

HW4:

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Exercise 1 :

Solution 1 :

The Algorithm " $\frac{4}{3}$ -approx-TSP" can be described as follows:

Algorithm 1: $\frac{4}{3}$ - approx - TSP.

* Input: a graph G whose edge weights are either 1 or 2
start point $v_0 \in V(G)$, a known "min-2-matching"
algorithm MIN-2-MATCHING for polynomial time.

* Output: a tour path S of TSP problem for G and v_0
o 1: utilize known MIN-2-MATCHING on G . to

get a optimal solution M for min-2-matching problem.
o 2: according to the defination of "2-matching".

we know that $M = \{E_1, E_2, \dots, E_k\}$, where $E_i \cap E_j = \emptyset$
and. E_i and E_j share no common vertex for $i \neq j$, while
for $\forall i \in \{1, 2, \dots, k\}$, \exists a connected graph G_i , s.t. $E_i = E(G_i)$.

o 3: $S = E_1$

04: for $2 \leq i \leq k$ do:

05: $e_1^* = \max_{w(e)} \{e \mid e \in S\}$

06: $e_2^* = \max_{w(e)} \{e \mid e \in E_k\}$

07: $V_1, V_2 = \text{Vertex}(e_1^*)$

08: $V_3, V_4 = \text{Vertex}(e_2^*)$

09: $e_3^* = \text{edge}(V_1, V_3)$

10: $e_4^* = \text{edge}(V_2, V_4).$

11: $S = S - \{e_1^*, e_2^*\} + \{e_3^*, e_4^*\}.$

12: return S

Prove the $\frac{4}{3}$ -approximation ratio for the Algorithm:

Prove:

define the notion $\Delta(i)$ means in i -th iteration

$$\Delta(i) = w(S - \{e_1^*, e_2^*\} + \{e_3^*, e_4^*\}) - w(S)$$

denote in the start of i -th iteration ($1 \leq i \leq k-1$)

$$S \hat{=} S_i.$$

denote in the end of i -th iteration ($1 \leq i \leq k-1$)

$$S \stackrel{\Delta}{=} S_{i+1}$$

So naturally we can induce that:

$$\Delta(i) = w(S_{i+1}) - w(S_i).$$

Let $T(i)$ denote the number of edges whose weight = 2 in S_i . ($1 \leq i \leq k$)

So obviously we can induce that

$$\textcircled{1} \quad \Delta(i) \leq 1, \quad \text{when } T(i) \geq 1$$

$$\textcircled{2} \quad T(i+1) = T(i) + \Delta(i)$$

So the following equation exists!

$$\begin{aligned} T(k) &= T(k-1) + \Delta(k-1) = \dots = T(1) + \Delta(1) + \Delta(2) + \dots + \Delta(k-1) \\ &= T(1) + \sum_{i=1}^{k-1} \Delta(i). \end{aligned}$$

$$\Rightarrow \sum_{i=1}^{k-1} \Delta(i) = T(k) - T(1)$$

According to the algorithm, We know that

$$\#(\text{weight=2 edges in } S_k) - \#(\text{weight=2 edges in } S_1) \leq k.$$

$$\Rightarrow \sum_{i=1}^{k-1} \Delta(i) \leq k$$

Considering that : for each $i \in \{1, 2, \dots, k\}$.

$$|\Xi_i| \geq 3$$

So we have that $|M| = |\bigcup_{i=1}^k E_i| = \sum_{i=1}^k |E_i| \geq 3k$.
 (because $E_i \cap E_j = \emptyset$)

So: [cost* denotes the cost of optimal solution].

$$\frac{\text{cost}(\text{Algo: } \frac{4}{3}\text{-approx-TSP})}{\text{cost}^*(\text{MIN-2-MATCHING})} = \frac{w(S)}{w(M)}$$

$$= \frac{w(M) + \sum_{i=1}^k \Delta(i)}{w(M)} = 1 + \frac{\sum_{i=1}^k \Delta(i)}{w(M)}$$

$$\leq 1 + \frac{k}{|M|} \leq 1 + \frac{k}{3k} = \frac{4}{3}$$

and.

$$\text{cost}^*(\text{TSP}) \geq \text{cost}^*(\text{MIN-2-MATCHING}),$$

for each solution p for TSP,

We know that p is a solution for
 MIN-2-MATCHING.

