

In summary, we found that $\mathcal{D}(P) \geq 2C$ is necessary & sufficient
 for stable recovery.
 (proved only injectivity)

3 regimes

$$1. m = cs \quad \begin{cases} \text{FRI} \\ \text{multi-band} \end{cases} \quad \begin{matrix} m \dots \# \text{ measurements} \\ s \dots \text{sparse level} \end{matrix}$$

$$2. m = c's^2 \quad \begin{matrix} \text{square-root bottleneck} \\ \text{coherence-based recovery thresholds} \end{matrix}$$

$$3. m = c' \log n \quad \leftarrow \text{Today}$$

$$y = \widehat{\Phi} x + v \quad \begin{matrix} nx1 \\ mx1 \\ \downarrow \text{noise} \end{matrix}$$

Def. For each integer $s = 1, 2, \dots$, define the isometry constant δ_s of a matrix $\widehat{\Phi}$ as the smallest number $s.f.$

$$(1 - \delta_s) \|x\|_2^2 \leq \|\widehat{\Phi}x\|_2^2 \leq (1 + \delta_s) \|x\|_2^2$$

Holds for all s -sparse vectors x . A vector x is s -sparse if at most s of its entries are nonzero.

Theorem 7.2. Let $y = \widehat{\Phi}x$. Assume that $\delta_{2s} < \sqrt{2} - 1$. Then, the solution x^* to

$$\min_{\widehat{x} \in \mathbb{R}^n} \|\widehat{x}\|_1 \quad \text{subject to } \widehat{\Phi}\widehat{x} = y$$

obeys

$$\|x^* - x\|_1 \leq C_0 \|x - x_s\|_1$$

and

$$\|x^* - x\|_2 \leq C_0 s^{-1/2} \|x - x_s\|_1$$

for some C_0 specified in the proof of the statement. Here, x_s

\hat{x} is the vector obtained by setting all but the s largest (in $| \cdot |$) entries of x equal to zero.

Theorem 7.3. Let $y = \Phi x + n$. Assume that $\|n\|_2 < \sqrt{2} - 1$ and $\|nx\|_2 \leq \varepsilon$. Then, the solution x^* to

$$\min_{\hat{x} \in \mathbb{R}^n} \|\hat{x}\|_1 \quad \text{subject to} \quad \|y - \Phi \hat{x}\|_2 \leq \varepsilon$$

obeys

$$\|x^* - x\|_2 \leq C_0 s^{-1/2} \|x - x_S\|_1 + C_1 \cdot \varepsilon.$$

$\binom{m}{s}$ subspaces

$$1 \leq \left(\frac{en}{s}\right)^s \Rightarrow \text{swf}\left(\frac{en}{s}\right)$$

x_S - covering

JL : set \mathcal{U} of m points in \mathbb{R}^n

embed these points into \mathbb{R}^s , with $s \ll n$ while approximately preserving pairwise distance between the points.

The JL states that any set of m points can be embedded in $s = \Theta(\log(m)/\varepsilon^2)$ dimensions while the distances between the points change by a factor of at most $1 \pm \varepsilon$.

Lemma 8.1- (JL - Lemma). Choose ε with $\varepsilon \in (0, 1)$ and suppose that \mathcal{U} satisfies

$$s \geq \frac{\delta}{\varepsilon^2 - \varepsilon^3} \log(2m).$$

Then, for every set \mathcal{U} of m points, there exists a map $f: \mathbb{R}^n \rightarrow \mathbb{R}^s$ s.t. for all $u, u' \in \mathcal{U}$, we have

$$(1 - \varepsilon) \|u - u'\|^2 \leq \|f(u) - f(u')\|^2 \leq (1 + \varepsilon) \|u - u'\|^2. \quad (\text{JL})$$

Lemma 8.2. Let $A \in \mathbb{R}^{d \times n}$ be a random matrix with i.i.d. $\mathcal{CN}(0, 1/\kappa)$ entries. Then, for ε with $\varepsilon \in (0, 1)$, and fixed $u \in \mathbb{R}^d$,

$$P(|\|Au\|^2 - \overbrace{\mathbb{E}[\|Au\|^2]}^{\|u\|^2}| \geq \varepsilon \|u\|^2) \leq 2 e^{-\frac{\varepsilon^2 - \varepsilon^3}{4}}$$

