

# CS215 DISCRETE MATH

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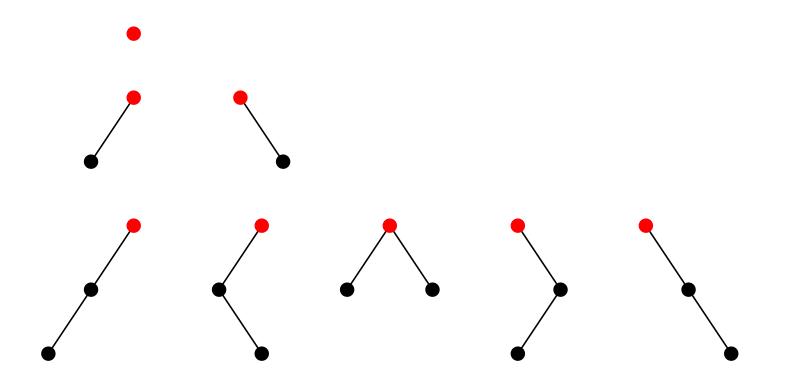
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• How many different binary tress are there with n vertices? We denote this number as  $C_n$ .

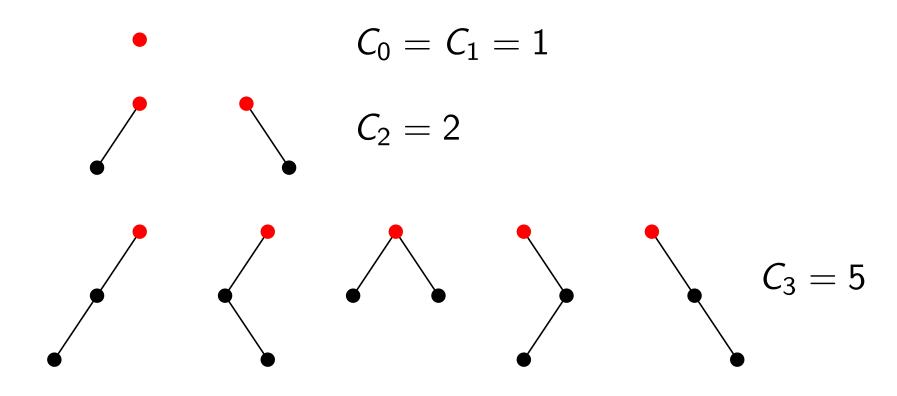


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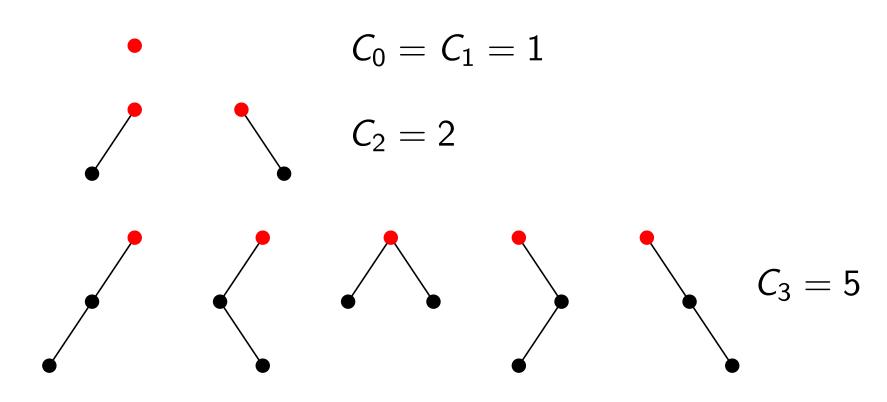


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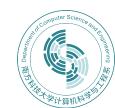




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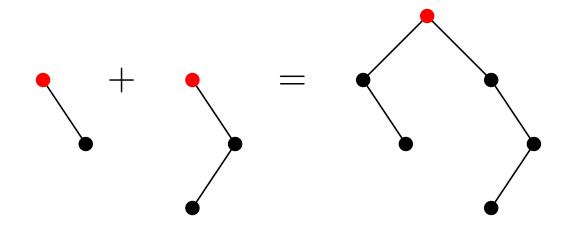
How to find a formula for  $C_n$ ?



