CS 344: Design and Analysis of Computer Algorithms

(Spring 2022 — Sections 5,6,7,8)

Lecture 25: NP-hardness Reductions

(Complexity) Classes P & NP

Classes P and NP

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- Class P:
 - ALL problems that can be solved in polynomial time
- Class NP:
 - ALL problems that can be verified in polynomial time

Classes P and

Problems we can solve efficiently

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- Class P:
 - ALL problems that can be solved in polynomial time
- Class NP:
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Problems we "hope" to be able to solve efficiently

Classes P and NP

- Clearly any problem in P is also in NP
 - If we can solve a problem in poly-time, we can definitely verify it in poly-time
- Big open question of Computer Science:

Is P=NP or not?

NP-Hard & NP-Complete problems

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- We want to show that Q is impossible to solve in polynomial time
- We do not know how to do that

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- Instead, we go for the next best thing:
 - Show that Q is really hard to solve in polynomial time
- A simple approach:
 - Show that if Q can be solved in polynomial time, then P = NP

NP-Hard and NP-Complete Problems

NP-hard problems:

 We say a problem R is NP-hard if designing a poly-time algorithm for R implies P=NP

NP-complete problems:

We say a problem R is NP-complete if (1) R is in NP itself, and
 (2) R is NP-hard

Circuit-SAT problem & Cook-Levin Theorem

Goal: Show that Q is NP-hard

Approach:

- Find any problem R which is already known to be NP-hard
- Show that R can be reduced to Q:
 - if Q can be solved in poly-time then R can also be solved in poly-time

Circuit-SAT Problem

 The very first NP-hard problem is called the circuit-satisfiability problem or circuit-SAT

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 The very first NP-hard problem is called the circuit-satisfiability problem or circuit-SAT

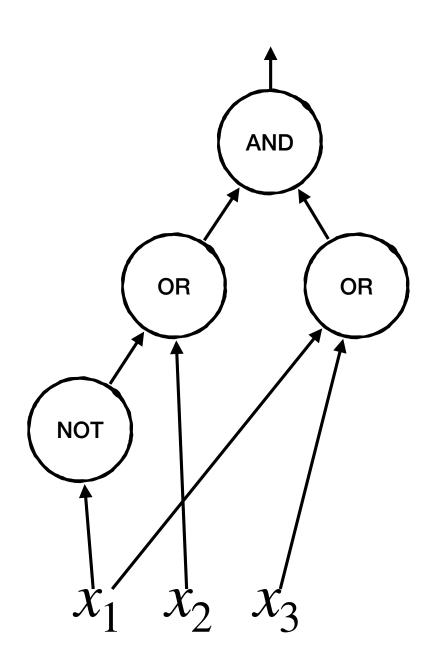
Input:

- A circuit C with binary AND and OR gates and unary NEGATE gates with n inputs in total
- For any $x \in \{0,1\}^n$ we use C(x) to denote the value of circuit on the input x

Output:

- Is there any x such that C(x) = True?

Circuit-SAT Problem: Example



Circuit-SAT

• Circuit-SAT is in NP

Circuit-SAT

- Circuit-SAT is in NP
- A poly-time verifier:
 - The proof is an assignment x such that C(x) = 1
 - We can evaluate x in C to compute the answer the evaluation is done bottom-up by computing value of each gate
- Cook-Levin Theorem: Circuit-SAT is NP-complete

Reductions

- We now know that circuit-SAT is NP-complete (and so NP-hard)
- We can use circuit-SAT in reductions to prove other problems are also NP-hard

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Example 1: 3-SAT is NP-Complete

Definition:

- Literal: a variable or its negation
- Clause: OR of a collection of literals
- CNF-Formula: AND of a collection of clauses

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 3-CNF formula: any CNF-formula whose clauses have at most three literals

Input:

• Output:

- Decide if there is an assignment of values in $\{0,1\}^n$ to the variables so that Φ evaluates to TRUE

3-SAT Problem: Example

- Examples:
- $\Phi = (X \vee Y \vee \bar{Z}) \wedge (\bar{X} \vee \bar{Y} \vee Z)$

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- Answer is YES: set (X,Y,Z) = (0,1,0)

3-SAT Problem: Example

• Examples:

- $\Phi = (X \vee Y \vee \bar{Z}) \wedge (\bar{X} \vee \bar{Y} \vee Z)$
- Answer is YES: set (X,Y,Z) = (0,1,0)
- $\Phi = (X \lor Y) \land (\bar{X} \lor \bar{Y}) \land (X \lor \bar{Y}) \land (\bar{X} \lor Y)$
- Answer is NO: any assignment makes (exactly) one of the clauses false

3-SAT Problem is in NP

3-SAT Problem is in NP

- We need a poly-time verifier
- Proof for verifier: if the answer is YES, give a satisfying assignment x to Φ
- We go over clauses one by one and make sure x satisfies every clause
- This takes only O(n+m) time so poly-time

3-SAT Problem is NP-Hard

3-SAT Problem is NP-Hard

 We have to show that if 3-SAT can be solved in poly-time then P=NP

- Recall our plan:
 - If 3-SAT can be solved in poly-time, then some NP-hard problem can also be solved in poly-time

3-SAT Problem is NP-Hard

 We have to show that if 3-SAT can be solved in poly-time then P=NP

- Recall our plan:
 - If 3-SAT can be solved in poly-time, then some NP-hard problem can also be solved in poly-time
 - At this point, the only NP-hard problem we know is Circuit-SAT

