

Preconditioning techniques in frame theory and probabilistic frames

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AMS Short Course on Finite Frame Theory: A Complete Introduction
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Outline

- 1 Preconditioning of finite frames: Scalable frames
 - Review of finite frame theory
 - Scalable Frames: Definition and basic examples
 - Basic properties of scalable frames
 - Characterization of scalable frames in \mathbb{R}^2
 - Characterization of scalable frames in \mathbb{R}^N
 - Fritz John's ellipsoid theorem and scalable frames
- 2 Probabilistic frames
 - The p^{th} frame potentials
 - Probabilistic frames: definition and basic properties
 - Probabilistic frame potential
 - Probabilistic p^{th} frame potential

Definition

Definition

$\Phi = \{\varphi_k\}_{k=1}^M \subseteq \mathbb{R}^N$ is a *frame* for \mathbb{R}^N if $\exists A, B > 0$ such that $\forall x \in \mathbb{R}^N$,

$$A\|x\|^2 \leq \sum_{k=1}^M |\langle x, \varphi_k \rangle|^2 \leq B\|x\|^2.$$

If, in addition, $\|\varphi_k\| = 1$ for each k , we say that Φ is a *unit-norm frame*. The set of frames for \mathbb{R}^N with M elements will be denoted by \mathcal{F} . In addition, we let \mathcal{F}_u the the subset of unit-norm frames.

Analysis and Synthesis with frame

Let $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$.

- 1 The *analysis operator*, is defined by

$$\mathbb{R}^N \ni x \mapsto \Phi^T x = \{\langle x, \varphi_k \rangle\}_{k=1}^M \in \mathbb{R}^M.$$

- 2 The *synthesis operator* is defined by

$$\mathbb{R}^M \ni c = (c_k)_{k=1}^M \mapsto \Phi c = \sum_{k=1}^M c_k \varphi_k \in \mathbb{R}^N.$$

- 3 The *frame operator* $S = \Phi\Phi^T$ is given by

$$\mathbb{R}^N \ni x \mapsto Sx = \sum_{k=1}^M \langle x, \varphi_k \rangle \varphi_k \in \mathbb{R}^N.$$

- 4 The *Gramian (operator)* $G = \Phi^T \Phi$ of the frame is the $M \times M$ matrix whose $(i, j)^{th}$ entry is $\langle \varphi_j, \varphi_i \rangle$.

Tight frames and FUNTFs

- 1 A frame Φ is a *tight frame* if we can choose $A = B$.
- 2 If $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^M$ is a frame then

$$\{\varphi_k^\dagger\}_{k=1}^M = \{S^{-1/2}\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$$

is a tight frame and for every $x \in \mathbb{R}^N$,

$$x = \sum_{k=1}^M \langle x, \varphi_k^\dagger \rangle \varphi_k^\dagger. \quad (1)$$

- 3 If Φ is a tight frame of unit-norm vectors, we say that Φ is a *finite unit-norm tight frame (FUNTF)*. In this case, the reconstruction formula (??) reduces to

$$\forall x \in \mathbb{R}^N, \quad x = \frac{N}{M} \sum_{k=1}^M \langle x, \varphi_k \rangle \varphi_k. \quad (2)$$

The frame potential

Theorem (Benedetto and Fickus, 2003)

For each $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$, such that $\|\varphi_k\| = 1$ for each k , we have

$$FP(\Phi) = \sum_{j=1}^M \sum_{k=1}^M |\langle \varphi_j, \varphi_k \rangle|^2 \geq \frac{M}{N} \max(M, N). \quad (3)$$

Furthermore,

- If $M \leq N$, the minimum of FP is M and is achieved by orthonormal systems for \mathbb{R}^N with M elements.
- If $M \geq N$, the minimum of FP is $\frac{M^2}{N}$ and is achieved by FUNTFs. FP(Φ) is the frame potential.

Why frames and FUNTFs

Remark

- 1 *Geometry of FUNTFs: N. Strawn.*
- 2 *Constructing all FUNTFs: D. Mixon.*
- 3 *Applications of FUNTFs and frames: P. Casazza; R. Balan; G. Chen and D. Needell; A. Powell and O. Yilmaz.*

Optimally conditioned frames

Remark

- 1 *FUNTFs can be considered “optimally conditioned” frames. In particular the condition number of the frame operator is 1.*
- 2 *There are many preconditioning methods to improve the condition number of a matrix, e.g., Matrix Scaling.*
- 3 *A matrix A is (row/column) scalable if there exist diagonal matrices D_1, D_2 with positive diagonal entries such that D_1A, AD_2 , or D_1AD_2 have constant row/column sum.*

Goals of this section

Remark

- 1 *How to transform a (non) tight frame into a tight one?*
- 2 *Give theoretical guarantees and algorithms.*
- 3 *What “transformations” are allowed?*
- 4 *For a given “transformation”, what happens if a frame cannot be transformed exactly?*

In this part of the lecture we will only consider one “transform” and mostly answer the first two questions.

Main question

Question

Given a (non-tight) frame $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ can one transform Φ into a tight frame? If yes can this be done algorithmically and can the class of all frames that allow such transformations be described?

Solution

- 1 If Φ denotes again the $N \times M$ synthesis matrix, a solution to the above problem is the associated canonical tight frame

$$\{S^{-1/2}\varphi_k\}_{k=1}^M.$$

Involves the inverse frame operator.

- 2 What "transformations" are allowed?

Choosing a transformation

Question

Given a (non-tight) frame $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ can one find nonnegative numbers $\{c_k\}_{k=1}^M \subset [0, \infty)$ such that $\tilde{\Phi} = \{c_k \varphi_k\}_{k=1}^M$ becomes a tight frame?

Definition

Definition

A frame $\Phi = \{\varphi_k\}_{k=1}^M$ in \mathbb{R}^N is *scalable*, if $\exists \{c_k\}_{k=1}^M \subset [0, \infty)$ such that $\{c_k \varphi_k\}_{k=1}^M$ is a tight frame for \mathbb{R}^N .

The set of scalable frames is denoted by $\mathcal{SC}(M, N)$.

In addition, if $\{c_k\}_{k=1}^M \subset (0, \infty)$, the frame is called *strictly scalable* and the set of strictly scalable frames is denoted by $\mathcal{SC}_+(M, N)$.

A more general definition

Definition

Given, $N \leq m \leq M$, a frame $\Phi = \{\varphi_k\}_{k=1}^M$ is said to be *m-scalable*, respectively, *strictly m-scalable*, if $\exists \Phi_I = \{\varphi_k\}_{k \in I}$ with $I \subseteq \{1, 2, \dots, M\}$, $\#I = m$, such that $\Phi_I = \{\varphi_k\}_{k \in I}$ is scalable, respectively, strictly scalable.

We denote the set of *m-scalable* frames, respectively, *strictly m-scalable* frames in $\mathcal{F}(M, N)$ by $\mathcal{SC}(M, N, m)$, respectively, $\mathcal{SC}_+(M, N, m)$.

Some basic examples

Example

- 1 When $M = N$, a frame $\Phi = \{\varphi_k\}_{k=1}^N \subset \mathbb{R}^N$ is scalable if and only if Φ is an orthogonal set.
- 2 When $M \geq N$, if Φ contains an orthogonal basis, then it is clearly N -scalable.
- 3 Thus, given $M \geq N$, the set $\mathcal{SC}(M, N, N)$ consists exactly of frames that contains an orthogonal basis for \mathbb{R}^N .

Useful remarks

Remark

We note that a frame $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ with $\varphi_k \neq 0$ for each $k = 1, \dots, M$ is scalable if and only if $\Phi' = \left\{ \frac{\varphi_k}{\|\varphi_k\|} \right\}_{k=1}^M$ is scalable.

Useful remarks

Remark

Given a frame $\Phi \subset \mathbb{R}^N$, assume that $\Phi = \Phi_1 \cup \Phi_2$ where

$$\Phi_1 = \{\varphi_k^{(1)} \in \Phi : \varphi_k^{(1)}(N) \geq 0\}$$

and

$$\Phi_2 = \{\varphi_k^{(2)} \in \Phi : \varphi_k^{(2)}(N) < 0\}.$$

Let

$$\Phi' = \Phi_1 \cup (-\Phi_2).$$

Φ is scalable if and only if Φ' is scalable.

We shall assume that all the frame vectors are in the upper-half space, i.e., $\Phi \subset \mathbb{R}^{N-1} \times \mathbb{R}_{+,0}$ where $\mathbb{R}_{+,0} = [0, \infty)$.

Elementary properties of scalable frames

Proposition

Let $M \geq N$, and $m \geq 1$ be integers.

- (i) If $\Phi \in \mathcal{F}$ is m -scalable then $m \geq N$.
- (ii) For any integers m, m' such that $N \leq m \leq m' \leq M$ we have that

$$\mathcal{SC}(M, N, m) \subset \mathcal{SC}(M, N, m'),$$

and

$$\mathcal{SC}(M, N) = \bigcup_{m=N}^M \mathcal{SC}(M, N, m).$$

- (iii) $\Phi \in \mathcal{SC}(M, N)$ if and only if $T(\Phi) \in \mathcal{SC}(M, N)$ for one (and hence for all) orthogonal transformation(s) T on \mathbb{R}^N .
- (iv) Let $\Phi = \{\varphi_k\}_{k=1}^{N+1} \in \mathcal{F}(N+1, N) \setminus \{0\}$ with $\varphi_k \neq \pm\varphi_\ell$ for $k \neq \ell$. If $\Phi \in \mathcal{SC}_+(N+1, N)$, then $\Phi \notin \mathcal{SC}_+(N+1, N+1)$.

Scalable frames: When and How?

Question

- 1 *When is a frame $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ scalable?*
- 2 *If $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ is scalable, how to find the coefficients?*
- 3 *If Φ is not scalable, how close to scalable is it?*
- 4 *What are the topological properties of $SC(M, N)$?*

A reformulation

Fact

Φ is (m -) scalable $\iff \exists \{x_k\}_{k \in I} \subset [0, \infty)$ with $\#I = m \geq N$ such that $\tilde{\Phi} = \Phi X$ satisfies

$$\tilde{\Phi} \tilde{\Phi}^T = \Phi X^2 \Phi^T = \tilde{A} I_N = \frac{\sum_{k \in I} x_k^2 \|\varphi_k\|^2}{N} I_N \quad (4)$$

where $X = \text{diag}(x_k)$.

(4) is equivalent to solving

$$\Phi Y \Phi^T = I_N \quad (5)$$

for $Y = \frac{1}{\tilde{A}} X^2$.

Scalable frame in \mathbb{R}^2

Question

When is $\Phi = \{\varphi_k\}_{k=1}^M \subset S^1$ is a scalable frame in \mathbb{R}^2 ?

Solution

Assume that $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R} \times \mathbb{R}_{+,0}$, $\|\varphi_k\| = 1$, and $\varphi_\ell \neq \varphi_k$ for $\ell \neq k$. Let $0 = \theta_1 < \theta_2 < \theta_3 < \dots < \theta_M < \pi$, then

$$\varphi_k = \begin{pmatrix} \cos \theta_k \\ \sin \theta_k \end{pmatrix} \in S^1.$$

Let $Y = (y_k)_{k=1}^M \subset [0, \infty)$, then (5) becomes

$$\begin{pmatrix} \sum_{k=1}^M y_k \cos^2 \theta_k & \sum_{k=1}^M y_k \sin \theta_k \cos \theta_k \\ \sum_{k=1}^M y_k \sin \theta_k \cos \theta_k & \sum_{k=1}^M y_k \sin^2 \theta_k \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}. \quad (6)$$

Scalable frame in \mathbb{R}^2

Solution

(6) is equivalent to

$$\begin{cases} \sum_{k=1}^M y_k \sin^2 \theta_k = 1 \\ \sum_{k=1}^M y_k \cos 2\theta_k = 0 \\ \sum_{k=1}^M y_k \sin 2\theta_k = 0. \end{cases}$$

Consequently, for Φ to be scalable we must find a nonnegative vector $Y = (y_k)_{k=1}^M$ in the kernel of the matrix whose k^{th} column is $\begin{pmatrix} \cos 2\theta_k \\ \sin 2\theta_k \end{pmatrix}$.

Scalable frame in \mathbb{R}^2

Solution

(6) is equivalent to

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Scalable frame in \mathbb{R}^2

Solution

The problem is equivalent to finding non-trivial nonnegative vectors in the nullspace of

$$\begin{pmatrix} 1 & \cos 2\theta_2 & \dots & \cos 2\theta_M \\ 0 & \sin 2\theta_2 & \dots & \sin 2\theta_M \end{pmatrix}. \quad (7)$$

Describing $\mathcal{SC}(3, 2)$

Example

We first consider the case $M = 3$. In this case, we have $0 = \theta_1 < \theta_2 < \theta_3 < \pi$, and the (7) becomes

$$\begin{pmatrix} 1 & \cos 2\theta_2 & \cos 2\theta_3 \\ 0 & \sin 2\theta_2 & \sin 2\theta_3 \end{pmatrix}. \quad (8)$$

Describing $\mathcal{SC}(3, 2)$

Example

If $\theta_{k_0} = \pi/2$ for $k_0 \in \{2, 3\}$, then the corresponding frame contains an ONB and, hence is scalable.

