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# Computation Complexity

**Lecture 27**

**Day 31/31**

**CS 154**

**Formal Languages and Computability**

**Spring 2018**

# Agenda of Day 31

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- About Final Exam
- Summary of Lecture 26
- Lecture 27: Teaching ...
  - Computation Complexity

# About Final Exam

Reminder 3

- **Value:** 20%
- **Topics:** Everything covered from the beginning of the semester
- **Type:** Closed all materials

	Section 1	Section 2	Section 3
Date	Thursday, May 17 <sup>th</sup>	Thursday, May 17 <sup>th</sup>	Tuesday, May 22 <sup>nd</sup>
Time	2:45 - 5:00 pm	5:15 - 7:30 pm	2:45 - 5:00 pm
Venue	MH 233	MH 233	SCI 311

- We won't need whole 2:15 hours.
- As usual, I'll announce officially the type and number of questions via Canvas. (study guide)

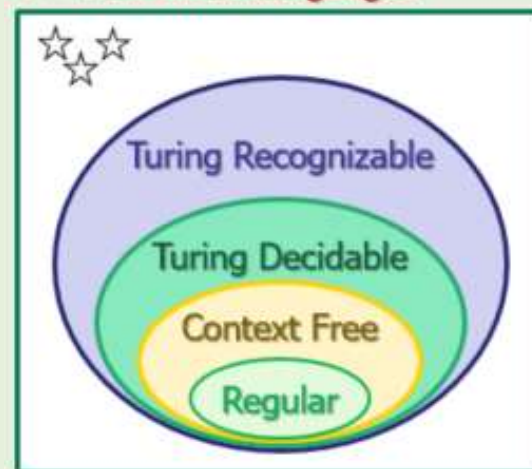
# Summary of Lecture 26: We learned ...

## Computability

- Turing Thesis
  - Any computation carried out by a mechanical procedure can be performed by a TM.
  - We cannot prove or refute it.
- A language is Turing-recognizable if there is a TM that accept it.
- We have problem with the rejecting of the strings of  $\overline{L}$ .
  - Because the TM might get stuck in a forever loop.
- We prefer TMs that always halt.
- We called these TMs as deciders.

- A language is called Turing-decidable if there is a decider for it.

U = All Formal Languages



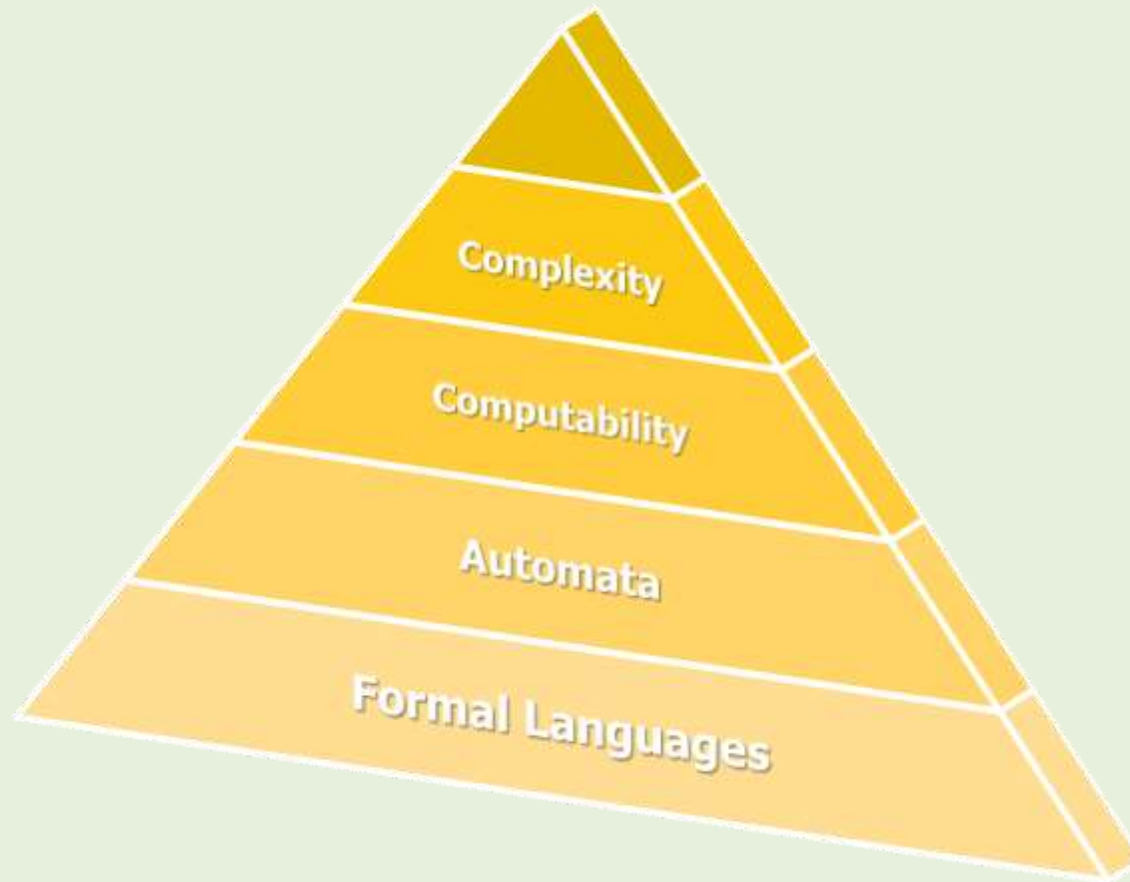
- Universal TM is a TM that can simulate other TMs.
- Halting problem shows the limitation of the theory of the computation.

**Any question?**

# Big Picture: Computer Science Foundation

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Recap



# Objective of This Lecture

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- What is complexity?
- What do we mean when we say:  
Computation A is more complex than computation B.
- How do we classify the problems based on their complexity?
- What classes of complexities do we have?

# Computation Complexity

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# What is Computation Complexity?

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- To answer this question, we need to be clear about two things:
  1. What is **computation** ?
  2. What is **complexity**?
- We've already defined **computation** as:
- The **sequence of configurations** from when the machine starts until it **halts**.
- Now, let's see what **complexity** is.

Recap





# What is Complexity?

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- Specifically, what do we mean when we say:

Computation A is more complex than computation B?

- It means, computation A needs more resources.
  
- What are the resources?
- Time and space
  
- We do have other resources such as energy, number of CPU, etc., but time and space are usually our main concerns.

# What is the Computation Complexity?

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- Since we have two major types of resources, "time" and "space", so, we can talk about two types of complexities:
  1. Time-complexity
  2. Space-complexity
- In this lecture we focus on "time-complexity" that is usually of more concerns.

# Time-Complexity

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# Assumptions

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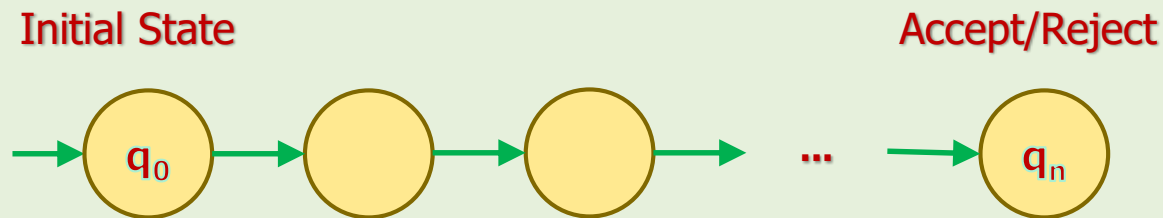
1. We are interested in "worst-cases" that needs the highest resources.
2. We define the efficiency of an algorithm as its complexity.  
The complexity of a computation = Efficiency of its algorithm

- Before going further, we need to have a clear understanding about the "computation time".

