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# Turo Car Sharing Platform: Report & Analysis

(Region: Arizona)

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**Abstract:** Given the use of a dataset provided from a popular car sharing website Turo.com, we derive a model based on factors that most contribute to the final price of a car trip. Using R, we attempt to explore this question by employing summary statistics, data cleaning and multiple linear regression to test a model of significant contributing factors.

**Sample Scope:** Data gathered is focused on patterns and insights from the state of Arizona.

**Analysis: (Walkthrough of Questions 1 – 6)**

*Question 1:*

**Load the data into RStudio.**

*Answer:*

The data is first loaded into a data frame using the built-in readRDS function and the provided turo.data.5140 dataset.

*Question 2:*

**Extract all the observations from the state your group is assigned to, and use this subset for the following tasks.**

*Answer:*

Next the Arizona data is isolated from the original dataset and read into a data frame for use throughout the remainder of the program using the readRDS function.

*Question 3:*

**Compute summary statistics and generate charts for ALL variables in the dataset, after excluding missing values. For each continuous variable, compute min, first quartile, medium, third quartile, max, mean, standard deviation, and skewness as summary statistics, and draw histogram. For each categorical variable, compute frequency and relative frequency distributions, and draw bar chart.**

*Answer:*

For this step, two list objects were created to store categorical and continuous variables separately. Using a for loop and a set of if statements, the first element of each column variable is tested (after having eliminated all NA values) to determine its classification status as either a continuous or a categorical variable.

```
# (3) Separate categorical and continuous data based on context.
continuous <- list()
categorical <- list()

for (name in names(az.df.clean)){
  # Separated According to First Value of Each Variable
  if (class(df[1, name]) == 'logical'){
    # Boolean are categorical
    categorical <- c(categorical, name)
  }
  else if(class(df[1, name]) == 'factor'){
    # Factors AKA strings are also categorical
    categorical <- c(categorical, name)
  }
…
print(paste("Continuous Variable Count: ", length(continuous)))
print(paste("Categorical Variable Count: ", length(categorical)))
```

After this is determined, separate charts and statistics are computed for each item corresponding to the respective continuous or categorical lists. For both sets of variables, by employing the use of a for loop the corresponding statistics are extracted and charts generated (Standard Deviation, Skewness and Histograms for continuous variables; frequency, relative frequency and bar charts for the categorical variables). In order to calculate the summary statistics their respective names are matched to their column positions in the dataframe.

```
### Number 3b: Summary Statistics

# extracting 'index positions'... (AKA: Column numbers)

continuous.pos <- match(continuous, names(df)) # index position of extracted columns classified as "continuous"

categorical.pos <- match(categorical, names(df)) # index position of extracted columns classified as "categorical"
```

Continuous Variable Statistics Code:

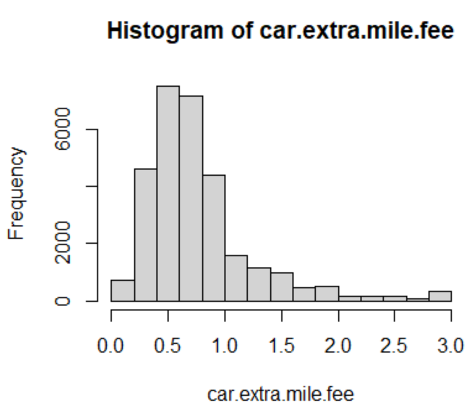
```
> # Continuous Variables : min, first and third quartiles, max, mean
>
> N <- nrow(az.df.clean)
>
> print(summary(df[, continuous.pos])) # min, first and third quartiles, max, mean
```

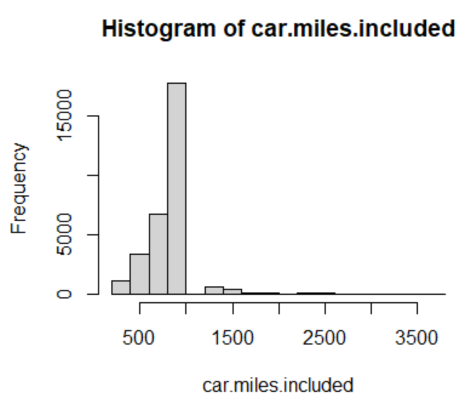
Continuous Variable Statistics Output:

