COT 5407: Introduction to Algorithms

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Analysis of Dijkstra's Algorithm

- O(n) calls to INSERT, EXTRACT-MIN
- O(m) calls to DECREASE-KEY

Approach	Insert	Dec-Key	Extract-Min	Total
PQ in Arrays	O(1)	O(1)	O(n)	$O(n^2)$
Heaps	O(log n)	O(log n)	O(log n)	O((m+n)log n)
Fibonacci Heaps	O(1)*	O(1)*	O(log n)*	O(m + n log n)*

*** Amortized Time Complexity**

Floyd-Warshall's Algorithm

- $SP_k(u,v)$, shortest paths between u and v that use at most k edges
- Old definition

- $SP_k(u,v)$, shortest paths between u and v that uses intermediate vertices from {1,2,…,k}
- New definition

Recurrence Relation

- Old Relation
- $SP_k(u,v) = \min (SP_{k-1}(u,v), \min_w \{SP_{k-1}(u,w) + SP_1(w,v)\})$
- New Relation
- $SP_k(u,v) = \min (SP_{k-1}(u,v), SP_{k-1}(u,k) + SP_{k-1}(k,v)\})$

Floyd-Warshall: Improved APSP

```
FLOYD-WARSHALL(W)
n = W.rows
D^(0) = W
for k = 1 to n
    let D^(k) = d_ij^(k)  be a new n   n matrix
    for i = 1 to n
        for j = 1 to n
            d_ij^(k) = min  d_ij^(k  1), d_ik^(k  1) + d_kj^(k  1)
return D^(n)
```

$O(n^3)$ time complexity

$$D^{(0)} = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi^{(0)} = \begin{pmatrix} \text{NIL} & 1 & 1 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & \text{NIL} & \text{NIL} \\ 4 & \text{NIL} & 4 & \text{NIL} & \text{NIL} \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(1)} = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi^{(1)} = \begin{pmatrix} \text{NIL} & 1 & 1 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & \text{NIL} & \text{NIL} \\ 4 & 1 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(2)} = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi^{(2)} = \begin{pmatrix} \text{NIL} & 1 & 1 & 2 & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & 2 & 2 \\ 4 & 1 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(3)} = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi^{(3)} = \begin{pmatrix} \text{NIL} & 1 & 1 & 2 & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & 2 & 2 \\ 4 & 3 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(4)} = \begin{pmatrix} 0 & 3 & -1 & 4 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix} \qquad \Pi^{(4)} = \begin{pmatrix} \text{NIL} & 1 & 4 & 2 & 1 \\ 4 & \text{NIL} & 4 & 2 & 1 \\ 4 & 3 & \text{NIL} & 2 & 1 \\ 4 & 3 & 4 & \text{NIL} & 1 \\ 4 & 3 & 4 & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(5)} = \begin{pmatrix} 0 & 1 & -3 & 2 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix} \qquad \Pi^{(5)} = \begin{pmatrix} \text{NIL} & 3 & 4 & 5 & 1 \\ 4 & \text{NIL} & 4 & 2 & 1 \\ 4 & 3 & \text{NIL} & 2 & 1 \\ 4 & 3 & 4 & \text{NIL} & 1 \\ 4 & 3 & 4 & 5 & \text{NIL} \end{pmatrix}$$

Figure 25.4 The sequence of matrices $D^{(k)}$ and $\Pi^{(k)}$ computed by the Floyd-Warshall algorithm for the graph in Figure 25.1.

Figure 14.38
Worst-case running times of various graph algorithms

Type of Graph Problem	Running Time	Comments
Unweighted	$O(\|E\|)$	Breadth-first search
Weighted, no negative edges	$O(\|E\| \log \|V\|)$	Dijkstra's algorithm
Weighted, negative edges	$O(\|E\| \cdot \|V\|)$	Bellman–Ford algorithm
Weighted, acyclic	$O(\|E\|)$	Uses topological sort

NP-Completeness

Polynomial-time computations

- An algorithm has time complexity $O(T(n))$ if it runs in time at most $cT(n)$ for <u>every</u> input of length n.
- An algorithm is a polynomial-time algorithm if its time complexity is $O(p(n))$, where $p(n)$ is polynomial in n.

