

Driving Range Prediction

R Markdown

In this model, we will try and predict the “Trip_Distance(km)” which is the dependent variables which signifies the Driving Range predicito. We will do some Exploratory Data Analysis to understand the data and do some prediciton modeling.

#Read The Input Data

```
library(data.table)
```

```
## Warning: package 'data.table' was built under R version 4.0.4
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.0.5
```

```
setwd("C:/Users/70302605/Desktop/Driving Range Prediction for Electric Vehicles")
df_ip = fread('Data-Final.csv')
```

Lets Check the Data Structure and checking for any null values

```
head(df_ip)
```

```

##   trip_distance(km) quantity(kWh)    tire_type city motor_way country_roads
## 1:          50       12.29 Winter tires  0       0       1
## 2:          43        8.68 Winter tires  0       1       1
## 3:          44        1.50 Winter tires  0       1       1
## 4:          76       14.44 Winter tires  0       1       0
## 5:          15        6.84 Winter tires  1       0       0
## 6:          63        7.10 Winter tires  0       1       0
##   driving_style consumption(kWh/100km) A/C park_heating avg_speed(km/h)
## 1:      Normal           15.5     0       1       47
## 2:      Normal           18.0     0       1       58
## 3:      Normal           16.1     0       1       43
## 4:      Normal           19.0     0       1       76
## 5:      Normal           16.1     0       1       23
## 6:      Fast             18.3     0       1       80
##   ecr_deviation
## 1:      -1.3
## 2:       1.2
## 3:      -0.7
## 4:       2.2
## 5:      -0.7
## 6:       1.5

```

```
dim(df_ip)
```

```
## [1] 3340 12
```

```
str(df_ip)
```

```

## Classes 'data.table' and 'data.frame': 3340 obs. of 12 variables:
## $ trip_distance(km) : num 50 43 44 76 15 63 85 71 76 80 ...
## $ quantity(kWh)    : num 12.29 8.68 1.5 14.44 6.84 ...
## $ tire_type        : chr "Winter tires" "Winter tires" "Winter tires" "Winter tires"
...
## $ city              : int 0 0 0 0 1 0 0 0 0 0 ...
## $ motor_way         : int 0 1 1 1 0 1 1 0 0 0 ...
## $ country_roads     : int 1 1 1 0 0 0 1 1 1 1 ...
## $ driving_style     : chr "Normal" "Normal" "Normal" "Normal" ...
## $ consumption(kWh/100km): num 15.5 18 16.1 19 16.1 18.3 18 19.4 15.8 14 ...
## $ A/C               : int 0 0 0 0 0 0 0 0 0 0 ...
## $ park_heating      : int 1 1 1 1 1 1 1 1 1 0 ...
## $ avg_speed(km/h)   : num 47 58 43 76 23 80 47 45 78 52 ...
## $ ecr_deviation     : num -1.3 1.2 -0.7 2.2 -0.7 1.5 1.2 2.6 -1 -2.8 ...
## - attr(*, ".internal.selfref")=<externalptr>

```

```
summary(df_ip)
```

```

## trip_distance(km) quantity(kwh) tire_type city
## Min.   : 0.50   Min.   : 0.010  Length:3340   Min.   :0.0000
## 1st Qu.: 20.00  1st Qu.: 1.790  Class  :character 1st Qu.:0.0000
## Median : 20.00  Median : 3.540  Mode   :character Median :1.0000
## Mean   : 42.08  Mean   : 5.911                               Mean   :0.6955
## 3rd Qu.: 57.00  3rd Qu.: 8.010                               3rd Qu.:1.0000
## Max.   :642.00  Max.   :84.600                               Max.   :1.0000
## motor_way      country_roads driving_style consumption(kWh/100km)
## Min.   :0.0000  Min.   :0.0000  Length:3340   Min.   : 4.00
## 1st Qu.:0.0000  1st Qu.:0.0000  Class  :character 1st Qu.:11.20
## Median :1.0000  Median :1.0000  Mode   :character Median :13.70
## Mean   :0.6653  Mean   :0.5871                               Mean   :13.92
## 3rd Qu.:1.0000  3rd Qu.:1.0000                               3rd Qu.:16.80
## Max.   :1.0000  Max.   :1.0000                               Max.   :76.00
## A/C          park_heating avg_speed(km/h) ecr_deviation
## Min.   :0.00000  Min.   :0.0000  Min.   : 2.00  Min.   :-12.80
## 1st Qu.:0.00000  1st Qu.:0.0000  1st Qu.: 37.00  1st Qu.: -5.60
## Median :0.00000  Median :0.0000  Median : 47.00  Median : -3.10
## Mean   :0.04491  Mean   :0.1886  Mean   : 46.76  Mean   : -2.88
## 3rd Qu.:0.00000  3rd Qu.:0.0000  3rd Qu.: 56.00  3rd Qu.:  0.00
## Max.   :1.00000  Max.   :1.0000  Max.   :100.00  Max.   : 59.20

```

```

#Checking for any Null Values.
#There are no Null values in the data
colSums(is.na(df_ip))

```

```

## trip_distance(km) quantity(kwh) tire_type
##          0           0           0
## city      motor_way    country_roads
##          0           0           0
## driving_style consumption(kWh/100km) A/C
##          0           0           0
## park_heating avg_speed(km/h) ecr_deviation
##          0           0           0

```

#Data Conversion into Factors

```

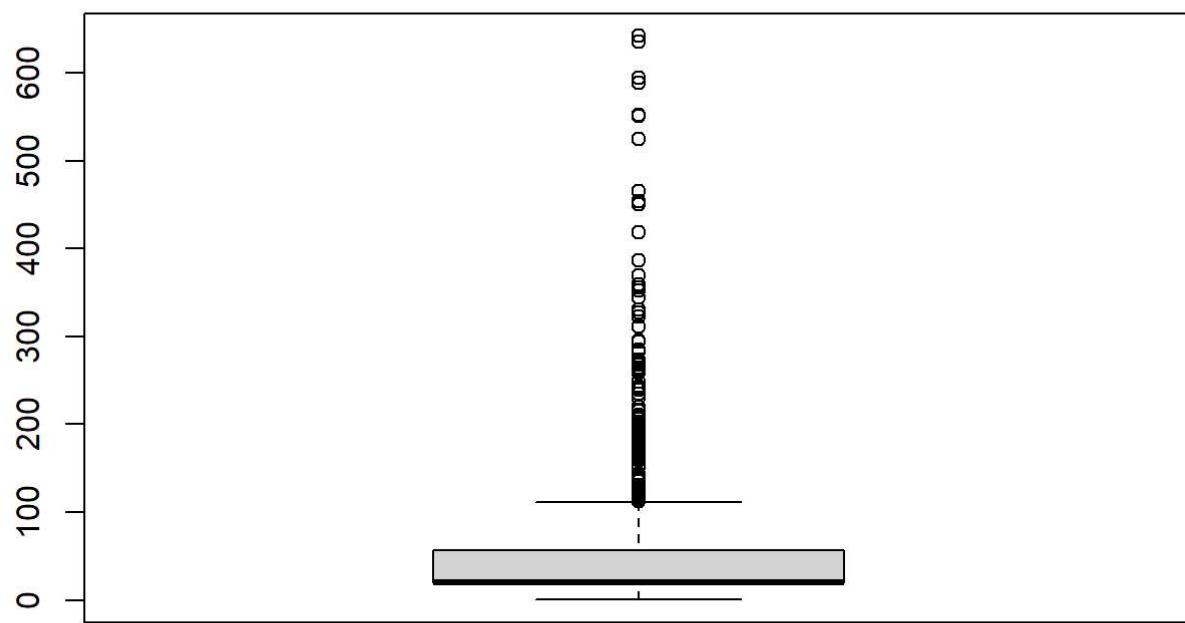
df_ip$city<-as.factor(df_ip$city)
df_ip$motor_way<-as.factor(df_ip$motor_way)
df_ip$country_roads<-as.factor(df_ip$country_roads)
df_ip$`A/C` <-as.factor(df_ip$`A/C`)
df_ip$park_heating<-as.factor(df_ip$park_heating)
df_ip<-as.data.frame(df_ip)
df1<-df_ip

```

Lets explore the Data using Univariate and Multivariate analysis

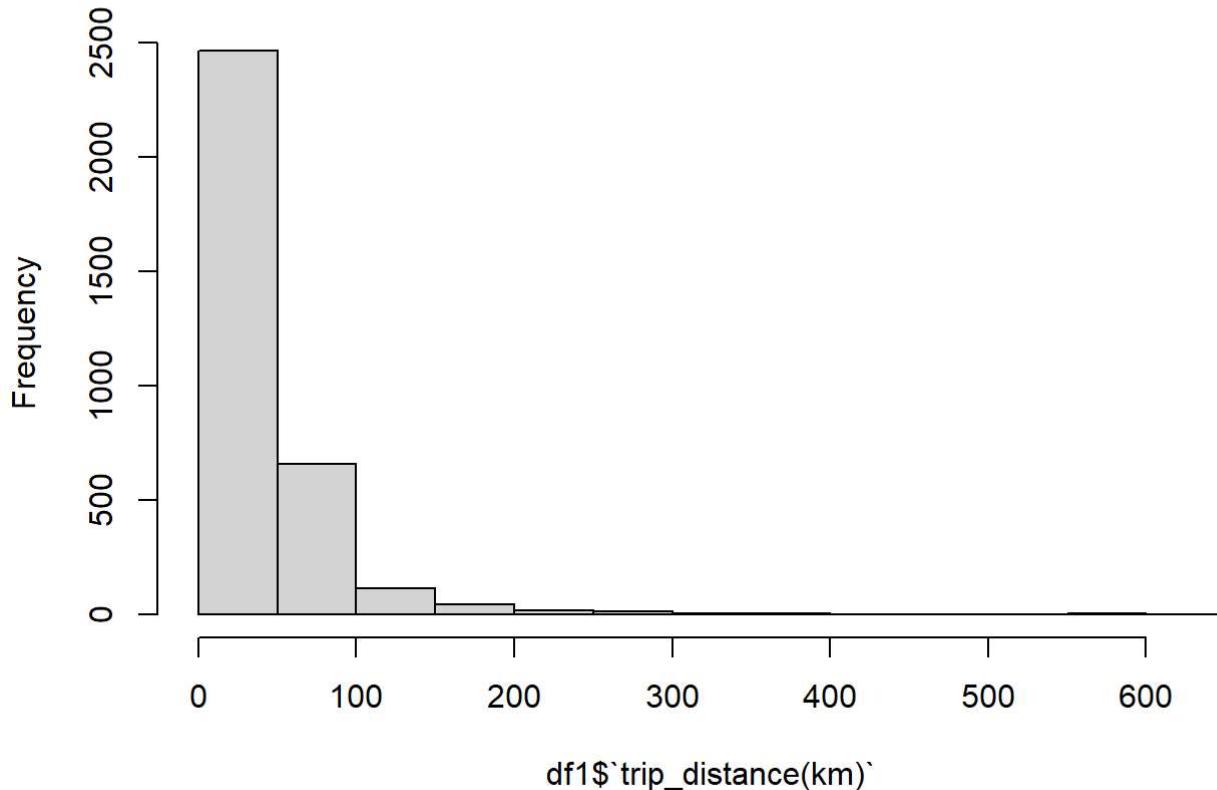
```

#DEPENDENT VARIABLE
boxplot(df1$`trip_distance(km)`)
```



```
hist(df1$`trip_distance(km)`)
```

Histogram of df1\$`trip_distance(km)`



```
#BOX and Histogram of the target variable show that there are Lot of outliers which have to be removed. based on the plots, any value >150 can be removed.
```

```
df1<-df1[df1$`trip_distance(km)`<=100,]
```

```
#In the Quantiy field, there seems to be some outliers. Hence, for this model, anything less than 15 needs to be removed.
```

```
df1<-df1[df1$`quantity(kwh)` <=15,]
```

```
#UNI-VARIATE ANALYSIS
```

```
library(DescTools)
```

```
## Warning: package 'DescTools' was built under R version 4.0.4
```

```
##
```

```
## Attaching package: 'DescTools'
```

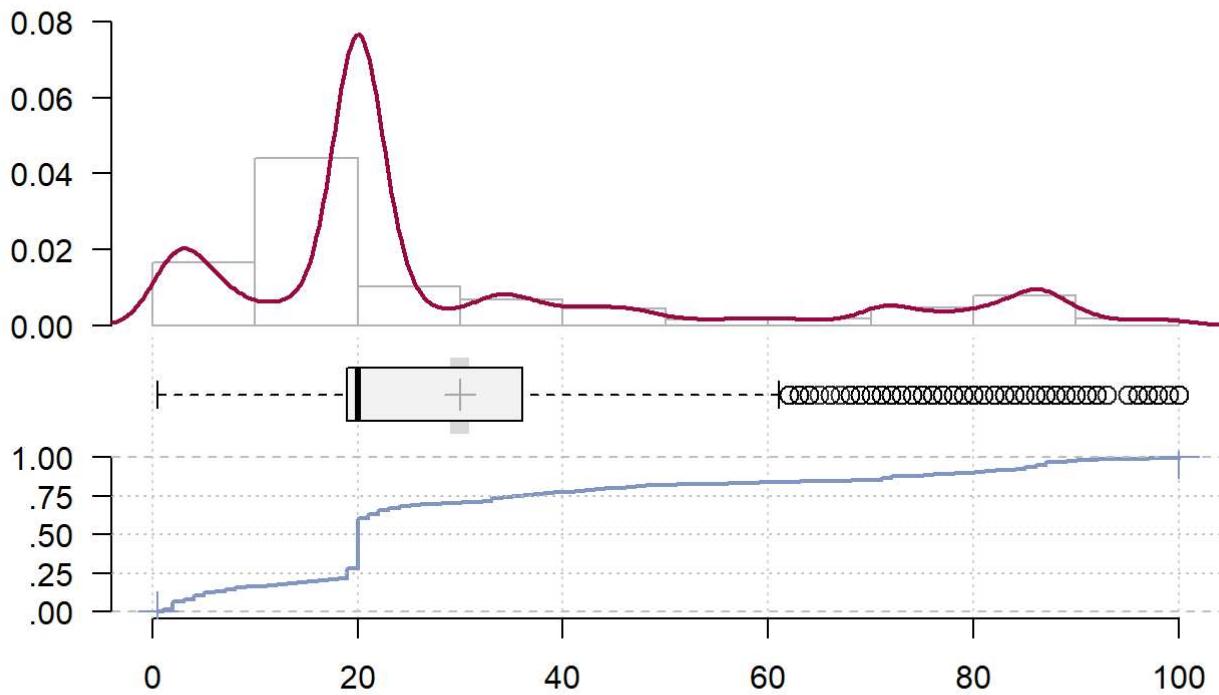
```
## The following object is masked from 'package:data.table':
```

```
##
```

```
##     %like%
```

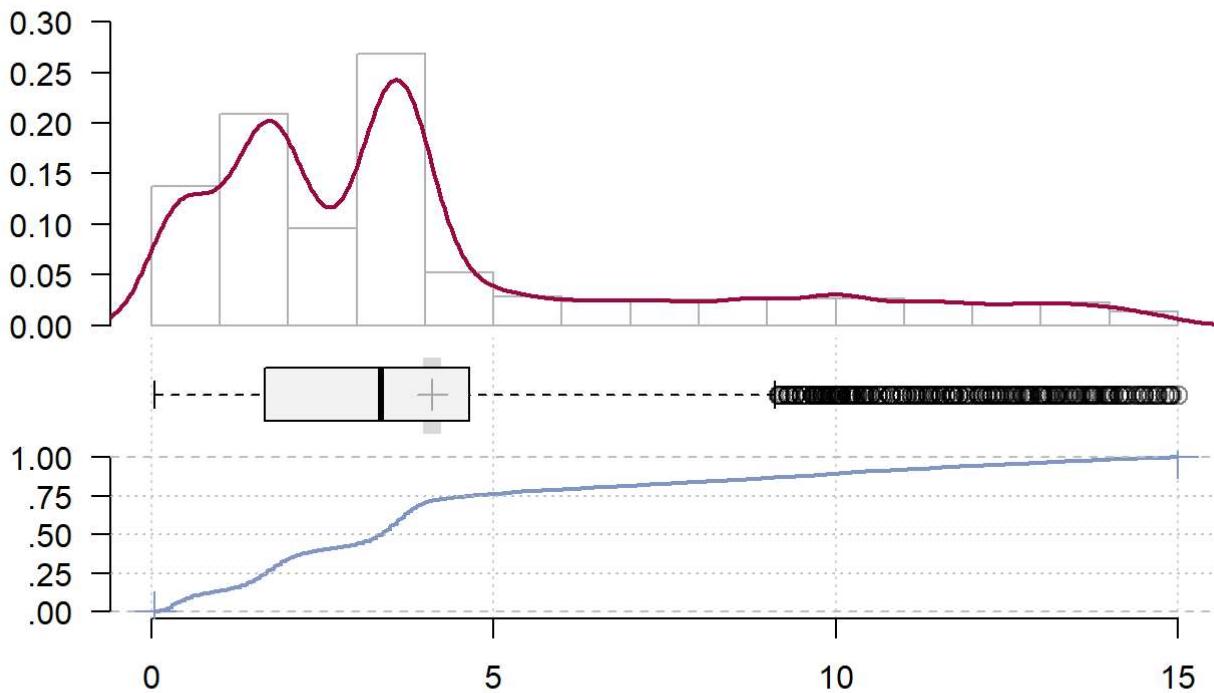
```
Desc(df1)
```

```
## -----
## Describe df1 (data.frame):
##
## data frame: 2953 obs. of 12 variables
##      2953 complete cases (100.0%)
##
##   Nr  ColName          Class     NAs  Levels
##   1  trip_distance(km)  numeric   .
##   2  quantity(kWh)     numeric   .
##   3  tire_type         character .
##   4  city               factor    . (2): 1-0, 2-1
##   5  motor_way          factor    . (2): 1-0, 2-1
##   6  country_roads     factor    . (2): 1-0, 2-1
##   7  driving_style      character .
##   8  consumption(kWh/100km) numeric   .
##   9  A/C                factor    . (2): 1-0, 2-1
##  10 park_heating        factor    . (2): 1-0, 2-1
##  11 avg_speed(km/h)    numeric   .
##  12 ecr_deviation      numeric   .
##
##
## -----
## 1 - trip_distance(km) (numeric)
##
##   length      n     NAs  unique      0s    mean  meanCI'
##   2'953    2'953     0     100      0  29.95  29.05
##           100.0%  0.0%           0.0%           30.86
##
##   .05      .10     .25  median     .75     .90     .95
##   2.00     4.00  19.00  20.00  36.00  80.00  86.00
##
##   range      sd   vcoef      mad     IQR    skew    kurt
##   99.50   25.16   0.84     7.41   17.00   1.30   0.55
##
## lowest : 0.5, 1.0 (50), 2.0 (145), 3.0 (51), 4.0 (77)
## highest: 96.0 (6), 97.0 (6), 98.0 (6), 99.0 (3), 100.0 (9)
##
## heap(?): remarkable frequency (32.8%) for the mode(s) (= 20)
##
## ' 95%-CI (classic)
```

