Population		Sample	
Mean	$\mu = \frac{\sum X}{N}$	Mean	$\bar{X} = \frac{X_i}{n}$
Variance	$\sigma^2 = \frac{\sum(X_i-\mu)^2}{N}$	Variance	$S^2 = \frac{\sum(X_i-\bar{x})^2}{n}$
Standard Deviation	$\sigma = \sqrt{\frac{\sum(X_i-\mu)^2}{N}}$	Standard Deviation	$S = \sqrt{\frac{\sum(X_i-\bar{x})^2}{n}}$

Calculating the Confidence Interval

$$|Z_1 = \frac{\bar{X} - \mu_{\bar{X}}}{\sigma_{\bar{X}}} = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

$$\mu = \bar{X} \pm Z_1 \sigma/\sqrt{n}$$

$$\overline{X} - Z_\alpha\left(\sigma/\sqrt{n}\right) \leq \mu \leq \overline{X} + Z_\alpha\left(\sigma/\sqrt{n}\right)$$

qnorm(p, mean = 0, sd = 1, lower.tail = TRUE)

where:

- **p:** The significance level to use
- **mean:** The mean of the normal distribution
- **sd:** The standard deviation of the normal distribution
- **lower.tail:** If TRUE, the probability to the left of **p** in the normal distribution is returned. If FALSE, the probability to the right is returned. Default is TRUE.

Standard Error Formula

The accuracy of a sample that describes a population is identified through the SE formula. The sample mean which deviates from the given population and that deviation is given as;

$$SE_{\bar{x}} = \frac{S}{\sqrt{n}}$$

Where S is the standard deviation and n is the number of observations.

Standard Error of Estimate (SEE)

The **standard error** of the **estimate** is the estimation of the accuracy of any predictions. It is denoted as SEE. The regression line depreciates the sum of squared deviations of prediction. It is also known as the sum of squares **error. SEE** is the square root of the average squared **deviation**. The deviation of some estimates from intended values is given by standard error of estimate formula.

$$SEE = \sqrt{\frac{\Sigma(x_i - \bar{x})}{n-2}}$$

Where x_i stands for data values, x bar is the mean value and n is the sample size.

Standard Error of the Mean (SEM)

The standard error of the mean also called the standard deviation of mean, is represented as the standard deviation of the measure of the sample mean of the population. It is abbreviated as SEM. For example, normally, the estimator of the population mean is the sample mean. But, if we draw another sample from the same population, it may provide a distinct value.

Thus, there would be a population of the sampled means having its distinct variance and mean. It may be defined as the standard deviation of such sample means of all the possible samples taken from the same given population. SEM defines an estimate of standard deviation which has been computed from the sample. It is calculated as the ratio of the standard deviation to the root of sample size, such as:

$$SEM = \frac{s}{\sqrt{n}}$$

Where 's' is the standard deviation and n is the number of observations.

Standard Error vs Standard Deviation

The below table shows how we can calculate the standard deviation (SD) using population parameters and standard error (SE) using sample parameters.

Population parameters	Formula for SD	Sample statistic	Formula for SE
Mean $\bar{x}$	$\frac{\sigma}{\sqrt{n}}$	Sample mean $\bar{x}$	$\frac{s}{\sqrt{n}}$
Sample proportion (P)	$\sqrt{\frac{P(1-P)}{n}}$	Sample proportion (p)	$\sqrt{\frac{p(1-p)}{n}}$
Difference between means $\bar{x}_1 - \bar{x}_2$	$\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_2^2}{n_2}}$	Difference between means $\bar{x}_1 - \bar{x}_2$	$\sqrt{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}$
Difference between proportions $P_1 - P_2$	$\sqrt{\frac{P_1(1-P_1)}{n_1}+\frac{P_2(1-P_2)}{n_2}}$	Difference between proportions $p_1 - p_2$	$\sqrt{\frac{p_1(1-p_1)}{n_1}+\frac{p_2(1-p_2)}{n_2}}$

Exponential Distribution Formula

The continuous random variable, say X is said to have an exponential distribution, if it has the following probability density function:

$$f_X(x|\lambda) = \begin{cases} \lambda e^{-\lambda x} & for\ x > 0 \\ 0 & for\ x \leq 0 \end{cases}$$

Where

λ is called the distribution rate.

Mean and Variance of Exponential Distribution

Mean:

The mean of the exponential distribution is calculated using the integration by parts.

$$Mean = E[X] = \int_0^\infty x\lambda e^{-\lambda x} dx$$

$$= \lambda \left[\left| \frac{-xe^{-\lambda x}}{\lambda} \right|_0^\infty + \frac{1}{\lambda} \int_0^\infty e^{-\lambda x} dx \right]$$

$$= \lambda \left[0 + \frac{1}{\lambda} \frac{-e^{-\lambda x}}{\lambda} \right]_0^\infty$$

$$= \lambda \frac{1}{\lambda^2}$$

$$= \frac{1}{\lambda}$$

Hence, the mean of the exponential distribution is $1/\lambda$.

Variance:

To find the variance of the exponential distribution, we need to find the second moment of the exponential distribution, and it is given by:

$E[X^2] = \int_0^\infty x^2 \lambda e^{-\lambda x} = \frac{2}{\lambda^2}$

Hence, the variance of the continuous random variable, X is calculated as:

Var (X) = E(X^2)- E(X)^2

Now, substituting the value of mean and the second moment of the exponential distribution, we get,

$Var(X) = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}$

Thus, the variance of the exponential distribution is 1/λ^2.