Deliverable 1

Data Processing, Description, Validation and Profiling

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Contents

1 Data description

- Description http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml
- Data Dictionary - SHL Trip Records -This data dictionary describes SHL trip data in visit http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml:

1.1 Variables

- VendorID
  - A code indicating the LPEP provider that provided the record.
  - Values:
    - 1= Creative Mobile Technologies, LLC
    - 2= VeriFone Inc.
- lpep_pickup_datetime
  - The date and time when the meter was engaged.
- lpep_dropoff_datetime
  - The date and time when the meter was disengaged.
- Passenger_count

  - The number of passengers in the vehicle.
  - This is a driver-entered value.

- Trip_distance
  - The elapsed trip distance in miles reported by the taximeter.

- Pickup_longitude
  - Longitude where the meter was engaged.

- Pickup_latitude
  - Latitude where the meter was engaged.

- RateCodeID
  - The final rate code in effect at the end of the trip.
  - Values:
    * 1=Standard rate

    * 2=JFK
    * 3=Newark
    * 4=Nassau or Westchester
    * 5=Negotiated fare
    * 6=Group ride

- Store_and_fwd_flag
  - This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka "store and forward," because the vehicle did not have a connection to the server:
  - Values
    * Y= store and forward trip

    * N= not a store and forward trip

- Dropoff_longitude
  - Longitude where the meter was timed off.

- Dropoff_latitude
  - Latitude where the meter was timed off.

- Payment_type
  - A numeric code signifying how the passenger paid for the trip.
  - Values:
    * 1= Credit card
    * 2= Cash
    * 3= No charge
    * 4= Dispute
- Fare_amount
  - The time-and-distance fare calculated by the meter.

- Extra
  - Miscellaneous extras and surcharges.

  - Currently, this only includes the $0.50 and $1 rush hour and overnight charges.
- MTA_tax
  - $0.50 MTA tax that is automatically triggered based on the metered rate in use.

- Improvement_surcharge
  - $0.30 improvement surcharge assessed on hailed trips at the flag drop.
  - The improvement surcharge began being levied in 2015.

- Tip_amount
  - This field is automatically populated for credit card tips.
  - Cash tips are not included.

- Tolls_amount
  - Total amount of all tolls paid in trip.

- Total_amount
  - The total amount charged to passengers.
  - Does not include cash tips.

- Trip_type
  - A code indicating whether the trip was a street-hail or a dispatch that is automatically assigned based on the metered rate in use but can be altered by the driver.
  - Values:
    * 1= Street-hail
    * 2= Dispatch

2 Load Required Packages for this deliverable

We load the necessary packages and set working directory

```
setwd("~/Documents/uni/FIB-ADEI-LAB/deliverable2")
#setwd("C:/Users/Claudia Sánchez/Desktop/FIB/TARDOR 2020-2021/ADEI/DELIVERABLE1/FIB-ADEI-LAB/deliverabl

# Load Required Packages
options(contrasts=c("contr.treatment","contr.treatment"))

requiredPackages <- c("missMDA","chemometrics","mvoutlier","effects","FactoMineR","car", "factoextra","F
missingPackages <- requiredPackages[!(requiredPackages %in% installed.packages()[,"Package"])]

if(length(missingPackages)) install.packages(missingPackages)
lapply(requiredPackages, require, character.only = TRUE)
```

2.1 Select a sample of 5000 records

From the proposed database, we need to select a sample of 5000 records randomly so we can start analyzing our data.

```
if(!is.null(dev.list())) dev.off()  # Clear plots
rm(list=ls())                       # Clean workspace
```

Data: green_tripdata_2016-01

```
setwd("~/Documents/uni/FIB-ADEI-LAB/deliverable2")
filepath<-"~/Documents/uni/FIB-ADEI-LAB/deliverable2"
#setwd("C:/Users/Claudia Sánchez/Desktop/FIB/TARDOR 2020-2021/ADEI/DELIVERABLE1/FIB-ADEI-LAB/deliverabl
#filepath<-"C:/Users/Claudia Sánchez/Desktop/FIB/TARDOR 2020-2021/ADEI/DELIVERABLE1/FIB-ADEI-LAB/delive
df<-read.table(paste0(filepath,"/green_tripdata_2016-01.csv"),header=T, sep=",")
# dim(df)       # Displays the sample size
# names(df)     # Displays the names of the sample variables
# summary(df)
```

Select your 5000 register sample (random sample). Use birthday of 1 member of the group –> Júlia's one

```
set.seed(180998)
sam<-as.vector(sort(sample(1:nrow(df),5000)))
```

Verification and storage of the sample

```
head(df)
```

```
##   VendorID lpep_pickup_datetime Lpep_dropoff_datetime Store_and_fwd_flag
## 1        2  2016-01-01 00:29:24   2016-01-01 00:39:36                  N
## 2        2  2016-01-01 00:19:39   2016-01-01 00:39:18                  N
## 3        2  2016-01-01 00:19:33   2016-01-01 00:39:48                  N
## 4        2  2016-01-01 00:22:12   2016-01-01 00:38:32                  N
## 5        2  2016-01-01 00:24:01   2016-01-01 00:39:22                  N
## 6        2  2016-01-01 00:32:59   2016-01-01 00:39:35                  N
##   RateCodeID Pickup_longitude Pickup_latitude Dropoff_longitude
## 1          1        -73.92864        40.68061         -73.92428
## 2          1        -73.95267        40.72318         -73.92392
```

```
## 3          1       -73.97161       40.67611         -74.01316
## 4          1       -73.98950       40.66958         -74.00065
## 5          1       -73.96473       40.68285         -73.94072
## 6          1       -73.89114       40.74646         -73.86774
##   Dropoff_latitude Passenger_count Trip_distance Fare_amount Extra MTA_tax
## 1         40.69804               1          1.46         8.0   0.5     0.5
## 2         40.76138               1          3.56        15.5   0.5     0.5
## 3         40.64607               1          3.79        16.5   0.5     0.5
## 4         40.68903               1          3.01        13.5   0.5     0.5
## 5         40.66301               1          2.55        12.0   0.5     0.5
## 6         40.74211               1          1.37         7.0   0.5     0.5
##   Tip_amount Tolls_amount Ehail_fee improvement_surcharge Total_amount
## 1       1.86            0        NA                   0.3        11.16
## 2       0.00            0        NA                   0.3        16.80
## 3       4.45            0        NA                   0.3        22.25
## 4       0.00            0        NA                   0.3        14.80
## 5       0.00            0        NA                   0.3        13.30
## 6       0.00            0        NA                   0.3         8.30
##   Payment_type Trip_type
## 1            1         1
## 2            2         1
## 3            1         1
## 4            2         1
## 5            2         1
## 6            2         1
```

```
df<-df[sam,]
summary(df)
```

```
##     VendorID     lpep_pickup_datetime Lpep_dropoff_datetime Store_and_fwd_flag
##  Min.   :1.000   Length:5000          Length:5000           Length:5000
##  1st Qu.:2.000   Class :character     Class :character      Class :character
##  Median :2.000   Mode  :character     Mode  :character      Mode  :character
##  Mean   :1.788
##  3rd Qu.:2.000
##  Max.   :2.000
##    RateCodeID  Pickup_longitude Pickup_latitude Dropoff_longitude
##  Min.   :1.0   Min.   :-75.39   Min.   : 0.00   Min.   :-75.31
##  1st Qu.:1.0   1st Qu.:-73.96   1st Qu.:40.70   1st Qu.:-73.97
##  Median :1.0   Median :-73.95   Median :40.75   Median :-73.94
##  Mean   :1.1   Mean   :-73.89   Mean   :40.72   Mean   :-73.80
##  3rd Qu.:1.0   3rd Qu.:-73.92   3rd Qu.:40.80   3rd Qu.:-73.91
##  Max.   :5.0   Max.   :  0.00   Max.   :41.04   Max.   :  0.00
##  Dropoff_latitude Passenger_count Trip_distance     Fare_amount
##  Min.   : 0.00    Min.   :0.000   Min.   : 0.000   Min.   :-52.0
##  1st Qu.:40.70    1st Qu.:1.000   1st Qu.: 1.020   1st Qu.:  6.0
##  Median :40.75    Median :1.000   Median : 1.800   Median :  9.0
##  Mean   :40.67    Mean   :1.375   Mean   : 2.765   Mean   : 11.9
##  3rd Qu.:40.79    3rd Qu.:1.000   3rd Qu.: 3.420   3rd Qu.: 14.5
##  Max.   :41.18    Max.   :6.000   Max.   :52.790   Max.   :200.0
##      Extra             MTA_tax           Tip_amount      Tolls_amount
##  Min.   :-1.0000   Min.   :-0.5000   Min.   : 0.000   Min.   : 0.00000
##  1st Qu.: 0.0000   1st Qu.: 0.5000   1st Qu.: 0.000   1st Qu.: 0.00000
##  Median : 0.5000   Median : 0.5000   Median : 0.000   Median : 0.00000
##  Mean   : 0.3517   Mean   : 0.4857   Mean   : 1.217   Mean   : 0.08369
##  3rd Qu.: 0.5000   3rd Qu.: 0.5000   3rd Qu.: 2.000   3rd Qu.: 0.00000
##  Max.   : 1.0000   Max.   : 0.5000   Max.   :96.000   Max.   :18.04000
##  Ehail_fee      improvement_surcharge  Total_amount     Payment_type
##  Mode:logical   Min.   :-0.3000       Min.   :-52.80   Min.   :1.00
##  NA's:5000      1st Qu.: 0.3000       1st Qu.:  7.80   1st Qu.:1.00
##                 Median : 0.3000       Median : 11.16   Median :2.00
##                 Mean   : 0.2914       Mean   : 14.33   Mean   :1.52
##                 3rd Qu.: 0.3000       3rd Qu.: 17.16   3rd Qu.:2.00
##                 Max.   : 0.3000       Max.   :260.00   Max.   :4.00
```

```
##    Trip_type
##  Min.   :1.000
##  1st Qu.:1.000
##  Median :1.000
##  Mean   :1.023
##  3rd Qu.:1.000
##  Max.   :2.000
```

Save the image

```
save.image("Taxi5000_raw.RData")
```

2.2 Some useful functions

```
calcQ <- function(x) { # Function to calculate the different quartiles
  s.x <- summary(x)
  iqr<-s.x[5]-s.x[2]
  list(souti=s.x[2]-3*iqr, mouti=s.x[2]-1.5*iqr, min=s.x[1], q1=s.x[2], q2=s.x[3],
       q3=s.x[5], max=s.x[6], mouts=s.x[5]+1.5*iqr, souts=s.x[5]+3*iqr )
}

countNA <- function(x) { # Function to count the NA values
  mis_x <- NULL
  for (j in 1:ncol(x)) {mis_x[j] <- sum(is.na(x[,j])) }
  mis_x <- as.data.frame(mis_x)
  rownames(mis_x) <- names(x)
  mis_i <- rep(0,nrow(x))
  for (j in 1:ncol(x)) {mis_i <- mis_i + as.numeric(is.na(x[,j])) }
  list(mis_col=mis_x,mis_ind=mis_i)
}

countX <- function(x,X) { # Function to count a specific number of appearences
  n_x <- NULL
  for (j in 1:ncol(x)) {n_x[j] <- sum(x[,j]==X) }
  n_x <- as.data.frame(n_x)
  rownames(n_x) <- names(x)
  nx_i <- rep(0,nrow(x))
  for (j in 1:ncol(x)) {nx_i <- nx_i + as.numeric(x[,j]==X) }
  list(nx_col=n_x,nx_ind=nx_i)
}
```

---

3 Initiating missings, outliers and errors

Initialization of counts for missings, outliers and errors. All numerical variables have to be checked before

```
imis<-rep(0,nrow(df))  # rows - trips
jmis<-rep(0,2*ncol(df))  # columns - variables

mis1<-countNA(df)
imis<-mis1$mis_ind
# mis1$mis_col # Number of missings for the current set of variables

iouts<-rep(0,nrow(df))  # rows - trips
jouts<-rep(0,2*ncol(df))  # columns - variables

ierrs<-rep(0,nrow(df))  # rows - trips
jerrs<-rep(0,2*ncol(df))  # columns - variables
```

4 Univariate Descriptive Analysis

```r
summary(df)
```

```
##     VendorID     lpep_pickup_datetime Lpep_dropoff_datetime Store_and_fwd_flag
##  Min.   :1.000   Length:5000          Length:5000           Length:5000       
##  1st Qu.:2.000   Class :character     Class :character      Class :character  
##  Median :2.000   Mode  :character     Mode  :character      Mode  :character  
##  Mean   :1.788                                                                
##  3rd Qu.:2.000                                                                
##  Max.   :2.000                                                                
##    RateCodeID  Pickup_longitude Pickup_latitude Dropoff_longitude
##  Min.   :1.0   Min.   :-75.39   Min.   : 0.00   Min.   :-75.31   
##  1st Qu.:1.0   1st Qu.:-73.96   1st Qu.:40.70   1st Qu.:-73.97   
##  Median :1.0   Median :-73.95   Median :40.75   Median :-73.94   
##  Mean   :1.1   Mean   :-73.89   Mean   :40.72   Mean   :-73.80   
##  3rd Qu.:1.0   3rd Qu.:-73.92   3rd Qu.:40.80   3rd Qu.:-73.91   
##  Max.   :5.0   Max.   :  0.00   Max.   :41.04   Max.   :  0.00   
##  Dropoff_latitude Passenger_count Trip_distance     Fare_amount   
##  Min.   : 0.00    Min.   :0.000   Min.   : 0.000   Min.   :-52.0  
##  1st Qu.:40.70    1st Qu.:1.000   1st Qu.: 1.020   1st Qu.:  6.0  
##  Median :40.75    Median :1.000   Median : 1.800   Median :  9.0  
##  Mean   :40.67    Mean   :1.375   Mean   : 2.765   Mean   : 11.9  
##  3rd Qu.:40.79    3rd Qu.:1.000   3rd Qu.: 3.420   3rd Qu.: 14.5  
##  Max.   :41.18    Max.   :6.000   Max.   :52.790   Max.   :200.0  
##      Extra             MTA_tax          Tip_amount      Tolls_amount    
##  Min.   :-1.0000   Min.   :-0.5000   Min.   : 0.000   Min.   : 0.00000  
##  1st Qu.: 0.0000   1st Qu.: 0.5000   1st Qu.: 0.000   1st Qu.: 0.00000  
##  Median : 0.5000   Median : 0.5000   Median : 0.000   Median : 0.00000  
##  Mean   : 0.3517   Mean   : 0.4857   Mean   : 1.217   Mean   : 0.08369  
##  3rd Qu.: 0.5000   3rd Qu.: 0.5000   3rd Qu.: 2.000   3rd Qu.: 0.00000  
##  Max.   : 1.0000   Max.   : 0.5000   Max.   :96.000   Max.   :18.04000  
##  Ehail_fee      improvement_surcharge Total_amount     Payment_type 
##  Mode:logical   Min.   :-0.3000       Min.   :-52.80   Min.   :1.00  
##  NA's:5000      1st Qu.: 0.3000       1st Qu.:  7.80   1st Qu.:1.00  
##                 Median : 0.3000       Median : 11.16   Median :2.00  
##                 Mean   : 0.2914       Mean   : 14.33   Mean   :1.52  
##                 3rd Qu.: 0.3000       3rd Qu.: 17.16   3rd Qu.:2.00  
##                 Max.   : 0.3000       Max.   :260.00   Max.   :4.00  
##    Trip_type    
##  Min.   :1.000  
##  1st Qu.:1.000  
##  Median :1.000  
##  Mean   :1.023  
##  3rd Qu.:1.000  
##  Max.   :2.000  
```

```r
names(df)
```

```
##  [1] "VendorID"              "lpep_pickup_datetime"  "Lpep_dropoff_datetime"
##  [4] "Store_and_fwd_flag"    "RateCodeID"            "Pickup_longitude"     
##  [7] "Pickup_latitude"       "Dropoff_longitude"     "Dropoff_latitude"     
## [10] "Passenger_count"       "Trip_distance"         "Fare_amount"          
## [13] "Extra"                 "MTA_tax"               "Tip_amount"           
## [16] "Tolls_amount"          "Ehail_fee"             "improvement_surcharge"
## [19] "Total_amount"          "Payment_type"          "Trip_type"            
```

