

## **Experiment 3.2**

1. **Aim:** Outlier detection using R programming.

2. **Objective:**

- To Identify and flag data points that deviate significantly from the norm.
- To Assess the impact of outliers on statistical analysis or modeling.

3. **Script:**

**What are outliers?**

- Data points far from the dataset's other points are considered outliers. This refers to the data values dispersed among other data values and upsetting the dataset's general distribution.

**Effects of an outlier on model:**

- The format of the data appears to be skewed.
- Modifies the mean, variance, and other statistical characteristics of the data's overall distribution.
- Leads to the model's accuracy level being biased.

**Dataset:**

The **day.csv** dataset provides information related to bike sharing and various environmental and temporal factors.

It contains the following variables:

1. instant: A unique identifier for each record.
2. dteday: The date of the record in yyyy-mm-dd format.
3. season: The season (1: spring, 2: summer, 3: fall, 4: winter).
4. yr: The year (0: 2011, 1: 2012).
5. mnth: The month (1 to 12).
6. holiday: A binary indicator of whether it is a holiday or not (1: holiday, 0: non-holiday).
7. weekday: The day of the week (0: Sunday, 1: Monday, ..., 6: Saturday).
8. workingday: A binary indicator of whether it is a working day or not (1: working day, 0: non-working day).
9. weathersit: The weather situation (1: clear, 2: mist/cloudy, 3: light rain/snow, 4: heavy rain/snow).
10. temp: The normalized temperature in Celsius.
11. atemp: The normalized feeling temperature in Celsius.
12. hum: The normalized humidity.
13. windspeed: The normalized wind speed.
14. casual: The number of casual (non-registered) bike users.
15. registered: The number of registered bike users.
16. cnt: The total count of bike rentals (casual + registered).

## 4. Code:

```
#Removed all the existing objects
rm(list = ls())

#Setting the working directory
setwd("D:/Documents")
getwd()

#Load the dataset
bike_data = read.csv("day.csv",header=TRUE)

# Missing Value Analysis
sum(is.na(bike_data))
summary(is.na(bike_data))
```

## Output:

Prior to outlier detection, we have performed missing value analysis just to check for the presence of any NULL or missing values. For the same, we have made use of `sum(is.na(data))` function.

```
> sum(is.na(bike_data))
[1] 0
> summary(is.na(bike_data))
instant      dteday      season      yr      mnth
Mode :logical Mode :logical Mode :logical Mode :logical Mode :logical
FALSE:731    FALSE:731    FALSE:731    FALSE:731    FALSE:731
holiday      weekday      workingday  weathersit    temp
Mode :logical Mode :logical Mode :logical Mode :logical Mode :logical
FALSE:731    FALSE:731    FALSE:731    FALSE:731    FALSE:731
atemp        hum          windspeed   casual       registered
Mode :logical Mode :logical Mode :logical Mode :logical Mode :logical
FALSE:731    FALSE:731    FALSE:731    FALSE:731    FALSE:731
cnt
Mode :logical
FALSE:731
```

#From the above result, the dataset contains NO Missing Values.

#Outlier Analysis -- DETECTION

# 1. Outliers in the data values exists only in continuous/numeric form of data variables. Thus, we need to store all the numeric and categorical independent variables into a separate array structure.

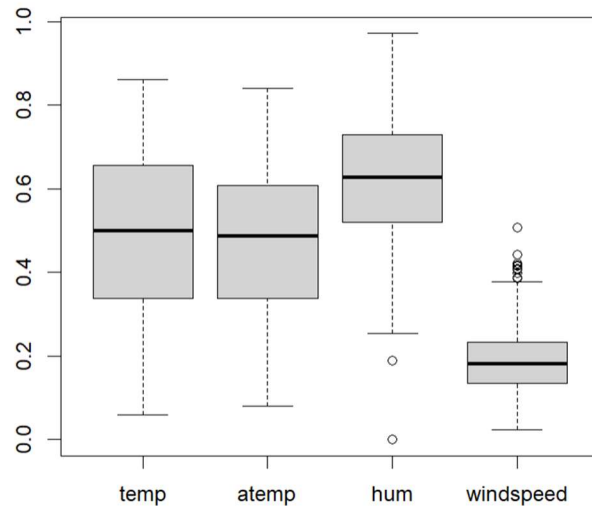
```
col = c('temp','cnt','hum','windspeed')
categorical_col = c("season","yr","mnth","holiday","weekday","workingday","weathersit")
```

# 2. Using BoxPlot to detect the presence of outliers in the numeric/continuous data columns.

```
boxplot(bike_data[,c('temp','atemp','hum','windspeed')])
```

## Output:

From the above visualization, the data variables 'hum' and 'windspeed' contains outliers in the data values.



#Now, we will replace the outlier data values with NULL.

```
for (x in c('hum','windspeed'))
{
  value = bike_data[,x][bike_data[,x] %in% boxplot.stats(bike_data[,x])$out]
  bike_data[,x][bike_data[,x] %in% value] = NA
}
```

```
#Checking whether the outliers in the above defined columns are replaced by NULL or not
sum(is.na(bike_data$hum))
sum(is.na(bike_data$windspeed))
as.data.frame(colSums(is.na(bike_data)))
```

## Output:

As a result, we have converted the 2 outlier points from the 'hum' column and 16 outlier points from the 'windspeed' column into missing(NA) values.

```
> sum(is.na(bike_data$hum))
[1] 2
> sum(is.na(bike_data$windspeed))
[1] 16
> as.data.frame(colSums(is.na(bike_data)))
      colSums(is.na(bike_data))
instant                0
dteday                 0
season                 0
yr                     0
mnth                   0
holiday                0
weekday                0
workingday              0
weathersit              0
temp                   0
atemp                  0
hum                     2
windspeed              16
casual                  0
registered              0
cnt                     0
> |
```

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```
#Removing the null values  
library(tidyr)  
bike_data = drop_na(bike_data)  
as.data.frame(colSums(is.na(bike_data)))
```

## Output:

At last, we treat the missing values by dropping the NULL values using [drop\\_na\(\) function](#) from the 'tidyr' library.

```
> #Removing the null values  
> library(tidyr)  
> bike_data = drop_na(bike_data)  
> as.data.frame(colSums(is.na(bike_data)))  
      colSums(is.na(bike_data))  
instant                0  
dteday                 0  
season                 0  
yr                     0  
mnth                  0  
holiday               0  
weekday              0  
workingday            0  
weathersit             0  
temp                  0  
atemp                 0  
hum                   0  
windspeed             0  
casual                0  
registered            0  
cnt                   0
```

```
#draw boxplot to verify whether outliers removed or not  
boxplot(bike_data[,c('temp','atemp','hum','windspeed')])
```

## Output:

