

# Compressed Sensing: Day 4

## Complete proof and more

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# Properties of this week

## Lemma (Small magnitude)

*For all  $t \in T^c$ , we have that  $|P(t)| < 1$  occurs with high probability.*

## Lemma (Invertibility)

*The operator  $\iota^* \iota - \frac{1}{|\Omega|} \iota^* H$  is invertible with high probability.*

# Sparsity

Recall that an assumption in the main theorem is  $\tau N \geq |T| \log N \frac{1}{\alpha(M)}$ , which can be written as

$E \ll \Omega$

$$|T| \leq \alpha(M) \frac{\tau N}{\log N}.$$

"f" is sparse enough

Last lecture, we had to ask that

$$|T| \leq \frac{(1 - \varepsilon_M)^2 \alpha^2}{\gamma^2} \tau N.$$

0.42 =  $\alpha$

$n = M \log N$

# Notation

$$n := M \log N .$$

$$\varepsilon_M := \sqrt{\frac{2M \log N}{\tau N}} = \sqrt{\frac{2n}{\tau N}} . \quad < 1$$

$$\alpha := 0.42 .$$

$$\underline{\tau \leq 0.44 .}$$

## Previous results

Under the previous assumptions,

$$\mathbb{P}(|\Omega| \geq (1 - \varepsilon_M)\tau N) \in 1 - O(N^{-M}).$$

$$\mathbb{P}(\|l^* H\|_F \leq (1 - \varepsilon_M)\alpha|\Omega|) \in 1 - O(N^{-M}).$$



0.42

# Properties of this week

## Lemma (Small magnitude)

For all  $t \in T^c$ , we have that  $|P(t)| < 1$  occurs with high probability.

## Lemma (Invertibility)

The operator  $\iota^* \iota - \frac{1}{|\Omega|} \iota^* H$  is invertible with high probability.

## Tuesday's recap

Define

$$R_n := \sum_{m=1}^{\infty} \left( \frac{1}{|\Omega|^n} (\iota^* H)^n \right)^m.$$

If  $\alpha \in (0, 1)$  and  $\|\iota^* H\|_F \leq \alpha |\Omega|$ , then

$$\|R_n\|_{\infty} \leq \sqrt{|T|} \frac{\alpha^n}{1 - \alpha^n}.$$

Also,

$$\left( \iota^* \iota - \frac{1}{|\Omega|} \iota^* H \right)^{-1} = (\iota^* \iota + R_n) \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m.$$

# Separation

We can write

$$\begin{aligned}
 P &= \left( \iota - \frac{1}{|\Omega|} H \right) \left( \iota^* \iota - \frac{1}{|\Omega|} \iota^* H \right)^{-1} \iota^* \text{sign } f \\
 &= \left( \iota - \frac{1}{|\Omega|} H \right) (\iota^* \iota + R_n) \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f.
 \end{aligned}$$

So that, for  $t \in T^c$ ,

$$\begin{aligned}
 P(t) &= -\frac{1}{|\Omega|} H \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t) \\
 &\quad - \frac{1}{|\Omega|} H R_n \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t) \\
 &= P_{n,0}(t) + P_{n,1}(t).
 \end{aligned}$$

Big

small



# Objective

## Definition

$$P_{n,0}(t) := -\frac{1}{|\Omega|} H \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t)$$

$$P_{n,1}(t) := -\frac{1}{|\Omega|} H R_n \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t)$$

Then, for  $t \in T^c$ ,

$$P(t) = \underbrace{P_{n,0}(t)} + \underbrace{P_{n,1}(t)}.$$

## Lemma (Small magnitude)

$$\mathbb{P} \left( \sup_{t \in T^c} |P(t)| \geq 1 \right) \in O(N^{-M}).$$

# The big and the small

## Lemma (Separation in big and small)

For all  $n, a \in (0, 1)$ ,

$$\mathbb{P} \left( \sup_{t \in T^c} |P(t)| \geq \underline{1} \right) \leq \overset{\text{big}}{\mathbb{P}(\|P_{n,0}\|_\infty \geq \underline{a})} + \overset{\text{small}}{\mathbb{P}(\|P_{n,1}\|_\infty \geq \underline{1-a})}$$

## Proof.

$$P(t) = P_{\{n, 0\}}(t) + P_{\{n, 1\}}(t)$$

$$\begin{aligned} \mathbb{P} \left( \sup_{t \in T^c} |P(t)| \geq 1 \right) &\leq \mathbb{P}(\|P_{n,0}\|_\infty + \|P_{n,1}\|_\infty \geq 1) \\ &\leq \mathbb{P}(\|P_{n,0}\|_\infty \geq a \text{ or } \|P_{n,1}\|_\infty \geq 1 - a) \\ &\leq \mathbb{P}(\|P_{n,0}\|_\infty \geq a) + \mathbb{P}(\|P_{n,1}\|_\infty \geq 1 - a). \end{aligned}$$



# The big and the small, in general

Consider  $X, Y$  positive random variables.

