SS 2024

Efficient Algorithms and Data Structures II

Harald Räcke

Fakultät für Informatik
TU München

https://www.moodle.tum.de/course/view.php?id=86234

Summer Term 2024

Part I

Organizational Matters

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- Modul: IN2004
- Name: "Efficient Algorithms and Data Structures II"
  "Effiziente Algorithmen und Datenstrukturen II"
- ECTS: 8 Credit points
- Lectures:
  - 4 SWS
    Wed 10:15–11:45 (Room 00.13.009A)
    Fri 10:15–11:45 (MS HS3)

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The Lecturer

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

Tutorials

- Tutor:
  - Omar AbdelWanis
  - omar.abdelwanis@tum.de
  - per appointment
- Room: 03.11.018
- Time: Mon 14:00–16:00

Assessment

- In order to pass the module you need to pass an exam.
- Exam:
  - 2.5 hours
  - There are no resources allowed, apart from a hand-written piece of paper (A4).
  - Answers should be given in English, but German is also accepted.

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1 Contents

Part 1: Linear Programming

Part 2: Approximation Algorithms

2 Literatur

- V. Chvatal:
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  Complexity and Approximation,
  Springer, 1999

Part II

Linear Programming

Brewery Problem

Brewery brews ale and beer.

- Production limited by supply of corn, hops and barley malt
- Recipes for ale and beer require different amounts of resources

	Corn (kg)	*Hops (kg)*	*Malt (kg)*	*Profit (€)*
ale (barrel)	5	4	35	13
beer (barrel)	15	4	20	23
supply	480	160	1190	

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How can brewer maximize profits?

- only brew ale: 34 barrels of ale
- only brew beer: 32 barrels of beer
- 7.5 barrels ale, 29.5 barrels beer
- 12 barrels ale, 28 barrels beer

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How can brewer maximize profits?

- only brew ale: 34 barrels of ale $\Longrightarrow$ 442 €
- only brew beer: 32 barrels of beer $\Longrightarrow$ 736 €
- 7.5 barrels ale, 29.5 barrels beer $\Longrightarrow$ 776 €
- 12 barrels ale, 28 barrels beer $\Longrightarrow$ 800 €

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Brewery Problem

Linear Program

- Introduce variables a and b that define how much ale and beer to produce.
- Choose the variables in such a way that the objective function (profit) is maximized.
- Make sure that no constraints (due to limited supply) are violated.

$$\begin{array}{lrcrl}
\text{max} & 13a & + & 23b & \\
\text{s.t.} & 5a & + & 15b & \leq 480 \\
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Standard Form LPs

LP in standard form:

- input: numbers a_{ij}, c_j, b_i
- output: numbers x_j
- $n = \#$decision variables, $m = \#$constraints
- maximize linear objective function subject to linear (in)equalities

$$\begin{array}{lrcll} \max & \sum_{j=1}^{n} c_j x_j & & & \\ \text{s.t.} & \sum_{j=1}^{n} a_{ij} x_j & = & b_i & 1 \le i \le m \\ & x_j & \ge & 0 & 1 \le j \le n \end{array}$$

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less or equal to equality:

greater or equal to equality:

min to max:

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- **less or equal to equality:**

$$a - 3b + 5c \leq 12 \implies \begin{aligned} a - 3b + 5c + s &= 12 \\ s &\geq 0 \end{aligned}$$

- **greater or equal to equality:**

$$a - 3b + 5c \geq 12 \implies \begin{aligned} a - 3b + 5c - s &= 12 \\ s &\geq 0 \end{aligned}$$

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- **equality to greater or equal:**

$$a - 3b + 5c = 12 \implies \begin{array}{r} a - 3b + 5c \ge 12 \\ -a + 3b - 5c \ge -12 \end{array}$$

- **unrestricted to nonnegative:**

$$x \text{ unrestricted} \implies x = x^+ - x^-,\ x^+ \ge 0,\ x^- \ge 0$$

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It is easy to transform variants of LPs into (any) standard form:

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Observations:

- a linear program does not contain x^2, $\cos(x)$, etc.
- transformations between standard forms can be done efficiently and only change the size of the LP by a small constant factor
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Fundamental Questions

Definition 1 (Linear Programming Problem (LP))

Let $A \in \mathbb{Q}^{m \times n}$, $b \in \mathbb{Q}^m$, $c \in \mathbb{Q}^n$, $\alpha \in \mathbb{Q}$. Does there exist $x \in \mathbb{Q}^n$ s.t. $Ax = b$, $x \geq 0$, $c^T x \geq \alpha$?

Questions:

- Is LP in NP?
- Is LP in co-NP?
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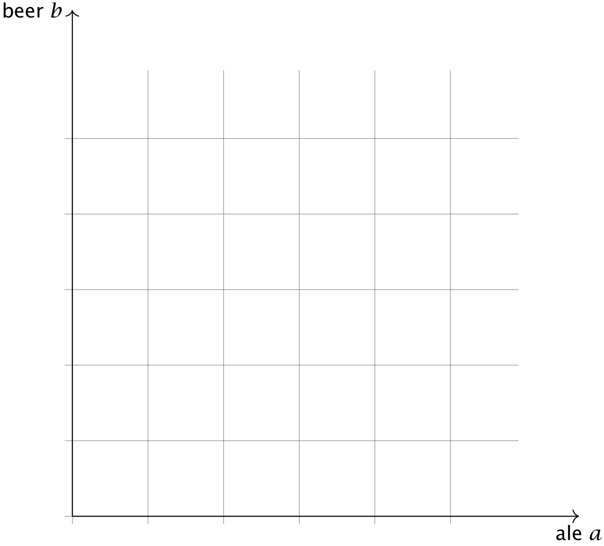

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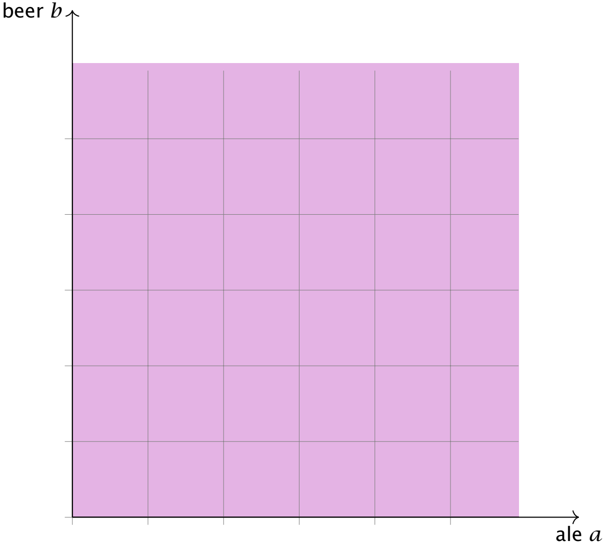

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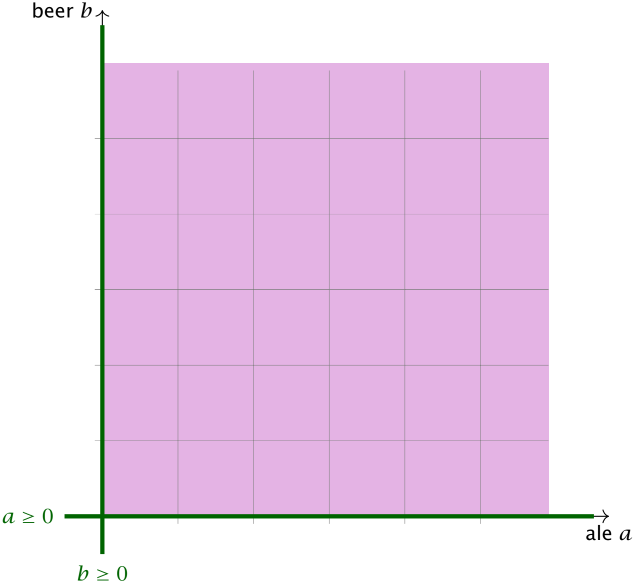

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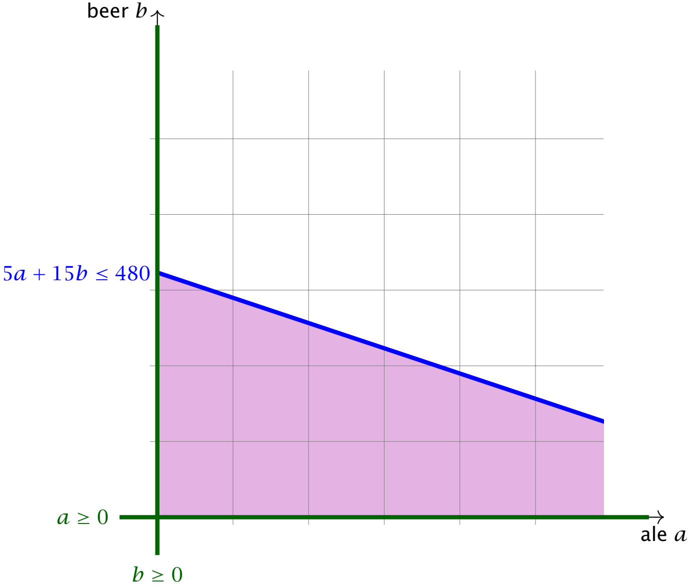

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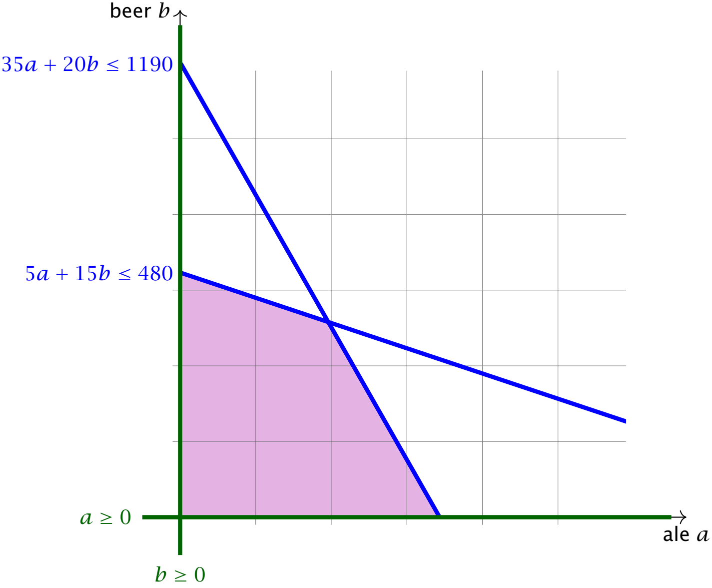

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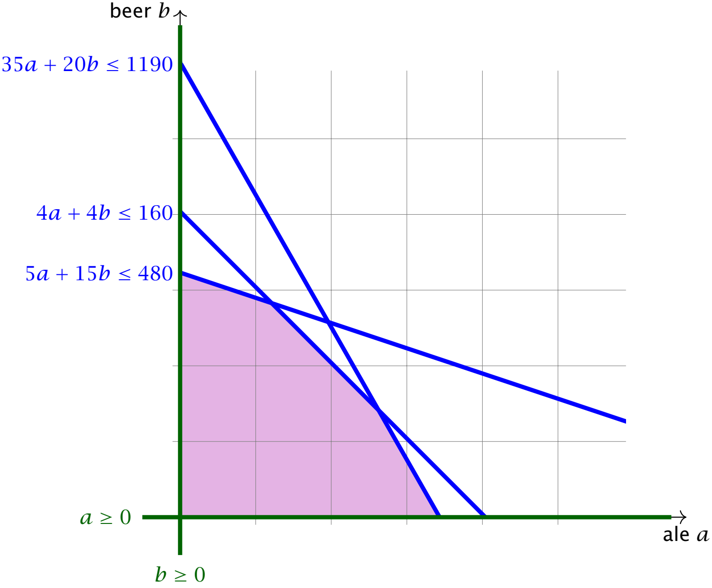

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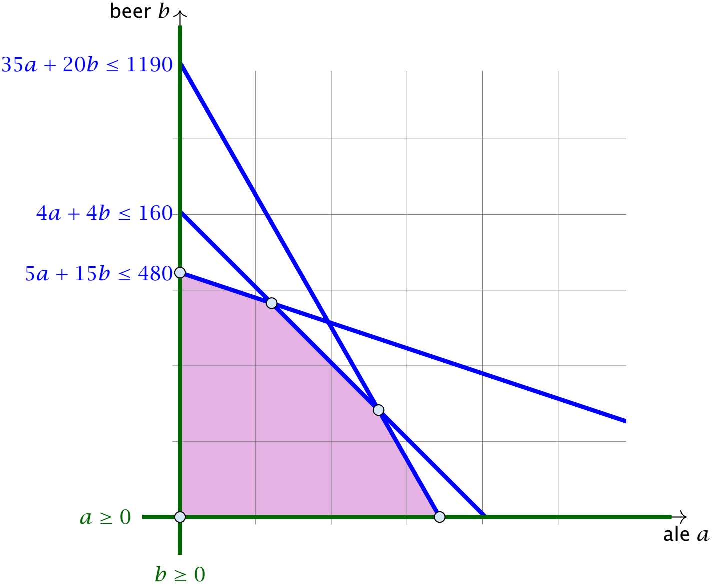

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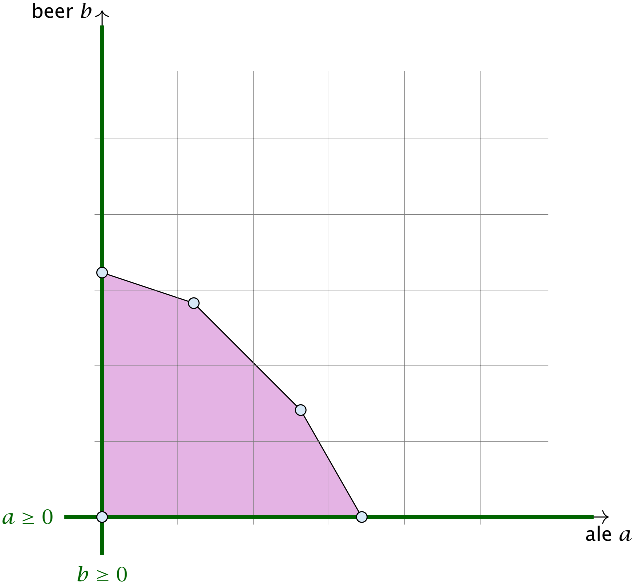

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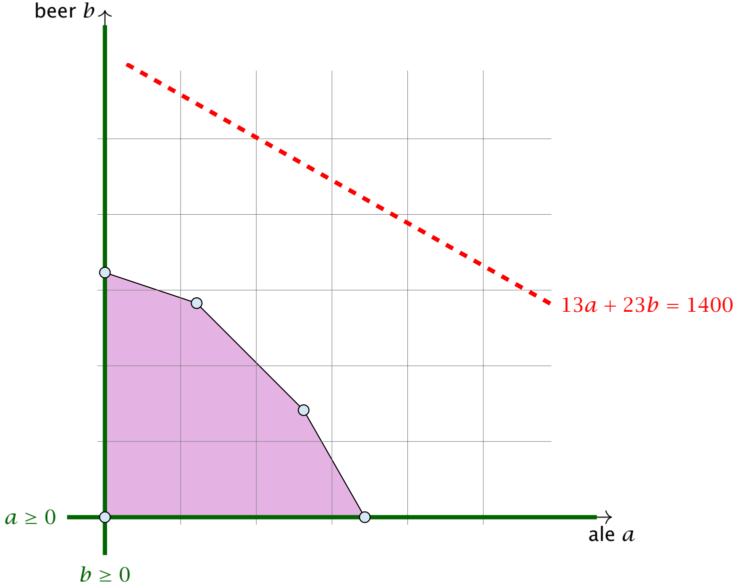

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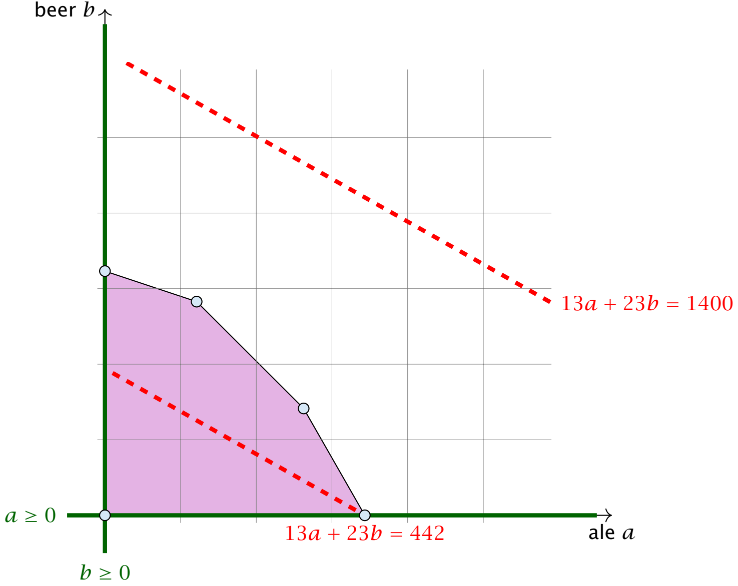

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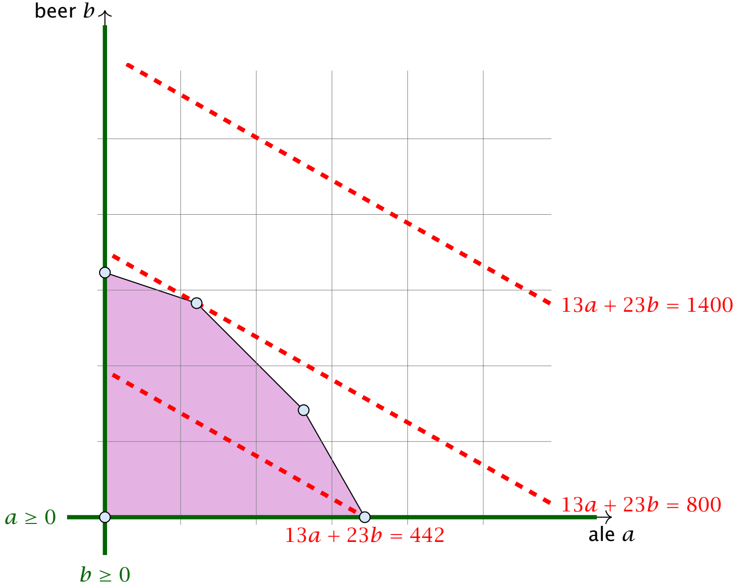

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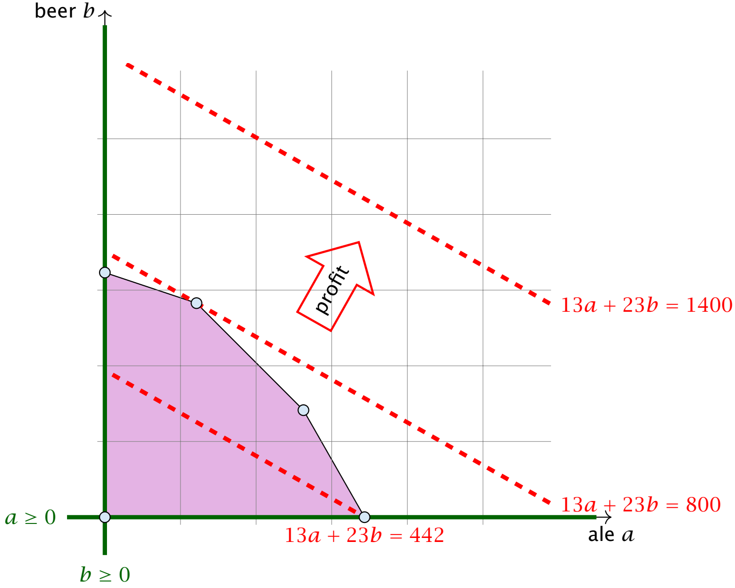

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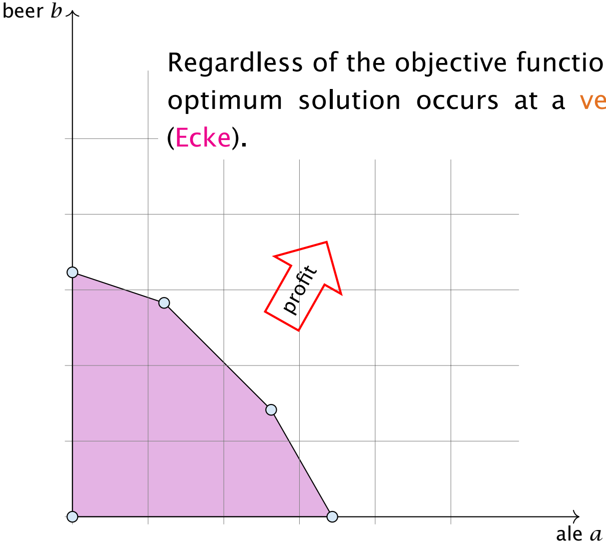

Regardless of the objective function an optimum solution occurs at a vertex (Ecke).

Definitions

Let for a Linear Program in standard form $P = \{x \mid Ax = b, x \geq 0\}$.

- P is called the feasible region (Lösungsraum) of the LP.
- A point $x \in P$ is called a feasible point (gültige Lösung).
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Definition 2

Given vectors/points $x_1, \ldots, x_k \in \mathbb{R}^n$, $\sum \lambda_i x_i$ is called

- linear combination if $\lambda_i \in \mathbb{R}$.
- affine combination if $\lambda_i \in \mathbb{R}$ and $\sum_i \lambda_i = 1$.
- convex combination if $\lambda_i \in \mathbb{R}$ and $\sum_i \lambda_i = 1$ and $\lambda_i \geq 0$.
- conic combination if $\lambda_i \in \mathbb{R}$ and $\lambda_i \geq 0$.

Note that a combination involves only finitely many vectors.

Definition 3

A set $X \subseteq \mathbb{R}^n$ is called

- a linear subspace if it is closed under linear combinations.
- an affine subspace if it is closed under affine combinations.
- convex if it is closed under convex combinations.
- a convex cone if it is closed under conic combinations.

Note that an affine subspace is **not** a vector space

Definition 4

Given a set $X \subseteq \mathbb{R}^n$.

- $\mathrm{span}(X)$ is the set of all linear combinations of X (linear hull, span)
- $\mathrm{aff}(X)$ is the set of all affine combinations of X (affine hull)
- $\mathrm{conv}(X)$ is the set of all convex combinations of X (convex hull)
- $\mathrm{cone}(X)$ is the set of all conic combinations of X (conic hull)

Definition 5

A function $f : \mathbb{R}^n \to \mathbb{R}$ is convex if for $x, y \in \mathbb{R}^n$ and $\lambda \in [0, 1]$ we have

$$f(\lambda x + (1 - \lambda)y) \le \lambda f(x) + (1 - \lambda)f(y)$$

Lemma 6

If $P \subseteq \mathbb{R}^n$, and $f : \mathbb{R}^n \to \mathbb{R}$ convex then also

$$Q = \{x \in P \mid f(x) \le t\}$$

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Dimensions

Definition 7
The dimension $\dim(A)$ of an affine subspace $A \subseteq \mathbb{R}^n$ is the dimension of the vector space $\{x - a \mid x \in A\}$, where $a \in A$.

Definition 8
The dimension $\dim(X)$ of a convex set $X \subseteq \mathbb{R}^n$ is the dimension of its affine hull $\mathrm{aff}(X)$.

Definition 9

A set $H \subseteq \mathbb{R}^n$ is a hyperplane if $H = \{x \mid a^T x = b\}$, for $a \neq 0$.

Definition 10

A set $H' \subseteq \mathbb{R}^n$ is a (closed) halfspace if $H = \{x \mid a^T x \leq b\}$, for $a \neq 0$.

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Definitions

Definition 11
A polytop is a set $P \subseteq \mathbb{R}^n$ that is the convex hull of a finite set of points, i.e., $P = \text{conv}(X)$ where $|X| = c$.

Definitions

Definition 12

A polyhedron is a set $P \subseteq \mathbb{R}^n$ that can be represented as the intersection of finitely many half-spaces $\{H(a_1, b_1), \ldots, H(a_m, b_m)\}$, where

$$H(a_i, b_i) = \{x \in \mathbb{R}^n \mid a_i x \le b_i\} \ .$$

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A polyhedron P is bounded if there exists B s.t. $\|x\|_2 \le B$ for all $x \in P$.

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Definitions

Theorem 14

P is a bounded polyhedron iff P is a polytop.

Definition 15

Let $P \subseteq \mathbb{R}^n$, $a \in \mathbb{R}^n$ and $b \in \mathbb{R}$. The hyperplane

$$H(a,b) = \{x \in \mathbb{R}^n \mid a^T x = b\}$$

is a supporting hyperplane of P if $\max\{a^T x \mid x \in P\} = b$.

Definition 16

Let $P \subseteq \mathbb{R}^n$. F is a face of P if $F = P$ or $F = P \cap H$ for some supporting hyperplane H.

Definition 17

Let $P \subseteq \mathbb{R}^n$.

- a face v is a vertex of P if $\{v\}$ is a face of P.
- a face e is an edge of P if e is a face and $\dim(e) = 1$.
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Equivalent definition for vertex:

Definition 18

Given polyhedron P. A point $x \in P$ is a vertex if $\exists c \in \mathbb{R}^n$ such that $c^T y < c^T x$, for all $y \in P$, $y \neq x$.

Definition 19

Given polyhedron P. A point $x \in P$ is an extreme point if $\nexists a, b \neq x$, $a, b \in P$, with $\lambda a + (1 - \lambda) b = x$ for $\lambda \in [0, 1]$.

Lemma 20

A vertex is also an extreme point.

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Observation

The feasible region of an LP is a Polyhedron.

Convex Sets

Theorem 21
If there exists an optimal solution to an LP (in standard form) then there exists an optimum solution that is an extreme point.

Proof

- suppose x is optimal solution that is not extreme point
- there exists direction $d \neq 0$ such that $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- Wlog. assume $c^Td \geq 0$ (by taking either d or $-d$)
- Consider $x + \lambda d$, $\lambda > 0$

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- Wlog. assume $c^T d \geq 0$ (by taking either d or $-d$)
- Consider $x + \lambda d$, $\lambda > 0$

Convex Sets

Theorem 21

If there exists an optimal solution to an LP (in standard form) then there exists an optimum solution that is an extreme point.

Proof

- suppose x is optimal solution that is not extreme point
- there exists direction $d \neq 0$ such that $x \pm d \in P$
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Convex Sets

Case 1. [$\exists j$ s.t. $d_j < 0$]

- increase λ to λ' until first component of $x + \lambda d$ hits 0
- $x + \lambda' d$ is feasible. Since $A(x + \lambda' d) = b$ and $x + \lambda' d \geq 0$
- $x + \lambda' d$ has one more zero-component ($d_k = 0$ for $x_k = 0$ as $x \pm d \in P$)
- $c^T x' = c^T(x + \lambda' d) = c^T x + \lambda' c^T d \geq c^T x$

Case 2. [$d_j \geq 0$ for all j and $c^T d > 0$]

- $x + \lambda d$ is feasible for all $\lambda \geq 0$ since $A(x + \lambda d) = b$ and $x + \lambda d \geq x \geq 0$
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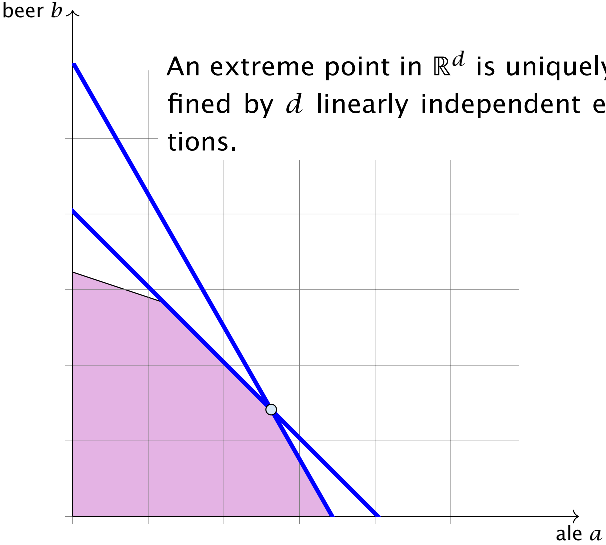
Algebraic View



An extreme point in $\mathbb{R}^d$ is uniquely defined by d linearly independent equations.

Notation

Suppose $B \subseteq \{1 \dots n\}$ is a set of column-indices. Define A_B as the subset of columns of A indexed by B.

Theorem 22

*Let $P = \{x \mid Ax = b, x \geq 0\}$. For $x \in P$, define $B = \{j \mid x_j > 0\}$. Then x is extreme point **iff** A_B has linearly independent columns.*

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Proof ($\Leftarrow$)

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- there exists direction d s.t. $x \pm d \in P$
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- define $B' = \{j \mid d_j \neq 0\}$
- $A_{B'}$ has linearly dependent columns as $Ad = 0$
- $d_j = 0$ for all j with $x_j = 0$ as $x \pm d \geq 0$
- Hence, $B' \subseteq B$, $A_{B'}$ is sub-matrix of A_B

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Theorem 23

Let $P = \{x \mid Ax = b, x \geq 0\}$. For $x \in P$, define $B = \{j \mid x_j > 0\}$. If A_B has linearly independent columns then x is a vertex of P.

- define $c_j = \begin{cases} 0 & j \in B \\ -1 & j \notin B \end{cases}$
- then $c^T x = 0$ and $c^T y \leq 0$ for $y \in P$
- assume $c^T y = 0$; then $y_j = 0$ for all $j \notin B$
- $b = Ay = A_B y_B = Ax = A_B x_B$ gives that $A_B(x_B - y_B) = 0$;
- this means that $x_B = y_B$ since A_B has linearly independent columns
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- then $c^Tx = 0$ and $c^Ty \leq 0$ for $y \in P$
- assume $c^Ty = 0$; then $y_j = 0$ for all $j \notin B$
- $b = Ay = A_By_B = Ax = A_Bx_B$ gives that $A_B(x_B - y_B) = 0$;
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Observation

For an LP we can assume wlog. that the matrix A has full row-rank. This means $\text{rank}(A) = m$.

- assume that $\text{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \ldots, A_m$;
  - if now $b_1 = \sum_{i=2}^{m} \lambda_i \cdot b_i$ then
  - if $b_1 \neq \sum_{i=2}^{m} \lambda_i \cdot b_i$ then the LP is infeasible, since for all x that fulfill constraints $A_2, \ldots, A_m$ we have

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- assume that $\operatorname{rank}(A) < m$
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$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i \text{, for suitable } \lambda_i$$

C1 if now $b_1 = \sum_{i=2}^{m} \lambda_i \cdot b_i$ then for all x with $A_i x = b_i$ we also have $A_1 x = b_1$; hence the first constraint is superfluous

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From now on we will always assume that the constraint matrix of a standard form LP has full row rank.

Theorem 24

Given $P = \{x \mid Ax = b, x \geq 0\}$. x *is extreme point iff there exists* $B \subseteq \{1, \ldots, n\}$ *with* $|B| = m$ *and*

- A_B is non-singular
- $x_B = A_B^{-1}b \geq 0$
- $x_N = 0$

where $N = \{1, \ldots, n\} \setminus B$.

Proof

Take $B = \{j \mid x_j > 0\}$ and augment with linearly independent columns until $|B| = m$; always possible since $\operatorname{rank}(A) = m$.

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Basic Feasible Solutions

$x \in \mathbb{R}^n$ is called basic solution (Basislösung) if $Ax = b$ and $\operatorname{rank}(A_J) = |J|$ where $J = \{j \mid x_j \neq 0\}$;

x is a basic **feasible** solution (gültige Basislösung) if in addition $x \geq 0$.

A basis (Basis) is an index set $B \subseteq \{1, \ldots, n\}$ with $\operatorname{rank}(A_B) = m$ and $|B| = m$.

$x \in \mathbb{R}^n$ with $A_B x_B = b$ and $x_j = 0$ for all $j \notin B$ is the basic solution associated to basis B (die zu B assoziierte Basislösung)

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Basic Feasible Solutions

A BFS fulfills the m equality constraints.

In addition, at least $n - m$ of the x_i's are zero. The corresponding non-negativity constraint is fulfilled with equality.

Fact:
In a BFS at least n constraints are fulfilled with equality.

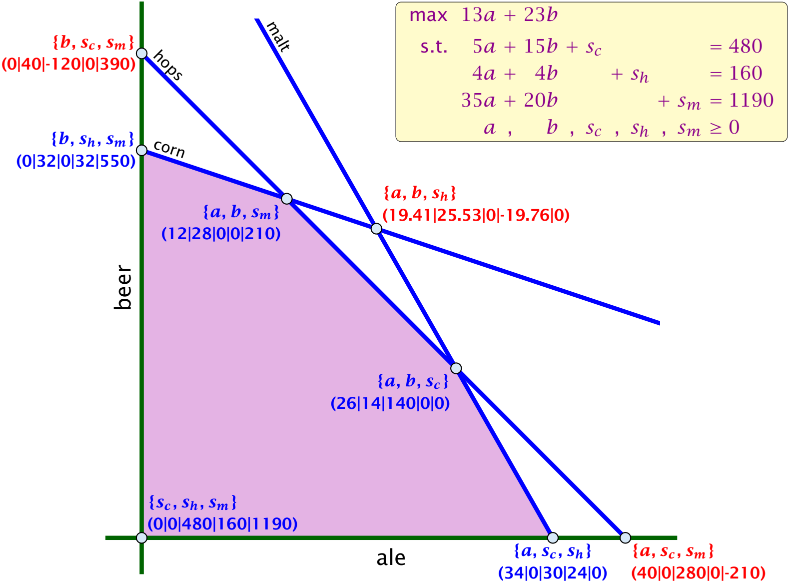
Basic Feasible Solutions

Definition 25

For a general LP ($\max\{c^Tx \mid Ax \le b\}$) with n variables a point x is a basic feasible solution if x is feasible and there exist n (linearly independent) constraints that are tight.

Algebraic View

$$\begin{array}{llllllll}
\max & 13a + 23b & & & & & & \\
\text{s.t.} & 5a + 15b & + s_c & & & & = & 480 \\
& 4a + 4b & & + s_h & & & = & 160 \\
& 35a + 20b & & & + s_m & & = & 1190 \\
& a \;,\; b & ,\; s_c & ,\; s_h & ,\; s_m & & \geq & 0
\end{array}$$



Fundamental Questions

Linear Programming Problem (LP)
Let $A \in \mathbb{Q}^{m\times n}$, $b \in \mathbb{Q}^m$, $c \in \mathbb{Q}^n$, $\alpha \in \mathbb{Q}$. Does there exist $x \in \mathbb{Q}^n$ s.t. $Ax = b$, $x \geq 0$, $c^Tx \geq \alpha$?

Questions:

- Is LP in NP? yes!
- Is LP in co-NP?
- Is LP in P?

Proof:

- Given a basis B we can compute the associated basis solution by calculating $A_B^{-1}b$ in polynomial time; then we can also compute the profit.

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Observation

We can compute an optimal solution to a linear program in time $\mathcal{O}\left(\binom{n}{m} \cdot \text{poly}(n, m)\right)$.

- there are only $\binom{n}{m}$ different bases.
- compute the profit of each of them and take the maximum

What happens if LP is unbounded?

4 Simplex Algorithm

Enumerating all basic feasible solutions (BFS), in order to find the optimum is slow.

Simplex Algorithm [George Dantzig 1947]
Move from BFS to adjacent BFS, without decreasing objective function.

Two BFSs are called adjacent if the bases just differ in one variable.

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$$
\begin{aligned}
& \text{max } Z \\
& 13a + 23b - Z = 0 \\
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basis $= \{s_c, s_h, s_m\}$

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Pivoting Step

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- Choose variable with coefficient > 0 as entering variable.

max Z

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5a & + & 15\boldsymbol{b} & + & s_c & & & & & & & = & 480 \\
4a & + & 4\boldsymbol{b} & & & + & s_h & & & & & = & 160 \\
35a & + & 20\boldsymbol{b} & & & & & + & s_m & & & = & 1190 \\
a & , & \boldsymbol{b} & , & s_c & , & s_h & , & s_m & & & \geq & 0
\end{array}$$

basis $= \{s_c, s_h, s_m\}$
$a = b = 0$
$Z = 0$

$s_c = 480$
$s_h = 160$
$s_m = 1190$

- Choose variable with coefficient > 0 as entering variable.
- If we keep $a = 0$ and increase b from 0 to $\theta > 0$ s.t. all constraints ($Ax = b, x \geq 0$) are still fulfilled the objective value Z will strictly increase.

max Z

$$\begin{array}{rcrcccccl} 13a & + & 23\boldsymbol{b} & & & & & -Z & = 0 \\ 5a & + & 15\boldsymbol{b} & + s_c & & & & & = 480 \\ 4a & + & 4\boldsymbol{b} & & + s_h & & & & = 160 \\ 35a & + & 20\boldsymbol{b} & & & + s_m & & & = 1190 \\ a & , & \boldsymbol{b} & , s_c & , s_h & , s_m & & & \geq 0 \end{array}$$

basis $= \{s_c, s_h, s_m\}$
$a = b = 0$
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- If we keep $a = 0$ and increase b from 0 to $\theta > 0$ s.t. all constraints ($Ax = b, x \geq 0$) are still fulfilled the objective value Z will strictly increase.
- For maintaining $Ax = b$ we need e.g. to set $s_c = 480 - 15\theta$.

max Z

$$\begin{array}{rcrcrcrcrcrcl}
13a & + & 23b & & & & & & & - & Z & = & 0 \\
5a & + & 15\boldsymbol{b} & + & s_c & & & & & & & = & 480 \\
4a & + & 4b & & & + & s_h & & & & & = & 160 \\
35a & + & 20b & & & & & + & s_m & & & = & 1190 \\
a & , & b & , & s_c & , & s_h & , & s_m & & & \geq & 0
\end{array}$$

basis $= \{s_c, s_h, s_m\}$
$a = b = 0$
$Z = 0$

$s_c = 480$
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- Choose variable with coefficient > 0 as entering variable.
- If we keep $a = 0$ and increase b from 0 to $\theta > 0$ s.t. all constraints ($Ax = b, x \geq 0$) are still fulfilled the objective value Z will strictly increase.
- For maintaining $Ax = b$ we need e.g. to set $s_c = 480 - 15\theta$.
- Choosing $\theta = \min\{480/15, 160/4, 1190/20\}$ ensures that in the new solution one current basic variable becomes 0, and no variable goes negative.

max Z

$$
\begin{array}{rcrcccccl}
13a & + & 23b & & & & & - Z & = 0 \\
5a & + & 15\boldsymbol{b} & + & \boldsymbol{s_c} & & & & = 480 \\
4a & + & 4b & & & + s_h & & & = 160 \\
35a & + & 20b & & & & + s_m & & = 1190 \\
a & , & b & , & s_c & , s_h & , s_m & & \geq 0
\end{array}
$$

basis $= \{s_c, s_h, s_m\}$

$a = b = 0$

$Z = 0$

$s_c = 480$

$s_h = 160$

$s_m = 1190$

- Choose variable with coefficient > 0 as entering variable.
- If we keep $a = 0$ and increase b from 0 to $\theta > 0$ s.t. all constraints ($Ax = b, x \geq 0$) are still fulfilled the objective value Z will strictly increase.
- For maintaining $Ax = b$ we need e.g. to set $s_c = 480 - 15\theta$.
- Choosing $\theta = \min\{480/15, 160/4, 1190/20\}$ ensures that in the new solution one current basic variable becomes 0, and no variable goes negative.
- The basic variable in the row that gives $\min\{480/15, 160/4, 1190/20\}$ becomes the leaving variable.

max Z

$$\begin{array}{rrrrrrr}
13a & + 23b & & & & -Z & = 0 \\
5a & + 15b & + s_c & & & & = 480 \\
4a & + 4b & & + s_h & & & = 160 \\
35a & + 20b & & & + s_m & & = 1190 \\
a, & b, & s_c, & s_h, & s_m & & \geq 0
\end{array}$$

basis $= \{s_c, s_h, s_m\}$

$a = b = 0$

$Z = 0$

$s_c = 480$

$s_h = 160$

$s_m = 1190$

max Z

$$
\begin{array}{rcrcccccccl}
13a & + & 23\boldsymbol{b} & & & & & & & -\; Z & = 0 \\
5a & + & 15\boldsymbol{b} & + & s_c & & & & & & = 480 \\
4a & + & 4\boldsymbol{b} & & & + & s_h & & & & = 160 \\
35a & + & 20\boldsymbol{b} & & & & & + & s_m & & = 1190 \\
a & , & \boldsymbol{b} & , & s_c & , & s_h & , & s_m & & \geq 0
\end{array}
$$

basis $= \{s_c, s_h, s_m\}$

$a = b = 0$

$Z = 0$

$s_c = 480$

$s_h = 160$

$s_m = 1190$

Substitute $b = \frac{1}{15}(480 - 5a - s_c)$.

max Z

$$\begin{array}{rcl}
13a + 23\boldsymbol{b} & - Z & = 0 \\
5a + 15\boldsymbol{b} + s_c & & = 480 \\
4a + 4\boldsymbol{b} + s_h & & = 160 \\
35a + 20\boldsymbol{b} + s_m & & = 1190 \\
a\ ,\ \boldsymbol{b}\ ,\ s_c\ ,\ s_h\ ,\ s_m & & \geq 0
\end{array}$$

basis $= \{s_c, s_h, s_m\}$

$a = b = 0$

$Z = 0$

$s_c = 480$

$s_h = 160$

$s_m = 1190$

Substitute $b = \frac{1}{15}(480 - 5a - s_c)$.

max Z

$$\begin{array}{rcl}
\frac{16}{3}a - \frac{23}{15}s_c & - Z & = -736 \\
\frac{1}{3}a + b + \frac{1}{15}s_c & & = 32 \\
\frac{8}{3}a - \frac{4}{15}s_c + s_h & & = 32 \\
\frac{85}{3}a - \frac{4}{3}s_c + s_m & & = 550 \\
a\ ,\ b\ ,\ s_c\ ,\ s_h\ ,\ s_m & & \geq 0
\end{array}$$

basis $= \{b, s_h, s_m\}$

$a = s_c = 0$

$Z = 736$

$b = 32$

$s_h = 32$

$s_m = 550$

max Z

$$\begin{aligned}
\tfrac{16}{3}a \phantom{{}+b} - \tfrac{23}{15}s_c \phantom{{}+s_h+s_m} - Z &= -736 \\
\tfrac{1}{3}a + b + \tfrac{1}{15}s_c \phantom{{}+s_h+s_m-Z} &= 32 \\
\tfrac{8}{3}a \phantom{{}+b} - \tfrac{4}{15}s_c + s_h \phantom{{}+s_m-Z} &= 32 \\
\tfrac{85}{3}a \phantom{{}+b} - \tfrac{4}{3}s_c \phantom{{}+s_h} + s_m \phantom{{}-Z} &= 550 \\
a\ ,\ b\ ,\ s_c\ ,\ s_h\ ,\ s_m &\geq 0
\end{aligned}$$

basis = $\{b, s_h, s_m\}$
$a = s_c = 0$
$Z = 736$

$b = 32$
$s_h = 32$
$s_m = 550$

max Z

$$\begin{aligned}
\tfrac{16}{3}\boldsymbol{a} \qquad\quad - \tfrac{23}{15}s_c \qquad\qquad\qquad - Z &= -736\\
\tfrac{1}{3}\boldsymbol{a} + b + \tfrac{1}{15}s_c \qquad\qquad\qquad\qquad &= 32\\
\tfrac{8}{3}\boldsymbol{a} \qquad\quad - \tfrac{4}{15}s_c + s_h \qquad\qquad\qquad &= 32\\
\tfrac{85}{3}\boldsymbol{a} \qquad\quad - \tfrac{4}{3}s_c \qquad + s_m \qquad\quad &= 550\\
\boldsymbol{a}\ ,\ b\ ,\quad s_c\ ,\ s_h\ ,\ s_m \qquad\quad &\geq 0
\end{aligned}$$

basis $= \{b, s_h, s_m\}$

$a = s_c = 0$

$Z = 736$

$b = 32$

$s_h = 32$

$s_m = 550$

Choose variable a to bring into basis.

max Z

$$\begin{array}{rcrcrcrcrcrcl}
\frac{16}{3}a & & & - & \frac{23}{15}s_c & & & & & - & Z & = & -736 \\
\frac{1}{3}a & + & b & + & \frac{1}{15}s_c & & & & & & & = & 32 \\
\frac{8}{3}a & & & - & \frac{4}{15}s_c & + & s_h & & & & & = & 32 \\
\frac{85}{3}a & & & - & \frac{4}{3}s_c & & & + & s_m & & & = & 550 \\
a & , & b & , & s_c & , & s_h & , & s_m & & & \geq & 0
\end{array}$$

basis = $\{b, s_h, s_m\}$

$a = s_c = 0$

$Z = 736$

$b = 32$

$s_h = 32$

$s_m = 550$

Choose variable a to bring into basis.

Computing $\min\{3 \cdot 32, {}^{3\cdot 32}/_{8}, {}^{3\cdot 550}/_{85}\}$ means pivot on line 2.

max Z

$$\begin{array}{rcccccccl}
\frac{16}{3}a & & - & \frac{23}{15}s_c & & & - Z & = & -736 \\
\frac{1}{3}a & + b & + & \frac{1}{15}s_c & & & & = & 32 \\
\frac{8}{3}\boldsymbol{a} & & - & \frac{4}{15}s_c & + s_h & & & = & 32 \\
\frac{85}{3}a & & - & \frac{4}{3}s_c & & + s_m & & = & 550 \\
a & , b & , & s_c & , s_h & , s_m & & \geq & 0
\end{array}$$

basis = $\{b, s_h, s_m\}$

$a = s_c = 0$

$Z = 736$

$b = 32$

$s_h = 32$

$s_m = 550$

Choose variable a to bring into basis.

Computing $\min\{3 \cdot 32, {}^{3 \cdot 32}/_{8}, {}^{3 \cdot 550}/_{85}\}$ means pivot on line 2.

Substitute $a = \frac{3}{8}(32 + \frac{4}{15}s_c - s_h)$.

max Z

$$\begin{array}{rcrcrcrcrcrcl}
\frac{16}{3}a & & & - & \frac{23}{15}s_c & & & & & - & Z & = & -736 \\
\frac{1}{3}a & + & b & + & \frac{1}{15}s_c & & & & & & & = & 32 \\
\frac{8}{3}\boldsymbol{a} & & & - & \frac{4}{15}s_c & + & s_h & & & & & = & 32 \\
\frac{85}{3}a & & & - & \frac{4}{3}s_c & & & + & s_m & & & = & 550 \\
a & , & b & , & s_c & , & s_h & , & s_m & & & \geq & 0
\end{array}$$

basis $= \{b, s_h, s_m\}$
$a = s_c = 0$
$Z = 736$

$b = 32$
$s_h = 32$
$s_m = 550$

Choose variable a to bring into basis.

Computing $\min\{3 \cdot 32, {}^{3\cdot 32}/{}_{8}, {}^{3\cdot 550}/{}_{85}\}$ means pivot on line 2.

Substitute $a = \frac{3}{8}(32 + \frac{4}{15}s_c - s_h)$.

max Z

$$\begin{array}{rcrcrcrcrcrcl}
 & & & - & s_c & - & 2s_h & & & - & Z & = & -800 \\
 & & b & + & \frac{1}{10}s_c & - & \frac{1}{8}s_h & & & & & = & 28 \\
a & & & - & \frac{1}{10}s_c & + & \frac{3}{8}s_h & & & & & = & 12 \\
 & & & & \frac{3}{2}s_c & - & \frac{85}{8}s_h & + & s_m & & & = & 210 \\
a & , & b & , & s_c & , & s_h & , & s_m & & & \geq & 0
\end{array}$$

basis $= \{a, b, s_m\}$
$s_c = s_h = 0$
$Z = 800$

$b = 28$
$a = 12$
$s_m = 210$

4 Simplex Algorithm

Pivoting stops when all coefficients in the objective function are non-positive.

Solution is optimal:

- any feasible solution satisfies all equations in the tableaux
- in particular: $Z = 800 - s_c - 2s_h$, $s_c \geq 0, s_h \geq 0$
- hence optimum solution value is at most 800
- the current solution has value 800

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Matrix View

Let our linear program be

$$\begin{array}{rcrcl} c_B^T x_B & + & c_N^T x_N & = & Z \\ A_B x_B & + & A_N x_N & = & b \\ x_B & , & x_N & \geq & 0 \end{array}$$

The simplex tableaux for basis B is

$$\begin{array}{rcrcl} & & (c_N^T - c_B^T A_B^{-1} A_N) x_N & = & Z - c_B^T A_B^{-1} b \\ I x_B & + & A_B^{-1} A_N x_N & = & A_B^{-1} b \\ x_B & , & x_N & \geq & 0 \end{array}$$

The BFS is given by $x_N = 0, x_B = A_B^{-1} b$.

If $(c_N^T - c_B^T A_B^{-1} A_N) \leq 0$ we know that we have an optimum solution.

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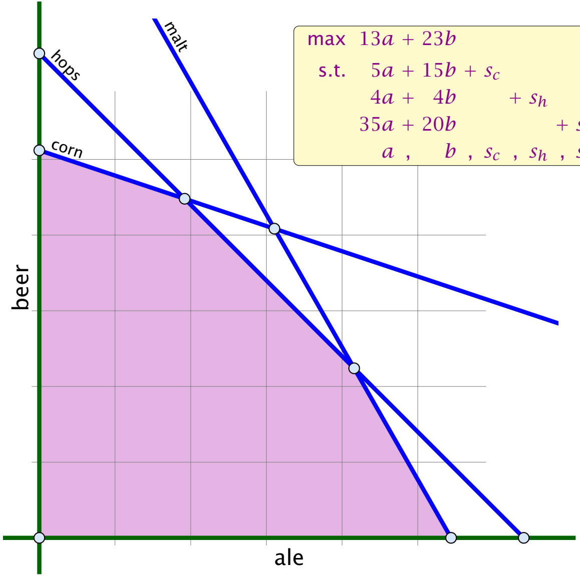
Geometric View of Pivoting



$$\begin{array}{lrcl}
\text{max} & 13a + 23b & & \\
\text{s.t.} & 5a + 15b + s_c & & = 480 \\
 & 4a + 4b \quad + s_h & & = 160 \\
 & 35a + 20b \quad\quad + s_m & & = 1190 \\
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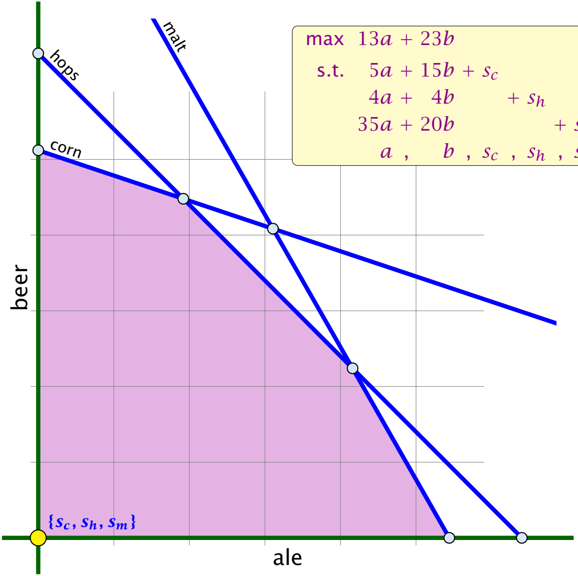
\end{array}$$

Geometric View of Pivoting



$$\begin{array}{ll} \text{max} & 13a + 23b \\ \text{s.t.} & \begin{array}{rcrcccccl} 5a & + & 15b & + & s_c & & & = & 480 \\ 4a & + & 4b & & & + s_h & & = & 160 \\ 35a & + & 20b & & & & + s_m & = & 1190 \\ a & , & b & , & s_c & , s_h & , s_m & \geq & 0 \end{array} \end{array}$$

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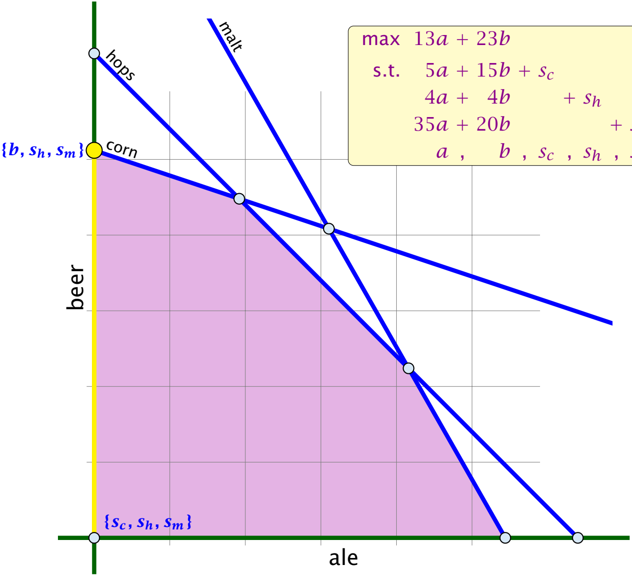

$$
\begin{array}{rrcrcccccl}
\text{max} & 13a & + & 23b & & & & & & \\
\text{s.t.} & 5a & + & 15b & + & s_c & & & & = 480 \\
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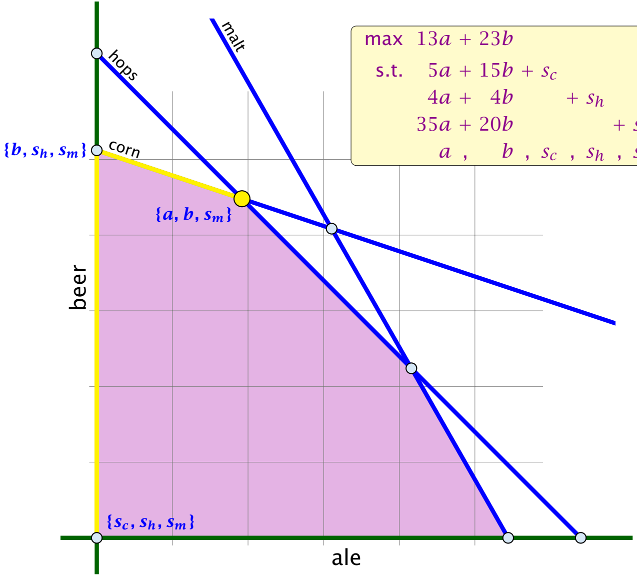

$$\begin{array}{lrcrcrcrcrcl}
\text{max} & 13a & + & 23b & & & & & & & & \\
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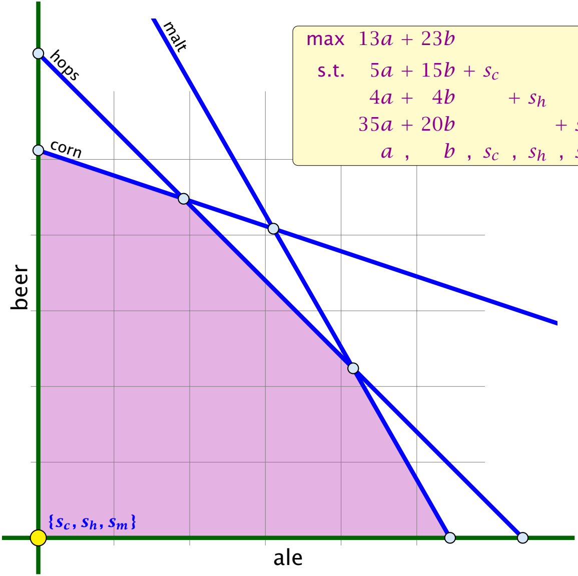

$$
\begin{array}{lrcrcccccl}
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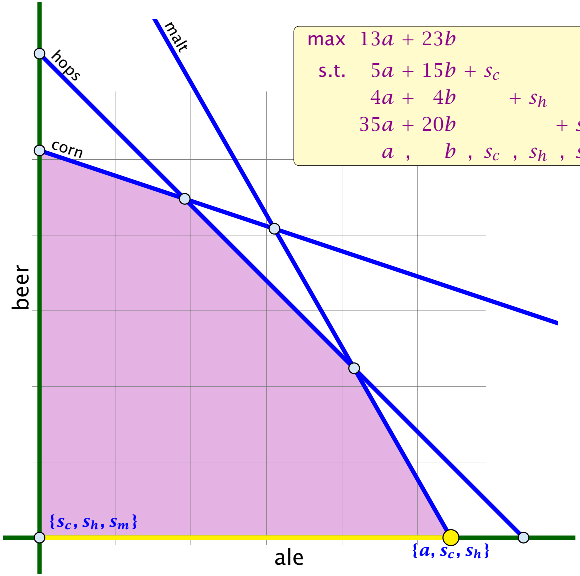

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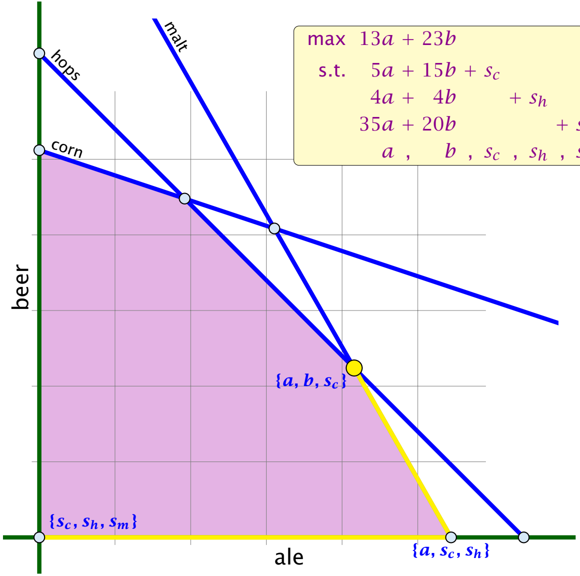

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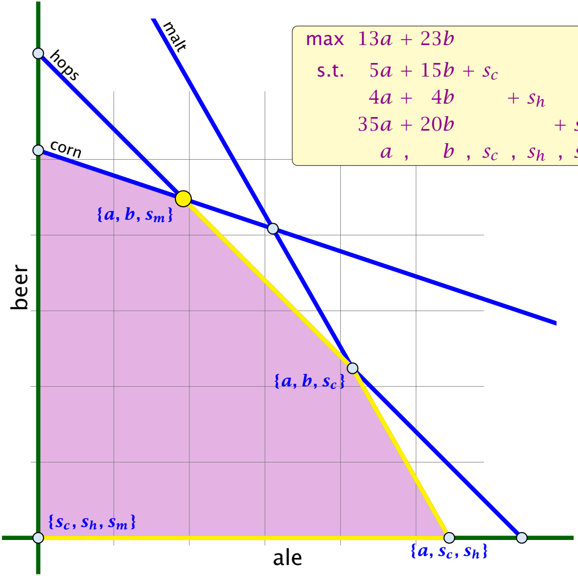

$$
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 & a & , & b & , & s_c & , & s_h & , & s_m & \geq & 0
\end{array}
$$

Algebraic Definition of Pivoting

- Given basis B with BFS x^*.
- Choose index $j \notin B$ in order to increase x_j^* from 0 to $\theta > 0$.
  - Other non-basis variables should stay at 0.
  - Basis variables change to maintain feasibility.
- Go from x^* to $x^* + \theta \cdot d$.