Polynomials

- If f(n) = polynomial function in n,
  then $f(n) = O(n^c)$, for some fixed constant c
- If f(n) = exponential (super-poly) function in n,
  then $f(n) = \omega(n^c)$, for any constant c
- Composition of polynomial functions are also polynomial, i.e.,
  f(g(n)) = polynomial if f() and g() are polynomial
- If an algorithm calls another polynomial-time subroutine a polynomial number of times, then the time complexity is polynomial.

The class $\mathcal{P}$

- A problem is in $\mathcal{P}$ if there exists a polynomial-time algorithm that solves the problem.
- Examples of $\mathcal{P}$
  - *DFS*: Linear-time algorithm exists
  - *Sorting*: O(n log n)-time algorithm exists
  - *Bubble Sort*: Quadratic-time algorithm $O(n^2)$
  - *APSP*: Cubic-time algorithm $O(n^3)$
- $\mathcal{P}$ is therefore a class of problems (not algorithms)!

The class $\mathcal{NP}$

- A problem is in $\mathcal{NP}$ if there exists a **non-deterministic** polynomial-time algorithm that solves the problem.
- A problem is in $\mathcal{NP}$ if there exists a (**deterministic**) polynomial-time algorithm that **verifies** a solution to the problem.
- All problems that are in $\mathcal{P}$ are also in $\mathcal{NP}$
- All problems that are in $\mathcal{NP}$ <u>may not</u> be in $\mathcal{P}$

TSP: Traveling Salesperson Problem

- **Input:**
  - Weighted graph, **G**
  - Length bound, **B**
- **Output:**
  - Is there a traveling salesperson tour in **G** of length at most **B**?
- Is TSP in $\mathcal{NP}$?
  - **YES**. Easy to verify a given solution.
- Is TSP in $\mathcal{P}$?
  - **OPEN**!
  - One of the greatest unsolved problems of this century!
  - Same as asking: Is $\mathcal{P} = \mathcal{NP}$?

So, what is *NP-Complete*?

- *NP-Complete* problems are the "hardest" problems in *NP*.
- We need to formalize the notion of "hardest".

Terminology

- Problem:
  - An abstract problem is a function (relation) from a set I of instances of the problem to a set S of solutions.

    p: I → S
  - An instance of a problem p is obtained by assigning values to the parameters of the abstract problem.
  - Thus, describing set of all instances (I.e., possible inputs) and set of corresponding outputs defines a problem.
- Algorithm:
  - An algorithm that solves problem p must give correct solutions to all instances of the problem.
- Polynomial-time algorithm:

Terminology (Cont'd)

- Input Length:
  - **length** of an <u>encoding</u> of an instance of the problem.
  - Time and space complexities are written in terms of it.
- Worst-case time/space complexity of an algorithm
  - Is the **maximum** time/space required by the algorithm on any input of length n.
- Worst-case time/space complexity of a problem
  - **UPPER BOUND**: worst-case time complexity of best existing algorithm that solves the problem.
  - **LOWER BOUND**: (provable) worst-case time complexity of best algorithm (need not exist) that could solve the problem.
  - **LOWER BOUND $\leq$ UPPER BOUND**
- Complexity Class $\mathcal{P}$:
  - Set of all problems *p* for which polynomial-time algorithms exist

Terminology (Cont'd)

- Decision Problems:
  - These are problems for which the solution set is {yes, no}
  - Example: Does a given graph have an odd cycle?
  - Example: Does a given weighted graph have a TSP tour of length at most B?
- Complement of a decision problem:
  - These are problems for which the solution is "complemented".
  - Example: Does a given graph NOT have an odd cycle?
  - Example: Is every TSP tour of a given weighted graph of length greater than B?
- Optimization Problems:
  - These are problems where one is maximizing (or minimizing) some objective function.
  - Example: Given a weighted graph, find a MST.
  - Example: Given a weighted graph, find an optimal TSP tour.
- Verification Algorithms:
  - Given a problem instance i and a certificate s, is s a solution for instance i?

Terminology (Cont'd)

- Complexity Class $\mathcal{P}$:
  - Set of all problems p for which polynomial-time algorithms exist.
- Complexity Class $\mathcal{NP}$:
  - Set of all problems p for which polynomial-time verification algorithms exist.
- Complexity Class *co*-$\mathcal{NP}$:
  - Set of all problems p for which polynomial-time verification algorithms exist for their complements, i.e., their complements are in $\mathcal{NP}$.

