

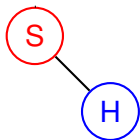
CS 170: Algorithms

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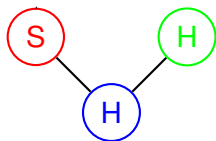
CS 170: Algorithms



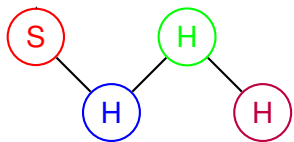
CS 170: Algorithms



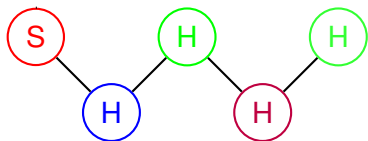
CS 170: Algorithms



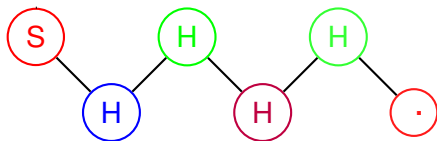
CS 170: Algorithms



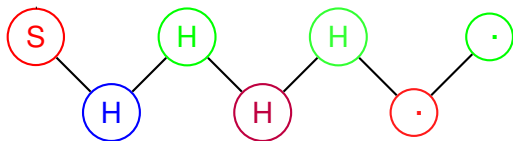
CS 170: Algorithms



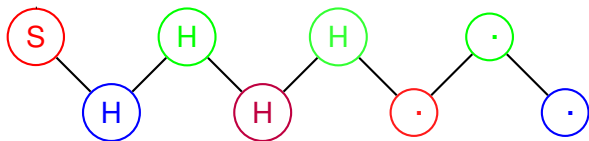
CS 170: Algorithms



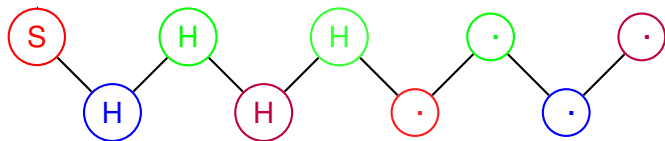
CS 170: Algorithms



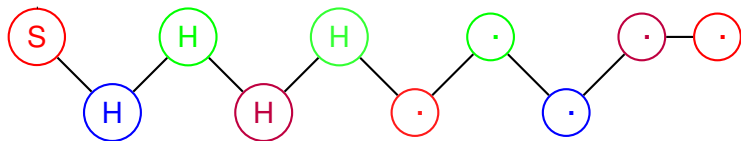
CS 170: Algorithms



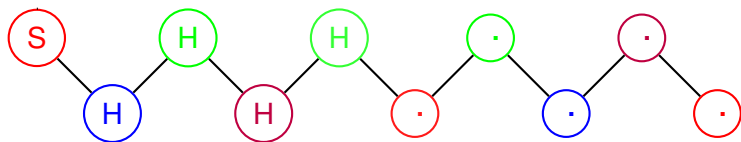
CS 170: Algorithms



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CS 170: Algorithms



Lecture in a minute

Maximum flow.

“Greedy” augment path...

Except reverse old decisions ..

Reverse residual capacities.

: Optimality?

No augmenting path \implies

$s - t$ cut size = flow value.

Find flow and $s - t$ cut with equal value!

Lecture in a minute

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 - Find flow and $s - t$ cut with equal value!

Maximum Matching.

- $G = (V, E)$, find subset of one-to-one matches.

- Reduction to max flow.

- Augmenting Alternating Path

- Algorithm \equiv Simplex.

Maximum flow

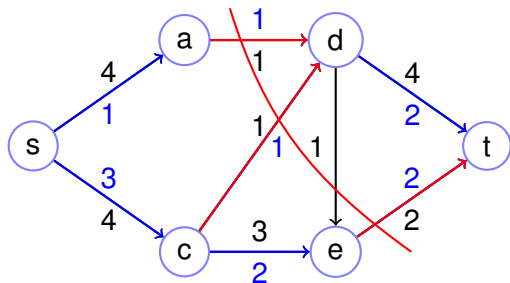
Flow network $G = (V, E)$, source s , sink $t \in V$, capacities $c_e > 0$.

Maximum flow

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Find Flow: f_e

1. $0 \leq f_e \leq c_e$. "Capacity constraints." $3 = f_{s,c} \leq c_{s,c} = 4$.

2. If u is not s or t

$$\sum_{(w,u) \in E} f_{wu} = \sum_{(u,w) \in E} f_{uw}. \quad 3 = f_{s,c} = f_{c,d} + f_{c,e} = 2 + 1.$$

$$\text{Maximize: } \text{size}(f) = \sum_{(s,u) \in E} f_{su}. \quad f_{sa} + f_{sc} = 1 + 3 = 4$$

Optimal? $c_{ad} + c_{cd} + c_{et} = 1 + 1 + 2 = 4$.

S-T cut.

An $s - t$ cut is a partition of V into S and T where $s \in S$ and $t \in T$. Its capacity is the total capacity of edges from S to T .

Do you know the definition?

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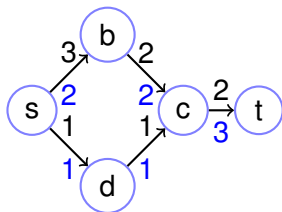
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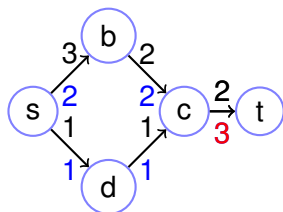
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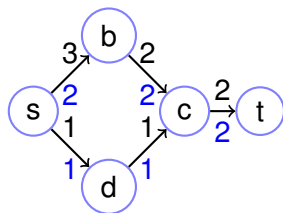
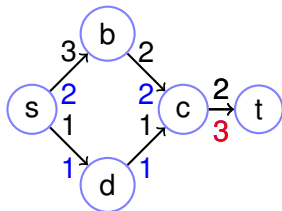
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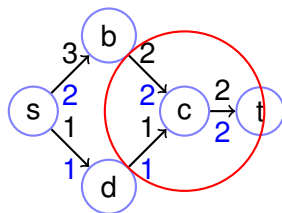
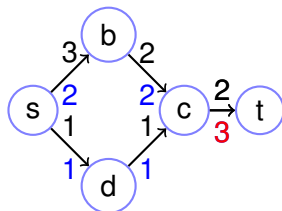
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$$2 + 1 \neq 2$$

Algorithms.

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Linear program!

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Variables f_e , linear constraints, linear optimization function.

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Note...

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Note...

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Vertex solution to linear program must be integral!

Ford-Fulkerson.

“Simplex” method.

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Add to flow variables along path.

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Update remaining capacity.

Ford-Fulkerson.

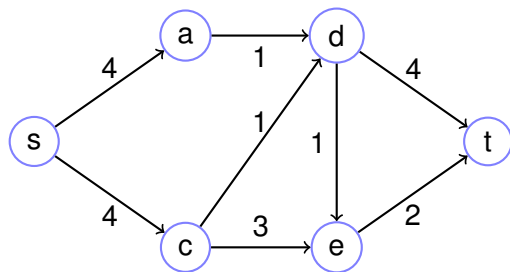
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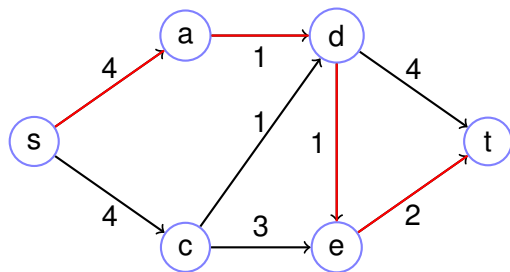
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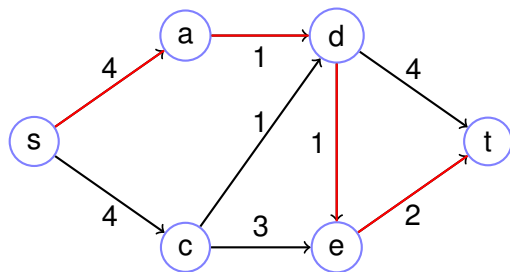
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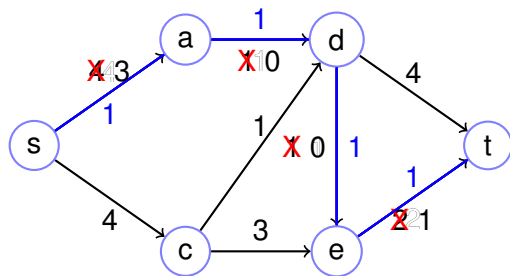
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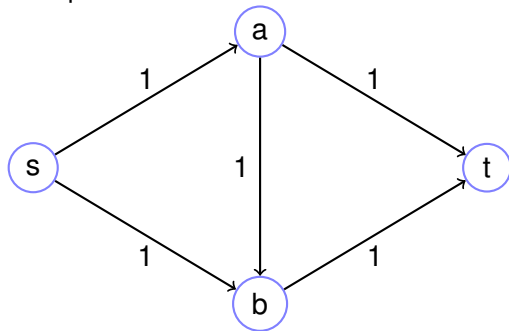
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Repeat.



