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CSE 421

Polynomial Time Reductions NP Completeness

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P, NP, EXP

P. Decision problems for which there is a **poly-time algorithm**.

EXP. Decision problems for which there is an **exponential-time algorithm**.

NP. Decision problems for which there is a **poly-time certifier**.

Claim. $P \subseteq NP$.

Pf. Consider any problem X in P .

By definition, there exists a poly-time algorithm $A(x)$ that solves X .

Certificate: $t = \text{empty string}$, certifier $C(x, \emptyset) = A(x)$. ■

Claim. $NP \subseteq EXP$.

Pf. Consider any problem X in NP .

By definition, there exists a poly-time certifier $C(x, t)$ for X .

To solve input x , run $C(x, t)$ on all strings t with length polyn in $|x|$

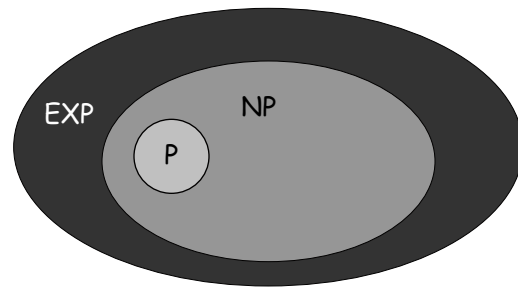
Return yes , if $C(x, t)$ returns yes for any of these.

The main question: P vs NP

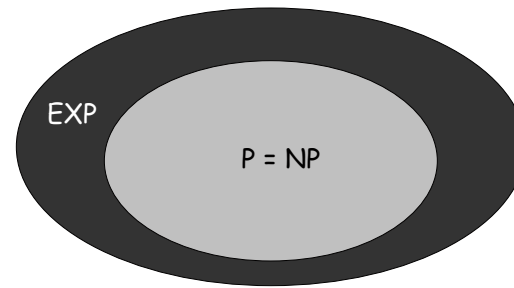
Does $P = NP$? [Cook 1971, Edmonds, Levin, Yablonski, Gödel]

Is the decision problem as easy as the certification problem?

Clay \$1 million prize.



If $P \neq NP$



If $P = NP$

If yes: Efficient algorithms for 3-COLOR, TSP, FACTOR, SAT, ...

If no: No efficient algorithms possible for 3-COLOR, TSP, SAT, ...

What do we know about NP?

- Nobody knows if all problems in NP can be done in polynomial time, i.e. does $P=NP$?
 - one of the most important open questions in all of science.
 - Huge practical implications specially if answer is yes
- To show Hamil-cycle $\notin P$ we have to prove that there is no poly-time algorithm for it even using all mathematical theorem that will be discovered in **future!**

NP Completeness

Complexity Theorists Approach: We don't know how to prove any problem in NP is hard. So, let's find **hardest** problems in NP.

NP-hard: A problem B is NP-hard iff for any problem $A \in NP$, we have $A \leq_p B$

NP-Completeness: A problem B is NP-complete iff B is NP-hard and $B \in NP$.

Motivations:

- If $P \neq NP$, then every NP-Complete problems is not in P. So, we shouldn't try to design Polytime algorithms
- To show $P = NP$, it is enough to design a polynomial time algorithm for just one NP-complete problem.

Cook-Levin Theorem

Theorem (Cook 71, Levin 73): 3-SAT is NP-complete, i.e., for all problems $A \in NP$, $A \leq_p$ 3-SAT.

- So, 3-SAT is the hardest problem in NP.

What does this say about other problems of interest? Like Independent set, Vertex Cover, ...

Fact: If $A \leq_p B$ and $B \leq_p C$ then, $A \leq_p C$

Pf idea: Just compose the reductions from A to B and B to C

So, if we prove $3\text{-SAT} \leq_p$ Independent set, then Independent Set, Clique, Vertex cover, Set cover are all NP-complete