Terminology (Cont'd)

- **Reductions:** $p_1 \rightarrow p_2$
  - A problem p_1 is reducible to p_2, if there exists an algorithm R that takes an instance i_1 of p_1 and outputs an instance i_2 of p_2, with the constraint that the solution for i_1 is YES if and only if the solution for i_2 is YES.
  - Thus, R converts YES (NO) instances of p_1 to YES (NO) instances of p_2.
- **Polynomial-time reductions:** $p_1 \xrightarrow{P} p_2$
  - R

- If $p_1 \xrightarrow{P} p_2$, then
  - If p_2 is easy, then so is p_1. $p_2 \in \mathcal{P} \Rightarrow p_1 \in \mathcal{P}$
  - If p_1 is hard, then so is p_2. $p_1 \notin \mathcal{P} \Rightarrow p_2 \notin \mathcal{P}$

What are *NP-Complete* problems?

- These are the hardest problems in *NP*.
- A problem **p** is *NP-Complete* if
  - there is a polynomial-time reduction from every problem in *NP* to **p**.
  - **p** $\in$ *NP*
- How to prove that a problem is *NP-Complete*?

> • **Cook's Theorem**: [1972]
>
> –The SAT problem is *NP-Complete*.

Steve Cook, Richard Karp, Leonid Levin

NP-Complete VS *NP-Hard*

- A problem **p** is *NP-Complete* if
  - there is a polynomial-time reduction from <u>every</u> problem in *NP* to **p**.
  - **p** $\in$ *NP*
- A problem **p** is *NP-Hard* if
  - there is a polynomial-time reduction from <u>every</u> problem in *NP* to **p**.

The SAT Problem: an example

- Consider the boolean expression:

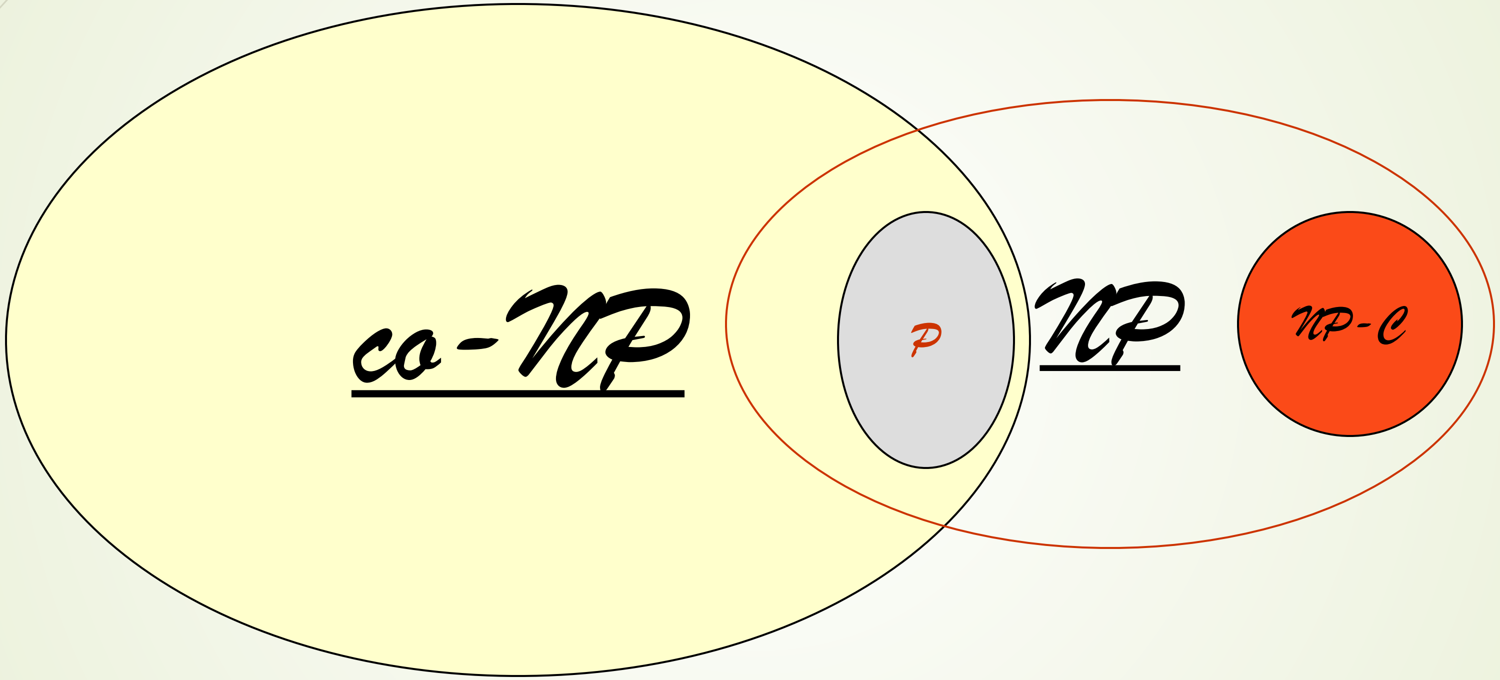
  $C = (a \vee \neg b \vee c) \wedge (\neg a \vee d \vee \neg e) \wedge (a \vee \neg d \vee \neg c)$
- Is C satisfiable?
- Does there exist a True/False assignments to the boolean variables a, b, c, d, e, such that C is True?
- Set a = True and d = True. The others can be set arbitrarily, and C will be true.
- If C has 40,000 variables and 4 million clauses, then it becomes hard to test this.
- If there are n boolean variables, then there are 2^n different truth value assignments.
- However, a solution can be quickly verified!

