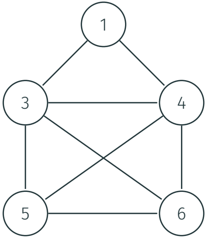
Pre-lecture brain teaser

Consider the following algorithm which takes in a undirected graph (G) and a vertex s

```
FindClique (G, s)
    C = s
    for each vertex v ∈ V
        flag = 1
        for each vertex u ∈ C
            if (u, v) ∉ E
                flag = 0
        if flag == 1
            C = C ∪ {v}
    return C
```

The algorithm is a represents a greedy algorithm which finds a clique depending on a start vertex s.

- How fast is this algorithm?



ECE-374-B: Lecture 20 - P/NP and NP-completeness

Instructor: Nickvash Kani

University of Illinois at Urbana-Champaign

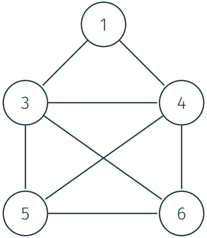
Pre-lecture brain teaser

Consider the following algorithm which takes in a undirected graph (G) and a vertex s

```
FindClique (G, s)
    C = s
    for each vertex v ∈ V
        flag = 1
        for each vertex u ∈ C
            if (u, v) ∉ E
                flag = 0
        if flag == 1
            C = C ∪ {v}
    return C
```

The algorithm is a represents a greedy algorithm which finds a clique depending on a start vertex s.

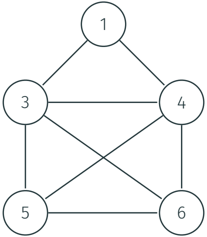
- How fast is this algorithm?



Pre-lecture brain teaser

Consider the following algorithm which takes in a undirected graph (G) and a vertex s

```
FindClique (G, s)
    C = s
    for each vertex v ∈ V
        flag = 1
        for each vertex u ∈ C
            if (u, v) ∉ E
                flag = 0
        if flag == 1
            C = C ∪ {v}
    return C
```

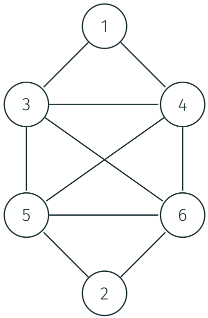


The Clique-problem is NP-complete. But this algorithm provides us with the maximal clique containing s. If we run it $|V|$ times, does that solve the clique-problem.

Pre-lecture brain teaser

Consider the following algorithm which takes in a undirected graph (G) and a vertex s

```
FindClique (G, s)
    C = s
    for each vertex v ∈ V
        flag = 1
        for each vertex u ∈ C
            if (u, v) ∉ E
                flag = 0
        if flag == 1
            C = C ∪ {v}
    return C
```



The Satisfiability Problem (SAT)

Propositional Formulas

Definition
Consider a set of boolean variables $x_1, x_2, \ldots x_n$.

- A literal is either a boolean variable x_i or its negation $\neg x_i$.
- A clause is a disjunction of literals.
  For example, $x_1 \vee x_2 \vee \neg x_4$ is a clause.
- A formula in conjunctive normal form (CNF) is propositional formula which is a conjunction of clauses
  - $(x_1 \vee x_2 \vee \neg x_4) \wedge (x_2 \vee \neg x_3) \wedge x_5$ is a CNF formula.

Propositional Formulas

Definition
Consider a set of boolean variables $x_1, x_2, \ldots x_n$.

- A literal is either a boolean variable x_i or its negation $\neg x_i$.
- A clause is a disjunction of literals.
  For example, $x_1 \vee x_2 \vee \neg x_4$ is a clause.
- A formula in conjunctive normal form (CNF) is propositional formula which is a conjunction of clauses
  - $(x_1 \vee x_2 \vee \neg x_4) \wedge (x_2 \vee \neg x_3) \wedge x_5$ is a CNF formula.
- A formula φ is a 3CNF:
  A CNF formula such that every clause has **exactly** 3 literals.
  - $(x_1 \vee x_2 \vee \neg x_4) \wedge (x_2 \vee \neg x_3 \vee x_1)$ is a 3CNF formula, but $(x_1 \vee x_2 \vee \neg x_4) \wedge (x_2 \vee \neg x_3) \wedge x_5$ is not.

