

Economics 103 – Statistics for Economists

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Lecture # 9

Discrete RVs – Part III

Definition of Conditional PMF

How does the distribution of y change with x ?

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

Conditional PMF of Y given $X = 2$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8

$$p_{Y|X}(1|2) = \frac{p_{XY}(2,1)}{p_X(2)} = \frac{0}{3/8} = 0$$

$$p_{Y|X}(2|2) = \frac{p_{XY}(2,2)}{p_X(2)} = \frac{1/4}{3/8} = 2/3$$

$$p_{Y|X}(3|2) = \frac{p_{XY}(2,3)}{p_X(2)} = \frac{1/8}{3/8} = 1/3$$

What is $p_{X|Y}(1|2)$?



		Y			
		1	2	3	
X	0	1/8	0	0	
	1	0	1/4	1/8	
	2	0	1/4	1/8	
	3	1/8	0	0	
		1/4	1/2	1/4	

What is $p_{X|Y}(1|2)$?



		Y			
		1	2	3	
X	0	1/8	0	0	
	1	0	1/4	1/8	
	2	0	1/4	1/8	
	3	1/8	0	0	
		1/4	1/2	1/4	

$$p_{X|Y}(1|2) = \frac{p_{XY}(1,2)}{p_Y(2)} = \frac{1/4}{1/2} = 1/2 \quad (1)$$

What is $p_{X|Y}(1|2)$?



		Y			
		1	2	3	
X	0	1/8	0	0	
	1	0	1/4	1/8	
	2	0	1/4	1/8	
	3	1/8	0	0	
		1/4	1/2	1/4	

$$p_{X|Y}(1|2) = \frac{p_{XY}(1,2)}{p_Y(2)} = \frac{1/4}{1/2} = 1/2 \quad (1)$$

Similarly:

$$p_{X|Y}(0|2) = 0, \quad p_{X|Y}(2|2) = 1/2, \quad p_{X|Y}(3|2) = 0$$

Independent RVs: Joint Equals Product of Marginals

Definition

Two discrete RVs are **independent** if and only if

$$p_{XY}(x, y) = p_X(x)p_Y(y)$$

for all pairs (x, y) in the support.

Equivalent Definition

$$p_{Y|X}(y|x) = p_Y(y) \text{ and } p_{X|Y}(x|y) = p_X(x)$$

for all pairs (x, y) in the support.

Are X and Y Independent?



(A = YES, B = NO)

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

Are X and Y Independent?



(A = YES, B = NO)

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

$$p_{XY}(2, 1) = 0$$

$$p_X(2) \times p_Y(1) = (3/8) \times (1/4) \neq 0$$

Therefore X and Y are *not* independent.

Conditional Expectation

Intuition

$E[Y|X]$ = “best guess” about realization of Y after observing realization of X .

$E[Y|X]$ is a Random Variable

While $E[Y]$ is a constant, $E[Y|X]$ is a function of X , hence a **Random Variable**.

$E[Y|X = x]$ is a Constant

The constant $E[Y|X = x]$ is the “guess” of Y if we see $X = x$.

Calculating $E[Y|X = x]$

Take the mean of the conditional pmf of Y given $X = x$.

Conditional Expectation: $E[Y|X = 2]$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

We showed above that the conditional pmf of $Y|X = 2$ is:

$$p_{Y|X}(1|2) = 0 \quad p_{Y|X}(2|2) = 2/3 \quad p_{Y|X}(3|2) = 1/3$$

Hence

$$E[Y|X = 2] = 2 \times 2/3 + 3 \times 1/3 = 7/3$$

Conditional Expectation: $E[Y|X = 0]$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

The conditional pmf of $Y|X = 0$ is

$$p_{Y|X}(1|0) = 1 \quad p_{Y|X}(2|0) = 0 \quad p_{Y|X}(3|0) = 0$$

Hence $E[Y|X = 0] = 1$

Calculate $E[Y|X = 3]$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

The conditional pmf of $Y|X = 3$ is

$$p_{Y|X}(1|3) = 1 \quad p_{Y|X}(2|3) = 0 \quad p_{Y|X}(3|3) = 0$$

Hence $E[Y|X = 3] = 1$

Calculate $E[Y|X = 1]$



		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

Calculate $E[Y|X = 1]$



		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

The conditional pmf of $Y|X = 1$ is

$$p_{Y|X}(1|1) = 0 \quad p_{Y|X}(2|1) = 2/3 \quad p_{Y|X}(3|1) = 1/3$$

Hence

$$E[Y|X = 1] = 2 \times 2/3 + 3 \times 1/3 = 7/3$$

$E[Y|X]$ is a Random Variable

For this example:

$$E[Y|X] = \begin{cases} 1 & X = 0 \\ 7/3 & X = 1 \\ 7/3 & X = 2 \\ 1 & X = 3 \end{cases}$$

