# Computational Complexity; slides 3, HT 2022 Deterministic complexity classes 

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## Measuring Complexity

Our general interest: detailed classification of decidable languages.
Goal: Classify languages according to the amount of resources needed to solve them.

Resources: In this lecture we will primarily consider

- time - the running time of algorithms (steps on a Turing machine)
- space - the amount of additional memory needed (cells on the Turing tapes)

Next: basic complexity classes, polynomial-time reductions

## Measuring Complexity

Definition.
Let $M$ be a Turing acceptor and let $S, T: \mathbb{N} \rightarrow \mathbb{N}$ be functions.
(1) $M$ is $T$-time bounded if it halts on every input $w \in \Sigma^{*}$ after $\leq T(|w|)$ steps.
(2) $M$ is $S$-space bounded if it halts on every input $w \in \Sigma^{*}$ using $\leq S(|w|)$ cells on its tapes.
(Here we assume that the Turing machines have a separate input tape that we do not count in measuring space complexity.)

## Deterministic Complexity Classes

## Definition.

Let $T, S: \mathbb{N} \rightarrow \mathbb{N}$ be monotone increasing functions. Define
(1) $\operatorname{DTIME}(T)$ as the class of languages $\mathcal{L}$ for which there is a $T$-time bounded $k$-tape Turing acceptor deciding $\mathcal{L}$, for some $k \geq 1$.
(2) $\operatorname{DSPACE}(S)$ as the class of languages $\mathcal{L}$ for which there is a $S$-space bounded $k$-tape Turing acceptor deciding $\mathcal{L}, k \geq 1$.

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## Important Complexity Classes:

- Time classes:
- $\mathbf{P}\left(\right.$ or PTIME) $:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(n^{d}\right) \quad$ polynomial time
- EXP $:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(2^{n^{d}}\right) \quad$ exponential time
- 2-EXP $:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(2^{2^{n^{d}}}\right)$ double exp time
- Space classes:
- LOGSPACE $:=\bigcup_{d \in \mathbb{N}} \operatorname{DSPACE}(d \log n)$
- PSPACE := $\bigcup_{d \in \mathbb{N}} \operatorname{DSPACE}\left(n^{d}\right)$
- EXPSPACE $:=\bigcup_{d \in \mathbb{N}} \operatorname{DSPACE}\left(2^{n^{d}}\right)$


## But wait...

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Do these classes depend on exact def of "Turing machine"?
Yes, for $\operatorname{DTIME}(T), \operatorname{DSPACE}(S)$;
No for the others
Indeed, usually don't need to refer explicitly to "Turing machine". But watch out for nondeterminism (details later)

## Time Complexity Classes

Important Time Complexity Classes:

- $\mathbf{P}:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(n^{d}\right)$
polynomial time
- EXP $:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(2^{n^{d}}\right) \quad$ exponential time

Not quite so important:

- 2-EXP $:=\bigcup_{d \in \mathbb{N}} \operatorname{DTIME}\left(2^{2^{n^{d}}}\right) \quad$ double exp time

Note: these are all classes of decision problems, i.e. languages.
Observation:

$$
\mathbf{P} \subseteq E X P \subseteq 2-E X P \subseteq \cdots \subseteq i-E X P \subseteq \ldots
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Alternative definition/notation:

$$
\mathbf{P}:=\mathrm{DTIME}\left(n^{O(1)}\right)
$$

## Linear Speed-Up

Theorem. (Linear Speed-Up Theorem)
Let $k>1$ and $c>0$
$T: \mathbb{N} \rightarrow \mathbb{N}$
$\mathcal{L} \subseteq \Sigma^{*}$ be a language.