Problem: SAT

> **Instance:** A CNF formula φ.
> **Question:** Is there a truth assignment to the variable of φ such that φ evaluates to true?

Problem: 3SAT

> **Instance:** A 3CNF formula φ.
> **Question:** Is there a truth assignment to the variable of φ such that φ evaluates to true?

Satisfiability

SAT
Given a CNF formula φ, is there a truth assignment to variables such that φ evaluates to true?

Example

- $(x_1 \vee x_2 \vee \neg x_4) \wedge (x_2 \vee \neg x_3) \wedge x_5$ is satisfiable; take $x_1, x_2, \ldots x_5$ to be all true
- $(x_1 \vee \neg x_2) \wedge (\neg x_1 \vee x_2) \wedge (\neg x_1 \vee \neg x_2) \wedge (x_1 \vee x_2)$ is not satisfiable.

3SAT
Given a 3CNF formula φ, is there a truth assignment to variables such that φ evaluates to true?

Importance of SAT and 3SAT

- SAT and 3SAT are basic constraint satisfaction problems.
- Many different problems can reduced to them because of the simple yet powerful expressively of logical constraints.
- Arise naturally in many applications involving hardware and software verification and correctness.
- As we will see, it is a fundamental problem in theory of NP-Completeness.

$SAT \leq_P 3SAT$

How SAT is different from 3SAT?
In SAT clauses might have arbitrary length: $1, 2, 3, \ldots$ variables:

$$\left(x \vee y \vee z \vee w \vee u\right) \wedge \left(\neg x \vee \neg y \vee \neg z \vee w \vee u\right) \wedge \left(\neg x\right)$$

In 3SAT every clause must have exactly 3 different literals.

How SAT is different from 3SAT?
In SAT clauses might have arbitrary length: $1, 2, 3, \ldots$ variables:

$$\left(x \vee y \vee z \vee w \vee u\right) \wedge \left(\neg x \vee \neg y \vee \neg z \vee w \vee u\right) \wedge \left(\neg x\right)$$

In 3SAT every clause must have exactly 3 different literals.

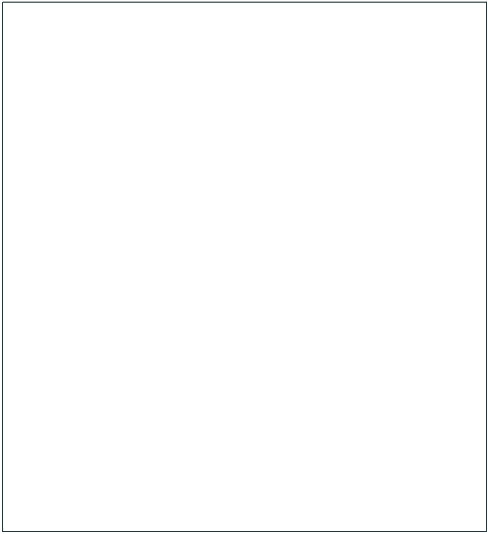
To reduce from an instance of SAT to an instance of 3SAT, we must make all clauses to have exactly 3 variables...

Basic idea

- Pad short clauses so they have 3 literals.
- Break long clauses into shorter clauses.
- Repeat the above till we have a 3CNF.

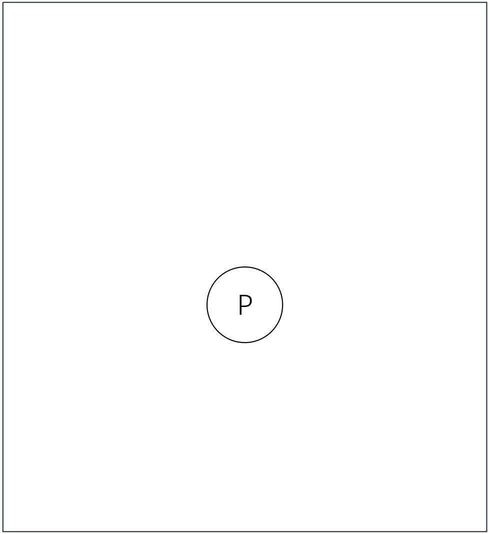
Overview of Complexity Classes

Algorithmic Complexity Space



This represents all problems that exist.