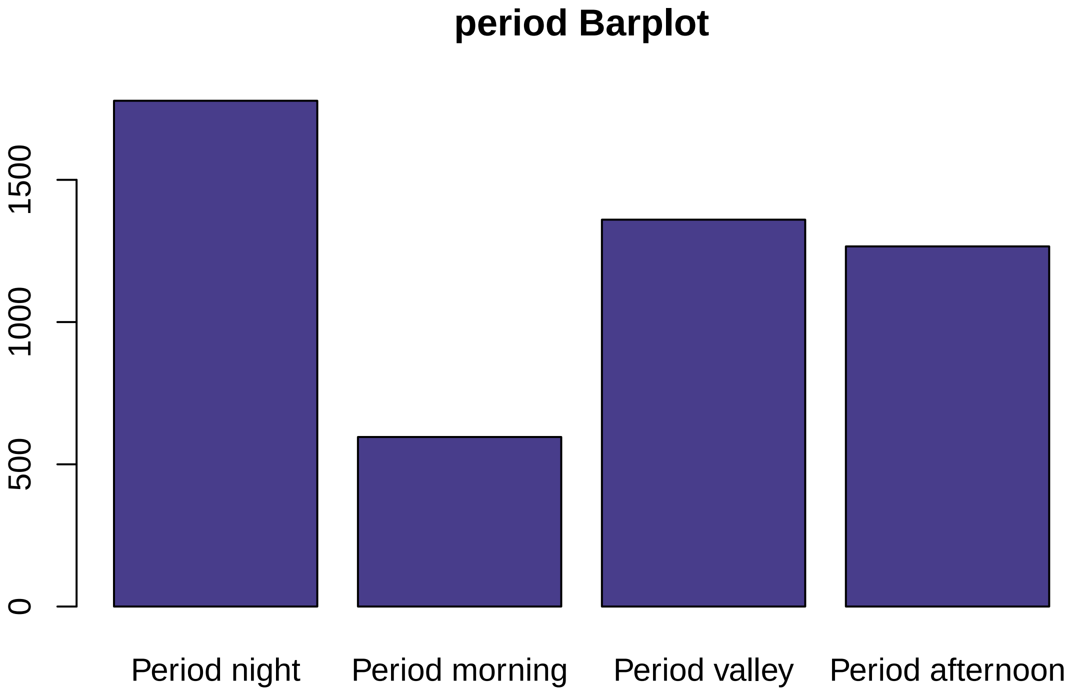
4.1 Qualitative Variables (Factors) / Categorical

Description: Original numeric variables corresponding to qualitative concepts have to be converted to factors. New factors grouping original levels will be considered very positively.

We need to do an analysis of all the variables to be able to identify missings, errors and outliers. We will also try to factorize each variable to make it easier to understand the sample.

4.1.1 New variable: Period

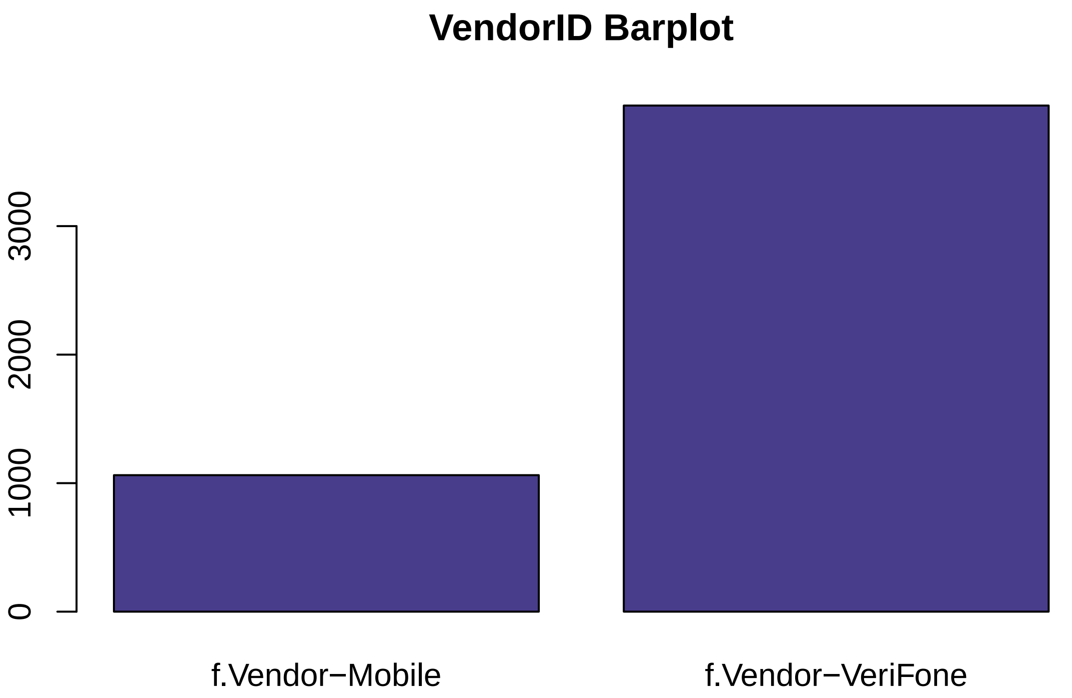
```
df$hour<-as.numeric(substr(strptime(df$lpep_pickup_datetime, "%Y-%m-%d %H:%M:%S"),12,13))
df$period<-1
df$period[df$hour>7]<-2
df$period[df$hour>10]<-3
df$period[df$hour>16]<-4
df$period[df$hour>20]<-1
df$period<-factor(df$period,labels=paste("Period",c("night","morning","valley","afternoon")))
barplot(summary(df$period),main="period Barplot",col = "DarkSlateBlue")
```



4.1.2 1. VendorID

This variable expresses the Creative Mobile Technologies, LLC as 1 and Verifone Inc as 2, so we create a factor to make it more readable. With the initial summary we see that this variable does not have any missing value, so we proceed to factor it.

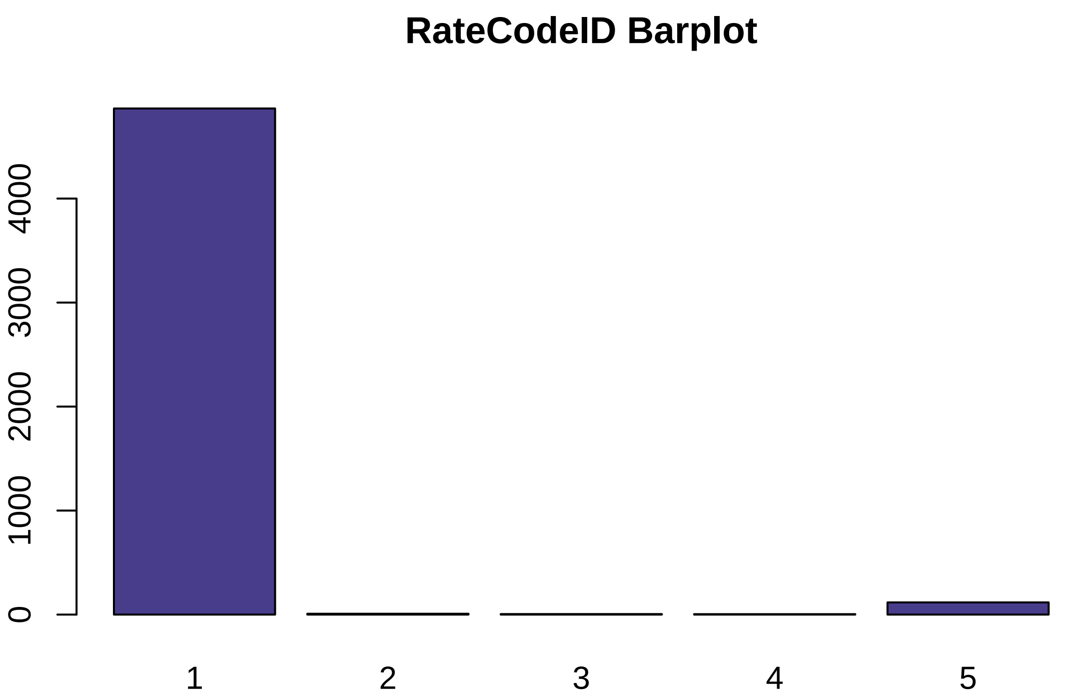
```
df$VendorID<-factor(df$VendorID,labels=c("Mobile","VeriFone"))
# nlevels(df$VendorID)
levels(df$VendorID)<-paste0("f.Vendor-",levels(df$VendorID))
# summary(df$VendorID)
barplot(summary(df$VendorID),main="VendorID Barplot",col = "DarkSlateBlue")
```



4.1.3 8. RateCodeID

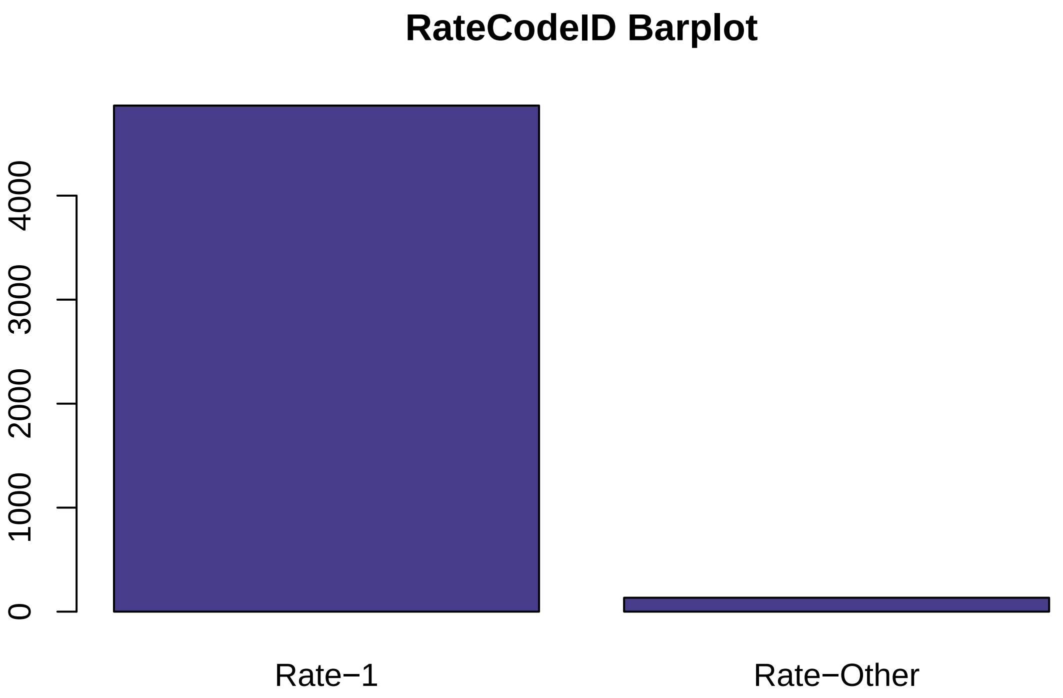
This variable expresses the different RateCodeIDs that we can have as numerical values, so we need to categorize them in order to be able to work with them.

```
# summary(df$RateCodeID)
df$RateCodeID<-factor(df$RateCodeID)
barplot(summary(df$RateCodeID),main="RateCodeID Barplot",col = "DarkSlateBlue")
```



We see that most samples are in RateCodeID = 1, which is what we are interested in. Therefore, we factorize and create only two groups, the one with RateCodeID = 1 and the rest.

```
df$RateCodeID[df$RateCodeID != 1] = 2
df$RateCodeID <- factor(df$RateCodeID, labels =c("Rate-1","Rate-Other"))
barplot(summary(df$RateCodeID),main="RateCodeID Barplot",col = "DarkSlateBlue")
```



Now is more balanced.

4.1.4 9. Store_and_fwd_flag

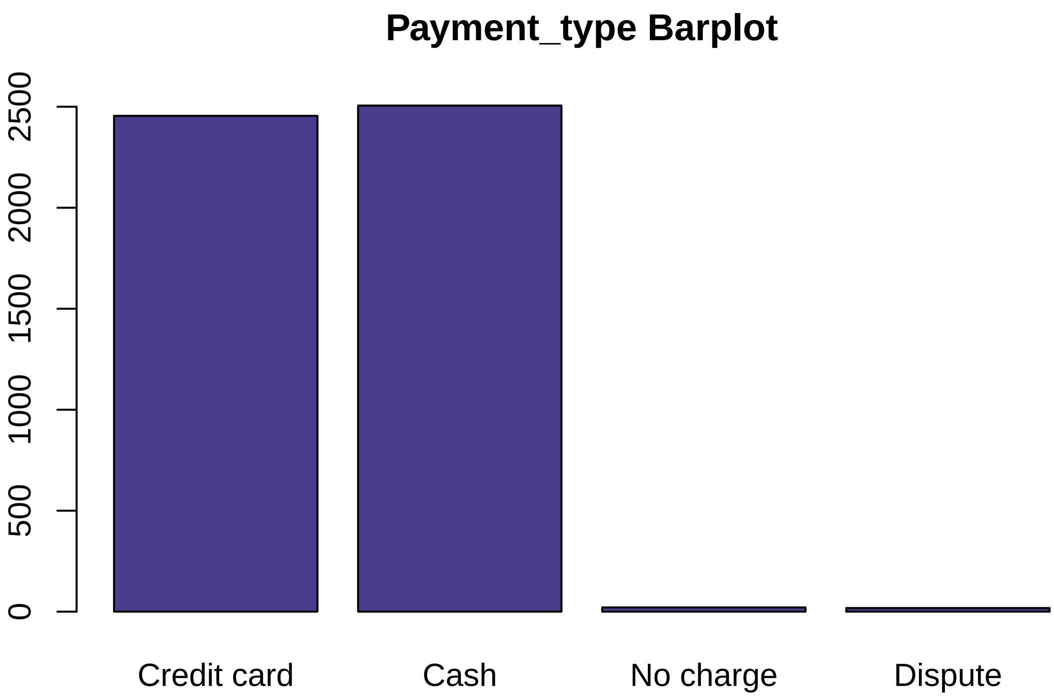
This is a categorical variable with the values Y and N, so we need to factor it.

```
# summary(df$Store_and_fwd_flag)
df$Store_and_fwd_flag<-factor(df$Store_and_fwd_flag)
barplot(summary(df$Store_and_fwd_flag),main="Store_and_fwd_flag Barplot",col = "DarkSlateBlue")
```

4.1.5 12. Payment_type

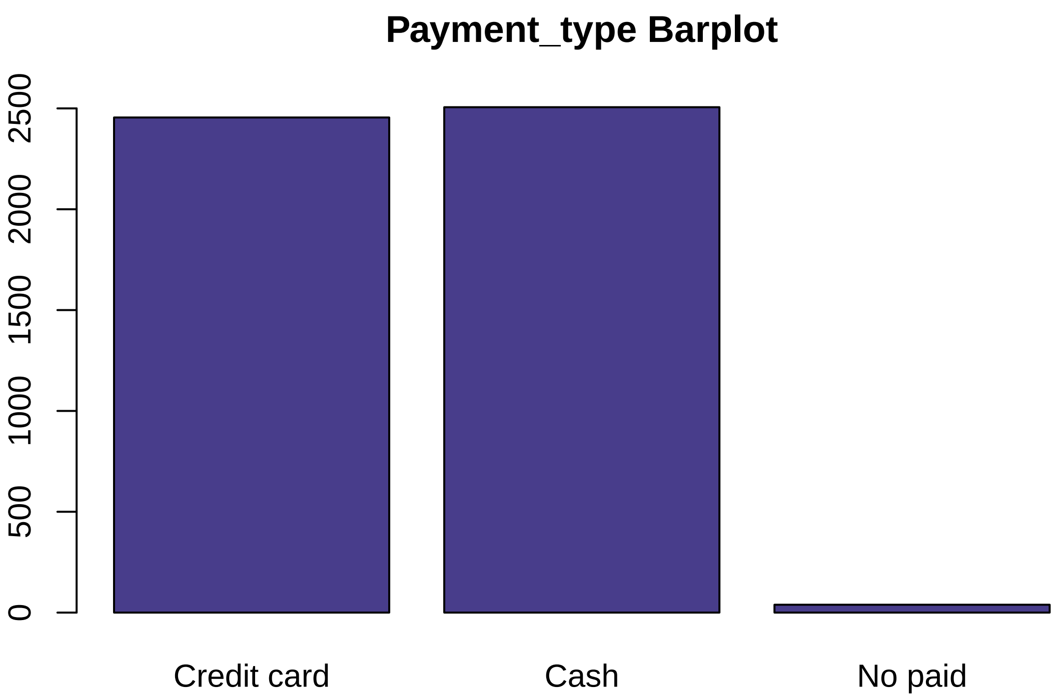
This variable is categorical but it is expressed as numerical, so we need to factor it in order to be able to work with it.

```
df$Payment_type<-factor(df$Payment_type,labels=c("Credit card","Cash","No charge","Dispute"))
# summary(df$Payment_type)
barplot(summary(df$Payment_type),main="Payment_type Barplot",col = "DarkSlateBlue")
```



As we can see, there are few values with "No charge" or "Dispute" category, so we decided to categorize it into a new category ("No paid").

