Gaussian Comparison Lemmas and Convex-Optimization

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joint work with
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2016 Conference on Applied Mathematics
The Universty of Hong Kong, August 23, 2016

Outline

- **Introduction**
  - structured signal recovery
  - non-smooth convex optimization
  - LASSO and generalized LASSO; BPSK signal recovery
- **Comparison Lemmas**
  - Slepian, Gordon
- **Main Result**
  - squared error of generalized LASSO
  - Gaussian widths, statistical dimension
  - optimal parameter tuning
- **Generalizations**
  - other loss functions (Moreau envelopes)
  - other random matrix ensembles, universality
  - nonlinear measurements (one-bit compressed sensing)
- **Summmary and Conclusion**

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- In this setting, it is important to have signal recovery algorithms that are computationally efficient and that need not access the entire data directly (hence compressed recovery)

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- The generic problem is

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  - how does the convex approach compare to one with no computational constraints?
  - how to choose the regularizer $\lambda \geq 0$? (or the constraint bounds c_1 and c_2?)

Example: Noisy Compressed Sensing

Consider a "desired" signal $x \in \mathcal{R}^n$, which is k-sparse, i.e., has only $k < n$ (often $k \ll n$) non-zero entries. Suppose we make m noisy measurements of x using the $m \times n$ measurement matrix A to obtain

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- Suppose each set of m columns of A are linearly independent. Then, if $m > k$, we can always find the *best k-sparse* solution to

$$\min_x \|y - Ax\|_2^2 ,$$

via exhaustive search of $\left(\begin{array}{c} n \\ k \end{array} \right)$ *such least-squares problems*

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Thus, the *information-theoretic* problem is perhaps not so challenging/interesting. The *computational problem*, however, is:

- Can we do this more efficiently? And for what values of m?
- What about problems (such as low rank matrix recovery) where it is not possible to enumerate all structured signals?

LASSO

The LASSO algorithm was introduced by Tibshirani in 1996:

$$\hat{x} = \arg\min_{x} \frac{1}{2} \|y - Ax\|_2^2 + \lambda \|x\|_1,$$

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- What is the performance of the algorithm? For example, what is $E\|x - \hat{x}\|^2$?

Generalized LASSO

The generalized LASSO algorithm can be used to enforce other types of structures

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- If the noise is bounded:

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Turns out *we can*.....

Example

$\mathbf{X}_0 \in \mathbb{R}^{n \times n}$ is rank r. Observe, $\mathbf{y} = A \cdot \text{vec}(\mathbf{X}_0) + \mathbf{z}$, solve the Matrix LASSO,

$$\min_{\mathbf{X}} \{\|\mathbf{y} - A \cdot \text{vec}(\mathbf{X})\|_2 + \lambda \|\mathbf{X}\|_\star\}$$

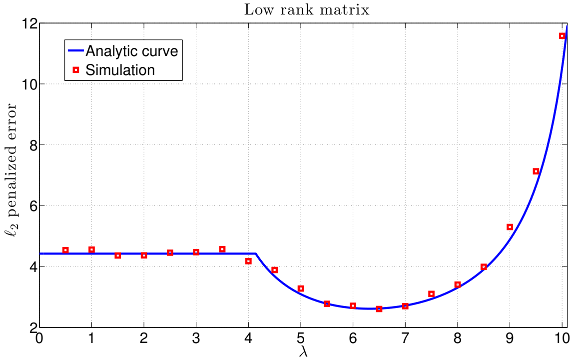

Figure: $n = 45$, $r = 6$, measurements $m = 0.6n^2$.

Recovering BPSK Signals

Consider

$$y = As + v,$$

where

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \quad , \quad s = \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix} \quad , \quad A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad , \quad v = \begin{bmatrix} v_1 \\ \vdots \\ v_m \end{bmatrix}$$

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$$\hat{s} = \arg \min_{s_i \in \{\pm 1\}} \|y - As\|_2.$$

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This method is quite popular and referred to as *box relaxation*. But what is the BER?