For example, when $k_0 = 2$, then $0 = \theta_1 < \theta_2 = \pi/2 < \theta_3 < \pi$. In this case, the fame is 2–scalable but not 3–scalable.

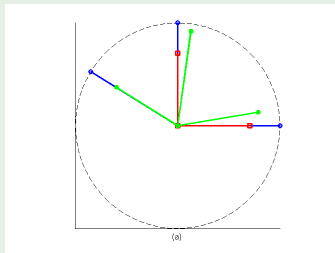


Figure : Blue=original frame; Red=the frames obtained by scaling;
 Green=associated canonical tight frame.

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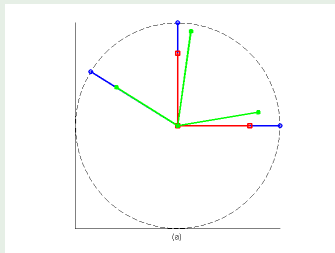


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Describing $\mathcal{SC}(3, 2)$

Example

Suppose $\theta_k \neq \pi/2$ for $k = 2, 3$. If $\theta_3 < \pi/2$, then the frame cannot be scalable. Indeed, $u = (z_1, z_2, z_3)$ belongs to the kernel of (8) if and only if

$$\begin{cases} z_1 &= \frac{\sin 2(\theta_3 - \theta_2)}{\sin 2\theta_2} z_3, \\ z_2 &= -\frac{\sin 2\theta_3}{\sin 2\theta_2} z_3, \end{cases} \quad (9)$$

where $z_3 \in \mathbb{R}$. The choice of the angles implies that $z_2 z_3 < 0$, unless $z_3 = 0$.

Describing $\mathcal{SC}(3, 2)$

Example

This is illustrated by

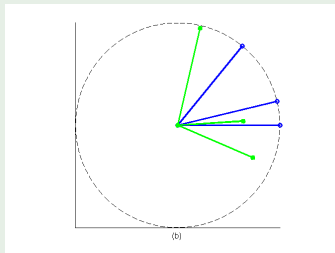


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Describing $\mathcal{SC}(3, 2)$

Example

Suppose that $0 = \theta_1 < \theta_2 < \pi/2 < \theta_3 < \pi$. From (9) $z_2 > 0$ for all $z_3 > 0$ and $z_1 > 0$ for all $z_3 > 0$ if and only if $\theta_3 - \theta_2 < \pi/2$.

Consequently, when $0 = \theta_1 < \theta_2 < \pi/2 < \theta_3 < \pi$ the frame $\Phi \in \mathcal{SC}_+(3, 2, 3)$ if and only if $0 < \theta_3 - \theta_2 < \pi/2$.

Describing $\mathcal{SC}(3, 2)$

Example

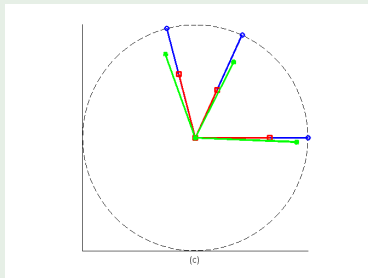


Figure : Blue=original frame; Red=the frames obtained by scaling;
Green=associated canonical tight frame.

Describing $\mathcal{SC}(4, 2)$

Example

When $M = 4$ we are lead to seek nonnegative non-trivial vectors in the null space of

$$\begin{pmatrix} 1 & \cos 2\theta_2 & \cos 2\theta_3 & \cos 2\theta_4 \\ 0 & \sin 2\theta_2 & \sin 2\theta_3 & \sin 2\theta_4 \end{pmatrix}.$$

Describing $\mathcal{SC}(4, 2)$

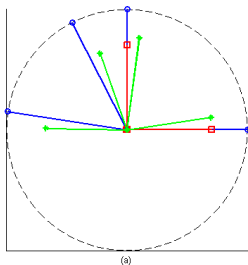


Figure : Blue=original frame; Red=the frames obtained by scaling;
Green=associated canonical tight frame.

Describing $\mathcal{SC}(4, 2)$

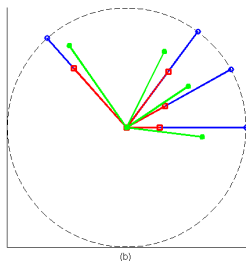


Figure : Blue=original frame; Red=the frames obtained by scaling;
Green=associated canonical tight frame.

Describing $\mathcal{SC}(4, 2)$

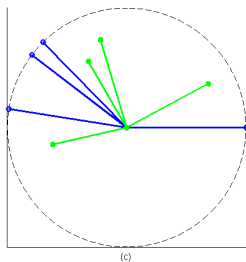


Figure : Blue=original frame; Red=the frames obtained by scaling;
Green=associated canonical tight frame.

A more general reformulation

Setting

Let $F : \mathbb{R}^N \rightarrow \mathbb{R}^d$, $d := (N - 1)(N + 2)/2$, defined by

$$F(x) = \begin{pmatrix} F_0(x) \\ F_1(x) \\ \vdots \\ F_{N-1}(x) \end{pmatrix}$$

$$F_0(x) = \begin{pmatrix} x_1^2 - x_2^2 \\ x_1^2 - x_3^2 \\ \vdots \\ x_1^2 - x_N^2 \end{pmatrix}, \dots, F_k(x) = \begin{pmatrix} x_k x_{k+1} \\ x_k x_{k+2} \\ \vdots \\ x_k x_N \end{pmatrix}$$

and $F_0(x) \in \mathbb{R}^{N-1}$, $F_k(x) \in \mathbb{R}^{N-k}$, $k = 1, 2, \dots, N - 1$.

The map F when $N = 2$

Example

When $N = 2$ the map F reduces to

$$F \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x^2 - y^2 \\ xy \end{pmatrix}.$$

Note that in the examples given above we consider

$$\tilde{F} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x^2 - y^2 \\ 2xy \end{pmatrix}.$$

When is a frame scalable: A generic solution

Question

When is $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ scalable?

Proposition

A frame Φ for \mathbb{R}^N is m -scalable, respectively, strictly m -scalable, if and only if there exists a nonnegative $u \in \ker F(\Phi) \setminus \{0\}$ with $\|u\|_0 \leq m$, respectively, $\|u\|_0 = m$, and where $F(\Phi)$ is the $d \times M$ matrix whose k^{th} column is $F(\varphi_k)$.