■ We first give an important *observation* on the recursive relation.

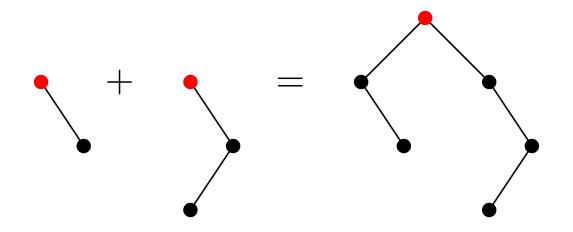


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  - = two smaller binary trees (possibly empty) + one extra root





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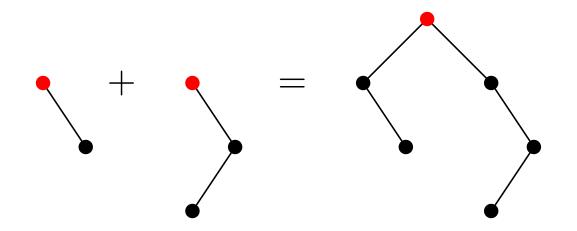
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We have  $C_n = \sum_{i=0}^{n-1} C_i C_{n-i-1}$ 

For example,  $C_3 = C_0C_2 + C_1C_1 + C_2C_0 = 1*2+1*1+2*1 = 5$ .



Let  $f(x) = \sum_{i=0}^{\infty} C_i x^i$ . We now consider  $f^2$ .



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The coefficient of  $x^n$  in  $f^2$  is:  $[x^n]_{f^2} = \sum_{i=0}^n C_i C_{n-i}$ , since the following is the sum of all possible terms of  $x^n$ 

 $C_0 \cdot C_n x^n + C_1 x \cdot C_{n-1} x^{n-1} + \cdots + C_n x^n \cdot C_n$ 



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Then we have  $xf^2 + 1 = f$ , which gives  $f = \frac{1 \pm \sqrt{1 - 4x}}{2x}$  for  $x \neq 0$ .



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Since 
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 $C_n$  – the coefficient of  $x^n$  in the expansion of f.



 $f = \frac{1-\sqrt{1-4x}}{2x}$ , by the extended Binomial Theorem,

$$\sqrt{1-4x} = (1+(-4x))^{1/2} = \sum_{n=0}^{\infty} {1/2 \choose n} (-4x)^n.$$



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Then we have  $C_n = \frac{1}{n+1} {2n \choose n}$ .

This is called the *n*-th *Catalan number*.



#### Catalan Numbers: Related Problems

**Theorem** The number of sequences  $a_1, \ldots, a_{2n}$  of 2n terms that can be formed using exactly n+1's and exactly n-1's whose partial sums are always nonnegative, i.e.,  $a_1 + a_2 + \cdots + a_k \ge 0$  for any  $1 \le k \le 2n$ , equals the n-th Catalan number  $C_n$ .



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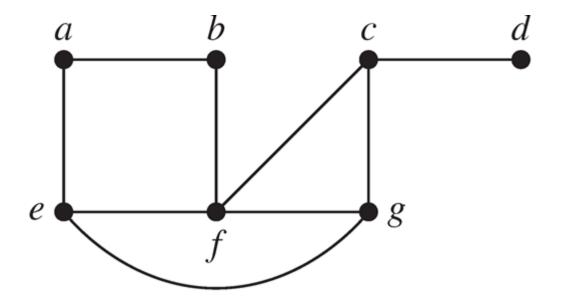
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  - R. Stanley, Catalan Numbers, Cambridge University Press, 2015. Includes 214 combinatorial interpretations of  $C_n$ , and 68 additional problems!



**Definition** Let G be a simple graph. A *spanning tree* of G is a subgraph of G that is a tree containing every vertex of G.