$3\text{-SAT} \leq_p$ Independent Set \leq_p Vertex Cover \leq_p Set Cover

Summary

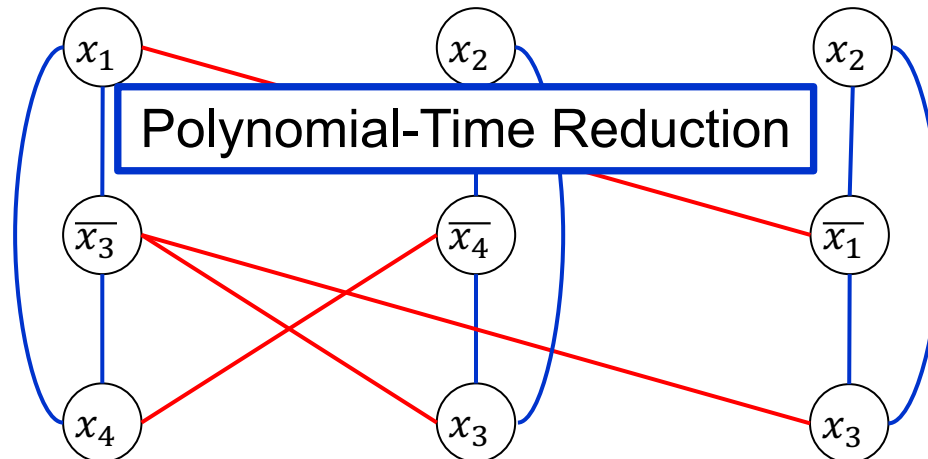
- If a problem is NP-hard it does not mean that all instances are hard, e.g., Vertex-cover has a polynomial-time algorithm on trees or bipartite graphs
- We learned the crucial idea of polynomial-time reduction. This can be even used in algorithm design, e.g., we know how to solve max-flow so we reduce image segmentation to max-flow
- NP-Complete problems are the hardest problem in NP
- NP-hard problems may not necessarily belong to NP.
- Polynomial-time reductions are transitive relations

3-SAT \leq_p Independent Set

Map a 3-CNF to (G,k) . Say m is number of clauses

- Create a vertex for each literal
- Join two literals if
 - They belong to the same clause (blue edges)
 - The literals are negations, e.g., x_i, \bar{x}_i (red edges)
- Set $k=m$

$$(x_1 \vee \bar{x}_3 \vee x_4) \wedge (x_2 \vee \bar{x}_4 \vee x_3) \wedge (x_2 \vee \bar{x}_1 \vee x_3)$$



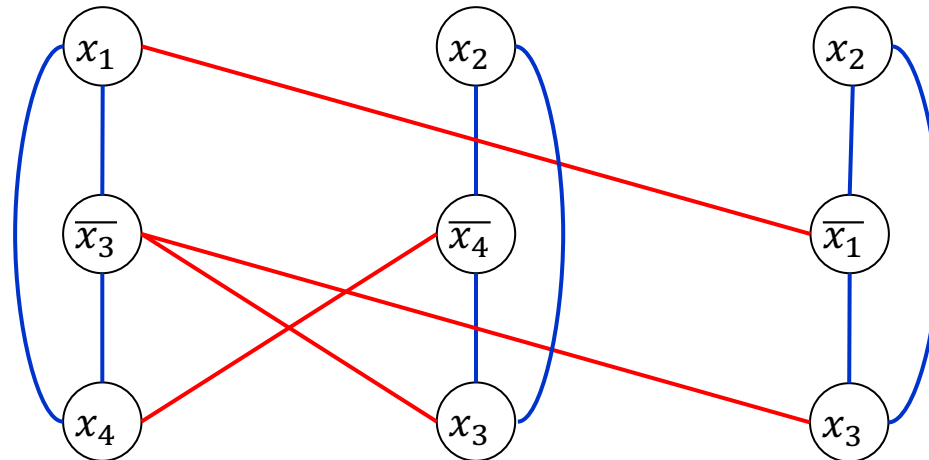
Correctness of $3\text{-SAT} \leq_p \text{Indep Set}$

F satisfiable \Rightarrow An independent of size m

Given a satisfying assignment, Choose one node from each clause where the literal is satisfied

$$(x_1 \vee \bar{x}_3 \vee x_4) \wedge (x_2 \vee \bar{x}_4 \vee x_3) \wedge (x_2 \vee \bar{x}_1 \vee x_3)$$

Satisfying assignment: $x_1 = T, x_2 = F, x_3 = T, x_4 = F$



- S has exactly one node per clause \Rightarrow No blue edges between S
- S follows a truth-assignment \Rightarrow No red edges between S
- S has one node per clause $\Rightarrow |S|=m$

