

Last time: Underdetermined linear systems  
 $y = Ax$ ,  $x \in \mathbb{R}^N$ ,  $A \in \mathbb{R}^{m \times N}$ ,  $y \in \mathbb{R}^m$

(i)  $m < N$ , (ii)  $A$  has full (row) rank.

$J(x)$ : Cost:  $\mathbb{R}^+ \rightarrow \mathbb{R}$

- $\min_{x \in \mathbb{R}^N} J(x)$  s.t.  $y = Ax$
- $J(x) = \|x\|_2^2$ , unique globally optimal closed form soln.
- $J(x) = \|x\|_p^p$ ,  $p > 1$ , " " " " soln. but not closed form for  $p \neq 2$ .
- $J(x) = \|x\|_1$ , convex but not strictly convex
  - Set of solns. form a bounded convex set
  - $\exists$  at least 1 soln. which has at most  $m$  nonzero.
- $J(x) = \|x\|_p^p$ ,  $p < 1$ : Nonconvex cost.
- $\ell_1$  min.  $\equiv$  linear program.

[Chapter 2]:

Notation:  $[N] = \{1, 2, \dots, N\}$   
 $|S|$  or  $\text{Card}(S) \equiv$  Cardinality of set  $S$   
 $\bar{S}$  or  $S^c = [N] \setminus S$ .

For  $x \in \mathbb{C}^N$ ,  $\text{supp}(x) = \{j \in [N] : x_j \neq 0\}$ .

$x \in \mathbb{C}^N$  is  $s$ -sparse if

$$\|x\|_0 = |\text{supp}(x)| \leq s.$$

$$\|x\|_p^p = \sum_{j \in [N]} |x_j|^p \stackrel{p > 0}{\approx} \sum_{j \in [N]} \mathbb{1}_{\{x_j \neq 0\}} = |\{j \in [N] : x_j \neq 0\}|.$$

Defn. For  $p > 0$ , the  $\ell_p$  error in the best  $s$ -term approx to  $x \in \mathbb{C}^N$  is

$$\sigma_s(x)_p \triangleq \inf \{ \|x - z\|_p : z \in \mathbb{C}^N, z \text{ s-sparse} \}.$$

The infimum is achieved by an  $s$ -sparse vec.  $z \in \mathbb{C}^N$  whose nonzero entries equal the  $s$ -largest absolute entries of  $x$ .

- $z$  need not be unique
- The optimum  $z$  is independent of  $p$ .

Informally,  $x \in \mathbb{C}^N$  is "compressible" if  $\sigma_s(x)_p$  decays very quickly with  $s$ . Turnout: this happens if  $x \in B_p^N \triangleq \{z \in \mathbb{C}^N : \|z\|_p \leq 1\}$  for small  $p > 0$ .



$B_p^N$ ,  $p < 1$  is a good model for compressible vecs.

Defn. A nonincreasing rearrangement of  $x \in \mathbb{C}^N$  is a vec.  $x^* \in \mathbb{R}_+^N$  for which

$$x_1^* \geq x_2^* \geq \dots \geq x_N^* \geq 0$$

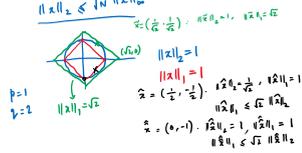
and there is a permutation  $\pi: [N] \rightarrow [N]$  with  $x_j^* = |x_{\pi(j)}|$ ,  $j=1, 2, \dots, N$ .

For  $0 < p < q$ ,

$$\|x\|_q \geq \|x\|_p \quad [\|x\|_1 \geq \|x\|_2]$$

opposite ineq:  $\|x\|_1 \leq \sqrt{N} \|x\|_2$  [ $N$  is the dim. of  $x$ ]

$$\|x\|_2 \leq \sqrt{N} \|x\|_\infty$$



For  $0 < p < q$ , the sphere with radius  $\sqrt{N}$  and  $\|\cdot\|_p$  describes the sphere of radius 1 with  $\|\cdot\|_q$ .

