Design and Analysis of Algorithms NP-Completeness

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What is polynomial-time?

- Polynomial-time: running time is $O(n^k)$, where k is a constant.
- Are they polynomial-time running time?

$$-T(n) = 3$$

$$-T(n)=n$$

$$-T(n) = nlg(n)$$

$$-T(n)=n^3$$

What is polynomial-time?

Are the polynomial-time?

$$-T(n) = 5^{n}$$
• No
$$-T(n) = n!$$
• No

- Problems with polynomial-time algorithms are considered as tractable
- With polynomial-time, we can define P problems, and NP problems

What are P and NP?

P problems

- (The original definition) Problems that can be solved by deterministic Turing machine in polynomial-time.
- (A equivalent definition) Problems that are solvable in polynomial time.

NP problems

- (The original definition) Problems that can be solved by non-deterministic Turing machine in polynomial-time.
- (A equivalent definition) Problems that are verifiable in polynomial time.
 - Given a solution, there is a polynomial-time algorithm to tell if this solution is correct.

Why we study NPC?

- One of the most important reasons is:
 - If you see a problem is NPC, you can stop from spending time and energy to develop a fast polynomial-time algorithm to solve it.
- Just tell your boss it is a NPC problem
- How to prove a problem is a NPC problem?
 - Will discuss later ahead.

What if a NPC problem needs to be solved?

- Buy a more expensive machine and wait
 - (could be 1000 years)
- Turn to approximation algorithms
 - Algorithms that produce near optimal solutions

Approximation algorithms for NP-complete problems

- If a problem is NP-complete, there is very likely no polynomial-time algorithm to find an optimal solution
- The idea of approximation algorithms is to develop polynomial-time algorithms to find a near optimal solution

- E.g.: develop a greedy algorithm without proving the greedy choice property and optimal substructure.
- Are those solution found near-optimal?
- How near are they?

• Approximation ratio ho(n)

- Define the cost of the optimal solution as C*
- The cost of the solution produced by a approximation algorithm is C

$$-\boldsymbol{\rho}(\boldsymbol{n}) \geq max(\frac{c}{c^*}, \frac{c^*}{c})$$

• The approximation algorithm is then called a $\rho(n)$ -approximation algorithm.

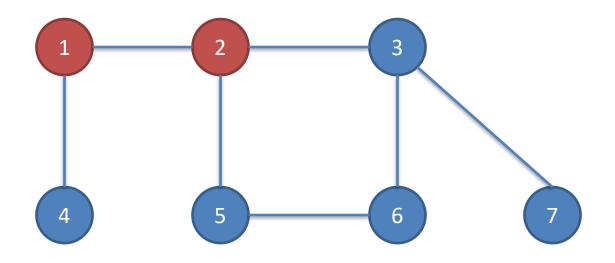
• E.g.:

- If the total weigh of a MST of graph G is 20
- A algorithm can produce some spanning trees,
 and they are not MSTs, but their total weights are
 always smaller than 25
- What is the approximation ratio?
 - 25/20 = 1.25
- This algorithm is called?
 - A 1.25-approximation algorithm

- What if $\rho(n)=1$?
- It is an algorithm that can always find a optimal solution

Vertex-cover problem

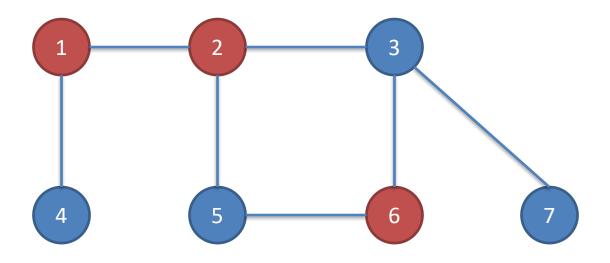
- What is a vertex-cover?
- Given a undirected graph G=(V, E), vertexcover V':
 - $-V'\subseteq V$
 - for each edge (u, v) in E, either u ∈ V' or v ∈ V' (or both)
- The size of a vertex-cover is |V'|



Are the red vertices a vertex-cover?

No. why?

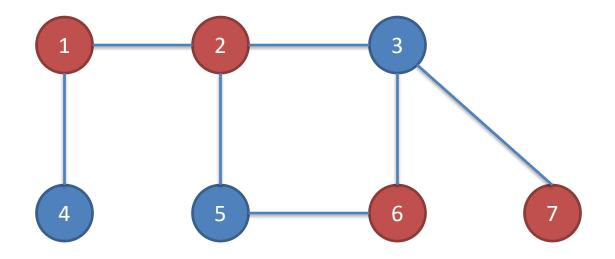
Edges (5, 6), (3, 6) and (3, 7) are not covered by it



Are the red vertices a vertex-cover?

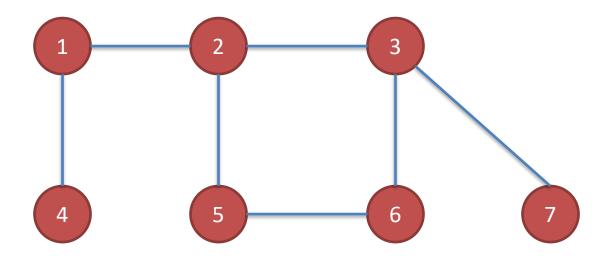
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Edge (3, 7) is not covered by it



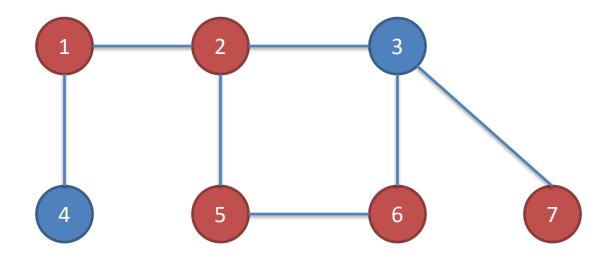
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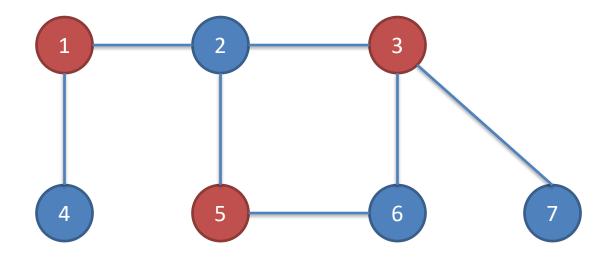
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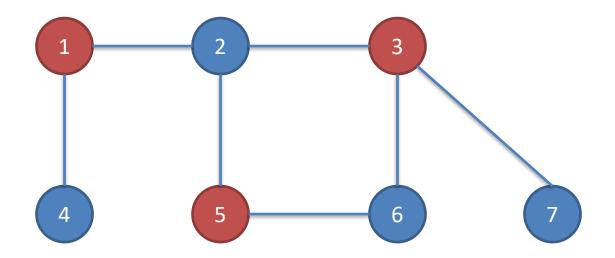


Are the red vertices a vertex-cover?

Yes

Vertex-cover problem

 Given a undirected graph, find a vertex cover with minimum size.



