Sufficient; Factorization theorem Multinomial n_i = the number of times we get outcome i=1,...,k of $f_{\vec{\theta}}(\vec{n})=n!\prod_{i=1}^k\frac{\theta_i^{n_i}}{1}\{\sum_{N_i=n}\} T(\vec{N})=(N_1,...,N_{k-1},n-\sum_{i=1}^{k-1}N_i)$ is equivalent with $(N_1,...,N_{k-1})$ is sufficient for θ . $p(x,\theta)=\frac{1}{\sigma}\exp\{-\frac{x^{-\mu}}{\sigma}\}\mathbf{1}_{\{x_i\geq\mu\}}\theta=(\mu,\sigma)-\infty<\mu<\infty,\sigma>0$ $x_{(1)}$ is sufficient for μ when σ is fixed. $h(x)=\sigma^{-n}\exp[-\frac{\sum_{i=1}^{n}x}{\sigma}]$, $g(T(x),\mu)=\exp[\frac{n\mu}{\sigma}]\prod_{i=1}^n\mathbf{1}_{\{x_i\geq\mu\}}$ $T(x)=\sum_{i=1}^nx_i$ is sufficient for σ when μ is fixed. $h(x)=\prod_{i=1}^n\mathbf{1}_{\{x_i\geq\mu\}}$, $g(T(x),\sigma)=\sigma^{-n}\exp[-\frac{\sum_{i=1}^nx}{\sigma}+\frac{n\mu}{\sigma}]$ $T(x)=(x_{(1)},\sum_{i=1}^nx_i)$ is a two-dimensional sufficient h(x)=1, $g(T(x),\mu,\sigma)=\sigma^{-n}\exp[-\frac{\sum_{i=1}^nx}{\sigma}+\frac{n\mu}{\sigma}]\prod_{i=1}^n\mathbf{1}_{\{x_{(1)}\geq\mu\}}$ $\exp[\eta(\theta)T(x)-\theta(\theta)]$, $x\in\mathcal{X}\subset\mathbb{R}$ free of θ $X=[Z,Y]^T$, where $Y=Z+\theta W,\theta>0$, $Z\perp W\sim N(0,1)$ $f(x,\theta)=f(z,y,\theta)=f(z)f_{\theta}(y|z)=\phi(z)\theta^{-1}\phi(\frac{y-z}{\theta})$ $=\frac{1}{2\pi}\exp[\frac{1}{2}z^2]\exp[-\frac{1}{2\rho^2}(y-z)^2-\ln\theta]$ $U(\theta_1,\theta_2)$, let h(x)=1, $a(\theta)=(\theta_2-\theta_1)^{-1}$ $g(T(x),\theta_1,\theta_2)=\prod_{i=1}^n[1_{\{x_{(n)}\leq\theta_i\}}\mathbf{1}_{\{x_{(1)}\geq\theta_i\}}][\theta_2-\theta_1]^{-n}$, h'(x)=1 $T(x)=(x_{(1)},x_{(n)})$ is a two-dimensional sufficient of θ in the $U[\theta_1,\theta_2]$ family u(x)=0 u

$$N(\mu, \sigma^{2}) = \frac{1}{\rho^{2}} \underbrace{\frac{x}{\Gamma(x)}}_{\eta(\mu)} \underbrace{\frac{\mu^{2}}{\Gamma(x)}}_{T(x)} \underbrace{\frac{\mu^{2}}{B(\mu)}}_{B(\mu)} \underbrace{\frac{x^{2}}{h(x)}}_{h(x)} \underbrace{\frac{\mu}{\mu} \operatorname{fixed}}_{h(x)} \underbrace{\exp\left[-\frac{1}{2\sigma^{2}} \underbrace{(x-\mu)^{2} - \ln\left(\sqrt{2\pi}\sigma\right)}_{B(\sigma^{2})} \underbrace{1_{\{x \in \mathbb{R}\}}}_{h(x)} \right]}_{h(x)}$$

$$\Gamma(p, \lambda) = \frac{p \operatorname{fixed}}{\lambda \operatorname{fixed}} \underbrace{\exp\left[-\frac{\lambda}{\mu} \underbrace{x}_{T(x)} - \frac{-\ln\left(\frac{\lambda^{p}}{\Gamma p}\right)}_{B(\sigma^{2})} \underbrace{1_{\{x \in (0,\infty)\}}}_{h(x)} \right]}_{h(x)}$$

$$\lambda \operatorname{fixed} = \underbrace{\exp\left[(p-1)\ln(x) - -\ln\left(\frac{\lambda^{p}}{\Gamma p}\right)\right]}_{\eta(p)} \underbrace{\exp\left[-\lambda x + (p-1)\ln x - -\ln\left(\frac{\lambda^{p}}{\Gamma p}\right)\right]}_{h(x)} \underbrace{1_{\{x \in (0,\infty)\}}}_{h(x)}$$

$$\exp\left[-\frac{\lambda x + (p-1)\ln x - -\ln\left(\frac{\lambda^{p}}{\Gamma p}\right)\right]}_{\eta(p,\lambda)T(x)} \underbrace{1_{\{x \in (0,\infty)\}}}_{B(p)} \underbrace{1_{\{x \in (0,\infty)\}}}_{h(x)}$$

$$s \operatorname{fixed} = \exp\left[(s-1)\ln(1-x) - \ln(B(r,s))\right] \underbrace{(1-x)^{s-1}1}_{\{x \in (0,1)\}}$$

$$\exp\left[(r-1)\ln(x) + (s-1)\ln(1-x) - \ln(B(r,s))\right] \underbrace{1_{\{x \in (0,1)\}}}_{h(x)}$$

$$\exp\left[(r-1)\ln(x) + (s-1)\ln(1-x) - \ln(B(r,s))\right] \underbrace{1_{\{x \in (0,1)\}}}_{h(x)}$$

Geometric $G(\theta)$ the number of failures before the first success in a sequence

Canonical $q(x,\eta)=h(x)\exp[\eta T(x)-A(\eta)], x\in\mathcal{X}\subset\mathbb{R}$ free of θ $A(\eta)=\ln(\int_{\mathcal{X}}h(x)\exp[\eta T(x)]dx); \int_{\mathcal{X}}h(x)\exp[\eta(\theta)T(x)-B(\theta)]dx=B$ $Bino:p(x,\theta)=,\eta=\ln p1-p, p=\frac{e^{\eta}}{1+e^{\eta}}, 1-p=\frac{1}{1+e^{\eta}}$ $A(\eta)=-n\ln(\frac{1}{1+e^{\eta}})=n\ln(1+e^{\eta})$ finite $\forall \eta\in\mathbb{R}$ $A(\eta)=-n\ln(\frac{1}{1+e^{\eta}})=n\ln(1+e^{\eta})$ finite $\forall \eta\in\mathbb{R}$ $A(\eta)=-n\ln(\frac{1}{1+e^{\eta}})=n\ln(1+e^{\eta})$ finite $\forall \eta\in\mathbb{R}$ $A(\eta)=-n\ln(e^{\eta})=n\ln(e^$

 $\mathbf{B}(\mu, \sigma^{2}) = -\frac{\mu^{2}}{2\sigma^{2}} + \ln(\sqrt{2\pi}\sigma) = -\frac{\eta_{1}^{2}}{4\eta_{2}} - \frac{1}{2}\ln(-\eta_{2}) + \ln(\sqrt{\pi}) = \mathbf{A}(\eta_{1}, \eta_{2})$ $\dot{A}(\eta) = (\frac{-\eta_{1}}{2\eta_{2}}, \frac{-1}{2\eta_{2}} + \frac{\eta_{1}^{2}}{4\eta_{2}^{2}})^{T} = (\mu, \mu^{2} + \sigma^{2})^{T}$ $\ddot{A}(\eta) = \begin{bmatrix} \frac{-1}{2\eta_{2}} & \frac{\eta_{1}}{2\eta_{2}^{2}} \\ \frac{\eta_{1}}{2\eta_{2}^{2}} & \frac{1}{2\eta_{2}} - \frac{\eta_{1}^{2}}{2\eta_{2}^{2}} \end{bmatrix} = \begin{bmatrix} \sigma^{2} & 2\mu\sigma^{2} \\ 2\mu\sigma^{2} & 2\mu\sigma^{4} + 4\mu^{2}\sigma^{2} \end{bmatrix}$

```
 \begin{aligned} & \frac{\operatorname{calculous}}{(\frac{w}{u})'} = \frac{u'v - uv'}{v^2}; (uv)' = u'v - uv', \int udv = uv - \int vdu; \\ & (\frac{w}{u})' = a^{\mu}\ln(a), \int a^{\chi} \ln a = a^{\chi}; \int xe^{\chi} dx = xe^{\chi} - \int e^{\chi} dx = xe^{\chi} - e^{\chi}; \\ & (e^{\mu x})' = a^{\mu}\ln(a), \int a^{\chi} \ln a = a^{\chi}; \int xe^{\chi} dx = xe^{\chi} - \int e^{\chi} dx = xe^{\chi} - e^{\chi}; \\ & (e^{\mu x})' = a^{\mu}\ln(a), \int a^{\chi} \ln a = a^{\chi}; \int xe^{\chi} dx = xe^{\chi} - \int e^{\chi} dx = xe^{\chi} - e^{\chi}; \\ & (e^{\mu x})' = ae^{\mu x}, \int e^{\mu u} = \frac{1}{a} e^{\mu u}; (x \ln x - x)' = \ln x, \int \ln u = u \ln u - u; \\ & (x^{n})' = nx^{n-1}, \int x^{n} = \frac{1}{n+1}; (\ln x)' = \frac{1}{\chi}, \int \frac{1}{ax+b} = \frac{\ln |ax+b|}{a}; \\ & (x^{n})' = \frac{1}{n+1}, \int x^{n} = \frac{(tx)^{n}}{n+1} = e^{t\chi}; \\ & (x^{n})' = \frac{1}{n+1}; (n-1)(n-1), \Gamma(1/2) = \sqrt{\pi}, \\ & \Gamma(n) = (n-1)! = (n-1)\Gamma(n-1), \Gamma(1/2) = \sqrt{\pi}, \\ & \Gamma(n) = (n-1)! = (n-1)\Gamma(n-1), \Gamma(1/2) = \sqrt{\pi}, \\ & \Gamma(n) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} e^{-\chi} dx, \int_{0}^{1} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ & \Gamma(t) = \int_{0}^{\infty} x^{t-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}; \\ &
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               MOM \hat{\mu} = EX = \bar{x}_i \hat{\sigma}^2 = E[X^2] - EX^2 = \frac{\sum x_i^2}{n} - \bar{x}^2
7.2.2 MLE - Indecator in
F(x) = (\frac{2}{\theta})^2, 0 \le x < \theta
