

Lecture 8:

$$y = R, p = 2$$

linear models, $H = \{ w_0 + w_1 x_1 + w_2 x_2 : \vec{w} \in \mathbb{R}^3 \}$

$$D := (X, Y) \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \end{bmatrix} \in \mathbb{R}^{n \times 3}$$

Algorithm will return one \vec{w}

and all \hat{y} 's can be via:

$$\vec{\hat{y}} = X \vec{w}$$

$$SSE = \sum e_i^2$$

$$\vec{e} = \vec{y} - \vec{\hat{y}}$$

$$= \vec{e}^T \vec{e} \quad [\text{dot / inner Product}]$$

$$A: \vec{b} = \underset{\vec{w} \in \mathbb{R}^3}{\text{argmin}} \{ \vec{e}^T \vec{e} \}$$

A: OLS

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

$$\left(\begin{bmatrix} 1 & x_{11} & x_{12} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \end{bmatrix} \right)^T \left(\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} - \begin{bmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_n \end{bmatrix} \right) = (\vec{y}^T - \vec{\hat{y}}^T) (\vec{y} - \vec{\hat{y}})$$

$$= \vec{y}^T \vec{y} - \vec{\hat{y}}^T \vec{y} - \vec{y}^T \vec{\hat{y}} + \vec{\hat{y}}^T \vec{\hat{y}}$$

$$= \vec{y}^T \vec{y} - 2 \vec{\hat{y}}^T \vec{y} + \vec{\hat{y}}^T \vec{\hat{y}}$$

$$\text{A. } \vec{b} = \arg \min_{\vec{w} \in \mathbb{R}^3} \{ \vec{e}^T \vec{e} \}$$

$$= \vec{y}^T \vec{y} - 2 \vec{w}^T \vec{X}^T + \vec{w}^T \vec{X}^T \vec{X} \vec{w}$$

$$= SSE$$

$$b_0: \frac{\partial}{\partial w_0} [SSE] \stackrel{\text{set}}{=} 0$$

$$b_1: \frac{\partial}{\partial w_1} [SSE] \stackrel{\text{set}}{=} 0$$

$$b_2: \frac{\partial}{\partial w_2} [SSE] \stackrel{\text{set}}{=} 0$$

$$\frac{\partial}{\partial \vec{w}} (SSE) = \begin{bmatrix} \frac{\partial}{\partial w_0} (SSE) \\ \frac{\partial}{\partial w_1} (SSE) \\ \frac{\partial}{\partial w_2} (SSE) \end{bmatrix} \stackrel{\text{set}}{=} \vec{0}_3$$

Back to math 231:-

Let $\vec{x} \in \mathbb{R}^n$; a scalar constant
w.r.t. + all x_j 's.

with
respected
to

$$\frac{\partial}{\partial \vec{x}} [a] = \vec{0}_n$$

Let $\vec{x} \in \mathbb{R}^n$, \vec{a} ^{column} vector constant w.r.t.
all x_j 's

$$\frac{\partial}{\partial \vec{x}} [\vec{a}^T \vec{x}] = \begin{bmatrix} \frac{\partial}{\partial x_1} [a_1 x_1 + a_2 x_2 + \dots + a_n x_n] \end{bmatrix}$$

$$= \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \vec{a}$$

f, g are both $\mathbb{R}^n \rightarrow \mathbb{R}$ func., a, b constant.

$$\frac{\partial}{\partial \vec{x}} [a f(\vec{x}) + b g(\vec{x})],$$

$$= a \frac{\partial}{\partial \vec{x}} [f(\vec{x})] + b \frac{\partial}{\partial \vec{x}} [g(\vec{x})]$$

$$\rightarrow \begin{bmatrix} \frac{\partial}{\partial x_1} [a f_1(\vec{x}) + b g(\vec{x})] \\ \vdots \\ \frac{\partial}{\partial x_n} [a f_n(\vec{x}) + b g(\vec{x})] \end{bmatrix}$$

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Let $A \in \mathbb{R}^{n \times n}$ be a ~~real~~ symmetric matrix of constants w.r.t. x_j 's;

$$\frac{\partial}{\partial \vec{x}} \left[\overset{1 \times n}{\vec{x}^T} \overset{n \times n}{A} \overset{n \times 1}{\vec{x}} \right] \quad (\text{dimen } (1/1))$$