Reduction

- Given a circuit C as input to the Circuit-SAT problem, we create a new input
 Ф for the 3-SAT problem such that:
 - The answer to Circuit-SAT on C is the same as the answer to 3-SAT on Φ
- We then assume that 3-SAT can be solved in poly-time and we run any algorithm for that to solve this instance Φ
- This then gives us a poly-time algorithm for any instance of Circuit-SAT also
- So 3-SAT should be NP-hard too

Reduction

Given the circuit C, define a new variable for every wire in C including the input wires

Reduction

- For every AND gate in C:
 - Let a be the variable of output wire and b and c be the ones for input wires, so we want $a = (b \land c)$
 - Add the following clauses to Φ :

$$(a \lor \bar{b} \lor \bar{c}) \land (\bar{a} \lor b) \land (\bar{a} \lor c)$$

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Note: in any assignment that makes Φ TRUE, we have $a = (b \land c)$

- For every OR gate in C:
 - Let a be the variable of output wire and b and c be the ones for input wires, so we want $a = (b \lor c)$
 - Add the following clauses to Φ :

$$(\bar{a} \lor b \lor c) \land (a \lor \bar{b}) \land (a \lor \bar{c})$$

- For every OR gate in C:
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$$(\bar{a} \lor b \lor c) \land (a \lor \bar{b}) \land (a \lor \bar{c})$$

Note: in any assignment that makes Φ TRUE, we have $a = (b \lor c)$

- For every NOT gate in C:
 - Let a be the variable of output wire and b be the one for input wire, so we want $a = \bar{b}$
 - Add the following clauses to Φ :

$$(a \lor b) \land (\bar{a} \lor \bar{b})$$

- For every NOT gate in C:
 - Let a be the variable of output wire and b be the one for input wire, so we want $a = \bar{b}$
 - Add the following clauses to Φ :

$$(a \lor b) \land (\bar{a} \lor \bar{b})$$

Note: in any assignment that makes Φ TRUE, we have $a = \bar{b}$

- For the output wire in C:
 - Let a be the variable of output wire
 - Add the following clauses to Φ :

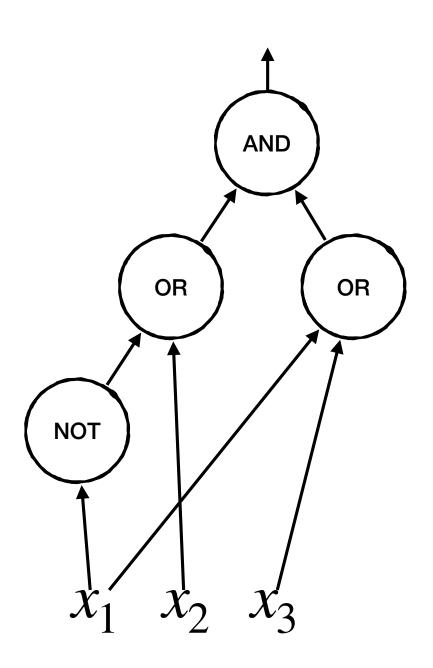
(a)

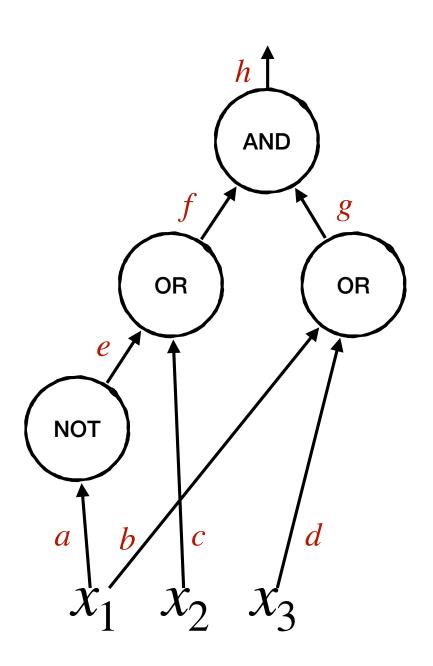
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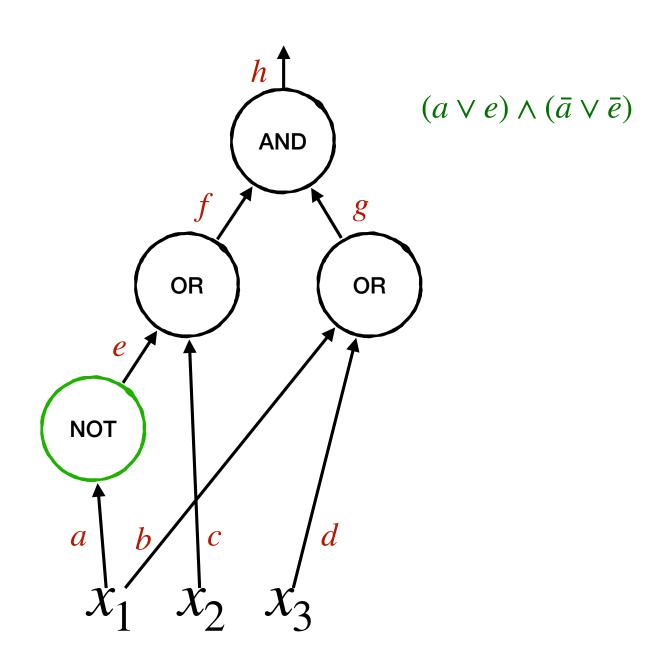
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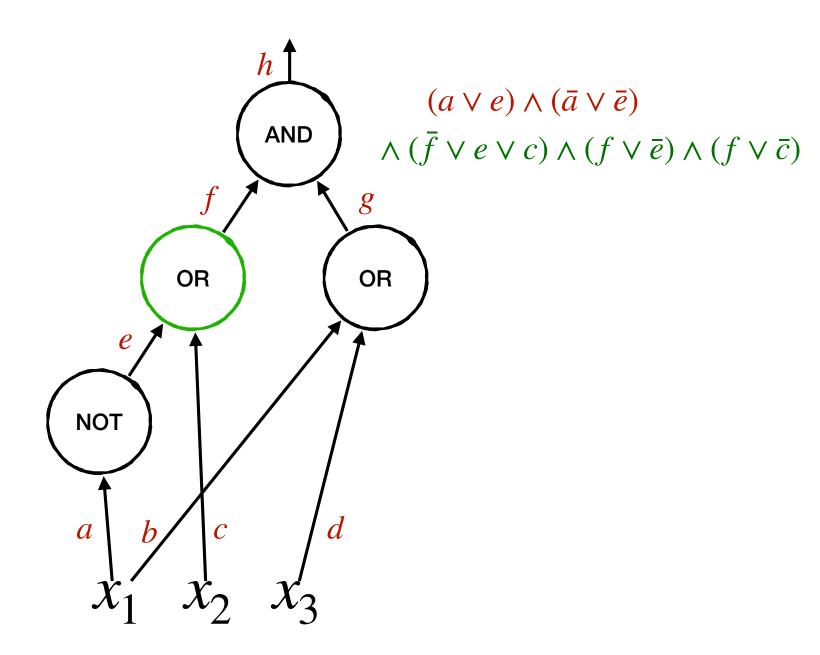
Note: in any assignment that makes Φ TRUE, we have a=1

