# BBM402-Lecture 17: Applications of Network Flows 

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Resources for the presentation:
https://courses.engr.illinois.edu/cs473/fa2016/lectures.html

## Is the flow always integral?

Let G be an integral instance of network flow (i.e., all numbers are integers). Consider the following statements:
(I) The value of the maximum flow is an integer number.
(II) If $f$ is a maximum flow, then $f(e)$ is an integer, for any edge $e \in E(G)$.
(III) There always exists a max flow $\boldsymbol{g}$, such that $g$ is a maximum flow, and $g(e)$ is an integer, for any edge $e \in E(G)$.
We have the following:
(A) All the above statements are false.
(B) All the above statements are true.
(C) (I) is true, (II) and (III) are false.
(D) (I) and (II) are true, and (III) is false.
(E) (I) and (III) are true, and (II) is false.

## Why max-flow does not have to be integral...

.but the one we compute always is!

Consider the graph with all capacities being one.


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One possible max flow:


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but the one we compute always is!

Consider the graph with all capacities being one.


One possible max flow:


Max flow as computed by algEdmondsKarp or algFordFulkerson:


## Network Flow: Facts to Remember

Flow network: directed graph $\boldsymbol{G}$, capacities $\boldsymbol{c}$, source $\boldsymbol{s}$, sink $\boldsymbol{t}$.
(1) Maximum s-t flow can be computed:
(1) Using Ford-Fulkerson algorithm in $\mathbf{O}(\boldsymbol{m C})$ time when capacities are integral and $C$ is an upper bound on the flow.
(2) Using variant of algorithm, in $\boldsymbol{O}\left(\boldsymbol{m}^{2} \log C\right)$ time, when capacities are integral. (Polynomial time.)
(3) Using Edmonds-Karp algorithm, in $\boldsymbol{O}\left(\boldsymbol{m}^{2} \boldsymbol{n}\right)$ time, when capacities are rational (strongly polynomial time algorithm).
(1) There is an $\boldsymbol{O}(\mathbf{m n})$ time algorithm due to Orlin which is the currently fastest strongly polynomial-time algorithm.

## Network Flow

## 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 $\boldsymbol{v}$. Integral flow implies integral flow on paths.
(3) Maximum flow is equal to the minimum cut and minimum cut can be found in $O(m+n)$ time given any maximum flow.

## Paths, Cycles and Acyclicity of Flows

## Definition

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

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Question:Given a flow $\boldsymbol{f}$, can there by cycles in its support?


## How fast can we detect a cycle in the flow

Given a flow network $G$ with $\boldsymbol{n}$ vertices, and $\boldsymbol{m}$ edges, and a flow $\boldsymbol{f}$ on it, then detecting a cycle in the flow can be done in time
(A) $O(m+n)$.
(B) $O(m C)$.
(C) $O(m n)$.
(D) $O\left(m^{2} n\right)$.
(E) $O\left(m n^{2}\right)$.

## Acyclicity of Flows

## Proposition

In any flow network, if $f$ is a flow then there is another flow $f^{\prime}$ such that the support of $f^{\prime}$ is an acyclic graph and $v\left(f^{\prime}\right)=v(f)$. Further if $f$ is an integral flow then so is $f^{\prime}$.

## Proof.

(1) $E^{\prime}=\{e \in E \mid f(e)>0\}$, support of $f$.
(2) Suppose there is a directed cycle $C$ in $E^{\prime}$
(0) Let $e^{\prime}$ be the edge in $C$ with least amount of flow
(1) For each $e \in C$, reduce flow by $f\left(e^{\prime}\right)$. Remains a flow. Why?
(0) Flow on $\boldsymbol{e}^{\prime}$ is reduced to $\mathbf{0}$.
( Claim: Flow value from $s$ to $t$ does not change. Why?
( - Iterate until no cycles

## Example



## Example



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



Throw away edge with no flow on it

## Example



Find a cycle in the support/flow

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Reduce flow on cycle as much as possible

## Example



Throw away edge with no flow on it

## Example



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


## 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 $f^{\prime}: \mathcal{P} \cup \mathcal{C} \rightarrow \mathbb{R}^{\geq 0}$ such that:
(1) $|\mathcal{P} \cup \mathcal{C}| \leq m$
(2) for each $e \in E, \sum_{P \in \mathcal{P}: e \in P} f^{\prime}(P)+\sum_{c \in \mathcal{C}: e \in C} f^{\prime}(C)=f(e)$
(0) $v(f)=\sum_{P \in \mathcal{P}} f^{\prime}(P)$.
(0) if $f$ is integral then so are $f^{\prime}(P)$ and $f^{\prime}(C)$ for all $P$ and $C$

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- $v(f)=\sum_{P \in \mathcal{P}} f^{\prime}(P)$.
- if $f$ is integral then so are $f^{\prime}(P)$ and $f^{\prime}(C)$ 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.