# What is Computation Time?

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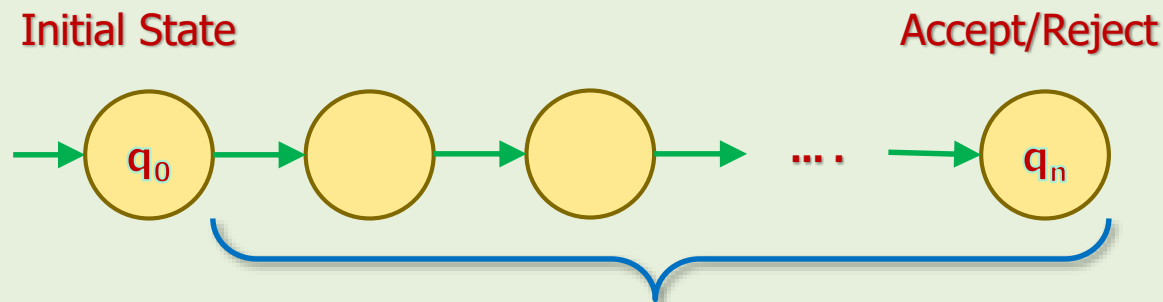
- For any computation, the machine makes some transitions starting from the initial state until it halts.
  - Recall that if it doesn't halt, there won't be any computation!
- For example, the following "one-dimensional projection" shows a computation for a process.



# Computation Time of a Process

## Definition

- ❗ The computation time of a process is the number of transitions from when the process starts until it halts.



Computation Time = Number of Transitions

- 💡 What would be the computation time when a machine gets stuck in an infinite-loop?

# Computation Time of Nondeterministic TMs

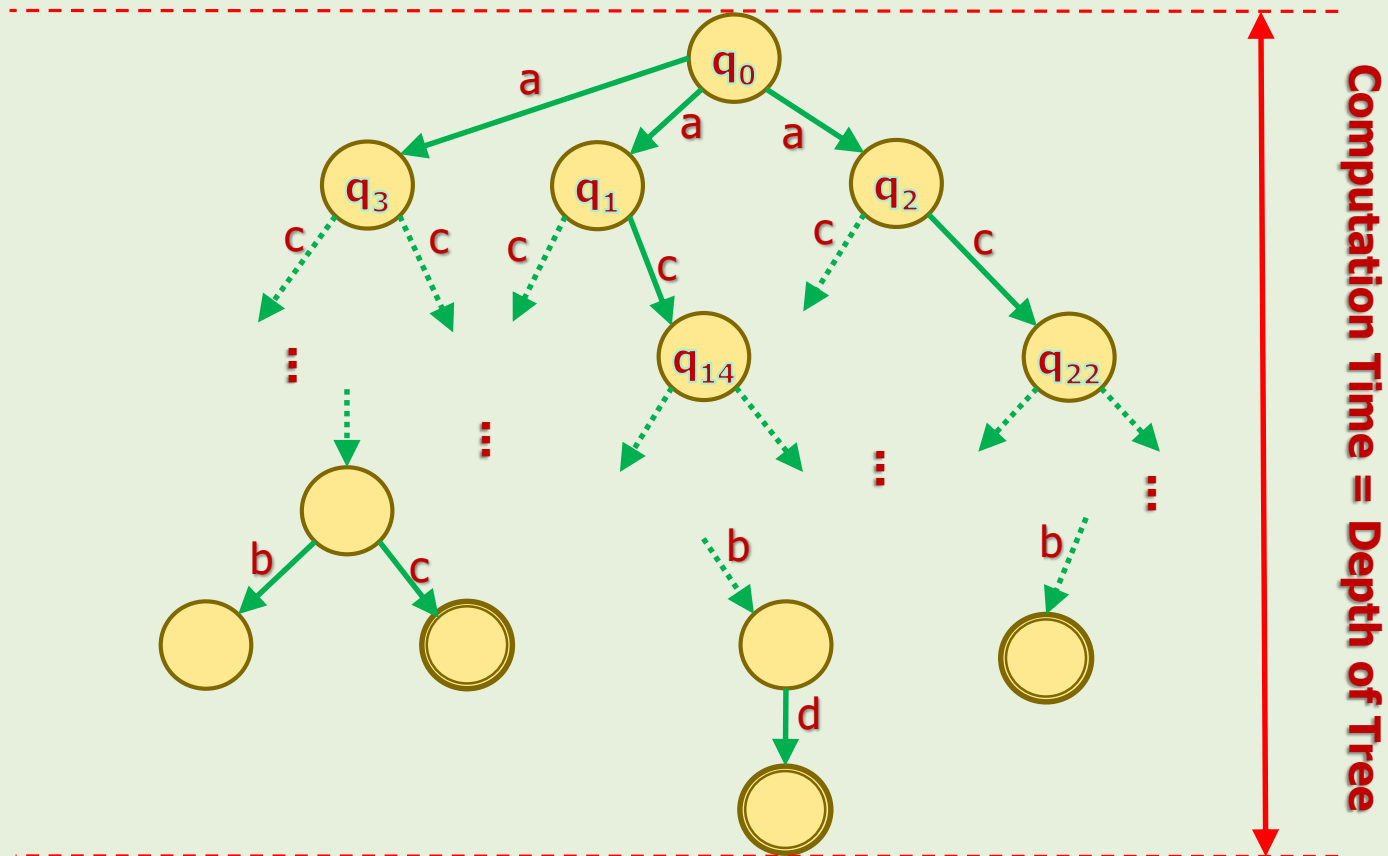
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- Note that we defined the computation time for a **single process**.
  - **Standard TMs use a single process**, so the definition of computation time covers them.

## What is the **computation time of nondeterministic TMs**?

- Ⓢ ▪ Since **all processes** of a nondeterministic TM run **concurrently**, then the computation time would be the computation time of the **longest process**.
- In the next slide, we **combined all processes** of a nondeterministic TM in a **tree**.
- The **computation time** would be the **depth of the tree**.

# Computation Time of Nondeterministic TMs



- Note that just **input symbol** of the labels are shown for readability purpose.





## Our Primary Concern

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- How fast the resources requirements grow when the input size becomes larger.
- This is called "growth rate of resources".
- Definitely, slower growth of the resources requirements is desirable.
- To understand this concept, let's be more precise!

# Growth Rate of Resources

- Consider the following **deterministic automaton**:



- We define the **worst case computation time** of this machine by  $f(n)$  that is a function of the input size  $n$ .



- What does  $f(n)$  look like for different types of automata?
- For example, if  $M$  is a **DFA**, how  $f(n)$  looks like?

$$f(n) = n$$



- How about for TMs?

