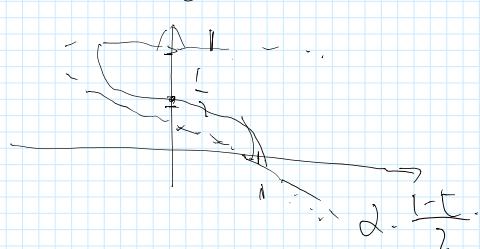


Max cut. Find a (S, T) that maximizes $|E(S, T)|$.
 Need to show that $\Pr(v_i, v_j \text{ is a cut}) \geq \alpha \cdot \frac{\|x_i - x_j\|^2}{4}$.
 $\alpha = 0.878$.

$\Pr(v_i, v_j \text{ is a cut}) = \arccos(\langle v_i, v_j \rangle) / \pi$. Let $t = \langle v_i, v_j \rangle \in [-1, 1]$.

$$\alpha \cdot \frac{\|x_i - x_j\|^2}{4} = \alpha \cdot \frac{1 - 2\langle x_i, x_j \rangle + 1}{4} = \alpha \cdot \frac{1 - t}{2}$$

wts. $\frac{\arccos t}{\pi} \geq \alpha \cdot \frac{1-t}{2}$ find the max α .



w+find α st. the line lies below the curve.

$$\Rightarrow \alpha = 0.878 \dots$$

Prop. $\Sigma \geq 0$. Let \mathbb{Z} be the number of edges over algo cuts. wts

$$\Pr(\mathbb{Z} \geq (\alpha - \xi) \cdot \text{OPT}) \geq \xi/2$$

$$\text{pf: } \mathbb{E}(\mathbb{Z}) \geq \alpha \cdot \text{OPT}. \quad \mathbb{E}(\mathbb{Z}) = \mathbb{E}(\mathbb{Z} | \mathbb{Z} \geq (\alpha - \xi) \cdot \text{OPT}) \cdot \Pr(\mathbb{Z} \geq (\alpha - \xi) \cdot \text{OPT}) \\ + \mathbb{E}(\mathbb{Z} | \mathbb{Z} < (\alpha - \xi) \cdot \text{OPT}) \cdot \Pr(\mathbb{Z} < (\alpha - \xi) \cdot \text{OPT}).$$

$$\Rightarrow \mathbb{E}(\mathbb{Z}) \leq \text{OPT}. \quad \Pr(\mathbb{Z} \geq (\alpha - \xi) \cdot \text{OPT}) + (\alpha - \xi) \cdot \text{OPT}. \Pr(\mathbb{Z} < (\alpha - \xi) \cdot \text{OPT}) \\ = \text{OPT} \cdot p + (\alpha - \xi) \cdot (1-p) \cdot \text{OPT} \\ = (\alpha - \xi) \cdot \text{OPT} + (1 - \alpha + \xi) \cdot \text{OPT} \cdot p.$$

$$\Rightarrow \xi \cdot \text{OPT} \leq (1 - \alpha + \xi) \cdot \text{OPT} \cdot p \Rightarrow p \geq \frac{\xi}{1 - \alpha + \xi}$$

$$\text{or. } \mathbb{E}(\mathbb{Z}) \leq m \cdot p + (\alpha - \xi) \cdot (1-p) \cdot \text{OPT}$$

$$\Leftrightarrow \mathbb{E}(\mathbb{Z}) \cdot \xi \cdot \text{OPT} \leq m \cdot \Pr(\mathbb{Z} \geq (\alpha - \xi) \cdot \text{OPT})$$

$$\Rightarrow p \geq \frac{\frac{\text{OPT}}{\text{OPT} \cdot m} \cdot \xi}{\xi} \cdot \xi. \quad \text{since } \exists \text{ algo st. } \text{OPT} \geq \frac{m}{2}$$

$$\Rightarrow p \geq \frac{\xi}{2}$$

$$\max \sum_{(i,j) \in E} \frac{(x_i - x_j)^2}{4}, \quad \text{where } x_i \in \{-1, 1\}^3$$

$\max \sum a_{ij} x_i x_j. \quad x_i \in \{-1, 1\}^3, y_j \in \{-1, 1\}^3. \quad A = (a_{ij})$ is an arbitrary $n \times n$ matrix.

$$\max \sum a_{ij} \langle v_i, v_j \rangle.$$

$$\text{st. } \|u_i\| = 1, \|v_j\| = 1.$$

this is relaxation of above problem since we can just take $u_i = x_i \cdot e, v_j = y_j \cdot e$ where e is a unit vector.