To conclude:

$$\frac{\text{cost}(\text{Algo: } \frac{4}{3}\text{-approx-TSP})}{\text{cost}^*(\text{TSP})} \leq \frac{\text{cost}(\text{Algo: } \frac{4}{3}\text{-approx-TSP})}{\text{cost}^*(\text{MIN-2-MATCHING})} \leq \frac{4}{3}$$

Exercise 2:

Solution 2:

First I would give a proof showing that the LP-FACILITY LOCATION algorithm achieves a 10-approximation ratio for this case.

Proof:

After running the LP-FACILITY LOCATION in this case, the service cost for client j in cluster k is at most:

$$\begin{aligned} C_{ik,j}^2 &\leq (C_{ij} + C_{ijk} + C_{ikjk})^2 \\ &= (C_{ij}^2 + C_{ijk}^2 + C_{ikjk}^2) \cdot (1^2 + 1^2 + 1^2) \dots \text{Cauchy inequality.} \\ &\leq (V_j^2 + V_{jk}^2 + V_{jk}^2) \cdot (1+1+1) \dots \text{complementary slackness} \\ &\leq 9 \cdot V_j^2 \dots \text{according to the description of Algorithm.} \end{aligned}$$

the bound of facility is the same as the proof in Lecture 10,

$$f_{ik} = f_{ik} \cdot \sum_{i: \text{neighbor of } jk} x_{ijk}^* \leq \sum_{i: \text{neighbor of } jk} f_i \cdot x_{ijk}^*$$
$$\leq \sum_{i: v} f_i \cdot y_i^*$$

Since $j_k, j_{k'}$ cannot have a common neighbor for $k \neq k'$, the total facility cost is,

$$\sum_k f_{ik} \leq \sum_k \sum_{i: \text{neighbor of } jk} f_i \cdot y_i^* \leq \sum_{i \in F} f_i \cdot y_i^*$$

So the total cost is at most

$$q \cdot \sum_{j \in O} V_j^* + \sum_{i \in F} f_i \cdot y_i^*$$

$$\leq q \cdot OPT_{LP} + OPT_{LP} \quad \text{--- Weak duality,}$$

$$\leq (0 \cdot OPT) \quad (\text{Integer LP} \subseteq \text{LP})$$

Where OPT is the optimal solution for ILP.

To conclude, We proved that the algorithm LP-FACILITY LOCATION is a 10-approx algorithm for this case $\#$.

Exercise 3.

[P.S. I looked up to 'cs.princeton.edu/courses/archive/fall14/cos521/lectnotes/lec15.pdf'
☆ for references.]

Solution: first, we introduce the corresponding define n+1 vectors: SDP. problem.

u_0, u_1, \dots, u_n , the first vector u_0 is a dummy vector (fixed), Let us set $\|u_0\|^2 = 1$.

and consider a general-clause-form: $y_i \vee y_j$.

We would like to say that if $u_i = u_0$, this means Set $y_i = \text{TRUE}$, if $u_i = -u_0$, this means set $y_i = \text{FALSE}$.

