

Polynomial Time Reductions

Lecture 20

April 7, 2011

Part I

Introduction to Reductions

Reductions

A reduction from Problem **X** to Problem **Y** means (informally) that if we have an algorithm for Problem **Y**, we can use it to find an algorithm for Problem **X**.

Using Reductions

- We use reductions to find algorithms to solve problems.
- We also use reductions to show that we *can't* find algorithms for some problems. (We say that these problems are *hard*.)

Also, the right reductions might win you a million dollars!

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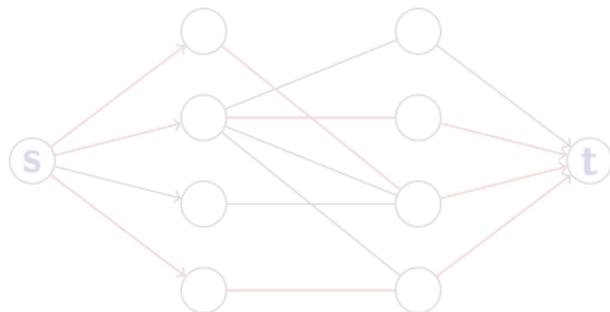
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Example 1: Bipartite Matching and Flows

How do we solve the BIPARTITE MATCHING Problem?

Given a bipartite graph $G = (U \cup V, E)$ and number k , does G have a matching of size $\geq k$?



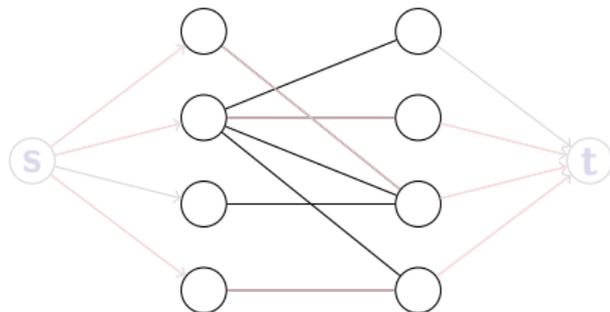
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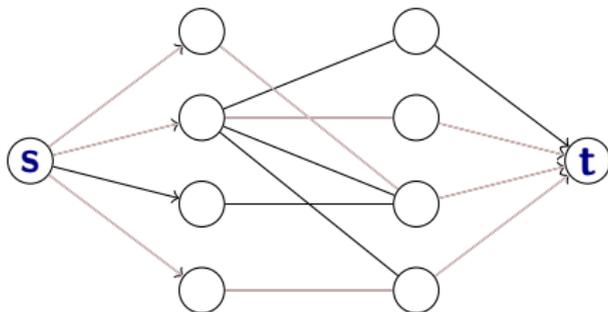
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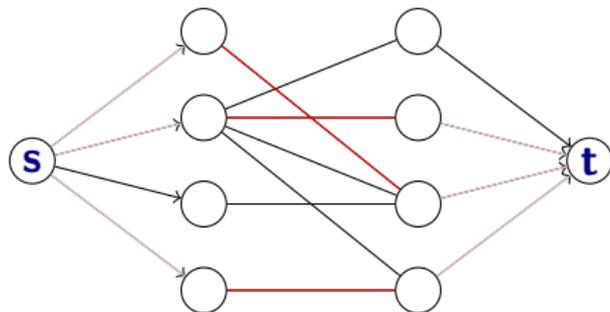
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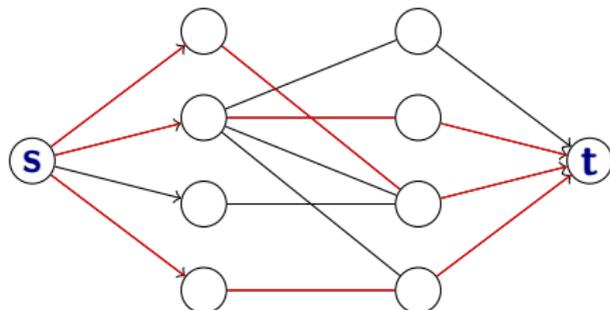
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Types of Problems

Decision, Search, and Optimization

- Decision problems (example: given n , is n prime?)
- Search problems (example: given n , find a factor of n if it exists)
- Optimization problems (example: find the smallest prime factor of n .)

For MAX-FLOW, the Optimization version is: Find the Maximum flow between s and t . The Decision Version is: Given an integer k , is there a flow of value $\geq k$ between s and t ?

While using reductions and comparing problems, we typically work with the decision versions. Decision problems have Yes/No answers. This makes them easy to work with.

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Problems vs Instances

- A **problem** Π consists of an *infinite* collection of inputs $\{I_1, I_2, \dots, \}$. Each input is referred to as an **instance**.
- The **size** of an instance I is the number of bits in its representation.
- For an instance I , $\mathbf{sol}(I)$ is a set of **feasible solutions** to I .
- For optimization problems each solution $s \in \mathbf{sol}(I)$ has an associated **value**.

