

# Hypothesis Testing

Most statistical inference centers around the parameters of a population( often the mean, standard deviation). Methods of drawing inferences about parameters are of two types:

- ▶ Actually estimate the value of the parameters
- ▶ Make decisions concerning the value of the parameters

When we estimate the value of the parameters we are using the method of estimations. Decisions concerning the value of the parameter are obtained by hypothesis testing.

The hypothesis testing procedure is a method for choosing between two competing hypotheses the so-called null hypothesis ( $H_o$ ) and alternative hypothesis( $H_a$ ).

# Null Vs. Alternative Hypotheses

**Null Hypothesis ( $H_o$ ):** A null hypothesis is a claim (or statement) about a population parameter that is assumed to be true until it is declared false.

**Alternative Hypothesis( $H_a$ ):** An alternative hypothesis is a claim about population parameters that will be true if the null hypothesis is false.

A statistical test is

i) **left- tailed** if  $H_a$  states that the parameter is less than the value claimed in  $H_o$

$$H_0 : \mu \geq \mu_0$$

$$H_a : \mu < \mu_0$$

ii) **right- tailed** if  $H_a$  states that the parameter is greater than the value claimed in  $H_o$

$$H_0 : \mu \leq \mu_0$$

$$H_a : \mu > \mu_0$$

iii) **two- tailed** if  $H_a$  states that the parameter is different from the value claimed in  $H_o$ .

$$H_0 : \mu = \mu_0$$

$$H_a : \mu \neq \mu_0$$

# Guidelines for Hypothesis Testing

- ▶ When testing a hypothesis concerning the value of some parameter, the statement of equality will always be included in  $H_o$ .
- ▶ Whatever is to be detected or supported is the alternative hypothesis.
- ▶ Since our research hypothesis is  $H_a$ , it is hoped that the evidence leads us to reject  $H_o$  and thereby to accept  $H_a$

Once a sample has been selected and the data have been collected, a decision must be made. The decision will be one of the following

- ▶ Reject  $H_0$
- ▶ Fail to reject  $H_0$

**Definition:** The decision is made by observing the value of some statistic whose probability distribution is known under assumption that the null value is the true value of the parameter. Such statistic is called the **test statistic**.

**Definition:** A rejection region is the region that specifies the values of the observed test statistic for which the null hypothesis will be rejected.

Few steps to perform hypothesis test

- ▶ Determine the parameter of interest.
- ▶ Determine the null hypothesis  $H_0$ .
- ▶ Determine the alternative hypothesis  $H_a$
- ▶ Choose the appropriate test statistic.
- ▶ Determine the rejection region using the significance level.
- ▶ Determine if the test statistic falls into the rejection region or not.
- ▶ Draw your conclusion:
  - ▶ Reject the null hypothesis
  - ▶ Fail to reject the null hypothesis

A type I error occurs when a true null hypothesis is rejected. The probability of committing a type I error is called the level of significance of the test and is denoted by  $\alpha$ . Hence

$$\alpha = P(\text{Type I error}) = P(\text{Reject } H_0 | H_0 \text{ is true})$$

A type II error occurs when a false null hypothesis is not rejected. The probability of committing Type II error is denoted by  $\beta$ . Hence,

$$\begin{aligned}\beta &= P(\text{Type II error}) = P(\text{Fail to Reject } H_0 | H_0 \text{ is false}) \\ \text{Power} &= 1 - \beta\end{aligned}$$



## Hypothesis Testing using p-value

A p-value is the probability of observing a value of the test statistic as extreme or more extreme than the observed one, assuming the null hypothesis is true. This means the p-value is the smallest significance level at which the null hypothesis is rejected. For this reason, the p-value is sometimes called the observed significance level.

- If the computed p-value is smaller than  $\alpha$ , reject the null hypothesis.
- If the computed p-value is greater than  $\alpha$ , fail to reject the null hypothesis.

Remark: The p-value for a two sided hypothesis we simply double the tail probability of the test statistic. For example , suppose we are testing the following hypothesis:

$$H_o : \mu = 5$$

$$H_1 : \mu \neq 5$$

further suppose the computed test statistics is  $z = 2.31$

Then the tail area associated with the test statistics is 0.0104. To compute the p-value, for a two sided hypothesis tests , we have  $P\text{-value} = 0.0104 + 0.0104 = 0.0208$ .

The p-value of 0.0208 is the likelihood of observing a value of the test statistic greater than 2.31 or less than -2.31 given the null hypothesis is true.

The p-value answers the following question:

If the null hypothesis is true, how likely is it that our observed test statistic takes the value we observed or more extreme? If this probability is small, then we reject the null hypothesis. If the p-value is not small, then we do not reject the null hypothesis.

