Algorithms

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6.5 Reductions

- introduction
- designing algorithms
- establishing lower bounds
- classifying problems
- intractability

Overview: introduction to advanced topics

Main topics. [next 2 lectures]

- Reduction: design algorithms, establish lower bounds, classify problems.
- Intractability: problems beyond our reach.
- Combinatorial search: coping with intractability.

Shifting gears.

- From individual problems to problem-solving models.
- From linear/quadratic to polynomial/exponential scale.
- From details of implementation to conceptual framework.

Goals.

- Place algorithms we've studied in a larger context.
- Introduce you to important and essential ideas.
- Inspire you to learn more about algorithms!

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6.5 Reductions

- introduction
- designing algorithms
- establishing lower bounds
- classifying problems
- intractability

Bird's-eye view

Desiderata. Classify problems according to computational requirements.

complexity	order of growth	examples
linear	N	min, max, median, Burrows-Wheeler transform, ...
linearithmic	$N \log N$	sorting, element distinctness, convex hull, closest pair, ...
quadratic	N^2	?
⋮	⋮	⋮
exponential	c^N	?

Frustrating news. Huge number of problems have defied classification.

Bird's-eye view

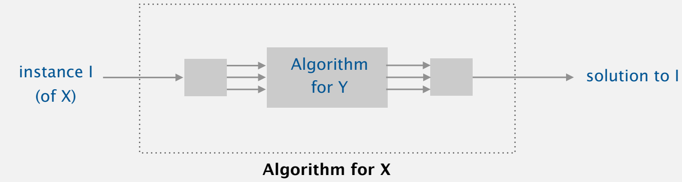
Desiderata. Classify problems according to computational requirements.

Desiderata'.
Suppose we could (could not) solve problem X efficiently.
What else could (could not) we solve efficiently?

> *" Give me a lever long enough and a fulcrum on which to place it, and I shall move the world. "* — *Archimedes*

Reduction

Def. Problem X reduces to problem Y if you can use an algorithm that solves Y to help solve X.



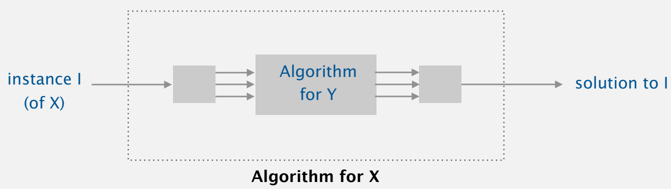
Cost of solving X = total cost of solving Y + cost of reduction.

perhaps many calls to Y on problems of different sizes

preprocessing and postprocessing

Reduction

Def. Problem X reduces to problem Y if you can use an algorithm that solves Y to help solve X.

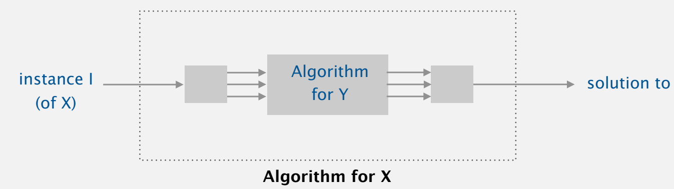


Ex 1. [finding the median reduces to sorting]
To find the median of N items:
- Sort N items.
- Return item in the middle.

Cost of solving finding the median. $\underbrace{N \log N}_{\text{cost of sorting}} + \underbrace{1}_{\text{cost of reduction}}$.

Reduction

Def. Problem X reduces to problem Y if you can use an algorithm that solves Y to help solve X.



Ex 2. [element distinctness reduces to sorting]
To solve element distinctness on N items:
- Sort N items.
- Check adjacent pairs for equality.

Cost of solving element distinctness. $\underbrace{N \log N}_{\text{cost of sorting}} + \underbrace{N}_{\text{cost of reduction}}$.

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6.5 Reductions

Reduction: design algorithms

Def. Problem X reduces to problem Y if you can use an algorithm that solves Y to help solve X.

Design algorithm. Given algorithm for Y, can also solve X.

More familiar reduction examples.

- 3-collinear reduces to sorting.
- CPM reduces to topological sort.
- Arbitrage reduces to shortest paths.
- Baseball elimination reduces to maxflow.
- Burrows-Wheeler transform reduces to suffix sort.
- …

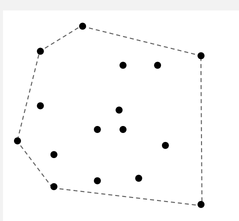
Mentality. Since I know how to solve Y, can I use that algorithm to solve X?

programmer's version: I have code for Y. Can I use it for X?

Convex hull reduces to sorting

Sorting. Given N distinct integers, rearrange them in ascending order.

Convex hull. Given N points in the plane, identify the extreme points of the convex hull (in counterclockwise order).



convex hull

1251432
2861534
3988818
8111033
13546464
89885444
43434213
34435312

sorting

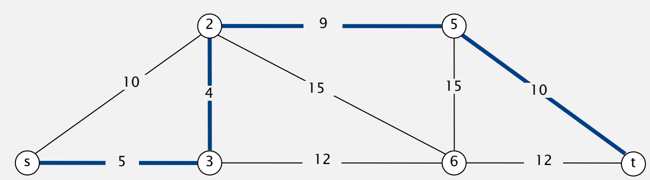
Proposition. Convex hull reduces to sorting.
Pf. Graham scan algorithm.

Cost of convex hull. $N \log N + N$.

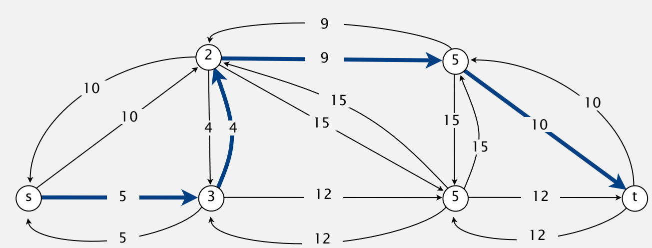
cost of sorting
cost of reduction

Shortest paths on edge-weighted graphs and digraphs

Proposition. Undirected shortest paths (with nonnegative weights) reduces to directed shortest path.

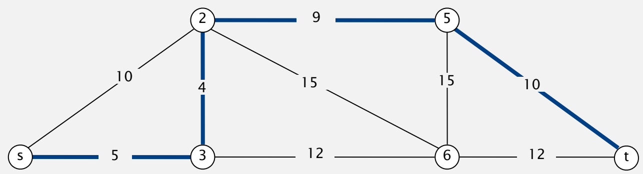


Pf. Replace each undirected edge by two directed edges.



Shortest paths on edge-weighted graphs and digraphs

Proposition. Undirected shortest paths (with nonnegative weights) reduces to directed shortest path.



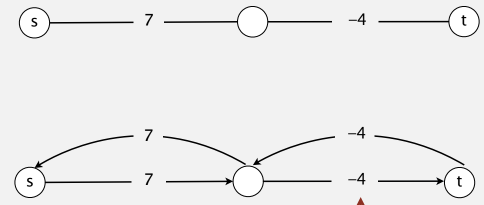
cost of shortest paths in digraph

cost of reduction

Cost of undirected shortest paths. $E \log V + E$.

Shortest paths with negative weights

Caveat. Reduction is invalid for edge-weighted graphs with negative weights (even if no negative cycles).



reduction creates negative cycles

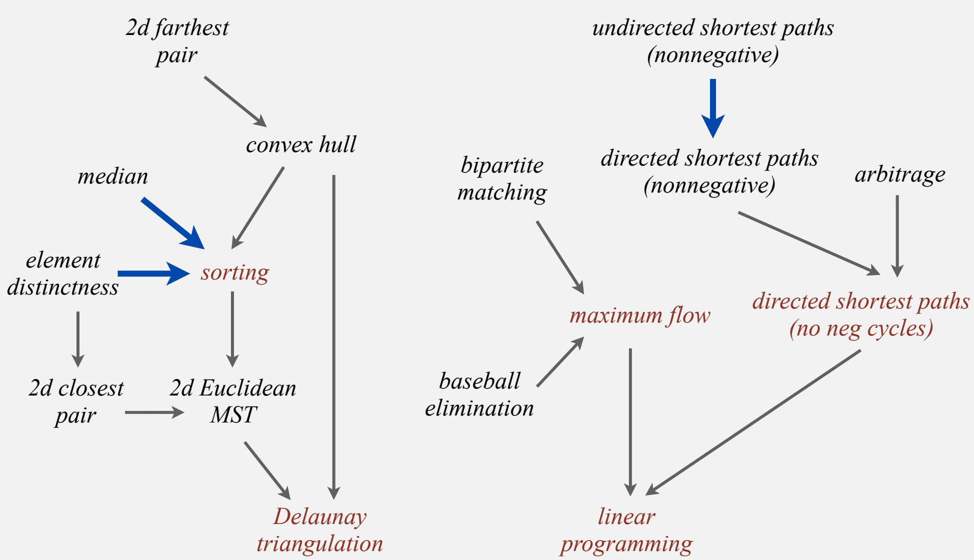
Remark. Can still solve shortest-paths problem in undirected graphs (if no negative cycles), but need more sophisticated techniques.

reduces to weighted non-bipartite matching (!)

Some reductions involving familiar problems

computational geometry

combinatorial optimization



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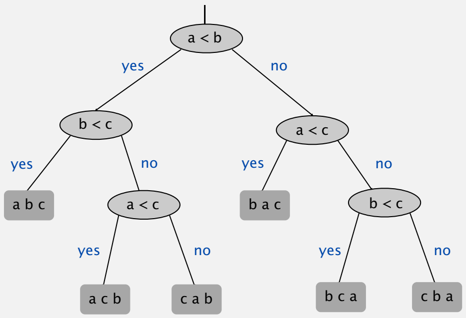
6.5 Reductions

- *introduction*
- *designing algorithms*
- *establishing lower bounds*
- *classifying problems*
- *intractability*

Bird's-eye view

Goal. Prove that a problem requires a certain number of steps.
Ex. In decision tree model, any compare-based sorting algorithm requires $\Omega(N \log N)$ compares in the worst case.



argument must apply to all conceivable algorithms

Bad news. Very difficult to establish lower bounds from scratch.
Good news. Spread $\Omega(N \log N)$ lower bound to Y by reducing sorting to Y.

assuming cost of reduction is not too high

Linear-time reductions

Def. Problem X linear-time reduces to problem Y if X can be solved with:
- Linear number of standard computational steps.
- Constant number of calls to Y.

Ex. Almost all of the reductions we've seen so far. [Which ones weren't?]

Establish lower bound:
- If X takes $\Omega(N \log N)$ steps, then so does Y.
- If X takes $\Omega(N^2)$ steps, then so does Y.

Mentality.
- If I could easily solve Y, then I could easily solve X.
- I can't easily solve X.
- Therefore, I can't easily solve Y.

Lower bound for convex hull

Proposition. In quadratic decision tree model, any algorithm for sorting N integers requires $\Omega(N \log N)$ steps.

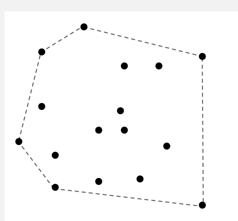
allows linear or quadratic tests:
$x_i < x_j$ or $(x_j - x_i)(x_k - x_l) - (x_j)(x_j - x_i) < 0$

Proposition. Sorting linear-time reduces to convex hull.
Pf. [see next slide]

lower-bound mentality:
I can't sort in linear time,
so I can't solve convex hull
in linear time either

1251432
2861534
3988818
4190745
8111033
13546464
89885444
43434213
34435312

sorting



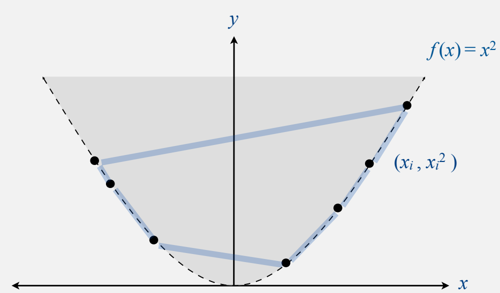
convex hull

linear or quadratic tests

Implication. Any ccw-based convex hull algorithm requires $\Omega(N \log N)$ ops.

Sorting linear-time reduces to convex hull

Proposition. Sorting linear-time reduces to convex hull.
- Sorting instance: $x_1, x_2, \ldots, x_N$.
- Convex hull instance: $(x_1, x_1^2), (x_2, x_2^2), \ldots, (x_N, x_N^2)$.



Pf.
- Region $\{ x : x^2 \geq x \}$ is convex $\Rightarrow$ all N points are on hull.
- Starting at point with most negative x, counterclockwise order of hull points yields integers in ascending order.

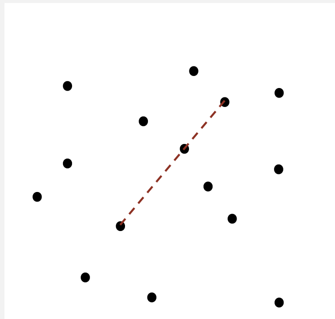
Lower bound for 3-COLLINEAR

3-SUM. Given N distinct integers, are there three that sum to 0?

3-COLLINEAR. Given N distinct points in the plane, are there 3 that all lie on the same line?

```
590584
-23439854
1251432
-2861534
3988818
-4190745
333255
13546464
89885444
-43434213
11998833
```

3-sum



3-collinear

Lower bound for 3-COLLINEAR

3-SUM. Given N distinct integers, are there three that sum to 0?

3-COLLINEAR. Given N distinct points in the plane, are there 3 that all lie on the same line?

Proposition. *3-SUM* linear-time reduces to *3-COLLINEAR*.
Pf. [next two slides]

lower-bound mentality: if I can't solve 3-sum in $N^{1.99}$ time, I can't solve 3-collinear in $N^{1.99}$ time either

Conjecture. Any algorithm for *3-SUM* requires $\Omega(N^2)$ steps.
Implication. No sub-quadratic algorithm for *3-COLLINEAR* likely.

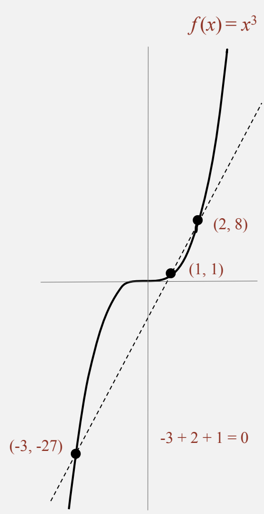
your $N^2 \log N$ algorithm was pretty good

3-SUM linear-time reduces to 3-COLLINEAR

Proposition. *3-SUM* linear-time reduces to *3-COLLINEAR*.

- *3-SUM* instance: $x_1, x_2, \ldots, x_N$.
- *3-COLLINEAR* instance: $(x_1, x_1^3), (x_2, x_2^3), \ldots, (x_N, x_N^3)$.

Lemma. If $a, b,$ and c are distinct, then $a + b + c = 0$ if and only if $(a, a^3), (b, b^3)$, and (c, c^3) are collinear.



3-SUM linear-time reduces to 3-COLLINEAR

Proposition. *3-SUM* linear-time reduces to *3-COLLINEAR*.

- *3-SUM* instance: $x_1, x_2, \ldots, x_N$.
- *3-COLLINEAR* instance: $(x_1, x_1^3), (x_2, x_2^3), \ldots, (x_N, x_N^3)$.

Lemma. If $a, b,$ and c are distinct, then $a + b + c = 0$ if and only if $(a, a^3), (b, b^3)$, and (c, c^3) are collinear.

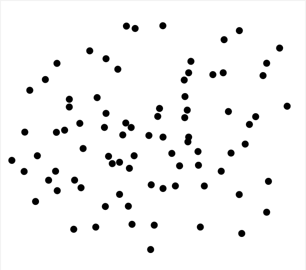
Pf. Three distinct points $(a, a^3), (b, b^3)$, and (c, c^3) are collinear iff:

$$\begin{aligned} 0 &= \begin{vmatrix} a & a^3 & 1 \\ b & b^3 & 1 \\ c & c^3 & 1 \end{vmatrix} \\ &= a(b^3 - c^3) - b(a^3 - c^3) + c(a^3 - b^3) \\ &= (a-b)(b-c)(c-a)(a+b+c) \end{aligned}$$

Establishing lower bounds: summary

Establishing lower bounds through reduction is an important tool in guiding algorithm design efforts.

Q. How to convince yourself no linear-time convex hull algorithm exists?
A1. [hard way] Long futile search for a linear-time algorithm.
A2. [easy way] Linear-time reduction from sorting.



convex hull

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6.5 Reductions

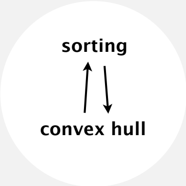
Classifying problems: summary

Desiderata. Problem with algorithm that matches lower bound.
Ex. Sorting and convex hull have complexity $N \log N$.

Desiderata'. Prove that two problems X and Y have the same complexity.

- First, show that problem X linear-time reduces to Y.
- Second, show that Y linear-time reduces to X.
- Conclude that X and Y have the same complexity.

even if we don't know what it is!



Integer arithmetic reductions

Integer multiplication. Given two N-bit integers, compute their product.
Brute force. N^2 bit operations.

								1	1	0	1	0	1	0	1
							×	0	1	1	1	1	1	0	1
								1	1	0	1	0	1	0	1
							0	0	0	0	0	0	0	0	
						1	1	0	1	0	1	0	1		
					1	1	0	1	0	1	0	1			
				1	1	0	1	0	1	0	1				
			1	1	0	1	0	1	0	1					
		1	1	0	1	0	1	0	1						
	0	0	0	0	0	0	0	0							
0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1

Integer arithmetic reductions

Integer multiplication. Given two N-bit integers, compute their product.
Brute force. N^2 bit operations.

problem	arithmetic	order of growth
integer multiplication	$a \times b$	M(N)
integer division	a / b, $a \bmod b$	M(N)
integer square	a^2	M(N)
integer square root	$\lfloor \sqrt{a} \rfloor$	M(N)

integer arithmetic problems with the same complexity as integer multiplication

Q. Is brute-force algorithm optimal?

History of complexity of integer multiplication

year	algorithm	order of growth
?	brute force	N^2
1962	Karatsuba	$N^{1.585}$
1963	Toom-3, Toom-4	$N^{1.465}$, $N^{1.404}$
1966	Toom-Cook	$N^{1+\varepsilon}$
1971	Schönhage–Strassen	$N \log N \log \log N$
2007	Fürer	$N \log N \, 2^{\log^* N}$
?	?	N

number of bit operations to multiply two N-bit integers

used in Maple, Mathematica, gcc, cryptography, ...

Remark. GNU Multiple Precision Library uses one of five different algorithm depending on size of operands.

GMP
«Arithmetic without limitations»

Linear algebra reductions

Matrix multiplication. Given two N-by-N matrices, compute their product.
Brute force. N^3 flops.

$$\begin{array}{c}\\ \\ \text{row } i\\ \\ \\ \end{array}\begin{bmatrix} 0.1 & 0.2 & 0.8 & 0.1 \\ 0.5 & 0.3 & 0.9 & 0.6 \\ 0.1 & 0.0 & 0.7 & 0.4 \\ 0.0 & 0.3 & 0.3 & 0.1 \end{bmatrix} \times \begin{array}{c} \text{column } j \\ \begin{bmatrix} 0.4 & 0.3 & 0.1 & 0.1 \\ 0.2 & 0.2 & 0.0 & 0.6 \\ 0.0 & 0.0 & 0.4 & 0.5 \\ 0.8 & 0.4 & 0.1 & 0.9 \end{bmatrix}\end{array} = \begin{array}{c}\\ \\ i\\ \\ \\ \end{array}\begin{array}{c} j \\ \begin{bmatrix} 0.16 & 0.11 & 0.34 & 0.62 \\ 0.74 & 0.45 & 0.47 & 1.22 \\ 0.36 & 0.19 & 0.33 & 0.72 \\ 0.14 & 0.10 & 0.13 & 0.42 \end{bmatrix}\end{array}$$

$0.5 \cdot 0.1 + 0.3 \cdot 0.0 + 0.9 \cdot 0.4 + 0.6 \cdot 0.1 = 0.47$

Linear algebra reductions

Matrix multiplication. Given two N-by-N matrices, compute their product.
Brute force. N^3 flops.

problem	linear algebra	order of growth
matrix multiplication	$A \times B$	MM(N)
matrix inversion	A^{-1}	MM(N)
determinant	$\lvert A \rvert$	MM(N)
system of linear equations	$Ax = b$	MM(N)
LU decomposition	$A = LU$	MM(N)
least squares	$\min \lVert Ax - b \rVert_2$	MM(N)

numerical linear algebra problems with the same complexity as matrix multiplication

Q. Is brute-force algorithm optimal?

History of complexity of matrix multiplication

year	algorithm	order of growth
?	brute force	N^{3}
1969	Strassen	$N^{2.808}$
1978	Pan	$N^{2.796}$
1979	Bini	$N^{2.780}$
1981	Schönhage	$N^{2.522}$
1982	Romani	$N^{2.517}$
1982	Coppersmith-Winograd	$N^{2.496}$
1986	Strassen	$N^{2.479}$
1989	Coppersmith-Winograd	$N^{2.376}$
2010	Strother	$N^{2.3737}$
2011	Williams	$N^{2.3727}$
?	?	$N^{2+\varepsilon}$

number of floating-point operations to multiply two N-by-N matrices

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6.5 Reductions

Bird's-eye view

Def. A problem is intractable if it can't be solved in polynomial time.

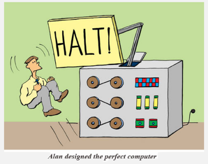
Desiderata. Prove that a problem is intractable.

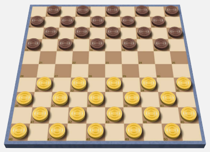
input size = c + lg K

Two problems that provably require exponential time.

- Given a constant-size program, does it halt in at most K steps?
- Given N-by-N checkers board position, can the first player force a win?

using forced capture rule





Frustrating news. Very few successes.

A key problem: satisfiability

SAT. Given a system of boolean equations, find a solution.

Ex.

$$
\begin{aligned}
\neg x_1 \text{ or } x_2 \text{ or } x_3 &= \text{true} \\
x_1 \text{ or } \neg x_2 \text{ or } x_3 &= \text{true} \\
\neg x_1 \text{ or } \neg x_2 \text{ or } \neg x_3 &= \text{true} \\
\neg x_1 \text{ or } \neg x_2 \text{ or } x_4 &= \text{true} \\
x'_2 \text{ or } x_3 \text{ or } x_4 &= \text{true}
\end{aligned}
$$

x_1	x_2	x_3	x_4
T	T	F	T

3-SAT. All equations of this form (with three variables per equation).

Key applications.

- Automatic verification systems for software.
- Mean field diluted spin glass model in physics.
- Electronic design automation (EDA) for hardware.
- ...

Satisfiability is conjectured to be intractable

Q. How to solve an instance of *3-SAT* with n variables?
A. Exhaustive search: try all 2^n truth assignments.

Q. Can we do anything substantially more clever?

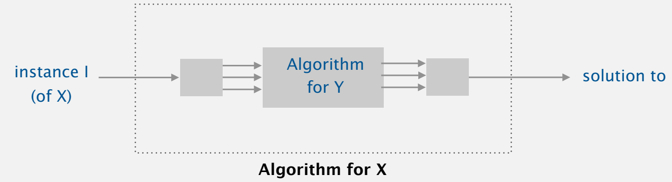
Conjecture (P ≠ NP). *3-SAT* is intractable (no poly-time algorithm).

consensus opinion

Polynomial-time reductions

Problem X poly-time (Cook) reduces to problem Y if X can be solved with:

- Polynomial number of standard computational steps.
- Polynomial number of calls to Y.



Establish intractability. If *3-SAT* poly-time reduces to Y, then Y is intractable.
(assuming *3-SAT* is intractable)

Mentality.

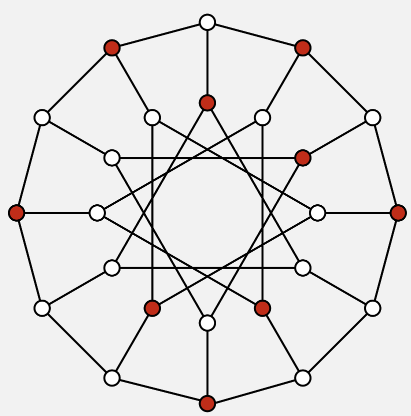
- If I could solve Y in poly-time, then I could also solve *3-SAT* in poly-time.
- *3-SAT* is believed to be intractable.
- Therefore, so is Y.

Independent set

An independent set is a set of vertices, no two of which are adjacent.

IND-SET. Given graph G and an integer k, find an independent set of size k.

k = 9



Applications. Scheduling, computer vision, clustering, ...

3-satisfiability reduces to independent set

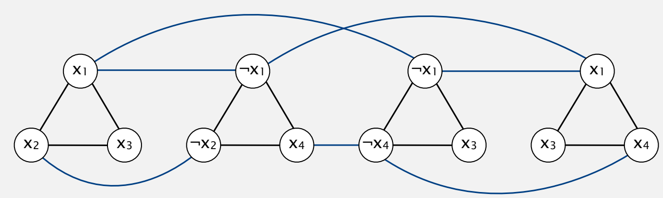
Proposition. *3-SAT* poly-time reduces to *IND-SET*.

lower-bound mentality:
if I could solve IND-SET efficiently,
I could solve 3-SAT efficiently

Pf. Given an instance Φ of *3-SAT*, create an instance G of *IND-SET*:

- For each clause in Φ, create 3 vertices in a triangle.
- Add an edge between each literal and its negation.

k = 4



$$\Phi = (x_1 \text{ or } x_2 \text{ or } x_3) \text{ and } (\neg x_1 \text{ or } \neg x_2 \text{ or } x_4) \text{ and } (\neg x_1 \text{ or } x_3 \text{ or } \neg x_4) \text{ and } (x_1 \text{ or } x_3 \text{ or } x_4)$$

3-satisfiability reduces to independent set

Proposition. *3-SAT* poly-time reduces to *IND-SET*.

Pf. Given an instance Φ of *3-SAT*, create an instance G of *IND-SET*:

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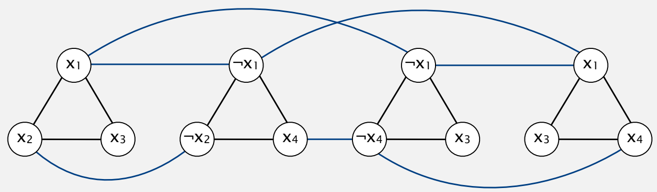


$$\Phi = (x_1 \text{ or } x_2 \text{ or } x_3) \text{ and } (\neg x_1 \text{ or } \neg x_2 \text{ or } x_4) \text{ and } (\neg x_1 \text{ or } x_3 \text{ or } \neg x_4) \text{ and } (x_1 \text{ or } x_3 \text{ or } x_4)$$

- Φ satisfiable $\Rightarrow$ G has independent set of size k.

for each of k clauses, include in independent set one vertex corresponding to a true literal

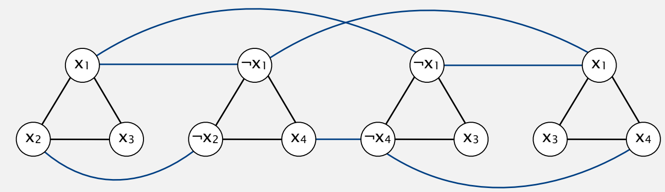
3-satisfiability reduces to independent set

Proposition. *3-SAT* poly-time reduces to *IND-SET*.

Pf. Given an instance Φ of *3-SAT*, create an instance G of *IND-SET*:

- For each clause in Φ, create 3 vertices in a triangle.
- Add an edge between each literal and its negation.

k = 4



$$\Phi = (x_1 \text{ or } x_2 \text{ or } x_3) \text{ and } (\neg x_1 \text{ or } \neg x_2 \text{ or } x_4) \text{ and } (\neg x_1 \text{ or } x_3 \text{ or } \neg x_4) \text{ and } (x_1 \text{ or } x_3 \text{ or } x_4)$$

- Φ satisfiable $\Rightarrow$ G has independent set of size k.
- G has independent set of size k $\Rightarrow$ Φ satisfiable.

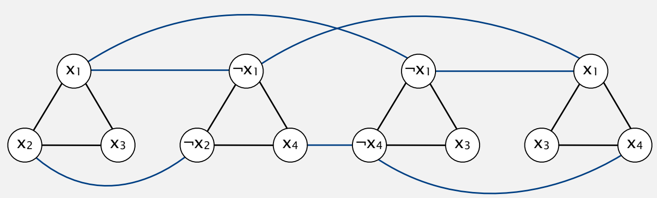
set literals corresponding to k vertices in independent set to true
(set remaining literals in any consistent manner)

3-satisfiability reduces to independent set

Proposition. *3-SAT* poly-time reduces to *IND-SET*.

Implication. Assuming *3-SAT* is intractable, so is *IND-SET*.

k = 4



$$\Phi = (x_1 \text{ or } x_2 \text{ or } x_3) \text{ and } (\neg x_1 \text{ or } \neg x_2 \text{ or } x_4) \text{ and } (\neg x_1 \text{ or } x_3 \text{ or } \neg x_4) \text{ and } (x_1 \text{ or } x_3 \text{ or } x_4)$$

Integer linear programming

ILP. Given a system of linear inequalities, find an integral solution.

$$3x_1 + 5x_2 + 2x_3 + x_4 + 4x_5 \geq 10$$
$$5x_1 + 2x_2 + 4x_4 + 1x_5 \leq 7$$
$$x_1 + x_3 + 2x_4 \leq 2$$
$$3x_1 + 4x_3 + 7x_4 \leq 7$$
$$x_1 + x_4 \leq 1$$
$$x_1 + x_3 + x_5 \leq 1$$
$$\text{all } x_i = \{ 0, 1 \}$$

linear inequalities

integer variables

yes instance:

x_1	x_2	x_3	x_4	x_5
0	1	0	1	1

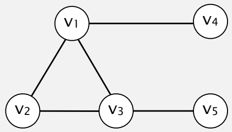
Context. Cornerstone problem in operations research.

Remark. Finding a real-valued solution is tractable (linear programming).

Independent set reduces to integer linear programming

Proposition. *IND-SET* poly-time reduces to *ILP*.

Pf. Given instance $\{ G, k \}$ of *IND-SET*, create an instance of *ILP* as follows:



is there an independent set of size 3?

$$x_1 + x_2 + x_3 + x_4 + x_5 \;=\; 3$$

number of vertices selected

$$x_1 + x_2 \le 1$$
$$x_2 + x_3 \le 1$$
$$x_1 + x_3 \le 1$$
$$x_1 + x_4 \le 1$$
$$x_3 + x_5 \le 1$$

at most one vertex selected from each edge

$$\text{all } x_i \;=\; \{ 0, 1 \}$$

binary variables

is there a feasible solution?

Intuition. $x_i = 1$ if and only if vertex v_i is in independent set.

3-satisfiability reduces to integer linear programming

Proposition. *3-SAT* poly-time reduces to *IND-SET*.

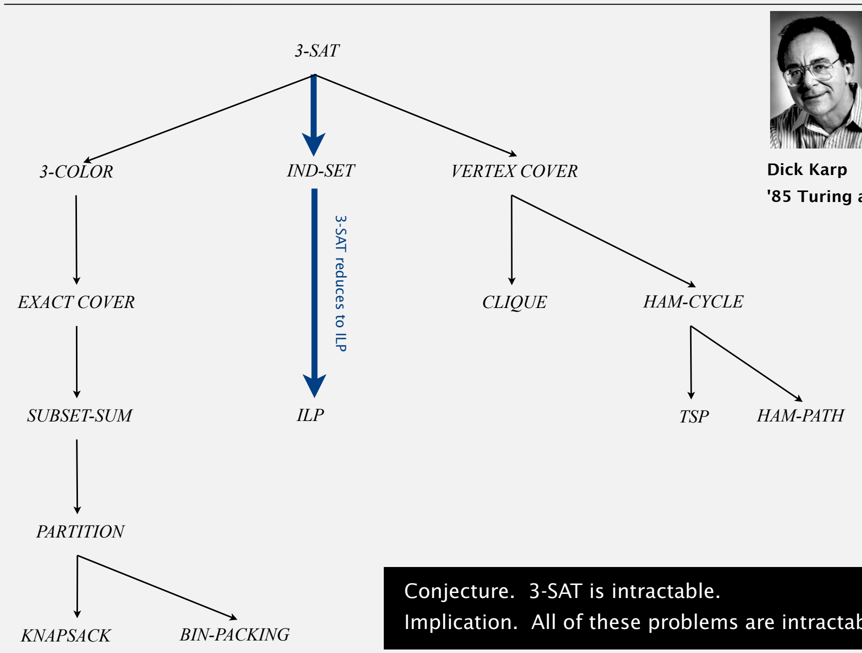
Proposition. *IND-SET* poly-time reduces to *ILP*.

Transitivity. If X poly-time reduces to Y and Y poly-time reduces to Z, then X poly-time reduces to Z.

Implication. Assuming *3-SAT* is intractable, so is *ILP*.

lower-bound mentality:
if I could solve ILP efficiently,
I could solve IND-SET efficiently;
if I could solve IND-SET efficiently,
I could solve 3-SAT efficiently

More poly-time reductions from 3-satisfiability



Dick Karp
'85 Turing award

Conjecture. 3-SAT is intractable.
Implication. All of these problems are intractable.

Implications of poly-time reductions from 3-satisfiability

Establishing intractability through poly-time reduction is an important tool in guiding algorithm design efforts.

Q. How to convince yourself that a new problem is (probably) intractable?

A1. [hard way] Long futile search for an efficient algorithm (as for *3-SAT*).

A2. [easy way] Reduction from *3-SAT*.

Caveat. Intricate reductions are common.

Search problems

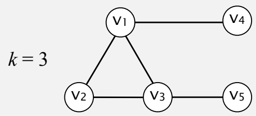
Search problem. Problem where you can check a solution in poly-time.

Ex 1. *3-SAT*.

$$\Phi = (x_1 \text{ or } x_2 \text{ or } x_3) \text{ and } (\neg x_1 \text{ or } \neg x_2 \text{ or } x_4) \text{ and } (\neg x_1 \text{ or } x_3 \text{ or } \neg x_4) \text{ and } (x_1 \text{ or } x_3 \text{ or } x_4)$$

x_1 = true, x_2 = true, x_3 = true, x_4 = true

Ex 2. *IND-SET*.



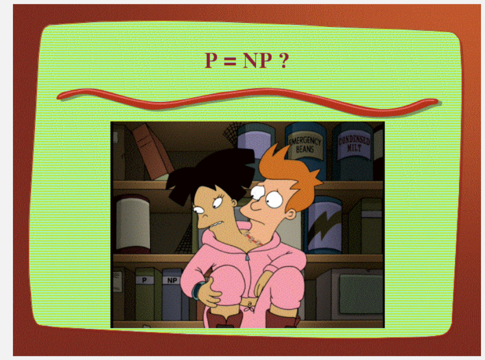
{ v_2 , v_4, v_5 }

P vs. NP

P. Set of search problems solvable in poly-time.
Importance. What scientists and engineers can compute feasibly.

NP. Set of search problems.
Importance. What scientists and engineers aspire to compute feasibly.

Fundamental question.



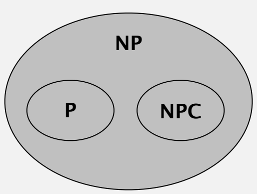
Consensus opinion. No.