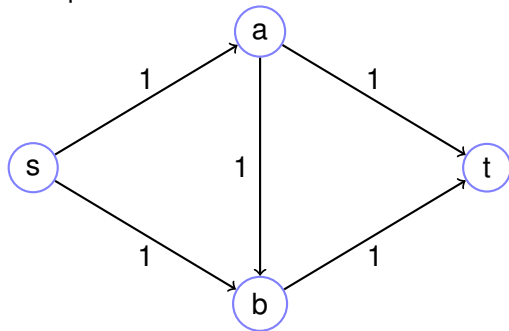
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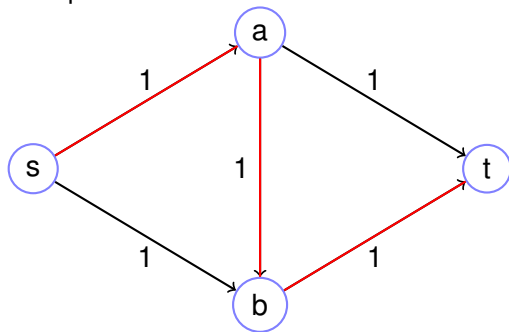
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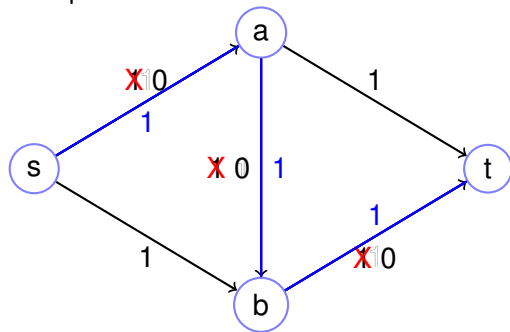
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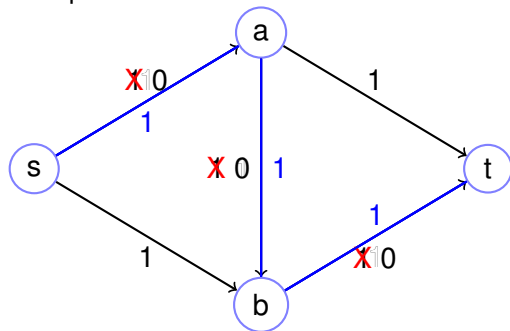
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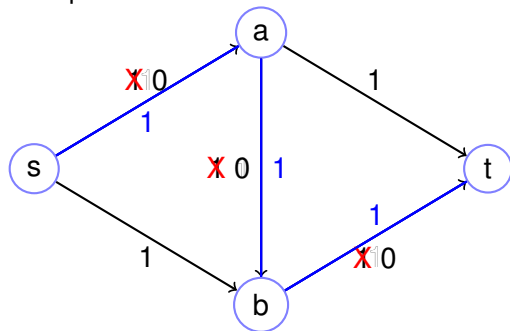
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No remaining path. Uh oh! Optimal is 2! (At most 2 due to cut.)

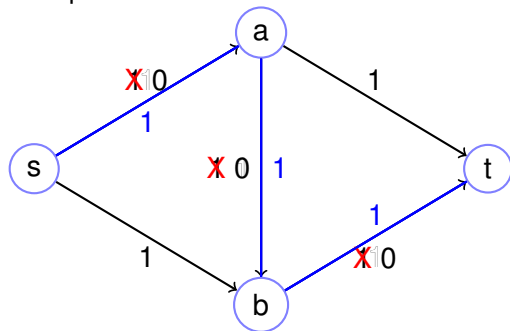
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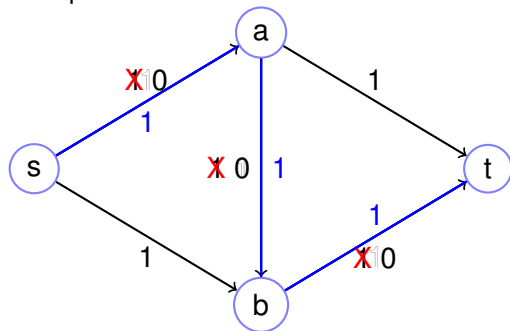
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Find s to t path with remaining capacity.

Add to flow along path. Or reduce flow on reverse edge.

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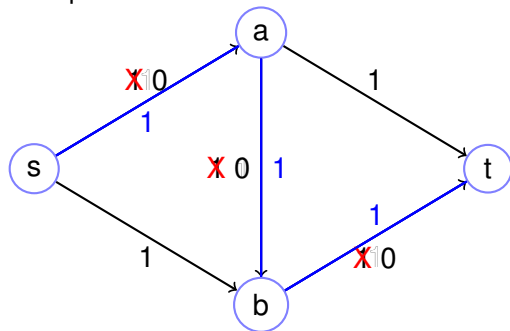
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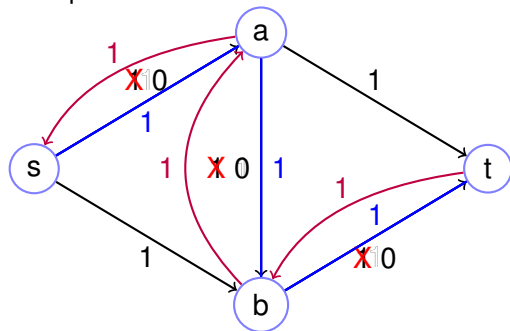
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and add reverse $r_{uv} = f_{vu}$

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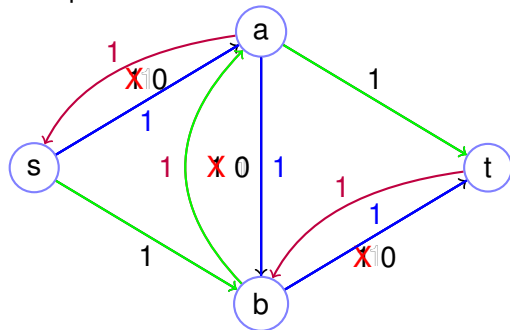
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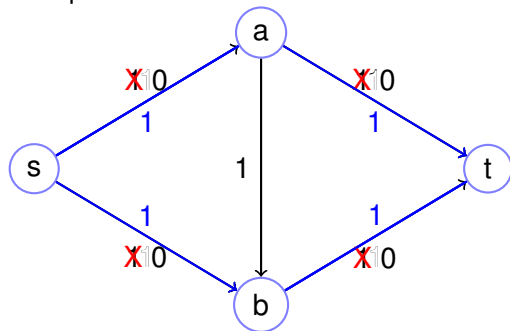
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Bigger Example.

Find s to t path with remaining capacity.

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Update residual capacities: $r_e = c_e - f_e$; $r_{uv} = f_{vu}$.

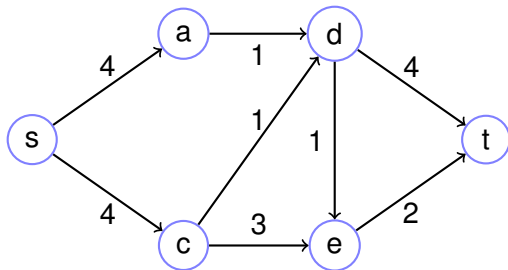
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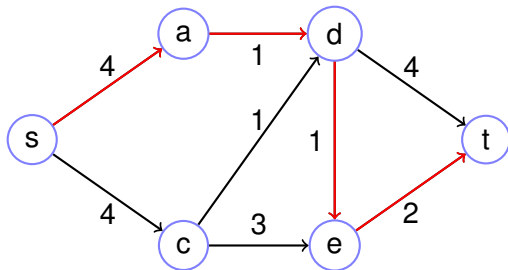
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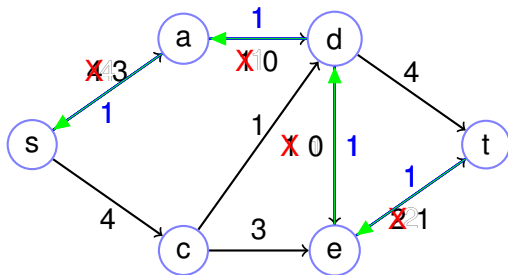
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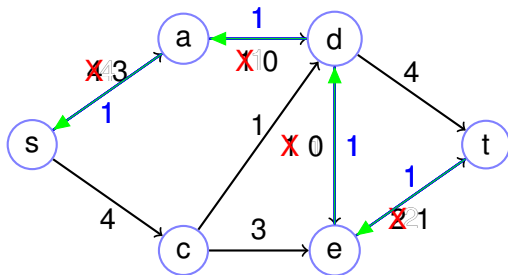
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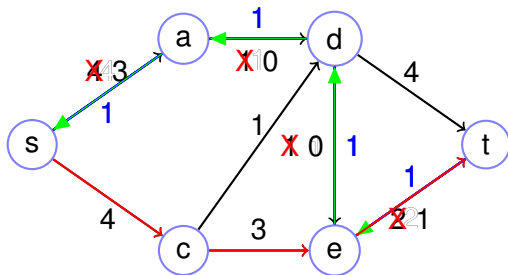
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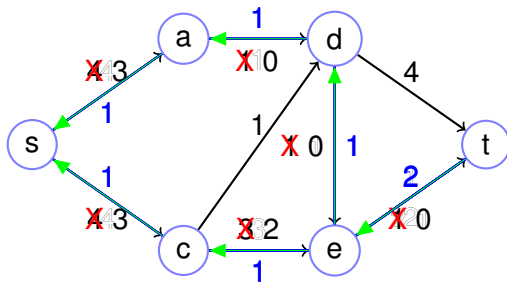
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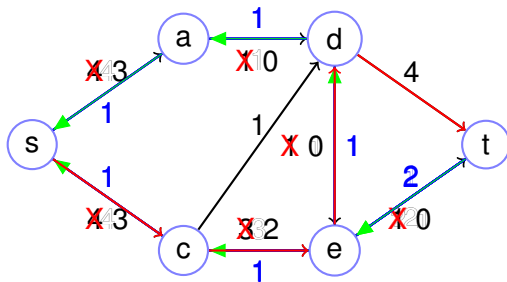
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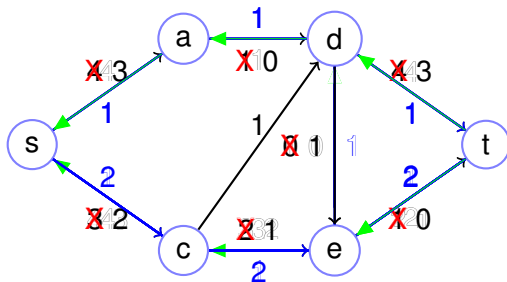
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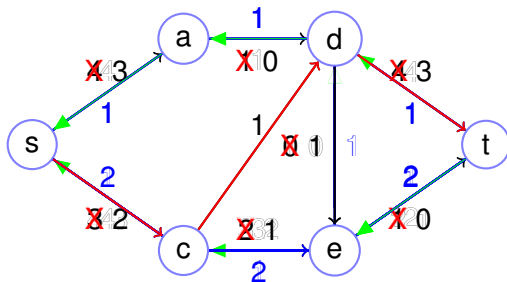
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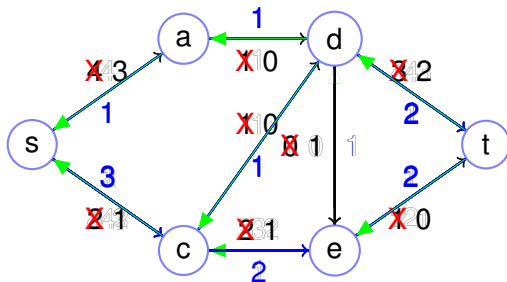
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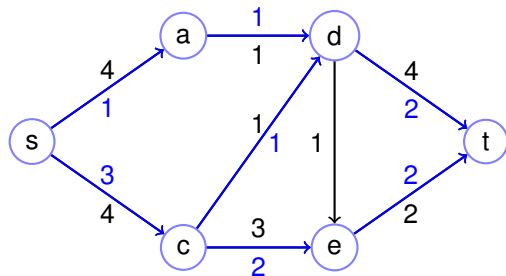
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Check Result...