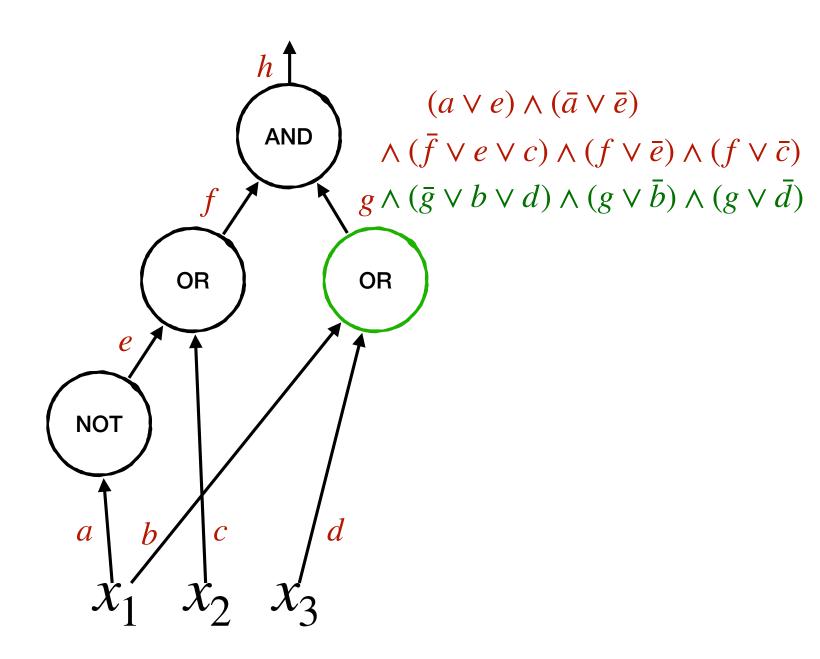
- After creating Φ this way, we run any algorithm for 3-SAT on Φ
- Return the same answer to the original Circuit-SAT problem

