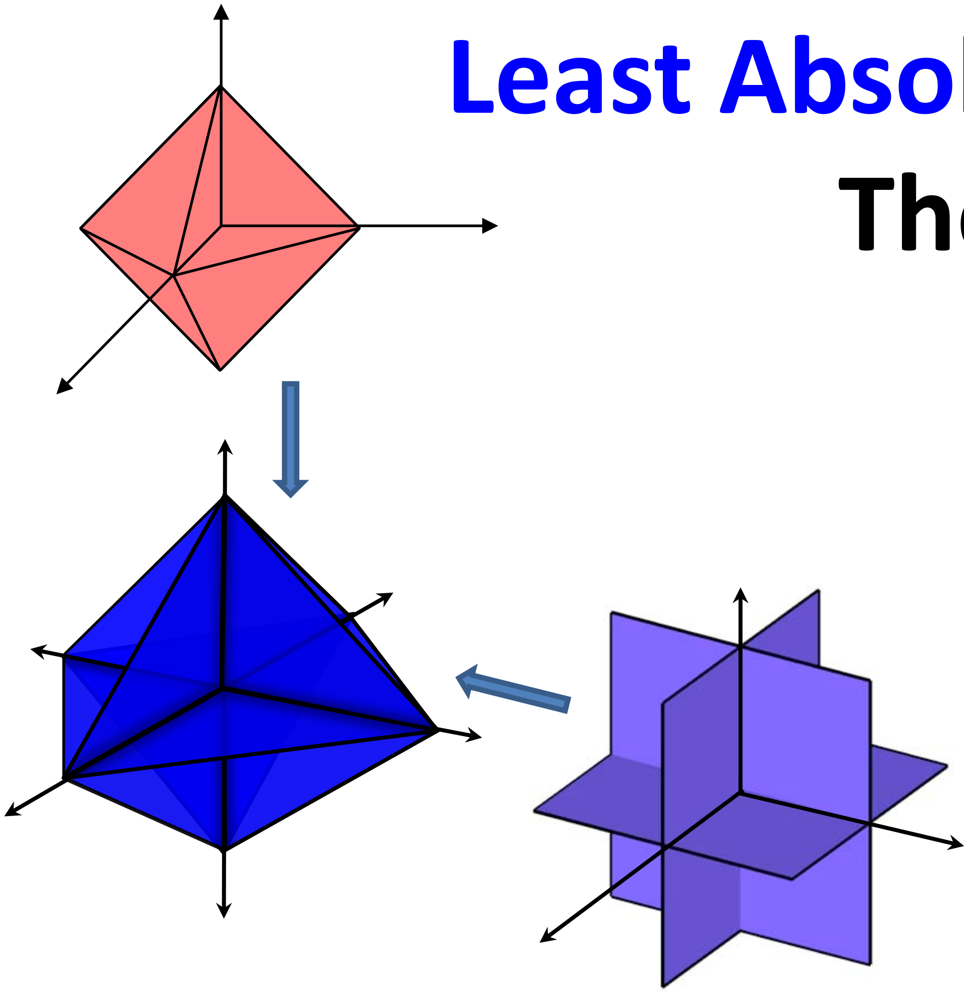
Combinatorial Selection and Least Absolute Shrinkage via The *CLASH* Operator



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joint work with my PhD student

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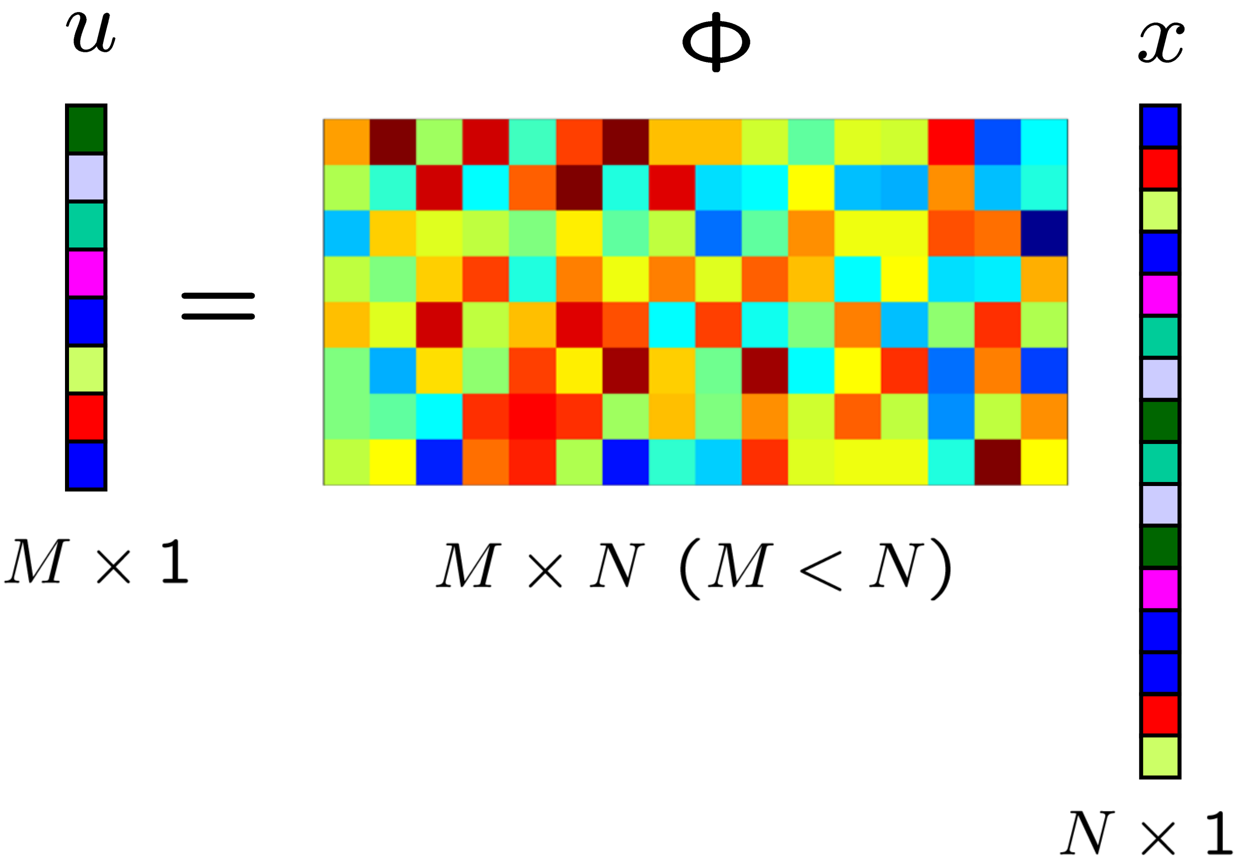
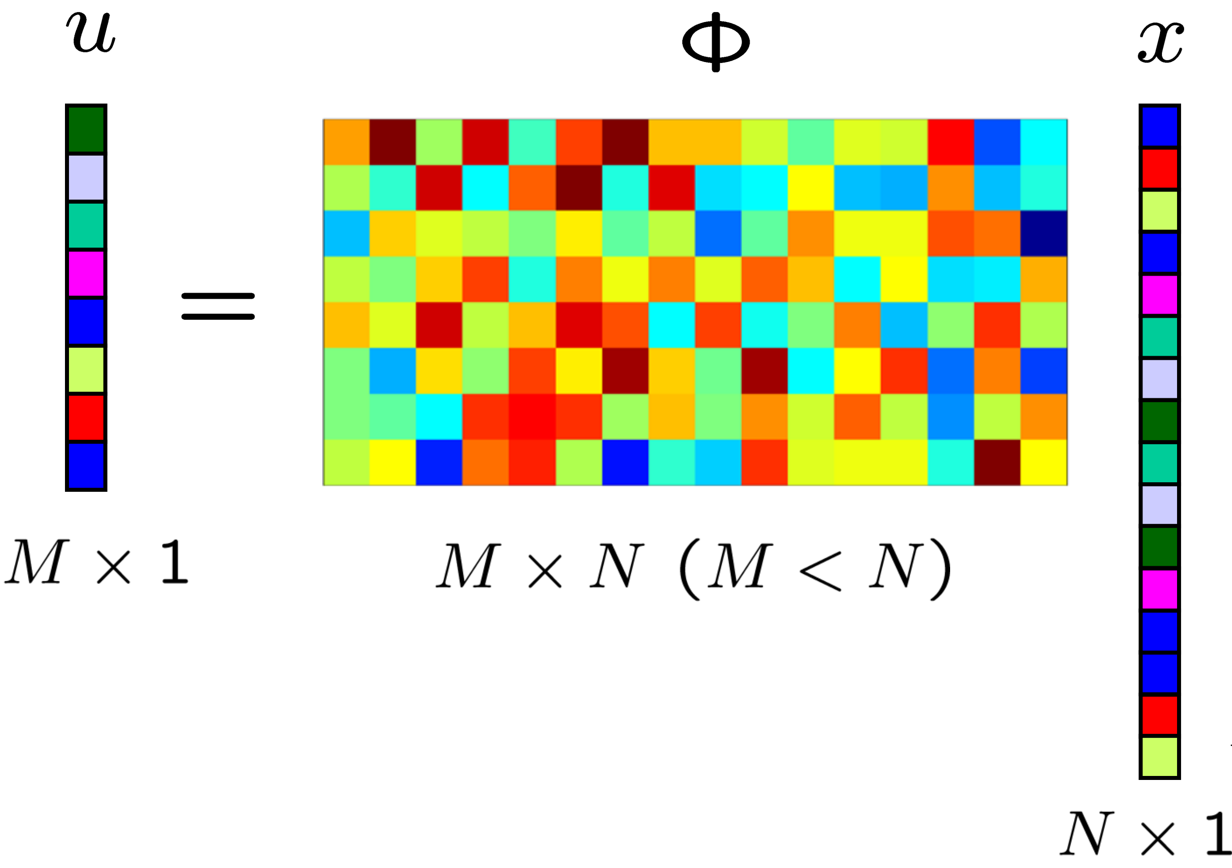
MARIE CURIE ACTIONS DARPA RICE UNIVERSITY DSP idiap RESEARCH INSTITUTE EPFL

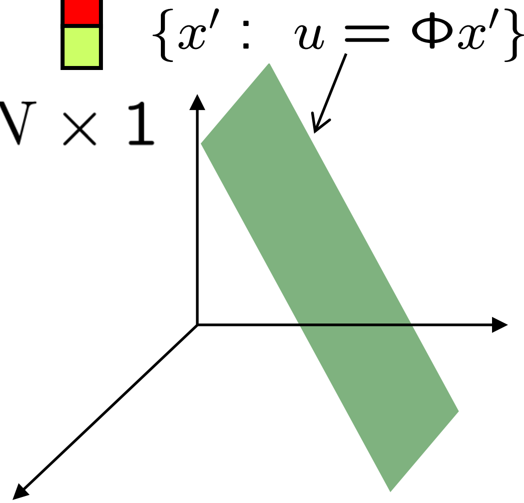
Linear Inverse Problems



Machine learning	dictionary of features
Compressive sensing	non-adaptive measurements
Information theory	coding frame
Theoretical computer science	sketching matrix / expander

Linear Inverse Problems

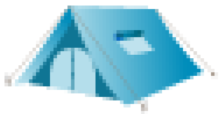




- **Challenge:** Null space of Φ: $\mathcal{N}(\Phi)$

$$x' = x + v \Rightarrow u, \ \forall v \in \mathcal{N}(\Phi)$$

Approaches

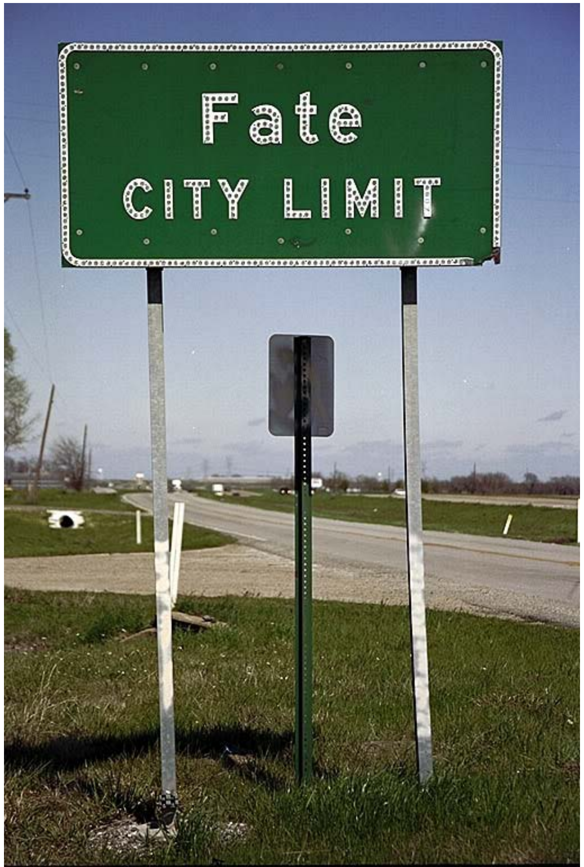
	 **Deterministic**	 **Probabilistic**
Prior	Sparsity compressibility	$f(x)$
Metric	ℓ_p-norm*	likelihood function

$$* : \|x\|_p = \left(\sum_i |x_i|^p\right)^{1/p}$$

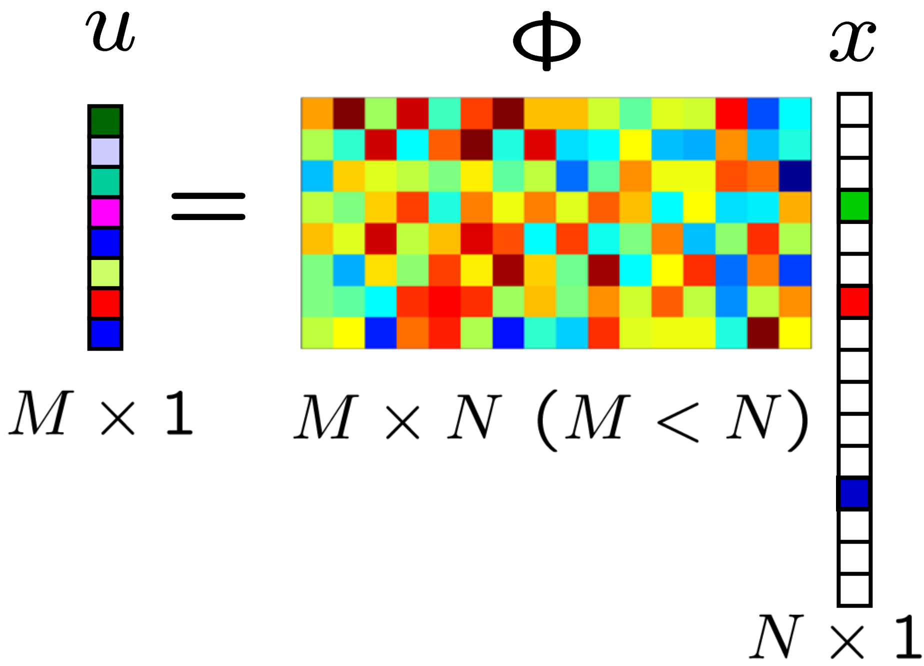
A Deterministic View

Model-based CS

(circa Aug 2008)



