

# Tutorial on Fine-Grained Complexity

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**DIMACS**

Center for Discrete Mathematics and Theoretical Computer Science  
Founded as a National Science Foundation Science and Technology Center



**INSAIT**

Institute for Computer Science,  
Artificial Intelligence and Technology

# Lecture 0: Welcome and Overview

- ▶ Welcome & Logistics
- ▶ Intro and quick overview
- ▶ Remarks about the tutorial

# Complexity Theory

NP-hard

k-SAT

Travelling Salesman

Independent Set

Subset Sum

Protein Folding

...

in P

Linear Programming

All Pairs Shortest Paths

Fourier Transform

Edit-Distance

Context-Free Grammar Parsing

...

*What about the problems inside P?*

# Complexity Theory

Popular since 1970's

(Traditional) Complexity:

“Polynomial Time = Efficient”

*Polynomial vs. exponential?*

*A theory for Small Data*

Popular since 2010's

Fine-Grained Complexity:

“Near-linear Time = Efficient”

*$O(n)$ ,  $O(n^{1.5})$ ,  $O(n^2)$ , ...?*

*A theory for Big Data*

# Longest Common Subsequence (LCS)

Input: two sequences of length  $n$

S = cddcab**bb**abcbaa  
          /  /  /  |  |  \  
T = ad**bb**bcab**ac**dd

Output: the length of the longest common subsequence

Dynamic Programming:  $O(n^2)$

$$M[i, j] = \max \begin{cases} M[i - 1, j - 1] + (S[i] == T[j]), \\ M[i - 1, j], \\ M[i, j - 1] \end{cases}$$

[Masek - Paterson '80]

$O(n^2 / \log^2 n)$

Can we do better?

Why care about  $n$  vs.  $n^2$  vs.  $n^3$ ...?

Here's one example where it matters...

## Local Alignment

Input: two (DNA) sequences of length  $n$  and a scoring matrix.

AGCCCGTCTACG T GCAACCGGGGAAAGTATA  
AAACGTGACGAGAGAGAGAACCCATTACGAA

Output: The optimal alignment of two substrings.

C C G - T C T A C G  
C C C A T - T A C G  
+1 +1 -0.5 -1 +1 -1 +1 +1 +1 +1 = +4.5

	A	C	G	T	-
A	+1	-1.4	-1.8	-0.7	-1
C	-1.4	+1	-0.5	-1	-1
G	-1.8	-0.5	+1	-1.9	-1
T	-0.7	-1	-1.9	+1	-1
-	-1	-1	-1	-1	$-\infty$

Typically:  $n \gg 10^6$

[Smith-Waterman '81]  $O(n^2)$  with dynamic programming - too slow!

Why care about  $n$  vs.  $n^2$  vs.  $n^3$ ...?

