

# On Support Sizes of Restricted Isometry Constants

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# Compressed Sensing

Let  $x \in \mathbb{R}^N$  be a given **signal**.

Suppose we obtain a vector  $b = Ax \in \mathbb{R}^n$  of **linear measurements** where  $A \in \mathbb{R}^{n \times N}$  is the **measurement matrix**.

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**Algorithm for the sparsest solution:**

$$\min \|x\|_0 \text{ subject to } Ax = b.$$

# $l_1$ -Minimization and the RIP

Suppose we solve instead the  $l_1$ -minimization:

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**Restricted Isometry Constants:**

$$L_k := \min_{c \geq 0} c \text{ subject to } (1 - c)\|x\|_2^2 \leq \|Ax\|_2^2 \text{ for all } k\text{-sparse } x$$

$$U_k := \min_{c \geq 0} c \text{ subject to } (1 + c)\|x\|_2^2 \geq \|Ax\|_2^2 \text{ for all } k\text{-sparse } x$$

$$R_k := \max\{L_k, U_k\}$$

# Conditions for $l_1$ to recover $l_0$

Chartrand (2007)  $bR_{(b+1)k} + R_{bk} < b - 1; \quad b > 2$

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What do these results mean quantitatively? Which is better?

# Gaussian RIP Upper Bounds

(Blanchard, Cartis and Tanner, 2009)

**Theorem:** Let  $A$  be a matrix of size  $n \times N$  whose entries are drawn i.i.d. from  $\mathcal{N}(0, \frac{1}{n})$ .

Let  $(k, n, N) \rightarrow \infty$  with  $\frac{k}{n} \rightarrow \rho$  and  $\frac{n}{N} \rightarrow \delta$ .

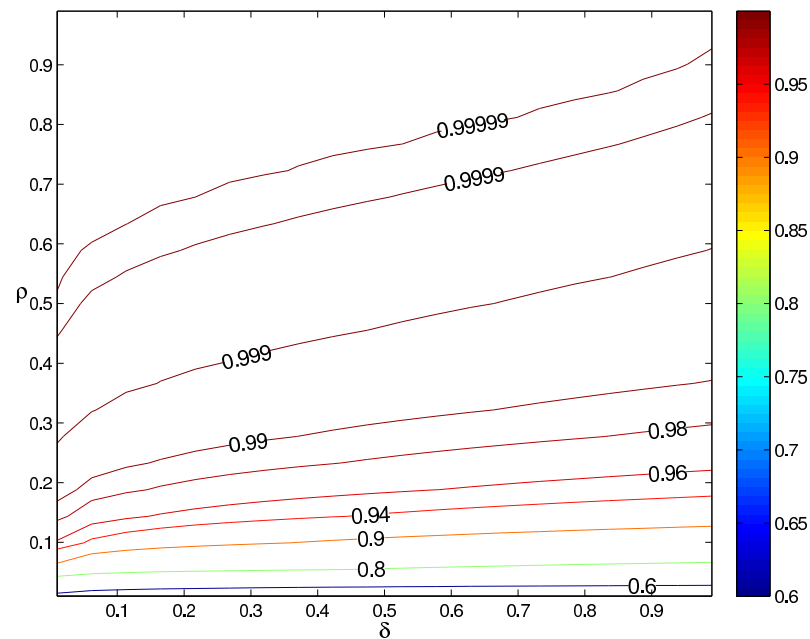
Then there exist numerically computable functions  $L(\delta, \rho)$  and  $U(\delta, \rho)$  such that, for any  $\epsilon > 0$ ,

$$\mathbb{P}\{L(k, n, N) < L(\delta, \rho) + \epsilon\} \rightarrow 1,$$

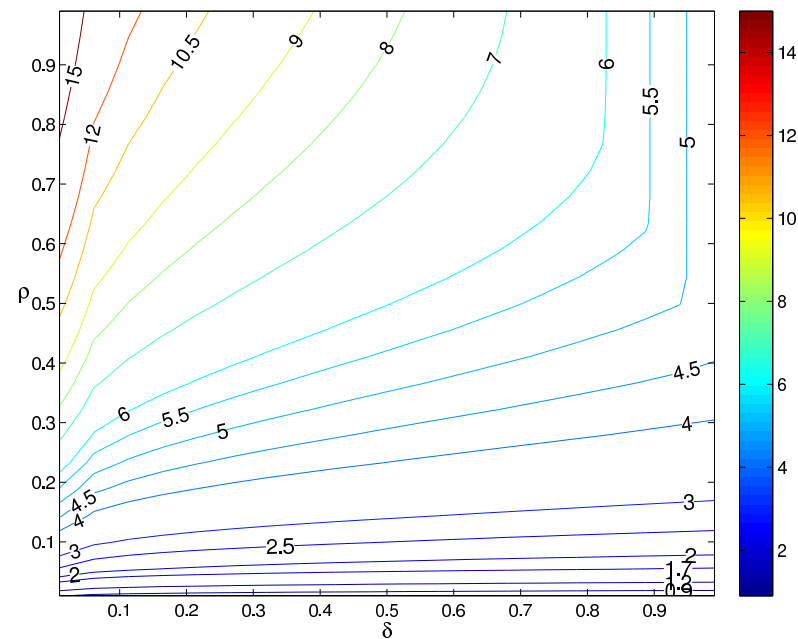
$$\mathbb{P}\{U(k, n, N) < U(\delta, \rho) + \epsilon\} \rightarrow 1.$$

