Predicting a waiter's tip amount in Dollars based on the customers total bill, gender(sex), time of the day, if the customer is a smoker or not and size of the group.

QIYU HUANG

Dec 21st 2020

Github

Code and data supporting this analysis is available at: https://github.com/cybernavily/Final.git'

Keywords

Linear Regression, Robust Algorithms, Data Analysis, Descriptive Analytics, p-value, t-statistic, R2 value, significance level, supervised learning.

Abstract.

An Analysis of Waiters tip amounts given the customers total bill, gender(sex), time of the day, smoker and size of the group. This study seeks to analyse the factors that influence the tipping behavior of customers: The likelihood of a customer giving a tip and the size of the tip. 244 eating events were recorded in a restaurant used for this analysis. The data was reported in a collection of case studies for business statistics. The report indicates that the average tipping rate is 7.048% of the total bill. The overall analysis demonstrates that customers tipping decisions and tip sizes are functions of their social interest. It is safe to conclude that customers consider tipping more of a social norm rather than self-interested rational behavior.

Specifying the Research Question

Is it possible to predict a waiters amount of tip in dollars based on the customers total bill, gender(sex), time of the day, smoker and size of the group

Introduction

Tipping is the norm in restaurants all over the world. According to Lynn et al. (1993)The amount of tip varies depending on the nature of the customer and quality of service received. According to Azar (2007), the tip amount ranges from 15% to 20% of the total bill for excellent service. The aim of this project is to use machine learning, collaborative data filterting and Supervised learning to solve tabular data problems. We will analyse a dataset with 244 records with one waiters tips over a few months working in a restaurant.

Studying customers tipping behavior can be helpful in measuring customer satisfaction (Rathore, 2015) and in turn restaurant managers can leverage such information to improve the quality of their services. Based on previous studies, tip size is reportedly increased by friendly service, good suggestions, excellent food, prompt delivery of the main course and check, a self-introduction by the waiter, and receiving separate checks("Introduction: The promise of collaborative public service delivery," 2019). The tip is decreased by waiting a long time for a beverage and being seated in a bad location.

Servers also show that there are no differences in tipping behavior. However, they have expressed that the effort required for some social groups in order to receive the same amount of tip is higher(Toporek, 2015). If this is the case then they would be more motivated to engage in cost-based statistical discrimination against groups that require more effort to serve.

The independent variable is the amount of tip in Dollars. Dependent variables are:

The customers total bill. Customers gender(sex). Time of day. Is the customer a smoker or not? The size of the group

Methodology

Thorough Data Cleaning In this step, we clean the dataset by checking for missing values.None was found. we also check for duplicates. Only one record was found but we shall use it since it is very likely to have duplicate records based on the variables in the data. We then ensure that each column has the correct datatype in preparation for further analysis and modelling.

Univariate analysis Here we check the distribution of each and every column in a bid to understand how each varies. We also analyse the measures of central tendency for numerical columns and vlaue counts for categorical columns.

Bivariate Analysis Analysing the relationships between variables in pairs. Some of the pairs include: Total_bill vs the tip amount, Gender distribution, gender vs smoker

Regression Modelling: modelling the data using a multiple Linear Regression model.

Conclusion Documenting the findings, reports and references. Was the analysis successful? Was the data sufficient? Was the statistical approach appropriate? How relevant is the analysis and who are the beneficiaries?

Data Source and relevance

Data: https://www.kaggle.com/jsphyg/tipping

One data set will be used to investigate the factors that influence how customers tip in restaurants.The dataset is from kaggle which is a credible data source for data science projects. The data has 244 rows and 7 columns which is enough to train and test the results of our model. One waiter recorded information about each tip he received over a period of a few months working in one restaurant.

Can you predict the tip amount?

Model

A Multiple Linear Regression was used for this analysis since we have more than one predictor variable. The coefficients then indicate which variables affect the dependent variable the most. Postive values depict a positive correlation while negative coefficients indicate low or no correlation. The coefficients are then used to predict the response variable. The general equation for a multiple linear regression is

y = a + b1x1 + b2x2 +... bnxn.

y is the response variable.

a, b1, b2... bn are the coefficients.

x1, x2, ... xn are the predictor variables.

Data Cleaning

```r
library("readr")
df <- read.csv("tips.csv")
head(df)
```

Loading the dataset

```
##   total_bill  tip    sex smoker day   time size
## 1      16.99 1.01 Female     No Sun Dinner    2
## 2      10.34 1.66   Male     No Sun Dinner    3
## 3      21.01 3.50   Male     No Sun Dinner    3
## 4      23.68 3.31   Male     No Sun Dinner    2
## 5      24.59 3.61 Female     No Sun Dinner    4
## 6      25.29 4.71   Male     No Sun Dinner    4
```

```r
tips_df <- data.frame(df)
head(tips_df)
```

Previewing the top of the dataset

```
##   total_bill  tip    sex smoker day   time size
## 1      16.99 1.01 Female     No Sun Dinner    2
## 2      10.34 1.66   Male     No Sun Dinner    3
## 3      21.01 3.50   Male     No Sun Dinner    3
## 4      23.68 3.31   Male     No Sun Dinner    2
## 5      24.59 3.61 Female     No Sun Dinner    4
## 6      25.29 4.71   Male     No Sun Dinner    4
```

```r
summary(tips_df)
```

