

## MARTINGALES & CONDITIONAL EXPECTATION

→ MARKOV PROPERTY :  $(X_n)_{n \geq 0}$

$$\begin{aligned} P(X_{n+1} = x | X_n = y, X_{n-1} = i_{n-1}, \dots, X_1 = i_1, X_0 = i_0) \\ = P(X_{n+1} = x | X_n = y) \end{aligned}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad \text{if } P(B) > 0$$

Markov property → Condition on exact position at time  $n$

$$P(\dots | X_n = y)$$

$$\begin{aligned} P(X_{n+1} = x | X_n \geq 0, X_{n-1} = i_{n-1}, \dots) \\ \neq P(X_{n+1} = x | X_n \geq 0) \end{aligned}$$

In general ↑ not true for a Markov chain.

$\{X_n \geq 0\}$  event carries less information than  $\{X_n = y\}$

MARTINGALE ≈ a stochastic process  $(X_n)_{n \geq 0}$  (DISCRETE TIME)

such that expectation of  $X_{n+1}$ , knowing

"the information" of  $X_n$  is equal to  $X_n$

## CONDITIONAL EXPECTATION

Let  $X : \Omega \rightarrow \mathbb{R}$  r.v. on  $(\Omega, \mathcal{A}, P)$

- $E[X] \approx$  best approximation of r.v.  $X$  with a constant.

Given a r.v.  $Y : \Omega \rightarrow \mathbb{R}$ , we want to define

$E[X|Y]$  CONDITIONAL EXPECTATION of  $X$  given  $Y$

$E[X|Y] \approx$  approximation of  $X$  as a random variable  
which looks like  $Y$

$\approx$  best approximation as a function of  $Y$

- if  $Y$  takes 2 values then  $E[X|Y]$  is the best

- if  $Y$  takes 2 values then  $E[X|Y]$  is the best approximation of  $X$  as a r.v. taking 2 values.

Example RANDOM IMAGE.



$$X : \Omega \rightarrow \{\text{PIXELS}\} \quad 10^8 = \# \text{PIXELS}$$

$$X(w) = \text{color}$$

approximation with monochrome image with less pixels  $\sim 100$   
is  $E[X|Y] : \Omega \rightarrow \{100 \text{ pixels}\}$   
 $\hookrightarrow$  conditional expectation

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## • DISCRETE RANDOM VARIABLES

$X$  and  $Y$  discrete  $X, Y : \Omega \rightarrow \mathbb{R}$

finite or countable state space

What is  $E[X|Y] = h(Y)$ ? Function of  $Y$

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

Consider the r.v.  $X|Y=y$

What is its density?

$$p_{X|Y=y}(x) = \frac{P(X=x | Y=y)}{P(Y=y)} = \frac{p_{X,Y}(x,y)}{p_Y(y)}$$

joint density

Denote  $p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$

CONDITIONAL DENSITY

Compute expectation of the r.v.  $X|Y=y$

$$\text{Note } \sum_x p_{X|Y}(x|y) = \frac{\sum_x p_{X,Y}(x,y)}{p_Y(y)} = \frac{p_Y(y)}{p_Y(y)} = 1$$

$$E[X|Y=y] = \sum_x x p_{X|Y}(x|y) = h(y)$$

$\hookrightarrow$  function of  $y$

$$\text{Then } E[X|Y] = h(Y)$$

- $X | Y = y$  is a r.v. with density  
 $p_{X|Y=y}(x) = p_{X|Y}(x, y)$
- $E[X | Y = y]$  is a number, is the expectation of the r.v.  $X | Y = y$   
 $E[X | Y = y] = h(y) = \sum_x x p_{X|Y}(x)$
- $h : \mathbb{R} \rightarrow \mathbb{R}$  function (on the discrete sets)
- $E[X | Y]$  is a random variable  
 $E[X | Y] : \Omega \rightarrow \mathbb{R}$   
 $\omega \mapsto E[X | Y](\omega) = h(Y(\omega))$