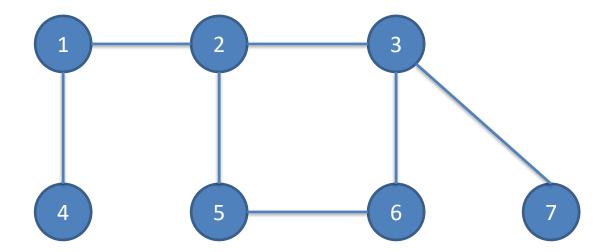
A minimum vertex-cover

- Vertex-cover problem is NP-complete
- A 2-approximation polynomial time algorithm is as the following:
- APPROX-VERTEX-COVER(G)

```
C = Ø;
E'=G.E;
while(E' ≠ Ø){
   Randomly choose a edge (u,v) in E', put u and v into C;
   Remove all the edges that covered by u or v from E'
}
Return C;
```

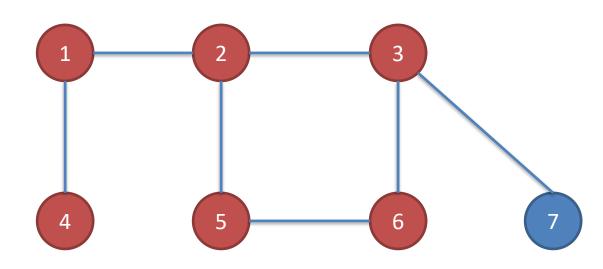
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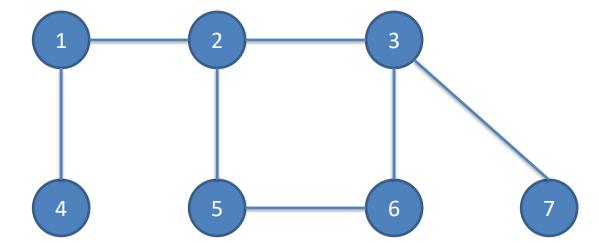
It is then a vertex cover

Size? 6

How far from optimal one? Max(6/3, 3/6) = 2

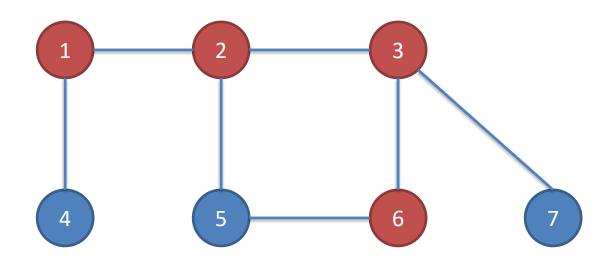
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It is then a vertex cover

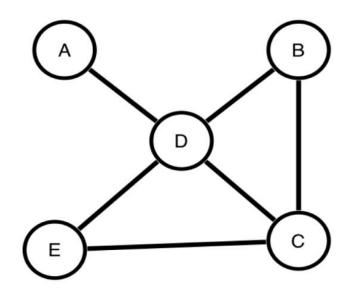
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Size?

How far from optimal one? Max(4/3, 3/4) = 1.33

Applications of Vertex Cover Problem (VC)

- Minimum Vertex Cover (MVC) problem comes into play in scheduling problems.
- A scheduling problem can be modeled as a graph, where the vertices represent tasks or times, and an edge between vertices means that a conflict exists between those times or tasks.
- Finding the minimum number of tasks that needs to be removed in order to resolve all conflicts is equivalent to finding a minimum vertex cover.
- [Carruthers, Sarah, Ulrike Stege, and Michael Masson. "Human performance on hard non-Euclidean graph problems: Vertex cover." (2012).]



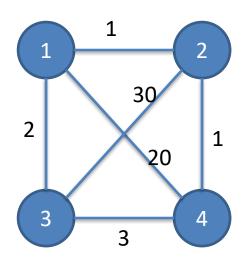
- **APPROX-VERTEX-COVER**(G) is a 2-approximation algorithm
- When the size of minimum vertex-cover is s
- The vertex-cover produced by APPROX-VERTEX-COVER is at most 2s

Proof:

- Assume a minimum vertex-cover is U*
- A vertex-cover produced by APPROX-VERTEX-COVER(G) is U
- The edges chosen in APPROX-VERTEX-COVER(G) is A
- A vertex in U* can only cover 1 edge in A
 So |U*|>= |A|
- For each edge in A, there are 2 vertices in U
 - So |U| = 2|A|
- So $|U^*| >= |U|/2$
- So $\frac{|U|}{|U^*|} \le 2$

Traveling-salesman problem (TSP):

 Given a weighted, undirected graph with V >= 3, start from certain vertex, find a minimum route visit each vertices once, and return to the original vertex.



- TSP is a NP-complete problem
- There is no polynomial-time approximation algorithm with a constant approximation ratio
- Another strategy to solve NPC problem:
 - Solve a special case

- Triangle inequality:
 - Weight(u, v) <= Weight(u, w) + Weight(w, v)</p>
- E.g.:
 - If all the edges are defined as the distance on a 2D map, the triangle inequality is true
- For the TSPs where the triangle inequality is true:
 - There is a 2-approximation polynomial time algorithm

Metric TSP

- Metric TSP is an special case of the TSP that satisfies the triangle inequality.
- Each vertex should be connected with every other vertex.

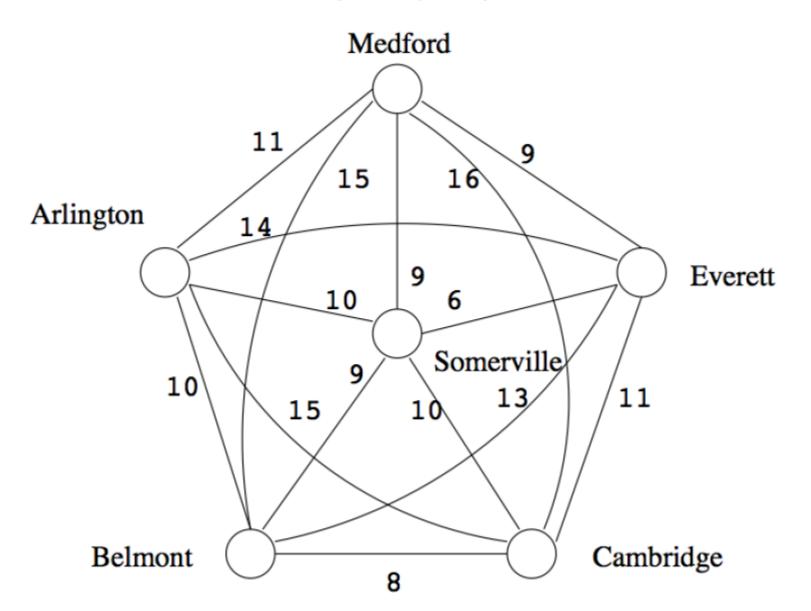
APPROX-TSP-TOUR(G)

Minimum Spanning Tree;

