#### NP-hardness of Nuclear Norm for Tensors

Shmuel Friedland

Univ. Illinois at Chicago

Joint work with Lek-Heng Lim

November 11, 2014, Simons Institute, Berkeley

#### Overview

- Norms
- Spectral and nuclear norms for matrices and tensors
- Weak membership and weak validity problems in unit ball of norms
- Approximation of norms
- NP-hardness of tensor and nuclear norms

## A primer on norms

$$\begin{split} \mathbb{F} &= \mathbb{C}, \mathbb{R}, \text{- basic fields, } \mathbb{F}^m \text{ column space of vectors } \mathbf{x} = (x_1, \dots, x_m)^\top \\ \nu : \mathbb{F}^n &\to [0, \infty) \text{ a norm if} \\ \nu(\mathbf{x}) &> 0 \text{ if } \mathbf{x} \neq \mathbf{0}, \, \nu(\mathbf{x} + \mathbf{y}) \leq \nu(\mathbf{x}) + \nu(\mathbf{y}), \, \nu(a\mathbf{x}) = |a|\nu(\mathbf{x}) \\ B_\nu :&= \{\mathbf{x} \in \mathbb{F}^n, \nu(\mathbf{x}) \leq 1\} \text{-unit ball, } S_\nu := \{\mathbf{x} \in \mathbb{F}^n, \nu(\mathbf{x}) = 1\} \text{-unit sphere} \\ \nu^\vee \text{-the dual norm: } \nu^\vee(\mathbf{x}) = \max\{\Re(\mathbf{y}^*\mathbf{x}), \mathbf{y} \in B_\nu\} = \max\{|\mathbf{y}^*\mathbf{x}|, \mathbf{y} \in S_\nu\} \\ &= \max\{Re(\mathbf{y}^*\mathbf{x}), \mathbf{y} \in \operatorname{Ext} B_\nu\}, \, \operatorname{Ext} B_\nu \text{-extreme points of } B_\nu \\ (\nu^\vee)^\vee &= \nu \\ \text{If } \nu(\mathbf{x}) = \max\{\Re\mathbf{y}^*\mathbf{x}, \mathbf{y} \in S\} \, \forall \mathbf{x} \in \mathbb{F}^n \text{ and a compact balanced } S \in \mathbb{F}^n \\ (aS = S \, \forall a \in \mathbb{F}, |a| = 1), \, \text{then } B_{\nu^\vee} = \operatorname{conv} S \end{split}$$

Eucledian norm 
$$\|\mathbf{x}\| := \sqrt{\mathbf{x}^*\mathbf{x}}$$
 is self dual

$$B(\mathbf{x},r):=\{\mathbf{y}\in\mathbb{F}^n,\|\mathbf{y}-\mathbf{x}\|\leq r\},\,r\geq0$$

### Spectral and Nuclear Norm for Matrices

$$\mathbb{F}^{m\times n} \text{ - space of } m\times n \text{ matrices } A = [a_{ij}]_{i=j=1}^{m,n}$$
 
$$\langle A,B\rangle := \operatorname{Tr}(AB^*), \ \|A\|_F = \sqrt{\operatorname{Tr} AA^*} \text{-Frobenius norm}$$
 
$$\|A\| = \sigma_1(A) := \max_{\|\mathbf{x}\| \le 1} \|A\mathbf{x}\| \text{ - spectral, or operator, or } \ell_2 \text{ norm of } A$$
 
$$\Omega_{m,n,\mathbb{F}} := \{\mathbf{u}\mathbf{v}^* \in \mathbb{F}^{m\times n}, \|\mathbf{u}\| = \|\mathbf{v}\| = 1\} \text{ balanced compact set}$$
 
$$\|A\| = \max\{\Re(\operatorname{Tr}(A\mathbf{v}\mathbf{u}^*)) = \Re(\mathbf{u}^*A\mathbf{v}), \mathbf{u}\mathbf{v}^* \in \Omega_{m,n,\mathbb{F}}\}$$

