

9/27/23

## Lecture 7: SoS for tensor decomposition (I)

Tensor norms:

Frobenius:

$$\|T\|_F = \left( \sum_{i,j,k} T_{ijk}^2 \right)^{1/2}$$

Injective (tensor analogue of operator norm):

$$\|T\|_{\text{inj}} = \max_{\|x\|_2=1} |\langle T, x^{ \otimes 3} \rangle|$$

(NP-hard even to approximate to within  $n^{o(1)}$  factor)

Note:

$$\begin{aligned} \langle T, x^{ \otimes 3} \rangle^2 &= \left( \sum_{i,j,k} T_{ijk} x_i x_j x_k \right)^2 \\ &\leq \left( \sum_{i,j,k} T_{ijk}^2 \right) \left( \sum_{i,j,k} x_i^2 x_j^2 x_k^2 \right) \\ &= \|T\|_F^2 \cdot \left( \sum_i x_i^2 \right)^3 = \|T\|_F, \end{aligned}$$

So  $\boxed{\|T\|_{\text{inj}} \leq \|T\|_F}$ .

Note: This was a degree-6 proof!

SoS norm : For  $t \geq 6$  even,

$$\|T\|_{Sos_t} \triangleq \max_{\mathbb{E}} \mathbb{E} \langle T, x^{\otimes 3} \rangle$$

where  $\mathbb{E}$  ranges over deg-t pseudo-expectations over SoS variable  $x$  satisfying  $\|x\|_2^2 = 1$ .

Note as  $t \rightarrow \infty$ , SoS norm approaches injective norm:

$$\|T\|_{Sos_6} \geq \|T\|_{Sos_8} \geq \dots \geq \|T\|_{Sos_+} \geq \|T\|_{inj}$$

Note:  $\|T\|_F \geq \|T\|_{Sos_6}$  b/c proof of

$\|T\|_F \geq \|T\|_{inj}$  was deg 6 SoS proof.

Norm of reshaping: Let  $M$  be reshaping of  $T$

into  $d \times d^2$  matrix, i.e.

$$M_{i,jk} = T_{ijk}.$$

$$\|T\|_{\{13, \{2,3\}\}} = \|M\|_{op}$$

$$\begin{aligned}
 \left( \sum_{ijk} T_{ijk} x_i x_j x_k \right)^2 &= \left( \underbrace{\sum_{ijk} x_j x_k}_{\parallel} \underbrace{\sum_i T_{ijk} x_i}_{\parallel} \right)^2 \\
 &\leq \left( \sum_{j,k} x_j^2 x_k^2 \right) \cdot \sum_{j,k} \left( \sum_i T_{ijk} x_i \right)^2 \\
 &= \|M^T x\|_2^2 \leq \|M\|_{op}^2
 \end{aligned}$$

Note: This is a deg-6 SOS proof, so

$$\|\mathcal{T}\|_{\{1,2,3\}} \geq \|\mathcal{T}\|_{SOS_6}$$

Today: (Very) Noisy Orthogonal tensor decomposition

$$\mathcal{T} = \sum_{i=1}^d u_i^{\otimes 3} + E$$

↑  
noise

$u_1, \dots, u_d \in \mathbb{R}^d$  orthonormal

Previously:

if every entry of  $E$  had magnitude  $\frac{1}{\sqrt{c}}$  for large enough constant  $c > 0$ , then Jennrich's succeeds.

What if  $E$  somewhat large?

