

# Model Selection for Low Complexity Priors

**Samuel Vaiter**<sup>1</sup>, Jalal Fadili and Gabriel Peyré

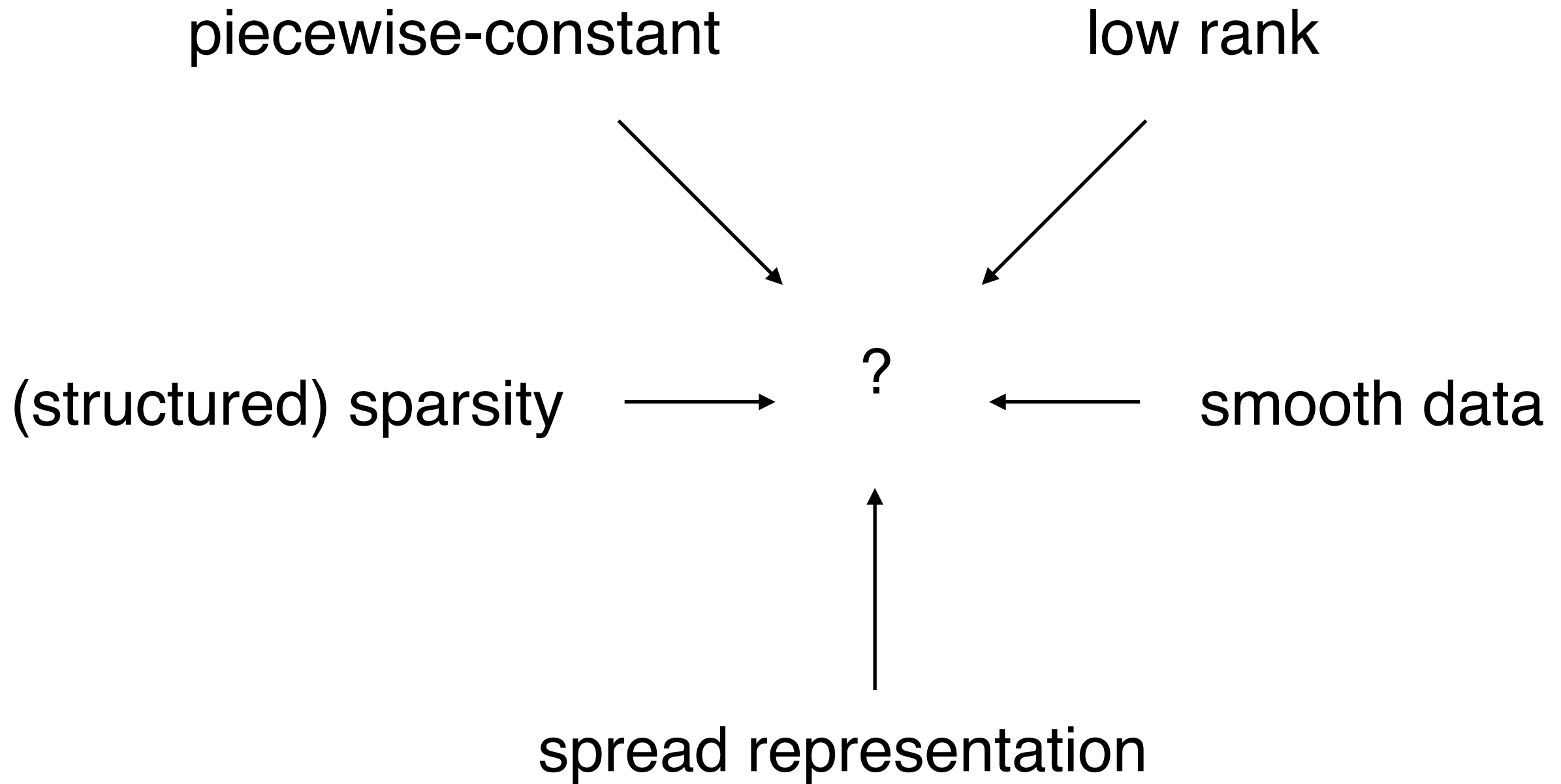
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@SIAM IS



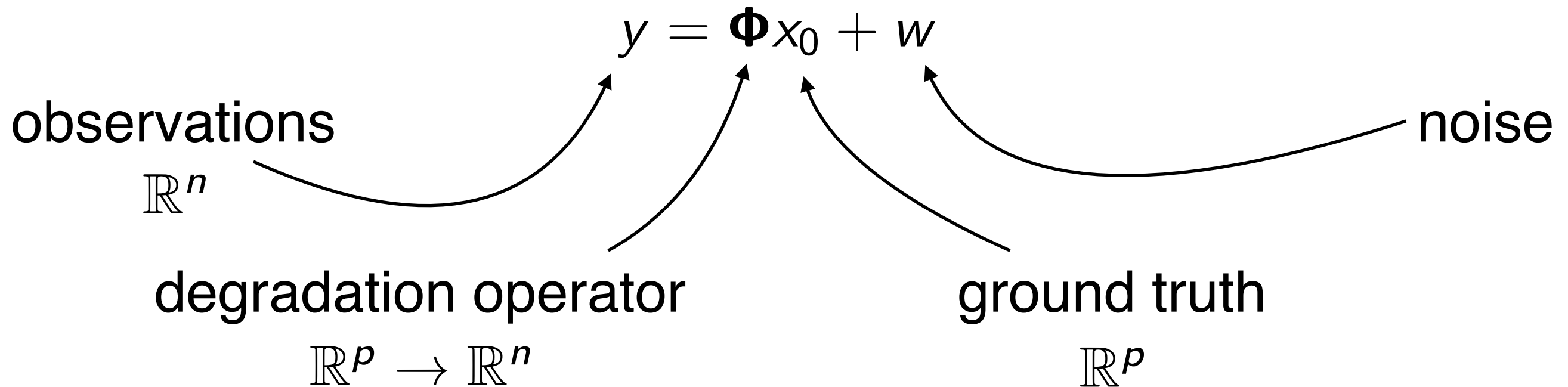
# Context

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# Inverse Problem and Variational Methods