From above the marginal distribution of X is:

$$P(X = 0) = 1/8 \quad P(X = 1) = 3/8$$

$$P(X = 2) = 3/8 \quad P(X = 3) = 1/8$$

$E[Y|X]$ takes the value 1 with prob. 1/4 and 7/3 with prob. 3/4.

The Law of Iterated Expectations

$E[Y|X]$ is an RV so what is its expectation?

For any RVs X and Y

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

Law of Iterated Expectations for Our Example

Marginal pmf of Y

$$P(Y = 1) = 1/4$$

$$P(Y = 2) = 1/2$$

$$P(Y = 3) = 1/4$$

$$\begin{aligned} E[Y] &= 1 \times 1/4 + 2 \times 1/2 + 3 \times 1/4 \\ &= 2 \end{aligned}$$

$E[Y|X]$

$$E[Y|X] = \begin{cases} 1 & \text{w/ prob. } 1/4 \\ 7/3 & \text{w/ prob. } 3/4 \end{cases}$$

$$\begin{aligned} E[E[Y|X]] &= 1 \times 1/4 + 7/3 \times 3/4 \\ &= 2 \end{aligned}$$

Expectation of Function of Two Discrete RVs

$$E[g(X, Y)] = \sum_x \sum_y g(x, y) p_{XY}(x, y)$$

Some Extremely Important Examples

Same For Continuous Random Variables

Let $\mu_X = E[X]$, $\mu_Y = E[Y]$

Covariance

$$\sigma_{XY} = \text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

Correlation

$$\rho_{XY} = \text{Corr}(X, Y) = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$

Shortcut Formula for Covariance

Much easier for calculating:

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

I'll mention this again in a few slides...

Calculating $\text{Cov}(X, Y)$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
		1/4	1/2	1/4	

$$E[X] = 3/8 + 2 \times 3/8 + 3 \times 1/8 = 3/2$$

$$E[Y] = 1/4 + 2 \times 1/2 + 3 \times 1/4 = 2$$

Calculating $\text{Cov}(X, Y)$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
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$$E[X] = 3/8 + 2 \times 3/8 + 3 \times 1/8 = 3/2$$

$$E[Y] = 1/4 + 2 \times 1/2 + 3 \times 1/4 = 2$$

$$\begin{aligned} E[XY] &= 1/4 \times (2 + 4) + 1/8 \times (3 + 6 + 3) \\ &= 3 \end{aligned}$$

Calculating $\text{Cov}(X, Y)$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
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$$E[X] = 3/8 + 2 \times 3/8 + 3 \times 1/8 = 3/2$$

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

Calculating $\text{Cov}(X, Y)$

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$$\begin{aligned} E[XY] &= 1/4 \times (2 + 4) + 1/8 \times (3 + 6 + 3) \\ &= 3 \end{aligned}$$

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &= 3 - 3/2 \times 2 = 0 \end{aligned}$$

Calculating $\text{Cov}(X, Y)$

		Y			
		1	2	3	
X	0	1/8	0	0	1/8
	1	0	1/4	1/8	3/8
	2	0	1/4	1/8	3/8
	3	1/8	0	0	1/8
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$$E[X] = 3/8 + 2 \times 3/8 + 3 \times 1/8 = 3/2$$

$$E[Y] = 1/4 + 2 \times 1/2 + 3 \times 1/4 = 2$$

$$\begin{aligned} E[XY] &= 1/4 \times (2 + 4) + 1/8 \times (3 + 6 + 3) \\ &= 3 \end{aligned}$$

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &= 3 - 3/2 \times 2 = 0 \end{aligned}$$

$$\text{Corr}(X, Y) = \text{Cov}(X, Y) / [SD(X)SD(Y)] = 0$$

Zero Covariance versus Independence

- ▶ From this example we learn that zero covariance (correlation) *does not* imply independence.
- ▶ However, it turns out that independence *does* imply zero covariance (correlation).

Linearity of Expectation, Again

Holds for Continuous RVs as well, but different proof.