## 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 $\mathbf{0}$ flow on them can not be used as they are no longer in the support of the flow.

## Example



Compute remaining flow

## Example



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

## Example



Compute remaining flow

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

## Example



Compute remaining flow

## Example



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 $\boldsymbol{m}$ flows on paths and cycles.

## Flow Decomposition

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(1) $|\mathcal{P} \cup \mathcal{C}| \leq m$
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( $v(f)=\sum_{P \in \mathcal{P}} f^{\prime}(P)$.
(1) if $f$ is integral then so are $f^{\prime}(P)$ and $f^{\prime}(C)$ for all $P$ and $C$.

Above flow decomposition can be computed in $O(m n)$ time.
Exercise: Naive implementation of flow-decomposition takes $O\left(m^{2}\right)$ time. Show how to implement in $O(m n)$ time.

## Flow decomposition into paths and cycles

Consider an integral flow network $G$, and two maximum flows $f$ and $\boldsymbol{g}$ in G. Assume both $\boldsymbol{f}$ and $\boldsymbol{g}$ are acyclic. Let $\boldsymbol{P}_{\boldsymbol{f}}$ and $P_{g}$ be the decomposition of the two flows into paths. Then:
(A) $P_{f}=P_{g}$ (paths are the same).
(B) $\left|P_{f}\right|=\left|P_{g}\right|$ (i.e., number of paths is the same).
(C) $\left|P_{f}\right|+\left|P_{g}\right|=m$.
(D) $\left|P_{f}\right| *\left|P_{g}\right|=n m$.
(E) None of the above.

## Part I

## Network Flow Applications I

## Edge-Disjoint Paths in Directed Graphs

## Definition



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## 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.

## 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 $\mathbf{1}$, 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 $\boldsymbol{k}$ in $\mathbf{G}$.

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## Proof.

Set $f(e)=\mathbf{1}$ 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 $\boldsymbol{k}$.

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## Proof.

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

## Running Time

## Theorem

The number of edge disjoint paths in a simple graph $G$ can be found in $O(m n)$ time.

## Proof.

(1) Set capacities of edges in $G$ to $\mathbf{1}$.
(2) Run Ford-Fulkerson algorithm.
(0) Maximum value of flow is $n$ and hence run-time is $O(n m)$.
(9) Decompose flow into $k$ paths $(k \leq n)$. Takes $O(k \times m)=O(k m)=O(m n)$ time.

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## Remark

The algorithm also computes a set of edge-disjoint paths realizing this optimal solution.

## Menger's Theorem

Theorem
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 $t$.

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## Proof.

Maxflow-mincut theorem and integrality of flow.

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## 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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(1) create directed graph $H$ by adding directed edges $(u, v)$ and $(\boldsymbol{v}, \boldsymbol{u})$ for each edge $\boldsymbol{u} \boldsymbol{v}$ in $G$.
(2) compute maximum s-t flow in $\boldsymbol{H}$.

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Problem: Both edges $(\boldsymbol{u}, \boldsymbol{v})$ and $(\boldsymbol{v}, \boldsymbol{u})$ may have non-zero flow!

## Edge Disjoint Paths in Undirected Graphs

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(2) compute maximum s-t flow in $H$.

Problem: Both edges $(u, v)$ and $(v, u)$ may have non-zero flow!
Not a Problem! Can assume maximum flow in $\boldsymbol{H}$ is acyclic and hence cannot have non-zero flow on both $(\boldsymbol{u}, \boldsymbol{v})$ and $(\boldsymbol{v}, \boldsymbol{u})$. Reduction works. See book for more details.

## Node Disjoint Paths and Meger's theorem

## Definition

A set of $\boldsymbol{s}$ - $\boldsymbol{t}$ paths $\mathcal{P}$ are internally node-disjoint if no two paths in $\mathcal{P}$ share a node other than $s, t$.


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## Theorem

Let $G$ be an undirected graph. The minimum number of nodes in $V \backslash\{s, t\}$ whose removal disconnects $s$ from $t$ is equal to the maximum number of internally node-disjoint paths in $G$ between $s$ and $t$.

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## Theorem

The max number of internally node-disjoint paths between $s$ and $t$ in $G$ can be computed in $O(m n)$ time.

Via reductions to directed graph edge-disjoint case!

## Multiple Sources and Sinks

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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Maximum Flow: Send as much flow as possible from the sources to the sinks. Sinks don't care which source they get flow from.

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Minimum Cut: Find a minimum capacity set of edge $E^{\prime}$ such that removing $E^{\prime}$ disconnects every source from every sink.

## Multiple Sources and Sinks: Formal Definition

Input:
(1) A directed graph $G$ with edge capacities $c(e)$.
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(9) Sources and sinks are disjoint.

A function $f: E \rightarrow \mathbb{R}^{\geq 0}$ 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 $f^{\text {in }}(v)=f^{\text {out }}(v)$.

Goal: $\max \sum_{i=1}^{k}\left(f^{\text {out }}\left(s_{i}\right)-f^{\text {in }}\left(s_{i}\right)\right)$, that is, flow out of sources.

## Reduction to Single-Source Single-Sink

(1) Add a source node $s$ and a sink node $t$.
(2) Add edges $\left(s, s_{1}\right),\left(s, s_{2}\right), \ldots,\left(s, s_{k}\right)$.
(3) Add edges $\left(t_{1}, t\right),\left(t_{2}, t\right), \ldots,\left(t_{\ell}, t\right)$.
(9) Set the capacity of the new edges to be $\infty$.


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## Supplies and Demands

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

Question: is there a flow from source to sinks such that supplies are not exceeded and demands are met? Formally we have the additional constraints that $f^{\text {out }}\left(s_{i}\right)-f^{\text {in }}\left(s_{i}\right) \leq S_{i}$ for each source $s_{i}$ and $f^{\text {in }}\left(t_{j}\right)-f^{\text {out }}\left(t_{j}\right) \geq D_{j}$ for each sink $t_{j}$.


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## Matching

## Problem (Matching)

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Goal: Find a matching of maximum cardinality.


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Goal: Find a matching of maximum cardinality.

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



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Maximum matching has 4 edges

## Reduction of bipartite matching to max-flow

## Max-Flow Construction

Given graph $G=(L \cup R, E)$ create flow-network $G^{\prime}=\left(V^{\prime}, E^{\prime}\right)$ as follows:


## Reduction of bipartite matching to max-flow

## Max-Flow Construction

Given graph $G=(L \cup R, E)$ create flow-network $G^{\prime}=\left(V^{\prime}, E^{\prime}\right)$ as follows:

(1) $V^{\prime}=L \cup R \cup\{s, t\}$ where $s$ and $t$ are the new source and sink.

## Reduction of bipartite matching to max-flow

## Max-Flow Construction

Given graph $G=(L \cup R, E)$ create flow-network $G^{\prime}=\left(V^{\prime}, E^{\prime}\right)$ as follows:

(1) $V^{\prime}=L \cup R \cup\{s, t\}$ 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 $t$.

## Reduction of bipartite matching to max-flow

## Max-Flow Construction

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(1) $V^{\prime}=L \cup R \cup\{s, t\}$ 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 $t$.
(0) Capacity of every edge is $\mathbf{1}$.

## Correctness: Matching to Flow

## Proposition

If $\boldsymbol{G}$ has a matching of size $\boldsymbol{k}$ then $\boldsymbol{G}^{\prime}$ has a flow of value $\boldsymbol{k}$.

$a^{\prime}$


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If $G$ has a matching of size $\boldsymbol{k}$ then $\boldsymbol{G}^{\prime}$ has a flow of value $\boldsymbol{k}$.

## Proof.

Let $M$ be matching of size $k$. Let $M=\left\{\left(u_{1}, v_{1}\right), \ldots,\left(u_{k}, v_{k}\right)\right\}$. Consider following flow $f$ in $G^{\prime}$ :
(1) $f\left(s, u_{i}\right)=1$ and $f\left(v_{i}, t\right)=1$ for $1 \leq i \leq k$
(2) $f\left(u_{i}, v_{i}\right)=1$ for $1 \leq i \leq k$
(0) for all other edges flow is zero.

Verify that $\boldsymbol{f}$ is a flow of value $\boldsymbol{k}$ (because $M$ is a matching).

