

Duality

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

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

Note that a lower bound is easy to derive. Every choice of $a, b \geq 0$ 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 $y_i \geq 0$) such that $\sum_i y_i a_{ij} \geq c_j$ then $\sum_i y_i b_i$ will be an upper bound.

Definition 2

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

The linear program D defined by

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

is called the **dual problem**.

Lemma 3

The dual of the dual problem is the primal problem.

Proof:

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

The dual problem is

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

Weak Duality

Let $z = \max\{c^T x \mid Ax \leq b, x \geq 0\}$ and
 $w = \min\{b^T y \mid A^T y \geq c, y \geq 0\}$ be a primal dual pair.

x is primal feasible iff $x \in \{x \mid Ax \leq b, x \geq 0\}$

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

Theorem 4 (Weak Duality)

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

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

Weak Duality

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

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

This gives

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

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.

5.2 Simplex and Duality

The following linear programs form a primal dual pair:

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

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

Proof

Primal:

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

Dual:

$$\begin{aligned} & \min\{[b^T \ -b^T]y \mid [A^T \ -A^T]y \geq c, y \geq 0\} \\ &= \min\left\{[b^T \ -b^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \mid [A^T \ -A^T] \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \geq c, y^- \geq 0, y^+ \geq 0\right\} \\ &= \min\{b^T \cdot (y^+ - y^-) \mid A^T \cdot (y^+ - y^-) \geq c, y^- \geq 0, y^+ \geq 0\} \\ &= \min\{b^T y' \mid A^T y' \geq c\} \end{aligned}$$

Proof of Optimality Criterion for Simplex

Suppose that we have a basic feasible solution with **reduced cost**

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

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** $\min\{b^T y \mid A^T y \geq c\}$.

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

Hence, the solution is optimal.

5.3 Strong Duality

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

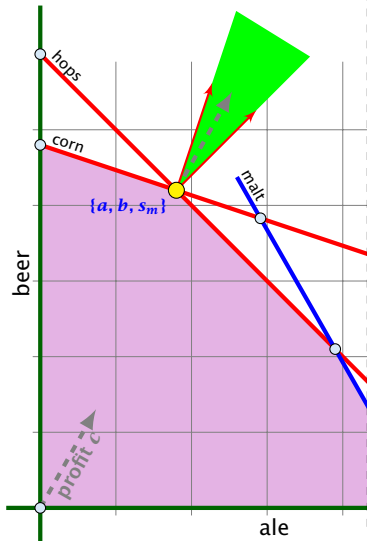
n_A : number of variables, m_A : number of constraints

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

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

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

5.3 Strong Duality



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

$$c^T x = (\bar{A}^T y)^T x = y^T \bar{A} x \leq y^T \bar{b}$$

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

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

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 5 (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

$$z^* = w^*$$

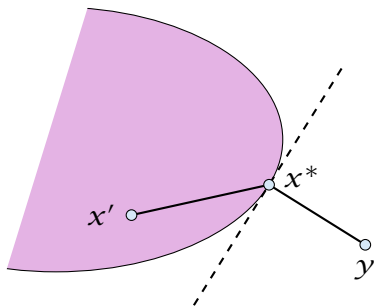
Lemma 6 (Weierstrass)

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)

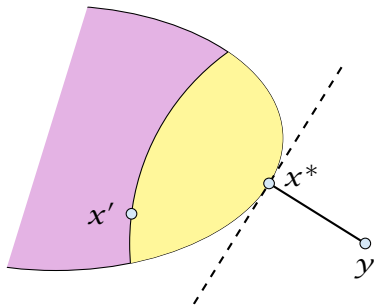
Lemma 7 (Projection Lemma)

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.



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 $0 \leq \epsilon \leq 1$.

