



# Design and Analysis of Algorithms

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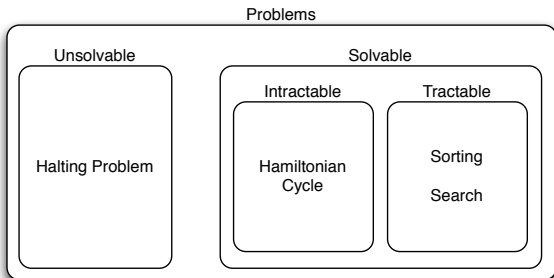
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# Theory of $NP$ —Completeness

## Classification of the Problems

- **Unsolvable:** There is no algorithm to solve them.
- **Intractable:** Solvable in theory, but not solvable in practice, because of the huge amounts of required time.
- **Tractable:** Solvable both in theory and in practice.



Here we will focus on **Intractable** problems.

## Deterministic vs. Nondeterministic

- **Deterministic Algorithm:** The next state of the algorithm execution can be definitely determined by the current state.
- **Nondeterministic Algorithm:** The next state of the algorithm execution can not be determined by the current state.

Based on the above principles, two classes of problems are as follows:

- **P:** The class of problems, for which a deterministic Polynomial-time algorithm exists.
- **NP:** The class of problems, for which a **N**ondeterministic Polynomial-time algorithm exists.

**Question:** How we can express a Nondeterministic Algorithm?

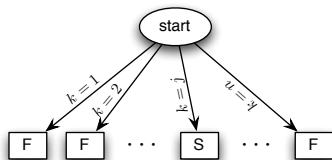
## Express a Nondeterministic Algorithm

In order to express a nondeterministic algorithm, three functions, all with  $O(1)$  time complexity are introduced as follows:

- **choose( $S$ ):** Concurrently create  $|S|$  copies of the machine and assign one element of  $S$  to each copy.
- **success():** Halt the machine with finding a solution.
- **failure():** Halt the machine without finding a solution.

**Example:** Nondeterministic Search with  $O(1)$  time complexity!

```
1: NSearch ( $A[1 \cdots n], x$ )  
2:  $k \leftarrow \text{choose}(\{1, 2, \cdots, n\})$  ;  
3: if  $A[k] = x$  then  
4:   success() ;  
5: else  
6:   failure() ;  
7: end if  
8: end.
```



## Express a Nondeterministic Algorithm

**Example:** Nondeterministic Sort with  $O(n)$  time complexity!

```
1: NSearch ( $A[1 \cdots n]$ )
2: Array  $B[1 \cdots n] \leftarrow \{0\}$  ;
3: for  $i \leftarrow 1$  to  $n$  do
4:    $j \leftarrow \text{choose}(\{1, 2, \cdots, n\})$  ;
5:   if  $B[j] \neq 0$  then
6:     failure() ;
7:   end if
8:    $B[j] \leftarrow A[i]$  ;
9: end for
10: for  $i \leftarrow 1$  to  $n - 1$  do
11:   if  $B[i] \neq B[i + 1]$  then
12:     failure() ;
13:   end if
14: end for
15: print( $B$ ) ;
16: success() ;
17: end.
```

A problem belongs to *NP* if one of the following holds.

- There is a nondeterministic polynomial-time algorithm for it.
- Verifying (deterministically and polynomially) whether a given solution to that problem is correct or not .

## Optimization vs. Decision

- Different optimization problems may have different outputs.
- In order to compare these problems, we need to have the same output for them.
- Any **optimization problem** can be converted to the corresponding **decision problem** by adding a bounding value.
- The answer of any decision problem is either **yes** or **no**.

### Example (Knapsack Problem)

Suppose that we have  $n$  objects, say  $o_i$  ( $i = 1, 2, \dots, n$ ), each with corresponding weight ( $w_i$ ) and profit ( $p_i$ ), and a weight bound  $b$ .

