

EC504 ALGORITHMS AND DATA STRUCTURES  
FALL 2020 MONDAY & WEDNESDAY  
2:30 PM - 4:15 PM

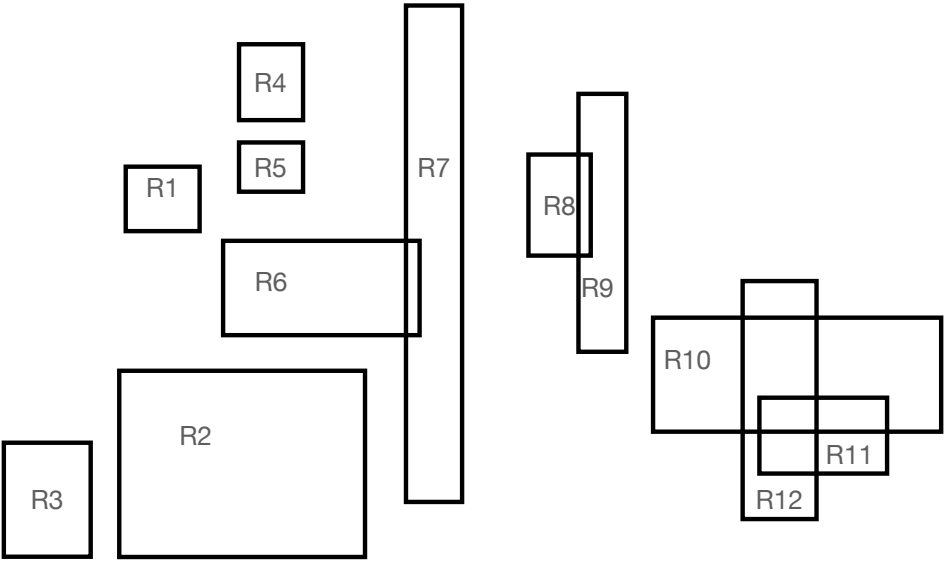
g 6 6 t

Prof: David Castañón, [dac@bu.edu](mailto:dac@bu.edu)

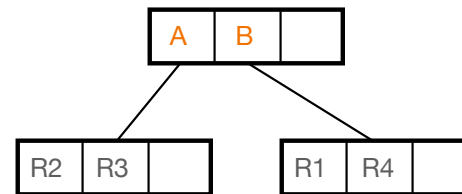
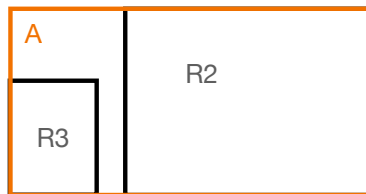
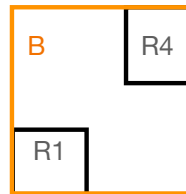
GTF: Mert Toslali, [toslali@bu.edu](mailto:toslali@bu.edu)

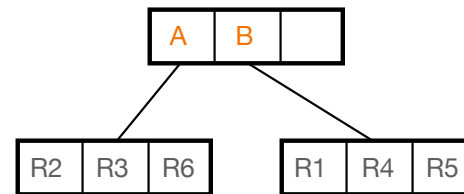
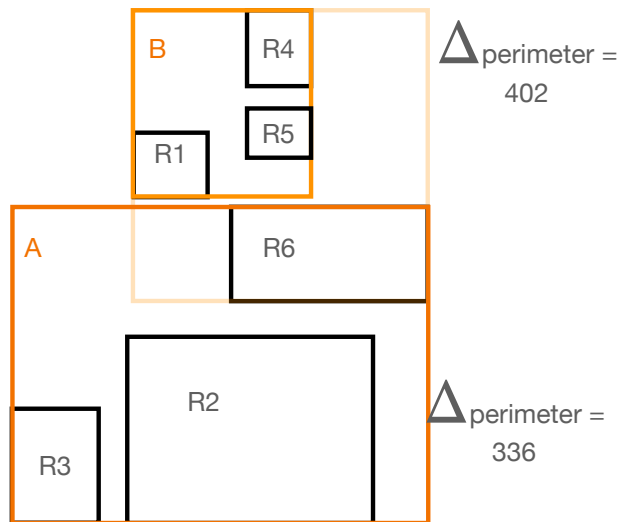
Haoyang Wang: [haoyangw@bu.edu](mailto:haoyangw@bu.edu)

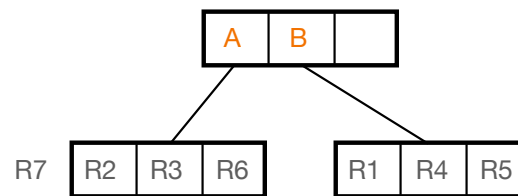
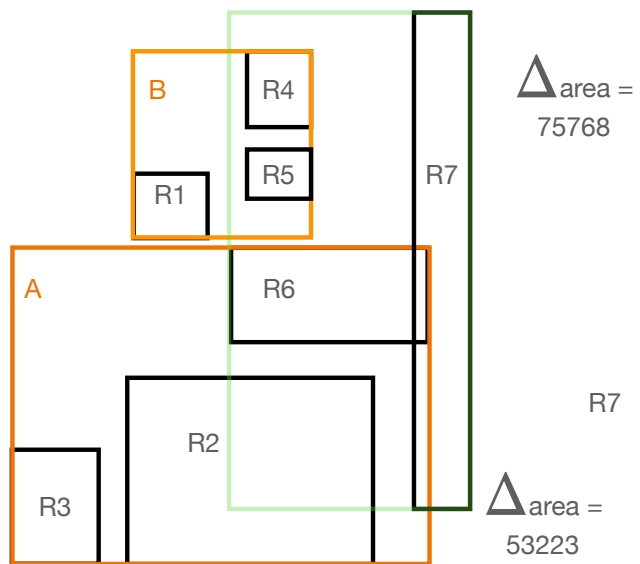
Christopher Liao: [cliao25@bu.edu](mailto:cliao25@bu.edu)

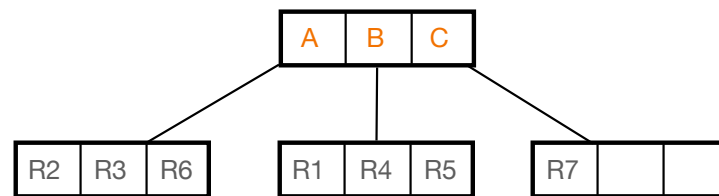
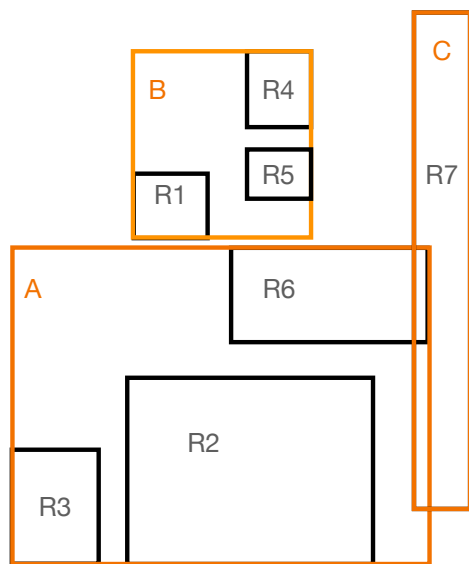


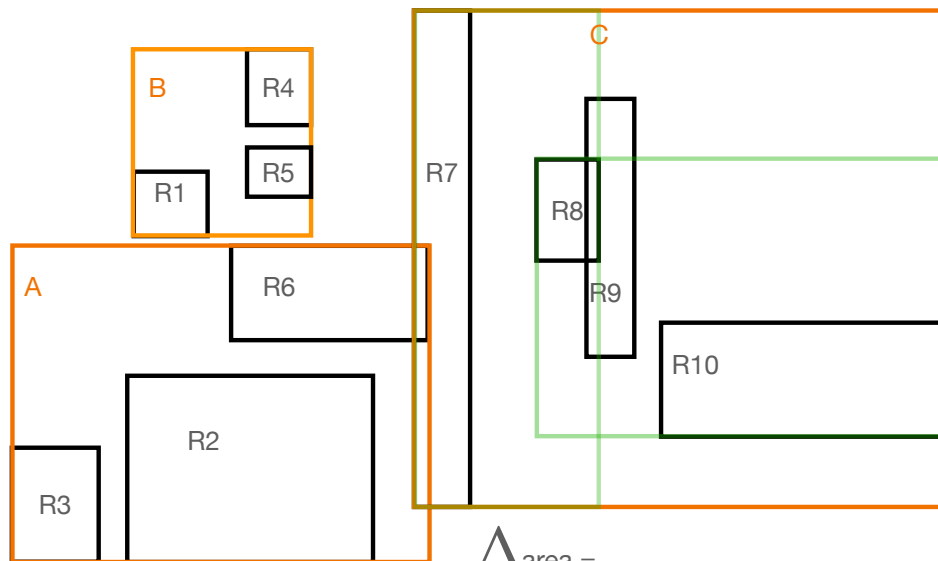
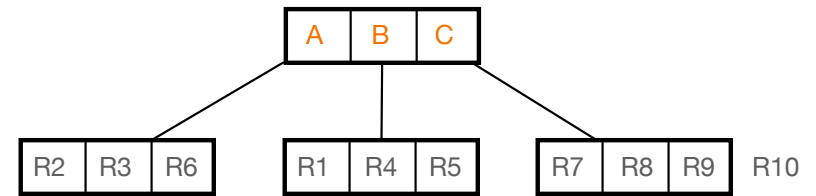
Seeds R3, R4  
for split







