

Lec 11 Math 340.4 3/12/10

Prediction in linear regression models:

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

made mistake
last time (w/ T)
Since obs's are
row vectors and \vec{b}
is a col. vec.

Empolator.

What if $\vec{x}^* \notin \text{Range}(X)$?

Define $\text{Range}(X) = \underbrace{[x_{1,\min}, x_{1,\max}]}_{\text{min/max of first predictor}} \times \underbrace{[x_{2,\min}, x_{2,\max}]}_{\text{min/max of second predictor}} \times \dots \times \underbrace{[x_{p,\min}, x_{p,\max}]}_{\text{min/max of last predictor}}$

If you run g on such an \vec{x}^* , you will likely get a wrong answer. (also)
It is suspect if it's towards the tails of the dist of the predictors too. It depends on how close the tails are.

Warning: most people ignore this!!

Review of Lec 10: $\vec{y} \in \mathbb{R}^n$, $X \in \mathbb{R}^{n \times (p+1)}$. The least squares linear model fit is given by $\vec{b} = (X^T X)^{-1} X^T \vec{y}$

$\vec{y} = \begin{bmatrix} \leftarrow \vec{y}_1 \rightarrow \\ \leftarrow \vec{y}_2 \rightarrow \\ \vdots \\ \leftarrow \vec{y}_n \rightarrow \end{bmatrix}$ $\vec{b} = X \vec{b} = \underbrace{X (X^T X)^{-1} X^T}_{H} \vec{y} = H \vec{y}$ "hat matrix" because it turns $\vec{y} \rightarrow \hat{\vec{y}}$

What is $\text{rank}(H)$? $p+1$. Why? $\vec{y}_i = b_0 + b_1 x_{i1} + \dots + b_p x_{ip}$ which lies in a $p+1$ dim. space.

Proof of this comes later.

How to get R^2 RMSE?

Recall $y = g(\vec{x}) + e \Rightarrow \vec{y} = \hat{\vec{y}} + \vec{e} \Rightarrow \vec{e} = \vec{y} - \hat{\vec{y}}$

$\text{SSE} := \|\vec{e}\|^2 = \sum_{i=1}^n e_i^2$, $\text{RMSE} = \sqrt{\frac{1}{n-p-1} \text{SSE}} \Rightarrow \text{RMSE} = \sqrt{\text{MSE}}$

$R^2 = \frac{s_y^2 - s_e^2}{s_y^2}$ doesn't change!

DEMO

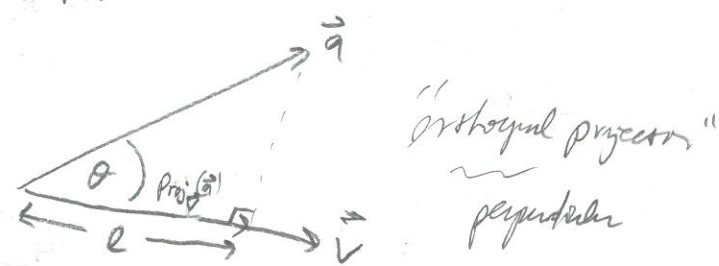
$p+1 =$
degrees of freedom. Why?
 $\text{Dim}(\text{Colsp}(X))$! How many dim
does model represent?

$$\vec{y} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad \vec{b} = X\vec{b} = X(X^T X)^{-1} X^T \vec{y} = H\vec{y}$$

$H \in \mathbb{R}^{n \times n}$
the hat matrix

What is $\text{rank}(H)$? It takes \vec{y} which is n -dim and lays it onto a $p+1$ -dim subspace
 $\Rightarrow \text{rank}(H) = p+1$. How do we know? Let's do some lin. alg.:

Let's do some pure lin algebra...
 Let's project two vectors $\in \mathbb{R}^d$



By law

of cosines, $\cos(\theta) = \frac{\vec{a} \cdot \vec{v}}{\|\vec{a}\| \|\vec{v}\|}$

but l is length of projection. Using 9th grade trig,

$$l = \|\vec{a}\| \cos(\theta) = \frac{\vec{a} \cdot \vec{v}}{\|\vec{v}\|}$$

Now we take l and give it the correct direction:

$$\text{Proj}_v(\vec{a}) = l \frac{\vec{v}}{\|\vec{v}\|} = \frac{\vec{a} \cdot \vec{v}}{\|\vec{v}\|^2} \vec{v} = \frac{\vec{a} \cdot \vec{v}}{\vec{v} \cdot \vec{v}} \vec{v} = \frac{\vec{v} \vec{v}^T \vec{a}}{\vec{v}^T \vec{v}} = \frac{\vec{v} \vec{v}^T}{\vec{v}^T \vec{v}} \vec{a} = H \vec{a}$$

unit vector in \vec{v} dir $\in \mathbb{R}^{d \times d}$ \uparrow projection matrix $\|\vec{v}\|^2$

Note if $\|\vec{v}\|=1$
 $\Rightarrow H = \vec{v} \vec{v}^T$

Let's project \vec{a} onto $V = \text{colsp}(V)$



You know $\text{Proj}_V(\vec{a}) = V\vec{w}$ let $V = [\vec{v}_1 \dots \vec{v}_k]$ all lin ind.
 Since $\vec{a} - V\vec{w} \in \text{colsp}(\vec{v}_1, \dots, \vec{v}_k)$

$$\vec{v}_i - \vec{a} \perp \text{each } \vec{v}_1, \dots, \vec{v}_k$$

$$\vec{v}_1^T (\vec{v}_2 - \vec{a}) = 0$$

$$\vec{v}_2^T (\vec{v}_2 - \vec{a}) = 0$$

$$\vdots$$

$$\vec{v}_k^T (\vec{v}_k - \vec{a}) = 0$$

$$\Rightarrow V^T (\vec{v}_k - \vec{a}) = 0$$

$$\Rightarrow V^T V \vec{w} = V^T \vec{a}$$

$$\Rightarrow \vec{w} = (V^T V)^{-1} V^T \vec{a}$$

$$\Rightarrow V \vec{w} = V (V^T V)^{-1} V^T \vec{a}$$

$$\Rightarrow \text{Proj}_V(\vec{a}) = \underbrace{V (V^T V)^{-1} V^T}_{H} \vec{a}$$

H is called a proj. matrix.

Properties:

(a) symmetric

$$H^T = (V (V^T V)^{-1} V^T)^T = V^T (V^T V)^{-1} V = V^T (V^T V)^{-1} V = H$$

Fact:
 $(A^T)^{-1} = (A^{-1})^T$

(b) idempotent $HH = H$

$$(V (V^T V)^{-1} V^T) (V (V^T V)^{-1} V^T) = V (V^T V)^{-1} (V^T V) (V^T V)^{-1} V^T = H$$