#### SVD decomposition:

$$A = U\Sigma V^*, UU^* = I_m, VV^* = I_n, \Sigma = \operatorname{diag}(\sigma_1, \dots, \sigma_{\min(m,n)})$$

$$A = \sum_{i=1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^*, \sigma_1 \ge \ldots \ge \sigma_r > 0, r = \text{rank } A$$

Nuclear norm: 
$$||A||_1 := \sum_{i=1}^{\min(m,n)} \sigma_i(A)$$
, F-norm:  $||A||_F^2 = \sum \sigma_i^2$ 

If A is real valued then ||A||,  $||A||_1$  over real same as over complex

Complexity of computation of ||A||,  $||A||_1$  is O(mn),  $O(\min(m, n)mn)$ 

Importance of matrix nuclear norm in missing entry completion:

#### Netflex problem



### Minimal characterization of matrix nuclear norm

$$B_{nuc} := \{ A \in \mathbb{F}^{m \times n} : \|A\|_1 = \sum_{i=1}^r \sigma_i \le 1 \}$$

$$A = ||A||_1 \sum_{i=1}^r \frac{\sigma_i}{||A||_1} \mathbf{u}_i \mathbf{v}_i^*$$

The set of extreme points of  $B_{nuc}$  is  $\Omega_{m,n,\mathbb{F}}$ 

Characterization of spectral norm gives  $\|\cdot\|^{\vee} = \|\cdot\|_1$ 

$$||A||_1 = \min\{\sum_{i=1}^N ||\mathbf{x}_i|| ||\mathbf{y}_i^*||, \sum_{i=1}^N \mathbf{x}_i \mathbf{y}_i^* = A\}$$

Proof 
$$||A||_1 = ||\sum_{i=1}^N \mathbf{x}_i \mathbf{y}_i^*|| \le \sum_{i=1}^N ||\mathbf{x}_i \mathbf{y}_i^*||_1 = \sum_{i=1}^N ||\mathbf{x}_i||||\mathbf{y}_i^*||$$

Caratheodory: dim 
$$\mathbb{F}^{m \times n} = mn \Rightarrow$$
 it is sufficinient  $N = mn + 1$ 

Alternating Minimization Method (AMM) for computing  $||A||_1$ :

Choose 
$$y_1, \dots, y_N \in \mathbb{F}^n \setminus \{\mathbf{0}\}$$
 in general position (at random)

$$L(A, \mathbf{y}_1, \dots, \mathbf{y}_N) := \{X := [\mathbf{x}_1 \dots \mathbf{x}_N] \in \mathbb{F}^{m \times N}, A = \sum_{i=1}^N \mathbf{x}_i \mathbf{y}_i^* \}$$

Find 
$$\min_{X \in L(A, \mathbf{y}_1, ..., \mathbf{y}_N)} \|X\|_y = [\mathbf{x}_{1,1} \dots \mathbf{x}_{N,1}], \|X\|_y := \sum_{i=1}^n \|\mathbf{x}_i\| \|y_i\|$$

Now repeat this minization with respect to  $y_1, \dots, y_n$  and so on



### **Notations**

Indices: 
$$\mathbf{m} = (m_1, \dots, m_d) \in \mathbb{N}^d$$
,  $[m] := \{1, \dots, m\}$ 

$$J = \{j_1, \dots, j_k\} \subset [d]$$
Tensors:  $\bigotimes_{i=1}^d \mathbb{F}^{m_i} = \mathbb{F}^{m_1 \times \dots \times m_d} = \mathbb{F}^{\mathbf{m}}$ 
Contraction of  $\mathcal{T} = [t_{i_1, \dots, i_d}] \in \mathbb{F}^{\mathbf{m}}$  with  $\mathcal{X} = [x_{j_1, \dots, j_k}] \in \bigotimes_{j_p \in J} \mathbb{F}^{m_{j_p}}$ :
$$\mathcal{T} \times \mathcal{X} = \sum_{j_p \in [m_{j_p}], j_p \in J} t_{i_1, \dots, i_d} x_{j_1, \dots, j_k} \in \bigotimes_{l \in [d] \setminus J} \mathbb{F}^{m_l}$$

is a vector in 
$$\mathbb{F}^{m_k}$$

$$\|\mathcal{T}\| = \sqrt{\mathcal{T} \times \bar{\mathcal{T}}}$$
 - Hilbert-Schmidt norm of  $\mathcal{T} \in \mathbb{C}^{\mathbf{m}}$ 

Example  $\mathcal{T} \times (\mathbf{x}_1 \otimes \ldots \otimes \mathbf{x}_{k-1} \otimes \mathbf{x}_{k+1} \otimes \ldots \otimes \mathbf{x}_d) =$ 

$$\langle \mathcal{T}, \mathcal{S} \rangle := \mathcal{T} \times \bar{\mathcal{S}} \text{ inner product in } \mathbb{C}^{\boldsymbol{m}}$$

 $\sum_{i:\in[m_i],i\in[d]\setminus\{k\}} t_{i_1,\ldots,i_d} \prod_{j\in[d]\setminus\{k\}} x_{i_j,j}$ 



### Tensor nuclear and spectral norms - 3-tensor

$$\mathcal{A} \in \mathbb{F}^{l \times m \times n}, \quad \Omega_{m,n,l,\mathbb{F}} := \{ \mathbf{x} \otimes \mathbf{y} \otimes \mathbf{z} \in \mathbb{F}^{m \times n \times l}, \|\mathbf{x}\| \|\mathbf{y}\| \|\mathbf{z}\| = 1 \}$$
$$\|\mathcal{A}\|_{\sigma,\mathbb{F}} := \max_{\mathbf{x},\mathbf{y},\mathbf{z} \neq 0} \frac{\Re \langle \mathcal{A},\mathbf{x} \otimes \mathbf{y} \otimes \mathbf{z} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\| \|\mathbf{z}\|} =$$

 $\text{max}\{|\langle \mathcal{A}, \textbf{x} \otimes \textbf{y} \otimes \textbf{z} \rangle|, \textbf{x} \otimes \textbf{y} \otimes \textbf{z} \in \Omega_{\textit{m,n,l},\mathbb{F}}\} \text{ -spectral norm}$ 

$$\begin{split} \|\mathcal{A}\|_{*,\mathbb{F}} &:= \min \Big\{ \sum_{i=1}^{r} \|\mathbf{x}_{i}\| \|\mathbf{y}_{i}\| \|\mathbf{z}_{i}\| : \mathcal{A} = \sum_{i=1}^{r} \mathbf{x}_{i} \otimes \mathbf{y}_{i} \otimes \mathbf{z}_{i}, \ r \in \mathbb{N} \Big\} \\ \|\cdot\|_{*,\mathbb{F}} &= \|\cdot\|_{\sigma,\mathbb{F}}^{\vee}, \operatorname{Ext} B_{\|\cdot\|_{*,\mathbb{F}}} = \Omega_{m,n,l,\mathbb{F}}. \end{split}$$

Hillar-Lim: Spectral norm is NP-hard to compute

Theorem: Nuclear norm is NP-hard to compute

Problem: For real tensors do we we have equalities (as for matrices)

$$\|\mathcal{A}\|_{\sigma,\mathbb{R}} = \|\mathcal{A}\|_{\sigma,\mathbb{C}}, \quad \|\mathcal{A}\|_{*,\mathbb{R}} = \|\mathcal{A}\|_{*,\mathbb{C}}?$$