Lemma (Separation in big and small)

For all  $a \in (0, 1)$ ,

$$\mathbb{P}(X + Y \geq 1) \leq \mathbb{P}(X \geq a) + \mathbb{P}(Y \geq 1 - a)$$

Proof.

$$\begin{aligned} \mathbb{P}(X + Y \geq 1) &\leq \mathbb{P}(X \geq a \text{ or } Y \geq 1 - a) \\ &\leq \mathbb{P}(X \geq a) + \mathbb{P}(Y \geq 1 - a) . \end{aligned}$$



# The big and the small, example

Consider  $X, Y \sim \text{Exp}(1)$ . Then,

$\text{Gamma}(2, 1)$

0.606

0.606

$$\mathbb{P}(X + Y \geq 1) \approx 0.735 \leq 1.212 \approx \mathbb{P}(X \geq 1/2) + \mathbb{P}(Y \geq 1/2).$$

In the other hand, if  $X = Y$ , then

$$\mathbb{P}(X + Y \geq 1) \approx 0.606 \leq 1.212 \approx \mathbb{P}(X \geq 1/2) + \mathbb{P}(Y \geq 1/2).$$

$2Y$

## The big and the small, example II

Consider  $X, Y \sim \begin{cases} 1/2 & w.p.1/2 \\ 0 & w.p.1/2. \end{cases}$

Then

$$\mathbb{P}(X + Y \geq 1) = 0.25 \leq 1.00 \approx \overset{0.5}{\mathbb{P}(X \geq 1/2)} + \overset{0.5}{\mathbb{P}(Y \geq 1/2)}.$$

In the other hand, if  $X = Y$ , then

$$\mathbb{P}(X + Y \geq 1) \approx \underset{2Y}{0.50} \leq 1.00 \approx \mathbb{P}(X \geq 1/2) + \mathbb{P}(Y \geq 1/2).$$

## The big and the small

Recall that, for all  $n$ ,  $a \in (0, 1)$ ,

Lemma (Separation in big and small)

$$\mathbb{P} \left( \sup_{t \in T^c} |P(t)| \geq 1 \right) \leq \mathbb{P} (\|P_{n,0}\|_\infty \geq a) + \mathbb{P} (\|P_{n,1}\|_\infty \geq 1 - a)$$

By choosing  $a = 0.91$ , we have to prove the following.

Lemma (Bounding the big)

$$\mathbb{P} (\|P_{n,0}\|_\infty \geq 0.91) \in O(N^{-M}).$$

Lemma (Bounding the small)

$$\mathbb{P} (\|P_{n,1}\|_\infty \geq 0.09) \in O(N^{-M}).$$

## Partitioning the sum

Recall that

$$\begin{aligned} P_{n,0}(t) &:= -\frac{1}{|\Omega|} H \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t) \\ &= -\sum_{m=1}^n \left( \frac{1}{|\Omega|} H \iota^* \right)^m \text{sign } f(t). \end{aligned}$$

Since the sum of many (random) vectors might be too complex, we will look at each term separately.

### Definition

$$Y_m := \left| \left( \frac{1}{|\Omega|} H \iota^* \right)^m \text{sign } f(t) \right|.$$

## Partitioning 0.91

Fix  $t \in T^c$ .

Consider  $(b_m)_{m \in [1..n]}$  such that  $b_i > 0$  and  $\sum_m b_m = 0.91$ . Then,

$$\mathbb{P} \left( |P_{n,0}(t)| \leq \sum_{m=1}^n Y_m \geq 0.91 \right) \leq \sum_{m=1}^n \mathbb{P}(Y_m \geq b_m).$$

If we had bounds on the moments of  $Y_m$ , we could use Markov inequalities to get an overall bound.



