

BASIC STATISTICS

1. SAMPLES, RANDOM SAMPLING AND SAMPLE STATISTICS

1.1. Random Sample. The random variables X_1, X_2, \dots, X_n are called a random sample of size n from the population $f(x)$ if X_1, X_2, \dots, X_n are mutually independent random variables and the marginal probability density function of each X_i is the same function of $f(x)$. Alternatively, X_1, X_2, \dots, X_n are called independent and identically distributed random variables with pdf $f(x)$. We abbreviate independent and identically distributed as iid.

Most experiments involve $n > 1$ repeated observations on a particular variable, the first observation is X_1 , the second is X_2 , and so on. Each X_i is an observation on the same variable and each X_i has a marginal distribution given by $f(x)$. Given that the observations are collected in such a way that the value of one observation has no effect or relationship with any of the other observations, the X_1, X_2, \dots, X_n are mutually independent. Therefore we can write the joint probability density for the sample X_1, X_2, \dots, X_n as

$$f(x_1, x_2, \dots, x_n) = f(x_1)f(x_2) \cdots f(x_n) = \prod_{i=1}^n f(x_i) \quad (1)$$

If the underlying probability model is parameterized by θ , then we can also write

$$f(x_1, x_2, \dots, x_n | \theta) = \prod_{i=1}^n f(x_i | \theta) \quad (2)$$

Note that the same θ is used in each term of the product, or in each marginal density. A different value of θ would lead to a different properties for the random sample.

1.2. Statistics. Let X_1, X_2, \dots, X_n be a random sample of size n from a population and let $T(x_1, x_2, \dots, x_n)$ be a real valued or vector valued function whose domain includes the sample space of (X_1, X_2, \dots, X_n) . Then the random variable or random vector $Y = (X_1, X_2, \dots, X_n)$ is called a statistic. A statistic is a map from the sample space of (X_1, X_2, \dots, X_n) call it \mathbf{X} , to some space of values, usually R^1 or R^n . T is what we compute when we observe the random variable X take on some specific values in a sample. The probability distribution of a statistic $Y = T(X)$ is called the sampling distribution of Y . Notice that $T(\cdot)$ is a function of sample values only, it does not depend directly on any underlying parameters, θ .

1.3. Some Commonly Used Statistics.

1.3.1. Sample mean. The sample mean is the arithmetic average of the values in a random sample. It is usually denoted

$$\bar{X}(X_1, X_2, \dots, X_n) = \frac{X_1 + X_2 + \dots + X_n}{n} = \frac{1}{n} \sum_{i=1}^n X_i$$

The observed value of \bar{X} in any sample is demoted by the lower case letter, i.e., \bar{x} .

1.3.2. *Sample variance.* The sample variance is the statistic defined by

$$S^2(X_1, X_2, \dots, X_n) = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (3)$$

The observed value of S^2 in any sample is demoted by the lower case letter, i.e., s^2 .

1.3.3. *Sample standard deviation.* The sample standard deviation is the statistic defined by

$$S = \sqrt{S^2} \quad (4)$$

1.3.4. *Sample midrange.* The sample mid-range is the statistic defined by

$$\frac{\max(X_1, X_2, \dots, X_n) - \min(X_1, X_2, \dots, X_n)}{2}$$

1.3.5. *Empirical distribution function.* The empirical distribution function is defined by

$$\hat{F}(X_1, X_2, \dots, X_n)(x) = \frac{1}{n} \sum_{i=1}^n I(X_i < x)$$

where $\hat{F}(X_1, X_2, \dots, X_n)(x)$ means we are evaluating the statistic $\hat{F}(X_1, X_2, \dots, X_n)$ at the particular value x . The random sample X_1, X_2, \dots, X_n is assumed to come from a probability defined on R^1 and $I(A)$ is the indicator of the event A . This statistic takes values in the set of all distribution functions on R^1 . It estimates the function valued parameter F defined by its evaluation at $x \in R^1$

$$F(P)(x) = P[X < x]$$

2. DISTRIBUTION OF SAMPLE STATISTICS

2.1. Theorem 1 on squared deviations and sample variances.

Theorem 1. Let x_1, x_2, \dots, x_n be any numbers and let $\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$. Then the following two items hold.

$$\begin{aligned} \text{a) } \min_a \sum_{i=1}^n (x_i - a)^2 &= \sum_{i=1}^n (x_i - \bar{x})^2 \\ \text{b) } (n-1)s^2 &= \sum_{i=1}^n (x_i - \bar{x})^2 = \sum_{i=1}^n x_i^2 - n\bar{x}^2 \end{aligned}$$

Part a) says that the sample mean is the value about which the sum of squared deviations is minimized. Part b) is a simple identity that will prove immensely useful in dealing with statistical data.

Proof. First consider part a of theorem 1. Add and subtract \bar{x} from the expression on the lefthand side in part a and then expand as follows

$$\sum_{i=1}^n (x_i - \bar{x} + \bar{x} - a)^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + 2 \sum_{i=1}^n (x_i - \bar{x})(\bar{x} - a) + \sum_{i=1}^n (\bar{x} - a)^2 \quad (5)$$

Now write out the middle term in 5 and simplify:

$$\sum_{i=1}^n (x_i - \bar{x})(\bar{x} - a) = (\bar{x} - a) \sum_{i=1}^n (x_i - \bar{x}) = (\bar{x} - a) \cdot 0 = 0$$

We can then write 5 as

$$\sum_{i=1}^n (x_i - a)^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{i=1}^n (\bar{x} - a)^2 \quad (6)$$

Equation 6 is clearly minimized when $a = \bar{x}$. Now consider part b) of theorem 1. Expand the second expression in part b) and simplify:

$$\begin{aligned} \sum_{i=1}^n (x_i - \bar{x})^2 &= \sum_{i=1}^n x_i^2 + \sum_{i=1}^n \bar{x}^2 - 2 \sum_{i=1}^n x_i \bar{x} \\ &= \sum_{i=1}^n x_i^2 + n\bar{x}^2 - 2n\bar{x}^2 \\ &= \sum_{i=1}^n x_i^2 - n\bar{x}^2 \end{aligned}$$

□

2.2. Theorem 2 on expected values and variances of sums.

Theorem 2. Let X_1, X_2, \dots, X_n be a random sample from a population and let $g(x)$ be a function such that $Eg(X_1)$ and $Var g(X_1)$ exist. Then following two items hold.

a) $E \left(\sum_{i=1}^n g(X_i) \right) = n(Eg(X_1))$

b) $Var \left(\sum_{i=1}^n g(X_i) \right) = n(Var g(X_1))$

Proof. First consider part a) of Theorem 2. Write the expected value of the sum as the sum of the expected values and then note that $Eg(X_1) = Eg(X_2) = \dots Eg(X_i) = \dots Eg(X_n)$ because the X_i are all from the same distribution.

$$E \left(\sum_{i=1}^n g(X_i) \right) = \sum_{i=1}^n E(g(X_i)) = n(Eg(X_1)) \quad (7)$$

Then consider part b) of Theorem 2. Write the definition of the variance for a variable z as $E(z - E(z))^2$ and then combine terms in the summation sign.

$$\begin{aligned} Var \left(\sum_{i=1}^n g(X_i) \right) &= E \left[\left(\sum_{i=1}^n g(X_i) \right) - E \left(\sum_{i=1}^n g(X_i) \right) \right]^2 \\ &= E \left[\left(\sum_{i=1}^n g(X_i) \right) - \sum_{i=1}^n E(g(X_i)) \right]^2 \\ &= E \left[\sum_{i=1}^n (g(X_i) - E(g(X_i))) \right]^2 \end{aligned} \quad (8)$$