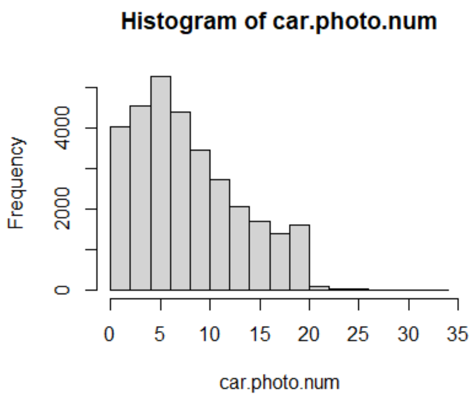
```
car.extra.mile.fee car.miles.included car.photo.num    car.trip.price      car.year
 Min.   :0.0100     Min.   : 350       Min.   : 1.000   Min.   :  91.0   Min.   :1929
 1st Qu.:0.4800     1st Qu.: 750       1st Qu.: 4.000   1st Qu.: 294.0   1st Qu.:2013
 Median :0.6800     Median :1000       Median : 7.000   Median : 448.0   Median :2016
 Mean   :0.7815     Mean   : Inf       Mean   : 8.295   Mean   : 641.1   Mean   :2015
 3rd Qu.:0.9500     3rd Qu.:1000       3rd Qu.:12.000   3rd Qu.: 714.0   3rd Qu.:2018
 Max.   :3.0000     Max.   : Inf       Max.   :34.000   Max.   :6993.0   Max.   :2020
 NA's   :1275       NA's   :449        NA's   :42       NA's   :47
 host.tenure.in.weeks
 Min.   :  4.429
 1st Qu.: 52.286
 Median :112.857
 Mean   :126.728
 3rd Qu.:186.857
 Max.   :461.000
 NA's   :119
```

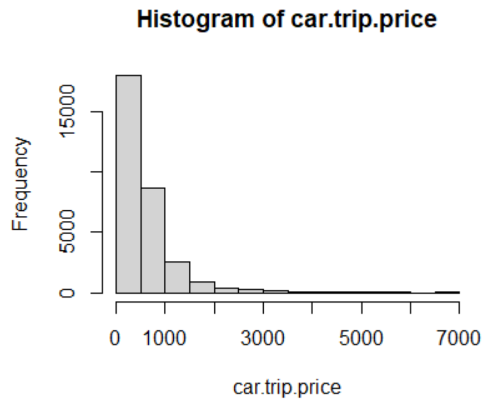
Continuous Variables Standard Deviation, Skewness & Histograms:

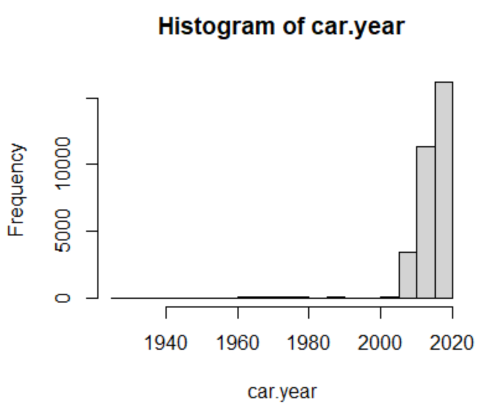
```
> for (column in continuous){ # Standard Deviation and Skewness
+   print(paste(column,"': ","Standard Deviation: '", sqrt(N - 1 / N) * sd(df[, column],
na.rm = TRUE))) # <<<<<<<<< !!!!!!! See NOTES FOR LONGFORM !!!!!!
+   print(paste(column,"': ", "Skewness: '", skewness(df[, column], na.rm = TRUE)))
+   hist(df[, column], main = paste("Histogram of",column), xlab = column)
+ }
[1] "car.extra.mile.fee ':  Standard Deviation: ' 16.522521766424"
[1] "car.extra.mile.fee ':  Skewness: ' 1.99167355884491"
[1] "car.miles.included ':  Standard Deviation: ' NaN"
[1] "car.miles.included ':  Skewness: ' NaN"
[1] "car.photo.num ':  Standard Deviation: ' 178.320381278836"
[1] "car.photo.num ':  Skewness: ' 0.608224551790603"
[1] "car.trip.price ':  Standard Deviation: ' 22583.0659105013"
[1] "car.trip.price ':  Skewness: ' 4.11023554579958"
[1] "car.year ':  Standard Deviation: ' 151.484724737546"
[1] "car.year ':  Skewness: ' -4.8662168534807"
[1] "host.tenure.in.weeks ':  Standard Deviation: ' 2966.91525528998"
[1] "host.tenure.in.weeks ':  Skewness: ' 0.684016843441089"
```

