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	

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	

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	

Brewery Problem

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

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

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

Brewery Problem

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

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 €

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.

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

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.

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

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.

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

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.

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

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.

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

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

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

$$\begin{aligned} \max \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \ge 0 \end{aligned}$$

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

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

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

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

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

$$\begin{aligned} \max \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \ge 0 \end{aligned}$$

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

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

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

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

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

$$\begin{array}{llcl} \max & c^T x & & \\ \text{s.t.} & Ax & = & b \\ & x & \ge & 0 \end{array}$$

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

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

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

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

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

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

Standard Form LPs

Original LP

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

Standard Form

Add a slack variable to every constraint.

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

Standard Form LPs

Original LP

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

Standard Form

Add a slack variable to every constraint.

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

Standard Form LPs

There are different standard forms:

standard form

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

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

standard maximization form

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

standard minimization form

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

Standard Form LPs

There are different standard forms:

standard form

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

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

standard maximization form

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

standard minimization form

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

Standard Form LPs

There are different standard forms:

standard form

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

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

standard maximization form

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

standard minimization form

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

Standard Form LPs

There are different standard forms:

standard form

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

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

standard maximization form

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

standard minimization form

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

Standard Form LPs

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

- less or equal to equality:

- greater or equal to equality:

- min to max:

Standard Form LPs

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

- **less or equal to equality:**

$$a - 3b + 5c \le 12 \implies \begin{array}{rl} a - 3b + 5c + s &= 12 \\ s &\ge 0 \end{array}$$

- **greater or equal to equality:**

$$a - 3b + 5c \ge 12 \implies \begin{array}{rl} a - 3b + 5c - s &= 12 \\ s &\ge 0 \end{array}$$

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **less or equal to equality:**

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

- **greater or equal to equality:**

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

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **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:**

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

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **less or equal to equality:**

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

- **greater or equal to equality:**

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

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **less or equal to equality:**

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

- **greater or equal to equality:**

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

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **less or equal to equality:**

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

- **greater or equal to equality:**

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

- **min to max:**

$$\min a - 3b + 5c \implies \max -a + 3b - 5c$$

Standard Form LPs

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

- **equality to less or equal:**

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

- **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:**

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

Standard Form LPs

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

- **equality to less or equal:**

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

- **equality to greater or equal:**

- **unrestricted to nonnegative:**

Standard Form LPs

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

- **equality to less or equal:**

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

- **equality to greater or equal:**

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

- **unrestricted to nonnegative:**

Standard Form LPs

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

- **equality to less or equal:**

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

- **equality to greater or equal:**

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

- **unrestricted to nonnegative:**

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

Standard Form LPs

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

- **equality to less or equal:**

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

- **equality to greater or equal:**

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

- **unrestricted to nonnegative:**

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

Standard Form LPs

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

- **equality to less or equal:**

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

- **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:**

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

Standard Form LPs

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
- for the standard minimization or maximization LPs we could include the nonnegativity constraints into the set of ordinary constraints; this is of course not possible for the standard form

Standard Form LPs

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
- for the standard minimization or maximization LPs we could include the nonnegativity constraints into the set of ordinary constraints; this is of course not possible for the standard form

Standard Form LPs

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
- for the standard minimization or maximization LPs we could include the nonnegativity constraints into the set of ordinary constraints; this is of course not possible for the standard form

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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?
- Is LP in P?

Input size:

- n number of variables, m constraints, L number of bits to encode the input

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. $Ax = b$, $x \geq 0$, $c^T x \geq \alpha$?