# Growth Rate of Resources

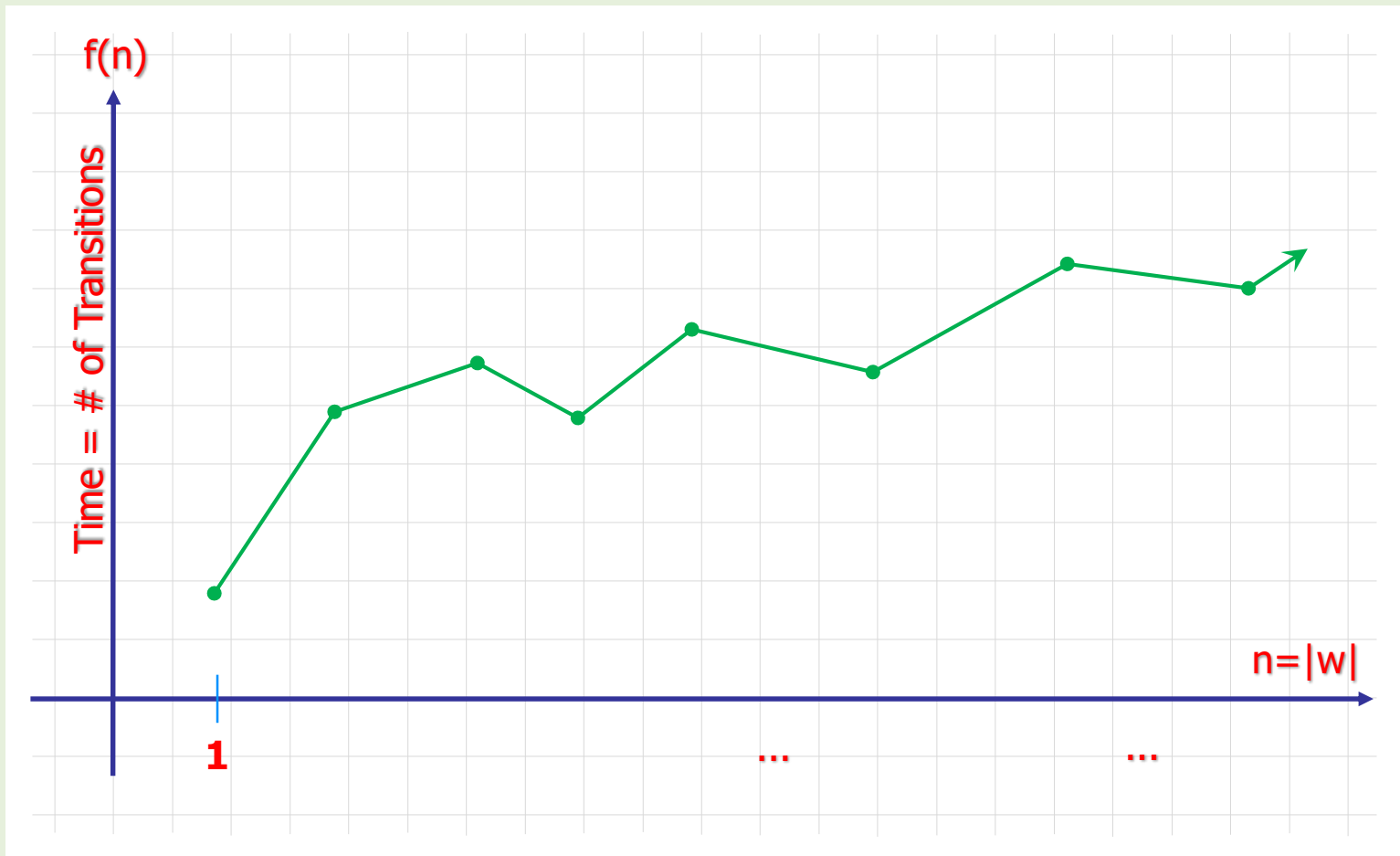
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- For TMs, the computation time for  $w$ 's with the same size might vary.
- For **example**, a TM might have the following values for **input size 3**:

$$f(3) = \begin{cases} 3 & \text{if } w = aaa \\ 5 & \text{if } w = aba \\ 5 & \text{if } w = baa \\ \dots & \dots \\ 4 & \text{if } w = bbb \end{cases}$$

- In this case, **we pick the worst case that is the longest one, 5, for  $f(3)$ .**
- If we do this for all sizes of  $w$ , we get  $f(n)$ .
- Next slide shows an example of  $f(n)$  for a TM.

# Example of a TM's Computation Graph

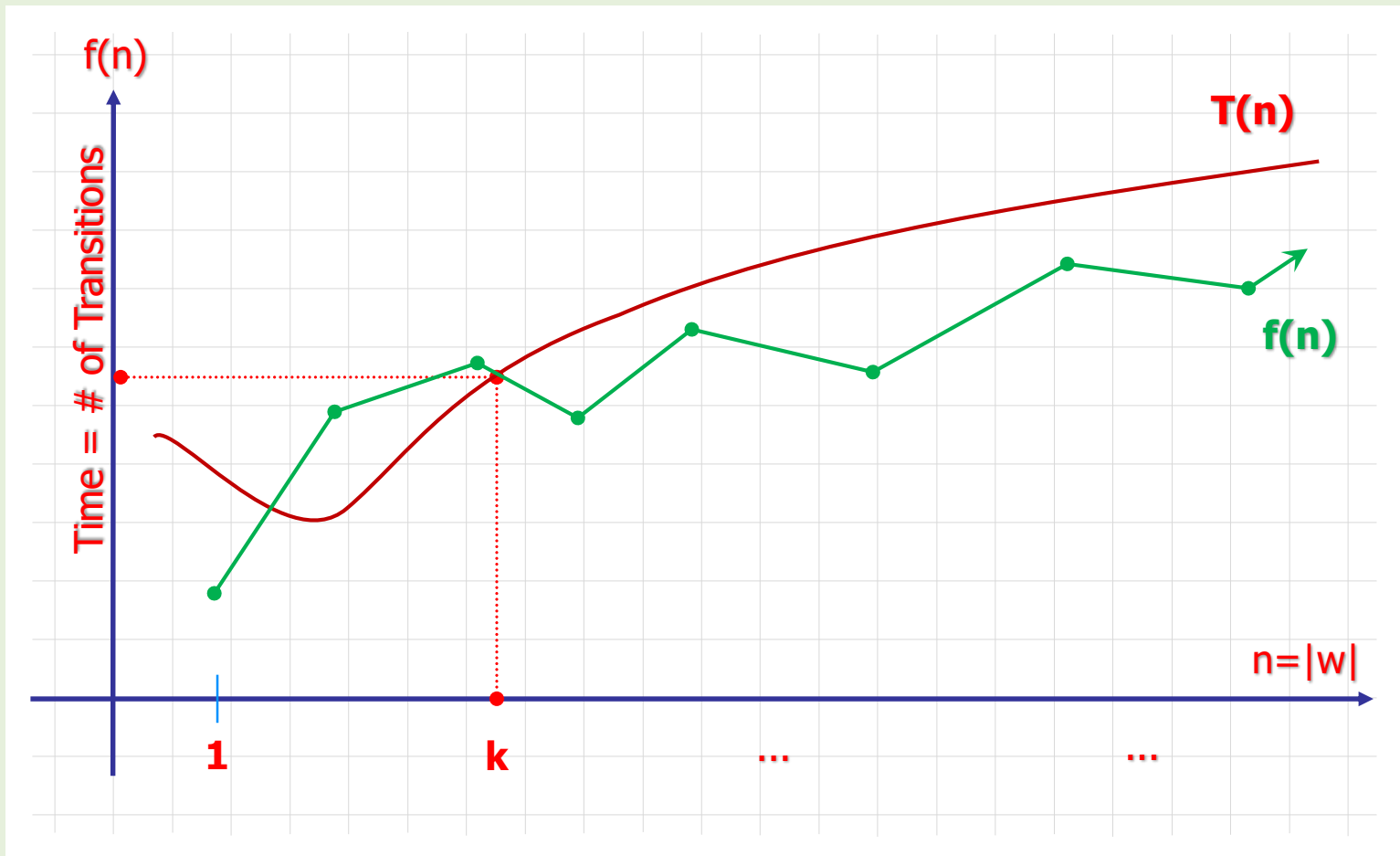


# Growth Rate of Resources

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- Almost always, the function  $f(n)$  is an unknown function.
  - Know functions such as  $f(n) = n$ , or  $\sin n$ , ...
- But most of times, we can approximate it with a known function as the next slide shows.

