

Dec 10 :

27th Jan

$X$ : Geometric random variable ( $\phi$ ): # of tosses until you see a head.

Prob of seeing a head =  $\phi$ .

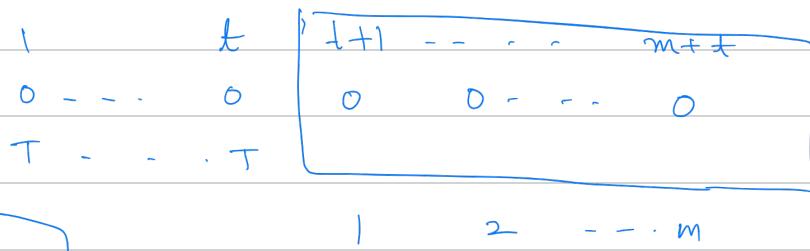
$$P(X = k) = (1 - \phi)^{k-1} \phi.$$

Memoryless property: RV  $X$  is said to have memoryless property if

$$P(X > m+t | X > t)$$

$$= P(X > m) \quad \forall m, t.$$

Upon seeing tails for first  $t$  instances, Expected # tosses to see a head is  $t + E[X]$



$$\begin{aligned} P(X > m) &= \sum_{x=m+1}^{\infty} P_X(x) = \sum_{x=m+1}^{\infty} (1 - \phi)^{x-1} \phi \\ &= (1 - \phi)^m \end{aligned}$$

$$\begin{aligned} &= (1 - \phi)^m \left[ 1 + (1 - \phi) + \dots \right] \\ &\quad \text{using the formula for the sum of an infinite geometric series: } S = \frac{a}{1 - r} \end{aligned}$$

$$P(X > m+t | X > t)$$

$$= P(1 - \phi)^m \left[ 1 + (1 - \phi) + \dots \right]$$

$$= \frac{P(X > m+t, X > t)}{P(X > t)} = (1 - \phi)^m.$$

$$= \frac{P(X > m+t)}{P(X > t)}$$

$$\begin{aligned} A &= \{X > m+t\} \\ B &= \{X > t\} \\ A &\subseteq B \end{aligned}$$

$$= \frac{(1 - \phi)^{m+t}}{(1 - \phi)^t} = (1 - \phi)^m = P(X > m).$$

Example: Using total law of expectation to find mean  $X$  is Geometric( $p$ ) R.V.

$$E[X] = P(A) E[X|A] + P(A^c) E[X|A^c]$$

$$A = \{X > 1\}$$

$$A^c = \{X \leq 1\}$$

$$= \{X = 1\}$$

$$P(A) = (1-p)$$

$$P(A^c) = p$$

$$E[X|A^c] = E[X | X \leq 1]$$

$$= 1.$$

$$P_{X|A^c}(x) = \begin{cases} 1 & \text{if } x=1 \\ 0 & \text{o.w.} \end{cases}$$

$$E[X|A] = E[X | X > 1].$$

$$E[X|A] = 1.$$

$$= 1 + E[X].$$

Confirming this using conditional probabilities

	1	2	3	4		
0	0	0	0	- - -		
	1	2	3	- - -		
						$\omega$

$$E[X | X > 1] = \sum_{x=1}^{\infty} x P_{X|A}(x) = \sum_{x=2}^{\infty} x \cdot P_X(x-1)$$

Conditional probability

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

$$E[X | X > 1] = \sum_{x=2}^{\infty} x P_X(x-1)$$

$$= \left\{ \begin{array}{ll} 0 & x=1 \\ \frac{P(\{X=2\})}{(1-p)} & x=2 \\ \vdots & \vdots \\ P_X(k-1). & x=k. \end{array} \right.$$