Examples

An instance of BIPARTITE MATCHING is a bipartite graph, and an integer k . The solution to this instance is “YES” if the graph has a matching of size $\geq k$, and “NO” otherwise.

An instance of MAX-FLOW is a graph G with edge-capacities, two vertices s, t , and an integer k . The solution to this instance is “YES” if there is a flow from s to t of value $\geq k$, else “NO”.

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Decision Problems and Languages

- A finite **alphabet** Σ . Σ^* is set of all finite strings on Σ .
- A **language** L is simply a subset of Σ^* ; a set of strings.

For every language L there is an associated decision problem Π_L and conversely, for every decision problem Π there is an associated language L_Π .

- Given L , Π_L is the following problem: given $x \in \Sigma^*$, is $x \in L$?
Each string in Σ^* is an instance of Π_L and L is the set of instances for which the answer is YES.
- Given Π the associated language
 $L_\Pi = \{I \mid I \text{ is an instance of } \Pi \text{ for which answer is YES}\}.$

Thus, decision problems and languages are used interchangeably.

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Example

Reductions, revised.

For decision problems X , Y , a reduction from X to Y is:

- An algorithm ...
- that takes I_X , an instance of X as input ...
- and returns I_Y , an instance of Y as output ...
- such that the solution (YES/NO) to I_Y is the same as the solution to I_X .

(Actually, this is only one type of reduction, but this is the one we'll use most often.)

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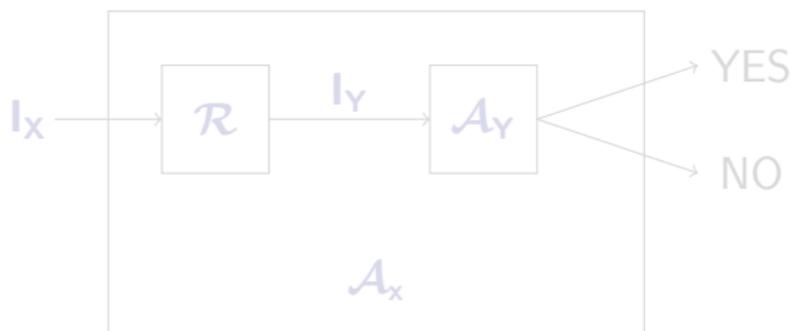
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Using reductions to solve problems

Given a reduction \mathcal{R} from \mathbf{X} to \mathbf{Y} , and an algorithm \mathcal{A}_Y for \mathbf{Y} :
We have an algorithm \mathcal{A}_X for \mathbf{X} ! Here it is:

Given an instance I_X of \mathbf{X} , use \mathcal{R} to produce an instance I_Y of \mathbf{Y} .
Now, use \mathcal{A}_Y to solve I_Y , and output the answer of \mathcal{A}_Y .

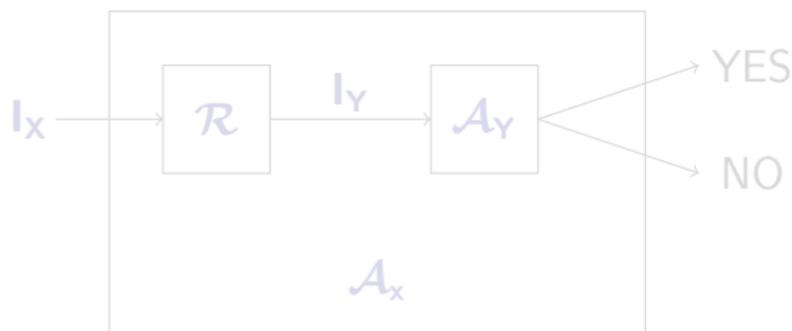


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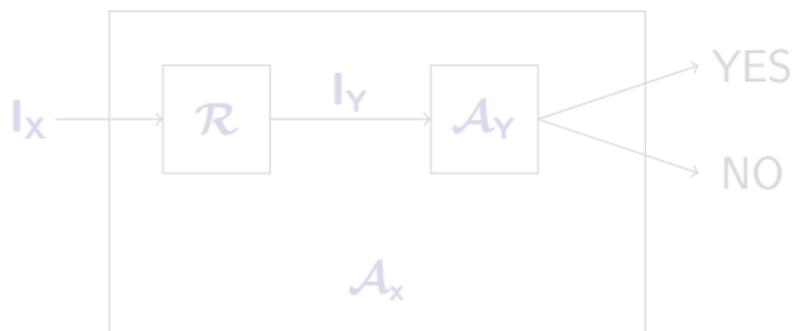


