

## LECTURE 13: Conditional expectation and variance revisited;

### Application: Sum of a random number of independent r.v.'s

- A more abstract version of the conditional expectation
  - view it as a random variable
  - the law of iterated expectations
- A more abstract version of the conditional variance
  - view it as a random variable
  - the law of total variance
- Sum of a random number of independent r.v.'s
  - mean
  - variance

## Conditional expectation as a random variable

- Function  $h$   
e.g.,  $h(x) = x^2$ , for all  $x$
- Random variable  $X$ ; what is  $h(X)$ ?  
 $= x^2$
- $h(X)$  is the r.v. that takes the value  $x^2$ , if  $X$  happens to take the value  $x$
- $\underline{g(y)} = \mathbf{E}[X | Y = y] = \sum_x x p_{X|Y}(x | y)$   
(integral in continuous case)
- $g(Y)$ : is the r.v. that takes the value  $\mathbf{E}[X | Y = y]$ , if  $Y$  happens to take the value  $y$
- Remarks:
  - It is a function of  $Y$
  - It is a random variable
  - Has a distribution, mean, variance, etc.

**Definition:**  $\underline{\mathbf{E}[X|Y]} = g(Y)$

## The mean of $E[X | Y]$ : Law of iterated expectations

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

$$E[E[X | Y]] = E[X]$$

$$E[X | Y] \triangleq g(Y)$$

$$E[E[X | Y]] = E[g(Y)]$$

$$= \sum_{\gamma} g(\gamma) P_Y(\gamma)$$

exp. value rule

$$= \sum_{\gamma} E[X | Y = \gamma] P_Y(\gamma)$$

• total exp thm

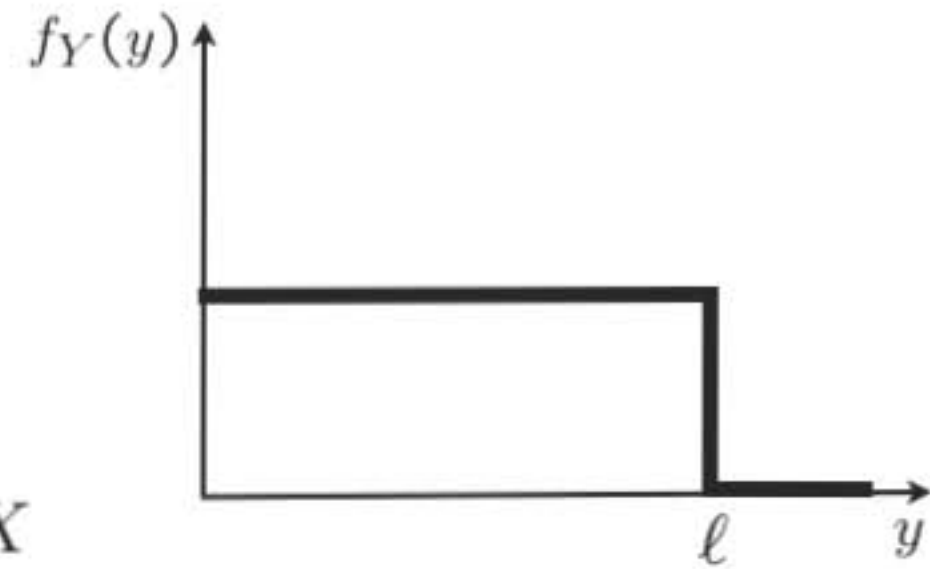