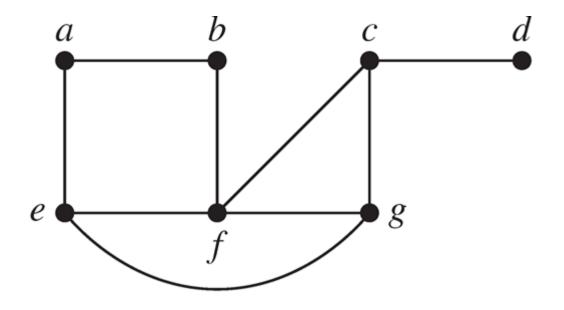


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- Form a path by successively adding vertices and edges.
  Continue adding to this path as long as possible.



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### Depth-First Search

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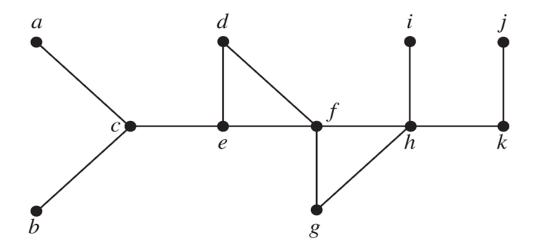
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- ♦ If the path goes through all vertices of the graph, the tree is a spanning tree.
- Otherwise, move back to some vertex to repeat this procedure (backtracking)



