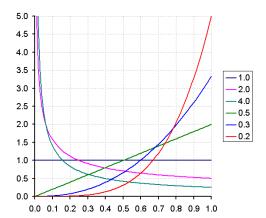
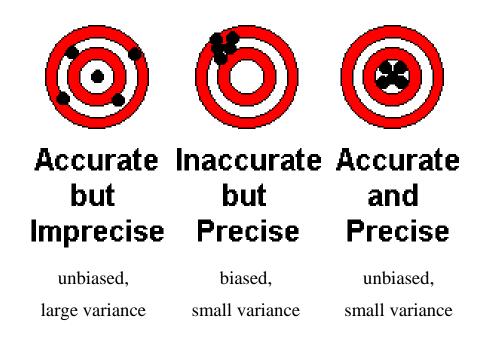
4. Let $X_1, X_2, ..., X_n$ be a random sample of size *n* from the distribution with probability density function

$$f(x;\theta) = \begin{cases} \frac{1-\theta}{\theta} & 0 \le x \le 1\\ 0 & \text{otherwise} \end{cases}$$
$$0 < \theta < \infty.$$



Recall: Maximum likelihood estimator of θ is $\hat{\theta} = -\frac{1}{n} \cdot \sum_{i=1}^{n} \ln X_i$. Method of moments estimator of θ is $\tilde{\theta} = \frac{1-\overline{X}}{\overline{X}} = \frac{1}{\overline{X}} - 1$. $E(X) = \frac{1}{1+\theta}$.

Def An estimator $\hat{\theta}$ is said to be **unbiased for** θ if $E(\hat{\theta}) = \theta$ for all θ .



d) Is $\hat{\theta}$ unbiased for θ ? That is, does $E(\hat{\theta})$ equal θ ?

$$\mathbf{E}(\ln \mathbf{X}_1) = \int_{-\infty}^{\infty} \ln x \cdot f_{\mathbf{X}}(x;\theta) dx = \int_{0}^{1} \left(\ln x \cdot \frac{1}{\theta} \cdot x \right) dx.$$

Integration by parts:

Choice of *u*:

$$\int_{a}^{b} u \, dv = u \, v \begin{vmatrix} b & b \\ a & - \int_{a}^{b} v \, du \end{vmatrix}$$
L ogarithmic
A lgebraic
T rigonometric
E xponential

$$u = \ln x, \qquad dv = \frac{1}{\theta} \cdot x^{1-\theta/\theta} dx = \frac{1}{\theta} \cdot x^{\theta-1} dx,$$
$$du = \frac{1}{x} dx, \qquad v = x^{1/\theta}.$$

$$\mathbf{E}\left(\ln \mathbf{X}_{1}\right) = \int_{0}^{1} \left(\ln x \cdot \frac{1}{\theta} \cdot x\right) dx = \left(\ln x \cdot x\right) \left| \begin{array}{c} 1 \\ 0 \\ 0 \end{array} - \int_{0}^{1} \left(\frac{1}{x} \cdot x\right) dx \right| dx$$

$$= -\int_{0}^{1} \left(\frac{1}{x} \cdot x \right) dx = -\int_{0}^{1} \frac{1}{\theta} dx = - \left(\frac{1}{1/\theta} \cdot x \right) \left| \begin{array}{c} 1 \\ 0 \end{array} \right|_{0}^{1} = -\theta.$$

Therefore,

$$\mathbf{E}\left(\hat{\theta}\right) = -\frac{1}{n} \cdot \sum_{i=1}^{n} \mathbf{E}\left(\ln \mathbf{X}_{i}\right) = -\frac{1}{n} \cdot \sum_{i=1}^{n} \left(-\theta\right) = \theta,$$

that is, $\hat{\theta}$ is an unbiased estimator for $\theta.$

Jensen's Inequality:

= =

If g is convex on an open interval I and X is a random variable whose support is contained in I and has finite expectation, then

$$\mathbf{E}[g(\mathbf{X})] \ge g[\mathbf{E}(\mathbf{X})].$$

If g is strictly convex then the inequality is strict, unless X is a constant random variable.

$$\Rightarrow E(X^{2}) \ge [E(X)]^{2} \qquad \Leftrightarrow \qquad Var(X) \ge 0$$

$$\Rightarrow E(e^{tX}) \ge e^{tE(X)} \qquad \Rightarrow \qquad M_{X}(t) \ge e^{t\mu}$$

$$\Rightarrow E\left(\frac{1}{X}\right) \ge \frac{1}{E(X)} \qquad \text{for a positive random variable } X$$

$$\Rightarrow E[X^{3}] \ge [E(X)]^{3} \qquad \text{for a non-negative random variable } X$$

$$\Rightarrow E\left[\ln X\right] \le \ln E(X) \qquad \text{for a positive random variable } X$$

$$\Rightarrow E\left[\sqrt{X}\right] \le \sqrt{E(X)} \qquad \text{for a non-negative random variable } X$$

$$\Rightarrow E\left[\sqrt{X}\right] \le \sqrt{E(X)} \qquad \text{for a non-negative random variable } X$$

e) Is $\tilde{\theta}$ unbiased for θ ? That is, does $E(\tilde{\theta})$ equal θ ?

Since $g(x) = \frac{1-x}{x} = \frac{1}{x} - 1$, 0 < x < 1, is strictly convex, and \overline{X} is not a constant random variable, by Jensen's Inequality,

$$\mathrm{E}(\widetilde{\theta}) = \mathrm{E}(g(\overline{\mathrm{X}})) > g(\mathrm{E}(\overline{\mathrm{X}})) = \theta.$$

 $\widetilde{\theta}~$ is NOT an unbiased estimator for $~\theta.$

6. Let $X_1, X_2, ..., X_n$ be a random sample of size *n* from a population with mean μ and variance σ^2 . Show that the sample mean \overline{X} and the sample variance S^2 are unbiased for μ and σ^2 , respectively.

$$\overline{\mathbf{X}} = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \dots + \mathbf{X}_n}{n}$$

$$\mathbf{E}(\mathbf{X}_1 + \mathbf{X}_2 + \dots + \mathbf{X}_n) = n \cdot \mu \qquad \Rightarrow \qquad \mathbf{E}(\overline{\mathbf{X}}) = \mu$$

$$\mathbf{E}(\mathbf{X}^2) = \operatorname{Var}(\mathbf{X}) + [\mathbf{E}(\mathbf{X})]^2 = \mu^2 + \sigma^2.$$

$$\operatorname{Var}(\mathbf{X}_1 + \mathbf{X}_2 + \dots + \mathbf{X}_n) = n \cdot \sigma^2 \qquad \Rightarrow \qquad \operatorname{Var}(\overline{\mathbf{X}}) = \frac{\sigma^2}{n}$$

$$\mathbf{E}\left(\left(\overline{\mathbf{X}}\right)^2\right) = \operatorname{Var}(\overline{\mathbf{X}}) + [\mathbf{E}(\overline{\mathbf{X}})]^2 = \mu^2 + \frac{\sigma^2}{n}.$$

$$\mathbf{S}^2 = \frac{1}{n-1} \sum \left(\mathbf{X}_i - \overline{\mathbf{X}}\right)^2 = \frac{1}{n-1} \left[\sum \mathbf{X}_i^2 - n \cdot (\overline{\mathbf{X}})^2\right]$$

$$\mathbf{E}(\mathbf{S}^2) = \frac{1}{n-1} \left[\sum \mathbf{E}\left(\mathbf{X}_i^2\right) - n \cdot \mathbf{E}\left((\overline{\mathbf{X}})^2\right)\right]$$

$$= \frac{1}{n-1} \left[n \cdot \left(\mu^2 + \sigma^2\right) - n \cdot \left(\mu^2 + \frac{\sigma^2}{n}\right)\right] = \sigma^2 \qquad \checkmark$$