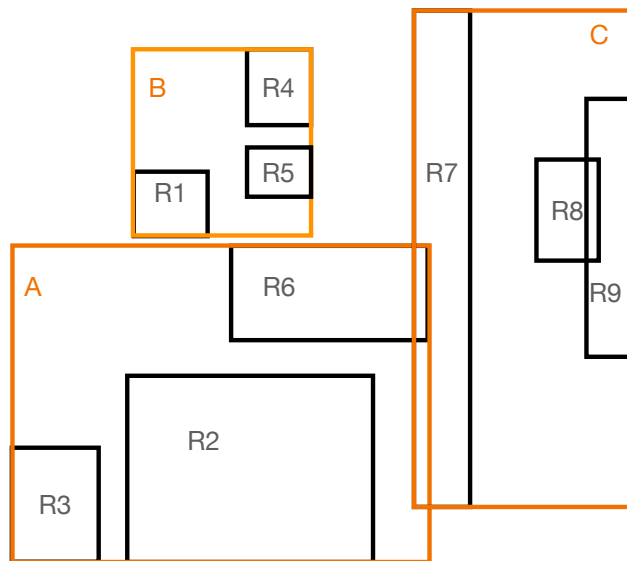




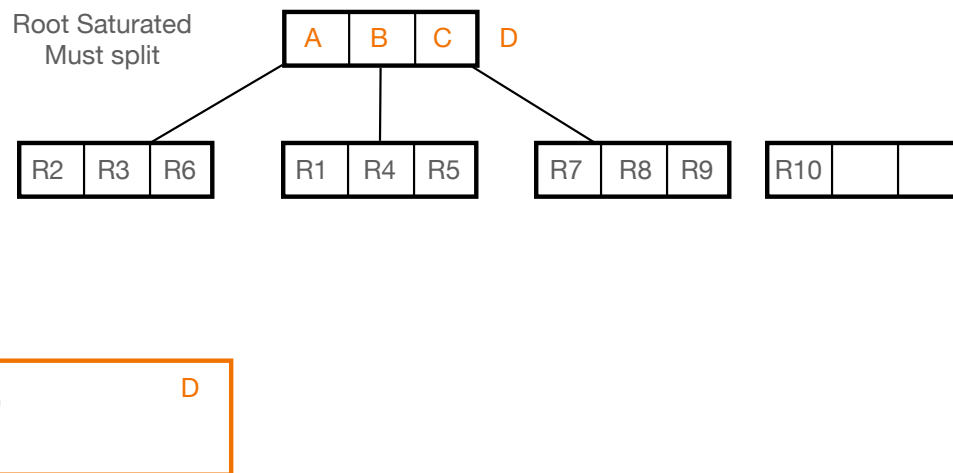
$\Delta_{\text{area}} =$   
52316

Split seeds  
R7, R10

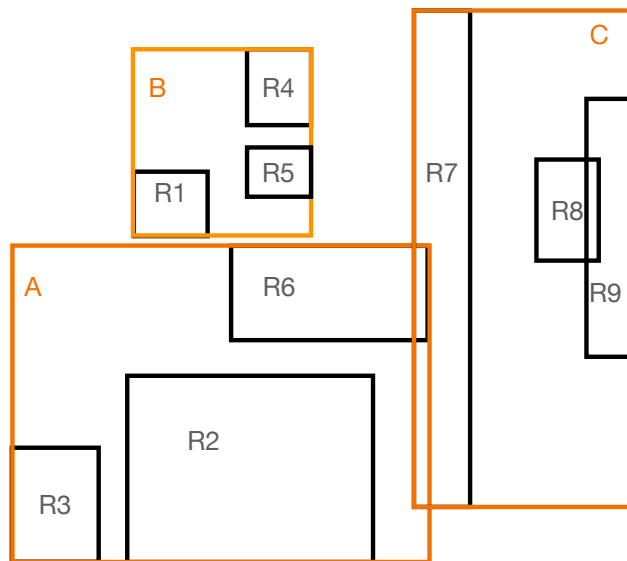
$\Delta_{\text{area}} =$   
142252



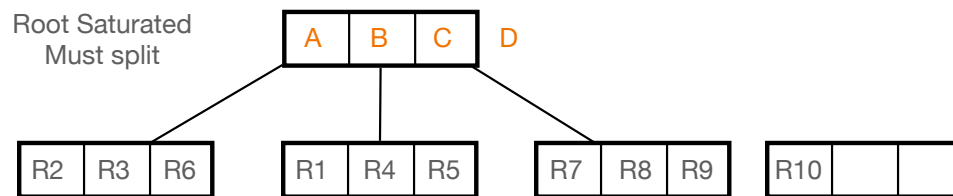
Root Saturated  
Must split







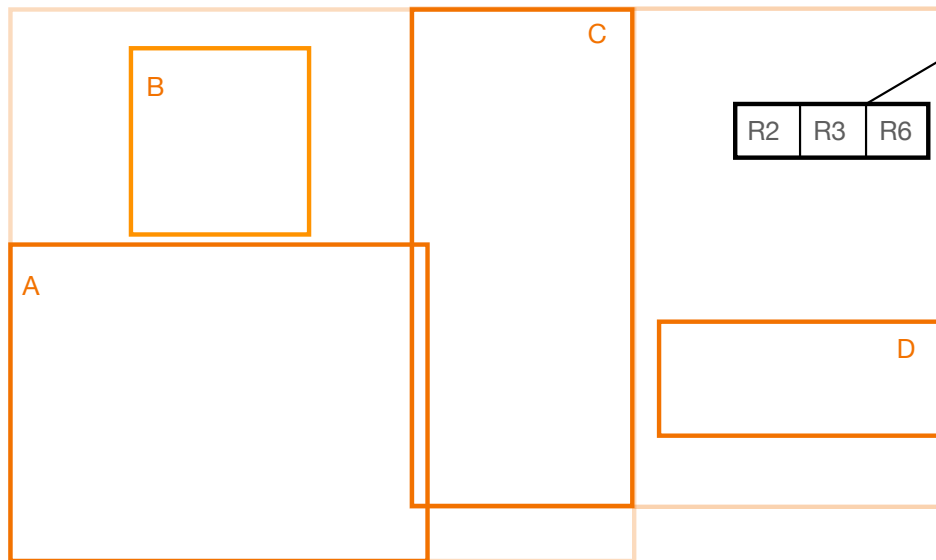
Root Saturated  
Must split



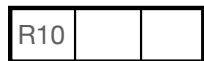
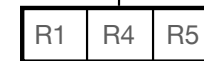
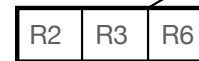
Split seeds  
A, D



$\Delta_{\text{area}} =$   
175294



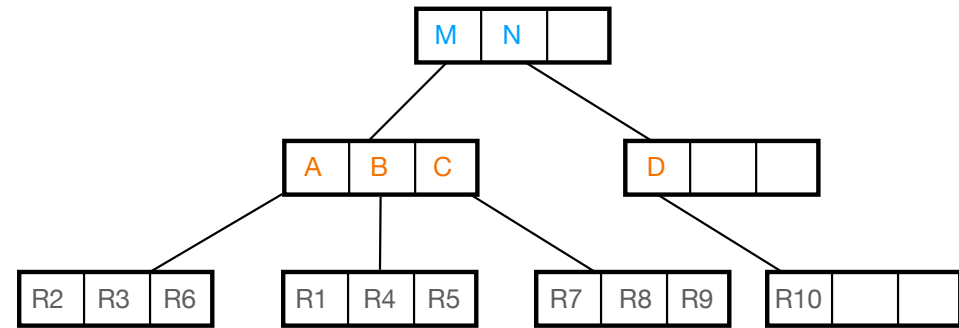
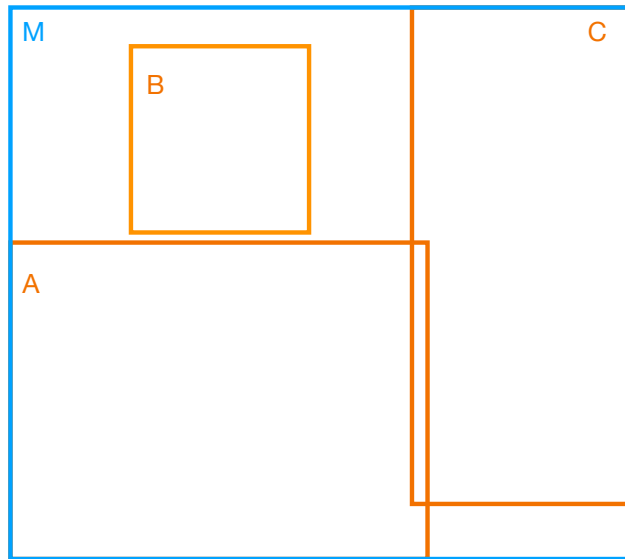
Root Saturated  
Must split



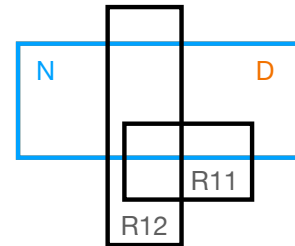
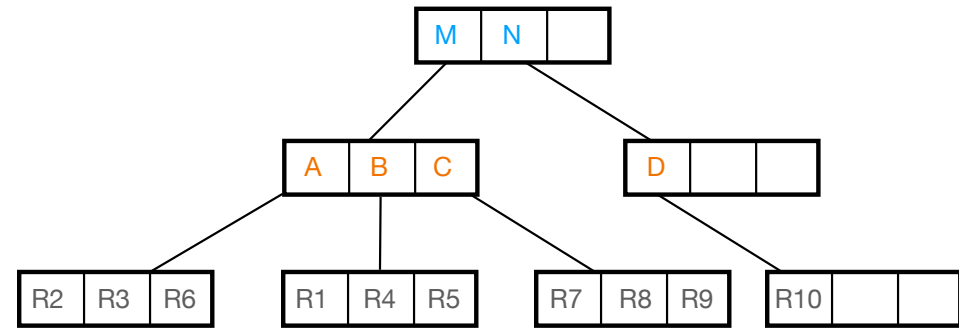
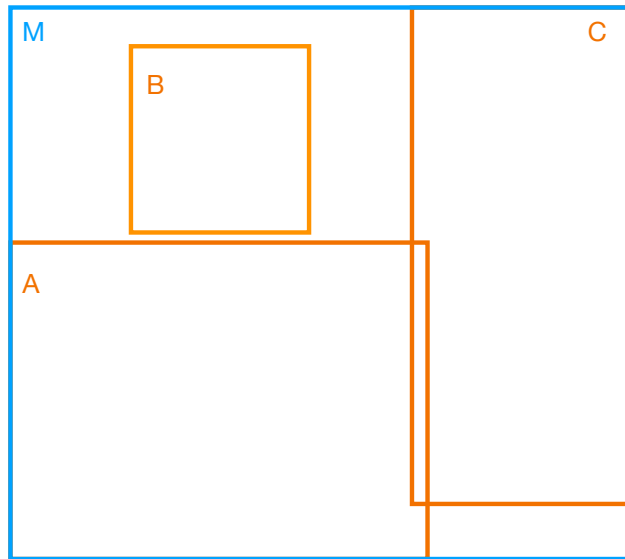
Split seeds  
A, D

$\Delta_{\text{area}} =$   
192876

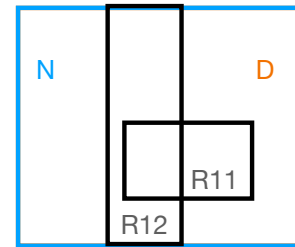
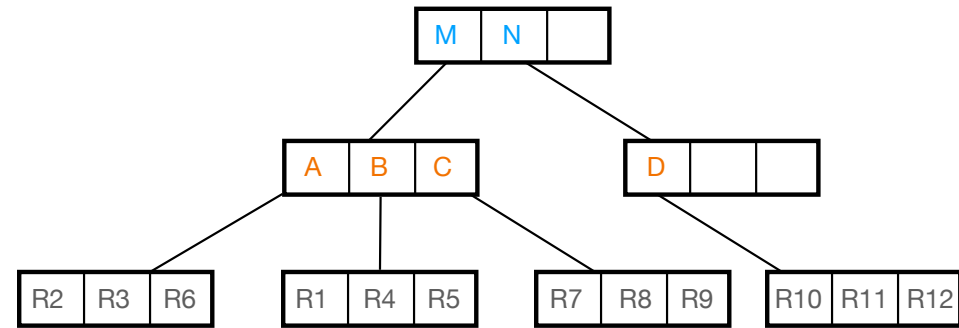
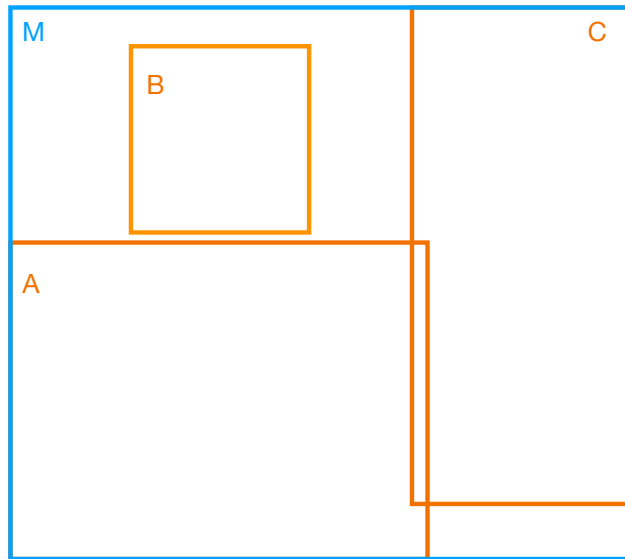
$\Delta_{\text{area}} =$   
175294



$\Delta_{\text{area}} =$   
175294



$\Delta$  area =  
175294



# A Theory of Computation

- While we have introduced many problems with polynomial-time algorithms...
  - We haven't formally defined what this means
  - And not all problems enjoy fast computation
- Given a set  $I$  of problem instances, and a set  $S$  of problem solutions, an abstract problem is a binary relationship in  $I \times S$ . That is, a set of pairs  $(i,s)$ 
  - The problem shortest path associates each instance of a graph and an origin-destination with a sequence of vertices which connect the origin and destination
- **Decision** problems have a yes or no solution. Abstract decision problem is a function which maps problem instances  $I$  into  $\{\text{yes}, \text{no}\}$ .
  - e.g. Is the shortest path in this graph between nodes 0 and nodes 30 have length  $> 10$ ?

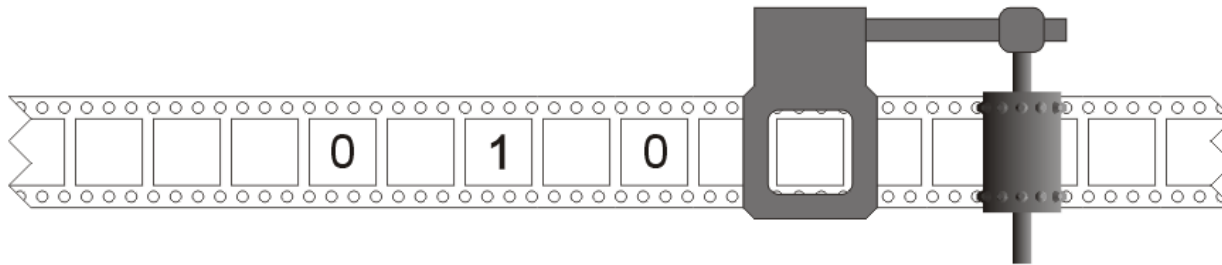
# Decision Problem Instance

- If a machine is to solve an instance of a problem, the input must be specified in terms of a string of bits
  - We must encode problem instance  $I$  into a sequence of binary inputs
  - This helps understand the “size” of the problem instance
  - A concrete problem is an encoding of the set of problem instances to the set of binary strings
  - And not all problems enjoy fast computation
- An algorithm is a procedure that processes an concrete problem instance of size  $n$  and generates the correct answer
  - In what computer model?
  - Turing machine (1936) — Alan Turing (developed decoders for German coders (WW II))

# Turing machine 1

The Turing machine has four components:

- An arbitrary-length tape
- **A head that can**
  - Read a symbol off the tape,
  - Write a symbol to the tape, and/or
  - Move to the next entry to the left or the right

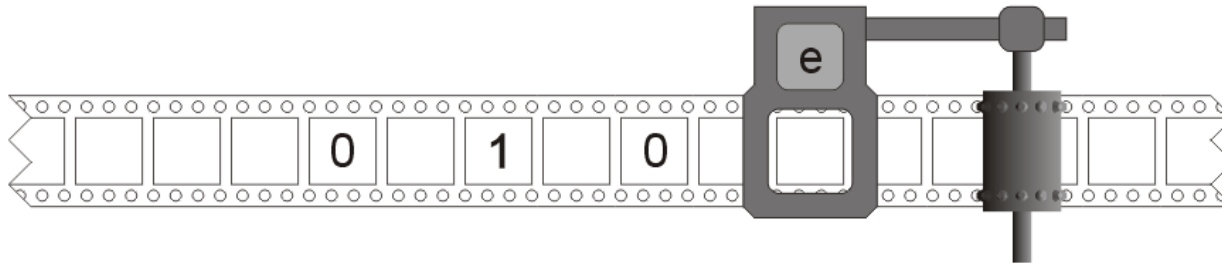




# Turing machine 2

The Turing machine has four components:

- An arbitrary-length tape
- A head
- **A state**
  - The state is one of a finite set of symbols  $Q$
  - In this example,  $Q = \{b, c, e, f\}$
  - The initial state of the machine is denoted  $q_0 \in Q$
  - Certain states may halt the computation



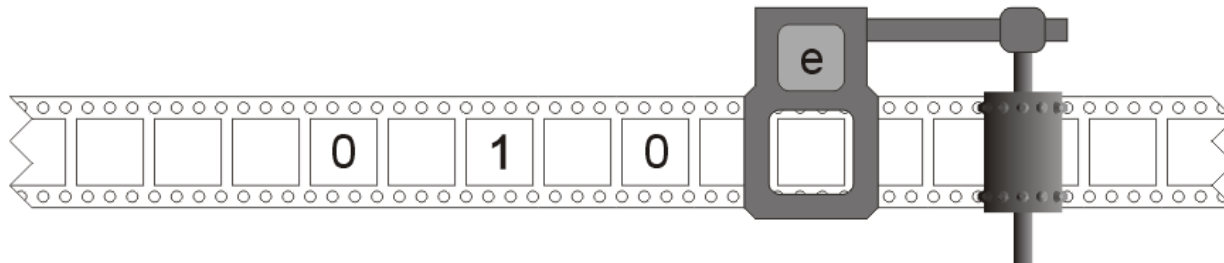
# Turing machine 3

The Turing machine has four components:

- An arbitrary-length tape
- A head
- A state
- **A transition table** (this is your program!)
  - $Q \times \Gamma \rightarrow Q \times \Gamma \times \{L, R, N\}$
  - **L** moves one entry to the left
  - **R** moves one entry to the right
  - **N** indicates no shift

Current		New		
State	Symbol read	State	Symbol to write	Direction
<i>b</i>	<b>B</b>	<i>c</i>	0	<b>R</b>
<i>c</i>	<b>B</b>	<i>e</i>	<b>B</b>	<b>R</b>
<i>e</i>	<b>B</b>	<i>f</i>	1	<b>R</b>
<i>f</i>	<b>B</b>	<i>b</i>	<b>B</b>	<b>R</b>

There is at most one entry in this table for each pair of current settings

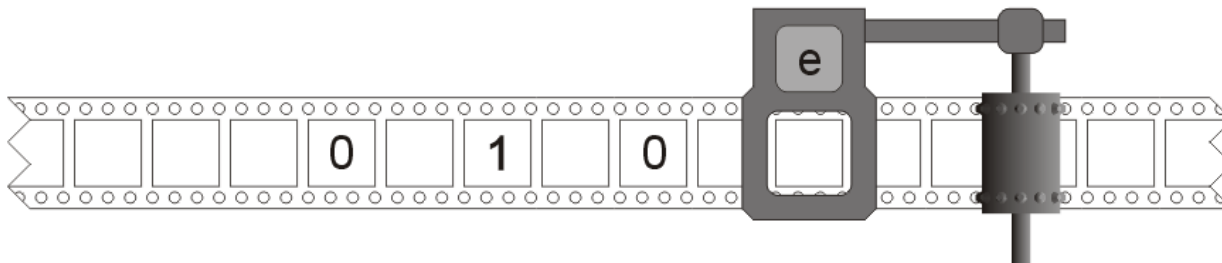


## Example (Turing, '36)

A program to write 0 1 0 1 0 1 0 ...

Currently, the state is  $e$  and the symbol under the head is  $B$

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	$B$	$c$	0	R
$c$	$B$	$e$	$B$	R
$e$	$B$	$f$	1	R
$f$	$B$	$b$	$B$	R

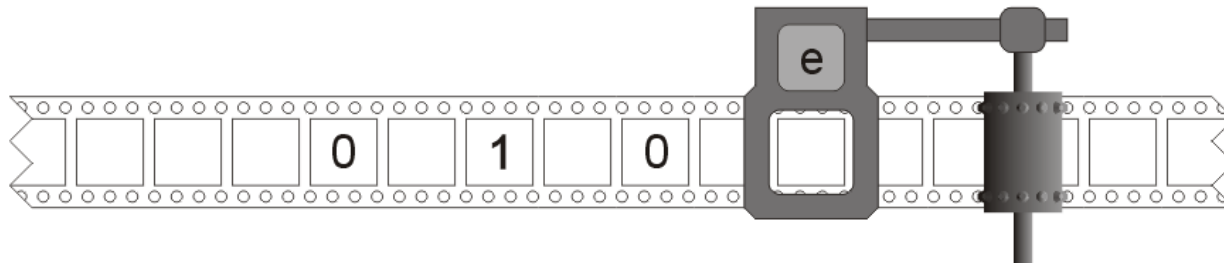


## Example - 2

The transition table dictates that the machine must:

- The state is set to  $f$
- Print symbol 1 onto the tape
- Move one entry to the right

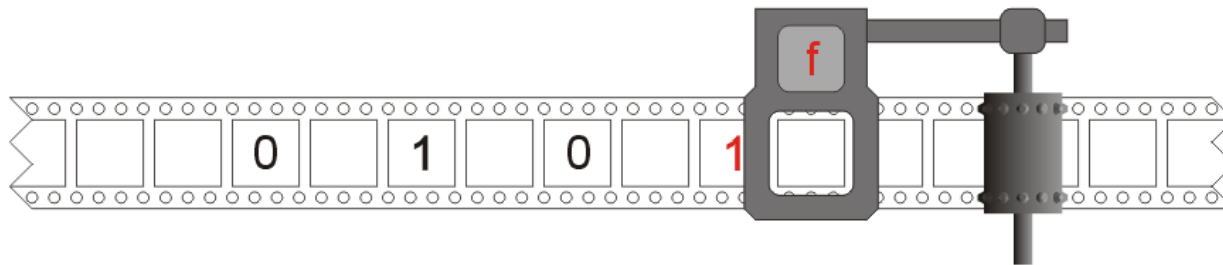
Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	$B$	$c$	0	R
$c$	$B$	$e$	$B$	R
$e$	$B$	$f$	1	R
$f$	$B$	$b$	$B$	R



## Example - 3

The state and symbol under the head have been updated

Current		Next		
State	Symbol read	State	Symbol to write	Direction
<i>b</i>	<b><i>B</i></b>	<i>c</i>	0	<b>R</b>
<i>c</i>	<b><i>B</i></b>	<i>e</i>	<b><i>B</i></b>	<b>R</b>
<i>e</i>	<b><i>B</i></b>	<i>f</i>	1	<b>R</b>
<i>f</i>	<b><i>B</i></b>	<i>b</i>	<b><i>B</i></b>	<b>R</b>

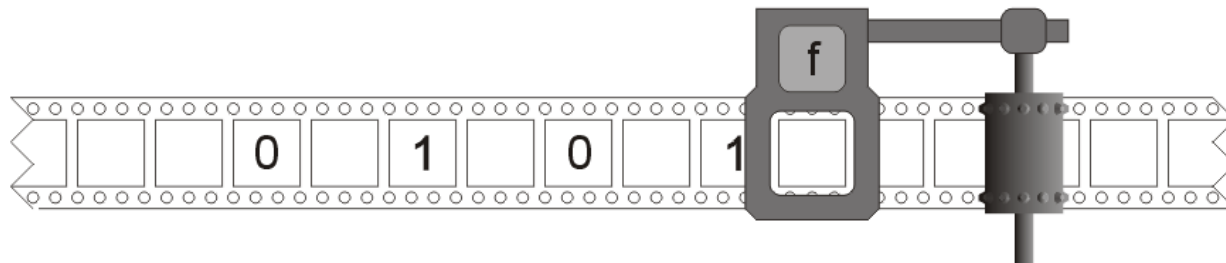


## Example - 4

The state is  $f$  and the symbol under the head is the blank  $B$ :t

- The state is set to  $b$
- A blank is printed to the tape
- Move one entry to the right

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	$B$	$c$	0	R
$c$	$B$	$e$	$B$	R
$e$	$B$	$f$	1	R
$f$	$B$	$b$	$B$	R

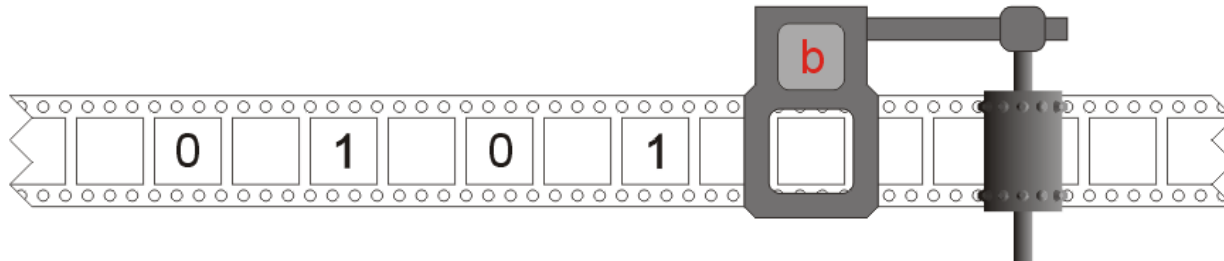


## Example - 5

Again, the state is  $b$ , the symbol a blank, and therefore:

- Set the state to  $c$
- Print the symbol 0 to the tape
- Move one entry to the right

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	$B$	$c$	0	<b>R</b>
$c$	$B$	$e$	$B$	<b>R</b>
$e$	$B$	$f$	1	<b>R</b>
$f$	$B$	$b$	$B$	<b>R</b>

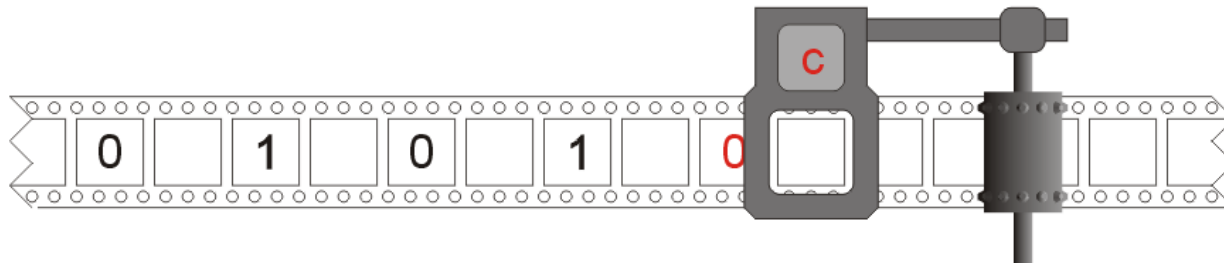


## Example - 6

The result is the state  $c$  and a blank symbol is under the head:

- Set the state to  $e$
- Write a blank to the tape
- Move one entry to the right

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	$B$	$c$	0	<b>R</b>
$c$	$B$	$e$	$B$	<b>R</b>
$e$	$B$	$f$	1	<b>R</b>
$f$	$B$	$b$	$B$	<b>R</b>



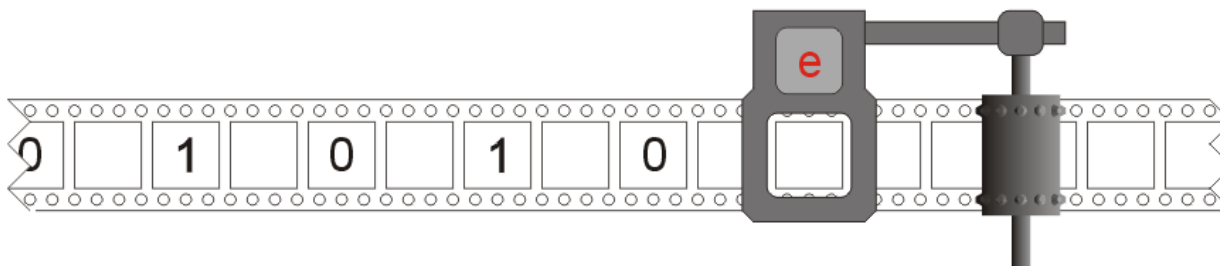


## Example - 7

The result is the state  $e$  and a blank symbol **B** under the head

- This is the state we were in four steps ago
- This machine never halts...

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$b$	<b>B</b>	$c$	0	<b>R</b>
$c$	<b>B</b>	$e$	<b>B</b>	<b>R</b>
$e$	<b>B</b>	$f$	1	<b>R</b>
$f$	<b>B</b>	$b$	<b>B</b>	<b>R</b>



# Another Example

This Turing machine does **what**?