For  $A \ge 0$  first equality holds - triangle inequality



## Tensor nuclear and spectral norms - d-tensor

$$\mathbb{F}^{m_1 \times ... \times m_d} = \bigotimes_{i=1}^d \mathbb{F}^{m_i}$$
 space of *d*-mode tensors

$$\textit{B}(\textit{m},\mathbb{F}) := \{ \textbf{x} \in \mathbb{F}^{\textit{m}}, \ \|\textbf{x}\| \leq 1 \}, \quad \textit{S}(\textit{m},\mathbb{F}) := \{ \textbf{x} \in \mathbb{F}^{\textit{m}}, \ \|\textbf{x}\| = 1 \}$$

$$\|\mathcal{A}\|_{\sigma,\mathbb{F}}:= \max\Bigl\{|\langle \mathcal{A}, \otimes_{j\in [d]} \mathbf{x}_j \rangle|, \ \mathbf{x}_j \in \mathcal{S}(m_j,\mathbb{F}^{m_j}), j \in [d]\Bigr\}$$

$$\|\mathcal{A}\|_{*,\mathbb{F}} := \text{min}\Big\{\textstyle\sum_{i=1}^r \prod_{j=1}^d \|\boldsymbol{x}_{i,j}\| : \mathcal{A} = \textstyle\sum_{i=1}^r \otimes_{j=1}^d \boldsymbol{x}_{i,j} \ r \in \mathbb{N}\Big\}$$

#### Spectral and nuclear norms are dual

$$\|\mathcal{A}\|_{\sigma} := \|\mathcal{A}\|_{\sigma,\mathbb{C}}, \|\mathcal{A}\|_* := \|\mathcal{A}\|_{*,\mathbb{C}}$$

$$\|\mathcal{A}\|_{\sigma,\mathbb{F}} \leq \|\mathcal{A}\|_{\sigma} \text{ for } \mathcal{A} \in \mathbb{R}^{m_1 \times ... \times m_d}, \quad \|\mathcal{A}\|_{*,\mathbb{F}} \geq \|\mathcal{A}\|_{\sigma,\mathbb{F}}$$

For 
$$\mathbf{x} = (x_1, \dots, x_N)^T \in \mathbb{C}^N$$
 let  $|\mathbf{x}| := (|x_1|, \dots, |x_N|)^T$ .

Claim 
$$\|A\|_{\sigma} \leq \||A|\|_{\sigma}$$

For  $A \geq 0$  in characterization of  $||A||_{\sigma,\mathbb{R}}$  use  $\mathbf{x}_i \geq 0$ 

Even for matrices one may have  $\|A\|_* > \||A|\|_*$ 

# AMM for spectral and nuclear norms

Maximal characterization  $\max\Bigl\{|\langle\mathcal{A},\otimes_{j\in[d]}\mathbf{x}_j\rangle|,\;\mathbf{x}_j\in S(m_j,\mathbb{F}^{m_j}),j\in[d]\Bigr\}$ applied to x; yields AMM algo, usually converges to a local minimum  $(\mathbf{x}_1^{\star}, \dots, \mathbf{x}_d^{\star})$  - a fixed point of corresponding map yields Newton method: Friedland-Venu 2014 Let  $N(>\prod_{i=1}^d m_i)$ ,  $\mathbf{x}_{k,j} \in \mathbb{F}^{m_j} \setminus \{\mathbf{0}\}, k \in [N]$  in general pos.  $j \in [d] \setminus \{i\}$  $L(\mathcal{A}, \mathbf{x}, i) := \{X_i = [\mathbf{x}_{1,i} \dots \mathbf{x}_{N,i}] \in \mathbb{F}^{m_i \times N}, \mathcal{A} = \sum_{k=1}^N \otimes_{i=1}^d \mathbf{x}_{k,j}\}$ Min. convex function  $||X_i||_X := \sum_{k=1}^N ||\mathbf{x}_{k,i}|| \otimes_{i \in [d] \setminus \{i\}} ||\mathbf{x}_{k,i}||$  on  $L(\mathcal{A}, \mathbf{x}, i)$ 

Alternate all variables

# 4-tensors and bi-partite density matrices

$$\mathbb{C}^{m\times m}\supset\mathbb{H}^{m\times m}\supset\mathbb{H}_{+}^{m\times m}\supset\mathbb{H}_{+,1}^{m\times m}$$

