

Algorithm design and analysis — Tractability and Intractability —

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Patterns

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- \triangleright Dynamic programming.
- \blacktriangleright Duality.

 \triangleright Greed. $O(n \log n)$ interval scheduling. \triangleright Divide-and-conquer. $O(n \log n)$ closest pair of points. ²) edit distance. ³) maximum flow and minimum cuts.

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Anti-patterns

- \triangleright NP-completeness.
- \blacktriangleright PSPACE-completeness.
-

 (k) algorithm unlikely. (k) certification algorithm unlikely. Indecidability. The Undecidability and the Undecidability.

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Polynomial time Probably not

Shortest path Longest path Matching 3-D matching Minimum cut Maximum cut 2-SAT 3-SAT Planar four-colour Planar three-colour Bipartite vertex cover Vertex cover Primality testing Factoring

- In Classify problems based on whether they admit efficient solutions or not.
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- \triangleright Some extremely hard problems cannot be solved efficiently (e.g., chess on an n -by- n board).
- \triangleright However, classification is unclear for a very large number of discrete computational problems.
- \triangleright We can prove that these problems are fundamentally equivalent and are manifestations of the same problem!

Algorithm design and analysis

— Reductions —

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Polynomial-Time Reduction

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Y is polynomial-time reducible to X ($Y \leq_P X$)

if an arbitrary instance of Y can be solved using a polynomial number of standard operations, plus a polynomial number of calls to a black box that solves problem X .

- \triangleright Y \leq_P X implies that X is at least as hard as Y.
- ▶ Such reductions are Cook reductions. Karp reductions allow only one call to the black box that solves X.

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- ► If $X \leq_P Y$ and $Y \leq_P X$, we use notation $X \equiv_P Y$ in order to express the equivalance. The express the equivalence express the equivalence

Problem X polynomial reduces (Cook) to problem Y if arbitrary instances of problem X can be solved using:

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Polynomial transformation is polynomial reduction with just one call to oracle for Y, exactly at the end of the algorithm for X. Almost all previous reductions were of this form.

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The problems have a similar underling structure and it is used to design new Algorithms

- \blacktriangleright Simple equivalence.
- \blacktriangleright Special case to general case.
- \blacktriangleright Encoding with gadgets.
- \triangleright So far, we have developed algorithms that solve optimization problems.
	- \triangleright Compute the largest flow.
	- \triangleright Find the closest pair of points.
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	- \triangleright Find the schedule with the least completion time.
- \triangleright Now, we will focus on decision versions of problems, e.g.,

Is there a flow with value at least k , for a given value of k ?

Independent sets

- A subset $S \subseteq V$ is an independent set if $\forall u, v \in S$ there exist an edge $(u, v) \in \overline{E}$.
- ► Given G and an integer k, is there a subset of vertices $S \subseteq V$ such that $|S| > k$, and for each edge at most one of its endpoints is in S?

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- A subset $S \subseteq V$ is an vertex cover if $\forall (u, v) \in E$, either $u \in S$ or $v \in S$.
- \triangleright Given a graph G and an integer k, is there a subset of vertices $S \subset V$ such that $|S| \leq k$, and for each edge, at least one of its endpoints is in S?

Let $G = (V, E)$ be an undirected connected graph.

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Silvio Guimarães [Tractability and Intractability](#page-0-0) 17 de 50

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Let $G = (V, E)$ be an undirected connected graph, and S a vertex cover of G

As S is a vertex cover of G, then \sqrt{S} is an independent set.

- ► Given an undirected graph $G(V, E)$, a subset $S \subseteq V$ is an independent set if no two vertices in S are connected by an edge.
- \triangleright Given an undirected graph $G(V, E)$, a subset $S ⊂ V$ is a vertex cover if every edge in E is incident on at least one vertex in S .

 \triangleright S is an independent set in G iff $V - S$ is a vertex cover in G.

- \triangleright S is an independent set in G iff $V S$ is a vertex cover in G.
- INDEPENDENT SET \leq_P VERTEX COVER and VERTEX COVER \leq_P INDEPENDENT SET.

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- \blacktriangleright Let S be any independent set.
- \triangleright Consider an arbitrary edge (u, v).
- \triangleright S independent $\Rightarrow u \notin S$ or $v \notin S \Rightarrow u \in V S$ or $v \in V S$.
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- \triangleright Thus, V S covers (u, v).
- \triangleright Let V S be any vertex cover.
- \triangleright Consider two nodes $u \in S$ and $v \in S$.
- ▶ Observe that $(u, v) \notin E$ since V S is a vertex cover.
- \triangleright Thus, no two nodes in S are joined by an edge \Rightarrow S independent set

Given a set U of elements, a collection $S = \{S_1, S_2, \cdots, S_m\}$ of subsets of U.

- A subset $C \subseteq S$ is a set cover if the union of elements of C is equal to U.
- \triangleright Given U, S, and an integer k, does there exist a collection of \leq k of these sets whose union is equal to U?

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Sample application:

- \blacktriangleright m available pieces of software
- \triangleright Set U of *n* capabilities that we would like our system to have
- ► The i^{th} piece of software provides the set $S_i \subseteq U$ of capabilities.
- \triangleright The goal is to achieve all *n* capabilities using fewest pieces of software .

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Sample application:

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

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S_1 = \{3, 7\} \qquad S_4 = \{2, 4\} S_2 = \{3, 4, 5, 6\} \qquad S_5 = \{5\} S_3 = \{1\} \qquad S_6 = \{1, 2, 6, 7\}
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Vertex Cover and Set Cover

- \triangleright Set cover is a packing problem: pack as many vertices as possible, subject to constraints (the edges).
- I Vertex Cover is a covering problem: cover all edges in the graph with as few vertices as possible.
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VERTEX COVER \leq_P SET COVER

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- Input to Vertex Cover is an undirected graph $G = (V, E)$ with *n* vertices.
- \triangleright Create an instance of Set Cover in which
	- \triangleright $k = k$, $U = E$, $S_v = \{e \in E : e \text{ incident to } v\}$

 \triangleright U can be covered with fewer than k subsets iff G has a vertex cover with at most k nodes.

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- \triangleright Abstract problems formulated in Boolean notation.
- \triangleright Often used to specify problems, e.g., in AI.
- \triangleright We are given a set $X = \{x_1, x_2, \ldots, x_n\}$ of *n* Boolean variables.
- \blacktriangleright Each variable can take the value 0 or 1.
- A term is a variable x_i or its negation $\overline{x_i}$.
- \triangleright A clause of length *l* is a disjunction of *l* distinct terms $t_1 \vee t_2 \vee \cdots t_l.$
- A truth assignment for X is a function $\nu : X \to \{0, 1\}$.
- An assignment satisfies a clause C if it causes C to evaluate to 1 under the rules of Boolean logic.
- An assignment **satisfies** a collection of clauses C_1, C_2, \ldots, C_k if it causes $C_1 \wedge C_2 \wedge \cdots C_k$ to evaluate to 1.
	- \triangleright ν is a **satisfying assignment** with respect to $C_1, C_2, \ldots C_k$.
	- \triangleright set of clauses $C_1, C_2, \ldots C_k$ is **satisfiable**.

SAT and 3-SAT

SATISFIABILITY PROBLEM (SAT)

INSTANCE A set of clauses C_1, C_2, \ldots, C_k over a set $X = \{x_1, x_2, \ldots, x_n\}$ of n variables.

QUESTION Is there a satisfying truth assignment for X with respect to C ?

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3-Satisfiability Problem (3-SAT)

- **INSTANCE** A set of clauses $C_1, C_2, \ldots C_k$ each of length 3 over a set $X =$ $\{x_1, x_2, \ldots x_n\}$ of *n* variables.
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- ▶ SAT and 3-SAT are fundamental combinatorial search problems.
- \triangleright We have to make *n* independent decisions (the assignments for each variable) while satisfying a set of constraints.
- \triangleright Satisfying each constraint in isolation is easy, but we have to make our decisions so that all constraints are satisfied simultaneously.

3-SAT and Independent Set

- \triangleright We want to prove $3\text{-SAT} \leq_P \text{INDEPENDENT SET}$.
- \blacktriangleright Two ways to think about 3-SAT:
	- 1. Make an independent 0/1 decision on each variable and succeed if we achieve one of three ways in which to satisfy each clause.
	- 2. Choose (at least) one term from each clause . Find a truth assignment that causes each chosen term to evaluate to 1. Ensure that no two terms selected ${\sf conflict}$, i.e., select x_i and $\overline{x_i}.$

Proving $3-SAT _P$ INDEPENDENT SET

$3-SAT < p$ INDEPENDENT SET

Given an instance Φ of 3-SAT, we construct an instance (G, k) of independent set that has an independent set of size k iff Φ is satisfiable.

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Given an instance Φ of 3-SAT, we construct an instance (G, k) of independent set that has an independent set of size k iff Φ is satisfiable. Construction.

- \triangleright G contains 3 nodes for each clause (k=3), one for each literal.
- \triangleright Connect 3 literals in a clause in a triangle.
- \triangleright Connect literal to each of its negations.

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Proving $3\text{-SAT} \leq_{\text{P}}$ INDEPENDENT SET

$3-SAT < p$ INDEPENDENT SET

Given an instance Φ of 3-SAT, we construct an instance (G, k) of independent set that has an independent set of size k iff Φ is satisfiable. Construction.

- \triangleright G contains 3 nodes for each clause (k=3), one for each literal.
- \triangleright Connect 3 literals in a clause in a triangle.
- \triangleright Connect literal to each of its negations.

 $\Phi = (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_2} \vee x_1 \vee x_3) \wedge (\overline{x_1} \vee x_2 \vee x_4)$

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G contains independent set of size $k = |\Phi|$ iff Φ is satisfiable.

 \Rightarrow Let S be independent set of size k.

- \triangleright S must contain exactly one vertex in each triangle.
- \triangleright Set these literals to true.
- \triangleright Truth assignment is consistent and all clauses are satisfied.

 ϵ Given satisfying assignment, select one true literal from each triangle. This is an independent set of size k.

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Proving $3\text{-SAT} \leq_P \text{INDEPENDENT SET}$

Conflict

- \triangleright We are given an instance of 3-SAT with k clauses of length three over *n* variables.
- \triangleright Construct a graph $G = (V, E)$ with 3k nodes.
	- ► For each clause $C_i, 1 \leq i \leq k$, add a triangle of three nodes v_{i1} , v_{i2} , v_{i3} and three edges to G.
	- ► Label each node $v_{ij}, 1 \leq j \leq 3$ with the *j*-th term in C_i .
	- \triangleright Add an edge between each pair of nodes whose labels correspond to terms that conflict.

Proving $3\text{-SAT} \leq_P \text{INDEPENDENT SET}$

Conflict

 \triangleright Claim: 3-SAT instance is satisfiable iff G has an independent set of size at $\overline{\text{least }k}$.

Proving $3-SAT \leq_{p}$ INDEPENDENT SET

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Proving $3-SAT \leq_{p}$ INDEPENDENT SET

- \triangleright Claim: 3-SAT instance is satisfiable iff G has an independent set of size at least k .
- **>** Satisfiable assignment \rightarrow independent set of size $\geq k$ Each triangle in G has at least one node whose label evaluates to 1. These nodes form an independent set of size k. Why?

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- Independent set of size $\geq k \rightarrow$ satisfiable assignment

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> Satisfiable assignment \rightarrow independent set of size $\geq k$ Each triangle in G has at least one node whose label evaluates to 1. These nodes form an independent set of size k . Why?

Independent set of size $\geq k \rightarrow$ satisfiable assignment the size of this set is k . How do we construct a satisfying truth assignment from the nodes in the independent set?

Basic reduction strategies.

- \triangleright Simple equivalence: INDEPENDENT SET \equiv_P VERTEX cover.
- \triangleright Special case to general case: VERTEX COVER \leq_P SET cover.
- Encoding with gadgets: $3-SAT \leq p$ INDEPENDENT SET.

