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When “Exact Recovery” is Exact Recovery in Compressed Sensing Simulation

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Measurements $\mathbf{u}$ come from sensing $\mathbf{x}$ by sensing matrix $\Phi$: $\mathbf{u} = \Phi \mathbf{x} + \mathbf{n}$. We use a recovery algorithm to build $\hat{\mathbf{x}}$ given $\mathbf{u}$ and $\Phi$, e.g., OMP, BP.

**Exact Recovery**

- In theory, we have no trouble asking $\hat{\mathbf{x}} \overset{?}{=} \mathbf{x}$.
- In practice, we must use a different criterion.
- At least two different criteria have been used in the simulation of compressed sensing recovery algorithms.
One exact recovery criterion in CS simulation: Support

Let $\Omega$ index the columns of $\Phi$, and define the support of $x$ as

$$S(x) := \{i \in \Omega : x_i \neq 0\}.$$ 

$x$ is exactly recovered with respect to support if

$$S(\hat{x}) = S(x).$$

This has been used in simulations of CS recovery in, e.g.,


One exact recovery criterion in CS simulation: Support


For $N = 512$. (a) Empirical prob. exact recovery as fun. of $M$ (ord.), $K/M$ (abs.). White is 1.0. (b) Empirical prob. of exact recovery for $M = 64$ as function of $K/M$. 
One exact recovery criterion in CS simulation: Support


Fig. 1. The percentage of 1000 input signals correctly recovered as a function of the number $N$ of measurements for different sparsity levels $m$ in dimension $d = 256$. 
One exact recovery criterion in CS simulation: Support


Fig. 1. Simulated success probability of ML detection for $n = 20$ and many values of $k$, $m$, SNR, and MAR. Each subfigure gives simulation results for $k \in \{1, 2, \ldots, 5\}$ and $m \in \{1, 2, \ldots, 40\}$ for one (SNR, MAR) pair. Each subfigure heading gives (SNR, MAR). Each point represents at least 500 independent trials. Overlaid on the color-intensity plots is a black curve representing (6).
Another exact recovery criterion: Normalized $\ell_2$-norm Error

Define a $0 \leq \epsilon^2 < 1$.

$x$ is exactly recovered with respect to normalized squared error if

$$\frac{\|x - \hat{x}\|^2_2}{\|x\|^2_2} \leq \epsilon^2 \quad (\epsilon^2 C)$$

This has been used in simulations of CS recovery in, e.g.,

Another exact recovery criterion: Normalized $\ell_2$-norm Error

Another exact recovery criterion: Normalized $\ell_2$-norm Error


Fig. 1. Empirical noiseless PTCs for Bernoulli-Gaussian signals and theoretical PTC for Lasso.
Another exact recovery criterion: Normalized $\ell_2$-norm Error

Two Criteria for Exact Recovery

1. \( \hat{x} \) is exactly recovered \textit{with respect to support} if
   \[
   S(\hat{x}) = S(x)
   \]  
   (SC)

2. \( \hat{x} \) is exactly recovered \textit{with respect to normalized squared error} if
   \[
   \frac{\|x - \hat{x}\|_2^2}{\|x\|_2^2} \leq \epsilon^2
   \]  
   (\( \epsilon^2 \)C)

One does not necessarily imply the other. There are instances, however, when one must be true if the other is true.

My Aims

With regards to running and comparing \textit{simulations of CS recovery}:

- Given a pair \((\hat{x}, x)\), when does “exact recovery” occur with respect to only one or both criteria?
- What is the role of \( \epsilon^2 \), and how should we define it?
Presentation Outline

1. Noiseless Case
   - $x \sim$ Bernoulli-Rademacher sparse signals
   - $x \sim$ Bernoulli-Gaussian sparse signals
   - Simulations

2. Noisy Case
   - $x \sim$ Bernoulli-Rademacher sparse signals
   - Simulations

3. Conclusions
Noiseless Case

Measurements $u$ come from sensing $x$ by the sensing matrix $\Phi$, $\|n\| = 0$:

$$u = \Phi x + n.$$ 

- Given $\hat{x}$, the weights minimizing the measurement modeling error are

$$y_{ls} := \arg \min_{y'} \|u - \Phi S(\hat{x})y'\|_2^2 = \Phi_{S(\hat{x})}^\dagger u.$$ 

With $\hat{x}$ composed of $y_{ls}$, if (SC) then for any $\epsilon^2 \in [0, 1]$ ($\epsilon^2 C$).

- If, however, ($\epsilon^2 C$) for $\epsilon^2 = 0$ then necessarily (SC).

Now we analyze the behavior of these criteria for signals distributed Bernoulli-Rademacher, Gaussian, and empirically in other ways.
Consider the **best case scenario** for sparsity $s$

- $S(\mathbf{x}) = \{1, 2, \ldots, s\}$;
- $\hat{\mathbf{x}}$ lacks the first $0 < k < s$ elements, i.e., for $n \in \{1, \ldots, k\}(\hat{x}_n = 0)$;
- $\hat{\mathbf{x}}$ has all the others, i.e., $n \in \Omega \backslash \{1, \ldots, k\}(\hat{x}_n = x_n)$.