# Markov inequality

Fix  $t \in T^c$ . Assume  $n = 2^J - 1$ .  $= M \log N$

Lemma ( $P_{n,0}$  can be bounded)

If  $\mathbb{E}[Y_m^{2K_j}] \leq c_n$  for  $K_j = 2^{J-j}$  and  $m \in [2^j .. (2^{j+1} - 1)]$ , then there exists  $a_0 \in (0, 1)$  such that

$$\mathbb{P} \left( |P_{n,0}(t)| \geq \sum_{m=1}^n Y_m \geq 0.91 \right) \leq n a_0^{2^n} c_n.$$

## Proof

 $b_m \rightarrow a_j$ 

Proof.

Choose  $(a_j)_{j \in [1..(J-1)]}$  such that  $a_j^{-K_j} = a_0^{-n}$  and  $\sum_{j=0}^{J-1} 2^j a_j \leq 0.91$ . Notice that

$$\begin{aligned}
 \mathbb{P} \left( \sum_{m=1}^n Y_m \geq 0.91 \right) &\leq \sum_{j=0}^{J-1} \sum_{m=2^j}^{2^{j+1}-1} \mathbb{P} (Y_m \geq a_j^{2K_j}) && ; \text{union bound} \\
 &\leq \sum_{j=0}^{J-1} \sum_{m=2^j}^{2^{j+1}-1} a_j^{-2K_j} \mathbb{E} \left[ Y_m^{2K_j} \right] && ; \text{Markov ineq.} \\
 &\leq \sum_{j=0}^{J-1} \sum_{m=2^j}^{2^{j+1}-1} a_0^{-2n} C_n && ; \text{assumption} \\
 &\leq (\dots)
 \end{aligned}$$

# Proof

Proof.

Choose  $(a_j)_{j \in [1..(J-1)]}$  such that  $a_j^{-K_j} = a_0^{-n}$  and  $\sum_{j=0}^{J-1} 2^j a_j \leq 0.91$ . Notice that

$$\mathbb{P} \left( \sum_{m=1}^n Y_m \geq 0.91 \right) \leq \sum_{j=0}^{J-1} \sum_{m=2^j}^{2^{j+1}-1} a_0^{-2n} c_n \quad ; \text{assumption}$$

$$\leq n a_0^{-2n} c_n .$$

By choosing  $a_0 = 0.42$ , we indeed have that

$$\sum_{j=0}^{J-1} 2^j a_j = \sum_{j=0}^{J-1} 2^j a_0^{n/K_j} \leq 0.91. \quad \square$$

# Markov inequality

Fix  $t \in T^c$ . Assume  $n = 2^J - 1$ .

Lemma ( $P_{n,0}$  can be bounded)

If  $\mathbb{E}[Y_m^{2K_j}] \leq c_n$  for  $K_j = 2^{J-j}$  and  $m \in [2^j .. (2^{j+1} - 1)]$ , then there exists  $a_0 \in (0, 1)$  such that

$$a_0 = 0.42$$

$$\mathbb{P} \left( |P_{n,0}(t)| \geq \sum_{m=1}^n Y_m \geq 0.91 \right) \leq n a_0^{2^n} c_n.$$

## Bound on moments

We will take as given the following result.

### Lemma

For  $m \in [1 .. n]$ , denote  $j$  for the integer such that  $m \in [2^j .. (2^{j+1} - 1)]$  and define  $K_j := 2^{J-j}$ , where  $n < 2^J < 2n$ .  
Then,

$$\mathbb{E}[Y_m^{2K_j}] \leq c_n \in O(e^{-n}) = O(N^{-M})$$

$n = M \lfloor \log N$

### Proof.

See [CRT06, Appendix, page 36]. □

## Overall bound

Notice that the bound is  $O(e^{-n})$ .

