

MATH 3235 Probability Theory

9/19/22

Last Time:

Expectation and Variance

of several examples of r.v.

Conditional Expectation

If P is a probability and

B is an event with $P(B) > 0$

Then

$P(\cdot | B)$ is a probability.

If X is a r.v. we can

define

$$p(x | B) = P(X = x | B)$$

$p(\cdot | B)$ is a p.m.f.

$$E(X | B) = \sum_x x p(x | B) =$$

$$= \sum_x x \mathbb{P}(X=x | B)$$

Conditional expectation of X given B .

Th: If $B_i, i=1, 2, \dots$ form a partition of Ω with $\mathbb{P}(B_i) > 0$ for every i Then

$$\mathbb{E}(X) = \sum_i \mathbb{E}(X | B_i) \mathbb{P}(B_i)$$

Proof:

$$\sum_i \mathbb{E}(X | B_i) \mathbb{P}(B_i) =$$

$$\sum_i \sum_x x \mathbb{P}(X=x | B_i) \mathbb{P}(B_i) =$$

$$\sum_x x \sum_i \mathbb{P}(X=x | B_i) \mathbb{P}(B_i) =$$

$$\sum_x x \mathbb{P}(X=x) = \mathbb{E}(X).$$

Flip a coin with prob. of H equal to p . How long is the initial sequence of equal flips?

X

H H H T

$$X = 3$$

T T T T H

$$X = 4$$

$$E(X \mid \text{first flip is H}) = \frac{1}{q}$$

$$E(X \mid \text{first flip is T}) = \frac{1}{p}$$

$$E(X) = E(X \mid H) P(H) +$$

$$E(X \mid T) P(T) =$$

$$= \frac{p}{q} + \frac{q}{p} = \frac{1}{pq} - 2$$

$$\text{if } p = \frac{1}{2} \Rightarrow E(X) = 2$$

Multivariate discrete distributions.

You have 2 dice. Roll them.

They are different.

$$\Omega = \{ (i, j) \mid 1 \leq i, j \leq 6 \}$$

$$\omega = (i, j)$$

$$X(\omega) = i \quad Y(\omega) = j$$

$$P(\{(i, j)\}) = \frac{1}{36}$$

Joint p.m.f. of X and Y

$$p(x, y) = P(X=x \& Y=y)$$

	1	2	3	4	5	6
1	$\frac{1}{36}$	$\frac{1}{36}$...			
2	$\frac{1}{36}$	$\frac{1}{36}$...			
3	⋮	⋮	⋮	⋮		
4	⋮	⋮		⋮		
⋮						

X and Y are called jointly distributed r.v.

$P(x, y)$ is The joint p.m.f.

Education and Income

X education	0	1	2
	h.s	g	pg
Y income	0	1	2
	low	med.	high

	0	1	2
0	0.2	0.1	0
1	0.1	0.3	0.1
2	0	0.1	0.1

$P(x, y)$ according To The Table.

Properties

$$p(x, y) \geq 0$$

$$\sum_{x, y} p(x, y) = 1$$

What if I only care for one of the two? Let's say X .

$$\begin{aligned} P_X(x) &= \mathbb{P}(X=x) = \\ &= \sum_y \mathbb{P}(X=x \& Y=y) = \\ &= \sum_y p(x, y) \end{aligned}$$

Example 1 (dice)

$$P_X(x) = \frac{1}{6} \quad x = 1, 2, \dots, 6$$

$$P_Y(y) = \frac{1}{6} \quad y = 1, 2, \dots, 6$$

Example 2: sample X

		0	1	2	P_Y
Y	0	0.2	0.1	0	0.3
	1	0.1	0.3	0.1	0.5
	2	0	0.1	0.1	0.2
	P_X	0.3	0.5	0.2	

$$P_X(0) = p(0,0) + p(0,1) + p(0,2) = 0.3$$

$$P_X(x) = \sum_y p(x,y)$$

Marginal of $p(x,y)$
over x

x -marginal of $p(x,y)$

$$P_Y(y) = \sum_x p(x,y)$$

y -marginal of $p(x,y)$

Expected values.