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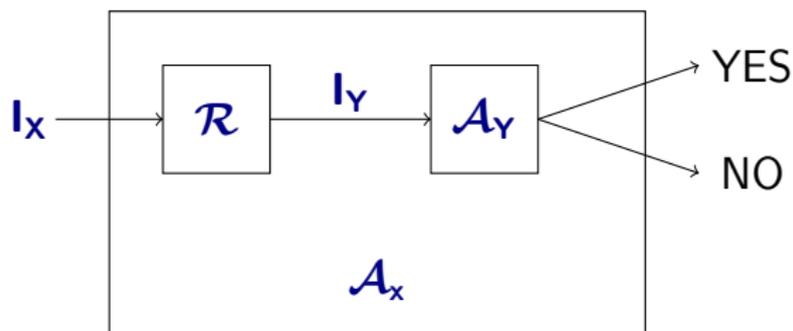


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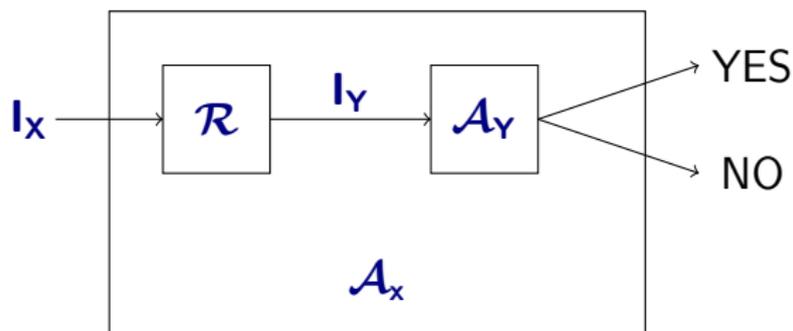


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Comparing Problems

- Reductions allow us to formalize the notion of “Problem **X** is no harder to solve than Problem **Y**”.
- If Problem **X** reduces to Problem **Y** (we write $X \leq Y$), then **X** cannot be harder to solve than **Y**.
- $\text{BIPARTITE MATCHING} \leq \text{MAX-FLOW}$. Therefore, $\text{BIPARTITE MATCHING}$ cannot be harder than MAX-FLOW .
- Equivalently, MAX-FLOW is at least as hard as $\text{BIPARTITE MATCHING}$.
- More generally, if $X \leq Y$, we can say that **X** is no harder than **Y**, or **Y** is at least as hard as **X**.

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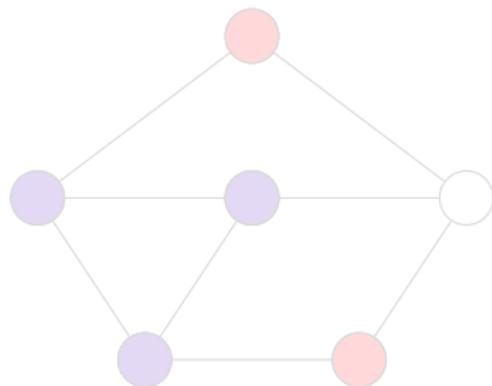
Part II

Examples of Reductions

Independent Sets and Cliques

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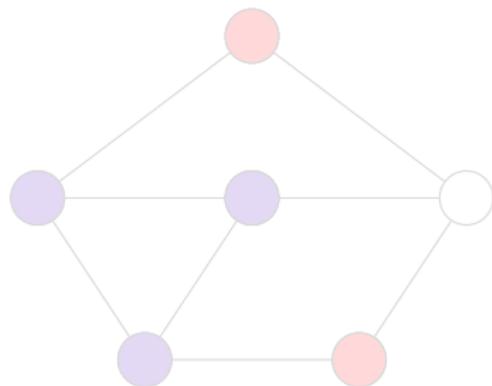
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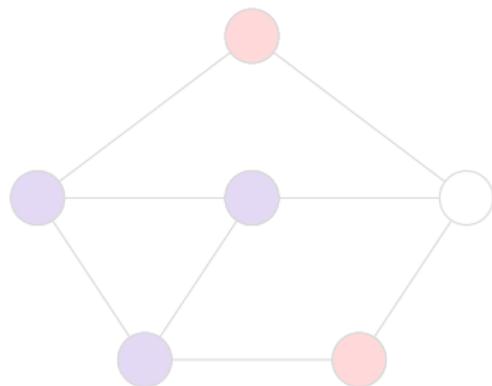
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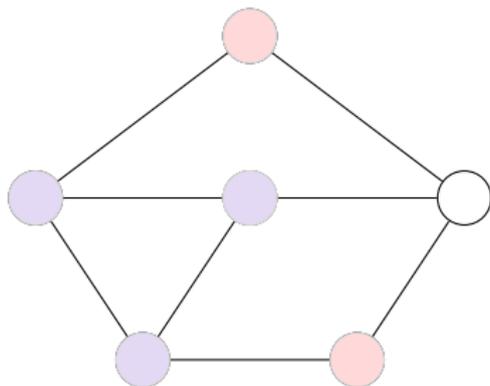
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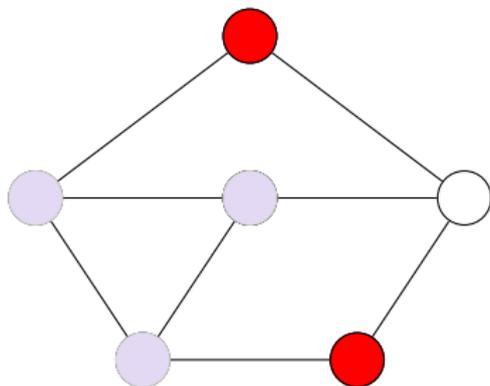
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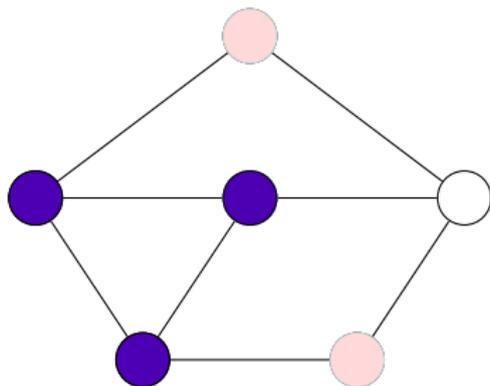
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Goal Decide whether **G** has an independent set of size $\geq k$.