My Insights on Compressive Sensing



1. Sparse or compressible x

   not sufficient alone

2. Projection Φ

   information preserving
   (stable embedding / special null space)

3. Decoding algorithms

   tractable

Signal Priors

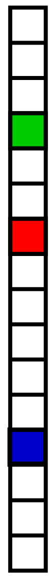
- **Sparse** signal: only K out of N coordinates nonzero
  - model: union of all K-dimensional subspaces aligned w/ coordinate axes

support:

$$\Omega = \{i : x_i \neq 0\}$$

$$|\Omega| = K$$

x

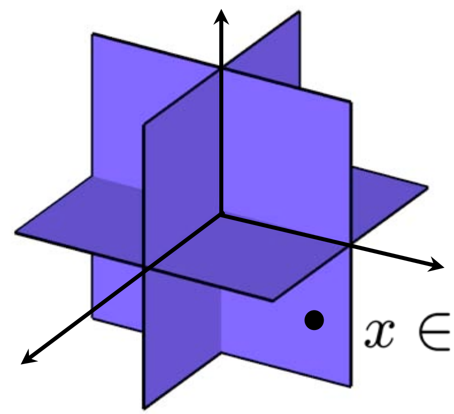


$N \times 1$

Example: 2-sparse in 3-dimensions

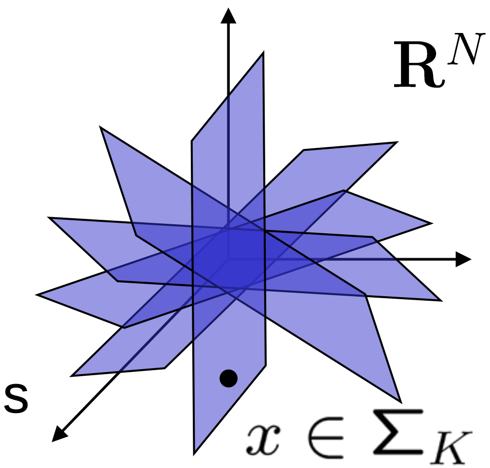
$K = 2$

$\mathbf{R}^3$



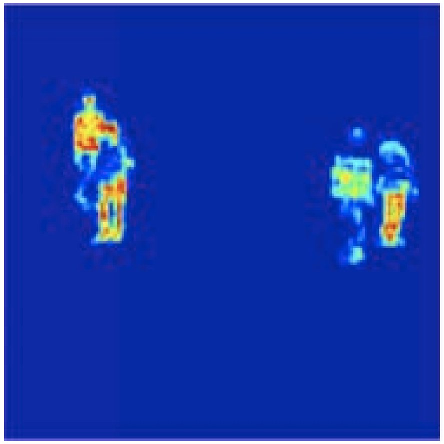
$x \in \Sigma_2$

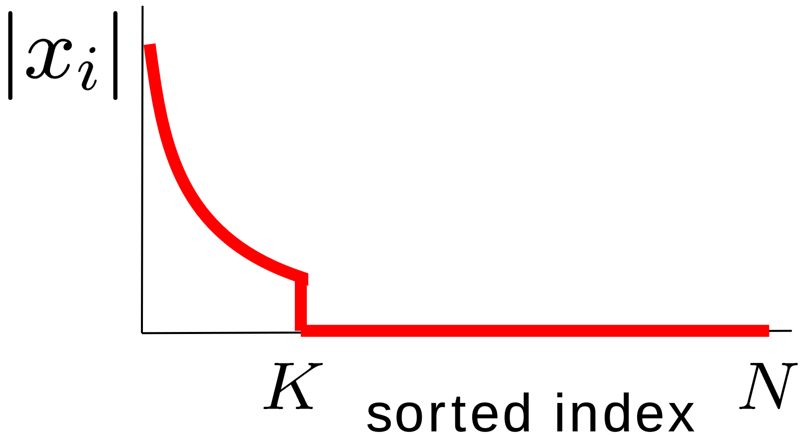
Signal Priors

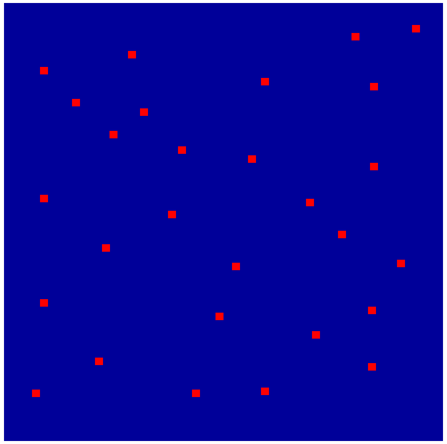


- **Sparse** signal: only K out of N coordinates nonzero
  - model: union of all K-dimensional subspaces aligned w/ coordinate axes

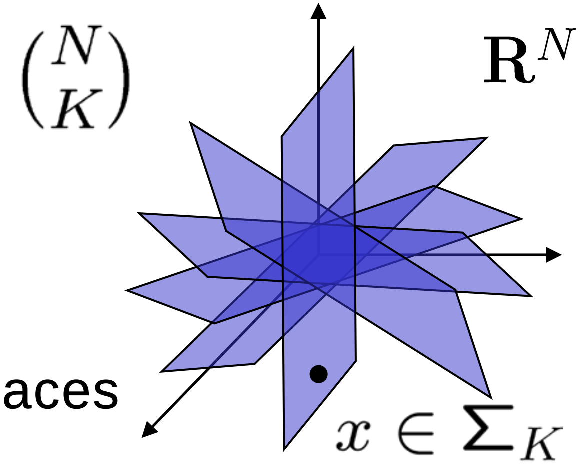
- **Structured sparse** signal: reduced set of subspaces **(or model-sparse)**
  - model: a particular union of subspaces ex: clustered or dispersed sparse patterns







Signal Priors



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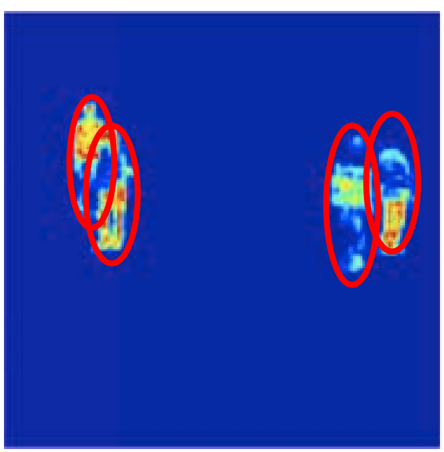
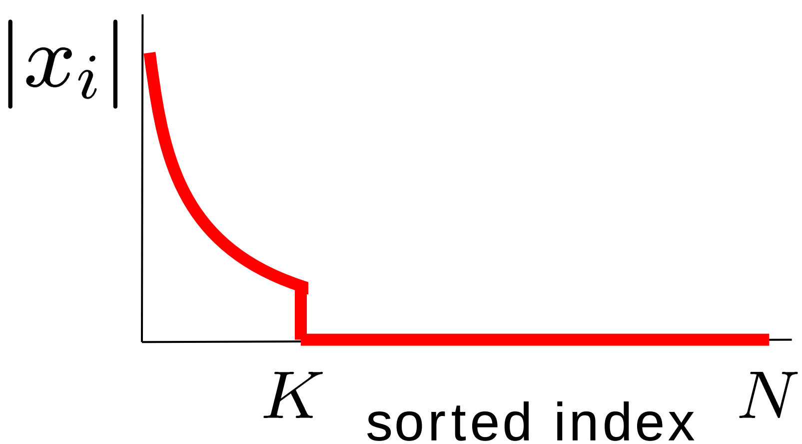
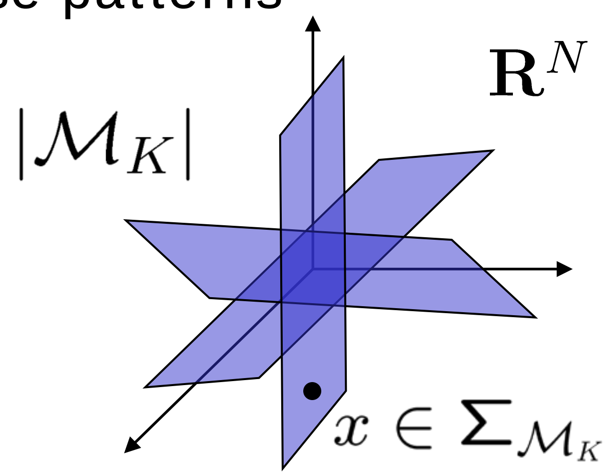






Sparse Recovery Algorithms

- **Goal:** given $u = \Phi x + n$

  recover x

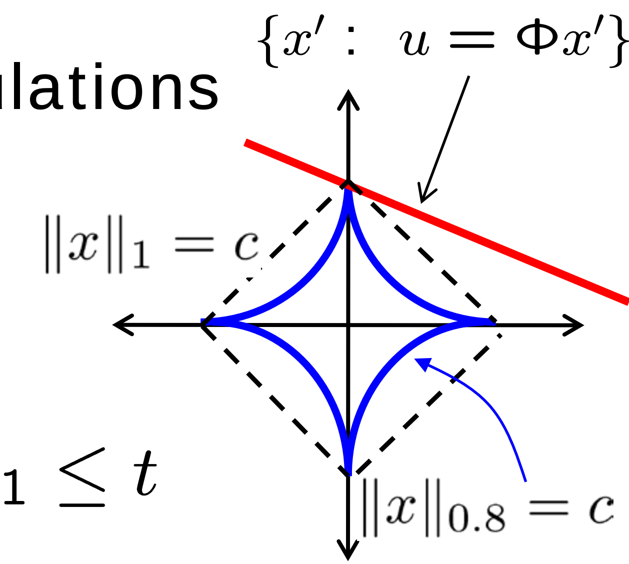
- $\ell_{q:q\leq 1}$ and convex optimization formulations
  - basis pursuit, Lasso, BP denoising...

$$\widehat{x} = \arg\min \|x\|_1 \text{ s.t. } u = \Phi x$$

$$\widehat{x} = \arg\min \|u - \Phi x\|_2 \text{ s.t. } \|x\|_1 \leq t$$

$$\widehat{x} = \arg\min \|u - \Phi x\|_2^2 + \mu \|x\|_1$$

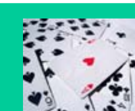
  - iterative re-weighted $\ell_1 \& \ell_2$ algorithms



- Hard thresholding algorithms: ALPS, CoSaMP, SP,...
- Greedy algorithms: OMP, MP,...

http://lions.epfl.ch/ALPS

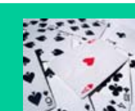
Sparse Recovery Algorithms

	Geometric 	**Combinatorial** $\binom{N}{K}$	**Probabilistic** 
Encoding	atomic norm / convex relaxation	non-convex union-of-subspaces	compressible / sparse priors
Example	$\min_{x:\|x\|_1 \leq \lambda} \|\|u - \Phi x\|\|^2$	$\min_{x:\|x\|_0 \leq K} \|\|u - \Phi x\|\|^2$	$E\{x\|u\}$
Algorithm	Basis pursuit, Lasso, basis pursuit denoising...	IHT, CoSaMP, SP, ALPS, OMP...	Variational Bayes, EP, Approximate message passing (AMP)...

$$\|x\|_0 = \#\{x_i \neq 0\}$$

Sparse Recovery Algorithms

The Clash Operator

	Geometric 	Combinatorial $\binom{N}{K}$	Probabilistic 
Encoding	atomic norm / convex relaxation	non-convex union-of-subspaces	compressible / sparse priors
Example	$\min_{x:\|x\|_1\leq\lambda}\|u-\Phi x\|^2$	$\min_{x:\|x\|_0\leq K}\|u-\Phi x\|^2$	$E\{x\|u\}$
Algorithm	Basis pursuit, Lasso, basis pursuit denoising...	IHT, CoSaMP, SP, ALPS, OMP...	Variational Bayes, EP, Approximate message passing (AMP)...

$$\widehat{x}_{\text{Clash}} = \arg\min_{x:\|x\|_1\leq\lambda,\|x\|_0\leq K}\|u-\Phi x\|^2$$