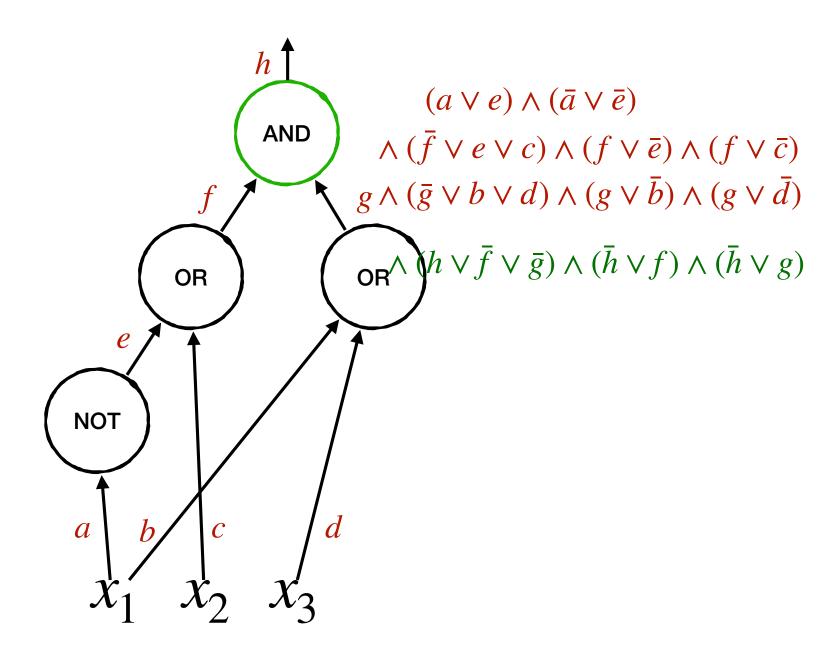


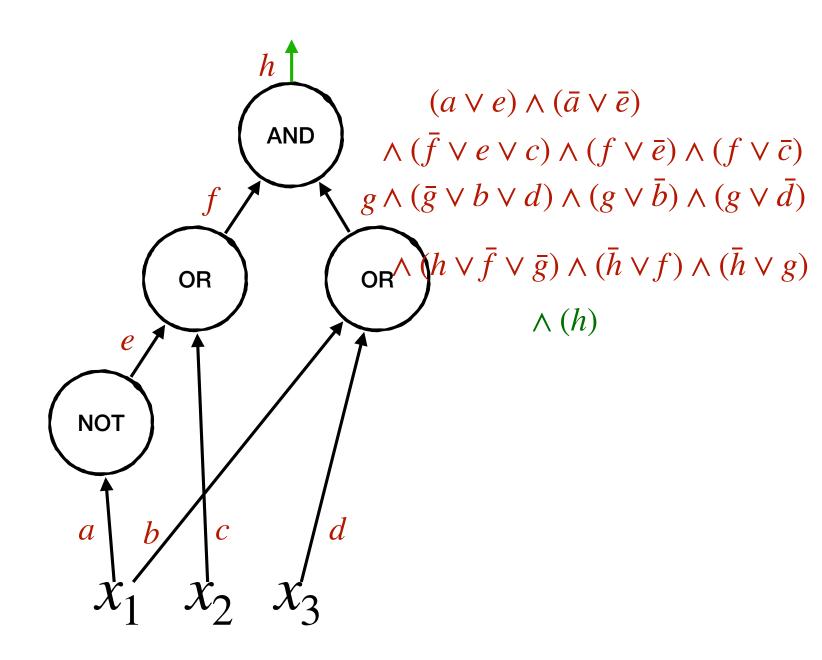


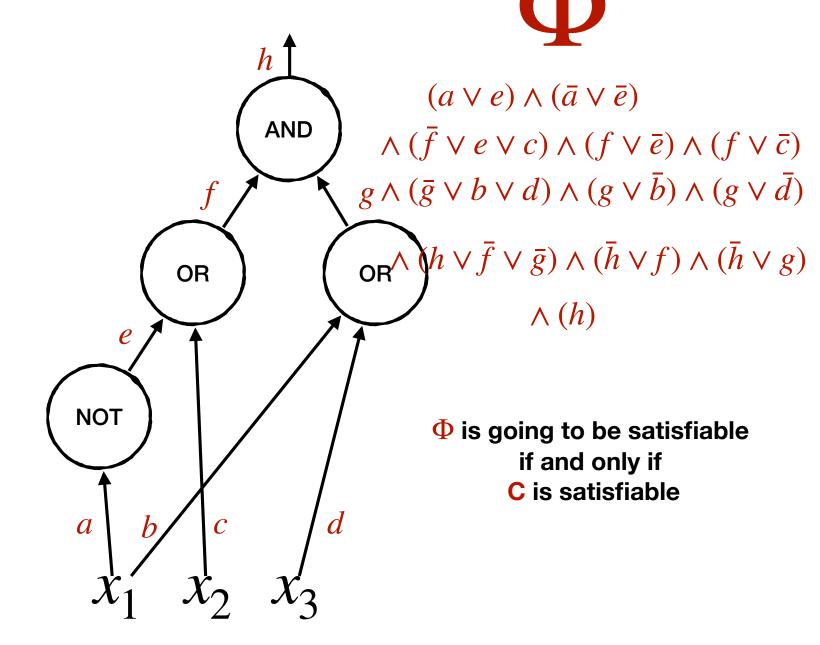












Reduction: Proof of Correctness

- Part one: If Φ is satisfiable then C is also satisfiable
- Pick a satisfying assignment y to Φ
- Let x be the assignment of variables to input wires in y
- C(x) must be TRUE so C is also satisfiable

Reduction: Proof of Correctness

- Pick a satisfying assignment x to C
- Let y be the assignment to all variables of Φ corresponding to the values of all wires in C(x)
- $\Phi(y)$ must be TRUE so Φ is also satisfiable

Reduction: Runtime Analysis

- **IF** we have a poly-time algorithm for 3-SAT we also get a poly-time reduction this way.
- Size of Φ is just a constant factor larger than the input circuit (at most three clause per wire)

Reduction: Conclusion

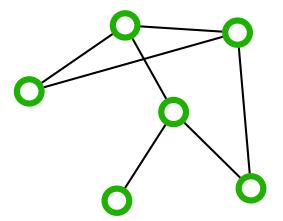
- So if 3-SAT can be solved in poly-time Circuit-SAT can also be solved in poly-time
- This means if 3-SAT can be solved in poly-time then P=NP because Circuit-SAT is NP-hard
- So 3-SAT is also NP-hard

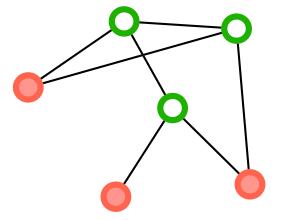
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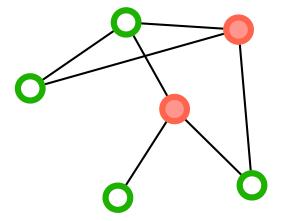
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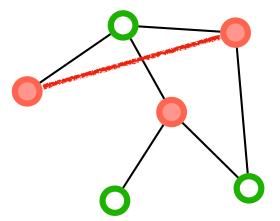
Since 3-SAT is also in NP, it is actually NP-complete

Example 2: Maximum Independent Set is NP-Hard









Maximum Independent Set Problem

Input:

An undirected graph G=(V,E)

Output:

Size of the largest independent set in G

For simplicity, we are going to call this problem MaxIndSet

MaxIndSet

• Is MaxIndSet in NP?