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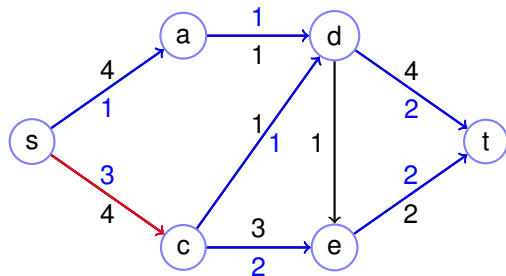
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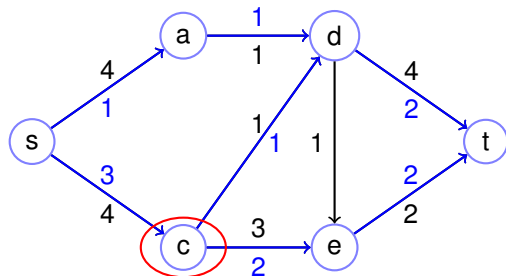
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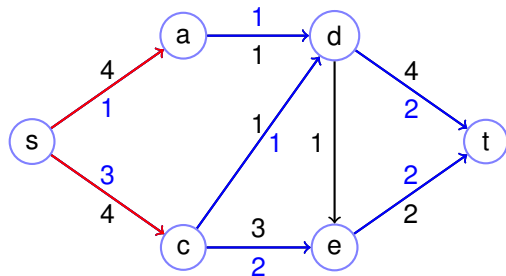


Find Flow: f_e

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 $\sum_{(w,u) \in E} f_{wu} = \sum_{(u,w) \in E} f_{uw}$. $3 = f_{s,c} = f_{c,d} + f_{c,e} = 2 + 1$.

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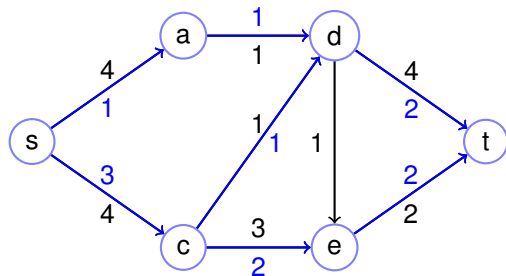


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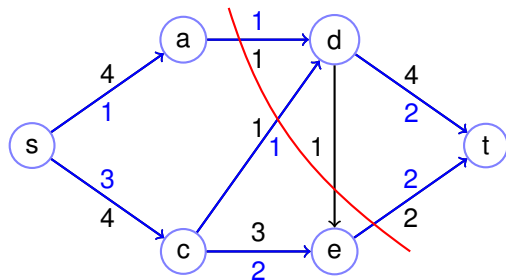
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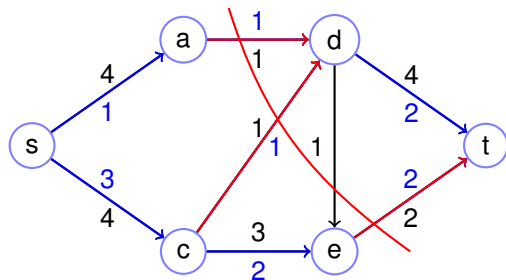
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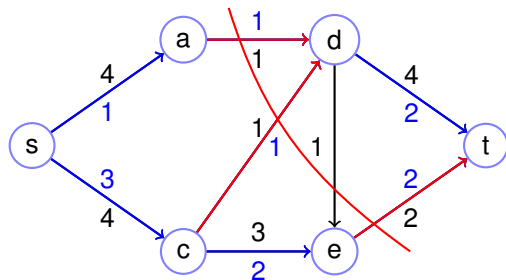
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Any $s - t$ cut gives an upper bound.

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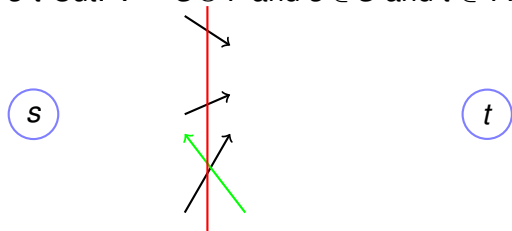
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Each internal node has f in, and f out.

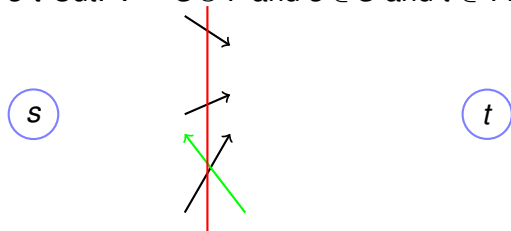
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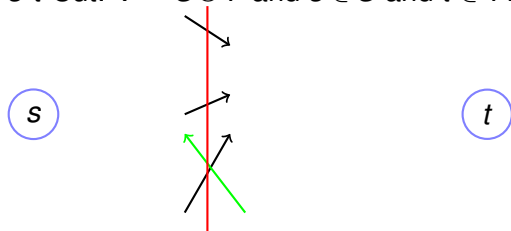
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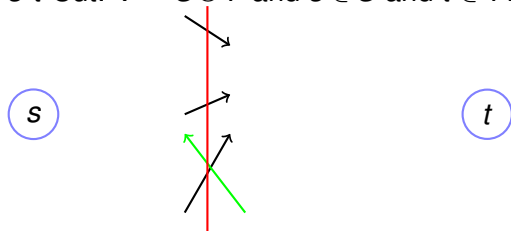


