

WS 2018/19

Efficient Algorithms and Data Structures

Harald Räcke

Fakultät für Informatik
TU München

<http://www14.in.tum.de/lehre/2018WS/ea/>

Winter Term 2018/19

Part I

Organizational Matters

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- ▶ **Modul: IN2003**
- ▶ Name: “Efficient Algorithms and Data Structures”
“Effiziente Algorithmen und Datenstrukturen”
- ▶ ECTS: 8 Credit points
- ▶ Lectures:
 - ▶ 4 SWS
 - Mon 10:00–12:00 (Room Interim2)
 - Fri 10:00–12:00 (Room Interim2)
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▶ IN0001, IN0003

“Introduction to Informatics 1/2”

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▶ IN0007

“Fundamentals of Algorithms and Data Structures”

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The Lecturer

- ▶ Harald Räcke
- ▶ Email: raecke@in.tum.de
- ▶ Room: 03.09.044
- ▶ Office hours: (by appointment)

Tutorials

A01 Monday, 12:00–14:00, 00.08.038 (Lederer)

A02 Monday, 12:00–14:00, 00.09.038 (Stotz)

A03 Monday, 14:00–16:00, 02.09.023 (Lederer)

B04 Tuesday, 10:00–12:00, 00.08.053 (Czerner)

D05 Thursday, 10:00–12:00, 03.11.018 (Stotz)

E06 Friday, 12:00–14:00, 00.13.009 (Czerner)

Assignment sheets

In order to pass the module you need to pass an exam.

Assessment

Assignment Sheets:

- ▶ An assignment sheet is usually made available on Monday on the module webpage.
- ▶ Solutions have to be handed in in the following week before the lecture on Monday.
- ▶ You can hand in your solutions by putting them in the mailbox "Efficient Algorithms" on the basement floor in the MI-building.
- ▶ Solutions have to be given in English.
- ▶ Solutions will be discussed in the tutorial of the week when the sheet has been handed in, i.e, sheet may not be corrected by this time.
- ▶ You should submit solutions in groups of up to 2 people.

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Assignment Sheets:

- ▶ Submissions must be handwritten by a member of the group. Please indicate who wrote the submission.
- ▶ Don't forget name and student id number for each group member.

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Assignment can be used to improve you grade

Requirements for Bonus

- ▶ 50% of the points are achieved on submissions 2-8,
- ▶ 50% of the points are achieved on submissions 9-14,
- ▶ each group member has written at least 4 solutions.

1 Contents

- ▶ Foundations
 - ▶ Machine models
 - ▶ Efficiency measures
 - ▶ Asymptotic notation
 - ▶ Recursion
- ▶ Higher Data Structures
 - ▶ Search trees
 - ▶ Hashing
 - ▶ Priority queues
 - ▶ Union/Find data structures
- ▶ Cuts/Flows
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2 Literatur

-  Alfred V. Aho, John E. Hopcroft, Jeffrey D. Ullman:
The design and analysis of computer algorithms,
Addison-Wesley Publishing Company: Reading (MA), 1974
-  Thomas H. Cormen, Charles E. Leiserson, Ron L. Rivest,
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-  Michael T. Goodrich, Roberto Tamassia:
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examples*,
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2. Auflage, Addison-Wesley, 1994
-  Volker Heun:
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-  Jon Kleinberg, Eva Tardos:
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-  Donald E. Knuth:
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3. Auflage, Addison-Wesley, 1997



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Prentice Hall, 1982



Uwe Schöning:

Algorithmik,

Spektrum Akademischer Verlag, 2001



Steven S. Skiena:

The Algorithm Design Manual,

Springer, 1998

Part II

Foundations

3 Goals

- ▶ Gain knowledge about efficient algorithms for important problems, i.e., learn how to solve certain types of problems efficiently.
- ▶ Learn how to analyze and judge the efficiency of algorithms.
- ▶ Learn how to design efficient algorithms.

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4 Modelling Issues

What do you measure?

- ▶ **Memory requirement**
- ▶ Running time
- ▶ Number of comparisons
- ▶ Number of multiplications
- ▶ Number of hard-disc accesses
- ▶ Program size
- ▶ Power consumption
- ▶ ...

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4 Modelling Issues

How do you measure?

- ▶ Implementing and testing on representative inputs
 - ▶ How do you choose your inputs?
 - ▶ May be very time-consuming.
 - ▶ Very reliable results if done correctly.
 - ▶ Results only hold for a specific machine and for a specific set of inputs.
- ▶ Theoretical analysis in a specific **model of computation**.
 - ▶ Gives a **lower bound** like "this algorithm always runs in $\Omega(n^2)$ time".
 - ▶ Typically focuses on the **number of comparisons**.
 - ▶ Can this lower bound also be **computation-based** (sorting algorithm needs at least $\Omega(n \log n)$ comparisons in the worst case)?

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Quick question: How many times does this algorithm always run in n ?

Typical answer: $O(n^2)$

Can this lower bound be any computer-**independent** sorting algorithm needs at least $\frac{n \log n}{2}$ comparisons in the worst case?

Yes, it can!

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 - ▶ Results only hold for a specific machine and for a specific set of inputs.
- ▶ Theoretical analysis in a specific model of computation.
 - ▶ Question: How long does this algorithm always run for?
 - ▶ Typical model: RAM
 - ▶ Can this lower bounds like any computer-based sorting algorithm needs at least $\Omega(n \log n)$ comparisons in the worst case?

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Quick question: How many times does this algorithm always run in $\Theta(n^2)$?

Answer: $\Theta(n^2)$ times. (The answer is $\Theta(n^2)$ for all $n \geq 1$.)

Can you answer this question by using a computer-based sorting algorithm? (The answer is $\Theta(n^2)$ for all $n \geq 1$.)

May be useful: <https://www.youtube.com/watch?v=U31111111111>

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Input length

The theoretical bounds are usually given by a function $f: \mathbb{N} \rightarrow \mathbb{N}$ that maps the **input length** to the running time (or storage space, comparisons, multiplications, program size etc.).

The **input length** may e.g. be

the size of the input (number of bits)

the number of arguments

the number of nodes in the input tree

the number of nodes in the input graph

the number of nodes in the input DAG

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Suppose n numbers from the interval $\{1, \dots, N\}$ have to be sorted. In this case we usually say that the input length is n instead of e.g. $n \log N$, which would be the number of bits required to encode the input.

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How to measure performance

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1. Calculate running time and storage space etc. on a simplified, idealized model of computation, e.g. Random Access Machine (RAM), Turing Machine (TM), . . .
2. Calculate number of certain basic operations: comparisons, multiplications, harddisc accesses, . . .

Version 2. is often easier, but focusing on one type of operation makes it more difficult to obtain meaningful results.

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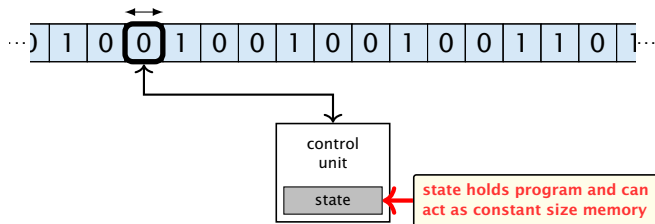
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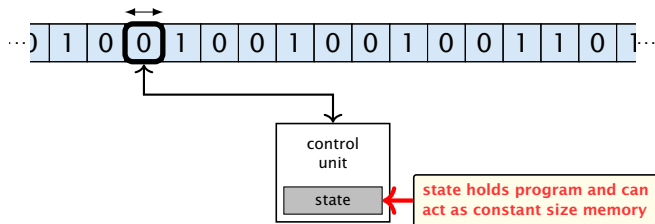
Turing Machine

- ▶ Very simple model of computation.
 - ▶ Only the “current” memory location can be altered.
 - ▶ Very good model for discussing computability, or polynomial vs. exponential time.
 - ▶ Some simple problems like recognizing whether input is of the form x^x , where x is a string, have quadratic lower bound.
- ⇒ Not a good model for developing efficient algorithms.



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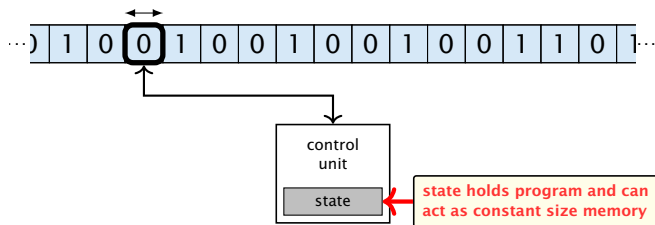
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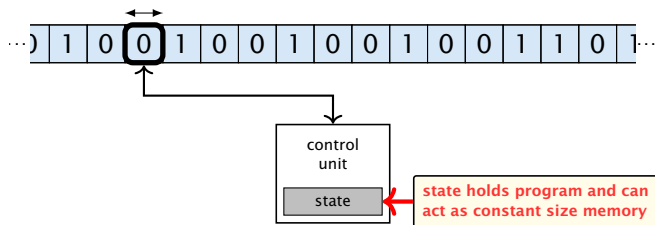
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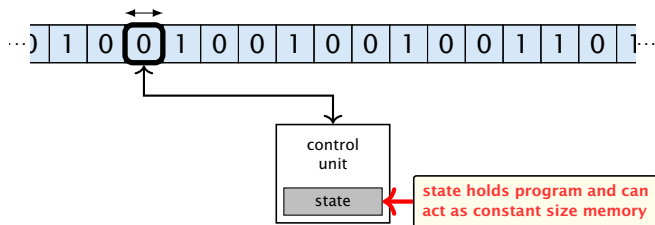
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Turing Machine

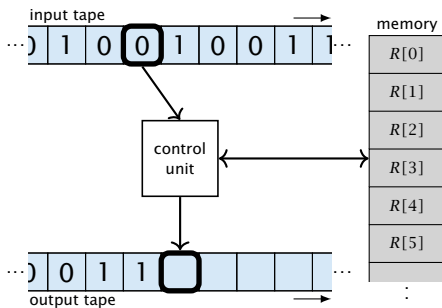
- ▶ Very simple model of computation.
- ▶ Only the “current” memory location can be altered.
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Random Access Machine (RAM)

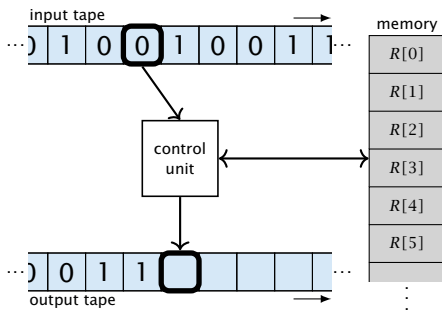
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Note that in the picture on the right the tapes are one-directional, and that a READ- or WRITE-operation always advances its tape.

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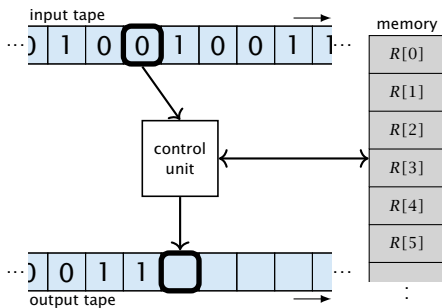
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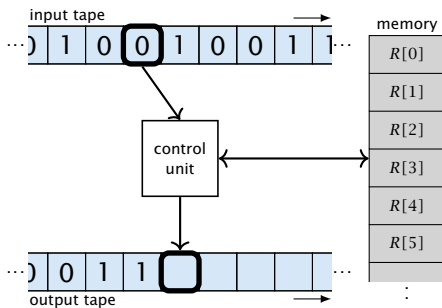
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- ▶ **uniform** cost model

Every operation takes time 1.

- ▶ **logarithmic** cost model

The cost depends on the content of memory cells:

- ▶ The time for a step is equal to the largest operand involved.
- ▶ The amount of memory required is equal to the length of the largest operand.
- ▶ The cost of a step is equal to the length of the largest operand.

Bounded word RAM model: cost is uniform but the largest value stored in a register may not exceed 2^w , where usually $w = \log_2 n$.

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Formal Definition

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- ▶ $o(f) = \{g \mid \forall c > 0 \exists n_0 \in \mathbb{N}_0 \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$
(set of functions that asymptotically grow **slower** than f)
- ▶ $\omega(f) = \{g \mid \forall c > 0 \exists n_0 \in \mathbb{N}_0 \forall n \geq n_0 : [g(n) \geq c \cdot f(n)]\}$
(set of functions that asymptotically grow **faster** than f)

Asymptotic Notation

There is an equivalent definition using limes notation (**assuming that the respective limes exists**). f and g are functions from \mathbb{N}_0 to \mathbb{R}_0^+ .

$$\blacktriangleright g \in \mathcal{O}(f): 0 \leq \lim_{n \rightarrow \infty} \frac{g(n)}{f(n)} < \infty$$

- Note that for the version of the Landau notation defined here, we assume that f and g are positive functions.
- There also exist versions for arbitrary functions, and for the case that the limes is not infinity.

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Abuse of notation

1. People write $f = \mathcal{O}(g)$, when they mean $f \in \mathcal{O}(g)$. This is **not** an equality (how could a function be equal to a set of functions).
2. People write $f(n) = \mathcal{O}(g(n))$, when they mean $f \in \mathcal{O}(g)$, with $f : \mathbb{N} \rightarrow \mathbb{R}^+, n \mapsto f(n)$, and $g : \mathbb{N} \rightarrow \mathbb{R}^+, n \mapsto g(n)$.
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How do we interpret an expression like:

$$2n^2 + 3n + 1 = 2n^2 + \Theta(n)$$

Here, $\Theta(n)$ stands for an anonymous function in the set $\Theta(n)$ that makes the expression true.

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The $\Theta(i)$ -symbol on the left represents **one** anonymous function $f : \mathbb{N} \rightarrow \mathbb{R}^+$, and then $\sum_i f(i)$ is computed.

How do we interpret an expression like:

$$\sum_{i=1}^n \Theta(i) = \Theta(n^2)$$

Careful!

“It is understood” that every occurrence of an Θ -symbol (or $\Theta, \Omega, o, \omega$) on the left represents **one** anonymous function.

Hence, the left side is **not** equal to

$$\Theta(1) + \Theta(2) + \dots + \Theta(n-1) + \Theta(n)$$

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Asymptotic Notation in Equations

We can view an expression containing asymptotic notation as generating a set:

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n)$$

represents

$$\{f : \mathbb{N} \rightarrow \mathbb{R}^+ \mid f(n) = n^2 \cdot g(n) + h(n)\}$$

with $g(n) \in \mathcal{O}(n)$ and $h(n) \in \mathcal{O}(\log n)$

Recall that according to the previous slide e.g. the expressions $\sum_{i=1}^n \mathcal{O}(i)$ and $\sum_{i=1}^{n/2} \mathcal{O}(i) + \sum_{i=n/2+1}^n \mathcal{O}(i)$ generate different sets.

Asymptotic Notation in Equations

Then an asymptotic equation can be interpreted as containment btw. two sets:

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n) = \Theta(n^2)$$

represents

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n) \subseteq \Theta(n^2)$$

Note that the equation does not hold.

Asymptotic Notation

Lemma 3

Let f, g be functions with the property

$\exists n_0 > 0 \forall n \geq n_0 : f(n) > 0$ (the same for g). Then

- ▶ $c \cdot f(n) \in \Theta(f(n))$ for any constant c
- ▶ $\mathcal{O}(f(n)) + \mathcal{O}(g(n)) = \mathcal{O}(f(n) + g(n))$
- ▶ $\mathcal{O}(f(n)) \cdot \mathcal{O}(g(n)) = \mathcal{O}(f(n) \cdot g(n))$
- ▶ $\mathcal{O}(f(n)) + \mathcal{O}(g(n)) = \mathcal{O}(\max\{f(n), g(n)\})$

The expressions also hold for Ω . Note that this means that $f(n) + g(n) \in \Theta(\max\{f(n), g(n)\})$.

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Comments

- ▶ Do not use asymptotic notation within induction proofs.
- ▶ For any constants a, b we have $\log_a n = \Theta(\log_b n)$.
Therefore, we will usually ignore the base of a logarithm within asymptotic notation.
- ▶ In general $\log n = \log_2 n$, i.e., we use 2 as the default base for the logarithm.

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In general asymptotic classification of running times is a good measure for comparing algorithms:

- ▶ If the running time analysis is tight and actually occurs in practise (i.e., the asymptotic bound is not a purely theoretical worst-case bound), then the algorithm that has better asymptotic running time will always outperform a weaker algorithm for large enough values of n .
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 - ▶ Algorithm A. Running time $f(n) = 1000 \log n = \mathcal{O}(\log n)$.
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Clearly $f = o(g)$. However, as long as $\log n \leq 1000$ Algorithm B will be more efficient.

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6 Recurrences

Algorithm 2 mergesort(list L)

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1:  $n \leftarrow \text{size}(L)$ 
2: if  $n \leq 1$  return  $L$ 
3:  $L_1 \leftarrow L[1 \cdots \lfloor \frac{n}{2} \rfloor]$ 
4:  $L_2 \leftarrow L[\lfloor \frac{n}{2} \rfloor + 1 \cdots n]$ 
5: mergesort( $L_1$ )
6: mergesort( $L_2$ )
7:  $L \leftarrow \text{merge}(L_1, L_2)$ 
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This algorithm requires

$$T(n) = T\left(\left\lceil \frac{n}{2} \right\rceil\right) + T\left(\left\lfloor \frac{n}{2} \right\rfloor\right) + \mathcal{O}(n) \leq 2T\left(\left\lceil \frac{n}{2} \right\rceil\right) + \mathcal{O}(n)$$

comparisons when $n > 1$ and 0 comparisons when $n \leq 1$.

Recurrences

How do we bring the expression for the number of comparisons (\approx running time) into a **closed form**?

For this we need to **solve** the recurrence.

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Methods for Solving Recurrences

1. Guessing+Induction

Guess the right solution and prove that it is correct via induction. It needs experience to make the right guess.

2. Master Theorem

For a lot of recurrences that appear in the analysis of algorithms this theorem can be used to obtain tight asymptotic bounds. It does not provide exact solutions.

3. Characteristic Polynomial

Linear homogenous recurrences can be solved via this method.

4. Generating Functions

A more general technique that allows to solve certain types of linear inhomogenous relations and also sometimes non-linear recurrence relations.

5. Transformation of the Recurrence

Sometimes one can transform the given recurrence relations so that it e.g. becomes linear and can therefore be solved with one of the other techniques.

6.1 Guessing+Induction

First we need to get rid of the \mathcal{O} -notation in our recurrence:

$$T(n) \leq \begin{cases} 2T(\lceil \frac{n}{2} \rceil) + cn & n \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

Informal way:

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One way of solving such a recurrence is to **guess** a solution, and check that it is correct by plugging it in.

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$$\begin{aligned}T(n) &\leq 2T\left(\frac{n}{2}\right) + cn \\&\leq 2\left(d\frac{n}{2}\log\frac{n}{2}\right) + cn \\&= dn(\log n - 1) + cn \\&= dn \log n + (c - d)n \\&\leq dn \log n\end{aligned}$$

if we choose $d \geq c$.

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if we choose $d \geq c$.

Formally, this is not correct if n is not a power of 2. Also even in this case one would need to do an induction proof.

6.1 Guessing+Induction

$$T(n) \leq \begin{cases} 2T(\frac{n}{2}) + cn & n \geq 16 \\ b & \text{otw.} \end{cases}$$

- Note that this proves the statement for $n \in \mathbb{N}_{\geq 2}$, as the statement is wrong for $n = 1$.
- The base case is usually omitted, as it is the same for different recurrences.

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- Note that this proves the statement for $n \in \mathbb{N}_{\geq 2}$, as the statement is wrong for $n = 1$.
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Hence, statement is **true** if we choose $d \geq c$.

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Note that we can do this as for constant-sized inputs the running time is always some constant (b in the above case).

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$$\boxed{\log \frac{9}{16}n = \log n + (\log 9 - 4)} = dn \log n + (\log 9 - 4)dn + 2d \log n + cn$$

$$\boxed{\log n \leq \frac{n}{4}} \leq dn \log n + (\log 9 - 3.5)dn + cn$$

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for a suitable choice of d .

6.2 Master Theorem

Note that the cases do not cover all possibilities.

Lemma 4

Let $a \geq 1$, $b \geq 1$ and $\epsilon > 0$ denote constants. Consider the recurrence

$$T(n) = aT\left(\frac{n}{b}\right) + f(n) .$$

Case 1.

If $f(n) = \mathcal{O}(n^{\log_b(a)-\epsilon})$ then $T(n) = \Theta(n^{\log_b a})$.

Case 2.

If $f(n) = \Theta(n^{\log_b(a)} \log^k n)$ then $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$,
 $k \geq 0$.

Case 3.

If $f(n) = \Omega(n^{\log_b(a)+\epsilon})$ and for sufficiently large n
 $af\left(\frac{n}{b}\right) \leq cf(n)$ for some constant $c < 1$ then $T(n) = \Theta(f(n))$.

6.2 Master Theorem

We prove the Master Theorem for the case that n is of the form b^{ℓ} , and we assume that the non-recursive case occurs for problem size 1 and incurs cost 1 .

The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:

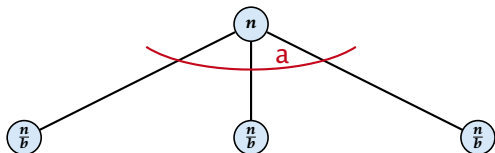
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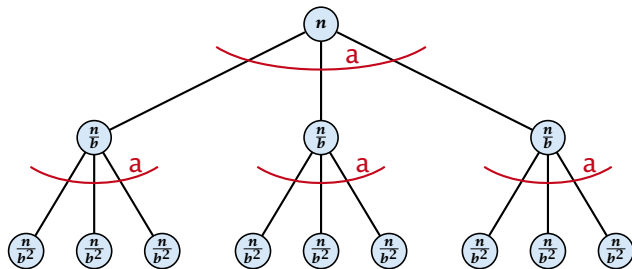
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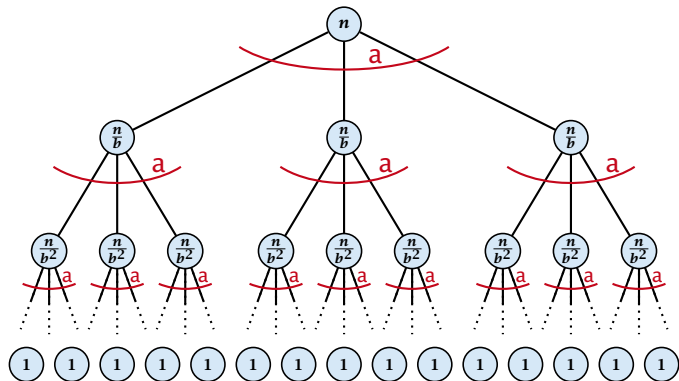
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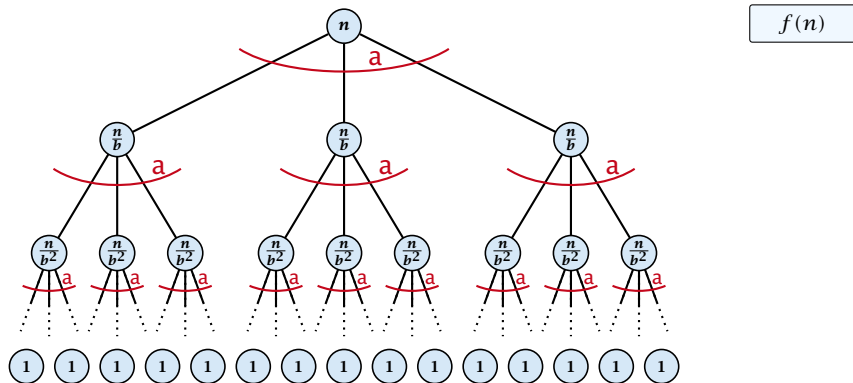
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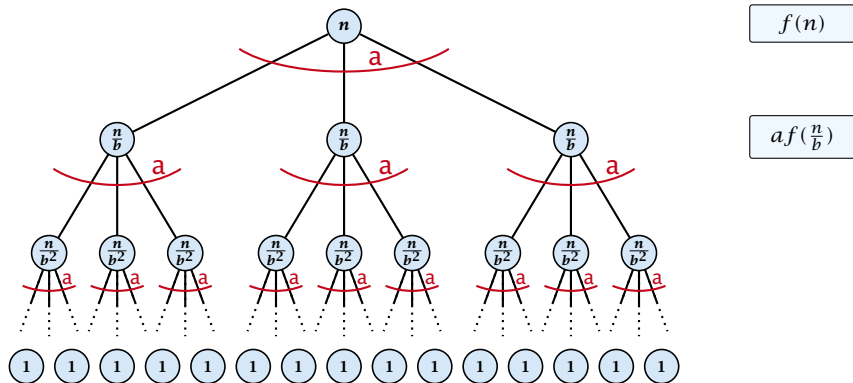
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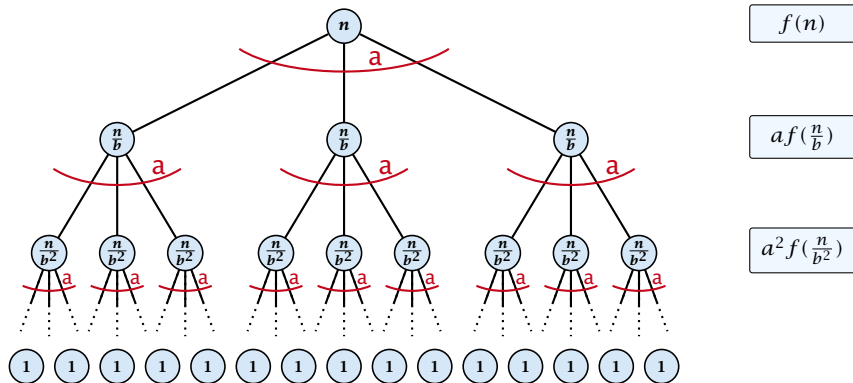
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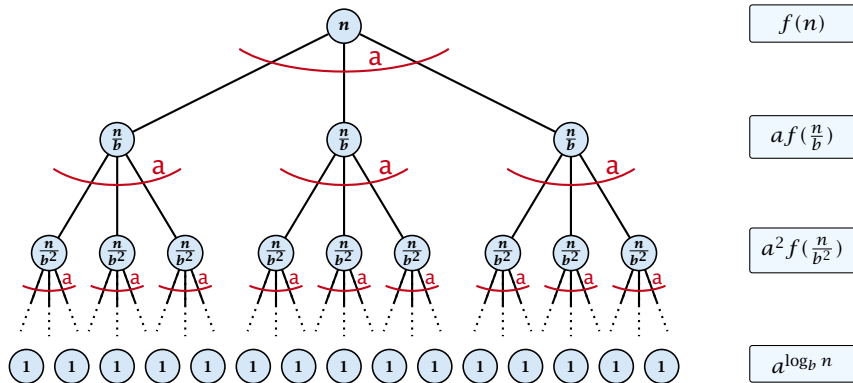
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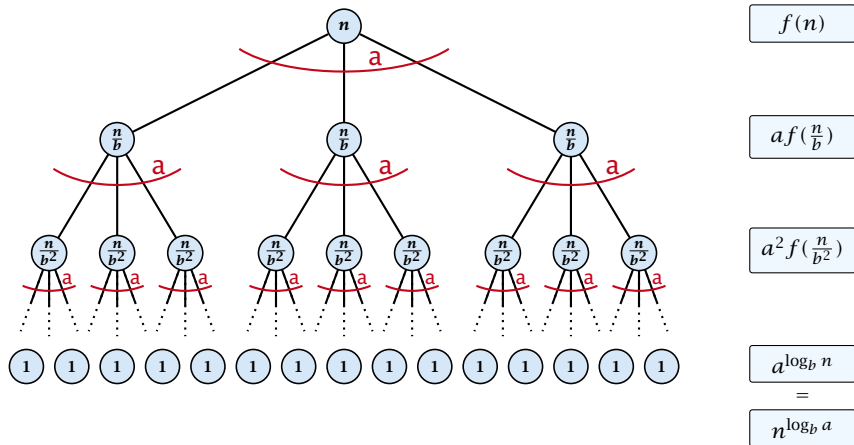
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The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:



6.2 Master Theorem

This gives

$$T(n) = n^{\log_b a} + \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right).$$

Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

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$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \end{aligned}$$

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$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}$$

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$$\Rightarrow T(n) = \mathcal{O}(n^{\log_b a} \log^{k+1} n).$$

Case 3. Now suppose that $f(n) \geq dn^{\log_b a + \epsilon}$, and that for sufficiently large n : $af(n/b) \leq cf(n)$, for $c < 1$.

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$$\begin{array}{r} 1\ 1\ 0\ 1\ 1\ 0\ 1\ 0\ 1\ A \\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1\ B \\ \hline \end{array}$$

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

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1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
<hr/>									

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1	0	0	0	1	0	0	1	1	B
<hr/>									
								0	

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1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
<hr/>								1	
									0

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For this we first need to be able to add two integers A and B :

1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
							1	1	
							0	0	

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For this we first need to be able to add two integers A and B :

1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
<hr/>									
						1	1		
								0	0

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For this we first need to be able to add two integers A and B :

1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
<hr/>						0	0	0	

The diagram illustrates the addition of two 9-bit integers, A and B. The bits of A are 1 1 0 1 1 0 1 0 1 and the bits of B are 1 0 0 0 1 0 0 1 1. A horizontal line is drawn under the 6th bit of B. The result of the addition is shown below the line, with a carry of 0 for the 7th, 8th, and 9th bits. The 7th bit of the result is 0, the 8th bit is 0, and the 9th bit is 0. The 7th, 8th, and 9th bits of the result are highlighted in a light blue box.

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & & & 1 & 1 & 1 & & \\ & & & & & & 0 & 0 & 0 & \end{array}$$

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For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & & & 0 & 1 & 1 & 1 & & \\ & & & & & 1 & 0 & 0 & 0 & & \end{array}$$

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & & 0 & 1 & 1 & 1 & & \\ & & & & & 1 & 0 & 0 & 0 & \end{array}$$

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & & 0 & 1 & 0 & 0 & 0 & \end{array}$$

The diagram illustrates the addition of two 9-bit integers, A and B, using a ripple carry adder. The bits of A are 1 1 0 1 1 0 1 0 1 and the bits of B are 1 0 0 0 1 0 0 1 1. A horizontal line separates the inputs from the output. The output bits are 0 1 0 0 0. A vertical box highlights the 5th bit position (index 4 from the right), where the carry-in is 1 and the carry-out is 0. Small subscripts '1' and '0' are placed below the 4th and 5th bits of the input rows, respectively, indicating the carry propagation.

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
				1	0	1	1	1	
				0	1	0	0	0	

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & 0 & 0 & 1 & 0 & 0 & 0 & \end{array}$$

The diagram illustrates the addition of two 9-bit integers, A and B, to produce a 9-bit result. The numbers are aligned to the right. A vertical box highlights the 4th bit position (from the right), which contains a '1' from A and a '0' from B. Below the horizontal line, the result bits are shown: '0' in the 4th position, '0' in the 5th, '1' in the 6th, '0' in the 7th, '0' in the 8th, and '0' in the 9th. Small subscripts are present below some bits: '1' under the 3rd bit of A, '1' under the 4th bit of A, '0' under the 5th bit of B, '1' under the 6th bit of B, '1' under the 7th bit of B, and '1' under the 8th bit of B.

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & 1 & 1 & 0 & 1 & 1 & 1 & \\ & & & 0 & 0 & 1 & 0 & 0 & 0 & \end{array}$$

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For this we first need to be able to add two integers A and B :

$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & 1 & 0 & 0 & 1 & 0 & 0 & 0 & \end{array}$$

Note: In the original image, the bit '0' in the second column of the result row is positioned below the '0' in the second column of the second row. The bit '1' in the third column of the result row is positioned below the '0' in the third column of the second row. The bit '1' in the fourth column of the result row is positioned below the '0' in the fourth column of the second row. The bit '0' in the fifth column of the result row is positioned below the '1' in the fifth column of the second row. The bit '0' in the sixth column of the result row is positioned below the '0' in the sixth column of the second row. The bit '1' in the seventh column of the result row is positioned below the '0' in the seventh column of the second row. The bit '0' in the eighth column of the result row is positioned below the '1' in the eighth column of the second row. The bit '0' in the ninth column of the result row is positioned below the '1' in the ninth column of the second row.

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

1	1	0	1	1	0	1	0	1	A
1	0	0	0	1	0	0	1	1	B
<hr/>									
		1	0	0	1	0	0	0	

Note: In the original image, a vertical box highlights the first two bits of A and B (1 and 1), and the carry bit 0 is shown below the first bit of B.

Example: Multiplying Two Integers

Suppose we want to multiply two n -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers A and B :

	1	1	0	1	1	0	1	0	1	A
	1	0	0	0	1	0	0	1	1	B
	<small>0</small>	<small>0</small>	<small>1</small>	<small>1</small>	<small>0</small>	<small>1</small>	<small>1</small>	<small>1</small>		
<hr/>										
	1	1	0	0	1	0	0	0		

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1	0	0	0	1	0	0	1	1	B
<hr/>									
	1	1	0	0	1	0	0	0	

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	1	0	0	1	1	0	1	1	1		A
	1	0	0	0	1	0	0	1	1		B
	<hr/>										
	0	1	1	0	0	1	0	0	0		

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	<hr/>									
	0	1	1	0	0	1	0	0	0	

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	<hr/>									
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This gives that two n -bit integers can be added in time $\mathcal{O}(n)$.

Example: Multiplying Two Integers

Suppose that we want to multiply an n -bit integer A and an m -bit integer B ($m \leq n$).

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Example: Multiplying Two Integers

Suppose that we want to multiply an n -bit integer A and an m -bit integer B ($m \leq n$).

$$\begin{array}{r} 10001 \\ \times 1011 \\ \hline \end{array}$$

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$$\begin{array}{r} 1\ 0\ 0\ 0\ 1 \times 1\ 0\ 1\ 1 \\ \hline 1\ 0\ 0\ 0\ 1 \\ 1\ 0\ 0\ 0\ 1\ 0 \\ 0\ 0\ 0\ 0\ 0\ 0\ 0 \\ 0\ 0\ 0 \end{array}$$

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Example: Multiplying Two Integers

Suppose that we want to multiply an n -bit integer A and an m -bit integer B ($m \leq n$).

$$\begin{array}{r} 10001 \times 1011 \\ \hline 10001 \\ 100010 \\ 0000000 \\ 10001000 \\ \hline 110001100 \end{array}$$

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$$\begin{array}{r} 10001 \times 1011 \\ \hline 10001 \\ 100010 \\ 0000000 \\ 10001000 \\ \hline 10111011 \end{array}$$

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Time requirement:

Example: Multiplying Two Integers

Suppose that we want to multiply an n -bit integer A and an m -bit integer B ($m \leq n$).

$$\begin{array}{r} 1\ 0\ 0\ 0\ 1 \times 1\ 0\ 1\ 1 \\ \hline 1\ 0\ 0\ 0\ 1 \\ 1\ 0\ 0\ 0\ 1\ 0 \\ 0\ 0\ 0\ 0\ 0\ 0\ 0 \\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0 \\ \hline 1\ 0\ 1\ 1\ 1\ 0\ 1\ 1 \end{array}$$

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Time requirement:

- ▶ Computing intermediate results: $\mathcal{O}(nm)$.

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- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Time requirement:

- ▶ Computing intermediate results: $\mathcal{O}(nm)$.
- ▶ Adding m numbers of length $\leq 2n$:
 $\mathcal{O}((m+n)m) = \mathcal{O}(nm)$.

Example: Multiplying Two Integers

A recursive approach:

Suppose that integers A and B are of length $n = 2^k$, for some k .

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Suppose that integers A and B are of length $n = 2^k$, for some k .

$$\boxed{b_{n-1} \quad \dots \quad b_0} \times \boxed{a_{n-1} \quad \dots \quad a_0}$$

Example: Multiplying Two Integers

A recursive approach:

Suppose that integers A and B are of length $n = 2^k$, for some k .

$$\boxed{b_{n-1} \quad \cdots \quad b_{\frac{n}{2}} \quad b_{\frac{n}{2}-1} \quad \cdots \quad b_0} \times \boxed{a_{n-1} \quad \cdots \quad a_{\frac{n}{2}} \quad a_{\frac{n}{2}-1} \quad \cdots \quad a_0}$$

Example: Multiplying Two Integers

A recursive approach:

Suppose that integers A and B are of length $n = 2^k$, for some k .

$$\begin{array}{|c|c|} \hline B_1 & B_0 \\ \hline \end{array} \times \begin{array}{|c|c|} \hline A_1 & A_0 \\ \hline \end{array}$$

Example: Multiplying Two Integers

A recursive approach:

Suppose that integers A and B are of length $n = 2^k$, for some k .



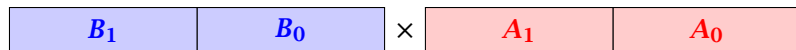
Then it holds that

$$A = A_1 \cdot 2^{\frac{n}{2}} + A_0 \text{ and } B = B_1 \cdot 2^{\frac{n}{2}} + B_0$$

Example: Multiplying Two Integers

A recursive approach:

Suppose that integers A and B are of length $n = 2^k$, for some k .



Then it holds that

$$A = A_1 \cdot 2^{\frac{n}{2}} + A_0 \text{ and } B = B_1 \cdot 2^{\frac{n}{2}} + B_0$$

Hence,

$$A \cdot B = A_1 B_1 \cdot 2^n + (A_1 B_0 + A_0 B_1) \cdot 2^{\frac{n}{2}} + A_0 B_0$$

Example: Multiplying Two Integers

Algorithm 3 $\text{mult}(A, B)$

```
1: if  $|A| = |B| = 1$  then  
2:   return  $a_0 \cdot b_0$   
3: split  $A$  into  $A_0$  and  $A_1$   
4: split  $B$  into  $B_0$  and  $B_1$   
5:  $Z_2 \leftarrow \text{mult}(A_1, B_1)$   
6:  $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$   
7:  $Z_0 \leftarrow \text{mult}(A_0, B_0)$   
8: return  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$ 
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```

$\mathcal{O}(1)$

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$\mathcal{O}(1)$

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$\mathcal{O}(1)$

3: split A into A_0 and A_1

4: split B into B_0 and B_1

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$\mathcal{O}(n)$

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Example: Multiplying Two Integers

Algorithm 3 $\text{mult}(A, B)$

- 1: **if** $|A| = |B| = 1$ **then** $\mathcal{O}(1)$
- 2: **return** $a_0 \cdot b_0$ $\mathcal{O}(1)$
- 3: split A into A_0 and A_1 $\mathcal{O}(n)$
- 4: split B into B_0 and B_1 $\mathcal{O}(n)$
- 5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$
- 6: $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$
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Algorithm 3 $\text{mult}(A, B)$

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$\mathcal{O}(n)$

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$\mathcal{O}(n)$

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$T(\frac{n}{2})$

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8: **return** $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

Example: Multiplying Two Integers

Algorithm 3 $\text{mult}(A, B)$

1: **if** $|A| = |B| = 1$ **then**

$\mathcal{O}(1)$

2: **return** $a_0 \cdot b_0$

$\mathcal{O}(1)$

3: split A into A_0 and A_1

$\mathcal{O}(n)$

4: split B into B_0 and B_1

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5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$

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We get the following recurrence:

$$T(n) = 4T\left(\frac{n}{2}\right) + \mathcal{O}(n) .$$

Example: Multiplying Two Integers

Master Theorem: Recurrence: $T[n] = aT(\frac{n}{b}) + f(n)$.

- ▶ Case 1: $f(n) = \mathcal{O}(n^{\log_b a - \epsilon})$ $T(n) = \Theta(n^{\log_b a})$
- ▶ Case 2: $f(n) = \Theta(n^{\log_b a} \log^k n)$ $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$
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In our case $a = 4$, $b = 2$, and $f(n) = \Theta(n)$. Hence, we are in Case 1, since $n = \mathcal{O}(n^{2-\epsilon}) = \mathcal{O}(n^{\log_b a - \epsilon})$.

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We get a running time of $\mathcal{O}(n^2)$ for our algorithm.

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⇒ Not better than the “school method”.

Example: Multiplying Two Integers

We can use the following identity to compute Z_1 :

A more precise
(correct) analysis
would say that
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We can use the following identity to compute Z_1 :

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Example: Multiplying Two Integers

We get the following recurrence:

$$T(n) = 3T\left(\frac{n}{2}\right) + \mathcal{O}(n) .$$

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Again we are in Case 1. We get a running time of $\Theta(n^{\log_2 3}) \approx \Theta(n^{1.59})$.

A huge improvement over the "school method".

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6.3 The Characteristic Polynomial

Consider the recurrence relation:

$$c_0T(n) + c_1T(n-1) + c_2T(n-2) + \dots + c_kT(n-k) = f(n)$$

This is the general form of a **linear** recurrence relation of **order k** with constant coefficients ($c_0, c_k \neq 0$).

The recurrence is **linear** as there are no products of T values. The recurrence is of **order k** as the recurrence relation is of order k .

The recurrence is **linear** as there are no products of T values. If $f(n) = 0$, then the recurrence relation becomes a **linear homogeneous** recurrence relation of order k .

Note that we ignore **boundary conditions** for the moment.

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This is the general form of a **linear** recurrence relation of **order k** with constant coefficients ($c_0, c_k \neq 0$).

- ▶ $T(n)$ only depends on the k preceding values. This means the recurrence relation is of **order k** .
- ▶ The recurrence is linear as there are no products of $T[n]$'s.
- ▶ If $f(n) = 0$ then the recurrence relation becomes a linear, **homogenous** recurrence relation of order k .

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The Homogenous Case

The solution space

$$S = \left\{ \mathcal{T} = T[1], T[2], T[3], \dots \mid \mathcal{T} \text{ fulfills recurrence relation} \right\}$$

is a **vector space**. This means that if $\mathcal{T}_1, \mathcal{T}_2 \in S$, then also $\alpha\mathcal{T}_1 + \beta\mathcal{T}_2 \in S$, for arbitrary constants α, β .

How do we find a non-trivial solution?

We guess that the solution is of the form λ^n , $\lambda \neq 0$, and see what happens. In order for this guess to fulfill the recurrence we need

$$c_0\lambda^n + c_1\lambda^{n-1} + c_2 \cdot \lambda^{n-2} + \dots + c_k \cdot \lambda^{n-k} = 0$$

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Dividing by λ^{n-k} gives that all these constraints are identical to

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This means that if λ_i is a root (Nullstelle) of $P[\lambda]$ then $T[n] = \lambda_i^n$ is a solution to the recurrence relation.

Let $\lambda_1, \dots, \lambda_k$ be the k (complex) roots of $P[\lambda]$. Then, because of the vector space property

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Lemma 5

Assume that the characteristic polynomial has k *distinct* roots $\lambda_1, \dots, \lambda_k$. Then *all* solutions to the recurrence relation are of the form

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Proof.

There is one solution for every possible choice of boundary conditions for $T[1], \dots, T[k]$.

We show that the above set of solutions contains one solution for every choice of boundary conditions.

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Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the α'_i 's such that these conditions are met:

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We show that the column vectors are linearly independent. Then the above equation has a solution.

Computing the Determinant

$$\begin{vmatrix} \lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\ \lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\ \vdots & \vdots & & \vdots & \vdots \\ \lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \end{vmatrix} =$$

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$$\begin{vmatrix} 1 & 0 & \cdots & 0 & 0 \\ 1 & (\lambda_2 - \lambda_1) \cdot 1 & \cdots & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-3} & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-2} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & (\lambda_k - \lambda_1) \cdot 1 & \cdots & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-3} & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-2} \end{vmatrix}$$

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$$\prod_{i=2}^k (\lambda_i - \lambda_1) \cdot \begin{vmatrix} 1 & \lambda_2 & \cdots & \lambda_2^{k-3} & \lambda_2^{k-2} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & \lambda_k & \cdots & \lambda_k^{k-3} & \lambda_k^{k-2} \end{vmatrix}$$

Computing the Determinant

Repeating the above steps gives:

$$\begin{vmatrix} \lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\ \lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\ \vdots & \vdots & & \vdots & \vdots \\ \lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \end{vmatrix} = \prod_{i=1}^k \lambda_i \cdot \prod_{i>\ell} (\lambda_i - \lambda_\ell)$$

Hence, if all λ_i 's are different, then the determinant is non-zero.

The Homogeneous Case

What happens if the roots are not all distinct?

Suppose we have a root λ_i with multiplicity (Vielfachheit) at least 2. Then not only is λ_i^n a solution to the recurrence but also $n\lambda_i^{n-1}$.

To see this consider the polynomial

$$P[\lambda] \cdot \lambda^{n-k} = c_0\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \dots + c_k\lambda^{n-k}$$

Since λ_i is a root we can write this as $Q[\lambda] \cdot (\lambda - \lambda_i)^2$.

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Suppose we have a root λ_i with multiplicity (**Vielfachheit**) at least 2. Then not only is λ_i^n a solution to the recurrence but also $n\lambda_i^{n-1}$.

To see this consider the polynomial

$$P[\lambda] \cdot \lambda^{n-k} = c_0\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \dots + c_k\lambda^{n-k}$$

Since λ_i is a root we can write this as $Q[\lambda] \cdot (\lambda - \lambda_i)^2$.

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This means

$$c_0 n \lambda_i^{n-1} + c_1 (n-1) \lambda_i^{n-2} + \dots + c_k (n-k) \lambda_i^{n-k-1} = 0$$

Hence,

$$\underbrace{c_0 n \lambda_i^n}_{T[n]} + \underbrace{c_1 (n-1) \lambda_i^{n-1}}_{T[n-1]} + \dots + \underbrace{c_k (n-k) \lambda_i^{n-k}}_{T[n-k]} = 0$$

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(after taking the derivative; multiplying with λ ; plugging in λ_i)

Doing this again gives

$$c_0 n^2 \lambda_i^n + c_1 (n-1)^2 \lambda_i^{n-1} + \dots + c_k (n-k)^2 \lambda_i^{n-k} = 0$$

We can continue $j-1$ times.

Hence, $n^\ell \lambda_i^n$ is a solution for $\ell \in 0, \dots, j-1$.

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We can continue $j-1$ times.

Hence, $n^\ell \lambda_i^n$ is a solution for $\ell \in 0, \dots, j-1$.

The Homogeneous Case

Lemma 6

Let $P[\lambda]$ denote the characteristic polynomial to the recurrence

$$c_0T[n] + c_1T[n-1] + \dots + c_kT[n-k] = 0$$

Let $\lambda_i, i = 1, \dots, m$ be the (complex) roots of $P[\lambda]$ with multiplicities ℓ_i . Then the general solution to the recurrence is given by

$$T[n] = \sum_{i=1}^m \sum_{j=0}^{\ell_i-1} \alpha_{ij} \cdot (n^j \lambda_i^n) .$$

The full proof is omitted. We have only shown that any choice of α_{ij} 's is a solution to the recurrence.

Example: Fibonacci Sequence

$$T[0] = 0$$

$$T[1] = 1$$

$$T[n] = T[n - 1] + T[n - 2] \text{ for } n \geq 2$$

The characteristic polynomial is

$$\lambda^2 - \lambda - 1$$

Finding the roots, gives

$$\lambda_{1/2} = \frac{1}{2} \pm \sqrt{\frac{1}{4} + 1} = \frac{1}{2} (1 \pm \sqrt{5})$$

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$$\alpha \left(\frac{1 + \sqrt{5}}{2} \right) + \beta \left(\frac{1 - \sqrt{5}}{2} \right) = 1 \implies \alpha - \beta = \frac{2}{\sqrt{5}}$$

Example: Fibonacci Sequence

Hence, the solution is

$$\frac{1}{\sqrt{5}} \left[\left(\frac{1 + \sqrt{5}}{2} \right)^n - \left(\frac{1 - \sqrt{5}}{2} \right)^n \right]$$

The Inhomogeneous Case

Consider the recurrence relation:

$$c_0T(n) + c_1T(n-1) + c_2T(n-2) + \cdots + c_kT(n-k) = f(n)$$

with $f(n) \neq 0$.

While we have a fairly general technique for solving **homogeneous**, linear recurrence relations the inhomogeneous case is different.

The Inhomogeneous Case

The general solution of the recurrence relation is

$$T(n) = T_h(n) + T_p(n) ,$$

where T_h is **any** solution to the homogeneous equation, and T_p is **one** particular solution to the inhomogeneous equation.

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The Inhomogeneous Case

Example:

$$T[n] = T[n - 1] + 1 \quad T[0] = 1$$

Then,

$$T[n - 1] = T[n - 2] + 1 \quad (n \geq 2)$$

Subtracting the first from the second equation gives,

$$T[n] - T[n - 1] = T[n - 1] - T[n - 2] \quad (n \geq 2)$$

or

$$T[n] = 2T[n - 1] - T[n - 2] \quad (n \geq 2)$$

I get a completely determined recurrence if I add $T[0] = 1$ and $T[1] = 2$.

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$T[1] = 2$ gives $1 + \beta = 2 \Rightarrow \beta = 1$.

The Inhomogeneous Case

If $f(n)$ is a polynomial of degree r this method can be applied $r + 1$ times to obtain a homogeneous equation:

$$T[n] = T[n - 1] + n^2$$

Shift:

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Difference:

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Shift:

$$T[n - 1] = 2T[n - 2] - T[n - 3] + 2(n - 1) - 1$$

$$T[n] = 2T[n - 1] - T[n - 2] + 2n - 1$$

Shift:

$$\begin{aligned} T[n - 1] &= 2T[n - 2] - T[n - 3] + 2(n - 1) - 1 \\ &= 2T[n - 2] - T[n - 3] + 2n - 3 \end{aligned}$$

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and so on...

6.4 Generating Functions

Definition 7 (Generating Function)

Let $(a_n)_{n \geq 0}$ be a sequence. The corresponding

- ▶ **generating function** (Erzeugendenfunktion) is

$$F(z) := \sum_{n \geq 0} a_n z^n;$$

- ▶ **exponential generating function** (exponentielle Erzeugendenfunktion) is

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1. The generating function of the sequence $(1, 0, 0, \dots)$ is

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2. The generating function of the sequence $(1, 1, 1, \dots)$ is

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6.4 Generating Functions

There are two different views:

A generating function is a **formal power series** (formale Potenzreihe).

Then the generating function is an **algebraic object**.

Let $f = \sum_{n \geq 0} a_n z^n$ and $g = \sum_{n \geq 0} b_n z^n$.

- ▶ **Equality:** f and g are equal if $a_n = b_n$ for all n .
- ▶ **Addition:** $f + g := \sum_{n \geq 0} (a_n + b_n) z^n$.
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- ▶ **Addition:** $f + g := \sum_{n \geq 0} (a_n + b_n) z^n$.
- ▶ **Multiplication:** $f \cdot g := \sum_{n \geq 0} c_n z^n$ with $c_n = \sum_{p=0}^n a_p b_{n-p}$.

There are no convergence issues here.

6.4 Generating Functions

The arithmetic view:

We view a power series as a function $f : \mathbb{C} \rightarrow \mathbb{C}$.

Then, it is important to think about convergence/convergence radius etc.

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What does $\sum_{n \geq 0} z^n = \frac{1}{1-z}$ mean in the algebraic view?

It means that the power series $1 - z$ and the power series $\sum_{n \geq 0} z^n$ are invers, i.e.,

$$(1 - z) \cdot \left(\sum_{n \geq 0} z^n \right) = 1 .$$

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Hence, the generating function of the sequence $a_n = n + 1$ is $1/(1-z)^2$.

Formally the derivative of a formal power series $\sum_{n \geq 0} a_n z^n$ is defined as $\sum_{n \geq 0} n a_n z^{n-1}$.

The known rules for differentiation work for this definition. In particular, e.g. the derivative of $\frac{1}{1-z}$ is $\frac{1}{(1-z)^2}$.

Note that this requires a proof if we consider power series as algebraic objects. However, we did not prove this in the lecture.

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Hence, the generating function of the sequence

$$a_n = (n+1)(n+2) \text{ is } \frac{2}{(1-z)^3} .$$

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The generating function of the sequence $a_n = \binom{n+k}{k}$ is $\frac{1}{(1-z)^{k+1}}$.

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The generating function of the sequence $a_n = n$ is $\frac{z}{(1-z)^2}$.

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We know

$$\sum_{n \geq 0} y^n = \frac{1}{1-y}$$

Hence,

$$\sum_{n \geq 0} a^n z^n = \frac{1}{1-az}$$

The generating function of the sequence $f_n = a^n$ is $\frac{1}{1-az}$.

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Example: $a_n = a_{n-1} + 1$, $a_0 = 1$

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Hence, $a_n = n + 1$.

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Solving Recursions with Generating Functions

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6. The coefficients of the resulting power series are the a_n .

Example: $a_n = 2a_{n-1}$, $a_0 = 1$

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This leads to the following conditions:

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This leads to the following conditions:

$$A + B + C = 1$$

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which gives

$$A = \frac{7}{4} \quad B = -\frac{1}{4} \quad C = -\frac{1}{2}$$

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6. This means $a_n = \frac{7}{4}3^n - \frac{1}{2}n - \frac{3}{4}$.

6.5 Transformation of the Recurrence

Example 9

$$f_0 = 1$$

$$f_1 = 2$$

$$f_n = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2 .$$

6.5 Transformation of the Recurrence

Example 9

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Define

$$g_n := \log f_n .$$

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$$f_n = 2^{F_n}$$

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Then:

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6 Recurrences

We get

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$$\begin{aligned}g_k &= 3 [g_{k-1}] + 2^k \\&= 3 [3g_{k-2} + 2^{k-1}] + 2^k \\&= 3^2 [g_{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^2 [3g_{k-3} + 2^{k-2}] + 3 \cdot 2^{k-1} + 2^k\end{aligned}$$

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$$\begin{aligned}g_k &= 3[g_{k-1}] + 2^k \\&= 3[3g_{k-2} + 2^{k-1}] + 2^k \\&= 3^2[g_{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^2[3g_{k-3} + 2^{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^3 g_{k-3} + 3^2 2^{k-2} + 3 \cdot 2^{k-1} + 2^k \\&= 2^k \cdot \sum_{i=0}^k \left(\frac{3}{2}\right)^i\end{aligned}$$

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$$\begin{aligned}g_k &= 3 [g_{k-1}] + 2^k \\&= 3 [3g_{k-2} + 2^{k-1}] + 2^k \\&= 3^2 [g_{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^2 [3g_{k-3} + 2^{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^3 g_{k-3} + 3^2 2^{k-2} + 3 \cdot 2^{k-1} + 2^k \\&= 2^k \cdot \sum_{i=0}^k \left(\frac{3}{2}\right)^i \\&= 2^k \cdot \frac{\left(\frac{3}{2}\right)^{k+1} - 1}{1/2}\end{aligned}$$

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6 Recurrences

Let $n = 2^k$:

$$g_k = 3^{k+1} - 2^{k+1}, \text{ hence}$$

$$f_n = 3 \cdot 3^k - 2 \cdot 2^k$$

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Part III

Data Structures

Abstract Data Type

An abstract data type (ADT) is defined by an interface of operations or methods that can be performed and that have a defined behavior.

The data types in this lecture all operate on objects that are represented by a [key, value] pair.

- ▶ The **key** comes from a totally ordered set, and we assume that there is an efficient comparison function.
- ▶ The **value** can be anything; it usually carries satellite information important for the application that uses the ADT.

Dynamic Set Operations

- ▶ **S . search(k):** Returns pointer to object x from S with $\text{key}[x] = k$ or null.
- ▶ S . insert(x): Inserts object x into set S . $\text{key}[x]$ must not currently exist in the data-structure.
- ▶ S . delete(x): Given pointer to object x from S , delete x from the set.
- ▶ S . minimum(): Return pointer to object with smallest key-value in S .
- ▶ S . maximum(): Return pointer to object with largest key-value in S .
- ▶ S . successor(x): Return pointer to the next larger element in S or null if x is maximum.
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- ▶ **S . union(S'):** Sets $S := S \cup S'$. The set S' is destroyed.
- ▶ S . merge(S'): Sets $S := S \cup S'$. Requires $S \cap S' = \emptyset$.
- ▶ S . split(k, S'):
 $S := \{x \in S \mid \text{key}[x] \leq k\}$, $S' := \{x \in S \mid \text{key}[x] > k\}$.
- ▶ S . concatenate(S'): $S := S \cup S'$.
Requires $\text{key}[S.\text{maximum}()] \leq \text{key}[S'.\text{minimum}()]$.
- ▶ S . decrease-key(x, k): Replace $\text{key}[x]$ by $k \leq \text{key}[x]$.

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Requires $\text{key}[S.\text{maximum}()] \leq \text{key}[S'.\text{minimum}()]$.
- ▶ **S.decrease-key(x, k)**: Replace $\text{key}[x]$ by $k \leq \text{key}[x]$.

Dynamic Set Operations

- ▶ **S. union(S'):** Sets $S := S \cup S'$. The set S' is destroyed.
- ▶ **S. merge(S'):** Sets $S := S \cup S'$. Requires $S \cap S' = \emptyset$.
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Examples of ADTs

Stack:

- ▶ **S .push(x)**: Insert an element.
- ▶ **S .pop()**: Return the element from S that was inserted most recently; delete it from S .
- ▶ **S .empty()**: Tell if S contains any object.

Queue:

- ▶ S .enqueue(x): Insert an element.
- ▶ S .dequeue(): Return the element that is longest in the structure; delete it from S .
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Priority-Queue:

- ▶ S .insert(x): Insert an element.
- ▶ S .delete-min(): Return the element with lowest key-value; delete it from S .

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7 Dictionary

Dictionary:

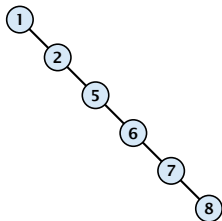
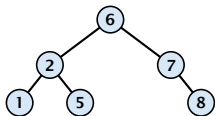
- ▶ **S .insert(x)**: Insert an element x .
- ▶ **S .delete(x)**: Delete the element pointed to by x .
- ▶ **S .search(k)**: Return a pointer to an element e with $\text{key}[e] = k$ in S if it exists; otherwise return **null**.

7.1 Binary Search Trees

An (**internal**) **binary search tree** stores the elements in a binary tree. Each tree-node corresponds to an element. All elements in the left sub-tree of a node v have a smaller key-value than $\text{key}[v]$ and elements in the right sub-tree have a larger-key value. We assume that all key-values are different.

(**External** Search Trees store objects only at leaf-vertices)

Examples:

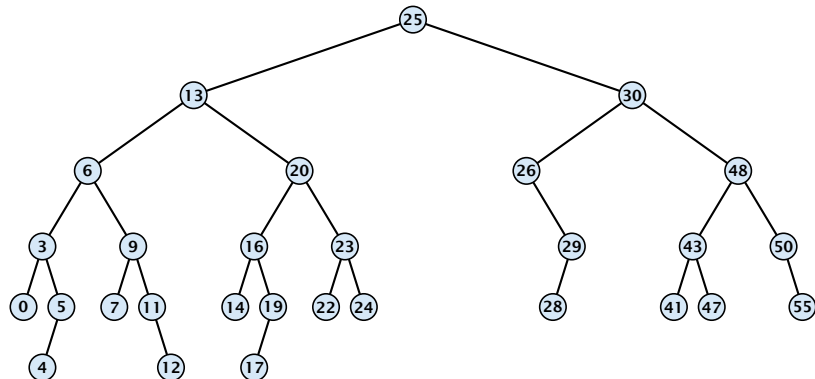


7.1 Binary Search Trees

We consider the following operations on binary search trees. Note that this is a super-set of the dictionary-operations.

- ▶ $T.\text{insert}(x)$
- ▶ $T.\text{delete}(x)$
- ▶ $T.\text{search}(k)$
- ▶ $T.\text{successor}(x)$
- ▶ $T.\text{predecessor}(x)$
- ▶ $T.\text{minimum}()$
- ▶ $T.\text{maximum}()$

Binary Search Trees: Searching

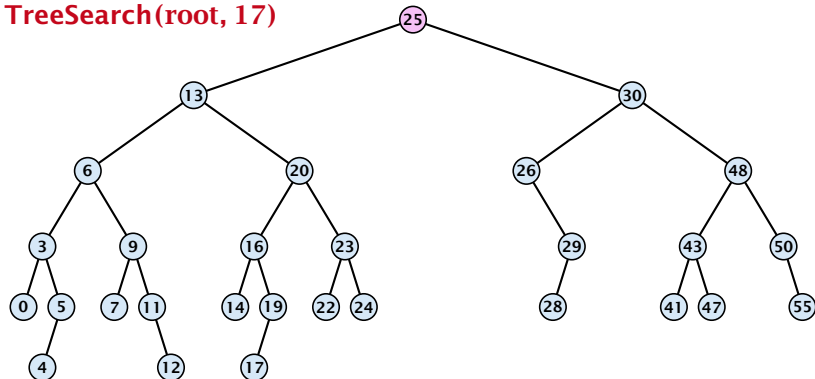


Algorithm 1 TreeSearch(x, k)

- 1: **if** $x = \text{null}$ **or** $k = \text{key}[x]$ **return** x
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Binary Search Trees: Searching

TreeSearch(root, 17)

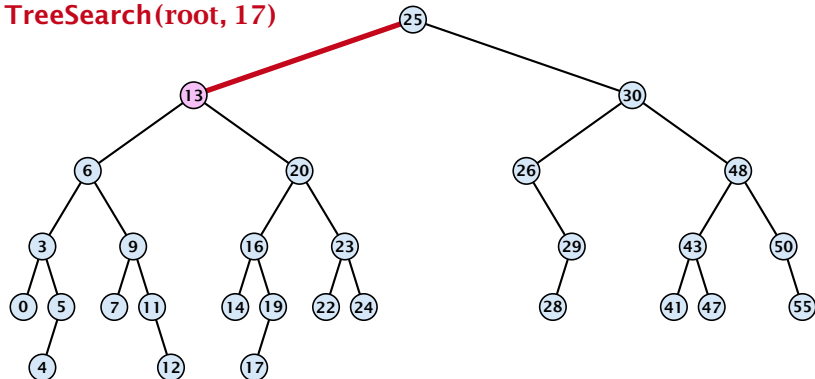


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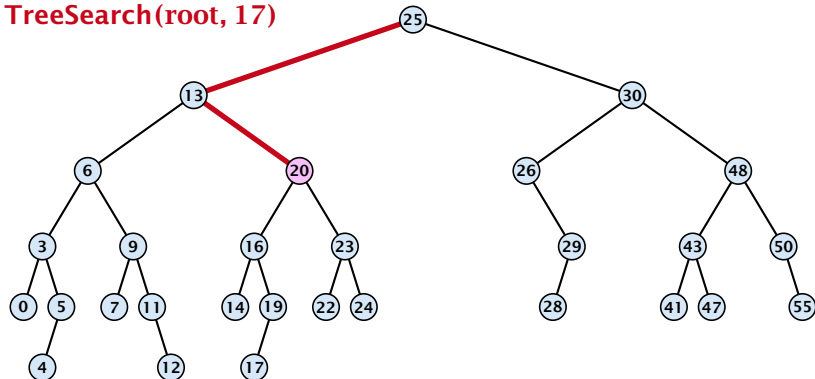


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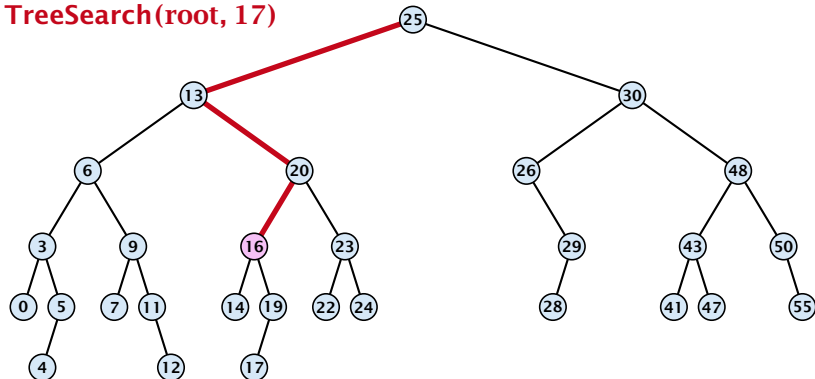


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Binary Search Trees: Searching

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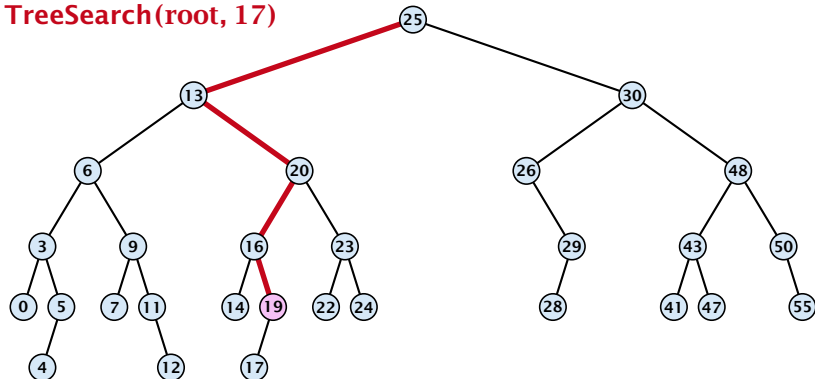


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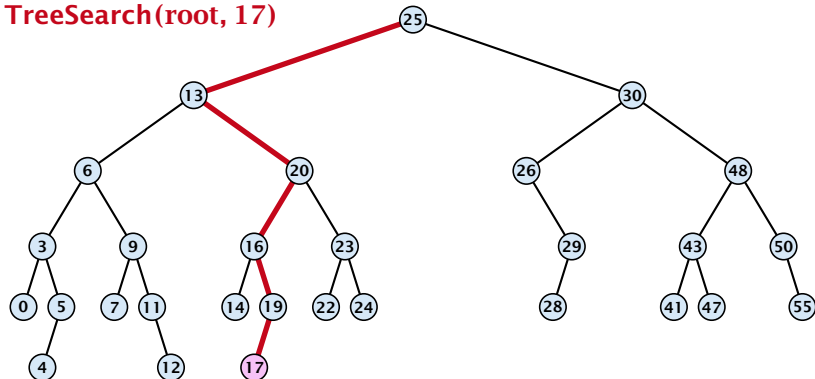


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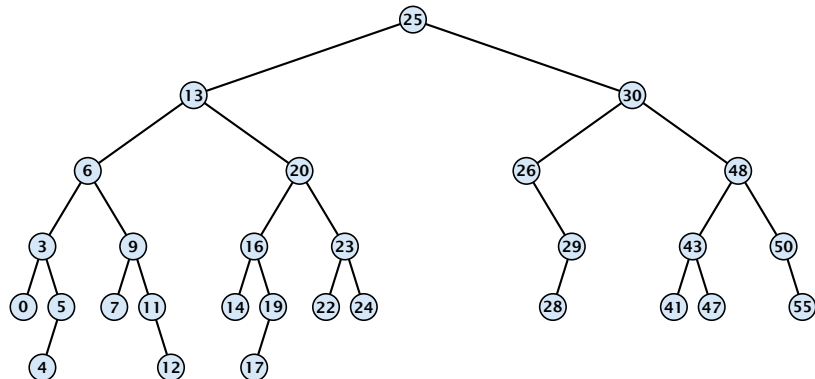
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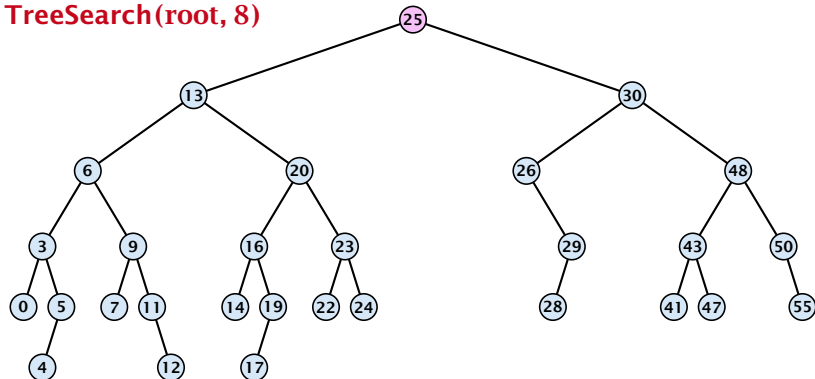


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Binary Search Trees: Searching

TreeSearch(root, 8)

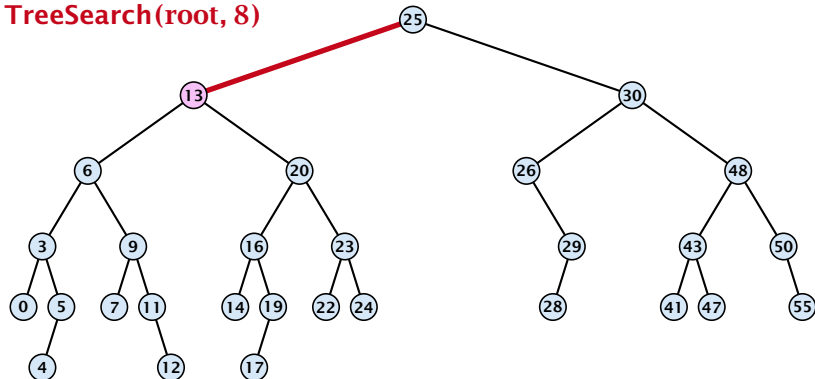


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Binary Search Trees: Searching

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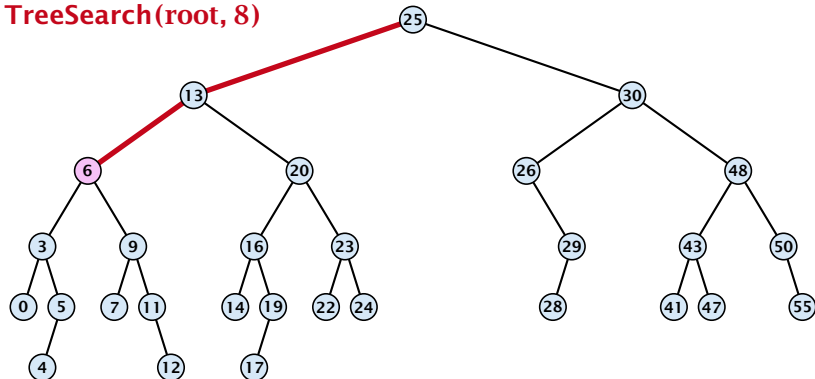


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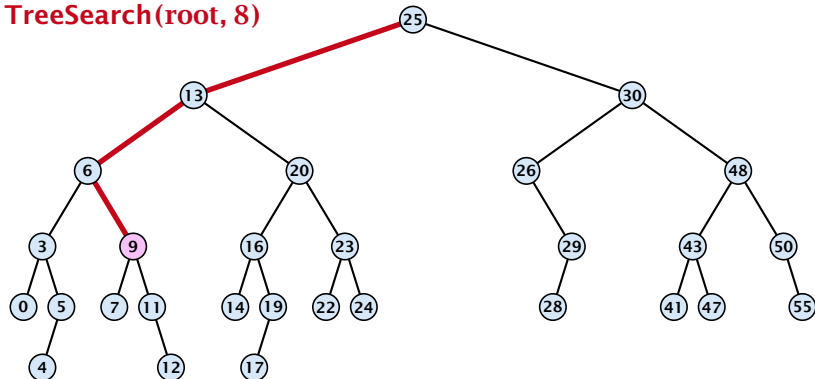


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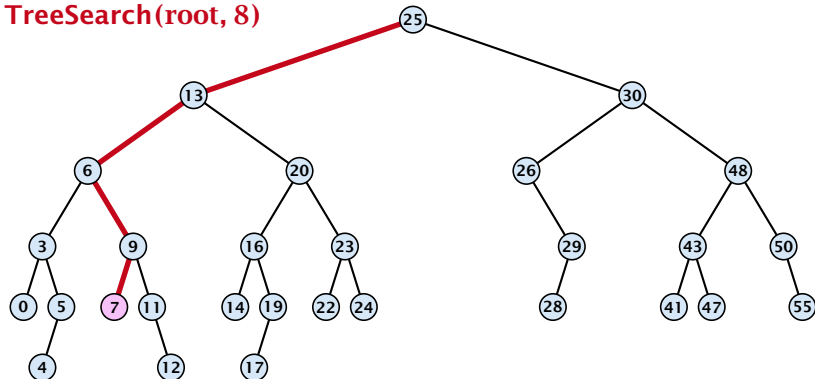


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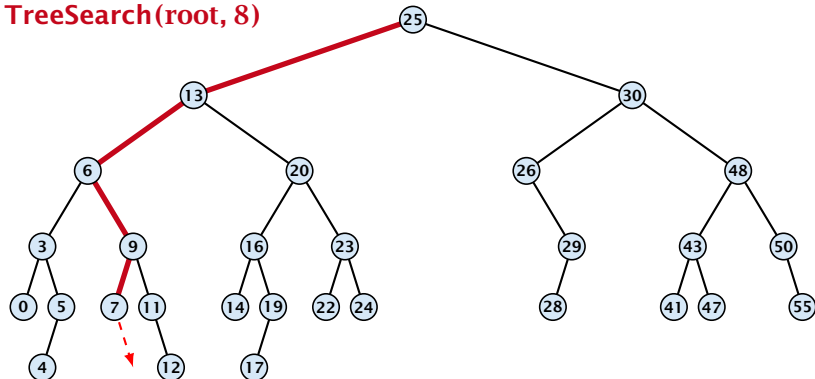


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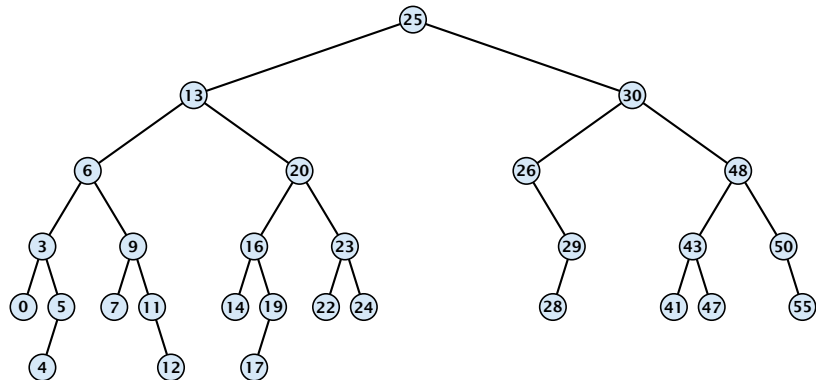
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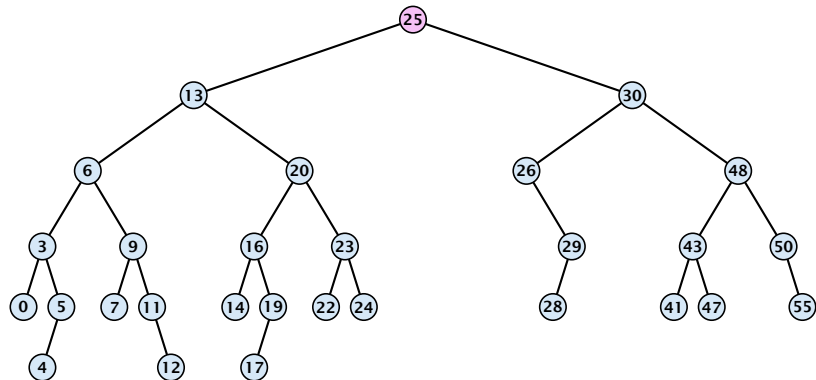
Binary Search Trees: Minimum



Algorithm 2 TreeMin(x)

- 1: **if** $x = \text{null}$ **or** $\text{left}[x] = \text{null}$ **return** x
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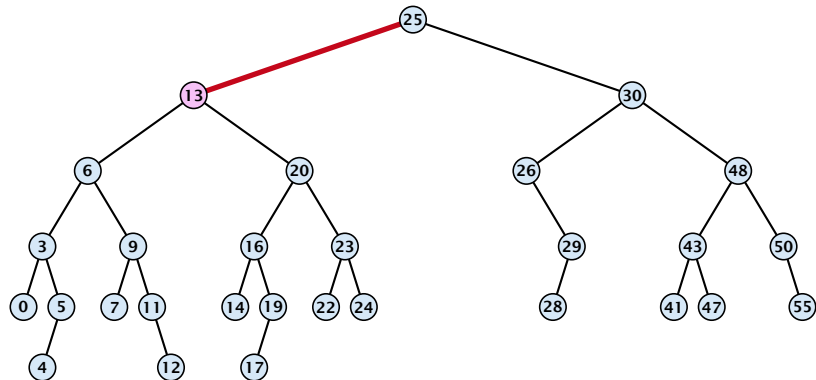
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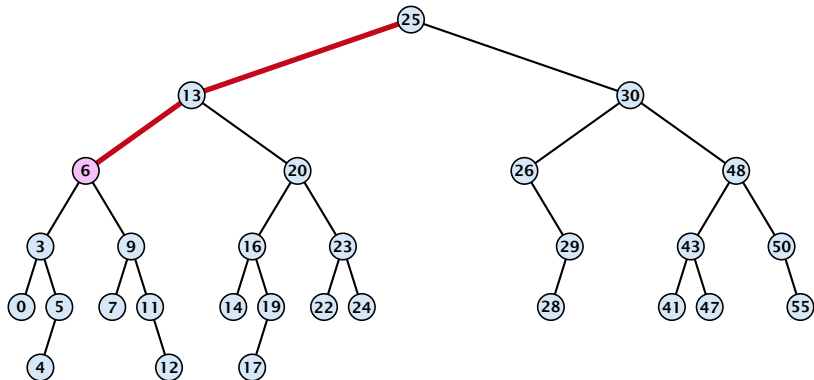
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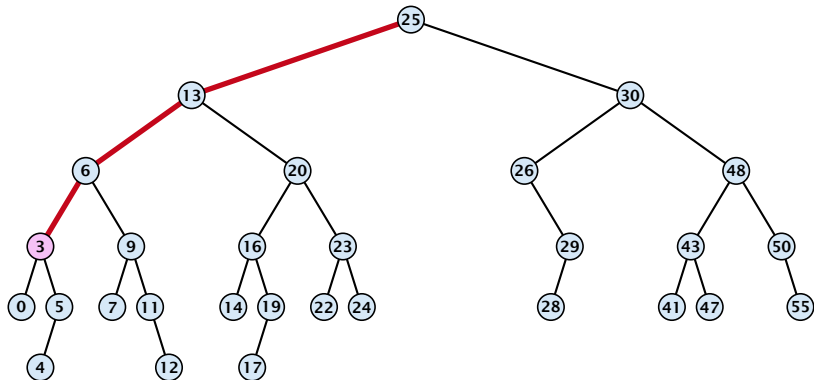
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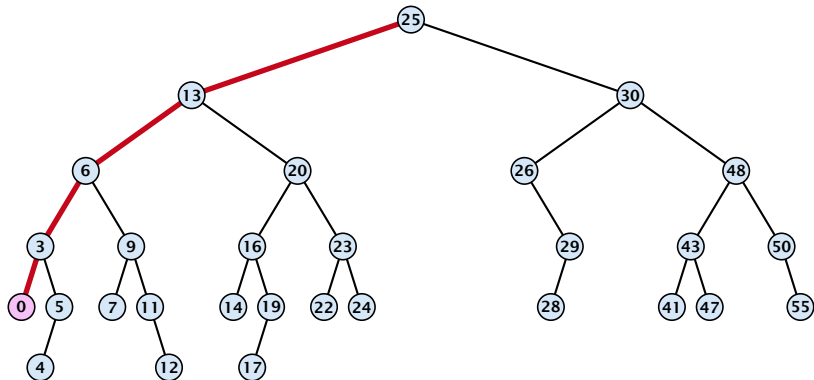
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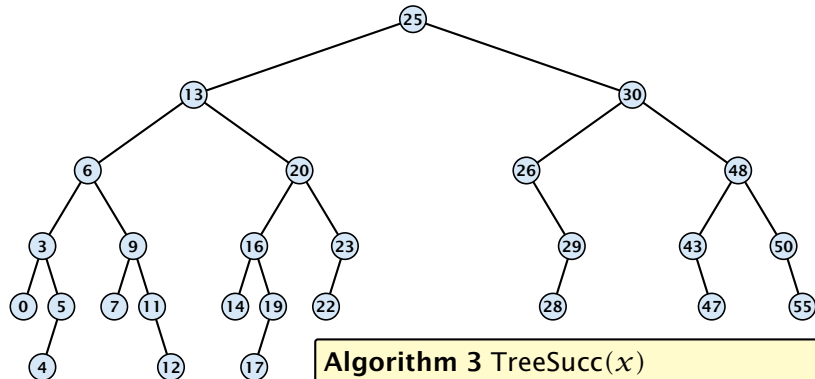
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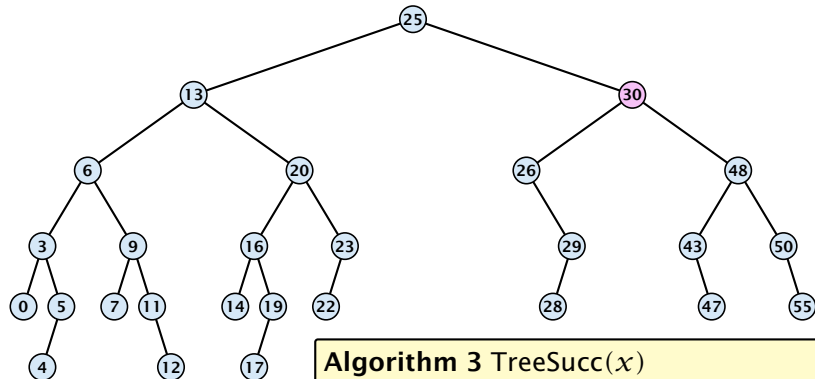
Binary Search Trees: Successor



Algorithm 3 TreeSucc(x)

- 1: **if** $\text{right}[x] \neq \text{null}$ **return** $\text{TreeMin}(\text{right}[x])$
- 2: $y \leftarrow \text{parent}[x]$
- 3: **while** $y \neq \text{null}$ **and** $x = \text{right}[y]$ **do**
- 4: $x \leftarrow y; y \leftarrow \text{parent}[x]$
- 5: **return** y ;

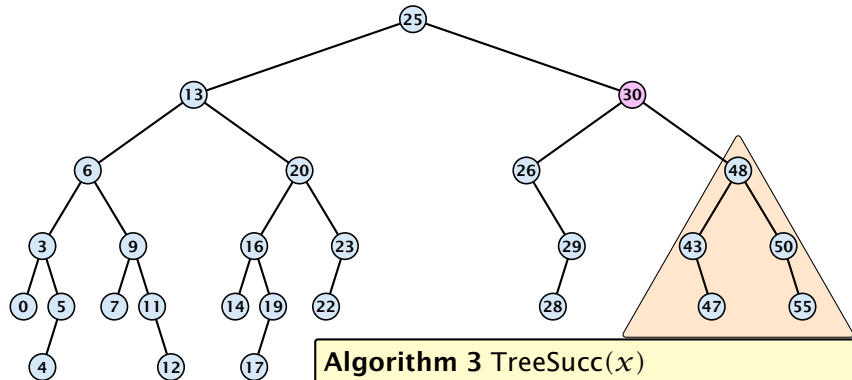
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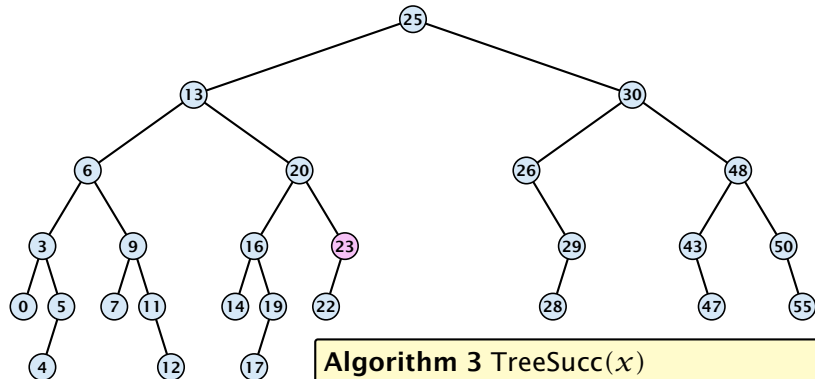
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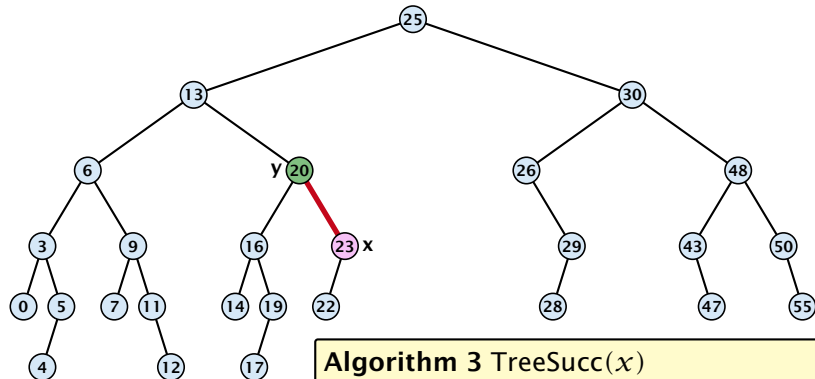
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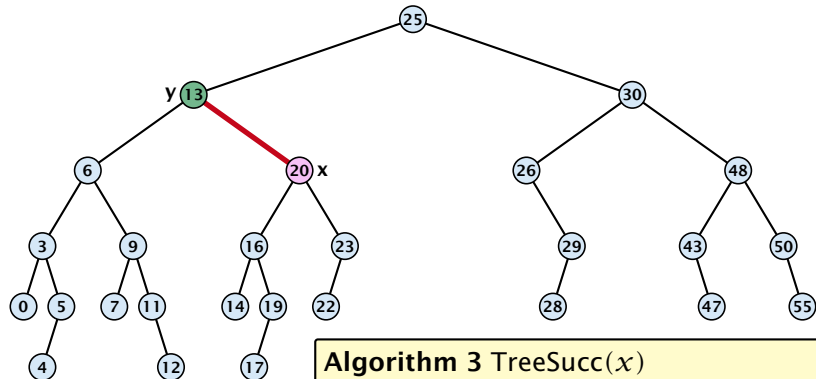
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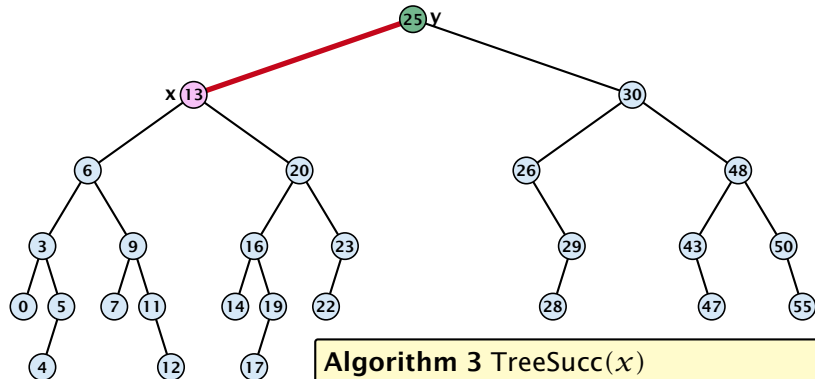
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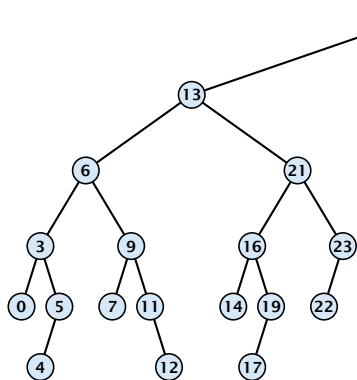
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Binary Search Trees: Insert

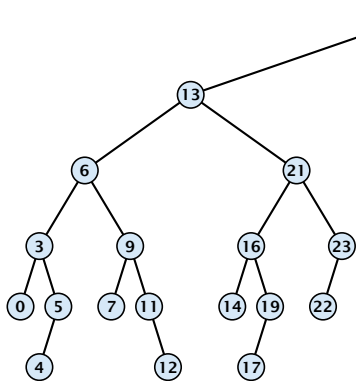


Algorithm 4 TreeInsert(x, z)

```
1: if  $x = \text{null}$  then
2:      $\text{root}[T] \leftarrow z$ ;  $\text{parent}[z] \leftarrow \text{null}$ ;
3:     return;
4: if  $\text{key}[x] > \text{key}[z]$  then
5:     if  $\text{left}[x] = \text{null}$  then
6:          $\text{left}[x] \leftarrow z$ ;  $\text{parent}[z] \leftarrow x$ ;
7:     else TreeInsert( $\text{left}[x], z$ );
8: else
9:     if  $\text{right}[x] = \text{null}$  then
10:         $\text{right}[x] \leftarrow z$ ;  $\text{parent}[z] \leftarrow x$ ;
11:    else TreeInsert( $\text{right}[x], z$ );
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Binary Search Trees: Insert

Insert element **not** in the tree.

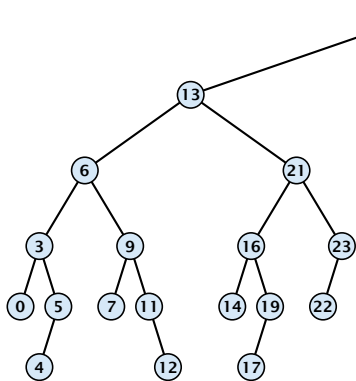


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Binary Search Trees: Insert

Insert element **not** in the tree.



Search for z . At some point the search stops at a null-pointer. This is the place to insert z .

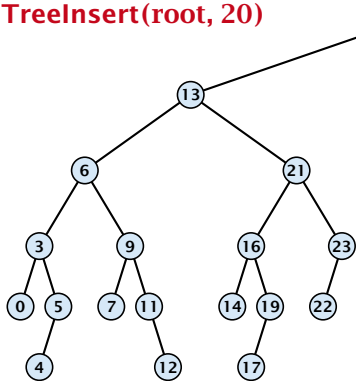
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3:   return;
4: if key[ $x$ ] > key[ $z$ ] then
5:   if left[ $x$ ] = null then
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7:   else TreeInsert(left[ $x$ ],  $z$ );
8: else
9:   if right[ $x$ ] = null then
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11:   else TreeInsert(right[ $x$ ],  $z$ );
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Binary Search Trees: Insert

Insert element **not** in the tree.

TreeInsert(root, 20)



Search for z . At some point the search stops at a null-pointer. This is the place to insert z .

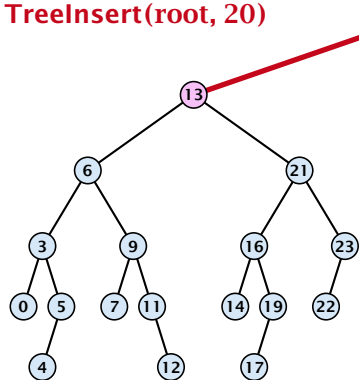
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- 3: **return**;
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- 5: **if** $\text{left}[x] = \text{null}$ **then**
- 6: $\text{left}[x] \leftarrow z$; $\text{parent}[z] \leftarrow x$;
- 7: **else** TreeInsert($\text{left}[x], z$);
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Insert element **not** in the tree.

TreeInsert(root, 20)



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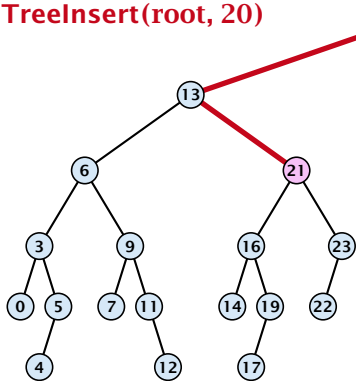
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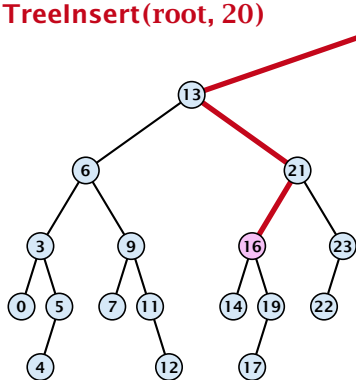
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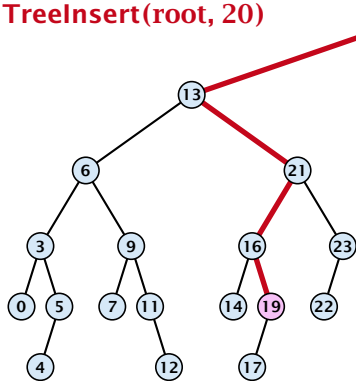
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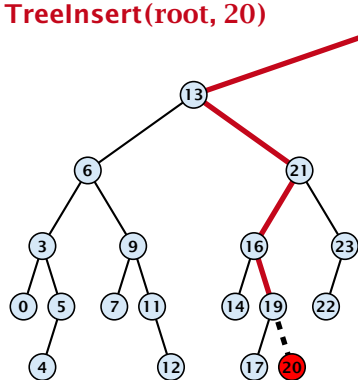
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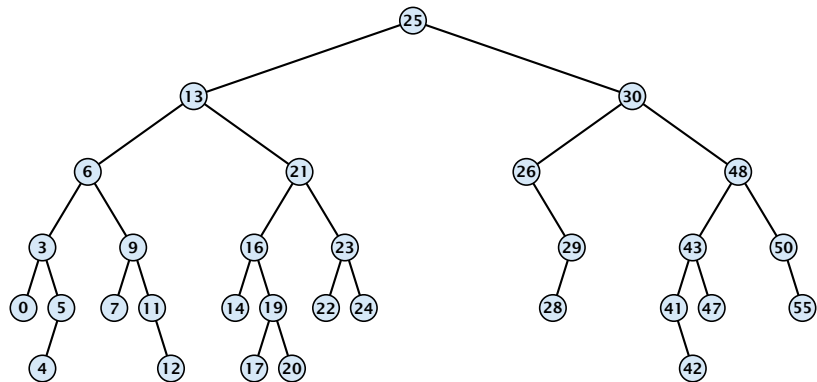


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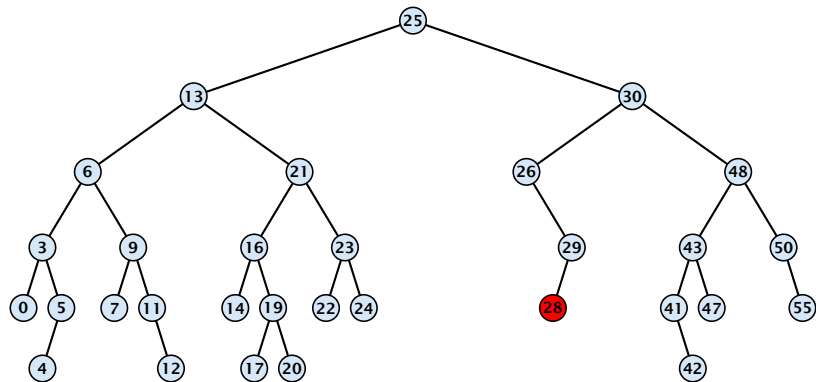
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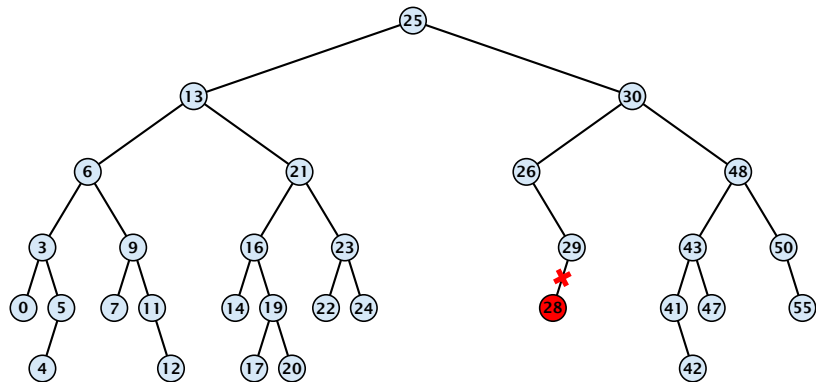


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Element does not have any children

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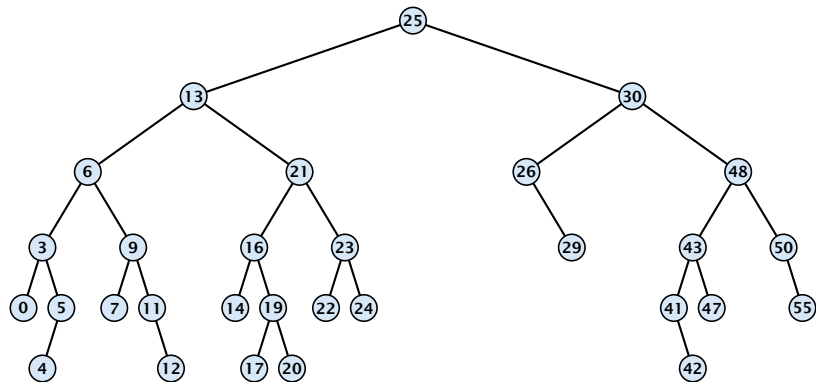


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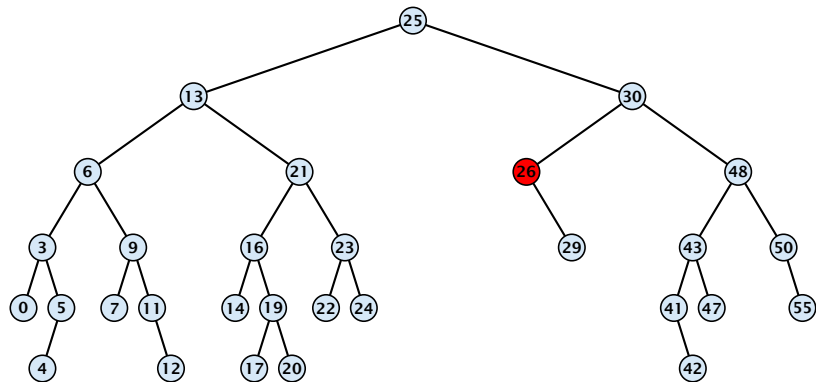


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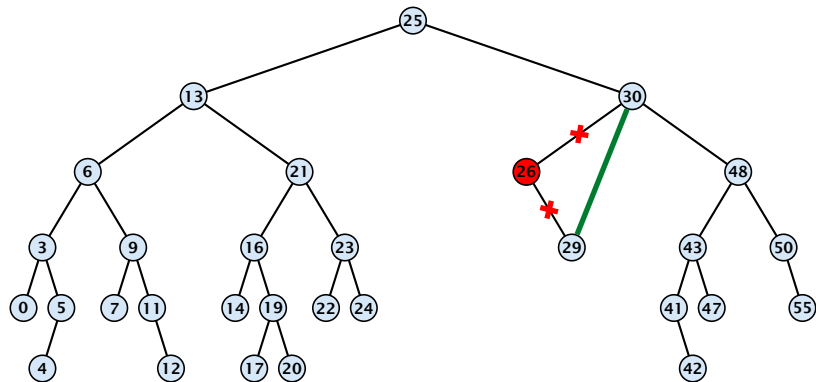


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Element has exactly one child

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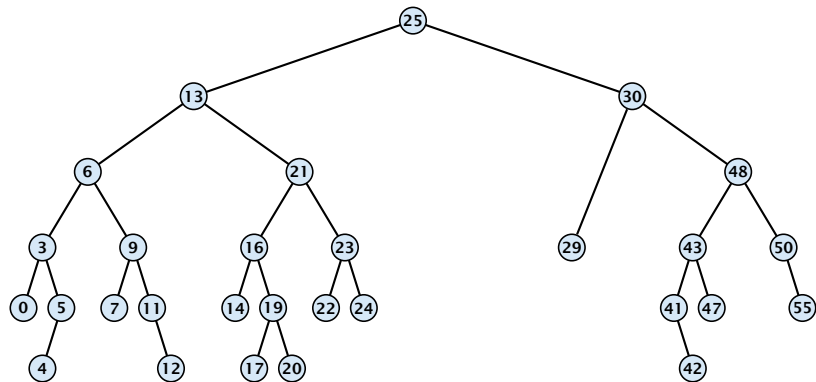


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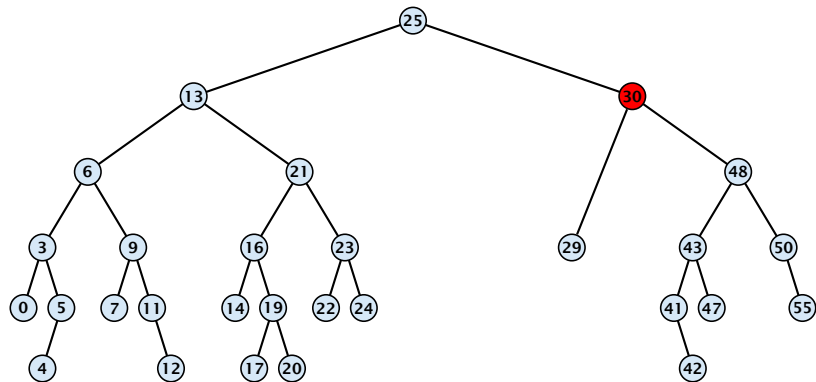


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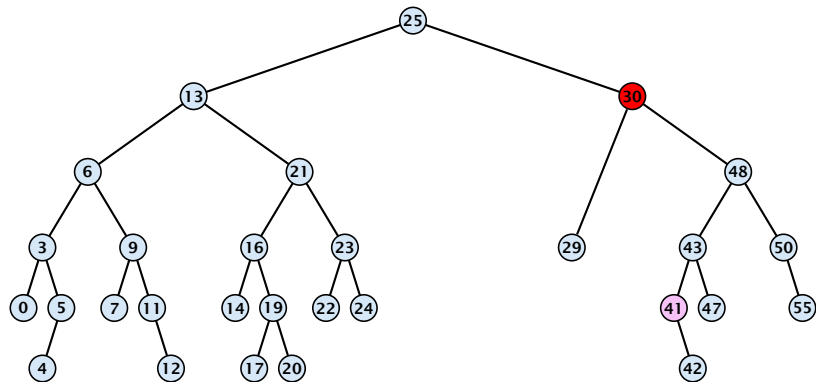


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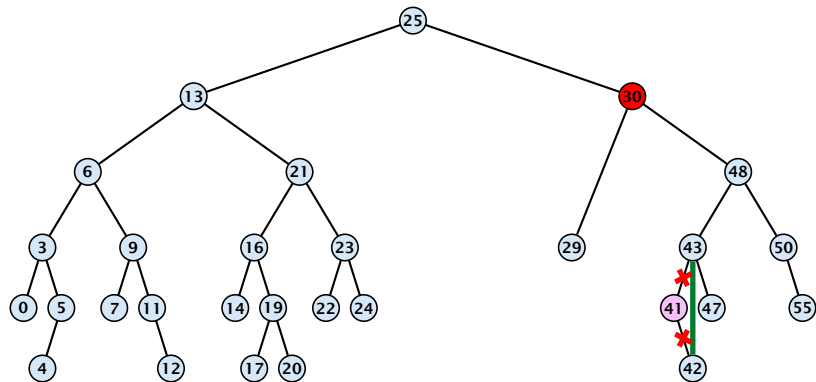


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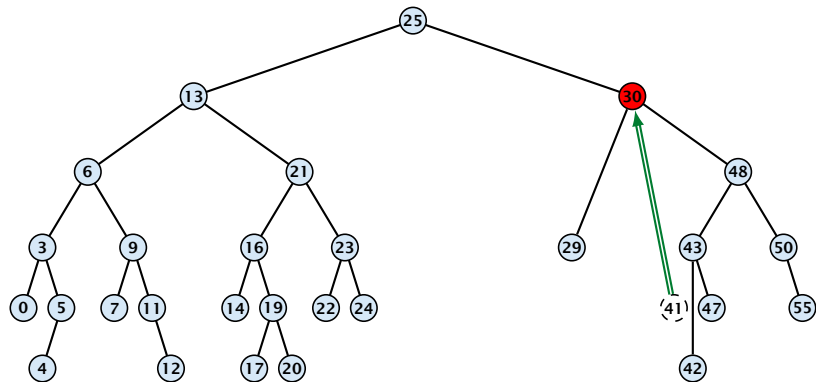


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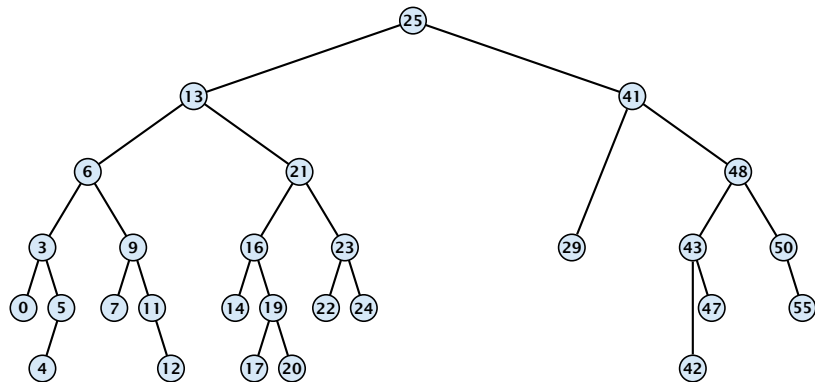


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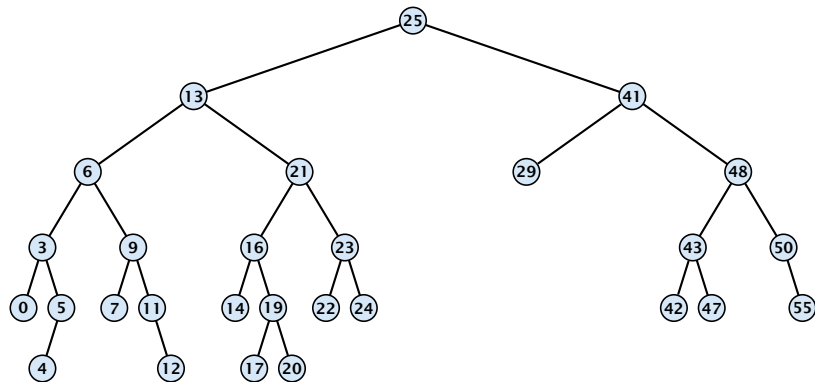


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- ▶ Splice successor out of the tree
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Binary Search Trees: Delete

Algorithm 9 TreeDelete(z)

```
1: if left[ $z$ ] = null or right[ $z$ ] = null
2:   then  $y \leftarrow z$  else  $y \leftarrow \text{TreeSucc}(z)$ ;   select  $y$  to splice out
3:   if left[ $y$ ]  $\neq$  null
4:     then  $x \leftarrow \text{left}[y]$  else  $x \leftarrow \text{right}[y]$ ;  $x$  is child of  $y$  (or null)
5:   if  $x \neq \text{null}$  then parent[ $x$ ]  $\leftarrow$  parent[ $y$ ];   parent[ $x$ ] is correct
6:   if parent[ $y$ ] = null then
7:     root[ $T$ ]  $\leftarrow x$ 
8:   else
9:     if  $y = \text{left}[\text{parent}[y]]$  then
10:      left[parent[ $y$ ]]  $\leftarrow x$ 
11:    else
12:      right[parent[ $y$ ]]  $\leftarrow x$ 
13:   if  $y \neq z$  then copy  $y$ -data to  $z$ 
```

} fix pointer to x

Balanced Binary Search Trees

All operations on a binary search tree can be performed in time $\mathcal{O}(h)$, where h denotes the height of the tree.