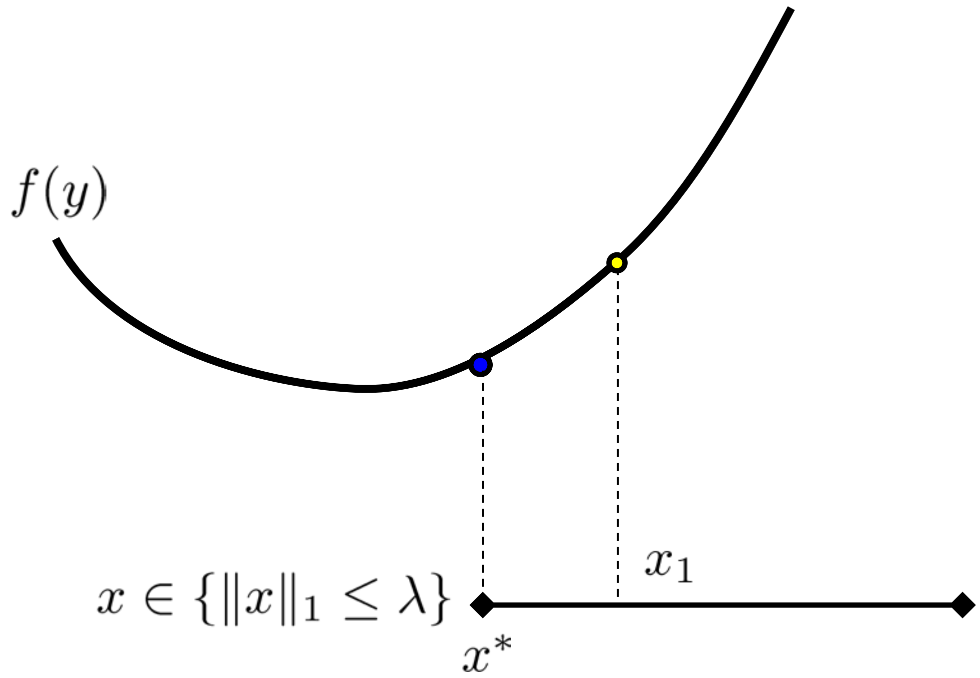
$$\|x\|_0 = \#\{x_i \neq 0\}$$

A Tale of Two Algorithms

- Soft thresholding

$f(x) = \|u - \Phi x\|^2$

$\min_{x:\|x\|_1 \leq \lambda} f(x)$



A Tale of Two Algorithms

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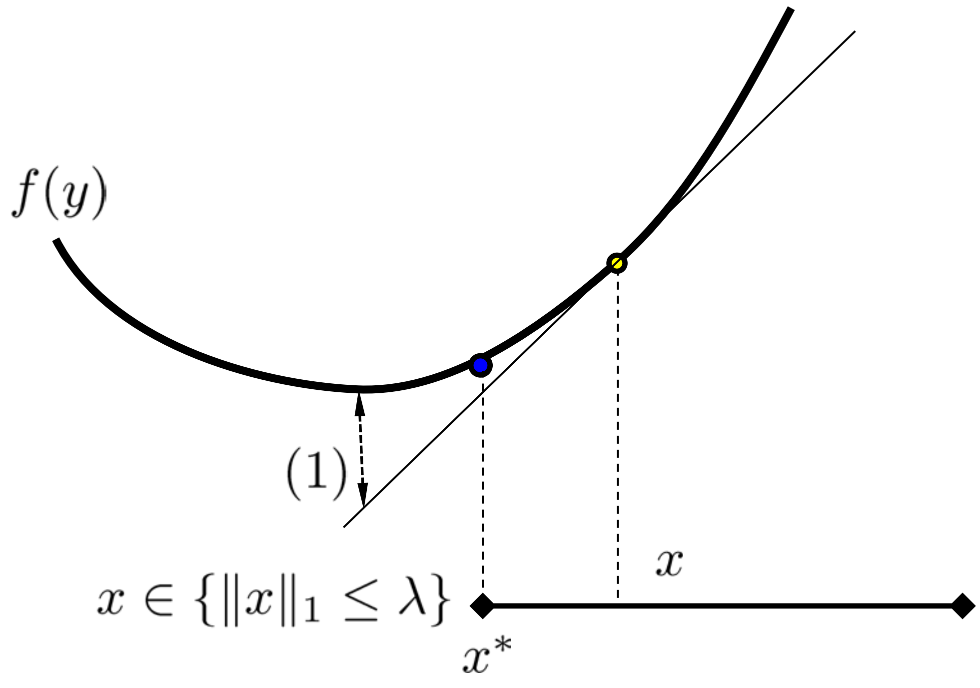


Structure in optimization:

Bregman distance

$$(1) \qquad \underbrace{f(y) - f(x) - \langle \nabla f(x), y - x \rangle}_{\text{Bregman distance}} = \|\Phi(y - x)\|^2 \qquad \forall x, y \in \mathcal{R}^N,$$

A Tale of Two Algorithms

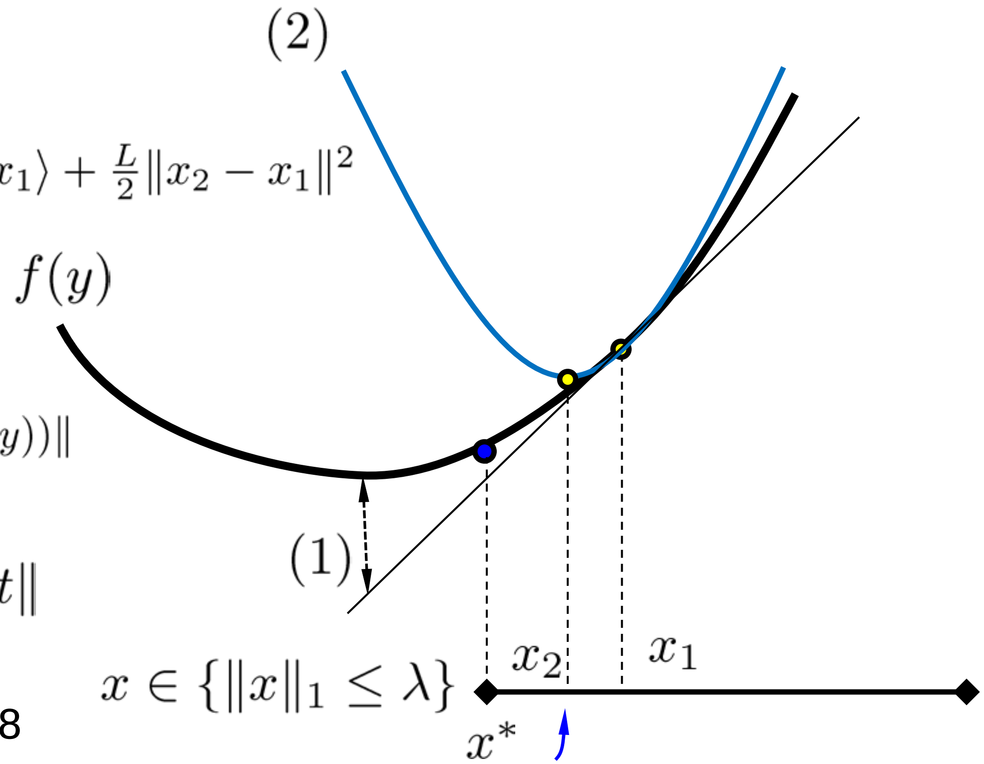
- Soft thresholding

$$f(x) = \|u - \Phi x\|^2$$

$$\min_{x:\|x\|_1 \leq \lambda} f(x)$$

$$U(x_2, x_1) = f(x_1) + \langle \nabla f(x_1), x_2 - x_1 \rangle + \frac{L}{2}\|x_2 - x_1\|^2$$

majorization-minimization



$$\arg \min_{\|x\|_1 \leq \lambda} U(x, y) = \arg \min_{\|x\|_1 \leq \lambda} \|x - (y - \frac{1}{L}\nabla f(y))\|$$

$$\text{St}_{\{\|x\|_1 \leq \lambda\}}(t) = \arg \min_{\|x\|_1 \leq \lambda} \|x - t\|$$

$$x_{i+1} = \text{St}_{\{\|x\|_1 \leq \lambda\}}\left(x_i - \frac{1}{L}\nabla f(x_i)\right)$$

ALGO: cf. J. Duchi et al. ICML 2008

Bregman distance

$$\begin{array}{llll} (1) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle & = & \|\Phi(y - x)\|^2 & \forall x, y \in \mathcal{R}^N, \\ (2) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle & \leq & \frac{L}{2}\|y - x\|^2 & L = 2\|\Phi\|, \forall x, y \in \mathcal{R}^N, \end{array}$$

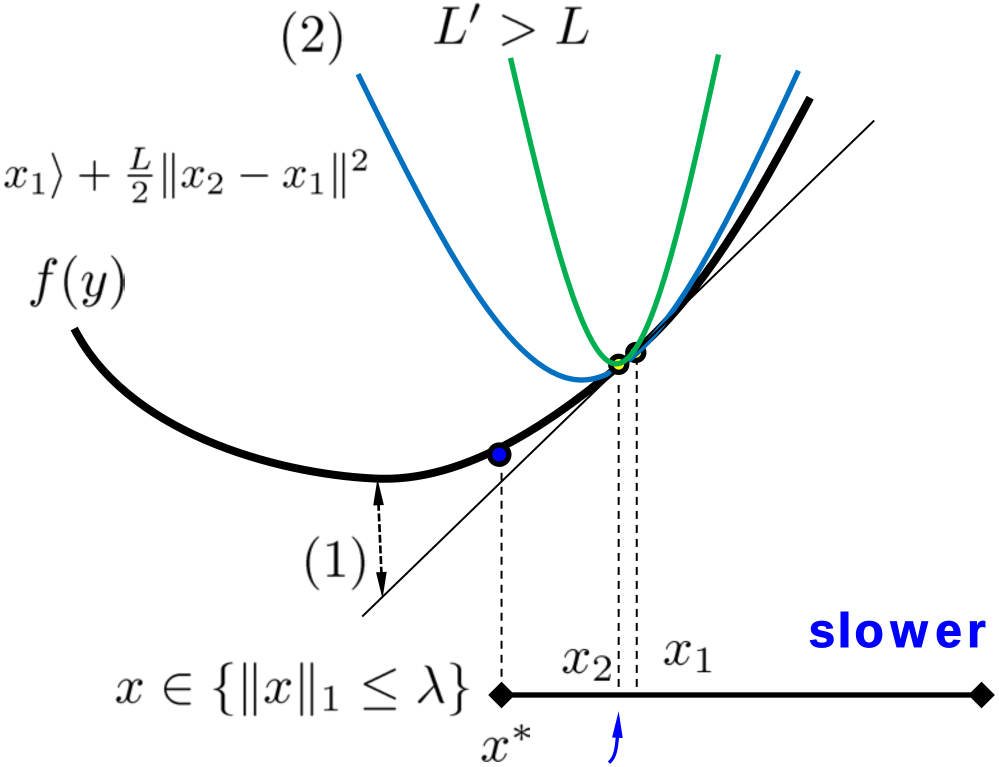
A Tale of Two Algorithms

- Soft thresholding

$$f(x) = \|u - \Phi x\|^2$$

$$\min_{x:\|x\|_1 \leq \lambda} f(x)$$

$$U(x_2, x_1) = f(x_1) + \langle \nabla f(x_1), x_2 - x_1 \rangle + \frac{L}{2}\|x_2 - x_1\|^2$$



$$x_{i+1} = \mathrm{St}_{\{\|x\|_1 \leq \lambda\}}\left(x_i - \frac{1}{L'}\nabla f(x_i)\right)$$

Bregman distance

$$\begin{array}{llcll} (1) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle & = & \|\Phi(y - x)\|^2 & \forall x, y \in \mathcal{R}^N, \\ (2) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle & \leq & \frac{L}{2}\|y - x\|^2 & L = 2\|\Phi\|, \forall x, y \in \mathcal{R}^N, \end{array}$$

A Tale of Two Algorithms

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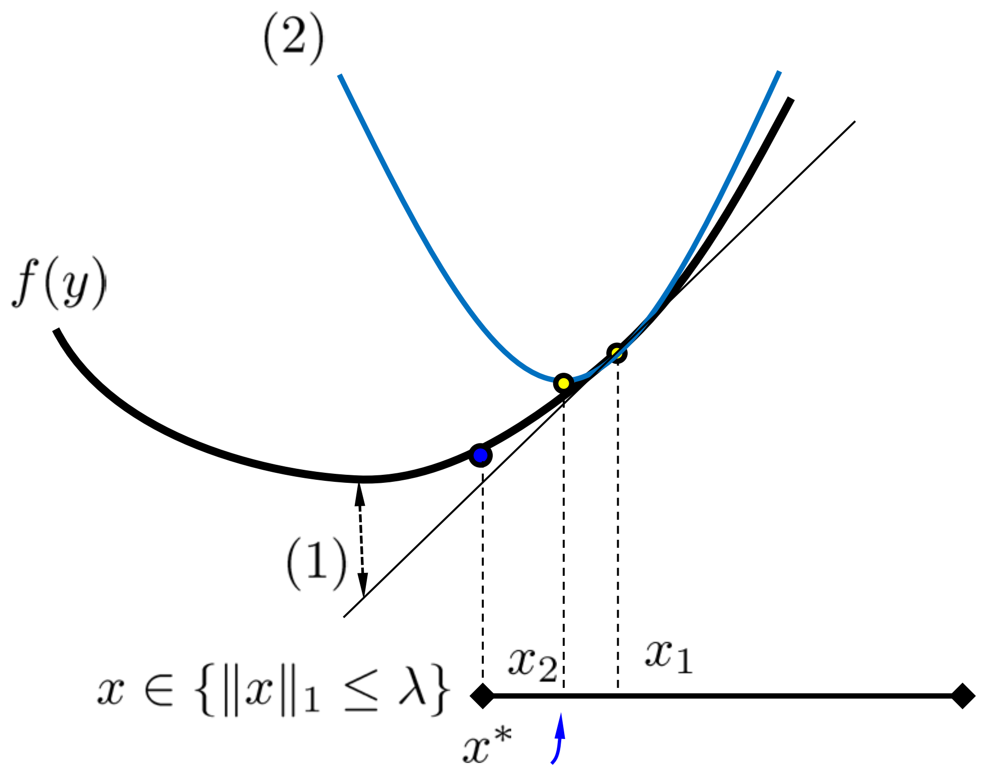


$x_{i+1} = \mathrm{St}_{\{\|x\|_1 \le \lambda\}} \left(x_i - \frac{1}{L} \nabla f(x_i) \right)$