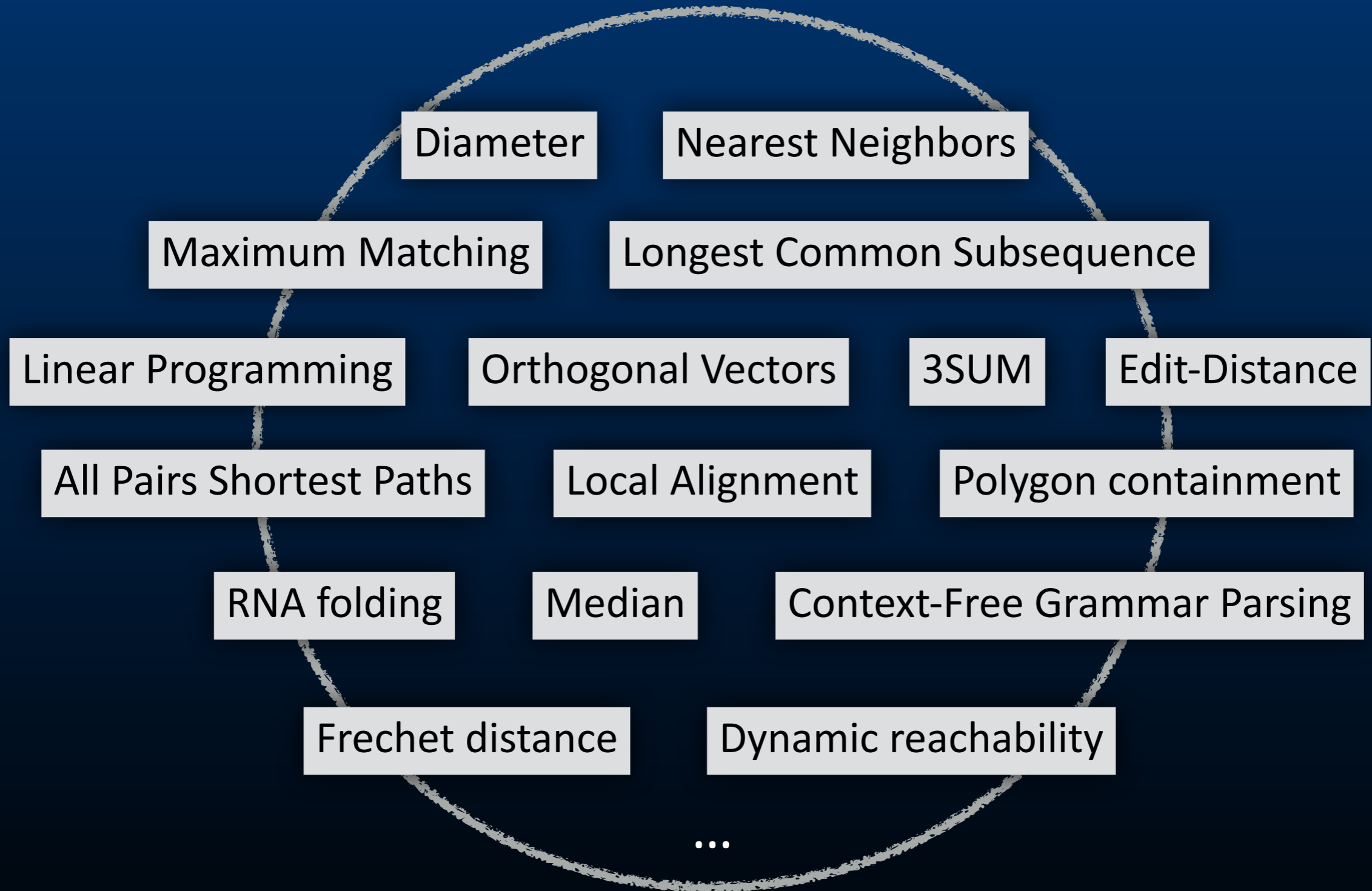
**BLAST: A heuristic, linear time algorithm for Local Alignment.**

The screenshot shows a Google Scholar search interface. The search bar contains the text 'local alignment' and a search button. Below the search bar, it indicates 'Articles' and 'About 4,600,000 results (0.10 sec)'. On the left side, there are filters for 'Any time', 'Since 2024', 'Since 2023', 'Since 2020', and 'Custom range...'. The main search result is titled 'Basic local alignment search tool' by 'SF Altschul, W Gish, W Miller, EW Myers...' from the 'Journal of molecular ...', 1990 - Elsevier. The abstract snippet reads: '... local alignment search tool (BLAST), directly approximates alignments that optimize a measure of local ... well as the statistical significance of alignments it generates. The basic algorithm ...'. Below the abstract, there are links for 'Save', 'Cite', 'Cited by 110181', 'Related articles', and 'All 43 versions'. The 'Cite' and 'Cited by 110181' links are circled in red.

110k citations!

Are there fast algorithms with optimality guarantees?

# The Class P



Goal: Understand the time complexity of important problems.



# Fine-Grained Complexity or: Hardness in P

Take a problem  $X$  in  $P$ , say in  $O(n^2)$  time.

And prove that:

“ $X$  probably *cannot* be solved in  $O(n^{2-\epsilon})$  time.”

*But how?*

How do we get  $n^2$  and  $n^3$  lower bounds?

Unconditional polynomial lower bounds?

*“Any Turing Machine has to spend  $\Omega(n^2)$  time...”*

Time Hierarchy Thm (1965): Some (artificial) problems require  $\Omega(n^2)$  time.

But  $\Omega(n^2)$  for natural problems, even for SAT, is far out of reach of current techniques. **Best lower bound is  $3.1n$ .**

Lower bounds for restricted algorithms?

e.g.  $\Omega(n \log n)$  for sorting in the comparisons-only model.

