

Frequently Asked Questions

1. Briefly explain a Likelihood ratio test procedure

Answer:

Suppose a composite null hypothesis $H_0 : \theta \in \Theta_0$ is to be tested against a composite alternative hypothesis $H_1 : \theta \in \Theta_1$

For testing the above null hypothesis a test procedure called Likelihood ratio test procedure is followed which is explained below.

Let a random sample x_1, x_2, \dots, x_n of size n be drawn from the given population with p.d.f $f(x, \theta)$

$$\text{Let } \lambda = \frac{\sup_{\theta \in \Theta_0} L(\theta, x_1, x_2, \dots, x_n)}{\sup_{\theta \in \Theta} L(\theta, x_1, x_2, \dots, x_n)}$$

Since the supremum in the denominator is over a larger set of numbers. $\lambda \leq 1$. Also likelihood functions are nonnegative and hence $\lambda \geq 0$. Thus $0 \leq \lambda \leq 1$.

That is the test procedure is as follows:

If λ is very large that is $\lambda \geq \lambda_\alpha$ the null hypothesis is accepted and if λ is very small that is $\lambda < \lambda_\alpha$ the null hypothesis is to be rejected. The constant λ_α is so chosen that the size of the test is α

2. In practical situation how do you test the average of a Normal population?

Answer:

To test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu \neq \mu_0$, when the variance is known $\left| \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right|$ is computed and compared with the tabulated value $Z_{\alpha/2}$

That is when the computed value of $\left| \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right|$ exceeds $Z_{\alpha/2}$ we reject the null hypothesis.

To test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu \neq \mu_0$ when the

variance is unknown, $\left| \frac{\bar{x} - \mu_0}{s / \sqrt{n}} \right|$ is computed and if it exceeds the tabulated value of $t_\alpha (n-1)$ we reject the null hypothesis.

3. What is the test criterion to test the variance of a Normal population in practical cases?

Answer:

In practice, to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma \neq \sigma_0$, when the mean is

known, $\frac{\sum (x_i - \mu)^2}{\sigma_0^2}$ is computed and compared with the tabulated value. That is we reject

the null hypothesis if $\frac{\sum (x_i - \mu)^2}{\sigma_0^2} > \chi_{\alpha/2}^2(n)$ or $\frac{\sum (x_i - \mu)^2}{\sigma_0^2} < \chi_{1-\alpha/2}^2(n)$

To test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma \neq \sigma_0$, when the mean is unknown

$\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is computed and compared with the tabulated value. That is we reject the null

hypothesis if $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > \chi_{\alpha/2}^2(n-1)$ or $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} < \chi_{1-\alpha/2}^2(n-1)$

4. For a normal population with a known variance σ^2 derive LRTP to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu \neq \mu_0$

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu \in \Theta_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{\mu \in \Omega} L(\mu, x_1, x_2, \dots, x_n)}$$

Where λ_α is such that

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{ ---- (*)}$$

$$\lambda = \frac{\sup_{\mu = \mu_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{-\infty < \mu < \infty} L(\mu, x_1, x_2, \dots, x_n)}$$

$$\lambda = \frac{\sup_{\mu = \mu_0} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{-\infty < \mu < \infty} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

The denominator attains the maximum value when the unknown parameter is substituted by its maximum likelihood estimate. Thus substituting μ by \bar{x} , a sample mean in the denominator we can make it to attain its maximum value. Therefore

$$\lambda = \frac{\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \bar{x})^2}}$$

$$= e^{-\frac{1}{2\sigma^2} [\sum_i (x_i - \mu_0)^2 - \sum_i (x_i - \bar{x})^2]}$$

$$\Rightarrow e^{\frac{-1}{2\sigma^2} [\sum_i x_i^2 + n\mu_0^2 - 2\mu_0 \sum_i x_i - (\sum_i x_i^2 + n\bar{x}^2 - 2\bar{x} \sum_i x_i)]}$$

$$\Rightarrow e^{\frac{-1}{2\sigma^2} [n\mu_0^2 + n\bar{x}^2 - 2n\bar{x}\mu_0]}$$

$$\Rightarrow e^{\frac{-n}{2\sigma^2} [\mu_0^2 + \bar{x}^2 - 2\bar{x}\mu_0]} \Rightarrow e^{\frac{-n}{2\sigma^2} [\bar{x} - \mu_0]^2}$$

