An introduction to chaining, and applications to sublinear algorithms

Jelani Nelson
Harvard

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Disclaimer: This is an educational talk, about ideas which aren't mine.

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- **This talk:** four progressively tighter ways to bound $\mathfrak{g}(T)$, then applications of techniques to some TCS problems

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&\leq u_* + |T|\cdot e^{-u_*^2/2} \\
&\lesssim \sqrt{\log|T|} \ (\text{set } u_* = \sqrt{2\log|T|})
\end{aligned}$$

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- $\lesssim \sqrt{\log |S_\varepsilon|} + \varepsilon (\mathbb{E}_g \|g\|_2^2)^{1/2}$
- $\lesssim \log^{1/2} \underbrace{\mathcal{N}(T, \ell_2, \varepsilon)}_{\text{smallest } \varepsilon-\text{net size}} + \varepsilon \sqrt{n}$
- Choose ε to optimize bound; can never be worse than last slide (which amounts to choosing $\varepsilon = 0$)

Gaussian mean width bound 3: ε-net sequence

- S_k is a $(1/2^k)$-net of T, $k \geq 0$

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- $$\begin{aligned}|\{\Delta_k x : x \in T\}| &\leq \mathcal{N}(T, \ell_2, 1/2^k) \cdot \mathcal{N}(T, \ell_2, 1/2^{k-1}) \\ &\leq (\mathcal{N}(T, \ell_2, 1/2^k))^2\end{aligned}$$

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- $$\begin{aligned} \mathfrak{g}(T) &\lesssim \sum_{k=1}^{\infty} (1/2^k) \cdot \log^{1/2} \mathcal{N}(T, \ell_2, 1/2^k) \\ &\lesssim \int_0^{\infty} \log^{1/2} \mathcal{N}(T, \ell_2, u)\, du \text{ (Dudley's theorem)} \end{aligned}$$

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- Again, wlog $|T| < \infty$. Define $T_0 \subseteq T_1 \subseteq \cdots \subseteq T_{k_*} = T$
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- Fernique'76*: can pull the $\sup_x$ *outside* the sum
- $\mathfrak{g}(T) \lesssim \inf_{\{T_k\}} \sup_{x \in T} \sum_{k=1}^{\infty} 2^{k/2} \cdot d_{\ell_2}(x, T_k) \stackrel{\text{def}}{=} \gamma_2(T, \ell_2)$

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  $*$ equivalent upper bound proven by Fernique (who minimized some integral over all measures over T), but reformulated in terms of admissible sequences by Talgarand

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Proof of Fernique's bound

$$\mathfrak{g}(T) \leq \underbrace{\mathop{\mathbb{E}}_{g} \sup_{x \in T} \langle g, \pi_0 x \rangle}_{0} + \mathop{\mathbb{E}}_{g} \sup_{x \in T} \sum_{k=1}^{\infty} \underbrace{\langle g, \Delta_k x \rangle}_{Y_k} \text{ (from before)}$$

- $\forall t$, $\mathbb{P}(Y_k > t 2^{k/2} \|\Delta_k x\|_2) \leq e^{t^2 2^k/2}$ (gaussian decay)

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(change of variables: $u = t \sup_{x \in T} \sum_k 2^{k/2} \|\Delta_k x\|_2 \simeq t\gamma_2(T, \ell_2)$)

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$$\leq \gamma_2(T, \ell_2) \cdot [2 + \int_2^\infty \left(\sum_{k=1}^\infty (2^{2^k})^2 e^{-t^2 2^k/2} \right) dt]$$

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- Conclusion: $\mathfrak{g}(T) \lesssim \gamma_2(T, \ell_2)$
- Talagrand: $\mathfrak{g}(T) \simeq \gamma_2(T, \ell_2)$ (won't show today) ("Majorizing measures theorem")

Are these bounds really different?

- $\gamma_2(T, \ell_2)$**:** $\inf_{\{T_k\}} \sup_{x \in T} \sum_{k=1}^{\infty} 2^{k/2} \cdot d_{\ell_2}(x, T_k)$
- **Dudley:** $\inf_{\{T_k\}} \sum_{k=1}^{\infty} 2^{k/2} \cdot \sup_{x \in T} d_{\ell_2}(x, T_k)$
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- Dudley: $\log \mathcal{N}(B_{\ell_1^n}, \ell_2, u) \simeq (1/u^2) \log n$ for u not too small (consider just covering $(1/u^2)$-sparse vectors with u^2 in each coordinate). Dudley can only give $\mathfrak{g}(B_{\ell_1^n}) \lesssim \log^{3/2} n$.

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- Simple vanilla ε-net argument gives $\mathfrak{g}(B_{\ell_1^n}) \lesssim \mathrm{poly}(n)$.