BER

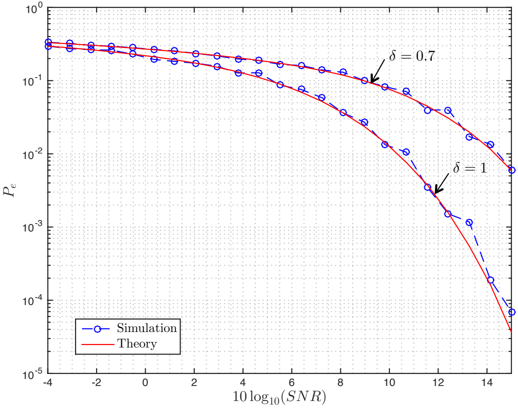

Figure: $n = 512$, $m = 358, 512$: Probability-of-error as a function of SNR

Where did this all come from....?

Slepian's Comparison Lemma (1962)

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Let X_i and Y_i be two Gaussian processes with the same mean μ_i and variance σ_i^2, such that $\forall\ i, i'$

- $E(X_i - \mu_i)(X_{i'} - \mu_{i'}) \geq E(Y_i - \mu_i)(Y_{i'} - \mu_{i'})$

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$$\text{Prob}\left(\max_i X_i \geq c\right) \overset{?}{\gtrless} \text{Prob}\left(\max_i Y_i \geq c\right)$$

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Slepian's Comparison Lemma (1962)

- proof not too difficult, but not trivial, either
- lemma not generally true for non-Gaussian processes

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Let $A \in \mathcal{R}^{m \times n}$ be a matrix with iid $N(0,1)$ entries and consider its maximum singular value:

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Define the two Gaussian processes

$$X_{uv} = u^T A v + \gamma \quad \text{and} \quad Y_{uv} = u^T g + v^T h,$$

where $\gamma \in \mathcal{R}$, $g \in \mathcal{R}^m$ and $h \in \mathcal{R}^n$ have iid $N(0,1)$ entries.

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where $\gamma \in \mathcal{R}$, $g \in \mathcal{R}^m$ and $h \in \mathcal{R}^n$ have iid $N(0,1)$ entries. Then it is not hard to see that both processes have zero mean and variance 2.

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Now,

$$EX_{uv}X_{u'v'} - EY_{uv}Y_{u'v'} = u^T u' v^T v' + 1 - u^T u' - v^T v' = (1 - u^T u')(1 - v^T v') \geq 0.$$

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Therefore from Slepian's lemma:

$$\underbrace{\text{Prob}\left(\max_{\|u\|=1}\max_{\|v\|=1} u^T A v + \gamma \geq c\right)}_{=\text{Prob}(\|A\|+\gamma\geq c)\geq\frac{1}{2}\text{Prob}(\|A\|\geq c)} \leq \underbrace{\text{Prob}\left(\max_{\|u\|=1}\max_{\|v\|=1} u^T g + v^T h \geq c\right)}_{\text{Prob}(\|g\|+\|h\|\geq c)}.$$

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Therefore from Slepian's lemma:

$$\underbrace{\text{Prob}\left(\max_{\|u\|=1}\max_{\|v\|=1} u^T Av + \gamma \geq c\right)}_{=\text{Prob}(\|A\|+\gamma\geq c)\geq\frac{1}{2}\text{Prob}(\|A\|\geq c)} \leq \underbrace{\text{Prob}\left(\max_{\|u\|=1}\max_{\|v\|=1} u^T g + v^T h \geq c\right)}_{\text{Prob}(\|g\|+\|h\|\geq c)}.$$

Since $\|g\| + \|h\|$ concentrates around $\sqrt{m} + \sqrt{n}$, this implies that the probability that $\|A\|$ (significantly) exceeds $\sqrt{m} + \sqrt{n}$ is very small.

Minimum Singular Value of a Gaussian Matrix

Let $A \in \mathcal{R}^{m \times n}$ $(m \leq n)$ be a matrix with iid $N(0,1)$ entries and consider its minimum singular value:

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It took 24 years for there to be progress...