# Gaussian RIP Upper Bounds

$$L(\delta, \rho)$$



$$U(\delta, \rho)$$



# Quantitative Sufficient Conditions

Chartrand (2007):

$$bL([b + 1]k, n, N) + U(bk, n, N) < b - 1; \quad b > 2$$

Candès (2008):

$$(1 + \sqrt{2})L(2k, n, N) + U(2k, n, N) < \sqrt{2}$$

Foucart, Lai (2009):

$$\frac{1 + U(2k, n, N)}{1 - L(2k, n, N)} < 4\sqrt{2} - 3$$

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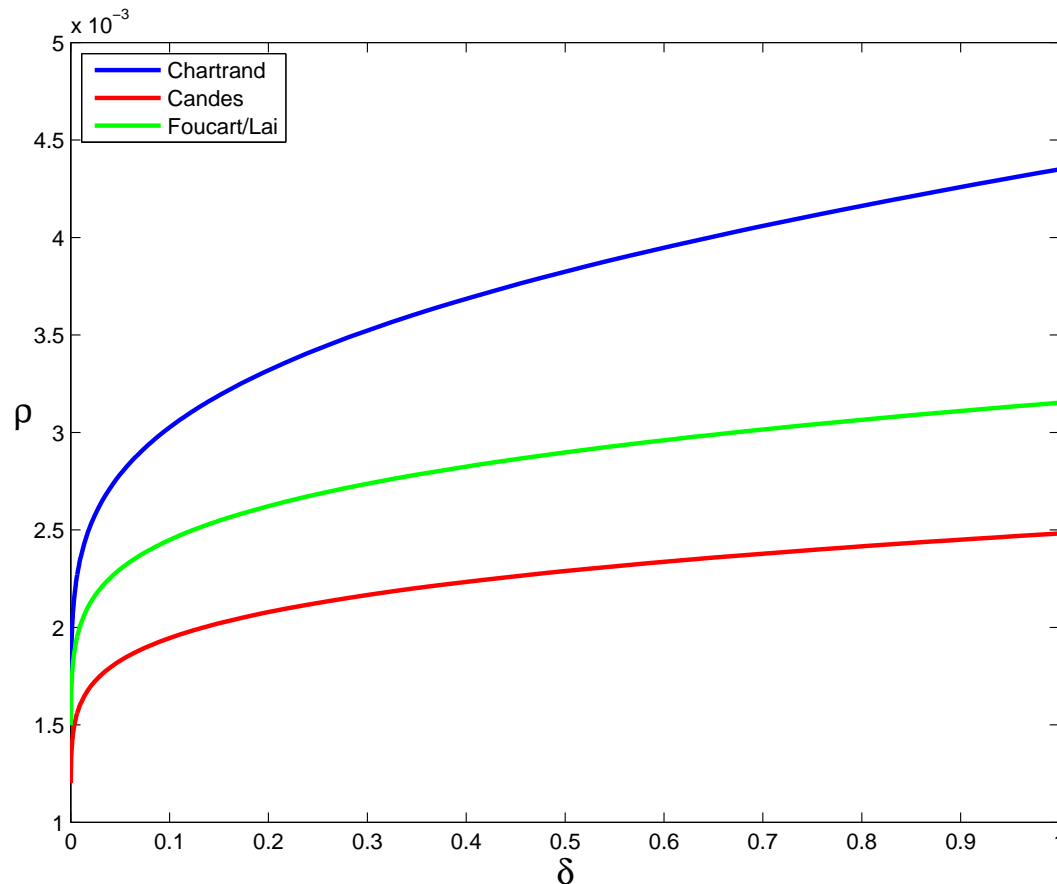
Candès (2008):

$$(1 + \sqrt{2})L(\delta, 2\rho) + U(\delta, 2\rho) < \sqrt{2}$$

Foucart, Lai (2009):

$$\frac{1 + U(\delta, 2\rho)}{1 - L(\delta, 2\rho)} < 4\sqrt{2} - 3$$

# Comparison of $l_1$ Phase Transitions



The highest phase transitions are obtained by taking  $b \approx 11$  in the result by Chartrand:  $11L(12k, n, N) + U(11k, n, N) < 10$ .