$$= E[X]$$



## Stick-breaking example

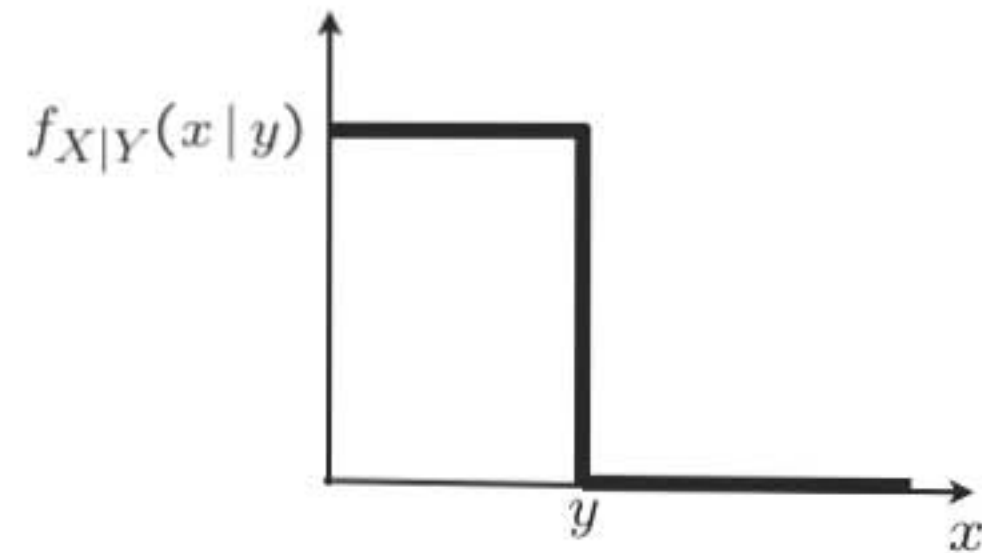
- Stick example: stick of length  $\ell$   
break at uniformly chosen point  $Y$

break what is left at uniformly chosen point  $X$



- $E[X | Y = y] = y/2$

- $E[X | Y] = Y/2$



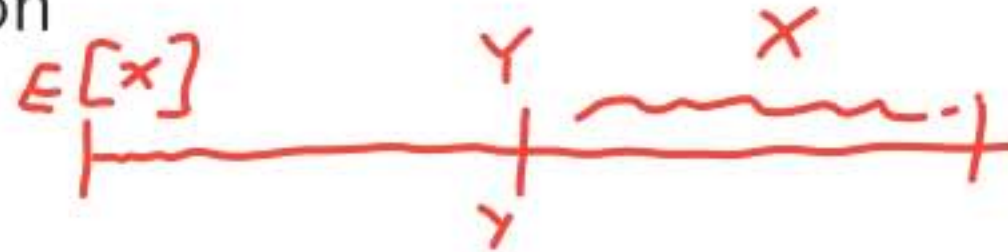
$$E[X] = E[E[X|Y]] = E[Y/2] = \frac{1}{2} E[Y] = \frac{1}{2} \cdot \frac{\ell}{2} = \frac{\ell}{4}$$

## Forecast revisions

$$E[E[X|Y]] = E[X]$$

- Suppose forecasts are made by calculating expected value, given any available information

- $X$ : February sales



- Forecast in the beginning of the year:  $E[X]$
- End of January: will get new information, value  $y$  of  $Y$

Revised forecast:  $E[X|Y=y]$        $E[X|Y]$

- Law of iterated expectations:

$$E[\text{revised forecast}] = E[X] = \text{original forecast}$$

## The conditional variance as a random variable

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

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

$\text{var}(X | Y)$  is the r.v. that takes the value  $\text{var}(\bar{X} | Y = y)$ , when  $Y = y$

- Example:  $X$  uniform on  $[0, Y]$

$$\text{var}(X | Y = y) = y^2/12$$

$$\text{var}(X | Y) = Y^2/12$$

**Law of total variance:**  $\text{var}(X) = \mathbf{E}[\text{var}(X | Y)] + \text{var}(\mathbf{E}[X | Y])$



## Derivation of the law of total variance

$$\text{var}(X) = \mathbf{E}[\text{var}(X | Y)] + \text{var}(\mathbf{E}[X | Y])$$