Reform SDP · Solution. (Kannan's work, 1977).

$$u_i \rightarrow X \quad \theta = \arccos \langle u_i, v_j \rangle.$$

$$v_j \rightarrow Y. \quad \|u_i\| = \|v_j\| = 1.$$

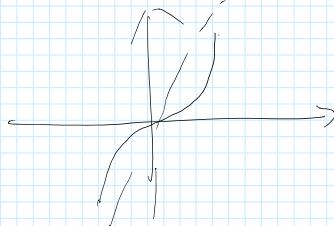
two vectors. tend to $\{+1, -1\}$. take arbitrary hyperplane belongs to upper +1 lower -1.

$$\begin{aligned} E(XY) &= \Pr(XY=1) - \Pr(XY=-1) \\ &= \Pr(X=1, Y=1) + \Pr(X=-1, Y=-1) - \Pr(X=1, Y=-1) - \Pr(X=-1, Y=1) \\ &= \frac{\pi - \theta - \theta}{\pi} = \frac{\pi - 2\theta}{\pi} \\ &= 1 - \frac{2}{\pi} \arccos \langle u_i, v_j \rangle = \frac{2}{\pi} \left(\frac{\pi}{2} - \arccos \langle u_i, v_j \rangle \right) \\ &= \frac{2}{\pi} \arcsin \langle u_i, v_j \rangle. \end{aligned}$$

Attempt 1:

$$E(\sum a_{ij} x_i y_j) = \sum a_{ij} E(x_i y_j) = \sum a_{ij} \cdot \frac{2}{\pi} \arcsin \langle u_i, v_j \rangle.$$

$\sum_{\text{wts}} \alpha \cdot \underbrace{\sum a_{ij} \langle u_i, v_j \rangle}_{\geq d - \text{OPT}}$



$\langle u_i, v_j \rangle$. no matter which z -line we choose. it lies both above/below \arcsin . this is a problem.

Fail.

Lem. For a set of unit vectors $u_1, \dots, u_n, v_1, \dots, v_n$, there exists unit vectors $\tilde{u}_1, \dots, \tilde{u}_n, \tilde{v}_1, \dots, \tilde{v}_n$ st.

$$\langle \tilde{u}_i, \tilde{v}_j \rangle = \sin(c \cdot \langle u_i, v_j \rangle), \text{ where } c = \ln(1 + \sqrt{2}).$$

1) solve the SDP.

2) transform vector.

3) apply. (nw. procedure to vectors $\tilde{u}_1, \dots, \tilde{u}_n, \tilde{v}_1, \dots, \tilde{v}_n$.

4) obtain solution $x_1, \dots, x_n, y_1, \dots, y_n$.

$$\begin{aligned} E(\sum a_{ij} x_i y_j) &= \sum a_{ij} E(x_i y_j) = \sum a_{ij} \cdot \frac{2}{\pi} \arcsin \langle \tilde{u}_i, \tilde{v}_j \rangle \\ &= \frac{2}{\pi} \sum a_{ij} \arcsin(\sin \langle u_i, v_j \rangle). \end{aligned}$$

$$= \frac{2C}{\pi} \cdot \sum a_{ij} \langle u_i, v_j \rangle = \frac{2C}{\pi} \cdot \text{SPP} \geq \frac{2C}{\pi} \cdot \text{OPT}$$

$u \in \mathbb{R}^n, v \in \mathbb{R}^m$.