The SAT (Satisfiability) Problem

- **Input**: Boolean expression **C** in Conjunctive normal form (CNF) in **n** variables and **m** clauses.
- **Question**: Is **C** satisfiable?
  - Let C = $C_1 \wedge C_2 \wedge \ldots \wedge C_m$
  - Where each C_i = $(y_1^i \vee y_2^i \vee \cdots \vee y_{k_i}^i)$
  - And each y_j^i $\in \{x_1, \neg x_1, x_2, \neg x_2, \ldots, x_n, \neg x_n\}$
  - We want to know if there exists a truth assignment to all the variables in the boolean expression **C** that makes it true.
- **Steve Cook** showed that the problem of deciding whether a non-deterministic Turing machine **T** accepts an input **w** or not can be written as a boolean expression C_T for a SAT problem. The boolean expression will have length bounded by a polynomial in the size of **T** and **w**.

> - How to now prove Cook's theorem? Is SAT in *NP*?
> - Can every problem in *NP* be poly. reduced to it ?

The problem classes and their relationships



More *NP-Complete* problems

3SAT

- **Input**: Boolean expression C in Conjunctive normal form (CNF) in n variables and m clauses. Each clause has at most three literals.
- **Question**: Is C satisfiable?
  - Let $C = C_1 \wedge C_2 \wedge \ \ldots \ \wedge C_m$
  - Where each $C_i = (y_1^i \vee y_2^i \vee y_3^i)$
  - And each $y_j^i \in \{x_1, \neg x_1, x_2, \neg x_2, \ldots, x_n, \neg x_n\}$
  - We want to know if there exists a truth assignment to all the variables in the boolean expression C that makes it true.

3SAT is *NP-Complete.*

More *NP-Complete* problems?

2SAT

- **Input**: Boolean expression **C** in Conjunctive normal form (CNF) in **n** variables and **m** clauses. Each clause has at most three literals.
- **Question**: Is **C** satisfiable?
  - Let $C = C_1 \wedge C_2 \wedge \ldots \wedge C_m$
  - Where each C_i = $(y_1^i \vee y_2^i)$
  - And each y_j^i $\in \{x_1, \neg x_1, x_2, \neg x_2, \ldots, x_n, \neg x_n\}$
  - We want to know if there exists a truth assignment to all the variables in the boolean expression **C** that makes it true.

2SAT is in $\mathcal{P}$.

3SAT is *NP-Complete*

- 3SAT is in *NP.*
- SAT can be reduced in polynomial time to 3SAT.
- This implies that every problem in *NP* can be reduced in polynomial time to 3SAT. Therefore, 3SAT is *NP-Complete*.
- So, we have to design an algorithm such that:
- Input: an instance C of SAT
- Output: an instance C' of 3SAT such that satisfiability is retained. In other words, C is satisfiable if and only if C' is satisfiable.

