Applications of Network Flows

Lecture 19

April 2, 2015

19.1: Important Properties of Flows

Network flow, what we know...

1. G: Network flow with n vertices and m edges.
2. **algFordFulkerson** computes max-flow if capacities are integers.
3. If total capacity is C, running time of **algFordFulkerson** is $O(mC)$.
4. **algFordFulkerson** is not polynomial time.
5. **algFordFulkerson** might not terminate if capacities are real numbers.
6. ...see end of the slides in previous lectures for detailed example.

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Part I

Edmonds-Karp algorithm

Edmonds-Karp algorithm

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algEdmondsKarp
    for every edge e, f(e) = 0
    G_f is residual graph of G with respect to f
    while G_f has a simple s-t path do
        Perform BFS in G_f
        P: shortest s-t path in G_f
        f = augment(f, P)
        Construct new residual graph G_f.
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Theorem

Given a network flow G with n vertices and m edges, and capacities that are real numbers, the algorithm **algEdmondsKarp** *computes the maximum flow in G.*
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19.2: Computing a minimum cut...

Finding a Minimum Cut

1. Question: How do we find an actual minimum s-t cut?
2. Proof gives the algorithm!
   1. Compute an s-t maximum flow f in G
   2. Obtain the residual graph G_f
   3. Find the nodes A reachable from s in G_f
   4. Output the cut $(A, B) = \{(u, v) \mid u \in A, v \in B\}$. Note: The cut is found in G while A is found in G_f
3. Running time is essentially the same as finding a maximum flow.
4. Note: Given G and a flow f there is a linear time algorithm to check if f is a maximum flow and if it is, outputs a minimum cut. How?

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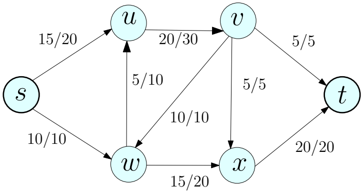

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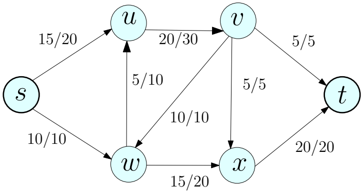

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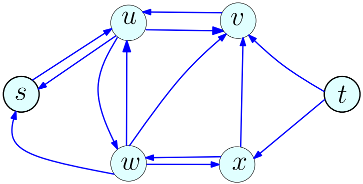

Residual network

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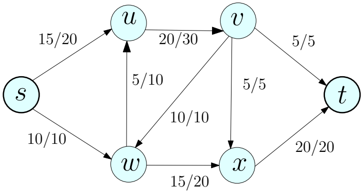

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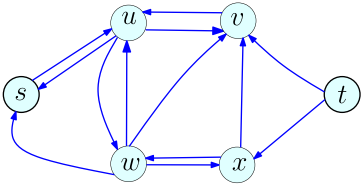

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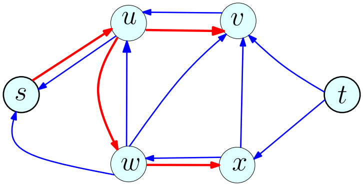
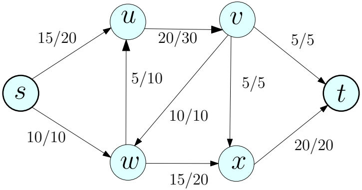


Reachable vertices from *s*

Min cut from max-flow



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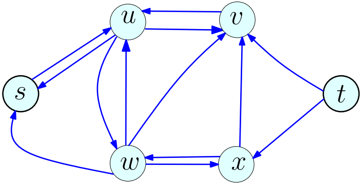

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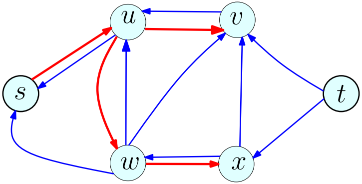

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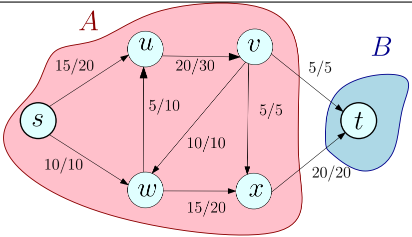

Resulting min-cut **(A, B)**

Network Flow: Facts to Remember

Flow network: directed graph G, capacities c, source s, sink t.

1. Maximum s-t flow can be computed:
    1. Using Ford-Fulkerson algorithm in $O(mC)$ time when capacities are integral and C is an upper bound on the flow.
    2. Using variant of algorithm, in $O(m^2 \log C)$ time, when capacities are integral. (Polynomial time.)
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Even more facts to remember

1. If capacities are integral then there is a maximum flow that is integral and above algorithms give an integral max flow. This is known as **integrality of flow**.
2. Given a flow of value v, can decompose into $O(m+n)$ flow paths of same total value v. Integral flow implies integral flow on paths.
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Paths, Cycles and Acyclicity of Flows

Definition

Given a flow network $G = (V, E)$ and a flow $f : E \to \mathbb{R}^{\geq 0}$ on the edges, the **support** of f is the set of edges $E' \subseteq E$ with non-zero flow on them. That is, $E' = \{e \in E \mid f(e) > 0\}$.

