

p.m.f. or p.d.f. $f(x; \theta)$, $\theta \in \Omega$. Ω – parameter space.

1. Suppose $\Omega = \{1, 2, 3\}$ and the p.m.f. $f(x; \theta)$ is

$$\theta = 1: \quad f(1; 1) = 0.6, \quad f(2; 1) = 0.1, \quad f(3; 1) = 0.1, \quad f(4; 1) = 0.2.$$

$$\theta = 2: \quad f(1; 2) = 0.2, \quad f(2; 2) = 0.3, \quad f(3; 2) = 0.3, \quad f(4; 2) = 0.2.$$

$$\theta = 3: \quad f(1; 3) = 0.3, \quad f(2; 3) = 0.4, \quad f(3; 3) = 0.2, \quad f(4; 3) = 0.1.$$

What is the maximum likelihood estimate of θ (based on only one observation of X) if ...

a) $X = 1$;

$$\begin{array}{l} f(1; 1) = 0.6 \leftarrow \\ f(1; 2) = 0.2 \\ f(1; 3) = 0.3 \end{array} \Rightarrow \hat{\theta} = \mathbf{1}.$$

b) $X = 2$;

$$\begin{array}{l} f(2; 1) = 0.1 \\ f(2; 2) = 0.3 \\ f(2; 3) = 0.4 \leftarrow \end{array} \Rightarrow \hat{\theta} = \mathbf{3}.$$

c) $X = 3$;

$$\begin{array}{l} f(3; 1) = 0.1 \\ f(3; 2) = 0.3 \leftarrow \\ f(3; 3) = 0.2 \end{array} \Rightarrow \hat{\theta} = \mathbf{2}.$$

d) $X = 4$.

$$\begin{array}{l} f(4; 1) = 0.2 \leftarrow \\ f(4; 2) = 0.2 \leftarrow \\ f(4; 3) = 0.1 \end{array} \Rightarrow \hat{\theta} = \mathbf{1 \text{ or } 2}.$$

(maximum likelihood estimate may not be unique)

Likelihood function:

$$L(\theta) = L(\theta; x_1, x_2, \dots, x_n) = \prod_{i=1}^n f(x_i; \theta) = f(x_1; \theta) \cdot \dots \cdot f(x_n; \theta)$$

It is often easier to consider $\ln L(\theta) = \sum_{i=1}^n \ln f(x_i; \theta)$.

Maximum Likelihood Estimator: $\hat{\theta} = \arg \max L(\theta) = \arg \max \ln L(\theta)$.

Method of Moments:

$$E(X) = g(\theta). \quad \text{Set } \bar{X} = g(\tilde{\theta}). \quad \text{Solve for } \tilde{\theta}.$$

0. Consider a single observation X of a Binomial random variable with n trials and probability of “success” p . That is,

$$P(X = k) = {}_n C_k p^k (1-p)^{n-k}, \quad k = 0, 1, \dots, n.$$

a) Obtain the method of moments estimator of p , \tilde{p} .

$$\text{Binomial: } E(X) = np$$

$$X = n\tilde{p} \quad \Rightarrow \quad \tilde{p} = \frac{X}{n}.$$

b) Obtain the maximum likelihood estimator of p , \hat{p} .

$$L(p) = {}_n C_X p^X (1-p)^{n-X}$$

$$\ln L(p) = \ln {}_n C_X + X \ln p + (n-X) \ln (1-p)$$

$$\frac{d}{dp} \ln L(p) = \frac{X}{p} - \frac{n-X}{1-p} = \frac{X - Xp - np + Xp}{p(1-p)} = \frac{X - np}{p(1-p)}$$

$$\frac{d}{dp} \ln L(\hat{p}) = 0 \quad \Rightarrow \quad \hat{p} = \frac{X}{n}.$$

2. Let X_1, X_2, \dots, X_n be a random sample of size n from a Poisson distribution with mean λ , $\lambda > 0$. That is,

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \quad k = 0, 1, 2, 3, \dots$$

- a) Obtain the method of moments estimator of λ , $\tilde{\lambda}$.