\max L(\theta) = 2^n \theta^{-2n} \prod x_i I_{(-\infty,\theta)}(x_{(n)}) I_{(0,\infty)}(x_{(1)})
\min \theta_{MLE} = X_{(n)} = nf()[F()]^{n-1} = \frac{2n}{\theta^n} x^{2n-1} \sim Beta(2n,1)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              \begin{split} \hat{\lambda}_{u} \frac{n-1}{T}; V \hat{\theta}_{u} \frac{\lambda^{2}}{n-2}; I_{\lambda} &= \frac{1}{\lambda^{2}} \cdot \operatorname{effi} \frac{n-2}{n} \\ e^{-(x-\theta)}, n &= 10; H_{0}: \theta = 0, H_{1}: \theta > 0; T = X_{(1)} \geq C \end{split}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                Let Y = X - \theta, Y_{(1)} \sim Expo(10), \Gamma(1, \frac{1}{10}); 20Y_{(1)} \sim \chi_2^2;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              P_{H_0}(X_{(1)} \ge C) = P_{H_0}(20Y_{(1)} \ge 20C) \stackrel{set}{=} 0.05,20C = 5.991; P_{H_1}(X_{(1)} \ge 0.2996) = P_{H_1}(Y_{(1)} \ge -0.7) = 1, \min \beta at H_0 is unbia A test whose power never drops below \alpha is unbiased
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   EX_{(n)} = \frac{2n}{2n+1}\theta ; Or = \int_0^\theta x f_{X_{(n)}}(x) dx
\lim_{n \to \infty} [EX_{(n)} - \theta] = 0; \lim_{n \to \infty} P(X_{(n)} - \theta) \ge \varepsilon = 0;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  Expo(\frac{1}{\mu}); H_0: \mu = 5, H_1: \mu \neq 5
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       \lim_{n \to \infty} V[X_{(n)}] = \lim_{n \to \infty} \frac{n \to \infty}{(2n+1)^2(n+1)} \theta^2 = 0
Y_i \sim \lim_{n \to \infty} Y[x_i] = Y[x_i], x_i \text{ known constants,}

\Lambda = \frac{L(\mu_0)}{L(\mu_1)} = (\frac{\mu_1}{5})^n e^{(\frac{1}{\mu_1} - \frac{1}{5})} \sum x_i \le c

\mu_1 < 5.\Lambda \nearrow \sum x_i \le c'; \mu_1 > 5.\Lambda \searrow \sum x_i \ge c';

T = \sum x_i \sim Gamma(10, \mu), \frac{2}{\mu} T \sim \chi_{20}^2;

P_{H_0} (\frac{2T}{5} \le \chi_{20,0.975}^2(9.59)) + P_{H_0} (\frac{2T}{5} \ge \chi_{20,0.025}^2(34.2)) = 0.05;

= 2.2
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               \begin{split} & \|\mathbf{Y}_i \sim POSL(\mu_i = \gamma \mathbf{x}_i), \mathbf{x}_i \text{ shown constant,} \\ & \hat{\gamma}_{mle} = \sum_{l=1}^{l=1} \frac{\mathbf{y}_i}{\mathbf{y}_{l-1}} \hat{\mathbf{x}}_i : \mathbb{E}[\gamma_{mle}] = \gamma_i V[\hat{\gamma}_{mle}] = \frac{\gamma}{\sum_{l=1}^{l} \mathbf{x}_i} \\ & \mathbf{7.2.3 \ Bayes estimator.} \\ & \mathbf{X}_n \text{ iid} \mathbf{E} \mathbf{x}_p o(\theta), \mathbf{\pi}(\theta) \sim \mathbf{E} \mathbf{x}_p o(\Lambda) \\ & \mathbf{\pi}(\theta|\tilde{\mathbf{x}}) = \frac{\mathbf{x}(\tilde{\mathbf{x}}|\theta)}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)} \frac{\mathbf{x}(\tilde{\mathbf{x}}|\theta)h(\theta)}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \Gamma(n+1, \frac{1}{\lambda + \sum_{i} \gamma}) \\ & \mathbf{x}_i = \frac{1}{\lambda_i} \sum_{i=1}^{l} \frac{1}{\mathbf{y}(\tilde{\mathbf{x}}|\theta)h(\theta)} \sim \mathbf{L}(\theta)h(\theta) \sim \mathbf{L}(\theta)h(\theta) \sim \mathbf{L}(\theta)h(\theta) \sim \mathbf{L}(\theta)h(\theta) \sim \mathbf{L}(\theta)h(\theta) 
\Gamma(\frac{2k+1}{2}) = \frac{(2k)!\sqrt{\pi}}{4^k k!}, k > 0; \frac{(-4)^{-k}(-k)!\sqrt{\pi}}{(-2k)!}, k < 0
                                                                                                                                                                                                                                                                                                                                                                                                        \frac{|Z_1|}{|Z_2|}; f(u) = \int_{-\infty}^{\infty} f(1)f(2)|v|dv = 2\int_{0}^{\infty} = \frac{1}{\pi(u^2+1)} \sim Cauch(0,1)
                                                                                                                                                                                                                                                                                                                                                                                                                    \sim Cauchy(0,\sigma), \sum^{n} X \sim Cauchy(0,n\sigma); Z^{2} \sim \chi_{1}^{2}
\sum_{n=0}^{\infty} ar^n = \frac{a}{1-r}, |r| < 1; \sum_{k=0}^{n-1} ar^n = \frac{a(1-r^n)}{1-r};
Finite

Binomial
                                                                                                                                                                                                                                                                                                                                                                                                        \begin{array}{lll} \lambda \sim Cau(n,y_1(y_2,r),2) & & & \\ \frac{X-\mu}{S^2/\sqrt{n}}, & \frac{S_\chi^2}{\sqrt{2}^2/\sigma_\chi^2}, t_{n-1}, & \frac{S_\chi^2}{S_\chi^2/\sigma_\chi^2}, t_{n-1,m-1}, & \frac{S_\chi^2}{\sigma_\chi^2}, \chi^2; F_{(p,q)}, & \frac{p}{q} \chi, & B(\frac{p}{2},\frac{q}{2}) \\ t_1, Cau(0,1); \chi_2^2, Exp(2); \chi_p^2, \Gamma(\frac{p}{2},2); U+V, \chi_{m+1}^2; & \Gamma_{(q)}^2, F_{(1,q)}; \end{array}
\sum_{k=1}^{n} k = \frac{n(n+1)}{2}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              \begin{array}{ll} P_{H_1}(\frac{2T}{\mu_1} \leq \frac{5x_{20,095}^2}{\mu_1}) + P_{H_1}(\frac{2T}{\mu_1} \geq \frac{5x_{20,0025}^2}{\mu_1}) \\ = P_{H_1}(\frac{2T}{\mu_1} \leq \frac{5x_{20,0025}^2}{\mu_1}) + P_{H_1}(\frac{2T}{\mu_1} \geq \frac{5x_{20,0025}^2}{\mu_1}) \\ = P_{H_0}(x_1 + x_2) = P_{H_0}(x_1 > 0.95); \end{array}
                                                                                                                                                          \sum_{k=0}^{n} \binom{n}{k} = 2^n
\sum_{k=1}^{n} (2k-1) = n^2
                                                                                                                                                              \sum_{k=0}^{n} {r+k \choose k} = {r+n+1 \choose n}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   \mathcal{L}_{\theta}(\hat{\theta}) = (\hat{\theta} - \theta)^2, to minPosterior risk E[\mathcal{L}_{\theta}(\hat{\theta}|\vec{x})], Posterior me