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

$$\text{var}(X | Y = y) = E[x^2 | Y = y] - (E[x | Y = y])^2 \text{ for all } y$$

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

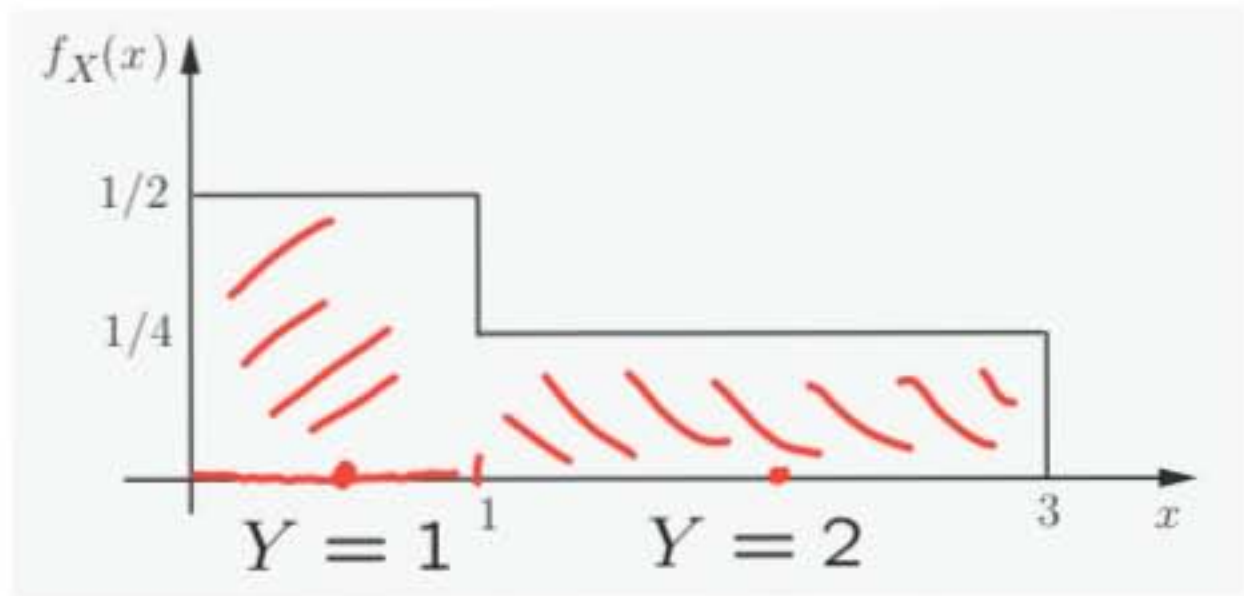
$$\mathbf{E}[\text{var}(X | Y)] = E[x^2] - E[(E[x | Y])^2]$$

$$+ \text{var}(\mathbf{E}[X | Y]) = E[(E[x | Y])^2] - (E[E[x | Y]])^2$$
$$= E[x^2] - (E[x])^2$$

## A simple example

$$\text{var}(X) = \mathbf{E}[\text{var}(X | Y)] + \text{var}(\mathbf{E}[X | Y]) = \frac{37}{48}$$

$$= \frac{5}{24} + \frac{9}{16}$$



$$\text{var}(X | Y) = \begin{cases} \frac{1}{2} & \text{var}(X | Y = 1) = \frac{1}{12} \\ \frac{1}{2} & \text{var}(X | Y = 2) = \frac{2^2}{12} = \frac{4}{12} \end{cases}$$

$$\mathbf{E}[\text{var}(X | Y)] = \frac{1}{2} \cdot \frac{1}{12} + \frac{1}{2} \cdot \frac{4}{12} = \frac{5}{24}$$

$$\mathbf{E}[X | Y] = \begin{cases} \frac{1}{2} & \mathbf{E}[X | Y = 1] = \frac{1}{2} \\ \frac{1}{2} & \mathbf{E}[X | Y = 2] = 2 \end{cases}$$

$$\text{var}(\mathbf{E}[X | Y]) = \frac{1}{2} \left( \frac{1}{2} - \frac{5}{4} \right)^2$$

$$+ \frac{1}{2} \left( 2 - \frac{5}{4} \right)^2 = \frac{9}{16}$$

$$\mathbf{E}[\mathbf{E}[X | Y]] = \frac{1}{2} \cdot \frac{1}{2} + \frac{1}{2} \cdot 2 = \frac{5}{4} = \mathbf{E}[X]$$



## Section means and variances

- Two sections of a class:  $y = 1$  (10 students);  $y = 2$  (20 students)

$x_i$ : score of student  $i$

- Experiment: pick a student at random (uniformly)

random variables:  $X$  and  $Y$

- Data:  $y = 1 : \frac{1}{10} \sum_{i=1}^{10} x_i = 90$        $y = 2 : \frac{1}{20} \sum_{i=11}^{30} x_i = 60$