Now write out the bottom expression in equation 8 as follows

$$\begin{aligned}
 \text{Var} \left(\sum_{i=1}^n g(X_i) \right) &= E [g(X_1) - E(g(X_1))]^2 + E [g(X_1) - E(g(X_1))] E [g(X_2) - E(g(X_2))] \quad (9) \\
 &\quad + E [g(X_1) - E(g(X_1))] E [g(X_3) - E(g(X_3))] + \cdots \\
 &\quad + E [g(X_2) - E(g(X_2))] E [g(X_1) - E(g(X_1))] + E [g(X_2) - E(g(X_2))]^2 \\
 &\quad + E [g(X_2) - E(g(X_2))] E [g(X_3) - E(g(X_3))] + \cdots \\
 &\quad + \cdots \\
 &\quad + E [g(X_n) - E(g(X_n))] E [g(X_1) - E(g(X_1))] + \cdots + E [g(X_n) - E(g(X_n))]^2
 \end{aligned}$$

Each of the squared terms in the summation is a variance. Specifically

$$E [g(X_i) - E(g(X_i))]^2 = \text{Var } g(X_i) = \text{Var } g(X_1) \quad (10)$$

The other terms in the summation in 9 are covariances of the form

$$E [g(X_i) - E(g(X_i))] E [g(X_j) - E(g(X_j))] = \text{Cov} [g(X_i), g(X_j)] \quad (11)$$

Now we can use the fact that the X_1 and X_j in the sample X_1, X_2, \dots, X_n are independent to assert that each of the covariances in the sum in 9 is zero. We can then rewrite 9 as

$$\begin{aligned}
 \text{Var} \left(\sum_{i=1}^n g(X_i) \right) &= E [g(X_1) - E(g(X_1))]^2 + E [g(X_2) - E(g(X_2))]^2 + \cdots + E [g(X_n) - E(g(X_n))]^2 \\
 &= \text{Var}(g(X_1)) + \text{Var}(g(X_2)) + \text{Var}(g(X_3)) + \cdots \\
 &= \sum_{i=1}^n \text{Var } g(X_i) = \sum_{i=1}^n \text{Var } g(X_1) = n \text{Var } g(X_1)
 \end{aligned}$$

□

2.3. Theorem 3 on expected values of sample statistics.

Theorem 3. Let X_1, X_2, \dots, X_n be a random sample from a population with mean μ and variance $\sigma^2 < \infty$. Then

a) $E\bar{X} = \mu$

b) $\text{Var } \bar{X} = \frac{\sigma^2}{n}$

c) $ES^2 = \sigma^2$

Proof. Proof of part a). In theorem 2 let $g(X) = g(X_i) = \frac{X_i}{n}$. This implies that $Eg(X_i) = \frac{\mu}{n}$. Then we can write

$$E\bar{X} = E \left(\frac{1}{n} \sum_{i=1}^n X_i \right) = E \left(\sum_{i=1}^n \frac{X_i}{n} \right) = E \left(\sum_{i=1}^n g(X_i) \right) = nE(g(X_i)) = n \frac{\mu}{n} = \mu \quad (12)$$

Proof of part b). In theorem 2 let $g(X) = g(X_i) = \frac{X_i}{n}$. This implies that $\text{Var } g(X_i) = \frac{\sigma^2}{n^2}$. Then we can write

$$\text{Var } \bar{X} = \text{Var} \left(\frac{1}{n} \sum_{i=1}^n X_i \right) = \text{Var} \left(\sum_{i=1}^n \frac{X_i}{n} \right) = \text{Var} \left(\sum_{i=1}^n g(X_i) \right) = n(\text{Var } g(X_1)) = n \frac{\sigma^2}{n^2} = \frac{\sigma^2}{n} \quad (13)$$

Proof of part c). As in part b) of theorem 1, write S^2 as a function of the sum of square of X_i minus n times the mean of X_i squared and then simplify

$$\begin{aligned} ES^2 &= E\left(\frac{1}{n-1}\left[\sum_{i=1}^n X_i^2 - n\bar{X}^2\right]\right) \\ &= \frac{1}{n-1}(nEX_1^2 - nE\bar{X}^2) \\ &= \frac{1}{n-1}\left(n(\sigma^2 + \mu^2) - n\left(\frac{\sigma^2}{n} + \mu^2\right)\right) = \sigma^2 \end{aligned} \quad (14)$$

The last line follows from the definition of the variance of a random variable, i.e.,

$$\begin{aligned} Var X &= \sigma_X^2 = EX^2 - (EX)^2 \\ &= EX^2 - \mu_X^2 \\ \Rightarrow EX^2 &= \sigma_X^2 + \mu_X^2 \end{aligned}$$

□

2.4. Unbiased Statistics. We say that a statistic $T(X)$ is an unbiased statistic for the parameter θ of the underlying probability distribution if $ET(X) = \theta$. Given this definition, \bar{X} is an unbiased statistic for μ , and S^2 is an unbiased statistic for σ^2 in a random sample.

3. METHODS OF ESTIMATION

Let Y_1, Y_2, \dots, Y_n denote a random sample from a parent population characterized by the parameters $\theta_1, \theta_2, \dots, \theta_k$. It is assumed that the random variable Y has an associated density function $f(\cdot; \theta_1, \theta_2, \dots, \theta_k)$.

3.1. Method of Moments.

3.1.1. Definition of Moments. If Y is a random variable, the r^{th} moment of Y , usually denoted by μ'_r , is defined as

$$\begin{aligned} \mu'_r &= E(Y^r) \\ &= \int_{-\infty}^{\infty} y^r f(y; \theta_1, \theta_2, \dots, \theta_k) dy \end{aligned}$$

if the expectation exists. Note that $\mu'_1 = E(Y) = \mu_Y$, the mean of Y . Moments are sometimes written as functions of θ .

$$E(Y^r) = \mu'_r = g_r(\theta_1, \theta_2, \dots, \theta_k)$$

3.1.2. Definition of Central Moments. If Y is a random variable, the r^{th} central moment of Y about a is defined as $E[(Y - a)^r]$. If $a = \mu_Y$, we have the r^{th} central moment of Y about μ_Y , denoted by μ_r , which is

$$\begin{aligned} \mu_r &= E[(Y - \mu_Y)^r] \\ &= \int_{-\infty}^{\infty} (y - \mu_y)^r f(y; \theta_1, \theta_2, \dots, \theta_k) dy \end{aligned}$$

Note that $\mu_1 = E[(Y - \mu_Y)] = 0$ and $\mu_2 = E[(Y - \mu_Y)^2] = Var[Y]$. Also note that all odd numbered moments of Y around its mean are zero for symmetrical distributions, provided such moments exist.

3.1.3. *Sample Moments about the Origin.* The r^{th} sample moment about the origin is defined as

$$\hat{\mu}'_r = \bar{x}_n^r = \frac{1}{n} \sum_{i=1}^n y_i^r$$

3.1.4. *Estimation Using the Method of Moments.* In general μ'_r will be a known function of the parameters $\theta_1, \theta_2, \dots, \theta_k$ of the distribution of Y , that is $\mu'_r = g_r(\theta_1, \theta_2, \dots, \theta_k)$. Now let y_1, y_2, \dots, y_n be a random sample from the density $f(\cdot; \theta_1, \theta_2, \dots, \theta_k)$. Form the K equations

$$\begin{aligned} \mu'_1 &= g_1(\theta_1, \theta_2, \dots, \theta_k) = \hat{\mu}'_1 = \frac{1}{n} \sum_{i=1}^n y_i \\ \mu'_2 &= g_2(\theta_1, \theta_2, \dots, \theta_k) = \hat{\mu}'_2 = \frac{1}{n} \sum_{i=1}^n y_i^2 \\ &\vdots \\ \mu'_K &= g_K(\theta_1, \theta_2, \dots, \theta_k) = \hat{\mu}'_K = \frac{1}{n} \sum_{i=1}^n y_i^K \end{aligned}$$

The estimators of $\theta_1, \theta_2, \dots, \theta_k$, based on the method of moments, are obtained by solving the system of equations for the K parameter estimates $\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_K$.