MaxIndSet

- Is **MaxIndSet** in NP?
- No because it is NOT a decision problem

MaxIndSet is NP-hard

- We are going to show that it is NP-hard
- This requires proving if MaxIndSet can be solved in poly-time, then P=NP
- Using reductions, this requires showing that a poly-time algorithm for MaxIndSet can solve another NP-hard problem in poly-time

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We use 3-SAT for this purpose

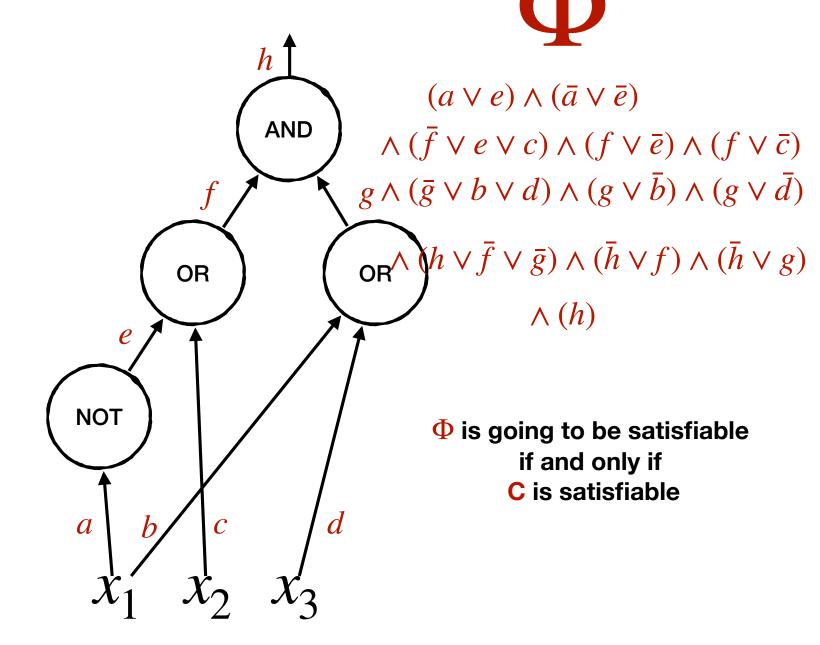
MaxIndSet: Reduction From 3-SAT

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- - For any clause in Φ , we add one vertex per literal of the clause
 - We connect all vertices in a clause together
 - We connect a vertex u to a vertex v if the literal of u is the negation of the literal of v

MaxIndSet: Reduction From 3-SAT

- - For any clause in Φ , we add one vertex per literal of the clause
 - We connect all vertices in a clause together
 - We connect a vertex u to a vertex v if the literal of u is the negation of the literal of v
- After creating G, we run any algorithm for MaxIndSet on G
- If size of the returned independent set is equal to the number of clauses, we return Φ is satisfiable, and otherwise it is not.



$$\Phi = (a \lor e) \land (\bar{a} \lor \bar{e}) \land (\bar{f} \lor e \lor c) \land (f \lor \bar{e}) \land (f \lor \bar{c}) \land (\bar{g} \lor b \lor d) \land (g \lor \bar{b}) \land (g \lor \bar{d})$$
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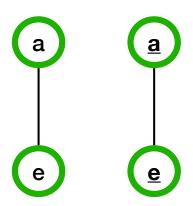


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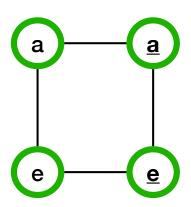


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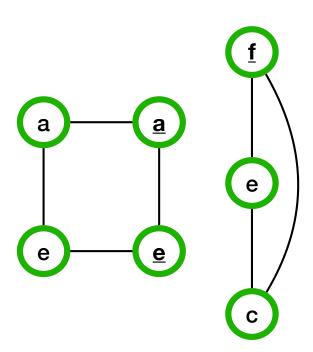




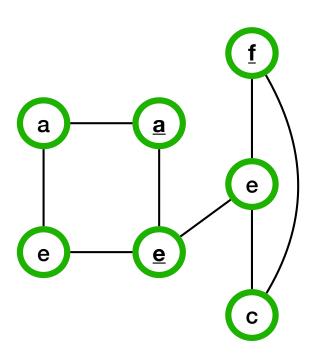
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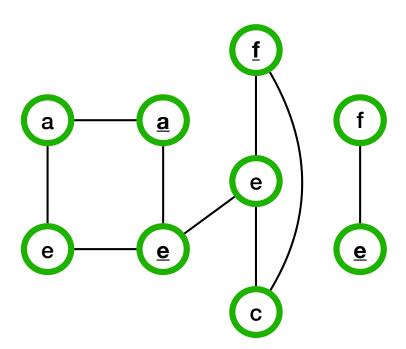