$$E(X) = \lambda \quad \Rightarrow \quad \tilde{\lambda} = \bar{X}$$

- b) Obtain the maximum likelihood estimator of λ , $\hat{\lambda}$.

$$L(\lambda) = \prod_{i=1}^n f(X_i; \lambda) = \prod_{i=1}^n \left(\frac{\lambda^{X_i} e^{-\lambda}}{X_i!} \right).$$

$$\ln L(\lambda) = \left(\sum_{i=1}^n X_i \right) \cdot \ln \lambda - n\lambda - \sum_{i=1}^n \ln(X_i!).$$

$$\frac{d \ln L(\lambda)}{d \lambda} = \frac{1}{\lambda} \cdot \left(\sum_{i=1}^n X_i \right) - n = 0. \quad \Rightarrow \quad \hat{\lambda} = \frac{\sum_{i=1}^n X_i}{n} = \bar{X}.$$

Let $\hat{\theta}$ be the maximum likelihood estimate (m.l.e.) of θ . Then the m.l.e. of any function $h(\theta)$ is $h(\hat{\theta})$. (The Invariance Principle)

- c) Obtain the maximum likelihood estimator of $P(X = 2)$.

$$P(X = 2) = h(\lambda) = \frac{\lambda^2 e^{-\lambda}}{2!} \quad \hat{\lambda} = \bar{X} \quad h(\hat{\lambda}) = \frac{\bar{X}^2 e^{-\bar{X}}}{2!}.$$

3. Let X_1, X_2, \dots, X_n be a random sample of size n from a Geometric distribution with probability of “success” p , $0 < p < 1$. That is,

$$P(X = k) = (1 - p)^{k-1} p, \quad k = 1, 2, 3, \dots$$

- a) Obtain the method of moments estimator of p , \tilde{p} .

$$E(X) = 1/p. \quad \bar{X} = 1/\tilde{p} \quad \text{so} \quad \tilde{p} = 1/\bar{X} = n / \sum_{i=1}^n X_i$$

- b) Obtain the maximum likelihood estimator of p , \hat{p} .

$$L(p) = (1 - p)^{\sum_{i=1}^n X_i - n} p^n$$

$$\ln L(p) = \left(\sum_{i=1}^n X_i - n \right) \ln(1 - p) + n \ln p$$

$$\frac{d}{dp} \ln L(p) = \frac{n}{p} - \frac{\sum_{i=1}^n X_i - n}{1 - p} = \frac{n - p \sum_{i=1}^n X_i}{p(1 - p)}$$

$$\frac{d}{dp} \ln L(\hat{p}) = 0 \quad \Rightarrow \quad \hat{p} = n / \sum_{i=1}^n X_i = 1/\bar{X}$$

$\hat{p} = \tilde{p}$ equals the number of successes, n , divided by the number of Bernoulli trials, $\sum_{i=1}^n X_i$;

- c)* Is \hat{p} an unbiased estimator for p ?

Since $g(x) = 1/x$, $x \geq 1$, is strictly convex, and \bar{X} is not a constant random variable, by Jensen's Inequality,

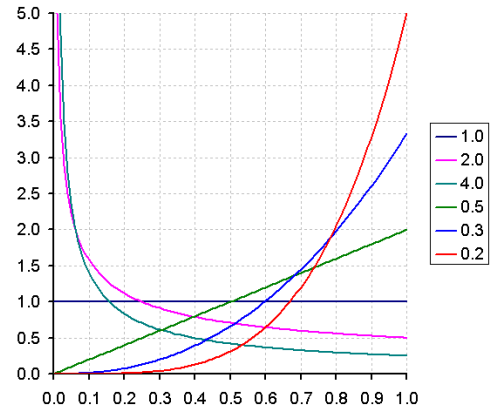
$$E(\hat{p}) = E(g(\bar{X})) > g(E(\bar{X})) = g(1/p) = p.$$

\hat{p} is NOT an unbiased estimator for p .