*Inverse problem / regression setting*



*Variational methods*

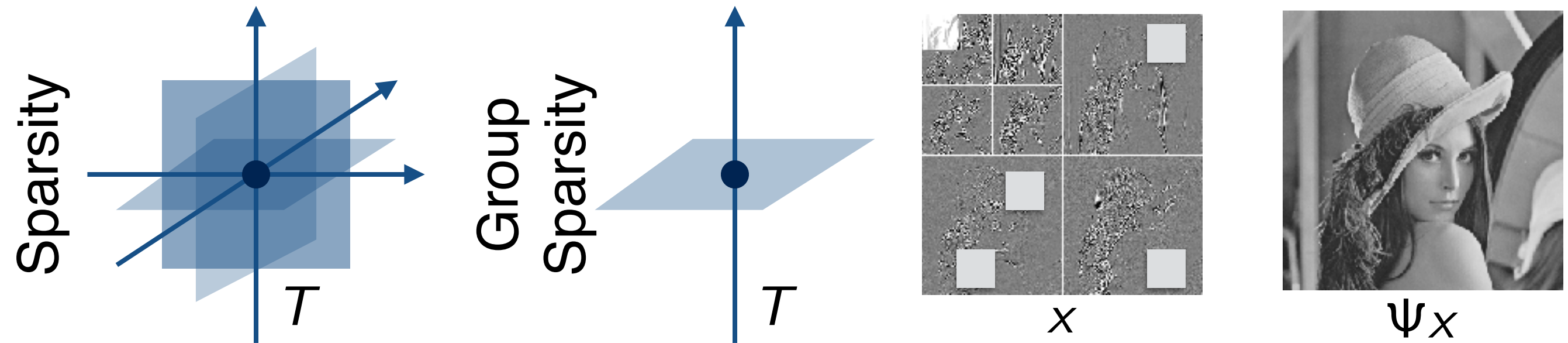
compromise

$$\hat{x}_\lambda(y) \in \underset{x \in \mathbb{R}^p}{\text{Argmin}} F(\Phi x, y) + \lambda J(x)$$

data fidelity "regularization"

BPDN / LASSO  
Total Variation  
Nuclear  
...

# Union of Models



- combinatorial candidate  $\|x\|_0 = |\text{supp}(x)|$
- convex candidate  $\|x\|_1 = \sum |x_i|$

How to relate the model  $T$  and the functional  $J$  ?

# What kind of results ?

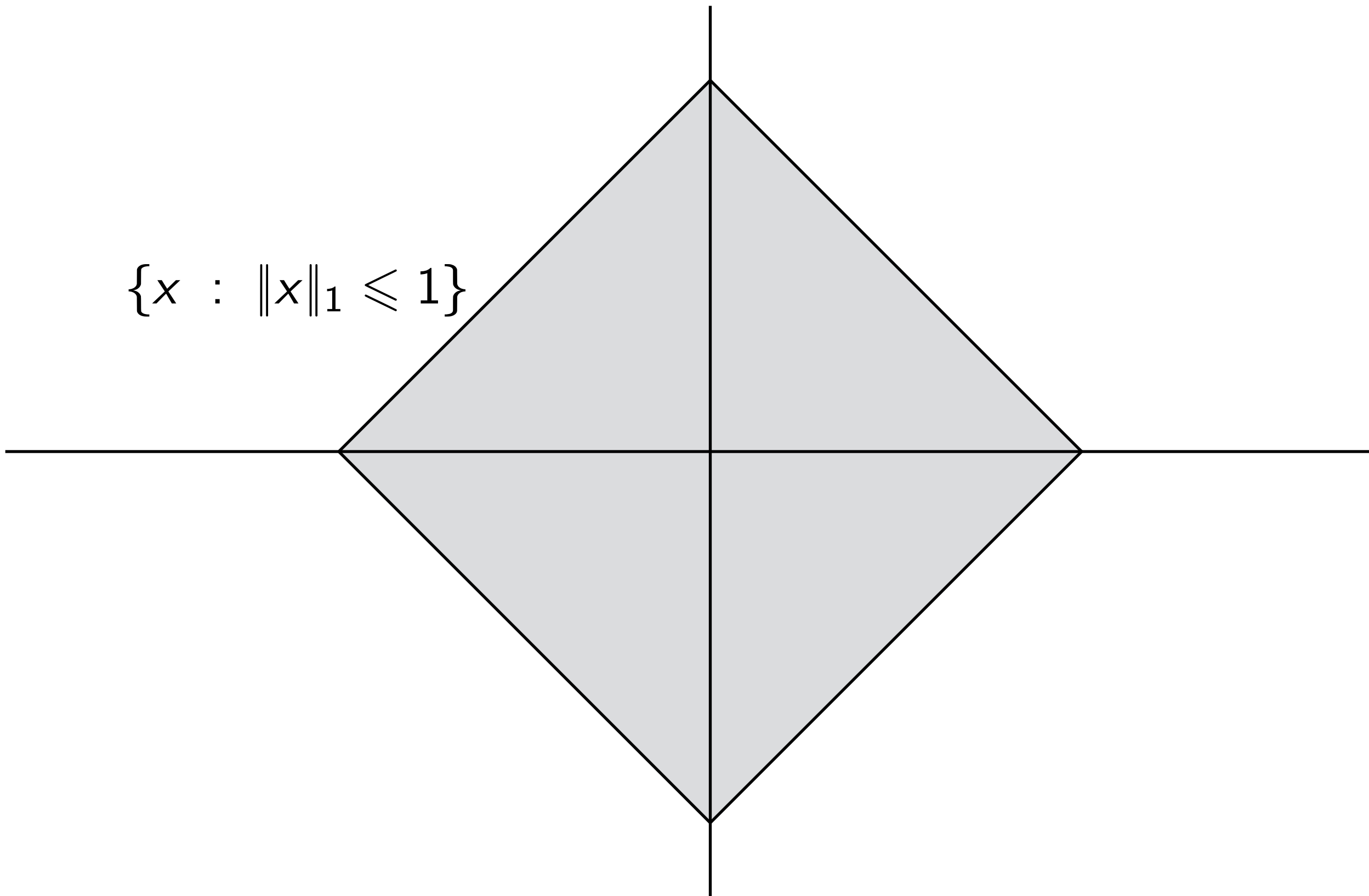
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- (deterministic and non-uniform)  $\ell^2$  stability
- (random/deterministic and non-uniform) model stability
- degrees of freedom (DoF) computation
- efficient risk estimation