## Correctness: Flow to Matching

## Proposition

If $G^{\prime}$ has a flow of value $k$ then $G$ has a matching of size $k$.

## Proof.

Consider flow $\boldsymbol{f}$ of value $\boldsymbol{k}$.
(1) Can assume $\boldsymbol{f}$ 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) $\boldsymbol{M}$ has $\boldsymbol{k}$ 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 $\boldsymbol{M}$ incident upon it. Why?

## Correctness of Reduction

## Theorem <br> The maximum flow value in $G^{\prime}=$ maximum cardinality of matching in $G$.

## Consequence

Thus, to find maximum cardinality matching in $G$, we construct $G^{\prime}$ and find the maximum flow in $G^{\prime}$. 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 $G^{\prime}$ has $O(n+m)$ edges, and $O(n)$ vertices.
(1) Generic Ford-Fulkerson: Running time is $O(m C)=O(n m)$ since $C=n$.
(2) Capacity scaling: Running time is $O\left(m^{2} \log C\right)=O\left(m^{2} \log n\right)$.

## Running Time

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(2) Capacity scaling: Running time is $O\left(m^{2} \log C\right)=O\left(m^{2} \log n\right)$.
Better running time is known: $O(m \sqrt{n})$.

## Perfect Matchings

## Definition

A matching $M$ is said to be 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 $X$.


## 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 $|N(X)| \geq|X|$.

## Hall's Theorem

## Theorem (Frobenius-Hall)

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

One direction is the necessary condition.

$$
|x| d
$$


$|v| d$

## Hall's Theorem

## Theorem (Frobenius-Hall)

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

One direction is the necessary condition.
For the other direction we will show the following:
(1) Create flow network $G^{\prime}$ from $G$.
(2) If $|N(X)| \geq|X|$ for all $X$, show that minimum s-t cut in $G^{\prime}$ is of capacity $n=|L|=|R|$.
(0) Implies that $G$ has a perfect matching.

## Proof of Sufficiency

Assume $|N(X)| \geq|X|$ for any $X \subseteq L$. Then show that min $s$ - $\boldsymbol{t}$ cut in $G^{\prime}$ is of capacity at least $\boldsymbol{n}$.

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Let $(A, B)$ be an arbitrary s-t cut in $G^{\prime}$
(1) Let $X=A \cap L$ and $Y=A \cap R$.

## Proof of Sufficiency

Assume $|N(X)| \geq|X|$ for any $X \subseteq L$. Then show that min s- $t$ cut in $\boldsymbol{G}^{\prime}$ is of capacity at least $\boldsymbol{n}$.

Let $(A, B)$ be an arbitrary s-t cut in $G^{\prime}$
(1) Let $X=A \cap L$ and $Y=A \cap R$.
(2) Cut capacity is at least $(|L|-|X|)+|Y|+|N(X) \backslash Y|$


## Because there are...

(1) $|\boldsymbol{L}|-|X|$ edges from $s$ to $L \cap B$.
(2) $|\boldsymbol{Y}|$ edges from $\boldsymbol{Y}$ to $\boldsymbol{t}$.
(3) there are at least $|\boldsymbol{N}(X) \backslash \boldsymbol{Y}|$ edges from $\boldsymbol{X}$ to vertices on the right side that are not in $\boldsymbol{Y}$.

## Proof of Sufficiency

## Continued...

(1) By the above, cut capacity is at least

$$
\alpha=(|L|-|X|)+|Y|+|N(X) \backslash Y|
$$

(2) $|N(X) \backslash Y| \geq|N(X)|-|Y|$.
(This holds for any two sets.)
(3) By assumption $|N(X)| \geq|X|$ and hence

$$
|N(X) \backslash Y| \geq|N(X)|-|Y| \geq|X|-|Y|
$$

(4) Cut capacity is therefore at least

$$
\begin{aligned}
\alpha & =(|L|-|X|)+|Y|+|N(X) \backslash Y| \\
& \geq|L|-|X|+|Y|+|X|-|Y| \geq|L|=n
\end{aligned}
$$

(5) Any $\boldsymbol{s}$ - $\boldsymbol{t}$ cut capacity is at least $\boldsymbol{n} \Longrightarrow$ max flow at least $\boldsymbol{n}$ units $\Longrightarrow$ perfect matching.