# Growth Rate of Resources



- The approximate function  $T(n)$  should have the same "growth rate", from a point afterward (e.g.  $k$ ).

# Big-O Notation

## Recap

- If we find such function, then we use a special notation called "Big-O" (aka "Order of magnitude") to represent it.

$$f(n) = O(T(n))$$

- The meaning of the above notation is:
  - $c \cdot T(n)$  is an upper-bound for the growth rate of  $f(n)$ .  
Where  $c$  is a positive real number.
- The above equal sign is an "asymptotic notation", not the regular equal sign.
  - That's why it is a very confusing notation.

How to prove that  $T(n)$  and  $f(n)$  have the **same growth rate**?

- We should calculate the following **calculus equation**:

$$\lim_{n \rightarrow \infty} \frac{T(n)}{f(n)} = ?$$

- If the result is a **constant**  $> 0$ , it means both have the **same growth rate**.
- If it is **zero**, it means  $f(n)$  grows faster.
- If it is  **$+\infty$** , it means  $T(n)$  grows faster.



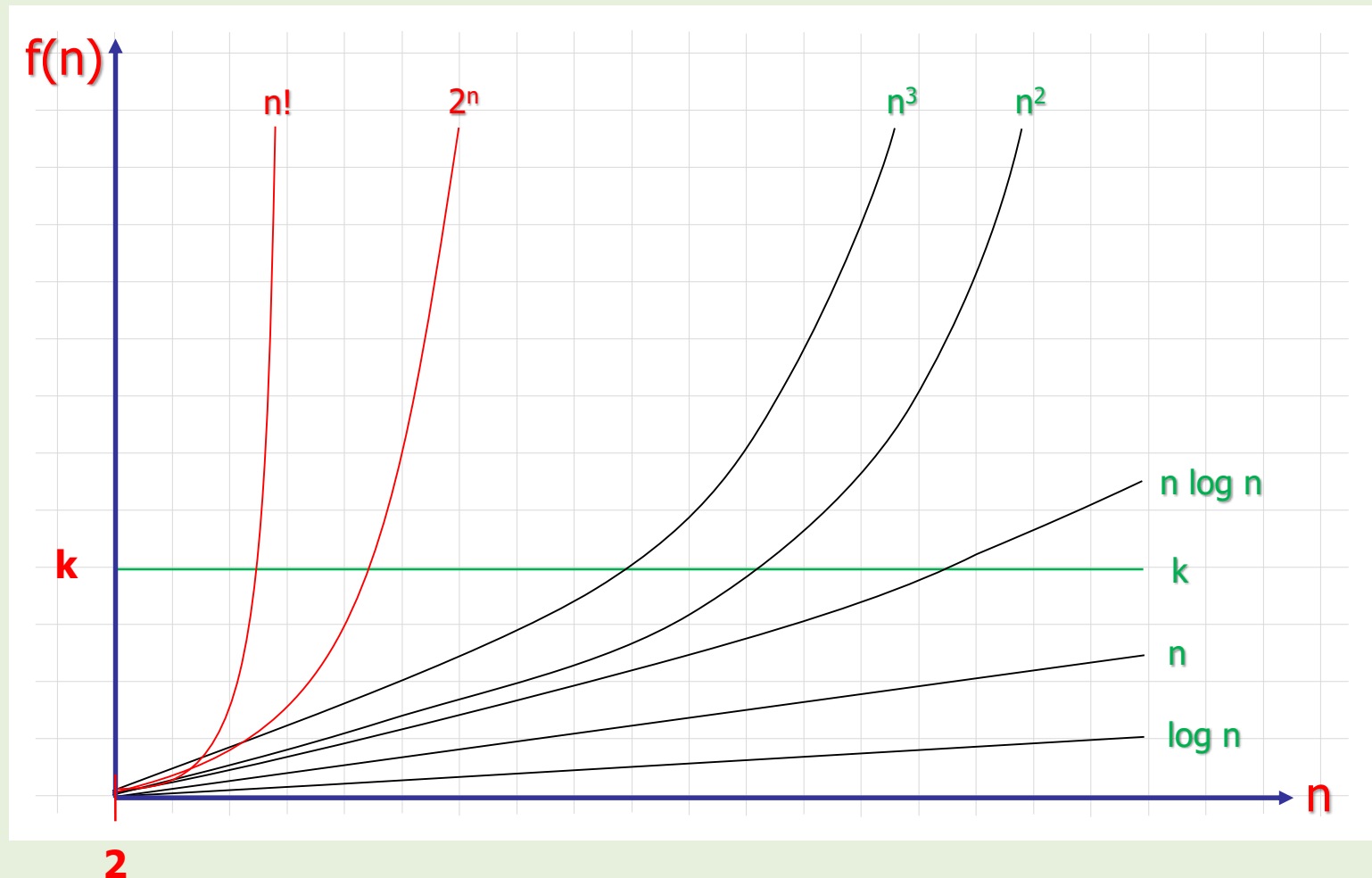
# Growth Rate of Some Functions

- The following table shows how different functions grow when the input size grows.

n	k	n	$n^2$	$n^3$	$2^n$
1	k	1	1	1	2
2	k	2	4	8	4
3	k	3	9	27	8
...	...	...	...	...	...
10	k	10	100	1000	1024
...	...	...	...	...	...
100	k	100	10,000	1,000,000	$2^{100} = ???$

- Next slide shows the graphs of some known functions.

# Growth Rate of Some Functions



# Computation Complexity Comparison

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- To be able to compare complexities, we need to quantify them.
- In computer science, it's been proven that Big-O is the best notation to quantify complexities.

## Example 1

- Problem A needs  $O(n^2)$  resources.
  - Problem B needs  $O(n)$  resources.
  - Which problem is more complex?
- 
- Problem A ...
  - ... because the resource requirement of problem A grows faster than problem B.

# Time-Complexity Classes

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# Time-Complexity Classes

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- In this section, we'll classify problems (languages) based on their complexities.
- The goal of this classification is:  
To have an engineering feeling about the types of problems that we encounter.
- To solve problems, we can use standard (deterministic) TM or nondeterministic TM.
  - As we'll see later, there is a huge difference between them.
- Let's start with "deterministic TM".

# Complexity Class DTIME( $n$ )

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- Our first complexity class is called DTIME( $n$ ).
- It contains all problems that can be decided in  $O(n)$  time.
  - The "D" at the beginning of DTIME shows that we are using "deterministic" TMs.
- Let's see what problems we can put in this class.

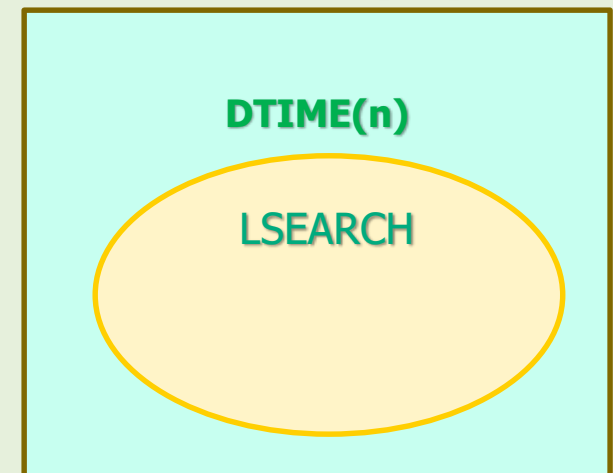
# Complexity Class **DTIME(n)**

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## Example 2

- Given an **unsorted list of numbers**  $x_1, x_2, \dots, x_n$  and a **key number**  $k$ .
- **Search in the list and determine if it contains  $k$  (LSEARCH).**
- In the **worst-case**, we need  **$n$  comparisons**.
- So, the **time-complexity** of this problem is  **$O(n)$** .
- Note that we assume each comparison needs **constant amount of time  $k$** .
- So, **total time needed is  $n \cdot k$** .
- In big-O notation, we eliminate constants.

