

NEW TOOLS FOR SMOOTHED ANALYSIS:

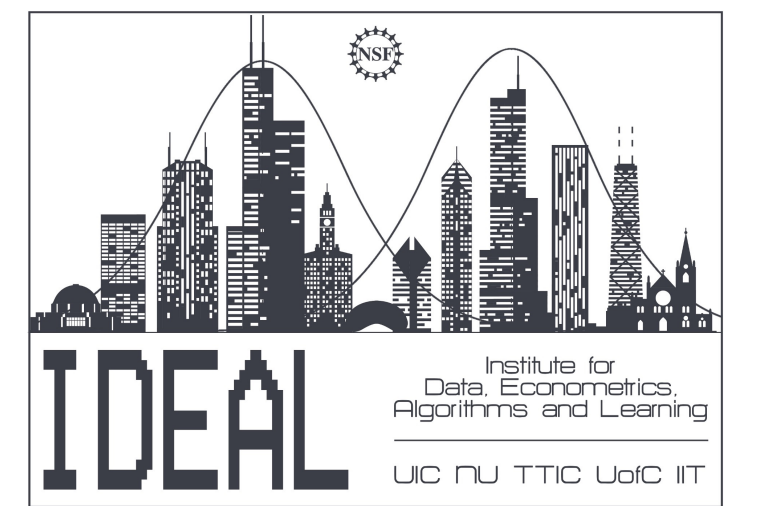
Least Singular Value Bounds for Random Matrices with Dependent Entries



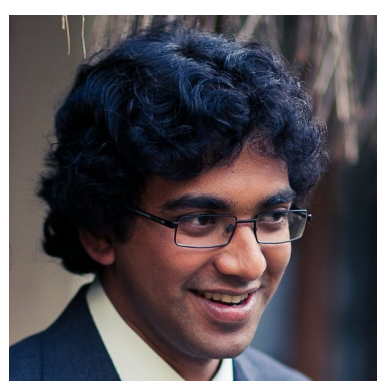
Aditya Bhaskara
University of Utah
IDEAL visitor 2022-23



Eric Ewert
University of Florida
(prev. Northwestern Math
+ Computer Science)



Vaidehi Srinivas
Northwestern
Computer Science



Aravindan Vijayaraghavan
Northwestern
Computer Science

STOC '24

PERTURBED MATRICES

Underlying base variables $\vec{x} = (x_1, \dots, x_n)$

$$M = \begin{bmatrix} P_{11}(\vec{x}) & P_{12}(\vec{x}) \\ P_{21}(\vec{x}) & \ddots \\ & & P_{m,m_2}(\vec{x}) \end{bmatrix} \quad \text{matrix of polynomial entries in } \vec{x}$$

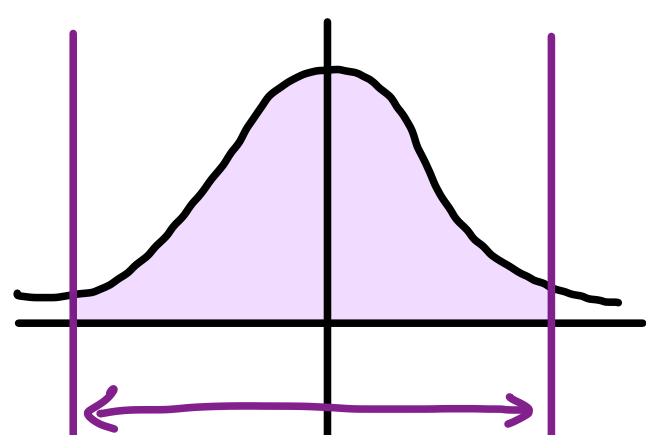
Draw values: $x_i = v_i + \eta_i$
arbitrary v_i + η_i "perturbation"
 $\eta_i \sim \mathcal{N}(0, \rho^2)$

WANT TO SHOW: M is robustly full-rank

CHALLENGE: Entries of M are highly dependent!

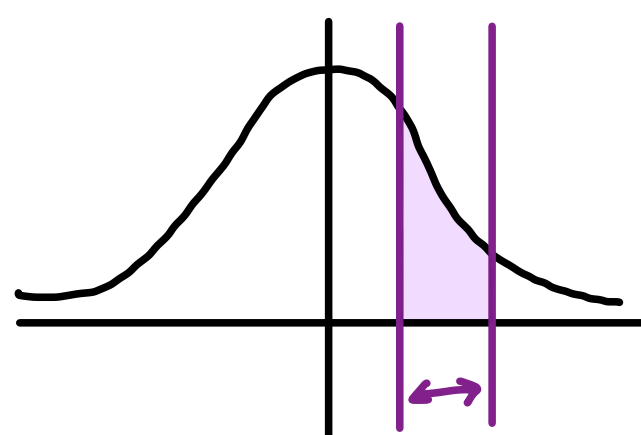
MATRIX ANTI-CONCENTRATION

Concentration



"likely to fall in this big window"

Anti-concentration



"unlikely to fall in any fixed small window"

matrix

"action of M unlikely to be too far from 0 matrix"

$$\sigma_{\max}(M) \leq \text{poly}(n, \rho) \quad \text{with high probability}$$