- Is x* what we are looking for?

  local “unverifiable” assumptions:

  – ERC/URC condition

  – compatibility condition …

(local → global / dual certification / random signal models)

$\binom{N}{K}$ A Tale of Two Algorithms

- Hard thresholding

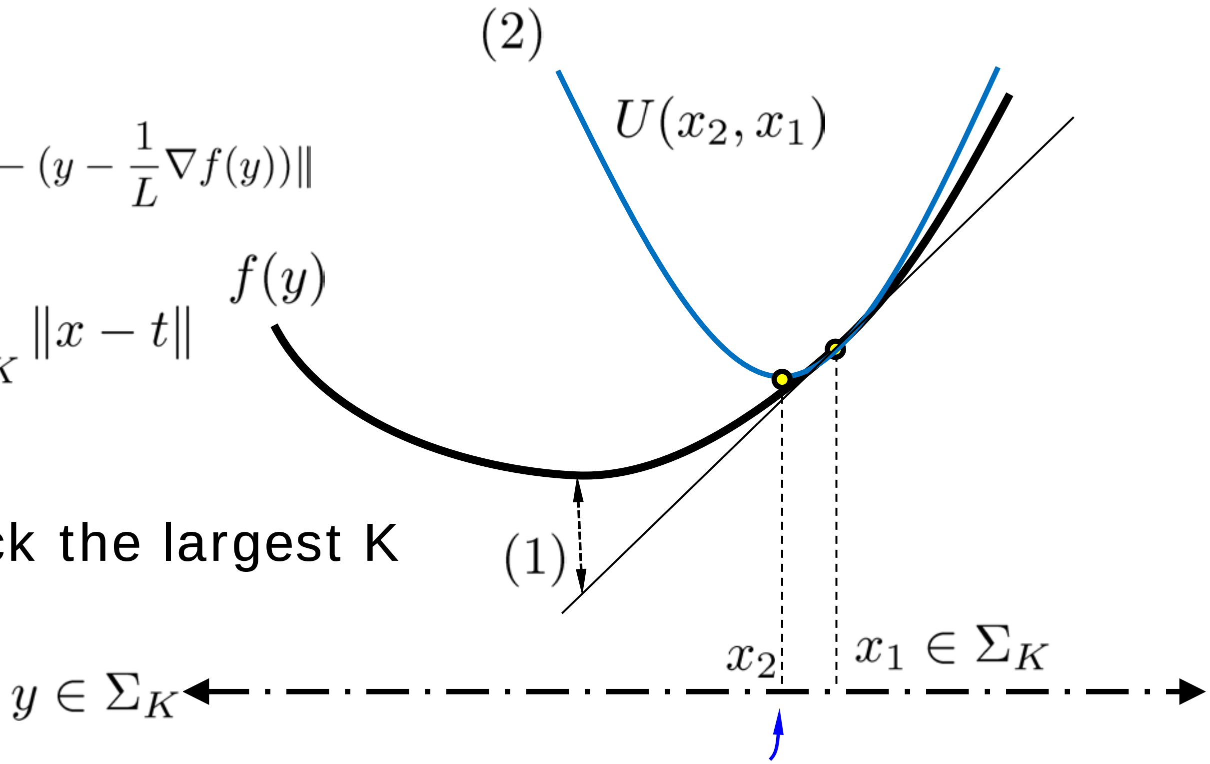
$$f(x) = \|u - \Phi x\|^2$$

$$\min_{x:\|x\|_0 \le K} f(x)$$

$$\arg\min_{\|x\|_0 \le K} U(x,y) = \arg\min_{\|x\|_0 \le K} \|x - (y - \frac{1}{L}\nabla f(y))\|$$

$$\mathrm{H}_{\{\|x\|_0 \le K\}}(t) = \arg\min_{\|x\|_0 \le K} \|x - t\|$$

ALGO: sort and pick the largest K



$$x_{i+1} = \mathrm{H}_{\{\|x\|_0 \le K\}}\left(x_i - \tfrac{1}{L}\nabla f(x_i)\right)$$

$\binom{N}{K}$ # A Tale of Two Algorithms

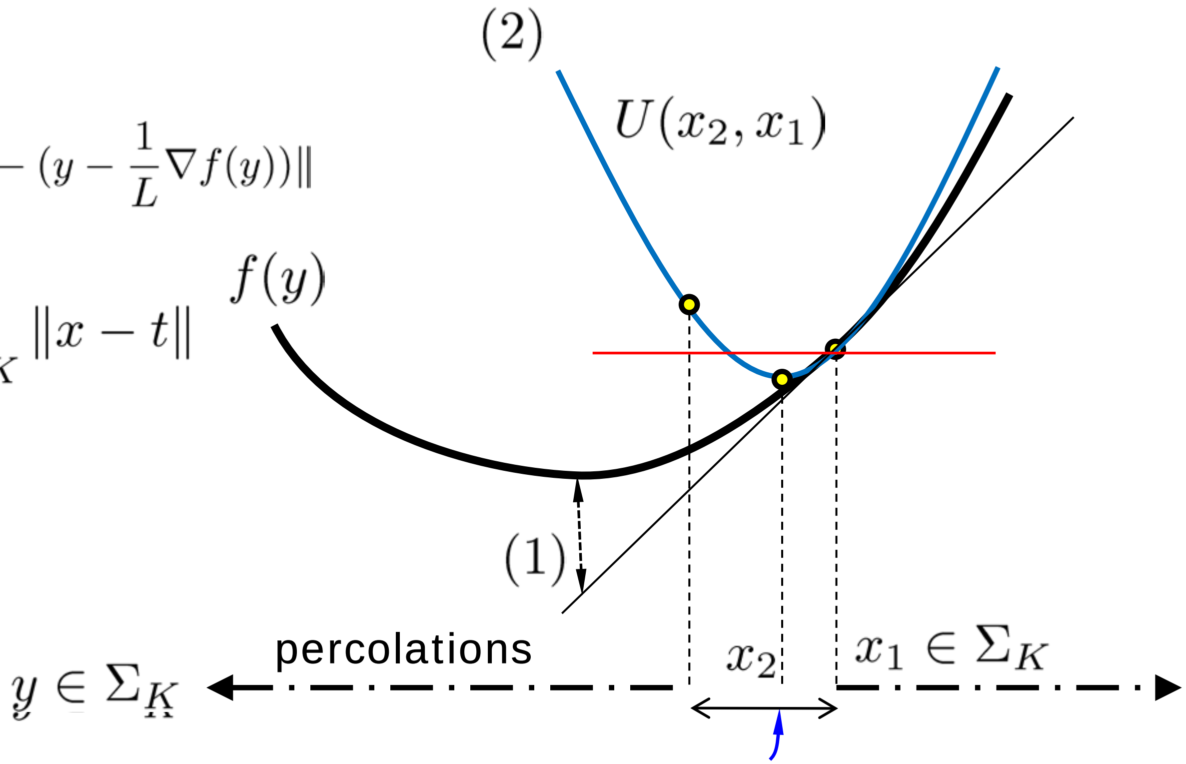
- Hard thresholding

$f(x) = \|u - \Phi x\|^2$

$\min_{x:\|x\|_0 \leq K} f(x)$

$$\arg\min_{\|x\|_0 \leq K} U(x,y) = \arg\min_{\|x\|_0 \leq K} \|x - (y - \frac{1}{L}\nabla f(y))\|$$

$$\mathrm{H}_{\{\|x\|_0 \leq K\}}(t) = \arg\min_{\|x\|_0 \leq K} \|x - t\|$$



$$x_{i+1} = \mathrm{H}_{\{\|x\|_0 \leq K\}}\left(x_i - \tfrac{1}{L}\nabla f(x_i)\right)$$

What could possibly go wrong with this naïve approach?

$\binom{N}{K}$ A Tale of Two Algorithms

- Hard thresholding

$$f(x) = \|u - \Phi x\|^2$$

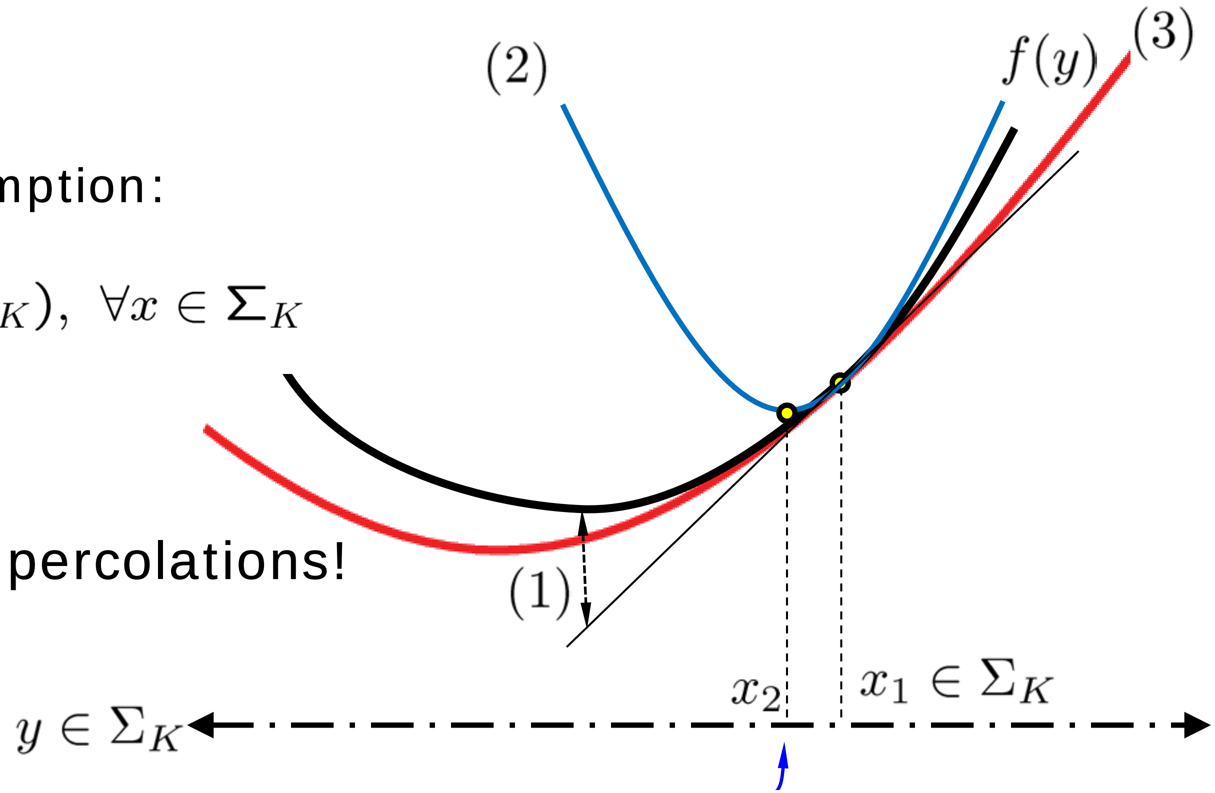
$$\min_{x:\|x\|_0 \leq K} f(x)$$

Global “unverifiable” assumption:

$$(1 - \delta_K) \leq \frac{\|\Phi x\|_2^2}{\|x\|_2^2} \leq (1 + \delta_K), \;\; \forall x \in \Sigma_K$$

$\Rightarrow$ we can tiptoe among percolations!

$$\delta_{2K} < 1/3$$

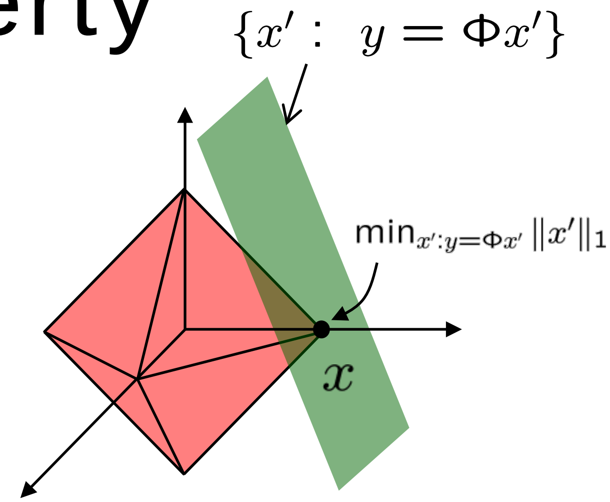


another variant has $\delta_{3K} < 1/2$

GraDes: $x_{i+1} = \mathrm{H}_{\{\|x\|_0 \leq K\}} \left(x_i - \frac{1}{L_{2K}} \nabla f(x_i) \right)$

$$
\begin{array}{llll}
(1) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle = \|\Phi(y-x)\|^2 & & \forall x, y \in \mathcal{R}^N, \\
(2) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle \leq \frac{L_{2K}}{2}\|y - x\|^2 & & L_{2K} = 2(1+\delta_{2K}), \forall x, y \in \Sigma_K, \\
(3) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle \geq \frac{\mu_{2K}}{2}\|y - x\|^2 & & \mu_{2K} = 2(1-\delta_{2K}), \forall x, y \in \Sigma_K,
\end{array}
$$