Example:  $E_{ijk} \sim N(0, \frac{1}{d^{0.9}})$

Jenrich's: Sample  $g \sim N(0, \text{Id})$  and consider

$$\tilde{T}(g, ::) = \underbrace{\sum_{i=1}^d \langle g, u_i \rangle u_i u_i^\top}_{\text{signal}} + \underbrace{\sum_{i=1}^d g_i E_{i::}}_{\text{noise}}$$

Every entry of  $\sum_{i=1}^d g_i E_{i::} \approx N(0, \frac{1}{d^{0.9}})$ .

$$\|N(0, \text{Id})^{d \times d}\|_{\text{op}} \approx \sqrt{d}, \text{ so}$$

$$\left\| \sum_i g_i E_{i::} \right\|_{\text{op}} \approx \sqrt{d} \cdot \sqrt{\frac{1}{d^{0.9}}} = d^{0.05} \gg 1$$

whereas

$$\left\| \underbrace{\sum_{i=1}^d \langle g, u_i \rangle u_i u_i^\top}_{\approx 1} \right\|_{\text{op}} \approx 1$$

i.e.  $\text{Noise} \gg \text{Signal}$ , so Jenrich's fails!

Fact (Hopkins-Schramm-Stewer '15): With high prob,

$$\|N(0, \sigma^2)^{d \times d \times d}\|_{SOS_6} \leq \sigma d^{3/4} \cdot \text{polylog}(d),$$

so  $\|E\|_{SOS_6}$  in example above is  $\leq \frac{1}{d^{0.2}}$ .

In fact, we will show that as long as  $\|E\|_{SOS_6} \ll 1$ , there is an algorithm to recover  $u_1, \dots, u_d$ !

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Let  $T = \sum_{i=1}^d u_i^{\otimes 3} + E$  for  $\|E\|_{SOS_6} = o(1)$ .

Define  $p_3(x) \triangleq \sum_{i=1}^d \langle u_i, x \rangle^3$ .

Goal: maximize  $p_3$

Alg (attempt #1):

SOS variables:  $x$  ( $d$ -dimensional)

Constraints :  $\|x\|_2^2 \leq 1$

Objective :  $\max_E \hat{\mathbb{E}} \langle T, x^{\otimes 3} \rangle$

Lemma: Optimal  $\hat{\mathbb{E}}$  for the above satisfies

$$\hat{\mathbb{E}}[p_3(x)] \geq 1 - o(1) \quad (\dagger)$$

Pf: Note that for pseudo-exp given by uniform dist over  $\{u_1, \dots, u_k\}$ , call it  $\mathbb{F}[\cdot]$ ,

$$\hat{\mathbb{E}}[\rho_3(x)] = \hat{\mathbb{E}}\left[\sum_i \langle u_i, x \rangle^3\right] = \frac{1}{d} \sum_j \left( \sum_i \langle \underbrace{u_i}_{=j}, u_j \rangle^3 \right) = \frac{1}{d} \cdot \sum_j 1 = 1,$$

$\mathbf{1}[i=j]$

$$\begin{aligned} \text{so } \hat{\mathbb{E}}[\langle T, x^{(3)} \rangle] &= \hat{\mathbb{E}}[\rho_3(x)] + \hat{\mathbb{E}}[\langle E, x^{(3)} \rangle] \\ &\geq 1 - \|\mathbb{E}\|_{SOS_6} = 1 - o(1) \end{aligned}$$

$$\begin{aligned} \text{so LHS of (b)} &= \hat{\mathbb{E}}[\langle T, x^{(3)} \rangle] + \hat{\mathbb{E}}[\langle E, x^{(3)} \rangle] \\ &\stackrel{\text{(by maximality of } \hat{\mathbb{E}}\text{)}}{\geq} 1 - o(1) - \|\mathbb{E}\|_{SOS_6} \\ &= 1 - o(1). \quad \square \end{aligned}$$

