

Lecture 10

(5 September 2024)

Recap,

RVs x_1, x_2, \dots, x_n are independent if

$$p_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n) = \prod_{i=1}^n p_{x_i}(x_i)$$

$$\forall x_1, x_2, \dots, x_n,$$

Linearity of Expectation:

$$E\left[\sum_{i=1}^n x_i\right] = \sum_{i=1}^n E[x_i]$$

If x_1, x_2, \dots, x_n are independent RVs

$$\text{var}\left(\sum_{i=1}^n x_i\right) = \sum_{i=1}^n \text{var}(x_i).$$

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

$$p_{x|y}(x|y) = p_{x,y}(x,y) / p_y(y)$$

$$p_{x,y}(x,y) = p_{x|y}(x|y) p_y(y) = p_{y|x}(y|x) p_x(x)$$

Conditional Expectation

The conditional expectation of X given $Y=y$ is defined as

$$E[X|Y=y] = \sum_x x p_{X|Y}(x|y).$$

Similarly for an event A with $P(A) > 0$

$$E[X|A] = \sum_x x p_{X|A}(x).$$

Theorem, $E[g(X)|A] = \sum_x g(x) p_{X|A}(x).$

The proof is exactly similar to the proof of $E[g(X)] = \sum_x g(x) p_X(x).$

Total Expectation Theorem:

If the events A_1, A_2, \dots, A_n form a partition of the sample space, with $P(A_i) > 0$ for all i then

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

Proof.

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

$$= \sum_{i=1}^n P(A_i) \sum_x x P_{X|A_i}(x)$$

$$= \sum_x x \sum_{i=1}^n \frac{P(A_i) P(X=x \cap A_i)}{P(A_i)}$$

$$= \sum_x x P(\{X=x\} \cap \Omega)$$

$$= \sum_x x P_X(x) = E[X].$$

Taking $\{X=y\}$ $y \in Y$ as the partition of Ω the total expectation theorem gives

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

Conditional Expectation as a RV:

$$\text{Let } \phi(y) = E[X|Y=y]$$

Y is a RV, $\phi(Y)$ is also a RV.

We denote $\phi(Y) \equiv E[X|Y]$.

$E[X|Y]$ is a function of RV Y .

$$E[\phi(Y)] = E[E[X|Y]]$$

$$= \sum_y P_Y(y) \phi(y)$$

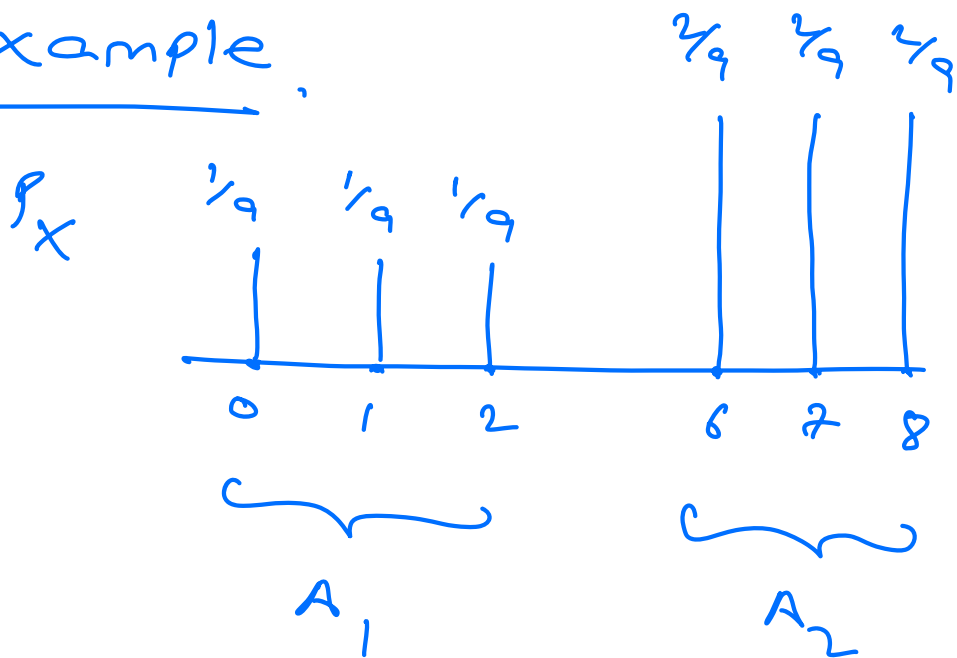
$$= \sum_y P_Y(y) E[X|Y=y]$$

$$= E[X]$$

(by total expectation theorem).