However the height of the tree may become as large as $\Theta(n)$.

Balanced Binary Search Trees

With each insert- and delete-operation perform local adjustments to guarantee a height of $\mathcal{O}(\log n)$.

AVL-trees, Red-black trees, Scapegoat trees, 2-3 trees, B-trees, AA trees, Treaps

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7.2 Red Black Trees

Definition 11

A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that

1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data

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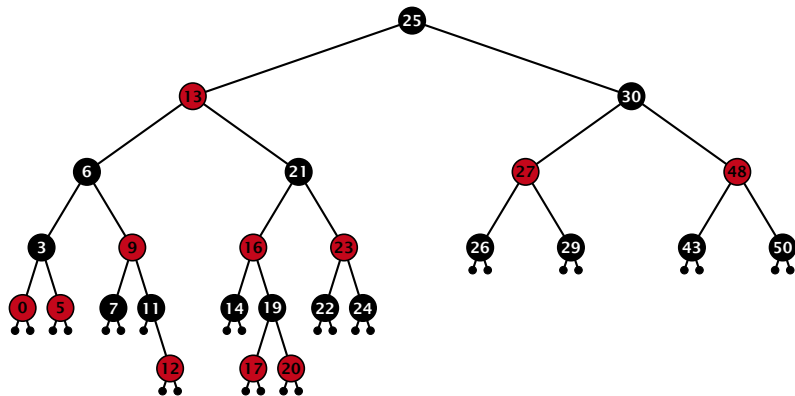
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Red Black Trees: Example



7.2 Red Black Trees

Lemma 12

A red-black tree with n internal nodes has height at most $\mathcal{O}(\log n)$.

Definition 13

The black height $\text{bh}(v)$ of a node v in a red black tree is the number of black nodes on a path from v to a leaf vertex (not counting v).

We first show:

Lemma 14

A sub-tree of black height $\text{bh}(v)$ in a red black tree contains at least $2^{\text{bh}(v)} - 1$ internal vertices.

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Proof of Lemma 14.

Induction on the height of v .

base case ($\text{height}(v) = 0$)

if $b(v) = 0$ (maximum distance from v to a node in the sub-tree rooted at v) is 0, then v is a leaf.

The black height of v is 0.

The sub-tree rooted at v contains 0 black nodes (inner nodes).

□

7.2 Red Black Trees

Proof of Lemma 14.

Induction on the height of v .

base case ($\text{height}(v) = 0$)

If v is a leaf (maximum distance from root) and a node in the sub-tree rooted at v is a red node, then v is a leaf.

The black height of v is 1.

The sub-tree rooted at v contains exactly one black node.

Q.E.D.

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- ▶ The black height of v is 0.
- ▶ The sub-tree rooted at v contains $0 = 2^{\text{bh}(v)} - 1$ inner vertices.

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7.2 Red Black Trees

Proof (cont.)

induction step

- Suppose x is a node with 2 children y and z .
- If x has two children with strictly smaller height, then x has two children y and z either both of which are black or both of which are red.
- By induction hypothesis both y - and z -trees contain at least $\frac{1}{2}n$ nodes.
- Then x is internal node.
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7.2 Red Black Trees

Proof (cont.)

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- ▶ Suppose v is a node with $\text{height}(v) > 0$.
- ▶ v has two children with strictly smaller height.
- ▶ These children (c_1, c_2) either have $\text{bh}(c_i) = \text{bh}(v)$ or $\text{bh}(c_i) = \text{bh}(v) - 1$.
- ▶ By induction hypothesis both sub-trees contain at least $2^{\text{bh}(v)-1} - 1$ internal vertices.
- ▶ Then T_v contains at least $2(2^{\text{bh}(v)-1} - 1) + 1 \geq 2^{\text{bh}(v)} - 1$ vertices.



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Hence, the black height of the root is at least $h/2$.

The tree contains at least $2^{h/2} - 1$ internal vertices. Hence,
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Hence, the black height of the root is at least $h/2$.

The tree contains at least $2^{h/2} - 1$ internal vertices. Hence,
 $2^{h/2} - 1 \leq n$.

Hence, $h \leq 2 \log(n + 1) = O(\log n)$. □

7.2 Red Black Trees

Proof of Lemma 12.

Let h denote the height of the red-black tree, and let P denote a path from the root to the furthest leaf.

At least half of the nodes on P must be black, since a red node must be followed by a black node.

Hence, the black height of the root is at least $h/2$.

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Hence, $h \leq 2 \log(n + 1) = \mathcal{O}(\log n)$. □

7.2 Red Black Trees

Definition 1

A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that

1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

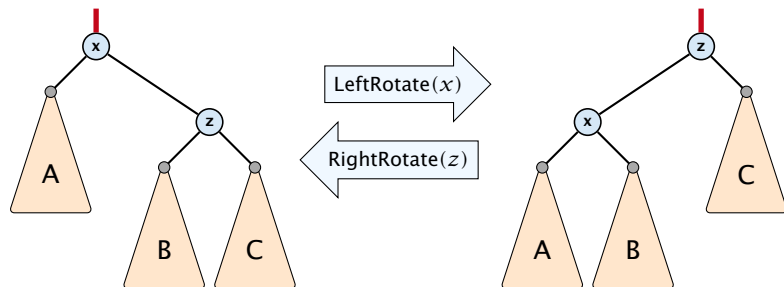
The **null**-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.

7.2 Red Black Trees

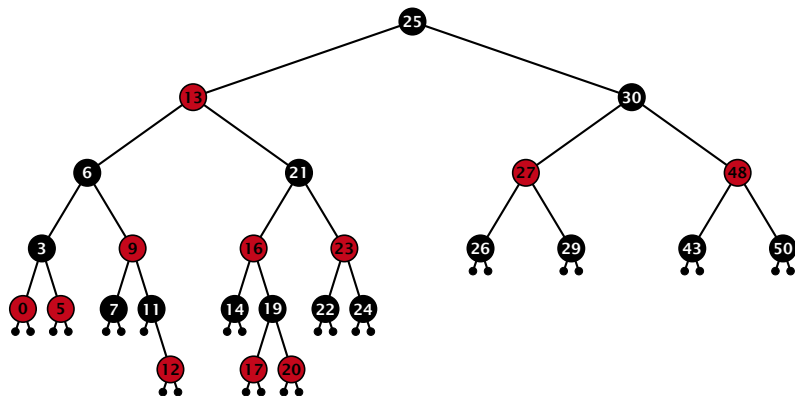
We need to adapt the insert and delete operations so that the red black properties are maintained.

Rotations

The properties will be maintained through rotations:



Red Black Trees: Insert

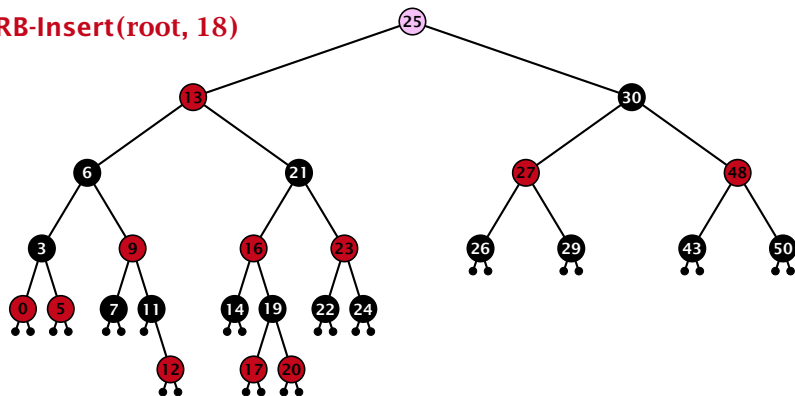


Insert:

- ▶ first make a normal insert into a binary search tree
- ▶ then fix red-black properties

Red Black Trees: Insert

RB-Insert(root, 18)

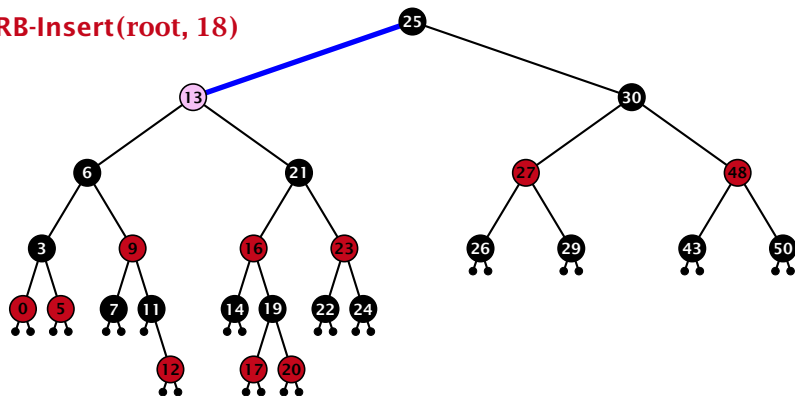


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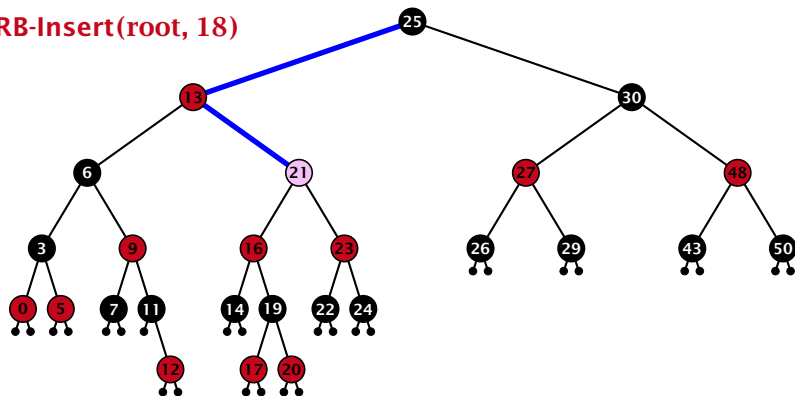


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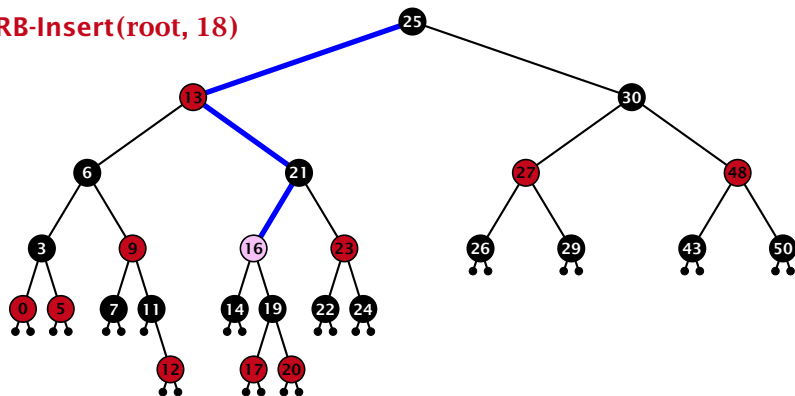


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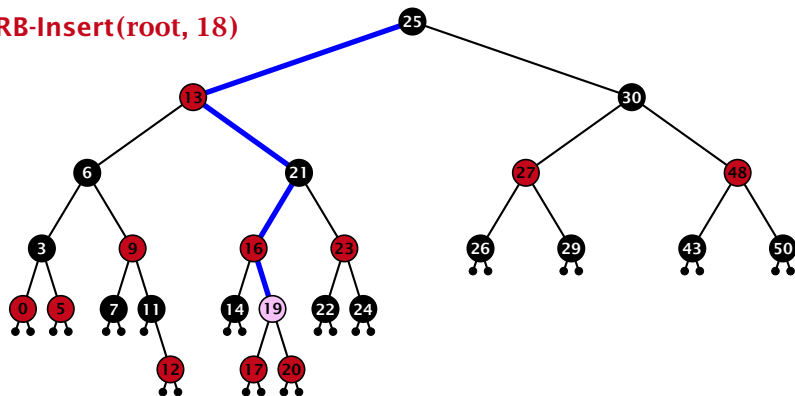


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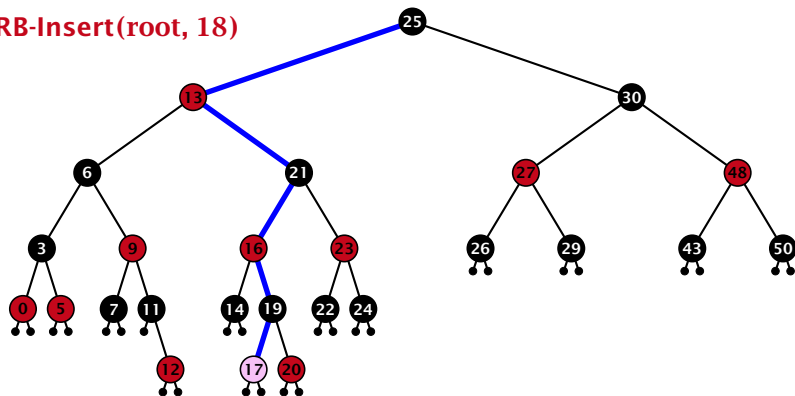


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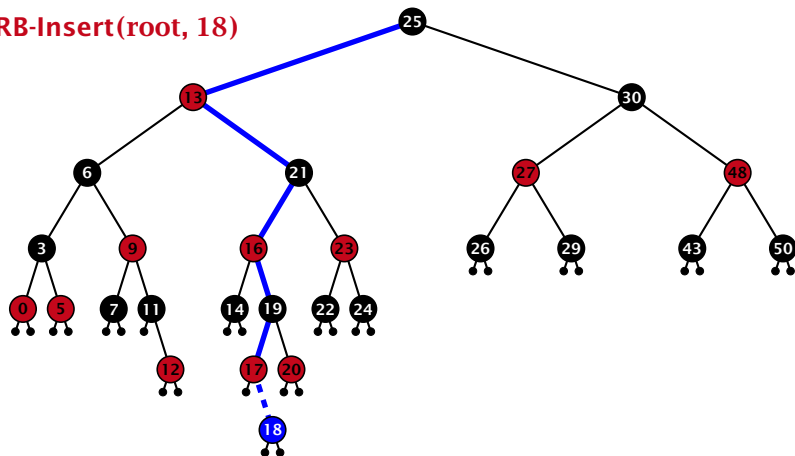


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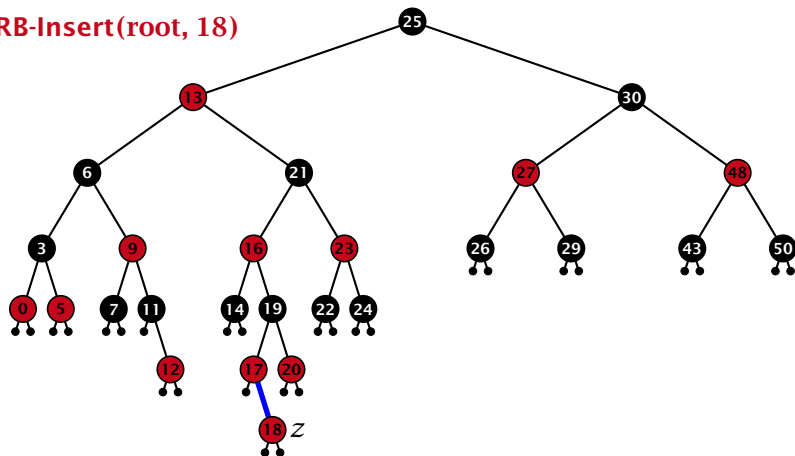


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Red Black Trees: Insert

Invariant of the fix-up algorithm:

- ▶ z is a red node
- ▶ the black-height property is fulfilled at every node
- ▶ the only violation of red-black properties occurs at z and $\text{parent}[z]$
 - either both of them are red (most important case)
 - or the parent does not exist (violation since root must be black)

If z has a parent but no grand-parent we could simply color the parent/root black; however this case never happens.

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Red Black Trees: Insert

Algorithm 10 InsertFix(z)

```
1: while parent[ $z$ ]  $\neq$  null and col[parent[ $z$ ]] = red do
2:   if parent[ $z$ ] = left[gp[ $z$ ]] then
3:      $uncle \leftarrow$  right[grandparent[ $z$ ]]
4:     if col[ $uncle$ ] = red then
5:       col[p[ $z$ ]]  $\leftarrow$  black; col[ $u$ ]  $\leftarrow$  black;
6:       col[gp[ $z$ ]]  $\leftarrow$  red;  $z \leftarrow$  grandparent[ $z$ ];
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8:       if  $z$  = right[parent[ $z$ ]] then
9:          $z \leftarrow$  p[ $z$ ]; LeftRotate( $z$ );
10:      col[p[ $z$ ]]  $\leftarrow$  black; col[gp[ $z$ ]]  $\leftarrow$  red;
11:      RightRotate(gp[ $z$ ]);
12:   else same as then-clause but right and left exchanged
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1: while parent[ $z$ ]  $\neq$  null and col[parent[ $z$ ]] = red do
2:   if parent[ $z$ ] = left[gp[ $z$ ]] then  $z$  in left subtree of grandparent
3:      $uncle \leftarrow$  right[grandparent[ $z$ ]]
4:     if col[ $uncle$ ] = red then
5:       col[p[ $z$ ]]  $\leftarrow$  black; col[ $u$ ]  $\leftarrow$  black;
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4:     if col[ $uncle$ ] = red then Case 1: uncle red
5:       col[p[ $z$ ]]  $\leftarrow$  black; col[ $u$ ]  $\leftarrow$  black;
6:       col[gp[ $z$ ]]  $\leftarrow$  red;  $z \leftarrow$  grandparent[ $z$ ];
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Red Black Trees: Insert

Algorithm 10 InsertFix(z)

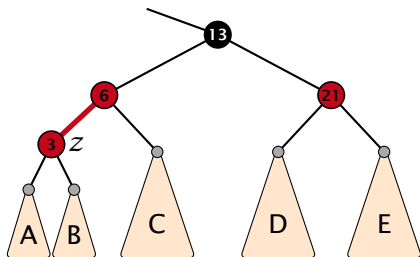
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1: while parent[ $z$ ]  $\neq$  null and col[parent[ $z$ ]] = red do
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11:        RightRotate(gp[ $z$ ]);
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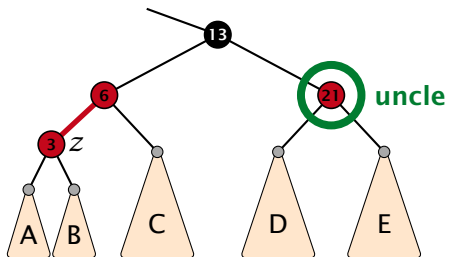
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10:      col[p[ $z$ ]]  $\leftarrow$  black; col[gp[ $z$ ]]  $\leftarrow$  red; 2b:  $z$  left child
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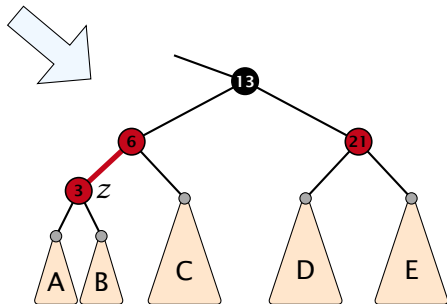
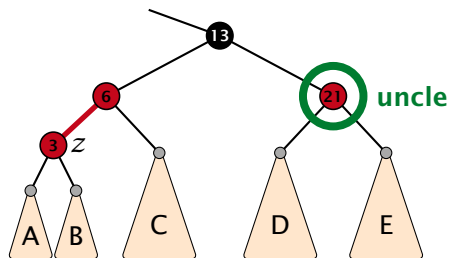
Case 1: Red Uncle



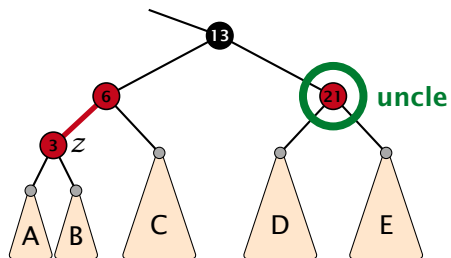
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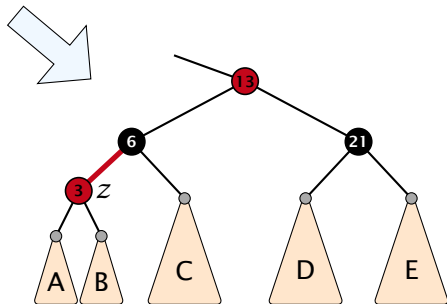
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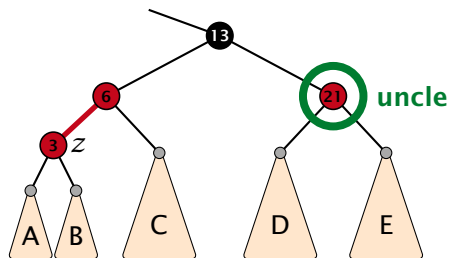
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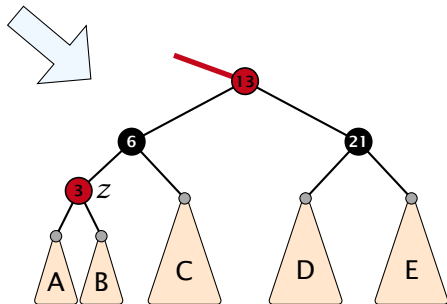
1. recolour



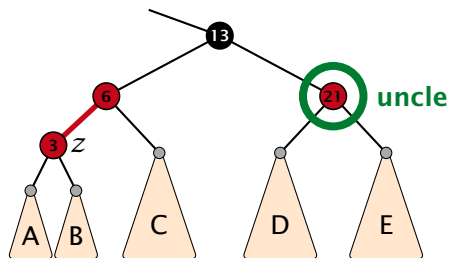
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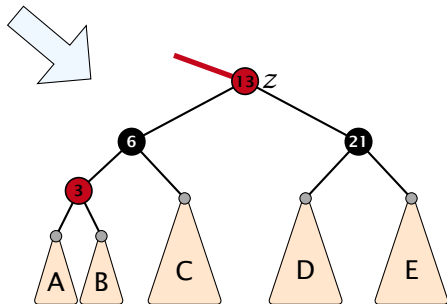
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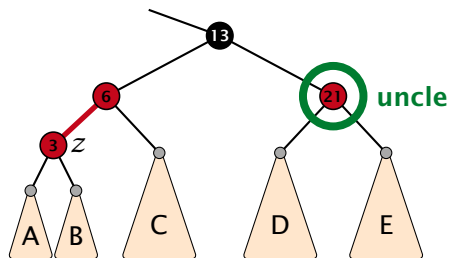
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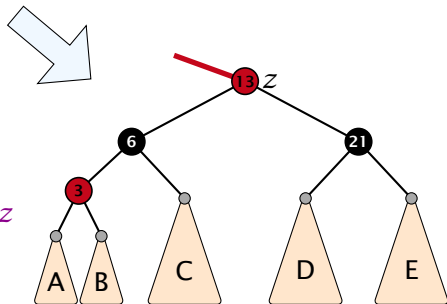
1. recolour
2. move z to grand-parent



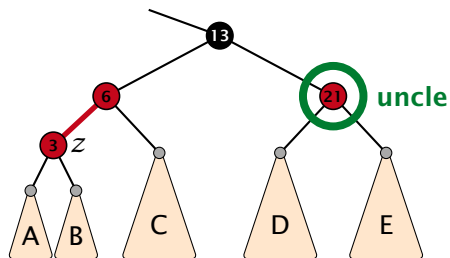
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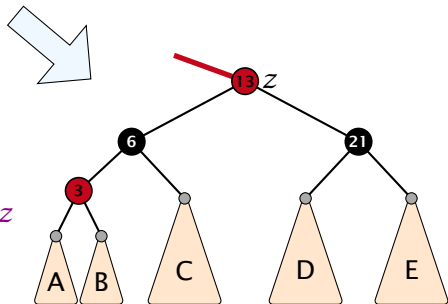
1. recolour
2. move z to grand-parent
3. invariant is fulfilled for new z



Case 1: Red Uncle

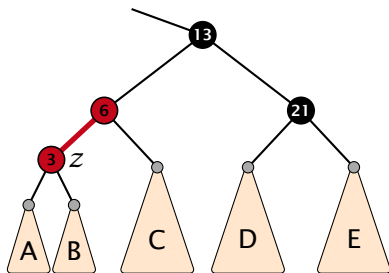


1. recolour
2. move z to grand-parent
3. invariant is fulfilled for new z
4. you made progress



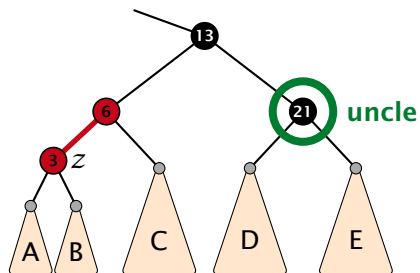
Case 2b: Black uncle and z is left child

1. rotate around grandparent
2. re-colour to ensure that black height property holds
3. you have a red black tree



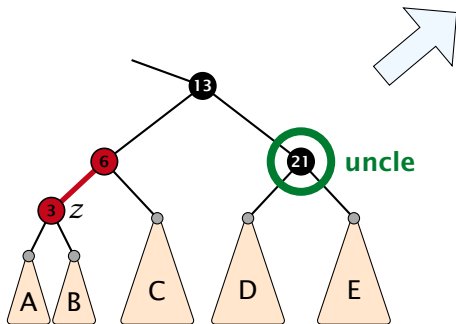
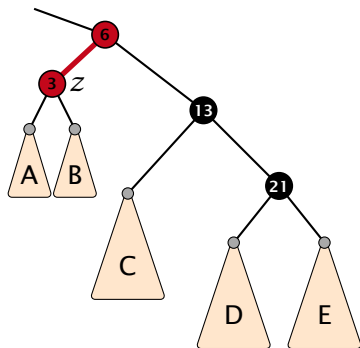
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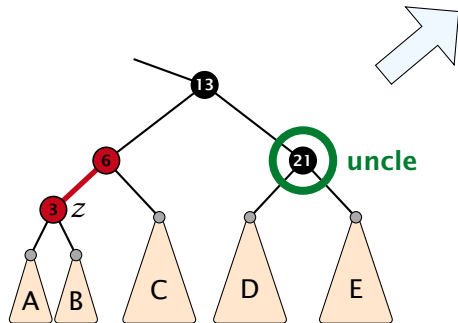
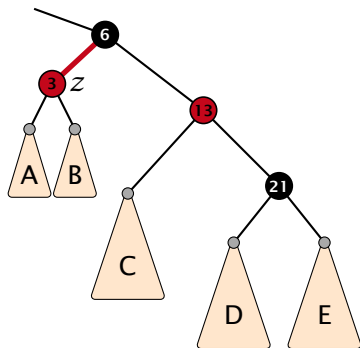
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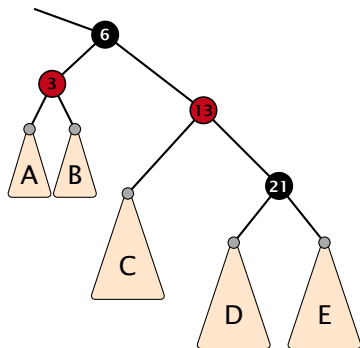
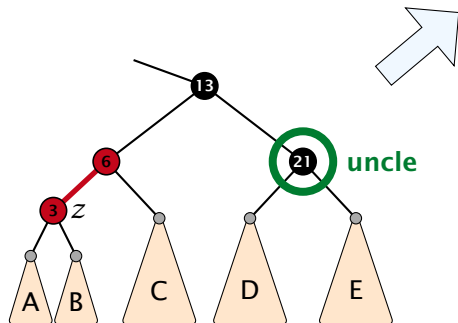
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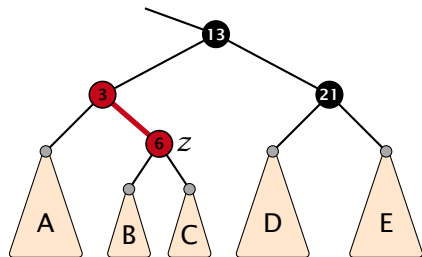
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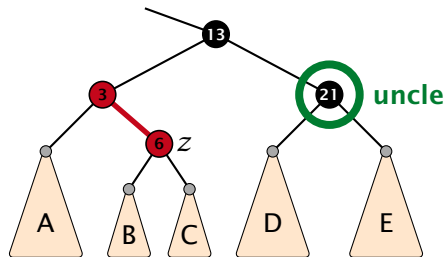
Case 2a: Black uncle and z is right child

1. rotate around parent
2. move z downwards
3. you have Case 2b.



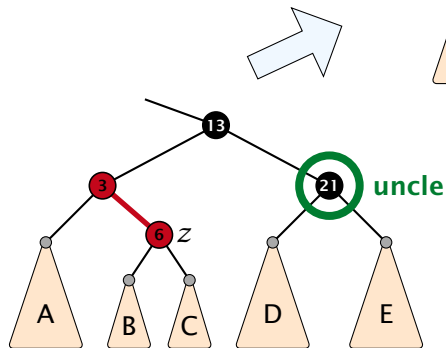
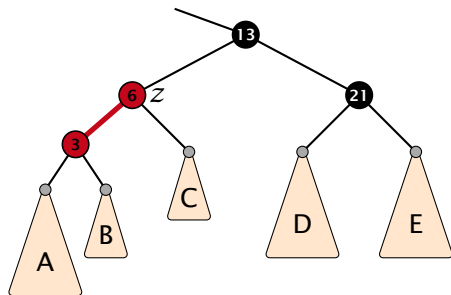
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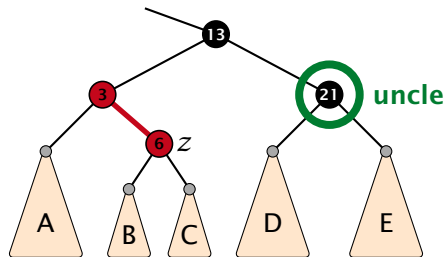
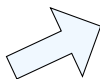
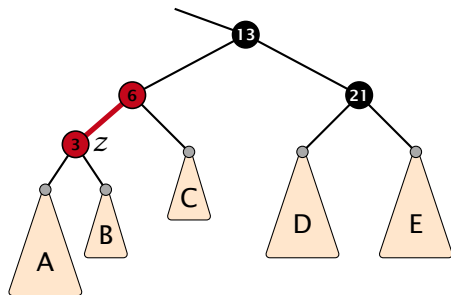
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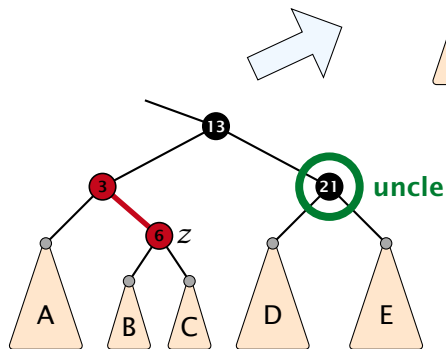
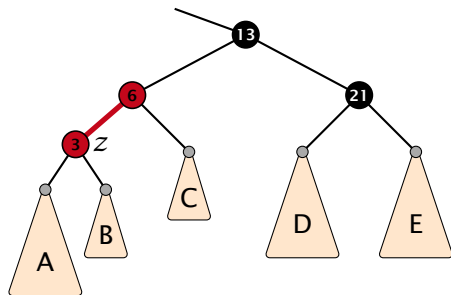
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3. you have Case 2b.



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Red Black Trees: Insert

Running time:

- ▶ Only Case 1 may repeat; but only $h/2$ many steps, where h is the height of the tree.
- ▶ Case 2a → Case 2b → red-black tree
- ▶ Case 2b → red-black tree

Performing Case 1 at most $\mathcal{O}(\log n)$ times and every other case at most once, we get a red-black tree. Hence $\mathcal{O}(\log n)$ re-colorings and at most 2 rotations.

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Performing Case 1 at most $\mathcal{O}(\log n)$ times and every other case at most once, we get a red-black tree. Hence $\mathcal{O}(\log n)$ re-colorings and at most 2 rotations.

Red Black Trees: Delete

First do a standard delete.

If the spliced out node x was red everything is fine.

If it was black there may be the following problems.

• If parent and child of x were red; two adjacent red vertices.

• If you delete the root, the root may now be red.

• Every path from an ancestor of x to a descendant leaf of x changes the number of black nodes. Black height property might be violated.

Red Black Trees: Delete

First do a standard delete.

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1. Parent and child of x were red; two adjacent red nodes.

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3. Every path from an ancestor of x to a descendant leaf changes the number of black nodes. Black height property might be violated.

Red Black Trees: Delete

First do a standard delete.

If the spliced out node x was red everything is fine.

If it was black there may be the following problems.

1. Parent and child of x were red, two adjacent red nodes.

2. x was the root, the root may now be red.

3. x had both an ancestor of a tree depth that is not a multiple of 2, and a child.

4. x was the root, the number of black nodes (Black Height) is not a multiple of 2.

5. x was the root, height is not a multiple of 2.

Red Black Trees: Delete

First do a standard delete.

If the spliced out node x was red everything is fine.

If it was black there may be the following problems.

- ▶ Parent and child of x were red; two adjacent red vertices.
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Red Black Trees: Delete

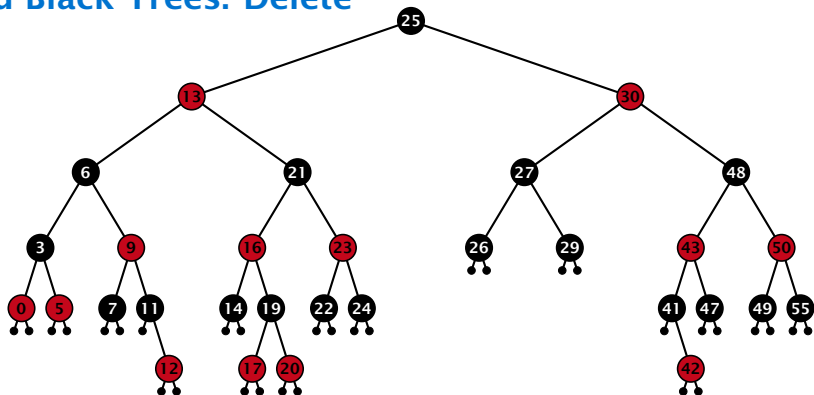
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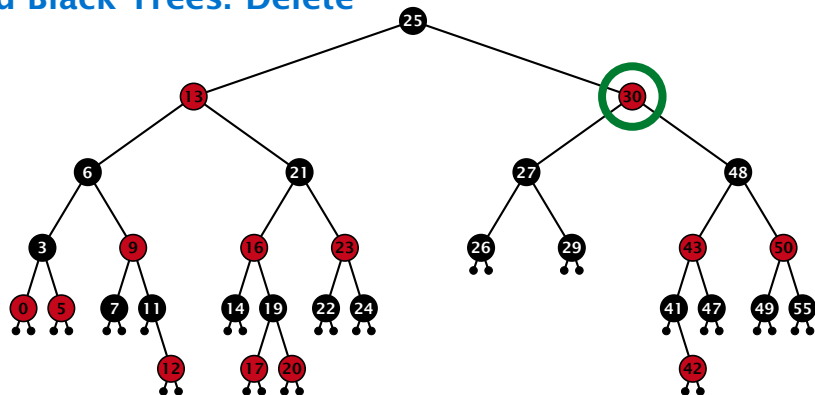
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Red Black Trees: Delete



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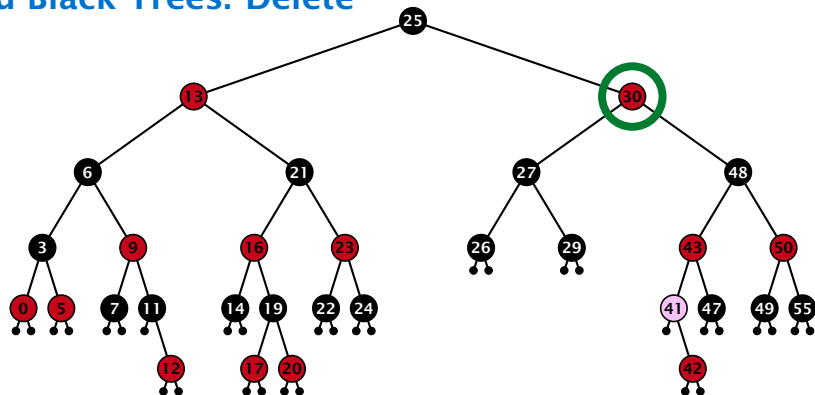


Case 3:

Element has two children

- ▶ do normal delete
- ▶ when replacing content by content of successor, don't change color of node

Red Black Trees: Delete

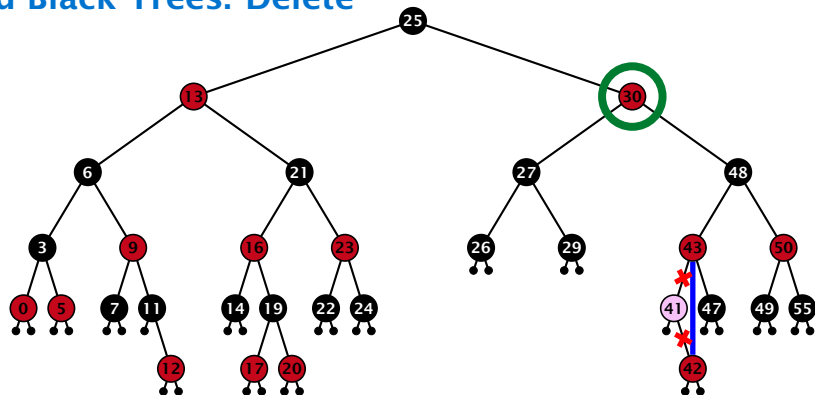


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Red Black Trees: Delete

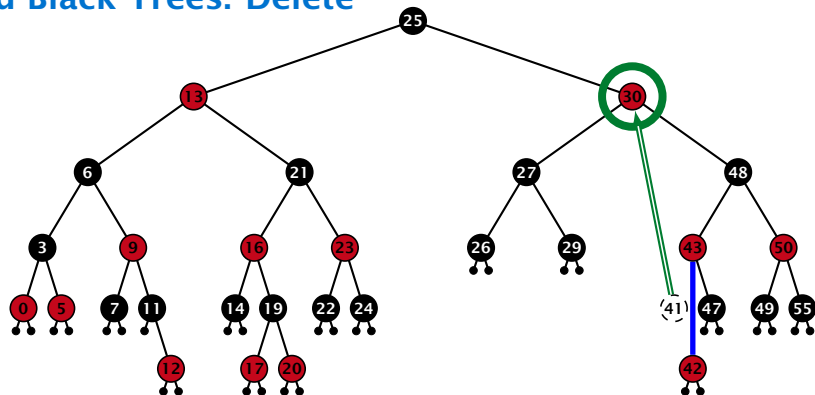


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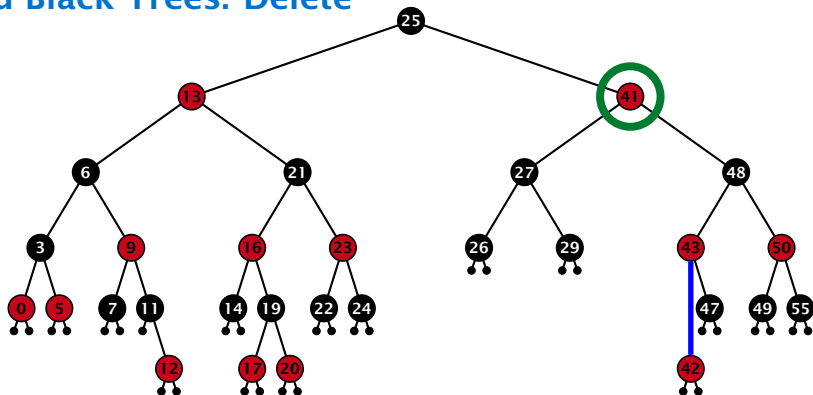


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Red Black Trees: Delete

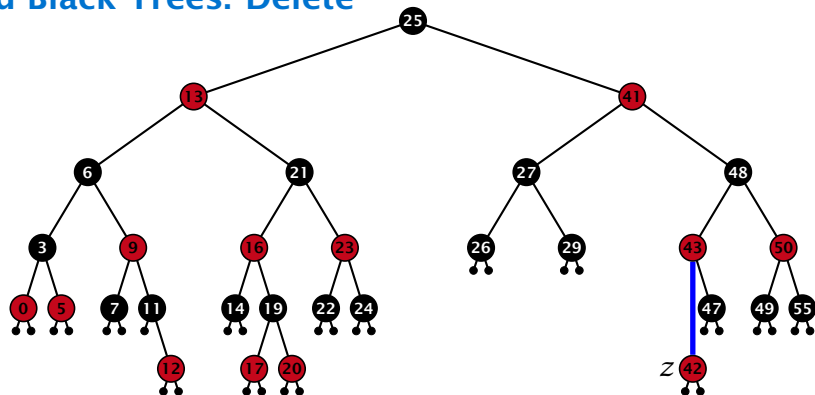


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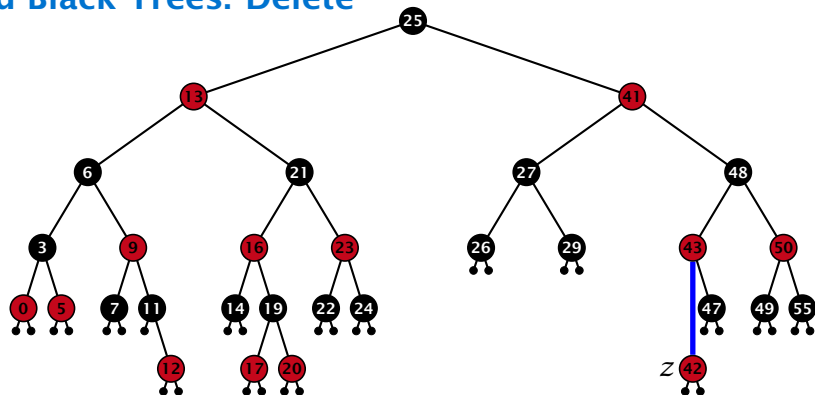
Red Black Trees: Delete



Delete:

- ▶ deleting black node messes up black-height property
- ▶ if z is red, we can simply color it black and everything is fine
- ▶ the problem is if z is black (e.g. a dummy-leaf); we call a fix-up procedure to fix the problem.

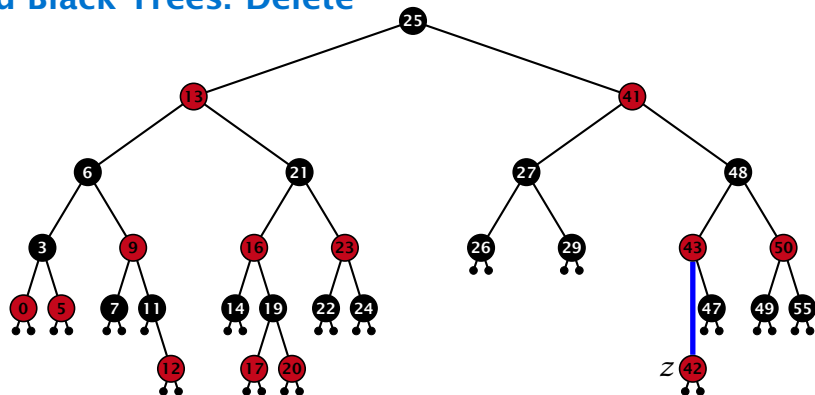
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Red Black Trees: Delete

Invariant of the fix-up algorithm

- ▶ the node z is black
- ▶ if we “assign” a fake black unit to the edge from z to its parent then the black-height property is fulfilled

Goal: make rotations in such a way that you at some point can remove the fake black unit from the edge.

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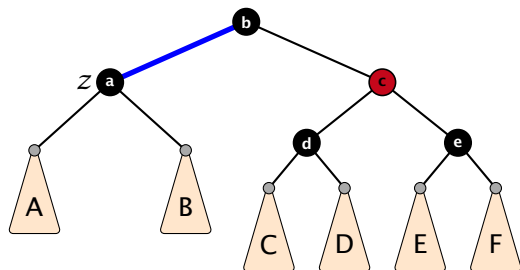
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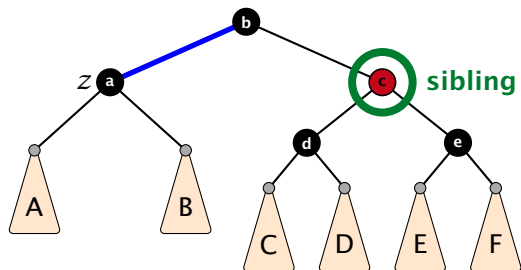
Case 1: Sibling of z is red



1. left-rotate around parent of z
2. recolor nodes b and c
3. the new sibling is black
(and parent of z is red)
4. Case 2 (special),
or Case 3, or Case 4



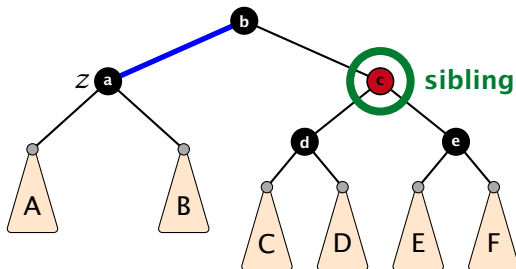
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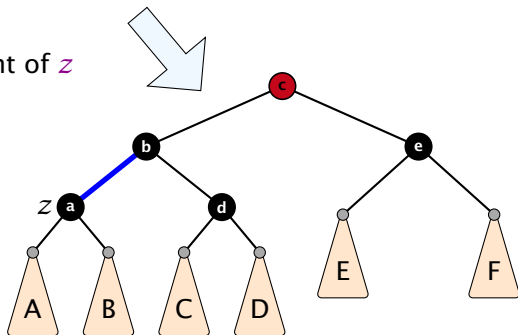
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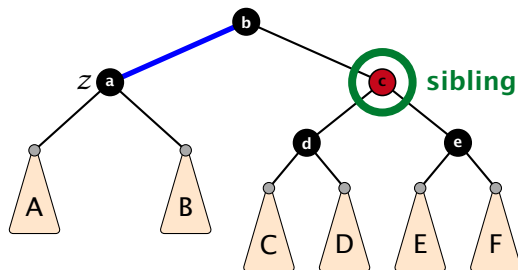
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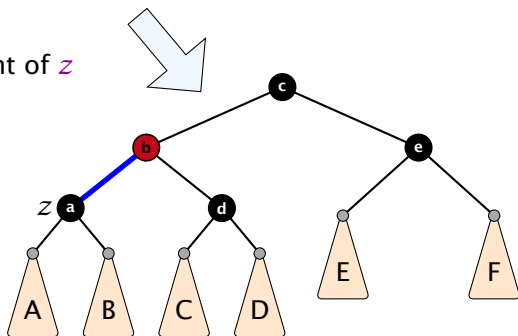
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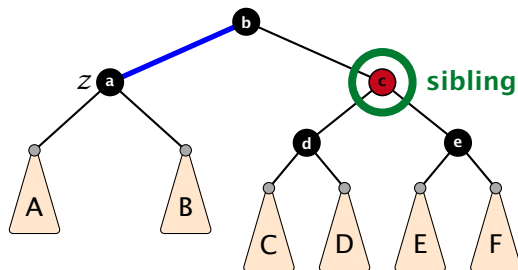
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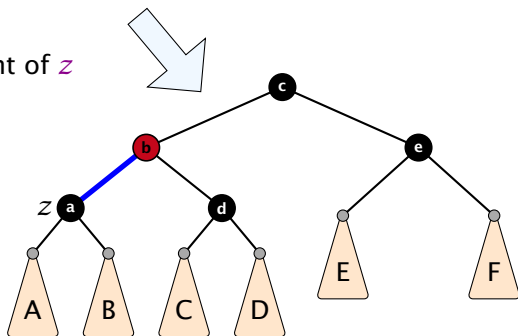
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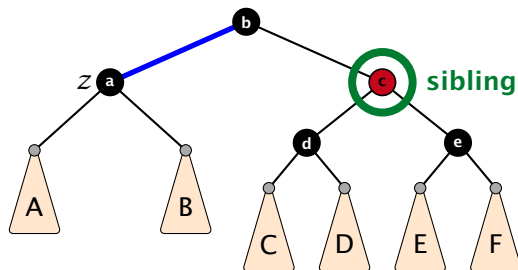
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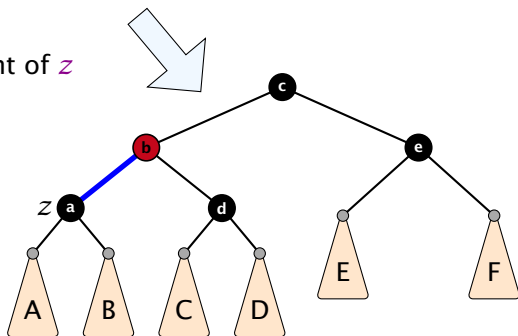
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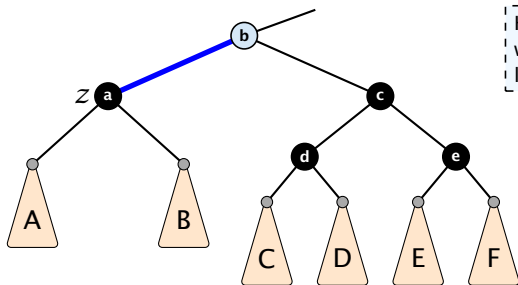
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Case 2: Sibling is black with two black children

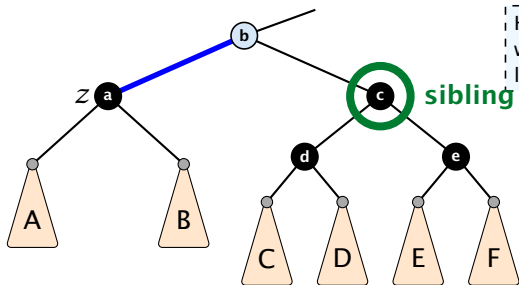


Here b is either black or red. If it is red we are in a special case that directly leads to a red-black tree.

1. re-color node c
2. move fake black unit upwards
3. move z upwards
4. we made progress
5. if b is red we color it black and are done



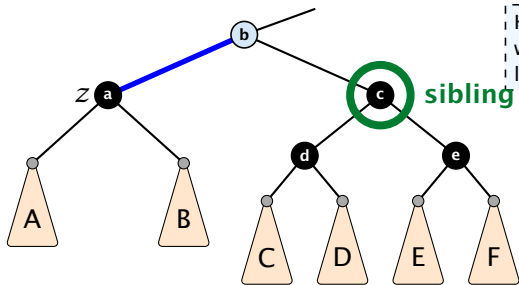
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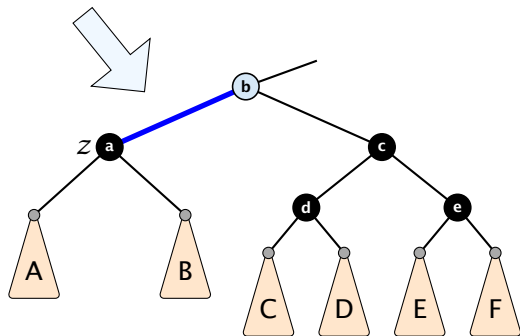


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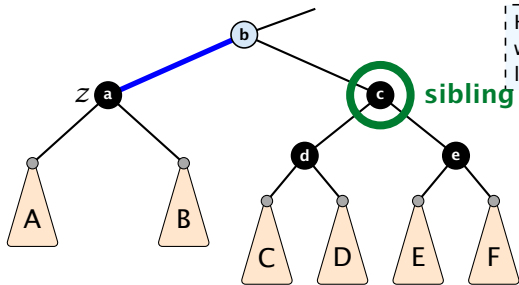


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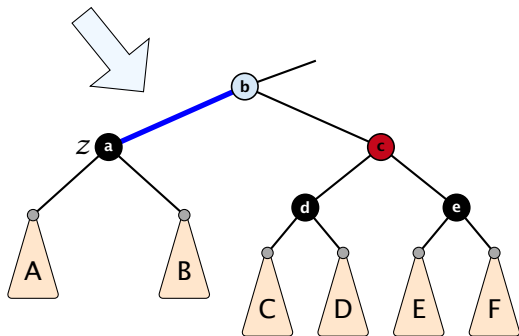


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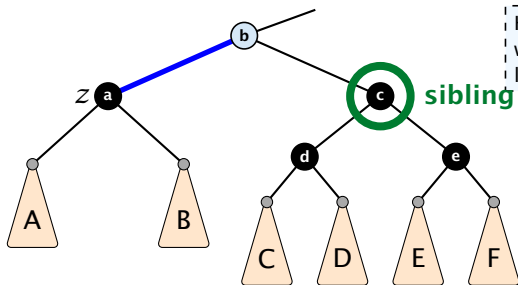


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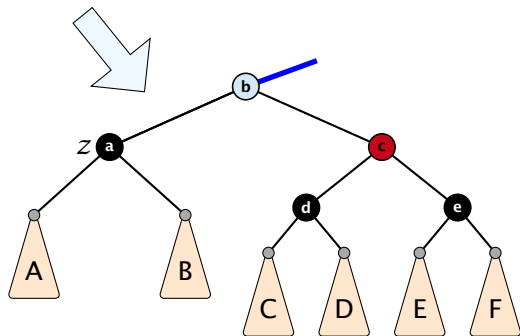


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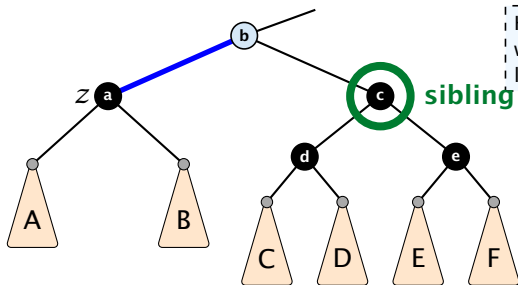


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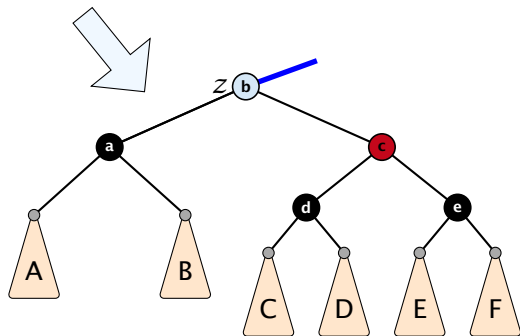


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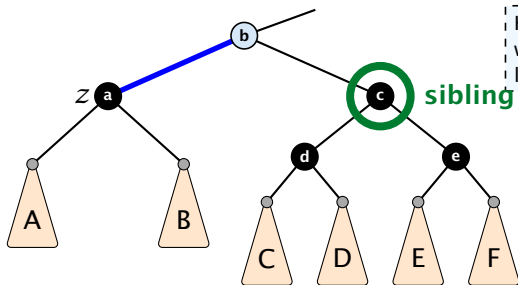


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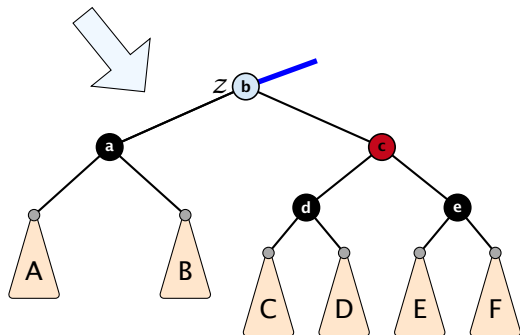


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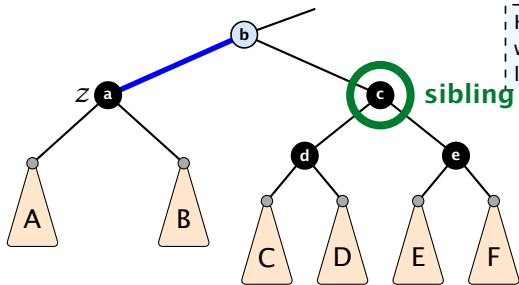


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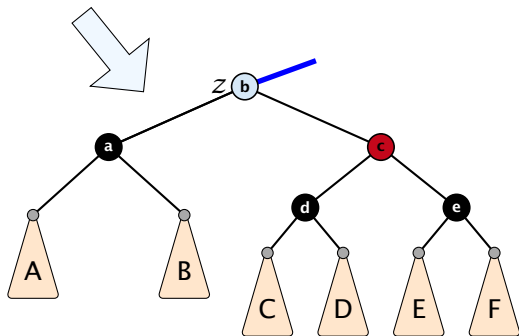


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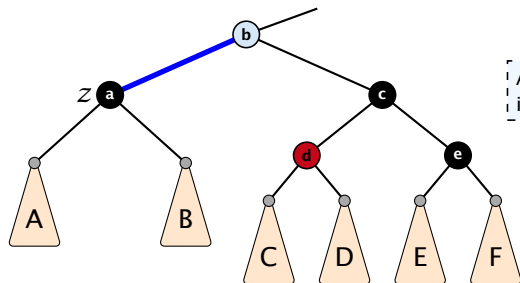
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Case 3: Sibling black with one black child to the right

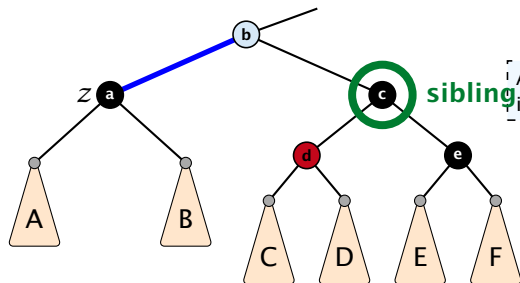
1. do a right-rotation at sibling
2. recolor c and d
3. new sibling is black with red right child (Case 4)



Again the blue color of b indicates that it can either be black or red.

Case 3: Sibling black with one black child to the right

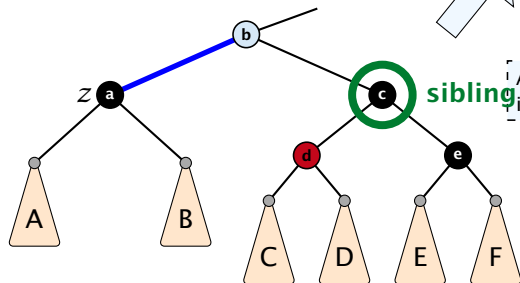
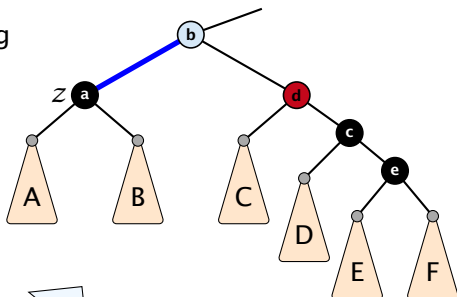
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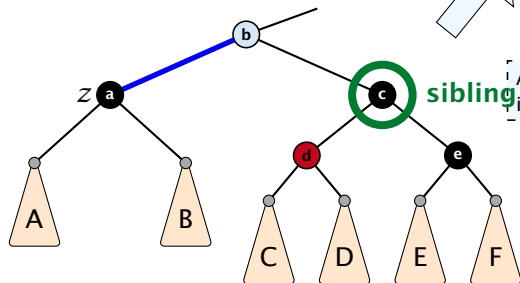
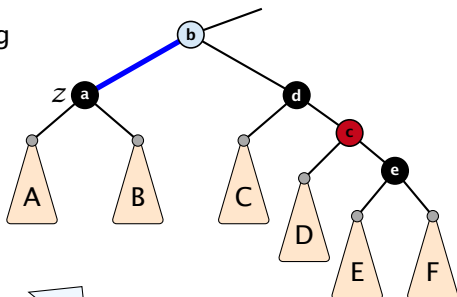
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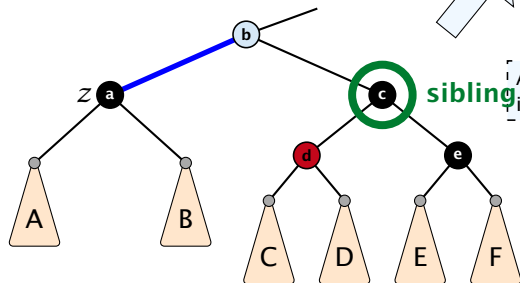
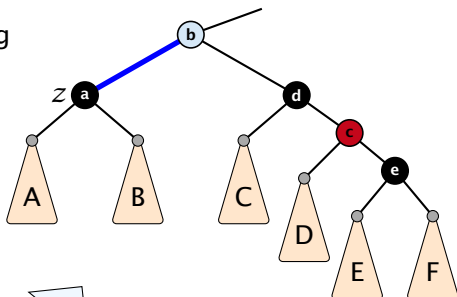
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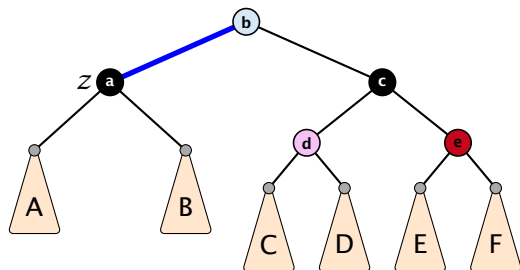
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1. do a right-rotation at sibling
2. recolor c and d
3. new sibling is black with red right child (Case 4)



Again the blue color of b indicates that it can either be black or red.

Case 4: Sibling is black with red right child

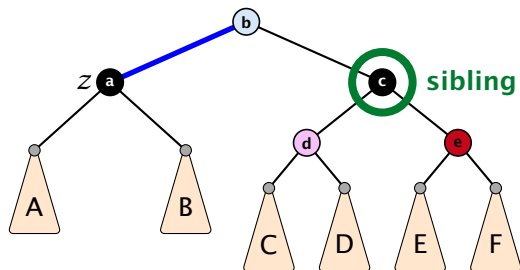


- Here b and d are either red or black but have possibly different colors.
- We recolor c by giving it the color of b .

1. left-rotate around b
2. remove the fake black unit
3. recolor nodes b , c , and e
4. you have a valid red black tree



Case 4: Sibling is black with red right child

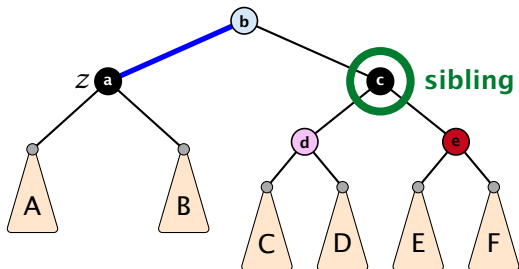


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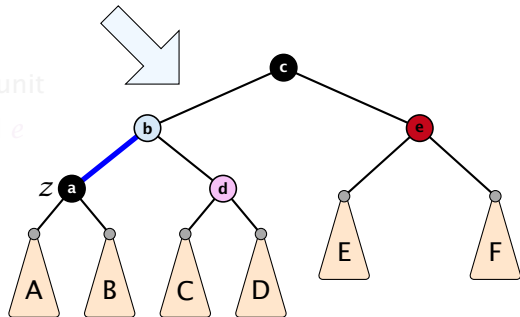


Case 4: Sibling is black with red right child

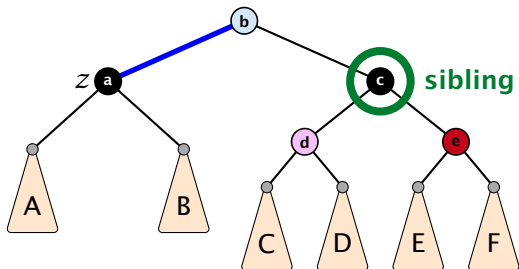


- Here **b** and **d** are either red or black but have possibly different colors.
- We recolor **c** by giving it the color of **b**.

1. left-rotate around **b**
2. remove the fake black unit
3. recolor nodes **b**, **c**, and **e**
4. you have a valid red black tree

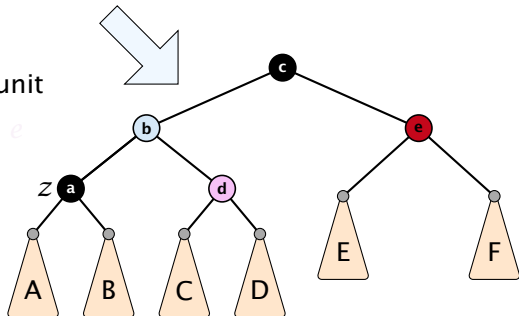


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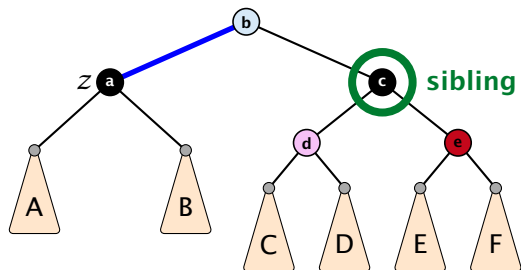


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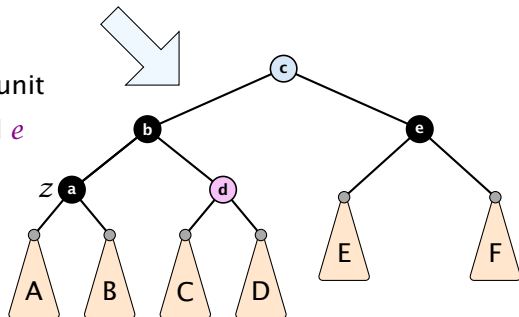


Case 4: Sibling is black with red right child

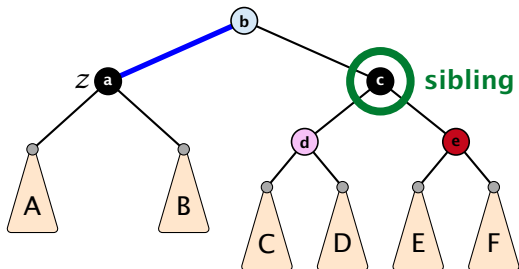


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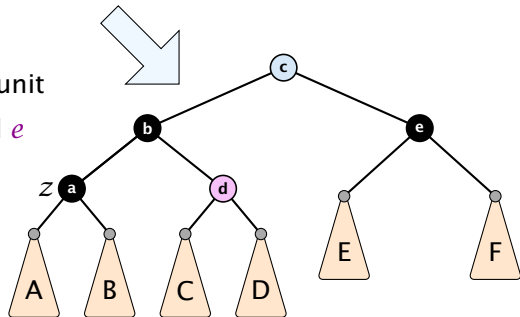


Case 4: Sibling is black with red right child



- Here **b** and **d** are either red or black but have possibly different colors.
- We recolor **c** by giving it the color of **b**.

1. left-rotate around **b**
2. remove the fake black unit
3. recolor nodes **b**, **c**, and **e**
4. you have a valid red black tree



Running time:

- ▶ only Case 2 can repeat; but only h many steps, where h is the height of the tree
- ▶ Case 1 → Case 2 (special) → red black tree
- ▶ Case 1 → Case 3 → Case 4 → red black tree
- ▶ Case 1 → Case 4 → red black tree
- ▶ Case 3 → Case 4 → red black tree
- ▶ Case 4 → red black tree

Performing Case 2 at most $\mathcal{O}(\log n)$ times and every other step at most once, we get a red black tree. Hence, $\mathcal{O}(\log n)$ re-colorings and at most 3 rotations.

Running time:

- ▶ only Case 2 can repeat; but only h many steps, where h is the height of the tree
- ▶ Case 1 → Case 2 (special) → red black tree
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Performing Case 2 at most $\mathcal{O}(\log n)$ times and every other step at most once, we get a red black tree. Hence, $\mathcal{O}(\log n)$ re-colorings and at most 3 rotations.

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Splay Trees

Disadvantage of balanced search trees:

- worst case; no advantage for easy inputs
- additional memory required
- complicated implementation

Splay Trees:

- after access, an element is moved to the root (splay)
- repeated accesses are faster
- only amortized guarantee
- read-only queries change the tree

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– repeated accesses are faster

– only amortized guarantees

– local rotations change the tree

Splay Trees

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- additional memory required
- complicated implementation

Splay Trees:

– when accessing an element is moved to the root (splay op.)

– repeated accesses are faster

– only amortized guarantees

– need to carefully analyze the tree

Splay Trees

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- complicated implementation

Splay Trees:

What happens if elements are inserted in the order 1, 2, 3, 4, 5, 6, 7, 8, 9, 10?

What happens if elements are inserted in the order 10, 9, 8, 7, 6, 5, 4, 3, 2, 1?

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What happens if elements are inserted in the order 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1?

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Splay Trees:

- + after access, an element is moved to the root; $\text{splay}(x)$
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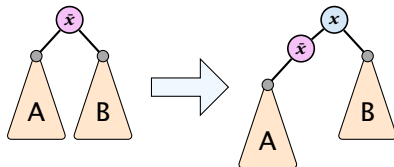
find(x)

- ▶ search for x according to a search tree
- ▶ let \tilde{x} be last element on search-path
- ▶ splay(\tilde{x})

Splay Trees

insert(x)

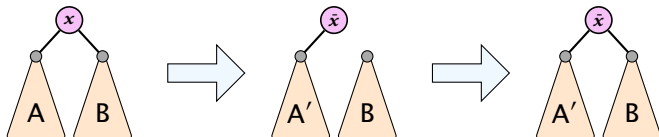
- ▶ search for x ; \bar{x} is last visited element during search (successor or predecessor of x)
- ▶ splay(\bar{x}) moves \bar{x} to the root
- ▶ insert x as new root



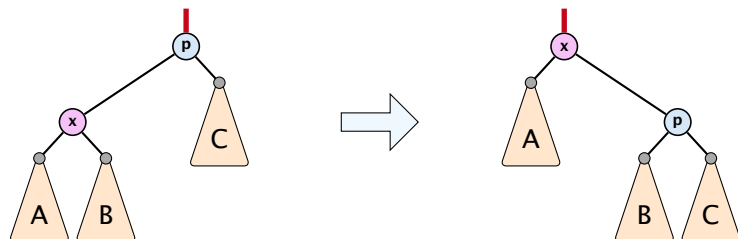
Splay Trees

delete(x)

- ▶ search for x ; splay(x); remove x
- ▶ search largest element \bar{x} in A
- ▶ splay(\bar{x}) (on subtree A)
- ▶ connect root of B as right child of \bar{x}



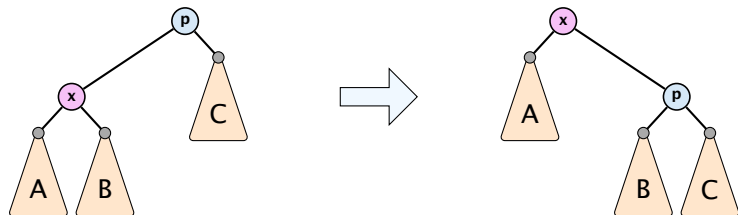
Move to Root



How to bring element to root?

- ▶ one (bad) option: `moveToRoot(x)`
- ▶ iteratively do rotation around parent of x until x is root
- ▶ if x is left child do right rotation otw. left rotation

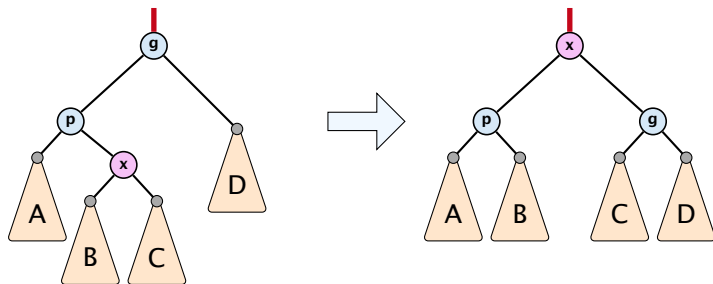
Splay: Zig Case



better option $\text{splay}(x)$:

- ▶ zig case: if x is child of root do left rotation or right rotation around parent

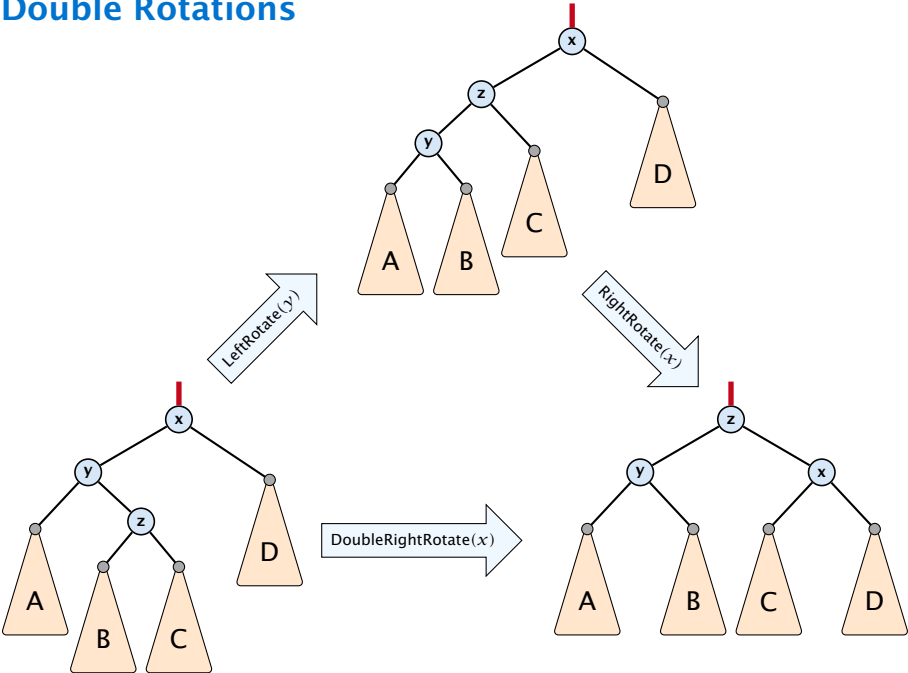
Splay: Zigzag Case



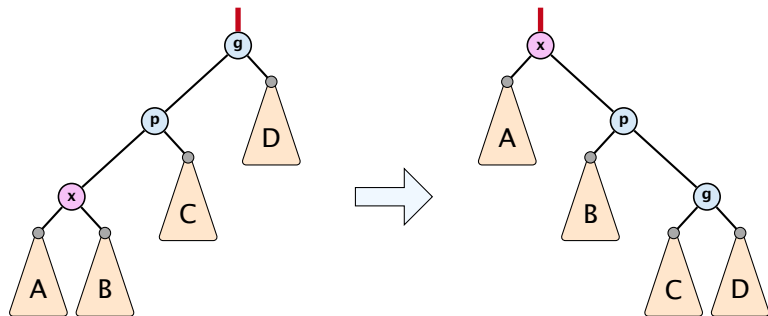
better option $\text{splay}(x)$:

- ▶ zigzag case: if x is right child and parent of x is left child (or x left child parent of x right child)
- ▶ do double right rotation around grand-parent (resp. double left rotation)

Double Rotations



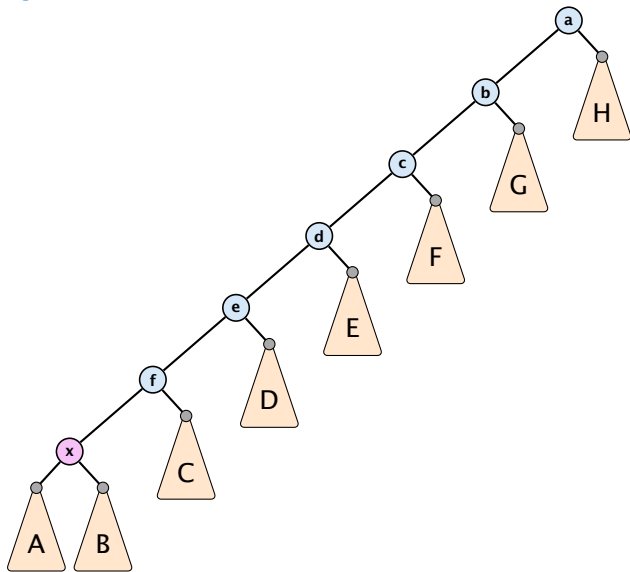
Splay: Zigzig Case



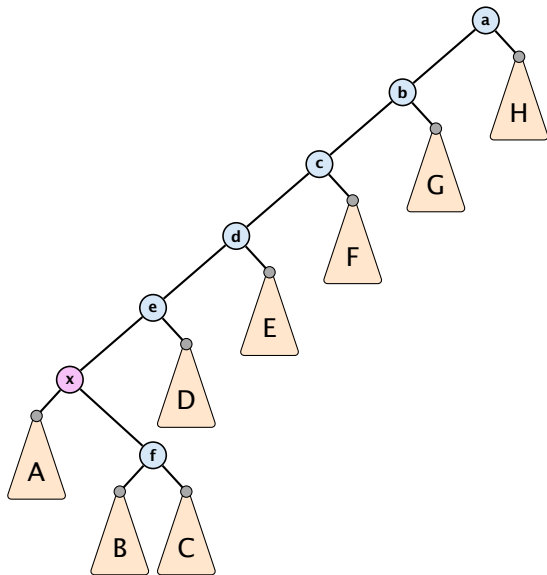
better option $\text{splay}(x)$:

- ▶ zigzig case: if x is left child and parent of x is left child (or x right child, parent of x right child)
- ▶ do right rotation around grand-parent followed by right rotation around parent (resp. left rotations)

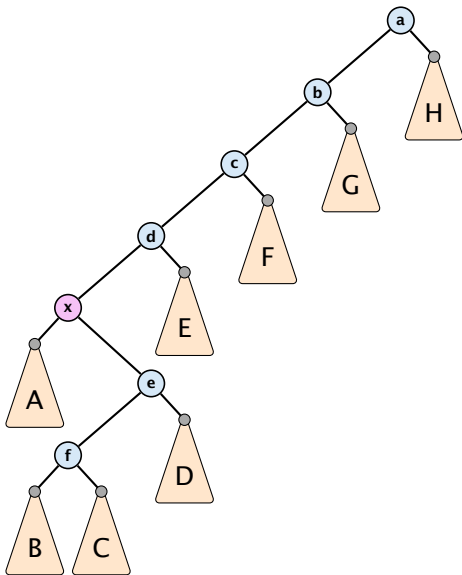
Splay vs. Move to Root



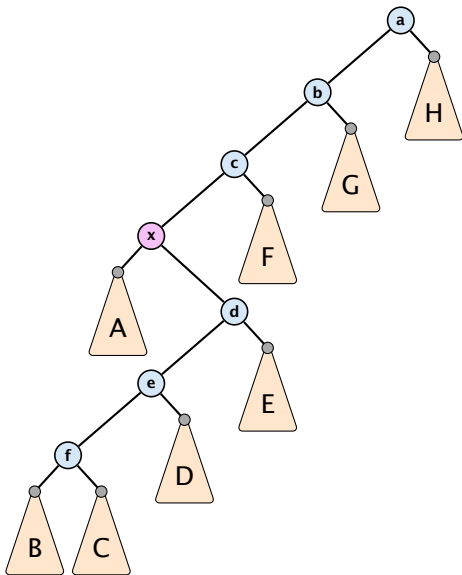
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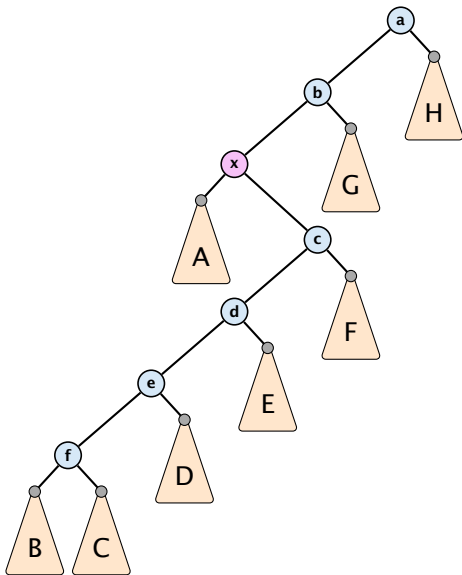
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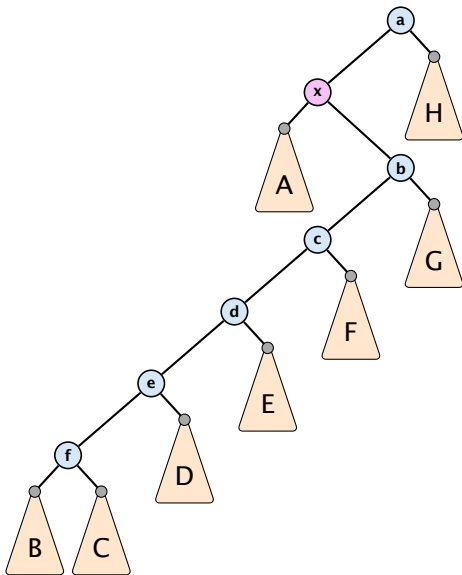
Splay vs. Move to Root



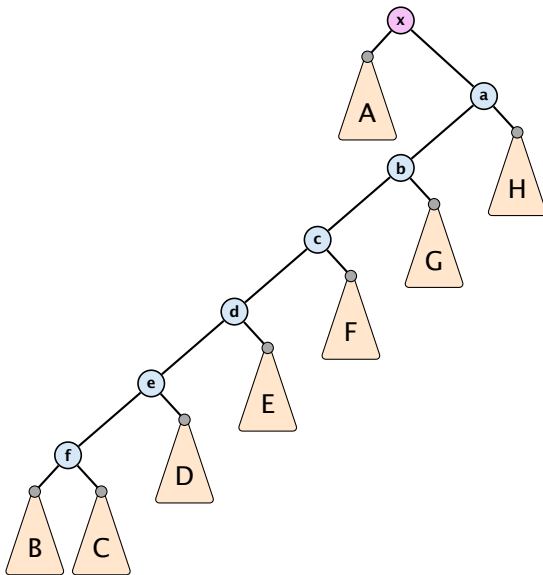
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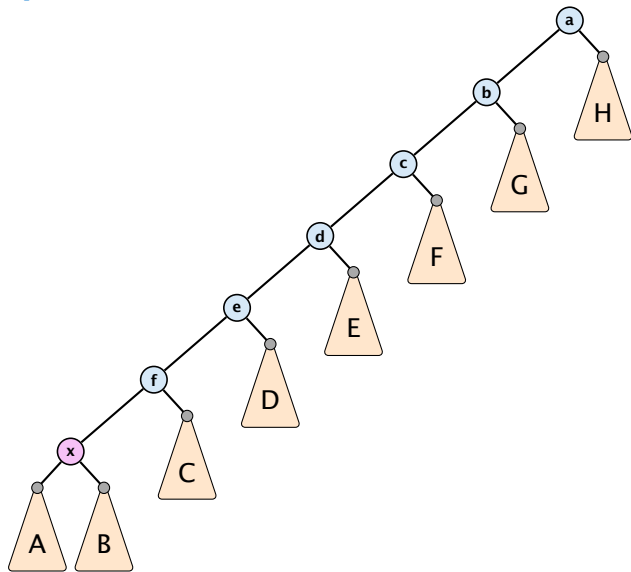
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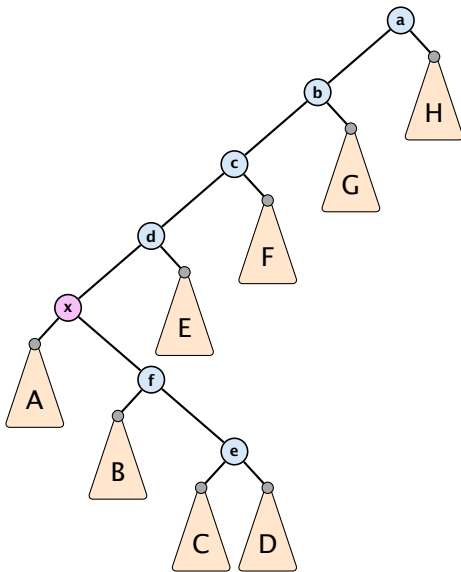
Splay vs. Move to Root



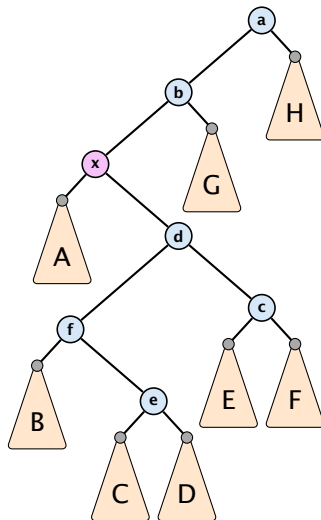
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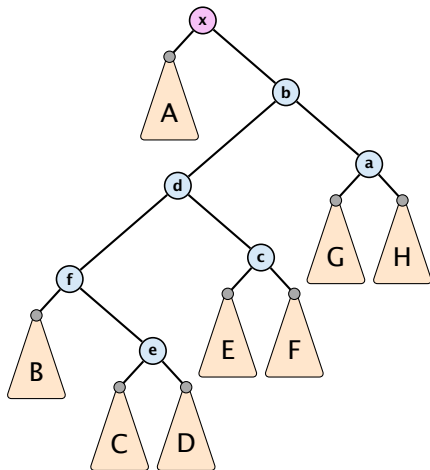
Splay vs. Move to Root



Splay vs. Move to Root



Splay vs. Move to Root



Static Optimality

Suppose we have a sequence of m find-operations. $\text{find}(x)$ appears h_x times in this sequence.

The cost of a **static** search tree T is:

$$\text{cost}(T) = m + \sum_x h_x \text{depth}_T(x)$$

The total cost for processing the sequence on a splay-tree is $\mathcal{O}(\text{cost}(T_{\min}))$, where T_{\min} is an **optimal static search tree**.

Dynamic Optimality

Let S be a sequence with m find-operations.

Let A be a data-structure based on a search tree:

- ▶ the cost for accessing element x is $1 + \text{depth}(x)$;
- ▶ after accessing x the tree may be re-arranged through rotations;

Conjecture:

A splay tree that only contains elements from S has cost $\mathcal{O}(\text{cost}(A, S))$, for processing S .

Lemma 15

*Splay Trees have an **amortized** running time of $\mathcal{O}(\log n)$ for all operations.*

Amortized Analysis

Definition 16

A data structure with operations $\text{op}_1(), \dots, \text{op}_k()$ has amortized running times t_1, \dots, t_k for these operations if the following holds.

Suppose you are given a sequence of operations (**starting with an empty data-structure**) that operate on at most n elements, and let k_i denote the number of occurrences of $\text{op}_i()$ within this sequence. Then the actual running time must be at most $\sum_i k_i \cdot t_i(n)$.

Potential Method

Introduce a potential for the data structure.

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Then

$$\sum_{i=1}^k c_i \leq \sum_{i=1}^k c_i + \Phi(D_k) - \Phi(D_0) = \sum_{i=1}^k \hat{c}_i$$

This means the amortized costs can be used to derive a bound on the total cost.

Example: Stack

Stack

- ▶ $S.\text{push}()$
- ▶ $S.\text{pop}()$
- ▶ $S.\text{multipop}(k)$: removes k items from the stack. If the stack currently contains less than k items it empties the stack.
- ▶ The user has to ensure that pop and multipop do not generate an underflow.

Actual cost:

- ▶ $S.\text{push}()$: cost 1.
- ▶ $S.\text{pop}()$: cost 1.
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$$\hat{C}_{\text{push}} = C_{\text{push}} + \Delta\Phi = 1 + 1 \leq 2 .$$

- ▶ $S.\text{pop}()$: cost

$$\hat{C}_{\text{pop}} = C_{\text{pop}} + \Delta\Phi = 1 - 1 \leq 0 .$$

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Incrementing a binary counter:

Consider a computational model where each bit-operation costs one time-unit.

Incrementing an n -bit binary counter may require to examine n -bits, and maybe change them.

Actual cost:

- ▶ Changing bit from 0 to 1: cost 1.
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Example: Binary Counter

Choose potential function $\Phi(x) = k$, where k denotes the number of ones in the binary representation of x .

Amortized cost:

Let z denote the number of consecutive ones in the least significant bit positions. An increment involves z operations, and one $\text{O}(1)$ operation.

Hence, the amortized cost is

Example: Binary Counter

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- ▶ Changing bit from 0 to 1:

$$\hat{C}_{0 \rightarrow 1} = C_{0 \rightarrow 1} + \Delta\Phi = 1 + 1 \leq 2 .$$

- ▶ Changing bit from 1 to 0:

$$\hat{C}_{1 \rightarrow 0} = C_{1 \rightarrow 0} + \Delta\Phi = 1 - 1 \leq 0 .$$

- ▶ **Increment:** Let k denotes the number of consecutive ones in the least significant bit-positions. An increment involves k (1 \rightarrow 0)-operations, and one (0 \rightarrow 1)-operation.

Hence, the amortized cost is $k\hat{C}_{1 \rightarrow 0} + \hat{C}_{0 \rightarrow 1} \leq 2$.

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Splay Trees

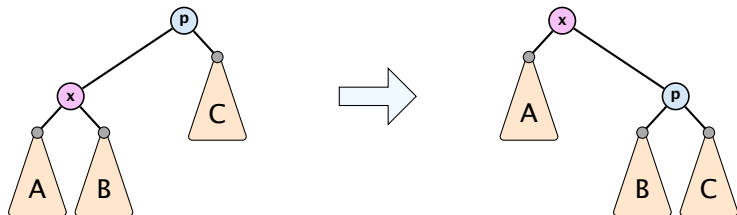
potential function for splay trees:

- ▶ size $s(x) = |T_x|$
- ▶ rank $r(x) = \log_2(s(x))$
- ▶ $\Phi(T) = \sum_{v \in T} r(v)$

amortized cost = real cost + potential change

The cost is essentially the cost of the splay-operation, which is 1 plus the number of rotations.

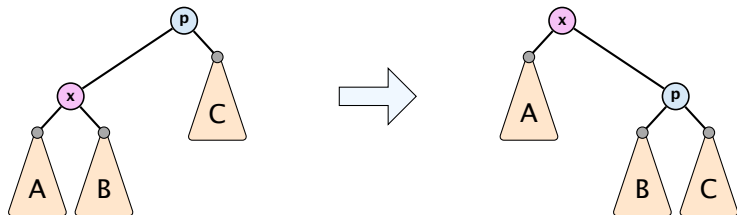
Splay: Zig Case



$$\begin{aligned}\Delta\Phi &= r'(x) + r'(p) - r(x) - r(p) \\ &= r'(p) - r(x) \\ &\leq r'(x) - r(x)\end{aligned}$$

$$\text{cost}_{\text{zig}} \leq 1 + 3(r'(x) - r(x))$$

Splay: Zig Case



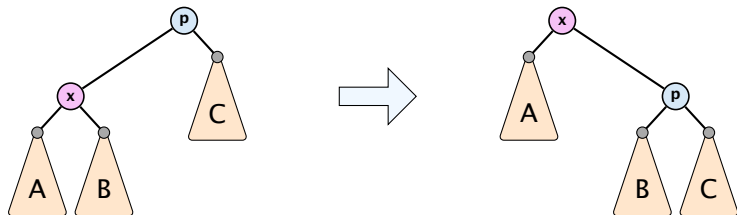
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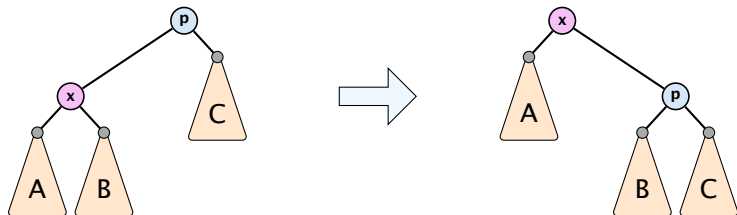
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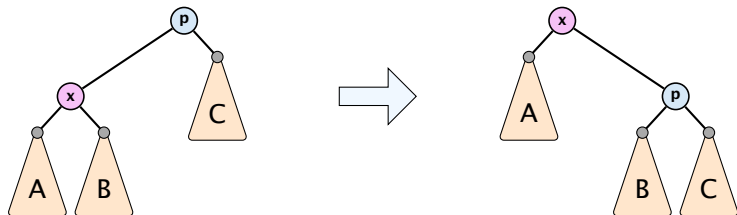
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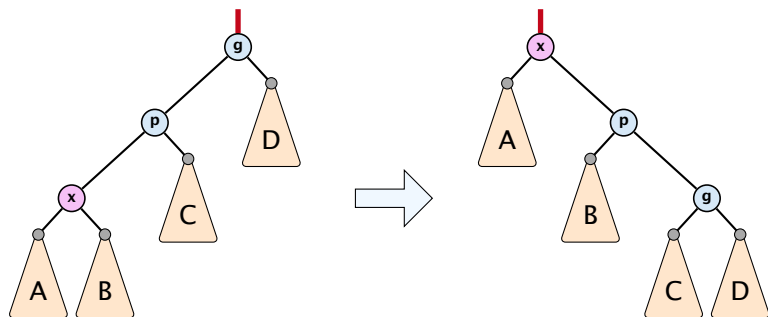
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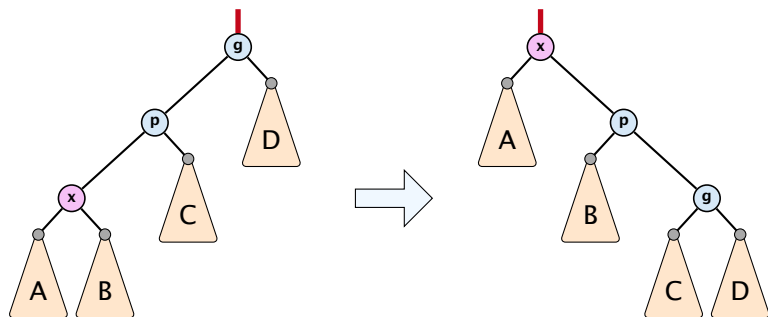
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Splay: Zigzig Case



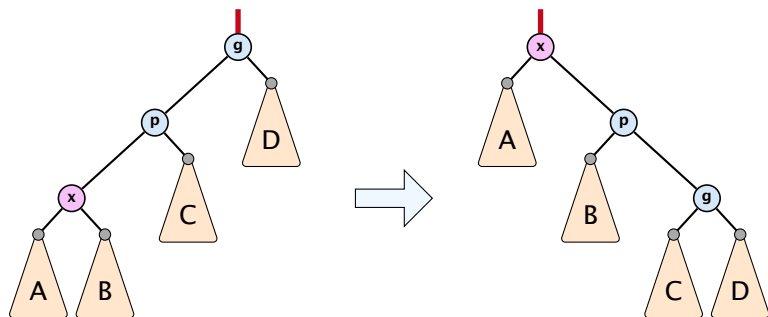
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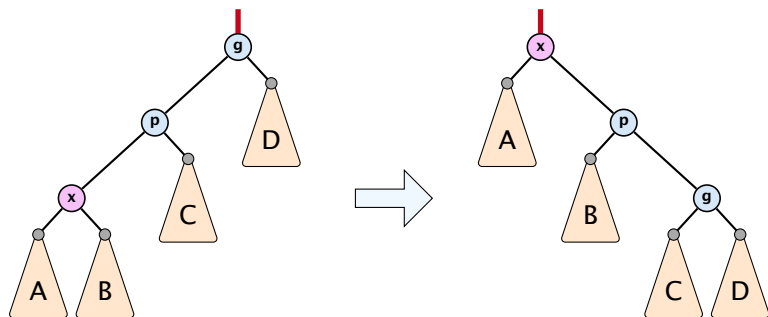
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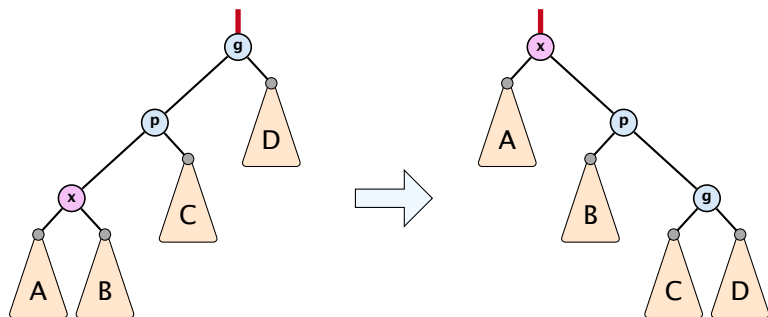
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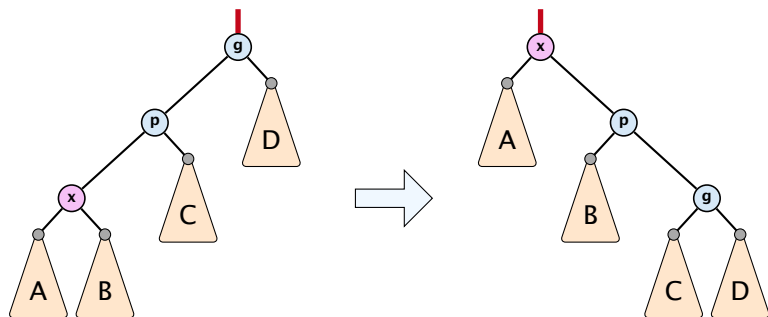
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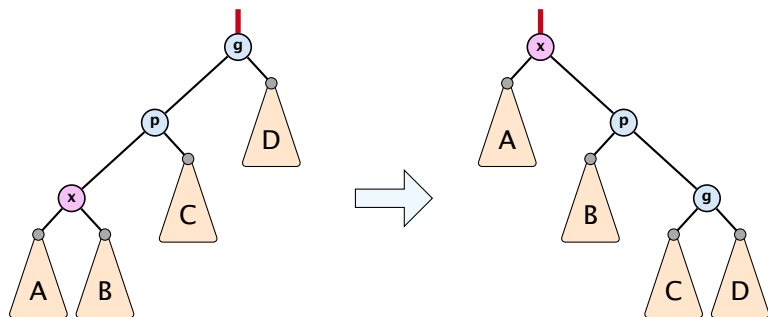
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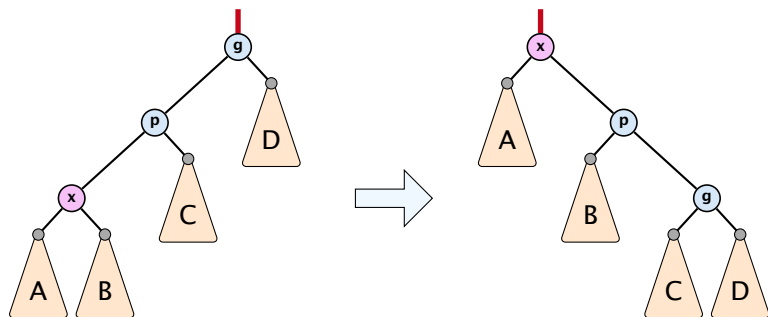
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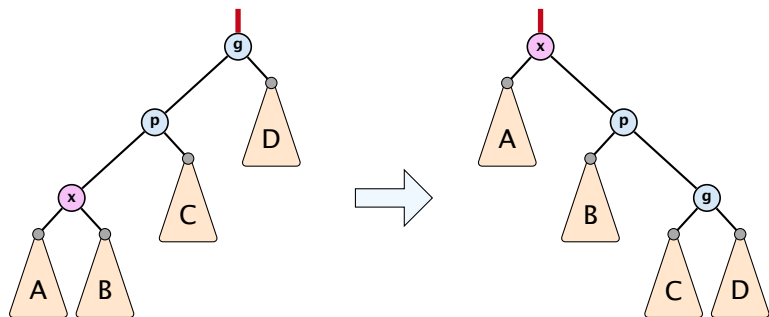
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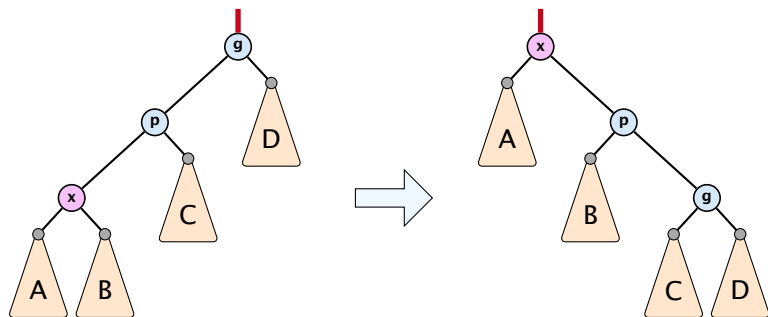
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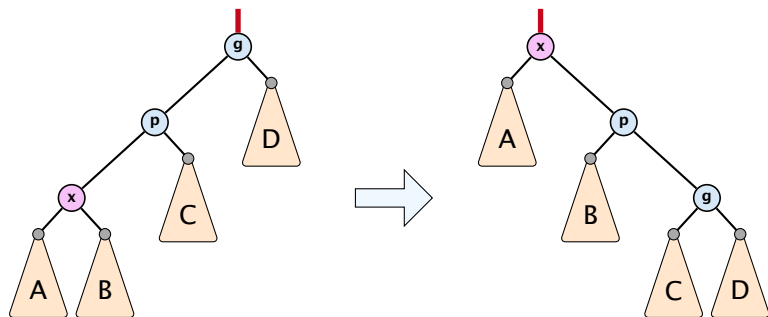
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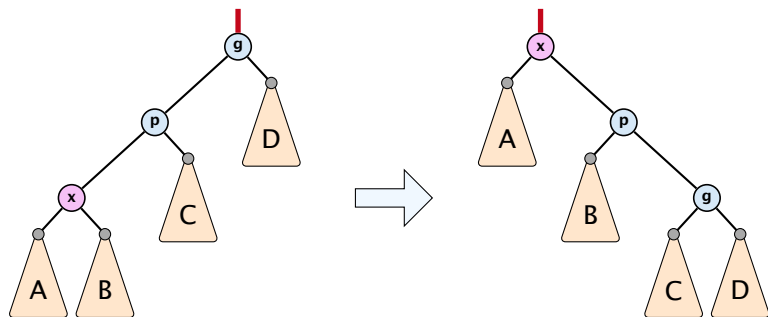
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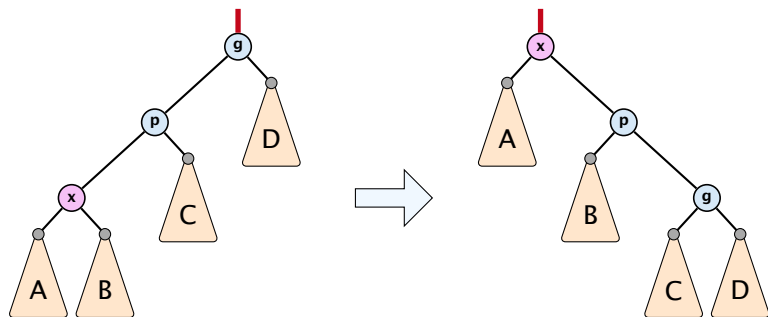
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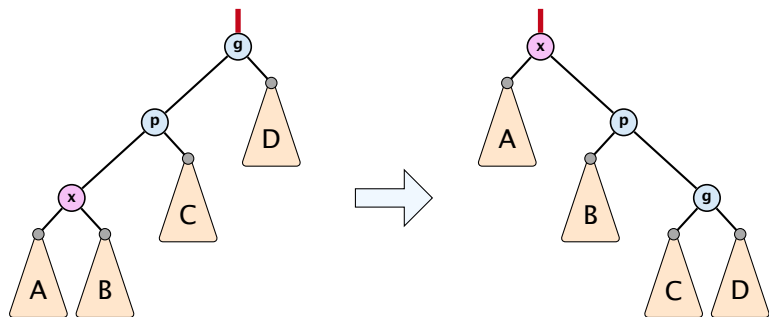
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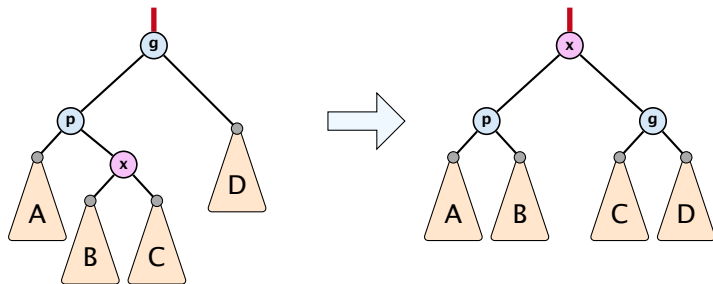
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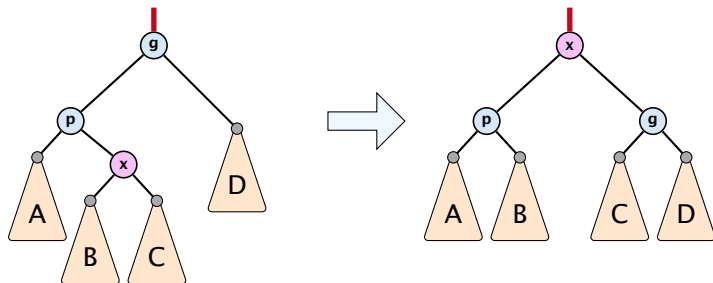
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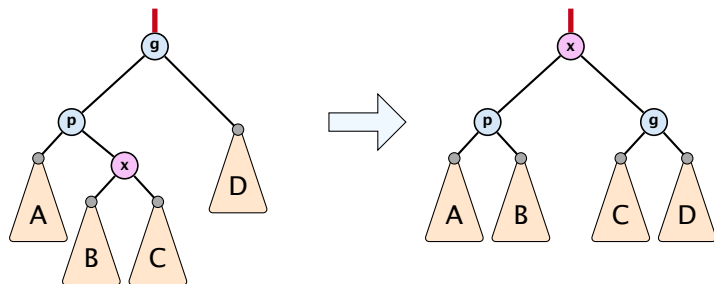
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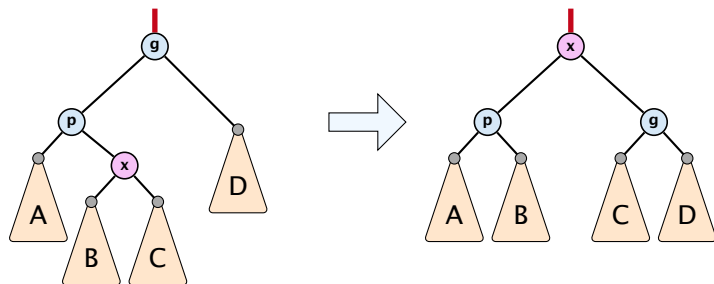
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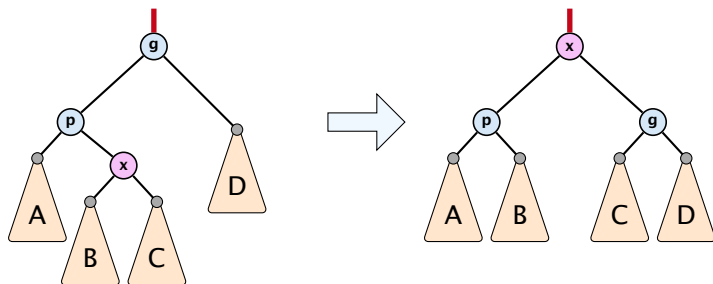
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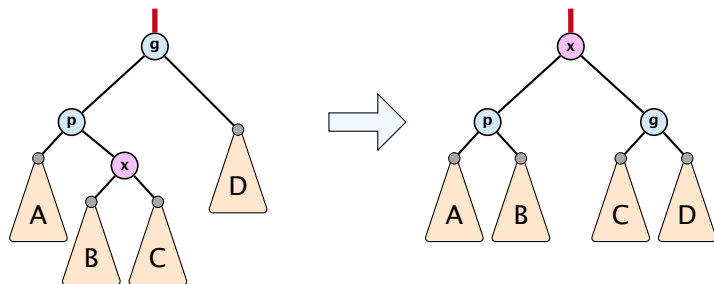
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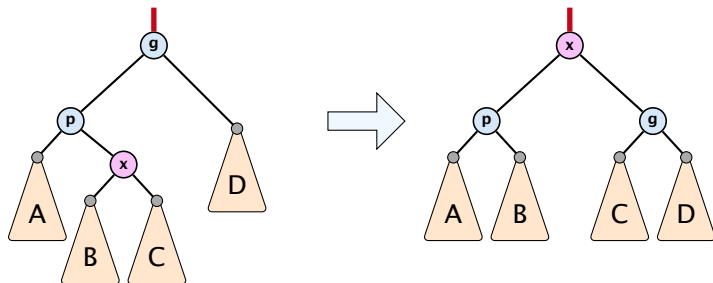
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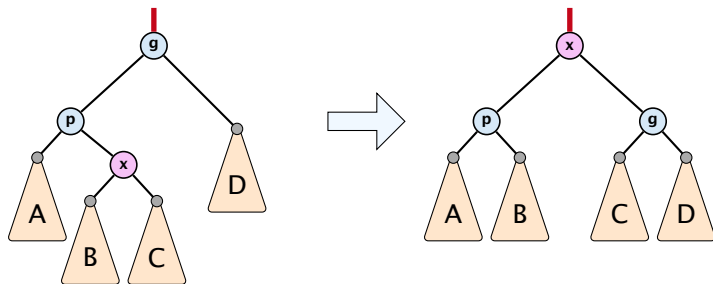
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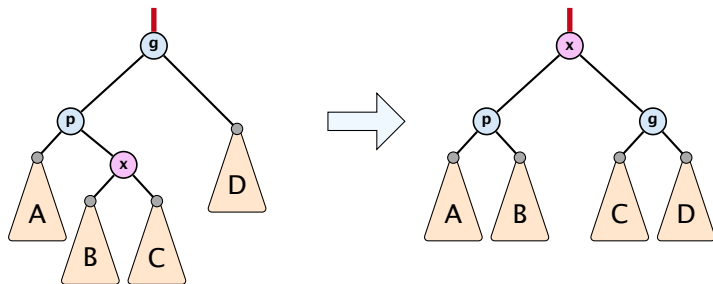
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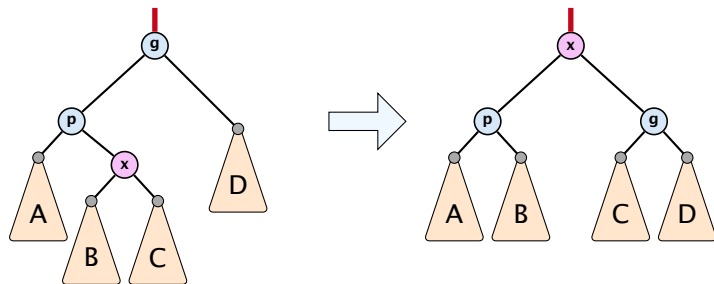
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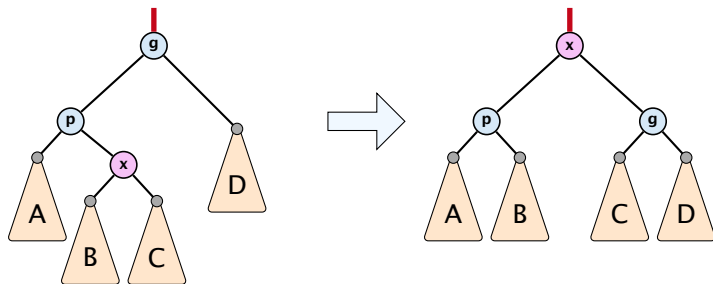
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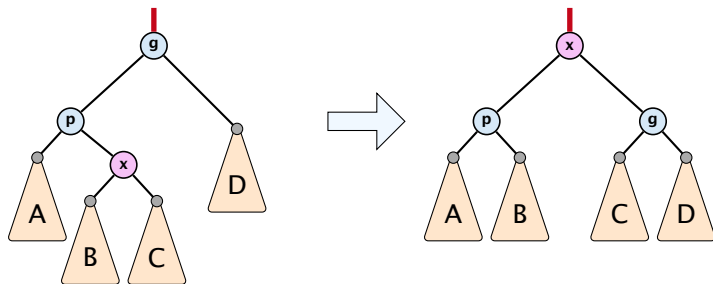
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Amortized cost of the whole splay operation:

$$\begin{aligned} &\leq 1 + 1 + \sum_{\text{steps } t} 3(r_t(x) - r_{t-1}(x)) \\ &= 2 + 3(r(\text{root}) - r_0(x)) \\ &\leq \mathcal{O}(\log n) \end{aligned}$$

7.4 Augmenting Data Structures

Suppose you want to develop a data structure with:

- ▶ **Insert(x)**: insert element x .
- ▶ **Search(k)**: search for element with key k .
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How to augment a data-structure

1. choose an underlying data-structure
2. determine additional information to be stored in the underlying structure
3. verify/show how the additional information can be maintained for the basic modifying operations on the underlying structure.
4. develop the new operations

- Of course, the above steps heavily depend on each other. For example it makes no sense to choose additional information to be stored (Step 2), and later realize that either the information cannot be maintained efficiently (Step 3) or is not sufficient to support the new operations (Step 4).
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Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time $\mathcal{O}(\log n)$.

1. We choose a red-black tree as the underlying data-structure.
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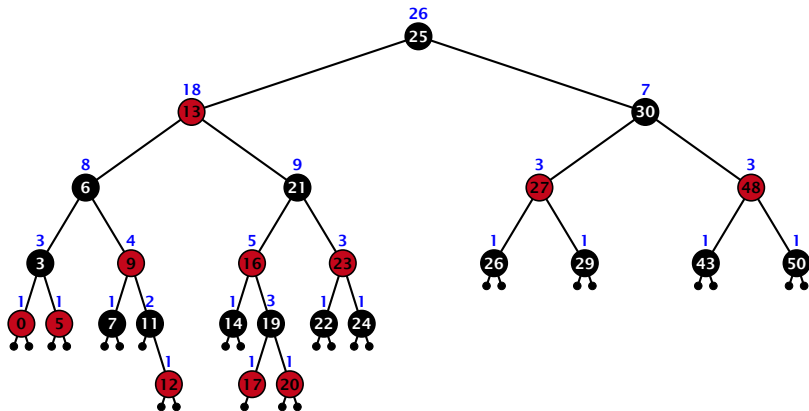
4. How does find-by-rank work?

Find-by-rank(k) := Select(root, k) with

Algorithm 11 Select(x, i)

