

LECTURE #15

CS 170

Spring 2021



Last time:

Maximizing flow in a network (graph with capacities)

Max Flow reduces to Linear Programming

Direct algorithm based on augmenting paths in residual network

Max-Flow Min-Cut Theorem:

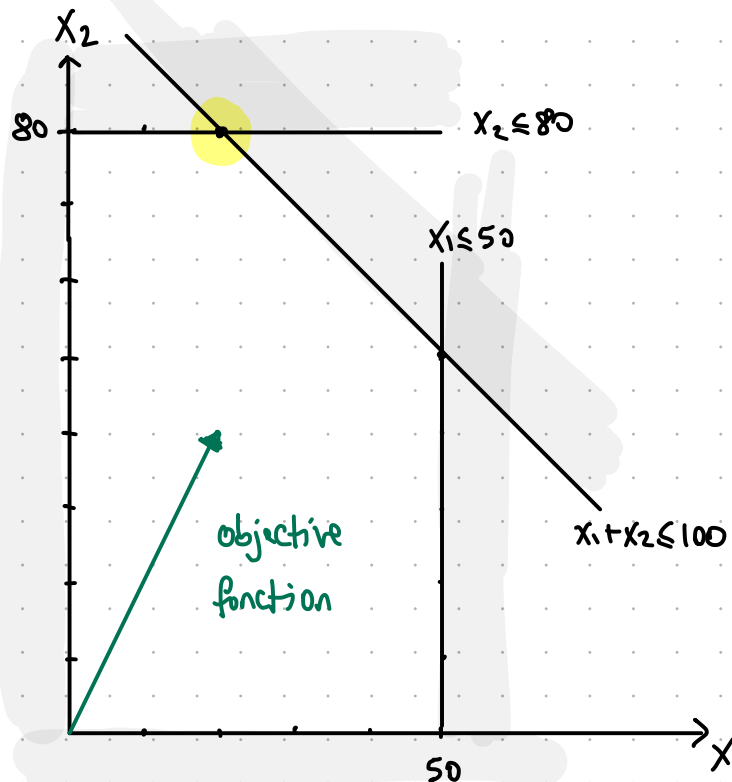
$$\max_{\text{flow } f} \text{val}(f) = \min_{\text{cut } (L,R)} \text{capacity}(L,R)$$

Today:

Duality in Linear Programming

↑
this is an example of duality

Recall example from LP lecture:



$$\begin{aligned} \max \quad & 2x_1 + 4x_2 \quad \text{s.t.} \quad x_1, x_2 \geq 0 \\ & x_1 \leq 50, x_2 \leq 80 \\ & x_1 + x_2 \leq 100 \end{aligned}$$

The solution was $(x_1, x_2) = (20, 80)$
with value $2x_1 + 4x_2 = 2 \cdot 20 + 4 \cdot 80 = 360$.

We can prove that the solution is optimal:

$$\begin{aligned} & 0 \cdot (x_1 \leq 50) \\ & + 2 \cdot (x_2 \leq 80) \\ & + 2 \cdot (x_1 + x_2 \leq 100) \\ \hline & 2x_1 + 4x_2 \leq 360 \end{aligned}$$

Where does this
optimality certificate
come from?

A more systematic approach: introduce variables y_1, y_2, y_3 and consider

$$\begin{aligned} & y_1 \cdot (x_1 \leq 50) \\ & + y_2 \cdot (x_2 \leq 80) \\ & + y_3 \cdot (x_1 + x_2 \leq 100) \end{aligned}$$

& $y_1, y_2, y_3 \geq 0$ (or else inequalities flip)

$$\underbrace{(y_1 + y_3)}_{=2} x_1 + \underbrace{(y_2 + y_3)}_{=4} x_2 \leq 50 y_1 + 80 y_2 + 100 y_3$$

$= 2$ $= 4$ \leftarrow to match objective function
 ≥ 2 ≥ 4 \leftarrow also ok

Hence: $2x_1 + 4x_2 \leq 50y_1 + 80y_2 + 100y_3$ if $\begin{cases} y_1, y_2, y_3 \geq 0 \\ y_1 + y_3 \geq 2 \\ y_2 + y_3 \geq 4 \end{cases}$.

want to MINIMIZE for best upper bound

In sum the dual LP to the original (primal) LP is:

$$\min \quad 50y_1 + 80y_2 + 100y_3$$

$$\text{s.t.} \quad y_1, y_2, y_3 \geq 0$$

$$y_1 + y_3 \geq 2$$

$$y_2 + y_3 \geq 4$$

If we have solutions to primal LP and to dual LP that have same value then they are both optimal.

Eg $(x_1, x_2) = (20, 80)$ & $(y_1, y_2, y_3) = (0, 2, 2)$ both have 360.