If $\mathcal{L}$ can be decided by a $T(n)$ time-bounded $k$-tape TM

$$
M:=\left(Q, \Sigma, \Gamma, q_{0}, \delta, F\right)
$$

then $\mathcal{L}$ can be decided by a $\left(\frac{1}{c} \cdot T(n)+n+2\right)$ time-bounded $k$-tape TM

$$
M^{*}:=\left(Q^{\prime}, \Sigma, \Gamma^{\prime}, q_{0}^{\prime}, \delta^{\prime}, F^{\prime}\right)
$$

## Linear Speed-Up

Proof idea. Let $\Gamma^{\prime}:=\Sigma \cup \Gamma^{s}$ where $s:=6 c$. To construct $M^{*}$ :
Step 1: Compress M's input.
Copy (in $n+2$ steps) the input onto tape 2 , compressing $s$ symbols into one (i.e., each symbol corresponds to an s-tuple from $\Gamma^{s}$ )

Step 2: Simulate M's computation, $s$ steps at once.
(1) Read (in 4 steps) symbols to the left, right and the current position and "store" (using $\left|Q \times\{1, \ldots, s\}^{k} \times \Gamma^{3 s k}\right|$ extra states).
(2) Simulate (in 2 steps) the next $s$ steps of $M$ (as $M$ can only modify the current position and one of its neighbours)
(3) $M^{*}$ accepts (rejects) if $M$ accepts (rejects)
(see Papadimitriou Thm 2.2, page 32)

## A Hierarchy of Complexity Classes?

Questions we will study:

- Can we always solve more problems if we have more resources?
- If not, how much more resources do we need to be able to solve strictly more problems?
- How do the complexity classes relate to each other?
- How do we show that some problem is in one of these classes but not in another?
- Are there any other interesting models of computation?
- Non-deterministic computation
- Randomised algorithms

Next: robustness of $\mathbf{P}$

## Robustness of the definition of $\mathbf{P}$

If $\mathbf{P}$ is to be the mathematical model of efficient computation, it should not depend on

- the exact computation-model we are using,
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Different Models of Computation:
(1) We can simulate $t$ steps of a $k$-tape Turing machine with an equivalent 1 -tape TM in $t^{2}$ steps.
(2) We can simulate $t$ steps of a two-way infinite $k$-tape Turing machine with an equivalent standard $k$-tape TM in $O(t)$ steps.
(3) We can simulate $t$ steps of a RAM-machine with a 3-tape TM in $O\left(t^{3}\right)$ steps. Vice-versa in $O(t)$ steps.

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Consequence: $\mathbf{P}$ is the same for all these models (unlike linear time)

## Different Encodings

## Observation.

(1) For any $n \in \mathbb{N}$, the length of the encoding of $n$ in base $b_{1}$ and base $b_{2}$ are related by a constant factor, for all $b_{1}, b_{2} \geq 2$.
(2) For any graph $G$, the length of its encoding as an

- adjacency matrix
- list of edges
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- adjacency matrix
- list of edges
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are all related by a polynomial factor.

Consequence: (for problems on numbers, graphs) $\mathbf{P}$ is the same for all these encoding (unlike linear time)

## Robustness of the definition of $\mathbf{P}$

Strong Church-Turing Hypothesis
Any function which can be computed by any well-defined procedure can be computed by a Turing machine with only polynomial overhead.

## (but doesn't apply to quantum or randomised algorithms)

I also pointed out that "in P" corresponds well to existence of a practical algorithm; problem is "tractable"

## Growth Rate of Functions (Garey/Johnson '79)

| Time complexity function | Size $n$ |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 10 | 20 | 30 | 40 | 50 | 60 |
| $n$ | $.00001$ second | .00002 second | .00003 second | . 00004 second | .00005 second | .00006 second |
| $n^{2}$ | .0001 second | $\begin{gathered} .0004 \\ \text { second } \\ \hline \end{gathered}$ | $\begin{gathered} .0009 \\ \text { second } \end{gathered}$ | $.0016$ second | $\begin{gathered} .0025 \\ \text { second } \end{gathered}$ | $.0036$ second |
| $n^{3}$ | .001 second | $\begin{gathered} .008 \\ \text { second } \end{gathered}$ | $\begin{aligned} & .027 \\ & \text { second } \end{aligned}$ | .064 second | $\begin{aligned} & .125 \\ & \text { second } \end{aligned}$ | $\begin{aligned} & .216 \\ & \text { second } \end{aligned}$ |
| $n^{5}$ | $\begin{aligned} & .1 \\ & \text { second } \end{aligned}$ | 3.2 seconds | $24.3$ <br> seconds | $\begin{aligned} & 1.7 \\ & \text { minutes } \end{aligned}$ | $\begin{gathered} 5.2 \\ \text { minutes } \end{gathered}$ | 13.0 minutes |
| $2^{n}$ | .001 second | 1.0 second | $\begin{gathered} 17.9 \\ \text { minutes } \end{gathered}$ | $\begin{aligned} & 12.7 \\ & \text { days } \end{aligned}$ | 35.7 years | 366 centuries |
| $3^{n}$ | $\begin{gathered} .059 \\ \text { second } \end{gathered}$ | $\begin{gathered} 58 \\ \text { minutes } \end{gathered}$ | $\begin{aligned} & 6.5 \\ & \text { years } \end{aligned}$ | 3855 centuries | $2 \times 10^{8}$ <br> centuries | $1.3 \times 10^{13}$ <br> centuries |