This principle of estimation is based upon the convention of picking the estimators of θ_i in such a manner that the corresponding population (theoretical) moments are equal to the sample moments. These estimators are consistent under fairly general regularity conditions, but are not generally efficient. Method of moments estimators may also not be unique.

3.1.5. *Example using density function* $f(y) = (p+1)y^p$. Consider a density function given by

$$f(y) = \begin{cases} (p+1)y^p & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Let Y_1, Y_2, \dots, Y_n denote a random sample from the given population. Express the first moment of Y as a function of the parameters.

$$\begin{aligned} E(Y) &= \int_{-\infty}^{\infty} y f(y) dy = \int_0^1 y (p+1) y^p dy = \int_0^1 y^{p+1} (p+1) dy \\ &= \left. \frac{y^{p+2} (p+1)}{(p+2)} \right|_0^1 = \frac{p+1}{p+2} \end{aligned}$$

Then set this expression of the parameters equal to the first sample moment and solve for p .

$$\begin{aligned}\mu'_1 &= E(Y) = \frac{p+1}{p+2} \\ \Rightarrow \frac{p+1}{p+2} &= \frac{1}{n} \sum_{i=1}^n y_i = \bar{y} \\ \Rightarrow p+1 &= (p+2)\bar{y} = p\bar{y} + 2\bar{y} \\ \Rightarrow p - p\bar{y} &= 2\bar{y} - 1 \\ \Rightarrow p(1 - \bar{y}) &= 2\bar{y} - 1 \\ \Rightarrow \hat{p} &= \frac{2\bar{y} - 1}{1 - \bar{y}}\end{aligned}$$

3.1.6. *Example using the Normal Distribution.* Let Y_1, Y_2, \dots, Y_n denote a random sample from a normal distribution with mean μ and variance σ^2 . Let $(\theta_1, \theta_2) = (\mu, \sigma^2)$. Recall that

$$\begin{aligned}\mu'_1 &= E(Y) = \mu \\ \mu'_2 &= E(Y^2) = \sigma^2 + E^2[Y] = \sigma^2 + \mu^2\end{aligned}$$

Now set the first population moment equal to its sample analogue to obtain

$$\mu = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y} \quad (15)$$

$$\Rightarrow \hat{\mu} = \bar{y}$$

Now set the second population moment equal to its sample analogue

$$\sigma^2 + \mu^2 = \frac{1}{n} \sum_{i=1}^n y_i^2 \quad (16)$$

$$\Rightarrow \sigma^2 = \frac{1}{n} \sum_{i=1}^n y_i^2 - \mu^2$$

$$\Rightarrow \sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2 - \mu^2}$$

Now replace μ in equation 16 with its estimator from equation 15 to obtain

$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2 - \bar{y}^2} = \sqrt{\sum_{i=1}^n \frac{(y_i - \bar{y})^2}{n}}$$

This is, of course, different from the sample standard deviation defined in equations 3 and 4.

3.1.7. *Example using the Gamma Distribution.* Let X_1, X_2, \dots, X_n denote a random sample from a gamma distribution with parameters α and β . The density function is given by

$$f(x; \alpha, \beta) = \begin{cases} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} & 0 \leq x < \infty \\ 0 & \text{otherwise} \end{cases}$$

Find the first moment of the gamma distribution by integrating as follows

$$E(X) = \int_0^{\infty} x \frac{1}{\beta^{\alpha} \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} dx = \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \int_0^{\infty} x^{(1+\alpha)-1} e^{-\frac{x}{\beta}} dx$$

If we multiply by $\beta^{1+\alpha} \Gamma(1 + \alpha)$ we obtain

$$E(X) = \frac{\beta^{1+\alpha} \Gamma(1 + \alpha)}{\beta^{\alpha} \Gamma(\alpha)} \int_0^{\infty} \frac{1}{\beta^{1+\alpha} \Gamma(1 + \alpha)} x^{(1+\alpha)-1} e^{-\frac{x}{\beta}} dx \quad (17)$$

The integrand of equation 17 is a gamma density with parameters β and $1 + \alpha$. This integrand will integrate to one so that we obtain the expression in front of the integral sign as $E(X)$.

$$E(X) = \frac{\beta^{1+\alpha} \Gamma(1 + \alpha)}{\beta^{\alpha} \Gamma(\alpha)} = \frac{\beta \Gamma(1 + \alpha)}{\Gamma(\alpha)}$$

The gamma function has the property that $\Gamma(t) = (t - 1)\Gamma(t - 1)$ or $\Gamma(v + 1) = v\Gamma(v)$. Replacing $\Gamma(1 + \alpha)$ with $\alpha \Gamma(\alpha)$, we obtain

$$E(X) = \frac{\beta \Gamma(1 + \alpha)}{\Gamma(\alpha)} = \frac{\beta \alpha \Gamma(\alpha)}{\Gamma(\alpha)} = \beta \alpha$$

We can find the second moment by finding $E(X^2)$. To do this we multiply the gamma density by x^2 instead of x . Carrying out the computation we obtain

$$E(X^2) = \int_0^{\infty} x^2 \frac{1}{\beta^{\alpha} \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} dx = \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \int_0^{\infty} x^{(2+\alpha)-1} e^{-\frac{x}{\beta}} dx$$

If we then multiply and divide by $\beta^{2+\alpha} \Gamma(2 + \alpha)$ we obtain

$$\begin{aligned} E(X^2) &= \frac{\beta^{2+\alpha} \Gamma(2 + \alpha)}{\beta^{\alpha} \Gamma(\alpha)} \int_0^{\infty} \frac{1}{\beta^{2+\alpha} \Gamma(2 + \alpha)} x^{(2+\alpha)-1} e^{-\frac{x}{\beta}} dx \\ &= \frac{\beta^{2+\alpha} \Gamma(2 + \alpha)}{\beta^{\alpha} \Gamma(\alpha)} = \frac{\beta^2 (\alpha + 1) \Gamma(1 + \alpha)}{\Gamma(\alpha)} = \frac{\beta^2 \alpha (\alpha + 1) \Gamma(\alpha)}{\Gamma(\alpha)} \\ &= \beta^2 \alpha (\alpha + 1) \end{aligned}$$

Now set the first population moment equal to the sample analogue to obtain

$$\begin{aligned} \beta \alpha &= \frac{1}{n} \sum_{i=1}^n x_i = \bar{x} \\ \Rightarrow \hat{\alpha} &= \frac{\bar{x}}{\beta} \end{aligned}$$

Now set the second population moment equal to its sample analogue

$$\begin{aligned}
 \beta^2 \alpha(\alpha + 1) &= \frac{1}{n} \sum_{i=1}^n x_i^2 \\
 \Rightarrow \beta^2 &= \frac{\sum_{i=1}^n x_i^2}{n \alpha(\alpha + 1)} \\
 \Rightarrow \beta^2 &= \frac{\sum_{i=1}^n x_i^2}{n \left(\frac{\bar{x}}{\beta}\right) \left(\left(\frac{\bar{x}}{\beta}\right) + 1\right)} = \frac{\sum_{i=1}^n x_i^2}{\left(\frac{n\bar{x}^2}{\beta^2}\right) + \left(\frac{n\bar{x}}{\beta}\right)} \\
 \Rightarrow n\bar{x}^2 + n\bar{x}\beta &= \sum_{i=1}^n x_i^2 \\
 \Rightarrow n\bar{x}\beta &= \sum_{i=1}^n x_i^2 - n\bar{x}^2 \\
 \Rightarrow \beta &= \frac{\sum_{i=1}^n x_i^2 - n\bar{x}^2}{n\bar{x}} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}{\bar{x}}
 \end{aligned}$$