Algorithmic Complexity Space



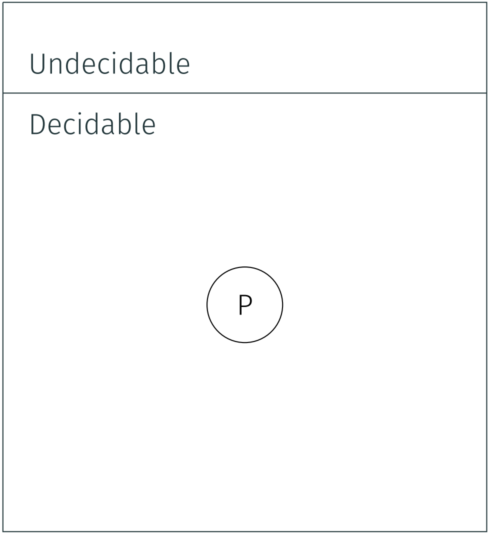
All problems solvable in a polynomial amount of time.

Most of the problems we discussed in the second part of the course.

P problems:

- Longest whatever subsequence
- Various shortest path problems
- Graph connectivity

Algorithmic Complexity Space



Set of all problems that can be computed by a TM (or not).

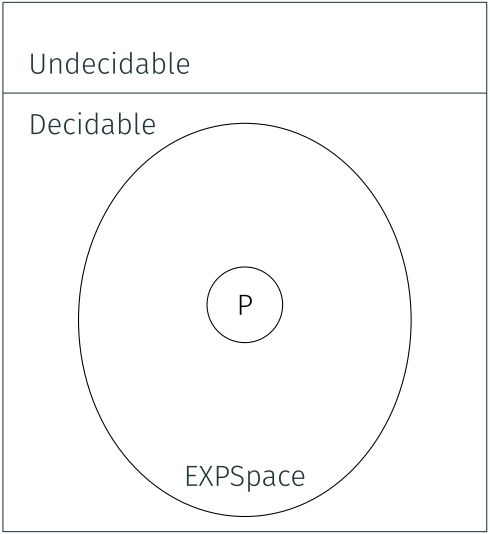
Decidable problems:

- Anything you can compute

Undecidable problems:

- Halting problem
- TM equivalence
- All non-trivial programs (Rice's theorem)

Algorithmic Complexity Space



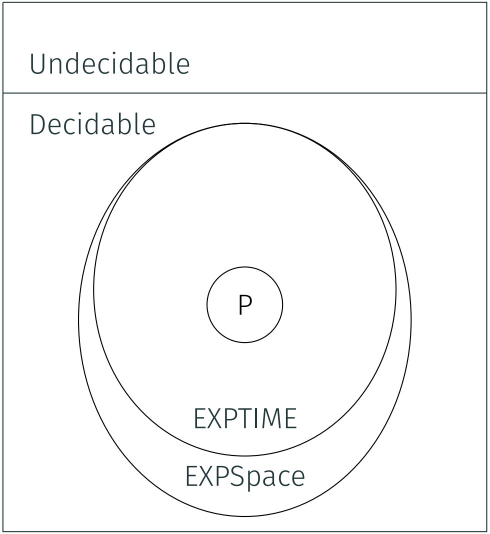
Set of all decision problem solvable by a TM in $O^{p(n)}$ *space*.

EXPSPACE problems:

- Given regular expressions r_1 and r_2, does $L(r_1) \equiv L(r_2)$
- Convertibility and reachability for Petri Nets

Equivalent to NEXPSPACE (Savitch's theorem), and

Algorithmic Complexity Space

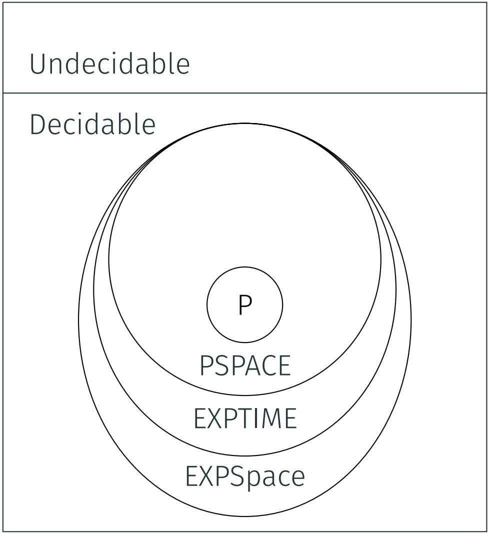


Set of all decision problem solvable by a TM in $O^{p(n)}$ *time*.