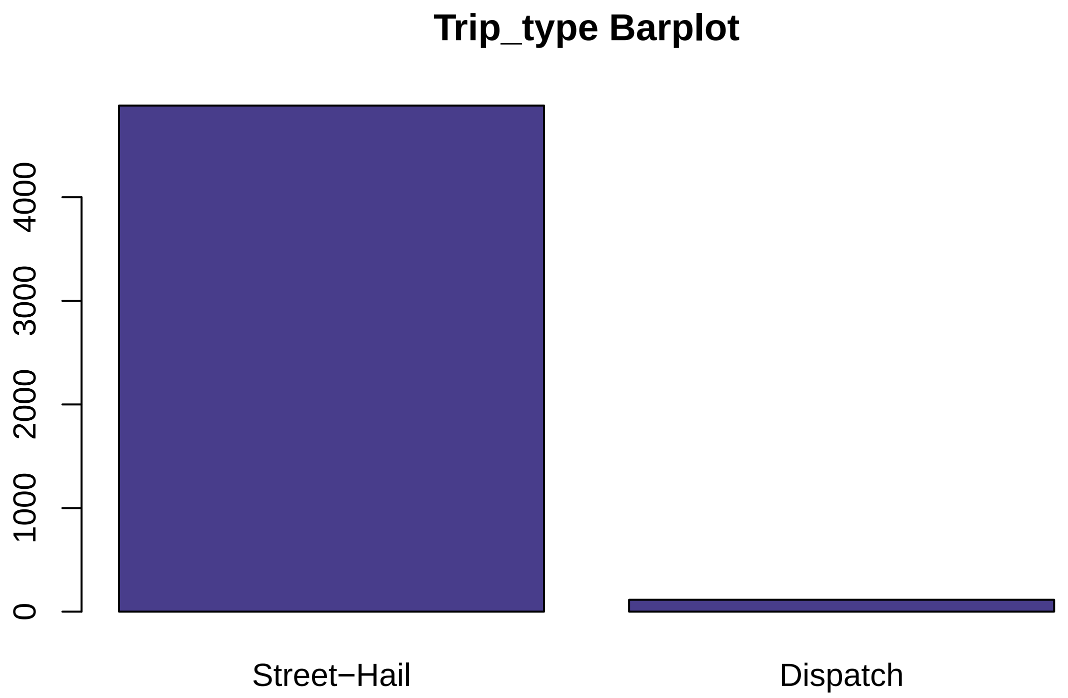
```
levels(df$Payment_type) <- c("Credit card","Cash","No paid","No paid")
# summary(df$Payment_type)
barplot(summary(df$Payment_type),main="Payment_type Barplot",col = "DarkSlateBlue")
```



4.1.6 21. Trip_type

This variable is categorical but it is expressed as numerical, so we need to factor it in order to be able to work with it.

```
df$Trip_type<-factor(df$Trip_type,labels=c("Street-Hail","Dispatch"))
barplot(summary(df$Trip_type),main="Trip_type Barplot",col = "DarkSlateBlue")
```




```
# summary(df$Trip_type)
```

4.2 Quantitative Variables

Description: Original numeric variables corresponding to real quantitative concepts are kept as numeric but additional factors should also be created as a discretization of each numeric variable.

We only keep the hours (variables 2 and 3) to be able to work with time slots in the future.

Create new variables derived from the original ones, as effective speed, travel time, hour of request, period of request, effective trip distance (in km)

4.2.1 New variables: Trip Length in km, Travel time un min and Effective speed

```
df$tlenkm<-df$Trip_distance*1.609344 # Miles to km
```

4.2.1.1 Trip length in km

```
df$traveltime<-(as.numeric(as.POSIXct(df$Lpep_dropoff_datetime)) - as.numeric(as.POSIXct(df$lpep_pickup_
```

4.2.1.2 Travel time in min

```
df$espeed<-(df$tlenkm/(df$traveltime))*60
```

4.2.1.3 Effective speed in km/h

```
sel<-which(is.na(df$espeed<=0)) #;length(sel)
imis[sel]<-imis[sel]+1
jmis[26]<-length(sel)
```

4.2.1.4 Missing data

4.2.1.5 Error detection

We detect as error those speeds smaller than 0 and bigger than 200

```
summary(df$espeed)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00   14.60   18.58   23.07   23.70 3881.74       2
```

```r
sel<-which((df$espeed<=0)|(df$espeed > 200))
ierrs[sel]<-ierrs[sel]+1
jerrs[26]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with “0” as value for longitude

```r
df[sel,"espeed"]<-NA
```

```r
# summary(df$espeed)
calcQ(df$espeed)
```

4.2.1.6 Check outliers

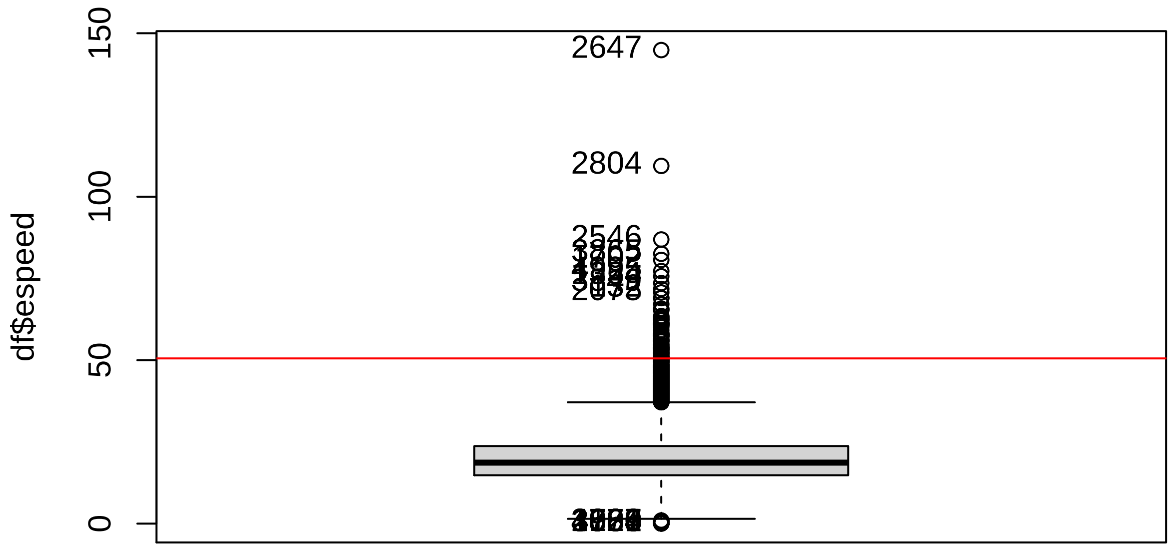
```
## $souti
##   1st Qu.
## -12.00637
##
## $mouti
##  1st Qu.
## 1.394097
##
## $min
##       Min.
## 0.03530885
##
## $q1
##  1st Qu.
## 14.79457
##
## $q2
##   Median
## 18.65269
##
## $q3
##  3rd Qu.
## 23.72821
##
## $max
##    Max.
## 144.841
##
## $mouts
##  3rd Qu.
## 37.12868
##
## $souts
##  3rd Qu.
## 50.52915
```

```r
Boxplot(df$espeed)
```

4.2.1.7 Outlier detection

```
##  [1] 4780 3001 3066 1936  120 3578 1767 4824 2685 3009 2647 2804 2546 3865 1702
## [16] 4995 1354 3849  132 2075
```

```r
var_out<-calcQ(df$espeed)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```




```
llout<-which((df$espeed<=3)|(df$espeed>80))
iouts[llout]<-iouts[llout]+1
jouts[26]<-length(llout)
df[llout,"espeed"]<-NA
```

4.2.2 2. lpep_pickup_datetime

We just keep the hours

```
df$pickup<-substr(strptime(df$lpep_pickup_datetime, "%Y-%m-%d %H:%M:%S"), 12, 13) # table(df$pickup)
```

4.2.3 3. lpep_dropoff_datetime

We just keep the hours

```
df$dropoff<-substr(strptime(df$Lpep_dropoff_datetime, "%Y-%m-%d %H:%M:%S"), 12, 13) # table(df$pickup)
```

4.2.4 4. Passenger_count

```
summary(df$Passenger_count)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   1.000   1.375   1.000   6.000
```

We set the 0 as an error because it is not possible to have a trip without passengers

```
sel<-which(df$Passenger_count == 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[10]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with "0" as value for passengers

```
df[sel,"Passenger_count"]<-NA
```

4.2.5 5. Trip_distance

```
summary(df$Trip_distance)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.020   1.800   2.765   3.420  52.790
```

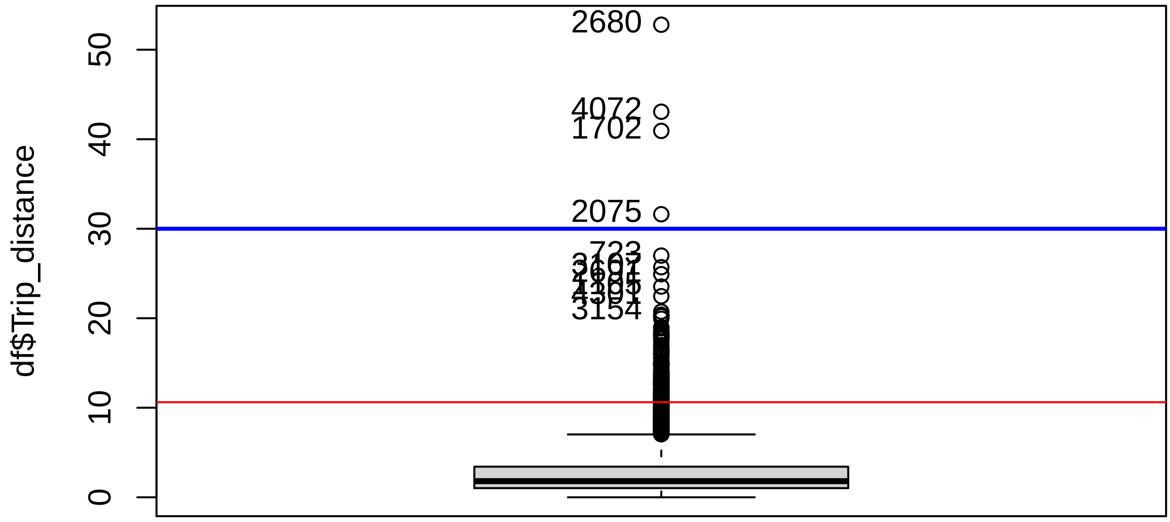
We see on the summary that there are not NA values, so we proceed to the outlier and error detection.

4.2.5.1 Outlier detection In order to evalute or data, we decide to set the maximum trip distance to 30, so we proceed to delete the outliers.

```r
Boxplot(df$Trip_distance)
```

```
##  [1] 2680 4072 1702 2075  723 3107 2691 1105 4301 3154
```

```r
var_out<-calcQ(df$Trip_distance)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
abline(h=30,col="blue",lwd=2)
```




```r
llout<-which(df$Trip_distance>30)
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[11]<-length(llout)
```

4.2.5.2 Error detection

We decide that an incorrect trip distance is the one with 0 miles or less. In order to be aware of this error we store it at ierrs, and jerrs. ierrs stores the number of errors in a row, and jerrs stores the total amount of errors in a variable.

```r
sel<-which(df$Trip_distance <= 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[11]<-length(sel)
# sel
```

4.2.5.3 Errors and outliers

Now, we set NA values in order to remove errors and outliersfrom the dataset

```r
setNA<-which((df$Trip_distance<=0) | (df$Trip_distance > 30))
df[setNA,"Trip_distance"]<-NA
```

4.2.5.4 Caterogial variable for Trip_distance

We are going to set a categorical variable for the Trip_distancerange. We decided to create 3 levels: "Short_dist", "Medium_dist" and"Long_dist". - Short_dist <= 2.5 - Medium_dist 2.5 < Trip_distance <= 5 - Long_dist > 5

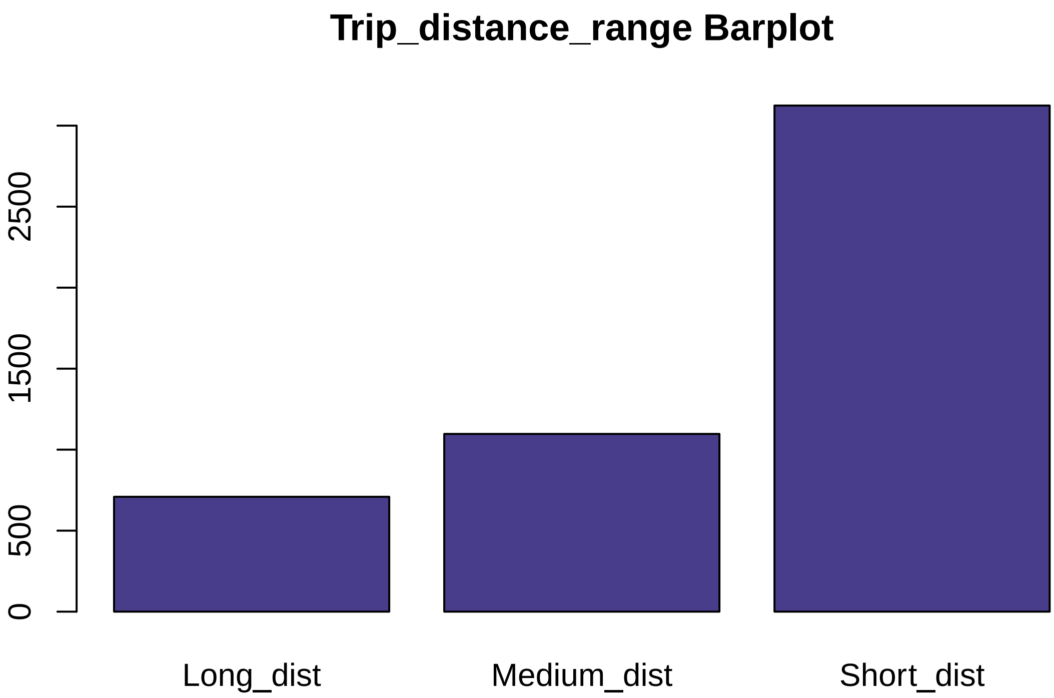
```r
df$Trip_distance_range[df$Trip_distance <= 2.5] = "Short_dist"
df$Trip_distance_range[(df$Trip_distance > 2.5) & (df$Trip_distance <= 5)] = "Medium_dist"
df$Trip_distance_range[df$Trip_distance > 5] = "Long_dist"
# summary(df$Trip_distance_range)
```

We see, though, that it is not a factor yet, so we factor it.

