# EE16A - Lecture 24 Notes

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### Review

- Redundant (Overcomplete) Dictionary of vectors  $D = \{\phi_l\}, \phi_l \in \mathbb{R}^N$
- N = length of each player's message
- $\operatorname{span}\{\phi_l\} = \mathbb{R}^N$
- $\bullet$  D contains no fewer than N lin. ind. vectors
- $y = \sum_{l=1}^{m-1} \alpha_l \vec{z}_l$ 
  - $-\vec{z_l}$ : message form the *l*th player
  - $-\alpha_l$ : scalars
  - Simplified model: ignoring time delay  $S^{N_k}$
  - of the L=2000 players, very few are talking to us at any given time window
  - Assume: All  $\|\phi_l\| = 1$ , if not, normalize
- Use Matching Pursuit Algorithm to solve for y
  - Continuously match with the best vector in the dictionary
  - Minimize residual vector each time using local optimization

# Another View of Matching Pursuit Algorithm

- Initialize:
  - Residual= y at iteration 0:  $r_0 = y$
  - $-A_0 = [$  ], placeholder matrix for the matched distingary vectors
- While  $r_m \geq \varepsilon$ , continue (Here:  $\varepsilon = 0$ )
  - 1. Look for the vector that gives the best match:  $k = \operatorname{argmax}_i |\langle r_m, \vec{z}_i, \rangle|$
  - 2. k is the largest projection between the current residual and all the vectors in the dictionary D.
  - 3.  $\vec{v}_m = \vec{z}_k$  is the vector in the dictionary the gives the projection k
  - 4. Augment matrix A with  $\vec{v}_m$  as a new column:  $A_m = \begin{bmatrix} A_{m-1} & \vec{v}_m \end{bmatrix}$
  - 5. Model received signal as a linear combination of the columns of the A matrix up to this point + error term:
    - $\vec{y} = A_m \vec{\alpha}_m + \vec{r}_m$
    - $-A_1\alpha_1$  is the best estimate at iteration 1 of the received signal  $\vec{y}$ :  $A_m\alpha_M = \vec{y}_m$
    - Best  $\alpha$  for answer is given by the Least Squares formula:  $\alpha_m = (A_M^T A_m)^{-1} A_m^T \vec{y}$
  - 6.  $\vec{r}_m = \vec{y} \vec{y}_m = y A_m \alpha_m$
- Problem:
  - Matrix A keeps getting wider on every iteration

- Each iteration you have to compute  $(A_m^T A_m)^{-1}$ , which is too costly
- Solution:
  - Try to construct matrix A at each iteration that has orthonormal columns
  - $\alpha_m = (A_M^T A_m)^{-1} A_m^T \bar{y}$
  - $\vec{y}_m = A_m (A_M^T A_m)^{-1} A_m^T \vec{y}$
  - If  $A_m$  has orthonormal cols, (if all  $\vec{v}_k$ 's are orthonormal):  $A_m^T A_m = T$
  - Thus,  $\vec{y}_m = A_m(A_m^T y) = \sum_{i=1}^m \langle \vec{v}_i, \vec{y} \rangle \vec{v}_i$

## Gram-Schmidt Orthogonlization (Orthonormalization)

- Have  $\vec{v}_1, \ldots, \vec{v}_m$  lin. ind. vectors  $V_m = \operatorname{span}\{\vec{v}_1, \ldots, \vec{v}_m\}$
- Claim: We can find another set of vectors  $\vec{z}_1, \ldots, \vec{z}_m$  that are mutually orthogonal and for which  $Z_m = \operatorname{span}\{\vec{z}_1, \ldots, \vec{z}_m\} = \operatorname{span}\{\vec{v}_1, \ldots, \vec{v}_m\} = V_m$ 
  - Once we have  $\vec{z}_1,\dots,\vec{z}_m$ , we can construct vectors  $\vec{q}_i=\frac{\vec{z}_i}{\|\vec{z}_i\|}, i=1,\dots,m$
  - $-Q_m = \operatorname{span}\{\vec{q}_1, \dots, \vec{q}_m\} = V_m = Z_m \text{ where } \langle \vec{q}_l, \vec{q}_k \rangle = 1 \text{ when } k = l \text{ and } \langle \vec{q}_l, \vec{q}_k \rangle = 0 \text{ when } k \neq l$
  - All  $\vec{q_i}$ 's are orthonormal
- **Proof** (By construction):
  - $-\vec{v}_1, \vec{v}_2, \vec{v}_3$  are linearly independent
  - Let  $\vec{z}_1 = \vec{v}_1$ : 1st principal direction of the orthogonal set
  - $-\vec{z}_2 = \vec{v}_2 \alpha \vec{z}_1 \text{ s.t. } \vec{z}_2 \perp \vec{z}_1$ 
    - \*  $\langle \vec{z}_2, \vec{z}_1 \rangle = \langle \vec{v}_2 \alpha \vec{z}_1, \vec{z}_1 \rangle = 0$
    - $* \langle \vec{v}_2, \vec{z}_1 \rangle \alpha \langle \vec{z}_1, \vec{z}_1 \rangle = 0 \implies \frac{\langle \vec{v}_2, \vec{z}_1 \rangle}{\langle \vec{z}_1, \vec{z}_1 \rangle}$
    - \*  $\vec{z}_2 = \vec{v}_2 \frac{\langle \vec{v}_2, \vec{z}_1 \rangle}{\langle \vec{z}_1, \vec{z}_1 \rangle} \vec{z}_1$
    - \*  $\vec{z}_2$  is the 2nd principal direction in the orthogonal set

