

①

$$\text{Form-I: } \max \left( \sum_{e \in \delta^+(s)} f_e \right) \longrightarrow 1.1$$

$$\sum_{e \in \delta^-(v)} f_e = \sum_{e \in \delta^+(v)} f_e \quad \forall v \neq s, t \longrightarrow 1.2$$

$$f_e \leq u_e \quad \forall e \in E \longrightarrow 1.3$$

$$f_e \geq 0 \quad \forall e \in E \longrightarrow 1.4$$

Form-II:

$$\max \left( \sum_{p \in P} f_p \right) \longrightarrow 2.1$$

$$\sum_{p \in P: e \in p} f_p \leq u_e \quad \forall e \in E \longrightarrow 2.2$$

$$f_p \geq 0 \quad \forall p \in P \longrightarrow 2.3$$

→ Proof strategy:

Lemma 1: If  $\{f_p\}_{p \in P}$  is a feasible solution to 'Form-II', then there is a feasible solution for 'Form-I' of the same cost.

Lemma 2: If  $\{f_e\}_{e \in \delta^+(s)}$  is a feasible solution to 'Form-I', then there is a feasible solution to 'Form-II' of the same cost.

→ Lemma 1 and 2 implies that these two linear programs always have equal optimal objective function value.

→ Proof of Lemma 1:

In form-II,  $\sum_{p \in P: e \in p} f_p$  means the sum of the flows of all paths that uses the edge 'e'

We alternatively define it in terms of nodes as:

$$f(u, v) := \sum_{P \in \mathcal{P}: (u, v) \in P} f_p$$

Inequality 2.2 implies it satisfies capacity constraints.

To show conservation constraint, we pivot node  $v$ .

Then sum over all edges incident on it:

$$\sum_{u: (u, v) \in E} f(u, v) = \sum_{P \in \mathcal{P}: v \in P} f_p \quad \textcircled{a}$$

Same holds for edges coming out of  $v$ ,

$$\sum_{w: (v, w) \in E} f(v, w) = \sum_{P \in \mathcal{P}: v \in P} f_p \quad \textcircled{b}$$

Equation  $\textcircled{a} = \textcircled{b}$  implies conservation for edge  $v$  in the network.

Different s-t path passing through vertex  $v$ .  
Summing over these paths gives equation  $(a)$  and  $(b)$

→ Proof of Lemma 2:

This can be inferred from Flow decomposition theorem (FDT).

FDT: Let  $f_1, \dots, f_k$  be feasible flow while  $P_1, \dots, P_k$  be s-t path in a flow network.

Then  $k \leq |E|$  and flow  $f_i$  sends positive flow only on the edges of  $P_i$ .

$$\begin{aligned} \sum_{e \in S^-(v)} f_e \\ = \sum_{e \in S^+(v)} f_e \end{aligned}$$

Through any vertex  $v'$ , all the flow across it corresponds to some path  $\{P_i\}$ .

Thus sum of such s-t path amounts to  $\sum_{P \in \mathcal{P}: v \in P} f_p \leq u_v$

Also,  $f_e \geq f_p$

②

Maximum multi-commodity flow (MMCF)

$$\max \left( \sum_{i=1}^k f^{(i)} \right)$$

Capacity constraints :  $\sum_{i=1}^k f_{uv}^{(i)} \leq c(u,v) ; \forall (u,v) \in V$

flow of commodity 'i' from vertex u to v.

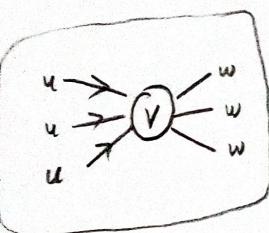
Conservation constraints :

$$\sum_{u \in V} f_{uv}^{(i)} = \sum_{w \in V} f_{vw}^{(i)} ; \forall i = \{1, \dots, k\} ; \forall v \in V / \{s_i, t_i\}$$

Positivity constraint :

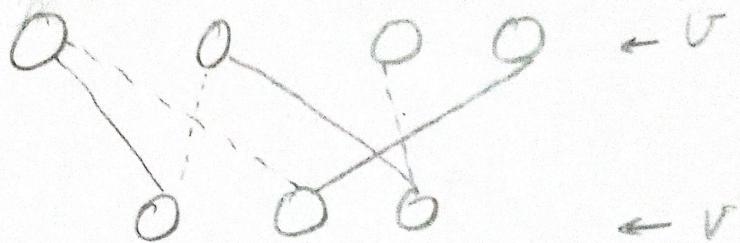
$$f_{uv}^{(i)} \geq 0$$

The above linear program output maximum possible value of  
multi-commodity flow.



### ③ Maximum Bipartite Matching (MBM)

(a) Given graph  $G = (U \cup V; E)$  where  $E \subseteq U \times V$



Let 'M' be solution set for MBM

$x_e = 1$  iff edge 'e'  $\in M$

$$\text{objective : } \max \left( \sum_{e \in E} x_e \right)$$

Constrain : for matching in Bipartite graph

Set of edges incident on vertex 'v'

$$\left\{ \begin{array}{ll} \sum_{e \in \delta(v)} x_e \leq 1 & \forall v \in (U \cup V) \\ x_e \geq 0 & \forall e \in E \\ x_e \leq 1 & \forall e \in E \end{array} \right.$$

(3)

(b)