So, $y_i \vee y_j$ can be expressed as follows:

$$1 - \frac{1}{4} (u_0 - u_i)(u_0 - u_j) = \begin{cases} 0, & u_i = u_j = -u_0 \\ 1, & u_i = u_0 \text{ OR } u_j = u_0 \end{cases}$$

(*)

So, the SDP problem is to find these vectors satisfying $\|\mathbf{u}_i\|^2 = 1$, for all i as to maximize $\sum_{\text{clause } l} v_l$, where v_l is the expression for l th clause. (X)

So, the Algorithm 'SDP-MAX-2SAT' could be described as follows:

Algorithm SDP-MAX-2SAT

- 1. Solve the above SDP problem to obtain the optimal solution. $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n$
- 2: choose a uniformly random unit vector $\vec{r} \in \mathbb{R}^n$.
- 3: $\left\{ \begin{array}{l} \text{if } \langle \vec{r}, \vec{u}_0 \rangle \cdot \langle \vec{r}, \vec{u}_i \rangle \geq 0, \text{ set } \hat{y}_i = \text{TRUE} \\ \text{Otherwise, set } y_i = \text{FALSE} \end{array} \right.$
- 4: Output $\{y_1, y_2, \dots, y_n\}$.

Then, we will prove that the above algorithm is a 0.878-approximation.

Proof,

e.g. for $y_i V y_j$.

Tips: \hat{u}_i represent: rounded
 u_i represent: relaxed

$$1 - \frac{1}{4}(\hat{u}_0 - \hat{u}_i) \cdot (\hat{u}_0 - \hat{u}_j) = \frac{1}{4}(1 + \hat{u}_0 \cdot \hat{u}_j) + \frac{1}{4}(1 + \hat{u}_0 \cdot \hat{u}_i) + \frac{1}{4}(1 - \hat{u}_i \cdot \hat{u}_j)$$

We will consider the above expression term by term.

e.g.

$$1 + \hat{u}_0 \hat{u}_j = \begin{cases} 2 & , \hat{u}_j = \hat{u}_0 \\ 0 & , \hat{u}_j = -\hat{u}_0 \end{cases}$$

$$\begin{aligned} \Rightarrow E[1 + \hat{u}_0 \hat{u}_j] &= 2 \cdot P(\hat{u}_j = \hat{u}_0) \\ &= 2 \cdot \frac{\pi - \theta_{j,0}}{\pi} = 2 \cdot \frac{\pi - \theta_{j,0}}{\pi(1 + \cos \theta_{j,0})} \cdot (1 + \cos \theta_{j,0}) \\ &\geq 0.878 \cdot (1 + \cos \theta_{j,0}) \\ &= 0.878 \cdot (1 + u_0 \cdot u_j) \cdot \textcircled{1} \end{aligned}$$

$$1 - \hat{u}_i \hat{u}_j = \begin{cases} 2 & , \hat{u}_i = -\hat{u}_j \\ 0 & , \hat{u}_i = \hat{u}_j \end{cases}$$

$$\Rightarrow \begin{cases} \hat{u}_i = \hat{u}_j \Leftrightarrow \langle u_i, r \rangle \cdot \langle u_j, r \rangle \geq 0 \\ \hat{u}_i = -\hat{u}_j \Leftrightarrow \langle u_i, r \rangle \cdot \langle u_j, r \rangle \leq 0. \end{cases}$$

$$\begin{aligned} \text{从而 } E[-\hat{u}_i \hat{u}_j] &= \frac{2\theta_{ij}}{\pi} = \frac{2\theta_{i,j}}{\pi(1-\cos\theta_{i,j})} (1-\cos\theta_{i,j}) \\ &\geq 0.878 (1-\cos\theta_{i,j}) \\ &= 0.878 (-u_i \cdot u_j) \quad \textcircled{2} \end{aligned}$$

结合①, ②可知:

$$\begin{aligned} E\left[\frac{1}{4}(1+\hat{u}_i \cdot \hat{u}_0) + \frac{1}{4}(1+\hat{u}_j \cdot \hat{u}_0) + \frac{1}{4}(-\hat{u}_i \cdot \hat{u}_j)\right] \\ = \frac{1}{4} \times \left\{ 0.878 \left[(1+u_i u_0) + (-u_i u_j) + (1+u_j u_0) \right] \right\} \\ = 0.878 \times \text{OPT}_{SDP} \geq 0.878 \cdot \text{OPT}_{\text{MAX-2SAT.}} \# \end{aligned}$$