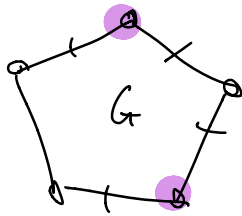


MaxCut: We will use convex programming  
 (linear programming over semidefinite matrices)  
 to get a 0.878... approximation of maxcut.  
 This is a famous result of Goemans & Williamson

Input: graph  $G = (V, E)$ .

For  $S \subset V$ , define  $\text{cut}(S) = \#\{(a,b) \text{ s.t. } | \{a,b\} \cap S | = 1\}$   
 $\text{maxcut}(G) = \max_S \text{cut}(S)$ .



$$\text{cut}(S) = 4$$

In our previous notation,  $\text{cut}(S) = |\partial(S)|$

Easy results first. Define  $m = |E|$ .

lem1  $\text{maxcut}(G) \geq m/2$

proof Consider choosing  $S$  unif. at random

$\forall a \in V \Pr[a \in S] = \frac{1}{2}$ , independently.

For  $\forall (a,b) \in E$

$$\begin{aligned} \Pr[(a,b) \in \partial(S)] &= \Pr[(a \in S \text{ and } b \notin S) \text{ or } (a \notin S \text{ and } b \in S)] \\ &= \Pr[a \in S \text{ and } b \notin S] + \Pr[a \notin S \text{ and } b \in S] \\ &= \frac{1}{4} + \frac{1}{4} = \frac{1}{2} \end{aligned}$$

$$\mathbb{E}_S \text{cut}(S) = \sum_{(a,b) \in E} \Pr[(a,b) \in \partial(S)] = \frac{m}{2}$$

max  $\geq$  average, so  $\exists S$  s.t.  $\text{cut}(S) \geq m/2$

Can turn this into an algorithm. But there's a simpler algorithm.

Let's describe it in terms of  $\{\pm 1\}^n$  vectors, where  $n = |U|$ .  
 $x \in \{\pm 1\}^n$ ,  $S_x = \{a : x(a) = 1\}$

### Local Search

Start with any  $x \in \{\pm 1\}^n$  (like  $\mathbb{1}$ , or random)

while  $\exists a$  st.  $x(a) \sum_{b:(a,b) \in E} x(b) > 0$  most neighbors of  $a$  are on same side

$$x(a) = -x(a).$$

Return  $x$  (or  $S_x = \{a : x(a) = 1\}$ )

Idea: if moving  $a$  into or out of  $S$  increases the cut, do it.

Claim 1  $\text{cut}(S_x) = \frac{1}{2} \sum_{(a,b) \in E} |1 - x(a)x(b)|$

proof

Claim 2 If  $\hat{x}$  is vector after moving  $a$ ,  
 $\text{cut}(S_{\hat{x}}) = \text{cut}(S_x) + x(a) \sum_{b:(a,b) \in E} x(b)$

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### Local Search

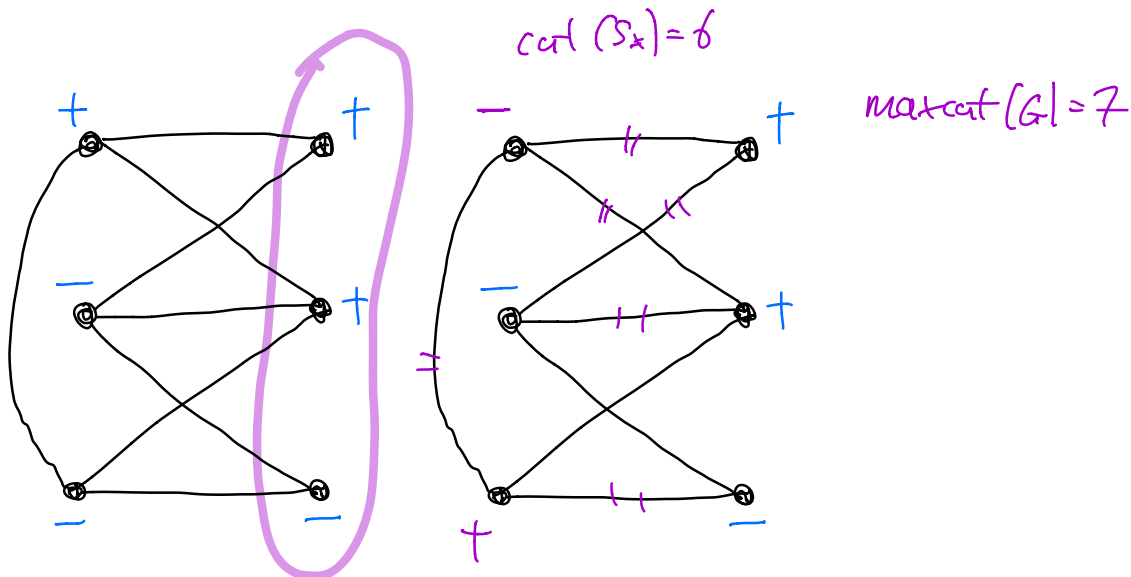
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Idea: if moving  $a$  into or out of  $S$  increases the cut, do it.