Lemma 2: optimal  $\hat{\mathbb{E}}$  also satisfies:

$$\hat{\mathbb{E}}[\rho_4(x)] \geq 1 - o(1) \quad (\text{b}')$$

Pf:

$$1 - o(1) \leq \hat{\mathbb{E}}[\rho_3(x)^2] = \hat{\mathbb{E}}\left[\sum_i \langle u_i, x \rangle^3\right]^2 \leq \hat{\mathbb{E}}\left[\left(\sum_i \langle u_i, x \rangle^3\right)^2\right]$$

pseudo-exp.  
Cauchy  
Schwarz

Note that if deg- $b$  SOS:

$$\left(\sum_i \langle u_i, x \rangle^3\right)^2 \leq \underbrace{\left(\sum_i \langle u_i, x \rangle^2\right)}_{\|x\|^2=1} \cdot \left(\sum_i \langle u_i, x \rangle^4\right)$$

$$= P_4(x),$$

so  $\hat{E}[P_4(x)] \geq 1 - o(1)$

□

How to round  $\hat{E}$  to a solution?

What if we ran Jenrich's, but on  $\hat{E}[x^{\otimes 3}]$  instead of on  $T$ ?

Issue: Suppose  $\hat{E}$  is an actual distribution

that places  $\frac{1}{\sqrt{d}}$  mass on an arbitrary vector  $W \perp u$ ,

and  $\frac{1-1/\sqrt{d}}{d}$  for  $u_1, \dots, u_d$ .

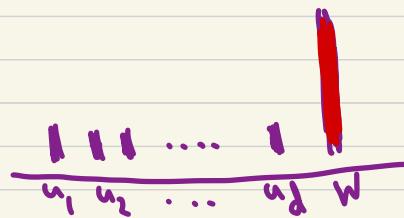
$$\tilde{T} \triangleq \tilde{\oplus}[x^{\otimes 3}] = \frac{1 - 1/\sqrt{d}}{\sqrt{d}} \sum_{i=1}^d u_i^{\otimes 3} + \frac{1}{\sqrt{d}} w^{\otimes 3}$$

$$\tilde{T}(g; \cdot) = \frac{1 - 1/\sqrt{d}}{\sqrt{d}} \sum_{i=1}^d \langle u_i, g \rangle u_i u_i^\top + \frac{1}{\sqrt{d}} \langle w, g \rangle w w^\top$$

eigenvectors are  $u_1, \dots, u_d, w$   
 w/ eigenvalues  $\approx \Theta(\frac{1}{d}), \dots, \Theta(\frac{1}{d}), \Theta(\frac{1}{\sqrt{d}})$

So top eigenvector completely useless! :)

Issue: This  $\tilde{\oplus}$  is very "low-entropy"



Idea: add constraints that force entropy to be high

## Algorithm (attempt 2):

Same SOS program as before but,

$$\max_{\tilde{E}} \tilde{E}[T, x^{\otimes 3}]$$

over deg-6 pseudo-exp.  $\tilde{E}$ 's which satisfy the SOS program constraints and additionally

$$1) \|\tilde{E}[xx^\top]\|_{op} \leq 1/\alpha \quad (1)$$

$$2) \|\tilde{E}[(x \otimes x)(x \otimes x)^\top]\|_{op} \leq 1/\alpha \quad (2)$$

$$3) \|\tilde{E}[(x \otimes x \otimes x)(x \otimes x \otimes x)^\top]\|_{op} \leq 1/\alpha \quad (3)$$

(note: this holds for  $\tilde{E}$  the uniform dist over  $u_1, \dots, u_d$ )

Lemma 3: For optimal  $\tilde{E}$  in the above,

for  $1 - o(1)$  fraction of  $i \in [d]$ ,

$$\tilde{E} \langle u_i, x \rangle^4 \geq \frac{1}{\lambda} (1 - o(1))$$

Pf: By Lemma 2,

$$\sum_{i=1}^d \tilde{E} \langle u_i, x \rangle^4 = 1 - o(1),$$

Suppose for  $\mathcal{F} = \mathcal{L}(1)$  fraction of i's,  
we have  $\hat{\mathbb{E}}(u_i, x)^4 \leq \frac{1-\delta}{d}$ .

