

## Lecture 20 — March 31

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## 20.1 Topics covered

- Sparse Representation in Over Complete Basis
- Finding Sparse Representation using  $\ell_1$  minimization

## 20.2 Sparse representation in overcomplete basis

### 20.2.1 Motivation from digital signal processing

Let  $\Phi$  be a matrix whose columns are composed of the basis functions/ vectors for the frequency domain. Let  $\Psi$  be a matrix similarly formed using the basis functions/ vectors for the time domain.

Consider the signal shown in figure 20.1. We have added together two signals with sparse representations in  $\Phi$  and  $\Psi$  alone to produce a signal which is sparse in neither. In other words, this resultant signal does not have a sparse representation in  $\Phi$  alone or in  $\Psi$  alone. But, it can be seen to have a sparse representation in  $\Phi$  and  $\Psi$  together.

It must be noted, however that the columns of  $[\Phi \ \Psi]$  are not linearly independent. So,  $[\Phi \ \Psi]$  forms an 'overcomplete basis'. This motivates the following problem.

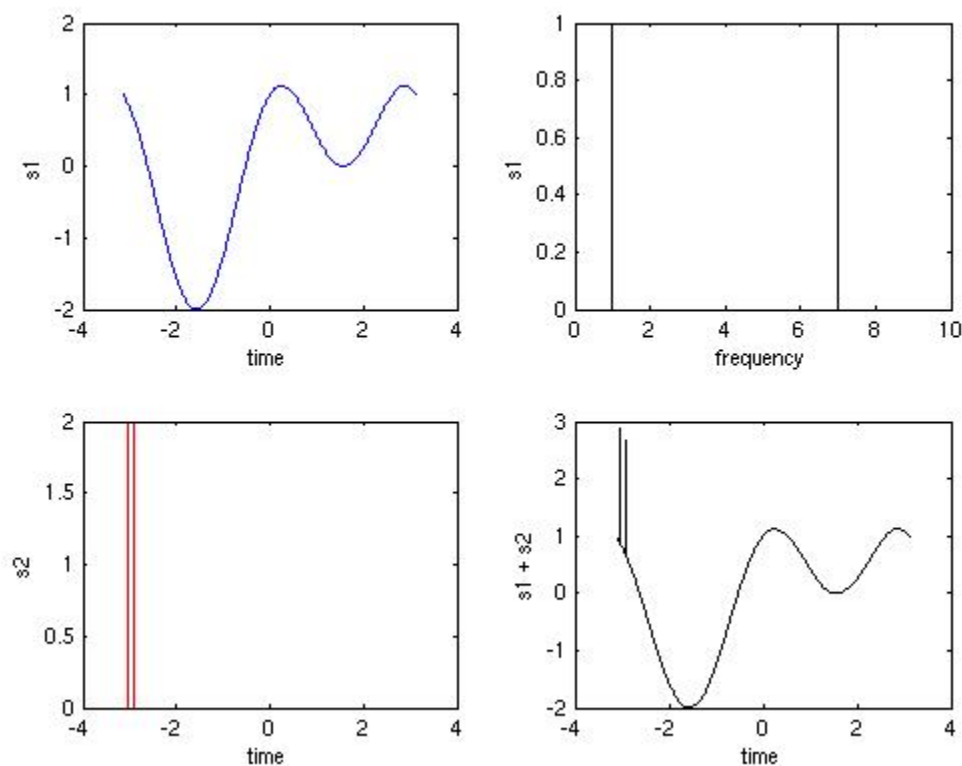
### 20.2.2 Problem

Given a signal (or a vector  $x$  in general), when can we find a sparse representation in the 'overcomplete basis'  $[\Phi \ \Psi]$ ?

#### Ill posedness/ non-uniqueness

There are an infinite number of representations for any signal in a pair of bases. Looking for sparsity in representation may help, but this is not enough to guarantee uniqueness.