EXPSPACE problems:

- Succinct circuits

Algorithmic Complexity Space

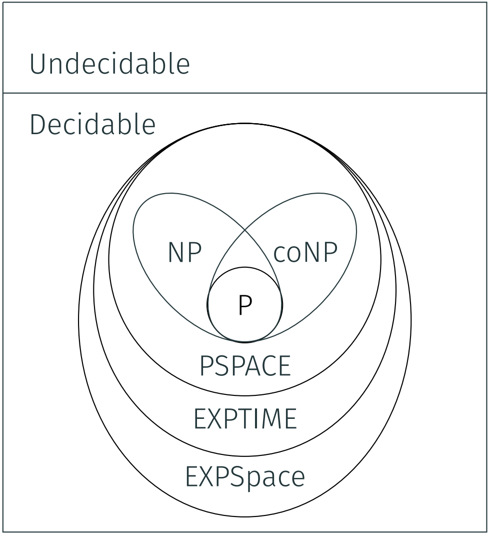


Set of all decision problem solvable by a TM using a polynomial amount of space.

PSPACE problems:

- Given a regular expression r_1, is $L(r_1) = \Sigma^*$
- Quantified boolean problem
- Reconfiguration problems
- Various puzzle problems

Algorithmic Complexity Space



Set of all decision problem solvable by a NTM in a polynomial amount of time. Alternatively, NP contains the problems whose YES instances are checkable in a polynomial amount of time by a TM (DTM). coNP is same for NO instances.

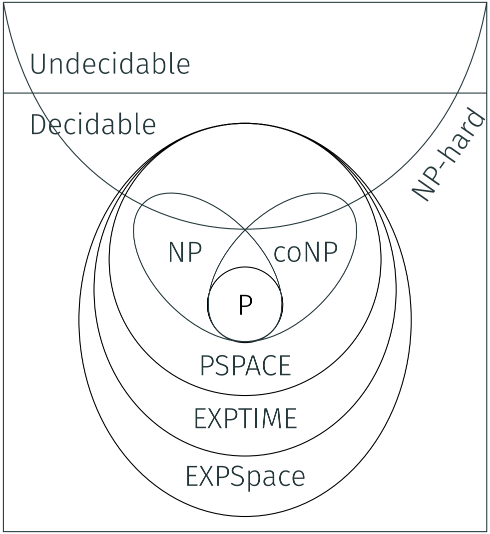
NP problems:

- SAT, 3SAT, ...
- Integer factorization

coNP problems:

- Tautology (opposite of SAT)
- Integer factorization

Algorithmic Complexity Space

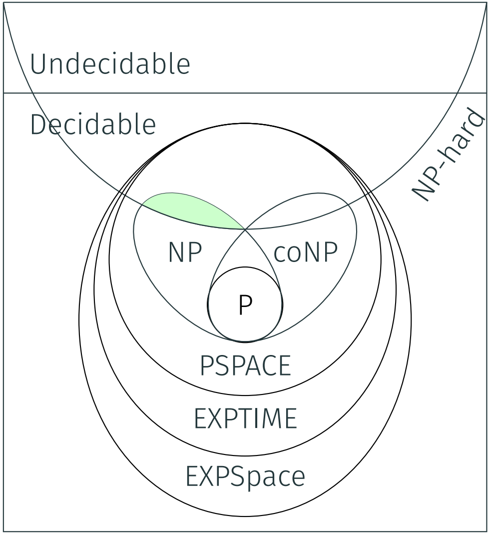


Class of problems that are atleast as hard as the hardest problems in NP.

NP-hard problems:

- SAT, 3SAT, ...
- Clique, Independent set
- Hamiltonian path/cycle
- 3+ Coloring

Algorithmic Complexity Space



The intersection of NP-hard and NP is called **NP-complete**. These are all the NP problems which all other NP problems can reduce to.

NP-complete problems:

- 3+ SAT, SAT
- Clique, Independent set
- 3+ Coloring

Non-deterministic polynomial time - NP

P and NP and Turing Machines

- P: set of decision problems that have polynomial time algorithms.
- NP: set of decision problems that have polynomial time non-deterministic algorithms.