Restricted Isometry Property

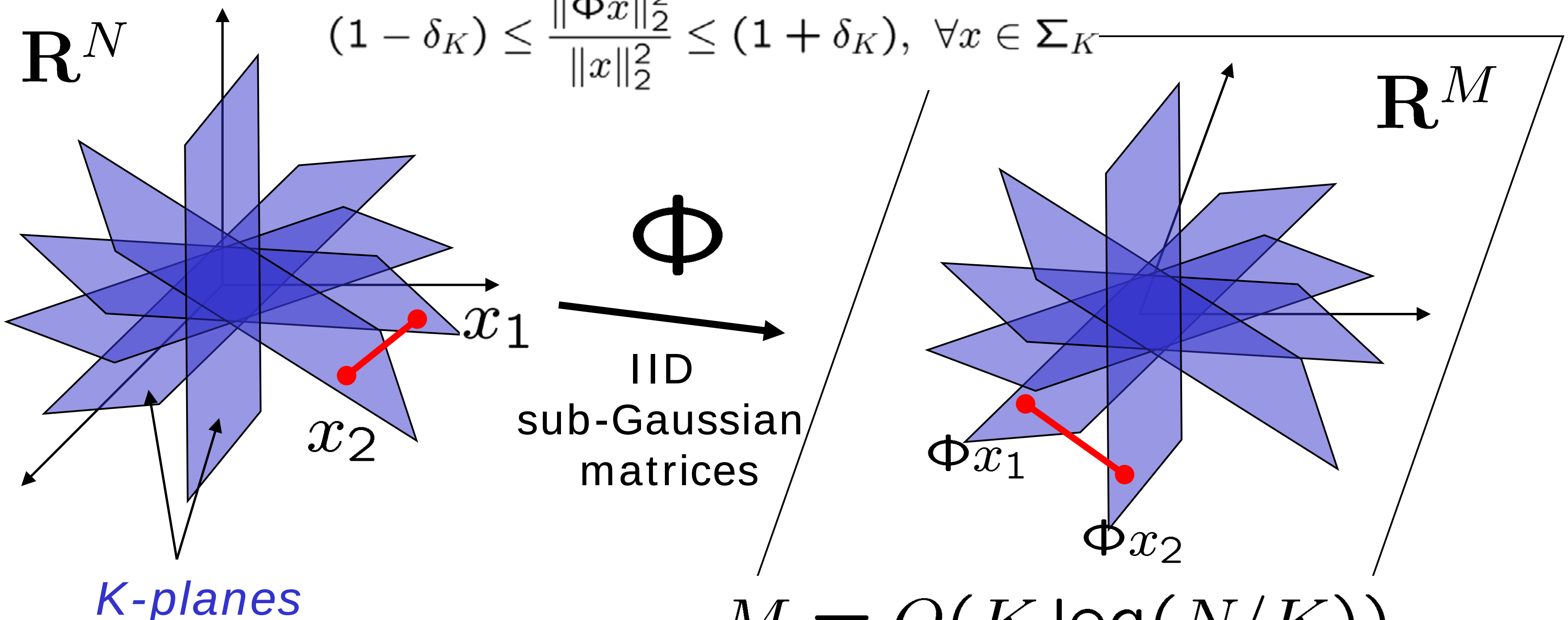


- **Model:** *K*-sparse coefficients

  Remark: implies convergence of convex relaxations also
  e.g., $\delta_{2K} < .465$ is sufficient for BP

- **RIP:** stable embedding

$$(1-\delta_K) \leq \frac{\|\Phi x\|_2^2}{\|x\|_2^2} \leq (1+\delta_K), \ \forall x \in \Sigma_K$$



$$M = O(K \log(N/K))$$

$|\mathcal{M}_K|$ A Model-based CS Algorithm

- Model-based hard thresholding $f(x) = \|u - \Phi x\|^2$

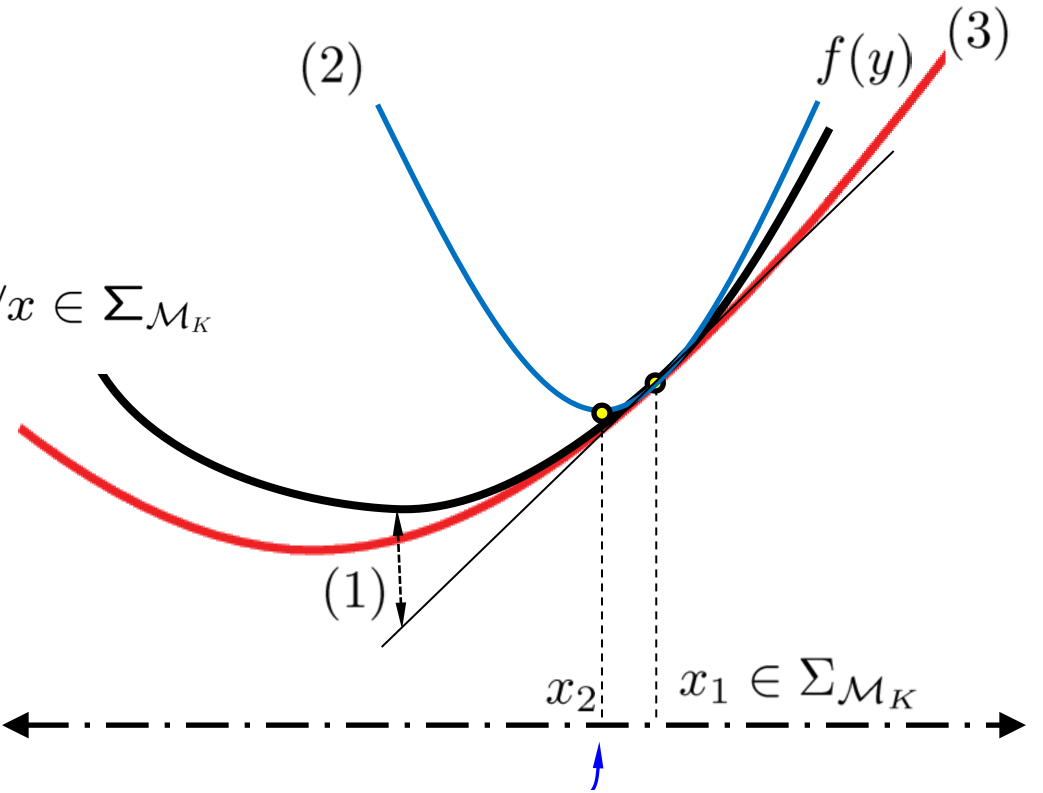
$\min_{x: x \in \Sigma_{\mathcal{M}_K}} f(x)$

Global "unverifiable" assumption:

$$(1-\delta_{\mathcal{M}_K}) \leq \frac{\|\Phi x\|_2^2}{\|x\|_2^2} \leq (1+\delta_{\mathcal{M}_K}), \;\; \forall x \in \Sigma_{\mathcal{M}_K}$$

$$\mathrm{H}_{\Sigma_{\mathcal{M}_K}}(t) = \arg \min_{x: x \in \mathcal{M}_K} \|x - t\|$$

$\delta_{\mathcal{M}_{2K}} < 1/3$



$$x_{i+1} = \mathrm{H}_{\Sigma_{\mathcal{M}_K}}\left(x_i - \frac{1}{L_{\mathcal{M}_{2K}}} \nabla f(x_i)\right)$$

$$
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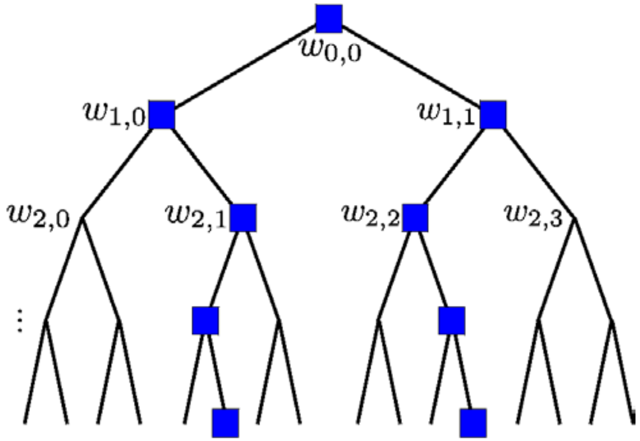
(2) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle \leq \frac{L_{\mathcal{M}_{2K}}}{2}\|y-x\|^2 & L_{\mathcal{M}_{2K}} = 2(1+\delta_{\mathcal{M}_{2K}}), & \forall x, y \in \Sigma_{\mathcal{M}_{2K}}, \\
(3) & f(y) - f(x) - \langle \nabla f(x), y - x \rangle \geq \frac{\mu_{\mathcal{M}_{2K}}}{2}\|y-x\|^2 & \mu_{\mathcal{M}_{2K}} = 2(1-\delta_{\mathcal{M}_{2K}}), & \forall x, y \in \Sigma_{\mathcal{M}_{2K}},
\end{array}
$$

Tree-Sparse

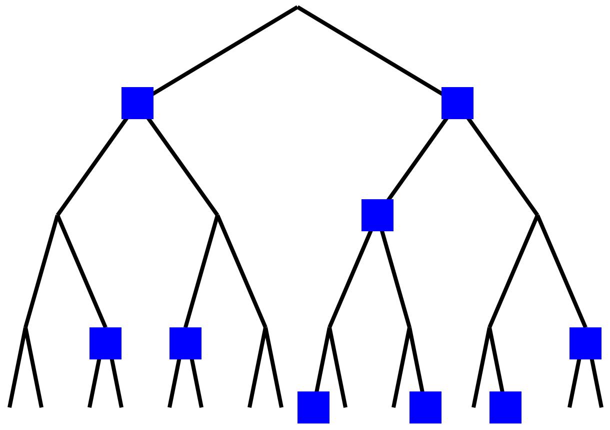


- **Model:** *K*-sparse coefficients
  + significant coefficients lie on a rooted subtree

- **Sparse approx:** find best set of coefficients
  - sorting
  - hard thresholding

- **Tree-sparse approx:** find best rooted subtree of coefficients
  - condensing sort and select [Baraniuk]
  - dynamic programming [Donoho]

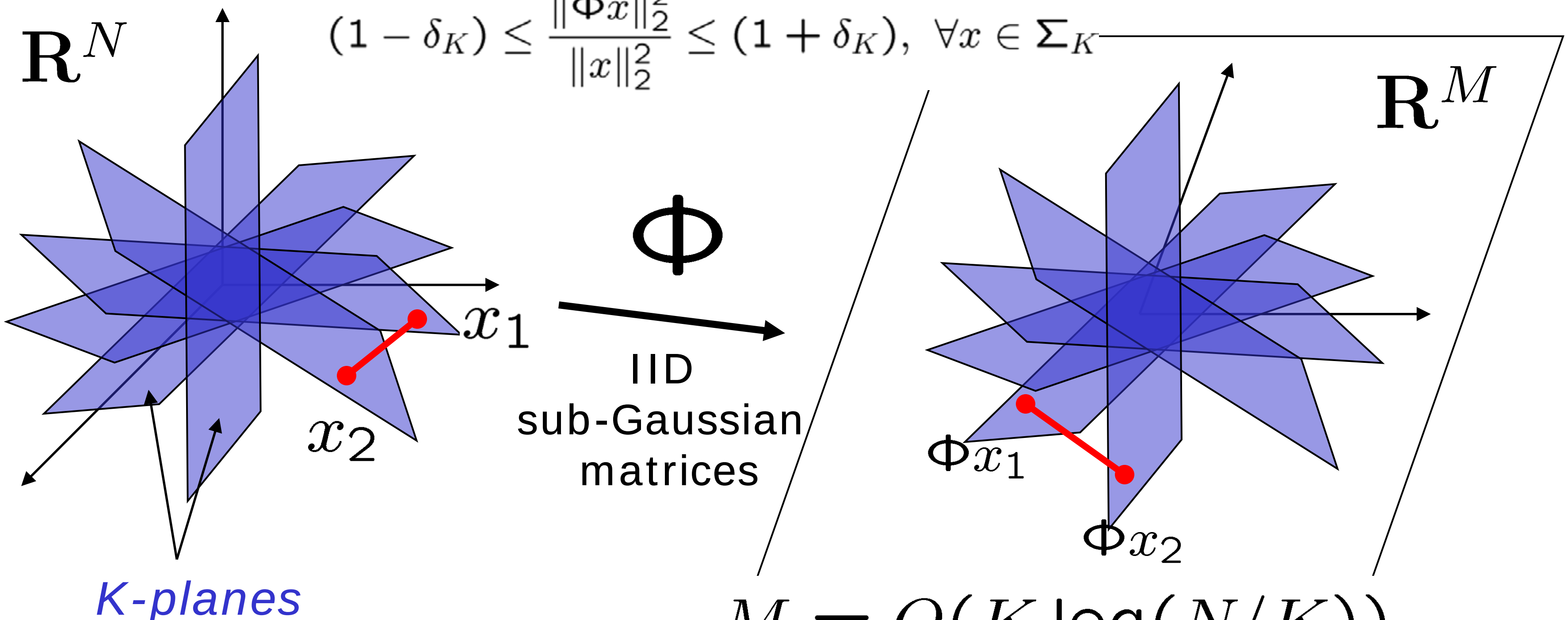
Sparse



- **Model:** *K*-sparse coefficients

- **RIP:** stable embedding

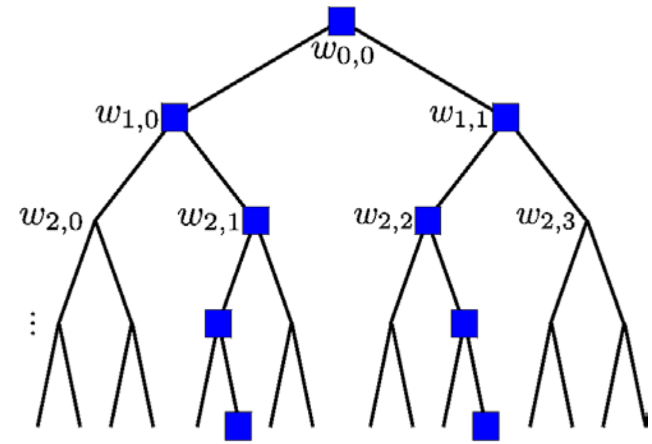
$$(1-\delta_K) \leq \frac{\|\Phi x\|_2^2}{\|x\|_2^2} \leq (1+\delta_K), \ \forall x \in \Sigma_K$$