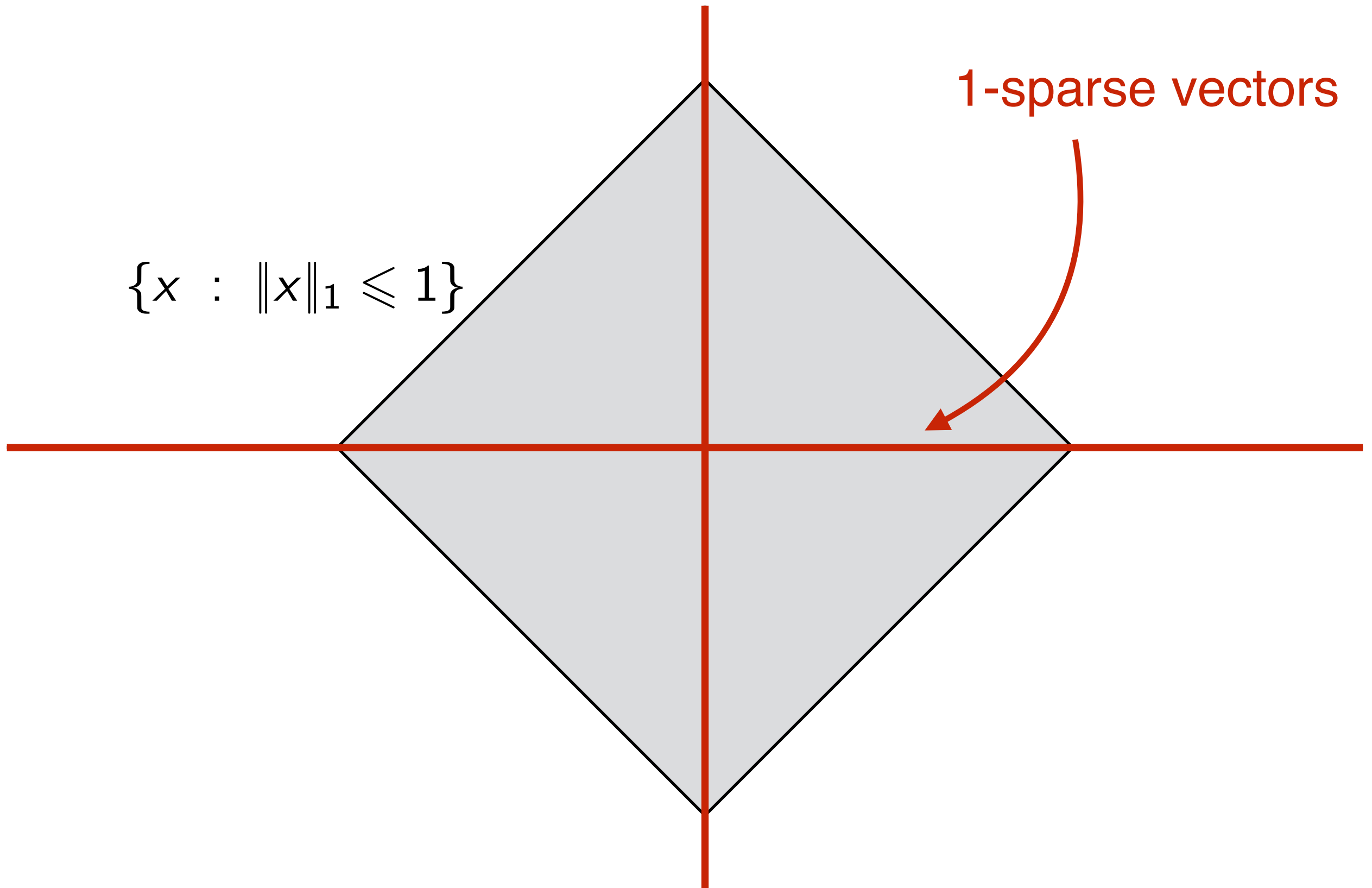
# Combinatorial and Convex Objects

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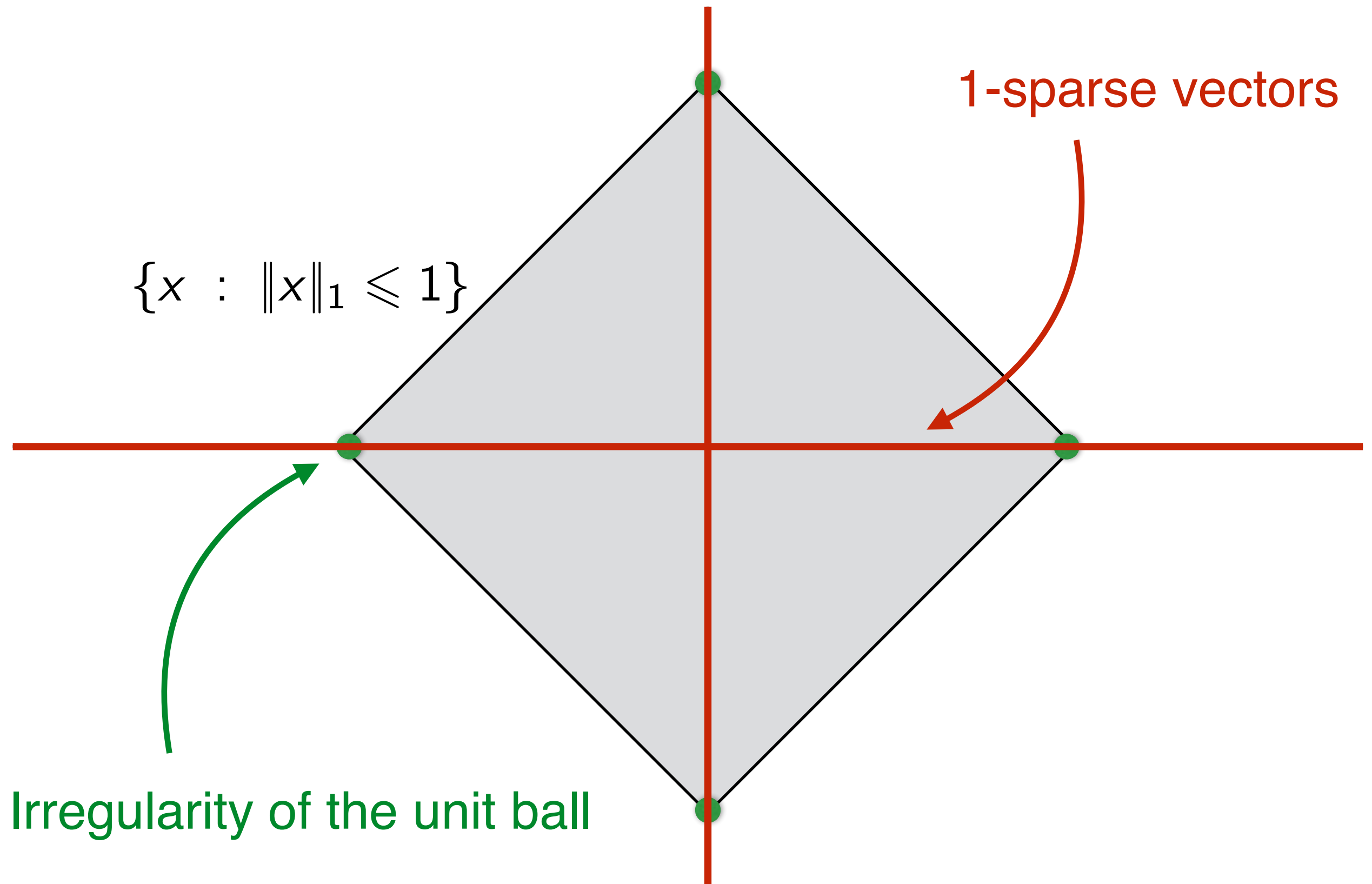
$$\{x : \|x\|_1 \leq 1\}$$



# Combinatorial and Convex Objects



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# A Decomposability Point of View

Proposition

$$\partial \|\cdot\|_1(x) = \{\eta \in \mathbb{R}^n : \eta_I = \text{sign}(x)_I \text{ and } \|\eta_J\|_\infty \leq 1\}$$

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## Definition (*Decomposable norm* [Candes-Recht '12])

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## Proposition [V. et al. '15]