$$-\vec{z}_2 = \vec{z}_3 - \alpha_1 \vec{z}_1 - \alpha_2 \vec{z}_2 = \vec{v}_3 - \sum_{l=1}^{2} \alpha_l \vec{z}_l \text{ s.t. } \vec{z}_3 \perp \vec{z}_1 \& \vec{z}_3 \perp \vec{z}_2$$

- \*  $\langle \vec{z}_3, \vec{z}_1 \rangle = \langle \vec{v}_3 \alpha_1 \vec{z}_1 \alpha_2 \vec{z}_2, \vec{z}_1 \rangle = 0$
- $* \langle \vec{z}_3, \vec{z}_2 \rangle = \langle \vec{v}_3 \alpha_1 \vec{z}_1 \alpha_2 \vec{z}_2, \vec{z}_2 \rangle = 0$
- \* Solve for  $\vec{z}_3 = \vec{v}_3 \frac{\langle \vec{v}_3, \vec{z}_1 \rangle}{\langle \vec{z}_1, \vec{z}_1 \rangle} \vec{z}_1 \frac{\langle \vec{v}_3, \vec{z}_2 \rangle}{\langle \vec{z}_2, \vec{z}_2 \rangle} \vec{z}_2$
- \*  $\vec{z}_3$  is the 3nd principal direction in the orthogonal set
- Continuing in this way:  $\vec{z}_n = \vec{v}_n \sum_{i=1}^{n-1} \frac{\langle \vec{v}_n, \vec{z}_i \rangle}{\langle \vec{z}_i, \vec{z}_i \rangle} \vec{z}_i$
- Gets the Orthogonal set, but still need to normalize
  - \* Get orthonormalized set  $\vec{q}_1,\dots,\vec{q}_m$  where  $\vec{q}_l=\frac{\vec{z}_l}{\|\vec{z}_l\|}$
  - \* Orthonormal Representation of Principal Direction:
    - $\cdot \alpha_l = \frac{\langle \vec{v}_m, \vec{z}_l \rangle}{\langle \vec{z}_l, \vec{z}_l \rangle}$
    - $\cdot \vec{z}_l = \|\vec{z}_l\|\vec{q}_l$
    - $\cdot \vec{v}_m = \vec{z}_m + \sum_{l=1}^{m-1} \alpha_l \vec{z}_l = \|\vec{z}_m\| \vec{q}_m + \sum_{l=1}^{m-1} \alpha_l \|\vec{z}_l\| \vec{q}_l = \sum_{l=1}^m \alpha_l \|\vec{z}_l\| \vec{q}_l = \sum_{l=1}^m r_{lm} \vec{q}_l$
- This gets A = QR where:
  - \* R is composed of elements  $r_{lm}$  and is upper triangular
  - \* Q is the orthonormalized matrix  $\begin{bmatrix} \vec{q}_1 & \dots & \vec{q}_m \end{bmatrix}$
  - \* A is the original principal direction matrix  $[\vec{v}_1 \ldots \vec{v}_m]$
  - $* Q^TQ = I$

#### **Gram Schmidt Orthogonalization:**

1st principal direction in the orthogonal set

$$\vec{z}_1 = \vec{v}_1 \tag{1}$$

n-th principal direction in the orthogonal set

$$\vec{z}_n = \vec{v}_n - \sum_{i=1}^{n-1} \frac{\langle \vec{v}_n, \vec{z}_i \rangle}{\langle \vec{z}_i, \vec{z}_i \rangle} \vec{z}_i \tag{2}$$

## Orthonormal Representation of Principal Direction

R is composed of elements  $r_{lm}$  and is upper triangular

Q is the orthonormalized matrix  $\begin{bmatrix} \vec{q}_1 & \dots & \vec{q}_m \end{bmatrix}$ 

A is the original principal direction matrix  $\begin{bmatrix} \vec{v}_1 & \dots & \vec{v}_m \end{bmatrix}$ 

$$A = QR \tag{3}$$

$$\vec{v}_m = \sum_{l=1}^m r_{lm} \vec{q}_l \tag{4}$$