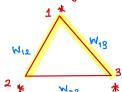
Ans 1

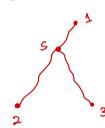
Consider the graph H given as



without loss of generality, consider

Then weight of Steiner tree obtained,

Now, consider the optimal Steiner tree and let 3 vertex be connected to path joining 1,2 at s.



Let path length from 
$$5 \text{ to } 1 = 2$$
  
 $5 \text{ to } 2 = y$   
 $5 \text{ to } 3 = 2$ 

But minimum path length arguement shows,

$$x + y \ge W_{12}$$
 —(1)

$$4 + 2 \ge w_{23}$$
 — (2)

$$\chi + 2 \geq W_{13} \qquad -(3)$$

(1) + (2) + (3)  

$$\Rightarrow$$
 (x+y+z)  $2 \ge w_{12} + w_{23} + w_{13}$  -(\*\*)

Now ALG 
$$\leq \omega_{12} + \omega_{13}$$

and 
$$w_{12} \leq w_{13} \leq w_{23}$$

Using (\*) and (\*\*), we get

$$ALQ \leq \frac{2}{3}(w_4 + w_{13} + w_{23}) \leq \frac{4}{3}(x+y+2) \leq \frac{4}{3}OPT$$

And 2 Defn: USV is a separating cut if for some i, SiEU, ti & U Dual LP LP relaxation max En yo min Zweke yu ≥ 0 xe≥o ∑ yυ ≤ we Z re > 1, U is sep. cut csimilar to e E & (U) set of cut-edges spanning and U is sep-cut tree limiting Primal dual Algo. 087 (1) F ← Ø y - 0 do f · Let C1, C2,..., Cn be the connected components in the tight edge subgraph, which separate some terminal pair, then increase ye,, yez,..., yen simultaneously · Include tight edges one-by-one not creating cycles in F till every (si, ti) pair is connected Pruning: Remove any edge from F that can be removed Now, analysis of this algorithm for 2 pairs. Proof of 3-approx claim: w(F) ≤ 3 Zygv DD = increment in dual objective  $\frac{\text{Proof}}{\text{N}}$ : We show, in each step,  $\frac{\Delta w(F)}{\Delta N} \leq \frac{3}{2}$ . Let number of connected components be q tight. w(F) = 2 we eff Σ 2 yν eep u: ee&(v) Now, for the final forest, these +60 components each have exactly 1 path blu any pair. Hence, Dw(F) = increase in weight of edges included in the final tree Final tree chosen by algorithm. with connected comp. contracted.  $=2(q-1)\varepsilon$ 

components in tight edge subgraph = 4  $\Rightarrow \frac{\Delta \omega(F)}{\Delta D} = \frac{(q-1)2\epsilon}{9\epsilon} \leq \frac{3}{4} \cdot \frac{2\epsilon}{\epsilon} = \frac{3}{2}$ Ans 3 Linear Program can be written as,  $\max \sum_{i=1}^{n} (1-y_i) P_i + \sum_{(i,j) \in E} Z_{(i,j)} Q_{(i,j)}$ +1,j ≤ 1; + 1j \ \ (i, j) e E 0 = 70 = 1  $0 \leq \lambda! \leq 7$  A! Let the optimal solution be given as (y\*, 2\*) Rounding Scheme Pick vertex : w.p. (1-2) + 24;\* Now, since algorithm is randomized, we consider expectation value of objective  $\mathbb{E}\left[\sum_{i \notin S} P_i + \sum_{(i,j) \in E} Q_{i,j}\right] = \sum_{i} P_r(i \notin S) P_i' + \sum_{(i,j) \in E} P_r(i \in S \text{ or } j \in S) Q_{i,j}$ ies or ies where  $P_{\sigma}(i \notin S) = |-(1-\lambda) - \lambda y_i^* = \lambda (1-y_i^*)$ Pr(ies or jes) = 1-Pr(ies) Pr(jes). (since ies are independent = 1 - 2(1-y; \*)(1- 3; \*)  $= \sum_{i} \lambda(1-y_{i}^{*}) P_{i} + \sum_{(i,j) \in E} (1-\lambda^{2}(1-y_{i}^{*})(1-y_{j}^{*})) Q_{i,j}$ Claim:  $1-\lambda^2(1-y_i^*)(1-y_i^*) \geq (1-\frac{\lambda^2}{4}) \neq i,j$ Case 1: 4; \* + 4; \* > 1

