

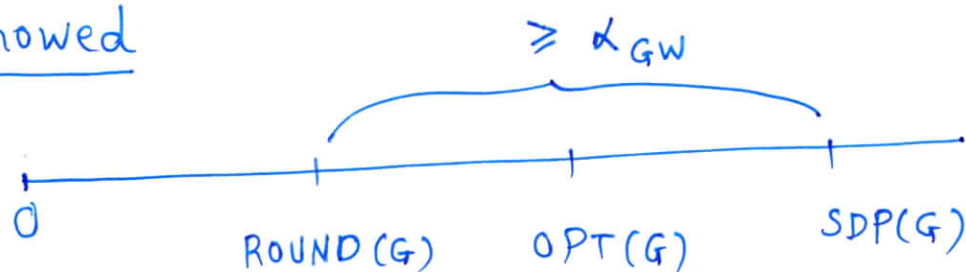
Integrality Gap for Max-Cut / GW SDP.

$G(V, E)$. $V = \{1, 2, \dots, n\}$.

$$\text{OPT}(G) = \text{Max} \sum_{(i,j) \in E} \frac{1 - x_i x_j}{2} \quad \left| \quad \text{SDP}(G) = \text{Max} \sum_{(i,j) \in E} \frac{1 - v_i \cdot v_j}{2}$$

$\forall i, x_i \in \{-1, 1\}$. $\forall i, \|v_i\| = 1$.

We showed



[Karloff, Feige Schechtman]

- $\exists \{G_k\}$ s.t. $\lim_{k \rightarrow \infty} \frac{\text{ROUND}(G_k)}{\text{SDP}(G_k)} = \alpha_{GW}$.

- $\exists \{G_k\}$ s.t. $\lim_{k \rightarrow \infty} \frac{\text{OPT}(G_k)}{\text{SDP}(G_k)} = \alpha_{GW}$.

i.e. the "integrality gap" of the SDP is α_{GW} .

Def.

Integrality Gap $^{\beta}$
(of specific SDP relaxⁿ) = $\inf_G \frac{\text{OPT}(G)}{\text{SDP}(G)}$.

Usually if integrality gap is β then it is taken as evidence that the problem is hard to β -approximate (via the specific SDP; this is a weaker criterion of hardness than NP-hardness).

— x —

We'll construct a graph $G(V, E)$ s.t.

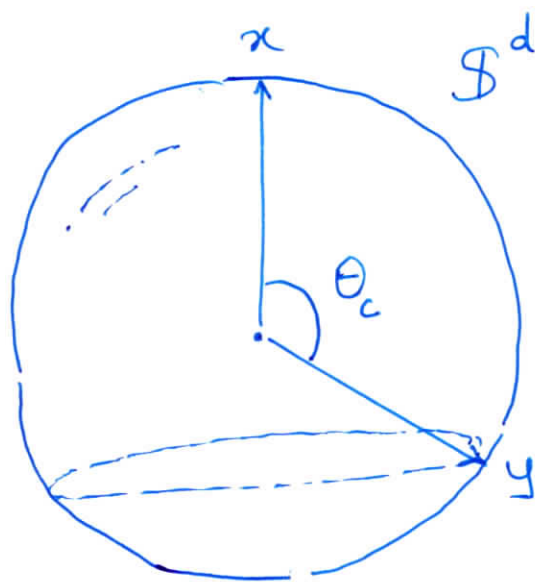
$$\frac{\text{OPT}(G)}{\text{SDP}(G)} \leq \alpha_{\text{GW}} + o(1).$$

[Description is imprecise; details omitted].