1 - trip_distance(km) (numeric)

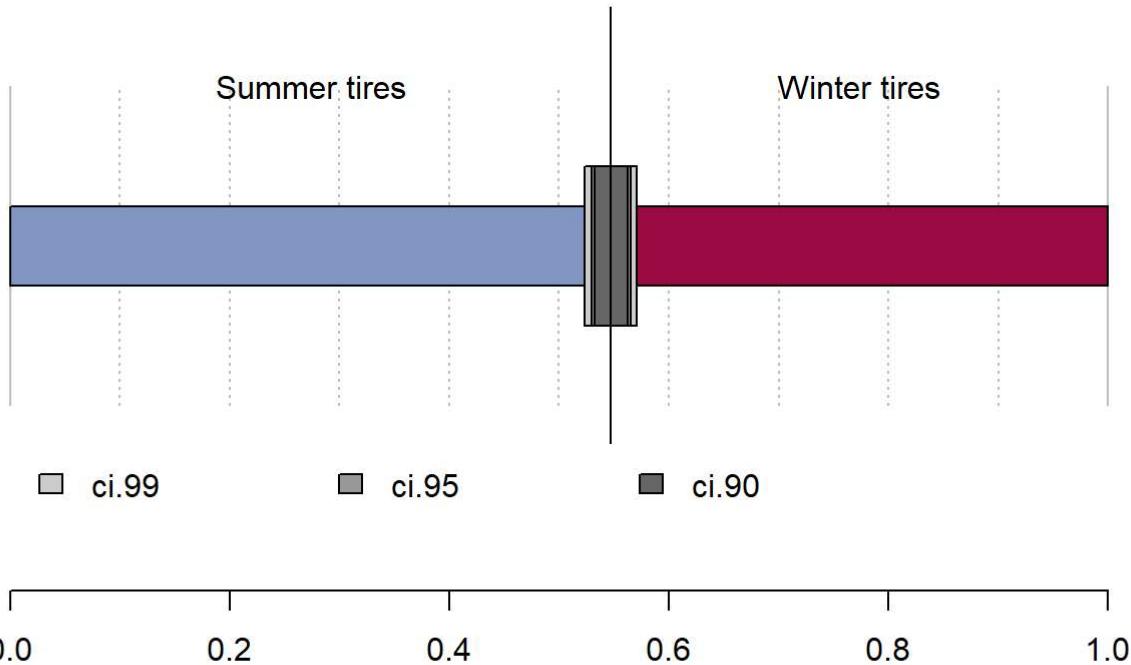
```
## -----
## 2 - quantity(kWh) (numeric)
##
##      length     n    NAs   unique    0s    mean  meanCI'
##      2'953  2'953      0     805      0  4.10   3.98
##                 100.0%  0.0%           0.0%          4.23
##
##      .05     .10    .25   median    .75    .90    .95
##      0.33    0.60   1.66    3.36   4.65  10.18  12.28
##
##      range      sd vcoef      mad    IQR    skew    kurt
##      14.95    3.54  0.86    2.46   2.99   1.34    0.95
##
## lowest : 0.05, 0.09 (3), 0.1 (15), 0.11 (6), 0.12 (3)
## highest: 14.81 (2), 14.85, 14.88 (4), 14.91, 15.0
##
## ' 95%-CI (classic)
```

2 - quantity(kWh) (numeric)

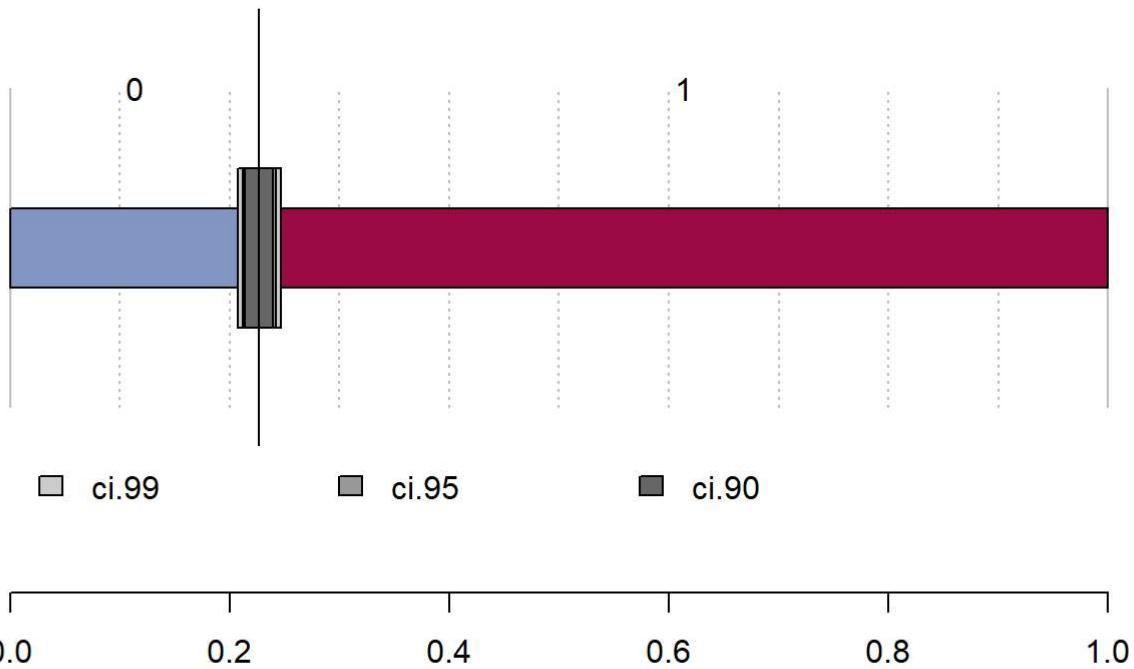


```
## -----
## 3 - tire_type (character - dichotomous)
##
##      length     n     NAs unique
##      2'953  2'953      0      2
##      100.0%  0.0%
##
##                  freq    perc   lci.95   uci.95'
## Summer tires  1'616  54.7%  52.9%  56.5%
## Winter tires  1'337  45.3%  43.5%  47.1%
##
## ' 95%-CI (Wilson)
```

3 - tire_type (character - dichotomous)

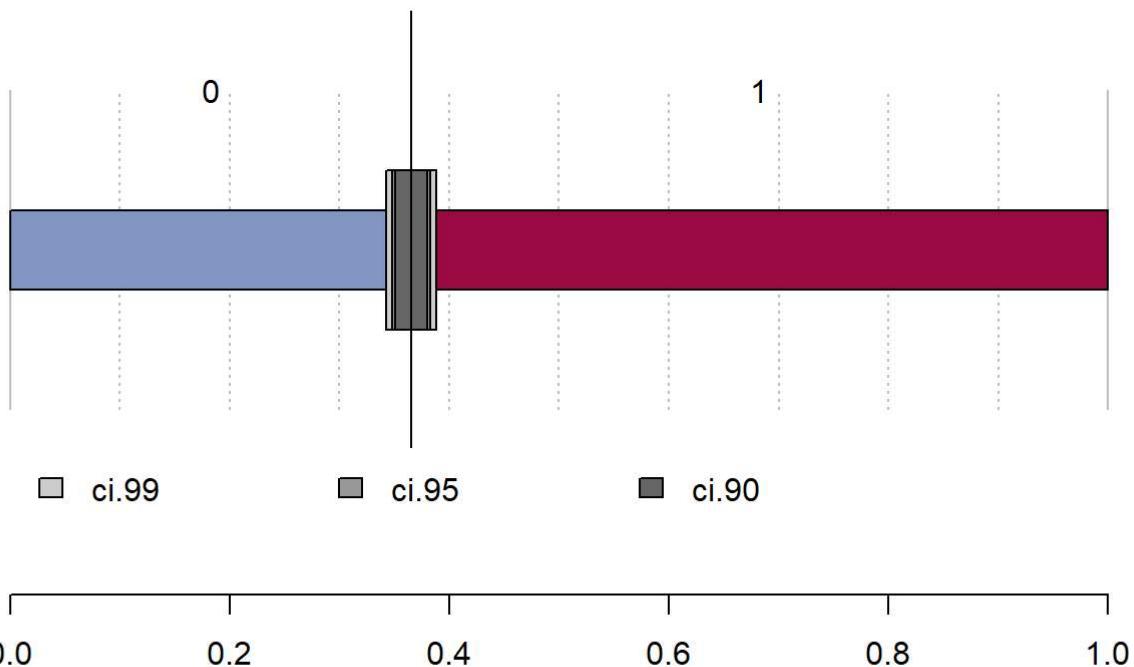


```
## -----
## 4 - city (factor - dichotomous)
##
##   length     n     NAs unique
##   2'953  2'953      0      2
##   100.0%  0.0%
##
##   freq    perc   lci.95   uci.95'
## 0    669  22.7%  21.2%  24.2%
## 1  2'284  77.3%  75.8%  78.8%
##
## ' 95%-CI (Wilson)
```

4 - city (factor - dichotomous)

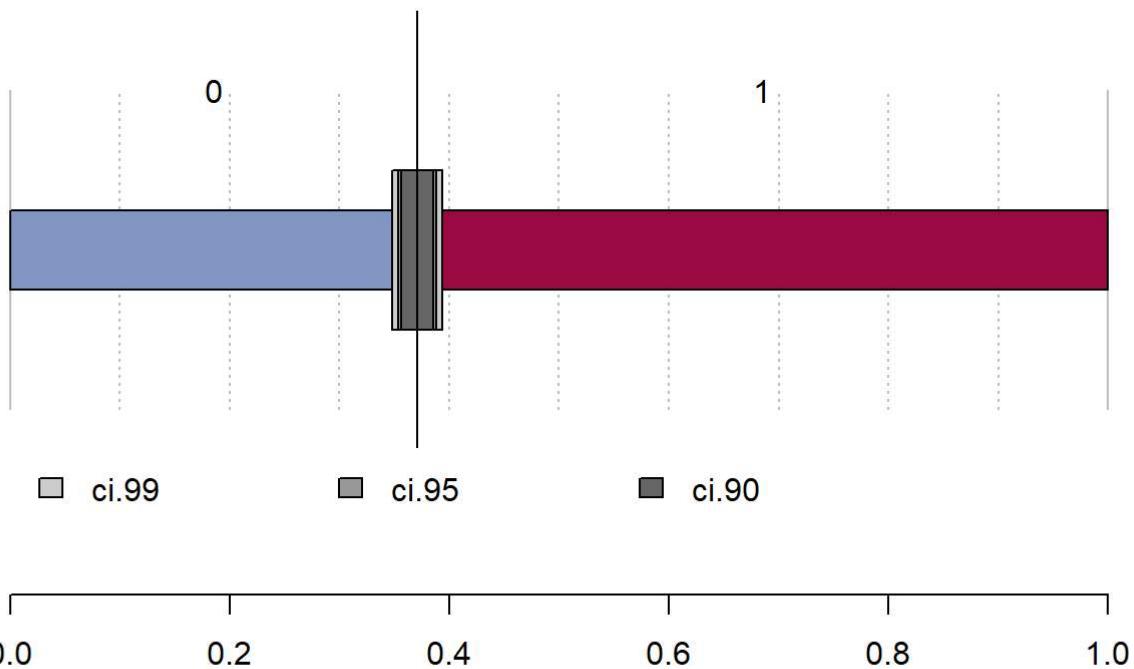
```
## -----
## 5 - motor_way (factor - dichotomous)
##
##   length     n     NAs unique
##   2'953  2'953      0      2
##           100.0%  0.0%
##
##   freq    perc   lci.95  uci.95'
## 0  1'078  36.5%  34.8%  38.3%
## 1  1'875  63.5%  61.7%  65.2%
##
## ' 95%-CI (Wilson)
```

5 - motor_way (factor - dichotomous)



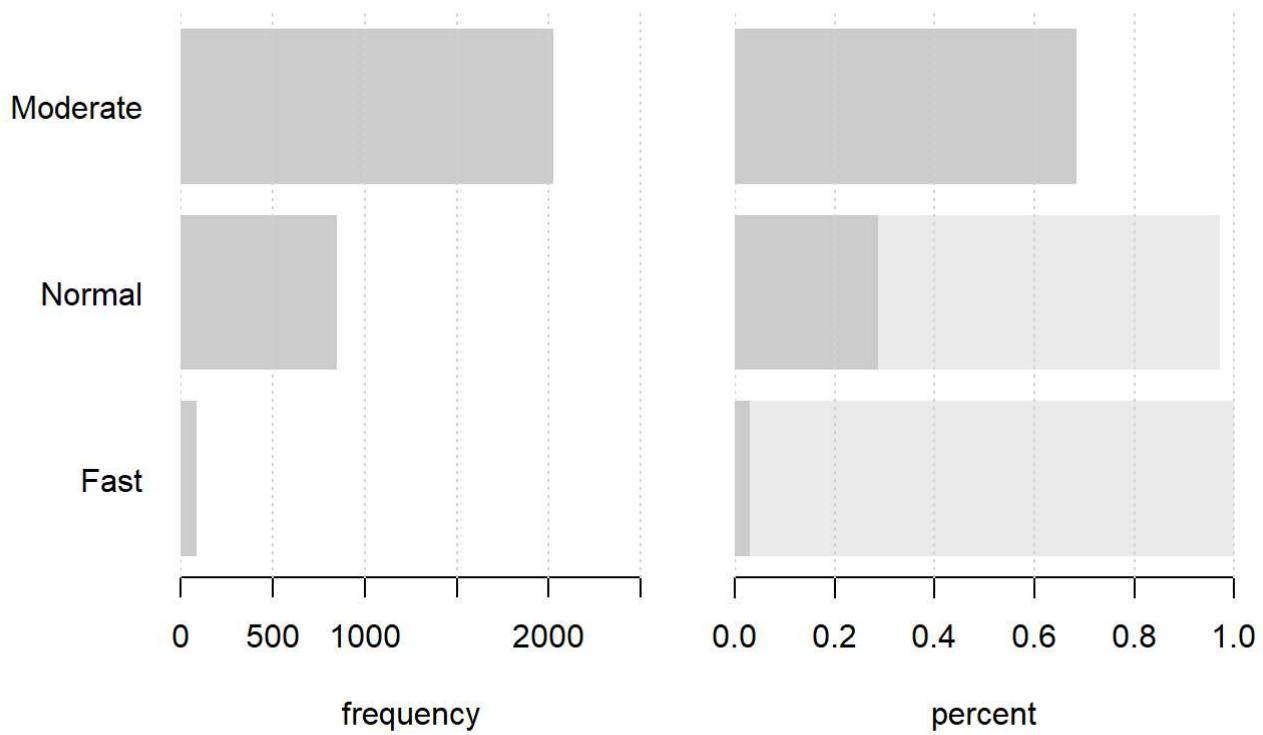
```
## -----
## 6 - country_roads (factor - dichotomous)
##
##   length     n    NAs unique
##   2'953  2'953      0      2
##           100.0%  0.0%
##
##   freq    perc   lci.95   uci.95'
## 0  1'094  37.0%  35.3%  38.8%
## 1  1'859  63.0%  61.2%  64.7%
##
## ' 95%-CI (Wilson)
```