- $E[X] = \frac{1}{30} \sum_{i=1}^{30} x_i = \frac{1}{30} (90 \cdot 10 + 60 \cdot 20) = 70$

$$E[X | Y = 1] = 90$$

$$E[X | Y = 2] = 60$$

$$E[X | Y] = \begin{array}{l} \frac{1}{3} \cdot 90 \\ \frac{2}{3} \cdot 60 \end{array}$$

- $E[E[X | Y]] = \frac{1}{3} \cdot 90 + \frac{2}{3} \cdot 60 = 70$

## Section means and variances (ctd.)

$$\mathbf{E}[X | Y] = \begin{cases} 90, & \text{w.p. } 1/3 \\ 60, & \text{w.p. } 2/3 \end{cases} \quad \mathbf{E}[\mathbf{E}[X | Y]] = 70 = \mathbf{E}[X]$$
$$\text{var}(\mathbf{E}[X | Y]) = \frac{1}{3}(90-70)^2 + \frac{2}{3}(60-70)^2 = 200$$

• More data:  $\frac{1}{10} \sum_{i=1}^{10} (x_i - 90)^2 = 10$        $\frac{1}{20} \sum_{i=11}^{30} (x_i - 60)^2 = 20$

$$\text{var}(X | Y = 1) = 10 \quad \text{var}(X | Y) = \frac{1/3}{2/3} \begin{matrix} 10 \\ 20 \end{matrix}$$

$$\text{var}(X | Y = 2) = 20 \quad \mathbf{E}[\text{var}(X | Y)] = \frac{1}{3} \cdot 10 + \frac{2}{3} \cdot 20 = \frac{50}{3}$$

$$\text{var}(X) = \mathbf{E}[\text{var}(X | Y)] + \text{var}(\mathbf{E}[X | Y]) = 50/3 + 200$$

$\text{var}(X) = (\text{average variability **within** sections}) + (\text{variability **between** sections})$



## Sum of a random number of independent r.v.'s

$$\mathbf{E}[Y] = \mathbf{E}[N] \cdot \mathbf{E}[X]$$

- $N$ : number of stores visited  
( $N$  is a nonnegative integer r.v.)
- Let  $Y = X_1 + \dots + X_N$
- $X_i$ : money spent in store  $i$ 
  - $X_i$  independent, identically distributed
  - independent of  $N$

$$\begin{aligned} \mathbf{E}[Y | N = n] &= \mathbf{E}[X_1 + \dots + X_n | N = n] = \mathbf{E}[X_1 + \dots + X_n | N = n] \\ &= \mathbf{E}[X_1 + \dots + X_n] = n \mathbf{E}[X] \end{aligned}$$

$\hookrightarrow \mathbf{E}[Y | N] = N \mathbf{E}[X]$

- Total expectation theorem:

$$\mathbf{E}[Y] = \sum_n p_N(n) \mathbf{E}[Y | N = n] = \sum_n p_N(n) n \mathbf{E}[X] = \mathbf{E}[N] \mathbf{E}[X]$$

- Law of iterated expectations:

$$\mathbf{E}[Y] = \mathbf{E}[\mathbf{E}[Y | N]] = \mathbf{E}[N \mathbf{E}[X]] = \mathbf{E}[N] \mathbf{E}[X]$$



## Variance of sum of a random number of independent r.v.'s

$$Y = X_1 + \dots + X_N$$

•

$$\text{var}(Y) = \mathbf{E}[\text{var}(Y | N)] + \text{var}(\mathbf{E}[Y | N])$$

$$\text{var}(Y) = \mathbf{E}[N] \text{var}(X) + (\mathbf{E}[X])^2 \text{var}(N)$$

•  $\mathbf{E}[Y | N] = N \mathbf{E}[X]$

•  $\text{var}(\mathbf{E}[Y | N]) = \text{var}(N \mathbf{E}[X]) = (\mathbf{E}[X])^2 \text{var}(N)$

•  $\text{var}(Y | N = n) = \text{var}(X_1 + \dots + X_n | N = n) = \text{var}(X_1 + \dots + X_n) = n \text{var}(X)$

$\text{var}(Y | N) = N \text{var}(X)$

•  $\mathbf{E}[\text{var}(Y | N)] = \mathbf{E}[N \text{var}(X)] = \mathbf{E}[N] \text{var}(X)$

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<https://ocw.mit.edu>

Resource: Introduction to Probability

John Tsitsiklis and Patrick Jaillet

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