

Semidefinite Programming

(1)

Max Cut: Given $G=(V,E)$ find a cut containing as many edges as possible.

① Random assignment / greedy algorithm:

$1/2$ -approximation.

② Linear programming

are ij in different parts?

$$\max \sum_{(i,j) \in E} d_{ij}$$

$$d_{ij} + d_{jk} + d_{ki} \leq 2 \quad \forall i,j,k$$

$$d_{ij} + d_{jk} \geq d_{ik}$$

$$1 \geq d_{ij} \geq 0$$

$$\forall i,j$$

Lem Integrality gap = $\frac{1}{2}$

Today A stronger technique!



Max-cut is captured by a quadratic program:

(2)

$$\max \frac{|E|}{2} \sum_{(i,j) \in E} v_i v_j$$

s.t.

$$v_i \in \{\pm 1\}$$

is v_i in 1'st part?

Idea Let v_i 's be vectors in \mathbb{R}^n .

Relaxation:

$$\max \frac{|E|}{2} - \frac{1}{2} \sum_{(i,j) \in E} \langle v_i, v_j \rangle$$

$$\text{s.t. } \|v_i\|^2 = 1$$

This is an instance of "semidefinite programming".

It turns out that we can (approx) solve such programs in polynomial time.

Thm (positive semidefinite matrix)

(3)

The following are equivalent for an $n \times n$ matrix P :

(1) \exists $m \times n$ matrix V s.t. $P = V^T V$

(2) $\forall x \in \mathbb{R}^n \quad x^T P x \geq 0$

Note: can efficiently
compute V from P
(Cholesky decomposition)

(3) All eigenvalues of P are non-negative.

When those conditions hold we say that P is positive semidefinite and denote $P \succeq 0$.

Note that (1) is the property we needed.

(2) shows that this property is equivalent to linear constraints.

Issue: there are infinitely many constraints.

Solution: efficient separation oracle using (3):

Eigenvalues of P can be computed efficiently

so we can check whether (3) holds.

If not, eigenvector corresponding to negative eigenvalue gives unsat constraint.

Comments ① eigenvectors / eigenvalues / solutions

④

So SDP may not have poly-size representations!

However -

- If feasible region is nonempty & contained in a poly size ball centered at origin.

We can get an approximation up to additive ϵ , ^{arbitrarily small}

② SDP solver only guarantees vectors in some dimension. Wlog this dimension is $\leq n$.

Back to Max-Cut

(5)

Solving relaxation yields $\vec{v}_i \in \mathbb{R}^n \quad 1 \leq i \leq n$

$$\text{s.t.} \quad \frac{|E|}{2} - \frac{1}{2} \sum_{(i,j) \in E} \langle \vec{v}_i, \vec{v}_j \rangle \geq \max \# \text{ edges cut.}$$

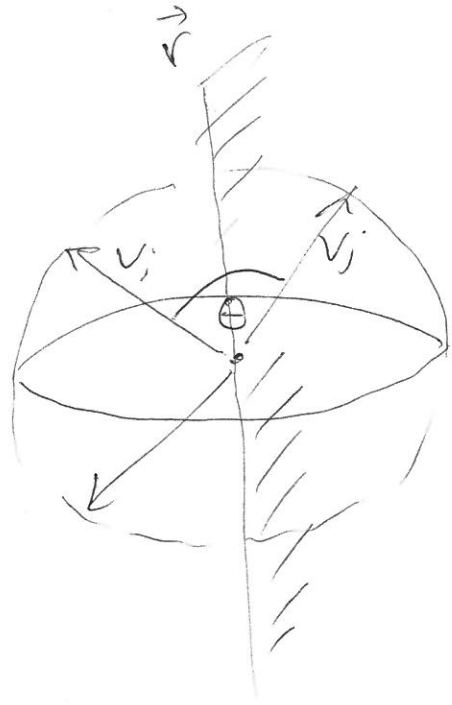
$$\|\vec{v}_i\|^2 = 1$$

Recall: $\langle v_i, v_j \rangle = \cos \angle(v_i, v_j)$

$$\langle v_i, v_j \rangle = 0 \rightarrow \cos \angle = 0$$

$$\langle v_i, v_j \rangle = 1 \rightarrow \cos \angle = 1$$

$$\langle v_i, v_j \rangle = -1 \rightarrow \cos \angle = -1$$



Randomized Rounding Pick a random $\vec{r} \in \mathbb{R}^n$
 $\|\vec{r}\|^2 = 1$