Requirements for d:

- $d_j = 1$ (normalization)
- $d_\ell = 0$, $\ell \notin B$, $\ell \neq j$
- $A(x^* + \theta d) = b$ must hold. Hence $Ad = 0$.
- Altogether: $A_B d_B + A_{*j} = Ad = 0$, which gives $d_B = -A_B^{-1} A_{*j}$.

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Algebraic Definition of Pivoting

- Given basis B with BFS x^*.
- Choose index $j \notin B$ in order to increase x_j^* from 0 to $\theta > 0$.
  - Other non-basis variables should stay at 0.
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- Go from x^* to $x^* + \theta \cdot d$.

Requirements for d:

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Algebraic Definition of Pivoting

Definition 26 (j-th basis direction)

Let B be a basis, and let $j \notin B$. The vector d with $d_j = 1$ and $d_\ell = 0, \ell \notin B, \ell \neq j$ and $d_B = -A_B^{-1}A_{*j}$ is called the j-th basis direction for B.

Going from x^* to $x^* + \theta \cdot d$ the objective function changes by

$$\theta \cdot c^T d = \theta(c_j - c_B^T A_B^{-1} A_{*j})$$

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Definition 27 (Reduced Cost)
For a basis B the value

$$\tilde{c}_j = c_j - c_B^T A_B^{-1} A_{*j}$$

is called the reduced cost for variable x_j.

Note that this is defined for every j. If $j \in B$ then the above term is 0.

Algebraic Definition of Pivoting

Let our linear program be

$$\begin{array}{rcrcl} c_B^T x_B & + & c_N^T x_N & = & Z \\ A_B x_B & + & A_N x_N & = & b \\ x_B & , & x_N & \geq & 0 \end{array}$$

The simplex tableaux for basis B is

$$\begin{array}{rcrcl} & & (c_N^T - c_B^T A_B^{-1} A_N) x_N & = & Z - c_B^T A_B^{-1} b \\ I x_B & + & A_B^{-1} A_N x_N & = & A_B^{-1} b \\ x_B & , & x_N & \geq & 0 \end{array}$$

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4 Simplex Algorithm

Questions:

- What happens if the min ratio test fails to give us a value θ by which we can safely increase the entering variable?
- How do we find the initial basic feasible solution?
- Is there always a basis B such that

$$(c_N^T - c_B^T A_B^{-1} A_N) \le 0 \ ?$$

  Then we can terminate because we know that the solution is optimal.
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Min Ratio Test

The min ratio test computes a value $\theta \geq 0$ such that after setting the entering variable to θ the leaving variable becomes 0 and all other variables stay non-negative.

For this, one computes b_i/A_{ie} for all constraints i and calculates the minimum positive value.

What does it mean that the ratio b_i/A_{ie} (and hence A_{ie}) is negative for a constraint?

This means that the corresponding basic variable will increase if we increase b. Hence, there is no danger of this basic variable becoming negative

What happens if **all** b_i/A_{ie} are negative? Then we do not have a leaving variable. Then the LP is unbounded!

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Because a variable x_ℓ with $\ell \in B$ is already 0.

The set of inequalities is degenerate (also the basis is degenerate).

Definition 28 (Degeneracy)

A BFS x^* is called degenerate if the set $J = \{j \mid x_j^* > 0\}$ fulfills $|J| < m$.

It is possible that the algorithm cycles, i.e., it cycles through a sequence of different bases without ever terminating. Happens, very rarely in practise.

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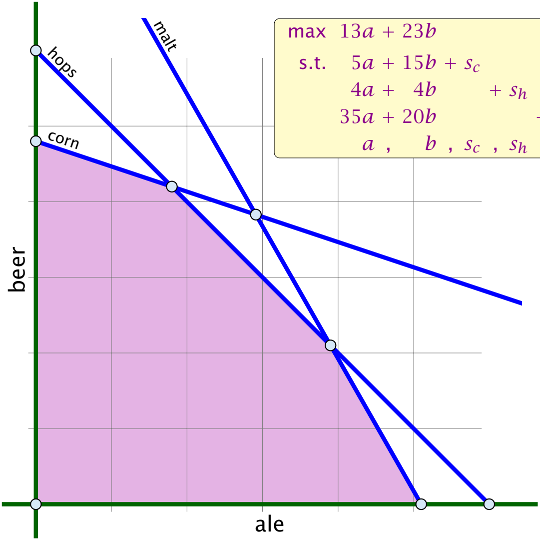
Non Degenerate Example



$$\begin{array}{llcccccl}
\text{max} & 13a + 23b & & & & & & \\
\text{s.t.} & 5a + 15b & + s_c & & & = & 480 \\
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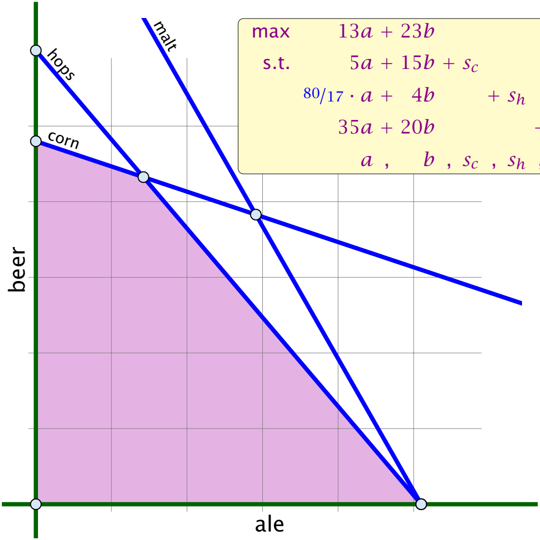

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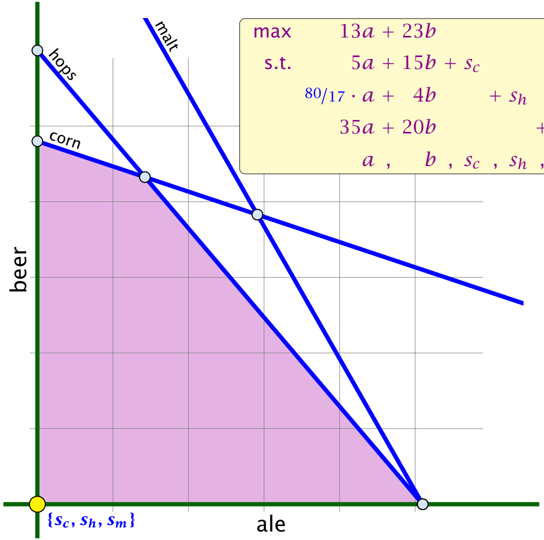

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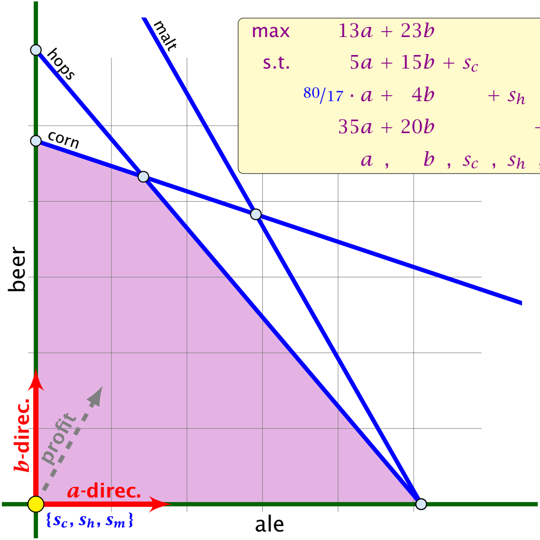

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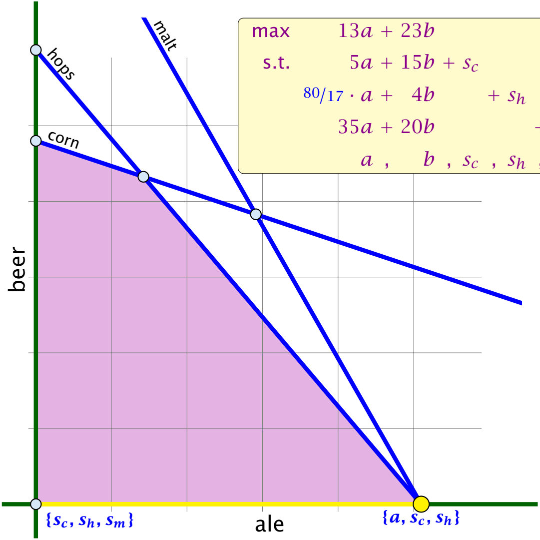

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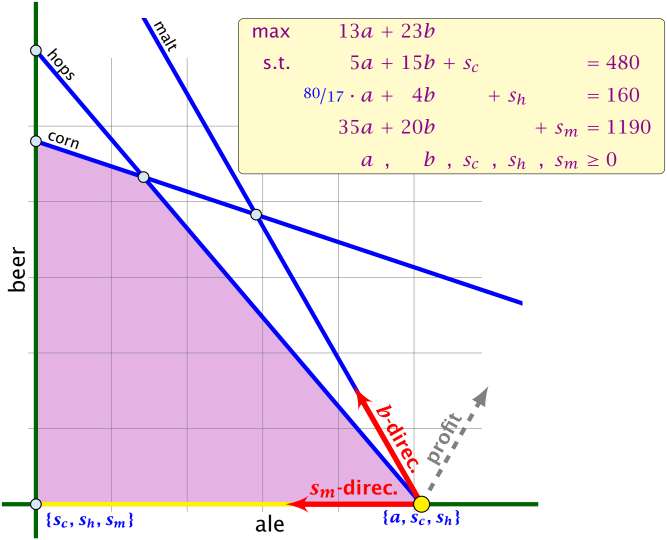

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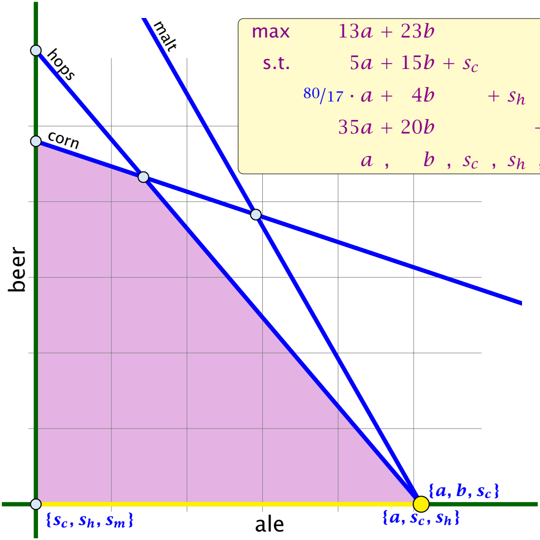

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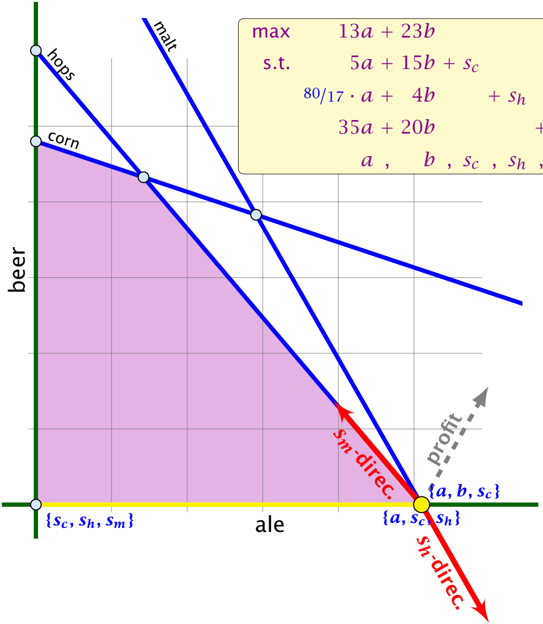

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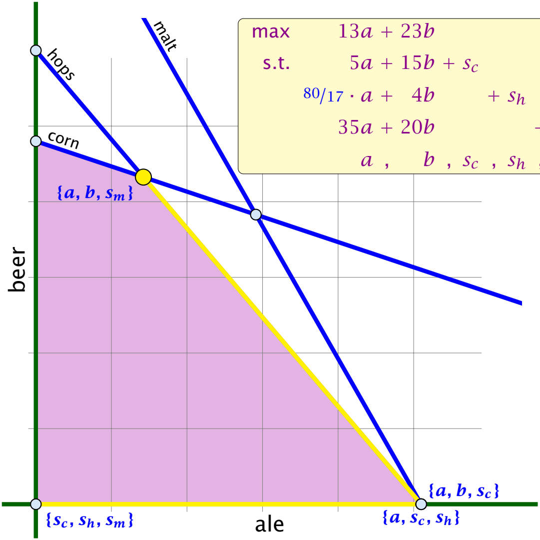

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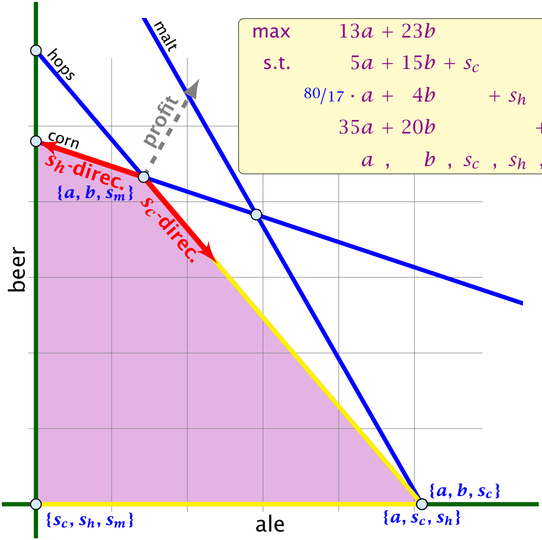

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Summary: How to choose pivot-elements

- We can choose a column e as an entering variable if $\tilde{c}_e > 0$ ($\tilde{c}_e$ is reduced cost for x_e).
- The standard choice is the column that maximizes $\tilde{c}_e$.
- If $A_{ie} \leq 0$ for all $i \in \{1, \ldots, m\}$ then the maximum is not bounded.
- Otw. choose a leaving variable ℓ such that $b_\ell / A_{\ell e}$ is minimal among all variables i with $A_{ie} > 0$.
- If several variables have minimum $b_\ell / A_{\ell e}$ you reach a degenerate basis.
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- Otw. choose a leaving variable ℓ such that $b_\ell / A_{\ell e}$ is minimal among all variables i with $A_{ie} > 0$.
- If several variables have minimum $b_\ell / A_{\ell e}$ you reach a degenerate basis.
- Depending on the choice of ℓ it may happen that the algorithm runs into a cycle where it does not escape from a degenerate vertex.

Summary: How to choose pivot-elements

- We can choose a column e as an entering variable if $\tilde{c}_e > 0$ ($\tilde{c}_e$ is reduced cost for x_e).
- The standard choice is the column that maximizes $\tilde{c}_e$.
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Termination

What do we have so far?
Suppose we are given an initial feasible solution to an LP. If the LP is non-degenerate then Simplex will terminate.

Note that we either terminate because the min-ratio test fails and we can conclude that the LP is unbounded, or we terminate because the vector of reduced cost is non-positive. In the latter case we have an optimum solution.

How do we come up with an initial solution?

- $Ax \le b, x \ge 0$, and $\boldsymbol{b} \ge \boldsymbol{0}$.
- The standard slack form for this problem is $Ax + Is = b, x \ge 0, s \ge 0$, where s denotes the vector of slack variables.
- Then $s = b$, $x = 0$ is a basic feasible solution (how?).
- We directly can start the simplex algorithm.

How do we find an initial basic feasible solution for an arbitrary problem?

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How do we find an initial basic feasible solution for an arbitrary problem?

Two phase algorithm

Suppose we want to maximize c^Tx s.t. $Ax = b, x \geq 0$.

1. Multiply all rows with $b_i < 0$ by -1.
2. maximize $-\sum_i v_i$ s.t. $Ax + Iv = b$, $x \geq 0$, $v \geq 0$ using Simplex. $x = 0$, $v = b$ is initial feasible.
3. If $\sum_i v_i > 0$ then the original problem is infeasible.
4. Otw. you have $x \geq 0$ with $Ax = b$.
5. From this you can get basic feasible solution.
6. Now you can start the Simplex for the original problem.

Two phase algorithm

Suppose we want to maximize $c^T x$ s.t. $Ax = b, x \geq 0$.

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Optimality

Lemma 29

Let B be a basis and x^* a BFS corresponding to basis B. $\tilde{c} \leq 0$ implies that x^* is an optimum solution to the LP.

Duality

How do we get an upper bound to a maximization LP?

$$\begin{array}{rrcrl}
\text{max} & 13a & + & 23b & \\
\text{s.t.} & 5a & + & 15b & \le 480 \\
 & 4a & + & 4b & \le 160 \\
 & 35a & + & 20b & \le 1190 \\
 & & & a, b & \ge 0
\end{array}$$

Note that a lower bound is easy to derive. Every choice of $a, b \ge 0$ gives us a lower bound (e.g. $a = 12, b = 28$ gives us a lower bound of 800).

If you take a conic combination of the rows (multiply the i-th row with $y_i \ge 0$) such that $\sum_i y_i a_{ij} \ge c_j$ then $\sum_i y_i b_i$ will be an upper bound.

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Duality

Definition 30
Let $z = \max\{c^T x \mid Ax \le b, x \ge 0\}$ be a linear program P (called the primal linear program).

The linear program D defined by

$$w = \min\{b^T y \mid A^T y \ge c, y \ge 0\}$$

is called the dual problem.

Duality

Lemma 31

The dual of the dual problem is the primal problem.

Proof:

- $w = \min\{b^Ty \mid A^Ty \geq c, y \geq 0\}$
- $w = -\max\{-b^Ty \mid -A^Ty \leq -c, y \geq 0\}$

The dual problem is

- $z = -\min\{-c^Tx \mid -Ax \geq -b, x \geq 0\}$
- $z = \max\{c^Tx \mid Ax \leq b, x \geq 0\}$

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Weak Duality

Let $z = \max\{c^Tx \mid Ax \le b, x \ge 0\}$ and $w = \min\{b^Ty \mid A^Ty \ge c, y \ge 0\}$ be a primal dual pair.

x is primal feasible iff $x \in \{x \mid Ax \le b, x \ge 0\}$

y is dual feasible, iff $y \in \{y \mid A^Ty \ge c, y \ge 0\}$.

Theorem 32 (Weak Duality)

Let $\hat{x}$ be primal feasible and let $\hat{y}$ be dual feasible. Then

$$c^T\hat{x} \le z \le w \le b^T\hat{y}\ .$$

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Weak Duality

$A^T\hat{y} \geq c \Rightarrow \hat{x}^TA^T\hat{y} \geq \hat{x}^Tc \ (\hat{x} \geq 0)$

$A\hat{x} \leq b \Rightarrow y^TA\hat{x} \leq \hat{y}^Tb \ (\hat{y} \geq 0)$

This gives

$$c^T\hat{x} \leq \hat{y}^TA\hat{x} \leq b^T\hat{y} \ .$$

Since, there exists primal feasible $\hat{x}$ with $c^T\hat{x} = z$, and dual feasible $\hat{y}$ with $b^T\hat{y} = w$ we get $z \leq w$.

If P is unbounded then D is infeasible.

Weak Duality

$A^T\hat{y} \geq c \Rightarrow \hat{x}^T A^T \hat{y} \geq \hat{x}^T c$ $(\hat{x} \geq 0)$

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If P is unbounded then D is infeasible.

5.2 Simplex and Duality

The following linear programs form a primal dual pair:

$$
\begin{aligned}
z &= \max\{c^T x \mid Ax = b, x \geq 0\} \\
w &= \min\{b^T y \mid A^T y \geq c\}
\end{aligned}
$$

This means for computing the dual of a standard form LP, we do not have non-negativity constraints for the dual variables.

Proof

Primal:

$$\max\{c^Tx \mid Ax = b, x \geq 0\}$$

Proof

Primal:

$$\begin{aligned}&\max\{c^Tx \mid Ax = b, x \geq 0\}\\&\qquad = \max\{c^Tx \mid Ax \leq b, -Ax \leq -b, x \geq 0\}\end{aligned}$$

Proof

Primal:

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\begin{aligned}
&\max\{c^Tx \mid Ax = b, x \geq 0\}\\
&\qquad = \max\{c^Tx \mid Ax \leq b, -Ax \leq -b, x \geq 0\}\\
&\qquad = \max\{c^Tx \mid \begin{bmatrix} A \\ -A \end{bmatrix} x \leq \begin{bmatrix} b \\ -b \end{bmatrix}, x \geq 0\}
\end{aligned}
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Proof

Primal:

$$\begin{aligned}
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\end{aligned}$$

Dual:

$$\min\{[b^T \; -b^T]y \mid [A^T \; -A^T]y \ge c, y \ge 0\}$$

Proof

Primal:

$$\begin{aligned}&\max\{c^Tx \mid Ax = b, x \geq 0\}\\&\quad = \max\{c^Tx \mid Ax \leq b, -Ax \leq -b, x \geq 0\}\\&\quad = \max\{c^Tx \mid \begin{bmatrix} A \\ -A \end{bmatrix} x \leq \begin{bmatrix} b \\ -b \end{bmatrix}, x \geq 0\}\end{aligned}$$

Dual:

$$\begin{aligned}&\min\{[b^T \; -b^T]y \mid [A^T \; -A^T]y \geq c, y \geq 0\}\\&\quad = \min\left\{[b^T \; -b^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \,\middle|\, [A^T \; -A^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \geq c, y^- \geq 0, y^+ \geq 0\right\}\end{aligned}$$

Proof

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&\qquad = \max\{c^Tx \mid Ax \leq b, -Ax \leq -b, x \geq 0\}\\
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\end{aligned}$$

Dual:

$$\begin{aligned}
&\min\{[b^T\ -b^T]y \mid [A^T\ -A^T]y \geq c, y \geq 0\}\\
&\qquad = \min\left\{[b^T\ -b^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \middle| [A^T\ -A^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \geq c, y^- \geq 0, y^+ \geq 0\right\}\\
&\qquad = \min\left\{b^T \cdot (y^+ - y^-) \middle| A^T \cdot (y^+ - y^-) \geq c, y^- \geq 0, y^+ \geq 0\right\}
\end{aligned}$$

Proof

Primal:

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&\qquad = \min\left\{b^T \cdot (y^+ - y^-) \;\middle|\; A^T \cdot (y^+ - y^-) \geq c, y^- \geq 0, y^+ \geq 0\right\}\\
&\qquad = \min\left\{b^Ty' \;\middle|\; A^Ty' \geq c\right\}
\end{aligned}
$$

Proof of Optimality Criterion for Simplex

Suppose that we have a basic feasible solution with reduced cost

$$\tilde{c} = c^T - c_B^T A_B^{-1} A \le 0$$

This is equivalent to $A^T (A_B^{-1})^T c_B \ge c$

$y^* = (A_B^{-1})^T c_B$ is solution to the dual $\min\{b^T y | A^T y \ge c\}$.

$$\begin{aligned} b^T y^* &= (Ax^*)^T y^* = (A_B x_B^*)^T y^* \\ &= (A_B x_B^*)^T (A_B^{-1})^T c_B = (x_B^*)^T A_B^T (A_B^{-1})^T c_B \\ &= c^T x^* \end{aligned}$$

Hence, the solution is optimal.

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$$\tilde{c} = c^T - c_B^T A_B^{-1} A \leq 0$$

This is equivalent to $A^T (A_B^{-1})^T c_B \geq c$

$y^* = (A_B^{-1})^T c_B$ is solution to the dual $\min\{b^T y | A^T y \geq c\}$.

$$\begin{aligned} b^T y^* &= (Ax^*)^T y^* = (A_B x_B^*)^T y^* \\ &= (A_B x_B^*)^T (A_B^{-1})^T c_B = (x_B^*)^T A_B^T (A_B^{-1})^T c_B \\ &= c^T x^* \end{aligned}$$

Hence, the solution is optimal.

Proof of Optimality Criterion for Simplex

Suppose that we have a basic feasible solution with reduced cost

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Hence, the solution is optimal.

5.3 Strong Duality

$P = \max\{c^T x \mid Ax \le b, x \ge 0\}$

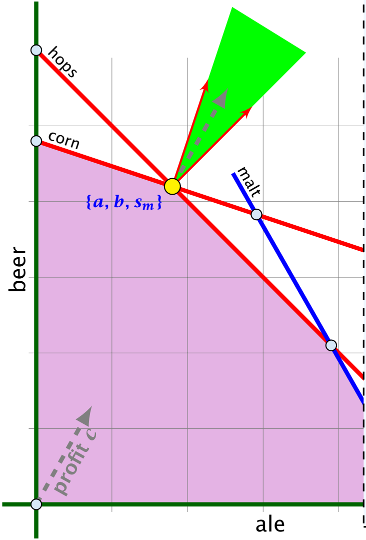
n_A: number of variables, m_A: number of constraints

We can put the non-negativity constraints into A (which gives us unrestricted variables): $\bar{P} = \max\{c^T x \mid \bar{A}x \le \bar{b}\}$

$n_{\bar{A}} = n_A$, $m_{\bar{A}} = m_A + n_A$

Dual $D = \min\{\bar{b}^T y \mid \bar{A}^T y = c, y \ge 0\}$.

5.3 Strong Duality



If we have a conic combination y of c then b^Ty is an upper bound of the profit we can obtain (weak duality):

$$c^Tx = (\bar{A}^Ty)^Tx = y^T\bar{A}x \le y^T\bar{b}$$

If x and y are optimal then the duality gap is 0 (strong duality). This means

$$\begin{aligned} 0 &= c^Tx - y^T\bar{b} \\ &= (\bar{A}^Ty)^Tx - y^T\bar{b} \\ &= y^T(\bar{A}x - \bar{b}) \end{aligned}$$

The last term can only be 0 if y_i is 0 whenever the i-th constraint is not tight. This means we have a conic combination of c by normals (columns of $\bar{A}^T$) of *tight* constraints.

Conversely, if we have x such that the normals of tight constraint (at x) give rise to a conic combination of c, we know that x is optimal.

The profit vector c lies in the cone generated by the normals for the hops and the corn constraint (the tight constraints).

Strong Duality

Theorem 33 (Strong Duality)

Let P and D be a primal dual pair of linear programs, and let z^* and w^* denote the optimal solution to P and D, respectively. Then

$$z^* = w^*$$

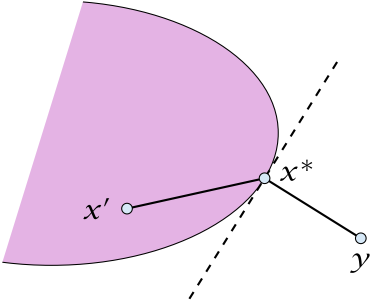
Lemma 34 (Weierstrass)

Let X be a compact set and let $f(x)$ be a continuous function on X. Then $\min\{f(x) : x \in X\}$ exists.

(without proof)

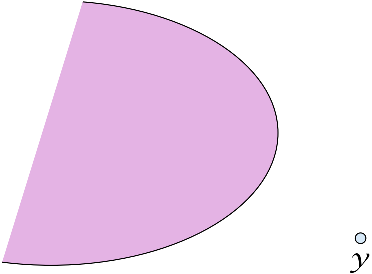
Lemma 35 (Projection Lemma)

Let $X \subseteq \mathbb{R}^m$ be a non-empty convex set, and let $y \notin X$. Then there exist $x^* \in X$ with minimum distance from y. Moreover for all $x \in X$ we have $(y - x^*)^T (x - x^*) \leq 0$.



Proof of the Projection Lemma

- Define $f(x) = \|y - x\|$.
- We want to apply Weierstrass but X may not be bounded.
- $X \neq \emptyset$. Hence, there exists $x' \in X$.
- Define $X' = \{x \in X \mid \|y - x\| \leq \|y - x'\|\}$. This set is closed and bounded.
- Applying Weierstrass gives the existence.



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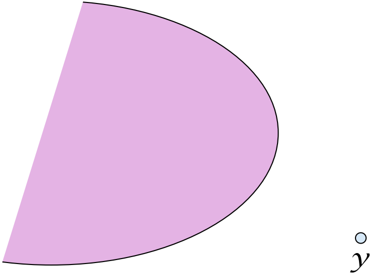

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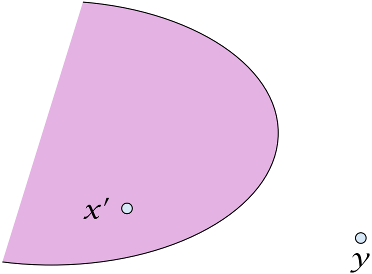

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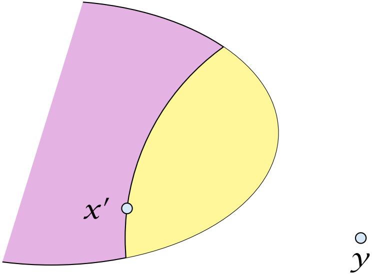

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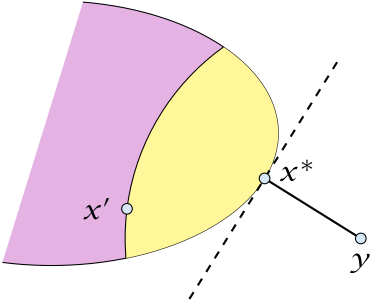

Proof of the Projection Lemma (continued)

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x^* is minimum. Hence $\|y - x^*\|^2 \leq \|y - x\|^2$ for all $x \in X$.

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By convexity: $x \in X$ then $x^* + \epsilon(x - x^*) \in X$ for all $0 \le \epsilon \le 1$.

Proof of the Projection Lemma (continued)

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$\|y - x^*\|^2$

Proof of the Projection Lemma (continued)

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By convexity: $x \in X$ then $x^* + \epsilon(x - x^*) \in X$ for all $0 \leq \epsilon \leq 1$.

$$\|y - x^*\|^2 \leq \|y - x^* - \epsilon(x - x^*)\|^2$$

Proof of the Projection Lemma (continued)

x^* is minimum. Hence $\|y - x^*\|^2 \leq \|y - x\|^2$ for all $x \in X$.

By convexity: $x \in X$ then $x^* + \epsilon(x - x^*) \in X$ for all $0 \leq \epsilon \leq 1$.

$$\begin{aligned}\|y - x^*\|^2 &\leq \|y - x^* - \epsilon(x - x^*)\|^2 \\ &= \|y - x^*\|^2 + \epsilon^2\|x - x^*\|^2 - 2\epsilon(y - x^*)^T(x - x^*)\end{aligned}$$

Proof of the Projection Lemma (continued)

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Hence, $(y - x^*)^T(x - x^*) \le \frac{1}{2}\epsilon\|x - x^*\|^2$.

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Hence, $(y - x^*)^T(x - x^*) \le \frac{1}{2}\epsilon\|x - x^*\|^2$.

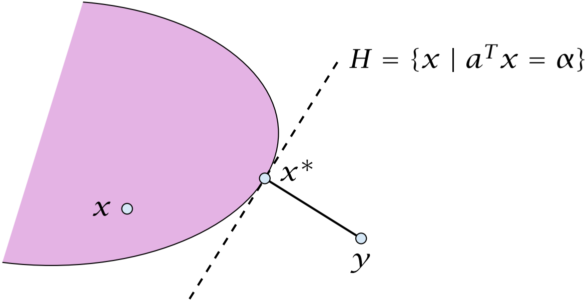
Letting $\epsilon \to 0$ gives the result.

Theorem 36 (Separating Hyperplane)

Let $X \subseteq \mathbb{R}^m$ be a non-empty closed convex set, and let $y \notin X$. Then there exists a separating hyperplane $\{x \in \mathbb{R} : a^T x = \alpha\}$ where $a \in \mathbb{R}^m$, $\alpha \in \mathbb{R}$ that separates y from X. ($a^T y < \alpha$; $a^T x \geq \alpha$ for all $x \in X$)

Proof of the Hyperplane Lemma

- Let $x^* \in X$ be closest point to y in X.
- By previous lemma $(y - x^*)^T(x - x^*) \leq 0$ for all $x \in X$.
- Choose $a = (x^* - y)$ and $\alpha = a^T x^*$.
- For $x \in X : a^T(x - x^*) \geq 0$, and, hence, $a^T x \geq \alpha$.
- Also, $a^T y = a^T(x^* - a) = \alpha - \|a\|^2 < \alpha$



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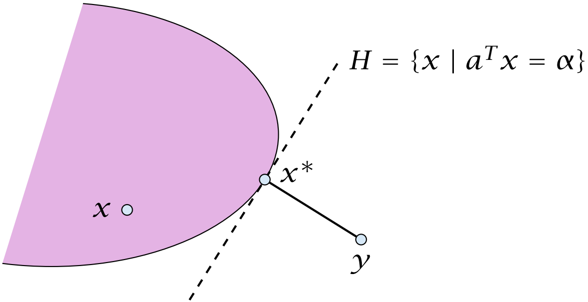

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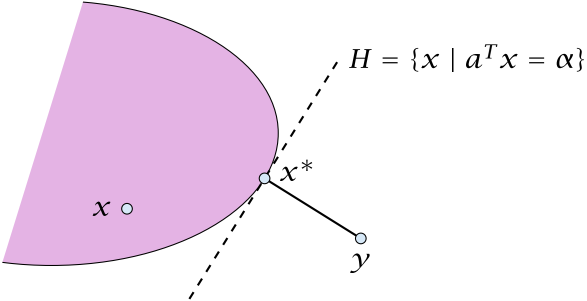

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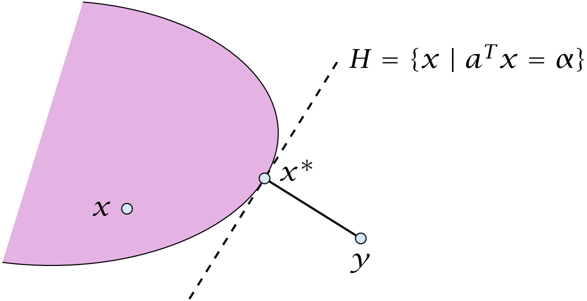

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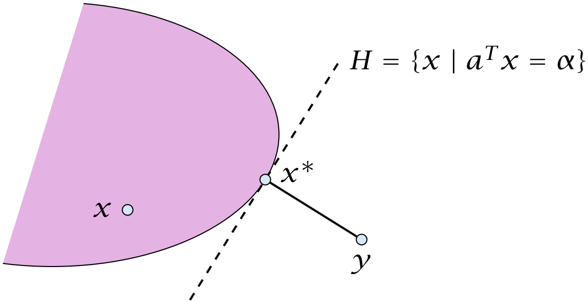

Lemma 37 (Farkas Lemma)

Let A be an $m \times n$ matrix, $b \in \mathbb{R}^m$. Then exactly one of the following statements holds.

1. $\exists x \in \mathbb{R}^n$ *with* $Ax = b$, $x \geq 0$
2. $\exists y \in \mathbb{R}^m$ *with* $A^T y \geq 0$, $b^T y < 0$

Assume $\hat{x}$ satisfies 1. and $\hat{y}$ satisfies 2. Then

$$0 > y^T b = y^T A x \geq 0$$

Hence, at most one of the statements can hold.

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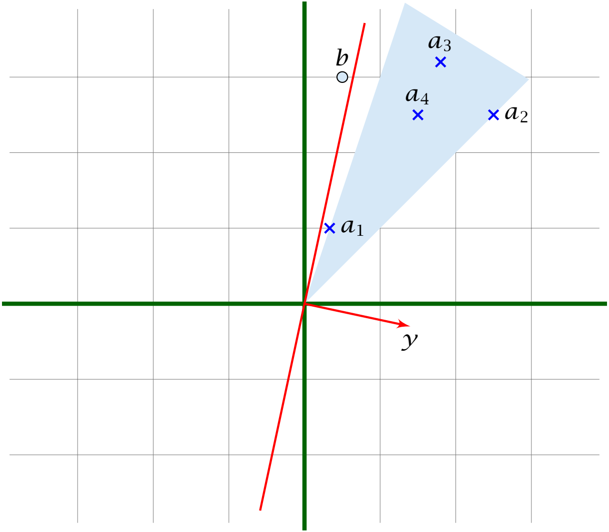
Farkas Lemma



If b is not in the cone generated by the columns of A, there exists a hyperplane y that separates b from the cone.

Proof of Farkas Lemma

Now, assume that 1. does not hold.

Consider $S = \{Ax : x \geq 0\}$ so that S closed, convex, $b \notin S$.

We want to show that there is y with $A^Ty \geq 0$, $b^Ty < 0$.

Let y be a hyperplane that separates b from S. Hence, $y^Tb < \alpha$ and $y^Ts \geq \alpha$ for all $s \in S$.

$0 \in S \Rightarrow \alpha \leq 0 \Rightarrow y^Tb < 0$

$y^TAx \geq \alpha$ for all $x \geq 0$. Hence, $y^TA \geq 0$ as we can choose x arbitrarily large.

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$0 \in S \Rightarrow \alpha \leq 0 \Rightarrow y^T b < 0$

$y^T Ax \geq \alpha$ for all $x \geq 0$. Hence, $y^T A \geq 0$ as we can choose x arbitrarily large.

Proof of Farkas Lemma

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$0 \in S \Rightarrow \alpha \leq 0 \Rightarrow y^T b < 0$

$y^T Ax \geq \alpha$ for all $x \geq 0$. Hence, $y^T A \geq 0$ as we can choose x arbitrarily large.

Lemma 38 (Farkas Lemma; different version)

Let A be an $m \times n$ matrix, $b \in \mathbb{R}^m$. Then exactly one of the following statements holds.

1. $\exists x \in \mathbb{R}^n$ *with* $Ax \leq b$, $x \geq 0$
2. $\exists y \in \mathbb{R}^m$ *with* $A^T y \geq 0$, $b^T y < 0$, $y \geq 0$

Rewrite the conditions:

1. $\exists x \in \mathbb{R}^n$ with $\begin{bmatrix} A \; I \end{bmatrix} \cdot \begin{bmatrix} x \\ s \end{bmatrix} = b$, $x \geq 0$, $s \geq 0$
2. $\exists y \in \mathbb{R}^m$ with $\begin{bmatrix} A^T \\ I \end{bmatrix} y \geq 0$, $b^T y < 0$

Lemma 38 (Farkas Lemma; different version)

Let A be an $m \times n$ matrix, $b \in \mathbb{R}^m$. Then exactly one of the following statements holds.

1. $\exists x \in \mathbb{R}^n$ *with* $Ax \leq b$, $x \geq 0$
2. $\exists y \in \mathbb{R}^m$ *with* $A^T y \geq 0$, $b^T y < 0$, $y \geq 0$

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Proof of Strong Duality

$P\colon\ z = \max\{c^Tx \mid Ax \leq b, x \geq 0\}$

$D\colon\ w = \min\{b^Ty \mid A^Ty \geq c, y \geq 0\}$

Theorem 39 (Strong Duality)

Let P and D be a primal dual pair of linear programs, and let z and w denote the optimal solution to P and D, respectively (i.e., P and D are non-empty). Then

$$z = w\ .$$

Proof of Strong Duality

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$z \leq w$: follows from weak duality

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We show $z < \alpha$ implies $w < \alpha$.

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We show $z < \alpha$ implies $w < \alpha$.

$$
\begin{array}{lrcl}
\exists x \in \mathbb{R}^n & & & \\
\text{s.t.} & Ax & \leq & b \\
 & -c^T x & \leq & -\alpha \\
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$$\begin{array}{lrcl} \exists y \in \mathbb{R}^m; v \in \mathbb{R} & & & \\ \text{s.t.} & A^T y - cv & \ge & 0 \\ & b^T y - \alpha v & < & 0 \\ & y, v & \ge & 0 \end{array}$$

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From the definition of α we know that the first system is infeasible; hence the second must be feasible.

Proof of Strong Duality

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If the solution y, v has $v = 0$ we have that

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is feasible. By Farkas lemma this gives that LP P is infeasible. Contradiction to the assumption of the lemma.

Proof of Strong Duality

Hence, there exists a solution y, v with $v > 0$.

We can rescale this solution (scaling both y and v) s.t. $v = 1$.

Then y is feasible for the dual but $b^T y < \alpha$. This means that $w < \alpha$.

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Fundamental Questions

Definition 40 (Linear Programming Problem (LP))

Let $A \in \mathbb{Q}^{m \times n}$, $b \in \mathbb{Q}^m$, $c \in \mathbb{Q}^n$, $\alpha \in \mathbb{Q}$. Does there exist $x \in \mathbb{Q}^n$ s.t. $Ax = b$, $x \geq 0$, $c^T x \geq \alpha$?

Questions:

- Is LP in NP?
- Is LP in co-NP? yes!
- Is LP in P?

Proof:

- Given a primal maximization problem P and a parameter α. Suppose that $\alpha > \text{opt}(P)$.
- We can prove this by providing an optimal basis for the dual.
- A verifier can check that the associated dual solution fulfills all dual constraints and that it has dual cost $< \alpha$.

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Complementary Slackness

Lemma 41
Assume a linear program $P = \max\{c^T x \mid Ax \le b; x \ge 0\}$ *has solution* x^* *and its dual* $D = \min\{b^T y \mid A^T y \ge c; y \ge 0\}$ *has solution* y^*.

1. *If* $x_j^* > 0$ *then the* j*-th constraint in* D *is tight.*
2. *If the* j*-th constraint in* D *is not tight than* $x_j^* = 0$.
3. *If* $y_i^* > 0$ *then the* i*-th constraint in* P *is tight.*
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If we say that a variable x_j^* (y_i^*) has slack if $x_j^* > 0$ ($y_i^* > 0$), (i.e., the corresponding variable restriction is not tight) and a contraint has slack if it is not tight, then the above says that for a primal-dual solution pair it is not possible that a constraint **and** its corresponding (dual) variable has slack.

Proof: Complementary Slackness

Analogous to the proof of weak duality we obtain

$$c^T x^* \le y^{*T} A x^* \le b^T y^*$$

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From the constraint of the dual it follows that $y^T A \geq c^T$. Hence the left hand side is a sum over the product of non-negative numbers. Hence, if e.g. $(y^T A - c^T)_j > 0$ (the j-th constraint in the dual is not tight) then $x_j = 0$ (2.). The result for (1./3./4.) follows similarly.

Interpretation of Dual Variables

- Brewer: find mix of ale and beer that maximizes profits

$$\begin{array}{rrcrl}
\text{max} & 13a & + & 23b & \\
\text{s.t.} & 5a & + & 15b & \leq 480 \\
& 4a & + & 4b & \leq 160 \\
& 35a & + & 20b & \leq 1190 \\
& & & a, b & \geq 0
\end{array}$$

- Entrepeneur: buy resources from brewer at minimum cost
  C, H, M: unit price for corn, hops and malt.

$$\begin{array}{rrcrcrl}
\text{min} & 480C & + & 160H & + & 1190M & \\
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Note that brewer won't sell (at least not all) if e.g. $5C + 4H + 35M < 13$ as then brewing ale would be advantageous.

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Interpretation of Dual Variables

Marginal Price:

- How much money is the brewer willing to pay for additional amount of Corn, Hops, or Malt?
- We are interested in the marginal price, i.e., what happens if we increase the amount of Corn, Hops, and Malt by ε_C, ε_H, and ε_M, respectively.

The profit increases to $\max\{c^Tx \mid Ax \le b + \varepsilon; x \ge 0\}$. Because of strong duality this is equal to

$$\begin{array}{lrcl} \min & (b^T + \epsilon^T)y & & \\ \text{s.t.} & A^Ty & \ge & c \\ & y & \ge & 0 \end{array}$$

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If ϵ is “small” enough then the optimum dual solution y^* might not change. Therefore the profit increases by $\sum_i \varepsilon_i y_i^*$.

Therefore we can interpret the dual variables as marginal prices.

Note that with this interpretation, complementary slackness becomes obvious.

- If the brewer has slack of some resource (e.g. corn) then he is not willing to pay anything for it (corresponding dual variable is zero).
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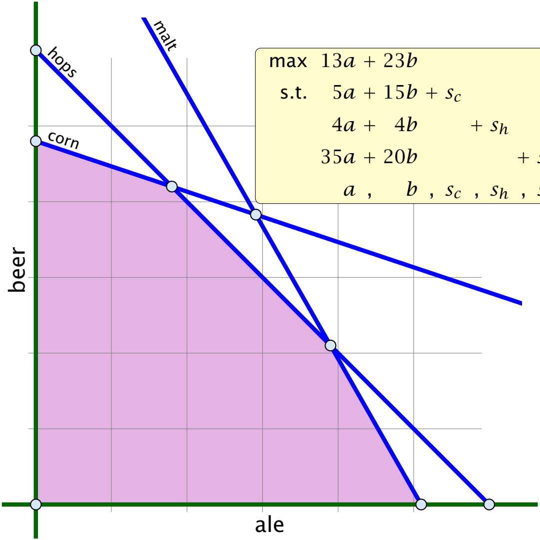
Example



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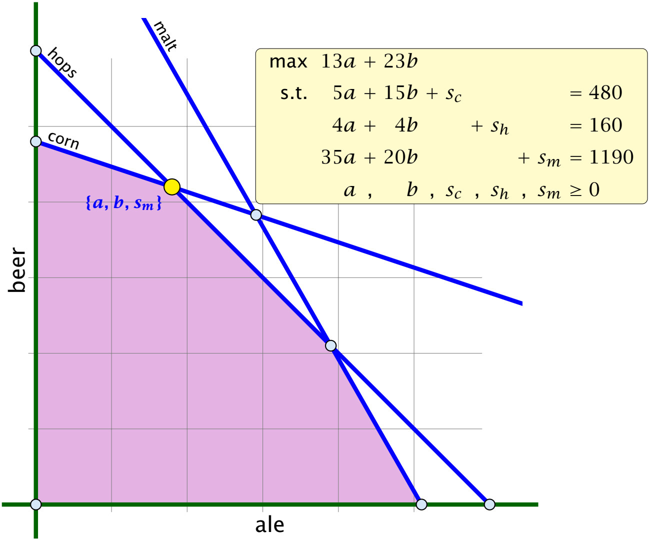

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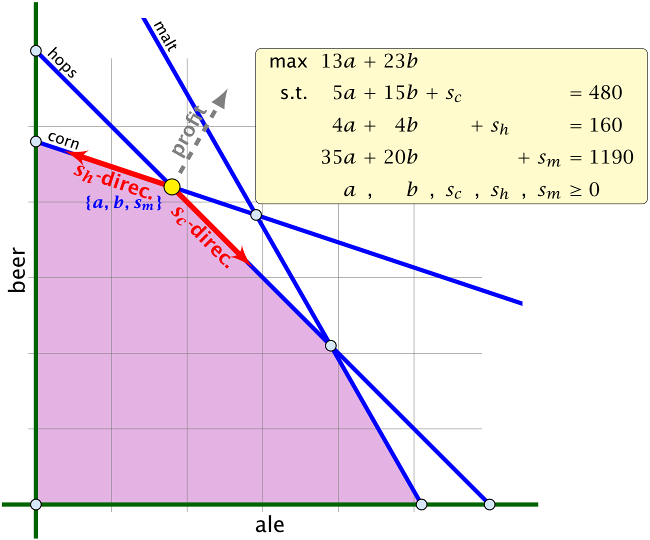

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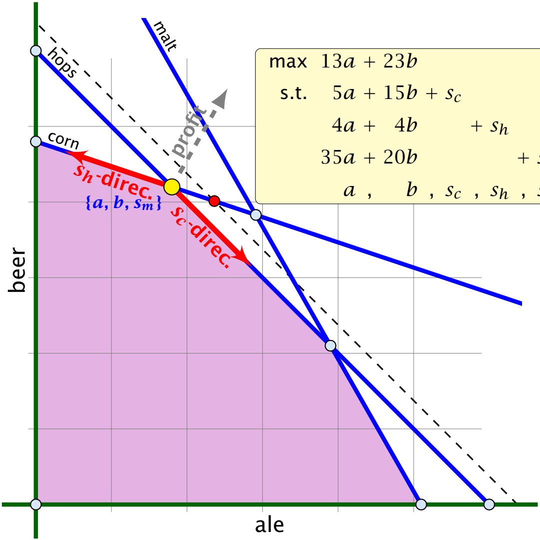

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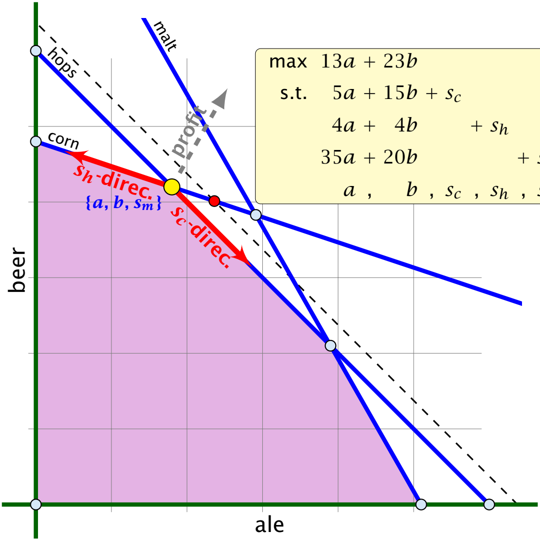

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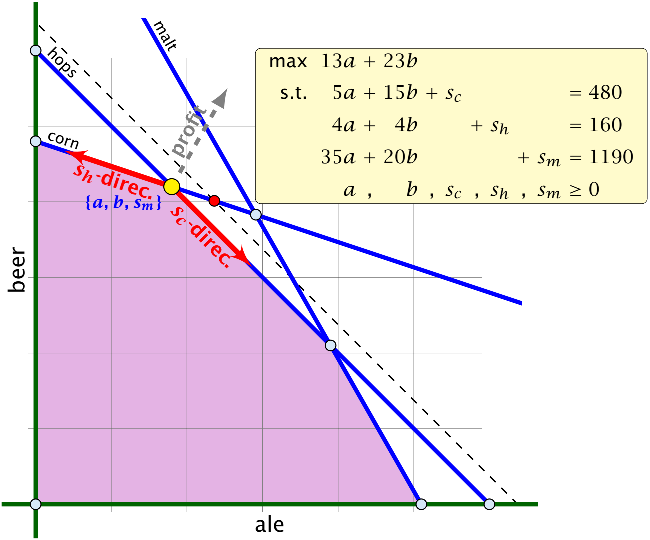

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The change in profit when increasing hops by one unit is

$= c_B^T A_B^{-1} e_h$.