### Interpreting p-values.

Here are some rough guidelines for interpreting p-values which can be used in any testing scenario (not just for testing hypotheses about the mean). Let  $p$  denote the p-value of a test:

- If  $p \leq 0.01$ , then one has very strong evidence against the null hypothesis.
- If  $0.01 < p \leq 0.05$ , then one has strong evidence against the null hypothesis.
- If  $0.05 < p < 0.10$ , then the evidence against the null hypothesis is moderate to weak.
- If  $0.10 \leq p < 0.20$  then the evidence against the null hypothesis is quite weak.
- If  $p > 0.20$ , then there is no evidence against null hypothesis.

There are three forms of test of hypotheses on the mean of a distribution:

## Right Tailed test

$$H_0 : \mu \leq \mu_o, \quad H_a : \mu > \mu_o$$

## Left Tailed test

$$H_0 : \mu \geq \mu_o, \quad H_a : \mu < \mu_o$$

## Two Tailed test

$$H_0 : \mu = \mu_o, \quad H_a : \mu \neq \mu_o$$

In order to test a hypothesis on a parameter , say  $\mu$ , we must find a statistic whose probability distribution is known at least under the null hypothesis. This statistic is called the test statistic.

If  $\sigma$  is known we have the test statistic

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$$

which follows standard normal distribution.

Decision criteria:

Hypothesis	Rejection Criteria
$H_o : \mu = \mu_o$ Vs. $H_a : \mu > \mu_0$	$Z > Z_\alpha$
$H_o : \mu = \mu_o$ Vs. $H_a : \mu < \mu_0$	$Z < -Z_\alpha$
$H_o : \mu = \mu_o$ Vs. $H_a : \mu \neq \mu_0$	$ Z  > Z_{\alpha/2}$

The p-value is the smallest significance level at which the null hypothesis would still be rejected.

1. The p-value is the  $\alpha$  that we can compute if we use the actual value of our test statistic as  $z$ .
2. For a  $z$  test (with normal or approximately normal populations) the p-value is
  - ▶  $p = 1 - \Phi(z)$  for an upper tailed test  
 $p = 1 - \text{pnorm}(z)$
  - ▶  $p = \Phi(z)$  for lower tailed test  
 $p = \text{pnorm}(z)$
  - ▶  $p = 2(1 - \Phi(|z|))$  for two tailed test  
 $p = 2(1 - \text{pnorm}(|z|))$

## Example

A new type of body armor is tested if it satisfies the specification of at most  $\mu_0 = 1.9$  in of displacement when hit with a certain type of bullet. The manufacturer tests by firing one round each at 36 samples of the new armor and measuring the displacement upon impact. The result is a sample mean displacement of 1.91 in. Assume the displacements are normally distributed with mean  $\mu$  and a standard deviation of 0.06 in. Test if the armor is up to specifications at the 10% significance level.

*Solution: Parameter of interest is  $\mu$  the true mean displacement.*

*Null hypothesis:  $H_0 : \mu = 1.9$*

*Alternative hypothesis:  $H_a : \mu > 1.9$*

*The test statistic is*

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} = \frac{1.91 - 1.9}{0.06/\sqrt{36}} = 1$$

*Rejection region: We use an upper tailed test and the critical value is  $Z_{0.1} = 1.2815$ .*

*Decision: Fail to reject the null hypothesis as  $1 < 1.2815$*

We need to install new package "TeachingDemos" or "BSDA"

`z.test` {TeachingDemos} R Documentation

Z test for known population standard deviation

```
z.test(x,mu =0,stdev,alternative=c("two.sided","less","greater"),  
       sd = stdev, conf.level = 0.95, ...)
```

Example:

```
x <- rnorm(25, 100, 5)
```

```
z.test(x, 99, 5)
```

## Example

A new type of body armor is tested if it satisfies the specification of at most  $\mu_0 = 1.9$  in of displacement when hit with a certain type of bullet. The manufacturer tests by firing one round each at 36 samples of the new armor and measuring the displacement upon impact. The result is a sample mean displacement of 1.91 in. Assume the displacements are normally distributed with mean  $\mu$  and a standard deviation of 0.06 in. Test if the armor is up to specifications at the 10% significance level.

*Solution: Parameter of interest is  $\mu$  the true mean displacement.*

*Null hypothesis:  $H_0 : \mu = 1.9$*

*Alternative hypothesis:  $H_a : \mu > 1.9$*

```
>library(BSDA)
>zsum.test(mean.x=1.91,sigma.x=0.06,n.x=36, mu=1.9,alt="greater")
      One-sample z-Test
data:  Summarized x
z = 1, p-value = 0.1587
alternative hypothesis: true mean is greater than 1.9
```

*Decision: Fail to reject the null hypothesis as  $p\text{-value} > \alpha$*



If  $\sigma$  is unknown and  $n$  is small we have the test statistic

$$T = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$$

which follows  $t$ -distribution with  $n - 1$  degrees of freedom.

