# Introduction to Theoretical Computer Science 

Lecture 11: (Polynomial) Complexity

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## Time Complexity

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The time complexity of a (deterministic) machine $M$ that halts on all inputs is a function $f: \mathbb{N} \rightarrow \mathbb{N}$ where $f(n)$ is the maximum number of steps that $M$ uses on any input of size $n$.

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Recall that $\left\{0^{i} 1^{i} \mid i \in \mathbb{N}\right\}$ is a CFL and decidable by e.g. a TM $M_{1}$ that given input $w$ :
1 Scan $w$ and reject if anything not in $\{\sqcup, 0,1\}$ or 10 is found.
2 While there are 0s and 1s left in the tape:

- Scan across and replace with blanks both the leftmost 0 and the rightmost 1.
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2 While there are 0s and 1s left in the tape:

- Scan across and replace with blanks both the leftmost 0 and the rightmost 1.
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Time complexity measure:

| $w$ | $\varepsilon$ | 01 | $0^{2} 1^{2}$ | $0^{3} 1^{3}$ | $0^{4} 1^{4}$ | $0^{5} 1^{5}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $f(\|w\|)$ | 2 | 8 | 19 | 34 | 53 | 76 |

## Big Letters

Recall from previous courses...

## Big $O$ and $\Omega$

Let $f, g: \mathbb{N} \rightarrow \mathbb{R}_{\geq 0}$. Say that $f(n) \in \mathcal{O}(g(n))$ if there exists c, $n_{0}>0$ such that for all $n>n_{0}$ :

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f(n) \leq c \cdot g(n)
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Similarly $f(n) \in \Omega(g(n))$ if:

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## Example

$f(n)=5 n^{3}+2 n^{2}+22 n+6$ is $\in \mathcal{O}\left(n^{3}\right)$.

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## Example

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$M_{1}$ 's complexity is $\mathcal{O}\left(n^{2}\right)$.

## Logarithms

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## Omitting the bases

We may safely omit the base of the logarithms here because:

$$
\log _{a} n=\frac{\log _{b} n}{\log _{b} a}
$$

## Model Concerns

Addition of two numbers is $\mathcal{O}(n)$ in our RM models.

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In TMs, addition is $\mathcal{O}(\log n)$ (e.g. consider binary addition).
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$\Rightarrow$ exponential penalty for RMs!
If we extend our RMs with $\operatorname{ADD}(i, j) \operatorname{SUB}(i, j)$ which instantly add/subtract $R_{j}$ from/to $R_{i}$, putting the result in $R_{i}$ :

Less inaccurate.. but
Now addition is $\mathcal{O}(1)$ instead of $\mathcal{O}(\log n)$, but this is a smaller inaccuracy than the exponential penalty from before.

## Variations in Models

## Problem?

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- What about control flow or memory access costs? In RMs this can be fast, but in TMs we have to move symbol by symbol.
- As we've seen, addition has different complexities based on the model.


## Question

Can we ignore these differences? How?

## What counts as different?

While complexity is useful, the measures are slightly bogus:
■ If a problem is $\mathcal{O}(n)$ on some model, it's surely easy on any model.

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Actually: There are problems that are much worse than this, but still solvable for real examples. We'll see later.
- What about something that is $\mathcal{O}\left(n^{10}\right)$ or $\Omega\left(n^{10}\right)$ ? An $\Omega\left(n^{10}\right)$ problem seems practically insoluble.


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- There's also our coefficients. If $f(n) \geq 10^{100} \log n$, that's only $\mathcal{O}(\log n)$.
However this isn't common.


## Complexity Classes

## Definition

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We'll give a more precise definition of time in terms of bounded machines later.

## Example

Recall $A=\left\{0^{i} 1^{i} \mid i \in \mathbb{N}\right\}$. Our TM $M_{1}$ can decide this in $\mathcal{O}\left(n^{2}\right)$. Therefore $A \in \operatorname{TIME}\left(n^{2}\right)$.

## Can we do better?

Can we come up with a machine $M_{2}$ that shows $A$ is in $\operatorname{TIME}(t(n))$ for some $t(n)$ that is asymptotically $<n^{2}$ ?

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## Example

Given w input:
1 Scan $w$ left to right and reject if 10 is found.
2 Repeat as long as there are 0s and 1s on the tape:
2.1 Scan from right to left and reject if there is an odd number of non-Xs on the tape.
2.2 Scan from left to right and replace every other 0 by an X, beginning from the first 0 . Then, do the same for 1 s .
3 If neither 0 s nor 1 s are left, accept. Else, reject.
Steps 1, 2.1, 2.2, and 3 are all $\mathcal{O}(n)$. Step 2 runs the substeps $\mathcal{O}(\log n)$ times. So this is $\mathcal{O}(n \log n)$.