                                                                                                                                                                                                                                                                                                                                                                                                      \begin{aligned} & \{_1, Cau(0, 1); \chi_2^c, Exp(2)\chi_p^c, \Gamma(\frac{c}{2}, 2); U + V, \chi_m + n; T_{(q)}^c, F_{(1,q)}; \\ & \{_2, N(\mu, \sigma^2) \perp Y \sim N(\gamma, \sigma^2), U = X + Y \perp V = X - Y \\ & \{_3, N(\mu, \sigma^2) \perp Y \sim N(\gamma, \sigma^2), U = X + Y \perp V = X - Y \\ & \{_4, N(\mu, \gamma, \sigma^2)\} \sim N(\mu, \gamma, \sigma^2), V \sim N(\mu, \gamma, \sigma^
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 \hat{\theta}_{L_2Bayes} = E[\pi(\theta|\vec{x})] = \frac{n+1}{\lambda + \sum x_i} = \frac{\lambda(\frac{1}{\lambda}, E[\theta])}{\lambda + n\bar{x}} + \frac{n\bar{x}(\frac{1}{\lambda}, \hat{\theta}_{MLE})}{\lambda + n\bar{x}};
\sum_{k=1}^{n} k^2 = \frac{n(n+1)(2n+1)}{6} \sum_{k=0}^{n} {n \choose m} = {n+1 \choose m+1}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            \begin{aligned} &\mathbf{x} = P_{H_0}(x_1 + x_2 > c) = P_{H_0}(x_1 > 0.95); \\ &\mathbf{c}_c^2 f(z) dz = \frac{c_2}{2} - 2c + 2 = \int_{0.95}^{1} f(x) dx = 0.05 \\ &\mathbf{c} = \frac{c_1}{1} \pm \sqrt{2^2 - 4 \cdot \frac{c_1}{2} \cdot 1.95}, \text{choose } 2 - 0.3162 = 1.6838} \\ &\mathbf{10 \, \, Consistency} \\ &\text{Asym unbiased } \lim_{n \to \infty} Bias(\hat{\theta}) = 0 \\ &\lim_{n \to \infty} Var_{\theta}[W_n] = 0, \lim_{n \to \infty} Bias_{\theta}[W_n] = 0, \\ &\lim_{n \to \infty} P(\tau(\hat{\theta}_{MLE}) - \tau(\theta) \geq \varepsilon) = 0 \end{aligned}
\sum_{k=1}^{n} k^3 = (\frac{n(n+1)}{2})^2
                                                                                                                                                          \sum_{k=0}^{r} \binom{m}{k} \binom{n}{r-k} = \binom{m+n}{r}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   absolute error loss |a - \theta|, post-median\hat{\theta}_{L_1 Bayes} = F^{-1}(\frac{1}{2});
\sum_{k=0}^{n} c^{k} = \frac{c^{n+1}-1}{c-1}
1 Basic_____
                                                                                                                                                        \sum_{k=0}^{n} \binom{n}{k} a^{n-k} b^k = (a+b)^n
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            binary0, \hat{\theta} = \theta; 1, o.w. po-mode\hat{\theta}_{L_0Bayes} = (\alpha - 1)\beta, \Gamma' \stackrel{set}{=} 0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               X \sim Pois(\theta), \theta \sim \Gamma(\alpha, \beta) (known
1 Basic P(X \le y | X \ge c) = \frac{P(X \le y, X \ge c)}{P(X \ge c)} = \frac{P(c \le X \le y)}{1 - P(X \le c)} = \frac{F(y) - F(c)}{1 - F(c)} CDF nondecreasing, right-continuou; \lim_{x \to \infty} F(x) = 1; \lim_{x \to -\infty} F(x) = 1
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   \pi(\theta|\vec{x}) \sim \Gamma(\alpha + \sum_{i}, \frac{\alpha}{n\beta + 1}); \hat{\theta}_{L_2} Bayes = \frac{(\alpha + \sum_{i})\beta}{n\beta + 1}
X \sim Bino(n, \theta), \theta \sim Beta(\alpha, \beta);
Z = X + Y_{i}X \perp Y_{i}g(z) = \int_{-\infty}^{\infty} f_{X}(w)f_{Y}(z - w)dw
                                                                                                                                                                                                                                                                                                                                                                                                       \begin{array}{l} || X + b \gamma \sim n(a\mu_X + b\mu_Y, a^-\mu_X^- + b^-\mu_Y^- + 2ab\rho\sigma_X\sigma_Y) \\ || X + 5Co_Y Co_T - Cov(X, Y)| = \sigma_{XY} = E((X - \mu_X)(Y - \mu_Y)) = E[XY] - \mu_X\mu_Y \\ || Cov(aX, bY)| = abCov(X, Y); Cov(X, Y + Z) = Cov(X, Y) + Cov(X, Z), n(\theta, \sigma^2), \theta \sim n(\mu, \tau^2); f(\theta|x) \sim N(\frac{\tau^2 x + \sigma^2 \mu}{\tau^2 + \sigma^2}, \frac{\sigma^2 \tau^2}{\sigma^2 + \tau^2}) \\ || Cov(X, c)| = 0; Cov(X, X) = E[X^2] - \mu_Y^2; X \perp Y, Cov(X + Y, X - Y) = \\ || Cov(X, X)| - Cov(Y, Y)| = V[X] - V
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         \pi(\theta|x) \sim B(\alpha + x, \beta - n + x); \hat{\theta}_{L_2Bayes} = \frac{\alpha + x}{\alpha + \beta + n}
\begin{array}{l} 5*0.99 \\ 5*0.99 + 995*0.02 \end{array} = 0.1992; V[X|Y] = E[X - E(X|Y)^2|Y] \\ Pois(3), E[30 - 3X - X^2] = 30 - 3EX - EX^2 = 9; \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    \lim_{i\to\infty} \frac{CRLB}{Var(\hat{\theta})}; U(a,b), m_n \approx N(M, \frac{1}{4nf^2(M)}), V[\bar{X}] = \frac{(b-a)^2}{12n},
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 7.3.1 MSE 

MSE = E[(T - \theta)^2] = V[S_k^2] + Bias^2 = \left[\frac{2(n-1)}{k^2} + (\frac{n-1}{k} - 1)^2\right]\sigma^4;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          V[m_n] = \frac{(b-a)^2}{4n}; \text{ ARE of } m_n \text{ to } \bar{X} = \lim_{n \to \infty} \frac{V[\bar{X}]}{Var[m_n]} = \frac{1}{3}
U(0,1), E[Y] = E(E[Y|X]) = \alpha + \beta EX^2 = \alpha + \beta/3
 \int f_T(t) = \frac{1}{1.5} e^{-\frac{1}{1.5}t}; 0
                                                                                                                                                                                                                                                                                                                                                                                                          \begin{aligned} & Cov(X,Y) - \frac{Cov(X,Y) - v_{1}}{\sqrt{Var(X)Var(Y)}}, \rho_{XY} \frac{v_{1}^{2}}{\sqrt{v_{1}^{2}VY}}, \frac{1/3 - (7/12)^{2}}{11/144}, -\frac{1}{11} \\ & Cov[\bar{X},X_{n}] = \frac{Cov[\sum_{X}^{N},X_{n}]}{1} = \frac{\sigma^{2}}{11/144}, cov[\sum_{X}^{N},X_{n}] = \frac{\sigma^{2}}{\sigma\sigma^{2}/n} = \frac{1}{\sqrt{n}} \end{aligned}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     S_{k}^{2} = \frac{\sum (X_{i} - \bar{X})^{2}}{k}; \frac{\partial MSE}{\partial k} \stackrel{set}{=} 0, S_{n+1}^{2} \min_{v \in \{1,2,\dots,n\}} (MSE)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  Asym effi of MLE: \sqrt{n}[\tau(\hat{\theta}_{MLE}) - \tau(\theta)] \stackrel{D}{\rightarrow} N(0, \frac{1}{I_0})