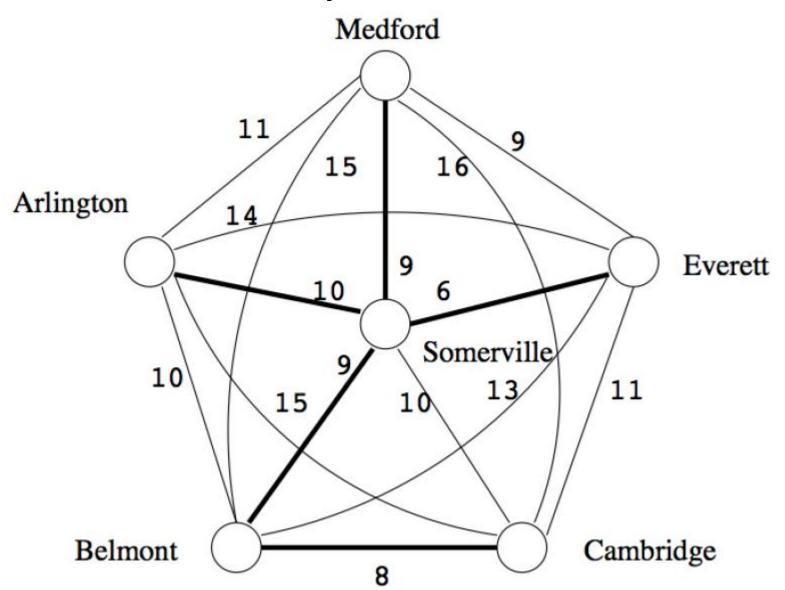
Creating a Cycle;

Removing Redundant Visits;

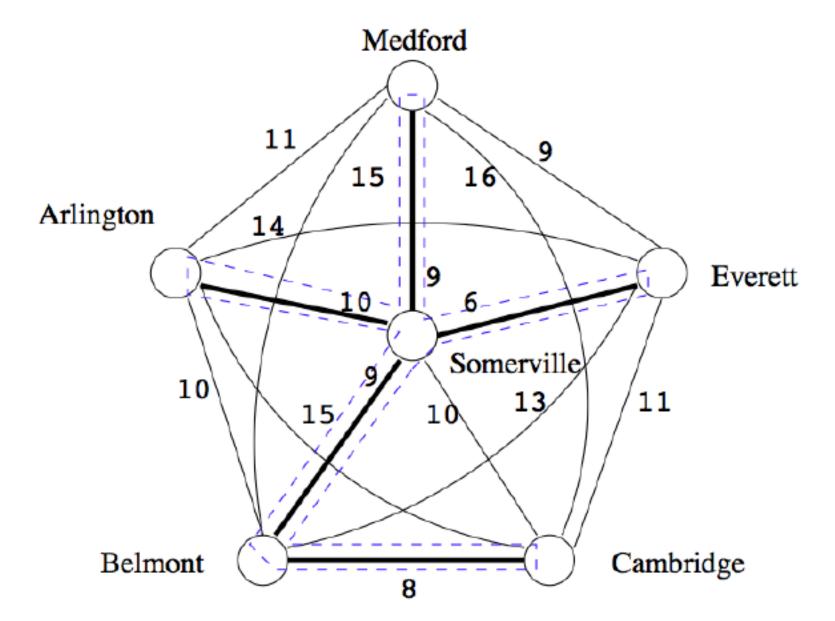
Metric TSP



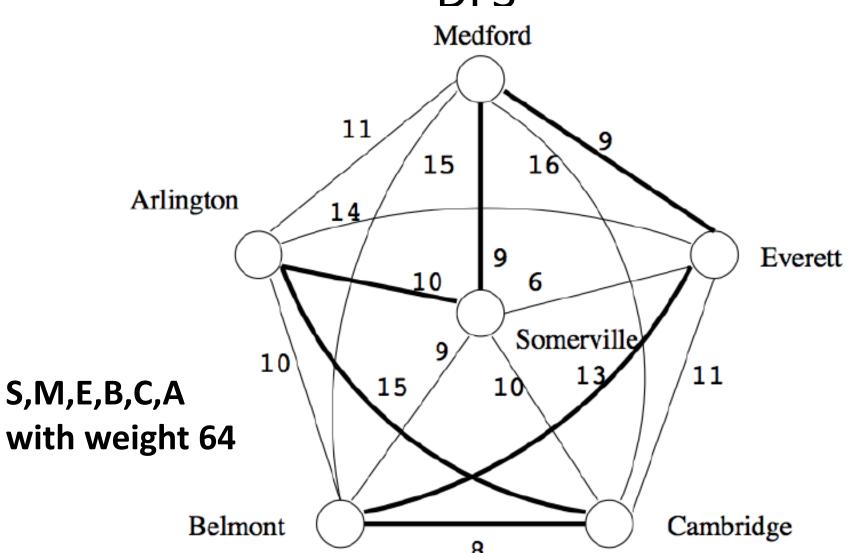
Step 1: MST



Step 2: Creating a cycle - using DFS



Step 3: Removing Redundant Visits of DFS

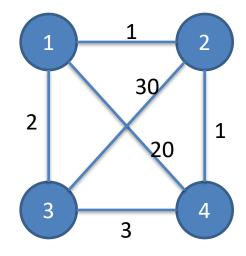


2 Approximation Algorithm

- Claim: The weight of the MST M is less than OPT, the weight of the TSP solution T.
 - i.e. OPT = w(T)
- Take T and remove an edge e. T is now a spanning tree.
- Because M is the MST,
 - $w(M) \le w(T-e)$
 - $w(M) \le w(T) w(e)$
 - $w(M) \le OPT-w(e)$
- Therefore, w(M) < OPT.
- Because each edge is used exactly twice during a depth first search on a tree (once descending, once ascending)
- w(W) = 2 * w(M) < 2 * OPT.

Traveling-salesman problem

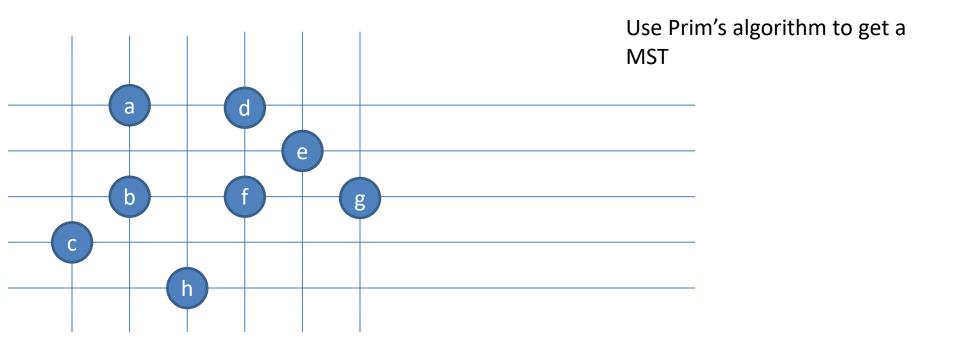
Can we apply the approximation algorithm on this one?



No. The triangle inequality is violated.

