

Approximation Algorithms

- There are two classes of problems:
 - 1) Problems whose solution is by a polynomial time algorithm
 - 2) Problems for which no polynomial time algorithm is known
- The first group consists of problems whose solution is bounded by a polynomial of small degree. e.g., Binary searching in $O(\log n)$, sorting $O(n \log n)$, and matrix multiplication $O(n^{2.81})$.
- The second group contains problems whose best known algorithms are nonpolynomial, e.g., traveling salesperson in $O(n^2 2^n)$, knapsack problem in $O(2^{n^{1/2}})$
- The theory of NP-completeness does not provide a method of obtaining polynomial time algorithms in the second group. It cannot also say that polynomial time algorithms do not exist.
- Instead, it can say that many of the problems for which there is no known polynomial time algorithm are computationally related.
- **Decision Problem:** Any problem for which the answer is 0 or 1 is called decision problem and the corresponding algorithm is called decision algorithm.
- **Optimization Problem:** Any problem which seeks for an optimal solution is called optimization problem and the corresponding algorithm is called optimization algorithm.

- In fact, we shall establish two classes of problems. These will be given the names NP-hard and NP-complete.
- A problem which is NP-complete will have the property that it can be solved in polynomial time iff all other NP-complete problems can also be solved in polynomial time.
- If an NP-hard problem can be solved in polynomial time then all NP-complete problems can be solved in polynomial time.
- All NP-complete problems are NP-hard but all NP-hard problems are not NP-complete.

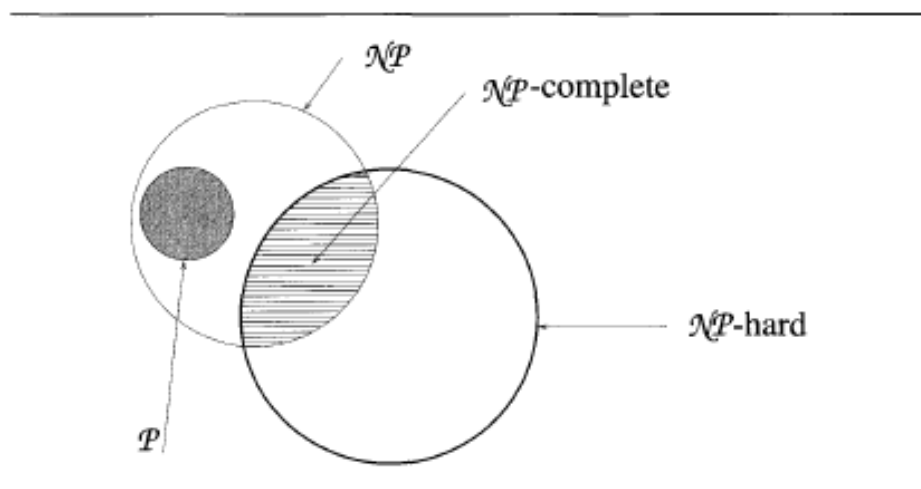


Figure 11.2 Commonly believed relationship among \mathcal{P} , \mathcal{NP} , \mathcal{NP} -complete, and \mathcal{NP} -hard problems

Note 2: What we do not know, and what has become perhaps the most famous unsolved problem in computer science is whether $P = NP$ or $P \neq NP$.

What is an Approximation Algorithm?

An algorithm that returns near optimal solution.

What is the Motivation? NP-complete problems.

Two approaches:

- 1) For small size problem, an exponential running time algorithm may be satisfactory.
- 2) Find a near optimal algorithm.

Comment: The second approach gives the birth of an approximation algorithm.

How to evaluate it?

Performance bound: An approximation algorithm has a ratio bound of $f(n)$ if

$$\text{Max}(\frac{C}{C^*}, \frac{C^*}{C}) \leq f(n)$$

where n is input size, C : Cost of the approximation algorithm and C^* : Cost of the optimal solution.