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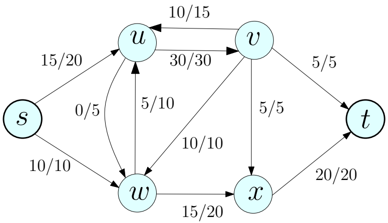

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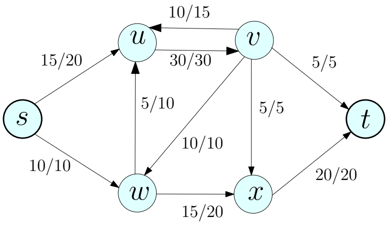

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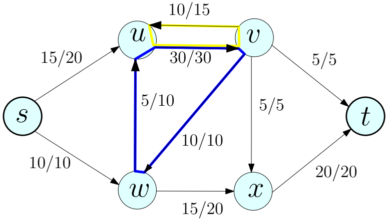

Acyclicity of Flows

Proposition

In any flow network, if f is a flow then there is another flow f' such that the support of f' is an acyclic *graph and $v(f') = v(f)$. Further if f is an integral flow then so is f'.*

Proof.

1. $E' = \{e \in E \mid f(e) > 0\}$, support of f.
2. Suppose there is a directed cycle C in E'
3. Let e' be the edge in C with least amount of flow
4. For each $e \in C$, reduce flow by $f(e')$. Remains a flow. Why?
5. Flow on e' is reduced to 0.
6. Claim: Flow value from s to t does not change. Why?
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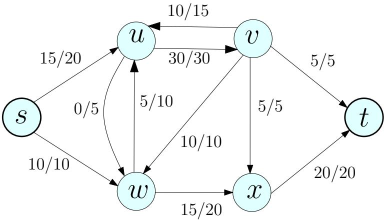
Example



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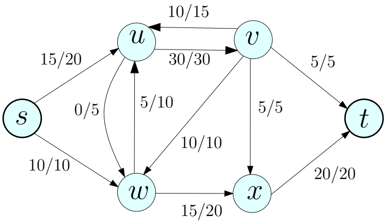
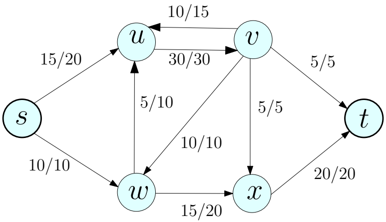
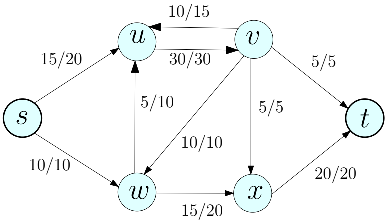
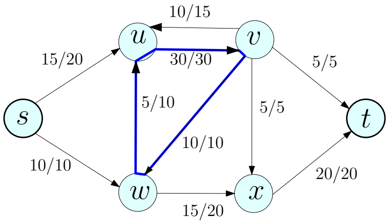




Throw away edge with no flow on it

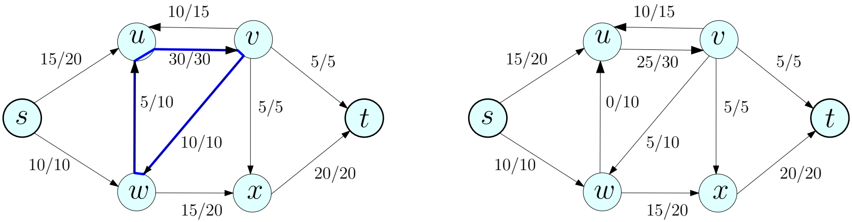
Example





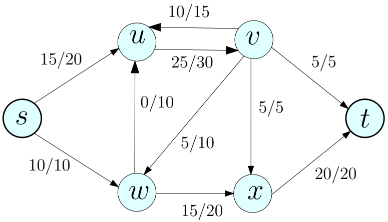
Find a cycle in the support/flow

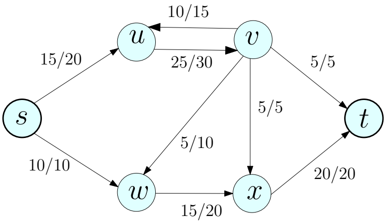
Example



Reduce flow on cycle as much as possible

Example





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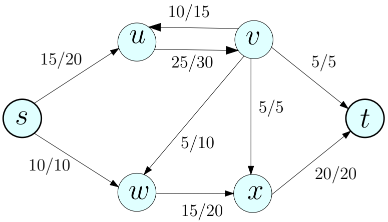
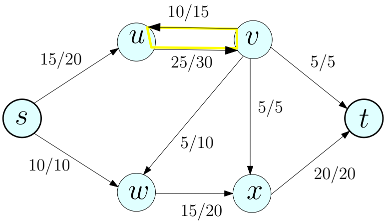
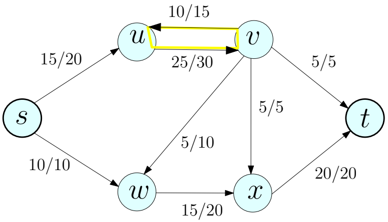
Example