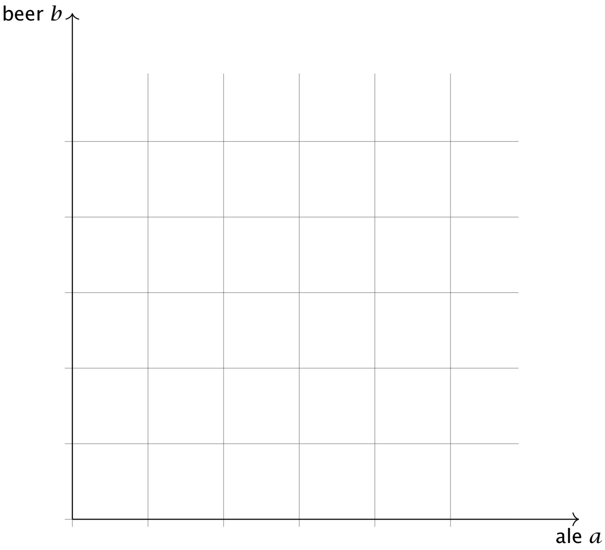
Questions:

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

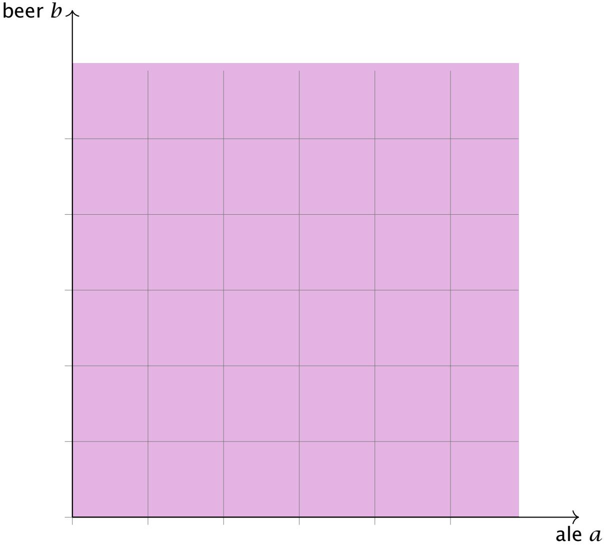
Input size:

- n number of variables, m constraints, L number of bits to encode the input

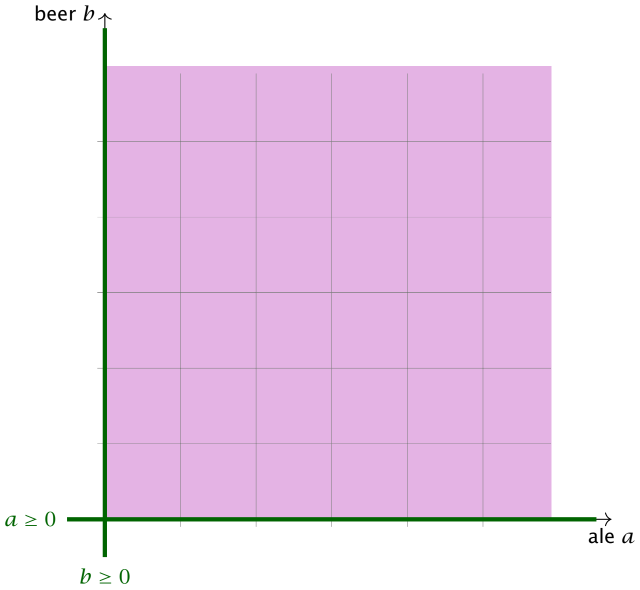
Geometry of Linear Programming



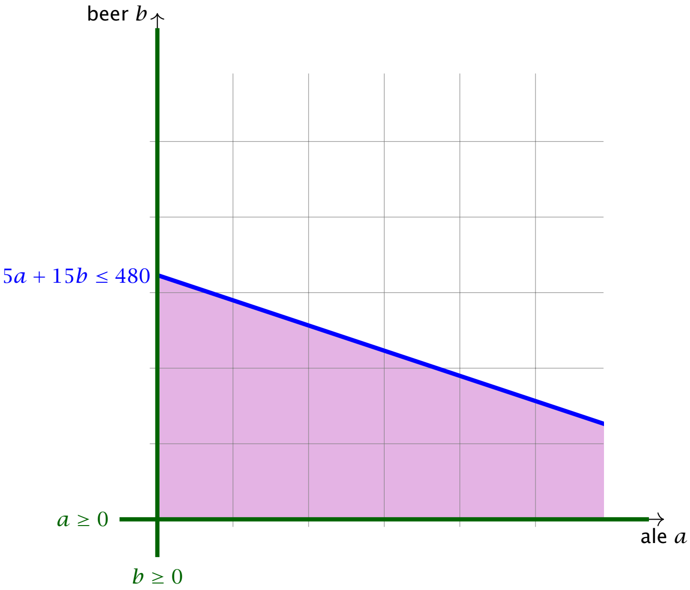
Geometry of Linear Programming



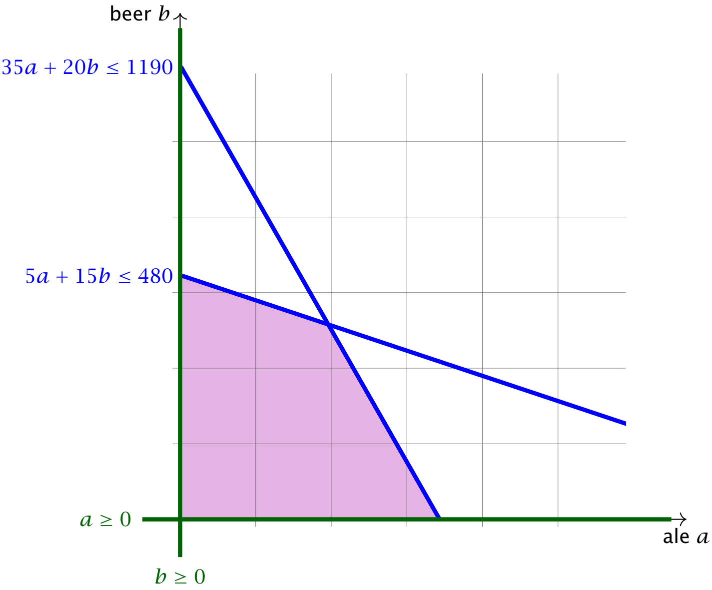
Geometry of Linear Programming



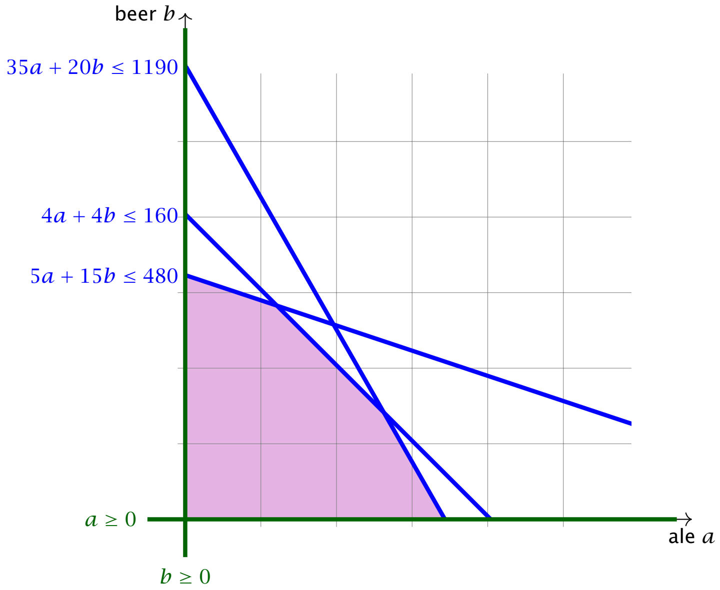
Geometry of Linear Programming



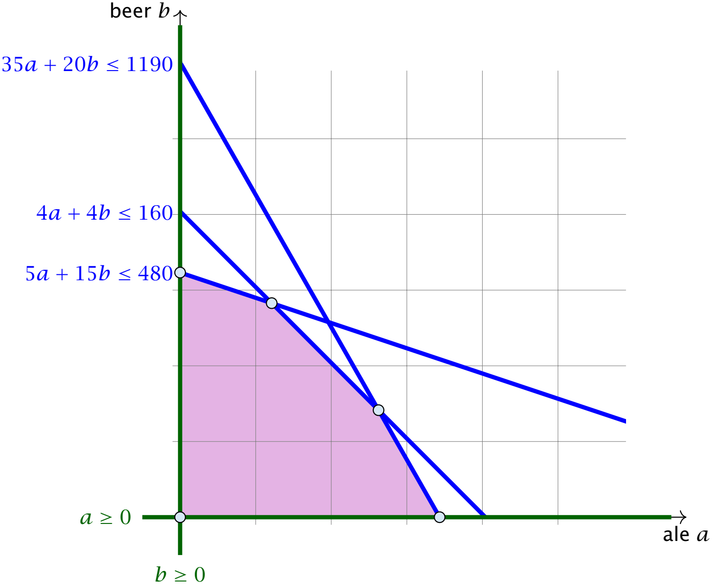
Geometry of Linear Programming



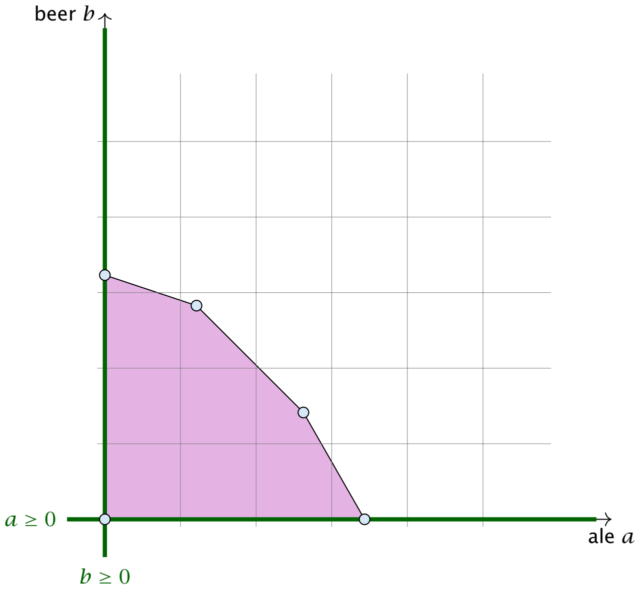
Geometry of Linear Programming



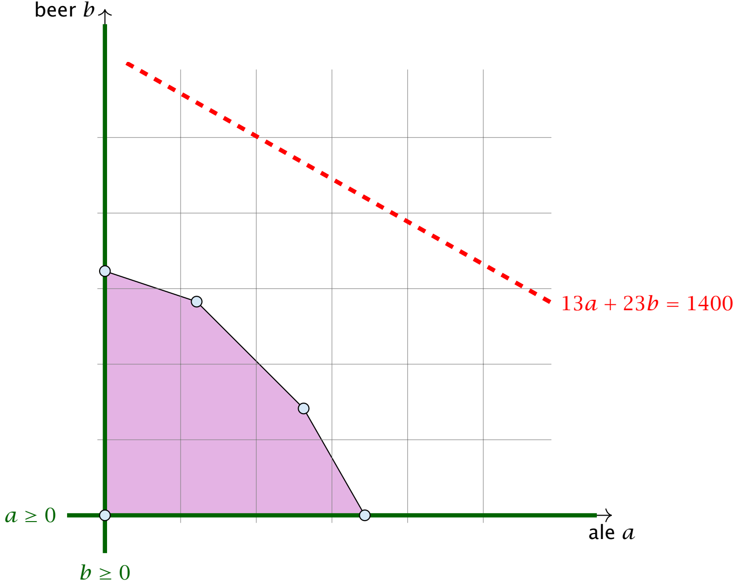
Geometry of Linear Programming



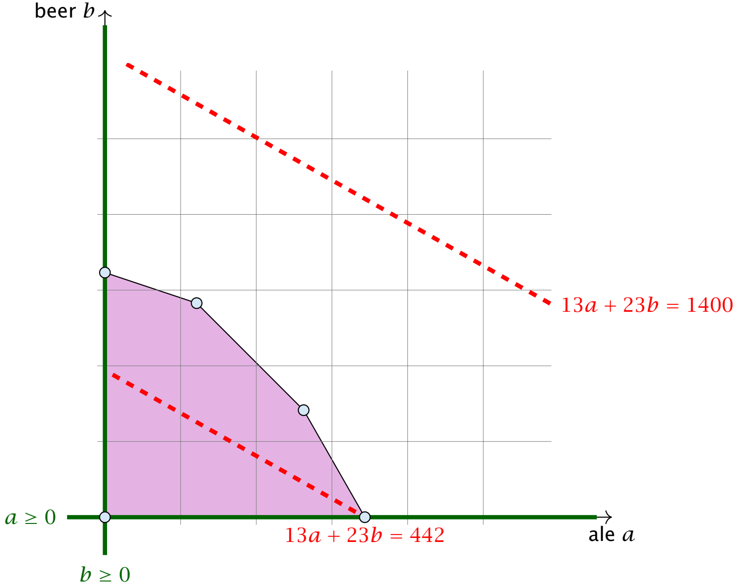
Geometry of Linear Programming



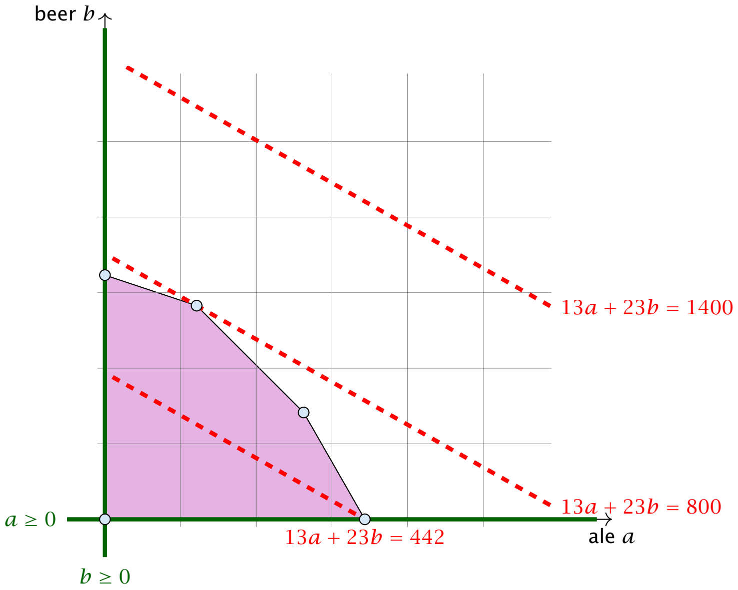
Geometry of Linear Programming



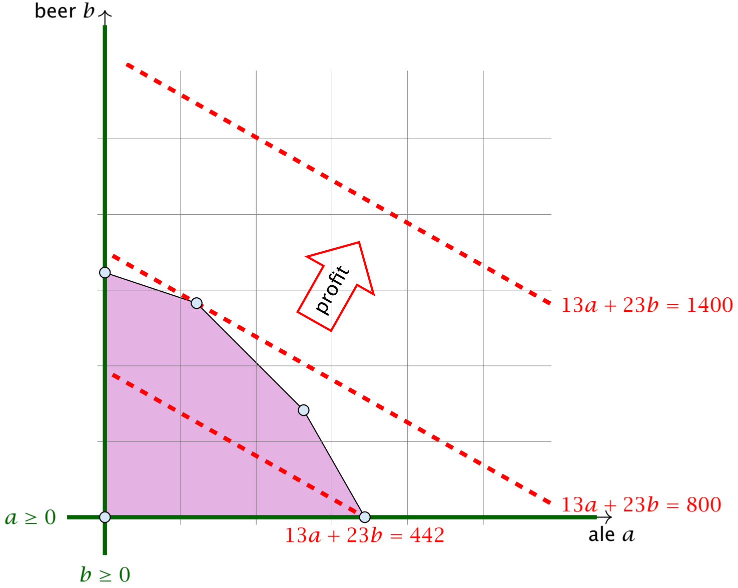
Geometry of Linear Programming