Previewing the summary of the dataset

```
##    total_bill         tip               sex                smoker         
##  Min.   : 3.07   Min.   : 1.000   Length:244         Length:244        
##  1st Qu.:13.35   1st Qu.: 2.000   Class :character   Class :character  
##  Median :17.80   Median : 2.900   Mode  :character   Mode  :character  
##  Mean   :19.79   Mean   : 2.998                                        
##  3rd Qu.:24.13   3rd Qu.: 3.562                                        
##  Max.   :50.81   Max.   :10.000                                        
##      day                time                size     
##  Length:244         Length:244         Min.   :1.00  
##  Class :character   Class :character   1st Qu.:2.00  
##  Mode  :character   Mode  :character   Median :2.00  
##                                        Mean   :2.57  
##                                        3rd Qu.:3.00  
##                                        Max.   :6.00
```

Properties of the dataset

```r
dim(tips_df)
```

Dimensions

```
## [1] 244   7
```

```r
#The dataframe has 244 row entries and 7 columns
```

```r
colnames(tips_df)
```

Column Names

```
## [1] "total_bill" "tip"        "sex"        "smoker"     "day"
## [6] "time"       "size"
```

```r
#The seven column names are:
```

```r
sapply(tips_df, class)
```

Column data types

```
##  total_bill         tip         sex      smoker         day        time
##   "numeric"   "numeric" "character" "character" "character" "character"
##        size
##   "integer"
```

Data Cleaning

Missing values

```r
#Checking the sum of missing values per column
colSums(is.na(tips_df))
```

```
## total_bill        tip        sex     smoker        day       time       size
##          0          0          0          0          0          0          0
```

```r
#there are no misssing values in the data
```

Duplicates

```r
duplicated_rows <- tips_df[duplicated(tips_df),]
duplicated_rows
```

```
##     total_bill tip    sex smoker  day  time size
## 203         13   2 Female    Yes Thur Lunch    2
```

```r
#there is one duplicate entry in the data
#we shall retain the duplicate record because based on the coulmn values it is possible to have similar
```

Checking the appropriate datatypes for each column

```
sapply(tips_df, class)
```

```
##  total_bill         tip         sex      smoker         day        time
##   "numeric"   "numeric" "character" "character" "character" "character"
##        size
##   "integer"
```

Univarite analysis

```
#install.packages("pacman")
figure_nums <- captioner::captioner(prefix = "Fig")
```

```
#Checking customer spending in the restaurant (Bill)

# mean
mean(tips_df$total_bill)
```

Total Bill

```
## [1] 19.78594
```

```
# median
median(tips_df$total_bill)
```

```
## [1] 17.795
```

```
# mode
x <- tips_df$total_bill
#sort(x)
names(table(x))[table(x)==max(table(x))]
```

```
## [1] "13.42"
```

```
#each of the values printed below appear thrice in the dataset


#distribution
hist(x, col=c("darkorange"))
```

Most of the customers spend between 10 and 25 dollars in the restaurant

The users spend an average 19.78594 dollars for their meals.

The modal amount spent on the site "13.42"

The median amount spent is 17.795.