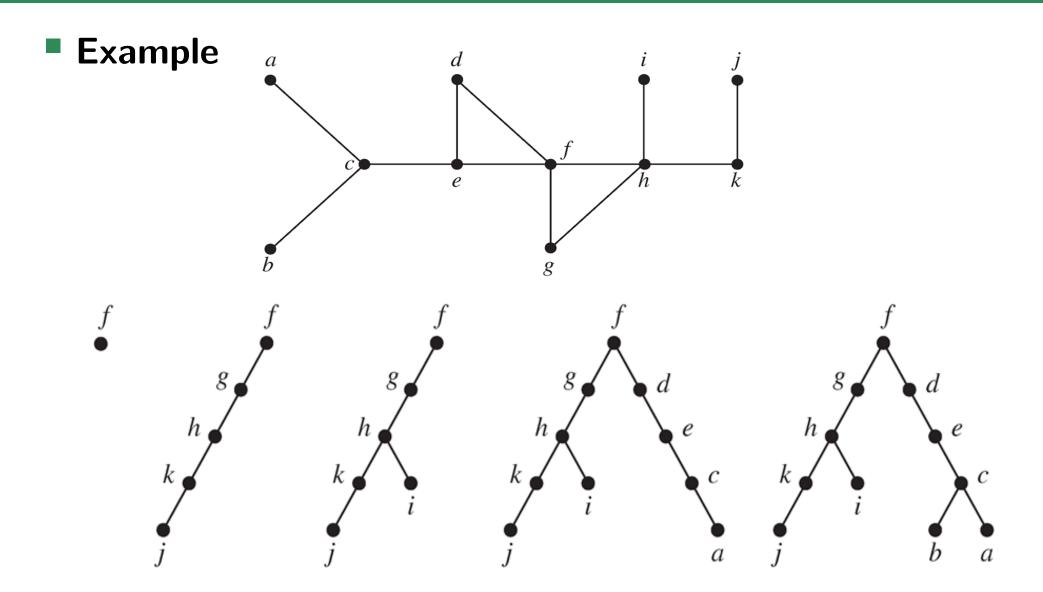
# Depth-First Search

Example





# Depth-First Search





# Depth-First Search Algorithm

```
procedure DFS(G: connected graph with vertices v<sub>1</sub>, v<sub>2</sub>, ..., v<sub>n</sub>)
T := tree consisting only of the vertex v<sub>1</sub>
visit(v<sub>1</sub>)

procedure visit(v: vertex of G)
for each vertex w adjacent to v and not yet in T
  add vertex w and edge {v,w} to T
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time complexity: O(e)



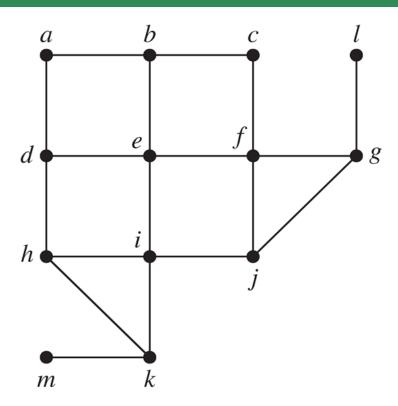
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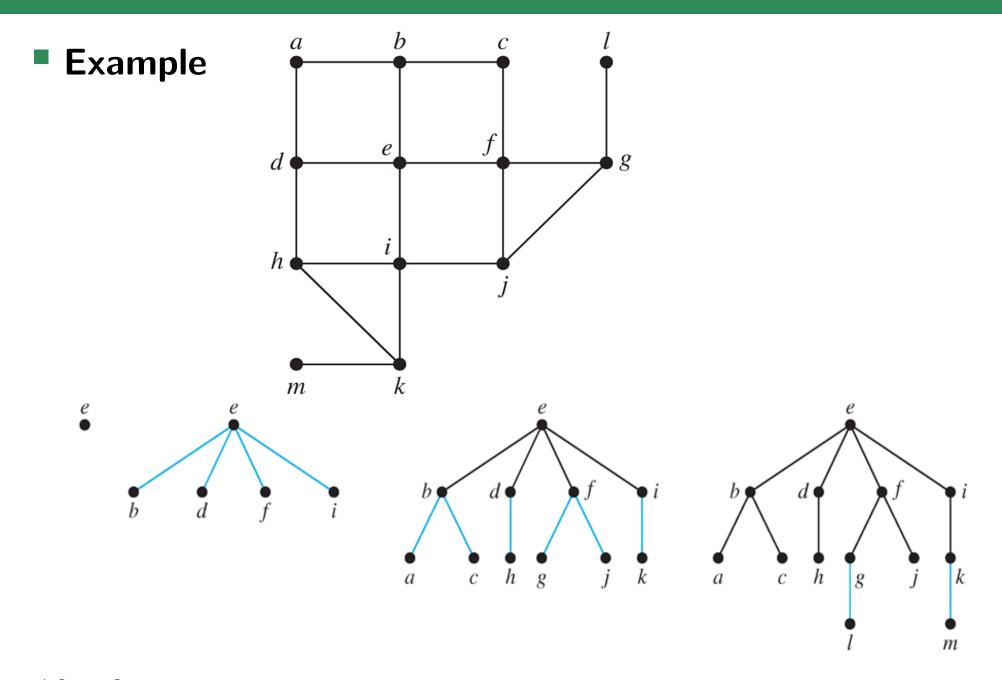


- This is the second algorithm that we build up spanning trees by successively adding edges.
  - First arbitrarily choose a vertex of the graph as the root.
  - ♦ Form a path by adding all edges incident to this vertex and the other endpoint of each of these edges
  - ⋄ For each vertex added at the previous level, add edge incident to this vertex, as long as it does not produce a simple circuit.
  - Continue in this manner until all vertices have been added.



Example





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procedure BFS(G: connected graph with vertices v<sub>1</sub>, v<sub>2</sub>, ..., v<sub>n</sub>)
T := tree consisting only of the vertex v<sub>1</sub>
L := empty list visit(v<sub>1</sub>)
put v<sub>1</sub> in the list L of unprocessed vertices
while L is not empty
remove the first vertex, v, from L
for each neighbor w of v
    if w is not in L and not in T then
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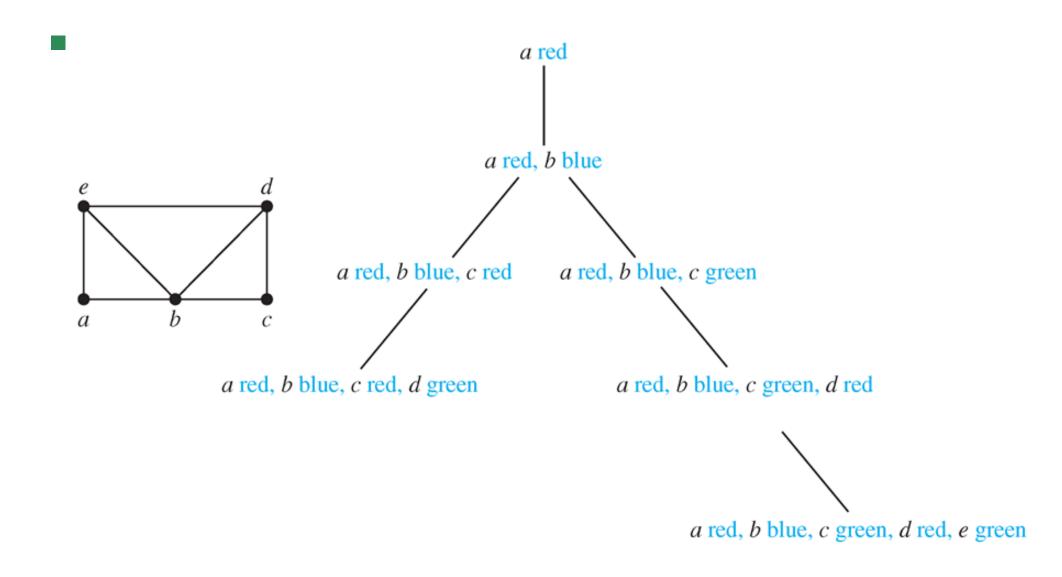


• find paths, circuits, connected components, cut vertices, ...

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graph coloring, sums of subsets, ...







find Sum = 0find {27} {31} grap Sum = 31Sum = 27 ${31, 5}$  $\{27, 7\}$  ${31, 7}$ {27, 11} Sum = 38Sum = 36Sum = 38Sum = 34 $\{27, 7, 5\}$ Sum = 39