Figure 1.2 Comparison of several polynomial and exponential time complexity

## Proving a problem is in $\mathbf{P}$

Good news: proofs of "in P" are often cleaner than detailed runtime analysis;
"in $\mathbf{P}$ " less specific than, e.g. "in $\operatorname{DTIME}\left(n^{2}\right)$ "; some technical details are avoided

- The most direct way to show that a problem is in $\mathbf{P}$ is to exhibit a polynomial time algorithm that solves it.
- Even a naive polynomial-time algorithm often provides a good insight into how the problem can be solved efficiently.
- Because of robustness, we do not generally need to specify all the details of the machine model or the encoding.
$\rightsquigarrow$ pseudo-code is sufficient.


## Example: Satisfiability

Some of the most important problems concern logical formulae Recall propositional logic

Formulae of propositional logic are built up inductively

- Variables: $X_{i} \quad i \in \mathbb{N}$
- Boolean connectives: If $\varphi, \psi$ are propositional formulae then so are
- $(\psi \vee \varphi)$
- $(\psi \wedge \varphi)$
- $\neg \varphi$

Example:
$\left(X_{1} \vee X_{2} \vee \neg X_{5}\right) \wedge\left(\neg X_{2} \vee \neg X_{4} \vee \neg X_{5}\right) \wedge\left(X_{2} \vee X_{3} \vee X_{4}\right)$

## Conjunctive Normal Form

Formula $\varphi$ is in conjunctive normal form (CNF) if

$$
\varphi:=C_{1} \wedge \cdots \wedge C_{m}
$$

where each $C_{i}$ is a clause, that is, a disjunction of literals

$$
C_{i}:=\left(L_{i 1} \vee \cdots \vee L_{i k}\right)
$$

A literal is a variable $X_{i}$ or a negated variable $\neg X_{i}$
k-CNF: CNF $\varphi$ with at most $k$ literals per clause.
3-CNF example:
$\left(X_{1} \vee X_{2} \vee \neg X_{5}\right) \wedge\left(\neg X_{2} \vee \neg X_{4}\right) \wedge\left(X_{2} \vee X_{3} \vee X_{4}\right) \wedge X_{6}$

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common CNF notation:
$\varphi:=\left\{\left\{X_{1}, X_{2}, \neg X_{5}\right\}, \quad\left\{\neg X_{2}, \neg X_{4}\right\}, \quad\left\{X_{2}, X_{3}, X_{4}\right\}, \quad\left\{X_{6}\right\}\right\}$

## Satisfiability

Definition. A formula $\varphi$ is satisfiable if there is a satisfying assignment (a.k.a. model) for $\varphi$.

In the case of formulae in CNF:
An assignment $\beta$ assigning values 0 or 1 to the variables of $\varphi$ so that every clause contains at least

- one variable to which $\beta$ assigns 1 or
- one negated variable to which $\beta$ assigns 0 .

