

Last time:  
Thm. Let  $0 < \epsilon < 1$ ,  $A \in \mathbb{R}^{n \times M}$ ,  $A_{ij} \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \frac{\epsilon}{n})$ .  
If  $m \geq k \log(\frac{M}{\epsilon})$ , then  $A$  satisfies RIP  
of order  $k$  with the probability  $\delta$  exceeding  $1 - \frac{\delta}{2}$  with probability  $\frac{\delta}{2}$  exceeding  $1 - \frac{\delta}{2}$ ,  
where  $\delta, \mu$  arbitrary and  $\delta_2 = \frac{\delta^2}{24} - \frac{1}{\mu}$ .

Proof outline:  
Need  $\delta$  s.t.  $(1-\epsilon)\|x\|_2 \leq \|Ax\|_2 \leq (1+\epsilon)\|x\|_2$   
 $\forall x \in \mathbb{R}^k, \delta \leq \epsilon$  (w.p.  $\frac{\delta}{2}$ ),  $\|x\|_2 = 1$ .  
Choose a net of pts  $\mathcal{Q}, |\mathcal{Q}| \leq \frac{1}{\epsilon^2} \log(\frac{M}{\epsilon})$  for any  $x \in \mathbb{R}^k$ ,  $\text{supp}(x)=T$   
s.t.  $\min_{y \in \mathcal{Q}} \|x-y\|_2 \leq \frac{\epsilon}{4}$  for any  $x \in \mathbb{R}^k$  with  $\|x\|_2=1$ .  
 $\mathcal{Q} \subseteq \bigcup_i \mathcal{Q}_i$ . Note:  $\|y_i\|_2=1, \forall y_i \in \mathcal{Q}_i$ .

Use Lemma 1 s.t.  $(1-\epsilon)\|y\|_2 \leq \|Ay\|_2 \leq (1+\epsilon)\|y\|_2, \forall y \in \mathcal{Q}$   
w.p.  $\frac{\delta}{2} \Rightarrow 1 - \epsilon \leq e^{-mG(\epsilon)}$   
Set  $\delta = \frac{\epsilon}{2}$  and choose that the prob. can be further  
lower held as follows:  
 $1 - 2\epsilon^{-mG(\epsilon)} \geq 1 - \frac{\epsilon}{2} \Rightarrow \frac{\epsilon}{2} \geq \frac{\epsilon}{2} e^{-mG(\epsilon)}$   
- Used the assumption that  $m \geq k \log(\frac{M}{\epsilon})$ .  
- We thus have the desired prob. over the net of pts.  
Need to still let  $A$  satisfy RIP w.t.  $\delta$ .

Defined  $\delta_k =$  smallest  $\delta$  s.t.  $\|Ax\|_2 \leq \sqrt{1+\delta_k} \|x\|_2, \forall x \in \mathbb{R}^k, \|x\|_2=1$ .  
Need Lemma 2 s.t.  $\forall x \in \mathbb{R}^k, \|x\|_2=1$ ,  
 $\|Ax\|_2 \leq \sqrt{1+\frac{\delta_k}{2}} + \sqrt{1+\frac{\delta_k}{2}} \frac{\delta_k}{4}$   
Since  $\delta_k$  is the smallest  $\delta$  s.t.  $\|Ax\|_2 \leq \sqrt{1+\delta_k} \|x\|_2, \forall x \in \mathbb{R}^k, \|x\|_2=1$ ,  
we must have  
 $\sqrt{1+\delta_k} \leq \sqrt{1+\frac{\delta_k}{2}} + \sqrt{1+\frac{\delta_k}{2}} \frac{\delta_k}{4}$   
 $\Rightarrow \sqrt{\delta_k} \leq \frac{\delta_k}{4}$   
Similarly,  $\|Ax\|_2 \geq \sqrt{1-\frac{\delta_k}{2}} - \sqrt{1-\frac{\delta_k}{2}} \frac{\delta_k}{4} \geq \sqrt{1-\delta_k}$   
 $\forall x \in \mathbb{R}^k, \|x\|_2=1$ .  
Thus,  $\forall x \in \mathbb{R}^k, (1-\delta_k)\|x\|_2 \leq \|Ax\|_2 \leq (1+\delta_k)\|x\|_2$   
holds w.p. exceeding  $1 - 2 \left(\frac{\delta_k}{2}\right)^k e^{-\epsilon m}$ ,  
where  $\delta_k = \frac{\delta^2}{24} - \frac{1}{\mu}$ , provided  $m \geq k \log(\frac{M}{\epsilon})$ .