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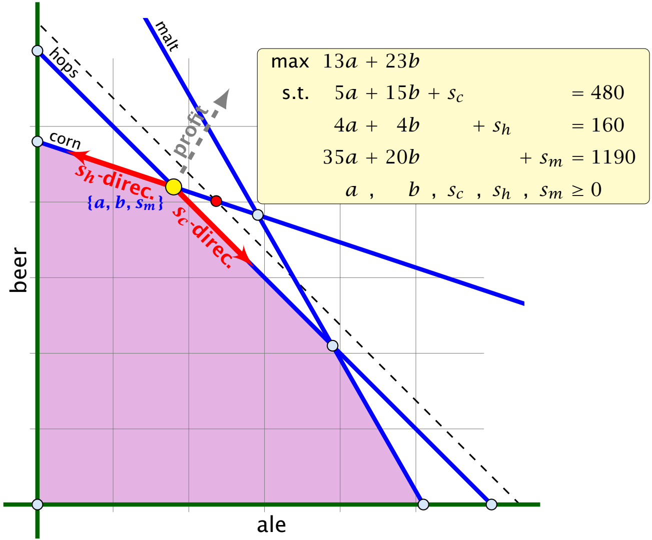

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$= \underbrace{c_B^T A_B^{-1}}_{y^*} e_h$.

Of course, the previous argument about the increase in the primal objective only holds for the non-degenerate case.

If the optimum basis is degenerate then increasing the supply of one resource may not allow the objective value to increase.

Flows

Definition 42

An (s,t)-flow in a (complete) directed graph $G=(V,V\times V,c)$ is a function $f:V\times V\mapsto\mathbb{R}_0^+$ that satisfies

1. For each edge (x,y)
$$0\le f_{xy}\le c_{xy}\enspace .$$
(capacity constraints)

2. For each $v\in V\setminus\{s,t\}$
$$\sum_x f_{vx}=\sum_x f_{xv}\enspace .$$
(flow conservation constraints)

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2. For each $v \in V \setminus \{s,t\}$
$$\sum_x f_{vx} = \sum_x f_{xv} \enspace .$$
(flow conservation constraints)

Flows

Definition 43
The value of an (s,t)-flow f is defined as

$$\mathrm{val}(f) = \sum_x f_{sx} - \sum_x f_{xs} \quad .$$

Maximum Flow Problem:
Find an (s,t)-flow with maximum value.

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LP-Formulation of Maxflow

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\begin{array}{llrcll}
\max & & \sum_z f_{sz} - \sum_z f_{zs} & & & \\
\text{s.t.} & \forall (z,w) \in V \times V & f_{zw} & \leq & c_{zw} & \ell_{zw} \\
 & \forall w \neq s,t & \sum_z f_{zw} - \sum_z f_{wz} & = & 0 & p_w \\
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\begin{array}{lllcl}
\text{min} & & \sum_{(xy)} c_{xy}\ell_{xy} & & \\
\text{s.t.} & f_{xy}\ (x,y \neq s,t): & 1\ell_{xy} - 1p_x + 1p_y & \ge & 0 \\
 & f_{sy}\ (y \neq s,t): & 1\ell_{sy} \qquad + 1p_y & \ge & 1 \\
 & f_{xs}\ (x \neq s,t): & 1\ell_{xs} - 1p_x & \ge & -1 \\
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with $p_t = 0$ and $p_s = 1$.

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\end{array}$$

We can interpret the ℓ_{xy} value as assigning a length to every edge.

The value p_x for a variable, then can be seen as the distance of x to t (where the distance from s to t is required to be 1 since $p_s = 1$).

The constraint $p_x \leq \ell_{xy} + p_y$ then simply follows from triangle inequality ($d(x,t) \leq d(x,y) + d(y,t) \Rightarrow d(x,t) \leq \ell_{xy} + d(y,t)$).

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Degeneracy Revisited

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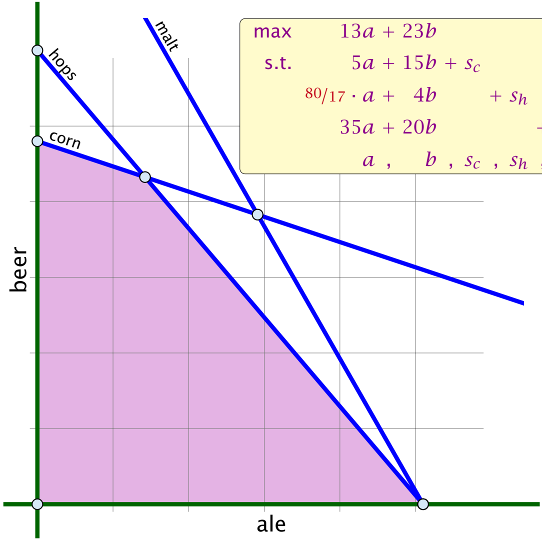
Degenerate Example



$$
\begin{array}{llcccccl}
\max & 13a + 23b & & & & & & \\
\text{s.t.} & 5a + 15b & + s_c & & & = & 480 \\
 & {}^{80}/_{17} \cdot a + 4b & & + s_h & & = & 160 \\
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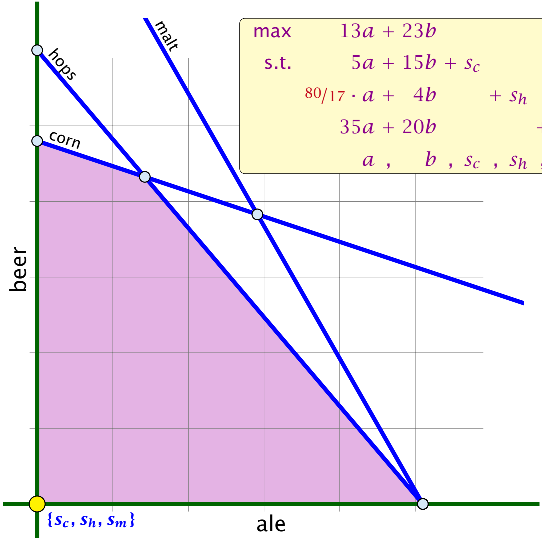

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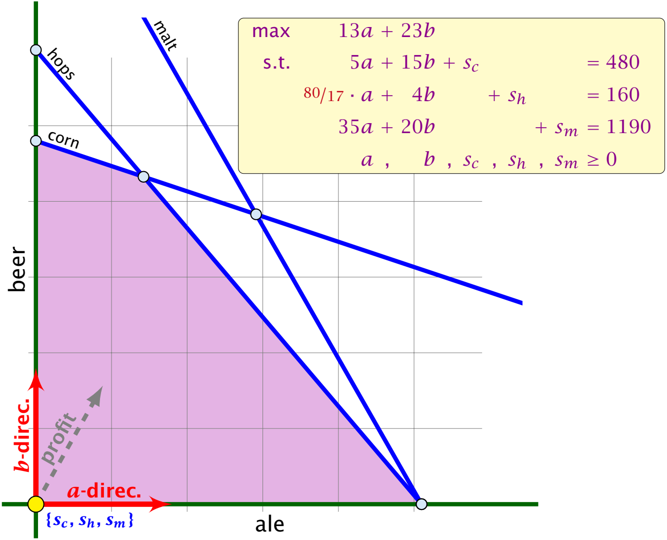

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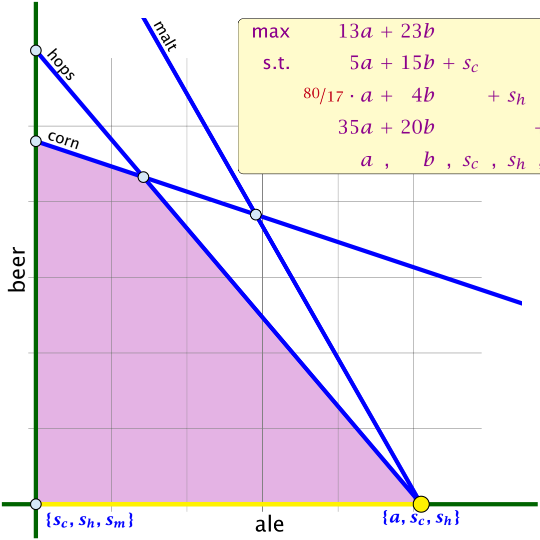

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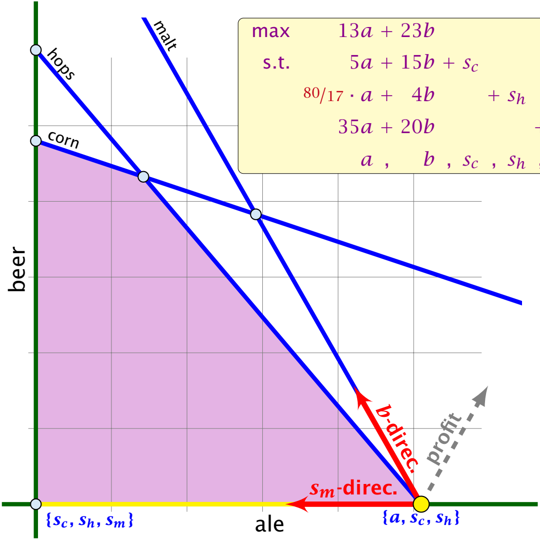

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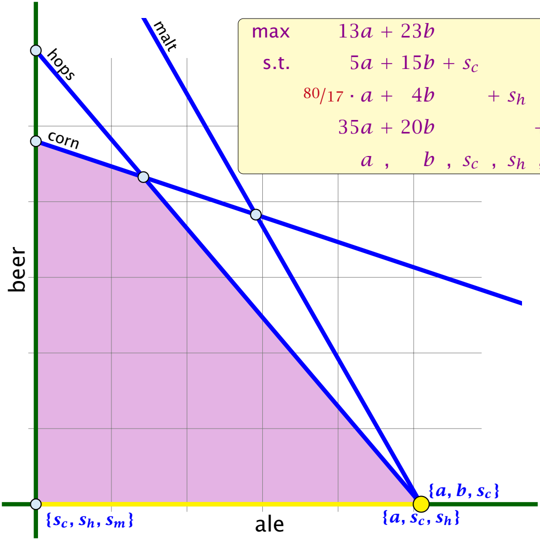

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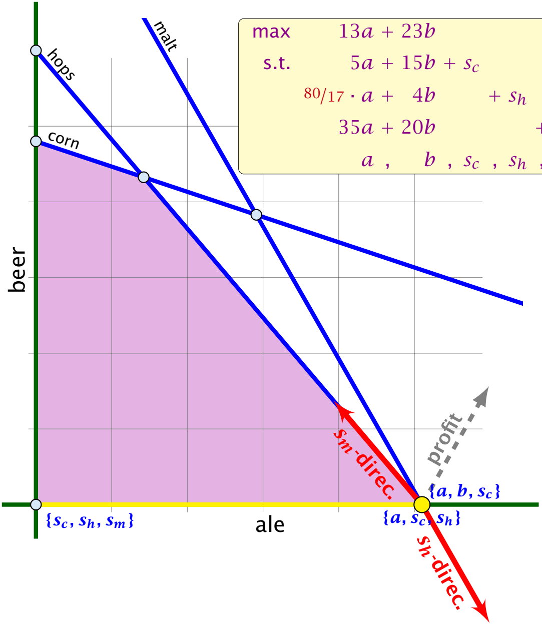

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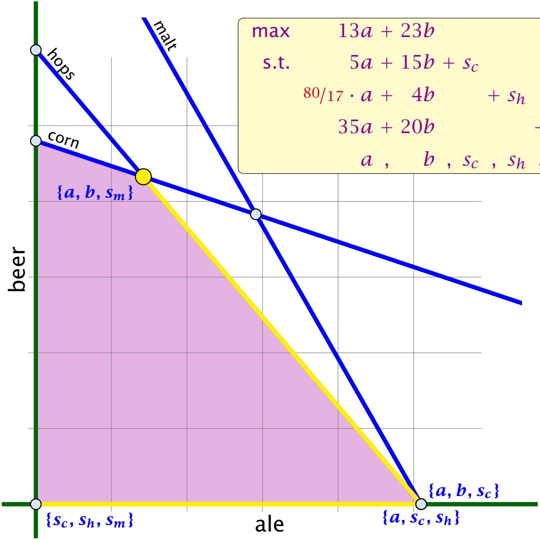

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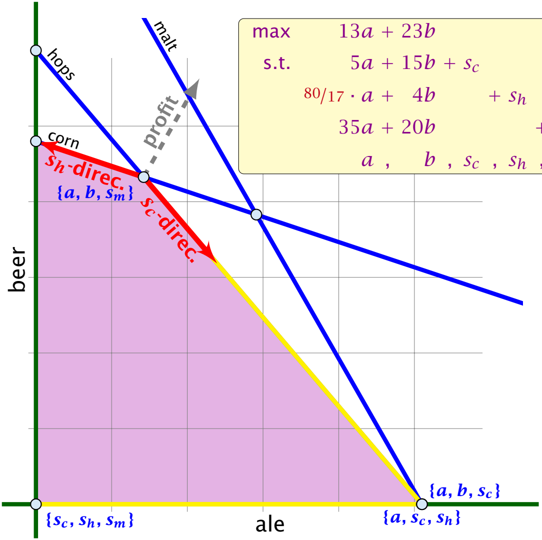

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If a basis variable is 0 in the basic feasible solution then we may not make progress during an iteration of simplex.

Idea:

Given feasible $\mathrm{LP} := \max\{c^Tx, Ax = b; x \geq 0\}$. Change it into $\mathrm{LP}' := \max\{c^Tx, Ax = b', x \geq 0\}$ such that

- LP' is feasible
- If a set B of basis variables corresponds to an infeasible basis (i.e. $A_B^{-1}b \not\geq 0$) then B corresponds to an infeasible basis in LP' (note that columns in A_B are linearly independent).
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Perturbation

Let B be index set of some basis with basic solution

$$x_B^* = A_B^{-1}b \geq 0, x_N^* = 0 \quad \text{(i.e. } B \text{ is feasible)}$$

Fix

$$b' := b + A_B \begin{pmatrix} \varepsilon \\ \vdots \\ \varepsilon^m \end{pmatrix} \text{ for } \varepsilon > 0 \ .$$

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The new LP is feasible because the set B of basis variables provides a feasible basis:

$$A_B^{-1}\left(b + A_B\begin{pmatrix}\varepsilon\\ \vdots\\ \varepsilon^m\end{pmatrix}\right) = x_B^* + \begin{pmatrix}\varepsilon\\ \vdots\\ \varepsilon^m\end{pmatrix} \geq 0\ .$$

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Hence, $\tilde{B}$ is not feasible.

Property III

Let $\tilde{B}$ be a basis. It has an associated solution

$$x^*_{\tilde{B}} = A_{\tilde{B}}^{-1} b + A_{\tilde{B}}^{-1} A_B \begin{pmatrix} \varepsilon \\ \vdots \\ \varepsilon^m \end{pmatrix}$$

in the perturbed instance.

We can view each component of the vector as a polynom with variable ε of degree at most m.

$A_{\tilde{B}}^{-1} A_B$ has rank m. Therefore no polynom is 0.

A polynom of degree at most m has at most m roots (Nullstellen).

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- If it terminates because the reduced cost vector fulfills

  $$\tilde{c} = (c^T - c_B^T A_B^{-1} A) \leq 0$$

  then we have found an optimal basis. Note that this basis is also optimal for LP, as the above constraint does not depend on b.
- If it terminates because it finds a variable x_j with $\tilde{c}_j > 0$ for which the j-th basis direction d, fulfills $d \geq 0$ we know that LP' is unbounded. The basis direction does not depend on b. Hence, we also know that LP is unbounded.

Lexicographic Pivoting

Doing calculations with perturbed instances may be costly. Also the right choice of ε is difficult.

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Simulate behaviour of LP' without explicitly doing a perturbation.

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We choose the entering variable arbitrarily as before ($\tilde{c}_e > 0$, of course).

If we do not have a choice for the leaving variable then LP' and LP do the same (i.e., choose the same variable).

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In the following we assume that $b \geq 0$. This can be obtained by replacing the initial system $(A \mid b)$ by $(A_B^{-1}A \mid A_B^{-1}b)$ where B is the index set of a feasible basis (found e.g. by the first phase of the Two-phase algorithm).

Then the perturbed instance is

$$b' = b + \begin{pmatrix} \varepsilon \\ \vdots \\ \varepsilon^m \end{pmatrix}$$

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Matrix View

Let our linear program be

$$\begin{array}{ccccc} c_B^T x_B & + & c_N^T x_N & = & Z \\ A_B x_B & + & A_N x_N & = & b \\ x_B & , & x_N & \geq & 0 \end{array}$$

The simplex tableaux for basis B is

$$\begin{array}{ccrcl} & & (c_N^T - c_B^T A_B^{-1} A_N) x_N & = & Z - c_B^T A_B^{-1} b \\ I x_B & + & A_B^{-1} A_N x_N & = & A_B^{-1} b \\ x_B & , & x_N & \geq & 0 \end{array}$$

The BFS is given by $x_N = 0, x_B = A_B^{-1} b$.

If $(c_N^T - c_B^T A_B^{-1} A_N) \leq 0$ we know that we have an optimum solution.

Lexicographic Pivoting

LP chooses an arbitrary leaving variable that has $\hat{A}_{\ell e} > 0$ and minimizes

$$\theta_\ell = \frac{\hat{b}_\ell}{\hat{A}_{\ell e}} = \frac{(A_B^{-1}b)_\ell}{(A_B^{-1}A_{*e})_\ell} \enspace .$$

ℓ is the index of a leaving variable within B. This means if e.g. $B = \{1, 3, 7, 14\}$ and leaving variable is 3 then $\ell = 2$.

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Lexicographic Pivoting

Definition 44

$u \leq_{\text{lex}} v$ if and only if the first component in which u and v differ fulfills $u_i \leq v_i$.

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$$= \frac{\ell\text{-th row of } A_B^{-1}(b \mid I)}{(A_B^{-1}A_{*e})_\ell}\begin{pmatrix}1\\ \varepsilon\\ \vdots\\ \varepsilon^m\end{pmatrix}$$

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This means you can choose the variable/row ℓ for which the vector

$$\frac{\ell\text{-th row of } A_B^{-1}(b \mid I)}{(A_B^{-1}A_{*e})_\ell}$$

is lexicographically minimal.

Of course only including rows with $(A_B^{-1}A_{*e})_\ell > 0$.

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Can we obtain a better analysis?

Number of Simplex Iterations

Observation

Simplex visits every feasible basis at most once.

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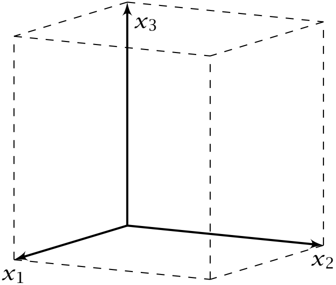
Simplex visits every feasible basis at most once.

However, also the number of feasible bases can be very large.

Example

$$\begin{aligned} \max\ & c^T x \\ \text{s.t.}\ & 0 \le x_1 \le 1 \\ & 0 \le x_2 \le 1 \\ & \quad\vdots \\ & 0 \le x_n \le 1 \end{aligned}$$



$2n$ constraint on n variables define an n-dimensional hypercube as feasible region.

The feasible region has 2^n vertices.

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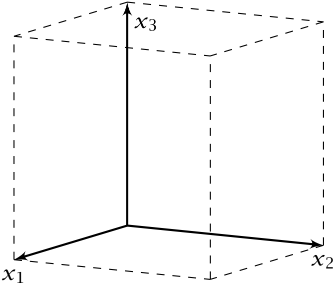

However, Simplex may still run quickly as it usually does not visit all feasible bases.

In the following we give an example of a feasible region for which there is a bad Pivoting Rule.

Pivoting Rule

A Pivoting Rule defines how to choose the entering and leaving variable for an iteration of Simplex.

In the non-degenerate case after choosing the entering variable the leaving variable is unique.

Klee Minty Cube

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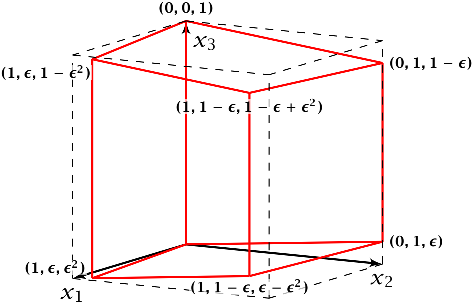
& \epsilon x_1 \le x_2 \le 1 - \epsilon x_1 \\
& \epsilon x_2 \le x_3 \le 1 - \epsilon x_2 \\
& \vdots \\
& \epsilon x_{n-1} \le x_n \le 1 - \epsilon x_{n-1} \\
& x_i \ge 0
\end{aligned}
$$



Observations

- We have $2n$ constraints, and $3n$ variables (after adding slack variables to every constraint).
- Every basis is defined by $2n$ variables, and n non-basic variables.
- There exist degenerate vertices.
- The degeneracies come from the non-negativity constraints, which are superfluous.
- In the following all variables x_i stay in the basis at all times.
- Then, we can uniquely specify a basis by choosing for each variable whether it should be equal to its lower bound, or equal to its upper bound (the slack variable corresponding to the non-tight constraint is part of the basis).
- We can also simply identify each basis/vertex with the corresponding hypercube vertex obtained by letting $\epsilon \rightarrow 0$.

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Analysis

- In the following we specify a sequence of bases (identified by the corresponding hypercube node) along which the objective function strictly increases.
- The basis $(0, \dots, 0, 1)$ is the unique optimal basis.
- Our sequence S_n starts at $(0, \dots, 0)$ ends with $(0, \dots, 0, 1)$ and visits every node of the hypercube.
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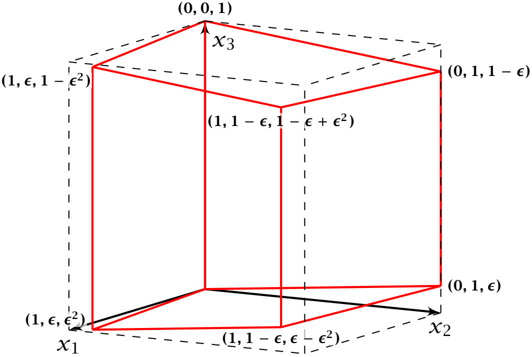

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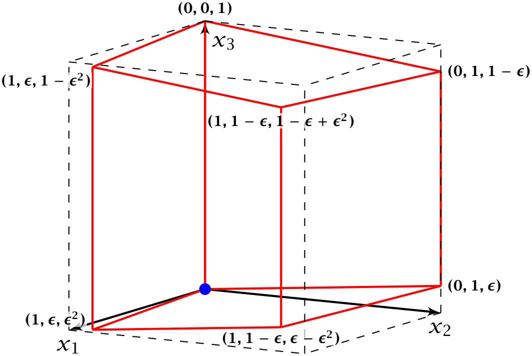

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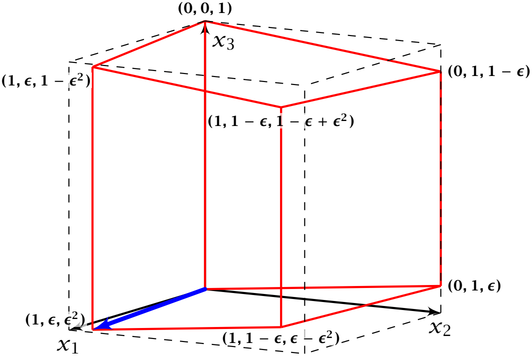

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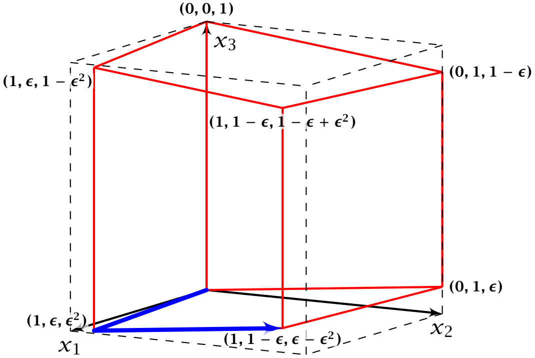

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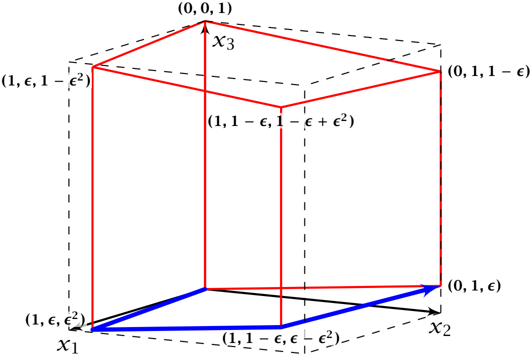

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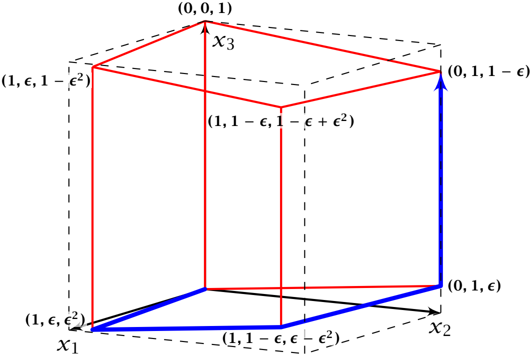

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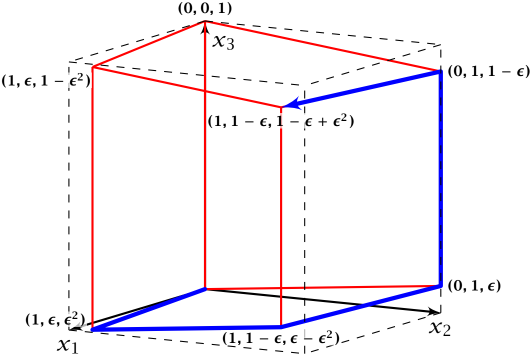

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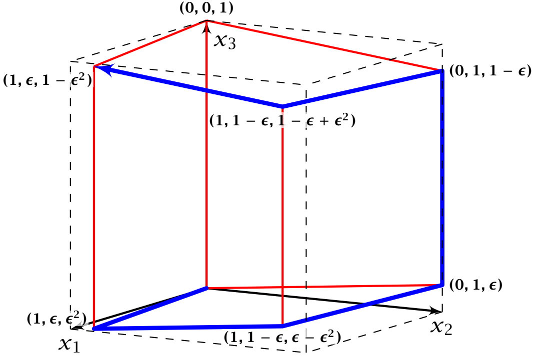

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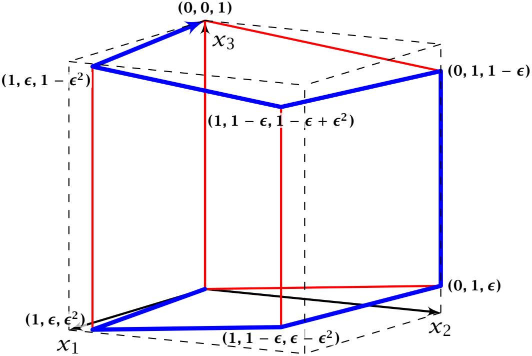

Analysis

The sequence S_n that visits every node of the hypercube is defined recursively

$$\begin{tikzcd}
(0,\ldots,0,0,0) \arrow[d, squiggly, "S_{n-1}"] & {} \arrow[ddd, squiggly, "S_n"] \\
(0,\ldots,0,1,0) \arrow[d] & \\
(0,\ldots,0,1,1) \arrow[d, squiggly, "S_{n-1}^{\text{rev}}"] & \\
(0,\ldots,0,0,1) & {}
\end{tikzcd}$$

The non-recursive case is $S_1 = 0 \to 1$

Analysis

Lemma 45

The objective value x_n is increasing along path S_n.

Proof by induction:

$n = 1$: obvious, since $S_1 = 0 \to 1$, and $1 > 0$.

$n - 1 \to n$

- For the first part the value of $x_n = \epsilon x_{n-1}$.
- By induction hypothesis x_{n-1} is increasing along S_{n-1}, hence, also x_n.
- Going from $(0, \ldots, 0, 1, 0)$ to $(0, \ldots, 0, 1, 1)$ increases x_n for small enough ϵ.
- For the remaining path S_{n-1}^{rev} we have $x_n = 1 - \epsilon x_{n-1}$.
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Analysis

Lemma 45

The objective value x_n is increasing along path S_n.

Proof by induction:

$\boldsymbol{n = 1}$: obvious, since $S_1 = 0 \to 1$, and $1 > 0$.

$\boldsymbol{n - 1 \to n}$

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Remarks about Simplex

Observation

The simplex algorithm takes at most $\binom{n}{m}$ iterations. Each iteration can be implemented in time $\mathcal{O}(mn)$.

In practise it usually takes a linear number of iterations.

Remarks about Simplex

Theorem
For almost all known deterministic pivoting rules (rules for choosing entering and leaving variables) there exist lower bounds that require the algorithm to have exponential running time ($\Omega(2^{\Omega(n)})$) (e.g. Klee Minty 1972).

Remarks about Simplex

Theorem
For some standard randomized pivoting rules there exist subexponential lower bounds ($\Omega(2^{\Omega(n^{\alpha})})$ for $\alpha > 0$) (Friedmann, Hansen, Zwick 2011).

Remarks about Simplex

Conjecture (Hirsch 1957)
The edge-vertex graph of an m-facet polytope in d-dimensional Euclidean space has diameter no more than $m - d$.

The conjecture has been proven wrong in 2010.

But the question whether the diameter is perhaps of the form $\mathcal{O}(\mathrm{poly}(m, d))$ is open.

8 Seidels LP-algorithm

- Suppose we want to solve $\min\{c^Tx \mid Ax \geq b; x \geq 0\}$, where $x \in \mathbb{R}^d$ and we have m constraints.
- In the worst-case Simplex runs in time roughly $\mathcal{O}(m(m+d)\binom{m+d}{m}) \approx (m+d)^m$. (slightly better bounds on the running time exist, but will not be discussed here).
- If d is much smaller than m one can do a lot better.
- In the following we develop an algorithm with running time $\mathcal{O}(d! \cdot m)$, i.e., linear in m.

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Setting:

- We assume an LP of the form

$$\boxed{\begin{array}{lrcl} \min & c^T x & & \\ \text{s.t.} & Ax & \geq & b \\ & x & \geq & 0 \end{array}}$$

- We assume that the LP is bounded.

Ensuring Conditions

Given a standard minimization LP

$$\begin{array}{lrcl} \min & c^Tx & & \\ \text{s.t.} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

how can we obtain an LP of the required form?

- **Compute a lower bound on c^Tx for any basic feasible solution.**

Computing a Lower Bound

Let s denote the smallest common multiple of all denominators of entries in A, b.

Multiply entries in A, b by s to obtain integral entries. This does not change the feasible region.

Add slack variables to A; denote the resulting matrix with $\bar{A}$.

If B is an optimal basis then x_B with $\bar{A}_B x_B = \bar{b}$, gives an optimal assignment to the basis variables (non-basic variables are 0).

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Theorem 46 (Cramers Rule)

Let M be a matrix with $\det(M) \neq 0$. Then the solution to the system $Mx = b$ is given by

$$x_i = \frac{\det(M_j)}{\det(M)} \enspace ,$$

where M_i is the matrix obtained from M by replacing the i-th column by the vector b.

Proof:

- Define

$$X_j = \begin{pmatrix} | & & | & | & | & & | \\ e_1 & \cdots & e_{j-1} & x & e_{j+1} & \cdots & e_n \\ | & & | & | & | & & | \end{pmatrix}$$

- Further, we have

$$MX_j = \begin{pmatrix} | & & | & | & | & & | \\ Me_1 & \cdots & Me_{j-1} & Mx & Me_{j+1} & \cdots & Me_n \\ | & & | & | & | & & | \end{pmatrix} = M_j$$

- Hence,

$$x_j = \det(X_j) = \frac{\det(M_j)}{\det(M)}$$

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Bounding the Determinant

Let Z be the maximum absolute entry occuring in $\bar{A}, \bar{b}$ or c. Let C denote the matrix obtained from $\bar{A}_B$ by replacing the j-th column with vector $\bar{b}$ (for some j).

Observe that

$$|\det(C)|$$

Here $\mathrm{sgn}(\pi)$ denotes the sign of the permutation, which is 1 if the permutation can be generated by an even number of transpositions (exchanging two elements), and -1 if the number of transpositions is odd.
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$$|\det(C)| = \left| \sum_{\pi \in S_m} \operatorname{sgn}(\pi) \prod_{1 \le i \le m} C_{i\pi(i)} \right|$$

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$$\begin{aligned}|\det(C)| &= \left| \sum_{\pi \in S_m} \operatorname{sgn}(\pi) \prod_{1 \le i \le m} C_{i\pi(i)} \right| \\ &\le \sum_{\pi \in S_m} \prod_{1 \le i \le m} |C_{i\pi(i)}|\end{aligned}$$

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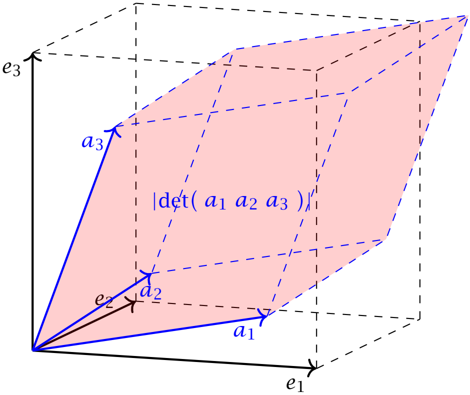
|\det(C)| &\le \prod_{i=1}^{m} \|C_{*i}\| \le \prod_{i=1}^{m} (\sqrt{m}Z) \\
&\le m^{m/2} Z^m \enspace .
\end{aligned}
$$

Hadamards Inequality



Hadamards inequality says that the volume of the red parallelepiped (Spat) is smaller than the volume in the black cube (if $\|e_1\| = \|a_1\|$, $\|e_2\| = \|a_2\|$, $\|e_3\| = \|a_3\|$).

Ensuring Conditions

Given a standard minimization LP

$$\begin{array}{lrcl} \min & c^T x & & \\ \text{s.t.} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

how can we obtain an LP of the required form?

- **Compute a lower bound on $c^T x$ for any basic feasible solution.** Add the constraint $c^T x \geq -dZ(m! \cdot Z^m) - 1$. Note that this constraint is superfluous unless the LP is unbounded.

Ensuring Conditions

Compute an optimum basis for the new LP.

- If the cost is $c^Tx = -(dZ)(m! \cdot Z^m) - 1$ we know that the original LP is unbounded.
- Otw. we have an optimum basis.

In the following we use $\mathcal{H}$ to denote the set of all constraints apart from the constraint $c^Tx \geq -dZ(m! \cdot Z^m) - 1$.

We give a routine SeidelLP$(\mathcal{H}, d)$ that is given a set $\mathcal{H}$ of explicit, non-degenerate constraints over d variables, and minimizes c^Tx over all feasible points.

In addition it obeys the implicit constraint $c^Tx \geq -(dZ)(m! \cdot Z^m) - 1$.

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if $d = 1$ then solve 1-dimensional problem and return;
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if $\hat{x}^* =$ infeasible then
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else
    add the value of $x_\ell$ to $\hat{x}^*$ and return the solution
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8 Seidels LP-algorithm

Note that for the case $d = 1$, the asymptotic bound $\mathcal{O}(\max\{m, 1\})$ is valid also for the case $m = 0$.

- If $d = 1$ we can solve the 1-dimensional problem in time $\mathcal{O}(\max\{m, 1\})$.
- If $d > 1$ and $m = 0$ we take time $\mathcal{O}(d)$ to return d-dimensional vector x.
- The first recursive call takes time $T(m-1, d)$ for the call plus $\mathcal{O}(d)$ for checking whether the solution fulfills h.
- If we are unlucky and $\hat{x}^*$ does not fulfill h we need time $\mathcal{O}(d(m+1)) = \mathcal{O}(dm)$ to eliminate x_ℓ. Then we make a recursive call that takes time $T(m-1, d-1)$.
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- If $d = 1$ we can solve the 1-dimensional problem in time $\mathcal{O}(\max\{m, 1\})$.
- If $d > 1$ and $m = 0$ we take time $\mathcal{O}(d)$ to return d-dimensional vector x.
- The first recursive call takes time $T(m-1, d)$ for the call plus $\mathcal{O}(d)$ for checking whether the solution fulfills h.
- If we are unlucky and $\hat{x}^*$ does not fulfill h we need time $\mathcal{O}(d(m+1)) = \mathcal{O}(dm)$ to eliminate x_ℓ. Then we make a recursive call that takes time $T(m-1, d-1)$.
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This gives the recurrence

$$T(m,d) = \begin{cases} \mathcal{O}(\max\{1,m\}) & \text{if } d = 1 \\ \mathcal{O}(d) & \text{if } d > 1 \text{ and } m = 0 \\ \mathcal{O}(d) + T(m-1,d) + & \\ \frac{d}{m}(\mathcal{O}(dm) + T(m-1,d-1)) & \text{otw.} \end{cases}$$

Note that $T(m,d)$ denotes the expected running time.

8 Seidels LP-algorithm

Let C be the largest constant in the $\mathcal{O}$-notations.

$$T(m,d)=\begin{cases} C\max\{1,m\} & \text{if } d=1\\ Cd & \text{if } d>1 \text{ and } m=0\\ Cd+T(m-1,d)+ & \\ \frac{d}{m}(Cdm+T(m-1,d-1)) & \text{otw.}\end{cases}$$

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if $f(d) \geq df(d-1) + 2d^2$.

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- Define $f(1) = 3 \cdot 1^2$ and $f(d) = df(d-1) + 3d^2$ for $d > 1$.

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since $\sum_{i\ge 1}\frac{i^2}{i!}$ is a constant.

$$\sum_{i\ge 1}\frac{i^2}{i!} = \sum_{i\ge 0}\frac{i+1}{i!} = e + \sum_{i\ge 1}\frac{i}{i!} = 2e$$

Complexity

LP Feasibility Problem (LP feasibility A)
Given $A \in \mathbb{Z}^{m \times n}$, $b \in \mathbb{Z}^m$. Does there exist $x \in \mathbb{R}^n$ with $Ax \le b$, $x \ge 0$?

LP Feasiblity Problem (LP feasibility B)
Given $A \in \mathbb{Z}^{m \times n}$, $b \in \mathbb{Z}^m$. Find $x \in \mathbb{R}^n$ with $Ax \le b$, $x \ge 0$!

LP Optimization A
Given $A \in \mathbb{Z}^{m \times n}$, $b \in \mathbb{Z}^m, c \in \mathbb{Z}^n$. What is the maximum value of $c^T x$ for a feasible point $x \in \mathbb{R}^n$?

LP Optimization B
Given $A \in \mathbb{Z}^{m \times n}$, $b \in \mathbb{Z}^m, c \in \mathbb{Z}^n$. Return feasible point $x \in \mathbb{R}^n$ with maximum value of $c^T x$?

Note that allowing A, b to contain rational numbers does not make a difference, as we can multiply every number by a suitable large constant so that everything becomes integral but the feasible region does not change.

The Bit Model

Input size

- The number of bits to represent a number $a \in \mathbb{Z}$ is

$$\lceil \log_2(|a|) \rceil + 1$$

- Let for an $m \times n$ matrix M, $L(M)$ denote the number of bits required to encode all the numbers in M.

$$\langle M \rangle := \sum_{i,j} \lceil \log_2(|m_{ij}|) + 1 \rceil$$

- In the following we assume that input matrices are encoded in a standard way, where each number is encoded in binary and then suitable separators are added in order to separate distinct number from each other.
- Then the input length is $L = \Theta(\langle A \rangle + \langle b \rangle)$.

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- In the following we sometimes refer to $L := \langle A\rangle + \langle b\rangle$ as the input size (even though the real input size is something in $\Theta(\langle A\rangle + \langle b\rangle)$).
- Sometimes we may also refer to $L := \langle A\rangle + \langle b\rangle + n\log_2 n$ as the input size. Note that $n\log_2 n = \Theta(\langle A\rangle + \langle b\rangle)$.
- In order to show that LP-decision is in NP we show that if there is a solution x then there exists a small solution for which feasibility can be verified in polynomial time (polynomial in L).

Note that $m\log_2 m$ may be much larger than $\langle A\rangle + \langle b\rangle$.

Suppose that $\bar{A}x = b$; $x \geq 0$ is feasible.

Then there exists a basic feasible solution. This means a set B of basic variables such that

$$x_B = \bar{A}_B^{-1} b$$

and all other entries in x are 0.

In the following we show that this x has small encoding length and we give an explicit bound on this length. So far we have only been handwaving and have said that we can compute x via Gaussian elimination and it will be short...

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Size of a Basic Feasible Solution

Note that n in the theorem denotes the number of columns in A which may be much smaller than m.

- A: original input matrix
- $\bar{A}$: transformation of A into standard form
- $\bar{A}_B$: submatrix of $\bar{A}$ corresponding to basis B

Lemma 47

Let $\bar{A}_B \in \mathbb{Z}^{m\times m}$ and $b \in \mathbb{Z}^m$. Define $L = \langle A\rangle + \langle b\rangle + n\log_2 n$. Then a solution to $\bar{A}_B x_B = b$ has rational components x_j of the form $\frac{D_j}{D}$, where $|D_j| \le 2^L$ and $|D| \le 2^L$.

Proof:

Cramers rules says that we can compute x_j as

$$x_j = \frac{\det(\bar{A}_B^j)}{\det(\bar{A}_B)}$$

where $\bar{A}_B^j$ is the matrix obtained from $\bar{A}_B$ by replacing the j-th column by the vector b.

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&\le n! \cdot 2^{\langle A \rangle + \langle b \rangle} \le 2^L \enspace .
\end{aligned}
$$

Bounding the Determinant

Let $X = \bar{A}_B$. Then

$$\begin{aligned}|\det(X)| &= |\det(\bar{X})|\\ &= \left|\sum_{\pi\in S_{\tilde{n}}} \operatorname{sgn}(\pi) \prod_{1\le i\le\tilde{n}} \bar{X}_{i\pi(i)}\right|\\ &\le \sum_{\pi\in S_{\tilde{n}}} \prod_{1\le i\le\tilde{n}} |\bar{X}_{i\pi(i)}|\\ &\le n!\cdot 2^{\langle A\rangle+\langle b\rangle} \le 2^L \enspace .\end{aligned}$$

Here $\bar{X}$ is an $\tilde{n}\times\tilde{n}$ submatrix of A with $\tilde{n}\le n$.

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Analogously for $\det(A_B^j)$.

When computing the determinant of $X = \bar{A}_B$ we first do expansions along columns that were introduced when transforming A into standard form, i.e., into $\bar{A}$.

Such a column contains a single 1 and the remaining entries of the column are 0. Therefore, these expansions do not increase the absolute value of the determinant. After we did expansions for all these columns we are left with a square sub-matrix of A of size at most $n \times n$.

Reducing LP-solving to LP decision.

Given an LP $\max\{c^T x \mid Ax \le b; x \ge 0\}$ do a binary search for the optimum solution

(Add constraint $c^T x \ge M$). Then checking for feasibility shows whether optimum solution is larger or smaller than M).

If the LP is feasible then the binary search finishes in at most

$$\log_2\left(\frac{2n2^{2L'}}{1/2^{L'}}\right) = \mathcal{O}(L') \ ,$$

as the range of the search is at most $-n2^{2L'}, \ldots, n2^{2L'}$ and the distance between two adjacent values is at least $\frac{1}{\det(A)} \ge \frac{1}{2^{L'}}$.

Here we use $L' = \langle A\rangle + \langle b\rangle + \langle c\rangle + n\log_2 n$ (it also includes the encoding size of c).

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How do we detect whether the LP is unbounded?

Let $M_{\max} = n2^{2L'}$ be an upper bound on the objective value of a basic feasible solution.

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Ellipsoid Method

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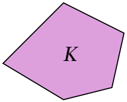

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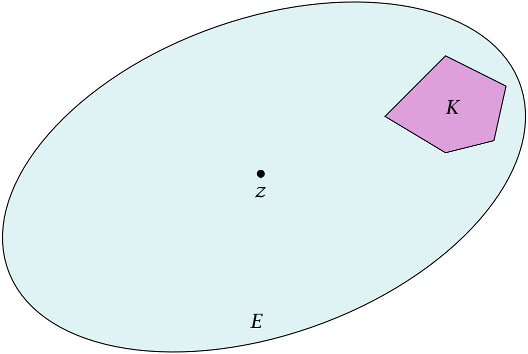

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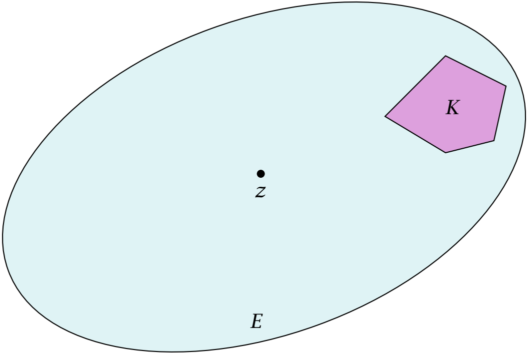

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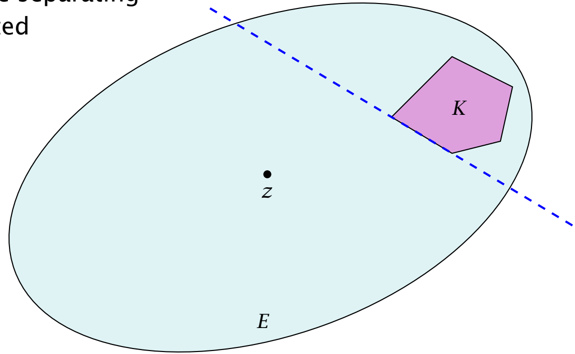

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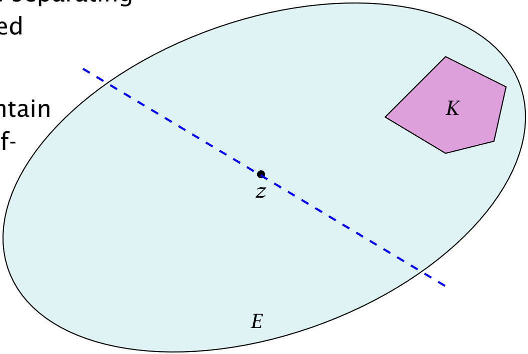

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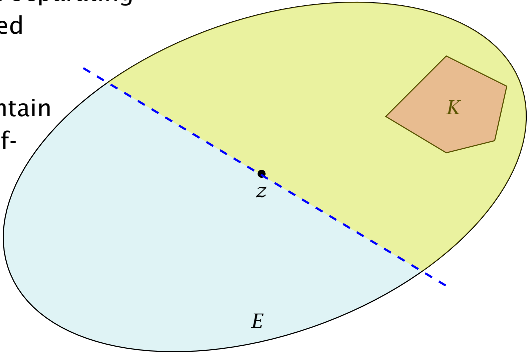

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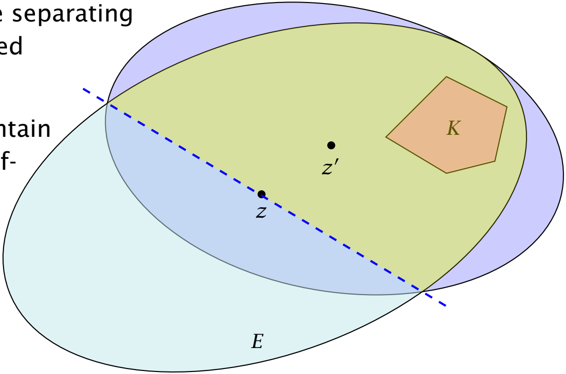

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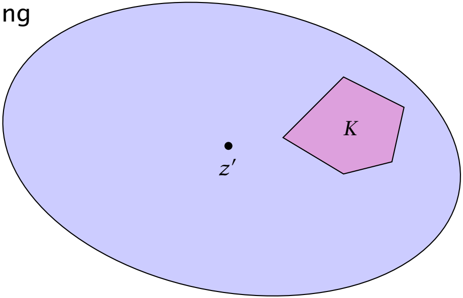

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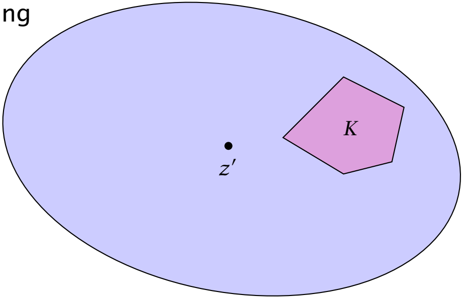
- REPEAT



Issues/Questions:

- How do you choose the first Ellipsoid? What is its volume?
- How do you measure progress? By how much does the volume decrease in each iteration?
- When can you stop? What is the minimum volume of a non-empty polytop?

Definition 48

A mapping $f : \mathbb{R}^n \to \mathbb{R}^n$ with $f(x) = Lx + t$, where L is an invertible matrix is called an affine transformation.

Definition 49

A ball in $\mathbb{R}^n$ with center c and radius r is given by

$$\begin{aligned} B(c,r) &= \{x \mid (x-c)^T(x-c) \le r^2\} \\ &= \{x \mid \sum_i (x-c)_i^2/r^2 \le 1\} \end{aligned}$$

$B(0,1)$ is called the unit ball.

Definition 50

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\begin{aligned}
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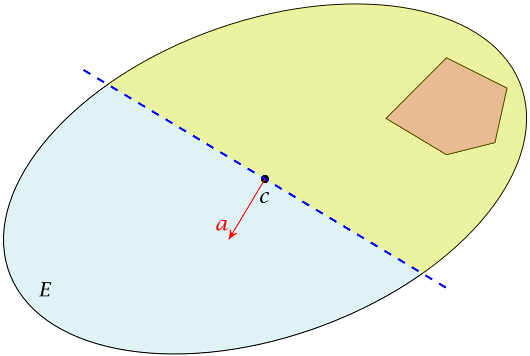
where $Q = LL^T$ is an invertible matrix.

How to Compute the New Ellipsoid



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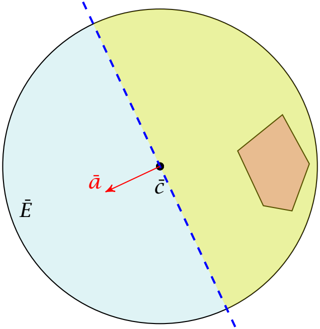
- Use f^{-1} (recall that $f = Lx + t$ is the affine transformation of the unit ball) to rotate/distort the ellipsoid (back) into the unit ball.



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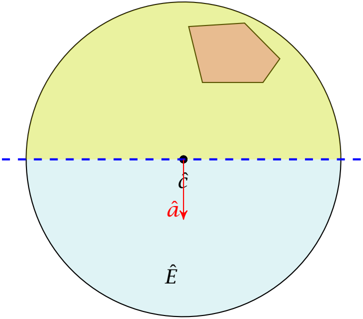

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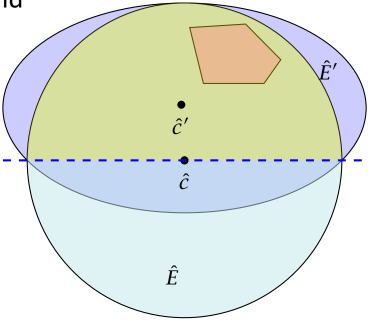

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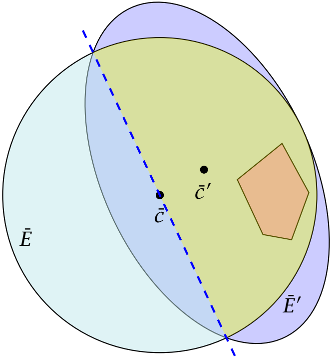

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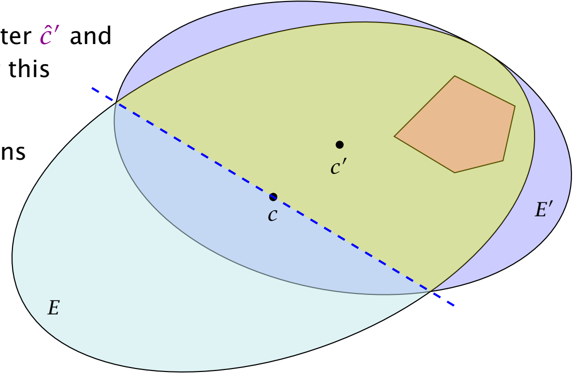
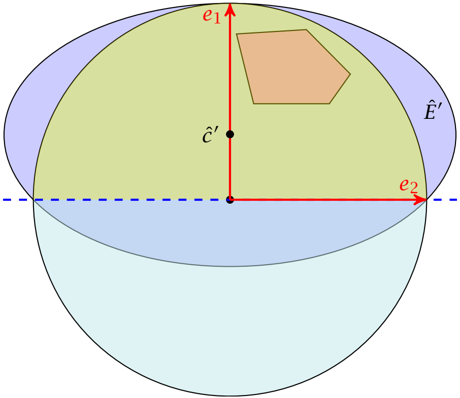


The Easy Case



- The new center lies on axis x_1. Hence, $\hat{c}' = te_1$ for $t > 0$.
- The vectors $e_1, e_2, \dots$ have to fulfill the ellipsoid constraint with equality. Hence $(e_i - \hat{c}')^T \hat{Q}'^{-1} (e_i - \hat{c}') = 1$.

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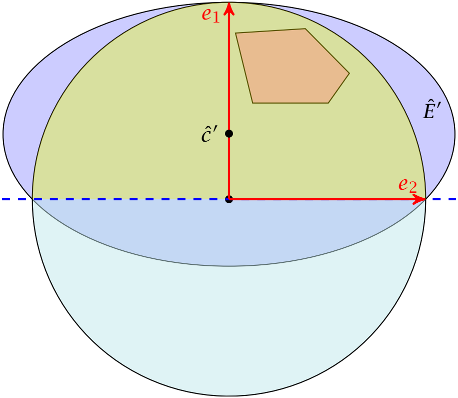

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- To obtain the matrix $\hat{Q}'^{-1}$ for our ellipsoid $\hat{E}'$ note that $\hat{E}'$ is axis-parallel.
- Let a denote the radius along the x_1-axis and let b denote the (common) radius for the other axes.
- The matrix

$$\hat{L}' = \begin{pmatrix} a & 0 & \dots & 0 \\ 0 & b & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & b \end{pmatrix}$$

  maps the unit ball (via function $\hat{f}'(x) = \hat{L}'x$) to an axis-parallel ellipsoid with radius a in direction x_1 and b in all other directions.

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- As $\hat{Q}' = \hat{L}'\hat{L}'^t$ the matrix $\hat{Q}'^{-1}$ is of the form

$$\hat{Q}'^{-1} = \begin{pmatrix} \frac{1}{a^2} & 0 & \dots & 0 \\ 0 & \frac{1}{b^2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \frac{1}{b^2} \end{pmatrix}$$

The Easy Case

- $(e_1 - \hat{c}')^T \hat{Q}'^{-1} (e_1 - \hat{c}') = 1$ gives

$$\begin{pmatrix} 1-t \\ 0 \\ \vdots \\ 0 \end{pmatrix}^T \cdot \begin{pmatrix} \frac{1}{a^2} & 0 & \dots & 0 \\ 0 & \frac{1}{b^2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \frac{1}{b^2} \end{pmatrix} \cdot \begin{pmatrix} 1-t \\ 0 \\ \vdots \\ 0 \end{pmatrix} = 1$$

- This gives $(1-t)^2 = a^2$.