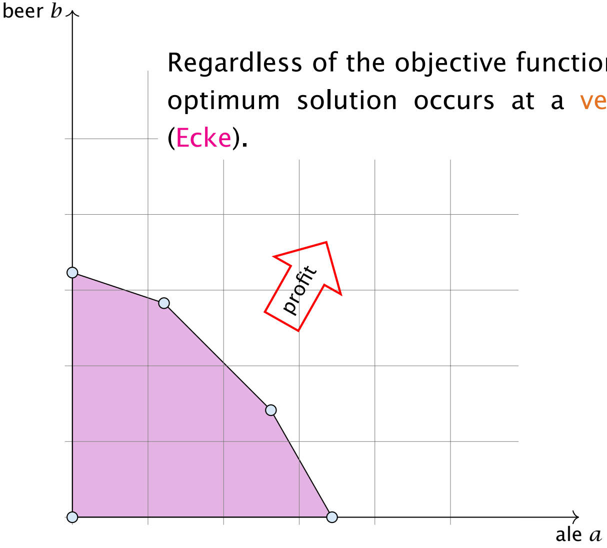
Geometry of Linear Programming



Geometry of Linear Programming



Geometry of Linear Programming



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

Definitions

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

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.

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).

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).
- If $P \neq \emptyset$ then the LP is called feasible (erfüllbar). Otherwise, it is called infeasible (unerfüllbar).
- An LP is bounded (beschränkt) if it is feasible and
  - $c^T x < \infty$ for all $x \in P$ (for maximization problems)
  - $c^T x > -\infty$ for all $x \in P$ (for minimization problems)

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).