Correctness of $3\text{-SAT} \leq_p \text{Indep Set}$

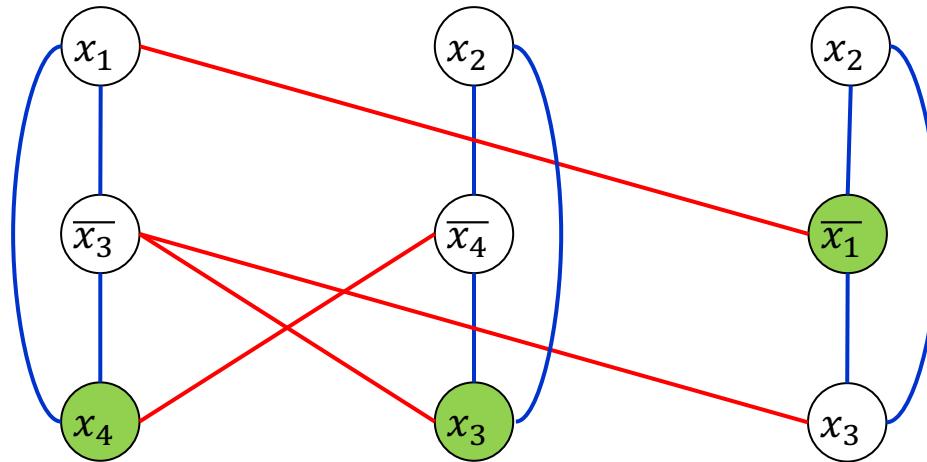
An independent set of size $m \Rightarrow$ A satisfying assignment

Given an independent set S of size m .

S has exactly one vertex per clause (because of blue edges)

S does not have x_i, \bar{x}_i (because of red edges)

So, S gives a satisfying assignment



Satisfying assignment: $x_1 = F, x_2 = ?, x_3 = T, x_4 = T$
 $(x_1 \vee \bar{x}_3 \vee x_4) \wedge (x_2 \vee \bar{x}_4 \vee x_3) \wedge (x_2 \vee \bar{x}_1 \vee x_3)$

Project Selection

Project Selection

can be positive or negative



Projects with prerequisites.

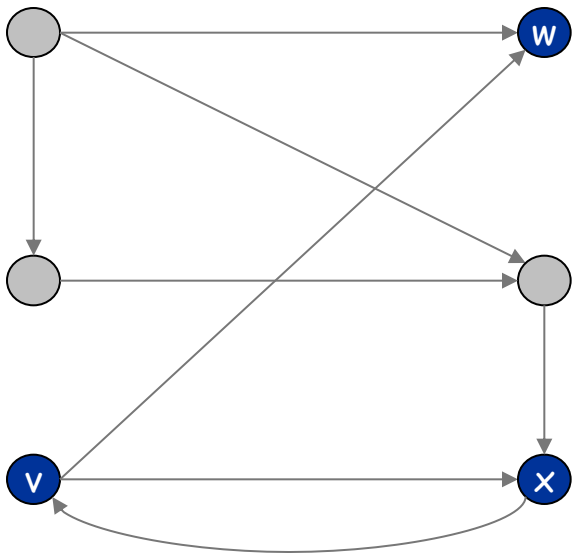
- Set P of possible projects. Project v has associated revenue p_v .
 - some projects generate money: create interactive e-commerce interface, redesign web page
 - others cost money: upgrade computers, get site license
- Set of prerequisites E . If $(v, w) \in E$, can't do project v and unless also do project w .
- A subset of projects $A \subseteq P$ is **feasible** if the prerequisite of every project in A also belongs to A .

Project selection. Choose a feasible subset of projects to maximize revenue.