3.1.8. *Example with unknown distribution but known first and second moments.* Let Y_1, Y_2, \dots, Y_n denote a random sample from an unknown distribution with parameters β and σ . We know the following about the distribution of Y .

$$\begin{aligned}
 Y &= \beta + u \\
 E(u) &= 0 \\
 E(u^2) &= \text{Var}(u) = \sigma^2
 \end{aligned}$$

Consider estimators for β and σ^2 . In a given sample

$$\begin{aligned}
 y_i &= \hat{\beta} + \hat{u}_i \\
 \Rightarrow \hat{u}_i &= y_i - \hat{\beta}
 \end{aligned} \tag{18}$$

The sample moments are then as follows

$$\begin{aligned}
 \text{First sample moment} &= \frac{\sum_{i=1}^n \hat{u}_i}{n} \\
 \text{Second sample moment} &= \frac{\sum_{i=1}^n \hat{u}_i^2}{n}
 \end{aligned}$$

Substituting from expression 18 we obtain

$$\begin{aligned}
 \text{First sample moment} &= \frac{\sum_{i=1}^n (y_i - \hat{\beta})}{n} \\
 \text{Second sample moment} &= \frac{\sum_{i=1}^n (y_i - \hat{\beta})^2}{n}
 \end{aligned}$$

If we set the first sample moment equal to the first population moment we obtain

$$\begin{aligned}\frac{\sum_{i=1}^n (y_i - \hat{\beta})}{n} &= 0 \\ \Rightarrow \sum_{i=1}^n y_i &= n\hat{\beta} \\ \Rightarrow \hat{\beta} &= \frac{\sum_{i=1}^n y_i}{n} = \bar{y}\end{aligned}$$

If we set the second sample moment equal to the second population moment we obtain

$$\begin{aligned}\frac{\sum_{i=1}^n (y_i - \hat{\beta})^2}{n} &= \sigma^2 \\ \Rightarrow \hat{\sigma}^2 &= \frac{\sum_{i=1}^n (y_i - \hat{\beta})^2}{n} = \frac{\sum_{i=1}^n (y_i - \hat{\beta})^2}{n}\end{aligned}$$

3.2. Method of least squares estimation.

3.2.1. *Example with one parameter.* Consider the situation in which the Y_i from the random sample can be written in the form

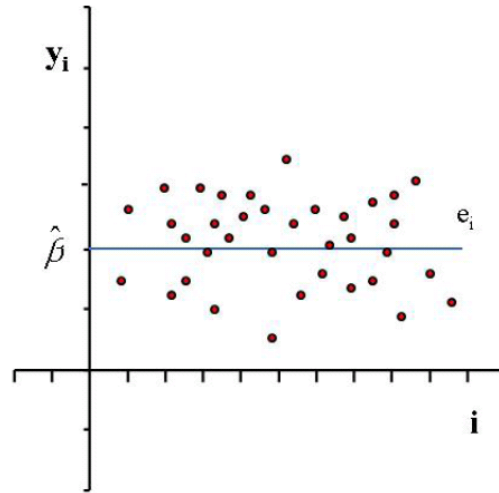
$$Y_i = \beta + \epsilon_i$$

where $E(\epsilon_i) = 0$ and $Var(\epsilon_i) = \sigma^2$ for all i . This is equivalent to stating that the population from which y_i is drawn has a mean of β and a variance of σ^2 .

The least squares estimator of β is obtained by minimizing the sum of squares errors, SSE, defined by

$$SSE = \sum_{i=1}^n (y_i - \hat{\beta})^2 \tag{19}$$

The idea is to pick the value of $\hat{\beta}$ to estimate β which minimizes SSE. Pictorially we select the value of $\hat{\beta}$ which minimizes the sum of squares of the vertical deviations



The solution is obtained by finding the value of β that minimizes equation 19:

$$\begin{aligned} \frac{\partial SSE}{\partial \beta} &= 2 \sum_{i=1}^n (y_i - \hat{\beta})(-1) = 0 \\ \Rightarrow \hat{\beta} &= \frac{1}{n} \sum_{i=1}^n y_i = \bar{y} \end{aligned}$$

This method chooses values of the parameters of the underlying distribution, β , such that the distance between the elements of the random sample and “predicted” values are minimized.

3.2.2. *Example with two parameters.* Consider the model

$$\begin{aligned} y_t &= \beta_1 + \beta_2 x_t + \varepsilon_t \\ &= \hat{\beta}_1 + \hat{\beta}_2 x_t + e_t \\ \Rightarrow e_t &= y_t - \hat{\beta}_1 - \hat{\beta}_2 x_t \end{aligned}$$

where $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$ for all t . This is equivalent to stating that the population from which y_t is drawn has a mean of $\beta_1 + \beta_2 x_t$ and a variance of σ^2 .

Now if these estimated errors are squared and summed we obtain

$$SSE = \sum_{t=1}^n e_t^2 = \sum_{t=1}^n (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_t)^2$$

This sum of squares of the vertical distances between y_t and the predicted y_t on the sample regression line is abbreviated SSE. Different values for the parameters give different values of SSE. The

idea is to pick values of β_1 and β_2 that minimize SSE. This can be done using calculus. Specifically

$$\begin{aligned}\frac{\partial SSE}{\partial \hat{\beta}_1} &= 2 \sum_t (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_t)(-1) = -2 \sum_t e_t = 0 \\ \frac{\partial SSE}{\partial \hat{\beta}_2} &= 2 \sum_t (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_t)(-x_t) \\ &= -2 \sum_t (y_t x_t - \hat{\beta}_1 x_t - \hat{\beta}_2 x_t^2) = -2 \sum_t e_t x_t = 0\end{aligned}$$

Setting these derivatives equal to zero implies

$$\begin{aligned}\sum_t e_t &= 0 \\ \sum_t e_t x_t &= 0.\end{aligned}$$

These equations are often referred to as the normal equations. Note that the normal equations imply that the sample mean of the residuals is equal to zero and that the sample covariance between the residuals and x is zero since the mean of e_t is zero. The easiest method of solution is to solve the first normal equation for $\hat{\beta}_1$ and then substitute into the second. Solving the first equation gives

$$\begin{aligned}\sum_t (y_t - \hat{\beta}_1 - \hat{\beta}_2 x_t) &= 0 \\ \Rightarrow \sum_t y_t &= n \hat{\beta}_1 + \hat{\beta}_2 \sum_t x_t \\ \Rightarrow \hat{\beta}_1 &= \frac{\sum_t y_t}{n} - \hat{\beta}_2 \frac{\sum_t x_t}{n} = \bar{y} - \hat{\beta}_2 \bar{x}\end{aligned}$$