$U = \text{All Formal Languages}$



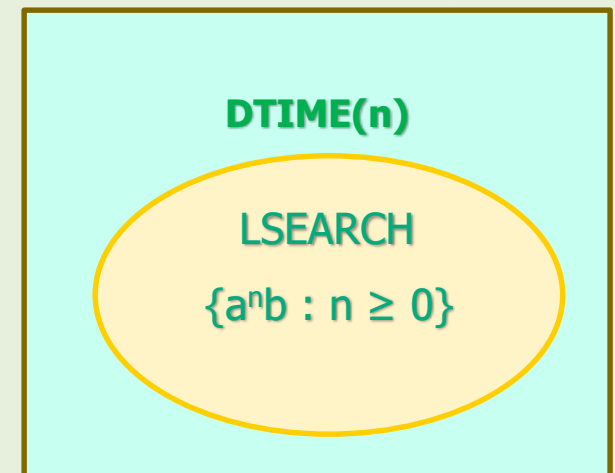
# Complexity Class DTIME(n)

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## Example 3

- Given  $L = \{a^n b : n \geq 0\}$
- What is the **time-complexity** of accepting this language?
- $L$  can be decided in  **$O(n)$**  by using a **deterministic TM**.

$U = \text{All Formal Languages}$



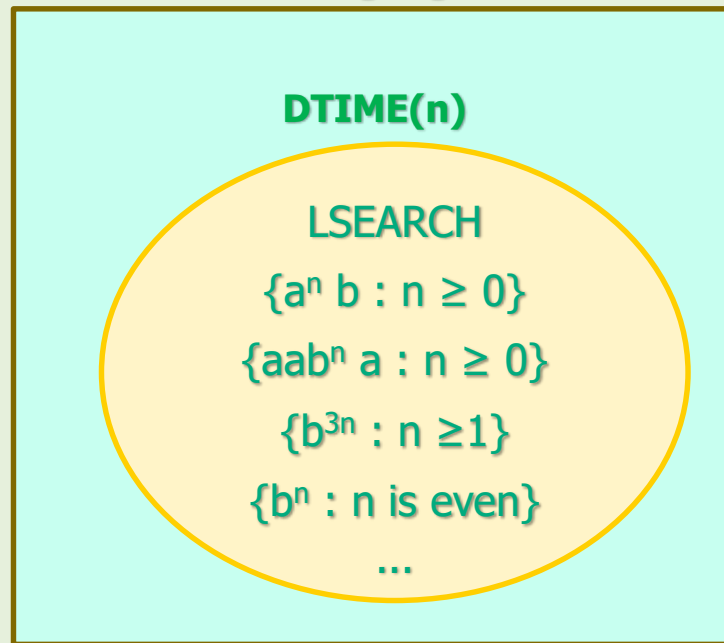


# Complexity Class **DTIME(n)**

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- Also, the following languages can be decided in  $O(n)$  by using a **deterministic TM**.

$U = \text{All Formal Languages}$



# Time-Complexity Classes

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- What are the complexities of the following languages?

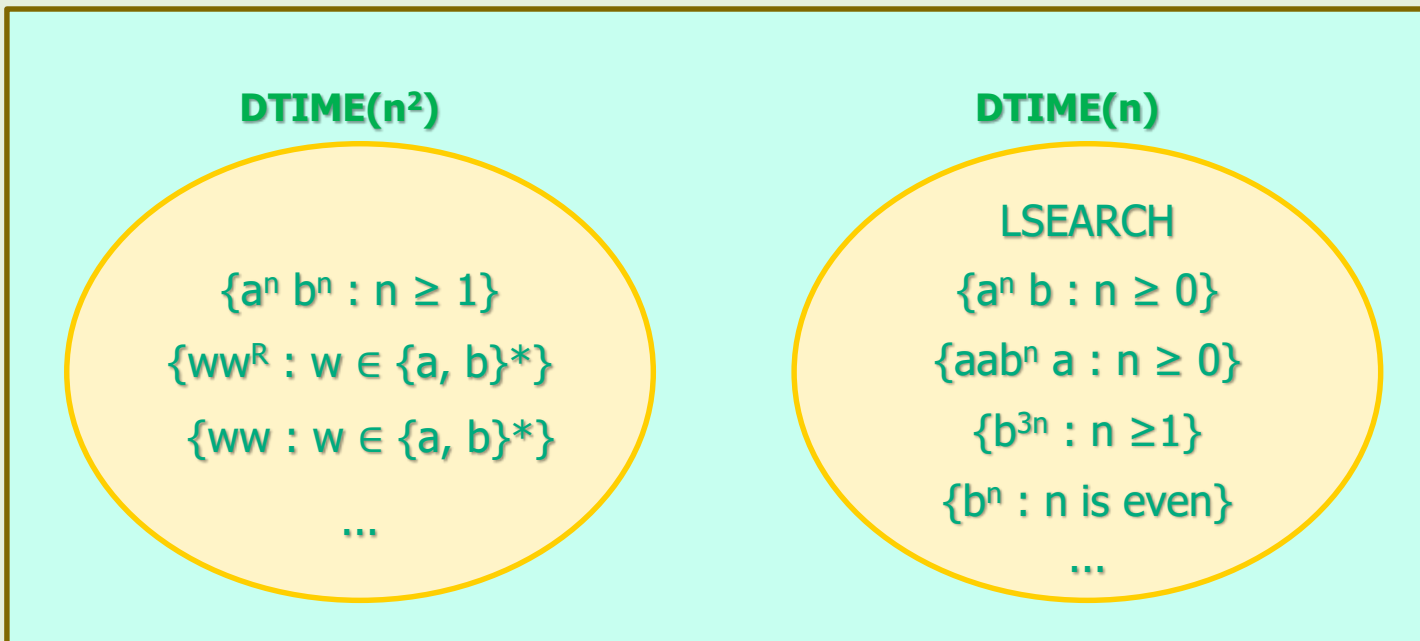


- $L = \{a^n b^n : n \geq 0\}$
- $L = \{ww^R : w \in \{a, b\}^*\}$
- $L = \{ww : w \in \{a, b\}^*\}$
- $O(n^2)$
- So, we need a new class of complexity.

# Complexity Class **DTIME( $n^2$ )**

- We create a new class called **DTIME( $n^2$ )** and put them in this new class.

