

9/18/23

Lecture 4 : Smoothed analysis of tensor decompositions

$U, V \in \mathbb{R}^{d \times k}$ arbitrary

$$\tilde{U} \triangleq U + \frac{\rho}{\sqrt{d}} \cdot N(0, \text{Id})^{d \otimes k}$$

$$\tilde{V} \triangleq V + \frac{\rho}{\sqrt{d}} \cdot N(0, \text{Id})^{d \otimes k}$$

Def : $\tilde{U} \circ \tilde{V} \in \mathbb{R}^{d^2 \times k}$ is the Khatri-Rao product :

$$(\tilde{U} \circ \tilde{V})_{:,j} = \text{vec}(U_{:,j} \otimes V_{:,j})$$

Thm : If $k \leq 0.99d^2$, then with probability $1 - k \exp(-\Omega(d))$,

$$\sigma_{\min}(\tilde{U} \circ \tilde{V}) \geq \Omega\left(\frac{\rho^2}{d^3}\right)$$

(1) : Reduce to "leave-one-out distance"

Def : Given $M \in \mathbb{R}^{n \times k}$ with columns M_1, \dots, M_k , the leave-one-out distance $l(M)$ is given by

$$l(M) \triangleq \min_{i \in [k]} \| \Pi_i^\perp M_i \|,$$

where Π_i^\perp is projection to orthogonal complement of $\text{span}(M_1, \dots, M_{i-1}, M_{i+1}, \dots, M_k)$.

Fact: $\ell(M) \leq \sqrt{k} \cdot \sigma_{\min}(M)$

Proof: Let $u \in \mathbb{S}^{k-1}$ be min. sing. vector so

$\|Mu\| = \sigma_{\min}(M)$. wLOG suppose u_1 is entry w/ largest magnitude, so $|u_1| \geq \frac{1}{\sqrt{k}}$. Then

$$\begin{aligned}\ell(M) &\leq \|\Pi_1^\perp M_1\| = \inf_{v \in \text{span}(M_2, \dots, M_k)} \|M_1 - v\| \\ &\leq \|M_1 + \underbrace{\sum_{i>1} \frac{u_i}{u_1} M_i}_{\in \text{span}(M_2, \dots, M_k)}\| = \frac{1}{|u_1|} \cdot \|Mu\| \leq \sigma_{\min}(M) \cdot \sqrt{k}. \quad \square\end{aligned}$$

So suffices to lower bound $\ell(\tilde{U} \circ \tilde{V})$. In fact, will lower bound $\|\Pi(\tilde{U} \circ \tilde{V})\|$ for Π a projector to an arbitrary subspace of dimension $\geq d^2 - k + 1 \geq 0.01d^2$, for every $i \in [k]$.

Then can just union bound over $i \in [k]$, taking $\Pi = \Pi_i^\perp$ (note: Π_i^\perp and $(\tilde{U} \circ \tilde{V})_i$ random but their randomness is independent)

50 w.t.s :

$$\begin{matrix} U_{:j} & V_{:j} \\ \downarrow & \downarrow \end{matrix}$$

Lemma: For $u, v \in \mathbb{R}^d$ arbitrary, $W \subset \mathbb{R}^{d^2}$ arbitrary
Subspace of dimension $D \geq 0.01d^2$, if

$\tilde{u} = u + \frac{\rho}{\sqrt{d}} N(0, \text{Id})$ and $\tilde{v} = v + \frac{\rho}{\sqrt{d}} N(0, \text{Id})$, then

$$\|\Pi_W (\tilde{u} \otimes \tilde{v})\| \geq \underline{L}(\rho^2/d^2)$$

w.p. at least $1 - \exp(-\underline{L}(d))$.

1.5 Warmup w/ one vector:

Baby lemma: For $u \in \mathbb{R}^d$ be arbitrary, $W \subset \mathbb{R}^d$ arbitrary
Subspace of dimension $D \geq 0.01d$, if

$\tilde{u} = u + \frac{\rho}{\sqrt{d}} N(0, \text{Id})$, then

$$\|\Pi_W \tilde{u}\| \geq \underline{L}(\rho/\sqrt{d})$$

w.p. at least $1 - \exp(-\underline{L}(d))$.

Easy proof that doesn't generalize:

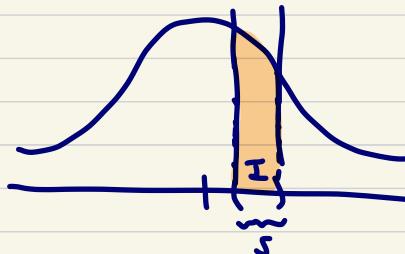
Pick any orthonormal basis $\{w_1, \dots, w_p\}$ for W , so

$$\|\Pi_W \vec{u}\| = \|(\langle w_1, \vec{u} \rangle, \dots, \langle w_p, \vec{u} \rangle)\|.$$

Note $\langle w_i, \vec{u} \rangle = \underbrace{\langle w'_i, \vec{u} \rangle}_{\text{arbitrary}} + \frac{\rho}{\sqrt{\delta}} N(0, 1)$, so

$\langle w_i, \vec{u} \rangle$ is Gaussian w/ variance $\frac{\rho^2}{\delta}$.

Fact [Gaussian anti-concentration]: for any interval I of length s , $\Pr_{g \sim N(0, 1)}[g \in I] \leq O(s)$.