```r
df$Trip_distance_range <- factor(df$Trip_distance_range)
```

We see a barplot for the factor we created.

```r
barplot(table(df$Trip_distance_range),main="Trip_distance_range Barplot",col = "DarkSlateBlue")
```



4.2.6 6. Pickup_longitude

We know that New York's longitude is -73.9385, so values that differ a lot from this value is an error or an outlier.

```
summary(df$Pickup_longitude)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -75.39  -73.96  -73.95  -73.89  -73.92    0.00
```

0.00 looks to be an error Seeing the individuals with this "0" value: df[which(df[,"Pickup_longitude"]==0),] it is a quantitive variable. Non-possible values will be recoded as errors, so will be transformed to NA.

```
sel<-which(df$Pickup_longitude == 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[6]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with "0" as value for longitude.

```
df[sel,"Pickup_longitude"]<-NA
```

Non-possible values are replaced by NA, missing value symbol in R.

4.2.6.1 Which trips are not running in New-York? Consider if, at least, one of the pick-up and drop-off points belong to New-York area. if not, this trip is an "out-of-scope" individual and has to be eliminated of the basis. Nevertheless, you have to justify thiselimination and count how many individuals were in this situation. Look at that!! possibly, starting from the outliers. . . "0" is missing value, outliers can help to detect trips running outside of New York. . .

We are deleting trips from outside New York. This means we are not using longitudes bigger than -73.80 and smaller than -74.02.

```
llout <-which((df$Pickup_longitude < -74.02) | (df$Pickup_longitude > -73.80))
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[6]<-length(llout)
```

Now that we have the outliers, we are setting them as NA

```
df[llout,"Pickup_longitude"]<-NA
```

4.2.7 7. Pickup_latitude

We know that New York's latitude is 40.6643, so values that differ a lot from this value is an error or an outlier.

```r
summary(df$Pickup_latitude)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   40.70   40.75   40.72   40.80   41.04
```

0.00 looks to be an error. Seeing the individuals with this "0" value: df[which(df[,"Pickup_latitude"]==0),] it is a quantitive variable. non-possible values will be recoded as errors, so will be transformed to NA.

```r
sel<-which(df$Pickup_latitude == 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[7]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with "0" as value for longitude

```r
df[sel,"Pickup_longitude"]<-NA
```

Non-possible values are replaced by NA, missing value symbol in R. We are deleting trips from outside New York. This means we are not using latitudes bigger than 40.54 and smallerthan 40.86

```r
llout <-which((df$Pickup_latitude < 40.54) | (df$Pickup_latitude > 40.86))
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[7]<-length(llout)
```

Now that we have the outliers, we are setting them as NA

```r
df[llout,"Pickup_latitude"]<-NA
```

4.2.8 10. Dropoff_longitude

We know that New York's longitude is -73.9385, so values that differ a lot from this value is an error or an outlier.

```r
summary(df$Dropoff_longitude)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -75.31  -73.97  -73.94  -73.80  -73.91    0.00
```

0.00 looks to be an error Seeing the individuals with this "0" value: df[which(df[,"Dropoff_longitude"]==0),] it is a quantitive variable.
Non-possible values will be recoded as errors, so will be transformed to NA.

```r
sel<-which(df$Dropoff_longitude == 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[8]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with "0" as value for longitude

```r
df[sel,"Dropoff_longitude"]<-NA
```

Non-possible values are replaced by NA, missing value symbol in R. We are deleting trips from outside New York. This means we are not using longitudes bigger than -73.80 and smaller than -74.02.

```r
llout <-which((df$Dropoff_longitude < -74.02) | (df$Dropoff_longitude > -73.80))
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[8]<-length(llout)
# llout
```

Now that we have the outliers, we are setting them as NA

```r
df[llout,"Dropoff_longitude"]<-NA
```

4.2.9 11. Dropoff_latitude

We know that New York's latitude is 40.6643, so values that differ a lot from this value is an error or an outlier.

```r
summary(df$Dropoff_latitude)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   40.70   40.75   40.67   40.79   41.18
```

0.00 looks to be an error Seeing the individuals with this "0" value: df[which(df[,"Dropoff_latitude"]==0),] it is a quantitive variable. Non-possible values will be recoded as errors, so will be transformed to NA.

```
sel<-which(df$Dropoff_latitude == 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[8]<-length(sel)
# sel
```

Sel contains the rownames of the individuals with "0" as value for longitude

```
df[sel,"Dropoff_latitude"]<-NA
```

Non-possible values are replaced by NA, missing value symbol in R. We are deleting trips from outside New York. This means we are not using latitude bigger than 40.54 and smaller than 40.86

```
llout <-which((df$Dropoff_latitude < 40.54) | (df$Dropoff_latitude > 40.86))
iouts[llout]<-iouts[llout]+1
#names(df)
jouts[9]<-length(llout)
# llout
```

Now that we have the outliers, we are setting them as NA

```
df[llout,"Dropoff_latitude"]<-NA
```

4.2.10 13. Fare_amount

We know that the fare should be positive, as it is the price of the trip, so we'll treat as error those values. The next we'll do is decide the outliers.

```
summary(df$Fare_amount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   -52.0     6.0     9.0    11.9    14.5   200.0
```

```
sel<-which(df$Fare_amount <= 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[12]<-length(sel)
# sel
```

```
df[sel,"Fare_amount"]<-NA
```

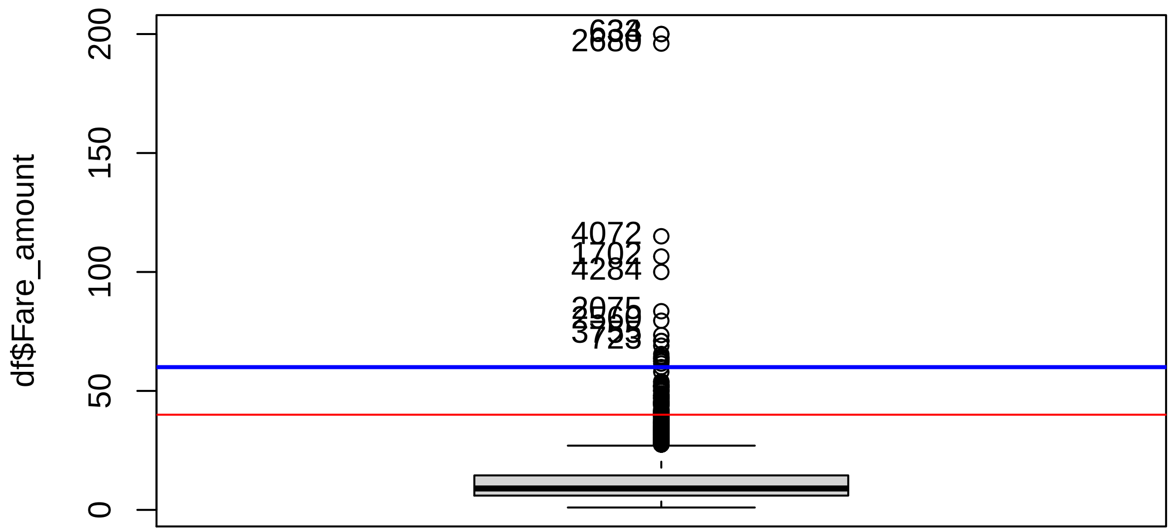
Non-possible values are replaced by NA, missing value symbol in R

```

Boxplot(df$Fare_amount)
```

4.2.10.1 Outlier detection

```
##  [1]  633  634 2680 4072 1702 4284 2075 2560 3755  723
```

```
var_out<-calcQ(df$Fare_amount)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
abline(h=60,col="blue",lwd=2)
```



We decide to set outliers for fare amounts bigger than 60, because the majority of the values are concentrated between 0 and 60.

```
llout<-which(df$Fare_amount>60)
iouts[llout]<-iouts[llout]+1
jouts[12]<-length(llout)
df[llout,"Fare_amount"]<-NA
# llout
```

4.2.11 14. Extra

As this variable is price related, it cannot have negative values, so this individuals will be treated as errors.

```
summary(df$Extra)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.0000  0.0000  0.5000  0.3517  0.5000  1.0000
```

We execute table in order to see every different value in the sample

```
table(df$Extra)
```

```
##
##   -1 -0.5    0  0.5    1
##    2    5 2296 1868  829
```

As it is a price related variable, negative values should be treated as errors, and the other values are the ones defined for this variable, so there are not outliers.

```
# df[which(df[, "Extra"] < 0),]
sel<-which(df$Extra < 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[13]<-length(sel)
df[sel,"Extra"]<-NA
# sel
```

4.2.12 15. MTA_tax

This variable corresponds to a tax that must be charged in every trip and its cost is $0.50, so values different from this are errors, and we don't have to take into account outliers because after the errors detection all values should be the MTA_tax.

```
summary(df$MTA_tax)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.5000  0.5000  0.5000  0.4857  0.5000  0.5000
```

```
# df[which(df[, "MTA_tax"] != 0.50),]
```

Important note: We assume that when this tax is smaller than 0, it is an error. If tax is 0, we say that payment in these cases is equivalent to "no paid".

```
sel<-which(df$MTA_tax < 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[14]<-length(sel)
df[sel,"MTA_tax"]<-NA
# sel
```

4.2.13 16. Improvement_surcharge

This variable corresponds to a charge that must be charged in every trip and its cost is $0.30, so values smaller than 0 are errors, and we don't have to take into account outliers because after the errors detection all values should be the Improvement surcharge.

```
summary(df$improvement_surcharge)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.3000  0.3000  0.3000  0.2914  0.3000  0.3000
```

```
table(df$improvement_surcharge)
```

```
##
## -0.3    0  0.3
##   11  121 4868
```

We know that this surcharge was leived in 2015, so we need to check if the 0 values correspond to trips before this year. That is what we are going to do.

```
df$yearGt2015[(df$lpep_pickup_datetime >= "2015-01-01 00:00:00") & (df$improvement_surcharge == 0.3)] =
df$yearGt2015[(df$lpep_pickup_datetime < "2015-01-01 00:00:00") | (df$improvement_surcharge != 0.3)] = (

table(df$yearGt2015)
```

```
##
##    0    1
##  132 4868
```

We see that the 0 individuals are errors.

```
sel<-which(df$improvement_surcharge < 0)
ierrs[sel]<-ierrs[sel]+1
# names(df)
jerrs[18]<-length(sel)
df[sel,"improvement_surcharge"]<-NA
# sel
```

4.2.14 17. Ehail_fee

We don't take this into account because every value of our sample is NA.

```
summary(df$Ehail_fee)
```

```
##    Mode    NA's
## logical    5000
```

4.2.15 18. Tip_amount

As this is a price related variable, negative values should be considered as errors, and big tips should be considered as outliers. Also tip amounts bigger than 0 for individuals with payment_type = "Cash" should be considered as errors as well.

```
summary(df$Tip_amount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   0.000   1.217   2.000  96.000
```

We proceed to check if the 0 values are related with payment_type = "Credit card" and the passenger did not tip.

```
df$CashTips[(df$Tip_amount > 0) & (df$Payment_type == "Cash")] = 1
df$CashTips[(df$Payment_type == "Credit card")] = 0
table(df$CashTips)
```

```
##
##    0
## 2455
```

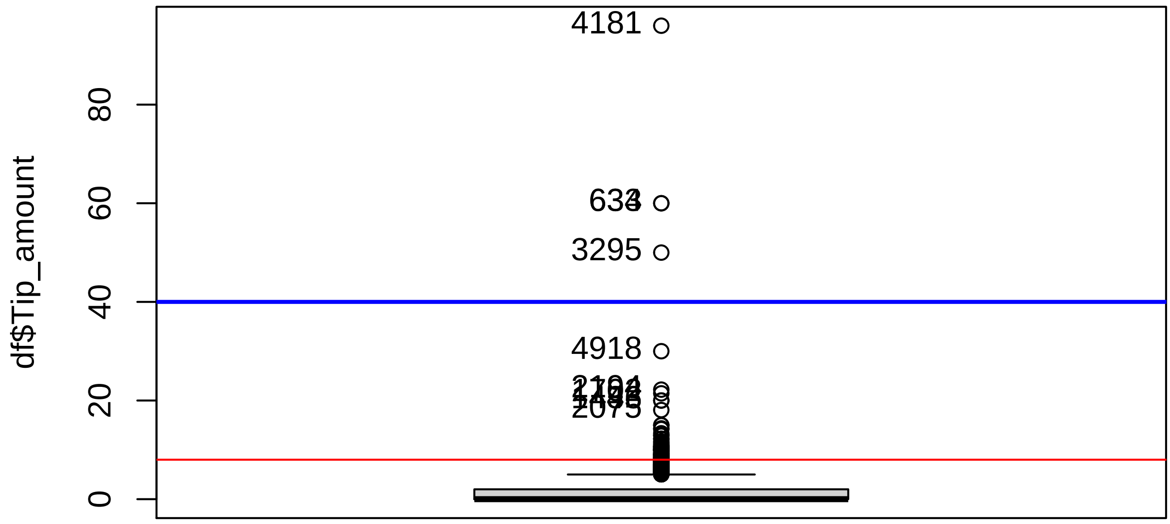
Now, we proceed to the outlier detection.

```r
Boxplot(df$Tip_amount)
```

4.2.15.1 Outlier detection

```
##  [1] 4181  633  634 3295 4918 2194 1702   46 1433 2075
```

```r
var_out<-calcQ(df$Tip_amount)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
abline(h=40,col="blue",lwd=2)
```




```r
llout<-which(df$Tip_amount>40)
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[15]<-length(llout)
df[llout,"Tip_amount"]<-NA
# llout
```

4.2.16 19. Tolls_amount

As this is a price related variable, negative values should be considered as errors.

```r
summary(df$Tolls_amount)
```

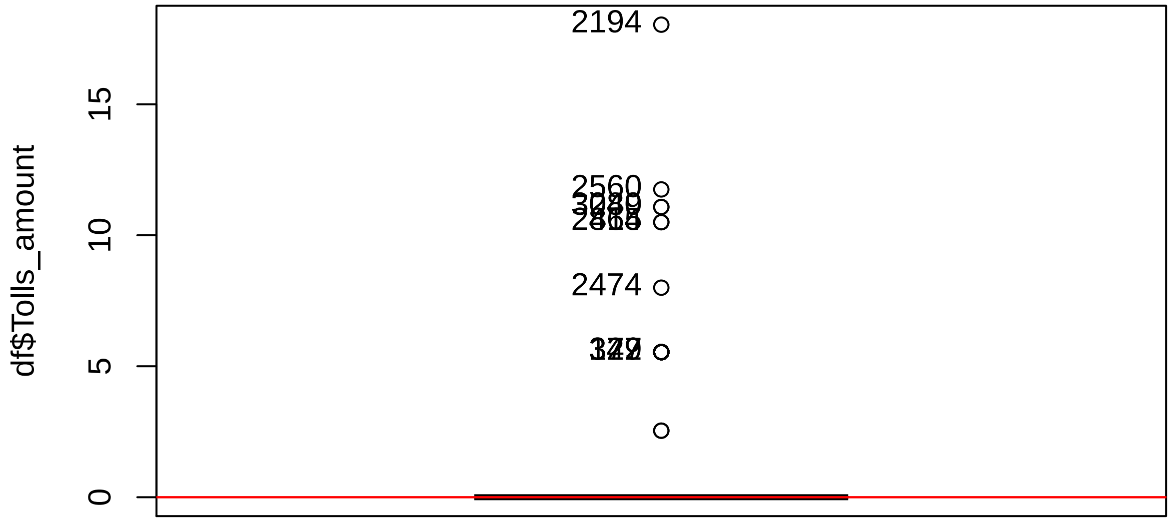
```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  0.00000  0.00000  0.00000  0.08369  0.00000 18.04000
```

We see that there are not negative values, so we do not have errors. We proceed now to the outlier detection.

```r
Boxplot(df$Tolls_amount)
```

```
##  [1] 2194 2560 3040 3289  415 2864 2474  122  347  379
```

```r
var_out<-calcQ(df$Tolls_amount)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```




```r
table(df$Tolls_amount)
```

```
##
##     0  2.54  5.54     8  10.5 11.08 11.75 18.04
##  4931     2    60     1     2     2     1     1
```

As we see in the boxplot and the table, the majority of the individuals are 0, so the values bigger than 5.54 will be outliers. After having the outliers, we proceed to categorize this variable to see if an individual has paid or not for a toll.