6 - country_roads (factor - dichotomous)

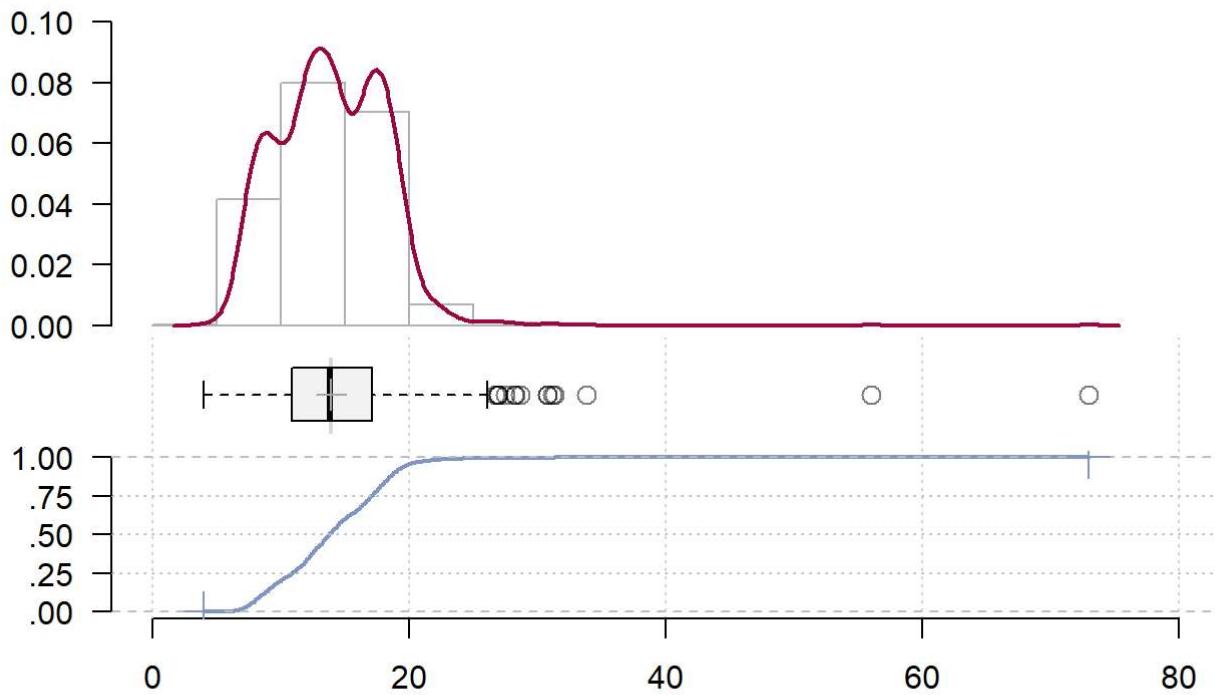


```
## -----
## 7 - driving_style (character)
##
##   length     n      NAs unique levels  dupes
##   2'953  2'953      0       3       3      y
##   100.0%  0.0%
##
##      level    freq     perc   cumfreq   cumperc
## 1 Moderate  2'022  68.5%    2'022   68.5%
## 2 Normal    847  28.7%    2'869   97.2%
## 3 Fast      84   2.8%    2'953  100.0%
```

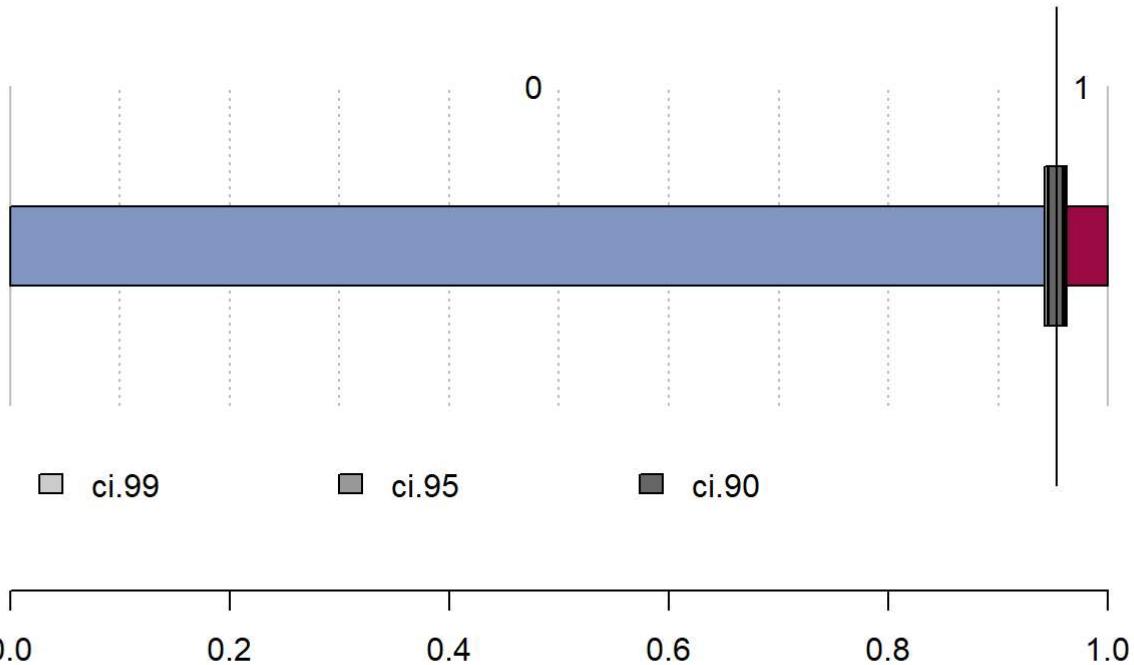
7 - driving_style (character)



```
## -----
## 8 - consumption(kWh/100km) (numeric)
##
##   length      n     NAs   unique     0s    mean  meanCI'
##   2'953    2'953      0     213      0  13.91  13.76
##             100.0%  0.0%           0.0%           14.07
##
##   .05      .10     .25 median     .75     .90     .95
##   7.60    8.32  10.90   13.80  17.10  18.80  19.74
##
##   range      sd vcoef      mad     IQR    skew    kurt
##   69.00    4.24  0.30     4.60    6.20    1.43   15.50
##
## lowest : 4.0, 4.5 (2), 5.2, 5.4, 5.5 (2)
## highest: 31.2, 31.3, 33.8, 56.0, 73.0
##
## ' 95%-CI (classic)
```

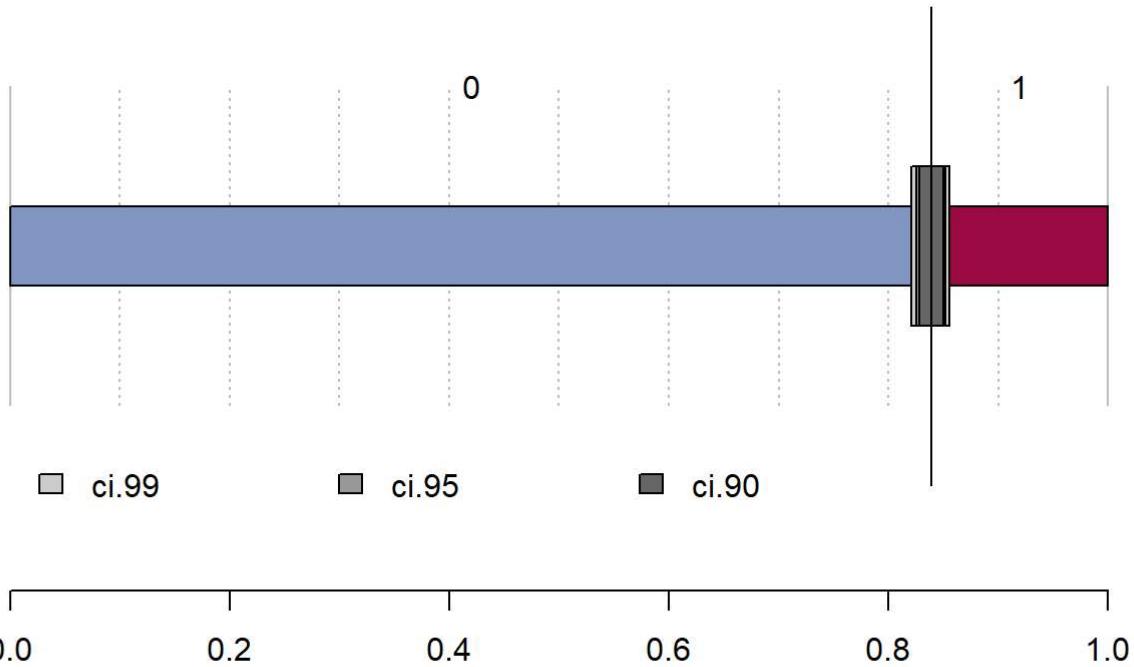
8 - consumption(kWh/100km) (numeric)

```
## -----
## 9 - A/C (factor - dichotomous)
##
##   length     n      NAs unique
##   2'953  2'953       0       2
##           100.0%  0.0%
##
##   freq    perc   lci.95  uci.95'
## 0  2'815  95.3%  94.5%  96.0%
## 1    138   4.7%   4.0%   5.5%
##
## ' 95%-CI (Wilson)
```

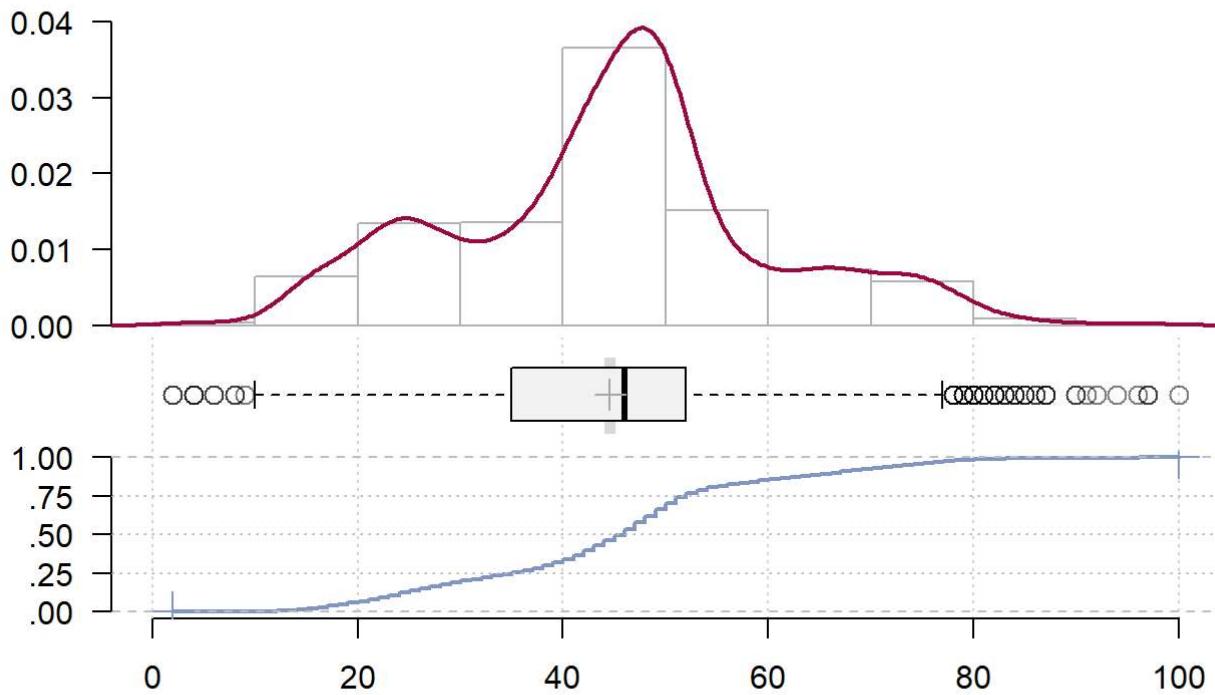
9 - A/C (factor - dichotomous)

```
## -----
## 10 - park_heating (factor - dichotomous)
##
##   length     n     NAs unique
##   2'953  2'953      0      2
##           100.0%  0.0%
##
##   freq    perc   lci.95  uci.95'
## 0  2'479  83.9%  82.6%  85.2%
## 1    474  16.1%  14.8%  17.4%
##
## ' 95%-CI (Wilson)
```

10 - park_heating (factor - dichotomous)

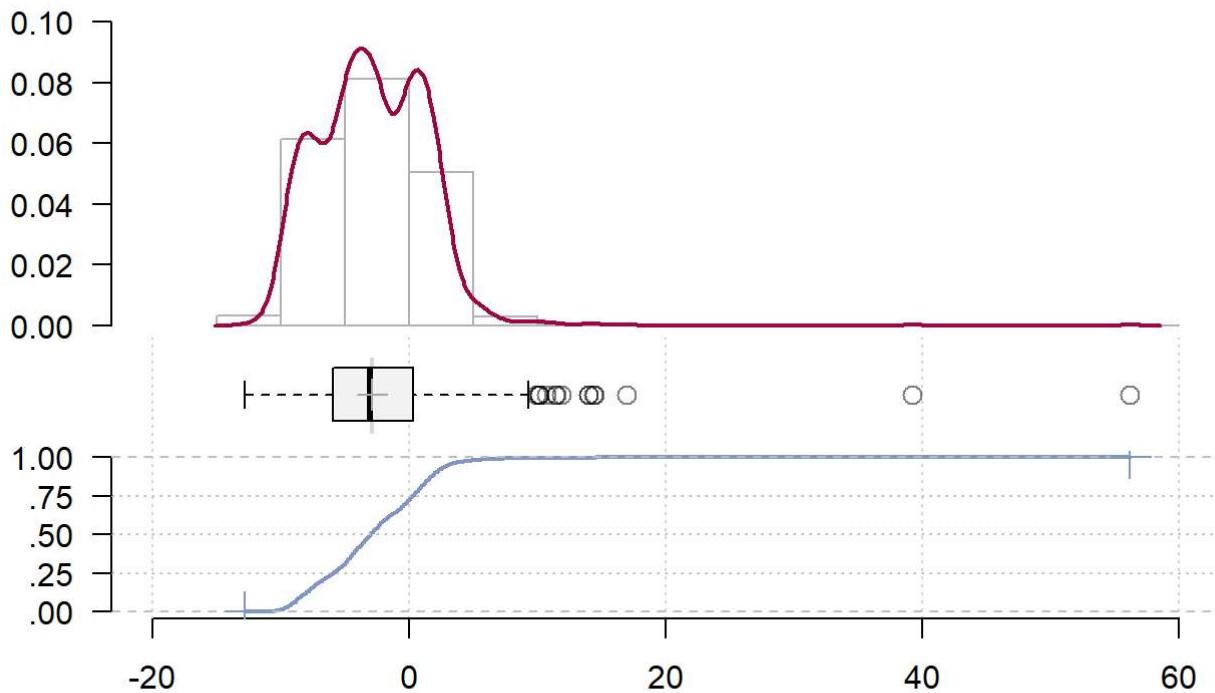


```
## -----
## 11 - avg_speed(km/h) (numeric)
##
##   length      n     NAs   unique      0s    mean  meanCI'
##   2'953    2'953      0      99      0  44.57  44.01
##             100.0%  0.0%                  0.0%          45.13
##
##   .05      .10      .25   median      .75      .90      .95
##   19.00    23.00   35.00    46.00   52.00   66.00   73.00
##
##   range      sd    vcoef      mad      IQR    skew    kurt
##   98.00   15.57    0.35   11.86   17.00    0.17    0.04
##
## lowest : 2.0 (2), 4.0 (3), 6.0 (2), 8.0 (2), 9.0
## highest: 92.0, 94.0, 96.0, 97.0 (2), 100.0
##
## ' 95%-CI (classic)
```

11 - avg_speed(km/h) (numeric)

```
## -----
## 12 - ecr_deviation (numeric)
##
##   length      n     NAs  unique    0s    mean  meanCI'
##   2'953    2'953      0    213     19   -2.89   -3.04
##             100.0%  0.0%                   0.6%           -2.73
##
##   .05      .10     .25 median    .75     .90     .95
##   -9.20   -8.48  -5.90   -3.00   0.30    2.00    2.94
##
##   range      sd vcoef      mad    IQR    skew    kurt
##   69.00    4.24 -1.47    4.60   6.20   1.43   15.50
##
## lowest : -12.80, -12.30 (2), -11.60, -11.40, -11.30 (2)
## highest: 14.4, 14.5, 17.0, 39.2, 56.2
##
## ' 95%-CI (classic)
```

12 - ecr_deviation (numeric)



```
#BI-VARIATE ANALYSIS
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.0.4
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:data.table':
##
##     between, first, last
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(DT)
```

```
## Warning: package 'DT' was built under R version 4.0.4
```

