

EE16A

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To do:

Gram-Schmidt process

1. Motivation

2. steps

3. application O.M.P.

Reading: application of "sparsity".

Google scholar search:

Sparse MRI, M. Lustig et al. Magnetic Resonance in Medicine, 2007

OMP Intuition

$$A \vec{x} = \vec{y}$$

$$\begin{bmatrix} | & | & \dots & | \\ \vec{a}_1 & \vec{a}_2 & \dots & \vec{a}_n \\ | & | & \dots & | \end{bmatrix}$$

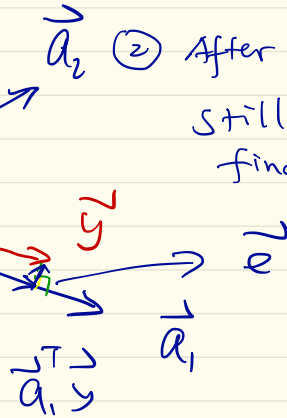
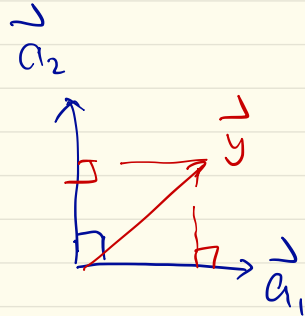
* generally \vec{a}_1, \vec{a}_2 not orthogonal.

$$n=2$$

* if $\vec{a}_1 \perp \vec{a}_2$

much easier.

Just do projections.



① If finding one code only, the closest one is \vec{a}_1

② After finding \vec{a}_1 , there's still residual error, find next.

Motivation

1. L.S. $\hat{\vec{x}} = (A^T A)^{-1} A^T \vec{y}$

$$A^T A \in \mathbb{R}^{n \times n} \quad \sim O(n^3)$$

2. O.M.P. $\hat{\vec{x}} = (A^T A)^{-1} A^T \vec{y}$

$$\vec{e} = \vec{y} - A \hat{\vec{x}} = \vec{y} - \underbrace{A(A^T A)^{-1} A^T}_{\text{red underline}} \vec{y}$$

In general, computation grows as # of iterations increases

* exception:

if columns of A are orthogonal, $A(A^T A)^{-1} A^T \vec{y} \rightarrow$ simple.

Let's see how

Given $A \vec{x} = \vec{y}$

$$A = \begin{bmatrix} | & | & & | \\ \vec{a}_1 & \vec{a}_2 & \dots & \vec{a}_n \\ | & | & & | \end{bmatrix}, \quad \vec{a}_i^T \vec{a}_j = 0, \quad i \neq j$$

"orthogonal"

$$A^T A = \begin{bmatrix} -\vec{a}_1^T & - \\ -\vec{a}_2^T & - \\ \vdots & \vdots \\ -\vec{a}_n^T & - \end{bmatrix} \begin{bmatrix} | & | & & | \\ \vec{a}_1 & \vec{a}_2 & \dots & \vec{a}_n \\ | & | & & | \end{bmatrix} = \begin{bmatrix} I & \\ & \\ & \\ & \end{bmatrix}, \quad \text{diagonalized?}$$

$$= \begin{bmatrix} \vec{a}_1^T \vec{a}_1 & & & \\ & \vec{a}_2^T \vec{a}_2 & & 0 \\ & & \dots & \\ 0 & & & \vec{a}_n^T \vec{a}_n \end{bmatrix},$$

$$= \begin{bmatrix} \|\vec{a}_1\|_2^2 & & & \\ & \|\vec{a}_2\|_2^2 & & 0 \\ & & \dots & \\ 0 & & & \|\vec{a}_n\|_2^2 \end{bmatrix}$$

$$(A^T A)^{-1} = \begin{bmatrix} \frac{1}{\|\vec{a}_1\|_2^2} & & & 0 \\ & \frac{1}{\|\vec{a}_2\|_2^2} & & \\ & & \dots & \\ 0 & & & \frac{1}{\|\vec{a}_n\|_2^2} \end{bmatrix};$$

$$A(A^T A)^{-1} A^T \vec{y}$$



$$\begin{bmatrix} \vec{a}_1^T \vec{y} \\ \vec{a}_2^T \vec{y} \\ \vdots \\ \vec{a}_n^T \vec{y} \end{bmatrix}$$



$$\begin{bmatrix} \frac{\vec{a}_1^T \vec{y}}{\|\vec{a}_1\|_2^2} \\ \frac{\vec{a}_2^T \vec{y}}{\|\vec{a}_2\|_2^2} \\ \vdots \\ \frac{\vec{a}_n^T \vec{y}}{\|\vec{a}_n\|_2^2} \end{bmatrix}$$