- Tape symbols:  $\Gamma = \{B, 1\}$
- States:  $Q = \{a, b, c, d, e, H\}$
- Initial state:  $q_0 = a$
- Halting state:  $H$

Note there is exactly one entry for each pair in  $Q \setminus \{H\} \times \Gamma$

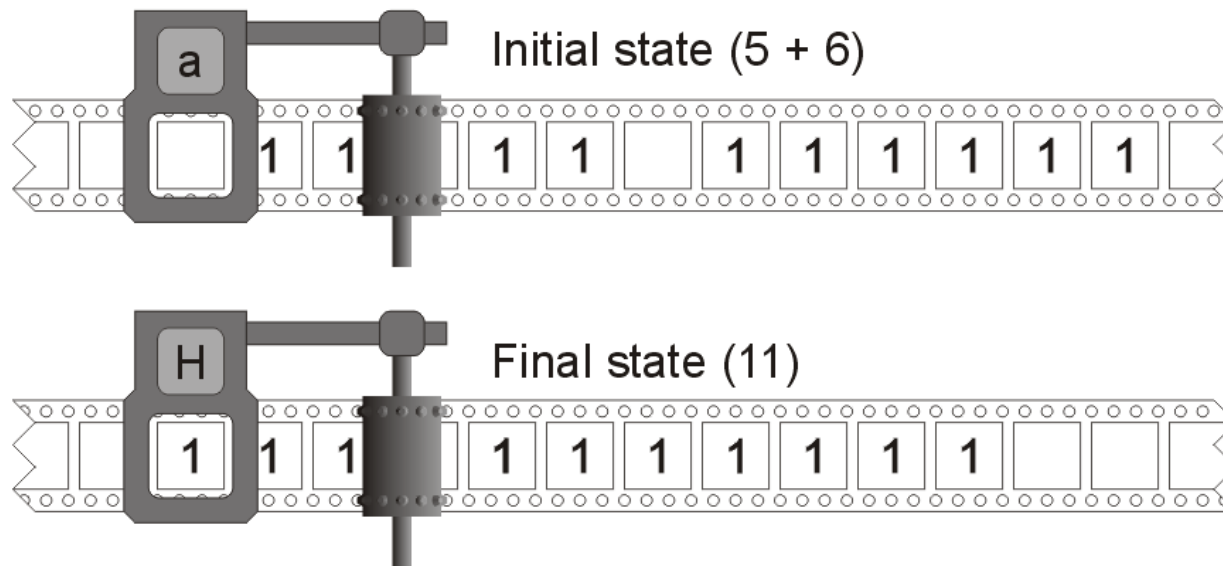
- It may not be necessary to have one for each, but you cannot have more than one transition for a given state and symbol
- **Deterministic** program

Current		Next		
State	Symbol read	State	Symbol to write	Direction
$a$	$B$	$a$	$B$	$R$
$a$	1	$b$	1	$R$
$b$	$B$	$c$	1	$R$
$b$	1	$b$	1	$R$
$c$	$B$	$d$	$B$	$L$
$c$	1	$b$	1	$R$
$d$	$B$	$d$	$B$	$L$
$d$	1	$e$	$B$	$L$
$e$	$B$	$H$	$B$	$R$
$e$	1	$e$	1	$L$

## Example 2

After 22 steps, a group of five ones and a group of six ones are merged into a single group of eleven ones

- This represents  $5 + 6 = 11$
- It is the simplest addition machine (no boolean representation of numbers)



# Non-deterministic algorithms

A Turing machine is non-deterministic if the transition table can contain more than one entry per state-letter pair

- When more than one transition is possible, a non-deterministic Turing machine branches and creating a new sequence of computation for each possible transition

A non-deterministic algorithm can be implemented on a deterministic machine in one of three manners:

- Assuming execution along any branch ultimately stops, perform a depth-first traversal by choosing one of the two or more options and if one does not find a solution, continue with the next option
- Create a copy of the currently executing process and have each copy work on one of the next possible steps
  - These can be performed either on separate processors or as multiple processes or threads on a single processor
- Randomly choose one of the multiple options

# Turing-Church Conjecture

Alan Turing and Alonzo Church (Turing's PhD mentor at Princeton):

- For any algorithm which can be calculated given arbitrary amounts of time and storage, there is an equivalent Turing machine for that algorithm
- Formally: a function on the natural numbers can be calculated by an effective method if and only if it is computable by a Turing machine
  - 'Effective method': each step of which is precisely predetermined and which is certain to produce the answer in a finite number of steps

A computational system is said to be *Turing complete* if it can compute every function computable on a Turing machine

- e.g., a programming language compiled into machine code and run on a process

# Decision Problem Instance

- An algorithm solves a concrete problem in time  $O(T(n))$  if, when provided with a problem instance of size  $n$  bits, it produces the correct answer to the question in  $O(T(n))$  time
- **Polynomially solvable** problems:  $T(n) = n^k$  for some  $k > 0$
- Size of the input:
  - Integers represented in binary
  - Sets represented in bits related to the number of elements in the set times the number of bits per element

# P and NP

- A decision problem belongs to the class **P** if there is a algorithm solving the problem with a running time on a deterministic machine that is polynomial in the input size.
- A decision problem belongs to the class **NP** (non-deterministic polynomial) if:
  - Any solution  $y$  leading to 'yes' can be encoded in polynomial space with respect to the size of the input  $x$ .
  - Checking whether a given solution leads to 'yes' can be done in polynomial time with respect to the size of  $x$  and  $y$
  - problem is solvable in polynomial time in a non-deterministic machine
    - Can explore all possible solutions in parallel
    - Oracle selects best possible solution to check

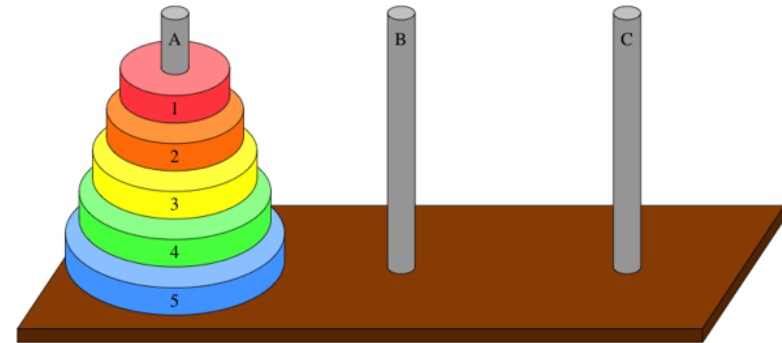
## Slightly more formal:

- Problem  $Q$  belongs to the class **NP**, if there exists a polynomial-time 2-argument algorithm  $A$ , such that:
  - For each instance  $i$ ,  $i$  is a yes-instance to  $Q$ , if and only if, there is a polynomial-size certificate  $c$  for which  $A(i,c) = \text{true}$ .

# Examples

- Tower of Hanoi

- Number of moves to solve is exponential in number of disks
- Can't describe solution in polynomial number of moves
- Not in NP



- Shortest path problem

- Is the length of a shortest path from a to b less than a threshold?
- Can answer in polynomial time in the size of the description of the network —> It is in **P**

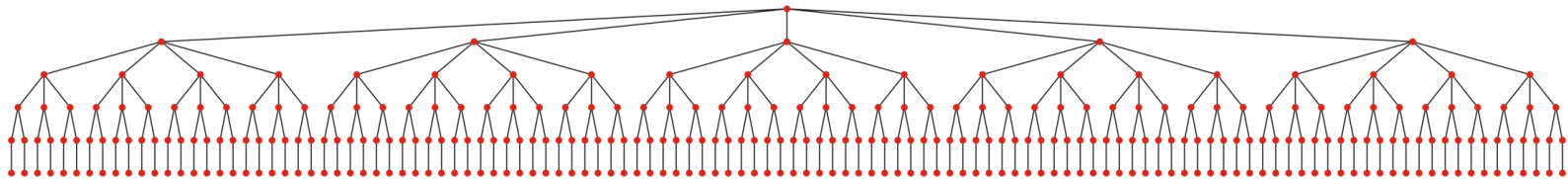
- Traveling salesperson problem

- Is the length of a complete traveling salesperson tour less than a threshold?
- A tour can be described in polynomial space, and we can verify the length of the tour in polynomial time —> it is in **NP**



# Non-deterministic polynomial-time algorithms

- The traveling salesman problem can be solved non-deterministically:
  - At each step, spawn a thread for each possible path
  - As you finish, compare them and determine if any of them have length less than  $k$
  - The run time is now  $\Theta(|V|)$
  - This is a brute-force search



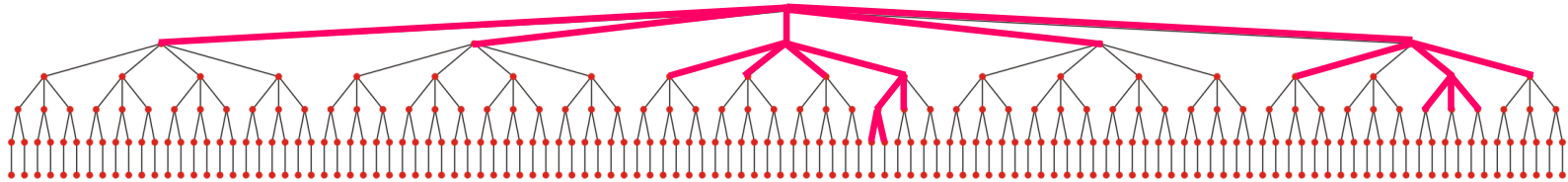
# Non-deterministic polynomial-time algorithms

Consider the following decision problem:

“Is there a path between vertices  $a$  and  $b$  with weight no greater than  $K$ ?”

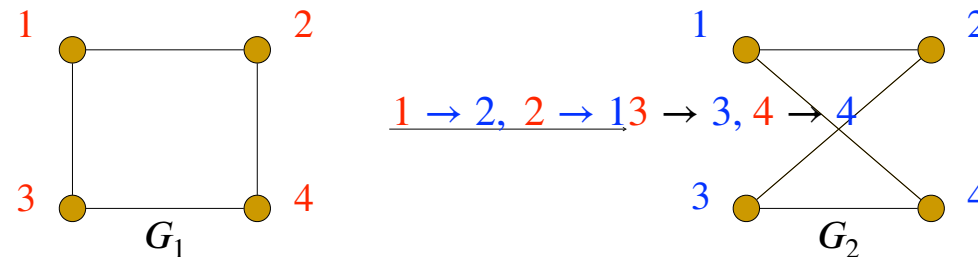
Dijkstra’s algorithm can answer this in polynomial time

- Dijkstra’s algorithm also solves the optimization problem



# Examples of NP problems

- **Factoring**: factor a given number  $n$ .
- Decision version: Given  $(n, k)$ , decide whether  $n$  has a factor less than  $k$
- Factoring is in **NP**: For any candidate factor  $m \leq k$ , it's **easy to check** whether  $m \mid n$ .
- **Graph Isomorphism**: Given two graphs  $G_1$  and  $G_2$ , decide whether we can permute vertices of  $G_1$  to get  $G_2$ .



- Easy to check: For any given permutation, easy to permute  $G_1$  according to it and then compare to  $G_2$ .

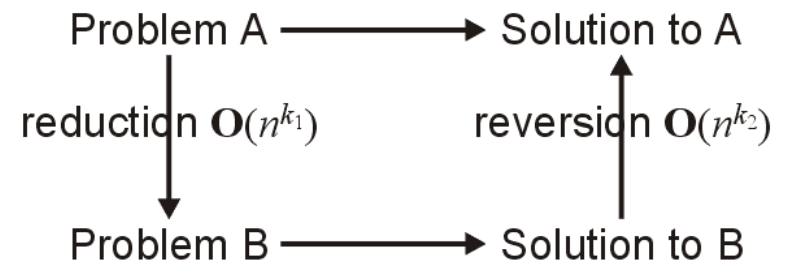
# Reduction and completeness

- Decision problem for language  $A$  is **reducible** to that for language  $B$  in time  $t$  if  $\exists f: \text{Domain}(A) \rightarrow \text{Domain}(B)$  s.t.  $\forall$  input instance  $x$  for  $A$ ,
  1.  $x \in A \Leftrightarrow f(x) \in B$ , and
  2. one can compute  $f(x)$  in time  $t(|x|)$
- Thus to solve  $A$ , it is enough to solve  $B$ .
  - First compute  $f(x)$
  - Run algorithm for  $B$  on  $f(x)$ .
  - If the algorithm outputs  $f(x) \in B$ , then output  **$x \in A$** .

# Reduction

- Reduction converts the solution of a problem to the solution of another problem

- Graphically, we may think of the following image:



- To solve Problem A, we:
  - Reduce the problem to Problem B in polynomial time
  - Solve Problem B
  - Revert the solution back into a solution for Problem A
- We want the reduction and reversion algorithms to be of polynomial complexity: **polynomial reduction**

## Example: Polynomial reduction

- Multiply two  $n$  digit decimal numbers:
  - Reduction: convert the two numbers into binary numbers
  - Multiply the two binary numbers
  - Reversion: convert the solution back into a decimal number
- Both the reduction and the reversion run in  $\Theta(n)$  time
- Observe: if a decision problem is reduced to a decision problem, the corresponding reversion algorithm is trivial and is in  $\Theta(1)$  time

# Polynomial reduction

- Another example: Does a list have a duplicate element?
  - Reduction: Sort the list
  - Simpler problem: Does a sorted list have a duplicate element?
  - Reversion: Return `true` or `false`, as is
- Both the reduction and the reversion run in  $\Theta(n)$  time
  - If a decision problem is reduced to a decision problem, the reversion is therefore  $\Theta(1)$ 
    - Either the solution or its negation

# Examples: Polynomial reduction

- Example: Does an  $n$  by  $n$  assignment problem have minimum cost less than  $K$ ?
  - Polynomial Reduction: Reduce to the solution of  $n$  sequential shortest path problems in non-negative weight graphs with  $O(2n)$  vertices
  - Reversion: Convert the decision of the successive shortest path algorithm
- Example: Given two sequences  $a_1, a_2, \dots, a_n$  and  $b_1, b_2, \dots, b_n$ , is there a permutation  $j(i)$  such that  $\sum_{i=1}^n a_i b_{j(i)} \geq K$ ?
  - Polynomial Reduction: sort both sequences increasing order, multiply the sorted sequences and verify product is greater than or equal to  $K$
  - Another polynomial reduction: convert to assignment problem!