#Average Driving Range by City

#From the summaries below we can see that City has high predictive power. However we also have to check for classification imbalance

```
Range_City= df1 %>%
  group_by(city) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_City)
```

Show 10 ▾ entries

Search:

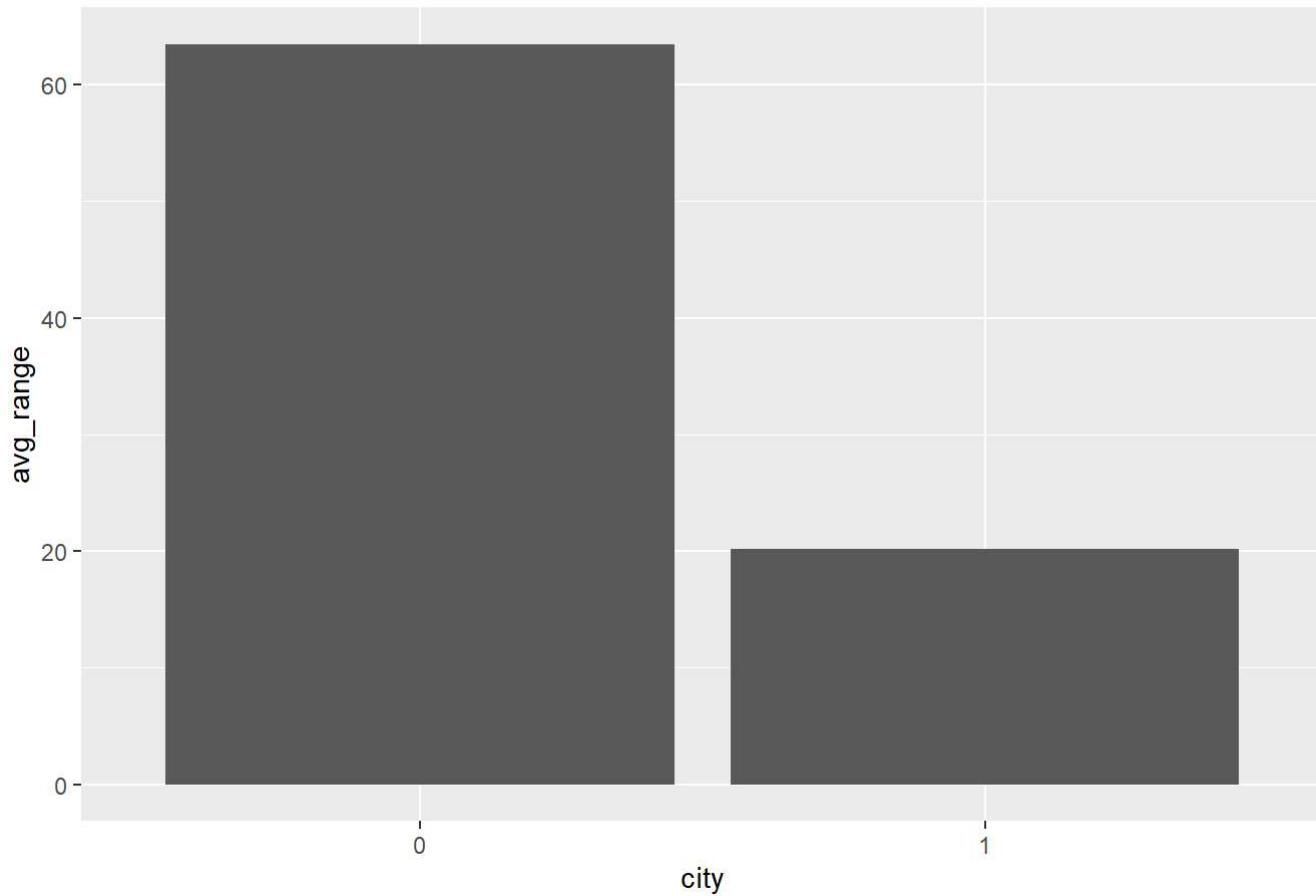
	city	avg_range
1	0	63.4723467862481
2	1	20.1355078809107

Showing 1 to 2 of 2 entries

Previous Next

```
plt_city = df1 %>% group_by(city) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=city,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by City")
plot(plt_city)
```

Average Driving Range by City



```
#Average Driving Range by Tire Type
#As it can be seen, there is no much difference in the average driving Range with the Tire_Type.
This variable can be ignored in the model
Range_tiretype= df1 %>%
  group_by(tire_type) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_tiretype)
```

Show 10 ▾ entries

Search:

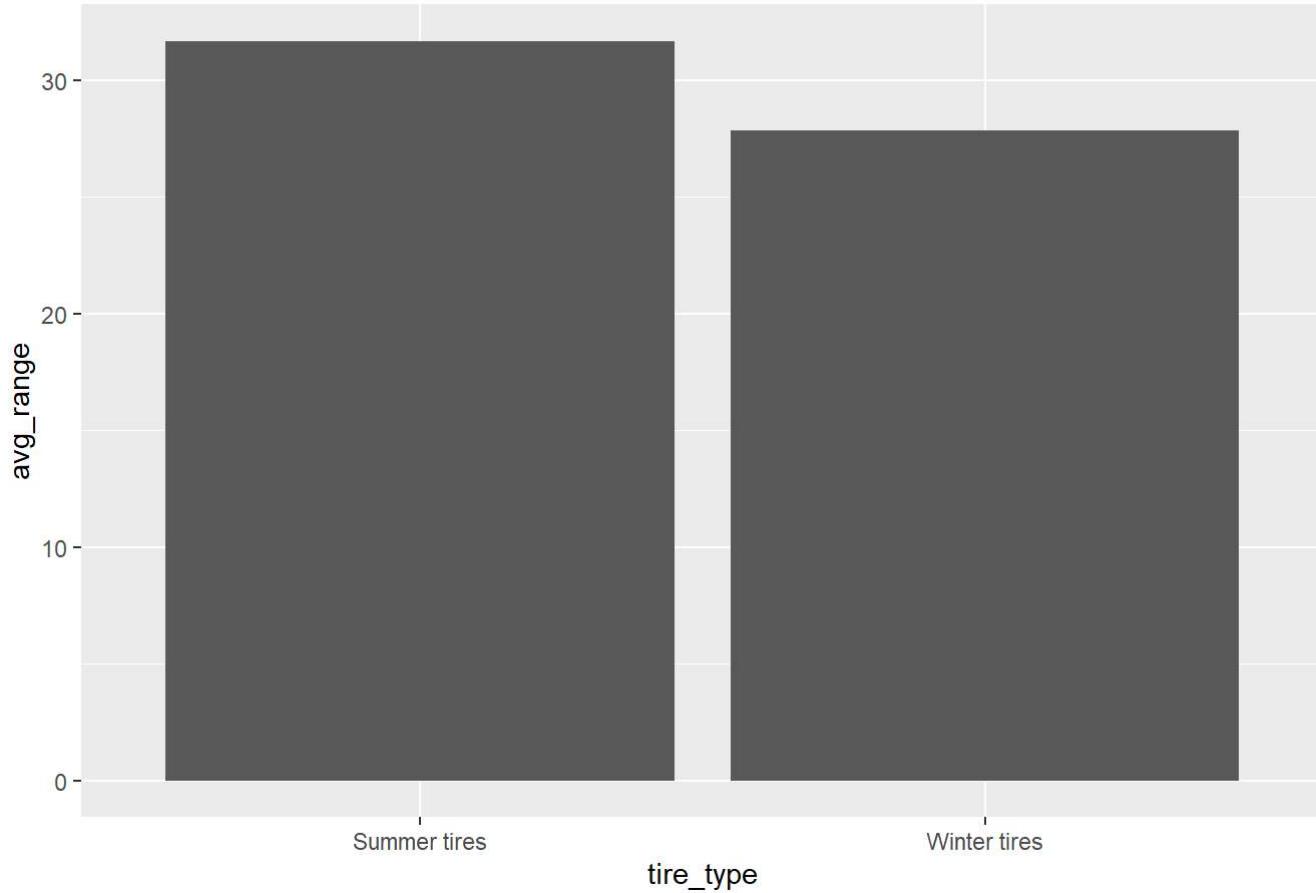
	tire_type	avg_range
1	Summer tires	31.6939975247525
2	Winter tires	27.8496634255797

Showing 1 to 2 of 2 entries

Previous Next

```
plt_tire = df1 %>% group_by(tire_type) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=tire_type,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by tire_type")
plot(plt_tire)
```

Average Driving Range by tire_type



```
#Average Driving Range by Motor Way
#Motor way has a good predictive power for Driving Range. This variable will be used for the model
Range_MotorWay= df1 %>%
  group_by(motor_way) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_MotorWay)
```

Show 10 entries

Search:

	motor_way	avg_range
1	1	34.944
2	0	21.2731910946197

Showing 1 to 2 of 2 entries

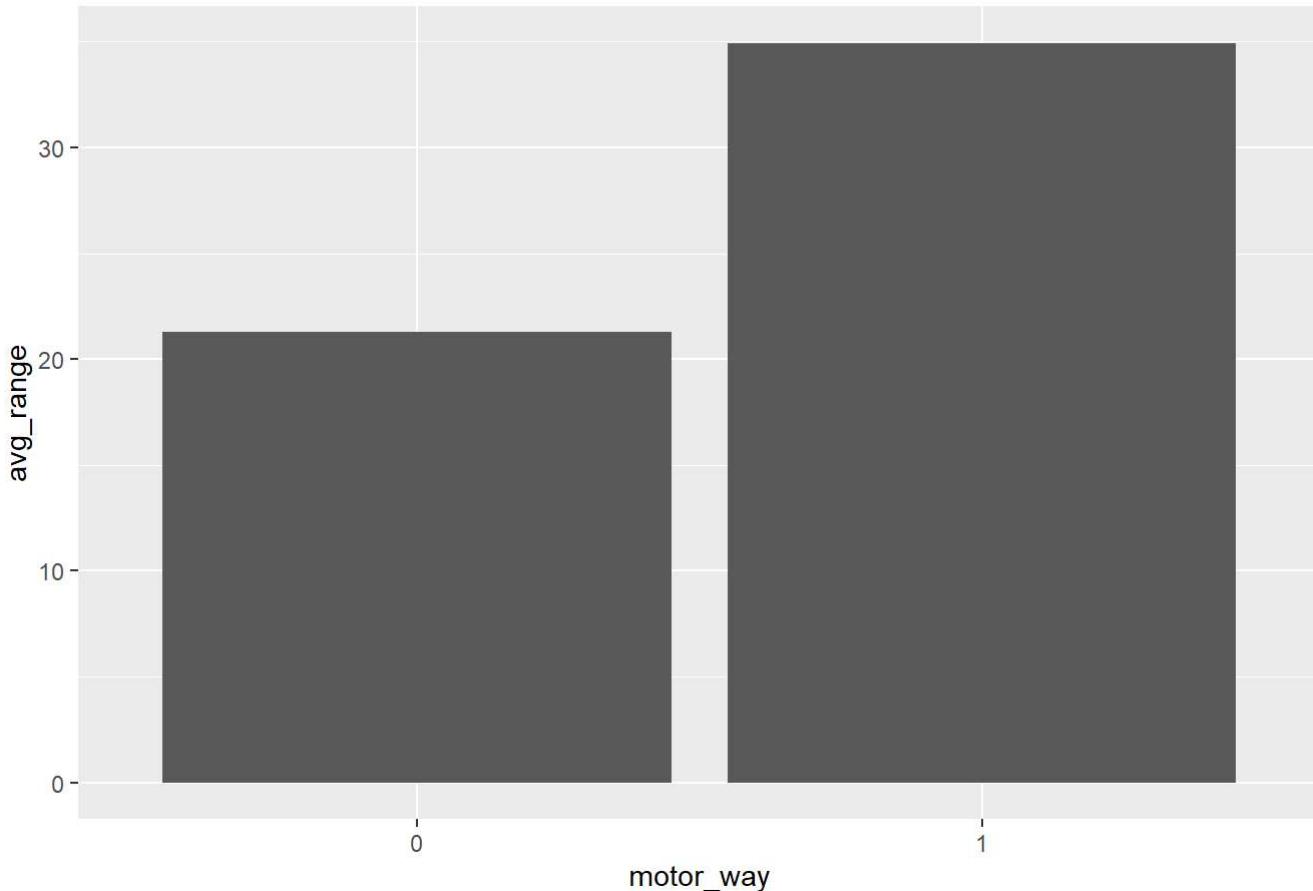
Previous

1

Next

```
plt_motor = df1 %>% group_by(motor_way) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=motor_way,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by motor_way")
plot(plt_motor)
```

Average Driving Range by motor_way



```
#Average Driving Range by Country Road
#From the Summaries below, Country Road will be used in the model as it has significant results.
Range_CountryRoad= df1 %>%
  group_by(country_roads) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_CountryRoad)
```

Show 10 entries

Search:

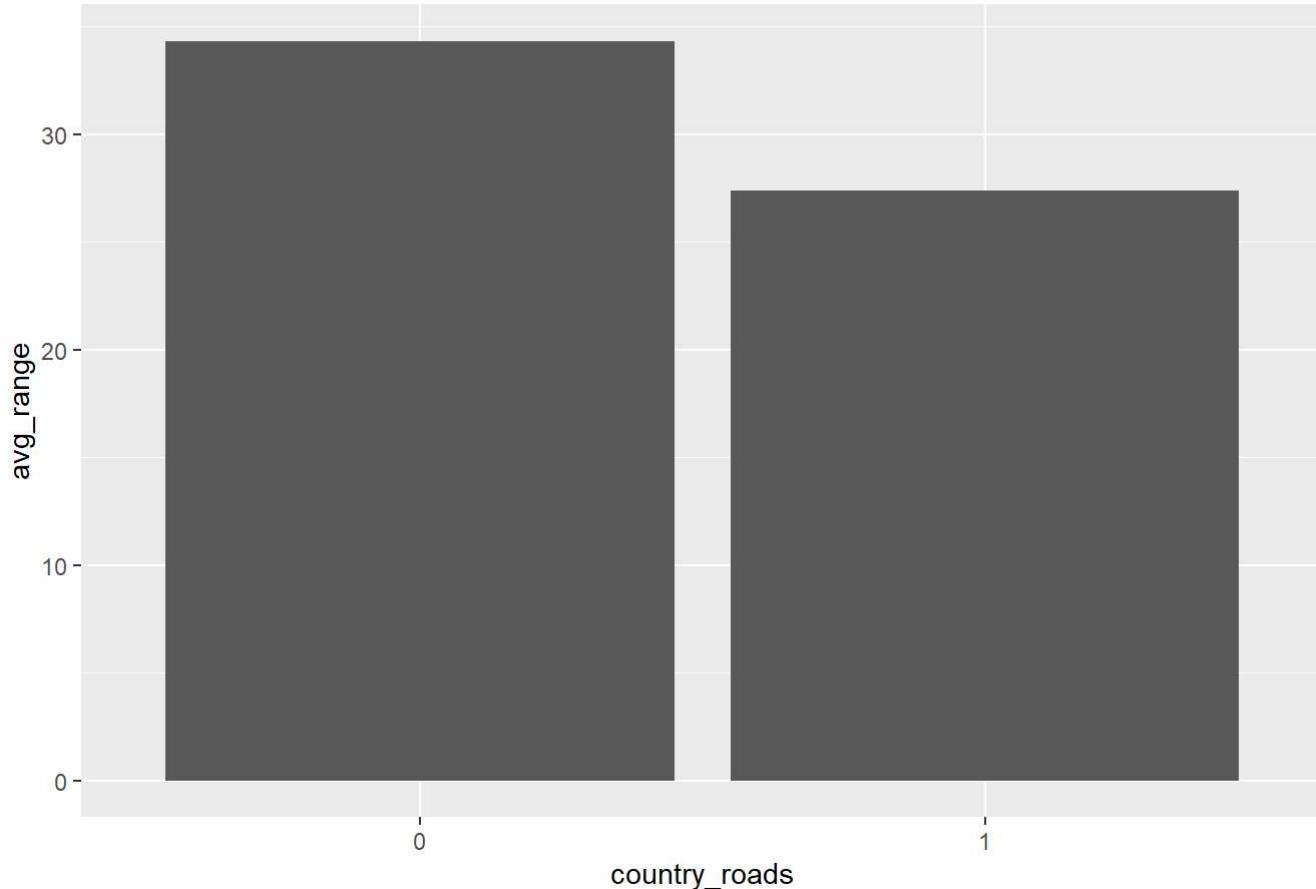
	country_roads	avg_range
1	0	34.3350091407678
2	1	27.3749327595481

Showing 1 to 2 of 2 entries

Previous 1 Next

```
plt_CountryRoad = df1 %>% group_by(country_roads) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=country_roads,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by country_roads")
plot(plt_CountryRoad)
```

Average Driving Range by country_roads



```
#Average Driving Range by Driving Style
#as it can be seen, the average driving range reduces as the driving style moves from Fast, Mode
rate to Normal. Hence, this variable should be used for the model.
Range_DrivingStyle= df1 %>%
  group_by(driving_style) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_DrivingStyle)
```

Show 10 entries

Search:

	driving_style	avg_range
1	Fast	33.1190476190476
2	Moderate	30.1043521266073

driving_style	avg_range
3 Normal	29.2792207792208

Showing 1 to 3 of 3 entries

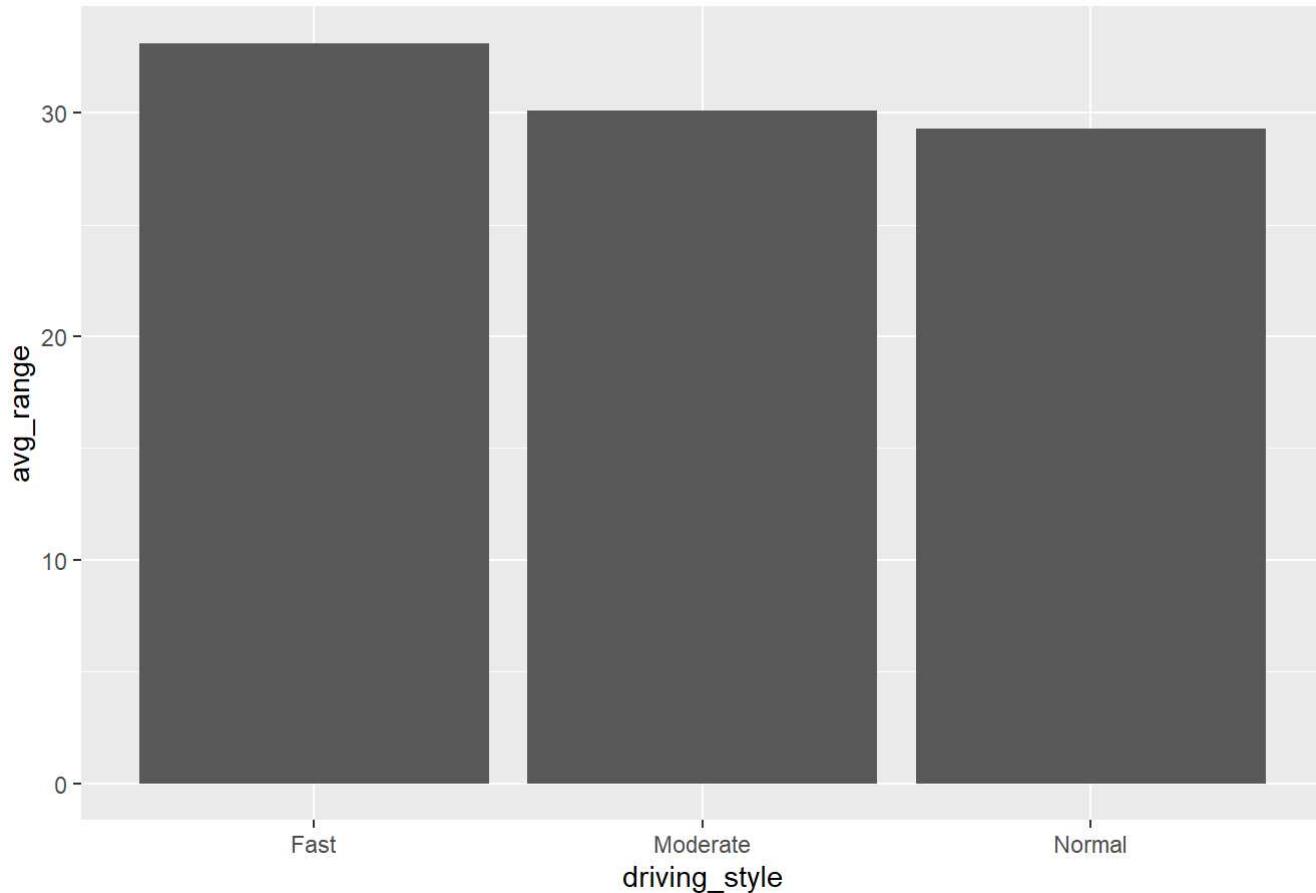
Previous

1

Next

```
plt_dvngstyle = df1 %>% group_by(driving_style) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=driving_style,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by driving_style")
plot(plt_dvngstyle)
```

Average Driving Range by driving_style



```
#Average Driving Range by A/C
#As seen below, A/C is an important variable. However, as seen above from its univariate analysis, this has a high classification imbalance issue. Hence this variable will NOT be considered.
Range_AC= df1 %>%
  group_by(`A/C`) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_AC)
```

Show 10 ▾ entries

Search:

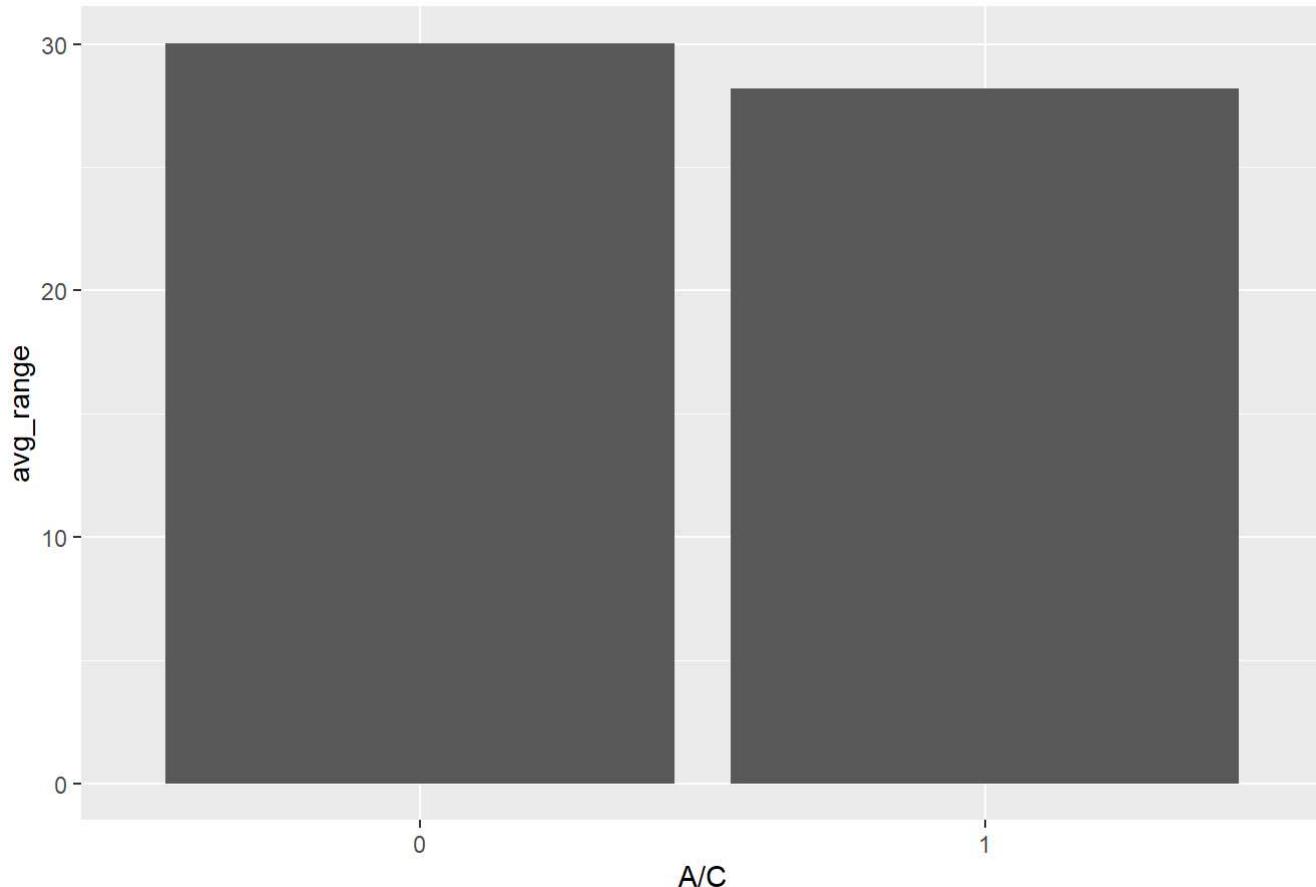
	A/C	avg_range
1	0	30.0399644760213
2	1	28.1884057971014

Showing 1 to 2 of 2 entries

Previous 1 Next

```
plt_AC = df1 %>% group_by(`A/C`) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=`A/C`,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by `A/C`")
plot(plt_AC)
```

Average Driving Range by `A/C`



#Average Driving Range by Park Heating

#As it can seen that the Driving Range of the vehicle increases if there is a Park Heating. Hence, this variable will be considered for the model.

```
Range_ParkHeating= df1 %>%
  group_by(park_heating) %>%
  summarise(avg_range = mean(`trip_distance(km)`)) %>%
  arrange(desc(avg_range))

DT::datatable(Range_ParkHeating)
```

Show 10 entries

Search:

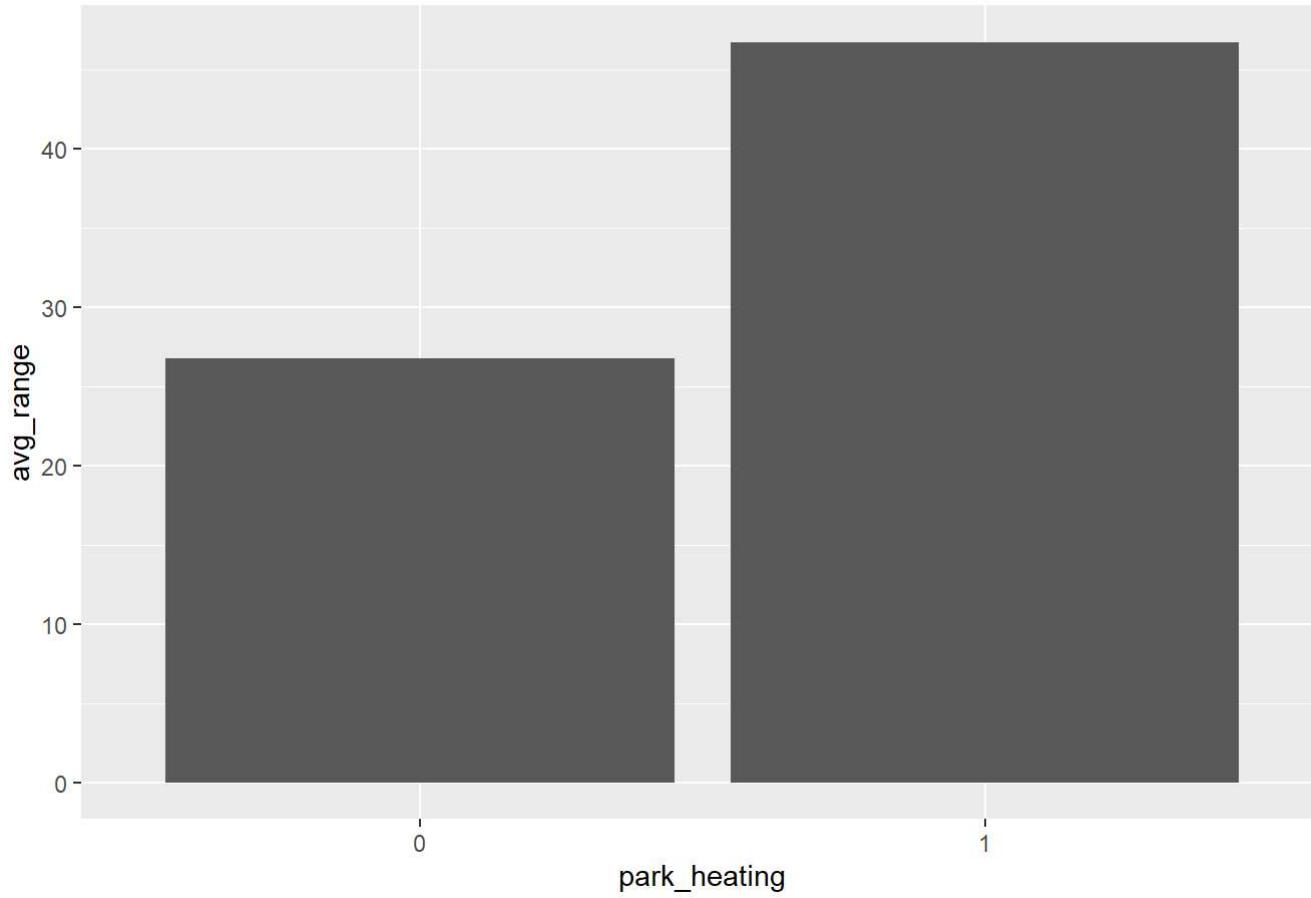
	park_heating	avg_range
1	1	46.7489451476793
2	0	26.742033077854

Showing 1 to 2 of 2 entries

Previous Next

```
plt_parkheating = df1 %>% group_by(park_heating) %>% summarise(avg_range = mean(`trip_distance(km)`)) %>%
  ggplot(aes(x=park_heating,y=avg_range)) + geom_bar(stat="identity") +
  labs(title = "Average Driving Range by park_heating")
plot(plt_parkheating)
```

Average Driving Range by park_heating

**### Correlation overview-**

As seen in Correlation Chart and Scatter plots below, quantity(kWh) and avg_speed(km/h) seem to have too much correlation with the Target variable. Hence, these 2 variables will be considered for the model. The other 2 numerical variables such as "consumption(kWh/100km)" and "ecr_deviatiion" dont have any correlation, hence will be removed.

```
library(correlation)
```

```
## Warning: package 'correlation' was built under R version 4.0.5
```

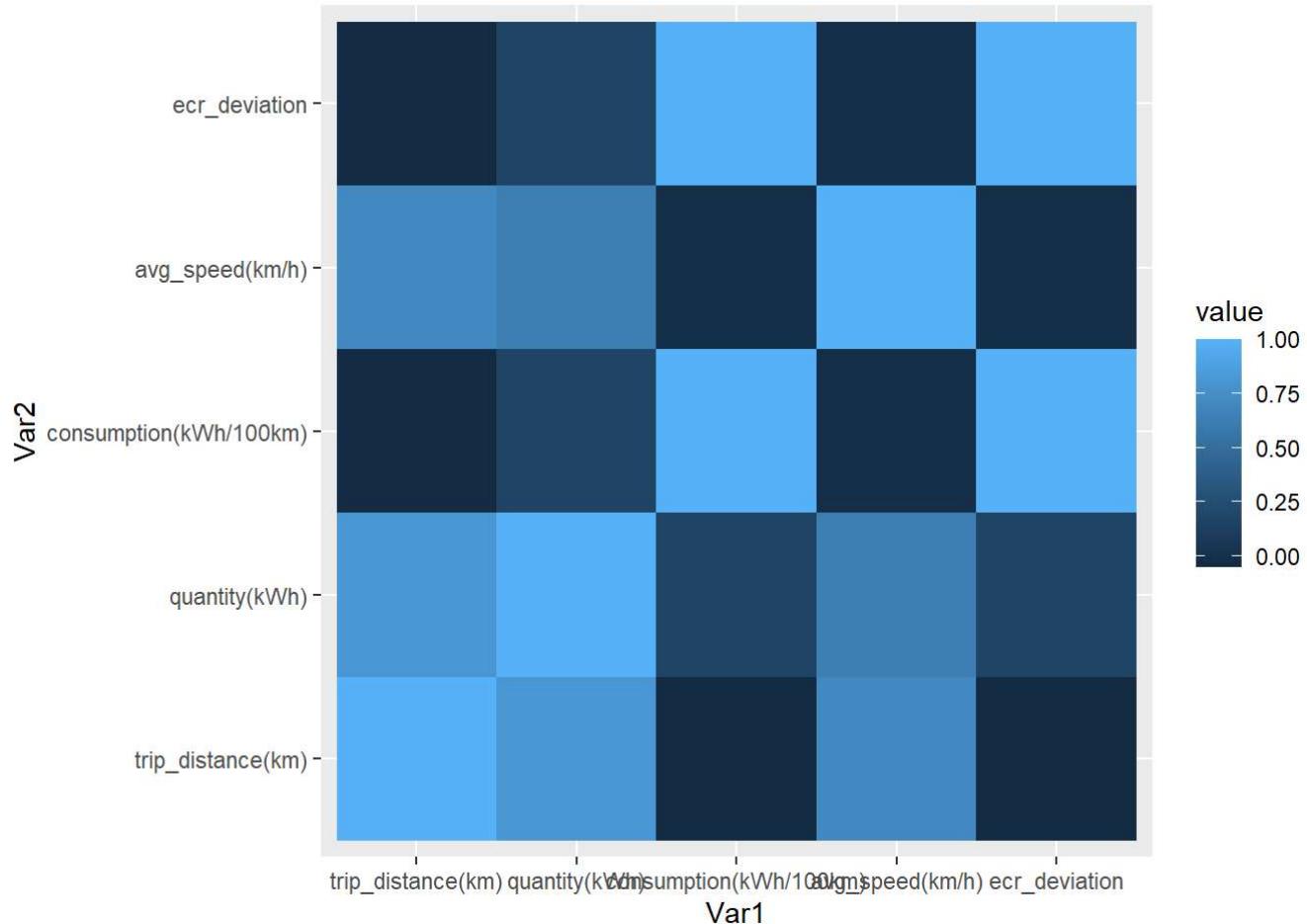
```
num_col<-sapply(df1, is.numeric)
df_num_cols<-df1[, num_col]
cor(df_num_cols)
```

	trip_distance(km)	quantity(kWh)	consumption(kWh/100km)
## trip_distance(km)	1.0000000	0.8087108	-0.04876906
## quantity(kWh)	0.80871076	1.0000000	0.16913134
## consumption(kWh/100km)	-0.04876906	0.1691313	1.00000000
## avg_speed(km/h)	0.70909194	0.6307378	-0.01267947
## ecr_deviation	-0.04876906	0.1691313	1.00000000
## avg_speed(km/h)	0.70909194	-0.04876906	
## quantity(kWh)	0.63073784	0.16913134	
## consumption(kWh/100km)	-0.01267947	1.00000000	
## avg_speed(km/h)	1.00000000	-0.01267947	
## ecr_deviation	-0.01267947	1.00000000	