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recall $A =$

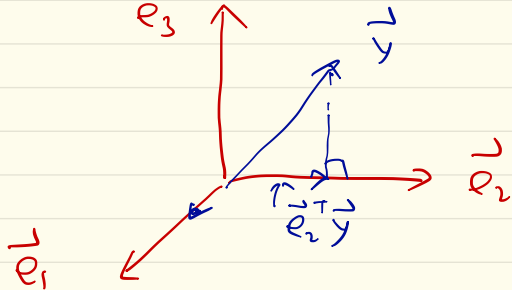
$$\begin{bmatrix} | & | & & | \\ \vec{a}_1 & \vec{a}_2 & \dots & \vec{a}_n \\ | & | & & | \\ \frac{\vec{a}_1^T \vec{y}}{\|\vec{a}_1\|_2^2} & \uparrow & \dots & \uparrow \end{bmatrix}$$

Linear combination of columns of A

$$A(A^T A)^{-1} A^T \vec{y}$$
$$= \frac{\vec{a}_1^T \vec{y}}{\|\vec{a}_1\|^2} \vec{a}_1 + \frac{\vec{a}_2^T \vec{y}}{\|\vec{a}_2\|^2} \vec{a}_2 + \dots + \frac{\vec{a}_n^T \vec{y}}{\|\vec{a}_n\|^2} \vec{a}_n$$

define $\frac{\vec{a}_1}{\|\vec{a}_1\|} = \vec{e}_1$, $\|\vec{e}_1\| = 1$

$$= \underbrace{(\vec{e}_1^T \vec{y})}_{\Delta} \vec{e}_1 + \underbrace{(\vec{e}_2^T \vec{y})}_{\vec{e}_3} \vec{e}_2 + \dots + (\vec{e}_n^T \vec{y}) \vec{e}_n$$

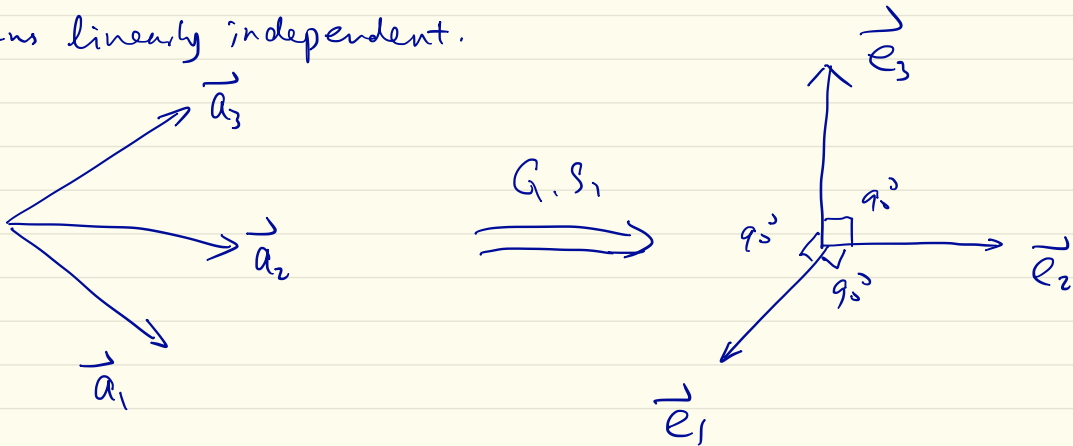


No matrix inversion
needed !!
Simply projection.

* Gram Schmidt Process

$A \in \mathbb{R}^{m \times n}$, columns are not orthogonal

columns linearly independent.



$$\text{span}(\{\vec{a}_1, \vec{a}_2, \vec{a}_3\}) = \text{span}(\{\vec{e}_1, \vec{e}_2, \vec{e}_3\})$$

* property: \vec{v}_1, \vec{v}_2 are linearly independent

$$\begin{aligned}
& \text{span}(\vec{v}_1, \vec{v}_2) \\
&= \text{span}(\vec{v}_1, \alpha \vec{v}_2) \quad , \quad \alpha \text{ is a "scalar"} \\
&= \text{span}(\vec{v}_1, \vec{v}_1 + \vec{v}_2) \\
&= \text{span}(\vec{v}_1, \vec{v}_1 - \vec{v}_2) = \text{span}(\vec{v}_1, \vec{v}_2 - \vec{v}_1) \\
&= \text{span}(\vec{v}_1, \vec{v}_2 - \alpha \vec{v}_1)
\end{aligned}$$

can I find an α , such that $\vec{v}_1 \perp (\vec{v}_2 - \alpha \vec{v}_1)$?

