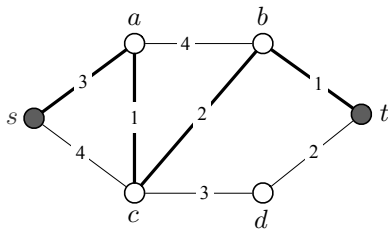


Module 3: Duality through examples (Weak Duality)

Recap: Feasible Widths

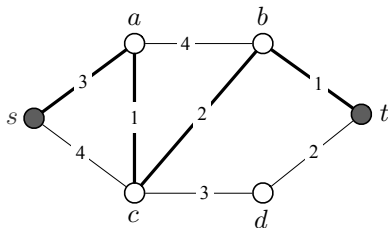
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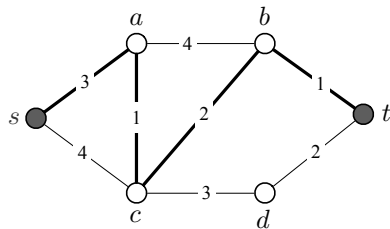
- a **graph** $G = (V, E)$,
- a non-negative length c_e for each edge $e \in E$, and
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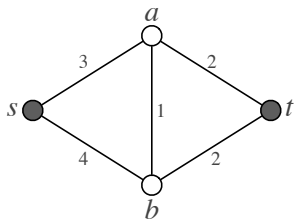
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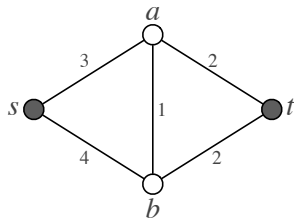
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and this is **feasible** if the total width of cuts containing edge e is no more than c_e , for all $e \in E$.

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Proposition

If y is a **feasible width assignment**, then any s, t -path must have length at least

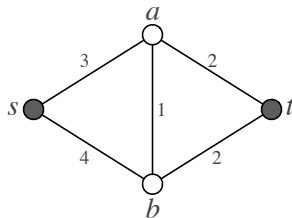
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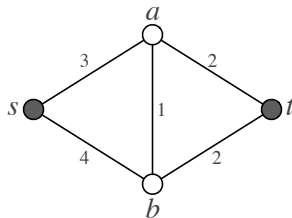
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Seemingly, we used an **ad hoc argument**, taylor-made for shortest paths. . .

but, as we will now see, there is a **constructive** and quite **mechanical** way to derive the Proposition via **linear programming**!

An Instructive Example LP

The LP on the right is feasible...

$$\min (2, 3)x$$

$$\text{s.t. } \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} x \geq \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix}$$

$$x \geq 0$$

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E.g., $x^1 = (8, 16)^\top$ and
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Can we find a good **lower-bound** on
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Deriving Valid Inequalities

Let's suppose that x is feasible for the LP on the right.

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Additionally, it satisfies

$$\begin{aligned} & y_1 \cdot (2, 1)x \geq y_1 \cdot 20 \\ & + y_2 \cdot (1, 1)x \geq y_2 \cdot 18 \\ & + y_3 \cdot (-1, 1)x \geq y_3 \cdot 8 \\ \hline & = (2y_1 + y_2 - y_3, y_1 + y_2 + y_3)x \\ & \geq 20y_1 + 18y_2 + 8y_3 \end{aligned}$$

for $y_1, y_2, y_3 \geq 0$.

So, if x is feasible for the LP on the right, it also satisfies

$$(y_1, y_2, y_3) \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} x \geq \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix}$$

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E.g., for $y = (0, 2, 1)^\top$, we obtain

$$(1, 3)x \geq 44$$

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Therefore,

$$\begin{aligned} z(x) &= (2, 3)x \\ &\geq (2, 3)x + 44 - (1, 3)x \\ &= 44 + (1, 0)x \end{aligned}$$

Since $x \geq 0$, it follows that

$$z(x) \geq 44$$

for every feasible solution x !

State of Affairs

We now know that

$$\begin{aligned} \min \quad & (2, 3)x \\ \text{s.t.} \quad & \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} x \geq \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix} \\ & x \geq 0 \end{aligned}$$

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We now know that

- (i) $x^2 = (5, 13)^\top$ is a solution to the LP of **value 49** and

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Can we find a better **lowerbound** on $z(x)$ for a feasible x ?

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Lowerbounding $z(x)$ **Systematically!**

We know that a feasible x satisfies

$$0 \geq (y_1, y_2, y_3) \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix} - (y_1, y_2, y_2) \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} x$$

for any $y_1, y_2, y_3 \geq 0$.