This means that

- $S(\hat{\mathbf{x}}) \subset S(\mathbf{x})$, i.e., $\hat{\mathbf{x}}$ has no false detections;
- the missed detections do not influence our estimation of the values of the recovered support.

In this case, $(\epsilon^2C)$ and not $(SC)$ becomes for $1 \leq k \leq s$

\[
\frac{1}{\|\mathbf{x}\|_2^2} \sum_{n=1}^{k} x_n^2 \leq \epsilon^2.
\] (1)
Bernoulli-Rademacher Signals

If \( x \sim \text{Bernoulli-Rademacher} \), its non-zero elements are iid equiprobable in \( \{-1, 1\} \). In this case, \( \|x\|_2^2 = s \), so

\[
P\{ (\epsilon^2 C) \land \neg (SC) \} = \begin{cases} 1, & k/s \leq \epsilon^2 \\ 0, & \text{else} \end{cases}
\]  

(2)

For Bernoulli-Rademacher sparse signals \textit{in the best case scenario:}

The parameter \( \epsilon^2 \) limits the number of missed detections \( k \) for a sparsity \( s \).

- As long as \( s < \epsilon^{-2} \) for \( x \sim \text{Bernoulli-Rademacher} \), \( (\epsilon^2 C) \rightarrow (SC) \).
- In Maleki et al. 2010, where \( s < 800 \) and \( \epsilon^2 = 10^{-4} \), \( (\epsilon^2 C) \rightarrow (SC) \). However, if for this \( \epsilon^2 \) the sparsity \( s > 10000 \), then the two conditions are no longer equivalent.
Bernoulli-Gaussian Signals

Let the $s$ non-zero elements of $\mathbf{x} \sim \mathcal{N}(0, \sigma^2_y)$ with variance $\sigma^2_y > 0$. Define the independent chi-squared rvs

$$Y_k := \sum_{n=1}^{k} \frac{x_n}{\sigma_y}^2 \sim \chi^2(k), \quad Z_{s-k} := \sum_{n=k+1}^{s} \frac{x_n}{\sigma_y}^2 \sim \chi^2(s-k)$$

Since $Y_k$ and $Z_{s-k}$ are independent, $F_{k,s-k} := \frac{Y_k/k}{Z_{s-k}/(s-k)} \sim \mathcal{F}(k, s-k)$. Thus, in the best case scenario

$$P\{(\epsilon^2 C) \wedge \neg(SC)\} = P\left\{F_{k,s-k} < \frac{\epsilon^2}{1 - \epsilon^2} \frac{1 - k/s}{k/s}\right\}. \quad (3)$$

If $k/s > \epsilon^2$, then, for $s \geq 2k$, $P\{F_{k,s-k} < 1 + \delta\} > 0.5$ for $\delta > 0$.

For Bernoulli-Gaussian signals in the best case scenario:

The parameter $\epsilon^2$ limits the number of missed detections $k$ before $((\epsilon^2 C) \wedge \neg(SC))$ is false in a majority sense.
Experiments for several $\epsilon^2$ (labeled) & sparsities (legend)

(a) Zero-mean Gaussian (theoretical)

(b) Laplacian (empirical)

(c) Uniform (empirical)

(d) Bimodal Gaussian (empirical)
Noisy Case (assuming (SC))

Measurements $u$ come from sensing $x$ by the sensing matrix $\Phi$, $\|n\| > 0$:

$$u = \Phi x + n.$$

Assume (SC), and $\hat{x}$ is built from $\Phi^\dagger_{S(x)} u$. The weights in real solution are

$$y := \arg\min_{y'} \|u - n - \Phi_{S(x)} y'\|_2^2 = \Phi^\dagger_{S(x)} (u - n).$$

Then, $(\epsilon^2 C)$ becomes

$$\frac{\|y - \Phi^\dagger_{S(x)} u\|_2^2}{\|y\|_2^2} = \frac{\|\Phi^\dagger_{S(x)} (u - n) - \Phi^\dagger_{S(x)} u\|_2^2}{\|y\|_2^2} = \frac{\|\Phi^\dagger_{S(x)} n\|_2^2}{\|y\|_2^2} \leq \epsilon^2. \quad (4)$$

Hence, for any $\epsilon^2 \in (0, 1]$ we can find an $n$ such that $((\text{SC}) \land \neg (\epsilon^2 C))$.

