

Basic concepts - LP II

- A solution to LP satisfies Ax = b.
- A feasible solution to LP satisfies $Ax = b \land x \ge 0$.
- An optimal solution to LP, x^{*} is a feasible solution satisfying that for any other feasible solution x̄
 cx^{*} ≥ cx̄
- A **basis** for A is a set of m linearly independent columns from A.
- The basic solution corresponding to the basis

$$B = A_{:B} = \{A_{j1}, \dots, A_{jm}\}$$

is the solution obtained from Ax = b by setting $x_j = 0, j \notin \{j_1, ..., j_m\}$. This is unique.

• A basic solution \tilde{x} to LP is a solution, for which a basis *B* exists such that \tilde{x} is the basic solution corresponding to *B*.

Basic concepts - LP III

Consider now the basis

$$B = \{A_{j1}, ..., A_{jm}\}$$

The variables $x_{j_1}, ..., x_{j_m}$ are called **basic variables**, the other variables ($x_j = 0, j \notin \{j_1, ..., j_m\}$ are **non-basic variables**.

The basic solution corresponding to B is found by

- 1. set all non-basic variables to 0 in Ax = b.
- 2. solve the "remaining system:

$$Bx = b \Leftrightarrow x = B^{-1}b$$

3. value ? - insert !



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\begin{array}{rcl} \max & cx \\ & Ax &= b \\ & x &\geq 0 \end{array} & \mapsto \\ \max & c_B x_B + c_N x_N \\ & Bx_B + N x_N &= b \\ & x_B, \ x_N &\geq 0 \end{array}
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Solving LP-problems - Algebra II. Left-multiply with B^{-1} and move terms to the right: $c_B x_B + c_N x_N$ max $Ix_B + B^{-1}Nx_N = B^{-1}b \mapsto$ $x_B, x_N \geq 0$ max $c_B x_B + c_N x_N$ $x_B = B^{-1}b - B^{-1}Nx_N \mapsto$ $x_B, x_N \geq 0$ Insert the expression for x_B into the objective fctn: $\max c_B(B^{-1}b - B^{-1}Nx_N) + c_Nx_N$ $= B^{-1}b - B^{-1}Nx_N \quad \mapsto \quad$ x_B > 0 x_B, x_N Collect terms: $\max \quad 0x_B + (c_N - c_B B^{-1} N) x_N + c_B B^{-1} b$ $Ix_B + B^{-1}Nx_N = B^{-1}b$ $x_B, x_N \geq 0$

The j'th reduced cost: $\overline{c_j} = c_j - (c_B B^{-1} N)_j$. What is the contents of the Simplex tableau ?







In standard form:

$$max \ 7x_1 + 11x_2 \quad (+18) \ NB!$$
$$-2x_1 + x_2 + x_3 = 1$$
$$x_1 + x_2 + x_4 = 7$$
$$x_2 + x_5 = 2.5$$
$$x_1, x_2, x_3, x_4, x_5 \ge 0$$

The variables x_3, x_4, x_5 are called **slack variables** and are introduced to obtain a system in standard form.





increased to 1. Find Simplex tableau wrt. the basis $\{2,4,5\}$.







The Simplex Algorithm for LP I

The procedure just completed is called the Simplex Algorithm and can be described as follows:

Input: A maximization-LP-problem in canonical form with respect to a basis, i.e. such that the columns of the basic variables are unit vectors, and that each basic variable has 0 as coefficient in the objective function.

- optimal := unbounded := "no" ;
- while optimal = "no" and unbounded = "no" do
 - if $\overline{c_j} \leq 0$ for all j then optimal := "yes" else
 - choose s with c_s > 0 (often largest positive); *)
 j is pivot column
 - if $\overline{a_{is}} \leq 0$ for all *i* then unbounded := "yes" else
 - * find $q = min_{i:\overline{a_{is}}>0} \{\overline{b_i}/\overline{a_{is}}\} = \overline{b_r}/\overline{a_{rs}}$ **r** is pivot row, q is the increase in objective function value from the current basic solution to new (to be constructed).
 - * pivot on $\overline{a_{rs}}$

*): If the problem in question is a minimization problem, then " $\overline{c_j} > 0$ (often largest positive)" is to be " $\overline{c_j} < 0$ (often smallest negative)".

Pivot ? - Exact description ?

The Simplex Algorithm for LP - pivoting

The Pivot operation on $\overline{a_{rs}}$:

- 1. Divide row r with $\overline{a_{rs}}$ to produce tableau with a 1 in row r, column s $\overline{a_{rj}} := \overline{a_{rj}}/\overline{a_{rs}}, \quad j \in \{1, ..., n\}$
- 2. For each other row p (including the "objective function row"), subtract a multiplum of row r such that $\overline{a_{ps}}$ becomes 0 in the new tableau:

•
$$\overline{a_{pj}} := \overline{a_{pj}} - (\overline{a_{rj}}/\overline{a_{rs}}) \cdot \overline{a_{ps}} \quad j \in \{1, ..., n\}$$

• $\overline{b_p} := \overline{b_p} - (\overline{b_r}/\overline{a_{rs}}) \cdot \overline{a_{ps}}$



The problem is **unbounded** - x_3 can be increased infinitely, increasing the objective function all the way ...







Pairs of primal and Dual LPs.

The connection between the structure of an LP-problem and its dual can be described through the following table. The dual of the dual to a given problem is the problem itself. Equivalent forms of a primal problem have equivalent dual problems.