From prior slide:

$$\begin{aligned} \max \quad & 2x_1 + 4x_2 \quad \text{s.t.} \quad x_1, x_2 \geq 0 \\ & x_1 \leq 50, x_2 \leq 80 \\ & x_1 + x_2 \leq 100 \end{aligned}$$

The general case

$k = \# \text{ variables}$

$m = \# \text{ constraints} = |I| + |E|$ (N is separate)

• PRIMAL $\max C_1 X_1 + \dots + C_k X_k$ s.t. $\forall i \in I \quad a_{i1} X_1 + \dots + a_{ik} X_k \leq b_i$
 $\forall i \in E \quad a_{i1} X_1 + \dots + a_{ik} X_k = b_i$
 $\forall j \in N \quad X_j \geq 0$

• Transformation:

$$\forall i \in I \quad y_i \cdot (a_{i1} X_1 + \dots + a_{ik} X_k \leq b_i) \quad \text{with } y_i \geq 0$$

$$\forall i \in E \quad y_i \cdot (a_{i1} X_1 + \dots + a_{ik} X_k = b_i) \quad \text{with } y_i \text{ anything}$$

$$\sum_{j \in N} \left(\underbrace{\sum_{i \in I \cup E} a_{ij} y_i}_{= C_j} \right) X_j + \sum_{j \notin N} \left(\underbrace{\sum_{i \in I \cup E} a_{ij} y_i}_{= C_j} \right) X_j \leq \underbrace{\sum_{i \in I} b_i y_i + \sum_{i \in E} b_i y_i}_{\text{MINIMIZE (best upper bound)}}$$

WANT: $\geq C_j$
(because $X_j \geq 0$)

$= C_j$
(because X_j can be neg)

MINIMIZE (best upper bound)

In sum:

- 1 multiplier variable per primal constraint
- 1 constraint per primal variable (coefficient \geq or $=$)
- minimize the induced RHS of the sum

$$m = \# \text{ variables} = |I| + |E|$$

$$k = \# \text{ constraints (I is separate)}$$

• DUAL

$$\min b_1 y_1 + \dots + b_m y_m \quad \text{s.t.} \quad \begin{aligned} \forall j \in N \quad a_{1j} y_1 + \dots + a_{mj} y_m &\geq c_j \\ \forall j \notin N \quad a_{1j} y_1 + \dots + a_{mj} y_m &= c_j \\ \forall i \in I \quad y_i &\geq 0 \end{aligned}$$

A notable special case:

- all constraints are inequalities
- all variables are non-negative

In this case the dual is easy to summarize:

Primal LP

$$\max \langle c, x \rangle$$

$$\text{s.t.} \quad \begin{aligned} Ax &\leq b \\ x &\geq 0 \end{aligned}$$

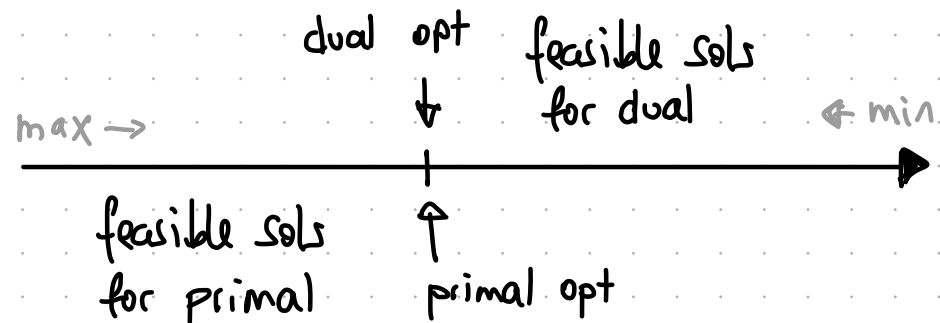
Dual LP

$$\min \langle b, y \rangle$$

$$\text{s.t.} \quad \begin{aligned} A^T y &\geq c \\ y &\geq 0 \end{aligned}$$

DUALITY THEOREM

If the primal LP has a bounded max,
then the dual LP has a bounded min,
and the two values are equal.



We will not prove the (strong) duality theorem.

Visualizing Duality

Compute the shortest path from s to t in an undirected graph G w/ positive lengths l .
 \Rightarrow We can use Dijkstra's algorithm.

An alternative:

Physical model where V balls are connected according to E via strings, and each string from u to v has length $l(u,v)$.
The shortest path from s to t is found as follows:
pull s away from t until no longer possible

We are maximizing distance, while "shortest path" is about minimization. (!)
Why? We are solving the dual LP of shortest paths.

$\max X_t$ s.t.

- $X_s = 0$
- $\forall (u,v) \in E: X_v \leq X_u + l(u,v)$

\leftarrow claim: optimum X_t^* is s.t. $X_t^* = \text{dist}(s,t)$

$X_t^* \geq \text{dist}(s,t)$: the constraints are satisfied by
 $\forall v \in V \quad X_v := \text{dist}(s,v)$.

$X_t^* \leq \text{dist}(s,t)$: let (s, v_1, \dots, v_k, t) be a path with length $\text{dist}(s,t)$.

Then $X_s = 0 \wedge X_{v_1} \leq X_s + l(s, v_1) \wedge X_{v_2} \leq X_{v_1} + l(v_1, v_2) \wedge \dots \Rightarrow X_t \leq l(s, v_1) + l(v_1, v_2) + \dots = \text{dist}(s,t)$.