The CLIQUE Problem:

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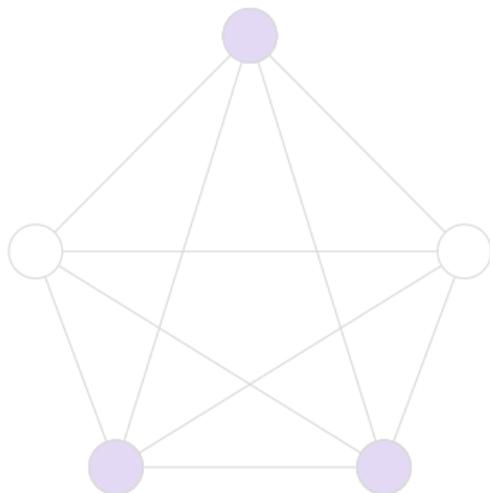
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Convert G to \bar{G} , in which (u, v) is an edge iff (u, v) is **not** an edge of G . (\bar{G} is the *complement* of G .)

We use \bar{G} and k as the instance of CLIQUE.

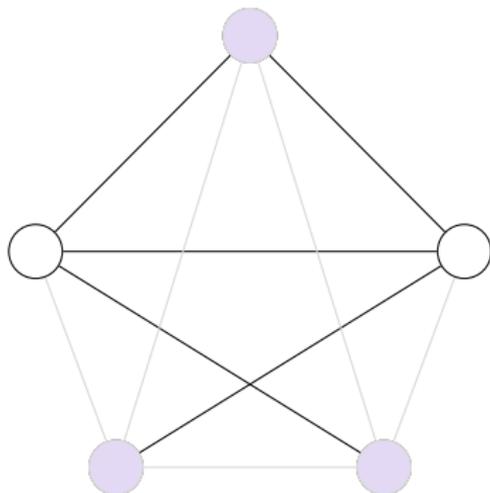


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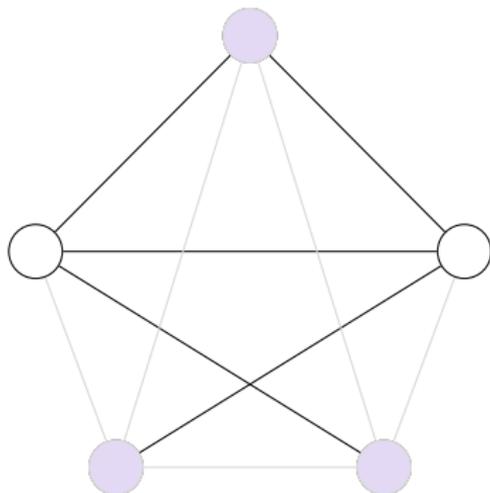


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Convert G to \overline{G} , in which (u, v) is an edge iff (u, v) is **not** an edge of G . (\overline{G} is the *complement* of G .)

We use \overline{G} and k as the instance of CLIQUE.