$u \otimes v \in \mathbb{R}^{n \times m}$. $\langle \dots \rangle \oplus \langle \dots \rangle = \langle \dots \rangle$.

$$\begin{pmatrix} 1 \\ 1 \end{pmatrix} \oplus \begin{pmatrix} 0 \\ 3 \end{pmatrix} = \begin{pmatrix} 1 \\ -1 \\ 0 \\ 3 \end{pmatrix}$$

$$\langle u_1 \otimes u_2, v_1 \otimes v_2 \rangle = \langle u_1, v_1 \rangle + \langle u_2, v_2 \rangle.$$

$$u \in \mathbb{R}^n, v \in \mathbb{R}^m, u \otimes v \in \mathbb{R}^{n \times m}, u = (u_1 \dots u_n),$$

$$u \otimes v = uv^T = (a_i \cdot b_j)_{ij}, \quad v = (b_1 \dots b_m)$$

$n \times m$ matrix. tensor product.

$$\begin{aligned} \langle u_1 \otimes u_2, v_1 \otimes v_2 \rangle &= \sum_{ij} u_i^{(1)} v_i^{(1)} \cdot u_j^{(2)} \cdot v_j^{(2)} \\ &= \sum_{ij} (u_i^{(1)} v_i^{(1)}) (u_j^{(2)} v_j^{(2)}) \\ &= (\sum_i (u_i^{(1)} v_i^{(1)})) (\sum_j (u_j^{(2)} v_j^{(2)})) \\ &= \langle u_1, v_1 \rangle \cdot \langle u_2, \end{aligned}$$

$$L(u) = u \oplus \underbrace{\frac{u^{\otimes 3}}{3!}}_{\text{odd}} \oplus \underbrace{\frac{u^{\otimes 5}}{5!}}_{\text{odd}} \oplus \dots$$

$$R(v) = v \oplus -\underbrace{\frac{v^{\otimes 3}}{3!}}_{\text{odd}} \oplus \underbrace{\frac{v^{\otimes 5}}{5!}}_{\text{odd}} \oplus -\underbrace{\frac{v^{\otimes 7}}{7!}}_{\text{odd}} \oplus \dots$$

$$\begin{aligned} \langle L(u), R(v) \rangle &= \sum_{k \text{ odd}} \frac{\langle u^{\otimes k}, v^{\otimes k} \rangle}{\frac{k!}{2k-1} \cdot \frac{k!}{2k+1}} \cdot (-1)^{\frac{k-1}{2}} \\ &= \sum_k \frac{\langle u, v \rangle^k}{k!} \cdot (-1)^{\frac{k-1}{2}} \\ &= \sin(\langle u, v \rangle). \end{aligned}$$

$$\|L(u)\| = 1.$$

$$u_i \rightarrow L(u_i) \quad v_j \rightarrow R(v_j).$$

6/30.

$$\max \sum a_{ij} x_i y_j \quad \forall i \in S^{\pm 1}, y_i \in S^{\pm 1}.$$

$$\begin{aligned} \max \sum a_{ij} x_i y_j &= \max \sum a_{ij} x_i \underbrace{\frac{y_j^{\otimes 3}}{3!}}_{\text{odd}} + \underbrace{\frac{y_j^{\otimes 5}}{5!}}_{\text{odd}} \dots \\ L(u) &= u \oplus \underbrace{\frac{u^{\otimes 3}}{3!}}_{\text{odd}} \oplus \dots \quad R(v) = v \oplus \underbrace{\frac{v^{\otimes 3}}{3!}}_{\text{odd}} \oplus \underbrace{\frac{v^{\otimes 5}}{5!}}_{\text{odd}} \oplus \dots \end{aligned}$$

$$\max \sum a_{ij} x_i y_j$$

$$L(u) = u \oplus \frac{u^{\otimes 3}}{3!} \oplus \frac{u^{\otimes 5}}{5!} \dots R(v) = v \oplus \frac{v^{\otimes 3}}{3!} \oplus \frac{v^{\otimes 5}}{5!} \dots$$

$$\langle L(u), R(v) \rangle = \sin(\langle u, v \rangle)$$

x, y, z generalization.

$$\sum a_{ijk} x_i y_j z_k + \sum b_{ik} x_i z_k + \sum c_{jk} y_j z_k$$

can also generalize to n variables.

Ex. $\langle t_i, t_i \rangle = 1$.

$$\langle t_i, t_j \rangle = -1/2 \text{ for } i \neq j$$

$$\|t_1 + t_2 + t_3\|^2 = 0$$

$$s_i = \frac{e}{\sqrt{2}} \quad s_i \text{ are equal.}$$

Three transformations:

$$Ax(u) = (u \otimes s_1) \oplus \frac{(u \otimes t_1)}{3!} \oplus \frac{(u \otimes s_2)}{5!} \oplus \dots$$

$$Ay(u) = (u \otimes s_2) \oplus \frac{(u \otimes t_2)}{3!} \oplus \frac{(u \otimes s_3)}{5!} \oplus \dots$$

$$u \mapsto Ax(u)$$

$$\max. \sum a_{ij} x_i y_j \quad x_i, y_j \in \{-1, 1\} \quad A = (a_{ij}) \text{ psd.}$$

$\max \sum a_{ij} x_i y_j$ if $x_i = y_j \forall i$. then solved problem above.