This implies that the regression line goes through the point (\bar{x}, \bar{y}) . The slope of the sample regression line is obtained by substituting $\hat{\beta}_1$ into the second normal equation and solving for $\hat{\beta}_2$. This will give

$$\begin{aligned}\sum_t (y_t x_t - \hat{\beta}_1 x_t - \hat{\beta}_2 x_t^2) &= 0 \\ \Rightarrow \sum_t y_t x_t &= \hat{\beta}_1 \sum_t x_t + \hat{\beta}_2 \sum_t x_t^2 = (\bar{y} - \hat{\beta}_2 \bar{x}) \sum_t x_t + \hat{\beta}_2 \sum_t x_t^2 \\ &= (\bar{y} - \hat{\beta}_2 \bar{x}) n \bar{x} + \hat{\beta}_2 \sum_t x_t^2 = n \bar{y} \bar{x} - n \hat{\beta}_2 \bar{x}^2 + \hat{\beta}_2 \sum_t x_t^2 \\ &= n \bar{y} \bar{x} + \hat{\beta}_2 \left(\sum_t x_t^2 - n \bar{x}^2 \right) \\ \Rightarrow \hat{\beta}_2 &= \frac{\sum_t y_t x_t - n \bar{x} \bar{y}}{\sum_t x_t^2 - n \bar{x}^2} = \frac{\sum_t (y_t - \bar{y})(x_t - \bar{x})}{\sum_t (x_t^2 - \bar{x})^2}\end{aligned}$$

3.2.3. *Method of moments estimation for example in 3.2.2.* Let Y_1, Y_2, \dots, Y_n denote a random sample from an unknown distribution with parameters β_1, β_2 , and σ . We know the following about the

distribution of Y :

$$\begin{aligned} Y &= \beta_1 + \beta_2 X + u \\ E(u) &= 0 \\ E(u^2) &= \text{Var}(u) = \sigma^2 \\ E(u \cdot x) &= 0 \end{aligned}$$

Consider estimators for β_1, β_2 , and σ^2 . In a given sample

$$\begin{aligned} y_i &= \hat{\beta}_1 + \hat{\beta}_2 x_i + \hat{u}_i \\ \Rightarrow \hat{u}_i &= y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i \end{aligned} \tag{20}$$

The sample moments are then as follows

$$\begin{aligned} \text{First sample moment} &= \frac{\sum_{i=1}^n \hat{u}_i}{n} \\ \text{Second sample moment} &= \frac{\sum_{i=1}^n \hat{u}_i^2}{n} \\ \text{Cross sample moment} &= \frac{\sum_{i=1}^n x_i \hat{u}_i}{n} \end{aligned}$$

Substituting from equation 20 we obtain:

$$\begin{aligned} \text{First sample moment} &= \frac{\sum_{i=1}^n (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)}{n} \\ \text{Second sample moment} &= \frac{\sum_{i=1}^n (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)^2}{n} \\ \text{Cross sample moment} &= \frac{\sum_{i=1}^n x_i (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)}{n} \end{aligned}$$

If we set the first sample moment equal to the first population moment we obtain:

$$\begin{aligned} \frac{\sum_{i=1}^n (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)}{n} &= 0 \\ \Rightarrow \sum_{i=1}^n y_i &= n\hat{\beta}_1 + \hat{\beta}_2 \sum_{i=1}^n x_i \\ \Rightarrow \sum_{i=1}^n y_i - \hat{\beta}_2 \sum_{i=1}^n x_i &= n\hat{\beta}_1 \\ \Rightarrow \bar{y} - \hat{\beta}_2 \bar{x} &= \hat{\beta}_1 \end{aligned}$$

Now use the cross sample moment to solve for $\hat{\beta}_2$:

$$\begin{aligned}
0 &= \frac{\sum_{i=1}^n x_i (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)}{n} \\
&\Leftrightarrow \sum_{i=1}^n x_i y_i = \hat{\beta}_1 \sum_{i=1}^n x_i + \hat{\beta}_2 \sum_{i=1}^n x_i^2 = (\bar{y} - \hat{\beta}_2 \bar{x}) \sum_{i=1}^n x_i + \hat{\beta}_2 \sum_{i=1}^n x_i^2 \\
&= (\bar{y} - \hat{\beta}_2 \bar{x}) \sum_{i=1}^n x_i + \hat{\beta}_2 \sum_{i=1}^n x_i^2 = (\bar{y} - \hat{\beta}_2 \bar{x}) n \bar{x} + \hat{\beta}_2 \sum_{i=1}^n x_i^2 \\
&= n \bar{x} \bar{y} + \hat{\beta}_2 \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right) \\
&\Leftrightarrow \hat{\beta}_2 \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right) = \sum_{i=1}^n x_i y_i - n \bar{y} \bar{x} \\
&\Leftrightarrow \hat{\beta}_2 = \frac{\sum_{i=1}^n x_i y_i - n \bar{y} \bar{x}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}
\end{aligned}$$

We obtain an estimate for σ^2 by equating the second sample moment to the second moment

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - \hat{\beta}_1 - \hat{\beta}_2 x_i)^2}{n}$$

3.3. Method of maximum likelihood estimation (MLE). Least squares is independent of a specification of a density function for the parent population. Now assume that

$$y_i \sim f(\cdot; \theta = (\theta_1, \dots, \theta_K)), \forall i.$$

3.3.1. Motivation for the MLE method. If a random variable Y has a probability density function $f(\cdot; \theta)$ characterized by the parameters $\theta = (\theta_1, \dots, \theta_k)$, then the maximum likelihood estimators (MLE) of $(\theta_1, \dots, \theta_k)$ are the values of these parameters which would have most likely generated the given sample.

3.3.2. Theoretical development of the MLE method. The joint density of a random sample y_1, y_2, \dots, y_n is given by $L = g(y_1, \dots, y_n; \theta) = f(y_1; \theta) \cdot f(y_2; \theta) \cdot f(y_3; \theta) \cdots f(y_n; \theta)$. Given that we have a random sample, the joint density is just the product of the marginal density functions. This is referred to as the *likelihood function*. The MLE of the θ_i are the θ_i which maximize the likelihood function.

The necessary conditions for an optimum are:

$$\frac{\partial L}{\partial \theta_i} = 0, \quad i = 1, 2, \dots, k$$

This gives k equations in k unknowns to solve for the k parameters $\theta_1, \dots, \theta_k$. In many instances it will be convenient to maximize $\ell = \ln L$ rather than L given that the log of a product is the sum of the logs.

3.3.3. *Example 1.* Let the random variable X_i be distributed as a normal $N(\mu, \sigma^2)$ so that its density is given by

$$f(x_i; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{1}{2}\left(\frac{x_i - \mu}{\sigma}\right)^2}$$

Its likelihood function is given by

$$\begin{aligned} L &= \prod_{i=1}^n f(x_i; \mu, \sigma^2) = f(x_1) f(x_2) \cdots f(x_n) & (21) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{-\frac{1}{2}\left(\frac{x_1 - \mu}{\sigma}\right)^2} e^{-\frac{1}{2}\left(\frac{x_2 - \mu}{\sigma}\right)^2} \cdots e^{-\frac{1}{2}\left(\frac{x_n - \mu}{\sigma}\right)^2} \\ &= \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2} \\ \Rightarrow \ln L = \ell &= \frac{-n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \end{aligned}$$

The MLE of μ and σ^2 are obtained by taking the partial derivatives of equation 21

$$\begin{aligned} \frac{\partial \ell}{\partial \mu} &= \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu) = 0 \Rightarrow \hat{\mu} = \frac{\sum_{i=1}^n x_i}{n} = \bar{x} \\ \frac{\partial \ell}{\partial \sigma^2} &= \frac{-n}{2} \left[\frac{2\pi}{2\pi\sigma^2} \right] - \left(\frac{1}{2}\right) (-1)(\sigma^2)^{-2} \sum_{i=1}^n (x_i - \hat{\mu})^2 = 0 \\ \Rightarrow \frac{n}{2\hat{\sigma}^2} &= \frac{1}{(2\hat{\sigma}^2)^2} \sum_{i=1}^n (x_i - \hat{\mu})^2 \\ \Rightarrow n &= \frac{1}{\hat{\sigma}^2} \sum_{i=1}^n (x_i - \hat{\mu})^2 \\ \Rightarrow \hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 = \left(\frac{n-1}{n}\right) s^2 \end{aligned}$$

The MLE of σ^2 is equal to the sample variance and not S^2 ; hence, the MLE is not unbiased as can be seen from equation 14. The MLE of μ is the sample mean.