Comes from Memoryless property  
 $P(X=x | X > 1) = P(X=x-1)$

$$= \underbrace{\sum_{k=1}^{\infty} k P_X(k)}_{E[X]} + 1$$

$$E[X] = P(A) E[X|A] + P(A^c) E[X|A^c]$$

$$E[X] = (1-p) [E[X]+1] + p \cdot 1.$$

$$\Rightarrow p E[X] = (1-p) + p = 1 \Rightarrow E[X] = \frac{1}{p}.$$

$$E[x] = \sum_{i=1}^n P(A_i) E[x|A_i]$$

$$E[g(x)] = \sum_{i=1}^n P(A_i) E[g(x)|A_i].$$

$$E[x^2] = P(A) \underbrace{E[x^2|A]}_{\downarrow} + P(A^c) \underbrace{E[x^2|A^c]}_1$$

A:  $x > 1$

$$E[(x+1)^2]$$

$$E[x^2|A] = \sum_{x=1}^{\infty} x^2 \underline{P_{x|A}(x)}$$

$$= \sum_{x=1}^{\infty} x^2 P_x(x-1) \quad \begin{matrix} E[x^2] \\ + 2E[x] + 1 \end{matrix}$$

$$= \sum_{k=1}^{\infty} (k+1)^2 P_x(k) = E[(x+1)^2]$$

$$\begin{aligned} E[x^2] &= \underbrace{(1-p)}_{P(A)} E[x^2|A] + p \underbrace{E[x^2|A^c]}_{=1} \\ &= (1-p) [E[x^2] + 2E[x] + 1] + p \cdot 1 \end{aligned}$$

$$\begin{aligned} E[x^2] &= 2(1-p) E[x] + (1-p) + p \\ &= 2(1-p) \frac{1}{p} + 1. \end{aligned}$$

$$E[x^2] = \frac{2(1-p)}{p^2} + \frac{1}{p}.$$

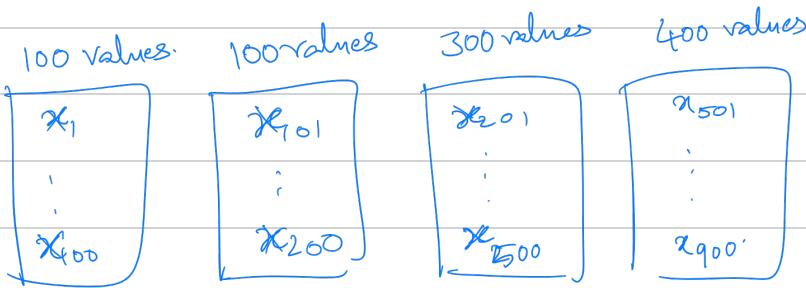
$$\text{Var}(x) = E[x^2] - (E[x])^2$$

$$= \frac{2}{p^2} - \frac{2}{p} + \frac{1}{p} - \frac{1}{p^2}$$

$$= \frac{1}{p^2} - \frac{1}{p} = \frac{(1-p)}{p^2}.$$

## Conditional Variance

and law of total variation



$$d = \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} \quad P_Y(y) = \begin{matrix} \frac{100}{900} \\ \frac{100}{900} \\ \frac{300}{900} \\ \frac{400}{900} \end{matrix}$$

$$E[X] = E \left[ E[X|Y] \right]$$

local mean value

each node  $y$  is providing you  $E[X|Y=y]$  and it is also

providing variance given by

$$\boxed{\text{Var}(X|Y=y) = E[(X - E[X|Y=y])^2]}$$

How do we find  $\text{Var}(X)$  ?

$$E[X] = \sum_y P_Y(y) E[X|Y=y]$$

Total Law of Variance

$$\boxed{\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]).}$$

Proof:

$$E[\text{Var}(X|Y)] = \sum_y P_Y(y) \text{Var}(X|Y=y).$$

$$= \sum_y P_Y(y) [E[X^2|Y=y] - (E[X|Y=y])^2]$$

$$E[g(x)] = \sum_i P(A_i) E[g(x)|A_i]$$

$$E[g(x)] = \sum_y P_Y(y) E[g(x)|Y=y]$$

$$= E[E[g(x)|Y]]$$

$$= \underbrace{E[X^2]}_{= E[X^2]} - \underbrace{\sum_y P_Y(y) (f(y))^2}_{f(y)}$$

