

Polynomial Time Reductions

Lecture 20

April 9, 2013

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

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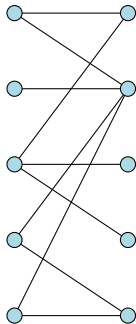
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Also, the right reductions might win you a million dollars!

Example 1: Bipartite Matching and Flows

How do we solve the
Bipartite Matching
Problem?

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



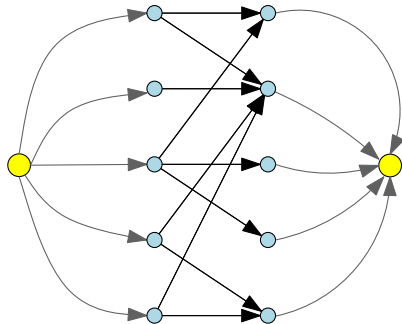
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Reduce it to **Max-Flow**. \mathbf{G} has a matching of size $\geq \mathbf{k}$ iff there is a flow from \mathbf{s} to \mathbf{t} of value $\geq \mathbf{k}$.

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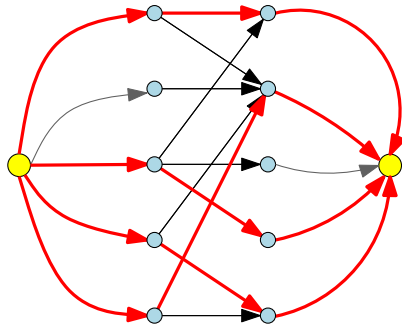
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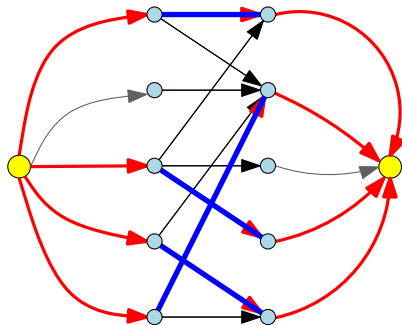
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Types of Problems

Decision, Search, and Optimization

- 1 **Decision problem.** Example: given n , is n prime?.
- 2 **Search problem.** Example: given n , find a factor of n if it exists.
- 3 **Optimization problem.** Example: find the smallest prime factor of n .

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Optimization and Decision problems

For max flow...

Problem (**Max-Flow** optimization version)

Given an instance G of network flow, find the maximum flow between s and t .

Problem (**Max-Flow** decision version)

Given an instance G of network flow and a parameter K , is there a flow in G , from s to t , of value at least K ?

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

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

Examples

Example

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.

Example

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”.

What is an algorithm for a decision Problem **X**?

It takes as input an instance of **X**, and outputs either “YES” or “NO”.

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Encoding an instance into a string

- 1 **I**; Instance of some problem.
- 2 **I** can be fully and precisely described (say in a text file).
- 3 Resulting text file is a binary string.
- 4 \implies Any input can be interpreted as a binary string **S**.
- 5 ... Running time of algorithm: Function of length of **S** (i.e., **n**).

Decision Problems and Languages

- 1 A finite **alphabet** Σ . Σ^* is set of all finite strings on Σ .
- 2 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 .

- 1 Given L , Π_L is the following decision 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.
- 2 Given Π the associated language is

$$L_\Pi = \{ I \mid I \text{ is an instance of } \Pi \text{ for which answer is YES} \}.$$

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Example

- 1 The decision problem **Primality**, and the language

$$L = \{ \#p \mid p \text{ is a prime number} \}.$$

Here $\#p$ is the string in base **10** representing p .

- 2 **Bipartite** (is given graph is bipartite. The language is

$$L = \{ \mathcal{S}(G) \mid G \text{ is a bipartite graph} \}.$$

Here $\mathcal{S}(G)$ is the string encoding the graph G .

Reductions, revised.

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

- 1 An algorithm ...
- 2 Input: I_X , an instance of X .
- 3 Output: I_Y an instance of Y .
- 4 Such that:

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- 2 \mathcal{A}_Y : algorithm for \mathbf{Y} :
- 3 \implies New algorithm for \mathbf{X} :

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 $\mathcal{A}_X(I_X)$ :  
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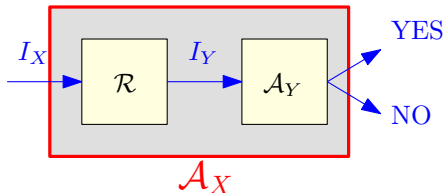
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Comparing Problems

- 1 "Problem **X** is no harder to solve than Problem **Y**".
- 2 If Problem **X** reduces to Problem **Y** (we write $X \leq Y$), then **X** cannot be harder to solve than **Y**.
- 3 **Bipartite Matching** \leq **Max-Flow**.
Bipartite Matching cannot be harder than **Max-Flow**.
- 4 Equivalently,
Max-Flow is at least as hard as **Bipartite Matching**.
- 5 $X \leq Y$:
 - 1 **X** is no harder than **Y**, or
 - 2 **Y** is at least as hard as **X**.

