

$$V = [\vec{v}_1, \vec{v}_2]$$

$$\text{colsp}[V] := \text{span}[\{\vec{v}_1, \vec{v}_2\}]$$

$$\text{proj}_V(\vec{a}) \neq \text{proj}_{\vec{v}_1}(\vec{a}) + \text{proj}_{\vec{v}_2}(\vec{a})$$

$$H\vec{a} = H_1\vec{a} + H_2\vec{a}$$

$$\text{is } H_1 + H_2 \text{ orthogonal}$$

$$1) \text{proj}_V(\vec{a}) = c_1\vec{v}_1 + c_2\vec{v}_2 \in \text{colsp}[V]$$

$$2) \text{proj}_V(\vec{a}) \perp \vec{a} - \text{proj}_V(\vec{a})$$

$$\hookrightarrow \text{proj}_V(\vec{a})^T (\vec{a} - \text{proj}_V(\vec{a})) = 0$$

$$\hookrightarrow 2 \|H_1\vec{a}\| \|H_2\vec{a}\| \neq$$

$$\cos(\theta(\vec{H}_1\vec{a}, \vec{H}_2\vec{a})) = 0$$

$$\text{proj}_V(\vec{a}) = \text{proj}_{\vec{v}_1}(\vec{a}) + \dots + \text{proj}_{\vec{v}_d}(\vec{a})$$

$$H\vec{a} = H_1\vec{a} + \dots + H_d\vec{a}$$

$$= \frac{\vec{v}_1\vec{v}_1^T}{\|\vec{v}_1\|^2} \vec{a} + \dots + \frac{\vec{v}_d\vec{v}_d^T}{\|\vec{v}_d\|^2} \vec{a}$$

$$= \left( \frac{\vec{v}_1\vec{v}_1^T}{\|\vec{v}_1\|^2} + \dots + \frac{\vec{v}_d\vec{v}_d^T}{\|\vec{v}_d\|^2} \right) \vec{a}$$

$$\text{let } \|\vec{v}_i\| = \dots = \|\vec{v}_d\| = 1 \quad H\vec{a}$$

$$Q = [\vec{v}_1 | \dots | \vec{v}_d] \quad \text{proj}_V(\vec{a}) = (\vec{v}_1\vec{v}_1^T + \dots + \vec{v}_d\vec{v}_d^T) \vec{a}$$

orthogonal basis  
"orthonormal"

unit length &  
orthogonal

$$\text{if } \text{colsp}[V] = \text{colsp}[Q] \\ V(V^TV)^{-1}V^T = QQ^T$$

$$= [\vec{v}_1, \vec{v}_2, \dots, \vec{v}_d] \begin{bmatrix} \vec{v}_1^T \\ \vec{v}_2^T \\ \vdots \\ \vec{v}_d^T \end{bmatrix} = QQ^T = H = V(V^TV)^{-1}V^T$$

eliminate double counting  
(orthonormalizing)

$$X \in \mathbb{R}^{n \times (p+1)}$$

change of basis

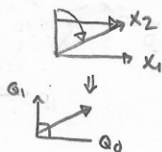
$$X \rightarrow Q$$

$$X = QR \quad Q = X R^{-1}$$

$n \times p+1$   $n \times p+1$   $p+1 \times p+1$   
full rank full rank

R is upper triangular

$$X = QR = Q \begin{bmatrix} c & d & e \\ 0 & f & g \\ 0 & 0 & h \end{bmatrix}$$



$$\begin{aligned} \vec{b} &= (X^TX)^{-1}X^Ty \\ (X^TX)\vec{b} &= X^Ty \\ ((QR)^T(QR)\vec{b}) &= (QR)^T y \\ R^T Q^T Q R \vec{b} &= R^T Q^T y \\ R^T R \vec{b} &= R^T \vec{z} \\ R^{-1} R^T R \vec{b} &= R^{-1} R^T \vec{z} \\ R \vec{b} &= \vec{z} \\ \begin{bmatrix} c & d & e \\ 0 & f & g \\ 0 & 0 & h \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} &= \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} \\ b_1 &= \frac{z_2 - g b_0}{f} \end{aligned}$$

review

$$SST = SSR + SSE$$

$$\sum (y_i - \bar{y})^2$$

$$SST = SSR + SSE$$

↑

↓

$$R^2 \uparrow \quad RMSE \downarrow$$

Fixed function of V  
(does not change)