To finish the proof, need to prove the two lemmas.  
Lemma 1:  $A \in \mathbb{R}^{n \times M}, A_{ij} \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \frac{\epsilon}{n})$ . Then,  
for any fixed  $x \in \mathbb{R}^k$ ,  
 $\Pr\{\|Ax\|_2 - \|x\|_2 \geq \epsilon\} \leq e^{-mG(\epsilon)}$   
 $\forall 0 < \epsilon < 1$ , where  $G(\epsilon) = \frac{\epsilon^2}{2} - \frac{\epsilon^3}{6}$ .  
[ $G(\epsilon) = \frac{\epsilon^2}{2}$  works too.]

Lemma 2: Let  $\epsilon \in (0, 1)$ .  $\exists$  a set of pts  $\mathcal{Q} \in \mathbb{R}^k$   
s.t.  $\|y_i\|_2=1, \forall y_i \in \mathcal{Q}$ ,  $|\mathcal{Q}| < \left(\frac{2}{\epsilon}\right)^k$ , and  
for any  $x \in \mathbb{R}^k, \|x\|_2=1$ ,  $\min_{y \in \mathcal{Q}} \|x-y\|_2 \leq \epsilon$ .

Proof of Lemma 1:  
Suffices to show:  
 $\Pr\{\|Ax\|_2 \geq (1+\epsilon)\|x\|_2\} \leq e^{-mG(\epsilon)}$   
 $\Pr\{\|Ax\|_2 \leq (1-\epsilon)\|x\|_2\} \leq e^{-mG(\epsilon)}$   
 $\Pr\{\|Ax\|_2 - \|x\|_2 \geq \epsilon\} \leq e^{-mG(\epsilon)}$   
 $\leq \Pr\{\|Ax\|_2 \geq (1+\epsilon)\|x\|_2\} + \Pr\{\|Ax\|_2 \leq (1-\epsilon)\|x\|_2\}$   
 $\leq e^{-mG(\epsilon)} + e^{-mG(\epsilon)} = 2e^{-mG(\epsilon)}$   
Suffices to consider  $x$  s.t.  $\|x\|_2=1$ .  
Let  $x = \sum_{i=1}^k x_i e_i$ . Then,  $y_j \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$   
 $\Rightarrow y_j \sim \sum_{i=1}^k x_i y_{ji}$  is  $x_i^2$  distributed.  
MGF:  $E\{e^{tY}\} = \frac{1}{(1-2t)^{1/2}}$ ,  $|t| < \frac{1}{2}$ .  
Hence,  $\Pr\{Y \geq (1+\epsilon)m\} = \Pr\{e^{tY} \geq \frac{e^{t(1+\epsilon)m}}{e^{t(1+\epsilon)m}}\}$   
 $\leq \frac{E\{e^{tY}\}}{e^{t(1+\epsilon)m}}$  (Markov Ineq.)  
 $= \frac{1}{(1-2t)^{1/2} e^{t(1+\epsilon)m}}$ .  
Can min. RHS w.r.t.  $t$ , at  $0 < t < \frac{1}{2}$ .  
 $\Rightarrow \max_{0 < t < \frac{1}{2}} \frac{1}{(1-2t)^{1/2} e^{t(1+\epsilon)m}} = \frac{1}{\sqrt{1-\epsilon}} e^{-\frac{\epsilon}{2} m}$   
 $\Rightarrow \Pr\{Y \geq (1+\epsilon)m\} \leq \frac{1}{\sqrt{1-\epsilon}} e^{-\frac{\epsilon}{2} m}$   
Now  $\log(1+\epsilon) \leq \frac{\epsilon}{2} - \frac{\epsilon^2}{8}$  [Show!]  
 $\Rightarrow \Pr\{Y \geq (1+\epsilon)m\} \leq \frac{1}{\sqrt{1-\epsilon}} e^{-\frac{\epsilon}{2} m} e^{-\frac{\epsilon^2}{8} m} = \frac{1}{\sqrt{1-\epsilon}} e^{-\frac{3\epsilon^2}{8} m}$   
 $= \frac{1}{\sqrt{1-\epsilon}} \left(\frac{1}{e}\right)^{\frac{3\epsilon^2}{8} m} \leq e^{-\frac{m}{16}}$  (slow!)  
for  $0 < \epsilon < 1$ .  
Proof for  $\Pr\{Y \leq (1-\epsilon)m\}$  is similar (H.W.).  
Hence,  $\Pr\{|Y-m| \geq \epsilon m\} \leq 2e^{-\frac{m}{16}}$ .