To see this, consider a basis  $\Psi$  which differs from  $\Phi$  in only two basis vectors, but is the same as  $\Phi$  otherwise. Then, sparsity of  $x$  in  $\Psi$  is equivalent to sparsity in  $\Phi$ ; and it is even hard for an  $x$  which is sparse in  $\Psi$  or  $\Phi$  alone, to have a unique representation in the overcomplete basis  $[\Phi \ \Psi]$ . For example, suppose that both  $\Phi$  and  $\Psi$  include the basis vectors  $\{\phi_1, \phi_2\}$ , and consider  $x = \phi_1 + \phi_2$ .  $x$  has an infinite number of sparse representations in the basis  $[\Phi \ \Psi]$ .



**Figure 20.1.** The signal  $s_1$  has a sparse representation in the frequency domain.  $s_2$  has a sparse representation in the time domain. But, the signal  $(s_1 + s_2)$  has a sparse representation in an overcomplete basis, but not in either the frequency or time domain alone.

So, we must add an additional condition:  $\Phi$  and  $\Psi$  must be 'different' enough. This property is usually referred to as 'incoherence'.

### 20.2.3 Basic uncertainty principle

**Theorem 20.1.** Let  $\Phi$  and  $\Psi$  be two orthonormal bases for a vector space. For any vector  $s \neq 0$ , let  $s = \Phi a$  and  $s = \Psi b$ . Let  $M = \max_{i,j} |\langle \phi_i, \psi_j \rangle|$ . Then:

$$\frac{\|a\|_0 + \|b\|_0}{2} \geq \sqrt{\|a\|_0 \|b\|_0} \geq M^{-1}$$

.

**Proof:** The first inequality comes from the well known AM-GM inequality, so we prove  $\sqrt{\|a\|_0 \|b\|_0} \geq M^{-1}$ .

Without loss of generality, suppose that  $s^T s = 1$ .

$$1 = a^T \Phi^T \Psi b \leq \sum_{i,j} |a_i| |\langle \phi_i, \psi_j \rangle| |b_j| \leq M \sum_i |a_i| \sum_j |b_j|$$

Let  $A = \|a\|_0, B = \|b\|_0$ . From  $s^T s = 1$ , we have that  $\sum_i |a_i|^2 = 1 = \sum_i |b_i|^2$ . Also,  $\forall i : |a_i| \leq 1, |b_i| \leq 1$ . So:

$$\sum_i |a_i| \leq \sqrt{A}, \sum_i |b_i| \leq \sqrt{B}$$

Substituting this into the earlier inequality, we have  $\sqrt{\|a\|_0 \|b\|_0} \geq M^{-1}$ .  $\square$

From this, we have the following theorem, whose proof is left as a homework exercise.

**Theorem 20.2.** *If  $s = [\Phi \ \Psi]g_1, s = [\Phi \ \Psi]g_2$ , then  $\|g_1\|_0 + \|g_2\|_0 \geq \frac{2}{M}$ .*

From this, we have the following corollary:

**Corollary 20.3.** *Suppose that  $s = [\Phi \ \Psi]g_1$ , and  $\|g_1\|_0 < M^{-1}$ . Then, there does not exist a  $g_2$  such that  $s = [\Phi \ \Psi]g_2$  and  $\|g_2\|_0 < M^{-1}$ .*

Incoherence is the situation where  $M$  is small. Thus, incoherence ensures uniqueness for the sparsest representation. In other words, any other representation will have more non-zeros.

This motivates the following question: If  $s$  has a unique sparse representation, how do we find it? The answer to this is explored in the next section.

## 20.3 Sparse Representation using $\ell_1$ minimization

Suppose we want to find the sparsest  $\gamma$  such that  $[\Phi \ \Psi]\gamma = s$ . The set of all feasible  $\gamma$  is an affine subspace of  $\mathbb{R}^n$ . We want to know when  $\ell_1$  minimization gives us the sparsest solution.

