

SET-UP

$X \in \mathbb{R}^p$ real valued RV of covariates
 $Y \in \mathbb{R}$ response
 $p(X, Y)$

Aim: find $f(X)$ to predict Y
 $L(Y, f(X))$ is our loss function

Find $f(X)$ to minimize the $EPE(f)$
 \uparrow
expected prediction error

$$EPE(f) = E_{X,Y}(L(Y, f(X))) \quad \text{assume } Y \text{ and } X \text{ continuous}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} L(y, f(x)) p(x, y) dx dy$$

\uparrow usually $f(x, y)$ but we use f for our func. of interest

Q: why not $\int \int L(y, f(x)) p(f(x), y) df(x) dy$?

"law of the unconscious statistician" $E(g(X, Y)) = \int \int g(x, y) p(x, y) dx dy$

With squared loss: $L(Y, f(X)) = (Y - f(X))^2$ L_2 -loss

$$EPE(f) = E[(Y - f(X))^2] = \int_x \int_y (y - f(x))^2 p(x, y) dy dx$$

← really 2 integrals

$$= \int_x \int_y (y - f(x))^2 p(y|x) p(x) dy dx = \int_x p(x) \cdot \underbrace{\int_y (y - f(x))^2 p(y|x) dy}_{E_{Y|X}[(Y - f(X))^2 | X]} dx$$

$$E_X \left[E_{Y|X}[(Y - f(X))^2 | X] \right]$$

What does this mean? Try optimize $f(X)$ at each $X=x$ at a time (partwise)

$EPE(f)$ at $X=x$ found by minimizing with respect to $f(x)$

$$E_{Y|X}((Y - f(X))^2 | X) = \int_y (y - f(x))^2 p(y|x) dy$$

$$0 = \frac{d}{df} \int_y (y - f(x))^2 p(y|x) dy \stackrel{\circledast}{=} \int \frac{d}{df} (y - f)^2 p(y|x) dy$$

$$= \int -2(y - f) p(y|x) dy = -2E(Y | X=x) + 2f(x) \underbrace{\int p(y|x) dy}_1$$

$$\underline{\underline{E(Y | X=x) = f(x)}}$$

⊛ if we may change the order of \int and $\frac{d}{df}$

But, do we know $E(Y|X=x)$?

Sometimes? What if $\begin{bmatrix} Y \\ X \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_Y \\ \mu_X \end{bmatrix}, \begin{bmatrix} \Sigma_{YY} & \Sigma_{YX} \\ \Sigma_{XY} & \Sigma_{XX} \end{bmatrix}\right)$?

Find $E(Y|X=x)$

From TMA4267 we know that $Y|X=x \sim N$ with

$$E(Y|X=x) = \mu_Y + \Sigma_{YX}\Sigma_{XX}^{-1}(x - \mu_X)$$

$$\text{and } \text{Var}(Y|X=x) = \Sigma_Y - \Sigma_{YX}\Sigma_{XX}^{-1}\Sigma_{XY}$$

What can we observe? $E(Y|X=x)$ is a linear func in x and
 $\text{Var}(Y|X=x)$ is not depd of x

\Rightarrow "main" reason for why we love MLR so much!

Rule

$$\frac{d X^T \beta}{d \beta} = X$$

$$d \frac{\beta^T X^T X \beta}{d \beta} = 2 X^T X \beta$$