set assignment to i to be $\text{sign} \langle \vec{r}, \vec{v}_i \rangle$

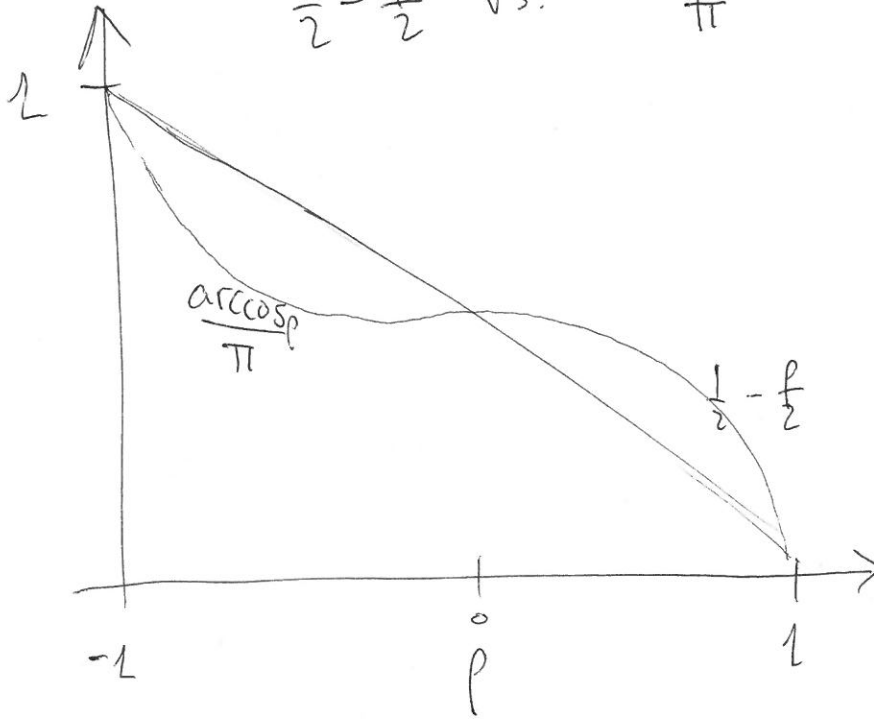
$$\mathbb{E}[\# \text{ edges cut}] = \mathbb{E} \sum_{(i,j) \in E} p(i,j \text{ cut}) = \frac{\angle(\vec{v}_i, \vec{v}_j)}{\pi} =$$

$$\frac{\arccos \langle \vec{v}_i, \vec{v}_j \rangle}{\pi}$$

OPT vs. Rounded

(6)

$$\frac{1}{2} - \frac{f}{2} \text{ vs. } \frac{\arccos p}{\pi}$$



The largest gap is $\min \frac{\arccos p}{\pi} \approx 0.878$.

Therefore, get an approx factor of $\frac{\arccos p}{\pi}$ for Max-Cut.

Integrality Gap

It turns out that the Goemans-Williamson rounding procedure is optimal!

consider the graph whose vertices are points $\vec{v} \in \mathbb{R}^n$ on the unit sphere,


and where edges connect \vec{v} and \vec{u} iff $\langle \vec{v}, \vec{u} \rangle = p^*$ where p^* minimizes $\frac{\arccos p}{\pi}$
 ~~$\frac{1}{2} - \frac{p}{2}$~~

(graph should be suitably discretized).

By construction SDP value = $\frac{1}{2} - \frac{p^*}{2}$.

We claim that no cut has value better than $\approx \frac{\arccos p}{\pi}$.

Cut = set on unit sphere

#edges cut = boundary of set w/ steps 

Thm [Feige-Schechtman] best cut is a hemisphere (cap through origin)
I.e. GW rounding is optimal. It achieves $\frac{\arccos p}{\pi}$.