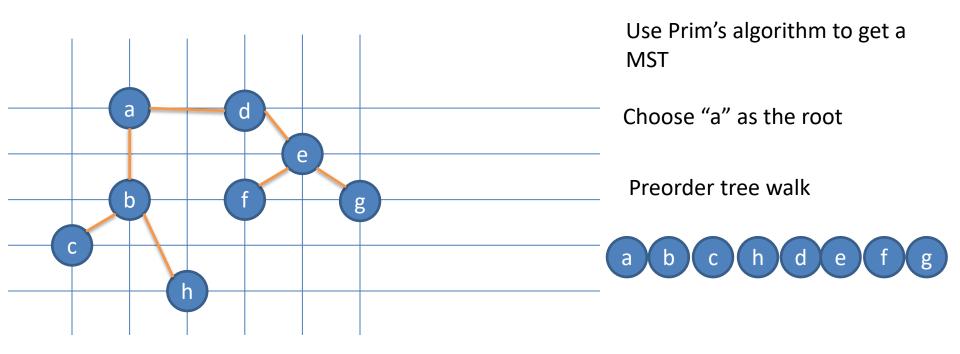
APPROX-TSP-TOUR(G)

```
Find a MST m;
Choose a vertex as root r;
return preorderTreeWalk(m, r);
```



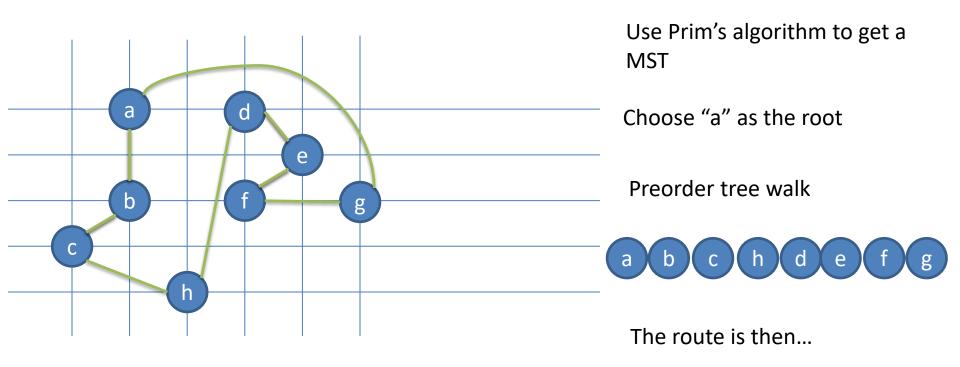
For any pair of vertices, there is a edge and the weight is the Euclidean distance

Triangle inequality is true, we can apply the approximation algorithm



For any pair of vertices, there is a edge and the weight is the Euclidean distance

Triangle inequality is true, we can apply the approximation algorithm



Because it is a 2-approximation algorithm

A TSP solution is found, and the total weight is at most twice as much as the optimal one

Set-covering problem

- Given a set X, and a family F of subsets of X, where F covers X, i.e. $X = \bigcup_{S \in F} S$.
- Find a subset of F that covers X and with minimum size

{f1, f3, f4} is a subset of F covering X

F:

f1: a b

f5: (a

{f1, f2, f3, f4} is a subset of F covering X

f2: b

{f2, f3, f4, f5} is a subset of F covering X

f3: c h

Here, {f1, f3, f4} is a minimum cover set

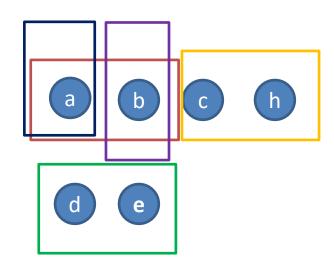
f4: d e

- Set-covering problem is NP-complete.
- If the size of the largest set in F is m, there is a $\sum_{i=1}^{m} 1/i$ approximation polynomial time algorithm to solve it.

GREEDY-SET-COVER(X, F)

```
U=X;
C=Ø;
While(U \neq \emptyset){
   Select S∈F that maximizes |S∩U|;
   U=U-S;
   C=CU\{S\};
return C;
```

X:



We can choose from f1, f3 and f4

Choose f1

We can choose from f3 and f4

Choose f3

We can choose from f4

Choose f4

F:

f1: a b

f2: b

f3: c h

f4: d e

f5: (a)

I: a b c h d

C: f1: a b

f3: Ch

f4: d e

Set Cover and its generalizations and variants are fundamental problems with numerous applications. Examples include:

- selecting a small number of nodes in a network to store a file so that all nodes have a nearby copy,
- selecting a small number of sentences to be uttered to tune all features in a speech-recognition model [11],
- selecting a small number of telescope snapshots to be taken to capture light from all galaxies in the night sky,
- finding a short string having each string in a given set as a contiguous sub-string.

What exactly NP is?

What is polynomial-time?

- Polynomial-time: running time is $O(n^k)$, where k is a constant. (Also written as: $n^{O(1)}$)
- Are they polynomial-time running time?

$$-T(n)=3$$

$$-T(n)=n$$

$$-T(n) = nlg(n)$$

$$-T(n)=n^3$$

Revision

What is polynomial-time?

Are the polynomial-time?

$$-T(n) = 5^{n}$$
• No
$$-T(n) = n!$$
• No

- Problems with polynomial-time algorithms are considered as tractable
- With polynomial-time, we can define P problems, and NP problems



P problems

- (The original definition) Problems that can be solved by deterministic Turing machine in polynomial-time.
- (A equivalent definition) Problems that are solvable in polynomial time

Examples

- A set of decision problem with yes/no answer
- Calculating the greatest common divisor
- sorting n numbers in ascending or descending order
- search the element in the list



- NP problems
 - (The original definition) Problems that can be solved by non-deterministic Turing machine in polynomial-time.
 - (A equivalent definition) Problems that are verifiable in polynomial time.
 - Given a solution, there is a polynomial-time algorithm to tell if this solution is correct
 - Examples
 - (i) Integer Factorization
 - (ii) Graph Isomorphism

- Polynomial-time verification can be used to easily tell if a problem is a NP problem
- E.g.:
 - Sorting, n-integers
 - A candidate: an array
 - Verification: scan it once
 - Max-heapify, n-nodes:
 - A candidate: a complete binary search tree
 - Verification: scan all the nodes once
 - Find all the sub sets of a given set A, |A|=n
 - A candidate: a set of set
 - Verification: check each set

NP Problems

- NP = {Decision problems solvable in polynomial time via a "lucky" algorithm}. The "lucky" algorithm can make lucky guesses always "right" without trying all options.
 - Stage 1 Non-deterministic model (Guessing): algorithm makes guesses.
 - Stage 2: Deterministic ("verification") says YES or
 NO () guesses guaranteed to lead to YES outcome if possible (no otherwise).

NP Problems: verification stage is polynomial

- Based on the definition of P and NP, which statements are correct?
 - "NP means non-polynomial"
 - No!
 - $-P \cap NP = \emptyset$
 - No. $P \subseteq NP$
 - A P problem is also a NP problem
 - Yes. $P \subseteq NP$

• any problem solvable by a deterministic Turing machine in polynomial time is also solvable by a nondeterministic Turing machine in polynomial time. Thus, $\mathbf{P} \subseteq \mathbf{NP}$

P = NP means whether an NP problem can belong to class P problem. In other words whether every problem whose solution can be verified by a computer in polynomial time can also be solved by a computer in polynomial time

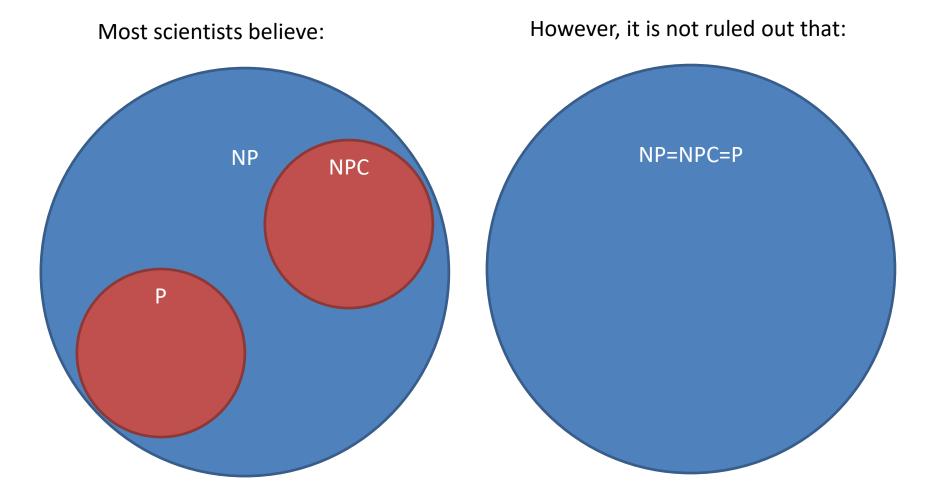
In order to prove that $P \neq NP$, we would need to prove that there exists a set of problems X such that:

- •X falls in **NP**. There exists an algorithm with which a nondeterministic Turing machine could solve problems in X in polynomial time
- •X does not fall in **P**. There exists no algorithm whatsoever with which a deterministic Turing machine could solve problems in X in polynomial time

What are NP-complete problems?

