



Design and Analysis of Algorithms (XIV)

Various Problems

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Poly-Time Reductions

Algorithm design patterns and antipatterns

Algorithm design patterns.

Algorithm design patterns and antipatterns

Algorithm design patterns.

- Divide and conquer.
- Dynamic programming.
- Greedy.
- Duality.
- **Reductions.**
- Local search.
- Approximation.
- Randomization.

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No algorithm possible.

Classify problems according to computational requirements

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A **working definition**. Those with poly-time algorithms.



von Neumann
(1953)



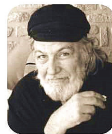
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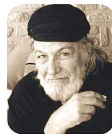
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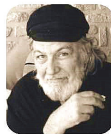
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Practice. Poly-time algorithms scale to huge problems.

Classify problems according to computational requirements

Q. Which problems will we be able to solve in practice?

A *working definition*. Those with poly-time algorithms.

yes	probably no
shortest path	longest path
min cut	max cut
2-satisfiability	3-satisfiability
planar 4-colorability	planar 3-colorability
bipartite vertex cover	vertex cover
2D-matching	3D-matching
primality testing	factoring
linear programming	integer linear programming

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Frustrating news. Huge number of fundamental problems have defied classification for decades.

Poly-time reductions

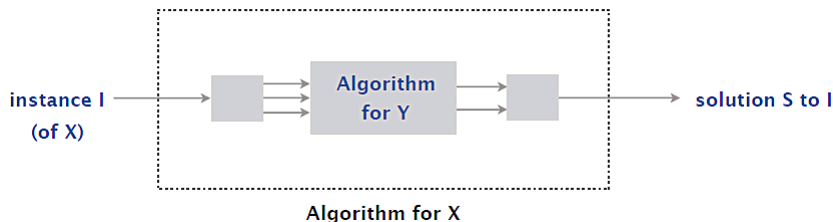
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Reduction. Problem X polynomial-time (Cook) reduces to problem Y if arbitrary instances of problem X can be solved using:

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Novice mistake. Confusing $X \leq_P Y$ with $Y \leq_P X$.

Suppose that $X \leq_P Y$. Which of the following can we infer?

- A. If X can be solved in polynomial time, then so can Y .
- B. X can be solved in poly time iff Y can be solved in poly time.
- C. If X cannot be solved in polynomial time, then neither can Y .
- D. If Y cannot be solved in polynomial time, then neither can X .

Which of the following poly-time reductions are known?

- A. $\text{FIND-MAX-FLOW} \leq_P \text{FIND-MIN-CUT}$.
- B. $\text{FIND-MIN-CUT} \leq_P \text{FIND-MAX-FLOW}$.
- C. Both A and B.
- D. Neither A nor B.

Poly-time reductions

Design algorithms. If $X \leq_P Y$ and Y can be solved in polynomial time, then X can be solved in polynomial time.

Poly-time reductions

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Establish intractability. If $X \leq_P Y$ and X cannot be solved in polynomial time, then Y cannot be solved in polynomial time.

Establish equivalence. If both $X \leq_P Y$ and $Y \leq_P X$, we use notation $X \equiv_P Y$. In this case, X can be solved in polynomial time iff Y can be.

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Bottom line. Reductions classify problems according to **relative** difficulty.

Packing and Covering Problems

Independent set

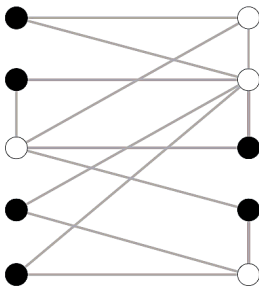
INDEPENDENT SET. Given a graph $G = (V, E)$ and an integer k , is there a subset of k (or more) vertices such that no two are adjacent?

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Example. Is there an independent set of size ≥ 6 ?

Example. Is there an independent set of size ≥ 7 ?



Vertex cover

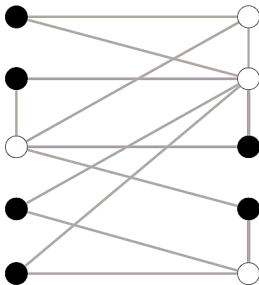
Vertex Cover. Given a graph $G = (V, E)$ and an integer k , is there a subset of k (or fewer) vertices such that each edge is incident to at least one vertex in the subset?

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Example. Is there a vertex cover of size ≤ 4 ?