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## Definition (*Partly smooth wrt linear model* [V. et al. '15])

$T_x, e_x, f_x$  “Lipschitz”-continuous

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## Proposition [V. et al. '15]

Almost all regularizers are PSL ... **except** the nuclear norm :(

# Combinatorial and Convex Objects

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$\text{Sym}_2(\mathbb{R})$

$$\begin{pmatrix} a & b \\ b & c \end{pmatrix}$$



$\mathbb{R}^3$

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

Matrix of rank 1 (+ zero vector)

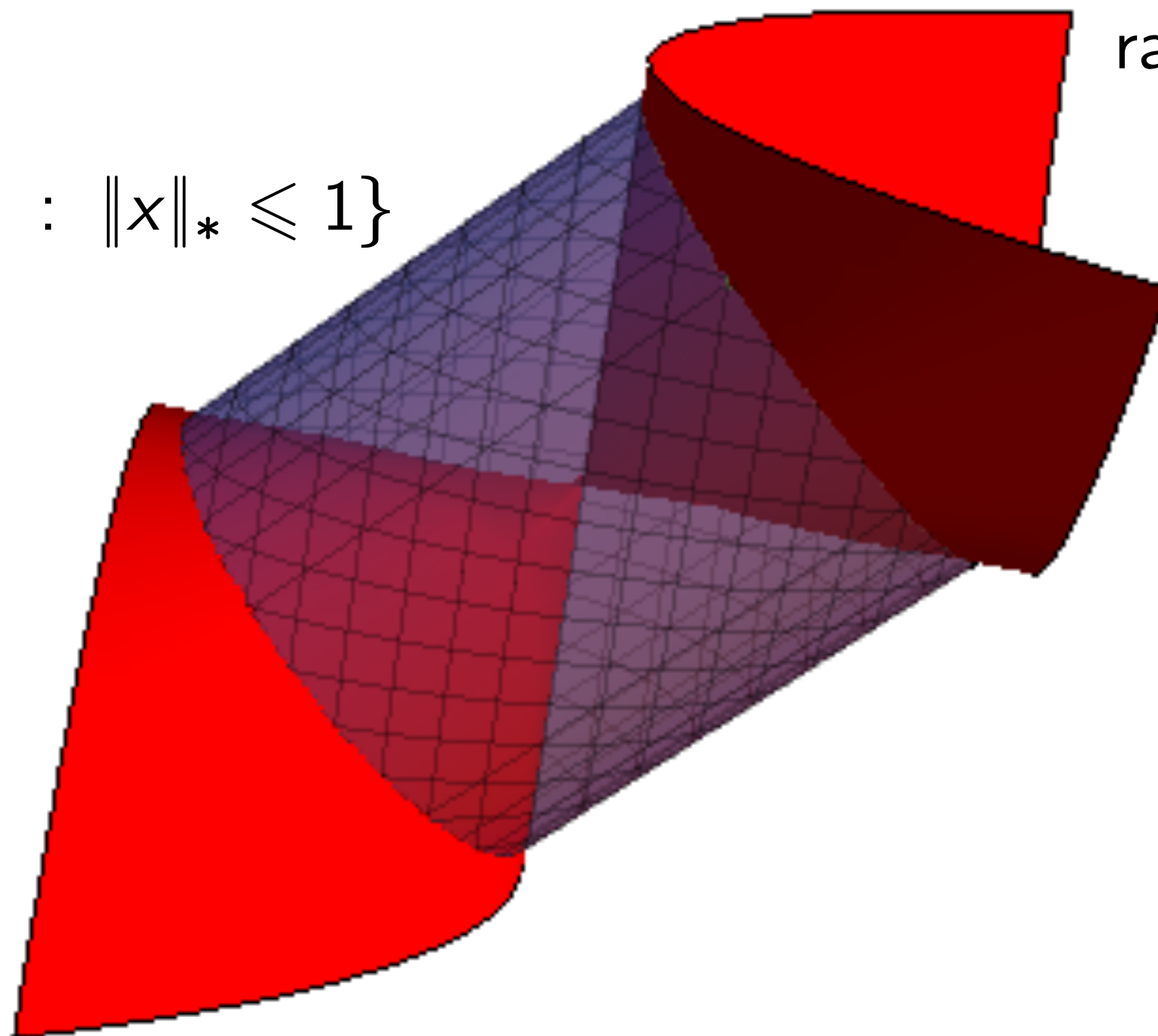
$$ac - b^2 = 0 \rightarrow \text{curve of degree 2}$$