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 $3-SAT < p$ INDEPENDENT SET $\leq p$ VERTEX COVER \leq_P SET COVER

Algorithm design and analysis

 \longrightarrow $\Lambda \mathcal{P}$ —

Silvio Guimarães

Graduate Program in Informatics – PPGINF Image and Multimedia Data Science Laboratory – IMScience Pontifical Catholic University of Minas Gerais – PUC Minas

- \triangleright Is it easy to check if a given set of vertices in an undirected graph forms an independent set of size at least k ?
- \triangleright Is it easy to check if a particular truth assignment satisfies a set of clauses?
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- \triangleright Is it easy to check if a particular truth assignment satisfies a set of clauses?
- \triangleright We draw a contrast between finding a solution and checking a solution (in polynomial time).

We have not been able to develop efficient algorithms to solve many decision problems, let us turn our attention to whether we can check if a proposed solution is correct.

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- \triangleright A has a polynomial running time if there is a polynomial function $p(\cdot)$ such that for every input string s, A terminates on s in at most $O(p(|s|))$ steps, e.g., there is an algorithm such that $p(|s|) = |s|^8$ for PRIMES

 \triangleright P : set of problems X for which there is a polynomial time algorithm.

Efficient Certification

- \triangleright A checking algorithm for a decision problem X has a different structure from an algorithm that solves X .
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- An algorithm B is an efficient certifier for a problem X if
	- 1. B is a polynomial time algorithm that takes two inputs s and t and 2. there is a polynomial function p so that for every string s , we have $s \in X$ iff there exists a string t such that $|t| \leq p(|s|)$ and $B(s,t) = \text{ves}.$
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- ► Certifier's job is to take a candidate short proof (t) that $s \in X$ and check in polynomial time whether t is a correct proof.

Certifier does not care about how to find these proofs.

 $3-SAT \in \mathcal{NP}$

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Certificance
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x_1 = 1
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, $x_2 = 1$, $x_3 = 0$ and $x_4 = 1$

3-SAT \in NP t is a truth assignment; B evaluates the clauses with respect to the assignment.

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$$
\textbf{Set}~ \textbf{Cover} \in \mathcal{NP}
$$

$$
U = \{1, 2, 3, 4, 5, 6, 7\} \text{ and } k = 2
$$

\n
$$
S_1 = \{3, 7\}
$$

\n
$$
S_2 = \{3, 4, 5, 6\}
$$

\n
$$
S_3 = \{1\}
$$

\n
$$
S_4 = \{2, 4\}
$$

\n
$$
S_5 = \{5\}
$$

\n
$$
S_6 = \{1, 2, 6, 7\}
$$

NP is the set of all problems for which there exists an efficient certifier

3-SAT \in NP t is a truth assignment; B evaluates the clauses with respect to the assignment.

INDEPENDENT SET \in NP t is a set of at least k vertices: B checks that no pair of these vertices are connected by an edge. **SET COVER** \in NP t is a list of k sets from the collection; B checks if their union is U.

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P vs. $N P$

P Decision problems for which there is a poly-time algorithm **EXP** Decision problems for which there is an exponential-time algorithm $\overline{\mathcal{NP}}$ Decision problems for which there is a poly-time certifier

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One of the major unsolved problems in computer science .

- \triangleright $\overline{NP} \subset \overline{EXP}$. Consider any problem X in \overline{NP} .
	- \triangleright By definition, there exists a poly-time certifier C(s, t) for X.
	- ► To solve input s, run C(s, t) on all strings t with $|t| \le p(|s|)$.
	- Return yes, if $C(s, t)$ returns yes for any of these.

A decision problem belongs to the class \mathcal{NP} if we can check whether a given solution leads to 'yes' can be done in polynomial time with respect to the size of (x,y) .

Class P – Class of decision problems, for which there exists a Deterministic Turing Machine that can solve any instance in polynomial time.

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Class $N \mathcal{P}$ – Class of decision problems, for which there exists a Non- Deterministic Turing Machine that can solve any yes instance in polynomial time. The machine guesses a yes solution and then verifies that it is a yes solution

Never tell to an expert in Computational Complexity – tractability – that you think that $N P$ stands for Non Polynomial

 \mathcal{NP} STANDS for Non-deterministic Polynomial

Does $P = NP$? [Cook 1971, Edmonds, Levin, Yablonski, Gödel]

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Is the decision problem as easy as the certification problem?