The Vertex Cover Problem:

Statement: A vertex cover of an undirected graph $G = (V, E)$ is a subset $V' \subseteq V$ such that if $(u, v) \in E$, then either $u \in V'$ or $v \in V'$ or both. It is to find a vertex cover of minimum size.

Algorithm APPROX-VERTEX COVER (G)

```
{  
   $C = \Phi$   
   $E' = E [G]$   
  While  $E' \neq \Phi$  do  
    Let  $(u, v)$  be an arbitrary edge of  $E'$   
     $C = C \cup \{u, v\}$   
    Remove from  $E'$  every edge incident on either  $u$  or  $v$   
  Return  $C$   
}
```

Running Time: $O(|E|)$

Near Optimality: The above algorithm returns a vertex cover whose size is guaranteed to be no more than twice the size of an optimal vertex cover.

An Illustration:

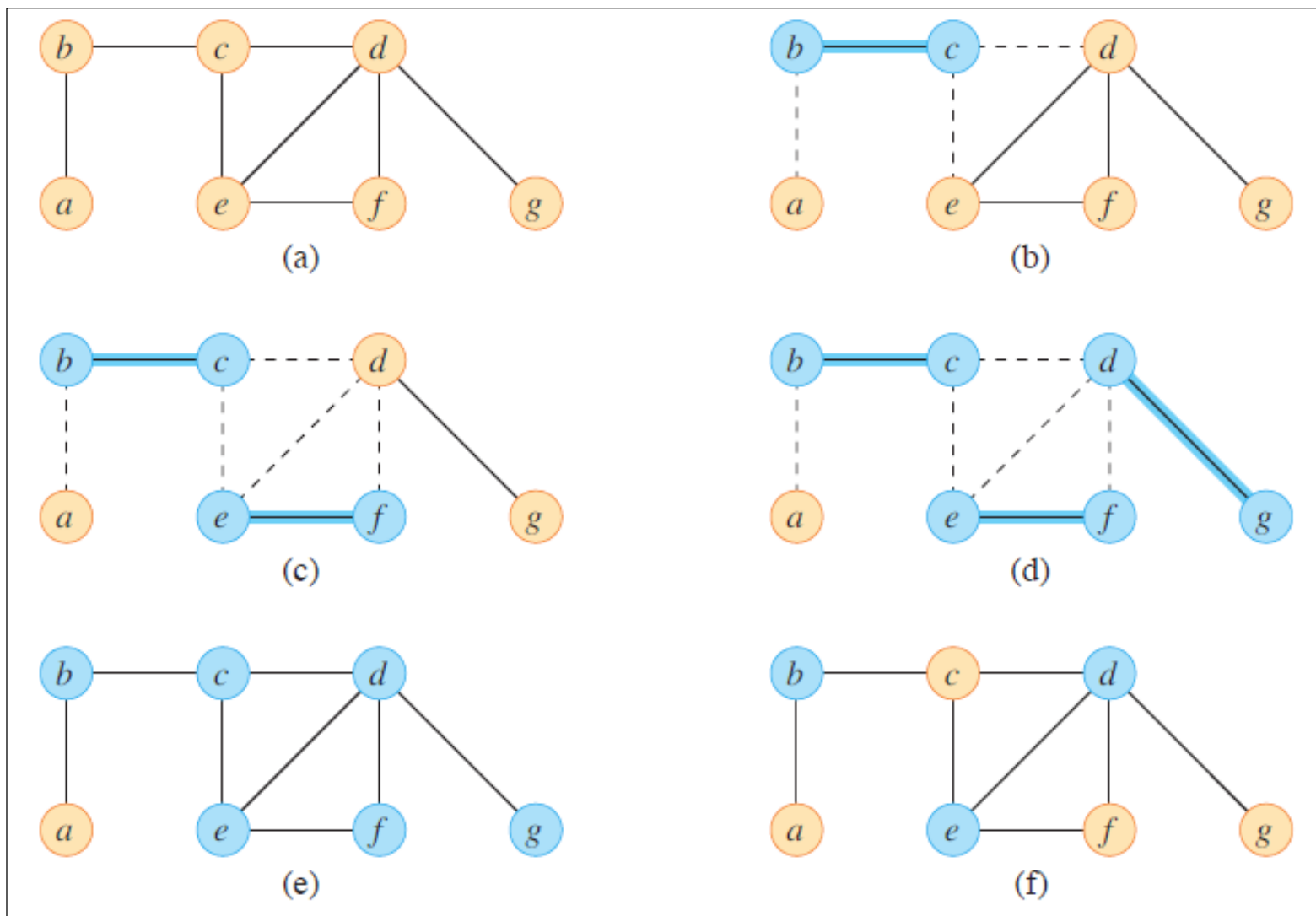


Fig. (a):Input Graph

Fig. (e): Final Vertex Cover $C = \{b, c, e, f, d, g\}$

Fig. (f): The Optimal vertex cover $\{b, e, d\}$

Comments: Optimal Sol. is almost half of Approx. Sol.

Theorem: APPROX-VERTEX-COVER is a polynomial-time 2-approximation algorithm.

Proof:

We have already shown that APPROX-VERTEX-COVER runs in polynomial time. The set C of vertices that is returned by APPROX-VERTEX-COVER is a vertex cover, since the algorithm loops until every edge in $E[G]$ has been covered by some vertex in C .