Matrix of unit nuclear norm

finite cylinder

# Combinatorial and Convex Objects

$$\{x : \|x\|_* \leq 1\}$$

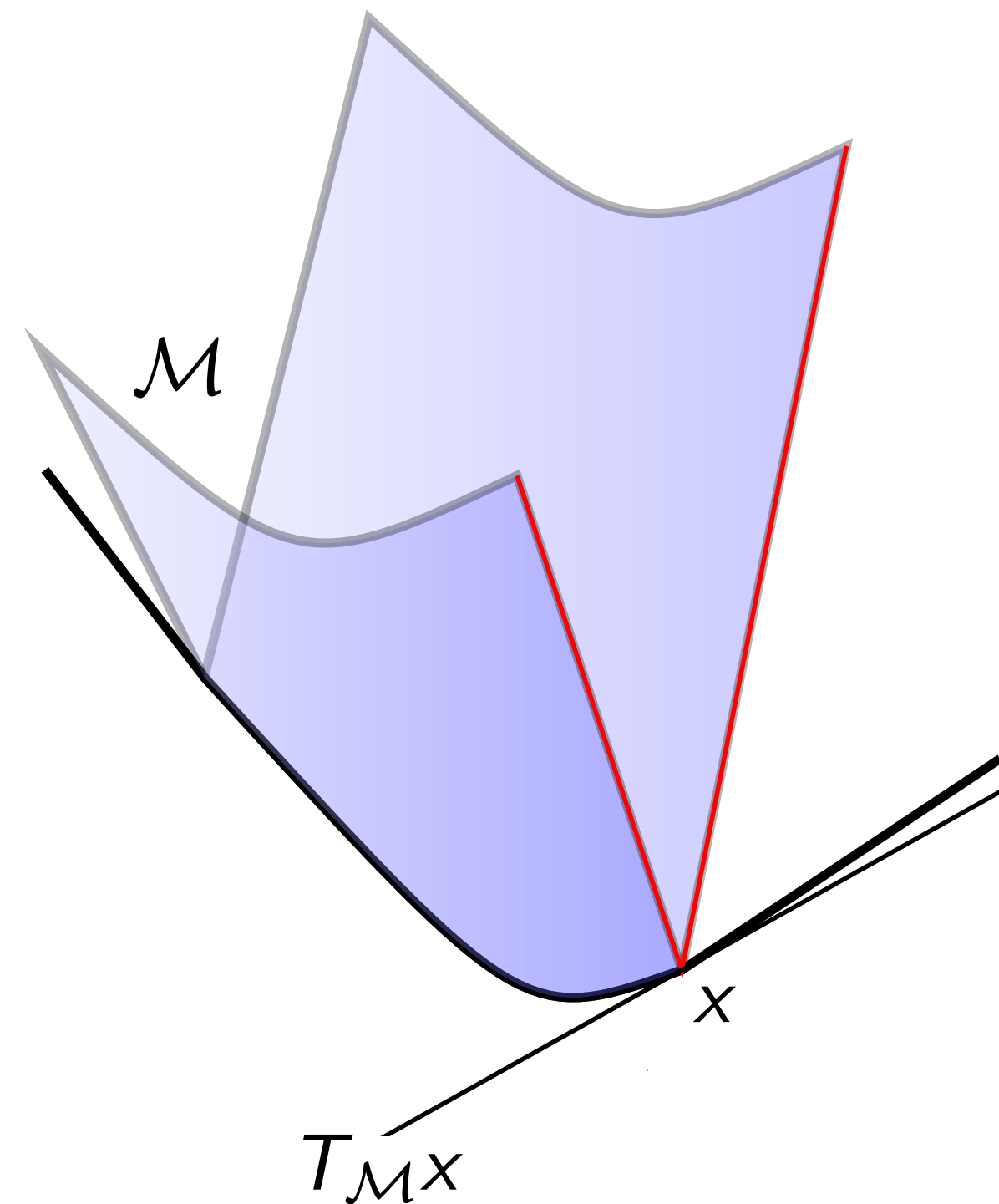


rank  $x = 1$



# Partial Smoothness

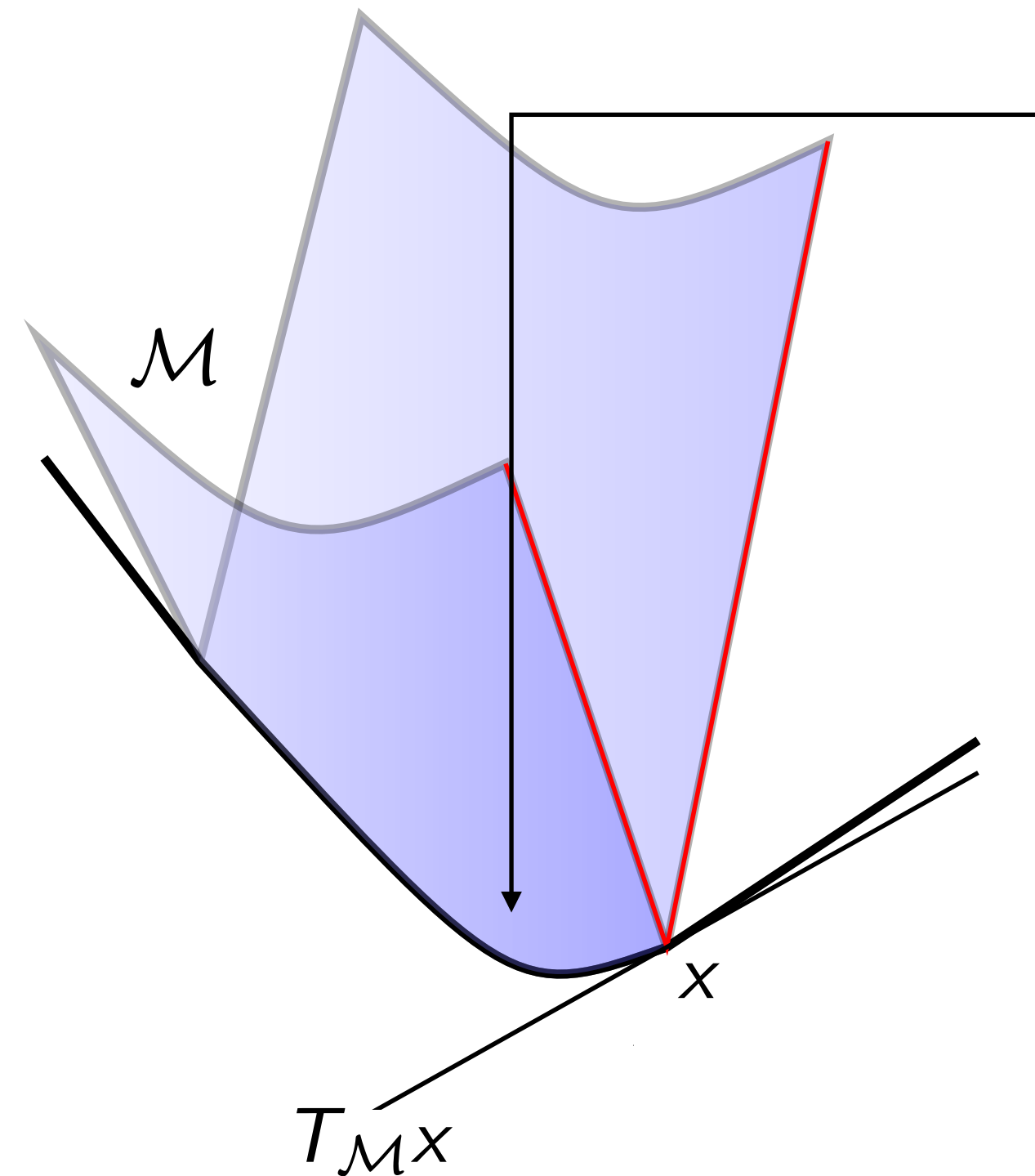
*Partly smooth function* [Lewis '02]