A key tool: The Farkas Lemma

Lemma

For every real $N \times M$ -matrix A exactly one of the following cases occurs:

- (i) The system of linear equations $Ax = 0$ has a nontrivial nonnegative solution $x \in \mathbb{R}^M$, i.e., all components of x are nonnegative and at least one of them is strictly positive.*
- (ii) There exists $y \in \mathbb{R}^N$ such that $y^T A$ is a vector with all entries strictly positive.*

Farkas lemma with $N = 2$, $M = 4$

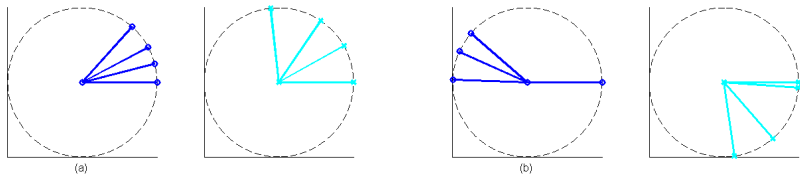


Figure : Bleu=original frame; Green=image by the map F . Both of these examples result in non scalable frames.

Farkas lemma with $N = 2$, $M = 4$

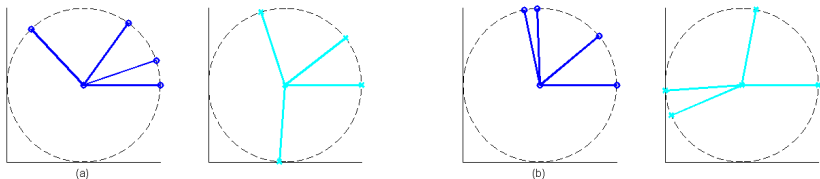


Figure : Bleu=original frame; Green=image by the map F . Both of these examples result in scalable frames.

Some convex geometry notions

Fact

Let $X = \{x_i\}_{k=1}^M \subset \mathbb{R}^N$.

- 1 The polytope generated by X is the convex hull of X , denoted by P_X (or $\text{co}(X)$).
- 2 The affine hull generated by X is denoted by $\text{aff}(X)$.
- 3 The relative interior of the polytope $\text{co}(X)$ denoted by $\text{ri co}(X)$, is the interior of $\text{co}(X)$ in the topology induced by $\text{aff}(X)$.
- 4 It is true that $\text{ri co}(X) \neq \emptyset$ whenever $\#X \geq 2$, and

$$\text{ri co}(X) = \left\{ \sum_{k=1}^M \alpha_k x_k : \alpha_k > 0, \sum_{k=1}^M \alpha_k = 1 \right\},$$

Scalable frames and Farkas's lemma

Theorem

Let $M \geq N \geq 2$, and let m be such that $N \leq m \leq M$. Assume that $\Phi = \{\varphi_k\}_{k=1}^M \in \mathcal{F}^*(M, N)$ is such that $\varphi_k \neq \pm\varphi_\ell$ when $k \neq \ell$. Then the following statements are equivalent:

- (i) Φ is m -scalable, respectively, strictly m -scalable,
- (ii) There exists a subset $I \subset \{1, 2, \dots, M\}$ with $\#I = m$ such that $0 \in \text{co}(F(\Phi_I))$, respectively, $0 \in \text{ri co}(F(\Phi_I))$.
- (iii) There exists a subset $I \subset \{1, 2, \dots, M\}$ with $\#I = m$ for which there is no $h \in \mathbb{R}^d$ with $\langle F(\varphi_k), h \rangle > 0$ for all $k \in I$, respectively, with $\langle F(\varphi_k), h \rangle \geq 0$ for all $k \in I$, with at least one of the inequalities being strict.

A useful property of F

For $x = (x_k)_{k=1}^N \in \mathbb{R}^N$ and $h = (h_k)_{k=1}^d \in \mathbb{R}^d$, we have that

$$\langle F(x), h \rangle = \sum_{\ell=2}^N h_{\ell-1} (x_1^2 - x_\ell^2) + \sum_{k=1}^{N-1} \sum_{\ell=k+1}^N h_{k(N-1-(k-1)/2)+\ell-1} x_k x_\ell. \quad (10)$$

Consequently, fixing $h \in \mathbb{R}^d$, $\langle F(x), h \rangle$ is a homogeneous polynomial of degree 2 in x_1, x_2, \dots, x_N . The set of all polynomials of this form can be identified with the subspace of real symmetric $N \times N$ matrices whose trace is 0.

A useful property of F

Remark

$\langle F(x), h \rangle = \langle Q_h x, x \rangle = 0$ defines a quadratic surface in \mathbb{R}^N , and condition (iii) in the last Theorem stipulates that for Φ to be scalable, one cannot find such a quadratic surface such that the frame vectors (with index in I) all lie on (only) “one side” of this surface.

A geometric characterization of scalable frames

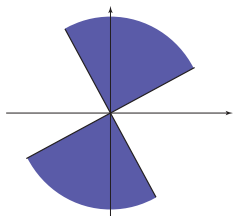
Theorem (G. Kutyniok, F. Philipp, K. Tuley, K.O. (2012))

Let $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N \setminus \{0\}$ be a frame for \mathbb{R}^N . Then the following statements are equivalent.

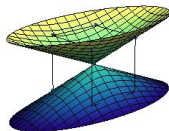
- (i) Φ is not scalable.
- (ii) There exists a symmetric $M \times M$ matrix Y with $\text{trace}(Y) < 0$ such that $\langle \varphi_j, Y\varphi_j \rangle \geq 0$ for all $j = 1, \dots, M$.
- (iii) There exists a symmetric $M \times M$ matrix Y with $\text{trace}(Y) = 0$ such that $\langle \varphi_j, Y\varphi_j \rangle > 0$ for all $j = 1, \dots, M$.

Scalable frames in \mathbb{R}^2 and \mathbb{R}^3

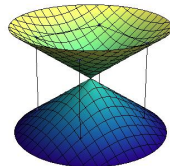
Figures show sample regions of vectors of a non-scalable frame in \mathbb{R}^2 and \mathbb{R}^3 .



(a)



(b)



(c)

Figure : (a) shows a sample region of vectors of a non-scalable frame in \mathbb{R}^2 .
 (b) and (c) show examples of sets in \mathcal{C}_3 which determine sample regions in \mathbb{R}^3 .

Fritz John's Theorem

Theorem (F. John (1948))

Let $K \subset B = B(0, 1)$ be a convex body with nonempty interior. There exists a unique ellipsoid \mathcal{E}_{min} of minimal volume containing K .

Moreover, $\mathcal{E}_{min} = B$ if and only if there exist $\{\lambda_k\}_{k=1}^m \subset (0, \infty)$ and $\{u_k\}_{k=1}^m \subset \partial K \cap S^{N-1}$, $m \geq N + 1$ such that

- (i) $\sum_{k=1}^m \lambda_k u_k = 0$
- (ii) $x = \sum_{k=1}^m \lambda_k \langle x, u_k \rangle u_k, \forall x \in \mathbb{R}^N$

where ∂K is the boundary of K and S^{N-1} is the unit sphere in \mathbb{R}^N .

