

# Robert Morris CSCI Data Analytics

## Stability of Statistical Estimators

1. Prove theoretically that the sample variance,  $s^2$ , is unbiased.

$$\begin{aligned}
 E(s^2) &= E\left[\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2\right] \\
 &= \left(\frac{1}{n-1}\right) E\left[\sum (x_i - \bar{x})^2\right] \\
 &= \left(\frac{1}{n-1}\right) E\left[\sum ((x_i - \bar{x})(x_i - \bar{x}))\right] \\
 &= \left(\frac{1}{n-1}\right) E\left[\sum (\bar{x}^2 - 2x_i\bar{x} + \bar{x}^2)\right] = \left(\frac{1}{n-1}\right) E\left[\sum x_i^2 - \sum 2x_i\bar{x} + \sum \bar{x}^2\right] \quad \text{constants} \\
 &= \left(\frac{1}{n-1}\right) E\left[\sum x_i^2 - 2\bar{x} \sum x_i + n\bar{x}^2\right] \quad \text{note: } \bar{x} = \frac{\sum x_i}{n} = n\bar{x} \\
 &= \left(\frac{1}{n-1}\right) E\left[\sum x_i^2 - 2\bar{x}n\bar{x} + n\bar{x}^2\right] = E\left[\sum x_i^2 - n\bar{x}^2\right] \\
 &\quad - 2n\bar{x}^2 + n\bar{x}^2 = \sum E(x_i^2) - E(n\bar{x}^2) \\
 &= \left(\frac{1}{n-1}\right) \sum E(x_i^2) - nE(\bar{x}^2) \quad \left[ \begin{array}{l} \text{note: } E(x_i^2) = \sigma^2 + \mu^2 \\ E(\bar{x}^2) = \frac{\sigma^2}{n} + \mu^2 \end{array} \right] \\
 &= \left(\frac{1}{n-1}\right) \sum (\sigma^2 + \mu^2) - n\left(\frac{\sigma^2}{n} + \mu^2\right) \\
 &= \left(\frac{1}{n-1}\right) n\sigma^2 + n\mu^2 - \sigma^2 - n\mu^2 \rightarrow = \sigma^2(n-1)\left(\frac{1}{n-1}\right)
 \end{aligned}$$

Since  $\left(\frac{1}{n-1}\right)$  and  $(n-1) = 1$ , we are left with  $\sigma^2$

• Hence  $E(s^2)$  is an unbiased estimator of  $\sigma^2$

2. Prove theoretically that the sample variance,  $s^2$ , is consistent.

$$\begin{aligned}
 \text{Var}(s^2) &= \text{Var}\left(\frac{\sum (x_i - \bar{x})^2}{n-1}\right) = \frac{1}{(n-1)^2} \text{Var}\left(\sum (x_i - \bar{x})^2\right) = \frac{2\sigma^4}{n-1} \\
 \text{(n becomes very large)} \quad \lim_{n \rightarrow \infty} \text{Var}(s^2) &= 0 \therefore s^2 \text{ is consistent}
 \end{aligned}$$

★ note:  $\sum \rightarrow$  all cases of  $\sum = \sum_{i=1}^n$   
 note:  $\bar{x} = \frac{\sum x_i}{n} = n\bar{x} = \sum x_i$

Notes: Sample mean  $\rightarrow \hat{\mu} = \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$   
 "Biased" Sample Variance  $\rightarrow \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$  ( $\sigma^2 = E[(x - \mu)^2]$ )  
 "Unbiased" Sample Variance  $\rightarrow s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$

Defn: The bias of an estimator  $\hat{\theta}$  is  $\text{bias}(\hat{\theta}) = E\hat{\theta} - \theta$

Defn: The estimator  $\hat{\theta}$  is unbiased if  $\text{bias}(\hat{\theta}) = 0$

$$E(\sum x_i) = \sum E(x_i), E(cX) = cE(X),$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$E(X^2) = \sigma^2 + \mu^2$$

$$\text{Var}(\bar{x}) = E(\bar{x}^2) - [E(\bar{x})]^2$$

$$E(\bar{x}^2) = \frac{\sigma^2}{n} + \mu^2$$