If yes Efficient algorithms for 3-COLOR, TSP, FACTOR, SAT, \cdots . If no No efficient algorithms possible for 3-COLOR, TSP, SAT, \cdots .

Does $P = \mathcal{NP}$? [Cook 1971, Edmonds, Levin, Yablonski, Gödel]

Is the decision problem as easy as the certification problem?

If yes Efficient algorithms for 3-COLOR, TSP, FACTOR, SAT, If no No efficient algorithms possible for 3-COLOR, TSP, SAT, \cdots . Consensus opinion on $P = NP$? Probably no .

The Simpson's: $P = NP$?

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Algorithm design and analysis $-\mathcal{NP}$ -Complete —

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Corollary: If there is any problem in \mathcal{NP} that cannot be solved in polynomial time, then no \mathcal{NP} -Complete problem can be solved in polynomial time.

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Corollary: If there is any problem in \mathcal{NP} that cannot be solved in polynomial time, then no \mathcal{NP} -Complete problem can be solved in polynomial time.

- Are there any \mathcal{NP} -Complete problems?
	- 1. Perhaps there are two problems X_1 and X_2 in \mathcal{NP} such that there is no problem $X \in \mathcal{NP}$ where $X_1 \leq_P X$ and $X_2 \leq_P X$.
	- 2. Perhaps there is a sequence of problems X_1, X_2, X_3, \ldots in \mathcal{NP} , each strictly harder than the previous one.

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CIRCUIT SATISFIABILITY

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- Cook-Levin Theorem CIRCUIT SATISFIABILITY is $\mathcal N\mathcal P$ -Complete.
- \triangleright A circuit K is a labelled, directed acyclic graph such that
	- 1. the **sources** in K are labelled with constants (0 or 1) or the name of a distinct variable (the **inputs** to the circuit).
	- 2. every other node is labelled with one Boolean operator ∧, ∨, or ¬.
	- 3. a single node with no outgoing edges represents the **output** of K .

CIRCUIT SATISFIABILITY

- INSTANCE A circuit K.
- QUESTION Is there a truth assignment to the inputs that causes the output to have value 1?

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- \triangleright Claim we will not prove: any algorithm that takes a fixed number *n* of bits as input and produces a yes/no answer
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 $X <_{P}$ CIRCUIT SATISFIABILITY.

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- \triangleright View $B(\cdot, \cdot)$ as an algorithm on $n + p(n)$ bits.
- \triangleright Convert B to a polynomial-sized circuit K with $n + p(n)$ sources.
	- 1. First n sources are hard-coded with the bits of s .
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- \triangleright $s \in X$ iff there is an assignment of the input bits of K that makes K satisfiable.

\triangleright Does a graph G on n nodes have a two-node independent set?

- \triangleright Does a graph G on n nodes have a two-node independent set?
- \triangleright s encodes the graph G with $\binom{n}{2}$ $\binom{n}{2}$ bits.
- t encodes the independent set with n bits.
- **Certifier needs to check if**
	- 1. at least two bits in t are set to 1 and
	- 2. no two bits in t are set to 1 if they form the ends of an edge (the corresponding bit in s is set to 1).

If Y is NP-Complete and $X \in \mathcal{NP}$ such that $Y \leq_P X$, then X is \mathcal{NP} -Complete.

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 \triangleright Given a new problem X, a general strategy for proving that X is \mathcal{NP} -Complete can be defined as follows

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- \triangleright If we use Karp reductions, we can refine the strategy:
	- 1. Prove that $X \in \mathcal{NP}$.
	- 2. Select a problem Y known to be $N \mathcal{P}$ -Complete.
	- 3. Consider an arbitrary instance s_Y of problem Y. Show how to construct, in polynomial time, an instance s_x of problem X such that
		- (a) If $s_Y \in Y$, then $s_X \in X$ and
		- (b) If $s_X \in X$, then $s_Y \in Y$.

\mathcal{NP} -Completeness