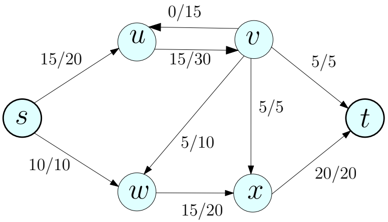
Find a cycle in the support/flow

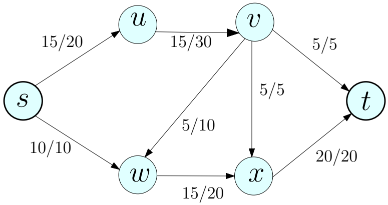
Example



Reduce flow on cycle as much as possible

Example





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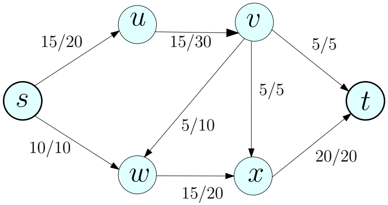
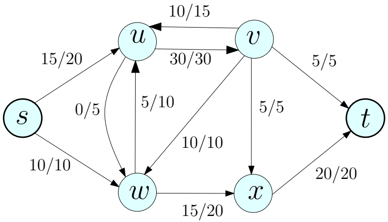


Viola!!! An equivalent flow with no cycles in it. Original flow:



Flow Decomposition

Lemma

Given an edge based flow $f : E \to \mathbb{R}^{\geq 0}$, *there exists a collection of paths* $\mathcal{P}$ *and cycles* $\mathcal{C}$ *and an assignment of flow to them* $f' : \mathcal{P} \cup \mathcal{C} \to \mathbb{R}^{\geq 0}$ *such that:*

1. $|\mathcal{P} \cup \mathcal{C}| \leq m$
2. *for each* $e \in E$, $\sum_{P \in \mathcal{P}: e \in P} f'(P) + \sum_{C \in \mathcal{C}: e \in C} f'(C) = f(e)$
3. $v(f) = \sum_{P \in \mathcal{P}} f'(P)$.
4. *if* f *is integral then so are* $f'(P)$ *and* $f'(C)$ *for all* P *and* C

Proof Idea.

1. Remove all cycles as in previous proposition.
2. Next, decompose into paths as in previous lecture.
3. Exercise: verify claims.

□

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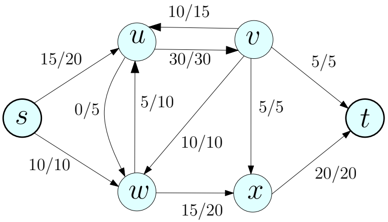
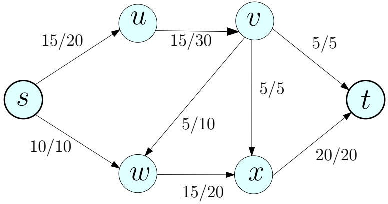
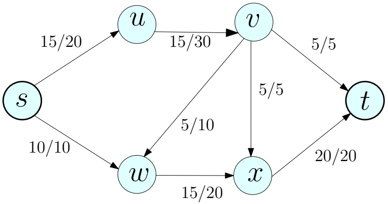
Example

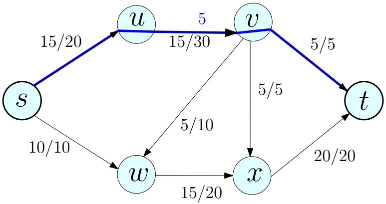




Find cycles as shown before

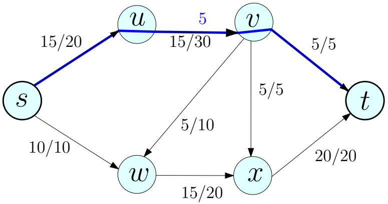
Example

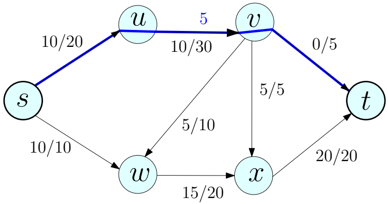




Find a source to sink path, and push max flow along it (5 unites)

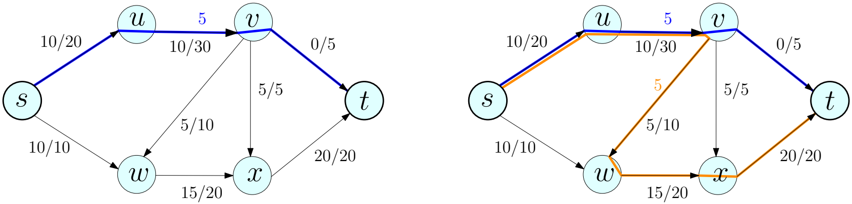
Example





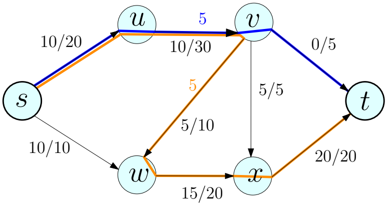
Compute remaining flow

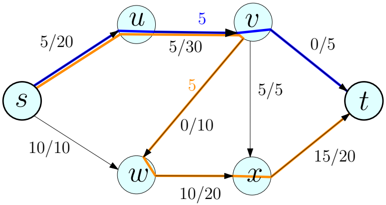
Example



Find a source to sink path, and push max flow along it (5 unites). Edges with **0** flow on them can not be used as they are no longer in the support of the flow.