Now

$$\lambda \leq \lambda_\alpha \Rightarrow e^{\frac{-n}{2\sigma^2} [\bar{x} - \mu_0]^2} \leq \lambda_\alpha$$

$$\Rightarrow \frac{-n}{2\sigma^2} [\bar{x} - \mu_0]^2 \leq \ln \lambda_\alpha$$

$$\Rightarrow \left(\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right)^2 \left(\frac{-1}{2} \right) \leq \ln \lambda_\alpha$$

$$\Rightarrow \left(\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right)^2 > -2 \ln \lambda_\alpha$$

$$\Rightarrow \left| \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right| > \sqrt{-2 \ln \lambda_\alpha} = \lambda_1 \text{ (say)}$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P\left[\left| \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right| > \lambda_1 \right] = \alpha$$

When x_i follows Normal with parameters μ and σ^2 , a sample mean

$\bar{x} \sim N(\mu, \sigma^2 / n)$. Then $\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \sim N(0,1)$ under Null hypothesis

$$\Rightarrow P[|N(0,1)| > \lambda_1] = \alpha$$

Now from the table of Normal Probabilities we can read $\lambda_1 = Z_{\alpha/2}$. Using the relation

among λ_α and $\lambda_1 = Z_{\alpha/2}$, λ_α and hence the test can be determined.

5. Deduce LRTP to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu > \mu_0$ when the variance is given

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu \in \Theta_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{\mu \in \Omega} L(\mu, x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{ ----- (*)}$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\mu=\mu_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{-\infty < \mu < \infty} L(\mu, x_1, x_2, \dots, x_n)}$$

$$\lambda = \frac{\sup_{\mu=\mu_0} \left(\frac{1}{\sigma\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{-\infty < \mu < \infty} \left(\frac{1}{\sigma\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

If μ_0 is greater than the sample mean, estimate of μ is μ_0 in the denominator then $\lambda=1$, in which case the null hypothesis should surely be accepted.

If μ_0 is less than the sample mean then the maximum likelihood estimate of μ is \bar{x} . Thus substituting μ by \bar{x} , a sample mean in the denominator we can make it to attain its maximum value as above we get

$$\lambda = \frac{\left(\frac{1}{\sigma\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\sigma\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \bar{x})^2}}$$

Now

$$\lambda \leq \lambda_\alpha \Rightarrow$$

$$\Rightarrow \left(\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} \right)^2 > -2 \ln \lambda_\alpha$$

$$\Rightarrow \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} > \sqrt{-2 \ln \lambda_\alpha} = \lambda_1 \text{ (say)}$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P\left[\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} > \lambda_1 \right] = \alpha$$

$$\Rightarrow P[N(0,1) > \lambda_1] = \alpha$$

Now from the table of Normal Probabilities we can read $\lambda_1 = Z_\alpha$. Using the relation among λ_α and $\lambda_1 = Z_\alpha$, λ_α and hence the test can be determined. For our practical purposes to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu > \mu_0$, $\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$ is

computed and compared with the tabulated value Z_{α} . That is we reject the null hypothesis if

$$\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \text{ exceeds } Z_{\alpha}$$

6. To test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu < \mu_0$, derive LRTP when variance of the population is known

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu \in \Theta_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{\mu \in \Omega} L(\mu, x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_{\alpha} / H_0] = \alpha \text{-----} (*)$$

Where λ_{α} is such that

$$\lambda = \frac{\sup_{\mu = \mu_0} L(\mu, x_1, x_2, \dots, x_n)}{\sup_{-\infty < \mu < \infty} L(\mu, x_1, x_2, \dots, x_n)}$$

$$\lambda = \frac{\sup_{\mu = \mu_0} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{-\infty < \mu < \infty} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

$$\lambda = \frac{\sup_{\mu = \mu_0} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\mu \leq \mu_0} \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

If μ_0 is less than the sample mean, estimate of μ is μ_0 in the denominator then $\lambda=1$, in which case the null hypothesis should surely be accepted.

