

## 1 Probability and Statistics

$$\begin{aligned} \binom{n}{r} &= \binom{n-1}{r} + \binom{n-1}{r-1} \\ \binom{-x}{r} &= (-1)^r \binom{x+r-1}{r} \\ \binom{n}{r_1, r_2, \dots, r_k} &= \binom{n}{r_1} \cdots \binom{n-r_1-\cdots-r_{k-1}}{r_k} \\ \binom{x}{r} &= \frac{x(x-1)\cdots(x-r+1)}{r!} \\ \binom{a}{0} \binom{b}{n} + \binom{a}{1} \binom{b}{n-1} + \cdots + \binom{a}{n} \binom{b}{0} &= \binom{a+b}{n} \\ \text{Bernoulli}(p) &= p^x(1-p)^{1-x} \\ p \mid p(1-p) \mid 1-p + pe^t \\ \text{Binomial}(n, p) &= \binom{n}{x} p^x(1-p)^{n-x} \\ np \mid np(1-p) \mid (1-p + pe^t)^n \\ \text{Poisson}(\lambda) &= \frac{\lambda^x e^{-\lambda}}{x!} \mid \lambda \mid \lambda \mid e^{\lambda(e^t-1)} \\ \text{Geometric}(p) &= (1-p)^{x-1} p \\ \frac{1}{p} \mid \frac{1-p}{p^2} \mid \frac{pe^t}{1-(1-p)e^t} \\ \text{Uniform}(a, b) &= \frac{1}{b-a} \\ \frac{a+b}{2} \mid \frac{(b-a)^2}{12} \mid \frac{e^{tb}-e^{ta}}{t(b-a)} \\ \text{Normal}(\mu, \sigma^2) &= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \\ \text{E}(Z^{2r+1}) = 0 \mid \text{E}(Z^{2r}) &= \frac{(2r)!}{(2^r r!)} \\ \mu \mid \sigma^2 \mid e^{\mu t + \frac{1}{2}\sigma^2 t^2} \\ \text{Gamma}(\alpha, \beta) &= \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \\ \frac{\alpha}{\beta} \mid \frac{\alpha}{\beta^2} \mid \left(\frac{\beta}{\beta-t}\right)^\alpha \\ \text{E}(\ln(X)) &= \frac{\Gamma'(\alpha)}{\Gamma(\alpha)} - \ln(\beta) \\ \theta = \frac{1}{\beta} \mid \sum \Gamma(\alpha_i, \beta) &= \Gamma\left(\sum \alpha_i, \beta\right) \\ \Gamma(1, \beta) = \text{Exponential}(\beta) \mid \Gamma\left(\frac{n}{2}, \frac{1}{2}\right) &= \chi_n^2 \end{aligned}$$

$$\begin{aligned} Y \sim \text{Gamma}(\alpha, \beta), cY &\sim \text{Gamma}(\alpha, \frac{\beta}{c}) \\ \text{Beta}(\alpha, \beta) &= \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)} \\ \frac{\alpha}{\alpha+\beta} \mid \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \mid \varnothing \\ \text{B}(a, b) &= \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)} \\ \text{Beta}(1, 1) = \text{U}[0, 1] \mid \mu'_r = \text{E}(X^r) \\ \text{ZIP}(\phi, \lambda) &:= ZX|(1-\phi)\lambda|(1-\phi)\lambda(1+\phi\lambda) \\ Z = \text{Bernoulli}(1-\phi), X &= \text{Poisson}(\lambda) \\ \text{M}_{\text{ZIP}}(t) &= \phi + (1-\phi)e^{\lambda(e^t-1)} \\ \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2}\right)} &= \frac{\frac{U}{M}}{\frac{V}{n}} \sim \text{F}(m, n), U \sim \chi^2(m), V \sim \chi^2(n) \\ X_1|X_2 \mid \mu_1 + \rho\frac{\sigma_1}{\sigma_2}(x_2 - \mu_2) \mid \sigma_1^2(1-\rho^2) \\ \text{Skewness} = \frac{\mu_3}{\sigma^3} \mid \text{Kurtosis} &= \frac{\mu_4}{\sigma^4} \\ \text{P}(g(X) \geq c) &\leq \frac{\text{E}(g(x))}{C} \\ \text{P}(|X - \mu| \geq c\sigma) &\leq \frac{1}{c^2} \\ \text{P}(|X - \mu| \geq c) &\leq \frac{\text{E}(|X|^r)}{c^r} \\ \text{E}(XY)^2 &\leq \text{E}(X^2)\text{E}(Y^2) \\ \text{E}(g(X)) &\geq g(\text{E}(X)), \forall \text{凸函数 } g(x^2) \\ \text{E}(X) &= \text{E}[\text{E}(X|Y)] \\ \text{Var}(X) &= \text{E}[\text{Var}(X|Y)] + \text{Var}[\text{E}(X|Y)] \\ \text{q 分位数}\xi_q &:= \text{F}(\xi_q) = \text{P}(X \leq \xi_q) \geq q \\ \text{pgf} := \text{G}_X(z) = \text{E}(z^X) &= \sum_{x \in \mathbb{S}} z^x \text{P}_X(X = x) \\ \text{Additivity : N, Poisson, NB, Binomial} \\ \text{IBF} := f_X(x) &\propto \frac{f_{X|Y}(x|y_0)}{f_{Y|X}(y_0|x)} \end{aligned}$$