Hermitian, positive definite and density matrices

$$A = [a_{ij}] \in \mathbb{F}^{m \times n}$$
,  $B = [b_{kl}] \in \mathbb{F}^{p \times q}$ , Kronecker product  $A \otimes B$ 

$$\begin{bmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & \vdots & \vdots \\ a_{m1}B & \dots & a_{mn}B \end{bmatrix} = [c_{(i,k)(j,l)}] \in \mathbb{F}^{(mp)\times(nq)}, c_{(i,k)(j,l)} = a_{ij}b_{kl}$$

Viewing 
$$\mathcal{C} := [c_{(i,k)(j,l)}] \in \mathbb{F}^{m \times p \times n \times q}$$
 we get  $\mathbb{F}^{m \times n} \otimes \mathbb{F}^{p \times q} \sim \mathbb{F}^{m \times p \times n \times q}$ 

$$\mathcal{C} = [\mathbf{c}_{i,k,j,l}] \in \mathbb{C}^{m \times n \times m \times n}$$
 is called:

Bi-symmetric: 
$$c_{i,k,j,l} = c_{j,l,i,k}$$
 for all  $i,j,k,l-C = [c_{(i,k)(j,l)}]$  symmetric

Bi-hermitian: 
$$c_{i,k,j,l} = \bar{c}_{j,l,i,k}$$
 for all  $i, j, k, l - C = [c_{(i,k)(j,l)}]$  hermitian

Positive definite: *C* is hermitian positive semi-definite,

bi-partite density matrix: Tr C = 1



## Bi-partite separable states and nuclear norm

#### Separable states in $\mathbb{C}^{m \times n \times m \times n}$ :

$$S(m,n) := \operatorname{conv} ((\mathbf{x} \otimes \mathbf{x}^*) \otimes (\mathbf{y} \otimes \mathbf{y}^*), \mathbf{x} \in S(m,\mathbb{C}), \mathbf{y} \in S(n,\mathbb{C})) \subset \mathbb{H}_{mn,+,1}$$

For 
$$\mathcal{A} = [a_{ikjl}] \in \mathbb{C}^{m \times n \times m \times n}$$
 define  $\operatorname{tr}(\mathcal{A}) := \sum_{i,j} a_{ijij}$  (= Tr  $\mathcal{C}$ )

Note 
$$\operatorname{Tr} \otimes_{j=1}^4 x_j = (\mathbf{x}_3^{\top} \mathbf{x}_1) (\mathbf{x}_4^{\top} \mathbf{x}_1) \leq \prod_{i=1}^4 \|\mathbf{x}_i\|$$

THM: 
$$|\operatorname{Tr} A| \leq ||A||_*$$
 equality iff  $A = tB$ ,  $B \in S(m, n)$ 

Cor. A bipartite density matrix is separable iff its nuclear norm is 1

Gurvits 2003: Weak membership in S(m, n) is NP-hard  $\Rightarrow$ :

Membership in the unit ball of nuclear norm on  $\mathbb{C}^{m \times n \times m \times n}$  NP-hard

Friedland-Lim: Weak membership is NP-hard



# Clique number and spectral norm of 4-tensors

G-graph on n vertices, A(G),  $\kappa(G)$ -adjacency matrix, clique number

Motzkin-Strassen 1965:  $1 - \frac{1}{\kappa(G)} = \max \mathbf{x}^{\top} A(G) \mathbf{x}$ ,  $\mathbf{x}$  probab. vector

COR: It is NP-hard to approximate  $\kappa(G)$  up to order  $\frac{1}{n^2}$ 

F-L: G induces 4-nonnegative symmetric positive definite tensor

 $\mathcal{B}(G) \in \mathbb{C}^{n \times n \times n \times n}$  whose spectral norm is  $1 - \frac{1}{\kappa(G)}$ 

So spectral norm is NP-hard to approximate within arbitrary  $\delta$ 

- 1. We show that this is equivalent to NP-hardness of weak membership in unit ball of spectral norm
- 2. Weak membership in  $B_{\nu}$  is polynomial iff weak membership in  $B_{\nu}$  is polynomial



#### Unit ball of a norm

Norm 
$$\nu: \mathbb{R}^n \to [0, \infty)$$
,  $\nu\text{-ball } B_{\nu}:=\{x\in \mathbb{R}^M, \ \nu(x)\leq 1\}$  all norms in  $\mathbb{R}^n$  are equivalent :  $\exists$  rational  $K(\nu)\geq k(\nu)>0$ :  $k(\nu)\|x\|\leq \nu(x)\leq K(\nu)\|x\|$  for all  $\mathbf{x}\in \mathbb{R}^n$   $< k(\nu)>, < K(\nu)>$  number of bits encoding  $k(\nu), K(\nu)$   $< B_{\nu}>:=< k(\nu)>+< K(\nu)>$   $\frac{1}{\prod_{i=1}^d m_i}\|A\|\leq \frac{1}{\sqrt{\prod_{i=1}^d m_i}}\|A\|\leq \|A\|$   $\sigma\leq \|A\|$ ,  $A\in \mathbb{F}^{m_1\times \ldots \times m_d}$   $\|A\|\leq \|A\|_*\leq \sqrt{\prod_{i=1}^d m_i}\|A\|\leq \prod_{i=1}^d m_i\|A\|$   $< K(\|\cdot\|_\sigma)>+< k(\|\cdot\|_\sigma)>=< K(\|\cdot\|_*)>+< k(\|\cdot\|_*)><< \prod_{i=1}^d m_i>$  For  $\epsilon>0$ :  $S(B_{\nu},\epsilon)$  closed  $\epsilon$ -neighborhood of  $B_{\nu}$ 

 $S(B_{\nu}, -\epsilon)$ -a closed subset of  $B_{\nu}$  s.t.  $S(S(B_{\nu}, -\epsilon), \epsilon) = B_{\nu}$ 

# Weak membership and validity problems

Given  $\mathbf{y} \in \mathbb{R}^n$  and rational  $\delta > 0, \gamma, \mathbf{c}$ 

Membership problem (MEM) for  $B_{\nu}$ : determine if **y** in  $B_{\nu}$ 

Weak membership problem (WMEM) for  $B_{\nu}$ 

assert either  $\mathbf{y} \in S(B_{\nu}, \delta)$  or  $\mathbf{y} \not\in S(B_{\nu}, -\delta)$ 

(Membership implies weak membership)

Weak validity problem (WVAL) problem for  $B_{\nu}$ :

assert either 
$$\mathbf{c}^T \mathbf{x} \leq \gamma + \epsilon$$
 for all  $\mathbf{x} \in \mathcal{S}(\mathcal{B}_{\nu}, -\epsilon)$ ,

or 
$$\mathbf{c}^T \mathbf{x} \geq \gamma - \epsilon$$
 for some  $\mathbf{x} \in S(B_{\nu}, \epsilon)$ 

Yudin-Nemirovski: If there exists a deterministic algorithm solving

WMEM problem for 
$$B_{
u}, \mathbf{y}, \delta$$
 in Poly( $< B_{
u} > + < \delta >$ )

then there exists a deterministic algorithm solving WVAL problem for

$$B_{
u}, \mathbf{c}, \gamma, \delta$$
 in Poly $(\langle B_{
u} \rangle + \langle \mathbf{c} \rangle + \langle \gamma \rangle + \langle \delta \rangle)$ 

# Equivalence of weak membership in $B_{\nu}$ and $B_{\nu^{\vee}}$ in $\mathbb{R}^n$

For compact 
$$K \subset \mathbb{R}^n$$
,  $\mathbf{c} \in \mathbb{R}^n$  set  $M(K, \mathbf{c}) := \max_{\mathbf{x} \in K} \mathbf{c}^T x$ .