High probability

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- Usual approach: bound $\mathbb{E}_g \sup_{x \in T} Z_x^p$ for large p and do Markov ("moment method")

  Can bound moments using chaining too; see (Dirksen'13)

Applications in computer science

- Fast RIP matrices (Candès, Tao'06), (Rudelson, Vershynin'06), (Cheragchi, Guruswami, Velingker'13), (N., Price, Wootters'14), (Bourgain'14), (Haviv, Regev'15)
- Fast JL (Ailon, Liberty'11), (Krahmer, Ward'11), (Bourgain, Dirksen, N.'15), (Oymak, Recht, Soltanolkotabi'15)
- Instance-wise JL bounds (Gordon'88), (Klartag, Mendelson'05), (Mendelson, Pajor, Tomczak-Jaegermann'07), (Dirksen'14)
- Approximate nearest neighbor (Indyk, Naor'07)
- Deterministic algorithm to estimate graph cover time (Ding, Lee, Peres'11)
- List-decodability of random codes (Wootters'13), (Rudra, Wootters'14)
- ...

A chaining result for quadratic forms

Theorem

[Krahmer, Mendelson, Rauhut'14] Let $\mathcal{A} \subset \mathbb{R}^{n \times n}$ be a family of matrices, and let $\sigma_1, \ldots, \sigma_n$ be independent subgaussians. Then

$$\begin{aligned}\mathbb{E} \sup_{A \in \mathcal{A}} &\left| \|A\sigma\|_2^2 - \mathop{\mathbb{E}}_{\sigma} \|A\sigma\|_2^2 \right| \\ &\lesssim \gamma_2^2(\mathcal{A}, \|\cdot\|_{\ell_2 \to \ell_2}) + \gamma_2(\mathcal{A}, \|\cdot\|_{\ell_2 \to \ell_2}) \cdot \Delta_F(\mathcal{A}) + \Delta_{\ell_2 \to \ell_2}(\mathcal{A}) \cdot \Delta_F(\mathcal{A})\end{aligned}$$

(Δ_X is diameter under X-norm)

A chaining result for quadratic forms

Theorem

[Krahmer, Mendelson, Rauhut'14] Let $\mathcal{A} \subset \mathbb{R}^{n\times n}$ be a family of matrices, and let $\sigma_1, \ldots, \sigma_n$ be independent subgaussians. Then

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(Δ_X is diameter under X-norm)

Won't show proof today, but it is similar to bounding $\mathfrak{g}(T)$ (with some extra tricks). See `http://people.seas.harvard.edu/~minilek/madalgo2015/`, Lecture 3.

Instance-wise bounds for JL

Corollary (Gordon'88, Klartag-Mendelson'05, Mendelson, Pajor, Tomczak-Jaegermann'07, Dirksen'14)

For $T \subseteq S^{n-1}$ and $0 < \varepsilon < 1/2$, let $\Pi \in \mathbb{R}^{m \times n}$ have independent subgaussian independent entries with mean zero and variance $1/m$ for $m \gtrsim {}^{(\mathfrak{g}^2(T)+1)}/_{\varepsilon^2}$. Then

$$\mathop{\mathbb{E}}_{\Pi} \sup_{x \in T} \left| \|\Pi x\|_2^2 - 1 \right| < \varepsilon$$

Proof of Gordon's theorem

- For $x \in T$ let A_x denote the $m \times mn$ matrix:

$$A_x = \frac{1}{\sqrt{m}} \cdot \begin{bmatrix} x_1 & \cdots & x_n & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & 0 & x_1 & \cdots & x_n & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & x_1 & \cdots & x_n \end{bmatrix}.$$

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- Then $\|\Pi x\|_2^2 = \|A_x \sigma\|_2^2$, where σ is formed by concatenating rows of Π (multiplied by $\sqrt{m}$).

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  $\Rightarrow \gamma_2(\mathcal{A}_T, \|\cdot\|_{\ell_2 \to \ell_2}) = \gamma_2(T, \ell_2) \simeq \mathfrak{g}(T)$

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- Thus $\mathbb{E}_\Pi \sup_{x \in T} |\|\Pi x\|_2^2 - 1| \lesssim \mathfrak{g}^2(T)/m + \mathfrak{g}(T)/\sqrt{m} + 1/\sqrt{m}$

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- $\Delta_F(\mathcal{A}_T) = 1$, $\Delta_{\ell_2 \to \ell_2}(\mathcal{A}_T) = 1/\sqrt{m}$
- Thus $\mathbb{E}_\Pi \sup_{x \in T} |\|\Pi x\|_2^2 - 1| \lesssim \mathfrak{g}^2(T)/m + \mathfrak{g}(T)/\sqrt{m} + 1/\sqrt{m}$
- Set $m \gtrsim (\mathfrak{g}^2(T)+1)/\varepsilon^2$

Consequences of Gordon's theorem

$m \gtrsim {(\mathfrak{g}^2(T)+1)}/{\varepsilon^2}$

- $|T| < \infty$: $\mathfrak{g}^2(T) \lesssim \log|T|$ (JL)
- T a d-dim subspace: $\mathfrak{g}^2(T) \simeq d$ (subspace embeddings)
- T all k-sparse vectors: $\mathfrak{g}^2(T) \simeq k\log(n/k)$ (RIP)

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- T all k-sparse vectors: $\mathfrak{g}^2(T) \simeq k \log(n/k)$ (RIP)
- more applications to constrained least squares, manifold learning, model-based compressed sensing, ...