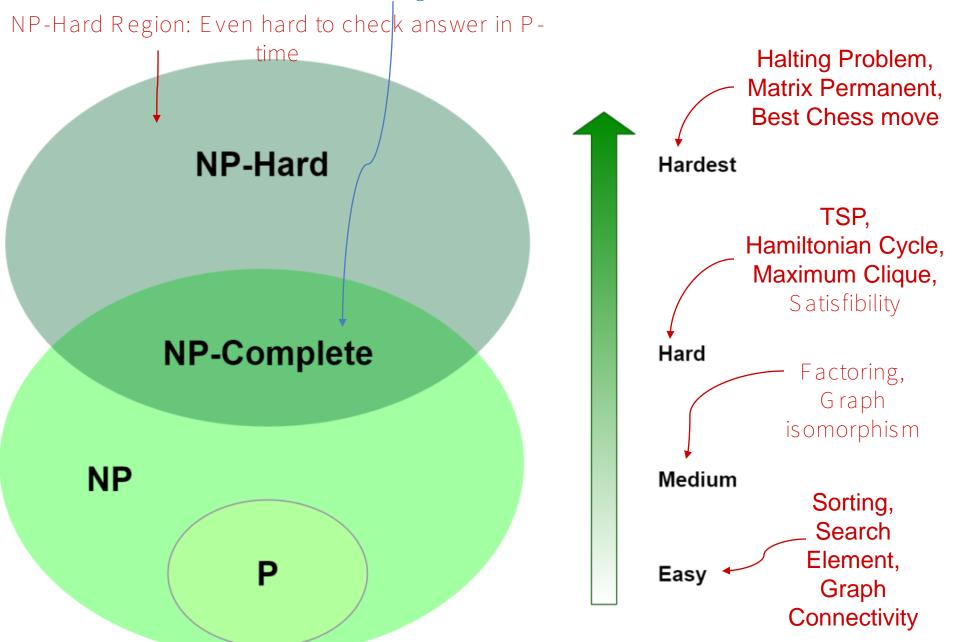
- A NP-complete problem(NPC) is
 - a NP problem
 - harder than all equal to all NP problems
- In other words, NPC problems are the hardest NP problems
- So far, no polynomial time algorithms are found for any of NPC problems

What are NP-complete problems?



NP-Hard problems: problems harder than or equal to NPC problems

NP-Hard Region: Can be verified in P-time



NP-Completeness

NP-Hard
NP-Complete

NP

- A problem B is NP-complete if:
 - (1) $B \in NP$
 - (2) $A \leq_p B$ for all $A \in \mathbf{NP}$
- If B satisfies only property (2) we say that B is NP-hard
- No polynomial time algorithm has been discovered for an NP-Complete problem
- No one has ever proven that no polynomial time algorithm can exist for any NP-Complete problem
- if any NP-complete problem can be solved in polynomial time, then every problem in NP has a polynomial-time solution.

Examples

Hamiltonian Paths

Optimization Problem: Given a graph, find a path that passes through every vertex exactly once

Decision Problem: Does a given graph have a Hamiltonian Path?

Traveling Salesman

Optimization Problem: Find a minimum weight Hamiltonian Path

Decision Problem: Given a graph and an integer k, is there a Hamiltonian Path with a total weight at most k?

<u>Factoring and Graph isomorphism:</u> are NP Problems which means we can verify solution in P time. But these problems still can not reduce to any existing NP-complete problem (so these problems are not hard as NP-complete problems). Therefore may be in the computational complexity class NP-intermediate.

NP-Hard

- An example of an NP-hard problem is Travelling Salesman Problem (TSP)
 - A special case of TSP, i.e. Metric TSP happens to be NPcomplete.
- There are decision problems that are NP-hard but not NP-complete such as the halting problem. That is the problem which asks "given a program and its input, will it run forever?"
 - The halting problem is not in NP since all problems in NP are decidable in a finite number of operations, but the halting problem, in general, is undecidable.

[https://en.wikipedia.org/wiki/NP-hardness]

Why we study NPC?

- For new computational problems we encounter:
- 1. We try for a while to develop an efficient algorithm; and if this fails,
- 2. We then try to prove it NP-complete.
- 3. Find Approximate Algorithms (sub-optimal solution) if required.

How to prove a problem is a NPC problem?

How to prove a problem is a NPC problem?

- A common method is to prove that it is not easier than a known NPC problem.
- To prove problem A is a NPC problem
 - Choose a NPC problem B
 - Develop a polynomial-time algorithm translate A to B
- A reduction algorithm
- If A can be solved in polynomial time, then B can be solved in polynomial time. It is contradicted with B is a NPC problem.
- So, A cannot be solved in polynomial time, it is also a NPC problem.



What if a NPC problem needs to be solved?

- Buy a more expensive machine and wait
 - (could be 1000 years)
- Turn to approximation algorithms
 - Algorithms that produce near optimal solutions

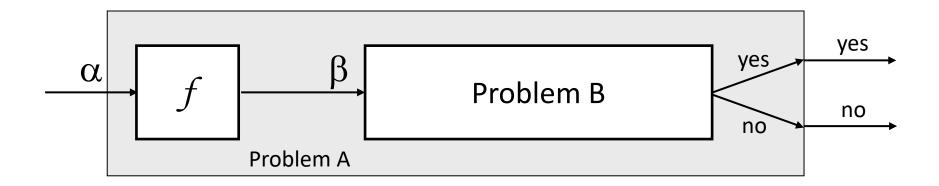
NP-Completeness Reduction

Reduction

- Reduction is a way of saying that one problem is "easier" than another.
- We say that problem A is easier than problem B, (i.e., we write "A ≤ B")

if we can solve A using the algorithm that solves B.

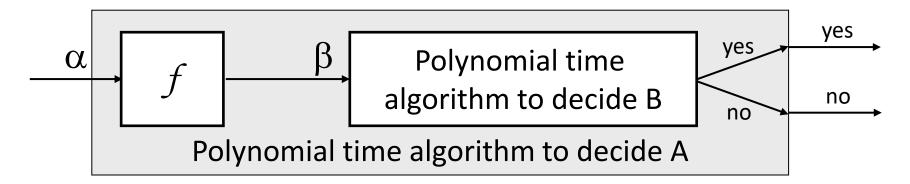
• Idea: transform the inputs of A to inputs of B



Polynomial Reduction

Given two problems A, B, we say that A is polynomially reducible to B $(A \le_p B)$ if:

There exists a function f that converts the input of A to inputs of B in polynomial time



- 1. Use a polynomial time reduction algorithm to transform A into B
- 2. Run a known **polynomial time** algorithm for B
- 3. Use the answer for B as the answer for A

Reduction

Reduction can be used to show:

1. Problem is tractable (solvable)

- 2. Problem is intractable (unsolvable)
 - To spread hardness.