Thus $E[E[X|Y]] = E[X]$ — called the law of iterated expectations.

Example.



$$P(A_1) = \frac{1}{3} \quad P(A_2) = \frac{2}{3}$$

$$E[X|A_1] = 0 \cdot \frac{1}{3} + 1 \cdot \frac{1}{3} + 2 \cdot \frac{1}{3} = 1$$

$$E[X|A_2] = \frac{6+7+8}{3} = 7$$

$$E[X] = \frac{1}{3} \cdot 1 + \frac{2}{3} \cdot 7 = 5.$$

Conditional Independence

Two random variables x and y are conditionally independent given an event A if

$$P_{xy|A}(x, y) = P_{x|A}(x) P_{y|A}(y) \quad \forall x, y.$$

Note that
$$P_{xy|A}(x, y) = \frac{P(X=x \cap Y=y \cap A)}{P(A)}.$$

Exercise, Consider the following P_{xy} .

	1	2	3	4
1	0	$\frac{1}{20}$	0	0
2	0	$\frac{1}{20}$	$\frac{3}{20}$	$\frac{1}{20}$
3	$\frac{2}{20}$	$\frac{4}{20}$	$\frac{1}{20}$	$\frac{2}{20}$
4	$\frac{1}{20}$	$\frac{2}{20}$	$\frac{2}{20}$	0

Are x and y independent?

Are x and y conditionally independent given

$$A = \{x \geq 3, y \leq 2\}?$$

Conditional Variance

Recall variance of x ,

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

$\sigma_x = \sqrt{\text{Var}(x)}$ is called standard deviation,

$$\text{Var}(x|y=y) = \psi(y)$$

$$= E[(x - E[x|y=y])^2 | y=y]$$

$$= E[x^2 + E[x|y=y]^2 - 2xE[x|y=y] | y=y]$$

$$= E[x^2 | y=y] + E[x|y=y]^2 - 2E[x|y=y]^2$$

$$= E[x^2 | y=y] - E[x|y=y]^2.$$

$\text{Var}(x|y) = \psi(y)$ is a RV,

Theorem (Law of total variance),

$$\text{Var}(x) = E[\text{Var}(x|y)] + \text{Var}(E[x|y])$$

Proof,

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

$$= E[E[x^2|y]] - E[x]^2$$

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

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

$$= E[\text{Var}(x|y)] + \text{Var}(E[x|y]).$$

Problems

Q) Consider $\text{Bin}(n=100, p=0.01)$. Find the probability of 5 successes in 100 trials, approximately [Note n is large],

Sol. - We use Poisson's approximation,

$$\lambda = np = 1.$$

$$P_x(5) = \frac{e^{-1} 1^5}{5!} = \frac{e^{-1}}{5!} \approx 0.003.$$

2) Let x be a geometric random variable with parameter p .

$$P(X > n) = \sum_{i=n+1}^{\infty} (1-p)^{i-1} p$$

$$= p \cdot \frac{(1-p)^n}{p} = (1-p)^n$$

$$P(X > m+n | X > m) \quad [m, n \in \mathbb{N}]$$

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

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

$$\therefore P(X > m+n | X > m) = P(X > n).$$

This is called memoryless property of the geometric random variable.

Q) You are allowed to take a certain test three times and your final score will be the maximum of the test scores.

$X = \max\{x_1, x_2, x_3\}$, where x_1, x_2, x_3 are the three test scores and X is the final score. Assume that your score in each test takes one of the values from 1 to 10 with equal probability $1/10$ - independently of the scores in other tests. Find the PMF of the final score.

Sol:- $F_X(k) = P(X \leq k)$

$$= P(\max\{x_1, x_2, x_3\} \leq k)$$

$$= P(x_1 \leq k, x_2 \leq k, x_3 \leq k)$$

$$= P(x_1 \leq k) P(x_2 \leq k) P(x_3 \leq k)$$

[as x_1, x_2 and x_3 are independent]

$$= F_{x_1}(k) F_{x_2}(k) F_{x_3}(k)$$

$$P_x(k) = F_x(k) - F_x(k-1)$$

$$= F_{x_1}(k) F_{x_2}(k) F_{x_3}(k) - F_{x_1}(k-1) F_{x_2}(k-1) F_{x_3}(k-1)$$

$$= \frac{k^3 - (k-1)^3}{1000} \quad , \quad k = 1, 2, \dots$$