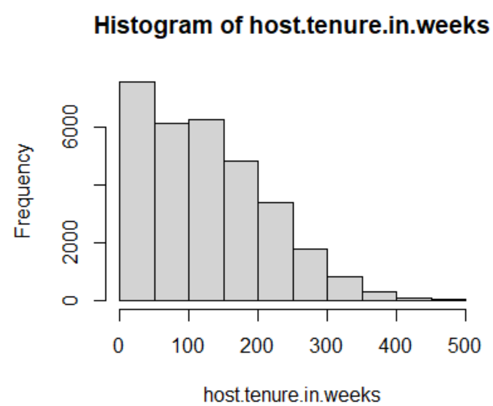




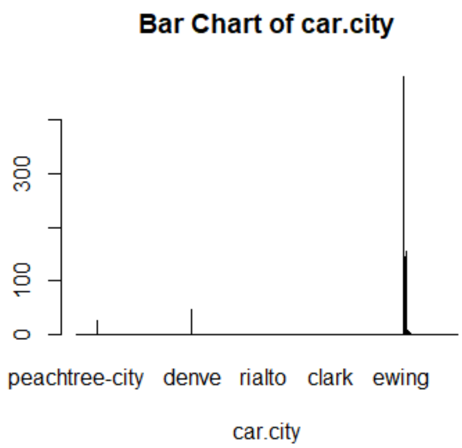



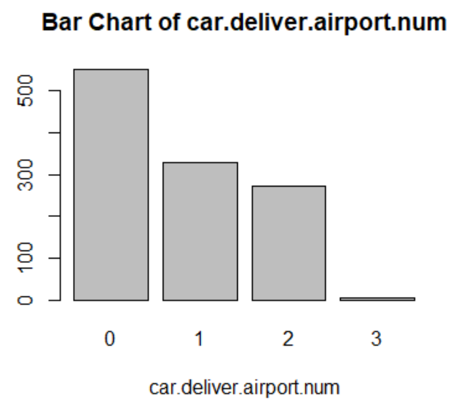



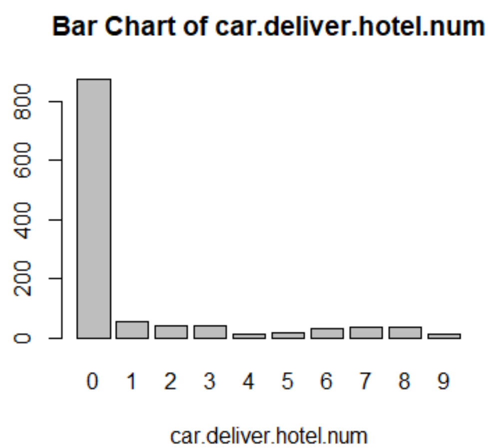

## Categorical Variables: Freq & Relative Freq

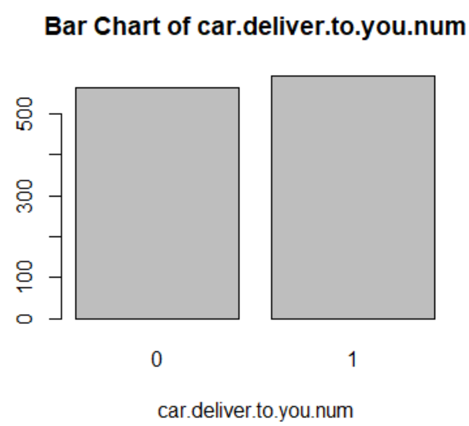
```
for (column in categorical){ # freq and relative freq distribution

  freq <- table(az.df.clean[,column])

  rel.freq <- table(column) / length(N)

  barplot(freq, main = paste("Bar Chart of",column), xlab = column)
```