F. John's characterization of scalable frames

Setting

Let $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ be a frame for \mathbb{R}^N . We apply F. John's theorem to the convex body $K = P_\Phi = \text{conv}(\{\pm\varphi_k\}_{k=1}^M)$. Let \mathcal{E}_Φ denote the ellipsoid of minimal volume containing P_Φ , and $V_\Phi = \text{Vol}(\mathcal{E}_\Phi)/\omega_N$ where ω_N is the volume of the euclidean unit ball.

Theorem

Let $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ be a frame. Then Φ is scalable if and only if $V_\Phi = 1$. In this case, the ellipsoid \mathcal{E}_Φ of minimal volume containing $P_\Phi = \text{conv}(\{\pm\varphi_k\}_{k=1}^M)$ is the euclidean unit ball B .

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A measure of scalability

Remark

Let $\Phi \subset S^{N-1}$ be a frame. Then V_Φ is a “measure of scalability”: the closer it is to 1 the more scalable is the frame.

A quadratic programming approach to scalability

Setting

$$\Phi = \{\varphi_i\}_{i=1}^M \text{ is scalable} \iff \exists \{c_i\}_{i=1}^M \subset [0, \infty) : \Phi C \Phi^T = I,$$

where $C = \text{diag}(c_i)$.

$$C_\Phi = \left\{ \Phi C \Phi^T = \sum_{i=1}^M c_i \varphi_i \varphi_i^T : c_i \geq 0 \right\}$$

is the (closed) cone generated by $\{\varphi_i \varphi_i^T\}_{i=1}^M$.

$$\Phi = \{\varphi_i\}_{i=1}^M \text{ is scalable} \iff I \in C_\Phi.$$

$$D_\Phi := \min_{C \geq 0 \text{ diagonal}} \|\Phi C \Phi^T - I\|_F$$

A second measure of scalability

Remark

Let $\Phi \subset S^{N-1}$ be a frame. Then D_Φ is a “measure of scalability”: the closer it is to 0 the more scalable is the frame.

Comparing the measures of scalability

Values of V_Φ and D_Φ for randomly generated frames of M vectors in \mathbb{R}^4 .

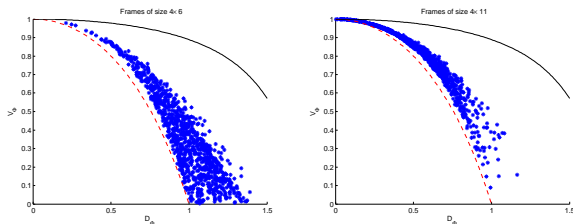


Figure : Relation between V_Φ and D_Φ with $M = 6, 11$. The black line indicates the upper bound in the last theorem, while the red dash line indicates the lower bound.

Comparing the measures of scalability

Values of V_Φ and D_Φ for randomly generated frames of M vectors in \mathbb{R}^4 .

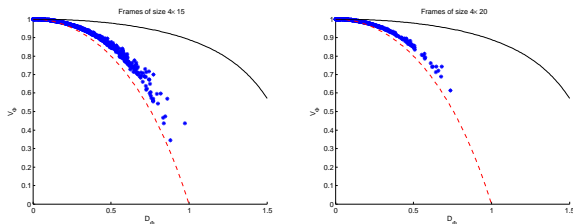


Figure : Relation between V_Φ and D_Φ with $M = 15, 20$. The black line indicates the upper bound in the last theorem, while the red dash line indicates the lower bound.

Concluding remarks on scalable frames

- 1 The problem can be reformulated as a linear programming one leading to numerical solutions.
- 2 When frame not scalable, one can define how close or far to being scalable it is: Notion of “almost scalable.”
- 3 Role of redundancy.
- 4 Size of $SC(M, N)$.
- 5 Other methods of frame preconditioning

Goals of this section

Remark

- 1 *Standard tools used in frame theory include: Functional and Harmonic Analysis, Operator Theory, Linear Algebra, Differential Geometry, Differential Equations.*
- 2 *Identifying frames with probability measures leads analyzing frames in the setting of the Wasserstein metric spaces.*
- 3 *For example, gradient flow methods from optimal transport theory can be used to minimize certain common potentials in frame theory.*

Motivation: The Welch bound

Theorem

For any frame $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ we have

$$\max_{k \neq \ell} |\langle \varphi_k, \varphi_\ell \rangle| \geq \sqrt{\frac{M-N}{N(M-1)}}, \quad (11)$$

and equality hold if and only if Φ is an ETF.

Furthermore, equality can hold only when $M \leq \frac{N(N+1)}{2}$.

Definition of the p^{th} frame potential

Definition

Let M be a positive integer, and $0 < p < \infty$. Given a collection of unit vectors $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$, the p -frame potential is the functional

$$\text{FP}_{p,M}(\Phi) = \sum_{k,\ell=1}^M |\langle \varphi_k, \varphi_\ell \rangle|^p. \quad (12)$$

When, $p = \infty$, the definition reduces to

$$\text{FP}_{\infty,M}(\Phi) = \max_{k \neq \ell} |\langle \varphi_k, \varphi_\ell \rangle|.$$

Special cases

- 1 $p = 2$ corresponds to the frame potential whose minimizers are the FUNTFs
- 2 For $p = \infty$ and fixed M , the minimizers of $FP_{\infty, M}$ are called Grassmanian frames.
- 3 The potential $FP_{\infty, M}$ always has a minimum but constructing these minimizers is challenging.

Question

What are the minimizers of $FP_{p, M}$?

Example: $M = 3, N = 2$

Question

Find the minimizers of

$$\text{FP}_{p,3}(\Phi) = \sum_{k,\ell=1}^3 |\langle \varphi_k, \varphi_\ell \rangle|^p$$

when $p \in (0, \infty]$ and $\Phi = \{\varphi_k\}_{k=1}^3 \subset S^1$.

Solution for $p = 2$ and $p = \infty$

Solution

- 1 When $p = 2$,

$$\text{FP}_{2,3}(\Phi) = \sum_{k,\ell=1}^3 |\langle \varphi_k, \varphi_\ell \rangle|^2 \geq 9/2$$

with equality if and only if $\Phi = \{\varphi_k\}_{k=1}^3 \subset S^1$ is a FUNTF. A minimizer of $\text{FP}_{2,3}$ is the MB-frame, see next slide.