Not general enough, and only gives partial answers.

NP-hardness is not fine-grained enough...

# Complexity Theory

*How do we prove hardness results?*

Popular since 1970's  
(Traditional) Complexity:

*Polynomial vs. exponential?*

Reductions!



**P ≠ NP:**

“k-SAT cannot be solved  
in polynomial time.”

Popular since 2010's  
Fine-Grained Complexity:

*$O(n)$ ,  $O(n^{1.5})$ ,  $O(n^2)$ , ...?*

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My problem is in P



$P = NP$



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Fine-Grained Reductions!

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Fine-Grained Reductions!



**SETH:**

“k-SAT cannot be solved  
even in  $O(1.99^n)$  time.”

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Fine-Grained Complexity:

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Fine-Grained Reductions!

My problem is linear



SETH is false



# An Example of a Fine-Grained Lower Bound

**Theorem [AVW'14]:**

“If for some  $\varepsilon > 0$ , we can solve Local Alignment in  $O(n^{2-\varepsilon})$  time, then we can solve k-SAT in  $O((2 - \delta)^n)$  time for some  $\delta > 0$  and all  $k > 0$ .”

Faster  
Local Alignment

e.g.  
 $O(n^{1.99})$



Faster  
k-SAT

e.g.  
 $O(1.99^n)$



SETH  
is false

**$P \neq NP$ :** “k-SAT cannot be solved in polynomial time.”

**ETH:** “k-SAT cannot be solved even in  $2^{o(n)}$  time.”

**SETH (The Strong Exponential Time Hypothesis):**

“k-SAT cannot be solved even in  $O(1.99^n)$  time.”

# SETH

**k-SAT**: given a k-CNF formula on  $n$  variables and  $m$  clauses, is it satisfiable?

$$\phi = (x_1 \vee x_2 \vee \bar{x}_3 \vee x_{10}) \wedge \cdots \wedge (x_2 \vee \bar{x}_1 \vee x_4)$$

Fastest algorithms:

$$O\left(2^{\left(1-\frac{1}{ck}\right)\cdot n}\right)$$

$$k=3: 1.308^n$$

$$k=4: 1.504^n$$

$$k=5: 1.592^n$$

$$\dots k \rightarrow \infty : 2^n$$

**The Strong Exponential Time Hypothesis (SETH):**

[Impagliazzo-Paturi'01]