So each $\langle w_i, \vec{u} \rangle$ has $\leq O(1)$ chance of having magnitude $\leq O(\rho/\sqrt{\delta})$, so

$$\begin{aligned} \Pr[\|\Pi_W \vec{u}\| \leq O(\rho/\sqrt{\delta})] &\leq \Pr[K w_i, \vec{u}] \leq O(\rho/\sqrt{\delta}) \\ &\leq \exp(-\underline{L}(\delta)). \end{aligned}$$

Alternative proof that will generalize:

Define "row echelon" basis for W

$$w_1 = (1, *, *, \dots, *)$$

$$w_2 = (0, 1, *, \dots, *)$$

$$w_3 = (0, 0, 1, *, \dots, *)$$

$$\vdots$$

$$w_D = (0, \dots, 0, 1, *, \dots, *)$$

\uparrow
0th entry

$\left. \begin{array}{l} \\ \\ \\ \\ \end{array} \right\} \in W$

s.t. all $|w_i|'$'s ≤ 1 , so $\|w_i\| \leq \sqrt{\lambda} \forall i$.

Consider "revealing" $\langle w_i, \tilde{u} \rangle$'s in reverse order.

$$\langle w_i, \tilde{u} \rangle = \langle w_i, u \rangle + \frac{p}{\sqrt{\lambda}} g_i + \frac{p}{\sqrt{\lambda}} \sum_{j > i} (w_i)_j g_j,$$

So conditioned on $\langle w_0, \tilde{u} \rangle, \langle w_1, \tilde{u} \rangle, \dots, \langle w_{i+1}, \tilde{u} \rangle$, there is still some "leftover" randomness in conditional distribution over $\langle w_i, \tilde{u} \rangle$. By Gaussian anti-conc., conditional prob that $|\langle w_i, \tilde{u} \rangle| \leq O(p/\sqrt{\lambda})$ is $\leq O(1)$, so this holds for all i with probability $\exp(-\Omega(\lambda))$.

Recall $\|w_i\| \leq \sqrt{\lambda}$, so for $\hat{w}_i \triangleq \frac{w_i}{\|w_i\|}$,

$$\|\Pi_w \tilde{u}\| \leq |\langle \hat{w}_i, \tilde{u} \rangle| = \frac{1}{\|w_i\|} \cdot |\langle w_i, \tilde{u} \rangle| \geq O(p/\lambda).$$

N.B.: We are assuming for every $i \in [D]$, exists $w \in W$ s.t. $w_i \neq 0$. This is WLOG: if not, permute coordinates.

Note, we lost a factor of $\frac{1}{\sqrt{d}}$
(i.e. $\frac{P}{d}$ vs $\frac{P}{\sqrt{d}}$) in this alternative proof, but what we gain is that this alternative proof generalizes.

Back to (non-baby) Lemma:

Need "2D" version of row echelon basis, and "ordering" specifying how we condition on randomness.

Given $S \subseteq [d] \times [d]$, let $R \subseteq [d]$ denote row indices,
i.e. $R \triangleq \{i : \exists (i,j) \in S\}$.

Also $R_i \triangleq \{j : (i,j) \in S\}$

For simplicity, let's pretend $R = \{1, \dots, D'\}$ for some

$$D' \leq D^*$$



recall $D = \Theta(d^2)$

N.B.: As in 1D case on prev. page, might need to permute coordinates first

Lemma:

Can construct S , basis $\{w^{(i,j)}\}_{(i,j) \in S}$ for W ,
and total ordering \prec on each R_i s.t.:

1). $w^{(i,j)}$ has max entry 1 in entry (i,j)

2) $w^{(i,j)}$ has zero for every entry $(i';j')$ s.t.

$$i' < i \text{ or } j' < j$$

3). $|R| \geq \Omega(d)$ and $|R_i| \geq \Omega(d) \forall i \in R$.

Pf: omitted, see [Anari et al. '18]

e.g. if $|R| = \sqrt{D}$ and $R_i = \{1, \dots, \sqrt{D}\}$, and

if \prec were the natural ordering on $\{1, \dots, \sqrt{D}\}$, then

$$w^{(2,3)} = \begin{pmatrix} 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & * & \cdots & * \\ 0 & 0 & 0 & * & \cdots & * \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & * & * & \cdots & * \end{pmatrix}$$

In general \prec for different rows might not be related

To use this to complete the proof, note we w.t.s
there is some $(i,j) \in S$ s.t.

$$\|\tilde{u}^\top w^{(i,j)} \tilde{v}\| \geq \Omega(\rho^2/d) \quad (\dagger)$$

For every $i \in R$, consider

$$e_i^T W^{(i,j)} \tilde{v}.$$

Note $\{W^{(i,j)^T} e_i\}_{j \in R}$ are in "row echelon" form, because $(W^{(i,j)^T} e_i)_j = 1$, and for all $j' < j$, $(W^{(i,j)^T} e_i)_{j'} = 0$.

So by 1D argument, w/ all but $\exp(-\Omega(\lambda))$ prob.,

$\exists j \in R$; st.

$$|e_i^T W^{(i,j)} \tilde{v}| \geq \Omega(\rho/\sqrt{\lambda}). \quad (\star\star)$$

Let $v^{(i)} \triangleq W^{(i,j)} \tilde{v}$ for such j maximizing $|e_i^T W^{(i,j)} \tilde{v}|$.

Note $\left\{ \frac{v^{(i)}}{\|v^{(i)}\|_\infty} \right\}$ is in row echelon form, so

by again applying 1D argument, w/ all but $\exp(-\Omega(\lambda))$ prob., $\exists i \in R$ st.

$$\left\langle \frac{v^{(i)}}{\|v^{(i)}\|_\infty}, \tilde{u} \right\rangle \geq \Omega(\rho/\sqrt{\lambda}) \quad (\star\star\star)$$

So by (18) and (19), recalling $v^{(i)} = w^{(i,j)} \hat{v}$,

$$\left| \hat{u}^\top w^{(i,j)} \hat{v} \right| \leq \Omega(\rho^2/\alpha),$$

establishing (2).

□