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FYI: Quadratic form

$$= \frac{\partial}{\partial \vec{x}} \left[\vec{x}^T \begin{bmatrix} \leftarrow \vec{a}_1 \rightarrow \\ \leftarrow \vec{a}_2 \rightarrow \\ \leftarrow \vec{a}_n \rightarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \vec{x} \\ \downarrow \end{bmatrix} \right]$$

$$= \frac{\partial}{\partial \vec{x}} \left[\vec{x}^T \begin{bmatrix} \vec{a}_1 \vec{x} \\ \vec{a}_2 \vec{x} \\ \vec{a}_n \vec{x} \end{bmatrix} \right]$$

$$= \frac{\partial}{\partial \vec{x}} \left[\begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} \vec{a}_1 \vec{x} \\ \vdots \\ \vec{a}_n \vec{x} \end{bmatrix} \right]$$

$$= \frac{\partial}{\partial \vec{x}} \left[x_1 \vec{a}_1 \vec{x} + x_2 \vec{a}_2 \vec{x} + \dots + x_n \vec{a}_n \vec{x} \right]$$

$$= \frac{\partial}{\partial \vec{x}} \left[x_1 (a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n) \right.$$

$$+ x_2 (a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n)$$

$$+ \dots + x_n (a_{n1}x_1 + a_{n2}x_2 + \dots$$

$$+ a_{nn}x_n) \left. \right]$$

$$= \frac{\partial}{\partial \vec{x}} \left[a_{11}x_1^2 + a_{12}x_1x_2 + \dots + a_{1n}x_1x_n + a_{21}x_2x_1 \right.$$

$$+ a_{22}x_2^2 + \dots + a_{2n}x_2x_n + a_{n1}x_nx_1$$

$$+ a_{nn}x_n^2 \left. \right]$$

before.
 $\frac{d}{dx_1} [\dots]$

$$= 2a_{11}x_1 + a_{12}x_2 + a_{1n}x_n + \underbrace{a_{21}x_2 + a_{31}x_3 + \dots + a_{n1}x_n}_{\text{equals in } A = A^T}$$

$$= 2a_{11}x_1 + 2a_{21}x_2 + \dots + 2a_{n1}x_n$$

$$= 2 \vec{a}_1 \cdot \vec{x}$$

$$\frac{\partial}{\partial x_2} (\dots) = 2 \vec{a}_2 \cdot \vec{x}$$

$$\frac{\partial}{\partial \vec{x}} [\vec{x}^T A \vec{x}] =$$

$$= \begin{bmatrix} 2 \vec{a}_1 \cdot \vec{x} \\ 2 \vec{a}_2 \cdot \vec{x} \\ \vdots \\ 2 \vec{a}_n \cdot \vec{x} \end{bmatrix} = 2 \begin{bmatrix} \vec{a}_1 \cdot \vec{x} \\ \vec{a}_2 \cdot \vec{x} \\ \vdots \\ \vec{a}_n \cdot \vec{x} \end{bmatrix}$$

$$= 2 \begin{bmatrix} \vec{a}_1 \\ \vec{a}_2 \\ \vdots \\ \vec{a}_n \end{bmatrix} \vec{x} = 2 A \vec{x}$$

$$X \in \mathbb{R}^{n \times 3}$$

$$\frac{\partial}{\partial \vec{w}} [SSE] = \frac{\partial}{\partial \vec{w}} [\vec{y}^T \vec{y} - 2 \underbrace{\vec{w}^T X^T \vec{y}}_{(\vec{X}^T \vec{y})^T \vec{w}} + \vec{w}^T \underbrace{X^T X}_{\text{matrix}} \vec{w}]$$

$$\begin{aligned} & (\vec{X}^T \vec{X})^T \\ &= \vec{X}^T (\vec{X}^T)^T \\ &= \vec{X}^T \vec{X} \end{aligned}$$

$$= \vec{0}_3 - 2 \vec{X}^T \vec{y} + 2 \vec{X}^T \vec{X} \vec{w}$$

$$\vec{0}_3 - 2 \vec{X}^T \vec{y} + 2 \vec{X}^T \vec{X} \vec{w} \stackrel{SSE}{=} \vec{0}_3$$