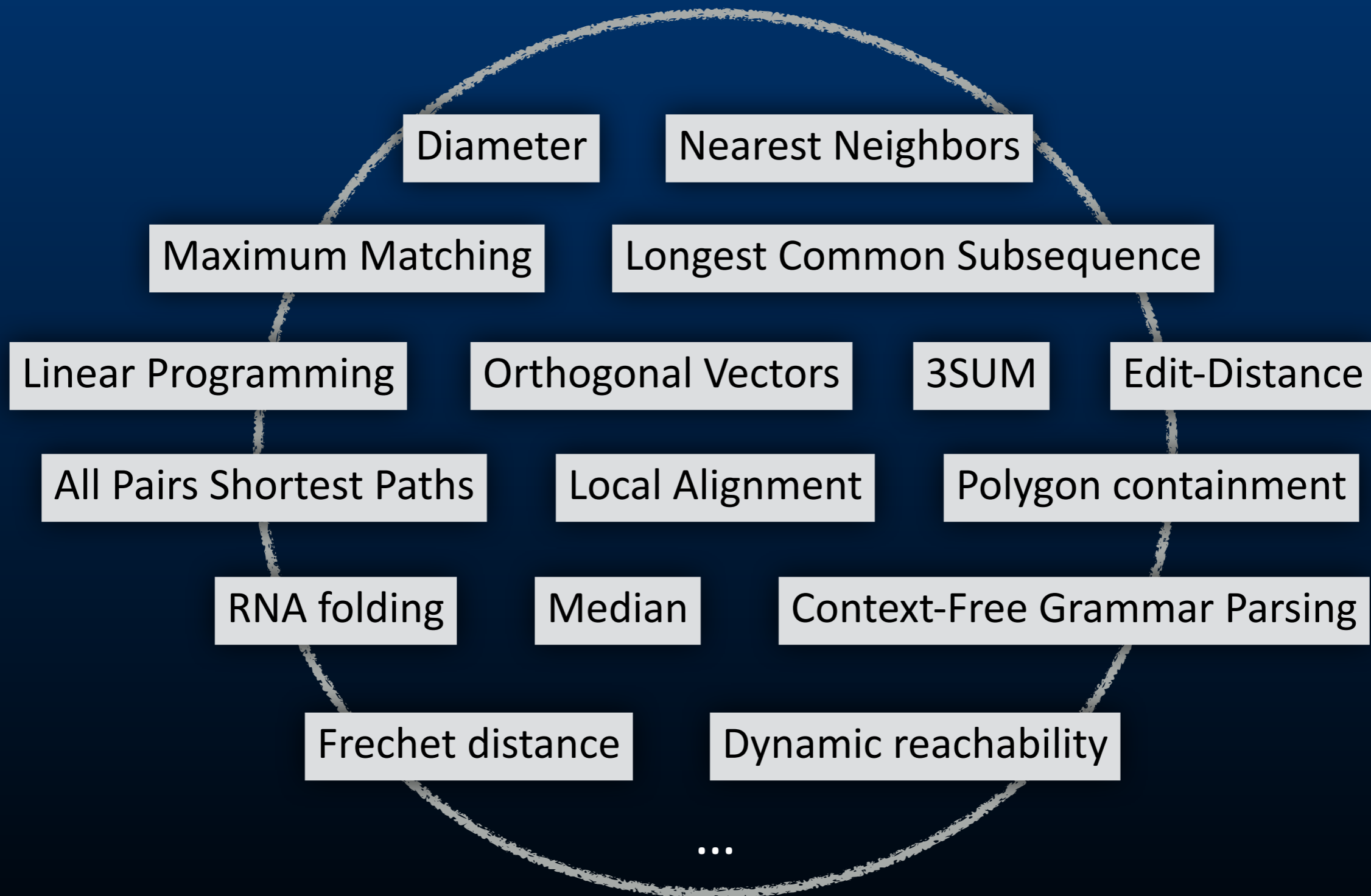
There is no  $\varepsilon > 0$  such that for all  $k > 2$ ,

**k-SAT** can be solved in  $O((2 - \varepsilon)^n)$  time.

SETH: “k-SAT cannot be solved in  $O(1.99^n)$  time.”



# The Class P (before)



# The Class P (after)



SETH



*Problem domains:*  
Graph Algorithms  
Pattern Matching  
Bioinformatics  
Computational Geometry  
Data Structures  
Machine Learning  
Formal Languages  
...

Many problems remain unclassified...

# The Class P (after)



**SETH**

SAT on  $n$  variable formulas requires  $\Omega((2 - \epsilon)^n)$  time.

Closest Pair  
Local Alignment  
Dynamic Reachability  
Single-Source Max-Flow  
Subtree Isomorphism  
Stable Matching  
Edit-Distance  
Frechet  
LCS  
...



**3SUM**

Finding 3 that sum to zero among  $n$  numbers requires  $\Omega(n^{2-\epsilon})$  time.

Polygon Containment  
Strips Cover Rectangle  
Triangle Enumeration  
Compressed Inner Product  
Dynamic Max Matching  
Set Intersection  
...



**APSP**

Computing all distances in  $n$  node graphs requires  $\Omega(n^{3-\epsilon})$  time.

Dynamic Max Matching  
Stochastic Context-Free Grammar Parsing  
Negative Triangle  
Dynamic Max Flow  
Replacement Paths  
Median  
...

Many problems remain unclassified...

# 3SUM

**3SUM:** Given  $n$  integers, are there 3 that sum to 0?

-15	-6	33	8	1	-21	4	-30	7	...	107
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*A famous conjecture in computational geometry:*

The 3-SUM Conjecture:  
“3-SUM cannot be solved in  $O(n^{1.99})$  time.”

# The Class P



SETH



3SUM



Diameter

Closest Pair

Local Alignment

Dynamic Reachability

Single-Source Max-Flow

Subtree Isomorphism

Stable Matching

Edit-Distance

Frechet

LCS

...