- **Optimization:** Find an  $X = (x_1, x_2, \dots, x_n)$  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  $X = (x_1, x_2, \dots, x_n)$ , where  $\sum_{i=1}^n x_i p_i \geq k$ ?

## Optimization vs. Decision

### Example (Max-Clique Problem)

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

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

### Example (Min-Vertex Cover Problem)

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

- **Optimization:** Find a minimal subset  $V' \subseteq V$ , such that for each  $e = (v_1, v_2) \in E$ , either  $v_1 \in V'$  or  $v_2 \in V'$  ( $V'$  covers the  $E$ ).
- **Decision:** For a given  $k$ , is there a subset  $V' \subseteq V$  with  $|V'| \leq k$ , such that  $V'$  covers the  $E$ ?

# Optimization vs. Decision

## Relation between Optimization and Decision problems

- If the optimization problem is easy to solve, then the corresponding decision problem is also easy.
- Conversely, If the decision problem is hard to solve, then the corresponding optimization problem is also hard.

## Corollary

- *In order to show that the optimization problem is hard to solve, it is enough to show that the corresponding decision problem is hard!*
- *Dealing with decision problems is much easier than the optimization problems.*

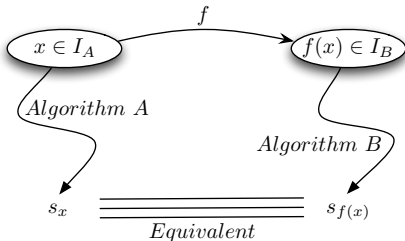


# The principle of Reduction

## Definition

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

- $x \in \text{Instance}(A) \implies f(x) \in \text{Instance}(B)$ .
- $x$  is a **yes**-instance of  $A \iff f(x)$  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*–Completeness

## Definition

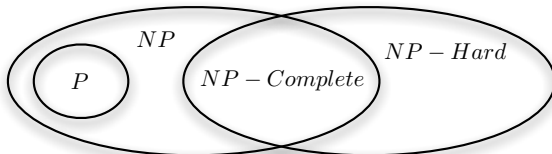
A problem  $L$  is called *NP*–Hard if all *NP* problems are reduced to  $L$ , i.e.

$$L \in NP - Hard \iff \forall L' \in NP : L' \preceq_P L.$$

## Definition

A problem  $L$  is called *NP*–Complete if all *NP* problems are reduced to  $L$  and  $L \in NP$ , i.e.

$$L \in NP - Complete \iff L \in NP \cap NP - Hard.$$



# The theory of $NP$ –Completeness

- Question: How we can prove that a problem is  $NP$ –Complete?
- Answer: Use the definition (**very hard**).

## Theorem

*The reduction has the transitive property, i.e.*

$$A \preceq_P B \ \& \ B \preceq_P C \implies A \preceq_P C.$$

- Question: How we can prove that a problem is  $NP$ –Complete?
- Answer: Use the above theorem (**relatively easy**). But we need at least one known  $NP$ –Complete problem.

## Theorem (Cook Theorem)

*The **Satisfiability problem** is an  $NP$ –Complete problem.*

# The theory of *NP*–Completeness

## Definition (Satisfiability problem)

Suppose that a formula  $\phi$  over the  $n$  binary variables is given as follows:

$$\phi = \bigwedge_{i=1}^m C_i, \quad C_i = \bigvee_{j=1}^{k_i} \ell_{ij}, \quad \ell_{ij} \in \{x_{ij}, \bar{x}_{ij}\}, \quad k_i \in \mathbb{N}^+.$$

Is there an assignment  $X = [x_1, x_2, \dots, x_n] \in \{0, 1\}^n$  such that  $\phi$  is satisfied by the assignment  $X$ ?

## Definition (*k*SAT)

A SAT is called *k*SAT if  $k_i = k$ , for all  $i = 1, 2, \dots, m$ .