find a subset of  $\{31, 27, 15, 11, 7, 5\}$  with the sum 39



## Minimum Spanning Trees

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two greedy algorithms: Prim's Algorithm, Kruscal's Algorithm



#### ALGORITHM 1 Prim's Algorithm.

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procedure Prim(G: weighted connected undirected graph with n vertices)
T := a minimum-weight edge
for i := 1 to n - 2
e := an edge of minimum weight incident to a vertex in T and not forming a simple circuit in T if added to T
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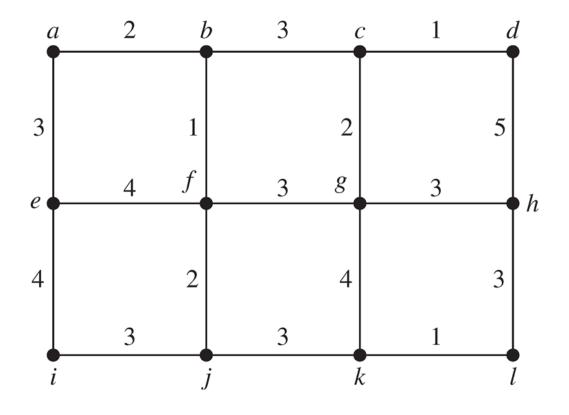
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We can maintain a *heap* of all the edges with at least one endpoint in T, and in each iteration, we do Extract-Mins until we see an edge that has one endpoint in T and one endpoint not in T.

time complexity: e log v

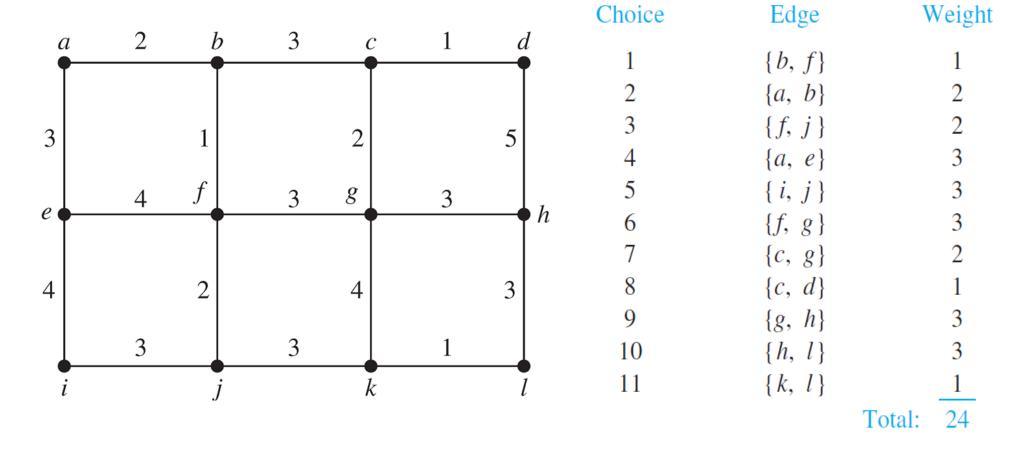


#### Example





#### Example





**Proof** by *induction*.



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i.h.: After each iteration, the tree T is a subgraph of some MST M. This is trivially true for the basic step, since intially T has only one vertex and no edges.



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Since Prim's algorithm has chosen to add e, we have  $w(e) \leq w(e')$ . So if we add e to M and remove e' from M, we will have a new tree M' whose total weight  $\leq$  that of M, and  $T \cup \{e\} \subset M'$ .



#### ALGORITHM 2 Kruskal's Algorithm.

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procedure Kruskal(G: weighted connected undirected graph with n vertices)
T := empty graph
for i := 1 to n - 1
e := any edge in G with smallest weight that does not form a simple circuit when added to T
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time complexity:  $e \log e$  Union-Find



