

$$y = W^H \xrightarrow{A} W \cdot \text{image}$$

↓ sparse

$10^6 \times 10^6$  orth. wavelet transform

$$y = \mathcal{D} x$$

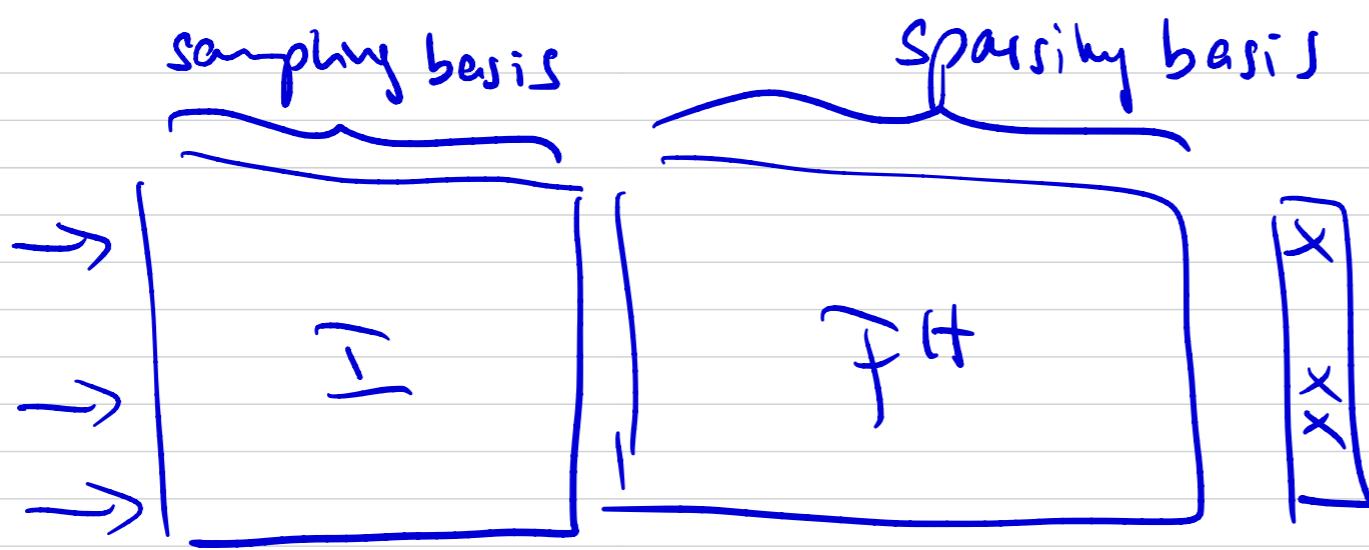
↓

$$\mathcal{D} = [d_1 \ d_2 \ \dots \ d_n]$$

$$y = \mathcal{D}x = \sum_{i=1}^s d_i x_i$$

observation  $\Rightarrow \mathcal{F}^H$

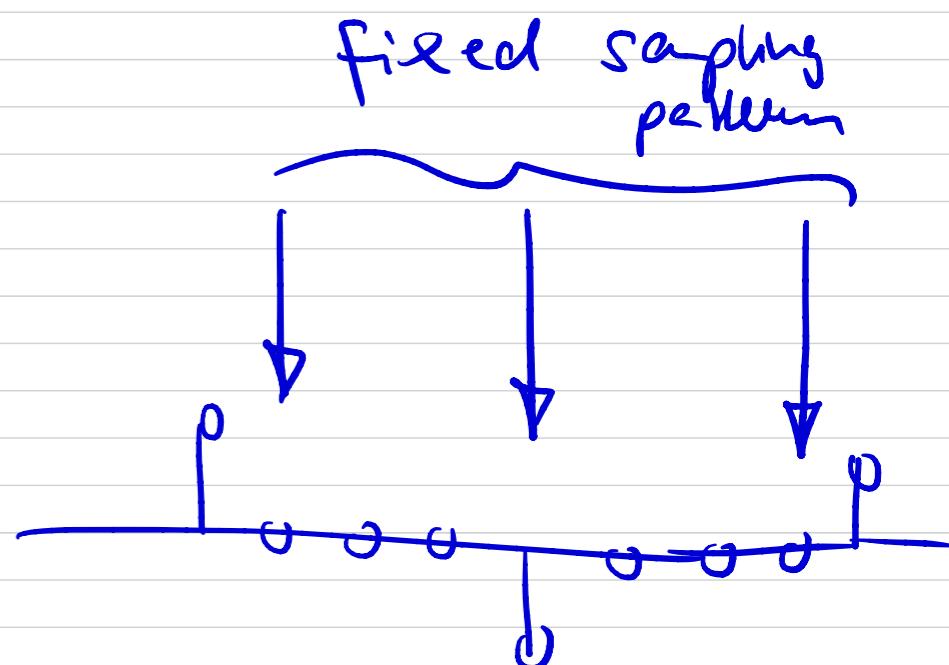
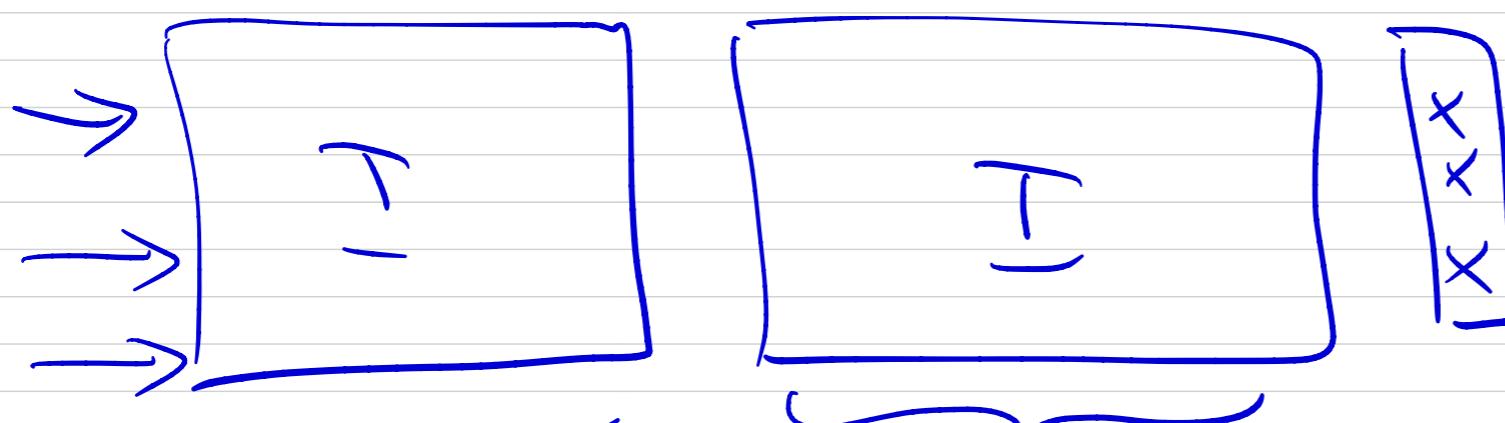
$x(t) = \int_{-\infty}^{\infty} \hat{x}(f) e^{i\pi f t} df$



$$y = \mathcal{D}x$$

$$\left( \rightarrow \begin{bmatrix} I \\ I \end{bmatrix} \mathcal{D} = \begin{bmatrix} x \\ x \end{bmatrix} \right)$$

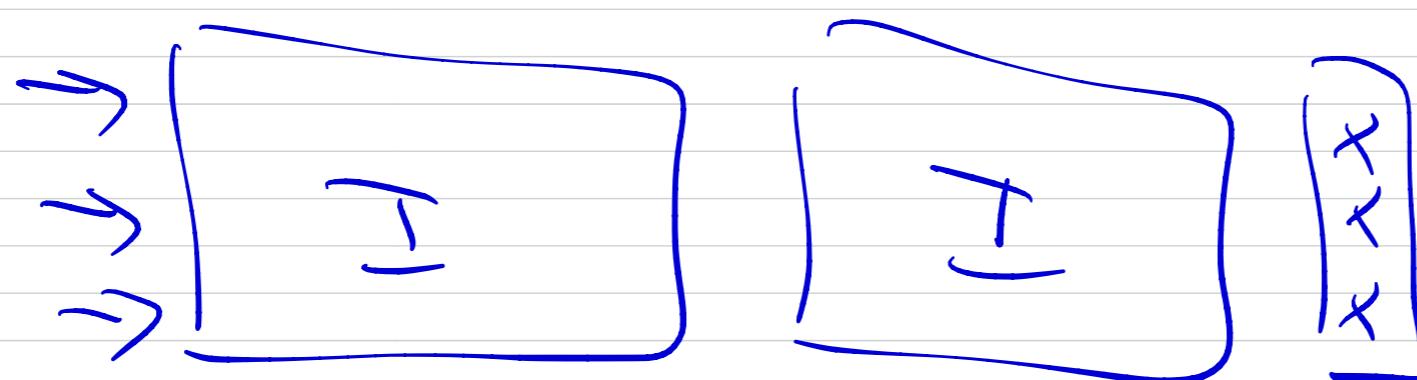
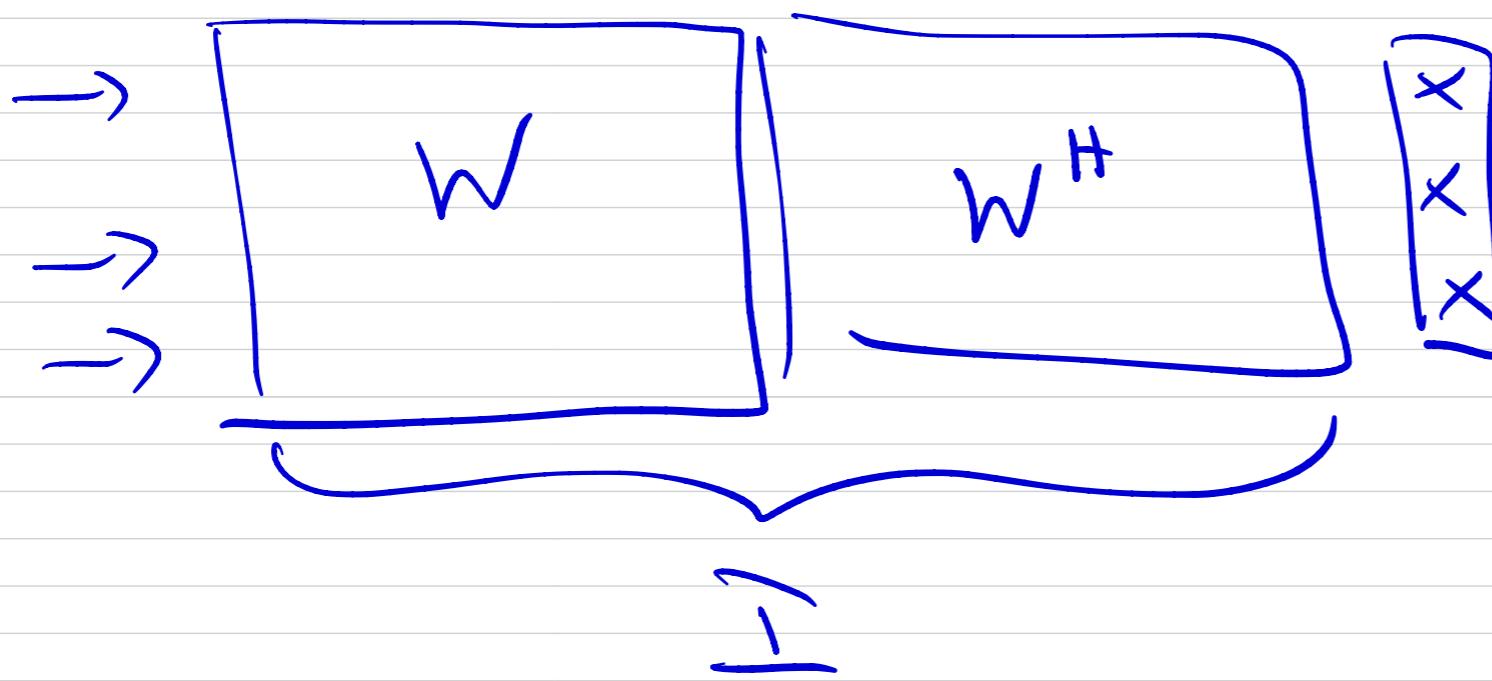
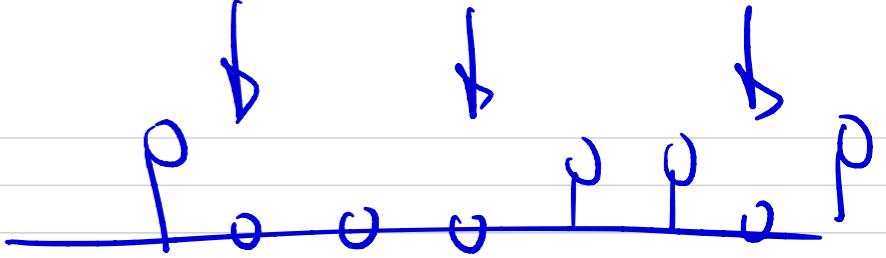
a



Sampling basis

$$I^H = I$$

$$W^H = W$$



### 3.2.2. The general problem

$$\mathcal{D} = \boxed{\text{(Sub)sampling}} \quad \boxed{\text{sparsity basis}} = \boxed{\quad}$$

e.g.  $\mathcal{F}^H, W^H$

$$y = \mathcal{D} x$$

□

Uniqueness of recovery

$$y_1 = \mathcal{D} x_1$$

$$\|x_1\|_0 \leq s, \|x_2\|_0 \leq s$$

$$y_2 = \mathcal{D} x_2$$

$$\text{if } x_1 \neq x_2 \Rightarrow y_1 \neq y_2$$

want to ensure that the following does not happen

$$y_1 = y_2 = y : 0 = y - y = \mathcal{D} x_1 - \mathcal{D} x_2 = \mathcal{D} (\underbrace{x_1 - x_2})$$

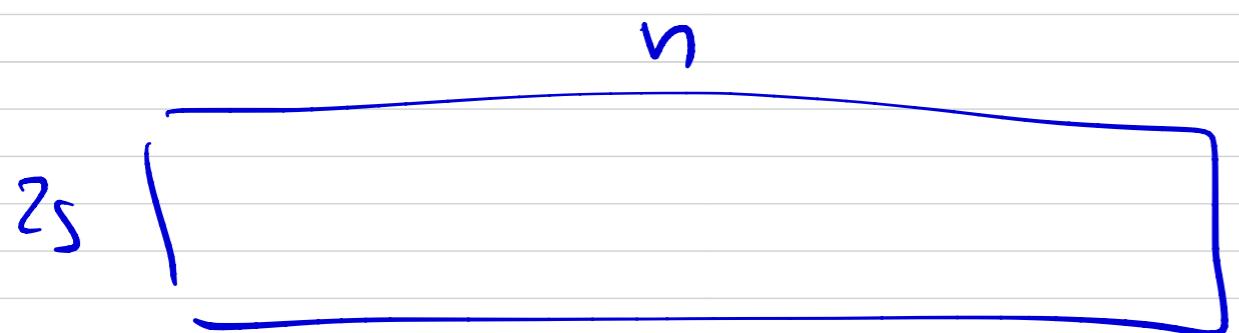
$$\|x_1 - x_2\|_0 \leq 2s$$

- need to ensure that every set of 2s or fewer columns of  $\mathcal{D}$  is linearly independent.

Def. 3.1. The spark of a matrix  $A$ , denoted by  $\text{spark}(A)$ , is defined

as the cardinality of the smallest set of linearly dependent columns of  $\mathcal{D}$ .

To get uniqueness of recovery, we need  $\mathcal{D}$  to have  $\geq 2s$  rows, this is often referred to as "sampling" at the Landau rate.



$$\text{Uniqueness of recovery} \Rightarrow s < \frac{\text{spars}(\mathcal{D})}{2}$$

### 3.3. The (PO) recovery algorithm

$$y = \mathcal{D}x_{\text{true}}$$

If  $x$  is  $s$ -sparse and

$$s < \frac{\text{spars}(\mathcal{D})}{2}$$

we can recover  $x$  through a combinatorial search:

$$(\text{PO}) \quad \text{find } x \text{ s.t. } \|x\|_0 \text{ subject to } y = \mathcal{D}x$$

Proof of (P0) delivering the correct solution:

Suppose that  $\|x\|_0 \leq s$  and  $s < \frac{\text{spark}(\mathcal{D})}{2}$ . Consider  $\hat{x} \neq x$  with  $\|\hat{x}\|_0 \leq s$  and  $y = \mathcal{D}\hat{x}$ .