Property  $E[E[X | Y]] = E[X]$  TOWER PROPERTY

Proof  $E[E[X | Y]] = E[h(Y)] = \sum_y h(y) p_Y(y)$

$$= \sum_y \left( \sum_x x p_{X|Y}(x|y) \right) p_Y(y)$$

$$= \sum_y \sum_x x \frac{p_{X,Y}(x,y)}{p_Y(y)} \cdot p_Y(y)$$

$$= \sum_x x \underbrace{\sum_y p_{X|Y}(x|y)}_{= p_X(x)} = \sum_x x p_X(x) = E[X]$$

### Absolutely Continuous R.V.

$(X, Y)$  is absolutely continuous random vector

- $X | Y = y$  is an absolutely continuous r.v.  
with density  $f_{X|Y}(x|y) = \begin{cases} f_{X,Y}(x,y) & \text{if } f_Y(y) > 0 \\ 0 & \text{if } f_Y(y) = 0 \end{cases}$

•  $F[X | Y = y] = \int_{-\infty}^{+\infty} \dots d_{\dots, \dots, \dots} |_{y|_Y} dx = D(y)$

- $E[X | Y = y] = \int_{-\infty}^{+\infty} x f_{X|Y}(x|y) dx = h(y)$   
 $h: \mathbb{R} \rightarrow \mathbb{R}$
- $E[X|Y]: \Omega \rightarrow \mathbb{R}$  (random variable)  
 $\omega \mapsto E[X|Y](\omega) = h(Y(\omega))$

### Exercise

$$X \perp\!\!\!\perp Y \quad X, Y \sim \text{Bin}(n, p)$$

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

$X | X+Y = m$  is r.v. with density

$$\begin{aligned} p_{X|X+Y}(k|m) &= P(X=k | X+Y=m) \\ &= \frac{P(X=k, X+Y=m)}{P(X+Y=m)} \end{aligned}$$

$$X, Y \in \{0, 1, \dots, n\} \quad m \in \{0, \dots, 2n\} \quad 0 \leq k \leq m$$

$$0 \leq k \leq \min\{n, m\} \quad 0 \leq k \leq n$$

Note that  $X+Y \sim \text{Bin}(2n, p)$

$$\begin{aligned} p_{X|X+Y}(k|m) &= \frac{P(X=k, Y=m-k)}{P(X+Y=m)} \\ &\stackrel{\text{INDEPENDENT}}{=} \frac{P(X=k) P(Y=m-k)}{P(X+Y=m)} \\ &= \frac{P(\text{Bin}(n, p) = k) P(\text{Bin}(n, p) = m-k)}{P(\text{Bin}(2n, p) = m)} \end{aligned}$$

$$= \frac{\binom{n}{k} p^k (1-p)^{n-k} \binom{n}{m-k} p^{m-k} (1-p)^{n-(m-k)}}{\binom{2n}{m} p^m (1-p)^{2n-m}}$$

$$= \frac{\binom{n}{k} \binom{n}{m-k}}{\binom{2n}{m}} \quad \rightarrow \text{density of HYPERGEOMETRIC r.v.}$$

$$\binom{2n}{m} \xrightarrow{\text{# draws}} Z \sim H_p(m, 2n, n) \xrightarrow{\text{# balls}} P(Z = k) = \frac{\binom{k}{m} \binom{2n-m}{2n-k}}{\binom{2n}{m}}$$

$Z = \# \text{ RED balls in } m \text{ draws without replacement}$   
 $\text{in an urn with } 2n \text{ balls and } n \text{ RED balls}$

$$E[Z] = m \cdot \frac{n}{2n} = \frac{m}{2}$$

$$\rightarrow X | X+Y = m \sim H_p(m, 2n, n)$$

$$E[X | X+Y = m] = \frac{m}{2} = h(m)$$

$$\Rightarrow E[X | X+Y] = h(X+Y) = \frac{X+Y}{2}$$

### Exercise

$$(X, Y) \text{ ABS. CONT. } f_{X,Y}(x, y) = \frac{e^{-\frac{x}{y}} e^{-y}}{y} \mathbb{1}_{\{x>0, y>0\}}$$