If μ_0 is greater than the sample mean then the maximum likelihood estimate of μ is \bar{x} . Thus

substituting μ by \bar{x} , a sample mean in the denominator we can make it to attain its maximum value as above we get

$$\lambda = \frac{\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \bar{x})^2}}$$

Now

$$\lambda \leq \lambda_\alpha \Rightarrow$$

$$\Rightarrow \left(\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \right)^2 > -2 \ln \lambda_\alpha$$

$$\Rightarrow \frac{\mu_0 - \bar{x}}{\sigma / \sqrt{n}} > \sqrt{-2 \ln \lambda_\alpha} = \lambda_1 \text{ (say)}$$

$$\Rightarrow \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \leq -\sqrt{-2 \ln \lambda_\alpha} = -\lambda_1$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P\left[\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}} \leq -\lambda_1\right] = \alpha$$

$$\Rightarrow P[N(0,1) \leq -\lambda_1] = \alpha$$

Using the relation among λ_α , and $\lambda_1 = Z_\alpha$, λ_α and hence the test can be determined. For our practical purposes to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis

$H_1: \mu < \mu_0$, $\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$ is computed and compared with the tabulated value $-Z_\alpha$. That is we reject

the null hypothesis if $\frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$ is less than $-Z_\alpha$

7. Let $x \sim N(\mu, \sigma^2)$ Obtain LRTP to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu \neq \mu_0$, with an unknown variance σ^2

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu = \mu_0} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma^2, \mu} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{ --- (*)}$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\sigma^2, \mu = \mu_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma^2, \mu} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

$$\sum (x_i - \mu_0)^2$$

Under the null hypothesis the m.l.e of σ^2 is $\frac{\sum (x_i - \mu_0)^2}{n}$ otherwise the m.l.e's of μ and σ^2

are \bar{x} and $\frac{\sum (x_i - \bar{x})^2}{n}$. In the expression of λ substituting the parameters by m.l.e's so that numerator and denominator attains its supremum we have

$$\lambda = \frac{\left(\frac{1}{\frac{\sum (x_i - \mu_0)^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \mu_0)^2}{n}} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\frac{\sum (x_i - \bar{x})^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \bar{x})^2}{n}} \sum_i (x_i - \bar{x})^2}}$$

$$= \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \mu_0)^2} \right)^{\frac{n}{2}}$$

Consider

$$\sum (x_i - \mu_0)^2 =$$

$$\sum [(x_i - \bar{x}) + (\bar{x} - \mu_0)]^2 = \sum (x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2 \text{ because } \sum (x_i - \bar{x}) = 0$$

$$\lambda = \left(\frac{\sum (xi - \bar{x})^2}{\sum (xi - \bar{x})^2 + n(\bar{x} - \mu_0)^2} \right)^{\frac{n}{2}} = \left(\frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{\sum (xi - \bar{x})^2}} \right)^{\frac{n}{2}}$$

Now

$$\lambda \leq \lambda_\alpha \Rightarrow \left(\frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{\sum (xi - \bar{x})^2}} \right)^{\frac{n}{2}} \leq \lambda_\alpha$$

$$\Rightarrow \left(\frac{1}{1 + \frac{t^2}{n-1}} \right)^{\frac{n}{2}} \leq \lambda_\alpha \Rightarrow \left(\frac{1}{1 + \frac{t^2}{n-1}} \right) \leq \lambda_\alpha^{\frac{2}{n}}$$

Where $t = \frac{(\bar{x} - \mu_0)}{s/\sqrt{n}}$ and $s^2 = \frac{\sum (xi - \bar{x})^2}{n-1}$ then $\frac{t^2}{n-1} = \frac{n(\bar{x} - \mu_0)^2}{\sum (xi - \bar{x})^2}$

$$\Rightarrow \left(1 + \frac{t^2}{n-1} \right) > \lambda_\alpha^{\frac{-2}{n}} \Rightarrow t^2 \geq (n-1)(\lambda_\alpha^{\frac{-2}{n}} - 1)$$

$$\Rightarrow |t| \geq \sqrt{(n-1)(\lambda_\alpha^{\frac{-2}{n}} - 1)} = \lambda_1 \text{ (say)}$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P[|t| > \lambda_1] = \alpha$$

The quantity λ_1 can be read from the table of probabilities of Student's t distribution for (n-1) degrees of freedom as $\lambda_1 = t_{\alpha}(n-1)$. Using the relation among λ_1 and λ_α , the test can be determined.