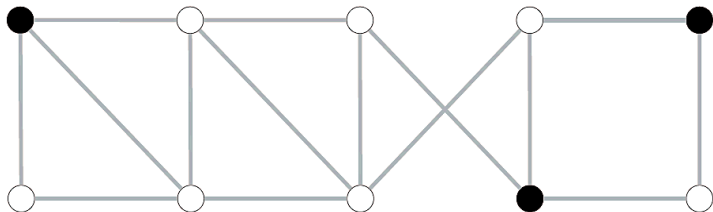
Example. Is there a vertex cover of size ≤ 3 ?



Quiz

Consider the following graph G . Which are true?

- A. The white vertices are a vertex cover of size 7.
- B. The black vertices are an independent set of size 3.
- C. Both A and B.
- D. Neither A nor B.



Vertex cover and independent set reduce to one another

Theorem

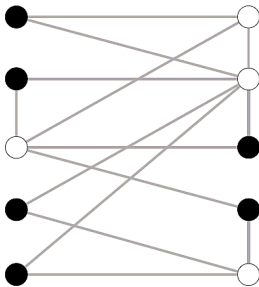
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Independent Set \equiv_P *Vertex Cover*.

Proof. We show S is an independent set of size k iff $V - S$ is a vertex cover of size $n - k$.



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- Let S be any independent set of size k .
- $V - S$ is of size $n - k$.
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S independent \Rightarrow either $u \notin S$, or $v \notin S$, or both.

\Rightarrow either $u \in V - S$, or $v \in V - S$, or both.

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- Thus, $V - S$ covers (u, v) .

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- Thus, S is an independent set.

CLIQUE. Given a graph $G = (V, E)$ and an integer k , is there a subset of k (or more) vertices such that each of two are adjacent?

Set cover

SET COVER. Given a set U of elements, a collection S of subsets of U , and an integer k , are there $\leq k$ of these subsets whose union is equal to U ?

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Sample application.

- m available pieces of software.
- Set U of n capabilities that we would like our system to have.
- The i^{th} piece of software provides the set $S_i \subseteq U$ of capabilities.
- **Goal:** achieve all n capabilities using fewest pieces of software.

$$U = \{1, 2, 3, 4, 5, 6, 7\}$$

$$S_a = \{3, 7\}$$

$$S_b = \{2, 4\}$$

$$S_c = \{3, 4, 5, 6\}$$

$$S_d = \{5\}$$

$$S_e = \{1\}$$

$$S_f = \{1, 2, 6, 7\}$$

$$k = 2$$

Given the universe $U = \{1, 2, 3, 4, 5, 6, 7\}$ and the following sets, which is the minimum size of a set cover?

- A. 1
- B. 2
- C. 3
- D. None of the above.

$$U = \{1, 2, 3, 4, 5, 6, 7\}$$

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Proof. Given a VERTEX COVER instance $G = (V, E)$ and k , we construct a SET COVER instance (U, S, k) that has a set cover of size k iff G has a vertex cover of size k .

Vertex cover reduces to set cover

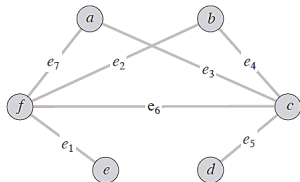
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Construction.

- Universe $U = E$.
- Include one subset for each node $v \in V : S_v = \{e \in E : e \text{ incident to } v\}$.



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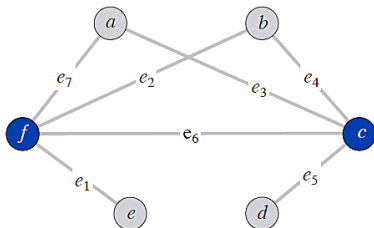
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Proof. \Rightarrow

Let $X \subseteq V$ be a vertex cover of size k in G , then $Y = \{S_v : v \in X\}$ is a set cover of size k .



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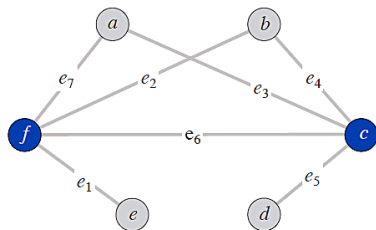
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Lemma

$G = (V, E)$ contains a vertex cover of size k iff (U, S, k) contains a set cover of size k .

Proof. \Leftarrow

Let $Y \subseteq S$ be a set cover of size k in (U, S, k) , then $X = \{v : S_v \in Y\}$ is a vertex cover of size k in G .