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

- $X | Y = y$  is r.v. with density  $f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$

$$\begin{aligned} f_Y(y) &= \int_{-\infty}^{+\infty} f(x, y) dx = \int_0^{+\infty} \frac{e^{-\frac{x}{y}} e^{-y}}{y} dx \\ &= \frac{e^{-y}}{y} \int_0^{+\infty} e^{-\frac{1}{y}x} dx = \frac{e^{-y}}{y} \left[ -\frac{1}{y} e^{-\frac{1}{y}x} \right]_{x=0}^{x \rightarrow +\infty} \\ &= \frac{e^{-y}}{y} \left[ -ye^{-\infty} + y \right] = e^{-y} \end{aligned}$$

$$f_Y(y) = e^{-y} \mathbb{1}_{\{y>0\}} \Rightarrow Y \sim \text{Exp}(1)$$

$$\begin{aligned} f_{X|Y}(x|y) &= \frac{e^{-\frac{x}{y}} e^{-y}}{y} = \frac{1}{y} e^{-\frac{x}{y}} \mathbb{1}_{\{x>0\}} \\ (\text{if } x, y > 0) \end{aligned}$$

$$\Rightarrow X | Y = y \sim \text{Exp}\left(\frac{1}{y}\right)$$

$$\left[ Z \sim \text{Exp}(\lambda) \Rightarrow f_Z(z) = \lambda e^{-\lambda z} \mathbb{1}_{\{z>0\}} \right]$$

$$[Z \sim \text{Exp}(\lambda) \Rightarrow f_Z(z) = \lambda e^{-\lambda z} \mathbb{1}_{\{z \geq 0\}}]$$

$$E[X|Y=y] = \frac{1}{f_Y(y)} = y = h(y)$$

$$\Rightarrow E[X|Y] = h(Y) = Y$$

### • CONDITIONAL EXPECTATION $E[X|Y]$

$X, Y : \Omega \rightarrow \mathbb{R}$  r.v.  $\rightarrow$  general setting

$(\Omega, \mathcal{A}, P)$  probability space  $X, Y \in L^1(\Omega)$

$$\hookrightarrow E[X] < \infty$$

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

$\hookrightarrow$  best approximation of  $X$  as a function of  $Y$

How to define  $E[X|Y]$  in general?

Consider  $\sigma(Y)$   $\sigma$ -ALGEBRA GENERATED by  $Y$

$Y : \Omega \rightarrow \mathbb{R}$  s.t. the event  $Y^{-1}(B) = \{Y \in B\} \in \mathcal{A}$

for any  $B \in \mathcal{B}(\mathbb{R})$  (enough to consider  $B$  intervals)

$\sigma(Y) = \sigma$ -algebra generated by (minimal  $\sigma$ -algebra which contains)

the set  $\{A : \exists B \text{ s.t. } A = \{X \in B\}\}$

$\sigma(Y)$  minimal  $\sigma$ -algebra for which  $Y$  is measurable  
(i.e. a random variable)

$\sigma(Y)$  contains all the information carried by  $Y$

$$E[cX] = cE[X] \quad \forall c \in \mathbb{R}$$

Let  $A \in \sigma(Y)$

$$E[X \mathbb{1}_A] \stackrel{\text{TOWER PROPERTY}}{=} E[E[X \mathbb{1}_A | Y]] = E[\mathbb{1}_A E[X|Y]]$$

expect to move outside of  
conditional expectation

Def  $X, Y \in L^1(\Omega)$ . The CONDITIONAL EXPECTATION of

$X$  given  $Y$ , denoted  $E[X|Y]$ , is a function of  $Y$   
 $E[X|Y] = h(Y)$  having the property that  
 $E[X \mathbf{1}_A] = E[h(Y) \mathbf{1}_A] \quad \forall A \in \sigma(Y)$

Property  $E[X|Y]$  is  $\sigma(Y)$  measurable ( $=$  function of  $Y$ )  
 $E[X|Y]$  exists and is unique