

PhD Course in KTH - Sparse Signal Processing

Slides 2

Discussion Topic - Uniqueness and Uncertainty

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Questions

$$(P_0) : \quad \arg \min_{\mathbf{x} \in \mathbb{R}^m} \|\mathbf{x}\|_0 \quad \text{subject to } \mathbf{b} = \mathbf{Ax}. \quad (1)$$

- 1 Can uniqueness of a solution be claimed? Under what conditions?
- 2 If a candidate solution is available, can we say it is globally minimum?

Treating two-ortho case

- ① In (P_0) problem, we seek answers for two questions.
- ② Rather than answering the questions directly, we first consider special matrices \mathbf{A} for which the analysis seems to be easier, and then extend our endeavor to general \mathbf{A} .

Special \mathbf{A} : Let us assume that \mathbf{A} is concatenation two orthogonal bases Ψ and Φ as $\mathbf{A} = [\Psi \ \Phi]$.

An example: Let $\Psi = \mathbf{I}$ and $\Phi = \mathbf{F}$ (Fourier matrix). That means \mathbf{b} is a linear combination of few spikes and sinusoids.

Uncertainty principle

- 1 Classic uncertainty principle: Two conjugate variables can not be both known with arbitrary precision
- 2 Examples: Variables that are Fourier pair: Time and frequency, position and momentum
- 3 There is a lower bound:

$$\int x^2 |f(x)|^2 dx \cdot \int \omega^2 |g(\omega)|^2 d\omega \geq \frac{1}{2} \quad (2)$$

Comparable claim

Remark

$\mathbf{b} \in \mathbb{R}^n$, and Ψ and Φ are two orthogonal complete bases. So, we can write $\mathbf{b} = \Psi\alpha$ and $\mathbf{b} = \Phi\beta$. Then, the *uncertainty claim* is as follows: α and β can not be both very sparse.

To understand the above, an important point is to consider how dissimilar the two matrices are.

Definition

For an arbitrary pair of orthogonal bases Ψ and Φ that construct $\mathbf{A} = [\Psi \Phi]$, we define the mutual coherence $\mu(\mathbf{A})$ as the maximal inner product between the columns of these two bases.

$$\text{similarity}(\Psi, \Phi) = \mu(\mathbf{A}) = \max_{1 \leq i, j \leq m} |\psi_i^T \phi_j| \quad (3)$$

Remark

Bounds: $\mu(\mathbf{A})$ satisfies $\frac{1}{\sqrt{n}} \leq \mu(\mathbf{A}) \leq 1$

Proof: [We work out](#)

Theorem

Uncertainty principle 1: For an arbitrary pair of orthogonal bases Ψ and Φ with mutual coherence $\mu(\mathbf{A})$, and $\mathbf{b} \in \mathbb{R}^n$ and $\mathbf{b} = \Psi\alpha = \Phi\beta$, the following inequality holds true:

$$\|\alpha\|_0 + \|\beta\|_0 \geq \frac{2}{\mu(\mathbf{A})} \quad (4)$$

Simpler proof: [We work out](#)

More involving proof: [We work out](#). In this proof, we see an **uncertainty relation with l_1 norm**: $\|\alpha\|_1 + \|\beta\|_1 \geq \frac{2}{\sqrt{\mu(\mathbf{A})}}$

Remark

When $\Psi = \mathbf{I}$ and $\Phi = \mathbf{F}$ (Fourier matrix: Discrete Fourier Transform), then $\mu(\mathbf{A}) = \frac{1}{\sqrt{n}}$. Then, in that case

$$\|\alpha\|_0 + \|\beta\|_0 \geq 2\sqrt{n}$$

Proof: [Homework](#)

Uncertainty of redundant solutions

Theorem

Uncertainty principle 2: Any two distinct solutions $\mathbf{x}_1, \mathbf{x}_2$ of $\mathbf{Ax} = [\Psi \Phi] \mathbf{x} = \mathbf{b}$ can not be both very sparse, governed by the following uncertainty principle:

$$\|\mathbf{x}_1\|_0 + \|\mathbf{x}_2\|_0 \geq \frac{2}{\mu(\mathbf{A})}. \quad (5)$$

We refer to this result as “Uncertainty of redundant solutions”.