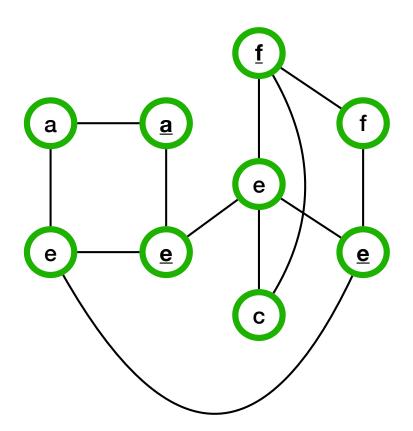




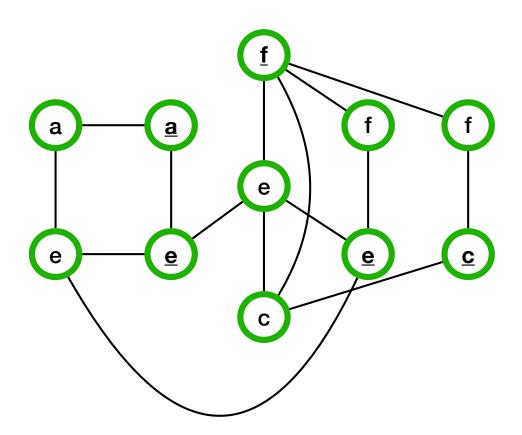




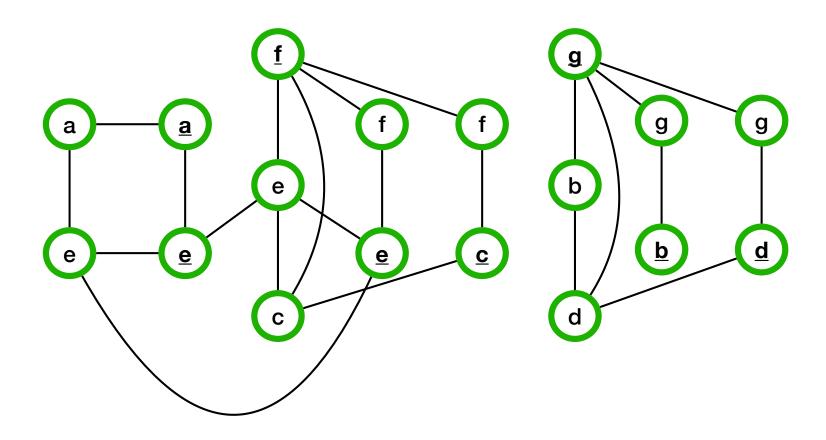


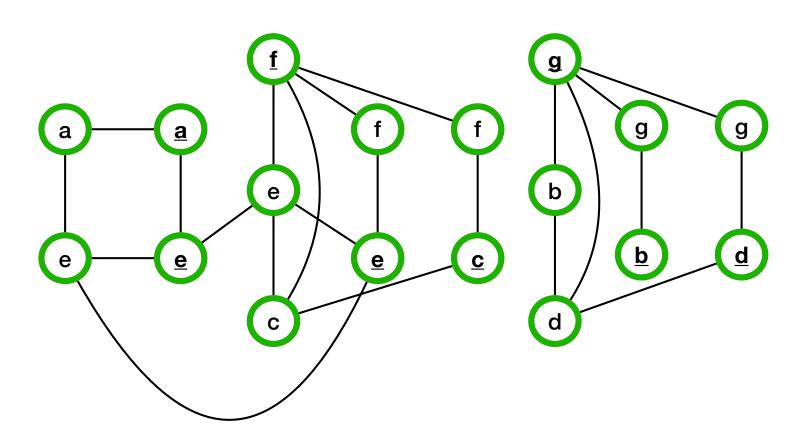






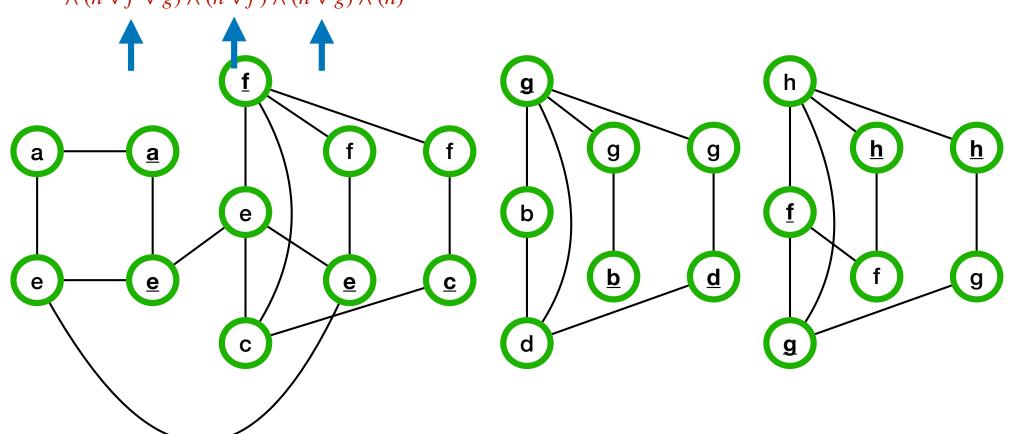






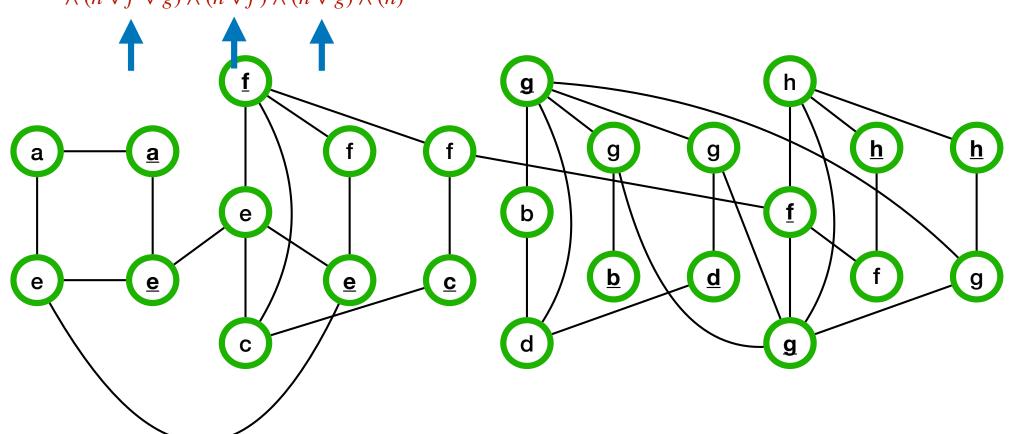
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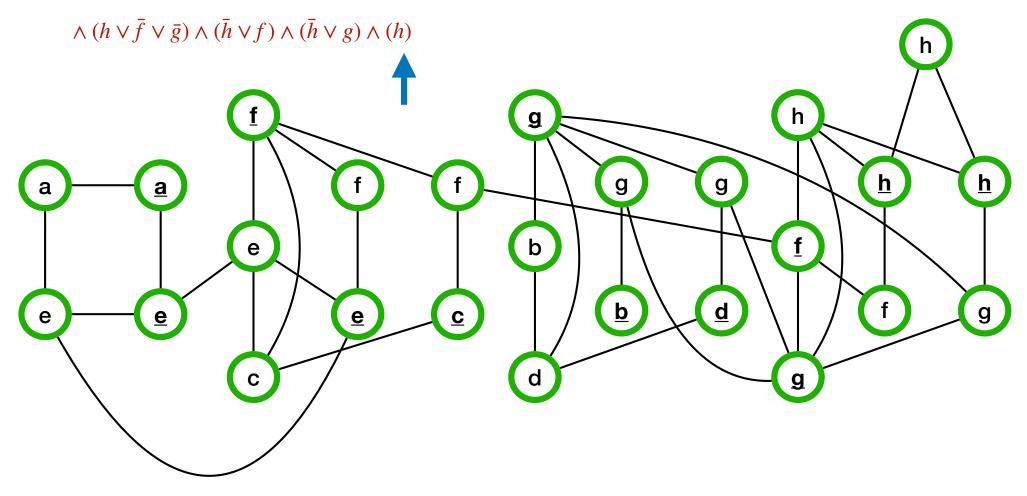


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- Part one: If maximum independent set size in G is equal to the number of clauses, then Φ is satisfiable
- Pick a largest independent set S in G
- There is exactly one vertex per each clause
- No literal and its negation can be picked simultaneously in S
- Define an assignment x of Φ : each positive literal chosen in S is set to 1 and each negative literal is set to 0 (remaining variables arbitrary)
- $\Phi(x)$ must be TRUE so Φ is also satisfiable

- Part two: If

 is satisfiable, then maximum independent set size in G
 is equal to the number of clauses.
- Pick a satisfying assignment x of Φ
- Define a set T of vertices: from each clause, pick one literal-vertex whose literal is 1 in x
- T is an independent set because we only pick one vertex per clause and we never pick a literal and its negation
- So T is an independent set with size equal to the number of clauses
