

35. Approximation Algorithms

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An algorithm that returns near-optimal solutions is called an *approximation algorithm*.

Performance bounds for approximation algorithms



We say an approximation algorithm for the problem has a ratio bound of $\rho(n)$ if for any input size n, the cost C of the solution produced by the approximation algorithm is within a factor of $\rho(n)$ of the C^* of the optimal solution:

$$\max\{\frac{C}{C^*}, \frac{C^*}{C}\} = \rho(n)$$

This definition applies for both minimization and maximization problems.

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An *approximation scheme* for an optimization problem is an approximation algorithm that takes as input not only an instance of the problem, but also a value $\varepsilon > 0$ such that for any fixed ε , the scheme is a $(1+\varepsilon)$ -approximation algorithm.



We say that an approximation scheme is a **polynomial-time** approximation scheme if for any fixed $\varepsilon > 0$, the scheme runs in time polynomial in the size n of its input instance.

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We say that an approximation scheme is a *polynomial-time* approximation scheme if for any fixed $\mathcal{E} > 0$, the scheme runs in polynomial in size n of its input instance..

For example, the scheme might have a running time of $O((1/\varepsilon)^2 n^3)$.



We say that an approximation scheme is *fully polynomial-time approximation scheme* if its running time is polynomial both in $\frac{1}{\varepsilon}$ and in the size n of the input instance, where ε is the relative error bound for the scheme.

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The *vertex cover problem* is to find a vertex cover of minimum size in a given undirected graph. We call such a vertex cover an *optimal vertex cover*.

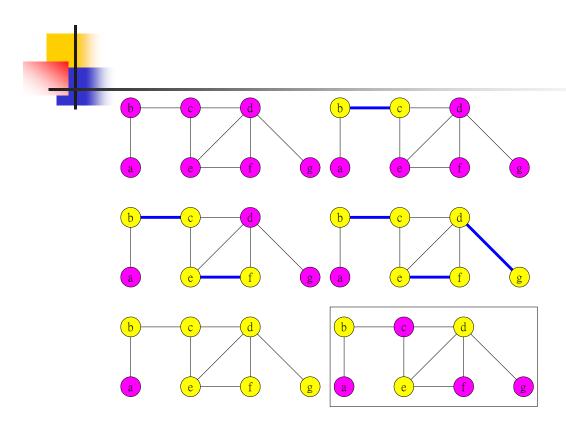


$APPROX_VERTEX_COVER(G)$

- 1 $C \leftarrow \phi$
- $2 E' \leftarrow E(G)$
- 3 while $E' \neq \phi$
- 4 do let (u,v) be an arbitrary edge of E'
- 5 $C \leftarrow C \cup (u,v)$
- 6 remove from E' every edge incident on either u or v
- 7 return C

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Chapter 35 Complexity: O(E)



Theorem 35.1 APPROX_VERTEX_COVER has ratio bound of 2.

Proof.

Let *A* be the set of selected edges.

$$|A| \leq |C^*|$$

$$\Rightarrow |C| \leq 2|C^*|$$

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35.2The traveling salesman problem

triangle inequality

$$c(u,w) \le c(u,v) + c(v,w) \quad \forall u,v,w$$



35.2.1 The TSP with triangle inequality

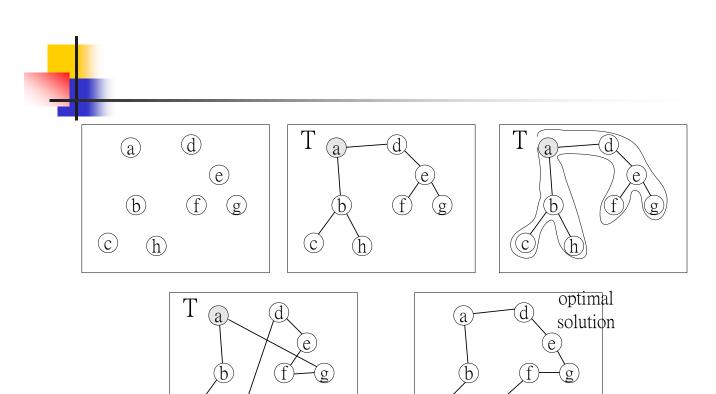
$APPROX_TSP_TOUR(G,c)$

- 1 Select a vertex $r \in V[G]$ to be a root vertex
- 2 grow a MST *T* for *G* from root *r* using MST_PRIM(*G*,*c*,*r*)
- 3 Let *L* be the list of vertices visited in a preorder walk of *T*.
- 4 **return** the hamiltonian cycle H that visit the vertices in the order L.