Example





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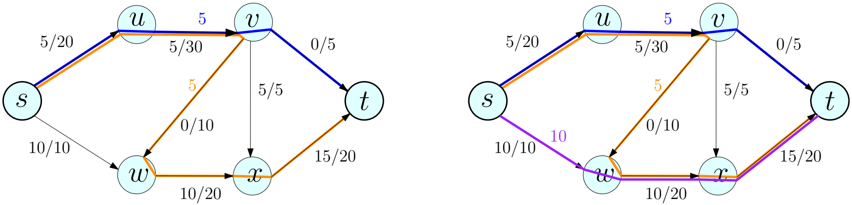
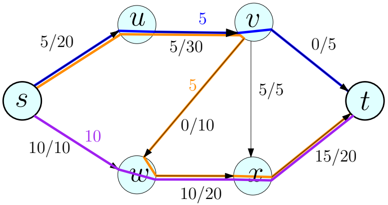
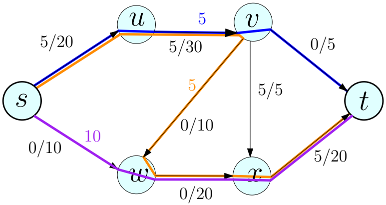


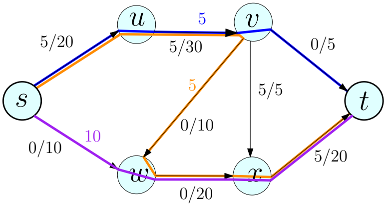
Find a source to sink path, and push max flow along it (10 unites).

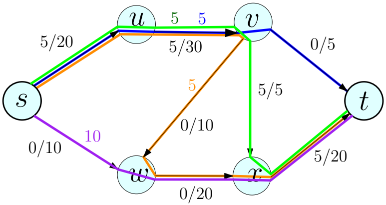
Example





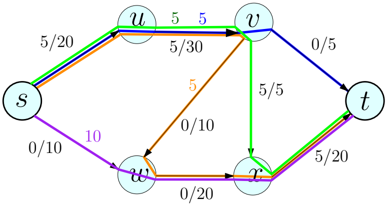
Compute remaining flow

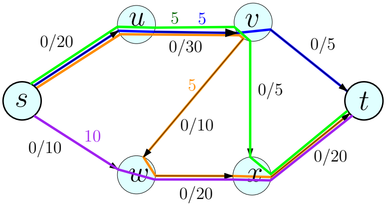




Find a source to sink path, and push max flow along it (5 unites).

Example





Compute remaining flow

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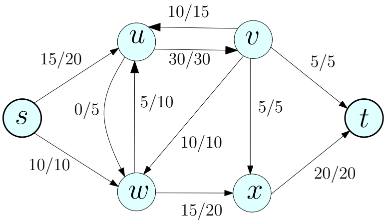

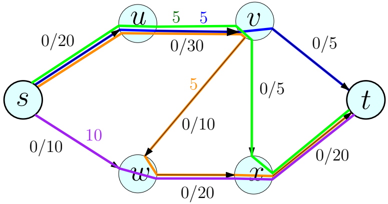

No flow remains in the graph. We fully decomposed the flow into flow on paths. Together with the cycles, we get a decomposition of the original flow into ***m*** flows on paths and cycles.

Flow Decomposition

Lemma

Given an edge based flow $f : E \rightarrow \mathbb{R}^{\geq 0}$, *there exists a collection of paths* $\mathcal{P}$ *and cycles* $\mathcal{C}$ *and an assignment of flow to them* $f' : \mathcal{P} \cup \mathcal{C} \rightarrow \mathbb{R}^{\geq 0}$ *such that:*

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Above flow decomposition can be computed in $O(m^2)$ *time.*

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Part II

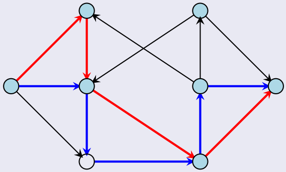
Network Flow Applications I

19.3: Edge Disjoint Paths

19.3.1: Directed Graphs

Edge-Disjoint Paths in Directed Graphs

Definition



A set of paths is **edge disjoint** if no two paths share an edge.

Problem

Given a directed graph with two special vertices s and t, find the *maximum* number of edge disjoint paths from s to t.

Applications: Fault tolerance in routing — edges/nodes in networks can fail. Disjoint paths allow for planning backup routes in case of failures.

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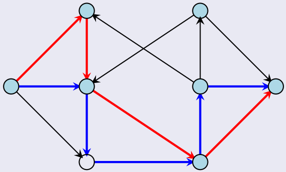

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19.3.2: Reduction to Max-Flow

Reduction to Max-Flow

Problem

Given a directed graph G with two special vertices s and t, find the maximum number of edge disjoint paths from s to t.

Reduction

Consider G as a flow network with edge capacities 1, and compute max-flow.

Correctness of Reduction

Lemma

If G has k edge disjoint paths $P_1, P_2, \ldots, P_k$ then there is an s-t flow of value k in G.

Proof.

Set $f(e) = 1$ if e belongs to one of the paths $P_1, P_2, \ldots, P_k$; other-wise set $f(e) = 0$. This defines a flow of value k. □

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Proof.