The distribution above is right-skewed.

```
# mean
mean(tips_df$tip)
```

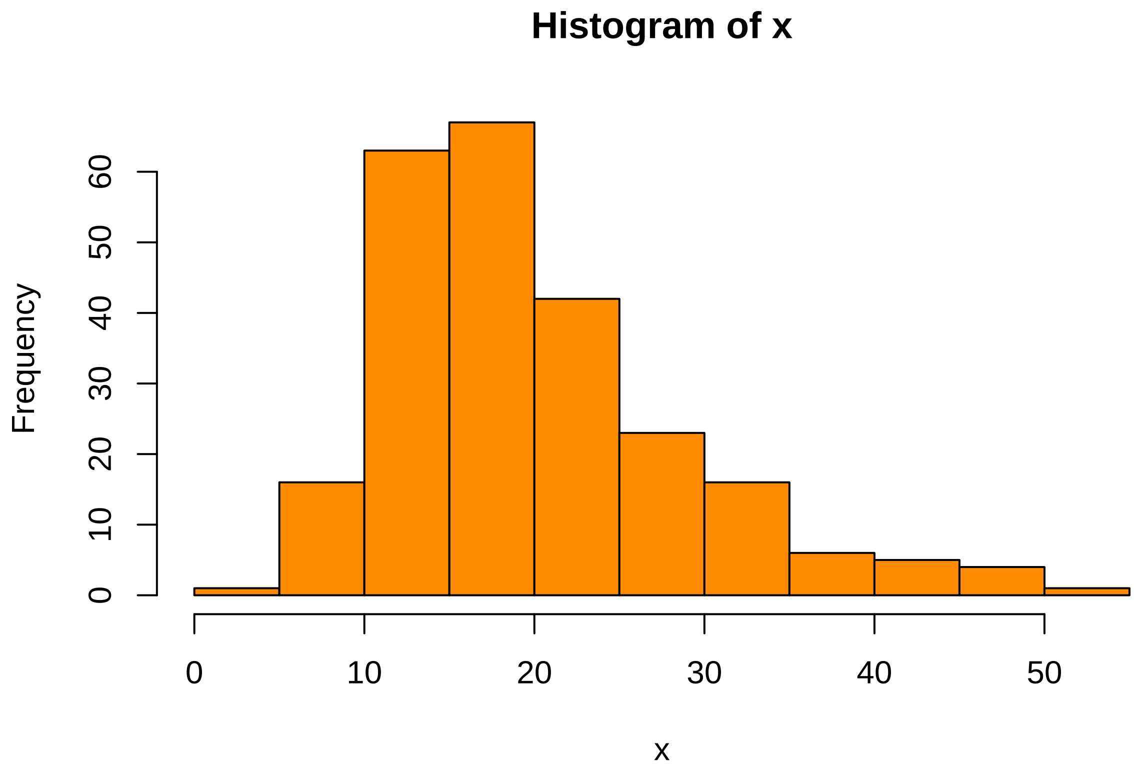

Figure 1: Plot1: Histogram of Total bill

Tip

```
## [1] 2.998279
```

```
# median
median(tips_df$tip)
```

```
## [1] 2.9
```

```
# mode
a <- tips_df$tip
#sort(x)
names(table(a))[table(a)==max(table(a))]
```

```
## [1] "2"
```

```
#distribution
hist(a, col=c("pink"))
```

The average amount of tips is 2.998279 dollars

The modal tip is 2 dollars

The median tip is 2.9 dollars.

The distribution above is right-skewed.

The highest frequency is 0-5 dollars.

The highest tip given is 7 dollars.

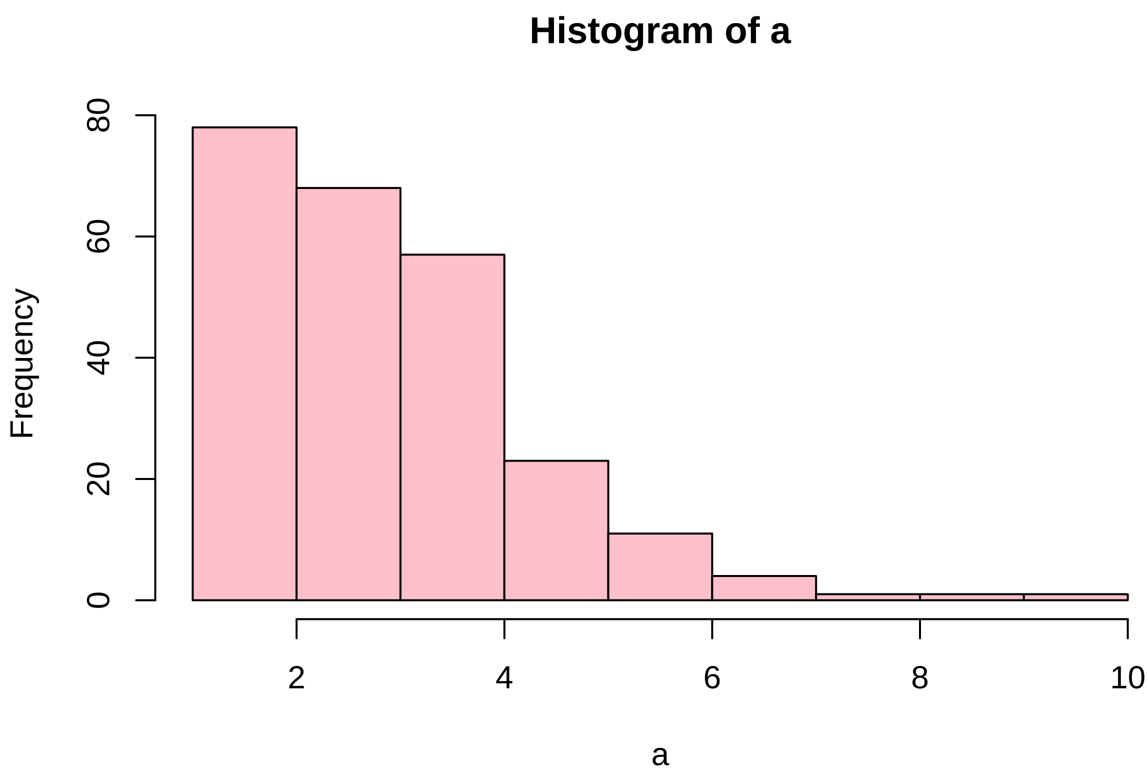

Figure 2: Plot2: Histogram of Tips

Sex

```
#gender of the user
# measures of central tendency

unique(factor(tips_df$sex))
```

Male

```
## [1] Female Male
## Levels: Female Male
```

```
gender_df <- table(tips_df$sex)
#distribution
barplot(gender_df, main="Gender Distribution",col=c("darkgreen"),xlab="Gender")
```

The gender distribution is not equal. The males are twice the females.