Now we have to see that APPROX-VERTEX-COVER returns a vertex cover that is at most twice the size of an optimal cover.

Let A denote the set of edges that were picked in line 4 of APPROX-VERTEX-COVER. In order to cover the edges in A , any vertex cover—in particular, an optimal cover C^* —must include at least one endpoint of each edge in A . No two edges in A share an endpoint, since once an edge is picked in line 4, all other edges that are incident on its endpoints are deleted from E_- in line 6. Thus, no two edges in A are covered by the same vertex from C^* , and we have the lower bound

$$|C^*| \geq |A| \tag{1}$$

on the size of an optimal vertex cover. Each execution of line 4 picks an edge for which neither of its endpoints is already in C , yielding an upper bound (an exact upper bound, in fact) on the size of the vertex cover returned:

$$|C| = 2 |A| \tag{2}$$

Combining equations (1) and (2), we obtain

$$\begin{aligned} |C| &= 2 |A| \\ &\leq 2 |C^*| \end{aligned}$$

Hence the proof.

The Travelling Sales Person Problem:

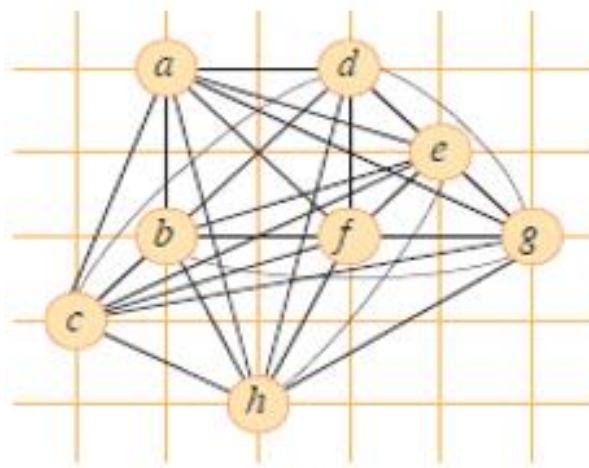
Statement: Given a complete undirected graph $G = (V, E)$ that has a non-negative integer cost $C(u, v)$ associated with each edge $(u, v) \in E$, find a Hamiltonian cycle of G with minimum cost.