3SAT is *NP-Complete*

- Let C be an instance of SAT with clauses $C_1, C_2, \ldots, C_m$
- Let C_i be a disjunction of $k > 3$ literals.

$$C_i = \quad y_1 \vee y_2 \vee \ldots \vee y_k$$

- Rewrite C_i as follows:

$$\begin{aligned} C'_i = \quad & (y_1 \vee y_2 \vee z_1) \wedge \\ & (\neg z_1 \vee y_3 \vee z_2) \wedge \\ & (\neg z_2 \vee y_4 \vee z_3) \wedge \\ & \ldots \\ & (\neg z_{k-3} \vee y_{k-1} \vee y_k) \end{aligned}$$

- Claim: C_i is satisfiable if and only if C'_i is satisfiable.

2SAT is in $\mathcal{P}$

- If there is only one literal in a clause, it must be set to true.
- If there are two literals in some clause, and if one of them is set to false, then the other must be set to true.
- Using these constraints, it is possible to check if there is some inconsistency.
- How? Homework problem!

The CLIQUE Problem

- A clique is a completely connected subgraph.

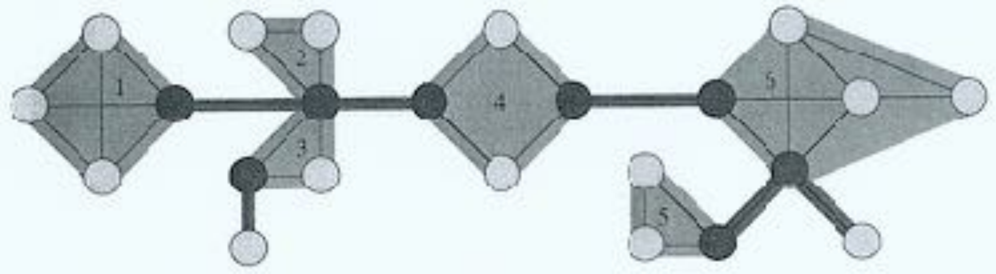


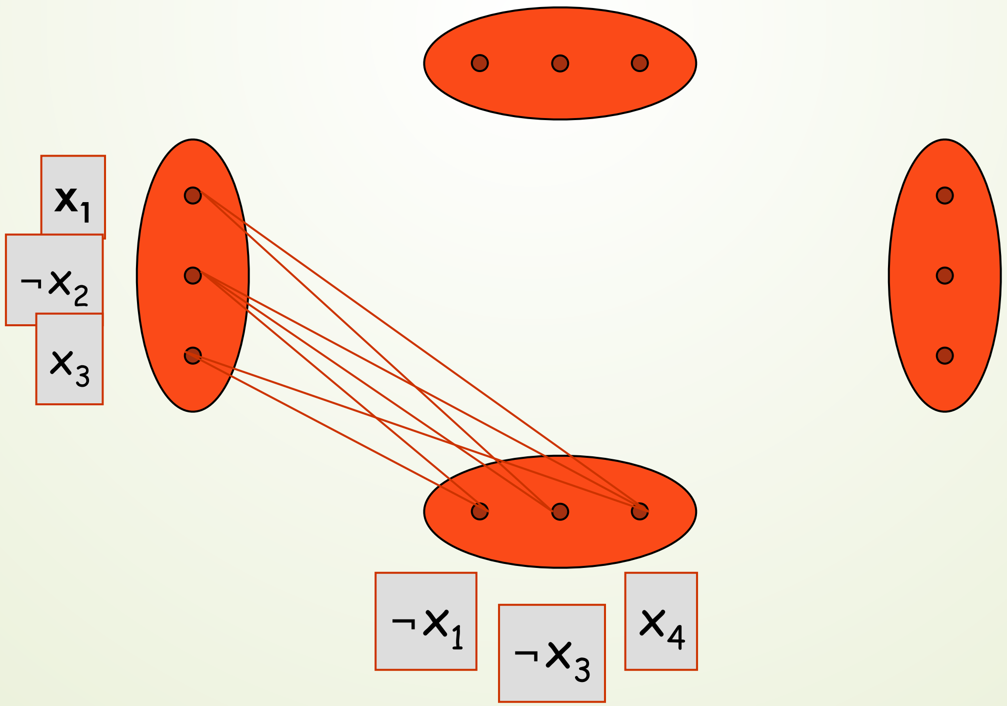
Figure 22.10 The articulation points, bridges, and biconnected components of a connected, undirected graph for use in Problem 22-2. The articulation points are the heavily shaded vertices, the bridges are the heavily shaded edges, and the biconnected components are the edges in the shaded regions, with a *bcc* numbering shown.