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for any $y_1, y_2, y_3 \geq 0$. **Therefore,**

$$z(x) \geq (y_1, y_2, y_3) \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix} + \left((2, 3) - (y_1, y_2, y_2) \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} \right) x \quad (\star)$$

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We want the second term to be **non-negative**. Since $x \geq 0$, this amounts to choosing y such that

$$(y_1, y_2, y_2) \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} \leq (2, 3)$$

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With such a y we then have from (\star) :

$$z(x) \geq (y_1, y_2, y_3) \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix}$$

Lowerbounding $z(x)$ **Systematically!**

So, we choose $y \geq 0$ such that

$$(y_1, y_2, y_3) \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} \leq (2, 3) \quad (\star)$$

yields

$$z(x) \geq (y_1, y_2, y_3) \begin{pmatrix} 20 \\ 18 \\ 8 \end{pmatrix} \quad (\diamond)$$

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Idea

Find the best possible lower-bound on z .

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Find the best possible lower-bound on z . I.e., find $y \geq 0$ such that (\star) holds, and the right-hand side of (\diamond) is maximized!

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Find the best possible lower-bound on z . I.e., find $y \geq 0$ such that (\star) holds, and the right-hand side of (\diamond) is maximized!

This is a **Linear Program**:

$$\begin{aligned} \max \quad & (20, 18, 8)y \\ \text{s.t.} \quad & \begin{pmatrix} 2 & 1 \\ 1 & 1 \\ -1 & 1 \end{pmatrix} y \leq (2, 3) \\ & y \geq 0 \end{aligned}$$

Lowerbounding $z(x)$ Systematically!

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Solving it gives:

$$\begin{aligned} \bar{y}_1 &= 0 \\ \bar{y}_2 &= 5/2 \\ \bar{y}_3 &= 1/2 \end{aligned}$$

and the **objective value** is 49.

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There is **no feasible solution** x to

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which has an objective value smaller than 49.

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Since $x^2 = (5, 13)^\top$ is a feasible solution with value 49, it **must be optimal!**

A General Argument

Suppose now we are given the LP

$$\min \quad c^\top x$$

$$\text{s.t.} \quad Ax \geq b$$

$$x \geq 0$$

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Any **feasible** solution x must satisfy

$$y^\top Ax \geq y^\top b,$$

for $y \geq 0$, and hence also

$$0 \geq y^\top b - y^\top Ax$$

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Therefore,

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If we also know that

$$A^\top y \leq c$$

then $x \geq 0$ implies that $z(x) \geq y^\top b$.

A General Argument

Suppose now we are given the LP

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

Any **feasible** solution x must satisfy

$$y^\top Ax \geq y^\top b,$$

for $y \geq 0$, and hence also

$$0 \geq y^\top b - y^\top Ax$$

Therefore,

$$\begin{aligned} z(x) &= c^\top x \\ &\geq c^\top x + y^\top b - y^\top Ax \\ &= y^\top b + (c^\top - y^\top A)x \end{aligned}$$

If we also know that

$$A^\top y \leq c$$

then $x \geq 0$ implies that $z(x) \geq y^\top b$.

The best **lower-bound on $z(x)$** can be found by the following LP:

$$\begin{array}{ll} \max & b^\top y \\ \text{s.t.} & A^\top y \leq c \\ & y \geq 0 \end{array}$$

The Dual LP

The linear program

$$\max \quad b^T y \quad (D)$$

$$\text{s.t.} \quad A^T y \leq c$$

$$y \geq 0$$

is called the **dual** of **primal** LP

$$\min \quad c^T x \quad (P)$$

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Theorem

[**Weak Duality**] If \bar{x} is feasible for (P) and \bar{y} is feasible for (D), then $b^T \bar{y} \leq c^T \bar{x}$.

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Proof:

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

as $\bar{y} \geq 0$ and $b \leq A\bar{x}$,

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as $\bar{y} \geq 0$ and $b \leq A\bar{x}$, as $\bar{x} \geq 0$ and $A^T \bar{y} \leq c$. □

Lowerbounding the Length of s, t -Paths

Recap: Shortest Path LP

Given a **shortest path** instance $G = (V, E)$, $s, t \in V$, $c_e \geq 0$ for all $e \in E$, the shortest-path LP is

$$\min \sum (c_e x_e : e \in E)$$

$$\text{s.t. } \sum (x_e : e \in \delta(U)) \geq 1 \quad (U \subseteq V, s \in U, t \notin U)$$

$$x \geq 0, x \text{ integer}$$

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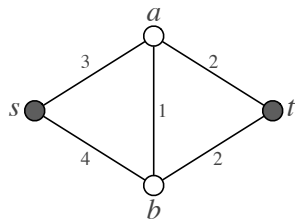
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Let's look at an **example**!