- 2 When $p = \infty$,

$$\text{FP}_{\infty,3}(\Phi) = \max_{k \neq \ell} |\langle \varphi_k, \varphi_\ell \rangle| \geq 1/\sqrt{2}$$

with equality if and only if $\Phi = \{\varphi_k\}_{k=1}^3 \subset S^1$ is an ETF. Hence a solution is also given by the MB frame

the MB-frame

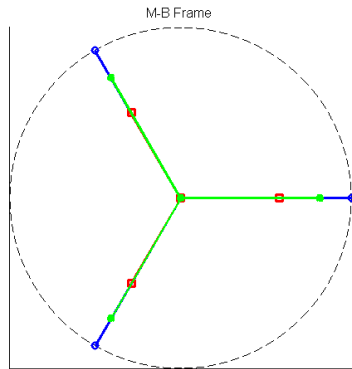


Figure : An example of Equiangular FUNTF: the MB-frame.

Minimizers of $FP_{p,3}$ for $p \in (0, \infty]$

Proposition

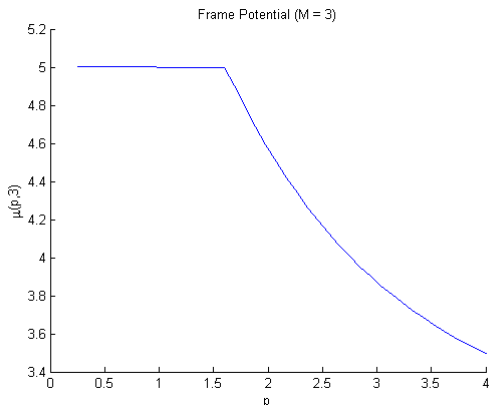
Let $p_0 = \frac{\log(3)}{\log(2)}$. Then $FP_{p_0,3}(\Phi) \geq 5$, with equality holding if and only if $\Phi = \{\varphi_k\}_{k=1}^3$ is an orthonormal basis plus one repeated vector or an ETF. Furthermore,

- (1) for $0 < p < p_0$, and $\Phi = \{\varphi_k\}_{k=1}^3 \subset S^1$, we have $FP_{p,3}(\Phi) \geq 5$, and equality holds if and only if $\Phi = \{\varphi_k\}_{k=1}^3$ is an orthonormal basis plus one repeated vector,
- (2) for $p > p_0$, and $\Phi = \{\varphi_k\}_{k=1}^3 \subset S^1$, we have $FP_{p,3}(\Phi) \geq 2^{\frac{p}{p_0}} (6)^{1-\frac{p}{p_0}} + 3$, and equality holds if and only if $\Phi = \{\varphi_k\}_{k=1}^3$ is an ETF.

Minimizers of $FP_{p,3}$ for $p \in (0, \infty)$

Remark

$$\mu_{p,3,2} = \min\{FP_{p,2}(\Phi) : \Phi = \{\varphi_k\}_{k=1}^3 \subset S^1\}$$



Minimizers of $\text{FP}_{p,N+1}$ for $p \in (0, \infty)$

Theorem

Let $p \in (0, \infty]$, and N be positive integer. Let $\Phi = \{\varphi_k\}_{k=1}^{N+1} \subset S^{N-1}$. Set $p_0 = \frac{\log(\frac{N(N+1)}{2})}{\log(N)}$. Assume that $\text{FP}_{p_0,N+1}(\Phi) \geq N + 3$, with equality holding if and only if $\Phi = \{\varphi_k\}_{k=1}^{N+1}$ is an orthonormal basis plus one repeated vector or an ETF. Then,

- (1) for $0 < p < p_0$, and $\Phi = \{\varphi_k\}_{k=1}^{N+1} \subset S^{N-1}$, we have $\text{FP}_{p,N+1}(\Phi) \geq N + 3$, and equality holds if and only if $\Phi = \{\varphi_k\}_{k=1}^{N+1}$ is an orthonormal basis plus one repeated vector,
- (2) for $p_0 < p < 2$, and $\Phi = \{\varphi_k\}_{k=1}^{N+1} \subset S^{N-1}$, we have $\text{FP}_{p,N+1}(\Phi) \geq 2^{\frac{p}{p_0}} (N(N+1))^{1-\frac{p}{p_0}} + N + 1$, and equality holds if and only if $\Phi = \{\varphi_k\}_{k=1}^{N+1}$ is an ETF.

Remarks on the Theorem

Remark

- 1 *The hypothesis of the last theorem can be verified when $N = 2$. But for $N \geq 3$ it is not known if this hypothesis is true.*
- 2 *There seems to be some “universality” of the minimizers of these potentials. With p_0 given above, any orthonormal basis plus one repeated vector minimizes $\text{FP}_{p,N+1}$ for $0 < p \leq p_0$ and any ETF minimizes $\text{FP}_{p,N+1}$ for $p_0 \leq p \leq \infty$.*

Partial results on minimizing $FP_{p,M}$ for $p \in (0, \infty)$

Proposition

Let $p \in (0, \infty]$, M, N be positive integers. Let $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ we have:

(a) If $M \geq N$ and $2 < p < \infty$, then

$$FP_{p,M}(\Phi) \geq M(M-1) \left(\frac{M-N}{N(M-1)} \right)^{p/2} + N,$$

and equality holds if and only if Φ is an ETF.

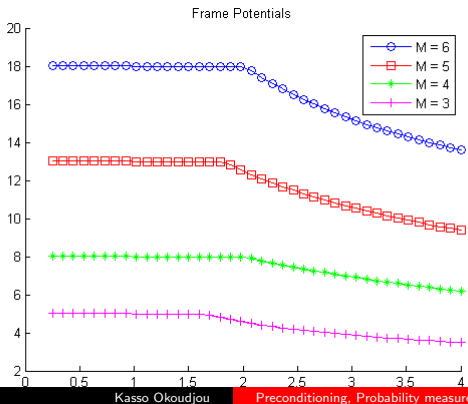
(b) Let $0 < p < 2$ and assume that $M = kN$ for some positive integer k . Then the minimizers of the p -frame potential are exactly the k copies of any orthonormal basis modulo multiplications by ± 1 . The minimum of (12) over all sets of $M = kN$ unit norm vectors is $k^2 N$.

Numerical simulations for $N = 2$

Remark

We let

$$\mu_{p,M,2} = \min\{\text{FP}_{p,2}(\Phi) : \Phi = \{\varphi_k\}_{k=1}^M \subset S^1\}$$



The p^{th} frame potential and t -design

Definition

Let t be a positive integer. A *spherical t -design* is a finite subset $\{x_i\}_{i=1}^M$ of the unit sphere S^{N-1} in \mathbb{R}^N , such that,

$$\frac{1}{M} \sum_{i=1}^M h(x_i) = \int_{S^{N-1}} h(x) d\sigma(x),$$

for all homogeneous polynomials h of total degree equals or less than t in N variables and where σ denotes the uniform surface measure on S^{N-1} normalized to have mass one.