8. To test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu > \mu_0$, the variance unknown obtain LRTP.

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\sigma^2, \mu} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma^2, \mu} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\sigma^2, \mu} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma^2, \mu} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

$$\sum (x_i - \mu_0)^2$$

Under the null hypothesis the m.l.e of σ^2 is $\frac{\sum (x_i - \mu_0)^2}{n}$ otherwise the m.l.e's of μ and σ^2

$$\sum (x_i - \bar{x})^2$$

are \bar{x} and $\frac{\sum (x_i - \bar{x})^2}{n}$. In the expression of λ substituting the parameters by m.l.e's so that

numerator and denominator attains its supremum we have

$$\lambda = \frac{\left(\frac{1}{\sum (x_i - \mu_0)^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \sum (x_i - \mu_0)^2} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\sum (x_i - \bar{x})^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \sum (x_i - \bar{x})^2} \sum_i (x_i - \bar{x})^2}}$$

$$= \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \mu_0)^2} \right)^{\frac{n}{2}}$$

Consider

$$\sum (xi - \mu_0)^2 =$$

$$\sum [(xi - \bar{x}) + (\bar{x} - \mu_0)]^2 = \sum (xi - \bar{x})^2 + n(\bar{x} - \mu_0)^2 \text{ because } \sum (xi - \bar{x}) = 0$$

$$\lambda = \left(\frac{\sum (xi - \bar{x})^2}{\sum (xi - \bar{x})^2 + n(\bar{x} - \mu_0)^2} \right)^{\frac{n}{2}} = \left(\frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{\sum (xi - \bar{x})^2}} \right)^{\frac{n}{2}}$$

$$\lambda \leq \lambda_\alpha \Rightarrow \frac{\bar{x} - \mu_0}{s/\sqrt{n}} > \lambda_1$$

Now size of the test = $\alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P\left[\frac{\bar{x} - \mu_0}{s/\sqrt{n}} > \lambda_1\right] = \alpha$$

$$\Rightarrow P[t > \lambda_1] = \alpha$$

Now from the table of probabilities of t distribution we can read $\lambda_1 = t_{2\alpha}(n-1)$ For our practical purposes to test the null hypothesis

$H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu > \mu_0$, $\frac{\bar{x} - \mu_0}{s/\sqrt{n}}$ is computed and compared with the tabulated value $t_{2\alpha}(n-1)$

That is we reject the null hypothesis if $\frac{\bar{x} - \mu_0}{s/\sqrt{n}}$ exceeds $t_{2\alpha}(n-1)$

9. Obtain a test procedure to test the null hypothesis $H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu < \mu_0$ for an unknown variance.

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\sigma^2, \mu = \mu_0} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma^2, \mu} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{ ----- (*)}$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\sigma^2, \mu} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma^2, \mu} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

Under the null hypothesis the m.l.e of σ^2 is $\frac{\sum (x_i - \mu_0)^2}{n}$ otherwise the m.l.e's of μ and

σ^2 are \bar{x} and $\frac{\sum (x_i - \bar{x})^2}{n}$. In the expression of λ substituting the parameters by m.l.e's so that numerator and denominator attains its supremum we have

$$\lambda = \frac{\left(\frac{1}{\frac{\sum (x_i - \mu_0)^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \mu_0)^2}{n}} \sum_i (x_i - \mu_0)^2}}{\left(\frac{1}{\frac{\sum (x_i - \bar{x})^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \bar{x})^2}{n}} \sum_i (x_i - \bar{x})^2}}$$

$$= \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \mu_0)^2} \right)^{\frac{n}{2}}$$

Consider

$$\sum (x_i - \mu_0)^2 =$$

$$\sum [(x_i - \bar{x}) + (\bar{x} - \mu_0)]^2 = \sum (x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2 \text{ because } \sum (x_i - \bar{x}) = 0$$

$$\lambda = \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2} \right)^{\frac{n}{2}} = \left(\frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{\sum (x_i - \bar{x})^2}} \right)^{\frac{n}{2}} \quad \text{To test the null}$$