Claim 1 cut  $(S_x) = \frac{1}{2} \sum_{(a,b) \in E} |1 - x(a)x(b)|$   $\frac{1}{2}(1 - (-1)) = 1$

proof  $x(a)x(b) = -1$  if  $(a,b) \in \partial(S_x)$   $\frac{1}{2}(1 - 1) = 0$   
 $= 1$  o.w.

Claim 2 If  $\hat{x}$  is vector after moving  $a$ ,

$$\underline{\text{cut}}(S_{\hat{x}}) = \underline{\text{cut}}(S_x) + x(a) \sum_{b:(a,b) \in E} x(b)$$

$$x: \quad \oplus \text{ --- } \oplus$$

$$\text{cut}(S_x) = 0$$

$$x(a)x(b) = 1$$

$$\hat{x}: \quad \ominus \text{ --- } \oplus$$

$$\text{cut}(S_{\hat{x}}) = 1$$

lem 2 local Search terminates, and returns  
 $x$  with  $\text{cut}(S_x) \geq \frac{m}{2}$

proof

When stops  $\forall a \sum_{b:(a,b) \in E} x(a)x(b) \leq 0$

$$\text{cut}(S_x) = \frac{1}{2} \sum_{(a,b) \in E} 1 - x(a)x(b) = \frac{m}{2} - \frac{1}{2} \sum_{(a,b) \in E} x(a)x(b) \text{ cuts} \geq \frac{m}{2}$$

need:  $\sum_{(a,b) \in E} x(a)x(b) \leq 0$

$$\sum_{(a,b) \in E} x(a)x(b) = \frac{1}{2} \sum_a \sum_{b:(a,b) \in E} x(a)x(b) \leq 0$$

How to do better?

Goemans & Williamson '95: relax  $x(a) \in \{\pm 1\}$

replace with  $u_a \in \mathbb{R}^n$ ,  $\|u_a\|_2 = 1$

$$\begin{aligned} x(a)x(b) &\rightarrow u_a^T u_b \\ \sum_{(a,b) \in E} (1 - x(a)x(b)) &\rightarrow \sum_{(a,b) \in E} (1 - u_a^T u_b) \end{aligned}$$

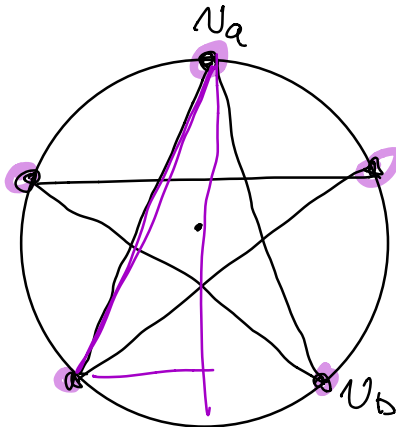
Solve the vector problem

$$\text{VP}(G) = \max_{\{u_a\}} \frac{1}{2} \sum_{(a,b) \in E} (1 - u_a^T u_b) \quad \text{s.t.} \quad \|u_a\|_2 = 1$$

$$u_a = 0$$

$$\frac{1}{2} m$$

Ex.