## 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.

## Assigning jobs to people

(1) $n$ jobs, $n / 2$ people
(2) For each job: a set of people who can do that job.
(0) Each person $j$ has to do exactly two jobs.
(- Goal: find an assignment of 2 jobs to each person, such that all jobs are assigned.
Solution: Build bipartite graph, compute maximum matching, remove it, compute another maximum matching. Both matchings together form a valid solution if it exists. This algorithm is
(A) Correct.
(B) Incorrect.

## Application: Assigning jobs to people

(1) $\boldsymbol{n}$ jobs or tasks
(2) $m$ people
(3) for each job a set of people who can do that job
(9) for each person $\boldsymbol{j}$ a limit on number of jobs $\boldsymbol{k}_{\boldsymbol{j}}$
(5) Goal: find an assignment of jobs to people so that all jobs are assigned and no person is overloaded

## Application: Assigning jobs to people

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(0) Goal: find an assignment of jobs to people so that all jobs are assigned and no person is overloaded
Reduce to max-flow similar to matching.
Arises in many settings. Using minimum-cost flows can also handle the case when assigning a job $i$ to person $j$ costs $c_{i j}$ and goal is assign all jobs but minimize cost of assignment.

## Reduction to Maximum Flow

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

## Matchings in General Graphs

Matchings in general graphs more complicated.
There is a polynomial time algorithm to compute a maximum matching in a general graph. Best known running time was until very recenlty $O(m \sqrt{n})$ due to Hopcroft and Karp. Now there is another algorithm that runs in $\tilde{O}\left(\boldsymbol{m}^{10 / 7}\right)$-time due to Madry (2015).

## Part I

## Baseball Pennant Race

## Pennant Race



## Pennant Race: Example

## Example

| Team | Won | Left |
| :--- | :---: | :---: |
| New York | 92 | 2 |
| Baltimore | 91 | 3 |
| Toronto | 91 | 3 |
| Boston | 89 | 2 |

Can Boston win the pennant?

## Pennant Race: Example

## Example

| Team | Won | Left |
| :--- | :---: | :---: |
| New York | 92 | 2 |
| Baltimore | 91 | 3 |
| Toronto | 91 | 3 |
| Boston | 89 | 2 |

Can Boston win the pennant?
No, because Boston can win at most 91 games.

## Another Example

## Example

| Team | Won | Left |
| :--- | :---: | :---: |
| New York | 92 | 2 |
| Baltimore | 91 | 3 |
| Toronto | 91 | 3 |
| Boston | 90 | 2 |

Can Boston win the pennant?

## Another Example

## Example

| Team | Won | Left |
| :--- | :---: | :---: |
| New York | 92 | 2 |
| Baltimore | 91 | 3 |
| Toronto | 91 | 3 |
| Boston | 90 | 2 |

Can Boston win the pennant?
Not clear unless we know what the remaining games are!

## Refining the Example

## Example

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 92 | 2 | - | 1 | 1 | 0 |
| Baltimore | 91 | 3 | 1 | - | 1 | 1 |
| Toronto | 91 | 3 | 1 | 1 | - | 1 |
| Boston | 90 | 2 | 0 | 1 | 1 | - |

Can Boston win the pennant?

## Refining the Example

## Example

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 92 | 2 | - | 1 | 1 | 0 |
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| Boston | 90 | 2 | 0 | 1 | 1 | - |

Can Boston win the pennant? Suppose Boston does

## Refining the Example

## Example

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 92 | 2 | - | 1 | 1 | 0 |
| Baltimore | 91 | 3 | 1 | - | 1 | 1 |
| Toronto | 91 | 3 | 1 | 1 | - | 1 |
| Boston | 90 | 2 | 0 | 1 | 1 | - |

Can Boston win the pennant? Suppose Boston does
(1) Boston wins both its games to get 92 wins

## Refining the Example

## Example

| Team | Won | Left | NY | Bal | Tor | Bos |
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Can Boston win the pennant? Suppose Boston does
(1) Boston wins both its games to get 92 wins
(2) New York must lose both games

## Refining the Example

## Example

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| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 92 | 2 | - | 1 | 1 | 0 |
| Baltimore | 91 | 3 | 1 | - | 1 | 1 |
| Toronto | 91 | 3 | 1 | 1 | - | 1 |
| Boston | 90 | 2 | 0 | 1 | 1 | - |

Can Boston win the pennant? Suppose Boston does
(1) Boston wins both its games to get 92 wins
(2) New York must lose both games; now both Baltimore and Toronto have at least 92

## Refining the Example

## Example

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 92 | 2 | - | 1 | 1 | 0 |
| Baltimore | 91 | 3 | 1 | - | 1 | 1 |
| Toronto | 91 | 3 | 1 | 1 | - | 1 |
| Boston | 90 | 2 | 0 | 1 | 1 | - |

Can Boston win the pennant? Suppose Boston does
(1) Boston wins both its games to get 92 wins
(2) New York must lose both games; now both Baltimore and Toronto have at least 92
(0) Winner of Baltimore-Toronto game has 93 wins!

