

Chapter-04 Mathematical Expectation

Mean for discrete Random variable:

$$\mu = E(x) = \sum_n n f(n)$$

Mean for continuous case:

$$\mu = E(x) = \int_{-\infty}^{\infty} n f(n) dn$$

variance of x: σ^2

variance for discrete Random variable:

$$\sigma^2 = \sum (n - \mu)^2 f(n)$$

variance for continuous case:

$$\sigma^2 = \int_{-\infty}^{\infty} (n - \mu)^2 f(n) dn$$

$f(n, y) \rightarrow$ given

$$\mu_x = E(x) = \sum_n n \cdot g(n)$$

$$\mu_y = E(y) = \sum_y y \cdot h(y)$$

$$E(g(x, y)) = \sum_n \sum_y g(n, y) f(n, y)$$

Two random variable x and y are independent the expected of $x \cdot y$:

$$E(xy) = E(x) E(y)$$

Chebyshev's Theorem :

$$\left\{ P(\mu - k\sigma < x < \mu + k\sigma) > 1 - \frac{1}{k^2} \right\}$$

↓

$$P(-k\sigma < x - \mu < k\sigma) > 1 - \frac{1}{k^2}$$

$$\left\{ P(|x - \mu| < k\sigma) > 1 - \frac{1}{k^2} \right\}$$

$$1 - P(|x - \mu| < k\sigma) \leq \frac{1}{k^2}$$

$$\left\{ P(|x - \mu| \geq k\sigma) \leq \frac{1}{k^2} \right\}$$

Chapter - 5 Binomial Distribution

binomial distribution:

$$b(x, n, p) = {}^n C_x p^x q^{n-x}$$

Multinomial distribution:

$$f(x_1, x_2, \dots, x_k; p_1, p_2, \dots, p_k; n) = \frac{n!}{x_1! \cdot x_2! \cdot \dots \cdot x_k!} \times p_1^{x_1} \cdot p_2^{x_2} \cdot \dots \cdot p_k^{x_k}$$

Hypergeometric distribution:

$$h(x, N, n, K) = \frac{{}^K C_x \cdot {}^{N-K} C_{n-x}}{{}^N C_n}$$

Multivariate hypergeometric distribution

$$f(x_1, x_2, \dots, x_k; a_1, a_2, \dots, a_k; N; n) = \frac{{}^{a_1} C_{x_1} \cdot {}^{a_2} C_{x_2} \cdot \dots \cdot {}^{a_k} C_{x_k}}{{}^N C_n}$$

Negative binomial distribution

$$b^*(x, k, p) = {}^{x-1} C_{k-1} p^k q^{x-k}$$

Geometric distribution:

$$g(x, p) = p q^{x-1}$$

Normal distribution:

$$n(x, \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} ; -\infty < x < \infty$$

Standard normal distribution:

$$Z = \frac{x - \mu}{\sigma}$$

Normal approx to binary:

$$\mu = np \quad \sigma^2 = npq$$

$$Z = \frac{x - np}{\sqrt{npq}}$$

$$P(x \leq n) = P\left(Z \leq \frac{n + 0.5 - \mu}{\sigma}\right)$$

$$P(x < n) = P\left(Z < \frac{n - 0.5 - \mu}{\sigma}\right)$$

Chapter - 03 Random variable and probability distribution

discrete probability distribution:

$$\rightarrow f(x) \geq 0$$

$$\rightarrow \sum_x f(x) = 1$$

$$\rightarrow P(X = x) = f(x)$$

Cumulative distribution function:

$$f(x) = P(X \leq x)$$

$$= \sum_{f \leq x} f(i)$$

$$f \leq x$$

$$P(a < X < b) = F(b) - F(a)$$

Continuous Probability distribution:

→ condⁿ 1:

$$f(x) > 0, \forall x \in \mathbb{R}$$

→ condⁿ 2:

$$\int_{-\infty}^{\infty} f(x) dx = 1$$

→ condⁿ 3:

$$\begin{aligned} P(a < x < b) &= P(a \leq x < b) \\ &= P(a < x \leq b) \\ &= P(a \leq x \leq b) \\ &= \int_a^b f(x) dx = F(b) \end{aligned}$$

cumulative distribution function:

$$F(x) = P(X \leq x)$$

$$F(x) = \int_{-\infty}^x f(t) dt$$

Joint Probability distribution:

(1) For discrete case:

$$\rightarrow f(x, y) > 0$$

$$\rightarrow \sum_x \sum_y f(x, y) = 1$$

$$\rightarrow P(X=x, Y=y) = f(x, y)$$

(2) For continuous case:

$$\rightarrow f(x, y) > 0$$

$$\rightarrow \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1$$

$$\rightarrow P(a < x < b, c < y < d) = \int_a^b \int_c^d f(x, y) dy dx$$

Marginal distribution: (discrete case)