Output: the better of the two solution x_i and y_j .

Prove: $x^T A x \geq x^T A y$ or $y^T A y \geq x^T A y$.

$$0 \leq (x - y)^T A (x - y) = x^T A x + y^T A y - 2x^T A y$$

Max k-SP problem with domain size ≤ 2

$$x_1, \dots, x_r \in \{\pm 1\} = \{-1, 1\}$$

Given a set of predicate r (Boolean functions).

f_1, \dots, f_m each depends on at most k variables.

Our goal is to find an assignment that maximizes the

#. of satisfied predicates.

E.g. 3 SAT problem.

$$x_1, \dots, x_n. (x_i \vee \bar{x}_j \vee x_k).$$

Max k-CSP(f) problem. Special version.

f_1, \dots, f_n predicates. and each predicate looks like.

$$f(x_{i_1+e_1}, x_{i_2+e_2}, \dots, x_{i_k+e_k})$$

$$f(x_1, \dots, x_k)$$

$$\frac{|\text{Supp}(f)|}{f^k}$$

$f=2$. domain size 2.

$$(\cdot \frac{k}{2^k} . 2 \cdot \frac{k}{2^k}) \text{ approx.}$$

$g \geq 2$. If $g > \log k$. we can get $\frac{c \cdot k g}{f^k}$.

$$\text{if } k \geq g. \frac{c \cdot k g}{f^k}. \quad \log g. \frac{c \cdot g^2}{f^k}.$$

$$\boxed{\text{Always. } c \cdot \frac{f}{g^k}}$$

Monday.

$$\exists? x. Ax \geq b. x \geq 0.$$

$$a_1 x \geq b_1 \dots a_m x \geq b_m.$$

$$x^{(+)}. a_1 x^{(+)} - b_1. \dots a_m x^{(+)} - b_m.$$

$$\frac{p_1^{(+)}, \dots, p_m^{(+)}}{p_1^{(+)}, \dots, p_m^{(+)}} \geq 0 \quad \text{ask. } \exists? x \text{ st. } \sum p_i^{(+)} (a_i x - b_i) \geq 0.$$

$$|a_i x - b_i| \leq p \forall i.$$

$$T = O\left(\frac{p^2 \log m}{\epsilon}\right) \quad x \rightarrow x^{(+)}$$

Set Cover.

$U = \{1, \dots, n\}$. $S_1, \dots, S_m \subset U$. pick minimal # of sets to cover U .

$$\min \sum_S x_S. \quad (x_S \in \{0, 1\}) \quad 0 \leq x_S \leq 1. \quad \forall S.$$

$$\forall i, \sum_{i \in S} x_i \geq 1.$$

Oracle: given $p_1 - p_m$. one for every set.

guess optimal g . try to find x achieves g .

$$x_S \geq 0 \text{ st. } \sum_{i \in S} p_i \cdot (\sum_{i \in S} x_i - 1) \geq 0, \sum x_i = g.$$

$$\Leftrightarrow \sum_{i \in S} x_i \cdot (\sum_{i \in S} p_i) \geq 1$$

$$\Leftrightarrow \text{st. } \sum_{i \in S} p_i \text{ minimum, } x_S = \frac{1}{\sum_{i \in S} p_i} \text{ or just } g. \\ \text{weight}(w(S)).$$

Oracle: For S which maximizes $\sum_{i \in S} p_i$. check if $g(\sum p_i) \geq 1$
 if yes. $x_S = g$ for this set S . and 0 for other S .
 if no, output Fail.