Primal LP: (Part 3(a))

$$\max \left( \sum_{e \in E} x_e \right)$$

$$\sum_{e \in \delta(v)} x_e \leq 1 ; \forall v \in (U \cup V)$$

$$\begin{array}{l} x_e \geq 0 \\ x_e \leq 1 \end{array} \quad \left. \begin{array}{l} \forall e \in E \\ \forall e = (u, v) \end{array} \right\}$$

This is not necessary

Dual LP

$$\min \left( \sum_{v \in (U \cup V)} y_v \right)$$

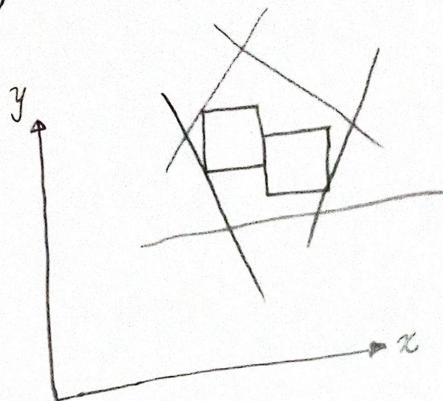
$$y_v + y_u \geq 1$$

 $e = (u, v)$  and  $\forall e \in E$ 

$$y_v, y_u \geq 0$$

- Meaning of dual variable  $y_v$ : It represents if a vertex  $v \in (U \cup V)$  is included in the solution set or not.
- Objective function represents the minimum possible set of vertices that satisfy the associated constraint.
- Dual problem represents minimum vertex cover in the given Bipartite graph.
- It can be inferred from the constraint  $y_v + y_u \geq 1$ . This makes sure that for every edge in the graph, atleast one of its vertex is included.
- Minimization of the objective function ensures that we pick fewest vertices still covering all edges.

(4)



$$a_i x + b_i y \leq c_i \quad \forall i = \{1, \dots\}$$

intersection of above lines  
form feasible region.

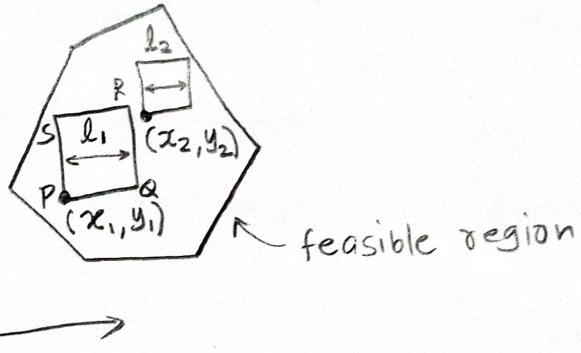
Since, squares are axis aligned.

Hence, we consider two cases.

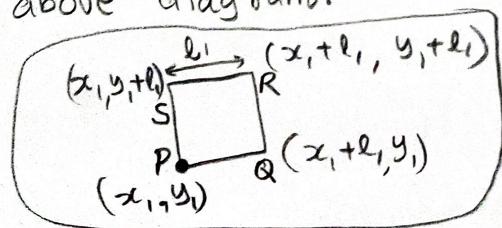
Both cases gives a linear program.

We compare the output of both cases  
and declare maximum among them as final  
output.

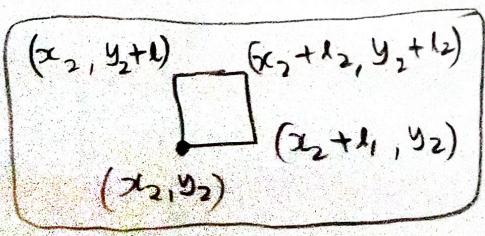
**Case-I:**  
[Left-Right  
alignment]



Let sides of squares are  $l_1$  and  $l_2$  as shown in the  
above diagram.



The left square lies in feasible  
region. [Constraint-I]



The right square shall lie inside  
feasible region, and its coordinate  
shall begin just after the left  
square finishes.

[constraint - II and III]

Objective: sum of areas =  $4\ell_1 + 4\ell_2$

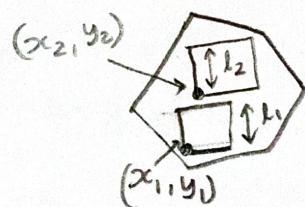
$$\left\{ \begin{array}{l} \boxed{\max(4\ell_1 + 4\ell_2)} \rightarrow (1) \\ a_i x_1 + b_i y_1 \leq c_i \rightarrow (2.1) \\ a_i(x_1 + \ell_1) + b_i(y_1) \leq c_i \rightarrow (2.2) \\ a_i(x_1) + b_i(y_1 + \ell_1) \leq c_i \rightarrow (2.3) \\ a_i(x_1 + \ell_1) + b_i(y_1 + \ell_1) \leq c_i \rightarrow (2.4) \end{array} \right.$$

Square PQRS      Orientation of two squares  $\left\{ x_1 + \ell_1 \leq x_2 \right. \rightarrow (3)$

For other square  $\left\{ \begin{array}{l} a_i x_2 + b_i y_2 \leq c_i \rightarrow (4.1) \\ a_i(x_2 + \ell_2) + b_i y_2 \leq c_i \rightarrow (4.2) \\ a_i(x_2) + b_i(y_2 + \ell_2) \leq c_i \rightarrow (4.3) \\ a_i(x_2 + \ell_2) + b_i(y_2 + \ell_2) \leq c_i \rightarrow (4.4) \end{array} \right.$

$$\ell_1, \ell_2 \geq 0 \rightarrow 5$$

Case-II: Top and down orientation



All equations from (1) to (5) remain same  
except eqn (3)

Replace eqn (3) by

$$y_1 + \ell_1 \leq y_2 \quad (3')$$