This also means that most people who eat in restaurants are male.

```
#This column indicates whether a customer is a smoker or not.

unique(factor(tips_df$smoker))
```

Smoker

```
## [1] No  Yes
```

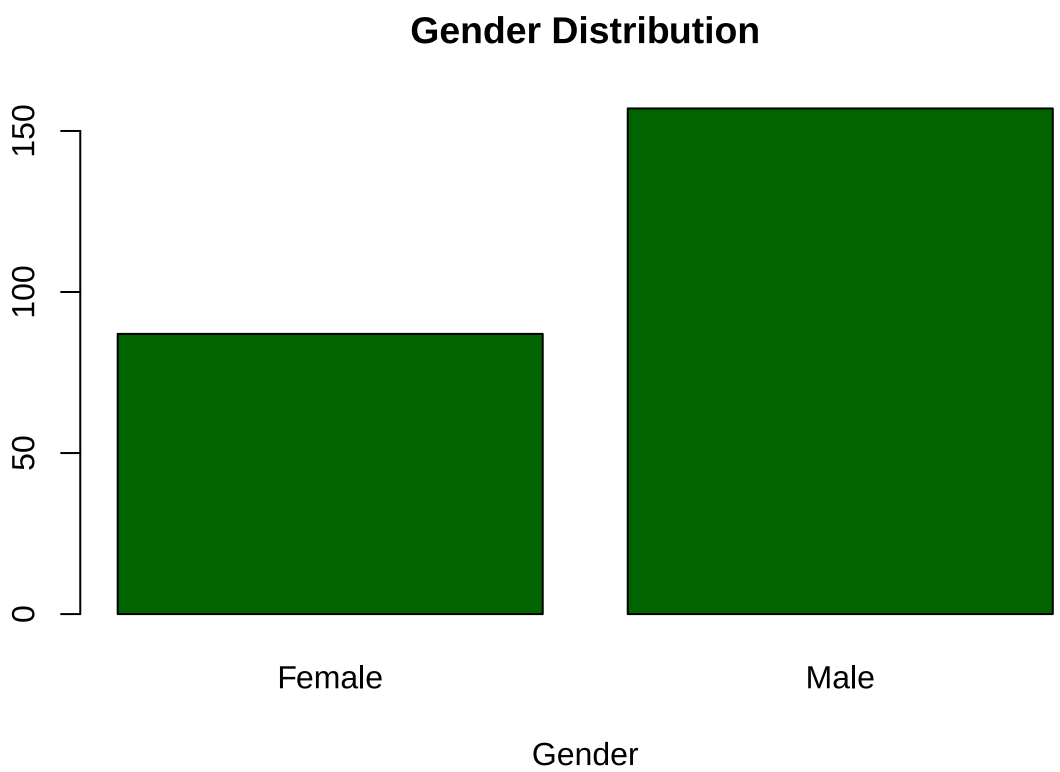

Figure 3: Plot3: Barplot of Gender

```
## Levels: No Yes
```

```
smoker_df <- table(tips_df$smoker)
#distribution
barplot(smoker_df, main="Smoker Distribution",col=c("brown"),xlab="Smoker")
```

Most of the customers who visit the restaurant are not smokers and the number of non-smokers are twice the number of smokers.

```

#Day of the week

unique(factor(tips_df$day))
```

Day

```
## [1] Sun  Sat  Thur Fri
## Levels: Fri Sat Sun Thur
```

```
day_df <- table(tips_df$day)
#distribution
barplot(day_df, main="Day of the Week",col=c("yellow"),xlab="Day")
```

The data was obtained from Thursday through to Sunday

Friday has the least number of customers.

Satruday has the most number of customers.

Saturday and Sunday are the busiest days.