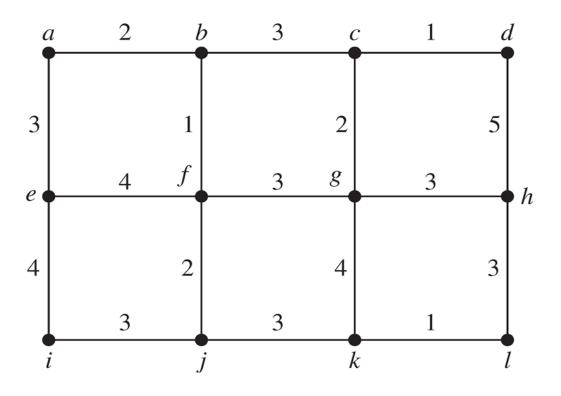
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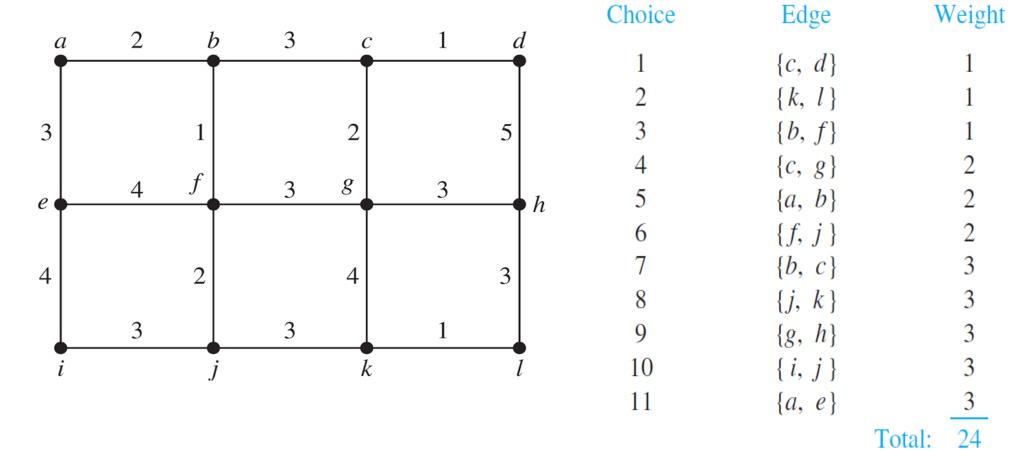


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## Kruscal's Algorithm: Correctness

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**Theorem** Let  $(S, \overline{S})$  be an arbitrary cut, and let e be an edge across the cut (one endpoint in S, the other in  $\overline{S}$ ) that has the smallest weight of all edges cross the cut. Then there must be an MST T containing e.

**Theorem** Let  $(S, \overline{S})$  be an arbitrary cut, and let E' be the set of edges across the cut of minimum weight (w(e) = w(e')) for any two edges  $e, e' \in E'$  and w(e) < w(e') for any  $e \in E'$  and  $e' \notin E'$ . Let T be an arbitrary MST. Then T must contain some edge in E'.



# NP-complete Problems

- Class NP vs Class P
  - P: decision problems solvable in polynomial time
  - NP: decision problems with certificates verifiable in polynomial time (polynomial time verification)



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  - CLRS / M. Sipser: Introduction to Theory of Computation
- Approximation Algorithm
  - Natural idea: settle for *non-optimal* solutions for these "hard" problems, if we can find such close-to-the-optimal solutions reasonably fast.



# Satisfiability Problem

 $\blacksquare$  Satisfiability (SAT) – one of the most important NP problems



# Satisfiability Problem

- $\blacksquare$  Satisfiability (SAT) one of the most important NP problems
- Definition A Boolean formula is a logical formula consisting of
  - Boolean variables (0 = false, 1 = true),
  - logical operations
    - $\diamond \neg x$ : Negation
    - $\diamond x \lor y$ : Disjunction
    - $\diamond x \land y$ : Conjunction

With the truth table defined by:

X	y	$\neg \chi$	$x \vee y$	$x \wedge y$