$$u(\mathbf{x}) = M(B_{
u^{\vee}}, \mathbf{x}), \quad K_{
u^{\vee}} = \frac{1}{k_{
u}}, \quad k_{
u^{\vee}} = \frac{1}{K_{
u}}$$

$$(1+k_{\nu}\delta)B_{\nu}\subseteq S(B_{\nu},\delta)\subseteq (1+K_{\nu}\delta)B_{\nu} \text{ for } 0<\delta\in\mathbb{Q}$$

$$(1 - K_{\nu}\delta)B_{\nu} \subseteq S(B_{\nu}, -\delta) \subseteq (1 - k_{\nu}\delta)B_{\nu}$$
 for  $K_{\nu}\delta < 1$ 

$$\left(1-rac{\delta}{\mathcal{K}_{
u}}
ight)
u(\mathbf{x})\geq extit{M}( extit{S}( extit{B}_{
u^ee},-\delta),\mathbf{x})\geq \left(1-rac{\delta}{\mathcal{K}_{
u}}
ight)
u(\mathbf{x})\quad ext{for }rac{\delta}{\mathcal{K}_{
u}}<1$$

$$\left(1 + \frac{\delta}{K_{\nu}}\right) \nu(\mathbf{x}) \leq M(\mathcal{S}(B_{\nu^{\vee}}, \delta), \mathbf{x}) \leq \left(1 + \frac{\delta}{K_{\nu}}\right) \nu(\mathbf{x})$$

**LEM**: For  $k_{\nu} \geq 2$  WVAL in  $B_{\nu^{\vee}}$  implies WMEM in  $B_{\nu}$ 

PRF Let 
$$x \in \mathbb{Q}^n$$
,  $\delta \in (0, \frac{1}{2})$ ,  $\gamma = 1$ 

If 
$$\mathbf{x}^{\top}\mathbf{y} \leq 1 + \delta \ \forall \mathbf{y} \in S(B_{\nu^{\vee}}, -\delta) \Rightarrow \mathbf{x} \in S(B_{\nu}, \delta)$$

If 
$$\mathbf{x}^{\top}\mathbf{y} > 1 - \delta$$
 for some  $y \in S(B_{\nu_*}, \delta)$  then  $\mathbf{x} \notin S(B_{\nu}, -\delta)$ 

WMEM in  $B_{\nu^{\vee}} \Rightarrow$  WVAL in  $B_{\nu^{\vee}} \Rightarrow$  WMEM in  $B_{\nu} \Rightarrow$  WMEM in  $B_{\nu}$ 

# Weak membership and norm approximation I

DEF:  $\nu$  is polynomially approximable if for all  $\|\mathbf{x}\| = 1, \epsilon \in (0, \kappa_{\nu}) \cap \mathbb{Q}$ 

 $\exists$  pol. time algo in  $n + \langle \delta \rangle + \langle K_{\nu} \rangle + \langle k_{\nu} \rangle$  for  $\omega(\mathbf{x})$ :

$$\omega(\mathbf{X}) - \epsilon < \nu(\mathbf{X}) < \omega(\mathbf{X}) + \epsilon$$

THM: THAE

- (1)  $\nu$  is polynomially approximable
- (2) Weak membership in  $B_{\nu}$  is polynomial

PRF: (1)
$$\Rightarrow$$
(2).  $\mathbf{x} \in \mathbb{R}^n$ ,  $0 < \delta \in \mathbb{Q}$  given

$$\|\mathbf{x}\| \leq \frac{1}{K_{\nu}} \Rightarrow \nu(\mathbf{x}) \leq 1 \Rightarrow \mathbf{x} \in \mathcal{S}(\mathcal{B}_{\nu}, \delta)$$

$$\|\mathbf{x}\| \geq \frac{1}{k_{\nu}} \Rightarrow \nu(\mathbf{x}) \geq 1 \Rightarrow \mathbf{x} \not\in S(B_{\nu}, -\delta)$$

$$\|\mathbf{x}\| \in (\frac{1}{K_{\nu}}, \frac{1}{k_{\nu}}), \mathbf{y} = \frac{1}{\|\mathbf{x}\|}\mathbf{x}, \epsilon = \frac{k_{\nu}^2 \delta}{2}$$

$$\|\mathbf{x}\|\omega(\mathbf{y}) \leq 1 + rac{k_{
u}\delta}{2} \Rightarrow \mathbf{x} \in \mathcal{S}(B_{
u}, \delta) \text{ otherwise } \mathbf{x} 
otin \mathcal{S}(B_{
u}, -\delta)$$