## Theorem

*3SAT* is an *NP*–Complete problem.

## Theorem

*2SAT* is a polynomial-time solvable problem.

# The theory of $NP$ –Completeness

## Theorem

*$k$ –Clique is an  $NP$ –Complete problem.*

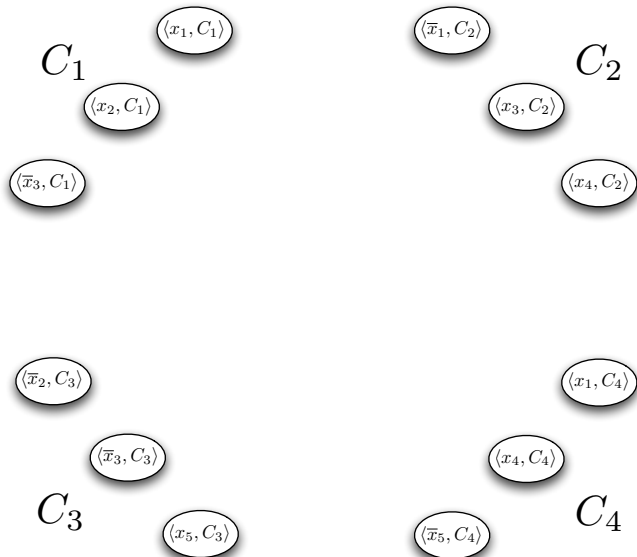
## Example

Consider the following 3SAT formula:

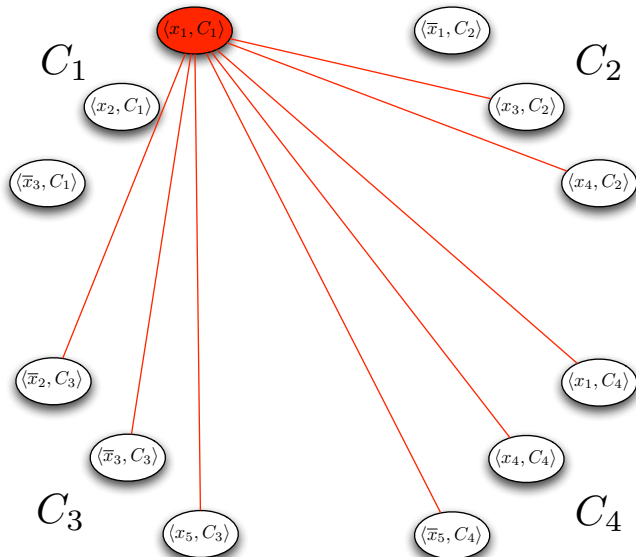
$$\phi = (x_1 \vee x_1 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_3 \vee x_4) \wedge (\bar{x}_2 \vee \bar{x}_3 \vee x_5) \wedge (x_1 \vee x_4 \vee \bar{x}_5).$$

We can construct the corresponding graph  $G(\phi)$  as follows (see the next slides).