Cook-Levin theorem

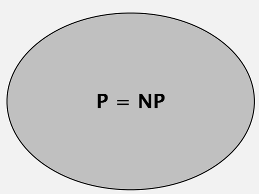
An NP problem is NP-COMPLETE if all problems in NP poly-time to reduce to it.

Cook-Levin theorem. *3-SAT* is NP-COMPLETE.
Corollary. *3-SAT* is tractable if and only if P = NP.

Two worlds.

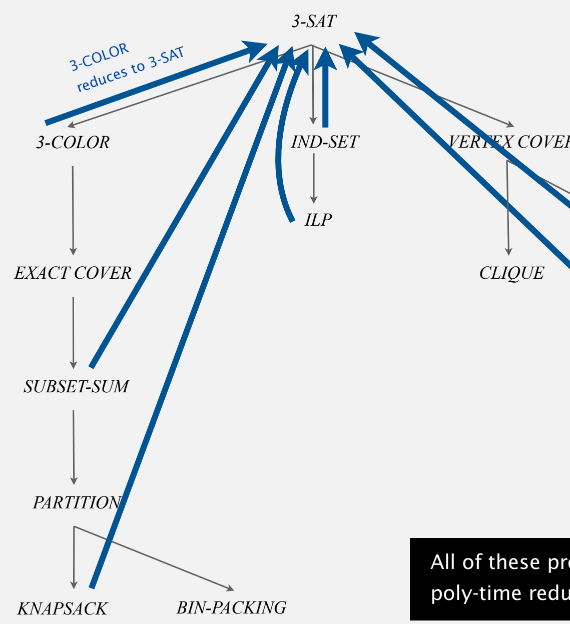


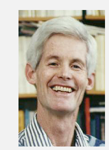
P ≠ NP



P = NP

Implications of Cook-Levin theorem



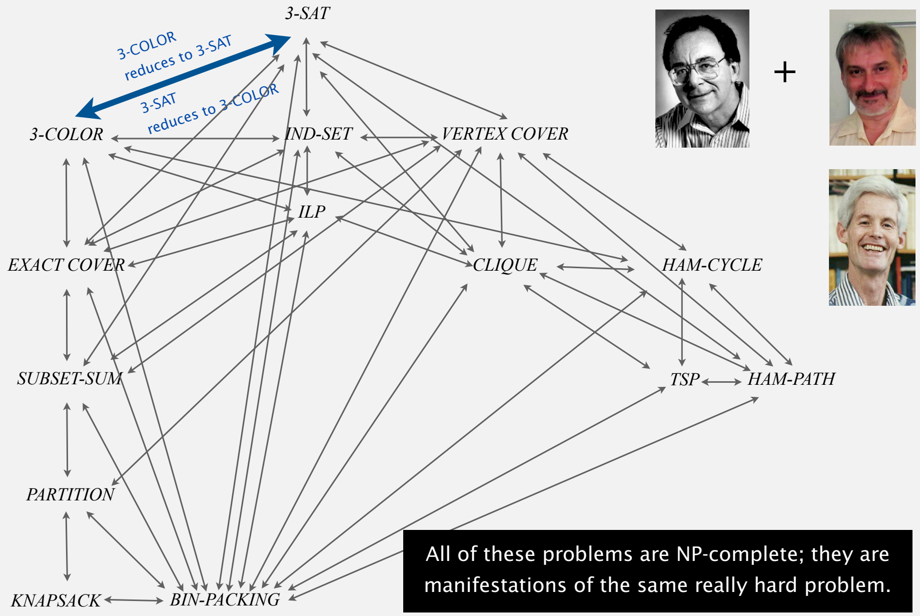


Stephen Cook
'82 Turing award

Leonid Levin

All of these problems (and many, many more) poly-time reduce to 3-SAT.

Implications of Karp + Cook-Levin



All of these problems are NP-complete; they are manifestations of the same really hard problem.

Birds-eye view: review

Desiderata. Classify problems according to computational requirements.

complexity	order of growth	examples
linear	N	min, max, median, Burrows-Wheeler transform, ...
linearithmic	N log N	sorting, element distinctness, convex hull, closest pair, ...
quadratic	N^2	?
⋮	⋮	⋮
exponential	c^N	?

Frustrating news. Huge number of problems have defied classification.

Birds-eye view: revised

Desiderata. Classify problems according to computational requirements.

complexity	order of growth	examples
linear	N	min, max, median,
linearithmic	N log N	sorting, convex hull,
M(N)	?	integer multiplication, division, square root, ...
MM(N)	?	matrix multiplication, Ax = b, least square, determinant, ...
⋮	⋮	⋮
NP-complete	probably not N^b	3-SAT, IND-SET, ILP, ...

Good news. Can put many problems into equivalence classes.

Complexity zoo

Complexity class. Set of problems sharing some computational property.

http://qwiki.stanford.edu/index.php/Complexity_Zoo

Bad news. Lots of complexity classes.

Summary

Reductions are important in theory to:

- Design algorithms.
- Establish lower bounds.
- Classify problems according to their computational requirements.

Reductions are important in practice to:

- Design algorithms.
- Design reusable software modules.
  - stacks, queues, priority queues, symbol tables, sets, graphs
  - sorting, regular expressions, suffix arrays
  - MST, shortest path, maxflow, linear programming
- Determine difficulty of your problem and choose the right tool.