## Comparing real times

Comparing the running times of $M_{1}$ and $M_{2}$ :

| $w$ | $\varepsilon$ | 01 | $0^{2} 1^{2}$ | $0^{3} 1^{3}$ | $0^{4} 1^{4}$ | $0^{5} 1^{5}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $f_{M_{1}}(\|w\|)$ | 2 | 8 | 19 | 34 | 53 | 76 |
| $f_{M_{2}}(\|w\|)$ | 1 | 15 | 45 | 63 | 117 | 141 |

$M_{2}$ has "better" complexity, but $M_{1}$ performs better for small $n$. ( $M_{2}$ will be faster for $0^{20} 1^{20}$ )

## Doing better

Could we do still better for $A$ ? I.e. a sub- $\mathcal{O}(n \log n)$ algorithm for $A$ ?

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## Example (Two tape TMs)

The answer is no, for a single-tape TM. But in a two tape TM, we can copy all os onto the second tape and then compare the number of 0 s to 1 s by moving the second tape head synchronously with the first.

## Polynomial Time

## Definition

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\mathbf{P}=\bigcup_{k \in \mathbb{N}} \operatorname{TIME}\left(n^{k}\right)
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■ Problems in $\mathbf{P}$ are called tractable.

- The class is robust: "Reasonable" changes in model don't change it, and "reasonable" translations between problems preserve membership in $\mathbf{P}$.
■ Any problem not in $\mathbf{P}$ is $\Omega\left(n^{k}\right)$ for every $k$, e.g. $2^{n}$ or $2^{\sqrt{n}}$.


## Outside P

## Definition

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A problem $Q$ is in $\mathbf{P}$ iff it is computed by polynomially-bounded RM.

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## Recall:

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## Definition

A polynomial reduction from $P_{1}=\left(D_{1}, Q_{1}\right)$ to $P_{2}=\left(D_{2}, Q_{2}\right)$ is a P-computable function $f: D_{1} \rightarrow D_{2}$ such that $d \in Q_{1}$ iff $f(d) \in Q_{2}$.

- If $P_{2}$ is in $\mathbf{P}$, then $P_{1}$ is in $\mathbf{P}$ straightforwardly.


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■ Therefore: To prove that a problem $P_{2}$ is not in $\mathbf{P}$, show that there is a polynomial reduction from a known non- $\mathbf{P}$ problem $P_{1}$ to $P_{2}$.
Question: Is this more like a mapping or Turing reduction?

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## Example (Hamiltonian Path Problem)

Given a graph $G=(V, E)$, is there a path that visits every vertex in $V$ exactly once?
We could solve this in $\mathcal{O}(|V|$ !), but this is not ideal..

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Given students taking exams, and timetable slots for exams, is it possible to schedule the exams so that there are no clashes? It also apparently requires looking at exponentially many possible assignments.
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Open problem: Are they really not in $\mathbf{P}$ ?

## Checking

Consider HPP (the Hamiltonian Path Problem) or timetabling. Both are apparently not in P.

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## Theorem

Any problem that can be checked in polynomial time on a deterministic RM/TM can be computed in polynomial time on a nondeterministic RM/TM.

## Nondeterminism

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## Example (generating a nondetermined number)

| beg: | CLEAR | $R_{0}$ |
| :--- | :--- | :--- |
| MAYBE | end |  |
| INC | 0 |  |
|  | GOTO | beg |

end :

## Non-nondeterminism

## Acceptance

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"Accepts" could mean halting, halting with 1 in $R_{0}$ or anything else.

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■ I sometimes like to think of MAYBE as FORK: the machine forks a copy of itself which takes the jump. If any copy accepts, it signals the OS, which kills off all the others.
Question: Do NRMs have the same deciding power as RMs?


## Comparing RMs and NRMs

## Power

NRMs have the same deciding power as RMs, because we can use the interleaving technique to simulate all runs of an NRM.
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## However!

In time $n$, an RM can explore only $\mathcal{O}(n)$ possibilities, but an NRM can explore $2^{\mathcal{O}(n)}$ possibilities.

NRMs are potentially exponentially faster than RMs

NP

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Let $t: \mathbb{N} \rightarrow \mathbb{R}_{\geq 0}$. Define $\operatorname{NTIME}(t(n))$ to be the collection of all problems that are decidable by an NRM in $\mathcal{O}(t(n))$ time.

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Is HPP in NP? Nondeterministically "guess" any path and check if it is Hamiltonian $(\mathcal{O}(n))$.

## A Short Aside

Can we implement nondeterminism or is it just a theoretical exercise?

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## Quantum Computing

Quantum computers can achieve a similar effect: an $n$-qubit computer computes on all $2^{n}$ values simultaneously. But it's hard to get many qubits; and there are subtleties-not every NP algorithm is quantum-computable (as far as we know).

## Is NP All?

Is every exponentially-bounded problem in NP? probably No!

## Tough problem

Given a machine $M$ and input $w$, determine if $M$ halts in less than $2^{|w|}$ steps.
There doesn't seem to be anything to do but run the machine $M$ for an exponential number of steps $\Rightarrow$ Probably not in NP.

