

Minimum Cost Flows & Related topics :

Statement of the problem

Input: A directed graph $G = [V; E]$; Real numbers (integers) $q_i; i \in V$; l_{ij}, u_{ij}, c_{ij} for each $(i,j) \in E$, $[u_{ij} \geq l_{ij} \forall (i,j) \in E]$; ~~f_{ij}~~

Desired out put : flows $f_{ij} \forall (i,j) \in E$ satisfying

$$l_{ij} \leq f_{ij} \leq u_{ij} \quad \forall (i,j) \in E$$

$$\sum_j f_{i,j} - \sum_j f_{j,i} = q_i \quad i \in V$$

$$\text{Min} \sum_j \sum_i c_{ij} f_{ij}$$

- l_{ij} : lower bound
- u_{ij} : upper bound
- q_i : external flow
- c_{ij} : Cost/unit

Special Cases : Shortest path: (assuming no negative cycles)

~~$u_{ij} = 0$~~ ; ~~f_{ij}~~ $l_{ij} = 0 \forall (i,j) \in E$;

$$q_i = \begin{cases} 1 & i = s \\ 0 & i \neq s, t \\ -1 & i = t \end{cases}$$

$u_{ij} = 1$ works
 $u_{ij} = \infty$ works
 assuming no neg. cycle.

Special Cases (contd)

(2)

Maximum flow

Add an edge (t, s) :

$$C_{ij} = 0 \quad \forall (i, j) \neq (t, s)$$

$$C_{t, s} = -1 ;$$

Transportation Problem:

$$\sum_j x_{i,j} = a_i \quad i=1 \dots m$$

$$\sum_i x_{i,j} = b_j \quad j=1 \dots n$$

$$x_{i,j} \geq 0; \quad \begin{matrix} i=1 \dots m \\ j=1 \dots n \end{matrix}$$

$$\text{Min } \sum_j \sum_i C_{i,j} x_{i,j}$$

When $m=n$ and $a_i = b_j = 1 \quad \forall i, j$ problem is known as The Assignment Problem (Also bipartite matching problem)

We now describe the basis for a "new" type of algorithm based on Linear Programming duality concepts.

Linear Programs & Duality Theory:

(3)

See my lecture notes under Linear Programming or Optimization. (In particular, section on "Duality Theory".)

Linear program:

This is an optimization problem with "linear" constraints and a linear function to be maximized (minimized). [Normally, we also assume that the number of variables and constraints are "finite"]. Hence, it is a problem each of whose constraints [m in total] look like

$$a_{i,1}x_1 + a_{i,2}x_2 + \dots + a_{i,n}x_n \quad (R_i) \quad b_i$$

$i=1 \dots m$

where $R_i \in \{ \geq, \leq, = \}$

and each variable x_i satisfies the relation

$$x_j \quad (R'_j) \quad 0 \quad j=1 \dots n$$

where $R'_j \in \{ \geq, \leq, \text{no relation to } 0 \}$
(could be +, -, or 0)

And the "goal" (objective function) is to max/min

$$\sum_{j=1}^n C_j x_j$$

$\{a_{i,j}\}, \{b_i\}, \{C_j\}$ are input data as are R_i, R'_j

There are several "Standard forms" for LP. For⁽⁴⁾ the purposes of Duality Theory:

$$\min cx : Ax \geq b, x \geq 0 \quad \textcircled{P}$$

is the one normally used.

$$\min \sum_{j=1}^n c_j x_j$$

$$y_i \geq 0 \quad \text{s.t.} \quad \sum_{j=1}^n a_{ij} x_j \geq b_i, \quad i=1, \dots, m$$

$$x_j \geq 0; \quad j=1, \dots, n$$

A standard form: Every LP can be written in this form.

"The" Dual of \textcircled{P} is another LP:

$$\max b^t y : A^t y \leq c^t; y \geq 0$$

\Leftrightarrow

\textcircled{D}

$$\max \sum_{i=1}^m b_i y_i$$

$$\text{s.t.} \quad \sum_{i=1}^m a_{ij} y_i \leq c_j \quad j=1, \dots, n$$

$$y_i \geq 0 \quad i=1, \dots, m$$

Which one is \textcircled{P} and which is \textcircled{D} depends on our "interest". Problem of interest is \textcircled{P}
"The Other" is \textcircled{D}

First we will demonstrate that this is indeed (5) "a standard" form. And show the relationship of the dual to the "general" LP.

General LP:

$$\begin{array}{ccc}
 x^1 \geq 0 & x^2 \leq 0 & x^3: \text{unrestd.} \\
 \begin{array}{|c|c|c|}
 \hline
 A_{11} & A_{12} & A_{13} \\
 \hline
 A_{21} & A_{22} & A_{23} \\
 \hline
 A_{31} & A_{32} & A_{33} \\
 \hline
 \end{array} & \begin{array}{l} \geq \\ \leq \\ = \end{array} & \begin{array}{|c|}
 \hline
 b^1 \\
 \hline
 b^2 \\
 \hline
 b^3 \\
 \hline
 \end{array} \\
 \text{Min } \begin{array}{|c|c|c|}
 \hline
 c^1 & c^2 & c^3 \\
 \hline
 \end{array} & &
 \end{array}$$

Transformation to Standard form.