0	0	1	0	0
0	1		1	0
1	0	0	1	0
1	1		1	1



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The assignment, x = 1, y = 1, z = 0 makes f(x, y, z) true, and hence it is satisfiable.

25 - 3

**Example.**  $f(x,y) = (x \lor y) \land (\neg x \lor y) \land (x \lor \neg y) \land (\neg x \lor \neg y)$ 

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There is no assignment that makes f(x, y) true, and hence it is NOT satisfiable.



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**Definition** For a fixed k, Boolean formulas in the following form are called k-conjunctive normal form (k-CNF):

$$f_1 \wedge f_2 \wedge \cdots \wedge f_n$$

where each  $f_i$  is of the form  $f_i = y_{i,1} \lor y_{i,2} \lor \cdots \lor y_{i,k}$ , and each  $y_{i,j}$  is a variable or the negation of a variable.

#### 2SAT

Instance: A 2-CNF formula *f* 

Problem: To decide whether f is satisfiable



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Theorem 2SAT ∈ Class P

**Proof**. We will show how to solve 2SAT efficiently using path searches in graphs.



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**Theorem** Given a graph G = (V, E) and two vertices  $u, v \in V$ , finding if there is a path from u to v in the graph G is polynomial-time decidable.



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#### Proof.

Use some basic search algorithms in graph theory (DFS/BFS).



- For a Boolean formula, use vertex to represent each variable and a negation of a variable
- There is an edge  $(x, y) \in E$  if and only if there exists a clause equivalent to  $(\neg x \lor y)$



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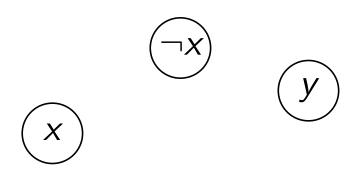
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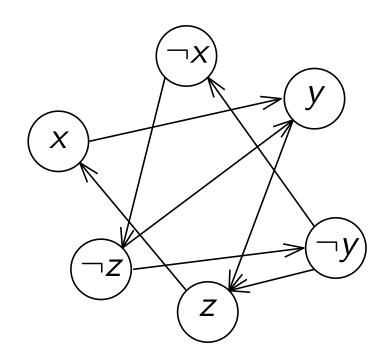




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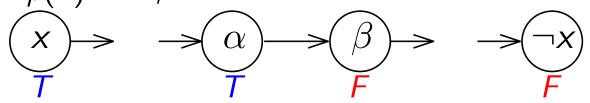