   P(V = 5) = P(t < 3) = \int_0^3 dt = 1 - e^{-2}
                                                                                                                                                                                                                                                                                        5 < v < 6
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            Robust if l'(\theta) = \sum \psi(x_l - \theta), W(x_l - \theta), \frac{\psi(x_l - \theta)}{x - \theta} bounded; n(\psi(x_l - \theta) = \frac{1}{\sigma^2} \times ; DE = \frac{sgn(x - \theta)}{x - \theta} \checkmark ; Cau = \frac{2}{1 + (x - \theta)^2} \checkmark Breakdown corrupt 1 (m) value in order to corrupt Mean(Median) Absolute Deviation \sum_{i=1}^{n} \frac{1}{|X_i - X|}, finite breakdown point is \frac{1}{n} (\frac{m}{n}) **Classical**
\begin{cases} P(V \le v) = P(2T < v) = \int_0^{v/2} dt = 1 - e^{-\frac{v}{3}} & 6 \le v \\ \frac{2}{9}(x+1), -1 \le x \le 2, Y = x^2; P(Y \le y) = P(X^2 \le y) = \frac{v}{9} \end{cases}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               \begin{array}{c} k S_{k+1}^2 = (n-1)S_k^2 + \frac{k}{k+1}(X_{k+1} - \bar{X}_k)^2 \\ 7.3.2 \text{ CRLB} \\ Var_0 W(\vec{X}) > \frac{(\frac{d}{d\theta} E_\theta W(\vec{X}))^2}{(\frac{d}{d\theta} E_\theta W(\vec{X}))^2} = [\underline{\tau} \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                          4.7 Inequity;Chebyshev;Cauchy-Schwarz;Jensen_
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               Var_{\theta}W(\vec{X}) \ge \frac{\left(\frac{d}{d\theta}E_{\theta}W(\vec{X})\right)^{2}}{nE_{\theta}\left[\left(\frac{\partial}{\partial\theta}\ln f(X|\theta)\right)^{2}\right]} = \frac{\left[\tau'(\theta)\right]^{2}}{nI_{\theta}}J_{\theta}(\theta) = E[W]
                                                                                                                                                                                                                                                                                                                                                                                                            g(x) \ge 0 \forall r > 0, P(g(X) \ge r) \le \frac{Eg(X)}{r}; P(|x - \mu| < t\sigma) \ge 1 - r
\begin{cases} P(1 \le X \le \sqrt{y}) = \int_{1}^{\sqrt{y}} f(x) dx = \frac{y}{y} + \frac{2\sqrt{y}}{9} - \frac{1}{3} & x \ge 1 \end{cases}
                                                                                                                                                                                                                                                                                                                                                                                                                r = 3, t = 2; P(-4 < x < 8) \ge \frac{3}{4}; \sigma = 2, t = \frac{5}{2}, P(-2 < x < 8) = \frac{1}{2}
\begin{cases} P(-\sqrt{y} \le X \le \sqrt{y}) = \int_{-\sqrt{y}}^{\sqrt{y}} f(x) dx = \frac{4\sqrt{y}}{9} \end{cases}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   *Expo(\theta),median0.5 = \int_0^{\hat{x}} f()dx, \tilde{x} = \frac{\ln 2}{\theta};
                                                                                                                                                                                                                                                                                                                                                                                                      \begin{aligned} &r = s, t = z; P(-4 < x < 8) \ge \frac{\pi}{4}; v = 2, t = \frac{\pi}{2}, P(-2 < x < 8) \\ &U(a,b), o^2 = \frac{(b-a)^2}{12}, P(|x-\mu| < 1.5\sigma) = P(+) - P(-) = \\ &\frac{\mu + 1.5\sigma}{b - a} - \frac{\mu - 1.5\sigma}{b - a} = \frac{3\sigma}{b - a} = 0.866 \ge 0.555 \text{ Che conservative} \\ &|EXY| \le E|XY| \le (E|X|^2) \cdot \frac{\pi}{2} (E|Y|^2) \cdot \frac{1}{2}; Cov(X, Y) \le \sigma_X^2 \sigma_Y^2; \end{aligned}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    *Classical** f(x;\theta) = (\theta+1)x^{\theta}, 0 < x < 1, B(\theta+1,1); H_0: \theta = 0.5, H_1: \theta > 0.5
f_{Y}(y) = \begin{cases} \frac{1}{9} + \frac{1}{9\sqrt{y}} & 1 \le y \le 4\\ \frac{2}{9\sqrt{y}} & 0 \le y \le 1 \end{cases}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   90^{th} \int_0^{g(\theta)} dx = 0.9; g(\theta) = \frac{\ln 10}{\theta}, VX_{(90)} \ge \frac{g'(\theta)^2}{n l_{\theta}} = \frac{(\ln 10)^2}{n \theta^2}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        mom = \frac{2\bar{X} - 1}{1 - X}; \hat{\theta}_{mle} = \frac{n}{-\sum \ln x_i} - 1; \hat{\theta}_{tt} = \frac{n - 1}{-\sum \ln x_i} - 1;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       X(\mu, \sigma^2), \frac{X_{(95)} - \mu}{\sigma} = Z_{(95)} = 1.645; X_{(95)} = \mu + 1.645\sigma;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              \begin{array}{ll} 1-X & mue & -\sum \ln x_i - 1; \theta u = \frac{n-1}{2} \ln x_i \\ \text{CRLB} & \frac{(\theta+1)^2}{n}; \sqrt{n}(\hat{\theta}-\theta) \sim N(0,(\theta+1)^2) \\ A = \frac{L(\theta_0)}{L(\theta_1)} = e^{(\theta_1-0.5)(-\sum \ln x_i)} \leq C \nearrow \text{MLR, T suff} \\ \ln x \sim E^{-\frac{n}{2}(\theta_1-x_1)} = e^{(\theta_1-\theta_2)(\theta_1-x_1)} = C \nearrow \text{MLR, T suff} \end{array}
2.3 Moment_
                                                                                                                                                                                                                                                                                                                                                                                                        Convex function Eg(X) \ge g(EX)