CLIQUE

- **Input**: Graph G(V,E) and integer k
- **Question**: Does G have a clique of size k?

CLIQUE is *NP-Complete*

- CLIQUE is in *NP*.
- Reduce 3SAT to CLIQUE in polynomial time.
- $F = (x_1 \lor \neg x_2 \lor x_3)\ (\neg x_1 \lor \neg x_3 \lor x_4)\ (x_2 \lor x_3 \lor \neg x_4)\ (\neg x_1 \lor \neg x_2 \lor x_3)$

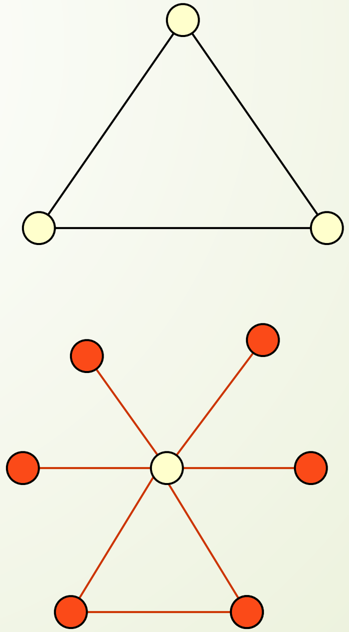


F is satisfiable if and only if G has a clique of size k where k is the number of clauses in F.

Vertex Cover

A **vertex cover** is a set of vertices that "covers" all the edges of the graph.

Examples

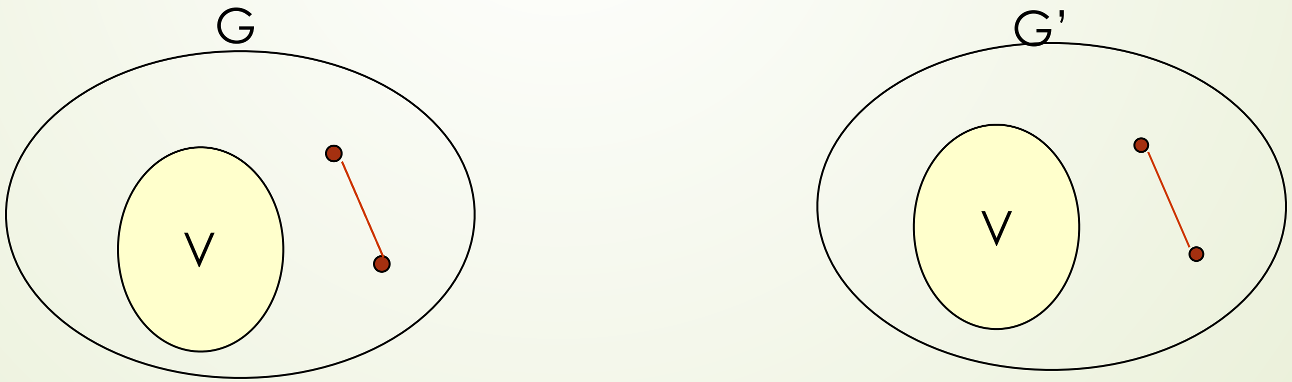


Vertex Cover (VC)

Input: Graph G, integer k

Question: Does G contain a **vertex cover** of size k?

- VC is in *NP*.
- polynomial-time reduction from CLIQUE to VC.
- Thus VC is *NP-Complete.*



Claim: G' has a clique of size k' if and only if G has a VC of size k = n – k'

Hamiltonian Cycle Problem (HCP)

Input: Graph G

Question: Does G contain a **hamiltonian** cycle?

- HCP is in *NP*.
- There exists a polynomial-time reduction from 3SAT to HCP.
- Thus HCP is *NP-Complete.*

- Notes/animations by a former student, Yi Ge!
- https://users.cs.fiu.edu/~giri/teach/UoM/7713/f98/yige/yi12.html