Part II

Examples of Reductions

Independent Sets and Cliques

Given a graph G , a set of vertices V' is:

- 1 **independent set**: no two vertices of V' connected by an edge.

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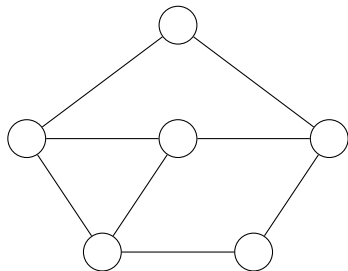
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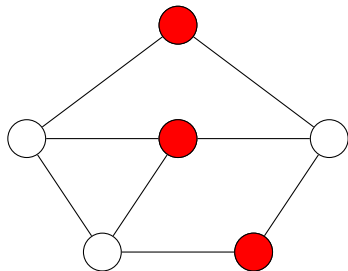
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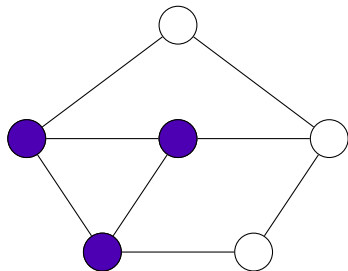
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The **Independent Set** and **Clique** Problems

Problem: **Independent Set**

Instance: A graph G and an integer k .

Question: Does G has an independent set of size $\geq k$?

Problem: **Clique**

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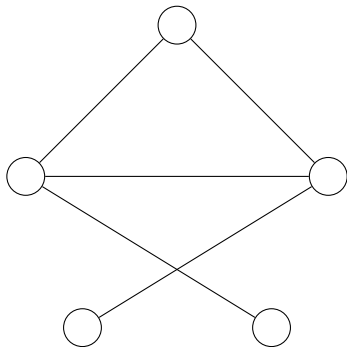
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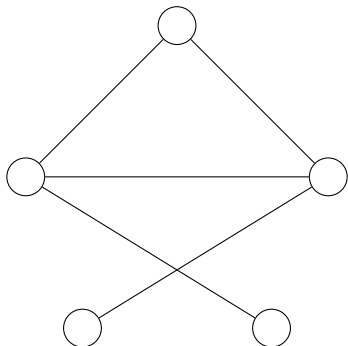


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Convert G to \bar{G} , in which (u, v) is an edge iff (u, v) is **not** an edge of G . (\bar{G} is the *complement* of G .)

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

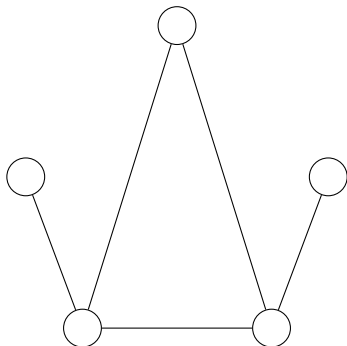


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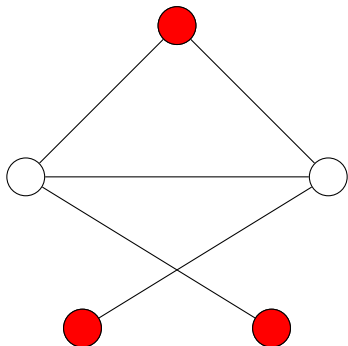


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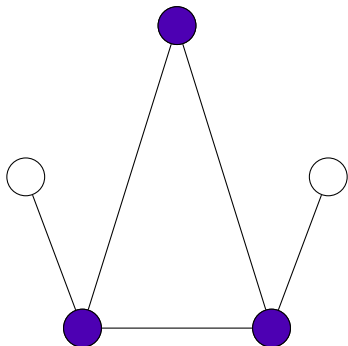


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What does this mean?

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DFAs (Remember 373?) are automata that accept regular languages. **NFA**s are the same, except that they are non-deterministic, while **DFA**s are deterministic.

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

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DFA Universality

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

Problem (DFA universality)

Input: A DFA M .

Goal: *Is M universal?*

How do we solve **DFA Universality**?

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

Alternatively, minimize M to obtain M' and see if M' has a single state which is an accepting state.

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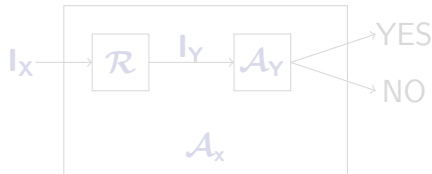
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Polynomial-time reductions

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 .

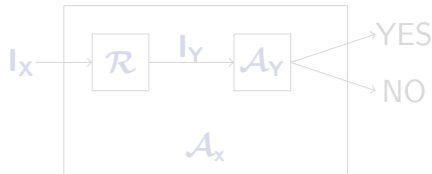


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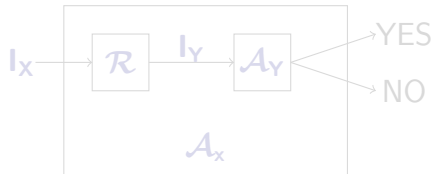


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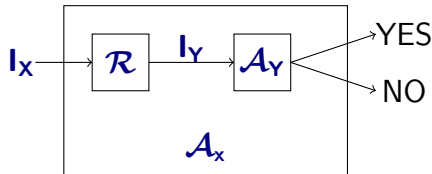


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Polynomial-time reductions and hardness

For decision problems X and Y , if $X \leq_P Y$, and Y has an efficient algorithm, X has an efficient algorithm.