5.4 Order.

X(k) = k{n \choose k} f(x) [F(x)]^{k-1} [1 - F(x)]^{n-k};
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               \sum_{i} \frac{\sum (X_{(95)} - \mu)^2}{n} = 1.645^2 \sigma^2 = g(\sigma^2); g'(\sigma^2) = 1.645^2
M_X(t) = E[e^{tX}]; M_{\bar{X}}(t) = [M_X(\frac{t}{n})]^n; M_X^{(n)}(0) = EX^n
\begin{aligned} & \underset{E[e^{tX}(1)]}{\text{Expo}(1)} = \int_{0}^{\infty} e^{tx} (ne^{-nx}) dx &= \frac{n}{n-t} \int_{0}^{\infty} (n-t)e^{-(n-t)x} dx \\ & E[e^{tX}(1)] = \int_{0}^{\infty} e^{tx} (ne^{-nx}) dx &= \frac{n}{n-t} \int_{0}^{\infty} (n-t)e^{-(n-t)x} dx \\ & X = e^{Z} \sim LN(0,1); (e^{n\mu + n^{2}\sigma^{2}/2}) \underbrace{M_{Z}(t)}_{1} = e^{\frac{1}{2}t^{2}}; \\ & 1 & 2 & 1 & 9 \end{aligned}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         /[\hat{\sigma}_{(05)}^2] \ge \frac{2(1.645\sigma)^4}{n} > \frac{2\sigma^4}{n}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          \ln x \sim Exp(\theta+1), -2(\theta+1) \sum \ln x \sim \Gamma(n,2), \chi^{2}_{2n}, n = 10
                                                                                                                                                                                                                                                                                                                                                                                                        X_{(1)} = nf(x)[1 - F(x)]^{n-1}; F = 1 - [1 - F(x)]^n;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  P_{H_0}(-3\sum \ln x_i \le \chi^2_{20,0.95}(10.851)) = 0.05
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   X_{(n)} = nf(x)[F(x)]^{n-1}; F = [F(x)]^n; f(1,..,n) = n! \prod f(x_i)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          \begin{array}{l} P_0 \\ P_{H_1 = 1} (-4 \sum \ln x_i \le \frac{4}{3} + 1.0851) = 1 - 0.806 \\ f'(x; \theta) = \theta(x + 1)^{-\theta - 1} \cdot x > 0, \theta > 2; \text{Let } y = \ln(x + 1), x = e^y - 1, \\ \frac{dx}{dy} = e^y, Y = \theta e^{-\theta y} \sim \text{Exp}(\theta), \Gamma(1, \frac{1}{\theta}); \end{array}
\begin{split} E[X^n] &= E[(e^Z)^n] = M_Z(n) = e^{\frac{1}{2}n^2}; E[X^{1/2,3}] = e^{\frac{1}{2}}, e^2, e^{\frac{9}{2}} \\ \text{skewness } E\frac{X-p^3}{\sigma^3} = (e+2)\sqrt{e-1} \end{split}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 If Suffi for \theta, EW = \tau(\theta), \phi(T) = E[W|T], then E\phi(V_{\phi}\phi(T) \leq V_{\phi}W. If Comply/Suffi for \theta, E\phi(T) = \tau(\theta), \phi(T) is UMVUE of \tau Pois(\lambda > 0), T = \sum x_1 \sim Pois(n\lambda) Comply/Suffi; E[\frac{T}{n}] = \lambda; E[T^2 - T] = VT + ET^2 - ET = n^2\lambda^2; \delta(x_1) = \begin{cases} 1 & X_1 = 0, 1, k \\ 0 & X_1 \neq 0, 1, k \end{cases}, \sum_{i=2}^{n} x_i \sim Pois((n-1)\lambda)
                                                                                                                                                                                                                                                                                                                                                                                                            \frac{n!f(u)f(v)}{(i-1)!(j-1-i)!(n-j)!}[F(u)]^{i-1}[F(v)-F(u)]^{j-1-i}[1-F(v)]^{n-j}
                                                                                                                                                                                                                                                                                                                                                                                                      |(u-1)!(J-1-1)!(n-J)!| < |(J-1)!(N-J)| < |(J
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              \frac{\overline{dy}}{\theta u} \frac{n-1}{\sum \ln(x+1)} \mathcal{N} \theta u \frac{\theta^2}{n-2} \mathcal{C} RLB \frac{\theta^2}{n} \lim_{n \to \infty} \frac{CRLB}{\mathcal{N} \theta u} = \lim_{n \to \infty} \frac{n-2}{n} = 1
\frac{e^{t}}{4-3e^{t}} \sim Geom(\frac{1}{4}); EX = \frac{1}{p} = 4; VarX = \frac{1-p}{p^{2}} = 12; \frac{\sigma}{\mu} = \frac{\sqrt{3}}{2}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            \begin{array}{ll} \sum_{\substack{n \in \mathcal{N} \\ |n| \\ 
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       E(\delta|t) = \frac{P(x_i = 0, 1, k' = t = t = t = t, t = 1, t = t)}{P(x_i = 0, 1, k) P(\sum_{i=1}^{n} x_i = t, t = 1, t = k)} \sim Bino(t, \frac{1}{n})
= (\frac{n-1}{n})^t, \frac{t(n-1)^{t-1}}{n^t}, \frac{t!}{k!(n-k)!}, \frac{(n-1)^{t-k}}{n^t}
*2B2W,pick,replace opposite, p=0, x=1,3,5;p=\frac{1}{4},x=2,4,6
                                                                                                                                                                                                                                                                                                                                                                                                              P(n(1-Y_n) < y) = 1 - P(Y_n < 1 - \frac{y}{n}) = 1 - \int_0^{1 - \frac{y}{n}} Y_n dy_n
X=all same color,Y=\frac{X}{2} \sim Geo(\frac{1}{4}); EX,2\frac{1}{p} = 8; VX,4\frac{1-p}{n^2} = 48
                                                                                                                                                                                                                                                                                                                                                                                                      P(nY_1 < y) = P(Y_1 < \frac{y}{n}) = \int_0^{\frac{y}{n}} Y_1 dy_1 = 1 - (1 - \frac{y}{n})^n;
*cpq^{x-1},x=a,a+1, F=c[\sum_{1}^{\infty}pq^{x-1} - \sum_{1}^{a-1}pq^{x-1}]^{p} = c[1-(1-c)]^{a}
                                                                                                                                                                                                                                                                                                                                                                                                        Or transf W_1 = ny_1 f(w) = f(\frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - y_n), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n})^{n-1} \frac{1}{n};
W_n = n(1 - \frac{w}{n}), f(w_n) = f(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(1 - \frac{w}{n}) |\frac{dy}{dw}| = n(
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           \lim_{n \to \infty} \frac{n!}{(n-k)!} \frac{n!}{n!}
\lim_{n \to \infty} (n, p), Y \operatorname{Compl/Suffi} E\left[\frac{Y}{n}\right] = p; E\left[\frac{Y^2 - Y}{n^2 - n}\right] = p^2
q^{a-1}]=1; X+1-a=Y~ Geo(p), EX=EY+a-1=\frac{1}{p}+a-1, VX=VY=\frac{1-p}{n^2}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 E[\frac{\gamma(n-Y)}{\eta(n-1)}] = pq; E[\frac{\gamma(n-Y)}{(\gamma-k)!(k-Y)!k!(n-k)!}] = \binom{n}{k}p^k(1-p)^{n-k} B Hypo test, Neyman-Pearson, M.R.; Karlin-Rubin Size\alpha_I = P_{H_0}(RR) Power = 1 - \beta_{II} = P_{H_1}(RR); Z_1 = \beta = -Z_\beta
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            EX = \int_0^{\theta x} f_X = \frac{1}{\theta - 1}, \int_1^{\infty} f_X = 1 + \frac{1}{\theta - 1} = \mu;
\theta_{mom} = 1 + \frac{1}{X}, 1 + \frac{1}{X - 1} = g(\bar{x});
           oins,toss even head p = \frac{1}{2}; X \ 2^{nd} success \sim NB(2, \frac{1}{2}); EX = VX = 4
                                                                                                                                                                                                                                                                                                                                                                                                      U(0,\theta): X_{(n)} = \frac{n}{\theta} \left(\frac{x}{\theta}\right)^{n-1} \sim Beta(n,1); V[X_n] = \frac{n\theta^2}{(n+1)^2(n+2)}
Pois Pois(\mu);x=1 uniq-mode; \frac{p_m}{p_{m-1}}, \frac{p_m}{p_{m+1}} \ge 1,x \in [\mu-1,\mu],\mu \in (1,2)
*Time:\Gamma(\alpha,\beta),Vist:Pois(\lambda = \frac{1}{\beta}),P(T > t) = P(X \le \alpha - 1)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                VX = \frac{\theta}{(\theta - 1)^2 (\theta - 2)} = \sigma^2; \sqrt{n} [\bar{x} - \mu] \stackrel{D}{\to} N(0, \sigma^2)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       H_0: \theta = \theta_0, H_1: \theta = \theta_1, \theta_0 < \theta_1, \operatorname{RR} \Lambda = \frac{\sup L(\theta_0)}{\sup L(\theta_1)} < \operatorname{C is MP}
                                                                                                                                                                                                                                                                                                                                                                                                              \mathrm{EX}_{(n)} = \frac{n\theta}{n+1}, E[\frac{n+1}{n}X_{(n)}] = \theta; E[\frac{n+2}{n}X_{(n)}^2] = \theta^2 is UMVUE
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 g(\mu) = 1 + \frac{1}{\mu} \cdot 1 + \frac{1}{\mu - 1} = \theta; g'(\mu) = \frac{-1}{\mu^2} \cdot \frac{-1}{(\mu - 1)^2} = -(\theta - 1)^2 \neq 0
C_i \sqrt{n} [\hat{\theta}_{mom} - \theta - \frac{\theta(\theta - 1)}{\theta(\theta - 2)}] \xrightarrow{D} N(0, \frac{\theta(\theta - 1)^2}{(\theta - 2)})
                                                                                                                                                                                                                                                                                                                                                                                                        \begin{cases} (n) & n+1 \cdot \kappa(-\frac{1}{n} - \kappa(n)) = \theta; E\lfloor \frac{n+\epsilon}{n} \times \frac{\kappa}{n} \rfloor = \theta^2 \text{is UMVUE} \\ frm & = \frac{n(n-1)\rho^{n-2}}{\theta^{n}} \cdot r \in (0,\theta), m \in (\frac{r}{2},\theta - \frac{r}{2}); \\ f_R & = \int_{\frac{r}{2}}^{\theta - \frac{r}{2}} \frac{dn}{\theta} = \frac{n(n-1)r^{n-2}(\theta - r)}{\theta^n}, r \in (0,\theta); \theta = 1, Beta(n-1,2); \end{cases}
10(\alpha) visits longer than 8(t) min, 1.5vist/min(\beta) =0.2424
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       Expo family g(t|\theta) = h(t)c(\theta)e^{W(\theta)t} T has MLR.