 $\Rightarrow \qquad \left(\left(-y_{i}^{*}\right)\left(\left(-y_{j}^{*}\right)\right) \leq \left(4\right) \Rightarrow 1-\lambda^{2}\left(\left(-y_{i}^{*}\right)\left(\left(-y_{j}^{*}\right)\right)\right) \geq 1-\frac{\lambda^{2}}{4} \geq \left(1-\frac{\lambda^{2}}{4}\right)\mathcal{Z}_{i,j}$ 

 $\Rightarrow \frac{1}{2} \geq \frac{1-y_i* + 1-y_j}{2} \Rightarrow \sqrt{(1-y_i*)(1-y_j*)}$ 

But, since we have only

two pairs (s1,t,), (s2, t2)

hence, number of connected

Case 2: 
$$y_i^* + y_j^* < 1$$
  
Then,  $z_{i,j}^* = y_i^* + y_j^*$  since increasing  $z_{i,j}$  increases objective function.

Now, 
$$1 - \lambda^{2} (1 - y_{i}^{*}) (1 - y_{j}^{*}) - (1 - \frac{\lambda^{2}}{4}) (y_{i}^{*} + y_{j}^{*})$$

$$\geq 1 - \lambda^{2} (\sqrt{(1 - y_{i}^{*})(1 - y_{j}^{*})})^{2} - (1 - \frac{\lambda^{2}}{4}) (y_{i}^{*} + y_{j}^{*})$$

 $\geq 1 - \lambda^2 \left( \frac{1 - y_i^* + 1 - y_j^*}{2} \right)^2 - \left( 1 - \frac{\lambda^2}{4} \right) \left( y_i^* + y_j^* \right)$ 

Putting yi\*+yj\* = x

Here,  $f(0) = (-\lambda^2 \ge 0)$ 

Now,  $\alpha = \min \left\{ \lambda, 1 - \frac{\lambda^2}{4} \right\}$ 

 $\lambda = 1 - \frac{\lambda^2}{4}$ 

 $\Rightarrow$   $4\lambda = 4 - \lambda^2$ 

 $\Rightarrow \lambda^2 + 4\lambda - 4 = 0$ 

Hence,  $f(x) \ge 0 + x \in [0, 1]$ 

A is an increasing  $f^{n}$ ,  $1-\frac{\lambda^{2}}{4}$  is decreasing

 $\Rightarrow \lambda = -4 + \sqrt{32} = -2 + 2\sqrt{2}$   $= 2(\sqrt{2} - 1)$ 

Hence best approx. factor is A s.t.

 $= 1 - \lambda^2 \left( 1 - \frac{2}{2} \right)^2 - \left( 1 - \frac{\lambda^2}{4} \right) \chi$ 

 $= -\lambda^2 \left(\frac{x^2}{4} - x + 1\right) - x \left(1 - \frac{\lambda^2}{4}\right) + 1$ 

 $f(1) = -\frac{\lambda^2}{4} + \frac{5}{4}\lambda^2 - 1 + 1 - \lambda^2 = 0$ 

 $= 1 - \lambda^{2} \left( 1 - y_{1}^{*} + y_{5}^{*} \right)^{2} - \left( 1 - \frac{\lambda^{2}}{4} \right) (y_{1}^{*} + y_{5}^{*})$ 

 $= -\lambda \frac{2}{4} \mu^2 + \chi \left(\frac{5}{4} \lambda^2 - 4\right) + (1 - \lambda^2) = f(\chi)$ 

Thus,  $1 - \lambda^2 (1 - y_i^*) (1 - y_j^*) - (1 - \frac{\lambda^2}{4}) (y_i^* + y_j^*) \ge 0$ .