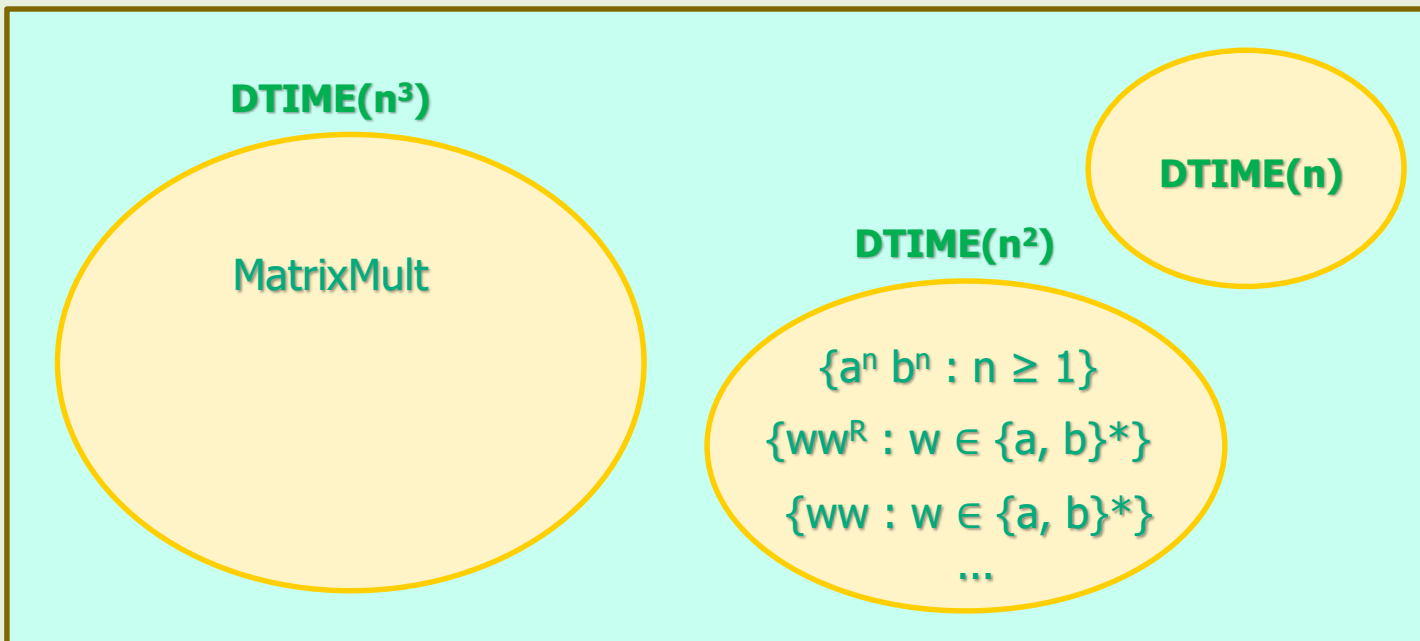
U = All Formal Languages



# Complexity Class **DTIME( $n^3$ )**

- Matrix multiplication problem can be decided in  $O(n^3)$  by using a deterministic TM.
- So, we need another class for  $O(n^3)$ .

U = All Formal Languages



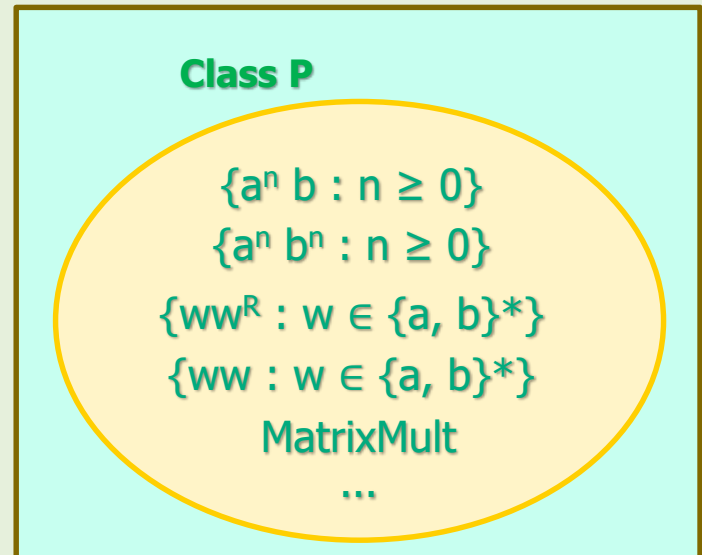
- We can continue this process for  $O(n^4)$ ,  $O(n^5)$ , ...,  $O(n^k)$ .



# Class P

- Classifying languages based on the degree of  $n$  has less practical benefit.
- We define a general class called "polynomial time-complexity" or just "class P".
- ♥ ▪ Class P is the set of problems that can be decided in  $O(n^k)$  by using a deterministic TM.
  - Where  $k \geq 0$
- ♥ ▪ Also, we call these problems "easy" (aka "tractable").
- We'll see within a few minutes why they are "easy"!

$U$  = All Formal Languages



# Exponential Time Algorithms

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# Introduction

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- We continue our study about the classification of complexities by focusing on "exponential algorithms".
- But first, we need to get familiar with some of those problems.
- In the next slides we'll take some examples of problems that need exponential time to be decided.

# Satisfiability Problem (SAT)

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## Problem

- As an **example**, consider the following **logical expression**:

$$X = (p \vee r) \wedge (\sim q \vee \sim r)$$

- For **what values of p, q, and r**, the expression X is satisfied (= true)?

## Solution

- Using "**truth table**" is the most **reliable way** to find all solutions.
- The expression has three variable p, q, and r.
- Therefore, there are  $2^3 = 8$  rows in the truth table.
- The **algorithm** should **evaluate X for all rows** to find all possible solutions.



# Satisfiability Problem (SAT)

$$X = (p \vee r) \wedge (\sim q \vee \sim r)$$

1.  $X = (T \vee T) \wedge (\sim T \vee \sim T) = F$

2.  $X = (T \vee F) \wedge (\sim T \vee \sim F) = T$

3.  $X = (T \vee T) \wedge (\sim F \vee \sim T) = T$

4.  $X = (T \vee F) \wedge (\sim F \vee \sim F) = T$

5.  $X = (F \vee T) \wedge (\sim T \vee \sim T) = F$

6.  $X = (F \vee F) \wedge (\sim T \vee \sim F) = F$

7.  $X = (F \vee T) \wedge (\sim F \vee \sim T) = T$

8.  $X = (F \vee F) \wedge (\sim F \vee \sim F) = F$

	p	q	r
1	T	T	T
2	T	T	F
3	T	F	T
4	T	F	F
5	F	T	T
6	F	T	F
7	F	F	T
8	F	F	F

# Satisfiability Problem (SAT)

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- In the previous example, we used an **exhaustive algorithm**.

## Algorithm

- Construct a truth table for 3 variables  $p, q, r$ .
  - Evaluate  $X$  for every row.
  - Pick those rows that  $X = \text{true}$ .
- 
- ⚠ ▪ So, **theoretically** this problem is **computable**.

# Efficiency of Satisfiability Problem (SAT)

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- If the number of variables is  $n$ , the truth table would have  $2^n$  rows .
- We assume the evaluation of one row needs constant time.
  - We ignore the constant coefficients in big-O notation.
- Therefore, the algorithm needs  $2^n$  evaluations.
- So, the efficiency of SAT problem is  $O(2^n)$ .

# Efficiency of Satisfiability Problem (SAT)

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- Is this algorithm **practically** feasible?
- What would happen if we had 100 variables?
- In this case, we'd need a table with  $2^{100}$  rows.
- Do you have any idea how **big** is this number?
- To answer this question, let's "**do some math**".



# Let's Do Some Math!

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## Example 4: A Practical Calculation for $2^{100}$

- Consider a truth table with 100 variables and  $2^{100}$  rows.
- If a computer processes each row in 1 Nano sec ( $10^{-9}$  sec), how long does it take for this computer to process entire table?

## Solution



# Let's Do Some Math!

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## Exhaustive Parsing Algorithm

$S \rightarrow SS \mid a S b \mid b S a \mid \lambda$

$w = abba\dots b; |w| = 50$

- Efficiency of exhaustive search parsing algorithm:  $O(|P|^{2|w|})$
- We have a deterministic computer that can process each substitution in 1 Nano sec ( $10^{-9}$  sec).
- How long does it take to parse a string of length 50?

