

Consider SDP relaxation of the MAX CUT QP. Since it does not involve linear terms we can use an SDP relaxation of size  $|V|$  (instead of size  $|V|+1$ ):

$$\text{sdp}(G, w) = \max \frac{1}{2} \sum_{\{i, j\} \in E} w_{ij} (1 - X_{ij})$$

$$X \in S_{\geq 0}^V$$

$$X_{ii} = 1 \text{ for } i \in V.$$

Clear:  $\text{mc}(G, w) \leq \text{sdp}(G, w)$ .

Every  $x \in \{-1, +1\}^V$  is a feasible solution for the MAX CUT QP. Then  $X = xx^T$  is a feasible solution for the SDP relaxation.

If  $\text{rank } X = 1$  and  $X$  is feasible for SDP-relaxation, then  $X = xx^T$  where  $x \in \{-1, +1\}^V$ . ( $\rightarrow$  Exercise 3.2)

How good is the SDP relaxation?

Theorem 5 (Goemans, Williamson, 1995)

$$\text{sdp}(G, w) \geq \text{mc}(G, w) \geq 0,878 \dots \text{sdp}(G, w).$$

Proof The proof of the inequality is algorithmic. It will yield a randomized polynomial time algorithm to approximate MAXCUT within a factor of  $0,878\dots$

Algorithm 1. Solve  $\text{sdp}(G, w)$ . Let  $X$  be an optimal solution.

2. Perform a Cholesky decomposition of  $X$ .

This gives normal vector  $v_i \in \mathbb{R}^V$ ,  $i \in V$ ,

with  $X_{ij} = v_i^T v_j$ ,  $i, j \in V$ .

randomized  
rounding

3. Choose  $\tau \in \mathbb{R}^V$ ,  $\|\tau\| = 1$ , randomly from the probability distribution on the unit sphere which is invariant under orthogonal transformation.

4. Define a cut  $S(S)$  by

$i \in S \iff \text{sign}(v_i^T \tau) \geq 0$  for  $i \in V$ .

That means  $x_i = \begin{cases} \text{sign}(v_i^T \tau), & \text{sign}(v_i^T \tau) \neq 0 \\ 1 & \text{otherwise.} \end{cases}$

5. If  $w(S(S)) < 0,878\dots \text{sdp}(G, w)$ :  
go back to step 3.

Now show:  $\mathbb{E}[w(S(S))] \geq 0,878\dots \text{sdp}(G, w)$ .

## Lemma 6 (Grothendieck's identity)

Let  $u, v \in \mathbb{R}^d$  be unit vectors. Let  $\pi \in \mathbb{R}^d$  be a random unit vector chosen from the  $O(d)$ -invariant probability distribution on the unit sphere. Then

$$(i) \quad \mathbb{P}[\text{sign}(u^T \pi) \neq \text{sign}(v^T \pi)] = \frac{\arccos(u^T v)}{\pi}$$

$$(ii) \quad \mathbb{E}[\text{sign}(u^T \pi) \text{sign}(v^T \pi)] = \frac{2}{\pi} \arcsin(u^T v).$$

Proof (i) If  $u = v$ , then  $\arccos(u^T v) = 0$

If  $u = -v$ , then  $\arccos(u^T v) = \pi$ .

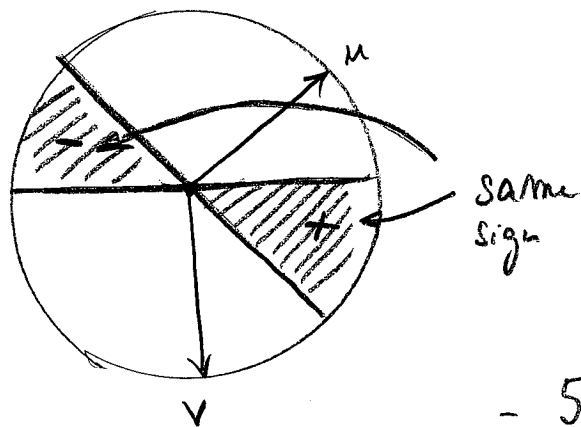
In both cases, the equality in (i) is obvious.

Now assume that  $W = \text{span}\{u, v\}$  has dimension 2.

Project  $\pi$  orthogonally onto  $W$ : this gives an  $s \in W$  such that  $u^T \pi = u^T s$ ,  $v^T \pi = v^T s$ . The unit vector  $\frac{s}{\|s\|}$  is

uniformly distributed on the unit circle by the  $O(d)$ -invariance of the probability distribution. Hence,

$$\mathbb{P}[\text{sign}(u^T \pi) \neq \text{sign}(v^T \pi)] = 2 \cdot \frac{1}{2\pi} \arccos(u^T v)$$



$$\begin{aligned}
(ii) \quad & \mathbb{E}[\text{sign}(u^T r) \text{sign}(v^T r)] \\
&= (+1) \mathbb{P}[\text{sign}(u^T r) = \text{sign}(v^T r)] + (-1) \mathbb{P}[\text{sign}(u^T r) \neq \text{sign}(v^T r)] \\
&= 1 - 2 \mathbb{P}[\text{sign}(u^T r) \neq \text{sign}(v^T r)] \\
&= 1 - 2 \frac{\arccos(u^T v)}{\pi} \\
&= \frac{2}{\pi} \arcsin(u^T v) \quad \text{because } \arcsin t + \arccos t = \frac{\pi}{2}.
\end{aligned}$$

Back to the proof of Theorem 5:

Let  $X$  be an optimal solution of  $\text{sdp}(G, w)$  and let  $v_i \in \mathbb{R}^V$ ,  $i \in V$ , be unit vectors with  $X_{ij} = v_i^T v_j$  constructed in Step 2.

Consider the cut  $S(S)$  determined in Step 4. Then:

$$\begin{aligned}
\mathbb{E}[w(S(S))] &= \sum_{\{i,j\} \in E} w_{ij} \mathbb{P}[\{i,j\} \in S(S)] \\
&= \sum_{\{i,j\} \in E} w_{ij} \mathbb{P}[\text{sign}(v_i^T r) \neq \text{sign}(v_j^T r)] \\
&= \sum_{\{i,j\} \in E} w_{ij} \frac{\arccos(v_i^T v_j)}{\pi} \\
&= \sum_{\{i,j\} \in E} w_{ij} \left( \frac{1 - v_i^T v_j}{2} \right) \cdot \underbrace{\left( \frac{2}{\pi} \frac{\arccos(v_i^T v_j)}{1 - v_i^T v_j} \right)}_{\geq 0.878\dots} \\
&\geq 0.878\dots \text{sdp}(G, w)
\end{aligned}$$

because  $\min_{t \in [-1, 1]} \frac{2}{\pi} \frac{\arccos t}{1-t} = 0.878\dots$

Since  $m_G(G, w) \geq \mathbb{E}[w(S(S))]$  Theorem 5  
in problem.  $\square$