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H*



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Theorem 35.2. APPROX_TSP_TOUR is an approximation algorithm with ratio bound of 2 for TSP with triangular inequality.

Proof.

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

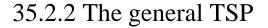
$$c(W) = 2c(T) \le 2c(H^*)$$

$$c(H) \le c(W)$$

$$\Rightarrow c(H) \le 2c(H^*)$$

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Theorem 35.3 If $NP \neq P$ and $\rho \geq 1$, there is no polynomial time approximation algorithm with ratio bound ρ for some general TSP.

Proof.

Let G = (V, E) be an instance of HC.

Let G' = (V, E') be the complete graph of V.

Set
$$c(u,v) = \begin{cases} 1 & \text{if } (u,v) \in E \\ \rho |V| + 1 & \text{otherwise} \end{cases}$$

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35.3The set-covering problem

An instance (X,F) of the *set-covering problem* consists of a finite set X and a family F of elements of X, such that every element of X belongs to at least one subset in F: $X = \bigcup S$. We say that a subset $S \in F$ *covers* its elements. $S \in F$

The problem is to find a minimum-size $C \subseteq F$ whose members covers all of X:

$$X = \bigcup_{S \in C} S. \quad (37.8)$$

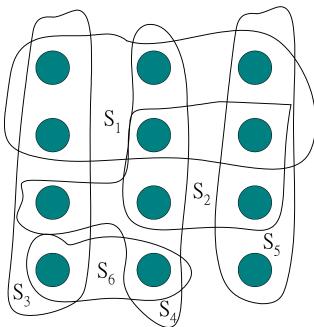
We say that any C satisfies equation (37.8) covers X.

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minimum-size set cover $C^*=\{S_3,S_4,S_5\}$

Greedy set cover $C^*=\{S_1,S_4,S_5,S_3\}$



$GREEDY_SET_COVER(X,F)$

- 1 $U \leftarrow X$
- 2 $C \leftarrow \phi$
- 3 **while** $C \neq \phi$
- 4 do select on $S \in F$ that maximize $|S \cap U|$
- 5 $U \leftarrow U S$
- 6 $C \leftarrow C \cup \{S\}$

7 return C

Chapter 35 running time: polynomial in |X| and |F|.

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Define $H_d = \sum_{i=1}^d \frac{1}{i}$

Theorem 35.4 GREEDY_SET_COVER has a ratio bound $H(max\{|S||S \in F\})$

Proof.

• Define
$$c_x = \frac{1}{|S_i - (S_1 \cup S_2 \cup ... \cup S_{i-1})|}$$
 if

$$x \in S_i - (S_1 \cup S_2 \cup ... \cup S_{i-1})$$

Then
$$|C| = \sum_{x \in X} c_x \le \sum_{S \in C^*} \sum_{x \in S} c_x$$



• Suppose $\sum_{x \in S} c_x \leq H(|S|)$.

Then
$$|C| \le \sum_{S \in C^*} H(|S|) \le |C^*| H(\max\{|S||S \in F\}).$$

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Proof $\sum_{x \in S} c_x \leq H(|S|)$.

Define

$$u_i = |S - (S_1 \cup S_2 \cup ... \cup S_i)|$$

$$u_0 = |S|$$

Let k be the least index such that $u_k = 0$. Hence

$$S \subseteq \bigcup_{i=1}^k S_i.$$



• $u_{i-1} \ge u_i$ and $u_{i-1} - u_i$ elements of S are covered for the first time by S_i for i=1,2,...,k.

$$\sum_{x \in S} c_x = \sum_{i=1}^k (u_{i-1} - u_i) \frac{1}{|S_i - (S_1 \cup S_2 \cup ... \cup S_{i-1})|}.$$

$$|S_i - (S_1 \cup S_2 \cup ... S_{i-1})| \ge |S - (S_1 \cup S_2 \cup ... S_{i-1})|$$

$$= u_{i-1}$$

$$\sum_{x \in S} c_x \le \sum_{i=1}^k (u_{i-1} - u_i) \frac{1}{u_{i-1}}.$$

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NOTE: For any two positive integer a>b, we have

$$H(b)-H(a) = \sum_{i=a+1}^{b} \frac{1}{i} \ge (b-a)\frac{1}{b}$$

$$\sum_{x \in S} c_x \le \sum_{i=1}^k (H(u_{i-1}) - H(u_i))$$

$$= H(u_0) - H(u_k) = H(u_0) - H(0)$$

$$= H(u_0) = H(|S|).$$



Corollary 35.5. GREEDY_SET_COVER has a ratio bound of (ln|X|+1).