```r
llout<-which(df$Tolls_amount>5.54)
iouts[llout]<-iouts[llout]+1
# names(df)
jouts[16]<-length(llout)
df[llout,"Tolls_amount"]<-NA
# llout

df$paidTolls[df$Tolls_amount == 0] = "No"
df$paidTolls[df$Tolls_amount > 0] = "Yes"
df$paidTolls <- factor(df$paidTolls)
```

4.2.17 20. Total_amount

This is a price related variable, so negative values should be treated as errors. Also, we need to sum the "Fare_amount", "Extra","MTA_tax", "Improvement_surcharge", "Tip_amount" and the "Tolls_amount" in order to see if the Total_amount matches with this sum.

```r
summary(df$Total_amount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -52.80    7.80   11.16   14.33   17.16  260.00
```

Negative values seem to be errors - 0 Total_amount is possible when Payment_type =="No charge"

We proceed to check if total amount is correctsumming the other variables and checking negatives values:

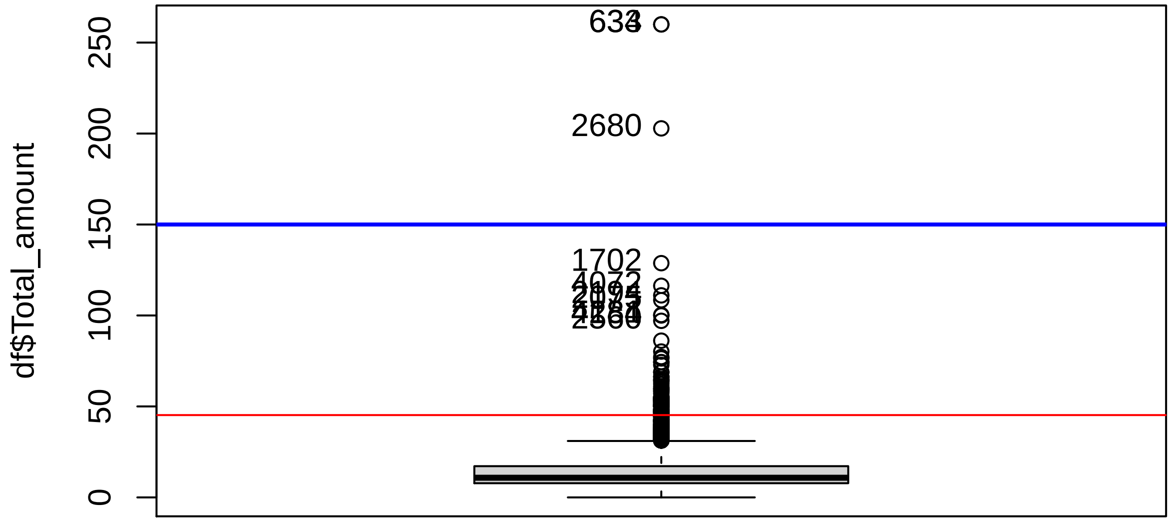
```r
df$Sum_total_amount = (df$Fare_amount + df$Extra + df$MTA_tax + df$improvement_surcharge + df$Tip_amount

sel<-which((df$Total_amount != df$Sum_total_amount) | (df$Total_amount<0))
# names(df)
if (length(sel)>0) {
  ierrs[sel]<-ierrs[sel]+1
  jerrs[19]<-length(sel)
}
# sel
df[sel,"Total_amount"]<-NA
```

```r
Boxplot(df$Total_amount)
```

4.2.17.1 Outlier detection

```
##  [1]  633  634 2680 1702 4072 2194 2075 4181 4284 2560
```

```r
var_out<-calcQ(df$Total_amount)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
abline(h=150,col="blue",lwd=2)
```




```r
llout<-which(df$Total_amount>150)
iouts[llout]<-iouts[llout]+1
jouts[19]<-length(llout)
df[llout,"Total_amount"]<-NA
```

---

5 Data Quality Report

5.1 Per variable

Per each variable, we have to count the following:

- number of missing values
- number of errors (including inconsistencies)
- number of outliers
- rank variables according the sum of missing values (and errors).

5.1.1 Number of missing values of each variable (with ranking)

```r
missings_ranking_sortlist <- sort.list(mis1$mis_col, decreasing = TRUE)
for (j in missings_ranking_sortlist) {
  print(paste(names(df)[j], " : ", mis1$mis_col$mis_x[j]))
}
```

```
## [1] "Ehail_fee  :  5000"
## [1] "VendorID  :  0"
## [1] "lpep_pickup_datetime  :  0"
## [1] "Lpep_dropoff_datetime  :  0"
## [1] "Store_and_fwd_flag  :  0"
## [1] "RateCodeID  :  0"
## [1] "Pickup_longitude  :  0"
## [1] "Pickup_latitude  :  0"
## [1] "Dropoff_longitude  :  0"
## [1] "Dropoff_latitude  :  0"
## [1] "Passenger_count  :  0"
## [1] "Trip_distance  :  0"
## [1] "Fare_amount  :  0"
## [1] "Extra  :  0"
## [1] "MTA_tax  :  0"
```

```
## [1] "Tip_amount  :  0"
## [1] "Tolls_amount  :  0"
## [1] "improvement_surcharge  :  0"
## [1] "Total_amount  :  0"
## [1] "Payment_type  :  0"
## [1] "Trip_type  :  0"
```

5.1.2 Number of errors per each variable (with ranking)

```
errors_ranking_sortlist <- sort.list(jerrs, decreasing = TRUE)
for (j in errors_ranking_sortlist) {
  if(!is.na(names(df)[j])) { print(paste(names(df)[j], " : ", jerrs[j])) }
}
```

```
## [1] "Total_amount  :  374"
## [1] "espeed  :  73"
## [1] "Trip_distance  :  66"
## [1] "Fare_amount  :  24"
## [1] "improvement_surcharge  :  11"
## [1] "MTA_tax  :  10"
## [1] "Dropoff_longitude  :  9"
## [1] "Extra  :  7"
## [1] "Pickup_longitude  :  3"
## [1] "Pickup_latitude  :  3"
## [1] "Passenger_count  :  2"
## [1] "VendorID  :  0"
## [1] "lpep_pickup_datetime  :  0"
## [1] "Lpep_dropoff_datetime  :  0"
## [1] "Store_and_fwd_flag  :  0"
## [1] "RateCodeID  :  0"
## [1] "Dropoff_latitude  :  0"
## [1] "Tip_amount  :  0"
## [1] "Tolls_amount  :  0"
## [1] "Ehail_fee  :  0"
## [1] "Payment_type  :  0"
## [1] "Trip_type  :  0"
## [1] "hour  :  0"
## [1] "period  :  0"
## [1] "tlenkm  :  0"
## [1] "traveltime  :  0"
## [1] "pickup  :  0"
## [1] "dropoff  :  0"
## [1] "Trip_distance_range  :  0"
## [1] "yearGt2015  :  0"
## [1] "CashTips  :  0"
## [1] "paidTolls  :  0"
## [1] "Sum_total_amount  :  0"
```

5.1.3 Number of outliers per each variable (with ranking)

```
errors_ranking_sortlist <- sort.list(jouts, decreasing = TRUE)
for (j in errors_ranking_sortlist) {
  if(!is.na(names(df)[j])) print(paste(names(df)[j], " : ", jouts[j]))
}
```

```
## [1] "Dropoff_latitude  :  116"
## [1] "Dropoff_longitude  :  113"
## [1] "Pickup_latitude  :  87"
## [1] "espeed  :  39"
## [1] "Fare_amount  :  20"
## [1] "Pickup_longitude  :  19"
## [1] "Tolls_amount  :  7"
## [1] "Trip_distance  :  4"
## [1] "Tip_amount  :  4"
```

```
## [1] "Total_amount  :  3"
## [1] "VendorID  :  0"
## [1] "lpep_pickup_datetime  :  0"
## [1] "Lpep_dropoff_datetime  :  0"
## [1] "Store_and_fwd_flag  :  0"
## [1] "RateCodeID  :  0"
## [1] "Passenger_count  :  0"
## [1] "Extra  :  0"
## [1] "MTA_tax  :  0"
## [1] "Ehail_fee  :  0"
## [1] "improvement_surcharge  :  0"
## [1] "Payment_type  :  0"
## [1] "Trip_type  :  0"
## [1] "hour  :  0"
## [1] "period  :  0"
## [1] "tlenkm  :  0"
## [1] "traveltime  :  0"
## [1] "pickup  :  0"
## [1] "dropoff  :  0"
## [1] "Trip_distance_range  :  0"
## [1] "yearGt2015  :  0"
## [1] "CashTips  :  0"
## [1] "paidTolls  :  0"
## [1] "Sum_total_amount  :  0"
```

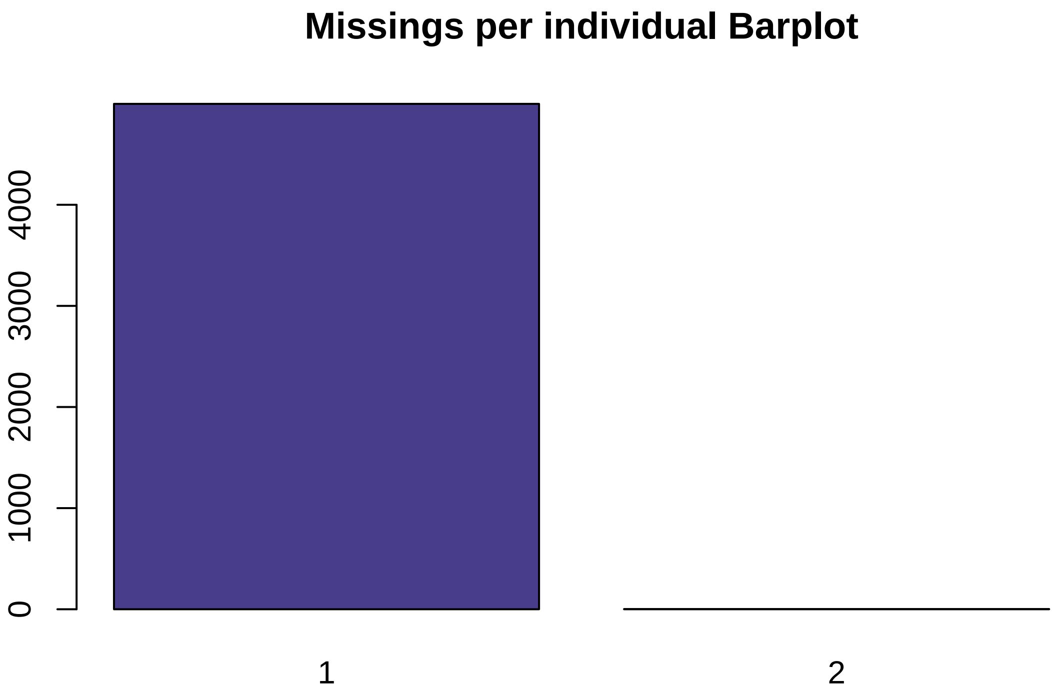
5.2 Per individual

Per each individuals, we have to count the following:

- number of missing values
- number of errors
- number of outliers

5.2.1 Number of missing values

```r
# table(imis)
barplot(table(imis),main="Missings per individual Barplot",col = "DarkSlateBlue")
```

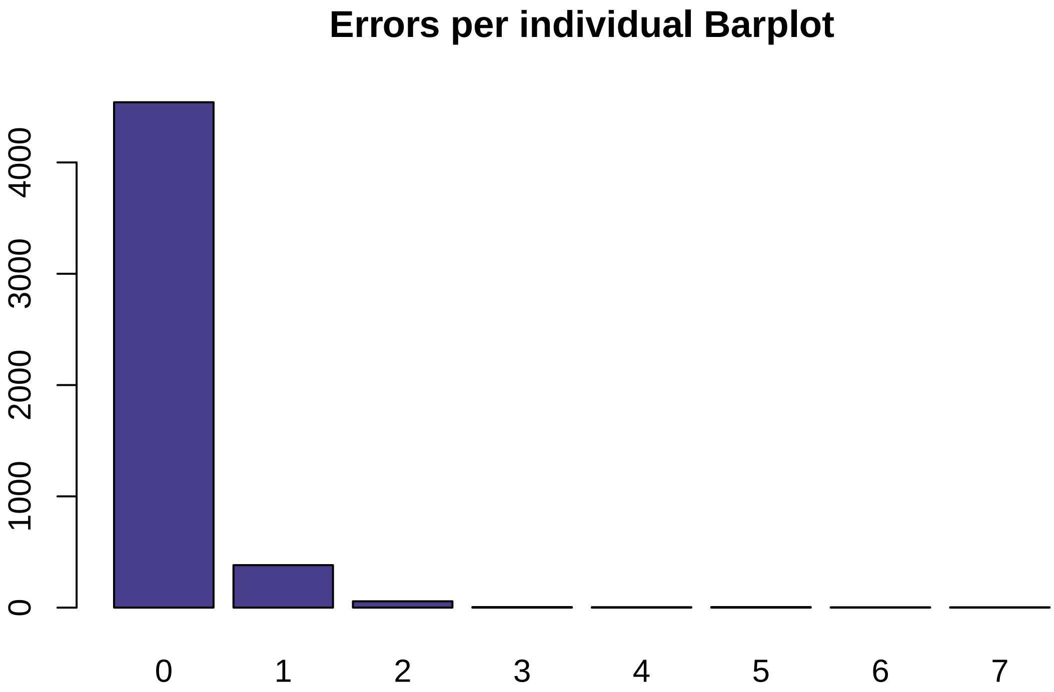


The one is from from the variable "Ehail_fee" and the observations that have two missing values are because of the "espeed" variable (maybe because the traveltime was 0 and nothing can be divided by 0).

5.2.2 Number of errors

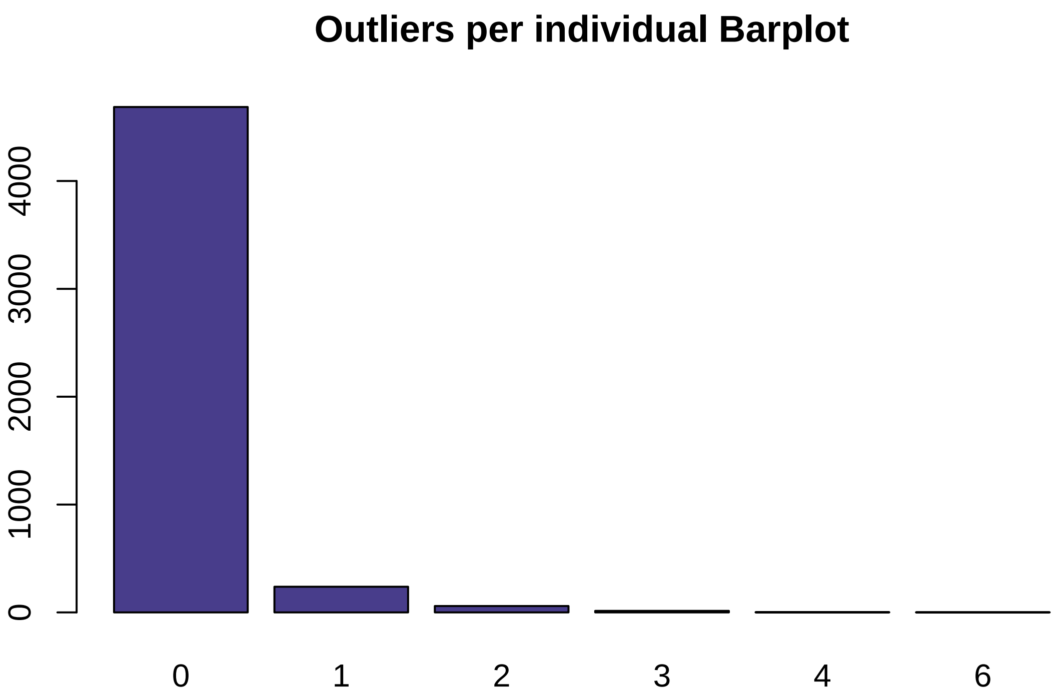
As we can see, most individuals have no mistakes. Those who do have errors, they tend to have more than one.

```
# table(ierrs)
barplot(table(ierrs),main="Errors per individual Barplot",col = "DarkSlateBlue")
```



5.2.3 Number of outliers

```
# table(iouts)
barplot(table(iouts),main="Outliers per individual Barplot",col = "DarkSlateBlue")
```



5.3 Create variable adding the total number missing values, outliers and errors

```
total_missings <- 0; total_outliers <- 0; total_errors <- 0;
for (m in imis) {total_missings <- total_missings + m}
for (o in iouts) {total_outliers <- total_outliers + o}
for (e in ierrs) {total_errors <- total_errors + e}
```

Now, let's print this variables:

```
total_missings
```

```
## [1] 5002
```

```
total_outliers
```

```
## [1] 412
```

```
total_errors
```

```
## [1] 591
```

---

6 Imputation

```
library(missMDA)
```

What we do with imputation is be able to eliminate all those values that may be missings, outliers or errors to turn them into values that can be realistic within our sample.

6.1 Numeric variables

We will now do the study by variables and try to impute the necessary observations.

Note: we do not include MTA_tax (14), Tolls_amount(16) nor improvement_surcharge(18). We proceed to delete NA values from Total_amount because it is our target variable, so we do not impute it, but we need to have this variable without NAs.

```
df <- df[!is.na(df$Total_amount),]

vars_quantitatives<-names(df)[c(10:13,15,24:26)]
```

```
summary(df[,vars_quantitatives])
```

```
##  Passenger_count Trip_distance     Fare_amount        Extra
##  Min.   :1.000   Min.   : 0.010   Min.   : 1.00   Min.   :0.0000
##  1st Qu.:1.000   1st Qu.: 1.020   1st Qu.: 6.00   1st Qu.:0.0000
##  Median :1.000   Median : 1.760   Median : 9.00   Median :0.5000
##  Mean   :1.371   Mean   : 2.719   Mean   :11.47   Mean   :0.3523
##  3rd Qu.:1.000   3rd Qu.: 3.420   3rd Qu.:14.50   3rd Qu.:0.5000
##  Max.   :6.000   Max.   :27.000   Max.   :60.00   Max.   :1.0000
##  NA's   :2       NA's   :62       NA's   :30
##    Tip_amount         tlenkm         traveltime           espeed
##  Min.   : 0.000   Min.   : 0.000   Min.   :    0.000   Min.   : 3.239
##  1st Qu.: 0.000   1st Qu.: 1.609   1st Qu.:    5.767   1st Qu.:14.826
##  Median : 0.000   Median : 2.800   Median :    9.550   Median :18.613
##  Mean   : 1.029   Mean   : 4.358   Mean   :   19.863   Mean   :20.490
##  3rd Qu.: 1.700   3rd Qu.: 5.472   3rd Qu.:   16.125   3rd Qu.:23.647
##  Max.   :30.000   Max.   :69.314   Max.   :1438.183   Max.   :75.657
##  NA's   :2                                            NA's   :105
```

```
res.imputation<-imputePCA(df[,vars_quantitatives],ncp=5)
summary(res.imputation$completeObs)
```

```
##  Passenger_count Trip_distance     Fare_amount         Extra
##  Min.   :1.000   Min.   :-0.670   Min.   :  1.00   Min.   :0.0000
##  1st Qu.:1.000   1st Qu.: 1.000   1st Qu.:  6.00   1st Qu.:0.0000
##  Median :1.000   Median : 1.760   Median :  9.00   Median :0.5000
##  Mean   :1.371   Mean   : 2.724   Mean   : 11.68   Mean   :0.3523
##  3rd Qu.:1.000   3rd Qu.: 3.400   3rd Qu.: 14.50   3rd Qu.:0.5000
##  Max.   :6.000   Max.   :40.469   Max.   :123.64   Max.   :1.0000
##    Tip_amount         tlenkm         traveltime           espeed
##  Min.   : 0.000   Min.   : 0.000   Min.   :    0.000   Min.   :-316.37
##  1st Qu.: 0.000   1st Qu.: 1.609   1st Qu.:    5.767   1st Qu.:  14.81
##  Median : 0.000   Median : 2.800   Median :    9.550   Median :  18.58
##  Mean   : 1.028   Mean   : 4.358   Mean   :   19.863   Mean   :  18.75
```

```
## 3rd Qu.: 1.700   3rd Qu.: 5.472   3rd Qu.:  16.125   3rd Qu.:  23.59
## Max.   :30.000   Max.   :69.314   Max.   :1438.183   Max.   : 100.59
```

We proceed now to fix all the numeric variables that have errors or outliers:

```
ll<-which(res.imputation$completeObs[,"Trip_distance"] < 0)
res.imputation$completeObs[ll,"Trip_distance"] <- 1
ll<-which(res.imputation$completeObs[,"Trip_distance"] > 30)
res.imputation$completeObs[ll,"Trip_distance"] <- 30
```

6.1.0.1 > Trip_distance

```
ll<-which(res.imputation$completeObs[,"Fare_amount"] > 60)
res.imputation$completeObs[ll,"Fare_amount"] <- 60
```

6.1.0.2 > Fare_amount

```
ll<-which(res.imputation$completeObs[,"Tip_amount"] > 17)
res.imputation$completeObs[ll,"Tip_amount"] <- 17
```

6.1.0.3 > Tip_amount We see that we have correct data, so we proceed to create the binary factor TipIsGiven.

```
df$TipIsGiven[(res.imputation$completeObs[,"Tip_amount"] > 0)] = "Yes"
df$TipIsGiven[(res.imputation$completeObs[,"Tip_amount"] == 0)] = "No"
df$TipIsGiven <- factor(df$TipIsGiven)
summary(df$TipIsGiven)
```

```
##   No  Yes
## 2882 1741
```

```
ll<-which(res.imputation$completeObs[,"tlenkm"] > 48.28)
res.imputation$completeObs[ll,"tlenkm"] <- 48.28
```

6.1.0.4 > tlenkm

```
ll<-which(res.imputation$completeObs[,"traveltime"] > 60)
res.imputation$completeObs[ll,"traveltime"] <- 60
```

6.1.0.5 > traveltime

```
ll<-which(res.imputation$completeObs[,"espeed"] < 3)
res.imputation$completeObs[ll,"espeed"] <- 3
ll<-which(res.imputation$completeObs[,"espeed"] > 55)
res.imputation$completeObs[ll,"espeed"] <- 55
```

6.1.0.6 > espeed

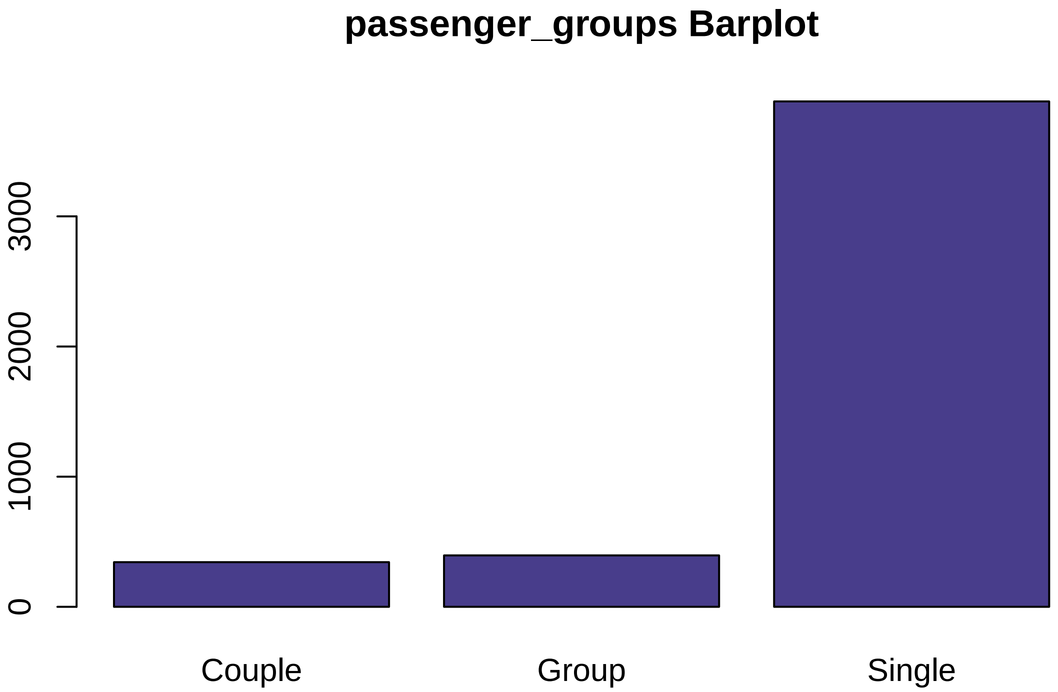
6.1.1 > Passenger_count

We decided to create categorical for this variable so we categorize it for single passengers, couple and groups (3 or more)

```
df$passenger_groups[df$Passenger_count == 1] = "Single"
df$passenger_groups[df$Passenger_count == 2] = "Couple"
df$passenger_groups[df$Passenger_count >= 3] = "Group"
df$passenger_groups <- factor(df$passenger_groups)
```

We see the barplot in order to see the distribution of passenger per trip

```r
barplot(table(df$passenger_groups),main="passenger_groups Barplot",col = "DarkSlateBlue")
```



6.1.2 > Extra

If we execute a table, we'll see that we have 0, 0'5 and 1 values, so we proceed to categorize this variable to see if has extra or not.

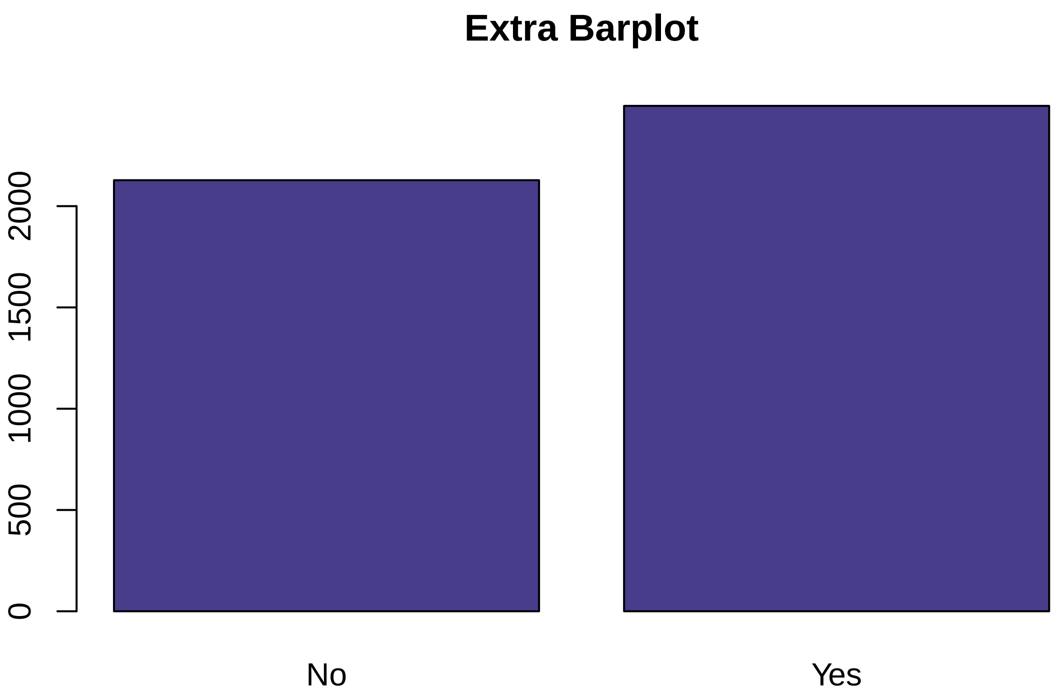
```r
table(df$Extra)
```

```
##
##    0  0.5    1
## 2128 1733  762
```

```r
df$Extra[df$Extra == 0] = 0
df$Extra[df$Extra > 0] = 1
df$Extra <- factor(df$Extra, labels =c("No","Yes"))
```

We see the barplot in order to see the distribution.

```r
barplot(table(df$Extra),main="Extra Barplot",col = "DarkSlateBlue")
```



6.1.3 > MTA_tax

If we execute a summary, we'll see that every value should be 0.5 or 0, so we proceed to categorize this variable in order to see if the tax has been paid or not.

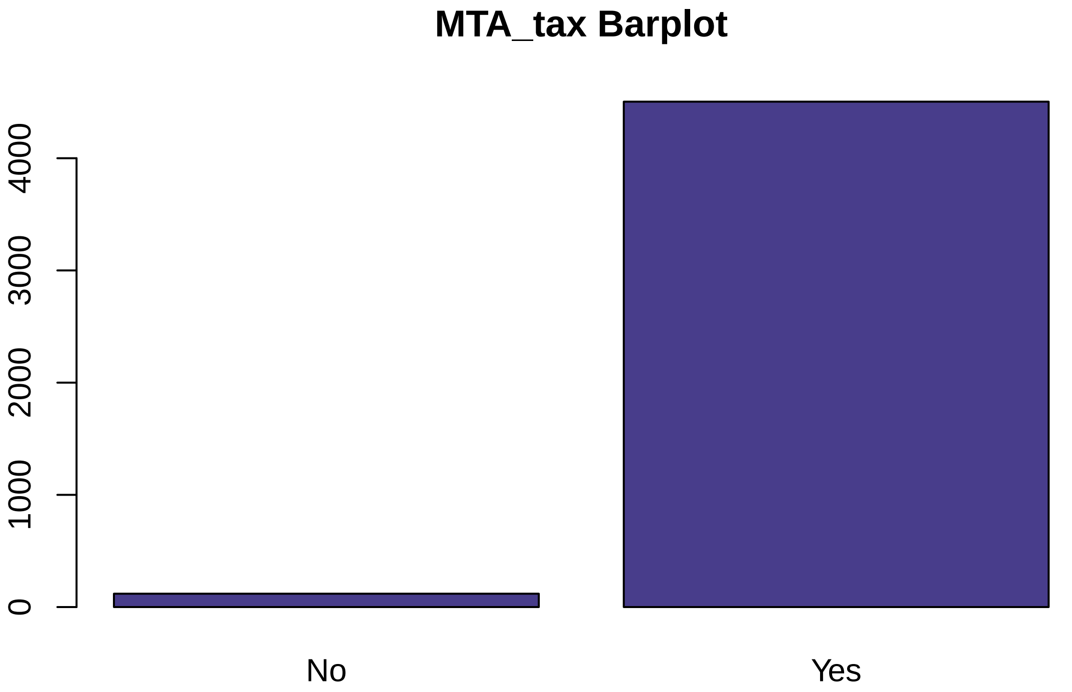
```
summary(df$MTA_tax)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.5000  0.5000  0.4871  0.5000  0.5000
```

```
df$MTA_tax <- factor(df$MTA_tax, labels =c("No","Yes"))
```

We see the barplot in order to see the distribution.