## Categorical Variables: Some Sample Barplots



*Question 4*:

**Use Inter Quartile Range (IQR) method to identify outliers of all continuous variables, then remove all observations containing outliers.**

*Answer:*

Initially, the total number of records in the dataset was 31,261 rows and 53 columns. The first step in detecting the outlier is removing all the observations with missing values, i.e., all rows with NA's are deleted. After removing NA's, the cleaned data set includes 1285 rows and 53 columns. Based on the definition of each variable, the categorical and continuous variables are identified. There are 6 continuous and 47 categorical variables in the cleaned dataset. The code to identify the continuous and categorical dataset is as shown:

```
# List all categorical and continuous data separately based on context.
continuous <- list()
categorical <- list()
for (name in names(az.df.clean)){
  # Separated According to First Value of Each Variable
  if (class(df[1, name]) == 'logical'){
    # Boolean are categorical
    categorical <- c(categorical, name)
  }
  else if(class(df[1, name]) == 'factor'){
    # Factors AKA strings are categorical
    categorical <- c(categorical, name)
  }
  else if(class(df[1, name]) == 'integer'){
 categorical <- c(categorical, name)
  }
  else if(df[1,name] == 0){
    categorical <- c(categorical, name)
  }
```

```
  else if(df[1,name] == 1){
    categorical <- c(categorical, name)
  }
  else if(name == "car.doors"){
    categorical <- c(categorical, name)
  }
  else{
    # All others belong in the list of continuous variables
    continuous <- c(continuous, name)
  }
}
print(paste("Continuous Variable Count: ", length(continuous)))
print(paste("Categorical Variable Count: ", length(categorical)))
```

Output:

```
> print(paste("Continuous Variable Count: ", length(continuous)))
[1] "Continuous Variable Count:  6"
> print(paste("Categorical Variable Count: ", length(categorical)))
[1] "Categorical Variable Count:  47"
```

Using loop control statements, the interquartile range, upper quantiles, and lower quantiles are calculated for each continuous variable. Thus, all those records above the (upper quantile + 1.5 x Interquartile range) or lower than the (lower Quantile -1.5 x Interquartile range) are considered outliers. The rows detected as outliers are cleaned and removed. The total number of observations detected as outliers is 102. Thus, after removing the outlier, the dataset has 1053 rows and 53 columns. The code to detect outliers is:

Code:

```
az.df<- az.df.clean
# The reduction of outlier is performed on az.df.clean.
# The dataset is retained in the dataframe az.df
for (column in continuous){
```

```
  iqr <- quantile(az.df[, column], 0.75) - quantile(az.df[, column],
0.25)
  lowerlimit <- quantile(az.df[, column], 0.25) - 1.5 * iqr
  upperlimit <- quantile(az.df[, column], 0.75) + 1.5 * iqr
  ### Remove all observations w/ missing values
  for (row in az.df.clean[, column]){
    if(row < lowerlimit | row > upperlimit){
      az.df.clean <- az.df.clean[-row,]
    }
  }}
print(paste("Dropped:", nrow(az.df) - nrow(az.df.clean), "rows!"))
print(paste("Row count w/o outliers:", nrow(az.df.clean)))
```

Output:

```
> print(paste("Dropped:", nrow(az.df) - nrow(az.df.clean), "rows!"))
[1] "Dropped: 102 rows!"
> print(paste("Row count w/o outliers:", nrow(az.df.clean)))
[1] "Row count w/o outliers: 951"
```