Gordon's Comparison Lemma (1988)

Let X_{ij} and Y_{ij} be two Gaussian processes with the same mean μ_{ij} and variance σ_{ij}^2, such that $\forall\ i, j, i', j'$

1. $E(X_{ij} - \mu_{ij})(X_{ij'} - \mu_{ij'}) \leq E(Y_{ij} - \mu_{ij})(Y_{ij'} - \mu_{ij'})$
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Then

$$\text{Prob}\left(\min_i \max_j X_{ij} \leq c\right) \overset{?}{\gtrless} \text{Prob}\left(\min_i \max_j Y_{ij} \leq c\right)$$

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$$\Phi(G,\gamma) = \min_{x\in S_x} \max_{y\in S_y} \; y^T Gx + \gamma\|x\|\cdot\|y\| + \psi(x,y),$$

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- Basis for "escape through mesh" and "Gaussian width"
- Can be used to show that $\sigma_{\min}(A)$ behaves as $\sqrt{n}-\sqrt{m}$

A Stronger Version of Gordon's Lemma (TOH 2015)

$$\begin{cases} \Phi(G) = \min_{x\in S_x}\max_{y\in S_y}\; y^T G x + \psi(x,y) & \text{(PO)} \\ \phi(g,h) = \min_{x\in S_x}\max_{y\in S_y}\; \|x\| g^T y + \|y\| h^T x + \psi(x,y) & \text{(AO)} \end{cases}$$

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4. *Under the above assumptions, $\hat{x}_\Phi$ and $\hat{x}_\phi$* asymptotically have the same empirical distribution.

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Then 3 shows that if $\|\hat{x}_\phi\|$ concentrates to c, $\|\hat{x}_\Phi\|$ concentrates to the same value.
- 4 can be used to evaluate the probability-of-error of the PO by analyzing the AO.

Analysis of the BER for Box Relaxation

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the AO is

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Using $\sqrt{x}=\min_{\beta>0}\frac{\beta x}{2}+\frac{1}{2\beta}$, we obtain

$$\min_{t_i\in[0,2],\beta>0} \frac{\beta}{2}(\|t\|^2+\sigma^2)m+\frac{1}{2\beta}+t^Th.$$

$$=\min_{\beta>0} \quad \frac{\beta mn}{2\mathrm{SNR}}+\frac{1}{2\beta}+\sum_{i=1}^{n}\min_{t_i\in[0,2]}\left(\frac{\beta m t_i^2}{2}+h_it_i\right).$$

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The optimization over t is now separable and straightforward:

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The summation concentrates to:

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Analysis of the AO

Redefining βm to β, after some algebra, we get

$$\hat{\beta} = \arg\min_{\beta > 0} \quad \frac{\beta}{2\mathrm{SNR}} + \frac{1}{2\beta}\left(1 - \frac{n}{2m}\right) + \frac{n}{2\beta m}\int_{2\beta}^{\infty} (h - 2\beta)^2 p(h)\,dh.$$

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Recall

$$BER = \text{Prob}(\hat{t}_i \geq 1) = \text{Prob}(-\frac{h_i}{\hat{\beta}} \geq 1) = \text{Prob}(-h_i \geq \hat{\beta}).$$

So that

$$\text{BER} = \int_{\hat{\beta}}^{\infty} \frac{e^{-h^2/2}}{\sqrt{2\pi}} dh = Q(\hat{\beta}).$$

BER

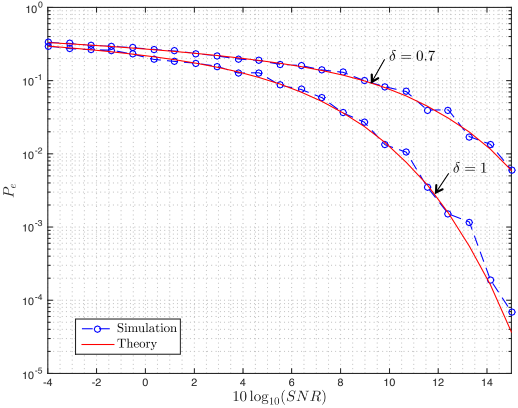

Figure: $n = 512$, $m = 358$: Probability-of-error as a function of SNR

Some Remarks

At high SNR, the value of $\hat{\beta}$ in the argument of the Q-function is large and therefore the intergral term in