$$0 = y - y = \mathcal{D}x - \mathcal{D}\hat{x} = \mathcal{D}(\underbrace{x - \hat{x}}_{\text{2}s-\text{sparse}}) \xrightarrow{\text{to}} \text{contradiction.}$$

$$\mu(\mathcal{D}) = \max_{r \neq e} |\langle \mathcal{D}e, \mathcal{D}r \rangle|$$

$\mathcal{D} \in \mathbb{C}^{m \times n}$

Theorem 3.2. (P0) applied to  $y = \mathcal{D}x$  recovers  $x$  if

$$\underbrace{\|x\|_0 \leq s}_{\text{sparsity is } s} < \frac{1}{2} \left( 1 + \frac{1}{\mu(\mathcal{D})} \right)$$

Proof. show that  $\text{spark}(\mathcal{D}) \geq 1 + \frac{1}{\mu(\mathcal{D})}$

$$\left( s < \frac{\text{spark}(D)}{2} \right)$$

consider  $x \in \mathbb{C}^n$ , with  $\|x\|_0 = \text{spark}(D)$  and  $Dx = 0$

$$Dx = \sum_{r=1}^n d_r x_r = 0$$

$$d_e x_l = - \sum_{\substack{r=1 \\ r \neq l}}^n d_r x_r \quad | \quad d_e^\#.$$

$$\underbrace{d_e^\# d_e}_{1} x_l = - \sum_{\substack{r=1 \\ r \neq l}}^n d_e^\# d_r x_r$$

$$\begin{aligned} |x_l| &= \left| \sum_{\substack{r=1 \\ r \neq l}}^n d_e^\# d_r x_r \right| \leq \sum_{\substack{r=1 \\ r \neq l}}^n |d_e^\# d_r| |x_r| \leq \\ &\leq \mu(D) \sum_{\substack{r=1 \\ r \neq l}}^n |x_r| \end{aligned}$$

add  $\mu(\mathcal{D})|x_e|$

$$(1 + \mu(\mathcal{D}))|x_e| \leq \mu(\mathcal{D}) \sum_{r=1}^n |x_r|$$

$\overbrace{\quad\quad\quad}^{||x||_1}$

Sum over all  $e$  for which  $x_e \neq 0$

$$(1 + \mu(\mathcal{D}))||x||_1 \leq \mu(\mathcal{D})||x||_1 \text{spark}(\mathcal{D})$$

$$\text{spark}(\mathcal{D}) \geq 1 + \frac{1}{\mu(\mathcal{D})}. \quad \square$$

### 3.4. Basis pursuit (BP)

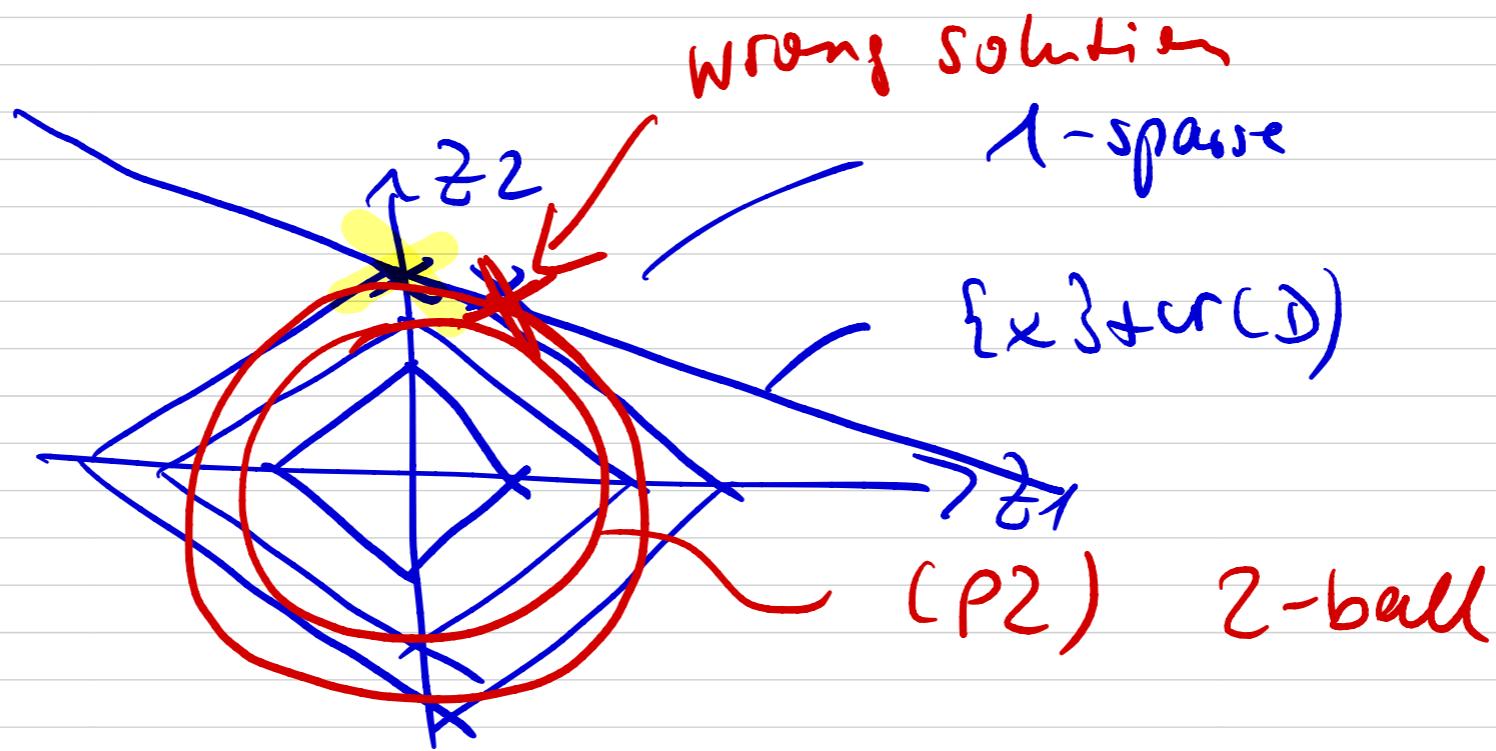
(P1) Find  $\arg \min ||x||_1$  subject to  $y = Dx$