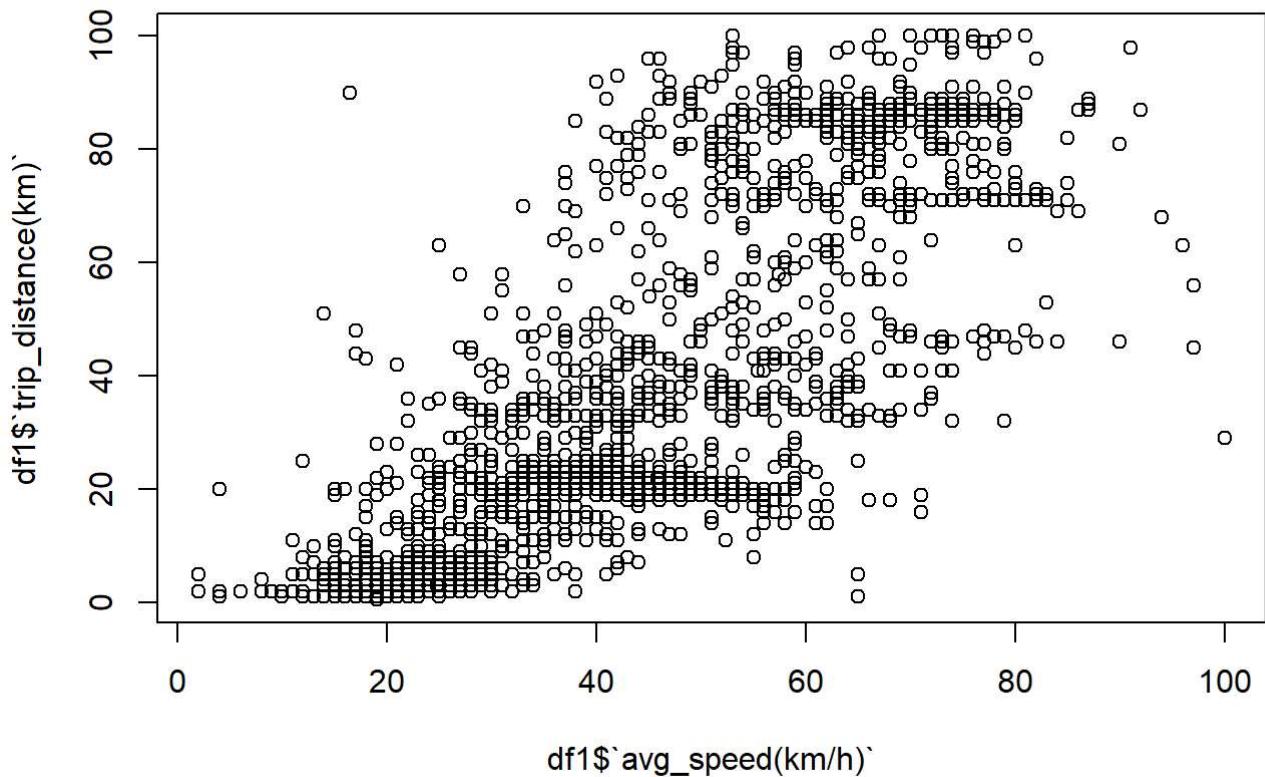
```
# Correlation Heat Chart
cormat <- round(cor(df_num_cols),3)
melted_cormat <- melt(cormat)
```

Warning in melt(cormat): The melt generic in data.table has been passed a matrix
 ## and will attempt to redirect to the relevant reshape2 method; please note that
 ## reshape2 is deprecated, and this redirection is now deprecated as well. To
 ## continue using melt methods from reshape2 while both libraries are attached,
 ## e.g. melt.list, you can prepend the namespace like reshape2::melt(cormat). In
 ## the next version, this warning will become an error.

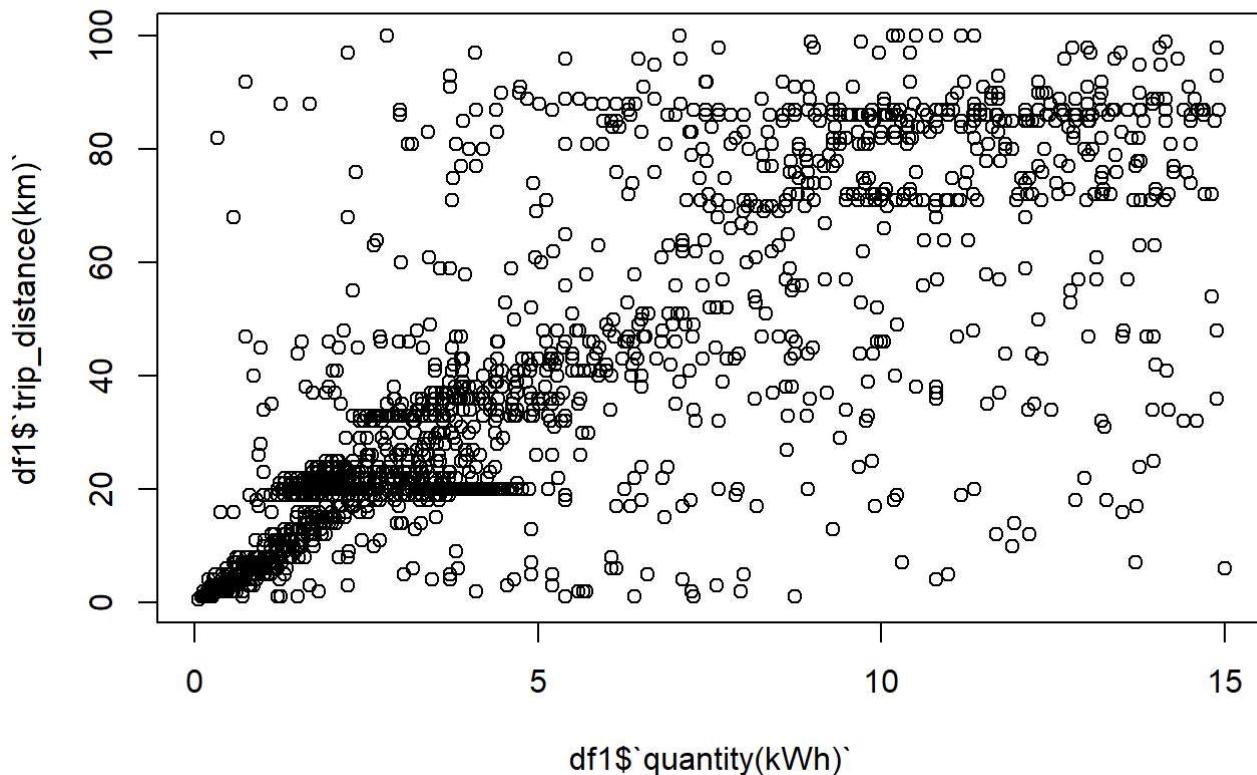
```
ggplot(data = melted_cormat, aes(x=Var1, y=Var2, fill=value)) +
  geom_tile()
```



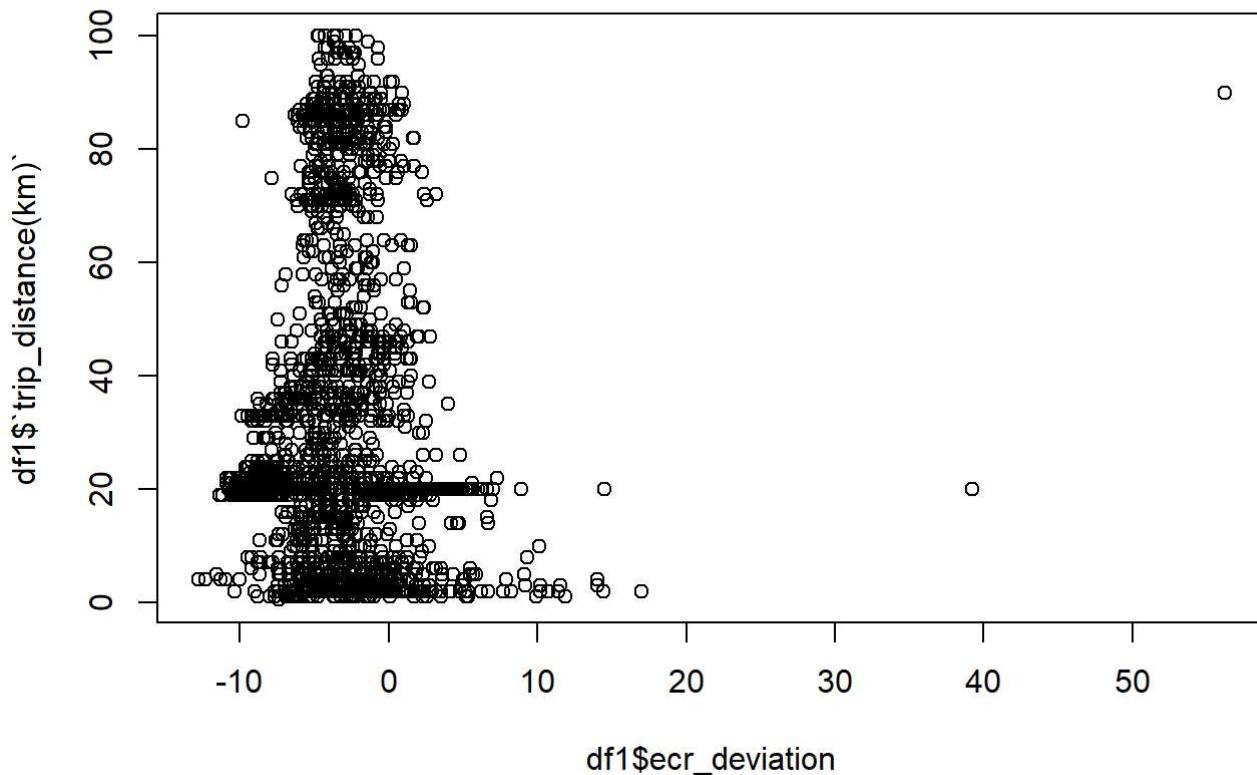
```
#Scatter Plots  
plot(df1$`avg_speed(km/h)` ,df1$`trip_distance(km)`)
```



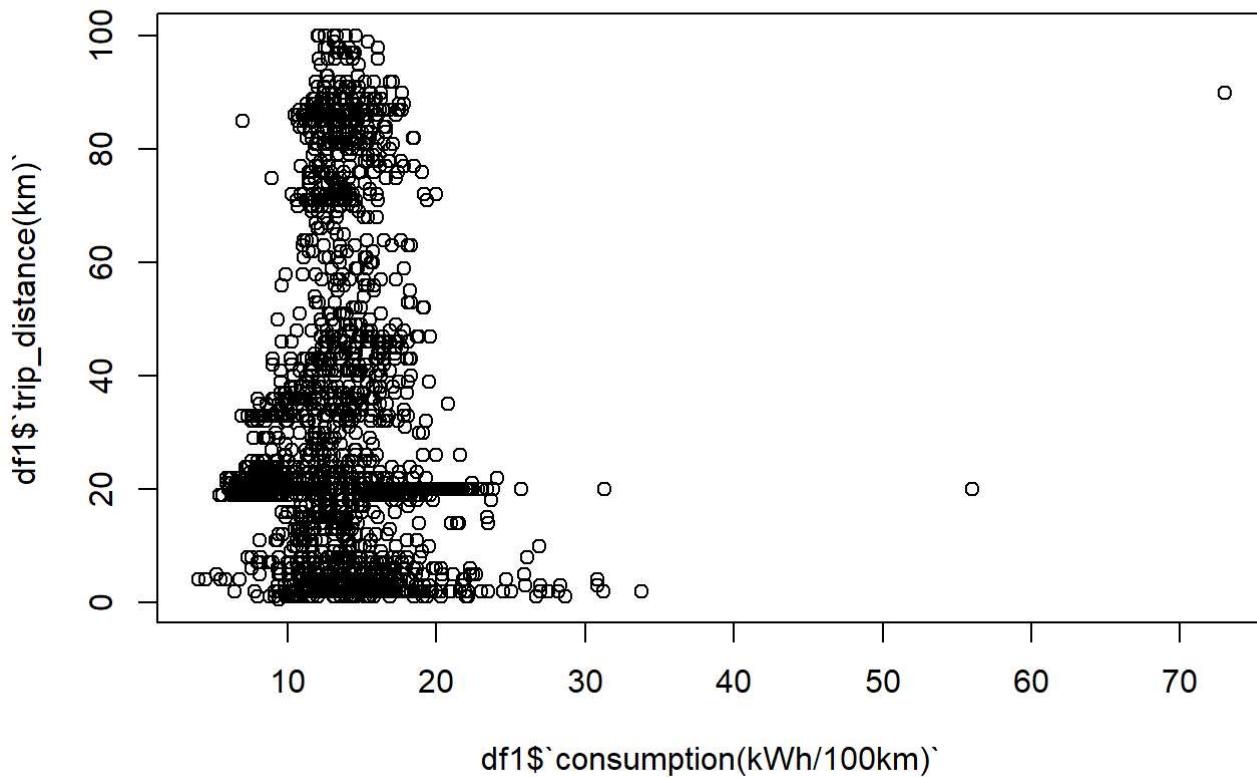
```
plot(df1$`quantity(kWh)` ,df1$`trip_distance(km)` )
```



```
plot(df1$`trip_distance(km)`)
```



```
plot(df1$`consumption(kWh/100km)`,df1$`trip_distance(km)`)
```



Hence, from the above Uni and Bi Variate Analysis, the following Variables will be Dropped from the model as they have very little or NO significance to predict the Dependent variable “trip_distance(km)” tire_type consumption(kWh/100km) A/C ecr_deviation

Removing the 4 variables from the dataframe. Now the Data is ready to build a predictive Model.

```
df_train<-within(df1, rm(tire_type, `A/C`, `consumption(kWh/100km)`, ecr_deviation))
```

LINEAR REGRESSION MODEL

```
#From the Model Output, Multiple R-squared:  0.7508 meaning, it is only 75% accurate. Lets try the Random Forest Model
dr_range<-lm(`trip_distance(km)`~`quantity(kWh)` + city + motor_way + country_roads + driving_style + park_heating + `avg_speed(km/h)` , data = df_train)
summary(dr_range)
```

```

## 
## Call:
## lm(formula = `trip_distance(km)` ~ `quantity(kWh)` + city + motor_way +
##     country_roads + driving_style + park_heating + `avg_speed(km/h)` ,
##     data = df_train)
##
## Residuals:
##    Min      1Q  Median      3Q     Max 
## -65.785  -5.337  -1.210   4.769  60.762 
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                2.296888   1.924529   1.193  0.23278    
## `quantity(kWh)`            3.404339   0.099006  34.385 < 2e-16 ***  
## city1                     -13.839055  0.911389 -15.185 < 2e-16 ***  
## motor_way1                 -3.464944  0.585158  -5.921 3.56e-09 ***  
## country_roads1             -0.004634  0.562093  -0.008  0.99342    
## driving_styleModerate      4.598693   1.412089   3.257  0.00114 **  
## driving_styleNormal        4.211156   1.444303   2.916  0.00358 **  
## park_heating1              -1.351352  0.695098  -1.944  0.05198 .  
## `avg_speed(km/h)`          0.503802   0.023933  21.051 < 2e-16 ***  
## ---                        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 
##
## Residual standard error: 12.58 on 2944 degrees of freedom
## Multiple R-squared:  0.7508, Adjusted R-squared:  0.7501 
## F-statistic: 1108 on 8 and 2944 DF,  p-value: < 2.2e-16

```

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.0.5
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
## 
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:dplyr':
```

```
## 
##     combine
```

```
## The following object is masked from 'package:ggplot2':
```

```
## 
##     margin
```

```
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.0.5
```

```
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 4.0.5
```

```
# Splitting data in train and test data
split <- sample.split(df_train, SplitRatio = 0.7)
split
```