Since  $n = M \log N$ ,  $O(e^{-n}) = O(N^{-M})$  and we have that, for each  $t \in T^c$ ,

$$\mathbb{P}(|P_{n,0}(t)| \geq 0.91) \leq n a_0^{2n} c_n \in O(N^{-M})$$

and, since  $a_0 = 0.42$  (and therefore  $a_0^2 < e^{-1}$ ),

$$\mathbb{P}(\|P_{n,0}\|_\infty \geq 0.91) \leq n \frac{N}{e^n} c_n \in O(N^{-M}),$$

for  $M \geq 1$ .

$$N / N^{\{M\}}$$

$$n \text{ integer} = \text{ceil}(M \log N)$$

## Discovering the small

Note that, for  $t \in T^c$ ,

small

$$\begin{aligned}
 P_{n,1}(t) &:= \frac{1}{|\Omega|} \underline{HR}_n \left[ \sum_{m=0}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \right] \iota^* \text{sign } f(t) \\
 &= \frac{1}{|\Omega|} HR_n \left( \iota^* \text{sign } f(t) + \sum_{m=1}^{n-1} \left( \frac{1}{|\Omega|} \iota^* H \right)^m \iota^* \text{sign } f(t) \right) \\
 &= \frac{1}{|\Omega|} HR_n \iota^* \left( \text{sign } f(t) + \sum_{m=1}^{n-1} \left( \frac{1}{|\Omega|} H \iota^* \right)^m \text{sign } f(t) \right) \\
 &= \frac{1}{|\Omega|} HR_n \iota^* (\text{sign } f(t) + \underbrace{P_{n-1,0}(t)}_{\text{Big}}) .
 \end{aligned}$$

Therefore,

$$\|P_{n,1}\|_{\infty} \leq \frac{1}{|\Omega|} \|H\|_{\infty} \|\underline{R}_n\|_{\infty} (1 + \|P_{n-1,0}\|_{\infty}) .$$

## Recalling the bounds

0.42

Recall that

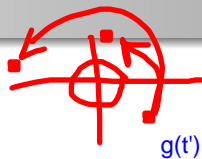
- $\mathbb{P}(\|l^* H\|_F < (1 - \varepsilon_M)\alpha|\Omega|) > 1 - O(N^{-M})$ .
- If  $\|l^* H\|_F < (1 - \varepsilon_M)\alpha|\Omega|$ , then  $\|R_n\|_\infty \leq \sqrt{|T|} \frac{\alpha^n}{1 - \alpha^n}$ .
- $\mathbb{P}(\|P_{n-1,0}\|_\infty \leq 0.91) > 1 - O(N^{-M})$ .

Then, with high probability,

$$\begin{aligned} \|P_{n,1}\|_\infty &\leq \frac{1}{|\Omega|} \|H\|_\infty \|R_n\|_\infty (1 + \|P_{n-1,0}\|_\infty) \\ &\leq \frac{1}{|\Omega|} \|H\|_\infty \sqrt{|T|} \frac{\alpha^n}{1 - \alpha^n} 2. \end{aligned}$$



# Magnitud of white noise



Recall that, for  $g \in \mathbb{C}^T$ ,

$$Hg(t) := - \sum_{\omega \in \Omega} \sum_{\substack{t' \in T \\ t' \neq t}} e^{i\omega(t-t')} g(t').$$

Therefore, if  $\|g\|_\infty \leq 1$ ,

$$\begin{aligned} |Hg(t)| &\leq \sum_{\omega \in \Omega} \sum_{\substack{t' \in T \\ t' \neq t}} |e^{i\omega(t-t')} g(t')| \\ &\leq \sum_{\omega \in \Omega} \sum_{\substack{t' \in T \\ t' \neq t}} 1 \leq |\Omega| |T|, \end{aligned}$$

so that

$$\frac{1}{|\Omega|} \|H\|_\infty \leq |T|.$$

# Overall bound

Then, with high probability,

$$\begin{aligned}\|P_{n,1}\|_{\infty} &\leq \frac{1}{|\Omega|} \|H\|_{\infty} \sqrt{|T|} \frac{\alpha^n}{1 - \alpha^n} 2 \\ &\leq |T|^{3/2} \frac{\alpha^n}{1 - \alpha^n} 2.\end{aligned}$$

Recall that  $n = M \log N$ . Then, if  $N^{3/2} \frac{\alpha^n}{1 - \alpha^n} 2 < 0.09$ , we would have that

$$\mathbb{P}(\|P_{n,1}\|_{\infty} \geq 0.09) \in O(N^{-M}).$$

small

## Relationship of $N$ and $M$

Consider the condition

$$N^{3/2} \frac{\alpha^n}{1 - \alpha^n} 2 = N^{3/2} \frac{\alpha^{M \log N}}{1 - \alpha^{M \log N}} 2 < 0.09$$