```
barplot(table(df$MTA_tax),main="MTA_tax Barplot",col = "DarkSlateBlue")
```



6.1.4 > Improvement_surcharge

If we execute a table, we'll see that every value should be 0.3 or 0, so we proceed to categorize this variable in order to see if the surcharge has been paid or not.

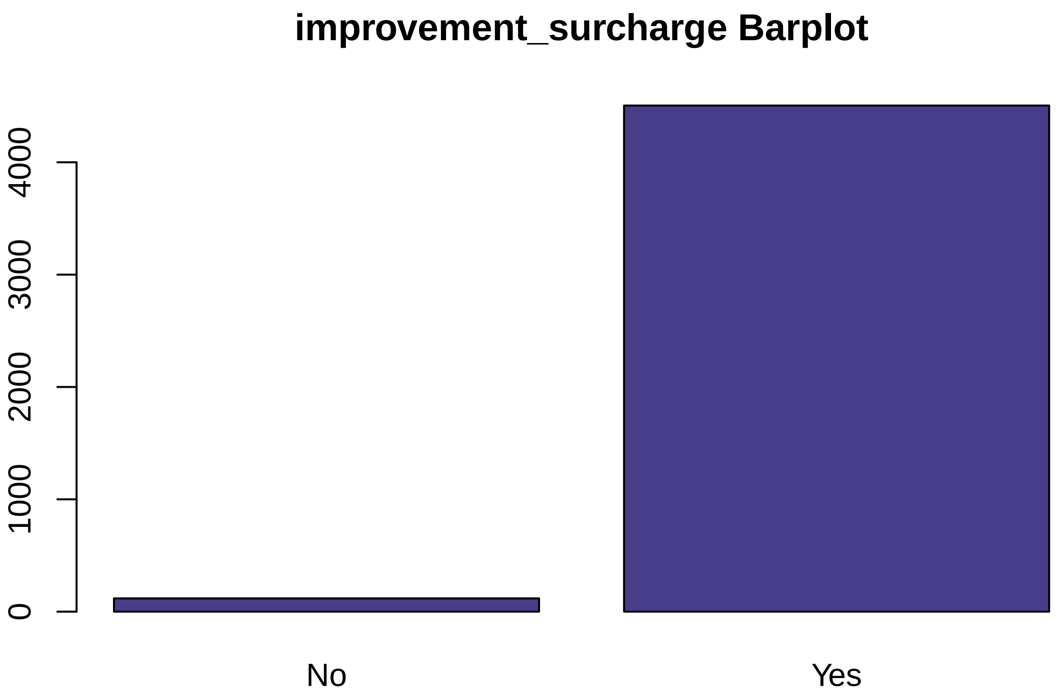
```
table(df$improvement_surcharge)
```

```
##
##    0  0.3
##  118 4505
```

```
df$improvement_surcharge <- factor(df$improvement_surcharge)
df$improvement_surcharge <- factor(df$improvement_surcharge, labels =c("No","Yes"))
```

We see the barplot in order to see the distribution.

```
barplot(table(df$improvement_surcharge),main="improvement_surcharge Barplot",col = "DarkSlateBlue")
```



We proceed to impute all NAs in our numerical variables that are stored in: `res.imputation$completeObs`

```
#summary(res.imputation$completeObs)
df[,vars_quantitatives] <- res.imputation$completeObs
```

6.2 Categorical variables / Factors

```
vars_categorical<-names(df)[c(1,4,5,20:21,23,29,35)]
summary(df[,vars_categorical])
```

```
##                VendorID    Store_and_fwd_flag      RateCodeID
##  f.Vendor-Mobile  : 973    N:4605               Rate-1     :4496
##  f.Vendor-VeriFone:3650    Y:  18               Rate-Other: 127
##
##
##       Payment_type         Trip_type                  period
##  Credit card:2096   Street-Hail:4511   Period night     :1642
##  Cash       :2497   Dispatch   : 112   Period morning   : 542
##  No paid    :  30                      Period valley    :1260
##                                        Period afternoon:1179
##   Trip_distance_range passenger_groups
##  Long_dist  : 645     Couple: 343
##  Medium_dist: 986     Group : 395
##  Short_dist :2930     Single:3883
##  NA's       :  62     NA's  :   2
```

```
#nb <- estim_ncpMCA(df[, vars_categorical],ncp.max=25)
res.input<-imputeMCA(df[,vars_categorical],ncp=10)
summary(res.input$completeObs)
```

```
##                VendorID    Store_and_fwd_flag      RateCodeID
##  f.Vendor-Mobile  : 973    N:4605               Rate-1     :4496
##  f.Vendor-VeriFone:3650    Y:  18               Rate-Other: 127
##
##
##       Payment_type         Trip_type                  period
##  Credit card:2096   Street-Hail:4511   Period night     :1642
##  Cash       :2497   Dispatch   : 112   Period morning   : 542
##  No paid    :  30                      Period valley    :1260
##                                        Period afternoon:1179
##   Trip_distance_range passenger_groups
##  Long_dist  : 665     Couple: 343
##  Medium_dist: 986     Group : 395
```

```
##   Short_dist :2972     Single:3885
##
```

We proceed to impute all NAs in our numerical variables that are stored in: `res.input$completeObs`

```r
# summary(res.input$completeObs)
df[,"VendorID"] <- res.input$completeObs[,"VendorID"]
df[,"Store_and_fwd_flag"] <- res.input$completeObs[,"Store_and_fwd_flag"]
df[,"RateCodeID"] <- res.input$completeObs[,"RateCodeID"]
df[,"Payment_type"] <- res.input$completeObs[,"Payment_type"]
df[,"Trip_type"] <- res.input$completeObs[,"Trip_type"]
df[,"period"] <- res.input$completeObs[,"period"]
df[,"Trip_distance_range"] <- res.input$completeObs[,"Trip_distance_range"]
df[,"passenger_groups"] <- res.input$completeObs[,"passenger_groups"]
```

6.3 Describe these variables, to which other variables exist higher associations

6.3.1 Compute the correlation with all other variables.

```r
library(mvoutlier)
library(FactoMineR)
res <- cor(df[,vars_quantitatives])
round(res, 2)
```

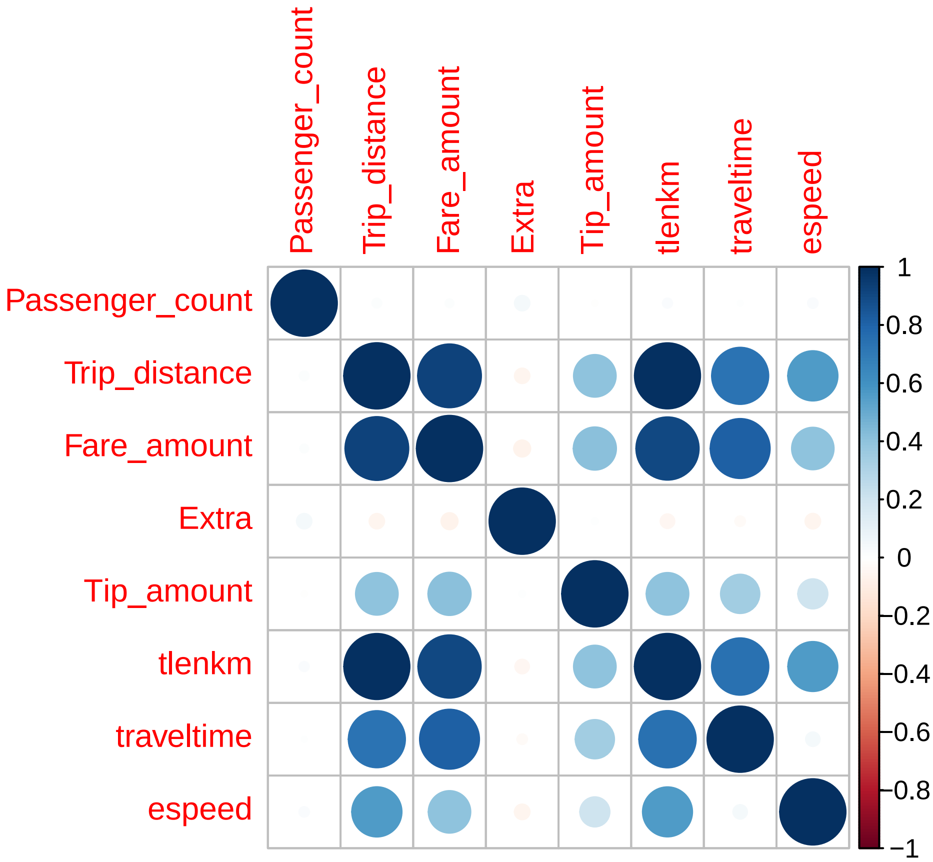
```
##                   Passenger_count Trip_distance Fare_amount Extra Tip_amount
## Passenger_count              1.00          0.02        0.01  0.05      -0.01
## Trip_distance                0.02          1.00        0.93 -0.05       0.41
## Fare_amount                  0.01          0.93        1.00 -0.06       0.42
## Extra                        0.05         -0.05       -0.06  1.00       0.01
## Tip_amount                  -0.01          0.41        0.42  0.01       1.00
## tlenkm                       0.02          0.99        0.91 -0.04       0.41
## traveltime                   0.01          0.74        0.82 -0.02       0.35
## espeed                       0.02          0.57        0.41 -0.05       0.20
##                   tlenkm traveltime espeed
## Passenger_count     0.02       0.01   0.02
## Trip_distance       0.99       0.74   0.57
## Fare_amount         0.91       0.82   0.41
## Extra              -0.04      -0.02  -0.05
## Tip_amount          0.41       0.35   0.20
## tlenkm              1.00       0.75   0.57
## traveltime          0.75       1.00   0.04
## espeed              0.57       0.04   1.00
```

6.3.2 Rank these variables according the correlation:

```r
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```r
corrplot(res)
```



As we can see in this graph, we have the correlation between all quantitative variables. We must say, however, that there are two variables (espeed and traveltime) which we had to modify when making the imputation.

In case of not having made the imputation of espeed and traveltime, we would have the following plot:

[insert image],

which means that there is a negative correlation between these two variables, since the longer the time, the slower the trip. However, we think it is necessary to remove the outliers we have had from these variables because they are unrealistic.

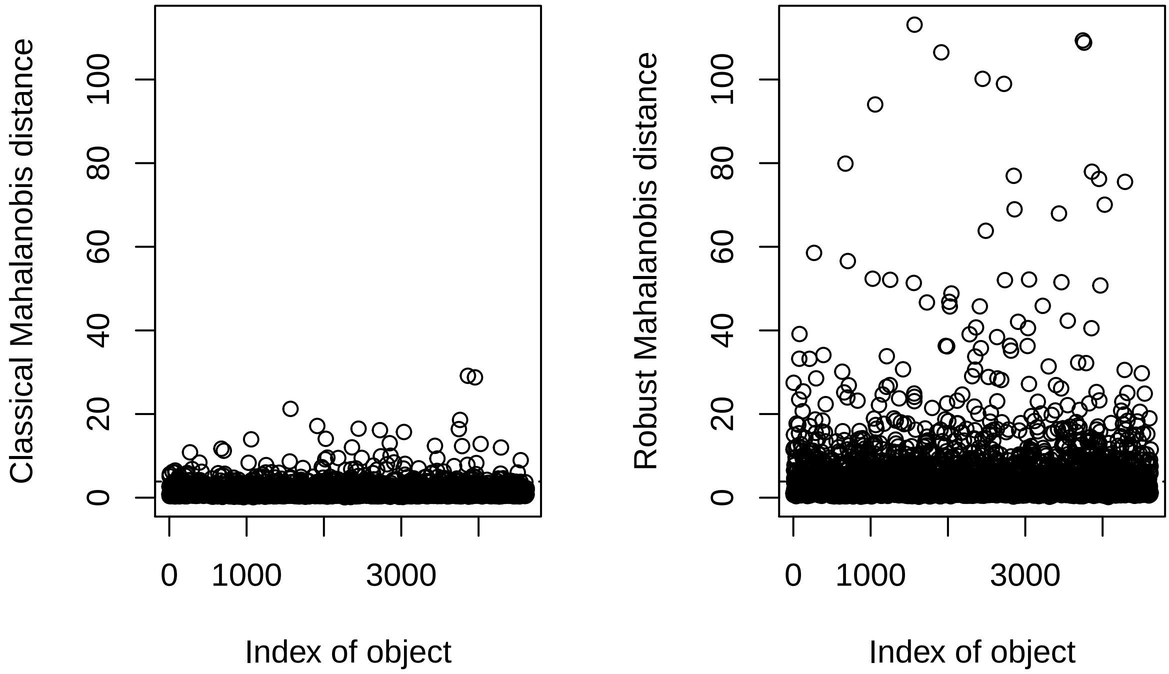
Now, let's describe each correlation we obtained in the first graph:

- Diagonals:
  - Being exactly the same variable, it is directly related to itself.
- Fare_amount + Trip_distance:
  - More distance, more time, therefore more price.
- Tip_amount + Trip_distance:
  - If the trip has been longer, there may be more reason to tip.
- Total_amount + Trip_distance:
  - As before, more distance, more time, therefore more price.
- tlenkm + Trip_distance:
  - They are exactly the same, only with a metric change.
- traveltime + Trip_distance:
  - The further away, the longer.
- espeed + Trip_distance:
  - The reason we think these variables are related to a direct and positive proportion is that since short trips have to be, logically cheaper, what taxi drivers do is slow down so that the trip take longer and thus charge more. Therefore, by increasing the distance of the journey, taxi drivers do not need to go so slow and therefore the speed increases.
- Amount_type + Amount_mount:
  - In the USA it is normal to give a tip proportional to the price of the service that has been offered.
- Total_amount + Fare_amount:
  - The variable Total_amount is equivalent to Fare_amount plus the fees, tips, among others, that have been applied to the trip.
- tlenkm + Fare_amount:
  - As before, more distance, more time, therefore more price.
- traveltime + Fare_amount:
  - More time, more price.

- espeed + Fare_amount:
  - As we said before, more speed means more distance, therefore more travel time, causing more price.
- Total_amount + Type_amount:
  - As before, in the USA it is normal to give a tip proportional to the price of the service that has been offered.
- tlenkm + Mount_type:
  - If the trip has been longer, there may be more reason to tip.
- traveltime + Tip_amount:
  - The longer it takes, the more price, and therefore the more tip given the proportionality.
- espeed + Tip_amount:
  - The more speed, as we said before, the more distance, and therefore the longer it takes. This causes more price and therefore more tip.
- tlenkm + Total_amount:
  - More distance, more time, therefore more price.
- traveltime + Total_amount:
  - More time, more price.
- espeed + Total_amount:
  - As we said before, more speed means more distance, therefore more travel time, causing more price.
- traveltime + tlenkm:
  - The more km to travel, the longer it takes.
- speed + tlenkm:
  - Same as for espeed + Trip_distance correlation.

6.3.3 Identify individuals considered as multivariant outliers

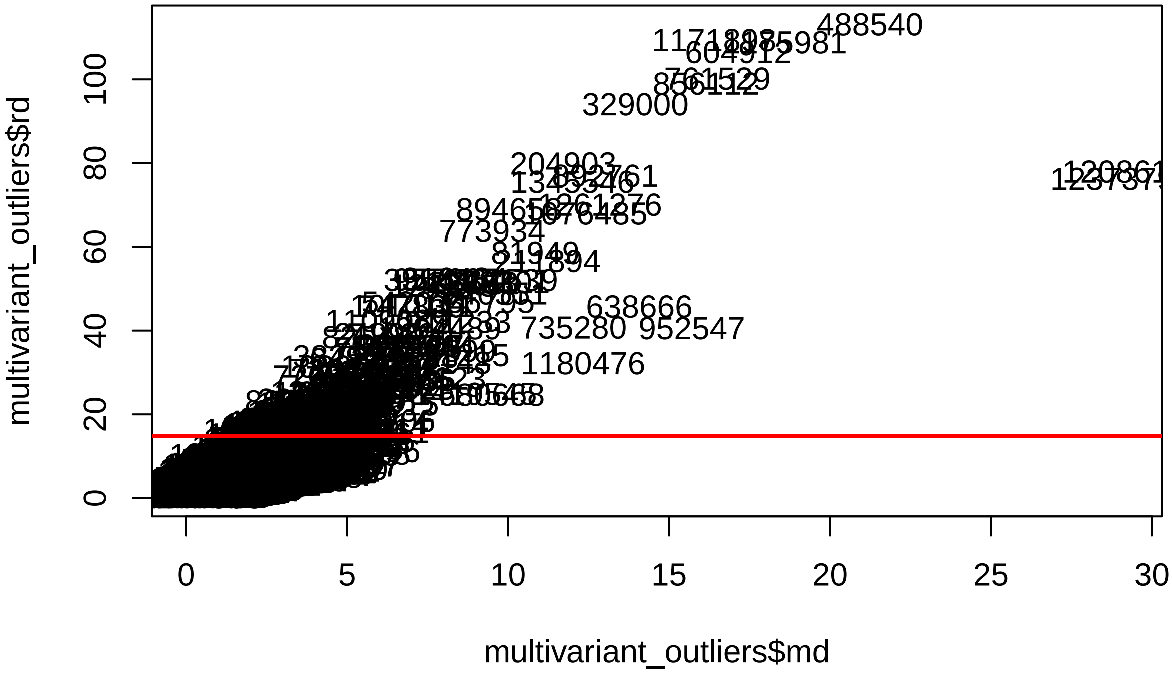
```
library(chemometrics)
multivariant_outliers <- Moutlier(df[, c(11:12, 19, 26)], quantile = 0.995)
```