```
1: if  $x = \text{null}$  then return error
2: if  $\text{left}[x] \neq \text{null}$  then  $r \leftarrow \text{left}[x].\text{size} + 1$  else  $r \leftarrow 1$ 
3: if  $i = r$  then return  $x$ 
4: if  $i < r$  then
5:     return Select( $\text{left}[x], i$ )
6: else
7:     return Select( $\text{right}[x], i - r$ )
```

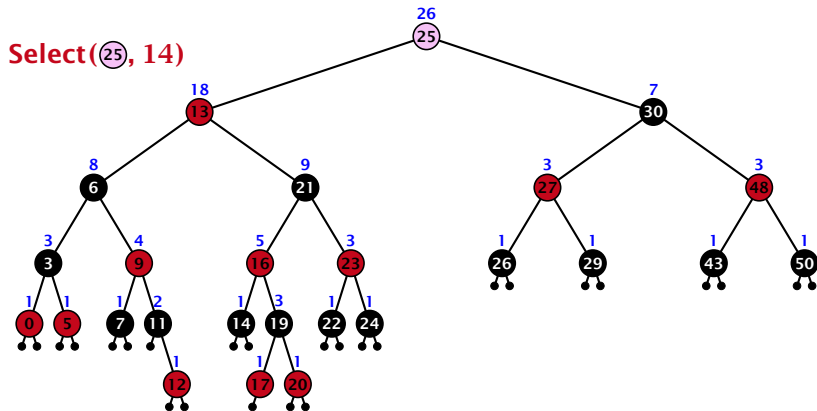
Select(x, i)



Find-by-rank:

- ▶ decide whether you have to proceed into the left or right sub-tree
- ▶ adjust the rank that you are searching for if you go right

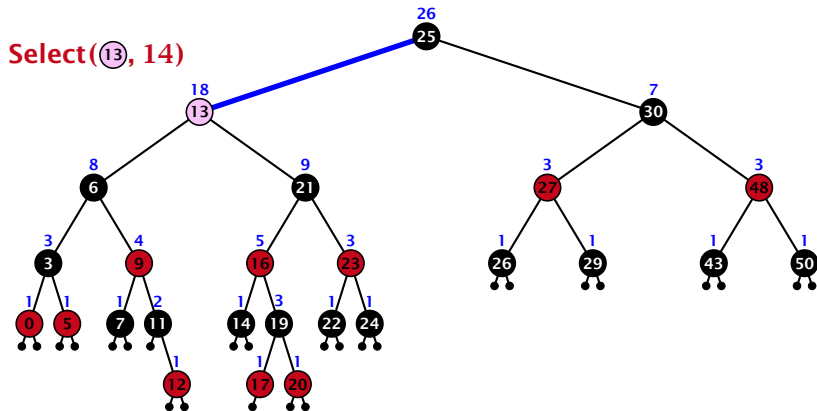
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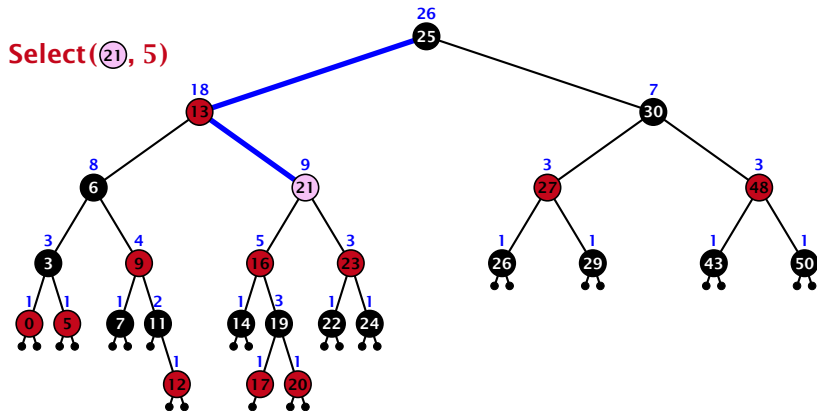
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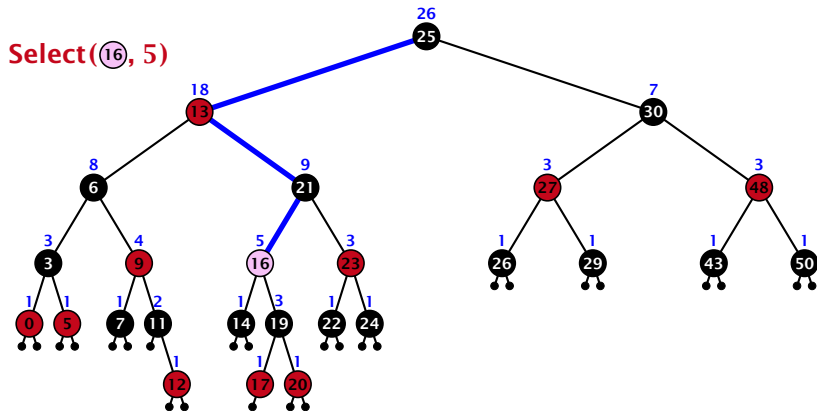
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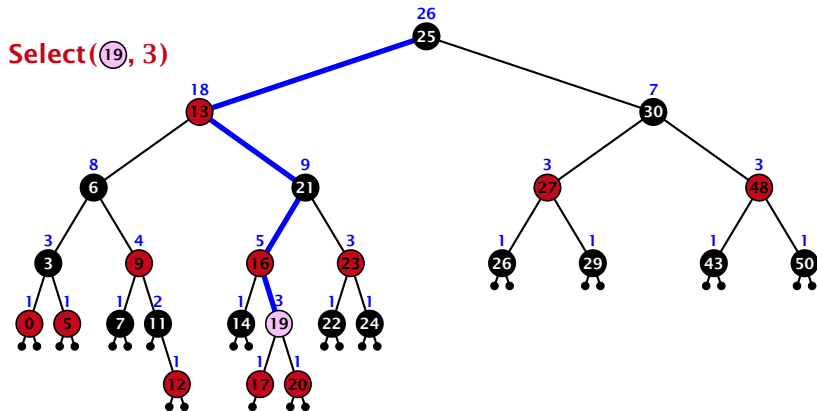
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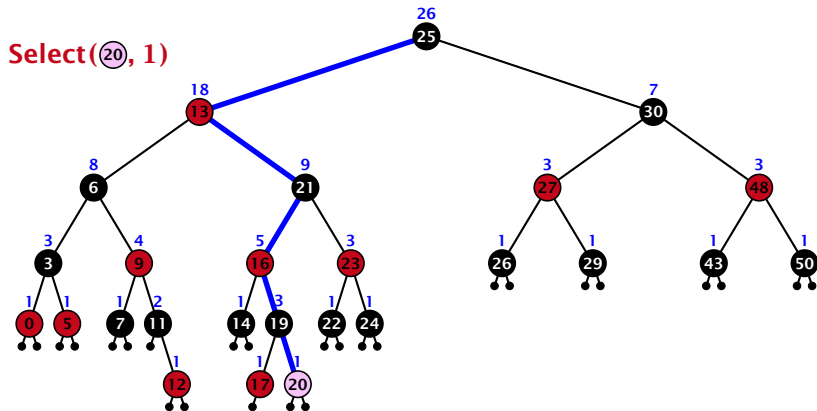
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Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time $\mathcal{O}(\log n)$.

3. How do we maintain information?

Search(k): Nothing to do.

Insert(x): When going down the search path increase the size field for each visited node. Maintain the size field during rotations.

Delete(x): Directly after splicing out a node traverse the path from the spliced out node upwards, and decrease the size counter on every node on this path. Maintain the size field during rotations.

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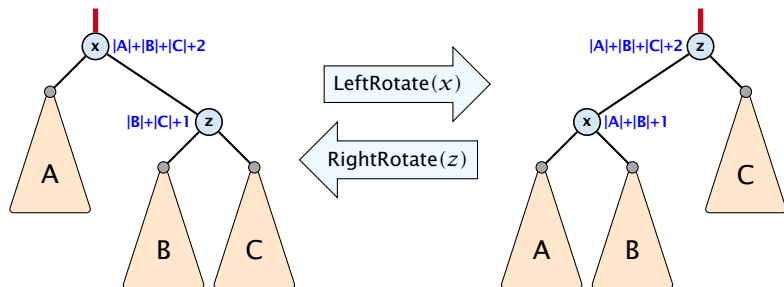
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Rotations

The only operation during the fix-up procedure that alters the tree and requires an update of the size-field:



The nodes x and z are the only nodes changing their size-fields.

The new size-fields can be computed **locally** from the size-fields of the children.

7.5 (a, b)-trees

Definition 17

For $b \geq 2a - 1$ an (a, b) -tree is a search tree with the following properties

1. all leaves have the same distance to the root
2. every internal non-root vertex v has at least a and at most b children
3. the root has degree at least 2 if the tree is non-empty
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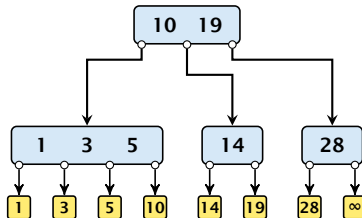
Each internal node v with $d(v)$ children stores $d - 1$ keys k_1, \dots, k_{d-1} . The i -th subtree of v fulfills

$$k_{i-1} < \text{key in } i\text{-th sub-tree} \leq k_i ,$$

where we use $k_0 = -\infty$ and $k_d = \infty$.

7.5 (a, b)-trees

Example 18



7.5 (a, b)-trees

Variants

- ▶ The dummy leaf element may not exist; it only makes implementation more convenient.
- ▶ Variants in which $b = 2a$ are commonly referred to as B -trees.
- ▶ A B -tree usually refers to the variant in which keys and data are stored at internal nodes.
- ▶ A B^+ tree stores the data only at leaf nodes as in our definition. Sometimes the leaf nodes are also connected in a linear list data structure to speed up the computation of successors and predecessors.
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Lemma 19

Let T be an (a, b) -tree for $n > 0$ elements (i.e., $n + 1$ leaf nodes) and height h (number of edges from root to a leaf vertex). Then

1. $2a^{h-1} \leq n + 1 \leq b^h$
2. $\log_b(n + 1) \leq h \leq 1 + \log_a\left(\frac{n+1}{2}\right)$

Proof.

The root has degree at least 2 and at most b children.

Each child has at least 1 and at most b children of its own.

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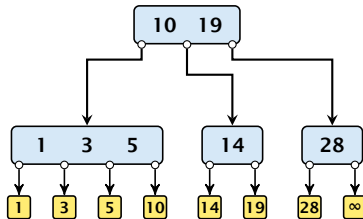
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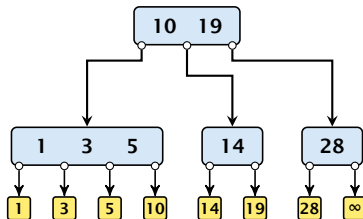


Search



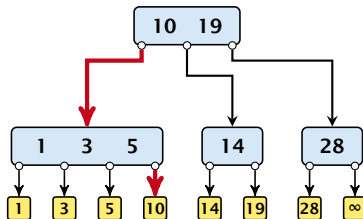
Search

Search(8)



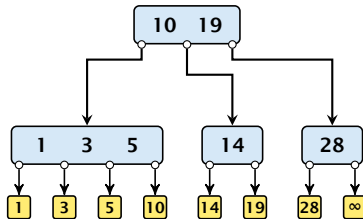
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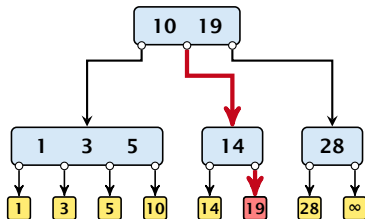
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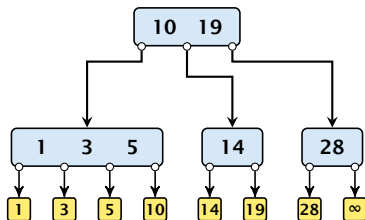


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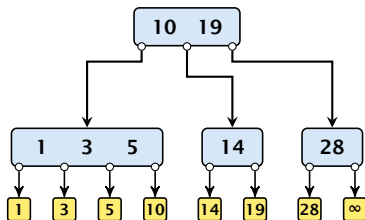


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Time: $\mathcal{O}(b \cdot h) = \mathcal{O}(b \cdot \log n)$, if the individual nodes are organized as linear lists.

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Insert element x :

- ▶ Follow the path as if searching for $\text{key}[x]$.
- ▶ If this search ends in leaf ℓ , insert x before this leaf.
- ▶ For this add $\text{key}[x]$ to the key-list of the last internal node v on the path.
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Rebalance(v):

- ▶ Let k_i , $i = 1, \dots, b$ denote the keys stored in v .
- ▶ Let $j := \lfloor \frac{b+1}{2} \rfloor$ be the middle element.
- ▶ Create two nodes v_1 , and v_2 . v_1 gets all keys k_1, \dots, k_{j-1} and v_2 gets keys k_{j+1}, \dots, k_b .
- ▶ Both nodes get at least $\lfloor \frac{b-1}{2} \rfloor$ keys, and have therefore degree at least $\lfloor \frac{b-1}{2} \rfloor + 1 \geq a$ since $b \geq 2a - 1$.
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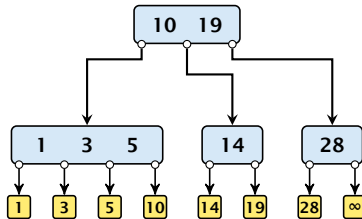
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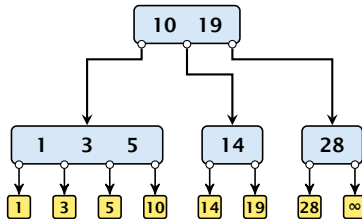
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Insert



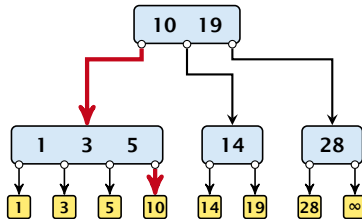
Insert

Insert(8)



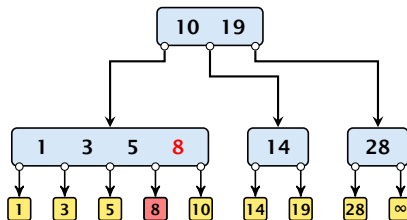
Insert

Insert(8)



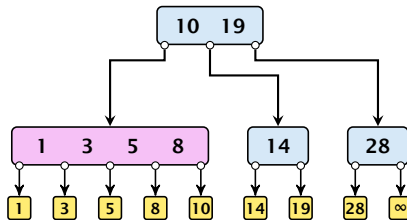
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Insert(8)



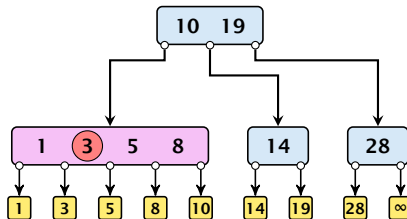
Insert

Insert(8)

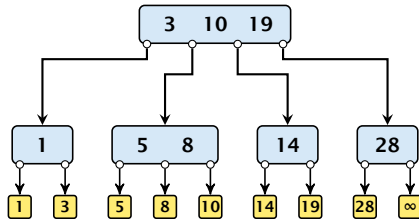


Insert

Insert(8)

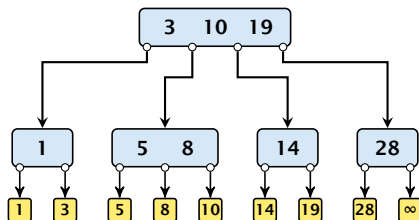


Insert



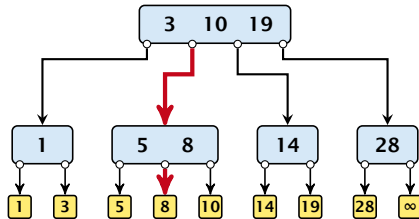
Insert

Insert(6)



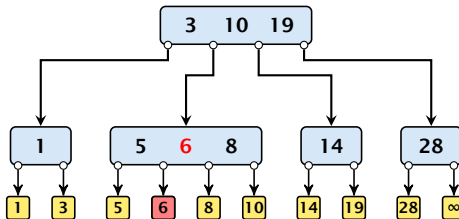
Insert

Insert(6)



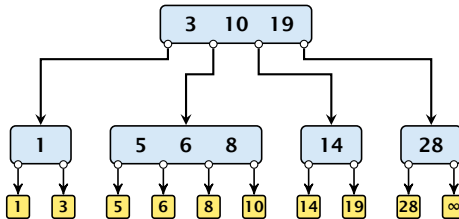
Insert

Insert(6)



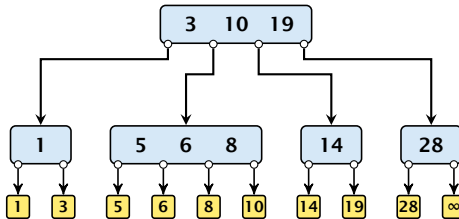
Insert

Insert(6)



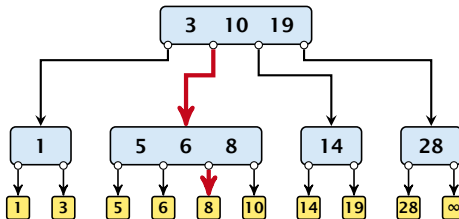
Insert

Insert(7)



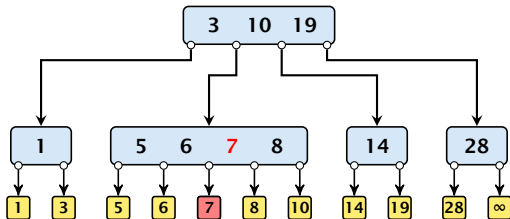
Insert

Insert(7)



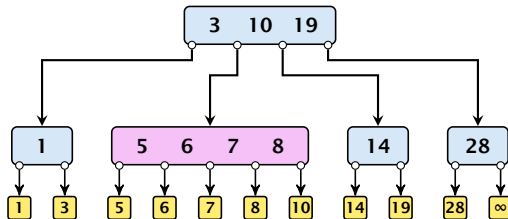
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Insert(7)



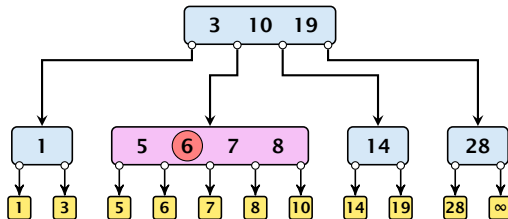
Insert

Insert(7)



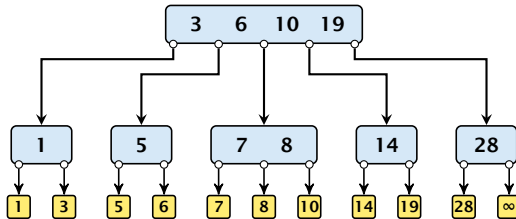
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Insert(7)



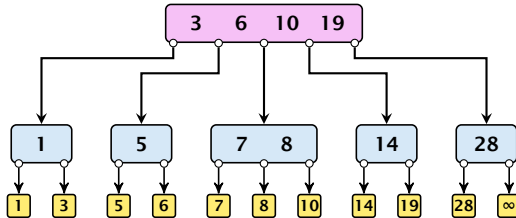
Insert

Insert(7)



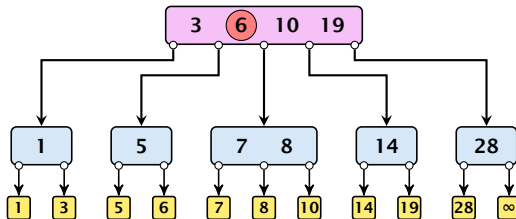
Insert

Insert(7)



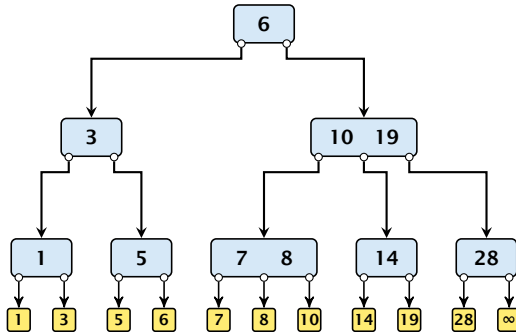
Insert

Insert(7)



Insert

Insert(7)



Delete

Delete element x (pointer to leaf vertex):

- ▶ Let v denote the parent of x . If $\text{key}[x]$ is contained in v , remove the key from v , and delete the leaf vertex.
- ▶ Otherwise delete the key of the predecessor of x from v ; delete the leaf vertex; and replace the occurrence of $\text{key}[x]$ in internal nodes by the predecessor key. (Note that it appears in exactly one internal vertex).
- ▶ If now the number of keys in v is below $a - 1$ perform $\text{Rebalance}'(v)$.

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Delete

Rebalance' (v):

- ▶ If there is a neighbour of v that has at least a keys take over the largest (if right neighbor) or smallest (if left neighbour) and the corresponding sub-tree.
- ▶ If not: merge v with one of its neighbours.
- ▶ The merged node contains at most $(a - 2) + (a - 1) + 1$ keys, and has therefore at most $2a - 1 \leq b$ successors.
- ▶ Then rebalance the parent.
- ▶ During this process the root may become empty. In this case the root is deleted and the height of the tree decreases.

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Rebalance' (v):

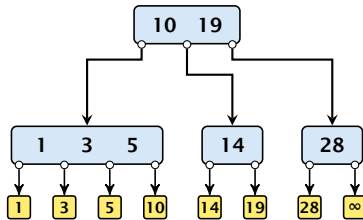
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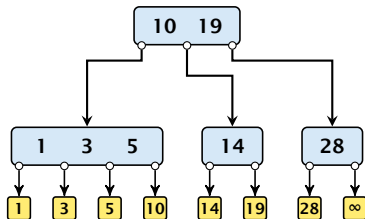
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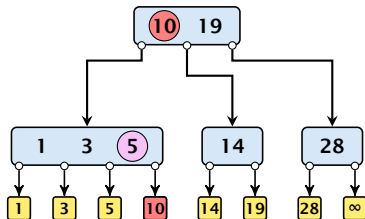
Delete

Delete(10)



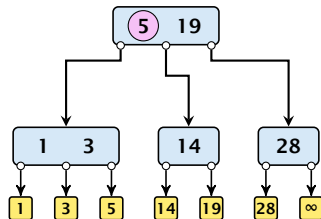
Delete

Delete(10)

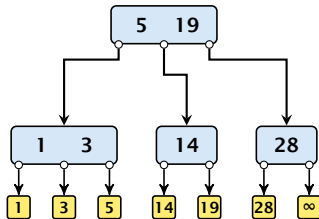


Delete

Delete(10)

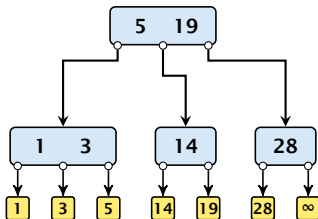


Delete



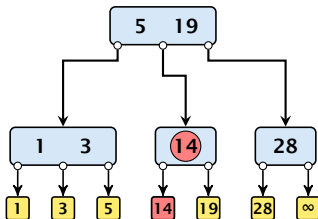
Delete

Delete(14)



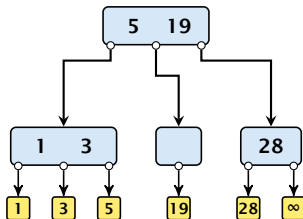
Delete

Delete(14)



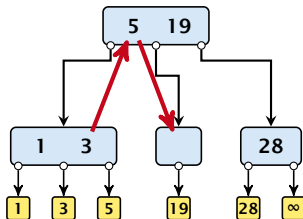
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Delete(14)



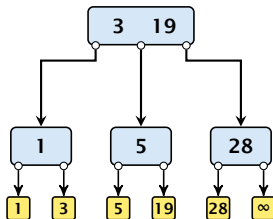
Delete

Delete(14)

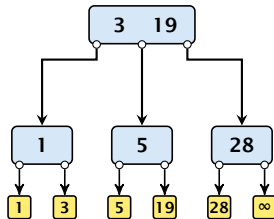


Delete

Delete(14)

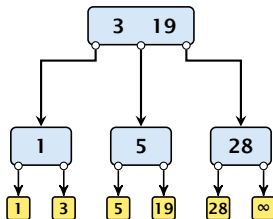


Delete



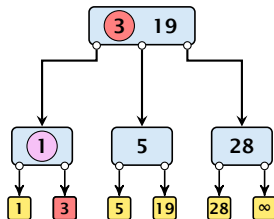
Delete

Delete(3)



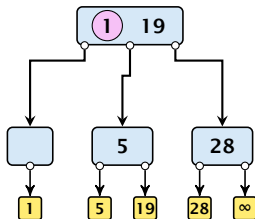
Delete

Delete(3)



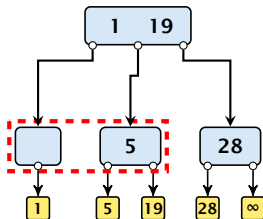
Delete

Delete(3)



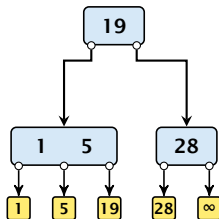
Delete

Delete(3)

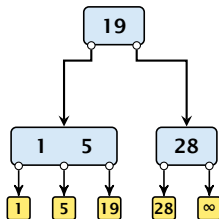


Delete

Delete(3)

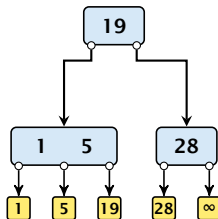


Delete



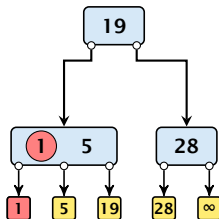
Delete

Delete(1)



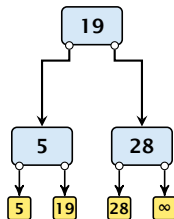
Delete

Delete(1)

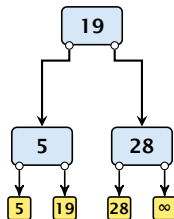


Delete

Delete(1)

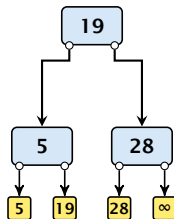


Delete



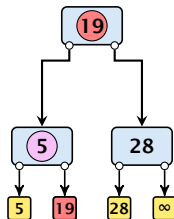
Delete

Delete(19)



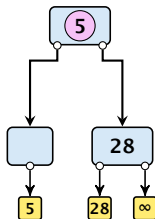
Delete

Delete(19)



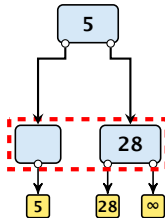
Delete

Delete(19)



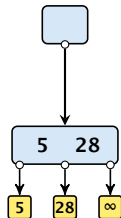
Delete

Delete(19)



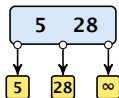
Delete

Delete(19)



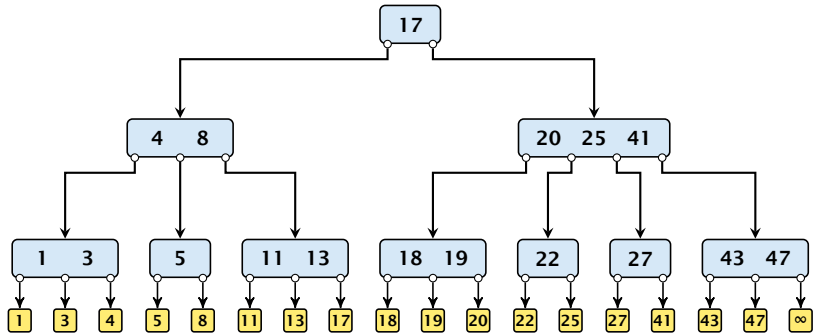
Delete

Delete(19)



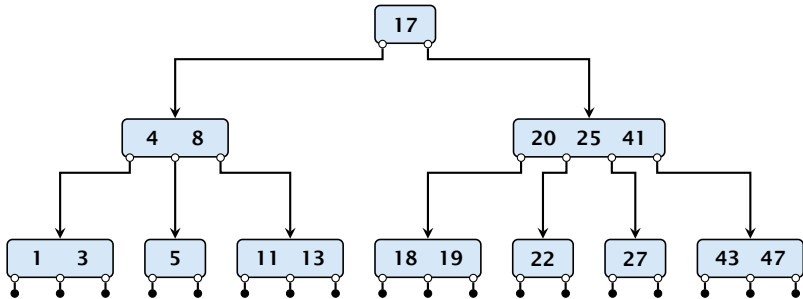
(2, 4)-trees and red black trees

There is a close relation between red-black trees and (2,4)-trees:



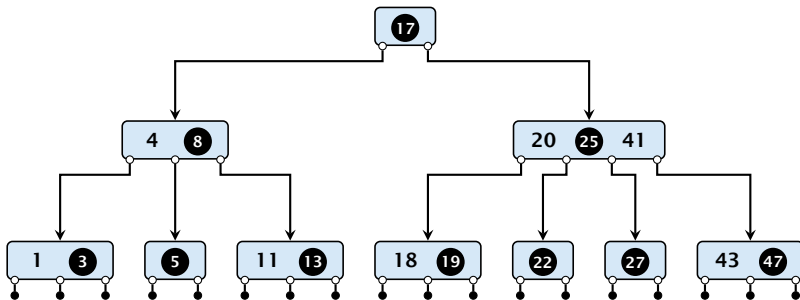
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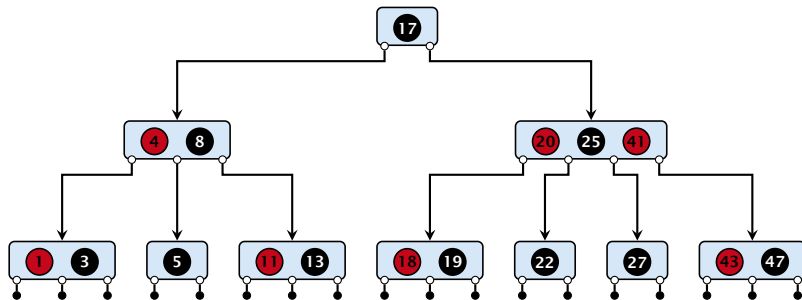
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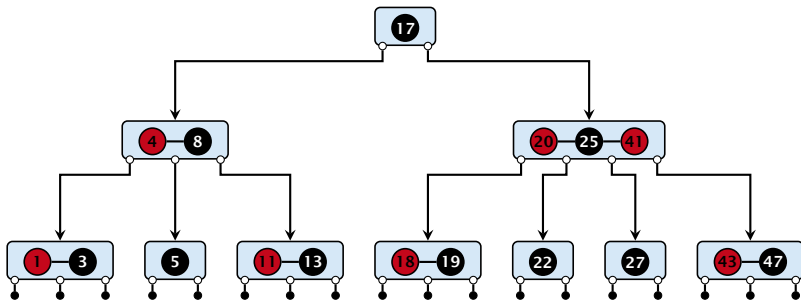
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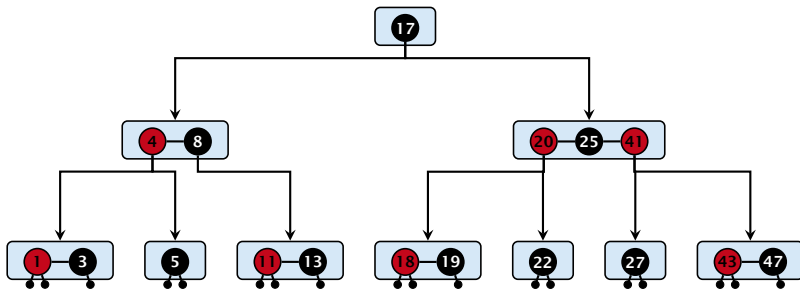
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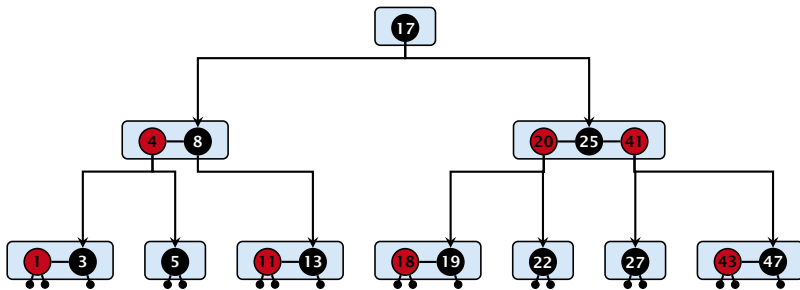
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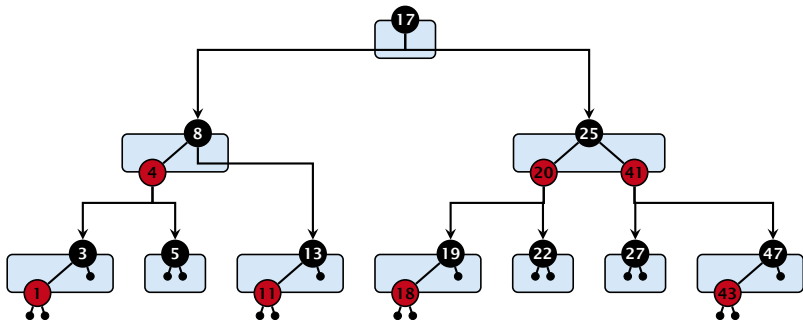
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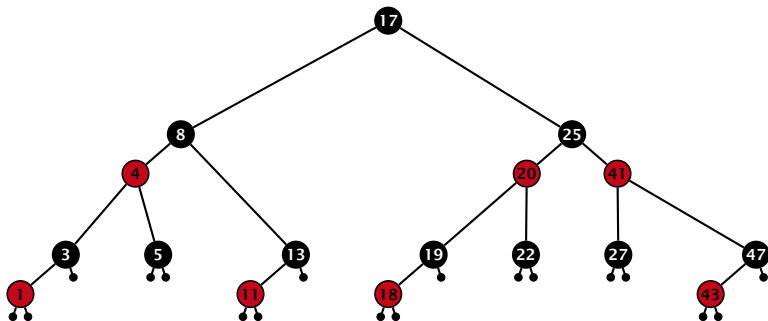
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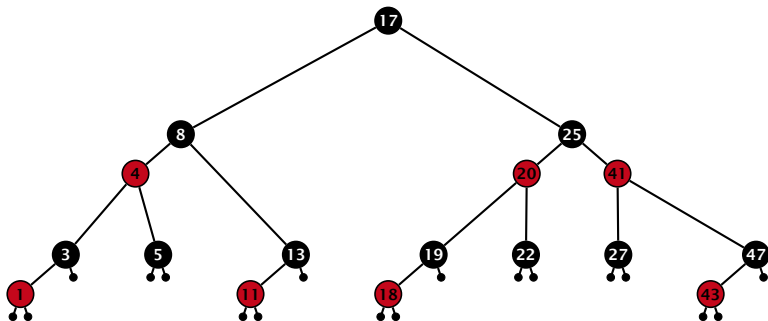
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(2, 4)-trees and red black trees

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Note that this correspondence is not unique. In particular, there are different red-black trees that correspond to the same (2, 4)-tree.

7.6 Skip Lists

Why do we not use a list for implementing the ADT Dynamic Set?

- ▶ time for search $\Theta(n)$
- ▶ time for insert $\Theta(n)$ (dominated by searching the item)
- ▶ time for delete $\Theta(1)$ if we are given a handle to the object, otw. $\Theta(n)$



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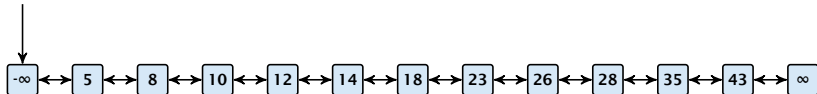
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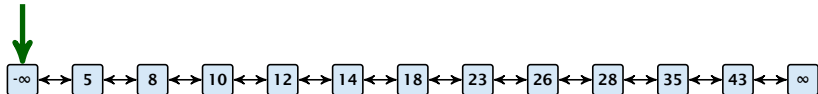
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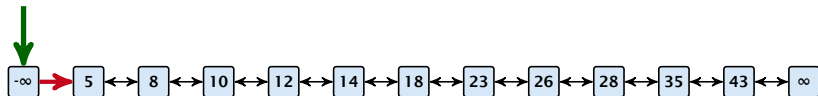
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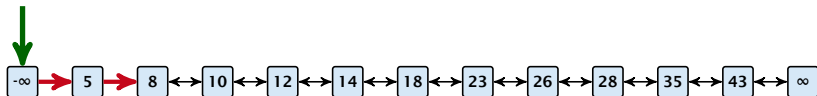
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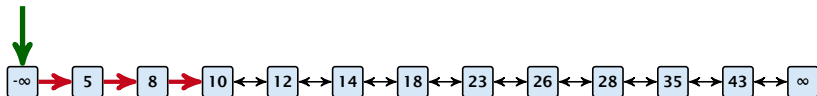
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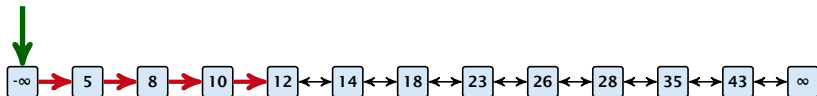
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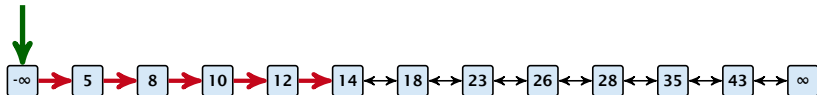
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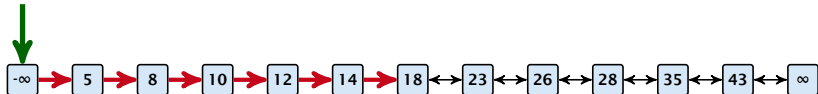
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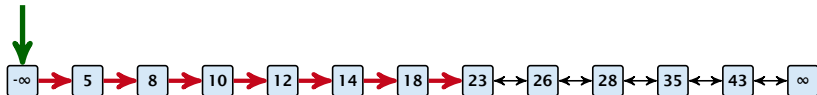
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- ▶ time for insert $\Theta(n)$ (dominated by searching the item)
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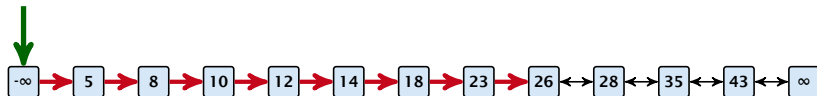
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7.6 Skip Lists

How can we improve the search-operation?

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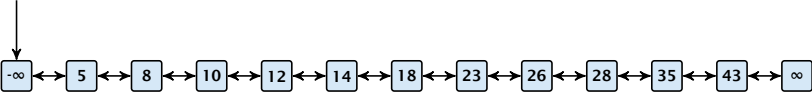
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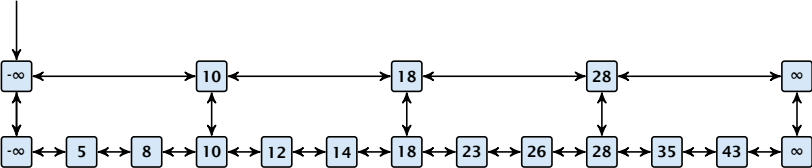
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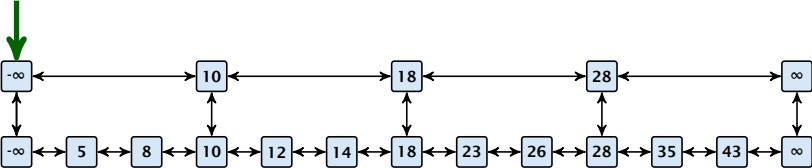
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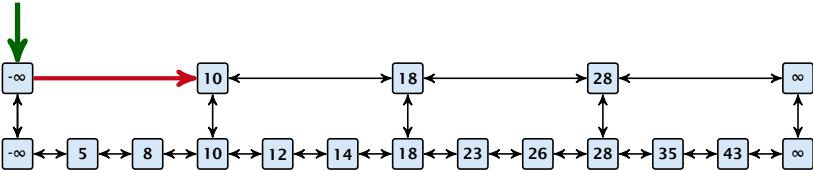
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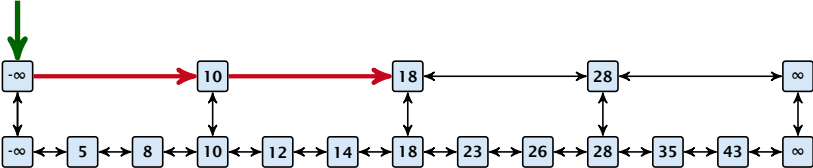
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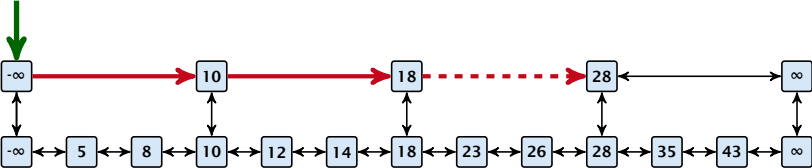
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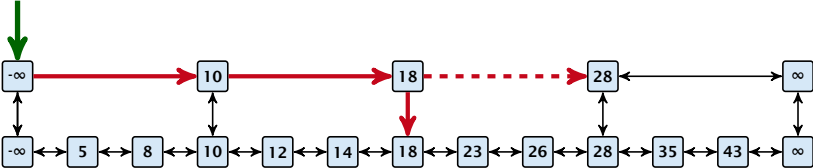
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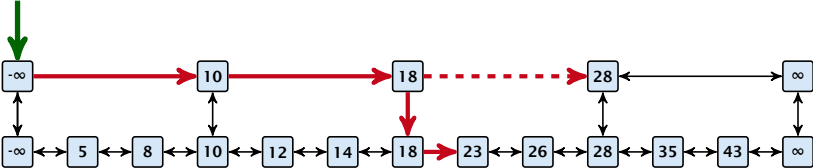
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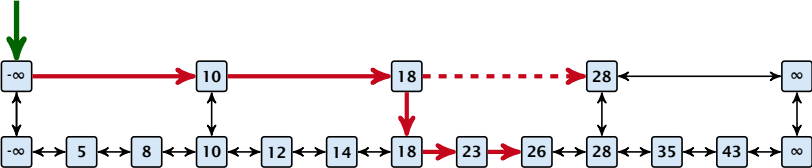
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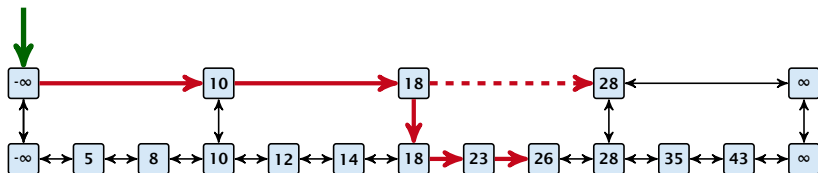
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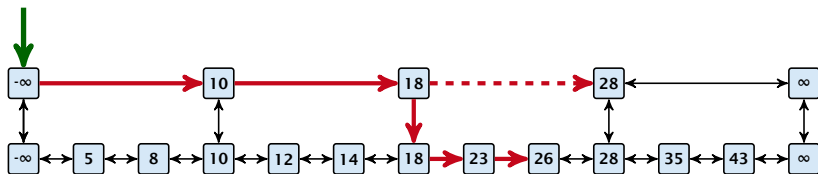


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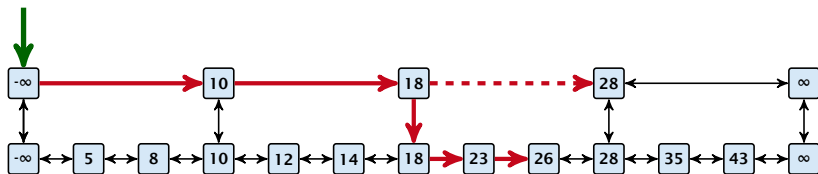
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Choose $|L_1| = \sqrt{n}$. Then search time $\Theta(\sqrt{n})$.

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Add more express lanes. Lane L_i contains roughly every $\frac{L_{i-1}}{L_i}$ -th item from list L_{i-1} .

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Choose ratios between list-lengths evenly, i.e., $\frac{|L_{i-1}|}{|L_i|} = r$, and, hence, $L_k \approx r^{-k}n$.

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Choosing $k = \Theta(\log n)$ gives a logarithmic running time.

7.6 Skip Lists

How to do insert and delete?

How many times do we have to traverse the list to find the position of elements to insert or delete? How many times do we have to reorganize the list?

Use randomization instead!

7.6 Skip Lists

How to do insert and delete?

- ▶ If we want that in L_i we always skip over roughly the same number of elements in L_{i-1} an insert or delete may require a lot of re-organisation.

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Insert:

- ▶ A search operation gives you the insert position for element x in every list.
- ▶ Flip a coin until it shows head, and record the number $t \in \{1, 2, \dots\}$ of trials needed.
- ▶ Insert x into lists L_0, \dots, L_{t-1} .

Delete:

- ▶ You get all predecessors via backward pointers.
- ▶ Delete x in all lists it actually appears in.

The time for both operations is dominated by the search time.

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Find all predecessor and successor pointers.

Remove all nodes which appear in it.

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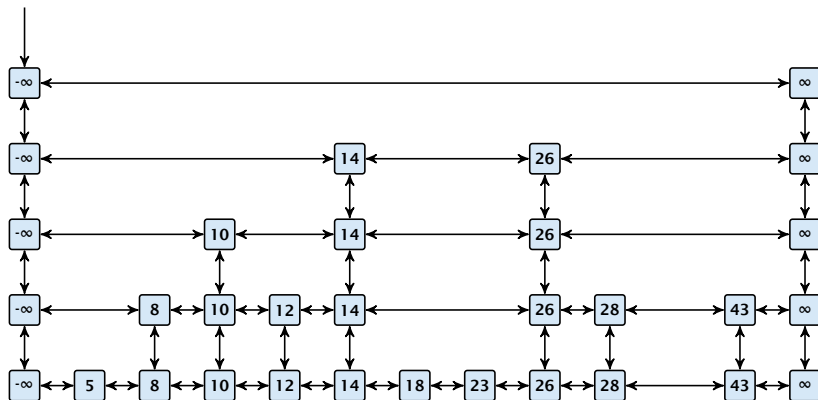
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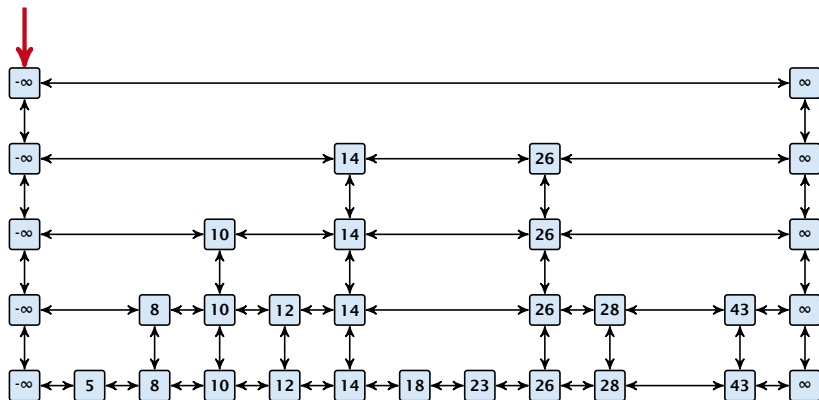
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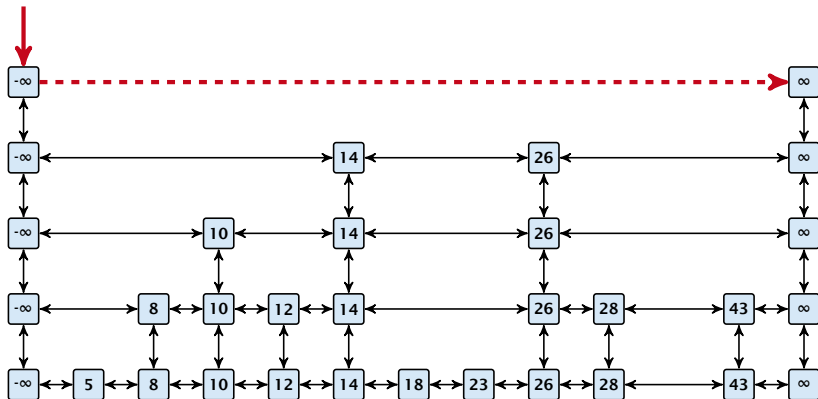
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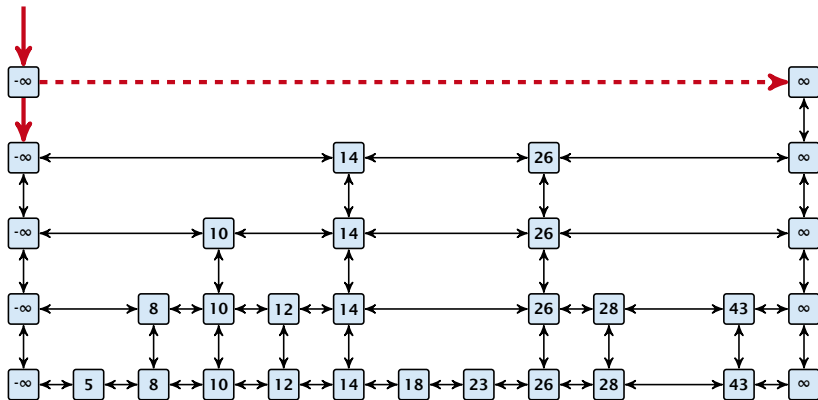
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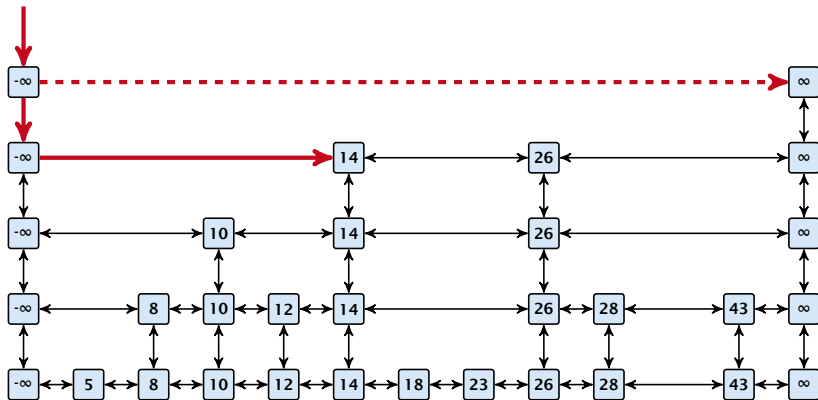
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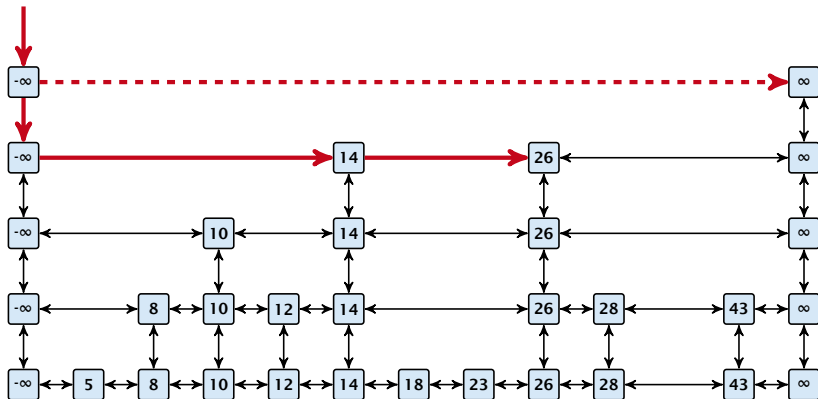
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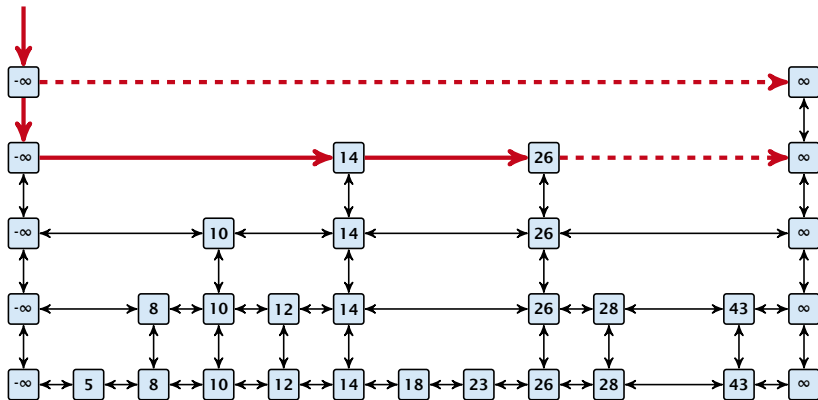
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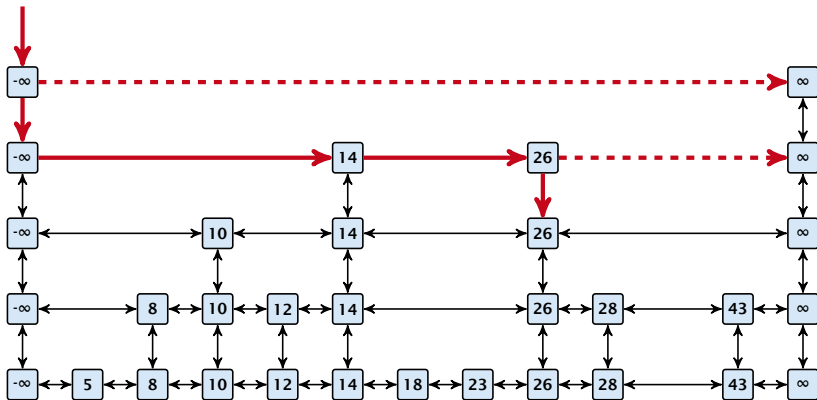
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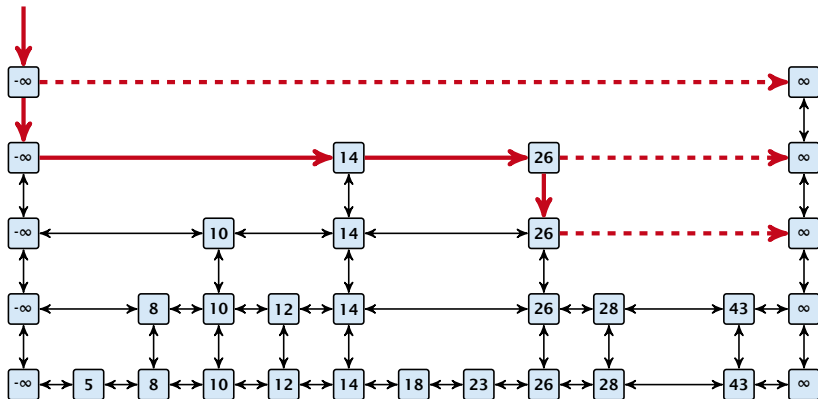
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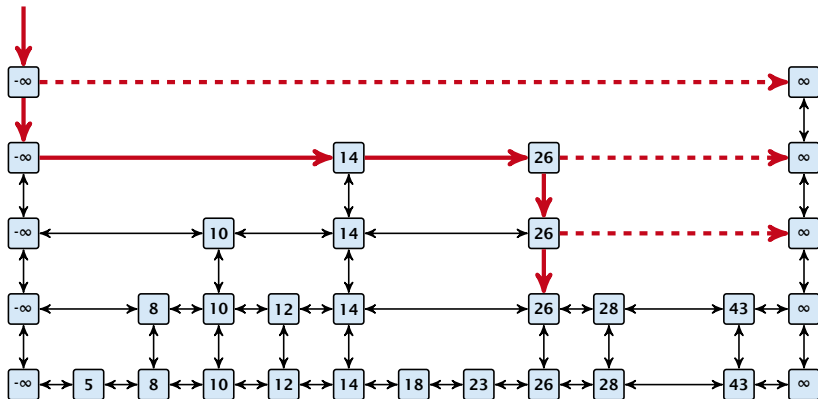
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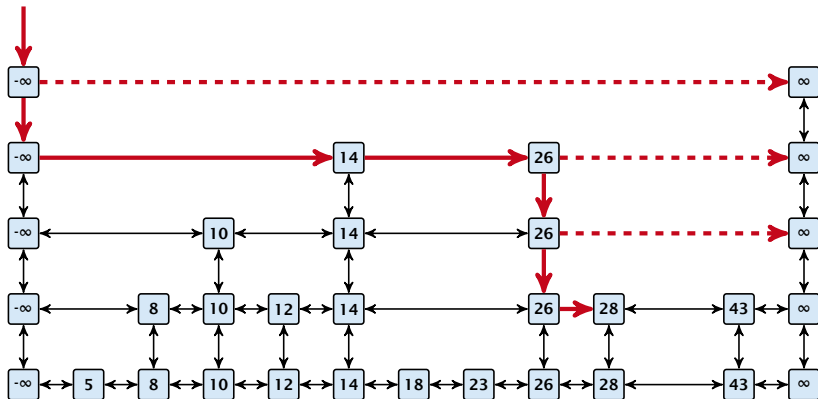
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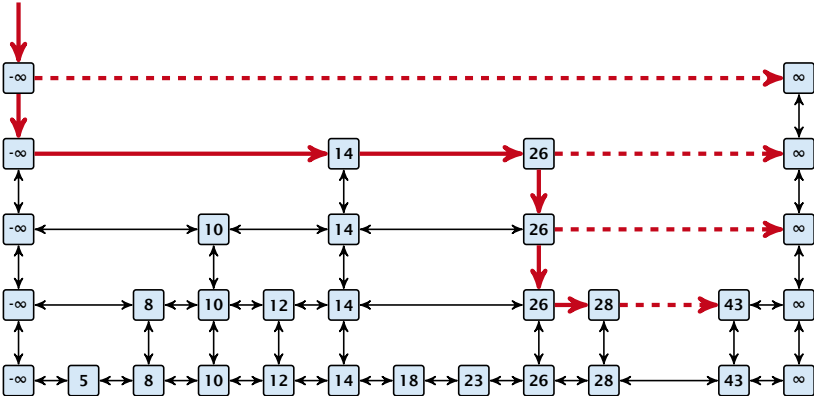
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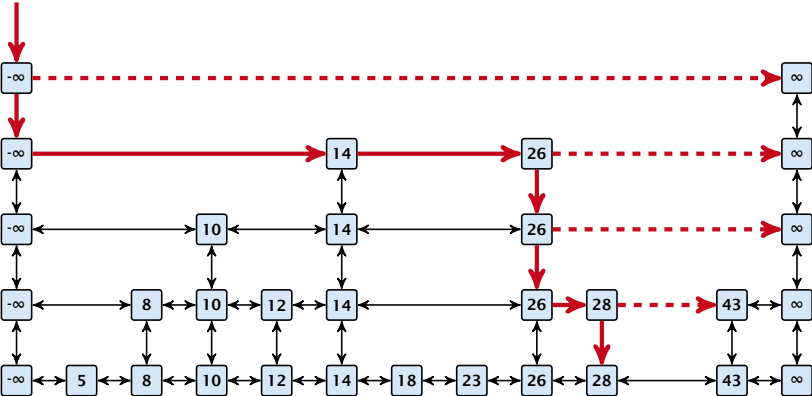
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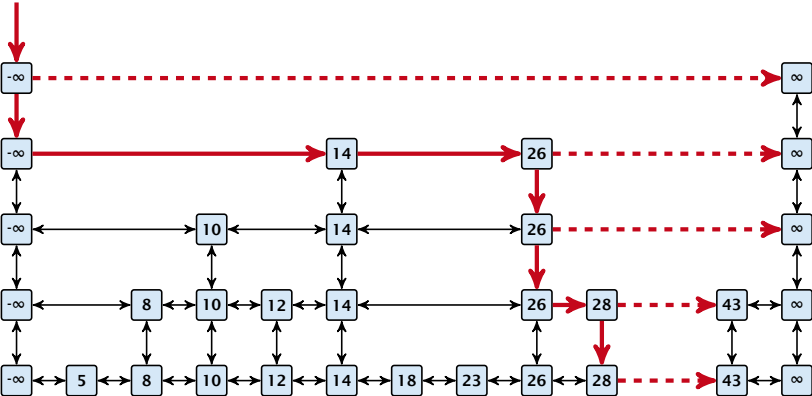
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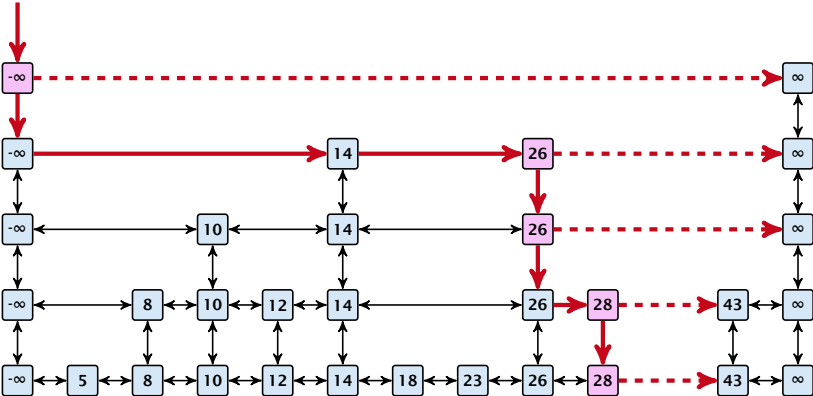
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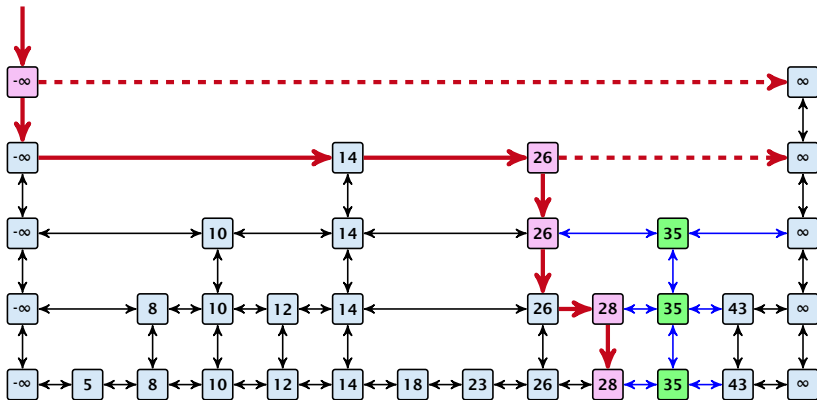
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High Probability

Definition 20 (High Probability)

We say a **randomized** algorithm has running time $\mathcal{O}(\log n)$ with **high probability** if for any constant α the running time is at most $\mathcal{O}(\log n)$ with probability at least $1 - \frac{1}{n^\alpha}$.

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High Probability

Suppose there are **polynomially** many events E_1, E_2, \dots, E_ℓ , $\ell = n^c$ each holding with high probability (e.g. E_i may be the event that the i -th search in a skip list takes time at most $\mathcal{O}(\log n)$).

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This means $\Pr[E_1 \wedge \dots \wedge E_\ell]$ holds with high probability.

7.6 Skip Lists

Lemma 21

A search (and, hence, also insert and delete) in a skip list with n elements takes time $\mathcal{O}(\log n)$ with high probability (w. h. p.).

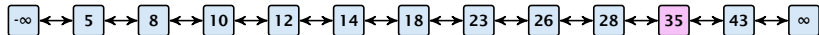
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Backward analysis:



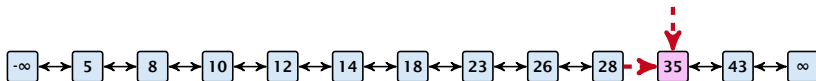
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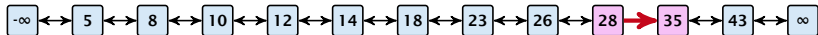
7.6 Skip Lists

Backward analysis:



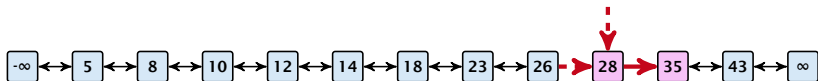
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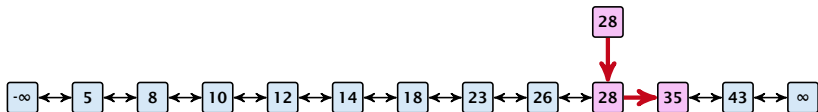
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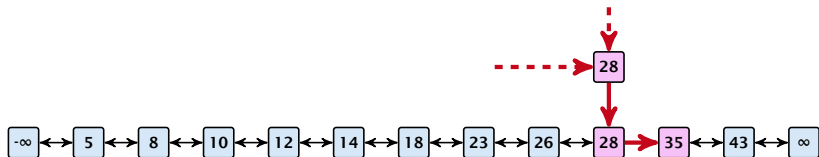
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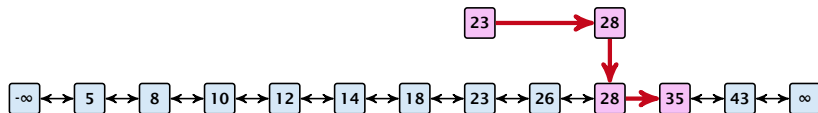
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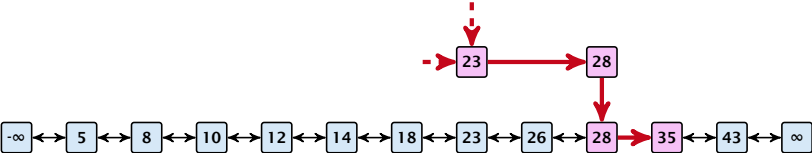
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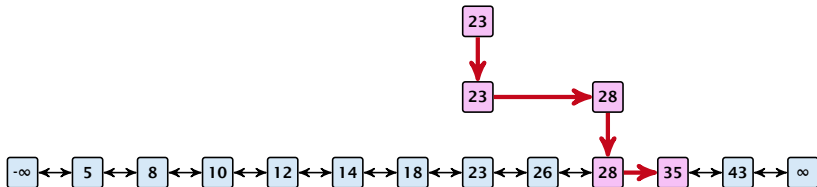
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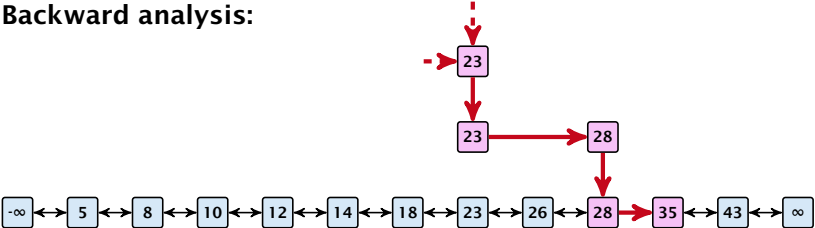
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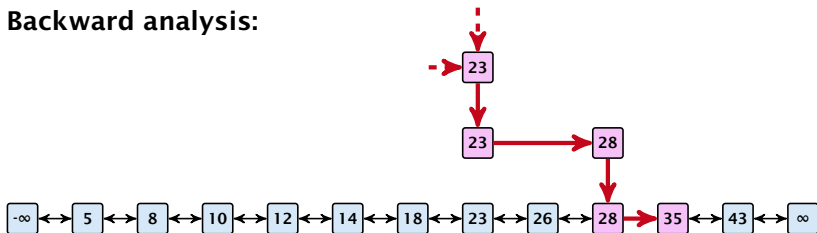
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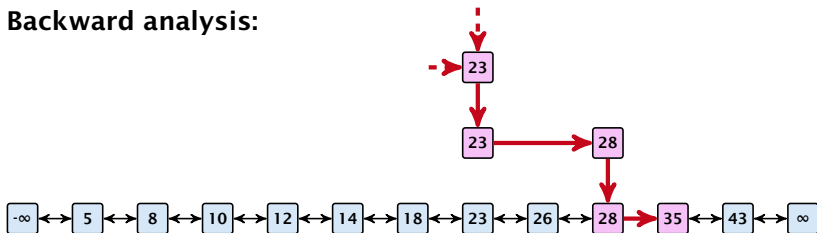
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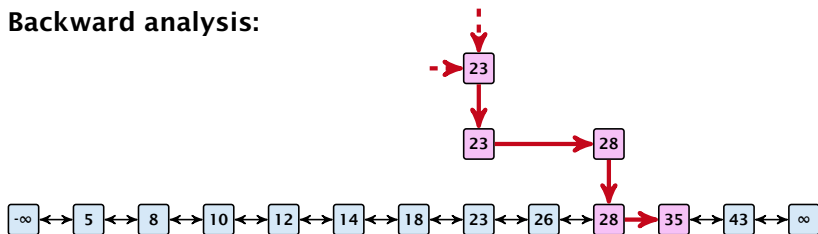
At each point the path goes up with probability $1/2$ and left with probability $1/2$.

We show that w.h.p:

- ▶ A “long” search path must also go very high.

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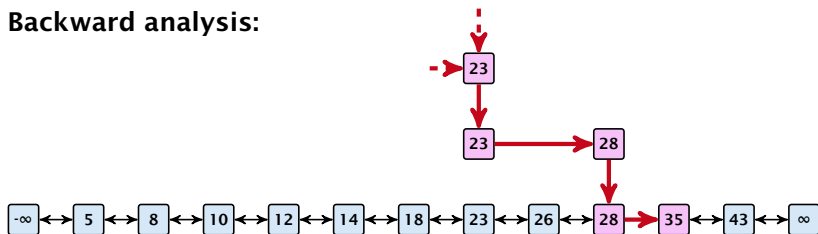
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We show that w.h.p:

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- ▶ There are no elements in high lists.

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At each point the path goes up with probability $1/2$ and left with probability $1/2$.

We show that w.h.p.:

- ▶ A “long” search path must also go very high.
- ▶ There are no elements in high lists.

From this it follows that w.h.p. there are no long paths.

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In particular, this means that during the construction in the backward analysis we see at most k heads (i.e., coin flips that tell you to go up) in z trials.

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This means, the search requires at most z steps, w. h. p.

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Dictionary:

- ▶ **$S.insert(x)$** : Insert an element x .
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- ▶ **$S.search(k)$** : Return a pointer to an element e with $key[e] = k$ in S if it exists; otherwise return **null**.

So far we have implemented the search for a key by carefully choosing split-elements.

Then the memory location of an object x with key k is determined by successively comparing k to split-elements.

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Definitions:

- ▶ Universe U of keys, e.g., $U \subseteq \mathbb{N}_0$. U very large.
- ▶ Set $S \subseteq U$ of keys, $|S| = m \leq |U|$.
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7.7 Hashing

Definitions:

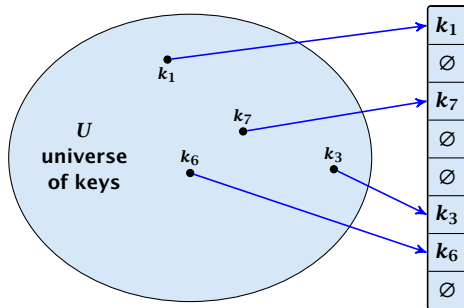
- ▶ Universe U of keys, e.g., $U \subseteq \mathbb{N}_0$. U very large.
- ▶ Set $S \subseteq U$ of keys, $|S| = m \leq |U|$.
- ▶ Array $T[0, \dots, n - 1]$ hash-table.
- ▶ Hash function $h : U \rightarrow [0, \dots, n - 1]$.

The hash-function h should fulfill:

- ▶ Fast to evaluate.
- ▶ Small storage requirement.
- ▶ Good distribution of elements over the whole table.

Direct Addressing

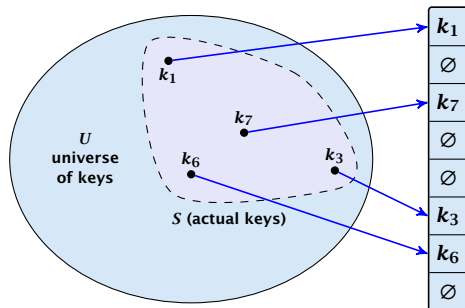
Ideally the hash function maps **all** keys to different memory locations.



This special case is known as **Direct Addressing**. It is usually very unrealistic as the universe of keys typically is quite large, and in particular larger than the available memory.

Perfect Hashing

Suppose that we **know** the set S of actual keys (no insert/no delete). Then we may want to design a **simple** hash-function that maps all these keys to different memory locations.



Such a hash function h is called a **perfect hash function** for set S .

Collisions

If we do not know the keys in advance, the best we can hope for is that the hash function distributes keys evenly across the table.

Problem: Collisions

Usually the universe U is much larger than the table-size n .

Hence, there may be two elements k_1, k_2 from the set S that map to the same memory location (i.e., $h(k_1) = h(k_2)$). This is called a **collision**.

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Collisions

Typically, collisions do not appear once the size of the set S of actual keys gets close to n , but already when $|S| \geq \omega(\sqrt{n})$.

Lemma 22

The probability of having a collision when hashing m elements into a table of size n under uniform hashing is at least

$$1 - e^{-\frac{m(m-1)}{2n}} \approx 1 - e^{-\frac{m^2}{2n}}.$$

Uniform hashing:

Choose a hash function uniformly at random from all functions $f: U \rightarrow [0, \dots, n-1]$.

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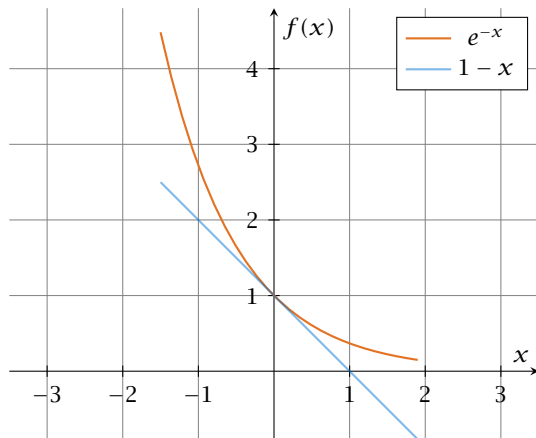
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Here the first equality follows since the ℓ -th element that is hashed has a probability of $\frac{n-\ell+1}{n}$ to not generate a collision under the condition that the previous elements did not induce collisions. □

Collisions



The inequality $1 - x \leq e^{-x}$ is derived by stopping the Taylor-expansion of e^{-x} after the second term.

Resolving Collisions

The methods for dealing with collisions can be classified into the two main types

- ▶ **open addressing**, aka. closed hashing
- ▶ **hashing with chaining**, aka. closed addressing, open hashing.

There are applications e.g. computer chess where you do not resolve collisions at all.

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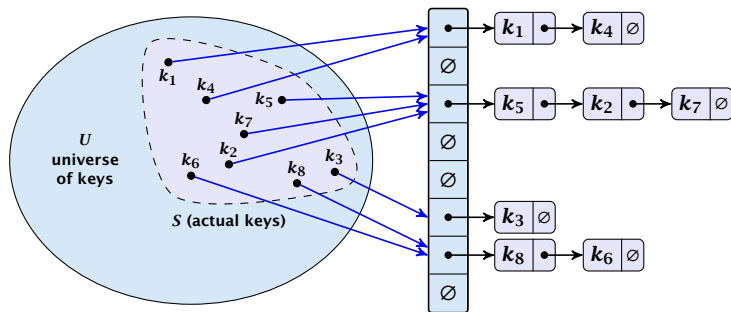
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Hashing with Chaining

Arrange elements that map to the same position in a linear list.

- ▶ Access: compute $h(x)$ and search list for $\text{key}[x]$.
- ▶ Insert: insert at the front of the list.



Hashing with Chaining

Let A denote a strategy for resolving collisions. We use the following notation:

- ▶ A^+ denotes the average time for a **successful** search when using A ;
- ▶ A^- denotes the average time for an **unsuccessful** search when using A ;
- ▶ We parameterize the complexity results in terms of $\alpha := \frac{m}{n}$, the so-called **fill factor** of the hash-table.

We assume **uniform hashing** for the following analysis.

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The time required for an unsuccessful search is 1 plus the length of the list that is examined. The average length of a list is $\alpha = \frac{m}{n}$. Hence, if A is the collision resolving strategy “Hashing with Chaining” we have

$$A^- = 1 + \alpha .$$

Hashing with Chaining

For a successful search observe that we do **not** choose a list at random, but we consider a random key k in the hash-table and ask for the search-time for k .

This is 1 plus the number of elements that lie before k in k 's list.

Let k_ℓ denote the ℓ -th key inserted into the table.

Let for two keys k_i and k_j , X_{ij} denote the indicator variable for the event that k_i and k_j hash to the same position. Clearly, $\Pr[X_{ij} = 1] = 1/n$ for uniform hashing.

The expected successful search cost is

$$E \left[\frac{1}{m} \sum_{i=1}^m \left(1 + \sum_{j=i+1}^m X_{ij} \right) \right]$$

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Hence, the expected cost for a successful search is $A^+ \leq 1 + \frac{\alpha}{2}$.

Hashing with Chaining

Disadvantages:

- ▶ pointers increase memory requirements
- ▶ pointers may lead to bad cache efficiency

Advantages:

- ▶ no à priori limit on the number of elements
- ▶ deletion can be implemented efficiently
- ▶ by using balanced trees instead of linked list one can also obtain worst-case guarantees.

Open Addressing

All objects are stored in the table itself.

Define a function $h(k, j)$ that determines the table-position to be examined in the j -th step. The values $h(k, 0), \dots, h(k, n - 1)$ must form a permutation of $0, \dots, n - 1$.

Search(k): Try position $h(k, 0)$; if it is empty your search fails; otw. continue with $h(k, 1), h(k, 2), \dots$.

Insert(x): Search until you find an empty slot; insert your element there. If your search reaches $h(k, n - 1)$, and this slot is non-empty then your table is full.

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Open Addressing

Choices for $h(k, j)$:

▶ **Linear probing:**

$$h(k, i) = h(k) + i \pmod n$$

(sometimes: $h(k, i) = h(k) + ci \pmod n$).

▶ Quadratic probing:

$$h(k, i) = h(k) + c_1 i + c_2 i^2 \pmod n.$$

▶ Double hashing:

$$h(k, i) = h_1(k) + ih_2(k) \pmod n.$$

For quadratic probing and double hashing one has to ensure that the search covers all positions in the table (i.e., for double hashing $h_2(k)$ must be relatively prime to n (teilerfremd); for quadratic probing c_1 and c_2 have to be chosen carefully).

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Linear Probing

- ▶ Advantage: **Cache-efficiency**. The new probe position is very likely to be in the cache.
- ▶ Disadvantage: **Primary clustering**. Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

Lemma 23

Let L be the method of linear probing for resolving collisions:

$$L^+ \approx \frac{1}{2} \left(1 + \frac{1}{1 - \alpha} \right)$$

$$L^- \approx \frac{1}{2} \left(1 + \frac{1}{(1 - \alpha)^2} \right)$$

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$$L^- \approx \frac{1}{2} \left(1 + \frac{1}{(1 - \alpha)^2} \right)$$

Linear Probing

- ▶ Advantage: **Cache-efficiency**. The new probe position is very likely to be in the cache.
- ▶ Disadvantage: **Primary clustering**. Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

Lemma 23

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Quadratic Probing

- ▶ Not as cache-efficient as Linear Probing.
- ▶ **Secondary clustering**: caused by the fact that all keys mapped to the same position have the same probe sequence.

Lemma 24

Let Q be the method of quadratic probing for resolving collisions:

$$Q^+ \approx 1 + \ln\left(\frac{1}{1-\alpha}\right) - \frac{\alpha}{2}$$

$$Q^- \approx \frac{1}{1-\alpha} + \ln\left(\frac{1}{1-\alpha}\right) - \alpha$$

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Double Hashing

- ▶ Any probe into the hash-table usually creates a cache-miss.

Lemma 25

Let A be the method of double hashing for resolving collisions:

$$D^+ \approx \frac{1}{\alpha} \ln \left(\frac{1}{1 - \alpha} \right)$$

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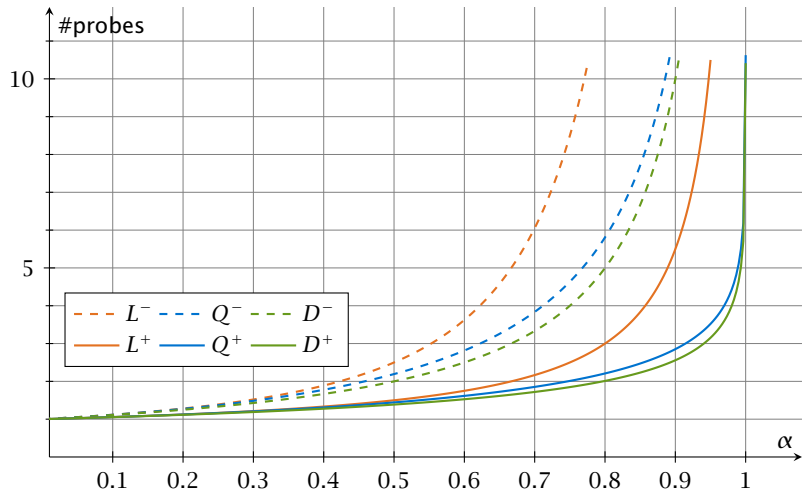
$$D^- \approx \frac{1}{1 - \alpha}$$

Open Addressing

Some values:

α	<i>Linear Probing</i>		<i>Quadratic Probing</i>		<i>Double Hashing</i>	
	L^+	L^-	Q^+	Q^-	D^+	D^-
0.5	1.5	2.5	1.44	2.19	1.39	2
0.9	5.5	50.5	2.85	11.40	2.55	10
0.95	10.5	200.5	3.52	22.05	3.15	20

Open Addressing



Analysis of Idealized Open Address Hashing

We analyze the time for a search in a very idealized Open Addressing scheme.

- ▶ The probe sequence $h(k, 0), h(k, 1), h(k, 2), \dots$ is equally likely to be any permutation of $\langle 0, 1, \dots, n - 1 \rangle$.

Analysis of Idealized Open Address Hashing



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Let X denote a random variable describing the number of probes in an **unsuccessful** search.

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$$\Pr[A_1 \cap A_2 \cap \dots \cap A_{i-1}]$$

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$$\begin{aligned} & \Pr[A_1 \cap A_2 \cap \dots \cap A_{i-1}] \\ &= \Pr[A_1] \cdot \Pr[A_2 \mid A_1] \cdot \Pr[A_3 \mid A_1 \cap A_2] \cdot \\ & \quad \dots \cdot \Pr[A_{i-1} \mid A_1 \cap \dots \cap A_{i-2}] \end{aligned}$$

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$$\Pr[X \geq i]$$

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Analysis of Idealized Open Address Hashing

$E[X]$

Analysis of Idealized Open Address Hashing

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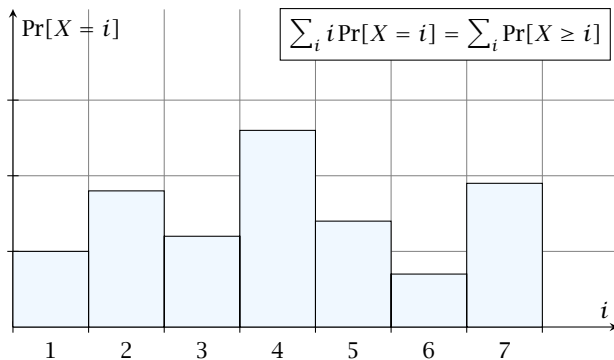
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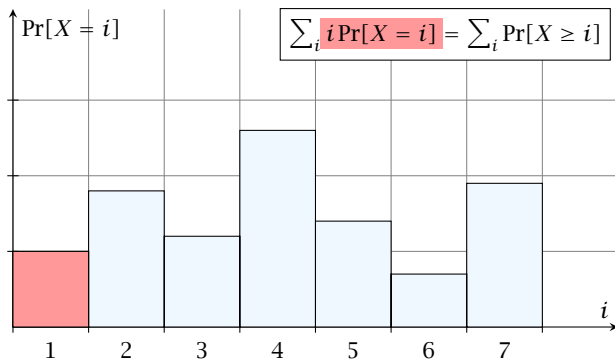
$$\frac{1}{1-\alpha} = 1 + \alpha + \alpha^2 + \alpha^3 + \dots$$

Analysis of Idealized Open Address Hashing



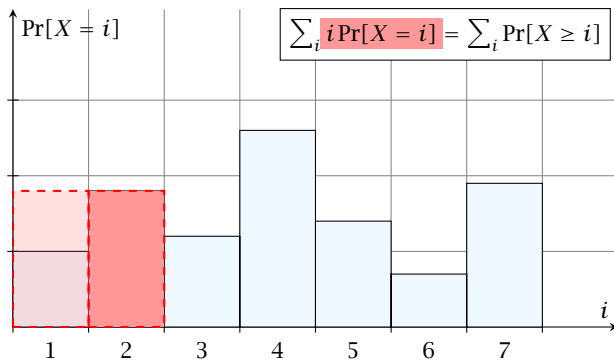
Analysis of Idealized Open Address Hashing

$i = 1$



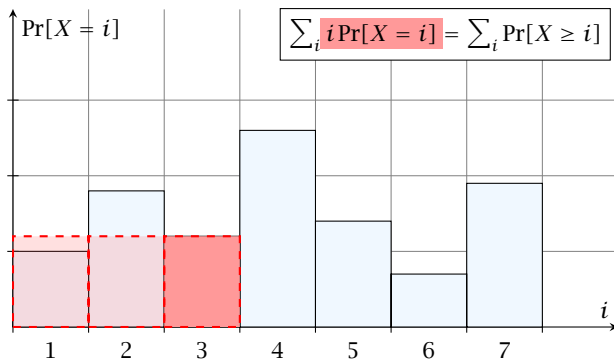
Analysis of Idealized Open Address Hashing

$i = 2$



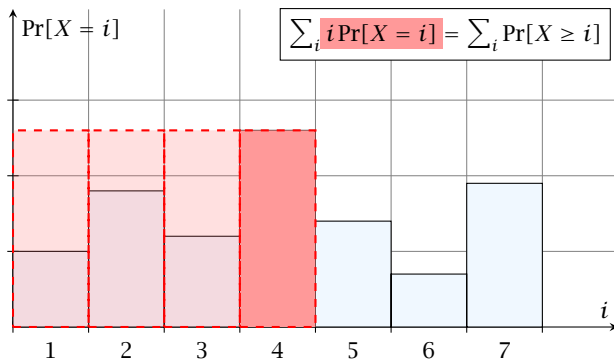
Analysis of Idealized Open Address Hashing

$i = 3$



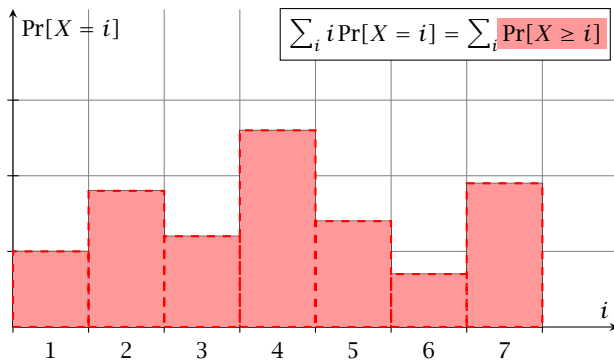
Analysis of Idealized Open Address Hashing

$i = 4$



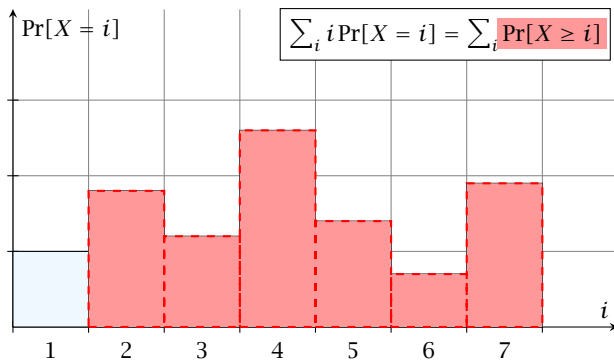
Analysis of Idealized Open Address Hashing

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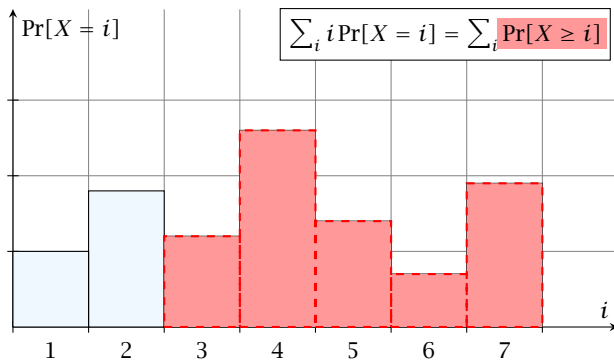
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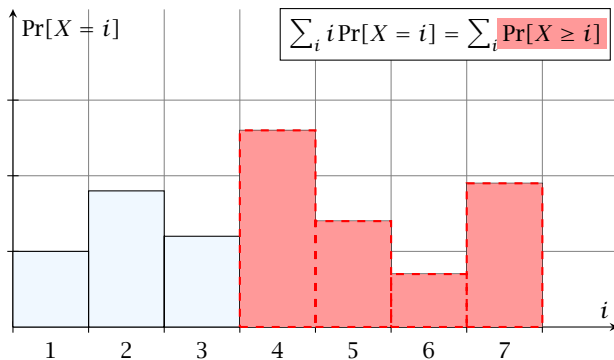
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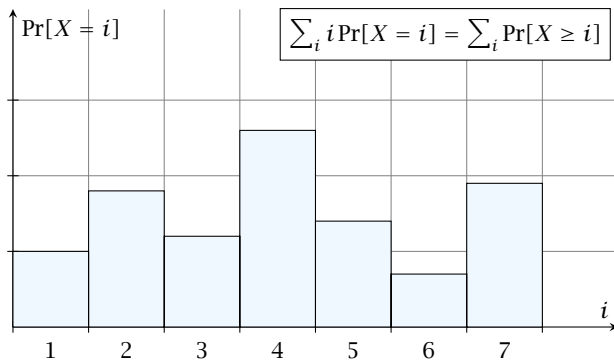


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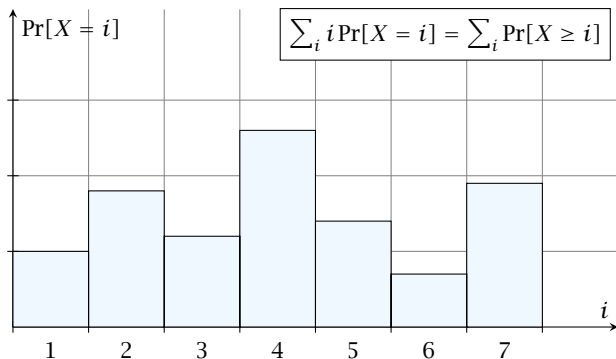
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Analysis of Idealized Open Address Hashing



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The j -th rectangle appears in both sums j times. (j times in the first due to multiplication with j ; and j times in the second for summands $i = 1, 2, \dots, j$)

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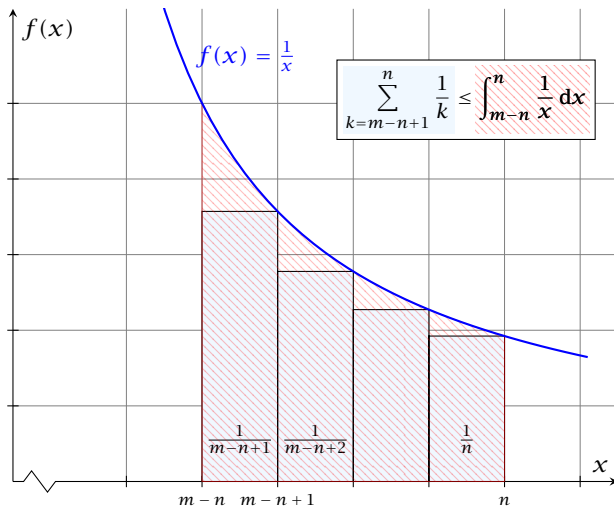
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How do we delete in a hash-table?

- ▶ For hashing with chaining this is not a problem. Simply search for the key, and delete the item in the corresponding list.
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Deletions in Hashtables

- ▶ Simply removing a key might interrupt the probe sequence of other keys which then cannot be found anymore.
- ▶ One can delete an element by replacing it with a **deleted-marker**.
 - ▶ Deleted markers are ignored by the probe sequence and the element can be found again.
 - ▶ Deleted markers do not interrupt the probe sequence of other keys.
- ▶ The table could fill up with deleted-markers leading to bad performance.
- ▶ If a table contains many deleted-markers (linear fraction of the keys) one can rehash the whole table and amortize the cost for this rehash against the cost for the deletions.

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Deletions for Linear Probing

Algorithm 12 delete(p)