Now

$$\lambda \leq \lambda_\alpha \Rightarrow \frac{\bar{x} - \mu_0}{s / \sqrt{n}} \leq -\lambda_1$$

Now size of the test = α

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \mu = \mu_0] = \alpha$$

$$\Rightarrow P\left[\frac{\bar{x} - \mu_0}{s / \sqrt{n}} \leq -\lambda_1\right] = \alpha$$

For our practical purposes to test the null hypothesis

$H_0: \mu = \mu_0$ against the alternative hypothesis $H_1: \mu < \mu_0$, $\frac{\bar{x} - \mu_0}{s / \sqrt{n}}$ is computed and compared with the tabulated value $t_{2\alpha}(n-1)$

That is we reject the null hypothesis if $\frac{\bar{x} - \mu_0}{s / \sqrt{n}}$ is less than $-t_{2\alpha}(n-1)$

10. Let $x \sim N(\mu, \sigma^2)$ with a known mean μ . Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma \neq \sigma_0$

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

The denominator attains the maximum value when the unknown parameter is substituted by

its maximum likelihood estimate. Thus substituting $\sigma^2 = \frac{\sum (xi - \mu_0)^2}{n}$ in the denominator we can make it to attain its maximum value. Therefore

$$\begin{aligned}\lambda &= \frac{\left(\frac{1}{\sigma_0^2}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{\frac{-1}{2\sigma_0^2} \sum_i (xi - \mu)^2}}{\left(\frac{1}{\frac{\sum (xi - \mu)^2}{n}}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{\frac{-1}{2 \frac{\sum (xi - \mu)^2}{n}} \sum_i (xi - \mu)^2}} \\&\Rightarrow \left(\frac{\sum (xi - \mu)^2}{\sigma_0^2}\right)^{\frac{n}{2}} n^{\frac{-n}{2}} e^{\frac{-n}{2} \frac{\sum (xi - \mu)^2}{\sigma_0^2}} \\&\Rightarrow e^{\frac{-u}{2} \frac{n}{u^2} k} \text{ where } u = \frac{\sum (xi - \mu)^2}{\sigma_0^2}, k = n^{\frac{-n}{2}} e^{\frac{n}{2}} \\&\lambda \leq \lambda_\alpha \Rightarrow e^{\frac{-u}{2} \frac{n}{u^2} k} \leq \lambda_\alpha \Rightarrow e^{\frac{-u}{2} \frac{n}{u^2}} \leq \frac{\lambda_\alpha}{k}\end{aligned}$$

Now

$$\Rightarrow u \leq c_1 \text{ or } u \geq c_2 \text{ where } e^{\frac{-c_1}{2} \frac{n}{c_1^2}} = e^{\frac{-c_2}{2} \frac{n}{c_2^2}} = \frac{\lambda_\alpha}{k}$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P[u \leq c_1 \text{ or } u \geq c_2 / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P[\chi^2_{(n)} \leq c_1] + P[\chi^2_{(n)} \geq c_2] = \alpha$$

When xi follows Normal with parameters μ and σ^2 ,

and when $\sigma = \sigma_0$, $\frac{\sum (x_i - \mu)^2}{\sigma_0^2} \sim \chi_{\alpha/2}^2(n)$. Therefore we find the constants C_1 and C_2

$$\text{such that } e^{-\frac{c_1}{2}} \frac{n}{c_1^2} = e^{-\frac{c_2}{2}} \frac{n}{c_2^2} = \frac{\lambda_\alpha}{k}$$

And $P[\chi^2(n) \leq c_1] + P[\chi^2(n) \geq c_2] = \alpha$ where $c_1 = \chi_{1-\alpha/2}^2(n)$ and $C_2 = \chi_{\alpha/2}^2(n)$

11. Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma > \sigma_0$ when the mean of a Normal population is known.