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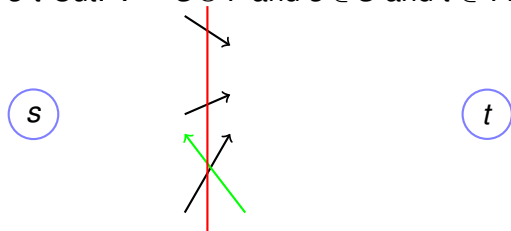
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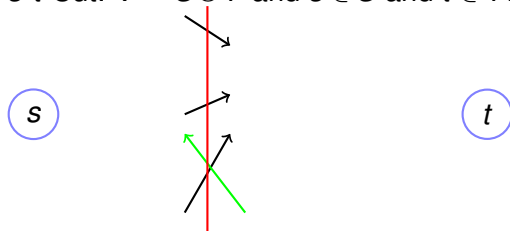
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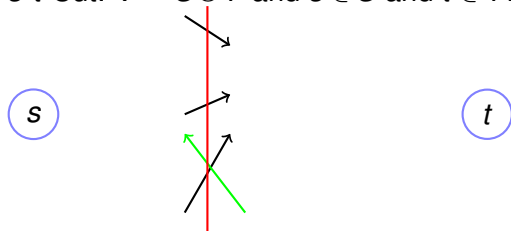
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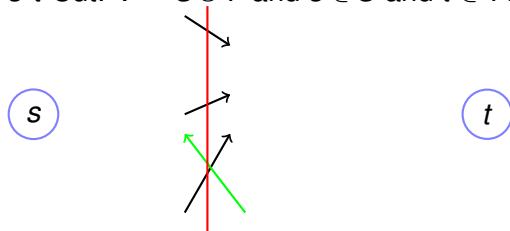
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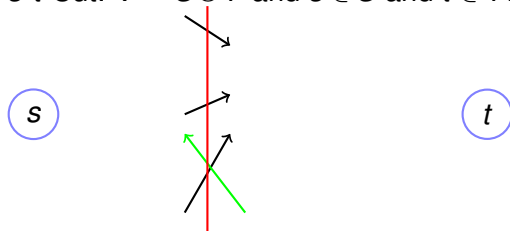
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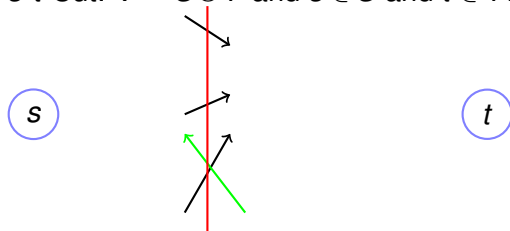
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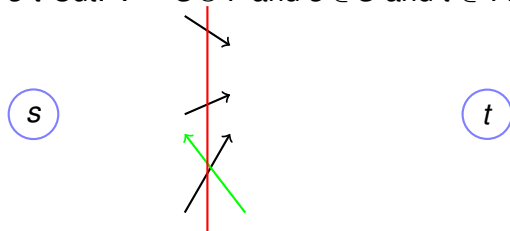
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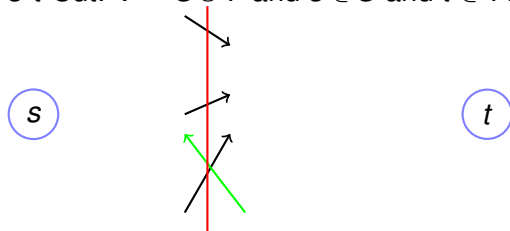
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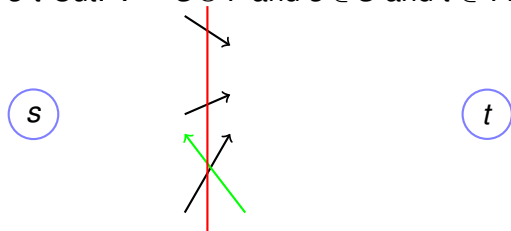
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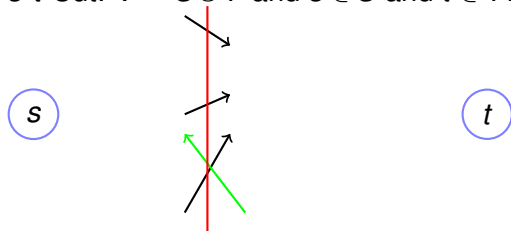
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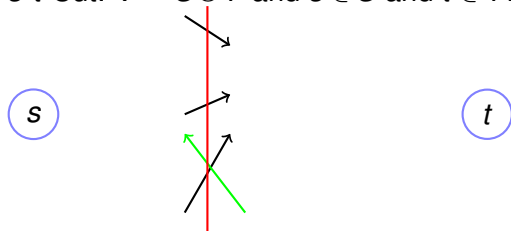
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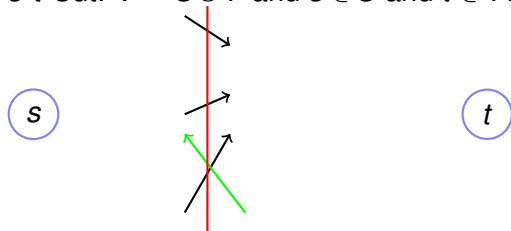
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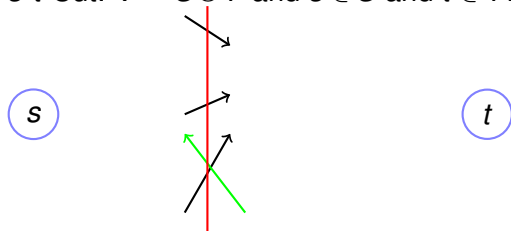
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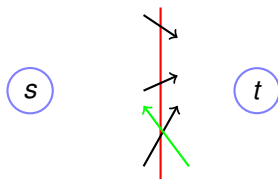
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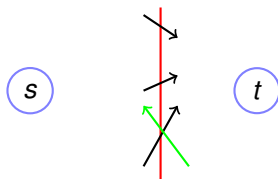


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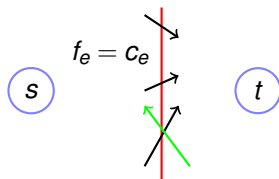
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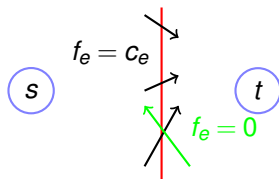
\implies All arcs leaving S are full.

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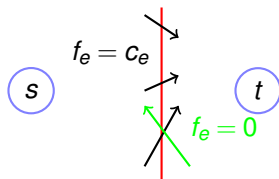
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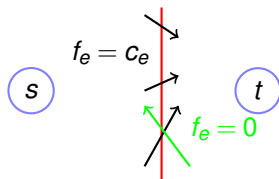
Total flow leaving S is $C(S, T)$.

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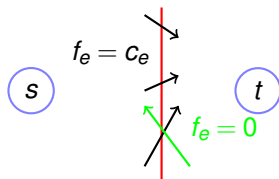
Valid flow \implies all that flow from source.

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No path with residual capacity!

Depth first search only starting at s does not reach t .



S be reachable nodes.

No arc with positive residual capacity leaving S

\implies All arcs leaving S are full.

\implies No arcs into S have flow.

Total flow leaving S is $C(S, T)$.

Valid flow \implies all that flow from source.

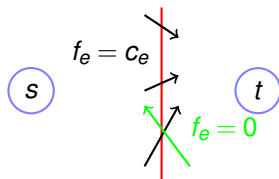
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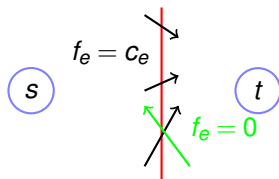
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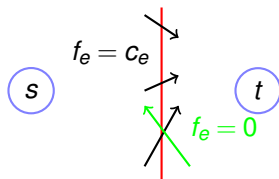
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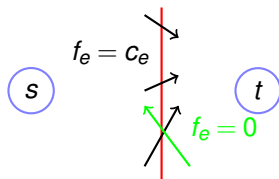
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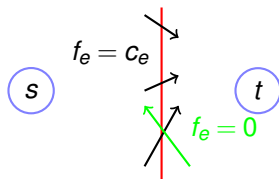
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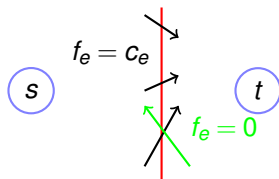
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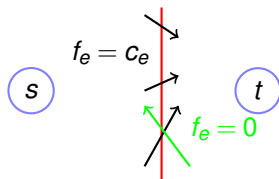
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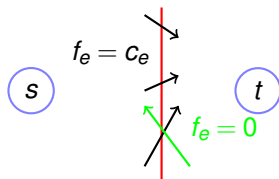
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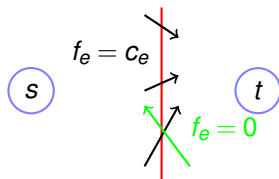
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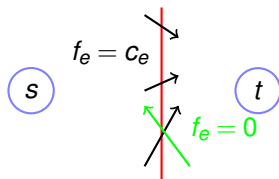
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“any flow” \leq “any cut” and this flow = this cut.

\rightarrow Maximum flow and minimum $s - t$ cut!

Celebrated max flow -minimum cut theorem.

Theorem: In any flow network, the maximum s - t flow is equal to the minimum cut.

Celebrated max flow -minimum cut theorem.

Theorem: In any flow network, the maximum s - t flow is equal to the minimum cut.

Celebrate!

Back to business: Algorithm Terminates?

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It will!!

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Flow keeps increasing.

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How long?

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One more unit every step!

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$O(mF)$ time

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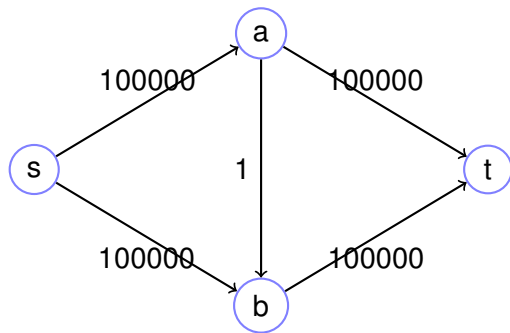
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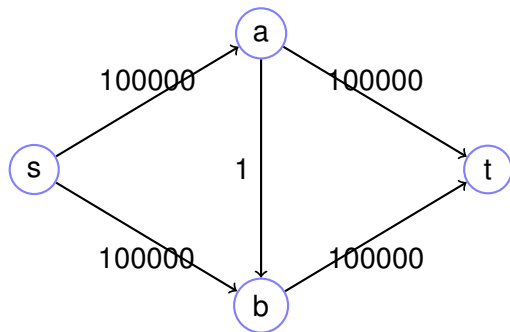
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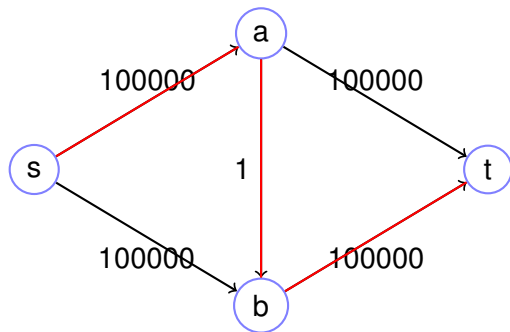
Efficiency.



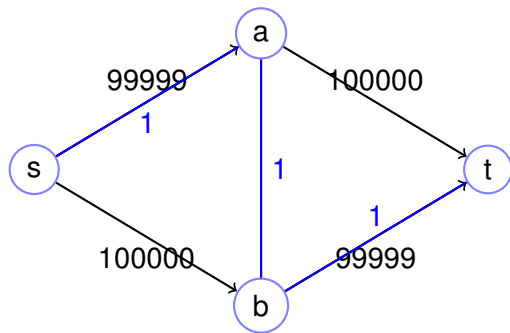
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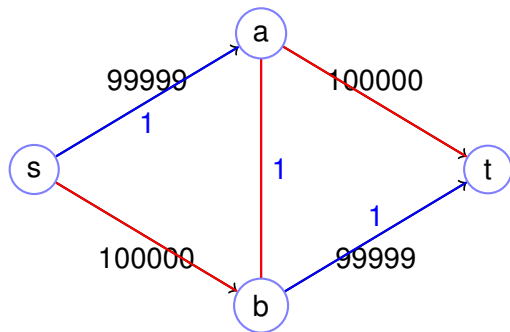
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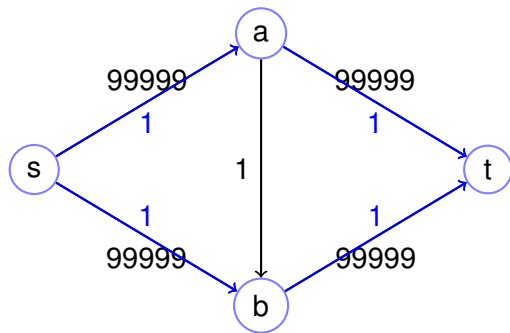
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Efficiency.



Edmonds-Karp

Augment along shortest path.

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Breadth first search!

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$O(|V||E|)$ augmentations.

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Only route flow on (u, v) if $d(u) \geq d(v)$.

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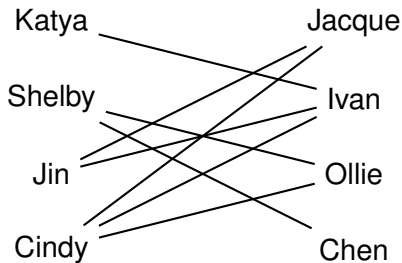
$O(|V||E|^2)$ time.

Bipartite Matching

Given a bipartite graph: $B = (L, R, E)$ where $E \subseteq L \times R$.

Bipartite Matching

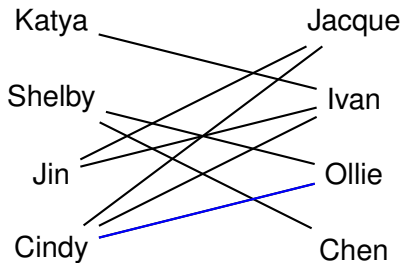
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Find largest subset of edges (“matches”) which are one to one.

Bipartite Matching

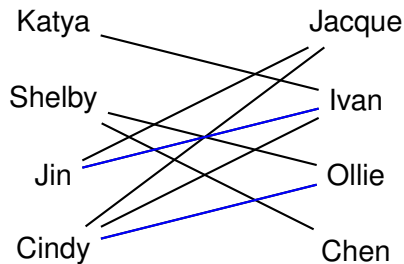
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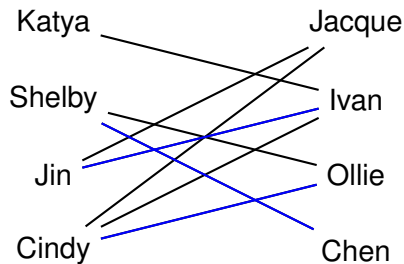
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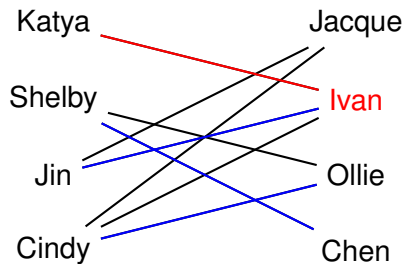
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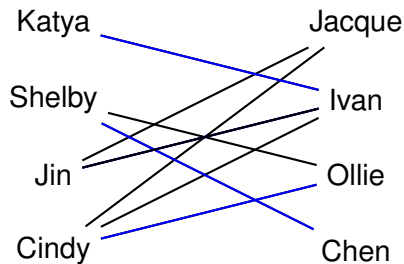
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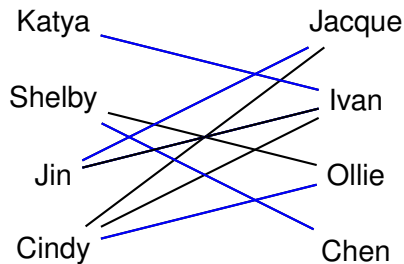
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Algorithm by “Reduction.”:

From matching problem produce flow problem.

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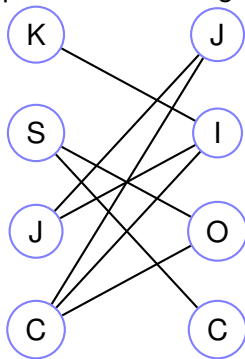
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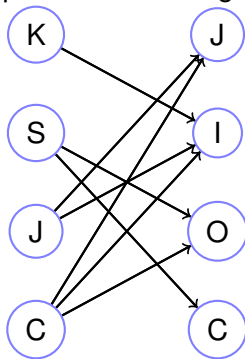


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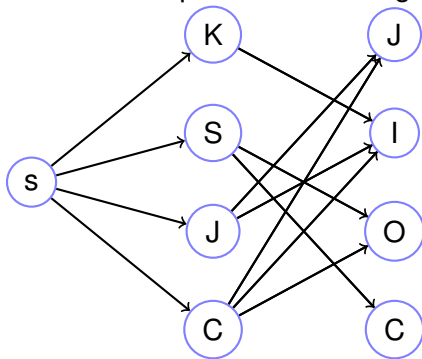


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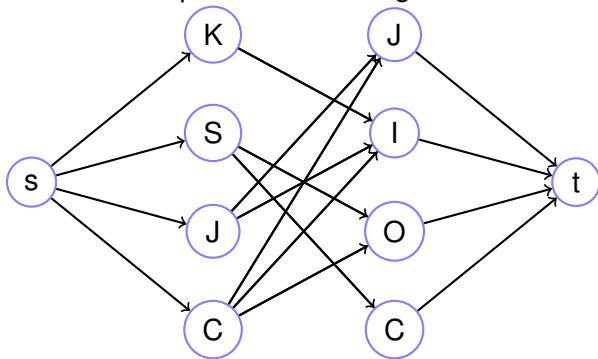


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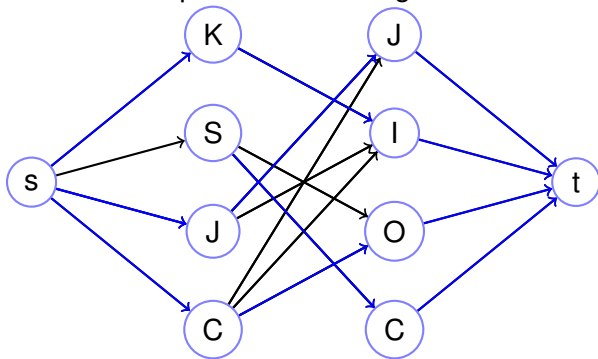


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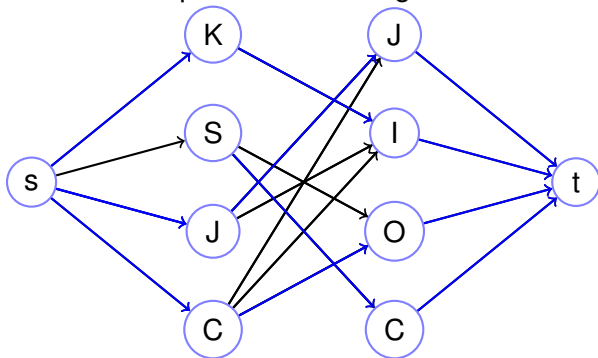


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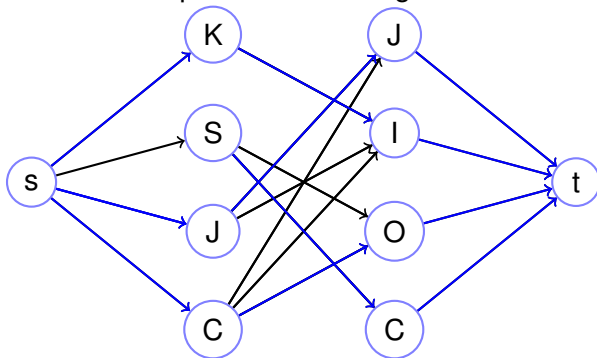
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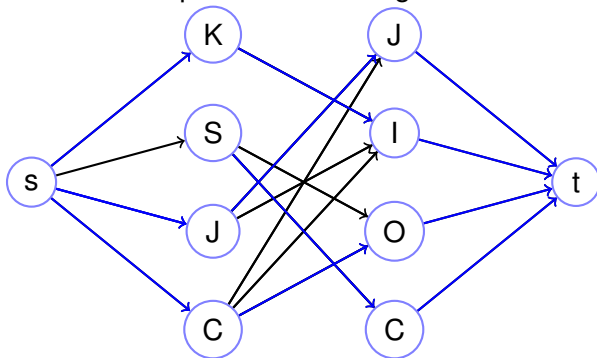
Flow is not integer necessarily....