## Can Boston win the penant?

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 3 | 6 | - | 2 | 3 | 1 |
| Baltimore | 5 | 4 | 2 | - | 1 | 1 |
| Toronto | 4 | 6 | 3 | 1 | - | 2 |
| Boston | 2 | 4 | 1 | 1 | 2 | - |

(A) Yes.
(B) No.

## Abstracting the Problem

Given
(1) A set of teams $S$
(2) For each $x \in S$, the current number of wins $w_{x}$
(3) For any $x, y \in S$, the number of remaining games $g_{x y}$ between $x$ and $y$
(9) A team $z$

Can $z$ win the pennant?

## Towards a Reduction

$\bar{z}$ can win the pennant if
(1) $\bar{z}$ wins at least $\boldsymbol{m}$ games
(2) no other team wins more than $\boldsymbol{m}$ games

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$\bar{z}$ can win the pennant if
(1) $\bar{z}$ wins at least $\boldsymbol{m}$ games
(1) to maximize $\bar{z}$ 's chances we make $\bar{z}$ win all its remaining games and hence $\boldsymbol{m}=\boldsymbol{w}_{\bar{z}}+\sum_{\boldsymbol{x} \in S} \boldsymbol{g}_{\boldsymbol{x} \bar{z}}$
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(2) no other team wins more than $\boldsymbol{m}$ games
(1) for each $\boldsymbol{x}, \boldsymbol{y} \in \boldsymbol{S}$ the $\boldsymbol{g}_{\boldsymbol{x y}}$ games between them have to be assigned to either $\boldsymbol{x}$ or $\boldsymbol{y}$.
(2) each team $\boldsymbol{x} \neq \overline{\mathbf{z}}$ can win at most $\boldsymbol{m}-\boldsymbol{w}_{\boldsymbol{x}}-\boldsymbol{g}_{\boldsymbol{x} \bar{z}}$ remaining games

Is there an assignment of remaining games to teams such that no team $x \neq \bar{z}$ wins more than $\boldsymbol{m}-\boldsymbol{w}_{\boldsymbol{x}}$ games?

## Flow Network: The basic gadget

(1) s: source
(2) $t: \sin k$
(3) $x, y$ : two teams
(1) $g_{x y}$ : number of games remaining between $x$ and $y$.
(5) $w_{x}$ : number of points $x$ has.
(6) $\boldsymbol{m}$ : maximum number of points $x$ can win before team of interest is eliminated.

## Flow Network: An Example

## Can Boston win?

| Team | Won | Left | NY | Bal | Tor | Bos |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| New York | 90 | 11 | - | 1 | 6 | 4 |
| Baltimore | 88 | 6 | 1 | - | 1 | 4 |
| Toronto | 87 | 11 | 6 | 1 | - | 4 |
| Boston | 79 | 12 | 4 | 4 | 4 | - |

(1) $m=79+12=91$ :

Boston can get at most 91 points.


## Constructing Flow Network

## Reduction

## Notations

(1) $S$ : set of teams,
(2) $w_{x}$ wins for each team, and
(3) $g_{x y}$ games left between $x$ and $y$.
( $m$ be the maximum number of wins for $\bar{z}$,

- and $S^{\prime}=S \backslash\{\bar{z}\}$.


## Construct the flow network $G$ as

 follows(1) One vertex $v_{x}$ for each team $x \in S^{\prime}$, one vertex $u_{x y}$ for each pair of teams $x$ and $y$ in $S^{\prime}$
(2) A new source vertex $s$ and $\operatorname{sink} t$
(3) Edges $\left(u_{x y}, v_{x}\right)$ and $\left(u_{x y}, v_{y}\right)$ of capacity $\infty$
(4) Edges $\left(s, u_{x y}\right)$ of capacity $g_{x y}$
(5) Edges $\left(v_{x}, t\right)$ of capacity equal $\boldsymbol{m}-\boldsymbol{w}_{\boldsymbol{x}}$

## Correctness of reduction

## Theorem

$\mathbf{G}^{\prime}$ has a maximum flow of value $\boldsymbol{g}^{*}=\sum_{x, y \in \boldsymbol{s}^{\prime}} g_{x y}$ if and only if $\bar{z}$ can win the most number of games (including possibly tie with other teams).