## ❗ Let's Do Some Math Again!

- Let's take another look at the table of **growth rate of functions**.
- Compare, for example, **one million rows of  $n^3$**  and the number that we just calculated for  $2^{100}$ .
- **One million rows can be processed within less than a second while  $2^{100}$  needs ....**
- ♥ ▪ That's why we call exponential algorithms as **"hard"** (aka **"intractable"**).

n	k	n	$n^2$	$n^3$	$2^n$
1	k	1	1	1	2
2	k	2	4	8	4
3	k	3	9	27	8
...	...	...	...	...	...
10	k	10	100	1000	1024
...	...	...	...	...	...
100	k	100	10,000	1,000,000	$2^{100} = ???$

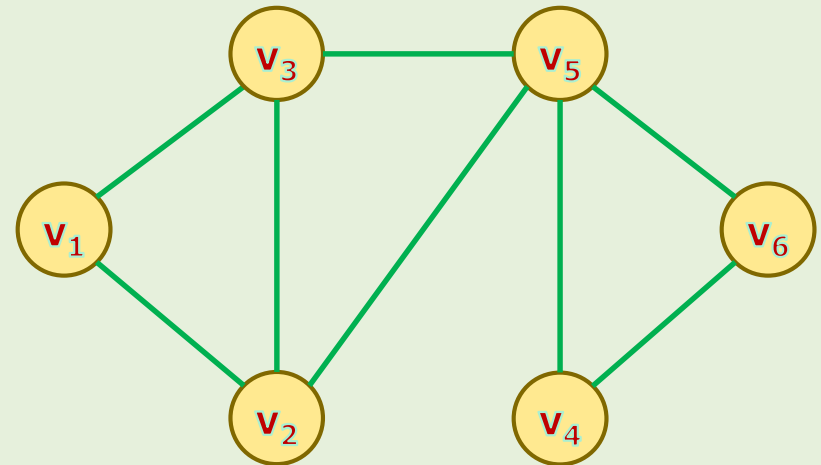
# Hamilton Path Problem (HAMPATH)

## Problem

- Given an undirected graph with  $n$  vertices  $v_1, v_2, \dots, v_n$ .
- Find a simple path that passes through all vertices.
  - This path, if exists, is called "Hamilton path".

## Example 6

- Is there any Hamilton path in the following graph?



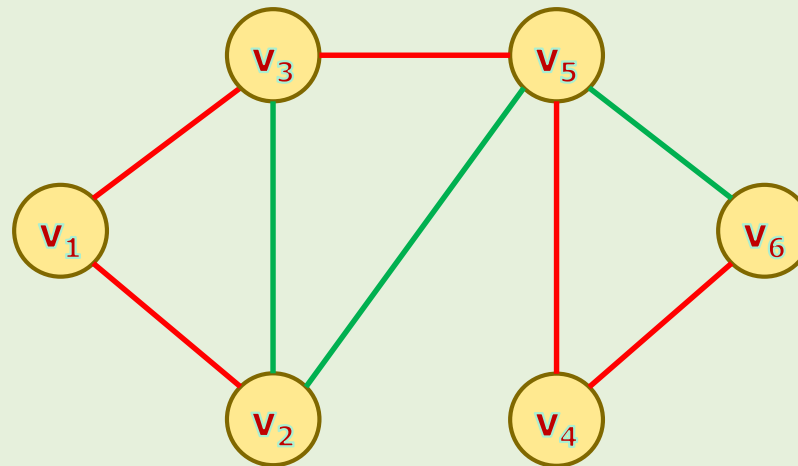


# Hamilton Path Problem (HAMPATH)

FYI

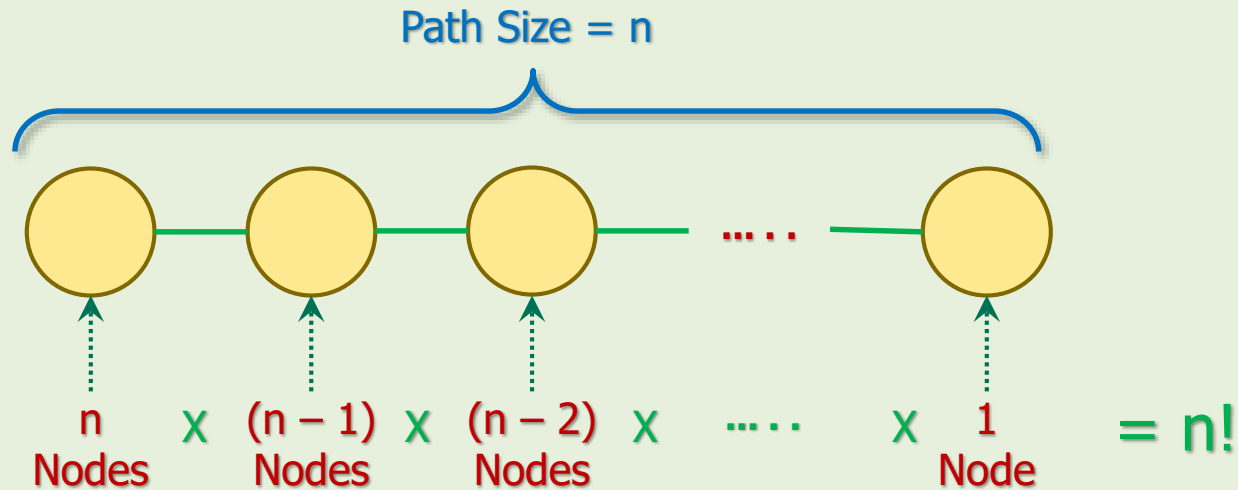
## Example 6 (cont'd)

- Yes,  $\{(v_2, v_1), (v_1, v_3), (v_3, v_5), (v_5, v_4), (v_4, v_6)\}$



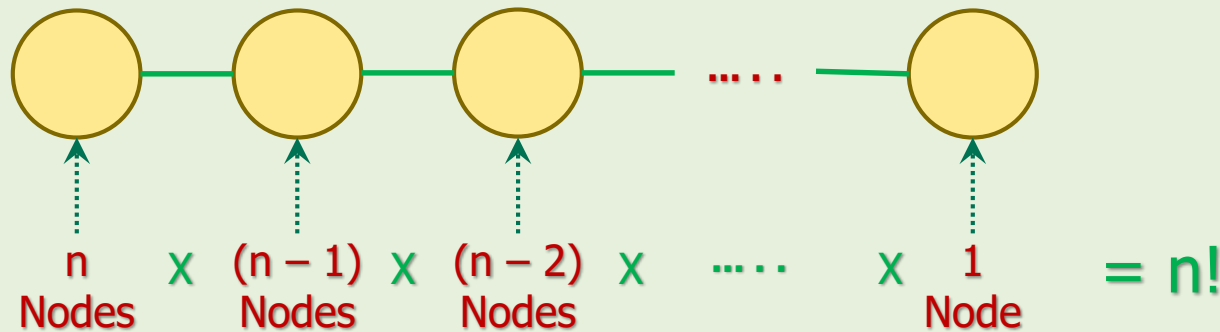
# Hamilton Path Problem Complexity

- Let's use an **exhaustive algorithm** to check all possible paths.
- **How many different paths** can we recognize?
- Since we need to visit all  $n$  vertices, so, all possible paths have size  $n$ .