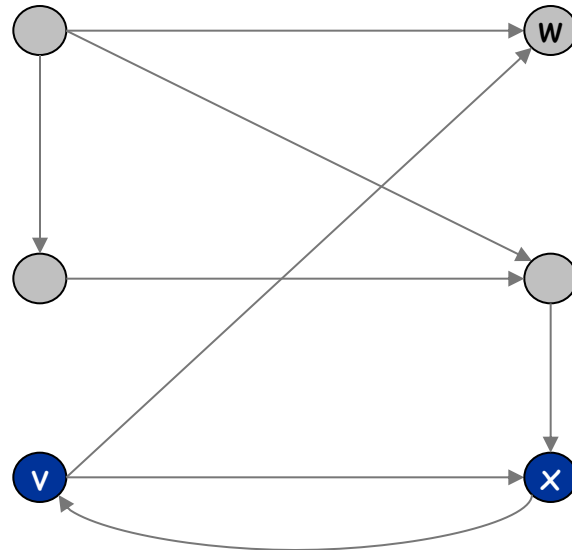
Project Selection: Prerequisite Graph

Prerequisite graph.

- Include an edge from v to w if can't do v without also doing w .
- $\{v, w, x\}$ is feasible subset of projects.
- $\{v, x\}$ is infeasible subset of projects.



feasible

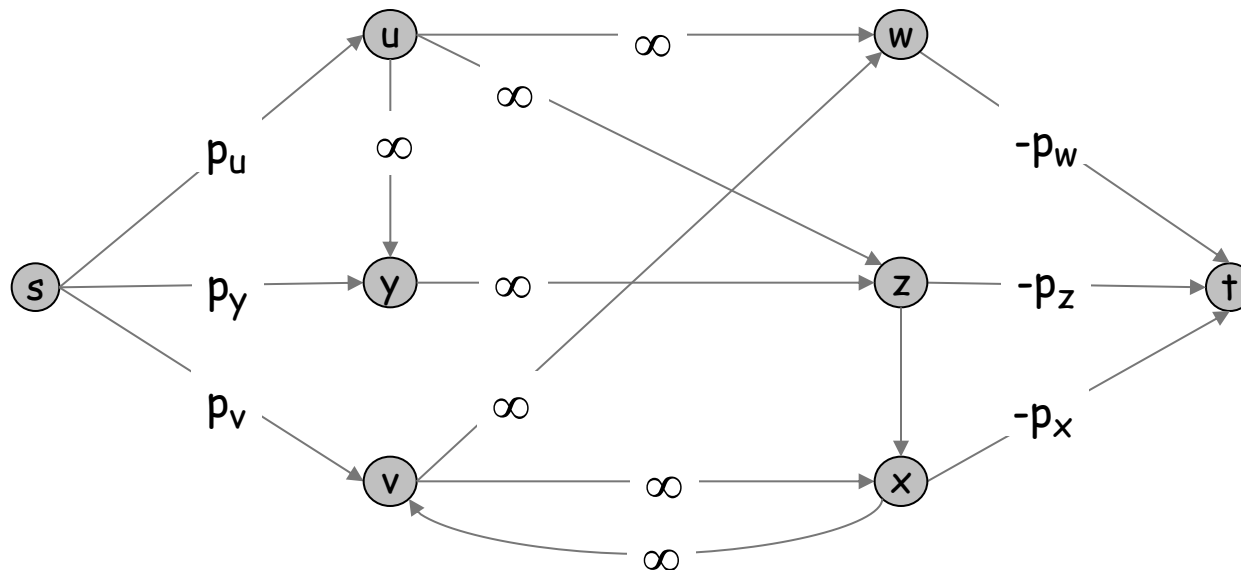


infeasible

Project Selection: Min Cut Formulation

Min cut formulation.

- Assign capacity ∞ to all prerequisite edge.
- Add edge (s, v) with capacity p_v if $p_v > 0$.
- Add edge (v, t) with capacity $-p_v$ if $p_v < 0$.
- For notational convenience, define $p_s = p_t = 0$.



