Expectation and Variance

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Expectation of D.R.V:

Let X be discrete random variable then its expectation of denoted by E(X) and defined as

$$E(X) = \sum_{i=1} x P[X = x_i]$$

provided that right hand series is absolutely convergent

Expectation of C.R.V:

Let X be continous random variable then its expectation of denoted by E(X) and defined as

 $E(X) = \int_{X} xf(x) dx$ provided that right hand integral is absolutely convergent

$$\sum_{i=1} |xP[X = x_i]| = \sum_{i=1} |x|P[X = x_i] < \infty$$
$$\int_{-\infty}^{\infty} |xf(x)| dx = \int_{-\infty}^{\infty} |x|f(x)dx < \infty$$

1. E(X) exist if E(|X|) exist

Expectation of function of D.R.V:

Let g(X) be function of discrete random variable then its expectation of denoted by E[g(X)] and defined as

$$E[g(x)] = \sum_{i=1}^{n} g(x_i) P[X = x_i]$$

Expectation of function of C.R.V:

Let X be continuous random variable then its expectation of denoted by E(X) and defined as

$$E[g(X)] = \int_{x} g(x)f(x)dx$$

Addition Theorem of Expectation

$$E(X+Y)=E(X)+E(Y)$$

Addition Theorem of Expectation:Generalisation

$$E(\sum_{i=1}^n X_i) = \sum_{i=1}^n E(X_i)$$

Multiplication Theorem of Expectation

If X and Y are independent random variables then

$$E(XY) = E(X)E(Y)$$

Multiplication Theorem of Expectation:Generalisation

$$E(\prod_{i=1}^n X_i) = \prod_{i=1}^n E(X_i)$$

If X is random variable and a is constant then

$$E(\psi(X) + a)) = E(\psi(X)) + a$$

$$E(a(\psi(X)) = a(E(\psi(X)))$$

If X is random variable a and b are constants then E(aX + b) = aE(X) + b

Let $X_1, X_2, ..., X_n$ be any *n* random variables and if $a_1, a_2, ..., a_n$ are any *n* constants, then

$$E(\sum_{i=1}^{n}a_{i}X_{i})=\sum_{i=1}^{n}E(a_{i})E(X_{i})$$

provided all the expectations exist

- 1. If $X \ge 0$ then $E(X) \ge 0$ If X and Y are two random variables such that $X \le Y$ then $E(X) \le E(Y)$
- 2. $|E(X)| \le E(|X|)$
- 3. If $\mu_r^{'}$ exists then $\mu_s^{'}$ exists for all $1 \leq s \leq r$
- 4. If X and Y are independent random variables then

$$E[h(x)k(y)] = E[h(x)]E[k(y)]$$

Variance:

Let X be random variable then its Variance is denoted by V(X) and defined as

$$V(X) = E[X - E(X)]^2 = E(X^2) - [E(X)^2]$$

1. If X is a random variable, then

$$V(aX+b)=a^2V(X)$$

1. If b = 0, then

$$V(aX) = a^2 V(X)$$

i.e. Variance is not independent by change of scale 2. If a = 0 , then

$$V(b) = 0$$

i.e. Variance of constant is zero 3. If a = 1 , then V(X + b) = V(X)

i.e. Variance is independent of change of origin.

Definition:Covariance

If X and Y are two random variables , then cavariance between them is defined as

Cov(X, Y) = E[X - E(X)Y - E(Y)] = E(XY) - E(X)E(Y)

1. If X and Y are independent then

$$Cov(X, Y) = 0$$

2.

$$Cov(aX, bY) = abCov(X, Y)$$



If X and Y are independent, Cov(X, Y) = 0, however converse is not true.

let $X_1, X_2, ..., X_n$ be *n* random variables then

$$V(\sum_{i=1}^{n} a_i X_i) = \sum_{i=1}^{n} (a_i)^2 V(X_i) + 2 \sum_{i=1}^{n} \sum_{j=1}^{n} a_j a_j Cov(X_i, X_j)$$

Important results related to Variance:

1. If $X_1, X_2, ..., X_n$ are independent random variables then

$$V(\sum_{i=1}^n (X_i)) = \sum_{i=1}^n V(X_i)$$

2.

$$V(X_1 + X_2) = V(X_1) + V(X_2) + 2Cov(X_1, X_2)$$

3. If X_1 and X_2 are random variables then

$$V(X_1 \pm X_2) = V(X_1) + V(X_2) \pm 2Cov(X_1, X_2)$$

4. If X_1 and X_2 are independent random variables then

$$V(X_1 \pm X_2) = V(X_1) + V(X_2)$$