Recalling that  $\alpha = 0.42$ , we will ask for  $M > \log_{\alpha}(e^{-3/2})$ , so that

$$\lim_{N \rightarrow \infty} N^{3/2} \alpha^{M \log N} = 0.$$

Notice that

$$\begin{aligned} \alpha^n &= e^{n \log \alpha} \\ &\leq e^{-0.87n} && ; \log(0.42) \approx -0.87 \\ &= N^{-0.87M} && ; n = M \log N. \end{aligned}$$

Then, we will ask for  $-0.87M < -3/2$ , i.e.

$$M > 1.724.$$

$$\begin{aligned} M &= 2 \\ &\rightarrow N > 17 \end{aligned}$$

## Overall bound

If  $N^{3/2} \frac{\alpha^n}{1-\alpha^n} 2 < 0.09$ , then

$$\mathbb{P}(\|P_{n,0}\|_\infty \geq 0.91), \mathbb{P}(\|P_{n,1}\|_\infty \geq 0.09) \in O(N^{-M}).$$

Therefore,

$$\mathbb{P}\left(\sup_{t \in T^c} |P(t)| \geq 1\right) \in O(N^{-M}).$$

And so we have proven that

### Lemma (Small magnitude)

For all  $t \in T^c$ , we have that  $|P(t)| < 1$  occurs with high probability.

## Reduction to $(P_1)$

Let  $f \in \mathbb{C}^N$  and  $\Omega$  non-empty. Denote  $T := \text{supp } f$ .

Lemma (Sufficient conditions)

If  $\mathcal{F}_{T \rightarrow \Omega} : \mathbb{C}^T \rightarrow \mathbb{C}^\Omega$  is injective and there exists  $P \in \mathbb{C}^N$  such that

$$\begin{cases} \hat{P}(\omega) = 0 & ; \omega \in \Omega^c \quad \blacksquare \\ P(t) = \text{sign } f(t) & ; t \in T \quad \blacksquare \\ |P(t)| < 1 & ; t \in T^c, \quad \blacksquare \end{cases}$$

then,  $f = f^\#$  is the unique minimizer of  $(P_1)$ .

# Clever construction

## Definition (Extrapolation)

Denote the extrapolation by zero by the operator  $\iota: \mathbb{C}^T \rightarrow \mathbb{C}^N$ .

Its adjoint  $\iota^*: \mathbb{C}^N \rightarrow \mathbb{C}^T$  is the restriction map. Note that  $\iota^*\iota: \mathbb{C}^T \rightarrow \mathbb{C}^T$  is the identity map.

We will prove that there is a suitable operator  $H: \mathbb{C}^T \rightarrow \mathbb{C}^N$  such that

$$P := \left( \iota - \frac{1}{|\Omega|} H \right) \left( \iota^* \iota - \frac{1}{|\Omega|} \iota^* H \right)^{-1} \iota^* \text{sign } f$$

works for our purposes.

## Reduction to $(P_1)$

Let  $f \in \mathbb{C}^N$  and  $\Omega$  non-empty. Denote  $T := \text{supp } f$ .

Lemma (Sufficient conditions)

If  $\mathcal{F}_{T \rightarrow \Omega} : \mathbb{C}^T \rightarrow \mathbb{C}^\Omega$  is injective and there exists  $P \in \mathbb{C}^N$  such that

$$\begin{cases} \hat{P}(\omega) = 0 & ; \omega \in \Omega^c \\ P(t) = \text{sign } f(t) & ; t \in T \\ |P(t)| < 1 & ; t \in T^c, \end{cases}$$

then,  $f = f^\#$  is the unique minimizer of  $(P_1)$ .

# Reconstruction with high probability

1.724

Fix  $f \in \mathbb{C}^N$ ,  $\tau \in (0, 1)$  and  $M > 0$ .

Theorem ([CRT06, Theorem 1.3])

Denote  $T := \text{supp } f$ . If

$$\tau N \geq |T| \log N \frac{1}{\alpha(M)},$$

then,  $f = f^\#$  with probability at least  $1 - O(N^{-M})$ .

Where

$$\alpha(M) := \frac{(1 - \varepsilon_M)^2 \alpha^2}{\gamma^2 M}$$



# Sensing and description basis

Theorem ([CR07, Theorem 1.1])

Denote  $T := \{\psi : \langle \psi, f \rangle \neq 0\}$ . If

$$\tau N \geq \mu^2(\Phi, \Psi) |T| \log N \frac{1}{\alpha(M)},$$

then,  $f = \underline{f}_{\Psi, \Phi}^{\#}$  with probability at least  $1 - O(N^{-M})$ .