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yes instance: $x_1 = \text{true}$, $x_2 = \text{true}$, $x_3 = \text{false}$ $x_4 = \text{false}$

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Key application. Electronic design automation (EDA).

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Donald J. Trump ✓

@realDonaldTrump

Following

Computer Scientists have so much funding and time and can't even figure out the boolean satisfiability problem. SAT!

RETWEETS

16,936

LIKES

50,195



6:31 AM - 17 Apr 2017



20K



17K



50K

<https://www.facebook.com/pg/npcompleteteens>

3-satisfiability reduces to independent set

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Proof.

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3-SAT \leq_P INDEPENDENT SET.

Proof. Given an instance Φ of 3-SAT, we construct an instance (G, k) of INDEPENDENT SET that has an independent set of size $k = |\Phi|$ iff Φ is satisfiable.

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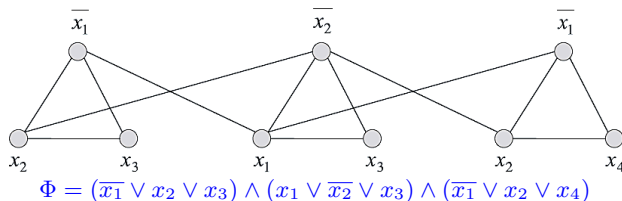
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Construction.

- G contains 3 nodes for each clause, one for each literal.
- Connect 3 literals in a clause in a triangle.
- Connect literal to each of its negations.



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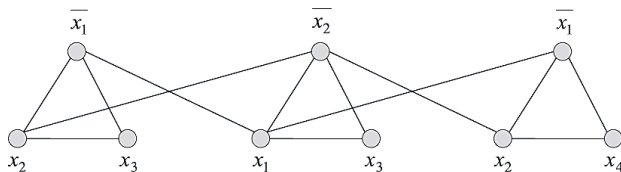
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Proof. \Rightarrow

Consider any satisfying assignment for Φ .

- Select one true literal from each clause/triangle.
- This is an independent set of size $k = |\Phi|$.



$$\Phi = (\overline{x_1} \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee x_3) \wedge (\overline{x_1} \vee x_2 \vee x_4)$$

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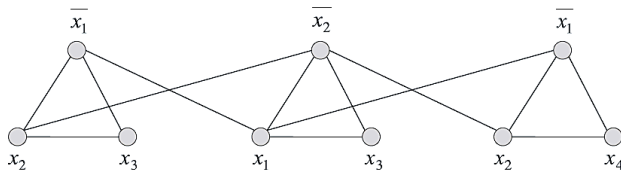
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Proof. \Leftarrow

Let S be independent set of size k .

- S must contain exactly one node in each triangle.
- Set these literals to **true** and remaining literals consistently.
- All clauses in Φ are satisfied.



$$\Phi = (\overline{x_1} \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee x_3) \wedge (\overline{x_1} \vee x_2 \vee x_4)$$

Basic reduction strategies.

- Simple equivalence: Independent Set \equiv_P Vertex Cover
- Special case to general case: Vertex Cover \leq_P Set Cover.
- Encoding with gadgets: 3-SAT \leq_P Independent Set.

Basic reduction strategies.

- Simple equivalence: Independent Set \equiv_P Vertex Cover
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Proof idea. Compose the two algorithms.

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Proof idea. Compose the two algorithms.

Example. 3-SAT \leq_P Independent Set \leq_P Vertex Cover \leq_P Set Cover.

Decision, search and optimization problems

Decision problem. Does there exist a vertex cover of size $\leq k$?

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Decision problem. Does there **exist** a vertex cover of size $\leq k$?

Search problem. **Find** a vertex cover of size $\leq k$.

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Goal. Show that all three problems poly-time reduce to one another.

Search problems VS. Decision problems

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Theorem. Vertex cover \equiv_P Find vertex cover.

Proof.

\leq_P . Decision problem is a special case of search problem.

\geq_P . To find a vertex cover of size $\leq k$:

- Determine if there exists a vertex cover of size $\leq k$.
- Find a vertex v such that $G - \{v\}$ has a vertex cover of size $\leq k - 1$. (any vertex in any vertex cover of size $\leq k$ will have this property)
- Include v in the vertex cover.
- Recursively find a vertex cover of size $\leq k - 1$ in $G - \{v\}$.

Optimization problems VS. Search problems VS. Decision problems



FIND VERTEX COVER. Find a vertex cover of size $\leq k$.