```
1:  $T[p] \leftarrow \text{null}$ 
2:  $p \leftarrow \text{succ}(p)$ 
3: while  $T[p] \neq \text{null}$  do
4:    $y \leftarrow T[p]$ 
5:    $T[p] \leftarrow \text{null}$ 
6:    $p \leftarrow \text{succ}(p)$ 
7:   insert( $y$ )
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p is the index into the table-cell that contains the object to be deleted.

Pointers into the hash-table become invalid.

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Universal Hashing

Regardless, of the choice of hash-function there is always an input (a set of keys) that has a very poor worst-case behaviour.

Therefore, so far we assumed that the hash-function is random so that regardless of the input the average case behaviour is good.

However, the assumption of uniform hashing that h is chosen randomly from all functions $f: U \rightarrow [0, \dots, n-1]$ is clearly unrealistic as there are $n^{|U|}$ such functions. Even writing down such a function would take $|U| \log n$ bits.

Universal hashing tries to define a set \mathcal{H} of functions that is much smaller but still leads to good average case behaviour when selecting a hash-function uniformly at random from \mathcal{H} .

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Definition 26

A class \mathcal{H} of hash-functions from the universe U into the set $\{0, \dots, n-1\}$ is called **universal** if for all $u_1, u_2 \in U$ with $u_1 \neq u_2$

$$\Pr[h(u_1) = h(u_2)] \leq \frac{1}{n} ,$$

where the probability is w. r. t. the choice of a random hash-function from set \mathcal{H} .

Note that this means that the probability of a collision between two arbitrary elements is at most $\frac{1}{n}$.

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A class \mathcal{H} of hash-functions from the universe U into the set $\{0, \dots, n-1\}$ is called **2-independent** (pairwise independent) if the following two conditions hold

- ▶ For any key $u \in U$, and $t \in \{0, \dots, n-1\}$ $\Pr[h(u) = t] = \frac{1}{n}$, i.e., a key is distributed uniformly within the hash-table.
- ▶ For all $u_1, u_2 \in U$ with $u_1 \neq u_2$, and for any two hash-positions t_1, t_2 :

$$\Pr[h(u_1) = t_1 \wedge h(u_2) = t_2] \leq \frac{1}{n^2} .$$

This requirement clearly implies a universal hash-function.

Universal Hashing

Definition 27

A class \mathcal{H} of hash-functions from the universe U into the set $\{0, \dots, n-1\}$ is called **2-independent** (pairwise independent) if the following two conditions hold

- ▶ For any key $u \in U$, and $t \in \{0, \dots, n-1\}$ $\Pr[h(u) = t] = \frac{1}{n}$, i.e., a key is distributed uniformly within the hash-table.
- ▶ For all $u_1, u_2 \in U$ with $u_1 \neq u_2$, and for any two hash-positions t_1, t_2 :

$$\Pr[h(u_1) = t_1 \wedge h(u_2) = t_2] \leq \frac{1}{n^2} .$$

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Definition 28

A class \mathcal{H} of hash-functions from the universe U into the set $\{0, \dots, n-1\}$ is called **k -independent** if for any choice of $\ell \leq k$ distinct keys $u_1, \dots, u_\ell \in U$, and for any set of ℓ not necessarily distinct hash-positions t_1, \dots, t_ℓ :

$$\Pr[h(u_1) = t_1 \wedge \dots \wedge h(u_\ell) = t_\ell] \leq \frac{1}{n^\ell} ,$$

where the probability is w. r. t. the choice of a random hash-function from set \mathcal{H} .

Universal Hashing

Definition 29

A class \mathcal{H} of hash-functions from the universe U into the set $\{0, \dots, n-1\}$ is called (μ, k) -independent if for any choice of $\ell \leq k$ distinct keys $u_1, \dots, u_\ell \in U$, and for any set of ℓ not necessarily distinct hash-positions t_1, \dots, t_ℓ :

$$\Pr[h(u_1) = t_1 \wedge \dots \wedge h(u_\ell) = t_\ell] \leq \frac{\mu}{n^\ell},$$

where the probability is w. r. t. the choice of a random hash-function from set \mathcal{H} .

Universal Hashing

Let $U := \{0, \dots, p-1\}$ for a prime p . Let $\mathbb{Z}_p := \{0, \dots, p-1\}$, and let $\mathbb{Z}_p^* := \{1, \dots, p-1\}$ denote the set of invertible elements in \mathbb{Z}_p .

Define

$$h_{a,b}(x) := (ax + b \bmod p) \bmod n$$

Lemma 30

The class

$$\mathcal{H} = \{h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p\}$$

is a universal class of hash-functions from U to $\{0, \dots, n-1\}$.

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Let $x, y \in U$ be two distinct keys. We have to show that the probability of a collision is only $1/n$.

► $ax + b \not\equiv ay + b \pmod{p}$

If $x \neq y$ then $(x - y) \not\equiv 0 \pmod{p}$.

Multiplying with $a \not\equiv 0 \pmod{p}$ gives

$$a(x - y) \not\equiv 0 \pmod{p}$$

where we use that \mathbb{Z}_p is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).

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- ▶ The hash-function does not generate collisions before the $(\text{mod } n)$ -operation. Furthermore, every choice (a, b) is mapped to a different pair (t_x, t_y) with $t_x := ax + b$ and $t_y := ay + b$.

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$$a \equiv (t_x - t_y)(x - y)^{-1} \pmod{p}$$

$$b \equiv t_y - ay \pmod{p}$$

Universal Hashing

There is a one-to-one correspondence between hash-functions (pairs (a, b) , $a \neq 0$) and pairs (t_x, t_y) , $t_x \neq t_y$.

Therefore, we can view the first step (before the mod n -operation) as choosing a pair (t_x, t_y) , $t_x \neq t_y$ uniformly at random.

What happens when we do the mod n operation?

Fix a value t_x . There are $p - 1$ possible values for choosing t_y .

From the range $0, \dots, p - 1$ the values $t_x, t_x + n, t_x + 2n, \dots$ map to t_x after the modulo-operation. These are at most $\lceil p/n \rceil$ values.

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As $t_y \neq t_x$ there are

possibilities for choosing t_y such that the final hash-value creates a collision.

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It is also possible to show that \mathcal{H} is an (almost) pairwise independent class of hash-functions.

$$\Pr_{t_x \neq t_y \in \mathbb{Z}_p^2} \left[\begin{array}{l} t_x \bmod n = h_1 \\ t_y \bmod n = h_2 \end{array} \right]$$

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It is also possible to show that \mathcal{H} is an (almost) pairwise independent class of hash-functions.

$$\frac{\left\lfloor \frac{p}{n} \right\rfloor^2}{p(p-1)} \leq \Pr_{t_x \neq t_y \in \mathbb{Z}_p^2} \left[\begin{array}{l} t_x \bmod n = h_1 \\ t_y \bmod n = h_2 \end{array} \right] \leq \frac{\left\lfloor \frac{p}{n} \right\rfloor^2}{p(p-1)}$$

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Note that the middle is the probability that $h(x) = h_1$ and $h(y) = h_2$. The total number of choices for (t_x, t_y) is $p(p-1)$. The number of choices for t_x (t_y) such that $t_x \bmod n = h_1$ ($t_y \bmod n = h_2$) lies between $\lfloor \frac{p}{n} \rfloor$ and $\lceil \frac{p}{n} \rceil$.

Universal Hashing

Definition 31

Let $d \in \mathbb{N}$; $q \geq (d + 1)n$ be a prime; and let $\bar{a} \in \{0, \dots, q - 1\}^{d+1}$. Define for $x \in \{0, \dots, q - 1\}$

$$h_{\bar{a}}(x) := \left(\sum_{i=0}^d a_i x^i \bmod q \right) \bmod n .$$

Let $\mathcal{H}_n^d := \{h_{\bar{a}} \mid \bar{a} \in \{0, \dots, q - 1\}^{d+1}\}$. The class \mathcal{H}_n^d is $(e, d + 1)$ -independent.

Note that in the previous case we had $d = 1$ and chose $a_d \neq 0$.

Universal Hashing

For the coefficients $\bar{a} \in \{0, \dots, q-1\}^{d+1}$ let $f_{\bar{a}}$ denote the polynomial

$$f_{\bar{a}}(x) = \left(\sum_{i=0}^d a_i x^i \right) \bmod q$$

The polynomial is defined by $d + 1$ distinct points.

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Universal Hashing

Fix $\ell \leq d + 1$; let $x_1, \dots, x_\ell \in \{0, \dots, q - 1\}$ be keys, and let t_1, \dots, t_ℓ denote the corresponding hash-function values.

Let $A^\ell = \{h_{\bar{a}} \in \mathcal{H} \mid h_{\bar{a}}(x_i) = t_i \text{ for all } i \in \{1, \dots, \ell\}\}$

Then

$$h_{\bar{a}} \in A^\ell \Leftrightarrow h_{\bar{a}} = f_{\bar{a}} \bmod n \text{ and}$$

$$f_{\bar{a}}(x_i) \in \underbrace{\{t_i + \alpha \cdot n \mid \alpha \in \{0, \dots, \lfloor \frac{q}{n} \rfloor - 1\}\}}_{=: B_i}$$

In order to obtain the cardinality of A^ℓ we choose our polynomial by fixing $d + 1$ points.

We first fix the values for inputs x_1, \dots, x_ℓ .

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$$|B_1| \cdot \dots \cdot |B_\ell|$$

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Now, we choose $d - \ell + 1$ other inputs and choose their value arbitrarily. We have $q^{d-\ell+1}$ possibilities to do this.

Therefore we have

$$|B_1| \cdot \dots \cdot |B_\ell| \cdot q^{d-\ell+1} \leq \left\lceil \frac{q}{n} \right\rceil^\ell \cdot q^{d-\ell+1}$$

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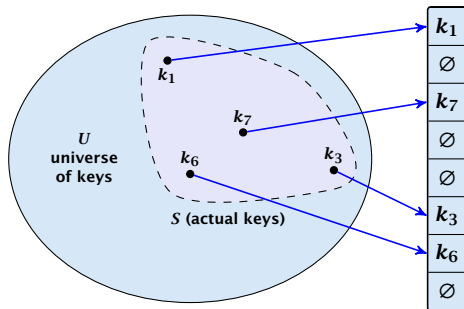
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This shows that the \mathcal{H} is $(e, d+1)$ -universal.

The last step followed from $q \geq (d+1)n$, and $\ell \leq d+1$.

Perfect Hashing

Suppose that we **know** the set S of actual keys (no insert/no delete). Then we may want to design a **simple** hash-function that maps all these keys to different memory locations.



Perfect Hashing

Let $m = |S|$. We could simply choose the hash-table size very large so that we don't get any collisions.

Using a universal hash-function the expected number of collisions is

$$E[\#\text{Collisions}] = \binom{m}{2} \cdot \frac{1}{n}.$$

If we choose $n = m^2$ the expected number of collisions is strictly less than $\frac{1}{2}$.

Can we get an upper bound on the probability of having collisions?

The probability of having 1 or more collisions can be at most $\frac{1}{2}$ as otherwise the expectation would be larger than $\frac{1}{2}$.

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We can find such a hash-function by a few trials.

However, a hash-table size of $n = m^2$ is very very high.

We construct a two-level scheme. We first use a hash-function that maps elements from S to m buckets.

Let m_j denote the number of items that are hashed to the j -th bucket. For each bucket we choose a second hash-function that maps the elements of the bucket into a table of size m_j^2 . The second function can be chosen such that all elements are mapped to different locations.

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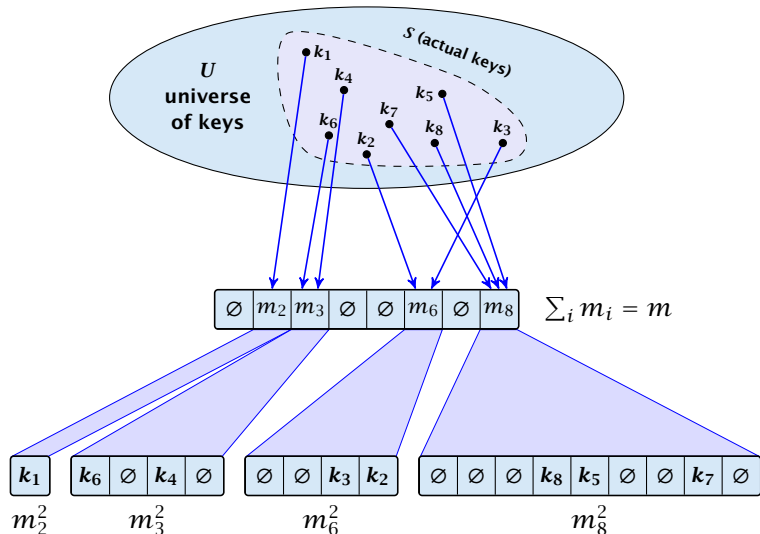
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$$= 2 \binom{m}{2} \frac{1}{m} + m = 2m - 1 .$$

Perfect Hashing

We need only $\mathcal{O}(m)$ time to construct a hash-function h with $\sum_j m_j^2 = \mathcal{O}(4m)$, because with probability at least $1/2$ a random function from a universal family will have this property.

Then we construct a hash-table h_j for every bucket. This takes expected time $\mathcal{O}(m_j)$ for every bucket. A random function h_j is collision-free with probability at least $1/2$. We need $\mathcal{O}(m_j)$ to test this.

We only need that the hash-functions are chosen from a universal family!!!

Cuckoo Hashing

Goal:

Try to generate a hash-table with constant worst-case search time in a dynamic scenario.

Two hash-tables T_1 and T_2 over \mathcal{U} and \mathcal{U} , with hash functions h_1 and h_2 .

An object x is either stored at location $T_1[h_1(x)]$ or $T_2[h_2(x)]$.

Search clearly takes constant time if the above conditions are met.

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Goal:

Try to generate a hash-table with constant worst-case search time in a dynamic scenario.

- ▶ Two hash-tables $T_1[0, \dots, n-1]$ and $T_2[0, \dots, n-1]$, with hash-functions h_1 , and h_2 .
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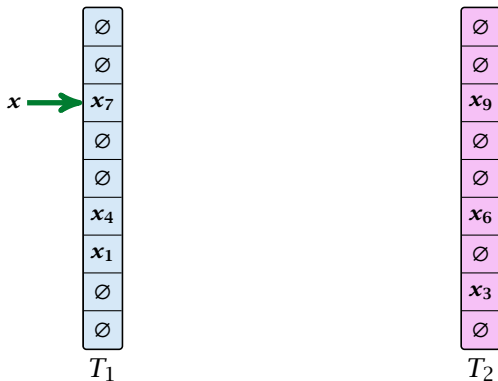
T_1



T_2

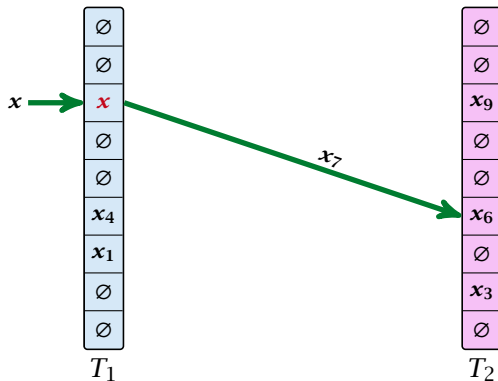
Cuckoo Hashing

Insert:



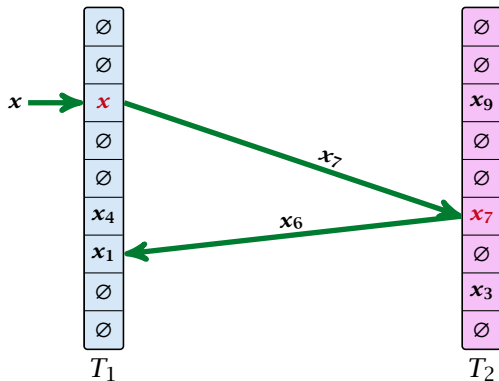
Cuckoo Hashing

Insert:



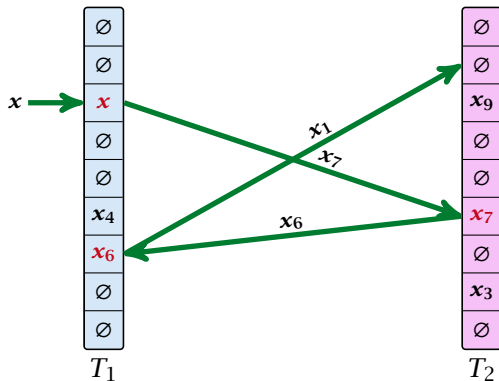
Cuckoo Hashing

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Algorithm 13 Cuckoo-Insert(x)

```
1: if  $T_1[h_1(x)] = x \vee T_2[h_2(x)] = x$  then return  
2: steps  $\leftarrow 1$   
3: while steps  $\leq$  maxsteps do  
4:   exchange  $x$  and  $T_1[h_1(x)]$   
5:   if  $x = \text{null}$  then return  
6:   exchange  $x$  and  $T_2[h_2(x)]$   
7:   if  $x = \text{null}$  then return  
8:   steps  $\leftarrow$  steps + 1  
9: rehash() // change hash-functions; rehash everything  
10: Cuckoo-Insert( $x$ )
```

Cuckoo Hashing

- ▶ We call one iteration through the while-loop a **step** of the algorithm.
- ▶ We call a sequence of iterations through the while-loop without the termination condition becoming true a **phase** of the algorithm.
- ▶ We say a phase is **successful** if it is not terminated by the **maxstep**-condition, but the while loop is left because $x = \text{null}$.

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What is the expected time for an insert-operation?

We first analyze the probability that we end-up in an infinite loop (that is then terminated after maxsteps steps).

Formally what is the probability to enter an infinite loop that touches s different keys?

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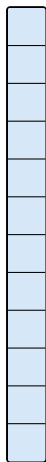
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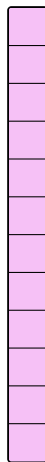
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Cuckoo Hashing: Insert

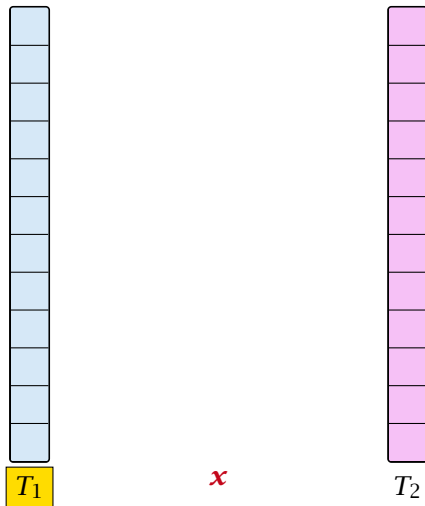


T_1

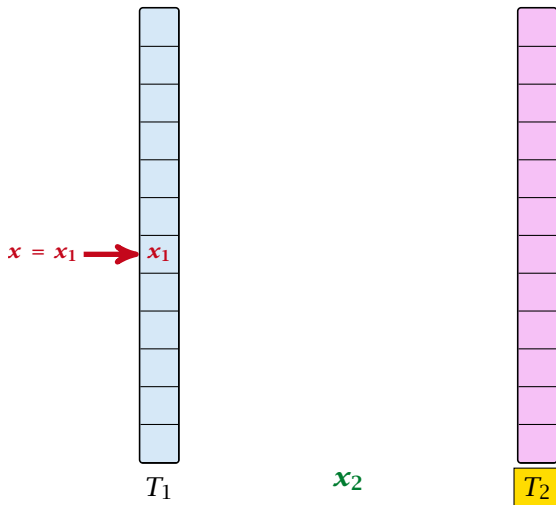


T_2

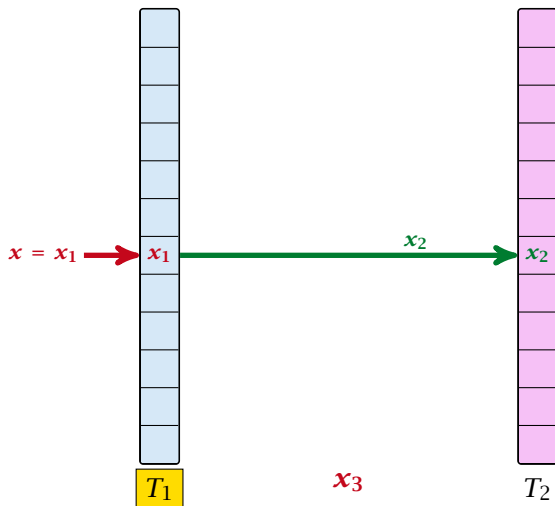
Cuckoo Hashing: Insert



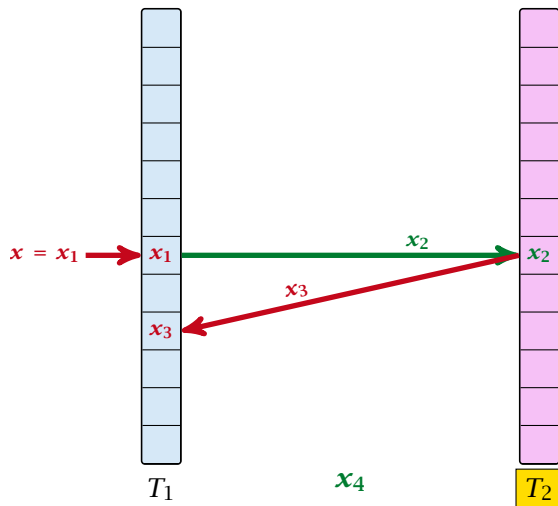
Cuckoo Hashing: Insert



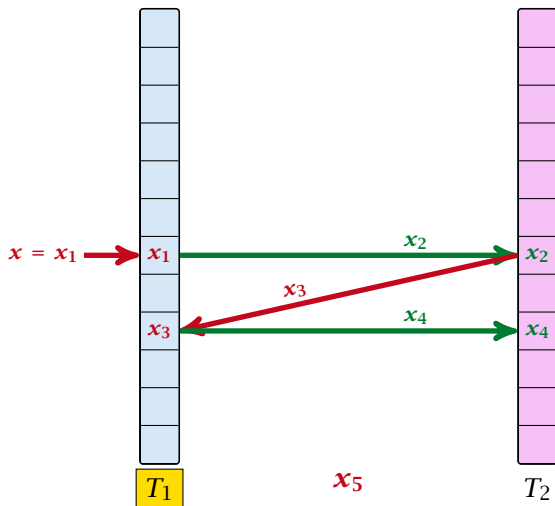
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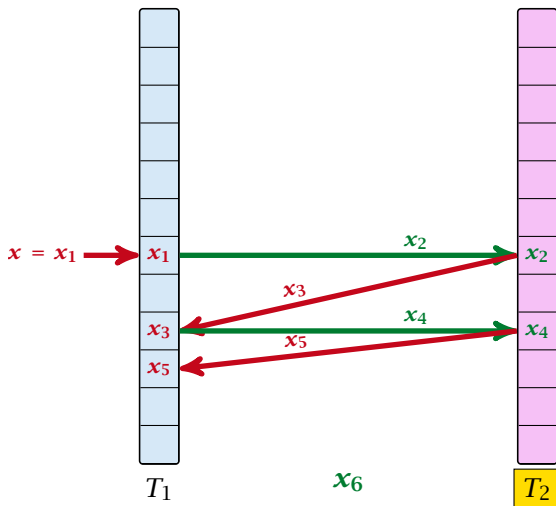
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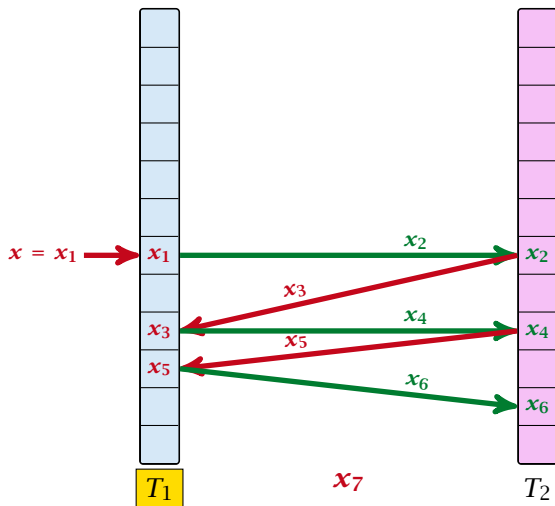
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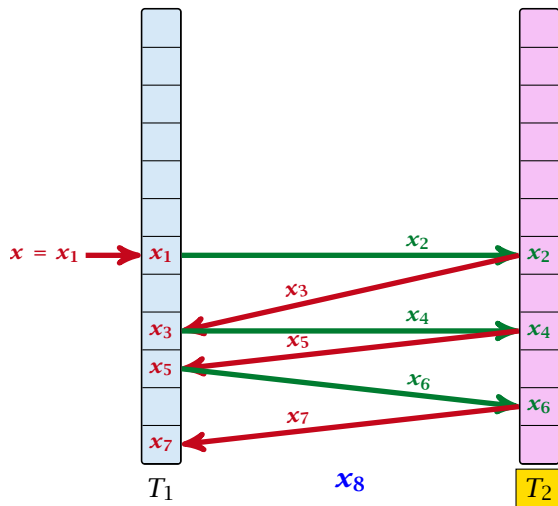
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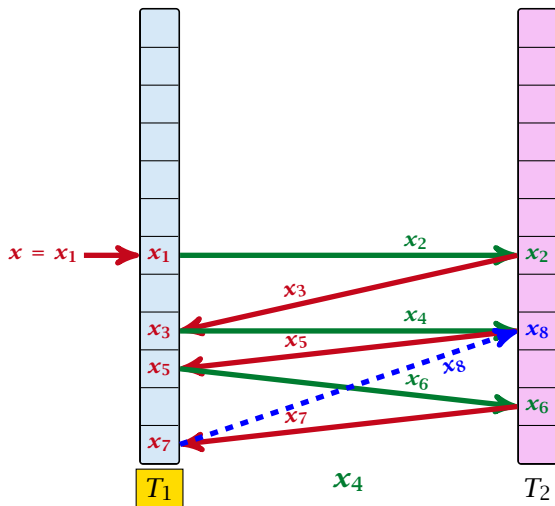
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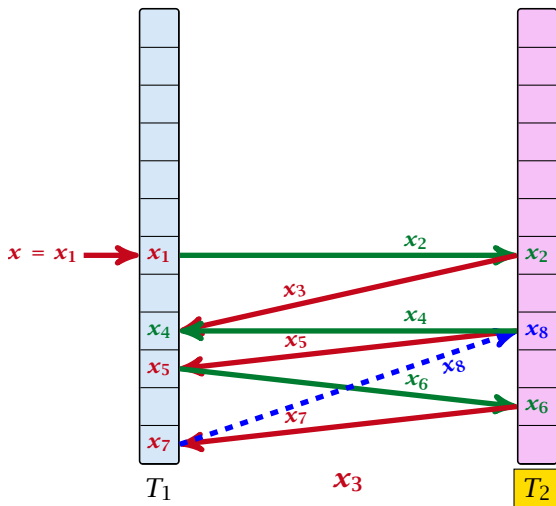
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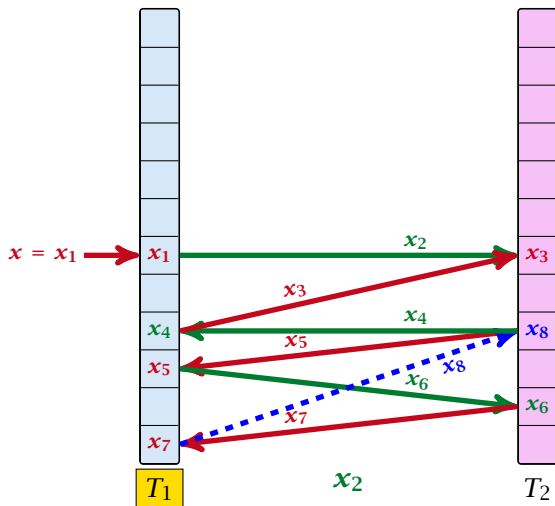
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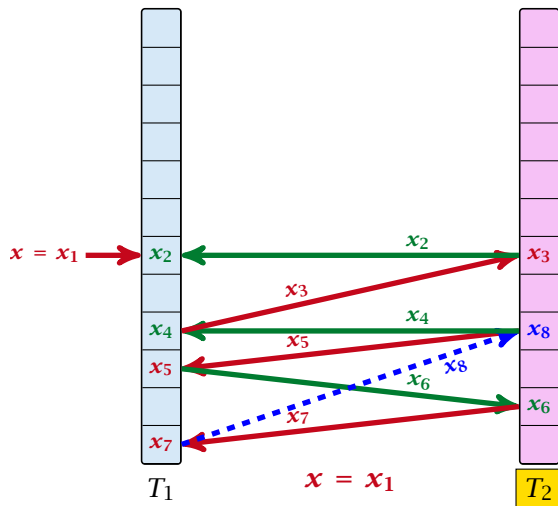
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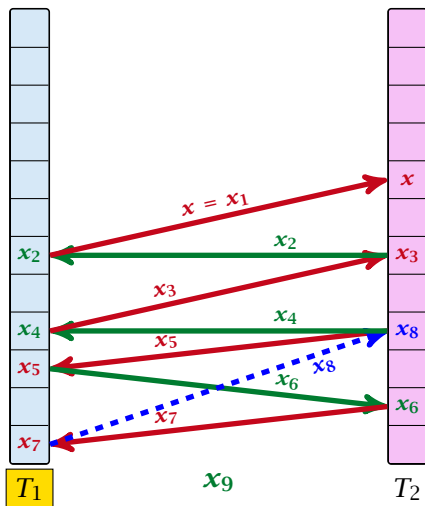
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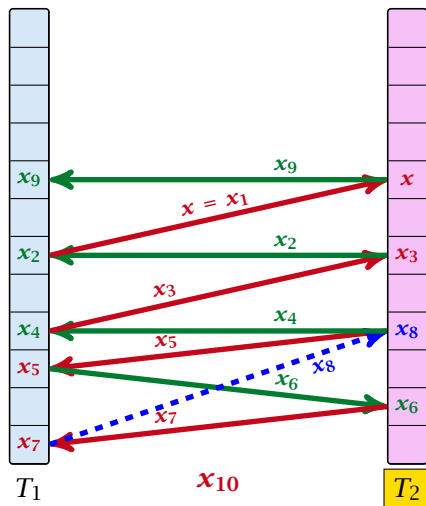
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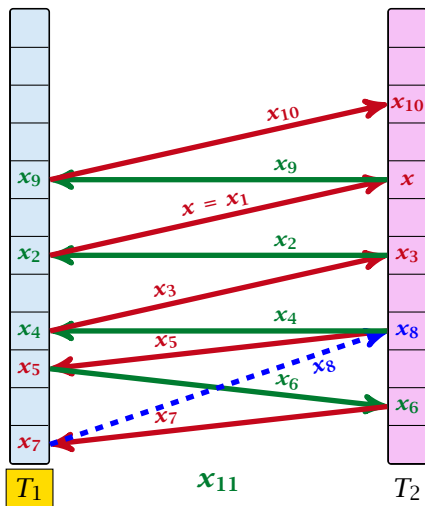
Cuckoo Hashing: Insert



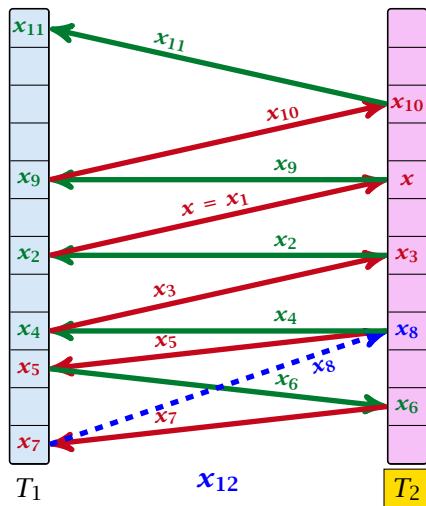
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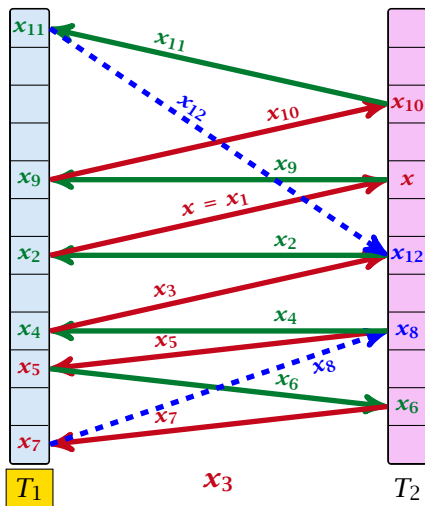
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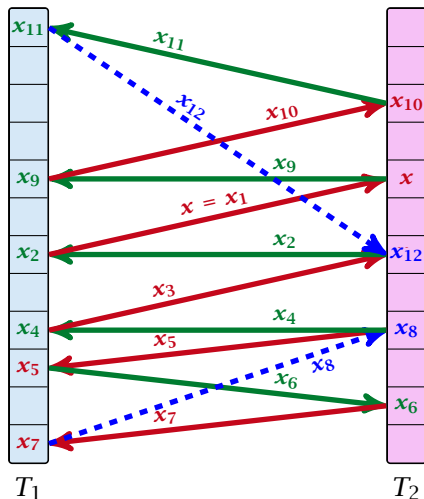
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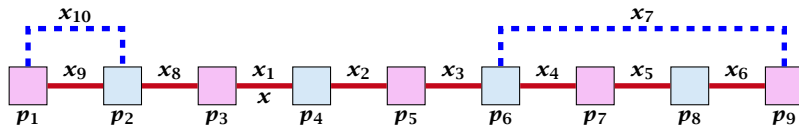
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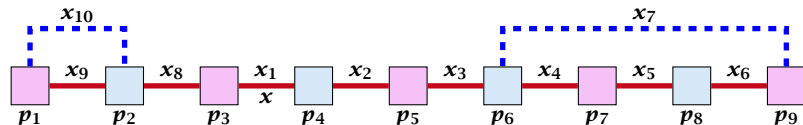


Cuckoo Hashing



A cycle-structure of size s is defined by

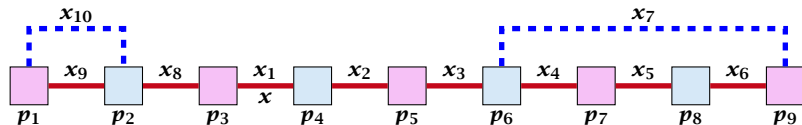
Cuckoo Hashing



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- ▶ $s - 1$ different cells (alternating btw. cells from T_1 and T_2).
- ▶ s distinct keys $x = x_1, x_2, \dots, x_s$, linking the cells.
- ▶ The leftmost cell is “linked forward” to some cell on the right.
- ▶ The rightmost cell is “linked backward” to a cell on the left.
- ▶ One link represents key x ; this is where the counting starts.

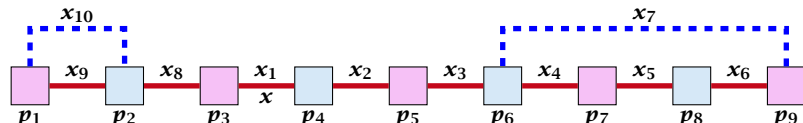
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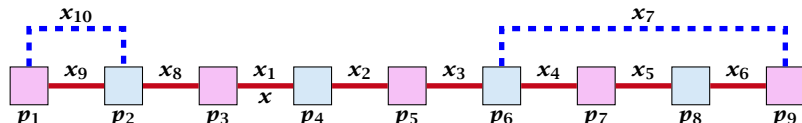
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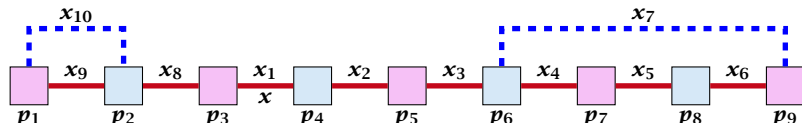
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- ▶ The leftmost cell is “linked forward” to some cell on the right.
- ▶ The rightmost cell is “linked backward” to a cell on the left.
- ▶ One link represents key x ; this is where the counting starts.

Cuckoo Hashing



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A cycle-structure is **active** if for every key x_ℓ (linking a cell p_i from T_1 and a cell p_j from T_2) we have

$$h_1(x_\ell) = p_i \quad \text{and} \quad h_2(x_\ell) = p_j$$

Observation:

If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size $s \geq 3$.

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Cuckoo Hashing

What is the probability that all keys in a cycle-structure of size s correctly map into their T_1 -cell?

This probability is at most $\frac{\mu}{n^s}$ since h_1 is a (μ, s) -independent hash-function.

What is the probability that all keys in the cycle-structure of size s correctly map into their T_2 -cell?

This probability is at most $\frac{\mu}{n^s}$ since h_2 is a (μ, s) -independent hash-function.

These events are independent.

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Cuckoo Hashing

The number of cycle-structures of size s is at most

$$s^3 \cdot n^{s-1} \cdot m^{s-1} .$$

There are s ways to pick the nodes that form the cycle, forward and backward links.

There are at most s possibilities to choose where to place

each of the s nodes in the cycle (forward or backward link)

There are n choices for each of the $s-1$ nodes

There are m choices for each of the $s-1$ nodes

Cuckoo Hashing

The number of cycle-structures of size s is at most

$$s^3 \cdot n^{s-1} \cdot m^{s-1} .$$

- ▶ There are at most s^2 possibilities where to attach the forward and backward links.
- ▶ There are at most s possibilities to choose where to place key x .
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The probability that there exists an active cycle-structure is therefore at most

$$\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \sum_{s=3}^{\infty} s^3 \left(\frac{m}{n}\right)^s$$

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Here we used the fact that $(1 + \epsilon)m \leq n$.

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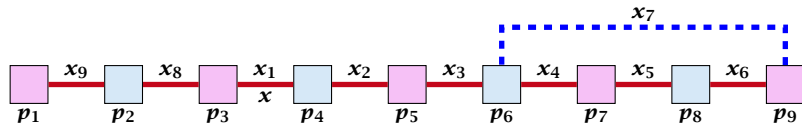
Hence,

$$\Pr[\text{cycle}] = \mathcal{O}\left(\frac{1}{m^2}\right).$$

Cuckoo Hashing

Now, we analyze the probability that a phase is not successful without running into a closed cycle.

Cuckoo Hashing



Sequence of visited keys:

$x = x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_3, x_2, x_1 = x, x_8, x_9, \dots$

Cuckoo Hashing

Consider the sequence of not necessarily distinct keys starting with x in the order that they are visited during the phase.

Lemma 32

If the sequence is of length p then there exists a sub-sequence of at least $\frac{p+2}{3}$ keys starting with x of distinct keys.

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Lemma 32

*If the sequence is of length p then there exists a sub-sequence of at least $\frac{p+2}{3}$ keys starting with x of *distinct* keys.*

Cuckoo Hashing

Proof.

Let i be the number of keys (including x) that we see before the first repeated key. Let j denote the total number of distinct keys.

The sequence is of the form:

$$x = x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_i \rightarrow x_r \rightarrow x_{r-1} \rightarrow \dots \rightarrow x_1 \rightarrow x_{i+1} \rightarrow \dots \rightarrow x_j$$

As $r \leq i - 1$ the length p of the sequence is

$$p = i + r + (j - i) \leq i + j - 1 .$$

Either sub-sequence $x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_i$ or sub-sequence $x_1 \rightarrow x_{i+1} \rightarrow \dots \rightarrow x_j$ has at least $\frac{p+2}{3}$ elements. □

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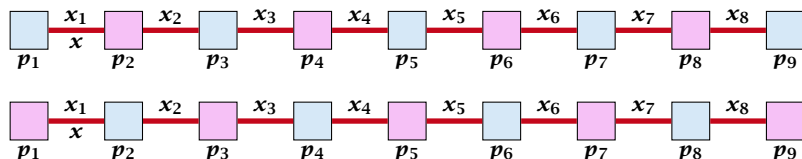
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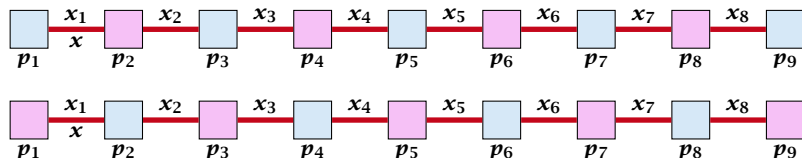
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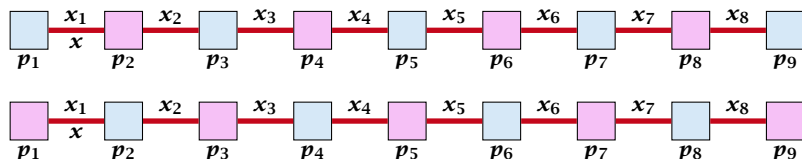
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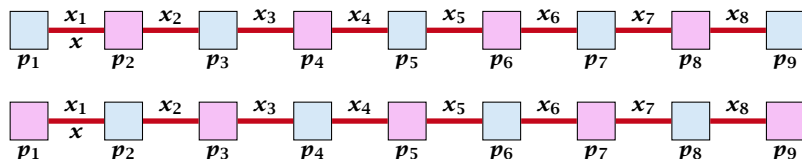
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Observation:

If a phase takes at least t steps without running into a cycle there must exist an active path-structure of size $(2t + 2)/3$.

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The probability that a given path-structure of size s is active is at most $\frac{\mu^2}{n^{2s}}$.

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This gives $\text{maxsteps} = \Theta(\log m)$.

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So far we estimated

$$\Pr[\text{cycle}] \leq \mathcal{O}\left(\frac{1}{m^2}\right)$$

and

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for a suitable constant $c > 0$.

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The expected number of complete steps in the **successful phase** of an insert operation is:

$$\begin{aligned} & E[\text{number of steps} \mid \text{phase successful}] \\ &= \sum_{t \geq 1} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}] \end{aligned}$$

We have

$$\begin{aligned} & \Pr[\text{search at least } t \text{ steps} \mid \text{successful}] \\ &= \Pr[\text{search at least } t \text{ steps} \wedge \text{successful}] / \Pr[\text{successful}] \\ &\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \wedge \text{successful}] / \Pr[\text{no cycle}] \\ &\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \wedge \text{no cycle}] / \Pr[\text{no cycle}] \\ &= \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}] . \end{aligned}$$

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This means the expected cost for a successful phase is constant (even after accounting for the cost of the incomplete step that finishes the phase).

Cuckoo Hashing

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is $q = \mathcal{O}(1/m^2)$ (probability $\mathcal{O}(1/m^2)$ of running into a cycle and probability $\mathcal{O}(1/m^2)$ of reaching maxsteps without running into a cycle).

A rehash try requires m insertions and takes expected constant time per insertion. It fails with probability $p := \mathcal{O}(1/m)$.

The expected number of unsuccessful rehashes is

$$\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \mathcal{O}(p).$$

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The expected cost for all rehashes is

$$E \left[\sum_i \sum_s Z_i X_i^s \right]$$

Note that Z_i is independent of X_j^s , $j \geq i$ (however, it is not independent of X_j^s , $j < i$). Hence,

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What kind of hash-functions do we need?

Since maxsteps is $\Theta(\log m)$ the largest size of a path-structure or cycle-structure contains just $\Theta(\log m)$ different keys.

Therefore, it is sufficient to have $(\mu, \Theta(\log m))$ -independent hash-functions.

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How do we make sure that $n \geq (1 + \epsilon)m$?

- ▶ Let $\alpha := 1/(1 + \epsilon)$.
- ▶ Keep track of the number of elements in the table. When $m \geq \alpha n$ we double n and do a complete re-hash (table-expand).
- ▶ Whenever m drops below $\alpha n/4$ we divide n by 2 and do a rehash (table-shrink).
- ▶ Note that right after a change in table-size we have $m = \alpha n/2$. In order for a table-expand to occur at least $\alpha n/2$ insertions are required. Similar, for a table-shrink at least $\alpha n/4$ deletions must occur.
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Lemma 33

Cuckoo Hashing has an expected constant insert-time and a worst-case constant search-time.

Note that the above lemma only holds if the fill-factor (number of keys/total number of hash-table slots) is at most $\frac{1}{2(1+\epsilon)}$.

The $1/(2(1+\epsilon))$ fill-factor comes from the fact that the total hash-table is of size $2n$ (because we have two tables of size n); moreover $m \leq (1+\epsilon)n$.

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8 Priority Queues

A **Priority Queue** S is a dynamic set data structure that supports the following operations:

- ▶ **S . build(x_1, \dots, x_n)**: Creates a data-structure that contains just the elements x_1, \dots, x_n .
- ▶ **S . insert(x)**: Adds element x to the data-structure.
- ▶ **element S . minimum()**: Returns an element $x \in S$ with minimum key-value $\text{key}[x]$.
- ▶ **element S . delete-min()**: Deletes the element with minimum key-value from S and returns it.
- ▶ **boolean S . is-empty()**: Returns true if the data-structure is empty and false otherwise.

Sometimes we also have

- ▶ **S . merge(S')**: $S := S \cup S'$; $S' := \emptyset$.

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An **addressable Priority Queue** also supports:

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8 Priority Queues

An **addressable Priority Queue** also supports:

- ▶ **handle S . insert(x)**: Adds element x to the data-structure, and returns a **handle** to the object for future reference.
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Dijkstra's Shortest Path Algorithm

Algorithm 14 Shortest-Path($G = (V, E, d), s \in V$)

```
1: Input: weighted graph  $G = (V, E, d)$ ; start vertex  $s$ ;  
2: Output: key-field of every node contains distance from  $s$ ;  
3:  $S.build()$ ; // build empty priority queue  
4: for all  $v \in V \setminus \{s\}$  do  
5:      $v.key \leftarrow \infty$ ;  
6:      $h_v \leftarrow S.insert(v)$ ;  
7:  $s.key \leftarrow 0$ ;  $S.insert(s)$ ;  
8: while  $S.is-empty() = false$  do  
9:      $v \leftarrow S.delete-min()$ ;  
10:    for all  $x \in V$  s.t.  $(v, x) \in E$  do  
11:        if  $x.key > v.key + d(v, x)$  then  
12:             $S.decrease-key(h_x, v.key + d(v, x))$ ;  
13:             $x.key \leftarrow v.key + d(v, x)$ ;
```