with

$$\mathbb{E}[\|Au\|^2] = \|u\|^2.$$

$$|\|Au\|^2 - \|u\|^2| \geq \varepsilon \|u\|^2$$

$$\|Au\|^2 - \|u\|^2 \geq \varepsilon \|u\|^2$$

$$\underline{\|Au\|^2 \geq (1+\varepsilon)\|u\|^2}$$

$$-\|Au\|^2 + \|u\|^2 \geq \varepsilon \|u\|^2$$

$$\underline{\|Au\|^2 \leq (1-\varepsilon)\|u\|^2}$$

→

Lemma 8.2 \Rightarrow JL Lemma

consider all $m(m-1)/2$ pairs $u, u' \in \mathcal{U}$

note that (JL) is violated with prob $2m^2 e^{-\frac{\varepsilon^2 - \varepsilon^3}{4}}$

$$2m^2 e^{-\frac{\varepsilon^2 - \varepsilon^3}{4}} < 1/2 \quad \leftarrow \text{prob. method}$$

$$\frac{\varepsilon^2 - \varepsilon^3}{4} \geq \omega_1(2m)$$

Proof of the concentration inequality:

a_j^\top is the j -th row of A and set $X_j = \frac{\varepsilon}{\|u\|} a_j^\top u$

$$\text{var}(X_j) = \frac{\varepsilon}{\|u\|^2} \frac{1}{\varepsilon} \|u\|^2 = 1.$$

\uparrow
 $\mathcal{CN}(0, 1/\kappa)$

$$X = \sum_{j=1}^{\frac{\varepsilon}{\|u\|}} X_j^2 = \frac{\varepsilon}{\|u\|^2} \sum_{j=1}^{\frac{\varepsilon}{\|u\|}} |a_j^\top u|^2$$

$$= \frac{\varepsilon}{\|u\|^2} \|Au\|^2$$

X_j are i.i.d. $\mathcal{CN}(0, 1)$

$$P(\|Au\|^2 \geq (1+\varepsilon)\|u\|^2) = P(X \geq (1+\varepsilon)\varepsilon)$$

$$X \sim \frac{\varepsilon}{\|u\|} \sim \mathcal{N}(0, 1) \quad = P(e^{\lambda X} \geq e^{\lambda(1+\varepsilon)\varepsilon})$$

$$\stackrel{\text{Markov}}{\leq} \frac{1}{e^{(1+\varepsilon)\lambda}} E[e^{\lambda X}]$$

$$= \frac{1}{e^{(1+\varepsilon)\lambda}} \prod_{i=1}^k E[e^{\lambda X_i}]$$

$$\stackrel{\text{i.i.d.}}{=} \frac{1}{e^{(1+\varepsilon)\lambda}} (E[e^{\lambda X_1}])^k$$

$$E[e^{\lambda X_1}] = \frac{1}{\sqrt{1-2\lambda}} \quad / \quad \lambda < 1/2.$$

$$P(\|A_{\mathcal{U}}\|^2 \geq (1+\varepsilon)\|a\|^2) \leq \left(\frac{e^{-2(1+\varepsilon)\lambda}}{\sqrt{1-2\lambda}}\right)^{k/2}$$

min. RHS over λ

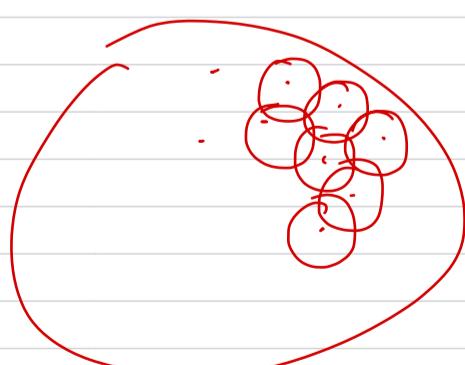
$$\lambda = \frac{\varepsilon}{2(1+\varepsilon)}$$

$$P(\|A_{\mathcal{U}}\|^2 \geq (1+\varepsilon)\|a\|^2) \leq ((1+\varepsilon)e^{-\varepsilon})^{k/2} < e^{-(\varepsilon^2 - \varepsilon^3)/4}$$

$$1 + \varepsilon \leq e^{\varepsilon - \frac{\varepsilon^2 - \varepsilon^3}{4}}$$

Taylor exp. of e^x

$$P(\|A_{\mathcal{U}}\|^2 \leq (1-\varepsilon)\|a\|^2) < e^{-(\varepsilon^2 - \varepsilon^3)/4}$$



Chapter 9. Verifying the Restr. Isom. Prop. through the JL Lemma

Lemma 9.1. Let $\widehat{A} \in \mathbb{R}^{m \times n}$ be an i.i.d. $\mathcal{C}(0, 1/m)$ matrix. Then, for any set S with $|S|=k \leq m$ and any $\delta \in (0, 1)$, we have

$$(1-\delta) \|x\| \leq \|(\bar{x})_x\| \leq (1+\delta) \|x\|, \quad \forall x \in \mathcal{X}_S$$

with prob.