Proof: [We work out](#)

From Uncertainty to Uniqueness

A direct consequence of the previous theorem is a uniqueness result.

Theorem

Uniqueness: For $\mathbf{Ax} = [\Psi \Phi] \mathbf{x} = \mathbf{b}$, if a candidate solution \mathbf{x} satisfies $\|\mathbf{x}\|_0 < \frac{1}{\mu(\mathbf{A})}$, then it is necessarily the sparsest and any other solution must be denser.

Proof: [By simple arguments](#)

Remark

- *This simple claim is wonderful and powerful. At least for special $\mathbf{A} = [\Psi \Phi]$, we have a complete answer for the two questions. We can claim uniqueness and global optimality.*
- *Notice that, in general for a non-convex problem a given solution can at best be verified as being locally optimal, and here we are able to verify global optimality.*

Treating general case: Uniqueness via Spark

- ♠ To characterize the null space of a general \mathbf{A} using l_0 norm
- ♠ Donoho and Elad coined and defined spark in 2003

Definition

Spark (Rank): The spark (rank) of a matrix \mathbf{A} is the smallest (largest) number of linearly dependent (independent) columns

$$\text{spark}(\mathbf{A}) = \min_{\mathbf{x} \in \mathbb{R}^m} \|\mathbf{x}\|_0 \text{ subject to } \mathbf{A}\mathbf{x} = \mathbf{0}, \mathbf{x} \neq \mathbf{0}. \quad (6)$$

Note: By definition, the non-zero vectors in the null space of \mathbf{A} , i.e., $\{\mathbf{x} : \mathbf{A}\mathbf{x} = \mathbf{0}, \mathbf{x} \neq \mathbf{0}\}$, must satisfy $\|\mathbf{x}\|_0 \geq \text{spark}(\mathbf{A})$

Uniqueness via Spark

Theorem

Uniqueness via Spark: For $\mathbf{Ax} = \mathbf{b}$, if a candidate solution \mathbf{x} satisfies $\|\mathbf{x}\|_0 < \frac{1}{2} \text{spark}(\mathbf{A})$, then it is necessarily the sparsest.

Proof: [We work out](#)

Remark

Range of Spark: $2 \leq \text{spark}(\mathbf{A}) \leq n + 1$

Proof: [We discuss](#)

Home work: For two-ortho identity-Fourier pair, prove that $\text{spark}(\mathbf{A}) = 2\sqrt{n}$

Uniqueness via Mutual Coherence

- 1 Finding 'spark' is again NP hard. So comes mutual coherence
- 2 In the two-ortho case, the gram matrix is

$$\mathbf{A}^T \mathbf{A} = \begin{bmatrix} \mathbf{I} & \boldsymbol{\Psi}^T \boldsymbol{\Phi} \\ \boldsymbol{\Phi}^T \boldsymbol{\Psi} & \mathbf{I} \end{bmatrix} \quad (7)$$

and the mutual coherence $\mu(\mathbf{A})$ is obtained as the maximum off-diagonal entry (in absolute value) in this Gram matrix.

- 3 Now we go for a generalization

Definition

Mutual coherence: Denoting the i -th column by \mathbf{a}_i

$$\mu(\mathbf{A}) = \max_{1 \leq i, j \leq m, i \neq j} \frac{|\mathbf{a}_i^T \mathbf{a}_j|}{\|\mathbf{a}_i\|_2 \|\mathbf{a}_j\|_2} \quad (8)$$

- ① For an orthogonal matrix, $\mu(\mathbf{A}) = 0$
- ② For two-ortho case: $\frac{1}{\sqrt{n}} \leq \mu(\mathbf{A}) \leq 1$
- ③ For a general $\mathbf{A} \in \mathbb{R}^{n \times m}$, we desire for a low $\mu(\mathbf{A})$ such that it exhibits a close behavior of an orthogonal matrix
- ④ Donoho and Huo's Work: For randomly constructed $\mathbf{A} \in \mathbb{R}^{n \times m}$ with full rank n , we have $\mu(\mathbf{A}) \geq \sqrt{\frac{m-n}{n(m-1)}}$.
 - When $m = n$, $\mu(\mathbf{A}) = 0$
 - As n decreases, $\mu(\mathbf{A})$ increases