## Proof of Correctness

## Proof.

Existence of $g^{*}$ flow $\Rightarrow \bar{z}$ wins pennant
(1) An integral flow saturating edges out of $s$, ensures that each remaining game between $x$ and $y$ is added to win total of either $x$ or $y$
(2) Capacity on $\left(v_{x}, t\right)$ edges ensures that no team wins more than m games
Conversely, $\bar{z}$ wins pennant $\Rightarrow$ flow of value $\boldsymbol{g}^{*}$
(1) Scenario determines flow on edges; if $x$ wins $k$ of the games against $y$, then flow on $\left(u_{x y}, v_{x}\right)$ edge is $k$ and on $\left(u_{x y}, v_{y}\right)$ edge is $g_{x y}-k$

## Proof that cannot with the pennant

(1) Suppose $\bar{z}$ cannot win the pennant since $g^{*}<g$. How do we prove to some one compactly that $\bar{z}$ cannot win the pennant?

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## Proof that cannot with the pennant

(1) Suppose $\bar{z}$ cannot win the pennant since $g^{*}<g$. How do we prove to some one compactly that $\bar{z}$ cannot win the pennant?
(2) Show them the min-cut in the reduction flow network!
(3) See Kleinberg-Tardos book for a natural interpretation of the min-cut as a certificate.

## The biggest loser?

Given an input as above for the pennant competition, deciding if a team can come in the last place can be done in
(A) Can be done using the same reduction as just seen.
(B) Can not be done using the same reduction as just seen.
(C) Can be done using flows but we need lower bounds on the flow, instead of upper bounds.
(D) The problem is NP-Hard and requires exponential time.
(E) Can be solved by negating all the numbers, and using the above reduction.
(F) Can be solved efficiently only by running a reality show on the problem.

## Part II

## An Application of Min-Cut to Project Scheduling

## Project Scheduling

Problem:
(1) $n$ projects/tasks $1,2, \ldots, n$
(2) dependencies between projects: $\boldsymbol{i}$ depends on $\boldsymbol{j}$ implies $\boldsymbol{i}$ cannot be done unless $j$ is done. dependency graph is acyclic
(0) each project $i$ has a cost/profit $p_{i}$
(0) $\boldsymbol{p}_{\boldsymbol{i}}<0$ implies $\boldsymbol{i}$ requires a cost of $-\boldsymbol{p}_{\boldsymbol{i}}$ units
(0) $\boldsymbol{p}_{\boldsymbol{i}}>\mathbf{0}$ implies that $\boldsymbol{i}$ generates $\boldsymbol{p}_{\boldsymbol{i}}$ profit

Goal: Find projects to do so as to maximize profit.

Example Coses

## Notation

For a set $\boldsymbol{A}$ of projects:
(1) $\boldsymbol{A}$ is a valid solution if $\boldsymbol{A}$ is dependency closed, that is for every $\boldsymbol{i} \in \boldsymbol{A}$, all projects that $\boldsymbol{i}$ depends on are also in $\boldsymbol{A}$.

## Notation

For a set $\boldsymbol{A}$ of projects:
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(2) $\operatorname{profit}(A)=\sum_{i \in A} \boldsymbol{p}_{\boldsymbol{i}}$. Can be negative or positive.

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Goal: find valid $A$ to maximize $\operatorname{profit}(A)$.

## Idea: Reduction to Minimum-Cut

Finding a set of projects is partitioning the projects into two sets: those that are done and those that are not done.

Can we express this is a minimum cut problem?

## Idea: Reduction to Minimum-Cut

Finding a set of projects is partitioning the projects into two sets: those that are done and those that are not done.

Can we express this is a minimum cut problem?
Several issues:
(1) We are interested in maximizing profit but we can solve minimum cuts.
(2) We need to convert negative profits into positive capacities.
(0) Need to ensure that chosen projects is a valid set.
( ( The cut value captures the profit of the chosen set of projects.

