

Week 11 notes

Recall some items related to conditional probability.

Conditioning definition:

$$P[- \mid A] = \frac{P[- \cap A]}{P[A]}$$

Multiplication rule:

$$P[AB] = P[A] P[B \mid A]$$

Division into Cases / Total Probability:

$$P[B] = P[B \mid A_1] P[A_1] + \cdots + P[B \mid A_n] P[A_n]$$

Conditional distribution

01 Theory

Conditional distribution, by a fixed event

Suppose X is a random variable and $A \subset \mathbb{R}$. The distribution of X **conditioned on A** describes the probabilities of values of X given the hypothesis that $X \in A$ is known.

Discrete case:

$$P_{X|A}(k) = \begin{cases} \frac{P_X(k)}{P[A]} & k \in A \\ 0 & k \notin A \end{cases}$$

Continuous case:

$$f_{X|A}(x) = \begin{cases} \frac{f_X(x)}{P[A]} & x \in A \\ 0 & x \notin A \end{cases}$$

We can also condition the CDF directly and derive the PDF from the CDF:

$$F_{X|A}(x) = P[X \leq x \mid A], \quad f_{X|A}(x) = \frac{dF_{X|A}(x)}{dx}$$

We can also translate Division into Cases / Total Probability into distributional terms:

$$P_X(k) = P_{X|A_1}(k) P[A_1] + \cdots + P_{X|A_n}(k) P[A_n]$$

$$f_X(x) = f_{X|A_1}(x) P[A_1] + \cdots + f_{X|A_n}(x) P[A_n]$$

Conditional distribution, by a variable event

Suppose X and Y are any two random variables. The **distribution of X conditioned on Y** describes the probabilities of values of X in terms of y , given the hypothesis that $Y = y$ is known.

Discrete case:

$$\begin{aligned} P_{X|Y}(k|\ell) &= P[X = k \mid Y = \ell] \\ &= \frac{P_{X,Y}(k, \ell)}{P_Y(\ell)} \quad (\text{assuming } P_Y(\ell) \neq 0) \end{aligned}$$

Continuous case:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x, y)}{f_Y(y)} \quad (\text{assuming } f_Y(y) \neq 0)$$

Notice:

- $P_{X,Y}(k, \ell)$ is the probability of “ $X = k$ and $Y = \ell$.”
- $P_{X|Y}(k|\ell)$ is the probability of $X = k$, given the hypothesis that $Y = \ell$ is known.

Sometimes it is useful to rewrite the formulas this way, for example to describe a “continuous probability tree:”

$$P_{X,Y}(k, \ell) = P_{X|Y}(k|\ell) P_Y(\ell)$$

$$f_{X,Y}(x, y) = f_{X|Y}(x|y) f_Y(y)$$

Extra - Deriving $f_{X|Y}(x|y)$

The density $f_{X|Y}$ ought to be such that $f_{X|Y}(x|y) dx$ gives the probability of $X \in [x, x + dx]$, on the hypothesis that $Y \in [y, y + dy]$ is known. Calculate this probability:

$$\begin{aligned} &P[x \leq X \leq x + dx \mid y \leq Y \leq y + dy] \\ \gg &\frac{P[x \leq X \leq x + dx, y \leq Y \leq y + dy]}{P[y \leq Y \leq y + dy]} \\ \gg &\frac{f_{X,Y}(x, y) dx dy}{f_Y(y) dy} \\ \gg &\frac{f_{X,Y}(x, y)}{f_Y(y)} dx \end{aligned}$$

Conditional expectation

02 Theory

Expectation conditioned by a fixed event

Suppose X is a random variable and $A \subset \mathbb{R}$. The **expectation of X conditioned on A** describes the typical value of X given the hypothesis that $X \in A$ is known.