## Deterministic sensing and random signal

Let  $C_0, C_1$  be fixed numerical constants. Fix  $\Phi, \Psi$  basis of  $\mathbb{C}^N$ ,  
 $T \subseteq \Psi$  and  $\Omega \subseteq \Phi$ .

Theorem ([CR07, Theorem 1.1])

Fix  $\delta > 0$ . If

$$|\Omega| \geq \max \left\{ C_0 \mu^2(\Phi, \Psi) |T| \log \left( \frac{N}{\delta} \right), C_1 \log^2 \left( \frac{N}{\delta} \right) \right\},$$

then,  $f = f_{\Psi, \Phi}^{\#}$  with probability at least  $1 - \delta$ .

Probability on what?  $f$  is random in its sign: choose the sign  $\langle \psi, f \rangle$  randomly for each  $\psi \in T$ . Then, the reconstruction holds independently of the magnitud of  $\langle \psi, f \rangle$ .

## Perturbed samples

Fix  $f \in \mathbb{C}^N$  and  $\Psi, \Phi$  description and sensing basis.  
Consider having access to, for all  $\phi \in \Omega$ ,

$$y_\phi := \langle f, \phi \rangle + \xi_\phi,$$

where  $\xi_\phi \sim \mathcal{N}(0, \varepsilon^2)$ .

Consider

$$(P_1(\Psi, \Phi)) \begin{cases} \min_{g \in \mathbb{C}^N} & \sum_{\psi \in \Psi} |\langle \psi, g \rangle| \\ \text{s.t.} & \langle \phi, g \rangle = y_\phi \quad \forall \phi \in \Omega \subseteq \Phi. \end{cases}$$

What is the relationship between  $f$  and  $f_{\Psi, \Phi}^\#$ ?

## Relevant support

With a general signal, we can rethink the support and define the following.

### Definition (Truncated signal)

Denote

$$f = \sum_{i=1}^N \langle \psi_i, f \rangle \psi_i,$$

where  $(|\langle \psi_i, f \rangle|)_{i \in [1..N]}$  is decreasing. Then, for  $T \in [1..N]$ , define

$$f_T := \sum_{i=1}^T \langle \psi_i, f \rangle \psi_i.$$

## Continuity in reconstruction

The general result states that there is a constant  $C_0 > 0$  such that

$$\|f - f_{\Psi, \Phi}^{\#}\|_2 \leq \frac{C_0}{\sqrt{|T|}} \|f - f_T\|_1$$

and

$$\|f - f_{\Psi, \Phi}^{\#}\|_1 \leq C_0 \|f_T - f_{\Psi, \Phi}^{\#}\|_1$$

with “high” probability, where “high” depends on  $\tau \in (0, 1)$  and  $T \in [1 .. N]$ .

## Correct minimization problem

How moral is to solve  $(P_1(\Psi, \Phi))$ ? Should we not solve

$$(\tilde{P}_1(\Psi, \Phi)) \begin{cases} \min_{g \in \mathbb{C}^N} & \sum_{\psi \in \Psi} |\langle \psi, g \rangle| \\ \text{s.t.} & \|\langle \phi, g \rangle - y_\phi\|_2 \leq \sqrt{N}\epsilon \quad \forall \phi \in \Omega \subseteq \Phi. \end{cases}$$

In this case, on can show that

$$\|f - \tilde{f}_{\Psi, \Phi}\|_2 \leq \frac{C_1}{\sqrt{|T|}} \|f - f_T\|_1 + C_2 \sqrt{N}\epsilon,$$

for some constants  $C_1, C_2 > 0$ .

# Reconstruction with high probability

Fix  $f \in \mathbb{C}^N$ ,  $\tau \in (0, 1)$  and  $M > 0$ .

Theorem ([CRT06, Theorem 1.3])

Denote  $T := \text{supp } f$ . If



$$\tau N \geq |T| \log N \frac{1}{\alpha(M)},$$

then,  $f = f^\#$  with probability at least  $1 - O(N^{-M})$ .

Where

$$\alpha(M) := \frac{(1 - \varepsilon_M)^2 \alpha^2}{\gamma^2 M}$$

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