Colinearity

Polygon Containment

Strips Cover Rectangle

Triangle Enumeration

Compressed Inner Product

Dynamic Max Matching

Set Intersection

...



# All Pairs Shortest Paths

APSP: Given a **weighted** graph on  $n$  nodes and  $n^2$  edges, compute the distance between every pair of nodes.

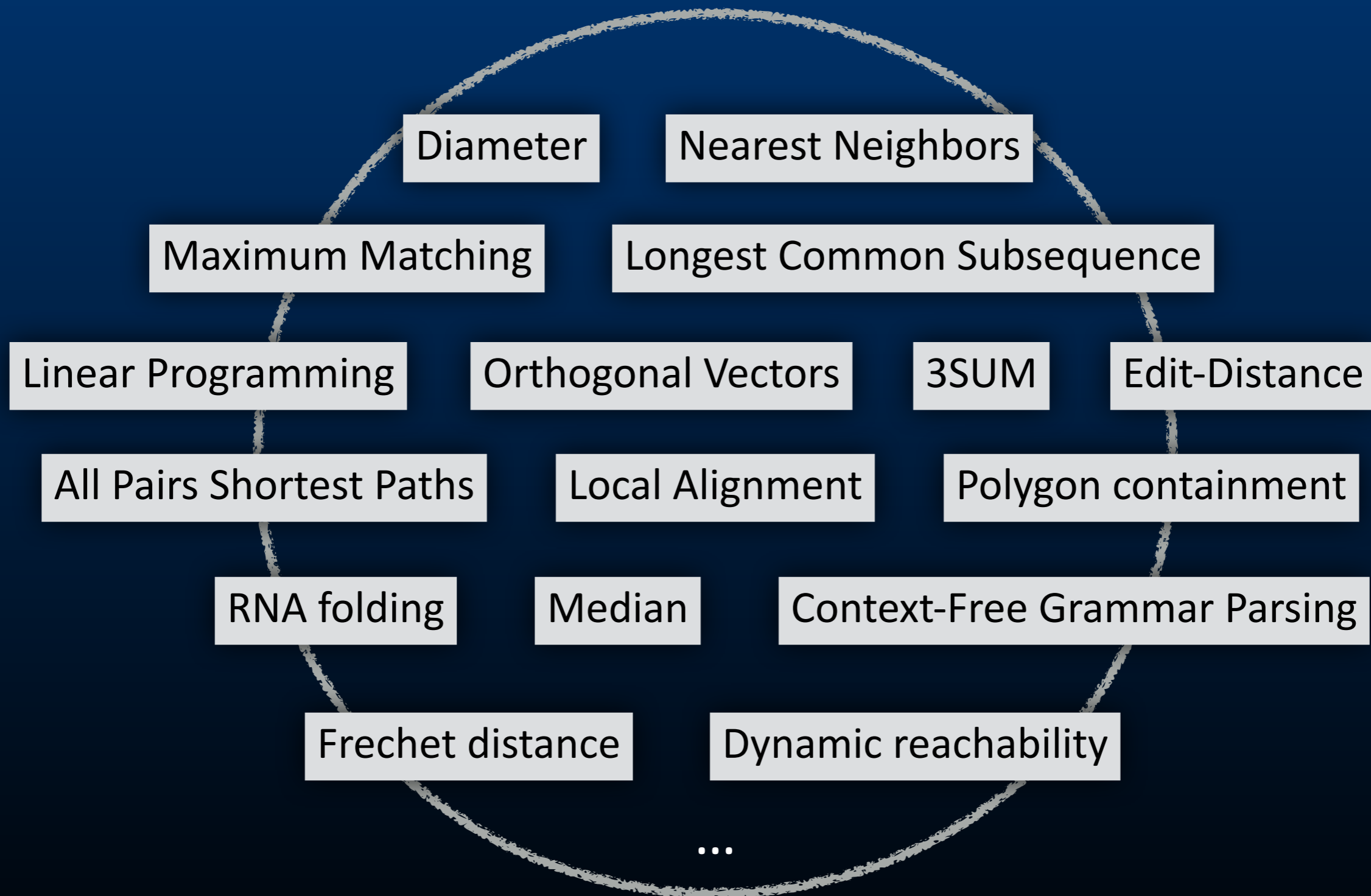
Author	Runtime	Year
Fredman	$n^3 \log \log^{1/3} n / \log^{1/3}$	1976
Takaoka	$n^3 \log \log^{1/2} n / \log^{1/2}$	1992
Dobosiewicz	$n^3 / \log^{1/2} n$	1992
Han	$n^3 \log \log^{5/7} n / \log^{5/7}$	2004
Takaoka	$n^3 \log \log^2 n / \log n$	2004
Zwick	$n^3 \log \log^{1/2} n / \log n$	2004
Chan	$n^3 / \log n$	2005
Han	$n^3 \log \log^{5/4} n / \log^{5/4}$	2006
Chan	$n^3 \log \log^3 n / \log^2 n$	2007
Han, Takaoka	$n^3 \log \log n / \log^2 n$	2012
Williams	$n^3 / 2^{\Omega(\sqrt{\log n})}$	2014

