

## Practical no 4

### Aim: Demonstration of Hypothesis testing

#### Theory:

Hypothesis testing is a form of statistical inference that uses data from a sample to draw conclusions about a population parameter or a population probability distribution.

First, a tentative assumption is made about the parameter or distribution. This assumption is called the null

hypothesis and is denoted by  $H_0$ . An alternative hypothesis (denoted  $H_a$ ), which is the opposite of what is

stated in the null hypothesis, is then defined. The hypothesis-testing procedure involves using sample data to

determine whether or not  $H_0$  can be rejected. If  $H_0$  is rejected, the statistical conclusion is that the alternative hypothesis  $H_a$  is true.

For example, assume that a radio station selects the music it plays based on the assumption that the average

age of its listening audience is 30 years. To determine whether this assumption is valid, a hypothesis test could

be conducted with the null hypothesis given as  $H_0: \mu = 30$  and the alternative hypothesis given as  $H_a: \mu \neq 30$ .

Based on a sample of individuals from the listening audience, the sample mean age,  $\bar{x}$ , can be computed and used to determine whether there is sufficient statistical evidence to reject  $H_0$ . Conceptually, a value of the sample mean that is “close” to 30 is consistent with the null hypothesis, while a value of the sample means that is “not close” to 30 provides support for the alternative hypothesis. What is considered “close” and “not close” is determined by using the sampling distribution of  $\bar{x}$ . Ideally, the hypothesis-testing procedure leads to the acceptance of  $H_0$  when  $H_0$  is true and the rejection of  $H_0$  when  $H_0$  is false. Unfortunately, since hypothesis tests are based on sample information, the possibility of errors must be considered. A type I error corresponds to rejecting  $H_0$  when  $H_0$  is actually true, and a type II error corresponds to accepting  $H_0$  when  $H_0$  is false. The probability of making a type I error is denoted by  $\alpha$ , and the probability of making a type II error is denoted by  $\beta$ .

**Steps:**

- Open Excel create a data
- Save it as .CSV(MS-DOS)
- Keep the dataset and R code in a same folder.

## Dataset:

1	Sr no	C1	Deviation	Deviation Square		
2	1	85.3	-12.2214	149.3633		
3	2	86.9	-10.6214	112.8147		
4	3	96.8	-0.72143	0.520459		
5	4	101.1667	3.645238	-61.2767		
6	5	106.9167	9.395238	-135.698		
7	6	112.6667	15.14524	-210.12		
8	7	118.4167	20.89524	-284.541		
9	8	124.1667	26.64524	-358.962		
10	9	129.9167	32.39524	-433.384		
11	10	135.6667	38.14524	-507.805		
12	11	141.4167	43.89524	-582.227		
13	12	147.1667	49.64524	-656.648		
14	13	152.9167	55.39524	-731.07		
15	14	158.6667	61.14524	-805.491		
16	15	164.4167	66.89524	-879.912		
17	16	170.1667	72.64524	-954.334		
18	17	175.9167	78.39524	-1028.76		
19	18	181.6667	84.14524	-1103.18		
20	19	187.4167	89.89524	-1177.6		
21	20	193.1667	95.64524	-1252.02		
22						
23						
24						