3.3.4. *Example 2 - Poisson.* The random variable X_i is distributed as a Poisson if the density of X_i is given by

$$f(x_i; \lambda) = \begin{cases} \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} & x_i \text{ is a non-negative integer} \\ 0 & \text{otherwise} \end{cases}$$

$$E(X) = \lambda$$

$$V(X) = \lambda$$

The likelihood function is given by

$$\begin{aligned} L &= \left[\frac{e^{-\lambda} \lambda^{x_1}}{x_1!} \right] \left[\frac{e^{-\lambda} \lambda^{x_2}}{x_2!} \right] \cdots \left[\frac{e^{-\lambda} \lambda^{x_n}}{x_n!} \right] \\ &= \frac{e^{-\lambda n} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!} \\ \Rightarrow \ln L &= \ell = -\lambda n + \sum_{i=1}^n x_i \ln \lambda - \ln \left(\prod_{i=1}^n x_i! \right) \end{aligned}$$

To obtain a MLE of λ , differentiate ℓ with respect to λ :

$$\begin{aligned} \frac{\partial \ell}{\partial \lambda} &= -n + \sum_{i=1}^n x_i \frac{1}{\lambda} = 0 \\ \Rightarrow \hat{\lambda} &= \frac{\sum_{i=1}^n x_i}{n} = \bar{x} \end{aligned}$$

3.3.5. *Example 3.* Consider the density function

$$f(y) = \begin{cases} (p+1)y^p & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

The likelihood function is given by

$$\begin{aligned} L &= \prod_{i=1}^n (p+1) y_i^p \tag{22} \\ \ln L &= \ell = \sum_{i=1}^n \ln [(p+1) y_i^p] = \sum_{i=1}^n (\ln(p+1) + \ln y_i^p) \\ &= \sum_{i=1}^n (\ln(p+1) + p \ln y_i) \end{aligned}$$

To obtain the MLE estimator differentiate 22 with respect to p

$$\begin{aligned} \frac{\partial \ell}{\partial p} &= \sum_{i=1}^n \left(\frac{1}{p+1} + \ln y_i \right) = 0 \\ \Rightarrow \sum_{i=1}^n \frac{1}{\hat{p}+1} &= \sum_{i=1}^n (-\ln y_i) \\ \Rightarrow \frac{n}{\hat{p}+1} &= \sum_{i=1}^n (-\ln y_i) \\ \Rightarrow \hat{p}+1 &= \frac{-n}{\sum_{i=1}^n \ln y_i} \\ \Rightarrow \hat{p} &= \frac{-n}{\sum_{i=1}^n \ln y_i} - 1 \end{aligned}$$

3.3.6. *Example 4.* Consider the density function

$$f(y_i) = p^{y_i} (1 - p)^{1 - y_i} \quad 0 \leq p \leq 1 \quad (23)$$

The likelihood function is given by

$$\begin{aligned} L &= \prod_{i=1}^n p^{y_i} (1 - p)^{1 - y_i} \\ &= p^{\sum_{i=1}^n y_i} (1 - p)^{n - \sum_{i=1}^n y_i} \\ \ln L &= \ell = \sum_{i=1}^n y_i \ln p + \left(n - \sum_{i=1}^n y_i \right) \ln(1 - p) \end{aligned} \quad (24)$$

To obtain the MLE estimator differentiate 24 with respect to p where we assume that $0 < p < 1$.

$$\begin{aligned} \frac{\partial \ell}{\partial p} &= \frac{\sum_{i=1}^n y_i}{p} - \frac{(n - \sum_{i=1}^n y_i)}{1 - p} = 0 \\ \Rightarrow \frac{\sum_{i=1}^n y_i}{p} &= \frac{(n - \sum_{i=1}^n y_i)}{1 - p} \\ \Rightarrow \sum_{i=1}^n y_i - p \sum_{i=1}^n y_i &= np - p \sum_{i=1}^n y_i \\ &\Rightarrow \sum_{i=1}^n y_i = np \\ &\Rightarrow \frac{\sum_{i=1}^n y_i}{n} = \hat{p} \end{aligned}$$

3.3.7. *Example 5.* Let Y_1, Y_2, \dots, Y_n denote a random sample from an unknown distribution with parameters β_1, β_2 , and σ . We know the following about the distribution of Y_i .

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

$$E(u_i) = 0$$

$$E(u_i^2) = \text{Var}(u_i) = \sigma^2$$

u_i and u_j are independent for all $i \neq j$

u_i and x_j are independent for all i and j

u_i are distributed normally for all i

This implies that the Y_i are independently and normally distributed with respective means $\beta_1 + \beta_2 X_i$ and a common variance σ^2 . The joint density of the a set of of observations, therefore, is

$$\begin{aligned}
 L &= \prod_{i=1}^n f(y_i; \beta_1, \beta_2, \sigma^2) = f(y_1) f(y_2) \cdots f(y_n) & (25) \\
 &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{1}{2\sigma^2} (y_1 - \beta_1 - \beta_2 x_1)^2} e^{-\frac{1}{2\sigma^2} (y_2 - \beta_1 - \beta_2 x_2)^2} \cdots e^{-\frac{1}{2\sigma^2} (y_n - \beta_1 - \beta_2 x_n)^2} \\
 &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2} \\
 \Rightarrow \ln L = \ell &= -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2 \\
 &= -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2
 \end{aligned}$$

The MLE of β_1 , β_2 , and σ^2 are obtained by taking the partial derivatives of equation 25

$$\begin{aligned}
 \frac{\partial \ell}{\partial \beta_1} &= \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i) \\
 \frac{\partial \ell}{\partial \beta_2} &= \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i) x_i \\
 \frac{\partial \ell}{\partial \sigma^2} &= -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2
 \end{aligned}$$

Solving for β_1 we obtain

$$\begin{aligned}
 \sum_i (y_i - \beta_1 - \beta_2 x_i) &= 0 \\
 \Rightarrow \sum_i y_i &= n\beta_1 + \beta_2 \sum_i x_i \\
 \Rightarrow \hat{\beta}_1 &= \frac{\sum_i y_i}{n} - \hat{\beta}_2 \frac{\sum_i x_i}{n} = \bar{y} - \hat{\beta}_2 \bar{x}
 \end{aligned}$$

We can find β_2 using $\frac{\partial \ell}{\partial \beta_2} = 0$ and substituting β_1 . This will give

$$\begin{aligned} \sum_i (y_i x_i - \beta_1 x_i - \beta_2 x_i^2) &= 0 \\ \Rightarrow \sum_i y_i x_i &= \beta_1 \sum_i x_i + \beta_2 \sum_i x_i^2 = (\bar{y} - \beta_2 \bar{x}) \sum_i x_i + \beta_2 \sum_i x_i^2 \\ &= (\bar{y} - \beta_2 \bar{x}) n \bar{x} + \beta_2 \sum_i x_i^2 = n \bar{y} \bar{x} - n \beta_2 \bar{x}^2 + \beta_2 \sum_i x_i^2 \\ &= n \bar{y} \bar{x} + \beta_2 \left(\sum_i x_i^2 - n \bar{x}^2 \right) \\ \Rightarrow \hat{\beta}_2 &= \frac{\sum_i y_i x_i - n \bar{x} \bar{y}}{\sum_i x_i^2 - n \bar{x}^2} = \frac{\sum_i (y_i - \bar{y})(x_i - \bar{x})}{\sum_i (x_i^2 - \bar{x}^2)} \end{aligned}$$