- Many natural problems we would like to solve are in *NP*.
- Every problem in *NP* has an exponential time algorithm
- $P \subseteq NP$
- Some problems in *NP* are in *P* (example, shortest path problem)

Big Question: Does every problem in *NP* have an efficient algorithm? Same as asking whether $P = NP$.

Problems with no known deterministic polynomial time algorithms

Problems

- Independent Set
- Vertex Cover
- Set Cover
- SAT

There are of course undecidable problems (no algorithm at all!) but many problems that we want to solve are of similar flavor to the above.

Question: What is common to above problems?

Problems with no known deterministic polynomial time algorithms

Problems

- Independent Set
- Vertex Cover
- Set Cover
- SAT

There are of course undecidable problems (no algorithm at all!) but many problems that we want to solve are of similar flavor to the above.

Question: What is common to above problems?

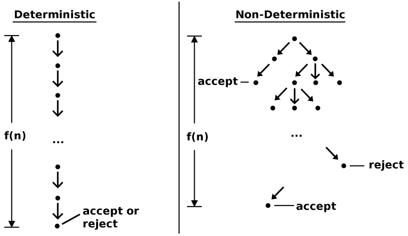
They can all be solved via a non-deterministic computer in polynomial time!

Non-determinism in computing

Non-determinism is a special property of algorithms.

An algorithm that is capable of taking multiple states concurrently. Whenever it reaches a choice, it takes both paths.

If there is a path for the string to be accepted by the machine, then the string is part of the language.



Problems with no known deterministic polynomial time algorithms

Problems

- Independent Set & Vertex Cover - Can build algorithm to check all possible collection of vertices
- Set Cover - Can check all possible collection of sets
- SAT -Can build a non-deterministic algorithm that checks every possible boolean assignment.

But we don't have access to a non-deterministic computer. So how can a deterministic computer verify that a algorithm is in NP?

Efficient Checkability

Above problems share the following feature:

Checkability
For any YES instance I_X of X there is a proof/certificate/solution that is of length poly($|I_X|$) such that given a proof one can efficiently check that I_X is indeed a YES instance.

Efficient Checkability

Above problems share the following feature:

Checkability
For any YES instance I_X of X there is a proof/certificate/solution that is of length poly($|I_X|$) such that given a proof one can efficiently check that I_X is indeed a YES instance.

Examples:

- **SAT** formula φ: proof is a satisfying assignment.
- **Independent Set** in graph G and k: a subset S of vertices.
- **Homework**

Certifiers

Definition
An algorithm $C(\cdot, \cdot)$ is a certifier for problem X if the following two conditions hold:

- For every $s \in X$ there is some string t such that $C(s, t) =$ "yes"
- If $s \notin X$, $C(s, t) =$ "no" for every t.

The string s is the problem instance. (Example: particular graph in independent set problem) The string t is called a certificate or proof for s.

Efficient (polynomial time) Certifiers

Definition (Efficient Certifier.)
A certifier C is an efficient certifier for problem X if there is a polynomial $p(\cdot)$ such that the following conditions hold:

- For every $s \in X$ there is some string t such that $C(s, t) =$ "yes" **and** $|t| \leq p(|s|)$.
- If $s \notin X$, $C(s, t) =$ "no" for every t.
- $C(\cdot, \cdot)$ runs in polynomial time.

Example: Independent Set

- Problem: Does $G = (V, E)$ have an independent set of size $\geq k$?
  - Certificate: Set $S \subseteq V$.
  - Certifier: Check $|S| \geq k$ and no pair of vertices in S is connected by an edge.

Example: SAT

- Problem: Does formula φ have a satisfying truth assignment?
  - Certificate: Assignment a of 0/1 values to each variable.
  - Certifier: Check each clause under a and say "yes" if all clauses are true.

Why is it called Nondeterministic Polynomial Time

A certifier is an algorithm $C(I, c)$ with two inputs:

- I: instance.
- c: proof/certificate that the instance is indeed a YES instance of the given problem.

One can think about C as an algorithm for the original problem, if:

- Given I, the algorithm guesses (non-deterministically, and who knows how) a certificate c.
- The algorithm now verifies the certificate c for the instance I.

