

概率论与数理统计 公式大全

一 概率论的基本概念

- 加法公式

- $$P(\bigcup_{i=1}^n A_i) = \sum_{i=1}^n P(A_i) - \sum_{1 \leq i < j \leq n} P(A_i A_j) + \sum_{1 \leq i < j < k \leq n} P(A_i A_j A_k) + \dots + (-1)^{n-1} P(A_1 A_2 \dots A_n)$$

- 条件概率

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

- 全概率公式

- $$P(A) = \sum_{j=1}^n P(B_j)P(A|B_j)$$

- 贝叶斯公式

- $$P(B_i|A) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A|B_i)}{\sum_{j=1}^n P(B_j)P(A|B_j)}$$

二 随机变量及其概率分布随机变量及其概率分布

- 概率密度

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

- 常见分布及期望和方差

- 0 – 1 分布

$$P(X = k) = p^k(1 - p)^{n-k}$$

- $$X \sim 0 - 1(p), E(X) = p, D(X) = p(1 - p)$$

- 泊松分布

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad (k = 0, 1, 2, \dots)$$

$$X \sim \pi(\lambda), E(X) = \lambda, D(X) = \lambda$$

◦ 正态分布

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$X \sim N(\mu, \sigma^2), E(X) = \mu, D(X) = \sigma^2$$

◦ 指数分布

$$f(x) = \lambda e^{-\lambda x} \quad x > 0$$

$$X \sim E(\lambda), E(X) = \frac{1}{\lambda}, D(X) = \frac{1}{\lambda^2}$$

◦ 二项分布

$$P(X = k) = C_n^k \cdot p^k \cdot (1-p)^{n-k}$$

$$X \sim B(n, p), E(X) = np, D(X) = np(1-p)$$

◦ 均匀分布

$$f(x) = \frac{1}{b-a} \quad a \leq x < b$$

$$X \sim U(a, b), E(X) = \frac{a+b}{2}, D(X) = \frac{(b-a)^2}{12}$$

• 随机变量函数的概率密度

◦ 若 $Y = g(x)$, $g'(x) > 0$ 或 $g'(x) < 0$

$$f_Y(y) = f_X(h(y)) \cdot |h'(y)| \quad \alpha < y < \beta$$

◦ $h(y)$ 是 $g(x)$ 的反函数

三 二元随机变量

• 当 X 与 Y 相互独立时, 若 $Z = X + Y$

$$f_Z(z) = \int_{-\infty}^{+\infty} f_X(z-y) f_Y(y) dy$$

• 二元连续型随机变量的条件概率密度

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}$$

• $Z = X + Y$ 的分布

◦

$$F_Z(z) = P(Z \leq z) = \iint_{x+y \leq z} f(x, y) dx dy$$

$$f_Z(z) = \int_{-\infty}^{+\infty} f(z-y, y) dy$$

◦ 正态分布

◦

$$c_0 + c_1 X_1 + c_2 X_2 + \dots + c_n X_n \sim N(c_0 + c_1 \mu_1 + \dots + c_n \mu_n, c_1^2 \sigma_1^2 + c_2^2 \sigma_2^2 + \dots + c_n^2 \sigma_n^2)$$

◦ 二项分布

◦

$$X + Y \sim B(n_1 + n_2, p)$$

◦ 泊松分布

◦

$$X + Y \sim \pi(\lambda_1 + \lambda_2)$$

• $\max(X, Y)$ 和 $\min(X, Y)$ 的分布

◦

$$f_{\max}(z) = f_X(z) f_Y(z)$$

◦

$$f_{\min}(z) = 1 - (1 - f_X(z))(1 - f_Y(z))$$

四 期望与方差

• 数学期望

◦

$$E(X) = \sum_{k=1}^{+\infty} x_k p_k$$

◦

$$E(X) = \sum_{k=1}^{+\infty} x_k p_k$$

◦

$$E(Y) = E[g(X)] = \sum_{k=1}^{\infty} g(x_k) p_k$$

◦

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

◦

$$E(Z) = E[h(X, Y)] = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} h(x_i, y_j) p_{ij}$$

◦

$$E(Z) = E[h(X, Y)] = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h(x, y) f(x, y) dx dy$$

$$\circ E(cX) = cE(X)$$

$$\circ E(XY) = E(X)E(Y) \quad (\text{要求独立})$$

• 方差

◦

$$D(X) = \sum_{i=1}^{+\infty} [x_i - E(X)]^2 p_i$$

$$D(X) = \int_{-\infty}^{+\infty} [x - E(X)]^2 f(x) dx$$

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

$$D(X + Y) = D(X) + D(Y) + 2 \cdot Cov$$

$$E(X^*) = 0$$

$$D(X^*) = 1$$

• 协方差

$$Cov(X, Y) = E\{[X - E(X)][Y - E(Y)]\}$$

$$Cov(X, Y) = E(XY) - E(X)E(Y)$$

$$Cov(aX, bY) = ab \cdot Cov(X, Y)$$

$$Cov(X_1 + X_2, Y) = Cov(X_1, Y) + Cov(X_2, Y)$$

$$\rho_{XY} = \frac{Cov(X, Y)}{\sqrt{D(X)D(Y)}}$$

$$\rho_{XY} = Cov(X^*, Y^*)$$

• 不相关与独立

$$\circ \text{ 不相关: } \rho_{XY} = 0$$

◦ 独立:

$$P(X = x_i, Y = y_j) = P(X = x_i)P(Y = y_j), \quad f(x, y) = f_X(x)f_Y(y)$$

• 常见分布及期望和方差

◦ 0-1 分布

$$P(X = k) = p^k(1 - p)^{n-k}$$

$$\circ \quad X \sim 0-1(p), E(X) = p, D(X) = p(1 - p)$$

◦ 泊松分布

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad (k = 0, 1, 2, \dots)$$

$$\circ \quad X \sim \pi(\lambda), E(X) = \lambda, D(X) = \lambda$$

◦ 正态分布

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- $X \sim N(\mu, \sigma^2), E(X) = \mu, D(X) = \sigma^2$

- 指数分布

$$f(x) = \lambda e^{-\lambda x} \quad x > 0$$

- $X \sim E(\lambda), E(X) = \frac{1}{\lambda}, D(X) = \frac{1}{\lambda^2}$

- 二项分布

$$P(X = k) = C_n^k \cdot p^k \cdot (1 - p)^{n-k}$$

- $X \sim B(n, p), E(X) = np, D(X) = np(1 - p)$

- 均匀分布

$$f(x) = \frac{1}{b-a} \quad a \leq x < b$$

- $X \sim U(a, b), E(X) = \frac{a+b}{2}, D(X) = \frac{(b-a)^2}{12}$

五 切比雪夫不等式，大数定律中心极限定理

- 切比雪夫不等式 Chebyshev's inequality

- $P\{|X - \mu| \geq \epsilon\} < \frac{\sigma^2}{\epsilon^2}$

- 伯努利大数定律

- $\lim_{n \rightarrow +\infty} P\{|\frac{nA}{n} - p| \geq \epsilon\} = 0$

- 独立同分布的中心极限定理 (CLT)

- 设 $X_1, X_2, \dots, X_n, \dots$ 相互独立且同分布, $E(X_i) = \mu, D(X_i) = \sigma^2, i = 1, 2, \dots$ 则对于充分大 n 的, 有

- $\sum_{i=1}^n X_i \sim^{\text{近似}} N(n\mu, n\sigma^2)$

- 德莫弗-拉普拉斯定理

- 即二项分布可以用正态分布逼近

- $n_A \sim^{\text{近似}} N(np, np(1-p))$

六 统计量与抽样分布

- 样本均值

- $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$

- $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$

- $\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1)$

- 样本方差

- $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$

- $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$

- $E(S^2) = \sigma^2$

- $D(S^2) = \frac{2\sigma^4}{n-1}$

- 样本矩

- $A_k = \frac{1}{n} \sum_{i=1}^n X_i^k$

- $B_k = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^k$

- χ^2 分布

- $\chi^2 = \sum_{i=1}^n X_i^2$

- $E(\chi^2) = n$

- $D(\chi^2) = 2n$

- $Y_1 + Y_2 \sim \chi^2(n_1 + n_2)$

- t 分布

- $T = \frac{X}{\sqrt{(Y/n)}}, X \sim N(0, 1), Y \sim \chi^2(n)$

- F 分布

- $F = \frac{X/n_1}{Y/n_2}, X \sim \chi^2(n_1), Y \sim \chi^2(n_2)$

- 两个正态总体的抽样分布

- $F = \frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2} = \frac{S_1^2}{S_2^2} \bigg/ \frac{\sigma_1^2}{\sigma_2^2} \sim F(n_1 - 1, n_2 - 1)$

-

$$\frac{(\bar{X} - \bar{Y}) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim N(0, 1)$$

$$\frac{(\bar{X} - \bar{Y}) - \mu_1 - \mu_2}{S_w \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(n_1 + n_2 - 2)$$

◦ 其中

$$S_w^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

七 参数估计

• 极大似然估计

$$L(\theta) = \prod_{i=1} p(x_i; \theta)$$

$$L(\theta) = \prod_{i=1} f(x_i; \theta)$$

$$\circ X \sim N(\mu, \sigma^2), \quad \hat{\mu} = \bar{X}, \quad \hat{\sigma}^2 = B_2$$

$$\circ X \sim U(a, b), \quad \hat{a} = \min\{X_1, \dots, X_n\}, \quad \hat{b} = \max\{X_1, \dots, X_n\}$$

• 置信区间

$$\circ P\{\theta_L(X_1, \dots, X_n) < \theta < \hat{\theta}_U(X_1, \dots, X_n)\} \geq 1 - \alpha$$

八 假设检验

• 拟合优度检验

$$\sum_{i=1}^k \frac{(n_i - np_i)^2}{np_i} \sim_{\text{近似}} \chi^2(k - r - 1)$$

◦ n_i 为实际频数, np_i 为理论频数