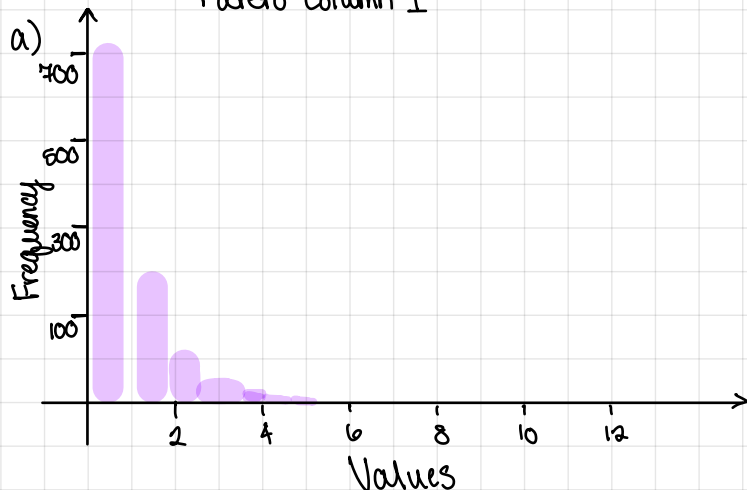


1. Pareto Column 1



b) MLE

$$L(\alpha) = \prod_{i=1}^n \alpha x_i^{-(\alpha+1)} = x_i^{-(\alpha+1)} \xrightarrow{\log} \ell(\alpha) = n \ln \alpha - (\alpha+1) \sum_{i=1}^n \ln x_i$$

$$\begin{aligned} \frac{\partial \ell}{\partial \alpha} &= \frac{n}{\alpha} - \sum_{i=1}^n \ln x_i = 0 \rightarrow \hat{\alpha}_{MLE} = \frac{n}{\sum_{i=1}^n \ln x_i} \\ \sum \ln x_i &= \log \text{sum} = \frac{n}{\hat{\alpha}_{MLE}} = \frac{1000}{2.972494} \approx 336.594 \checkmark \end{aligned}$$

$$\begin{aligned} c) \ln f(x_i) &= \ln \alpha - (\alpha+1) \ln x_i \rightarrow \frac{\partial \ln f}{\partial \alpha} = \frac{1}{\alpha} - \ln x \rightarrow \frac{\partial^2 \ln f}{\partial \alpha^2} = -\frac{1}{\alpha^2} \rightarrow I(\alpha) = \frac{n}{\alpha^2} \xrightarrow{\alpha=1000} \frac{1000}{\alpha^2} \\ &\rightarrow I(2.972494) = \frac{1000}{(2.972494)^2} \approx 113.181 \end{aligned}$$

$$\text{Standard error: } SE(\hat{\alpha}_{MLE}) = \sqrt{\frac{1}{I(\hat{\alpha}_{MLE})}} = \frac{\hat{\alpha}_{MLE}}{\sqrt{n}} = \frac{2.972494}{\sqrt{1000}} \approx 0.09397$$

$$\begin{aligned} CI &= 2.972494 \pm 1.96 \cdot 0.09397 \\ &\rightarrow 2.972494 \pm 0.184182 \\ &\approx (2.788312, 3.156676) \end{aligned}$$

$$d) E[X] = \frac{\alpha}{\alpha-1} \rightarrow \bar{x} = \frac{\hat{\alpha}_{MOM}}{\hat{\alpha}_{MOM}-1} \rightarrow \bar{x} \hat{\alpha}_{MOM} - \hat{\alpha}_{MOM} = \hat{\alpha}_{MOM} \rightarrow \hat{\alpha}_{MOM} = \frac{\bar{x}}{\bar{x}-1}$$

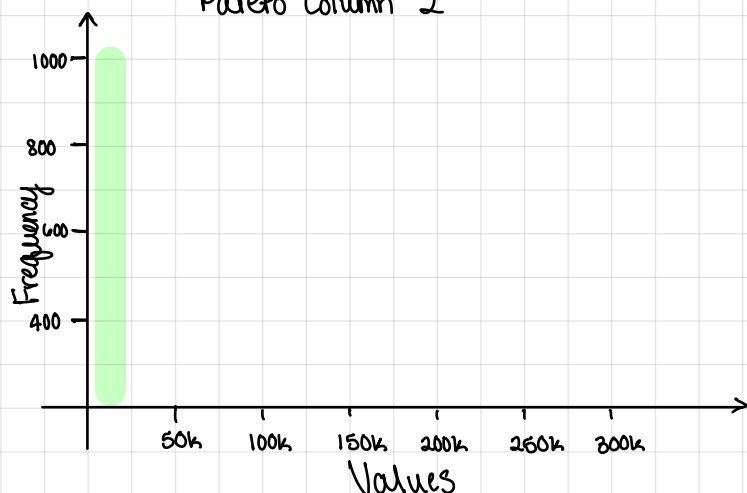
$$\hat{\alpha}_{MOM} = 1.509695 = \frac{\bar{x}}{\bar{x}-1} \rightarrow \bar{x}(1-1.509695) = -1.509695 \approx 1.509695$$

$$e) \hat{\alpha}_{boot} = \frac{\bar{x}^*}{\bar{x}^*-1} \rightarrow CI_{boot} = (\hat{\alpha}_{boot}, 0.025, \hat{\alpha}_{boot}, 0.975) \rightarrow (1.482697, 1.537991)$$