Bipartite Matching

Algorithm by “Reduction.”:

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Max flow = Max Matching Size.

Flow is not integer necessarily....

Augmenting path algorithm gives integer flow.

Maximum Matching Problem.

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Given a bipartite graph, $G = (U, V, E)$, find a maximum sized matching.

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Key Idea: Augmenting Alternating Paths.

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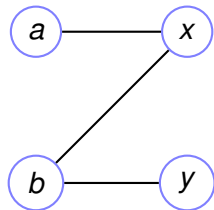
Example:

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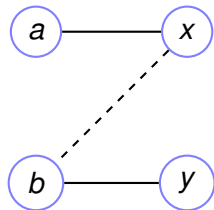


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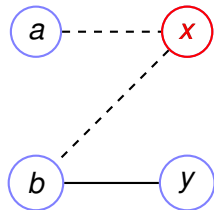


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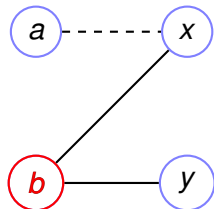


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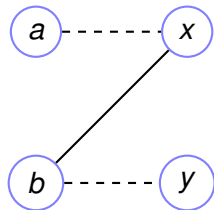
Start at unmatched node(s),
follow unmatched edge(s),
follow matched.
Repeat until an unmatched node.

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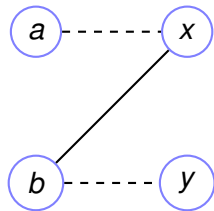


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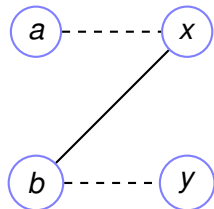
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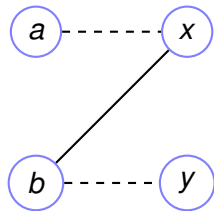
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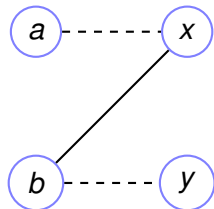
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Example:



Start at unmatched node(s),
follow unmatched edge(s),
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Repeat until an unmatched node.

No perfect matching

Algorithm:

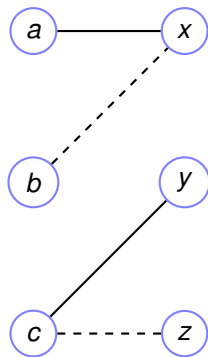
Given matching.

Direct unmatched edges U to V , matched V to U .

Find path between unmatched nodes on left to right. (BFS, DFS).

Until everything matched ... or output a cut.

No perfect matching



Can't increase matching size.
No alternating path from (a) to (y) .

Algorithm:

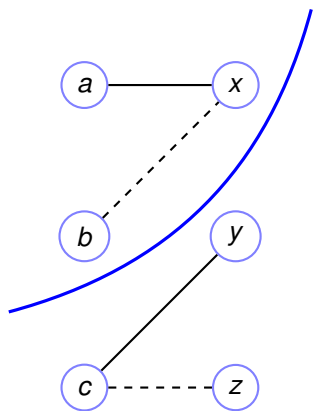
Given matching.

Direct unmatched edges U to V , matched V to U .

Find path between unmatched nodes on left to right. (BFS, DFS).

Until everything matched ... or output a cut.

No perfect matching



Can't increase matching size.

No alternating path from (a) to (y) .

Cut!

Algorithm:

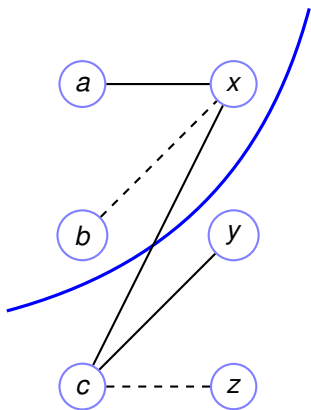
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No perfect matching



Can't increase matching size.

No alternating path from (a) to (y) .

Cut!

Still no augmenting path.

Still Cut?

Algorithm:

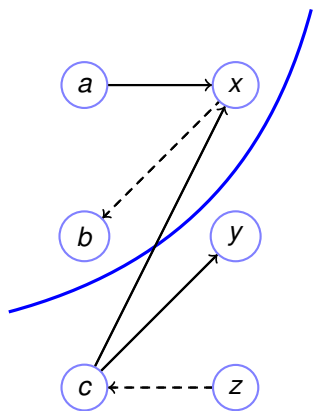
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Cut!

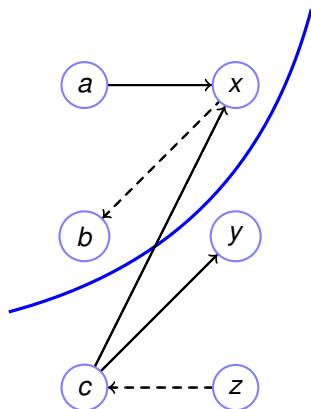
Still no augmenting path.

Still Cut?

Use directed graph!

Cut in this graph.

No perfect matching



Algorithm:

Can't increase matching size.

No alternating path from (a) to (y).

Cut!

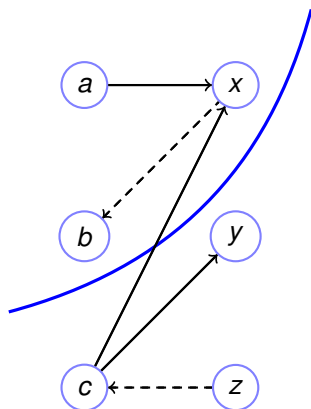
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Algorithm:
Given matching.

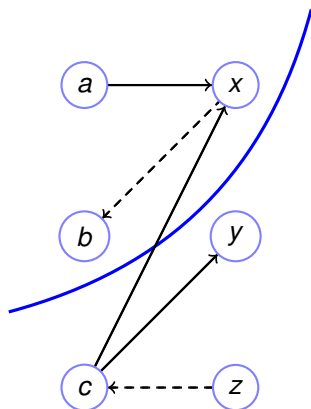
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Use directed graph!

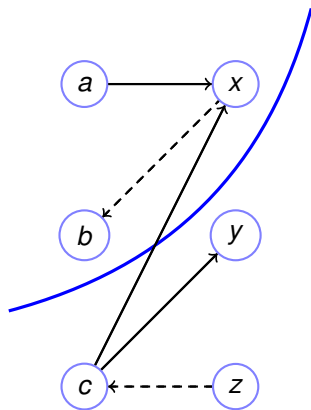
Cut in this graph.

Algorithm:

Given matching.

Direct unmatched edges U to V , matched V to U .

No perfect matching



Can't increase matching size.

No alternating path from (a) to (y).

Cut!

Still no augmenting path.

Still Cut?

Use directed graph!

Cut in this graph.

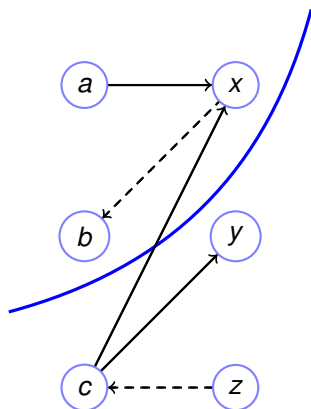
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Algorithm:

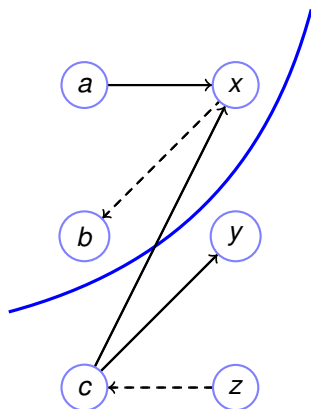
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Until everything matched ... or output a cut.

Simplex Algorithm

$$\max C \cdot X.$$

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$$Ax \leq b$$

$$x \geq 0$$

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Start at feasible point where n equations are satisfied.

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Another view: intersection of n hyperplanes.

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Another view: intersection of n hyperplanes.

Drop one equation:

Simplex Algorithm

$$\max C \cdot X.$$

$$Ax \leq b$$

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Start at feasible point where n equations are satisfied.

E.g., $x = 0$.

This is a point.

Another view: intersection of n hyperplanes.

Drop one equation:

Points on line satisfy $n - 1$ ind. equations.

Simplex Algorithm

$$\max C \cdot X.$$

$$Ax \leq b$$

$$x \geq 0$$

Start at feasible point where n equations are satisfied.

E.g., $x = 0$.

This is a point.

Another view: intersection of n hyperplanes.

Drop one equation:

Points on line satisfy $n - 1$ ind. equations.

Intersection of $n - 1$ hyperplanes.

Simplex Algorithm

$$\max C \cdot X.$$

$$Ax \leq b$$

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Another view: intersection of n hyperplanes.

Drop one equation:

Points on line satisfy $n - 1$ ind. equations.

Intersection of $n - 1$ hyperplanes.

Move in direction that increases objective.

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$$\max C \cdot X.$$

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Start at feasible point where n equations are satisfied.

E.g., $x = 0$.

This is a point.

Another view: intersection of n hyperplanes.

Drop one equation:

Points on line satisfy $n - 1$ ind. equations.