Prim's Minimum Spanning Tree Algorithm

Algorithm 15 Prim-MST($G = (V, E, d), s \in V$)

```
1: Input: weighted graph  $G = (V, E, d)$ ; start vertex  $s$ ;  
2: Output: pred-fields encode MST;  
3:  $S.build()$ ; // build empty priority queue  
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5:      $v.key \leftarrow \infty$ ;  
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13:             $x.key \leftarrow d(v, x)$ ;  
14:             $x.pred \leftarrow v$ ;
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Analysis of Dijkstra and Prim

Both algorithms require:

- ▶ 1 build() operation
- ▶ $|V|$ insert() operations
- ▶ $|V|$ delete-min() operations
- ▶ $|V|$ is-empty() operations
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How good a running time can we obtain?

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<i>Operation</i>	<i>Binary Heap</i>	<i>BST</i>	<i>Binomial Heap</i>	<i>Fibonacci Heap*</i>
build	n	$n \log n$	$n \log n$	n
minimum	1	$\log n$	$\log n$	1
is-empty	1	1	1	1
insert	$\log n$	$\log n$	$\log n$	1
delete	$\log n^{**}$	$\log n$	$\log n$	$\log n$
delete-min	$\log n$	$\log n$	$\log n$	$\log n$
decrease-key	$\log n$	$\log n$	$\log n$	1
merge	n	$n \log n$	$\log n$	1

Note that most applications use `build()` only to create an empty heap which then costs time 1.

The standard version of binary heaps is not addressable, and hence does not support a delete operation.

Fibonacci heaps only give an **amortized** guarantee.

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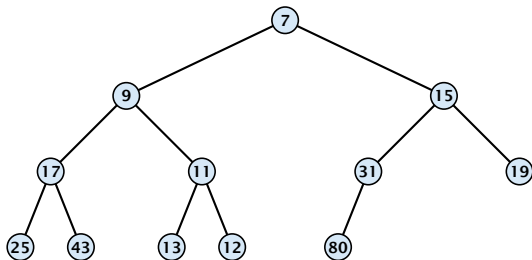
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8 Priority Queues

Using Binary Heaps, Prim and Dijkstra run in time $\mathcal{O}((|V| + |E|) \log |V|)$.

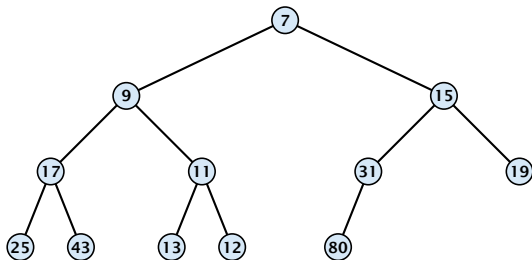
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8.1 Binary Heaps



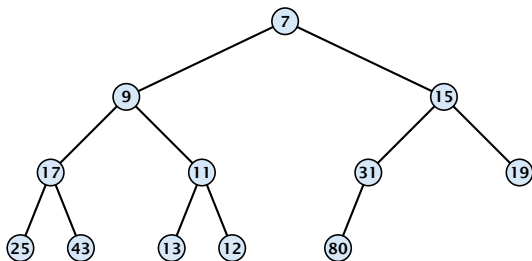
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- ▶ Nearly complete binary tree; only the last level is not full, and this one is filled from left to right.



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- ▶ Nearly complete binary tree; only the last level is not full, and this one is filled from left to right.
- ▶ **Heap property:** A node's key is not larger than the key of one of its children.



Binary Heaps

Operations:

- ▶ `minimum()`: return the root-element. Time $\mathcal{O}(1)$.
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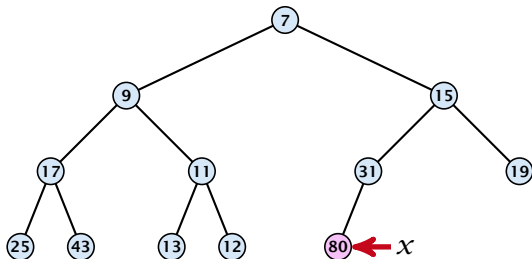
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Maintain a pointer to the **last element** x .

- ▶ We can compute the predecessor of x (last element when x is deleted) in time $\mathcal{O}(\log n)$.



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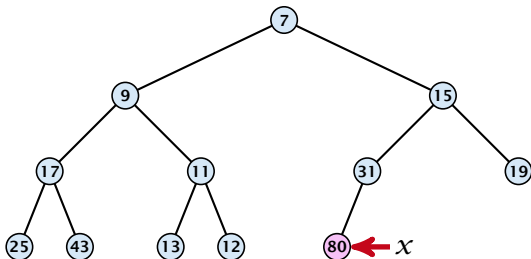
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go up until the last edge used was a right edge.

go left; go right until you reach a leaf

if you hit the root on the way up, go to the rightmost element



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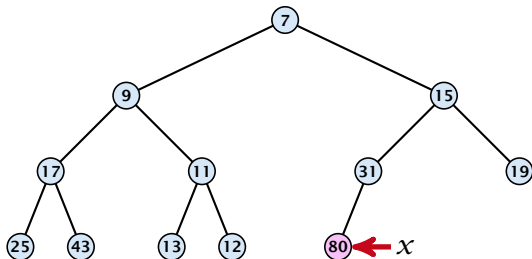
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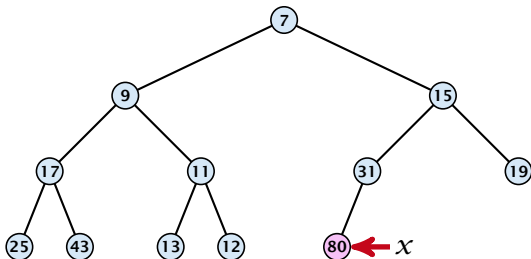
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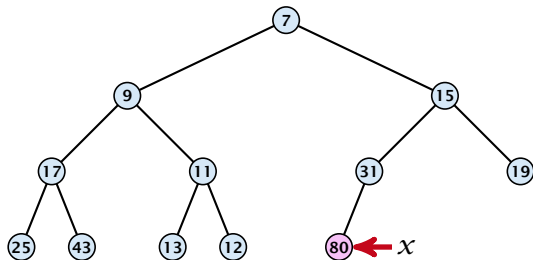
- ▶ We can compute the successor of x (last element when an element is inserted) in time $\mathcal{O}(\log n)$.

go up until the last edge used was left edge

if right edge used, swap

repeat until root or left edge used

swap with last element



8.1 Binary Heaps

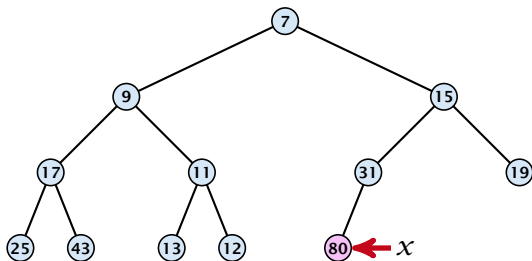
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go up until the last edge used was a left edge.

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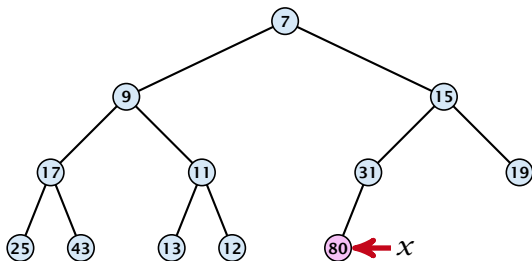
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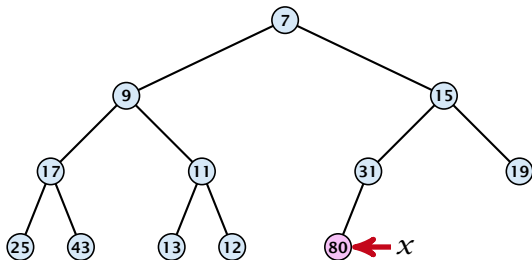
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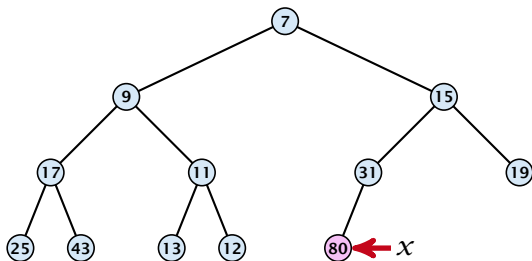
go right; go left until you reach a **null**-pointer.

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Insert

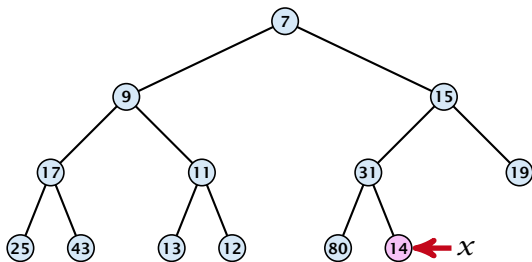
1. Insert element at successor of x .
2. Exchange with parent until heap property is fulfilled.



Note that an exchange can either be done by moving the data or by changing pointers. The latter method leads to an addressable priority queue.

Insert

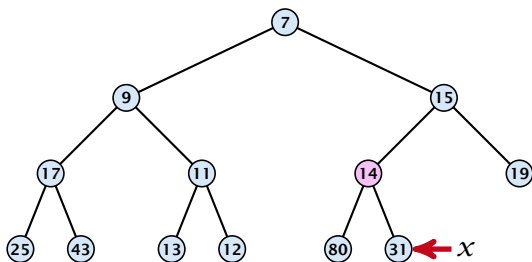
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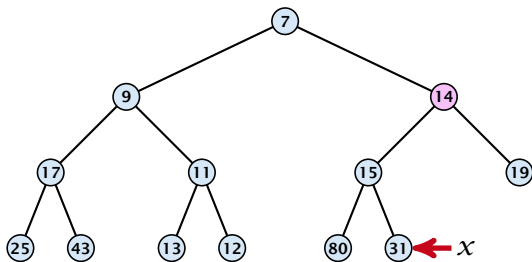
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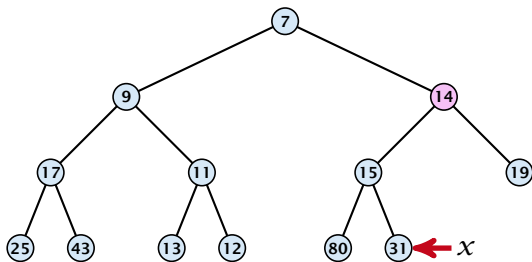
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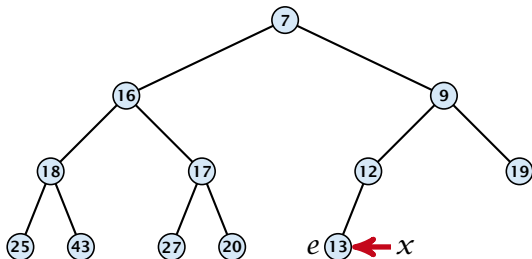
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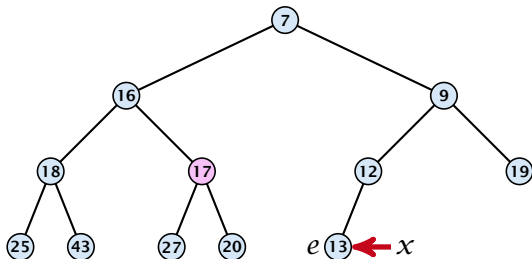
1. Exchange the element to be deleted with the element e pointed to by x .
2. Restore the heap-property for the element e .



At its new position e may either travel up or down in the tree (but not both directions).

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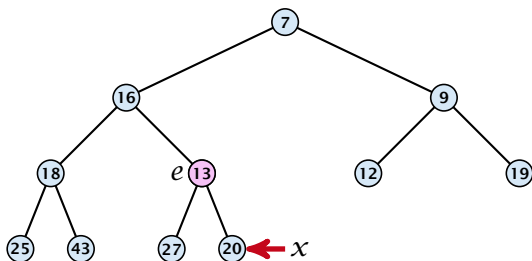
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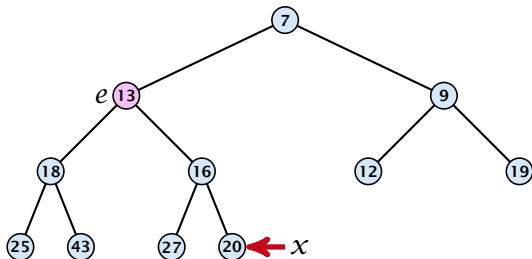
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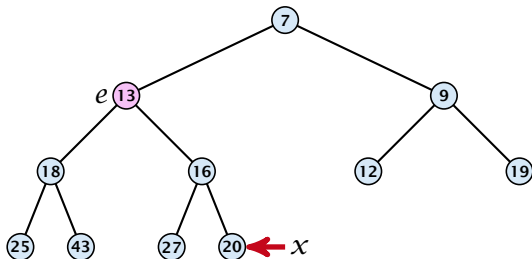
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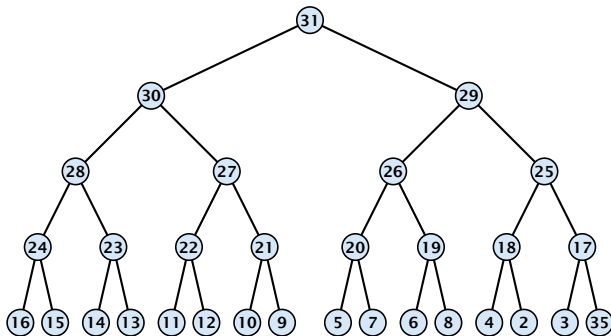
Binary Heaps

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- ▶ **minimum()**: return the root-element. Time $\mathcal{O}(1)$.
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Build Heap

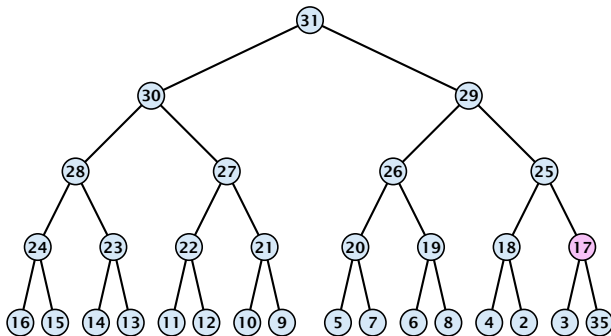
We can build a heap in linear time:



$$\sum_{\text{levels } \ell} 2^\ell \cdot (h - \ell) = \sum_i i 2^{h-i} = \mathcal{O}(2^h) = \mathcal{O}(n)$$

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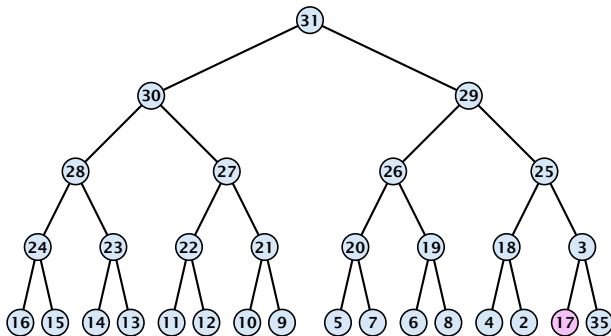
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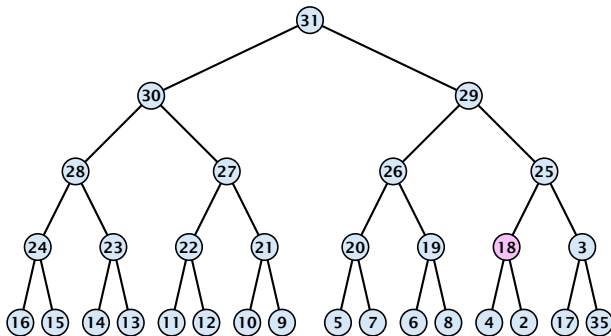
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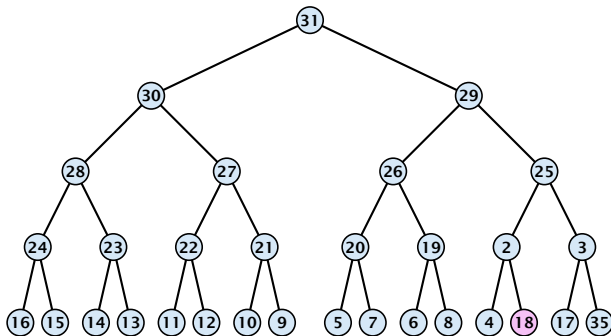
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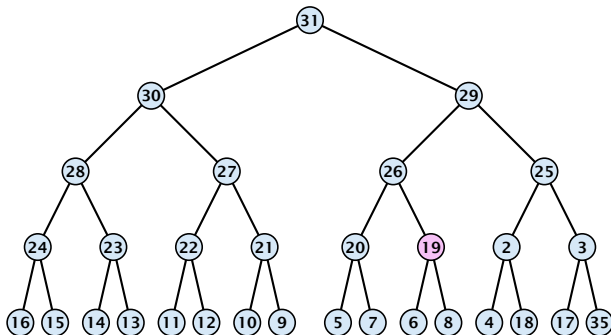
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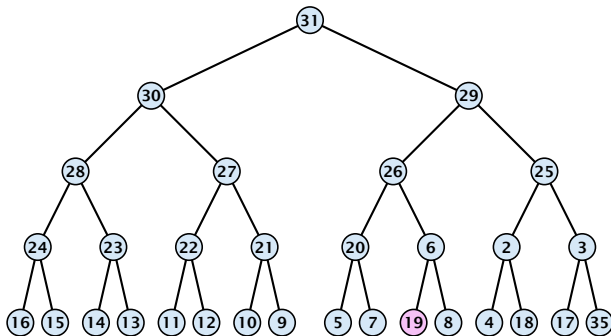
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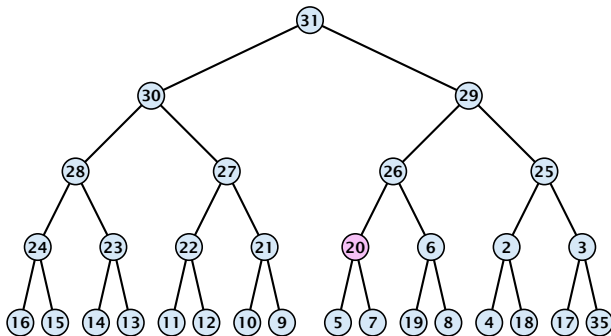
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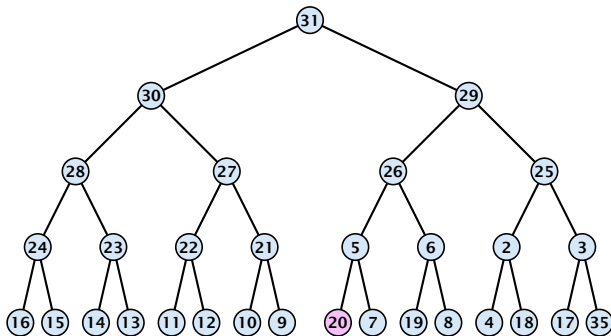
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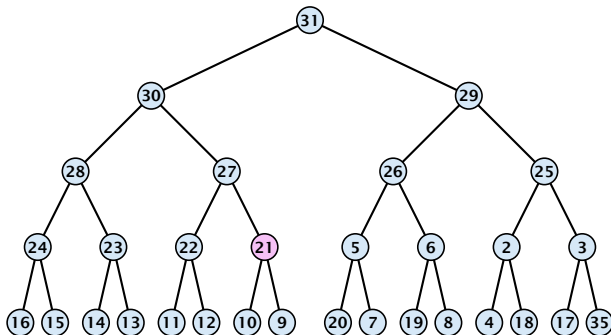
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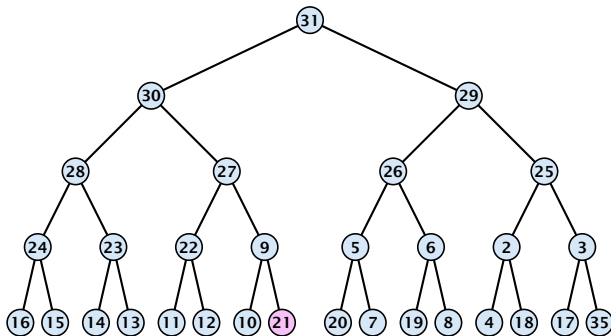
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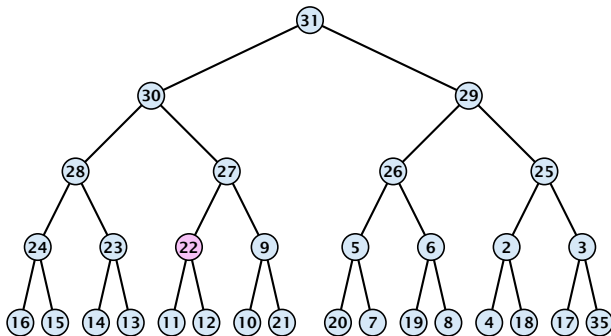
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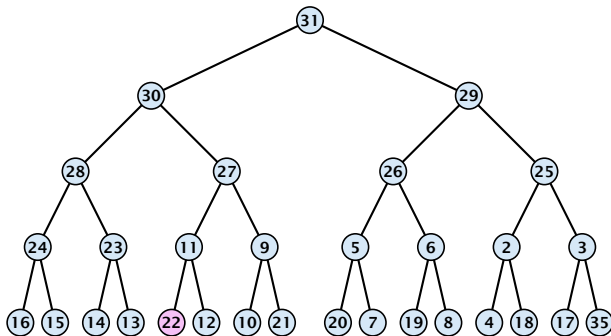
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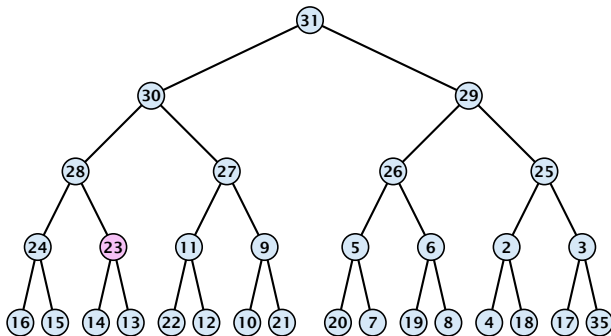
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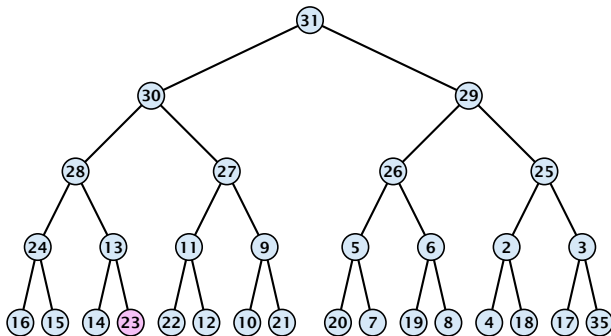
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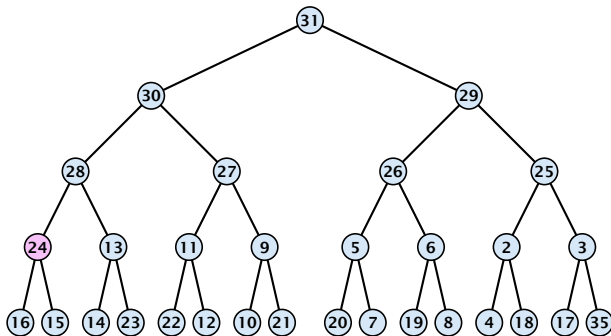
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Build Heap

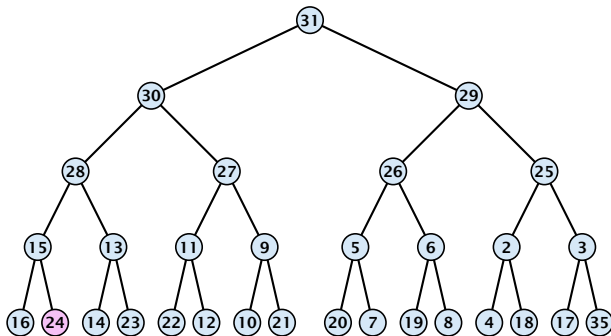
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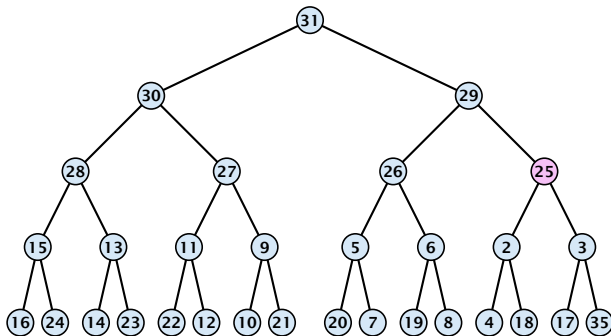
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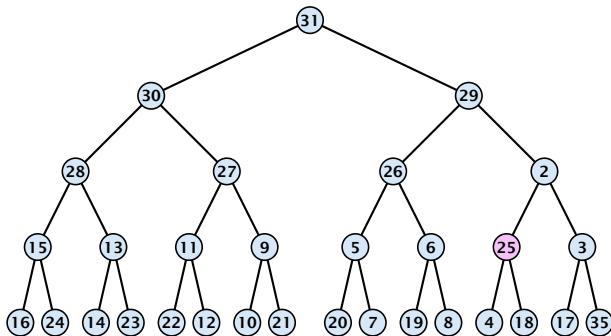
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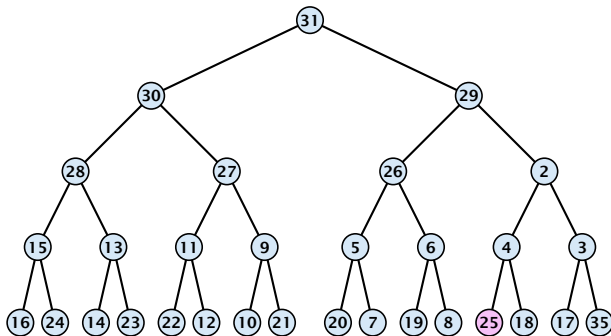
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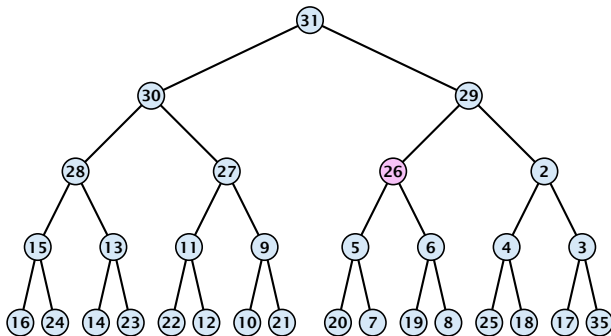
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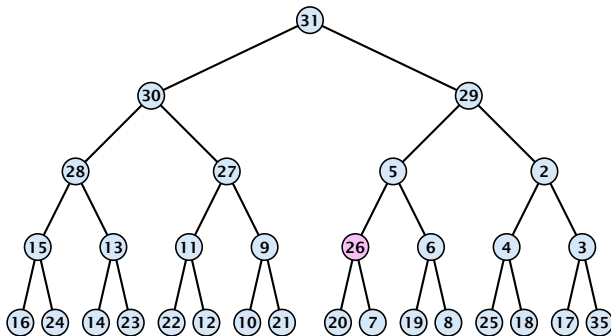
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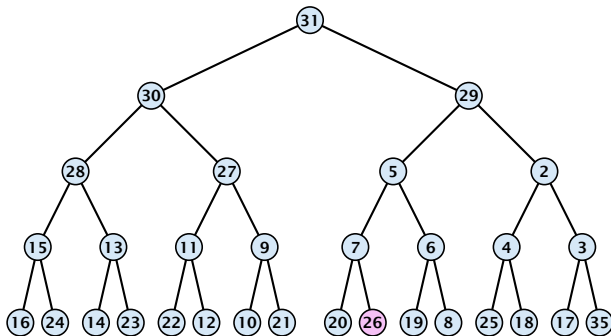
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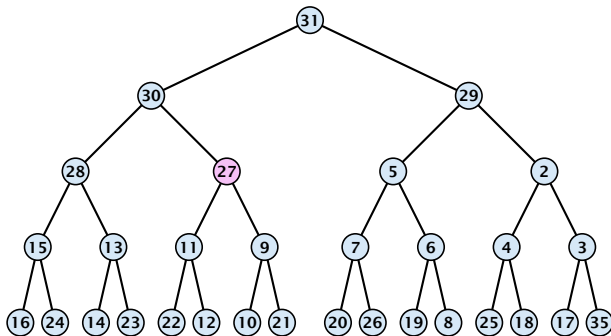
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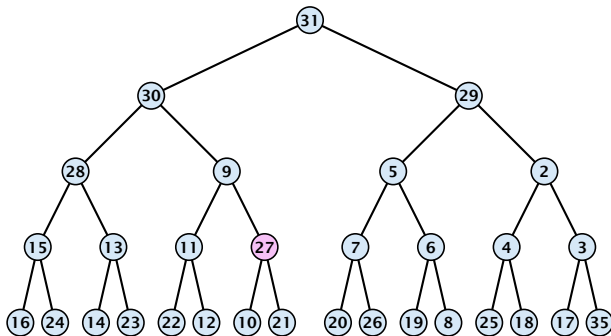
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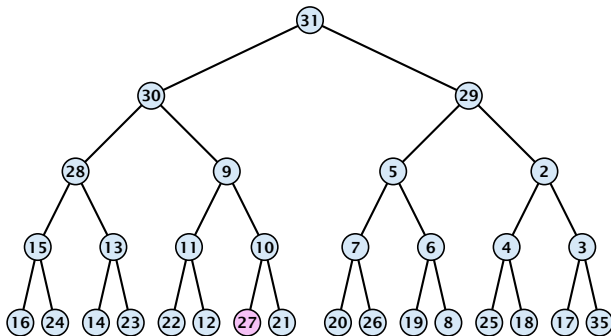
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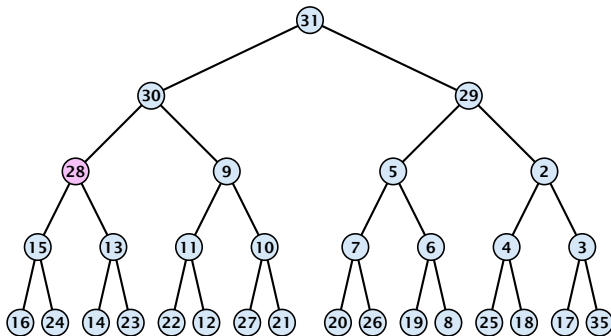
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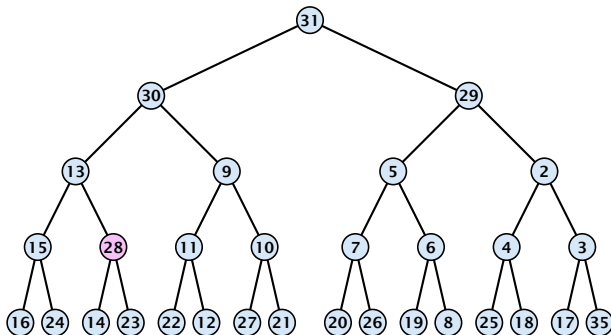
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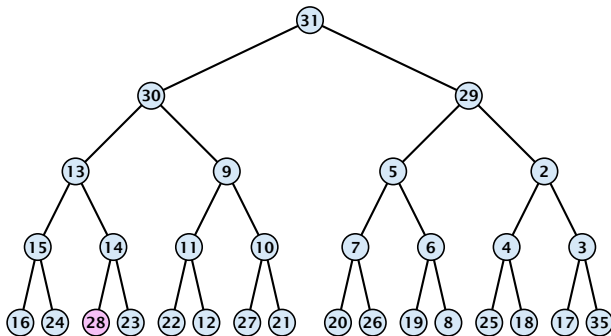
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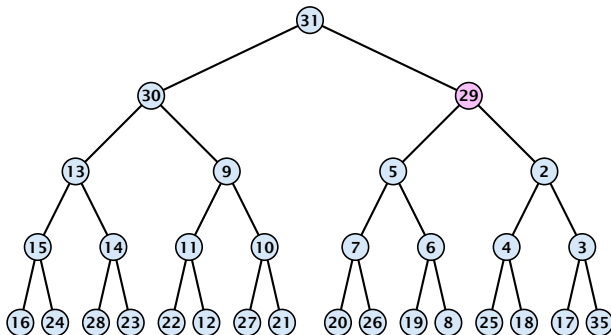
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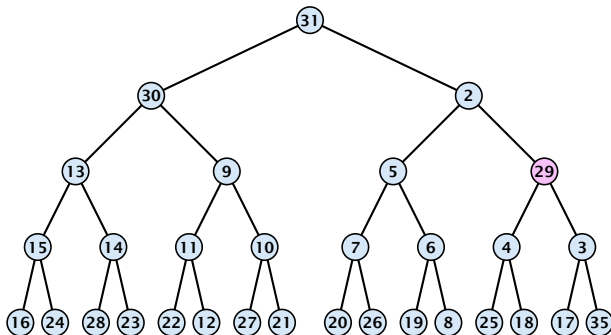
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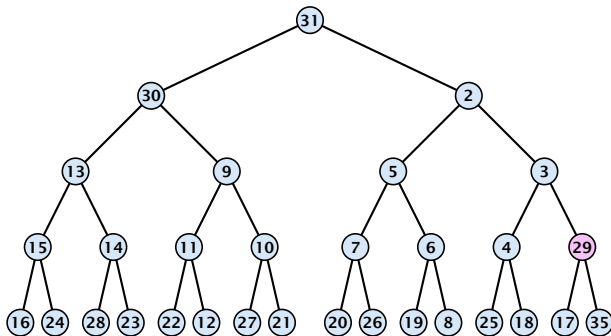
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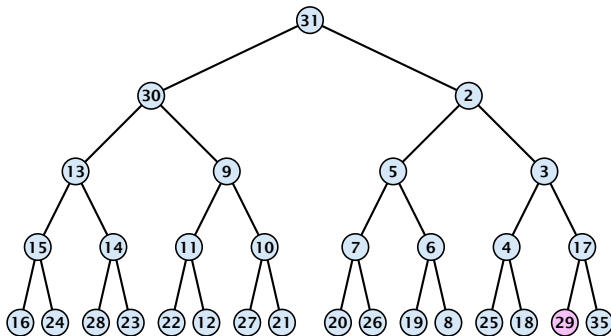
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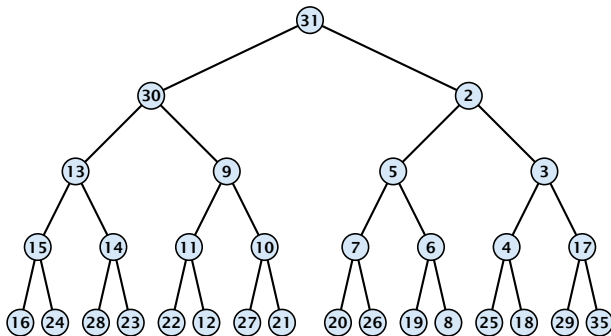
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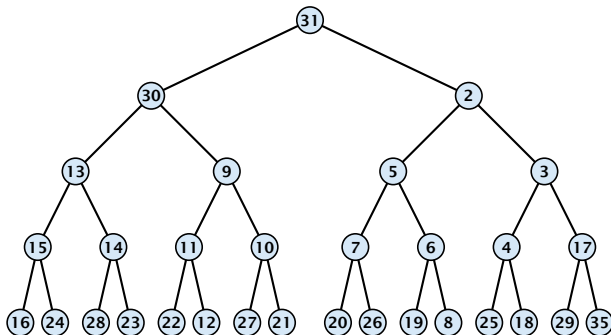
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Binary Heaps

Operations:

- ▶ **minimum()**: Return the root-element. Time $\mathcal{O}(1)$.
- ▶ **is-empty()**: Check whether root-pointer is **null**. Time $\mathcal{O}(1)$.
- ▶ **insert(k)**: Insert at x and bubble up. Time $\mathcal{O}(\log n)$.
- ▶ **delete(h)**: Swap with x and bubble up or sift-down. Time $\mathcal{O}(\log n)$.
- ▶ **build(x_1, \dots, x_n)**: Insert elements arbitrarily; then do sift-down operations starting with the lowest layer in the tree. Time $\mathcal{O}(n)$.

Binary Heaps

The standard implementation of binary heaps is via arrays. Let $A[0, \dots, n - 1]$ be an array

- ▶ The parent of i -th element is at position $\lfloor \frac{i-1}{2} \rfloor$.
- ▶ The left child of i -th element is at position $2i + 1$.
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Finding the successor of x is much easier than in the description on the previous slide. Simply increase or decrease x .

The resulting binary heap is not addressable. The elements don't maintain their positions and therefore there are no stable handles.

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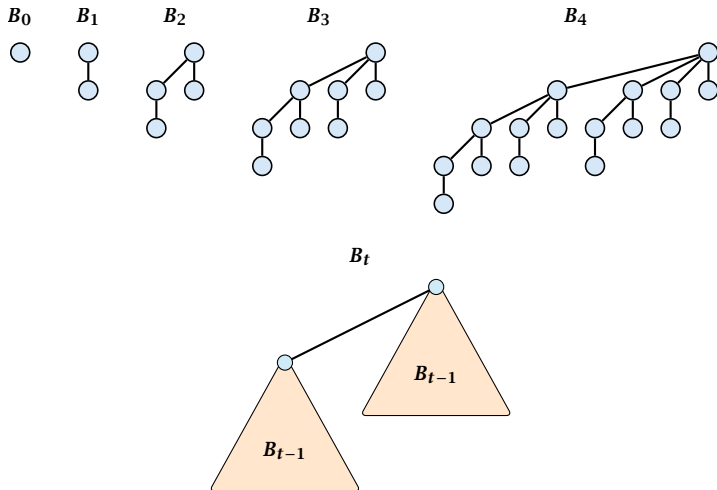
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8.2 Binomial Heaps

<i>Operation</i>	<i>Binary Heap</i>	<i>BST</i>	<i>Binomial Heap</i>	<i>Fibonacci Heap*</i>
build	n	$n \log n$	$n \log n$	n
minimum	1	$\log n$	$\log n$	1
is-empty	1	1	1	1
insert	$\log n$	$\log n$	$\log n$	1
delete	$\log n^{**}$	$\log n$	$\log n$	$\log n$
delete-min	$\log n$	$\log n$	$\log n$	$\log n$
decrease-key	$\log n$	$\log n$	$\log n$	1
merge	n	$n \log n$	$\log n$	1

Binomial Trees



Properties of Binomial Trees

- ▶ B_k has 2^k nodes.
- ▶ B_k has height k .
- ▶ The root of B_k has degree k .
- ▶ B_k has $\binom{k}{\ell}$ nodes on level ℓ .
- ▶ Deleting the root of B_k gives trees B_0, B_1, \dots, B_{k-1} .

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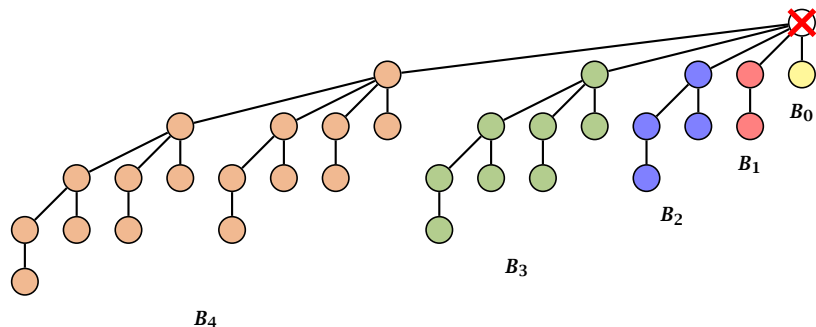
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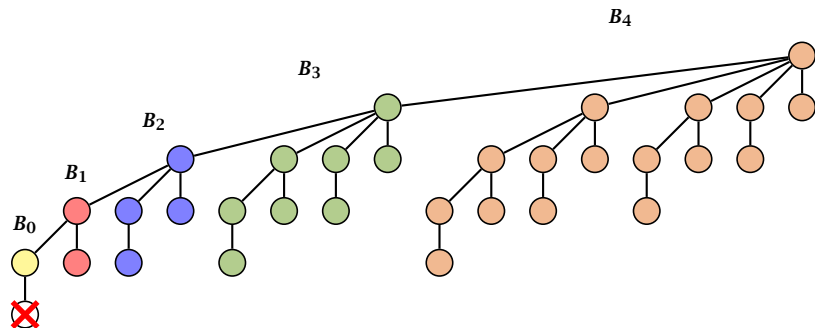
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Binomial Trees



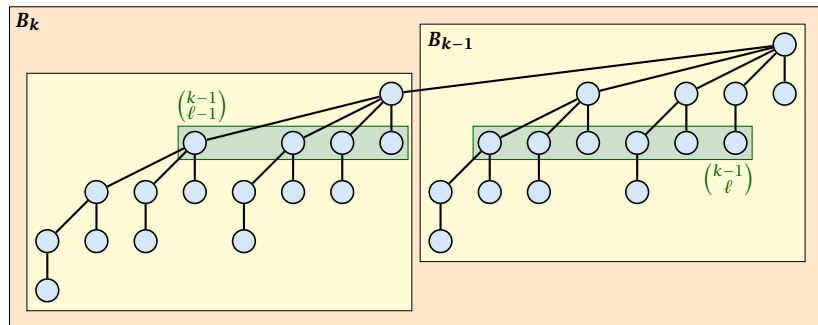
Deleting the root of B_5 leaves sub-trees B_4 , B_3 , B_2 , B_1 , and B_0 .

Binomial Trees



Deleting the leaf furthest from the root (in B_5) leaves a path that connects the roots of sub-trees B_4 , B_3 , B_2 , B_1 , and B_0 .

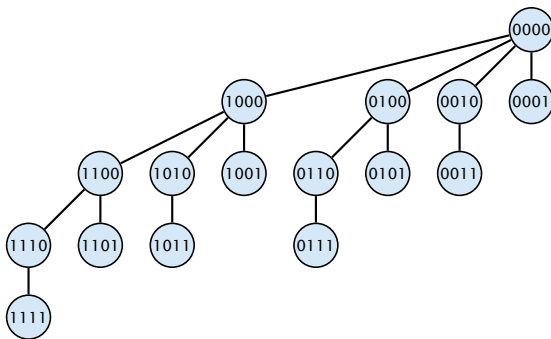
Binomial Trees



The number of nodes on level ℓ in tree B_k is therefore

$$\binom{k-1}{\ell-1} + \binom{k-1}{\ell} = \binom{k}{\ell}$$

Binomial Trees

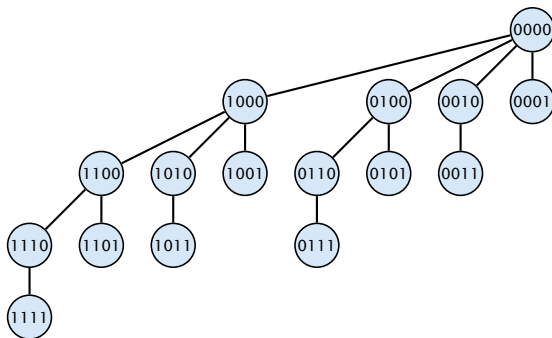


The binomial tree B_k is a sub-graph of the hypercube H_k .

The parent of a node with label b_k, \dots, b_1 is obtained by setting the least significant 1-bit to 0.

The ℓ -th level contains nodes that have ℓ 1's in their label.

Binomial Trees

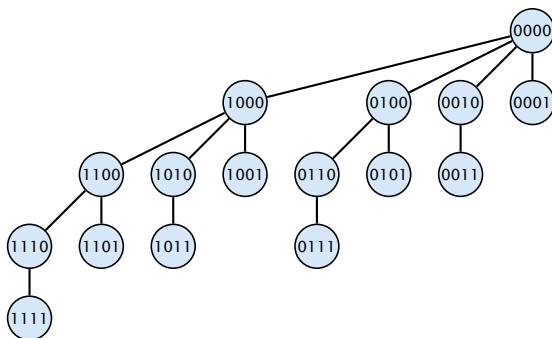


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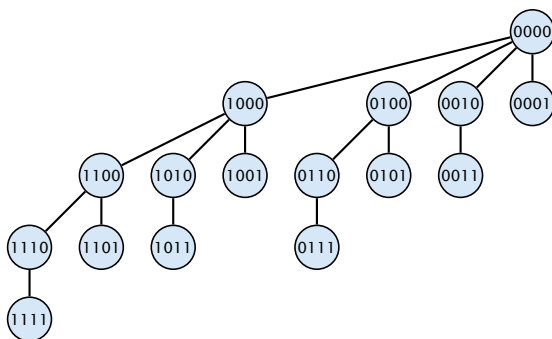


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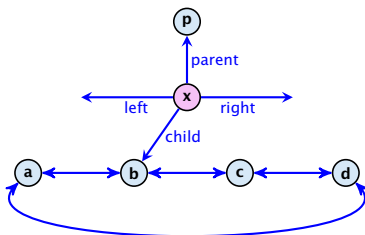
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8.2 Binomial Heaps

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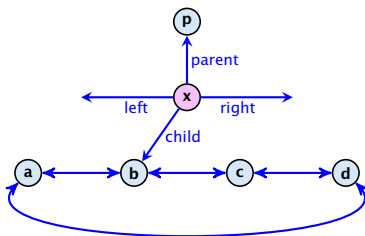
- ▶ The children of a node are arranged in a **circular linked list**.
- ▶ A child-pointer points to an arbitrary node within the list.
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- ▶ Pointers $x.left$ and $x.right$ point to the left and right sibling of x (if x does not have siblings then $x.left = x.right = x$).



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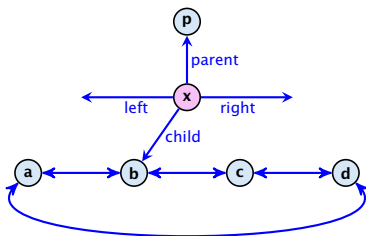
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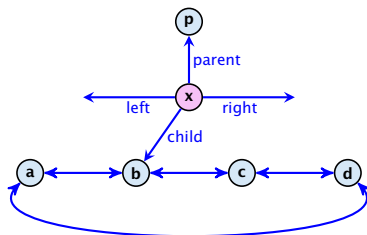
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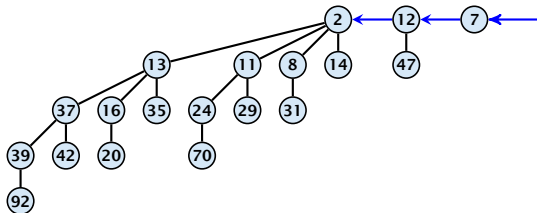
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8.2 Binomial Heaps

- ▶ Given a pointer to a node x we can splice out the sub-tree rooted at x in constant time.
- ▶ We can add a child-tree T to a node x in constant time if we are given a pointer to x and a pointer to the root of T .

Binomial Heap

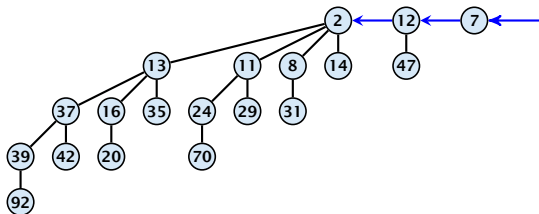


In a binomial heap the keys are arranged in a collection of binomial trees.

Every tree fulfills the heap-property

There is at most one tree for every dimension/order. For example the above heap contains trees B_0 , B_1 , and B_4 .

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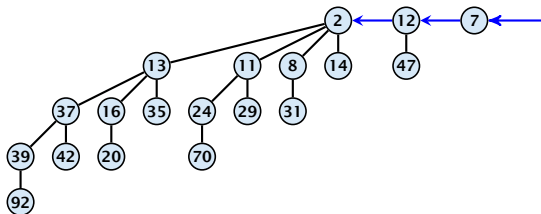


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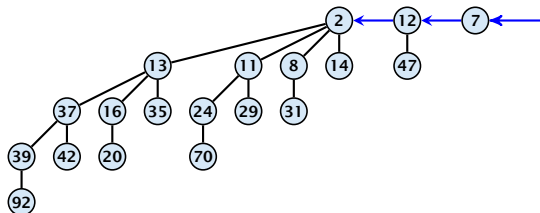


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Binomial Heap: Merge

Given the number n of keys to be stored in a binomial heap we can deduce the binomial trees that will be contained in the collection.

Let $B_{k_1}, B_{k_2}, B_{k_3}, k_i < k_{i+1}$ denote the binomial trees in the collection and recall that every tree may be contained at most once.

Then $n = \sum_i 2^{k_i}$ must hold. But since the k_i are all distinct this means that the k_i define the non-zero bit-positions in the binary representation of n .

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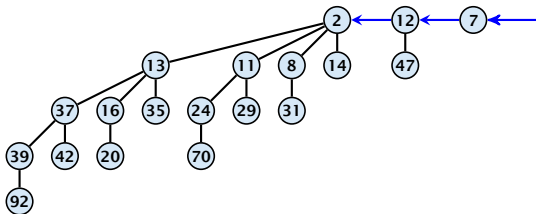
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Binomial Heap

Properties of a heap with n keys:

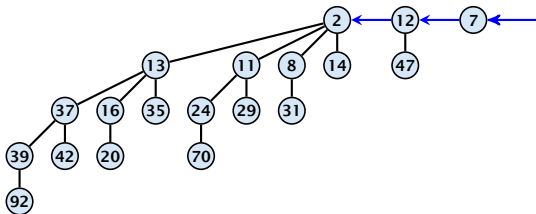
- ▶ Let $n = b_d b_{d-1} \dots b_0$ denote binary representation of n .
- ▶ The heap contains tree B_i iff $b_i = 1$.
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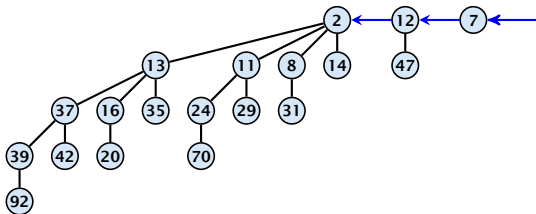
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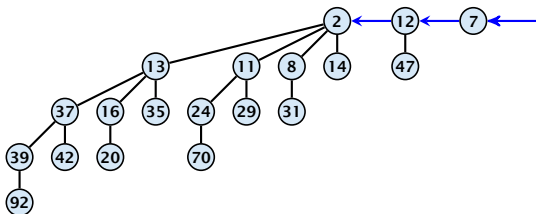
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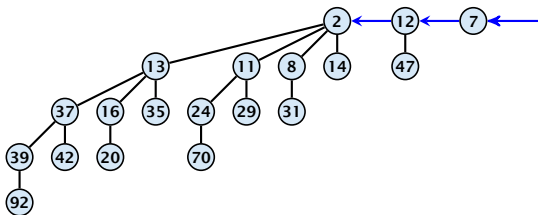
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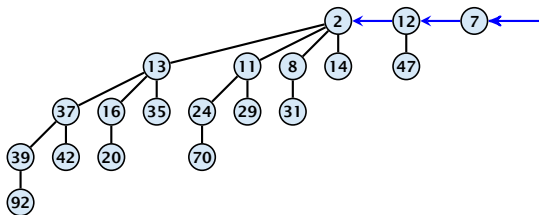
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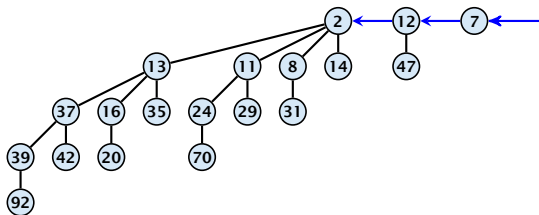
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Binomial Heap: Merge

The merge-operation is instrumental for binomial heaps.

A merge is easy if we have two heaps with different binomial trees. We can simply merge the tree-lists.

Otherwise, we cannot do this because the merged heap is not allowed to contain two trees of the same order.

Merging two trees of the same size: Add the tree with larger root-value as a child to the other tree.

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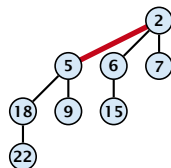
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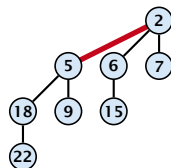
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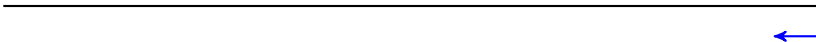
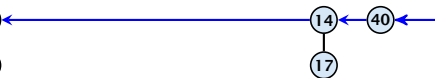
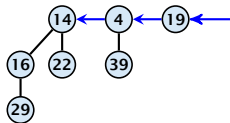
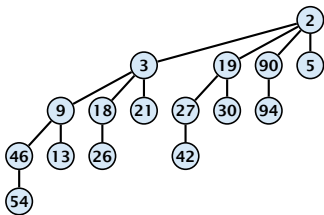
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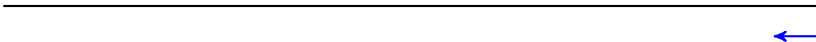
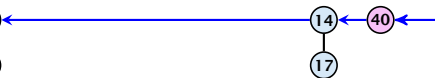
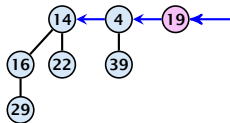
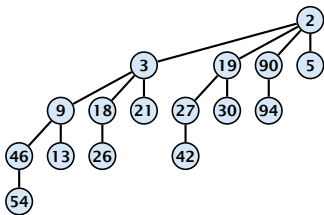
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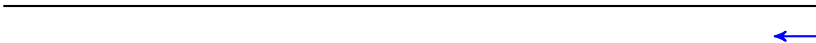
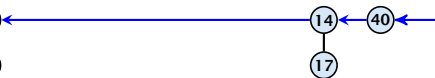
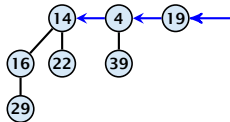
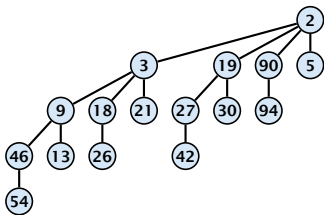
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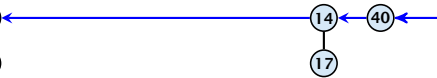
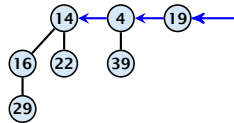
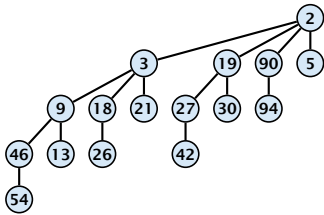
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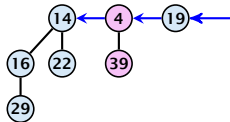
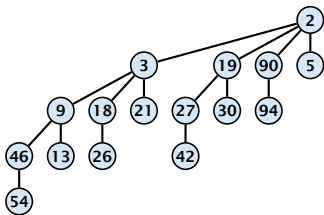


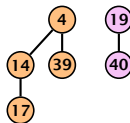
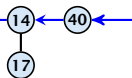
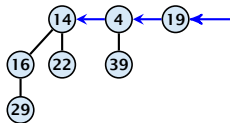
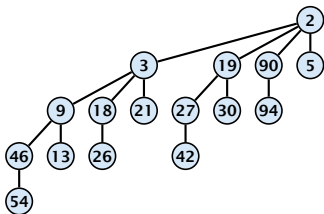


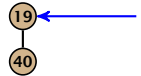
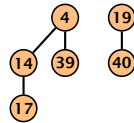
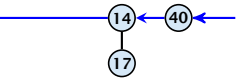
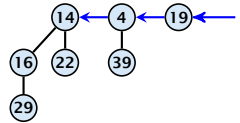
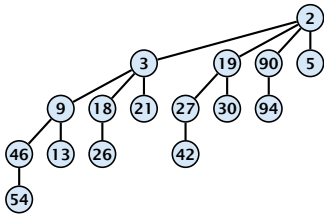


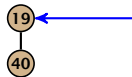
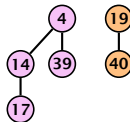
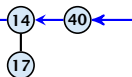
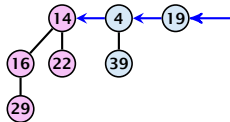
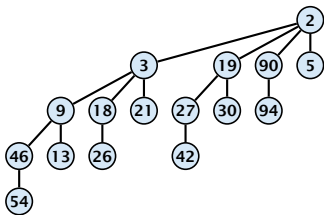


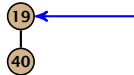
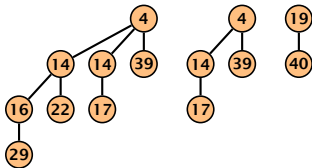
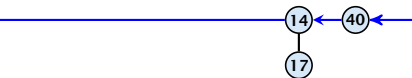
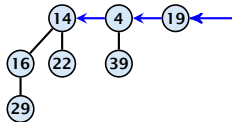
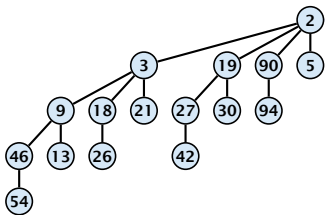


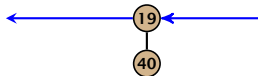
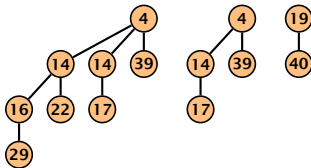
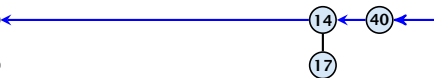
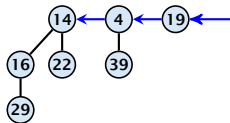
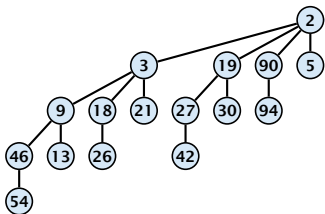


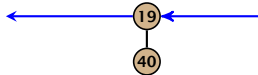
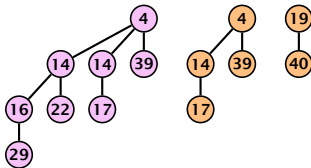
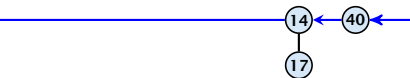
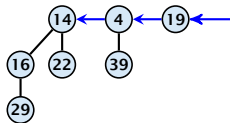
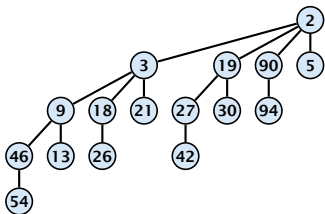


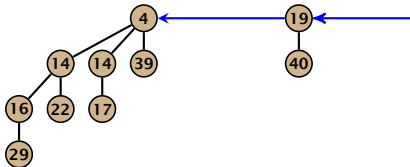
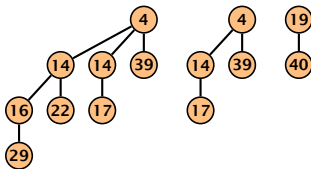
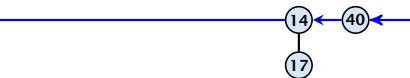
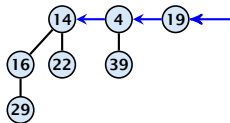
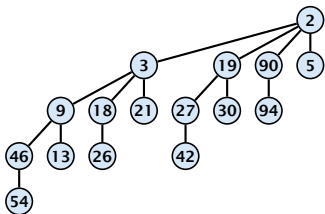




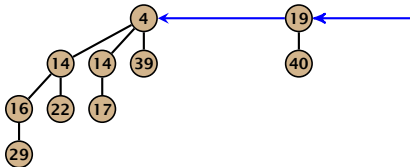
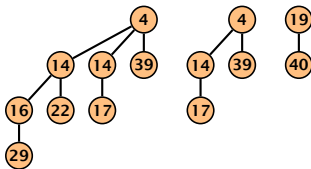
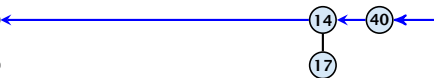
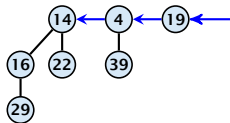
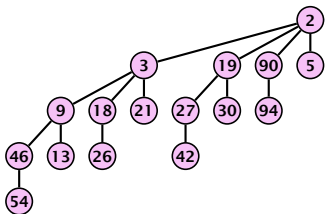




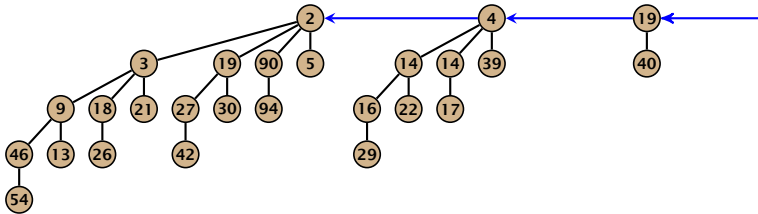
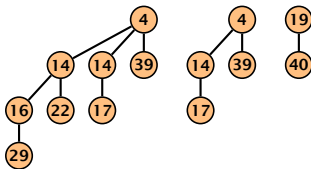
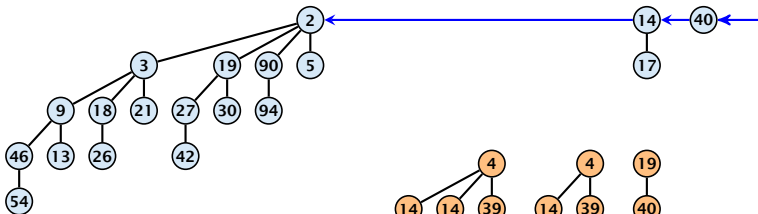


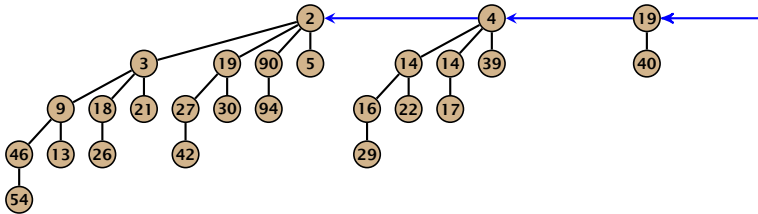
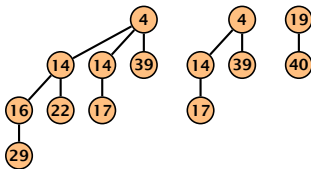
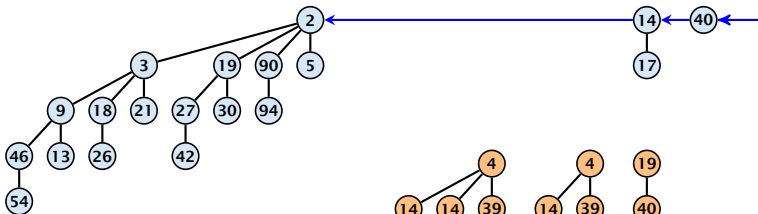


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- ▶ Create a new heap S' that contains the trees obtained from T_{\min} after deleting the root (note that these are just $\mathcal{O}(\log n)$ trees).
- ▶ Compute $S.\text{merge}(S')$.
- ▶ Time: $\mathcal{O}(\log n)$.

8.2 Binomial Heaps

S. delete-min():

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8.2 Binomial Heaps

S. decrease-key(handle h):

- ▶ Decrease the key of the element pointed to by h .
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8.2 Binomial Heaps

***S*. delete(handle *h*):**

- ▶ Execute *S*. decrease-key(*h*, $-\infty$).
- ▶ Execute *S*. delete-min().
- ▶ Time: $\mathcal{O}(\log n)$.

8.2 Binomial Heaps

S . delete(handle h):

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8.2 Binomial Heaps

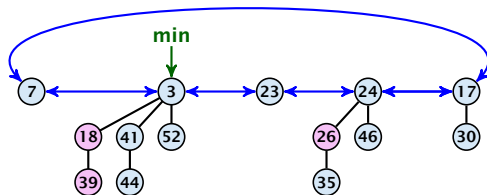
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8.3 Fibonacci Heaps

Collection of trees that fulfill the heap property.

Structure is much more relaxed than binomial heaps.



8.3 Fibonacci Heaps

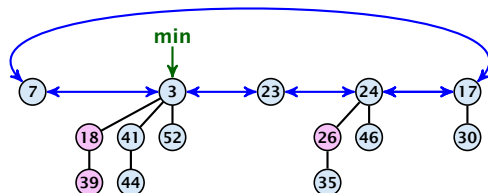
Additional implementation details:

- ▶ Every node x stores its degree in a field $x.degree$. Note that this can be updated in constant time when adding a child to x .
- ▶ Every node stores a boolean value $x.marked$ that specifies whether x is **marked** or not.

8.3 Fibonacci Heaps

The potential function:

- ▶ $t(S)$ denotes the number of trees in the heap.
- ▶ $m(S)$ denotes the number of marked nodes.
- ▶ We use the potential function $\Phi(S) = t(S) + 2m(S)$.



The potential is $\Phi(S) = 5 + 2 \cdot 3 = 11$.

8.3 Fibonacci Heaps

We assume that one unit of potential can pay for a constant amount of work, where the constant is chosen “big enough” (to take care of the constants that occur).

To make this more explicit we use c to denote the amount of work that a unit of potential can pay for.

8.3 Fibonacci Heaps

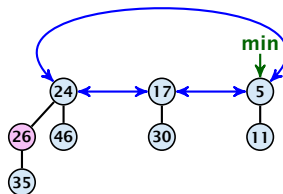
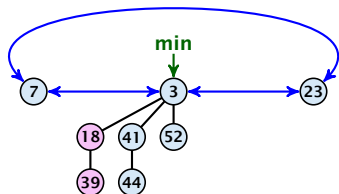
S. minimum()

- ▶ Access through the min-pointer.
- ▶ Actual cost $\mathcal{O}(1)$.
- ▶ No change in potential.
- ▶ Amortized cost $\mathcal{O}(1)$.

8.3 Fibonacci Heaps

S . merge(S')

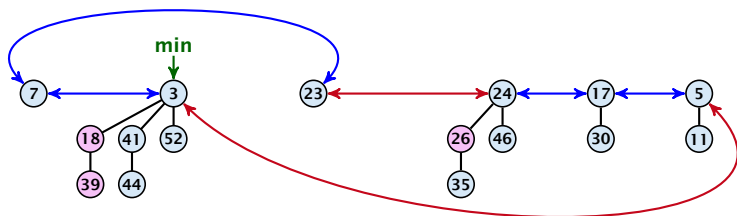
- ▶ Merge the root lists.
- ▶ Adjust the min-pointer



8.3 Fibonacci Heaps

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- ▶ Merge the root lists.
- ▶ Adjust the min-pointer



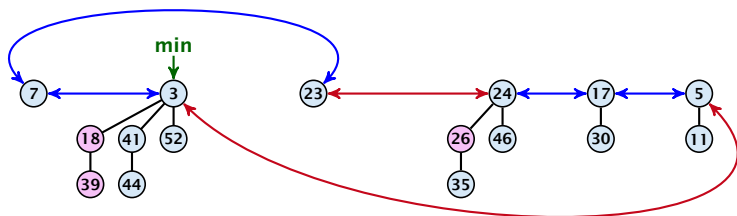
Running time:

- ▶ Actual cost $\mathcal{O}(1)$.

8.3 Fibonacci Heaps

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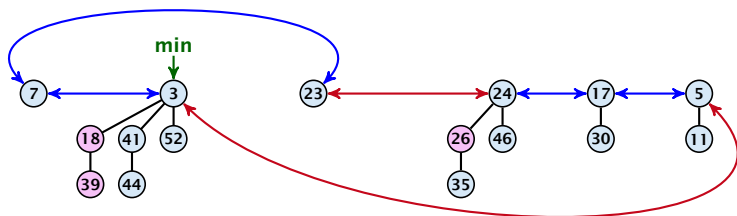
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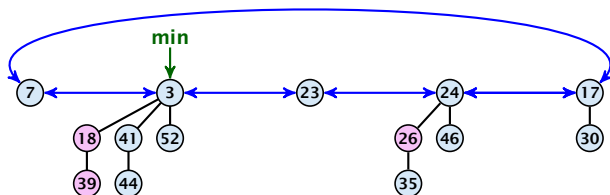
Running time:

- ▶ Actual cost $\mathcal{O}(1)$.
- ▶ No change in potential.
- ▶ Hence, amortized cost is $\mathcal{O}(1)$.

8.3 Fibonacci Heaps

S. insert(x)

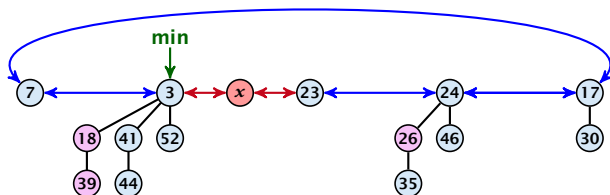
- ▶ Create a new tree containing x .
- ▶ Insert x into the root-list.
- ▶ Update min-pointer, if necessary.



8.3 Fibonacci Heaps

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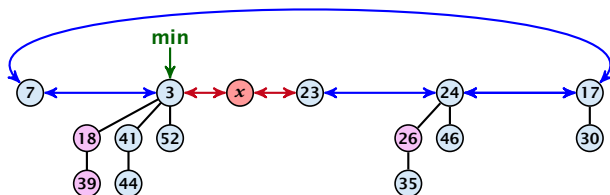
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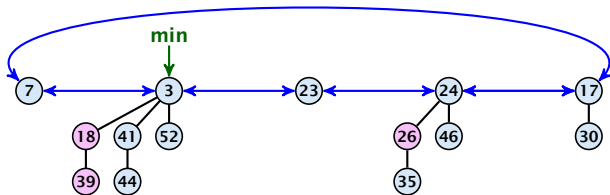


Running time:

- ▶ Actual cost $\mathcal{O}(1)$.
- ▶ Change in potential is $+1$.
- ▶ Amortized cost is $c + \mathcal{O}(1) = \mathcal{O}(1)$.

8.3 Fibonacci Heaps

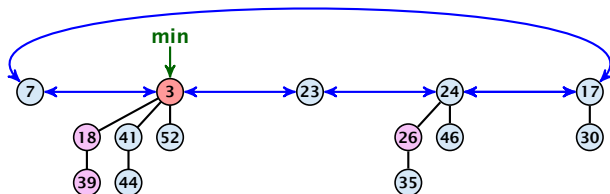
S. delete-min(x)



8.3 Fibonacci Heaps

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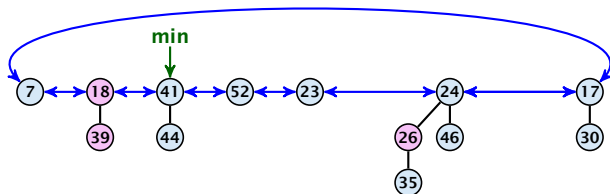
- ▶ Delete minimum; add child-trees to heap;
time: $D(\min) \cdot \mathcal{O}(1)$.



8.3 Fibonacci Heaps

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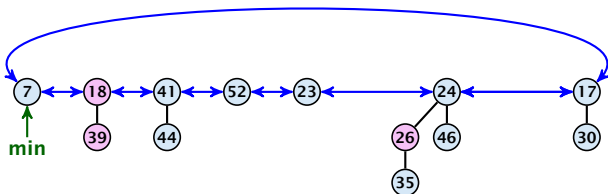
- ▶ Delete minimum; add child-trees to heap; time: $D(\min) \cdot \mathcal{O}(1)$.
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8.3 Fibonacci Heaps

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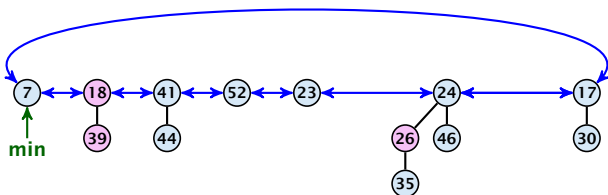
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8.3 Fibonacci Heaps

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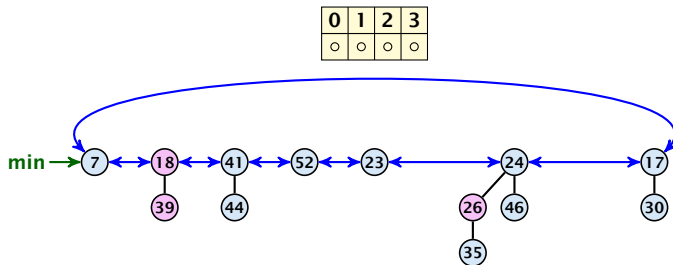
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- ▶ Consolidate root-list so that no roots have the same degree. Time $t \cdot \mathcal{O}(1)$ (see next slide).

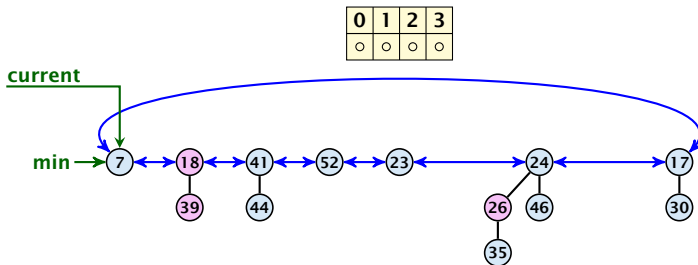
8.3 Fibonacci Heaps

Consolidate:



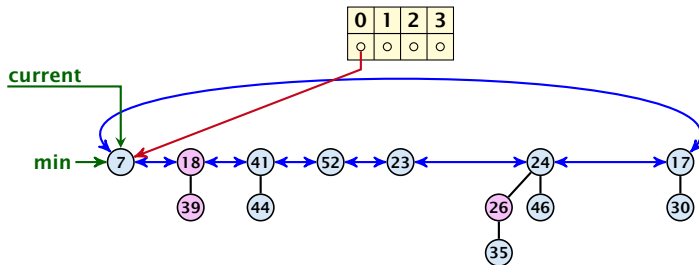
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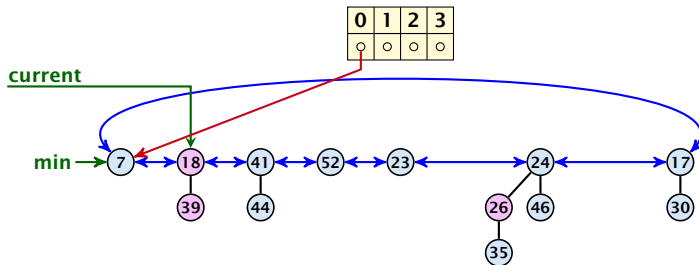
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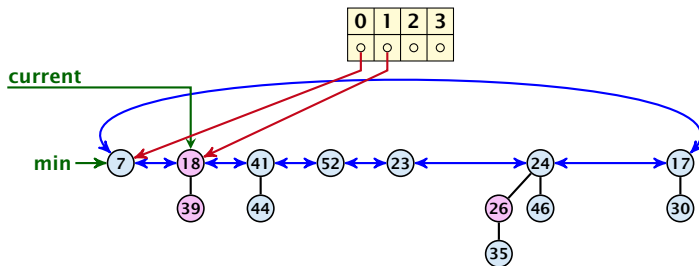
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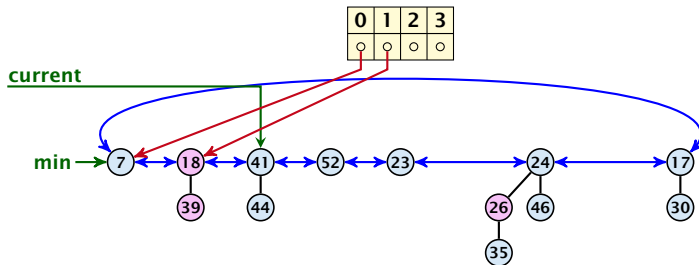
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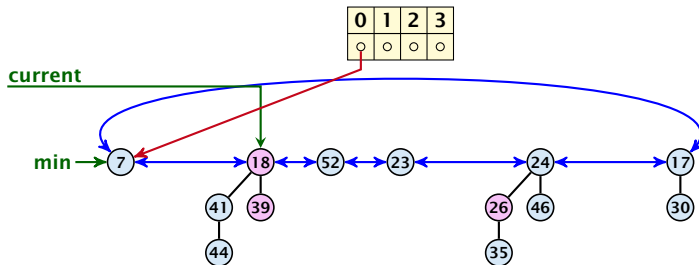
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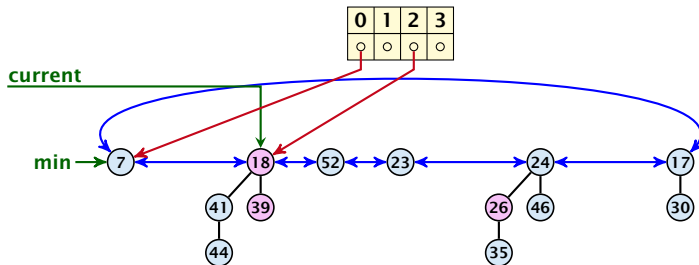
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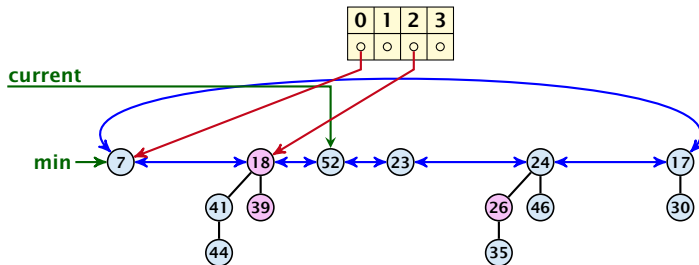
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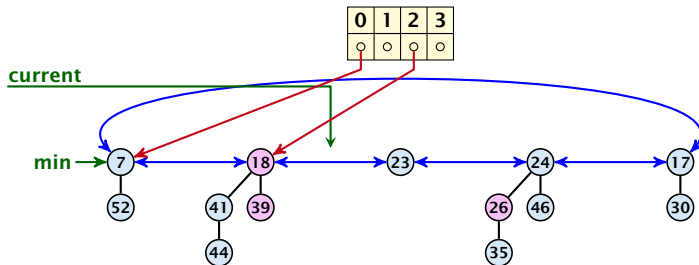
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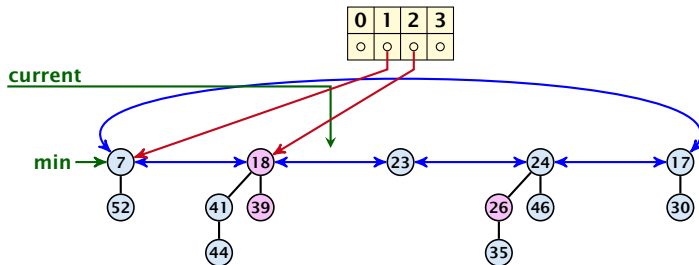
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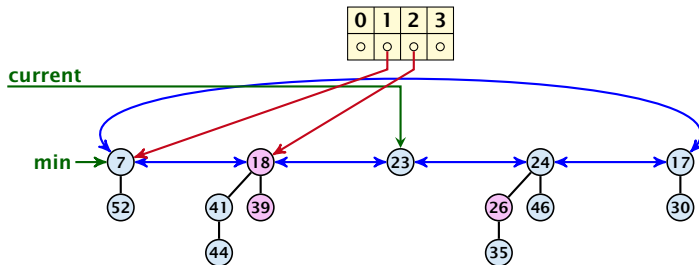
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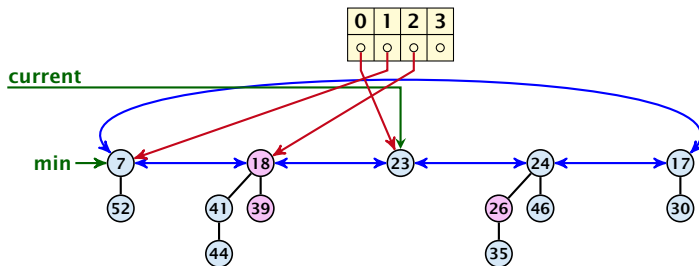
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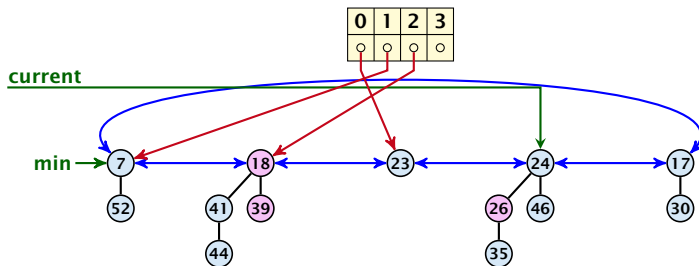
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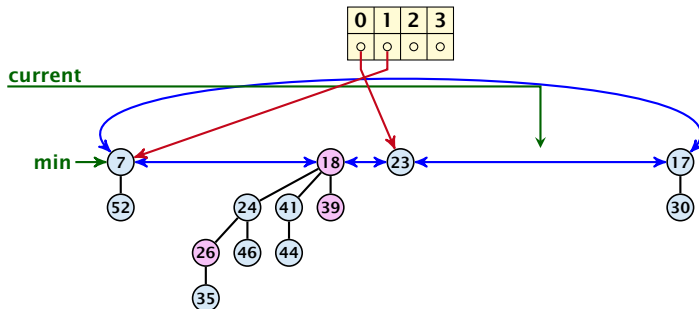
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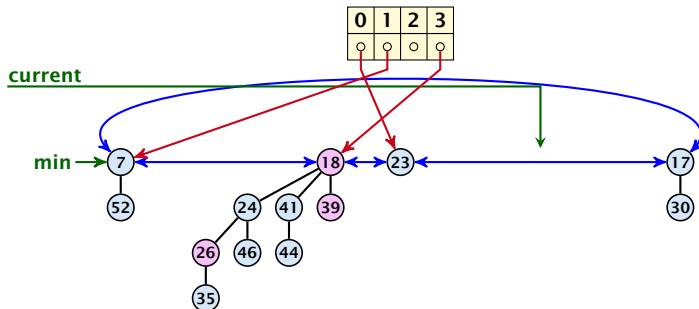
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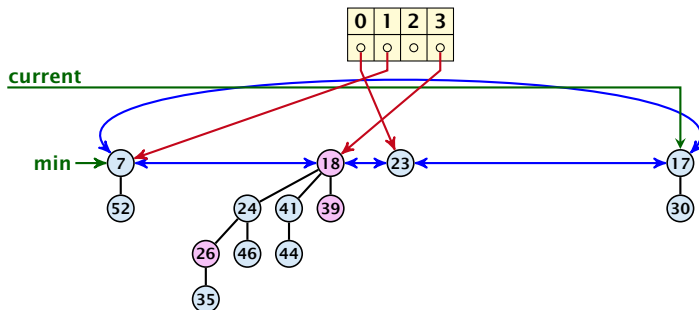
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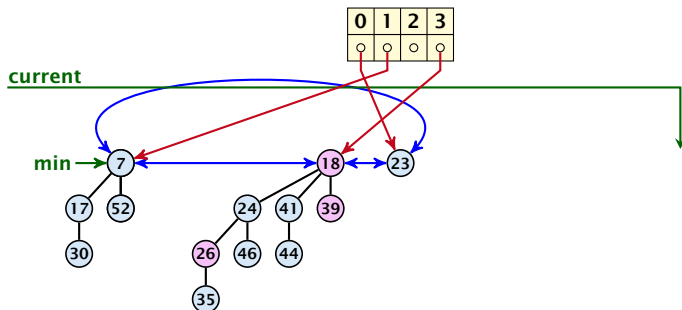
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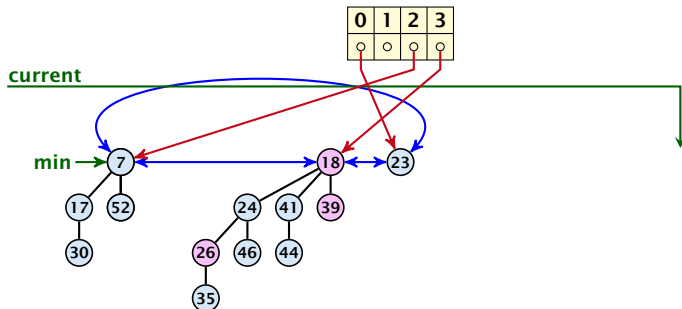
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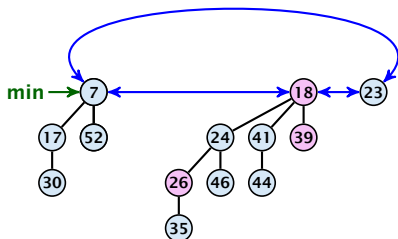
8.3 Fibonacci Heaps

Consolidate:



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8.3 Fibonacci Heaps

Actual cost for delete-min()

- ▶ At most $D_n + t$ elements in root-list before consolidate.

8.3 Fibonacci Heaps

Actual cost for delete-min()

- ▶ At most $D_n + t$ elements in root-list before consolidate.
- ▶ Actual cost for a delete-min is at most $\mathcal{O}(1) \cdot (D_n + t)$.
Hence, there exists c_1 s.t. actual cost is at most $c_1 \cdot (D_n + t)$.

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- ▶ $t' \leq D_n + 1$ as degrees are different after consolidating.
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for $c \geq c_1$.

8.3 Fibonacci Heaps

If the input trees of the consolidation procedure are binomial trees (for example only singleton vertices) then the output will be a set of distinct binomial trees, and, hence, the Fibonacci heap will be (more or less) a Binomial heap right after the consolidation.

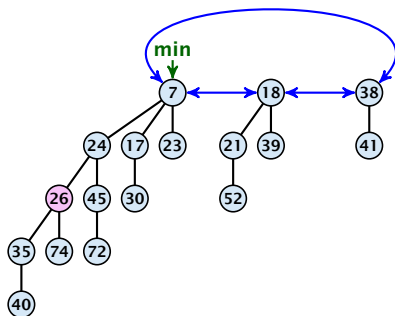
If we do not have delete or decrease-key operations then $D_n \leq \log n$.

8.3 Fibonacci Heaps

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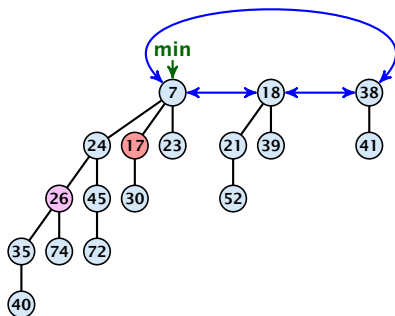
Fibonacci Heaps: decrease-key(handle h, v)



Case 1: decrease-key does not violate heap-property

- ▶ Just decrease the key-value of element referenced by h . Nothing else to do.

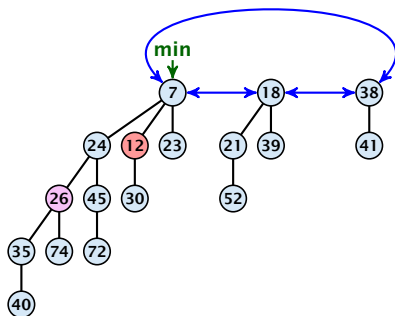
Fibonacci Heaps: decrease-key(handle h, v)



Case 1: decrease-key does not violate heap-property

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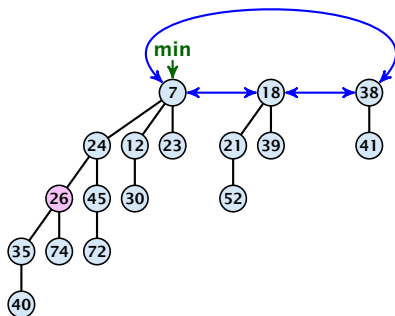
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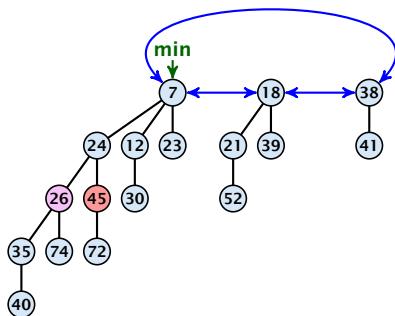
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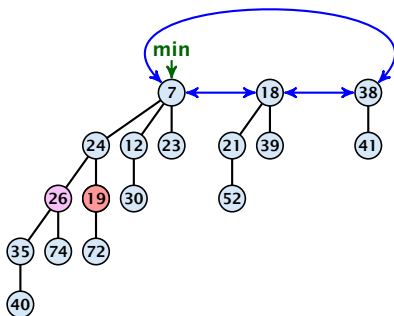
Fibonacci Heaps: decrease-key(handle h, v)



Case 2: heap-property is violated, but parent is not marked

- ▶ Decrease key-value of element x reference by h .
- ▶ If the heap-property is violated, cut the parent edge of x , and make x into a root.
- ▶ Adjust min-pointers, if necessary.
- ▶ Mark the (previous) parent of x (unless it's a root).

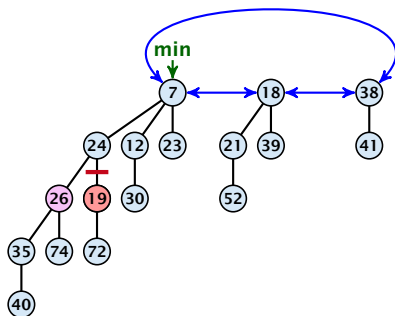
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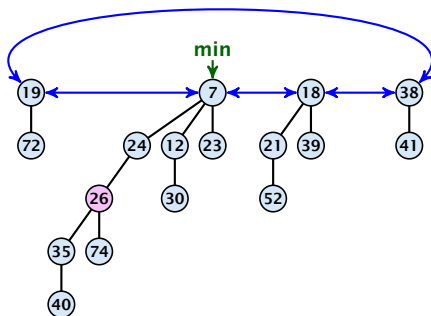
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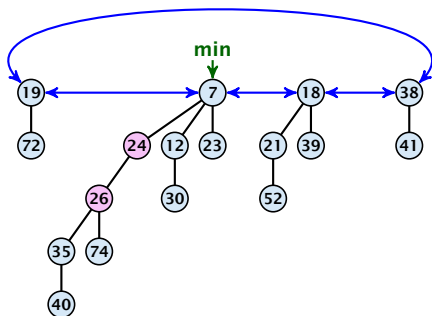
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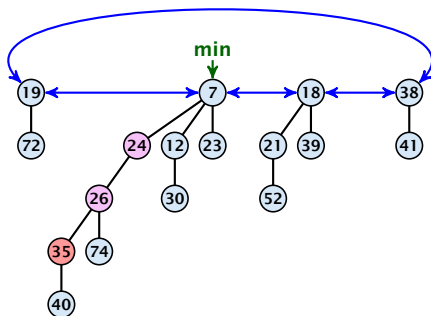
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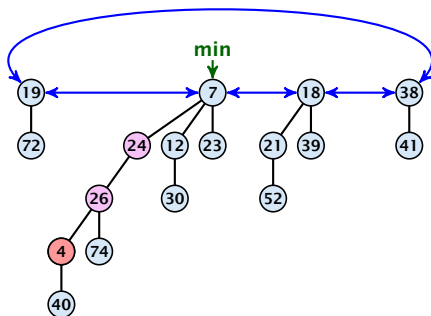
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- ▶ Decrease key-value of element x reference by h .
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- ▶ Adjust min-pointers, if necessary.
- ▶ Continue cutting the parent until you arrive at an unmarked node.

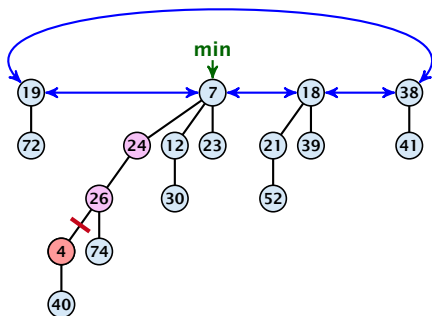
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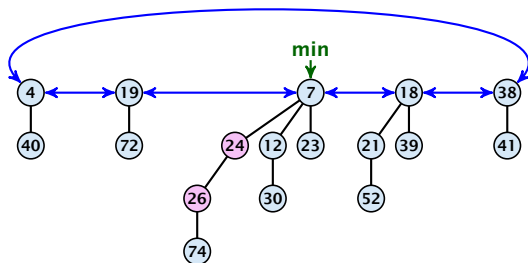
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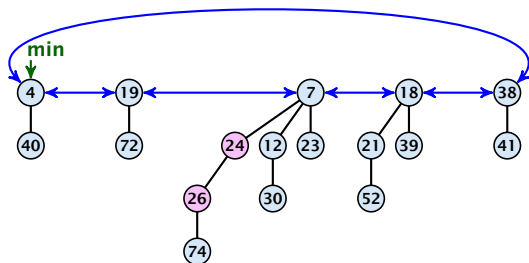
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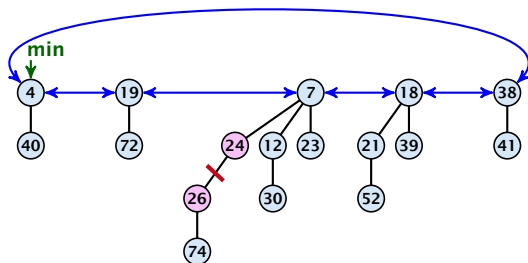
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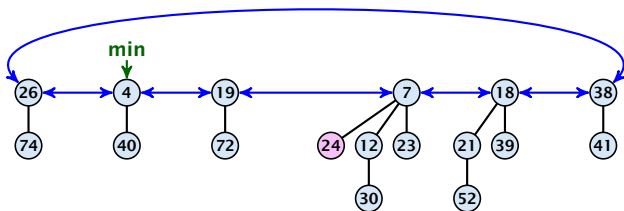
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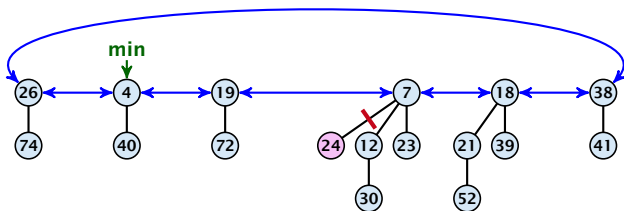
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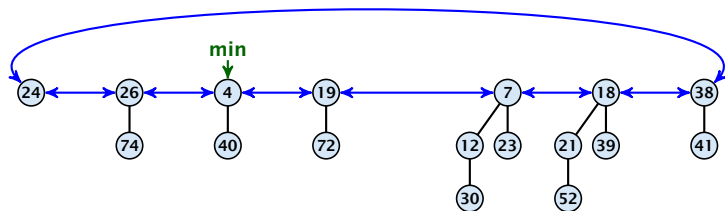
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- ▶ Decrease key-value of element x reference by h .
- ▶ Cut the parent edge of x , and make x into a root.
- ▶ Adjust min-pointers, if necessary.
- ▶ Execute the following:

```
 $p \leftarrow \text{parent}[x];$   
while ( $p$  is marked)  
     $pp \leftarrow \text{parent}[p];$   
    cut of  $p$ ; make it into a root; unmark it;  
     $p \leftarrow pp;$   
if  $p$  is unmarked and not a root mark it;
```

Fibonacci Heaps: decrease-key(handle h, v)

Actual cost:

- ▶ Constant cost for decreasing the value.
- ▶ Constant cost for each of ℓ cuts.
- ▶ Hence, cost is at most $c_2 \cdot (\ell + 1)$, for some constant c_2 .

Amortized cost:

- ▶ Each time we cut, we create one new root.
- ▶ Each time we cut, we mark a node, and all but the first cut marks a node, the last cut may mark a node.

- ▶ Amortized cost is at most

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Amortized cost:

- ▶ Every time we cut, we create one new root.
- ▶ Every time we cut, we create one new node.
- ▶ Every time we cut, we mark a node. The first cut marks a node, the last cut may mark a node.
- ▶ Amortized cost is $O(\ell)$.

Fibonacci Heaps: decrease-key(handle h, v)

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Amortized cost:

- ▶ Every cut creates one new root.
- ▶ Every root has at most ℓ children.
- ▶ Marks a root with ℓ credits.
- ▶ Amortized cost of ℓ cuts:

Fibonacci Heaps: decrease-key(handle h, v)

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Amortized cost:

- ▶ $t' = t + \ell$, as every cut creates one new root.
- ▶ $m' \leq m - (\ell - 1) + 1 = m - \ell + 2$, since all but the first cut unmarks a node; the last cut may mark a node.
- ▶ $\Delta\Phi \leq \ell + 2(-\ell + 2) = 4 - \ell$
- ▶ Amortized cost is at most

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$$c_2(\ell+1) + c(4-\ell) \leq (c_2 - c)\ell + 4c + c_2 = \mathcal{O}(1),$$

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Delete node

H. delete(x):

- ▶ decrease value of x to $-\infty$.
- ▶ delete-min.

Amortized cost: $\mathcal{O}(D_n)$

- ▶ $\mathcal{O}(1)$ for decrease-key.
- ▶ $\mathcal{O}(D_n)$ for delete-min.

8.3 Fibonacci Heaps

Lemma 34

Let x be a node with degree k and let y_1, \dots, y_k denote the children of x in the order that they were linked to x . Then

$$\text{degree}(y_i) \geq \begin{cases} 0 & \text{if } i = 1 \\ i - 2 & \text{if } i > 1 \end{cases}$$

8.3 Fibonacci Heaps

Proof

- ▶ When y_i was linked to x , at least y_1, \dots, y_{i-1} were already linked to x .
- ▶ Hence, at this time $\text{degree}(x) \geq i - 1$, and therefore also $\text{degree}(y_i) \geq i - 1$ as the algorithm links nodes of equal degree only.
- ▶ Since, then y_i has lost at most one child.
- ▶ Therefore, $\text{degree}(y_i) \geq i - 2$.

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$$s_k = 2 + \sum_{i=2}^k \text{size}(y_i)$$

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$$\begin{aligned} s_k &= 2 + \sum_{i=2}^k \text{size}(y_i) \\ &\geq 2 + \sum_{i=2}^k s_{i-2} \\ &= 2 + \sum_{i=0}^{k-2} s_i \end{aligned}$$

8.3 Fibonacci Heaps

$\phi = \frac{1}{2}(1 + \sqrt{5})$ denotes the *golden ratio*.
Note that $\phi^2 = 1 + \phi$.

Definition 35

Consider the following non-standard Fibonacci type sequence:

$$F_k = \begin{cases} 1 & \text{if } k = 0 \\ 2 & \text{if } k = 1 \\ F_{k-1} + F_{k-2} & \text{if } k \geq 2 \end{cases}$$

Facts:

1. $F_k \geq \phi^k$.
2. For $k \geq 2$: $F_k = 2 + \sum_{i=0}^{k-2} F_i$.

The above facts can be easily proved by induction. From this it follows that $s_k \geq F_k \geq \phi^k$, which gives that the maximum degree in a Fibonacci heap is logarithmic.

$$k=0: \quad 1 = F_0 \geq \Phi^0 = 1$$

$$k=1: \quad 2 = F_1 \geq \Phi^1 \approx 1.61$$

$$k-2, k-1 \rightarrow k: \quad F_k = F_{k-1} + F_{k-2} \geq \Phi^{k-1} + \Phi^{k-2} = \Phi^{k-2} \underbrace{(\Phi + 1)}_{\Phi^2} = \Phi^k$$

$$k=2: \quad 3 = F_2 = 2 + 1 = 2 + F_0$$

$$k-1 \rightarrow k: \quad F_k = F_{k-1} + F_{k-2} = 2 + \sum_{i=0}^{k-3} F_i + F_{k-2} = 2 + \sum_{i=0}^{k-2} F_i$$

9 Union Find

Union Find Data Structure \mathcal{P} : Maintains a partition of **disjoint** sets over elements.

- ▶ \mathcal{P} . **makeset**(x): Given an element x , adds x to the data-structure and creates a singleton set that contains only this element. Returns a locator/handle for x in the data-structure.
- ▶ \mathcal{P} . **find**(x): Given a handle for an element x ; find the set that contains x . Returns a representative/identifier for this set.
- ▶ \mathcal{P} . **union**(x, y): Given two elements x , and y that are currently in sets S_x and S_y , respectively, the function replaces S_x and S_y by $S_x \cup S_y$ and returns an identifier for the new set.

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9 Union Find

Algorithm 16 Kruskal-MST($G = (V, E), w$)

```
1:  $A \leftarrow \emptyset$ ;  
2: for all  $v \in V$  do  
3:    $v.\text{set} \leftarrow \mathcal{P}.\text{makeset}(v.\text{label})$   
4: sort edges in non-decreasing order of weight  $w$   
5: for all  $(u, v) \in E$  in non-decreasing order do  
6:   if  $\mathcal{P}.\text{find}(u.\text{set}) \neq \mathcal{P}.\text{find}(v.\text{set})$  then  
7:      $A \leftarrow A \cup \{(u, v)\}$   
8:      $\mathcal{P}.\text{union}(u.\text{set}, v.\text{set})$ 
```

List Implementation

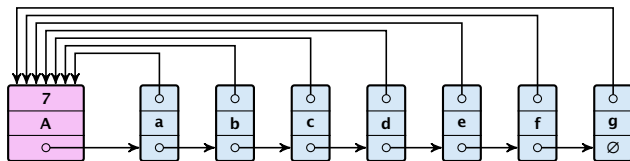
- ▶ The elements of a set are stored in a list; each node has a backward pointer to the head.
- ▶ The head of the list contains the identifier for the set and a field that stores the size of the set.



- ▶ `makeset(x)` can be performed in constant time.
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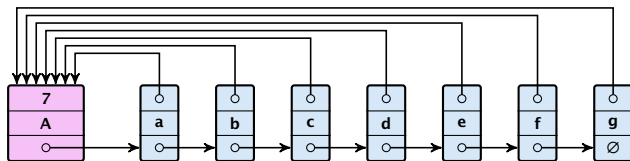
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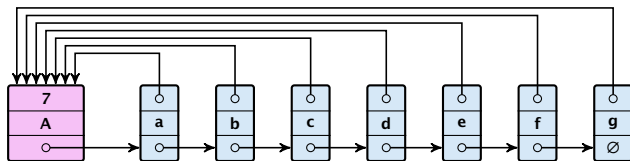
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List Implementation

union(x, y)

- ▶ Determine sets S_x and S_y .
- ▶ Traverse the smaller list (say S_y), and change all backward pointers to the head of list S_x .
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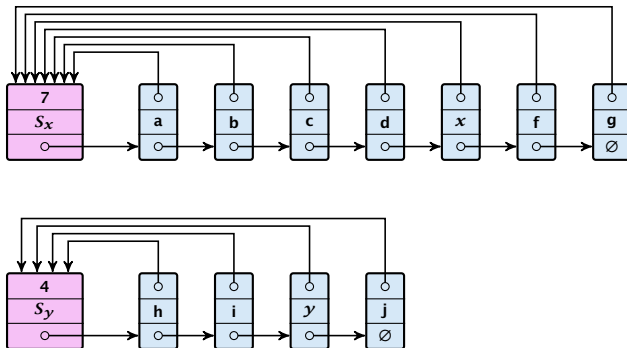
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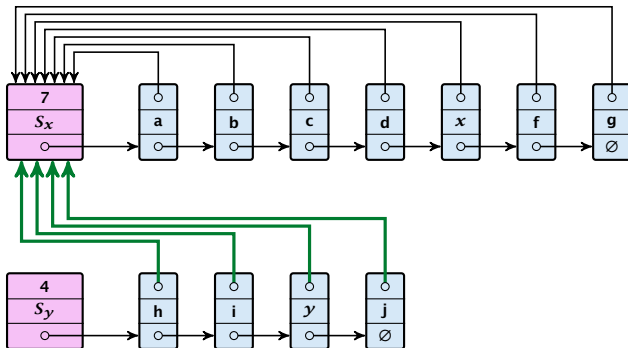
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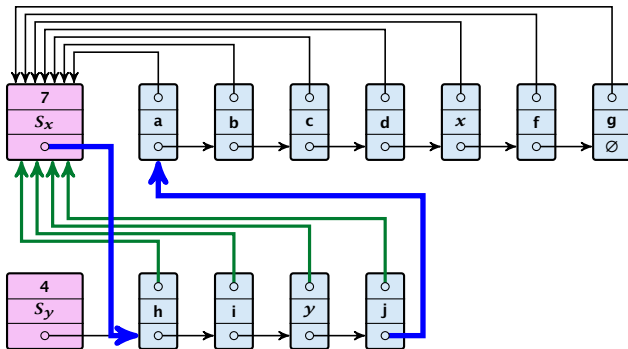
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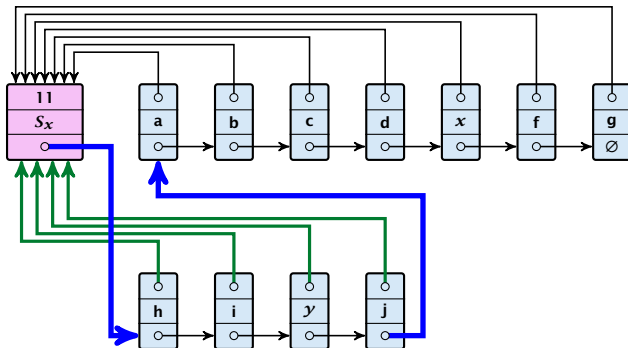
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Running times:

- ▶ $\text{find}(x)$: constant
- ▶ $\text{makeset}(x)$: constant
- ▶ $\text{union}(x, y)$: $\mathcal{O}(n)$, where n denotes the number of elements contained in the set system.

List Implementation

Lemma 36

The list implementation for the ADT union find fulfills the following amortized time bounds:

- ▶ $\text{find}(x): \mathcal{O}(1)$.
- ▶ $\text{makeset}(x): \mathcal{O}(\log n)$.
- ▶ $\text{union}(x, y): \mathcal{O}(1)$.

The Accounting Method for Amortized Time Bounds

- ▶ There is a bank account for every element in the data structure.
- ▶ Initially the balance on all accounts is zero.
- ▶ Whenever for an operation the amortized time bound exceeds the actual cost, the difference is credited to some bank accounts of elements involved.
- ▶ Whenever for an operation the actual cost exceeds the amortized time bound, the difference is charged to bank accounts of some of the elements involved.
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List Implementation

- ▶ For an operation whose actual cost exceeds the amortized cost we charge the **excess** to the elements involved.
- ▶ In total we will charge at most $\mathcal{O}(\log n)$ to an element (regardless of the request sequence).
- ▶ For each element a makeset operation occurs as the first operation involving this element.
- ▶ We inflate the amortized cost of the makeset-operation to $\Theta(\log n)$, i.e., at this point we fill the bank account of the element to $\Theta(\log n)$.
- ▶ Later operations charge the account but the balance never drops below zero.

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makeiset(x): The actual cost is $\mathcal{O}(1)$. Due to the cost inflation the amortized cost is $\mathcal{O}(\log n)$.

find(x): For this operation we define the amortized cost and the actual cost to be the same. Hence, this operation does not change any accounts. Cost: $\mathcal{O}(1)$.

union(x, y):

Let x and y be two disjoint sets. The cost to insert all elements of x into y is

$\sum_{x \in X} \log |y| = \log |y| \cdot |x|$. The actual cost is $|x|$.

Therefore, the amortized cost is $|x| \cdot (\log |y| + 1)$. Since $|y| \leq |x| + |y|$, the

amortized cost is $|x| \cdot (\log |x| + 1)$. The actual cost is $|x|$.

Therefore, the amortized cost is $\mathcal{O}(\log n)$.

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- ▶ Charge c to every element in set S_x .

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Lemma 37

An element is charged at most $\lfloor \log_2 n \rfloor$ times, where n is the total number of elements in the set system.

Proof.

Whenever an element x is charged the number of elements in x 's set doubles. This can happen at most $\lfloor \log n \rfloor$ times. \square

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Implementation via Trees

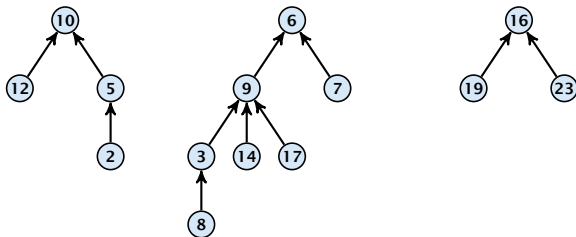
- ▶ Maintain nodes of a set in a tree.
- ▶ The root of the tree is the label of the set.
- ▶ Only pointer to parent exists; we cannot list all elements of a given set.
- ▶ Example:



Set system $\{2, 5, 10, 12\}$, $\{3, 6, 7, 8, 9, 14, 17\}$, $\{16, 19, 23\}$.

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Implementation via Trees

makeSet(x)

- ▶ Create a singleton tree. Return pointer to the root.
- ▶ Time: $\mathcal{O}(1)$.

find(x)

Start at element x in the tree, and repeatedly update x to be its parent until it reaches the root.

Time complexity: $\mathcal{O}(h)$, where h is the height of the tree.

Optimization: The root of the tree is the same for all elements in the same tree. We can store the root of the tree in a separate array, and update it when we create a new tree.

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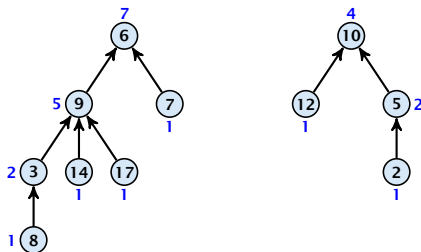
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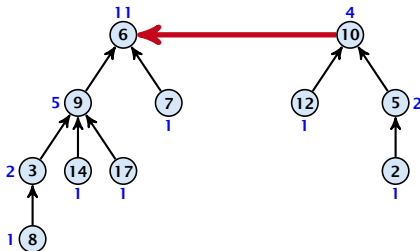


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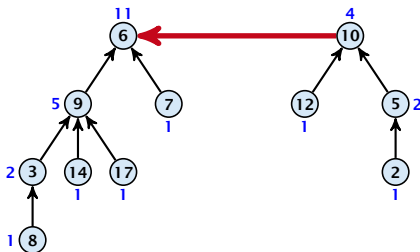


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- ▶ Time: constant for $\text{link}(a, b)$ plus two find-operations.

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The running time (non-amortized!!!) for $\text{find}(x)$ is $\mathcal{O}(\log n)$.

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Path Compression

find(x):

- ▶ Go upward until you find the root.
- ▶ Re-attach all visited nodes as children of the root.
- ▶ Speeds up successive find-operations.



Path compression: find(x) returns the root of x and re-attach all visited nodes as children of the root. This speeds up successive find-operations.

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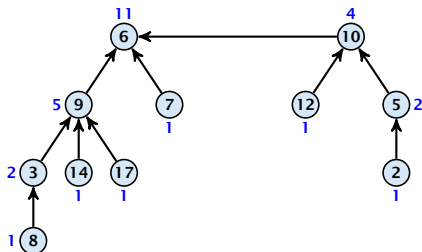
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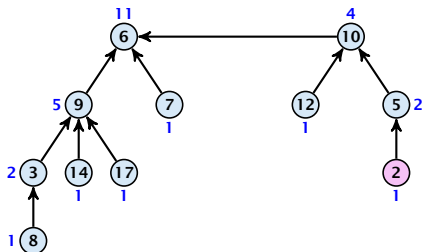


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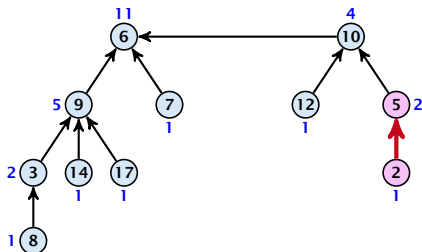


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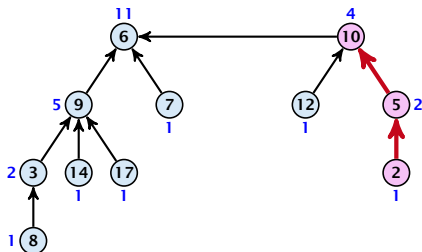


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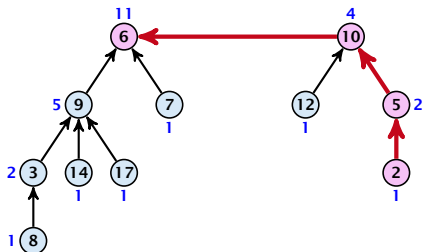


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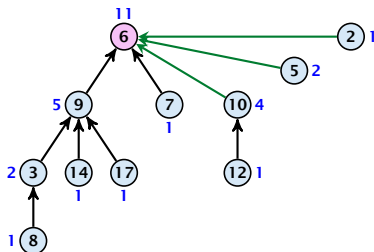


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find(x):

- ▶ Go upward until you find the root.
- ▶ Re-attach all visited nodes as children of the root.
- ▶ Speeds up successive find-operations.

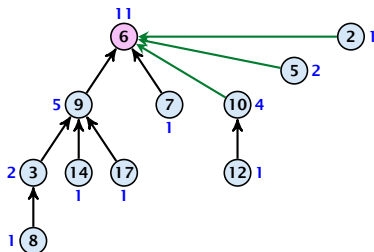


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Amortized Analysis

Definitions:

$n(x)$ = the number of nodes that were in the sub-tree rooted at x when x became the child of another node (i.e. the number of nodes if x is the root).

Note that this is the same as the size of x 's subtree in the case that there are no find-operations.

Lemma 39

The rank of a parent must be strictly larger than the rank of a child.

Amortized Analysis

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- ▶ $\text{size}(v) :=$ the number of nodes that were in the sub-tree rooted at v when v became the child of another node (or the number of nodes if v is the root).

Note that this is the same as the size of v 's subtree in the case that there are no find-operations.

- ▶ $\text{rank}(v) = \lfloor \log(\text{size}(v)) \rfloor$.
- ▶ $\Rightarrow \text{size}(v) \geq 2^{\text{rank}(v)}$.

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Amortized Analysis

Lemma 40

There are at most $n/2^s$ nodes of rank s .

Proof.

Let x be a node of rank s . Then x is the root of a tree of size 2^{s-1} . The root has two children.

Repeat this argument for each of rank $s-1$ children during the running time of the algorithm.

This holds because the rank sequence of the roots of the subtrees of x is strictly increasing during the running time of the algorithm. Thus, each node of rank $s-1$ has at most one child of rank $s-2$.

Therefore, each node of rank $s-1$ has at most one child of rank $s-2$. This rank sequence is even by at least $s-1$ different nodes. □

Amortized Analysis

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There are at most $n/2^s$ nodes of rank s .

Proof.

- ▶ Let's say a node v sees node x if v is in x 's sub-tree at the time that x becomes a child.
- ▶ A node v sees at most one node of rank s during the running time of the algorithm.
- ▶ This holds because the rank-sequence of the roots of the different trees that contain v during the running time of the algorithm is a strictly increasing sequence.
- ▶ Hence, every node sees at most one rank s node, but every rank s node is seen by at least 2^s different nodes. □

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We define

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Theorem 41

Union find with path compression fulfills the following amortized running times:

- ▶ $\text{makeset}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{find}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{union}(x, y) : \mathcal{O}(\log^*(n))$

Amortized Analysis

In the following we assume $n \geq 2$.

rank-group:

A node with rank r belongs to the rank-group r .

The rank-group r contains only nodes with rank $\geq r$.

rank

rank-group: \geq rank

no maximum number of rank-groups

no maximum number of nodes in a rank-group

total number of rank-groups is at most n

Amortized Analysis

In the following we assume $n \geq 2$.

rank-group:

- ▶ A node with rank $\text{rank}(v)$ is in **rank group** $\log^*(\text{rank}(v))$.
- ▶ The rank-group $g = 0$ contains only nodes with rank 0 or rank 1.
- ▶ A rank group $g \geq 1$ contains ranks $\text{tow}(g-1) + 1, \dots, \text{tow}(g)$.
- ▶ The maximum non-empty rank group is $\log^*(\lfloor \log n \rfloor) \leq \log^*(n) - 1$ (which holds for $n \geq 2$).
- ▶ Hence, the total number of rank-groups is at most $\log^* n$.

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Amortized Analysis

Accounting Scheme:

• Create an account for every find-operation

• Create an account for every node

The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

• If v is the root we charge the cost to the account of v .

• Otherwise:

• If the credit-number of v is 0, then use as that of $\text{parent}[v]$.

• If v has a credit-number > 0 (before starting path compression) we

charge the cost to the node-account of v and decrease the credit-

number of v by 1. Otherwise we charge the cost to the account of $\text{parent}[v]$.

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The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

- ▶ if v is the root we charge the cost to the account of the root
- ▶ if v is not the root we charge the cost to the account of $\text{parent}[v]$
- ▶ if the grand-father of v is the root we charge the cost to the account of the root
- ▶ if v is not the grand-father of the root (before working path compression) we charge the cost to the node $\text{grand-father}[v]$
- ▶ if v is the grand-father of the root we charge the cost to the account of the root

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- ▶ if the credit is not enough, we charge the cost to the account of the parent
- ▶ if we are working with path compression, we charge the cost to the account of the root

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- ▶ If $\text{parent}[v]$ is the root we charge the cost to the find-account.
- ▶ If the group-number of $\text{rank}(v)$ is the same as that of $\text{rank}(\text{parent}[v])$ (before starting path compression) we charge the cost to the node-account of v .
- ▶ Otherwise we charge the cost to the find-account.

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Amortized Analysis

Observations:

- The number of changed elements is bounded since for every element x the number of times it is changed when increasing the rank of x is bounded by $\log_2 \frac{m}{r(x)}$.
- The number of changed elements is bounded by $\log_2 \frac{m}{r(x)}$ by itself for the parent of x .
- The same changes to the parent will be in a lower rank group, and will need to be changed again.
- The total change made by a node in rank group i is at most

Amortized Analysis

Observations:

- ▶ A find-account is charged at most $\log^*(n)$ times (once for the root and at most $\log^*(n) - 1$ times when increasing the rank-group).
- ▶ After a node v is charged its parent-edge is re-assigned. The rank of the parent strictly increases.
- ▶ After some charges to v the parent will be in a larger rank-group. $\Rightarrow v$ will never be charged again.
- ▶ The total charge made to a node in rank-group g is at most $\text{tow}(g) - \text{tow}(g - 1) - 1 \leq \text{tow}(g)$.

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What is the total charge made to nodes?

- ▶ The total charge is at most

$$\sum_g n(g) \cdot \text{tow}(g),$$

where $n(g)$ is the number of nodes in group g .

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Amortized Analysis

Without loss of generality we can assume that all **makeset**-operations occur at the start.

This means if we inflate the cost of **makeset** to $\log^* n$ and add this to the node account of v then the balances of all node accounts will sum up to a positive value (this is sufficient to obtain an amortized bound).

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The analysis is not tight. In fact it has been shown that the amortized time for the union-find data structure with path compression is $\mathcal{O}(\alpha(m, n))$, where $\alpha(m, n)$ is the inverse Ackermann function which grows a lot lot slower than $\log^* n$. (Here, we consider the average running time of m operations on at most n elements).

There is also a lower bound of $\Omega(\alpha(m, n))$.

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$$A(x, y) = \begin{cases} y + 1 & \text{if } x = 0 \\ A(x - 1, 1) & \text{if } y = 0 \\ A(x - 1, A(x, y - 1)) & \text{otw.} \end{cases}$$

$$\alpha(m, n) = \min\{i \geq 1 : A(i, \lfloor m/n \rfloor) \geq \log n\}$$

- ▶ $A(0, y) = y + 1$
- ▶ $A(1, y) = y + 2$
- ▶ $A(2, y) = 2y + 3$
- ▶ $A(3, y) = 2^{y+3} - 3$
- ▶ $A(4, y) = \underbrace{2^{2^{2^2}}}_{y+3 \text{ times}} - 3$

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Part IV

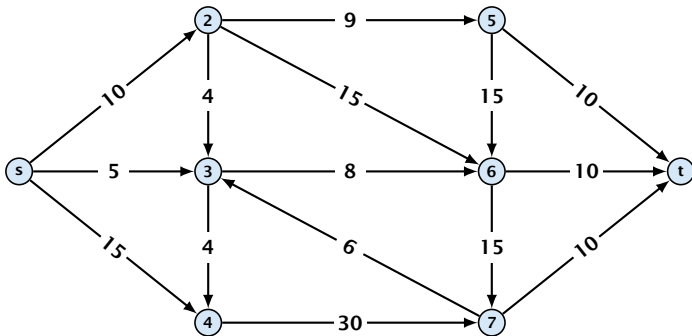
Flows and Cuts

The following slides are partially based on slides by Kevin Wayne.

10 Introduction

Flow Network

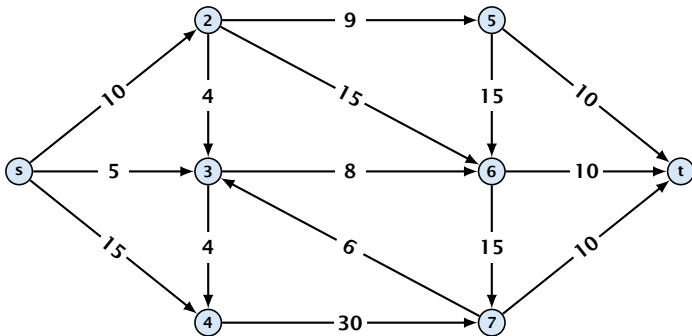
- ▶ directed graph $G = (V, E)$; edge capacities $c(e)$
- ▶ two special nodes: source s ; target t ;
- ▶ no edges entering s or leaving t ;
- ▶ at least for now: no parallel edges;



10 Introduction

Flow Network

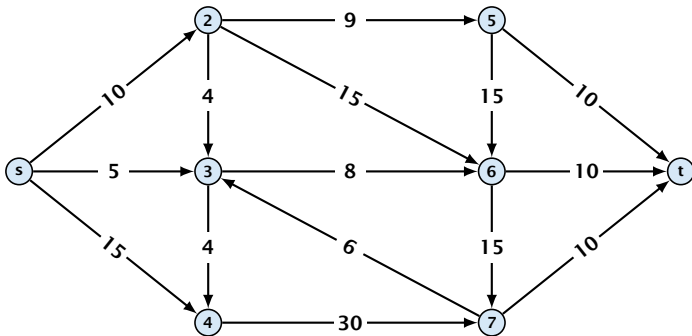
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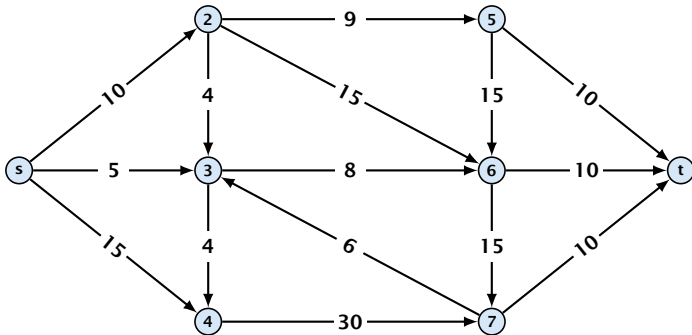
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Cuts

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The **capacity** of a cut A is defined as

$$\text{cap}(A, V \setminus A) := \sum_{e \in \text{out}(A)} c(e) ,$$

where $\text{out}(A)$ denotes the set of edges of the form $A \times V \setminus A$ (i.e. edges leaving A).

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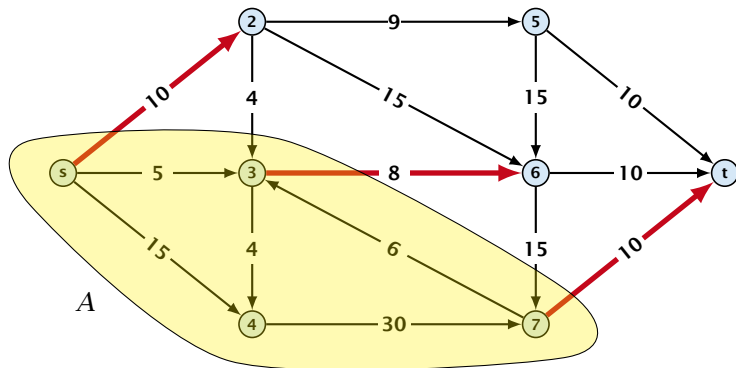
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Minimum Cut Problem: Find an (s, t) -cut with minimum capacity.

Cuts

Example 44



The capacity of the cut is $\text{cap}(A, V \setminus A) = 28$.

Definition 45

An (s, t) -flow is a function $f : E \mapsto \mathbb{R}^+$ that satisfies

1. For each edge e

$$0 \leq f(e) \leq c(e) .$$

(capacity constraints)

2. For each $v \in V \setminus \{s, t\}$

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The **value of an (s, t) -flow f** is defined as

$$\text{val}(f) = \sum_{e \in \text{out}(s)} f(e) .$$

Maximum Flow Problem: Find an (s, t) -flow with maximum value.

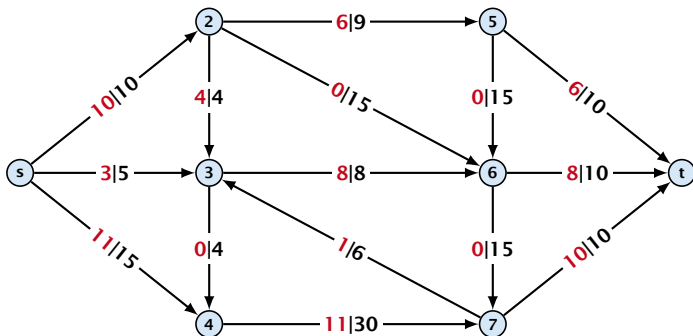
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Example 47



The value of the flow is $\text{val}(f) = 24$.

Lemma 48 (Flow value lemma)

Let f be a flow, and let $A \subseteq V$ be an (s, t) -cut. Then the *net-flow* across the cut is equal to the amount of flow leaving s , i.e.,

$$\text{val}(f) = \sum_{e \in \text{out}(A)} f(e) - \sum_{e \in \text{into}(A)} f(e) .$$

Proof.

$\text{val}(f)$

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$$\text{val}(f) = \sum_{e \in \text{out}(s)} f(e)$$

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$$\begin{aligned}\text{val}(f) &= \sum_{e \in \text{out}(s)} f(e) \\ &= \sum_{e \in \text{out}(s)} f(e) + \sum_{v \in A \setminus \{s\}} \left(\sum_{e \in \text{out}(v)} f(e) - \sum_{e \in \text{in}(v)} f(e) \right)\end{aligned}$$

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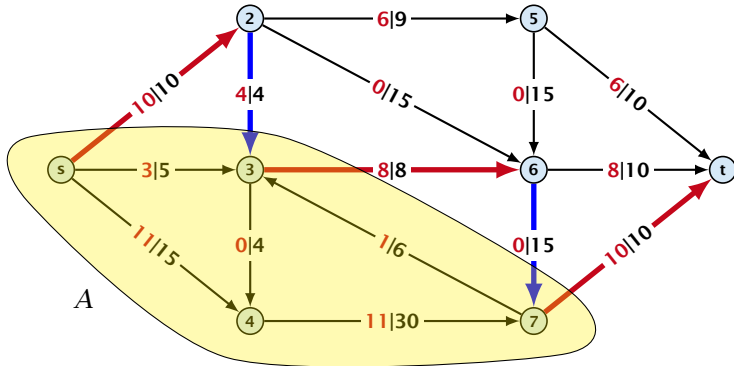
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The last equality holds since every edge with both end-points in A contributes negatively as well as positively to the sum in Line 2. The only edges whose contribution doesn't cancel out are edges leaving or entering A . \square

Example 49



Corollary 50

Let f be an (s, t) -flow and let A be an (s, t) -cut, such that

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Suppose that there is a flow f' with larger value. Then

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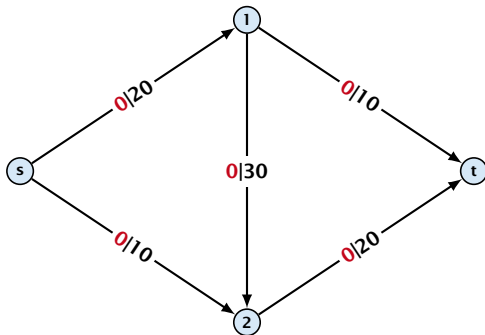
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□

11 Augmenting Path Algorithms

Greedy-algorithm:

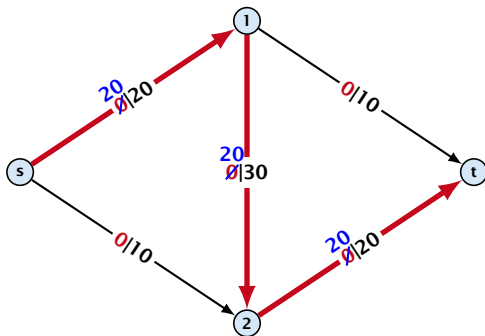
- ▶ start with $f(e) = 0$ everywhere
- ▶ find an s - t path with $f(e) < c(e)$ on every edge
- ▶ augment flow along the path
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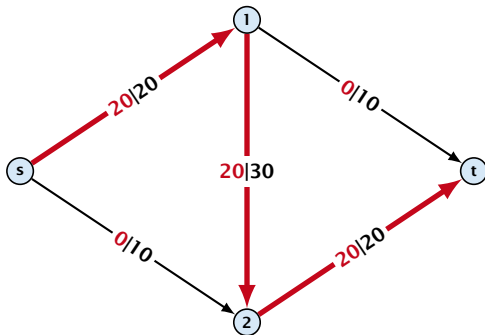
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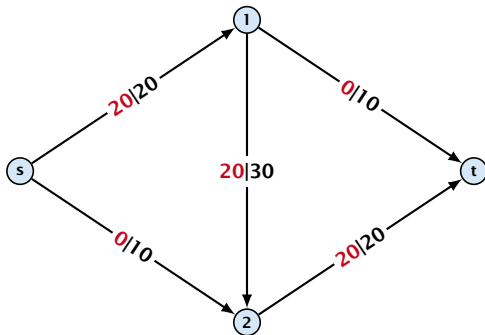
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The Residual Graph

From the graph $G = (V, E, c)$ and the current flow f we construct an auxiliary graph $G_f = (V, E_f, c_f)$ (the residual graph):

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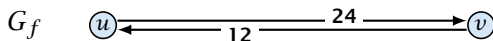
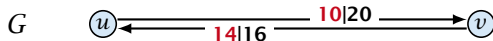
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Augmenting Path Algorithm

Definition 51

An **augmenting path** with respect to flow f , is a path from s to t in the auxiliary graph G_f that contains only edges with non-zero capacity.

Algorithm 1 FordFulkerson($G = (V, E, c)$)

- 1: Initialize $f(e) \leftarrow 0$ for all edges.
- 2: **while** \exists augmenting path p in G_f **do**
- 3: augment as much flow along p as possible.

Augmenting Path Algorithm

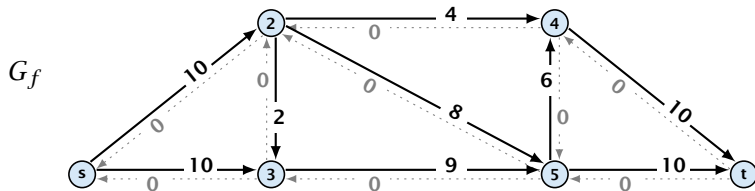
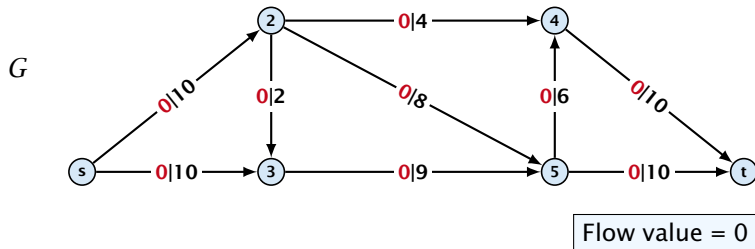
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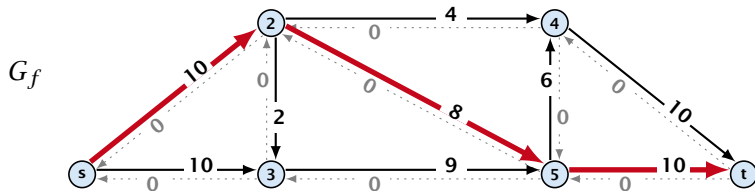
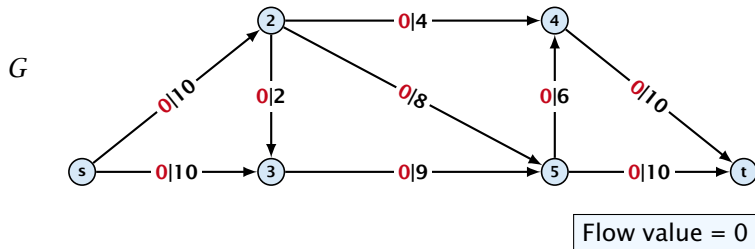
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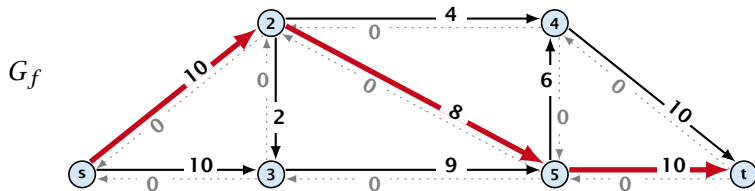
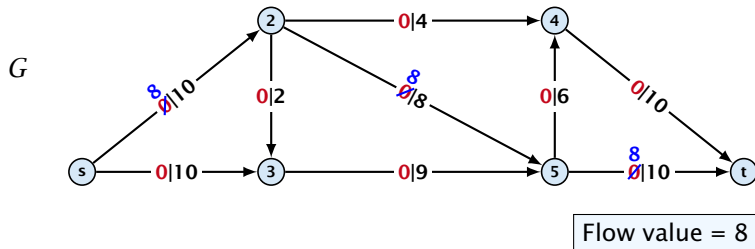
Augmenting Path Algorithm



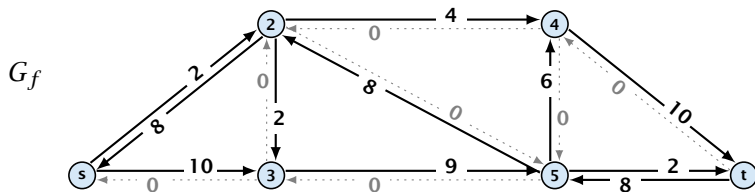
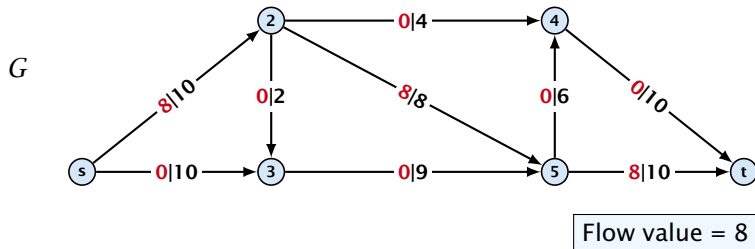
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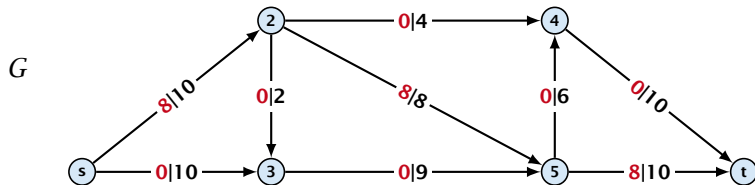
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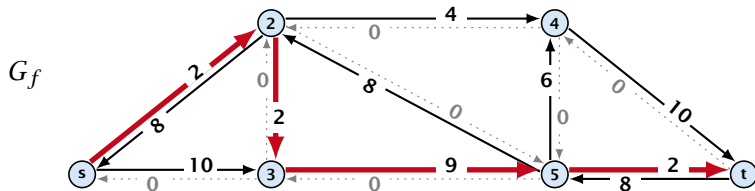
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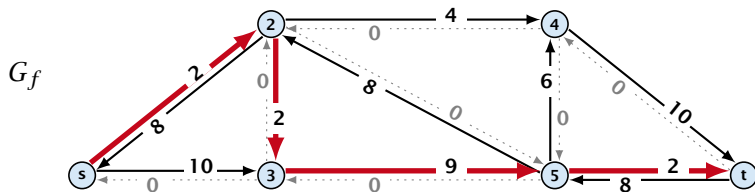
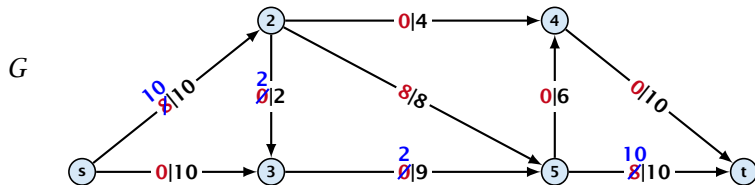
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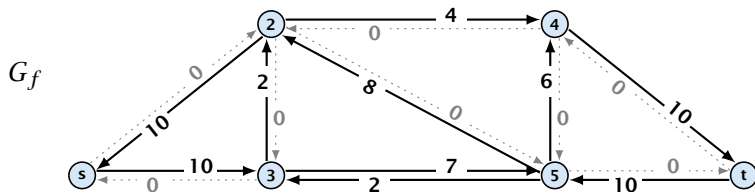
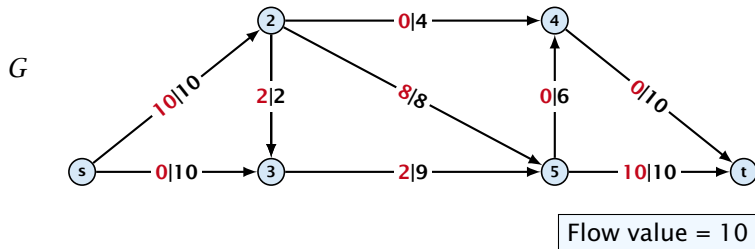
Flow value = 8



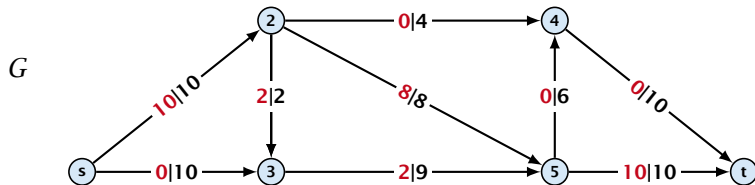
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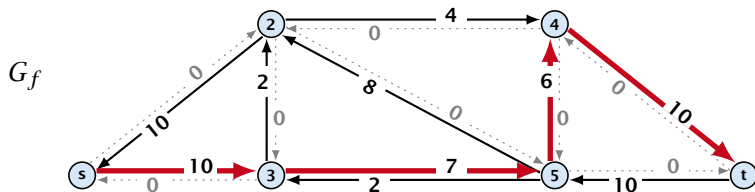
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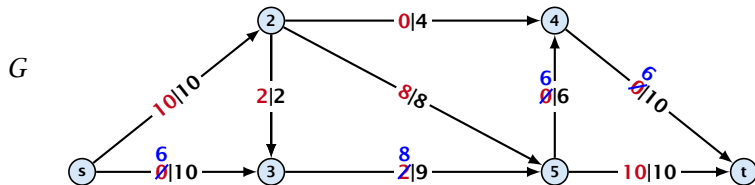
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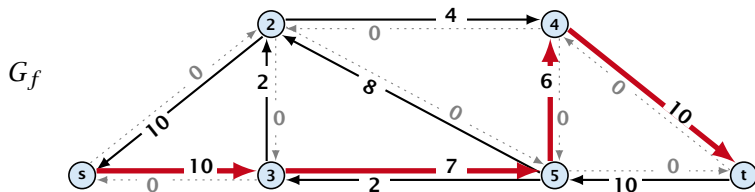
Flow value = 10



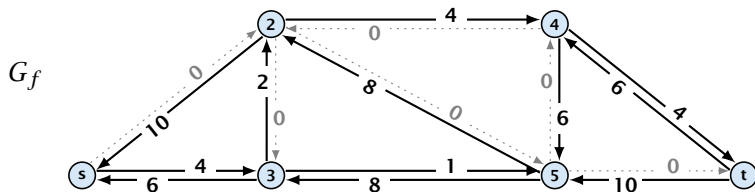
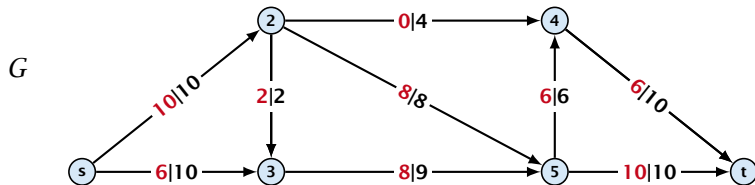
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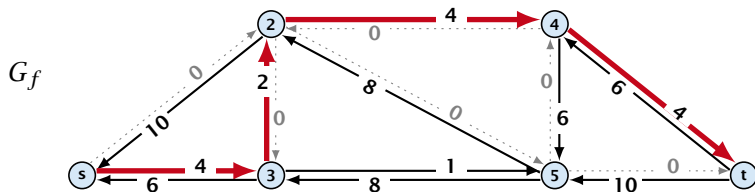
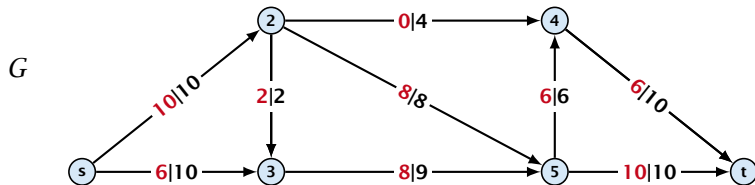
Flow value = 16



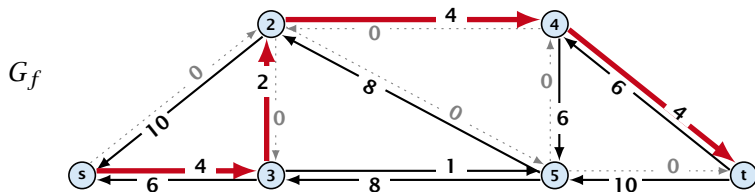
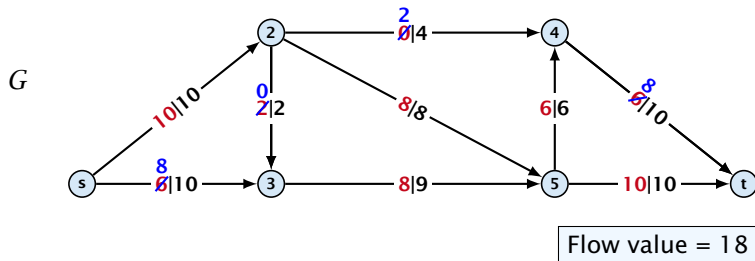
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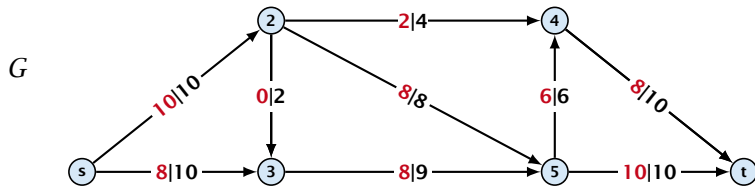
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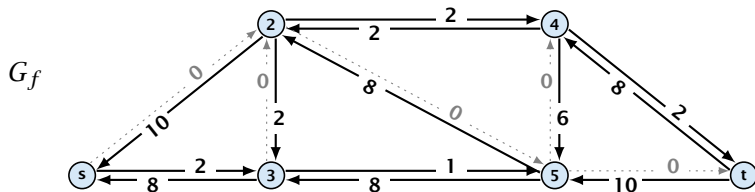
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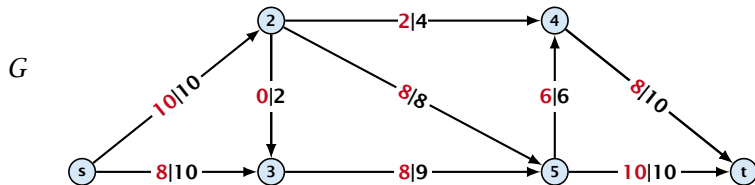
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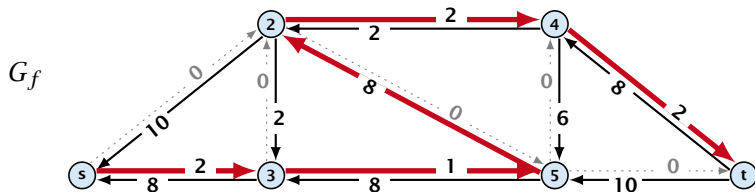
Flow value = 18



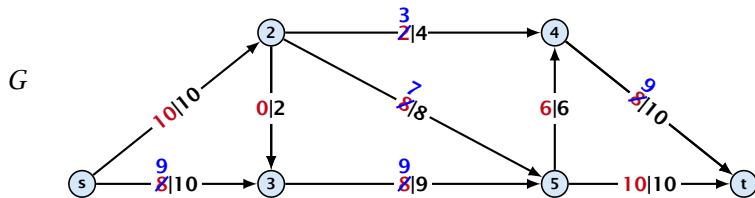
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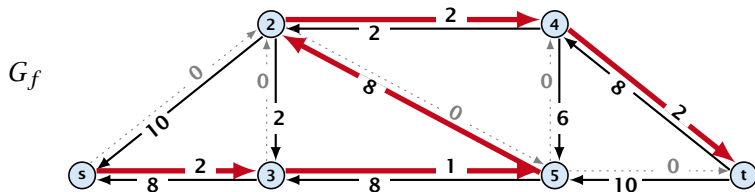
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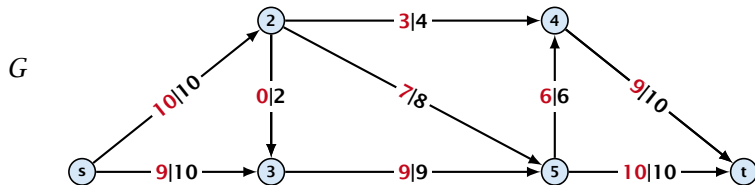
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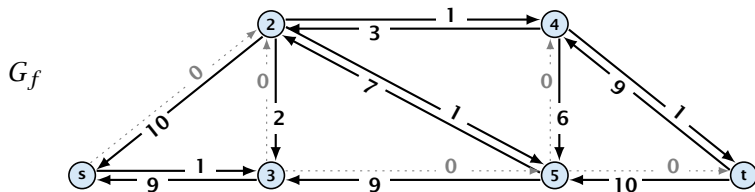
Flow value = 19



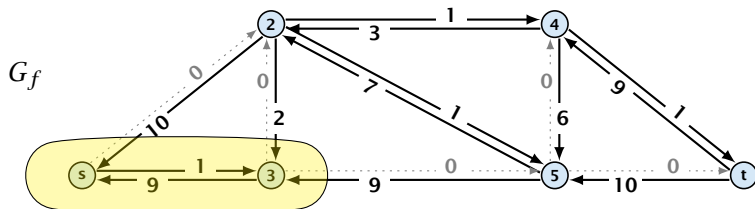
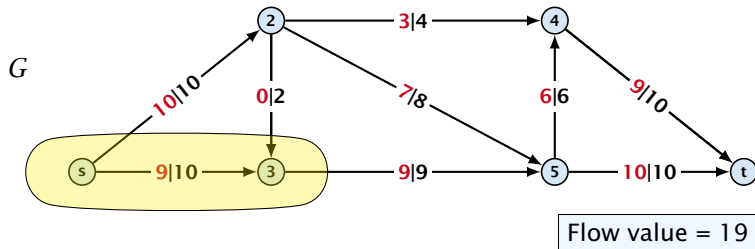
Augmenting Path Algorithm



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Augmenting Path Algorithm



Augmenting Path Algorithm

Theorem 52

A flow f is a maximum flow iff there are no augmenting paths.

Theorem 53

The value of a maximum flow is equal to the value of a minimum cut.

Proof.

Let f be a flow. The following are equivalent:

1. There exists a cut C such that $|f| = \text{val}(C)$.
2. f is a maximum flow.
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Augmenting Path Algorithm

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Augmenting Path Algorithm

Theorem 52

A flow f is a maximum flow **iff** there are no augmenting paths.

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The value of a maximum flow is equal to the value of a minimum cut.

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Let f be a flow. The following are equivalent:

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1. \Rightarrow 2.

This we already showed.

2. \Rightarrow 3.

If there were an augmenting path, we could improve the flow.
Contradiction.

3. \Rightarrow 1.

Let G_f be a flow with no augmenting paths.

Let S be the set of vertices reachable from s in the residual graph along non-saturated capacity edges.

Since there is no augmenting path, $t \notin S$.

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$\text{val}(f)$

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$$\text{val}(f) = \sum_{e \in \text{out}(A)} f(e) - \sum_{e \in \text{into}(A)} f(e)$$

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This finishes the proof.

Here the first equality uses the flow value lemma, and the second exploits the fact that the flow along incoming edges must be 0 as the residual graph does not have edges leaving A .

Analysis

Assumption:

All capacities are integers between 1 and C .

Invariant:

Every flow value $f(e)$ and every residual capacity $c_f(e)$ remains integral throughout the algorithm.

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The algorithm terminates in at most $\text{val}(f^*) \leq nC$ iterations, where f^* denotes the maximum flow. Each iteration can be implemented in time $\mathcal{O}(m)$. This gives a total running time of $\mathcal{O}(nmC)$.

Theorem 55

If all capacities are integers, then there exists a maximum flow for which every flow value $f(e)$ is integral.

Lemma 54

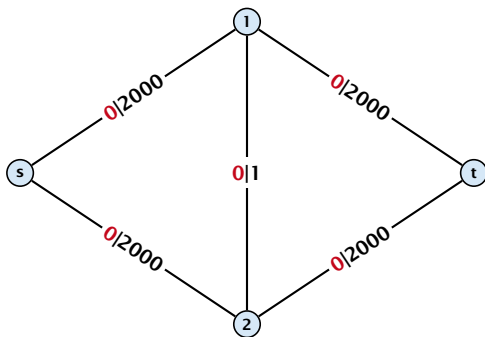
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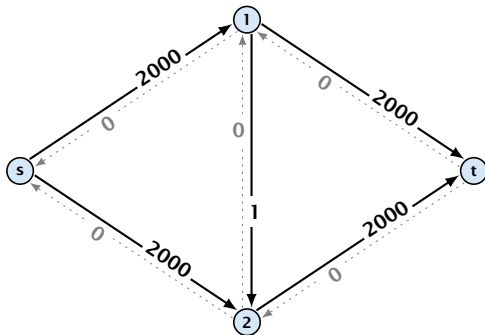
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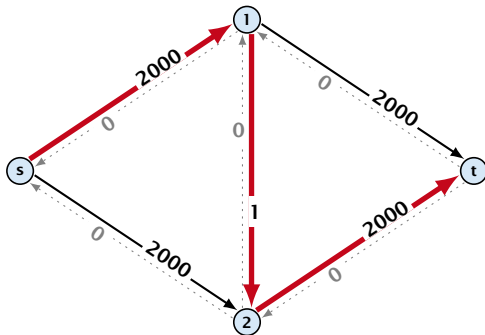


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Can we tweak the algorithm so that the running time is polynomial in the input length?

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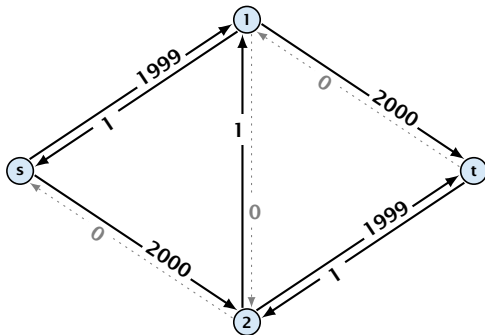


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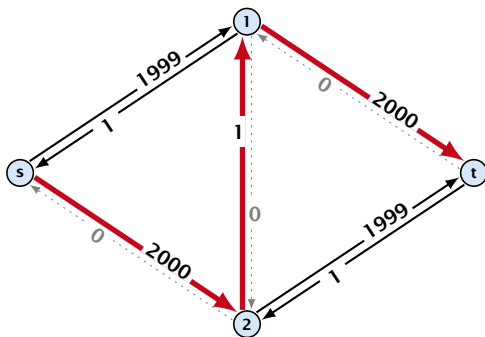


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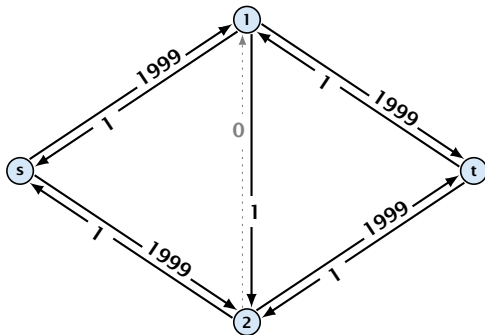


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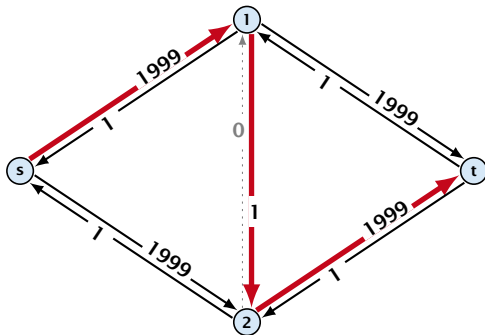


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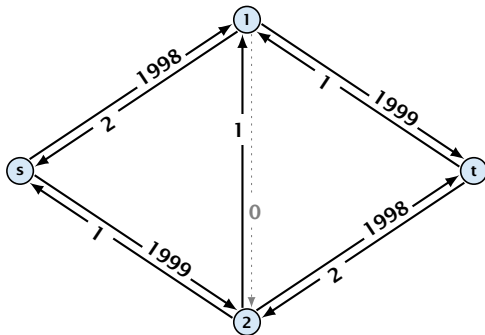


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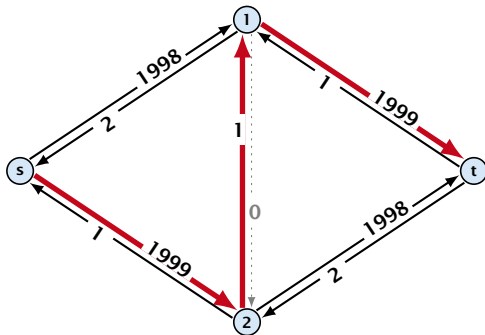


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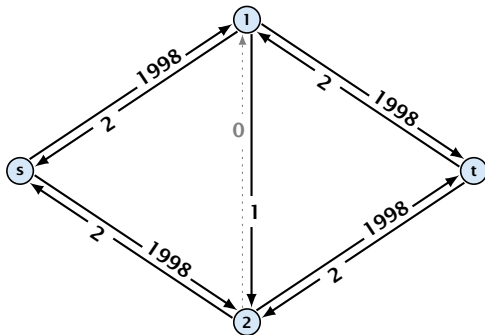


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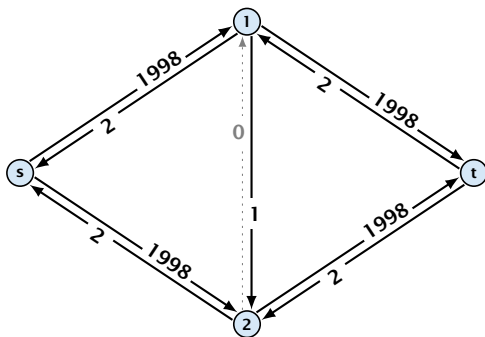


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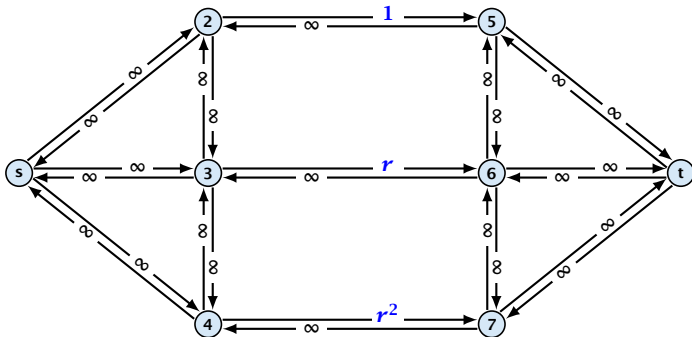


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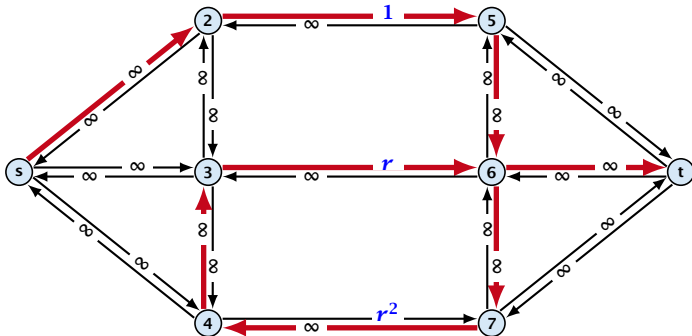
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Let $r = \frac{1}{2}(\sqrt{5} - 1)$. Then $r^{n+2} = r^n - r^{n+1}$.



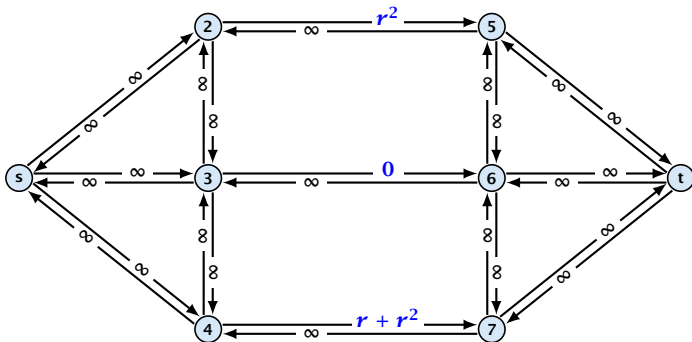
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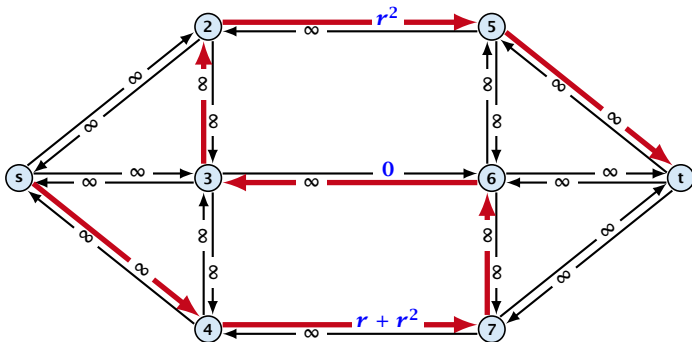
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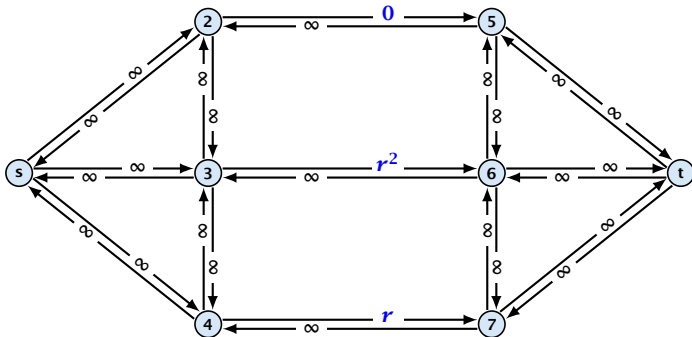
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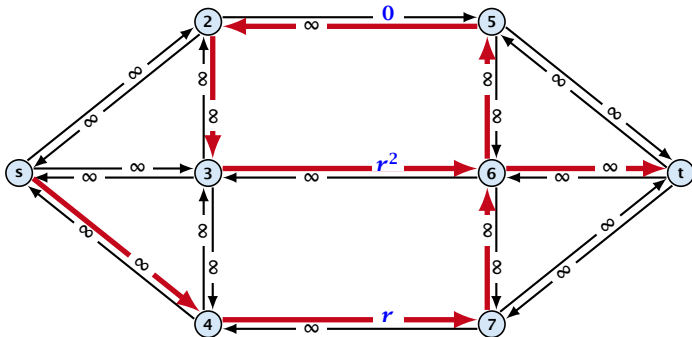
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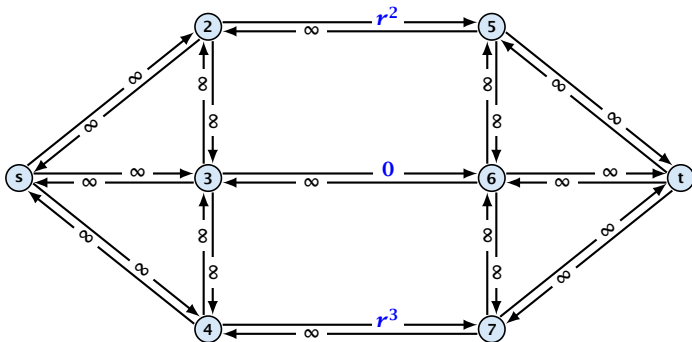
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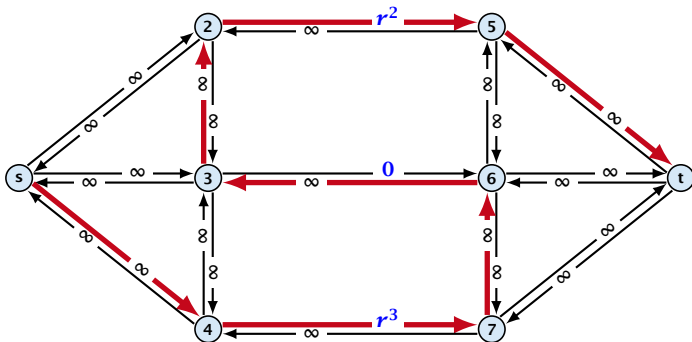
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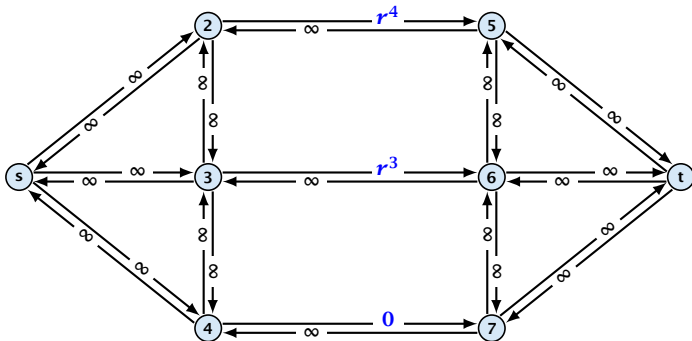
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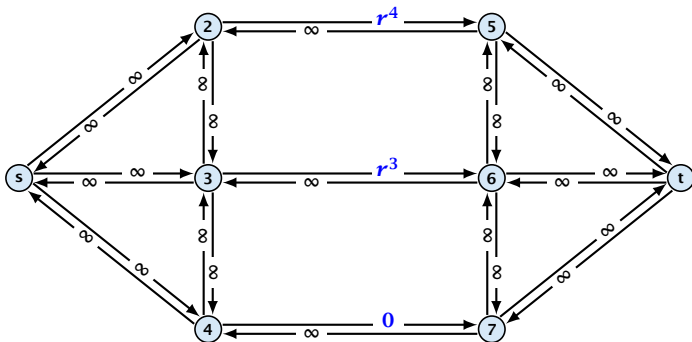
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Running time may be infinite!!!

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Lemma 56

The length of the shortest augmenting path never decreases.

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After at most $\mathcal{O}(m)$ augmentations, the length of the shortest augmenting path strictly increases.

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These two lemmas give the following theorem:

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The shortest augmenting path algorithm performs at most $\mathcal{O}(mn)$ augmentations. This gives a running time of $\mathcal{O}(m^2n)$.

Proof.

We can find the shortest augmenting paths in time $\mathcal{O}(m)$.

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There are at most $\mathcal{O}(mn)$ augmentations for paths of strictly increasing edges.

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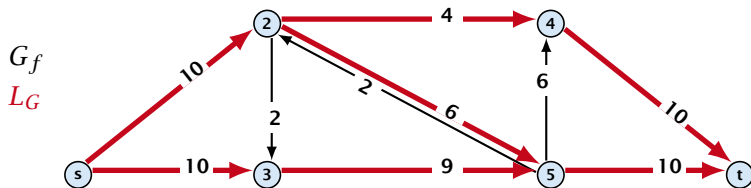
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In the following we assume that the residual graph G_f does not contain zero capacity edges.

This means, we construct it in the usual sense and then delete edges of zero capacity.

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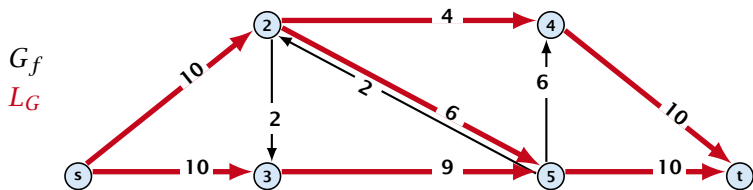
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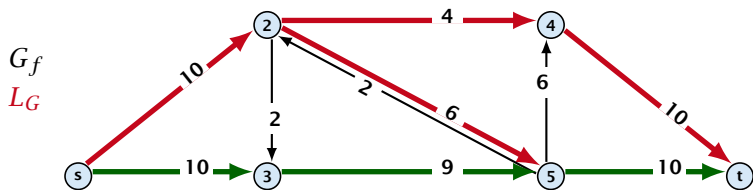
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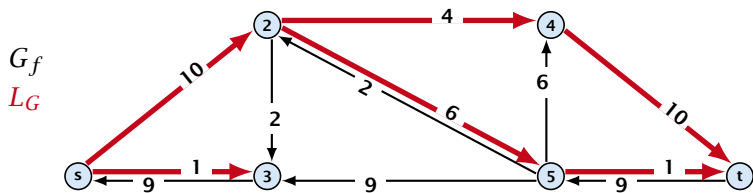
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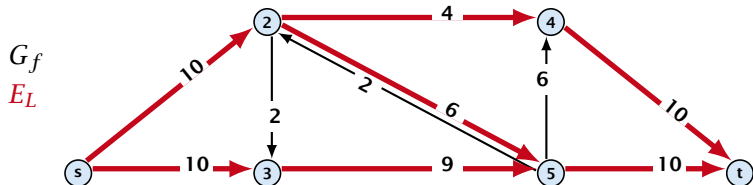
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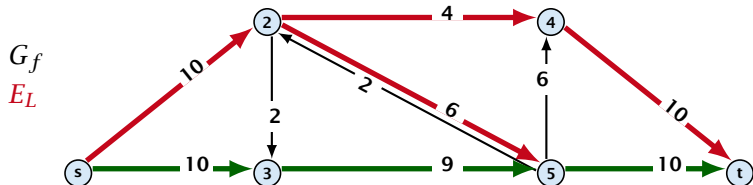
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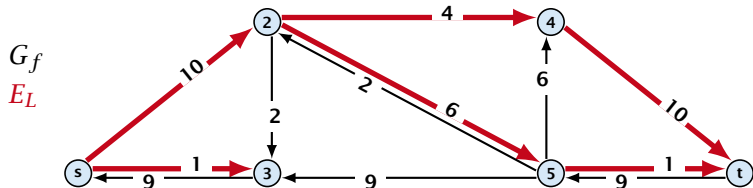
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Theorem 60 (without proof)

There exist networks with $m = \Theta(n^2)$ that require $\mathcal{O}(mn)$ augmentations, when we restrict ourselves to only augment along shortest augmenting paths.

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Note that E_L is not the set of edges of the level graph but a subset of level-graph edges.

Shortest Augmenting Paths

We maintain a subset E_L of the edges of G_f with the guarantee that a shortest $s-t$ path using only edges from E_L is a shortest augmenting path.

With each augmentation some edges are deleted from E_L .

When E_L does not contain an $s-t$ path anymore the distance between s and t strictly increases.

Note that E_L is not the set of edges of the level graph but a subset of level-graph edges.

Suppose that the initial distance between s and t in G_f is k .

E_L is initialized as the level graph L_G .

Perform a DFS search to find a path from s to t using edges from E_L .

Either you find t after at most n steps, or you end at a node v that does not have any outgoing edges.

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Let a phase of the algorithm be defined by the time between two augmentations during which the distance between s and t strictly increases.

Initializing E_L for the phase takes time $\mathcal{O}(m)$.

The total cost for searching for augmenting paths during a phase is at most $\mathcal{O}(mn)$, since every search (successful (i.e., reaching t) or unsuccessful) decreases the number of edges in E_L and takes time $\mathcal{O}(n)$.

The total cost for performing an augmentation during a phase is only $\mathcal{O}(n)$. For every edge in the augmenting path one has to update the residual graph G_f and has to check whether the edge is still in E_L for the next search.

There are at most n phases. Hence, total cost is $\mathcal{O}(mn^2)$.

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- ▶ Choose path with sufficiently large bottleneck capacity.
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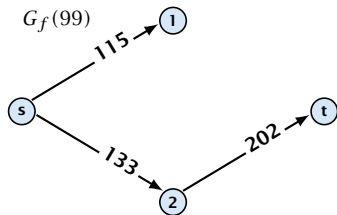
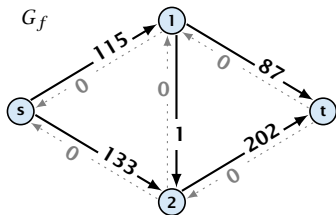
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Capacity Scaling

Algorithm 2 maxflow(G, s, t, c)

