

## LECTURE 16

- **Readings:** Sections 4.5, 4.6

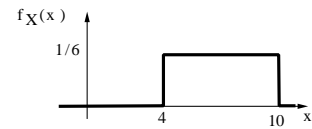
### Outline

- Least squares prediction
  - Conditional variance
  - Linear prediction

### Review

- $E[X | Y]$  is a random variable whose experimental value is  $E[X | Y = y]$  when  $Y = y$ 
  - It is a function of  $Y$
  - $E[E[X | Y]] = E[X]$

## Prediction in the absence of information

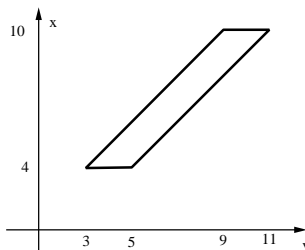
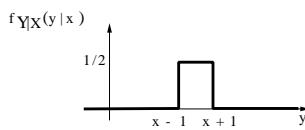
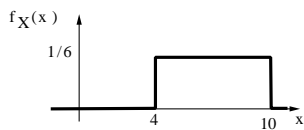


- prediction  $c$

$$\text{minimize } \mathbf{E}[(X - c)^2]$$

- $c = \mathbf{E}[X]$
- Optimal mean squared error:

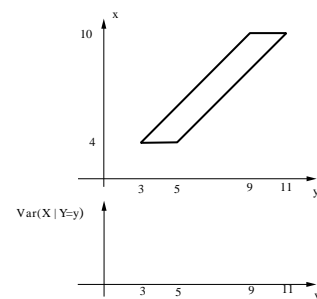
$$\mathbf{E}[(X - \mathbf{E}[X])^2] = \text{Var}(X)$$



## Conditional variance

- $\text{Var}(X | Y = y)$ : variance of the conditional distribution of  $X$

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



### Predicting $X$ based on $Y$

- Two r.v.'s  $X, Y$
- we observe that  $Y = y$ 
  - new universe: condition on  $Y = y$
- $\mathbf{E}[(X - c)^2 | Y = y]$  is minimized by  $c =$
- View predictor as a function  $g(y)$
- $\mathbf{E}[X | Y]$  minimizes

$$\mathbf{E}[(X - g(Y))^2]$$

over all predictors  $g(\cdot)$

### Prediction given several measurements

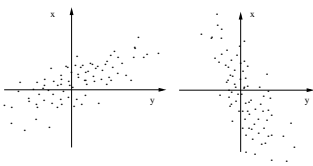
- Unknown r.v.  $X$
- Observe values of r.v.'s  $Y_1, \dots, Y_n$
- Best prediction:  $\mathbf{E}[X | Y_1, \dots, Y_n]$
- Can be hard to compute/implement
  - need model  $f_{X, Y_1, \dots, Y_n}$
  - even with model, computations are hard

### Linear prediction

- Form a predictor (of  $X$ ) of the form  $aY + b$
- Minimize  $\mathbf{E}[(X - aY - b)^2]$
- Best predictor:

$$\mathbf{E}[X] + \frac{\text{Cov}(X, Y)}{\text{var}(Y)}(Y - \mathbf{E}[Y])$$

$$\text{Cov}(X, Y) = \mathbf{E}[(X - \mathbf{E}[X])(Y - \mathbf{E}[Y])]$$



### Covariance and correlation

- Covariance:
$$\text{Cov}(X, Y) = \mathbf{E}[(X - \mathbf{E}[X])(Y - \mathbf{E}[Y])]$$
- Correlation (dimensionless version of covariance)
$$\rho = \mathbf{E}\left[\frac{(X - \mathbf{E}[X])}{\sigma_X} \cdot \frac{(Y - \mathbf{E}[Y])}{\sigma_Y}\right]$$
- $-1 \leq \rho \leq 1$
- Independence implies zero covariance (converse is not true)