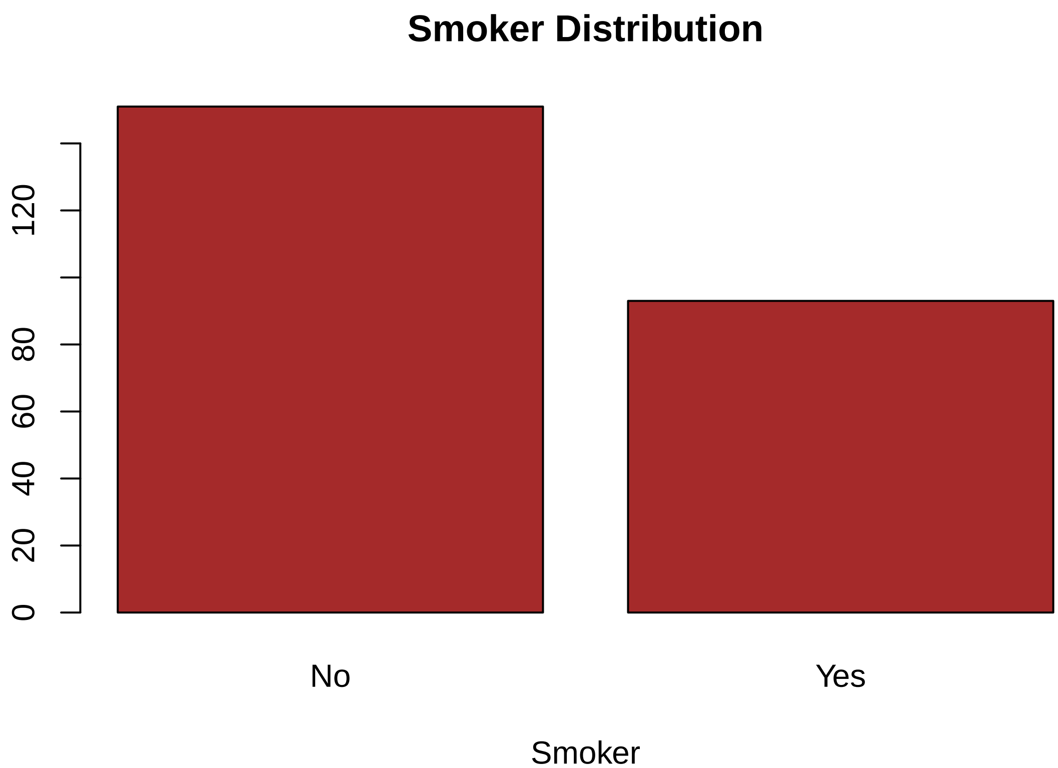

Figure 4: Plot4: Barplot of Smokers

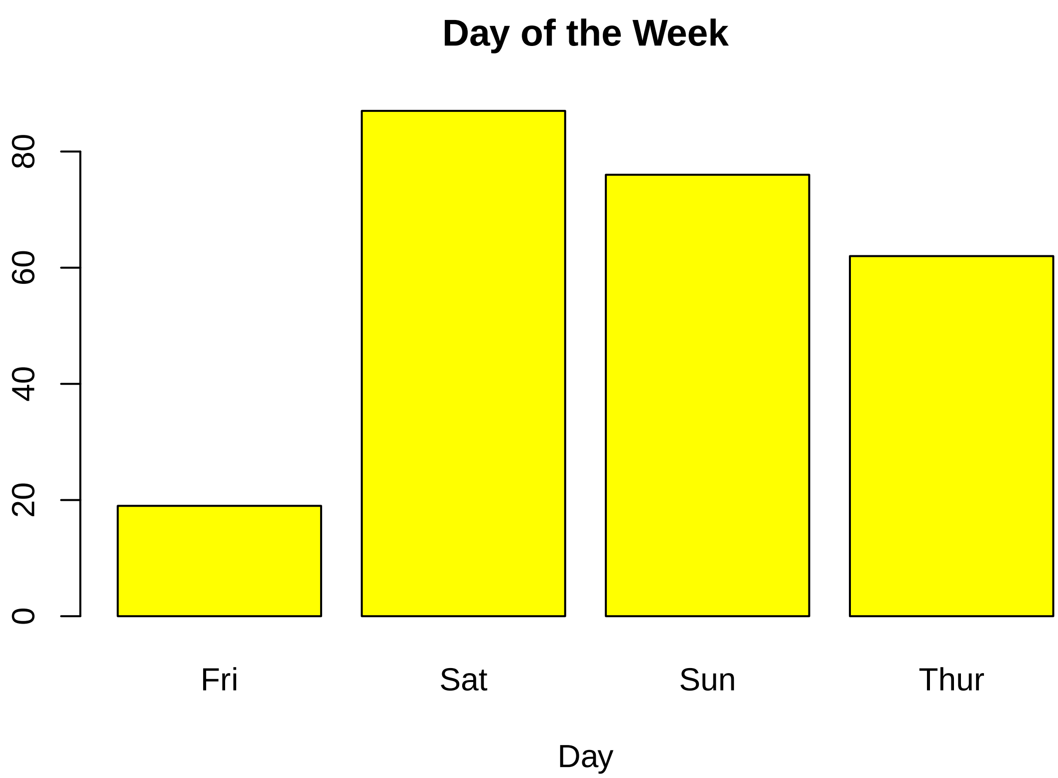

Figure 5: Plot5: Barplot of Days

```r
#Time of Day

unique(factor(tips_df$time))
```

Time

```
## [1] Dinner Lunch
## Levels: Dinner Lunch
```

```r
time_df <- table(tips_df$time)
#distribution
barplot(time_df, main="Time Distribution",col=c("darkblue"),xlab="Time")
```