Intersection of $n - 1$ hyperplanes.

Move in direction that increases objective.

Until new tight constraint.

Simplex Algorithm

$$\max C \cdot X.$$

$$Ax \leq b$$

$$x \geq 0$$

Start at feasible point where n equations are satisfied.

E.g., $x = 0$.

This is a point.

Another view: intersection of n hyperplanes.

Drop one equation:

Points on line satisfy $n - 1$ ind. equations.

Intersection of $n - 1$ hyperplanes.

Move in direction that increases objective.

Until new tight constraint.

No direction increases objective.

Hyperplane View

$$x + y + z \leq 1$$

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

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On one side of hyperplane.

Normal to hyperplane?

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$$x + y + z \leq 1$$

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Normal to hyperplane? $(1, 1, 1)$.

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Why?

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

(a', b', c') where $a' + b' + c' = 1$.

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

(a', b', c') where $a' + b' + c' = 1$.

$(a + 1, b + 1, c + 1) - (a, b, c) = (1, 1, 1)$.

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

(a', b', c') where $a' + b' + c' = 1$.

$(a + 1, b + 1, c + 1) - (a, b, c) = (1, 1, 1)$.

$(a' - a, b' - b, c' - c) \cdot (1, 1, 1) = (a' + b' + c' - (a + b + c)) = 0$.

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

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Normal to $mx + ny + pz = C$?

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

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Normal to $mx + ny + pz = C$? (m, n, p)

Hyperplane View

$$x + y + z \leq 1$$

On one side of hyperplane.

Normal to hyperplane? $(1, 1, 1)$.

Why?

(a, b, c) where $a + b + c = 1$.

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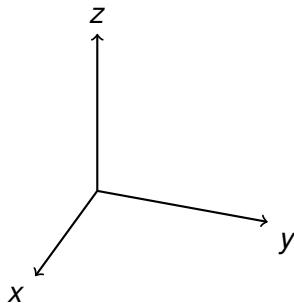
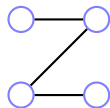
$(a + 1, b + 1, c + 1) - (a, b, c) = (1, 1, 1)$.

$(a' - a, b' - b, c' - c) \cdot (1, 1, 1) = (a' + b' + c' - (a + b + c)) = 0$.

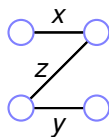
Normal to $mx + ny + pz = C$? (m, n, p)

Points in hyperplane are related by nullspace of row.

Maximum matching and simplex.



Maximum matching and simplex.



$$\max x + y + z$$

$$x \leq 1$$

$$x + z \leq 1$$

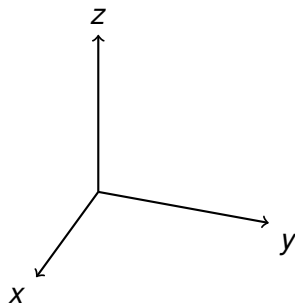
$$z + y \leq 1$$

$$y \leq 1$$

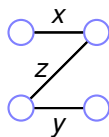
$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Maximum matching and simplex.



$$\max x + y + z$$

$$x \leq 1$$

$$x + z \leq 1$$

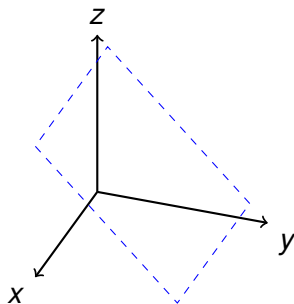
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

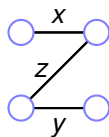
$$y \geq 0$$

$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.



$$\max x + y + z$$

$$x \leq 1$$

$$x + z \leq 1$$

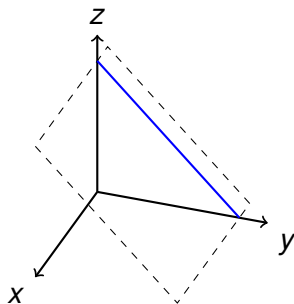
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

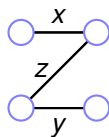
$$y \geq 0$$

$$z \geq 0$$



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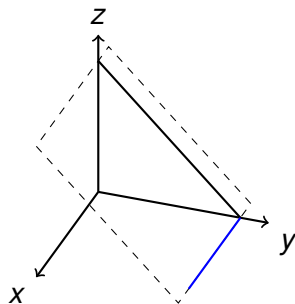
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

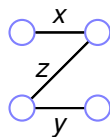
$$y \geq 0$$

$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.



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$$x + z \leq 1$$

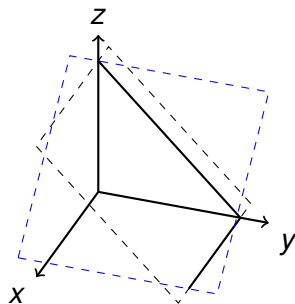
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

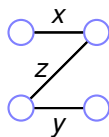
$$y \geq 0$$

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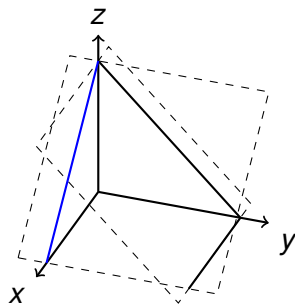
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.

$$\max x + y + z$$

$$x \leq 1$$

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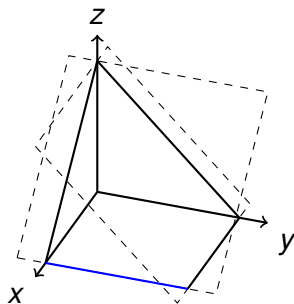
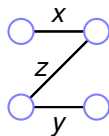
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

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$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.

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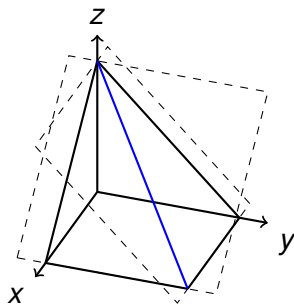
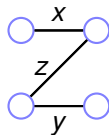
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

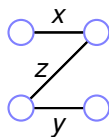
$$y \geq 0$$

$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.



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$$x \leq 1$$

$$x + z \leq 1$$

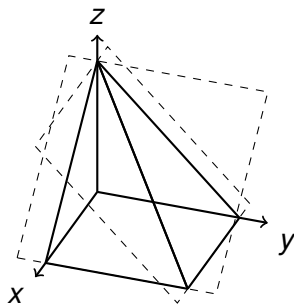
$$z + y \leq 1$$

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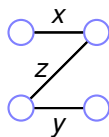
$$y \geq 0$$

$$z \geq 0$$



Blue constraints intersect.

Maximum matching and simplex.



$$\max x + y + z$$

$$x \leq 1$$

$$x + z \leq 1$$

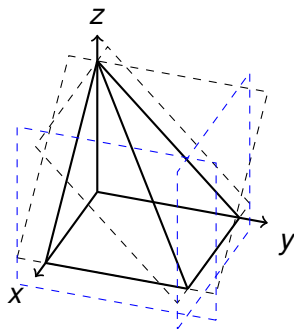
$$z + y \leq 1$$

$$y \leq 1$$

$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints redundant.

Maximum matching and simplex.

$$\max x + y + z$$

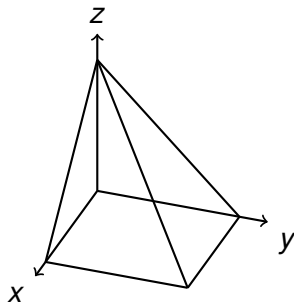
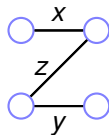
$$x + z \leq 1$$

$$z + y \leq 1$$

$$x \geq 0$$

$$y \geq 0$$

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Maximum matching and simplex.

$$\max x + y + z$$

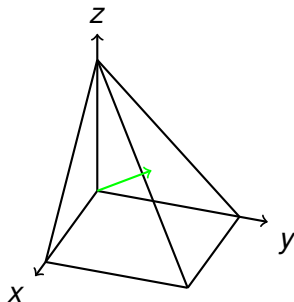
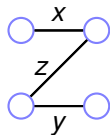
$$x + z \leq 1$$

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$$x \geq 0$$

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Maximum matching and simplex.

$$\max x + y + z$$

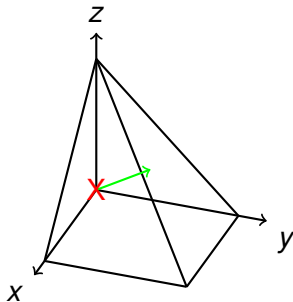
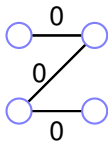
$$x + z \leq 1$$

$$z + y \leq 1$$

$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints tight.

Maximum matching and simplex.

$$\max x + y + z$$

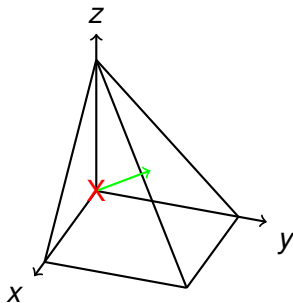
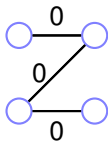
$$x + z \leq 1$$

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Blue constraints tight.

Maximum matching and simplex.