## Code:

```

1 datanew=read.csv("C:/Users/admin/Downloads/Desktop/Materials/COMPUTER SCIENCE/Sem 6/Data
2 datanew
3 boxplot(datanew)
4 m1=mean(datanew$C1)
5 m1
6 sd1=sd(datanew$C1)
7 sd1
8 plot(datanew$C1)
9 t.test(datanew$C1,alternative="greater",mu=100)
10
11

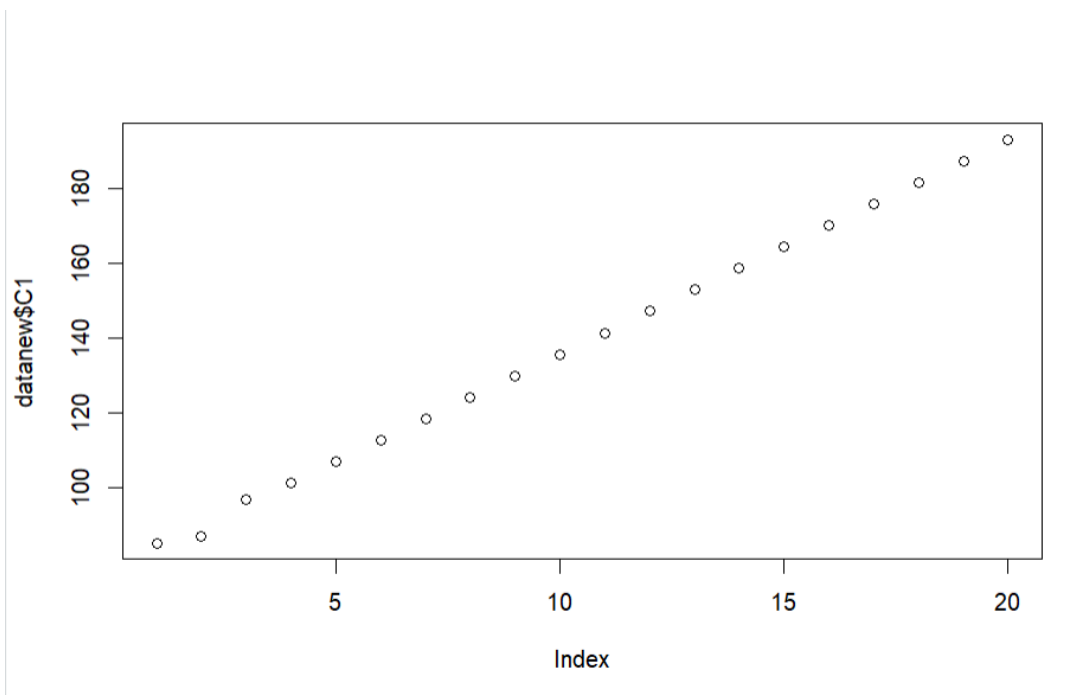
```

## Output:

```
> datanew
  Sr.no      C1      Deviation Deviation.Square
1     1  85.3000 -12.2214286      149.3633163
2     2  86.9000 -10.6214280      112.8147449
3     3  96.8000  -0.7214285       0.5204592
4     4 101.1667   3.6452384      -61.2766837
5     5 106.9167   9.3952384     -135.6981122
6     6 112.6667  15.1452385     -210.1195408
7     7 118.4167  20.8952385     -284.5409693
8     8 124.1667  26.6452385     -358.9623979
9     9 129.9167  32.3952386     -433.3838264
10    10 135.6667  38.1452386     -507.8052550
11    11 141.4167  43.8952386     -582.2266836
12    12 147.1667  49.6452387     -656.6481121
13    13 152.9167  55.3952387     -731.0695407
14    14 158.6667  61.1452387     -805.4909692
15    15 164.4167  66.8952388     -879.9123978
16    16 170.1667  72.6452388     -954.3338264
17    17 175.9167  78.3952388    -1028.7552550
18    18 181.6667  84.1452389    -1103.1766830
19    19 187.4167  89.8952389    -1177.5981120
20    20 193.1667  95.6452389    -1252.0195410
> boxplot(datanew)
> m1=mean(datanew$C1)
> m1
[1] 138.5417
> sd1=sd(datanew$C1)
> sd1
[1] 34.02634
> plot(datanew$C1)
> t.test(datanew$C1,alternative="greater",mu=100)

One Sample t-test

data: datanew$C1
t = 5.0656, df = 19, p-value = 3.434e-05
alternative hypothesis: true mean is greater than 100
95 percent confidence interval:
 125.3855      Inf
sample estimates:
mean of x
 138.5417
> |
```



**Conclusion: Hence we have successfully learnt & performed Hypothesis testing.**