The Easy Case

- For $i \neq 1$ the equation $(e_i - \hat{c}')^T \hat{Q}'^{-1}(e_i - \hat{c}') = 1$ looks like (here $i = 2$)

$$\begin{pmatrix} -t \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}^T \cdot \begin{pmatrix} \frac{1}{a^2} & 0 & \dots & 0 \\ 0 & \frac{1}{b^2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \frac{1}{b^2} \end{pmatrix} \cdot \begin{pmatrix} -t \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} = 1$$

- This gives $\frac{t^2}{a^2} + \frac{1}{b^2} = 1$, and hence

$$\frac{1}{b^2} = 1 - \frac{t^2}{a^2}$$

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$$\frac{1}{b^2} = 1 - \frac{t^2}{a^2} = 1 - \frac{t^2}{(1-t)^2} = \frac{1-2t}{(1-t)^2}$$

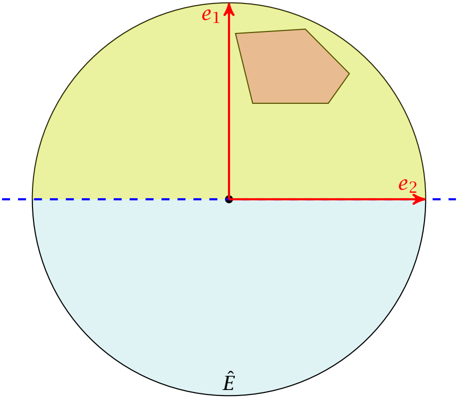
Summary

So far we have

$$a = 1 - t \quad \text{and} \quad b = \frac{1 - t}{\sqrt{1 - 2t}}$$

The Easy Case

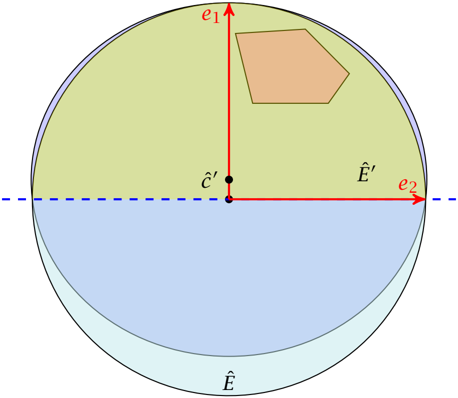
We still have many choices for t:



Choose t such that the volume of $\hat{E}'$ is minimal!!!

The Easy Case

We still have many choices for t:



Choose t such that the volume of $\hat{E}'$ is minimal!!!

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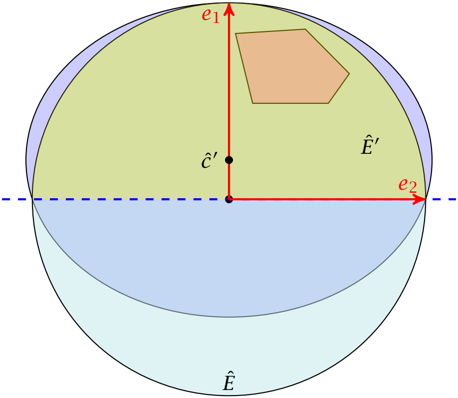

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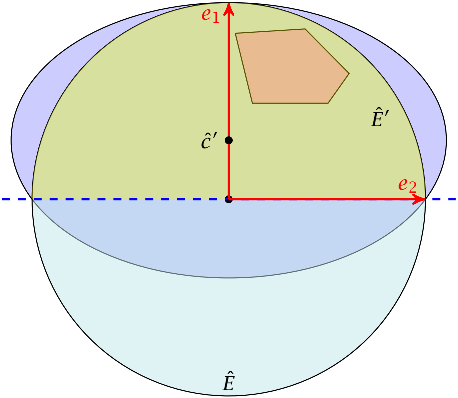

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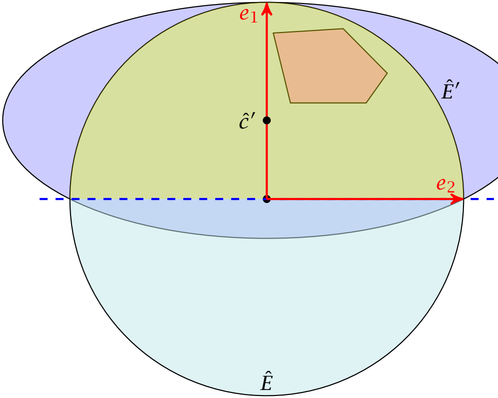

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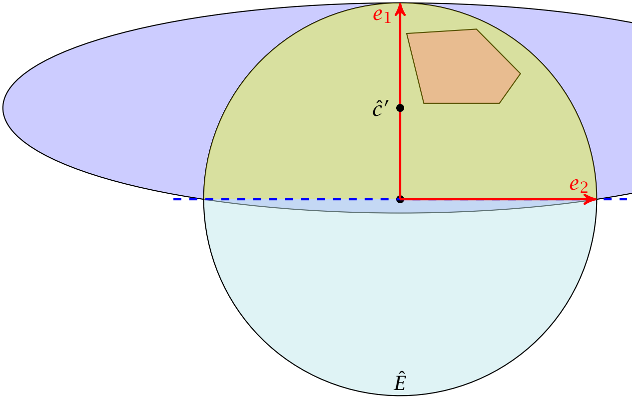

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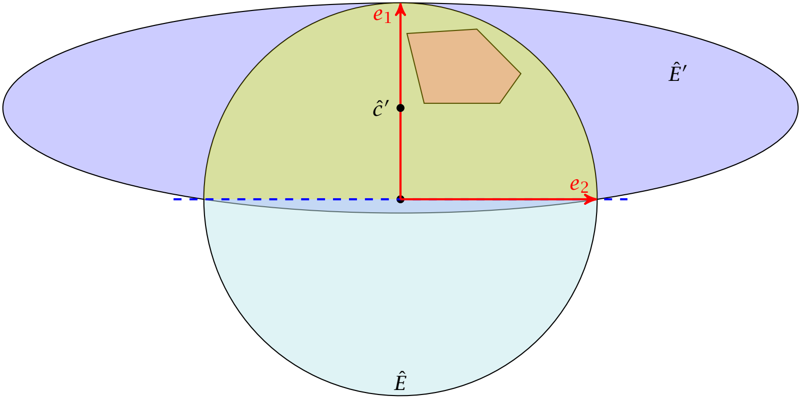

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We want to choose t such that the volume of $\hat{E}'$ is minimal.

Lemma 51

Let L be an affine transformation and $K \subseteq \mathbb{R}^n$. Then

$$\mathrm{vol}(L(K)) = |\det(L)| \cdot \mathrm{vol}(K) \ .$$

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Lemma 51
Let L be an affine transformation and $K \subseteq \mathbb{R}^n$. Then

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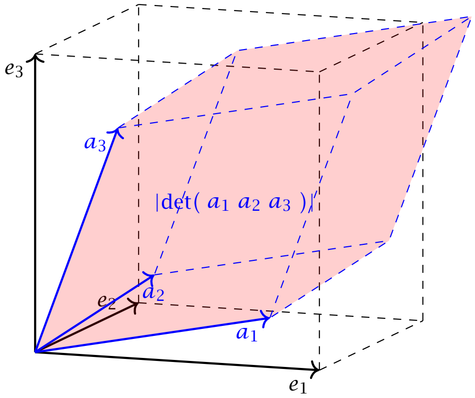
n-dimensional volume



The Easy Case

- We want to choose t such that the volume of $\hat{E}'$ is minimal.

$$\mathrm{vol}(\hat{E}') = \mathrm{vol}(B(0,1)) \cdot |\det(\hat{L}')| \ ,$$

- Recall that

$$\hat{L}' = \begin{pmatrix} a & 0 & \dots & 0 \\ 0 & b & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & b \end{pmatrix}$$

- Note that a and b in the above equations depend on t, by the previous equations.

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We use the shortcut $\Phi := \mathrm{vol}(B(0,1))$.

The Easy Case

$$\frac{\mathrm{d}\,\mathrm{vol}(\hat{E}')}{\mathrm{d}\,t}$$

The Easy Case

$$\frac{\mathrm{d}\,\mathrm{vol}(\hat{E}')}{\mathrm{d}\,t} = \frac{\mathrm{d}}{\mathrm{d}\,t}\left(\Phi\frac{(1-t)^n}{(\sqrt{1-2t})^{n-1}}\right)$$

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$$= \frac{\Phi}{N^2}$$

N = denominator

The Easy Case

$$\frac{\mathrm{d}\,\mathrm{vol}(\hat{E}')}{\mathrm{d}\,t} = \frac{\mathrm{d}}{\mathrm{d}\,t}\left(\Phi\frac{(1-t)^n}{(\sqrt{1-2t})^{n-1}}\right)$$

$$= \frac{\Phi}{N^2}\cdot\Bigg((-1)\cdot n(1-t)^{n-1}$$

derivative of numerator

The Easy Case

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$$= \frac{\Phi}{N^2}\cdot\Bigg((-1)\cdot n(1-t)^{n-1}\cdot\underbrace{(\sqrt{1-2t})^{n-1}}_{\text{denominator}}$$

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$$-\underbrace{(n-1)(\sqrt{1-2t})^{n-2}}_{\text{outer derivative}}$$

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$$= \frac{\Phi}{N^2}\cdot\Bigg((-1)\cdot n(1-t)^{n-1}\cdot(\sqrt{1-2t})^{n-1}$$

$$-(n-1)(\sqrt{1-2t})^{n-2}\cdot\frac{1}{2\sqrt{1-2t}}\cdot(-2)$$

inner derivative

The Easy Case

$$\frac{\mathrm{d}\,\mathrm{vol}(\hat{E}')}{\mathrm{d}\,t} = \frac{\mathrm{d}}{\mathrm{d}\,t}\left(\Phi\frac{(1-t)^n}{(\sqrt{1-2t})^{n-1}}\right)$$

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\begin{aligned}
\frac{\mathrm{d}\,\mathrm{vol}(\hat{E}')}{\mathrm{d}\,t} &= \frac{\mathrm{d}}{\mathrm{d}\,t}\left(\Phi\frac{(1-t)^n}{(\sqrt{1-2t})^{n-1}}\right)\\
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&\qquad -(n-1)(\sqrt{1-2t})^{n-2}\cdot\frac{1}{2\sqrt{1-2t}}\cdot(-2)\cdot(1-t)^n\Bigg)\\
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$$

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- We obtain the minimum for $t = \frac{1}{n+1}$.
- For this value we obtain

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The Easy Case

Let $\gamma_n = \frac{\mathrm{vol}(\hat{E}')}{\mathrm{vol}(B(0,1))} = ab^{n-1}$ be the ratio by which the volume changes:

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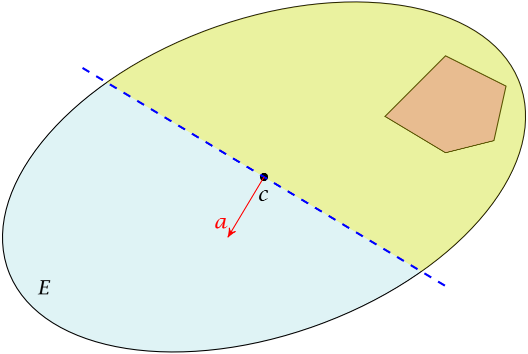
where we used $(1+x)^a \le e^{ax}$ for $x \in \mathbb{R}$ and $a > 0$.

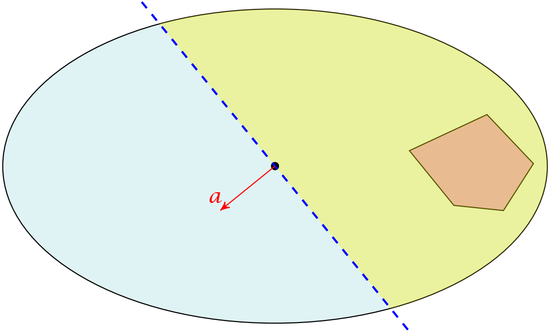
This gives $\gamma_n \le e^{-\frac{1}{2(n+1)}}$.

How to Compute the New Ellipsoid



How to Compute the New Ellipsoid

- Use f^{-1} (recall that $f = Lx + t$ is the affine transformation of the unit ball) to translate/distort the ellipsoid (back) into the unit ball.



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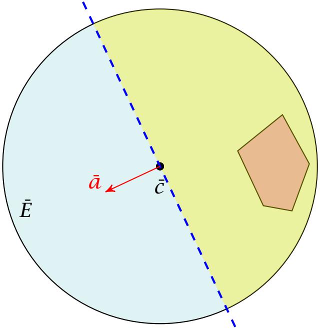
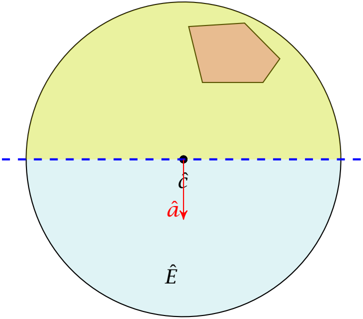


How to Compute the New Ellipsoid

- Use f^{-1} (recall that $f = Lx + t$ is the affine transformation of the unit ball) to translate/distort the ellipsoid (back) into the unit ball.
- Use a rotation R^{-1} to rotate the unit ball such that the normal vector of the halfspace is parallel to e_1.



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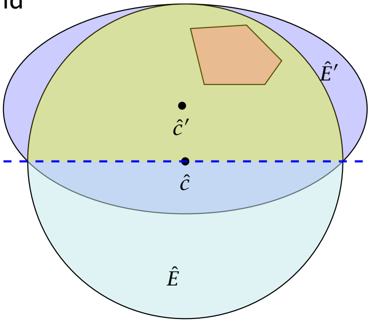
- Compute the new center $\hat{c}'$ and the new matrix $\hat{Q}'$ for this simplified setting.



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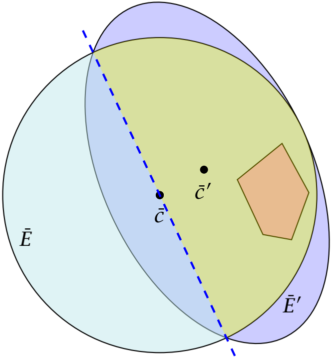

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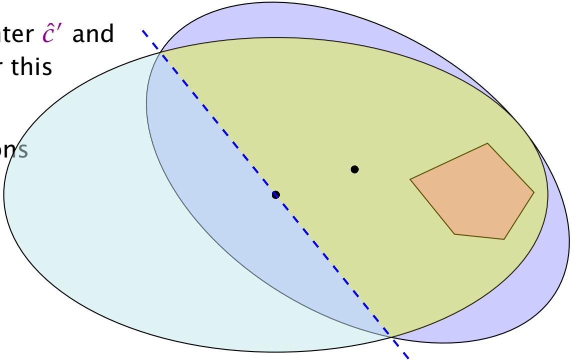

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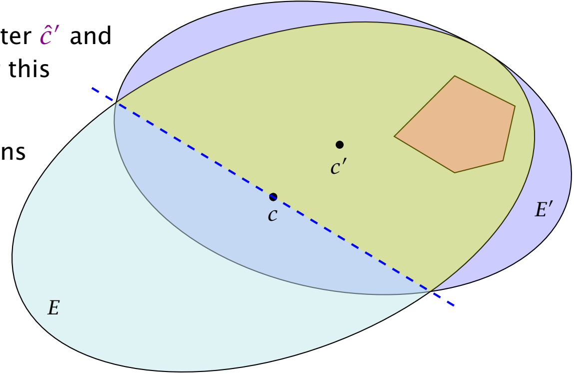

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Here it is important that mapping a set with affine function $f(x) = Lx + t$ changes the volume by factor $\det(L)$.

The Ellipsoid Algorithm

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This means $\bar{a} = L^T a$.

The center $\bar{c}$ is of course at the origin.

The Ellipsoid Algorithm

After rotating back (applying R^{-1}) the normal vector of the halfspace points in negative x_1-direction. Hence,

$$R^{-1}\Big(\frac{L^Ta}{\|L^Ta\|}\Big) = -e_1 \quad \Rightarrow \quad -\frac{L^Ta}{\|L^Ta\|} = R \cdot e_1$$

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For computing the matrix Q' of the new ellipsoid we assume in the following that $\hat{E}', \bar{E}'$ and E' refer to the ellispoids centered in the origin.

Recall that

$$\hat{Q}' = \begin{pmatrix} a^2 & 0 & \dots & 0 \\ 0 & b^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & b^2 \end{pmatrix}$$

This gives

$$\hat{Q}' = \frac{n^2}{n^2-1}\Big(I - \frac{2}{n+1}e_1e_1^T\Big)$$

Note that $e_1e_1^T$ is a matrix M that has $M_{11} = 1$ and all other entries equal to 0.

because for $a^2 = {}^{n^2}/_{(n+1)^2}$ and $b^2 = {}^{n^2}/_{n^2-1}$

$$\begin{aligned} b^2 - b^2\frac{2}{n+1} &= \frac{n^2}{n^2-1} - \frac{2n^2}{(n-1)(n+1)^2} \\ &= \frac{n^2(n+1) - 2n^2}{(n-1)(n+1)^2} = \frac{n^2(n-1)}{(n-1)(n+1)^2} = a^2 \end{aligned}$$

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9 The Ellipsoid Algorithm

$\bar{E}'$

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\end{aligned}
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9 The Ellipsoid Algorithm

Hence,

$$\bar{Q}'$$

Here we used the equation for Re_1 proved before, and the fact that $RR^T = I$, which holds for any rotation matrix. To see this observe that the length of a rotated vector x should not change, i.e.,

$$x^T I x = (Rx)^T (Rx) = x^T (R^T R) x$$

which means $x^T (I - R^T R) x = 0$ for every vector x. It is easy to see that this can only be fulfilled if $I - R^T R = 0$.

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Hence,

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9 The Ellipsoid Algorithm

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$$\begin{aligned}\bar{Q}' &= R\hat{Q}'R^T\\ &= R\cdot\frac{n^2}{n^2-1}\Big(I-\frac{2}{n+1}e_1e_1^T\Big)\cdot R^T\\ &= \frac{n^2}{n^2-1}\Big(R\cdot R^T-\frac{2}{n+1}(Re_1)(Re_1)^T\Big)\\ &= \frac{n^2}{n^2-1}\Big(I-\frac{2}{n+1}\frac{L^Taa^TL}{\|L^Ta\|^2}\Big)\end{aligned}$$

Here we used the equation for Re_1 proved before, and the fact that $RR^T = I$, which holds for any rotation matrix. To see this observe that the length of a rotated vector x should not change, i.e.,

$$x^TIx = (Rx)^T(Rx) = x^T(R^TR)x$$

which means $x^T(I - R^TR)x = 0$ for every vector x. It is easy to see that this can only be fulfilled if $I - R^TR = 0$.

9 The Ellipsoid Algorithm

E'

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$$E' = L(\bar{E}')$$

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$$\begin{aligned} E' &= L(\bar{E}') \\ &= \{L(x) \mid x^T \bar{Q}'^{-1} x \le 1\} \end{aligned}$$

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Incomplete Algorithm

```
Algorithm 1 ellipsoid-algorithm
input: point $c \in \mathbb{R}^n$, convex set $K \subseteq \mathbb{R}^n$
output: point $x \in K$ or “$K$ is empty”
$Q \leftarrow$ ???
repeat
    if $c \in K$ then return $c$
    else
        choose a violated hyperplane $a$
        $c \leftarrow c - \frac{1}{n+1}\frac{Qa}{\sqrt{a^TQa}}$
        $Q \leftarrow \frac{n^2}{n^2-1}\Big(Q - \frac{2}{n+1}\frac{Qaa^TQ}{a^TQa}\Big)$
    endif
until ???
return “$K$ is empty”
```

Repeat: Size of basic solutions

Lemma 52
Let $P = \{x \in \mathbb{R}^n \mid Ax \le b\}$ *be a bounded polyhedron. Let* $L := 2\langle A\rangle + \langle b\rangle + 2n(1+\log_2 n)$. *Then every entry* x_j *in a basic solution fulfills* $|x_j| = \frac{D_j}{D}$ *with* $D_j, D \le 2^L$.

In the following we use $\delta := 2^L$.

Proof:
We can replace P by $P' := \{x \mid A'x \le b; x \ge 0\}$ where $A' = \begin{bmatrix} A & -A \end{bmatrix}$. The lemma follows by applying Lemma 47, and observing that $\langle A'\rangle = 2\langle A\rangle$ and $n' = 2n$.

Repeat: Size of basic solutions

Lemma 52

Let $P = \{x \in \mathbb{R}^n \mid Ax \le b\}$ *be a bounded polyhedron. Let* $L := 2\langle A\rangle + \langle b\rangle + 2n(1 + \log_2 n)$*. Then every entry* x_j *in a basic solution fulfills* $|x_j| = \frac{D_j}{D}$ *with* $D_j, D \le 2^L$*.*

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How do we find the first ellipsoid?

For feasibility checking we can assume that the polytop P is bounded; it is sufficient to consider basic solutions.

Every entry x_i in a basic solution fulfills $|x_i| \leq \delta$.

Hence, P is contained in the cube $-\delta \leq x_i \leq \delta$.

A vector in this cube has at most distance $R := \sqrt{n}\delta$ from the origin.

Starting with the ball $E_0 := B(0, R)$ ensures that P is completely contained in the initial ellipsoid. This ellipsoid has volume at most $R^n \operatorname{vol}(B(0,1)) \leq (n\delta)^n \operatorname{vol}(B(0,1))$.

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When can we terminate?

Let $P := \{x \mid Ax \le b\}$ with $A \in \mathbb{Z}$ and $b \in \mathbb{Z}$ be a bounded polytop.

Consider the following polyhedron

$$P_\lambda := \left\{x \mid Ax \le b + \frac{1}{\lambda}\begin{pmatrix}1\\ \vdots\\ 1\end{pmatrix}\right\} ,$$

where $\lambda = \delta^2 + 1$.

Note that the volume of P_λ cannot be 0

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Making P full-dimensional

Lemma 53

P_λ *is feasible if and only if* P *is feasible.*

$\Longleftarrow$: obvious!

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P_λ is feasible if and only if P is feasible.

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Making P full-dimensional

$\Longrightarrow$:

Consider the polyhedrons

$$\bar{P} = \left\{ x \mid \begin{bmatrix} A & -A & I_m \end{bmatrix} x = b; x \geq 0 \right\}$$

and

$$\bar{P}_\lambda = \left\{ x \mid \begin{bmatrix} A & -A & I_m \end{bmatrix} x = b + \frac{1}{\lambda} \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}; x \geq 0 \right\} .$$

P is feasible if and only if $\bar{P}$ is feasible, and P_λ feasible if and only if $\bar{P}_\lambda$ feasible.

$\bar{P}_\lambda$ is bounded since P_λ and P are bounded.

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Let $\bar{A} = \begin{bmatrix} A & -A & I_m \end{bmatrix}$.

$\bar{P}_\lambda$ feasible implies that there is a basic feasible solution represented by

$$x_B = \bar{A}_B^{-1} b + \frac{1}{\lambda} \bar{A}_B^{-1} \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

(The other x-values are zero)

The only reason that this basic feasible solution is not feasible for $\bar{P}$ is that one of the basic variables becomes negative.

Hence, there exists i with

$$(\bar{A}_B^{-1} b)_i < 0 \le (\bar{A}_B^{-1} b)_i + \frac{1}{\lambda} (\bar{A}_B^{-1} \vec{1})_i$$

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By Cramers rule we get

$$(\bar{A}_B^{-1}b)_i < 0 \quad \Longrightarrow \quad (\bar{A}_B^{-1}b)_i \le -\frac{1}{\det(\bar{A}_B)} \le -1/\delta$$

and

$$(\bar{A}_B^{-1}\vec{1})_i \le \det(\bar{A}_B^j) \le \delta \ ,$$

where $\bar{A}_B^j$ is obtained by replacing the j-th column of $\bar{A}_B$ by $\vec{1}$.

But then

$$(\bar{A}_B^{-1}b)_i + \frac{1}{\lambda}(\bar{A}_B^{-1}\vec{1})_i \le -1/\delta + \delta/\lambda < 0 \ ,$$

as we chose $\lambda = \delta^2 + 1$. Contradiction.

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Lemma 54

If P_λ *is feasible then it contains a ball of radius* $r := 1/\delta^3$*. This has a volume of at least* $r^n \mathrm{vol}(B(0,1)) = \frac{1}{\delta^{3n}} \mathrm{vol}(B(0,1))$*.*

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Let $\vec{\ell}$ with $\|\vec{\ell}\| \leq r$. Then

$$(A(x + \vec{\ell}))_i$$

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Hence, $x + \vec{\ell}$ is feasible for P_λ which proves the lemma.

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&= 8n(n+1)\ln(\delta) + 2(n+1)n\ln(n)\\
&= \mathcal{O}(\mathrm{poly}(n)\cdot L)
\end{aligned}$$

Algorithm 1 ellipsoid-algorithm

```
input: point $c \in \mathbb{R}^n$, convex set $K \subseteq \mathbb{R}^n$, radii $R$ and $r$
        with $K \subseteq B(c,R)$, and $B(x,r) \subseteq K$ for some $x$
output: point $x \in K$ or "$K$ is empty"
$Q \leftarrow \mathrm{diag}(R^2,\dots,R^2)$ // i.e., $L = \mathrm{diag}(R,\dots,R)$
repeat
    if $c \in K$ then return $c$
    else
        choose a violated hyperplane $a$
        $c \leftarrow c - \frac{1}{n+1}\frac{Qa}{\sqrt{a^TQa}}$
        $Q \leftarrow \frac{n^2}{n^2-1}\Big(Q - \frac{2}{n+1}\frac{Qaa^TQ}{a^TQa}\Big)$
    endif
until $\det(Q) \le r^{2n}$ // i.e., $\det(L) \le r^n$
return "$K$ is empty"
```

Separation Oracle

Let $K \subseteq \mathbb{R}^n$ be a convex set. A separation oracle for K is an algorithm A that gets as input a point $x \in \mathbb{R}^n$ and either

- certifies that $x \in K$,
- or finds a hyperplane separating x from K.

We will usually assume that A is a polynomial-time algorithm.

In order to find a point in K we need

- a guarantee that a ball of radius r is contained in K,
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The Ellipsoid algorithm requires $\mathcal{O}(\text{poly}(n) \cdot \log(R/r))$ iterations. Each iteration is polytime for a polynomial-time Separation oracle.

Separation Oracle

Let $K \subseteq \mathbb{R}^n$ be a convex set. A separation oracle for K is an algorithm A that gets as input a point $x \in \mathbb{R}^n$ and either

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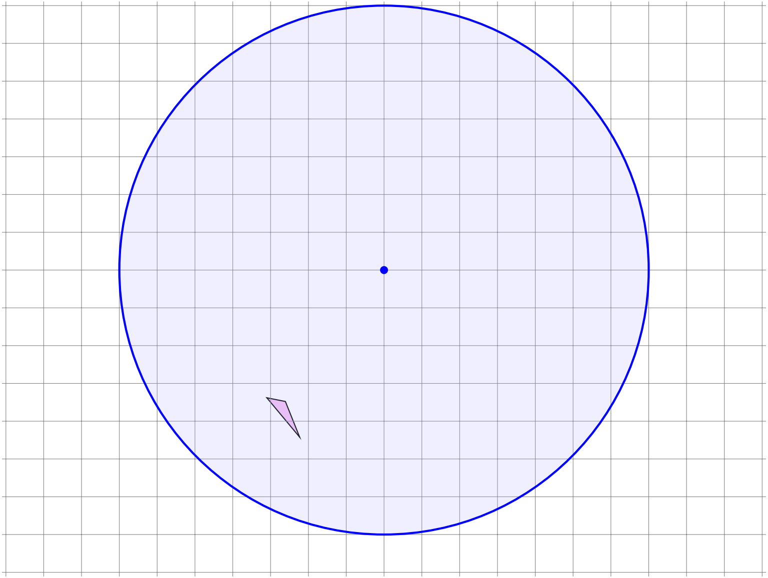

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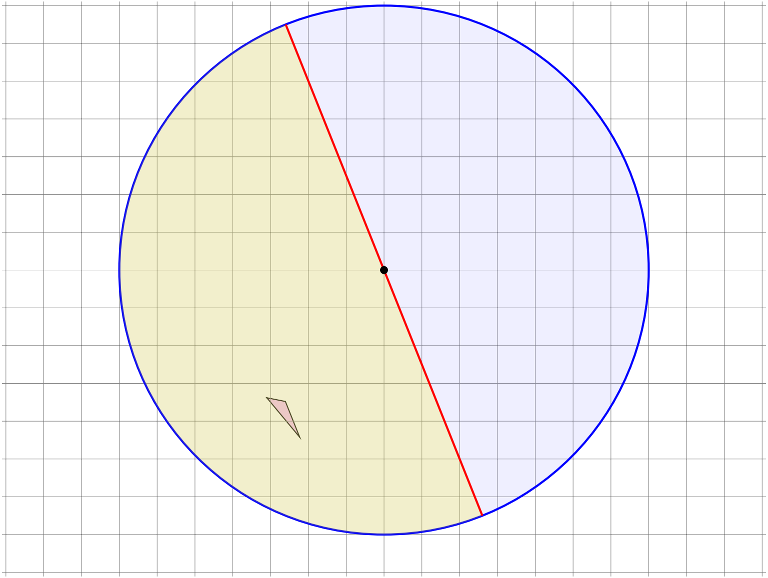

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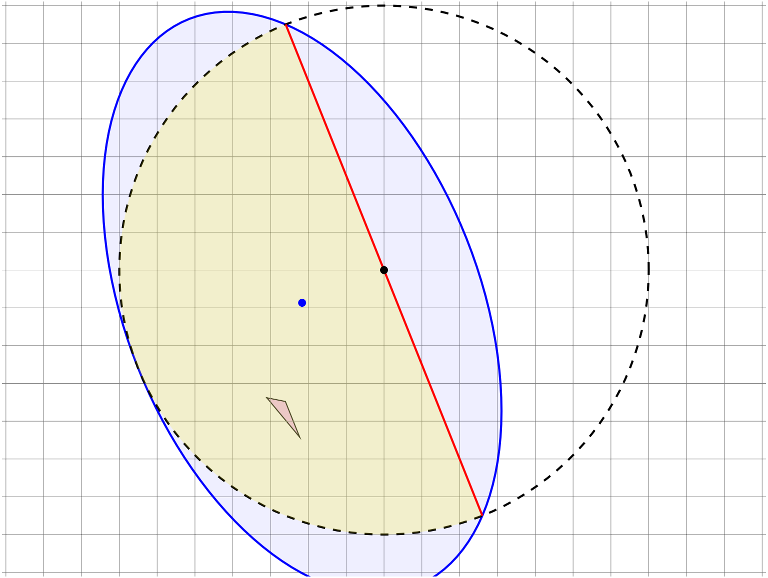

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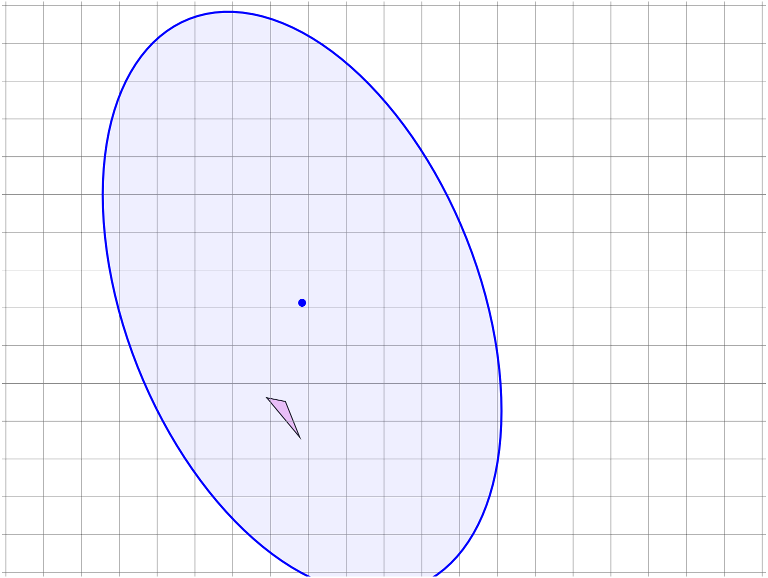

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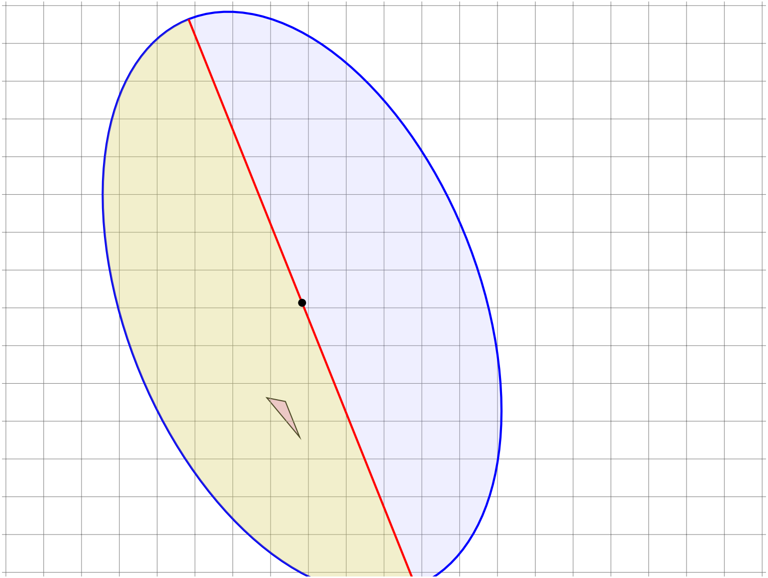

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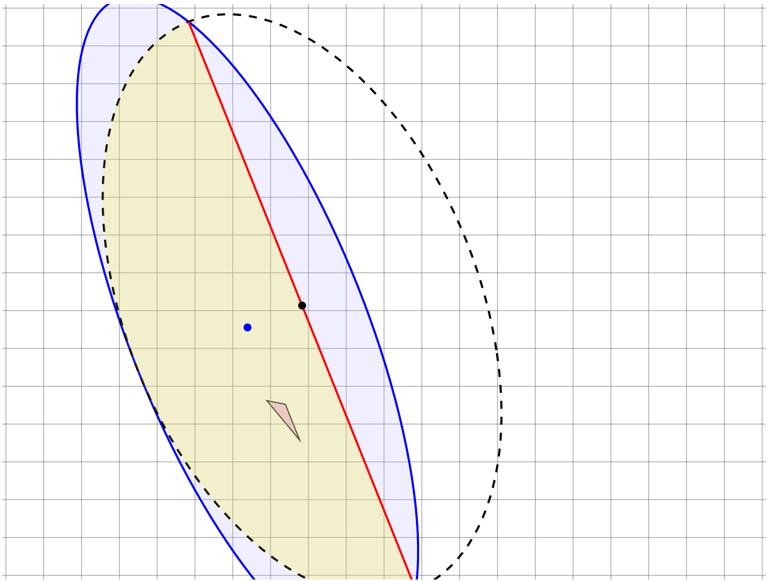

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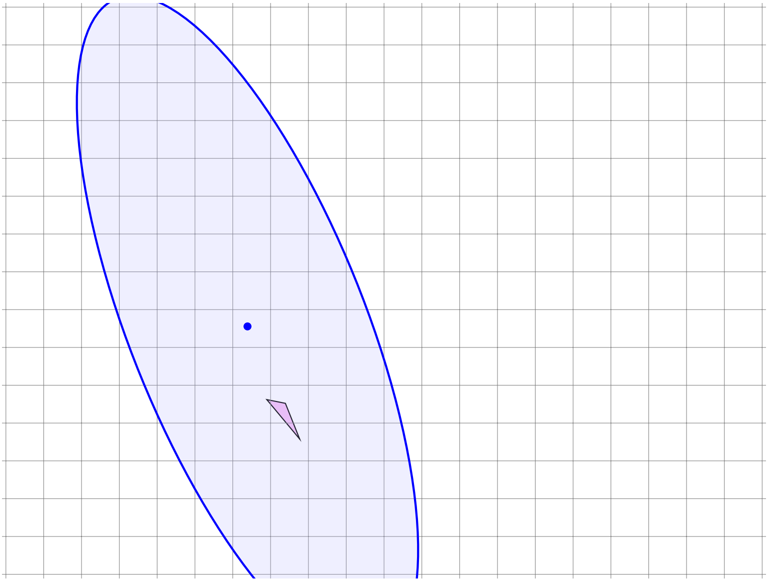

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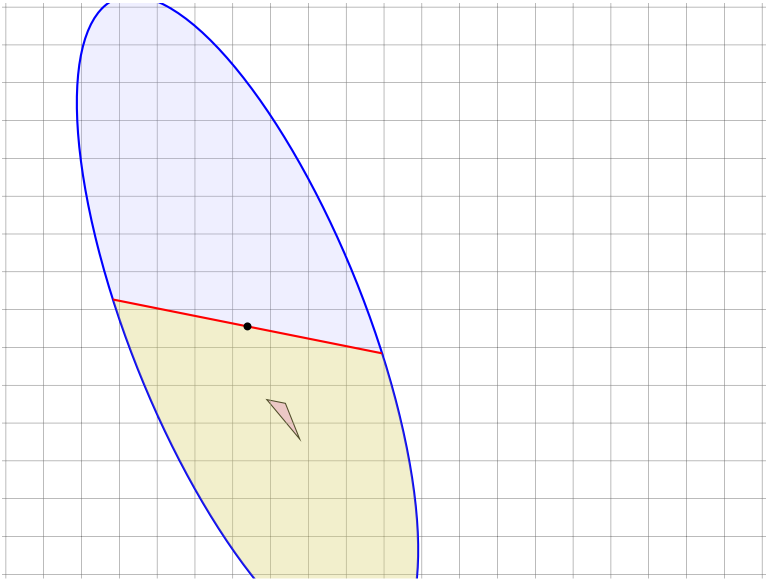

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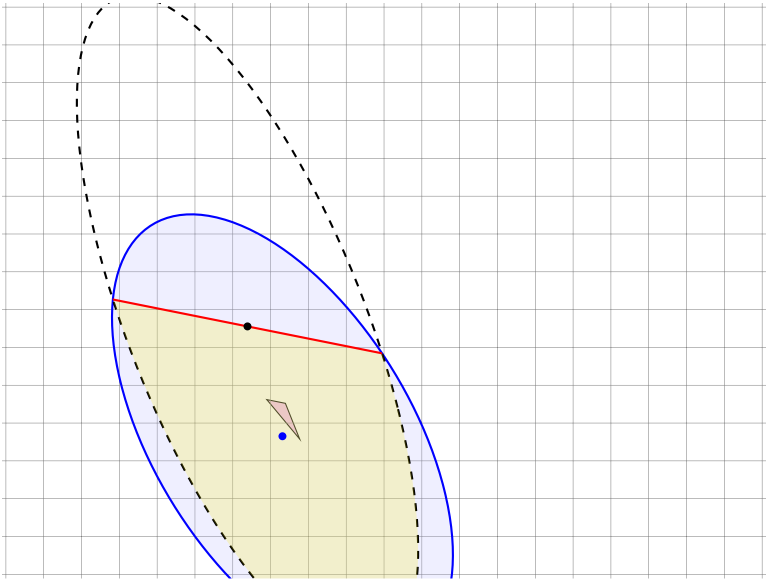

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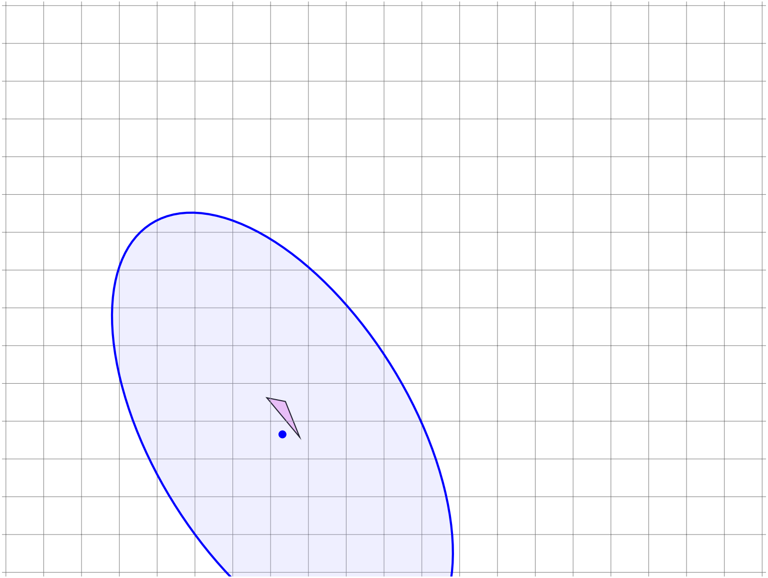

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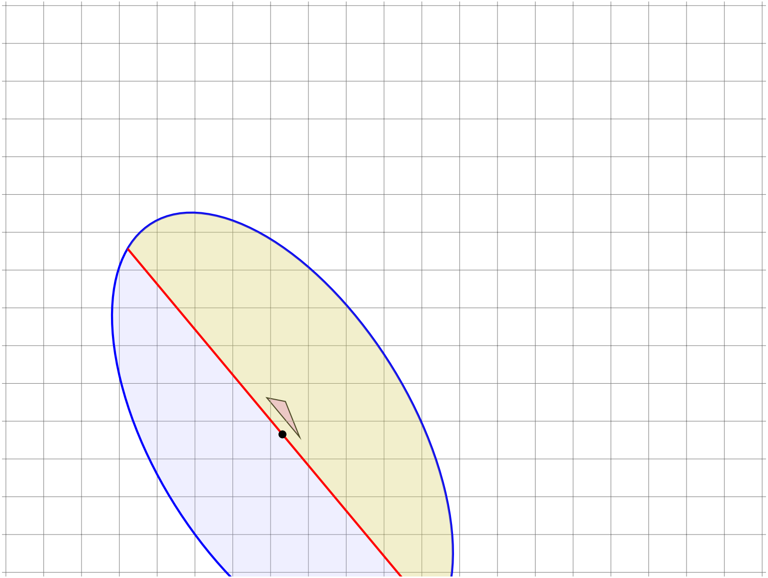

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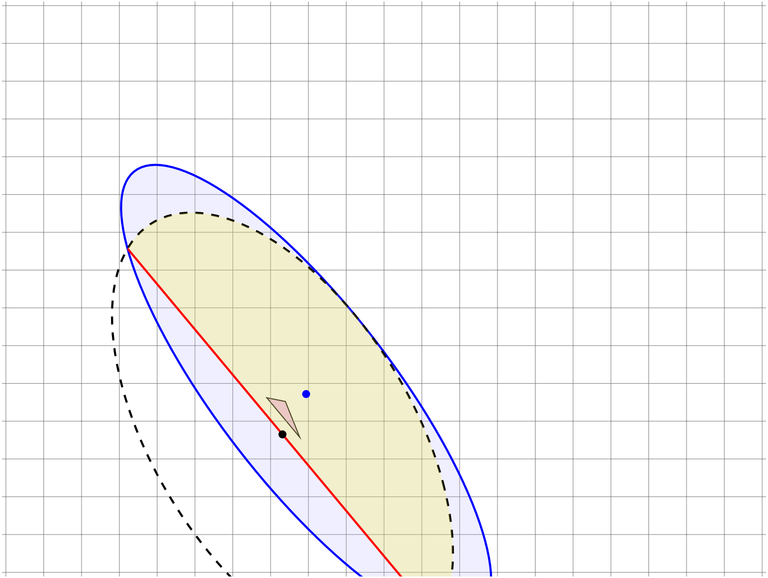

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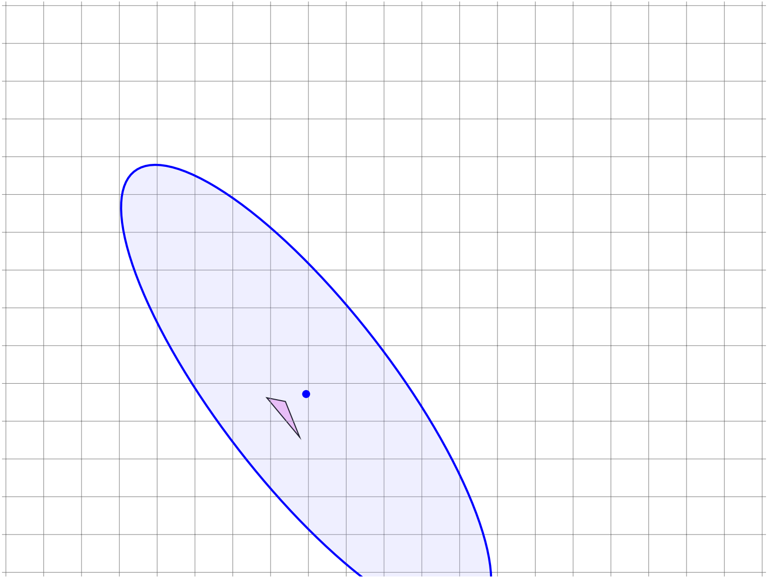

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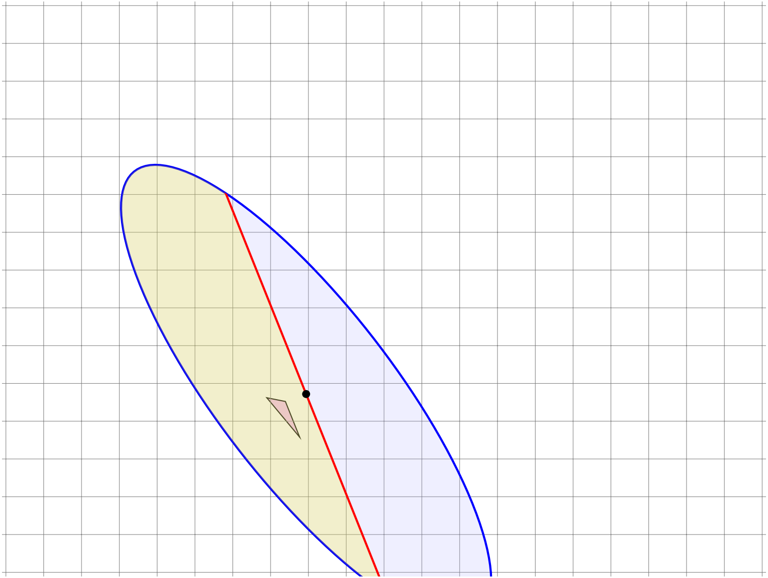

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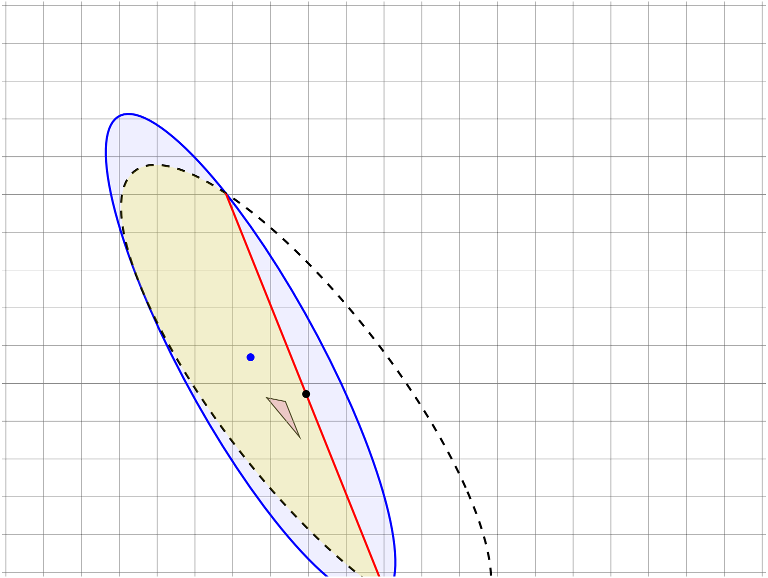

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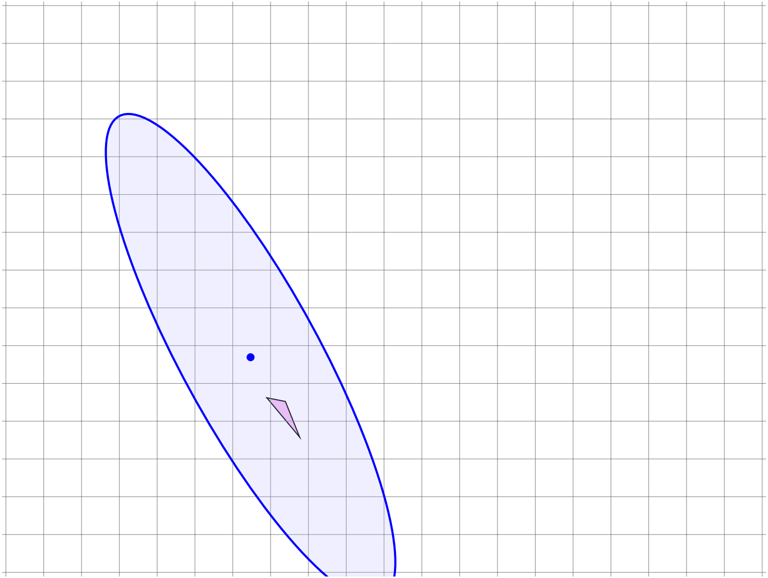

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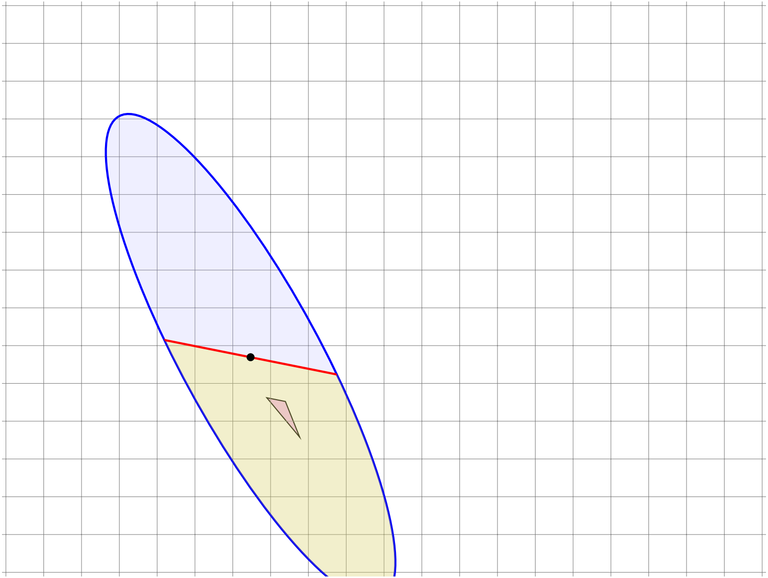

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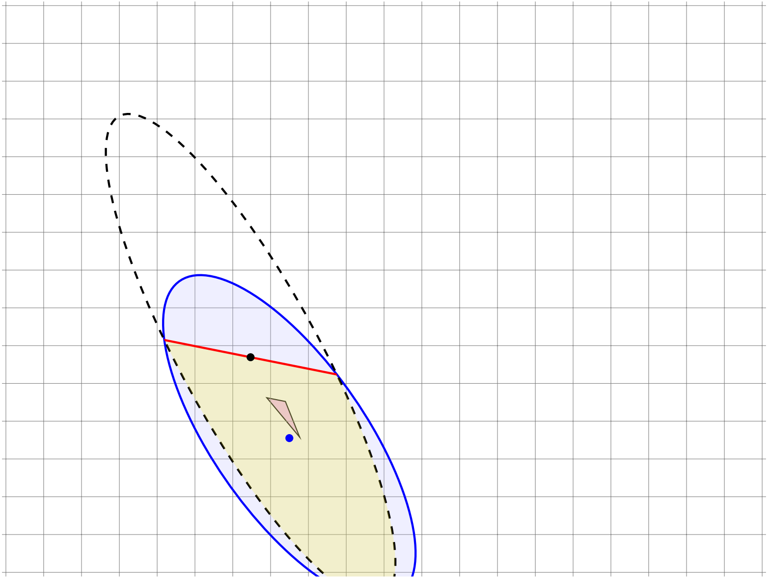

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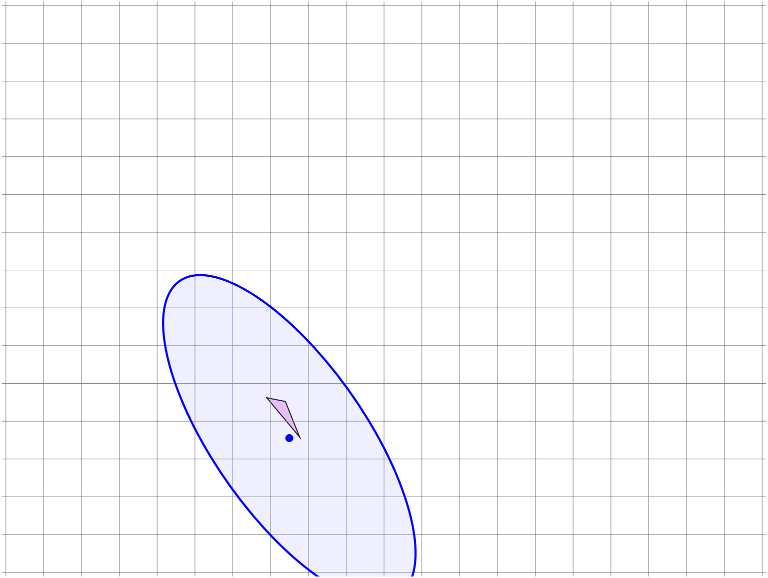

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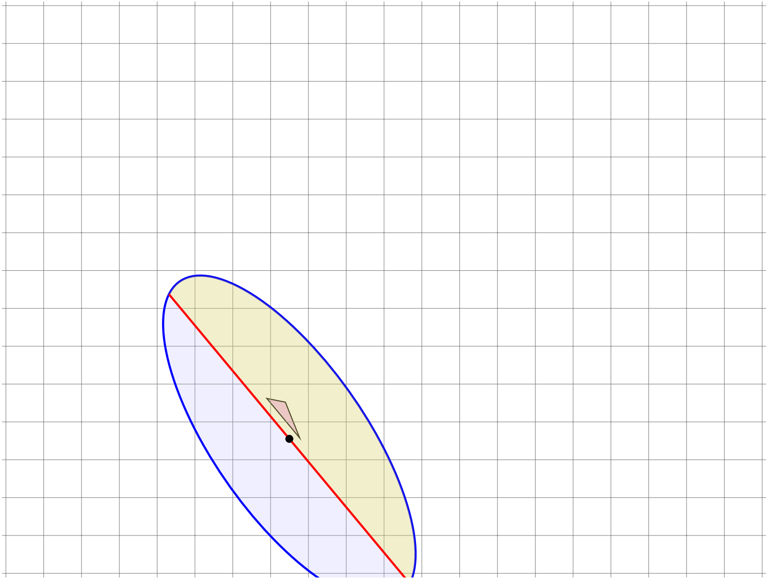