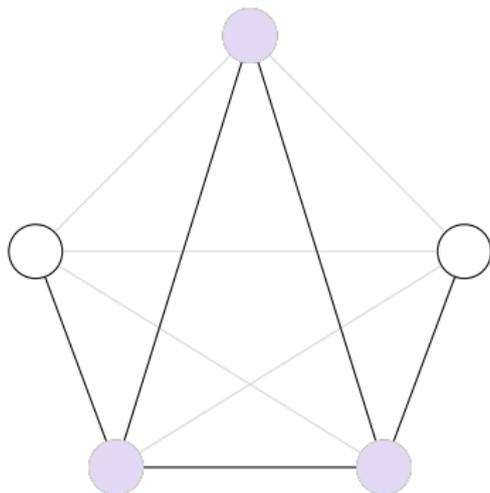


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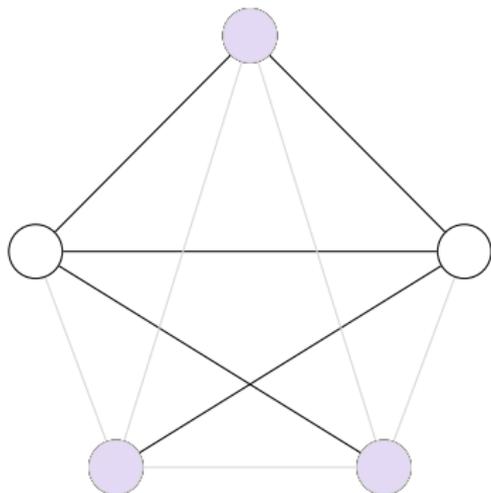


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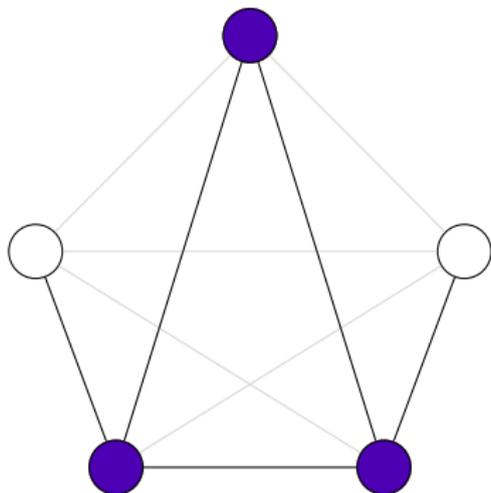


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DFAs and NFAs

DFAs (Remember 273?) are automata that accept regular languages. NFAs are the same, except that they are non-deterministic, while DFAs are deterministic.

Every NFA can be converted to a DFA that accepts the same language using the **subset construction**.

(How long does this take?)

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DFA Universality

A DFA M is said to be **universal** if it accepts every string. That is, $L(M) = \Sigma^*$, the set of all strings.

The DFA UNIVERSALITY Problem:

Input A DFA M

Goal Decide whether M is universal.

How do we solve DFA UNIVERSALITY?

We check if M has *any* reachable non-final state.

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Reduce it to DFA UNIVERSALITY?

Given an NFA \mathbf{N} , convert it to an equivalent DFA \mathbf{M} , and use the DFA UNIVERSALITY Algorithm.

The reduction takes **exponential time!**

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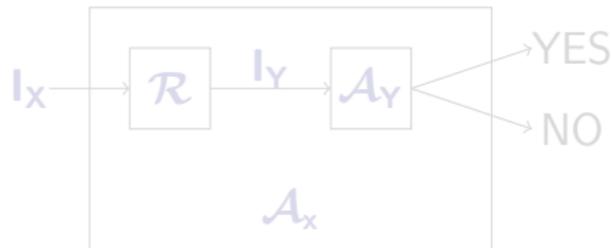
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Polynomial-time reductions

We say that an algorithm is **efficient** 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 A_Y for **Y**, we have a polynomial-time/efficient algorithm for **X**.

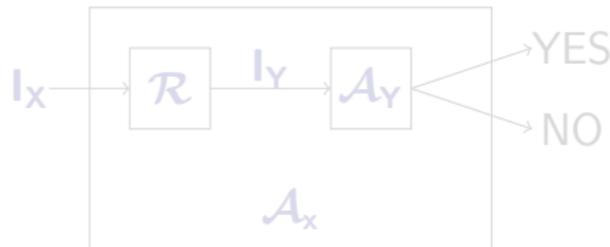


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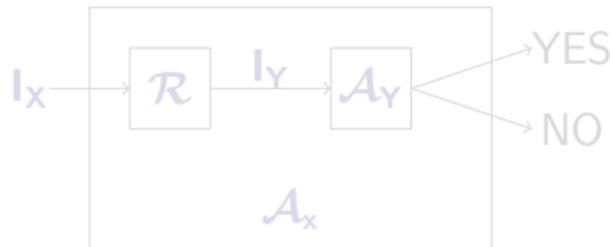


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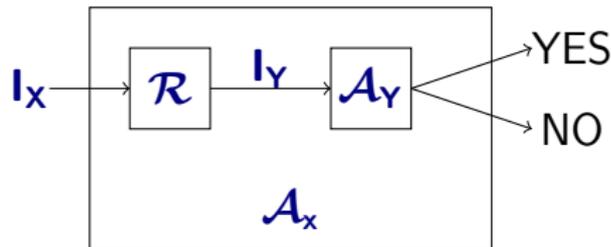


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A polynomial time reduction from a *decision* problem \mathbf{X} to a *decision* problem \mathbf{Y} is an *algorithm* \mathcal{A} that has the following properties:

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Proposition

If $\mathbf{X} \leq_p \mathbf{Y}$ then a polynomial time algorithm for \mathbf{Y} implies a polynomial time algorithm for \mathbf{X} .