Discrete case:

$$E[X | A] = \sum_k k P_{X|A}(k)$$

$$E[g(X) | A] = \sum_k g(k) P_{X|A}(k)$$

Continuous case:

$$E[X | A] = \int_{-\infty}^{+\infty} x f_{X|A}(x) dx$$

$$E[g(X) | A] = \int_{-\infty}^{+\infty} g(x) f_{X|A}(x) dx$$

Conditional variance:

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

Division into Cases / Total Probability applied to expectation:

$$E[X] = E[X | A_1] P[A_1] + \dots + E[X | A_n] P[A_n]$$

Linearity of conditional expectation:

$$E[aX_1 + bX_2 + c | Y = y] = a E[X_1 | Y = y] + b E[X_2 | Y = y] + c$$

Extra - Proof: Division of Expectation into Cases

We prove the discrete case only.

1. Expectation formula:

$$E[X] = \sum_k k P_X(k)$$

2. Division into Cases for the PMF:

$$P_X(k) = \sum_{i=1}^n P_{X|A_i}(k) P[A_i]$$

3. Substitute in the formula for $E[X]$:

$$\sum_k k P_X(k) \gg \sum_k k \sum_{i=1}^n P_{X|A_i}(k) P[A_i]$$

$$\gg \sum_{i=1}^n P[A_i] \sum_k k P_{X|A_i}(k)$$

$$\gg \sum_{i=1}^n P[A_i] E[X | A_i]$$

Expectation conditioned by a variable event

Suppose X and Y are any two random variables. The **expectation of X conditioned on $Y = y$** describes the typical of value of X in terms of y , given the hypothesis that $Y = y$ is known.

Discrete case:

$$E[X | Y = y] = \sum_k k P_{X|Y}(k|y) \quad (k \text{ over all poss. vals.})$$

$$E[g(X, Y) | Y = y] = \sum_k g(k, y) P_{X|Y}(k|y)$$

Continuous case:

$$E[X | Y = y] = \int_{-\infty}^{+\infty} x f_{X|Y}(x|y) dx$$

$$E[g(X, Y) | Y = y] = \int_{-\infty}^{+\infty} g(x, y) f_{X|Y}(x|y) dx$$

03 Illustration

≡ Example - Conditioning on a fixed event

Suppose X measures the lengths of some items and has the following PMF:

$$P_X(k) = \begin{cases} 0.15 & k = 1, 2, 3, 4 \\ 0.1 & k = 5, 6, 7, 8 \\ 0 & \text{otherwise} \end{cases}$$

Let L be the event that $X \geq 5$.

- Find the PMF of X conditioned on L .
- Find the conditional expected value and variance of X given L .

Solution

(a)

- By the definition:

$$P_{X|L}(x) = \begin{cases} \frac{P_X(x)}{P[L]} & x = 5, 6, 7, 8 \\ 0 & \text{otherwise} \end{cases}$$

- Adding exclusive probabilities:

$$P[L] = \sum_{k=5}^8 P_X(k) \gg \gg 0.4$$

- Note that $0.1/0.4 = 0.25$. Therefore:

$$P_{X|L}(k) = \begin{cases} 0.25 & k = 5, 6, 7, 8 \\ 0 & \text{otherwise} \end{cases}$$

(b)

1. Find $E[X | L]$:

$$E[X | L] = \sum_{k=5}^8 k P_{X|L}(k)$$

$$\gg \gg 5 \cdot (0.25) + 6 \cdot (0.25) + 7 \cdot (0.25) + 8 \cdot (0.25)$$

$$\gg \gg 6.5 \text{ min}$$

2. Find $E[X^2 | L]$:

$$E[X^2 | L] = \sum_{k=5}^8 k^2 P_{X|L}(k)$$

$$\gg \gg 5^2 \cdot (0.25) + 6^2 \cdot (0.25) + 7^2 \cdot (0.25) + 8^2 \cdot (0.25)$$

$$\gg \gg 43.5 \text{ min}^2$$

3. Find $\text{Var}[X | L]$:

$$\text{Var}[X | L] = E[X^2 | L] - E[X | L]^2 \gg \gg 1.25 \text{ min}^2$$

Example - Conditioning on variable events, discrete PMF function

Suppose X and Y have joint PMF given by:

$$P_{X,Y}(k, \ell) = \begin{cases} \frac{k+\ell}{21} & k = 1, 2, 3; \ell = 1, 2 \\ 0 & \text{otherwise} \end{cases}$$

Find $P_{X|Y}(k|\ell)$ and $P_{Y|X}(\ell, k)$.