FIND MIN VERTEX COVER. Find a vertex cover of minimum size.

Optimization problems VS. Search problems VS. Decision problems

FIND VERTEX COVER. Find a vertex cover of size $\leq k$.

FIND MIN VERTEX COVER. Find a vertex cover of minimum size.

Theorem. Find vertex cover \equiv_P Find min vertex cover.

Optimization problems VS. Search problems VS. Decision problems

FIND VERTEX COVER. Find a vertex cover of size $\leq k$.

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FIND VERTEX COVER. Find a vertex cover of size $\leq k$.

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Proof.

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\geq_P . To find vertex cover of minimum size:

FIND VERTEX COVER. Find a vertex cover of size $\leq k$.

FIND MIN VERTEX COVER. Find a vertex cover of minimum size.

Theorem. Find vertex cover \equiv_P Find min vertex cover.

Proof.

\leq_P . Search problem is a special case of optimization problem.

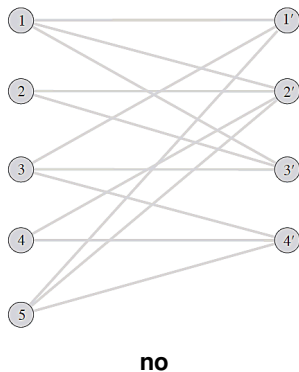
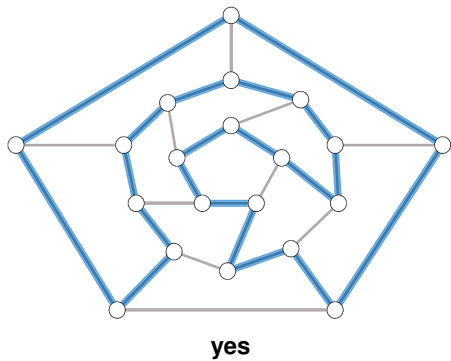
\geq_P . To find vertex cover of minimum size:

- Binary search (or linear search) for size k^* of min vertex cover.
- Solve search problem for given k^* .

Sequencing Problems

Hamilton cycle

HAMILTON CYCLE. Given an undirected graph $G = (V, E)$, does there exist a cycle Γ that visits every node exactly once?



Directed Hamilton cycle reduces to Hamilton cycle

DIRECTED HAMILTON CYCLE. Given a directed graph $G = (V, E)$, does there exist a directed cycle Γ that visits every node exactly once?

Theorem

DIRECTED HAMILTON CYCLE \leq_P HAMILTON CYCLE.

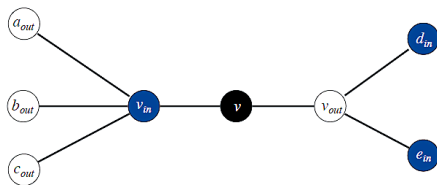
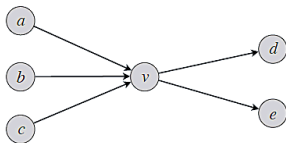
Directed Hamilton cycle reduces to Hamilton cycle

DIRECTED HAMILTON CYCLE. Given a directed graph $G = (V, E)$, does there exist a directed cycle Γ that visits every node exactly once?

Theorem

DIRECTED HAMILTON CYCLE \leq_P HAMILTON CYCLE.

Proof. Given a directed graph $G = (V, E)$, construct a graph G' with $3n$ nodes.



Directed Hamilton cycle reduces to Hamilton cycle

Lemma

G has a directed Hamilton cycle iff G' has a Hamilton cycle.

Directed Hamilton cycle reduces to Hamilton cycle

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G has a directed Hamilton cycle iff G' has a Hamilton cycle.

Proof.

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Proof.

\Rightarrow

- Suppose G has a directed Hamilton cycle Γ .
- Then G' has an undirected Hamilton cycle (same order).

Directed Hamilton cycle reduces to Hamilton cycle

Lemma

G has a directed Hamilton cycle iff G' has a Hamilton cycle.

Proof.

⇒

- Suppose G has a directed Hamilton cycle Γ .
- Then G' has an undirected Hamilton cycle (same order).

⇐

- Suppose G' has an undirected Hamilton cycle Γ' .
- Γ' must visit nodes in G' using one of following two orders:
... , black, white, blue, black, white, blue, black, white, blue, ...
... , black, blue, white, black, blue, white, black, blue, white, ...
- Black nodes in Γ' comprise either a directed Hamilton cycle Γ in G , or reverse of one.