## 2 Sampling Distributions

$$\begin{aligned} g(y_1, y_2) &= f(x_1, x_2) \times |\mathbf{J}| \\ \mathbf{J} &= \begin{vmatrix} \frac{\partial x_1}{\partial y_1} & \frac{\partial x_1}{\partial y_2} \\ \frac{\partial x_2}{\partial y_1} & \frac{\partial x_2}{\partial y_2} \end{vmatrix} \\ \bar{X} = \frac{1}{n} \sum X_i \mid S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2 \\ \bar{X} \sim \text{N}(\mu, \frac{\sigma^2}{n}) \mid \bar{X} \perp S^2 \\ \frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2 \mid \sum Z_i^2 \sim \chi^2(n) \\ T = \frac{Z}{\sqrt{\frac{Y}{n}}} \sim \text{t}(n), Y \sim \chi^2(n) \\ T = \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim \text{t}(n-1) \\ \text{F}(X_{(n)}) = [F(x)]^n \\ f_{X_{(r)}} = \frac{n!}{(r-1)!(n-r)!} f(x)[F(x)]^{r-1}[1-F(x)]^{n-r} \\ \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{L} Z \sim N(0, 1), \forall \text{随机变量} X \\ \textbf{3 Point Estimation} \\ L(\theta) = \prod_{i=1}^n f(x_i; \theta) \\ \ell(\theta) = \ln L(\theta) = \sum_{i=1}^n \ln f(x_i; \theta) \\ h(\theta) = h(\hat{\theta}), \forall \text{MLE } \hat{\theta} \\ \frac{1}{n} \sum X_i^2 - \bar{X}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \\ \hat{\mu}_k = \text{E}(X^k) \\ p(\theta|x) = \frac{f(x|\theta)\pi(\theta)}{f(x)} \propto f(x|\theta) \times \pi(\theta) \\ \text{Unbiasedness: E}(\hat{\theta}) = \theta \mid \text{Bias}(\hat{\theta}) = \text{E}(\hat{\theta}) - \theta \\ \text{MSE}(\hat{\theta}) = \text{E}[(\hat{\theta} - \theta)^2] = \text{Var}(\hat{\theta}) + [\text{Bias}(\hat{\theta})]^2 \\ \text{Fisher Information: } I_n(\theta) = E\left[-\frac{\partial^2 \log L(\theta)}{\partial \theta^2}\right] \\ \text{CRLB: } \textit{Var}(\hat{\theta}) \geq \frac{1}{I_n(\theta)} \end{aligned}$$

Sufficiency:  $f(x; \theta) = g(T(x), \theta) \times h(x), \forall \text{Statistics } T$

$$\begin{aligned} \hat{\theta}_n &\xrightarrow{P} \theta, n \xrightarrow{\infty} \\ \sqrt{nI(\theta)}(\hat{\theta}_n - \theta) &\xrightarrow{d} N(0, 1) \text{ or } \hat{\theta}_n \sim N\left(\theta, \frac{1}{I_n(\theta)}\right) \end{aligned}$$