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This is a quadratic equation for $\hat{\beta}$ that can be straightforwardly solved to obtain:

$$\mathrm{BER} = Q\left(\sqrt{\left(\frac{m}{n} - \frac{1}{2}\right)\mathrm{SNR}}\right).$$

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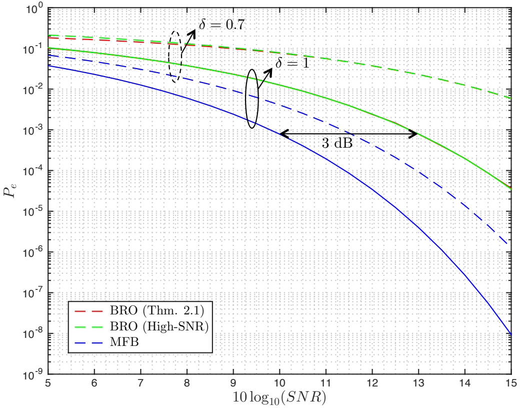
- In the AO, the events of making errors in each of the symbols were *independent*
- Therefor in the PO, for any fixed k symbols, the error events are also independent
- This fact has far-reaching consequences for algorithms that can be applied to the output of the box relaxation

BER



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Least-Squares

Suppose we are confronted with the *noisy* measurements:

$$y = Ax + z,$$

where $A \in \mathcal{R}^{m\times n}$ is the measurement matrix with iid $N(0,1)$ entries, $y \in \mathcal{R}^m$ is the measurement vector, $x_0 \in \mathcal{R}^n$ is the unknown desired signal, and $z \in \mathcal{R}^n$ is the unknown noise vector with iid $N(0,\sigma^2)$ entries.

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Let us analyze this using the stronger version of Gordon's lemma.

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To this end, define the estimation error $w = x_0 - x$, so that $y - Ax = Aw + z$.

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This satisfies all the conditions of the lemma. The simpler optimization is therefore:

$$\min_w \max_{\|u\|\le 1} \sqrt{\|w\|^2 + \sigma^2} g^T u + \|u\| \begin{bmatrix} h_w^T & h_\sigma \end{bmatrix} \begin{bmatrix} w \\ \sigma \end{bmatrix},$$

where $g = R^m$, $h_w = R^n$ and $h_\sigma \in R$ have iid $N(0,1)$ entries.

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Differentiating over α gives the solution:

$$\frac{\alpha^2}{\sigma^2} = \frac{\|h_w\|^2}{\|g\|^2 - \|h_w\|^2} \to \frac{n}{m-n}.$$

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Of course, in the least-squares case, we need not use all this machinery since the solutions are famously given by:

$$\hat{x} = \left(A^T A\right)^{-1} A^T y \quad \text{and} \quad E\|x_0 - \hat{x}\|_2^2 = \sigma^2 \text{trace}\left(A^T A\right)^{-1}.$$

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When A has iid $N(0,1)$ entries, A^TA is a *Wishart matrix* whose asymptotic eigendistribution is well known, from which we obtain

$$\frac{E\|x-\hat{x}\|_2^2}{\sigma^2} \to \frac{n}{m-n}.$$

Back to the Squared Error of Generalized LASSO

However, for generalized LASSO, we do not have closed form solutions and the machinery becomes very useful:

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While this can be analyzed in full generality, it is instructive to focus on the low noise, $\sigma \to 0$, case.

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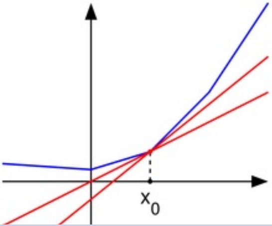
While this can be analyzed in full generality, it is instructive to focus on the low noise, $\sigma \to 0$, case. Here $\|w\|$ will be small and we may therefore write

$$f(x_0 - w) \gtrsim f(x_0) + \sup_{s \in \partial f(\mathbf{x}_0)} s^T(-w),$$

where $\partial f(\mathbf{x}_0)$ is the subgradient of $f(\cdot)$ evaluated at x_0, and defined as

$$\partial f(\mathbf{x}_0) = \left\{ s | f(x+x_0) \geq f(x_0) + s^T x, \forall x \right\}.$$