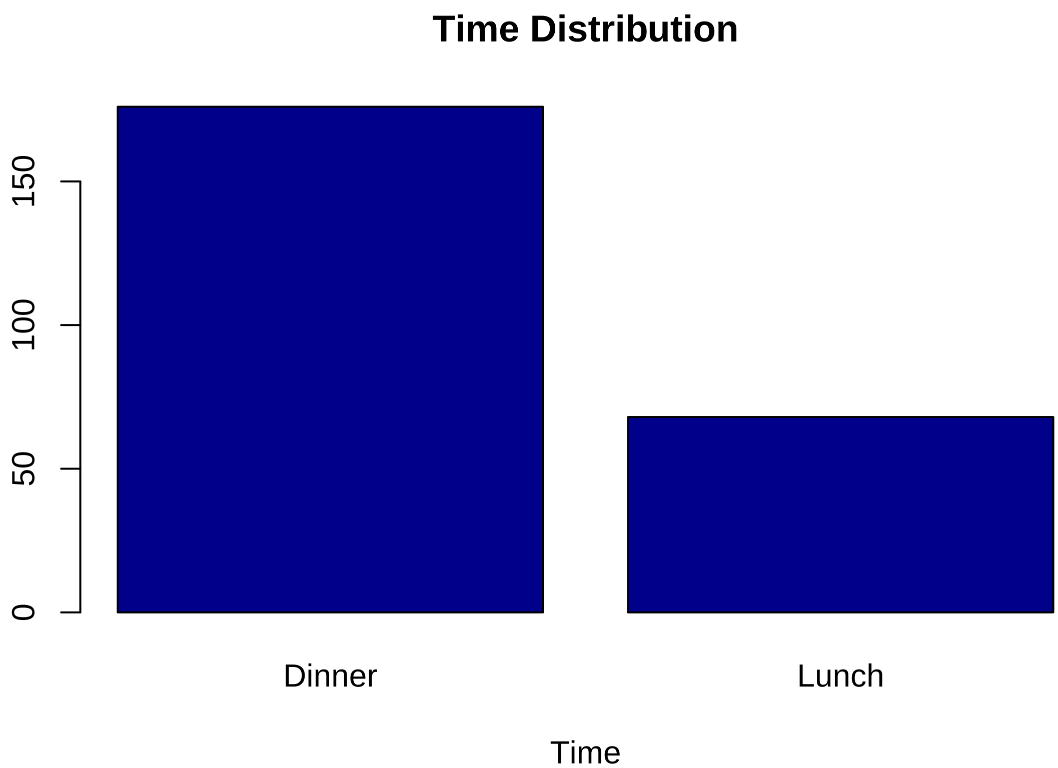

Figure 6: Plot6: Barplot of Time

Most of the clients have dinner at the restaurant as opposed to having lunch there.

```r
unique(factor(tips_df$size))
```

Size

```
## [1] 2 3 4 1 6 5
## Levels: 1 2 3 4 5 6
```

```r
size_df <- table(tips_df$size)
#distribution
barplot(size_df, main="Size Distribution",col=c("purple"),xlab="size")
```

The most popular number for the amount of diners is 2.

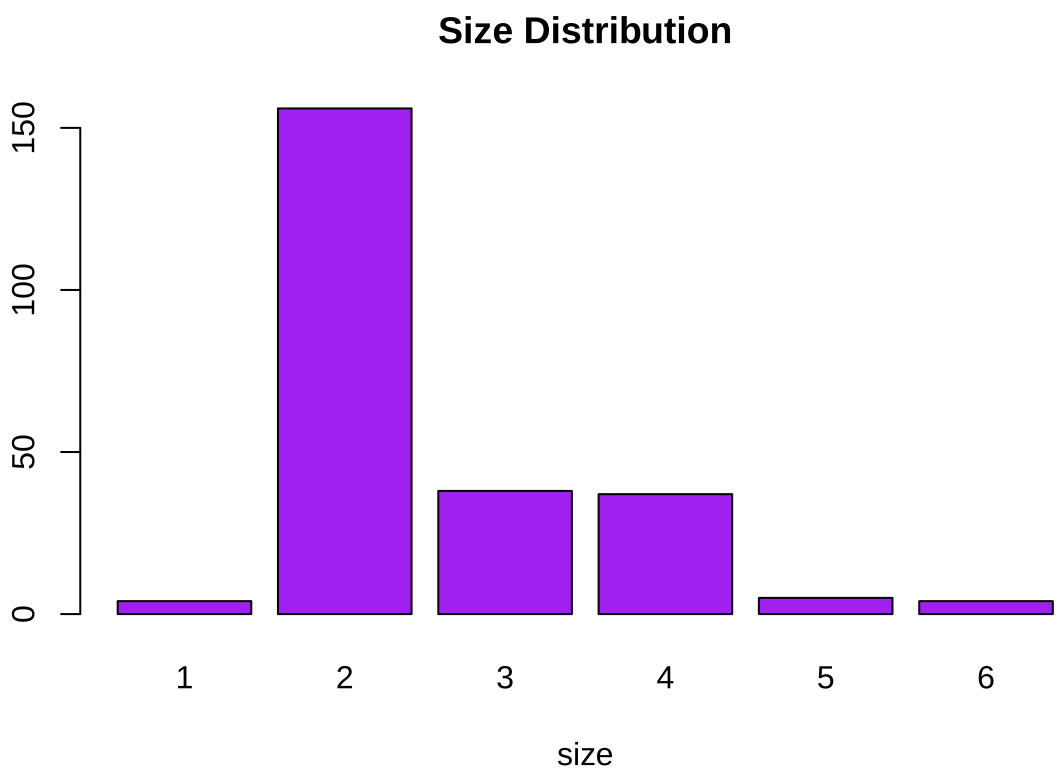

Figure 7: Plot7: Barplot of Size

very few customers visit the restaurant by themselves.

Groups of 3 and 4 are abit common.

there are no groups for more than six customers in one sitting.

