

Max-flow problem:

Monday 9/29/14

Input: Directed graph $G=(V,E)$
with specified $s \in V$ & $t \in V$
and for every edge $e \in E$ there is capacity $c_e > 0$

Output: Flow f specified by for every
edge $e \in E$ f_e
which maximizes

$$\text{size}(f) = \sum_{w: \overrightarrow{sw} \in E} f_{sw} = \text{flow-out of } s$$

to be a valid flow need that:

- for all $e \in E$: $0 \leq f_e \leq c_e$

- for all $v \in V - \{s, t\}$:

$$\text{flow-in to } v = \text{flow-out of } v$$

i.e.,
$$\sum_{u: \overrightarrow{uv} \in E} f_{uv} = \sum_{w: \overrightarrow{vw} \in E} f_{vw}$$

We saw last class how to solve max-flow
using LP.

Min st-cut:

input: same as for max-flow

A st-cut is a partition $V = L \cup R$ where:

$$s \in L, t \in R$$

The capacity of the st-cut (L, R) is

$$\text{capacity}(L, R) = \sum_{\substack{\vec{vw} \in E \\ v \in L, w \in R}} c_{vw} = \begin{array}{l} \text{total capacity} \\ \text{of edges from} \\ L \text{ to } R \end{array}$$

output: st-cut (L, R) with minimum capacity.

Last class we saw LP duality:

Primal LP:

n variables $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$

m constraints specified by $A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix}$

$$\begin{aligned} \max \quad & c^T x \\ Ax & \leq b \\ x & \geq 0 \end{aligned}$$

Dual LP:

m variables $y = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$ (one per constraint in primal LP)

n constraints specified by A^T

$$\begin{aligned} \min \quad & b^T y \\ A^T y & \geq c \\ y & \geq 0 \end{aligned}$$

Max-flow LP:

Variable f_e for each edge $e \in E$

$$\max \sum_{w: \vec{sw} \in E} f_{sw}$$

subject to:

- for all $e \in E$: $f_e \leq c_e$
- for all $v \in V - \{s, t\}$: $\sum_{u: \vec{vu} \in E} f_{vu} = \sum_{w: \vec{vw} \in E} f_{vw}$
- for all $e \in E$: $f_e \geq 0$

We'll consider an equivalent LP.

Equivalent in the sense that its objective value still equals the max-flow size.

But this is a HUGE LP — too many variables — so can't implement it. But we can use it to study properties of the max-flow problem.

The flow-preserving constraints (flow-in to v = flow-out of v) ensure no flow is "lost" along a path from s to t .

We'll avoid these constraints by specifying flow along the entire st -path.

Let \mathcal{P} = set of all paths from s to t .

Typically, $|\mathcal{P}|$ is exponentially large.

For each path $p \in \mathcal{P}$, have a variable x_p .

New LP:

$$\max \sum_{p \in \mathcal{P}} x_p$$

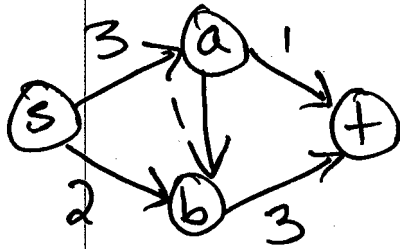
subject to:

• for all $e \in E$: $\sum_{p \in \mathcal{P}: e \in p} x_p \leq c_e$

• for all $p \in \mathcal{P}$: $x_p \geq 0$

Says: total flow over edge $e \leq c_e$

Example:



$P = \{P_a, P_{ab}, P_b\}$ = correspond to paths $s \rightarrow a \rightarrow t$
 $s \rightarrow a \rightarrow b \rightarrow t$
 $s \rightarrow b \rightarrow t$

$$\max P_a + P_{ab} + P_b$$

s.t.