## Reduction to Minimum-Cut

Note: We are reducing a maximization problem to a minimization problem.
(1) projects represented as nodes in a graph
(2) if $i$ depends on $j$ then $(i, j)$ is an edge
(3) add source $s$ and sink $t$

- for each $i$ with $p_{i}>0$ add edge $(s, i)$ with capacity $p_{i}$
© for each $\boldsymbol{i}$ with $p_{i}<\mathbf{0}$ add edge ( $i, t$ ) with capacity $-p_{i}$
- for each dependency edge ( $i, j$ ) put capacity $\infty$ (more on this later)


## Reduction: Flow Network Example



## Reduction contd

Algorithm:
(1) form graph as in previous slide
(2) compute s-t minimum cut $(A, B)$
(0) output the projects in $A-\{s\}$

## Understanding the Reduction

Let $C=\sum_{i: p_{i}>0} \boldsymbol{p}_{\boldsymbol{i}}$ : maximum possible profit.

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## Lemma

Suppose $(A, B)$ is an s-t cut of finite capacity (no $\infty$ ) edges. Then projects in $\boldsymbol{A}-\{s\}$ are a valid solution.

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Suppose $(A, B)$ is an s-t cut of finite capacity (no $\infty$ ) edges. Then projects in $\boldsymbol{A}-\{s\}$ are a valid solution.

## Proof.

If $\boldsymbol{A}-\{s\}$ is not a valid solution then there is a project $\boldsymbol{i} \in \boldsymbol{A}$ and a project $\boldsymbol{j} \notin \boldsymbol{A}$ such that $\boldsymbol{i}$ depends on $\boldsymbol{j}$

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Since $(i, j)$ capacity is $\infty$, implies $(A, B)$ capacity is $\infty$, contradicting assumption.

Example


Example


## Correctness of Reduction

Recall that for a set of projects $X, \operatorname{profit}(X)=\sum_{i \in X} \boldsymbol{p}_{i}$.

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Recall that for a set of projects $X, \operatorname{profit}(X)=\sum_{i \in X} \boldsymbol{p}_{\boldsymbol{i}}$.

## Lemma

Suppose $(A, B)$ is an s-t cut of finite capacity (no $\infty$ ) edges. Then $c(A, B)=C-\operatorname{profit}(A-\{s\})$.

## Proof.

Edges in $(A, B)$ :
(1) $(s, i)$ for $i \in B$ and $p_{i}>0$ : capacity is $p_{i}$
(2) (i,t) for $i \in A$ and $p_{i}<0$ : capacity is $-p_{i}$
(0) cannot have $\infty$ edges

## Proof contd

For project set $\boldsymbol{A}$ let
(1) $\operatorname{cost}(A)=\sum_{i \in A: p_{i}<0}-p_{i}$
(2) $\operatorname{benefit}(A)=\sum_{i \in A: p_{i}>0} p_{i}$
(0) $\operatorname{profit}(A)=\operatorname{benefit}(A)-\operatorname{cost}(A)$.

## Proof.

Let $A^{\prime}=A \cup\{s\}$.
$c\left(A^{\prime}, B\right)=\operatorname{cost}(A)+\operatorname{benefit}(B)$
$=\operatorname{cost}(A)-\operatorname{benefit}(A)+\operatorname{benefit}(A)+\operatorname{benefit}(B)$
$=-\operatorname{profit}(A)+C$
$=C-\operatorname{profit}(A)$

## Correctness of Reduction contd

We have shown that if $(A, B)$ is an $s$ - $t$ cut in $G$ with finite capacity then
(1) $A-\{s\}$ is a valid set of projects
(2) $c(A, B)=C-\operatorname{profit}(A-\{s\})$

## Correctness of Reduction contd

We have shown that if $(A, B)$ is an $s$ - $t$ cut in $G$ with finite capacity then
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Therefore a minimum s-t cut ( $\boldsymbol{A}^{*}, B^{*}$ ) gives a maximum profit set of projects $A^{*}-\{s\}$ since $C$ is fixed.

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Question: How can we use $\infty$ in a real algorithm?

## Correctness of Reduction contd

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(2) $c(A, B)=C-\operatorname{profit}(A-\{s\})$

Therefore a minimum s-t cut ( $A^{*}, B^{*}$ ) gives a maximum profit set of projects $A^{*}-\{s\}$ since $C$ is fixed.

Question: How can we use $\infty$ in a real algorithm?
Set capacity of $\infty$ arcs to $C+\mathbf{1}$ instead. Why does this work?