- There is no larger independent set in G as we can only pick one vertex per clause

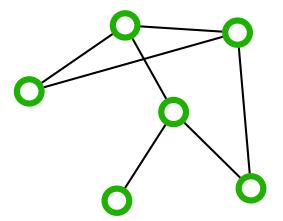
Reduction: Runtime Analysis

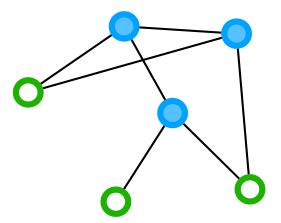
- IF we have a poly-time algorithm for MaxIndSet we also get a poly-time reduction this way.
- Size of G is just a constant factor larger than the input formula (at most three vertices per clause)
- Creating G takes time linear in the size of Φ

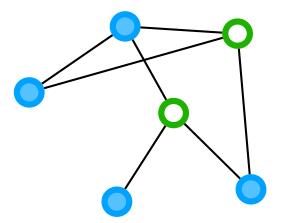
Reduction: Conclusion

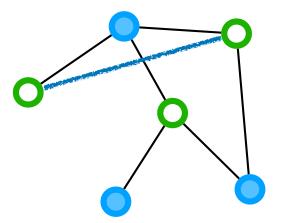
- So if MaxIndSet can be solved in poly-time 3-SAT can also be solved in poly-time
- This means if MaxIndSet can be solved in poly-time then P=NP because 3-SAT is NP-hard
- So MaxIndSet is also NP-hard

Example 3: Minimum Vertex Cover is NP-Hard









Minimum Vertex Cover Problem

• Input:

An undirected graph G=(V,E)

• Output:

Size of the smallest vertex cover in G

For simplicity, we are going to call this problem MinVC

MinVC

• Is MinVC in NP?

MinVC

- Is MinVC in NP?
- No because it is NOT a decision problem

MinVC is NP-hard

- We are going to show that it is NP-hard
- This requires proving if MinVC can be solved in poly-time, then P=NP
- Using reductions, this requires showing that a poly-time algorithm for MinVC can solve another NP-hard problem in poly-time