```
multivariant_outliers$cutoff
```

```
## [1] 3.854901
```

```
par(mfrow=c(1,1))
plot(multivariant_outliers$md, multivariant_outliers$rd, type="n")
text(multivariant_outliers$md, multivariant_outliers$rd, labels=rownames(df[, c(11:12, 19, 26)]))
abline(col="red",lwd=2, h=qchisq(0.995, ncol(df[, c(11:12, 19, 26)])))
```



As we can see, above the defined line we have all the possible observations that we call multivariate outliers. These mean that, viewed only from the point of view of a variable, it does not have to be an outlier, but that viewed with various dimensions (variables), it may be so.

We want to look at two observations that have caught our attention. The first is 488540 and the second is 1180476.

As we can see, observation 488540 is the one at the boundary of the two axes. So that means it's most likely a multivariate outlier. On the other hand, the 1180476 is not exactly very central on both axes. This may lead us to think that he is not as likely as the other observation to be a multivariate outlier.

```r
df[which(row.names(df)=="488540"), 1:35]
```

```
##                  VendorID lpep_pickup_datetime Lpep_dropoff_datetime
## 488540 f.Vendor-VeriFone  2016-01-11 06:57:31   2016-01-11 07:46:31
##        Store_and_fwd_flag RateCodeID Pickup_longitude Pickup_latitude
## 488540                  N     Rate-1        -73.91121              NA
##        Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 488540                NA               NA               1            30
##        Fare_amount Extra MTA_tax Tip_amount Tolls_amount Ehail_fee
## 488540          60     0     Yes         17            0        NA
##        improvement_surcharge Total_amount Payment_type   Trip_type hour
## 488540                   Yes       128.76  Credit card Street-Hail    6
##              period tlenkm traveltime espeed pickup dropoff Trip_distance_range
## 488540 Period night  48.28         49     55     06      07          Short_dist
##        yearGt2015 CashTips paidTolls Sum_total_amount TipIsGiven
## 488540          1        0        No               NA        Yes
##        passenger_groups
## 488540           Single
```

```r
df[which(row.names(df)=="1180476"), 1:35]
```

```
##                 VendorID lpep_pickup_datetime Lpep_dropoff_datetime
## 1180476 f.Vendor-Mobile  2016-01-27 05:48:11   2016-01-27 06:19:48
##         Store_and_fwd_flag RateCodeID Pickup_longitude Pickup_latitude
## 1180476                  N Rate-Other        -73.90414        40.85212
##         Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 1180476          -73.9847         40.75537               1          10.5
##         Fare_amount Extra MTA_tax Tip_amount Tolls_amount Ehail_fee
## 1180476    33.76959     0      No          0            0        NA
##         improvement_surcharge Total_amount Payment_type Trip_type hour
## 1180476                    No            0         Cash  Dispatch    5
##               period   tlenkm traveltime   espeed pickup dropoff
## 1180476 Period night 16.89811   31.61667 32.06811     05      06
##         Trip_distance_range yearGt2015 CashTips paidTolls Sum_total_amount
## 1180476           Long_dist          0       NA        No               NA
```

```
##         TipIsGiven passenger_groups
## 1180476         No           Single
```

---

7 Profiling

7.1 Numeric target: Total_amount

Profiling is used to finish profiling our sample.

We will now proceed to the profiling that asks us for our numeric target (Total_amount) and then we have to use the original variables and factors.

In order to observe the relationship of our numerical target with the other variables we use the condes tool that provides us with information about the relationships between the indicated variables and the target.

```
library(FactoMineR)
summary(df$Total_amount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    7.80   10.80   13.93   17.00  128.76
```

```
vars_res<-names(df)[c(19,34)]
res.condes <- condes(df[, c(vars_res,vars_quantitatives, vars_categorical)],1)
```

Let's now look at the correlations between our Total_amount target and the variables in the following groups. We will basically look at p.value, which we know that the smaller the correlation between the variables.

```
res.condes$quanti # Global association to numeric variables
```

7.1.0.1 > Numerical variables

```
##               correlation       p.value
## Fare_amount     0.9426421  0.000000e+00
## Trip_distance   0.8938806  0.000000e+00
## tlenkm          0.8803275  0.000000e+00
## traveltime      0.7620364  0.000000e+00
## Tip_amount      0.5660554  0.000000e+00
## espeed          0.3970258 2.214665e-174
```

- Fare_amount:
  - The variable Total_amount is equivalent to Fare_amount plus the fees, tips, among others, that have been applied to the trip.
- Trip_distance:
  - As before, more distance, more time, therefore more price.
- tlenkm
  - More distance, more time, therefore more price.
- traveltime
  - More time, more price.
- Tip_amount
  - The more you pay, since the tip is a proportion of the final price, the more it will increase.
- espeed
  - As we said before, more speed means more distance, therefore more travel time, causing more price.

```
res.condes$quali # Global association to factors
```

7.1.0.2 > Qualitative variables

```
##                              R2      p.value
## Trip_distance_range 0.556244056 0.000000e+00
## TipIsGiven          0.058775333 7.976817e-63
## Payment_type        0.053488291 7.096416e-56
## RateCodeID          0.013014975 7.244863e-15
## Trip_type           0.001221351 1.748826e-02
```

- Trip_distance_range

  - Obviously, the longer the journey, the longer it will take and the more price it will have.
- TipIsGiven
  - Like before, the more you pay, since the tip is a proportion of the final price, the more it will increase.
- Payment_type
  - This is the least related variable. However, we can predict that the more the trip is worth, the more likely it is to be paid by credit card.
- RateCodeID
  - As we have seen before, virtually all observations were of type 1. Therefore it is not worth looking at the correlation.

```
res.condes$category # Partial association to significative levels in factors
```

7.1.0.3 > Categorical variables

```
##                                   Estimate      p.value
## Trip_distance_range=Long_dist   11.421531 0.000000e+00
## TipIsGiven=Yes                    2.512982 7.976817e-63
## Payment_type=Credit card          2.653121 4.728144e-57
## RateCodeID=Rate-Other             3.505459 7.244863e-15
## Trip_type=Dispatch                1.141598 1.748826e-02
## Trip_type=Street-Hail            -1.141598 1.748826e-02
## RateCodeID=Rate-1                -3.505459 7.244863e-15
## Trip_distance_range=Medium_dist -1.609971 1.572556e-33
## Payment_type=Cash                -2.024634 1.858977e-56
## TipIsGiven=No                    -2.512982 7.976817e-63
## Trip_distance_range=Short_dist  -9.811560 0.000000e+00
```

- Trip_distance_range
  - We can see that, the further away, the more correlation, as it takes longer to travel.
- TipIsGiven
  - We see that it is more likely to tip if the price is high.
- Payment_type
  - We see that it is easier for the guy to be with CreditCard if the trip costs more.
- RateCodeID
  - As we have seen before, virtually all observations were of type 1. Therefore it is not worth looking at the correlation.
- period
  - We see that in the morning travel costs less.

7.2 Factor (Y.bin - TipIsGiven)

And now, we are profiling the qualitative target:

```
res.catdes <- catdes(df[, c(vars_res,vars_quantitatives, vars_categorical)],2)
```

Let's now look at the correlations between our TipIsGiven target and the variables in the following groups. We will basically look at p.value, which we know that the smaller the correlation between the variables.

```
res.catdes$test.chi2
```

7.2.0.1 > Test.Chi2

```
##                          p.value df
## Payment_type        0.000000e+00  2
## Trip_distance_range 1.622279e-22  2
## Trip_type           4.740323e-06  1
## RateCodeID          5.045642e-05  1
## period              8.478130e-05  3
```

- Payment_type
  - We see that it is very likely that there will be a tip if it is paid in a concise manner.
- Trip_distance_range
  - As we can see, there is tip as long as the trip is, or very short, or very long.
- Trip_type
  - We don't think the type of trip is important.

- RateCodeID
  - As we have seen before, virtually all observations were of type 1. Therefore it is not worth looking at the correlation.
- period
  - We see that in the morning people are not in a very good mood and are more inclined to tip the "valley".

```
res.catdes$quanti.var
```

7.2.0.2 > Quantitative variables

```
##                     Eta2      P-value
## Tip_amount    0.514077510 0.000000e+00
## Total_amount  0.058775333 7.976817e-63
## Fare_amount   0.014382526 2.803248e-16
## tlenkm        0.012684087 1.591459e-14
## Trip_distance 0.011969561 8.707794e-14
## traveltime    0.009494751 3.152093e-11
## espeed        0.007486324 3.805650e-09
```

- Tip_amount
  - If there is a tip, it must have value.
- Total_amount
  - We see that it is more likely to tip if the price is high.
- Fare_amount
  - We see that it is more likely to tip if the price is high.
- tlenkm
  - The more distance, the more time, therefore the more price. So, more chances of there being a tip.
- Trip_distance
  - Exactly the same as above.
- traveltime
  - The longer, therefore the more price. So, more chances of there being a tip.
- espeed
  - The faster you get to the site, the more satisfaction and therefore the likelihood of tipping.

```
res.catdes$category
```

7.2.0.3 > Categorical variables

```
## $No
##                                  Cla/Mod   Mod/Cla     Global      p.value
## Payment_type=Cash              100.00000 86.641221 54.0125460 0.000000e+00
## Trip_distance_range=Short_dist  67.63122 69.743234 64.2872594 3.721944e-23
## Payment_type=No paid           100.00000  1.040944  0.6489293 6.580800e-07
## Trip_type=Dispatch              83.03571  3.226926  2.4226693 1.522866e-06
## RateCodeID=Rate-Other           79.52756  3.504511  2.7471339 2.624700e-05
## period=Period valley            67.14286 29.354615 27.2550292 3.381957e-05
## period=Period morning           56.64207 10.652325 11.7239888 3.830184e-03
## RateCodeID=Rate-1               61.85498 96.495489 97.2528661 2.624700e-05
## Trip_type=Street-Hail           61.82665 96.773074 97.5773307 1.522866e-06
## Trip_distance_range=Medium_dist  53.85396 18.424705 21.3281419 7.981541e-10
## Trip_distance_range=Long_dist    51.27820 11.832061 14.3845987 3.316979e-10
## Payment_type=Credit card         16.93702 12.317835 45.3385248 0.000000e+00
##                                   v.test
## Payment_type=Cash                    Inf
## Trip_distance_range=Short_dist  9.911188
## Payment_type=No paid            4.973343
## Trip_type=Dispatch              4.808212
## RateCodeID=Rate-Other           4.203801
## period=Period valley            4.146094
## period=Period morning          -2.891819
## RateCodeID=Rate-1              -4.203801
## Trip_type=Street-Hail          -4.808212
```

```
## Trip_distance_range=Medium_dist -6.145294
## Trip_distance_range=Long_dist   -6.283189
## Payment_type=Credit card             -Inf
##
## $Yes
##                                  Cla/Mod    Mod/Cla     Global      p.value
## Payment_type=Credit card        83.06298 100.000000 45.3385248 0.000000e+00
## Trip_distance_range=Long_dist   48.72180  18.609994 14.3845987 3.316979e-10
## Trip_distance_range=Medium_dist 46.14604  26.134406 21.3281419 7.981541e-10
## Trip_type=Street-Hail           38.17335  98.908673 97.5773307 1.522866e-06
## RateCodeID=Rate-1               38.14502  98.506605 97.2528661 2.624700e-05
## period=Period morning           43.35793  13.497990 11.7239888 3.830184e-03
## period=Period valley            32.85714  23.779437 27.2550292 3.381957e-05
## RateCodeID=Rate-Other           20.47244   1.493395  2.7471339 2.624700e-05
## Trip_type=Dispatch              16.96429   1.091327  2.4226693 1.522866e-06
## Payment_type=No paid             0.00000   0.000000  0.6489293 6.580800e-07
## Trip_distance_range=Short_dist  32.36878  55.255600 64.2872594 3.721944e-23
## Payment_type=Cash                0.00000   0.000000 54.0125460 0.000000e+00
##                                   v.test
## Payment_type=Credit card             Inf
## Trip_distance_range=Long_dist   6.283189
## Trip_distance_range=Medium_dist 6.145294
## Trip_type=Street-Hail           4.808212
## RateCodeID=Rate-1               4.203801
## period=Period morning           2.891819
## period=Period valley           -4.146094
## RateCodeID=Rate-Other          -4.203801
## Trip_type=Dispatch             -4.808212
## Payment_type=No paid           -4.973343
## Trip_distance_range=Short_dist -9.911188
## Payment_type=Cash                   -Inf
```

- TipIsGiven
  - Same variable.
- Payment_type
  - We see that it is very likely that there will be a tip if it is paid in a concise manner.
- Trip_distance_range
  - As we can see, there is tip as long as the trip is, or very short, or very long.
- Trip_type
  - We don't think the type of trip is important.
- RateCodeID
  - As we have seen before, virtually all observations were of type 1. Therefore it is not worth looking at the correlation.
- period
  - We see that in the morning people are not in a very good mood and are more inclined to tip the "valley".