$$\text{or } \underline{\vec{v}_1^T (\vec{v}_2 - \alpha \vec{v}_1) = 0}$$

$$\Rightarrow \vec{v}_1^T \vec{v}_2 = \alpha \vec{v}_1^T \vec{v}_1 = \alpha \|\vec{v}_1\|_2^2$$

$$\Rightarrow \alpha = \frac{\vec{v}_1^T \vec{v}_2}{\|\vec{v}_1\|_2^2} \quad , \quad \vec{v}_2' = \vec{v}_2 - \alpha \vec{v}_1 = \vec{v}_2 - \frac{\vec{v}_1^T \vec{v}_2}{\|\vec{v}_1\|_2^2} \vec{v}_1$$

$$= \vec{v}_2 - \underbrace{\left(\vec{e}_1^T \vec{v}_2 \right)}_{\substack{\vec{v}_1 \\ \|\vec{v}_1\|_2}} \vec{e}_1$$

$$\vec{e}_2 = \frac{\vec{v}_2'}{\|\vec{v}_2'\|}$$

$$\text{span}(\vec{e}_1, \vec{e}_2) = \text{span}(\vec{v}_1, \vec{v}_2)$$

G.S.

step 1: compute $\vec{e}_1 = \frac{\vec{a}_1}{\|\vec{a}_1\|}$, unit vector

step 2: for $i = 2, \dots, n$

1) compute $\vec{q}_i = \vec{a}_i - \sum_{j=1}^{i-1} (\vec{e}_j^T \vec{a}_i) \vec{e}_j$

2) normalize $\vec{e}_i = \frac{\vec{q}_i}{\|\vec{q}_i\|}$

end.

$$\Rightarrow \text{span}(\{\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n\}) = \text{span}(\{\vec{e}_1, \vec{e}_2, \dots, \vec{e}_n\})$$

OMP Summary

$$\text{problem: } \vec{y} = x_1 \vec{S}_1^{(\tau_1)} + x_2 \vec{S}_2^{(\tau_2)} + \dots + x_n \vec{S}_n^{(\tau_n)}$$

$$\vec{y} \in \mathbb{R}^m, \vec{S}_i \in \mathbb{R}^m$$

also know: only k of $\{x_1, x_2, \dots, x_n\}$ are non-zero

OMP procedures with Gram Schmidt

$$* \text{ set } \vec{e} = \vec{y}, \quad j=1, \quad A = [], \quad F = \{\emptyset\}$$

$$\hookrightarrow Q = []$$

$$* \text{ while } [(j \leq k) \ \& \ (\|\vec{e}\| \geq \epsilon)]$$

$$1. \text{ circorr}(\vec{e}, \vec{S}_i) \text{ for all } i \in \{1, 2, \dots, n\}$$

\Rightarrow Find which i^* such that $\text{circorr}(\vec{e}, \vec{S}_{i^*})$ has largest peak correlation.

$$2. \text{ Add } i^* \text{ to } F = \{F, i^*\},$$

$$3. \text{ Add } \vec{S}_{i^*}^{(\tau_{i^*})} \text{ to } A, \quad A = [A \mid \vec{S}_{i^*}^{(\tau_{i^*})}], \text{ as a new column vector}$$

$$\text{G.S. } \hookrightarrow \vec{e}_0$$

$$Q = [Q \mid \vec{e}_j]$$

4. Estimate a new sol. $\hat{\vec{x}} = \underbrace{(A^T A)^{-1} A^T \vec{y}}$, $[\vec{e}_1^T \vec{y}, \vec{e}_2^T \vec{y}, \dots, \vec{e}_j^T \vec{y}]^T$

5. Update residual $\vec{e} = \vec{y} - A \hat{\vec{x}}$ $\hat{\vec{x}} \leftarrow [\hat{\vec{x}} \quad \vec{e}_j^T \vec{y}]^T$

6. $j = j + 1$,

is not \vec{e}_i' $\vec{y} - \underbrace{[(\vec{e}_1^T \vec{y}) \vec{e}_1 + (\vec{e}_2^T \vec{y}) \vec{e}_2 + \dots + (\vec{e}_j^T \vec{y}) \vec{e}_j]}_{\vec{e}}$

* stop if $j > k$, or $\|\vec{e}\| < \epsilon$

$$\vec{e} \leftarrow \vec{e} - (\vec{e}_j^T \vec{y}) \vec{e}_j$$

- With Gram Schmidt, the O.M.P. solves $A \hat{\vec{x}} = \vec{y}$ in an orthonormal basis, denote as $\hat{\vec{x}}'$
- To compute $\hat{\vec{x}}$ for the original codes $\vec{s}_1^{(\tau_1)}$, $\vec{s}_2^{(\tau_2)}$, ..., $\vec{s}_n^{(\tau_n)}$, we need to perform a change of basis, using the relations btw \vec{e}_i & $\vec{s}_i^{(\tau_i)}$ defined by Gram-Schmidt.