4. Let X_1, X_2, \dots, X_n be a random sample of size n from the distribution with probability density function

$$f(x; \theta) = \begin{cases} \frac{1}{\theta} \cdot x^{1-\theta/\theta} & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$0 < \theta < \infty.$$



- a) Obtain the method of moments estimator of θ , $\tilde{\theta}$.

$$\begin{aligned} E(X) &= \int_{-\infty}^{\infty} x \cdot f_X(x; \theta) dx = \int_0^1 \left(x \cdot \frac{1}{\theta} \cdot x^{1-\theta/\theta} \right) dx \\ &= \int_0^1 \left(\frac{1}{\theta} \cdot x^{1/\theta} \right) dx = \frac{1}{\theta} \cdot \left(\frac{1}{1/\theta + 1} \cdot x^{1/\theta + 1} \right) \Big|_0^1 = \frac{1}{1+\theta}. \end{aligned}$$

$$\bar{X} = \frac{1}{1+\theta}. \quad \tilde{\theta} = \frac{1}{\bar{X}} - 1 = \frac{1-\bar{X}}{\bar{X}}.$$

- b) Obtain the maximum likelihood estimator of θ , $\hat{\theta}$.

Likelihood function:

$$L(\theta) = \prod_{i=1}^n f_X(X_i; \theta) = \frac{1}{\theta^n} \cdot \left(\prod_{i=1}^n X_i \right)^{1-\theta/\theta}.$$

$$\ln L(\theta) = -n \cdot \ln \theta + \frac{1-\theta}{\theta} \cdot \sum_{i=1}^n \ln X_i = -n \cdot \ln \theta + \left(\frac{1}{\theta} - 1 \right) \cdot \sum_{i=1}^n \ln X_i.$$

$$\frac{d}{d\theta} (\ln L(\hat{\theta})) = -\frac{n}{\hat{\theta}} - \frac{1}{\hat{\theta}^2} \cdot \sum_{i=1}^n \ln X_i = 0. \quad \Rightarrow \quad \hat{\theta} = -\frac{1}{n} \cdot \sum_{i=1}^n \ln X_i.$$

- c) Suppose $n = 3$, and $x_1 = 0.2$, $x_2 = 0.3$, $x_3 = 0.5$. Compute the values of the method of moments estimate and the maximum likelihood estimate for θ .

$$\bar{X} = \frac{0.2+0.3+0.5}{3} = \frac{1}{3}. \quad \tilde{\theta} = \frac{1-\bar{X}}{\bar{X}} = \frac{1-\frac{1}{3}}{\frac{1}{3}} = 2.$$

$$\hat{\theta} = -\frac{1}{n} \cdot \sum_{i=1}^n \ln X_i = -\frac{1}{3} \cdot (\ln 0.2 + \ln 0.3 + \ln 0.5) \approx \mathbf{1.16885}.$$

- 5.** Let X_1, X_2, \dots, X_n be a random sample of size n from $N(\theta_1, \theta_2)$, where $\Omega = \{(\theta_1, \theta_2) : -\infty < \theta_1 < \infty, 0 < \theta_2 < \infty\}$. That is, here we let $\theta_1 = \mu$ and $\theta_2 = \sigma^2$.

- a) Obtain the maximum likelihood estimator of θ_1 , $\hat{\theta}_1$, and of θ_2 , $\hat{\theta}_2$.

$$\begin{aligned} L(\theta_1, \theta_2) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\theta_2}} \exp\left[-\frac{(X_i - \theta_1)^2}{2\theta_2}\right] \\ &= \left(\frac{1}{\sqrt{2\pi\theta_2}}\right)^n \exp\left[-\frac{\sum_{i=1}^n (X_i - \theta_1)^2}{2\theta_2}\right], \quad (\theta_1, \theta_2) \in \Omega. \end{aligned}$$

$$\ln L(\theta_1, \theta_2) = -\frac{n}{2} \ln(2\pi\theta_2) - \frac{\sum_{i=1}^n (X_i - \theta_1)^2}{2\theta_2}.$$

The partial derivatives with respect to θ_1 and θ_2 are

$$\frac{\partial(\ln L)}{\partial \theta_1} = \frac{1}{\theta_2} \sum_{i=1}^n (X_i - \theta_1)$$

and

$$\frac{\partial(\ln L)}{\partial \theta_2} = -\frac{n}{2\theta_2} + \frac{1}{2\theta_2^2} \sum_{i=1}^n (X_i - \theta_1)^2.$$

The equation $\partial(\ln L)/\partial \theta_1 = 0$ has the solution $\theta_1 = \bar{X}$.