For an estimator $\hat{\theta}$ of θ , define the **Mean Squared Error** of $\hat{\theta}$ by

$$MSE(\hat{\theta}) = E[(\hat{\theta} - \theta)^2].$$

$$E\left[\left(\hat{\theta} - \theta\right)^{2}\right] = \left(E\left(\hat{\theta}\right) - \theta\right)^{2} + Var\left(\hat{\theta}\right) = \left(bias\left(\hat{\theta}\right)\right)^{2} + Var\left(\hat{\theta}\right).$$

7. Let $X_1, X_2, ..., X_n$ be a random sample of size *n* from a distribution with probability density function

$$f_{\rm X}(x) = f_{\rm X}(x;\theta) = \frac{1+\theta x}{2}, \qquad -1 < x < 1, \qquad -1 < \theta < 1.$$

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

$$\mu = \mathbf{E}(\mathbf{X}) = \int_{-1}^{1} x \cdot \frac{1+\theta x}{2} dx = \left(\frac{x^2}{4} + \frac{\theta x^3}{6}\right) \Big|_{-1}^{1} = \frac{\theta}{3}.$$
$$\overline{\mathbf{X}} = \frac{\widetilde{\theta}}{3} \qquad \Rightarrow \qquad \widetilde{\theta} = 3 \, \overline{\mathbf{X}}.$$

b) Is $\tilde{\theta}$ an unbiased estimator for θ ? Justify your answer.

$$E(\tilde{\theta}) = E(3\overline{X}) = 3E(\overline{X}) = 3\mu = 3\frac{\theta}{3} = \theta.$$

 \Rightarrow $\tilde{\theta}$ an unbiased estimator for θ .

c) Find Var($\tilde{\theta}$).

$$E(X^{2}) = \int_{-1}^{1} x^{2} \cdot \frac{1+\theta x}{2} dx = \left(\frac{x^{3}}{6} + \frac{\theta x^{4}}{8}\right) \Big|_{-1}^{1} = \frac{1}{3}.$$

$$\sigma^{2} = Var(X) = \frac{1}{3} - \left(\frac{\theta}{3}\right)^{2} = \frac{3-\theta^{2}}{9}.$$

$$Var(\tilde{\theta}) = 9 Var(\overline{X}) = 9 \cdot \frac{\sigma^{2}}{n} = \frac{3-\theta^{2}}{n}. \qquad \Rightarrow \qquad MSE(\tilde{\theta}) = \frac{3-\theta^{2}}{n}.$$

8. Let X_1, X_2 be a random sample of size n = 2 from a distribution with probability density function

$$f_{\rm X}(x) = f_{\rm X}(x;\theta) = \frac{1+\theta x}{2}, \qquad -1 < x < 1, \qquad -1 < \theta < 1.$$

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

$$L(\theta) = \frac{1+\theta x_1}{2} \cdot \frac{1+\theta x_2}{2} = \frac{1+\theta(x_1+x_2)+\theta^2 x_1 x_2}{4}$$

L(
$$\theta$$
) is a parabola with vertex at $\frac{-b}{2a} = \frac{-(x_1 + x_2)}{2x_1x_2}$.

Case 1:
$$a = x_1 x_2 > 0$$
. Parabola has its "antlers" up.
 \Rightarrow The vertex is the minimum.

Subcase 1:
$$x_1 > 0, x_2 > 0.$$
 Vertex = $-\frac{x_1 + x_2}{2x_1 x_2} < 0.$

Maximum of $L(\theta)$ on $-1 < \theta < 1$ is at $\hat{\theta} = 1$.

Subcase 2:
$$x_1 < 0$$
, $x_2 < 0$. Vertex = $-\frac{x_1 + x_2}{2x_1 x_2} > 0$.