We want ρ . st. $\forall i |a_i^T x - b_i| \leq \rho$

$$|\sum x_i - 1| \leq g^{-1} \leq m.$$

$$\min c^T x.$$

Primal

$$a_i^T x \geq b_i, \dots, x \geq 0, y_i = a_i^T x - b_i \Leftrightarrow y_i \geq 0 \dots x \geq 0.$$

$$\sum_{i \in [m]} y_i (a_i^T x) \geq b^T y.$$

$$(x \geq b, \exists y \geq 0)$$

$$A \left(\begin{array}{c:c} : & : \\ \hline a_1^T x \geq b_1 & y_1 \geq 0 \end{array} \right) \quad x \geq 0.$$

$$a_m^T x \geq b_m \quad \exists y_m \geq 0.$$

$$\sum y_i (a_i^T x) \geq b^T y \Rightarrow y^T A x \geq b^T y.$$

$$\text{if } y^T A \leq c, \text{ then, } c^T x \geq y^T A x \geq b^T y.$$

max by $y^T A \leq c, y \geq 0$ - best lower bound.

Dual.

$$a_i^T x \geq b_i, \exists y_i$$

$$\vdots \quad \vdots$$

$\text{aux} \geq b_m \exists y_m$

Oracle': $\sum_i p_i(a_i x - b_i) \geq -\epsilon'$.

p_1, \dots, p_n .

$p_i^{(+)}, \dots, p_n^{(+)}$ Oracle' gives x st. $\sum_i p_i^{(+)}(a_i x - b_i) \geq -\epsilon'$.
 $\hookrightarrow x^{(++)}$.

take $\bar{x} = \frac{1}{T} \sum_{t=1}^T x^{(t)}$. for $T = O\left(\frac{\ell^2 \log m}{\epsilon'^2}\right) \Rightarrow \forall i \quad a_i \bar{x} - b_i \geq -\epsilon'$.

vii. we know $\frac{1}{T} \sum_i p_i^{(+)}(a_i x^{(t)}) \leq \frac{1}{T} \sum_i l_i^{(+)} + \epsilon \quad T \geq \frac{4\ell^2 \log m}{\epsilon'^2}$.

$$\frac{1}{T} \sum_{t=1}^T \sum_i p_i^{(+)}(a_i x^{(t)} - b_i) \leq \frac{1}{T} \sum_i (a_i x^{(t)} - b_i) + \epsilon$$

$$\min c \cdot x.$$

$$A_i \cdot x \geq b_i$$

:

$$A_m \cdot x \geq b_m$$

$$x \geq 0 \text{ psd.}$$

linear program.

$$\min c \cdot x$$

$$a_i \cdot x \geq b_i \quad \dots \quad x \geq 0$$

add. constraints linear
except this

$$\exists? A_i \cdot x \geq b_i$$

$$A_m \cdot x \geq b_m$$

$x \geq 0$, oracle handles the psd restraint

$$w_i^{(+)} = w_i^{(-1)} \cdot \exp(-\epsilon l_i^{(+)}) = \exp(-\epsilon \cdot \frac{t}{\sum_{j=1}^m l_j^{(t)}})$$

$$p_i^{(+)} = \frac{w_i^{(+)}}{\sum_{j=1}^m w_j^{(+)}} \quad l_i^{(+)} = A_i \cdot x - b_i$$

Oracle find x st. $\sum_i p_i^{(+)}(a_i x - b_i) \geq 0$. ~~$x \geq 0$~~ psd.

and vii. $|A_i x - b_i| \leq \rho$.

$$(A' \cdot X \geq b' \quad \wedge \quad \forall i \quad |A_i x - b_i| \leq \rho) \quad | \quad b_i$$

$$\left\{ \begin{array}{l} A \cdot X \geq b \\ X \geq 0 \\ \text{tr}(X) = 1 \end{array} \right. \quad \left(\begin{array}{c} \text{---} \\ \circ \end{array} \right) \quad \left(\begin{array}{c} \text{---} \\ \circ \end{array} \right) \quad \left(\begin{array}{c} \text{---} \\ b_{ij} \end{array} \right)$$

$$\sum a_{ik} x_{kj} = b_{ij}$$

$$a_{il} = \max a_{ik}, \quad x_{lj} = \frac{b_{ij}}{a_{il}}, \quad \sum x_{ii} \leq 1$$

$$A \cdot X = \begin{pmatrix} A_1 \cdot X \\ \vdots \\ A_m \cdot X \end{pmatrix}$$

$$A' \cdot X = \sum_{ij} A'_{ij} x_{ij}$$

Hint: eigenvalues

$$X = \tau_1 u_1 v_1^T + \tau_2 u_2 v_2^T + \dots + \tau_k u_k v_k^T$$

The eigenvalues τ_i eigen vectors
when $X = uu^T$. $\max A' u u^T = \sum A'_{ij} u_{ij}$.

$$= u^T A' u = \lambda_{\max}(A')$$

$\lambda_{\max}(A')$ we get

SDP for max cut.