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

The denominator attains the maximum value when the unknown parameter is substituted by

$$\frac{\sum (x_i - \mu_0)^2}{n}$$

its maximum likelihood estimate. Thus substituting $\sigma^2 = \frac{\sum (x_i - \mu_0)^2}{n}$ in the denominator

we can make it to attain its maximum value. Therefore

$$\lambda = \frac{\left(\frac{1}{\sigma_0^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma_0^2} \sum_i (x_i - \mu)^2}}{\left(\frac{1}{\frac{\sum (x_i - \mu)^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \mu)^2}{n}} \sum_i (x_i - \mu)^2}}$$

$$\Rightarrow \left(\frac{\sum (x_i - \mu)^2}{\sigma_0^2} \right)^{\frac{n}{2}} \frac{1}{n^{\frac{n}{2}} e^{\frac{n}{2}} e^{\frac{(-1)}{2} \frac{\sum (x_i - \mu)^2}{\sigma_0^2}}}$$

$$\Rightarrow e^{-\frac{u}{2}} \frac{1}{u^{\frac{n}{2}}} k \text{ where } u = \frac{\sum (x_i - \mu)^2}{\sigma_0^2}, k = n^{\frac{n}{2}} e^{\frac{n}{2}}$$

$$\lambda \leq \lambda_\alpha \Rightarrow \frac{\sum (x_i - \mu)^2}{\sigma_0^2} > C_1 = \chi_{\alpha}^2(n)$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P\left[\frac{\sum (x_i - \mu)^2}{\sigma_0^2} > \chi_{\alpha}^2(n)\right] = \alpha$$

In practice to test the null hypothesis

$H_0: \sigma = \sigma_0$ against $H_1: \sigma > \sigma_0$, the mean is known $\frac{\sum (x_i - \mu)^2}{\sigma_0^2}$ is computed and compared with

the tabulated value $\chi_{\alpha}^2(n)$. That is we reject the null hypothesis if $\frac{\sum (x_i - \mu)^2}{\sigma_0^2}$ exceeds $\chi_{\alpha}^2(n)$

12. Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma < \sigma_0$ when the mean of a Normal population is known.

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

Where λ_α is such that

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{ --- (*)}$$

$$\lambda = \frac{\sup_{\sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

The denominator attains the maximum value when the unknown parameter is substituted by

its maximum likelihood estimate. Thus substituting $\sigma^2 = \frac{\sum (x_i - \mu_0)^2}{n}$ in the denominator we can make it to attain its maximum value. Therefore

$$\lambda = \frac{\left(\frac{1}{\sigma_0^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma_0^2} \sum_i (x_i - \mu)^2}}{\left(\frac{1}{\frac{\sum (x_i - \mu)^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2 \frac{\sum (x_i - \mu)^2}{n}} \sum_i (x_i - \mu)^2}}$$

$$\Rightarrow \left(\frac{\sum (x_i - \mu)^2}{\sigma_0^2} \right)^{\frac{n}{2}} n^{\frac{n}{2}} e^{\frac{-n}{2}} e^{\frac{-1}{2} \frac{\sum (x_i - \mu)^2}{\sigma_0^2}}$$

$$\Rightarrow e^{\frac{-u}{2}} u^{\frac{n}{2}} k \text{ where } u = \frac{\sum (x_i - \mu)^2}{\sigma_0^2}, k = n^{\frac{n}{2}} e^{\frac{-n}{2}}$$

How the assumptions of the model can be tested using LRTP

$$\lambda \leq \lambda_\alpha \Rightarrow \frac{\sum (x_i - \mu)^2}{\sigma_0^2} < C_2 = \chi_{1-\alpha}^2(n)$$

Now size of the test = $\alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P\left[\frac{\sum (x_i - \mu)^2}{\sigma_0^2} < \chi_{1-\alpha}^2(n) \right] = \alpha$$

In practice to test the null hypothesis

$H_0: \sigma = \sigma_0$ against $H_1: \sigma < \sigma_0$, the mean is known $\frac{\sum (xi - \mu)^2}{\sigma_0^2}$ is computed and compared

with the tabulated value $\chi_{1-\alpha}^2(n)$. That is we reject the null hypothesis if $\frac{\sum (xi - \mu)^2}{\sigma_0^2}$ is less than $\chi_{1-\alpha}^2(n)$

13. Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma \neq \sigma_0$, with an unknown mean μ

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\mu, \sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

