Tractable downfall of basis pursuit in structured sparse optimization

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## Table of Contents

1 Introduction





#### 4 Concluding remarks

## Table of Contents

1 Introduction

2 Main Result

3 Visualization

4 Concluding remarks

Sparse minimization

$$V \in \mathbb{R}^{m \times n}, \ m < n, \ y \in \mathbb{R}^n$$



- Compressed Sensing & ML
- System Id. & Model Reduction
- Sensor & Actuator Selection
- Fuel Optimal Control

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$\ell_1$ Minimization	
	n
$\underset{u\in\mathbb{R}^{n}}{minimize}$	$  u  _{\ell_1} := \sum_{i=1}^n  u_i $
subject to	Vu = y.

#### Mutual Coherence and Restricted Isometry Property

• Mutual Coherence: For a matrix  $V \in \mathbb{R}^{m \times n}$  with columns  $v_1, \ldots, v_n$ , the mutual coherence is defined as

$$\mu(V) = \max_{1 \le i \ne j \le n} \frac{|\langle v_i, v_j \rangle|}{\|v_i\|_2 \|v_j\|_2} = \cos \theta_{ij}.$$

Lower  $\mu(V)$  indicates that the columns of V are less correlated. A solution is guaranteed to be sparse if  $\|u^*\|_0 < 1/2(1+1/\mu(V))$ 

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• Restricted Isometry Property (RIP): A matrix V satisfies the RIP of order s with constant  $\delta_s \in (0, 1)$  if, for every s-sparse vector x,

$$(1 - \delta_s) \|x\|_2^2 \le \|Vx\|_2^2 \le (1 + \delta_s) \|x\|_2^2.$$

This property ensures that V approximately preserves the  $\ell_2$ -norm of sparse signals.

 $\implies$  **Problem:** NP-hard to verify and often not practical!

# Fuel Optimal Control

# $\begin{array}{l} L_0 \text{ Minimization} \\ \\ \text{minimize } & \|u\|_{L_0} := \int_0^T |\text{sign}(u(t)| dt \\ \\ \text{subject to } & \dot{x} = Ax + bu \\ & x(0) = \xi, \; x(T) = 0 \end{array}$

 $L_1 \text{ Minimization}$ minimize  $||u||_{L_1} := \int_0^T |u(t)| dt$ subject to  $\dot{x} = Ax + bu$  $x(0) = \xi, \ x(T) = 0$ 



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## Table of Contents

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3 Visualization

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Alignment property:  $\|V^{\mathsf{T}}\beta^*\|_{\infty} = u^{*\mathsf{T}}\underbrace{V^{\mathsf{T}}\beta^*}_{\tilde{\beta}^*} = \|u^*\|_1$ 

2

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$$\tilde{\beta}^* \in \mathsf{Im}(V^{\mathsf{T}}) = \mathsf{Im}\left(\begin{bmatrix}I_m\\ \begin{bmatrix}V_{(1:m,:)}^{-1}V_{(:,m+1:n)}\end{bmatrix}^{\mathsf{T}}\end{bmatrix}\right).$$

8 / 20

#### Theorem

Let  $u^* \in \mathbb{R}^n$  be a solution to  $\ell_0$  problem, where  $V \in \mathbb{R}^{m \times n}$  is such that  $V_{(:,1:m)}$  is invertible. Then,  $u^*$  is not a solution of  $\ell_1$  problem if there exists an  $i^* \in (m+1:n)$  with  $u_i^* \neq 0$  and  $\|V_{(:,1:m)}^{-1}V_{(:,i^*)}\|_{\ell_1} < 1$ .

1

Alignment property: 
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$$\tilde{\boldsymbol{\beta}}^* \in \mathsf{Im}(\boldsymbol{V}^{\mathsf{T}}) = \mathsf{Im}\left( \begin{bmatrix} \boldsymbol{I}_m \\ \begin{bmatrix} \boldsymbol{V}_{(1:m,:)}^{-1} \boldsymbol{V}_{(:,m+1:n)} \end{bmatrix}^{\mathsf{T}} \end{bmatrix} \right)$$

#### Tractable removal of "unhelpful" entries

Goal: Systematic removal of "unhelpful" entries.

**Observation:** 

• If 
$$b = \mathbf{1}_m \in \mathbb{R}^m$$
,  $A = \text{diag}(\lambda_1, \dots, \lambda_m)$ ,  $\lambda_i \ge 0$  and  $V = \begin{bmatrix} b & Ab & \dots & A^Nb \end{bmatrix}$ , then  
 $p_i = \|V_{(1:m,:)}^{-1}V_{(::m+1:i)}\|_1 = \mathbf{1}_m^\mathsf{T}WV_{(1:m,:)}^{-1}V_{(::m+1:i)}$ 

is part of an impulse response.

 $\implies$  (Schur-)Stable A and large enough N,  $p_i < 1$  for  $i \ge I^*$ .

 $\bullet\,$  Tractability by unimodality of p



 $\implies$  Simple binary search to find smallest  $I^*$  with  $p_{I^*} < 1$ .

#### Variation & Unimodality

• Variation of a Vector: For  $p \in \mathbb{R}^n$ 

$$S(p) := \#$$
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Unimodality: Let (Δp)<sub>i</sub> := p<sub>i+1</sub> − p<sub>i</sub>, then p is unimodal if S(Δp) ≤ 1 and a possible sign change in Δp occurs from positive to negative.



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• Unimodality: Let  $(\Delta p)_i := p_{i+1} - p_i$ , then p is unimodal if  $S(\Delta p) \le 1$  and a possible sign change in  $\Delta p$  occurs from positive to negative.