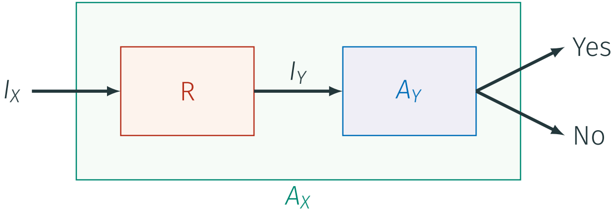
NP can be equivalently described using Turing machines.

Polynomial-time reductions

We say that an algorithm is <u>efficient</u> if it runs in polynomial-time.

To find efficient algorithms for problems, we are only interested in polynomial-time reductions. Reductions that take longer are not useful.

If we have a polynomial-time reduction from problem X to problem Y (we write $X \leq_P Y$), and a poly-time algorithm $\mathcal{A}_Y$ for Y, we have a polynomial-time/efficient algorithm for X.



Polynomial-time Reduction

A polynomial time reduction from a decision problem X to a decision problem Y is an algorithm $\mathcal{A}$ that has the following properties:

- given an instance I_X of X, $\mathcal{A}$ produces an instance I_Y of Y
- $\mathcal{A}$ runs in time polynomial in $|I_X|$.
- Answer to I_X YES $\iff$ answer to I_Y is YES.

Lemma
If $X \leq_P Y$ then a polynomial time algorithm for Y implies a polynomial time algorithm for X.

Such a reduction is called a Karp reduction. Most reductions we will need are Karp reductions.Karp reductions are the same as mapping reductions when specialized to polynomial time for the reduction step.

Review question: Reductions again...

Let X and Y be two decision problems, such that X can be solved in polynomial time, and $X \leq_P Y$. Then

(A) Y can be solved in polynomial time.

(B) Y can NOT be solved in polynomial time.

(C) If Y is hard then X is also hard.

(D) None of the above.

(E) All of the above.

Cook-Levin Theorem

“Hardest” Problems

Question
What is the hardest problem in NP? How do we define it?

Towards a definition

- Hardest problem must be in NP.
- Hardest problem must be at least as “difficult” as every other problem in NP.

NP-Complete Problems

Definition
A problem X is said to be **NP-Complete** if

- $X \in NP$, and
- (Hardness) For any $Y \in NP$, $Y \leq_P X$.

Lemma
Suppose X is NP-Complete. Then X can be solved in polynomial time if and only if $P = NP$.

Proof.

$\Rightarrow$ Suppose X can be solved in polynomial time

- Let $Y \in NP$. We know $Y \leq_P X$.
- We showed that if $Y \leq_P X$ and X can be solved in polynomial time, then Y can be solved in polynomial time.
- Thus, every problem $Y \in NP$ is such that $Y \in P$; $NP \subseteq P$.
- Since $P \subseteq NP$, we have $P = NP$.

$\Leftarrow$ Since $P = NP$, and $X \in NP$, we have a polynomial time algorithm for X. $\square$

NP-Hard Problems

Definition
A problem Y is said to be NP-Hard if

- (Hardness) For any $X \in NP$, we have that $X \leq_P Y$.

An NP-Hard problem need not be in NP!

Example: Halting problem is NP-Hard (why?) but not NP-Complete.

Consequences of proving NP-Completeness

If X is NP-Complete

- Since we believe $P \neq NP$,
- and solving X implies $P = NP$.

X is unlikely to be efficiently solvable.

At the very least, many smart people before you have failed to find an efficient algorithm for X.

Consequences of proving NP-Completeness

If X is NP-Complete

- Since we believe $P \neq NP$,
- and solving X implies $P = NP$.

X is unlikely to be efficiently solvable.

At the very least, many smart people before you have failed to find an efficient algorithm for X.

(This is proof by mob opinion — take with a grain of salt.)

NP-Complete Problems

Question
Are there any problems that are NP-Complete?

Answer
Yes! Many, many problems are NP-Complete.

Cook-Levin Theorem

Theorem (Cook-Levin)
SAT is NP-Complete.

Cook-Levin Theorem

Theorem (Cook-Levin)
SAT is NP-Complete.

Need to show

- SAT is in NP.
- every NP problem X reduces to SAT.

Steve Cook won the Turing award for his theorem.