- If $P \neq \emptyset$ then the LP is called feasible (erfüllbar). Otherwise, it is called infeasible (unerfüllbar).
- An LP is bounded (beschränkt) if it is feasible and
  - $c^T x < \infty$ for all $x \in P$ (for maximization problems)
  - $c^T x > -\infty$ for all $x \in P$ (for minimization problems)

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).
- If $P \neq \emptyset$ then the LP is called feasible (erfüllbar). Otherwise, it is called infeasible (unerfüllbar).
- An LP is bounded (beschränkt) if it is feasible and
  - $c^T x < \infty$ for all $x \in P$ (for maximization problems)
  - $c^T x > -\infty$ for all $x \in P$ (for minimization problems)

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).
- If $P \neq \emptyset$ then the LP is called feasible (erfüllbar). Otherwise, it is called infeasible (unerfüllbar).
- An LP is bounded (beschränkt) if it is feasible and
  - $c^T x < \infty$ for all $x \in P$ (for maximization problems)
  - $c^T x > -\infty$ for all $x \in P$ (for minimization problems)

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).
- If $P \neq \emptyset$ then the LP is called feasible (erfüllbar). Otherwise, it is called infeasible (unerfüllbar).
- An LP is bounded (beschränkt) if it is feasible and
  - $c^T x < \infty$ for all $x \in P$ (for maximization problems)
  - $c^T x > -\infty$ for all $x \in P$ (for minimization problems)

Definition 2

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

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

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

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

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 $a \neq 0$.