Shortest Path: **Example**

On the right, we see a sample instance of the shortest-path problem.



Shortest Path: Example

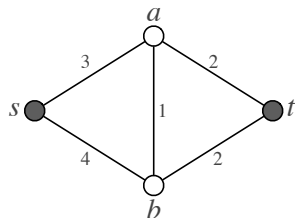
On the right, we see a sample instance of the shortest-path problem.

Here is the corresponding IP:

$$\min (3, 4, 1, 2, 2)x$$

$$\text{s.t.} \quad \begin{array}{l} \{s\} \\ \{s, a\} \\ \{s, b\} \\ \{s, a, b\} \end{array} \begin{pmatrix} sa & sb & ab & at & bt \\ \left(\begin{array}{ccccc} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{array} \right) x \geq \mathbb{1} \end{pmatrix}$$

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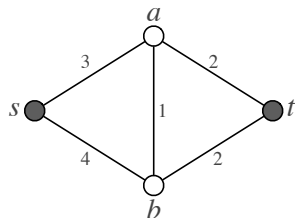
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Note that if P is an s, t -path, then letting

$$\bar{x}_e = \begin{cases} 1 & \text{if } e \text{ is an edge of } P \\ 0 & \text{otherwise.} \end{cases}$$

for all $e \in E$ yields a feasible IP solution and

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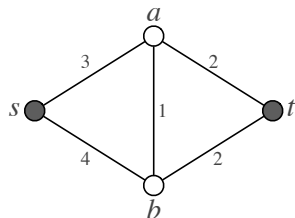
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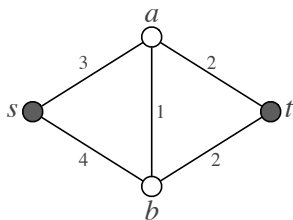
$$\bar{x}_e = \begin{cases} 1 & \text{if } e \text{ is an edge of } P \\ 0 & \text{otherwise.} \end{cases}$$

for all $e \in E$ yields a **feasible IP** solution and its **objective value** is $c(P)$.

$$\min (3, 4, 1, 2, 2)x$$

$$\text{s.t.} \quad \begin{matrix} & sa & sb & ab & at & bt \\ \{s\} & \left(\begin{array}{ccccc} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{array} \right) & x & \geq & \mathbb{1} \\ \{s, a\} & & & & & \\ \{s, b\} & & & & & \\ \{s, a, b\} & & & & & \end{matrix}$$

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Example:

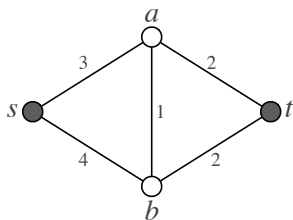
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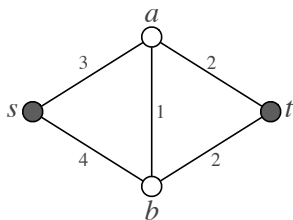
$$x = (1, 0, 1, 0, 1)^T$$

is feasible for the IP, and its value is 6.

$$\min (3, 4, 1, 2, 2)x$$

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Example:

$$P = sa, ab, bt$$

is an s, t -path.

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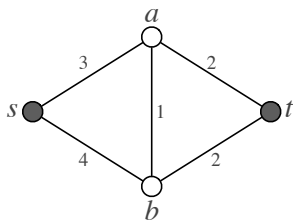
Remark

The optimal value of the shortest path IP is, at most, the length of a shortest s, t -path.

$$\min (3, 4, 1, 2, 2)x \quad (\text{P})$$

$$\text{s.t.} \quad \begin{matrix} & sa & sb & ab & at & bt \\ \{s\} & \left(\begin{array}{ccccc} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{array} \right) & x \geq \mathbb{1} \\ \{s, a\} \\ \{s, b\} \\ \{s, a, b\} \end{matrix}$$

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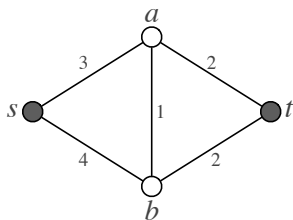


Note that dropping the **integrality** restriction can not increase the optimal value.

min $(3, 4, 1, 2, 2)x$ (P)

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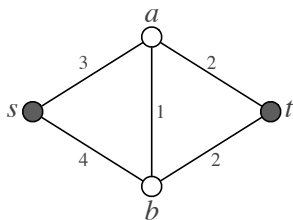
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The resulting LP is called the **linear programming relaxation** of the IP.