$$\geq 1 - 2(12\delta)^2 e^{-c\delta(2)m}$$

$$\text{where } c(x) = \frac{1}{4}(x^2 - x^3)$$

Proof. it suffices to consider $\|x\|=1$

covering \mathcal{Q}_S s.t. i) $\mathcal{Q}_S \subseteq \mathcal{X}_S$, $\|q\|=1$ for all $q \in \mathcal{Q}_S$

ii) for all $x \in \mathcal{X}_S$ with $\|x\|=1$, we have

$$\min_{q \in \mathcal{Q}_S} \|x - q\| \leq \delta/4.$$

$$\exists Q_S \text{ s.t. } |\mathcal{Q}_S| \leq (12\delta)^2.$$

$$(1 - \delta/2) \|q\|^2 \leq \|(\bar{x})_q\|^2 \leq (1 + \delta/2) \|q\|^2 \quad \forall q \in \mathcal{Q}_S$$

holds w.p.

$$\geq 1 - 2(12\delta)^2 e^{-c\delta(2)m}$$

$$c(x) = \frac{x^2 - x^3}{4}.$$

A is the smallest no. s.t.

$$\|(\bar{x})_x\| \leq (1+A) \|x\|, \quad \forall x \in \mathcal{X}_S$$

$$x \in \mathcal{X}_S \quad (\|x\|=1) \Rightarrow q \in \mathcal{Q}_S \text{ s.t. } \|x - q\| \leq \delta/4 \quad (\text{covering})$$

$$\begin{aligned} \|(\bar{x})_x\| &= \|(\bar{x})(q+x-q)\| \leq \underbrace{\|(\bar{x})_q\|}_{(1+A)\delta/4} + \underbrace{\|(\bar{x})(x-q)\|}_{\sqrt{1+\delta/2}} \\ &\leq \sqrt{1+\delta/2} \|q\|^2 \leq 1 + \delta/2 \\ &\leq 1 + \delta/2 + (1+A)\delta/4 \end{aligned}$$

$$A + A \leq A + \delta/2 + (1+A)\delta/4$$

$$A \leq \delta/2 + (1+A)\delta/4$$

$$A \leq \delta.$$

we therefore established that $\|(\bar{x})_x\| \leq (1+\delta) \|x\|$

$$\|(\bar{\Phi}x)\| \geq \|(\bar{\Phi}y)\| - \|(\bar{\Phi}(x-y))\| \geq (1-\delta/2) - (1+\delta)\delta/4$$

$\geq 1-\delta$. q.e.d.

$m \times n$

Theorem. Suppose that m, n , and $\delta \in (0, 1)$ are given. If the pdf generating $\bar{\Phi}$ satisfies the concentration inequality in Lemma 8.2, then there exist constants $c_1, c_2 > 0$, depending only on δ s.t. the rest. isom. prop. holds for $\bar{\Phi}$ with the prescribed δ and every $\gamma \leq \frac{c_1 m}{\log(n/\epsilon)}$ w.p. $\geq 1 - 2e^{-c_2 m \gamma}$.

$$\gamma \leq \frac{c_1 m}{\log(n/\epsilon)} \quad \begin{matrix} \text{If meas.} \\ \uparrow \\ \text{S} \end{matrix} \quad \Rightarrow \boxed{m \geq C S \log(n/\epsilon)} \quad \begin{matrix} \text{amb. dim.} \\ \uparrow \\ \text{S} \end{matrix}$$

Proof. We know that for each of the S -dim. subspaces X_S , the matrix $\bar{\Phi}$ will fail to satisfy

$$(1-\delta) \|x\| \leq \|(\bar{\Phi}x)\| \leq (1+\delta) \|x\|, \forall x \in X_S \quad \text{④}$$

$$\text{w. p. } \leq 2(12/\delta)^S e^{-C\delta/2} m.$$

Key idea: There are $\binom{n}{S} \leq (\frac{en}{S})^S$ such subspaces \Rightarrow by union bound ④ will fail to hold w.p.

$$\leq 2(\frac{en}{S})^S (12/\delta)^S e^{-C\delta/2} m.$$

\uparrow
Counting
subspaces
or equiv.
no. of support sets

\nwarrow distribution of given X_S

q.e.d.

$$y = Wx \quad \begin{matrix} \uparrow \\ \text{s-sparse} \end{matrix}$$

$$\bar{\Phi}y = \bar{\Phi}Wx \quad \begin{matrix} \uparrow \\ \text{i.i.d.} \end{matrix}$$