Bivariate Analysis and Multivariate Graphical Data Analysis

```
#substettng the data for further numerical analysis
tips_df2 <- subset(tips_df, select = c(total_bill,tip,size  ))

head(tips_df2)
```

```
##   total_bill  tip size
## 1      16.99 1.01    2
## 2      10.34 1.66    3
## 3      21.01 3.50    3
## 4      23.68 3.31    2
## 5      24.59 3.61    4
## 6      25.29 4.71    4
```

Correlation

```
#The default method is Pearson, but we can also compute Spearman or Kendall coefficients.
mydata = cor(tips_df2, method = c("spearman"))
```

```r
mydata1= cor(tips_df2, method = c("kendall"))
mydata2= cor(tips_df2, method = c("pearson"))

mydata #spearman
```

```
##            total_bill       tip      size
## total_bill  1.0000000 0.6789681 0.6047911
## tip         0.6789681 1.0000000 0.4682679
## size        0.6047911 0.4682679 1.0000000
```

```r
mydata1 #kendall
```

```
##            total_bill       tip      size
## total_bill  1.0000000 0.5171810 0.4843421
## tip         0.5171810 1.0000000 0.3781847
## size        0.4843421 0.3781847 1.0000000
```

```r
mydata2 #pearson
```

```
##            total_bill       tip      size
## total_bill  1.0000000 0.6757341 0.5983151
## tip         0.6757341 1.0000000 0.4892988
## size        0.5983151 0.4892988 1.0000000
```

Using the 3 correlation coefficients to get the correlation between the features, we can see that the correlation is average in most cases.

This means that most of the variables are somewhat dependent of each other

Significance levels (p-values) can also be generated using the rcorr function which is

found in the Hmisc package.

```r
#mydata.coeff = mydata.rcorr$r
#mydata.p = mydata.rcorr$P
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```r
corrplot(mydata)
```

A default correlation matrix plot (called a Correlogram) is generated. Positive

correlations are displayed in a blue scale while negative correlations are displayed

in a red scale

There is average positive correlation between the variables in the data.

The Plots below are scatterplots of a few pairs of variables

```r
# Libraries
library(ggplot2)

# create data
amount_spent <- tips_df$total_bill
Tip <- tips_df$tip
data <- data.frame(amount_spent,Tip)
```

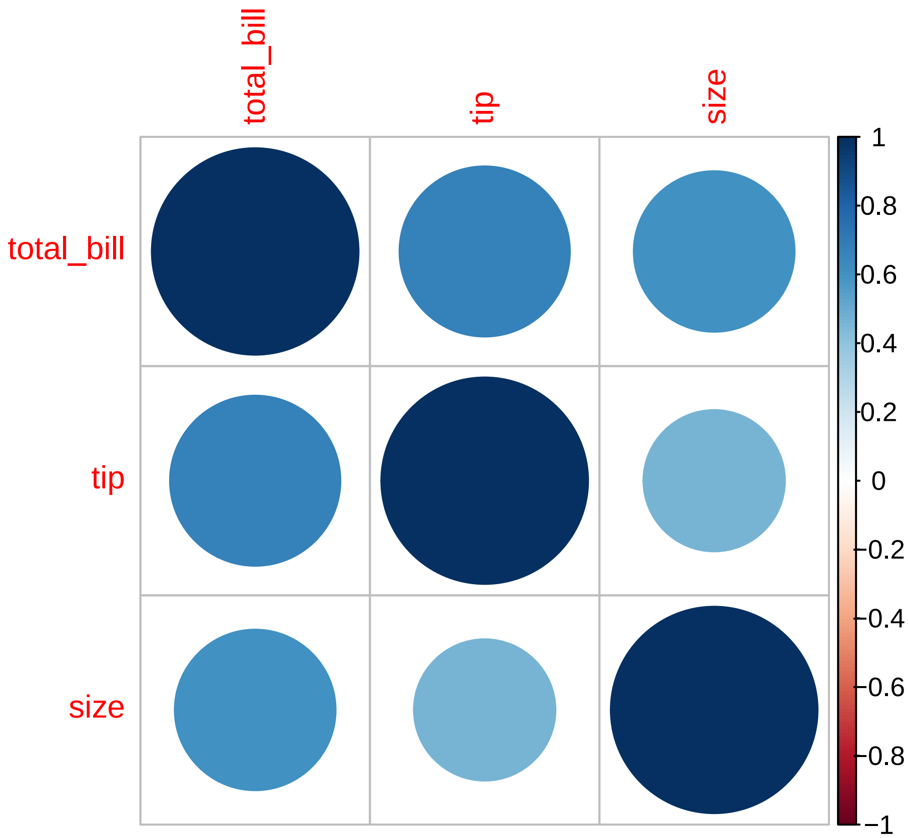

Figure 8: Plot8: Corrplot of Total_bill, Tips and Size

```r
# Plot
ggplot(data, aes(x=amount_spent, y=Tip)) + geom_point()
```