1. Capacities are all 1 and hence there is integer flow of value k, that is $f(e) = 0$ or $f(e) = 1$ for each e.
2. Decompose flow into paths.
3. Flow on each path is either 1 or 0.
4. Hence there are k paths $P_1, P_2, \ldots, P_k$ with flow of 1 each.
5. Paths are edge-disjoint since capacities are 1. □

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2. Decompose flow into paths.
3. Flow on each path is either 1 or 0.
4. Hence there are k paths $P_1, P_2, \ldots, P_k$ with flow of 1 each.
5. Paths are edge-disjoint since capacities are 1. □

Correctness of Reduction

Lemma

If G has a flow of value k then there are k edge disjoint paths between s and t.

Proof.

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Running Time

Theorem

The number of edge disjoint paths in G can be found in $O(mn)$ time.

Proof.

1. Set capacities of edges in G to 1.
2. Run Ford-Fulkerson algorithm.
3. Maximum value of flow is n and hence run-time is $O(nm)$.
4. Decompose flow into k paths ($k \leq n$).
   Takes $O(k \times m) = O(km) = O(mn)$ time. □

Remark

Algorithm computes set of edge-disjoint paths realizing opt. solution.

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19.3.3: Menger's Theorem

Menger's Theorem

Theorem (Menger [1927])

Let G be a directed graph. The minimum number of edges whose removal disconnects s from t (the minimum-cut between s and t) is equal to the maximum number of edge-disjoint paths in G between s and t.

Proof.

Maxflow-mincut theorem and integrality of flow. □

Menger proved his theorem before Maxflow-Mincut theorem!
Maxflow-Mincut theorem is a generalization of Menger's theorem to capacitated graphs.

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19.3.4: Undirected Graphs

Edge Disjoint Paths in Undirected Graphs

1. The problem:

Problem

Given an undirected graph G, find the maximum number of edge disjoint paths in G

2. Reduction:
   1. create directed graph H by adding directed edges (u, v) and (v, u) for each edge uv in G.
   2. compute maximum s-t flow in H.
3. Problem: Both edges (u, v) and (v, u) may have non-zero flow!
4. Not a Problem! Can assume maximum flow in H is acyclic and hence cannot have non-zero flow on both (u, v) and (v, u). Reduction works. See book for more details.

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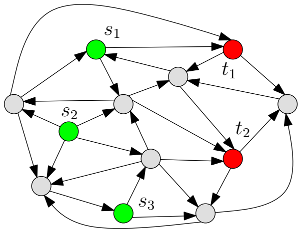
19.4: Multiple Sources and Sinks

Multiple Sources and Sinks

1. Input:
   1. A directed graph G with edge capacities $c(e)$.
   2. Source nodes $s_1, s_2, \ldots, s_k$.
   3. Sink nodes $t_1, t_2, \ldots, t_\ell$.
   4. Sources and sinks are *disjoint*.



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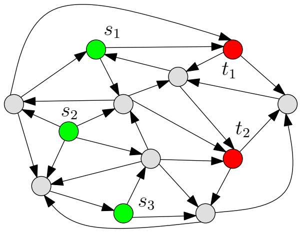

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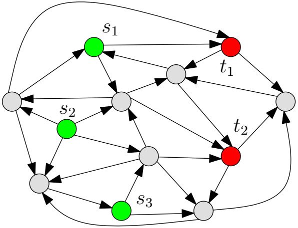

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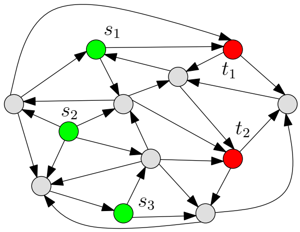

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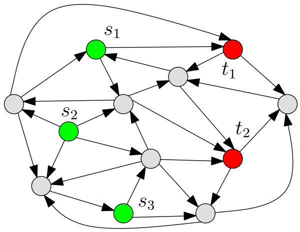

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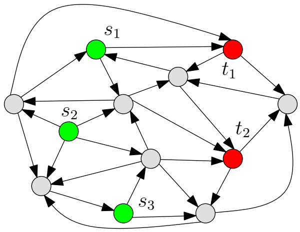

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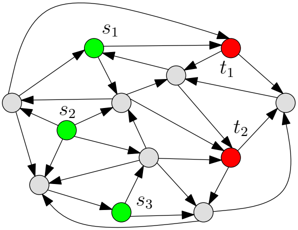

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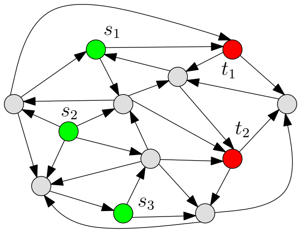

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2. A function $f : E \to \mathbb{R}^{\geq 0}$ is a **flow** if:
   1. For each $e \in E$, $f(e) \leq c(e)$, and
   2. for each v which is not a source or a sink $f^{\text{in}}(v) = f^{\text{out}}(v)$.
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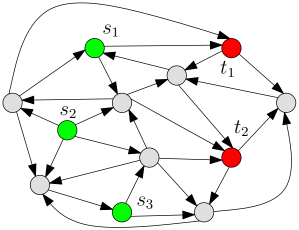
1. Add a **source** node s and a **sink** node t.
2. Add edges $(s, s_1), (s, s_2), \ldots, (s, s_k)$.
3. Add edges $(t_1, t), (t_2, t), \ldots, (t_\ell, t)$.
4. Set the capacity of the new edges to be ∞.