Where λ_α is such that

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (xi - \mu)^2}}{\sup_{\mu, \sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{\frac{-1}{2\sigma^2} \sum_i (xi - \mu)^2}}$$

Under the null hypothesis the m.l.e of $\mu = \bar{x}$ otherwise the m.l.e's of μ and σ^2 are \bar{x} and

$$\frac{\sum (xi - \bar{x})^2}{n}.$$

In the expression of λ substituting the parameters by m.l.e's so that numerator and denominator attains its supremum we have

$$\lambda = \frac{\left(\frac{1}{\sigma_0^2}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2\sigma_0^2} \sum_i (x_i - \bar{x})^2}}{\left(\frac{1}{\sum_i (x_i - \bar{x})^2}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2n} \sum_i (x_i - \bar{x})^2}}$$

$$\Rightarrow \left(\frac{\sum_i (x_i - \bar{x})^2}{\sigma_0^2}\right)^{\frac{n}{2}} n^{-\frac{n}{2}} e^{\frac{-1}{2} \frac{\sum_i (x_i - \bar{x})^2}{\sigma_0^2}}$$

$$\Rightarrow e^{\frac{-u}{2}} u^{\frac{n}{2}} k \text{ where } u = \frac{\sum_i (x_i - \bar{x})^2}{\sigma_0^2}, k = n^{-\frac{n}{2}} e^{\frac{n}{2}}$$

$$\lambda \leq \lambda_\alpha \Rightarrow e^{\frac{-u}{2}} u^{\frac{n}{2}} k \leq \lambda_\alpha \Rightarrow e^{\frac{-u}{2}} u^{\frac{n}{2}} \leq \frac{\lambda_\alpha}{k}$$

Now

$$\Rightarrow u \leq c_1 \text{ or } u \geq c_2 \text{ where } e^{\frac{-c_1}{2}} c_1^{\frac{n}{2}} = e^{\frac{-c_2}{2}} c_2^{\frac{n}{2}} = \frac{\lambda_\alpha}{k}$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P[u \leq c_1 \text{ or } u \geq c_2 / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P[\chi^2_{(n)} \leq c_1] + P[\chi^2_{(n)} \geq c_2] = \alpha$$

When x_i follows Normal with parameters μ and σ^2 and when $\sigma =$

$$\frac{\sum_i (x_i - \bar{x})^2}{\sigma_0^2} \sim \chi_{\alpha/2}^2(n-1)$$

σ_0

Therefore we find the constants C_1 and C_2 such that $e^{-\frac{c_1}{2}} \frac{n}{c_1^{\frac{n}{2}}} = e^{-\frac{c_2}{2}} \frac{n}{c_2^{\frac{n}{2}}} = \frac{\lambda_\alpha}{k}$

And $P[\chi^2_{(n-1)} \leq c_1] + P[\chi^2_{(n-1)} \geq c_2] = \alpha$ where $c_1 = \chi^2_{1-\alpha/2}(n-1)$ and

$$C_2 = \chi^2_{\alpha/2}(n-1)$$

In practice to test the null hypothesis

$H_0: \sigma = \sigma_0$ against $H_1: \sigma \neq \sigma_0$, $\frac{\sum (xi - \bar{x})^2}{\sigma_0^2}$ is computed and compared with the tabulated value.

That is we reject the null hypothesis if $\frac{\sum (xi - \bar{x})^2}{\sigma_0^2} > \chi^2_{\alpha/2}(n-1)$ or

$$\frac{\sum (xi - \bar{x})^2}{\sigma_0^2} < \chi^2_{1-\alpha/2}(n-1)$$

14. Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma > \sigma_0$, with an unknown mean μ

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\mu, \sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

Where λ_α is such that

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (xi - \mu)^2}}{\sup_{\mu, \sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (xi - \mu)^2}}$$

Under the null hypothesis the m.l.e of $\mu = \bar{x}$ otherwise the m.l.e's of μ and σ^2 are \bar{x} and $\frac{\sum (xi - \bar{x})^2}{n}$