$$\begin{aligned}
 SSR &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \sum_{i=1}^n \hat{y}_i^2 - 2\bar{y} \sum_{i=1}^n \hat{y}_i + \sum_{i=1}^n \bar{y}^2 = \|\hat{\vec{y}}\|^2 - 2n\bar{y}^2 + n\bar{y}^2 = \|\hat{\vec{y}}\|^2 - n\bar{y}^2 \\
 \sum \hat{y}_i &= \hat{\vec{y}}^T \vec{1}_n = (H\vec{y})^T \vec{1}_n = \vec{y}^T H^T \vec{1}_n = \vec{y}^T \vec{1}_n = \sum y_i = n\bar{y} \\
 X &= \begin{bmatrix} \uparrow & \uparrow & & \uparrow \\ | & | & & | \\ x_1 & x_2 & \dots & x_p \\ | & | & & | \\ \downarrow & \downarrow & & \downarrow \end{bmatrix} \xrightarrow{G.S.} Q = \begin{bmatrix} \uparrow & \uparrow & & \uparrow \\ | & | & & | \\ q_0 & q_1 & \dots & q_p \\ | & | & & | \\ \downarrow & \downarrow & & \downarrow \end{bmatrix} \\
 &\text{add new column to } X \\
 X &= \begin{bmatrix} \uparrow & \uparrow & & \uparrow & \uparrow \\ | & | & & | & | \\ x_1 & x_2 & \dots & x_p & x_{p+1} \\ | & | & & | & | \\ \downarrow & \downarrow & & \downarrow & \downarrow \end{bmatrix} \xrightarrow{G.S.} Q = \begin{bmatrix} q_0 & q_1 & \dots & q_p & \tilde{q}_* \end{bmatrix} \\
 &\geq 0 \quad \text{note: } \|\vec{a} + \vec{b}\|^2 = \|\vec{a}\|^2 + \|\vec{b}\|^2 \\
 &\geq 0 \quad = \|\text{proj}_{\vec{q}_0}(\vec{y})\|^2 + \|\text{proj}_{\vec{q}_1}(\vec{y})\|^2 + \dots + \|\text{proj}_{\vec{q}_p}(\vec{y})\|^2 - n\bar{y}^2
 \end{aligned}$$

$$\begin{aligned}
 SST &= SSR + SSE \\
 SSR &> SSR \\
 SSE &< SSE
 \end{aligned}$$

$$H = QQ^T$$

$$H_1 = I - H = Q_1 Q_1^T$$

lets add all  $n - (p+1)$  columns to get

$$X = \begin{bmatrix} \vdots \\ x_{p+1} \end{bmatrix} \in \mathbb{R}^{n \times n} \text{ full rank}$$

$$\hat{\vec{y}} = H\vec{y} = X(X^T X)^{-1} X^T \vec{y} = \underbrace{X X^{-1}}_I (\underbrace{X^T}_I)^{-1} X^T \vec{y} = I \vec{y} = \vec{y}$$

Is I orthogonal proj. matrix?

$$\begin{aligned}
 I^T &= I \\
 I I &= I
 \end{aligned}$$

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum 0^2 = 0$$

$$R^2 = 1; RMSE = 0$$

\* new columns are not related to  $\vec{y}$ 's  
ie. the causal inputs

"overfitting" (core concept in data science...)

predictive performance on ID

Aggregates ~~all~~ data science in the world  
generalization error affects future performance

$$\begin{aligned}
 y &= g(x) + \underbrace{(h^*(\vec{x}) - g(\vec{x}))}_{\text{estimation}} + \underbrace{(h^*(\vec{x}) - f(\vec{x}))}_{\text{mispecification}} + \underbrace{(f(\vec{x}) - g(x))}_{\text{ignorance}} \\
 &\quad \underbrace{\hspace{10em}}_e
 \end{aligned}$$

Assume overfit

$\Rightarrow f(\vec{x}) \approx h^*(\vec{x})$  is fixed

$$h^*(x) = x^T \vec{\beta} \Rightarrow \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p; f(x) = \sin(x_1 x_2) + x_3 + \dots$$

overfitting is estimation error

$$g(x) = x^T \vec{b}$$

asymptotic overfit

$$\vec{b} \approx \vec{\beta} \text{ diverge}$$

$$\begin{aligned}
 h^*(\vec{x}) - g(\vec{x}) &: \text{estimation error} \\
 \vec{x}^T \vec{\beta} - \vec{x}^T \vec{b} \\
 x(\vec{\beta} - \vec{b})
 \end{aligned}$$