A FINE-GRAINED APPROACH TO ALGORITHMS AND COMPLEXITY

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THE CENTRAL QUESTION OF ALGORITHMS RESEARCH

``How fast can we solve fundamental problems, in the worst case?"



ALGORITHMIC TECHNIQUES



HARD PROBLEMS

For many problems, the known techniques get stuck:

- Very important computational problems from diverse areas
- They have simple, often brute-force, classical algorithms
- No improvements in many decades!





A CANONICAL HARD PROBLEM

k-SAT

Input: variables $x_1, ..., x_n$ and a formula $F = C_1 \land C_2 \land ... \land C_m$ so that each C_i is of the form $\{y_1 \lor y_2 \lor ... \lor y_k\}$ and $\forall i, y_i$ is either x_t or $\neg x_t$ for some t.

Output: A boolean assignment to $\{x_1, ..., x_n\}$ that satisfies all the clauses, or NO if the formula is not satisfiable

Brute-force algorithm: try all 2^n assignments Best known algorithm: $O(2^{n-(cn/k)}n^d)$ time for const c,d

Goes to 2ⁿ as k grows.

222 ANOTHER HARD PROBLEM: LONGEST COMMON SUBSEQUENCE (LCS)

Given two strings on n letters

Example 2

ATCGGGTTCCTTAAGGG ATATIGGTACCTTCAGGG

Find a subsequence of both strings of maximum length.

Algorithms:

Classical O(n²) time

Best algorithm: $O(n^2 / \log^2 n)$ time [MP'80]

Applications both in computational biology and in spellcheckers.





THE REAL WORLD AND NP-HARD PROBLEMS LIKE K-SAT

l've got data. I want to solve this algorithmic problem but I'm stuck!

Ok, thanks, I feel better that none of my attempts worked. I'll use some heuristics. I'm sorry, this problem is NP-hard. A fast algorithm for it would resolve a hard problem in CS/math.



THE REAL WORLD AND EASIER PROBLEMS LIKE LCS

I've got data. I want to solve this algorithmic problem but I'm stuck!

> But my data size n is huge! Don't you have a faster algorithm?

?!? ... Should I wait? ... Or should I be satisfied with heuristics? Great news! Your problem is in P. Here's an O(n²) time algorithm!

Uhm, I don't know... This is already theoretically fast... For some reason I can't come up with a faster algorithm for it right now...



IN THEORETICAL CS, POLYNOMIAL TIME = EFFICIENT/EASY.

This is for a variety of reasons.

E.g. composing two efficient algorithms results in an efficient algorithm. Also, model-independence.

However, noone would consider an $O(n^{100})$ time algorithm efficient in practice.

If n is huge, then $O(n^2)$ can also be inefficient.

No $N^{2-\epsilon}$ time algorithms known for:

Many string matching problems: Edit distance, Sequence local alignment, LCS, jumbled indexing ...

General form: given two sequences of length n, how similar are they? All variants can be solved in $O(n^2)$ time by dynamic programming.

> ATCGGGTTCCTTAAGGG ATTGGTACCTTCAGG

No $N^{2-\epsilon}$ time algorithms known for:

Many string matching problems

Many problems in computational geometry: e.g
 Given n points in the plane, are any three colinear?
 A very important primitive!

No $N^{2-\epsilon}$ time algorithms known for:

- Many string matching problems
- Many problems in computational geometry
 Many graph problems in sparse graphs: e.g.

Given an n node, O(n) edge graph, what is its diameter? Fundamental problem. Even approximation algorithms seem hard!

No $N^{2-\epsilon}$ time algorithms known for:

Many string matching problems

Many problems in computational geometry
 Many graph problems in sparse graphs

Many other problems ...

Why are we stuck?

Are we stuck because of the same reason?



• Traditional hardness in complexity

• A fine-grained approach

• New Developments

COMPUTATIONAL COMPLEXITY



This traditional complexity class approach says little about runtime!

Contains the "1000-clique" problem; best runtime: $\Omega(n^{790})$

It also does not apply to problems in P!

WHY IS K-SAT HARD?

Theorem [Cook, Karp'72]: k-SAT is **NP-complete** for all $k \ge 3$. NP-completeness addresses runtime, but it is too coarsegrained!

That is, if there is an algorithm that solves k-SAT instances on n variables in **poly(n)** time, then all problems in NP have poly(N) time solutions, and so P=NP.

k-SAT (and all other NP-complete problems) are considered hard because fast algorithms for them imply fast algorithms for many important problems.

N – size of input

NP

TIME HIERARCHY THEOREMS

For most natural computational models one can prove:

for any constant c, there exist problems solvable in $O(n^c)$ time but not in $O(n^{c-\epsilon})$ time for any $\epsilon > 0$.

It is completely unclear how to show that a particular problem in $O(n^c)$ time is not in $O(n^{c-\epsilon})$ time for any $\epsilon > 0$.

Unconditional lower bounds seem hard.

In fact, it is not even known if SAT is in linear time!

We instead develop a *fine-grained theory of hardness* that is conditional and mimics NP-completeness.



• Traditional hardness in complexity

• A fine-grained approach

• Fine-grained reductions lead to new algorithms

FINE-GRAINED HARDNESS

Idea: Mimic NP-completeness

1. Identify key hard problems

2. Reduce these to all (?) other problems believed hard

3. Hopefully form equivalence classes

Goal:

understand the landscape of algorithmic problems

CNF SAT IS CONJECTURED TO BE REALLY HARD

Two popular conjectures about SAT on n variables [IPZ01]: ETH: 3-SAT requires $2^{\delta n}$ time for some constant $\delta > 0$.

SETH: for every $\varepsilon > 0$, there is a k such that k-SAT on n variables, m clauses cannot be solved in $2^{(1-\varepsilon)n}$ poly m time.

So we can use k-SAT as our hard problem and ETH or SETH as the conjecture we base hardness on.

Recent research [CGIMPS'16] suggests these problems are **not equivalent**!



Author	Runtime	Year
Floyd, Warshall	n ³	1962
Fredman	n ³	1976
Takaoka	n ³	1992
Dobosiewicz	n ³	1992
Han	n ³	2004
Takaoka	n ³	2004
Zwick	n ³	2004
Chan	n ³	2005
Han	n ³	2006
Chan	n ³	2007
Han, Takaoka	n ³	2012
Williams	n ³	2014

WORK ON APSP

Classical problem Long history

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FINE-GRAINED REDUCTIONS

Intuition: a(n),b(n) are the naive runtimes for A and B. A reducible to B implies that beating the naive runtime for B implies also beating the naive runtime for A.

- A is (a,b)-reducible to B if for every $\varepsilon > 0 \exists \delta > 0$, and an $O(a(n)^{1-\delta})$ time algorithm that adaptively transforms any A-instance of size n to B-instances of size n_1, \dots, n_k so that $\sum_i b(n_i)^{1-\varepsilon} < O(n)^{1-\delta}$.
- If B is in O(b(n)^{1-ε}) time,
 then A is in O(a(n)^{1-δ}) time.
- Focus on exponents.
- We can build equivalences.



Next: an example

AN EXAMPLE FINE-GRAINED EQUIVALENCE

b

THEOREM [VW'10]: Boolean matrix multiplication (BMM) is equivalent to Triangle detection under *subcubic* fine-grained reductions.

BMM: Given two n x n Boolean matrices X and Y, return an n x n matrix Z where for all i and j, $Z[i, j] = OR_k (X[i, k] AND Y[k, j])$.

Triangle detection: Given an n node graph G, does it contain three vertices a, b, c, such that (a, b), (b, c), (c, a) are all edges?

We will show that (1) an O(n^{3-e}) time alg for BMM can give an O(n^{3-e}) time triangle alg, and (2) an O(n^{3-e}) time alg for triangle can give an O(n^{3-e/3}) time BMM alg. BMM: Given two n x n Boolean matrices X and Y, return an n x n matrix Z where for all i and j, $Z[i, j] = OR_k (X[i, k] AND Y[k, j]).$ If one can multiply Boolean matrices in O(n^c) time, then one can find a triangle in a graph in O(n^c) time.

BMM CAN SOLVE TRIANGLE (ITAI, RODEH'1978)

G=(V,E) - n node graph. A – n x n adjacency matrix: for all pairs of nodes u,v

A[u, v] = 1 if (u, v) is an edge and 0 otherwise.

Say Z = Boolean product of A with itself. Then for all pairs of nodes $U \neq W$, Z[U, W] = $OR_v (A[U, v] AND A[v, w]) = - \begin{bmatrix} 1 & \text{if there is a path of length 2 from u to w.} \\ and \\ 0 & \text{otherwise.} \end{bmatrix}$ So G has a triangle iff there is some edge (u, w) in G s.t. Z[u, w] = 1. BMM: Given two n x n Boolean matrices X and Y, return an n x n matrix Z where for all i and j, $Z[i, j] = OR_k (X[i, k] AND Y[k, j]).$

A: rows of X, B: cols of X and rows of Y, C: cols of Y

Reduction from BMM to triangle finding:

Split A into pieces A₁,...,A_t of size n/t

 $t = n^{2/3}$

- Split B into pieces B_1, \ldots, B_t of size n/t
- Split C into pieces C_1, \ldots, C_t of size n/t
- Place an edge between every i in A and every j in C
- Z all zeros matrix
- For all **triples** A_p,B_q,C_r in turn:
 - While A_p [B_q [C_r has a triangle,
 - Let (i, j, k) be a triangle in $A_{\rm p}$ [$B_{\rm q}$ [$C_{\rm r}$
 - Set Z[i , j] = 1
 - Remove (i , j) from the graph.



Z – all zeros matrix For all **triples** A_p, B_q, C_r in turn: While $A_p [B_q [C_r has a triangle, Let (i, j, k) be a triangle in <math>A_p [B_q [C_r Set Z[i, j] = 1]$ Remove (i, j) from the graph.

BMM TO TRIANGLE REDUCTION

Correctness: Every triple of nodes i, j, k appears in some examined A_p [B_a [C_r

Runtime: Every call to the Triangle finding algorithm is due to either (1) Setting an entry Z[i, j] to 1, or

this happens at most once per pair i, j

(2) Determining that some triple $A_p [B_q [C_r doesn't have any more triangles]$

this happens at most once per triple A_p [B_a [C_r

If the runtime for detecting a triangle is $T(n) = O(n^{3-\epsilon})$, then the reduction time is $(n^2 + t^3) T(n/t)$. Setting $t=n^{2/3}$, we get: $O(n^{3-\epsilon/3})$.

FINE-GRAINED HARDNESS

Idea: Mimic NP-completeness

1. Identify key hard problems

2. Reduce these to all (?) other hard problems

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Goal:

understand the landscape of algorithmic problems

Using other hardness assumptions, one can unravel even more structure

N – input size n – number of variables or vertices

SOME STRUCTURE WITHIN P

Orthog.

Sparse graph diameter [RV'13], approximate graph eccentricities [AVW'16], local alignment, longest common substring* [AVW'14], Frechet distance [Br'14], Edit distance [BI'15], LCS, Dynamic time warping [ABV'15, BrK'15], subtree isomorphism [ABHVZ'15], ...

Ν2-ε

Many dynamic problems [P'10],[A**V**'14], [HKNS'15], [RZ'04]

Ν2-ε'

Ν^{1.5- ε'} η^{3- ε}

Ν2- ε'

Huge literature in comp. geom. [GO'95, BHP98, ...]: Geombase, 3PointsLine, 3LinesPoint, Polygonal Containment ...

String problems: Sequence local alignment [AVW'14], jumbled indexing [ACLL'14]



In dense graphs: radius, median, betweenness centrality [AGV'15], negative triangle, second shortest path, replacement paths, shortest cycle ... [VW'10],



• Traditional hardness in complexity

• A fine-grained approach

- New developments
 - The quest for more believable conjectures

THE QUEST FOR MORE PLAUSIBLE CONJECTURES

- Two problems harder than CNF-SAT,3SUM, and APSP
- Longest common subsequence, Formula SAT and Branching Programs

[Abboud-VW-Yu STOC'15]: Two hard problems for node-colored graphs



SOME STRUCTURE W

Ν2-ε'

Sparse graph diameter [RV'13], local alignment, longest common substring* [AVW'14], Frechet distance [Br'14], Edit distance [BI'15], LCS, Dynamic Time Warping [ABV'15, BrK'15]... Dynamic problems [P'10],[AV'14], [HKNS'15], [RZ'04]

> N^{1.5-}ε' n³⁻ε

Ν2-ε'

Huge literature in comp. geom. [GO'95, BH-P98, ...]: Geombase, 3PointsLine, 3LinesPoint, Polygonal Containment ...

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In dense graphs: radius, median, betweenness centrality [AGV'15], negative triangle, second shortest path, replacement paths, shortest cycle ... [VW'10],

S-T max flow, dynamic max flow, ... [AVY'15]

THE QUEST FOR MORE PLAUSIBLE CONJECTURES

- Two problems harder than CNF-SAT,3SUM, and APSP
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CIRCUIT-STRONG-ETH

- The most successful hypothesis has been SETH
- It is ultimately about SAT of linear size CNF-formulas
- There are more difficult satisfiability problems:
 - CIRCUIT-SAT
 - NC-SAT
 - NC1-SAT

C-SETH: satisfiability of circuits from circuit class C on n variables and size s requires 2^{n-o(n)} poly(s) time.

• [Williams'10,'11]: a $2^n/n^{10}$ time SAT algorithm implies circuit lower bounds for C (for E^{NP} and others); the bigger the class the stronger the lower bound

A VERY RECENT DEVELOPMENT

Theorem [Abboud-Hansen-VW-Williams'16]: There is an efficient reduction from **Satisfiability for non-deterministic branching programs** (BPs) of size **T** and width **W** and **n** input variables to the following string problems on strings of length $N = 2^{n/2} T^{O(\log W)}$:

Longest Common Subsequence, Edit Distance, Dynamic Time Warping, etc. THEOREM [ABBOUD-HANSEN-VW-WILLIAMS'15]: THERE IS AN EFFICIENT REDUCTION FROM SATISFIABILITY FOR NON-DETERMINISTIC BRANCHING PROGRAMS (BPS) OF SIZE T AND WIDTH W AND N INPUT VARIABLES TO THE FOLLOWING STRING PROBLEMS ON STRINGS OF LENGTH N = 2^{N/2} T^{O(LOG W)}: LONGEST COMMON SUBSEQUENCE, EDIT DISTANCE, DYNAMIC TIME WARPING, ETC.

A type of reachability question. Proof encodes a Savitch-like construction into the LCS/Edit distance instance.



BP: edge-labelled, directed, layered graph. Start node s, accept node t.
Width: W nodes per layer. Size: T layers.
Each layer labeled with a variable. A variable can label many layers.
Each edge labeled with 0 or 1.
An input 001 is accepted if it generates an s-t path.

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Longest Common Subsequence, Edit Distance, Dynamic Time Warping, etc.

[Barrington'85]: BPs with T=2 polylog n and W=5 capture NC. The above problems require N^{2-o(1)} time under NC-SETH.

Impressive SAT algs

BPs with T=2^{o(sqrt n)} and W=2^{o(sqrt n)} can represent any nondeterministic Turing machine using o(sqrt n) space

- Edit Distance (or LCS etc) in O(n^{2-ε}) time implies a nontrivial improvement over exhaustive search for checking SAT of complex objects that can easily implement e.g. cryptographic primitives
- Much more surprising than refuting SETH!

Circuit Lower Bounds

If Edit Distance (or LCS etc) has $O(n^{2-\epsilon})$ time algorithms for any $\epsilon > 0$, then **E^{NP}** does not have:

- Non-uniform 2°(n)-size Boolean Formulas we don't even know if the enormous $\Sigma_2 \text{EXP}$ has 2°(n)-size depth-3 circuits
- Non-uniform o(n)-depth circuits of bouded fan-in
- Non-uniform 2^{o(sqrt(n))}-size non-deterministic branching programs

"A POLYLOG SHAVED IS A LOWER BOUND MADE"

[Williams'14, Abboud-Williams-Yu'15]: APSP can be solved in n³ / log^{ω(1)} n time, OV can be solved in n²/log^{ω(1)} n time

Does Edit Distance (or LCS etc) have such an algorithm? (The current best algorithms run in ~ n^2/log^2 n time.)

PARTIAL ANSWER: An n² / $\log^{\omega(1)}$ n algorithm for Edit Distance (or LCS etc) implies that E^{NP} is not in NC1.

n²/log^{2.1} n?

Also meaningful for particular polylogs. E.g. if Edit Distance (or LCS etc) has an $n^2/log^{100} n$ time algorithm, then E^{NP} does not have non-uniform Boolean formulas of size n^5 .

Thank you!