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 $a \neq 0$.

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 $\{H(a_1, b_1), \dots, H(a_m, b_m)\}$, where

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

Definition 13

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

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

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

Definition 13
A polyhedron P is bounded if there exists B s.t. $\|x\|_2 \leq B$ for all $x \in P$.

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 $\dim(e) = 1$.
- a face F is a facet of P if F is a face and $\dim(F) = \dim(P) - 1$.

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 $\dim(e) = 1$.
- a face F is a facet of P if F is a face and $\dim(F) = \dim(P) - 1$.

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 $\dim(e) = 1$.
- a face F is a facet of P if F is a face and $\dim(F) = \dim(P) - 1$.

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.

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.

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 $c^T d \geq 0$ (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 $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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 $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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 $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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 $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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 $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- Wlog. assume $c^T d \geq 0$ (by taking either d or $-d$)
- Consider $x + \lambda d$, $\lambda > 0$

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 $x + \lambda d \geq x \geq 0$
- as $\lambda \to \infty$, $c^T(x + \lambda d) \to \infty$ as $c^T d > 0$

Convex Sets

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

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 $x + \lambda d \geq x \geq 0$
- as $\lambda \to \infty$, $c^T(x + \lambda d) \to \infty$ as $c^T d > 0$

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 $x + \lambda' d \geq 0$

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 $x + \lambda d \geq x \geq 0$
- as $\lambda \to \infty$, $c^T(x + \lambda d) \to \infty$ as $c^T d > 0$

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 $c^T d > 0$]

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 $c^T d > 0$]

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 $x + \lambda d \geq x \geq 0$
- as $\lambda \to \infty$, $c^T(x + \lambda d) \to \infty$ as $c^T d > 0$

Convex Sets

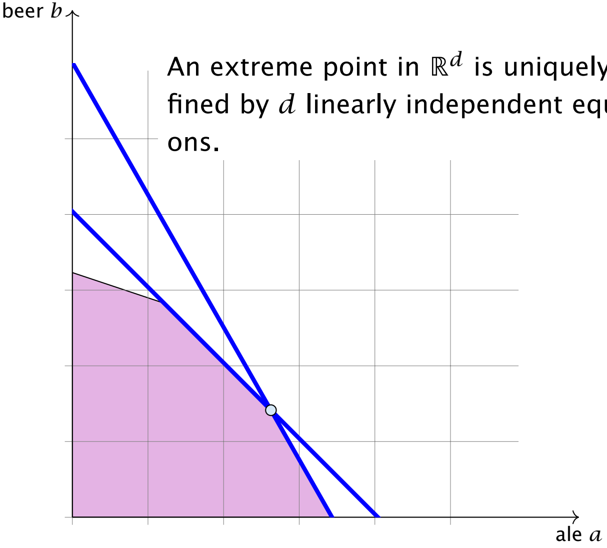
Case 1. [$\exists j$ s.t. $d_j < 0$]

- 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 $x + \lambda d \geq x \geq 0$
- as $\lambda \to \infty$, $c^T(x + \lambda d) \to \infty$ as $c^T d > 0$

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.*

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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof (⇐)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof (⇐)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Leftarrow$)

- assume x is not extreme point
- there exists direction d s.t. $x \pm d \in P$
- $Ad = 0$ because $A(x \pm d) = b$
- 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

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.*

Proof ($\Rightarrow$)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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.*

Proof (⇒)

- assume A_B has linearly dependent columns
- there exists $d \neq 0$ such that $A_B d = 0$
- extend d to $\mathbb{R}^n$ by adding 0-components
- now, $Ad = 0$ and $d_j = 0$ whenever $x_j = 0$
- for sufficiently small λ we have $x \pm \lambda d \in P$
- hence, x is not extreme point

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

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
- we get $y = x$
- hence, x is a vertex of P

Observation

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

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 $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

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 $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