Klein Lapp. 6.

$$\max_{u \in \mathbb{R}^n} \sum_{(i,j) \in E} \frac{\|u_i - u_j\|^2}{4}$$

$$\text{st. } \|u_i\|^2 = 1 \quad \forall i \in [n]$$

$$\max \frac{1}{4} (\bar{e}_{ii} + \bar{e}_{jj} - 2\bar{e}_{ij}) \cdot X$$

Laplacian of the graph.

$$\bar{e}_{ii} \cdot X \geq 1$$

$$\text{tr}(X) = n$$

Ex Solve above SDP. find width.

$$\mathcal{L} = D - A$$

↓

diagonal $D_{ii} = \deg(i)$.

$$\exists x \cdot \text{prove } \mathcal{L} \cdot x = \sum_{(i,j) \in E} (\bar{E}_{ii} + \bar{E}_{jj} - 2\bar{E}_{ij}) \cdot x.$$

$$\max \frac{1}{4} \mathcal{L} \cdot x.$$

$$\text{st. } \bar{E}_{ii} \cdot x \geq 1. \quad \text{tr}(x) = h. \quad x \text{ p.s.d.}$$

$$\max. \frac{n}{4g} \mathcal{L} \cdot z. \quad \text{st. } n\bar{E}_{ii} \cdot z \geq 1. \quad \forall i \in [n]. \quad \text{tr}(z) = 1. \quad z \text{ p.s.d.}$$

$$\exists z. \frac{n}{4g} \mathcal{L} \cdot z \geq 3 P_0^{(t)}.$$

$$n\bar{E}_{ii} \cdot z \geq 1. \quad \left\{ \begin{array}{l} P_i^{(t)} \\ \forall i \end{array} \right.$$

$$\text{tr}(z) = 1.$$

$$\text{find } z \text{ st. } \text{tr}(z) = 1. \quad z \geq 0.$$

$$(P_0^{(t)} \frac{n}{4g} \mathcal{L} + \sum_{i=1}^n P_i^{(t)} n \bar{E}_{ii}) \cdot z \geq 1. \quad A^{(t)} \cdot z \geq 1.$$

Quadratic.

$$- \text{Find. } \lambda_{\max}(A^{(t)})$$

$$- \lambda_{\max} \geq 1. \quad \left\{ \begin{array}{l} O(\frac{m \ln n}{\epsilon}) \\ \text{approximately} \end{array} \right. \quad z = u u^\top, \quad \text{where } u \text{ is the first eigenvector}$$

$$| \underbrace{\sum_{\substack{i \\ z_{ii} \leq 1}} n \bar{E}_{ii} \cdot z - 1 | \leq n - 1}$$

$$\mathcal{L} \cdot u^\top u = u^\top \mathcal{L} u.$$

$$| \frac{n}{4g} \mathcal{L} \cdot z - 1 | = O(m).$$

$$T = O\left(\frac{\epsilon^2 \ln n}{\epsilon^2}\right). \quad \text{Actually can get } O\left(\frac{\epsilon \ln m \ln n}{\epsilon^2}\right)$$

$$= O\left(\frac{\epsilon \ln n}{\epsilon^2} + \text{trule}\right) = O\left(\frac{m \ln m \ln n}{\epsilon^2}\right).$$

$$= O\left(\frac{mn^2}{\epsilon^2} + \text{rule}\right), = O\left(\frac{mn\ln n}{\epsilon^2}\right).$$

find $\bar{x} - \frac{1}{4g} \bar{L}x \geq 1 - \epsilon$.

$$\bar{t}_{ii} \cdot x \geq 1 - \epsilon.$$

$$\text{tr}(x) = n.$$

$$1 - \epsilon \leq x_{ii} \leq 1 + \epsilon$$

Then can produce SPP solution with value $(1 - \epsilon)r$ if $1 - \epsilon \leq x_i \leq 1 + \epsilon$.