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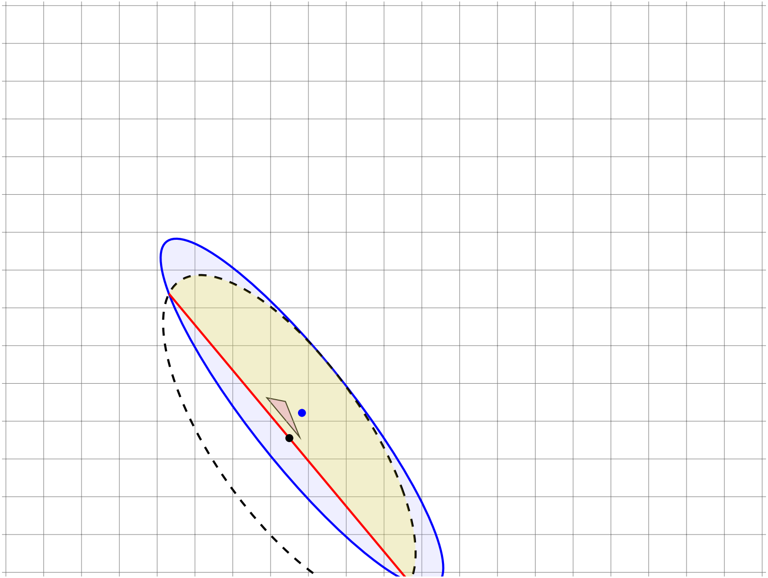

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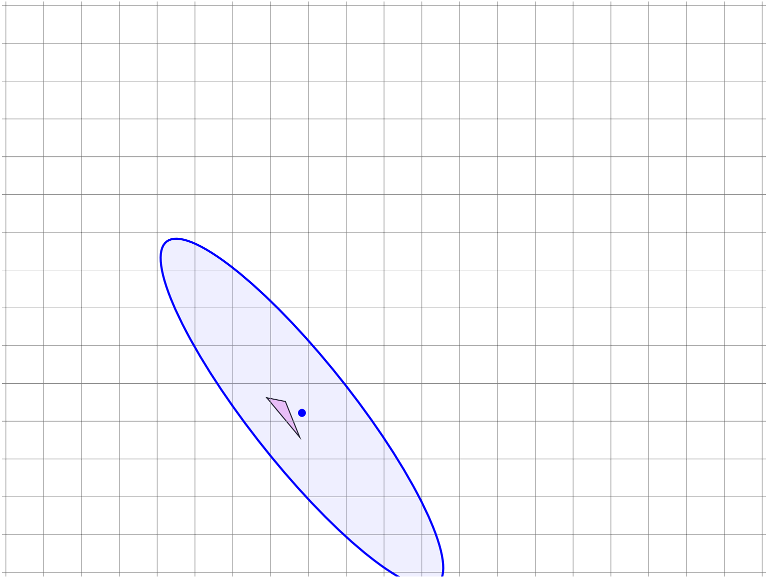

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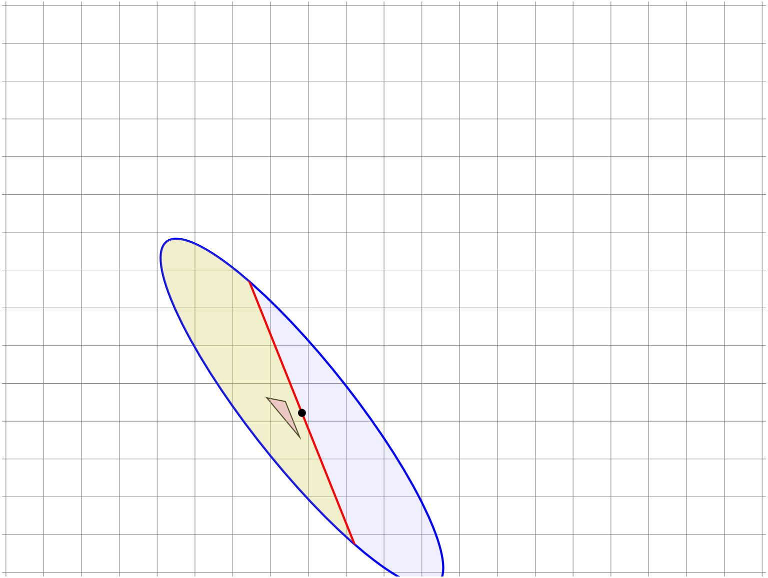

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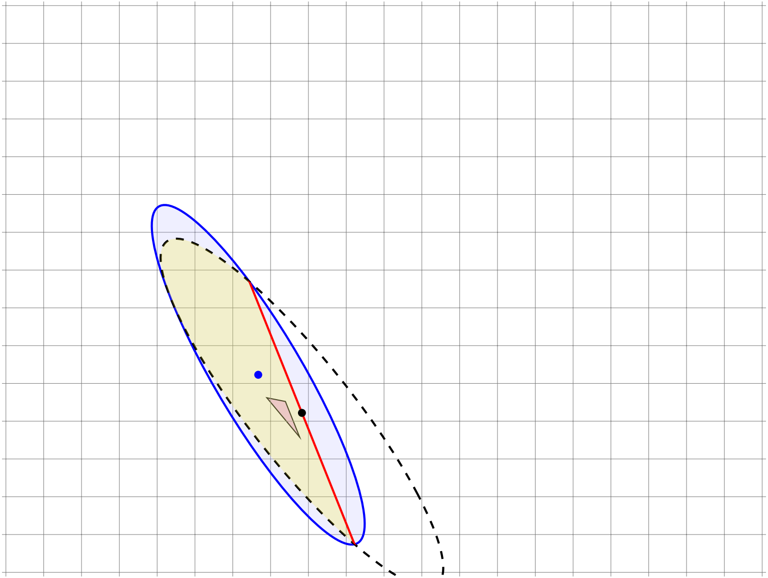

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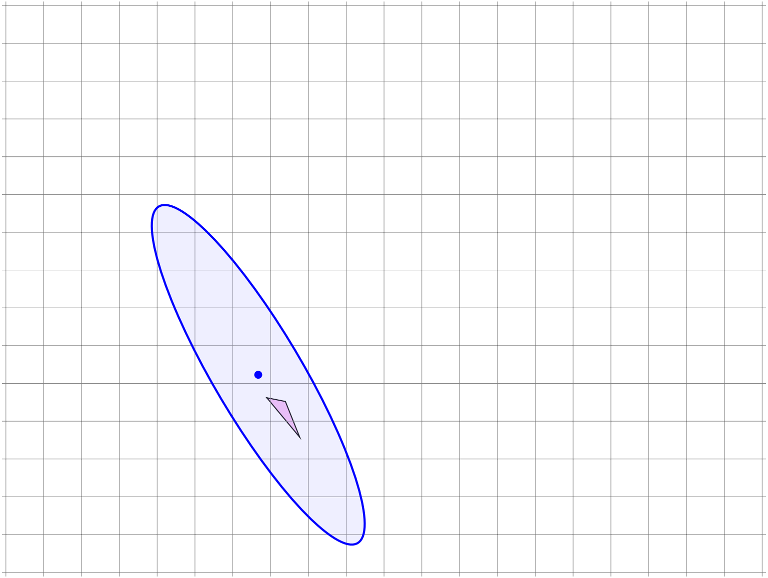

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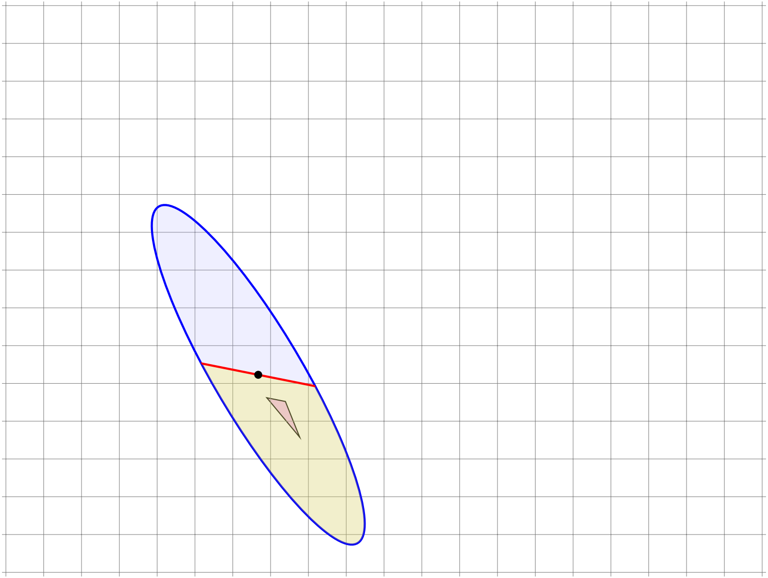

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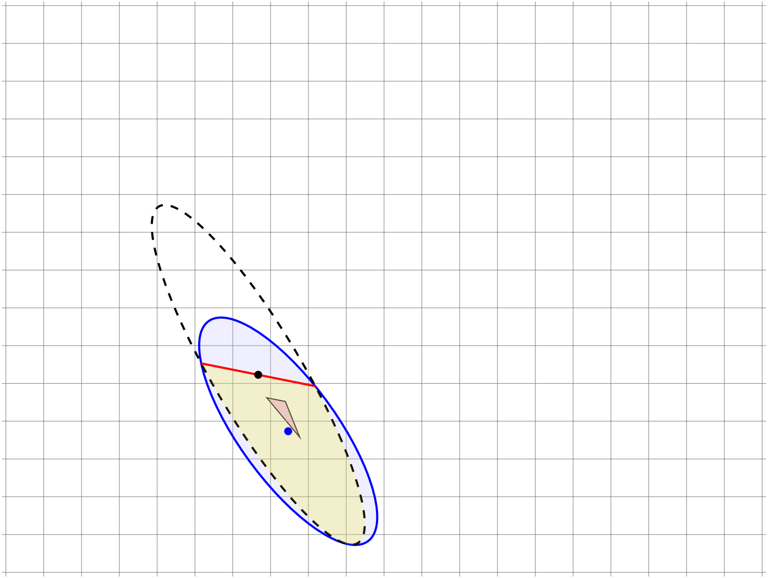

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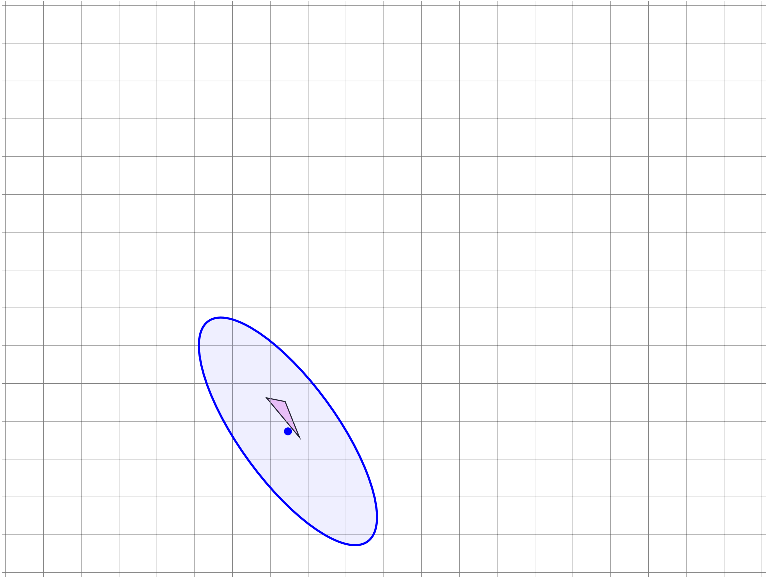

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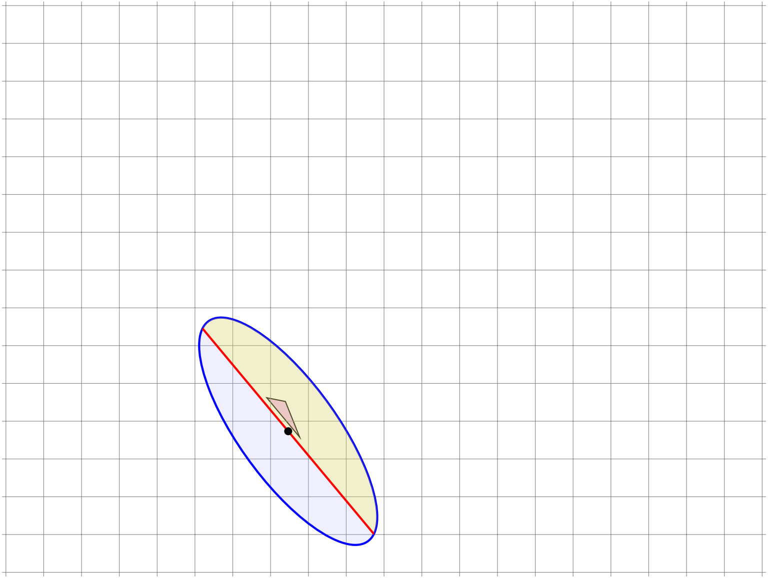

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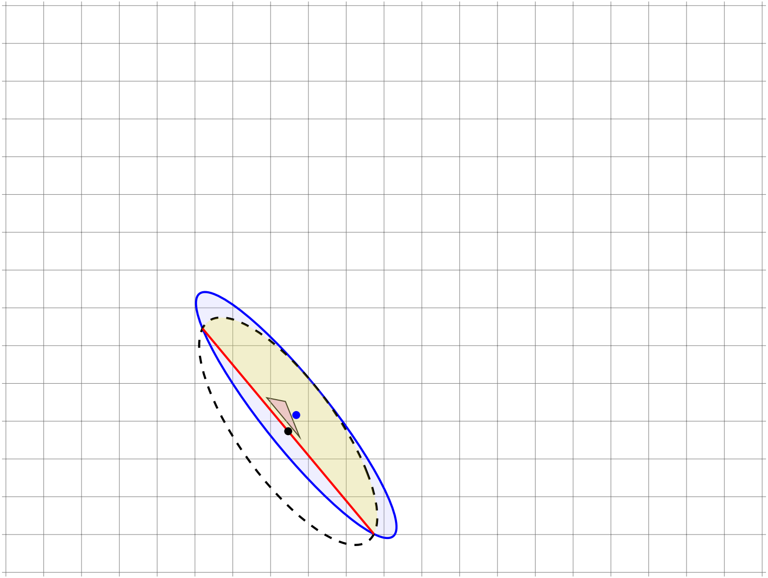

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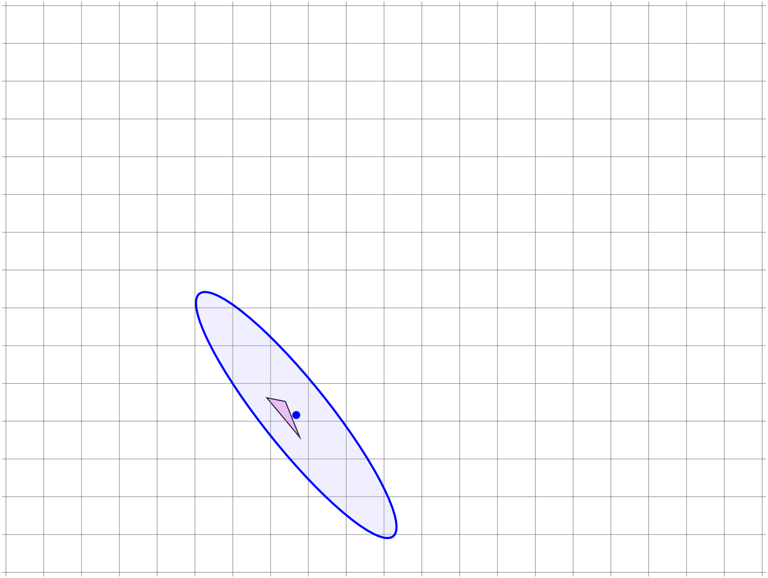

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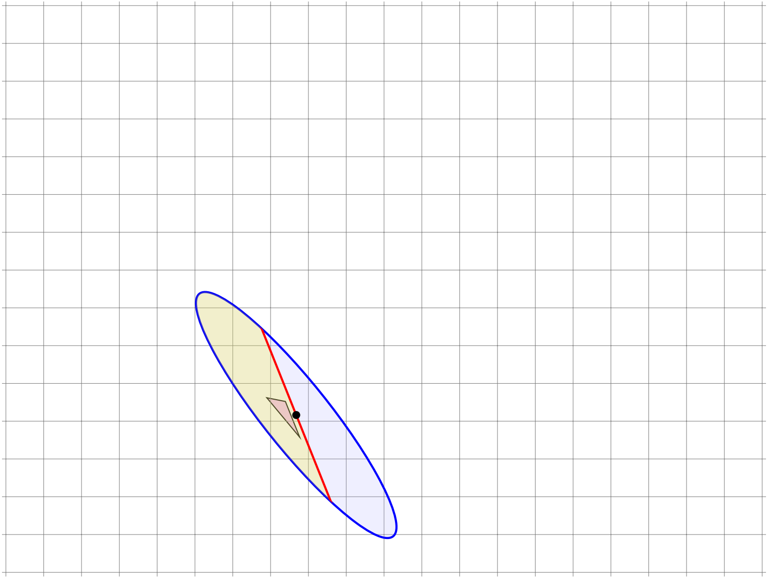

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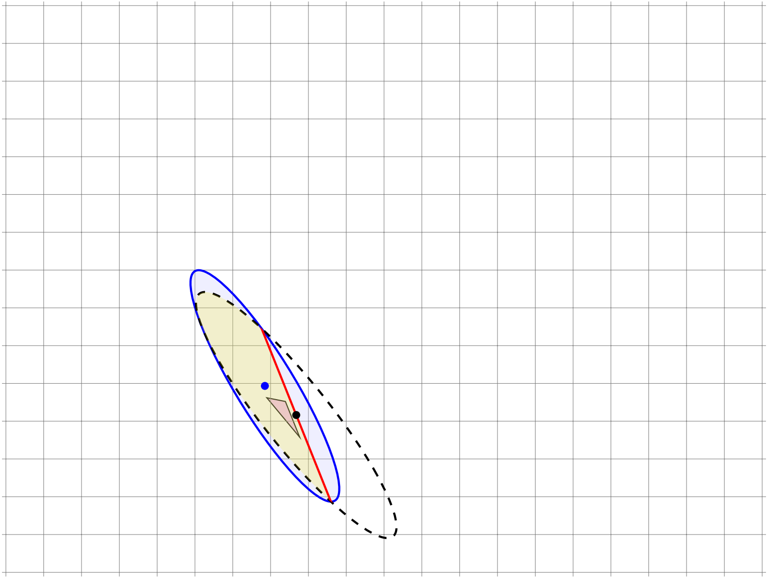

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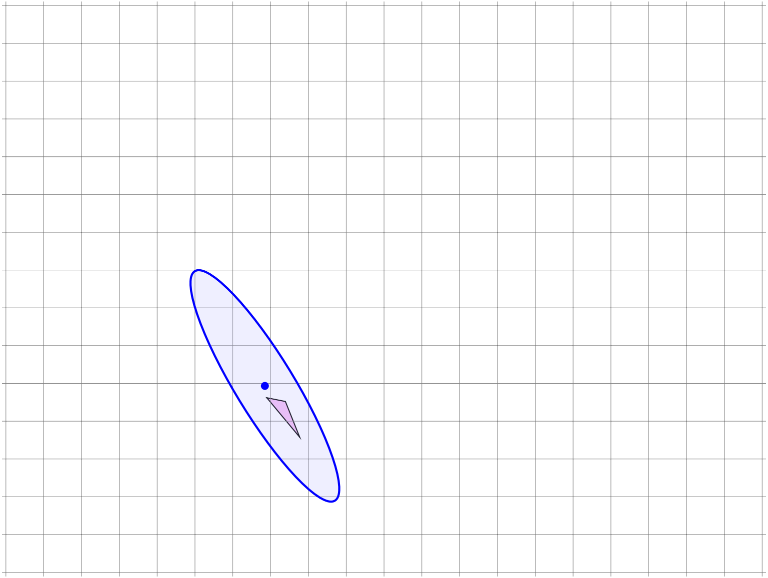

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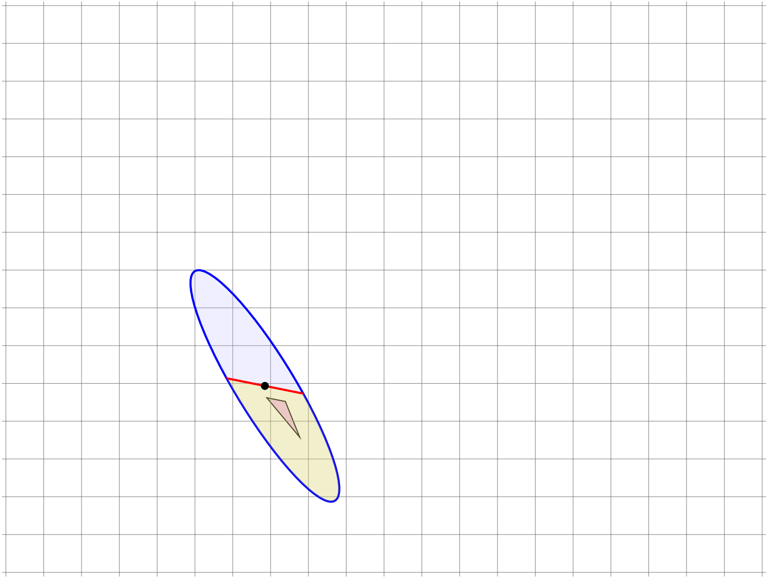

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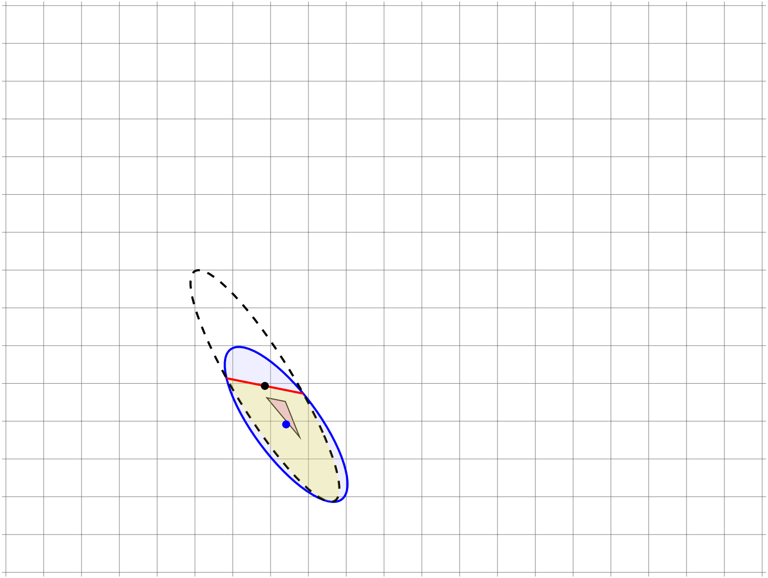

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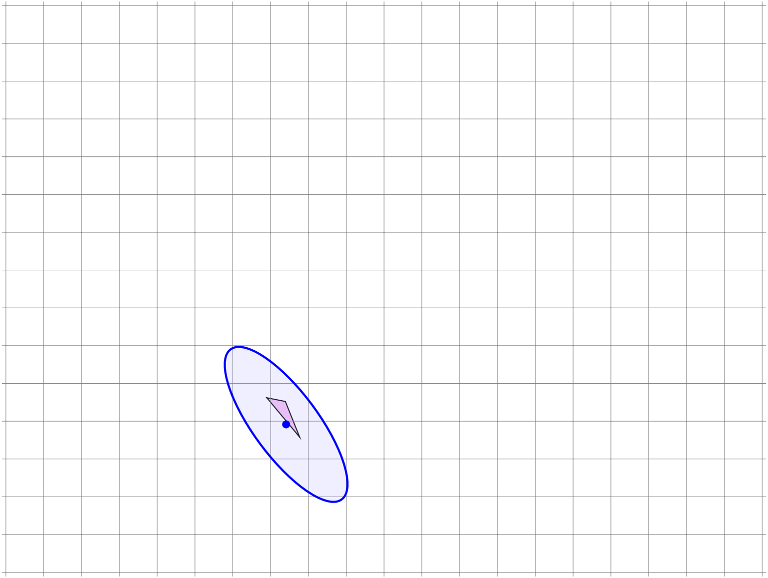

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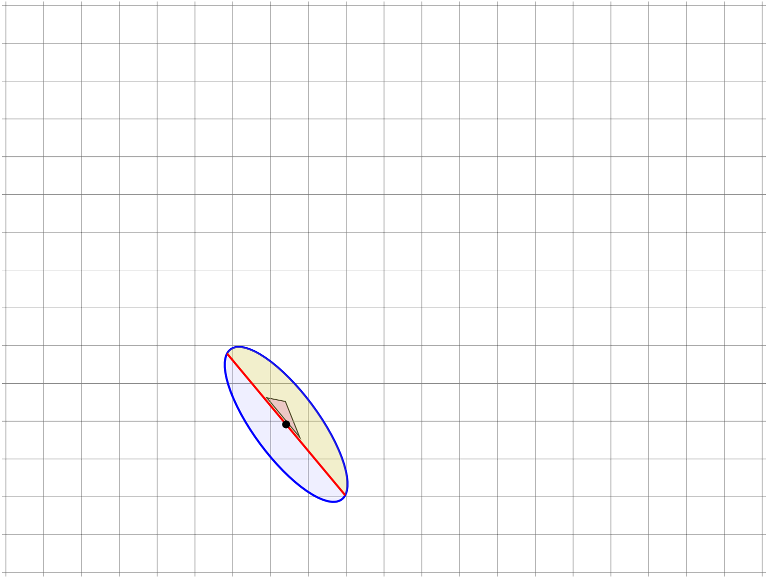

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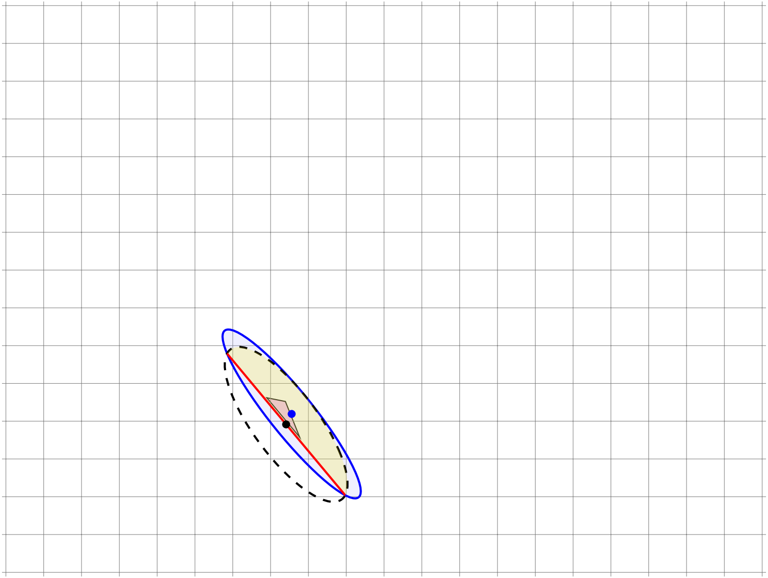

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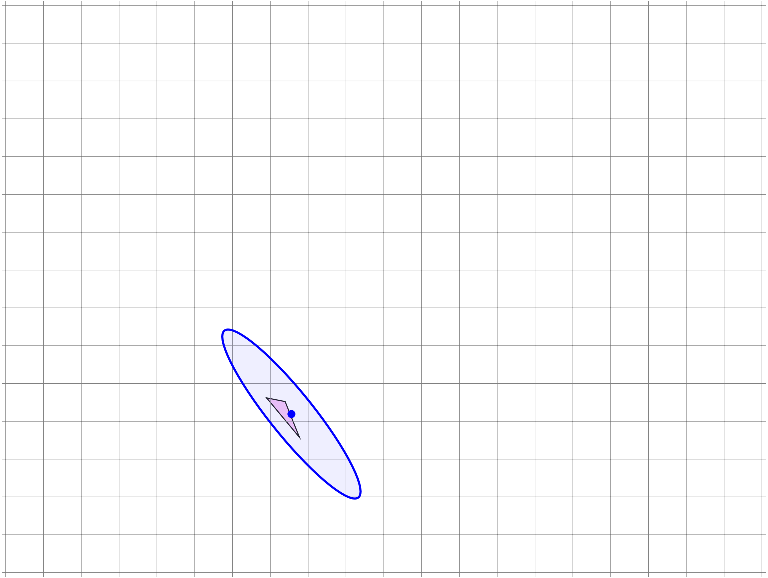

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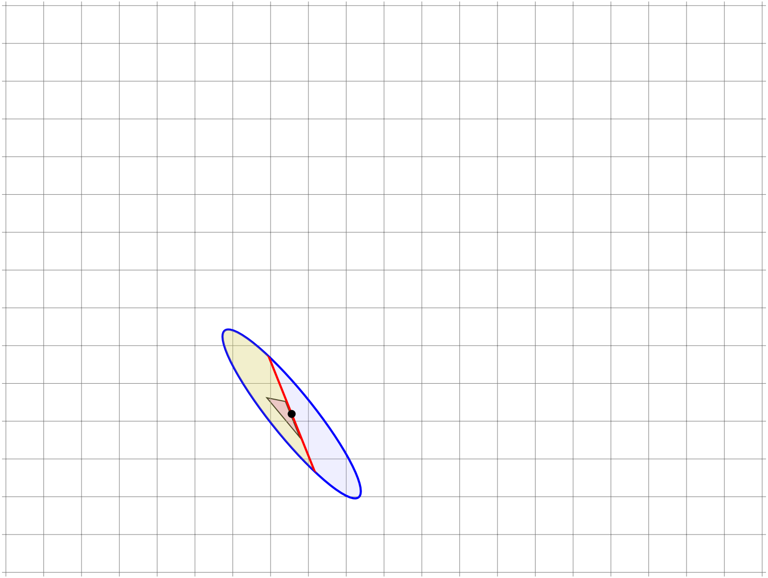

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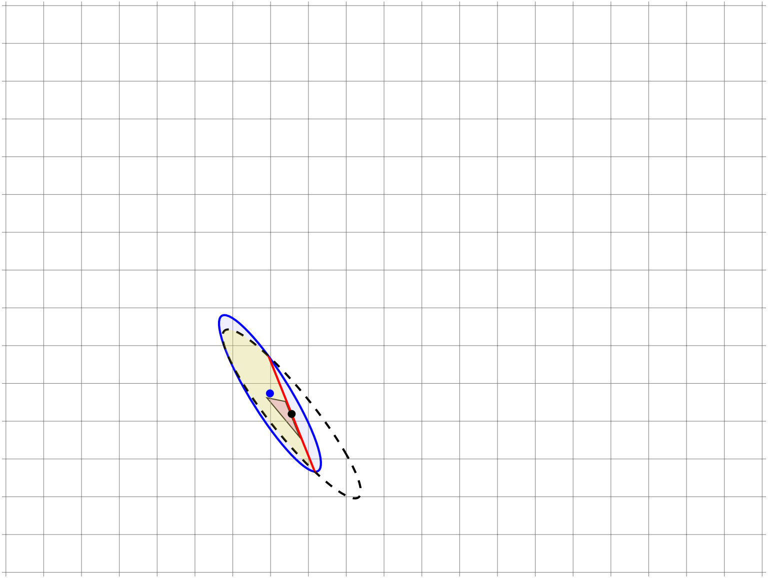

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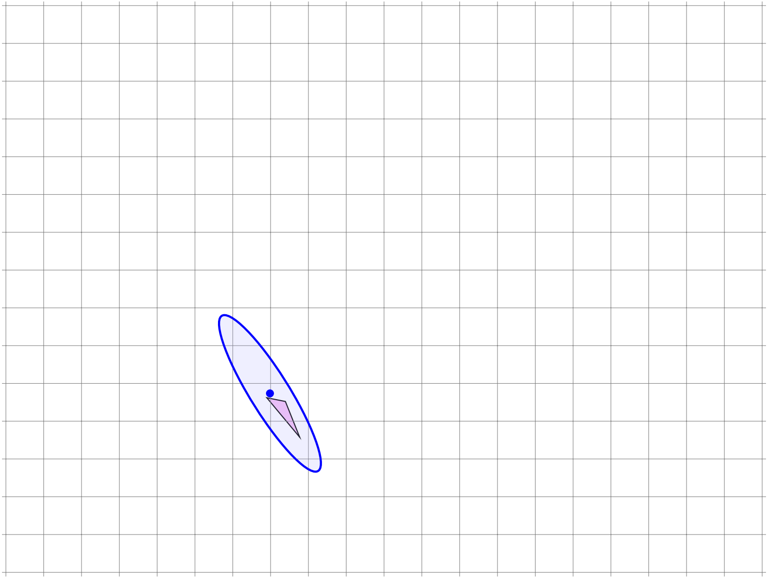

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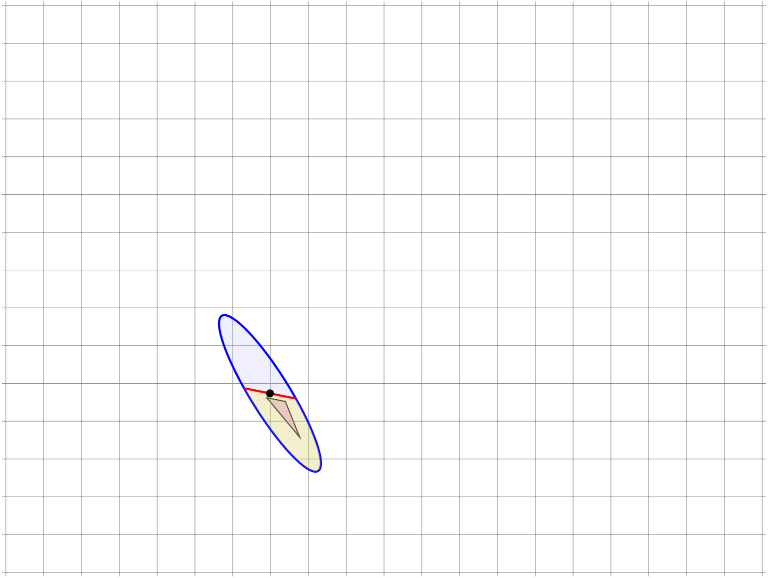

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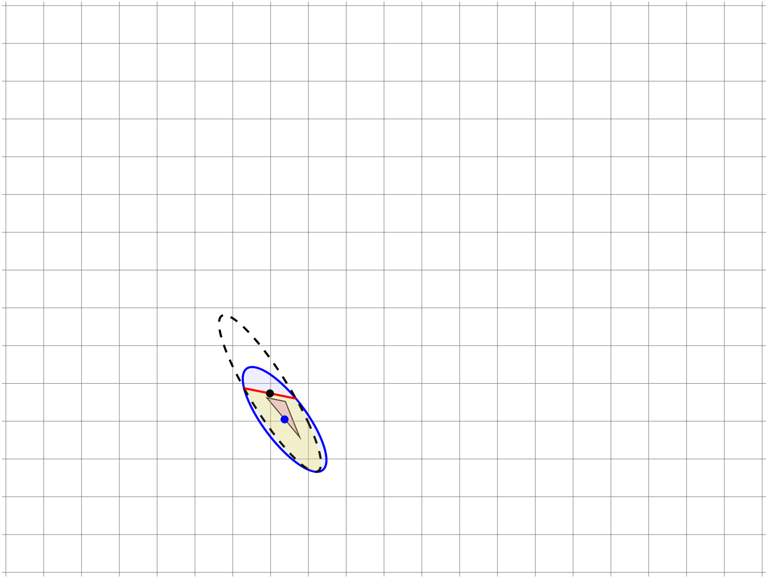

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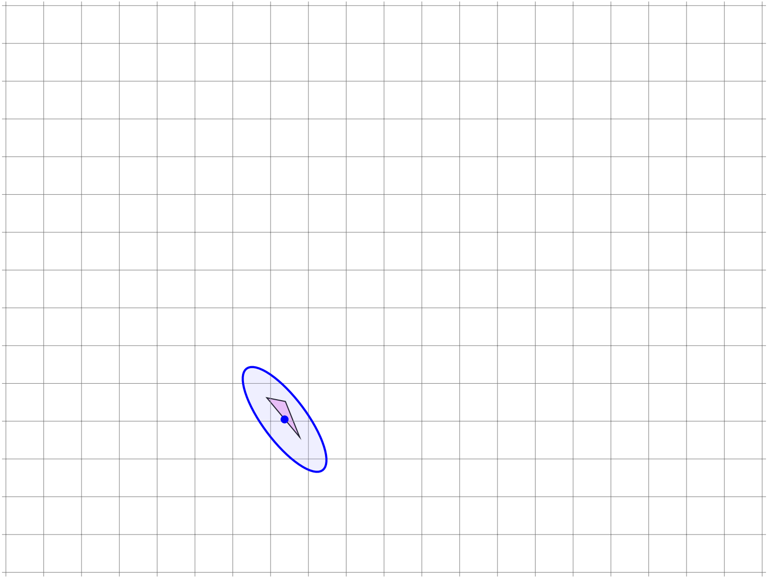

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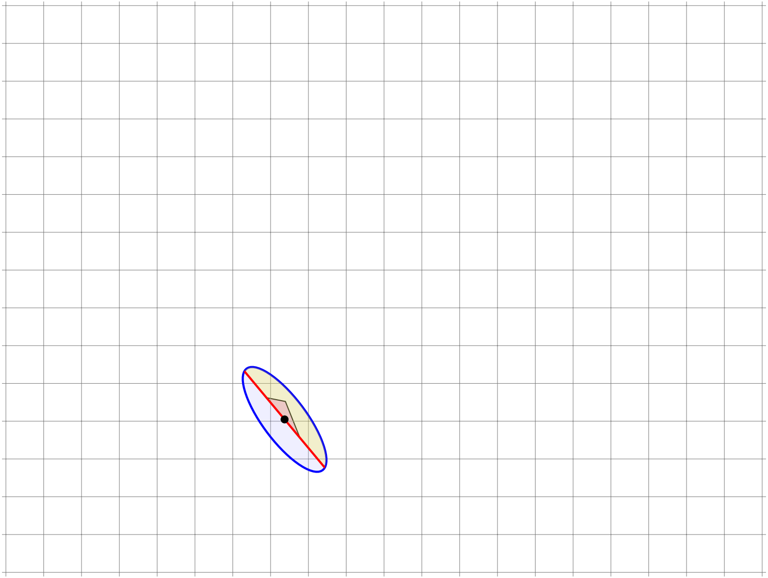

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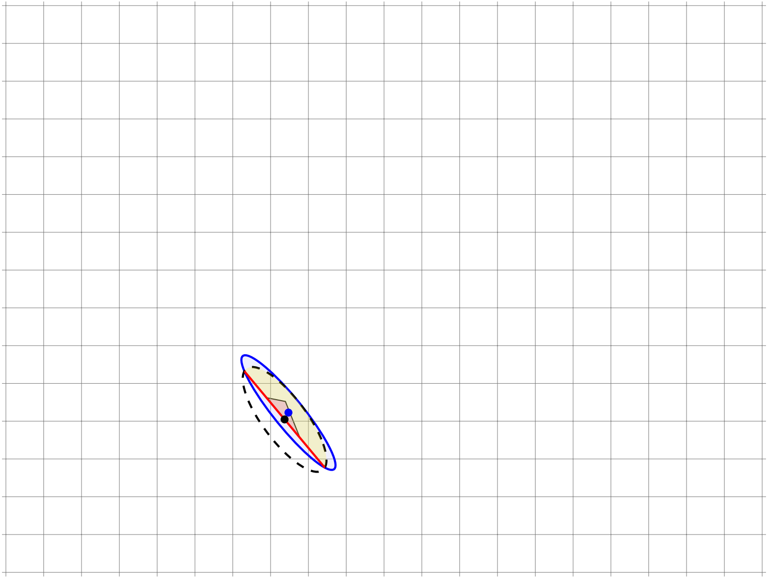

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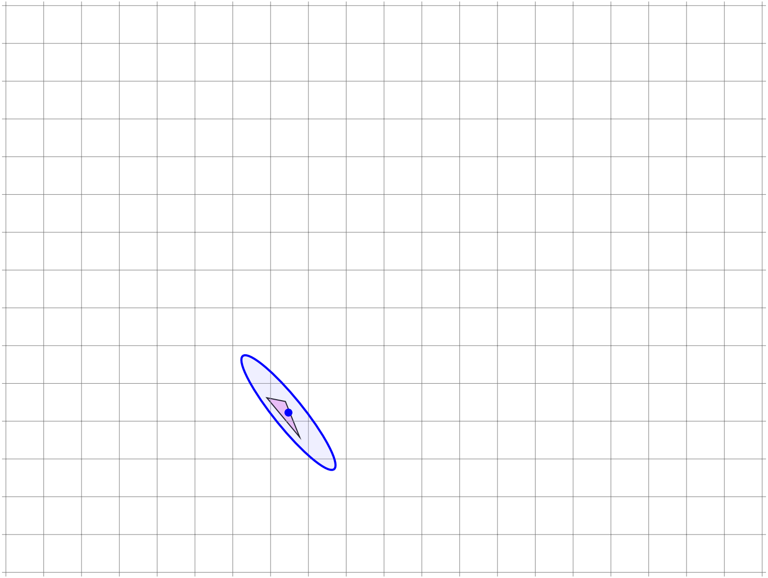

10 Karmarkars Algorithm

- inequalities $Ax \leq b$; $m \times n$ matrix A with rows a_i^T
- $P = \{x \mid Ax \leq b\}$; $P^\circ := \{x \mid Ax < b\}$
- interior point algorithm: $x \in P^\circ$ throughout the algorithm
- for $x \in P^\circ$ define
  $$s_i(x) := b_i - a_i^T x$$
  as the slack of the i-th constraint

logarithmic barrier function:

$$\phi(x) = -\sum_{i=1}^{m} \ln(s_i(x))$$

Penalty for point x; points close to the boundary have a very large penalty.

Throughout this section a_i denotes the i-th row as a column vector.

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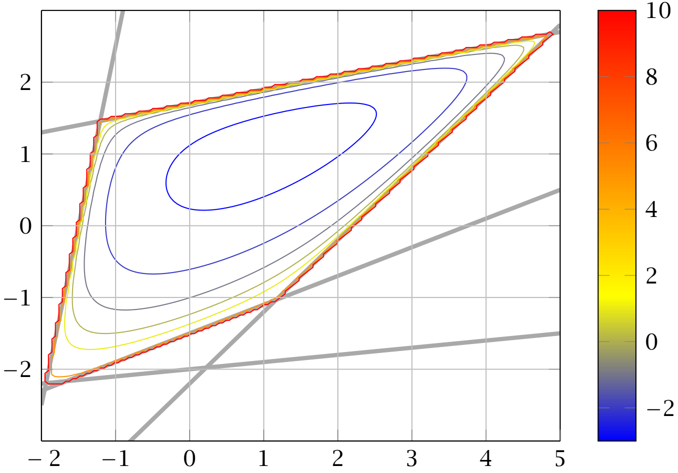

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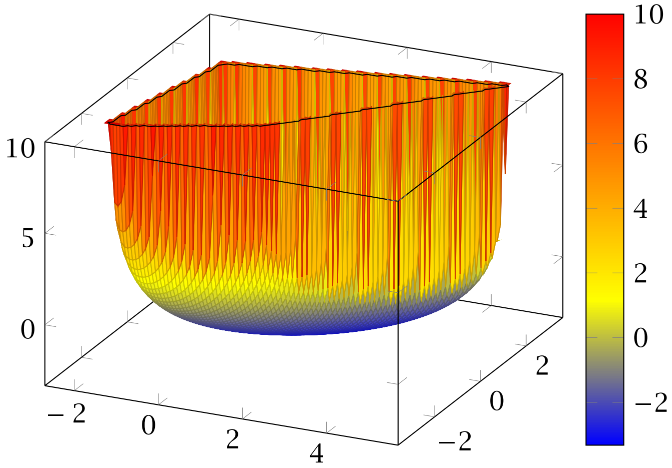

Gradient and Hessian

Taylor approximation:

$$\phi(x+\epsilon) \approx \phi(x) + \nabla\phi(x)^T\epsilon + \frac{1}{2}\epsilon^T\nabla^2\phi(x)\epsilon$$

Gradient:

$$\nabla\phi(x) = \sum_{i=1}^{m} \frac{1}{s_i(x)} \cdot a_i = A^T d_x$$

where $d_x^T = (1/s_1(x), \ldots, 1/s_m(x))$. ($d_x$ vector of inverse slacks)

Hessian:

$$H_x := \nabla^2\phi(x) = \sum_{i=1}^{m} \frac{1}{s_i(x)^2} a_i a_i^T = A^T D_x^2 A$$

with $D_x = \mathrm{diag}(d_x)$.

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$$\phi(x+\epsilon) \approx \phi(x) + \nabla\phi(x)^T\epsilon + \frac{1}{2}\epsilon^T\nabla^2\phi(x)\epsilon$$

Gradient:

$$\nabla\phi(x) = \sum_{i=1}^{m} \frac{1}{s_i(x)} \cdot a_i = A^T d_x$$

where $d_x^T = (1/s_1(x), \dots, 1/s_m(x))$. ($d_x$ vector of inverse slacks)

Hessian:

$$H_x := \nabla^2\phi(x) = \sum_{i=1}^{m} \frac{1}{s_i(x)^2} a_i a_i^T = A^T D_x^2 A$$

with $D_x = \mathrm{diag}(d_x)$.

Gradient and Hessian

Taylor approximation:

$$\phi(x+\epsilon) \approx \phi(x) + \nabla\phi(x)^T\epsilon + \frac{1}{2}\epsilon^T\nabla^2\phi(x)\epsilon$$

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Proof for Gradient

$$\begin{aligned}\frac{\partial\phi(x)}{\partial x_i} &= \frac{\partial}{\partial x_i}\Bigl(-\sum_r \ln(s_r(x))\Bigr)\\ &= -\sum_r \frac{\partial}{\partial x_i}\Bigl(\ln(s_r(x))\Bigr) = -\sum_r \frac{1}{s_r(x)}\frac{\partial}{\partial x_i}\Bigl(s_r(x)\Bigr)\\ &= -\sum_r \frac{1}{s_r(x)}\frac{\partial}{\partial x_i}\Bigl(b_r - a_r^T x\Bigr) = \sum_r \frac{1}{s_r(x)}\frac{\partial}{\partial x_i}\Bigl(a_r^T x\Bigr)\\ &= \sum_r \frac{1}{s_r(x)} A_{ri}\end{aligned}$$

The i-th entry of the gradient vector is $\sum_r 1/s_r(x)\cdot A_{ri}$. This gives that the gradient is

$$\nabla\phi(x) = \sum_r 1/s_r(x) a_r = A^T d_x$$

Proof for Hessian

$$\begin{aligned}\frac{\partial}{\partial x_j}\Big(\sum_r \frac{1}{s_r(x)}A_{ri}\Big) &= \sum_r A_{ri}\Big(-\frac{1}{s_r(x)^2}\Big)\cdot\frac{\partial}{\partial x_j}\Big(s_r(x)\Big)\\ &= \sum_r A_{ri}\frac{1}{s_r(x)^2}A_{rj}\end{aligned}$$

Note that $\sum_r A_{ri}A_{rj} = (A^TA)_{ij}$. Adding the additional factors $1/s_r(x)^2$ can be done with a diagonal matrix.

Hence the Hessian is

$$H_x = A^TD^2A$$

Properties of the Hessian

H_x is positive semi-definite for $x \in P^\circ$

$$u^T H_x u = u^T A^T D_x^2 A u = \|D_x A u\|_2^2 \geq 0$$

This gives that $\phi(x)$ is convex.

If $\operatorname{rank}(A) = n$, H_x is positive definite for $x \in P^\circ$

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Dikin Ellipsoid

$$E_x = \{y \mid (y-x)^T H_x (y-x) \le 1\} = \{y \mid \|y-x\|_{H_x} \le 1\}$$

Points in E_x are feasible!!!

$$\begin{aligned}(y-x)^T H_x (y-x) &= (y-x)^T A^T D_x^{-2} A (y-x)\\ &= \sum_{i=1}^{m} \frac{(a_i^T (y-x))^2}{s_i(x)^2}\\ &= \sum_{i=1}^{m} \frac{(\text{change of distance to } i\text{-th constraint going from } x \text{ to } y)^2}{(\text{distance of } x \text{ to } i\text{-th constraint})^2}\\ &\le 1\end{aligned}$$

In order to become infeasible when going from x to y one of the terms in the sum would need to be larger than 1.

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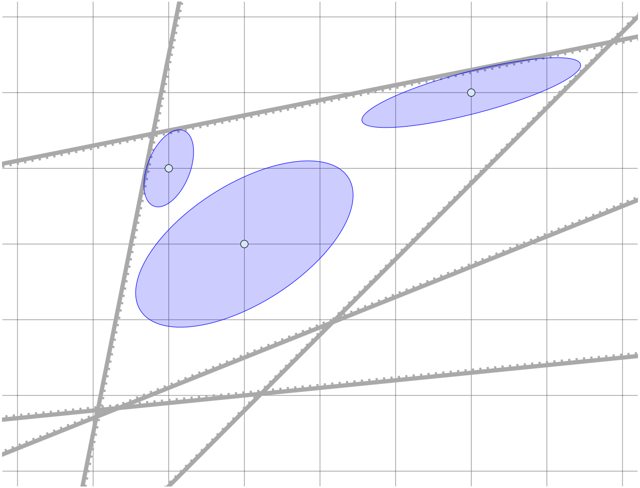
Dikin Ellipsoids



Analytic Center

$$x_{\text{ac}} := \arg\min_{x \in P^\circ} \phi(x)$$

- x_{ac} is solution to

$$\nabla \phi(x) = \sum_{i=1}^{m} \frac{1}{s_i(x)} a_i = 0$$

- depends on the description of the polytope
- x_{ac} exists and is unique iff P° is nonempty and bounded

Central Path

In the following we assume that the LP and its dual are strictly feasible and that $\text{rank}(A) = n$.

Central Path:
Set of points $\{x^*(t) \mid t > 0\}$ with

$$x^*(t) = \text{argmin}_x\{tc^Tx + \phi(x)\}$$

- $t = 0$: analytic center
- $t = \infty$: optimum solution

$x^*(t)$ exists and is unique for all $t \geq 0$.

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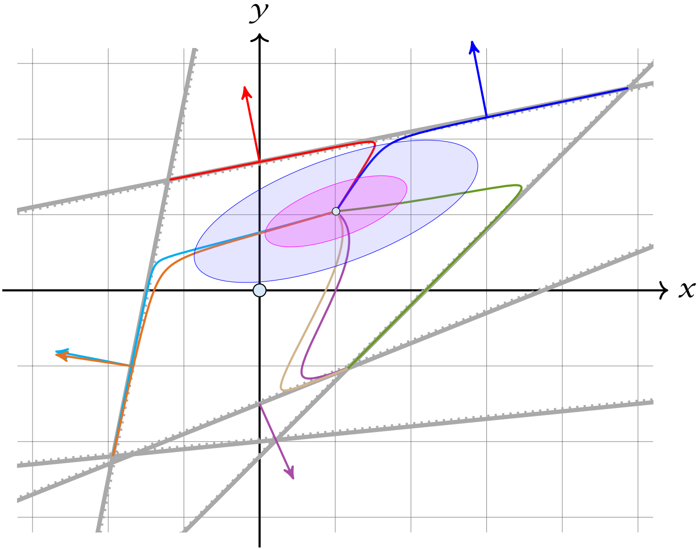
Different Central Paths



Central Path

Intuitive Idea:
Find point on central path for large value of t. Should be close to optimum solution.

Questions:

- Is this really true? How large a t do we need?
- How do we find corresponding point $x^*(t)$ on central path?

The Dual

primal-dual pair:

$$\begin{array}{rl} \text{min} & c^Tx \\ \text{s.t.} & Ax \le b \end{array}$$

$$\begin{array}{rl} \text{max} & -b^Tz \\ \text{s.t.} & A^Tz + c = 0 \\ & z \ge 0 \end{array}$$

Assumptions

- primal and dual problems are strictly feasible;
- $\mathrm{rank}(A) = n$.

Note that the right LP in standard form is equal to $\max\{-b^Ty \mid -A^Ty = c, x \ge 0\}$. The dual of this is $\min\{c^Tx \mid -Ax \ge -b\}$ (variables x are unrestricted).

Force Field Interpretation

Point $x^*(t)$ on central path is solution to $tc + \nabla\phi(x) = 0$

- We can view each constraint as generating a repelling force. The combination of these forces is represented by $\nabla\phi(x)$.
- In addition there is a force tc pulling us towards the optimum solution.

The “gravitational force” actually pulls us in direction $-\nabla\Phi(x)$. We are minimizing, hence, optimizing in direction $-c$.

How large should t be?

Point $x^*(t)$ on central path is solution to $tc + \nabla\phi(x) = 0$.

This means

$$tc + \sum_{i=1}^{m} \frac{1}{s_i(x^*(t))} a_i = 0$$

or

$$c + \sum_{i=1}^{m} z_i^*(t) a_i = 0 \quad \text{with} \quad z_i^*(t) = \frac{1}{ts_i(x^*(t))}$$

- $z^*(t)$ is strictly dual feasible: $(A^T z^* + c = 0; z^* > 0)$
- duality gap between $x := x^*(t)$ and $z := z^*(t)$ is

$$c^T x + b^T z = (b - Ax)^T z = \frac{m}{t}$$

- if gap is less than $1/2^{\Omega(L)}$ we can snap to optimum point

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How to find $x^*(t)$

First idea:

- start somewhere in the polytope
- use iterative method (Newtons method) to minimize $f_t(x) := tc^Tx + \phi(x)$

Newton Method

Quadratic approximation of f_t

$$f_t(x+\epsilon) \approx f_t(x) + \nabla f_t(x)^T \epsilon + \frac{1}{2}\epsilon^T H_{f_t}(x)\,\epsilon$$

Suppose this were exact:

$$f_t(x+\epsilon) = f_t(x) + \nabla f_t(x)^T \epsilon + \frac{1}{2}\epsilon^T H_{f_t}(x)\,\epsilon$$

Then gradient is given by:

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Note that for the one-dimensional case $g(\epsilon) = f(x) + f'(x)\epsilon + \frac{1}{2}f''(x)\epsilon^2$, then $g'(\epsilon) = f'(x) + f''(x)\epsilon$.

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Newton Method

Observe that $H_{f_t}(x) = H(x)$, where $H(x)$ is the Hessian for the function $\phi(x)$ (adding a linear term like $tc^T x$ does not affect the Hessian).

Also $\nabla f_t(x) = tc + \nabla\phi(x)$.

We want to move to a point where this gradient is 0:

Newton Step at $x \in P^\circ$

$$\begin{aligned}\Delta x_{\mathrm{nt}} &= -H_{f_t}^{-1}(x)\nabla f_t(x)\\ &= -H_{f_t}^{-1}(x)(tc + \nabla\phi(x))\\ &= -(A^T D_x^2 A)^{-1}(tc + A^T d_x)\end{aligned}$$

Newton Iteration:

$$x := x + \Delta x_{\mathrm{nt}}$$

Measuring Progress of Newton Step

Newton decrement:

$$\begin{aligned}\lambda_t(x) &= \|D_x A \Delta x_{\mathrm{nt}}\| \\ &= \|\Delta x_{\mathrm{nt}}\|_{H_x}\end{aligned}$$

Square of Newton decrement is linear estimate of reduction if we do a Newton step:

$$-\lambda_t(x)^2 = \nabla f_t(x)^T \Delta x_{\mathrm{nt}}$$

- $\lambda_t(x) = 0$ iff $x = x^*(t)$
- $\lambda_t(x)$ is measure of proximity of x to $x^*(t)$

Recall that Δx_{nt} fulfills $-H(x)\Delta x_{\mathrm{nt}} = \nabla f_t(x)$.