Primal: Min		Dual: Max	
a) i'th constraint	\geq	i'th variable	≥ 0
b) "	\leq	"	≤ 0
c) "	=	>>	free
d) j'th variable	≥ 0	j'th constraint	\geq
e) "	≤ 0	"	\geq
d) "	free	"	=
Primal: Max		Dual: Min	
Primal: Max a) i'th constraint	2	Dual: Min i'te variable	≤ 0
Primal: Max a) i'th constraint b) "	2 <	Dual: Min i'te variable "	≤ 0 ≥ 0
Primal: Max a) i'th constraint b) " c) "	> < =	Dual: Min i'te variable "	≤ 0 ≥ 0 free
Primal: Max a) i'th constraint b) " c) " d) j'th variable	≥ ≤ = ≥ 0	Dual: Min i'te variable " " j'th constraint	≤ 0 ≥ 0 free \geq
Primal: Max a) i'th constraint b) " c) " d) j'th variable e) "	$ \geq \\ \leq \\ = \\ \geq 0 \\ \leq 0 $	Dual: Min i'te variable " " j'th constraint "	$ \leq 0 \\ \geq 0 \\ free \\ \geq \\ \leq $
Primal: Maxa) i'th constraintb)c)d) j'th variablee)nd)	$ \geq \\ \leq \\ = \\ \geq 0 \\ \leq 0 \\ \text{free} $	Dual: Min i'te variable " " " j'th constraint " "	$ \leq 0 \\ \geq 0 \\ free \\ \geq \\ \leq \\ = $

Optimality conditions.

The Complementary Slackness Theorem is concerned with necessary and sufficient conditions for optimality of feasible solutions x and y to a pair of dual LP-problems: We consider a pair of dual LP-problems, P and DP:

$$(P) \qquad (DP)$$

$$\max cx \qquad \min yb$$

$$Ax \leq b \qquad yA \geq c$$

$$x \geq 0 \qquad y \geq 0$$

and a pair $\overline{x}, \overline{y}$ of *feasible* solutions to P resp. DP. \overline{x} and \overline{y} are **optimal** solution to P resp. DP *if and only if*:

$$(\mathbf{b} - \mathbf{A}\overline{\mathbf{x}}) \cdot \overline{\mathbf{y}} = \mathbf{0} \wedge (\overline{\mathbf{y}}\mathbf{A} - \mathbf{c}) \cdot \overline{\mathbf{x}} = \mathbf{0}$$

The conditions spelled out are:

$$\forall i : \overline{y}_i(b_i - A_i \cdot \overline{x}) = 0$$

$$\forall j : (\overline{y}A_{\cdot j} - c_j)\overline{x}_j = 0$$

Optimality conditions - revised.

We consider an LP-problem, P:

$$\begin{array}{cccc} \max & \operatorname{cx} & & \\ & A_1 \mathrm{x} & \geq & b_1 \\ & A_2 \mathrm{x} & = & b_2 \\ & & & \mathrm{x} & \mathrm{free} \end{array}$$

A given x^o is an optimal solution to P if and only if:

- 1) x^o is a feasible solution to P , and
- 2) there exists a vector (y_1, y_2) satisfying the following:

$$(y_{1}, y_{2}) \begin{pmatrix} A_{1} \\ A_{2} \end{pmatrix} = c (1)$$

$$y_{1}(b_{1} - A_{1}x^{o}) = 0 (2)$$

$$y_{2}(b_{2} - A_{2}x^{o}) = 0 (3)$$

$$((y_{1}, y_{2}) \begin{pmatrix} A_{1} \\ A_{2} \end{pmatrix} - c)x^{o} = 0 (4)$$

$$y_{1} \leq 0 (5)$$

(1)+(5): (y_1, y_2) is feasible for the dual problem of P. (2)+(3)+(4): the compl. slackness thm. holds for $x^o, (y_1, y_2)$. (3) holds due to the feasibility of x^o , and (4) holds due to (1). Thus (3) and (4) are superfluous.

Optimality conditions - Geometry I

We consider now an LP-problem, P:

$$\begin{array}{ccc} \max & \operatorname{cx} & & \\ & A\mathbf{x} & \geq & b \\ & & \mathbf{x} & \text{free} \end{array}$$

A given x^{o} is an optimal solution to P if and only if:

- 1) x^{o} is a feasible solution to P, and
- 2) there exists a vector (y) satisfying the following:

$$yA = c \quad (1)$$
$$y(b - Ax^{o}) = 0 \quad (2)$$
$$y \leq 0 \quad (3)$$

What is the geometric interpretation of (1), (2), and (3)?

The vector c is the **gradient** of the objective function cx, i.e. that direction for a move in \mathbb{R}^n , for which the objective function increases most rapidly.

Optimality conditions - Geometry II

The feasible region S for P, $\{x | Ax \ge b\}$, is defined by the functions

 $a_{11}x_1 + \ldots + a_{1n}x_n - b_1 \ge 0$, \ldots , $a_{m1}x_1 + \ldots + a_{mn}x_n - b_m \ge 0$. The gradients (a_{11}, \ldots, a_{1n}) , \ldots , (a_{m1}, \ldots, a_{mn}) for these functions point *into* S. Condition (1) and (3) state, that at the optimal point of S - an extreme point, Q - the gradient of the objective function must be a **non-positive linear combination** of the gradients of the constraints. For Q (which corresponds to a basic feasible solution), (2) states that the linear combination must be constructed using only the gradients of those constraints, which are **binding** at Q:

