

GEMS OF TCS

EXPONENTIAL-TIME ALGORITHMS

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EXACT ALGORITHMS

- We need to solve problem exactly

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- Problem takes exponential time solve exactly

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- We need to solve problem exactly
- Problem takes exponential time solve exactly
- Intelligent exhaustive search: finding optimal solution without going through all candidate solutions

RUNNING TIME

	<i>Streaming algs</i>	<i>poly time</i>	<i>Exp time</i>	
running time:	n	n^2	n^3	$n!$
less than 10^9 :	10^9	$10^{4.5}$	10^3	12
		<i>30k</i>		

RUNNING TIME

running time:	n	n^2	n^3	$n!$
less than 10^9 :	10^9	$10^{4.5}$	10^3	12

$$n! \approx 2^{n \log_2 n}$$

Exp-time algs

running time:	$n!$	4^n	2^n	1.308^n
less than 10^9 :	12	14	29	77



Lecture 1. Hand

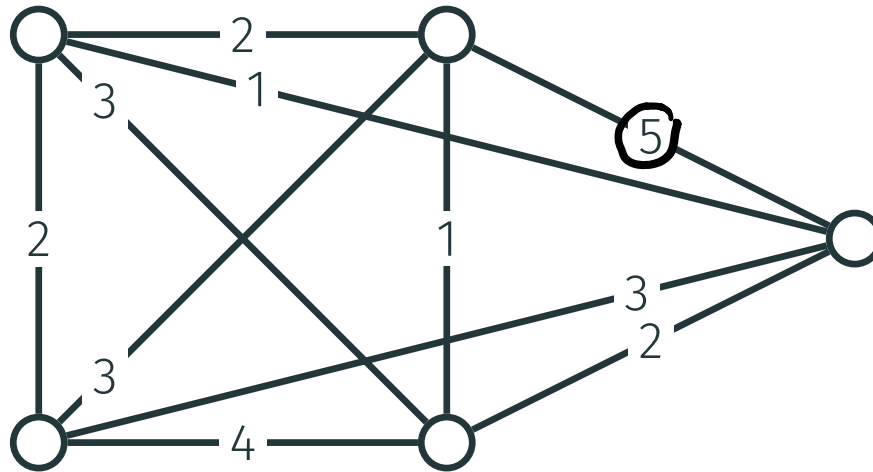
Lecture 2. Approximate soln in poly-time

Today. Exactly. Hand. How hard is it?

Traveling Salesman Problem (TSP)

TRAVELING SALESMAN PROBLEM

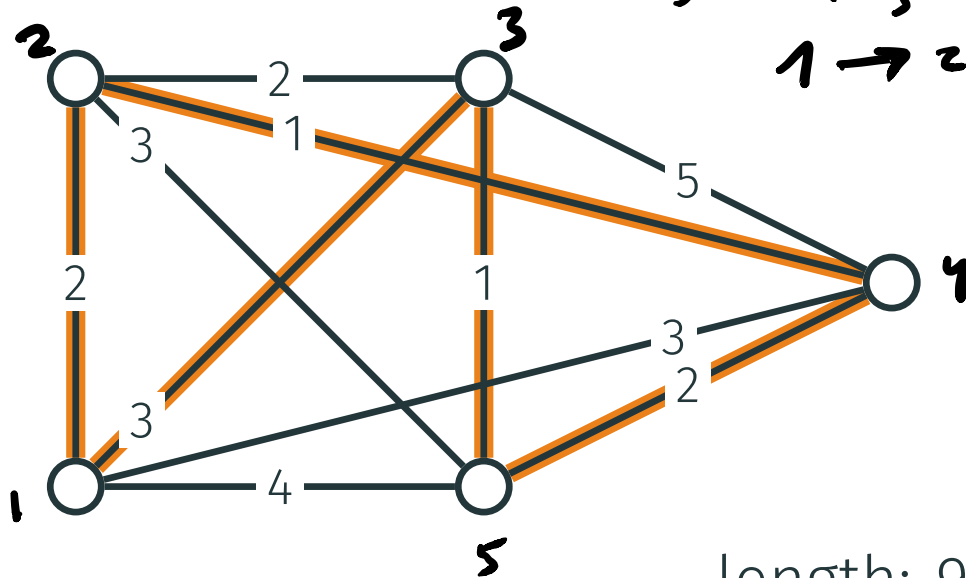
Given a complete weighted graph, find a cycle (or a path) of minimum total weight (length) visiting each node exactly once



length: 9

TRAVELING SALESMAN PROBLEM

Given a complete weighted graph, find a cycle (or a path) of minimum total weight (length) visiting each node exactly once



ALGORITHMS

- Classical optimization problem with countless number of real life applications (see Lecture 1)

ALGORITHMS

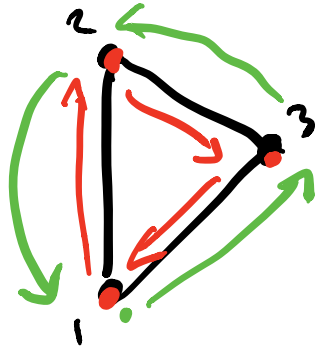
- Classical optimization problem with countless number of real life applications (see Lecture 1)
- No polynomial time algorithms known

ALGORITHMS

- Classical optimization problem with countless number of real life applications (see Lecture 1)
- No polynomial time algorithms known
- We'll see exact **exponential-time** algorithms

BRUTE FORCE SOLUTION

A naive algorithm just checks all possible $\sim \underline{\underline{n!}}$ cycles.



$n = 3$

1	2	3
1	3	2
2	1	3
2	3	1
3	1	2
3	2	1

BRUTE FORCE SOLUTION

A naive algorithm just checks all possible $\sim n!$ cycles.

$$n! \approx 2^{\frac{n \log_2 n}{1}} = e^{n \ln n}$$

We'll see

$$n! \approx n^n$$

- Use dynamic programming to solve TSP in $O(n^2 \cdot 2^n) \approx 2^n$

BRUTE FORCE SOLUTION

A naive algorithm just checks all possible $\sim n!$ cycles.

We'll see

- Use dynamic programming to solve TSP in $O(n^2 \cdot 2^n)$
- The running time is exponential, but is much better than $n!$

DYNAMIC PROGRAMMING

was invented for TSP

1962
*still remains
best known
for TSP*

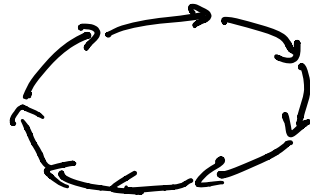
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DYNAMIC PROGRAMMING

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- Rough idea: express a solution for a problem through solutions for smaller subproblems

DYNAMIC PROGRAMMING

- Dynamic programming is one of the most powerful algorithmic techniques
- Rough idea: express a solution for a problem through solutions for smaller subproblems
- Solve subproblems one by one. Store solutions to subproblems in a table to avoid recomputing the same thing again

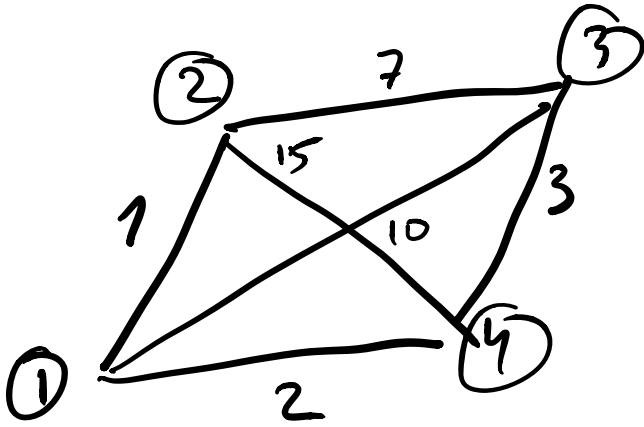


SUBPROBLEMS

Start at 1.
End at i

- For a subset of vertices $S \subseteq \{1, \dots, n\}$ containing the vertex 1 and a vertex $i \in S$, let $C(S, i)$ be the length of the shortest path that starts at 1, ends at i and visits all vertices from S exactly once





For any set $S \subseteq \{1, \dots, n\}$

For any vertex $i \in \{1, \dots, n\}$

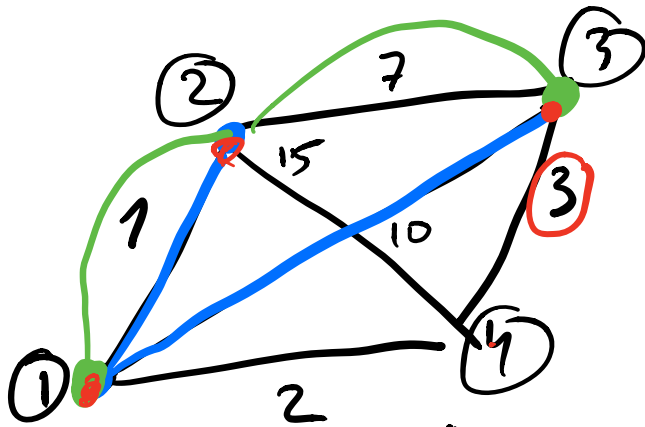
$C(S, i)$ = length of shortest path that.

1. Starts at 1

2. Ends at i

3. Visits every vertex

from S exactly once



$$C(\{1, 2\}, 2) = \underline{1}$$

$$C(\{1, 3\}, 3) = 10$$

$$C(\{1\}, 1) = 0$$

$$C(\{1, 2\}, 1) = +\infty$$

$$C(\{1, 2, 3\}, 1) = +\infty$$

$$C(\{1, 2, 3\}, 3) = 1 + 7 = 8$$

$$C(\{1, 2, 3\}, 2) = 10 + 7 = 17$$

$$C(\{1, 2, 3, 4\}, 4) = \min($$

$$C(\{1, 2, 3\}, 3) + 3,$$

$$C(\{1, 2, 3\}, 2) + 15).$$

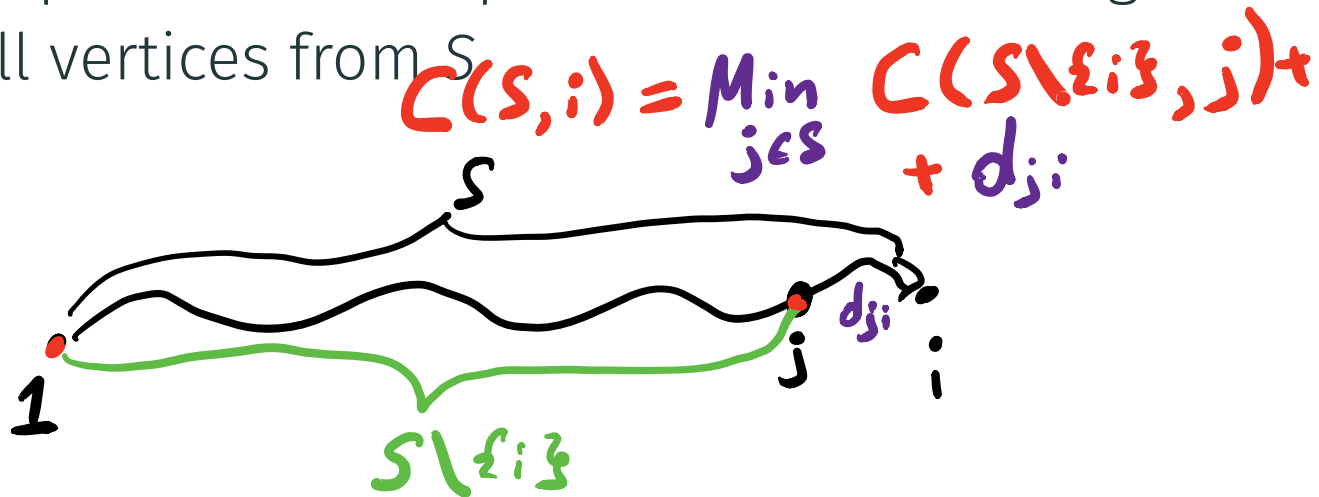
SUBPROBLEMS

- For a subset of vertices $S \subseteq \{1, \dots, n\}$ containing the vertex 1 and a vertex $i \in S$, let $C(S, i)$ be the length of the shortest path that starts at 1, ends at i and visits all vertices from S exactly once
- $C(\{1\}, 1) = 0$ and $C(S, 1) = +\infty$ when $|S| > 1$

$$C(S, i)$$

RECURRENCE RELATION

- Consider the second-to-last vertex j on the required shortest path from 1 to i visiting all vertices from S



subpath of shortest path is shortest

RECURRENCE RELATION

- Consider the second-to-last vertex j on the required shortest path from 1 to i visiting all vertices from S
- The subpath from 1 to j is the shortest one visiting all vertices from $S - \{i\}$ exactly once

RECURRENCE RELATION

- Consider the second-to-last vertex j on the required shortest path from 1 to i visiting all vertices from S
- The subpath from 1 to j is the shortest one visiting all vertices from $S - \{i\}$ exactly once
- Hence

$$C(\underline{S}, i) = \min_j \{C(S - \{i\}, \underline{j}) + \underline{d_{ji}}\}, \text{ where the minimum is over all } j \in S \text{ such that } j \neq i$$

ORDER OF SUBPROBLEMS

$$C(S, i)$$

- Need to process all subsets $S \subseteq \{1, \dots, n\}$ in an order that guarantees that when computing the value of $C(S, i)$, the values of $C(S - \{i\}, j)$ have already been computed

ORDER OF SUBPROBLEMS

- Need to process all subsets $S \subseteq \{1, \dots, n\}$ in an order that guarantees that when computing the value of $C(S, i)$, the values of $C(S - \{i\}, j)$ have already been computed
- For example, we can process subsets in order of increasing size

ALGORITHM

$$\underline{C(s, i)} \leftarrow +\infty$$

$$C(\{1\}, 1) \leftarrow 0$$

ALGORITHM

$C(*, *) \leftarrow +\infty$

$C(\{1\}, 1) \leftarrow 0$

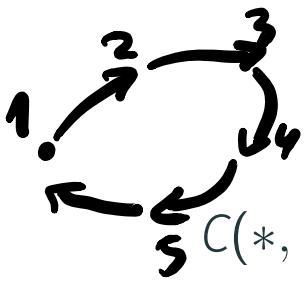
for s from 2 to n :

for all $1 \in \underline{S} \subseteq \{1, \dots, n\}$ of size s :

size of S : $s = |S|$

$C(S, i)$

ALGORITHM



$$C(*, *) \leftarrow +\infty$$

$$C(\{1\}, 1) \leftarrow 0$$

for s from 2 to n :

for all $1 \in S \subseteq \{1, \dots, n\}$ of size s :

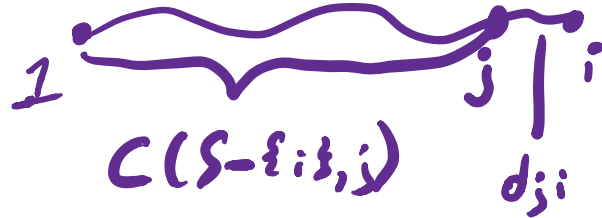
for all $i \in S, i \neq 1$:

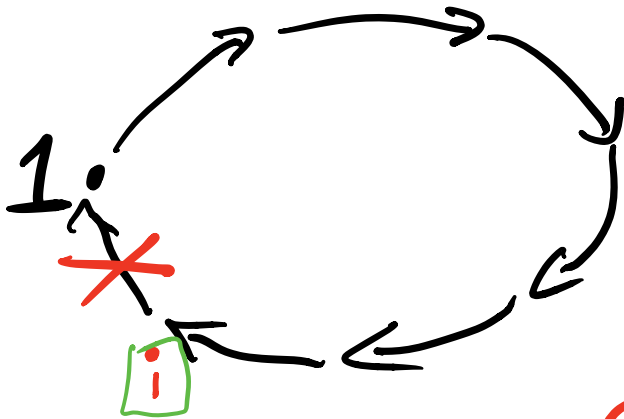
for all $j \in S, j \neq i$

$C(S, i)$ -

always $+1$

$$C(S, i) \leftarrow \min\{C(S, i), C(S - \{i\}, j) + d_{ji}\}$$





$$\text{length of cycle} = C(\{1, \dots, n\}, i) + d_{i,1}$$

length of shortest cycle =

$$= \min_i C(\{1, \dots, n\}, i) + d_{i,1}$$

ALGORITHM

$$C(*, *) \leftarrow +\infty$$

Run-time $\in 2^n \cdot n^3$

$$C(\{1\}, 1) \leftarrow 0$$

go over all subsets of $\{1, \dots, n\}$
 2^n

for s from 2 to n:

n

for all $1 \in \boxed{S} \subseteq \{1, \dots, n\}$ of size s: 2^n

for all i $\in S, i \neq 1$: n

for all j $\in S, j \neq i$ n

Run-time $\in 2^n \cdot n^2$

$$C(S, i) \leftarrow \min\{C(S, i), C(S - \{i\}, j) + d_{ji}\}$$

return $\min_i \{ \underbrace{C(\{1, \dots, n\}, i)}_{\text{shortest path}} + d_{i,1} \}$ shortest cycle

$\approx 2^n$

shortest path

Satisfiability Problem (SAT)

SAT

SAT

$$(X_1 \vee X_2 \vee X_3) \wedge (X_1 \vee \neg X_2) \wedge (\neg X_1 \vee X_3) \wedge (X_2 \vee \neg X_3)$$

$$(X_1 \vee X_2 \vee X_3) \wedge (X_1 \vee \neg X_2) \wedge (\neg X_1 \vee X_3) \wedge (X_2 \vee \neg X_3) \wedge (\neg X_1 \vee \neg X_2 \vee \neg X_3)$$

UNSAT

k -SAT

$$\begin{aligned} \phi(x_1, \dots, x_n) = & (x_1 \vee \neg x_2 \vee \dots \vee x_k) \wedge \\ & \dots \wedge \\ & (x_2 \vee \neg x_3 \vee \dots \vee x_8) \end{aligned}$$

k -SAT

$$\begin{aligned} \phi(x_1, \dots, x_n) = & (x_1 \vee \neg x_2 \vee \dots \vee x_k) \wedge \\ & \dots \wedge \\ & (x_2 \vee \neg x_3 \vee \dots \vee x_8) \end{aligned}$$

ϕ is **satisfiable** if

$$\exists x \in \{0, 1\}^n : \phi(x) = 1.$$

Otherwise, ϕ is **unsatisfiable**

k-SAT

$$\begin{aligned} \phi(x_1, \dots, x_n) = & (x_1 \vee \neg x_2 \vee \dots \vee \underline{x_k}) \wedge \\ & \dots \wedge \\ & (x_2 \vee \neg x_3 \vee \dots \vee x_8) \end{aligned}$$

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n Boolean vars, m clauses

k -SAT

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n Boolean vars, m clauses

k -SAT is SAT where clause length $\leq k$

k -SAT. EXAMPLES

3-SAT

$$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2) \wedge (\neg x_1 \vee x_3) \wedge (x_2 \vee \neg x_3)$$

k -SAT. EXAMPLES

$$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2) \wedge (\neg x_1 \vee x_3) \wedge (x_2 \vee \neg x_3)$$