Setting $\partial(\ln L)/\partial \theta_2 = 0$ and replacing θ_1 by \bar{X} yields

$$\theta_2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2.$$

Therefore, the maximum likelihood estimators of $\mu = \theta_1$ and $\sigma^2 = \theta_2$ are

$$\hat{\theta}_1 = \bar{X} \quad \text{and} \quad \hat{\theta}_2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2.$$

- b) Obtain the method of moments estimator of θ_1 , $\tilde{\theta}_1$, and of θ_2 , $\tilde{\theta}_2$.

$$E[X] = \mu = \theta_1.$$

$$E[X^2] = \text{Var}[X] + E[X]^2 = \sigma^2 + \mu^2 = \theta_2 + \theta_1^2.$$

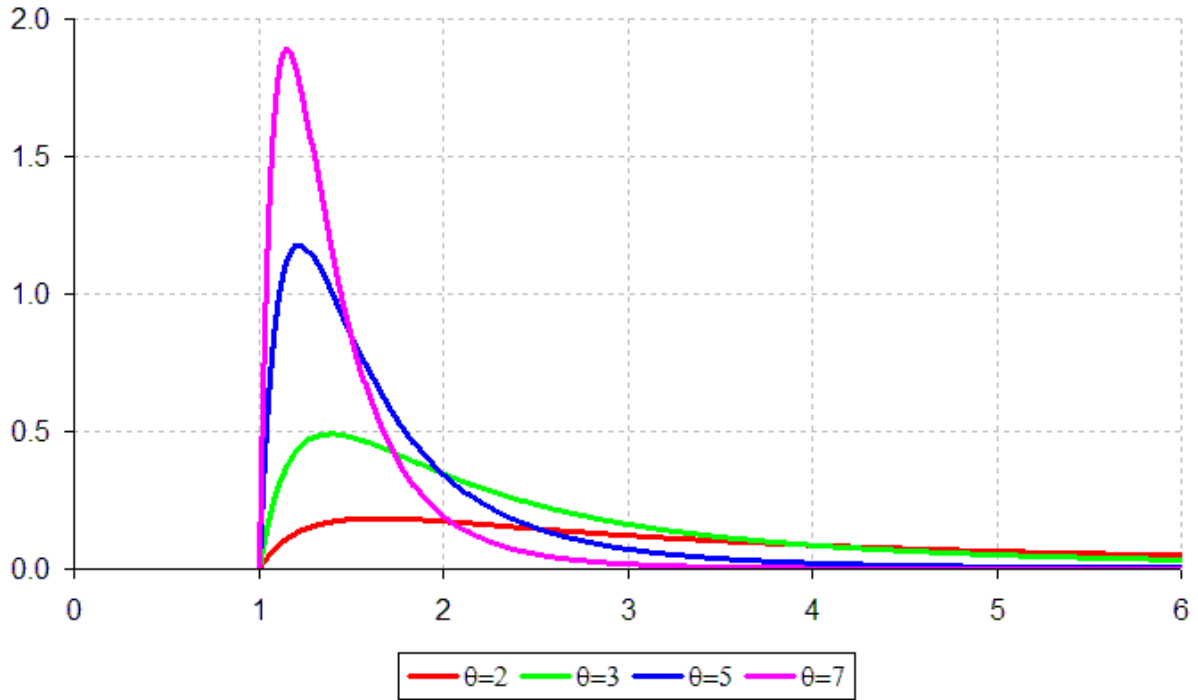
$$\text{Thus,} \quad \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i = \tilde{\theta}_1, \quad \overline{X^2} = \frac{1}{n} \sum_{i=1}^n X_i^2 = \tilde{\theta}_2 + \tilde{\theta}_1^2.$$

$$\text{Therefore,} \quad \tilde{\theta}_1 = \bar{X} \quad \text{and} \quad \tilde{\theta}_2 = \overline{X^2} - (\bar{X})^2.$$

5^{1/2}.

