

Appendix A

Proof that the statistic, $S^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$, is the unbiased estimator of the population parameter, σ^2 .

□ Let X_1, X_2, \dots, X_n be independent and identically distributed random variables, each with expected value, μ , and variance, σ^2 . For the entire population, $\sigma = \sqrt{\sigma^2}$ and $\sigma^2 = E(X_i - \mu)^2$. The variance is the theoretical expected value for the square of the distance from the mean to an individual data point (e.g., deviation). Thus, we want a statistic such that $E(S^2) = \sigma^2$. Intuitively, we would guess that S^2 is

$\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n}$ (the average of our sample deviations). Drawing on the algebra of expected values,

however, this statistic results in the following expected value:

$$E(S^2) = E\left(\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n}\right) = \frac{1}{n} E\left(\sum_{i=1}^n (X_i - \bar{X})^2\right) = \frac{1}{n} E\left(\sum_{i=1}^n ((X_i - \mu) - (\bar{X} - \mu))^2\right)$$

$$E(S^2) = \frac{1}{n} E\left(\sum_{i=1}^n ((X_i - \mu)^2) - 2\sum_{i=1}^n (X_i - \mu)(\bar{X} - \mu) + \sum_{i=1}^n ((\bar{X} - \mu)^2)\right) = \frac{1}{n} \left(\sum_{i=1}^n E((X_i - \mu)^2) - n \cdot E((\bar{X} - \mu)^2)\right)$$

Substituting $\sigma^2 = E(X_i - \mu)^2$ (initial assumption) and $E(\bar{X} - \mu)^2 = \frac{\sigma^2}{n}$ (from central limit theorem) results in the following:

$$E(S^2) = \frac{1}{n} \left(\sum_{i=1}^n \sigma^2 - n \cdot \frac{\sigma^2}{n}\right) = \frac{1}{n} (n\sigma^2 - \sigma^2) = \frac{n-1}{n} \sigma^2.$$

Thus, the expected value of our statistic, S^2 , is a *biased* estimate (a fraction) of σ^2 . Because the n in the denominator originated from our initial guess, replacing n with $n-1$ in the original formula

would result in an unbiased estimate of our population parameter. So, $S^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$ is the

statistic that is an unbiased estimator of the desired population parameter, σ^2 . ■