Such a reduction is called a Karp reduction. Most reductions we will need are Karp reductions

Polynomial-time reductions and hardness

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If $\mathbf{X} \leq_P \mathbf{Y}$ and \mathbf{X} does not have an efficient algorithm, \mathbf{Y} cannot have an efficient algorithm!

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Polynomial-time reductions and instance sizes

Proposition

Let \mathcal{R} be a polynomial-time reduction from \mathbf{X} to \mathbf{Y} . Then for any instance \mathbf{l}_X of \mathbf{X} , the size of the instance \mathbf{l}_Y of \mathbf{Y} produced from \mathbf{l}_X by \mathcal{R} is polynomial in the size of \mathbf{l}_X .

Proof.

\mathcal{R} is a polynomial-time algorithm and hence on input \mathbf{l}_X of size $|\mathbf{l}_X|$ it runs in time $p(|\mathbf{l}_X|)$ for some polynomial $p()$.

\mathbf{l}_Y is the output of \mathcal{R} on input \mathbf{l}_X

\mathcal{R} can write at most $p(|\mathbf{l}_X|)$ bits and hence $|\mathbf{l}_Y| \leq p(|\mathbf{l}_X|)$. □

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Transitivity of Reductions

Proposition

$X \leq_P Y$ and $Y \leq_P Z$ implies that $X \leq_P Z$.

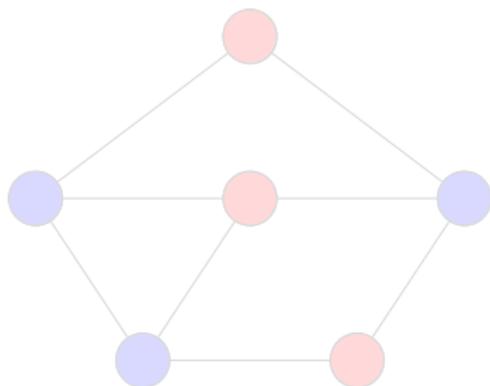
Note: $X \leq_P Y$ does not imply that $Y \leq_P X$ and hence it is very important to know the FROM and TO in a reduction.

To prove $X \leq_P Y$ you need to show a reduction FROM X TO Y
In other words show that an algorithm for Y implies an algorithm for X .

Vertex Cover

Given a graph $G = (V, E)$, a set of vertices S is:

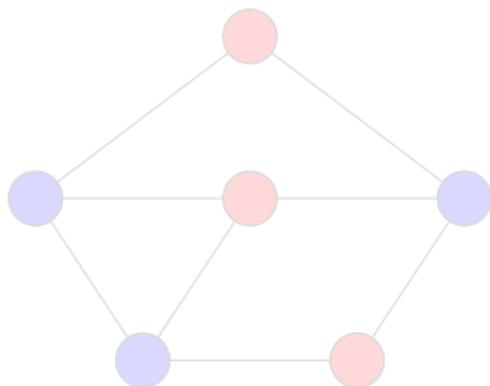
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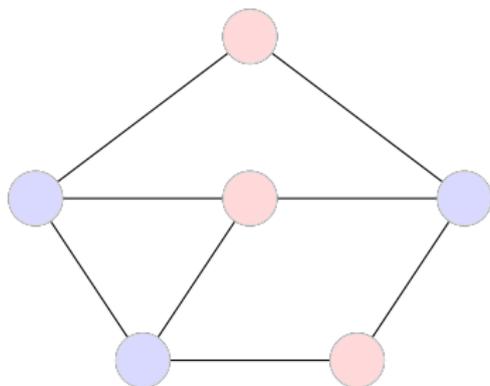
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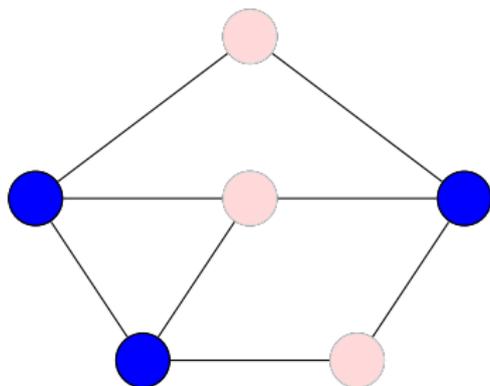
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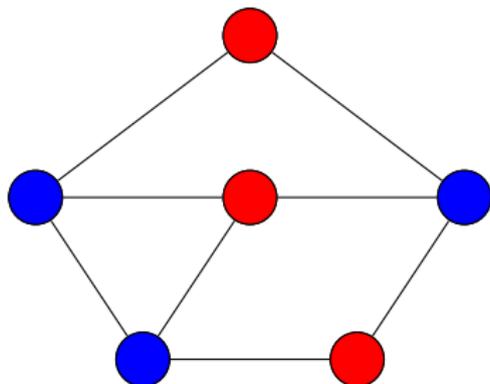
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Relationship between Vertex Cover and Independent Set