3-satisfiability reduces to directed Hamilton cycle

Theorem

3-SAT \leq_P DIRECTED HAMILTON CYCLE.

3-satisfiability reduces to directed Hamilton cycle

Theorem

3-SAT \leq_P DIRECTED HAMILTON CYCLE.

Proof.

3-satisfiability reduces to directed Hamilton cycle

Theorem

$3\text{-SAT} \leq_P \text{DIRECTED HAMILTON CYCLE}$.

Proof.

Given an instance Φ of 3-SAT , we construct an instance G of $\text{Directed Hamilton cycle}$ that has a Hamilton cycle iff Φ is satisfiable.

3-satisfiability reduces to directed Hamilton cycle

Theorem

3-SAT \leq_P DIRECTED HAMILTON CYCLE.

Proof.

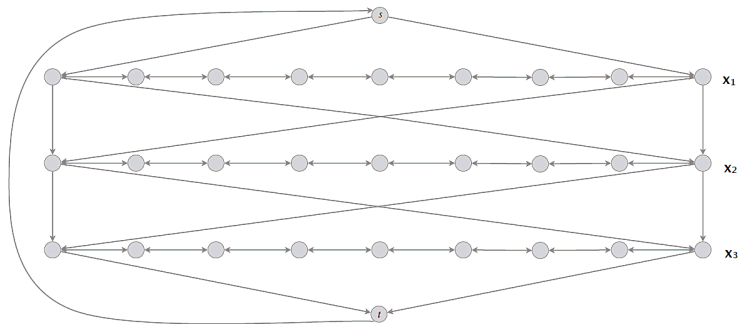
Given an instance Φ of 3-SAT, we construct an instance G of Directed Hamilton cycle that has a Hamilton cycle iff Φ is satisfiable.

Construction overview. Let n denote the number of variables in Φ . We will construct a graph G that has 2^n Hamilton cycles, with each cycle corresponding to one of the 2^n possible truth assignments.

3-satisfiability reduces to directed Hamilton cycle

Construction. Given 3-SAT instance Φ with n variables x_i and k clauses.

- Construct G to have 2^n Hamilton cycles.
- **Intuition:** traverse path i from left to right \Leftrightarrow set variables $x_i = \text{true}$



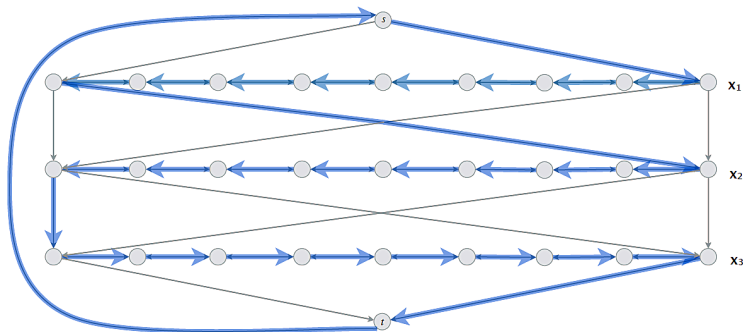
Which is truth assignment corresponding to Hamilton cycle below?

A. $x_1 = \text{true}, x_2 = \text{true}, x_3 = \text{true}$

B. $x_1 = \text{true}, x_2 = \text{true}, x_3 = \text{false}$

C. $x_1 = \text{false}, x_2 = \text{false}, x_3 = \text{true}$

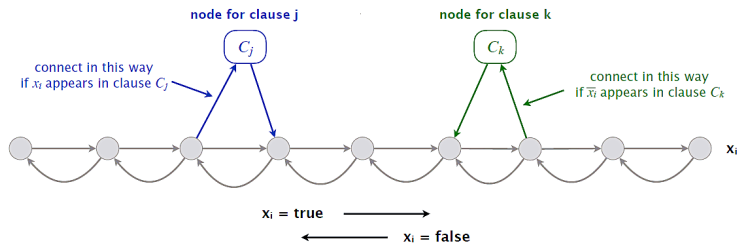
C. $x_1 = \text{false}, x_2 = \text{false}, x_3 = \text{false}$



3-satisfiability reduces to directed Hamilton cycle

Construction. Given 3-SAT instance Φ with n variables x_i and k clauses.