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Convergence of Newtons Method

Theorem 55

If $\lambda_t(x) < 1$ *then*

- $x_+ := x + \Delta x_{nt} \in P^\circ$ *(new point feasible)*
- $\lambda_t(x_+) \leq \lambda_t(x)^2$

This means we have quadratic convergence. Very fast.

Convergence of Newtons Method

feasibility:

- $\lambda_t(x) = \|\Delta x_{\mathsf{nt}}\|_{H_x} < 1$; hence x_+ lies in the Dikin ellipsoid around x.

Convergence of Newtons Method

bound on $\lambda_t(x^+)$:

we use $D := D_x = \mathrm{diag}(d_x)$ and $D_+ := D_{x^+} = \mathrm{diag}(d_{x^+})$

$$\begin{aligned}\lambda_t(x^+)^2 &= \|D_+ A\Delta x_{nt}^+\|^2\\ &\le \|D_+ A\Delta x_{nt}^+\|^2 + \|D_+ A\Delta x_{nt}^+ + (I - D_+^{-1}D)DA\Delta x_{nt}\|^2\\ &= \|(I - D_+^{-1}D)DA\Delta x_{nt}\|^2\end{aligned}$$

To see the last equality we use Pythagoras

$$\|a\|^2 + \|a+b\|^2 = \|b\|^2$$

if $a^T(a+b) = 0$.

Convergence of Newtons Method

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$$\begin{aligned}\lambda_t(x^+)^2 &= \|D_+ A\Delta x_{\mathrm{nt}}^+\|^2\\ &\le \|D_+ A\Delta x_{\mathrm{nt}}^+\|^2 + \|D_+ A\Delta x_{\mathrm{nt}}^+ + (I - D_+^{-1}D)DA\Delta x_{\mathrm{nt}}\|^2\\ &= \|(I - D_+^{-1}D)DA\Delta x_{\mathrm{nt}}\|^2\end{aligned}$$

To see the last equality we use Pythagoras

$$\|a\|^2 + \|a+b\|^2 = \|b\|^2$$

if $a^T(a+b) = 0$.

Convergence of Newtons Method

bound on $\lambda_t(x^+)$:
we use $D := D_x = \mathrm{diag}(d_x)$ and $D_+ := D_{x^+} = \mathrm{diag}(d_{x^+})$

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$$a^T(a+b)$$

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&= \Delta x_{\text{nt}}^{+T} A^T D_+ \Big(D_+ A \Delta x_{\text{nt}}^+ + (I - D_+^{-1}D) DA\Delta x_{\text{nt}} \Big)\\
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Convergence of Newtons Method

bound on $\lambda_t(x^+)$:

we use $D := D_x = \mathrm{diag}(d_x)$ and $D_+ := D_{x^+} = \mathrm{diag}(d_{x^+})$

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\lambda_t(x^+)^2 &= \|D_+ A\Delta x_{\mathsf{nt}}^+\|^2 \\
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&= \|(I - D_+^{-1}D)DA\Delta x_{\mathsf{nt}}\|^2 \\
&= \|(I - D_+^{-1}D)^2\vec{1}\|^2 \\
&\le \|(I - D_+^{-1}D)\vec{1}\|^4 \\
&= \|DA\Delta x_{\mathsf{nt}}\|^4 \\
&= \lambda_t(x)^4
\end{aligned}$$

The second inequality follows from $\sum_i y_i^4 \le \left(\sum_i y_i^2\right)^2$

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The second inequality follows from $\sum_i y_i^4 \le \left(\sum_i y_i^2\right)^2$

If $\lambda_t(x)$ is large we do not have a guarantee.

Try to avoid this case!!!

Path-following Methods

Try to slowly travel along the central path.

Algorithm 1 PathFollowing

```
start at analytic center
while solution not good enough do
    make step to improve objective function
    recenter to return to central path
```

Short Step Barrier Method

simplifying assumptions:

- a first central point $x^*(t_0)$ is given
- $x^*(t)$ is computed exactly in each iteration

ϵ is approximation we are aiming for

start at $t = t_0$, repeat until $m/t \le \epsilon$

- compute $x^*(\mu t)$ using Newton starting from $x^*(t)$
- $t := \mu t$

where $\mu = 1 + 1/(2\sqrt{m})$

Short Step Barrier Method

gradient of f_{t^+} at ($x = x^*(t)$)

$$\begin{aligned}\nabla f_{t^+}(x) &= \nabla f_t(x) + (\mu - 1)tc \\ &= -(\mu - 1)A^T D_x \vec{1}\end{aligned}$$

This holds because $0 = \nabla f_t(x) = tc + A^T D_x \vec{1}$.

The Newton decrement is

$$\begin{aligned}\lambda_{t^+}(x)^2 &= \nabla f_{t^+}(x)^T H^{-1} \nabla f_{t^+}(x) \\ &= (\mu - 1)^2 \vec{1}^T B(B^T B)^{-1} B^T \vec{1} \qquad B = D_x^T A \\ &\le (\mu - 1)^2 m \\ &= 1/4\end{aligned}$$

This means we are in the range of quadratic convergence!!!

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Number of Iterations

Explanation for previous slide

$P = B(B^TB)^{-1}B^T$ is a symmetric real-valued matrix; it has n linearly independent Eigenvectors. Since it is a projection matrix ($P^2 = P$) it can only have Eigenvalues 0 and 1 (because the Eigenvalues of P^2 are λ_i^2, where λ_i is Eigenvalue of P).

The expression

$$\max_v \frac{v^TPv}{v^Tv}$$

gives the largest Eigenvalue for P. Hence, $\vec{1}^TP\vec{1} \leq \vec{1}^T\vec{1} = m$

the number of Newton iterations per outer iteration is very small; in practise only 1 or 2

Number of outer iterations:

We need $t_k = \mu^k t_0 \geq m/\epsilon$. This holds when

$$k \geq \frac{\log(m/(\epsilon t_0))}{\log(\mu)}$$

We get a bound of

$$\mathcal{O}\left(\sqrt{m}\log\frac{m}{\epsilon t_0}\right)$$

We show how to get a starting point with $t_0 = 1/2^L$. Together with $\epsilon \approx 2^{-L}$ we get $\mathcal{O}(L\sqrt{m})$ iterations.

Damped Newton Method

We assume that the polytope (not just the LP) is bounded. Then $Av \leq 0$ is not possible.

For $x \in P^\circ$ and direction $v \neq 0$ define

$$\sigma_x(v) := \max_i \frac{a_i^T v}{s_i(x)}$$

$a_i^T v$ is the change on the left hand side of the i-th constraint when moving in direction of v.

If $\sigma_x(v) > 1$ then for one coordinate this change is larger than the slack in the constraint at position x.

By downscaling v we can ensure to stay in the polytope.

Observation:

$$x + \alpha v \in P \qquad \text{for } \alpha \in \{0, 1/\sigma_x(v)\}$$

Damped Newton Method

Suppose that we move from x to $x + \alpha v$. The linear estimate says that $f_t(x)$ should change by $\nabla f_t(x)^T \alpha v$.

The following argument shows that f_t is well behaved. For small α the reduction of $f_t(x)$ is close to linear estimate.

$$f_t(x + \alpha v) - f_t(x) = tc^T \alpha v + \phi(x + \alpha v) - \phi(x)$$

$$\begin{aligned} \phi(x + \alpha v) - \phi(x) &= -\sum_i \log(s_i(x + \alpha v)) + \sum_i \log(s_i(x)) \\ &= -\sum_i \log(s_i(x + \alpha v)/s_i(x)) \\ &= -\sum_i \log(1 - a_i^T \alpha v / s_i(x)) \end{aligned}$$

$$s_i(x + \alpha v) = b_i - a_i^T x - a_i^T \alpha v = s_i(x) - a_i^T \alpha v$$

Damped Newton Method

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Damped Newton Method

$$\nabla f_t(x)^T \alpha v = \Big(tc^T + \textstyle\sum_i a_i^T/s_i(x)\Big)\alpha v = tc^T\alpha v + \textstyle\sum_i \alpha w_i$$

Note that $\|w\| = \|v\|_{H_x}$.

Define $w_i = a_i^T v/s_i(x)$ and $\sigma = \max_i w_i$. Then

$$\begin{aligned} f_t(x+\alpha v) - f_t(x) - \nabla f_t(x)^T\alpha v &= -\textstyle\sum_i (\alpha w_i + \log(1-\alpha w_i)) \\ &\le -\sum_{w_i>0}(\alpha w_i + \log(1-\alpha w_i)) + \sum_{w_i<0}\frac{\alpha^2 w_i^2}{2} \\ &\le -\sum_{w_i>0}\frac{w_i^2}{\sigma^2}\Big(\alpha\sigma + \log(1-\alpha\sigma)\Big) + \frac{(\alpha\sigma)^2}{2}\sum_{w_i<0}\frac{w_i^2}{\sigma^2} \end{aligned}$$

For $|x| < 1$, $x \le 0$:

$$x + \log(1-x) = -\frac{x^2}{2} - \frac{x^3}{3} - \frac{x^4}{4} - \dots \ge -\frac{x^2}{2} = -\frac{y^2}{2}\frac{x^2}{y^2}$$

For $|x| < 1$, $0 < x \le y$:

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Damped Newton Method

$$\begin{aligned}\nabla f_t(x)^T\alpha v &= \Big(tc^T+\textstyle\sum_i a_i^T/s_i(x)\Big)\alpha v\\ &= tc^T\alpha v+\textstyle\sum_i \alpha w_i\end{aligned}$$

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Damped Newton Method

$$\begin{aligned}&\nabla f_t(x)^T\alpha v\\&\quad=\left(tc^T+\textstyle\sum_i a_i^T/s_i(x)\right)\alpha v\\&\quad=tc^T\alpha v+\textstyle\sum_i \alpha w_i\end{aligned}$$

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Damped Newton Method

For $x \ge 0$
$$\frac{x^2}{2} \le \frac{x^2}{2} + \frac{x^3}{3} + \frac{x^4}{4} + \cdots = -\Big(x + \log(1-x)\Big)$$

$$\le -\sum_i \frac{w_i^2}{\sigma^2}\Big(\alpha\sigma + \log(1-\alpha\sigma)\Big)$$

$$= -\frac{1}{\sigma^2}\|v\|_{H_x}^2\Big(\alpha\sigma + \log(1-\alpha\sigma)\Big)$$

Damped Newton Iteration:

In a damped Newton step we choose

$$x_+ = x + \frac{1}{1+\sigma_x(\Delta x_{\text{nt}})}\Delta x_{\text{nt}}$$

This means that in the above expressions we choose $\alpha = \frac{1}{1+\sigma}$ and $v = \Delta x_{\text{nt}}$. Note that it wouldn't make sense to choose α larger than 1 as this would mean that our real target $(x + \Delta x_{\text{nt}})$ is inside the polytope but we overshoot and go further than this target.

Damped Newton Method

For $x \geq 0$
$$\frac{x^2}{2} \leq \frac{x^2}{2} + \frac{x^3}{3} + \frac{x^4}{4} + \cdots = -\Big(x + \log(1-x)\Big)$$

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Damped Newton Method

Theorem:

In a damped Newton step the cost decreases by at least

$$\lambda_t(x) - \log(1 + \lambda_t(x))$$

Proof: The decrease in cost is

$$-\alpha \nabla f_t(x)^T v + \frac{1}{\sigma^2} \|v\|_{H_x}^2 (\alpha\sigma + \log(1 - \alpha\sigma))$$

Choosing $\alpha = \frac{1}{1+\sigma}$ and $v = \Delta x_{\text{nt}}$ gives

$$\frac{1}{1+\sigma} \lambda_t(x)^2 + \frac{\lambda_t(x)^2}{\sigma^2} \left(\frac{\sigma}{1+\sigma} + \log\left(1 - \frac{\sigma}{1+\sigma}\right)\right)$$

$$= \frac{\lambda_t(x)^2}{\sigma^2} (\sigma - \log(1 + \sigma))$$

With $v = \Delta x_{\text{nt}}$ we have $\|w\|_2 = \|v\|_{H_x} = \lambda_t(x)$; further recall that $\sigma = \|w\|_\infty$; hence $\sigma \leq \lambda_t(x)$.

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Damped Newton Method

The first inequality follows since the function $\frac{1}{x^2}(x - \log(1+x))$ is monotonically decreasing.

$$
\begin{aligned}
&\geq \lambda_t(x) - \log(1 + \lambda_t(x)) \\
&\geq 0.09
\end{aligned}
$$

for $\lambda_t(x) \geq 0.5$

Centering Algorithm:

Input: precision δ; starting point x

1. compute Δx_{nt} and $\lambda_t(x)$
2. if $\lambda_t(x) \leq \delta$ return x
3. set $x := x + \alpha \Delta x_{\text{nt}}$ with

$$
\alpha = \begin{cases} \frac{1}{1+\sigma_x(\Delta x_{\text{nt}})} & \lambda_t \geq 1/2 \\ 1 & \text{otw.} \end{cases}
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Centering

Lemma 56
The centering algorithm starting at x_0 *reaches a point with* $\lambda_t(x) \leq \delta$ *after*

$$\frac{f_t(x_0) - \min_y f_t(y)}{0.09} + \mathcal{O}(\log\log(1/\delta))$$

iterations.

This can be very, very slow...

How to get close to analytic center?

Let $P = \{Ax \leq b\}$ be our (feasible) polyhedron, and x_0 a feasible point.

We change $b \rightarrow b + \frac{1}{\lambda} \cdot \vec{1}$, where $L = \langle A \rangle + \langle b \rangle + \langle c \rangle$ (encoding length) and $\lambda = 2^{2L}$. Recall that a basis is feasible in the old LP iff it is feasible in the new LP.

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Lemma [without proof]
The inverse of a matrix M can be represented with rational numbers that have denominators $z_{ij} = \det(M)$.

For two basis solutions x_B, $x_{\bar{B}}$, the cost-difference $c^T x_B - c^T x_{\bar{B}}$ can be represented by a rational number that has denominator $z = \det(A_B) \cdot \det(A_{\bar{B}})$.

This means that in the perturbed LP it is sufficient to decrease the duality gap to $1/2^{4L}$ (i.e., $t \approx 2^{4L}$). This means the previous analysis essentially also works for the perturbed LP.

For a point x from the polytope (not necessarily BFS) the objective value $\bar{c}^T x$ is at most $n2^M 2^L$, where $M \leq L$ is the encoding length of the largest entry in $\bar{c}$.

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How to get close to analytic center?

Start at x_0.

Note that an entry in $\hat{c}$ fulfills $|\hat{c}_i| \leq 2^{2L}$. This holds since the slack in every constraint at x_0 is at least $\lambda = 1/2^{2L}$, and the gradient is the vector of inverse slacks.

Choose $\hat{c} := -\nabla\phi(x)$.

$x_0 = x^*(1)$ is point on central path for $\hat{c}$ and $t = 1$.

You can travel the central path in both directions. Go towards 0 until $t \approx 1/2^{\Omega(L)}$. This requires $O(\sqrt{m}L)$ outer iterations.

Let $x_{\hat{c}}$ denote this point.

Let x_c denote the point that minimizes

$$t \cdot c^T x + \phi(x)$$

(i.e., same value for t but different c, hence, different central path).

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Start at x_0.

Choose $\hat{c} := -\nabla\phi(x)$.

Note that an entry in $\hat{c}$ fulfills $|\hat{c}_i| \le 2^{2L}$. This holds since the slack in every constraint at x_0 is at least $\lambda = 1/2^{2L}$, and the gradient is the vector of inverse slacks.

$x_0 = x^*(1)$ is point on central path for $\hat{c}$ and $t = 1$.

You can travel the central path in both directions. Go towards 0 until $t \approx 1/2^{\Omega(L)}$. This requires $O(\sqrt{m}L)$ outer iterations.

Let $x_{\hat{c}}$ denote this point.

Let x_c denote the point that minimizes

$$t \cdot c^T x + \phi(x)$$

(i.e., same value for t but different c, hence, different central path).

How to get close to analytic center?

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$$\begin{aligned} & tc^T x_{\hat{c}} + \phi(x_{\hat{c}}) - tc^T x_c - \phi(x_c) \\ & \qquad \le t(c^T x_{\hat{c}} + \hat{c}^T x_c - \hat{c}^T x_{\hat{c}} - c^T x_c) \\ & \qquad \le 4tn2^{3L} \end{aligned}$$

For $t = 1/2^{\Omega(L)}$ the last term becomes constant. Hence, using damped Newton we can move from $x_{\hat{c}}$ to x_c quickly.

In total for this analysis we require $\mathcal{O}(\sqrt{m}L)$ outer iterations for the whole algorithm.

One iteration can be implemented in $\tilde{\mathcal{O}}(m^3)$ time.

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Part III

Approximation Algorithms

There are many practically important optimization problems that are NP-hard.

What can we do?

- Heuristics.
- Exploit special structure of instances occurring in practise.
- Consider algorithms that do not compute the optimal solution but provide solutions that are close to optimum.

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Definition 57

An α-approximation for an optimization problem is a polynomial-time algorithm that for all instances of the problem produces a solution whose value is within a factor of α of the value of an optimal solution.

Why approximation algorithms?

- We need algorithms for hard problems.
- It gives a rigorous mathematical base for studying heuristics.
- It provides a metric to compare the difficulty of various optimization problems.
- Proving theorems may give a deeper theoretical understanding which in turn leads to new algorithmic approaches.

Why not?

- Sometimes the results are very pessimistic due to the fact that an algorithm has to provide a close-to-optimum solution on every instance.

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Definition 58

An optimization problem $P = (\mathcal{I}, \mathrm{sol}, m, \mathrm{goal})$ is in **NPO** if

- $x \in \mathcal{I}$ can be decided in polynomial time
- $y \in \mathrm{sol}(\mathcal{I})$ can be verified in polynomial time
- m can be computed in polynomial time
- $\mathrm{goal} \in \{\min, \max\}$

In other words: the decision problem is there a solution y with $m(x, y)$ at most/at least z is in NP.

- x is problem instance
- y is candidate solution
- $m^*(x)$ cost/profit of an optimal solution

Definition 59 (Performance Ratio)

$$R(x,y) := \max\left\{\frac{m(x,y)}{m^*(x)}, \frac{m^*(x)}{m(x,y)}\right\}$$

Definition 60 (r-approximation)

An algorithm A is an r-approximation algorithm iff

$$\forall x \in \mathcal{I} : R(x, A(x)) \le r \ ,$$

and A runs in polynomial time.

Definition 61 (PTAS)
A PTAS for a problem P from NPO is an algorithm that takes as input $x \in \mathcal{I}$ and $\epsilon > 0$ and produces a solution y for x with

$$R(x, y) \le 1 + \epsilon \ .$$

The running time is polynomial in $|x|$.

approximation with arbitrary good factor... fast?

Problems that have a PTAS

Scheduling. Given m jobs with known processing times; schedule the jobs on n machines such that the MAKESPAN is minimized.

Definition 62 (FPTAS)

An FPTAS for a problem P from NPO is an algorithm that takes as input $x \in \mathcal{I}$ and $\epsilon > 0$ and produces a solution y for x with

$$R(x, y) \le 1 + \epsilon \enspace .$$

The running time is polynomial in $|x|$ and $1/\epsilon$.

approximation with arbitrary good factor... fast!

Problems that have an FPTAS

KNAPSACK. Given a set of items with profits and weights choose a subset of total weight at most W s.t. the profit is maximized.

Definition 63 (APX – approximable)

A problem P from NPO is in APX if there exist a constant $r \geq 1$ and an r-approximation algorithm for P.

constant factor approximation...

Problems that are in APX

MAXCUT. Given a graph $G = (V, E)$; partition V into two disjoint pieces A and B s. t. the number of edges between both pieces is maximized.

MAX-3SAT. Given a 3CNF-formula. Find an assignment to the variables that satisfies the maximum number of clauses.

Problems with polylogarithmic approximation guarantees

- Set Cover
- Minimum Multicut
- Sparsest Cut
- Minimum Bisection

There is an r-approximation with $r \leq \mathcal{O}(\log^c(|x|))$ for some constant c.

Note that only for some of the above problem a matching lower bound is known.

There are really difficult problems!

Theorem 64
For any constant $\epsilon > 0$ there does not exist an $\Omega(n^{1-\epsilon})$-approximation algorithm for the maximum clique problem on a given graph G with n nodes unless $\mathrm{P} = \mathrm{NP}$.

Note that an n-approximation is trivial.

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There are weird problems!
Asymmetric k-Center admits an $\mathcal{O}(\log^* n)$-approximation.

There is no $o(\log^* n)$-approximation to Asymmetric k-Center unless $NP \subseteq DTIME(n^{\log\log\log n})$.

Class APX not important in practise.

Instead of saying problem P is in APX one says problem P admits a 4-approximation.

One only says that a problem is APX-hard.

A crucial ingredient for the design and analysis of approximation algorithms is a technique to obtain an upper bound (for maximization problems) or a lower bound (for minimization problems).

Therefore Linear Programs or Integer Linear Programs play a vital role in the design of many approximation algorithms.

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An Integer Linear Program or Integer Program is a Linear Program in which all variables are required to be integral.

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A Mixed Integer Program is a Linear Program in which a subset of the variables are required to be integral.

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Note that solving Integer Programs in general is NP-complete!

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Note that solving Integer Programs in general is NP-complete!

Set Cover

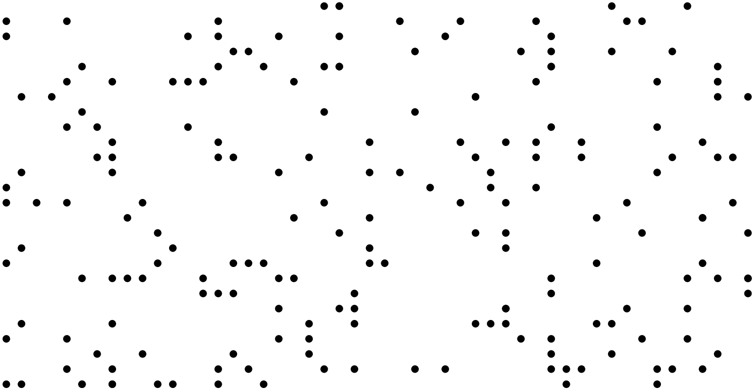
Given a ground set U, a collection of subsets $S_1, \dots, S_k \subseteq U$, where the i-th subset S_i has weight/cost w_i. Find a collection $I \subseteq \{1, \dots, k\}$ such that

$$\forall u \in U \exists i \in I : \; u \in S_i \quad \text{(every element is covered)}$$

and

$$\sum_{i \in I} w_i \quad \text{is minimized.}$$

Set Cover



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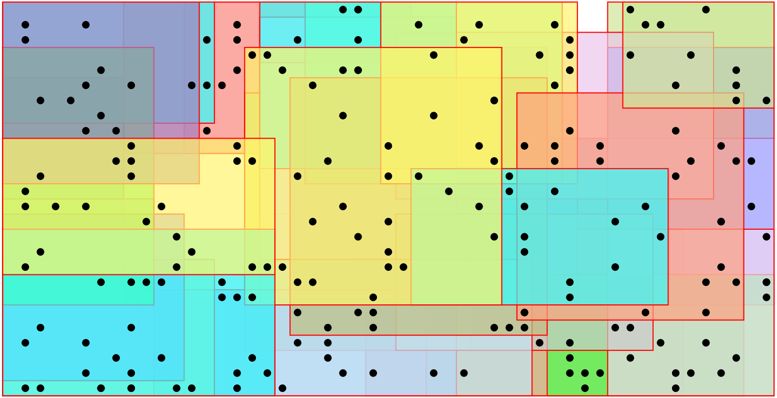

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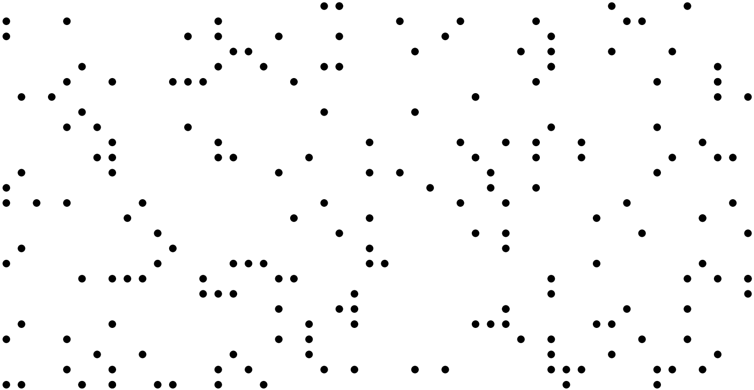

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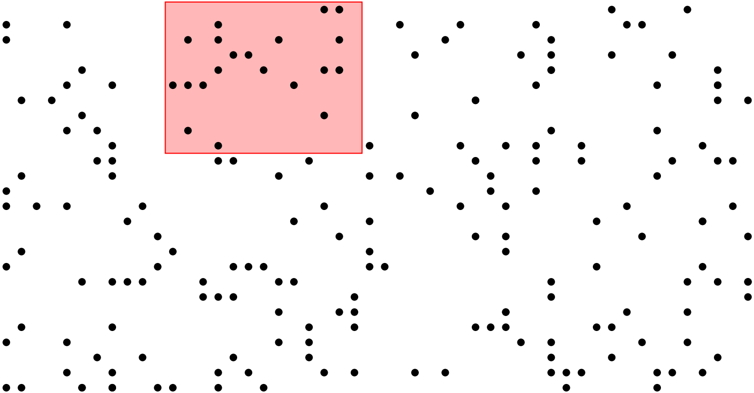

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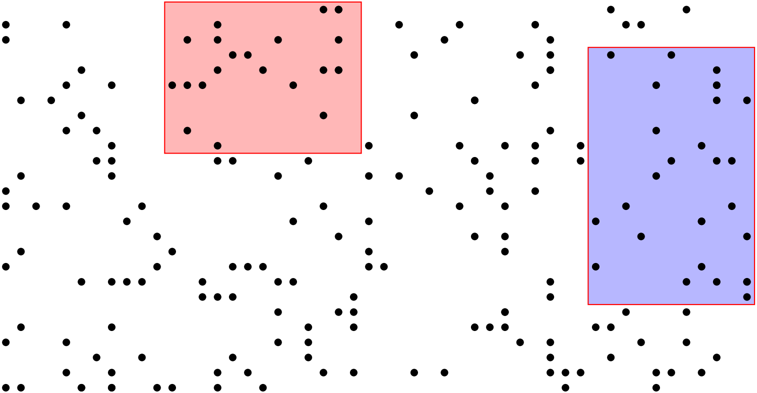

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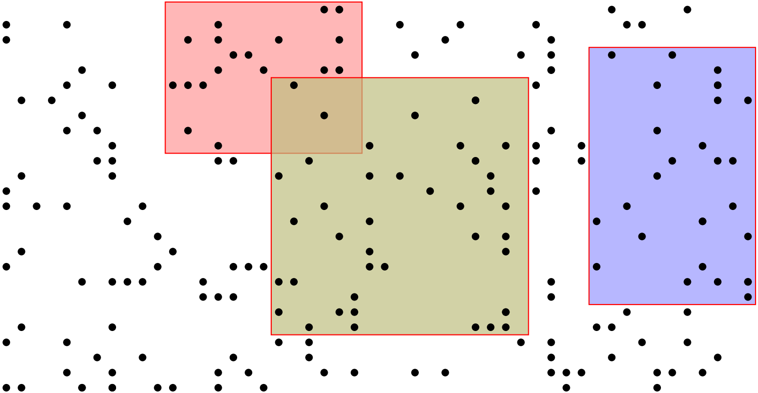

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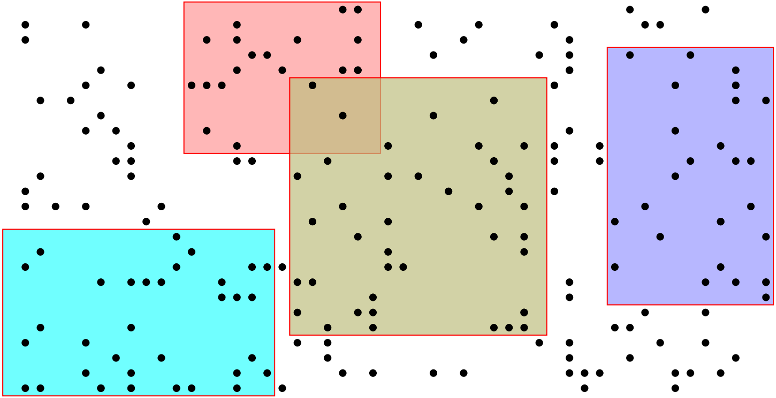

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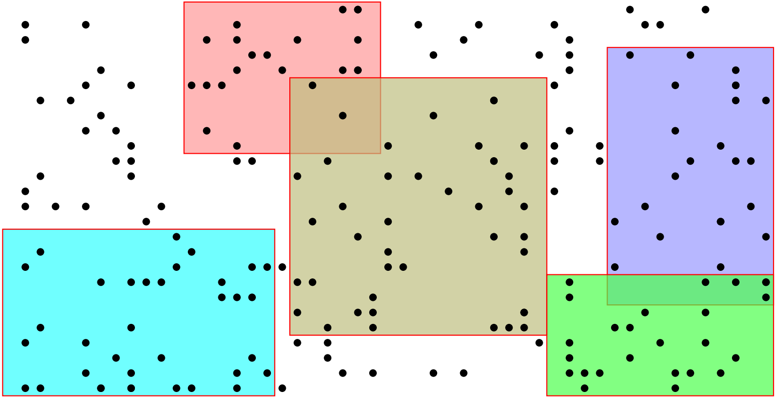

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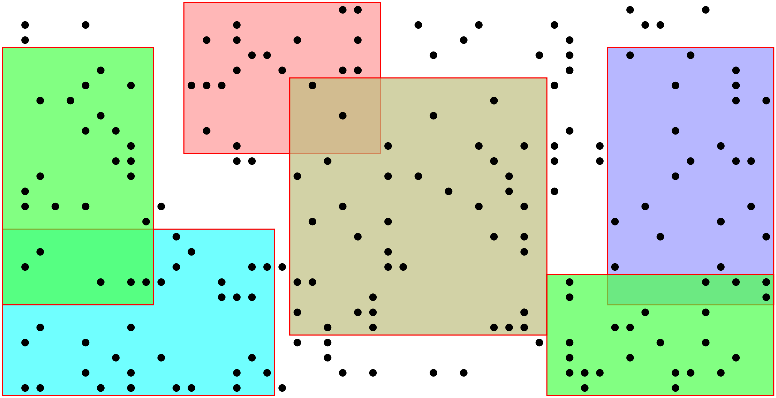

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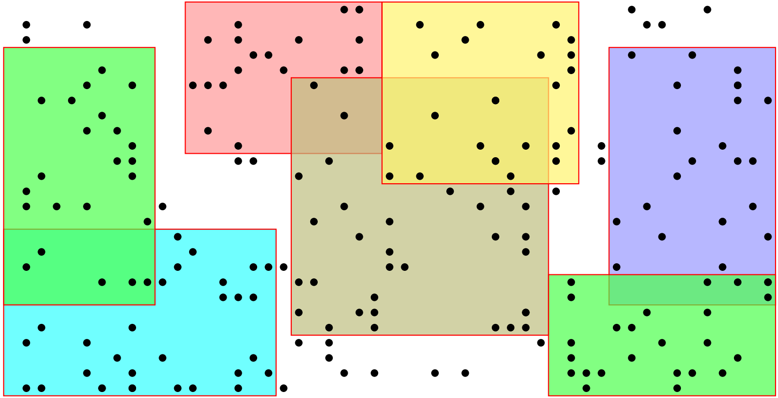

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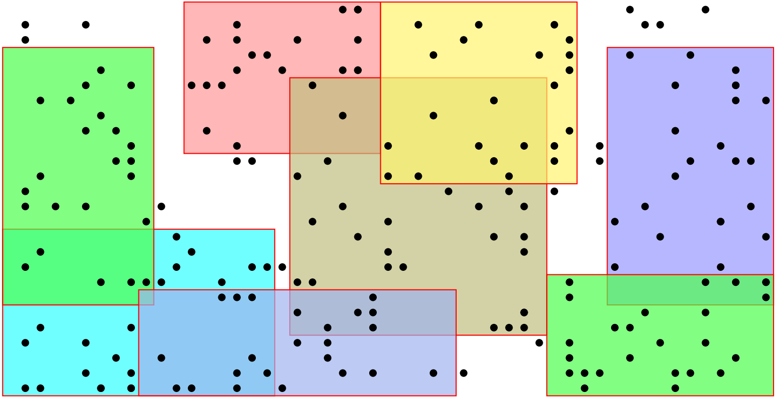

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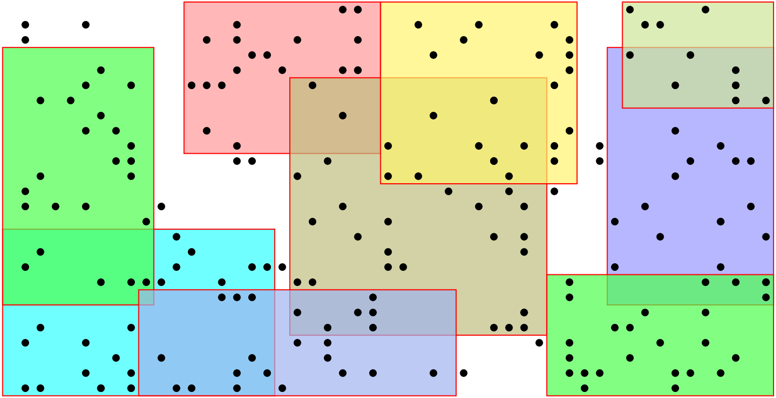

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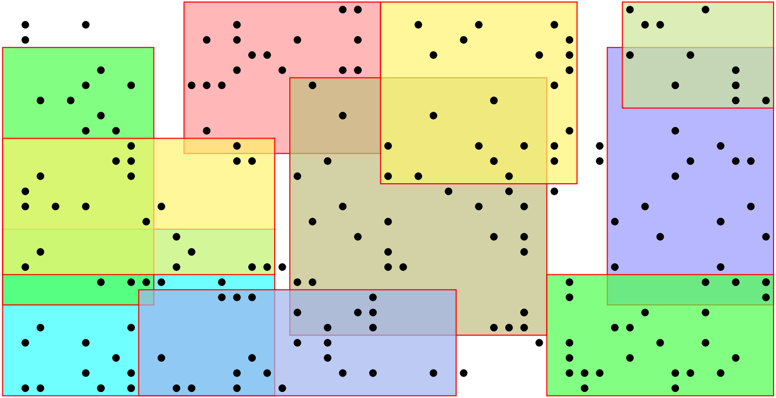

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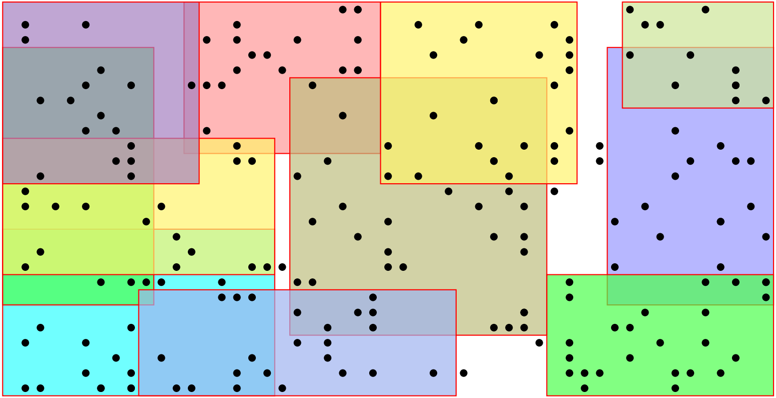

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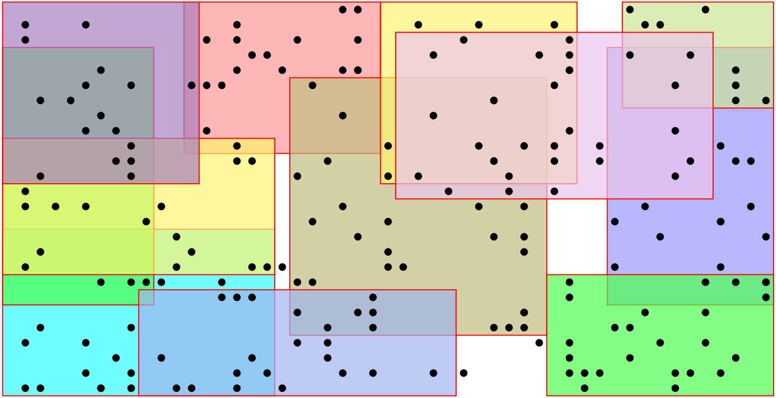

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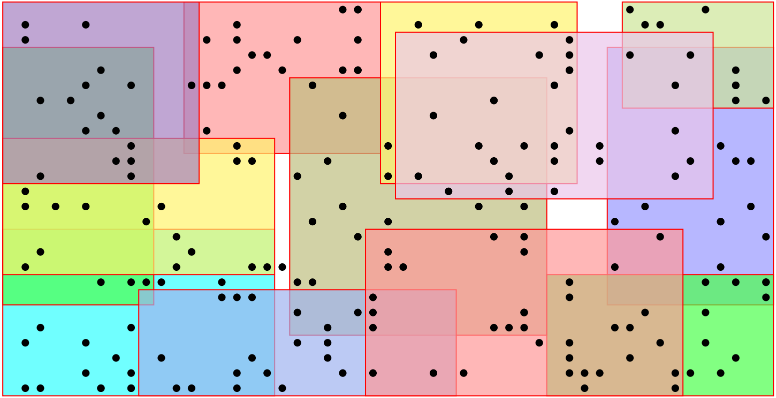

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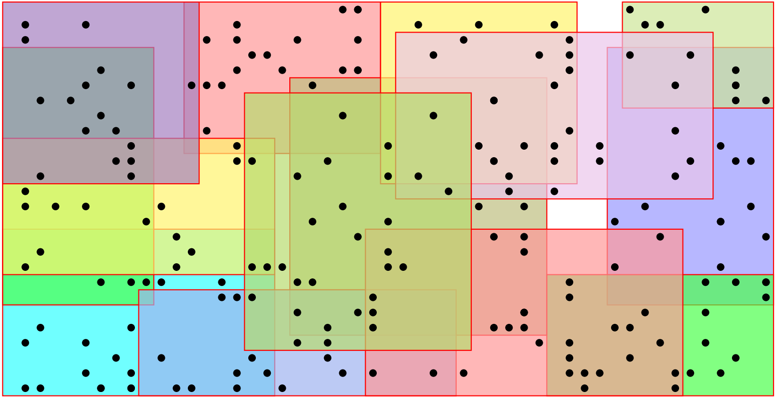

IP-Formulation of Set Cover

$$\begin{array}{llrcl}
\text{min} & & \sum_i w_i x_i & & \\
\text{s.t.} & \forall u \in U & \sum_{i:u\in S_i} x_i & \geq & 1 \\
 & \forall i \in \{1,\dots,k\} & x_i & \geq & 0 \\
 & \forall i \in \{1,\dots,k\} & x_i & \text{integral} &
\end{array}$$

Vertex Cover

Given a graph $G = (V, E)$ and a weight w_v for every node. Find a vertex subset $S \subseteq V$ of minimum weight such that every edge is incident to at least one vertex in S.

IP-Formulation of Vertex Cover

$$\begin{array}{llrcl}
\min & & \sum_{v\in V} w_v x_v & & \\
\textsf{s.t.} & \forall e=(i,j)\in E & x_i + x_j & \geq & 1 \\
 & \forall v\in V & x_v & \in & \{0,1\}
\end{array}$$

Maximum Weighted Matching

Given a graph $G = (V, E)$, and a weight w_e for every edge $e \in E$. Find a subset of edges of maximum weight such that no vertex is incident to more than one edge.

$$\begin{array}{llrcl} \max & & \sum_{e \in E} w_e x_e & & \\ \text{s.t.} & \forall v \in V & \sum_{e: v \in e} x_e & \leq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Maximum Weighted Matching

Given a graph $G = (V, E)$, and a weight w_e for every edge $e \in E$. Find a subset of edges of maximum weight such that no vertex is incident to more than one edge.

$$\begin{array}{llrcl} \max & & \sum_{e\in E} w_e x_e & & \\ \text{s.t.} & \forall v \in V & \sum_{e: v\in e} x_e & \le & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Maximum Independent Set

Given a graph $G = (V, E)$, and a weight w_v for every node $v \in V$. Find a subset $S \subseteq V$ of nodes of maximum weight such that no two vertices in S are adjacent.

$$\begin{array}{llrcl}
\max & & \multicolumn{3}{l}{\sum_{v\in V} w_v x_v} \\
\text{s.t.} & \forall e = (i,j) \in E & x_i + x_j & \le & 1 \\
 & \forall v \in V & x_v & \in & \{0,1\}
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Knapsack

Given a set of items $\{1,\dots,n\}$, where the i-th item has weight w_i and profit p_i, and given a threshold K. Find a subset $I \subseteq \{1,\dots,n\}$ of items of total weight at most K such that the profit is maximized.

$$
\begin{array}{lrcl}
\max & \sum_{i=1}^{n} p_i x_i & & \\
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Relaxations

Definition 67

A linear program LP is a relaxation of an integer program IP if any feasible solution for IP is also feasible for LP and if the objective values of these solutions are identical in both programs.

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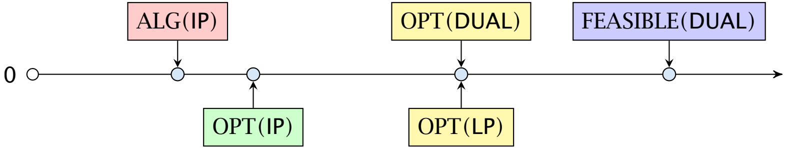
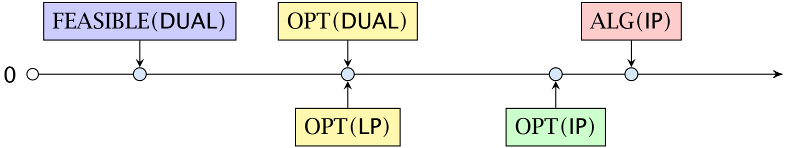
By solving a relaxation we obtain an upper bound for a maximization problem and a lower bound for a minimization problem.

Relations

Maximization Problems:



Minimization Problems:



Technique 1: Round the LP solution.

We first solve the LP-relaxation and then we round the fractional values so that we obtain an integral solution.

Set Cover relaxation:

$$\begin{array}{llrcl}
\min & & \sum_{i=1}^{k} w_i x_i & & \\
\text{s.t.} & \forall u \in U & \sum_{i:u\in S_i} x_i & \geq & 1 \\
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\end{array}$$

Let f_u be the number of sets that the element u is contained in (the frequency of u). Let $f = \max_u\{f_u\}$ be the maximum frequency.

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Technique 1: Round the LP solution.

Rounding Algorithm:
Set all x_i-values with $x_i \geq \frac{1}{f}$ to 1. Set all other x_i-values to 0.

Technique 1: Round the LP solution.

Lemma 68

The rounding algorithm gives an f-approximation.

Proof: Every $u \in U$ is covered.

- We know that $\sum_{i: u \in S_i} x_i \geq 1$.
- The sum contains at most $f_u \leq f$ elements.
- Therefore one of the sets that contain u must have $x_i \geq 1/f$.
- This set will be selected. Hence, u is covered.

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$$\sum_{i \in I} w_i \le \sum_{i=1}^{k} w_i (f \cdot x_i)$$

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Technique 2: Rounding the Dual Solution.

Relaxation for Set Cover

Primal:

$$\begin{array}{lr} \min & \sum_{i\in I} w_i x_i \\ \text{s.t. } \forall u & \sum_{i:u\in S_i} x_i \geq 1 \\ & x_i \geq 0 \end{array}$$

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Technique 2: Rounding the Dual Solution.

Rounding Algorithm:

Let I denote the index set of sets for which the dual constraint is tight. This means for all $i \in I$

$$\sum_{u:u\in S_i} y_u = w_i$$

Technique 2: Rounding the Dual Solution.

Lemma 69

The resulting index set is an f-approximation.

Proof:

Every $u \in U$ is covered.

- Suppose there is a u that is not covered.
- This means $\sum_{v: u \in S_i} y_v < w_i$ for all sets S_i that contain u.
- But then y_u could be increased in the dual solution without violating any constraint. This is a contradiction to the fact that the dual solution is optimal.

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Let I denote the solution obtained by the first rounding algorithm and I' be the solution returned by the second algorithm. Then

$$I \subseteq I' \ .$$

This means I' is never better than I.

- Suppose that we take S_i in the first algorithm. I.e., $i \in I$.
- This means $x_i \geq \frac{1}{f}$.
- Because of Complementary Slackness Conditions the corresponding constraint in the dual must be tight.
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Technique 3: The Primal Dual Method

The previous two rounding algorithms have the disadvantage that it is necessary to solve the LP. The following method also gives an f-approximation without solving the LP.

For estimating the cost of the solution we only required two properties.

1. The solution is dual feasible and, hence,
$$\sum_u y_u \le \text{cost}(x^*) \le \text{OPT}$$
where x^* is an optimum solution to the primal LP.
2. The set I contains only sets for which the dual inequality is tight.

Of course, we also need that I is a cover.

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Technique 3: The Primal Dual Method

Algorithm 1 PrimalDual

```
$y \leftarrow 0$
$I \leftarrow \emptyset$
while exists $u \notin \bigcup_{i \in I} S_i$ do
    increase dual variable $y_u$ until constraint for some
    new set $S_\ell$ becomes tight
    $I \leftarrow I \cup \{\ell\}$
```

Technique 4: The Greedy Algorithm

Algorithm 1 Greedy

```
$I \leftarrow \emptyset$
$\hat{S}_j \leftarrow S_j$    for all $j$
while $I$ not a set cover do
    $\ell \leftarrow \arg\min_{j:\hat{S}_j \neq 0} \frac{w_j}{|\hat{S}_j|}$
    $I \leftarrow I \cup \{\ell\}$
    $\hat{S}_j \leftarrow \hat{S}_j - S_\ell$    for all $j$
```

In every round the Greedy algorithm takes the set that covers remaining elements in the most cost-effective way.

We choose a set such that the ratio between cost and still uncovered elements in the set is minimized.

Technique 4: The Greedy Algorithm

Lemma 70

Given positive numbers $a_1, \dots, a_k$ *and* $b_1, \dots, b_k$, *and* $S \subseteq \{1, \dots, k\}$ *then*

$$\min_i \frac{a_i}{b_i} \le \frac{\sum_{i \in S} a_i}{\sum_{i \in S} b_i} \le \max_i \frac{a_i}{b_i}$$

Technique 4: The Greedy Algorithm

Let n_ℓ denote the number of elements that remain at the beginning of iteration ℓ. $n_1 = n = |U|$ and $n_{s+1} = 0$ if we need s iterations.

In the ℓ-th iteration

$$\min_j \frac{w_j}{|S_j|} \le \frac{\sum_{j\in\mathrm{OPT}} w_j}{\sum_{j\in\mathrm{OPT}} |S_j|} = \frac{\mathrm{OPT}}{\sum_{j\in\mathrm{OPT}} |S_j|} \le \frac{\mathrm{OPT}}{n_\ell}$$

since an optimal algorithm can cover the remaining n_ℓ elements with cost OPT.

Let $\hat{S}_j$ be a subset that minimizes this ratio. Hence, $w_j/|\hat{S}_j| \le \frac{\mathrm{OPT}}{n_\ell}$.

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Adding this set to our solution means $n_{\ell+1} = n_\ell - |\hat{S}_j|$.

$$w_j \le \frac{|\hat{S}_j|\mathrm{OPT}}{n_\ell} = \frac{n_\ell - n_{\ell+1}}{n_\ell} \cdot \mathrm{OPT}$$

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\begin{aligned}
\sum_{j\in I} w_j &\le \sum_{\ell=1}^{s} \frac{n_\ell - n_{\ell+1}}{n_\ell}\cdot \mathrm{OPT}\\
&\le \mathrm{OPT}\sum_{\ell=1}^{s}\left(\frac{1}{n_\ell}+\frac{1}{n_\ell-1}+\cdots+\frac{1}{n_{\ell+1}+1}\right)
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\sum_{j\in I} w_j &\le \sum_{\ell=1}^{s} \frac{n_\ell - n_{\ell+1}}{n_\ell}\cdot \mathrm{OPT} \\
&\le \mathrm{OPT} \sum_{\ell=1}^{s} \left(\frac{1}{n_\ell} + \frac{1}{n_\ell - 1} + \dots + \frac{1}{n_{\ell+1}+1}\right) \\
&= \mathrm{OPT} \sum_{i=1}^{n} \frac{1}{i} \\
&= H_n \cdot \mathrm{OPT} \le \mathrm{OPT}(\ln n + 1)\enspace .
\end{aligned}
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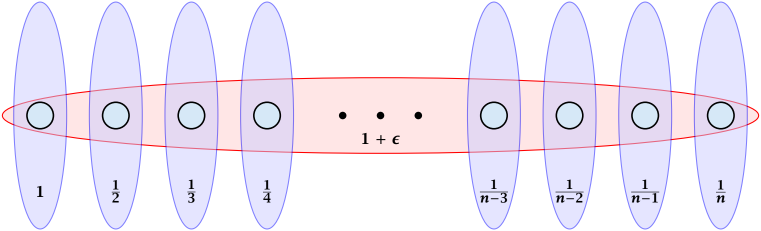
Technique 4: The Greedy Algorithm

A tight example:



Technique 5: Randomized Rounding

One round of randomized rounding:
Pick set S_j uniformly at random with probability $1 - x_j$ (for all j).

Version A: Repeat rounds until you nearly have a cover. Cover remaining elements by some simple heuristic.

Version B: Repeat for s rounds. If you have a cover STOP. Otherwise, repeat the whole algorithm.

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Probability that $u \in U$ is not covered (in one round):

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\end{aligned}
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Probability that $u \in U$ is not covered (after ℓ rounds):

$$
\Pr[u \text{ not covered after } \ell \text{ round}] \le \frac{1}{e^{\ell}} \enspace .
$$

$\Pr[\exists u \in U$ not covered after ℓ round$]$

$$\begin{aligned}&\Pr[\exists u \in U \text{ not covered after } \ell \text{ round}]\\&\quad = \Pr[u_1 \text{ not covered} \vee u_2 \text{ not covered} \vee \ldots \vee u_n \text{ not covered}]\end{aligned}$$

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Lemma 71

With high probability $\mathcal{O}(\log n)$ *rounds suffice.*

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Lemma 71

With high probability $\mathcal{O}(\log n)$ *rounds suffice.*

With high probability:

For any constant α the number of rounds is at most $\mathcal{O}(\log n)$ with probability at least $1-n^{-\alpha}$.

Proof: We have

$$\Pr[\#\text{rounds} \geq (\alpha+1)\ln n] \leq ne^{-(\alpha+1)\ln n} = n^{-\alpha} \ .$$

Expected Cost

- Version A.
  Repeat for $s = (\alpha + 1)\ln n$ rounds. If you don't have a cover simply take for each element u the cheapest set that contains u.

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  for $n \geq 2$ and $\alpha \geq 1$.

Randomized rounding gives an $\mathcal{O}(\log n)$ approximation. The running time is polynomial with high probability.

Theorem 72 (without proof)

There is no approximation algorithm for set cover with approximation guarantee better than $\frac{1}{2}\log n$ *unless* NP *has quasi-polynomial time algorithms (algorithms with running time* $2^{\mathrm{poly}(\log n)}$*).*

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Integrality Gap

The integrality gap of the SetCover LP is $\Omega(\log n)$.

- $n = 2^k - 1$
- Elements are all vectors $\vec{x}$ over $GF[2]$ of length k (excluding zero vector).
- Every vector $\vec{y}$ defines a set as follows

$$S_{\vec{y}} := \{\vec{x} \mid \vec{x}^T\vec{y} = 1\}$$

- each set contains 2^{k-1} vectors; each vector is contained in 2^{k-1} sets
- $x_i = \frac{1}{2^{k-1}} = \frac{2}{n+1}$ is fractional solution.

Integrality Gap

Every collection of $p < k$ sets does not cover all elements.

Hence, we get a gap of $\Omega(\log n)$.

Techniques:

- Deterministic Rounding
- Rounding of the Dual
- Primal Dual
- Greedy
- Randomized Rounding
- Local Search
- Rounding Data + Dynamic Programming

Scheduling Jobs on Identical Parallel Machines

Given n jobs, where job $j \in \{1,\dots,n\}$ has processing time p_j. Schedule the jobs on m identical parallel machines such that the Makespan (finishing time of the last job) is minimized.

$$\begin{array}{lrrcl}
\min & & & L & \\
\text{s.t.} & \forall \text{machines } i & \sum_j p_j \cdot x_{j,i} & \le & L \\
 & \forall \text{jobs } j & \sum_i x_{j,i} \ge 1 & & \\
 & \forall i,j & x_{j,i} & \in & \{0,1\}
\end{array}$$

Here the variable $x_{j,i}$ is the decision variable that describes whether job j is assigned to machine i.

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Lower Bounds on the Solution

Let for a given schedule C_j denote the finishing time of machine j, and let $C_{\max}$ be the makespan.

Let $C^*_{\max}$ denote the makespan of an optimal solution.

Clearly

$$C^*_{\max} \geq \max_j p_j$$

as the longest job needs to be scheduled somewhere.

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Local Search

A local search algorithm successively makes certain small (cost/profit improving) changes to a solution until it does not find such changes anymore.

It is conceptionally very different from a Greedy algorithm as a feasible solution is always maintained.

Sometimes the running time is difficult to prove.

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Local Search for Scheduling

Local Search Strategy: Take the job that finishes last and try to move it to another machine. If there is such a move that reduces the makespan, perform the switch.

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Local Search Analysis

Let ℓ be the job that finishes last in the produced schedule.

Let S_ℓ be its start time, and let C_ℓ be its completion time.

Note that every machine is busy before time S_ℓ, because otherwise we could move the job ℓ and hence our schedule would not be locally optimal.

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We can split the total processing time into two intervals one from 0 to S_ℓ the other from S_ℓ to C_ℓ.

The interval $[S_\ell, C_\ell]$ is of length $p_\ell \le C^*_{\max}$.