FUNTFs and 2-design

Proposition

$\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ is a spherical 2-design if and only if Φ is a FUNTF and $\sum_{k=1}^M \varphi_k = 0$.

t -designs as minimizers of p^{th} frame potentials

Theorem

Let $p = 2k$ be an even integer and $\{x_i\}_{i=1}^M = \{-x_i\}_{i=1}^M \subset S^{N-1}$, then

$$\text{FP}_{p,M}(\{x_i\}_{i=1}^M) \geq \frac{1 \cdot 3 \cdot 5 \cdots (p-1)}{N(N+2) \cdots (N+p-2)} M^2,$$

and equality holds if and only if $\{x_i\}_{i=1}^M$ is a spherical p -design.

Motivations

- Let $\Phi = \{\varphi_i\}_{i=1}^M$ be a frame in \mathbb{R}^N with bounds $0 < A \leq B < \infty$. Define

$$\mu_\Phi := \frac{1}{M} \sum_{i=1}^M \delta_{\varphi_i} \quad \text{then} \quad \int_{\mathbb{R}^N} |\langle x, y \rangle|^2 d\mu_\Phi(y) = \frac{1}{M} \sum_{k=1}^M |\langle x, \varphi_k \rangle|^2.$$

- For each $x \in \mathbb{R}^N$: $A/M\|x\|^2 \leq \int_{\mathbb{R}^N} |\langle x, y \rangle|^2 d\mu_\Phi(y) \leq B/M\|x\|^2$
- μ_Φ is an example of probabilistic frames.
- \mathcal{P} is the set of probability measures on \mathbb{R}^N , and

$$\mathcal{P}_2 = \left\{ \mu \in \mathcal{P} : M_2^2(\mu) = \int_{\mathbb{R}^N} \|y\|^2 d\mu(y) < \infty \right\}$$

Definition

Definition

A Borel probability measure $\mu \in \mathcal{P}$ is a *probabilistic frame* if there exist $0 < A \leq B < \infty$ such that

$$A\|x\|^2 \leq \int_{\mathbb{R}^N} |\langle x, y \rangle|^2 d\mu(y) \leq B\|x\|^2, \quad \text{for all } x \in \mathbb{R}^N. \quad (13)$$

When $A = B$, μ is called a *tight probabilistic frame*.

When is a probability measure a probabilistic frame?

Theorem

A Borel probability measure $\mu \in \mathcal{P}$ is a probabilistic frame if and only if $\mu \in \mathcal{P}_2$ and $E_\mu = \mathbb{R}^N$, where E_μ denotes the linear span of $\text{supp}(\mu)$ in \mathbb{R}^N . Moreover, if μ is a tight probabilistic frame, then the frame bound is given by

$$A = \frac{1}{N} M_2^2(\mu) = \frac{1}{N} \int_{\mathbb{R}^N} \|y\|^2 d\mu(y).$$

Examples

Example

- (a) Let $a = \{a_k\}_{k=1}^M \subset (0, \infty)$ with $\sum_{k=1}^M a_k = 1$. A set $\Phi = \{\varphi_k\}_{k=1}^M \subset \mathbb{R}^N$ is a frame if and only if the probability measure $\mu_{\Phi, a} = \sum_{k=1}^M a_k \delta_{\varphi_k}$ supported by the set Φ is a probabilistic frame.
- (c) The uniform distribution on the unit sphere S^{N-1} in \mathbb{R}^N is a tight probabilistic frame. That is, denoting the probability measure on S^{N-1} by $d\sigma$ we have that for all $x \in \mathbb{R}^N$,

$$\frac{\|x\|^2}{N} = \int_{\mathbb{R}^N} \langle x, y \rangle^2 d\sigma(y).$$

Probabilistic frame operator

Let $\mu \in \mathcal{P}$ be a probability measure.

- 1 The *probabilistic analysis operator* is given by

$$T_\mu : \mathbb{R}^N \rightarrow L^2(\mathbb{R}^N, \mu), \quad x \mapsto \langle x, \cdot \rangle.$$

- 2 The *probabilistic synthesis operator* is defined by

$$T_\mu^* : L^2(\mathbb{R}^N, \mu) \rightarrow \mathbb{R}^N, \quad f \mapsto \int_{\mathbb{R}^N} f(x) x d\mu(x).$$

- 3 The *probabilistic frame operator* of μ is

$$S_\mu = T_\mu^* T_\mu.$$

- 4 The *probabilistic Gram operator* of μ , is defined on $L^2(\mathbb{R}^N, \mu)$ by

$$G_\mu f(x) = T_\mu T_\mu^* f(x) = \int_{\mathbb{R}^N} \langle x, y \rangle f(y) d\mu(y).$$

Probabilistic frame operator

Fact

The probabilistic frame operator is given by

$$S_\mu : \mathbb{R}^d \rightarrow \mathbb{R}^d, \quad S_\mu(x) = \int_{\mathbb{R}^N} \langle x, y \rangle y d\mu(y)$$

and is the matrix of second moments of μ :

If $\{e_j\}_{j=1}^N$ is the canonical orthonormal basis for \mathbb{R}^N , then

$$S_\mu e_i = \sum_{j=1}^N m_{i,j}(\mu) e_j,$$

where

$$m_{i,j}(\mu) = \int_{\mathbb{R}^N} y^{(i)} y^{(j)} d\mu(y).$$

Probabilistic frame operator

Proposition

Let $\mu \in \mathcal{P}$, then S_μ is well-defined (and hence bounded) if and only if

$$M_2(\mu) < \infty.$$

Furthermore, μ is a probabilistic frame if and only if S_μ is positive definite.

Duality

If μ is a probabilistic frame then S_μ is positive definite.

- 1 The *push-forward* of μ through S_μ^{-1} is given by

$$\tilde{\mu}(B) = \mu((S_\mu^{-1})^{-1}B) = \mu(S_\mu B).$$

- 2 $\tilde{\mu}$ is a probabilistic frame called the *probabilistic canonical dual frame* of μ .
- 3 The push-forward of μ through $S_\mu^{-1/2}$ is given by

$$\mu^\dagger(B) = \mu(S^{1/2}B).$$

Reconstruction formula

Proposition

Let $\mu \in \mathcal{P}$ be a probabilistic frame with bounds $0 < A \leq B < \infty$. Then:

(a) $\tilde{\mu}$ is a probabilistic frame with frame bounds $1/B \leq 1/A$.

(b) μ^\dagger is a tight probabilistic frame.