$$P_a + P_{ab} \leq 3 \quad (\text{for edge } s \rightarrow a)$$

$$P_{ab} \leq 1 \quad (\text{for edge } a \rightarrow b)$$

$$P_a \leq 1 \quad (\text{for edge } a \rightarrow t)$$

$$P_b \leq 2 \quad (\text{for edge } s \rightarrow b)$$

$$P_{ab} + P_b \leq 3 \quad (\text{for edge } b \rightarrow t)$$

$$P_a, P_{ab}, P_b \geq 0$$

Example LP has: $x = \begin{pmatrix} P_a \\ P_{ab} \\ P_b \end{pmatrix}$ $c = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$

$$A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad b = \begin{pmatrix} 3 \\ 1 \\ 1 \\ \dots \\ \dots \\ \dots \end{pmatrix}$$

Dual LP has: $y = \begin{pmatrix} y_{sa} \\ y_{ab} \\ y_{at} \\ y_{sb} \\ y_{bt} \end{pmatrix}$

$$\min 3y_{sa} + y_{ab} + y_{at} + 2y_{sb} + y_{bt}$$

s.t.

$$y_{sa} + y_{at} \geq 1 \quad (\text{edges on } P_a)$$

$$y_{sa} + y_{ab} + y_{bt} \geq 1 \quad (\text{edges on } P_{ab})$$

$$y_{sb} + y_{bt} \geq 1 \quad (\text{edges on } P_b)$$

$$y_{sa}, y_{ab}, y_{at}, y_{sb}, y_{bt} \geq 0$$

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Dual LP:

for each edge $e \in E$, variable y_e

$$\min \sum_{e \in E} c_e y_e$$

subject to:

• for all $p \in P$: $\sum_{e \in P} y_e \geq 1$

• for all $e \in E$: $y_e \geq 0$

Lemma: Consider a st-cut (L, R) .

There is a feasible solution y where its objective value = capacity (L, R) .

Hence, the optimal value of the dual LP \leq min st-cut.

By duality theorem, optimal of Primal LP = optimal of dual LP \leq min st-cut
"max-flow"

Then we need to show that this is =, so need to show next that

optimal of dual LP \geq min st-cut

Proof of lemma: For the st-cut (L, R) ,

$$\text{let } y_{vw} = \begin{cases} 1 & \text{if } v \in L, w \in R \\ 0 & \text{otherwise} \end{cases}$$

Then, $\sum_{v \rightarrow w \in E} c_{vw} y_{vw} = \text{capacity}(L, R)$.

& this y is feasible because:

for a path P , since $s \in L, t \in R$, $\sum_{v \rightarrow w \in P} y_{vw} \geq 1$
have to cross $L \rightarrow R$ at least once.

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Lemma: Consider a feasible y . There is a st-cut (L, R) where

$$\text{capacity}(L, R) \leq \sum_{e \in E} c_e y_e$$

Proof: Think of y_{vw} as the weight for edge $v \rightarrow w$.

Now we have a graph with weights on edges.

For a vertex v , let

$Q(v)$ = length of shortest path from s to v .

Note, for any u where $u \rightarrow v$ is an edge then

$$Q(v) \leq Q(u) + y_{uv}$$

since we can get to v via u plus edge $u \rightarrow v$.

The dual constraints say: $\sum_{e \in P} y_e \geq 1$

Since every P ends at t , then

$$Q(t) \geq 1.$$

Choose T randomly from the interval $[0, 1)$.
Since $T < 1$ we know $T < d(t)$.

Let $L = \{v: d(v) \leq T\}$ & $R = V - L$.

Since $t \notin L$ (because $T < d(t)$) & $s \in L$
(since $d(s) = 0$)
then (L, R) is a st-cut.

Look at the expectation over T of the
capacity (L, R) :

$$E[\text{capacity}(L, R)] = \sum_{\vec{vw} \in E} c_{vw} \Pr(v \in L, w \in R)$$

$$\begin{aligned} \Pr(v \in L, w \in R) &= \Pr(d(v) \leq T < d(w)) \\ &= d(w) - d(v) \end{aligned}$$

But recall that $d(w) \leq d(v) + y_{vw}$

Hence, $\Pr(v \in L, w \in R) \leq y_{vw}$.

Therefore,

$$E[\text{capacity}(L, R)] \leq \sum_{\vec{vw} \in E} C_{vw} Y_{vw}$$

And there must be at least one choice of T
 with $\text{capacity}(L, R) \leq E[\text{capacity}(L, R)]$.
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