During the first interval $[0, S_\ell]$ all processors are busy, and, hence, the total work performed in this interval is

$$m \cdot S_\ell \le \sum_{j \ne \ell} p_j \ .$$

Hence, the length of the schedule is at most

$$p_\ell + \frac{1}{m}\sum_{j \ne \ell} p_j = (1 - \frac{1}{m})p_\ell + \frac{1}{m}\sum_j p_j \le (2 - \frac{1}{m})C^*_{\max}$$

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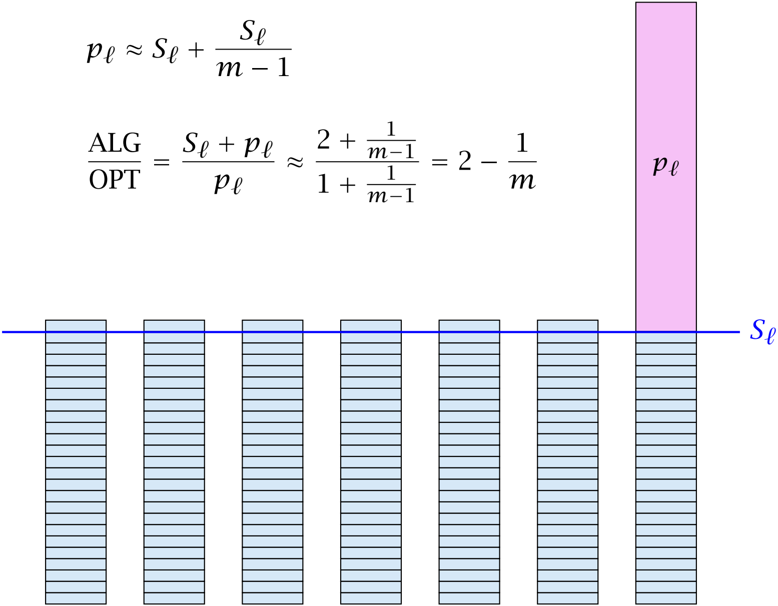
A Tight Example

$$p_\ell \approx S_\ell + \frac{S_\ell}{m-1}$$

$$\frac{\text{ALG}}{\text{OPT}} = \frac{S_\ell + p_\ell}{p_\ell} \approx \frac{2 + \frac{1}{m-1}}{1 + \frac{1}{m-1}} = 2 - \frac{1}{m}$$



A Greedy Strategy

List Scheduling:
Order all processes in a list. When a machine runs empty assign the next yet unprocessed job to it.

Alternatively:
Consider processes in some order. Assign the i-th process to the least loaded machine.

It is easy to see that the result of these greedy strategies fulfill the local optimally condition of our local search algorithm. Hence, these also give 2-approximations.

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A Greedy Strategy

Lemma 73

If we order the list according to non-increasing processing times the approximation guarantee of the list scheduling strategy improves to $4/3$.

Proof:

- Let $p_1 \geq \cdots \geq p_n$ denote the processing times of a set of jobs that form a counter-example.
- Wlog. the last job to finish is n (otw. deleting this job gives another counter-example with fewer jobs).
- If $p_n \leq C^*_{\max}/3$ the previous analysis gives us a schedule length of at most

$$C^*_{\max} + p_n \leq \frac{4}{3} C^*_{\max} \enspace .$$

  Hence, $p_n > C^*_{\max}/3$.
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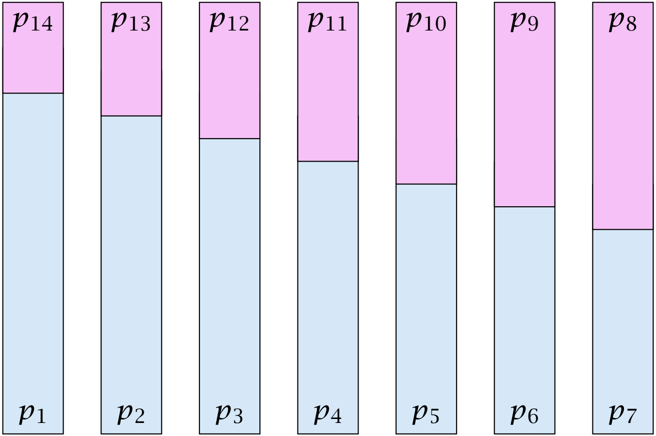
When in an optimal solution a machine can have at most 2 jobs the optimal solution looks as follows.



- We can assume that one machine schedules p_1 and p_n (the largest and smallest job).
- If not assume wlog. that p_1 is scheduled on machine A and p_n on machine B.
- Let p_A and p_B be the other job scheduled on A and B, respectively.
- $p_1 + p_n \leq p_1 + p_A$ and $p_A + p_B \leq p_1 + p_A$, hence scheduling p_1 and p_n on one machine and p_A and p_B on the other, cannot increase the Makespan.
- Repeat the above argument for the remaining machines.

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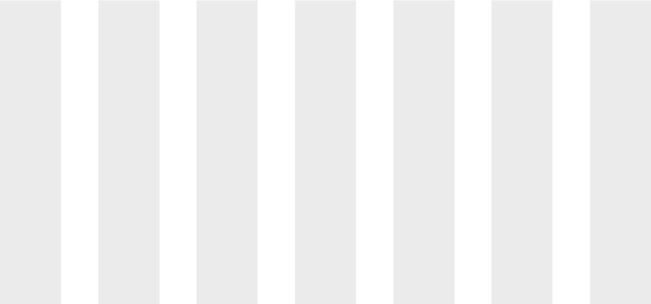
Tight Example

- $2m + 1$ jobs



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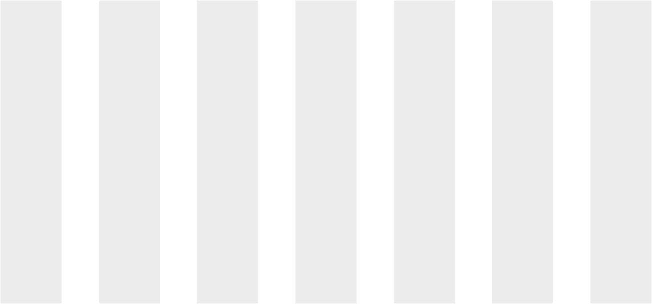
- $2m + 1$ jobs
- 2 jobs with length $2m, 2m - 2, \ldots, m + 1$ ($2m - 2$ jobs in total)



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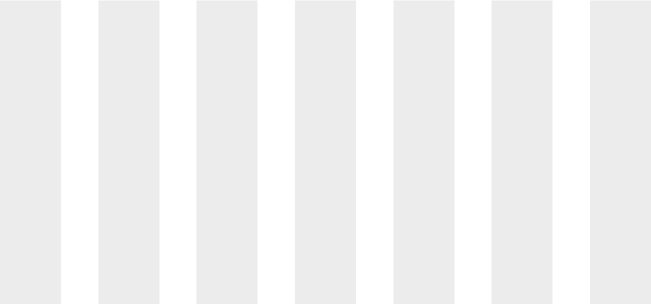

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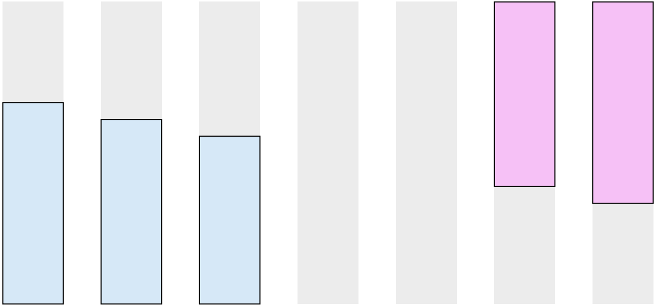

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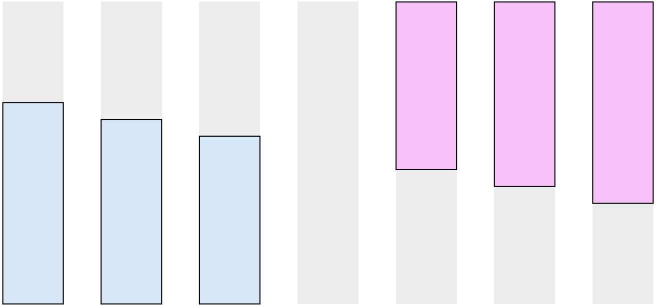

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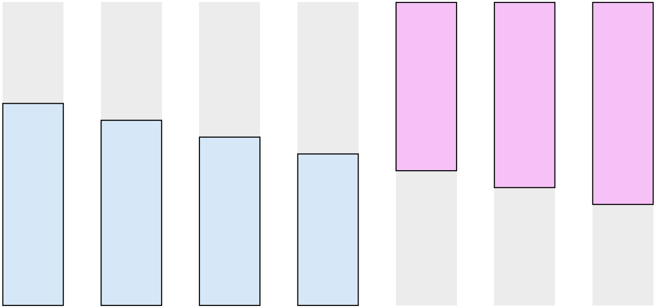

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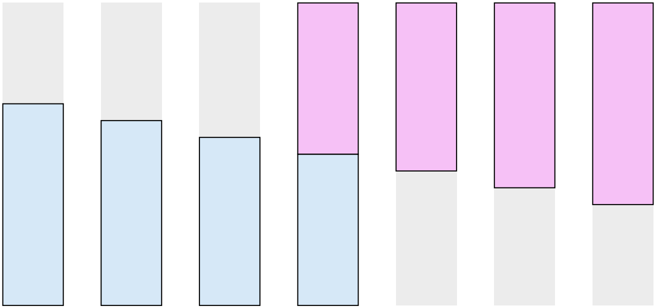

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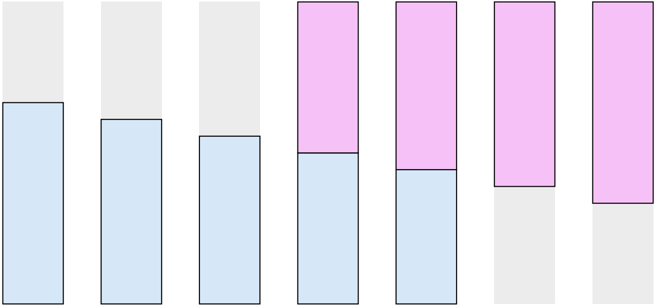

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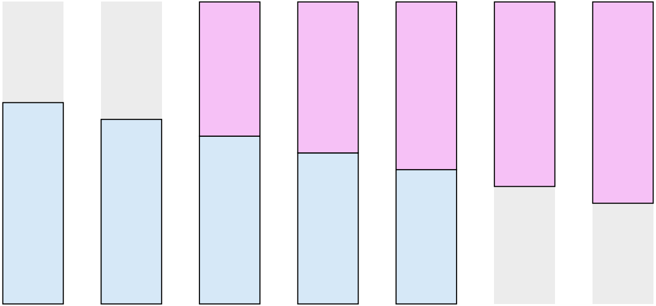

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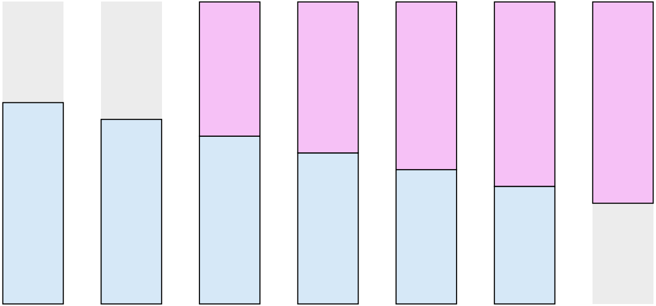

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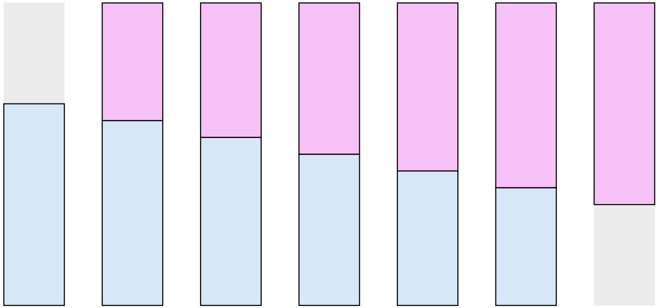

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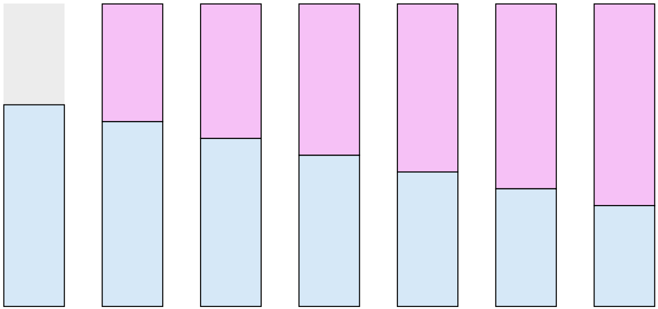

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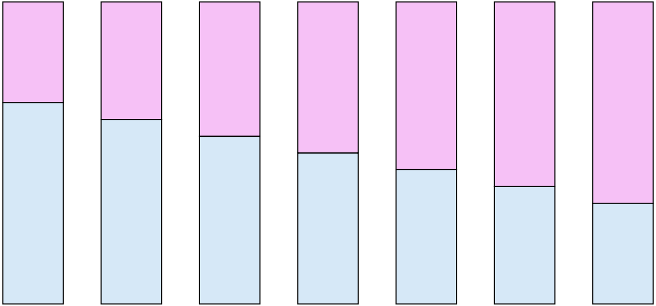

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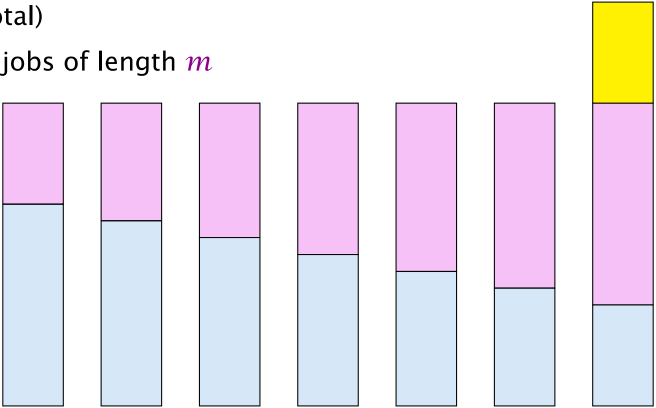

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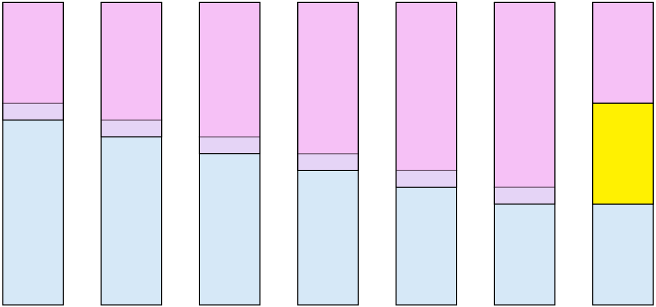

15 Rounding Data + Dynamic Programming

Knapsack:
Given a set of items $\{1,\ldots,n\}$, where the i-th item has weight $w_i \in \mathbb{N}$ and profit $p_i \in \mathbb{N}$, and given a threshold W. Find a subset $I \subseteq \{1,\ldots,n\}$ of items of total weight at most W such that the profit is maximized (we can assume each $w_i \leq W$).

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\max & & \sum_{i=1}^{n} p_i x_i & & \\
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15 Rounding Data + Dynamic Programming

Algorithm 1 Knapsack

```
A(1) ← [(0,0),(p_1,w_1)]
for j ← 2 to n do
    A(j) ← A(j-1)
    for each (p,w) ∈ A(j-1) do
        if w + w_j ≤ W then
            add (p + p_j, w + w_j) to A(j)
        remove dominated pairs from A(j)
return max_{(p,w)∈A(n)} p
```

The running time is $\mathcal{O}(n \cdot \min\{W, P\})$, where $P = \sum_i p_i$ is the total profit of all items. This is only pseudo-polynomial.

15 Rounding Data + Dynamic Programming

Definition 74

An algorithm is said to have pseudo-polynomial running time if the running time is polynomial when the numerical part of the input is encoded in unary.

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Scheduling Revisited

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Together with the obervation that if each $p_i \geq \frac{1}{3}C^*_{\max}$ then LPT is optimal this gave a $4/3$-approximation.

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Partition the input into long jobs and short jobs.

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Idea:

1. Find the optimum Makespan for the long jobs by brute force.
2. Then use the list scheduling algorithm for the short jobs, always assigning the next job to the least loaded machine.

We still have a cost of

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If ℓ is a short job its length is at most

$$p_\ell \leq \sum_j p_j/(mk)$$

which is at most $C^*_{\max}/k$.

Hence we get a schedule of length at most

$$\left(1+\frac{1}{k}\right)C^*_{\max}$$

There are at most km long jobs. Hence, the number of possibilities of scheduling these jobs on m machines is at most m^{km}, which is constant if m is constant. Hence, it is easy to implement the algorithm in polynomial time.

Theorem 75
The above algorithm gives a polynomial time approximation scheme (PTAS) for the problem of scheduling n jobs on m identical machines if m is constant.

We choose $k = \lceil \frac{1}{\epsilon} \rceil$.

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We first design an algorithm that works as follows:
On input of T it either finds a schedule of length $(1+\frac{1}{k})T$ or certifies that no schedule of length at most T exists (assume $T \geq \frac{1}{m}\sum_j p_j$).

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On input of T it either finds a schedule of length $(1+\frac{1}{k})T$ or certifies that no schedule of length at most T exists (assume $T \geq \frac{1}{m}\sum_j p_j$).

We partition the jobs into long jobs and short jobs:

- A job is long if its size is larger than T/k.
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- We round all long jobs down to multiples of T/k^2.
- For these rounded sizes we first find an optimal schedule.
- If this schedule does not have length at most T we conclude that also the original sizes don't allow such a schedule.
- If we have a good schedule we extend it by adding the short jobs according to the LPT rule.

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After the first phase the rounded sizes of the long jobs assigned to a machine add up to at most T.

There can be at most k (long) jobs assigned to a machine as otw. their rounded sizes would add up to more than T (note that the rounded size of a long job is at least T/k).

Since, jobs had been rounded to multiples of T/k^2 going from rounded sizes to original sizes gives that the Makespan is at most

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Running Time for scheduling large jobs: There should not be a job with rounded size more than T as otw. the problem becomes trivial.

Hence, any large job has rounded size of $\frac{i}{k^2}T$ for $i \in \{k, \dots, k^2\}$. Therefore the number of different inputs is at most n^{k^2} (described by a vector of length k^2 where, the i-th entry describes the number of jobs of size $\frac{i}{k^2}T$). This is polynomial.

The schedule/configuration of a particular machine x can be described by a vector of length k^2 where the i-th entry describes the number of jobs of rounded size $\frac{i}{k^2}T$ assigned to x. There are only $(k+1)^{k^2}$ different vectors.

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We have

$$\mathrm{OPT}(n_1,\dots,n_{k^2}) = \begin{cases} 0 & (n_1,\dots,n_{k^2}) = 0 \\ 1 + \min\limits_{(s_1,\dots,s_{k^2})\in C} \mathrm{OPT}(n_1 - s_1,\dots,n_{k^2} - s_{k^2}) & (n_1,\dots,n_{k^2}) \gneq 0 \\ \infty & \text{otw.} \end{cases}$$

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Scheduling on identical machines with the goal of minimizing Makespan is a strongly NP-complete problem.

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- Suppose we have an instance with polynomially bounded processing times $p_i \le q(n)$
- We set $k := \lceil 2nq(n) \rceil \ge 2\,\mathrm{OPT}$
- Then

$$\mathrm{ALG} \le \left(1 + \frac{1}{k}\right)\mathrm{OPT} \le \mathrm{OPT} + \frac{1}{2}$$

- But this means that the algorithm computes the optimal solution as the optimum is integral.
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More General

Let $\mathrm{OPT}(n_1, \ldots, n_A)$ be the number of machines that are required to schedule input vector $(n_1, \ldots, n_A)$ with Makespan at most T (A: number of different sizes).

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Bin Packing

Given n items with sizes $s_1, \dots, s_n$ where

$$1 > s_1 \geq \cdots \geq s_n > 0 \;.$$

Pack items into a minimum number of bins where each bin can hold items of total size at most 1.

Theorem 77

There is no ρ-approximation for Bin Packing with $\rho < 3/2$ unless $\mathrm{P} = \mathrm{NP}$.

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Proof

- In the partition problem we are given positive integers $b_1, \dots, b_n$ with $B = \sum_i b_i$ even. Can we partition the integers into two sets S and T s.t.

$$\sum_{i \in S} b_i = \sum_{i \in T} b_i \quad ?$$

- We can solve this problem by setting $s_i := 2b_i/B$ and asking whether we can pack the resulting items into 2 bins or not.
- A ρ-approximation algorithm with $\rho < 3/2$ cannot output 3 or more bins when 2 are optimal.
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Definition 78

An asymptotic polynomial-time approximation scheme (APTAS) is a family of algorithms $\{A_\epsilon\}$ along with a constant c such that A_ϵ returns a solution of value at most $(1+\epsilon)\mathrm{OPT}+c$ for minimization problems.

Note that for Set Cover or for Knapsack it makes no sense to differentiate between the notion of a PTAS or an APTAS because of scaling.

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Again we can differentiate between small and large items.

Lemma 79

Any packing of items into ℓ bins can be extended with items of size at most γ s.t. we use only $\max\{\ell, \frac{1}{1-\gamma}\text{SIZE}(I) + 1\}$ bins, where $\text{SIZE}(I) = \sum_i s_i$ is the sum of all item sizes.

If after Greedy we use more than ℓ bins, all bins (apart from the last) must be full to at least $1 - \gamma$.

Hence, $r(1 - \gamma) \le \text{SIZE}(I)$ where r is the number of nearly-full bins.

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Choose $\gamma = \epsilon/2$. Then we either use ℓ bins or at most

$$\frac{1}{1-\epsilon/2} \cdot \mathrm{OPT} + 1 \leq (1+\epsilon) \cdot \mathrm{OPT} + 1$$

bins.

It remains to find an algorithm for the large items.

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Linear Grouping:

Generate an instance I' (for large items) as follows.

- Order large items according to size.
- Let the first k items belong to group 1; the following k items belong to group 2; etc.
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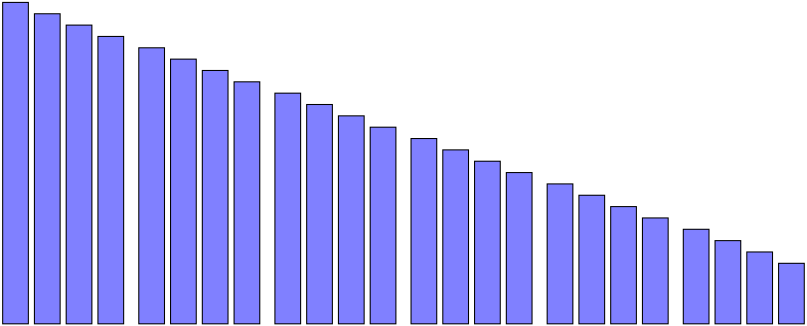

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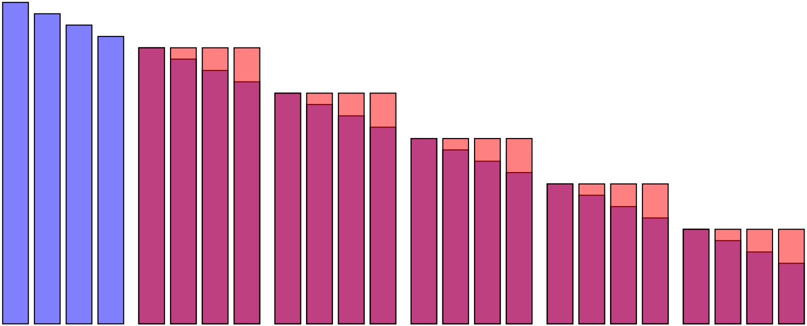

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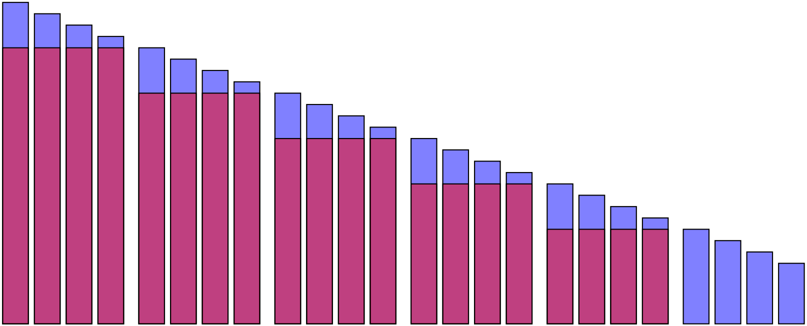

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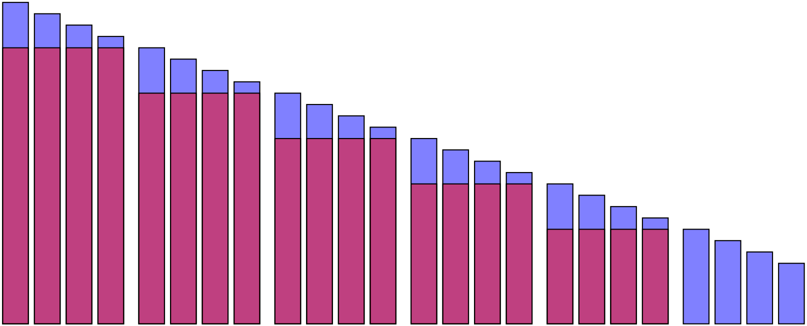

Lemma 80
$\mathrm{OPT}(I') \le \mathrm{OPT}(I) \le \mathrm{OPT}(I') + k$

Proof 1:

- Any bin packing for I gives a bin packing for I' as follows.
- Pack the items of group 2, where in the packing for I the items for group 1 have been packed;
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Hence, after grouping we have a constant number of piece sizes ($4/\epsilon^2$) and at most a constant number ($2/\epsilon$) can fit into any bin.

We can find an optimal packing for such instances by the previous Dynamic Programming approach.

- cost (for large items) at most

$$\mathrm{OPT}(I') + k \le \mathrm{OPT}(I) + \epsilon \mathrm{SIZE}(I) \le (1+\epsilon)\mathrm{OPT}(I)$$

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Change of Notation:

- Group pieces of identical size.
- Let s_1 denote the largest size, and let b_1 denote the number of pieces of size s_1.
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A possible packing of a bin can be described by an m-tuple $(t_1,\ldots,t_m)$, where t_i describes the number of pieces of size s_i. Clearly,

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Let N be the number of configurations (exponential).

Let $T_1, \dots, T_N$ be the sequence of all possible configurations (a configuration T_j has T_{ji} pieces of size s_i).

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\min & & \sum_{j=1}^{N} x_j & & \\
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How to solve this LP?

later...

We can assume that each item has size at least $1/\mathrm{SIZE}(I)$.

Harmonic Grouping

- Sort items according to size (monotonically decreasing).
- Process items in this order; close the current group if size of items in the group is at least 2 (or larger). Then open new group.
- I.e., G_1 is the smallest cardinality set of largest items s.t. total size sums up to at least 2. Similarly, for $G_2, \dots, G_{r-1}$.
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From the grouping we obtain instance I' as follows:

- Round all items in a group to the size of the largest group member.
- Delete all items from group G_1 and G_r.
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- Observe that $n_i \geq n_{i-1}$.

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The number of different sizes in I' is at most $\mathrm{SIZE}(I)/2$.

- Each group that survives (recall that G_1 and G_r are deleted) has total size at least 2.
- Hence, the number of surviving groups is at most $\mathrm{SIZE}(I)/2$.
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Lemma 83

The total size of deleted items is at most $\mathcal{O}(\log(\mathrm{SIZE}(I)))$.

- The total size of items in G_1 and G_r is at most 6 as a group has total size at most 3.
- Consider a group G_i that has strictly more items than G_{i-1}.
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$$3\frac{n_i - n_{i-1}}{n_i} \leq \sum_{j=n_{i-1}+1}^{n_i} \frac{3}{j}$$

since the average piece size is only $3/n_i$.

- Summing over all i that have $n_i > n_{i-1}$ gives a bound of at most

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Algorithm 1 BinPack

```
if $\mathrm{SIZE}(I) < 10$ then
    pack remaining items greedily
Apply harmonic grouping to create instance $I'$; pack discarded items in at most $\mathcal{O}(\log(\mathrm{SIZE}(I)))$ bins.
Let $x$ be optimal solution to configuration LP
Pack $\lfloor x_j \rfloor$ bins in configuration $T_j$ for all $j$; call the packed instance $I_1$.
Let $I_2$ be remaining pieces from $I'$
Pack $I_2$ via BinPack$(I_2)$
```

Analysis

$$\mathrm{OPT}_{\mathrm{LP}}(I_1) + \mathrm{OPT}_{\mathrm{LP}}(I_2) \le \mathrm{OPT}_{\mathrm{LP}}(I') \le \mathrm{OPT}_{\mathrm{LP}}(I)$$

Proof:

- Each piece surviving in I' can be mapped to a piece in I of no lesser size. Hence, $\mathrm{OPT}_{LP}(I') \le \mathrm{OPT}_{LP}(I)$
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Each level of the recursion partitions pieces into three types

1. Pieces discarded at this level.
2. Pieces scheduled because they are in I_1.
3. Pieces in I_2 are handed down to the next level.

Pieces of type 2 summed over all recursion levels are packed into at most $\mathrm{OPT}_{\mathrm{LP}}$ many bins.

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Pieces of type 1 are packed into at most

$$\mathcal{O}(\log(\mathrm{SIZE}(I))) \cdot L$$

many bins where L is the number of recursion levels.

Analysis

Each level of the recursion partitions pieces into three types

1. Pieces discarded at this level.
2. Pieces scheduled because they are in I_1.
3. Pieces in I_2 are handed down to the next level.

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We can show that $\text{SIZE}(I_2) \leq \text{SIZE}(I)/2$. Hence, the number of recursion levels is only $\mathcal{O}(\log(\text{SIZE}(I_{\text{original}})))$ in total.

The number of non-zero entries in the solution to the configuration LP for I' is at most the number of constraints, which is the number of different sizes ($\leq \text{SIZE}(I)/2$).

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How to solve the LP?

Let $T_1, \dots, T_N$ be the sequence of all possible configurations (a configuration T_j has T_{ji} pieces of size s_i).

In total we have b_i pieces of size s_i.

Primal

$$\begin{array}{llrcl} \min & & \sum_{j=1}^{N} x_j & & \\ \text{s.t.} & \forall i \in \{1 \dots m\} & \sum_{j=1}^{N} T_{ji} x_j & \geq & b_i \\ & \forall j \in \{1, \dots, N\} & x_j & \geq & 0 \end{array}$$

Dual

$$\begin{array}{llrcl} \max & & \sum_{i=1}^{m} y_i b_i & & \\ \text{s.t.} & \forall j \in \{1, \dots, N\} & \sum_{i=1}^{m} T_{ji} y_i & \leq & 1 \\ & \forall i \in \{1, \dots, m\} & y_i & \geq & 0 \end{array}$$

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Separation Oracle

Suppose that I am given variable assignment y for the dual.

How do I find a violated constraint?

I have to find a configuration $T_j = (T_{j1}, \dots, T_{jm})$ that

- is feasible, i.e.,

$$\sum_{i=1}^{m} T_{ji} \cdot s_i \le 1 ,$$

- and has a large profit

$$\sum_{i=1}^{m} T_{ji} y_i > 1$$

But this is the Knapsack problem.

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We have FPTAS for Knapsack. This means if a constraint is violated with $1+\epsilon' = 1 + \frac{\epsilon}{1-\epsilon}$ we find it, since we can obtain at least $(1-\epsilon)$ of the optimal profit.

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If the value of the computed dual solution (which may be infeasible) is z then

$$\mathrm{OPT} \le z \le (1+\epsilon')\mathrm{OPT}$$

How do we get good primal solution (not just the value)?

- The constraints used when computing z certify that the solution is feasible for DUAL'.
- Suppose that we drop all unused constraints in DUAL. We will compute the same solution feasible for DUAL'.
- Let DUAL'' be DUAL without unused constraints.
- The dual to DUAL'' is PRIMAL where we ignore variables for which the corresponding dual constraint has not been used.
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16.1 MAXSAT

Problem definition:

- n Boolean variables
- m clauses $C_1, \ldots, C_m$. For example

$$C_7 = x_3 \vee \bar{x}_5 \vee \bar{x}_9$$

- Non-negative weight w_j for each clause C_j.
- Find an assignment of true/false to the variables sucht that the total weight of clauses that are satisfied is maximum.

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Terminology:

- A variable x_i and its negation $\bar{x}_i$ are called literals.
- Hence, each clause consists of a set of literals (i.e., no duplications: $x_i \vee x_i \vee \bar{x}_j$ is **not** a clause).
- We assume a clause does not contain x_i and $\bar{x}_i$ for any i.
- x_i is called a positive literal while the negation $\bar{x}_i$ is called a negative literal.
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- Clauses of length one are called unit clauses.

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MAXSAT: Flipping Coins

Set each x_i independently to true with probability $\frac{1}{2}$ (and, hence, to false with probability $\frac{1}{2}$, as well).

Define random variable X_j with

$$X_j = \begin{cases} 1 & \text{if } C_j \text{ satisfied} \\ 0 & \text{otw.} \end{cases}$$

Then the total weight W of satisfied clauses is given by

$$W = \sum_j w_j X_j$$

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$E[W]$

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MAXSAT: LP formulation

- Let for a clause C_j, P_j be the set of positive literals and N_j the set of negative literals.

$$C_j = \bigvee_{i\in P_j} x_i \vee \bigvee_{i\in N_j} \bar{x}_i$$

$$\begin{array}{llrcl} \max & & & & \sum_j w_j z_j \\ \text{s.t.} & \forall j & \sum_{i\in P_j} y_i + \sum_{i\in N_j}(1-y_i) & \geq & z_j \\ & \forall i & y_i & \in & \{0,1\} \\ & \forall j & z_j & \leq & 1 \end{array}$$

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MAXSAT: Randomized Rounding

Set each x_i independently to true with probability y_i (and, hence, to false with probability $(1 - y_i)$).

Lemma 84 (Geometric Mean $\leq$ Arithmetic Mean)

For any nonnegative $a_1, \ldots, a_k$

$$\left(\prod_{i=1}^{k} a_i\right)^{1/k} \leq \frac{1}{k}\sum_{i=1}^{k} a_i$$

Definition 85

A function f on an interval I is concave if for any two points s and r from I and any $\lambda \in [0,1]$ we have

$$f(\lambda s + (1-\lambda)r) \geq \lambda f(s) + (1-\lambda)f(r)$$

Lemma 86

Let f be a concave function on the interval $[0,1]$, with $f(0) = a$ and $f(1) = a + b$. Then

$$\begin{aligned} f(\lambda) &= f((1-\lambda)0 + \lambda 1) \\ &\geq (1-\lambda)f(0) + \lambda f(1) \\ &= a + \lambda b \end{aligned}$$

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Definition 85

A function f on an interval I is concave if for any two points s and r from I and any $\lambda \in [0,1]$ we have

$$f(\lambda s + (1-\lambda)r) \geq \lambda f(s) + (1-\lambda)f(r)$$

Lemma 86

Let f *be a concave function on the interval* $[0,1]$*, with* $f(0) = a$ *and* $f(1) = a + b$*. Then*

$$\begin{aligned} f(\lambda) &= f((1-\lambda)0 + \lambda 1) \\ &\geq (1-\lambda)f(0) + \lambda f(1) \\ &= a + \lambda b \end{aligned}$$

for $\lambda \in [0,1]$*.*

$\Pr[C_j \text{ not satisfied}]$

$$\Pr[C_j \text{ not satisfied}] = \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i$$

$$\begin{aligned}\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i \\ &\le \left[\frac{1}{\ell_j}\left(\sum_{i\in P_j}(1-y_i)+\sum_{i\in N_j} y_i\right)\right]^{\ell_j}\end{aligned}$$

$$
\begin{aligned}
\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i \\
&\le \left[\frac{1}{\ell_j}\left(\sum_{i\in P_j}(1-y_i)+\sum_{i\in N_j} y_i\right)\right]^{\ell_j} \\
&= \left[1-\frac{1}{\ell_j}\left(\sum_{i\in P_j} y_i+\sum_{i\in N_j}(1-y_i)\right)\right]^{\ell_j}
\end{aligned}
$$

$$
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\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i \\
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&= \left[1-\frac{1}{\ell_j}\left(\sum_{i\in P_j} y_i+\sum_{i\in N_j}(1-y_i)\right)\right]^{\ell_j} \\
&\le \left(1-\frac{z_j}{\ell_j}\right)^{\ell_j} \quad .
\end{aligned}
$$

The function $f(z) = 1 - (1 - \frac{z}{\ell})^{\ell}$ is concave. Hence,

$$\Pr[C_j \text{ satisfied}]$$

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The function $f(z) = 1 - (1 - \frac{z}{\ell})^{\ell}$ is concave. Hence,

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$f''(z) = -\frac{\ell-1}{\ell}\left[1 - \frac{z}{\ell}\right]^{\ell-2} \leq 0$ for $z \in [0,1]$. Therefore, f is concave.

$E[W]$

$$E[W] = \sum_j w_j \Pr[C_j \text{ is satisfied}]$$

$$
\begin{aligned}
E[W] &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\
&\geq \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j} \right)^{\ell_j} \right]
\end{aligned}
$$

$$\begin{aligned} E[W] &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\ &\geq \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \\ &\geq \left(1 - \frac{1}{e}\right) \mathrm{OPT} \enspace . \end{aligned}$$

MAXSAT: The better of two

Theorem 87

Choosing the better of the two solutions given by randomized rounding and coin flipping yields a $\frac{3}{4}$*-approximation.*

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$E[\max\{W_1, W_2\}]$$

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$$
\begin{aligned}
&E[\max\{W_1, W_2\}] \\
&\qquad\qquad \ge E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2]
\end{aligned}
$$

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$\begin{aligned} &E[\max\{W_1, W_2\}] \\ &\qquad \geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2] \\ &\qquad \geq \frac{1}{2}\sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] + \frac{1}{2}\sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \end{aligned}$$

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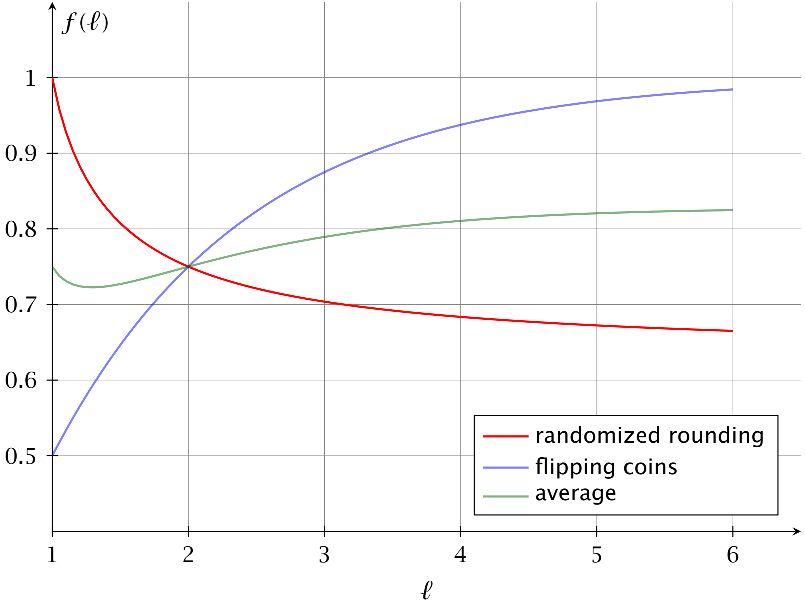
&\qquad \geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2] \\
&\qquad \geq \frac{1}{2}\sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] + \frac{1}{2}\sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\
&\qquad \geq \sum_j w_j z_j \Bigg[\underbrace{\frac{1}{2}\left(1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right) + \frac{1}{2}\left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)}_{\geq \frac{3}{4} \text{for all integers}}\Bigg]
\end{aligned}$$

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$
\begin{aligned}
E[\max\{W_1, W_2\}]
&\geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2] \\
&\geq \frac{1}{2}\sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] + \frac{1}{2}\sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\
&\geq \sum_j w_j z_j \left[\underbrace{\frac{1}{2}\left(1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right) + \frac{1}{2}\left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)}_{\geq \frac{3}{4} \text{ for all integers}}\right] \\
&\geq \frac{3}{4}\mathrm{OPT}
\end{aligned}
$$



$f(\ell)$
1
0.9
0.8
0.7
0.6
0.5
1
2
3
4
5
6
ℓ
randomized rounding
flipping coins
average

MAXSAT: Nonlinear Randomized Rounding

So far we used linear randomized rounding, i.e., the probability that a variable is set to 1/true was exactly the value of the corresponding variable in the linear program.

We could define a function $f : [0,1] \to [0,1]$ and set x_i to true with probability $f(y_i)$.

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MAXSAT: Nonlinear Randomized Rounding

Let $f : [0,1] \rightarrow [0,1]$ be a function with

$$1 - 4^{-x} \leq f(x) \leq 4^{x-1}$$

Theorem 88

Rounding the LP-solution with a function f of the above form gives a $\frac{3}{4}$-approximation.

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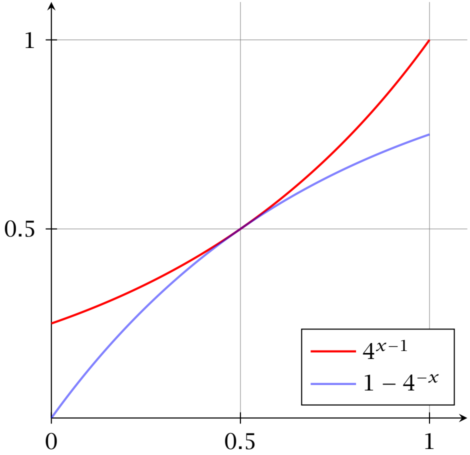
1
0.5
0
0.5
1
4^{x-1}
$1-4^{-x}$

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$$\Pr[C_j \text{ not satisfied}] = \prod_{i\in P_j}(1-f(y_i))\prod_{i\in N_j}f(y_i)$$

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\begin{aligned}
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&= 4^{-(\sum_{i\in P_j}y_i+\sum_{i\in N_j}(1-y_i))}
\end{aligned}$$

$$
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&\le \prod_{i\in P_j}4^{-y_i}\prod_{i\in N_j}4^{y_i-1}\\
&= 4^{-(\sum_{i\in P_j}y_i+\sum_{i\in N_j}(1-y_i))}\\
&\le 4^{-z_j}
\end{aligned}
$$

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$$\Pr[C_j \text{ satisfied}] \geq 1 - 4^{-z_j}$$

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Therefore,

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Therefore,

$$E[W] = \sum_j w_j \Pr[C_j \text{ satisfied}] \geq \frac{3}{4} \sum_j w_j z_j \geq \frac{3}{4} \mathrm{OPT}$$

Can we do better?

Not if we compare ourselves to the value of an optimum LP-solution.

Definition 89 (Integrality Gap)

The integrality gap for an ILP is the worst-case ratio over all instances of the problem of the value of an optimal IP-solution to the value of an optimal solution to its linear programming relaxation.

Note that the integrality is less than one for maximization problems and larger than one for minimization problems (of course, equality is possible).

Note that an integrality gap only holds for one specific ILP formulation.

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Note that an integrality gap only holds for one specific ILP formulation.

Lemma 90

Our ILP-formulation for the MAXSAT problem has integrality gap at most $\frac{3}{4}$.

$$
\begin{array}{llrcl}
\max & & \multicolumn{3}{c}{\sum_j w_j z_j} \\
\text{s.t.} & \forall j & \sum_{i\in P_j} y_i + \sum_{i\in N_j}(1-y_i) & \geq & z_j \\
 & \forall i & y_i & \in & \{0,1\} \\
 & \forall j & z_j & \leq & 1
\end{array}
$$

Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- any solution can satisfy at most 3 clauses
- we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
- hence, the LP has value 4.

Lemma 90

Our ILP-formulation for the MAXSAT problem has integrality gap at most $\frac{3}{4}$.

$$\begin{array}{llrcl} \max & & & & \sum_j w_j z_j \\ \text{s.t.} & \forall j & \sum_{i\in P_j} y_i + \sum_{i\in N_j}(1-y_i) & \geq & z_j \\ & \forall i & y_i & \in & \{0,1\} \\ & \forall j & z_j & \leq & 1 \end{array}$$

Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

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MaxCut

MaxCut
Given a weighted graph $G = (V, E, w)$, $w(v) \geq 0$, partition the vertices into two parts. Maximize the weight of edges between the parts.

Trivial 2-approximation

Semidefinite Programming

$$\begin{array}{rrrcl}
\max / \min & & \sum_{i,j} c_{ij} x_{ij} & & \\
\text{s.t.} & \forall k & \sum_{i,j,k} a_{ijk} x_{ij} & = & b_k \\
& \forall i,j & x_{ij} & = & x_{ji} \\
& & \multicolumn{3}{c}{X = (x_{ij}) \text{ is psd.}}
\end{array}$$

- linear objective, linear constraints
- we can constrain a square matrix of variables to be symmetric positive semidefinite

Note that wlog. we can assume that all variables appear in this matrix. Suppose we have a non-negative scalar z and want to express something like

$$\sum_{ij} a_{ijk} x_{ij} + z = b_k$$

where x_{ij} are variables of the positive semidefinite matrix. We can add z as a diagonal entry $x_{\ell\ell}$, and additionally introduce constraints $x_{\ell r} = 0$ and $x_{r\ell} = 0$.

Vector Programming

$$\begin{array}{lrlcl} \max / \min & & \sum_{i,j} c_{ij}(v_i^t v_j) & & \\ \text{s.t.} & \forall k & \sum_{i,j,k} a_{ijk}(v_i^t v_j) & = & b_k \\ & & v_i \in \mathbb{R}^n & & \end{array}$$

- variables are vectors in n-dimensional space
- objective functions and constraints are linear in inner products of the vectors

This is equivalent!

Fact [without proof]

We (essentially) can solve Semidefinite Programs in polynomial time...

Quadratic Programs

Quadratic Program for MaxCut:

$$\begin{array}{lll} \max & \frac{1}{2}\sum_{i,j} w_{ij}(1 - y_i y_j) & \\ \forall i & y_i \in \{-1, 1\} & \end{array}$$

This is exactly MaxCut!

Semidefinite Relaxation

$$\begin{array}{llrcl} \max & & \frac{1}{2}\sum_{i,j} w_{ij}(1 - v_i^t v_j) & & \\ & \forall i & v_i^t v_i & = & 1 \\ & \forall i & v_i & \in & \mathbb{R}^n \end{array}$$

- this is clearly a relaxation
- the solution will be vectors on the unit sphere

Rounding the SDP-Solution

- Choose a random vector r such that $r/\|r\|$ is uniformly distributed on the unit sphere.
- If $r^t v_i > 0$ set $y_i = 1$ else set $y_i = -1$

Rounding the SDP-Solution

Choose the i-th coordinate r_i as a Gaussian with mean 0 and variance 1, i.e., $r_i \sim \mathcal{N}(0,1)$.

Density function:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{x^2/2}$$

Then

$$\begin{aligned}\Pr[r = (x_1, \dots, x_n)] \\ &= \frac{1}{(\sqrt{2\pi})^n} e^{x_1^2/2} \cdot e^{x_2^2/2} \cdot \ldots \cdot e^{x_n^2/2} \, \mathrm{d}x_1 \cdot \ldots \cdot \mathrm{d}x_n \\ &= \frac{1}{(\sqrt{2\pi})^n} e^{\frac{1}{2}(x_1^2 + \ldots + x_n^2)} \, \mathrm{d}x_1 \cdot \ldots \cdot \mathrm{d}x_n\end{aligned}$$

Hence the probability for a point only depends on its distance to the origin.

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&\qquad = \frac{1}{(\sqrt{2\pi})^n} e^{\frac{1}{2}(x_1^2 + \ldots + x_n^2)} \, \mathrm{d}x_1 \cdot \ldots \cdot \mathrm{d}x_n
\end{aligned}$$

Hence the probability for a point only depends on its distance to the origin.

Rounding the SDP-Solution

Fact
The projection of r onto two unit vectors e_1 and e_2 are independent and are normally distributed with mean 0 and variance 1 iff e_1 and e_2 are orthogonal.

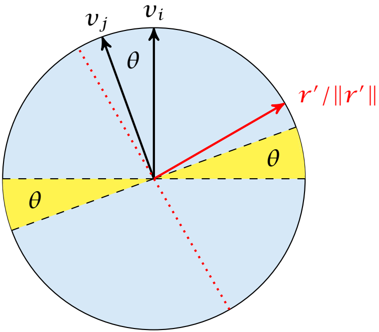
Note that this is clear if e_1 and e_2 are standard basis vectors.

Rounding the SDP-Solution

Corollary

If we project r onto a hyperplane its normalized projection ($r'/\|r'\|$) is uniformly distributed on the unit circle within the hyperplane.

Rounding the SDP-Solution



- if the normalized projection falls into the shaded region, v_i and v_j are rounded to different values
- this happens with probability θ/π

Rounding the SDP-Solution

- contribution of edge (i, j) to the SDP-relaxation:

$$\frac{1}{2}w_{ij}\left(1 - v_i^t v_j\right)$$

- (expected) contribution of edge (i, j) to the rounded instance $w_{ij}\arccos(v_i^t v_j)/\pi$
- ratio is at most

$$\min_{x\in[-1,1]} \frac{2\arccos(x)}{\pi(1-x)} \geq 0.878$$

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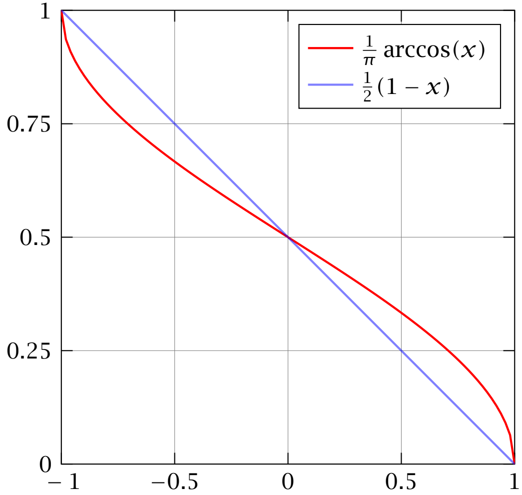
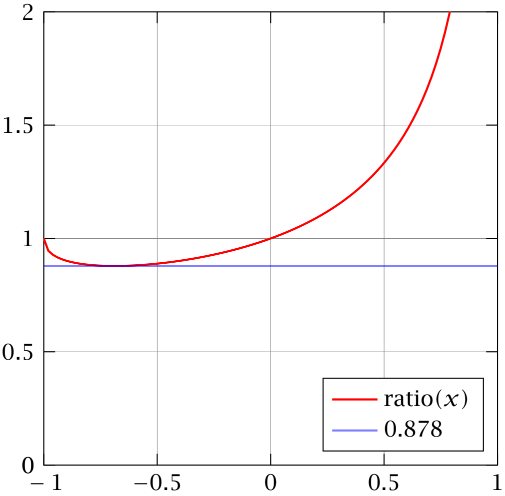


Rounding the SDP-Solution



Rounding the SDP-Solution

Theorem 91

Given the unique games conjecture, there is no α*-approximation for the maximum cut problem with constant*

$$\alpha > \min_{x\in[-1,1]} \frac{2\arccos(x)}{\pi(1-x)}$$

unless $\mathrm{P} = \mathrm{NP}$*.*

Repetition: Primal Dual for Set Cover

Primal Relaxation:

$$\begin{array}{llrcl} \min & & \sum_{i=1}^{k} w_i x_i & & \\ \text{s.t.} & \forall u \in U & \sum_{i: u \in S_i} x_i & \geq & 1 \\ & \forall i \in \{1, \ldots, k\} & x_i & \geq & 0 \end{array}$$

Dual Formulation:

$$\begin{array}{llrcl} \max & & \sum_{u \in U} y_u & & \\ \text{s.t.} & \forall i \in \{1, \ldots, k\} & \sum_{u: u \in S_i} y_u & \leq & w_i \\ & & y_u & \geq & 0 \end{array}$$

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Repetition: Primal Dual for Set Cover

Algorithm:

- Start with $y = 0$ (feasible dual solution).
  Start with $x = 0$ (integral primal solution that may be infeasible).
- While x not feasible
  - Identify an element e that is not covered in current primal integral solution.
  - Increase dual variable y_e until a dual constraint becomes tight (maybe increase by 0!).
  - If this is the constraint for set S_j set $x_j = 1$ (add this set to your solution).

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- Start with $y = 0$ (feasible dual solution).
  Start with $x = 0$ (integral primal solution that may be infeasible).
- While x not feasible
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Repetition: Primal Dual for Set Cover

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$$\begin{aligned}\sum_j w_j x_j = \sum_j \sum_{e\in S_j} y_e &= \sum_e |\{j : e \in S_j\}| \cdot y_e \\ &\le f \cdot \sum_e y_e \le f \cdot \mathrm{OPT}\end{aligned}$$

Note that the constructed pair of primal and dual solution fulfills primal slackness conditions.

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If we would also fulfill dual slackness conditions

$$y_e > 0 \Rightarrow \sum_{j: e \in S_j} x_j = 1$$

then the solution would be optimal!!!

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This is sufficient to show that the solution is an f-approximation.

Suppose we have a primal/dual pair

$$\begin{array}{llrcl} \min & & \sum_j c_j x_j & & \\ \text{s.t.} & \forall i & \sum_{j:} a_{ij} x_j & \geq & b_i \\ & \forall j & x_j & \geq & 0 \end{array}$$

$$\begin{array}{llrcl} \max & & \sum_i b_i y_i & & \\ \text{s.t.} & \forall j & \sum_i a_{ij} y_i & \leq & c_j \\ & \forall i & y_i & \geq & 0 \end{array}$$

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and solutions that fulfill approximate slackness conditions:

$$x_j > 0 \Rightarrow \sum_i a_{ij} y_i \geq \frac{1}{\alpha} c_j$$

$$y_i > 0 \Rightarrow \sum_j a_{ij} x_j \leq \beta b_i$$

Then

$$\sum_j c_j x_j$$

Then

$$\boxed{\sum_j c_j x_j}$$

primal cost

Then

$$\underbrace{\sum_j \overbrace{\boxed{c_j}}^{\text{right hand side of } j\text{-th dual constraint}} x_j}_{\text{primal cost}}$$

Then

$$\underbrace{\boxed{\sum_j c_j x_j}}_{\text{primal cost}} \leq \alpha \sum_j \left(\sum_i a_{ij} y_i \right) x_j$$

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primal cost

$$= \alpha \sum_i \left(\sum_j a_{ij} x_j \right) y_i$$

Then

$$\begin{aligned}\boxed{\sum_j c_j x_j} &\le \alpha \sum_j \left(\sum_i a_{ij} y_i\right) x_j \\ &= \alpha \sum_i \left(\sum_j a_{ij} x_j\right) y_i \\ &\le \alpha\beta \cdot \sum_i b_i y_i\end{aligned}$$

primal cost

Then

$$
\begin{aligned}
\underbrace{\boxed{\sum_j c_j x_j}}_{\text{primal cost}} &\leq \alpha \sum_j \left(\sum_i a_{ij} y_i \right) x_j \\
&= \alpha \sum_i \left(\sum_j a_{ij} x_j \right) y_i \\
&\leq \alpha\beta \cdot \underbrace{\boxed{\sum_i b_i y_i}}_{\text{dual objective}}
\end{aligned}
$$

Feedback Vertex Set for Undirected Graphs

- Given a graph $G = (V, E)$ and non-negative weights $w_v \geq 0$ for vertex $v \in V$.