In the expression of λ substituting the parameters by m.l.e's so that numerator and denominator attains its supremum we have

$$\lambda = \frac{\left(\frac{1}{\sigma_0^2}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2\sigma_0^2} \sum_i (x_i - \bar{x})^2}}{\left(\frac{1}{\sum (x_i - \bar{x})^2}\right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2 \sum (x_i - \bar{x})^2} \sum_i (x_i - \bar{x})^2}}$$

$$\Rightarrow \left(\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}\right)^{\frac{n}{2}} n^{-\frac{n}{2}} e^{\frac{n}{2} \left(\frac{-1}{2}\right) \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}}$$

$$\Rightarrow e^{\frac{-u}{2}} u^{\frac{n}{2}} k \text{ where } u = \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}, k = n^{-\frac{n}{2}} e^{\frac{n}{2}}$$

$$\lambda \leq \lambda_\alpha \Rightarrow \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > C_1 = \chi_\alpha^2 (n-1)$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_\alpha / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P\left[\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} > \chi_\alpha^2 (n-1)\right] = \alpha$$

In practice to test the null hypothesis

$H_0: \sigma = \sigma_0$ against $H_1: \sigma > \sigma_0$, the mean is unknown $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is computed and compared

with the tabulated value $\chi_\alpha^2 (n-1)$.

That is we reject the null hypothesis if $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ exceeds $\chi_\alpha^2 (n-1)$

15. Derive LRTP to test the null hypothesis $H_0: \sigma = \sigma_0$ against $H_1: \sigma < \sigma_0$, with an unknown mean μ

Answer:

Let x_1, x_2, \dots, x_n be a random sample of size n from a Normal population with parameters μ and σ^2

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} L(x_1, x_2, \dots, x_n)}{\sup_{\mu, \sigma \geq 0} L(x_1, x_2, \dots, x_n)}$$

Where λ_α is such that

$$P[\lambda \leq \lambda_\alpha / H_0] = \alpha \text{-----} (*)$$

$$\lambda = \frac{\sup_{\mu, \sigma = \sigma_0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}{\sup_{\mu, \sigma \geq 0} \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_i (x_i - \mu)^2}}$$

Under the null hypothesis the m.l.e of $\mu = \bar{x}$ otherwise the m.l.e's of μ and σ^2 are \bar{x} and $\frac{\sum (x_i - \bar{x})^2}{n}$.

In the expression of λ substituting the parameters by m.l.e's so that numerator and denominator attains its supremum we have

$$\begin{aligned} \lambda &= \frac{\left(\frac{1}{\sigma_0^2} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2\sigma_0^2} \sum_i (x_i - \bar{x})^2}}{\left(\frac{1}{\frac{\sum (x_i - \bar{x})^2}{n}} \right)^{\frac{n}{2}} \left(\frac{1}{\sqrt{2\pi}} \right)^n e^{-\frac{1}{2 \frac{\sum (x_i - \bar{x})^2}{n}} \sum_i (x_i - \bar{x})^2}} \\ &\Rightarrow \left(\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} \right)^{\frac{n}{2}} n^{\frac{-n}{2}} e^{\frac{n}{2}} e^{\left(\frac{-1}{2} \right) \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}} \\ &\Rightarrow e^{\frac{-u}{2}} n^{\frac{n}{2}} k \text{ where } u = \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}, k = n^{\frac{-n}{2}} e^{\frac{n}{2}} \end{aligned}$$

Now

$$\lambda \leq \lambda_{\alpha} \Rightarrow \frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} < C_2 = \chi_{1-\alpha}^2 (n-1)$$

Now size of the test $= \alpha \Rightarrow P[\text{Reject } H_0 / H_0 \text{ true}] = \alpha$

$$\Rightarrow P[\lambda \leq \lambda_{\alpha} / \sigma = \sigma_0] = \alpha$$

$$\Rightarrow P\left[\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2} < \chi_{1-\alpha}^2 (n-1)\right] = \alpha$$

In practice to test the null hypothesis

$H_0: \sigma = \sigma_0$ against $H_1: \sigma < \sigma_0$, the mean is unknown $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is computed and compared

with the tabulated value $\chi_{1-\alpha}^2 (n-1)$.

That is we reject the null hypothesis if $\frac{\sum (x_i - \bar{x})^2}{\sigma_0^2}$ is less than $\chi_{1-\alpha}^2 (n-1)$