

Lecture 10: Compressed Sensing

Lecturer: *Przemysław Uznański*

Scribe: -

1 Overview

A version of sparse recovery: given linear measurements, recover the signal. In general impossible if $m < n$, but is possible if we make additional assumptions.

Definition 1. Given $A \in \mathbb{R}^{m \times n}$, and $y = Ax \in \mathbb{R}^m$, recover $x \in \mathbb{R}^n$ given that x is k -sparse.

Rephrasing problem:

$$\begin{aligned} & \text{minimize} \quad \|x'\|_0 \\ & \text{subject to} \quad Ax' = Ax \end{aligned}$$

(this is hard problem, NP-hard?)

The approach: solve the following program

$$\begin{aligned} & \text{minimize} \quad \|x'\|_1 \\ & \text{subject to} \quad Ax' = Ax \end{aligned}$$

The insight is that signals with small $\|x'\|_1$ should be sparse (the weight of x' is concentrated on a few “optimal” coordinates). Particularly, optimizing $\|x'\|_2$ would not work.

(Adding noise: subject to $\|Ax - Ax'\|_2 \leq \varepsilon$.)

The program can be expressed as LP, with $n^{\Theta(1)}$ algorithm.

Theorem 2. Let $m = \Theta(k \log(n/k))$. Pick $A \in \mathbb{R}^{m \times n}$ with entries $\mathcal{N}(0, 1)$. W.h.p. the following holds for some C : the output x' of the LP satisfies

$$\|x' - x\|_2 \leq \frac{C}{\sqrt{k}} \min_{\|x''\|_0 \leq k} \|x - x''\|_1. \quad (1)$$

In fact any JL-type distribution works.

1.1 Restricted Isometry Property

Definition 3. We say that matrix A satisfies (k, ε) -RIP if for any k -sparse x there is

$$\|Ax\|_2 = (1 \pm \varepsilon)\|x\|_2.$$

Theorem 4. JL matrix with $m = \Theta(k \log(n/k))$ satisfies $(k, 1/3)$ -RIP.

Proof. Recall proof of subspace embeddings. Here as well it is enough to show the property for $\|x\|_2 = 1$. For any $K \subseteq [n]$, $|K| = k$, we take $B_K = \{x : \|x\|_2 = 1 \wedge \text{support}(x) \subseteq K\}$, that is vectors spanned on coordinates in K of length 1.

Pick $(1/7)$ -net N_K for B_K of size $2^{\mathcal{O}(k)}$. For any $x \in B_K$ there is $x = \sum_{i \geq 0} \alpha_i x_i$ where $\alpha_i \leq 7^{-i}$ and $x_i \in B_K$, and $\alpha_0 = 1$.

For A properly set (JL with constant $1/7$), there is

$$\|Ax\|_2 = \|A \sum_{i \geq 0} \alpha_i x_i\|_2 \leq \sum_i \alpha_i \|Ax_i\|_2 \leq \sum_i \frac{8}{7} \cdot 7^{-i} \leq \frac{4}{3}$$

and

$$\|Ax\|_2 = \|A \sum_{i \geq 0} \alpha_i x_i\|_2 \geq \|Ax_0\|_2 - \sum_{i \geq 1} \alpha_i \|Ax_i\|_2 \geq \frac{6}{7} - \sum_{i \geq 1} \frac{8}{7} 7^{-i} = \frac{6}{7} - \frac{4}{3} \cdot \frac{1}{7} = \frac{2}{3}$$

How large the m needs to be? It needs to work for union of all $1/7$ -nets. We have $|\bigcup N_K| \leq \binom{n}{k} \cdot 2^{\mathcal{O}(k)} = 2^{\mathcal{O}(k \log(n/k))}$. \square

1.2 Basis pursuit

Theorem 5. $(4k, 1/3)$ -RIP implies (1).

Proof. Denote $h = x' - x$. Let us reorder x so that x_1, \dots, x_k are the largest magnitude coefficients, and then so that h_{k+1}, \dots are sorted (ignoring that h_1, \dots, h_k might be arbitrary). Denote $A = \{1, \dots, k\}$ and $A_j = \{k + 5jk + 1, \dots, 6k + 5jk\}$ for $j \geq 0$.