*Question 6:*

**<u>Build a multiple linear regression model using car.trip.price as dependent variable. Select at least five independent variables. Treat each categorical variable as a single variable although it may be broken into multiple dummy variables. Try different models and choose the best one you can find.</u>**

*Answer:*

The steps we took to identify the best multiple regression model to estimate the car.trip.price using various combinations of independent variables are as follows:

1. First, all categorical variables with more than 40 categories are dropped. Thus, car.city, car.make, car.insurance, car.model, and car.state are excluded from modeling.
2. A full model is created with all of the independent variables is created using function lm() as shown below. This full model has many insignificant predictors, and the

model can predict 60.14% variation in car.trip.price by varying all of the predictors. To identify all of the significant predictors, the step function is used.

```
fit<- lm(formula = car.trip.price ~ ., data = az.lm)
```

3. The step function in R is used for stepwise detection of significant variables. It focuses on minimizing the AIC of the model. <u>Code</u>: step(fit) detects the final model:

```
Call:
lm(formula = car.trip.price ~ car.deliver.hotel.num + car.deliver.to.you.num +
    car.displayed.user.review.num.past.18m + car.displayed.user.review.num.past.6m +
    car.doors + car.extra.child.safety.seat + car.extra.cooler +
    car.extra.mile.fee + car.extra.num + car.extra.post.trip.cleaning +
    car.extra.prepaid.refuel + car.photo.num + car.power + car.transmission +
    car.year + host.verified.email, data = az.lm)

Coefficients:
                           (Intercept)                   car.deliver.hotel.num
                             34761.296                                   9.840
                car.deliver.to.you.num  car.displayed.user.review.num.past.18m
                               -45.763                                  -4.080
 car.displayed.user.review.num.past.6m                               car.doors
                               -12.314                                 -48.497
       car.extra.child.safety.seatTRUE                    car.extra.coolerTRUE
                               -66.228                                -117.937
                    car.extra.mile.fee                           car.extra.num
                              1006.081                                  25.441
      car.extra.post.trip.cleaningTRUE            car.extra.prepaid.refuelTRUE
                              -159.004                                 -74.434
                         car.photo.num                  car.powerGas (Regular)
                                -4.664                                -255.324
                          car.powerGas                  car.powerGas (Premium)
                              -202.239                                -186.024
                     car.powerElectric               car.powerHybrid (Premium)
                              -397.275                                -234.523
                        car.powerDiesel               car.powerHybrid (Regular)
                              -100.289                                -302.559
   car.transmissionManual transmission                                car.year
                               264.211                                 -16.976
               host.verified.emailTRUE
                              -100.238
```

The model with the above predictor is:

```
Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)                            34761.296   8044.950   4.321 1.70e-05 ***
car.deliver.hotel.num                      9.840      5.992   1.642 0.100867    
car.deliver.to.you.num                   -45.763     28.301  -1.617 0.106186    
car.displayed.user.review.num.past.18m    -4.080      2.172  -1.879 0.060575 .  
car.displayed.user.review.num.past.6m    -12.314      5.113  -2.409 0.016192 *  
car.doors                                -48.497     17.638  -2.750 0.006073 ** 
car.extra.child.safety.seatTRUE          -66.228     45.374  -1.460 0.144705    
car.extra.coolerTRUE                    -117.937     61.180  -1.928 0.054168 .  
car.extra.mile.fee                      1006.081     31.751  31.687  < 2e-16 ***
car.extra.num                             25.441     16.879   1.507 0.132062    
car.extra.post.trip.cleaningTRUE        -159.004     49.647  -3.203 0.001403 ** 
car.extra.prepaid.refuelTRUE             -74.434     44.505  -1.672 0.094731 .  
car.photo.num                             -4.664      2.828  -1.649 0.099363 .  
car.powerGas (Regular)                  -255.324    104.176  -2.451 0.014415 *  
car.powerGas                            -202.239    101.301  -1.996 0.046151 *  
car.powerGas (Premium)                  -186.024    104.308  -1.783 0.074814 .  
car.powerElectric                       -397.275    113.995  -3.485 0.000513 ***
car.powerHybrid (Premium)               -234.523    257.538  -0.911 0.362701    
car.powerDiesel                         -100.289    177.922  -0.564 0.573102    
car.powerHybrid (Regular)               -302.559    155.320  -1.948 0.051690 .  
car.transmissionManual transmission      264.211     74.364   3.553 0.000398 ***
car.year                                 -16.976      3.999  -4.245 2.39e-05 ***
host.verified.emailTRUE                 -100.238     39.718  -2.524 0.011761 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 408.8 on 1030 degrees of freedom
Multiple R-squared:  0.594,	Adjusted R-squared:  0.5853 
F-statistic:  68.5 on 22 and 1030 DF,  p-value: < 2.2e-16
```