Example:

$$
\left(X_{1} \vee X_{2} \vee \neg X_{5}\right) \wedge\left(\neg X_{2} \vee \neg X_{4} \vee \neg X_{5}\right) \wedge\left(X_{2} \vee X_{3} \vee X_{4}\right)
$$

Satisfying assignment:

$$
X_{1} \mapsto 1 \quad X_{2} \mapsto 0 \quad X_{3} \mapsto 1 \quad X_{4} \mapsto 0 \quad X_{5} \mapsto 1
$$

## The Satisfiability Problem

In association with propositional formulae, the following two problems are the most important:

## SAT <br> Input: Propositional formula $\varphi$ in CNF Problem: Is $\varphi$ satisfiable?

## k-SAT

Input: Propositional formula $\varphi$ in $k$-CNF Problem: Is $\varphi$ satisfiable?
(Let us also note CIRCUIT SAT: given a circuit with $n$ inputs, one output, can we set input values to get output=TRUE?)

## 2-SAT is in $\mathbf{P}$

Proof. The following algorithm solves the problem in poly time.
Let $\varphi$ be the input formula
Repeat
If $\varphi$ contains clauses $\{X\}$ and $\{\neg X\}$, halt and output "no";
If $\varphi$ contains clauses $\{X\}$ and $\{\neg X, Y\}$, add clause $\{Y\}$;
If $\varphi$ contains clauses $\{X, Y\}\{\neg X, Z\}$, add clause $\{Y, Z\}$;
Any clause $\{X, X\}$ simplifies to $\{X\}$
Output "yes".

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Any clause $\{X, X\}$ simplifies to $\{X\}$
Output "yes".
Poly-time:

- there are $O\left(n^{2}\right)$ iterations.
- Each "if" test searches for $O\left(n^{2}\right)$ items in $\varphi$
- Each search is linear in length of $\varphi$ above analysis is crude but does the job.


## Polynomial-Time Reductions

As for decidability we can use many-one reductions to show membership in $\mathbf{P}$.

Definition. A language $\mathcal{L}_{1} \subseteq \Sigma^{*}$ is polynomially reducible to $\mathcal{L}_{2} \subseteq \Sigma^{*}$, denoted $\mathcal{L}_{1} \leq_{p} \mathcal{L}_{2}$, if there is a polynomial-time computable function $f$ such that for all $w \in \Sigma^{*}$

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w \in \mathcal{L}_{1} \quad \Longleftrightarrow \quad f(w) \in \mathcal{L}_{2}
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Lemma. If $\mathcal{L}_{1} \leq_{p} \mathcal{L}_{2}$ and $\mathcal{L}_{2} \in \mathbf{P}$ then $\mathcal{L}_{1} \in \mathbf{P}$.
Proof idea. The sum and composition of polynomials is a polynomial.

Generally, members of $\mathbf{P}$ can be poly-time reduced to each other.

## Example: Colourability

Vertex Colouring:
A vertex colouring of $G$ with $k$ colours is a function

$$
c: V(G) \longrightarrow\{1, \ldots, k\}
$$

such that adjacent nodes have different colours
i.e. $\{u, v\} \in E(G)$ implies $c(u) \neq c(v)$

## k-COLOURABILITY <br> Input: Graph $G, k \in \mathbb{N}$ <br> Problem: Does $G$ have a vertex colouring with $k$ colours?

For $k=2$ this is the same as Bipartite.

## A reduction to 3-SAT

Lemma. $k$-Colourability $\leq_{p} 3$-SAT

## Proof.

Introduce $X_{v, c}$ to represent "in a solution, $v$ gets colour c".
clauses impose constraints, e.g. $X_{v c} \Rightarrow \neg X_{v c^{\prime}}$ (or rather,
$\left.\neg X_{v c} \vee \neg X_{v c^{\prime}}\right)$
$X_{v c} \Rightarrow \neg X_{v^{\prime} c}$ for $\left(v, v^{\prime}\right)$ any edge
$X_{v 1} \vee X_{v 2} \vee \ldots \vee X_{v k}$ for each $v$
can replace e.g. $X_{v 1} \vee X_{v 2} \vee X_{v 3} \vee X_{v 4}$ with $X_{v 1} \vee X_{v 2} \vee X_{\text {new }}$ and $\neg X_{\text {new }} \vee X_{v 3} \vee X_{v 4}$

Reducible to 2-SAt ??