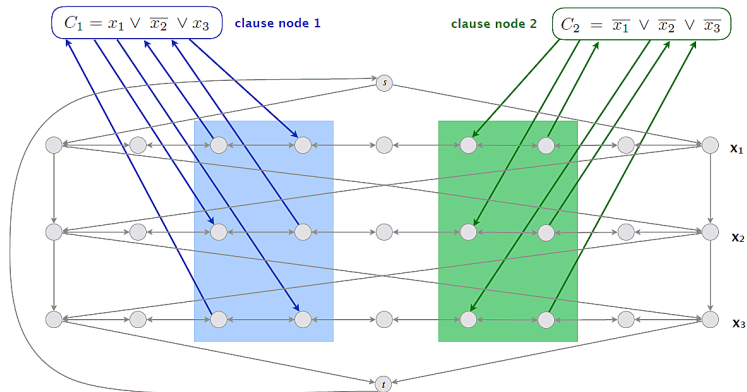
- For each clause: add a node and 2 edges per literal.



3-satisfiability reduces to directed Hamilton cycle

Construction. Given 3-SAT instance Φ with n variables x_i and k clauses.

- For each clause: add a node and 2 edges per literal.



3-satisfiability reduces to directed Hamilton cycle

Lemma

Φ is satisfiable iff G has a Hamilton cycle.

3-satisfiability reduces to directed Hamilton cycle

Lemma

Φ is satisfiable iff G has a Hamilton cycle.

Proof.

3-satisfiability reduces to directed Hamilton cycle

Lemma

Φ is satisfiable iff G has a Hamilton cycle.

Proof. \Rightarrow

- Suppose 3-SAT instance Φ has satisfying assignment x^* .
- Then, define Hamilton cycle Γ in G as follows:
 - if $x_i^* = true$, traverse row i from left to right.
 - if $x_i^* = false$, traverse row i from right to left.
 - for each clause C_j , there will be at least one row i in which we are going in “correct” direction to splice clause node C_j into cycle (and we splice in C_j exactly once)

3-satisfiability reduces to directed Hamilton cycle

Lemma

Φ is satisfiable iff G has a Hamilton cycle.

Proof.

3-satisfiability reduces to directed Hamilton cycle

Lemma

Φ is satisfiable iff G has a Hamilton cycle.

Proof. \Leftarrow

- Suppose G has a Hamilton cycle Γ .
- If Γ enters clause node C_j , it must depart on mate edge.
 - nodes immediately before and after C_j are connected by an edge $e \in E$.
 - removing C_j from cycle, and replacing it with edge e yields Hamilton cycle on $G - \{C_j\}$.
- Continuing in this way, we are left with a Hamilton cycle Γ' in $G - \{C_1, C_2, \dots, C_k\}$.
- Set $x_i^* = \text{true}$ if Γ' traverses row i left-to-right; otherwise, set $x_i^* = \text{false}$.
- traversed in “correct” direction, and each clause is satisfied.

Graph Coloring

Home reading!

Numerical Problems

Subset sum

SUBSET SUM. Given n natural numbers w_1, \dots, w_n and an integer W , is there a subset that adds up to exactly W ?

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Example. { 215, 215, 275, 275, 355, 355, 420, 420, 580, 580, 655, 655 }, $W = 1505$.

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Example. { 215, 215, 275, 275, 355, 355, 420, 420, 580, 580, 655, 655 }, $W = 1505$.

Yes. $215 + 355 + 355 + 580 = 1505$.

Subset sum

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Example. { 215, 215, 275, 275, 355, 355, 420, 420, 580, 580, 655, 655 }, $W = 1505$.

Yes. $215 + 355 + 355 + 580 = 1505$.

Remark. With arithmetic problems, input integers are encoded in binary. Poly-time reduction must be polynomial in **binary** encoding.

Theorem

3-SAT \leq_P SUBSET SUM.

Theorem

$3\text{-SAT} \leq_P \text{SUBSET SUM}$.

Proof. Given an instance Φ of 3-SAT , we construct an instance of **Subset sum** that has solution iff Φ is satisfiable.

3-satisfiability reduces to subset sum

Construction. Given 3-SAT instance Φ with n variables and k clauses, form $2n + 2k$ decimal integers, each having $n + k$ digits:

- Include one digit for each variable x_i and one digit for each clause C_j .
- Include two numbers for each variable x_i .
- Include two numbers for each clause C_j .

3-satisfiability reduces to subset sum

- Sum of each x_i digit is 1;
- Sum of each C_j digit is 4.

Key property. No carries possible \Rightarrow each digit yields one equation.