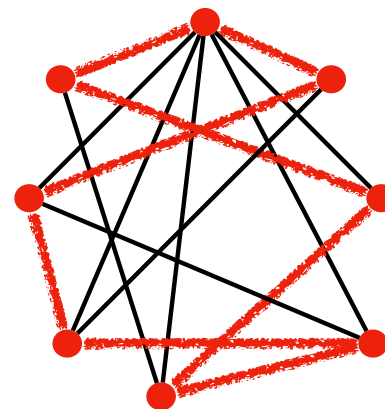
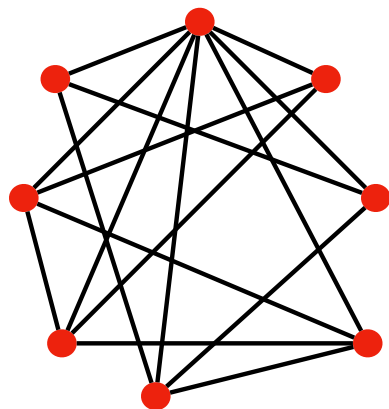


# Polynomially Reducible

- **Definition:** Problem A is polynomially reducible to problem B if there exists an algorithm for solving problem A in polynomial time if we could solve arbitrary instances of problem B at unit cost
  - Written as  $A \leq_p B$
  - If  $A \leq_p B$ , and  $B \leq_p A$ , then we write  $A =_p B$
- If  $A \in \mathbf{P}$  and  $B \leq_p A$ , then  $B \in \mathbf{P}$ 
  - e.g. Shortest path problem is in  $\mathbf{P}$ . Assignment problem is polynomially reducible to shortest path problem. Then Assignment problem is in  $\mathbf{P}$ .

# Polynomial Reduction

- Problem A: Traveling salesperson problem
  - Given a weighted directed graph, find a simple cycle that visits each vertex once and has total cost less than or equal to  $K$
- Problem B: Hamiltonian cycle problem
  - Given a directed graph, does there exist a simple cycle that includes every vertex once?



# Polynomial Reduction

- Claim:  $B \leq_p A$

Proof: Let graph for B be  $G(V,E)$ . We are going to construct a weighted graph  $G(V,E')$  with a weight function for Problem A, in polynomial time

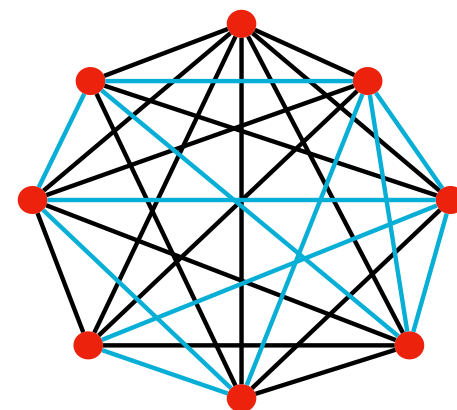
Let  $E'$  be the dense set of edge in  $V \times V$ . Assign weights as follows:  $w(e') = 0$  if  $e' \in E$ ,  $w(e') = 1$  if  $e' \notin E$

Reduction:  $O(|V|^2)$  is polynomial

TSP problem: Does there exist a simple cycle that visits every vertex in  $V$  once, and has total cost less than or equal to 0

If yes, it is a cycle with all edges in  $E$ , and so it is a Hamiltonian cycle

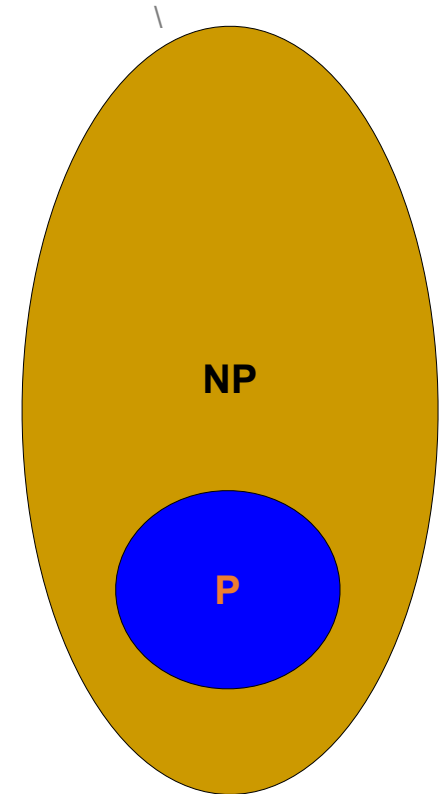
If no, no cycle exists with all edges in  $E$ , so no Hamiltonian cycle can be found



This shows Hamiltonian cycle  $\leq_p$  Traveling Salesperson Problem

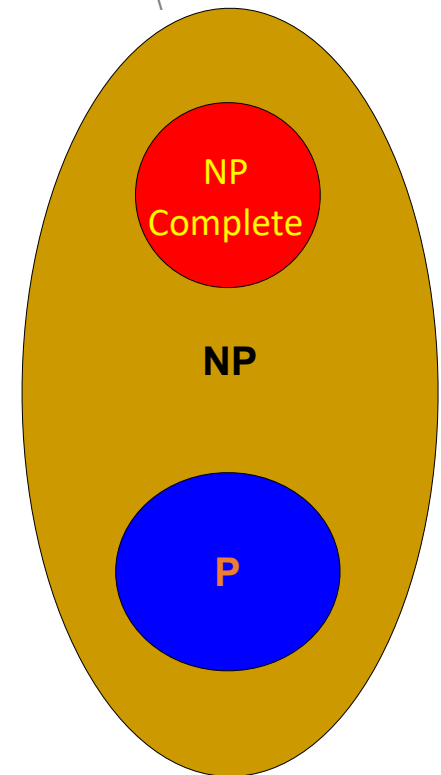
# NP Complete

- We know class **P** is a subset of class **NP**
  - TSP is not known to be in class **P** but is in **NP**
  - It is a conjecture that  $\mathbf{P} \neq \mathbf{NP}$ , but it has not been proven
  - We do know  $\mathbf{P} \subset \mathbf{NP}$
- **Definition:** a problem  $A$  is NP-complete, if  $A \in \mathbf{NP}$  and every problem  $B \in \mathbf{NP}$  can be polynomially reduced to  $A$ . That is,  $B \leq_P A$
- Do such problems exist? If so, **and** one of them was in class **P**, then every problem in class **NP** could be solved in polynomial time



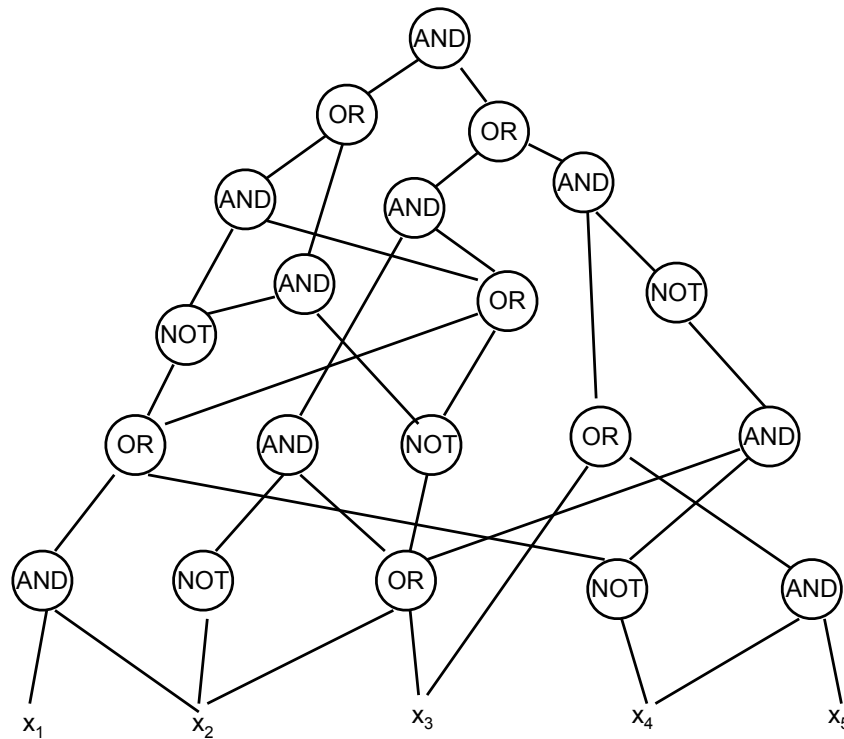
# Existence of NP-complete Problems

- Steven Cook and Leonid Levin (BU) proved in parallel that there exists an **NP** complete problem
  - Levin joined BU in 1980s
- Specifically: Boolean satisfiability (SAT)
  - Given a Boolean formula, is there an assignment of True and False to its variables so that the formula evaluates to True?
  - e.g. Can we find values of p, q, r, s so formula below is true?  
$$(p \vee q \vee r) \wedge (p \vee \neg q \wedge s) \wedge (\neg p) \wedge (\neg q \wedge s) \wedge (\neg s)$$
- Cook-Levin Theorem
  - If a polynomial-time deterministic algorithm can solve this problem, then polynomial-time deterministic algorithms can solve all NP problems



## /

- All the gates are ands, nots, ors



# SAT and $k$ -SAT

- SAT formula: **AND** of  $m$  clauses (Conjunctive Normal Form)
- $n$  **variables** (taking values 0 and 1)
- a **literal**: a variable  $x_i$  or its negation  $\bar{x}_i$
- $m$  **clauses**, each being **OR** of some literals.
  - $(x_1 \vee x_2 \vee \bar{x}_3) \wedge (x_1 \vee \bar{x}_2 \vee x_4) \wedge (\bar{x}_4) \wedge (\bar{x}_2 \vee x_3) \wedge (\bar{x}_3)$
- **SAT** Problem: Is there an **assignment** of variables s.t. the formula evaluates to 1?
- $k$ -SAT: same as SAT but each clause has at most  $k$  literals.
- SAT and  $k$ -SAT are in **NP**
  - Given any assignment, it's **easy to check** whether it satisfies all clauses.

# The 1<sup>st</sup> **NP**-complete problem: SAT

- Consider an arbitrary problem class  $Y$  in **NP**
- Given a problem instance  $y$ , with description length  $n$  bits, there is an algorithm which is polynomial in  $n$ ,  $p(n)$ , which can verify whether the answer to this instance  $y$  is true
  - The input description to this verification algorithm is a set of bits: Boolean variables
  - Verification algorithm manipulates Boolean variables into a yes or no decision: a Boolean output
- The algorithm can be specified as a Boolean formula in conjunctive normal form, involving  $p(n)$  terms
- Finding a set of inputs to this formula that makes it true is equivalent to determining whether there original problem instance has answer true
  - $Y \leq_p \text{SAT}$



# How Do We Find Other NP-Complete Problems

- Reduction! We want to find if problem Y in **NP** is NP-complete
- If  $SAT \leq_P Y$ , then Problem Y is NP-Complete! SAT is no easier than Y
- Note: to prove a problem A is in class **P**, we need to find a problem B in class **P** so that  $A \leq_P B$
- To prove a problem A is NP-complete class **P**, find an NP-complete problem so that  $B \leq_P A$
- Note the following: it is easy to show that  $SAT =_P 3\text{-SAT}$  using standard logic transformations

# Graph NP-Complete Problems

- Karp ('72) followed Cook's proof to show 3-D SAT can be reduced to 21 different graph problems
  - TSP, others
- Many others have continued to extend this to thousands of other problems
- Note: to prove a problem A is in class **P**, we need to find a problem B in class **P** so that  $A \leq_P B$
- To prove a problem A is NP-complete class **P**, find an NP-complete problem so that  $B \leq_P A$
- Note the following: it is easy to show that  $SAT =_P 3\text{-SAT}$  using standard logic transformations

# NP-complete problem 1: Clique

- **Clique**: Given a graph  $G$  and a number  $k$ , decide whether  $G$  has a clique of size  $\geq k$ .
  - Clique: a complete subgraph.
- Fact: Clique is **in NP**.
- Theorem: If one can solve **Clique** in polynomial time, then one can also solve **3-SAT** in polynomial time.
  - So Clique is at least as hard as 3-SAT.
- Corollary: Clique is **NP-complete**.