"action of M unlikely to be too close to 0 matrix"

$$\sigma_{\min}(M) \geq \text{poly}\left(\frac{1}{n}, \rho\right) \quad \text{with high probability}$$

SMOOTHED ANALYSIS

Worst-case analysis

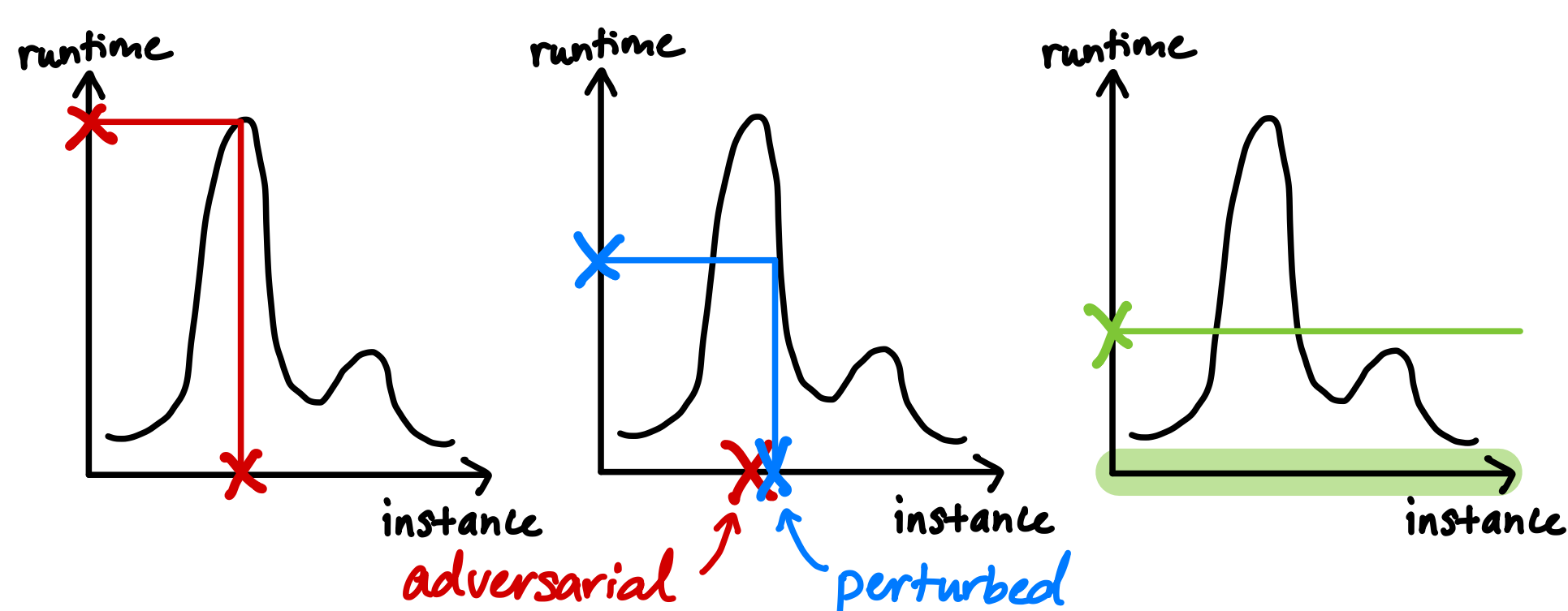
analyze algorithm on adversarially chosen instance

Smoothed analysis

analyze algorithm on perturbed instance

average-case analysis

analyze algorithm on instance drawn from fixed distribution



CONTRIBUTIONS

- ▷ 2 new approaches for proving anti-concentration/least singular value bounds for structured random matrices
 - ① New hierarchical net construction suited to anti-concentration
 - ② Inductive argument to analyze "smoothed modal contractions" of an arbitrary tensor
- ▷ New results and alternate proofs of known results
- ▷ Resolve conjectured smoothed analysis bounds for problems including
 - ▷ Subspace clustering [Garg Kayal Saha, FOCs '20]
 - [Chandra Garg Kayal Mittal Sinha, ITCS '24]
 - ▷ Computing linear sections of varieties [Johnston Lovitz Vijayaraghavan, FOCs '23]
 - ▷ Power-sum decompositions of polynomials [Bafna Hsieh Kothari Xu, FOCs '22]

SAMPLE THEOREM

The symmetric lift of a subspace V is

$$V^{\odot d} = \text{span} \{ a^{\odot d} : a \in V \}$$

where $a^{\odot d}$ is the outer product of a with itself d times, taken as a vector

Informal Theorem [BESV '24]

Let Φ be a projection of sufficiently high rank, \tilde{U} be an $n \times m$ matrix (for $n > m$) perturbed by magnitude ρ ,

and d be a constant,

then

$$\sigma_{\min}(\Phi \tilde{U}^{\odot d}) \geq \text{poly}\left(\frac{1}{n}, \rho\right)$$

with high probability.

" $\tilde{U}^{\odot d}$ is unlikely to nontrivially intersect the kernel of Φ ."

" Φ is likely invertible over the subspace $\tilde{U}^{\odot d}$."