**Theorem 20.4 (Donoho and Huo).** *If  $\|\gamma\|_0 < \frac{1}{2}(1 + \frac{1}{M})$  then  $\|\tilde{\gamma}\|_1 > \|\gamma\|_1$  for all  $\tilde{\gamma}$  such that  $[\Phi \ \Psi]\tilde{\gamma} = [\Phi \ \Psi]\gamma$*

**Proof:** Let  $\|\gamma\|_0 < \frac{1}{2}(1 + \frac{1}{M})$ . Consider any  $\tilde{\gamma}$  such that  $[\Phi \ \Psi]\tilde{\gamma} = [\Phi \ \Psi]\gamma$ . Let  $x = \tilde{\gamma} - \gamma$ . Then, we have  $[\Phi \ \Psi]x = 0$ .

$$\|\tilde{\gamma}\|_1 > \|\gamma\|_1$$

$$\Leftrightarrow \sum_{k \in \text{supp}(\gamma)} (|\gamma_k + x_k| - |\gamma_k|) + \sum_{k \notin \text{supp}(\gamma)} |x_k| > 0$$

$$\Leftarrow \sum_{k \in \text{supp}(\gamma)} -|x_k| + \sum_{k \notin \text{supp}(\gamma)} |x_k| > 0$$

$$\Leftrightarrow \frac{\sum_{\text{ON}} |x_k|}{\sum_{\text{ALL}} |x_k|} < \frac{1}{2}$$

$$\text{where } \sum_{\text{ON}} |x_k| = \sum_{k \in \text{supp}(\gamma)} |x_k| \text{ and } \sum_{\text{ALL}} |x_k| = \sum_k |x_k|.$$

We want this to be true for all supports of size less than  $\frac{1}{2}(1 + \frac{1}{M})$  and for all  $x$  such that  $[\Phi\Psi]x = 0$ . Let  $x \neq 0$  be any such vector and let  $i$  be such that  $|x_i| \geq |x_j|$  for all  $j$ . WLOG, by rescaling, we can assume  $x_i = v$  where  $v$  is a fixed number. For this, we have

$$\sum_{\text{ON}} |x_k| \leq \|x\|_0 |v|.$$

$$x = \begin{bmatrix} x^\Phi \\ x^\Psi \end{bmatrix}$$

$$\|x\|_1 = \|x^\Phi\|_1 + \|x^\Psi\|_1$$

WLOG, say  $i$  is in the  $\Phi$  part.

$$\Phi x^\Phi = -\Psi x^\Psi$$

$$x^\Phi = -\Phi^T \Psi x^\Psi$$

since  $\Phi$  is an orthonormal matrix. So we have,

$$|v| = |x_i| = |[\Phi^T \Psi]_i x^\Psi|$$

$$\leq M \|x^\Psi\|_1$$

$$\Rightarrow \|x^\Psi\|_1 \geq \frac{|v|}{M}$$

We also have,

$$\|x^\Phi\|_1 \geq |v|$$

$$\Rightarrow \sum_{\text{ALL}} |x_k| = \|x\|_1 \geq |v| \left(1 + \frac{1}{M}\right)$$

So for any  $x$  such that  $[\Phi\Psi]x = 0$ ,

$$\frac{\sum_{\text{ON}} |x_k|}{\sum_{\text{ALL}} |x_k|} \leq \frac{\|\gamma\|_0}{1 + \frac{1}{M}}$$

and since  $\|\gamma\|_0 < \frac{1}{2} \left(1 + \frac{1}{M}\right)$ , we have

$$\frac{\sum_{\text{ON}} |x_k|}{\sum_{\text{ALL}} |x_k|} < \frac{1}{2}$$

proving the result.

□

Elad and Bruckstein further refine the sufficient condition to  $\|\gamma\|_0 < \frac{\sqrt{2}-\frac{1}{2}}{M}$ . So under these conditions, if we solve  $\argmin \|\gamma\|_1$  s.t.  $[\Phi\Psi]\gamma = s$ , we are guaranteed to find the unique sparsest solution.