```
## [1] TRUE TRUE FALSE FALSE TRUE FALSE TRUE TRUE
```

```
train <- subset(df_train, split == "TRUE")
test <- subset(df_train, split == "FALSE")
```

```
dim(train)
```

```
## [1] 1846 8
```

```
dim(test)
```

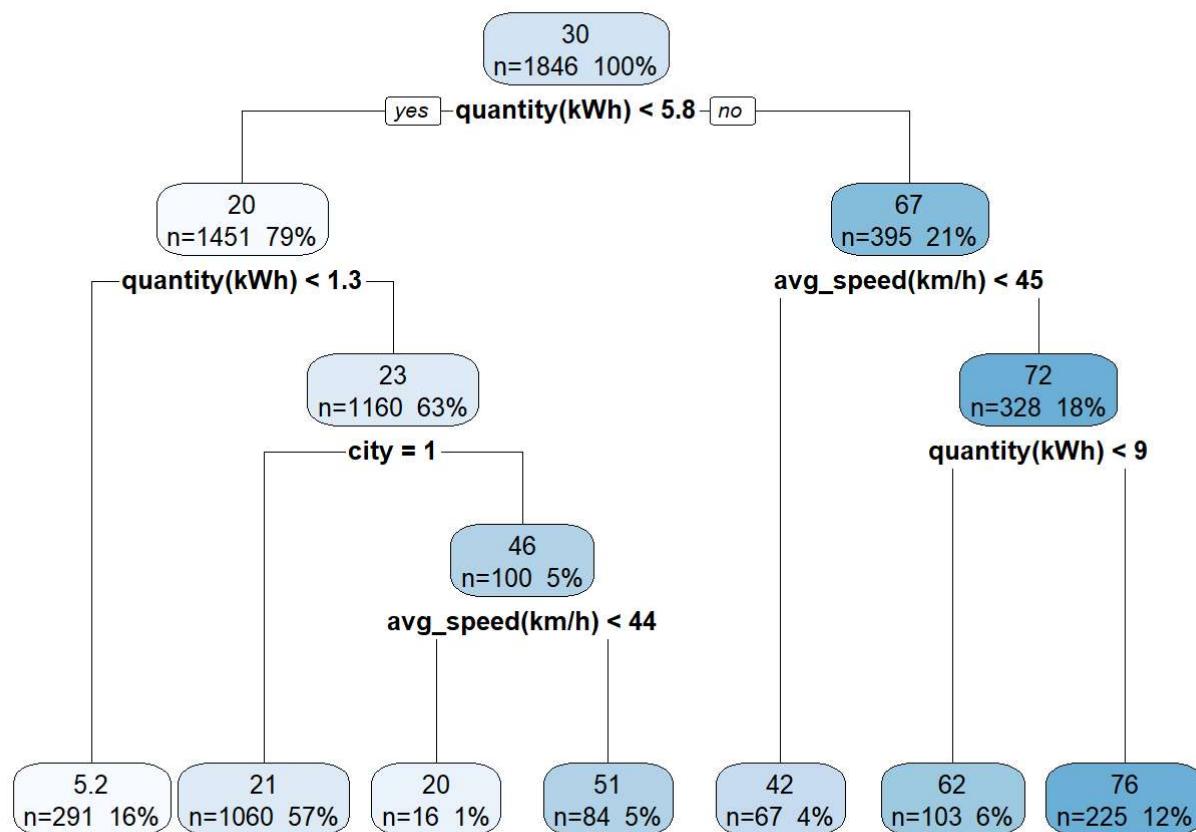
```
## [1] 1107 8
```

R-PART MODEL

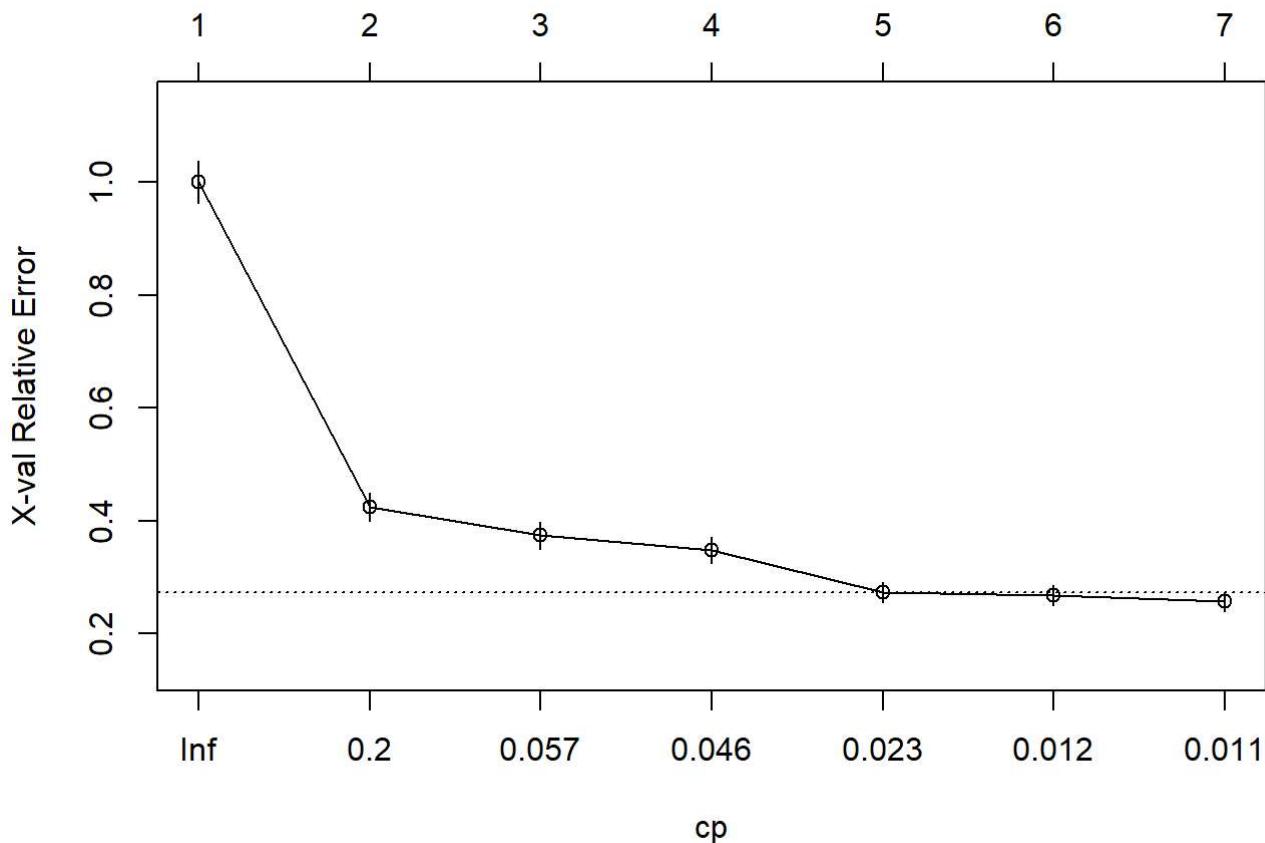
```
fit <- rpart(`trip_distance(km)`~., data = train, method = 'anova')
fit
```

```
## n= 1846
##
## node), split, n, deviance, yval
##      * denotes terminal node
##
## 1) root 1846 1170230.000 29.727790
##   2) quantity(kWh)< 5.765 1451  251804.900 19.654380
##     4) quantity(kWh)< 1.275 291   19741.490  5.201031 *
##     5) quantity(kWh)>=1.275 1160  156023.900 23.280170
##       10) city=1 1060   34630.600 21.099060 *
##       11) city=0 100    62898.000 46.400000
##         22) avg_speed(km/h)< 43.5 16   1956.938 19.937500 *
##         23) avg_speed(km/h)>=43.5 84   47602.700 51.440480 *
##     3) quantity(kWh)>=5.765 395  230319.600 66.731650
##       6) avg_speed(km/h)< 44.5 67   40888.420 41.686570 *
##       7) avg_speed(km/h)>=44.5 328  138820.400 71.847560
##     14) quantity(kWh)< 8.96 103   52580.990 61.990290 *
##     15) quantity(kWh)>=8.96 225   71649.840 76.360000 *
```

```
rpart.plot(fit, extra=101)
```



```
plotcp(fit)
```

size of tree

```
predict_rpart <- predict(fit, test)
predict_rpart
```

##	3	4	6	13	14	16	22	23
##	19.937500	76.360000	61.990291	19.937500	76.360000	76.360000	61.990291	21.099057
##	25	30	31	33	39	40	42	47
##	41.686567	21.099057	41.686567	51.440476	41.686567	61.990291	76.360000	61.990291
##	48	50	56	57	59	64	65	68
##	51.440476	51.440476	19.937500	76.360000	76.360000	41.686567	41.686567	76.360000
##	74	76	78	84	85	87	92	93
##	41.686567	61.990291	76.360000	76.360000	76.360000	21.099057	51.440476	61.990291
##	95	103	105	107	115	116	118	126
##	76.360000	76.360000	76.360000	51.440476	76.360000	76.360000	51.440476	76.360000
##	127	129	136	137	139	145	146	149
##	61.990291	41.686567	76.360000	51.440476	41.686567	76.360000	61.990291	76.360000
##	154	155	157	164	165	167	174	175
##	76.360000	5.201031	41.686567	76.360000	61.990291	61.990291	76.360000	76.360000
##	177	182	183	185	193	194	196	204
##	76.360000	76.360000	76.360000	76.360000	76.360000	61.990291	61.990291	76.360000
##	206	209	214	215	218	226	227	230
##	76.360000	76.360000	5.201031	76.360000	61.990291	61.990291	76.360000	76.360000
##	237	238	240	245	246	248	255	256
##	76.360000	19.937500	76.360000	61.990291	5.201031	5.201031	76.360000	76.360000
##	259	264	265	267	273	275	277	285
##	5.201031	51.440476	76.360000	76.360000	76.360000	61.990291	5.201031	76.360000
##	286	288	294	295	297	303	304	309
##	76.360000	76.360000	76.360000	51.440476	76.360000	76.360000	76.360000	19.937500
##	317	318	322	327	328	330	336	337
##	51.440476	76.360000	21.099057	5.201031	76.360000	76.360000	76.360000	76.360000
##	339	344	345	348	353	354	356	362
##	76.360000	61.990291	41.686567	76.360000	76.360000	61.990291	5.201031	5.201031
##	363	366	371	372	374	380	381	383
##	51.440476	76.360000	61.990291	76.360000	76.360000	76.360000	76.360000	5.201031
##	388	390	393	400	402	404	409	410
##	61.990291	76.360000	76.360000	51.440476	76.360000	21.099057	76.360000	61.990291
##	414	420	422	426	433	434	436	444
##	61.990291	76.360000	76.360000	76.360000	76.360000	21.099057	61.990291	76.360000
##	447	450	459	460	463	470	472	475
##	76.360000	76.360000	19.937500	76.360000	41.686567	61.990291	61.990291	51.440476
##	484	485	487	492	493	495	502	503
##	41.686567	76.360000	76.360000	19.937500	61.990291	76.360000	76.360000	76.360000
##	506	512	514	517	524	525	527	534
##	41.686567	51.440476	76.360000	51.440476	51.440476	76.360000	61.990291	61.990291
##	535	540	552	554	557	565	566	571
##	51.440476	76.360000	41.686567	5.201031	41.686567	76.360000	61.990291	76.360000
##	589	591	593	600	602	606	614	617
##	76.360000	21.099057	61.990291	76.360000	61.990291	76.360000	51.440476	76.360000
##	620	628	629	631	641	642	646	656
##	51.440476	21.099057	21.099057	76.360000	19.937500	76.360000	76.360000	51.440476
##	657	661	667	668	671	677	678	681
##	61.990291	76.360000	76.360000	61.990291	51.440476	76.360000	51.440476	61.990291
##	686	689	691	698	699	702	708	710
##	76.360000	41.686567	51.440476	5.201031	76.360000	76.360000	76.360000	41.686567
##	715	722	724	726	732	733	737	745
##	19.937500	61.990291	61.990291	51.440476	76.360000	76.360000	76.360000	76.360000

##	747	750	756	758	762	768	769	771
##	41.686567	51.440476	61.990291	21.099057	76.360000	76.360000	21.099057	61.990291
##	776	777	780	787	788	791	797	799
##	41.686567	61.990291	51.440476	76.360000	51.440476	41.686567	76.360000	61.990291
##	802	814	815	817	823	825	828	835
##	41.686567	61.990291	21.099057	41.686567	61.990291	51.440476	76.360000	61.990291
##	837	841	846	847	855	861	862	864
##	76.360000	61.990291	21.099057	5.201031	51.440476	41.686567	61.990291	5.201031
##	876	877	879	888	891	894	899	900
##	76.360000	19.937500	41.686567	76.360000	76.360000	76.360000	76.360000	51.440476
##	904	909	910	912	919	920	922	928
##	41.686567	51.440476	61.990291	61.990291	51.440476	19.937500	19.937500	76.360000
##	929	931	937	938	943	950	951	953
##	76.360000	21.099057	51.440476	76.360000	76.360000	76.360000	5.201031	5.201031
##	958	959	961	966	967	969	974	975
##	5.201031	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	977	982	983	985	990	991	993	998
##	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	999	1001	1006	1007	1009	1016	1017	1019
##	5.201031	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1024	1025	1027	1032	1033	1035	1042	1043
##	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057
##	1045	1051	1052	1054	1060	1061	1063	1068
##	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	5.201031	21.099057
##	1069	1071	1077	1078	1081	1086	1087	1089
##	21.099057	21.099057	76.360000	21.099057	21.099057	21.099057	21.099057	21.099057
##	1094	1097	1099	1104	1105	1107	1114	1115
##	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057
##	1118	1124	1125	1127	1132	1133	1135	1140
##	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1141	1143	1148	1149	1151	1156	1157	1159
##	76.360000	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1164	1165	1167	1174	1175	1177	1182	1186
##	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	76.360000	76.360000
##	1188	1193	1194	1196	1201	1202	1204	1209
##	21.099057	21.099057	5.201031	21.099057	5.201031	21.099057	21.099057	21.099057
##	1210	1212	1217	1218	1220	1225	1226	1228
##	5.201031	21.099057	5.201031	21.099057	21.099057	21.099057	5.201031	1252
##	1233	1234	1236	1241	1242	1244	1251	1252
##	5.201031	21.099057	5.201031	21.099057	5.201031	21.099057	21.099057	21.099057
##	1254	1259	1260	1262	1267	1268	1271	1277
##	21.099057	5.201031	5.201031	21.099057	21.099057	21.099057	5.201031	1324
##	1278	1280	1285	1286	1292	1299	1300	1303
##	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	61.990291	21.099057
##	1308	1309	1311	1316	1317	1319	1324	1326
##	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	61.990291
##	1328	1333	1334	1336	1341	1342	1344	1349
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1350	1352	1357	1358	1360	1365	1366	1368
##	5.201031	5.201031	21.099057	21.099057	5.201031	21.099057	21.099057	61.990291
##	1373	1374	1376	1381	1382	1384	1389	1392
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057

##	1394	1399	1400	1402	1407	1408	1410	1415
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1416	1418	1423	1424	1426	1433	1434	1436
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1443	1444	1446	1452	1455	1457	1462	1463
##	21.099057	5.201031	61.990291	5.201031	61.990291	61.990291	21.099057	21.099057
##	1465	1470	1471	1473	1478	1479	1481	1486
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057
##	1487	1489	1494	1496	1498	1504	1505	1507
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1512	1513	1515	1520	1521	1523	1528	1529
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1532	1538	1539	1541	1546	1547	1549	1554
##	5.201031	21.099057	21.099057	21.099057	5.201031	5.201031	21.099057	21.099057
##	1555	1557	1562	1563	1565	1570	1571	1573
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1581	1582	1584	1589	1590	1592	1597	1598
##	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057
##	1600	1607	1608	1610	1615	1616	1618	1623
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	76.360000	21.099057
##	1624	1626	1634	1635	1637	1642	1643	1645
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1650	1651	1653	1658	1659	1661	1666	1667
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	61.990291	21.099057
##	1669	1674	1675	1677	1683	1684	1686	1691
##	5.201031	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057
##	1692	1694	1700	1701	1703	1708	1709	1711
##	21.099057	5.201031	21.099057	21.099057	21.099057	5.201031	5.201031	21.099057
##	1716	1717	1719	1725	1726	1728	1733	1734
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1736	1742	1743	1745	1751	1752	1754	1759
##	5.201031	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057
##	1760	1764	1769	1770	1772	1778	1779	1781
##	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1786	1787	1789	1794	1795	1797	1804	1805
##	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057
##	1807	1815	1816	1818	1823	1824	1826	1831
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057
##	1832	1834	1841	1842	1844	1849	1850	1852
##	21.099057	21.099057	61.990291	21.099057	21.099057	5.201031	21.099057	21.099057
##	1858	1859	1861	1866	1867	1870	1875	1876
##	21.099057	21.099057	21.099057	21.099057	21.099057	41.686567	21.099057	21.099057
##	1878	1885	1886	1888	1893	1894	1896	1901
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057
##	1902	1904	1909	1910	1912	1917	1918	1920
##	21.099057	21.099057	5.201031	5.201031	21.099057	21.099057	5.201031	21.099057
##	1925	1926	1928	1933	1934	1936	1941	1942
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	1944	1949	1950	1952	1957	1958	1960	1965
##	21.099057	21.099057	61.990291	21.099057	21.099057	5.201031	5.201031	21.099057
##	1966	1968	1973	1974	1976	1982	1983	1985
##	21.099057	21.099057	61.990291	21.099057	61.990291	21.099057	21.099057	21.099057

##	1990	1991	1993	1998	1999	2001	2007	2008
##	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057
##	2010	2015	2016	2018	2026	2027	2029	2036
##	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057
##	2037	2039	2044	2045	2047	2052	2053	2055
##	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057
##	2060	2061	2064	2070	2071	2073	2078	2079
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	76.360000
##	2082	2087	2088	2090	2095	2096	2098	2103
##	21.099057	21.099057	5.201031	21.099057	41.686567	21.099057	21.099057	5.201031
##	2104	2106	2112	2113	2117	2125	2126	2128
##	21.099057	21.099057	41.686567	41.686567	5.201031	21.099057	21.099057	21.099057
##	2133	2134	2136	2142	2143	2145	2150	2151
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	2153	2160	2161	2163	2168	2169	2171	2176
##	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057
##	2177	2179	2184	2185	2187	2192	2193	2195
##	21.099057	41.686567	21.099057	21.099057	21.099057	21.099057	19.937500	76.360000
##	2200	2201	2203	2209	2210	2213	2218	2219
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031
##	2221	2226	2227	2229	2234	2235	2237	2242
##	21.099057	21.099057	21.099057	21.099057	76.360000	61.990291	21.099057	21.099057
##	2243	2245	2250	2251	2253	2258	2259	2261
##	21.099057	21.099057	21.099057	61.990291	61.990291	21.099057	21.099057	21.099057
##	2266	2267	2269	2274	2275	2277	2282	2283
##	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057
##	2285	2290	2291	2293	2298	2299	2301	2306
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	2307	2311	2316	2317	2319	2325	2326	2328
##	19.937500	61.990291	21.099057	5.201031	21.099057	5.201031	21.099057	21.099057
##	2333	2334	2336	2343	2344	2346	2351	2352
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	2355	2360	2361	2363	2368	2369	2371	2376
##	61.990291	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057
##	2377	2379	2384	2385	2387	2392	2393	2395
##	51.440476	21.099057	61.990291	5.201031	21.099057	21.099057	5.201031	51.440476
##	2400	2401	2403	2408	2409	2411	2416	2417
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	2420	2425	2426	2428	2433	2434	2436	2441
##	21.099057	21.099057	5.201031	21.099057	5.201031	21.099057	21.099057	5.201031
##	2442	2444	2449	2450	2452	2457	2458	2460
##	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	5.201031
##	2465	2467	2470	2475	2476	2478	2485	2486
##	21.099057	5.201031	21.099057	21.099057	5.201031	21.099057	5.201031	21.099057
##	2488	2493	2494	2496	2501	2502	2504	2510
##	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031
##	2511	2513	2518	2519	2521	2526	2527	2529
##	5.201031	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057
##	2534	2535	2537	2542	2543	2545	2550	2551
##	21.099057	21.099057	21.099057	21.099057	5.201031	51.440476	21.099057	21.099057
##	2553	2558	2559	2561	2566	2567	2569	2574
##	21.099057	21.099057	5.201031	5.201031	21.099057	21.099057	5.201031	76.360000

##	2577	2579	2584	2585	2587	2592	2593	2595
##	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057
##	2600	2601	2603	2608	2609	2611	2616	2617
##	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	21.099057	76.360000
##	2619	2624	2625	2627	2632	2633	2635	2640
##	21.099057	5.201031	21.099057	21.099057	21.099057	61.990291	21.099057	21.099057
##	2641	2643	2648	2649	2651	2656	2657	2659
##	5.201031	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057
##	2664	2665	2667	2672	2673	2675	2683	2684
##	5.201031	5.201031	41.686567	21.099057	5.201031	21.099057	21.099057	21.099057
##	2686	2691	2692	2694	2699	2700	2702	2707
##	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057
##	2708	2710	2715	2716	2718	2723	2724	2726
##	21.099057	21.099057	21.099057	5.201031	5.201031	21.099057	21.099057	5.201031
##	2731	2732	2734	2739	2740	2742	2747	2748
##	5.201031	5.201031	5.201031	21.099057	21.099057	5.201031	21.099057	21.099057
##	2750	2755	2756	2758	2763	2764	2766	2771
##	21.099057	76.360000	21.099057	5.201031	21.099057	5.201031	21.099057	5.201031
##	2772	2774	2779	2780	2782	2787	2788	2790
##	5.201031	5.201031	21.099057	5.201031	21.099057	61.990291	5.201031	5.201031
##	2795	2796	2798	2803	2804	2806	2811	2812
##	21.099057	21.099057	21.099057	5.201031	5.201031	21.099057	5.201031	21.099057
##	2814	2819	2820	2822	2827	2828	2830	2836
##	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057	41.686567
##	2837	2839	2844	2845	2847	2852	2853	2855
##	19.937500	21.099057	21.099057	21.099057	21.099057	21.099057	41.686567	5.201031
##	2860	2861	2863	2868	2869	2871	2878	2879
##	21.099057	21.099057	5.201031	61.990291	21.099057	5.201031	21.099057	21.099057
##	2881	2887	2888	2891	2896	2897	2899	2904
##	21.099057	5.201031	5.201031	21.099057	21.099057	5.201031	21.099057	5.201031
##	2905	2907	2912	2913	2915	2920	2921	2923
##	5.201031	5.201031	5.201031	21.099057	5.201031	61.990291	21.099057	5.201031
##	2928	2929	2931	2936	2937	2939	2944	2945
##	5.201031	5.201031	5.201031	21.099057	21.099057	21.099057	21.099057	21.099057
##	2947	2952	2953	2955	2963	2964	2966	2971
##	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057	5.201031	21.099057
##	2972	2975	2980	2981	2983	2990	2991	2993
##	21.099057	21.099057	21.099057	21.099057	21.099057	76.360000	21.099057	21.099057
##	2998	2999	3001	3007	3008	3010	3015	3016
##	21.099057	5.201031	21.099057	5.201031	21.099057	5.201031	21.099057	5.201031
##	3018	3023	3024	3026	3031	3032	3034	3039
##	21.099057	61.990291	5.201031	5.201031	21.099057	21.099057	61.990291	5.201031
##	3040	3044	3049	3050	3053	3058	3059	3061
##	19.937500	21.099057	21.099057	21.099057	21.099057	21.099057	5.201031	5.201031
##	3067	3068	3070	3077	3078	3080	3085	3086
##	5.201031	5.201031	5.201031	5.201031	5.201031	51.440476	5.201031	21.099057
##	3088	3093	3094	3096	3101	3102	3104	3109
##	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057	21.099057	21.099057
##	3110	3112	3117	3118	3120	3126	3127	3129
##	21.099057	5.201031	5.201031	5.201031	5.201031	21.099057	21.099057	5.201031
##	3134	3135	3137	3142	3143	3145	3150	3151
##	21.099057	5.201031	21.099057	21.099057	21.099057	5.201031	21.099057	21.099057