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Squared Error of Generalized LASSO $\sigma \to 0$

Returning back to the (AO):

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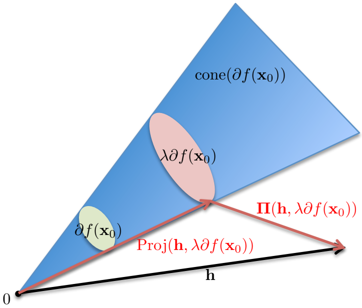
$$\lim_{\sigma \to 0} \frac{\alpha^2}{\sigma^2} = \frac{\text{dist}^2(h_w, \lambda \partial f(\mathbf{x}_0))}{m - \text{dist}^2(h_w, \lambda \partial f(\mathbf{x}_0))}.$$

Main Result: The Squared Error of Generalized LASSO

Generate an n-dimensional vector h with iid $N(0,1)$ entries and define:

$$D_f(x_0, \lambda) = E\text{dist}^2\left(h, \lambda \partial f(x_0)\right).$$



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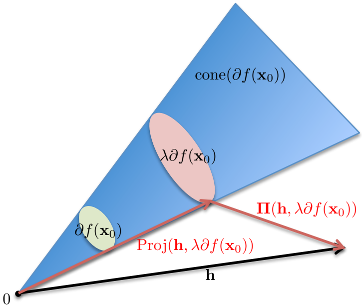

It turns out that $\text{dist}^2(h_w, \lambda\partial f(\mathbf{x}_0))$ concentrates to $D_f(x_0, \lambda)$, and that:

$$\lim_{\sigma\to 0} \frac{\|x_0 - \hat{x}\|^2}{\sigma^2} \to \frac{D_f(x_0, \lambda)}{m - D_f(x_0, \lambda)}.$$

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It is easy to see that

$$D_f(x_0, \lambda^*) = E\mathrm{dist}^2\left(h, \mathrm{cone}(\partial f(x_0))\right) \stackrel{\Delta}{=} \omega^2.$$

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- $$\omega^2 = E\text{dist}^2\left(h, \text{cone}(\partial f(x_0))\right)$$

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- The quantity ω^2 determines the minimum number of measurements required to recover a k-sparse signal using (appropriate) convex optimization. (The so-called *recovery thresholds*.)

Statistical Dimension

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- For BPSK signals and $f(x) = \|x\|_\infty$:

$$\omega^2 = \frac{n}{2} \quad , \quad \lim_{\sigma \to 0} \frac{\|x_0 - \hat{x}\|^2}{\|z\|^2} \to \frac{n/2}{m - n/2} = \frac{n}{2m - n}$$

Example

$\mathbf{X}_0 \in \mathbb{R}^{n \times n}$ is rank r. Observe, $\mathbf{y} = A \cdot \text{vec}(X_0) + \mathbf{z}$, solve the Matrix LASSO,

$$\min_{\mathbf{X}} \{\|\mathbf{y} - A \cdot \text{vec}(X)\|_2 + \lambda \|\mathbf{X}\|_\star\}$$

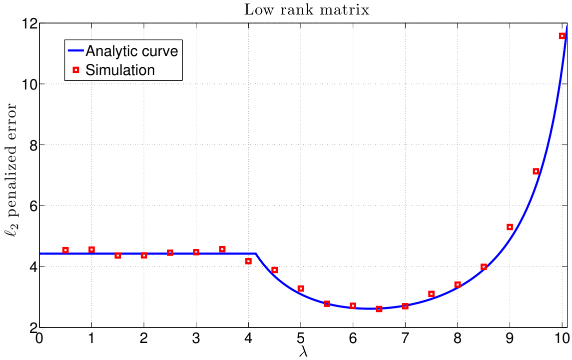

Figure: $n = 45$, $r = 6$, measurements $m = 0.6n^2$.