This is different from noiseless case.
Define $\mathbf{v} := \Phi_{\mathcal{S}(\mathbf{x})}^\dagger \mathbf{n}$, and assume its $|\mathcal{S}(\mathbf{x})|$ elements are iid $\mathcal{N}(0, \sigma_v^2)$ and independent of $\mathbf{y}$. Define the chi-squared-distributed rv

$$V_s := \sum_{n=1}^{s} \left[ \frac{v_n}{\sigma_v} \right]^2 \sim \chi^2(s).$$

If $s$ elements of $\mathbf{x} \sim$ Rademacher, the probability of $(\epsilon^2 \mathcal{C})$ given (SC)

$$P\{ (\epsilon^2 \mathcal{C}) | (\text{SC}) \} = P \left\{ V_s < \frac{\epsilon^2 s}{\sigma_v^2} \right\}. $$

Note $P \{ V_s < s + \delta \} > 0.5$ for $\delta > 0$.

For Bernoulli-Rademacher signals, in the best case scenario:

Given (SC), if $\epsilon^2 \geq \sigma_v^2$ then $(\epsilon^2 \mathcal{C})$ in a majority sense.
Bernoulli-Gaussian Signals Given (SC)

Assume $s$ non-zero elements of $x \sim \mathcal{N}(0, \sigma^2_y)$, independent of $v$. Define

$$X_s := \sum_{n=1}^{s} \left[ \frac{x_n}{\sigma_y} \right]^2 \sim \chi^2(s).$$  (7)

The ratio $V_s / X_s$ is an F-distributed rv $W_{s,s} := V_s / X_s \sim \mathcal{F}(s, s)$. Thus, the probability of $(\epsilon^2 C)$ given (SC) is

$$P\{(\epsilon^2 C) | (SC)\} = P \left\{ W_{s,s} < \frac{\sigma_y^2}{\sigma_v^2} \epsilon^2 \right\}. \quad (8)$$

Note $P \{ W_{s,s} < 1 + \delta \} > 0.5$ for $\delta > 0$.

For Bernoulli-Gaussian signals, in the best case scenario:

Given (SC), if $\epsilon^2 \geq \sigma_v^2 / \sigma_y^2$ then $(\epsilon^2 C)$ in a majority sense.
Experiments for several SNR (legend) given (SC)

(a) Rademacher (theoretical)

(b) Zero-mean Gaussian (theoretical)

(c) Zero-mean Laplacian (empirical)

(d) Zero-mean Uniform (empirical)
Noisy Case (assuming not (SC))

Consider \((\epsilon^2 C)\) is true but not (SC), and best case scenario for sparsity \(s\):
- \(S(x) = \{1, 2, \ldots, s\}\);
- \(\hat{x}\) lacks the first \(0 < k < s\) elements, i.e., for \(n \in \{1, \ldots, k\}\)\((\hat{x}_n = 0)\);
- \(\hat{x}\) has the others perturbed by \(v\): \(n \in \Omega \setminus \{1, \ldots, k\}\)(\(\hat{x}_n = x_n + v_n\)).

This means that:
- \(S(\hat{x}) \subset S(x)\), i.e., \(\hat{x}\) has no false detections;
- missed detections do not influence estimations of support recovered;
- values of true detections perturbed only by the noise.

Assume \(x\) and \(v\) are independent, \((\epsilon^2 C)\) given not (SC) becomes

\[
\frac{1}{\|x\|^2} \left[ \sum_{n=1}^{k} x_n^2 + \sum_{n=1}^{s-k} v_n^2 \right] \leq \epsilon^2. \tag{9}
\]
Bernoulli-Rademacher Signals (assuming not (SC))

Define the rv

$$G_{s-k} := \sum_{n=1}^{s-k} \left[ v_n / \sigma_v \right]^2 \sim \chi^2(s - k).$$  \hfill (10)

When the non-zero elements of $x$ are distributed Rademacher, and $v_n \sim \mathcal{N}(0, \sigma_v^2)$, $(\epsilon^2 C)$ given not (SC) becomes

$$P\{(\epsilon^2 C) \wedge \neg (SC)\} = P\left\{ G_{s-k} < \frac{\epsilon^2 s - k}{\sigma_v^2} \right\}. \hfill (11)$$

Note $P\{G_{s-k} < s - k + \delta\} > 0.5$ for $\delta > 0$.

For Bernoulli-Rademacher signals in the best case scenario:

If $\frac{\epsilon^2 s - k}{\sigma_v^2} < s - k$, then $(\epsilon^2 C)$ is false in a majority sense.
Experiments for several $\epsilon^2$ (labeled) & SNR (legend)

(a) Rademacher (theoretical)

(b) Zero-mean Gaussian (empirical)
In theory, we can test for exact recovery with $\hat{x} = x$.

In practice (finite precision), we must use a different criterion.

In the *simulation* of compressed sensing recovery algorithms, two different exact recovery criteria have been used:

1. $x$ is exactly recovered *with respect to support* if
   \[ S(\hat{x}) = S(x) \]  
   \[(SC)\]

2. $x$ is exactly recovered *with respect to normalized squared error* if
   \[ \frac{\|x - \hat{x}\|^2}{\|x\|^2} \leq \epsilon^2. \]  
   \[(\epsilon^2 C)\]

We have shown that each does not necessarily imply the other.

$\epsilon^2$ limits the acceptable number of missed detections.

See the paper for more useful tips!