```
##      3153      3158      3159      3161      3166      3167      3170      3175
## 21.099057 51.440476 21.099057 21.099057 5.201031 5.201031 21.099057 5.201031
##      3176      3178      3183      3184      3186      3191      3192      3194
## 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057
##      3200      3202      3204      3209      3210      3212      3218      3219
## 5.201031 21.099057 21.099057 21.099057 21.099057 5.201031 21.099057 21.099057
##      3221      3226      3227      3229      3234      3235      3237      3242
## 21.099057 5.201031 5.201031 21.099057 5.201031 21.099057 21.099057 21.099057
##      3243      3245      3251      3252      3254      3260      3261      3263
## 21.099057 21.099057 21.099057 21.099057 5.201031 5.201031 21.099057 21.099057
##      3268      3269      3271      3276      3277      3279      3284      3285
## 21.099057 5.201031 41.686567 21.099057 5.201031 21.099057 21.099057 5.201031
##      3287      3292      3293      3295      3300      3301      3303      3308
## 21.099057 5.201031 41.686567 5.201031 5.201031 21.099057 21.099057 21.099057
##      3309      3311      3316      3317      3319      3324      3327      3329
## 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057 21.099057
##      3334      3335      3337
## 21.099057 21.099057 41.686567
```

```
summary(predict_rpart)
```

```
##      Min. 1st Qu. Median Mean 3rd Qu. Max.
## 5.201 21.099 21.099 29.205 21.099 76.360
```

```
#Adding RPart Predicted values to the test dataframe
test$Rpart_Pred<-predict_rpart
```

RANDOM FOREST MODEL

```
set.seed(120) # Setting seed
classifier_RF = randomForest(x = train[-1],
                               y = train$`trip_distance(km)` ,
                               ntree = 500)

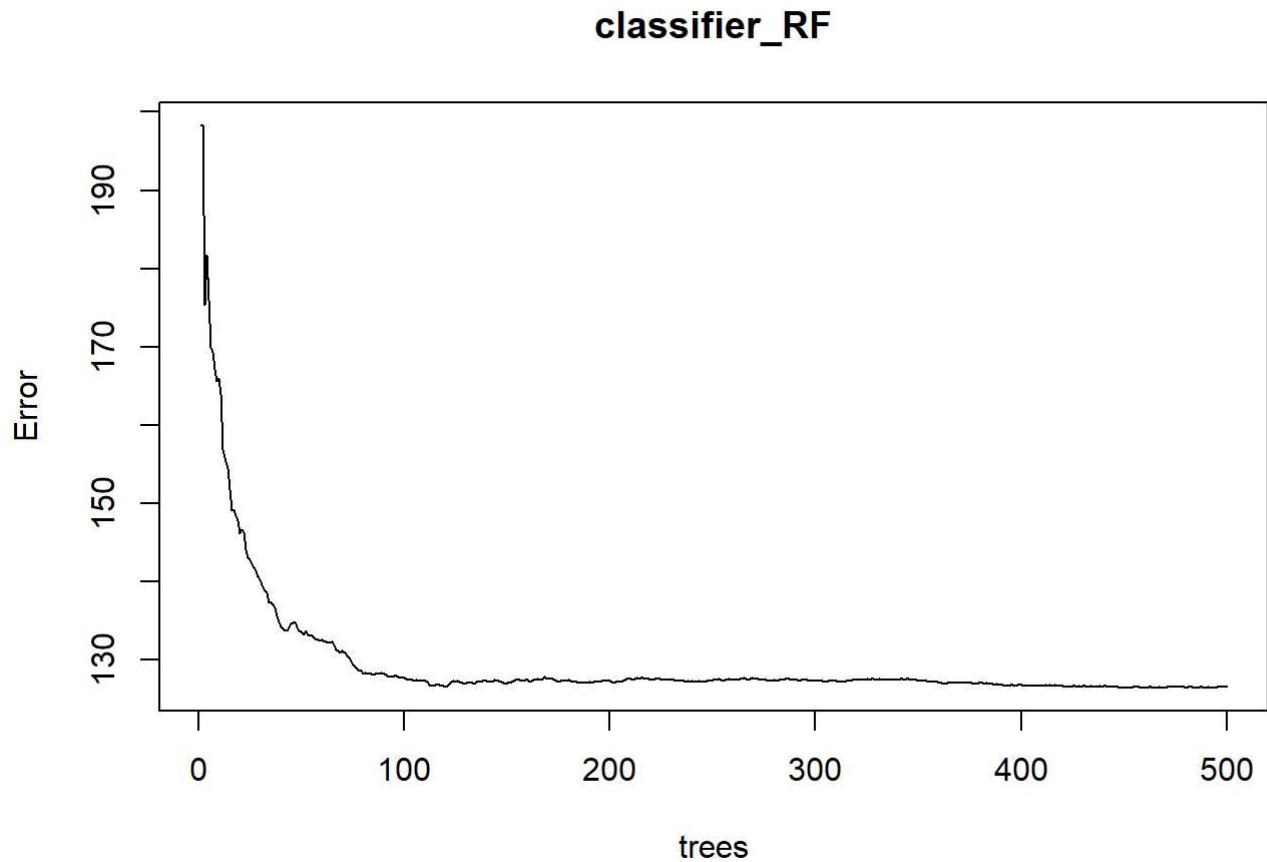
print(classifier_RF)
```

```
##
## Call:
## randomForest(x = train[-1], y = train$`trip_distance(km)` , ntree = 500)
##                 Type of random forest: regression
##                         Number of trees: 500
## No. of variables tried at each split: 2
##
##                 Mean of squared residuals: 126.6029
## % Var explained: 80.03
```

```
library(dplyr)
# Predicting the Test set results
y_pred = predict(classifier_RF, newdata = test[-1])

#Adding RF Predicted values to the test dataframe
test$RandomForest_Pred<-y_pred

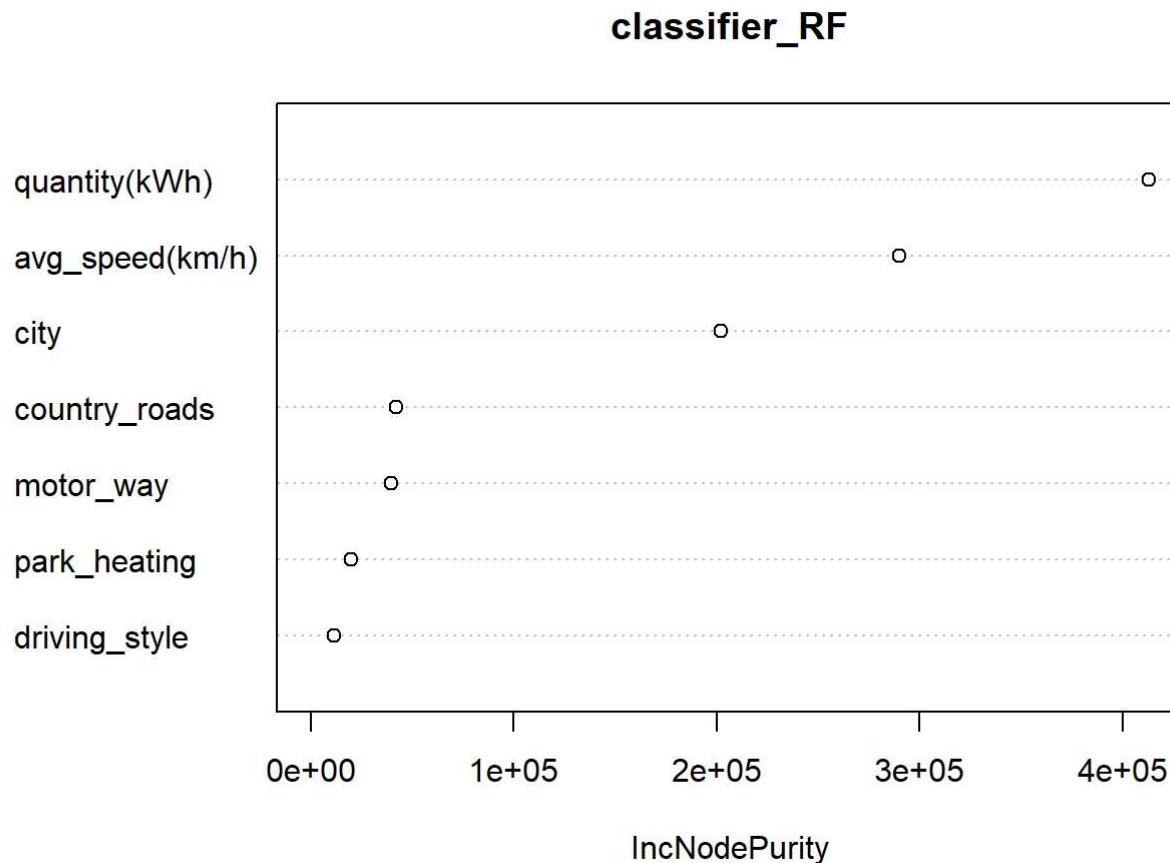
# Plotting model
plot(classifier_RF)
```



```
# Importance plot
importance(classifier_RF)
```

```
##           IncNodePurity
## quantity(kWh)      412961.07
## city                202194.15
## motor_way            39630.21
## country_roads        42186.58
## driving_style         11319.30
## park_heating          19878.51
## avg_speed(km/h)      290059.05
```

```
# Variable importance plot
varImpPlot(classifier_RF)
```



As seen from the above results, Random Forest model is performing better than LR or RPart models. The RF model is giving an accuracy of 81.47% which is descent enough. We can still increase the accuracy by looking at Deep Learning models or certain parameter tuning in the current RF Models.

Exporting the Predicted output data into Excel

```
library("writexl")
## Warning: package 'writexl' was built under R version 4.0.5
write_xlsx(test,"prediction_output.xlsx")
```

THANK YOU