

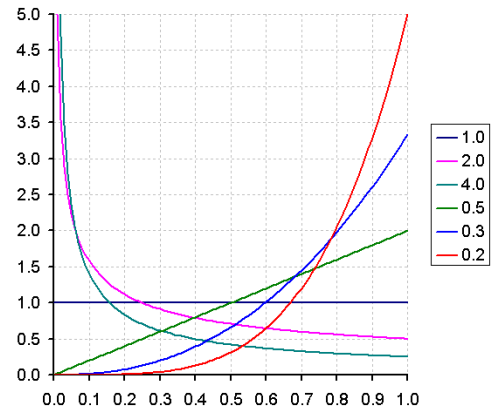
## 6.4 - Maximum Likelihood Estimation, Method of Moments (Part 2) – Estimator Properties

**Example 4:**

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

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

$0 < \theta < \infty.$



Recall: Maximum likelihood estimator of  $\theta$  is  $\hat{\theta} = -\frac{1}{n} \cdot \sum_{i=1}^n \ln X_i.$

Method of moments estimator of  $\theta$  is  $\tilde{\theta} = \frac{1-\bar{X}}{\bar{X}} = \frac{1}{\bar{X}} - 1. \quad E(X) = \frac{1}{1+\theta}.$

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



**Accurate  
but  
Imprecise**  
unbiased,

large variance



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

**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

$$E [ g ( X ) ] \geq g [ E ( X ) ].$$

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

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

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sample mean

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

sample variance

$$S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2$$

**Example 6:**

Let  $X_1, X_2, \dots, X_n$  be a random sample of size  $n$  from a population with mean  $\mu$  and variance  $\sigma^2$ . Show that the sample mean  $\bar{X}$  and the sample variance  $S^2$  are unbiased for  $\mu$  and  $\sigma^2$ , respectively.

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

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

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