Proving that a problem X is NP-Complete

To prove X is NP-Complete, show

- Show that X is in NP.
- Give a polynomial-time reduction from a known NP-Complete problem such as SAT to X

Proving that a problem X is NP-Complete

To prove X is NP-Complete, show

- Show that X is in NP.
- Give a polynomial-time reduction from a known NP-Complete problem such as SAT to X

SAT $\leq_P X$ implies that every NP-complete problem $Y \leq_P X$. Why?

3-SAT is NP-Complete

- 3-SAT is in NP
- SAT $\leq_P$ 3-SAT as we saw

NP-Completeness via Reductions

- SAT is NP-Complete due to Cook-Levin theorem
- SAT $\leq_P$ 3-SAT
- 3-SAT $\leq_P$ Independent Set
- Independent Set $\leq_P$ Vertex Cover
- Independent Set $\leq_P$ Clique
- 3-SAT $\leq_P$ 3-Color
- 3-SAT $\leq_P$ Hamiltonian Cycle

NP-Completeness via Reductions

- SAT is NP-Complete due to Cook-Levin theorem
- SAT $\leq_P$ 3-SAT
- 3-SAT $\leq_P$ Independent Set
- Independent Set $\leq_P$ Vertex Cover
- Independent Set $\leq_P$ Clique
- 3-SAT $\leq_P$ 3-Color
- 3-SAT $\leq_P$ Hamiltonian Cycle

Hundreds and thousands of different problems from many areas of science and engineering have been shown to be NP-Complete.

A surprisingly frequent phenomenon!

Reducing 3-SAT to Independent Set

Independent Set

Problem: Independent Set

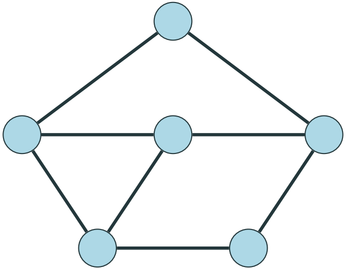
Instance: A graph G, integer k.

Question: Is there an independent set in G of size k?

Problem: Independent Set

Instance: A graph G, integer k.

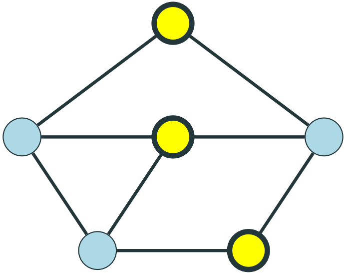
Question: Is there an independent set in G of size k?



Independent Set

Problem: Independent Set

Instance: A graph G, integer k.
Question: Is there an independent set in G of size k?



Interpreting 3SAT

There are two ways to think about 3SAT

- Find a way to assign 0/1 (false/true) to the variables such that the formula evaluates to true, that is each clause evaluates to true.
- Pick a literal from each clause and find a truth assignment to make all of them true. You will fail if two of the literals you pick are in conflict, i.e., you pick x_i and $\neg x_i$

We will take the second view of 3SAT to construct the reduction.

The Reduction

- G_φ will have one vertex for each literal in a clause
- 2- Connect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
- 4- Connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict
- 5- Take k to be the number of clauses

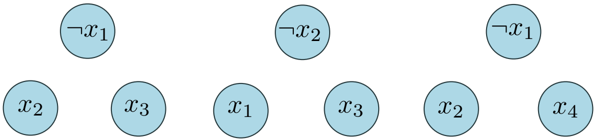


Figure 1: Graph for $\varphi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_4)$

The Reduction

- G_φ will have one vertex for each literal in a clause
- 2- Connect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
- 4- Connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict
- 5- Take k to be the number of clauses

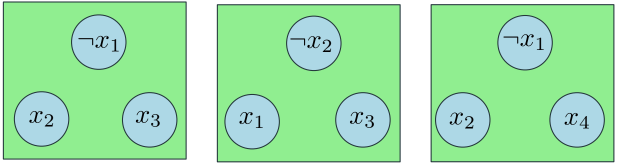


Figure 1: Graph for $\varphi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_4)$

The Reduction

- G_φ will have one vertex for each literal in a clause
- 2- Connect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
- 4- Connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict
- 5- Take k to be the number of clauses

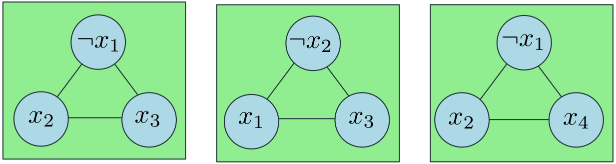


Figure 1: Graph for $\varphi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_4)$