MinVC is NP-hard

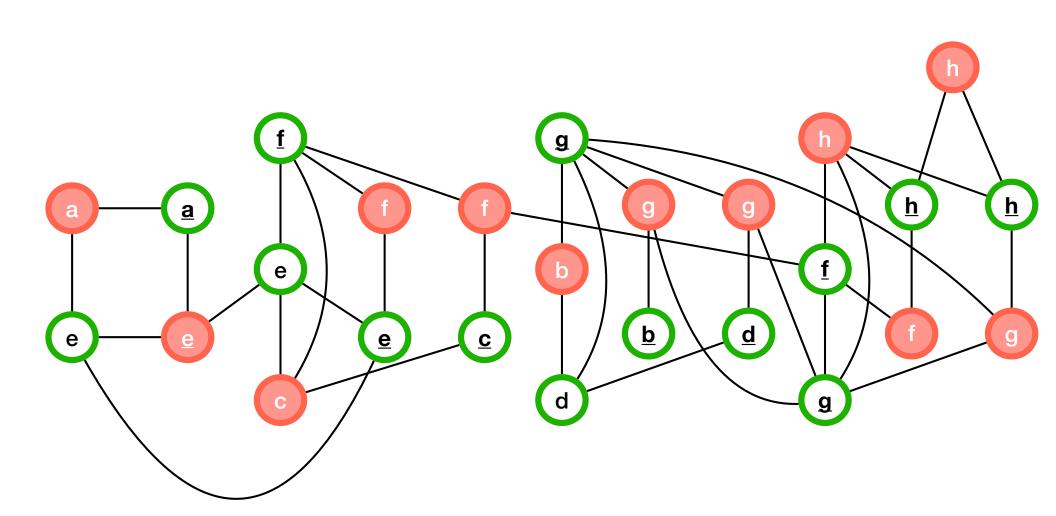
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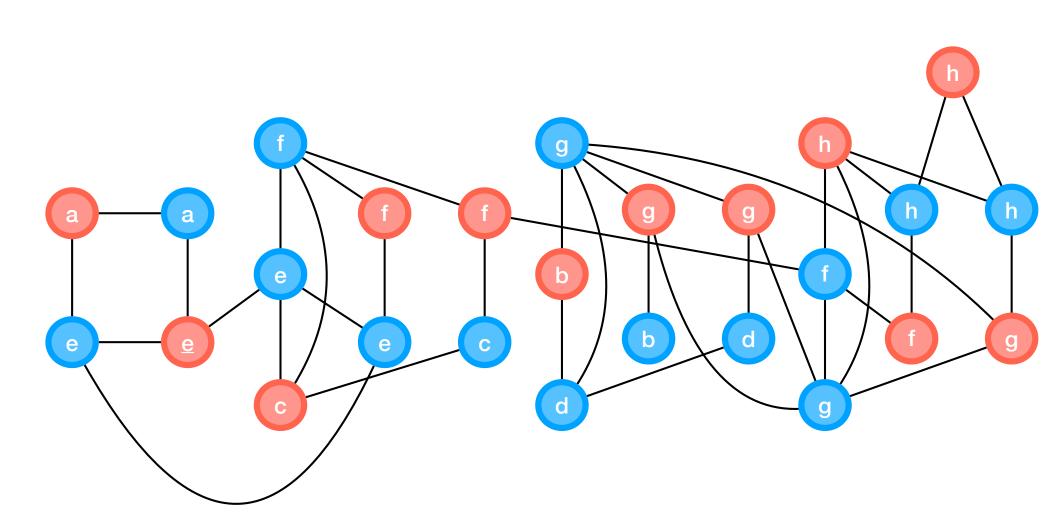
We use MaxIndSet for this purpose

MinVC: Reduction From MaxIndSet

- Given a graph G as input to the MaxIndSet problem:
 - Run any algorithm for MinVC on G to get k = size of a minimum vertex cover in G
 - Return n-k as the answer to MaxIndSet

 $\Phi = (a \lor e) \land (\bar{a} \lor \bar{e}) \land (\bar{f} \lor e \lor c) \land (f \lor \bar{e}) \land (f \lor \bar{c}) \land (\bar{g} \lor b \lor d) \land (g \lor \bar{b}) \land (g \lor \bar{d})$ $\wedge (h \vee \bar{f} \vee \bar{g}) \wedge (\bar{h} \vee f) \wedge (\bar{h} \vee g) \wedge (h)$ <u>h</u> <u>h</u> <u>b</u> <u>d</u> g





- In any graph G
 - T is an independent set if and only if S=V-T is a vertex cover

- In any graph G
 - T is an independent set if and only if S=V-T is a vertex cover
- Part one: If T is an independent set, then S=V-T is a vertex cover:
 - Suppose not, then there is an edge with no endpoint in S
 - So both endpoints in T, a contradiction

- In any graph G
 - T is an independent set if and only if S=V-T is a vertex cover
- Part two: If S is a vertex cover, then T=V-S is an independent set:
 - Suppose not, then there is an edge with both endpoints in T
 - So no endpoints in S, a contradiction

- In any graph G
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 So T is a maximum independent set in G if and only if S=V-T is a minimum vertex cover

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So answer to MaxIndSet is equal to n minus the answer to MinVC

Reduction: Runtime Analysis

• **IF** we have a poly-time algorithm for **MinVC** we also get a poly-time reduction this way.

Reduction: Conclusion

- So if MinVC can be solved in poly-time MaxIndSet can also be solved in poly-time
- This means if MinVC can be solved in poly-time then P=NP because MaxIndSet is NP-hard
- So MinVC is also NP-hard

Concluding Remarks on NP-Hardness

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- Our goal in this part of the course was to show some problems are hard to solve
- Reductions allow us to design an "efficient" algorithm for a problem to show that another problem likely does not have an efficient algorithm
- To prove problem B is hard, we pick a problem A which we know is hard and use ANY algorithm for B in a black-box way to get an algorithm for A also
- This means B should be hard as well

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- Our goal in this part of the course was to show some problems are hard to solve
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NP-hard

To prove problem B is hard, we pick a problem A which we know
is hard and use ANY algorithm for B in a black-box way to get an
NP-hard
algorithm for A also algorithm that runs in poly-time

NP-hard

This means B should be hard as well