Proof of Lemma 2  
Constructive proof. Greedy procedure for constructing  $\mathcal{Q}$ :  
1. Pick  $y_1 \in \mathbb{R}^k$  s.t.  $\|y_1\|_2=1$ .  
2. At step  $i$ , pick any  $y_i \in \mathbb{R}^k$  s.t.  $\|y_i\|_2=1$   
and  $\|y_i - y_j\|_2 \geq \frac{\epsilon}{2} \forall j < i$ .  
Add  $y_i$  to  $\mathcal{Q}$ .  
3. Repeat (2) till no more pts can be added.  
Want to bound  $|\mathcal{Q}|$ .  
...  $\Rightarrow |\mathcal{Q}| \leq \frac{2}{\epsilon^2} \log(\frac{M}{\epsilon})$  at each  $y_i$ .

Center balls of radius  $(\frac{1}{2})^k$ .  
 These balls are disjoint, and all balls lie inside a "big" ball with radius  $(1 + \frac{1}{2})^k$ .



Hence,  $|a| \leq \frac{1}{2^k} \leq \frac{1}{2^k} (1 + \frac{1}{2})^k$

where  $B_k(x)$  = Ball of radius  $x$  in  $\mathbb{R}^k$ .

Hence  $|a| \leq \frac{(1 + \frac{1}{2})^k}{2^k} \leq \frac{(3/2)^k}{2^k} = (\frac{3}{4})^k$ .

Then  $A \in \mathbb{R}^{m \times n}$ ,  $A_j = \sum_{i=1}^m x_i(a_i, \frac{1}{2})$ ,  $m \geq k$ ,  $k \log(\frac{M}{k})$ .  
 A satisfies RIP w.r.t.  $\geq 1 - 2e^{-k_2 m} (\frac{4k}{3})^k$ ,  
 where  $k_2 = \frac{3}{4} - \frac{1}{4}$ .

**Remark:** Often, we are interested in signals that are sparse (or compressible) in some other orthonormal basis  $\psi \neq I$ .  
 $\Rightarrow A\psi$  needs to satisfy RIP.  $\text{Ax} = \sum_{i=1}^k x_i \psi_i$   
 Choose the set of pts in the  $k$ -dim space spanned by set of  $k$  cols of  $\psi$ ! Then the proof goes through!  
 $\Rightarrow$  All matrices of the form  $A\psi$  satisfy RIP!

Gaussian measurement matrices are universal for taking compressive measurements.

Random meas. matrices  $\Rightarrow$  observations are "democratic", i.e., no one measurement is more imp. than others.  
 (In contrast, deterministic matrices do not share these two properties.)