The Reduction

- G_φ will have one vertex for each literal in a clause
- 2- Connect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
- 4- Connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict
- 5- Take k to be the number of clauses

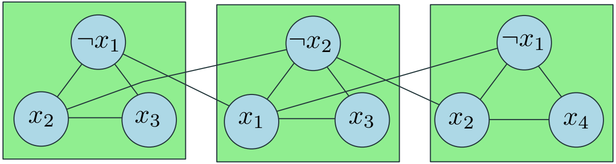


Figure 1: Graph for $\varphi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_4)$

- G_φ will have one vertex for each literal in a clause
- 2- Connect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
- 4- Connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict
- 5- Take k to be the number of clauses

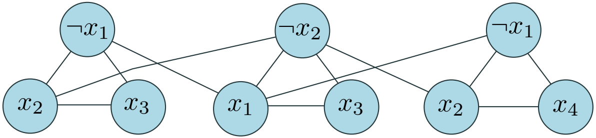


Figure 1: Graph for $\varphi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_4)$

Lemma

φ is satisfiable iff G_φ has an independent set of size k (= number of clauses in φ).

Proof.

$\Rightarrow$ Let a be the truth assignment satisfying φ

- 2- Pick one of the vertices, corresponding to true literals under a, from each triangle. This is an independent set of the appropriate size. Why? □

Correctness (contd)

Lemma
φ is satisfiable iff G_φ has an independent set of size k (= number of clauses in φ).

Proof.

$\Leftarrow$ Let S be an independent set of size k

- S must contain exactly one vertex from each clause triangle
- S cannot contain vertices labeled by conflicting literals
- Thus, it is possible to obtain a truth assignment that makes in the literals in S true; such an assignment satisfies one literal in every clause $\square$

Other NP-Complete problems

Graph Coloring

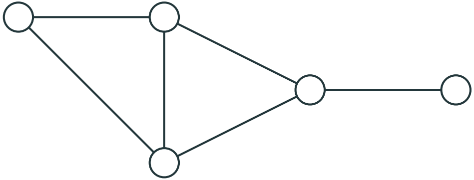
Problem: **Graph Coloring**

Instance: $G = (V, E)$: Undirected graph, integer k.
Question: Can the vertices of the graph be colored using k colors so that vertices connected by an edge do not get the same color?

Graph 3-Coloring

Problem: 3 Coloring

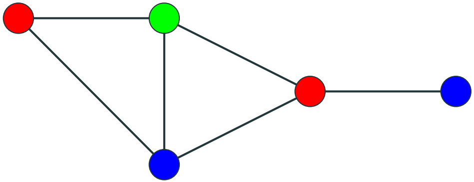
Instance: $G = (V, E)$: Undirected graph.
Question: Can the vertices of the graph be colored using 3 colors so that vertices connected by an edge do not get the same color?



Graph 3-Coloring

Problem: 3 Coloring

Instance: $G = (V, E)$: Undirected graph.
Question: Can the vertices of the graph be colored using 3 colors so that vertices connected by an edge do not get the same color?



‘

Graph Coloring

Observation: If G is colored with k colors then each color class (nodes of same color) form an independent set in G. Thus, G can be partitioned into k independent sets iff G is k-colorable.

Graph 2-Coloring can be decided in polynomial time.

G is 2-colorable iff G is bipartite! There is a linear time algorithm to check if G is bipartite using Breadth-first-Search

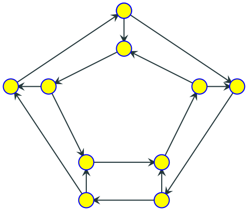
Hamiltonian Cycle

Directed Hamiltonian Cycle

Input Given a directed graph $G = (V, E)$ with n vertices

Goal Does G have a Hamiltonian cycle?

- 2- A Hamiltonian cycle is a cycle in the graph that visits every vertex in G exactly once



Directed Hamiltonian Cycle

Input Given a directed graph $G = (V, E)$ with n vertices

Goal Does G have a Hamiltonian cycle?

- 2- A Hamiltonian cycle is a cycle in the graph that visits every vertex in G exactly once