From $\frac{\partial \ell}{\partial \sigma^2} = 0$ we obtain:

$$\begin{aligned} \frac{\partial \ell}{\partial \sigma^2} &= \frac{-n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2 = 0 \\ \Rightarrow \frac{n}{2\sigma^2} &= \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2 \\ \Rightarrow n &= \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2 \\ \Rightarrow \hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_i)^2 \end{aligned}$$

4. FINITE SAMPLE PROPERTIES OF ESTIMATORS

4.1. Introduction to sample properties of estimators. In section 3 we discussed alternative methods of estimating the unknown parameters in a model. In order to compare the estimating techniques we will discuss some criteria which are frequently used in such a comparison. Let θ denote an unknown parameter and let $\hat{\theta}$ and $\tilde{\theta}$ be alternative estimators. Now define the bias, variance and mean squared error of $\hat{\theta}$ as

$$\begin{aligned} Bias(\hat{\theta}) &= E(\hat{\theta}) - \theta \\ Var(\hat{\theta}) &= E\left(\hat{\theta} - E(\hat{\theta})\right)^2 \\ MSE(\hat{\theta}) &= E\left(\hat{\theta} - \theta\right)^2 \\ &= Var(\hat{\theta}) + \left(Bias(\hat{\theta})\right)^2 \end{aligned} \tag{26}$$

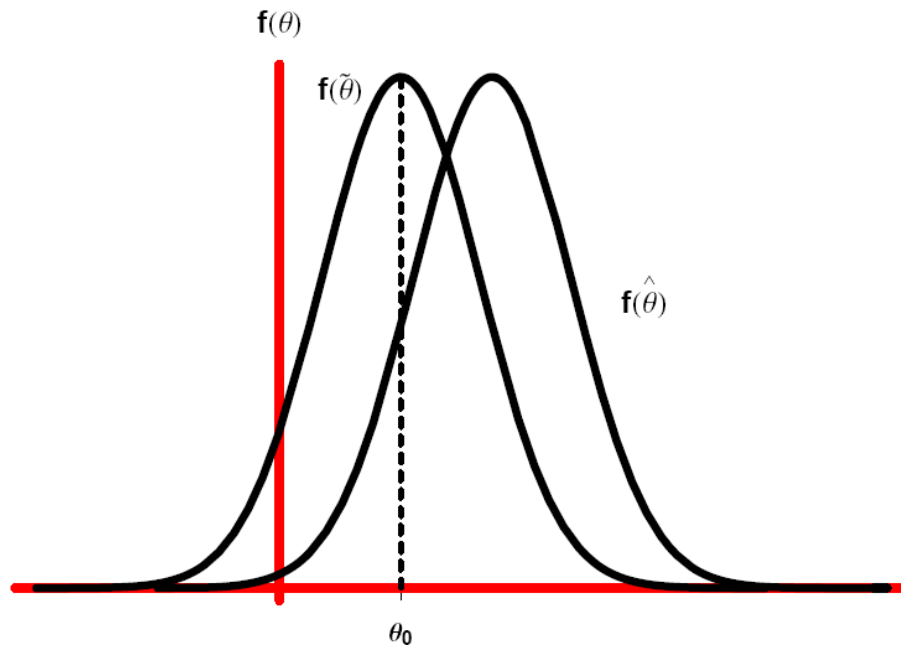
The result on mean squared error can be seen as follows

$$\begin{aligned} MSE(\theta) &= E\left(\hat{\theta} - \theta\right)^2 = E\left(\hat{\theta} - E(\hat{\theta}) + E(\hat{\theta}) - \theta\right)^2 \\ &= E\left(\left(\hat{\theta} - E(\hat{\theta})\right) + \left(E(\hat{\theta}) - \theta\right)\right)^2 \\ &= E\left(\hat{\theta} - E(\hat{\theta})\right)^2 + 2\left[E(\hat{\theta}) - \theta\right] E\left(\hat{\theta} - E(\hat{\theta})\right) + \left(E(\hat{\theta}) - \theta\right)^2 \\ &= E\left(\hat{\theta} - E(\hat{\theta})\right)^2 + \left(E(\hat{\theta}) - \theta\right)^2 = Var(\hat{\theta}) + \left(Bias(\hat{\theta})\right)^2 \end{aligned}$$

4.2. Specific properties of estimators.

4.2.1. *Unbiasedness.* $\hat{\theta}$ is said to be an *unbiased estimator* of θ if $E(\hat{\theta}) = \theta$.

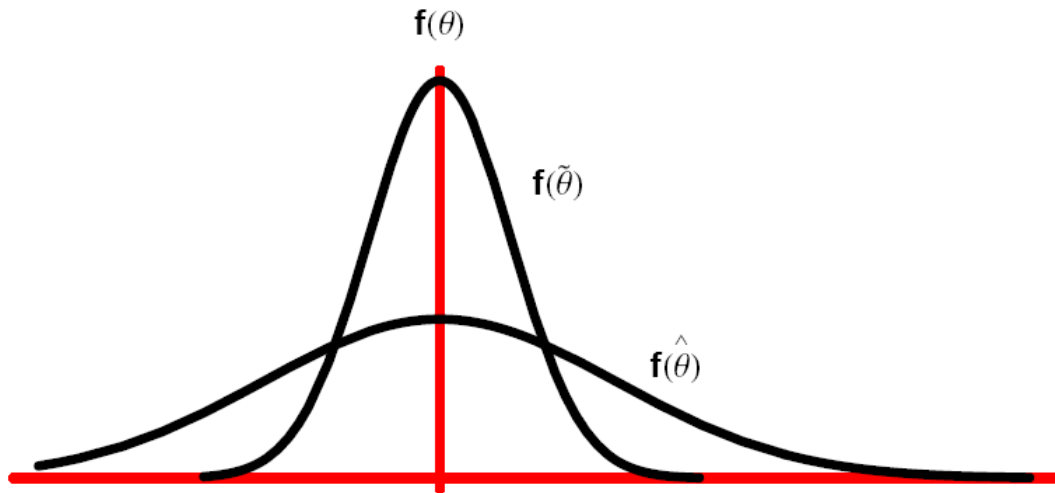
In the figure below, $\hat{\theta}$ is an unbiased estimator of θ , while $\tilde{\theta}$ is a biased estimator:



4.2.2. *Minimum variance.* $\hat{\theta}$ is said to be a *minimum variance estimator* of θ if

$$\text{Var}(\hat{\theta}) \leq \text{Var}(\tilde{\theta})$$

where $\tilde{\theta}$ is any other estimator of θ . This criterion has its disadvantages as can be seen by noting that $\hat{\theta} = \text{constant}$ has zero variance and yet completely ignores any sample information that we may have. In the figure below, $\tilde{\theta}$ has a lower variance than $\hat{\theta}$:



4.2.3. *Mean squared error efficient.* $\hat{\theta}$ is said to be a MSE *efficient* estimator of θ if

$$MSE(\hat{\theta}) \leq MSE(\tilde{\theta})$$

where $\tilde{\theta}$ is any other estimator of θ . This criterion takes into account both the variance and bias of the estimator under consideration.

