

rank $[X] = p+1$
 full rank
 "design matrix"

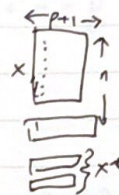
$$\Rightarrow \vec{b} = (X^T X)^{-1} X^T \vec{y}$$

$(p+1) \times n$ $(p+1) \times n$ $(p+1) \times n$ $n \times 1$

OLS estimates

$$\vec{b} \in \mathbb{R}^{p+1}$$

$$\vec{b} \in \mathcal{H} = \{ \vec{w} \cdot \vec{x} : \vec{w} \in \mathbb{R}^{p+1} \}$$



prediction

$$\hat{y}^* = g(\vec{x}^*) = b_0 + b_1 x_{*,1} + \dots + b_p x_{*,p} = \vec{x}^* \vec{b} \quad \square = \square$$

What if \vec{x}^* is far from all x ?

$$\text{Range}[X] = [X_{1,\min}, X_{1,\max}] \times [X_{2,\min}, X_{2,\max}] \times \dots \times [X_{p,\min}, X_{p,\max}]$$

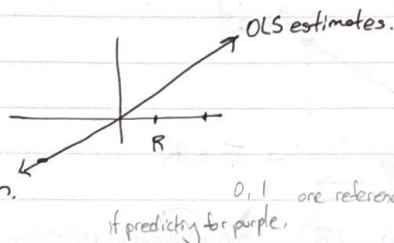
Continuous

 X {all levels of x_j } x

categorical

 $\vec{x}^* \notin \text{Range}[X]$ historical training data?

 $\hat{y} = g(\vec{x}^*)$ extrapolation is risky

 if $\vec{x}^* \in \text{Range}[X]$ prediction is an interpolation.


Note: supervised learning doesn't generally work when extrapolating. Further, different models extrapolate, very different.

How well does this model perform?

$$\text{SSE} = \sum_{i=1}^n e_i^2 = \sum (y_i - \hat{y}_i)^2 = (\vec{y} - \hat{\vec{y}})^T (\vec{y} - \hat{\vec{y}}) = \|\vec{e}\|^2$$

$$\hat{\vec{y}} = X \vec{b} = X (X^T X)^{-1} X^T \vec{y}$$

substitute OLS

$$\hat{\vec{y}} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} \vec{x}_1 \cdot \vec{b} \\ \vec{x}_2 \cdot \vec{b} \\ \vdots \\ \vec{x}_n \cdot \vec{b} \end{bmatrix} = \begin{bmatrix} \leftarrow \vec{x}_1 \rightarrow \\ \leftarrow \vec{x}_2 \rightarrow \\ \vdots \\ \leftarrow \vec{x}_n \rightarrow \end{bmatrix} \vec{b}$$

"has matrix" $\vec{y} \rightarrow \hat{\vec{y}}$
makes \vec{y} $\hat{\vec{y}}$ -hat

MAT 231: $A \in \mathbb{R}^{n \times n}$ (full rank)

$$\vec{v} \in \mathbb{R}^n$$

$$\vec{z} = A \vec{v} = \begin{bmatrix} a_{11}v_1 + a_{12}v_2 + \dots + a_{1n}v_n \\ \vdots \\ a_{n1}v_1 + a_{n2}v_2 + \dots + a_{nn}v_n \end{bmatrix}$$

if $\text{rank}[A] = n$

$$H \in \mathbb{R}^{n \times n}$$

$$\text{rank}[H] = p+1$$

"degrees of freedom" of model is (the number of dimension in the model)

$$p+1$$

 rank of H
 dimensionality of \vec{y}

dimension of col space

$$\hat{y} = Hy$$

$$\hat{y} = b_0 + b_1 x_1 + \dots + b_p x_p$$

$$\begin{bmatrix} \hat{y} \\ 1 \end{bmatrix} = b_0 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + b_1 \begin{bmatrix} x_1 \\ 1 \end{bmatrix} + \dots + b_p \begin{bmatrix} x_p \\ 1 \end{bmatrix}$$

if linearly combined.

$\vec{g} \in \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} x_1 \\ 1 \end{bmatrix}, \dots, \begin{bmatrix} x_p \\ 1 \end{bmatrix} \right\}$ weight scalar constants

rank 2

$$MSE = \frac{1}{n - (p+1)} SSE$$

unit of y

rank[H]

$$RMSE = \sqrt{MSE}$$

indicating intercept.
no intercept.

Line 93 $\Rightarrow 0 +$

$r^2 \Rightarrow 2$ variables.

$R^2 \Rightarrow$ fraction of residuals.

$$R^2 = 1 - \frac{SSE}{SST} = \frac{S_y^2 - S_e^2}{S_y^2}$$

unitless

multivariable regression performance
is evaluated same

practice Lab

Line 172 cbind(1, boston)

intercept.

data frame
needs to
coerce it
as matrix.

Line 212

solve(hatX) it's not full rank it's not invertible

Line 230 get column vector.

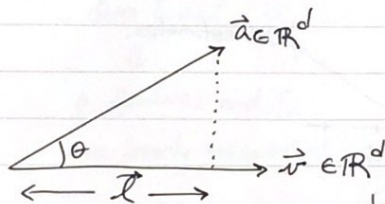
$\Rightarrow 3 \Rightarrow 4 \times 2$ look like

~ (take everything in Boston)

Line 344 row-mod = lm.fit(Xmm, y)

equals to $\hat{\beta} = (X^T X)^{-1} X^T y$

Next Unit



$\vec{l} = \text{proj}_{\vec{v}}(\vec{a})$ the orthogonal projection of \vec{a} onto \vec{v}

$$\text{Using the law of cosine} \Rightarrow \cos(\theta) = \frac{\vec{a} \cdot \vec{v}}{\|\vec{a}\| \|\vec{v}\|} = \frac{\|\vec{l}\|}{\|\vec{a}\|}$$

$$\Rightarrow \frac{\vec{a} \cdot \vec{v}}{\|\vec{v}\|} = \|\vec{l}\|$$

$$\Rightarrow \vec{l} = \|\vec{l}\| \frac{\vec{v}}{\|\vec{v}\|}$$

$$\Rightarrow \text{proj}_{\vec{v}}(\vec{a}) = \frac{\vec{a} \cdot \vec{v}}{\|\vec{v}\|^2} \vec{v} = \left(\frac{1}{\|\vec{v}\|^2} \vec{v} \vec{v}^T \right) \vec{a}$$

full space

$$\Rightarrow H\vec{a} = c\vec{v} \text{ for } c \in \mathbb{R}$$

"a projection matrix" of rank = 1