$C_1 =$	$\neg x_1$	\vee	x_2	\vee	x_3
$C_2 =$	x_1	\vee	$\neg x_2$	\vee	x_3
$C_3 =$	$\neg x_1$	\vee	$\neg x_2$	\vee	$\neg x_3$

dummies to get clause columns to sum to 4

	x_1	x_2	x_3	C_1	C_2	C_3	
x_1	1	0	0	0	1	0	100,010
$\neg x_1$	1	0	0	1	0	1	100,101
x_2	0	1	0	1	0	0	10,100
$\neg x_2$	0	1	0	0	1	1	10,011
x_3	0	0	1	1	1	0	1,110
$\neg x_3$	0	0	1	0	0	1	1,001
<hr/>							
}	0	0	0	1	0	0	100
	0	0	0	2	0	0	200
	0	0	0	0	1	0	10
	0	0	0	0	2	0	20
	0	0	0	0	0	1	1
	0	0	0	0	0	2	2
W	1	1	1	4	4	4	111,444

3-satisfiability reduces to subset sum

Lemma

Φ is satisfiable iff there exists a subset that sums to W .

3-satisfiability reduces to subset sum

Lemma

Φ is satisfiable iff there exists a subset that sums to W .

Proof.

3-satisfiability reduces to subset sum

Lemma

Φ is satisfiable iff there exists a subset that sums to W .

Proof. \Rightarrow Suppose 3-SAT instance Φ has satisfying assignment x^* . If $x_i^* = \text{true}$, select integer in row x_i , otherwise, select integer in row $\neg x_i$.

- Each x_i digit sums to 1.
- Since Φ is satisfiable, each C_j digit sums to at least 1 from x_i and $\neg x_i$ rows.
- Select dummy integers to make C_j digits sum to 4.

$$\begin{array}{l}
 C_1 = \neg x_1 \vee x_2 \vee x_3 \\
 C_2 = x_1 \vee \neg x_2 \vee x_3 \\
 C_3 = \neg x_1 \vee \neg x_2 \vee \neg x_3
 \end{array}$$

dummies to get clause columns to sum to 4

	x_1	x_2	x_3	C_1	C_2	C_3	
x_1	1	0	0	0	1	0	100,010
$\neg x_1$	1	0	0	1	0	1	100,101
x_2	0	1	0	1	0	0	10,100
$\neg x_2$	0	1	0	0	1	1	10,011
x_3	0	0	1	1	1	0	1,110
$\neg x_3$	0	0	1	0	0	1	1,001
	0	0	0	1	0	0	100
	0	0	0	2	0	0	200
	0	0	0	0	1	0	10
	0	0	0	0	2	0	20
	0	0	0	0	0	1	1
	0	0	0	0	0	2	2
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3-satisfiability reduces to subset sum

Lemma

Φ is satisfiable iff there exists a subset that sums to W .

Proof.

3-satisfiability reduces to subset sum

Lemma

Φ is satisfiable iff there exists a subset that sums to W .

Proof. \Leftarrow Suppose there exists a subset S^* that sums to W . Digit x_i forces subset S^* to select either row x_i or row $\neg x_i$ (but not both). If row x_i selected, assign $x_i^* = true$; otherwise, assign $x_i^* = false$.

Digit C_j forces subset S^* to select at least one literal in clause.

$$\begin{aligned}
 C_1 &= \neg x_1 \vee x_2 \vee x_3 \\
 C_2 &= x_1 \vee \neg x_2 \vee x_3 \\
 C_3 &= \neg x_1 \vee \neg x_2 \vee \neg x_3
 \end{aligned}$$

dummies to get clause
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	x_1	x_2	x_3	C_1	C_2	C_3	
x_1	1	0	0	0	1	0	100,010
$\neg x_1$	1	0	0	1	0	1	100,101
x_2	0	1	0	1	0	0	10,100
$\neg x_2$	0	1	0	0	1	1	10,011
x_3	0	0	1	1	1	0	1,110
$\neg x_3$	0	0	1	0	0	1	1,001
	0	0	0	1	0	0	100
	0	0	0	2	0	0	200
	0	0	0	0	1	0	10
	0	0	0	0	2	0	20
	0	0	0	0	0	1	1
	0	0	0	0	0	2	2
W	1	1	1	4	4	4	111,444

Subset sum reduces to knapsack

Subset sum. Given n natural numbers w_1, \dots, w_n and an integer W , is there a subset that adds up to exactly W ?