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35.5 The subset-sum problem

An exponential-time algorithm

$$L = \{1,2,3,5,9\}$$

$$L + 2 = \{3,4,5,7,11\}$$



EXACT_SUBSET_SUM(S,t)

- 1 $n \leftarrow |S|$
- 2 $L_0 \leftarrow < 0 >$
- 3 for $i \leftarrow 1$ to n
- 4 **do** $L_i \leftarrow MERGE_LIST(L_i, L_{i-1} + x_i)$
- 5 remove from L_i every element that is greater than t
- 6 return the largest element in L_n

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$$S = \{1,4,5\}$$

 $P_1 = \{0,1\}$
 $P_2 = \{0,1,4,5\}$
 $P_3 = \{0,1,4,5,6,10\}$

$$S = \{x_1, x_2, ..., x_k \}$$

$$P_i = P_{i-1} \cup (P_{i-1} + x_i)$$



A fully polynomial-time approximation scheme

Let $0 < \delta < 1$.

• To trim a list L by δ

y is removed from L if $\exists z \le y$ still in L' such that $\frac{y-z}{y} \le \delta \Leftrightarrow (1-\delta)y \le z \le y$

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Example:
$$\delta = 0.1$$

$$L = <10,11,12,15,20,21,22,23,24,29>$$



$Trim(L,\delta)$

- 1 $m \leftarrow |L|$
- $2 L' \leftarrow < y_1 >$
- 3 $last \leftarrow y_1$
- 4 for $i \leftarrow 2$ to m
- 5 **do if** $last < (1 \delta)y_i$
- 6 **then** append y_i onto the end of L'
- 7 $last \leftarrow y_i$

Chapter 35 8 return L'

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$\overline{\mathsf{APPROX_SUBSET_SUM}(S,t,\varepsilon)}$

- 1 $n \leftarrow |S|$
- 2 $L_0 \leftarrow <0>$
- 3 for $i \leftarrow 1$ to n
- 4 **do** $Li \leftarrow MERGE_LIST(L_{i-1}, L_{i-1} + x_i)$
- 5 $L_i \leftarrow TRIM(L_i, \frac{\varepsilon}{n})$
- 6 remove from L_i every element that is greater than t
- 7 let z be the largest value of L

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$$L = <104,102,201,101>$$

$$t = 308$$

$$\varepsilon = 0.20$$

$$\delta = \varepsilon / 4 = 0.05$$

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$$2 L_0 = <0>$$

4
$$L_1 = < 0.104 >$$

5
$$L_1 = < 0.104 >$$

6
$$L_1 = < 0.104 >$$

4
$$L_2 = <0,102,104,206>$$

5
$$L_2 = <0,102,206>$$

6
$$L_2 = <0,102,206>$$

4
$$L_3 = <0,102,201,206,303,407>$$

5
$$L_3 = <0,102,201,303,407>$$

6
$$L_3 = <0,102,201,303>$$

$$4 \quad L_4 = <0,101,102,201,203,302,303,404>$$

5
$$L_4 = <0,101,201,302,404>$$

6
$$L_4 = <0,101,201,302>$$



$$z = 302$$

 $z^* = 307 = 104 + 102 + 101$
 $\varepsilon = 2\%$

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Theorem 35.8. APPROX_SUBSET_SUM is a fully polynomial approximation scheme for the subset-sum problem.

Proof.

• By induction on i, one can show that for every element y in P_i that is at most t, there is a $z \in L_i$ such that $(1 - \frac{\varepsilon}{n})^i y \le z \le y$.



 $y^* \in P_n$ (optimal solution)

$$\Rightarrow (1 - \frac{\varepsilon}{n})^n y^* \le z \le y^*$$

Note
$$(1-\varepsilon) < (1-\frac{\varepsilon}{n})^n$$

•
$$for \frac{d}{dn} (1 - \frac{\varepsilon}{n})^n > 0 \Rightarrow (1 - \frac{\varepsilon}{n})^n is increasing$$

Thus
$$(1-\varepsilon) < (1-\frac{\varepsilon}{n})^n$$

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- Hence $(1-\varepsilon)y^* \le z \le y^*$
- Note that the successive element z and z' of L_i satisfy $\frac{z}{z'} > \frac{1}{1 \frac{\varepsilon}{n}}$. Thus the number of elements of L_i

is at most
$$\log_{\frac{1}{1-\frac{\varepsilon}{n}}} t = \frac{\ln t}{-\ln(1-\frac{\varepsilon}{n})} \le \frac{n \ln t}{\varepsilon}$$

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- The algorithm is polynomial in the number n of the input values given, the number of bits $\ln t$ and $\frac{1}{\varepsilon}$.
- APPROX_SUBSET_SUM running time is $P(n, \ln t, \frac{1}{\varepsilon})$.