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- In the ℓ_1 case the subgradient cone is polyhedral and Donoho and Tanner (2005) computed the Grassman angle to obtain the minimum number of measurements required to recover a k-sparse signal
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Replica-based analysis:

- Guo, Baron and Shamai (2009), Kabashima, Wadayama, Tanaka (2009), Rangan, Fletecher, Goyal (2012), Vehkapera, Kabashima, Chatterjee (2013), Wen, Zhang, Wong, Chen (2014)

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- Our approach is inspired by Stojnic (2013)
  - subsumes all earlier (noiseless and noisy results)
  - allows for much, much more (as we have seen and shall further see)
  - is the most natural way to study the problem

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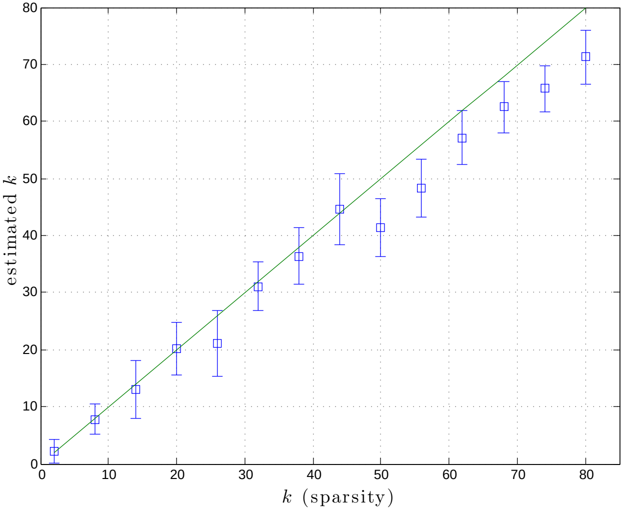
4. For this value of k find the optimal λ^*.

Estimating the Sparsity: $n = 520$, $m = 280$



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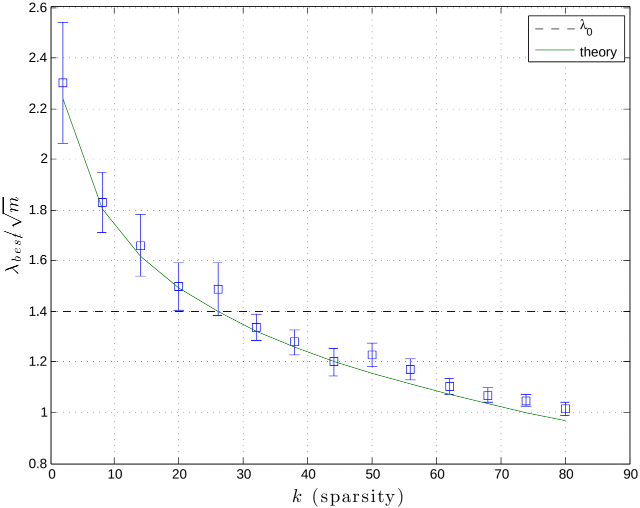
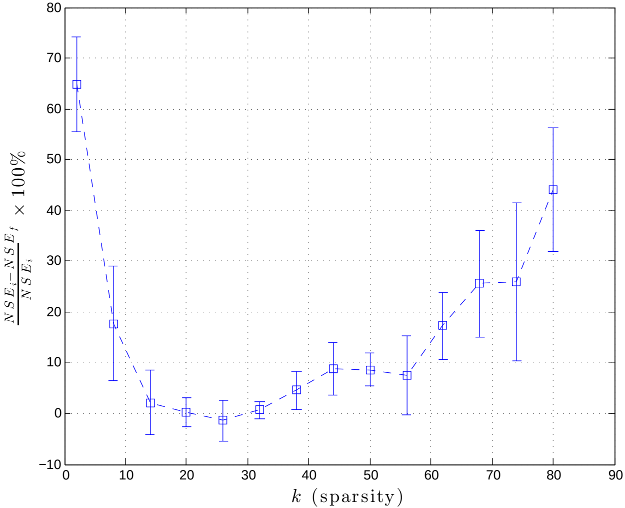


Improvement in NSE: $n = 520$, $m = 280$



Generalizations

Finite σ and General Loss Functions

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$$\mathcal{L}(y - Ax) = \max_u u^T(y - Ax) - \mathcal{L}^*(u) \quad \text{and} \quad f(x) = \max_v v^T x - f^*(v),$$

