

4 Modelling Issues

1 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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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**.

Ques: How many comparisons does this algorithm always require?

Ans: $\frac{n(n-1)}{2}$ comparisons. (This is the number of elements in the lower triangle of an $n \times n$ matrix.)

Typically focuses on the

Can this lower bound also be compared-based sorting algorithm needs at least $\frac{n(n-1)}{2}$ comparisons in the worst case.

Worst case

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Ques: How long will the Tims algorithm always run in?

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Can this lower bound be any comparison-based sorting algorithm needs at least $\Omega(n \log n)$ comparisons in the worst case.

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Ques: How many comparisons does this algorithm always take?

Typical answer: $\Theta(n^2)$

Can this lower bound be very computer-implementation dependent?
Algorithm needs at least $\frac{n(n-1)}{2}$ comparisons in the worst case.

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

Typical answer: $\Theta(n^2)$.

Can this lower bound be improved by using a more sophisticated sorting algorithm instead of `std::sort`? (The answer depends on the input data.)

Wrong again!

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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 (e.g. for binary trees)

the number of nodes in the input graph (e.g. for graph problems)

the number of nodes in the input DAG (e.g. for DAG problems)

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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

How to measure performance of a model of computation? It is not possible to measure the performance of a model of computation in a general sense. Performance is a relative term and depends on the context in which the model is used. For example, a model of computation that is efficient for a specific task may be inefficient for another task. Therefore, performance should be measured relative to a specific task or set of tasks.

The most common way to measure performance is by measuring the time taken to execute a given task. This is often done by measuring the number of operations or instructions executed. However, this is not always the best way to measure performance, as it does not take into account the complexity of the task or the resources used.

How to measure performance

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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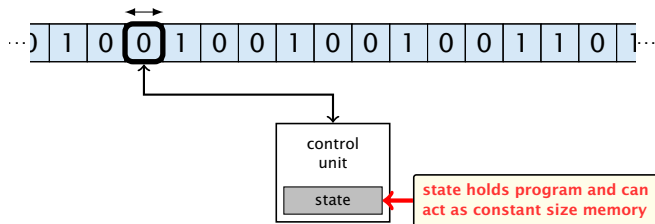
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Turing Machine

- ▶ 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.

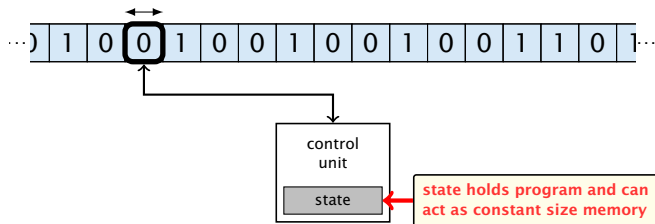
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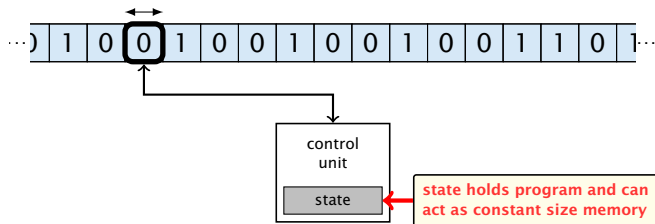
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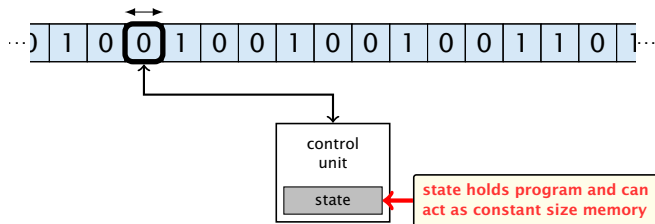
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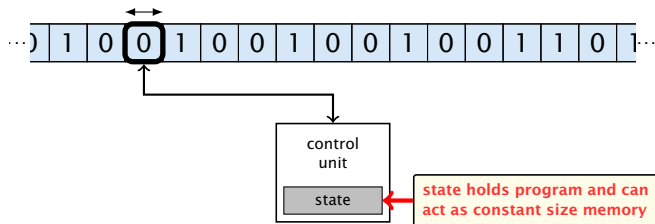
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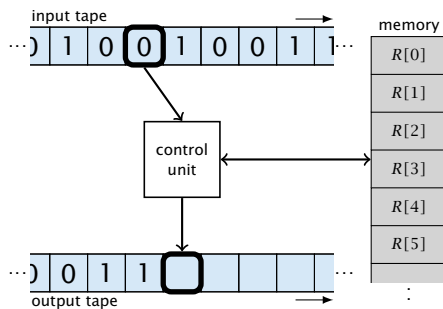
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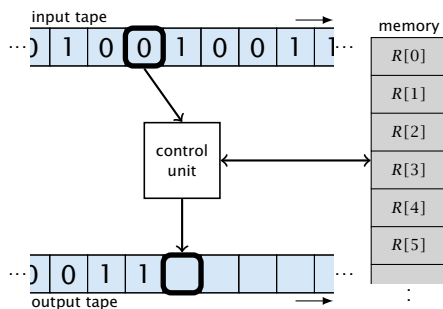
Random Access Machine (RAM)

- ▶ Input tape and output tape (sequences of zeros and ones; unbounded length).
- ▶ Memory unit: infinite but countable number of registers $R[0], R[1], R[2], \dots$
- ▶ Registers hold integers.
- ▶ Indirect addressing.



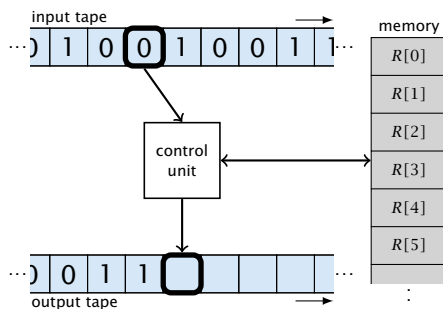
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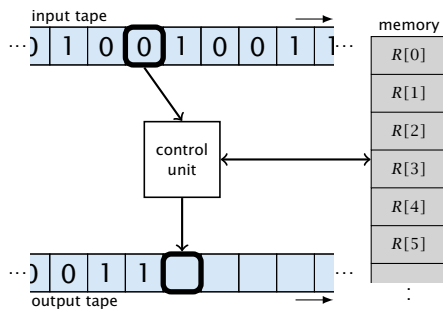
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 - ▶ $R[j] := R[R[i]]$
loads the content of the $R[i]$ -th register into the j -th register
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- ▶ branching (including loops) based on comparisons
 - ▶ `jump x`
jumps to position x in the program;
sets instruction counter to x ;
reads the next operation to perform from register $R[x]$
 - ▶ `jumpz x $R[i]$`
jump to x if $R[i] = 0$
if not the instruction counter is increased by 1;
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Model of Computation

- ▶ **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 word size of a register is equal to the length (in bits) of the largest value ever stored in it.

- ▶ The time for a step is equal to the word size.

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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Example 2

Algorithm 1 RepeatedSquaring(n)

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1:  $r \leftarrow 2$ ;  
2: for  $i = 1 \rightarrow n$  do  
3:    $r \leftarrow r^2$   
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 - ▶ logarithmic model: $1 + 2 + 4 + \dots + 2^n = 2^{n+1} - 1 = \Theta(2^n)$
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Usually easy to analyze, but not very meaningful.

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