$$f) \alpha = 0.5 \quad Z = \frac{0.4933142 - 0.5}{0.015597} \approx \frac{-0.0066858}{0.015597} \approx -0.4286 \quad p = 2 \cdot P(Z > 0.4286) \approx 2 \cdot 0.3341 = 0.6682$$

$$\begin{aligned} g) \ell(\hat{\alpha}_{MLE}) &= n \ln \hat{\alpha}_{MLE} - (\hat{\alpha}_{MLE}+1) \cdot \frac{n}{\hat{\alpha}_{MLE}} \rightarrow \ln(0.4933142) \approx -0.7067 \\ &\rightarrow \ell(0.5) \approx 1000 \cdot (-0.693147) - 1.5 \cdot 2027.65 \approx -693.147 - 3041.475 \approx -3734.622 \\ LRT &= 2[-3734.35 - (-3734.622)] = 2 \cdot 0.272 \approx 0.544 \quad p = P(\chi^2_2 > 0.544) \approx 0.4607 \end{aligned}$$

2. Pareto Column 2



b) MLE for a

$$\hat{\alpha}_{MLE} = \frac{n}{\sum_{i=1}^n \ln x_i} \rightarrow \frac{1000}{2027.45} = 0.4933$$

c) Fischer Info & 95% CI

$$I(\alpha) = n/\alpha^2 \rightarrow I(0.4933) = \frac{1000}{0.4933^2} \approx 4107.87$$

$$\text{Standard error: } 0.4933/\sqrt{4107.87} \approx 0.00768$$

$$\begin{aligned} CI \ 95\%: \hat{\alpha}_{MLE} \pm 1.96 \cdot SE &\rightarrow 0.4933 \pm 1.96(0.00768) \\ &\rightarrow (0.4782, 0.5084) \end{aligned}$$

d) MOM Estimator

$$\hat{\alpha}_{MOM} = \frac{\bar{x}}{\bar{x}-1} \rightarrow 2.0033/2.0033-1 \approx 1.0017$$

e) Bootstrap  $\rightarrow 1.0007 \neq 1.0070$

f) Wald-test  $\alpha = 0.5$

$$Z = \frac{\hat{\alpha}_{MLE} - 0.5}{SE} \rightarrow \frac{0.4933 - 0.5}{0.00768} \approx -0.8688$$

g) Likelihood Ratio Test  $\alpha = 0.5$

$$\log L(\alpha = 0.5) = 1000 \log(0.5) - 1.5 \cdot \sum \ln x_i$$

$$\log L(\hat{\alpha}) = 1000 \log(0.4933) - 1.4933 \cdot \sum \ln x_i$$

$$2(\log L(\hat{\alpha}) - \log L(0.5)) \approx 0.182$$

$$p = P(\chi^2_1 > 0.182) \approx 0.670$$

3.  $r \sqrt{X} \sim \text{NegBin}(r, p)$   $x_i \dots$

a) MLE of  $p$

$$L(p) = \prod_{i=1}^n \binom{k_i + r - 1}{k_i} (1-p)^{k_i} p^r$$

$$\log L(p) = \sum_{i=1}^n [\log \binom{k_i + r - 1}{k_i} + k_i \log(1-p) + r \log(p)]$$

$$\hookrightarrow \log L(p) = \text{const} + \left( \sum_{i=1}^n k_i \right) \log(1-p) + nr \log(p)$$

When  $S = \sum_{i=1}^n k_i$  then  $\log L(p) = \text{const} + S \log(1-p) + nr \log(p)$

derivative:  $\frac{d}{dp} \log L(p) = -\frac{S}{1-p} + \frac{nr}{p} = 0 \rightarrow -\frac{S}{1-p} + \frac{nr}{p} = 0 \rightarrow \frac{nr}{p} = \frac{S}{1-p}$

$$nr(1-p) = Sp \rightarrow nr - nrp = Sp \rightarrow nr = p(nr + S) \rightarrow \hat{p} = \frac{nr}{nr + \sum k_i}$$

$$\hat{p} = \frac{r}{r+k}$$

b)

$$\log L(p) = \text{const} + S \log(1-p) + nr \log(p)$$

$$\hookrightarrow \frac{d^2}{dp^2} \log L(p) = -\frac{S}{(1-p)^2} - \frac{nr}{p^2}$$

Fischer info is neg of 2nd der.

$$I(p) = E\left[-\frac{d^2}{dp^2} \log L(p)\right] \rightarrow E[S] = \sum E[X_i] = n \cdot \frac{r(1-p)}{p}$$

$$\hookrightarrow I(p) = \frac{nr(1-p)}{p^2} + \frac{nr}{p^2} = \frac{nr}{p^2(1-p)}$$

4. Discrete Uniform(1, k)

a) MOM Estimator

$$E[X] = (k+1)/2 \quad \bar{x} = (k+1)/2 \rightarrow k = 2\bar{x} - 1 \quad \hat{k}_{MOM} = 2\bar{x} - 1$$

b)  $L(k) = (1/k)^n$  for  $k \geq \max(x_i \dots)$

based on the PMF and likelihood function is a decreasing fun of  $k$ , meaning likelihood gets smaller as  $k$  gets larger

if  $k < \max$  observed value then likelihood = 0

if  $k > \max$  then likelihood exists but is smaller than necessary... max likelihood occurs @ smallest possible value of  $k$  that still makes an observed values possible  $\rightarrow \hat{k}_{MLE} = \max(x_i \dots)$