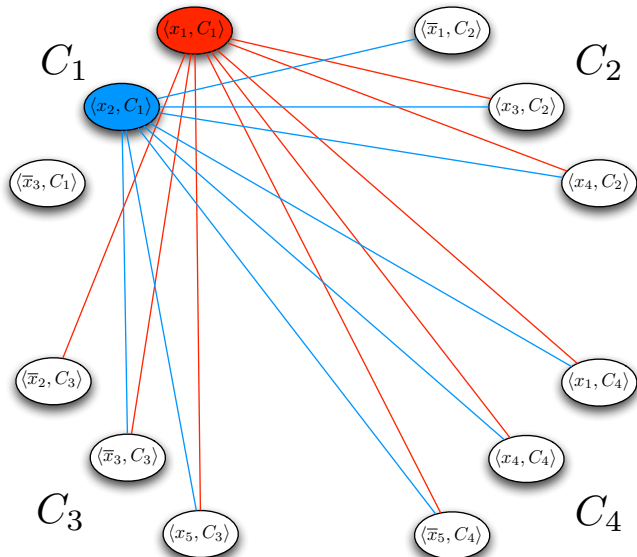
# The theory of $NP$ –Completeness



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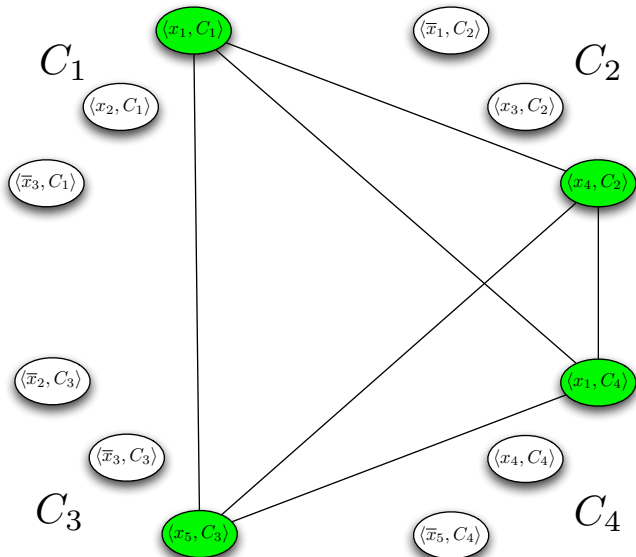


# The theory of $NP$ -Completeness





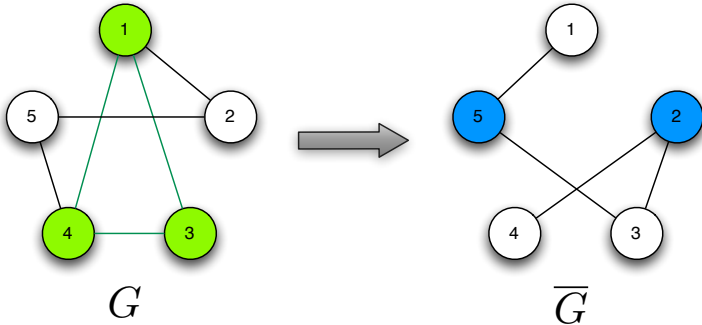
# The theory of $NP$ -Completeness



# The theory of $NP$ -Completeness

## Theorem

*$k$ -Vertex Cover is an  $NP$ -Complete problem.*



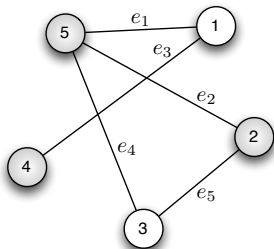
# The theory of $NP$ –Completeness

## Definition (Subset Sum Problem)

Suppose that a set  $S = \{x_1, x_2, \dots, x_n\}$  and a positive integer  $t$  are given. Is there a subset  $S' \subseteq S$  such that  $\sum_{x \in S'} x = t$ ?

## Theorem

*Subset Sum Problem* is an  $NP$ –Complete problem.



	$e_1$	$e_2$	$e_3$	$e_4$	$e_5$
$v_1$	1	0	1	0	0
$v_2$	0	1	0	0	1
$M = v_3$	0	0	0	1	1
$v_4$	0	0	1	0	0
$v_5$	1	1	0	1	0

## The theory of $NP$ –Completeness

	MSB	$e_1$	$e_2$	$e_3$	$e_4$	$e_5$	مبنای ۱۰
$x_1$	1	1	0	1	0	0	1296
$x_2$	1	0	1	0	0	1	1089
$x_3$	1	0	0	0	1	1	1029
$x_4$	1	0	0	1	0	0	1040
$x_5$	1	1	1	0	1	0	1348
$y_1$	0	1	0	0	0	0	256
$y_2$	0	0	1	0	0	0	64
$y_3$	0	0	0	1	0	0	16
$y_4$	0	0	0	0	1	0	4
$y_5$	0	0	0	0	0	1	1
$t$	$k$	2	2	2	2	2	3754

# The theory of $NP$ –Completeness

## Definition (Hamiltonian Path (Cycle))

For a given graph  $G = (V, E)$ , a path (cycle)  $p$  is called Hamiltonian path (cycle) if it passes through all vertices and visit each vertex exactly once.