4.2.4. *Best linear unbiased estimators.* $\hat{\theta}$ is the best linear unbiased estimator (BLUE) of θ if

$$\hat{\theta} = \sum_{i=1}^n a_i y_i \text{ linear}$$

$$E(\hat{\theta}) = \theta \text{ unbiased}$$

$$Var(\hat{\theta}) \leq Var(\tilde{\theta})$$

where the a_i are constants to be determined and $\tilde{\theta}$ is any other linear unbiased estimator of θ . For the class of unbiased estimators of θ , the efficient estimators will also be minimum variance estimators.

4.2.5. *Example.* Let Y_1, Y_2, \dots, Y_n denote a random sample drawn from a population having a mean μ and variance σ^2 . Now derive the best linear unbiased estimator (BLUE) of μ .

Let the proposed estimator be denoted by $\hat{\theta}$. It is linear so we can write it as follows.

$$\hat{\theta} = \sum_{i=1}^n a_i y_i$$

If the estimator is to be unbiased, there will be restrictions on the a_i . Specifically

$$\begin{aligned} E(\hat{\theta}) &= E\left(\sum_{i=1}^n a_i y_i\right) = \sum_{i=1}^n a_i E(y_i) \\ &= \sum_{i=1}^n a_i \mu = \mu \sum_{i=1}^n a_i \\ &\Rightarrow \sum_{i=1}^n a_i = 1 \end{aligned}$$

Now consider the variance of $\hat{\theta}$:

$$\begin{aligned} Var(\hat{\theta}) &= Var\left[\sum_{i=1}^n a_i y_i\right] \\ &= \sum a_i^2 Var(y_i) + \sum_{i \neq j} a_i a_j Cov(y_i y_j) \\ &= \sum_{i=1}^n a_i^2 \sigma^2 \end{aligned}$$

because the covariance between y_i and y_j ($i \neq j$) is equal to zero due to the fact that the y 's are drawn from a random sample.

The problem of obtaining a BLUE of μ becomes that of minimizing $\sum_{i=1}^n a_i^2$ subject to the constraint $\sum_{i=1}^n a_i = 1$. This is done by setting up a Lagrangian

$$L(a, \lambda) = \sum_{i=1}^n a_i^2 - \lambda \left(\sum_{i=1}^n a_i - 1 \right)$$

The necessary conditions for an optimum are

$$\begin{aligned} \frac{\partial L}{\partial a_1} &= 2a_1 - \lambda = 0 \\ &\cdot \\ &\cdot \\ &\cdot \\ \frac{\partial L}{\partial a_n} &= 2a_n - \lambda = 0 \\ \frac{\partial L}{\partial \lambda} &= -\sum_{i=1}^n a_i + 1 = 0 \end{aligned}$$

The first n equations imply that $a_1 = a_2 = a_3 = \dots a_n$ so that the last equation implies that

$$\begin{aligned} \sum_{i=1}^n a_i - 1 &= 0 \\ \Rightarrow n a_i - 1 &= 0 \\ \Rightarrow n a_i &= 1 \\ \Rightarrow a_i &= \frac{1}{n} \\ \Rightarrow \hat{\theta} &= \sum_{i=1}^n a_i y_i = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y} \end{aligned}$$

Note that equal weights are assigned to each observation.

4.2.6. *Example.* Let X_1, X_2, \dots, X_n denote a random sample drawn from a population having a population mean equal to μ and a population variance equal to σ^2 . The sample mean (estimator of μ) is calculated by the formula

$$\bar{X} = \sum_{i=1}^n \frac{X_i}{n}$$

and is an unbiased estimator of μ from theorem 3 and equation 12.

Two possible estimates of the population variance are

$$\begin{aligned}\hat{\sigma}^2 &= \sum_{i=1}^n \frac{(X_i - \bar{X})^2}{n} \\ S^2 &= \sum_{i=1}^n \frac{(X_i - \bar{X})^2}{n-1}\end{aligned}$$

We have shown previously in theorem 3 and equation 14 that $\hat{\sigma}^2$ is a biased estimator of σ^2 ; whereas S^2 is an unbiased estimator of σ^2 . Note also that

$$\begin{aligned}\hat{\sigma}^2 &= \left(\frac{n-1}{n}\right) S^2 \\ E(\hat{\sigma}^2) &= \left(\frac{n-1}{n}\right) E(S^2) \\ &= \left(\frac{n-1}{n}\right) \sigma^2\end{aligned}\tag{27}$$

Also from theorem 3 and equation 13, we have that

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$$

Now consider the mean square error of the two estimators \bar{X} and S^2 where X_1, X_2, \dots, X_n are a random sample from a normal population with a mean of μ and a variance of σ^2 .

$$\begin{aligned}\text{MSE}(\bar{X}) &= E(\bar{X} - \mu)^2 = \text{Var}(\bar{X}) = \frac{\sigma^2}{n} \\ \text{MSE}(S^2) &= E(S^2 - \sigma^2)^2 = \text{Var}(S^2) = \frac{2\sigma^4}{n-1}\end{aligned}$$

The variance of S^2 was derived in the lecture on sample moments. The variance of $\hat{\sigma}^2$ is easily computed given the variance of S^2 . Specifically,

$$\begin{aligned}\text{Var}(\hat{\sigma}^2) &= \text{Var}\left(\left(\frac{n-1}{n}\right) S^2\right) = \left(\frac{n-1}{n}\right)^2 \text{Var}(S^2) \\ &= \left(\frac{n-1}{n}\right)^2 \frac{2\sigma^4}{n-1} = \frac{2(n-1)\sigma^4}{n^2}\end{aligned}$$

We can compute the MSE of $\hat{\sigma}^2$ as follows

$$\begin{aligned}
 MSE \hat{\sigma}^2 &= E(\hat{\sigma}^2 - \sigma)^2 = E\left(\hat{\sigma}^2 - \left(\frac{n-1}{n}\right)\sigma^2 + \left(\frac{n-1}{n}\right)\sigma^2 - \sigma\right)^2 \\
 &= E\left(\hat{\sigma}^2 - \left(\frac{n-1}{n}\right)\sigma^2\right)^2 + E\left(\left(\frac{n-1}{n}\right)\sigma^2 - \sigma\right)^2 \\
 &\quad + 2E\left[\left(\hat{\sigma}^2 - \left(\frac{n-1}{n}\right)\sigma^2\right)\left(\left(\frac{n-1}{n}\right)\sigma^2 - \sigma\right)\right] \\
 &= Var(\hat{\sigma}^2) + \left(\left(\frac{n-1}{n}\right)\sigma^2 - \sigma\right)^2 \\
 &= \frac{2(n-1)\sigma^4}{n^2} + \left[\left(\frac{n-1}{n}\right)\sigma^2 - \sigma\right]^2 \\
 &= \frac{2(n-1)\sigma^4}{n^2} + \left(\frac{n-1}{n}\right)^2\sigma^4 - 2\left(\frac{n-1}{n}\right)\sigma^4 + \sigma^4 \\
 &= \sigma^4\left(\frac{2(n-1)}{n^2} + \frac{(n-1)^2}{n^2} - \frac{2n(n-1)}{n^2} + \frac{n^2}{n^2}\right) \\
 &= \sigma^4\left(\frac{2n-2+n^2-2n+1-2n^2+2n+n^2}{n^2}\right) \\
 &= \sigma^4\left(\frac{2n-1}{n^2}\right)
 \end{aligned}$$

Now compare the MSE's of S^2 and $\hat{\sigma}^2$:

$$MSE(\hat{\sigma}^2) = \sigma^4\left(\frac{2n-1}{n^2}\right) < \sigma^4\left(\frac{2}{n-1}\right) = MSE(S^2)$$

So $\hat{\sigma}^2$ is a biased estimator of σ^2 but has lower mean square error than S^2 .