$$V = \mathbb{S}^d$$

$$\theta_c \approx 117^\circ.$$

$$E = \{ (x, y) \mid \text{Angle}(x, y) = \theta_c \}$$



Claim $SDP(G) \geq \frac{1 - \cos \theta_c}{2}$

Proof Consider a vector solution

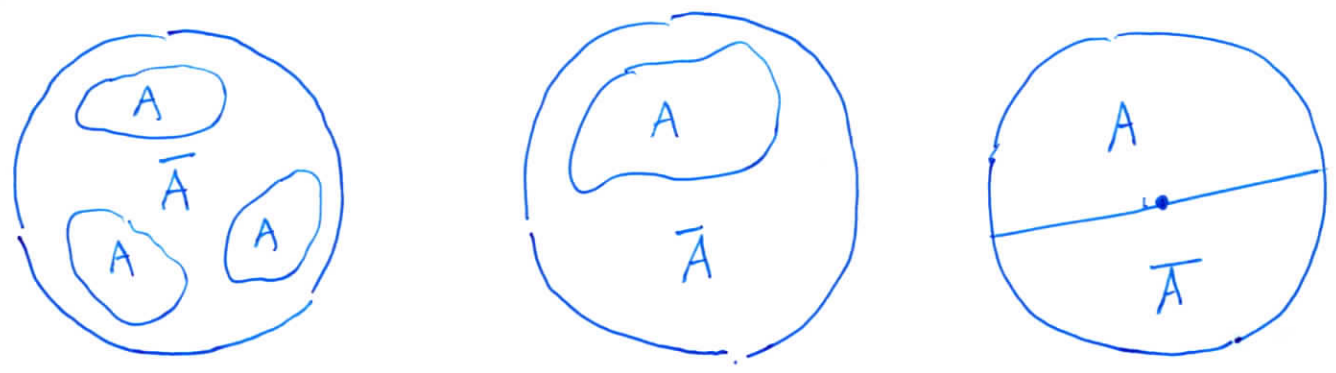
$x \rightarrow v_x$ (the vector x itself)

$$SDP(G) \geq \mathbb{E}_{(x,y) \in E} \left[\frac{1 - v_x \cdot v_y}{2} \right] = \frac{1 - \cos \theta_c}{2}$$

Claim $OPT(G) \leq \frac{\theta_c}{\pi}$

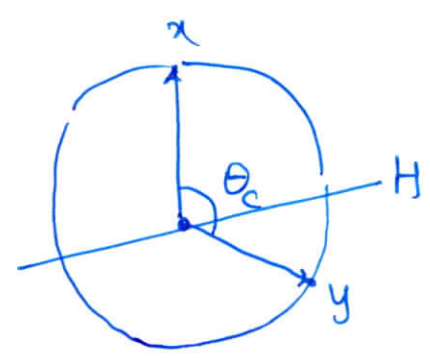
Proof

cut: $S^d = A \cup \bar{A}$



Theorem Among all cuts, max-cut is achieved by a half-sphere.

$$\begin{aligned} \text{Cut}_H &= \Pr_{(x,y) \in E} [(x,y) \text{ cut by } H] \\ &= \Pr_{H'} [(x,y) \text{ cut by } H'] \\ &= \theta_c / \pi. \end{aligned}$$



$$\therefore \text{OPT}(G) = \frac{\theta_c}{\pi}.$$

$$\therefore \frac{\text{OPT}(G)}{\text{SDP}(G)} \leq \frac{\theta_c / \pi}{\frac{1 - \cos \theta_c}{2}} = \alpha_{\text{GW}} + \underbrace{o(1)}$$

Details : - Discretization

- $d \rightarrow \infty$

- Actual geometric theorem is a bit different.

Hypercontractivity & Noisy Hypercube

Def For $f: \{-1, 1\}^n \rightarrow \mathbb{R}$ let $1 \leq p < \infty$

$$\|f\|_p = \left(\mathbb{E}_x [|f(x)|^p] \right)^{1/p}$$

Fact $\|f\|_p$ is increasing in p , i.e. if $p \leq q$ then $\|f\|_p \leq \|f\|_q$.

Proof $\mathbb{E}_x [|f(x)|^p]^{1/p} \leq \mathbb{E}_x [|f(x)|^q]^{1/q}$

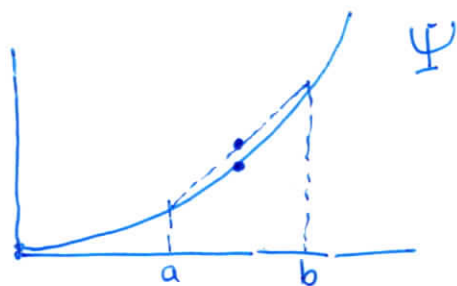
Let $g(x) = |f(x)|^p \geq 0$. Same as,

$$\mathbb{E}_x [g(x)]^{2/p} \leq \mathbb{E}_x [g(x)^{2/p}]$$

Same as

$$\Psi \left(\mathbb{E}_x [g(x)] \right) \leq \mathbb{E}_x [\Psi (g(x))]$$

where $\Psi(\theta) = \theta^{2/p}$ is convex since $2/p \geq 1$.