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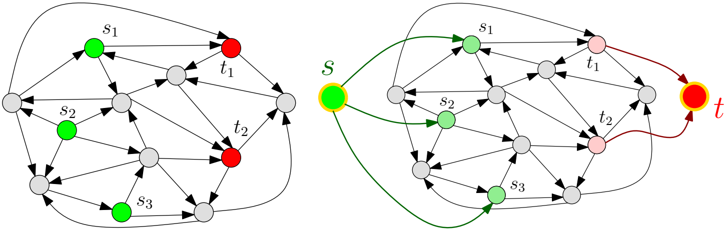

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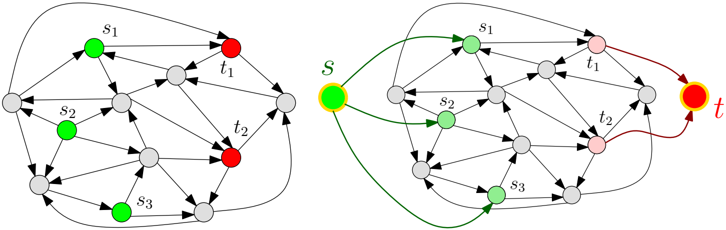

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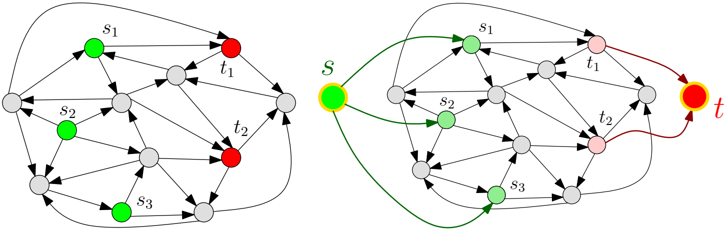
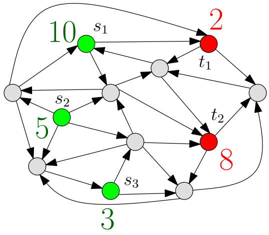


Supplies and Demands

1. A further generalization:
   1. source s_i has a supply of $S_i \geq 0$
   2. since t_j has a demand of $D_j \geq 0$ units
2. Question: is there a flow from source to sinks such that supplies are not exceeded and demands are met?
3. Formally: additional constraints that $f^{\text{out}}(s_i) - f^{\text{in}}(s_i) \leq S_i$ for each source s_i and $f^{\text{in}}(t_j) - f^{\text{out}}(t_j) \geq D_j$ for each sink t_j.



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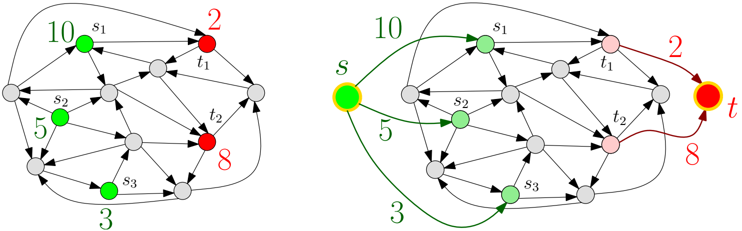

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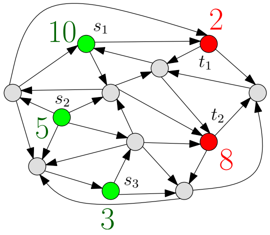

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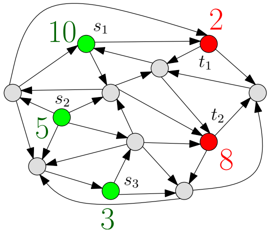

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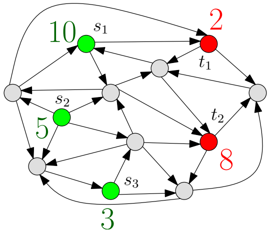


19.5: Bipartite Matching

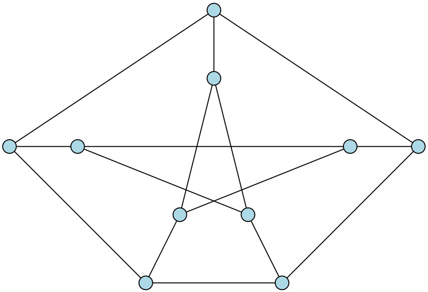
19.5.1: Definitions

Matching

Problem (Matching)

Input: *Given a (undirected) graph* $G = (V, E)$.
Goal: *Find a matching of maximum cardinality.*

1. *A matching is* $M \subseteq E$ *such that at most one edge in* M *is incident on any vertex*



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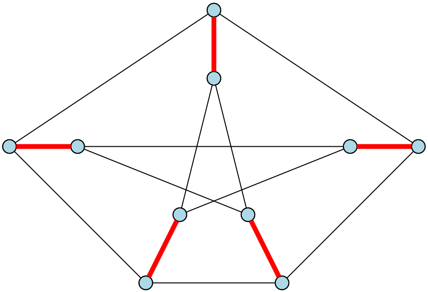

Bipartite Matching

Problem (Bipartite matching)

Input: *Given a bipartite graph* $G = (L \cup R, E)$.
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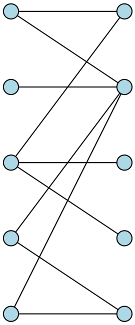

