

Matrix Concentration & Applications to Combinatorics

Khintchine / Bernstein's Inequality

$\varepsilon_1, \dots, \varepsilon_n \sim \{\pm 1\}$ uniform indep $\sigma = \sqrt{\sum_i a_i^2}$

a_1, \dots, a_n : arbitrary reals. \rightarrow std-dev

Then $\Pr \left[\left| \sum_i \varepsilon_i a_i \right| \geq t \cdot \sigma \right] \leq 2 \cdot e^{-\frac{t^2}{2}}$

define operator norm here

Non-Commutative Matrix Khintchine

$\varepsilon_1, \dots, \varepsilon_n \sim$ iid Rademachers

A_1, \dots, A_n : arbitrary $n \times n$ symm matrices.

$$\sigma = \left\| \sum_i A_i^2 \right\|_2$$

[Lust Piquard, Pisier '91]

$$P_v [\|\sum_i \varepsilon_i A_i\|_2 \geq t \cdot \sigma] \\ \leq 2 \cdot n \cdot e^{-\frac{t^2}{2}}$$

$$E [\|\sum_i \varepsilon_i A_i\|_2] \leq \sqrt{2 \log 2n} \cdot \sigma$$

Very useful inequality! In these 3 lectures, I want to tell you 3 applications of it to combinatorial facts.

↗ controls expected maximum

$$E \max_{\substack{u, v \\ \text{unit}}} [u^T (\sum_i \varepsilon_i A_i) v] \leq O(\sqrt{\log n}) \sigma$$

Won't prove it but want to tell you a few applications so that you

Can add it to your toolkit

The applications I chose are
in combinatorics.

Graph Sparsification.

Def: $G'(V, E')$ is an ϵ -cut
sparsifier for $G(V, E)$ if

$$\forall S \subseteq V, |E_{G'}(S, \bar{S})| \in (1 \pm \epsilon) |E_G(S, \bar{S})|$$

Thm: every G admits an ϵ -cut
sparsifier with $O\left(\frac{n}{\epsilon^2} \cdot \log n\right)$ edges.

Lap solvers
expander graphs $O\left(\frac{n}{\epsilon^2}\right)$! Batson-Spielman-Srivastava

Gurth problems [Bollobas'78]

[Alon-Hoory-Linial'02]

Every G with avg deg d has
a cycle of length $\leq \lceil 2 \cdot \log_{d-1}^{(n)} \rceil$.

Hypergraph Generalization [Feige]

→ lots of apps

Codes (Local Codes)

$E: \mathbb{F}_2^k \rightarrow \mathbb{F}_2^n$, q -LPC if
given an $i \in [k]$, y corr. codeword,

decode b_i by reading 3 bits of y .

what's the smallest $n = n(k)$ for
which such codes exist?

Why?

1. beautiful combinatorial result
2. generalizes expander graphs

$$= \sum_{e \in E} (x_i - x_j)^2$$

So $\forall x \in \{\pm 1\}^n, x^T L_G x = 4 \cdot \text{cut}(x)$

Thus: cut sparsification

$$x^T L_{G'} x \in (1 \pm \epsilon) \cdot x^T L_G x$$

~~$$\forall x \in \{\pm 1\}^n$$~~

Spectral sparsification: $\forall x$.

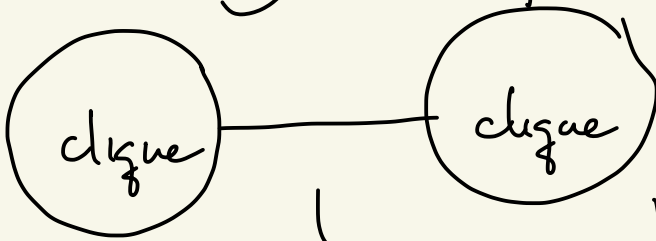
[Karger '93, Benczur-Karger '95]

$\forall G, \exists G'$ with $O(\frac{n \cdot \log n}{\epsilon^2})$ edges

st. G' is a ϵ -cut sparsifier of G .

Idea: "importance" sampling

Sample each edge independently



must
sample
this edge!

$$L_G = \sum_{e \in E} L_e.$$

Need: $x^T \left(\sum_{e \in E} w_e L_e \right) x$

$$= (1 \pm \epsilon) x^T \sum_{e \in E} L_e x$$

relative error

Key Idea

$$\tilde{L}_e = L_G^{-1/2} L_e L_G^{-1/2}$$

Note: $\sum \tilde{L}_e = \mathbb{I}_I$

$$\left\| \sum_{e \in E'} w_e \tilde{L}_e - \mathbb{I}_I \right\|_2 \leq \epsilon.$$

for unit u

$$\Leftrightarrow u^T \left(\sum_{E'} w_e \tilde{L}_e \right) u$$

$$\in (\pm \epsilon) \cdot \|u\|_2^2$$

Plug in $u = L_G^{1/2} u'$

$$\Leftrightarrow u'^T \left(\sum_{E'} w_e L_e \right) u' \in (\pm \epsilon) \cdot u'^T L_G u'$$