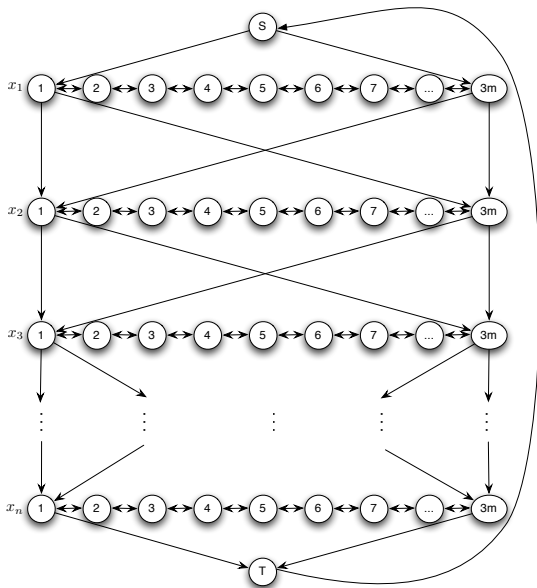
## Definition (Hamiltonian Cycle Problem)

For a given graph  $G = (V, E)$ , check weather  $G$  has a Hamiltonian cycle or not?

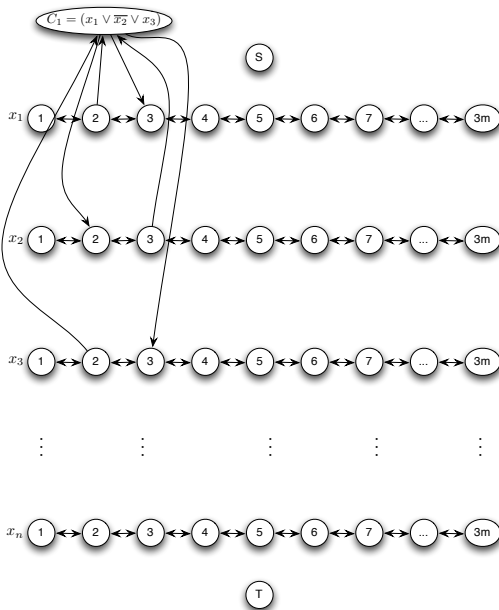
## Theorem

*Directed Hamiltonian Cycle (DHC) is an  $NP$ –Complete problem.*

# The theory of *NP*–Completeness



# The theory of *NP*–Completeness



# The theory of $NP$ –Completeness

## Definition (3Coloring Problem)

For a given graph  $G = (V, E)$ , check whether the vertices of  $G$  can be colored by three different colors in such a way that for all  $e = (v_1, v_2) \in E$ ,  $Color(v_1) \neq Color(v_2)$ ?

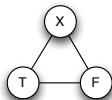
## Theorem

*3Coloring is an  $NP$ –Complete problem.*

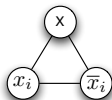


# The theory of *NP*–Completeness

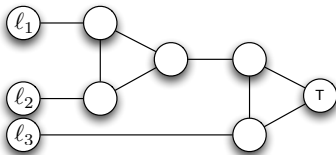
- Truth structure:



- Variable Structure:



- Clause Structure:



## The theory of *NP*–Completeness

$$\phi = (a \vee b \vee c) \wedge (b \vee \bar{c} \vee \bar{d}) \wedge (\bar{a} \vee c \vee d) \wedge (a \vee \bar{b} \vee \bar{d}).$$