Maximum matching has 4 edges

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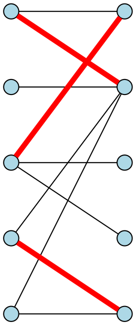

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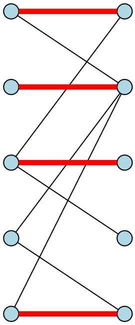

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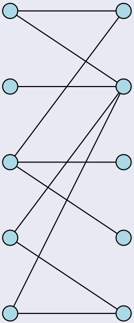
19.5.2: Reduction of bipartite matching to max-flow

Reduction of bipartite matching to max-flow

Max-Flow Construction

Given graph $G = (L \cup R, E)$ create flow-network $G' = (V', E')$ as follows:



1. $V' = L \cup R \cup \{s, t\}$ where s and t are the new source and sink.
2. Direct all edges in E from L to R, and add edges from s to all vertices in L and from each vertex in R to t.
3. Capacity of every edge is 1.

Reduction of bipartite matching to max-flow

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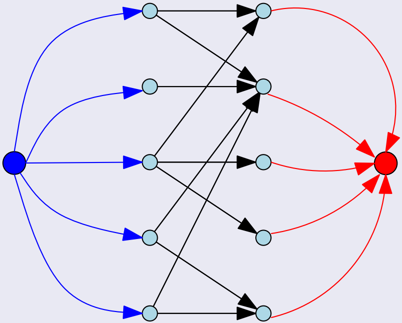

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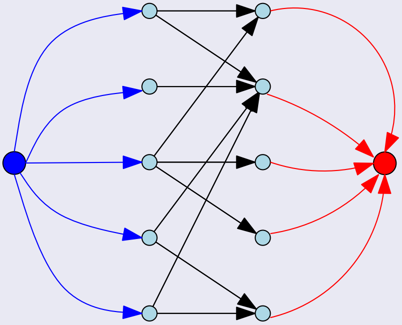

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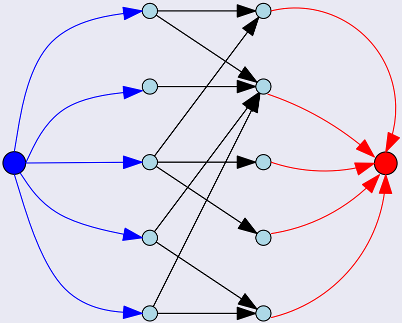

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3. Capacity of every edge is 1.

Correctness: Matching to Flow

Proposition

If G has a matching of size k then G' has a flow of value k.

Proof.

Let M be matching of size k. Let $M = \{(u_1, v_1), \ldots, (u_k, v_k)\}$.
Consider following flow f in G':

1. $f(s, u_i) = 1$ and $f(v_i, t) = 1$ for $1 \leq i \leq k$
2. $f(u_i, v_i) = 1$ for $1 \leq i \leq k$
3. for all other edges flow is zero.

Verify that f is a flow of value k (because M is a matching). □

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Correctness: Flow to Matching

Proposition

If G' has a flow of value k then G has a matching of size k.

Proof.

Consider flow f of value k.

1. Can assume f is integral. Thus each edge has flow $\mathbf{1}$ or $\mathbf{0}$.
2. Consider the set M of edges from L to R that have flow 1.
    1. M has k edges because value of flow is equal to the number of non-zero flow edges crossing cut $(L \cup \{s\}, R \cup \{t\})$
    2. Each vertex has at most one edge in M incident upon it. Why?

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□

Correctness of Reduction

Theorem

The maximum flow value in G' = maximum cardinality of matching in G.

Consequence

Thus, to find maximum cardinality matching in G, we construct G' and find the maximum flow in G'. Note that the matching itself (not just the value) can be found efficiently from the flow.

Running Time

For graph G with n vertices and m edges G' has $O(n + m)$ edges, and $O(n)$ vertices.

1. Generic Ford-Fulkerson: Running time is $O(mC) = O(nm)$ since $C = n$.
2. Capacity scaling: Running time is $O(m^2 \log C) = O(m^2 \log n)$.

Better running time is known: $O(m\sqrt{n})$.

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19.5.3: Perfect Matchings

Perfect Matchings

Definition

A matching M is **perfect** if every vertex has one edge in M incident upon it.

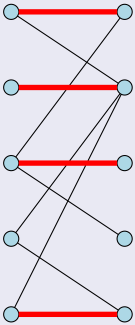

Figure: This graph does not have a perfect matching

Characterizing Perfect Matchings

Problem

When does a bipartite graph have a perfect matching?

1. Clearly $|L| = |R|$
2. Are there any necessary and sufficient conditions?

A Necessary Condition

Lemma

If $G = (L \cup R, E)$ *has a perfect matching then for any* $X \subseteq L$, $|N(X)| \geq |X|$, *where* $N(X)$ *is the set of neighbors of vertices in* X.

Proof.

Since G has a perfect matching, every vertex of X is matched to a different neighbor, and so $|N(X)| \geq |X|$. □

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Hall's Theorem

1. Frobenius-Hall theorem:

Theorem

Let $G = (L \cup R, E)$ be a bipartite graph with $|L| = |R|$. G has a perfect matching if and only if for every $X \subseteq L$, $|N(X)| \geq |X|$.