$$f(x, y) = x + y$$

$$g(x, y) = \begin{cases} 1 & x > y \\ 0 & \text{otherwise} \end{cases}$$

$$Z = f(X, Y)$$

$$\omega = (i, j)$$

$$Z(\omega) = i + j.$$

$$P(Z = z) = \sum_{\substack{(x, y) \\ f(x, y) = z}} p(x, y)$$

$$P(Z = 2) = P_Z(2) = \frac{1}{36}$$

$$P(Z = 3) = P_Z(3) = \frac{1}{18}$$

$$P_Z(4) = \frac{1}{12}$$

⋮

If X and Y are discrete r.v.

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$Z = f(X, Y)$ is a discrete r.v.

$$P_Z(z) = \sum_{(x,y) \in f^{-1}(z)} p(x,y)$$

Thm:

$$\mathbb{E}(f(X, Y)) =$$

$$\sum_{x,y} f(x,y) p(x,y)$$

Cor: if X and Y are r.v.

with j.p.m.f. $p(x,y)$ and

a, b are real numbers Then:

$$\mathbb{E}(aX + bY) =$$

$$a \mathbb{E}(X) + b \mathbb{E}(Y)$$

$$E(X) = \sum_x x P_X(x) = \sum_{x,y} x p(x,y)$$

$$E(Y) = \sum_y y P_Y(y) = \sum_{x,y} y p(x,y)$$

$$aE(X) + bE(Y) =$$

$$\sum_{x,y} (ax + by) p(x,y) =$$

$$E(aX + bY).$$

Are They independent?

X and Y are independent

iff for every x and y

$$P(x, y) = P_X(x) P_Y(y)$$

This means that

The events $\{X=x\}$ and $\{Y=y\}$
are independent

Remark: The eq.

$$P(x, y) = P_X(x) P_Y(y)$$

must be valid for every x and y .

In general independence involves
many conditions and is quite
hard to check!

Example 1: (dice)

$$\frac{1}{36} = P(x, y) = P_X(x) P_Y(y) = \frac{1}{6} \cdot \frac{1}{6} \quad \forall x, y$$

On The contrary: example 2.

$$0.2 = P(0,0) \neq P_X(0) P_Y(0) = 0.3 \cdot 0.3 = 0.09$$

Not independent.

Th. If X and Y are independent and f, g are functions $\mathbb{R} \rightarrow \mathbb{R}$ Then

a) $f(X)$ and $g(Y)$ are independent

$$b) E[f(X)g(Y)] = E[f(X)]E[g(Y)]$$

In particular

$$E[XY] = E[X]E[Y]$$

if $X \perp\!\!\!\perp Y$.

$$\begin{aligned}
\mathbb{E}(f(X)g(Y)) &= \sum_{x,y} f(x)g(y) p(x,y) = \\
&= \sum_{x,y} f(x)g(y) p_X(x) p_Y(y) = \\
&= \sum_x f(x) p_X(x) \sum_y g(y) p_Y(y) = \\
&= \mathbb{E}(f(X)) \mathbb{E}(g(Y))
\end{aligned}$$

It is also true that if

for every f and g

$$\mathbb{E}(f(X)g(Y)) = \mathbb{E}(f(X)) \mathbb{E}(g(Y))$$

Then

X and Y are independent.

If you have for example that X and Y have j.p.m.f. of the form

$$p(x,y) = e^{-(\lambda + \mu)} \frac{\lambda^x}{x!} \frac{\mu^y}{y!} =$$

$$= f(x) g(y)$$

$$f(x) = e^{-(\lambda + \mu)} \frac{\lambda^x}{x!}$$

$$P_X(x) = e^{-\lambda} \frac{\lambda^x}{x!}$$

$$g(y) = \frac{\mu^y}{y!}$$

$$P_Y(y) = e^{-\mu} \frac{\mu^y}{y!}$$

Th: if p can be written as

$$p(x,y) = f(x) g(y)$$

Then X and Y are independent.