let $c(A)$ denote the total cost of the edges in the subset $A \subseteq E$:

$$c(A) = \sum_{(u,v) \in A} c(u, v) .$$

It is always cheapest to go directly from a node u to another node v instead of going via an intermediate node w , i.e., it follows the triangle inequality:

$$c(u, v) \leq c(u, w) + c(w, v)$$



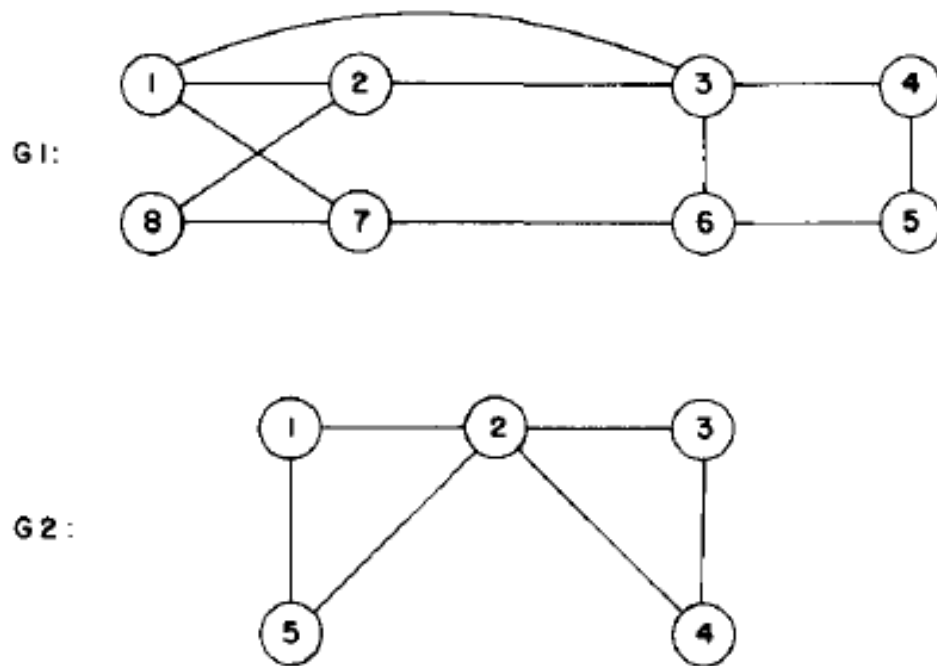


Fig. 1: Two graphs, one containing a Hamiltonian cycle, other does not have.

Approximation Algorithm with Triangle Inequality:

APPROX-TSP-TOUR (G, C)

1. Select a vertex $r \in V(G)$ to be a root vertex
2. Grow a minimum spanning tree T for G from the root r .
3. Let L be the list of vertices in a preorder walk of T .
4. Return the Hamiltonian cycle H that visits the vertices in the order L .

Time complexity: $O(|V|^2)$ as step 2 requires $O(|V|^2)$ time using prim's algorithm.

An Illustration:

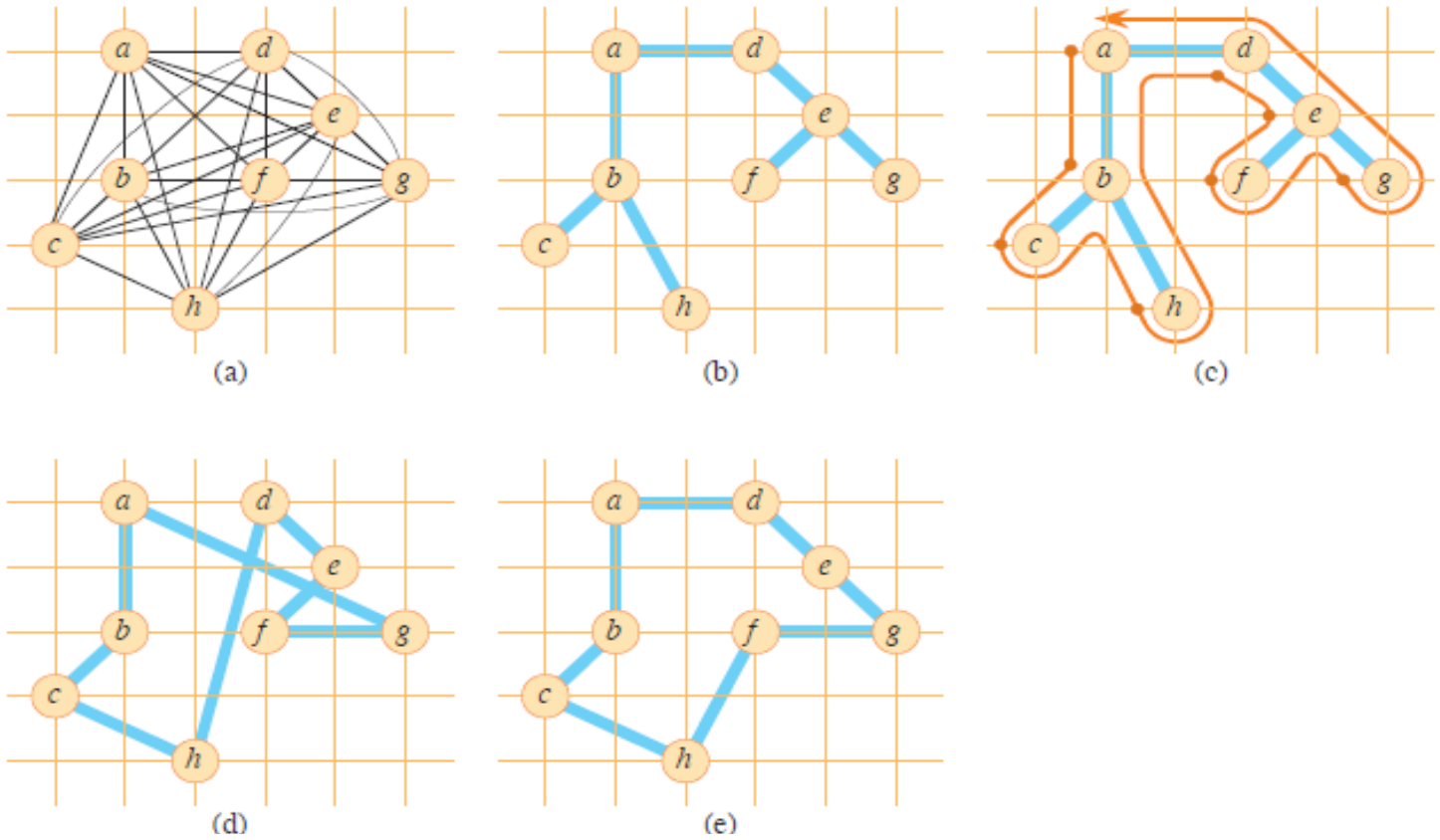


Fig. (a): Input Grid

(b): MST

(c): A preorder Walk $\{a, b, c, b, h, b, a, d, e, f, e, g, e, d, a\}$

(d): Approx. Tour $\{a, b, c, h, d, e, f, g, a\}$ of **Cost 19.074**

(e): **Optimal Tour of Cost 14.715**

Comment: The Optimal Tour Cost is **23 % shorter** than the Approx. Sol. Cost.

Theorem: Approx-TSP-Tour is a polynomial time 2-approximation algorithm for TSP with triangle inequality.

Proof: The algorithm is correct because it produces a Hamiltonian circuit.

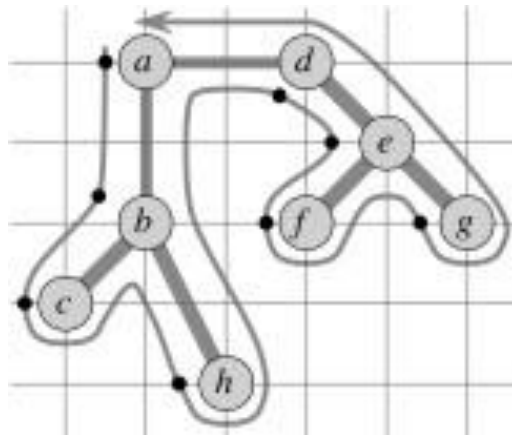
The algorithm is polynomial time because the most expensive operation is MST-Prim, which can be computed in $O(|V|^2)$

For the approximation result, let T be the spanning tree found in line 2, H be the tour found and H^* be an optimal tour for a given problem.

