

Last lecture

Correlation and covariance ([Ch 4.8](#))

- Examples

Minimum mean square error estimation ([Ch 4.9](#))

- Constant estimators
- Unconstrained estimators
- Linear estimators

Agenda

Minimum mean square error estimation ([Ch 4.9](#))

- Recap
 - Constant estimators
 - Unconstrained estimators
 - Linear estimators
- Examples

Joint Gaussian Distribution ([Ch 4.11](#))

- Motivation
- Facts
- Examples

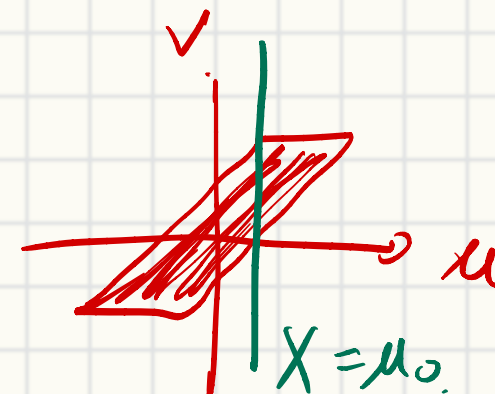
Estimators Recap

$$E[(Y - c')^2] \geq \text{Var}(Y)$$

- Constant estimator

- $c^* = E[Y],$

$$\text{MSE} = \text{Var}(Y)$$



- Unconstraint estimator

- $g^*(X) = E[Y|X]$

$$\text{MSE} = E[Y^2] - E[(E[Y|X])^2]$$

- Best estimator, but requires $f_{Y|X}$

$$E[(Y - g(X))^2] \geq E[(Y - g^*(X))^2]$$

- Linear estimator

- $\hat{E}[Y|X] = \mu_Y + \frac{\text{Cov}(X,Y)}{\text{Var}(X)}(X - \mu_X) = \mu_Y + \rho_{X,Y}\sigma_Y\left(\frac{X - \mu_X}{\sigma_X}\right)$

$$= aX + b.$$

- $\text{MSE} = \sigma_Y^2 - \frac{(\text{Cov}(X,Y))^2}{\text{Var}(X)} = \sigma_Y^2(1 - \rho_{X,Y}^2)$

$$\hat{E}[Y|X] = aX + b$$

Z

$$\operatorname{argmin}_{a,b} E[(Y - \hat{E})^2] = E[(Y - aX - b)^2]$$

$$b^* = E[Z] = \mu_Y - a\mu_X$$

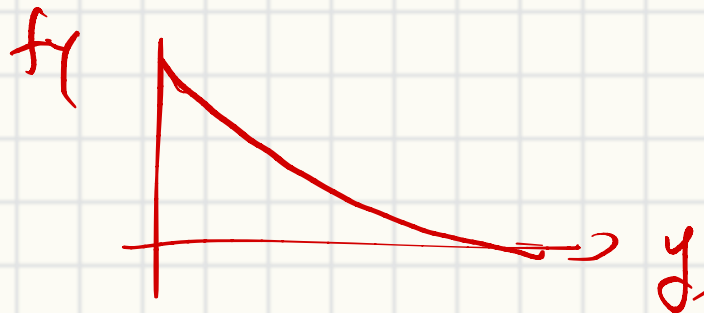
$$\Rightarrow E[(Y - aX - b)^2] = E[\underbrace{(Y - \mu_Y - a(X - \mu_X))^2}_f]$$

$$\frac{df}{da} = 0$$

$$\Rightarrow a^* = \frac{\operatorname{Cov}(X, Y)}{\operatorname{Var}(X)}$$

Example

$$Y = X + N$$



Let $X = Y + N$, $Y \sim \text{Exp}(\lambda)$ and $N \sim N(0, \sigma_N^2)$. Assume Y and N are independent

- Find $\hat{E}[Y|X]$

$$\begin{cases} \mu_Y = \frac{1}{\lambda} \\ \mu_X = \mu_Y + \mu_N = \frac{1}{\lambda} + 0 = \frac{1}{\lambda} \\ \text{Cov}(X, Y) = \text{Cov}(Y + N, Y) = \text{Var}(Y) = \frac{1}{\lambda^2} \\ \text{Var}(X) = \text{Cov}(Y + N, Y + N) = \text{Var}(Y) + \text{Var}(N) = \frac{1}{\lambda^2} + \sigma_N^2 \end{cases}$$

- Find the ~~best~~ unconstrained estimator of Y

better

$$\begin{aligned} \hat{E}[Y|X] &= \mu_Y + \frac{\text{Cov}(X, Y)}{\text{Var}(X)} (X - \mu_X) \\ &= \frac{1}{\lambda} + \frac{1}{1 + \lambda^2 \sigma_N^2} \left(X - \frac{1}{\lambda} \right) = \frac{X + \lambda \sigma_N^2}{1 + \lambda^2 \sigma_N^2} \end{aligned}$$

$$Y > 0, \quad \hat{E}[Y|X] = aX + b \neq 0,$$

$$g(x) = \max(0, \hat{E}[Y|X])$$

$$E[(Y - g(X))^2] < E[(Y - \hat{E}[Y|X])^2]$$

Example

Suppose X and Y are uniformly distributed in the triangle.