# Recent Results of Cai/Wang/Xu

$$R_{k+a} + \sqrt{\frac{k}{b}} R_{k+a+b} < 1$$

$$L_{k+a} + \frac{1}{2} \sqrt{\frac{k}{b}} (L_{k+a+b} + U_{k+a+b}) < 1$$

where  $2a \leq b \leq 4a$ .

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$$R_a + t R_{a+b} < 1$$

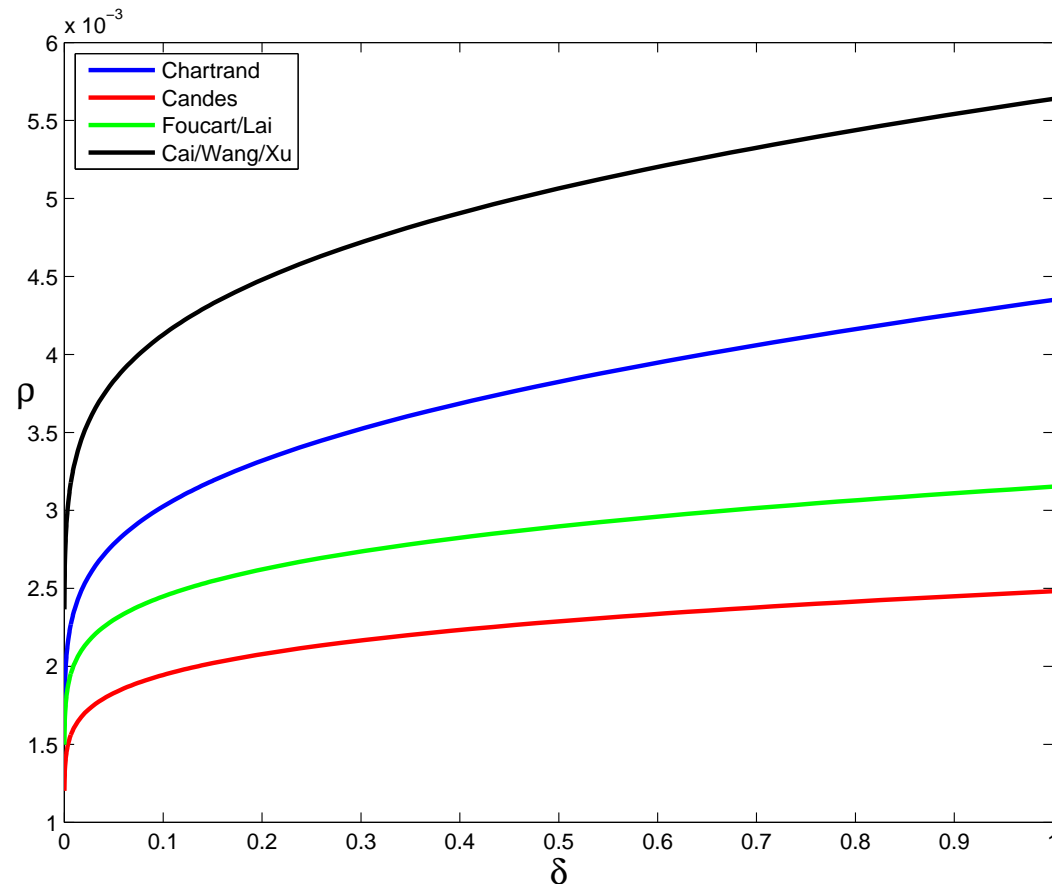
$$L_a + \frac{1}{2} t (L_{a+b} + U_{a+b}) < 1$$

where  $a \geq k$ ,  $8(a - k) \leq b$ , and

$$t = \sqrt{\frac{a}{b}} + \frac{1}{4} \sqrt{\frac{b}{a}} - \frac{2(a-k)}{\sqrt{ab}}.$$

$$\left[ \Rightarrow R_k < \frac{1}{1+\sqrt{5}} \approx 0.3090 \right]$$

# Comparison of $l_1$ Phase Transitions



Higher phase transitions can be obtained from the new results by again choosing large support sizes:

$$4L(2k, n, N) + L(6k, n, N) + U(6k, n, N) < 4.$$

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# Conclusions

- It is important to understand what RIP conditions mean quantitatively: the phase transition framework combined with RIP bounds for Gaussian matrices is a useful tool to investigate this.
- We observe that a results by Cai *et al.* with surprisingly high support sizes give the highest phase transitions for  $l_1$  minimization.
- It is not always quantitatively beneficial to have RIP results with the smallest possible support sizes.



Thank you for your attention!