# Weak membership and norm approximation II

(2) 
$$\Rightarrow$$
 (1). **x** given,  $\|\mathbf{x}\| = 1 \to \nu(\mathbf{x}) \in [k_{\nu}, K_{\nu}]$   
Set  $K_{\nu,0} = K_{\nu}, k_{\nu,0} = k_{\nu}, i = 0$  and assume  $\nu(\mathbf{x}) \in [k_{\nu,i}, K_{\nu,i}]$   
 $a_i = \frac{k_{\nu,i} + K_{\nu,i}}{2}, \quad \delta_i = \frac{K_{\nu,i} - k_{\nu,i}}{2K_{\nu,i}(K_{\nu,i} + k_{\nu,i})}, \quad \mathbf{y} = \frac{1}{a_i}\mathbf{x}$   
If  $\mathbf{y} \in S(B_{\nu}, \delta_i) \Rightarrow \nu(\mathbf{x}) = \leq \frac{3}{4}K_{\nu,i} + \frac{1}{4}k_{\nu,i}$   
set  $k_{\nu,i+1} = k_{\nu,i}, K_{\nu,i+1} = \frac{3}{4}K_{\nu,i} + \frac{1}{4}k_{\nu,i}$   
If  $\mathbf{y} \notin S(B_{\nu}, -\delta_i) \Rightarrow \nu(\mathbf{x}) = \geq \frac{3}{4}k_{\nu,i} + \frac{1}{4}K_{\nu,i}$   
set  $k_{\nu,i+1} = \frac{3}{4}k_{\nu,i} + \frac{1}{4}k_{\nu,i}, K_{\nu,i+1} = K_{\nu,i}$ 

Repeat this procedure 
$$O(\log \delta)$$
 times to get  $\omega(\mathbf{x}) = \frac{1}{2}(K_{\nu,i} + k_{\nu,i})$ 

Observe  $\nu(\mathbf{x}) \in [k_{\nu,i+1}, K_{\nu,i+1}]$  and  $K_{\nu,i+1} - k_{\nu,i+1} = \frac{3}{4}(K_{\nu,i} - k_{\nu,i})$ 



#### WMEM for nuclear tensor norm is NP-hard

Finding an  $\epsilon$  approximation to spectral norm is NP-hard

Equivalent to WMEM in the unit ball of nuclear norm

Finding an WMEM in the uni spectral norm is NP-hard

WMEM for nuclear norm is NP-hard

WMEM of nuclear norm is equivalent to approximation of nuclear norm

Approximation of nuclear norm is NP-hard

### References 1

- S. Banach, Über homogene polynome in (*L*<sup>2</sup>), *Studia Math.* 7 (1938), 36–44.
- B. Chen, S. He, Z. Li, and S, Zhang, Maximum block improvement and polynomial optimization, *SIAM J. Optimization*, 22 (2012), 87–107
- S. Friedland. Best rank one approximation of real symmetric tensors can be chosen symmetric, *Front. Math. China*, 8 (1) (2013), 19–40.
- S. Friedland and L.-H. Lim, Computational Complexity of Tensor Nuclear Norm, arXiv:1410.6072.
- S. Friedland and V. Tammali, Low-rank approximation of tensors, arXiv:1410.6089.

### References 2

- Grötschel, M., Lovàsz, L., Schrijver, A.: Geometric Algorithms and Combinatorial Optimization.
- L. Gurvits. Classical deterministic complexity of Edmonds problem and quantum entanglement, Proc. of the 35th ACM symp. on Theory of comp., pages 10–19, New York, 2003. ACM Press.
- G.J. Hillar and L.-H. Lim, "Most tensor problems are NP-hard," Journal of the ACM, 60 (2013), no. 6, Art. 45, 39 pp.
- L.-H. Lim. Singular values and eigenvalues of tensors: a variational approach. *Proc. IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing* (CAMSAP '05), 1 (2005), 129-132.