→ Marginal distribution along x:

$$g(x) = \sum_y f(x, y)$$

→ Marginal distribution along y:

$$h(y) = \sum_x f(x, y)$$

continuous case:

→ Marginal distribution along x:

$$g(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

→ Marginal distribution along y:

$$h(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

condⁿ distribution (y given x = x)

$$f(y|x) = \frac{f(x, y)}{g(x)}, \quad g(x) > 0$$

condⁿ distribution of (x given y = y)

$$f(x|y) = \frac{f(x, y)}{h(y)}, \quad h(y) > 0$$

→ discrete case:

$$\sum_{a < x < b} f(x|y)$$

→ continuous case:

$$P(a < x < b | y) = \int_a^b f(x|y) dx$$

2 independent Random variable:

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

Chapter-02 probability of an Event

A: Event

S: Sample space.

$$P(A) = \frac{|A|}{|S|}$$

$$P(\emptyset) = \frac{|\emptyset|}{|S|} = 0$$

$$P(S) = \frac{|S|}{|S|} = 1$$

↓

Largest
Set

Conditional probability: → Event A given B $P(A|B)$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad P(B) > 0$$

→ Event B given A $P(B|A)$

$$P(B|A) = \frac{P(A \cap B)}{P(A)}, \quad P(A) > 0$$

$$P(A|B) = P(A)$$

$$P(B|A) = P(B)$$

Independent event: two event A and B are indepen-

- dent iff and only if $P(A|B) = P(A)$, $P(B|A) = P(B)$

A and B are independent: $P(A \cap B) = P(A) \times P(B)$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad P(B) > 0 \quad \text{--- (I)}$$

$$P(B|A) = \frac{P(A \cap B)}{P(A)}, \quad P(A) > 0 \quad \text{--- (II)}$$

as two event A and B are independent $P(A|B) = P(A)$
 $P(B|A) = P(B)$

from (I)

$$P(A|B) = P(A) = \frac{P(A \cap B)}{P(B)}$$

$$\boxed{P(A \cap B) = P(A) P(B)}$$

from (II) $P(B|A) = P(B) = \frac{P(A \cap B)}{P(A)}$

$$\boxed{P(A \cap B) = P(A) P(B)}$$

Theorem: P(A' | B) shows that if 2 Events A and B are independent then their complements A' and B' are also independent.

$$\underline{\text{LHS}} \quad P(A' \cap B') = P((A \cup B)')$$

$$= 1 - P(A \cup B)$$

$$= 1 - [P(A) + P(B) - P(A \cap B)]$$

$$= 1 - P(A) - P(B) + P(A) P(B)$$

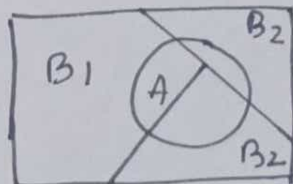
$$= 1 - P(A) - P(B) [1 - P(A)]$$

$$[1 - P(A)] [1 - P(B)]$$

$$P(A') P(B') \quad \underline{\text{RHS}}$$

Theorem of total probability

if the events B_1, B_2, \dots, B_k constitute a partition of a sample space S such that $P(B_i) \neq 0, \forall i = 1, 2, \dots, k$



for any event A of S:
$$\boxed{P(A) = \sum_{i=1}^k P(B_i \cap A)}$$

$$= \sum_{i=1}^k P(B_i) P(A|B_i)$$

Bayes's Rule: If the ^{events} ~~element~~ B_1, B_2, \dots, B_k constitute a partition of a sample space 'S' such that $P(B_i) \neq 0 \{i=1, 2, \dots, k\}$

$$P(A) \neq 0$$

$$P(B_i | A) = \frac{P(B_i \cap A)}{P(A)}$$
$$= \frac{P(B_i) P(A | B_i)}{\sum_{i=1}^k P(B_i) P(A | B_i)}$$

chapter - 01

Sample mean: $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i = \frac{1}{n} (x_1 + x_2 + \dots + x_n)$

Sample median:

$$\bar{x} = \begin{cases} x_{(\frac{n+1}{2})}, & n \text{ is odd} \\ \frac{1}{2} \left(x_{(\frac{n}{2})} + x_{(\frac{n}{2} + 1)} \right) \end{cases}$$

Sample variance:

$$S^2 = \frac{1}{n-1} \left[\sum_{i=1}^n (x_i - \bar{x})^2 \right], \text{ where } \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$
$$\frac{1}{n-1} \left[(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_n - \bar{x})^2 \right]$$

Sample standard deviation: $S = \sqrt{S^2}$