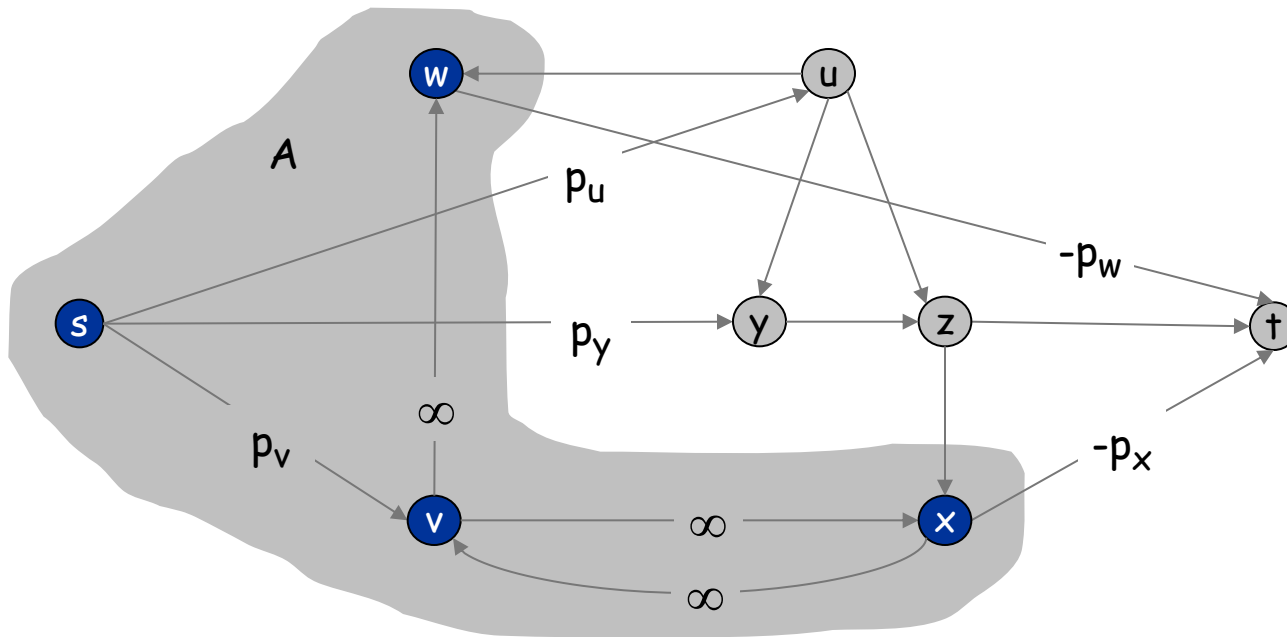
Project Selection: Min Cut Formulation

Claim. (A, B) is min cut iff $A - \{s\}$ is optimal set of projects.

- Infinite capacity edges ensure $A - \{s\}$ is feasible.

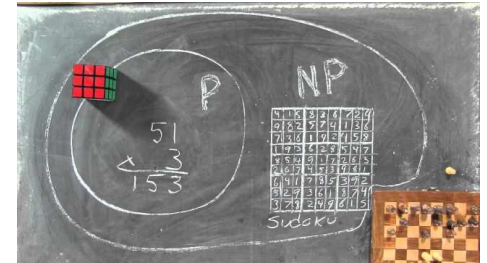
- Max revenue because:

$$\begin{aligned} \text{cap}(A, B) &= \sum_{v \in B: p_v > 0} p_v + \sum_{v \in A: p_v < 0} (-p_v) \\ &= \underbrace{\sum_{v: p_v > 0} p_v}_{\text{constant}} - \sum_{v \in A} p_v \end{aligned}$$



What is next?

- CSE 431 (Complexity Course)
 - How to prove lower bounds on algorithms?
- CSE 422 (Advanced Toolkit for Modern Alg)
 - SVD, Data structures, many programming tasks

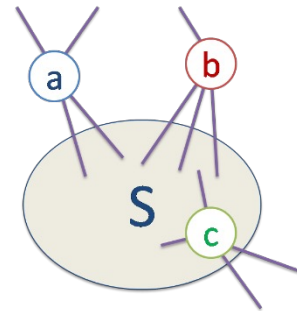


- CSE 521 (Graduate Algorithms Course)

Prereq: 312, Math 308

- How to design streaming algorithms?
- How to design algorithms for high dimensional data?
- How to use matrices/eigenvalues/eigenvectors to design algorithms
- How to use LPs to design algorithms?

$$p(a,S) = 2/8$$
$$p(b,S) = 3/8$$
$$p(c,S) = 6/8$$



- CSE 525 (Graduate Randomized Algorithms Course)

Prereq: CSE 521

- How to use randomization to design algorithms?
- How to use Markov Chains to design algorithms?



Course Evaluations

- How can we improve this course?
- Did you like sections? Should we keep having them? Any suggestion on how to improve sections?
- Did you like topics related to linear programming? Did you like to see more of that?
- Which topic was most/least interesting to you?
- Which problem sets did you like more?