C1 if now $b_1 = \sum_{i=2}^{m} \lambda_i \cdot b_i$ then

C2 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 $A_2, \dots, A_m$ we have

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 $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

Observation

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

- assume that $\mathrm{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \ldots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

Observation

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

- assume that $\operatorname{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

Observation

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

- assume that $\operatorname{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

Observation

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

- assume that $\operatorname{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

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 $A_2, \dots, A_m$; this means

$$A_1 = \textstyle\sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \textstyle\sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

Observation

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

- assume that $\operatorname{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \ldots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

Observation

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

- assume that $\operatorname{rank}(A) < m$
- assume wlog. that the first row A_1 lies in the span of the other rows $A_2, \dots, A_m$; this means

$$A_1 = \sum_{i=2}^{m} \lambda_i \cdot A_i, \text{ for suitable } \lambda_i$$

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

C2 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 $A_2, \dots, A_m$ we have

$$A_1 x = \sum_{i=2}^{m} \lambda_i \cdot A_i x = \sum_{i=2}^{m} \lambda_i \cdot b_i \neq b_1$$

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 $B \subseteq \{1, \dots, n\}$ with $|B| = m$ and

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

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

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

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 $\mathrm{rank}(A) = m$.

Basic Feasible Solutions

$x \in \mathbb{R}^n$ is called basic solution (Basislösung) if $Ax = b$ and $\text{rank}(A_J) = |J|$ 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 $B \subseteq \{1, \dots, n\}$ with $\text{rank}(A_B) = m$ 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)

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 $B \subseteq \{1, \dots, n\}$ 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)

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)

Basic Feasible Solutions

$x \in \mathbb{R}^n$ is called basic solution (Basislösung) if $Ax = b$ and $\mathrm{rank}(A_J) = |J|$ 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 $\mathrm{rank}(A_B) = m$ 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)

Basic Feasible Solutions

$x \in \mathbb{R}^n$ is called basic solution (Basislösung) if $Ax = b$ and $\mathrm{rank}(A_J) = |J|$ 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 $\mathrm{rank}(A_B) = m$ 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)

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.

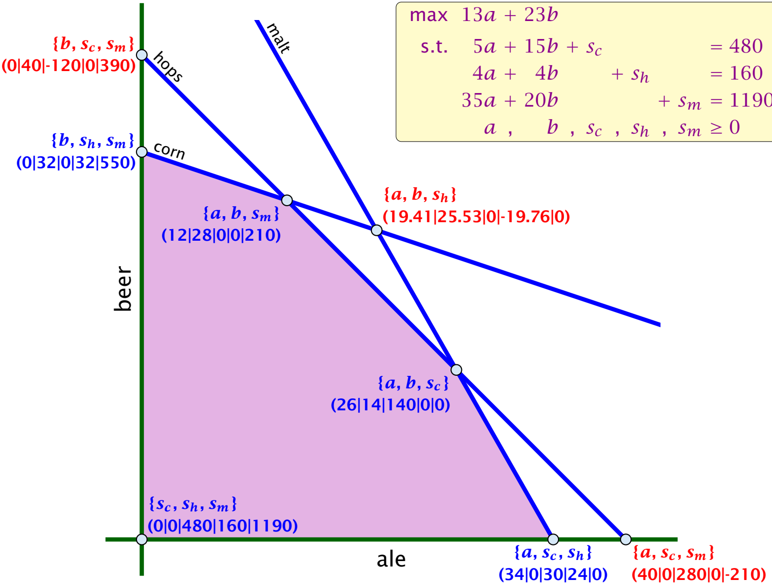
Basic Feasible Solutions

Definition 25

For a general LP ($\max\{c^T x \mid Ax \le b\}$) 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. $Ax = b$, $x \geq 0$, $c^T x \geq \alpha$?

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.

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. $Ax = b$, $x \geq 0$, $c^T x \geq \alpha$?

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.

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?