## P \& NP

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## The P Class

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- For convenience, let the input data be a word over an alphabet: $x \in \Sigma^{*}$.
- The size of input, $|x|$ is the length of $x$ in symbols.
- A decision problem is in the P class, if there exists an algorithm for solving it, whose worst case running time is bounded by $p(|x|)$.


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- The Turing machine may branch:

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- Angelic choice: if at least one execution trajectory yields "yes," then the answer is "yes."
- One can implement non-deterministic guess (say, guess the satisfying assignment for a 3-CNF or guess a Hamiltonian cycle in a graph).


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- $y$ is a hint, given by someone to help us solve the problem.
- Examples of $y$ : the satisfying assignment; the Hamiltonian cycle; ...


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- As an ersatz, the theory of NP-completeness was invented.
- Informally, NP-complete problems are the hardest possible problems in NP.
- In particular, if an NP-complete problem is solvable in poly time, then $P=N P$.
- Contraposition: if $P \neq N P$ (which highly likely), then any NP-complete problem is not in P .


## NP-Completeness

- m-reduction (Carp reduction): $A$ is
reducible to $B\left(A \leq_{m}^{P} B\right)$, if there exists a polytime computable function $f: \Sigma^{*} \rightarrow \Sigma^{*}$, such that $A(x)=1 \Longleftrightarrow B(f(x))=1$.
- The idea of reduction: if we can solve $B$, we can also solve $A$ : $A(x)=B(f(x))$.
- A problem $B$ is NP-hard if $A \leq_{m}^{P} B$ for any $A \in \mathrm{NP}$.
- $B$ is NP-complete if $B \in N P$ and $B$ is NP-hard.


## Complexity Picture

(if $P \neq N P$ )


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- Suppose we know $A$ to be already NP-hard.
- In order to prove NP-hardness of a problem $B$, we reduce the old problem $A$ to $B$.
- But how to bootstrap and obtain the first example of an NP-complete problem?


## Cook - Levin Theorem

## Theorem

SAT is NP-complete.

## Cook - Levin Theorem

Proof sketch.

- Suppose $A \in$ NP, let us show $A \leq_{m}^{P}$ SAT.
- We encode each configuration of the Turing machine for $A$ as a binary word:

$0^{m} \quad a_{1} \quad \ldots \quad 0^{m} \quad a_{i-1} \quad q \quad a_{i} \quad 0^{m} \quad a_{i+1} \quad \ldots$


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- The sequence of configurations (protocol) of $A$ on input $x$ is encoded by a binary matrix $\left(b_{i j}\right)$ of size $(m \cdot p(|x|)) \times p(|x|)$.


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- Next, we construct a formula $\varphi_{x}$ with variables $b_{00}, b_{01}, \ldots$ which expresses the fact that this matrix represents a correct protocol of a successful execution.


## Cook - Levin Theorem

$\varphi_{x}$ is a conjunction of the following claims:

1. the first row represents the configuration with $x$ on the tape, the machine observing its first letter;
2. each next row is obtained from the previous one by one of the rules of the machine;
3. the last row includes state $q_{F}$ and the answer "yes" (1).

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This is all expressible as Boolean formulae.

## Cook - Levin Theorem

- The reducing function is $f: x \mapsto \varphi_{x}$.
- $A(x)=1 \Leftrightarrow \varphi_{x}$ is satisfiable.
- Thus, $A \leq_{m}^{P}$ SAT.
- Since $A$ was taken arbitrarily, we get NP-hardness of SAT.
- On the other hand, SAT is in NP, so it is NP-complete.


## NP-completeness of 3-SAT

- 3-SAT is a special version of SAT, where only 3-CNFs are allowed.
- Trivially, 3-SAT $\leq_{m}^{P}$ SAT... but we need the opposite reduction!
- Let us show that SAT $\leq_{m}^{P} 3$-SAT.


## Tseitin's Transformations

## Theorem

For any Boolean formula $\varphi$, there exists an equisatisfiable 3-CNF $\psi$ of polynomial size.