$(a,b) \in E$

$$u_a^T u_b = \cos\left(\frac{4\pi}{5}\right) \approx -0.81$$

for all  $(a,b) \in E$

$$\frac{1}{2} \sum_{(a,b) \in E} (1 - u_a^T u_b) \approx 4.52 > \text{maxcat}(G) = 4$$

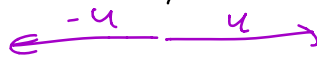
1. We can turn the solution into an approximate solution to maxcat.
2. We can approximately solve VP in polynomial time.

Claim 3  $VP(G) \geq \text{maxcut}(G)$   $x(a) \in \pm 1, \forall a$

proof consider  $N_a = \underline{u} \cdot x(a)$  for any unit vector  $u$ .

Now,  $N_a^T N_b = x(a)x(b)$ .

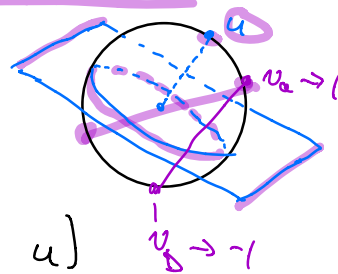
But we can choose  $N_a$  differently, and get a larger value.



To round vectors  $N_1, \dots, N_n$  into  $\pm 1$   $x(1), \dots, x(n)$ :

Choose a random unit vector  $u$ ,

set  $x(a) = \begin{cases} 1 & \text{if } u^T N_a \geq 0 \\ -1 & \text{o.w.} \end{cases}$

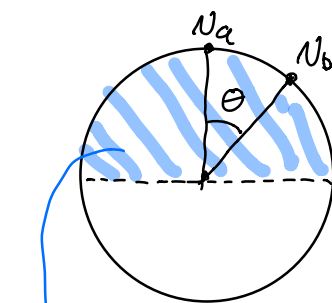
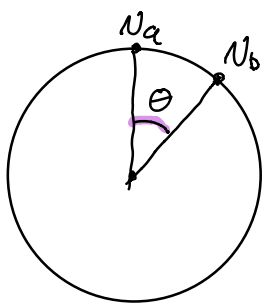


(is equivalent to use Gaussian random  $u$ )

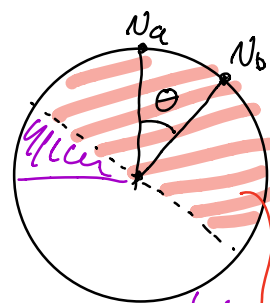
$\tau \sim N(0, I_n)$   $u = \tau / \|\tau\|$

Claim 4  $\Pr[(a,b) \in \partial(S_x)] = \frac{1}{\pi} \text{ang}(N_a, N_b) = \frac{\theta}{\pi} = \frac{2\theta}{2\pi}$

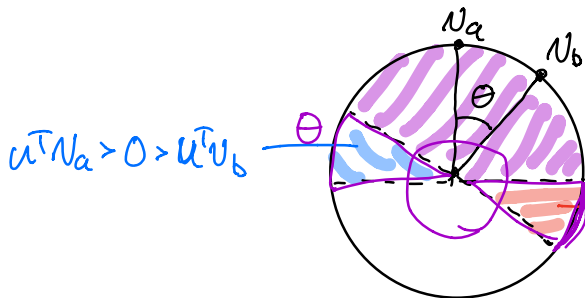
proof First, look at the 2D case



$\{u: u^T N_a > 0\}$



$\{u: u^T N_b > 0\}$



$u^T N_a > 0 > u^T N_b$

both slices have angle  $\theta$

$u^T N_b > 0 > u^T N_a$

In general, project  $u$  to span  $(u_a, u_b)$ , and apply this analysis.

$u_a^T u_b = \cos(\theta)$

$\swarrow$   $S_u$  or  $S_{x_u}$

Claim 5  $\mathbb{E}_u \text{cut}(S_x) = \frac{1}{\pi} \sum_{(a,b) \in E} a \cos(u_a^T u_b)$

proof  $u_a^T u_b = \cos \theta$ ,  $\theta = \arccos(u_a^T u_b)$

Claim 6  $\min_{-1 \leq t \leq 1} \frac{\frac{1}{\pi} \arccos(t)}{\frac{1}{2}(1-t)} \geq 0.878$