$$\begin{aligned} \text{Ex. } \| (1+\alpha)u_i - (1+\beta)v_j \|^2 &\geq (1 - \epsilon)r)^2 \| u_i - v_j \|^2 \text{ for} \\ \| u_i \|^2 &= \| v_j \|^2 = 1 \text{ and } |\alpha|, |\beta| \leq r. \end{aligned}$$

$$\max_c c \cdot x.$$

$$\text{st. } y_i A_i \cdot x \leq b_i, \quad i=1, \dots, m.$$

x p.s.d.

Dual for this S.PP.

$$(\sum y_i A_i) \cdot x \leq b \cdot y.$$

Ex. for A, B p.s.d. $A \cdot B$ p.s.d.

Dual:

$$\min_b b \cdot y$$

st. $\sum y_i A_i - C$ p.s.d. $y \geq 0$. results hot exactly.

dual for S.PP,

time t, have $X^{(+)}$, $\text{tr}(X^{(+)}) = 1$.

guess y is QPT.

Rule: find $y \geq 0$ st.

$$\sum y_i A_i \cdot X^{(+)} - C \cdot X^{(+)} \geq 0.$$

linear program for y .

$b \cdot y \leq g$.

$$\|\sum_i y_i A_i - c\| \leq \rho \quad \text{weight}$$

where $\|M\| = \max_{(i)} \{|\lambda_{\max}(M)|, |\lambda_{\min}(M)|\}$.

$$w^{(1)} = I, \quad x^{(1)} = \frac{w^{(1)}}{\text{tr}(w^{(1)})}$$

$$M^{(+)} = \frac{\sum_i y_i^{(+)} A_i - (1 + \rho)I}{2\rho}, \quad w^{(+)} = \exp\left(-(\sum_{\tau=1}^{t-1} M^{(\tau)})\right)$$

$$x^{(+)} = \frac{w^{(+)}}{\text{tr}(w^{(+)})}$$

$$\exp(A) = I + A + \frac{A^2}{2!} + \dots$$

Ex. If A symmetric. So is $\exp(A)$.

Ex For any. Symmetric A . $\exp(A)$ p.s.d.

$\text{tr}(e^{A+B}) \neq \text{tr}(e^A \cdot e^B)$. Matrices need not to commute.

Gohberg-Thompson: $\text{tr}(\exp(A+B)) \leq \text{tr}(e^A \otimes e^B)$.

Ex Analyze. matrix MW algorithm.

Ex. $\lambda_n(\sum_i y_i A_i - c) \geq -O(\epsilon)$. for T large enough

[AK 08]

Max-Cut.

$x_i, x_j \in \{-1\}$. $(i, j) \in E$. $x_i x_j = -1$. Is a cut.

$$\max_{\substack{(i,j) \in E \\ (i,j) \in E}} \sum_{(i,j) \in E} \left(\frac{1 - x_i x_j}{2} \right)$$

Max 3-XOR.

$x_i \in \{-1\}$. $x_i x_j x_k = b$. (1 or -1)

$$\hookrightarrow \sum_{(i,j,k) \in E} x_i x_j x_k$$

$$x_{(i,j)} = \underset{2}{\cancel{x_i x_j}} \Rightarrow x_i x_j x_k = x_{(i,j)} x_k.$$

$$\frac{1+b x_i x_j x_k}{2} = \frac{1+b \cancel{x_{(i,j)} x_k}}{2} \rightarrow \frac{1+b \langle u_{(i,j)}, u_k \rangle}{2}$$

$$\langle u_\phi, u_{(i,j)} \rangle = \langle u_i, u_j \rangle.$$

$$\sum_{S \subseteq [n], |S| \leq t} \|u_S\| = 1.$$

$$\langle u_S, u_T \rangle = \langle u_S, u_{T'} \rangle \text{ when } S \triangleleft T = S' \triangleleft T'.$$

$$\max. \sum_{i,j,k} \frac{1+b \langle u_{(i,j)}, u_k \rangle}{2} \quad \text{relaxation of original problem.}$$

Ex. $t=n$. exact.

Ex. Write relaxation for $c/1$ variables.