
EECS 16A Designing Information Devices and Systems I Discussion 13B
 Spring 2019

In Fall 2018, this discussion was not held haha

1. Orthogonal Matching Pursuit Lecture

Orthogonal Matching Pursuit (OMP) algorithm:

Inputs:

- A set of m songs, each of length n : $\mathbf{S} = \{\vec{S}_0, \vec{S}_1, \dots, \vec{S}_{m-1}\}$
- An n -dimensional received signal vector: \vec{r}
- The sparsity level k of the signal
- Some threshold, th . When the norm of the signal is below this value, the signal contains only noise.

Outputs:

- A set of songs that were identified, F , which will contain at most k elements
- A vector \vec{x} containing song messages (x_1, x_2, \dots) , which will be of length k or less
- An n -dimensional residual \vec{y}

Procedure:

- Initialize the following values: $\vec{y} = \vec{r}$, $j = 1$, k , $\mathbf{A} = []$, $F = \{\emptyset\}$
- while $((j \leq k) \text{ and } (\|\vec{y}\| \geq th))$:
 - (a) Cross-correlate \vec{y} with the shifted versions of all songs. Find the song index i and the shifted version of the song, \vec{S}_i^N , with which the received signal has the highest correlation value.
 - (b) Add i to the set of song indices F .
 - (c) Column concatenate matrix \mathbf{A} with the correctly shifted version of the song: $\mathbf{A} = [\mathbf{A} \mid \vec{S}_i^N]$
 - (d) Use least squares to obtain the message value: $\vec{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \vec{r}$
 - (e) Update the residual value \vec{y} by subtracting: $\vec{y} = \vec{r} - \mathbf{A} \vec{x}$
 - (f) Update the counter: $j = j + 1$

2. Orthogonal Matching Pursuit

Let's work through an example of the OMP algorithm. Suppose that we have a vector $\vec{x} \in \mathbb{R}^4$ that is sparse and we know that it has only 2 non-zero entries. In particular,

$$\mathbf{M}\vec{x} \approx \vec{y} \quad (1)$$

$$\begin{bmatrix} | & | & | & | \\ \vec{m}_1 & \vec{m}_2 & \vec{m}_3 & \vec{m}_4 \\ | & | & | & | \end{bmatrix} \vec{x} \approx \vec{y} \quad (2)$$

$$\begin{bmatrix} 1 & 0 & 2 & 1 \\ 0 & 1 & 2 & 0 \\ 0 & 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \approx \begin{bmatrix} 5 \\ 1 \\ 1 \end{bmatrix} \quad (3)$$

where exactly 2 of x_1 to x_4 are non-zero. Use Orthogonal Matching Pursuit to estimate x_1 to x_4 .

- Why can we not solve for \vec{x} directly?
- Why can we not apply the least squares process to obtain \vec{x} ?
- Let us start by reviewing the OMP procedure,

Inputs:

- A matrix \mathbf{M} , whose columns, \vec{m}_i , make up a set of vectors, $\{\vec{m}_i\}$, each of length n
- A vector \vec{y} of length n
- The sparsity level k of the signal

Outputs:

- A vector \vec{x} , that contains k non-zero entries.
- A error vector $\vec{e} = \vec{y} - \mathbf{M}\vec{x}$

Procedure:

- Initialize the following values: $\vec{e} = \vec{y}$, $j = 1$, k , $\mathbf{A} = [\quad]$
- while ($j \leq k$):
 - Compute the inner product for each vector in the set, \vec{m}_i , with \vec{e} : $c_i = \langle \vec{m}_i, \vec{e} \rangle$.
 - Column concatenate matrix \mathbf{A} with the column vector that had the maximum inner product value with \vec{e} , c_i : $\mathbf{A} = [\mathbf{A} \quad \vec{m}_i]$
 - Use least squares to compute \vec{x} given the \mathbf{A} for this iteration: $\vec{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \vec{y}$
 - Update the error vector: $\vec{e} = \vec{y} - \mathbf{A}\vec{x}$
 - Update the counter: $j = j + 1$
- Compute the inner product of every column with the \vec{y} vector. Which column has the largest inner product? This will be the first column of the matrix \mathbf{A} .
- Now, find the projection of \vec{y} onto the columns of \mathbf{A} (ie. $\text{proj}_{\text{Col}(\mathbf{A})} \vec{y} = \mathbf{A}(\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \vec{y}$). Use this to update the error vector.
- Now compute the inner product of every column with the new error vector. Which column has the largest inner product? This will be the second column of \mathbf{A} .
- We now have two non-zero entries for our vector, \vec{x} . Find the values of those two entries.

(Reminder: $\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$)