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If  $X \sim \text{Poisson}(\lambda)$ , what is  $E[X]$

$$p_X(i) = \frac{e^{-\lambda} \lambda^i}{i!} \quad (\text{pdf of } X \sim \text{Poisson}(\lambda)) \quad (0 \leq i < \infty)$$

$$E[X] = \sum_{i=0}^{\infty} i p_X(i) = \sum_{i=0}^{\infty} i \frac{e^{-\lambda} \lambda^i}{i!} = \sum_{i=1}^{\infty} i \frac{e^{-\lambda} \lambda^i}{i!}$$

$$= e^{-\lambda} \sum_{i=1}^{\infty} i \frac{\lambda^i}{i!} = \lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{i(i-1)(i-2)\dots 1} = \lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$$

$$= \lambda e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

Moment of an r.v. The  $i$ -th moment of r.v.  $X$ , denoted  $E[X^i]$  is

$$E[X^i] = \sum_x x^i p_X(x) \quad (\text{discrete case}) \quad x \quad X$$

$$E[X^i] = \int_{-\infty}^{\infty} x^i f_X(x) dx \quad (\text{continuous case})$$

More generally, the expectation of function  $g(\cdot)$  of the r.v.  $X$  is:

$$E[g(X)] = \sum_x g(x) p_X(x) \quad (\text{discrete case})$$

$$E[g(X)] = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

Example (p. 46 [H])

$$X = \begin{cases} 0 & \omega / \text{prob. } 0.2 \\ 1 & \omega / \text{prob } 0.5 \\ 2 & \omega / \text{prob } 0.3 \end{cases}$$

$$\begin{aligned} E[2X^2 + 3] &= \sum_x (2x^2 + 3) p_X(x) = (2 \cdot 0^2 + 3) p_X(0) + (2 \cdot 1^2 + 3) p_X(1) + \\ &+ (2 \cdot 2^2 + 3) p_X(2) = 3 \times 0.2 + 5 \times 0.5 + 11 \times 0.3 = \\ &= 0.6 + 2.5 + 3.3 = 6.4 \end{aligned}$$

Defn. 3.17 Variance

The square of how much we expect  $X$  to differ from its mean,  $E[X]$ .

$$\text{Var}(X) = E[(X - E[X])^2] = \sum_x (x - E[X])^2 p_X(x) \quad (\text{discrete case})$$

$$\Rightarrow \int_{-\infty}^{\infty} (x - E[X])^2 f_X(x) dx \quad (\text{continuous case})$$

If  $X \sim \text{Bernoulli}(p)$ , what is  $\text{Var}(X)$ ?

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

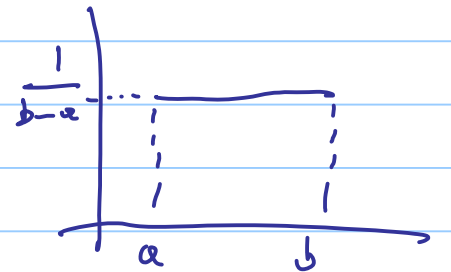
$$= E[(X - p)^2] = \sum_i (i - p)^2 p_X(i) = (0 - p)^2 p_X(0) + (1 - p)^2 p_X(1) =$$

$$= \underbrace{(0 - p)^2}_{(1-p)} + \underbrace{(1 - p)^2}_p = (1 - p)[p^2 + (1 - p)p] = (1 - p)(p^2 + p - p^2)$$

$$= p - p^2 = p(1 - p)$$

If  $X \sim \text{Uniform}(a, b)$ , what is  $\text{Var}(X)$ ?

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



$$E[X] = \int_a^b x \frac{1}{b-a} dx = \frac{1}{b-a} \int_a^b x dx = \frac{1}{b-a} \left. \frac{x^2}{2} \right|_a^b = \frac{1}{b-a} \left( \frac{b^2 - a^2}{2} \right)$$

$$= \frac{1}{\cancel{b-a}} \frac{\cancel{(b-a)}(b+a)}{2} = \frac{b+a}{2} = \frac{a+b}{2}$$

$$(*) E \left[ \left( X - \frac{a+b}{2} \right)^2 \right] = \int_a^b \left( x - \frac{a+b}{2} \right)^2 \frac{1}{b-a} dx = \dots = \frac{(b-a)^2}{12}$$

## Joint probability & independence (3.10 [H])

Def. 3.18 The joint probability mass function between discrete r.v.s  $X$  and  $Y$  (of)

$$p_{XY}(x, y) = \mathbb{P} \left\{ \underbrace{X=x, Y=y}_{\text{an event}} \right\}$$