Then for some other  $i$ , by averaging,

$$\hat{\mathbb{E}}(u_i, x)^4 \geq \frac{1}{d}.$$

$$\begin{aligned} & (u_i \otimes u_i)^\top \hat{\mathbb{E}}[(x \otimes x)(x \otimes x)^\top] (u_i \otimes u_i) \\ & \leq \|\hat{\mathbb{E}}[(x \otimes x)(x \otimes x)^\top]\|_{\text{op}} \leq \frac{1}{d}, \end{aligned}$$

by high entropy constraint

Contradiction!

□

We now prove that by running Jennrich's on  
 $\hat{\mathbb{E}}[x^{\otimes 4}]$

many times, we recover  $|-o(1)$  of the components  
 (see [Ma-Shi-Stewer '16] for how to  
 reverse to find the remaining  $o(1)$  fraction).

## Theorem (main rounding analysis) :

If  $a \in \mathbb{R}^d$  satisfies

$$\mathbb{E}[\langle a, x \rangle^4] \geq \frac{1}{d}(1 - o(1)),$$

then w.p.  $\geq \frac{1}{\text{poly}(d)}$  over  $g \sim N(0, \text{Id}_{d^2})$

the top eigenvector  $v$  of  $\mathbb{E}[\langle x \otimes x, g \rangle xx^\top]$

satisfies  $\langle v, a \rangle^2 \geq 0.99$ .

Pf : Write  $g = \gamma a \otimes a + \gamma^\perp$  for

$\gamma \sim N(0, 1)$  and  $\gamma^\perp \sim N(0, \text{Id}_{d^2} - (a \otimes a)(a \otimes a)^\top)$

Denote  $M_g \triangleq \mathbb{E}[\langle x \otimes x, g \rangle xx^\top]$  so that

$$M_g = \underbrace{\gamma M_{a \otimes a}}_{\textcircled{1}} + \underbrace{M_{\gamma^\perp}}_{\textcircled{2}}$$

$\textcircled{1}$   $\boxed{\text{will show } = \frac{1}{d} a a^\top + o(\frac{1}{d})}$

$\textcircled{2}$   $\boxed{\text{will show } \leq \frac{\sqrt{\lg d}}{d}}$

So if  $\gamma \geq 100\sqrt{\lg d}$  (happens w.p.  $\geq \frac{1}{\text{poly}(d)}$ ),

$$\text{then } M_g \approx \frac{\gamma}{d} (a a^\top + 0.01),$$

so top eigenvector has large constant correlation with  $a$  as desired.

①: To analyze  $M_{a \otimes a} = \mathbb{E}[(\langle x, a \rangle^2 x x^\top)],$

consider  $b \in \mathbb{S}^{d-1}$  orthogonal to  $a$ . Then:

$$b^\top M_{a \otimes a} b$$

$$= b^\top \left\{ \mathbb{E}[(\langle x, a \rangle^2 x x^\top)] \right\} b = \mathbb{E}[\langle x, a \rangle^2 \langle x, b \rangle^2]$$

note,  $\langle x, b \rangle^2 + \langle x, a \rangle^2 \leq \|x\|^2 = 1$ , so

$$\begin{aligned} &\leq \underbrace{\mathbb{E}[\langle x, a \rangle^2]}_{= a^\top \mathbb{E}[x \otimes x] a} - \underbrace{\mathbb{E}[\langle x, a \rangle^4]}_{\geq \frac{1}{d}(1-o(1))} \\ &\leq \|\mathbb{E}[x \otimes x]\|_{op} \\ &\leq 1/d \\ &\leq o(1/d). \end{aligned}$$

Also,

$$a^T (M_{a \otimes a}) a = \hat{\mathbb{E}} \left[ \langle x, a \rangle^4 \right] \geq \frac{1}{\kappa} (1).$$