## Approach: Reduction

- Given a 3-SAT formula  $\phi = C_1 \wedge \dots \wedge C_k$ , with conjunctions  $C_k$ , we construct a graph  $G$  s.t.
  - if  $\phi$  is satisfiable, then  $G$  has a clique of size  $k$ .
  - if  $\phi$  is unsatisfiable, then  $G$  has no clique of size  $\geq k$ .
  - Note:  $k$  is the number of clauses of  $\phi$ .
- If you can solve the Clique problem, then you can also solve the 3-SAT problem.

# Construction

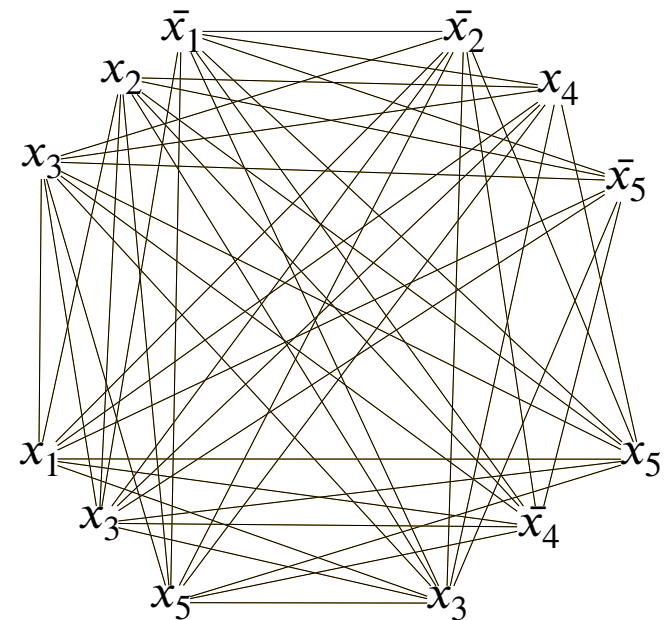
- Put each **literal** appearing in the formula as a **vertex**.

- Literal:  $x_i$  and  $\bar{x}_i$

- e.g.

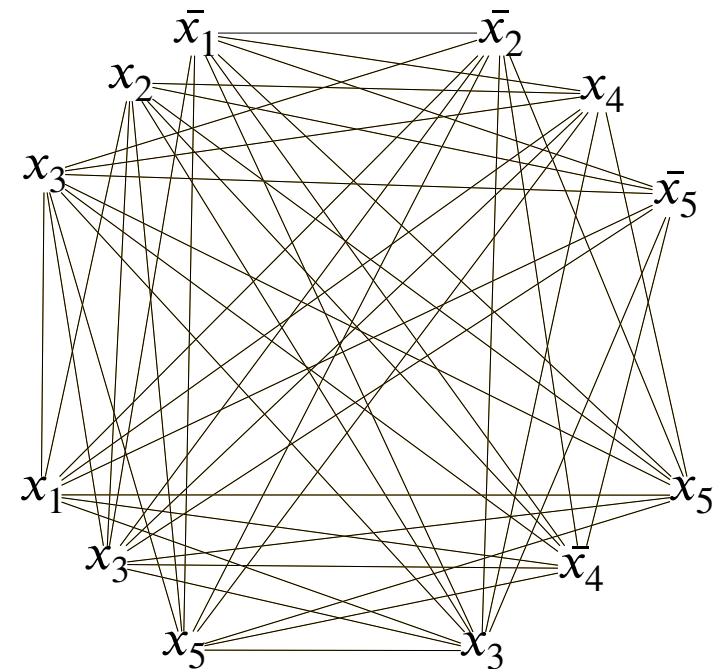
$$\phi = (\bar{x}_1 \vee x_2 \vee x_3) \wedge (\bar{x}_2 \vee x_3 \vee x_5) \wedge (x_1 \vee x_3 \vee x_5) \wedge (x_3 \vee \bar{x}_4 \vee x_5)$$

- Literals from the **same clause** are **not connected**
- Two literals from different clauses are **connected** if they are **not the negation** of each other
- 



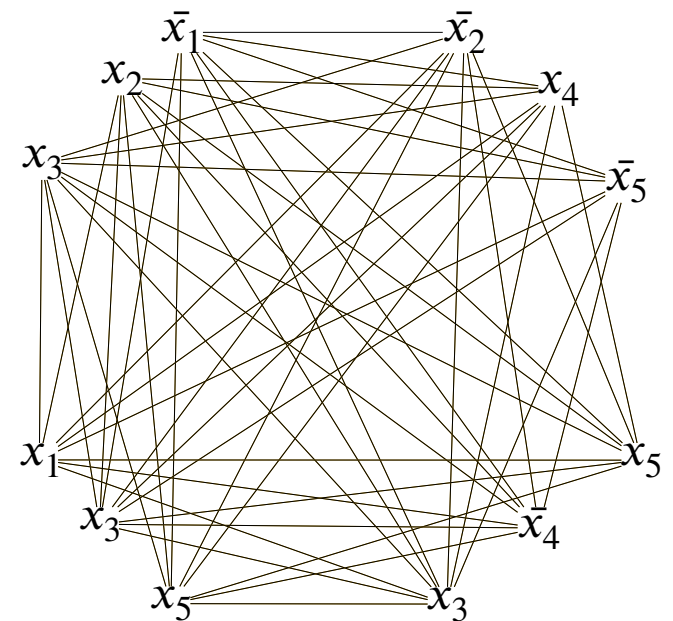
$\phi$  is satisfied  $\Rightarrow G$  has a  $k$ -clique

- If  $\phi$  is satisfied,
- then there is a satisfying assignment  $x_1 \dots x_n$  s.t. each clause has at least one literal being 1.
  - E.g.  $x = 00111$ , then pick  $\bar{x}_1, x_4, x_3, x_5$
- And those literals (one from each clause) are **consistent** because they all evaluate to 1
- So the subgraph with these vertices is **complete**. --- A clique of size  $k$ .



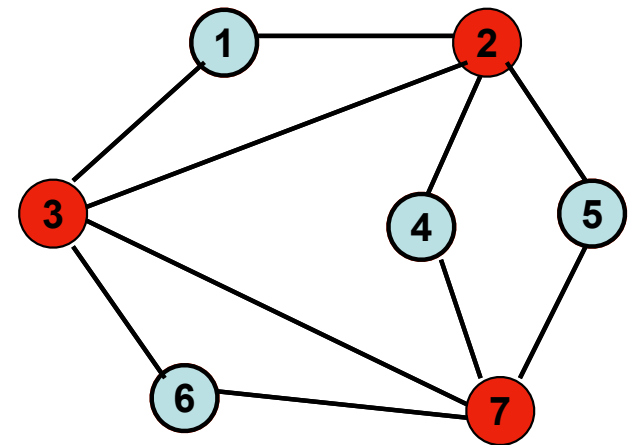
$G$  has a  $k$ -clique  $\Rightarrow \phi$  is satisfied

- If the graph has a clique of size  $k$ :
- It must be **one** vertex **from each** clause.
  - Vertices from the same clause don't connect.
- And these literals are **consistent**.
  - Otherwise they don't all connect.
- So we can pick the **assignment** by these vertices. It satisfies all clauses by satisfying at least one vertex in each clause
- Hence, it makes  $\phi$  true



## NP-complete problem 2: Vertex Cover

- **Vertex Cover**: Given a graph  $G$  and a number  $k$ , decide whether  $G$  has a **vertex cover** of size  $\leq k$ 
  - $V'$  is a vertex cover if all edges in  $G$  are “touched” by vertices from  $V'$
- Vertex Cover is **in NP**
  - Given a candidate subset  $S \subseteq V$ , it is easy to check whether “ $|S| \leq k$  and  $S$  touches all edges in  $E$ ”





# NP-complete

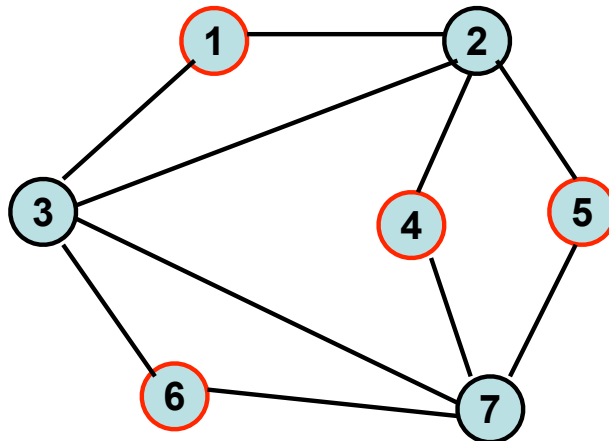
- To prove Vertex Cover is **NP-complete**, reduce **Clique** to Vertex Cover
- For any graph  $G$ , the **complement** of  $G$  is  $\bar{G}$ 
  - If  $G = (V, E)$ , then  $\bar{G} = (V, \bar{E})$
  - $\bar{E} = \{\{i, j\} : i \in V, j \in V, \{i, j\} \notin E\}$
  - Constructing  $\bar{G}$  from  $G$  is a polynomial operation
- **Theorem:**  $G$  has a  **$k$ -clique**  $\iff \bar{G}$  has a **vertex cover** of size  $n - k$ 
  - Will show In next slide
- Given this theorem, Clique can be reduced to Vertex Cover
- So Vertex Cover is **NP-complete**

## Proof of the theorem

- $G$  has a  $k$ -clique  $\iff \exists V' \subset V, |V'| = k, V'$  is a **clique in  $G$**
- Independent set in  $\bar{G}$ : For any  $u, v$  in  $V'$ ,  $\{u, v\} \notin \bar{E}$
- $V'$  is a clique in  $G \iff V'$  is an **independent set** in  $\bar{G}$
- $V'$  is an independent set in  $\bar{G} \iff V/V'$  is a **vertex cover** of  $\bar{G}$ ,  
because every edge in  $\bar{E}$  must touch a vertex in  $V/V'$
- Let  $V'' = V/V'$ . Then,  $|V''| = n - k$ , and  $V''$  is a **vertex cover** of  $\bar{G}$

## Another NP-Complete Problem: Independent Set

- **Independent Set**: Decide whether a given graph has an independent set of size at least  $k$
- The above argument shows that the **Independent Set** problem is also NP-Complete because  $\text{Clique} \leq_P \text{Independent set}$



## NP-complete problem 3: Integer Programming (IP)

- Any 3-SAT formula can be expressed by integer programming.
- Consider a conjunctive clause, for example,
  - $\bar{x}_1 \vee x_2 \vee x_3, \quad x_1, x_2, x_3 \in \{0,1\}$
  - This is equivalent to  $(1 - x_1) + x_2 + x_3 \geq 1, \quad x_1, x_2, x_3 \in \{0,1\}$
- Multiple conjunctive clauses:
  - Translate to multiple integer programming constraints which must be satisfied simultaneously
  - Finding a feasible solution to the set of integer programming inequalities would yield a feasible solution to 3-SAT

# Integer Programming example

- 3-SAT formula

$$(\bar{x}_1 \vee x_2 \vee x_3) \wedge (\bar{x}_2 \vee x_4 \vee \bar{x}_5) \wedge (x_1 \vee x_3 \vee x_5) \wedge (x_3 \vee \bar{x}_4 \vee x_5)$$

- Integer program inequalities

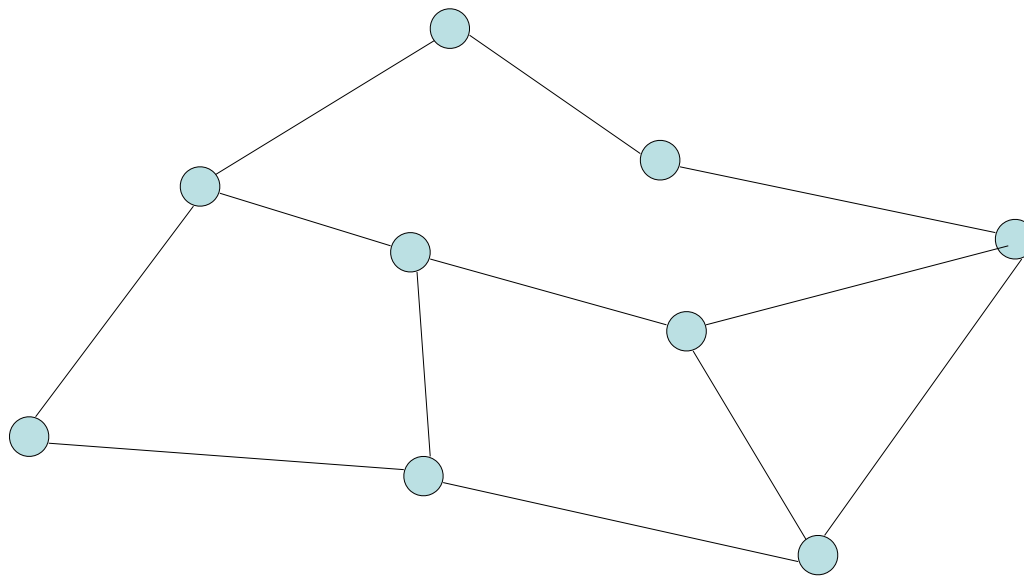
$$\begin{aligned} (1 - x_1) + x_2 + x_3 &\geq 1, \\ (1 - x_2) + x_4 + (1 - x_5) &\geq 1, \\ x_1 + x_3 + x_5 &\geq 1, \\ x_3 + (1 - x_4) + x_5 &\geq 1, \end{aligned}$$

$$x_1, x_2, x_3, x_4, x_5 \in \{0,1\}$$

- So if one can solve IP efficiently, then one can also solve 3-SAT efficiently
- $3\text{-SAT} \leq_P \text{Integer Programming}$