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Polynomial-time reductions and instance sizes

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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 $\mathbf{p}(|\mathbf{l}_X|)$ for some polynomial $\mathbf{p}()$.

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

- 1 A **vertex cover** if every $e \in E$ has at least one endpoint in S .

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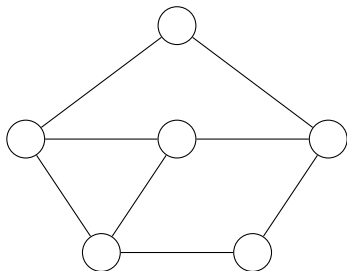
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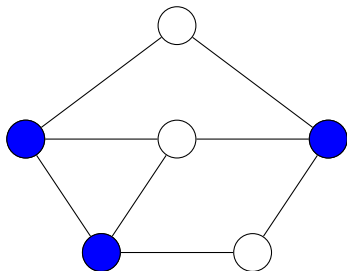
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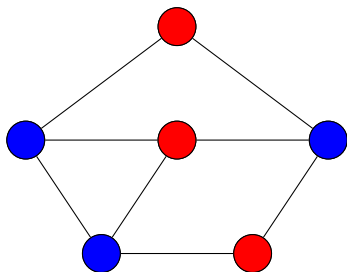
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Input: A graph G and integer k .

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Can we relate **Independent Set** and **Vertex Cover**?

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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

- 1 Consider any edge $uv \in E$.
- 2 Since S is an independent set, either $u \notin S$ or $v \notin S$.
- 3 Thus, either $u \in V \setminus S$ or $v \in V \setminus S$.
- 4 $V \setminus S$ is a vertex cover.

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

- 1 Consider $u, v \in S$
- 2 uv is not an edge of G , as otherwise $V \setminus S$ does not cover uv .
- 3 $\implies S$ is thus an independent set. □

Independent Set \leq_P Vertex Cover

- 1 **G**: graph with **n** vertices, and an integer **k** be an instance of the **Independent Set** problem.
- 2 **G** has an independent set of size $\geq k$ iff **G** has a vertex cover of size $\leq n - k$
- 3 **(G, k)** is an instance of **Independent Set**, and **(G, n - 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 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 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 U ?

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Input: Given a set U of n elements, a collection S_1, S_2, \dots, S_m of subsets of U , and an integer k .

Goal: Is there a collection of at most k of these sets S_i whose union is equal to U ?

Example

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

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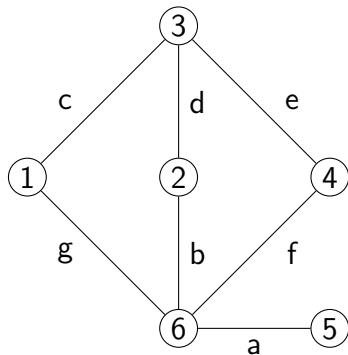
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Observe that G has vertex cover of size k if and only if $U, \{S_v\}_{v \in V}$ has a set cover of size k . (Exercise: Prove this.)

Vertex Cover \leq_P Set Cover: Example



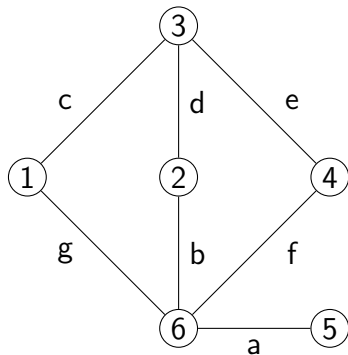
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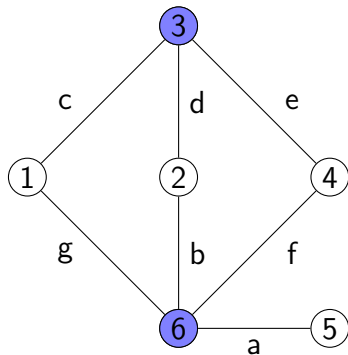
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Proving Reductions

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

- 1 Transforms an instance I_X of X into an instance I_Y of Y .
- 2 Satisfies the property that answer to I_X is YES iff I_Y is YES.
 - 1 typical easy direction to prove: answer to I_Y is YES if answer to I_X is YES
 - 2 **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).
- 3 Runs in **polynomial** time.

Example of incorrect reduction proof

Try proving **Matching** \leq_P **Bipartite Matching** via following reduction:

- ① Given graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ obtain a bipartite graph $\mathbf{G}' = (\mathbf{V}', \mathbf{E}')$ as follows.
 - ① 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})
 - ② $\mathbf{E}' = \{\mathbf{u}_1\mathbf{v}_2 \mid \mathbf{u} \neq \mathbf{v} \text{ and } \mathbf{uv} \in \mathbf{E}\}$
- ② 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.

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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 some examples of reductions between **Independent Set**, **Clique**, **Vertex Cover**, and **Set Cover**.

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