And because  $M_{a \otimes a}$  is psd,

$$\begin{aligned} |a^T M_{a \otimes a} b|^2 &\leq \underbrace{\left( a^T (M_{a \otimes a}) a \right)}_{\leq \frac{1}{\kappa}} \underbrace{\left( b^T (M_{a \otimes a}) b \right)}_{\leq o(\frac{1}{\kappa})} \\ &\leq o(1/\kappa), \end{aligned}$$

so  $\left\| \frac{1}{\kappa} aa^T - M_{a \otimes a} \right\|_{op} \leq o\left(\frac{1}{\kappa}\right)$ .  $\square$

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(2): To bound  $M_{\gamma^\perp} = \hat{\mathbb{E}} \left[ \langle \gamma^\perp, x \otimes x \rangle xx^T \right]$ ,

write  $\gamma^\perp = \frac{1}{2}(g_1 + g_2)$ , where

$$\begin{aligned} g_1 &= \gamma^\perp + \gamma' \\ g_2 &= \gamma^\perp - \gamma' \end{aligned} \quad \text{for } \gamma' \sim N(0, (a \otimes a)(a \otimes a)^T)$$

Note,  $g_1, g_2$  are marginally dist'd as  $N(0, \text{Id})$ .

So suffices to bound

$$M_h = \tilde{\mathbb{E}}(\langle h, x \otimes x \rangle xx^T)$$

for  $h \sim N(0, \text{Id})$ .

$$M_h = \sum_{i,j=1}^d h_{ij} \cdot A_{ij} \quad \text{for } A_{ij} \stackrel{\Delta}{=} \tilde{\mathbb{E}}[x_i x_j \cdot xx^T]$$

↑  
independent Gaussians

By Concentration of Matrix Gaussian Series

(see. e.g. Theorem 4.1.1 in Tropp "Intro to matrix concentration inequalities") ,

$$\|M_h\|_{\text{op}} \leq \left\| \sum_{ij} A_{ij}^2 \right\|_{\text{op}}^{1/2} \cdot O(\sqrt{\lg d}) \quad (\star\star)$$

with high probability.

$$\text{If } B = \tilde{\mathbb{E}}[x (x^{\otimes 3})^T] \in \mathbb{R}^{d \times d^3},$$

$$S = \tilde{\mathbb{E}}[x^{\otimes 4}],$$

$$\begin{aligned}
 \left( \sum_{i,j} A_{ij}^2 \right)_{ab} &= \sum_{c,i,j} S_{ijac} S_{ijcb} \\
 &\stackrel{\text{(symmetric)}}{=} \sum_{c,i,j} S_{ajic} S_{ijcb} \\
 &= \beta_a : \beta_b^T,
 \end{aligned}$$

$$\text{so } \sum_{i,j} A_{ij}^2 = \beta \beta^T$$

$$\text{and } \left\| \sum_{i,j} A_{ij}^2 \right\|_{op} = \|\beta\|_{op}$$

not for any  $z \in \mathbb{R}^d, z' \in \mathbb{R}^{d^3}$  of unit norm,

$$\begin{aligned}
 (z^T \beta z')^2 &= \hat{\mathbb{E}} [(\langle x, z \rangle \langle x^{\otimes 3}, z' \rangle)]^2 \\
 &\stackrel{\substack{\text{pseudo-exp.} \\ (\text{Gauß}) \\ (\text{Schwartz})}}{\leq} \hat{\mathbb{E}} [\langle x, z \rangle^2] \cdot \hat{\mathbb{E}} [\langle x^{\otimes 3}, z' \rangle^2] \\
 &= (z^T \hat{\mathbb{E}} [xx^T] z) \cdot (z' \hat{\mathbb{E}} [x^{\otimes 3} (x^{\otimes 3})^T] z') \\
 &\stackrel{\text{entropy bounds}}{\leq} \frac{1}{d^2}
 \end{aligned}$$

so  $\|\beta\|_{op} \leq 1/d_r$ , and (\*) yields

$$\|\mathcal{M}_n\| \leq 1/d \cdot \sqrt{\lg d}.$$

□