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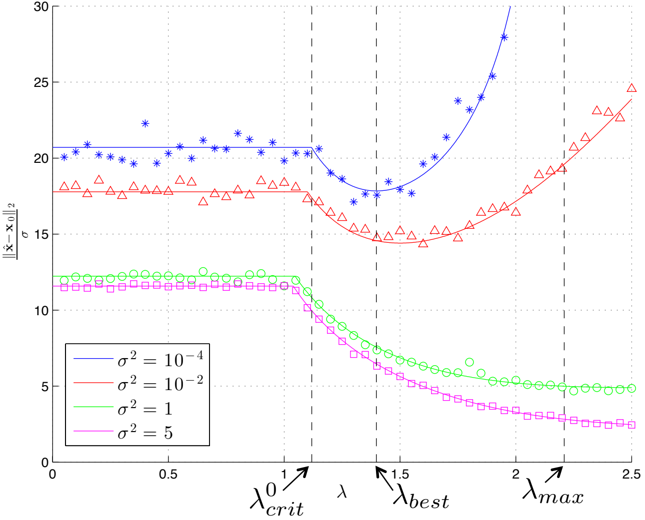
It turns out that the geometric quantities that show up in the analysis of the AO are the *expected Moreau envelopes*.

NSE for Finite σ: $n = 500$, $m = 150$, $k = 20$



Another Example: Least-Absolute Deviations (LAD)

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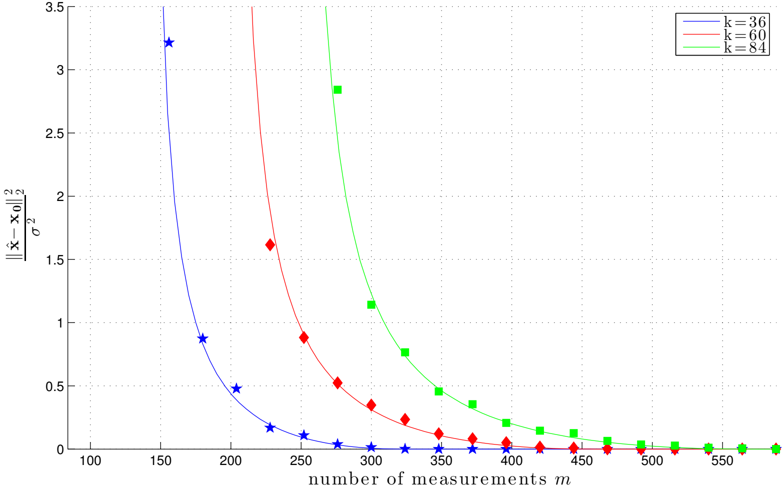
We can do other loss functions. For example,

$$\hat{x} = \arg\min_x \|y - Ax\|_1 + \lambda\|x\|_1,$$

which attempts to find a sparse signal in sparse noise and which is called *least absolute deviations* (LAD).

Squared Error vs Number of Measurements



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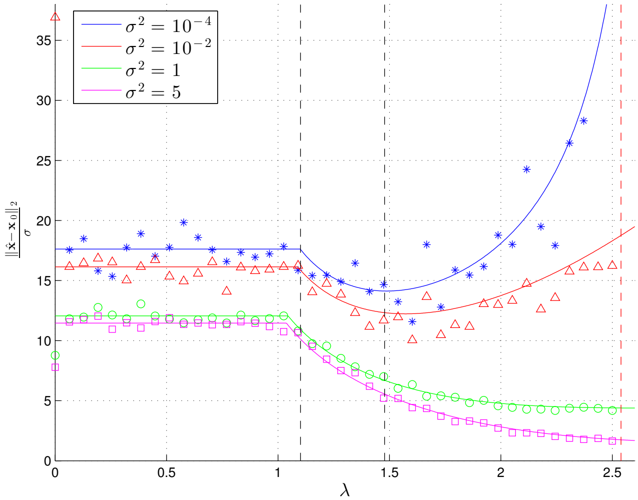
  concentrates for *any* A with iid zero-mean unit variance entries.
- Have yet to prove this for other loss functions and for the general (PO)