Convex optimization problem  $\Rightarrow$  numerous algorithms available

why does  $\ell_1$ -reconstruction work?

$\arg \min \|z\|_1$  subject to  $y = Ax$

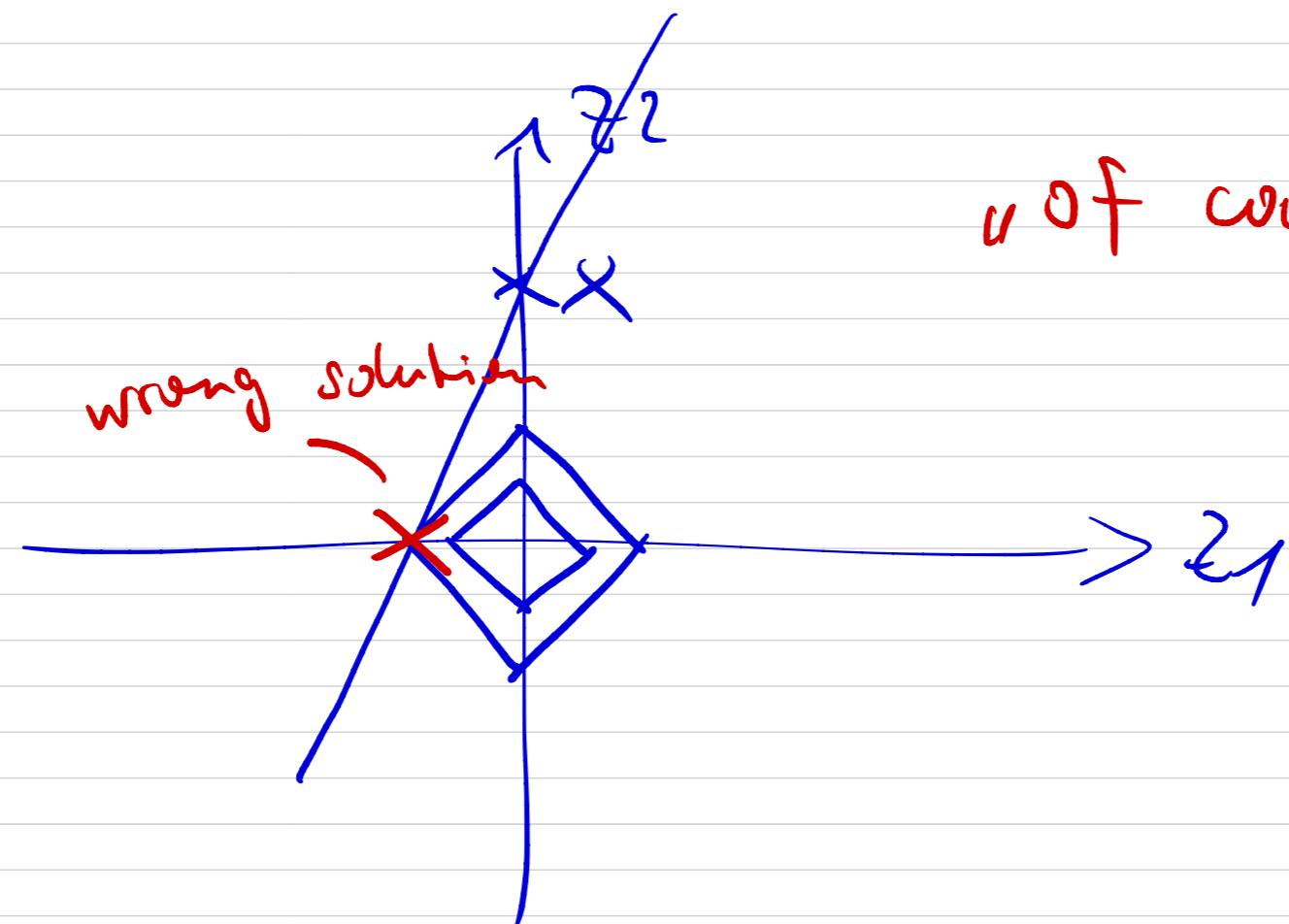
$\arg \min \|z\|_1$  subject to  $x \in \{x\} + r(D)$