Solution

First compute the marginal PMFs:

$$P_X(k) = \frac{2k+3}{21}, \quad k = 1, 2, 3$$

$$P_Y(\ell) = \frac{\ell+2}{7}, \quad \ell = 1, 2$$

Therefore, assuming $\ell = 1$ or 2 , then for any $k = 1, 2, 3$ we have:

$$P_{X|Y}(k, \ell) = \frac{P_{X,Y}(k, \ell)}{P_Y(\ell)} \gg \gg \frac{k+\ell}{3\ell+6}$$

And, assuming $k = 1, 2$, or 3 , then for any $\ell = 1, 2$ we have:

$$P_{Y|X}(\ell, k) = \frac{P_{Y,X}(\ell, k)}{P_X(k)} \gg \gg \frac{k+\ell}{2k+3}$$

04 Theory

Expectation conditioned by a random variable

Suppose X and Y are any two random variables. The **expectation of X conditioned on Y** is a random variable giving the typical value of X on the assumption that Y has value determined by an outcome of the experiment.

$$E[X | Y] = g(Y) \quad \text{where } g(y) = E[X | Y = y]$$

In other words, start by defining a function $g(y)$:

$$\begin{aligned} g : \mathbb{R} &\rightarrow \mathbb{R} \\ y &\mapsto E[X | Y = y] \end{aligned}$$

Now $E[X | Y]$ is defined as the composite random variable $g(Y)$.

Considered as a random variable, $E[X | Y]$ takes an outcome $s \in S$, computes $Y(s)$, sets $y = Y(s)$, then returns the expectation of X conditioned on $Y = y$.

Notice that X is *not* evaluated at s , only Y is.

Because the value of $E[X | Y]$ depends only on $Y(s)$, and not on any additional information about s , it is common to *represent* a conditional expectation $E[X | Y]$ using only the function g .

Iterated Expectation

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

Proof of Iterated Expectation, discrete case

$$\begin{aligned} E[E[X | Y]] &= \sum_{\ell} E[X | Y = \ell] P_Y(\ell) \\ &= \sum_{\ell} \sum_k g(\ell) P_Y(\ell) P_{X|Y}(k|\ell) \\ &= \sum_{\ell} \sum_k k P_{X,Y}(k, \ell) \\ &= \sum_k k P_X(k) = E[X] \end{aligned}$$

Handwritten notes:

- $P_{X|Y} = \frac{P_{X,Y}}{P_Y} \leadsto P_{X,Y} = P_Y \cdot P_{X|Y} = P_X \cdot P_{Y|X}$
- $P[A \cap B] = P[A] P[B|A] = P[B] \cdot P[A|B]$
- $= \sum_{\ell} \sum_k k P_{X,Y}(k, \ell)$
- $= E[X]$
- $X = g(Y)$

05 Illustration

Exercise - Proof of Iterated Expectation, continuous case

Prove Iterated Expectation for the continuous case.

Example - Conditional expectations from joint density

Suppose X and Y are random variables with joint density given by:

$$f_{X,Y}(x,y) = \begin{cases} \frac{1}{y} e^{-x/y} e^{-y} & x, y \in (0, \infty) \\ 0 & \text{otherwise} \end{cases}$$

Find $E[X | Y = y]$. Use this to compute $E[X]$.