  (see (Dirksen'14) and (Bourgain, Dirksen, N.'15))

Chaining isn't just for gaussians

Chaining without gaussians: RIP (Rudelson, Vershynin'06)

"Restricted isometry property" useful in compressed sensing.
$T = \{x : \|x\|_0 \leq k, \|x\|_2 = 1\}$.

Theorem (Candès-Tao'06, Donoho'06, Candés'08)

If Π satisfies (ε_*, k)-RIP for $\varepsilon_* < \sqrt{2} - 1$ then there is a linear program which, given Πx and Π as input, recovers $\tilde{x}$ in polynomial time such that $\|x - \tilde{x}\|_2 \leq O(1/\sqrt{k}) \cdot \min_{\|y\|_0 \leq k} \|x - y\|_1$.

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Of interest to show sampling rows of discrete Fourier matrix is RIP

Chaining without gaussians: RIP (Rudelson, Vershynin'06)

- (Unnormalized) Fourier matrix F, rows: $z_1^*, \ldots, z_n^*$
- $\delta_1, \ldots, \delta_n$ independent Bernoulli with expectation m/n

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- Want

$$\mathop{\mathbb{E}}_{\delta} \sup_{\substack{T \subset [n] \\ |T| \le k}} \| I_T - \frac{1}{m} \sum_{i=1}^{n} \delta_i z_i^{(T)} z_i^{(T)^*} \| < \varepsilon$$

Chaining without gaussians: RIP (Rudelson, Vershynin'06)

$$\text{LHS} = \mathop{\mathbb{E}}_{\delta} \sup_{\substack{T \subset [n] \\ |T| \le k}} \| \overbrace{\mathop{\mathbb{E}}_{\delta'} \frac{1}{m} \sum_{i=1}^{n} \delta'_i z_i^{(T)} z_i^{(T)^*}}^{I_T} - \frac{1}{m} \sum_{i=1}^{n} \delta_i z_i^{(T)} z_i^{(T)^*} \|$$

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$$\le \frac{1}{m} \mathop{\mathbb{E}}_{\delta,\delta'} \sup_{T} \| \sum_{i=1}^{n} (\delta'_i - \delta_i) z_i^{(T)} z_i^{(T)^*} \| \text{ (Jensen)}$$

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$$\begin{aligned}
\text{LHS} &= \mathop{\mathbb{E}}_{\delta} \sup_{\substack{T\subset[n]\\|T|\le k}} \| \overbrace{\mathop{\mathbb{E}}_{\delta'} \frac{1}{m}\sum_{i=1}^{n} \delta'_i z_i^{(T)} z_i^{(T)^*}}^{I_T} - \frac{1}{m}\sum_{i=1}^{n} \delta_i z_i^{(T)} z_i^{(T)^*} \| \\
&\le \frac{1}{m} \mathop{\mathbb{E}}_{\delta,\delta'} \sup_{T} \| \sum_{i=1}^{n} (\delta'_i - \delta_i) z_i^{(T)} z_i^{(T)^*} \| \text{ (Jensen)} \\
&= \sqrt{\frac{\pi}{2}} \cdot \frac{1}{m} \mathop{\mathbb{E}}_{\delta,\delta',\sigma} \sup_{T} \| \mathop{\mathbb{E}}_{g} \sum_{i=1}^{n} |g_i| \sigma_i (\delta'_i - \delta_i) z_i^{(T)} z_i^{(T)^*} \|
\end{aligned}$$

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&\le \sqrt{2\pi} \cdot \frac{1}{m} \mathop{\mathbb{E}}_{\delta,g} \sup_{T} \| \sum_{i=1}^{n} g_i \delta_i z_i^{(T)} z_i^{(T)^*} \| \text{ (Jensen+triangle ineq)}
\end{aligned}$$

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$$\le \frac{1}{m} \mathop{\mathbb{E}}_{\delta,\delta'} \sup_{T} \| \sum_{i=1}^{n} (\delta_i' - \delta_i) z_i^{(T)} z_i^{(T)^*} \| \text{ (Jensen)}$$

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$$\le \sqrt{2\pi} \cdot \frac{1}{m} \mathop{\mathbb{E}}_{\delta,g} \sup_{T} \| \sum_{i=1}^{n} g_i \delta_i z_i^{(T)} z_i^{(T)^*} \| \text{ (Jensen+triangle ineq)}$$

$$\simeq \frac{1}{m} \mathop{\mathbb{E}}_{\delta} \mathop{\mathbb{E}}_{g} \sup_{x\in B_2^{n,k}} | \sum_{i=1}^{n} g_i \delta_i \langle z_i, x\rangle^2 | \text{ (gaussian mean width!)}$$

The End

June 22nd+23rd: workshop on concentration of measure / chaining at Harvard, after STOC'16. Details+website forthcoming.