$$\|z\|_1 = |z_1| + |z_2| \leq c$$

$$|z_2| \leq c - |z_1|$$

The 1-norm does not always sparsify



fraction of L<sub>1</sub>-norm on S

Def. 3.3. We denote

$$P_1(S, \mathbb{D}) := \max_{x \in \mathbb{D}, x \geq 0} \frac{\sum_{s \in S} |x_s|}{\sum_s |x_s|}$$

Th. 3.4. Arbitrarily fix x with support set S and let y = Dx. If  $P_1(S, \mathbb{D}) < 1/2$ , then x is the unique solution to

(P1) : find any max 1-norm subject to  $y = \mathbf{J}^T \mathbf{x}$

Proof. need to establish that for all  $\alpha \in \text{C}(\mathcal{D})$ )

$$\underbrace{\sum_{\mathcal{S}} |x_{\mathcal{S}} + \alpha_{\mathcal{S}}|}_{\text{1-norm of competing solutions}} > \underbrace{\sum_{\mathcal{S}} |x_{\mathcal{S}}|}_{\sim \text{1-norm of correct solution}}$$

$$|\alpha + b| \geq |\alpha| - |b| \quad , \text{ reverse 1-norm eqn.}$$

$$\begin{aligned} \sum_{\mathcal{S}} |x_{\mathcal{S}} + \alpha_{\mathcal{S}}| &= \sum_{\mathcal{S} \notin S} |x_{\mathcal{S}} + \alpha_{\mathcal{S}}| + \sum_{\mathcal{S} \in S} |x_{\mathcal{S}} + \alpha_{\mathcal{S}}| \\ &= \sum_{\mathcal{S} \notin S} |\alpha_{\mathcal{S}}| + \underbrace{\sum_{\mathcal{S} \in S} |x_{\mathcal{S}} + \alpha_{\mathcal{S}}|}_{\geq \sum_{\mathcal{S} \in S} |x_{\mathcal{S}}| - \sum_{\mathcal{S} \in S} |\alpha_{\mathcal{S}}|} \end{aligned}$$

$$\geq \sum_{S \notin S} |k_S| + \cancel{\sum_{S \in S} |x_S|} - \sum_{S \in S} |k_S|$$

$$> \sum_{S \in S} |x_S|$$

$$\Rightarrow \sum_{S \notin S} |k_S| > \sum_{S \in S} |k_S| \quad \Big| + \sum_{S \in S} |k_S|$$

$$\sum_S |k_S| > 2 \sum_{S \in S} |k_S|$$

$$\frac{\sum_{S \in S} |k_S|}{\sum_S |k_S|} < \frac{1}{2}$$