In general, $E[g(X, Y)] \neq g(E[X], E[Y])$. The key exception is when g is a linear function:

$$E[aX + bY + c] = aE[X] + bE[Y] + c$$

where X, Y are random variables and a, b, c are constants.

Application: Shortcut Formula for Variance

By the Linearity of Expectation,

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

Application: Shortcut Formula for Variance

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$$\begin{aligned} \text{Var}(X) &= E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] \\ &= \end{aligned}$$

Application: Shortcut Formula for Variance

By the Linearity of Expectation,

$$\begin{aligned} \text{Var}(X) &= E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + \mu^2 \\ &= \end{aligned}$$

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$$\begin{aligned} \text{Var}(X) &= E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + \mu^2 \\ &= E[X^2] - 2\mu^2 + \mu^2 \\ &= \end{aligned}$$

Application: Shortcut Formula for Variance

By the Linearity of Expectation,

$$\begin{aligned}\text{Var}(X) &= E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + \mu^2 \\ &= E[X^2] - 2\mu^2 + \mu^2 \\ &= E[X^2] - \mu^2\end{aligned}$$

We saw in a previous lecture that it's typically much easier to calculate variances using the shortcut formula.

Another Application: Shortcut Formula for Covariance

Similar to Shortcut for Variance: in fact $\text{Var}(X) = \text{Cov}(X, X)$

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\ &= E[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y] \\ &\quad \vdots \\ &= E[XY] - E[X]E[Y]\end{aligned}$$

You'll fill in the details for homework...

Expected Value of Sum = Sum of Expected Values

Repeatedly applying the linearity of expectation,

$$E[X_1 + X_2 + \dots + X_n] = E[X_1] + E[X_2] + \dots + E[X_n]$$

regardless of how the RVs X_1, \dots, X_n are related to each other. In particular it **doesn't matter if they're dependent or independent.**

Independent and Identically Distributed (iid) RVs

Example

$$X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(p)$$

Independent

Realization of one of the RVs gives no information about the others.

Identically Distributed

Each X_i is the same kind of RV, with the same values for any parameters. (Hence same pmf, cdf, mean, variance, etc.)

Binomial(n, p) Random Variable

Definition

Sum of n independent Bernoulli RVs, each with probability of “success,” i.e. 1, equal to p

Parameters

p = probability of “success,” n = # of trials

Support

$\{0, 1, 2, \dots, n\}$

Using Our New Notation

Let $X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(p)$, $Y = X_1 + X_2 + \dots + X_n$.

Then $Y \sim \text{Binomial}(n, p)$.

Which of these is the PMF of a Binomial(n, p) RV?



(a) $p(x) = p^x(1 - p)^{n-x}$

(b) $p(x) = \binom{n}{x} p^x(1 - p)^{n-x}$

(c) $p(x) = \binom{x}{n} p^x$

(d) $p(x) = \binom{n}{x} p^{n-x}(1 - p)^x$

(e) $p(x) = p^n(1 - p)^x$

Which of these is the PMF of a Binomial(n, p) RV?



(a) $p(x) = p^x(1 - p)^{n-x}$

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(d) $p(x) = \binom{n}{x} p^{n-x}(1 - p)^x$

(e) $p(x) = p^n(1 - p)^x$

$$p(x) = \binom{n}{x} p^x(1 - p)^{n-x}$$

Expected Value of Binomial RV

Use the fact that a Binomial(n, p) RV is defined as the sum of n iid Bernoulli(p) Random Variables and the Linearity of Expectation:

$$\begin{aligned} E[Y] &= E[X_1 + X_2 + \dots + X_n] = E[X_1] + E[X_2] + \dots + E[X_n] \\ &= p + p + \dots + p \\ &= np \end{aligned}$$

Variance of a Sum \neq Sum of Variances!

$$\text{Var}(aX + bY) = E \left[\{(aX + bY) - E[aX + bY]\}^2 \right]$$

Variance of a Sum \neq Sum of Variances!

$$\begin{aligned}\text{Var}(aX + bY) &= E \left[\{(aX + bY) - E[aX + bY]\}^2 \right] \\ &= E \left[\{a(X - \mu_X) + b(Y - \mu_Y)\}^2 \right]\end{aligned}$$

Variance of a Sum \neq Sum of Variances!

$$\begin{aligned}\text{Var}(aX + bY) &= E \left[\{(aX + bY) - E[aX + bY]\}^2 \right] \\ &= E \left[\{a(X - \mu_X) + b(Y - \mu_Y)\}^2 \right] \\ &= E \left[a^2(X - \mu_X)^2 + b^2(Y - \mu_Y)^2 + 2ab(X - \mu_X)(Y - \mu_Y) \right]\end{aligned}$$