Theorem  $\mathbb{E}_u \text{cut}(S_x) \geq 0.878 \cdot \text{maxcut}(G)$

proof  $\mathbb{E}_u \text{cut}(S_x) = \frac{1}{\pi} \sum_{(a,b) \in E} a \cos(u_a^T u_b)$

$$\geq 0.878 \sum_{(a,b) \in E} \frac{1}{2} (1 - u_a^T u_b)$$

$$= 0.878 \text{UP}(G)$$

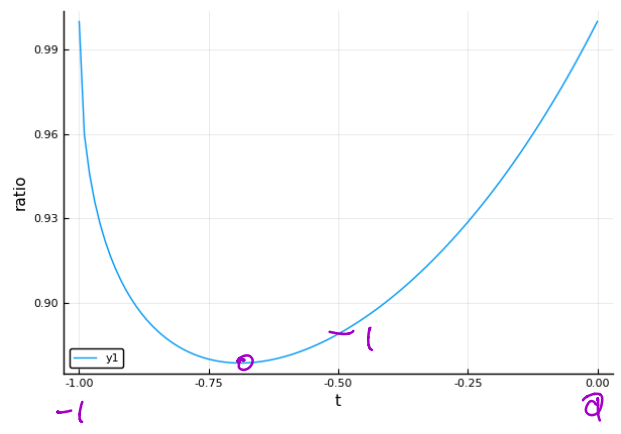
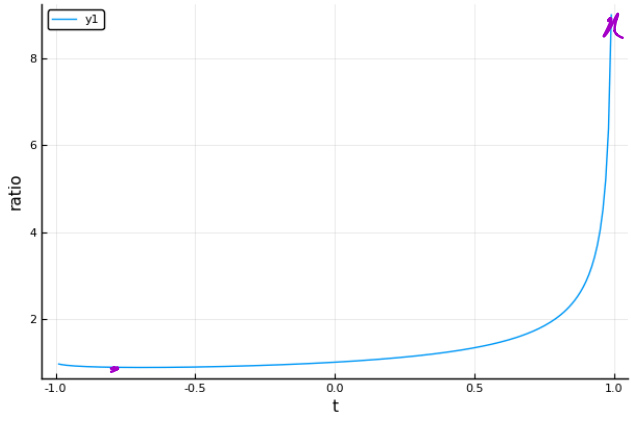
$$\geq 0.878 \text{maxcut}(G)$$

Proof of claim 6

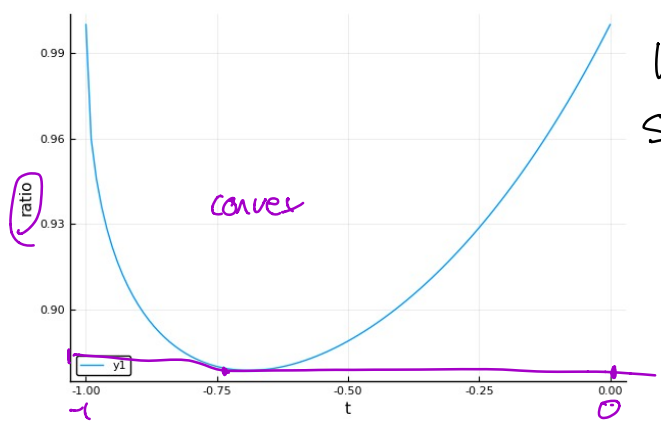
change to  $\theta = \arccos(t)$ , compute deriv, set to 0  
crit point  $\cos(\theta) + \theta \sin(\theta) = 1$



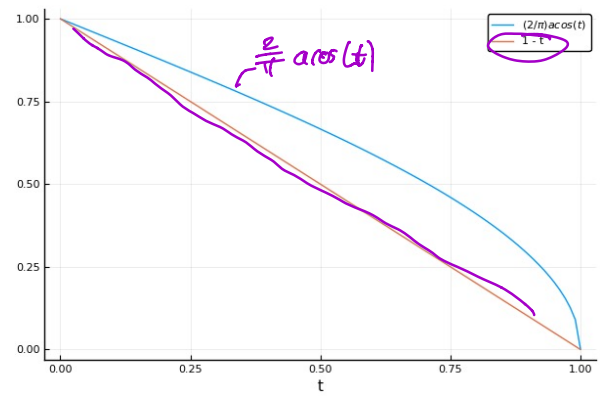
or, 2. plot it.