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

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

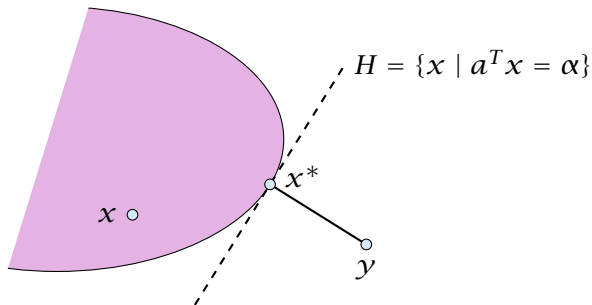
Letting $\epsilon \rightarrow 0$ gives the result.

Theorem 8 (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, $a^T y = a^T(x^* - a) = \alpha - \|a\|^2 < \alpha$



Lemma 9 (Farkas Lemma)

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

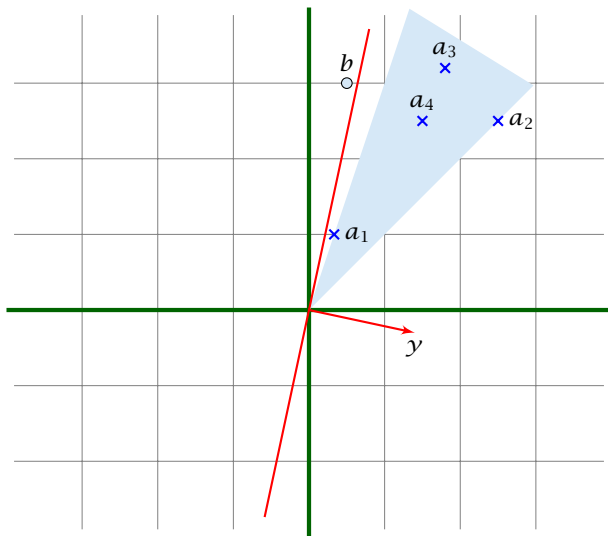
1. $\exists x \in \mathbb{R}^n$ with $Ax = b$, $x \geq 0$
2. $\exists y \in \mathbb{R}^m$ with $A^T y \geq 0$, $b^T y < 0$

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

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

Hence, at most one of the statements can hold.

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 $A^T y \geq 0$, $b^T y < 0$.

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

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

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

Lemma 10 (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 $\begin{bmatrix} A^T \\ I \end{bmatrix} y \geq 0, b^T y < 0$

Proof of Strong Duality

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

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

Theorem 11 (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

$$z = w \text{ .}$$

Proof of Strong Duality

$z \leq w$: follows from weak duality

$z \geq w$:

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

$$\exists x \in \mathbb{R}^n$$

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

$$\exists y \in \mathbb{R}^m; v \in \mathbb{R}$$

$$\begin{array}{lll} \text{s.t.} & A^T y - cv & \geq 0 \\ & b^T y - \alpha v & < 0 \\ & y, v & \geq 0 \end{array}$$

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

Proof of Strong Duality

$$\begin{array}{ll}\exists \mathbf{y} \in \mathbb{R}^m; v \in \mathbb{R} & \\ \text{s.t.} & A^T \mathbf{y} - c v \geq 0 \\ & b^T \mathbf{y} - \alpha v < 0 \\ & \mathbf{y}, v \geq 0\end{array}$$

If the solution $\mathbf{y}, v$ has $v = 0$ we have that

$$\begin{array}{ll}\exists \mathbf{y} \in \mathbb{R}^m & \\ \text{s.t.} & A^T \mathbf{y} \geq 0 \\ & b^T \mathbf{y} < 0 \\ & \mathbf{y} \geq 0\end{array}$$

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 $w < \alpha$.

Fundamental Questions

Definition 12 (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 $< \alpha$.

Complementary Slackness

Lemma 13

Assume a linear program $P = \max\{c^T x \mid Ax \leq b; x \geq 0\}$ has solution x^* and its dual $D = \min\{b^T y \mid A^T y \geq c; y \geq 0\}$ 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 then $x_j^* = 0$.
3. If $y_i^* > 0$ then the i -th constraint in P is tight.
4. If the i -th constraint in P is not tight then $y_i^* = 0$.