$$\Rightarrow \vec{X}^T \vec{X} \vec{w} = \vec{X}^T \vec{y}$$

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

SS und $\vec{X}^T \vec{X}$ sind invertierbar

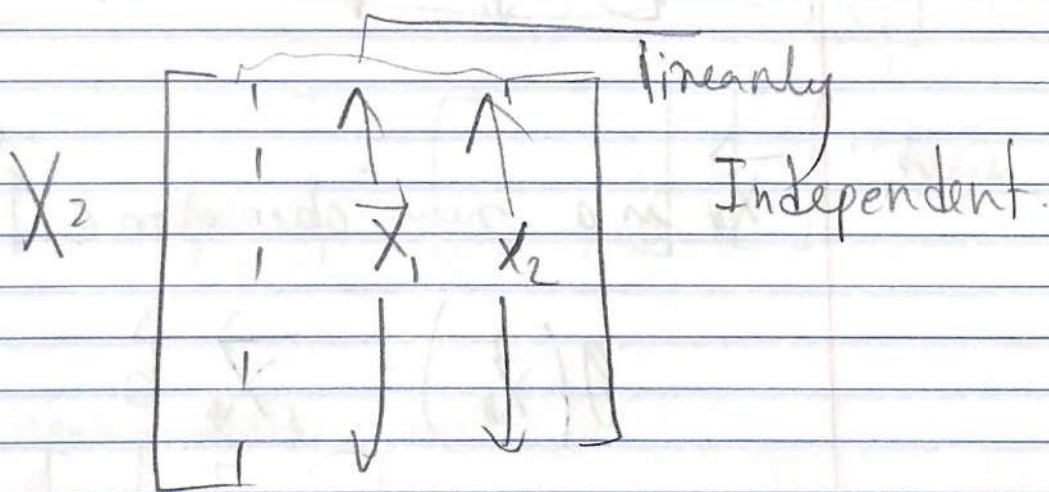
$$\vec{b} = (X^T X)^{-1} X^T \vec{y}$$

~~(P^{-1}) or (P^{-1}) \times n \times n \times 1~~

OLS estimate valid
for all P .

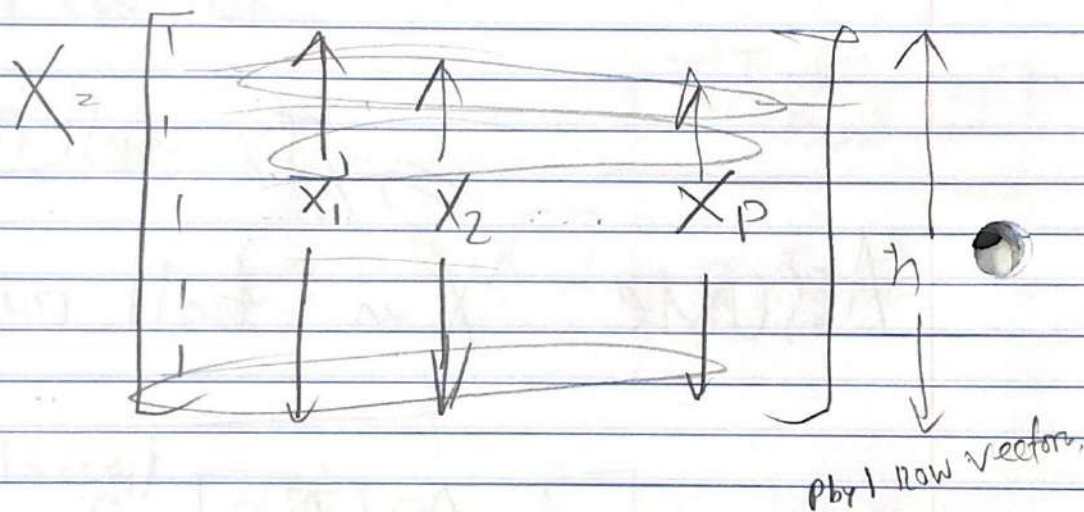
$\Rightarrow X^T X$ full rank

Assume X is full rank



In general, X is full rank.