$$= E[X^2] - E[(f(Y))^2]$$

$$\begin{aligned}
 \text{Var}(\mathbb{E}[x|Y]) &= \text{Var}(f(Y)) \\
 &= \mathbb{E}[(f(Y) - \mathbb{E}[f(Y)])^2] \\
 &= \mathbb{E}[(f(Y))^2] - (\mathbb{E}[f(Y)])^2
 \end{aligned}$$

$$\mathbb{E}[f(Y)] = \mathbb{E}[\mathbb{E}[x|Y]] = \mathbb{E}[x].$$

$$\begin{aligned}
 \text{Var}(\mathbb{E}[x|Y]) &= \mathbb{E}[(f(Y))^2] - \underline{(\mathbb{E}[x])^2} \\
 \Rightarrow \text{Var}(\mathbb{E}[x|Y]) + \mathbb{E}[\text{Var}(x|Y)] &= \text{Var}(x)
 \end{aligned}$$

### Independence of random variables

Random variable  $X$  is said to be independant of event  $A$  if

$$P_{X|A}(x) = P_X(x) \quad \text{for all } x \in \mathbb{R}.$$

or equivalently.

$$\frac{P(\{X=x\} \cap A)}{P(A)} = P_X(x)$$

$$P(\{X=x\} \cap A) = P_X(x) P(A).$$

### Independence of two R.Vs.

$X$  and  $Y$  are said to be independant if for every  $x, y$ .

$$P(X=x, Y=y) = P_X(x) P_Y(y).$$

Exercise:  $X, Y$  are R.Vs taking values in  $\{0, 1\}$  and  $P_{X,Y}(1,1) = P_X(1) P_Y(1)$ . Are  $X, Y$  independant?

## Independence of more than 2 RV's

$X_1, X_2, \dots, X_n$  are said to be independent if.

$$P(X_1=x_1, X_2=x_2, \dots, X_n=x_n) = \prod_{i=1}^n P_{X_i}(x_i)$$

for all  $(x_1, \dots, x_n) \in \mathcal{X}_1 \times \mathcal{X}_2 \times \dots \times \mathcal{X}_n$ .

If  $X_1, \dots, X_n$  are independent then any sub collection of them are independent.

For example: Let  $X_1, X_2, X_3$  be independent.  
 $\Rightarrow X_1, X_2$  are independent.

$$P_{X_1, X_2, X_3}(x_1, x_2, x_3) = \prod_{i=1}^3 P_{X_i}(x_i)$$

$$P_{X_1, X_2}(x_1, x_2) = \sum_{x_3 \in \mathcal{X}_3} P_{X_1, X_2, X_3}(x_1, x_2, x_3)$$

$$= \sum_{x_3 \in \mathcal{X}_3} P_{X_1}(x_1) P_{X_2}(x_2) P_{X_3}(x_3)$$

$$= P_{X_1}(x_1) P_{X_2}(x_2)$$

$$\left[ \sum_{x_3 \in \mathcal{X}_3} P_{X_3}(x_3) \right] = 1$$

If  $X$  and  $Y$  are independent then

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

$$E[X Y] = \sum_{x \in \mathcal{X}, y \in \mathcal{Y}} x \cdot y P_{X, Y}(x, y).$$

$$= \sum_x \sum_y x \cdot y P_X(x) P_Y(y)$$

$$= \left[ \sum_x x P_X(x) \right] \left[ \sum_y y P_Y(y) \right]$$

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

If  $E[XY] = E[X] E[Y]$  then the random variables  $X, Y$  are said to be "uncorrelated".

$X, Y$  uncorrelated does not imply  $X, Y$  are independent.

Example:

$$X \in \mathcal{X} = \{-1, 0, 1\}$$

$$P_X(x) = \frac{1}{3} \quad \forall x \in \mathcal{X}$$

$$Y(\omega) = \begin{cases} 1 & \text{if } X(\omega) = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$E[XY] = 0, \quad E[X] = \frac{1}{3}(-1) + 0 \cdot \left(\frac{1}{3}\right) + 1 \cdot \left(\frac{1}{3}\right)$$

$X, Y$  are uncorrelated.

$$P_{X|Y}(0|1) = 1$$

$$P_X(0) = \frac{1}{3}. \quad \therefore \text{not independent.}$$