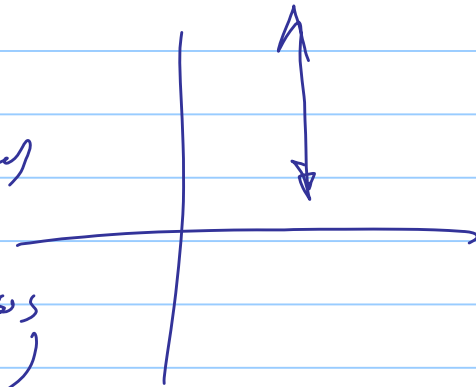
The joint probability density function.....

$$\int_c^d \int_a^b f_{XY}^{(x,y)} dx dy = \mathbb{P} \{ a < X < b, c < Y < d \}$$

Def. 3.19 r.v.  $X$  and  $Y$  are independent  
(written  $X \perp Y$ )

if  $p_{XY}(x,y) = p_X(x) \cdot p_Y(y)$  (discrete case)

or if  $f_{XY}(x,y) = f_X(x) \cdot f_Y(y)$  (continuous case)



Thm. 3.20 If  $X \perp Y$ , then  $E[XY] = E[X] \cdot E[Y]$

Proof (discrete):  $\sum_x \sum_y xy P\{X=x, Y=y\} =$  (defn. of joint prob. mass funcl)

$$= \sum_x \sum_y xy p_{XY}(x,y) = \sum_x \sum_y xy p_X(x) p_Y(y) =$$

3.19

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$$= \sum_x \sum_y x p_X(x) y p_Y(y) = \sum_x x p_X(x) \sum_y y p_Y(y) =$$

$$= \sum_x x p_X(x) E[Y] = E[X] E[Y]$$

$a \cdot b + a \cdot c = a(b+c)$  (distributivity of product over sum)

This generalizes to the continuous case & to this:

$$\text{If } X \perp Y, \text{ then } E[g(X)f(Y)] = E[g(X)]E[f(Y)]$$

The converse is not true:

If  $E[XY] = E[X]E[Y]$  it is not necessary that  $X \perp Y$ .



Defn. 3.21 r.v.  $X$  with p.m.f  $p_X(\cdot)$ . Let  $A$  be an event.

$p_{X|A}(\cdot)$  is the conditional p.m.f. of  $X$  given  $A$ ,

$$p_{X|A}(\cdot) = P\{X=x|A\} = \frac{P\{(X=x) \cap A\}}{P\{A\}}$$

A conditional probability involves a narrowing of the outcome space (from  $\Omega$  to  $A$ ).

Defn. 3.22 Let  $X$  be a discrete r.v. The conditional expectation of  $X$  given event  $A$  is;

$$E[X|A] = \sum_x x P_{X|A}(x) = \frac{P\{X=x \cap A\}}{P\{A\}}$$

The event  $A$  may be the event that corresponds to another r.v. having a particular value.

$$E[X|Y=y] = \sum_x x P_{X|Y}(x|y) = \frac{\sum_x P_{X,Y}(x,y)}{P\{Y=y\}} = \frac{\sum_x P_{X,Y}(x,y)}{P_Y(y)}$$

Ex. (pp. 50-51. [H])

$p_{X,Y}(x,y)$

$Y=2$	0	$\frac{1}{6}$	$\frac{1}{8}$
$Y=1$	$\frac{1}{8}$	$\frac{1}{6}$	$\frac{1}{8}$
$Y=0$	$\frac{1}{6}$	$\frac{1}{8}$	0
	$X=0$	$X=1$	$X=2$

$$E[X|Y=2] = \sum_x x p_{X|Y}(x|2) = \sum_x x \cdot P\{X=x|Y=2\} =$$

$$= 0 \cdot \frac{P\{X=0, Y=2\}}{P\{Y=2\}} + 1 \cdot \frac{P\{X=1, Y=2\}}{P\{Y=2\}} + 2 \cdot \frac{P\{X=2, Y=2\}}{P\{Y=2\}} =$$
$$= 0 + 1 \cdot \frac{\frac{1}{6}}{\frac{1}{6} + \frac{1}{8}} + 2 \cdot \frac{\frac{1}{8}}{\frac{1}{6} + \frac{1}{8}} = \frac{\frac{1}{6}}{\frac{14}{48}} + 2 \cdot \frac{\frac{1}{8}}{\frac{14}{48}} = \dots = \frac{10}{7}$$

Defn. 3.23 Conditional p.d.f.

$$f_{X|A}(x) = \begin{cases} \frac{f_X(x)}{P\{X \in A\}} & \text{if } x \in A \\ 0 & \text{otherwise} \end{cases}$$

Defn. 3.24 Conditional expectation of  $X$  given  $A$

$$E[X|A] = \int_{-\infty}^{\infty} x f_{X|A}(x) dx = \int_A x f_{X|A}(x) dx = \frac{1}{P\{X \in A\}} \int_A x f_X(x) dx$$