Reductions Spread Tractability

If problem A reduces to problem B and B can be solved by a polynomial-time algorithm, then A can also be solved by a polynomial-time algorithm (Figure 19.2).

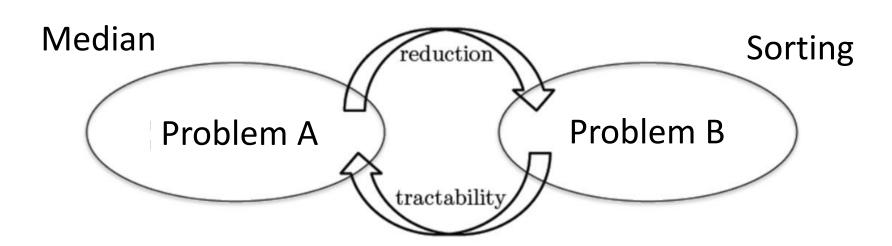


Figure 19.2: Spreading tractability from B to A: If problem A reduces to problem B and B is computationally tractable, then A is also computationally tractable.

If $A \leq_{p} B$ and $B \in P$, then $A \in P$

Reductions Spread Intractability

If problem A reduces to problem B and A is NP-hard, then B is also NP-hard (Figure 19.3).

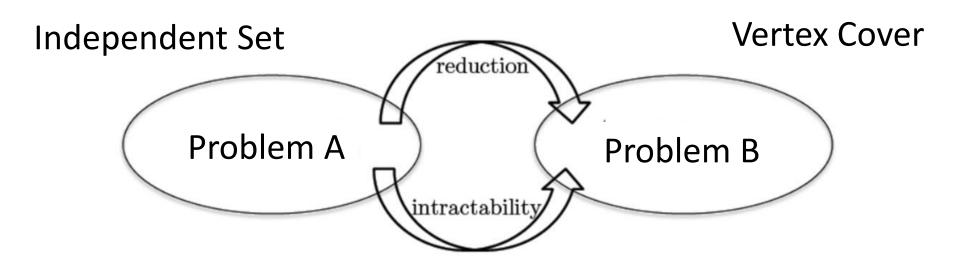
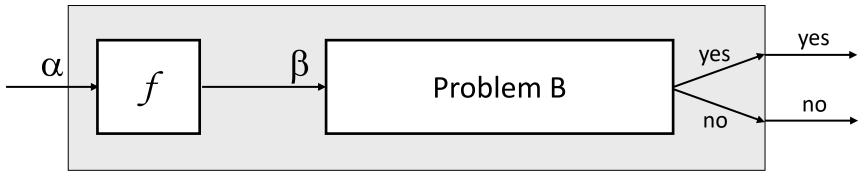


Figure 19.3: Spreading intractability in the opposite direction, from A to B: If problem A reduces to problem B and A is computationally intractable, then B is also computationally intractable.

if $A \leq_{p} B$ and $A \notin P$, then $B \notin P$

Implications of Reduction

 Problem A reduces to problem B if you can use an algorithm that solves B to help solve A.



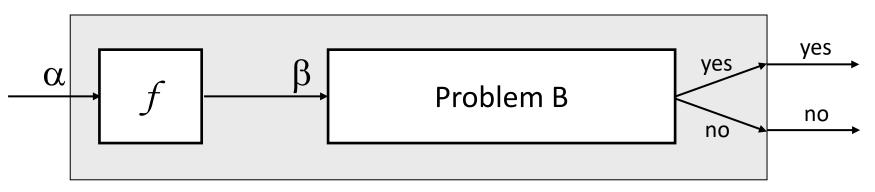
Algorithm for Problem A

- If $A \leq_p B$ and $B \in P$, then $A \in P$
- if $A \leq_p B$ and $A \notin P$, then $B \notin P$

Cost of solving A = total cost of solving B + cost of reduction.

Reductions (Tractable Examples)

 Problem A reduces to problem B if you can use an algorithm that solves B to help solve A.



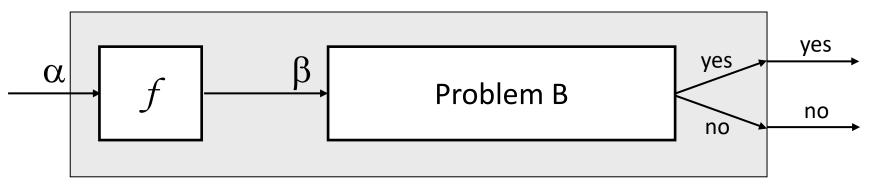
Algorithm for Problem A

- Example 1. [finding the median reduces to sorting]
- To find the median of N items:
 - Sort N items
- Return item in the middle: Cost of Sorting
 Cost of Reduction

 Cost of solving finding median = O(n log n) + 1

Reductions (Tractable Examples)

 Problem A reduces to problem B if you can use an algorithm that solves B to help solve A.



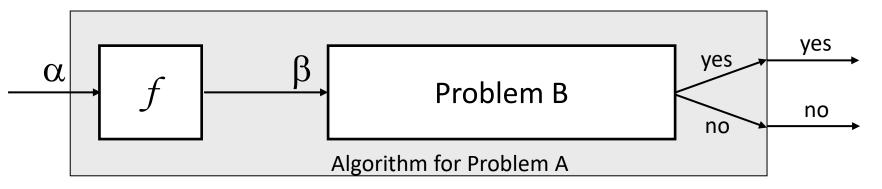
Algorithm for Problem A

- Example 2. [element distinctness reduces to sorting]
- To solve element distinctness on N items:
 - Sort N items
- Check adjacent pairs for equality. Cost of Sorting
 Cost of Reduction

 Cost of solving element distinctness = O(n log n) + O(n) ←

Reductions (Tractable Examples)

 Convex hull. Given N points in the plane, identify the extreme points of the convex hull (in counterclockwise order).



- Example 3. [Convex hull reduces to sorting.]
- To solve convex hull:
 - Choose point p with smallest (or largest) y-coordinate.
 - Sort points by polar angle with p.
 - Consider points in order, and discard those that would create a clockwise turn.

Cost of Sorting Cost of Reduction
$$\cos = O(n \log n) + O(n)$$

Cost of solving element distinctness = $O(n \log n) + O(n)$

RECIPE FOR PROVING PROBLEM Is NP-Complete

To Prove B Is NP-Complete

- 1. Prove that B is a member of the class NP. $B \in NP$
- 2. Choose an NP-complete problem A.

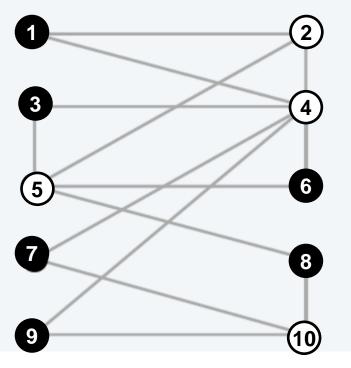
3. Prove that there is a Levin reduction from A to B.