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 constraint 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

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

Because of strong duality we then get

$$c^T x^* = y^{*T} A x^* = b^T y^*$$

This gives e.g.

$$\sum_j (y^T A - c^T)_j x_j^* = 0$$

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

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

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

$$\begin{array}{llllll} \min & 480C & + & 160H & + & 1190M \\ \text{s.t.} & 5C & + & 4H & + & 35M \geq 13 \\ & 15C & + & 4H & + & 20M \geq 23 \\ & & & & & C, H, M \geq 0 \end{array}$$

Note that brewer won't sell (at least not all) if e.g.

$5C + 4H + 35M < 13$ as then brewing ale would be advantageous.

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 $\max\{c^T x \mid Ax \leq b + \epsilon; x \geq 0\}$. Because of strong duality this is equal to

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

Interpretation of Dual Variables

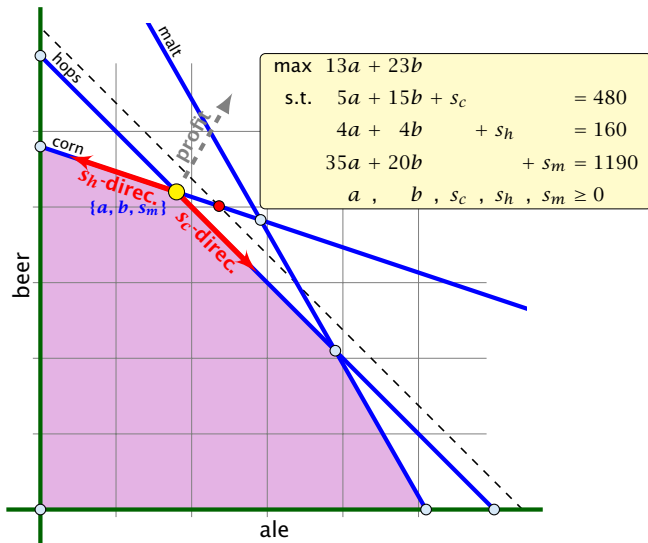
If ϵ is “small” enough then the optimum dual solution y^* might not change. Therefore the profit increases by $\sum_i \epsilon_i y_i^*$.

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).
- ▶ If the dual variable for some resource is non-zero, then an increase of this resource increases the profit of the brewer. Hence, it makes no sense to have left-overs of this resource. Therefore its slack must be zero.

Example



The change in profit when increasing hops by one unit is

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

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 14

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

1. For each edge (x, y)

$$0 \leq f_{xy} \leq c_{xy} .$$

(capacity constraints)

2. For each $v \in V \setminus \{s, t\}$

$$\sum_x f_{vx} = \sum_x f_{xv} .$$

(flow conservation constraints)

Definition 15

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

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

Maximum Flow Problem:

Find an (s, t) -flow with maximum value.

LP-Formulation of Maxflow

$$\begin{array}{ll}
 \max & \sum_z f_{sz} - \sum_z f_{zs} \\
 \text{s.t.} & \forall (z, w) \in V \times V \quad f_{zw} \leq c_{zw} \quad \ell_{zw} \\
 & \forall w \neq s, t \quad \sum_z f_{zw} - \sum_z f_{wz} = 0 \quad p_w \\
 & f_{zw} \geq 0
 \end{array}$$