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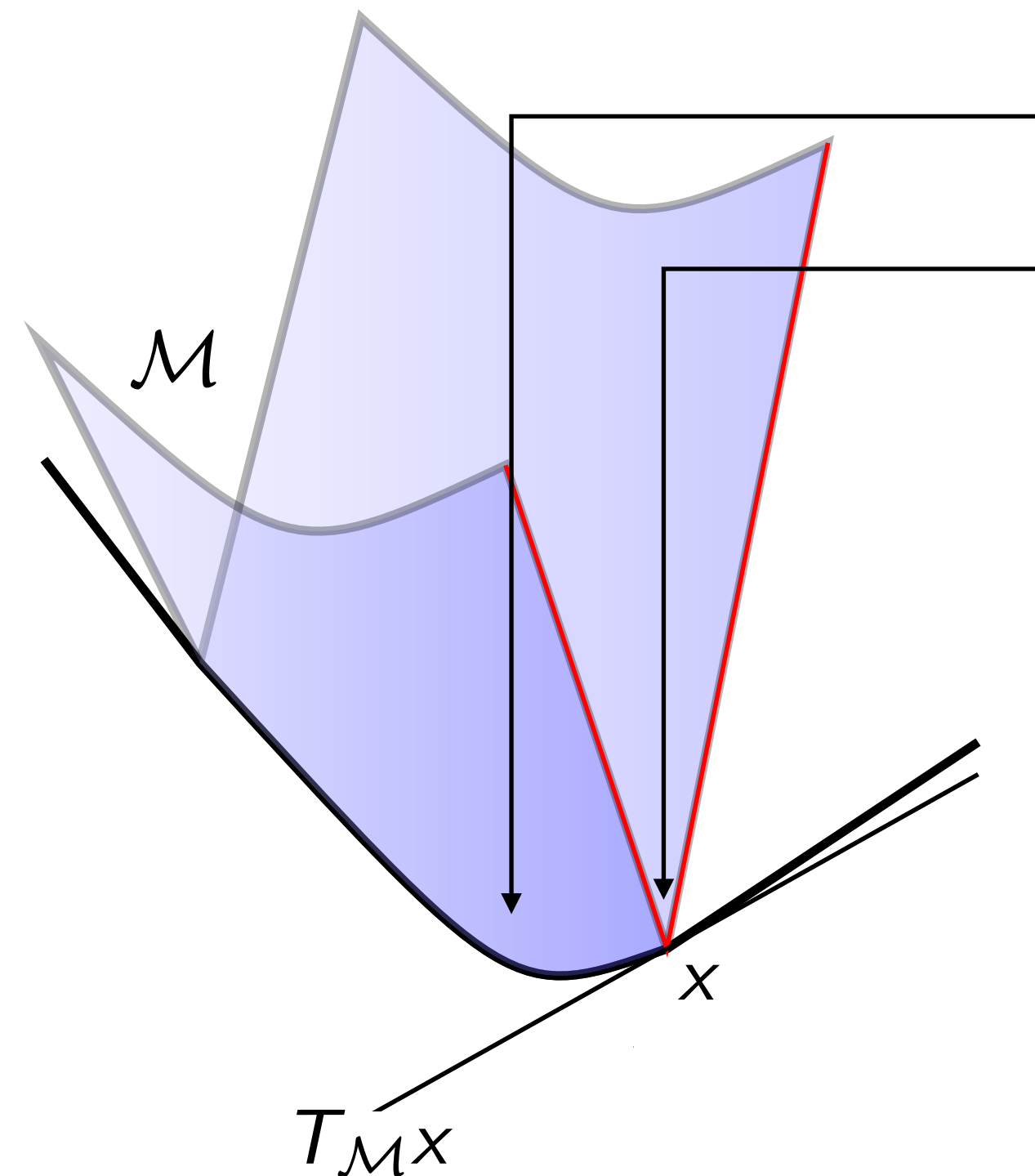
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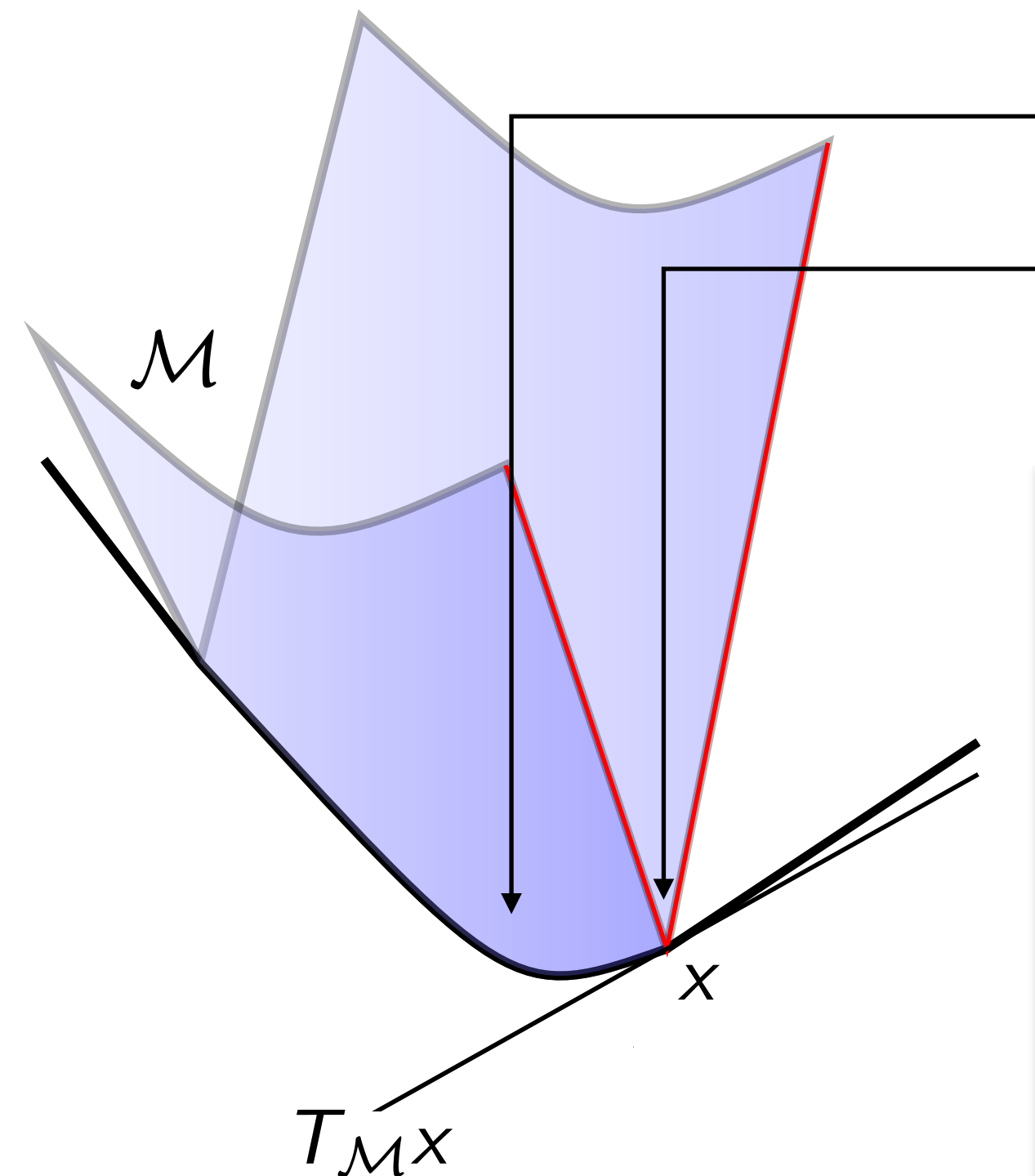


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$\forall h \in (T_{\mathcal{M}x})^\perp, t \mapsto J(x + th)$   
not smooth at 0

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*Examples*

$\|\cdot\|_1, \|\nabla \cdot\|_1, \|\cdot\|_{1,2}, \|\cdot\|_*, \|\cdot\|_\infty, \dots$

*Algebraic stability*

Sum, precomposition by a linear operator and spectral lift are stable within the class of PS.