free of \theta is Suffi, \Lambda = \frac{L(\theta_0)}{L(\theta_1)} has \nearrow MLR in T,T \le C \Lambda
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                \begin{array}{ll} \hat{\theta}_{mom} = \frac{\bar{x}}{\bar{x}-1} \approx \frac{\mu}{\mu-1} + \frac{1}{(\mu-1)^2} (\hat{x} - \mu) + \frac{1}{(\mu-1)^3} (\bar{x} - \mu)^2 \\ E[\hat{\theta}_{mom}] \approx \frac{\mu}{\mu-1} + 0 + \frac{1}{(\mu-1)^3} \frac{\sigma^2}{n^2} = \theta + \frac{\theta(\theta-1)}{n(\theta-2)} \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   P_{H_0}(RR) = \alpha \text{ is UMP; } -2\ln\Lambda \xrightarrow{D} \chi_1^2
 \sum_{i=1}^{N} \frac{(w_1, p_i), \alpha_i}{(w_1, p_i), \alpha_i} = \frac{(w_1, p_i), \alpha_i}{(w_1, q_i), \mu_i} \frac{(w_1, q_i);}{(w_1, q_i), \mu_i} \frac{(w_
                                                                                                                                                                                                                                                                                                                                                                                                                                           \int_{0}^{2m} dr = \frac{n(2m)^{n-1}}{\theta^{n}}, m \in (0, \frac{\theta}{2}); V[R] = \frac{1}{\lambda^{2}} \sum_{k=1}^{n-1} \frac{1}{k};
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         Beta(\theta,\theta), H_0: \theta = 1, H_1: \theta = 2 \text{ One Obs } X_1 < \frac{2}{3}
                                                                                                                                                                                                                                                                                                                                                                                                        \begin{split} & f m = f_0 \quad ar = \frac{1}{\theta^n} \quad m \in (0, \frac{\tau}{2}); \forall |\mathbf{K}| = \frac{1}{\lambda^2} \sum_{k=1}^{\tau} \frac{1}{k}; \\ & f m = f_0^{2(\theta-m)} dr = \frac{n[2(\theta-m)]^{n-1}}{\theta^n}, m \in (\frac{\theta}{2}, \theta); \mathbf{E}[\mathbf{R}] = \frac{1}{\lambda} \sum_{k=1}^{r-1} \frac{1}{k}; \\ & Exp(\lambda): X_{(1)} = n\lambda e^{-n\lambda X} \sim Exp(n\lambda); F = 1 - e^{-n\lambda X}; \\ & X_{(n)} = n\lambda e^{-\lambda X} (1 - e^{-\lambda X})^{n-1}; F = (1 - e^{-\lambda X})^n \\ & 5.5 \text{ Convergence; CLT; Slutsky} & \mathcal{P} \end{split}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              V[\hat{\theta}_{mom}] \approx V[\frac{\mu}{\mu - 1} + \frac{1}{(\mu - 1)^2}(\bar{x} - \mu)] = \frac{\theta(\theta - 1)^2}{n(\theta - 2)}
f(x, y) = 6(y - x), 0 < x < y < 1, Z = \frac{X + Y}{2}, W = Y; z < w < 2z;
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             = P_{\theta_0}(x_1 < \frac{2}{3}) = \int_0^{\frac{2}{3}} f(x|\theta_0) = \frac{2}{3}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         PowerP_{\theta_1}(x_1 < \frac{2}{3}) = 1 - \int_0^{\frac{2}{3}} f(x|\theta_1) = \frac{20}{27}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 \begin{split} & \text{Power}(\theta_1 \mid x_1 < \frac{\epsilon}{3}) = 1 - \int_0^3 f(x|\theta_1) = \frac{\epsilon y_1}{2} \\ & \times m \sim Expo(\frac{1}{\theta_1}) \times m \sim Expo(\frac{1}{\theta_2}) H_0 \cdot \theta_1 = \theta_2, H_1 \cdot \theta_1 \neq \theta_2; \\ & \frac{\theta_{MLE}}{\theta_1 + \sum_{i} + \sum_{j} t_i} \theta_1 = \sum_{i} \frac{x_i}{\theta_1} \cdot \xi_2 = \frac{\sum_{j} t_j}{\theta_1} \\ & T = \sum_{x_j + \sum_{j} t_j} \frac{\Gamma(m_j \theta_1) + \Gamma(n_j \theta_2)}{\Gamma(m_j \theta_1) + \Gamma(n_j \theta_2)} \text{ suff} \\ & \Delta = \frac{(m_j + t_j) m_j m_j}{m_j m_j m_j} T(1 - T)^{T_1} \propto B(m_j + 1, n_j + 1), F \leq C' \\ & \times N(\mu_j + 2S), H_0 \cdot \mu_j = 50, H_1 \cdot \mu_j = 55; Z_{0.05} = 1.645; Z_{0.11} = 1.28; \\ & P_{H_0}(X_0 \geq c) = 0.05; \frac{\sqrt{n}(X_n - 50)}{\sqrt{n}(X_n - 50)} \geq \frac{\sqrt{n}(c - 50)}{\sqrt{n}(c - 50)} = Z_{\alpha} = 1.645; \\ & R_{\alpha} \cdot (X_0 = x_j) = \frac{\sqrt{n}}{2} \left( \frac{\sqrt{n}}{2} (X_0 - 55) \right) \cdot \sqrt{n}(c - 55) \end{split}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |J| = 2,g(z,w) = 24(w-z),g(z) = \int_{z}^{2z} g(z,w)dw = 12z^{2}, 0 < z < \frac{1}{2}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                f_Z(z) = \int_z^1 g(z, w) dw = 12(z - 1)^2, \frac{1}{2} < z < 1
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          \begin{split} & y_{Z_1(z)} = \int_{\mathcal{Z}} g(z, w) dw = 12(z-1)^2, \frac{1}{2} < z < 1 \\ & f(x, y) = c(x + 2y), y \in (0, 1), x \in (0, 2), x = \frac{1}{4}, f\chi = \frac{1}{4}(x + 1), 0, o.w. \\ & f(y, y \leq 0, x \leq 0), 0, y \leq 0, 0, 0, x \in (0, 2), x \in (0, 1), x \in (0, 2) \\ & f_0^2 \int_0^y \int_0^y dy dx = \frac{x^2y}{8} + \frac{xy^2}{4} \quad y \in (0, 1), x \in (0, 2) \\ & f_0^2 \int_0^y dy dx = \frac{y^2}{2} + \frac{y}{2} \quad y \in (0, 1), 2 \leq x \\ & f_0^3 \int_0^1 dy dx = \frac{x^2}{8} + \frac{x}{4} \quad 1 \leq y, x \in (0, 2) \\ & Z = \frac{9}{9} \int_0^y dy dx = \frac{y^2}{8} z^{-2}, z \in (1, 9), 0, o.w. \end{split}
Gamma \begin{split} X_{\Gamma} &\sim \Gamma(n\alpha,\frac{\beta}{n}) : \chi_{V}^{2} \sim \Gamma(\frac{\nu}{2},2) \\ \text{Beta} &\qquad \qquad B(\alpha,\beta) : B(\alpha+\beta,\gamma), \ U = XY \sim B(\alpha,\beta+\gamma) \\ X_{\Gamma} &\sim B(\alpha,\beta) : B(\alpha+\beta,\gamma), \ U = XY \sim B(\alpha,\beta+\gamma) \\ X_{\Gamma} &\sim B(\alpha,\beta) : B(\alpha,\beta+\gamma) = B(\alpha,\beta+\gamma) \\ X_{\Gamma} &\sim B(\alpha,\beta) : B(\alpha,\beta+\gamma) = B(\alpha,\beta+\gamma) = B(\alpha,\beta+\gamma) \end{split}
                                                                                                                                                                                                                                                                                                                                                                                                          X_n \stackrel{a.s.}{\to} X_r P(\lim_{n \to \infty} |X_n - X| < \epsilon) = 1; \stackrel{\mathcal{P}}{\to} \lim_{n \to \infty} P(|X_n - X| < \epsilon) = 1