1-SAT

$$(x_1) \wedge (\neg x_2) \wedge (x_3) \wedge (\neg x_1)$$

COMPLEXITY OF SAT

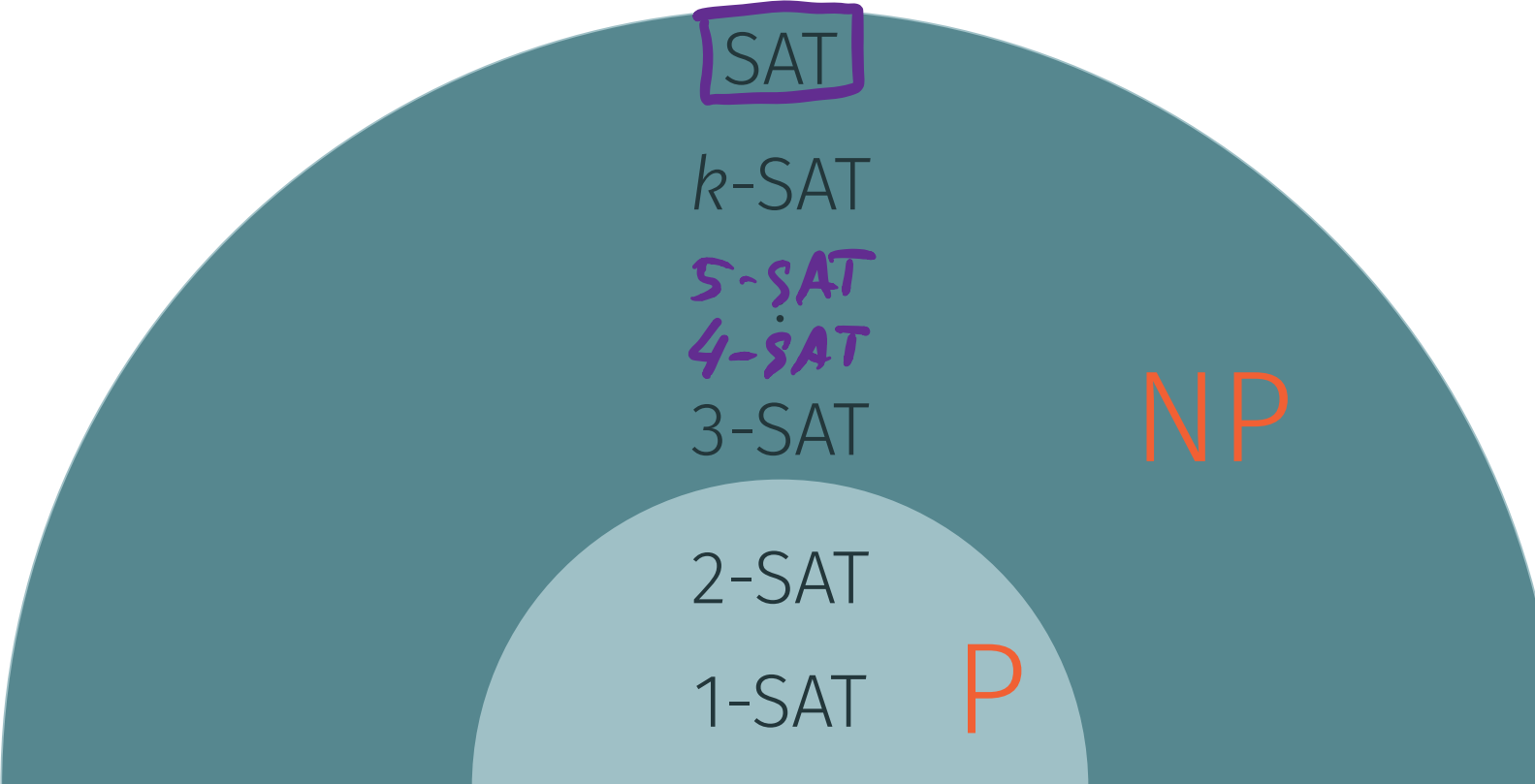
2-SAT

1-SAT

P



COMPLEXITY OF SAT



SAT

k-SAT

5-SAT

4-SAT

3-SAT

NP

2-SAT

1-SAT

P

But **how** hard is SAT?

SAT IN 2^n

- $O^*(\cdot)$ suppresses polynomial factors in the input length:

$$2^n n^{10} m^2 = O^*(2^n)$$

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- $O^*(\cdot)$ suppresses polynomial factors in the input length:

$$2^n n^{10} m^2 = O^*(2^n)$$

- SAT can be solved in time $O^*(2^n)$

$$x_1, \dots, x_n \in \{0, 1\}$$

— 2^n such assignments

For each assignment, in linear time check
assignment satisfies formula

SAT IN 2^n

- $O^*(\cdot)$ suppresses polynomial factors in the input length:

$$2^n n^{10} m^2 = O^*(2^n)$$

- SAT can be solved in time $O^*(2^n)$
- We don't know how to solve SAT exponentially faster: in time $O^*(1.999^n)$

Conjecture: every alg for SAT takes time $\geq 2^n$

3-SAT

- $(x_1 \vee x_2 \vee x_9) \wedge \dots \wedge (x_2 \vee \neg x_3 \vee x_8)$

3-SAT

- $(x_1 \vee x_2 \vee x_9) \wedge \dots \wedge (x_2 \vee \neg x_3 \vee x_8)$

x_1	x_2	x_3
0	0	0
0	0	1
0	1	0
0	1	1
1	0	0
1	0	1
1	1	0
1	1	1

Instead of checking $\{0,1\}^n$

can check only those
that don't have $x_1 = x_2 = x_3 = 0$

$2^n \cdot \frac{7}{8}$ assignments

can be extended

run-time $(7)^{n/3} \approx 1.92^n$

Case 1: $x_1 = 1$

Case 2: $x_1 = 0$ $x_2 = 1$

Case 3: $x_1 = 0$ $x_2 = 0$ $x_3 = 1$

3-SAT

• ~~$(x_1 \vee x_2 \vee x_9) \wedge \dots \wedge (x_2 \vee \neg x_3 \vee x_8)$~~

~~$(\neg x_1 \vee x_2 \vee x_5)$~~

• Consider three sub-problems:

- Case I:** $x_1 = 1$ Replace $x_i \rightarrow 1; \neg x_i \rightarrow 0$ 3-SAT($n-1$)
- Case II:** $x_1 = 0, x_2 = 1$ Replace $x_i \rightarrow 0; \neg x_i \rightarrow 1; x_2 \rightarrow 1; \neg x_2 \rightarrow 0$ 3-SAT($n-2$)
- Case III:** $x_1 = 0, x_2 = 0, x_9 = 1$ 3-SAT($n-3$)

3-SAT

- $(x_1 \vee x_2 \vee x_9) \wedge \dots \wedge (x_2 \vee \neg x_3 \vee x_8)$
- Consider three sub-problems:
 - $x_1 = 1$
 - $x_1 = 0, x_2 = 1$
 - $x_1 = 0, x_2 = 0, x_9 = 1$
- The original formula is SAT iff at least one of these formulas is SAT

3-SAT (Formula)

Pick a clause $(x \vee y \vee z)$

- 3-SAT (Formula $x=1$)
- 3-SAT (Formula $x=0 \ y=1$)
- 3-SAT (Formula $x=y=0 \ z=1$)

If one of these is TRUE,
Then RETURN TRUE

Else
Then RETURN FALSE

$T(n)$ - Run-time on formulas with n variables

$$T(n) \leq \underline{T(n-1)} + \underline{T(n-2)} + \underline{T(n-3)}$$

3-SAT. ANALYSIS

- $T(n) \leq T(n-1) + T(n-2) + T(n-3)$

Claim $T(n) \leq 1.85^n$

— Prove by induction on n

$$T(n-1) \leq 1.85^{n-1}$$

$$T(n-2) \leq 1.85^{n-2}$$

$$T(n-3) \leq 1.85^{n-3}$$

3-SAT. ANALYSIS

- $T(n) \leq T(n - 1) + T(n - 2) + T(n - 3)$
- $T(n) \leq 1.85^n$:

3-SAT. ANALYSIS

- $T(n) \leq T(n-1) + T(n-2) + T(n-3)$
- $T(n) \leq 1.85^n$:

$$\begin{aligned} T(n) &\leq T(n-1) + T(n-2) + T(n-3) \\ \text{ind hypothesis} &\leq \frac{1.85^{n-1}}{1} + \frac{1.85^{n-2}}{1} + \frac{1.85^{n-3}}{1} \\ &= \frac{1.85^n}{1.85} + \frac{1.85^n}{1.85^2} + \frac{1.85^n}{1.85^3} \\ &< \frac{1.85^n}{1} (0.999) \\ &< \frac{1.85^n}{1} \end{aligned}$$

$$T(n) \leq T(n-1) + T(n-2) + \dots + T(n-k)$$

\forall constant, k -SAT in $(2 - \epsilon_k)^n$
SAT in time 2^n

3-SAT. ANALYSIS

- $T(n) \leq T(n-1) + T(n-2) + T(n-3)$
- $T(n) \leq 1.85^n$:

$$\begin{aligned} T(n) &\leq T(n-1) + T(n-2) + T(n-3) \\ &\leq 1.85^{n-1} + 1.85^{n-2} + 1.85^{n-3} \\ &= 1.85^n \left(\frac{1}{1.85} + \frac{1}{1.85^2} + \frac{1}{1.85^3} \right) \\ &< 1.85^n (0.991) \\ &< 1.85^n \end{aligned}$$

- There are even faster algorithms: $\frac{1.308^n}{10^{-24}}$
[HKZZ19]

\uparrow
 10^{-24}

How hard can SAT be?

ALGORITHMIC COMPLEXITY OF SAT

2-SAT $O(m)$

1-SAT $O(m)$

ALGORITHMIC COMPLEXITY OF SAT

3-SAT 1.308^n

2-SAT $O(m)$

1-SAT $O(m)$

ALGORITHMIC COMPLEXITY OF SAT

k -SAT $2^{n(1-O(1/k))}$

⋮

3-SAT 1.308^n

2-SAT $O(m)$

1-SAT $O(m)$

ALGORITHMIC COMPLEXITY OF SAT

Conj

SAT 2^n

k -SAT $2^{n(1-O(1/k))}$

⋮

3-SAT 1.308^n

2-SAT $O(m)$

1-SAT $O(m)$