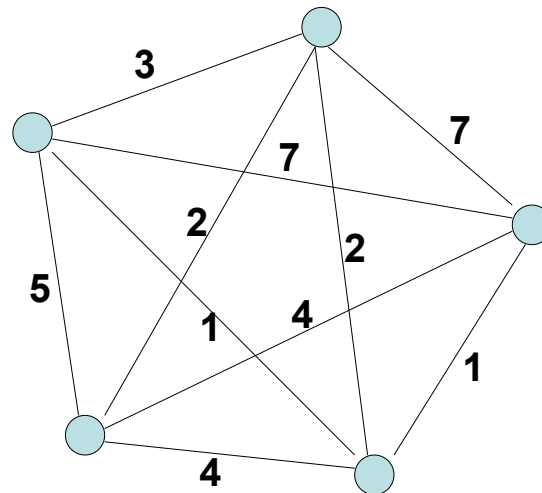
# Hamiltonian Circuit Problem

- Hamiltonian Circuit – does there exist a simple cycle including all the vertices of the graph?
- Can show Vertex Cover  $\leq_p$  Hamiltonian Circuit (very complicated construction)



# Traveling Salesman Problem

- Given a complete graph with edge weights, determine the shortest tour that includes all of the vertices (visit each vertex exactly once, and get back to the starting point)
  - Already proved Hamiltonian Circuit  $\leq_P$  TSP



Find the minimum cost tour

# Subset Sums

The subset sum problem

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

**Ex.**  $\{ 215, 215, 275, 275, 355, 355, 420, 420, 580, 580, 655, 655 \}$ ,  $W = 1505$

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

- Subset sum is in NP
  - Easy to verify whether a subset sums up to  $W$
- Important aspect: numbers are input in binary
  - Reduction must be polynomial in number of bits of input
  - Want to show  $3\text{-SAT} \leq_P \text{Subset Sum}$



# Subset Sum via Dynamic Programming

- Break up into smaller problems, build up to full problem
- $F(k,s)$  = True if there exists a subset of  $w_1, \dots, w_k$  that adds up to  $s$ , else false
- Initialization:  $F(k,0) = \text{True}$ ,  $k = 0, \dots, n$ ;  $F(0, s) = \text{False}$ ,  $s > 0$
- Dynamic Programming recursion:

$$F(k, s) = \begin{cases} F(k-1, s) & \text{if } w_k > s \\ F(k-1, s) \vee F(k-1, s - w_k) & \text{if } w_k \leq s \end{cases}$$

- Can fill table to get solution:  $O(n \times W)$
- But, this is not polynomial:  $W$  is exponential in the size of the binary description of  $W$  in bits
  - Requires exponential space and time

# SAT Reduction to Subset Sum

- Given 3-SAT instance with  $n$  variables and  $k$  clauses, form  $2n + 2k$  decimal integers, each having  $n + k$  digits as follows
  - For each variable  $x_i$ , construct numbers  $t_i$  and  $f_i$  of  $n + m$  digits: the  $i$ -th digit of  $t_i$  and  $f_i$  is equal to 1, other digits from 1 to  $n$  are 0
  - For  $n+1 \leq j \leq n+m$ , the  $j$ -th digit of  $t_i$  is equal to 1 if  $x_i$  is in clause  $c_{j-n}$   
For  $n+1 \leq j \leq n+m$ , the  $j$ -th digit of  $f_i$  is equal to 1 if  $\bar{x}_i$  is in clause  $c_{j-n}$
  - All other digits of  $t_i$  and  $f_i$  are 0
  - Example:  $(x_1 \vee x_2 \vee x_3) \wedge (\bar{x}_1 \vee \bar{x}_2 \vee x_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_3) \wedge (x_1 \vee \bar{x}_2 \vee x_3)$

Number	$i$			$j$			
	1	2	3	1	2	3	4
$t_1$	1	0	0	1	0	0	1
$f_1$	1	0	0	0	1	1	0
$t_2$	0	1	0	1	0	1	0
$f_2$	0	1	0	0	1	0	1
$t_3$	0	0	1	1	1	0	1
$f_3$	0	0	1	0	0	1	0

## SAT Reduction to Subset Sum - 2

- Given 3-SAT instance with  $n$  variables and  $k$  clauses, form  $2n + 2k$  decimal integers, each having  $n + k$  digits as follows
  - For each clause  $c_j$ , construct numbers  $z_j$  and  $y_j$  of  $n + m$  digits: The  $(n+j)$ -th digit of  $z_j$  and  $y_j$  is equal to 1, all other digits of  $z_j$  and  $y_j$  are 0
  - Example:  $(x_1 \vee x_2 \vee x_3) \wedge (\bar{x}_1 \vee \bar{x}_2 \vee x_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_3) \wedge (x_1 \vee \bar{x}_2 \vee x_3)$
  - Finally, construct a sum number  $s$  of  $n + m$  digits:  
For  $1 \leq j \leq n$ , the  $j$ -th digit of  $s$  is equal to 1  
For  $n + 1 \leq j \leq n + m$ , the  $j$ -th digit of  $s$  is equal to 3
  - e.g. 1113333
  -

	i			j			
Number	1	2	3	1	2	3	4
$t_1$	1	0	0	1	0	0	1
$f_1$	1	0	0	0	1	1	0
$t_2$	0	1	0	1	0	1	0
$f_2$	0	1	0	0	1	0	1
$t_3$	0	0	1	1	1	0	1
$f_3$	0	0	1	0	0	1	0
$z_1$	0	0	0	1	0	0	0
$y_1$	0	0	0	1	0	0	0
$z_2$	0	0	0	0	1	0	0
$y_2$	0	0	0	0	1	0	0
$z_3$	0	0	0	0	0	1	0
$y_3$	0	0	0	0	0	1	0
$z_4$	0	0	0	0	0	0	1
$y_4$	0	0	0	0	0	0	1
sum	1	1	1	3	3	3	3

# SAT Reduction to Subset Sum - 3

- If we find subset of rows that sum to the total sum, then we can convert the rows to Boolean variables  $x_i, i = 1, \dots, n$  such that every clause  $c_j, j = 1, \dots, m$  is true
  - $x_i$  true if  $t_i$  is in subset; otherwise,  $f_i$  must be in subset so  $x_i$  is false
  - Since the  $j$  columns sum to 3, at least one of the literals in  $c_j$  must be true because there are at most 2 in  $z_j, y_j$
- If there exists a true assignment, then there is a set of rows that sums to sum
  - For clause  $c_j$ , add rows  $y_j$  if two or less literals are true, add  $z_j$  if only one literal is true
- **Result:** 3-SAT  $\leq_P$  Subset Sum

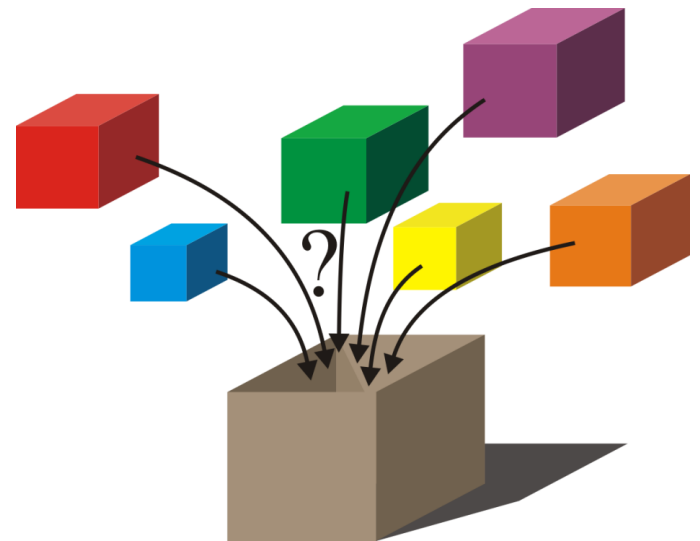
	i			j			
Number	1	2	3	1	2	3	4
$t_1$	1	0	0	1	0	0	1
$f_1$	1	0	0	0	1	1	0
$t_2$	0	1	0	1	0	1	0
$f_2$	0	1	0	0	1	0	1
$t_3$	0	0	1	1	1	0	1
$f_3$	0	0	1	0	0	1	0
$z_1$	0	0	0	1	0	0	0
$y_1$	0	0	0	1	0	0	0
$z_2$	0	0	0	0	1	0	0
$y_2$	0	0	0	0	1	0	0
$z_3$	0	0	0	0	0	1	0
$y_3$	0	0	0	0	0	1	0
$z_4$	0	0	0	0	0	0	1
$y_4$	0	0	0	0	0	0	1
sum	1	1	1	3	3	3	3

# Knapsack problem

The knapsack problem

- Suppose a container can hold a maximum weight  $W$
- Given a number of items with specified weights  $w_i$  and values  $v_i$ , is there some combination of items that has a total value greater than or equal to  $V$  without exceeding the maximum weight  $W$ ?

•



# Knapsack Decision Problem is NP-Complete \

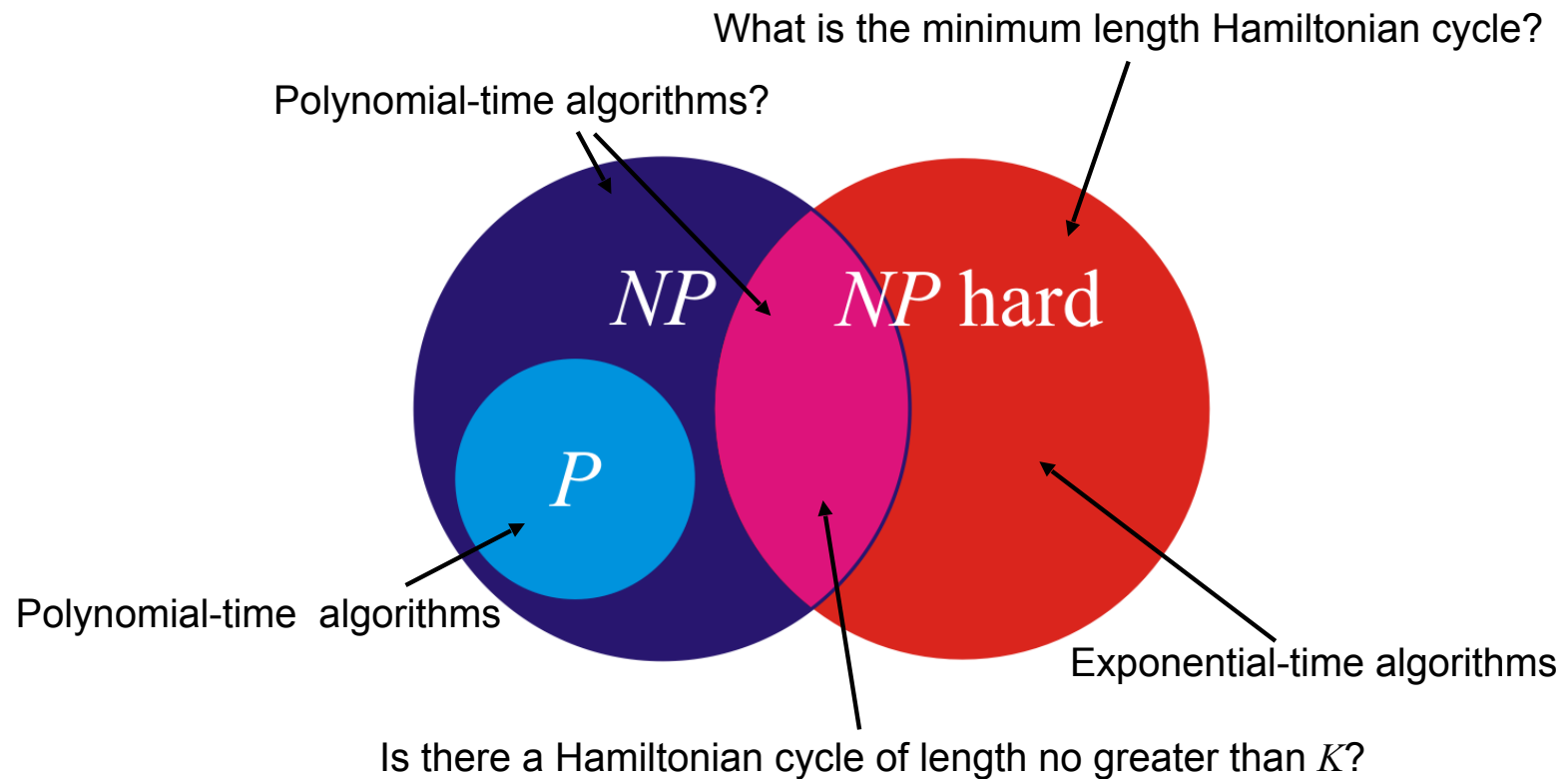
- Show that  $\text{Subset Sum} \leq_P \text{Knapsack}$
- Given subset sum problem instance with  $w_1, \dots, w_n$  and total weight  $W$ , form following Knapsack problem:
  - Let weight of object  $i$  be  $w_i$
  - Let value  $v_i$  of object  $i$  be  $v_i = w_i$
- Solve the following knapsack decision problem: Is there a subset of items  $S$  such that the value is greater than or equal to  $W$ , while the total weight is less than or equal to  $W$ ?
  - $\sum_{i \in S} v_i = \sum_{i \in S} w_i \geq W; \quad \sum_{i \in S} w_i \leq W;$
  - If answer is yes, then  $S$  is a subset with sum  $W$ . If no solution can be found for knapsack, then subset sum does not have a subset with sum  $W$