$$= p+1$$



$\vec{x}_\#$ is a new observation $\in \mathbb{R}^{p+1}$

$$g(\vec{x}_\#) = \vec{x}_\# \vec{b} = \hat{y}_\#$$

$$g(X_*) \in \mathbb{R}^{n_* \times (P+1)}$$

$$g(X_*) = X_* \vec{b} = \vec{\hat{y}}!$$

get back $\vec{\hat{y}}$ for all original subjects in \mathbb{D}

$$\vec{\hat{y}} = g(X) = X \cdot \vec{b}$$

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

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

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"Hat matrix"

$$= H \vec{y}$$

$$= T(\vec{y})$$

$$\begin{bmatrix} \end{bmatrix} = \begin{bmatrix} \end{bmatrix} \begin{bmatrix} \end{bmatrix} \quad \downarrow \text{linear function}$$

$$\text{rank} + \text{nullity} = n$$

$$\dim(\text{col space}) + \dim(\text{nullspace}) = n$$

$$\downarrow \text{IPH} \quad + \quad (n - (P+1)) = n$$

degrees of freedom

Feel it

$$\vec{e} = \vec{y} - \hat{\vec{y}} = \vec{y} - H\vec{y} = (I - H)\vec{y}$$

$$\vec{y} = \hat{\vec{y}} + \vec{e}$$

$$I\vec{y} = \underbrace{H\vec{y}}_{T(\vec{y})} + \underbrace{(I-H)\vec{y}}_{U(\vec{y})}$$

ARNA

$$SSE = \vec{e}^T \vec{e}$$

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

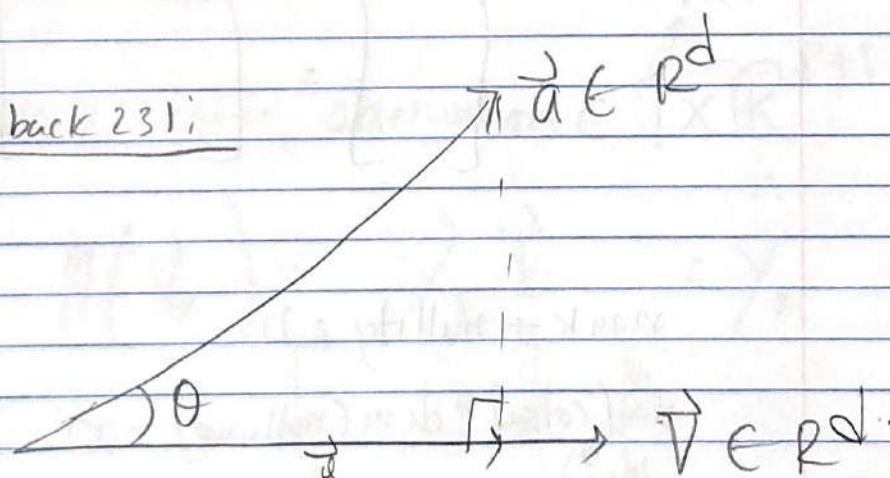
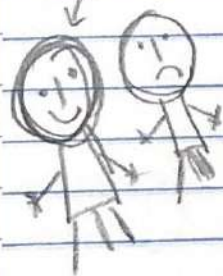
$$R^2 = 1 - \frac{SSE}{SST}$$

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$$RMSE = \sqrt{MSE}$$

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going back 231;



$$l := \text{Proj}_V(a)$$

orthogonal Projection

We want a formula for I as a function of inputs \vec{a}, \vec{v}

Recall the "law of cosines"

$$\cos(\theta) = \frac{\vec{a}^T \vec{v}}{\|\vec{a}\| \|\vec{v}\|} = \frac{\|\vec{x}\|}{\|\vec{a}\|}$$

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

$$\vec{x} = \|\vec{x}\| \frac{\vec{v}}{\|\vec{v}\|} \quad \downarrow \quad = \frac{\vec{a} \cdot \vec{v} \vec{v}}{\|\vec{v}\|^2}$$

$$= \frac{\overbrace{\vec{v} \vec{v}^T}^{dx \times dx \quad dx \times dx \quad dx \times dx}}{\|\vec{v}\|^2} \vec{a}$$

$$\boxed{H \vec{a} = \text{Proj}_{\vec{v}}(\vec{a})}$$

Formula.