                                                                                                                                                                                                                                                                                                                                                                                                          X_{n} \xrightarrow{\mathcal{D}} X_{1} \lim_{n \to \infty} F_{X_{n}}(x) = F_{X}(x); \frac{\sqrt{n}(X_{n} - \mu)}{\sigma} \xrightarrow{\mathcal{D}} N(0, 1);
X_{n} \xrightarrow{\mathcal{D}} X_{1}, Y_{n} \xrightarrow{\mathcal{P}} a_{1}X_{n}Y_{n} \xrightarrow{\mathcal{D}} a_{2}X_{n} + Y_{n} \xrightarrow{\mathcal{D}} X + a_{n}
                                                                                                                                                                                                                                                                                                                                                                                                        Delta Method: if \sqrt{n}(Y_n - \theta) \stackrel{D}{\rightarrow} N(0, \sigma^2),
VX = E[Var(X|P)] + Var[E(X|P)] = E[npq] + Var[np] = \frac{n\alpha\beta(\alpha+\beta+n)}{(\alpha+\beta+1)^2(\alpha+\beta+1)}
                                                                                                                                                                                                                                                                                                                                                                                                        g'(\theta) = 0, \sqrt{n}[g(Y_n) - g(\theta)] \stackrel{\mathcal{J}}{\rightarrow} N(0, \sigma^2[g'(\theta)]^2)
g'(\theta) = 0, \stackrel{\mathcal{J}}{\rightarrow} \sigma^2 \frac{g''(\theta)}{2} \chi_1^2)
\begin{array}{ll} P \sim B(\frac{1}{2},\frac{1}{2}), EX = \frac{n}{2}; VX = \frac{n(n+1)}{8}; \\ P \sim B(1,1), X \sim U(0,n+1), P|X \sim B(x+1,n-x+1) \\ \text{Pois-Bino.} \\ Pois(\lambda).S_{10} = \sum_{i=1}^{10} X_i \sim Pois(10\lambda). \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   P_{H_1}(\bar{X}_n \ge c) = 0.90; \frac{\sqrt{n}(\bar{X}_n - 55)}{5} \ge \frac{\sqrt{n}(c - 55)}{5} = -Z_\beta = -1.28
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      f(y_1, y_2) = c(1 - y_2), 0 \le y1 \le y2 \le 1; \int_0^1 \int_0^{y_2} dy_1 dy_2 = 1, c = 6; (y_1) = \int_{y_1}^1 dy_2 = 3(y_1 - 1)^2; f(y_2) = \int_0^{y_2} dy_1 = 6(y_2 - y_2^2)
                                                                                                                                                                                                                                                                                                                                                                                                      \begin{array}{l} g(x) = g(x_0) + g'(x_0)(x - x_0) + g''(x_0)\frac{(x - x_0)^2}{2} + R \\ \text{Stein } n(\theta, \sigma^2) \text{,} E[g(X)(X - \theta)] = \sigma^2 E[g'(X)]; \dots \dots \\ g(\mu) = \frac{1}{\mu} \text{,} E\mu(\frac{1}{X}) \approx \frac{1}{\mu} \text{,} Var_{\mu}(\frac{1}{X}) \approx (\frac{1}{\mu})^4 Var_{\mu}(X) \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         \mu = \left[ \frac{(Z_{\alpha} + Z_{\beta})\sigma}{\delta = \mu_1 - \mu_0} \right]^2 = \left[ \frac{(1.645 + 1.28)5}{55 - 50} \right]^2 = 8.56 \approx 9, c = 52.74 \, 87
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   M_{S_{10}}(t) = \prod_{i=1}^{10} M_X(t) = [e^{\lambda(e^t - 1)}]^{10} = e^{10\lambda(e^t - 1)}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  \begin{array}{ll} S_{10} = S = S_4 + S_6, P(S_4|S_{10}) = \frac{P(S_4, S_6 = S - S_{10})}{P(S_{10})} \sim Bino(s, \frac{2}{5}) \\ Pois(\lambda), Pois(3\lambda) P(x|x + y = 5) = \frac{P(x)P(y = 5 - x)}{P(x + y = 5)} \sim Bino(5, \frac{3}{3}); \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              T = \sum (x - 120)^2 \text{ suff};
                                                                                                                                                                                                                                                                                                                                                                                                            \sqrt{n}(\frac{1}{X} - \frac{1}{\mu}) \stackrel{D}{\rightarrow} N(0, (\frac{1}{\mu})^4 Var_{\mu}[X_1])
                                                                                                                                                                                                                                                                                                                                                                                                      \left| \widehat{Var} \left[ \frac{1}{X} \right] \approx \left( \frac{1}{X} \right)^4 S^2, \frac{\sqrt{n} \left( \frac{1}{X} - \frac{1}{\mu} \right)}{(1/X)^2 S} \stackrel{D}{\to} N(0, 1) \right|
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       \hat{X} = 6.7, n = 18, \sigma = 2, \frac{\hat{x} - \mu_0}{\sigma / \sqrt{n}} = 1.48 < 1.645
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              \begin{array}{l} \ddot{X} = 6.7, n = 18, \sigma = \mathcal{L}, \frac{\delta \sqrt{n}}{\sigma / \sqrt{n}} - \frac{\delta \sqrt{n}}{N}) = P(Z > 1.53) = 0.937 \\ \text{of } \mu_1 = 7.5, \text{Power-} P(Z > Z_{\alpha} - \frac{\delta \sqrt{n}}{N}) = P(Z > 1.53) = 0.937 \\ \text{*} N(\theta, 1), N(3\theta, 1); H_0 : \theta \leq 0, H_1 : \theta > 0; \text{Ti} \ddot{X} + 3\ddot{Y} - n(10\theta, \frac{10}{m}), \Lambda > 0 \\ \text{*} D = 0, N_1 : \rho - \frac{1}{N} \cdot \frac{1}{N} \cdot
Uniform.