Denote $\eta = \min_{\|x''\|_0 \leq k} \|x - x''\|_1 = \|x_{A^c}\|_1$.

First, bound:

$$\|x\|_1 \geq \|x'\|_1 = \|x + h\|_1 = \|x_A + h_A\|_1 + \|x_{A^c} + h_{A^c}\|_1 \geq \|x_A\|_1 - \|h_A\|_1 - \|x_{A^c}\|_1 + \|h_{A^c}\|_1$$

so

$$\|h_{A^c}\|_1 \leq \|h_A\|_1 + 2\|x_{A^c}\|_1 = \|h_A\|_1 + 2\eta \quad (2)$$

Then for any vector y with sorted coordinates, $|y_i| \leq \|y\|_1/i$. So

$$\|h_{(AA_0)^c}\|_2^2 \leq \|h_{A^c}\|_1^2 \sum_{j=5k}^{\infty} \frac{1}{j^2} \leq \|h_{A^c}\|_1^2 \frac{1}{\mathcal{O}(k)}$$

so, using (2)

$$\|h_{(AA_0)^c}\|_2 = \mathcal{O}\left(\frac{\|h_A\|_1 + \eta}{\sqrt{k}}\right) \quad (3)$$

Then

$$\begin{aligned} 0 &= \|A(x' - x)\|_2 = \|Ah\|_2 \geq \|Ah_{AA_0}\|_2 - \left\| \sum_{j \geq 1} Ah_{A_j} \right\|_2 \\ &\geq \|Ah_{AA_0}\|_2 - \sum_{j \geq 1} \|Ah_{A_j}\|_2 \\ &\geq \frac{2}{3} \|h_{AA_0}\|_2 - \frac{4}{3} \sum_{j \geq 1} \|h_{A_j}\|_2 \end{aligned}$$

Each term in $h_{A_{j+1}}$ is smaller than average term in h_{A_j} , so $\|h_{A_{j+1}}\|_2^2 \leq (5k) \frac{\|h_{A_j}\|_1^2}{(5k)^2} = \frac{\|h_{A_j}\|_1^2}{5k}$. So

$$\sum_{j \geq 1} \|h_{A_j}\|_2 \leq \sum_{j \geq 0} \frac{\|h_{A_j}\|_1}{\sqrt{5k}} = \frac{\|h_{A^c}\|_1}{\sqrt{5k}} = \frac{\|h_A\|_1 + 2\eta}{\sqrt{5k}} \leq \sqrt{\frac{k}{5k}} \|h_A\|_2 + \frac{2}{\sqrt{5k}} \eta \quad (4)$$

Combining we have

$$\frac{2}{3} \|h_{AA_0}\|_2 \leq \frac{4}{3\sqrt{5}} \|h_A\|_2 + \mathcal{O}\left(\frac{\eta}{\sqrt{k}}\right)$$

so since $\|h_A\|_2 \leq \|h_{AA_0}\|_2$ and $\frac{2}{3} < \frac{4}{3\sqrt{5}}$, there is

$$\|h_{AA_0}\|_2 = \mathcal{O}\left(\frac{\eta}{\sqrt{k}}\right)$$

and this bound also applies in the form of

$$\frac{\|h_A\|_1}{\sqrt{k}} = \mathcal{O}\left(\frac{\eta}{\sqrt{k}}\right).$$

By triangle inequality

$$\|h\|_2 \leq \|h_{AA_0}\|_2 + \|h_{(AA_0)^c}\|_2 = \mathcal{O}\left(\frac{\eta}{\sqrt{k}}\right)$$

□

1.3 Iterative Hard Thresholding [BD09]

Assume $y = Ax + e$, where e is some noise, and x is k -sparse.

The algorithm works as follow.

- $x^0 = 0$.
- $a^{i+1} = x^i + A^T(y - Ax^i)$
- $x^{i+1} = H_k[a^{i+1}]$ where H_k is projection onto top- k coefficients.

We expect x^t to converge onto $x \pm \mathcal{O}(e)$, in logarithmic number of iterations. Proof: denote $r^i = x - x^i$. Our goal is to show that r^i decreases by a constant factor at each step.