Decision criteria:

Hypothesis	Rejection Criteria
$H_o : \mu = \mu_o$ Vs. $H_a : \mu > \mu_0$	$T > T_{\alpha, n-1}$
$H_o : \mu = \mu_o$ Vs. $H_a : \mu < \mu_0$	$T < -T_{\alpha, n-1}$
$H_o : \mu = \mu_o$ Vs. $H_a : \mu \neq \mu_0$	$ T  > T_{\alpha/2, n-1}$

The p-value is the smallest significance level at which the null hypothesis would still be rejected.

1. The p-value is the  $\alpha$  that we can compute if we use the actual value of our test statistic as  $t$ .
2. For a t test (with normal or approximately normal populations) the p-value is
  - ▶  $p = P(T > t)$  for an upper tailed test  
 $p = 1 - \text{pt}(t, n)$
  - ▶  $p = P(T < t)$  for lower tailed test  
 $p = \text{pt}(t, n)$
  - ▶  $p = 2(P(T > t))$  for two tailed test  
 $p = 2(1 - \text{pt}(|t|), n)$

## Example

A certain medication is supposed to stay in the blood stream for at least 12 hours. A new pill design is tested in 25 patients. The sample average time the medication is detected at sufficient levels in the blood stream is 11.8 hours with a sample standard deviation of 0.5 hours. Does this data suggest that the actual mean time of sufficient levels in the blood stream is less than the desired 12 hours?

*Solution: Parameter of interest:  $\mu$  the actual mean time of sufficient levels in the blood stream*

$$H_0 : \mu = 12$$

$$H_a : \mu < 12$$

*The test statistic is*

$$t = \frac{\bar{X} - \mu_0}{s/\sqrt{n}} = \frac{11.8 - 12}{0.5/\sqrt{25}} = -2.0$$

*p-value: Because the test is lower tailed: We have  $DF = 24$ ,  
 $p = P(t \leq -2.0) = 0.0284$*

*Conclusion: At the 0.05 level,  $H_0$  would be rejected, at the 0.01 level it would not be rejected.*

## Example

Suppose a car manufacturer claims a model gets 25 mpg. A consumer group asks 10 owners of this model to calculate their mpg and the mean value was 22 with a standard deviation of 1.5. Is the manufacturer's claim supported?

We want to test

$$H_0 : \mu = 25$$

$$H_a : \mu < 25$$

To test using R we simply need to tell R about the type of test. We need to calculate the test statistic and then find the p-value.

```
## Compute the t statistic.  
> xbar=22; s=1.5;n=10  
> t = (xbar-25)/(s/sqrt(n))  
> t  
[1] -6.324555  
## use pt to get the distribution function of t  
> pt(t,df=n-1)  
[1] 6.846828e-05
```

p-value (0.000068) is small. Hence, the manufacturer's claim is suspicious.

## Example- t.test

A farmer want to test if a new brand of fertilizer increases his wheat yield per plot. He put the new fertilizer on 15 equal plots and records the yields for the 15 plots which are given below. If his traditional yield is two bushels per plot, conduct a test of significance for  $\mu$  at  $\alpha = 0.05$  significance level.

2.5, 3.0, 3.1, 4.0, 1.2, 5.0, 4.1, 3.9, 3.2, 3.3, 2.8, 4.1, 2.7, 2.9, 3.7

*Solution: We would like to test*

$$H_0 : \mu = 2$$

$$H_a : \mu > 2$$

```
> x=c(2.5,3.0,3.1,4.0,1.2,5.0,4.1,3.9,3.2,3.3,2.8,4.1,2.7,2.9,3.7)
```

```
> t.test(x, alternative="greater", mu=2)
```

One Sample t-test

data: x

t = 5.6443, df = 14, p-value = 3.026e-05

alternative hypothesis: true mean is greater than 2

95 percent confidence interval:

2.894334            Inf

sample estimates:

mean of x

3.3

## Example

A random sample, consisting of the values listed below, was taken from a population which is normally distributed. Test the hypothesis that mean is 25 at  $\alpha = 0.1$  and construct 90% confidence interval for population mean.

22, 23, 24, 22, 25, 26, 27, 25, 30, 26, 29

*Solution: We would like to test*

$$H_0 : \mu = 25$$

$$H_a : \mu \neq 25$$

```
y=c(22, 23, 24, 22, 25, 26, 27, 25,30,26,29)
> t.test(y, mu=25)
    One Sample t-test
data:  y
t = 0.4607, df = 10, p-value = 0.6549
alternative hypothesis: true mean is not equal to 25
95 percent confidence interval:
 23.60476 27.12251
sample estimates:
mean of x
 25.36364
```