$$M = O(K \log(N/K))$$

Tree-Sparse

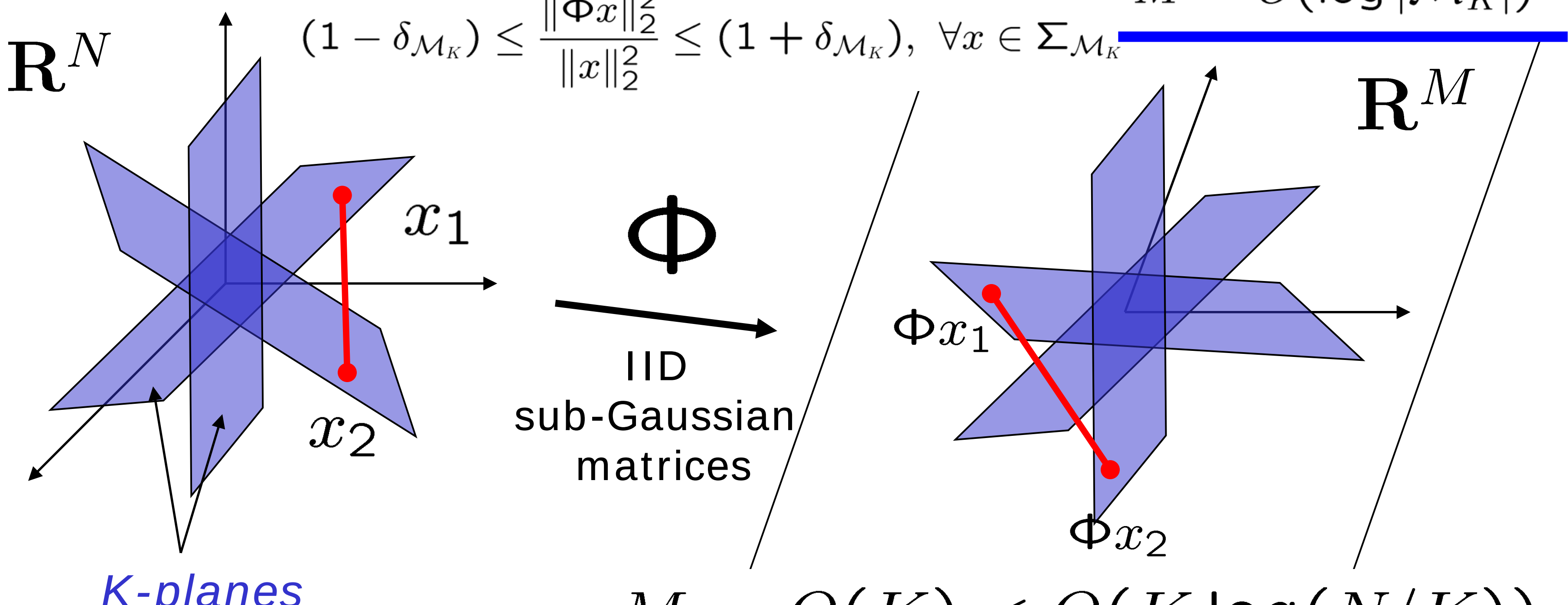
- **Model:** K-sparse coefficients
  + significant coefficients
  lie on a rooted subtree



- **Tree-RIP:** stable embedding

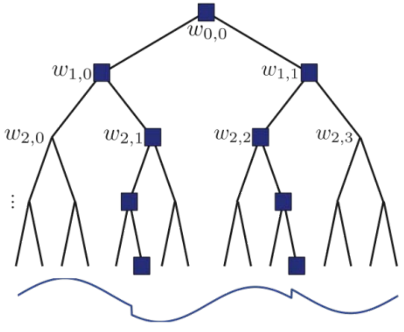
$M = O(\log|\mathcal{M}_K|)$

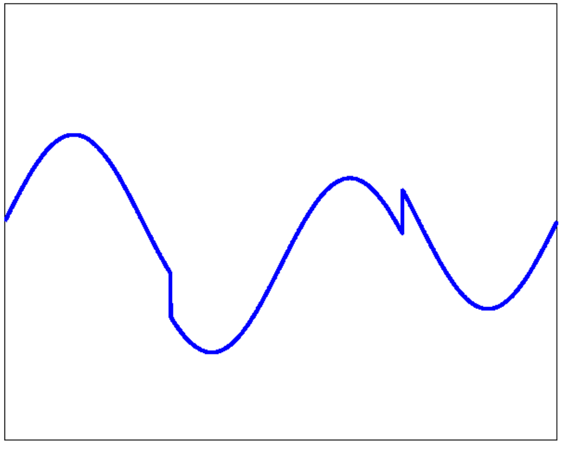
$$(1-\delta_{\mathcal{M}_K}) \leq \frac{\|\Phi x\|_2^2}{\|x\|_2^2} \leq (1+\delta_{\mathcal{M}_K}), \quad \forall x \in \Sigma_{\mathcal{M}_K}$$



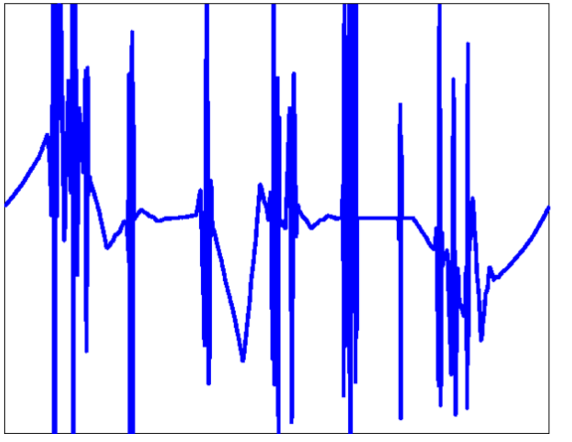
$M = O(K) < O(K\log(N/K))$

Tree-Sparse Signal Recovery



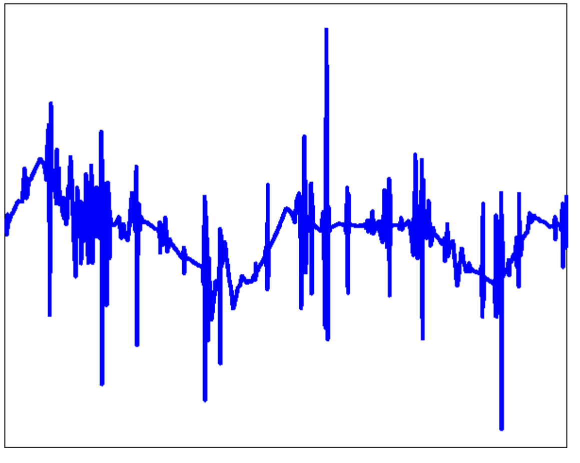


target signal

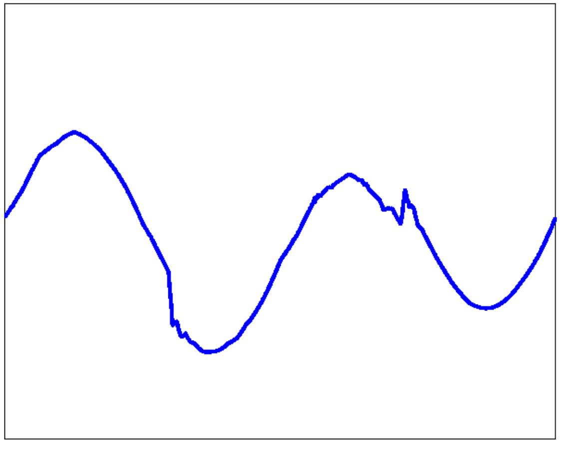


CoSaMP,
(MSE=1.12)

N=1024
M=80



L1-minimization
(MSE=0.751)



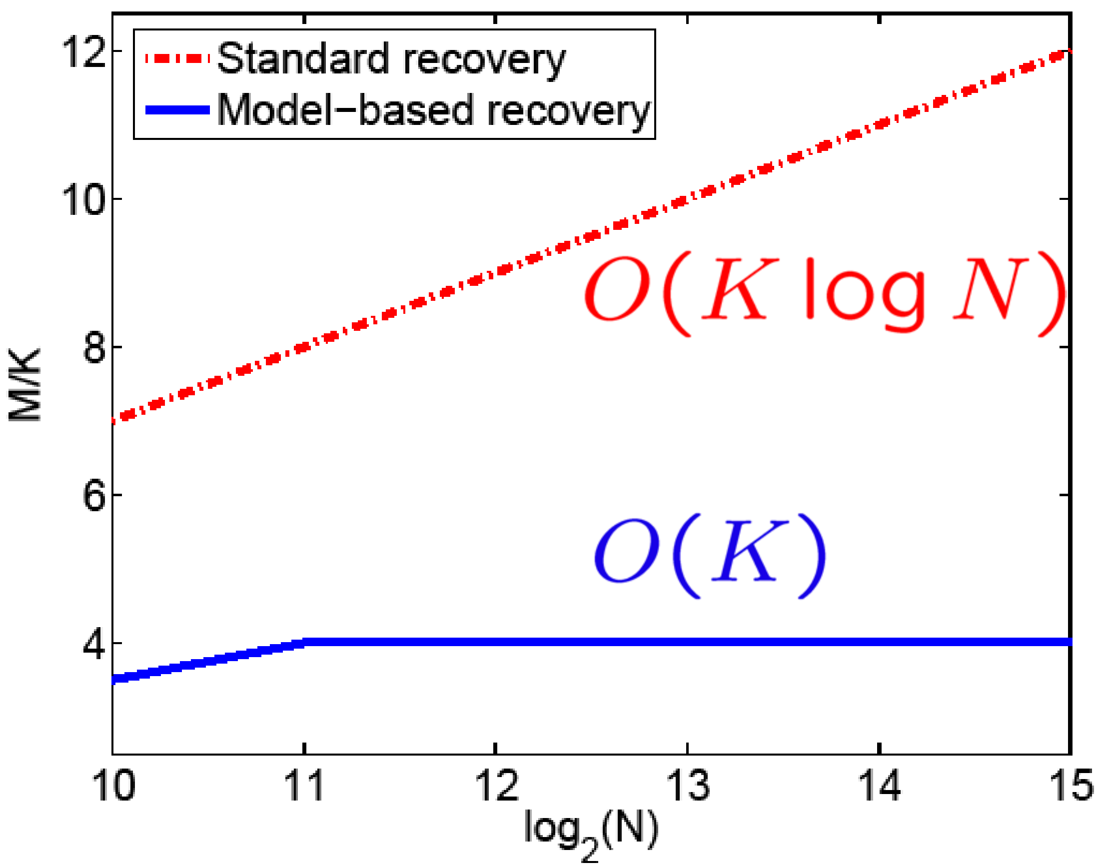
Tree-sparse CoSaMP
(MSE=0.037)

Tree-Sparse Signal Recovery

- Number samples for correct recovery

- Piecewise cubic signals + wavelets

- Models/algorithms:
  - compressible (CoSaMP)
  - tree-compressible (tree-CoSaMP)



Model CS in Context

- Basis pursuit and Lasso

  exploit geometry < > interplay of ℓ_1 ball and ℓ_2 error

  arbitrary selection < > *difficulty of interpretation*

  cannot leverage further structure

- Structured-sparsity ***inducing*** norms

  “customize” geometry for selection < > “mixing” of norms over groups / Lovasz extension of submodular set functions

  inexact selections

- Structured-sparsity via OMP / Model-CS

  greedy selection < > *cannot leverage geometry*

  exact selection < > *cannot leverage geometry*

Model CS in Context

- Basis pursuit and Lasso

exploit geometry	< >	interplay of ℓ_1 ball and ℓ_2 error
arbitrary selection	< >	*difficulty of interpretation*
		cannot leverage further structure

- Structured-sparsity ***inducing*** norms

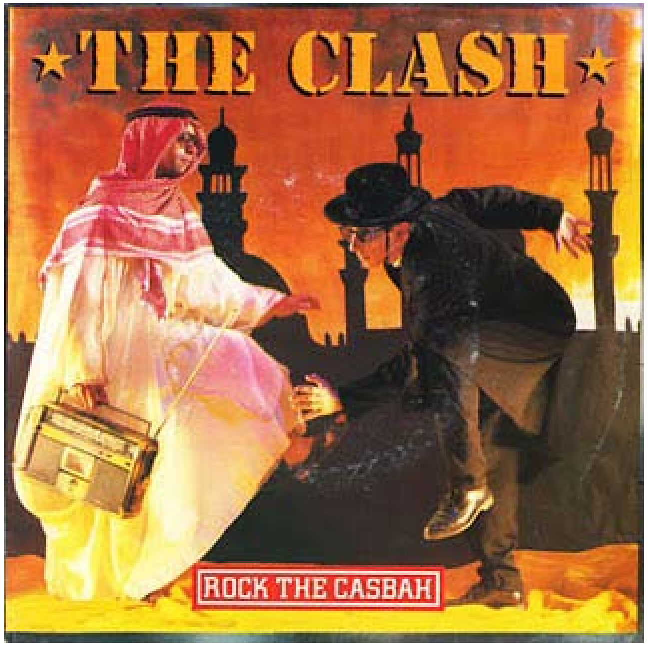
"customize" geometry for selection	< >	"mixing" of norms over groups / Lovasz extension of submodular set functions
		inexact selections

- Structured-sparsity via OMP / Model-CS

greedy selection	< >	*cannot leverage geometry*
exact selection	< >	**Or, can it?**