F \sim U(0,1), B(1,1); -\ln F, -\ln(1-F) \sim Exp(1), \Gamma(1,1);
                                                                                                                                                                                                                                                                                                                                                                                                            \operatorname{Exp}(\lambda), \sqrt{n}(\bar{X}_n - \frac{1}{\lambda}) \xrightarrow{D} N(0, \frac{1}{\lambda^2}), g(u) = u^2, g'(u) = 2u \neq 0
\begin{split} & r \sim u(u, 1), g(1, 1), & -u(r, -u)(r - r) \sim Exp(1), 1(1, 1), \\ & -\lambda \ln U \sim Exp(\lambda), -2 \sum^{u} \ln U \sim \chi_{2v}^{2}, \\ & -\beta \sum^{\alpha} \ln U \sim \Gamma(\alpha, \beta); \; \sum_{q=1}^{u} \frac{\ln U}{\ln U} \\ & u(0, 1), U = Y - X, 0 < x < y < 1, \; g(u, v) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 1, 0 < v < 1 - u, f_{U}(u) = 
                                                                                                                                                                                                                                                                                                                                                                                                            \sqrt{n}(\bar{X}_n^2 - (\frac{1}{\lambda})^2) \to n(0, \frac{4}{\lambda^4})
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   \sqrt{\frac{m}{10}} (\bar{X} + 3\bar{Y} - 10\theta) \stackrel{D}{\to} n(0,1); P_{\theta_0} (\sqrt{\frac{m}{10}} (\bar{X} + 3\bar{Y} - 10\theta_0 > Z_{\alpha}) = P_{\theta_1} (\sqrt{\frac{m}{10}} (\bar{X} + 3\bar{Y} - 10\theta_1 > Z_{\alpha} - (\theta_1 - \theta_0)\sqrt{10m})
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        \begin{array}{l} \sqrt{\gamma_1} = 2 - 2y_1 / f_{Y_2} = 2y_2 \\ E[Y_1 + Y_2] = \int_0^1 y_1 (2 - 2y_1) dy_1 + \int_0^1 y_2 (2y_2) dy_2 = \frac{1}{3} + \frac{2}{3} = 1 \\ P(Y_1 \leq \frac{3}{4} | Y_1 > \frac{1}{3}) = \frac{\int_1^{3/4}}{1 - \int_0^{1/3}} = \frac{55}{64} \\ {}^*f(x;y) = Cxy, 0 \leq x \leq 2, 0 \leq y \leq 2, x + y \leq 2; \\ 0 < x < 2 - y < 2, 0 < y < 2 - x < 2; \int_0^2 \int_0^{2 - x}, c = \frac{3}{2}; \\ f(x) = \int_0^{2 - x} f(x, y) dy = \frac{3}{4} x(x - 2)^2; f(y) \text{same} \\ P(X < Y) = P(X < Y, Y < 1) + P(X < Y, Y > 1) = P(X < Y < 1) + P(X < 2 - Y, 1 < Y < 2) = \int_0^1 \int_0^y dx dy + \int_1^2 \int_0^{2 - y} dx dy = \frac{1}{2} \\ {}^*f_{X} = 3kxe^{-3x^2}; k = 2; m = \sqrt{\frac{\ln 2}{3}}; f'_{X} = 0, \text{mode} = \frac{1}{\sqrt{6}} Y = X^2, f_{Y} = 3e^{-3y} \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                     Pois(\mu),g(\bar{X}n) = e^{-X}n, g(\mu) = e^{-\mu}, g'(\mu) = -e^{-\mu} \neq 0

\sqrt{n}(e^{-X}n - e^{-\mu}) \rightarrow n(0, \frac{[(e^{-\mu}t')^2]^2}{1(\mu)}) = n(0, \mu e^{-2\mu}))
6.2.1 Suffise.2.2 Mini Suffise.3.3 Ancillary Stat
\begin{array}{lll} u(0,1), u=1 & -\lambda, 0 & \lambda & < 1 & < 1, g(u,v) = 1,0 < \\ 1 & -u,0 & < u & < 1; f_{|U|}(u) = 2(1-u), E[|U|] = \frac{1}{3}; \\ U(0,1), U & = Y_1 + Y_2,0 & < u-v < 1, u-1 < v < \\ f_U(u) & = 0; F_U(u) = 0; o.w. \\ \int_0^u = u; \int_0^u = \frac{u^2}{2} & u \in \end{array}
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     Pois(\lambda) H_0: \lambda \leq 1, H_1: \lambda > 1 \Lambda = (\frac{\lambda_0}{\lambda_0}) \sum x_i e^{n(\lambda_1 - \lambda_0)} < C
T = \sum x_i \sim Pois(n\lambda), \Lambda \setminus_{\lambda} \alpha = P_{\theta_0}(T > C) = 0.05
                                                                                                                                                                                                                                                                                                                                                                                                          \frac{\prod f(\mathbf{x}|\theta)}{g(t|\theta)} = h(\vec{\mathbf{x}}) \text{ free of } \theta; \frac{f(\mathbf{x}|\theta)}{f(\mathbf{y}|\theta)} \text{ constant fn of } \theta \text{ if } T(\mathbf{x}) = T(\mathbf{y})
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       = 1 max \Lambda, P_{\theta_0}(T \ge 4) < 0.05 \text{ ifT=3let } 0.019 + \text{p0.061=0.05}, p = \frac{31}{61}
                                                                                                                                                                                                                                                                                                                                                                                                        g_{\mathbf{g}}(\vec{x}) = x_i + a, G = \{g_{\mathbf{g}}(\vec{x}) : a \in \mathbf{R}\} \text{ is a group, is invariant unde oc-paraθ} [Y_n - \vec{Y}]_{(g_{\mathbf{g}}(\vec{x}))} = Y_n + a - \frac{\sum (Y_j + a)}{n} = (Y_n - \vec{Y})_{(\vec{x})}
\int_{\mathbf{N}}^{0} \int_{u-1}^{u-1} = 2 - u; F_{U}(1) + \int_{1}^{u} 2u - \frac{u^{2}}{2} - 1 \quad u \in (1, 2)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       \theta x^{\theta-1} \sim Beta(\theta,1), -\ln x \sim Expo(\theta), -2\theta \sum \ln x \sim \Gamma(n,2), \chi_{2n}^2
                                                                                                                                                                                                                                                                                                                                                                                                      (g_{d}(\overline{x})) - i\eta + u - \frac{1}{n} = (Y_{n} - Y)_{(\overline{x})} Loca-scale famility g(x)\mu, \sigma = \frac{1}{d}f(\frac{x-\mu}{\sigma}), \mulocation-par,\sigmascale-par 6.2.4 Compl Suffi; Basu E[g(t)] = 0. \ \ \forall \lambda \text{ iff } P[g(t) = 0] = 1; f(x|\widetilde{\theta}) = h(x)c(\widetilde{\theta})e^{-\sum_{j=1}^{d}W_{j}(\widetilde{\theta})}f_{j}(x), \text{ t free of } \theta \text{ W open set in } \mathbb{R}^{k}; Expo famility t/n = Y is comp/suff, indep with Y_{n} - Y
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   \begin{aligned} &P_{\theta_1}(X>0.5) = 1 - \int_0^{0.5} \theta x^{\theta-1} dx = 1 - 0.5^{\theta} \\ &H_0: \theta=1, H_1: \theta > 1; \Lambda \nearrow P_{H_0}(-\ln y \le C) = \alpha \end{aligned}
\bar{\mathbf{N}}_{-n}^{\text{cut}} without normality; \bar{\mathbf{E}}[\bar{\mathbf{X}}] = \mu, V[\bar{\mathbf{X}}] = \frac{\sigma^2}{n}, E[S^2] = \sigma^2 without normality; \bar{\mathbf{X}} \sim n(\mu, \frac{\sigma^2}{n}); \bar{\mathbf{X}} \perp S^2; \frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 \begin{array}{l} H_0: \lambda = \frac{1}{2}, H_1: \lambda = 1; P_{H_0}\left(-\sum \ln x \leq \chi^2_{20,0.95}(10.85)\right) = 0.05; \\ P_{H_1}\left(-2\sum \ln x \leq 2*10.85\right) = 0.64; \end{array}
E(Z^{2k}) = \frac{(2k)!}{2^K K!}, k = 1, 2, ...; E(Z^{2k+1}) = 0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       \hat{\lambda}_{mle} \frac{n}{T} ; E \hat{\lambda}_{mle} \frac{n\lambda}{n-1} ; Bias \frac{\lambda}{n-1} ; V \frac{n^2\lambda^2}{(n-1)^2(n-2)} ; MSE \frac{(n+2)\lambda^2}{(n-1)(n-2)} ;
V[S^2] > CRLB > V[S_n^2]; \frac{2\sigma^4}{n-1} \ge \frac{2\sigma^4}{n} > \frac{2(n-1)\sigma^4}{n^2};
```