Independent Set (Example 1)

INDEPENDENT-SET. Given a graph G = (V, E) and an integer k, is there a subset of k (or more) vertices such that no two are adjacent?

Ex. Is there an independent set of size ≥ 6 ?

Ex. Is there an independent set of size ≥ 7 ?



{1} is independent Set

{2, 3} is independent Set

{1, 3} is independent Set

{1, 3, 6} is independent Set

[2, 5, 6, 7] is independent Set

{1, 3, 6, 7} is independent Set

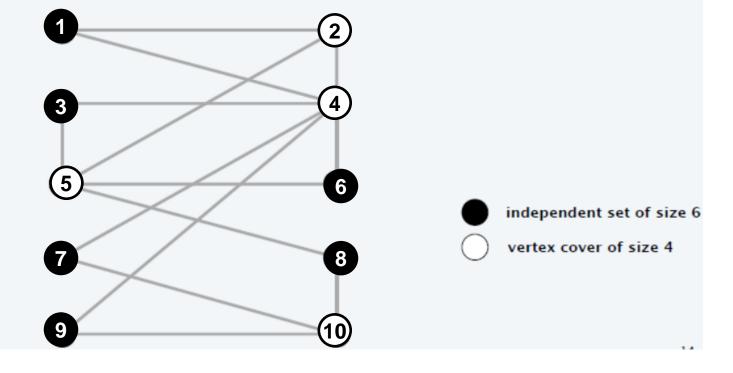
{1, 3, 6, 7, 8, 9} is independent Set

independent set of size 6

Vertex Cover (Example 1)

VERTEX-COVER. Given a graph G = (V, E) and an integer k, is there a subset of k (or fewer) vertices such that each edge is incident to at least one vertex in the subset?

- Ex. Is there a vertex cover of size ≤ 4 ?
- Ex. Is there a vertex cover of size ≤ 3 ?



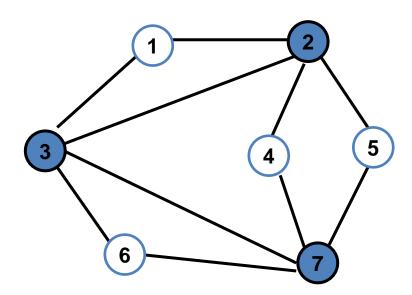
Vertex Cover is NP-Complete Recipe to Prove a Problem Is NP-Complete

- Prove that a Vertex Cover is NP-Complete
- Step 1. Vertex Cover ∈ NP
- Step 2. Choose an NP-Complete problem A (Independent Set).
 Prove that A (Independent set) reduces to B (Vertex Cover)
 INDEPENDENT-SET ≤_p VERTEX-COVER.

Step 1: Vertex Cover ∈ NP

Given Graph G = (V, E) contains Vertex cover of Size 3?

S is vertex cover if every edge in E has at least one endpoint in S. (Example V.C = $\{2,3,7\}$)



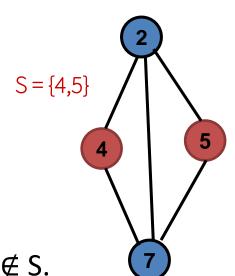
Vertex cover and independent set reduce to one another

- Lemma: INDEPENDENT-SET \leq_p VERTEX-COVER.
- **Proof:** We show *S* is an independent set of size k, iff V S is a vertex cover of size n k.
 - Let S be any independent set of size k.
 - Consider an arbitrary edge $(u, v) \in E$.





Thus, V – S covers (u, v). ■

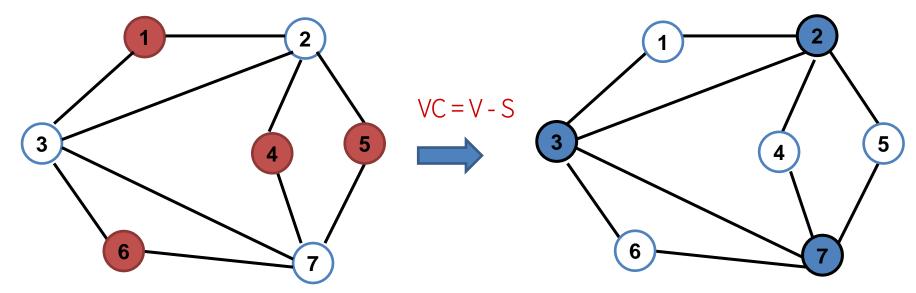


Independent Set (Example 2)

 S is independent if there are no edges between vertices in S. (Example I.S = {1,4,5,6})

$$V.C = V - S$$

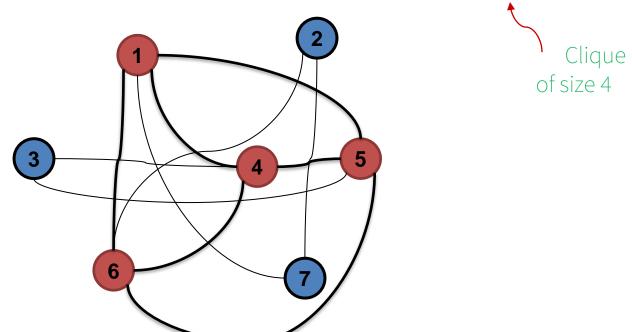
(V.C ={2,3,7})



Clique (Example 2)

Clique

— Graph G = (V, E), a subset S of the vertices is a clique if there is an edge between every pair of vertices in S. (Example Clique = {1,4,5,6})



Clique is NP-Complete

Recipe to Prove a Problem Is NP-Complete

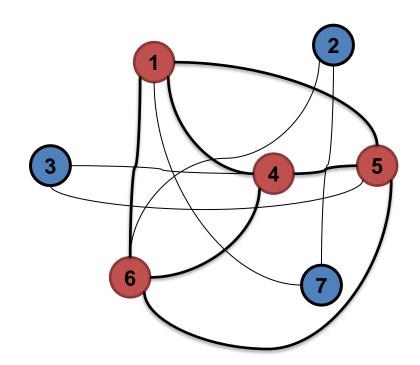
Prove that a Clique is NP-Complete

• Step 1. Clique \in NP.

Step 2. Choose known NP-Complete problem A (IS).
 Prove that A (IS) reduces to B (Clique)
 IS ≤_p Clique.

Step 1: Clique ∈ NP.

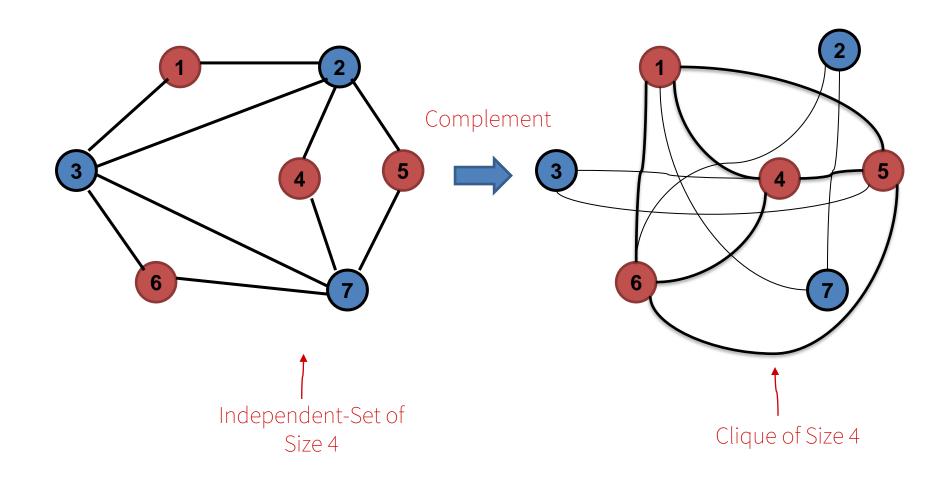
- Graph G = (V, E), a subset S of the vertices is a clique if there is an edge between every pair of vertices in S. (Example Clique = {1,4,5,6})
- Given graph contains Clique of size = 4?