# Hamilton Path Problem Complexity

- The paths can start from all  $n$  nodes.
- The second node in each path can be  $(n-1)$  remaining nodes.
- The third node in each path can be  $(n-2)$  remaining nodes, and so forth ...
- Based on "**multiplication rule of counting**", total number of possible paths would be:  $n \times (n-1) \times (n-2) \times \dots \times 2 \times 1 = n!$



# Hamilton Path Problem Complexity

- Therefore, the total number of paths in the worst-case is  $n!$ .
- So, investigating which path is Hamilton path needs  $O(n!)$  time.
- We usually don't have a clear feeling about how big is  $n!$ .
- So, we use Stirling's approximation for  $n!$ .

$$n! \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

## Conclusion

- Complexity of HAMPATH  $\approx O(n^n)$
- So, if we have 100 vertices, then we need to check  $100^{100}$  possibilities!
- Now you do the math!

# Using Nondeterministic TMs

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# Using Nondeterministic TM

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## Theorem

- If a **deterministic** TM solves a problem in an **exponential time**  $O(k^{an})$ , a **nondeterministic** TM solves it in a **polynomial time**  $O(n^p)$ .
- Where:
  - $p$ ,  $k$  and  $a$  are constants

# Using Nondeterministic TM

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## Example 8

- The SAT problem complexity =  $O(2^n)$  (by using deterministic TM)
- If we solve this problem by using a nondeterministic TM, the complexity would be  $O(n)$ .
- Do the math again!



## Class NP

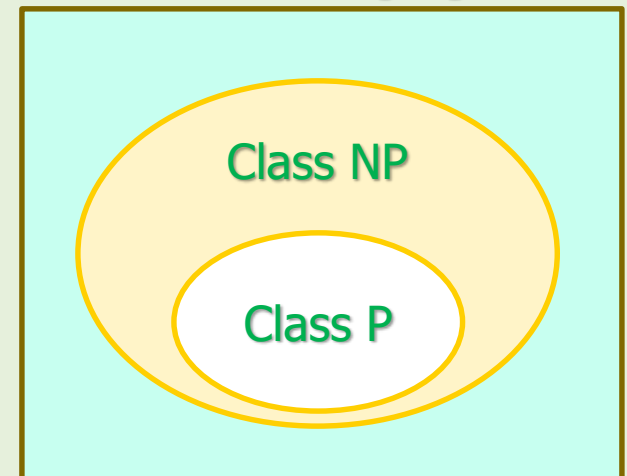


- Class NP is the set of problems that can be decided in polynomial time by using nondeterministic TMs.
- NP = Nondeterministic Polynomial Time-Complexity

### What is the relationship between class P and NP?

- All languages in class P can also be decided in polynomial time by using nondeterministic TM.
- So,  $P \subseteq NP$

U = All Formal Languages



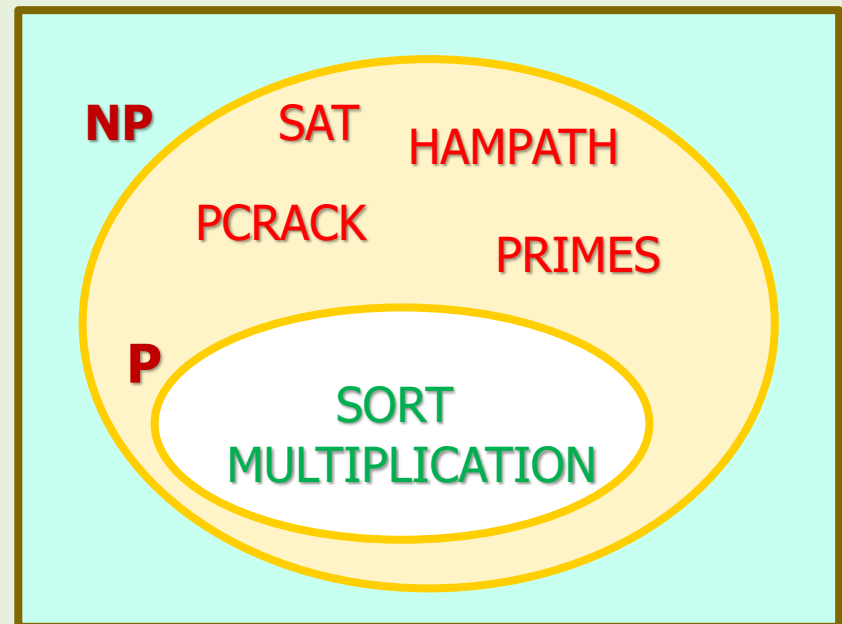


# P vs. NP

- Computer scientists found **polynomial time algorithms** for some problems such as **sorting, multiplication**.
- They found **exponential algorithms** for some others such as **SAT, HAMPATH, PRIMES** (finding prime numbers), **PCRACK** (password cracking), ...

- We were lucky to find a **polynomial time algorithm** for some of them like **PRIMES**. (Agrawal, Kayal, Saxena / 2004)
- So, we moved **PRIMES** to class P. (next slide)

U = All Formal Languages



# P vs. NP: An Open Question

- Now the question is:

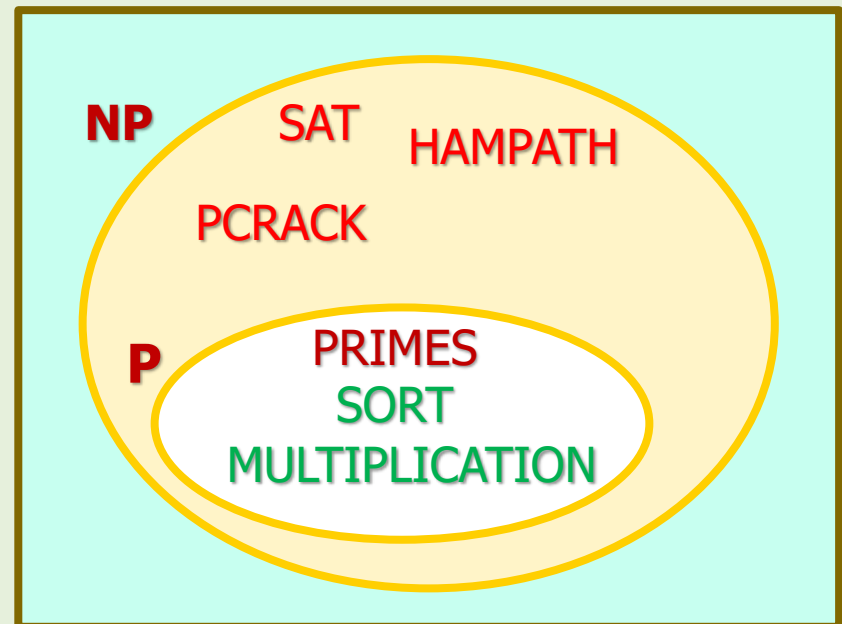
Can we find polynomial time algorithms for the rest of them?

- In other words, can we expect one day  $P = NP$ ?
- We don't know yet.

- This is another "open question" of computer science.

- \$1,000,000 for the solution!
- <http://www.claymath.org>

U = All Formal Languages



# Last Note

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- Note that **it is not the case** that we just have 2 or 3 classes.
- As of this moment, there are **535 known complexity classes!**
- For more information, take a look at the "**Complexity Zoo**" website at:  
[https://complexityzoo.uwaterloo.ca/Complexity\\_Zoo](https://complexityzoo.uwaterloo.ca/Complexity_Zoo)



# **The End**

# **I wish you all, the Bests!**

# References

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1. Linz, Peter, "An Introduction to Formal Languages and Automata, 5<sup>th</sup> ed.," Jones & Bartlett Learning, LLC, Canada, 2012
2. Michael Sipser, "Introduction to the Theory of Computation, 3<sup>rd</sup> ed.," CENGAGE Learning, United States, 2013  
ISBN-13: 978-1133187790