- Equisatisfiability means that $\psi$ is satisfiable iff $s o$ is $\varphi$.


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For any Boolean formula $\varphi$, there exists an equisatisfiable 3-CNF $\psi$ of polynomial size.

- Equisatisfiability means that $\psi$ is satisfiable iff $s o$ is $\varphi$.
- Constructing an equivalent 3-CNF of polynomial size is not always possible: even translation to CNF can lead to exponential blowup.


## Tseitin's Transformations

- Tseitin's transformations look like translation into 3-address (Assembler-like) code:
$(a+b) *(c+d)$ is translated to
"add $a b t_{1}$; add $c d t_{2}$; mul $t_{1} t_{2} r$ "


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$(a+b) *(c+d)$ is translated to "add $a b t_{1}$; add $c d t_{2}$; mul $t_{1} t_{2} r$ "
- For each subformula we introduce a new variable and write the corresponding equivalences.


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& \left(t_{1} \leftrightarrow(p \rightarrow q)\right) \wedge \\
& \left(t_{2} \leftrightarrow(p \rightarrow r)\right) \wedge \\
& \left(t_{3} \leftrightarrow\left(q \rightarrow t_{2}\right)\right) \wedge \\
& \left(t_{4} \leftrightarrow\left(t_{1} \vee t_{3}\right)\right) \wedge \\
& t_{4}
\end{aligned}
$$

## Tseitin's Transformations

## Transform into 3-CNF by the following table:

$$
\begin{array}{l|l}
t_{k} \leftrightarrow\left(t_{i} \wedge t_{j}\right) & \left(\neg t_{i} \vee \neg t_{j} \vee t_{k}\right) \wedge\left(t_{i} \vee \neg t_{k}\right) \wedge\left(t_{j} \vee \neg t_{k}\right) \\
t_{k} \leftrightarrow\left(t_{i} \vee t_{j}\right) & \left(t_{i} \vee t_{j} \vee \neg t_{k}\right) \wedge\left(\neg t_{i} \vee t_{k}\right) \wedge\left(\neg t_{j} \vee t_{k}\right) \\
t_{k} \leftrightarrow\left(t_{i} \rightarrow t_{j}\right) & \left(\neg t_{i} \vee t_{j} \vee \neg t_{k}\right) \wedge\left(t_{i} \vee t_{k}\right) \wedge\left(\neg t_{j} \vee t_{k}\right) \\
t_{k} \leftrightarrow \neg t_{i} & \left(t_{i} \vee t_{k}\right) \wedge\left(\neg t_{i} \vee \neg t_{k}\right)
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t_{k} \leftrightarrow \neg t_{i} & \begin{array}{l}
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\end{array}
\end{array}
$$

For our example, we get:

$$
\begin{aligned}
& \left(\neg p \vee q \vee \neg t_{1}\right) \wedge\left(p \vee t_{1}\right) \wedge\left(\neg q \vee t_{1}\right) \wedge \\
& \left(\neg p \vee r \vee \neg t_{2}\right) \wedge\left(p \vee t_{2}\right) \wedge\left(\neg r \vee t_{2}\right) \wedge \\
& \left(\neg q \vee t_{2} \vee \neg t_{3}\right) \wedge\left(q \vee t_{3}\right) \wedge\left(\neg t_{2} \vee t_{3}\right) \wedge \\
& \left(t_{1} \vee t_{3} \vee \neg t_{4}\right) \wedge\left(\neg t_{1} \vee t_{4}\right) \wedge\left(\neg t_{3} \vee t_{4}\right) \wedge t_{4}
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- Search problem: yield a witness or say "no."
- Counting problem (the \#P class): yield the number of witnesses.
- Finally, we could ask for all witnesses.


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- Dichotomy: take $\varphi\left[p_{1}:=0\right]$ and $\varphi\left[p_{1}:=1\right]$, find out which is satisfiable, then do the same for $p_{2}, p_{3}, \ldots$.


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- This gives a poly-time algorithm for the search problem for 2-CNF.
- The counting problem could be harder than the decision one (example: DNF-SAT).