Classical Algs:  $O(n^3)$

*Bellman-Ford, Dijkstra,...*

Conjecture:  
APSP cannot be solved  
in  $O(n^{3-\epsilon})$  time.

# The Class P (before)



# The Class P (after)



**SETH**



**3SUM**



**APSP**



Diameter

Closest Pair

Local Alignment

Dynamic Reachability

Single-Source Max-Flow

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Colinearity

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Radius

Dynamic Max Matching

Stochastic Context-Free

Grammar Parsing

Negative Triangle

Dynamic Max Flow

Replacement Paths

Median

...

Many problems remain unclassified...





# Technical Remarks

- ▶ We will ignore  $\log n$ ,  $\log^{O(1)} n$ ,  $2^{\sqrt{\log n}}$  or any  $n^{o(1)}$  factors.
  - ▶ Many reductions have such overheads.
- ▶ We allow randomness.
  - ▶ The conjectures are assumed to hold against randomized algorithms too.
  - ▶ Many reductions use randomness.
- ▶ We use the (standard) Word RAM model with  $w = O(\log n)$ .
  - ▶ You can do any operations on words in constant time: addition, multiplication, random access, hashing, etc.
  - ▶ Since we allow log factors and randomness, this is not too important.
- ▶ Numbers are assumed to be in a polynomial range.
  - ▶ Integers in  $\{-n^{O(1)}, \dots, +n^{O(1)}\}$ , real numbers with precision  $1/n^{O(1)}$ .

# Fine-Grained Reductions

Thm: If  $A \xrightarrow{a \rightarrow b} B$  and  $B$  is in  $O(n^{b-\varepsilon})$  time then  $A$  is in  $O(n^{a-\delta})$  time.

Thm: If  $A \xrightarrow{a \rightarrow b} B$  and  $B \xrightarrow{b \rightarrow c} C$  then also  $A \xrightarrow{a \rightarrow c} C$ .

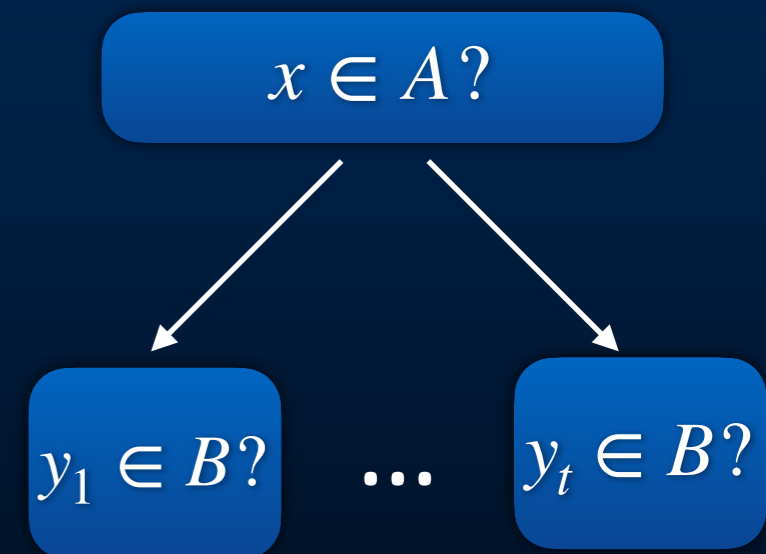
Definition:  $A \xrightarrow{a \rightarrow b} B$

A fine-grained  $(a, b)$ -reduction from  $A$  to  $B$  is an algorithm  $\mathcal{A}^B$  for  $A$  with oracle access to  $B$ , such that:

$\forall \varepsilon > 0 : \exists \delta > 0 :$  for all input  $x$  of size  $n$ :

1.  $\mathcal{A}^B(x)$  is correct w.p.  $\geq 1 - 1/n^{10}$
2.  $\mathcal{A}^B(x)$  runs in  $O(n^{a-\delta})$  time.
3. Let  $y_1, \dots, y_t$  be the oracle calls, then:

$$\sum_{i=1}^t |y_i|^{b-\varepsilon} = O(n^{a-\delta})$$



# Tutorial Objectives

- ▶ Goal 0: The ability to understand FGC results.
- ▶ Goal 1: The ability to prove your own FGC results.
  - ▶ We will highlight the simplest hard problems

**k-SAT**



**OV**



**3SUM**



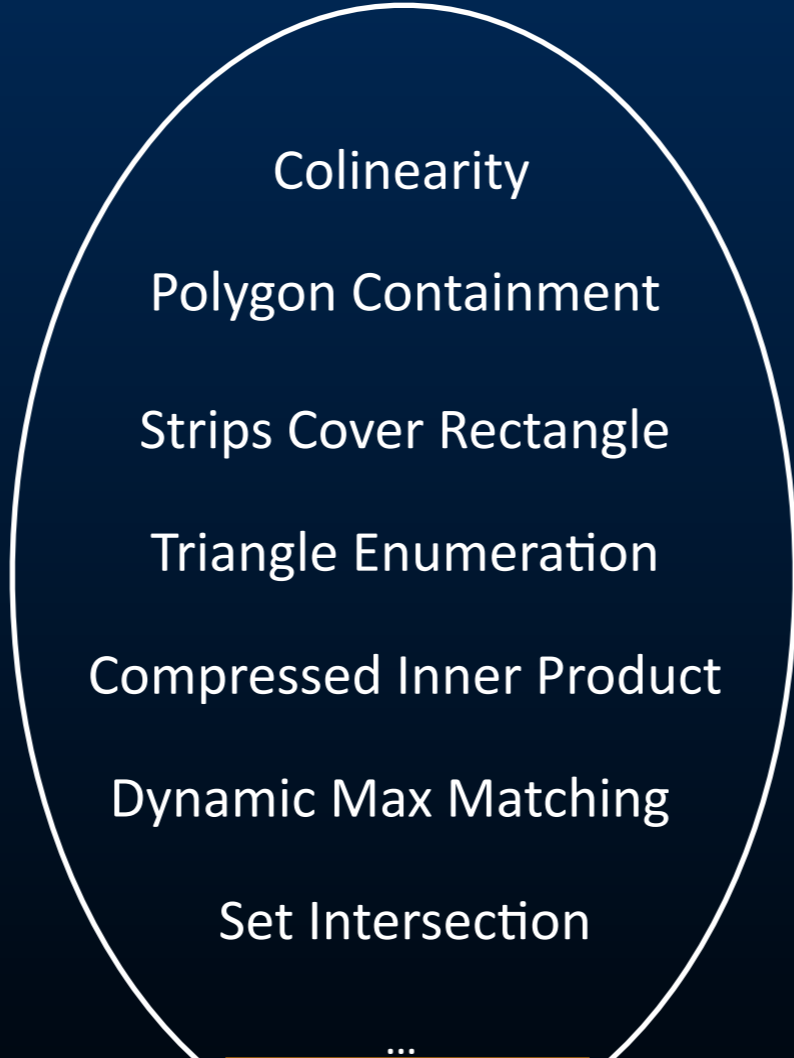
**APSP**



**Negative-Triangle**



**Wed + Thu**



**Monday**



**Tuesday**

# Tutorial Objectives

- ▶ Goal 0: The ability to understand FGC results.
- ▶ Goal 1: The ability to prove your own FGC results.
  - ▶ We will highlight the simplest hard problems
- ▶ Goal 2: Intimacy with the theory and with current research.
  - ▶ This is the purpose of the afternoon lectures (and Friday).
- ▶ *Most importantly: To have fun thinking about basic problems!*