```
1: foreach  $e \in E$  do  $f_e \leftarrow 0$ ;  
2:  $\Delta \leftarrow 2^{\lceil \log_2 C \rceil}$   
3: while  $\Delta \geq 1$  do  
4:    $G_f(\Delta) \leftarrow \Delta$ -residual graph  
5:   while there is augmenting path  $P$  in  $G_f(\Delta)$  do  
6:      $f \leftarrow \text{augment}(f, c, P)$   
7:      $\text{update}(G_f(\Delta))$   
8:    $\Delta \leftarrow \Delta/2$   
9: return  $f$ 
```

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All capacities are integers between 1 and C .

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- ▶ therefore after the last phase there are no augmenting paths anymore
- ▶ this means we have a maximum flow.

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There are $\lceil \log C \rceil + 1$ iterations over Δ .

Proof: obvious.

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- ▶ There must exist an s - t cut in $G_f(\Delta)$ of zero capacity.
- ▶ In G_f this cut can have capacity at most $m\Delta$.
- ▶ This gives me an upper bound on the flow that I can still add.

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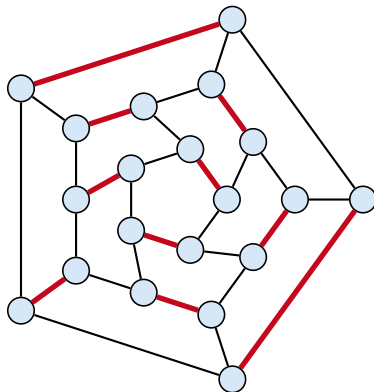
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Theorem 64

We need $\mathcal{O}(m \log C)$ augmentations. The algorithm can be implemented in time $\mathcal{O}(m^2 \log C)$.

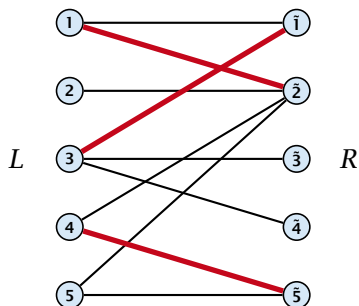
Matching

- ▶ Input: undirected graph $G = (V, E)$.
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- ▶ Maximum Matching: find a matching of maximum cardinality



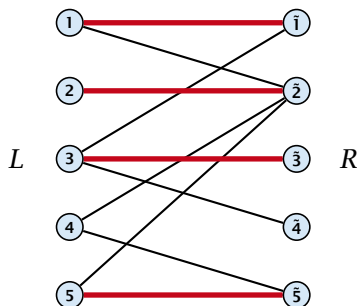
Bipartite Matching

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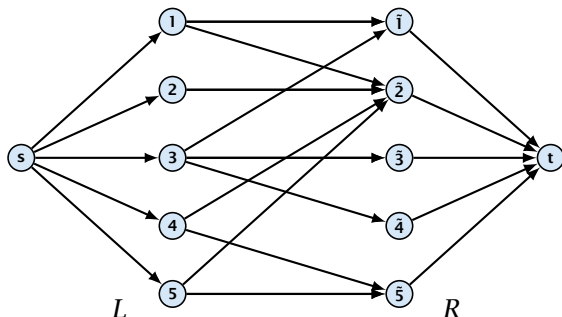
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Maxflow Formulation

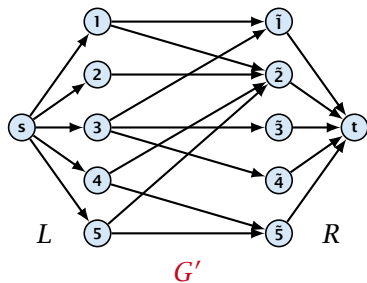
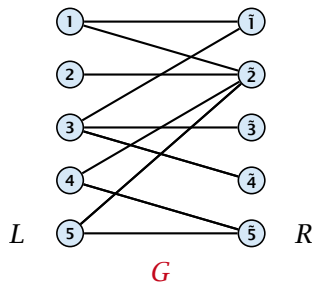
- ▶ Input: undirected, bipartite graph $G = (L \uplus R \uplus \{s, t\}, E')$.
- ▶ Direct all edges from L to R .
- ▶ Add source s and connect it to all nodes on the left.
- ▶ Add t and connect all nodes on the right to t .
- ▶ All edges have unit capacity.



Proof

Max cardinality matching in $G \leq$ value of maxflow in G'

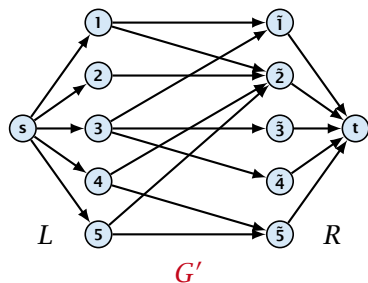
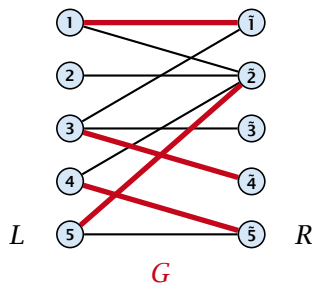
- ▶ Given a maximum matching M of cardinality k .
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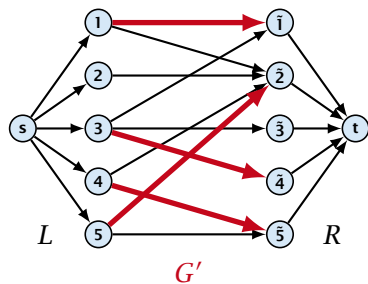
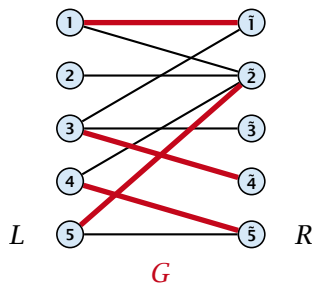
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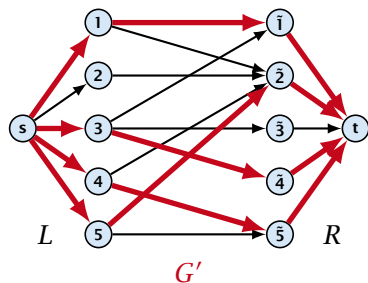
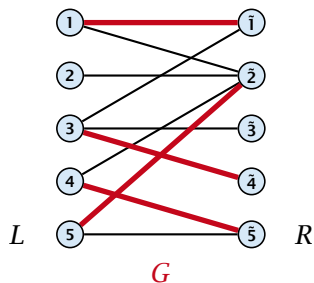
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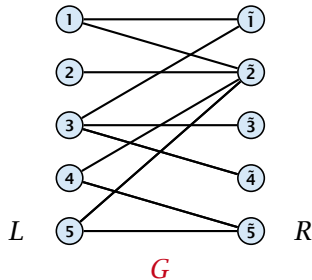
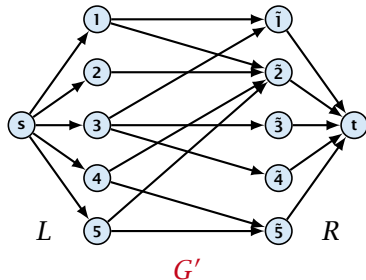
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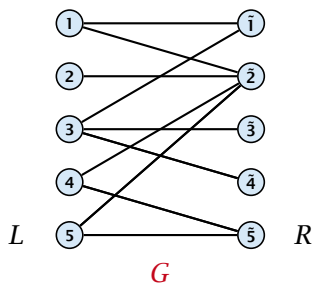
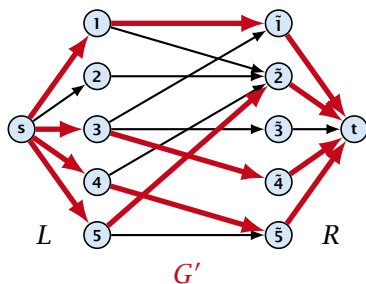
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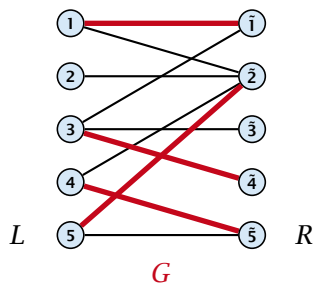
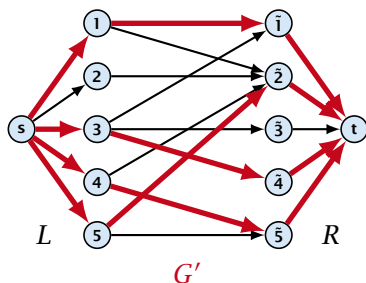
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12.1 Matching

Which flow algorithm to use?

- ▶ Generic augmenting path: $\mathcal{O}(m \text{val}(f^*)) = \mathcal{O}(mn)$.
- ▶ Capacity scaling: $\mathcal{O}(m^2 \log C) = \mathcal{O}(m^2)$.
- ▶ Shortest augmenting path: $\mathcal{O}(mn^2)$.

For **unit capacity simple graphs** shortest augmenting path can be implemented in time $\mathcal{O}(m\sqrt{n})$.

A graph is a **unit capacity simple graph** if

- ▶ every edge has capacity 1
- ▶ a node has either at most one leaving edge **or** at most one entering edge

Baseball Elimination

<i>team</i> <i>i</i>	<i>wins</i> w_i	<i>losses</i> ℓ_i	<i>remaining games</i>			
			<i>Atl</i>	<i>Phi</i>	<i>NY</i>	<i>Mon</i>
Atlanta	83	71	–	1	6	1
Philadelphia	80	79	1	–	0	2
New York	78	78	6	0	–	0
Montreal	77	82	1	2	0	–

Which team can end the season with most wins?

- ▶ Montreal is eliminated, since even after winning all remaining games there are only 80 wins.
- ▶ But also Philadelphia is eliminated. Why?

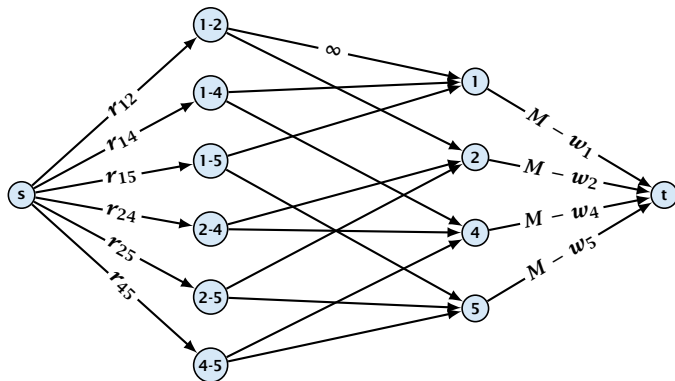
Baseball Elimination

Formal definition of the problem:

- ▶ Given a set S of teams, and one specific team $z \in S$.
- ▶ Team x has already won w_x games.
- ▶ Team x still has to play team y , r_{xy} times.
- ▶ Does team z still have a chance to finish with the most number of wins.

Baseball Elimination

Flow network for $z = 3$. M is number of wins Team 3 can still obtain.




Idea. Distribute the results of remaining games in such a way that no team gets too many wins.

Certificate of Elimination

Let $T \subseteq S$ be a subset of teams. Define

$$w(T) := \sum_{i \in T} w_i, \quad r(T) := \sum_{i, j \in T, i < j} r_{ij}$$



If $\frac{w(T)+r(T)}{|T|} > M$ then one of the teams in T will have more than M wins in the end. A team that can win at most M games is therefore eliminated.

Theorem 65

A team z is eliminated if and only if the flow network for z does not allow a flow of value $\sum_{i,j \in S \setminus \{z\}, i < j} r_{ij}$.

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- ▶ Consider the mincut A in the flow network. Let T be the set of team-nodes in A .

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- ▶ We don't find a flow that saturates all source edges:

$$r(S \setminus \{z\})$$

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$$\begin{aligned} r(S \setminus \{z\}) &> \text{cap}(A, V \setminus A) \\ &\geq \sum_{i < j: i \notin T \vee j \notin T} r_{ij} + \sum_{i \in T} (M - w_i) \end{aligned}$$

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$$\begin{aligned}r(S \setminus \{z\}) &> \text{cap}(A, V \setminus A) \\ &\geq \sum_{i < j: i \notin T \vee j \notin T} r_{ij} + \sum_{i \in T} (M - w_i) \\ &\geq r(S \setminus \{z\}) - r(T) + |T|M - w(T)\end{aligned}$$

Theorem 65

A team z is eliminated if and only if the flow network for z does not allow a flow of value $\sum_{i \in S \setminus \{z\}, i < j} r_{ij}$.

Proof (\Leftarrow)

- ▶ Consider the mincut A in the flow network. Let T be the set of team-nodes in A .
- ▶ If for node $x-y$ not both team-nodes x and y are in T , then $x-y \notin A$ as otherwise the cut would cut an infinite capacity edge.
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- ▶ This gives $M < (w(T) + r(T))/|T|$, i.e., z is eliminated.

Baseball Elimination

Proof (\Rightarrow)

- ▶ Suppose we have a flow that saturates all source edges.
- ▶ We can assume that this flow is *integral*.
- ▶ For every pairing x - y it defines how many games team x and team y should win.
- ▶ The flow leaving the team-node x can be interpreted as the additional number of wins that team x will obtain.
- ▶ This is less than $M - w_x$ because of capacity constraints.
- ▶ Hence, we found a set of results for the remaining games, such that no team obtains more than M wins in total.
- ▶ Hence, team z is not eliminated.

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Project Selection

Project selection problem:

- ▶ Set P of possible projects. Project v has an associated profit p_v (can be positive or negative).
- ▶ Some projects have requirements (taking course EA2 requires course EA1).
- ▶ Dependencies are modelled in a graph. Edge (u, v) means “can’t do project u without also doing project v .”
- ▶ A subset A of projects is **feasible** if the prerequisites of every project in A also belong to A .

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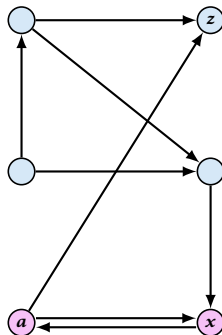
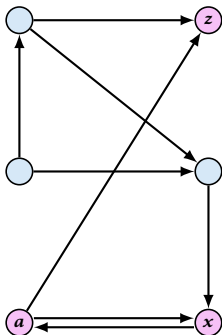
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The prerequisite graph:

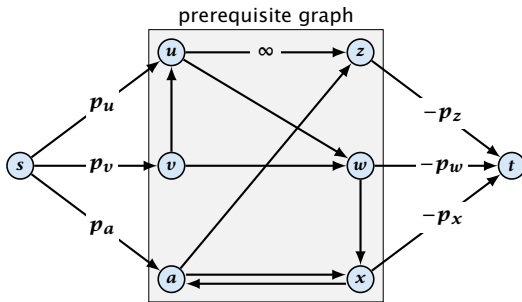
- ▶ $\{x, a, z\}$ is a feasible subset.
- ▶ $\{x, a\}$ is infeasible.



Project Selection

Mincut formulation:

- ▶ Edges in the prerequisite graph get infinite capacity.
- ▶ Add edge (s, v) with capacity p_v for nodes v with positive profit.
- ▶ Create edge (v, t) with capacity $-p_v$ for nodes v with negative profit.



Theorem 66

A is a mincut if $A \setminus \{s\}$ is the optimal set of projects.

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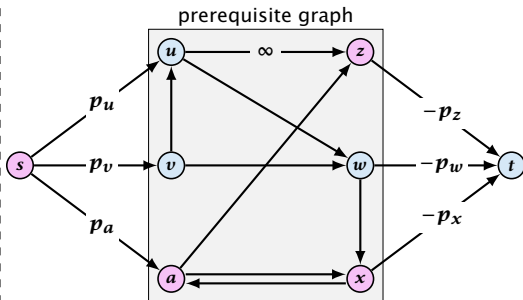
Proof.

- ▶ A is feasible because of capacity infinity edges.

For the formula we define $p_s := 0$.

The step follows by adding $\sum_{v \in A: p_v > 0} p_v - \sum_{v \in A: p_v > 0} p_v = 0$.

Note that minimizing the capacity of the cut $(A, V \setminus A)$ corresponds to maximizing profits of projects in A .



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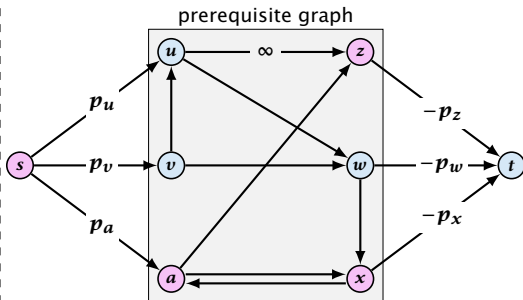
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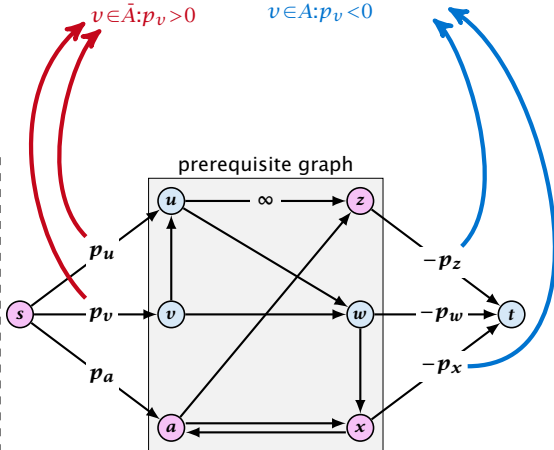
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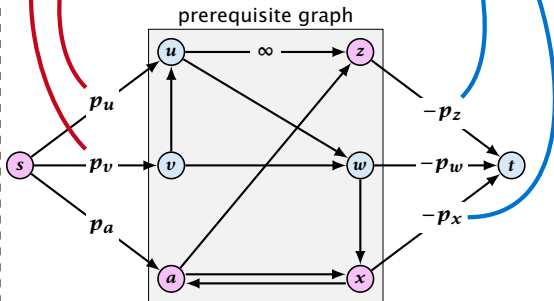
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Preflows

Definition 67

An (s, t) -preflow is a function $f : E \mapsto \mathbb{R}^+$ that satisfies

For each edge $e \in E$

$$0 \leq f(e) \leq c(e)$$

For each vertex $v \in V$

$$\sum_{e \in E^{\text{out}}(v)} f(e) - \sum_{e \in E^{\text{in}}(v)} f(e) \leq b(v)$$

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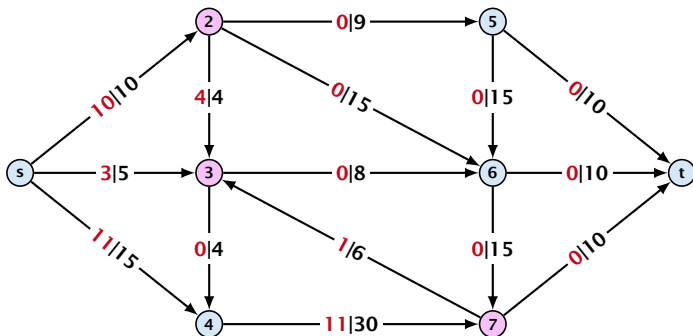
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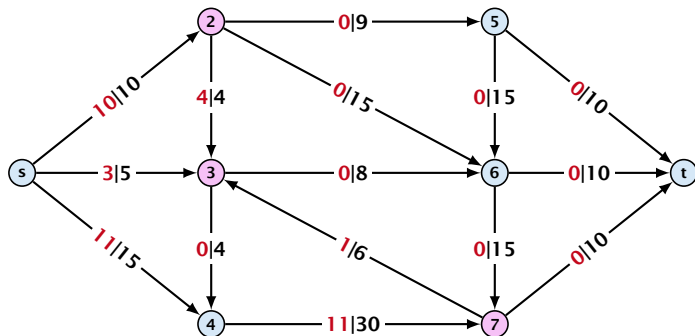
Preflows

Example 68



Preflows

Example 68



A node that has $\sum_{e \in \text{out}(v)} f(e) < \sum_{e \in \text{into}(v)} f(e)$ is called an **active node**.

Preflows

Definition:

A **labelling** is a function $\ell : V \rightarrow \mathbb{N}$. It is **valid** for preflow f if

- ▶ $\ell(u) \leq \ell(v) + 1$ for all edges (u, v) in the residual graph G_f (only non-zero capacity edges!!!)

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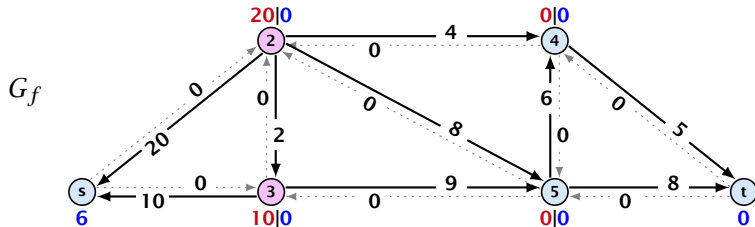
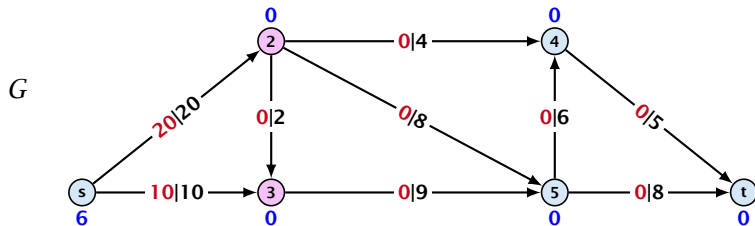
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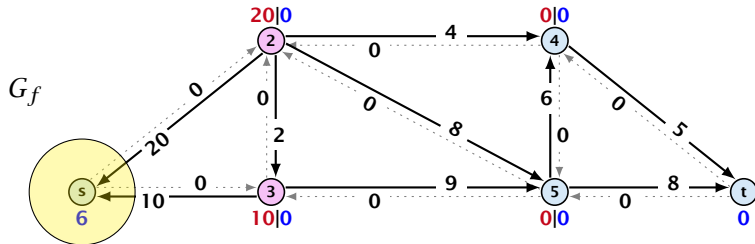
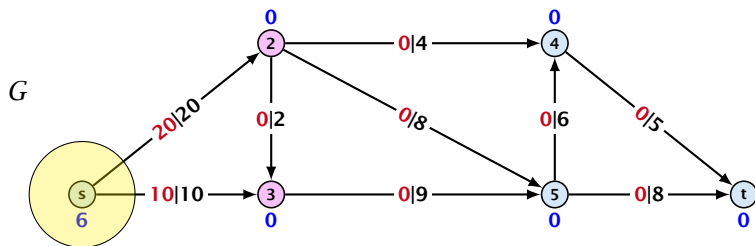
Intuition:

The labelling can be viewed as a height function. Whenever the height from node u to node v decreases by more than 1 (i.e., it goes very steep downhill from u to v), the corresponding edge must be saturated.

Preflows



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Preflows

Lemma 69

A *preflow* that has a valid labelling saturates a cut.

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Lemma 70

A *flow* that has a valid labelling is a maximum flow.

Push Relabel Algorithms



Push Relabel Algorithms

Idea:

- ▶ start with some preflow and some valid labelling

Note that this is somewhat dual to an augmenting path algorithm. The former maintains the property that it has a feasible flow. It successively changes this flow until it saturates some cut in which case we conclude that the flow is maximum. A preflow push algorithm maintains the property that it has a saturated cut. The preflow is changed iteratively until it fulfills conservation constraints in which case we can conclude that we have a maximum flow.

Push Relabel Algorithms

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Push Relabel Algorithms

Idea:

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- ▶ successively change the preflow while maintaining a valid labelling
- ▶ stop when you have a flow (i.e., no more active nodes)

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Changing a Preflow

An arc (u, v) with $c_f(u, v) > 0$ in the residual graph is **admissible** if $\ell(u) = \ell(v) + 1$ (i.e., it goes downwards w.r.t. labelling ℓ).

The push operation

Consider an active node u with **excess flow**

$f(u) = \sum_{e \in \text{into}(u)} f(e) - \sum_{e \in \text{out}(u)} f(e)$ and suppose $e = (u, v)$ is an admissible arc with residual capacity $c_f(e)$.

We can send flow $\min\{c_f(e), f(u)\}$ along e and obtain a new preflow. The old labelling is still valid (!!!).

The arc e is deleted from the residual graph.

The node u becomes inactive.

Note that a push-operation may be saturating and non-saturating at the same time.

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Increasing the label of u by 1 results in a valid labelling.

- ▶ Edges (w, u) incoming to u still fulfill their constraint $\ell(w) \leq \ell(u) + 1$.
- ▶ An outgoing edge (u, w) had $\ell(u) < \ell(w) + 1$ before since it was not admissible. Now: $\ell(u) \leq \ell(w) + 1$.

Push Relabel Algorithms

Intuition:

We want to send flow downwards, since the source has a height/label of n and the target a height/label of 0 . If we see an active node u with an admissible arc we push the flow at u towards the other end-point that has a lower height/label. If we do not have an admissible arc but excess flow into u it should roughly mean that the level/height/label of u should rise. (If we consider the flow to be water then this would be natural.)

Note that the above intuition is very incorrect as the labels are integral, i.e., they cannot really be seen as the height of a node.

Reminder

- ▶ In a **preflow** nodes may not fulfill conservation constraints; a node may have more incoming flow than outgoing flow.
- ▶ Such a node is called **active**.
- ▶ A labelling is **valid** if for every edge (u, v) in the residual graph $\ell(u) \leq \ell(v) + 1$.
- ▶ An arc (u, v) in residual graph is **admissible** if $\ell(u) = \ell(v) + 1$.
- ▶ A **saturating push** along e pushes an amount of $c(e)$ flow along the edge, thereby saturating the edge (and making it disappear from the residual graph).
- ▶ A **non-saturating push** along $e = (u, v)$ pushes a flow of $f(u)$, where $f(u)$ is the **excess flow** of u . This makes u inactive.

Push Relabel Algorithms

Algorithm 3 $\text{maxflow}(G, s, t, c)$

```
1: find initial preflow  $f$ 
2: while there is active node  $u$  do
3:     if there is admiss. arc  $e$  out of  $u$  then
4:          $\text{push}(G, e, f, c)$ 
5:     else
6:          $\text{relabel}(u)$ 
7: return  $f$ 
```

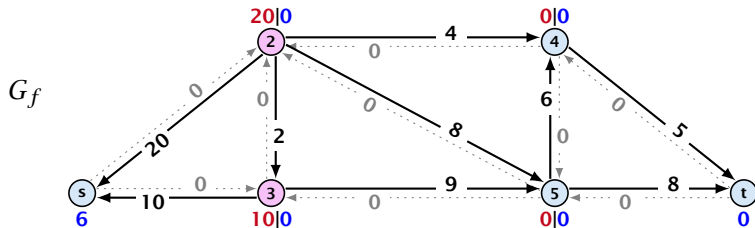
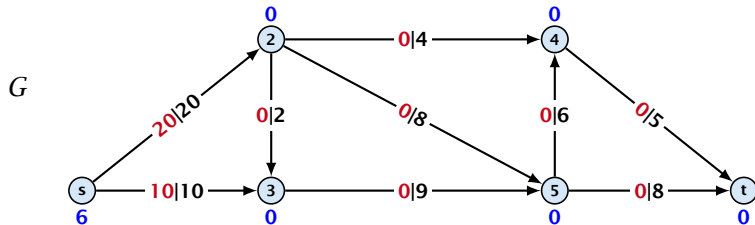
Push Relabel Algorithms

Algorithm 3 $\text{maxflow}(G, s, t, c)$

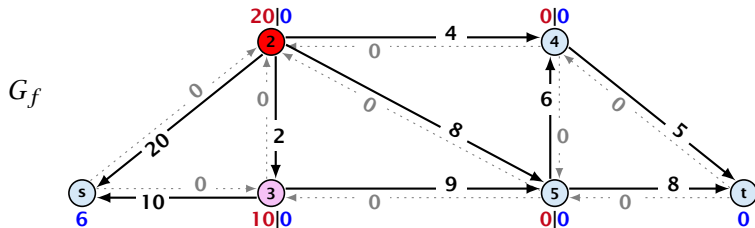
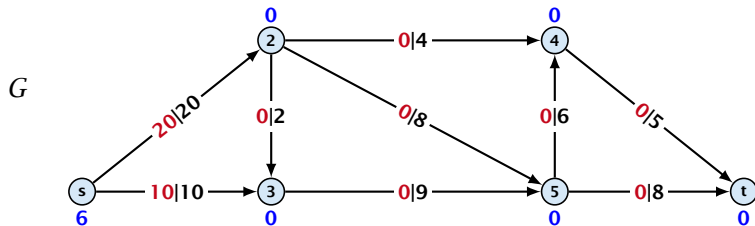
```
1: find initial preflow  $f$ 
2: while there is active node  $u$  do
3:     if there is admiss. arc  $e$  out of  $u$  then
4:          $\text{push}(G, e, f, c)$ 
5:     else
6:          $\text{relabel}(u)$ 
7: return  $f$ 
```

In the following example we always stick to the same active node u until it becomes inactive but this is not required.

Preflow Push Algorithm



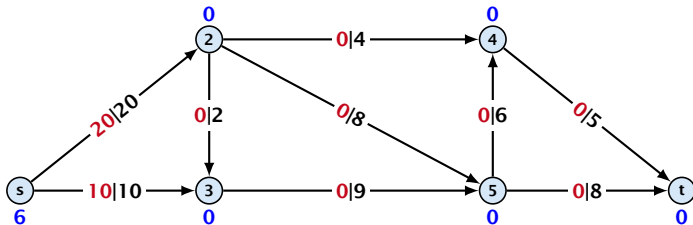
Preflow Push Algorithm



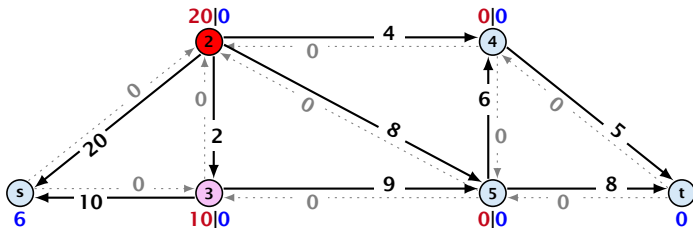
Preflow Push Algorithm

relabel

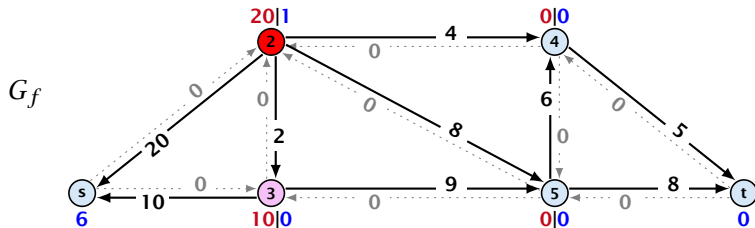
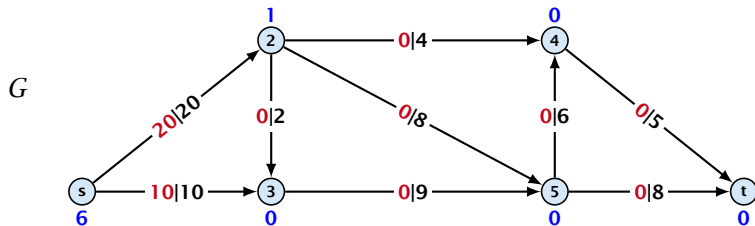
G



G_f



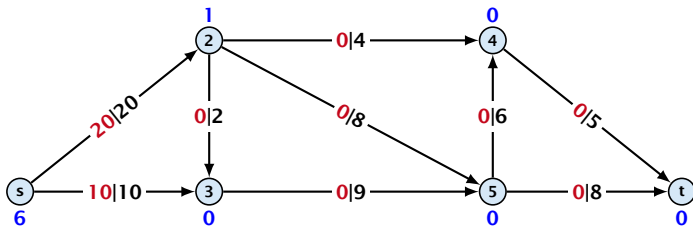
Preflow Push Algorithm



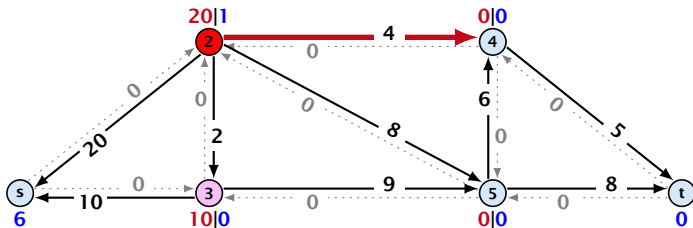
Preflow Push Algorithm

push

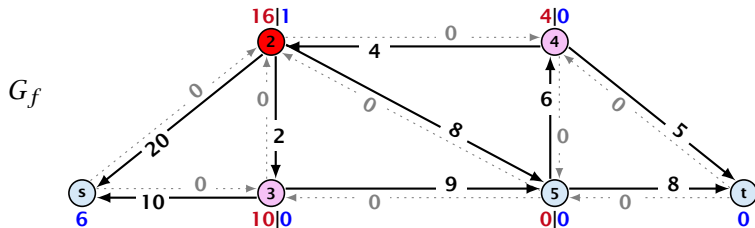
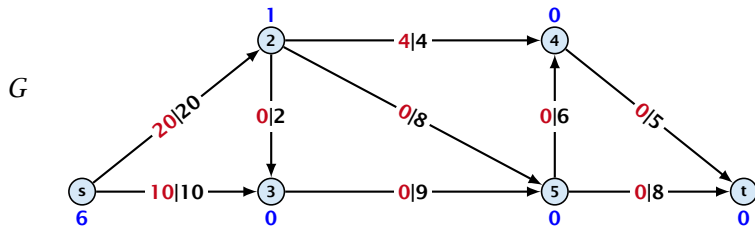
G



G_f



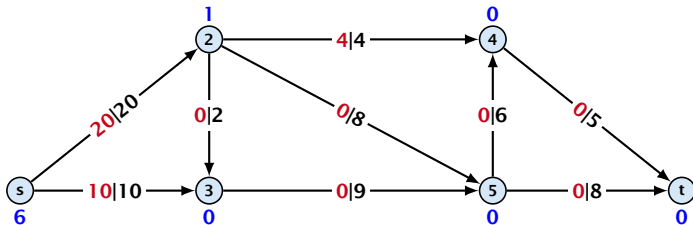
Preflow Push Algorithm



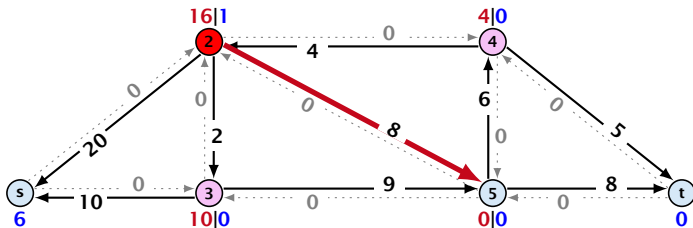
Preflow Push Algorithm

push

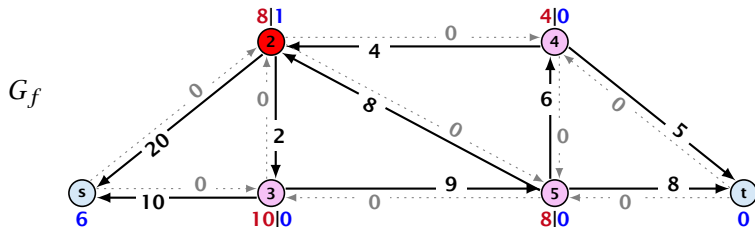
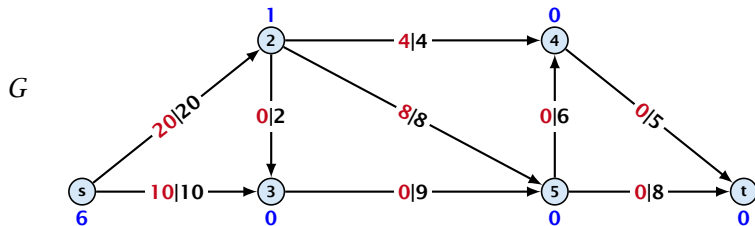
G



G_f



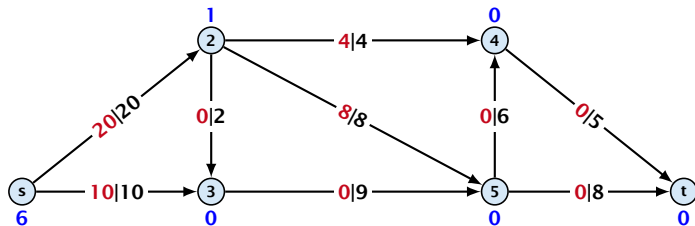
Preflow Push Algorithm



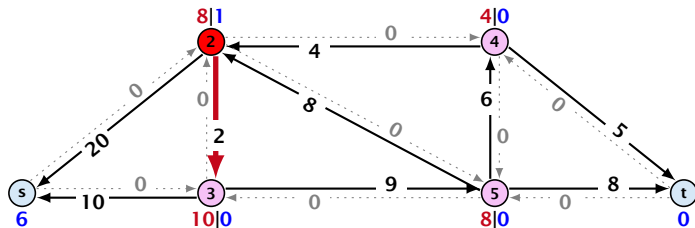
Preflow Push Algorithm

push

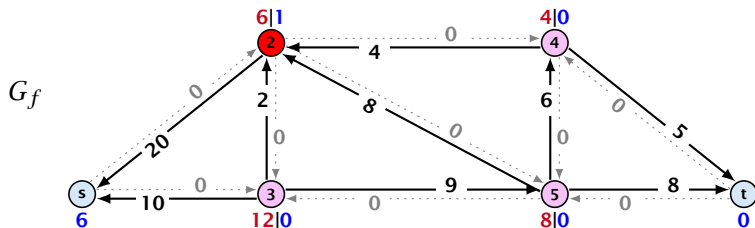
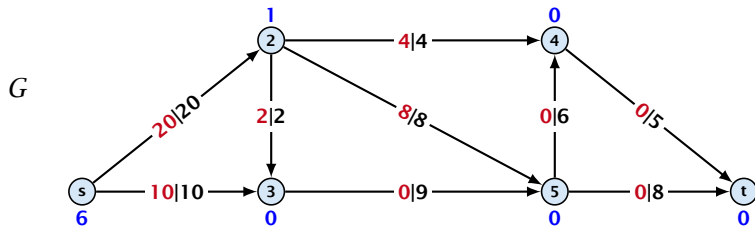
G



G_f



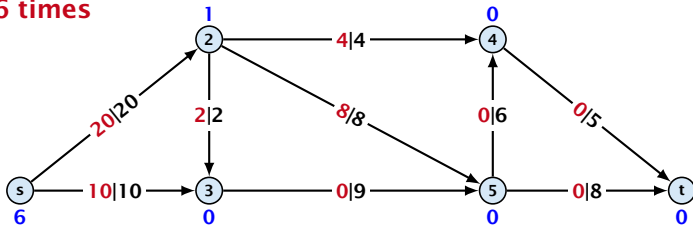
Preflow Push Algorithm



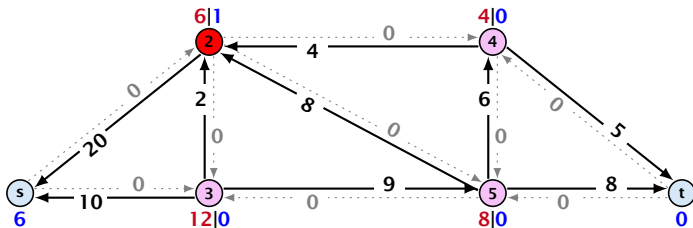
Preflow Push Algorithm

relabel 6 times

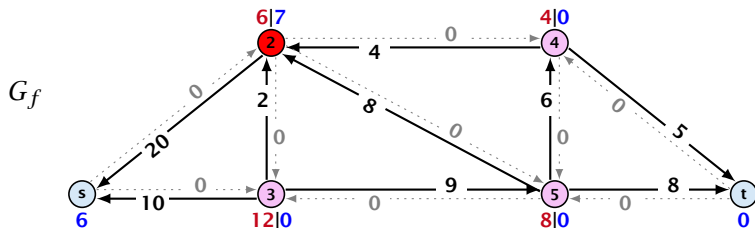
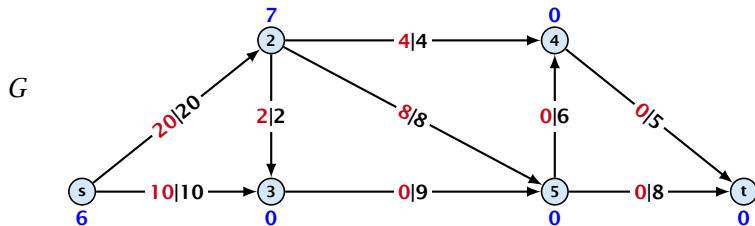
G



G_f



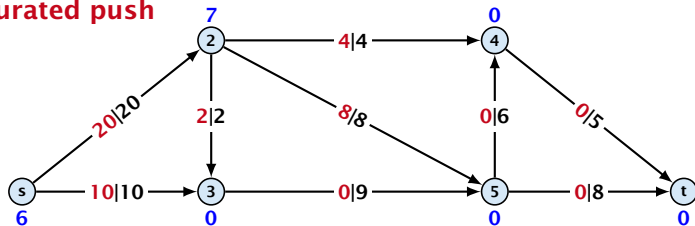
Preflow Push Algorithm



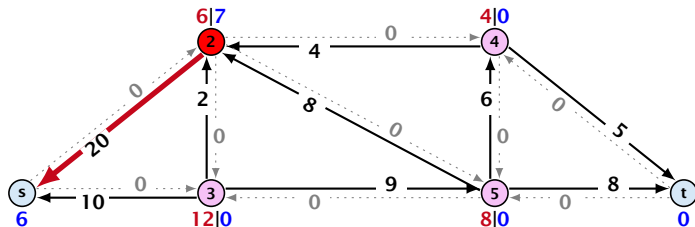
Preflow Push Algorithm

non-saturated push

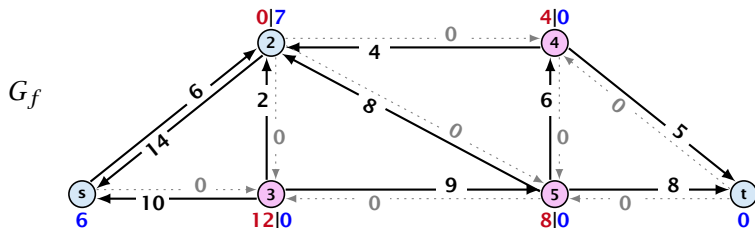
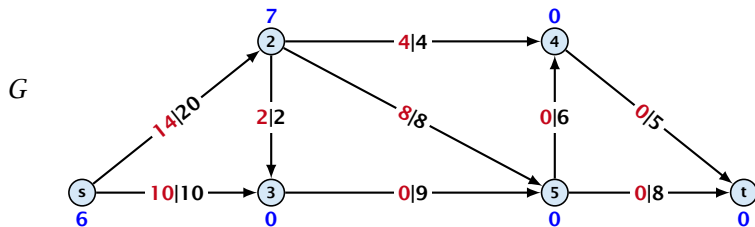
G



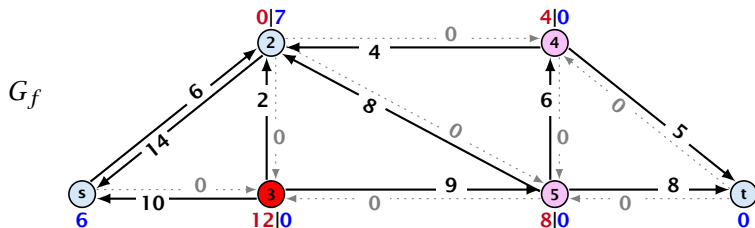
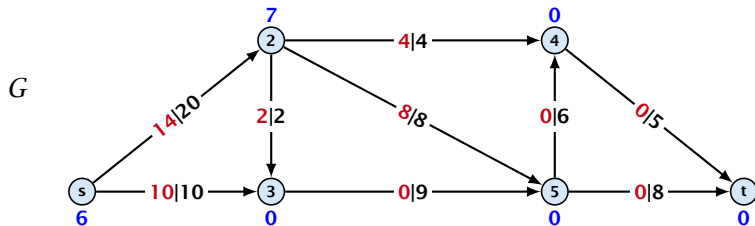
G_f



Preflow Push Algorithm



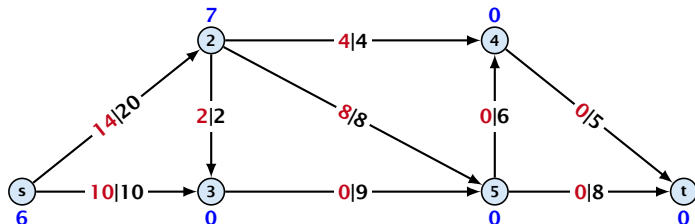
Preflow Push Algorithm



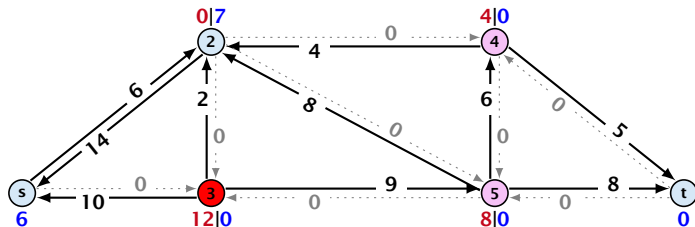
Preflow Push Algorithm

relabel

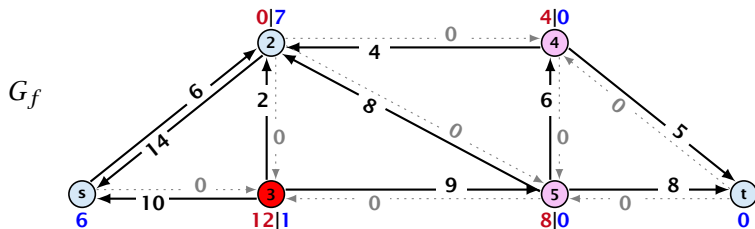
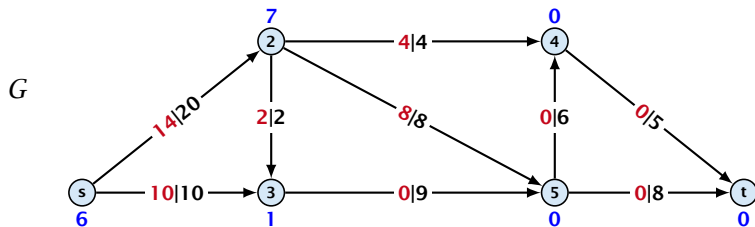
G



G_f



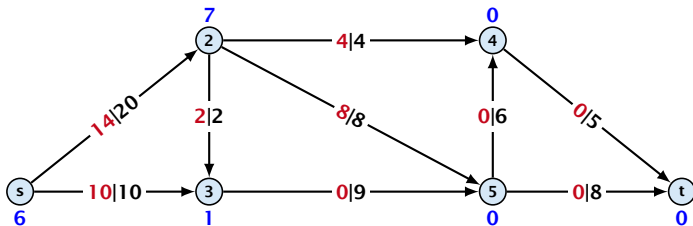
Preflow Push Algorithm



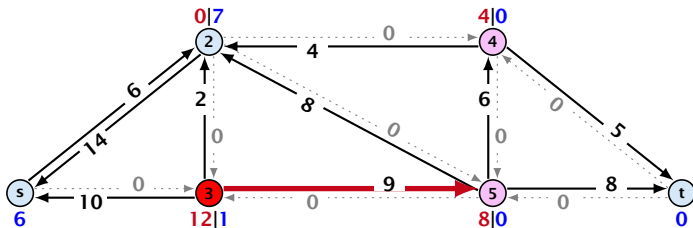
Preflow Push Algorithm

push

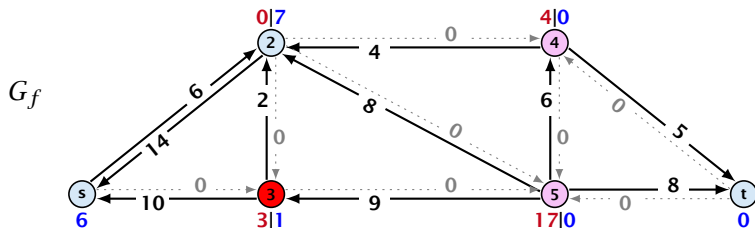
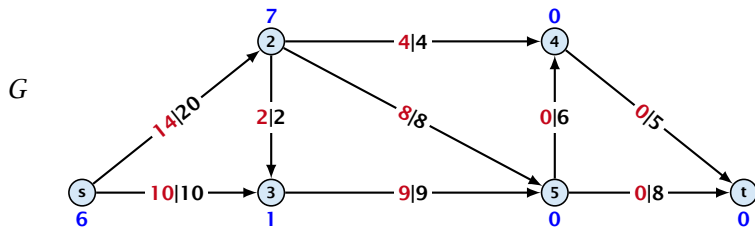
G



G_f



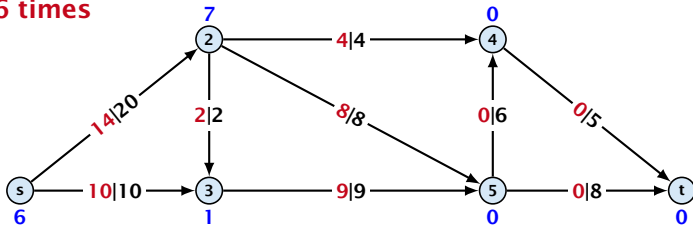
Preflow Push Algorithm



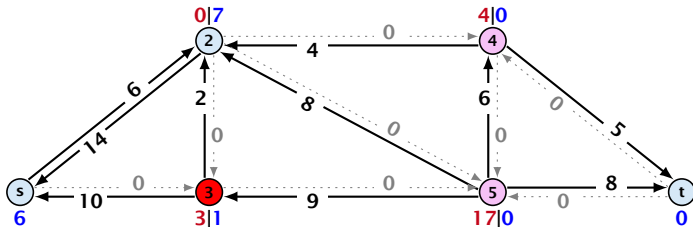
Preflow Push Algorithm

relabel 6 times

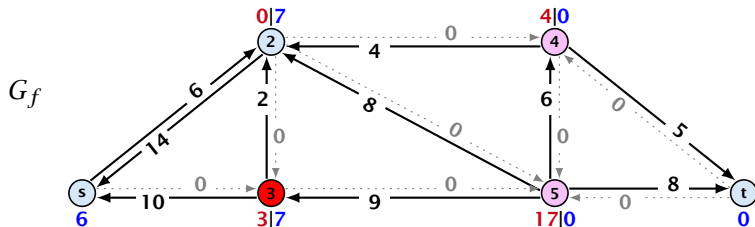
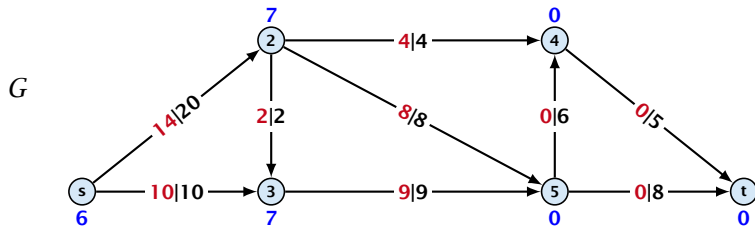
G



G_f



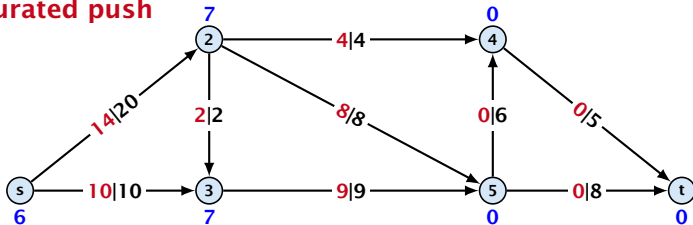
Preflow Push Algorithm



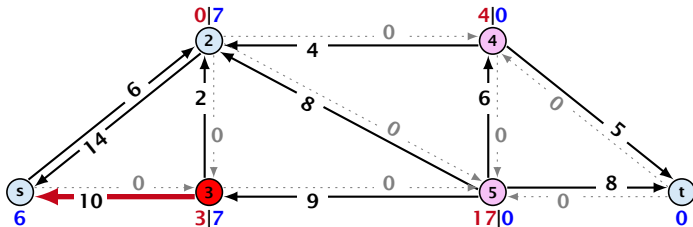
Preflow Push Algorithm

non-saturated push

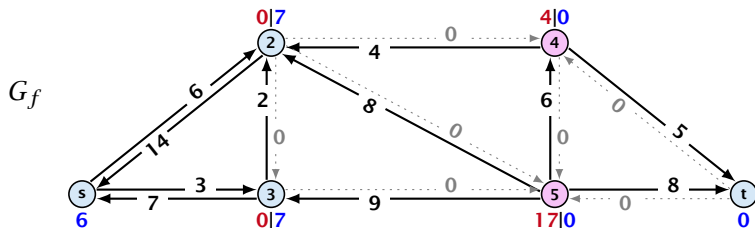
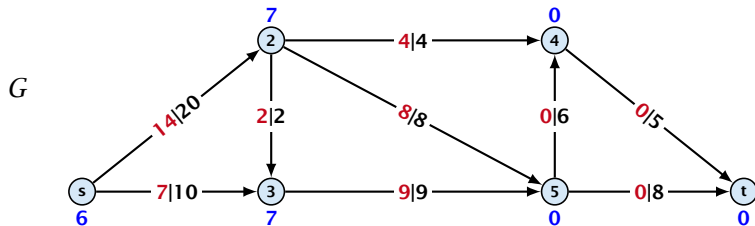
G



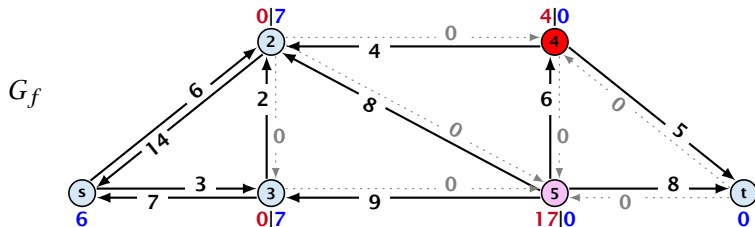
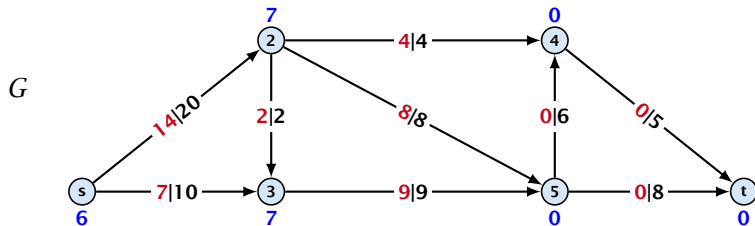
G_f



Preflow Push Algorithm



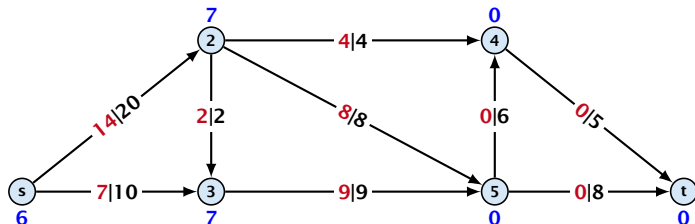
Preflow Push Algorithm



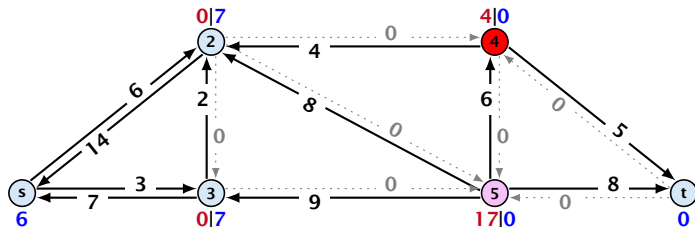
Preflow Push Algorithm

relabel

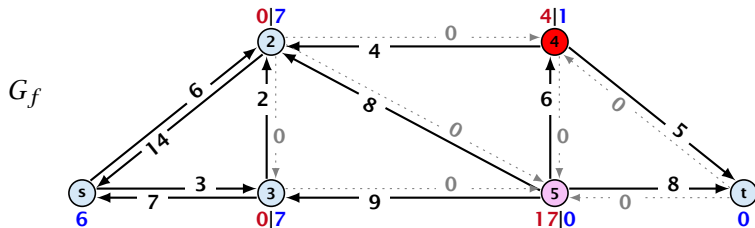
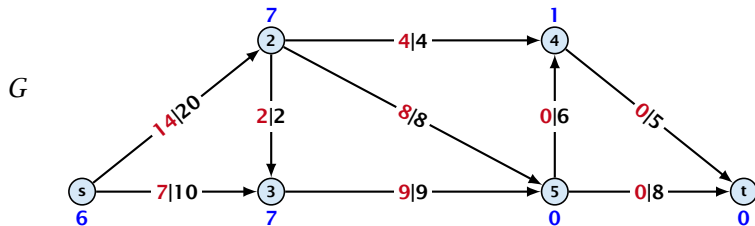
G



G_f

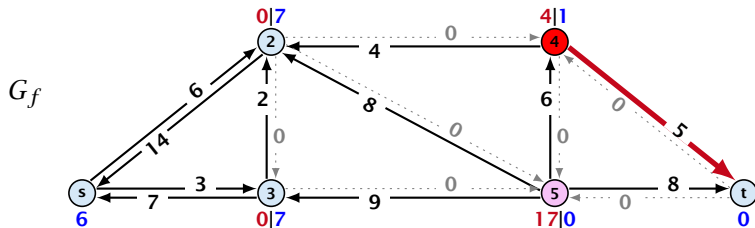
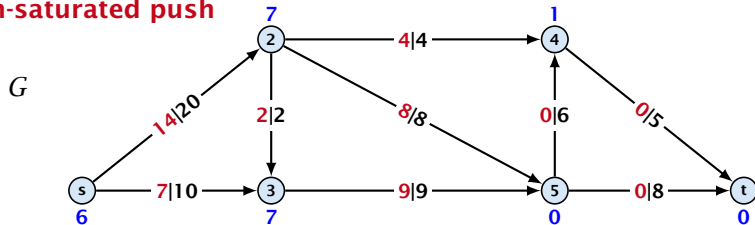


Preflow Push Algorithm

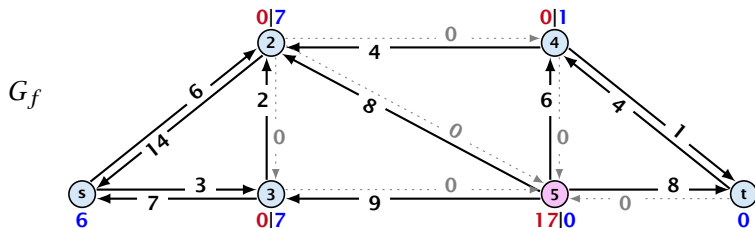
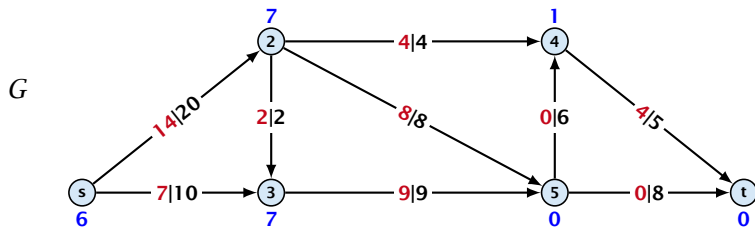


Preflow Push Algorithm

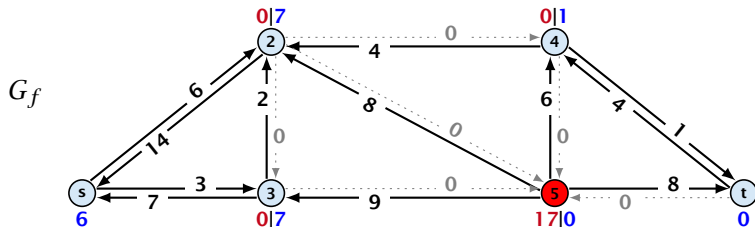
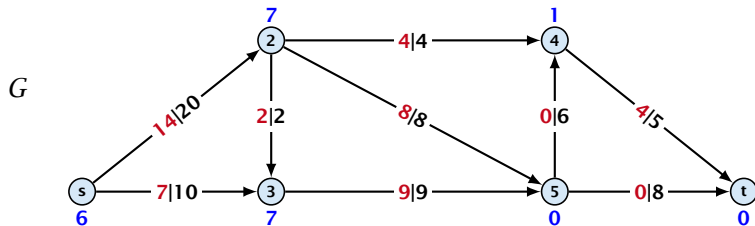
non-saturated push



Preflow Push Algorithm



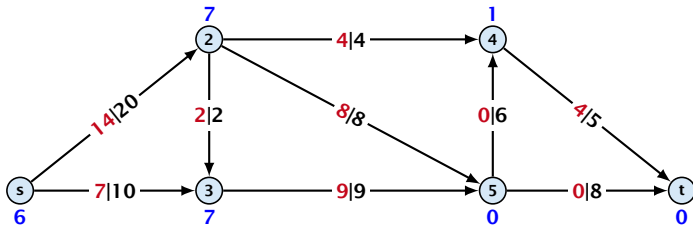
Preflow Push Algorithm



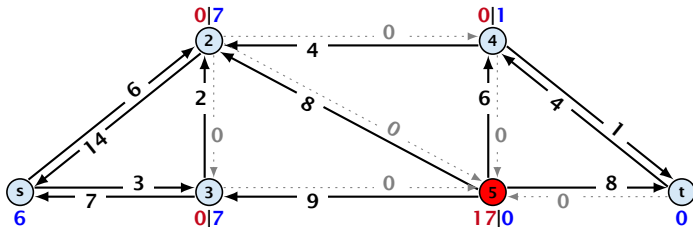
Preflow Push Algorithm

relabel

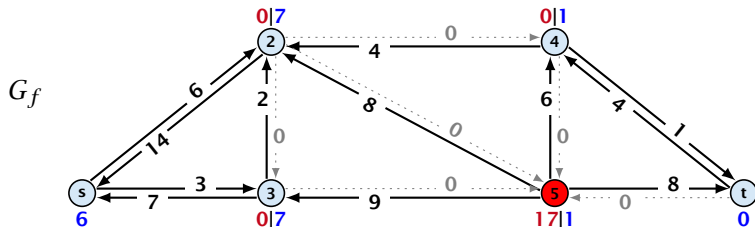
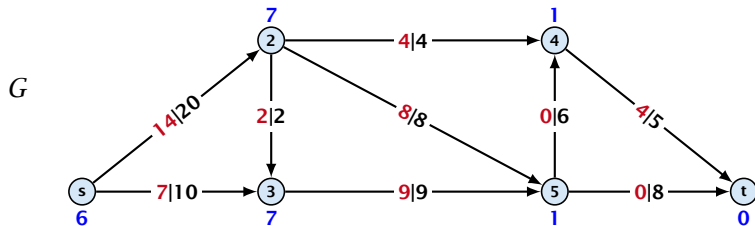
G



G_f



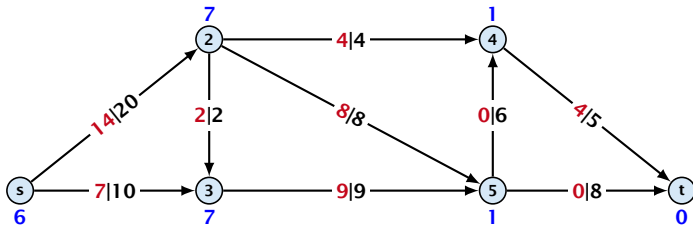
Preflow Push Algorithm



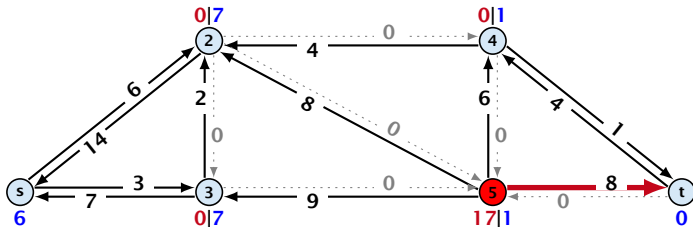
Preflow Push Algorithm

push

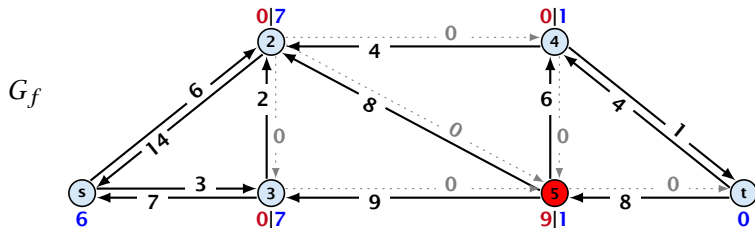
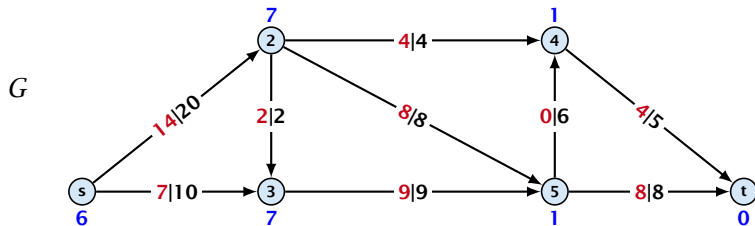
G



G_f



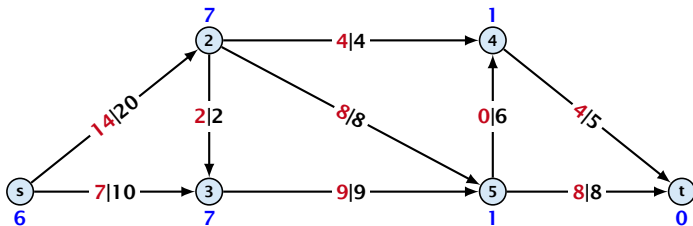
Preflow Push Algorithm



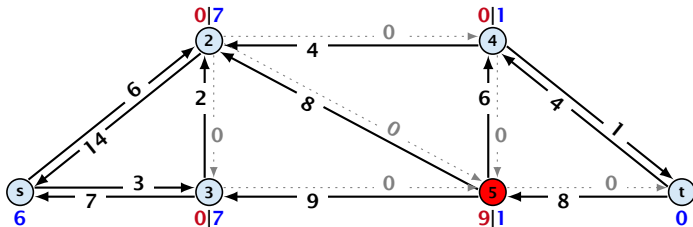
Preflow Push Algorithm

relabel

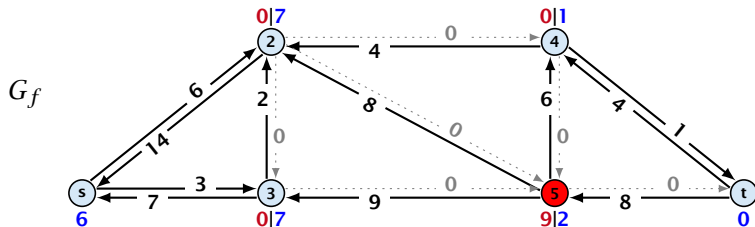
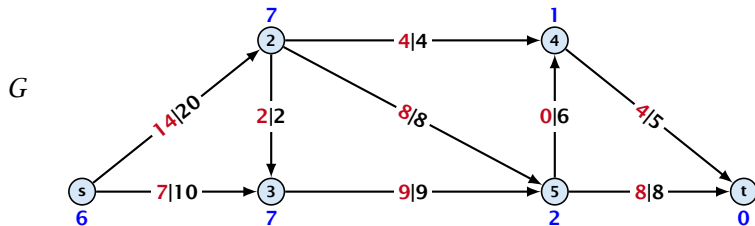
G



G_f

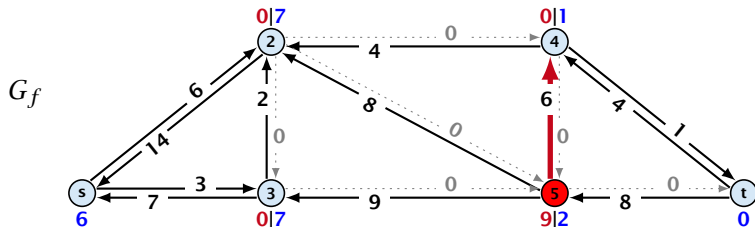
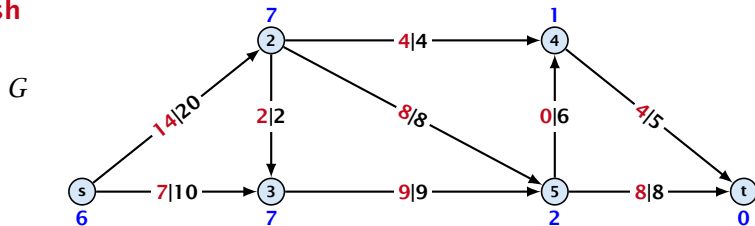


Preflow Push Algorithm

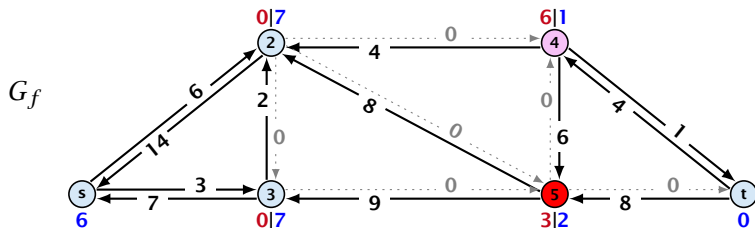
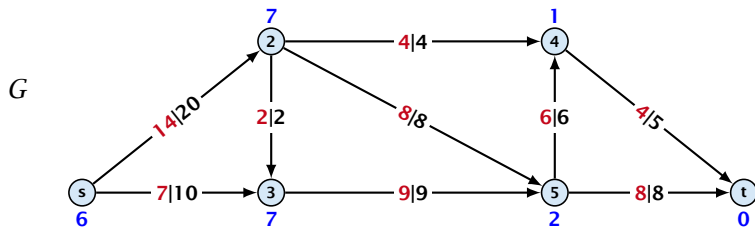


Preflow Push Algorithm

push



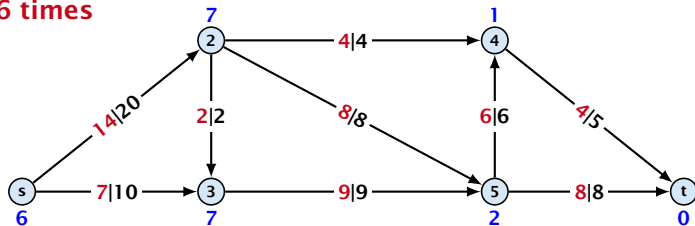
Preflow Push Algorithm



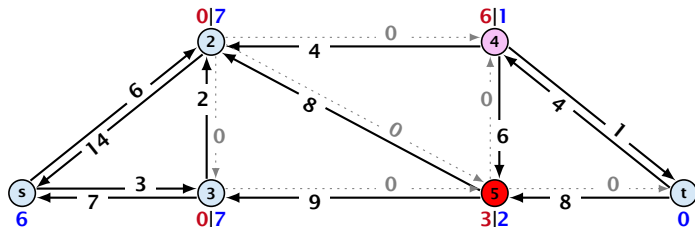
Preflow Push Algorithm

relabel 6 times

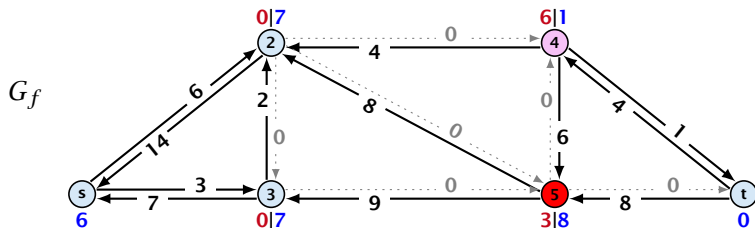
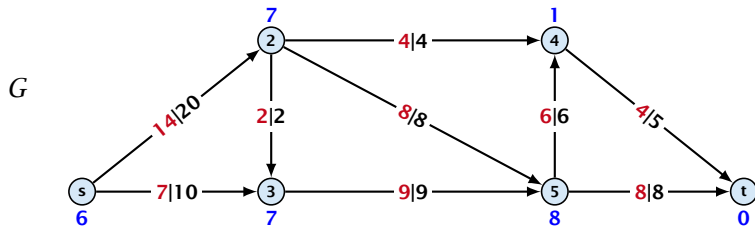
G



G_f



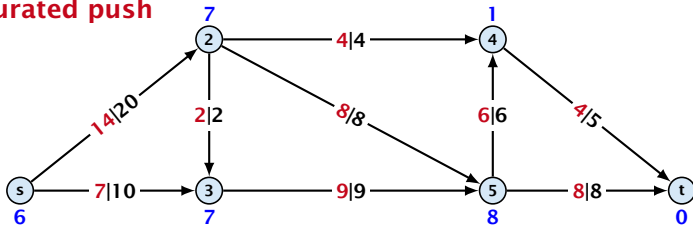
Preflow Push Algorithm



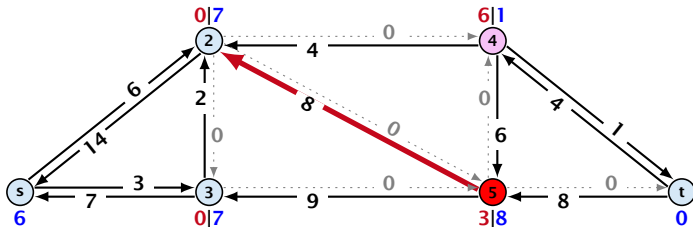
Preflow Push Algorithm

non-saturated push

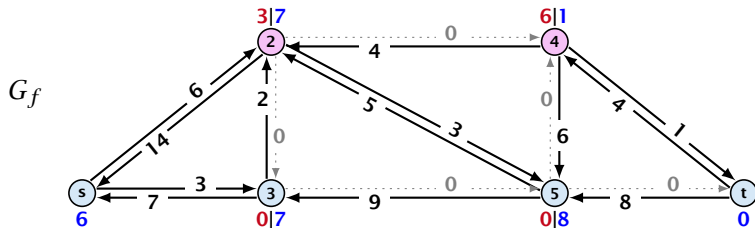
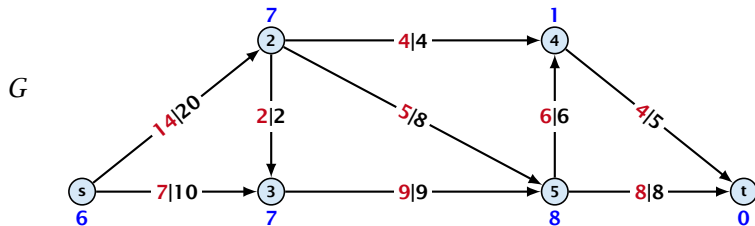
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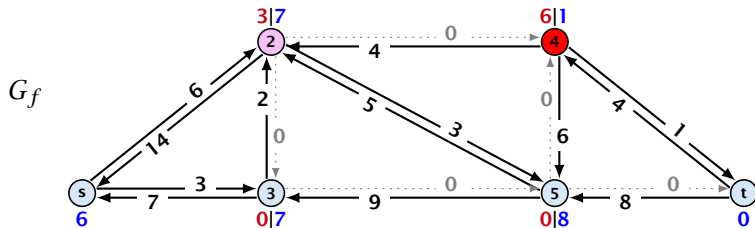
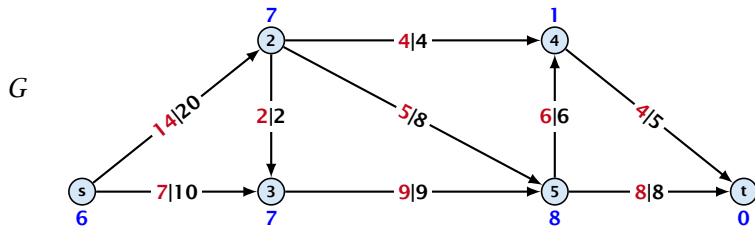
G_f



Preflow Push Algorithm



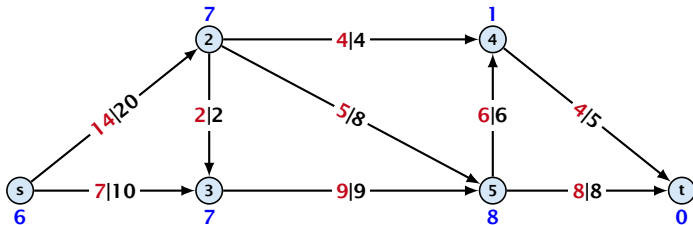
Preflow Push Algorithm



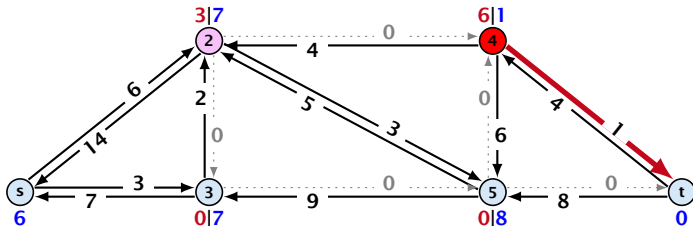
Preflow Push Algorithm

push

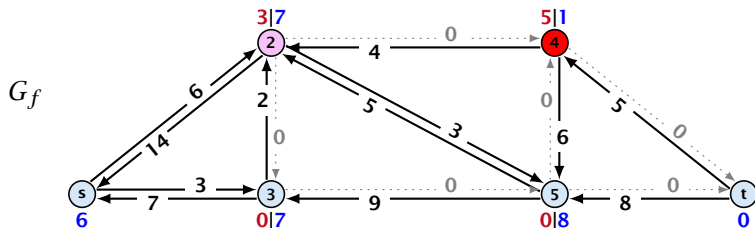
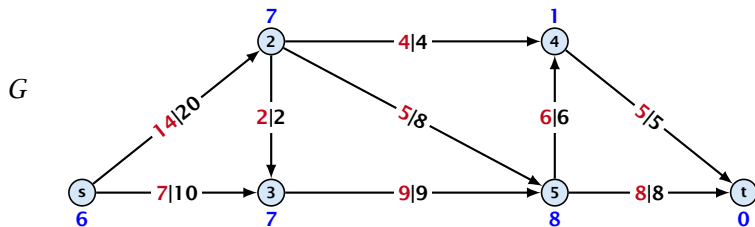
G



G_f



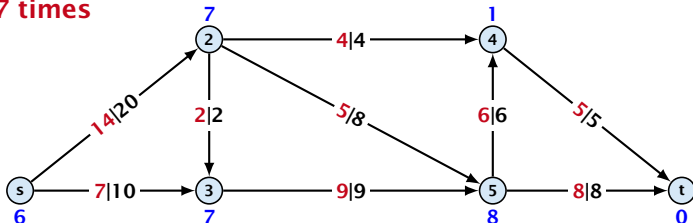
Preflow Push Algorithm



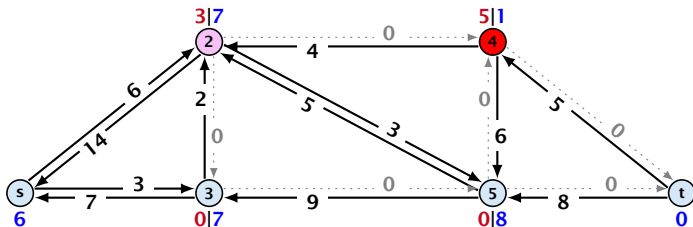
Preflow Push Algorithm

relabel 7 times

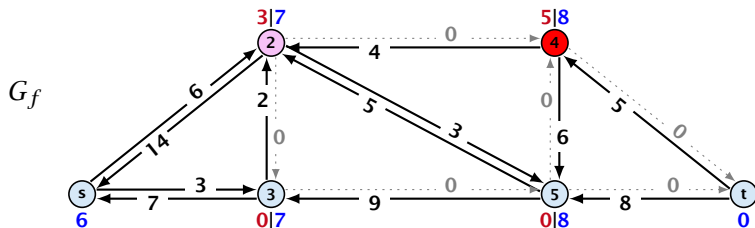
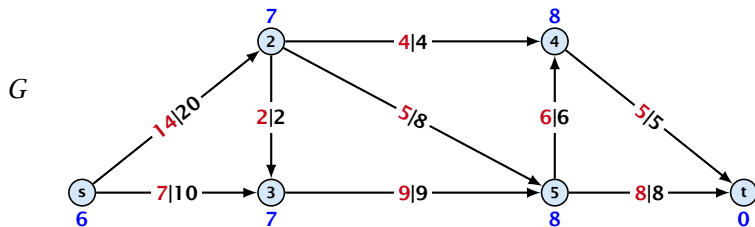
G



G_f

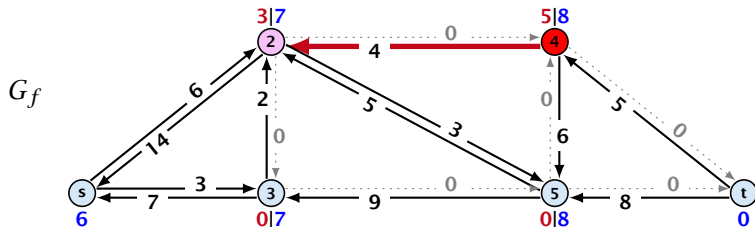
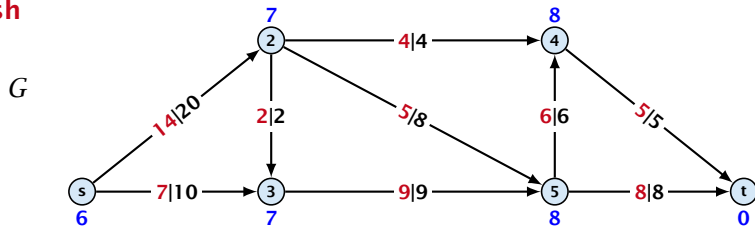


Preflow Push Algorithm

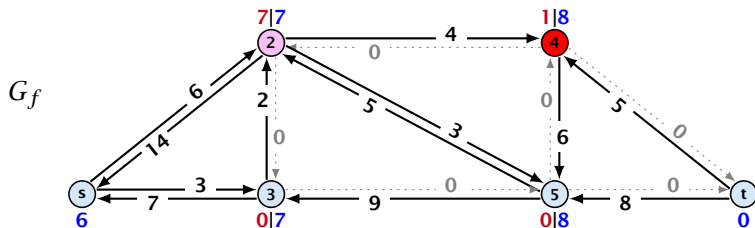
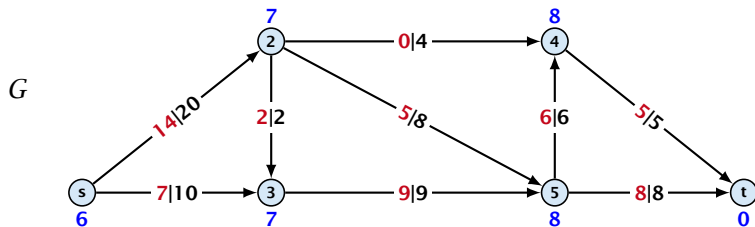


Preflow Push Algorithm

push



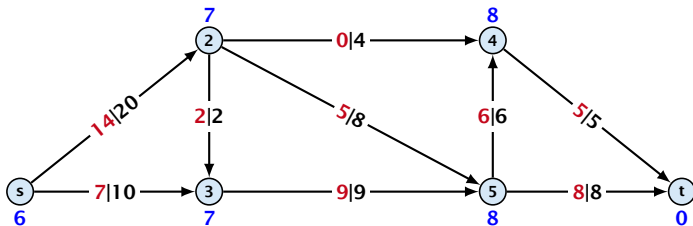
Preflow Push Algorithm



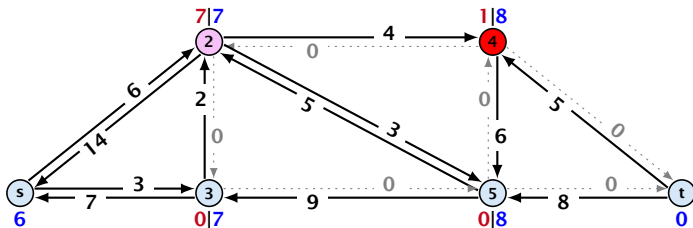
Preflow Push Algorithm

relabel

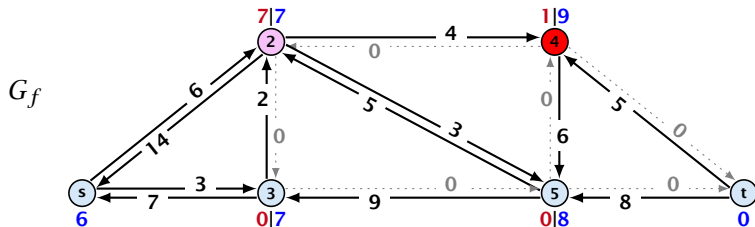
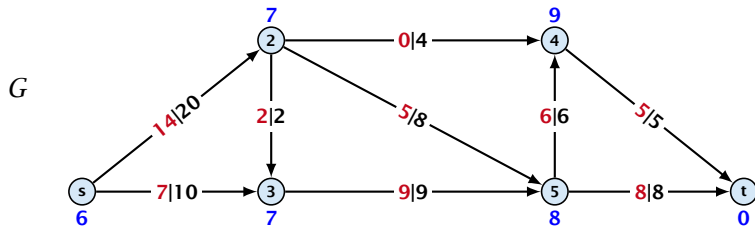
G



G_f



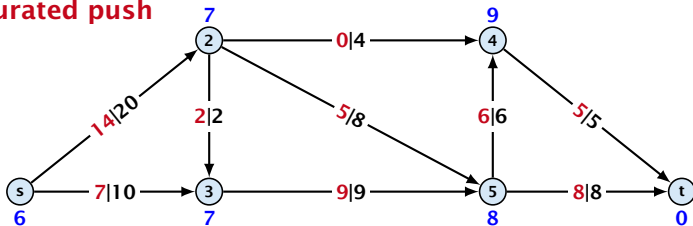
Preflow Push Algorithm



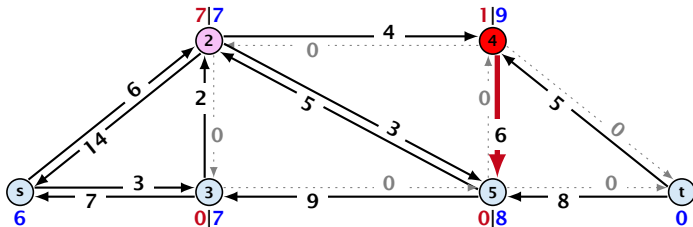
Preflow Push Algorithm

non-saturated push

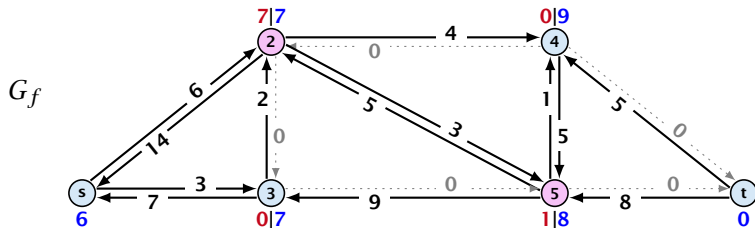
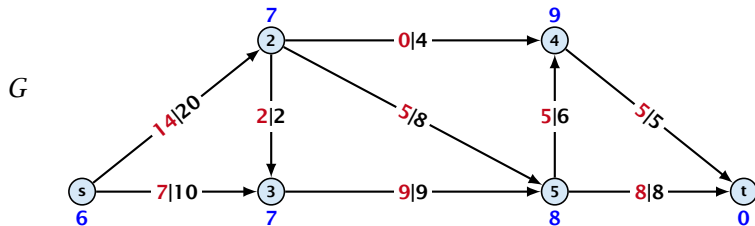
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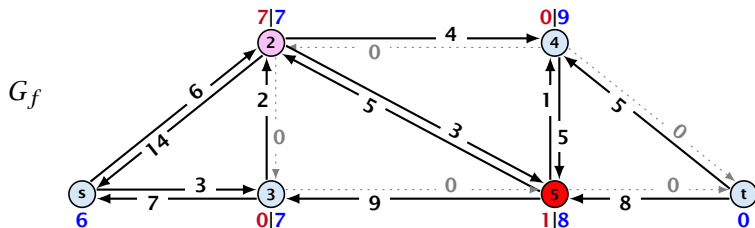
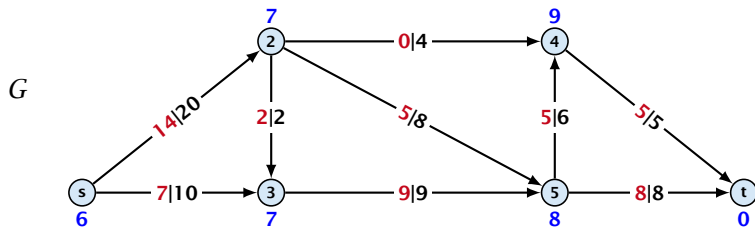
G_f



Preflow Push Algorithm



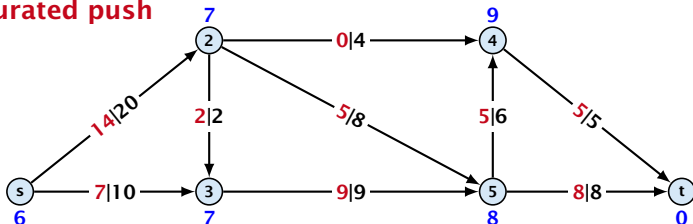
Preflow Push Algorithm



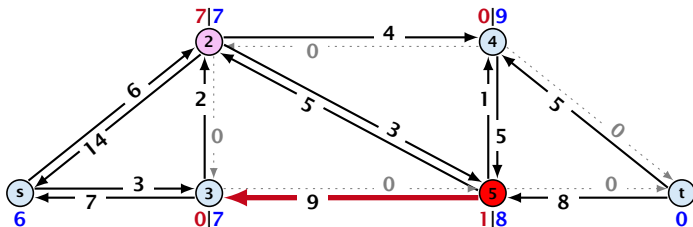
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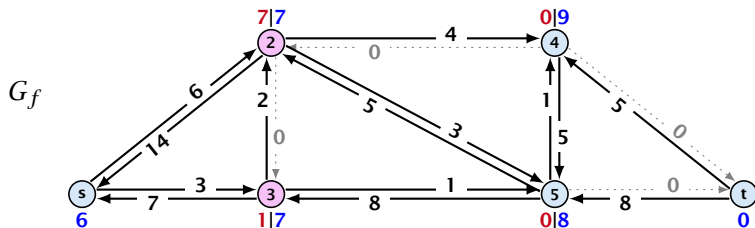
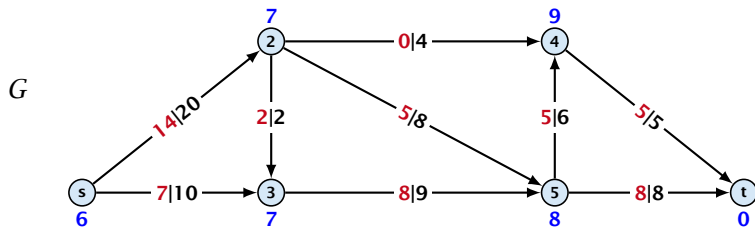
G



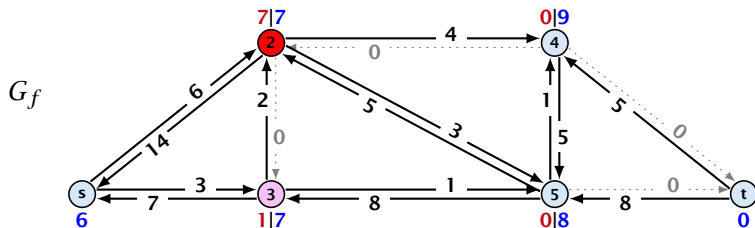
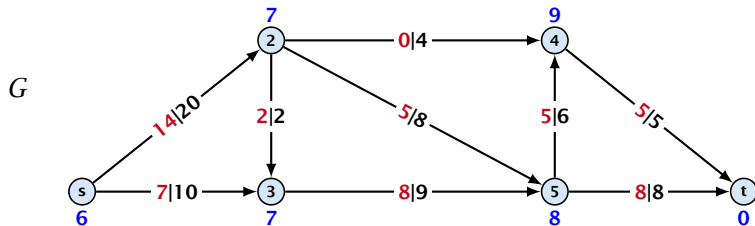
G_f



Preflow Push Algorithm



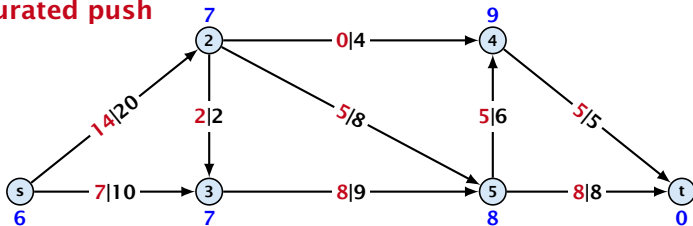
Preflow Push Algorithm



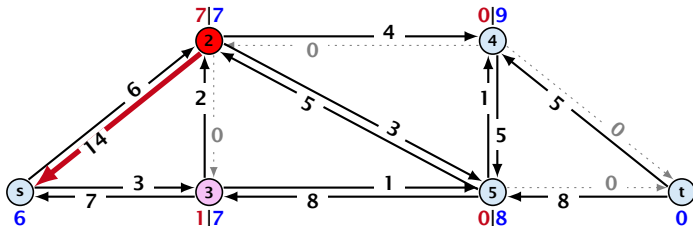
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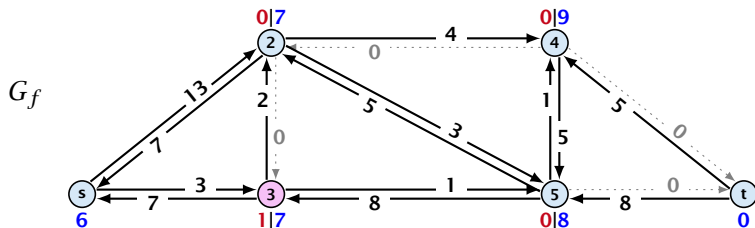
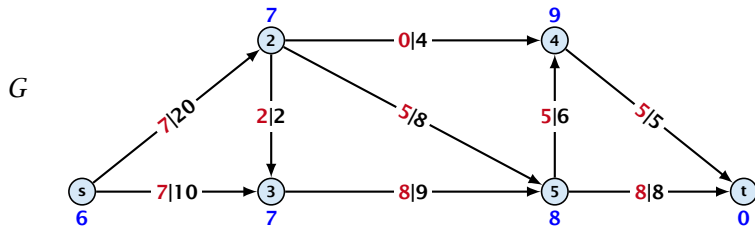
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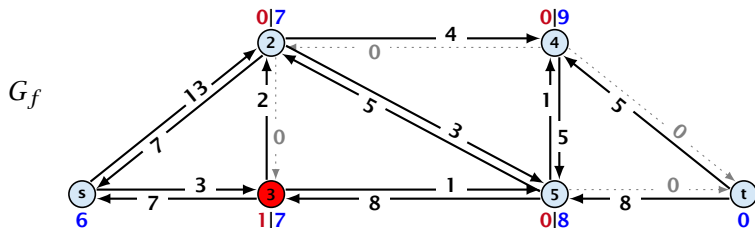
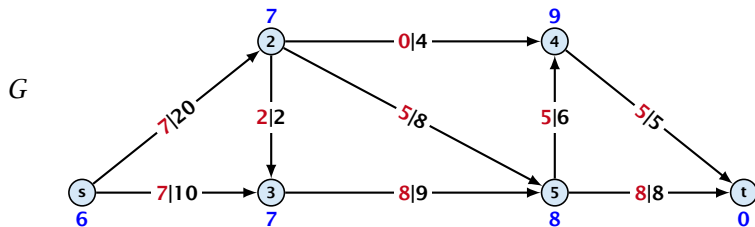
G_f



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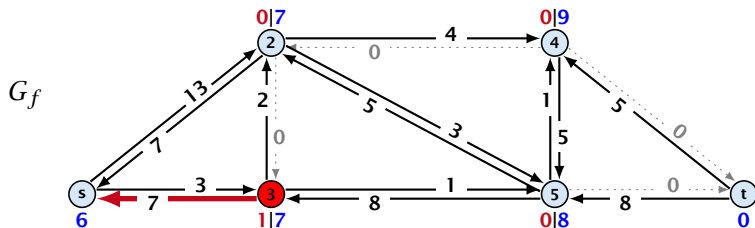
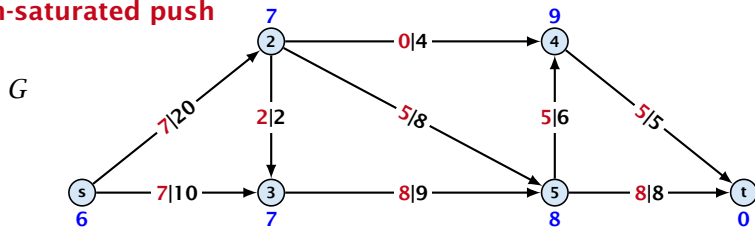


Preflow Push Algorithm

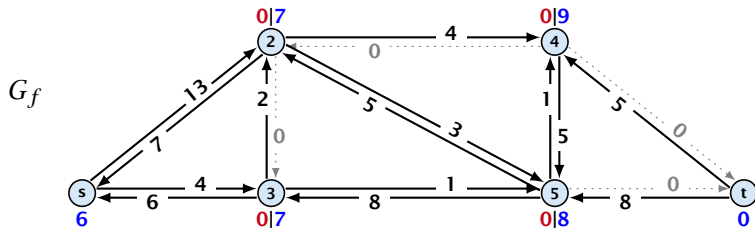
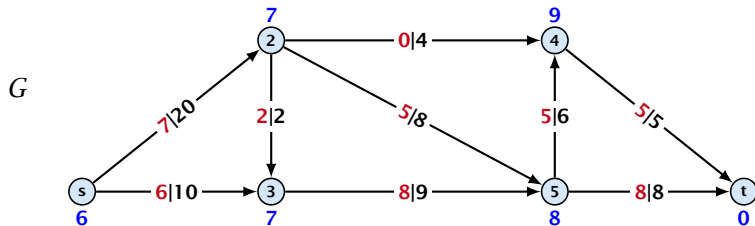


Preflow Push Algorithm

non-saturated push



Preflow Push Algorithm



Analysis

Note that the lemma is almost trivial. A node v having excess flow means that the current preflow ships something to v . The residual graph allows to *undo* flow. Therefore, there must exist a path that can undo the shipment and move it back to s . However, a formal proof is required.

Lemma 71

An active node has a path to s in the residual graph.

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Proof.

- ▶ Let A denote the set of nodes that can reach s , and let B denote the remaining nodes. Note that $s \in A$.

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- ▶ In the residual graph there are no edges into A , and, hence, no edges leaving A /entering B can carry any flow.
- ▶ Let $f(B) = \sum_{v \in B} f(v)$ be the excess flow of all nodes in B .

Let $f : E \rightarrow \mathbb{R}_0^+$ be a preflow. We introduce the notation

$$f(x, y) = \begin{cases} 0 & (x, y) \notin E \\ f((x, y)) & (x, y) \in E \end{cases}$$

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Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$.

Analysis

Lemma 72

The label of a node cannot become larger than $2n - 1$.

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Proof.

- ▶ When increasing the label at a node u there exists a path from u to s of length at most $n - 1$. Along each edge of the path the height/label can at most drop by 1 , and the label of the source is n .

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Lemma 73

There are only $\mathcal{O}(n^2)$ relabel operations.

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Lemma 74

The number of *saturating pushes* performed is at most $\mathcal{O}(mn)$.

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- ▶ For a push from v to u the edge (v, u) must become admissible. The label of v must increase by at least 2.

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- ▶ Hence, the edge (u, v) is deleted from the residual graph.
- ▶ For the edge to appear again, a push from v to u is required.
- ▶ Currently, $\ell(u) = \ell(v) + 1$, as we only make pushes along admissible edges.
- ▶ For a push from v to u the edge (v, u) must become admissible. The label of v must increase by at least 2.
- ▶ Since the label of v is at most $2n - 1$, there are at most n pushes along (u, v) .

Lemma 75

The number of *non-saturating pushes* performed is at most $\mathcal{O}(n^2m)$.

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- ▶ A non-saturating push decreases Φ by at least 1 as the node that is pushed from becomes inactive and has a label that is strictly larger than the target.
- ▶ Hence,

$$\begin{aligned} \# \text{non-saturating_pushes} &\leq \# \text{relabels} + 2n \cdot \# \text{saturating_pushes} \\ &\leq \mathcal{O}(n^2m) . \end{aligned}$$

Theorem 76

There is an implementation of the generic push relabel algorithm with running time $\mathcal{O}(n^2m)$.

Analysis

Proof:

For every node maintain a list of admissible edges starting at that node. Further maintain a list of active nodes.

A push along an edge (u, v) can be performed in constant time

- check whether edge (u, v) needs to be added to the list
- check whether v needs to be deleted (stopping push)
- check whether u becomes inactive and has to be deleted from the set of active nodes

A relabel at a node u can be performed in time $\mathcal{O}(n)$

- check for all outgoing edges if they become admissible
- check for all incoming edges if they become inadmissible

Analysis

Proof:

For every node maintain a list of admissible edges starting at that node. Further maintain a list of active nodes.

A push along an edge (u, v) can be performed in constant time
check whether v is an active node (edge (u, v) is admissible)
check whether v needs to be pushed (returning push)
check whether v becomes inactive and has to be deleted
from the set of active nodes

A relabel at a node u can be performed in time $\mathcal{O}(n)$
check for all outgoing edges if they become admissible
check for all incoming edges if they become non-admissible

Analysis

Proof:

For every node maintain a list of admissible edges starting at that node. Further maintain a list of active nodes.

A push along an edge (u, v) can be performed in constant time

- ▶ check whether edge (v, u) needs to be added to G_f
- ▶ check whether (u, v) needs to be deleted (saturating push)
- ▶ check whether u becomes inactive and has to be deleted from the set of active nodes

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- ▶ check for all outgoing edges if they become admissible
- ▶ check for all incoming edges if they become non-admissible

Analysis

For special variants of push relabel algorithms we organize the neighbours of a node into a linked list (possible neighbours in the residual graph G_f). Then we use the discharge-operation:

Algorithm 4 discharge(u)