Denote $S = \text{support}(x)$ and $S^i = \text{support}(x^i)$, and $B^i = S \cup S^i$.

We assume we have $(3k, \varepsilon)$ -RIP for sufficiently small ε (like, small constant).

Properties: (A_S denotes matrix with only columns in S kept, and all others zeroed out).

Lemma 6. For S such that $|S| \leq 3k$:

$$\|(I - A_S^T A_S)x_S\|_2 \leq \varepsilon \|x_S\|_2$$

Proof. Follows from A_S being subspace embedding for $3k$ -sparse vectors. □

Lemma 7. for any disjoint S, S' with $|S| + |S'| \leq 3k$

$$\|A_S^T A_{S'} x_{S'}\|_2 \leq \varepsilon \|x_{S'}\|_2$$

Proof.

$$\begin{aligned}\|A_S^T A_{S'}\|_2 &= \sup_{\|y\|=1} \|A_S^T A_{S'} y\|_2 = \sup_{\|x\|=1, \|y\|=1} x^T A_S^T A_{S'} y = \sup_{\|x\|=1, \|y\|=1} \langle A x_S, A y_{S'} \rangle \\ &= \sup_{\|x\|=1, \|y\|=1} (\langle x_S, y_{S'} \rangle \pm \varepsilon) \leq \varepsilon\end{aligned}$$

where we used that $\langle x_S, y_{S'} \rangle = 0$ and that linear combinations of $x_S, y_{S'}$ are also sparse. \square

Lemma 8.

$$\|A_S^T y\|_2^2 \leq (1 + \varepsilon) \|y\|_2^2$$

Proof. Follows from $\|A_S^T\|_2 = \|A_S\|_2 \leq (1 + \varepsilon)$, which follows from:

$$\|A_S\|_2 = \sum_{\|x\|_2=1} \|A_S x_S\|_2 \leq \sqrt{1 + \varepsilon} \|x_S\| = \sqrt{1 + \varepsilon}$$

\square

Now we bound $\|r^{i+1}\|_2$:

$$\|r^{i+1}\|_2 = \|x - x^{i+1}\|_2 = \|x_{B^{i+1}} - x_{B^{i+1}}^{i+1}\|_2 \leq \|x_{B^{i+1}} - a_{B^{i+1}}^{i+1}\|_2 + \|x_{B^{i+1}}^{i+1} - a_{B^{i+1}}^{i+1}\|_2$$

since $x_{B^{i+1}}^{i+1}$ is the best possible k -sparse approximation to $a_{B^{i+1}}^{i+1}$, and $x_{B^{i+1}}$ is k -sparse, we have

$$\begin{aligned}\|r^{i+1}\|_2 &\leq 2\|x_{B^{i+1}} - a_{B^{i+1}}^{i+1}\|_2 \\ &\leq 2\|x_{B^{i+1}} - x_{B^{i+1}}^i - A_{B^{i+1}}^T A r^i - A_{B^{i+1}}^T e\|_2 \\ &\leq 2\|r_{B^{i+1}}^i - A_{B^{i+1}}^T A r^i\|_2 + 2\|A_{B^{i+1}}^T e\|_2 \\ &\leq 2\|(I - A_{B^{i+1}}^T A_{B^{i+1}}) r_{B^{i+1}}^i\|_2 + 2\|A_{B^{i+1}}^T A_{B^i - B^{i+1}} r_{B^i - B^{i+1}}^i\|_2 + 2\sqrt{1 + \varepsilon} \|e\|_2 \\ &\leq 2\varepsilon \|r_{B^{i+1}}^i\|_2 + 2\varepsilon \|r_{B^i - B^{i+1}}^i\|_2 + 2\sqrt{1 + \varepsilon} \|e\|_2 \\ &\leq 4\varepsilon \|r^i\|_2 + 2\sqrt{1 + \varepsilon} \|e\|_2\end{aligned}$$

set $\varepsilon = 1/8$

$$\leq \frac{1}{2} \|r^i\|_2 + 3\|e\|_2$$

References

- [BD09] T. Blumensath and M. E. Davies. A simple, efficient and near optimal algorithm for compressed sensing. In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 3357–3360, April 2009.