# NP-Hard vs NP-Complete Problems

- The optimization version of NP-Complete problem is referred to as an **NP-Hard** problem
  - NP-complete problems are decision problems
  - E.g. finding the minimum length Hamiltonian circuit is NP-hard; finding whether there exists a Hamiltonian circuit with length less than  $L$  is NP-complete
  - Finding the maximum value that fits in a knapsack is NP-hard; finding whether we can fit value of at least  $V$  is NP-Complete
- Formally, a problem  $X$  is NP-hard, if there is an NP-complete problem  $Y$ , such that  $Y$  is reducible to  $X$  in polynomial time
  - But  $X$  does not have to be in NP, and does not have to be a decision problem

# $NP$ and $NP$ Hard

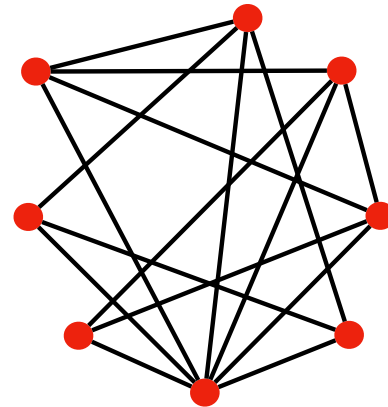
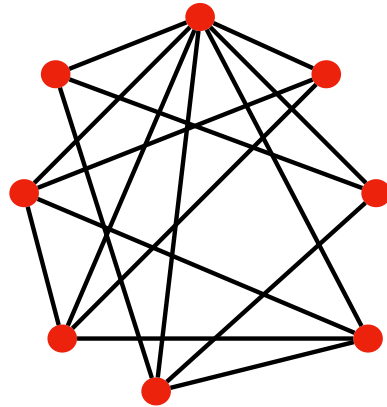
Consider this Venn diagram where  $P \subseteq NP$





# Problems in NP not in P or NP-Complete

- Graph Isomorphism
  - We don't have an algorithm to show problem is in **P**, and no reduction of an np-complete problem to it



## Other Complexity Concepts

- **Pseudopolynomial** complexity: If  $K$  is the size of the largest number, and  $n$  is the size of the input, then the worst case complexity is polynomial in  $n$  and  $K$ . (e.g. Integer Knapsack)
- **Strongly Polynomial** complexity: worst case complexity is polynomial in input size, independent of largest value of number in input.
- **Strongly NP-complete** problems: If one restricts the size of the largest number in the problem to  $K$ , where  $K$  is a polynomial in the input size  $n$ , then the problem is still NP-complete.
  - e.g. Clique
  - Hard to find approximate solutions

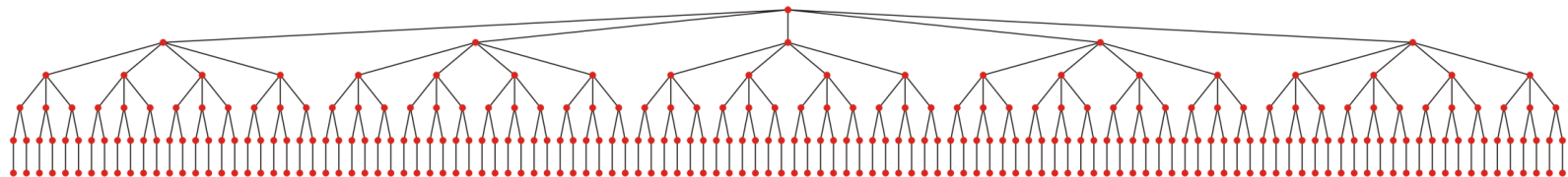
# Deterministic polynomial-time algorithms

Consider the traveling salesman problem:

In a complete weighed graph, what is the least weight Hamiltonian cycle?

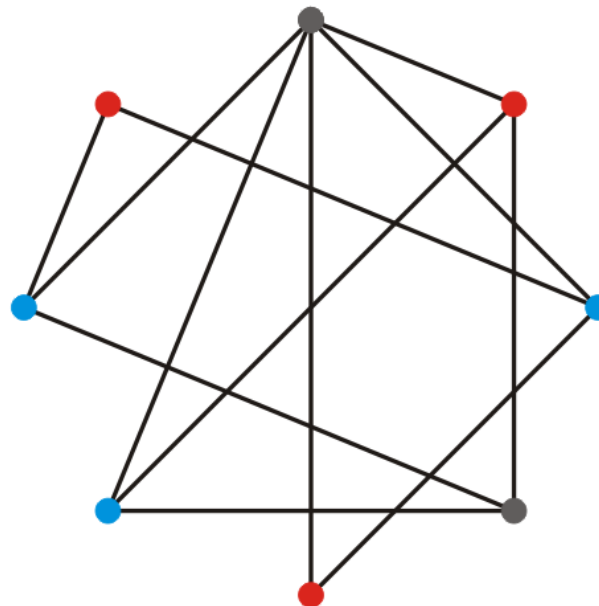
A deterministic algorithm to find a solution is to do tree traversal

- This tries every path
- The run time is  $\Theta(|V|!)$
- The Held-Karp algorithm runs in  $\Theta(|V|^2 2^{|V|})$  time
  - It uses dynamic programming
- To the best of our knowledge, this problem is not in  $P$



# NP-Hard: Graph colorings

- Given a graph and  $n$  colors, is it possible to assign one of the colors to each of the vertices so that no adjacent vertices have the same color?



- Complete graphs requires  $|V|$  colors
- Finding the smallest number of colors for a graph is *NP* Hard

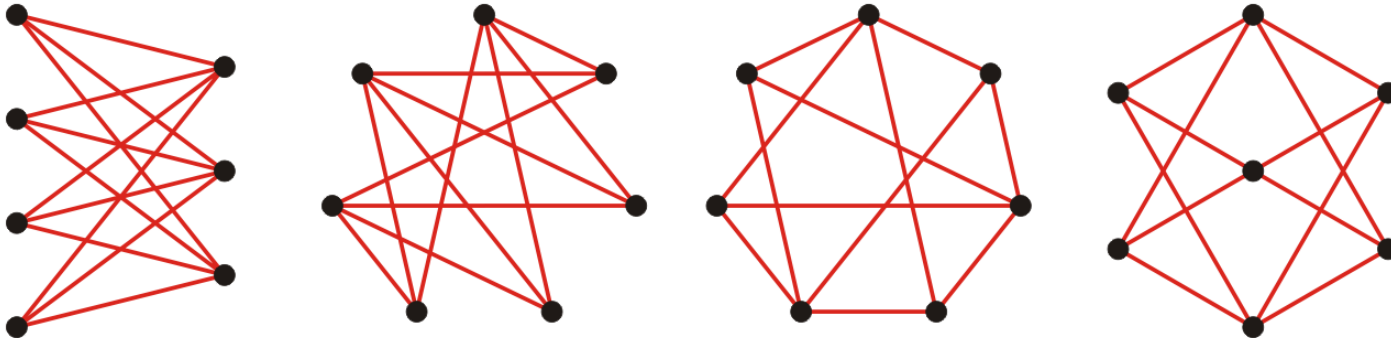
# NP-Complete: Graph isomorphisms

Recall the sub-graph isomorphism problem

- Given two graphs, is one graph isomorphic to a sub-graph of the other?

A possibly easier question is:

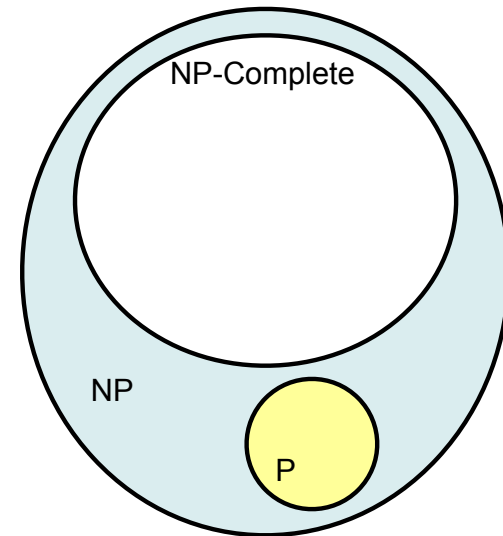
- Are two graphs isomorphic?



- So far, the best algorithm is  $2^{O(\sqrt{n \ln(n)})}$

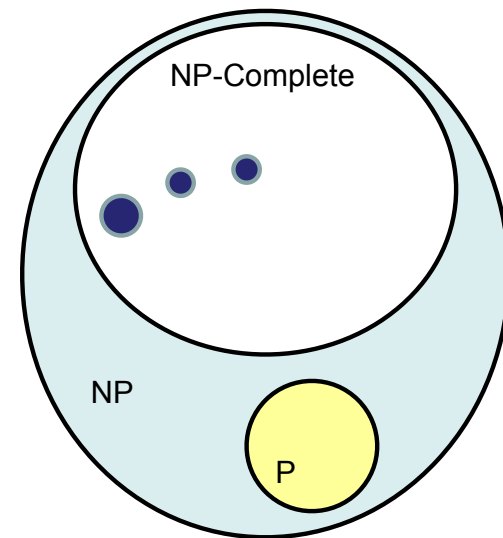
# Populating the NP-Completeness Universe

- Circuit Sat  $\leq_p$  3-SAT
- 3-SAT  $\leq_p$  Independent Set
- 3-SAT  $\leq_p$  Vertex Cover
- Independent Set  $\leq_p$  Clique
- 3-SAT  $\leq_p$  Hamiltonian Circuit
- Hamiltonian Circuit  $\leq_p$  Traveling Salesman
- 3-SAT  $\leq_p$  Integer Linear Programming
- 3-SAT  $\leq_p$  Graph Coloring
- 3-SAT  $\leq_p$  Subset Sum
- Subset Sum  $\leq_p$  Scheduling with Release times and deadlines



# Populating the NP-Completeness Universe

- Circuit Sat  $\leq_P$  3-SAT
- 3-SAT  $\leq_P$  Independent Set
- 3-SAT  $\leq_P$  Vertex Cover
- Independent Set  $\leq_P$  Clique
- 3-SAT  $\leq_P$  Hamiltonian Circuit
- Hamiltonian Circuit  $\leq_P$  Traveling Salesman
- 3-SAT  $\leq_P$  Integer Linear Programming
- 3-SAT  $\leq_P$  Graph Coloring
- 3-SAT  $\leq_P$  Subset Sum
- Subset Sum  $\leq_P$  Scheduling with Release times and deadlines



## Exercise

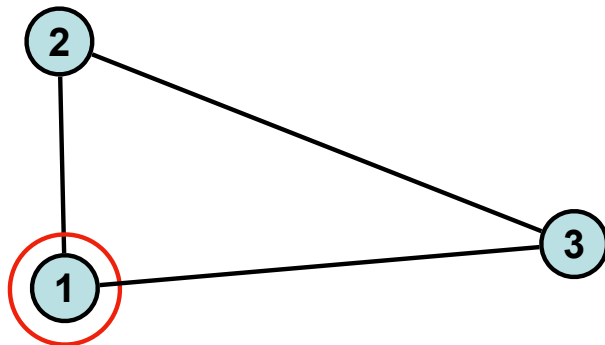
- *Dominating Set* problem: Given a graph  $G = (V, E)$  and an integer  $K$ , decide whether  $G$  contains a dominating set of size at most  $K$ .
  - Dominating set:  $S \subseteq V$  such that  $\forall v \in V$ , either  $v \in S$  or  $v$  has a neighbor in  $S$ .
  - Namely,  $S$  and  $S$ 's neighbors cover the entire  $V$ .
- Prove that Dominating Set is NP-complete.
- Hint: Reduction from Vertex Cover.



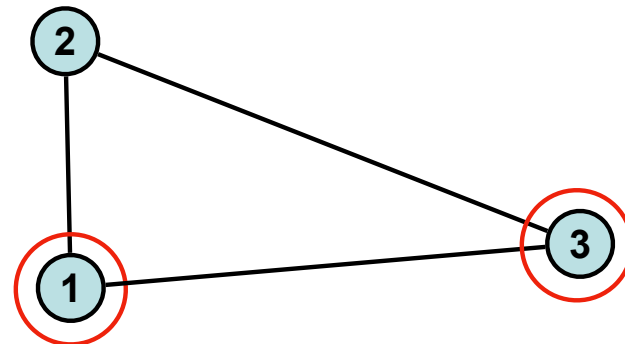
# Vertex Cover vs Dominating Set

- Every vertex cover is a dominating set (if graph is connected)
- But, size of minimal vertex cover is different from size of minimal dominating set! Minimal dominating set can be smaller...

Dominating Set



Vertex Cover.



# Reduction

- Add an extra vertex for every edge
- Minimum dominating set =  $k \iff$  minimum vertex cover is  $k - n_I$ , where  $n_I$  is number of isolated vertices