```
1: while  $u$  is active do  
2:    $v \leftarrow u.current\text{-neighbour}$   
3:   if  $v = \text{null}$  then  
4:     relabel( $u$ )  
5:      $u.current\text{-neighbour} \leftarrow u.neighbour\text{-list-head}$   
6:   else  
7:     if  $(u, v)$  admissible then push( $u, v$ )  
8:     else  $u.current\text{-neighbour} \leftarrow v.next\text{-in-list}$ 
```

Note that $u.current\text{-neighbour}$ is a global variable. It is only changed within the discharge routine, but keeps its value between consecutive calls to discharge.

Lemma 77

If $v = \text{null}$ in Line 3, then there is no outgoing admissible edge from u .

Proof.

- ▶ While pushing from u the current-neighbour pointer is only advanced if the current edge is not admissible.
- ▶ The only thing that could make the edge admissible again would be a relabel at u .
- ▶ If we reach the end of the list ($v = \text{null}$) all edges are not admissible. □

This shows that $\text{discharge}(u)$ is correct, and that we can perform a relabel in Line 4.

In order for e to become admissible the other end-point say v has to push flow to u (so that the edge (u, v) re-appears in the residual graph). For this the label of v needs to be larger than the label of u . Then in order to make (u, v) admissible the label of u has to increase.

13.2 Relabel to Front

Algorithm 1 relabel-to-front(G, s, t)

```
1: initialize preflow
2: initialize node list  $L$  containing  $V \setminus \{s, t\}$  in any order
3: foreach  $u \in V \setminus \{s, t\}$  do
4:    $u.current\text{-neighbour} \leftarrow u.neighbour\text{-list}\text{-head}$ 
5:  $u \leftarrow L.head$ 
6: while  $u \neq \text{null}$  do
7:    $old\text{-height} \leftarrow \ell(u)$ 
8:   discharge( $u$ )
9:   if  $\ell(u) > old\text{-height}$  then // relabel happened
10:    move  $u$  to the front of  $L$ 
11:    $u \leftarrow u.next$ 
```

13.2 Relabel to Front

Lemma 78 (Invariant)

In Line 6 of the relabel-to-front algorithm the following invariant holds.

- 1. The sequence L is topologically sorted w.r.t. the set of admissible edges; this means for an admissible edge (x, y) the node x appears before y in sequence L .*
- 2. No node before u in the list L is active.*

Proof:

► Initialization:

1. In the beginning s has label $n \geq 2$, and all other nodes have label 0. Hence, no edge is admissible, which means that any ordering L is permitted.
2. We start with u being the head of the list; hence no node before u can be active

► Maintenance:

1.
 - Pushes do not create any new admissible edges. Therefore, if `discharge()` does not relabel u , L is still topologically sorted.
 - After relabeling, u cannot have admissible incoming edges as such an edge (x, u) would have had a difference $\ell(x) - \ell(u) \geq 2$ before the re-labeling (such edges do not exist in the residual graph).
Hence, moving u to the front does not violate the sorting property for any edge; however it fixes this property for all admissible edges leaving u that were generated by the relabeling.

13.2 Relabel to Front

Proof:

► Maintenance:

2. If we do a relabel there is nothing to prove because the only node before u' (u in the next iteration) will be the current u ; the discharge(u) operation only terminates when u is not active anymore.

For the case that we do not relabel, observe that the only way a predecessor could be active is that we push flow to it via an admissible arc. However, all admissible arcs point to successors of u .

Note that the invariant means that for $u = \text{null}$ we have a preflow with a valid labelling that does not have active nodes. This means we have a maximum flow.

13.2 Relabel to Front

Lemma 79

There are at most $\mathcal{O}(n^3)$ calls to $\text{discharge}(u)$.

Every discharge operation without a relabel advances u (the current node within list L). Hence, if we have n discharge operations without a relabel we have $u = \text{null}$ and the algorithm terminates.

Therefore, the number of calls to discharge is at most $n(\#\text{relabels} + 1) = \mathcal{O}(n^3)$.

13.2 Relabel to Front

Lemma 80

The cost for all relabel-operations is only $\mathcal{O}(n^2)$.

A relabel-operation at a node is constant time (increasing the label and resetting *u .current-neighbour*). In total we have $\mathcal{O}(n^2)$ relabel-operations.

13.2 Relabel to Front

Note that by definition a saturating push operation ($\min\{c_f(e), f(u)\} = c_f(e)$) can at the same time be a non-saturating push operation ($\min\{c_f(e), f(u)\} = f(u)$).

Lemma 81

*The cost for all saturating push-operations that are **not** also non-saturating push-operations is only $\mathcal{O}(mn)$.*

Note that such a push-operation leaves the node u active but makes the edge e disappear from the residual graph. Therefore the push-operation is immediately followed by an increase of the pointer $u.current-neighbour$.

This pointer can traverse the neighbour-list at most $\mathcal{O}(n)$ times (upper bound on number of relabels) and the neighbour-list has only $degree(u) + 1$ many entries (+1 for null-entry).

13.2 Relabel to Front

Lemma 82

The cost for all non-saturating push-operations is only $\mathcal{O}(n^3)$.

A non-saturating push-operation takes constant time and ends the current call to `discharge()`. Hence, there are only $\mathcal{O}(n^3)$ such operations.

Theorem 83

The push-relabel algorithm with the rule relabel-to-front takes time $\mathcal{O}(n^3)$.

13.3 Highest Label

Algorithm 6 highest-label(G, s, t)

- 1: initialize preflow
- 2: **foreach** $u \in V \setminus \{s, t\}$ **do**
- 3: $u.current-neighbour \leftarrow u.neighbour-list-head$
- 4: **while** \exists active node u **do**
- 5: select active node u with highest label
- 6: discharge(u)

13.3 Highest Label

Lemma 84

When using highest label the number of non-saturating pushes is only $\mathcal{O}(n^3)$.

A push from a node on level ℓ can only “activate” nodes on levels strictly less than ℓ .

This means, after a non-saturating push from u a relabel is required to make u active again.

Hence, after n non-saturating pushes without an intermediate relabel there are no active nodes left.

Therefore, the number of non-saturating pushes is at most $n(\#relabels + 1) = \mathcal{O}(n^3)$.

13.3 Highest Label

Since a discharge-operation is terminated by a non-saturating push this gives an upper bound of $\mathcal{O}(n^3)$ on the number of discharge-operations.

The cost for relabels and saturating pushes can be estimated in exactly the same way as in the case of the generic push-relabel algorithm.

Question:

How do we find the next node for a discharge operation?

13.3 Highest Label

Maintain lists L_i , $i \in \{0, \dots, 2n\}$, where list L_i contains active nodes with label i (maintaining these lists induces only constant additional cost for every push-operation and for every relabel-operation).

After a discharge operation terminated for a node u with label k , traverse the lists L_k, L_{k-1}, \dots, L_0 , (in that order) until you find a non-empty list.

Unless the last (non-saturating) push was to s or t the list $k - 1$ must be non-empty (i.e., the search takes constant time).

13.3 Highest Label

Hence, the total time required for searching for active nodes is at most

$$\mathcal{O}(n^3) + n(\#non-saturating-pushes-to-s-or-t)$$

Lemma 85

The number of non-saturating pushes to s or t is at most $\mathcal{O}(n^2)$.

With this lemma we get

Theorem 86

The push-relabel algorithm with the rule highest-label takes time $\mathcal{O}(n^3)$.

13.3 Highest Label

Proof of the Lemma.

- ▶ We only show that the number of pushes to the source is at most $\mathcal{O}(n^2)$. A similar argument holds for the target.
- ▶ After a node v (which must have $\ell(v) = n + 1$) made a non-saturating push to the source there needs to be another node whose label is increased from $\leq n + 1$ to $n + 2$ before v can become active again.
- ▶ This happens for every push that v makes to the source. Since, every node can pass the threshold $n + 2$ at most once, v can make at most n pushes to the source.
- ▶ As this holds for every node the total number of pushes to the source is at most $\mathcal{O}(n^2)$.

Problem Definition:

$$\begin{aligned} \min \quad & \sum_e c(e)f(e) \\ \text{s.t.} \quad & \forall e \in E: 0 \leq f(e) \leq u(e) \\ & \forall v \in V: f(v) = b(v) \end{aligned}$$

Mincost Flow

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- ▶ $G = (V, E)$ is a **directed graph**.
- ▶ $u : E \rightarrow \mathbb{R}_0^+ \cup \{\infty\}$ is the **capacity function**.
- ▶ $c : E \rightarrow \mathbb{R}$ is the **cost function**
(note that $c(e)$ may be negative).
- ▶ $b : V \rightarrow \mathbb{R}, \sum_{v \in V} b(v) = 0$ is a **demand function**.

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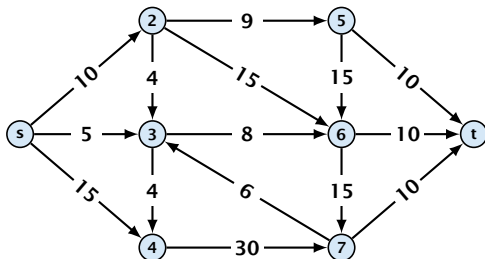
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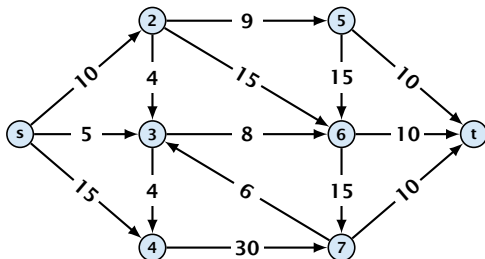
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Solve Maxflow Using Mincost Flow

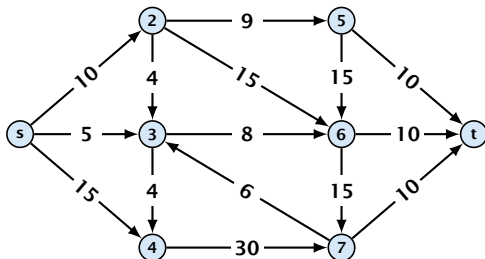


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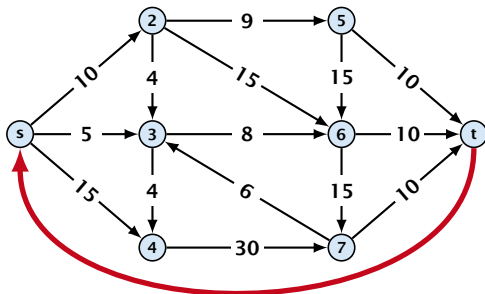
- ▶ Given a flow network for a standard maxflow problem.

Solve Maxflow Using Mincost Flow



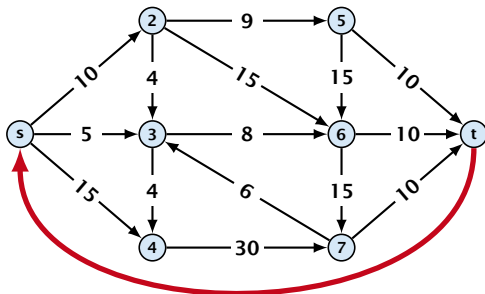
- ▶ Given a flow network for a standard maxflow problem.
- ▶ Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0.

Solve Maxflow Using Mincost Flow



- ▶ Given a flow network for a standard maxflow problem.
- ▶ Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0 .
- ▶ Add an edge from t to s with infinite capacity and cost -1 .

Solve Maxflow Using Mincost Flow



- ▶ Given a flow network for a standard maxflow problem.
- ▶ Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0 .
- ▶ Add an edge from t to s with infinite capacity and cost -1 .
- ▶ Then, $\text{val}(f^*) = -\text{cost}(f_{\min})$, where f^* is a maxflow, and f_{\min} is a mincost-flow.

Solve Maxflow Using Mincost Flow

Solve decision version of maxflow:

- ▶ Given a flow network for a standard maxflow problem, and a value k .
- ▶ Set $b(v) = 0$ for every node apart from s or t . Set $b(s) = -k$ and $b(t) = k$.
- ▶ Set edge-costs to zero, and keep the capacities.
- ▶ There exists a maxflow of value at least k if and only if the mincost-flow problem is feasible.

Solve Maxflow Using Mincost Flow

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Generalization

Our model:

$$\begin{aligned} \min \quad & \sum_e c(e)f(e) \\ \text{s.t.} \quad & \forall e \in E: 0 \leq f(e) \leq u(e) \\ & \forall v \in V: f(v) = b(v) \end{aligned}$$

where $b : V \rightarrow \mathbb{R}$, $\sum_v b(v) = 0$; $u : E \rightarrow \mathbb{R}_0^+ \cup \{\infty\}$; $c : E \rightarrow \mathbb{R}$;

A more general model?

$$\begin{aligned} \min \quad & \sum_e c(e)f(e) \\ \text{s.t.} \quad & \forall e \in E: \ell(e) \leq f(e) \leq u(e) \\ & \forall v \in V: a(v) \leq f(v) \leq b(v) \end{aligned}$$

where $a : V \rightarrow \mathbb{R}$, $b : V \rightarrow \mathbb{R}$; $\ell : E \rightarrow \mathbb{R} \cup \{-\infty\}$, $u : E \rightarrow \mathbb{R} \cup \{\infty\}$
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Differences

- ▶ Flow along an edge e may have non-zero lower bound $\ell(e)$.
- ▶ Flow along e may have negative upper bound $u(e)$.
- ▶ The demand at a node v may have lower bound $a(v)$ and upper bound $b(v)$ instead of just lower bound = upper bound = $b(v)$.

Reduction I

$$\begin{aligned} \min \quad & \sum_e c(e) f(e) \\ \text{s.t.} \quad & \forall e \in E: \ell(e) \leq f(e) \leq u(e) \\ & \forall v \in V: a(v) \leq f(v) \leq b(v) \end{aligned}$$

We can assume that $a(v) = b(v)$:

Add new node r

Add new edges (r, v) for all $v \in V$

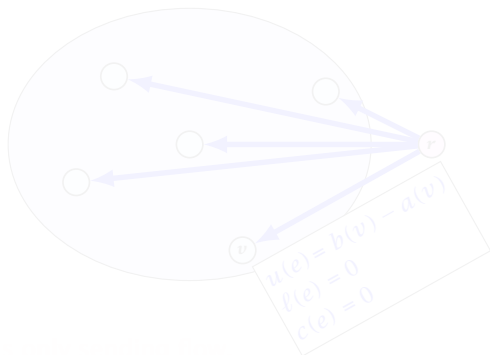
Set $u(e) = b(v) - a(v)$ for these

edges

Set $\ell(e) = 0$ for these

edges

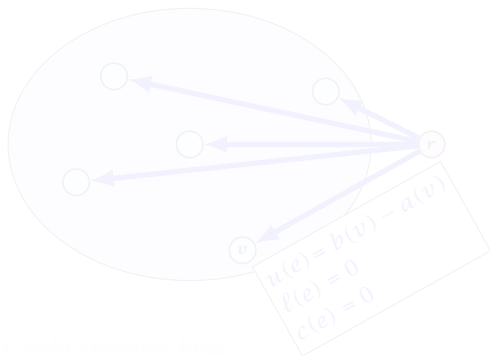
Set $c(e) = 0$ for all



Reduction I

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We can assume that $a(v) = b(v)$:

Add new node r .

Add edge (r, v) for all $v \in V$.

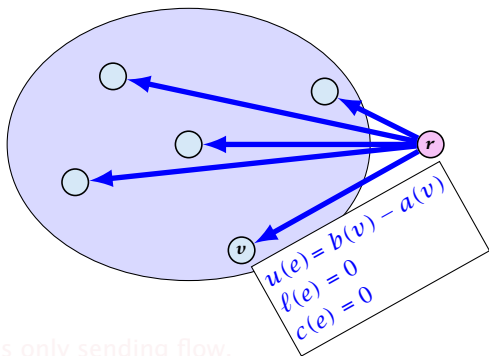
Set $\ell(e) = c(e) = 0$ for these edges.

Set $u(e) = b(v) - a(v)$ for edge (r, v) .

Set $a(v) = b(v)$ for all $v \in V$.

Set $b(r) = -\sum_{v \in V} b(v)$.

$-\sum_v b(v)$ is negative; hence r is only sending flow.



Reduction I

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We can assume that $a(v) = b(v)$:

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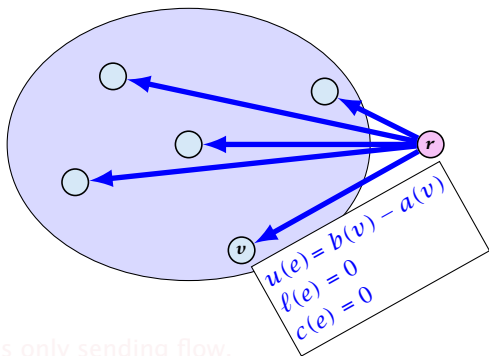
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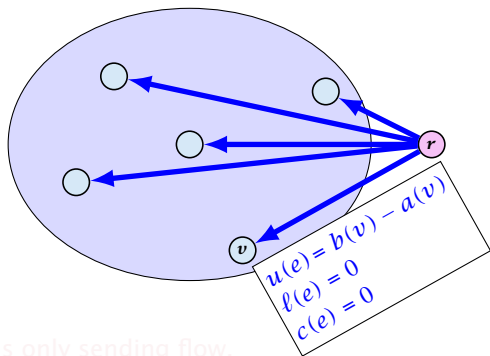
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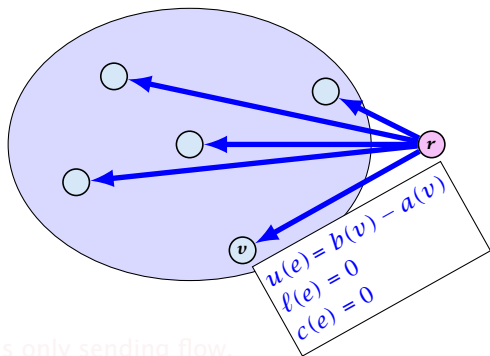
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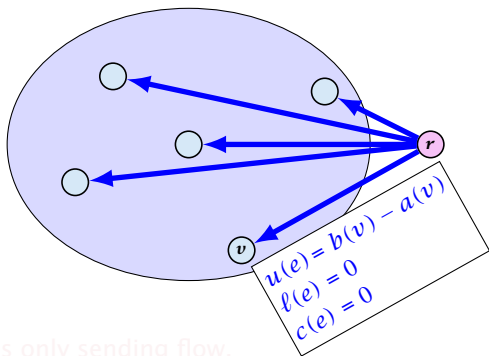
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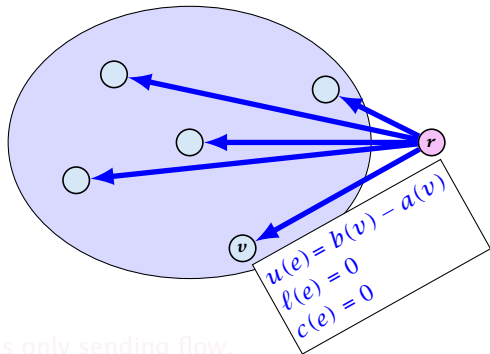
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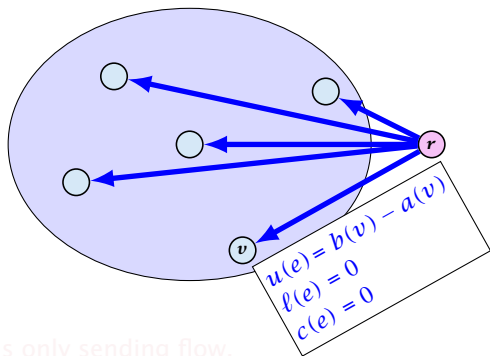
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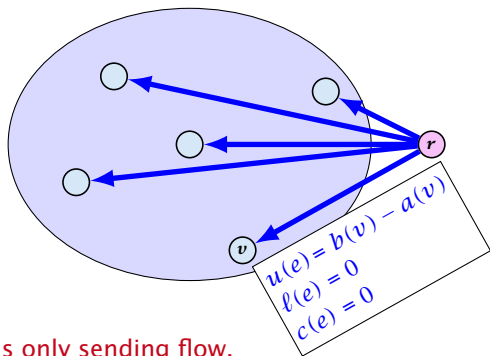
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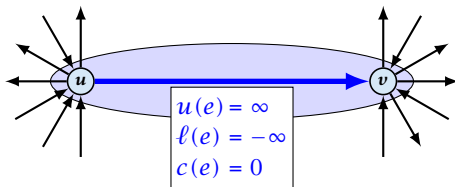
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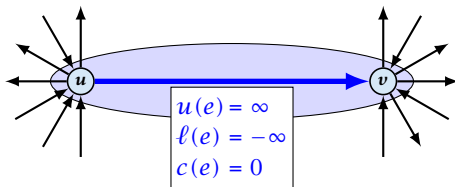
If $c(e) = 0$ we can contract the edge/identify nodes u and v .

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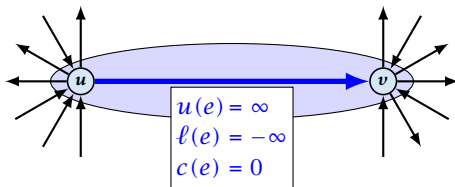
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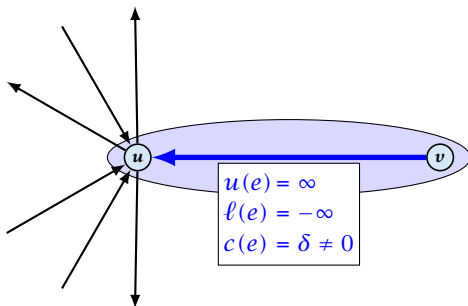


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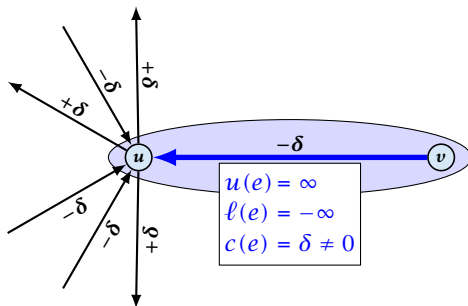
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Additionally we set $b(u) = 0$.

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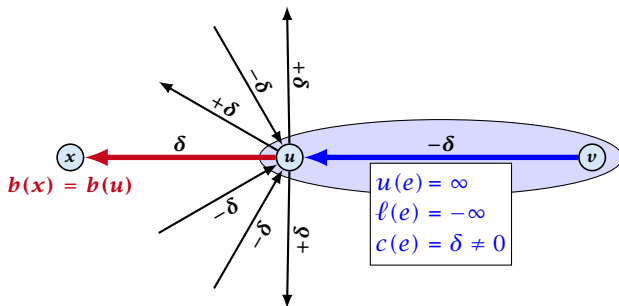
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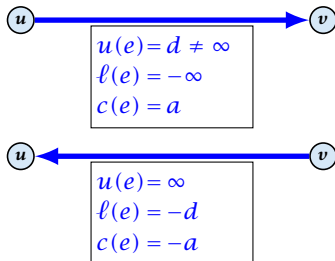


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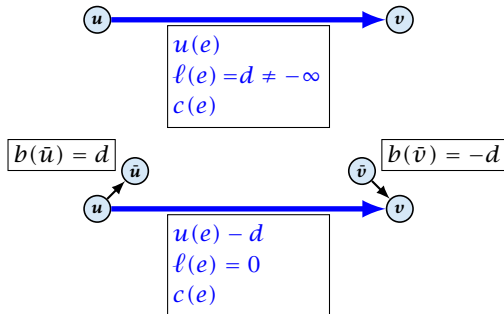


Replace the edge by an edge in opposite direction.

Reduction IV

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We can assume that $\ell(e) = 0$:



The added edges have infinite capacity and cost $c(e)/2$.

Caterer Problem

- ▶ She needs to supply r_i napkins on N successive days.
- ▶ She can buy new napkins at p cents each.
- ▶ She can launder them at a fast laundry that takes m days and cost f cents a napkin.
- ▶ She can use a slow laundry that takes $k > m$ days and costs s cents each.
- ▶ At the end of each day she should determine how many to send to each laundry and how many to buy in order to fulfill demand.
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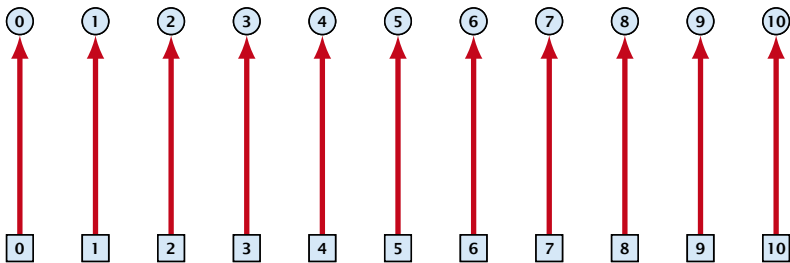
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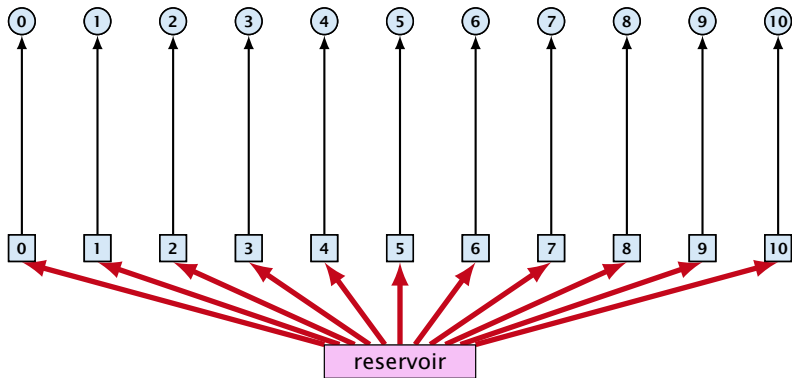
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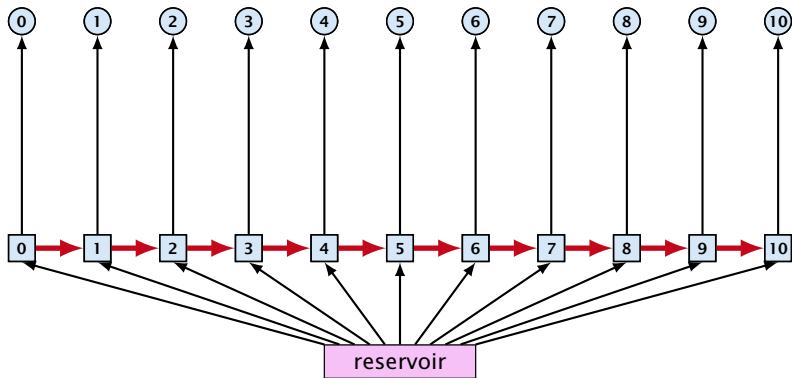


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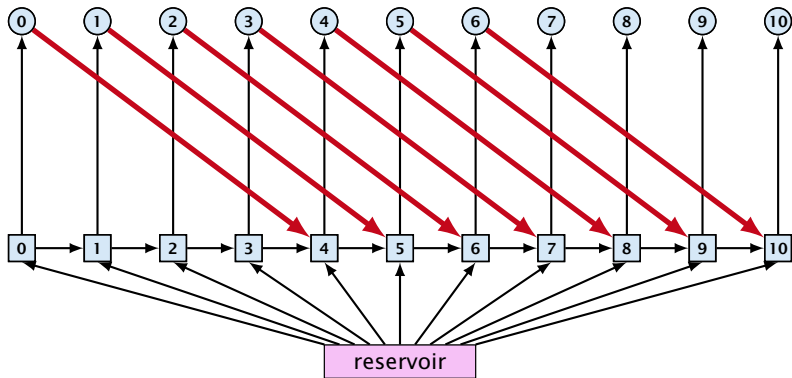
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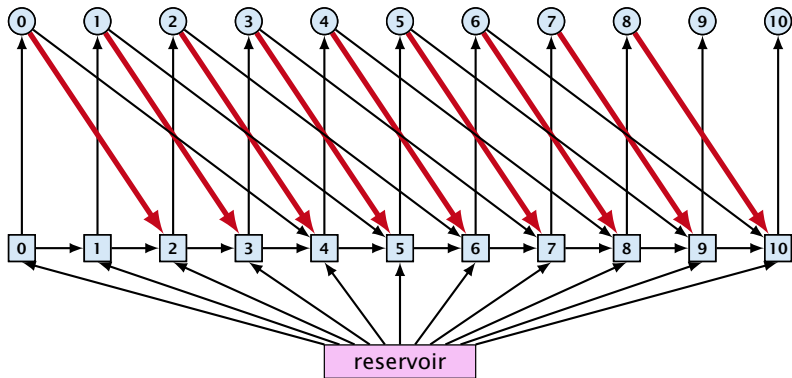
forward edges:

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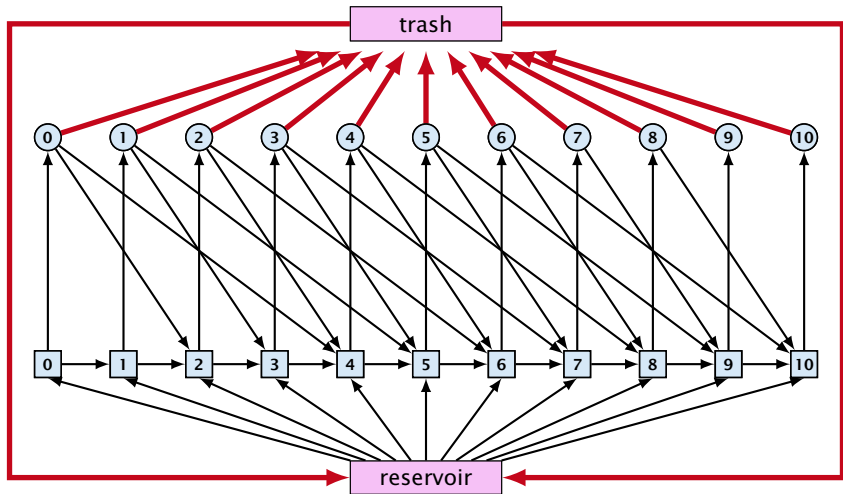
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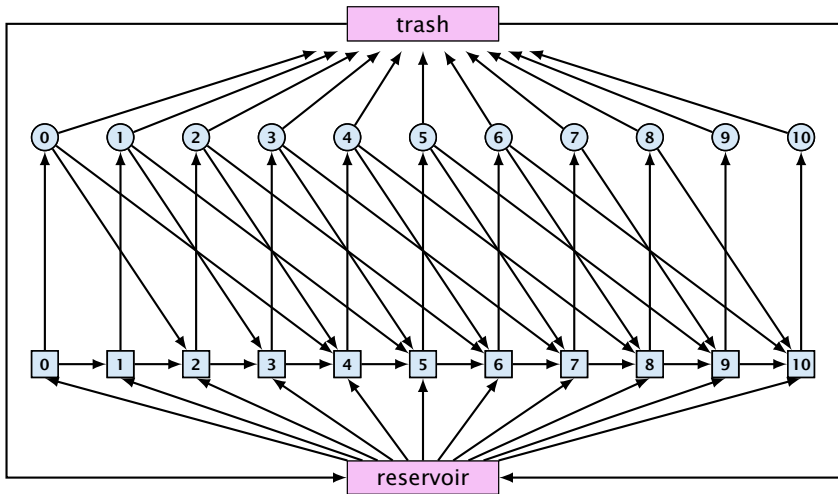
fast edges:

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 cost: $c(e) = f$



trash edges:

upper bound: $u(e_i) = \infty$;
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 cost: $c(e) = 0$



Residual Graph

Version A:

The residual graph G' for a mincost flow is just a copy of the graph G .

If we send $f(e)$ along an edge, the corresponding edge e' in the residual graph has its lower and upper bound changed to $\ell(e') = \ell(e) - f(e)$ and $u(e') = u(e) - f(e)$.

Version B:

The residual graph for a mincost flow is exactly defined as the residual graph for standard flows, with the only exception that one needs to define a cost for the residual edge.

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- ⇒ Suppose that g is a feasible circulation of negative cost in the residual graph.

Then $f + g$ is a feasible flow with cost $\text{cost}(f) + \text{cost}(g) < \text{cost}(f)$. Hence, f is not minimum cost.

- ⇐ Let f be a non-mincost flow, and let f^* be a min-cost flow. We need to show that the residual graph has a feasible circulation with negative cost.

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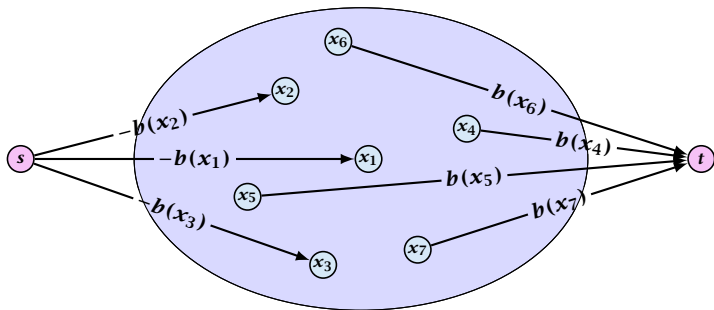
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14 Mincost Flow

Algorithm 23 CycleCanceling($G = (V, E), c, u, b$)

- 1: establish a feasible flow f in G
- 2: **while** G_f contains negative cycle **do**
- 3: use Bellman-Ford to find a negative circuit Z
- 4: $\delta \leftarrow \min\{u_f(e) \mid e \in Z\}$
- 5: augment δ units along Z and update G_f

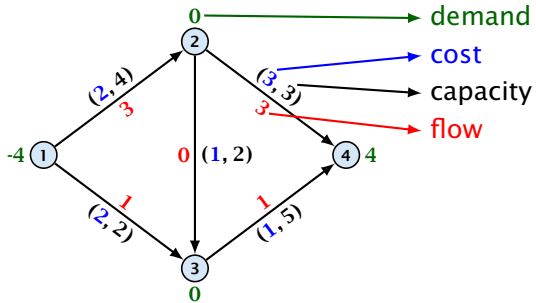
How do we find the initial feasible flow?



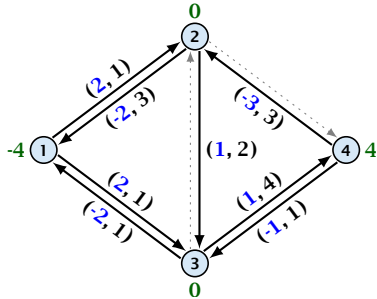
- ▶ Connect new node s to all nodes with negative $b(v)$ -value.
- ▶ Connect nodes with positive $b(v)$ -value to a new node t .
- ▶ There exist a feasible flow in the original graph iff in the resulting graph there exists an s - t flow of value

$$\sum_{v:b(v)<0} (-b(v)) = \sum_{v:b(v)>0} b(v) .$$

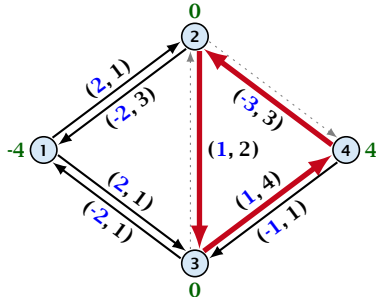
14 Mincost Flow



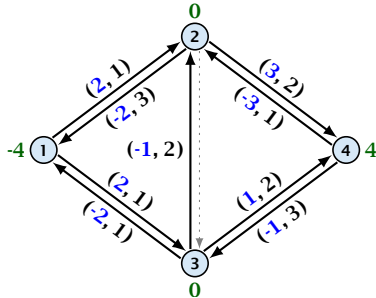
14 Mincost Flow



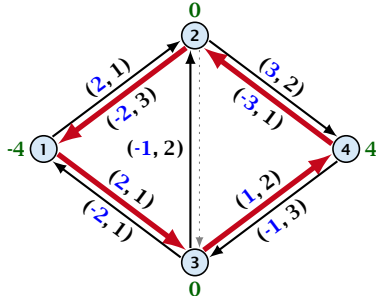
14 Mincost Flow



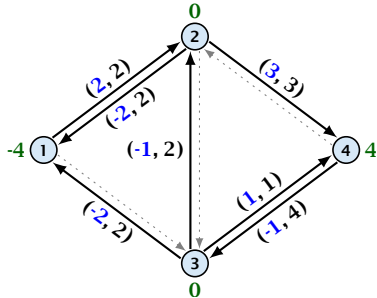
14 Mincost Flow



14 Mincost Flow



14 Mincost Flow



14 Mincost Flow

Lemma 89

The improving cycle algorithm runs in time $\mathcal{O}(nm^2CU)$, for integer capacities and costs, when for all edges e , $|c(e)| \leq C$ and $|u(e)| \leq U$.

- ▶ Running time of Bellman-Ford is $\mathcal{O}(mn)$.
- ▶ Pushing flow along the cycle can be done in time $\mathcal{O}(n)$.
- ▶ Each iteration decreases the total cost by at least 1.
- ▶ The true optimum cost must lie in the interval $[-mCU, \dots, +mCU]$.

Note that this lemma is weak since it does not allow for edges with infinite capacity.

14 Mincost Flow

A **general mincost flow problem** is of the following form:

$$\begin{aligned} \min \quad & \sum_e c(e) f(e) \\ \text{s.t.} \quad & \forall e \in E: \ell(e) \leq f(e) \leq u(e) \\ & \forall v \in V: a(v) \leq f(v) \leq b(v) \end{aligned}$$

where $a: V \rightarrow \mathbb{R}$, $b: V \rightarrow \mathbb{R}$; $\ell: E \rightarrow \mathbb{R} \cup \{-\infty\}$, $u: E \rightarrow \mathbb{R} \cup \{\infty\}$
 $c: E \rightarrow \mathbb{R}$;

Lemma 90 (without proof)

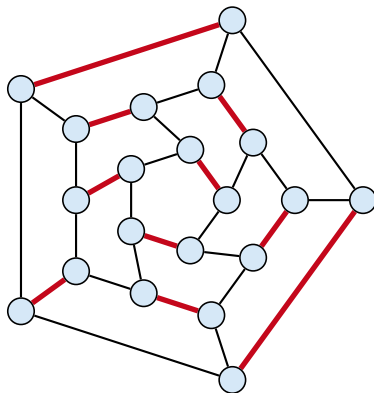
A general mincost flow problem can be solved in polynomial time.

Part V

Matchings

Matching

- ▶ Input: undirected graph $G = (V, E)$.
- ▶ $M \subseteq E$ is a **matching** if each node appears in at most one edge in M .
- ▶ Maximum Matching: find a matching of maximum cardinality



16 Bipartite Matching via Flows

Which flow algorithm to use?

- ▶ Generic augmenting path: $\mathcal{O}(m \text{val}(f^*)) = \mathcal{O}(mn)$.
- ▶ Capacity scaling: $\mathcal{O}(m^2 \log C) = \mathcal{O}(m^2)$.
- ▶ Shortest augmenting path: $\mathcal{O}(mn^2)$.

For **unit capacity simple graphs** shortest augmenting path can be implemented in time $\mathcal{O}(m\sqrt{n})$.

17 Augmenting Paths for Matchings

Definitions.

- ▶ Given a matching M in a graph G , a vertex that is not incident to any edge of M is called a **free vertex** w. r. .t. M .
- ▶ For a matching M a path P in G is called an **alternating path** if edges in M alternate with edges not in M .
- ▶ An alternating path is called an **augmenting path** for matching M if it ends at distinct free vertices.

Theorem 91

A matching M is a maximum matching if and only if there is no augmenting path w. r. t. M .

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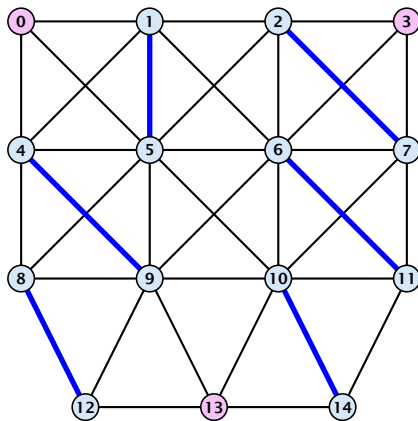
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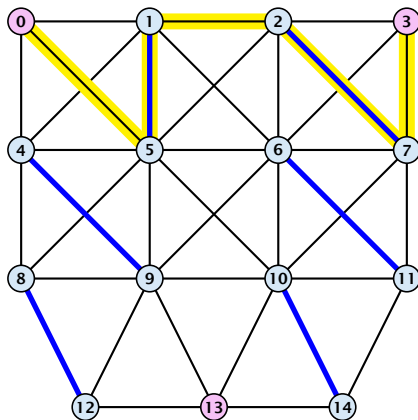
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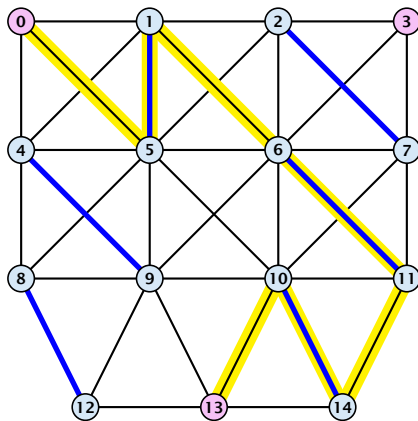
Augmenting Paths in Action



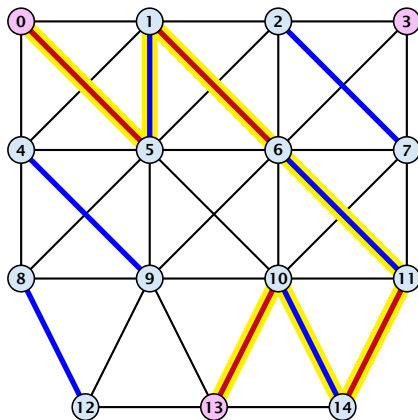
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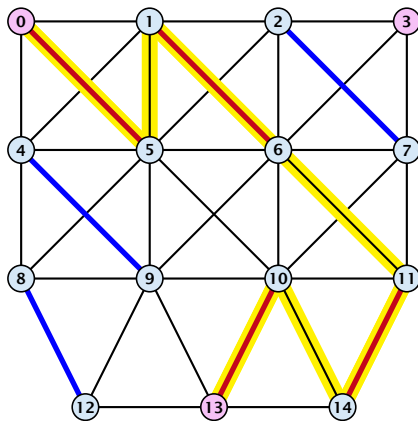
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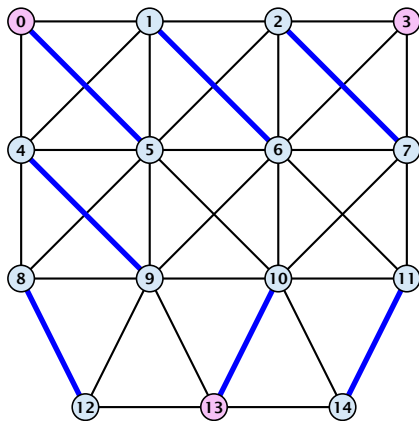
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Augmenting Paths in Action



17 Augmenting Paths for Matchings

Proof.

⇒ If M is maximum there is no augmenting path P , because we could switch matching and non-matching edges along P . This gives matching $M' = M \oplus P$ with larger cardinality.

⇐ Suppose there is a matching M' with larger cardinality. Consider the graph H with edge-set $M' \oplus M$ (i.e., only edges that are in either M or M' but not in both).

Each vertex can be incident to at most two edges (one from M and one from M'). Hence, the connected components are alternating cycles or alternating path.

As $|M'| > |M|$ there is one connected component that is a path P for which both endpoints are incident to edges from M' . P is an augmenting path.

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17 Augmenting Paths for Matchings

Algorithmic idea:

As long as you find an augmenting path augment your matching using this path. When you arrive at a matching for which no augmenting path exists you have a maximum matching.

Theorem 92

Let G be a graph, M a matching in G , and let u be a free vertex w.r.t. M . Further let P denote an augmenting path w.r.t. M and let $M' = M \oplus P$ denote the matching resulting from augmenting M with P . If there was no augmenting path starting at u in M then there is no augmenting path starting at u in M' .

The above theorem allows for an easier implementation of an augmenting path algorithm. Once we checked for augmenting paths starting from u we don't have to check for such paths in future rounds.

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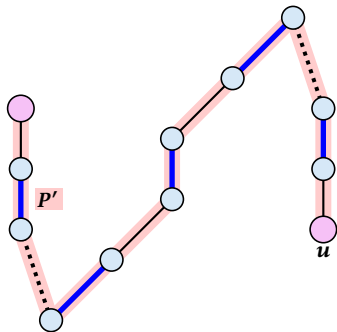
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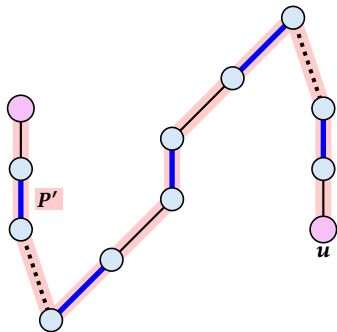
- ▶ Assume there is an augmenting path P' w.r.t. M' starting at u .



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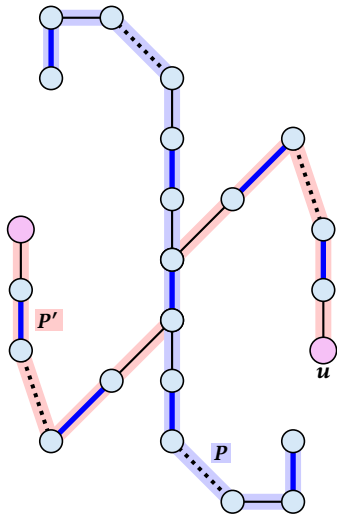
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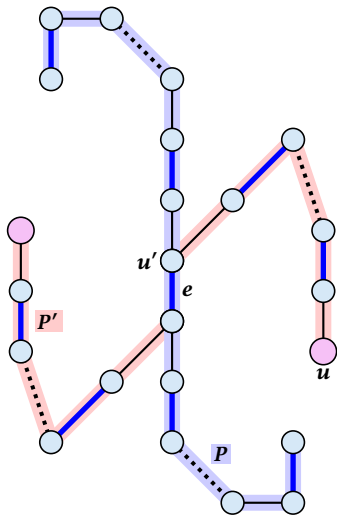
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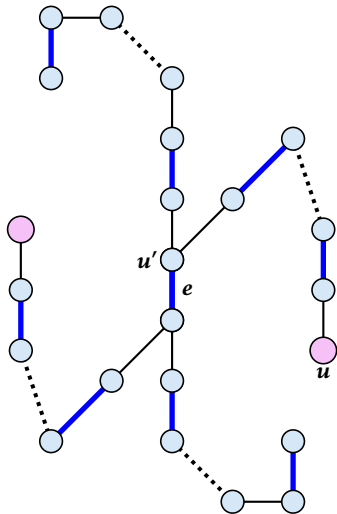
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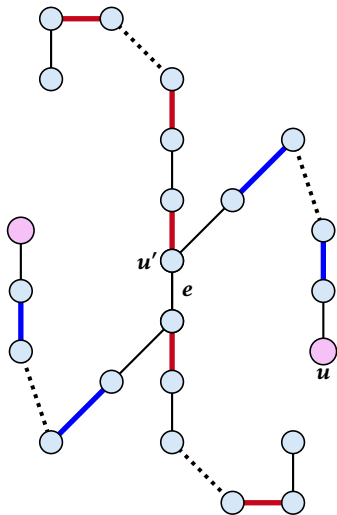
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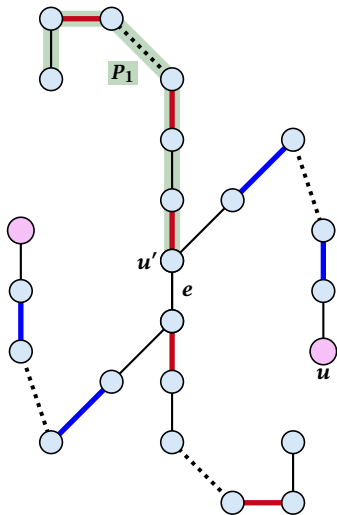
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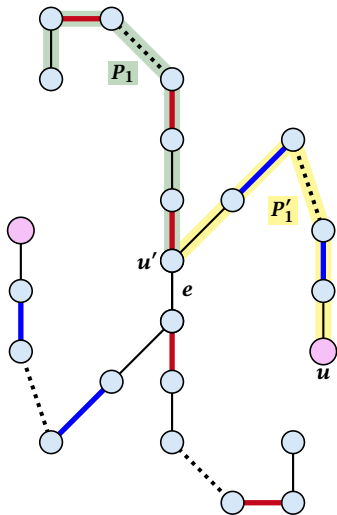
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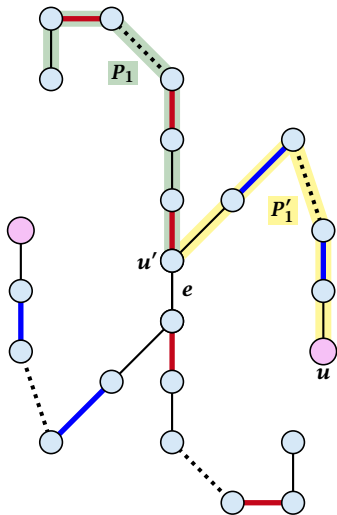
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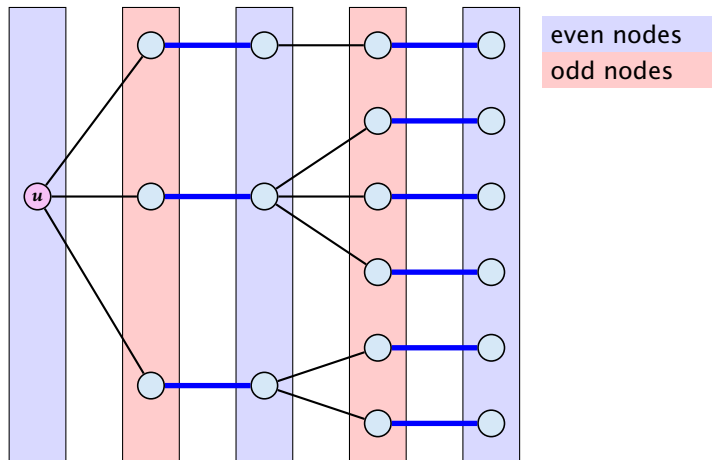
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- ▶ $P_1 \circ P'_1$ is augmenting path in M (\neq).



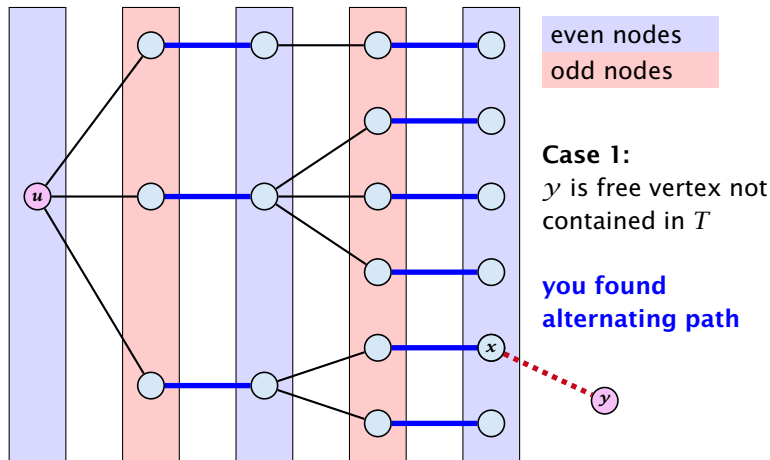
How to find an augmenting path?

Construct an alternating tree.



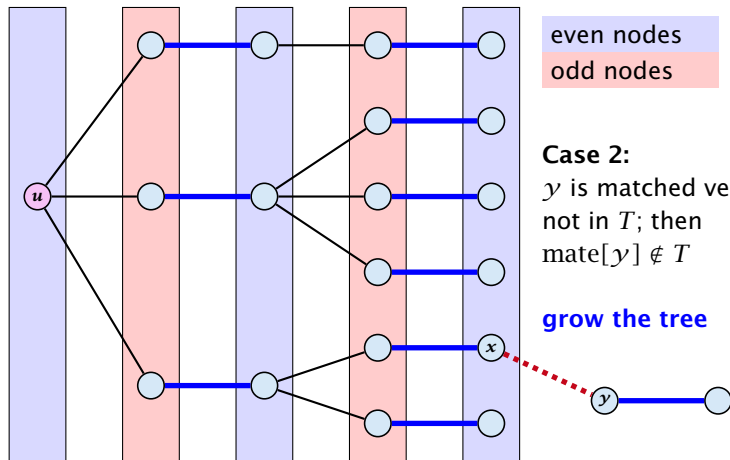
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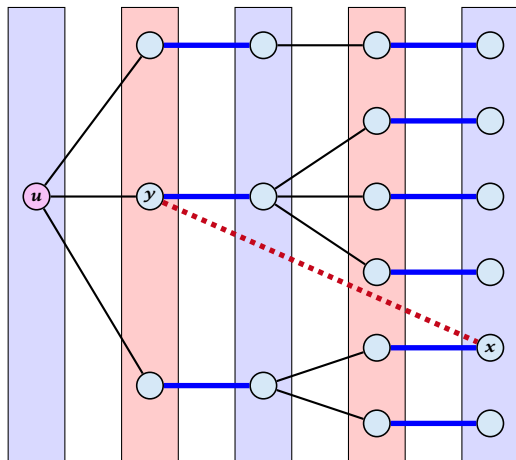
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How to find an augmenting path?

Construct an alternating tree.



even nodes

odd nodes

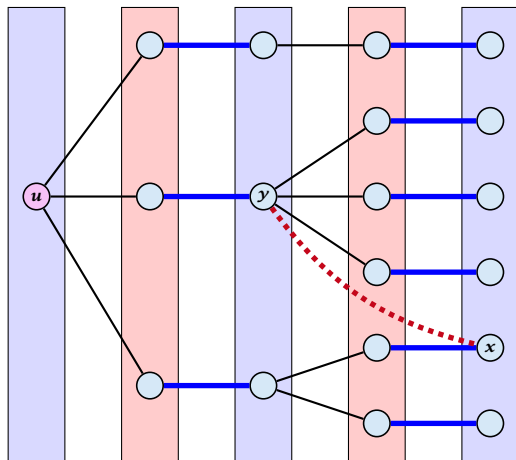
Case 3:

y is already contained
in T as an odd vertex

ignore successor y

How to find an augmenting path?

Construct an alternating tree.



even nodes

odd nodes

Case 4:

y is already contained
in T as an even vertex

can't ignore y

does not happen in
bipartite graphs

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
4:    $r \leftarrow r + 1$   
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8:     while  $aug = false$  and  $Q \neq \emptyset$  do  
9:        $x \leftarrow Q.dequeue()$ ;  
10:      for  $y \in A_x$  do  
11:        if  $mate[y] = 0$  then  
12:           $augm(mate, parent, y)$ ;  
13:           $aug \leftarrow true$ ;  
14:           $free \leftarrow free - 1$ ;  
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17:             $parent[y] \leftarrow x$ ;  
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```

graph $G = (S \cup S', E)$

$S = \{1, \dots, n\}$

$S' = \{1', \dots, n'\}$

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start with an
empty matching

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free: number of
unmatched nodes in
 S

r: root of current tree

Algorithm 24 BiMatch($G, match$)

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as long as there are
unmatched nodes and
we did not yet try to
grow from all nodes we
continue

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r is the new node that we grow from.

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12:           $augm(mate, parent, y)$ ;  
13:           $aug \leftarrow true$ ;  
14:           $free \leftarrow free - 1$ ;  
15:        else  
16:          if  $parent[y] = 0$  then  
17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

If r is free start tree construction

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
4:    $r \leftarrow r + 1$   
5:   if  $mate[r] = 0$  then  
6:     for  $i = 1$  to  $n$  do  $parent[i'] \leftarrow 0$   
7:      $Q \leftarrow \emptyset$ ;  $Q.append(r)$ ;  $aug \leftarrow false$ ;  
8:     while  $aug = false$  and  $Q \neq \emptyset$  do  
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16:          if  $parent[y] = 0$  then  
17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

Initialize an empty tree.
Note that only nodes i'
have parent pointers.

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
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17:             $parent[y] \leftarrow x$ ;  
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```

Q is a queue (BFS!!!).

aug is a Boolean that stores whether we already found an augmenting path.

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
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16:          if  $parent[y] = 0$  then  
17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

as long as we did not augment and there are still unexamined leaves continue...

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
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15:        else  
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17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

take next unexamined
leaf

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
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5:   if  $mate[r] = 0$  then  
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17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

if x has unmatched neighbour we found an augmenting path (note that $y \neq r$ because we are in a bipartite graph)

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```
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17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

do an augmentation...

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
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3: while  $free \geq 1$  and  $r < n$  do  
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11:        if  $mate[y] = 0$  then  
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13:           $aug \leftarrow true$ ;  
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15:      else  
16:        if  $parent[y] = 0$  then  
17:           $parent[y] \leftarrow x$ ;  
18:           $Q.enqueue(mate[y])$ ;
```

setting $aug = true$
ensures that the tree
construction will not
continue

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
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5:   if  $mate[r] = 0$  then  
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15:      else  
16:        if  $parent[y] = 0$  then  
17:           $parent[y] \leftarrow x$ ;  
18:           $Q.enqueue(mate[y])$ ;
```

reduce number of free
nodes

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
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15:        else  
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17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

if y is not in the tree yet

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
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17:             $parent[y] \leftarrow x$ ;  
18:             $Q.enqueue(mate[y])$ ;
```