Knapsack. Given a set of items X , weights $u_i \geq 0$, values $v_i \geq 0$, a weight limit U , and a target value V , is there a subset $S \subseteq X$ such that:

$$\sum_{i \in S} u_i \leq U, \quad \sum_{i \in S} v_i \geq V$$

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Recall. $O(nU)$ dynamic programming algorithm for knapsack.

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Recall. $O(nU)$ dynamic programming algorithm for knapsack.

Challenge. Prove subset sum \leq_P Knapsack.

SAT to 3SAT

From SAT problem to 3SAT problem

$$\left\{ \begin{array}{l} (a_1 \vee a_2 \vee \dots \vee a_k) \\ \text{is satisfied} \end{array} \right\} \iff \left\{ \begin{array}{l} \text{there is a setting of the } y_i\text{'s for which} \\ (a_1 \vee a_2 \vee y_1) (\bar{y}_1 \vee a_3 \vee y_2) \dots (\bar{y}_{k-3} \vee a_{k-1} \vee a_k) \\ \text{are all satisfied} \end{array} \right\}$$

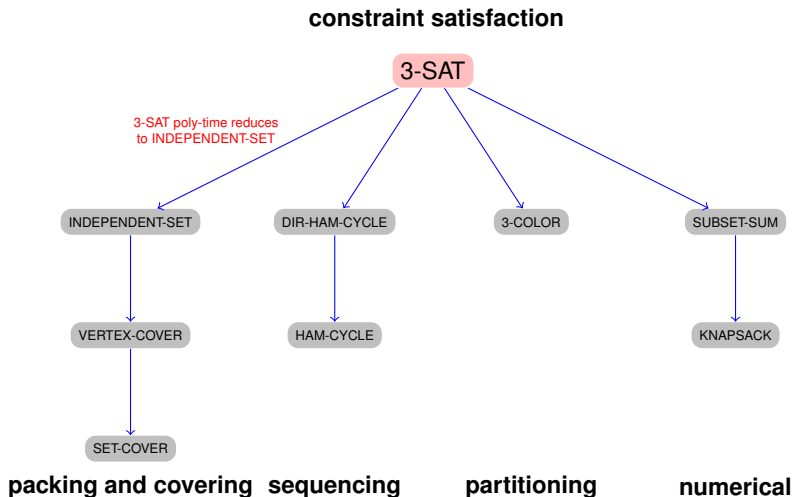
From SAT problem to 3SAT problem

$$\left\{ \begin{array}{l} (a_1 \vee a_2 \vee \dots \vee a_k) \\ \text{is satisfied} \end{array} \right\} \iff \left\{ \begin{array}{l} \text{there is a setting of the } y_i\text{'s for which} \\ (a_1 \vee a_2 \vee y_1) (\overline{y_1} \vee a_3 \vee y_2) \dots (\overline{y_{k-3}} \vee a_{k-1} \vee a_k) \\ \text{are all satisfied} \end{array} \right\}$$

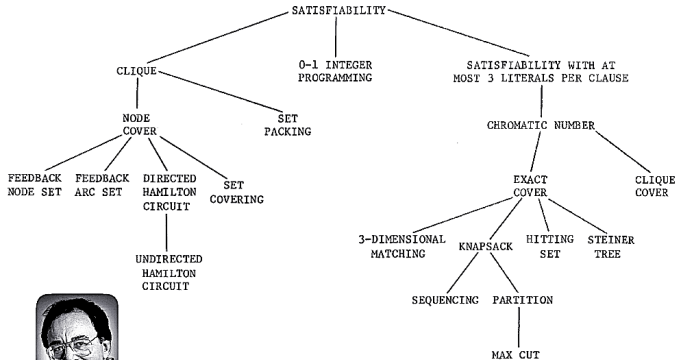
Suppose that the clauses on the right are all satisfied. Then **at least** one of the literals a_1, \dots, a_k must be **true**.

Otherwise y_1 would have to be **true**, which would in turn force y_2 to be **true**, and so on.

Conversely, if $(a_1 \vee a_2 \vee \dots \vee a_k)$ is **satisfied**, then some a_i must be **true**. Set y_1, \dots, y_{i-2} to **true** and the rest to **false**.



Karp's 20 poly-time reductions from satisfiability



Dick Karp (1972)
1985 Turing Award

FIGURE 1 - Complete Problems

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RICHARD M. KARP

Referred Materials

- Content of this lecture comes from Chapter 8 in [KT05].