$$\Psi \left(\frac{a+b}{2} \right) \leq \frac{\Psi(a) + \Psi(b)}{2}$$



Recall Beckner operator

$$T_{1-\gamma}(f) = \sum_S \hat{f}(s) (1-\gamma)^{|s|} \chi_S.$$

Equivalently $T_{1-\gamma}(f)(x) = \mathbb{E}_{y \sim_{1-\gamma}^x} [f(y)].$

Fact $\|T_{1-\gamma} f\|_p \leq \|f\|_p. \quad 1 \leq p.$

Proof

$$\begin{aligned} \|T_{1-\gamma} f\|_p^p &= \mathbb{E}_x \left[|T_{1-\gamma} f(x)|^p \right] \\ &= \mathbb{E}_x \left[\left| \mathbb{E}_{y \sim_{1-\gamma}^x} [f(y)] \right|^p \right] \\ &\leq \mathbb{E}_x \left[\mathbb{E}_{y \sim_{1-\gamma}^x} [|f(y)|^p] \right] \\ &= \mathbb{E}_y [|f(y)|^p] \quad \because \text{convexity} \\ &= \|f\|_p^p. \end{aligned}$$

$T_{1-\gamma}$ is
Contractive.



Theorem (Bonami-Beckner, Hyper contractivity).

$$\|T_{1-\gamma} f\|_2 \leq \|f\|_{1+(1-\gamma)^2}$$

Expansion of small sets in Noisy Hypercube

— $G(\{-1,1\}^n, E)$ weighted.

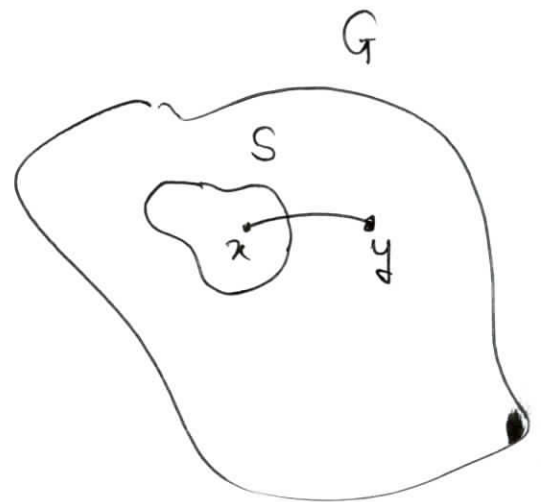
— For fixed $x \in \{-1,1\}^n$, a "random edge" (x,y) going out of x is sampled by $y \sim_{1-\gamma} x$.

Def Let $S \subseteq \{-1,1\}^n$.

$$|S| = \delta \cdot 2^n.$$

Expansion of S

$$\Phi(S) = \Pr_{\substack{x \in S \\ y \sim_{1-\gamma} x}} [y \notin S].$$



Fact $\Phi(s) \geq 1 - \delta^{1/2}$ ($\rightarrow 1$ as $\delta \rightarrow 0$).

Proof

$$1 - \Phi(s) = \Pr_{\substack{x \in S \\ y \sim_{1-\gamma} x}} [y \in S]$$

$$= \frac{\Pr_{x, y \sim_{1-\gamma} x} [x \in S, y \in S]}{\Pr_x [x \in S]}$$

$$\Pr_x [x \in S]$$

$$= \frac{1}{\delta} \cdot \mathbb{E}_{x, y \sim_{1-\gamma} x} [f(x) f(y)]$$

$$f = \mathbb{1}_S$$
$$f(x) = \begin{cases} 1 & x \in S \\ 0 & \text{oth} \end{cases}$$

$$= \frac{1}{\delta} \sum_S \hat{f}(s)^2 (1-\gamma)^{|S|}$$

$$= \frac{1}{\delta} \sum_S \left(\hat{f}(s) \sqrt{1-\gamma}^{|S|} \right)^2$$

$$= \frac{1}{\delta} \sum_S \left(T_{\sqrt{1-\gamma}}^{\wedge} f(s) \right)^2$$

$$\begin{aligned}
&= \frac{1}{\delta} \left\| \frac{T}{\sqrt{1-\gamma}} f \right\|_2^2 \\
&\leq \frac{1}{\delta} \|f\|_{1+1-\gamma}^2 \\
&= \frac{1}{\delta} \left(\underbrace{\mathbb{E} \left[|f(x)|^{2-\gamma} \right]}_{\frac{1}{2}} \right)^{\frac{1}{2-\gamma}} \\
&= \frac{1}{\delta} \cdot \delta^{\frac{2}{2-\gamma}} \\
&\leq \frac{1}{\delta} \delta^{1+\frac{\gamma}{2}} \qquad \frac{2}{2-\gamma} \geq 1+\frac{\gamma}{2} \\
&= \delta^{\frac{\gamma}{2}}.
\end{aligned}$$



"small sets in noisy hypercube expand nearly fully."