$$\begin{array}{ll}
 \min & \sum_{(xy)} c_{xy} \ell_{xy} \\
 \text{s.t.} & f_{xy} \ (x, y \neq s, t) : \quad 1\ell_{xy} - 1p_x + 1p_y \geq 0 \\
 & f_{sy} \ (y \neq s, t) : \quad 1\ell_{sy} \quad \quad + 1p_y \geq 1 \\
 & f_{xs} \ (x \neq s, t) : \quad 1\ell_{xs} - 1p_x \quad \quad \geq -1 \\
 & f_{ty} \ (y \neq s, t) : \quad 1\ell_{ty} \quad \quad + 1p_y \geq 0 \\
 & f_{xt} \ (x \neq s, t) : \quad 1\ell_{xt} - 1p_x \quad \quad \geq 0 \\
 & f_{st} : \quad \quad \quad 1\ell_{st} \quad \quad \geq 1 \\
 & f_{ts} : \quad \quad \quad 1\ell_{ts} \quad \quad \geq -1 \\
 & \quad \quad \quad \ell_{xy} \quad \quad \geq 0
 \end{array}$$

LP-Formulation of Maxflow

$$\begin{array}{ll} \min & \sum_{(x,y)} c_{xy} \ell_{xy} \\ \text{s.t.} & f_{xy} \ (x, y \neq s, t) : \quad 1\ell_{xy} - 1p_x + 1p_y \geq 0 \\ & f_{sy} \ (y \neq s, t) : \quad 1\ell_{sy} - \quad 1 + 1p_y \geq 0 \\ & f_{xs} \ (x \neq s, t) : \quad 1\ell_{xs} - 1p_x + \quad 1 \geq 0 \\ & f_{ty} \ (y \neq s, t) : \quad 1\ell_{ty} - \quad 0 + 1p_y \geq 0 \\ & f_{xt} \ (x \neq s, t) : \quad 1\ell_{xt} - 1p_x + \quad 0 \geq 0 \\ & f_{st} : \quad 1\ell_{st} - \quad 1 + \quad 0 \geq 0 \\ & f_{ts} : \quad 1\ell_{ts} - \quad 0 + \quad 1 \geq 0 \\ & \ell_{xy} \geq 0 \end{array}$$

LP-Formulation of Maxflow

$$\begin{array}{ll} \min & \sum_{(x,y)} c_{xy} \ell_{xy} \\ \text{s.t.} & f_{xy} \ (x, y \neq s, t) : \quad 1\ell_{xy} - 1p_x + 1p_y \geq 0 \\ & f_{sy} \ (y \neq s, t) : \quad 1\ell_{sy} - p_s + 1p_y \geq 0 \\ & f_{xs} \ (x \neq s, t) : \quad 1\ell_{xs} - 1p_x + p_s \geq 0 \\ & f_{ty} \ (y \neq s, t) : \quad 1\ell_{ty} - p_t + 1p_y \geq 0 \\ & f_{xt} \ (x \neq s, t) : \quad 1\ell_{xt} - 1p_x + p_t \geq 0 \\ & f_{st} : \quad 1\ell_{st} - p_s + p_t \geq 0 \\ & f_{ts} : \quad 1\ell_{ts} - p_t + p_s \geq 0 \\ & \ell_{xy} \geq 0 \end{array}$$

with $p_t = 0$ and $p_s = 1$.

LP-Formulation of Maxflow

$$\begin{array}{ll}\min & \sum_{(xy)} c_{xy} \ell_{xy} \\ \text{s.t.} & f_{xy} : \quad 1\ell_{xy} - 1p_x + 1p_y \geq 0 \\ & \ell_{xy} \geq 0 \\ & p_s = 1 \\ & p_t = 0\end{array}$$

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 ($d(x, t) \leq d(x, y) + d(y, t) \Rightarrow d(x, t) \leq \ell_{xy} + d(y, t)$).

One can show that there is an optimum LP-solution for the dual problem that gives an integral assignment of variables.

This means $p_x = 1$ or $p_x = 0$ for our case. This gives rise to a cut in the graph with vertices having value 1 on one side and the other vertices on the other side. The objective function then evaluates the capacity of this cut.

This shows that the Maxflow/Mincut theorem follows from linear programming duality.