Hölder's inequality

$$\sum_{i=1}^N |a_i| |b_i| \leq \left( \sum_{i=1}^N |a_i|^p \right)^{\frac{1}{p}} \left( \sum_{i=1}^N |b_i|^q \right)^{\frac{1}{q}}$$

Set  $|a_i| = |x_i|^p$ ,  $|b_i| = 1$ ,  $\frac{1}{p} + \frac{1}{q} = 1$ ,  $\frac{1}{q} = 1 - \frac{1}{p}$

$$\sum_{i=1}^N |x_i|^p \leq \left( \sum_{i=1}^N |x_i|^p \right)^{\frac{p}{p}} \left( \sum_{i=1}^N 1 \right)^{1 - \frac{p}{p}}$$

$$\text{RHS} = \left( \sum_{i=1}^N |x_i|^p \right)^{\frac{p}{p}} N^{1 - \frac{p}{p}} \quad \frac{1}{q} = 1 - \frac{1}{p}$$

$$\text{LHS} = \|x\|_p^p$$

$$\Rightarrow \|x\|_p^p \leq \left( \sum_{i=1}^N |x_i|^p \right)^{\frac{1}{p}} \left( \sum_{i=1}^N 1 \right)^{1 - \frac{1}{p}} = \|x\|_p \cdot N^{\frac{1}{p} - 1}$$

$$\|x\|_p \leq N^{\frac{1}{p} - 1} \|x\|_p \quad 0 < p < q$$

$$\|x\|_q \leq \|x\|_p \leq N^{\frac{1}{p} - \frac{1}{q}} \|x\|_q, \quad 0 < p < q.$$

In general,  $\exists c, c'$  s.t.  
 $c \|x\|_p \leq \|x\|_q \leq c' \|x\|_p$

Prop. For any  $q > p > 0$  and any  $x \in \mathbb{C}^N$ ,

$$\sigma_s(x)_q \leq \frac{1}{s^{\frac{1}{q} - \frac{1}{p}}} \|x\|_p \quad \left( \text{Use this inequality to see that } \sigma_s(x)_q \text{ is nec. for recovering all } s\text{-sparse vecs. from } y = Ax \right)$$

When  $p=1, q=2$

$$\sigma_s(x)_2 \leq \frac{1}{\sqrt{s}} \|x\|_1$$

When  $q=2, p < 2$ ,

$$\|x\|_2$$

$\sigma_p(x)_2 \leq \frac{1}{\lambda^{\frac{1}{p}-1}}$   
 $\Rightarrow$  Unit balls in the  $\ell_p$  quasi-norm for  $p < 1$   
 are good models for compressible vectors.



Proof: Let  $\pi \in \mathbb{R}_+^N$  be a noninc. rearrangement

of  $x \in \mathbb{C}^N$ . Then,  
 $\sigma_p(x)_V = \sum_{j=1}^N (x_j^*)^p \leq \underbrace{(\pi_1^*)^p \sum_{j=1}^N (\pi_j^*)^p}_{\text{RHS}}$

$$(\pi_1^*)^p = (\pi_1^*)^{q-p} (\pi_1^*)^p$$

$$\leq (\pi_1^*)^{q-p} (\pi_1^*)^p \quad \forall \Delta$$

$$\text{RHS} \leq \left( \frac{1}{\lambda} \sum_{j=1}^N (\pi_j^*)^q \right)^{\frac{q-p}{p}} \sum_{j=1}^N (\pi_j^*)^p$$

$$\underbrace{(\pi_j^*)^q, j=1,2,\dots,N \text{ are all } \geq (\pi_1^*)^q}_{\text{avg.} \geq (\pi_1^*)^q}$$

$$(\text{avg.})^{\frac{q-p}{p}} \geq (\pi_1^*)^{q-p}$$

$$\leq \left( \frac{1}{\lambda} \|\pi\|_p^p \right)^{\frac{q-p}{p}} \cdot \|\pi\|_p^p \quad (\text{Just adds more noisy terms})$$

$$= \left( \frac{1}{\lambda} \right)^{\frac{q-p}{p}} \cdot \|\pi\|_p^{q-p} \cdot \|\pi\|_p^p$$

$$\text{Thus, } \sigma_p(x)_V \leq \frac{1}{\lambda^{\frac{1}{p}-1}} \|\pi\|_p^q$$

$$\sigma_p(x)_V \leq \frac{1}{\lambda^{\frac{1}{p}-1}} \cdot \|\pi\|_p^q \quad \square$$