3. Use the plot to derive the bound. (see GW)



here, ratio is convex.  
So use a supporting plane to get a lower bound



here, ratio  $\geq 1$

How to solve VP:

$$\max_{v_1, \dots, v_n} \frac{1}{2} \sum_{(a,b)} 1 - v_a^T v_b \quad \text{s.t. } \underline{v_a^T v_a = 1, \text{ for all } a.}$$

This problem is linear in the Gram matrix:

$$\underline{M(a,b) = v_a^T v_b} \quad \underline{M = V^T V} \quad \text{where } V = \begin{pmatrix} v_1 & \dots & v_n \\ \vdots & & \vdots \end{pmatrix}$$

$$\text{problem becomes } \max \frac{1}{2} \sum_{(a,b) \in E} \underline{1 - M(a,b)} \quad \text{s.t. } \underline{M(a,a) = 1, \forall a}$$

and M is a Gram matrix.

Claim:

M is a Gram matrix iff M is positive semidefinite.

proof  $M = V^T V \Rightarrow \exists x \quad x^T M x = (Vx)^T (Vx) \geq 0, \forall x$

If M is psd, can find a "Cholesky" - factorization

$$M = LL^T \quad L = \begin{pmatrix} * & & 0 \\ * & * & \\ * & * & * \end{pmatrix} \quad \begin{pmatrix} * & 0 \\ * & * \\ * & 0 \end{pmatrix}$$

$$V = L^T \quad M \text{ is Gram matrix of } L^T$$

eigen:  $M = U \Lambda U^T \quad \Lambda = \text{diag, non-neg} \quad V = \underline{\Lambda^{1/2} U^T} \quad U^T V = M$

So, solve

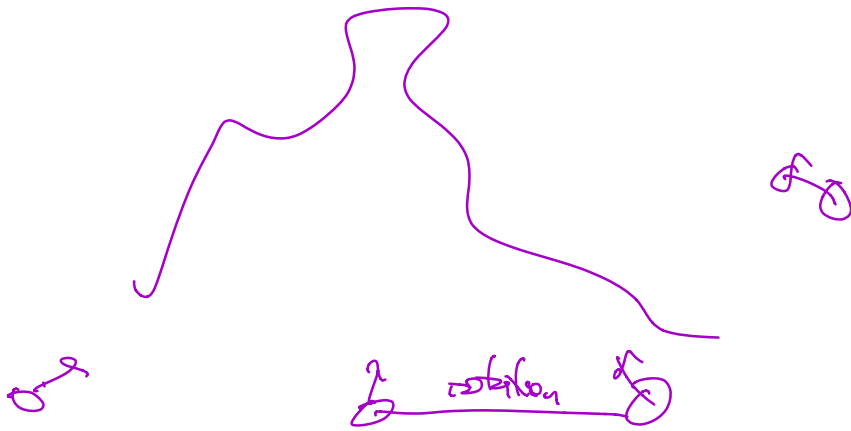
$$\max \frac{1}{2} \sum_{(a,b) \in E} \underline{1 - M(a,b)} \quad \text{s.t. } \underline{M \succeq 0}, \quad \underline{M(a,a) = 1, \forall a}$$

Cholesky factor  $\underline{M = LL^T}$  eigen decomp

$x = \text{sign}(u^T V)$  for a random vector u

Can find graphs for which alg  
does not beat 0.879

UGC  $\Rightarrow$  can't beat GW.



variables are  $\hat{M}^n$   $n^2$  variables...

for many problems solution has low rank  
are many special purpose algs.

Semidefinite Programming

$$\max \text{Tr}(C^T M) = \langle C, M \rangle$$

s.t.  $M \succeq 0$  pos def

$$\text{Tr}(B_i^T M) \leq b_i$$

$$N(0,1) \quad p(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

$$x = x_1, \dots, x_n$$

$$\begin{aligned} p(x) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-x_i^2/2} \\ &= (2\pi)^{-n/2} \prod_i e^{-x_i^2/2} \\ &= (2\pi)^{-n/2} e^{-\sum x_i^2/2} \\ &= \text{"} e^{-\frac{1}{2}\|x\|^2} \end{aligned}$$