• k-Variation Bounding (VB<sub>k</sub>): A matrix  $X \in \mathbb{R}^{k \times n}$  with k > n is k-variation bounding if for every  $u \in \mathbb{R}^n \setminus \{0\}$ ,

 $\mathsf{S}(Xu) \le k - 1.$ 

# Sign Consistency & Variation Bounding

For  $X \in \mathbb{R}^{m \times n}$ , m > n,

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**VB**<sub>m</sub> versus **SC**<sub>m</sub> (Lemma): For  $X \in \mathbb{R}^{m \times n}$  with m > n and  $\mathsf{rk}(X) = n$ , X is m-variation bounding (VB<sub>m</sub>) if and only if it is m-sign consistent (SC<sub>m</sub>).

#### Main result - Unimodality

#### Theorem

Let  $V \in \mathbb{R}^{m \times n}$ , m < n, be such that  $V \in SC_m$ ,  $\Delta((\mathbf{1}_m^{\mathsf{T}}V)^{\mathsf{T}}) \in VB_m$  and  $\det(V_{(:,1:m)}) \neq 0$ . Then,  $p \in \mathbb{R}^n$  defined by

$$p_k := \|V_{(:,1:m)}^{-1}V_{(:,\{k\})}\|_{\ell_1}, \ k \in (1:n)$$

is unimodal .

▶ By definition  $p_{(1:m)} = \mathbf{1}_m$ , does this implies  $S(\Delta p_{(m:n)}) \leq 1$ .

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• 
$$\Delta \mathbf{1}_m^\mathsf{T} W \in \mathsf{VB}_m \Rightarrow$$

$$\mathsf{S}(\Delta Q \, \mathbf{1}_m) = \mathsf{S}(\Delta W \, W_{(1:m,:)}^{-1} K_m \, \mathbf{1}_m) \le m - 1.$$

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▶ The first m rows of  $\Delta Q \mathbf{1}_m$  contribute m-2 sign changes

$$(\Delta Q)_{(1:m,:)} \mathbf{1}_m = \Delta K_m \, \mathbf{1}_m = \begin{bmatrix} \vdots \\ 2 \\ -2 \\ 2 \end{bmatrix}$$

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► 
$$p_{(m+1:n)} = Q_{(m+1:n,:)}$$
,  $\Rightarrow \mathsf{S}(\Delta p(m:n)) \le 1$ .

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- $\blacktriangleright p_{(m+1:n)} = Q_{(m+1:n,:)}, \Rightarrow \mathsf{S}(\Delta p(m:n)) \le 1.$
- Finally, the single sign change in  $\Delta p(m:n)$  must be due to a negative entry, which implies that p is unimodal.

# Corollary

#### Corollary

Let  $V \in \mathbb{R}^{m \times m}$  defined as in the previous theorem. Further, let  $T \in \mathbb{R}^{m \times m}$  be invertible,  $\overline{V} = TV$  and

$$p(k) := \|\mathbf{1}_m^{\mathsf{T}} \bar{V}_{(:,1:m)}^{-1} \bar{V}_{(:,m+k)}\|_{\ell_1}$$

for all  $k \ge 1$ . Then, the sequence  $\{p(k)\}_{k\ge 1}$  is unimodal.

- In other words: mpulse response is realization independent
- Applies to Hankel, Page, Toeplitz matrices, ...

#### Log-Concavity

#### Theorem

Let  $A \in \mathbb{R}^{m \times m}$  and  $b \in \mathbb{R}^m$  be such that A is diagonalizable and (A, b) controllable. Further, let  $V = C(A, b) \in SC_m$  and

$$g_{(i)}(k) := W_k^T e_i, \ i \in (1:m)$$
$$p(k) := W_k^T \mathbf{1}_m$$

where

$$W_k := K_m^T V_{(:,1:m)}^{-1} V_{(:,m+k)}, \ k \ge 1.$$

Then, the sequences  $\{g_{(i)}(k)\}_{k\geq 1}$  for each  $i \in (1:m)$  and  $\{p(k)\}_{k\geq 1}$  are log-concave.

#### Log-Concavity

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Then, the sequences  $\{g_{(i)}(k)\}_{k\geq 1}$  for each  $i \in (1:m)$  and  $\{p(k)\}_{k\geq 1}$  are log-concave.

**Hidden Gem:** The transformation induced by  $W_k$  yields the companion matrix of A.

#### Characteristic Polynomial

#### Theorem

Let  $A \in \mathbb{R}^{m \times m}$  have characteristic polynomial

$$\det(sI - A) = s^{m} + \alpha_{m-1}s^{m-1} + \dots + \alpha_{1}s + \alpha_{0},$$

with  $\sum_{i=0}^{m-1} |\alpha_i| < 1$ , and let  $b \in \mathbb{R}^m$  be such that the pair (A, b) is controllable. Then, for the controllability matrix V = C(A, b) it holds

$$\|V_{(:,1:m)}^{-1}V_{(:,m+k)}\|_{\ell_1} < 1$$
 for all  $k \ge 0$ .

## Table of Contents

1 Introduction

2 Main Result

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Sparse minimization (G)

$$V = \begin{bmatrix} b & Ab & \dots & A^{N-1}b \end{bmatrix} \begin{bmatrix} u(N-1) & \dots & u(0) \end{bmatrix}^{\mathsf{T}}$$



## Table of Contents

1 Introduction

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3 Visualization



- Deterministic framework that provides failure guarantees for basis pursuit for special matrix structures.
- Complements (conservative) success guarantees
- New avenue for study of sparse/low-rank optimization problems
- Future work: sparsity in terms of singular values and rank minimization.