If we delete any edge from H^* , we get a spanning tree that can be no cheaper than the *minimum* spanning tree T , because H^* has one more (nonnegative cost) edge than T :

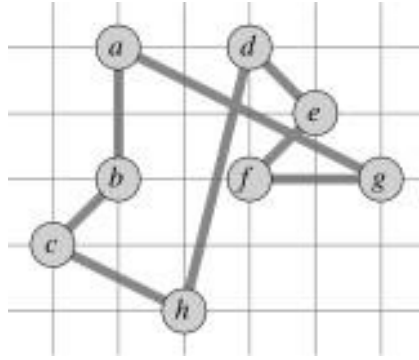
$$c(T) \leq c(H^*)$$

Consider the cost of the **full walk** W that traverses the edges of T exactly twice starting at the root. (For our example, W is $\langle \{a, b\}, \{b, c\}, \{c, b\}, \{b, h\}, \{h, b\}, \{b, a\}, \{a, d\}, \dots \{d, a\} \rangle$.)



Since each edge in T is traversed twice in W : $c(W) = 2 c(T)$

This walk W is not a tour because it visits some vertices more than once, but we can skip the redundant visits to vertices once we have visited them, producing the same tour H as in line 3. (For example, instead of $\langle \{a, b\}, \{b, c\}, \{c, b\}, \{b, h\}, \dots \rangle$, go direct: $\langle \{a, b\}, \{b, c\}, \{c, h\}, \dots \rangle$.)



By the triangle inequality, which says it can't cost any more to go direct between two vertices,

$$c(H) \leq c(W)$$

Noting that H is the tour constructed by Approx-TSP-Tour, and putting all of these together:

$$c(H) \leq c(W) = 2 c(T) \leq 2 c(H^*)$$

So, $c(H) \leq 2 c(H^*)$, and thus Approx-TSP-Tour is a 2-approximation algorithm for TSP. (The CLRS text notes that there are even better solutions, such as a 3/2-approximation algorithm.)

The set-covering problem

An instance (X, \mathcal{F}) of the *set-covering problem* consists of a finite set X and a family \mathcal{F} of subsets of X , such that every element of X belongs to at least one subset in \mathcal{F} :

$$X = \bigcup_{S \in \mathcal{F}} S.$$

We say that a subfamily $\mathcal{C} \subseteq \mathcal{F}$ *covers* a set of elements U if

$$U \subseteq \bigcup_{S \in \mathcal{C}} S.$$

The problem is to find a minimum-size subfamily $\mathcal{C} \subseteq \mathcal{F}$ whose members cover all of X :

$$X = \bigcup_{S \in \mathcal{C}} S.$$

An Illustration:

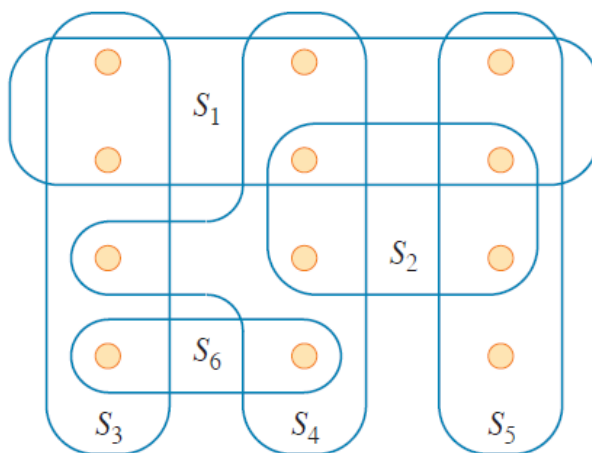


Figure 35.3 An instance (X, \mathcal{F}) of the set-covering problem, where X consists of the 12 tan points and $\mathcal{F} = \{S_1, S_2, S_3, S_4, S_5, S_6\}$. Each set $S_i \in \mathcal{F}$ is outlined in blue. A minimum-size set cover is $\mathcal{C} = \{S_3, S_4, S_5\}$, with size 3. The greedy algorithm produces a cover of size 4 by selecting either the sets S_1, S_4, S_5 , and S_3 or the sets S_1, S_4, S_5 , and S_6 , in order.

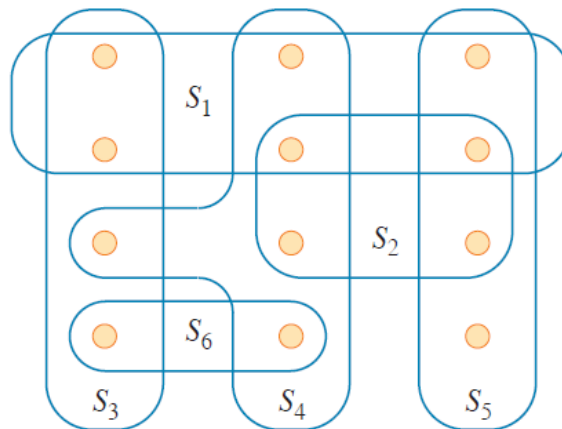
Note: The set-covering problem is an abstraction of many commonly arising combinatorial problems. As a simple example, suppose that X represents a set of skills that are needed to solve a problem and that we have a given set of people available to work on the problem. We wish to form a committee, containing as few people as possible, such that for every requisite skill in X , there is a member of the committee having that skill.

A greedy approximation algorithm

GREEDY-SET-COVER(X, \mathcal{F})

```

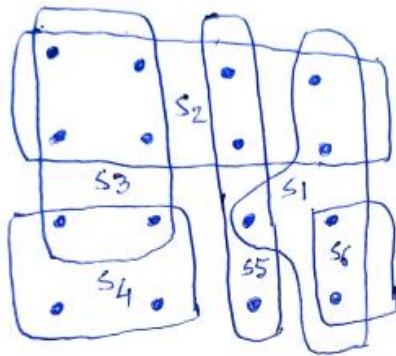
1   $U \leftarrow X$ 
2   $\mathcal{C} \leftarrow \emptyset$ 
3  while  $U \neq \emptyset$ 
4      do select an  $S \in \mathcal{F}$  that maximizes  $|S \cap U|$ 
5           $U \leftarrow U - S$ 
6           $\mathcal{C} \leftarrow \mathcal{C} \cup \{S\}$ 
7  return  $\mathcal{C}$ 
```



Result of the approximation algorithm: S_1, S_4, S_5, S_3 or S_1, S_4, S_5, S_6 in order.

Time Complexity: $O(|X| |\mathcal{F}|)$

Ex 1: Apply the approximation algorithm to solve set covering problem for the following graph by showing stepwise results.



$U = X = (\text{All black points})$

$F = \{S_1, S_2, S_3, S_4, S_5, S_6\}$

$T = \emptyset$

$S_2 \cap U$ is maximum.

$\therefore U = U - \text{all points in } S_2$

$T = \{S_2\}$

$S_4 \cap U$ is maximum

$\therefore U = U - \text{all points in } S_4$

$T = \{S_2, S_4\}$

$S_1 \cap U$ is maximum

$\therefore U = U - \text{all points in } S_1$

$T = \{S_2, S_4, S_1\}$

$S_5 \cap U$ is maximum

$U = U - \text{all points in } S_5$

$T = \{S_2, S_4, S_1, S_5\}$