Proposition

Let $G = (V, E)$ be a graph. S is an independent set if and only if $V \setminus S$ is a vertex cover

Proof.

(\Rightarrow) Let S be an independent set

- Consider any edge $(u, v) \in E$
- Since S is an independent set, either $u \notin S$ or $v \notin S$
- Thus, either $u \in V \setminus S$ or $v \in V \setminus S$
- $V \setminus S$ is a vertex cover

(\Leftarrow) Let $V \setminus S$ be some vertex cover

- Consider $u, v \in S$
- (u, v) is not edge, as otherwise $V \setminus S$ does not cover (u, v)

INDEPENDENT SET \leq_P VERTEX COVER

Let \mathbf{G} , a graph with \mathbf{n} vertices, and an integer \mathbf{k} be an instance of the INDEPENDENT SET problem.

\mathbf{G} has an independent set of size $\geq \mathbf{k}$ iff \mathbf{G} has a vertex cover of size $\leq \mathbf{n} - \mathbf{k}$

(\mathbf{G}, \mathbf{k}) is an instance of INDEPENDENT SET, and $(\mathbf{G}, \mathbf{n} - \mathbf{k})$ is an instance of VERTEX COVER with the same answer.

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A problem of Languages

Suppose you work for the United Nations. Let \mathbf{U} be the set of all **languages** spoken by people across the world. The United Nations also has a set of **translators**, all of whom speak English, and some other languages from \mathbf{U} .

Due to budget cuts, you can only afford to keep k translators on your payroll. Can you do this, while still ensuring that there is someone who speaks every language in \mathbf{U} ?

More General problem: Find/Hire a small group of people who can accomplish a large number of tasks.

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The SET COVER Problem

Input Given a set \mathbf{U} of n elements, a collection $\mathbf{S}_1, \mathbf{S}_2, \dots, \mathbf{S}_m$ of subsets of \mathbf{U} , and an integer k

Goal Is there is a collection of at most k of these sets \mathbf{S}_i whose union is equal to \mathbf{U} ?

Example

Let $\mathbf{U} = \{1, 2, 3, 4, 5, 6, 7\}$, $k = 2$ with

$$\begin{array}{ll} \mathbf{S}_1 = \{3, 7\} & \mathbf{S}_2 = \{3, 4, 5\} \\ \mathbf{S}_3 = \{1\} & \mathbf{S}_4 = \{2, 4\} \\ \mathbf{S}_5 = \{5\} & \mathbf{S}_6 = \{1, 2, 6, 7\} \end{array}$$

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- Number \mathbf{k} for the SET COVER instance is the same as the number \mathbf{k} given for the VERTEX COVER instance.
- $\mathbf{U} = \mathbf{E}$
- We will have one set corresponding to each vertex;
 $\mathbf{S}_v = \{e \mid e \text{ is incident on } v\}$

Observe that \mathbf{G} has vertex cover of size \mathbf{k} if and only if $\mathbf{U}, \{\mathbf{S}_v\}_{v \in \mathbf{V}}$ has a set cover of size \mathbf{k} . (Exercise: Prove this.)

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- We will have one set corresponding to each vertex;
 $\mathbf{S}_v = \{e \mid e \text{ is incident on } v\}$

Observe that \mathbf{G} has vertex cover of size \mathbf{k} if and only if $\mathbf{U}, \{\mathbf{S}_v\}_{v \in \mathbf{V}}$ has a set cover of size \mathbf{k} . (Exercise: Prove this.)