Steps: Multiply by -1 : inequalities that go \leq

Replace $=$ by \geq & \leq

Replace unrestd variables by difference of two nonnegative variables

$$\text{i.e. } x^3(\text{unrestd}) = x^3_+ - x^3_-$$

"

$$8 \longrightarrow (8, 0)$$

$$-8 \longrightarrow (0, +8)$$

This results in:

$x^1 \geq 0$ $-x^2 \geq 0$ $x^3_+ \geq 0$ $x^3_- \geq 0$

A_{11}	$-A_{12}$	A_{13}	$-A_{13}$	\geq	b^1
$-A_{21}$	$-A_{22}$	$-A_{23}$	$+A_{23}$	\geq	$-b^2$
A_{31}	$-A_{32}$	A_{33}	$-A_{33}$	\geq	b^3
$-A_{31}$	A_{32}	$-A_{33}$	A_{33}	\geq	$-b^3$
Min					
c^1	$-c^2$	c^3	$-c^3$		

P

Which is in standard form. Its dual is

$y^1 \geq 0$ $\tilde{y}^2 \geq 0$ $\tilde{y}^3_+ \geq 0$ $\tilde{y}^3_- \geq 0$

Combine {

A_{11}^t	$-A_{21}^t$	A_{31}^t	$-A_{31}^t$	\leq	$(c^1)^t$
$-A_{12}^t$	$-A_{22}^t$	$-A_{32}^t$	A_{32}^t	\leq	$(c^2)^t$
A_{13}^t	$-A_{23}^t$	A_{33}^t	$-A_{33}^t$	\leq	$(c^3)^t$
$-A_{13}^t$	A_{23}^t	$-A_{33}^t$	A_{33}^t	\leq	$(c^3)^t$
Max					
$(b^1)^t$	$(-b^2)^t$	$(b^3)^t$	$(-b^3)^t$		

Reversing Steps used in getting Standard form. (7)

Let $y^3 = y_+^3 - y_-^3$: unrestricted

$y^2 = -\tilde{y}^2 \leq 0$

Combining $\geq, \leq \rightarrow =$

We get

$y^1 \geq 0$	$y^2 \leq 0$	y^3 : unrestricted	
A_{11}^t	A_{21}^t	A_{31}^t	$\leq (c^1)^t$
A_{12}^t	A_{22}^t	A_{32}^t	$\geq (c^2)^t$
A_{13}^t	A_{23}^t	A_{33}^t	$= (c^3)^t$

Max $\left[(b^1)^t \mid (b^2)^t \mid (b^3)^t \right]$

This is "the process" of getting dual to General

LP.

Now to the "reason" for looking at dual
and relationship between (P) and (D).

Theorem 1. (Weak Duality Theorem)

Let x^0 be any feasible solution to (P) and
let y^0 be any " " " (D).

Then $c x^0 \geq b^t y^0$

Corollary : If x^0 is feas. to (P) and y^0 is feas. to (D)
Such that $c x^0 = b^t y^0$, then
these are "optimal" to (P) and (D) resp.

Pf. (Theorem 1) :

x^0 feas to (P) $\Leftrightarrow Ax^0 \geq b, x^0 \geq 0$.
 y^0 feas to (D) $\Rightarrow y^0 \geq 0$.
 $\Leftrightarrow \sum_{j=1}^n a_{ij} x_j \geq b_i$
 $i=1 \dots m$

$\sum_{i=1}^m y_i \sum_{j=1}^n a_{ij} x_j \leftarrow \therefore (y^0)^t Ax^0 \geq (y^0)^t b = b^t y^0$
(Red arrows and annotations: y_i and $\sum b \cdot y_i$)

$\sum_{j=1}^n x_j \sum_{i=1}^m a_{ij} y_i \leftarrow$ Similar $(x^0)^t Ay^0 \leq (x^0)^t c^t = c x^0$.

Combining we get the result.

Note $(y^0)^t Ax^0 = (x^0)^t Ay^0$

Theorem 2 (Strong Duality) If both (P) and (D) are
feasible, then they both have optimal solutions
and $c x^* = b^t y^*$ for all opt. solutions x^*, y^* .

Theorem 3: (Weak) Complementary Slackness Theorem ⁽⁹⁾

Let x^* be any optimal solution to (P) and
 y^* (D).

Then,

$$\left. \begin{array}{l} \sum_{j=1}^n a_{ij} x_j^* > b_i \Rightarrow y_i^* = 0 \\ \sum_{j=1}^n a_{ij} x_j^* = b_i \Leftrightarrow y_i^* > 0 \\ \sum_{i=1}^m a_{ij} y_i^* < c_j \Rightarrow x_j^* = 0 \\ \sum_{i=1}^m a_{ij} y_i^* = c_j \Leftrightarrow x_j^* > 0 \end{array} \right\} (*)$$

Moreover, ~~if~~ for any pair (x^*, y^*) that are
feas. to (P) and (D) respectively that satisfy $(*)$
are also optimal to (P) and (D) respectively.

It is this result that is basis for algorithms
to solve (P) and (D) **simultaneously**.

These are algorithms based on Duality Theory
of Linear Programming.