Enter
CLASH

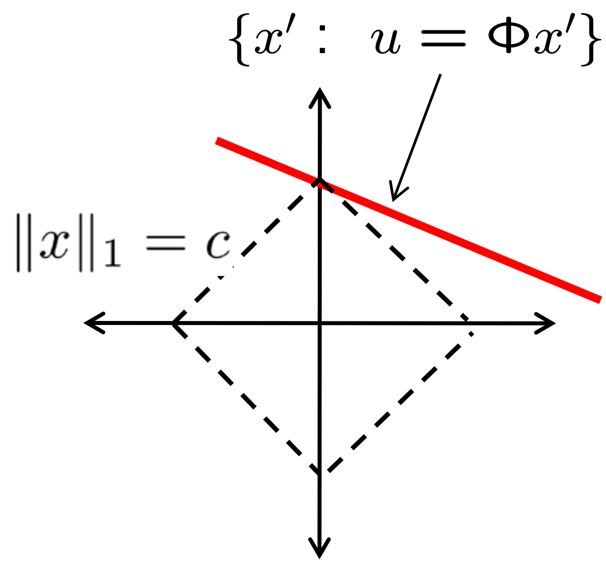
http://lions.epfl.ch/CLASH



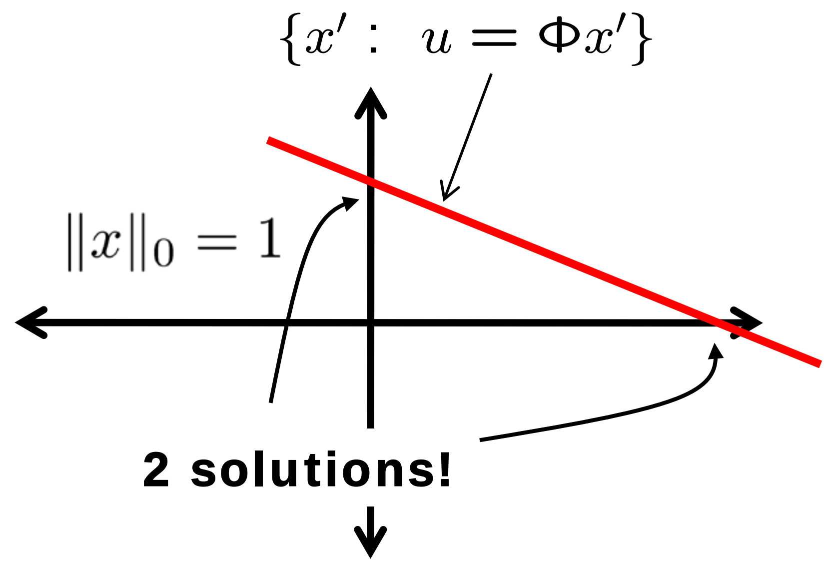
Importance of Geometry

- A subtle issue

$$\widehat{x} = \arg\min \|x\|_1 \text{ s.t. } u = \Phi x$$



$$\widehat{x} = \arg\min \|x\|_0 \text{ s.t. } u = \Phi x$$

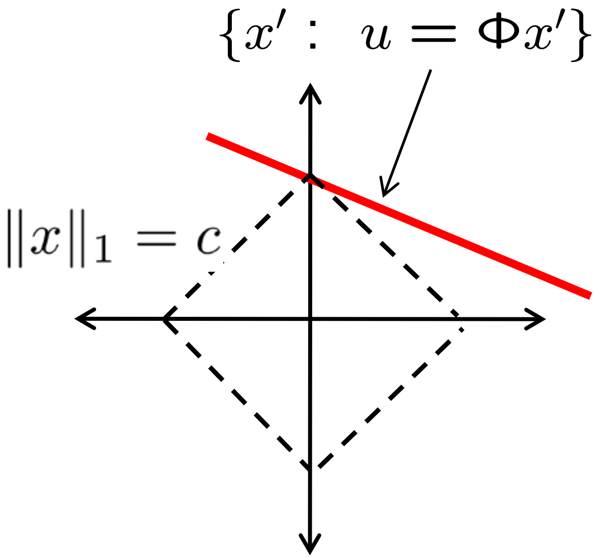


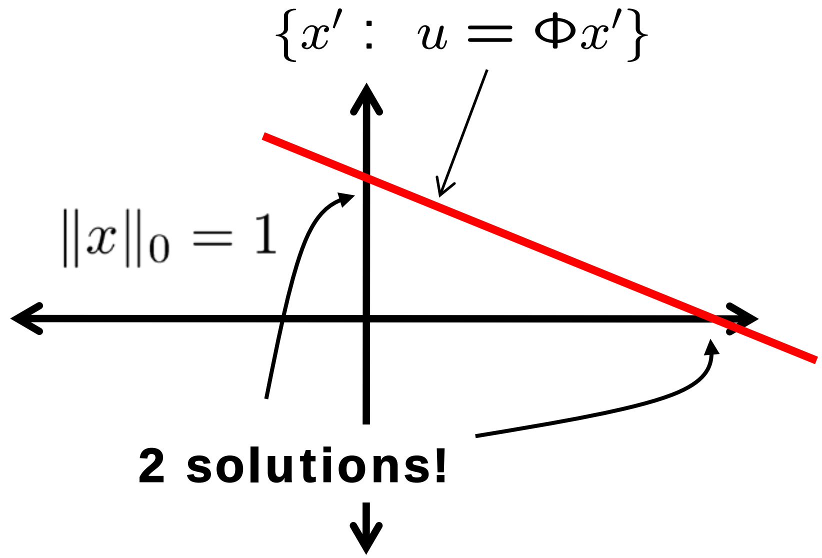
Which one is correct?

Importance of Geometry

- A subtle issue

$\widehat{x} = \arg\min \|x\|_1 \text{ s.t. } u = \Phi x$ $\qquad$ $\widehat{x} = \arg\min \|x\|_0 \text{ s.t. } u = \Phi x$



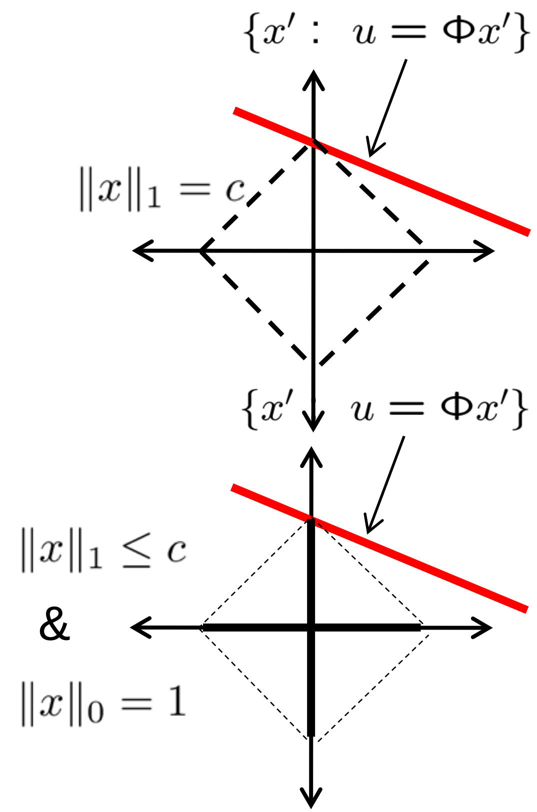


Which one is correct?

EPIC FAIL

CLASH Pseudocode

- Algorithm code @ http://lions.epfl.ch/CLASH
  - Active set expansion
  - Greedy descend
  - Combinatorial selection
  - Least absolute shrinkage
  - De-bias with convex constraint



Minimum 1-norm solution still makes sense!

CLASH Pseudocode

- Algorithm code @ http://lions.epfl.ch/CLASH
  - Active set expansion
  - Greedy descend
  - Combinatorial selection
  - Least absolute shrinkage
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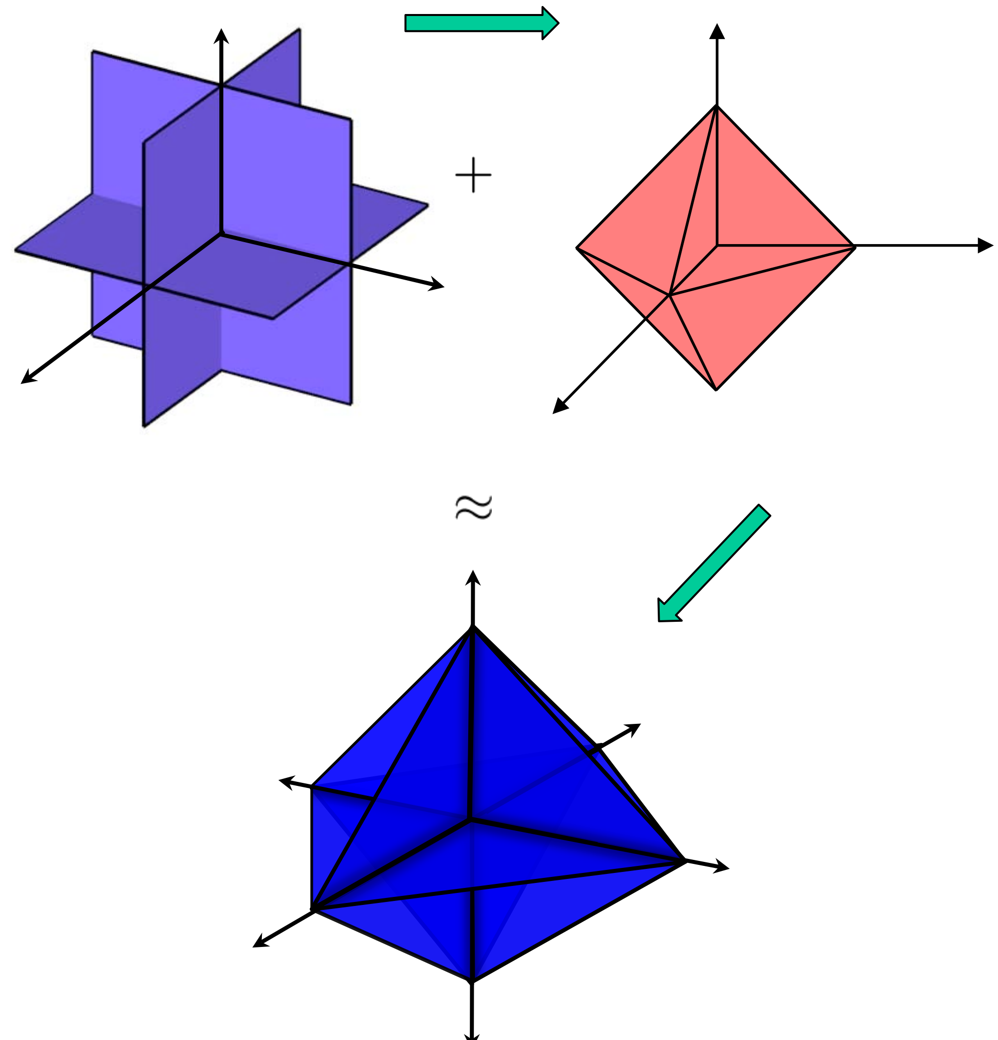
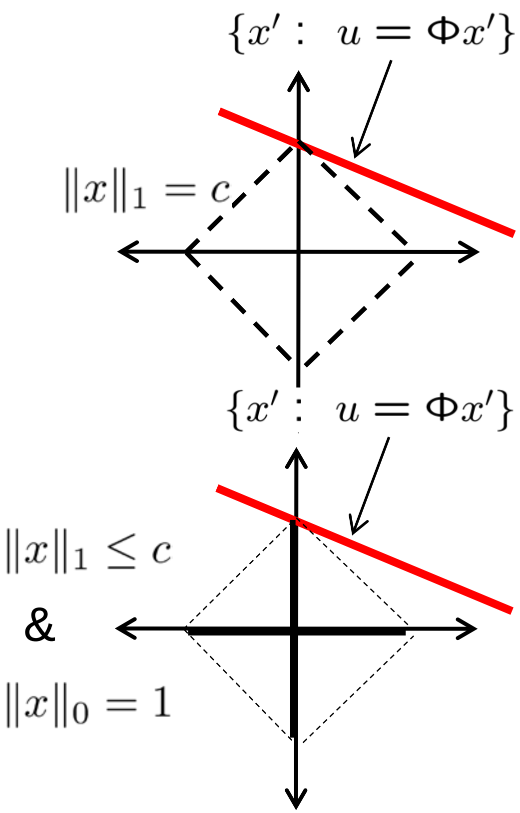


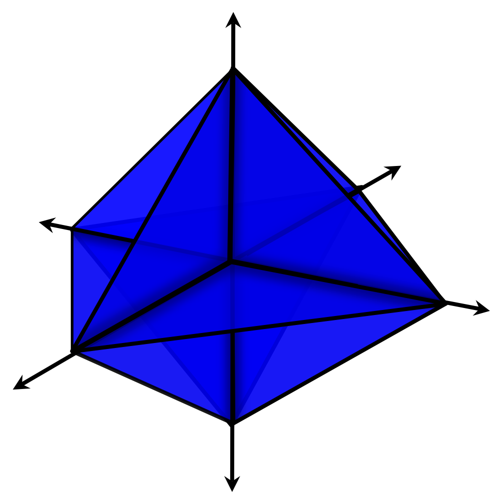
Geometry of CLASH

- Combinatorial selection
  +
  least absolute shrinkage

$$\mathrm{H}_{\{\|x\|_0 \leq K\}}(t) = \arg \min_{\|x\|_0 \leq K} \|x - t\|$$

$$\mathrm{St}_{\{\|x\|_1 \leq \lambda\}}(t) = \arg \min_{\|x\|_1 \leq \lambda} \|x - t\|$$