...put it into the tree

Algorithm 24 BiMatch($G, match$)

```
1: for  $x \in V$  do  $mate[x] \leftarrow 0$ ;  
2:  $r \leftarrow 0$ ;  $free \leftarrow n$ ;  
3: while  $free \geq 1$  and  $r < n$  do  
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```

add its buddy to the set
of unexamined leaves

18 Weighted Bipartite Matching

Weighted Bipartite Matching/Assignment

- ▶ Input: undirected, bipartite graph $G = L \cup R, E$.
- ▶ an edge $e = (\ell, r)$ has weight $w_e \geq 0$
- ▶ find a matching of maximum weight, where the weight of a matching is the sum of the weights of its edges

Simplifying Assumptions (wlog [why?]):

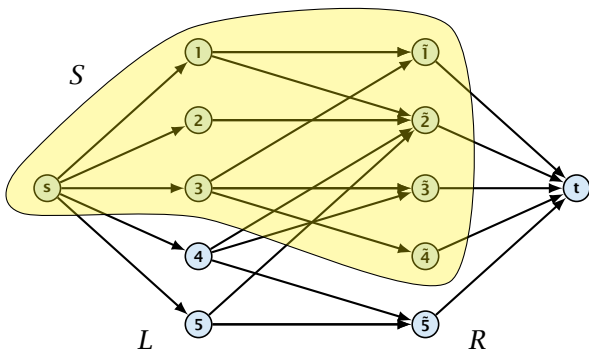
- ▶ assume that $|L| = |R| = n$
- ▶ assume that there is an edge between every pair of nodes $(\ell, r) \in V \times V$
- ▶ can assume goal is to construct maximum weight **perfect** matching

Weighted Bipartite Matching

Theorem 93 (Halls Theorem)

A bipartite graph $G = (L \cup R, E)$ has a perfect matching if and only if for all sets $S \subseteq L$, $|\Gamma(S)| \geq |S|$, where $\Gamma(S)$ denotes the set of nodes in R that have a neighbour in S .

18 Weighted Bipartite Matching



Halls Theorem

Proof:

- ← Of course, the condition is necessary as otherwise not all nodes in S could be matched to different neighbours.
- ⇒ For the other direction we need to argue that the minimum cut in the graph G' is at least $|L|$.

Halls Theorem

Proof:

- ⇐ Of course, the condition is necessary as otherwise not all nodes in S could be matched to different neighbours.
- ⇒ For the other direction we need to argue that the minimum cut in the graph G' is at least $|L|$.
 - ▶ Let S denote a minimum cut and let $L_S \cong L \cap S$ and $R_S \cong R \cap S$ denote the portion of S inside L and R , respectively.
 - ▶ Clearly, all neighbours of nodes in L_S have to be in S , as otherwise we would cut an edge of infinite capacity.
 - ▶ This gives $R_S \geq |\Gamma(L_S)|$.
 - ▶ The size of the cut is $|L| - |L_S| + |R_S|$.
 - ▶ Using the fact that $|\Gamma(L_S)| \geq |L_S|$ gives that this is at least $|L|$.

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Algorithm Outline

Idea:

We introduce a node weighting \vec{x} . Let for a node $v \in V$, $x_v \in \mathbb{R}$ denote the weight of node v .

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- ▶ Suppose that the node weights dominate the edge-weights in the following sense:

$$x_u + x_v \geq w_e \text{ for every edge } e = (u, v).$$

- ▶ Let $H(\vec{x})$ denote the subgraph of G that only contains edges that are **tight** w.r.t. the node weighting \vec{x} , i.e. edges $e = (u, v)$ for which $w_e = x_u + x_v$.
- ▶ Try to compute a perfect matching in the subgraph $H(\vec{x})$. If you are successful you found an optimal matching.

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- ▶ Try to compute a perfect matching in the subgraph $H(\vec{x})$. If you are successful you found an optimal matching.

Algorithm Outline

Reason:

- ▶ The weight of your matching M^* is

$$\sum_{(u,v) \in M^*} w_{(u,v)} = \sum_{(u,v) \in M^*} (x_u + x_v) = \sum_v x_v .$$

- ▶ Any other perfect matching M (in G , not necessarily in $H(\vec{x})$) has

$$\sum_{(u,v) \in M} w_{(u,v)} \leq \sum_{(u,v) \in M} (x_u + x_v) = \sum_v x_v .$$

Algorithm Outline

What if you don't find a perfect matching?

Then, Hall's theorem guarantees you that there is a set $S \subseteq L$, with $|\Gamma(S)| < |S|$, where Γ denotes the neighbourhood w.r.t. the subgraph $H(\vec{x})$.

Idea: reweight such that:

- ▶ the total weight assigned to nodes decreases
- ▶ the weight function still dominates the edge-weights

If we can do this we have an algorithm that terminates with an optimal solution (we analyze the running time later).

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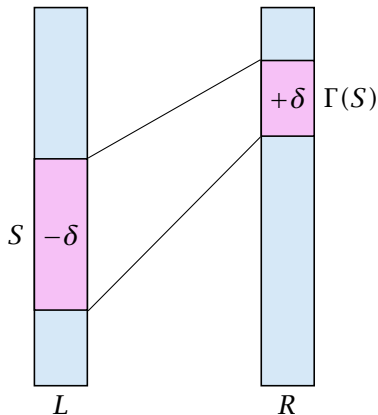
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Changing Node Weights

Increase node-weights in $\Gamma(S)$ by $+\delta$, and decrease the node-weights in S by $-\delta$.

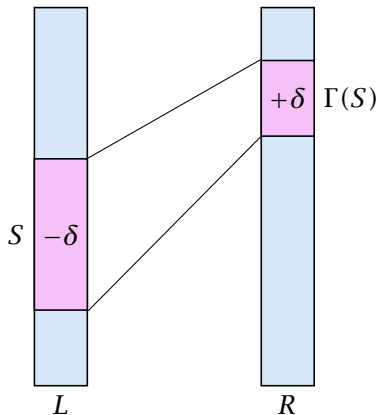
- ▶ Total node-weight decreases.
- ▶ Only edges from S to $R - \Gamma(S)$ decrease in their weight.
- ▶ Since, none of these edges is tight (otw. the edge would be contained in $H(\vec{x})$, and hence would go between S and $\Gamma(S)$) we can do this decrement for small enough $\delta > 0$ until a new edge gets tight.



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Increase node-weights in $\Gamma(S)$ by $+\delta$, and decrease the node-weights in S by $-\delta$.

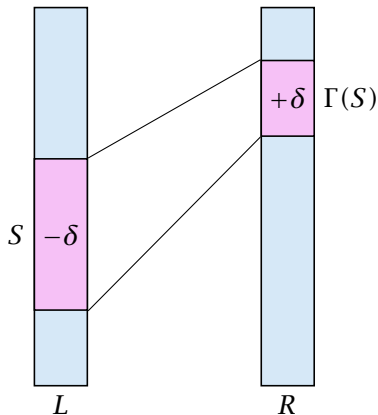
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Changing Node Weights

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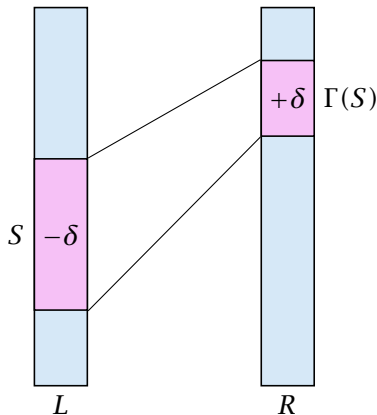
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Changing Node Weights

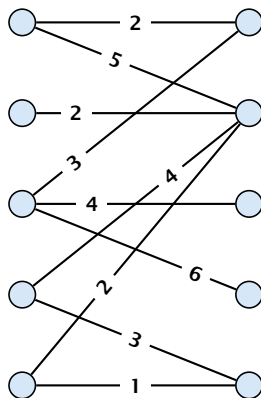
Increase node-weights in $\Gamma(S)$ by $+\delta$, and decrease the node-weights in S by $-\delta$.

- ▶ Total node-weight decreases.
- ▶ Only edges from S to $R - \Gamma(S)$ decrease in their weight.
- ▶ Since, none of these edges is tight (otw. the edge would be contained in $H(\vec{x})$, and hence would go between S and $\Gamma(S)$) we can do this decrement for small enough $\delta > 0$ until a new edge gets tight.



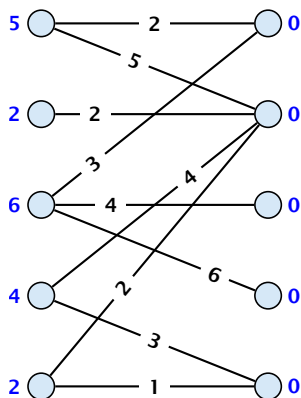
Weighted Bipartite Matching

Edges not drawn have weight 0.



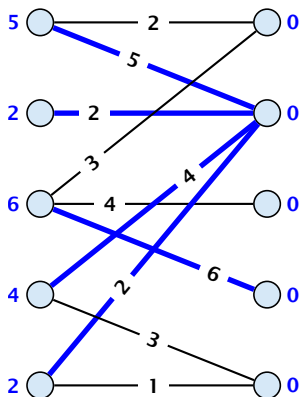
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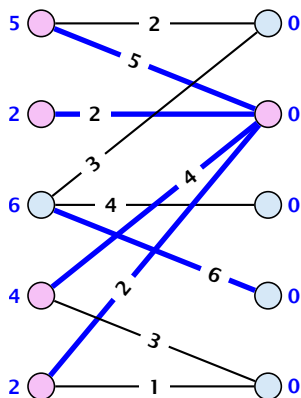
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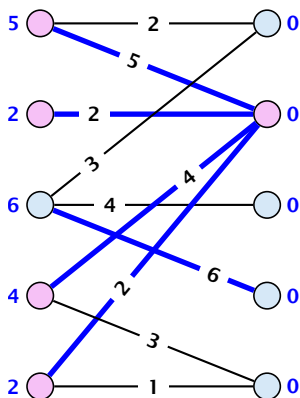
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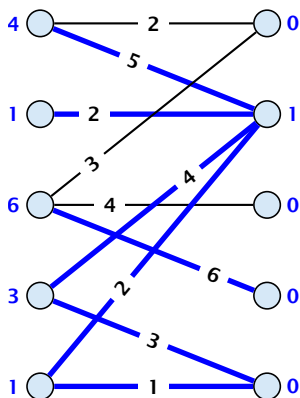
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$$\delta = 1$$



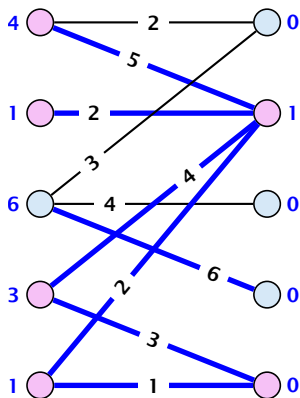
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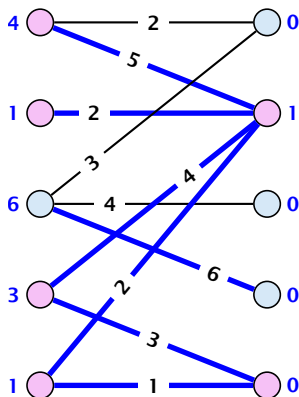
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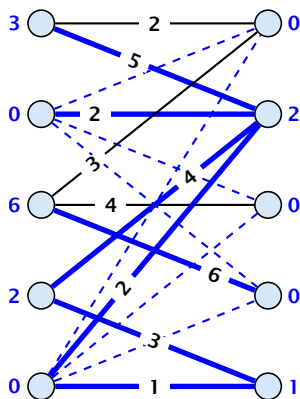
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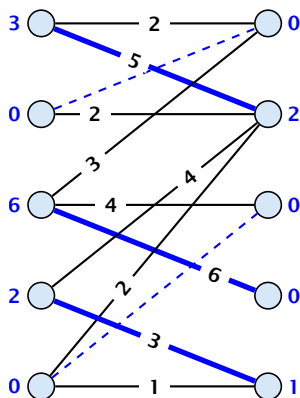
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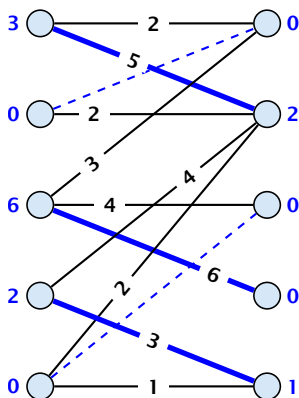
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Analysis

How many iterations do we need?

- ▶ One reweighting step increases the number of edges out of S by at least one.
- ▶ Assume that we have a maximum matching that saturates the set $\Gamma(S)$, in the sense that every node in $\Gamma(S)$ is matched to a node in S (we will show that we can always find S and a matching such that this holds).
- ▶ This matching is still contained in the new graph, because all its edges either go between $\Gamma(S)$ and S or between $L - S$ and $R - \Gamma(S)$.
- ▶ Hence, reweighting does not decrease the size of a maximum matching in the tight sub-graph.

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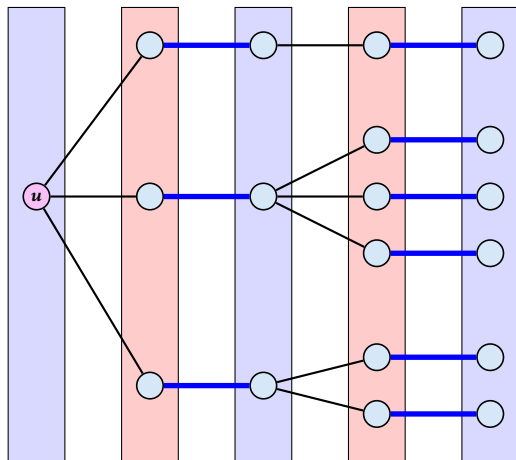
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- ▶ We will show that after at most n reweighting steps the size of the maximum matching can be increased by finding an augmenting path.
- ▶ This gives a polynomial running time.

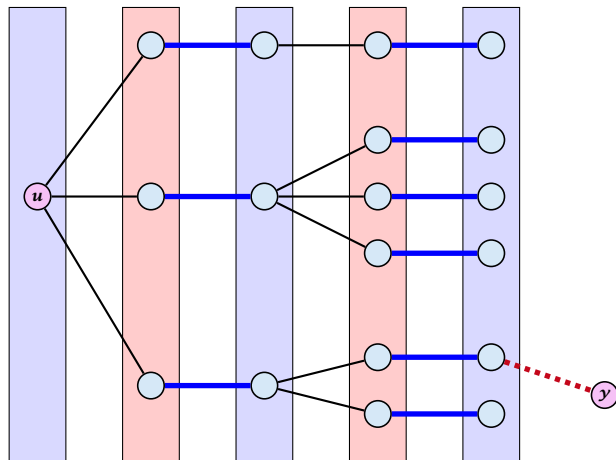
How to find an augmenting path?

Construct an alternating tree.



How to find an augmenting path?

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Analysis

How do we find S ?

- ▶ Start on the left and compute an alternating tree, starting at any free node u .
- ▶ If this construction stops, there is no perfect matching in the tight subgraph (because for a perfect matching we need to find an augmenting path starting at u).
- ▶ The set of even vertices is on the left and the set of odd vertices is on the right and contains all neighbours of even nodes.
- ▶ All odd vertices are matched to even vertices. Furthermore, the even vertices additionally contain the free vertex u . Hence, $|V_{\text{odd}}| = |E(V_{\text{even}})| < |V_{\text{even}}|$, and all odd vertices are saturated in the current matching.

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- ▶ The current matching does not have any edges from V_{odd} to $L \setminus V_{\text{even}}$ (edges that may possibly be deleted by changing weights).
- ▶ After changing weights, there is at least one more edge connecting V_{even} to a node outside of V_{odd} . After at most n reweights we can do an augmentation.
- ▶ A reweighting can be trivially performed in time $\mathcal{O}(n^2)$ (keeping track of the tight edges).
- ▶ An augmentation takes at most $\mathcal{O}(n)$ time.
- ▶ In total we obtain a running time of $\mathcal{O}(n^4)$.
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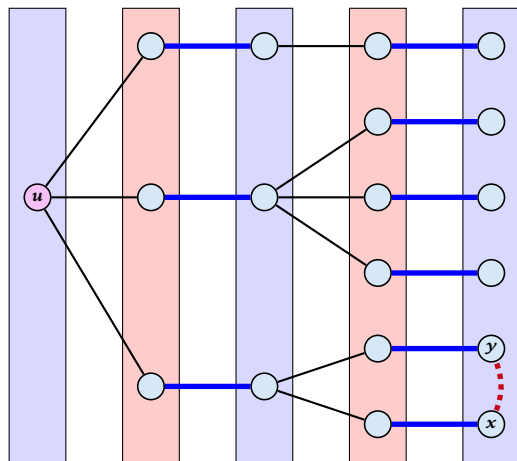
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How to find an augmenting path?

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even nodes

odd nodes

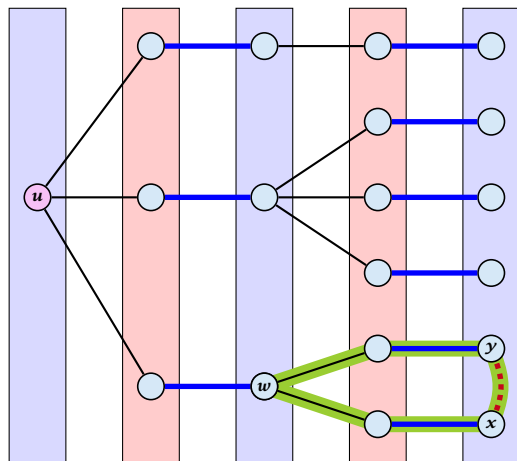
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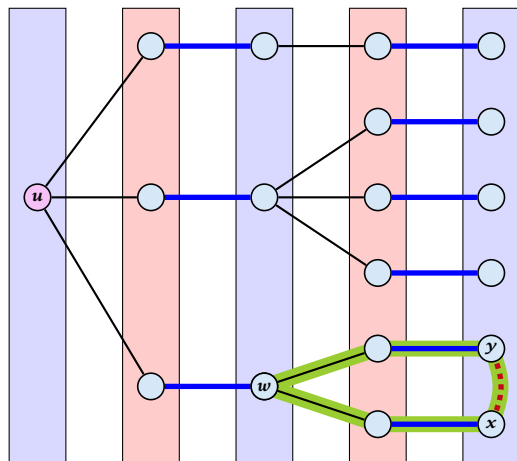
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The cycle $w \leftrightarrow y - x \leftrightarrow w$
is called a **blossom**.
 w is called the **base** of the
blossom (even node!!!).
The path $u-w$ is called the
stem of the blossom.

Flowers and Blossoms

Definition 94

A **flower** in a graph $G = (V, E)$ w.r.t. a matching M and a (free) root node r , is a subgraph with two components:

- ▶ A **stem** is an even length alternating path that starts at the root node r and terminates at some node w . We permit the possibility that $r = w$ (empty stem).
- ▶ A **blossom** is an odd length alternating cycle that starts and terminates at the terminal node w of a stem and has no other node in common with the stem. w is called the **base** of the blossom.

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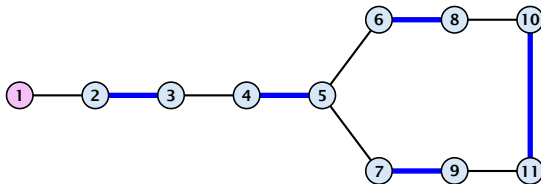
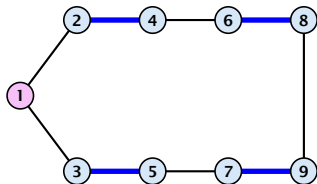
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Properties:

1. A stem spans $2\ell + 1$ nodes and contains ℓ matched edges for some integer $\ell \geq 0$.
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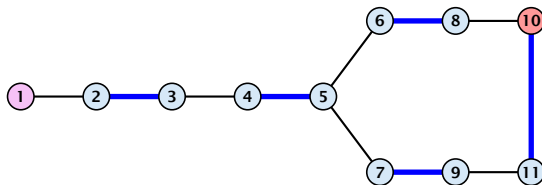
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Shrinking Blossoms

When during the alternating tree construction we discover a blossom B we replace the graph G by $G' = G/B$, which is obtained from G by contracting the blossom B .

- ▶ Delete all vertices in B (and its incident edges) from G .
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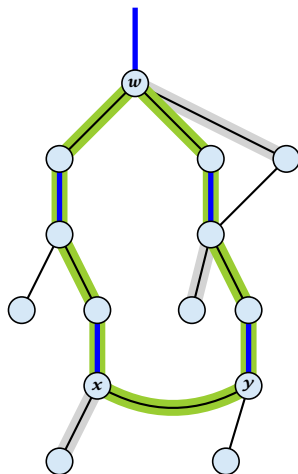
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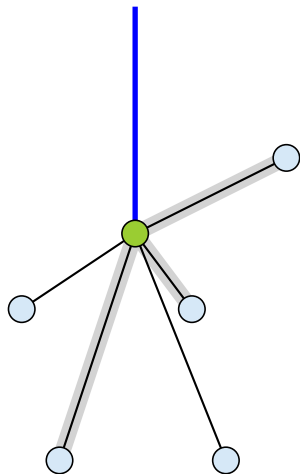
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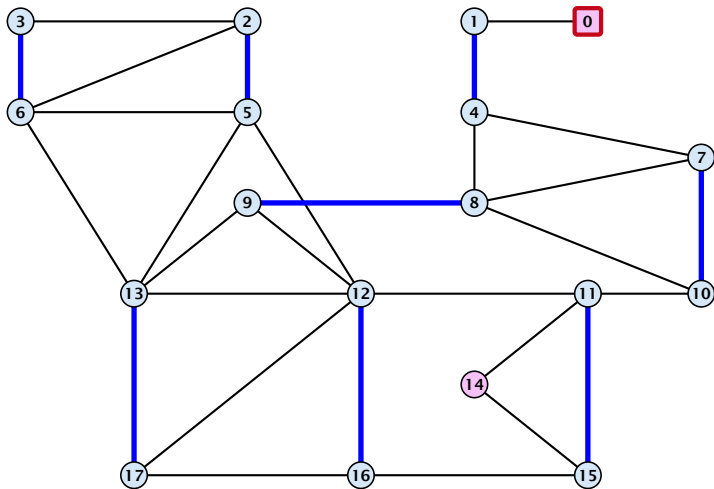


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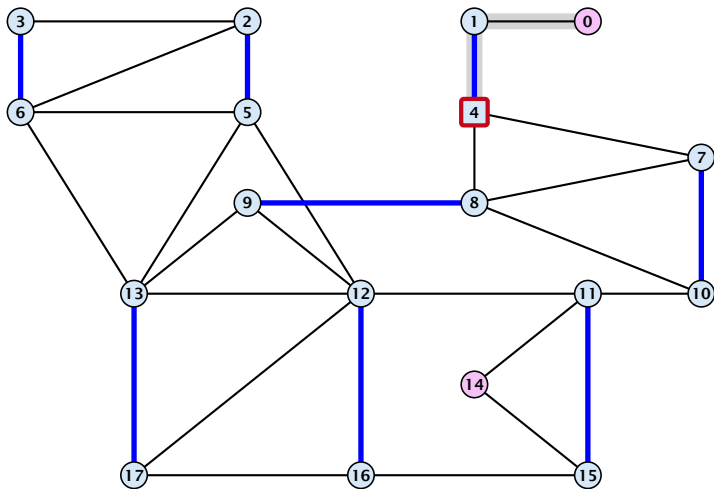
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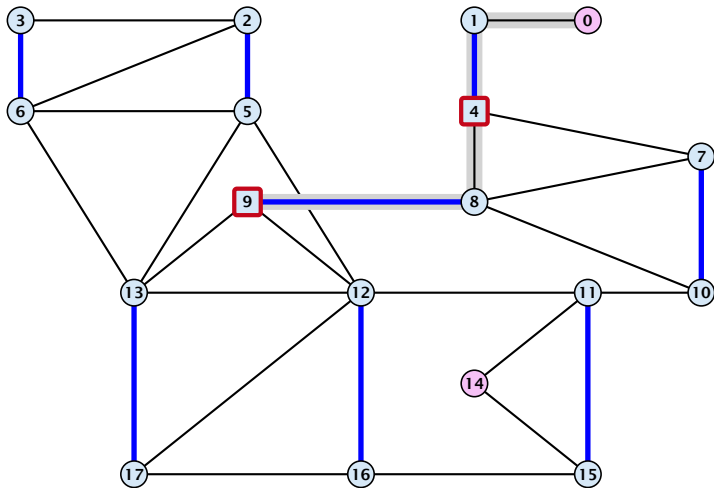
Example: Blossom Algorithm



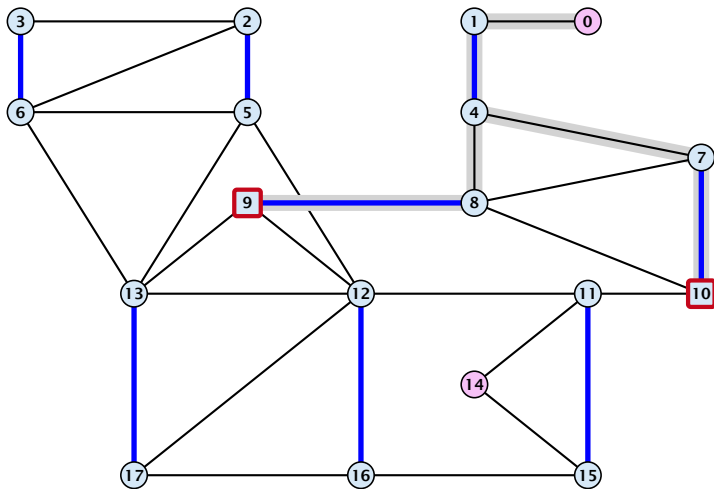
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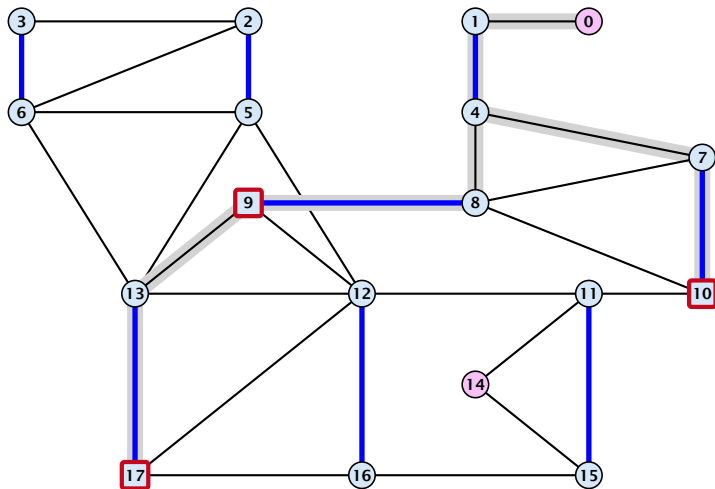
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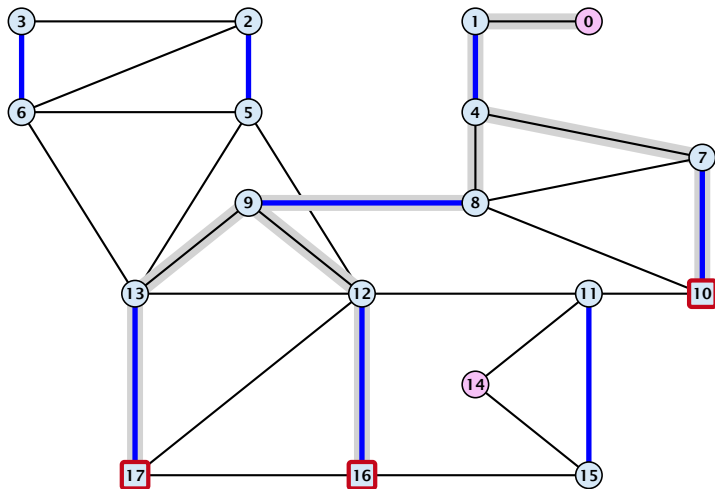
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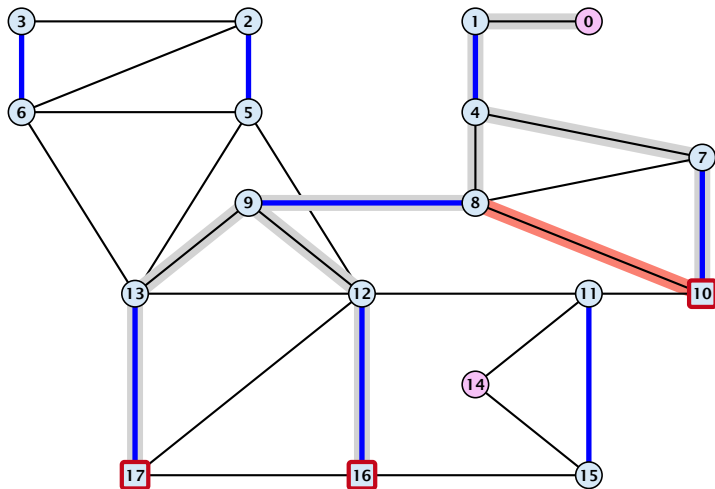
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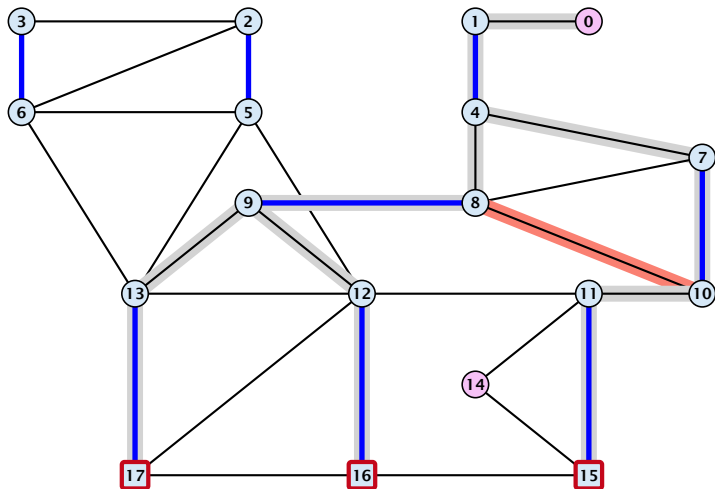
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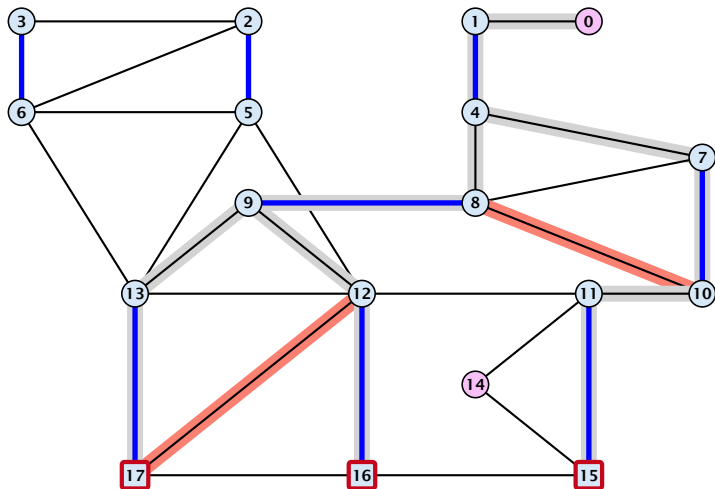
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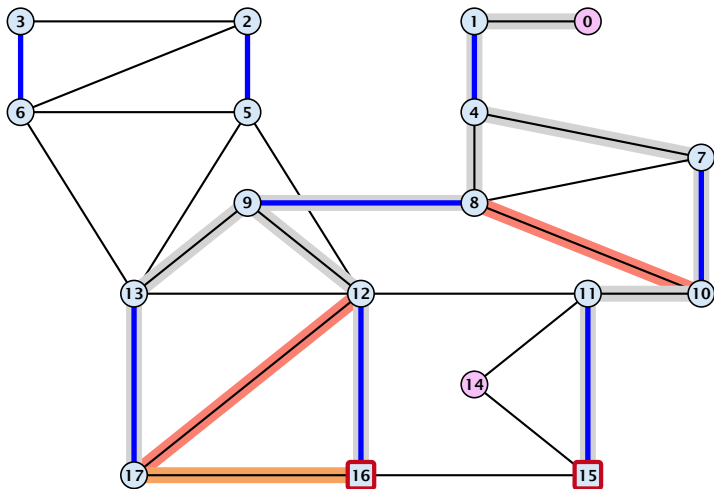
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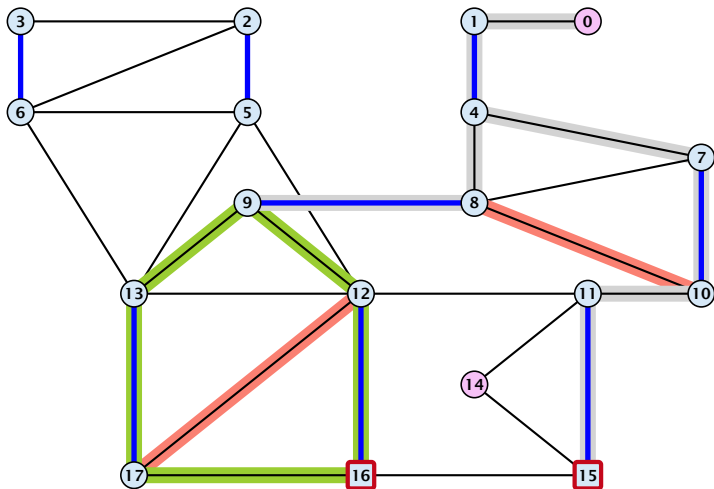
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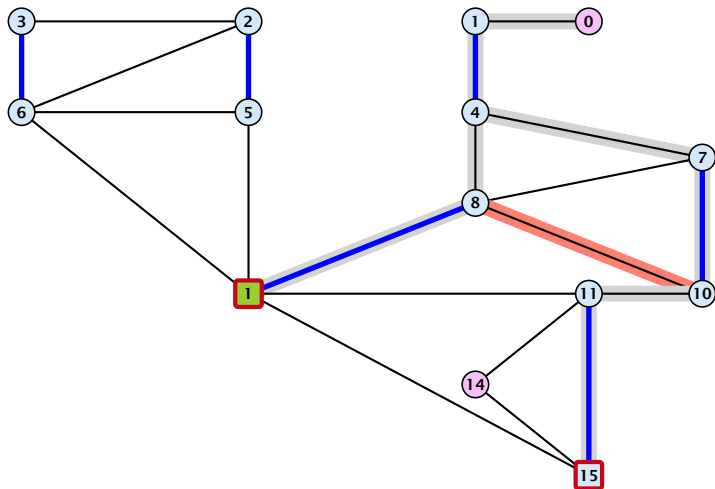
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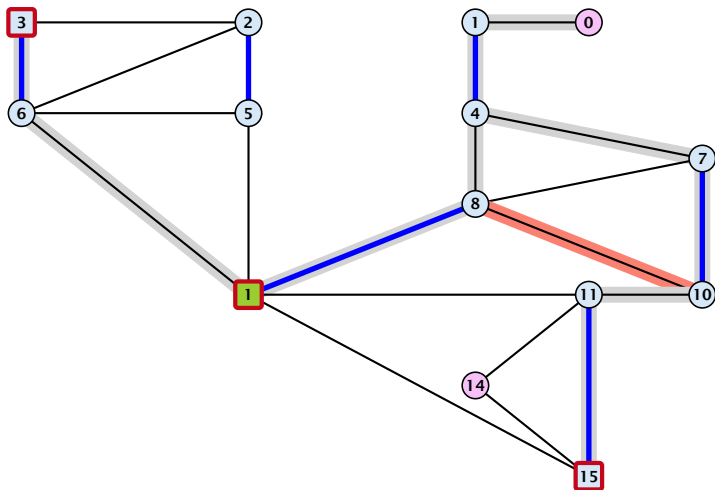
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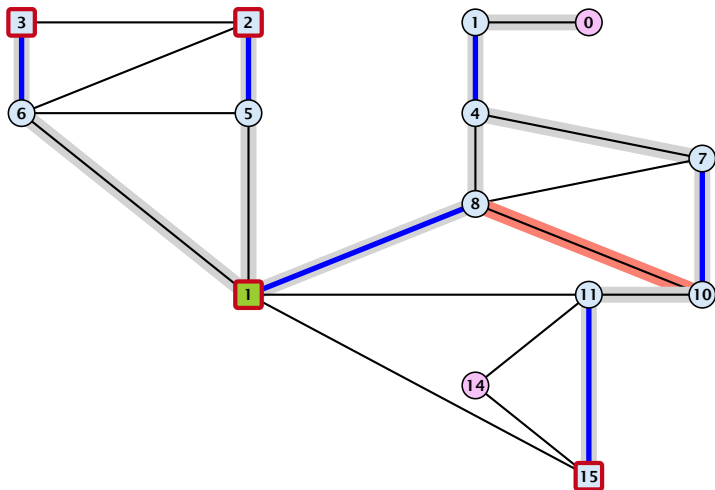
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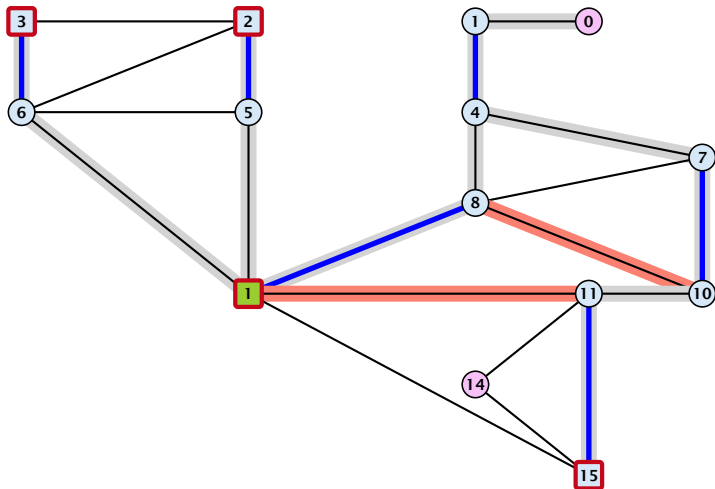
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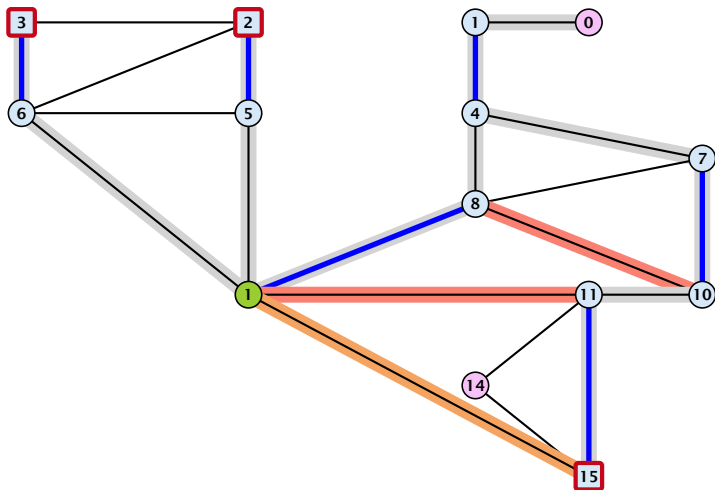
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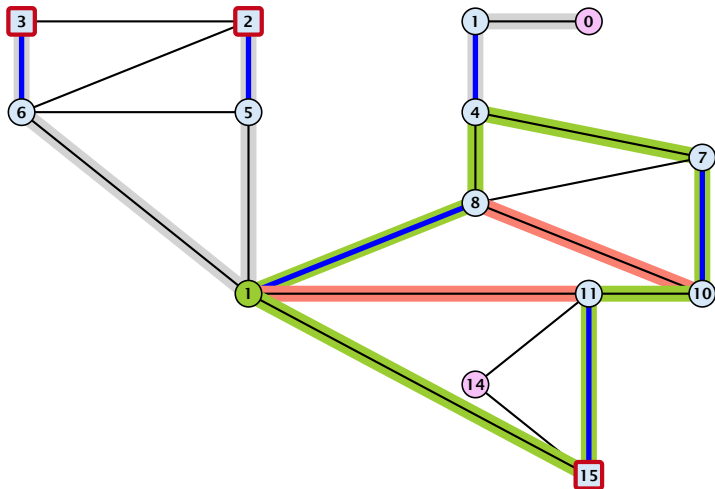
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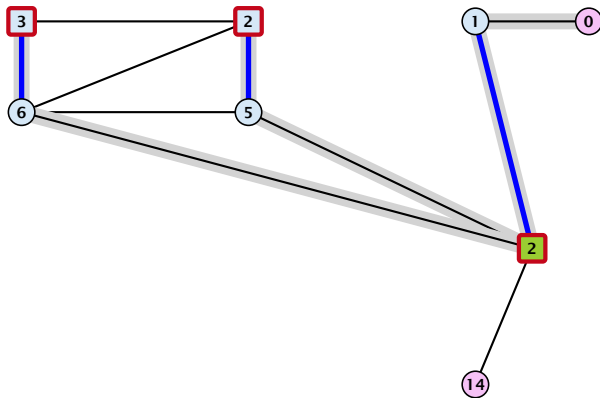
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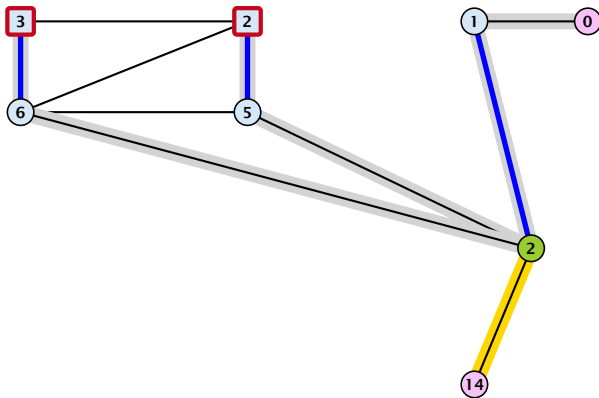
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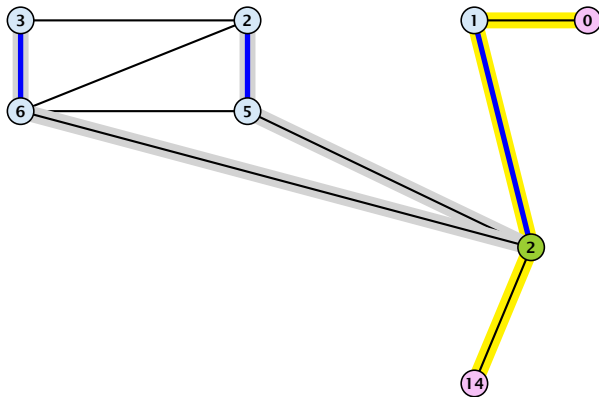
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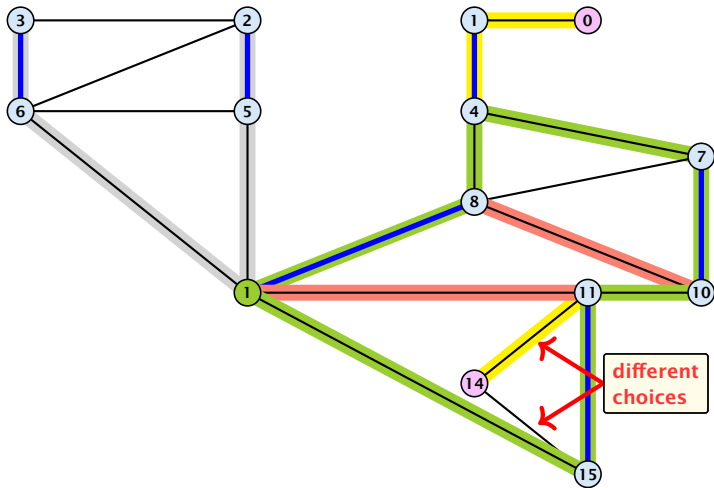
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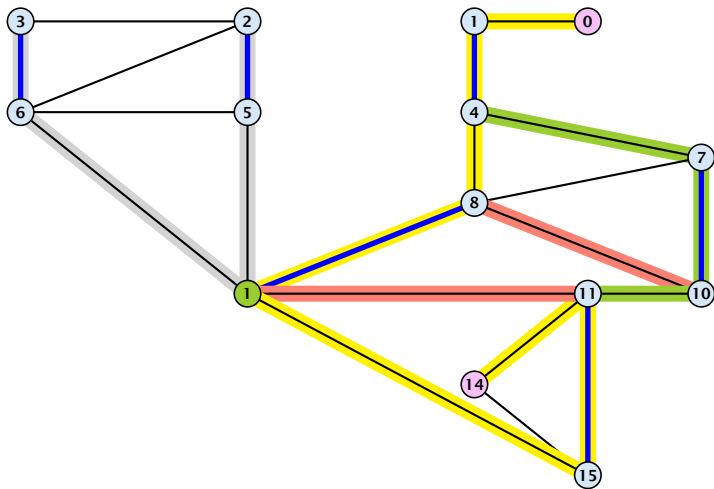
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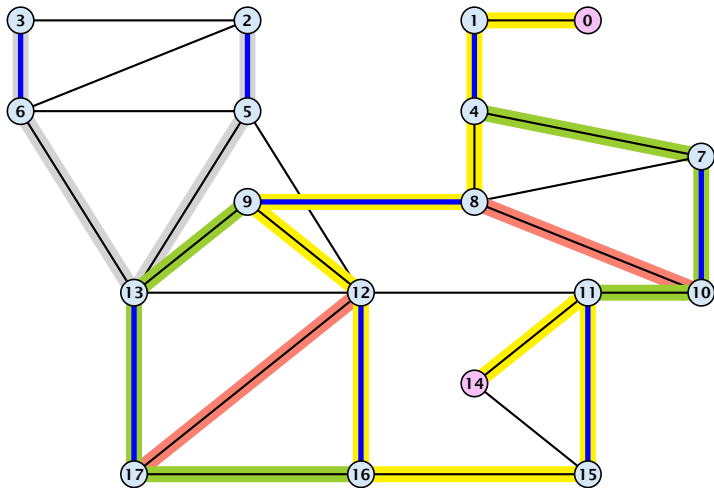
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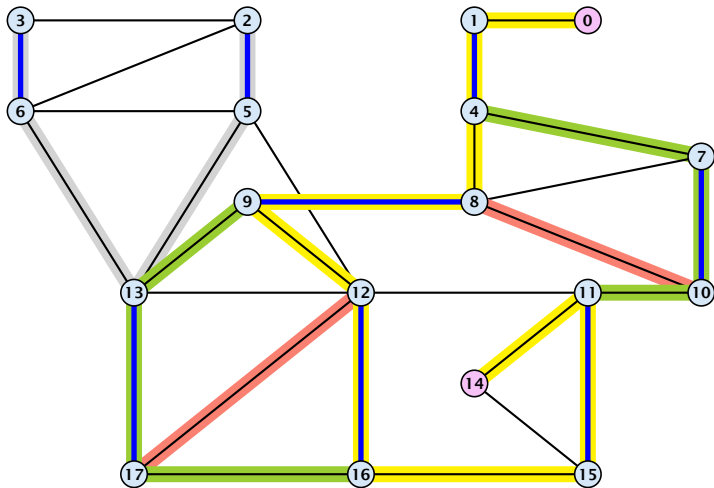
Example: Blossom Algorithm



Example: Blossom Algorithm



Example: Blossom Algorithm



Correctness

Assume that in G we have a flower w.r.t. matching M . Let r be the root, B the blossom, and w the base. Let graph $G' = G/B$ with pseudonode b . Let M' be the matching in the contracted graph.

Lemma 95

If G' contains an augmenting path P' starting at r (or the pseudo-node containing r) w.r.t. the matching M' then G contains an augmenting path starting at r w.r.t. matching M .

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Correctness

Proof.

If P' does not contain b it is also an augmenting path in G .

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Case 1: non-empty stem

- ▶ Next suppose that the stem is non-empty.

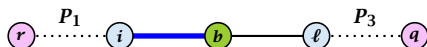
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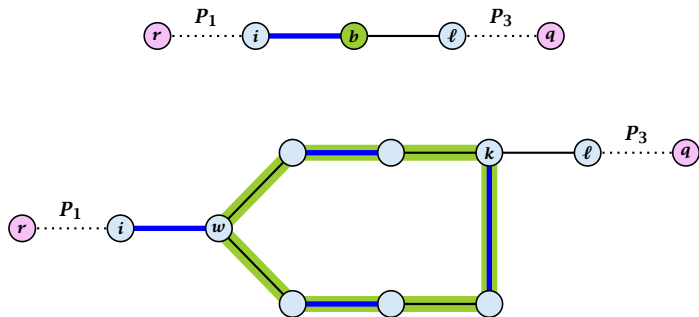
Correctness

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- ▶ Next suppose that the stem is non-empty.



Correctness

- ▶ After the expansion ℓ must be incident to some node in the blossom. Let this node be k .
- ▶ If $k \neq w$ there is an alternating path P_2 from w to k that ends in a matching edge.
- ▶ $P_1 \circ (i, w) \circ P_2 \circ (k, \ell) \circ P_3$ is an alternating path.
- ▶ If $k = w$ then $P_1 \circ (i, w) \circ (w, \ell) \circ P_3$ is an alternating path.

Correctness

Proof.

Case 2: empty stem

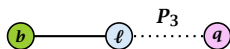
- ▶ If the stem is empty then after expanding the blossom,
 $w = r$.

Correctness

Proof.

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- ▶ If the stem is empty then after expanding the blossom,
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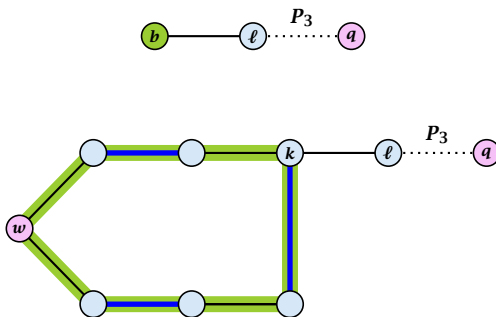


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- ▶ If the stem is empty then after expanding the blossom, $w = r$.

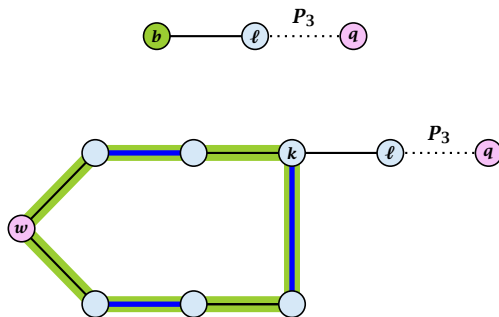


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Proof.

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- ▶ If the stem is empty then after expanding the blossom, $w = r$.



- ▶ The path $r \circ P_2 \circ (k, l) \circ P_3$ is an alternating path.

Lemma 96

If G contains an augmenting path P from r to q w.r.t. matching M then G' contains an augmenting path from r (or the pseudo-node containing r) to q w.r.t. M' .

Correctness

Proof.

- ▶ If P does not contain a node from B there is nothing to prove.
- ▶ We can assume that r and q are the only free nodes in G .

Case 1: empty stem

Let i be the last node on the path P that is part of the blossom.

P is of the form $P_1 \circ (i, j) \circ P_2$, for some node j and (i, j) is unmatched.

$(b, j) \circ P_2$ is an augmenting path in the contracted network.

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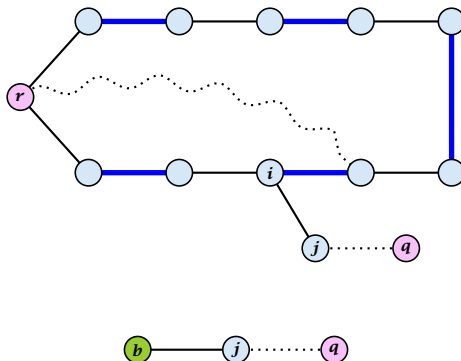
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Correctness

Illustration for Case 1:



Correctness

Case 2: non-empty stem

Let P_3 be alternating path from r to w ; this exists because r and w are root and base of a blossom. Define $M_+ = M \oplus P_3$.

In M_+ , r is matched and w is unmatched.

G must contain an augmenting path w.r.t. matching M_+ , since M and M_+ have same cardinality.

This path must go between w and q as these are the only unmatched vertices w.r.t. M_+ .

For M'_+ the blossom has an empty stem. Case 1 applies.

G' has an augmenting path w.r.t. M'_+ . It must also have an augmenting path w.r.t. M' , as both matchings have the same cardinality.

This path must go between r and q .

Correctness

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Algorithm 25 $\text{search}(r, \text{found})$

- 1: set $\bar{A}(i) \leftarrow A(i)$ for all nodes i
- 2: $\text{found} \leftarrow \text{false}$
- 3: unlabel all nodes;
- 4: give an even label to r and initialize $\text{list} \leftarrow \{r\}$
- 5: **while** $\text{list} \neq \emptyset$ **do**
- 6: delete a node i from list
- 7: $\text{examine}(i, \text{found})$
- 8: **if** $\text{found} = \text{true}$ **then return**

Search for an augmenting path
starting at r .

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- 7: examine(i, found)
- 8: **if** $\text{found} = \text{true}$ **then return**

$A(i)$ contains neighbours of node i .

We create a copy $\bar{A}(i)$ so that we later
can shrink blossoms.

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found is just a Boolean that allows
to abort the search process...

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In the beginning no node is in the tree.

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7: examine(i, found)

8: **if** $\text{found} = \text{true}$ **then return**

Put the root in the tree.

list could also be a set or a stack.

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7: $\text{examine}(i, \text{found})$

8: **if** $\text{found} = \text{true}$ **then return**

As long as there are nodes with
unexamined neighbours...

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- 8: **if** $\text{found} = \text{true}$ **then return**

...examine the next one

Algorithm 25 $\text{search}(r, \text{found})$

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- 5: **while** $\text{list} \neq \emptyset$ **do**
- 6: delete a node i from list
- 7: examine(i, found)
- 8: **if** $\text{found} = \text{true}$ **then return**

If you found augmenting path
abort and start from next root.

Algorithm 26 examine($i, found$)

```
1: for all  $j \in \bar{A}(i)$  do  
2:   if  $j$  is even then contract( $i, j$ ) and return  
3:   if  $j$  is unmatched then  
4:      $q \leftarrow j$ ;  
5:     pred( $q$ )  $\leftarrow i$ ;  
6:      $found \leftarrow \text{true}$ ;  
7:     return  
8:   if  $j$  is matched and unlabeled then  
9:     pred( $j$ )  $\leftarrow i$ ;  
10:    pred(mate( $j$ ))  $\leftarrow j$ ;  
11:    add mate( $j$ ) to list
```

Examine the neighbours of a node i

Algorithm 26 examine($i, found$)

```
1: for all  $j \in \bar{A}(i)$  do  
2:   if  $j$  is even then contract( $i, j$ ) and return  
3:   if  $j$  is unmatched then  
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6:      $found \leftarrow \text{true}$ ;  
7:     return  
8:   if  $j$  is matched and unlabeled then  
9:     pred( $j$ )  $\leftarrow i$ ;  
10:    pred(mate( $j$ ))  $\leftarrow j$ ;  
11:    add mate( $j$ ) to  $list$ 
```

For all neighbours j do...

Algorithm 26 examine($i, found$)

```
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3:   if  $j$  is unmatched then
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5:     pred( $q$ )  $\leftarrow i$ ;
6:      $found \leftarrow \text{true}$ ;
7:     return
8:   if  $j$  is matched and unlabeled then
9:     pred( $j$ )  $\leftarrow i$ ;
10:    pred(mate( $j$ ))  $\leftarrow j$ ;
11:    add mate( $j$ ) to  $list$ 
```

You have found a blossom...

Algorithm 26 examine($i, found$)

```
1: for all  $j \in \bar{A}(i)$  do  
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8:   if  $j$  is matched and unlabeled then  
9:     pred( $j$ )  $\leftarrow i$ ;  
10:    pred(mate( $j$ ))  $\leftarrow j$ ;  
11:    add mate( $j$ ) to  $list$ 
```

You have found a free node which gives you an augmenting path.

Algorithm 26 examine($i, found$)

```
1: for all  $j \in \bar{A}(i)$  do  
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8:   if  $j$  is matched and unlabeled then  
9:     pred( $j$ )  $\leftarrow i$ ;  
10:    pred(mate( $j$ ))  $\leftarrow j$ ;  
11:    add mate( $j$ ) to  $list$ 
```

If you find a matched node that is not
in the tree you grow...

Algorithm 26 $\text{examine}(i, \text{found})$

```
1: for all  $j \in \bar{A}(i)$  do  
2:   if  $j$  is even then  $\text{contract}(i, j)$  and return  
3:   if  $j$  is unmatched then  
4:      $q \leftarrow j$ ;  
5:      $\text{pred}(q) \leftarrow i$ ;  
6:      $\text{found} \leftarrow \text{true}$ ;  
7:     return  
8:   if  $j$  is matched and unlabeled then  
9:      $\text{pred}(j) \leftarrow i$ ;  
10:     $\text{pred}(\text{mate}(j)) \leftarrow j$ ;  
11:    add  $\text{mate}(j)$  to  $\text{list}$ 
```

$\text{mate}(j)$ is a new node from
which you can grow further.

Algorithm 27 $\text{contract}(i, j)$

- 1: trace pred-indices of i and j to identify a blossom B
- 2: create new node b and set $\bar{A}(b) \leftarrow \cup_{x \in B} \bar{A}(x)$
- 3: label b even and add to *list*
- 4: update $\bar{A}(j) \leftarrow \bar{A}(j) \cup \{b\}$ for each $j \in \bar{A}(b)$
- 5: form a circular double linked list of nodes in B
- 6: delete nodes in B from the graph

Contract blossom identified by
nodes i and j

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Get all nodes of the blossom.

Time: $\mathcal{O}(m)$

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Identify all neighbours of b .

Time: $\mathcal{O}(m)$ (how?)

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b will be an even node, and it has unexamined neighbours.

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Every node that was adjacent to a node
in B is now adjacent to b

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Only for making a blossom expansion easier.

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- 5: form a circular double linked list of nodes in B
- 6: delete nodes in B from the graph

Only delete links from nodes not in B to B .
When expanding the blossom again we can
recreate these links in time $\mathcal{O}(m)$.

Analysis

- ▶ A contraction operation can be performed in time $\mathcal{O}(m)$. Note, that any graph created will have at most m edges.
- ▶ The time between two contraction-operation is basically a BFS/DFS on a graph. Hence takes time $\mathcal{O}(m)$.
- ▶ There are at most n contractions as each contraction reduces the number of vertices.
- ▶ The expansion can trivially be done in the same time as needed for all contractions.
- ▶ An augmentation requires time $\mathcal{O}(n)$. There are at most n of them.
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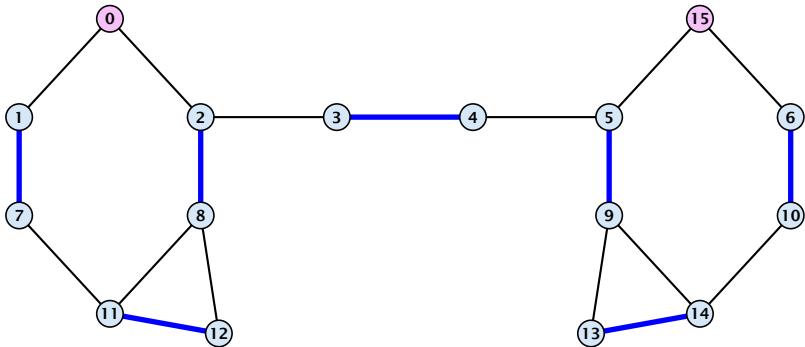
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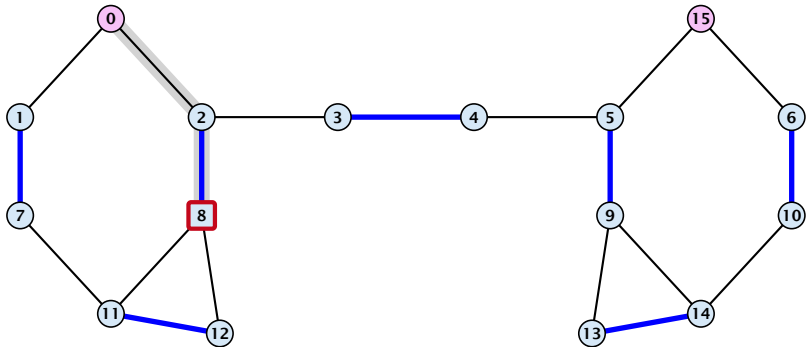
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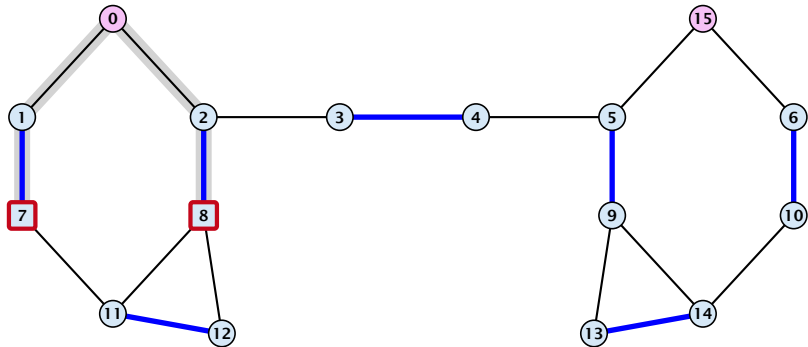
Example: Blossom Algorithm



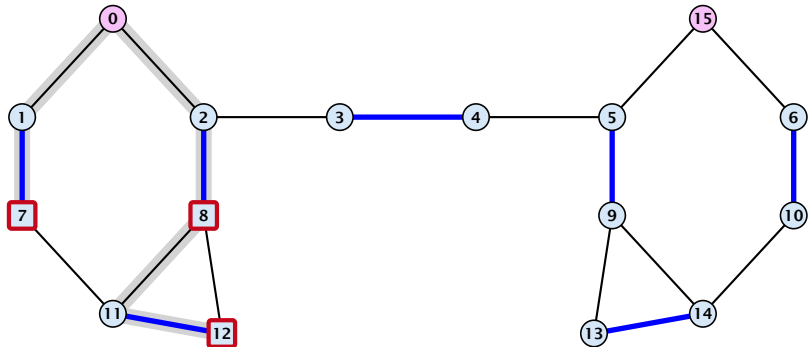
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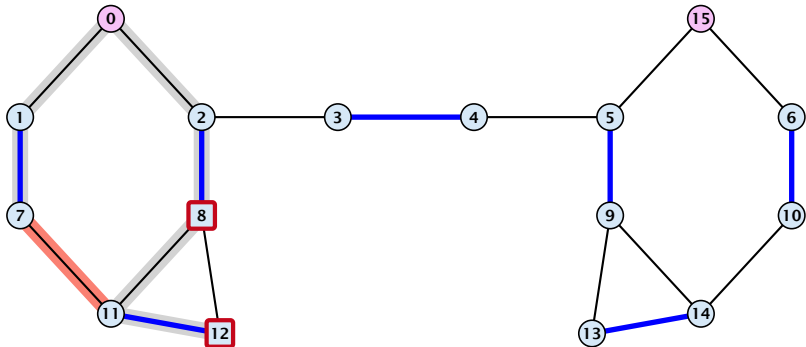
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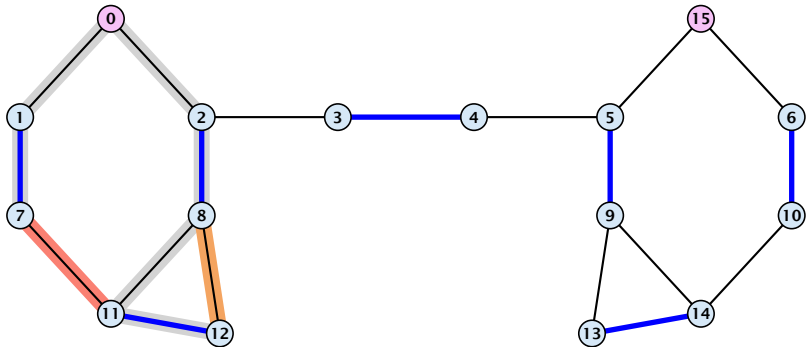
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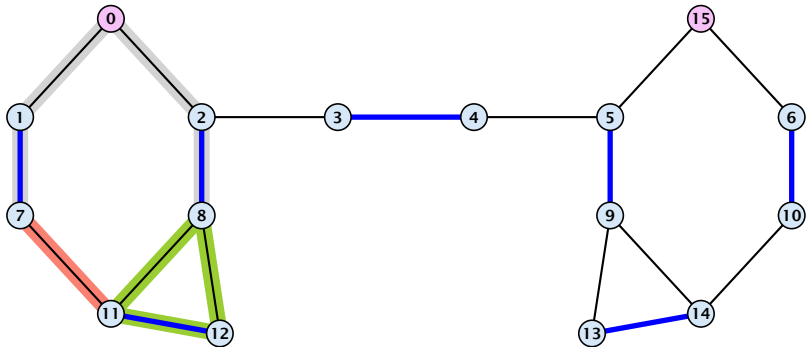
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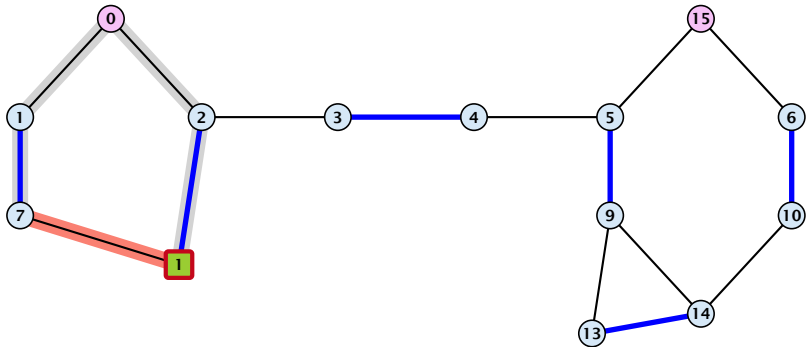
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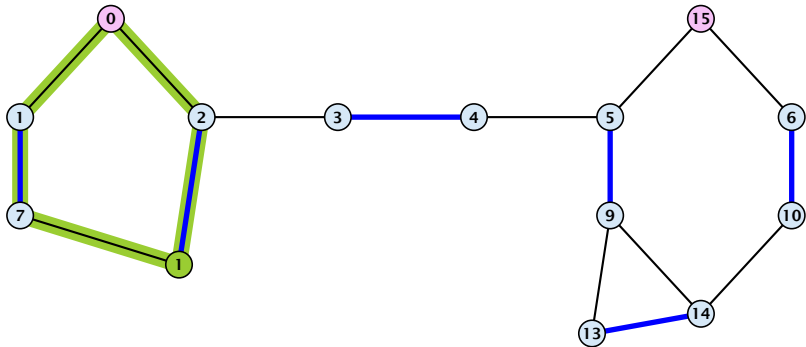
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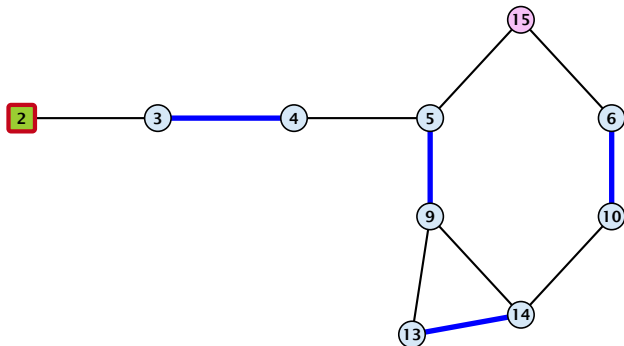
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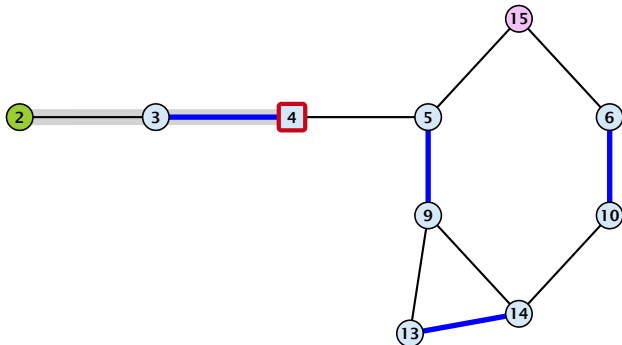
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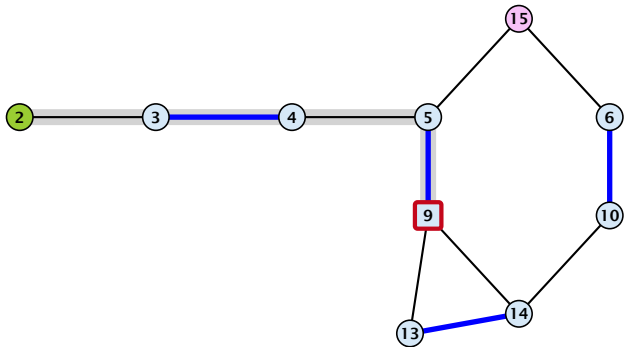
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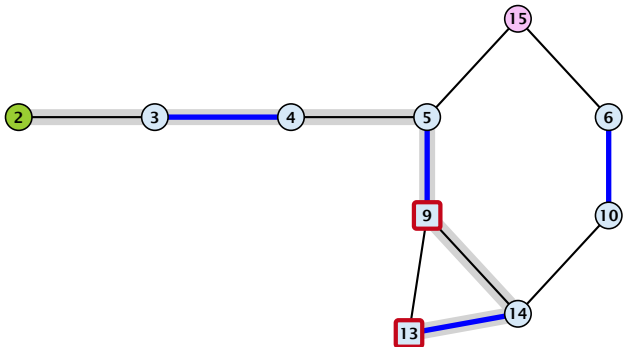
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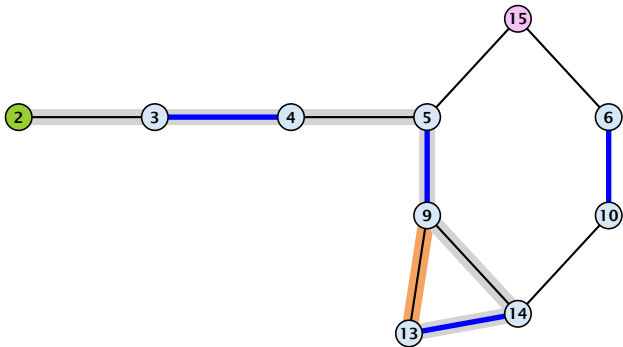
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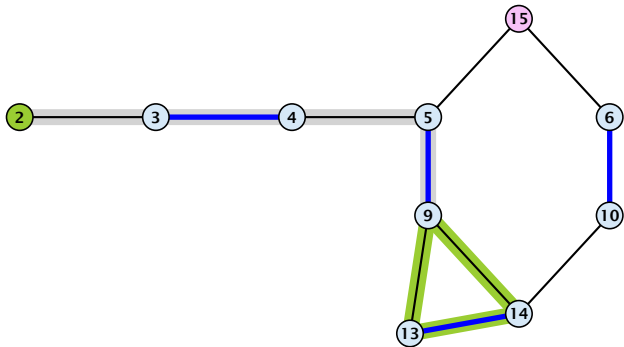
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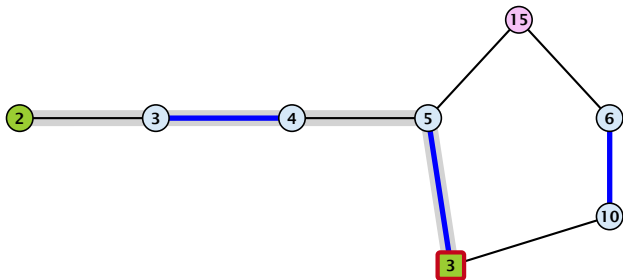
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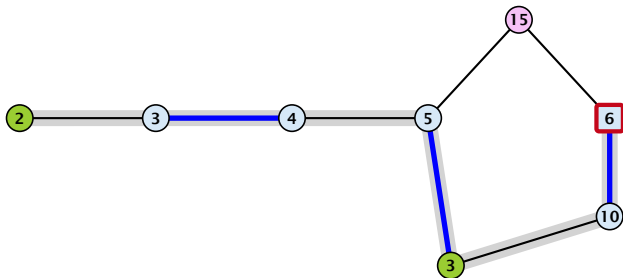
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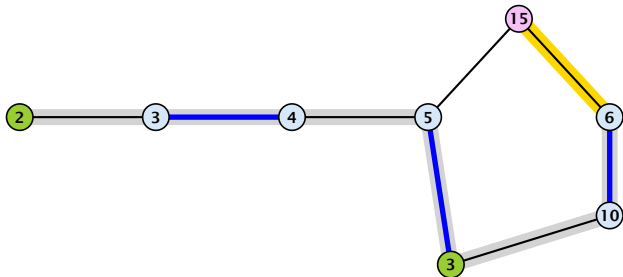
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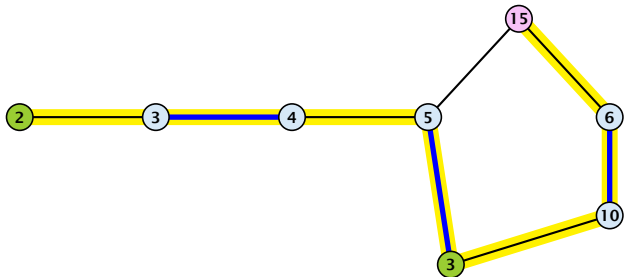
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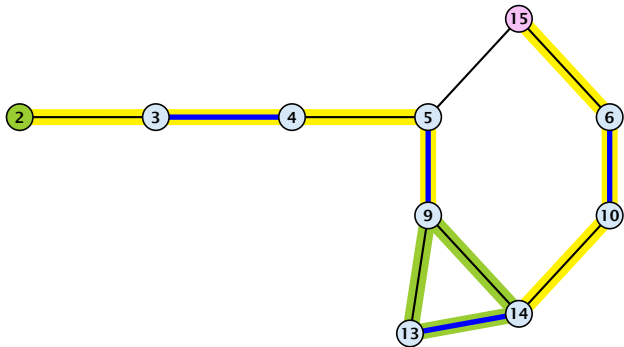
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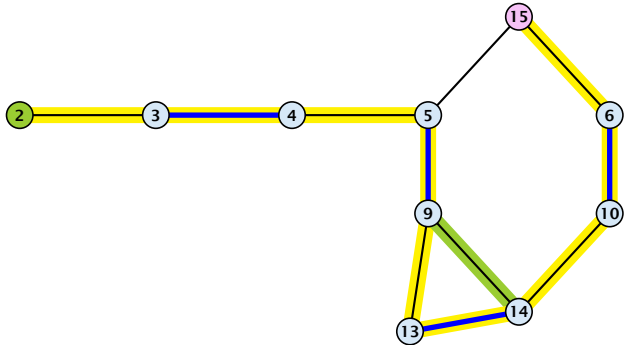
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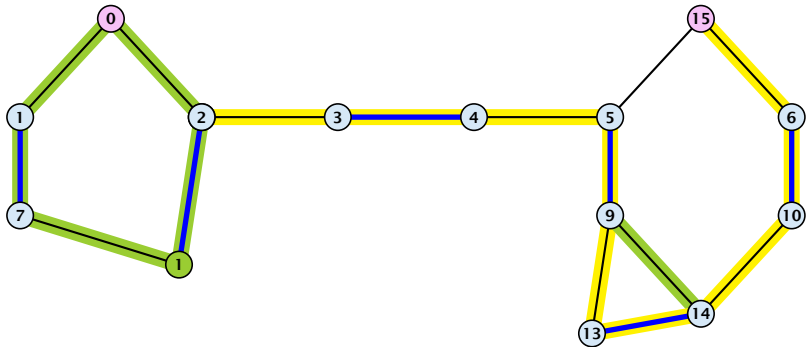
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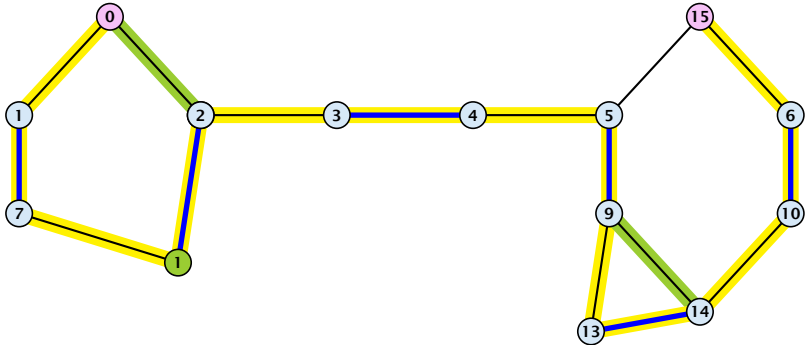
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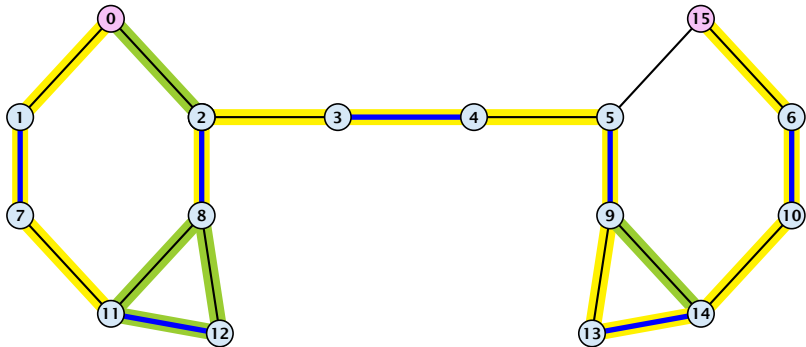
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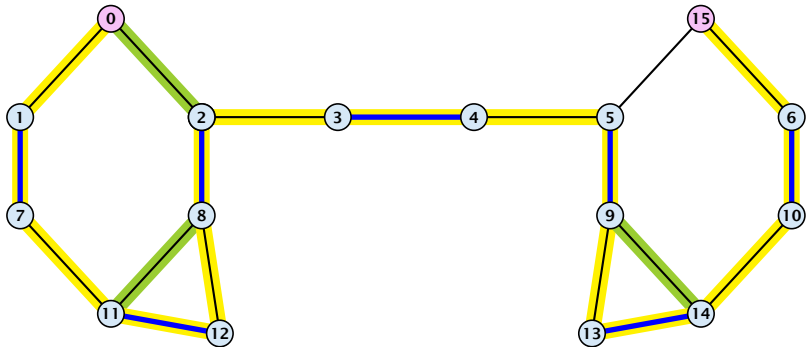
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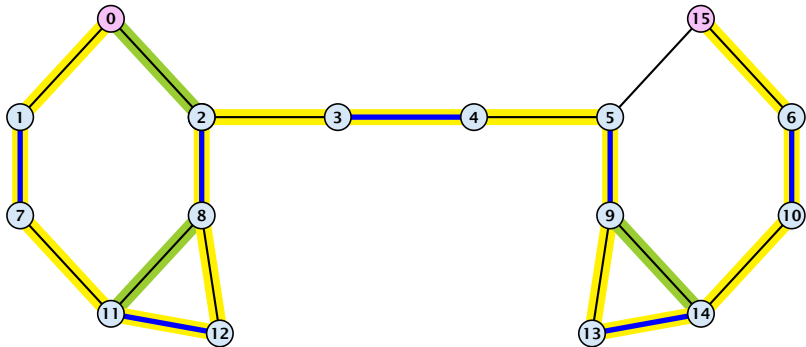
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A Fast Matching Algorithm

Algorithm 28 Bimatch-Hopcroft-Karp(G)

```
1:  $M \leftarrow \emptyset$ 
2: repeat
3:   let  $\mathcal{P} = \{P_1, \dots, P_k\}$  be maximal set of
4:   vertex-disjoint, shortest augmenting path w.r.t.  $M$ .
5:    $M \leftarrow M \oplus (P_1 \cup \dots \cup P_k)$ 
6: until  $\mathcal{P} = \emptyset$ 
7: return  $M$ 
```

We call one iteration of the repeat-loop a **phase** of the algorithm.

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Lemma 97

Given a matching M and a maximal matching M^* there exist $|M^*| - |M|$ *vertex-disjoint* augmenting path w.r.t. M .

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- ▶ Similar to the proof that a matching is optimal iff it does not contain an augmenting path.
- ▶ Consider the graph $G = (V, M \oplus M^*)$, and mark edges in this graph blue if they are in M and red if they are in M^* .
- ▶ The connected components of G are cycles and paths.
- ▶ The graph contains $k \leq |M^*| - |M|$ more red edges than blue edges.
- ▶ Hence, there are at least k components that form a path starting and ending with a red edge. These are augmenting paths w.r.t. M .

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- ▶ Let P_1, \dots, P_k be a maximal collection of vertex-disjoint, shortest augmenting paths w.r.t. M (let $\ell = |P_i|$).
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- ▶ Let P be an augmenting path in M' .

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The set $A \cong M \oplus (M' \oplus P) = (P_1 \cup \dots \cup P_k) \oplus P$ contains at least $(k+1)\ell$ edges.

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- ▶ Hence, the set contains at least $k + 1$ vertex-disjoint augmenting paths w.r.t. M as $|M'| = |M| + k + 1$.
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- ▶ Hence, $|A| \leq k\ell + |P| - 1$.
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Analysis Hopcroft-Karp

Lemma 100

The Hopcroft-Karp algorithm requires at most $2\sqrt{|V|}$ phases.

Proof.

- ▶ After iteration $\lfloor \sqrt{|V|} \rfloor$ the length of a shortest augmenting path must be at least $\lfloor \sqrt{|V|} \rfloor + 1 \geq \sqrt{|V|}$.
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Analysis Hopcroft-Karp

Lemma 101

One phase of the Hopcroft-Karp algorithm can be implemented in time $\mathcal{O}(m)$.

construct a “level graph” G' :

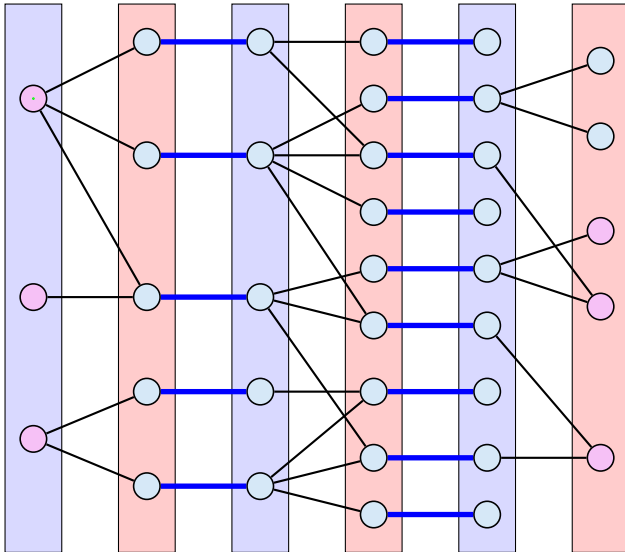
- ▶ construct Level 0 that includes all free vertices on left side L
- ▶ construct Level 1 containing all neighbors of Level 0
- ▶ construct Level 2 containing **matching** neighbors of Level 1
- ▶ construct Level 3 containing all neighbors of Level 2
- ▶ ...
- ▶ stop when a level (apart from Level 0) contains a free vertex

can be done in time $\mathcal{O}(m)$ by a modified BFS

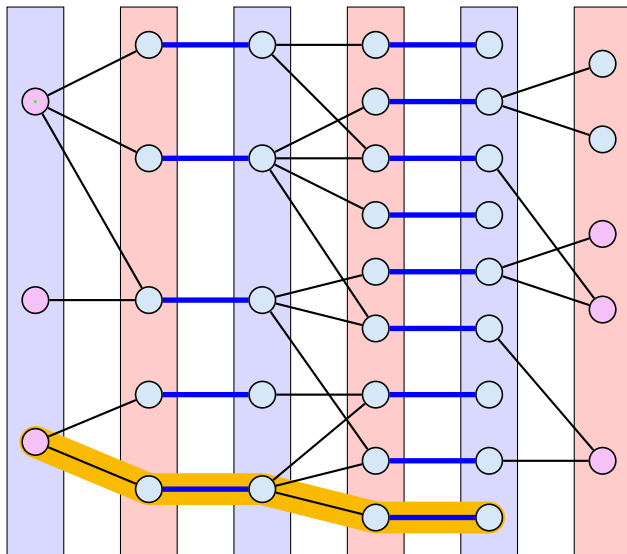
Analysis Hopcroft-Karp

- ▶ a shortest augmenting path **must** go from Level 0 to the last layer constructed
- ▶ it can only use edges between layers
- ▶ construct a maximal set of vertex disjoint augmenting path connecting the layers
- ▶ for this, go forward until you either reach a free vertex or you reach a “dead end” v
- ▶ if you reach a free vertex delete the augmenting path and all incident edges from the graph
- ▶ if you reach a dead end backtrack and delete v together with its incident edges

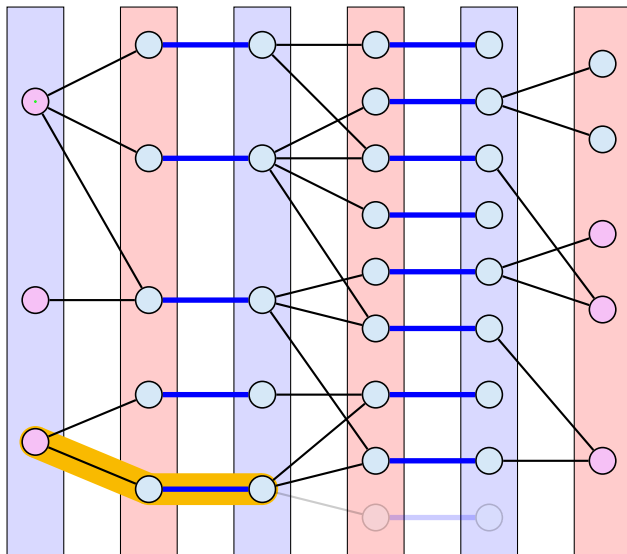
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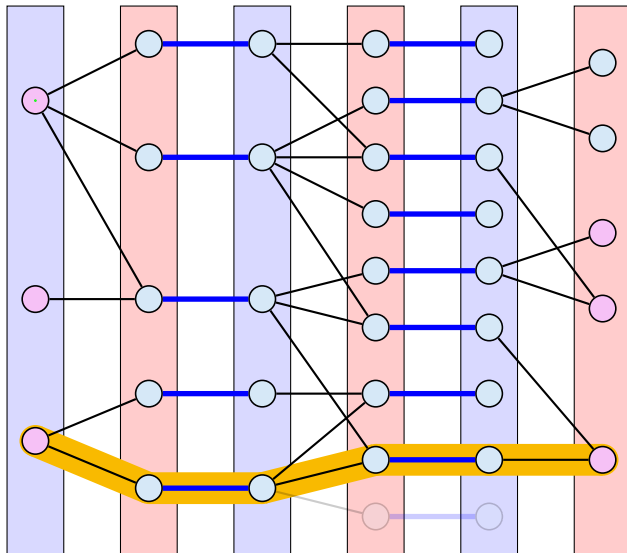
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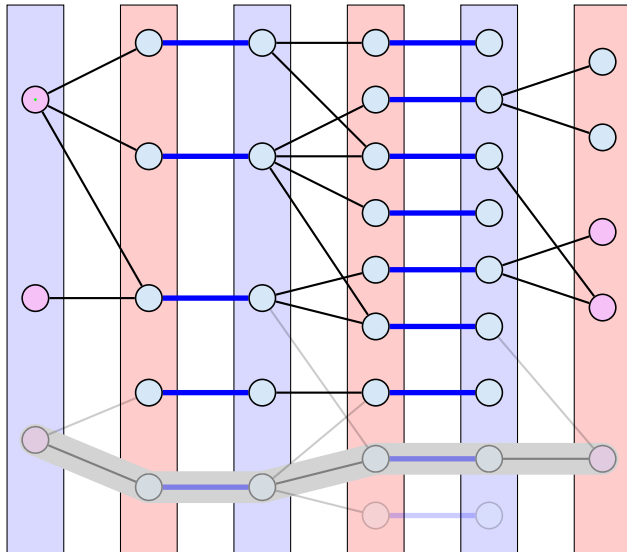
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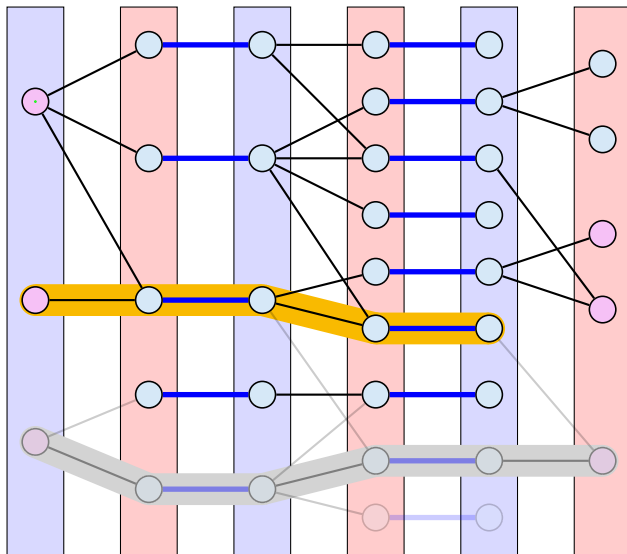
Analysis Hopcroft-Karp



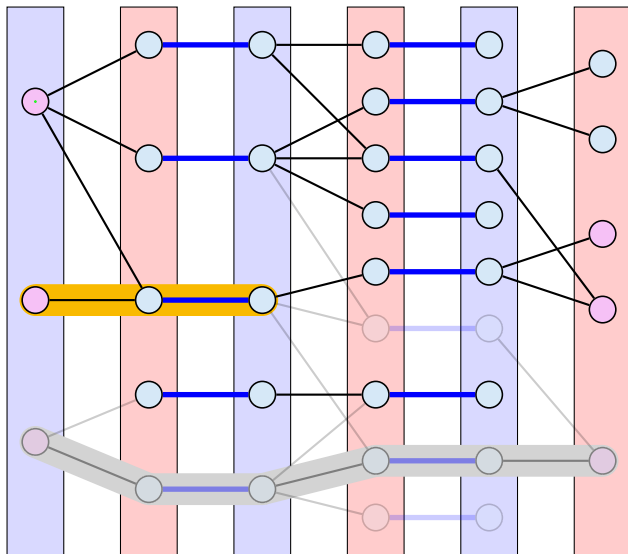
Analysis Hopcroft-Karp



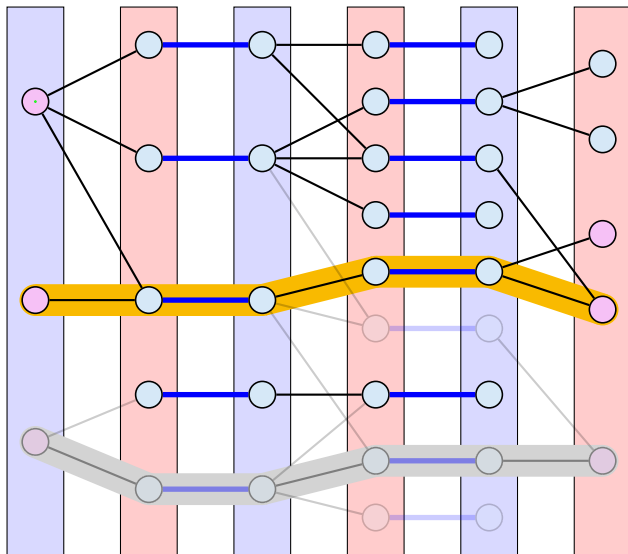
Analysis Hopcroft-Karp



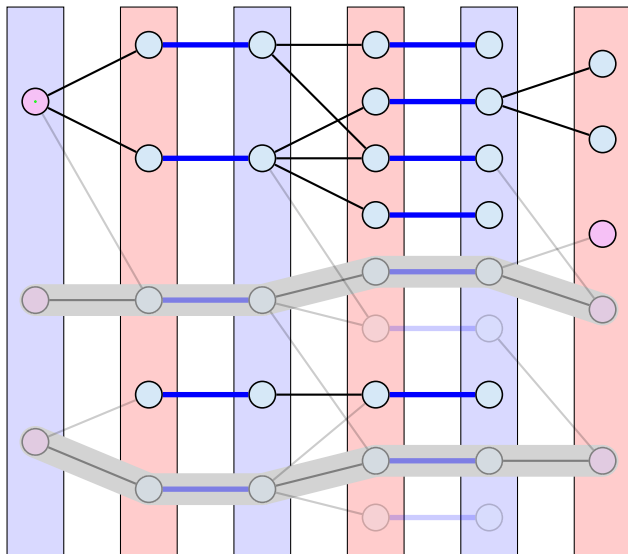
Analysis Hopcroft-Karp



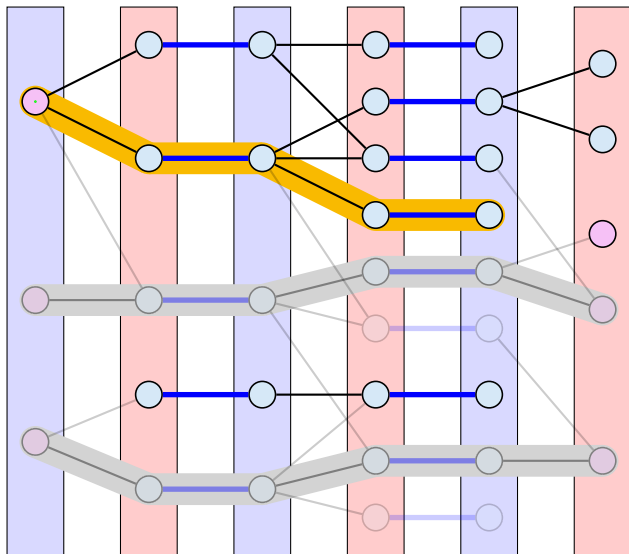
Analysis Hopcroft-Karp



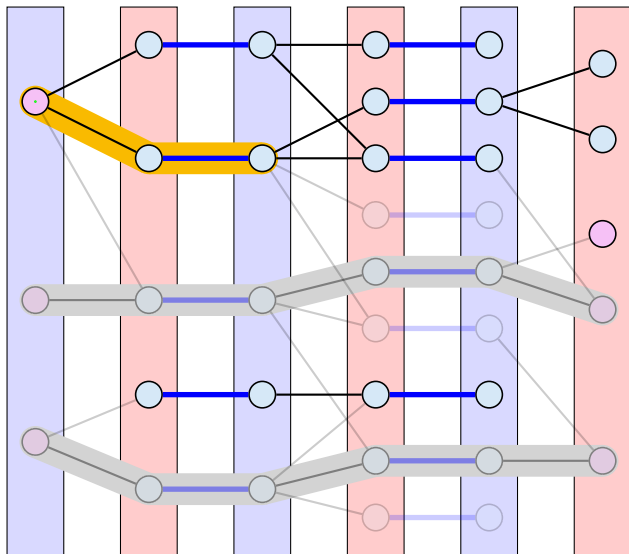
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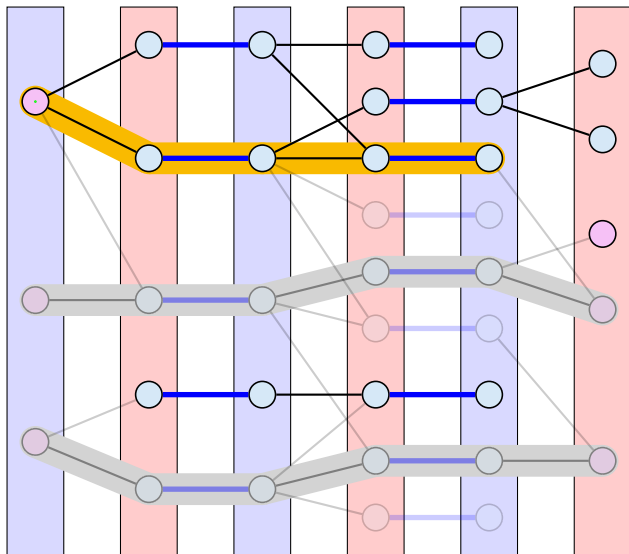
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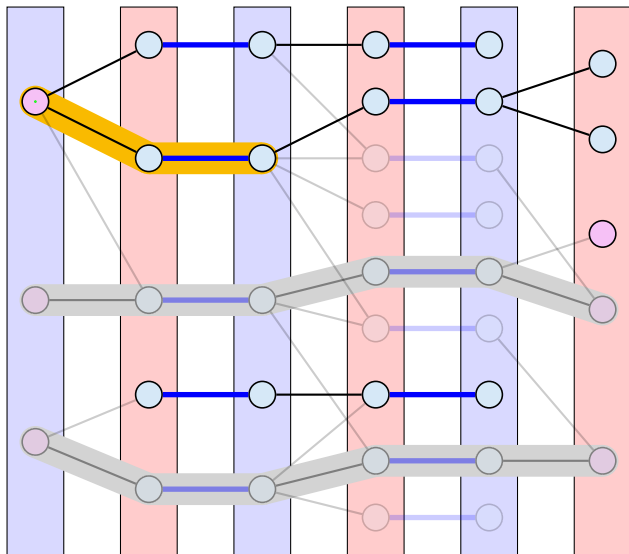
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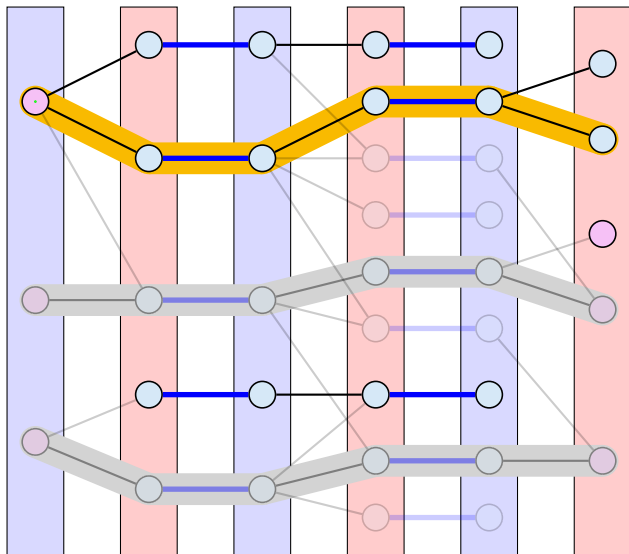
Analysis Hopcroft-Karp



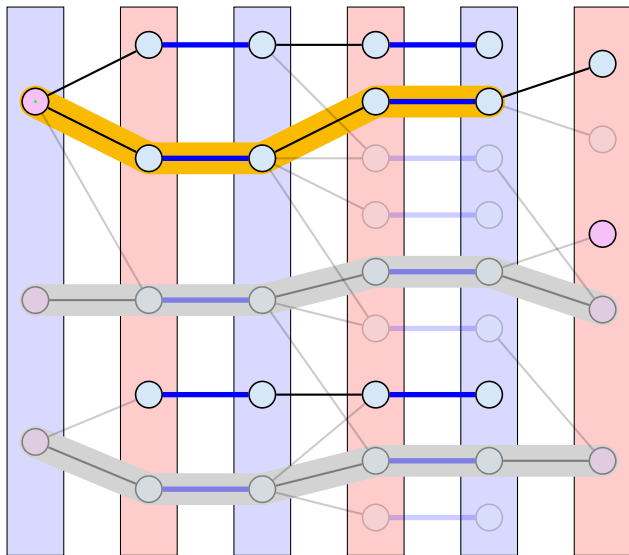
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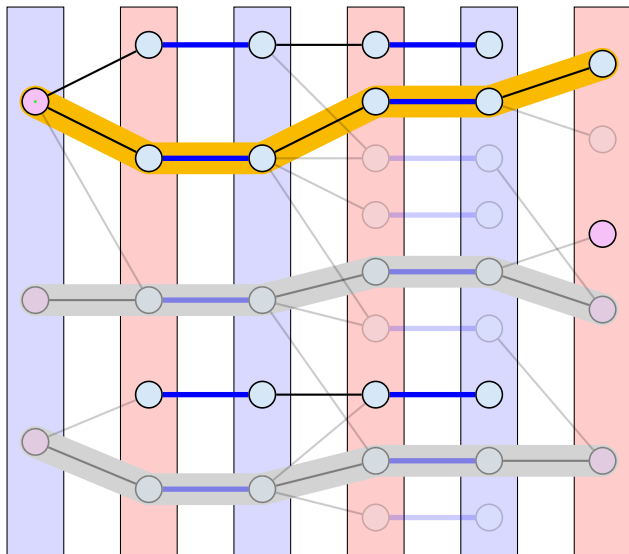
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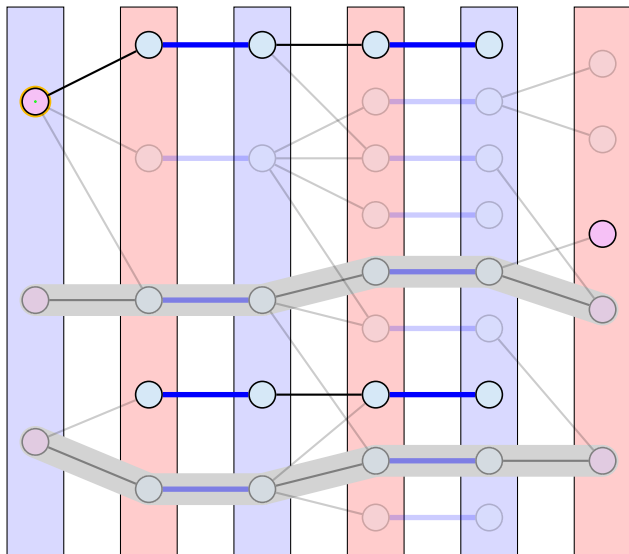
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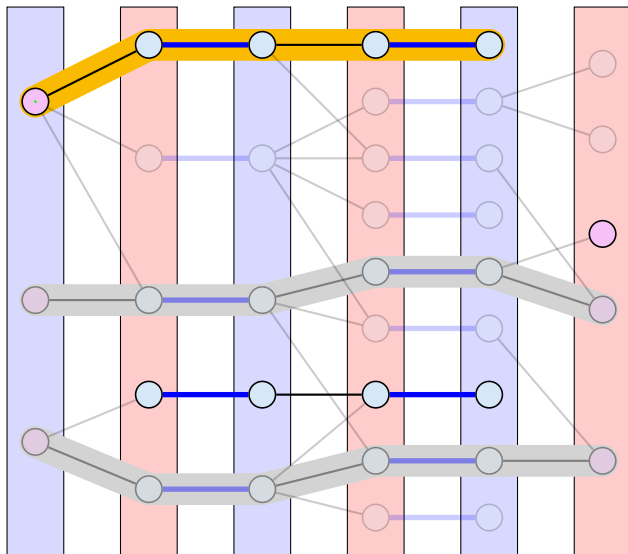
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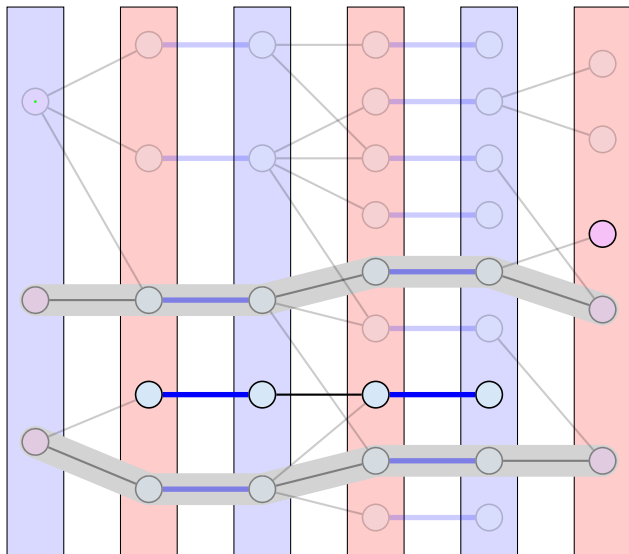
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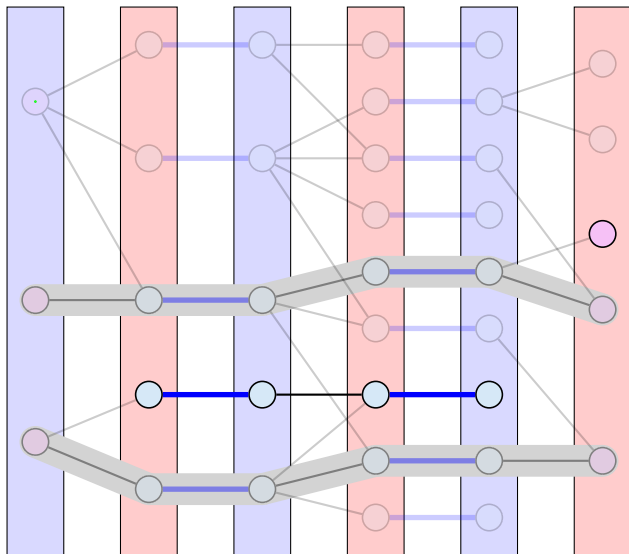
Analysis Hopcroft-Karp



Analysis Hopcroft-Karp



Analysis Hopcroft-Karp



Analysis: Shortest Augmenting Path for Flows

cost for searches during a phase is $\mathcal{O}(mn)$

- ▶ a search (successful or unsuccessful) takes time $\mathcal{O}(n)$
- ▶ a search deletes at least one edge from the level graph

there are at most n phases

Time: $\mathcal{O}(mn^2)$.

Analysis for Unit-capacity Simple Networks

cost for searches during a phase is $\mathcal{O}(m)$

- ▶ an edge/vertex is traversed at most twice

need at most $\mathcal{O}(\sqrt{n})$ phases

- ▶ after \sqrt{n} phases there is a cut of size at most \sqrt{n} in the residual graph
- ▶ hence at most \sqrt{n} additional augmentations required

Time: $\mathcal{O}(m\sqrt{n})$.