Solution

First derive the marginal density $f_Y(y)$:

$$f_Y(y) \gg \int_0^{+\infty} \frac{1}{y} e^{-x/y} e^{-y} dx$$

$$\gg -e^{-x/y} e^{-y} \Big|_{x=0}^{\infty} \gg e^{-y}$$

Use $f_Y(y)$ to compute $f_{X|Y}(x|y)$:

$$f_{X|Y}(x|y) \gg \frac{f_{X,Y}(x,y)}{f_Y(y)}$$

$$\gg \frac{1}{y} e^{-x/y} e^{-y} \cdot (e^{-y})^{-1} \gg \frac{1}{y} e^{-x/y}$$

Use $f_{X|Y}(x|y)$ to calculate expectation conditioned on the variable event:

$$g(y) = E[X | Y = y] \gg \int_{-\infty}^{+\infty} x f_{X|Y}(x|y) dx$$

$$\gg \int_0^{\infty} \frac{x}{y} e^{-x/y} dx \gg y = g(y)$$

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

So, set $g(y) = y$. By Iterated Expectation, we know that $E[X] = E[g(Y)]$.

Therefore:

$$\begin{aligned} E[E[X|Y]] &\gg E[Y] = \\ E[X] = E[g(Y)] &= \int_{-\infty}^{+\infty} g(y) f_Y(y) dy \\ &\gg \int_0^{+\infty} y e^{-y} dy \gg 1 \end{aligned}$$

Notice that $g(Y) = Y$, so $E[X | Y] = Y$, and Iterated Expectation says that $E[X] = E[Y]$.

v.e.w $X = g(X,Y)$

$$E[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y} dx dy$$

$$\gg E[X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{X,Y} dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \frac{1}{y} e^{-x/y} e^{-y} dx dy$$

$\gg ??$ Can you do this?

e.g.: "assuming $Y=2$,
expect $X=2$ "

Example - Flip coin, choose RV

$$E[Z] = \sum z P_Z(z)$$

$$1 \cdot \left(\frac{1}{2} \cdot \frac{1}{4} + \frac{1}{2} \cdot \frac{1}{3} \right) + 0 \cdot \left(\frac{1}{2} \cdot \frac{3}{4} + \frac{1}{2} \cdot \frac{2}{3} \right) = \frac{7}{24}$$

Suppose $X \sim \text{Ber}(1/3)$ and $Y \sim \text{Ber}(1/4)$ represent two biased coins, giving 1 for heads and 0 for tails.

Here is the experiment:

1. Flip a fair coin.
2. If heads, flip the X coin; if tails, flip the Y coin.
3. Record the outcome as Z .

What is $E[Z]$?

Solution

Let $G \sim \text{Ber}(1/2)$ describe the fair coin.

Then:

$$\begin{aligned} E[Z] &= E[E[Z | G]] \\ &\gg \gg E[Z | G = 0] P_G(0) + E[Z | G = 1] P_G(1) \\ &\gg \gg E[Y] P_G(0) + E[X] P_G(1) \\ &\gg \gg \frac{1}{4} \cdot \frac{1}{2} + \frac{1}{3} \cdot \frac{1}{2} \gg \gg \frac{7}{24} \end{aligned}$$

Example - Sum of random number of RVs

Let N denote the number of customers that enter a store on a given day.

Let X_i denote the amount spent by the i^{th} customer.

Assume that $E[N] = 50$ and $E[X_i] = \$8$ for each i .

What is the expected total spend of all customers in a day?

Solution

$$X = X_1 + X_2 + \dots + X_N$$

A formula for the total spend is $X = \sum_{i=1}^N X_i$.

By Iterated Expectation, we know $E[X] = E[E[X | N]]$.

Now compute $E[X | N]$ as a function of N :

$$\begin{aligned} E[X | N = n] &\gg \gg E\left[\left(\sum_{i=1}^N X_i\right) | N = n\right] && g(X, N) \rightsquigarrow g(X, n) \\ &\gg \gg E\left[\left(\sum_{i=1}^n X_i\right) | N = n\right] && \text{verified as iid question} \\ &\gg \gg \sum_{i=1}^n E[X_i | N = n] \\ &\gg \gg \sum_{i=1}^n E[X_i] \gg \gg 8n && E[X | N=n] \\ &&& \Rightarrow E[X | N] = 8N \end{aligned}$$

Therefore $g(n) = 8n$ and $g(N) = 8N$ and $E[X | N] = 8N$.

Then by Iterated Expectation, $E[X] = E[8N] = 8E[N] = \$400$.