

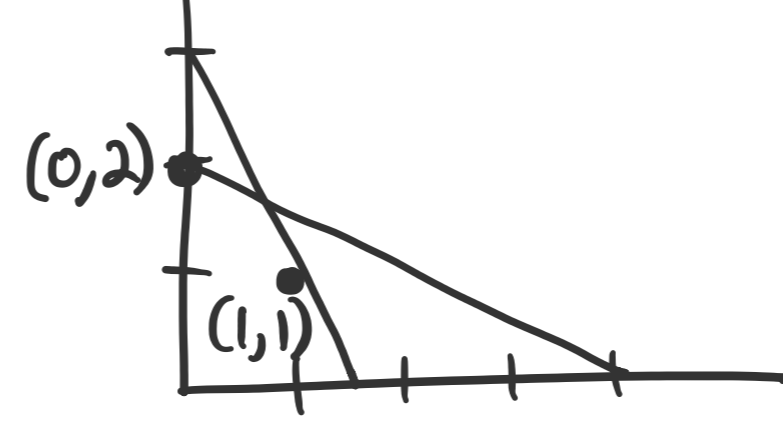
Example: a bakery sells cakes and cookies.

Each cake = \$3 profit, each cookie = \$2  
 Each cake uses 2 cups of flour, 1 cup of sugar  
 Each cookie uses 1 " " 2 " "

Inventory:

$x = \# \text{ cakes}, y = \# \text{ cookies}$

$$\begin{aligned} \max & 3x + 2y \\ \text{s.t.} & 2x + y \leq 3 \\ & x + 2y \leq 4 \\ & x \geq 0, y \geq 0 \end{aligned}$$



Integral optimal solution:  $(x,y) = (1,1)$ , value 5  
 This is called Integer Programming. NP-hard!

What if units can be fractional (e.g. sell milk vs. juice)

Fractional optimal solution:  $(x,y) = (\frac{2}{3}, \frac{5}{3})$ , value  $\frac{16}{3}$

So fractional optimum  $\geq$  integer optimum, can be  $\neq$ .

Theorem: can solve Linear Programming in polynomial time!

Max-Flow: represent each  $f(u,v)$  as variable  $x_{uv}$

$$\begin{aligned} \max & \sum_v x_{sv} - \sum_v x_{vs} \\ \text{s.t.} & \sum_u x_{uv} = \sum_v x_{vu} \quad \forall u \\ & 0 \leq x_{uv} \leq c_{uv} \quad \forall (u,v) \end{aligned} \left. \begin{array}{l} \\ \\ \end{array} \right\} \begin{array}{l} \text{all linear functions} \\ \text{on the variables } x_{uv} \end{array}$$

$\uparrow$  constant

Recall from Ford-Fulkerson: if capacities are integral, then max flow is integral.

So integral maximum = fractional maximum.  
 Such an LP is called integral.

Duality: Recall that max-flow  $\leq$  min-cut.

In fact, any cut is proof that max-flow  $\leq$  value of that cut.

In general, the dual of an LP is "proof" that optimum  $\leq$  ...

Recall the example  $\max 3x + 2y$

$$\begin{aligned} \text{s.t.} & 2x + y \leq 3 \\ & x + 2y \leq 4 \\ & x \geq 0, y \geq 0 \end{aligned}$$

Suppose I sum the inequalities:

$$3x + 3y \leq 7$$

So for any solution  $(x,y)$ , value =  $3x + 2y \leq 3x + 3y \leq 7$ .

What if I sum 2x first inequality + second inequality:

$$5x + 4y \leq 10 \quad x \frac{3}{5}: 3x + 2.4y \leq 6$$

So for any solution  $(x,y)$ , value =  $3x + 2y \leq 3x + 2.4y \leq 6$

I can make this systematic:

$$\begin{aligned} \max & 3x + 2y \\ \text{s.t.} & \begin{cases} 2x + y \leq 3 & \times a: \text{multiply by } a \geq 0 \\ x + 2y \leq 4 & \times b: \text{multiply by } b \geq 0 \\ x \geq 0, y \geq 0 \end{cases} \\ & \Rightarrow a(2x+y) + b(x+2y) \leq 3a + 4b \\ & \Leftrightarrow (2a+b)x + (a+2b)y \leq 3a + 4b \end{aligned}$$

For this to upper bound all  $x \geq 0, y \geq 0$ , I need

$$\begin{aligned} 2a + b & \geq 3 \\ a + 2b & \geq 2 \end{aligned}$$

For any satisfying  $(a,b)$ , value =  $3x + 2y \leq 3a + 4b$

For the tightest bound, I want to minimize  $3a + 4b$ .

The dual LP becomes

$$\begin{aligned} \min & 3a + 4b \\ \text{s.t.} & 2a + b \geq 3 \\ & a + 2b \geq 2 \\ & a \geq 0, b \geq 0 \end{aligned}$$

Weak duality theorem: dual optimum  $\geq$  primal optimum.

Strong duality theorem: dual optimum = primal optimum.

Matrix formulation of LPs:

$$\begin{aligned} \max & 3x + 2y & \max & \begin{bmatrix} 3 \\ 2 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \text{ entrywise } \geq \\ \text{s.t.} & \begin{cases} 2x + y \leq 3 \\ x + 2y \leq 4 \\ x \geq 0, y \geq 0 \end{cases} & \rightarrow & \text{s.t.} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \geq \begin{bmatrix} 3 \\ 4 \end{bmatrix} \\ & & & \begin{bmatrix} x \\ y \end{bmatrix} \geq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{aligned}$$

In general:  $\max \vec{c} \cdot \vec{x}$   
 $\text{s.t. } A\vec{x} \leq \vec{b}$   
 $\vec{x} \geq \vec{0}$

if  $\vec{a} \cdot \vec{x} \geq b$  constraint, convert to  $-\vec{a} \cdot \vec{x} \leq -b$ .  
 if  $\vec{a} \cdot \vec{x} = b$  constraint, convert to both  $\geq, \leq$ .

Example: flow LP

$$\begin{aligned} \max & \sum_v x_{sv} - \sum_v x_{vs} \\ \text{s.t.} & \sum_u x_{uv} = \sum_v x_{vu} \leftarrow \text{write as} \begin{cases} \sum_u x_{uv} - \sum_v x_{vu} \leq 0 \\ -\sum_u x_{uv} + \sum_v x_{vu} \leq 0 \end{cases} \\ & 0 \leq x_{uv} \leq c_{uv} \end{aligned}$$

The dual LP is  $\min \vec{b} \cdot \vec{y}$   
 $A^T \vec{y} \geq \vec{c}$   
 $\vec{y} \geq 0$

Weak Duality Theorem: for any primal solution  $\vec{x}$  and dual solution  $\vec{y}$ ,  
 $\vec{c} \cdot \vec{x} \leq \vec{b} \cdot \vec{y}$ .

Proof: From  $A^T \vec{y} \geq \vec{c}$  and  $\vec{x} \geq 0$ ,  $\vec{c}^T \vec{x} \leq (A^T \vec{y})^T \vec{x} = \vec{y}^T A \vec{x}$   
 From  $A \vec{x} \leq \vec{b}$  and  $\vec{y} \geq 0$ ,  $\vec{b}^T \vec{y} \geq (A \vec{x})^T \vec{y} = \vec{x}^T A \vec{y}$  are equal

Strong Duality is a deep theorem that generalizes max-flow/min-cut.