- Find $g^*(u) = E[Y|X = u]$ and the corresponding minimum MSE

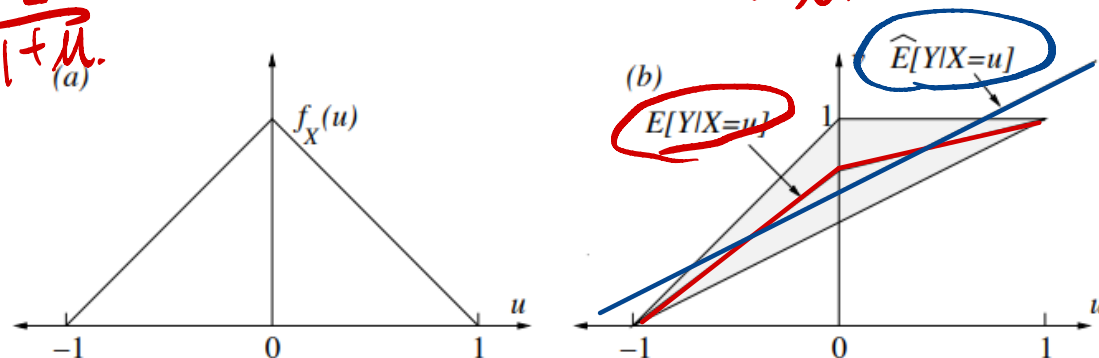
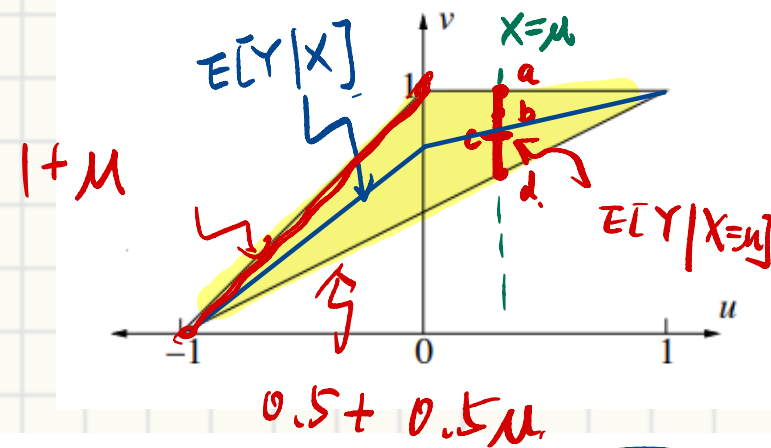
$$g^*(u) = \begin{cases} 0.75 + 0.75u & -1 < u \leq 0 \\ 0.75 + 0.25u & 0 < u < 1 \\ \text{undefined} & \text{else} \end{cases}$$

- Find $\hat{E}[Y|X = u]$, and compute MSE

$$E[Y|X=u] = \int v f_{Y|X}(v|u) dv$$

$\hookrightarrow \frac{2}{1+u}$ (a)

$$\mu_X, \mu_Y, \text{Cov}(X, Y), \text{Var}(X)$$



Final Review

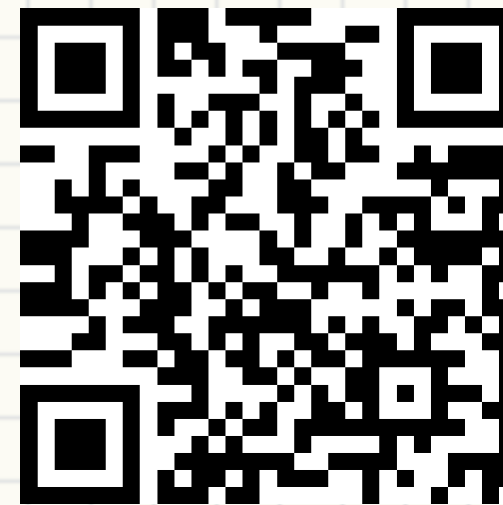
Next Wednesday class

↳ Input top 5 ~

↳ Final composition

60% 50% pre midterm 2

50% post midterm 2 (comprehensive)



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