VERTEX COVER \leq_P SET COVER

Given graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ and integer \mathbf{k} as instance of VERTEX COVER, construct an instance of SET COVER as follows:

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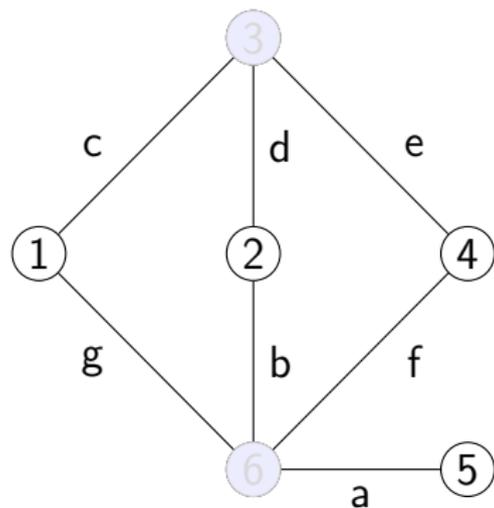
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VERTEX COVER \leq_P SET COVER: Example



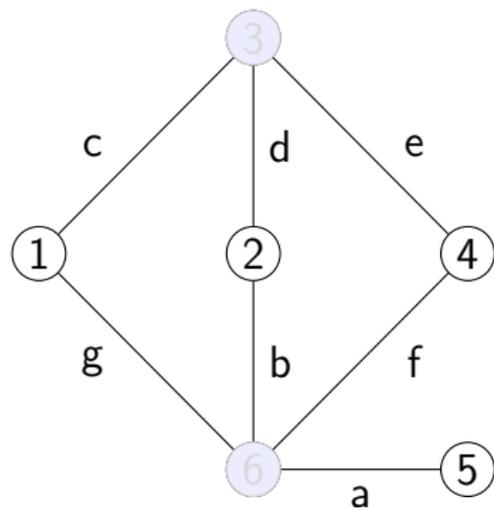
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$$\begin{aligned} S_1 &= \{c, g\} & S_2 &= \{b, d\} \\ S_3 &= \{c, d, e\} & S_4 &= \{e, f\} \\ S_5 &= \{a\} & S_6 &= \{a, b, f, g\} \end{aligned}$$

$\{S_3, S_6\}$ is a set cover

$\{3, 6\}$ is a vertex cover

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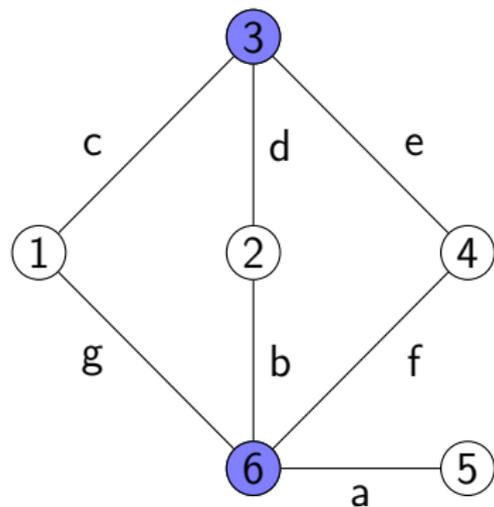
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Proving Reductions

To prove that $X \leq_P Y$ you need to give an algorithm \mathcal{A} that

- transforms an instance I_X of X into an instance I_Y of Y
- satisfies the property that answer to I_X is YES iff I_Y is YES
 - typical easy direction to prove: answer to I_Y is YES if answer to I_X is YES
 - **typical difficult direction to prove**: answer to I_X is YES if answer to I_Y is YES (equivalently answer to I_X is NO if answer to I_Y is NO)
- runs in *polynomial* time

Example of incorrect reduction proof

Try proving $\text{MATCHING} \leq_P \text{BIPARTITE MATCHING}$ via following reduction:

- Given graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ obtain a bipartite graph $\mathbf{G}' = (\mathbf{V}', \mathbf{E}')$ as follows.
 - Let $\mathbf{V}_1 = \{\mathbf{u}_1 \mid \mathbf{u} \in \mathbf{V}\}$ and $\mathbf{V}_2 = \{\mathbf{u}_2 \mid \mathbf{u} \in \mathbf{V}\}$. We set $\mathbf{V}' = \mathbf{V}_1 \cup \mathbf{V}_2$ (that is, we make two copies of \mathbf{V})
 - $\mathbf{E}' = \{(\mathbf{u}_1, \mathbf{v}_2) \mid \mathbf{u} \neq \mathbf{v} \text{ and } (\mathbf{u}, \mathbf{v}) \in \mathbf{E}\}$
- Given \mathbf{G} and integer \mathbf{k} the reduction outputs \mathbf{G}' and \mathbf{k} .

Example

“Proof”

Claim

Reduction is a poly-time algorithm. If G has a matching of size k then G' has a matching of size k .

Proof.

Exercise.

Claim

If G' has a matching of size k then G has a matching of size k .

Incorrect! Why? Vertex $u \in V$ has two copies u_1 and u_2 in G' . A matching in G' may use both copies!

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We looked at **polynomial-time reductions**.

Using polynomial-time reductions

- If $X \leq_p Y$, and we have an efficient algorithm for Y , we have an efficient algorithm for X .
- If $X \leq_p Y$, and there is no efficient algorithm for X , there is no efficient algorithm for Y .

We looked at some examples of reductions between INDEPENDENT SET, CLIQUE, VERTEX COVER, and SET COVER.

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