# Linearized Precertificate

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Minimal norm certificate

$$p_0 = \operatorname{argmin}_{\Phi^* p \in \partial J(x_0)} \|p\|$$

Linearized **pre**certificate

$$p_F = \operatorname{argmin}_{\Phi^* p \in \text{Aff} \partial J(x_0)} \|p\|$$

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*Example: Sparse Regularization (BPDN, Lasso)*

$$\Phi^* p_F \in \operatorname{ri} \partial \|\cdot\|_1(x_0) \Leftrightarrow \max_{j \in I^c} |\langle \Phi_j, \Phi_I (\Phi_I^* \Phi_I)^{-1} \operatorname{sign}(x_0)_I \rangle| < 1$$



# Model Stability

## Theorem

Assume  $J$  is PS at  $x_0$  relative to  $\mathcal{M}$ . Suppose

$$\Phi^* p_F \in \text{ri } \partial J(x_0) \quad \text{and} \quad \text{Ker } \Phi \cap T_{x_0} = \{0\}$$

There exists  $C > 0$  such that if  $\max(\lambda, \|w\|/\lambda) \leq C$ , the unique solution of  $x^*$  of  $(\mathcal{P}_{y,\lambda})$  satisfies

$$x^* \in \mathcal{M}_{x_0}$$

model stability

$$\|x^* - x_0\| = O(\|w\|)$$

$\ell^2$ -stability

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$$\begin{array}{ll} x^* \in \mathcal{M}_{x_0} & \text{model stability} \\ \|x^* - x_0\| = O(\|w\|) & \ell^2\text{-stability} \end{array}$$

## Tightness

If  $\Phi^* p_F \notin \partial J(x_0) \Rightarrow x^* \notin \mathcal{M}_{x_0}$  no model stability

If  $\Phi^* p_F \in \text{bd } \partial J(x_0) \Rightarrow \text{case-by-case}$

# Identification in Finite Time

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Forward—Backward scheme

$$x^{k+1} = \text{Prox}_{\rho J}(x^k - \rho \nabla F(x^k))$$

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There exists  $C > 0$  such that if  $\max(\lambda, \|w\|/\lambda) \leq C$ , and

$\rho < 2/\|\Phi\|$ , one has

$$x^k \rightarrow x_0$$

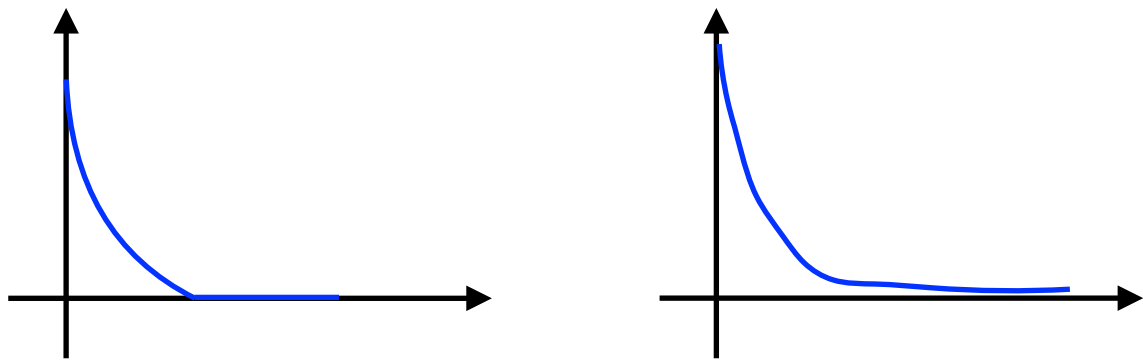
$$\exists k_0, \forall k \geq k_0, x^k \in \mathcal{M}_{x_0}$$

convergence

finite identification

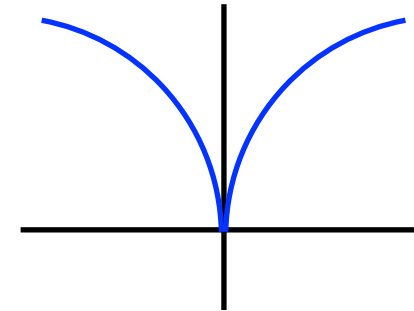
# Perspectives

*approximate model*



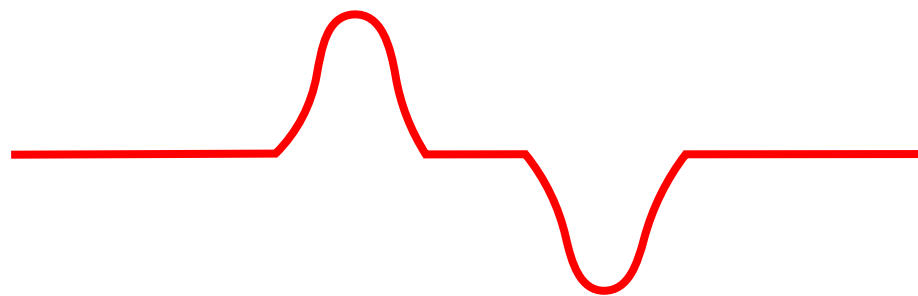
e.g. weak  $\ell^p$  space

*non-convex regularization*



e.g.  $\| \cdot \|_p$  with  $0 < p < 1$

*infinite dimension*



e.g. C-BP, C-ROF

*algorithmic implication*

other algorithms,  
accelerations

see Liang et al.

# Thanks for your attention

Want more ?

Review book chapter:

*V., G. Peyré, J. Fadili, Low Complexity Regularizations, LNCS, 2014*

Model selection/consistency:

*V., G. Peyré, J. Fadili, Manifold Consistency with Partly Smooth Regularizers, TIT 2017*

Special case for analysis sparsity:

*V., C. Dossal, G. Peyré, J. Fadili, Robust Sparse Analysis Regularization, TIT, 2013*

# *Example:* Nuclear Norm Regularization