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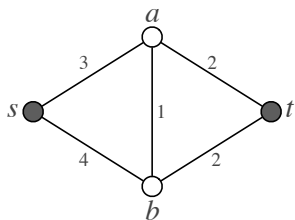
Straight from **Weak Duality** theorem, we have that:

Remark

The dual of (P) has optimal value no larger than that of (P)!

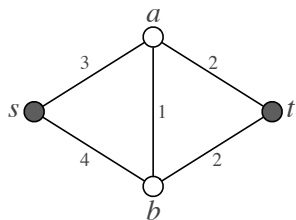
The **dual** of the shortest path LP on the previous slide is given by

$$\begin{array}{l}
 \max \quad \mathbb{1}^\top y \\
 \text{s.t.} \quad \begin{array}{cccc}
 & \{s\} & \{s, a\} & \{s, b\} & \{s, a, b\} \\
 sa & \left(\begin{array}{cccc}
 1 & 0 & 1 & 0 \\
 1 & 1 & 0 & 0 \\
 0 & 1 & 1 & 0 \\
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 0 & 0 & 1 & 1
 \end{array} \right) & y \leq & \begin{pmatrix} 3 \\ 4 \\ 1 \\ 2 \\ 2 \end{pmatrix} \\
 sb & & & & \\
 ab & & & & \\
 at & & & & \\
 bt & & & & \\
 y \geq & \mathbb{0} & & &
 \end{array}
 \end{array}$$



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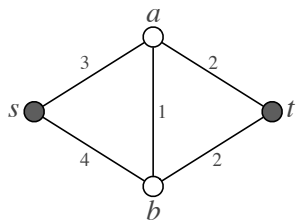
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 bt & & & & \\
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Note that dual solutions assign the value $y_U \geq 0$ to every s, t -cut $\delta(U)$!

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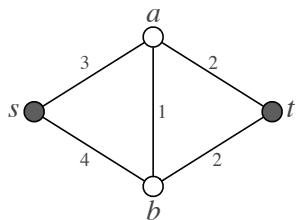
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$$y_{\{s,a\}} + y_{\{s,b\}} \leq 1$$

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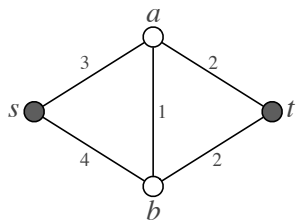
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The left-hand side is precisely the y -value assigned to s, t -cuts containing ab !

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Note that dual solutions assign the value $y_U \geq 0$ to every s, t -cut $\delta(U)$!

Remark

y is feasible for the above LP if and only if it is a feasible width assignment for the s, t -cuts in the given shortest path instance!

General Shortest Path Instances

Input: $G = (V, E)$, $c_e \geq 0$ for all $e \in E$, $s, t \in V$.

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Remark

Feasible solutions to (D) correspond precisely to feasible width assignments.

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Its dual is of the form

$$\begin{aligned} \max \quad & \mathbf{1}^T y && \text{(D)} \\ \text{s.t.} \quad & A^T y \leq c \\ & y \geq \mathbf{0} \end{aligned}$$

where

- (i) A has a column for every edge and a row for every s, t -cut $\delta(U)$.
- (ii) $A[U, e] = 1$ if $e \in \delta(U)$, and 0 otherwise.

Note that the dual has a constraint for every edge $e \in E$. The left-hand side of this constraint is

$$\sum (y_U : e \in \delta(U))$$

and the right-hand side is c_e .

Remark

Feasible solutions to (D) correspond precisely to feasible width assignments. **Weak duality** implies that $\sum y_U$ is, at most, the length of a shortest s, t -path!

Recap

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is given by

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- If x is feasible for (P) and y feasible for (D), then $b^T y \leq c^T x$.
- The **LP relaxation** of an integer program is obtained by dropping the **integrality restriction**.
- The **dual** of the **shortest path LP** is given by

$$\begin{aligned} \max \quad & \sum (y_U : \delta(U) \text{ s, t-cut}) \\ \text{s.t.} \quad & \sum (y_U : e \in \delta(U)) \leq c_e \quad (e \in E) \\ & y \geq 0 \end{aligned}$$