Step 2: $IS \leq_p Clique$

- Lemma: S is Independent in G iff S is a Clique in the complement of G
- To reduce IS to Clique, we compute the complement of the graph. The complement has a clique of size K iff the original graph has an independent set of size K.
- Construction of Complement of the graph can easily be done in polynomial time.

$IS \leq_p Clique (Example 2)$



Reduction: Independent Set, Vertex Cover, and Clique (Example 3)

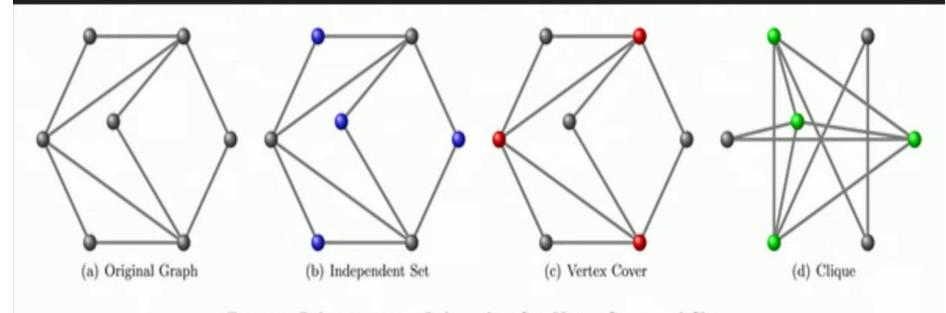


Figure 1: Relations among Independent Set, Vertex Cover, and Clique

INDEPENDENT-SET is NP-Complete Recipe to Prove a Problem Is NP-Complete

- To prove that a problem B (INDEPENDENT-SET) is NP-Complete:
- Step 1. INDEPENDENT-SET ∈ NP
- Step 2. Choose an NP-Complete problem A (3-SAT).
 Prove that A (3-SAT) reduces to B (INDEPENDENT-SET)
 3-SAT ≤₀ INDEPENDENT-SET

Satisfiability

Literal. A Boolean variable or its negation.

$$x_i$$
 or $\overline{x_i}$

Clause. A disjunction of literals.

$$C_j = x_1 \vee \overline{x_2} \vee x_3$$

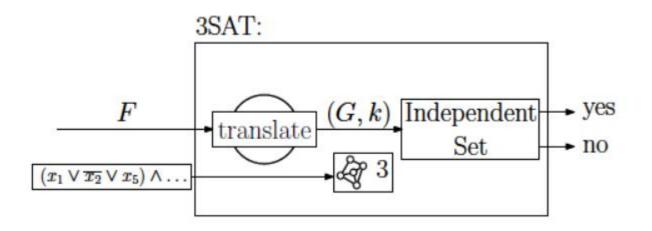
Conjunctive normal form (CNF). A propositional formula Φ that is a conjunction of clauses.

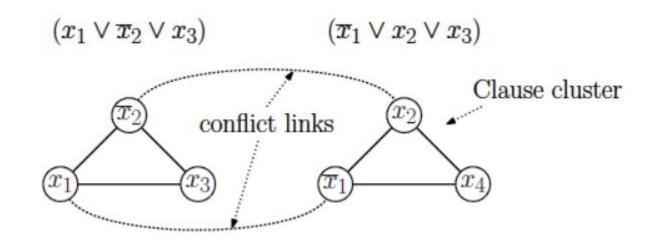
$$\Phi = C_1 \wedge C_2 \wedge C_3 \wedge C_4$$

SAT. Given a CNF formula Φ , does it have a satisfying truth assignment? 3-SAT. SAT where each clause contains exactly 3 literals (and each literal corresponds to a different variable).

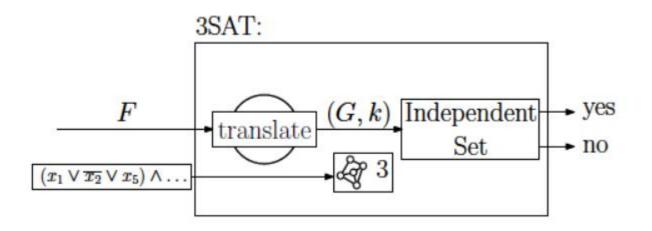
yes instance: $x_1 = \text{true}, x_2 = \text{true}, x_3 = \text{false}, x_4 = \text{false}$

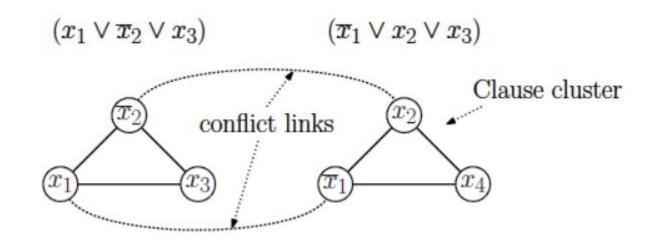
3-satisfiability reduces to independent set





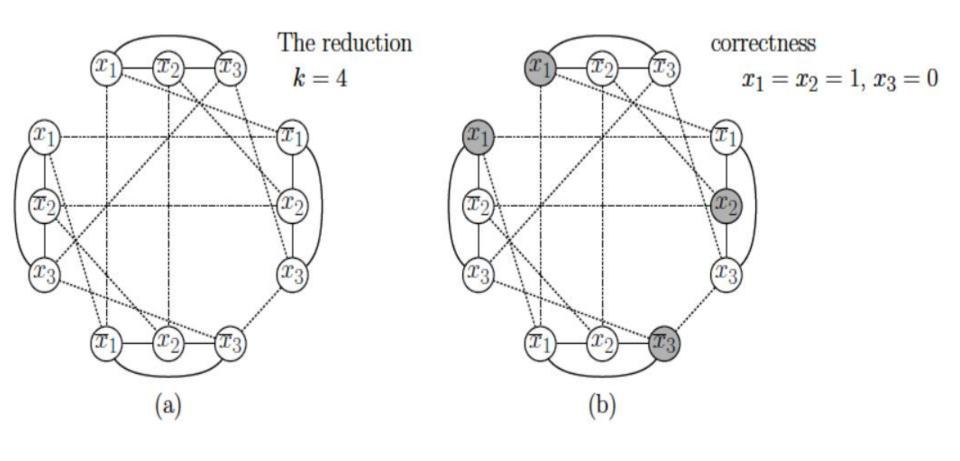
3-satisfiability reduces to independent set





3-satisfiability reduces to independent set

$$F = (x_1 \vee \overline{x_2} \vee \overline{x_3}) \wedge (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_1} \vee x_2 \vee \overline{x_3}) \wedge (x_1 \vee \overline{x_2} \vee x_3).$$



Cook-Levin theorem shows that 3-SAT is a "universal" problem