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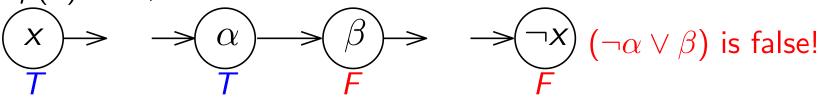
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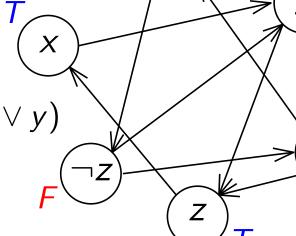
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**Theorem** A 2-CNF formula f is satisfiable if and only if there are no paths from x to  $\neg x$  or from  $\neg x$  to x for any literal x.



#### $2SAT \in P$

- An efficient algorithm for 2SAT is the following.
  - In the constructed graph G, for each variable x, check whether there is a path from x to  $\neg x$  and vice versa.
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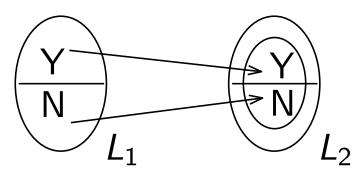
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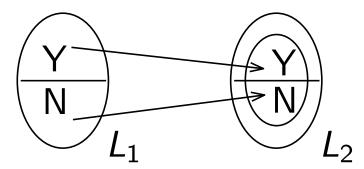


- Let  $L_1$  and  $L_2$  be two decision problems
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If such an f exists, we say that  $L_1$  is polynomial-time reducible to  $L_2$ , and write  $L_1 \leq_P L_2$ .



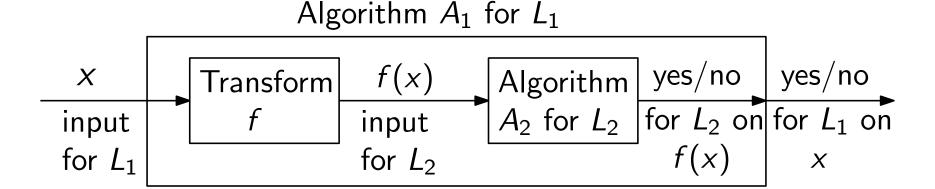
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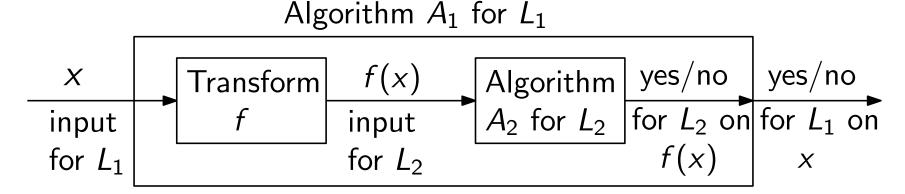


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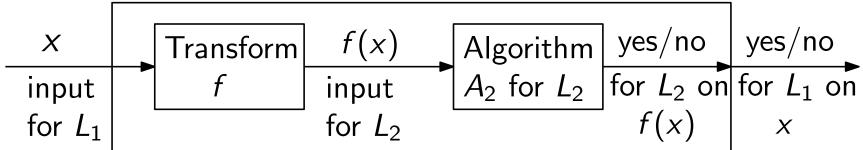


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**Theorem** If  $L_1 \leq_P L_2$  and  $L_2 \in P$ , then  $L_1 \in P$ 

**Lemma** If  $L_1 \leq_P L_2$  and  $L_2 \leq_P L_3$ , then  $L_1 \leq_P L_3$ .



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**Proof**. Let L'' be any problem in NP. Since  $L' \in NPC$ , by definition we have  $L'' \leq_P L'$ . Since  $L' \leq_P L$ , then by transitivity, we have  $L'' \leq_P L$ .

# $\overline{\mathsf{SAT}} \in NPC$ (Cook's Theorem)

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We will prove:  $3SAT \leq_P DCLIQUE$  $DCLIQUE \leq_P DVC$ 



#### Next Lecture

Graph NPC problems ...