This model can predict a 59.4% variation in the car.trip.price. Thus, the model's predictability is insignificantly reduced, with many predictors not included. However, the model still contains insignificant predictors as the p-value of many predictors are greater than 0.05.

4. The next step is to remove all of those insignificant predictors one by one, based on the p-values. The predictor with the highest p-value (highest p>0.05) is removed first, and the model is recreated.
5. If there remains any insignificant predictor after the recreation of the model, then step 4 is repeated until all of the remaining predictors remain significant. The final model with backward linear regression step is:

```
> summary(Finalfit)

Call:
lm(formula = car.trip.price ~ car.displayed.user.review.num.past.18m +
    car.displayed.user.review.num.past.6m + car.doors + car.extra.mile.fee +
    car.extra.post.trip.cleaning + car.transmission + car.year +
    host.verified.email, data = az.lm)

Residuals:
    Min      1Q  Median      3Q     Max
-1325.8  -187.9   -29.4   123.1  3796.4

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                           37573.838   7871.593   4.773 2.07e-06 ***
car.displayed.user.review.num.past.18m    -5.237      2.091  -2.504 0.012427 *
car.displayed.user.review.num.past.6m    -13.098      5.005  -2.617 0.009007 **
car.doors                                -59.717     16.929  -3.527 0.000438 ***
car.extra.mile.fee                       984.115     28.825  34.141  < 2e-16 ***
car.extra.post.trip.cleaningTRUE        -184.122     31.294  -5.884 5.40e-09 ***
car.transmissionManual transmission      284.146     74.270   3.826 0.000138 ***
car.year                                 -18.469      3.915  -4.717 2.72e-06 ***
host.verified.emailTRUE                 -107.206     39.556  -2.710 0.006834 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 412.1 on 1044 degrees of freedom
Multiple R-squared:  0.582,	Adjusted R-squared:  0.5788
F-statistic: 181.7 on 8 and 1044 DF,  p-value: < 2.2e-16
```

**Conclusion:** After conducting our analysis we determined that the resulting model can predict a 58.2% variation in the car.trip.price with an adjusted R squared of 0.5788, approximately the same as r-squared. Thus, the model's predictability is insignificantly reduced, with all of the predictors included in the model becoming significant. In other words, only those variables that are statistically significant are left in the model with all others being removed. With this model the predictability remains comparable to that of the initial model with all variables present. (Please see attached: Appendix 1 - R Code).

## Appendix 1

R Source Code:

- Cleaning, Detecting Outliers and Performing Multiple Linear Regression Analysis

```
- # Group Project Code: Multiple Regression Analysis
-
- # (1) Import Data set
- df = readRDS('turo.data.5140')
-
- # (2) Select the state
- az.df.clean <- df[df$car.state == 'az',]
- head(az.df.clean,1)
-
- # (5) Remove All NA's
- az.df.clean<- na.omit(az.df.clean)
-
- # (3) Separate categorical and continuous data based on context.
- continuous <- list()
- categorical <- list()
-
- for (name in names(az.df.clean)){
-   # Separated According to First Value of Each Variable
-   if (class(df[1, name]) == 'logical'){
-     # Boolean are categorical
-     categorical <- c(categorical, name)
-   }
-   else if(class(df[1, name]) == 'factor'){
-     # Factors AKA strings are also categorical
-     categorical <- c(categorical, name)
-   }
-   else if(class(df[1, name]) == 'integer'){
-     # In this case the int values are used to represent Binary Boolean values
(1's and 0's)
```

```
-       categorical <- c(categorical, name)
-     }
-     else if(df[1,name] == 0){
-       # Binary Boolean values (1's and 0's) are categorical
-       categorical <- c(categorical, name)
-     }
-     # Binary Boolean values (1's and 0's) are categorical
-     else if(df[1,name] == 1){
-       categorical <- c(categorical, name)
-     }
-     else if(name == "car.doors"){
-       categorical <- c(categorical, name)
-     }
-     else{
-       # All others belong in the list of continuous variables
-       continuous <- c(continuous, name)
-     }
-   }
-
-   print(paste("Continuous Variable Count: ", length(continuous)))
-   print(paste("Categorical Variable Count: ", length(categorical)))
-
-   ### Number 3b: Summary Statistics
-
-   # extracting 'index positions'... (AKA: Column numbers)
-   continuous.pos <- match(continuous, names(df)) # index positions of
    extracted columns classified as "continuous"
-   categorical.pos <- match(categorical, names(df)) # index positions of
    extracted columns classified as "categorical"
-
-   # Continuous Variables : Compute -> min, first and third quartiles, max,
    mean, sd & skewness; histograms
-
```

```
- N <- nrow(az.df.clean)
-
- print(summary(df[, continuous.pos])) # min, first and third quartiles, max, mean
-
- for (column in continuous){ # Standard Deviation and Skewness
-   print(paste(column,"': ","Standard Deviation: '", sqrt(N - 1 / N) * sd(df[, column], na.rm = TRUE))) # <<<<<<<<< !!!!!!! See NOTES FOR LONGFORM !!!!!!
-   print(paste(column,"': ", "Skewness: '", skewness(df[, column], na.rm = TRUE)))
-   hist(df[, column], main = paste("Histogram of",column), xlab = column)
- }
-
- # Categorical Variables: Compute -> frequency and relative frequency distributions; bar charts
-
- print(categorical) # extracted column names of the df classified as "continuous"
-
- for (column in categorical){ # freq and relative freq distribution
-   freq <- table(az.df.clean[,column])
-   rel.freq <- table(column) / length(N)
-   barplot(freq, main = paste("Bar Chart of",column), xlab = column)
- }
-
- # (4) Using the IQR method, detect and remove all the rows having outliers.
- az.df<- az.df.clean
- for (column in continuous){ # Standard Deviation and Skewness
-   iqrange <- quantile(az.df[, column], 0.75) - quantile(az.df[, column], 0.25)
-   lowerlimit <- quantile(az.df[, column], 0.25) - 1.5 * iqrange
-   upperlimit <- quantile(az.df[, column], 0.75) + 1.5 * iqrange
-
```

```
-    # (5) Remove all observations w/ missing values
-
-      for (row in az.df.clean[, column]){
-        if(row < lowerlimit | row > upperlimit){
-          az.df.clean <- az.df.clean[-row,]
-        }
-      }
-    }
-    print(paste("Dropped:", nrow(az.df) - nrow(az.df.clean), "rows!"))
-    print(paste("Row count w/o outliers:", nrow(az.df.clean)))
-
-    # Multiple Linear Regression
-    az.lm<-az.df.clean
-    az.lm$car.city<-NULL
-    az.lm$car.make<-NULL
-    az.lm$car.insurance<-NULL
-    az.lm$car.model<-NULL
-    az.lm$car.state<-NULL
-    fit<-lm(car.trip.price~.,az.lm)
-    step(fit)
-
-    # Backward Step method to remove insignificant variables.
-
-    Finalfit<-lm(formula = car.trip.price ~
     car.displayed.user.review.num.past.18m +
     car.displayed.user.review.num.past.6m +
-        car.doors + car.extra.mile.fee + car.extra.post.trip.cleaning
     +car.transmission +
-        car.year + host.verified.email, data = az.lm)
-    summary(Finalfit)
```