Maximum of
$$L(\theta)$$
 on $-1 < \theta < 1$ is at $\hat{\theta} = -1$.

<u>Case 2</u>: $a = x_1 x_2 < 0$. Parabola has its "antlers" down. \Rightarrow The vertex is the maximum.

Vertex is at
$$-\frac{x_1 + x_2}{2x_1 x_2}$$
.

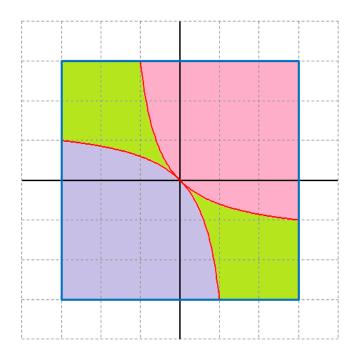
Subcase 1:
$$-\frac{x_1 + x_2}{2x_1 x_2} > 1$$
. That is, $x_2 > -\frac{x_1}{2x_1 + 1}$.
Maximum of $L(\theta)$ on $-1 < \theta < 1$ is at $\hat{\theta} = 1$.

Subcase 2:
$$-\frac{x_1 + x_2}{2x_1 x_2} < -1$$
. That is, $x_2 < \frac{x_1}{2x_1 - 1}$.

Maximum of L(θ) on $-1 < \theta < 1$ is at $\hat{\theta} = -1$.

Subcase 3:
$$-1 < -\frac{x_1 + x_2}{2x_1 x_2} < 1.$$

Maximum of L(θ) on $-1 < \theta < 1$ is at $\hat{\theta} = -\frac{X_1 + X_2}{2X_1 X_2}$.



Pink $\hat{\theta} = 1.$ Purple $\hat{\theta} = -1.$ Green $\hat{\theta} = -\frac{X_1 + X_2}{2X_1 X_2}.$ **9.** Let $X_1, X_2, ..., X_n$ be a random sample from the distribution with probability density function

$$f(x) = 4 \theta x^3 e^{-\theta x^4}$$
 $x > 0$ $\theta > 0$

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

$$L(\theta) = \prod_{i=1}^{n} \left(4\theta x_i^3 e^{-\theta x_i^4} \right)$$

$$\ln L(\theta) = n \cdot \ln \theta + \sum_{i=1}^{n} \ln \left(4x_i^3 \right) - \theta \cdot \sum_{i=1}^{n} x_i^4$$

$$\left(\ln L(\theta) \right)' = \frac{n}{\theta} - \sum_{i=1}^{n} x_i^4 = 0 \qquad \Rightarrow \qquad \hat{\theta} = \frac{n}{\sum_{i=1}^{n} x_i^4}.$$

b) Find
$$E(X^k)$$
, $k > -4$.

$$E(X^{k}) = \int_{0}^{\infty} x^{k} 4\theta x^{3} e^{-\theta x^{4}} dx \qquad u = \theta x^{4} \qquad du = 4\theta x^{3} dx$$
$$= \int_{0}^{\infty} \left(\frac{u}{\theta}\right)^{k/4} e^{-u} du = \frac{1}{\theta^{k/4}} \Gamma\left(\frac{k}{4} + 1\right).$$

c) Find the method of moments estimator of θ , $\tilde{\theta}$.

$$E(X) = E(X^{1}) = \frac{1}{\theta^{1/4}} \Gamma\left(\frac{1}{4}+1\right) = \frac{1}{\theta^{1/4}} \Gamma\left(1.25\right) \approx \frac{0.9064}{\theta^{1/4}}.$$
$$\overline{X} = \frac{\Gamma(1.25)}{\theta^{1/4}}.$$
$$\widetilde{\theta} = \left(\frac{\Gamma(1.25)}{\overline{X}}\right)^{4} \approx \frac{0.675}{\left(\overline{X}\right)^{4}}.$$