$$
\begin{aligned}
& \text { NP-Completeness } \\
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\end{aligned}
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Spring 2019

## Classification of the Problems

$\square$ Unsolvable: There is no algorithm to solve them (Halting Problem)
$\square$ Intractable: As they grow large, we are unable to solve them in reasonable time (Hamiltonian Cycle)
$\square$ Tractable: We are able to solve them in reasonable time (Sorting)
Q: What constitutes reasonable time?
A: Standard working definition: polynomial time

- On an input of size $n$, the worst-case running time is $\mathrm{O}\left(n^{k}\right)$ for some constant $k$
- Polynomial time: $\mathrm{O}\left(\mathrm{n}^{2}\right), \mathrm{O}\left(\mathrm{n}^{3}\right), \mathrm{O}(1), \mathrm{O}(\mathrm{n} \lg \mathrm{n})$
- Not in polynomial time: $\mathrm{O}\left(2^{n}\right), \mathrm{O}\left(n^{\mathrm{n}}\right), \mathrm{O}(n!)$


## P vs. NP

$\square$ P: The class of problems, for which a Polynomial-time algorithm exists.

- Ex: fractional knapsack, finding maximum subarray, rod cutting, etc.
$\square$ NP: The class of problems for which a solution can be verified in polynomial time
- Ex: Hamiltonian cycle, graph coloring, 3SAT, etc.


## Decision vs. Optimization

$\square$ Decision problem: a decision problem is a problem that can be posed as a yes-no question of the input values.
$\square$ Optimization problem: optimization problems are concerned with finding the best answer to a particular input.

## Decision vs. Optimization

## Example (Knapsack Problem)

Suppose that we have $n$ objects, say $o_{i}(i=1,2, \cdots, n)$, each with corresponding weight ( $w_{i}$ ) and profit ( $p_{i}$ ), and a weight bound $b$.

- Optimization: Find an $X=\left(x_{1}, x_{2}, \cdots, x_{n}\right)$ that maximize $\sum_{i=1}^{n} x_{i} p_{i}$ with respect to $\sum_{i=1}^{n} x_{i} w_{i} \leq b$.
- Decision: For a given $k$, is there a feasible solution, say $X=\left(x_{1}, x_{2}, \cdots, x_{n}\right)$, where $\sum_{i=1}^{n} x_{i} p_{i} \geq k$ ?


## Decision vs. Optimization

## Example (Max-Clique Problem)

Suppose that a graph $G=(V, E)$ is given.

- Optimization: Find a maximal subset $V^{\prime} \subseteq V$, such that the induced graph by $V^{\prime}$ is complete graph (The clique is a complete subgraph).
- Decision: For a given $k$, is there a subset $V^{\prime} \subseteq V$ with $\left|V^{\prime}\right| \geq k$, such that the induced graph by $V^{\prime}$ is complete graph (a clique of size at least $k)$ ?


## Decision vs. Optimization



## Decision vs. Optimization

## Example (Min-Vertex Cover Problem)

Suppose that a graph $G=(V, E)$ is given.

- Optimization: Find a minimal subset $V^{\prime} \subseteq V$, such that for each $e=\left(v_{1}, v_{2}\right) \in E$, either $v_{1} \in V^{\prime}$ or $v_{2} \in V^{\prime}\left(V^{\prime}\right.$ covers the $\left.E\right)$.
- Decision: For a given $k$, is there a subset $V^{\prime} \subseteq V$ with $\left|V^{\prime}\right| \leq k$, such that $V^{\prime}$ covers the $E$ ?


## Decision vs. Optimization



## The principle of Reduction

## Definition

Suppose that $A$ and $B$ are two decision problems. We say that $A$ is reduced to $B$ (denoted by $A \preccurlyeq P B$ ), if there exists a polynomial algorithm, say $f$, such that:

- $x \in \operatorname{Instance}(A) \Longrightarrow f(x) \in \operatorname{Instance}(B)$.
- $x$ is a yes-instance of $A \Longleftrightarrow f(x)$ is a yes-instance of $B$.


Application of reduction
The reduction defines an order over the decision problems with respect to their level of difficulties.

- If $B$ is easy to solve, then $A$ is also easy.
- Conversely, If $A$ is hard to solve, then $B$ is also hard.


## The theory of NP-Completness

## Definition

A problem $L$ is called $N P-$ Hard if all $N P$ problems are reduced to $L$, i.e.

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L \in N P-\text { Hard } \Longleftrightarrow \forall L^{\prime} \in N P: L^{\prime} \preccurlyeq P L .
$$

## Definition

A problem $L$ is called $N P$-Complete if all $N P$ problems are reduced to $L$ and $L \in N P$, i.e.
$L \in N P$ - Complete $\Longleftrightarrow L \in N P \cap N P$ - Hard.

## The theory of NP-Completness



## The theory of NP-Completness

- NP-Complete problems are the "hardest" problems in NP:
- If any one NP-Complete problem can be solved in polynomial time...
- ...then every NP-Complete problem can be solved in polynomial time...
- ... and in fact every problem in NP can be solved in polynomial time (which would show $\mathbf{P}=\mathbf{N P}$ )
- Thus: solve Hamiltonian-cycle in $\mathrm{O}\left(n^{100}\right)$ time, you've proved that $\mathbf{P}=\mathbf{N P}$. Retire rich $\&$ famous.


## Travelling Salesman Problem (TSP)

$\square$ The travelling salesman problem (TSP) asks the following question:

Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city and returns to the origin city?
$\square$ A very important question:
$\square$ Which complexity class does the TSP belong to? (NP-complete or NP-hard?)