 $\Rightarrow \min\left\{\lambda, 1-\frac{\lambda^2}{4}\right\}\left(\sum_{i}\left(1-\gamma_i*\right)^{i}\right)^{i} + \sum_{(i,j)}\sum_{i\in E}^{*} Q_{i,j}\right) = \min\left\{\lambda, 1-\frac{\lambda^2}{4}\right\} \ \text{LP-OPT}$ 

≥ min { \, 1 - \lambda^2 \} OPT

 $g(\lambda) = 1 - \frac{\lambda^2}{4}$ 

i.e.  $\alpha = 2(\sqrt{2}-1)$  is best.

Hence,  $\sum_{i} \lambda(1-y_i^*) P_i + \sum_{(i,j) \in E} (1-\lambda^2(1-y_i^*)(1-y_j^*)) Q_{i,j}$ 

$$(1-y_{1}^{2})^{2} = y_{1}^{2} + y_{2}^{2} - y_{3}^{2} + y_{3}^{2} - y_{3}^{2} + y_{3}^{2$$

$$-\lambda^{2}(1-y_{i}^{*})(1-y_{j}^{*}) - \left(1-\frac{\lambda^{2}}{4}\right)(y_{i}^{*}+y_{j}^{*})$$

$$1 - \lambda^{2} (1 - y_{i}^{*}) (1 - y_{j}^{*}) - (1 - \frac{\lambda^{2}}{4}) (y_{i}^{*} + y_{j}^{*})$$

And A Quadratic program is given as

Quadratic program is given as

max 
$$\sum_{i \neq j} d_{i,j} \left( \frac{1 - z_i z_j}{2} \right) + \sum_{i \neq j} \frac{c_{i,j}}{2} \left( \frac{1 + z_i z_j}{2} \right)$$

then SDP relaxation is given as

$$\max \sum_{i,j} d_{i,j} \left( \frac{1 - \langle v_{i,j} v_{j} \rangle}{2} \right) + \sum_{i,j} S_{i,j} \left( \frac{1 + \langle v_{i,j} v_{j} \rangle}{2} \right)$$

$$< x_i, x_i > = T$$
,  $X_i \in \mathbb{R}_u$   $\forall 1 \leq i \leq u$ 

Now, randomized hyperplane rounding gives 
$$\sum_{i,j} d_{i,j} \ Pr(i,j \text{ lie on app sides}) + \sum_{i,j} s_{i,j} \ Pr(i,j \text{ lie on same side})$$

$$\geq dij$$
  $(1,j)$  lie on opp tides  $(1+2ij)^{2ij}$   $(2,j)$  lie on same side

$$= \sum_{i,j} d_{i,j} \frac{\theta_{i,j}}{\pi} + \sum_{i,j} s_{i,j} \left( 1 - \theta_{i,j} \right)$$

$$\min_{\Theta} \frac{2\Theta}{(1-\cos\Theta)^{\pi}} = \propto \text{ gives } \propto = 0.878 \text{ (from proof of MAX-CUT)}$$

Putting 
$$\theta = \pi - \theta'$$

min  $\frac{2(1-\frac{\theta}{\pi})}{1+\cos\theta} = \alpha'$ 

$$\geq \sum_{i,j} d_{i,j} \quad \alpha \cdot \left( \frac{1 - \cos \theta}{2} \right) + \sum_{i,j} 2_{i,j} \cdot \alpha \cdot \left( \frac{1 + \cos \theta}{2} \right)$$

$$= \alpha \left( \sum_{i,j} d_{i,j} \left( \frac{1 - \langle V_i, V_j \rangle}{2} \right) + \sum_{i,j} 2ij \left( \frac{1 + \langle V_i, V_j \rangle}{2} \right) \right)$$

Hence, ALG 
$$\geq \alpha$$
 OPT-SDP  $\geq \alpha$  OPT-SP  $\geq \alpha$  OPT.  
i.e.  $ALG \geq \alpha$  OPT