So: goal "sample" $E' \subseteq E$ s.t.

$$\left\| \sum_{e \in E'} w_e \tilde{L}_e - \mathbb{I}_+ \right\|_2 \leq \epsilon.$$

Iterative halving strategy

0. $E_0 = E$

1. Take a uniformly random sign
 $S \in \{\pm 1\}^m$

2. $E_{i+1} = \{e \mid e \in E_i, s_e = +1\}.$

$$w_{i+1}(e) = \begin{cases} 2 \cdot w_i(e) & \text{if } e \in E_{i+1} \\ 0 & \text{o/w} \end{cases}$$

Error: $\left\| \sum_{e \in E_1} \tilde{L}_e \cdot 2 - \sum_{e \in E_0} \tilde{L}_e \right\|_2$
 $= \left\| \sum_{e \in E_0} s_e \tilde{L}_e \right\|_2$

Matrix Khintchine

A_1, \dots, A_N , $n \times n$, symmetric
deterministic

$$\mathbb{E} \|\sum b_i A_i\|_2 \leq \sigma \sqrt{\log n^4}$$

$$\text{for } \sigma^2 = \|\sum_i A_i^2\|_2$$

Matrix Analysis Facts:

1. If A is PSD, then so is A^2

2. If $\|A\|_2 = \rho$, then $A \preceq \rho \cdot I$.

3. $A^2 \preceq (\rho \cdot I) \cdot A$

Pf: $\sum \lambda_i^2 v_i v_i^T \preceq \sum \rho \cdot \lambda_i v_i v_i^T$.

Lemma: Suppose $\|\tilde{L}_e\|_2 \leq \rho \forall e$.

Then, $\|\sum_{e \in E_i} s_e \cdot \tilde{L}_e\|_2$
 $\lesssim \|\sum_e \tilde{L}_e^2\|_2^{1/2} \cdot \sqrt{\log n}$
 $\lesssim \rho^{1/2} \cdot \sqrt{\log n}$

$\sum_e \tilde{L}_e \tilde{L}_e$
 $\leq \sum_e (\rho \cdot \mathbb{I}) \cdot \tilde{L}_e$
 $= \rho \cdot \mathbb{I}_1$
So $\|\sum_e \tilde{L}_e^2\|_2 \leq \rho$

How small can ρ be?

$$\sum_{e \in E} \|\tilde{L}_e\|_2 = \sum_{e \in E} \text{Tr}(\tilde{L}_e)$$

\downarrow
rank 1

$$= \text{Tr}(\mathbb{I}_1)$$
$$= n-1$$

So "best value": $\rho \sim \frac{n-1}{m}$

In best case scenario, error:

$$C \cdot \sqrt{\log n} \left[\sqrt{\frac{n}{m}} + \sqrt{\frac{n}{m/2}} + \dots + \sqrt{\frac{n}{m_{\text{final}}}} \right]$$

$$\approx O \left(\sqrt{\frac{n}{m_{\text{final}}}} \right) \cdot \sqrt{\log n}$$

$$\approx \epsilon \text{ if } m_{\text{final}} \geq \frac{n}{\epsilon^2} \cdot \log(n)$$

So only remaining issue:

what if some q is large?

Idea: 1. Sort edges in ascending order of lev scores.

2. Apply the sign & halve trick to first half

Obsⁿ: $e_1 \text{ --- } e_m$

$$\rho_{\frac{2n}{m}} \leq \binom{2n}{m}$$

Pf: $\rho \cdot \frac{m}{2} \leq n !$

HW: work out the above argument.

[Spielman-Teng]

Today, an iterative construction

Lemma 1:

$$\begin{aligned} & \sum_e \|L_G^{-1/2} \cdot L_e \cdot L_G^{-1/2}\|_2 \\ &= \sum_e \text{Tr}(L_G^{-1/2} \cdot L_e \cdot L_G^{-1/2}) \\ &= \text{Tr}(\sum_e L_G^{-1/2} \cdot L_e \cdot L_G^{-1/2}) \\ &= \text{Tr}(\mathbb{I}_1) = n-1. \end{aligned}$$

Lemma 2: Sort the edges of G
in ascending order of $\|L_G^{-1/2} \cdot L_e \cdot L_G^{-1/2}\|_2$
 $e_1, \text{---} \frac{1}{\frac{n}{2}} \text{---}, e_m.$

Then $e_{\frac{n}{2}}$ has leverage $\leq \left(\frac{2n}{m}\right).$

Lemma 3:

Suppose $\max \text{lev score} \leq \rho$.

Then, for uniform $s \in \{\pm 1\}^m$

$$\mathbb{E} \left\| \sum s_e \tilde{L}_e \right\|_2$$

$$\leq \sqrt{\log n} \cdot \left\| \sum_e \tilde{L}_e^2 \right\|_2^{1/2}$$

$$= \sqrt{\log n} \cdot \rho$$

Note:

$$\left\| \sum_e \tilde{L}_e^2 \right\|_2 \leq \max_e \|\tilde{L}_e\|_2 \cdot \left\| \sum_e \tilde{L}_e \right\|_2$$

$$= \rho.$$