Lemma

For a matrix $\mathbf{A} \in \mathbb{R}^{n \times m}$, $\text{spark}(\mathbf{A}) \geq 1 + \frac{1}{\mu(\mathbf{A})}$

Proof: **We work out** (by using Gershgorin disk theorem). We learn the Gershgorin disk theorem and its relation with positive-definite property. Then we proceed with formal proof.

Challenge: Can students perform an alternate proof by using the facts that the resulting Gram matrix is symmetric, off-diagonal elements are upper bounded by mutual-coherence and the Gram matrix has to be full rank.

Theorem

Uniqueness via Mutual Coherence: For $\mathbf{Ax} = \mathbf{b}$, if a candidate solution \mathbf{x} satisfies $\|\mathbf{x}\|_0 < \frac{1}{2}(1 + \frac{1}{\mu(\mathbf{A})})$, then it is necessarily the sparsest.

Proof: **By simple arguments**

Uniqueness via Babel function

- 1 An intelligent approach by Joel Tropp
- 2 [Home Work](#): Understand the approach

Upper bounding the Spark

For sparsest uniqueness verification

- ① We can evaluate $\mu(\mathbf{A})$ and so the upper bound $\frac{1}{2}(1 + \frac{1}{\mu(\mathbf{A})})$.
- ② We may find a solution \mathbf{x} such that $\|\mathbf{x}\|_0 < \frac{1}{2}(1 + \frac{1}{\mu(\mathbf{A})})$ and conclude uniqueness. However, such a solution may not be guaranteed.
- ③ So comes the use of spark. We may find a solution \mathbf{x} such that $\|\mathbf{x}\|_0 < \frac{1}{2} \text{spark}(\mathbf{A})$ and conclude uniqueness.
- ④ However, computation of spark is NP hard.
- ⑤ So, in practice, we can upper bound the spark by a computable quantity and compare.

♠ Let us evaluate such an upper bound

Constructing Grassmannian matrices

Definition

A Grassmannian (real) matrix $\mathbf{A} \in \mathbb{R}^{n \times m}$ with $m \geq n$ and normalized columns satisfies that its Gram matrix $\mathbf{G} = \mathbf{A}^T \mathbf{A}$ has the following property

$$\forall i \neq j, |G_{i,j}| = \sqrt{\frac{m-n}{n(m-1)}}. \quad (9)$$

For a Grassmannian matrix, $\mu(\mathbf{A}) = \sqrt{\frac{m-n}{n(m-1)}}$.

- 1 Grassmannian is special as the angle between each and every pairs of columns is same and smallest possible.
- 2 It has strong connection with packing vectors/subspaces in \mathbb{R}^n .
- 3 Important in channel coding and wireless communication.
- 4 Hard to construct such matrix. A numerical method was proposed by Joel Tropp.

Home Work: Read the paper and simulate the algorithm.
Reproduce the experimental and/or numerical results in the paper.

Home Work Problems

- 1 Understand the proof for the claim related to (P_1) problem: There exist a sparse solution that has at-most n non-zeros (i.e., same as the number of constraints). According to Saikat, there is a problem in the proof. So, either identify the problem or get convinced that the proof is correct.
- 2 For identity-Fourier pair (two-ortho case), prove that $\mu(\mathbf{A}) = \frac{1}{\sqrt{n}}$ and $\|\alpha\|_0 + \|\beta\|_0 \geq 2\sqrt{n}$.
- 3 For identity-Fourier pair (two-ortho case), prove that $\text{spark}(\mathbf{A}) = 2\sqrt{n}$.
- 4 Understand 'Uniqueness via Babel Function' approach by Joel Tropp (From text book).
- 5 Construction of Grassmannian: Read the paper by Joel Tropp and simulate the algorithm. Reproduce the experimental and/or numerical results in the paper.