Feedback Vertex Set for Undirected Graphs

- Given a graph $G = (V, E)$ and non-negative weights $w_v \geq 0$ for vertex $v \in V$.
- Choose a minimum cost subset of vertices s.t. every cycle contains at least one vertex.

We can encode this as an instance of Set Cover

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- However, this encoding gives a Set Cover instance of non-polynomial size.
- The $O(\log n)$-approximation for Set Cover does not help us to get a good solution.

Let $\mathfrak{C}$ denote the set of all cycles (where a cycle is identified by its set of vertices)

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Primal Relaxation:

$$\begin{array}{llrcl} \min & & \sum_v w_v x_v & & \\ \text{s.t.} & \forall C \in \mathfrak{C} & \sum_{v \in C} x_v & \geq & 1 \\ & \forall v & x_v & \geq & 0 \end{array}$$

Dual Formulation:

$$\begin{array}{llrcl} \max & & \sum_{C \in \mathfrak{C}} y_C & & \\ \text{s.t.} & \forall v \in V & \sum_{C: v \in C} y_C & \leq & w_v \\ & \forall C & y_C & \geq & 0 \end{array}$$

If we perform the previous dual technique for Set Cover we get the following:

- Start with $x = 0$ and $y = 0$

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- Start with $x = 0$ and $y = 0$
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  - set $x_v = 1$.

Then

$$\sum_v w_v x_v$$

Then

$$\sum_v w_v x_v = \sum_v \sum_{C:v\in C} y_C x_v$$

Then

$$\begin{aligned}\sum_{v} w_v x_v &= \sum_{v} \sum_{C:v\in C} y_C x_v \\ &= \sum_{v\in S} \sum_{C:v\in C} y_C\end{aligned}$$

where S is the set of vertices we choose.

Then

$$\begin{aligned}\sum_v w_v x_v &= \sum_v \sum_{C:v\in C} y_C x_v \\ &= \sum_{v\in S} \sum_{C:v\in C} y_C \\ &= \sum_C |S\cap C| \cdot y_C\end{aligned}$$

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where S is the set of vertices we choose.

If every cycle is short we get a good approximation ratio, but this is unrealistic.

Algorithm 1 FeedbackVertexSet

```
y ← 0
x ← 0
while exists cycle $C$ in $G$ do
    increase $y_C$ until there is $v \in C$ s.t. $\sum_{C:v\in C} y_C = w_v$
    $x_v = 1$
    remove $v$ from $G$
    repeatedly remove vertices of degree 1 from $G$
```

Idea:

Always choose a short cycle that is not covered. If we always find a cycle of length at most α we get an α-approximation.

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Observation:

For any path P of vertices of degree 2 in G the algorithm chooses at most one vertex from P.

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If we always choose a cycle for which the number of vertices of degree at least 3 is at most α we get a 2α-approximation.

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Theorem 92

In any graph with no vertices of degree 1, there always exists a cycle that has at most $\mathcal{O}(\log n)$ vertices of degree 3 or more. We can find such a cycle in linear time.

This means we have

$$y_C > 0 \Rightarrow |S \cap C| \leq \mathcal{O}(\log n) \ .$$

Primal Dual for Shortest Path

Given a graph $G = (V, E)$ with two nodes $s, t \in V$ and edge-weights $c : E \to \mathbb{R}^+$ find a shortest path between s and t w.r.t. edge-weights c.

$$\begin{array}{llrcl} \min & & \sum_e c(e)x_e & & \\ \text{s.t.} & \forall S \in \mathcal{S} & \sum_{e:\delta(S)} x_e & \geq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Here $\delta(S)$ denotes the set of edges with exactly one end-point in S, and $\mathcal{S} = \{S \subseteq V : s \in S, t \notin S\}$.

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Primal Dual for Shortest Path

The Dual:

$$\begin{array}{llrcl}
\max & & \sum_S y_S & & \\
\textbf{s.t.} & \forall e \in E & \sum_{S: e \in \delta(S)} y_S & \le & c(e) \\
 & \forall S \in \mathcal{S} & y_S & \ge & 0
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Primal Dual for Shortest Path

We can interpret the value y_S as the width of a moat surounding the set S.

Each set can have its own moat but all moats must be disjoint.

An edge cannot be shorter than all the moats that it has to cross.

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Algorithm 1 PrimalDualShortestPath

```
$y \leftarrow 0$
$F \leftarrow \emptyset$
while there is no $s$-$t$ path in $(V, F)$ do
    Let $C$ be the connected component of $(V, F)$ containing $s$
    Increase $y_C$ until there is an edge $e' \in \delta(C)$ such that $\sum_{S: e' \in \delta(S)} y_S = c(e')$.
    $F \leftarrow F \cup \{e'\}$
Let $P$ be an $s$-$t$ path in $(V, F)$
return $P$
```

Lemma 93

At each point in time the set F forms a tree.

Proof:

- In each iteration we take the current connected component from (V, F) that contains s (call this component C) and add some edge from $\delta(C)$ to F.
- Since, at most one end-point of the new edge is in C the edge cannot close a cycle.

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$$\sum_{e \in P} c(e)$$

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\begin{aligned}
\sum_{e\in P} c(e) &= \sum_{e\in P}\sum_{S:e\in\delta(S)} y_S \\
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If we can show that $y_S > 0$ implies $|P\cap\delta(S)| = 1$ gives

$$\sum_{e\in P} c(e) = \sum_S y_S \le \mathrm{OPT}$$

by weak duality.

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Hence, we find a shortest path.

If $\delta(S)$ contains two edges from P then there must exist a subpath P' of P that starts and ends with a vertex from S (and all interior vertices are not in S).

When we increased y_S, S was a connected component of the set of edges F' that we had chosen till this point.

$F' \cup P'$ contains a cycle. Hence, also the final set of edges contains a cycle.

This is a contradiction.

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Steiner Forest Problem:
Given a graph $G = (V, E)$, together with source-target pairs s_i, t_i, $i = 1, \dots, k$, and a cost function $c : E \to \mathbb{R}^+$ on the edges. Find a subset $F \subseteq E$ of the edges such that for every $i \in \{1, \dots, k\}$ there is a path between s_i and t_i only using edges in F.

$$\begin{array}{llrcl} \min & & \sum_e c(e)x_e & & \\ \text{s.t.} & \forall S \subseteq V : S \in S_i \text{ for some } i & \sum_{e\in\delta(S)} x_e & \geq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

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\text{s.t.} & \forall e\in E & \sum_{S:e\in\delta(S)} y_S & \le & c(e) \\
 & & y_S & \ge & 0
\end{array}
$$

The difference to the dual of the shortest path problem is that we have many more variables (sets for which we can generate a moat of non-zero width).

Algorithm 1 FirstTry

```
$y \leftarrow 0$
$F \leftarrow \emptyset$
while not all $s_i$-$t_i$ pairs connected in $F$ do
    Let $C$ be some connected component of $(V,F)$ such that $|C \cap \{s_i,t_i\}| = 1$ for some $i$.
    Increase $y_C$ until there is an edge $e' \in \delta(C)$ s.t. $\sum_{S \in S_i : e' \in \delta(S)} y_S = c_{e'}$
    $F \leftarrow F \cup \{e'\}$
return $\bigcup_i P_i$
```

$$\sum_{e\in F} c(e)$$

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If we show that $y_S > 0$ implies that $|\delta(S)\cap F| \le \alpha$ we are in good shape.

However, this is not true:

- Take a complete graph on $k+1$ vertices $v_0, v_1, \dots, v_k$.

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- The i-th pair is v_0-v_i.
- The first component C could be $\{v_0\}$.
- We only set $y_{\{v_0\}} = 1$. All other dual variables stay 0.
- The final set F contains all edges $\{v_0, v_i\}$, $i = 1, \dots, k$.

$$\sum_{e\in F} c(e) = \sum_{e\in F}\sum_{S:e\in\delta(S)} y_S = \sum_{S} |\delta(S)\cap F|\cdot y_S \enspace .$$

If we show that $y_S > 0$ implies that $|\delta(S)\cap F| \le \alpha$ we are in good shape.

However, this is not true:

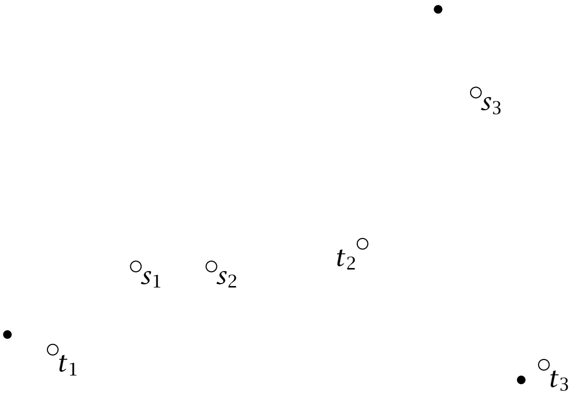
- Take a complete graph on $k+1$ vertices $v_0, v_1, \dots, v_k$.
- The i-th pair is v_0-v_i.
- The first component C could be $\{v_0\}$.
- We only set $y_{\{v_0\}} = 1$. All other dual variables stay 0.
- The final set F contains all edges $\{v_0, v_i\}$, $i = 1, \dots, k$.
- $y_{\{v_0\}} > 0$ but $|\delta(\{v_0\})\cap F| = k$.

Algorithm 1 SecondTry

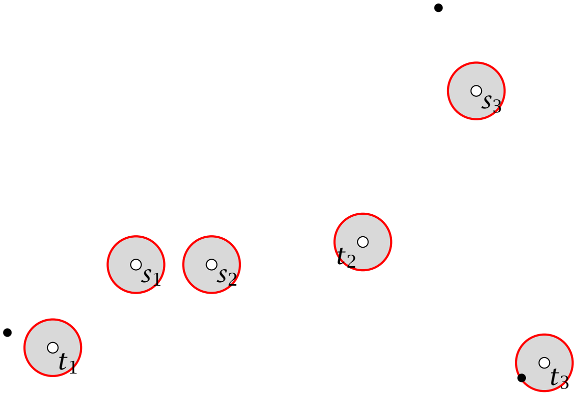
```
$y \leftarrow 0$; $F \leftarrow \emptyset$; $\ell \leftarrow 0$
while not all $s_i$-$t_i$ pairs connected in $F$ do
    $\ell \leftarrow \ell + 1$
    Let $\mathfrak{C}$ be set of all connected components $C$ of $(V, F)$
    such that $|C \cap \{s_i, t_i\}| = 1$ for some $i$.
    Increase $y_C$ for all $C \in \mathfrak{C}$ uniformly until for some edge
    $e_\ell \in \delta(C')$, $C' \in \mathfrak{C}$ s.t. $\sum_{S: e_\ell \in \delta(S)} y_S = c_{e_\ell}$
    $F \leftarrow F \cup \{e_\ell\}$
$F' \leftarrow F$
for $k \leftarrow \ell$ downto $1$ do // reverse deletion
    if $F' - e_k$ is feasible solution then
        remove $e_k$ from $F'$
return $F'$
```

The reverse deletion step is not strictly necessary this way. It would also be sufficient to simply delete all unnecessary edges in any order.

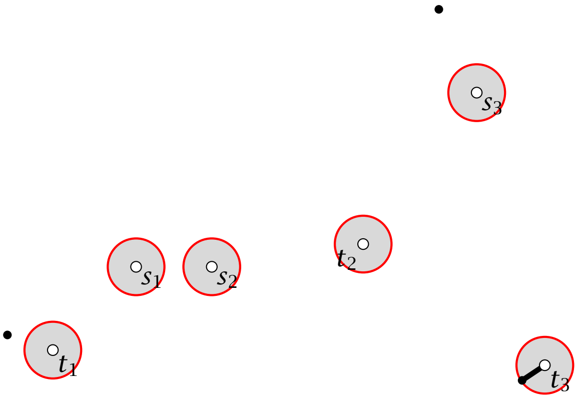
Example



Example



Example



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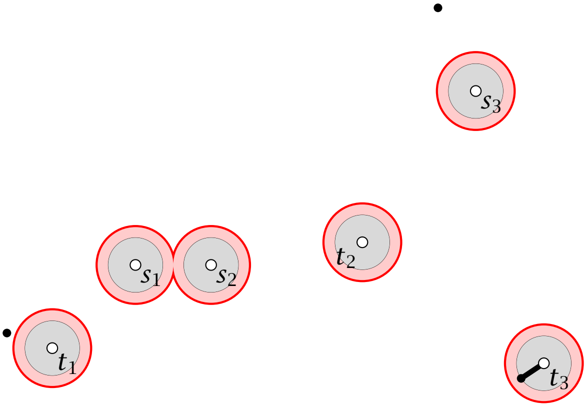

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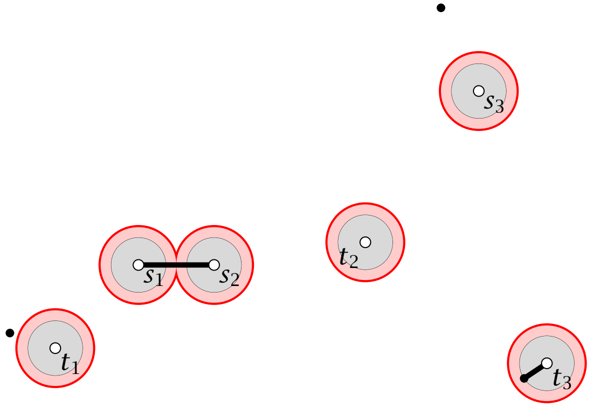

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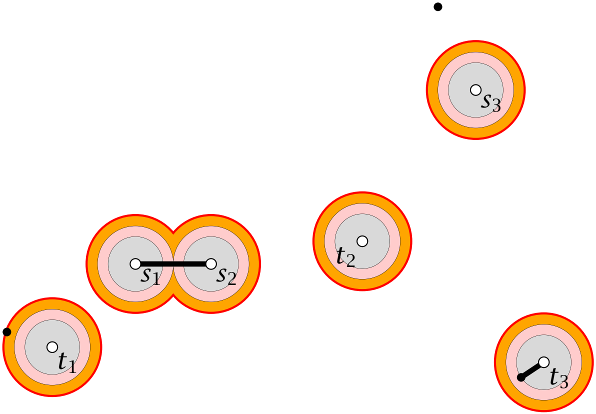

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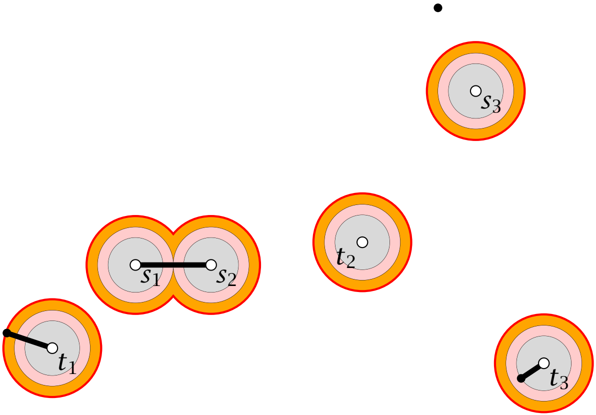

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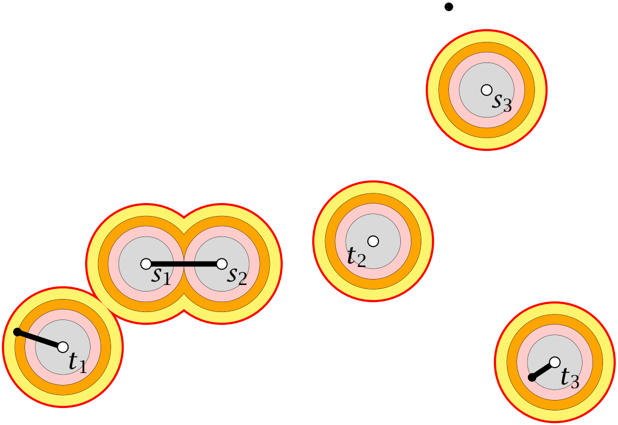

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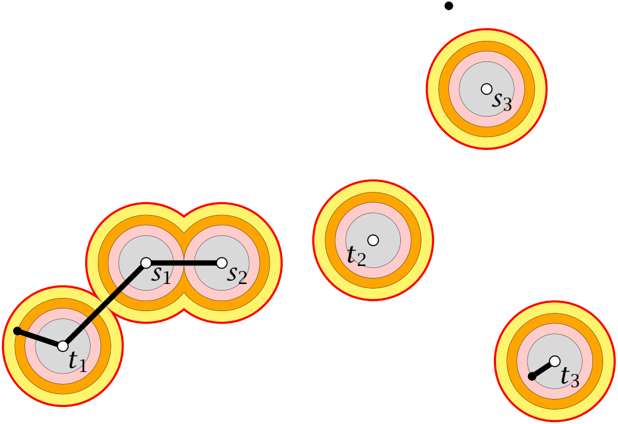

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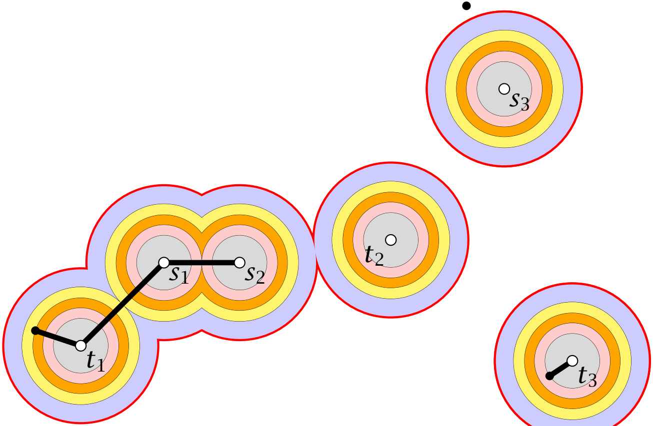

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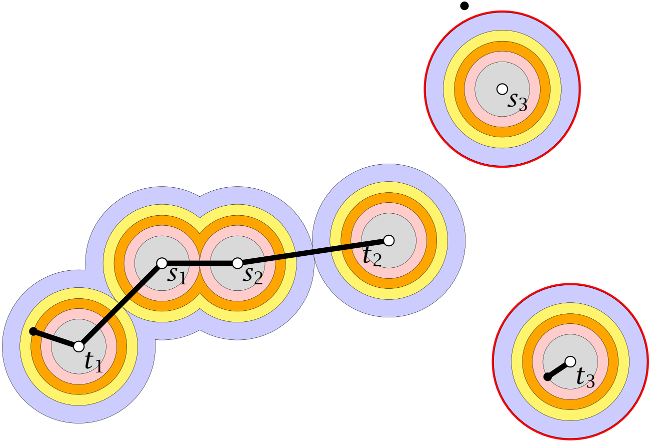

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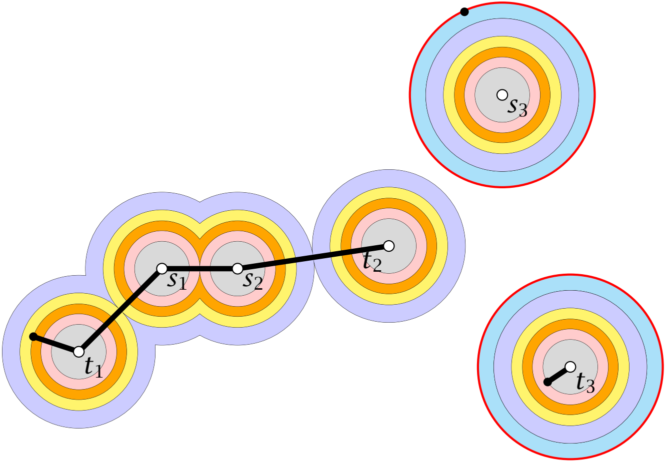

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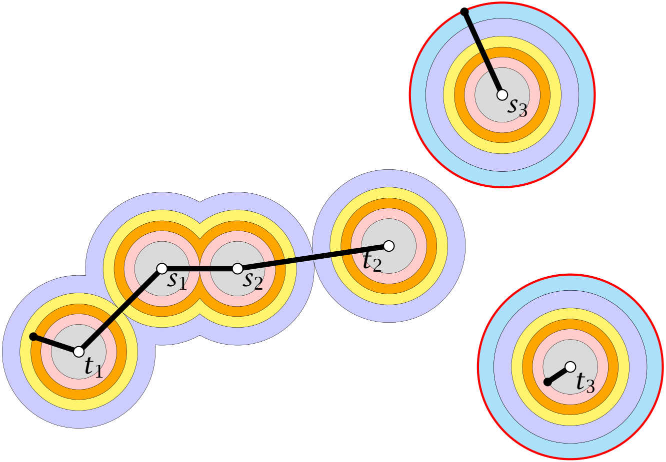
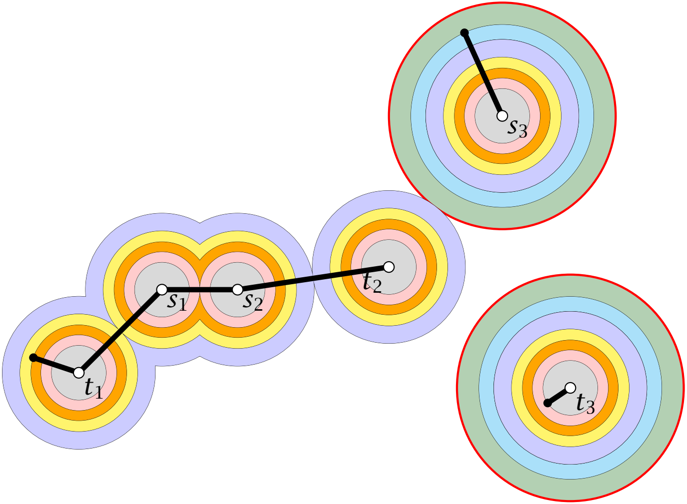


Example



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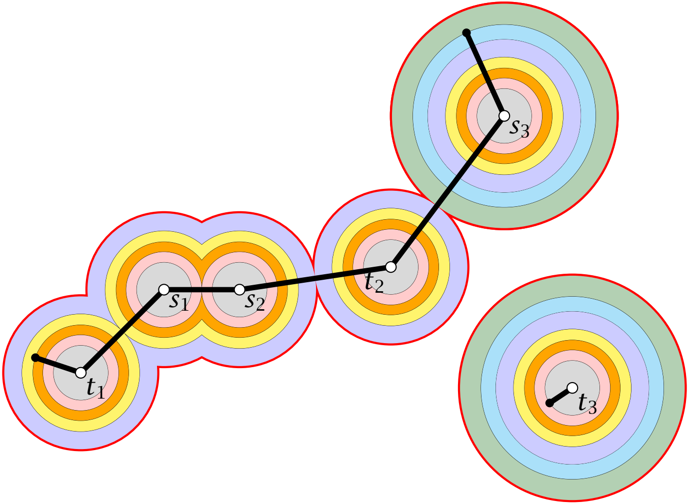

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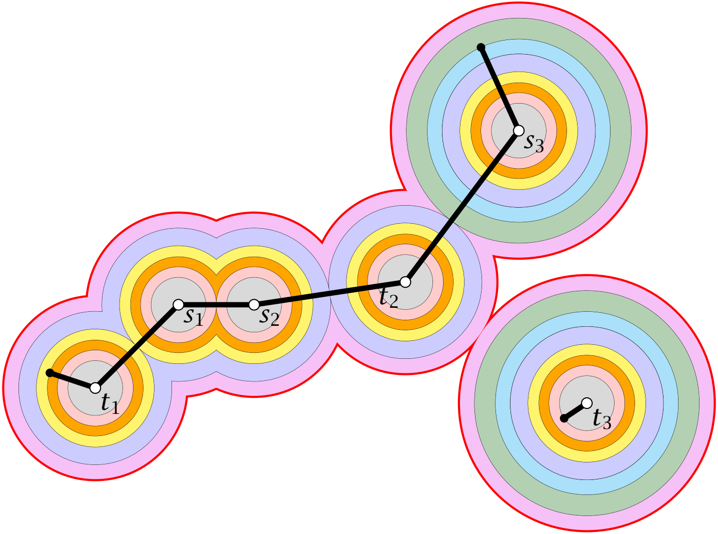

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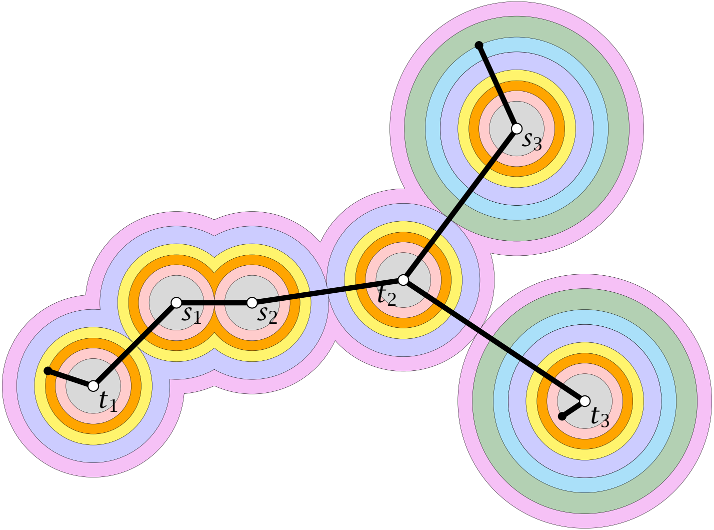

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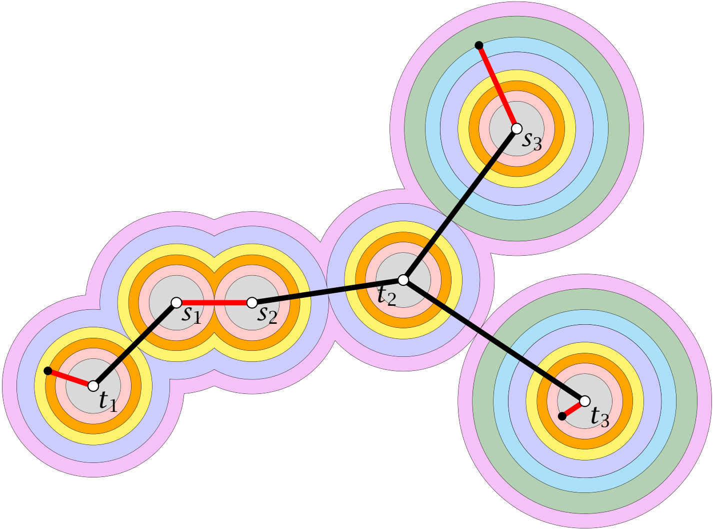

Lemma 94

For any $\mathfrak{C}$ in any iteration of the algorithm

$$\sum_{C\in\mathfrak{C}} |\delta(C)\cap F'| \le 2|\mathfrak{C}|$$

This means that the number of times a moat from $\mathfrak{C}$ is crossed in the final solution is at most twice the number of moats.

Proof: later...

$$\sum_{e\in F'} c_e = \sum_{e\in F'}\sum_{S:e\in\delta(S)} y_S = \sum_S |F'\cap\delta(S)|\cdot y_S\ .$$

We want to show that

$$\sum_S |F'\cap\delta(S)|\cdot y_S \le 2\sum_S y_S$$

- In the i-th iteration the increase of the left-hand side is

$$\epsilon\sum_{C\in\mathcal{C}} |F'\cap\delta(C)|$$

  and the increase of the right hand side is $2\epsilon|\mathcal{C}|$.
- Hence, by the previous lemma the inequality holds after the iteration if it holds in the beginning of the iteration.

$$\sum_{e\in F'} c_e = \sum_{e\in F'} \sum_{S:e\in\delta(S)} y_S = \sum_S |F' \cap \delta(S)| \cdot y_S \ .$$

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Lemma 95

For any set of connected components $\mathfrak{C}$ in any iteration of the algorithm

$$\sum_{C\in\mathfrak{C}} |\delta(C)\cap F'| \le 2|\mathfrak{C}|$$

Proof:

- At any point during the algorithm the set of edges forms a forest (why?).
- Fix iteration i. Let F_i be the set of edges in F at the beginning of the iteration.
- Let $H = F' - F_i$.
- All edges in H are necessary for the solution.

Lemma 95

For any set of connected components $\mathfrak{C}$ *in any iteration of the algorithm*

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- All edges in H are necessary for the solution.

- Contract all edges in F_i into single vertices V'.
- We can consider the forest H on the set of vertices V'.
- Let $\deg(v)$ be the degree of a vertex $v \in V'$ within this forest.
- Color a vertex $v \in V'$ red if it corresponds to a component from $\mathbb{C}$ (an active component). Otw. color it blue. (Let B the set of blue vertices (with non-zero degree) and R the set of red vertices)
- We have

$$\sum_{v\in R} \deg(v) \ge \sum_{C\in\mathbb{C}} |\delta(C) \cap F'| \overset{?}{\le} 2|\mathbb{C}| = 2|R|$$

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$$\begin{aligned}\sum_{v\in R}\deg(v) &= \sum_{v\in R\cup B}\deg(v) - \sum_{v\in B}\deg(v)\\ &\le 2(|R|+|B|) - 2|B|\end{aligned}$$

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  - But this means that the cluster corresponding to b must separate a source-target pair.
  - But then it must be a red node.

Traveling Salesman

Given a set of cities ($\{1,\ldots,n\}$) and a symmetric matrix $C = (c_{ij})$, $c_{ij} \geq 0$ that specifies for every pair $(i,j) \in [n] \times [n]$ the cost for travelling from city i to city j. Find a permutation π of the cities such that the round-trip cost

$$c_{\pi(1)\pi(n)} + \sum_{i=1}^{n-1} c_{\pi(i)\pi(i+1)}$$

is minimized.

Traveling Salesman

Theorem 96

There does not exist an $O(2^n)$-approximation algorithm for TSP.

Hamiltonian Cycle:
For a given undirected graph $G = (V, E)$ decide whether there exists a simple cycle that contains all nodes in G.

- Given an instance to HAMPATH we create an instance for TSP.
- If $(i, j) \notin E$ then set c_{ij} to $n2^n$ otw. set c_{ij} to 1. This instance has polynomial size.
- There exists a Hamiltonian Path iff there exists a tour with cost n. Otw. any tour has cost strictly larger than $n2^n$.
- An $O(2^n)$-approximation algorithm could decide btw. these cases. Hence, cannot exist unless $P = NP$.

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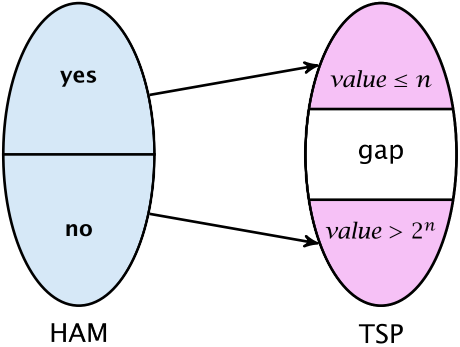
Gap Introducing Reduction



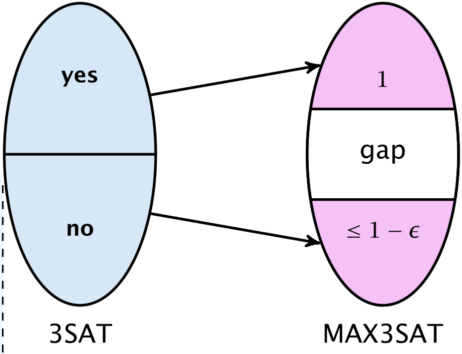
Reduction from Hamiltonian cycle to TSP

- instance that has Hamiltonian cycle is mapped to TSP instance with small cost
- otherwise it is mapped to instance with large cost
- $\Longrightarrow$ there is no $2^n/n$-approximation for TSP

PCP theorem: Approximation View

Theorem 97 (PCP Theorem A)

There exists $\epsilon > 0$ *for which there is gap introducing reduction between 3SAT and MAX3SAT.*



The standard formulation of the PCP theorem looks very different but the above theorem is equivalent. Originally, the PCP theorem is a result about interactive proof systems and its importance to hardness of approximation is somewhat a side effect.

Here the goal of the MAX3SAT-problem is to maximize the fraction of satisfied clauses. The above theorem implies that we cannot approximate MAX3SAT with a ratio better than $1 - \epsilon$.

PCP theorem: Proof System View

Definition 98 (NP)

A language $L \in \mathrm{NP}$ if there exists a polynomial time, deterministic verifier V (a Turing machine), s.t.

[$x \in L$] **completeness**
There exists a proof string y, $|y| = \mathrm{poly}(|x|)$, s.t. $V(x,y) =$ "accept".

[$x \notin L$] **soundness**
For any proof string y, $V(x,y) =$ "reject".

Note that requiring $|y| = \mathrm{poly}(|x|)$ for $x \notin L$ does not make a difference (**why?**).

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There exists a proof string y, $|y| = \mathrm{poly}(|x|)$, s.t. $V(x, y) =$ "accept".

[$x \notin L$] **soundness**
For any proof string y, $V(x, y) =$ "reject".

Note that requiring $|y| = \mathrm{poly}(|x|)$ for $x \notin L$ does not make a difference (**why?**).

Probabilistic Checkable Proofs

An Oracle Turing Machine M is a Turing machine that has access to an oracle.

Such an oracle allows M to solve some problem in a single step.

For example having access to a TSP-oracle π_{TSP} would allow M to write a TSP-instance x on a special oracle tape and obtain the answer (yes or no) in a single step.

For such TMs one looks in addition to running time also at query complexity, i.e., how often the machine queries the oracle.

For a proof string y, π_y is an oracle that upon given an index i returns the i-th character y_i of y.

Probabilistic Checkable Proofs

Non-adaptive means that e.g. the second proof-bit read by the verifier may not depend on the value of the first bit.

Definition 99 (PCP)

A language $L \in \mathrm{PCP}_{c(n),s(n)}(r(n),q(n))$ if there exists a polynomial time, non-adaptive, randomized verifier V, s.t.

[$x \in L$] There exists a proof string y, s.t. $V^{\pi_y}(x) =$ "accept" with probability $\geq c(n)$.

[$x \notin L$] For any proof string y, $V^{\pi_y}(x) =$ "accept" with probability $\leq s(n)$.

The verifier uses at most $\mathcal{O}(r(n))$ random bits and makes at most $\mathcal{O}(q(n))$ oracle queries.

Note that the proof itself does not count towards the input of the verifier. The verifier has to write the number of a bit-position it wants to read onto a special tape, and then the corresponding bit from the proof is returned to the verifier. The proof may only be exponentially long, as a polynomial time verifier cannot address longer proofs.

Probabilistic Checkable Proofs

$c(n)$ is called the completeness. If not specified otw. $c(n) = 1$. Probability of accepting a correct proof.

$s(n) < c(n)$ is called the soundness. If not specified otw. $s(n) = 1/2$. Probability of accepting a wrong proof.

$r(n)$ is called the randomness complexity, i.e., how many random bits the (randomized) verifier uses.

$q(n)$ is the query complexity of the verifier.

Probabilistic Checkable Proofs

RP = coRP = P is a commonly believed conjecture. RP stands for randomized polynomial time (with a non-zero probability of rejecting a YES-instance).

- P = PCP(0, 0)
  verifier without randomness and proof access is deterministic algorithm
- PCP($\log n$, 0) ⊆ P
  we can simulate $\mathcal{O}(\log n)$ random bits in deterministic, polynomial time
- PCP(0, $\log n$) ⊆ P
  we can simulate short proofs in polynomial time
- PCP(poly(n), 0) = coRP $\overset{?!}{=}$ P
  by definition; coRP is randomized polytime with one sided error (positive probability of accepting NO-instance)

Note that the first three statements also hold with equality

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Probabilistic Checkable Proofs

- $\mathrm{PCP}(0, \mathrm{poly}(n)) = \mathrm{NP}$
  by definition; NP-verifier does not use randomness and asks polynomially many queries
- $\mathrm{PCP}(\log n, \mathrm{poly}(n)) \subseteq \mathrm{NP}$
  NP-verifier can simulate $\mathcal{O}(\log n)$ random bits
- $\mathrm{PCP}(\mathrm{poly}(n), 0) = \mathrm{coRP} \overset{?!}{\subseteq} \mathrm{NP}$
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  hard part of the PCP-theorem

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PCP theorem: Proof System View

Theorem 100 (PCP Theorem B)

$\mathrm{NP} = \mathrm{PCP}(\log n, 1)$

Probabilistic Proof for Graph NonIsomorphism

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Verifier gets input (G_0, G_1) (two graphs with n-nodes)

It expects a proof of the following form:

- For any labeled n-node graph H the H's bit $P[H]$ of the proof fulfills

$$\begin{aligned} G_0 \equiv H &\implies P[H] = 0 \\ G_1 \equiv H &\implies P[H] = 1 \\ G_0, G_1 \not\equiv H &\implies P[H] = \text{arbitrary} \end{aligned}$$

Probabilistic Proof for Graph NonIsomorphism

Verifier:

- choose $b \in \{0, 1\}$ at random
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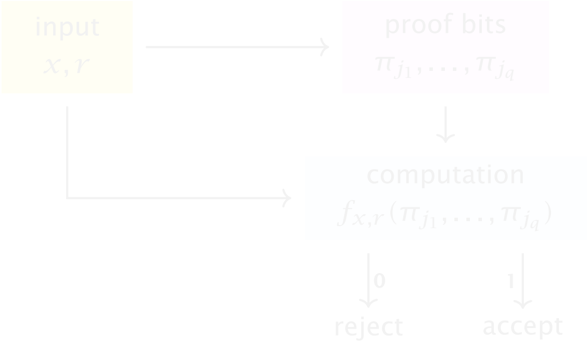
If $G_0 \not\equiv G_1$ then by using the obvious proof the verifier will always accept.

If $G_0 \equiv G_1$ a proof only accepts with probability $1/2$.

- suppose $\pi(G_0) = G_1$
- if we accept for $b = 1$ and permutation π_{rand} we reject for $b = 0$ and permutation $\pi_{\text{rand}} \circ \pi$

Version B $\implies$ Version A

- For 3SAT there exists a verifier that uses $c \log n$ random bits, reads $q = \mathcal{O}(1)$ bits from the proof, has completeness 1 and soundness $1/2$.
- fix x and r:



input

x, r

proof bits

$\pi_{j_1}, \dots, \pi_{j_q}$

computation

$f_{x,r}(\pi_{j_1}, \dots, \pi_{j_q})$

0

1

reject

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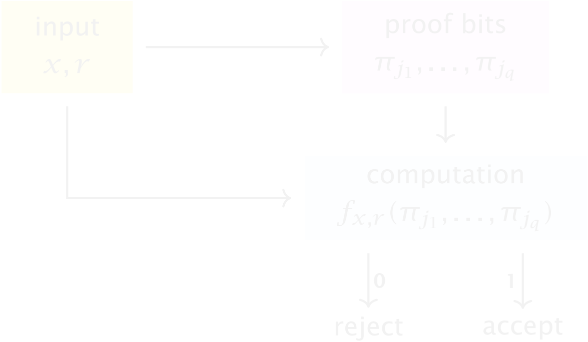

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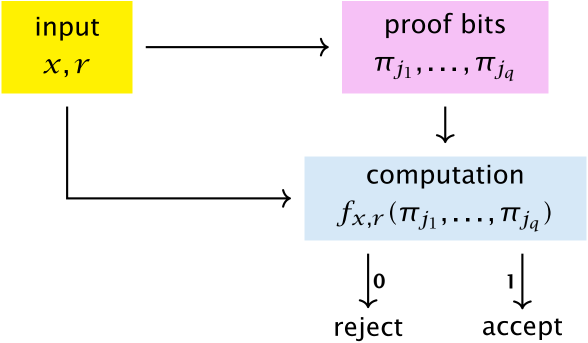

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Version B $\Longrightarrow$ Version A

- transform Boolean formula $f_{x,r}$ into 3SAT formula $C_{x,r}$ (constant size, variables are proof bits)
- consider 3SAT formula $C_x \coloneqq \bigwedge_r C_{x,r}$

[$x \in L$] There exists proof string y, s.t. all formulas $C_{x,r}$ evaluate to 1. Hence, all clauses in C_x satisfied.

[$x \notin L$] For any proof string y, at most 50% of formulas $C_{x,r}$ evaluate to 1. Since each contains only a constant number of clauses, a constant fraction of clauses in C_x are not satisfied.

- this means we have gap introducing reduction

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Version A $\Longrightarrow$ Version B

We show: Version A $\Longrightarrow \text{NP} \subseteq \text{PCP}_{1,1-\epsilon}(\log n, 1)$.

given $L \in \text{NP}$ we build a PCP-verifier for L

Verifier:

- 3SAT is NP-complete; map instance x for L into 3SAT instance I_x, s.t. I_x satisfiable iff $x \in L$
- map I_x to MAX3SAT instance C_x (PCP Thm. Version A)
- interpret proof as assignment to variables in C_x
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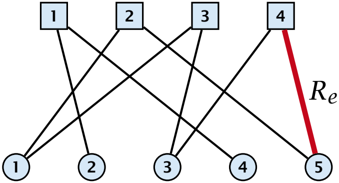
[$x \notin L$] For any proof string y, at most a $(1-\epsilon)$-fraction of clauses in C_x evaluate to 1. The verifier will reject with probability at least ϵ.

To show Theorem B we only need to run this verifier a constant number of times to push rejection probability above $1/2$.

Label Cover

Input:

- bipartite graph $G = (V_1, V_2, E)$
- label sets L_1, L_2
- for every edge $(u, v) \in E$ a relation $R_{u,v} \subseteq L_1 \times L_2$ that describe assignments that make the edge happy.
- maximize number of happy edges



$L_1 = \{$🟩, 🟥, 🟨, 🟦$\}$

$R_e = \{$(🟩, 🟢), (🟩, 🔵), (🟦, 🟣)$\}$

$L_2 = \{$🟢, 🔴, 🟡, 🔵, 🟣$\}$

The label cover problem also has its origin in proof systems. It encodes a 2PR1 (2 prover 1 round system). Each side of the graph corresponds to a prover. An edge is a query consisting of a question for prover 1 and prover 2. If the answers are consistent the verifer accepts otw. it rejects.

Label Cover

- an instance of label cover is (d_1, d_2)-regular if every vertex in L_1 has degree d_1 and every vertex in L_2 has degree d_2.
- if every vertex has the same degree d the instance is called d-regular

MAX E3SAT via Label Cover

instance:

$\Phi(x) = (x_1 \vee \bar{x}_2 \vee x_3) \wedge (x_4 \vee x_2 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_4)$

corresponding graph:

The verifier accepts if the labelling (assignment to variables in clauses at the top + assignment to variables at the bottom) causes the clause to evaluate to true and is consistent, i.e., the assignment of e.g. x_4 at the bottom is the same as the assignment given to x_4 in the labelling of the clause.

label sets: $L_1 = \{T, F\}^3, L_2 = \{T, F\}$ (T=true, F=false)

relation: $R_{C,x_i} = \{((u_i, u_j, u_k), u_i)\}$, where the clause C is over variables x_i, x_j, x_k and assignment (u_i, u_j, u_k) satisfies C

$$R = \{((F,F,F),F), ((F,T,F),F), ((F,F,T),T), ((F,T,T),T),$$
$$((T,T,T),T), ((T,T,F),F), ((T,F,F),F)\}$$

MAX E3SAT via Label Cover

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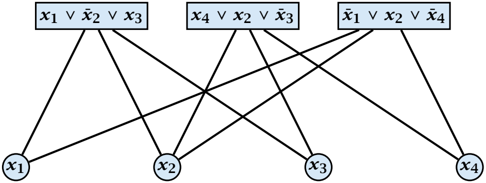

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label sets: $L_1 = \{T, F\}^3, L_2 = \{T, F\}$ (T=true, F=false)

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MAX E3SAT via Label Cover

instance:

$\Phi(x) = (x_1 \vee \bar{x}_2 \vee x_3) \wedge (x_4 \vee x_2 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_4)$

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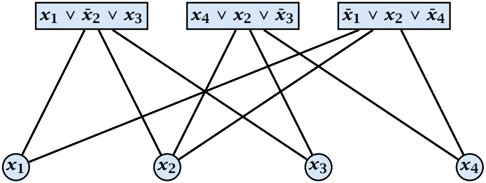

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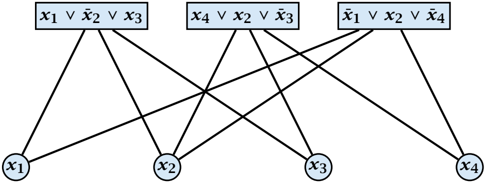

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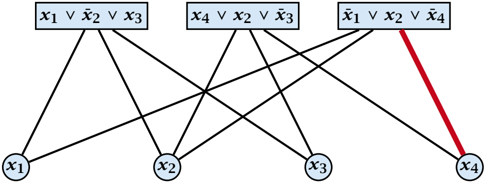

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MAX E3SAT via Label Cover

Lemma 101
If we can satisfy k out of m clauses in ϕ we can make at least $3k + 2(m - k)$ edges happy.

Proof:

- for V_2 use the setting of the assignment that satisfies k clauses
- for satisfied clauses in V_1 use the corresponding assignment to the clause-variables (gives $3k$ happy edges)
- for unsatisfied clauses flip assignment of one of the variables; this makes one incident edge unhappy (gives $2(m - k)$ happy edges)

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MAX E3SAT via Label Cover

Lemma 102

If we can satisfy at most k clauses in Φ we can make at most $3k + 2(m - k) = 2m + k$ edges happy.

Proof:

- the labeling of nodes in V_2 gives an assignment
- every unsatisfied clause in this assignment cannot be assigned a label that satisfies all 3 incident edges
- hence at most $3m - (m - k) = 2m + k$ edges are happy

MAX E3SAT via Label Cover

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Hardness for Label Cover

Here $\epsilon > 0$ is the constant from PCP Theorem A.

We cannot distinguish between the following two cases

- all $3m$ edges can be made happy
- at most $2m + (1-\epsilon)m = (3-\epsilon)m$ out of the $3m$ edges can be made happy

Hence, we cannot obtain an approximation constant $\alpha > \frac{3-\epsilon}{3}$.

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$(3,5)$-regular instances

Theorem 103

There is a constant ρ s.t. MAXE3SAT is hard to approximate with a factor of ρ even if restricted to instances where a variable appears in exactly 5 clauses.

Then our reduction has the following properties:

- the resulting Label Cover instance is $(3,5)$-regular
- it is hard to approximate for a constant $\alpha < 1$
- given a label ℓ_1 for x there is at most one label ℓ_2 for y that makes edge (x,y) happy (uniqueness property)

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$(3,5)$-regular instances

The previous theorem can be obtained with a series of gap-preserving reductions:

- MAX3SAT $\leq$ MAX3SAT(≤ 29)
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- MAX3SAT$(= 5)$ $\leq$ MAXE3SAT$(= 5)$

Here MAX3SAT(≤ 29) is the variant of MAX3SAT in which a variable appears in at most 29 clauses. Similar for the other problems.

Regular instances

We take the $(3,5)$-regular instance. We make 3 copies of every clause vertex and 5 copies of every variable vertex. Then we add edges between clause vertex and variable vertex iff the clause contains the variable. This increases the size by a constant factor. The gap instance can still either only satisfy a constant fraction of the edges or all edges. The uniqueness property still holds for the new instance.

Theorem 104

There is a constant $\alpha < 1$ *such if there is an* α*-approximation algorithm for Label Cover on 15-regular instances than P=NP.*

Given a label ℓ_1 for $x \in V_1$ there is at most one label ℓ_2 for y that makes (x, y) happy. (uniqueness property)

Parallel Repetition

We would like to increase the inapproximability for Label Cover.

In the verifier view, in order to decrease the acceptance probability of a wrong proof (or as here: a pair of wrong proofs) one could repeat the verification several times.

Unfortunately, we have a 2P1R-system, i.e., we are stuck with a single round and cannot simply repeat.

The idea is to use parallel repetition, i.e., we simply play several rounds in parallel and hope that the acceptance probability of wrong proofs goes down.

Parallel Repetition

Given Label Cover instance I with $G = (V_1, V_2, E)$, label sets L_1 and L_2 we construct a new instance I':

- $V_1' = V_1^k = V_1 \times \cdots \times V_1$
- $V_2' = V_2^k = V_2 \times \cdots \times V_2$
- $L_1' = L_1^k = L_1 \times \cdots \times L_1$
- $L_2' = L_2^k = L_2 \times \cdots \times L_2$
- $E' = E^k = E \times \cdots \times E$

An edge $((x_1, \dots, x_k), (y_1, \dots, y_k))$ whose end-points are labelled by $(\ell_1^x, \dots, \ell_k^x)$ and $(\ell_1^y, \dots, \ell_k^y)$ is happy if $(\ell_i^x, \ell_i^y) \in R_{x_i, y_i}$ for all i.

Parallel Repetition

If I is regular than also I'.

If I has the uniqueness property than also I'.

Did the gap increase?

- Suppose we have labelling ℓ_1, ℓ_2 that satisfies just an α-fraction of edges in I.
- We transfer this labelling to instance I':
  vertex $(x_1, \dots, x_k)$ gets label $(\ell_1(x_1), \dots, \ell_1(x_k))$,
  vertex $(y_1, \dots, y_k)$ gets label $(\ell_2(y_1), \dots, \ell_2(y_k))$.
- How many edges are happy?

Does this always work?

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Does this always work?

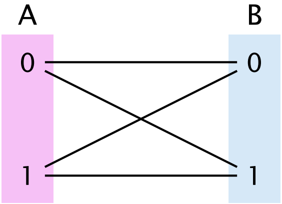
Counter Example

Non interactive agreement:

- Two provers A and B
- The verifier generates two random bits b_A, and b_B, and sends one to A and one to B.
- Each prover has to answer one of A_0, A_1, B_0, B_1 with the meaning $A_0 :=$ prover A has been given a bit with value 0.
- The provers win if they give the same answer and if the answer is correct.

Counter Example

The provers can win with probability at most $1/2$.



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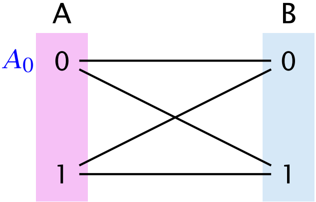

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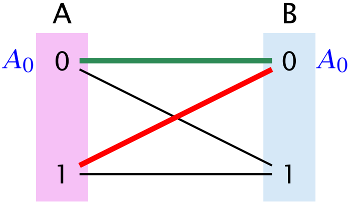

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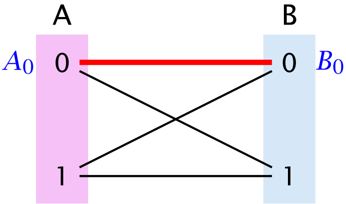

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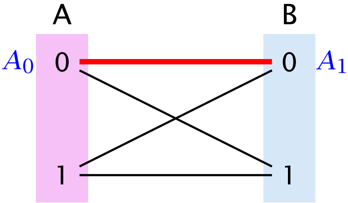

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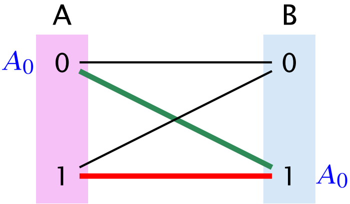

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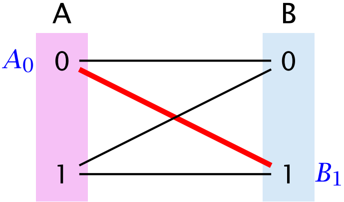

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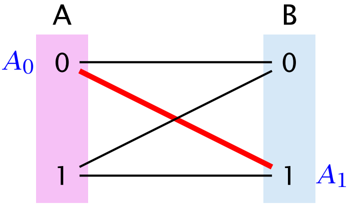

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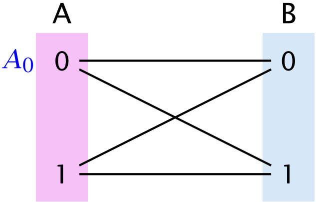

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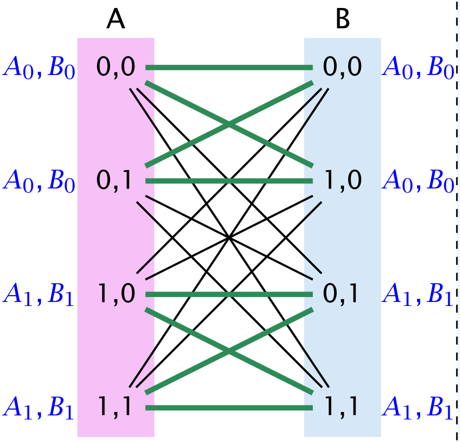
Counter Example

In the repeated game the provers can also win with probability $1/2$:



For the first game/coordinate the provers give an answer of the form "A has received..." (A_0 or A_1) and for the second an answer of the form "B has received..." (B_0 or B_1).

If the answer a prover has to give is about himself a prover can answer correctly. If the answer to be given is about the other prover the same bit is returned. This means e.g. Prover B answers A_1 for the first game iff in the second game he receives a 1-bit.

By this method the provers always win if Prover A gets the same bit in the first game as Prover B in the second game. This happens with probability $1/2$.

This strategy is not possible for the provers if the game is repeated sequentially. How should prover B know (for her answer in the first game) which bit she is going to receive in the second game?

Boosting

Theorem 105
There is a constant $c > 0$ *such if* $\mathrm{OPT}(I) = |E|(1-\delta)$ *then* $\mathrm{OPT}(I') \le |E'|(1-\delta)^{\frac{ck}{\log L}}$, *where* $L = |L_1| + |L_2|$ *denotes total number of labels in* I.

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Hardness of Label Cover

Theorem 106

There are constants $c > 0$, $\delta < 1$ s.t. for any k we cannot distinguish regular instances for Label Cover in which either

- $\mathrm{OPT}(I) = |E|$, *or*
- $\mathrm{OPT}(I) = |E|(1 - \delta)^{ck}$

unless each problem in NP has an algorithm running in time $\mathcal{O}(n^{\mathcal{O}(k)})$.

Corollary 107

There is no α-approximation for Label Cover for any constant α.

Advanced PCP Theorem

Here the verifier reads exactly three bits from the proof. Not $O(3)$ bits.

Theorem 108

For any positive constant $\epsilon > 0$*, it is the case that* $\mathrm{NP} \subseteq \mathrm{PCP}_{1-\epsilon,1/2+\epsilon}(\log n, 3)$*. Moreover, the verifier just reads three bits from the proof, and bases its decision only on the parity of these bits.*

It is NP-hard to approximate a MAXE3LIN problem by a factor better than $1/2 + \delta$, for any constant δ.

It is NP-hard to approximate MAX3SAT better than $7/8 + \delta$, for any constant δ.