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Definition

A family of vectors $F = \{f_i\}_{i=1}^N$ in $\mathbb{R}^m$ is called a frame for $\mathbb{R}^m$, if there exist constants $0 < A \leq B < \infty$ such that

$$A\left\|x\right\|^2 \leq \sum_{i=1}^{n} |\langle x, f_i\rangle|^2 \leq B\left\|x\right\|^2 \qquad (1)$$

- If $A = B$, then F is an $A-$tight frame.
- If $\|f_i\| = 1$ for all i and if there exist $\alpha \geq 0$ such that $|\langle f_i, f_j\rangle| = \alpha$ for all $i \neq j$ then F is an Equiangular
- Grassmannian frame is one that minimizes the maximal correlation $\langle f_i, f_j\rangle$ among all frames $F = \{f_i\}_{i=1}^N$

- Mutual coherence of a frame is largest absolute inner-product between different normalized elements of F
- This paper is concerned the problem of designing real frames with low mutual coherence
- One can find the solution for above mentioned problem by solving the following Optimization problem:

$$min_{\{F\}} max_{\{i \neq j\}} |\langle f_i, f_j \rangle| \; s.\ t \; \|f_i\|_2 = 1 \; for \; all \; i \tag{2}$$

- The authors have proceed to relax this problem and provide convex optimization formulations to solve it approximately
- The approach taken in this paper is for given a frame $H = \{h_i\}_{i=1}^N$ to find a new frame $F = \{f_i\}_{i=1}^N$ that is near to the initial one, with smaller mutual coherence by solving the following convex optimization problem: For all $i = 1, \ldots, N$

$$min_{\{f_i; \|f_i - h_i\|_2^2 \leq T_i\}} max_{\{j;\, j \neq i\}} |\langle h_j, f_i \rangle| \tag{3}$$

- The authors have developed a convex approach for sparse deconvolution that improves upon l_1-norm regularization
- They have posed the sparse deconvolution problem named as BISR in the following way:

$$\tilde{x} = arg\ min_{x \in \mathbb{R}^2} \left\{ f(x) = \frac{1}{2} \|y - Hx\|_2^2 + \lambda \Psi(x) \right\}, \qquad (4)$$

  where, $\lambda > 0$ and $\Psi(x) : \mathbb{R}^2 \to \mathbb{R}$ is a penalty function.
- This method is based on designing a non-convex penalty function $\Psi(x)$ so that the objective function is convex
- The new penalty overcomes limitations of separable regularization.
- They have given an algorithm for above mentioned problem. Further,this bivariate problem has been extended to an $N-$point linear inverse problem

Compressed nonnegative matrix factorization is fast and accurate

Mariano Tepper and Guillermo Sapiro

- In recent years, Nonnegative Matrix Factorization (NMF) has been frequently used since it provides a good way for modeling many real-life applications
- NMF seeks to represent a nonnegative matrix as the product of two nonnegative matrices
- One can find the solution of NMF by solving the following optimization problem:

$$min_{\{X \in \mathbb{R}^{m \times r}, Y \in \mathbb{R}^{r \times n}\}} \|A - XY\|_F^2 \ s.\ t\ X, Y \geq 0 \tag{5}$$

  where r is a parameter that controls the size of factors X and Y and, hence, the factorization's accuracy.
- In the general case, NMF is known to be NP-Hard

- However, there are matrices that exhibit a particular structure such that NMF can be solved efficiently
- A nonnegative matrix A is $r-$separable if there exists an index set $\mathcal{K}$ of cardinality r over the columns of A and a nonnegative matrix $Y \in \mathbb{R}^{r \times n}$, such that $A = (A)_{:\mathcal{K}} Y$
- When A presents this type of special structure, the NMF problem (now denoted as separable NMF, SNMF) can be simply modeled as

$$min_{\{\mathcal{K} \subset \{1,\ldots,n\}, Y \in \mathbb{R}^{r \times n}\}} \|A - (A)_{:\mathcal{K}} Y\|_F^2 \; s.\ t \; |\mathcal{K}| = r, Y \geq 0 \quad (6)$$

- The goal of this paper is to develop algorithms, based on structured random projections, for computing NMF for big data matrices
- The authors have showed that the resulting compressed techniques are faster than their uncompressed variants, vastly reduce memory demands

Other Interesting Papers

- Analysis of a Subset Selection Scheme for Wireless Sensor Networks in Time-Varying Fading Channels by S. H. Mousavi, et.al.
- Collaborative Multi-Sensor Classification Via Sparsity-Based Representation by M. Dao, et.al.

Thank you