2. One direction is the necessary condition.
3. For the other direction we will show the following:
   1. Create flow network G' from G.
   2. If $|N(X)| \geq |X|$ for all X, show that minimum s-t cut in G' is of capacity $n = |L| = |R|$.
   3. Implies that G has a perfect matching.

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Proof of Sufficiency

1. Assume $|N(X)| \geq |X|$ for any $X \subseteq L$. Then show that min s-t cut in G' is of capacity at least n.
2. Let (A, B) be an *arbitrary* s-t cut in G'
    1. Let $X = A \cap L$ and $Y = A \cap R$.
    2. Cut capacity is at least $(|L| - |X|) + |Y| + |N(X) \setminus Y|$

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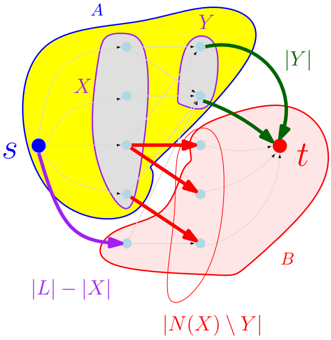

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1. $|L| - |X|$ edges from s to $L \cap B$.
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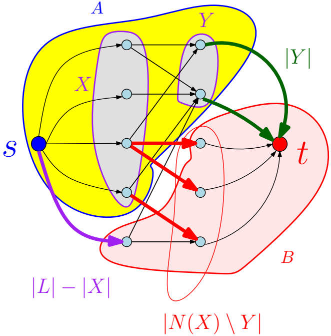

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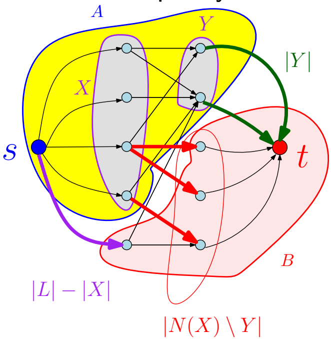

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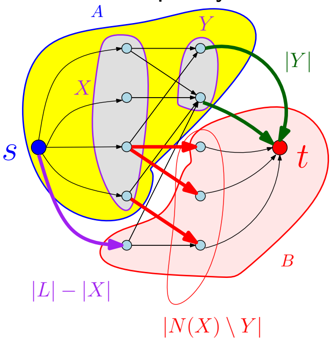

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3. there are at least $|N(X) \setminus Y|$ edges from X to vertices on the right side that are not in Y.

Proof of Sufficiency

Continued...

1. By the above, cut capacity is at least
$$\alpha = (|L| - |X|) + |Y| + |N(X) \setminus Y|.$$
2. $|N(X) \setminus Y| \geq |N(X)| - |Y|$.
(This holds for any two sets.)
3. By assumption $|N(X)| \geq |X|$ and hence
$$|N(X) \setminus Y| \geq |N(X)| - |Y| \geq |X| - |Y|.$$
4. Cut capacity is therefore at least
$$\begin{aligned}\alpha &= (|L| - |X|) + |Y| + |N(X) \setminus Y| \\ &\geq |L| - |X| + |Y| + |X| - |Y| \geq |L| = n.\end{aligned}$$
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Hall's Theorem: Generalization

Theorem (Frobenius-Hall)

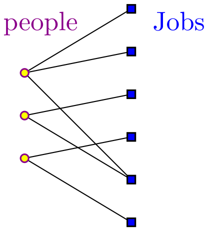
Let $G = (L \cup R, E)$ *be a bipartite graph with* $|L| \leq |R|$. G *has a matching that matches all nodes in* L *if and only if for every* $X \subseteq L$, $|N(X)| \geq |X|$.

Proof is essentially the same as the previous one.

Problem: Assigning jobs to people

Problem:

1. n jobs or tasks
2. m people.
3. for each job a set of people who can do that job.
4. for each person j a limit on number of jobs k_j.
5. Goal: find an assignment of jobs to people so that all jobs are assigned and no person is overloaded.



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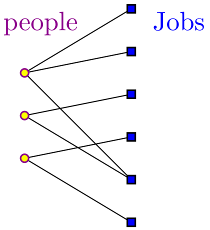

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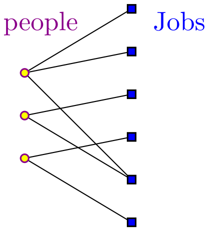

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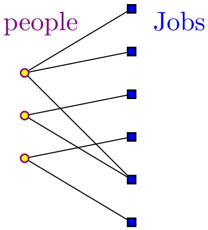

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Reduction to Maximum Flow

For assigning jobs to people

1. Create directed graph $G = (V, E)$ as follows
   1. $V = \{s, t\} \cup L \cup R$: L set of n jobs, R set of m people
   2. add edges (s, i) for each job $i \in L$, capacity 1
   3. add edges (j, t) for each person $j \in R$, capacity k_j
   4. if job i can be done by person j add an edge (i, j), capacity 1
2. Compute max s-t flow. There is an assignment if and only if flow value is n.

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1. Matchings in general graphs more complicated.
2. There is a polynomial time algorithm to compute a maximum matching in a general graph. Best known running time is $O(m\sqrt{n})$.

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K. Menger. Zur allgemeinen kruventheorie. *Fund. Math.*, 10:96–115, 1927.