Variance of a Sum \neq Sum of Variances!

$$\begin{aligned}\text{Var}(aX + bY) &= E \left[\{ (aX + bY) - E[aX + bY] \}^2 \right] \\&= E \left[\{ a(X - \mu_X) + b(Y - \mu_Y) \}^2 \right] \\&= E \left[a^2(X - \mu_X)^2 + b^2(Y - \mu_Y)^2 + 2ab(X - \mu_X)(Y - \mu_Y) \right] \\&= a^2 E[(X - \mu_X)^2] + b^2 E[(Y - \mu_Y)^2] + 2ab E[(X - \mu_X)(Y - \mu_Y)]\end{aligned}$$

Variance of a Sum \neq Sum of Variances!

$$\begin{aligned}\text{Var}(aX + bY) &= E \left[\{(aX + bY) - E[aX + bY]\}^2 \right] \\&= E \left[\{a(X - \mu_X) + b(Y - \mu_Y)\}^2 \right] \\&= E \left[a^2(X - \mu_X)^2 + b^2(Y - \mu_Y)^2 + 2ab(X - \mu_X)(Y - \mu_Y) \right] \\&= a^2 E[(X - \mu_X)^2] + b^2 E[(Y - \mu_Y)^2] + 2ab E[(X - \mu_X)(Y - \mu_Y)] \\&= a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y)\end{aligned}$$

Since $\sigma_{XY} = \rho\sigma_X\sigma_Y$, this is sometimes written as:

$$\text{Var}(aX + bY) = a^2\sigma_X^2 + b^2\sigma_Y^2 + 2ab\rho\sigma_X\sigma_Y$$

$$\text{Independence} \Rightarrow \text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$$

X and Y independent $\implies \text{Cov}(X, Y) = 0$. Hence, independence implies

$$\begin{aligned}\text{Var}(X + Y) &= \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y) \\ &= \text{Var}(X) + \text{Var}(Y)\end{aligned}$$

Also true for three or more RVs

If X_1, X_2, \dots, X_n are independent, then

$$\text{Var}(X_1 + X_2 + \dots + X_n) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_n)$$

Crucial Distinction

Expected Value

Always true that

$$E[X_1 + X_2 + \dots + X_n] = E[X_1] + E[X_2] + \dots + E[X_n]$$

Variance

Not true in general that

$$\text{Var}[X_1 + X_2 + \dots + X_n] = \text{Var}[X_1] + \text{Var}[X_2] + \dots + \text{Var}[X_n]$$

except in the special case where X_1, \dots, X_n are independent (or at least uncorrelated).

Variance of Binomial Random Variable

Definition from Sequence of Bernoulli Trials

If $X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(p)$ then

$$Y = X_1 + X_2 + \dots + X_n \sim \text{Binomial}(n, p)$$

Using Independence

$$\begin{aligned} \text{Var}[Y] &= \text{Var}[X_1 + X_2 + \dots + X_n] \\ &= \text{Var}[X_1] + \text{Var}[X_2] + \dots + \text{Var}[X_n] \\ &= \end{aligned}$$

Variance of Binomial Random Variable

Definition from Sequence of Bernoulli Trials

If $X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(p)$ then

$$Y = X_1 + X_2 + \dots + X_n \sim \text{Binomial}(n, p)$$

Using Independence

$$\begin{aligned}\text{Var}[Y] &= \text{Var}[X_1 + X_2 + \dots + X_n] \\ &= \text{Var}[X_1] + \text{Var}[X_2] + \dots + \text{Var}[X_n] \\ &= p(1 - p) + p(1 - p) + \dots + p(1 - p) \\ &= \end{aligned}$$

Variance of Binomial Random Variable

Definition from Sequence of Bernoulli Trials

If $X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(p)$ then

$$Y = X_1 + X_2 + \dots + X_n \sim \text{Binomial}(n, p)$$

Using Independence

$$\begin{aligned} \text{Var}[Y] &= \text{Var}[X_1 + X_2 + \dots + X_n] \\ &= \text{Var}[X_1] + \text{Var}[X_2] + \dots + \text{Var}[X_n] \\ &= p(1 - p) + p(1 - p) + \dots + p(1 - p) \\ &= np(1 - p) \end{aligned}$$