Consequently, for each $x \in \mathbb{R}^N$ we have:

$$\int_{\mathbb{R}^N} \langle x, y \rangle S_\mu y d\tilde{\mu}(y) = \int_{\mathbb{R}^N} \langle S_\mu^{-1} x, y \rangle y d\mu(y) = x, \quad (14)$$

and

$$\int_{\mathbb{R}^N} \langle x, y \rangle y d\mu^\dagger(y) = \int_{\mathbb{R}^N} \langle S_\mu^{-1/2} x, y \rangle S_\mu^{-1/2} y d\mu(y) = x. \quad (15)$$

Definition

Question

When is a probability measure μ a tight probabilistic frame?

Definition

The *probabilistic frame potential* is the nonnegative function defined on \mathcal{P} and given by

$$\text{PFP}(\mu) = \iint_{\mathbb{R}^N \times \mathbb{R}^N} |\langle x, y \rangle|^2 d\mu(x) d\mu(y), \quad (16)$$

for each $\mu \in \mathcal{P}$.

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for each $\mu \in \mathcal{P}$.

The probabilistic frame potential and Gramian operator

Proposition

Let $\mu \in \mathcal{P}$, then $\text{PFP}(\mu)$ is the Hilbert-Schmidt norm of the probabilistic Gramian operator G_μ , that is

$$\|G_\mu\|_{HS}^2 = \iint_{\mathbb{R}^d \times \mathbb{R}^d} \langle x, y \rangle^2 d\mu(x)d\mu(y).$$

Furthermore, if $\mu \in \mathcal{P}_2$, (which is the case when μ is a probabilistic frame) then we have

$$\text{PFP}(\mu) \leq M_2^4(\mu) < \infty.$$

Probabilistic tight frames as minimizers of the PFP

Theorem

Let $\mu \in \mathcal{P}_2$ be such that $M_2(\mu) = 1$ and set $E_\mu = \text{span}(\text{supp}(\mu))$, then the following estimate holds

$$\text{PFP}(\mu) \geq 1/n \quad (17)$$

where n is the number of nonzero eigenvalues of S_μ . Moreover, equality holds if and only if μ is a tight probabilistic frame for E_μ .

In particular, given any probabilistic frame $\mu \in \mathcal{P}_2$ with $M_2(\mu) = 1$, we have

$$\text{PFP}(\mu) \geq 1/N$$

and equality holds if and only if μ is a tight probabilistic frame.

Remark

When μ is a discrete measure, then $\text{PFP}(\mu)$ is the frame potential.

Definition

For $p \in (0, \infty)$ set

$$\mathcal{P}_p = \left\{ \mu \in \mathcal{P} : M_p^p(\mu) = \int_{\mathbb{R}^N} \|y\|^p d\mu(y) < \infty \right\}.$$

Definition

For each $p \in (0, \infty)$, the *probabilistic p -frame potential* is given by

$$\text{PFP}(\mu, p) = \iint_{\mathbb{R}^N \times \mathbb{R}^N} |\langle x, y \rangle|^p d\mu(x) d\mu(y). \quad (18)$$

When $\text{supp}(\mu) = \Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$, $\text{PFP}(\mu, p)$ reduces to $\text{FP}_{p, M}$.

Minimizers of the probabilistic p^{th} frame potential

Theorem

Let $0 < p < 2$, then the minimizers of (18) over all the probability measures supported on the unit sphere S^{N-1} are exactly those probability measures μ that satisfy

(i) there is an orthonormal basis $\{e_1, \dots, e_N\}$ for \mathbb{R}^N such that

$$\{e_1, \dots, e_N\} \subset \text{supp}(\mu) \subset \{\pm e_1, \dots, \pm e_N\}$$

(ii) there is $f : S^{N-1} \rightarrow \mathbb{R}$ such that $\mu(x) = f(x)\nu_{\pm x_1, \dots, \pm x_N}(x)$ and

$$f(x_i) + f(-x_i) = \frac{1}{N},$$

where the measure $\nu_{\pm x_1, \dots, \pm x_N}(x)$ represent the counting measure of the set $\{\pm x_i : i = 1, \dots, N\}$.

Probabilistic p -frame

Definition

For $0 < p < \infty$, we call $\mu \in \mathcal{M}(S^{N-1}, \mathcal{B})$ a *probabilistic p -frame* for \mathbb{R}^N if and only if there are constants $A, B > 0$ such that

$$A\|y\|^p \leq \int_{S^{N-1}} |\langle x, y \rangle|^p d\mu(x) \leq B\|y\|^p, \quad \forall y \in \mathbb{R}^N. \quad (19)$$

We call μ a *tight probabilistic p -frame* if and only if we can choose $A = B$.

Examples

Example

By symmetry considerations, it is not difficult to show that the uniform surface measure σ on S^{N-1} is always a tight probabilistic p -frame, for each $0 < p < \infty$.

Lemma

If μ is probabilistic frame, then it is a probabilistic p -frame for all $1 \leq p < \infty$. Conversely, if μ is a probabilistic p -frame for some $1 \leq p < \infty$, then it is a probabilistic frame.

Tight probabilistic p -frames and spherical t -designs

Theorem

Let p be an even integer. For any probability measure μ on S^{N-1} ,

$$\text{PFP}(\mu, p) \geq \frac{1 \cdot 3 \cdot 5 \cdots (p-1)}{N(N+2) \cdots (N+p-2)},$$

and equality holds if and only if μ is a probabilistic tight p -frame.

Tight probabilistic p -frames and spherical t -designs

Proposition

Let $p = 2k$ be an even positive integer. A set $\Phi = \{\varphi_k\}_{k=1}^M \subset S^{N-1}$ is a spherical p -design if and only if the probability measure $\mu_\Phi = \frac{1}{M} \sum_{k=1}^M \delta_{\varphi_k}$ is a probabilistic tight p -frame.

Concluding remarks on probabilistic frames

- The 2-Wasserstein metric given by

$$W_2^2(\mu, \nu) := \min \left\{ \int_{\mathbb{R}^N \times \mathbb{R}^N} \|x - y\|^2 d\gamma(x, y), \gamma \in \Gamma(\mu, \nu) \right\}, \quad (20)$$

where $\Gamma(\mu, \nu)$ is the set of all Borel probability measures γ on $\mathbb{R}^N \times \mathbb{R}^N$ whose marginals are μ and ν , respectively.

- (\mathcal{P}_2, W_2) form a metric space.
- Construction of frame path with various constraint.
- Optimization of frame related functionals, e.g., the probabilistic p^{th} frame potentials, in the context of the Wasserstein metrics.

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Thank You!

<http://www2.math.umd.edu/okoudjou>