Let X_1, X_2, \dots, X_n be a random sample of size n from the distribution with probability density function

$$f_X(x) = f_X(x; \theta) = (\theta - 1)^2 \cdot \frac{\ln x}{x^\theta}, \quad x > 1, \quad \theta > 1.$$



a) Find the maximum likelihood estimator $\hat{\theta}$ of θ .

$$L(\theta) = \prod_{i=1}^n (\theta - 1)^2 \cdot \frac{\ln x_i}{x_i^\theta}, \quad \ln L(\theta) = 2n \ln(\theta - 1) + \sum_{i=1}^n \ln \ln x_i - \theta \cdot \sum_{i=1}^n \ln x_i.$$

$$\frac{d \ln L(\theta)}{d\theta} = \frac{2n}{\theta - 1} - \sum_{i=1}^n \ln x_i = 0. \quad \Rightarrow \quad \hat{\theta} = 1 + \frac{2n}{\sum_{i=1}^n \ln X_i}.$$

- b) Suppose $n = 5$, and $x_1 = 5$, $x_2 = 1.2$, $x_3 = 2$, $x_4 = 12$, $x_5 = 1.5$.
Find the maximum likelihood estimate $\hat{\theta}$ of θ .

$$\sum_{i=1}^5 \ln x_i = \ln 216 \approx 5.3753.$$

$$\hat{\theta} \approx 1 + \frac{10}{5.3753} \approx \mathbf{2.86}.$$

- c) Suppose $\theta > 2$. Find the method of moments estimator $\tilde{\theta}$ of θ .

$$E(X) = \int_{-\infty}^{\infty} x \cdot f_X(x) dx = \int_1^{\infty} x \cdot (\theta - 1)^2 \cdot \frac{\ln x}{x^\theta} dx = \frac{(\theta - 1)^2}{(\theta - 2)^2}.$$

$$\frac{1}{n} \cdot \sum_{i=1}^n X_i = \bar{X} = \frac{(\theta - 1)^2}{(\theta - 2)^2}. \quad \Rightarrow \quad \tilde{\theta} = \frac{2\sqrt{\bar{X}} - 1}{\sqrt{\bar{X}} - 1}.$$

- d) Suppose $n = 5$, and $x_1 = 5$, $x_2 = 1.2$, $x_3 = 2$, $x_4 = 12$, $x_5 = 1.5$.
Find the method of moments estimate $\tilde{\theta}$ of θ .

$$\bar{x} = 4.34.$$

$$\tilde{\theta} = \frac{2\sqrt{4.34} - 1}{\sqrt{4.34} - 1} \approx \mathbf{2.923}.$$

For fun:

e) Find $E(X^k)$, $k < \theta - 1$.

$f_X(x; \beta) = (\beta - 1)^2 \cdot \frac{\ln x}{x^\beta}$ is a probability density function, $\beta > 1$.

$$\Rightarrow \int_1^{\infty} \frac{\ln x}{x^\beta} dx = \frac{1}{(\beta - 1)^2}, \quad \beta > 1.$$

$$\begin{aligned} E(X^k) &= \int_{-\infty}^{\infty} x^k \cdot f_X(x) dx = \int_1^{\infty} x^k \cdot (\theta - 1)^2 \cdot \frac{\ln x}{x^\theta} dx \\ &= (\theta - 1)^2 \cdot \int_1^{\infty} \frac{\ln x}{x^{\theta - k}} dx = \frac{(\theta - 1)^2}{(\theta - k - 1)^2}. \end{aligned}$$

For example, $E(X) = E(X^1) = \frac{(\theta - 1)^2}{(\theta - 1 - 1)^2} = \frac{(\theta - 1)^2}{(\theta - 2)^2}$.