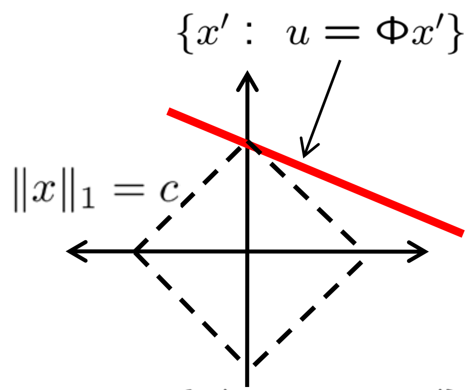


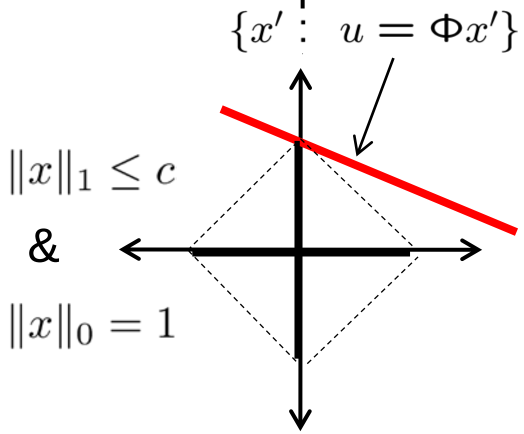
Geometry of CLASH

- Combinatorial selection
  +
  least absolute shrinkage

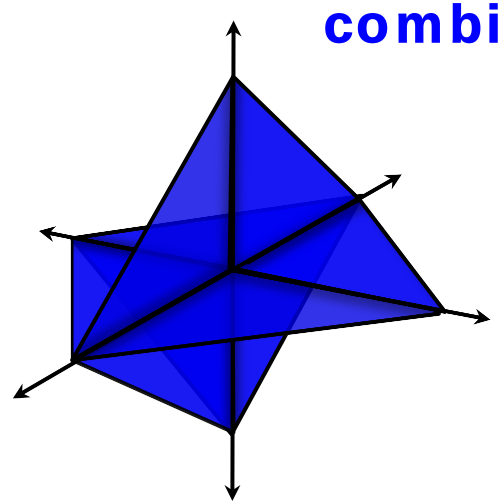
$$\mathrm{H}_{\Sigma_{\mathcal{M}_K}}(y) = \arg \min_{x : x \in \Sigma_{\mathcal{M}_K}} \|x - y\|$$

$$\mathrm{St}_{\{\|x\|_1 \leq \lambda\}}(t) = \arg \min_{\|x\|_1 \leq \lambda} \|x - t\|$$





combinatorial origami



Combinatorial Selection

- A different view of the model-CS workhorse

$$\mathrm{H}_{\Sigma_{\mathcal{M}_K}}(y) = \arg \min_{x : x \in \Sigma_{\mathcal{M}_K}} \|x - y\|$$

(Lemma) support of the solution < > modular approximation problem

$$\mathrm{supp}\left(\arg\min_{x:\mathrm{supp}(x)\in\mathcal{M}_K} \|x-y\|_2^2\right) = \arg\max_{\mathcal{S}:\mathcal{S}\in\bar{\mathcal{M}}_K} F(S;y)$$

indexing set

where $F(S;y) = \sum_{i\in\mathcal{S}} |y_i|^2.$

PMAP

- An algorithmic generalization of union-of-subspaces

  Polynomial time modular epsilon-approximation property: PMAP_ϵ

- Sets with PMAP-0 $F(\widehat{\mathcal{S}}_\epsilon; y) \geq (1-\epsilon) \max_{\mathcal{S}\in\bar{\mathcal{M}}_K} F(\mathcal{S}; y)$

  - **Matroids**

uniform matroids	< >	regular sparsity
partition matroids	< >	block sparsity (disjoint groups)
cographic matroids	< >	rooted connected tree group adapted hull model

  - **Totally unimodular systems**

mutual exclusivity	< >	neuronal spike model
interval constraints	< >	sparsity within groups

Model-CS is applicable for all these cases!

PMAP

- An algorithmic generalization of union-of-subspaces

  Polynomial time modular epsilon-approximation property: PMAP_ϵ

- Sets with PMAP-epsilon $F(\widehat{\mathcal{S}}_\epsilon; y) \geq (1-\epsilon)\max_{\mathcal{S}\in\bar{\mathcal{M}}_K} F(\mathcal{S}; y)$

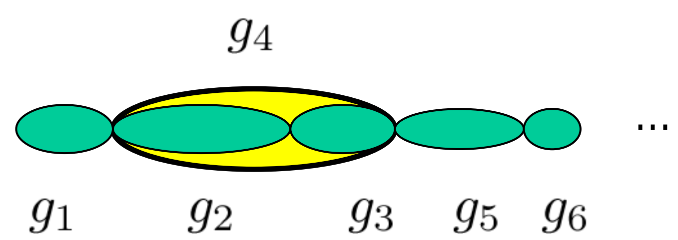
  - **Knapsack**

    multi-knapsack constraints

    weighted multi-knapsack

    quadratic knapsack (?)

  - Define algorithmically!



$$\sum_i z_i \leq G$$

selector variables

$$z_i \in \{0,1\}, \forall i$$

$$z_2 + z_3 \leq 1$$

$$z_2 + z_4 \leq 1$$

$$z_3 + z_4 \leq 1$$

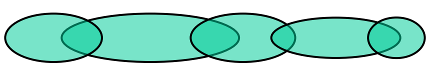
PMAP

- An algorithmic generalization of union-of-subspaces

  Polynomial time modular epsilon-approximation property: PMAP_ϵ

- Sets with PMAP-epsilon $F(\widehat{\mathcal{S}}_\epsilon; y) \geq (1-\epsilon)\max_{\mathcal{S}\in\bar{\mathcal{M}}_K} F(\mathcal{S}; y)$
  - **Knapsack**
  - Define algorithmically!

- Sets with PMAP-???



  - pairwise overlapping groups <> mincut with cardinality constraint

$$\max_{\mathcal{S}:\mathcal{S}\in\bar{\mathcal{M}}_K} F(S;\beta) = -\min\left\{\sum_{i>j}\|(\beta)_{g_i\cap g_j}\|_2^2 z_i z_j - \sum_i \|(\beta)_{g_i}\|_2^2 z_i : \sum_i z_i \leq G\right\}.$$

CLASH Approximation Guarantees

- PMAP / downward compatibility

$$\text{SNR} = \frac{\|x^*\|}{\sqrt{f(x^*)}}$$

$$\frac{\|x_{i+1} - x^*\|_2}{\|x^*\|_2} \leq \rho \frac{\|x_i - x^*\|_2}{\|x^*\|_2} + \frac{c_1(\delta_{2K}, \delta_{3K}, \epsilon)}{\text{SNR}} + c_2(\delta_{2K}, \delta_{3K}, \epsilon) + c_3(\delta_{2K}, \delta_{3K}, \epsilon)\sqrt{\frac{1}{\text{SNR}}}$$

$$\rho = \frac{\delta_{3K} + \delta_{2K} + \sqrt{\epsilon}(1+\delta_{2K})}{\sqrt{1-\delta_{2K}^2}} \sqrt{\frac{1+\left((1-\epsilon)+2\sqrt{1-\epsilon}\right)\delta_{3K}^2 + 2\delta_{3K}\sqrt{\epsilon}+\epsilon}{1-\delta_{3K}^2}}$$

$$c_2(\delta_{2K}, \delta_{3K}, \epsilon) = O(\delta_{3K}\sqrt{\epsilon} + \epsilon)$$

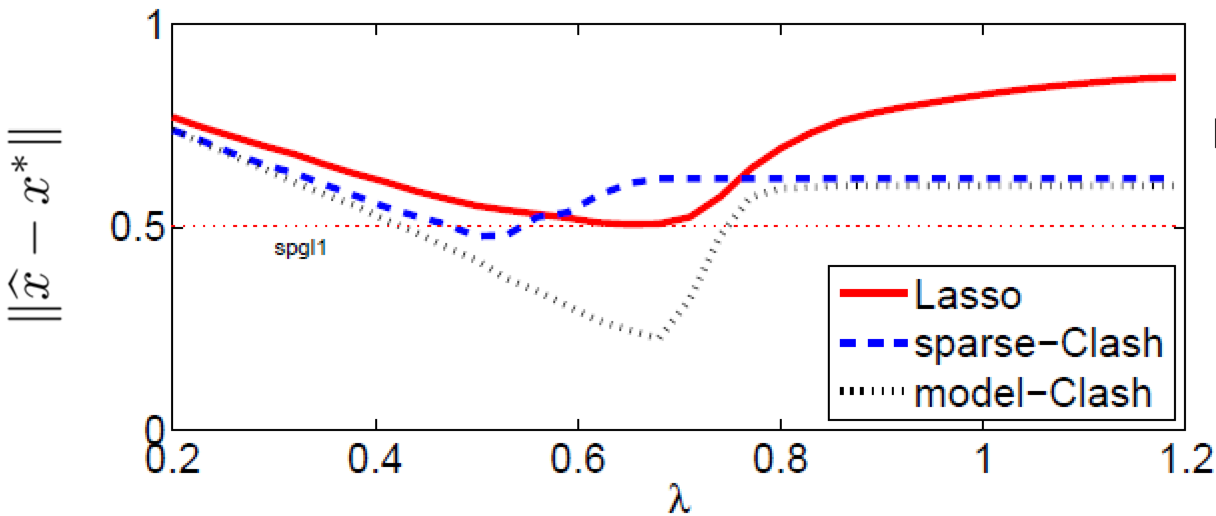
  - precise formulae are in the paper

  http://lions.epfl.ch/CLASH

- Isometry requirement (PMAP-0) <> $\delta_{3K} < 0.3658$

Examples

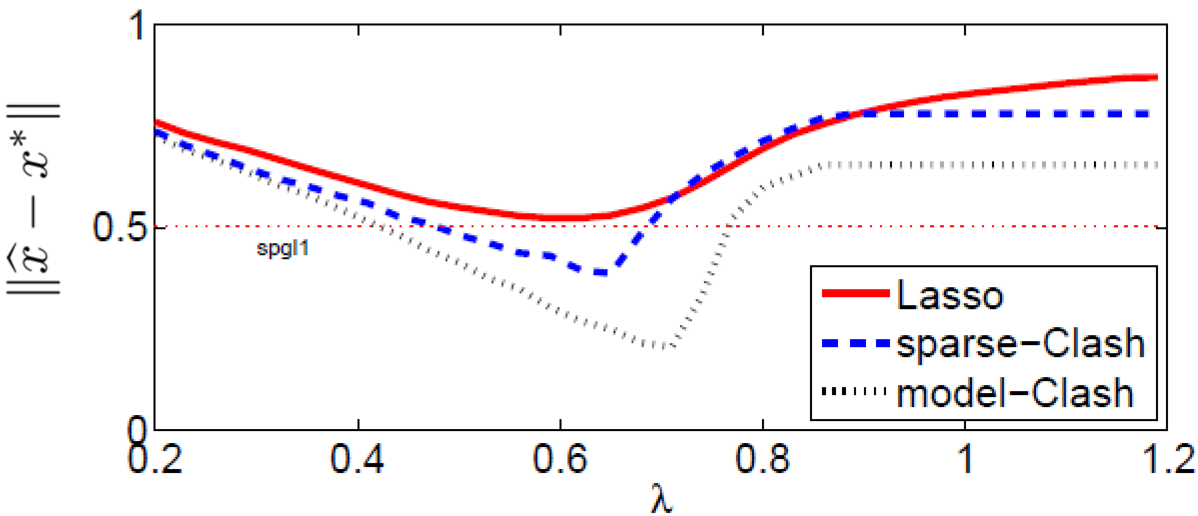
sparse matrix



Model: (K,C)-clustered model

O(KCN) – per iteration

~10-15 iterations

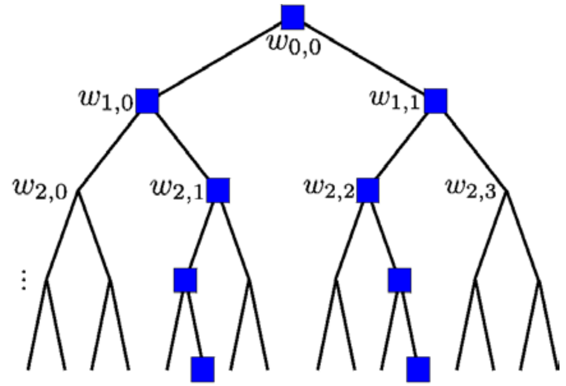


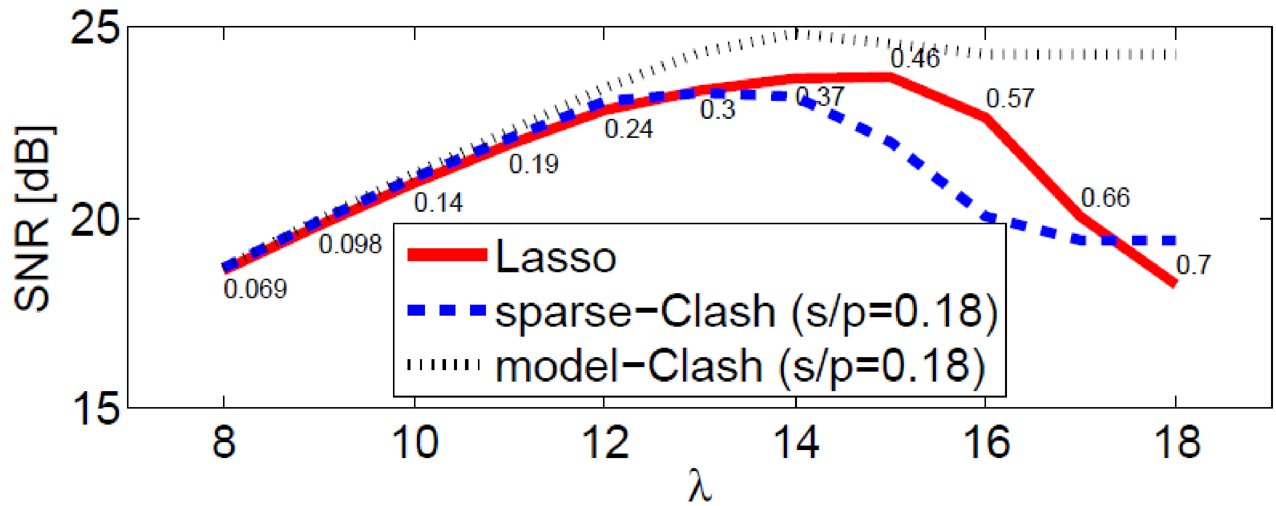
Model: partition model / TU

LP – per iteration

~20-25 iterations

Examples





CCD array readout via noiselets

Conclusions

- CLASH NEW! < > combinatorial selection
  +
  convex geometry
  $\lambda \to \infty \Rightarrow$ model-CS
- PMAP-epsilon NEW! < > inherent difficulty in combinatorial selection
  - beyond simple selection towards provable solution quality
    +
    runtime/space bounds
  - algorithmic definition of sparsity + many models
    matroids, TU, knapsack,...
- Postdoc position @ LIONS / EPFL

  contact: volkan.cevher@epfl.ch

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