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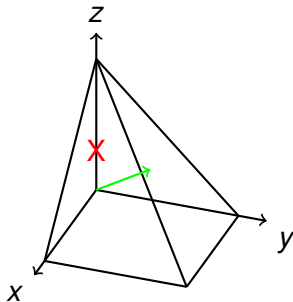
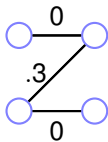
$$x + z \leq 1$$

$$z + y \leq 1$$

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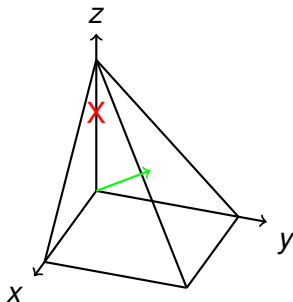
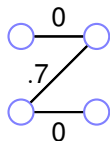
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$$z + y \leq 1$$

$$x \geq 0$$

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Maximum matching and simplex.

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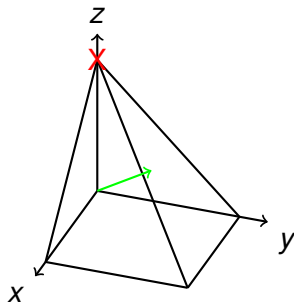
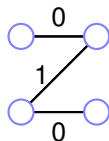
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Maximum matching and simplex.

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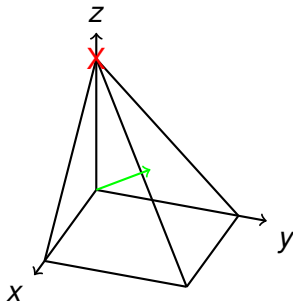
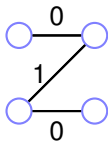
$$x + z \leq 1$$

$$z + y \leq 1$$

$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints tight.

Maximum matching and simplex.

$$\max x + y + z$$

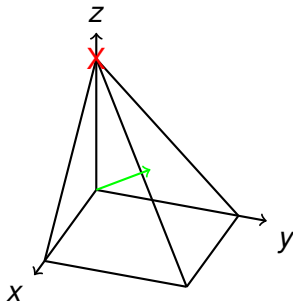
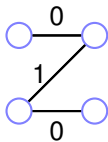
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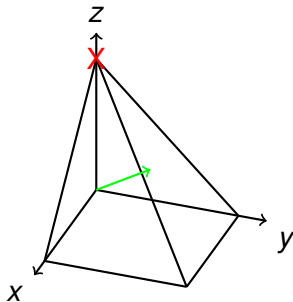
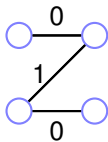
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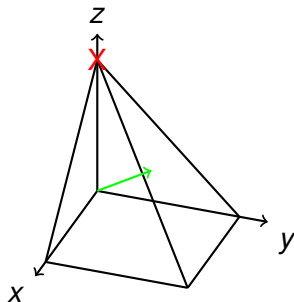
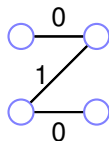
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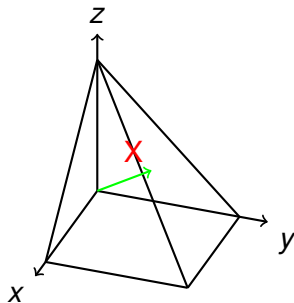
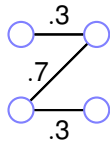
$$x + z \leq 1$$

$$z + y \leq 1$$

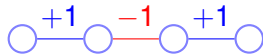
$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints tight.



Augmenting Path.

Maximum matching and simplex.

$$\max x + y + z$$

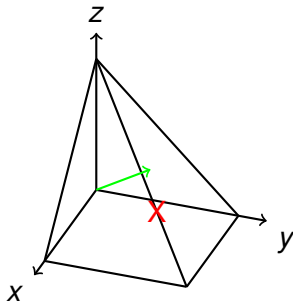
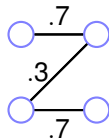
$$x + z \leq 1$$

$$z + y \leq 1$$

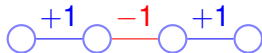
$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0$$



Blue constraints tight.



Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

$$\max x + y + z$$

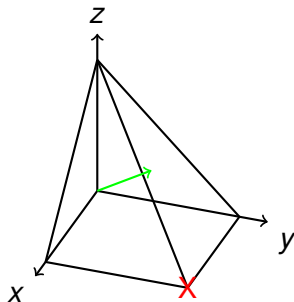
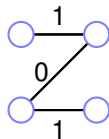
$$x + z \leq 1$$

$$z + y \leq 1$$

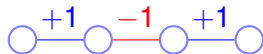
$$x \geq 0$$

$$y \geq 0$$

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Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

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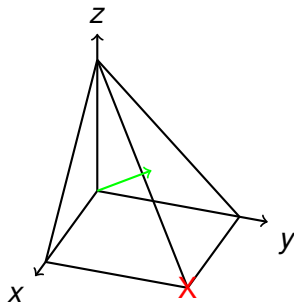
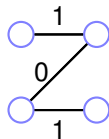
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$$z + y \leq 1$$

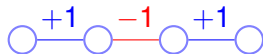
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Augmenting Path. Via Gaussian Elimination!

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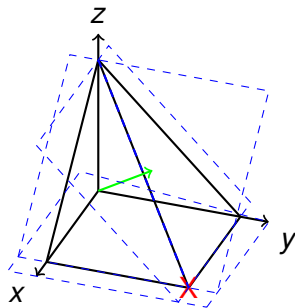
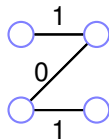
$$x + z \leq 1$$

$$z + y \leq 1$$

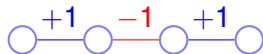
$$x \geq 0$$

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$$z \geq 0$$



Blue constraints tight.



Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

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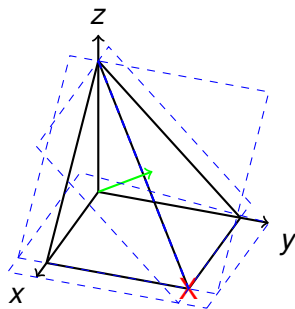
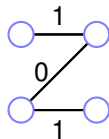
$$x + z \leq 1 \quad a$$

$$z + y \leq 1 \quad b$$

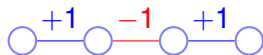
$$x \geq 0$$

$$y \geq 0$$

$$z \geq 0 \quad c$$



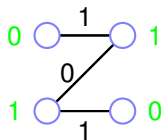
Blue constraints tight.



Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

$$\max x + y + z$$



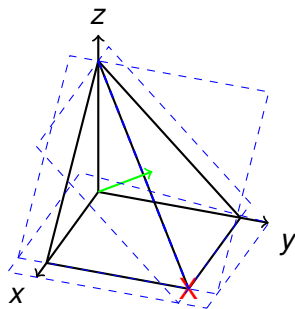
$$x + z \leq 1 \quad a = 1$$

$$z + y \leq 1 \quad b = 1$$

$$x \geq 0$$

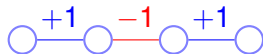
$$y \geq 0$$

$$z \geq 0 \quad c = 1$$



Blue constraints tight.

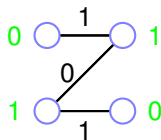
$$\text{Sum: } x + z + y.$$



Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

$$\max x + y + z$$



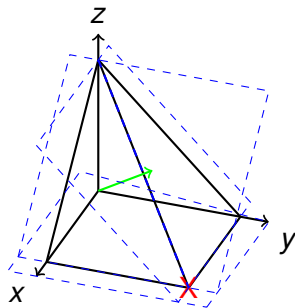
$$x + z \leq 1 \quad a = 1$$

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$$x \geq 0$$

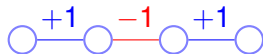
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Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

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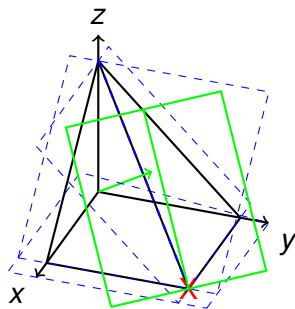
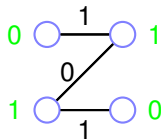
$$x + z \leq 1 \quad a = 1$$

$$z + y \leq 1 \quad b = 1$$

$$x \geq 0$$

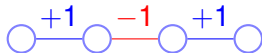
$$y \geq 0$$

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Blue constraints tight.

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Augmenting Path. Via Gaussian Elimination!

Maximum matching and simplex.

$$\max x + y + z$$

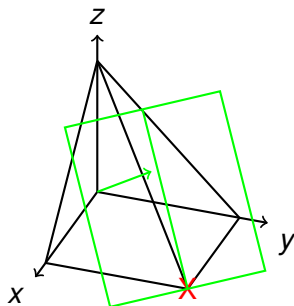
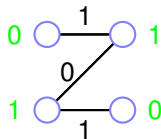
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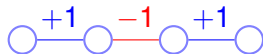
$$y \geq 0$$

$$z \geq 0 \quad c = 1$$



Blue constraints tight.

$$\text{Sum: } x + z + y.$$



Augmenting Path. Via Gaussian Elimination!

Lecture in a minute

Maximum flow.

“Greedy” augment path...

Except reverse old decisions ..

Reverse residual capacities.

: Optimality?

No augmenting path \implies

$s - t$ cut size = flow value.

Find flow and $s - t$ cut with equal value!

Lecture in a minute

Maximum flow.

- “Greedy” augment path...

 - Except reverse old decisions ..

 - Reverse residual capacities.

- : Optimality?

 - No augmenting path \implies

 - $s - t$ cut size = flow value.

 - Find flow and $s - t$ cut with equal value!

Maximum Matching.

- $G = (V, E)$, find subset of one-to-one matches.

- Reduction to max flow.

- Augmenting Alternating Path

- Algorithm \equiv Simplex.