NSE for iid Bernouli($\frac{1}{2}$): $n = 500$, $m = 150$, $k = 20$



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- For such random matrices, we have shown that the two optimization problems:

$$\begin{aligned} \Phi(Q,z) &= \min_w && \|\sigma z - Qw\| + \lambda f(w) && \text{(PO)} \\ \phi(g,h) &= \min_{w,l}\max_{\beta\geq 0} && \|\sigma v - w - l\| + \beta(\|l\|\cdot\|g\| - h^T l) + \lambda f(w) && \text{(AO)} \end{aligned}$$

where z, v, h and g have iid $N(0,1)$ entries, have the same optimal costs and statistically the same optimal minimizer.

Isotropically Random Unitary Matrices

- Using the above result, we have been able to show that

$$\lim_{\sigma \to 0} \frac{\|x_0 - \hat{x}\|^2}{\|z\|^2} \to \frac{D_f(x_0, \lambda)}{m - D_f(x_0, \lambda)} \cdot \frac{n - D_f(x_0, \lambda)}{n}.$$

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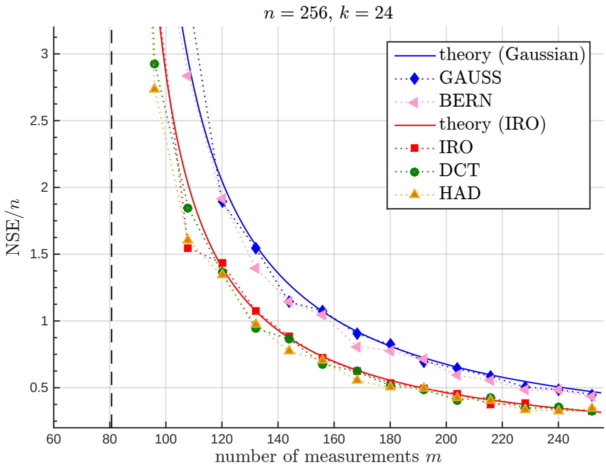
- Since $\frac{n - D_f(x_0, \lambda)}{n} < 1$, this is strictly better than the Gaussian case.

NSE for Isotropically Unitary Matrix: $n = 520$, $k = 20$



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This seems like a very naive thing to do. However, it was suggested by Brillinger for standard least-squares in the 1980's and very recently by Plan and Vershynin.

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Theorem (TAH 2015): *The MSE of generalized LASSO for nonlinear measurements of the form* $y = g(Ax_0 + v)$ *is asymptotically the same as the MSE of generalized LASSO for measurements of the form* $y = \mu A x_0 + \sigma v$*, where:*

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- We can show that, for q-bit quantization, the optimal quantizer is the celebrated LLoyd-Max quantizer.

One-Bit Quantization

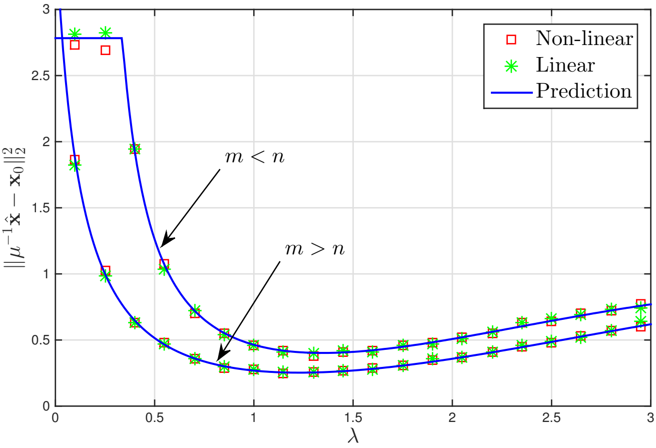

Figure: $n = 768$, $k = 115$, $m = 920 > n$ and $m = 576 < n$. The measurements were $y = \mathrm{sign}(Ax_0 + .3v)$ with the v_i iid $N(0, 1)$.

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