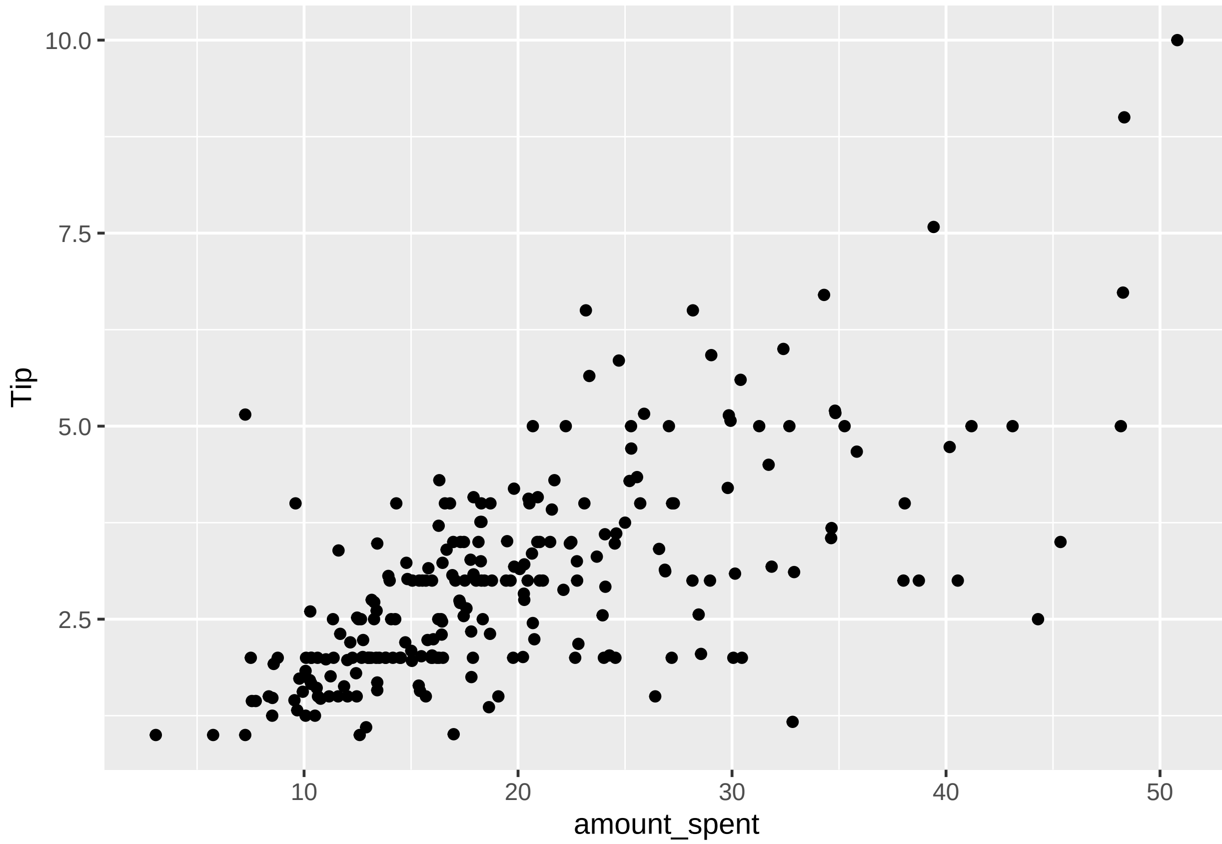

Figure 9: Plot9: Plot of Amount spent vs Tips

```r
#positive non-linear correlation

avg_tip_percentage <- transform(tips_df, new = amount_spent / Tip)
mean(avg_tip_percentage[["new"]])
```

Amount spent in the restaurant vs amount of tip

```
## [1] 7.048932
```

```r
#The average tipping rate is 7.048%
```

```r
library(tidyverse)
```

sex VS Smoker

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --

## v tibble  3.0.4     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v purrr   0.3.4     v forcats 0.5.0
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
#Male respondents who clicked on an add
dim(tips_df%>% filter(sex == 'Male', smoker == 'No'))
```

```
## [1] 97  7
```

```r
#97

#Male respondents did not click on an add
dim(tips_df%>% filter(sex == 'Female', smoker == 'No'))
```

```
## [1] 54  7
```

```r
#54

#Female respondents who clicked on an add
dim(tips_df%>% filter(sex == 'Male' , smoker == 'Yes'))
```

```
## [1] 60  7
```

```r
# 60

#Female respondents who clicked did not on an add
dim(tips_df%>% filter(sex == 'Female', smoker == 'Yes'))
```

```
## [1] 33  7
```

```r
# 33
```

```r
gender_vs_smoker <- c( 97 , 54 , 60 , 33 )

# barchart with added parameters
barplot(gender_vs_smoker, main = " gender_vs_smoker " , xlab = " Label ", ylab = " Count ",
names.arg = c("Male&Non-smoker Female&Non-smoker Male&Smoker Female&Smoker"),
col = "darkred",
horiz = FALSE)
```

There are more male smokers than female smokers.

The number of male non-smokers is also high indicating a gender bias in the data.

The number of female non-smokers is higher than that of female smokers.

Multivariate Analysis

```r
# A glimpse of the data
library(dplyr)
glimpse(tips_df2)
```

```
## Rows: 244
## Columns: 3
## $ total_bill <dbl> 16.99, 10.34, 21.01, 23.68, 24.59, 25.29, 8.77, 26.88, 1...
## $ tip        <dbl> 1.01, 1.66, 3.50, 3.31, 3.61, 4.71, 2.00, 3.12, 1.96, 3....
## $ size       <int> 2, 3, 3, 2, 4, 4, 2, 4, 2, 2, 2, 4, 2, 4, 2, 2, 3, 3, 3,...
```

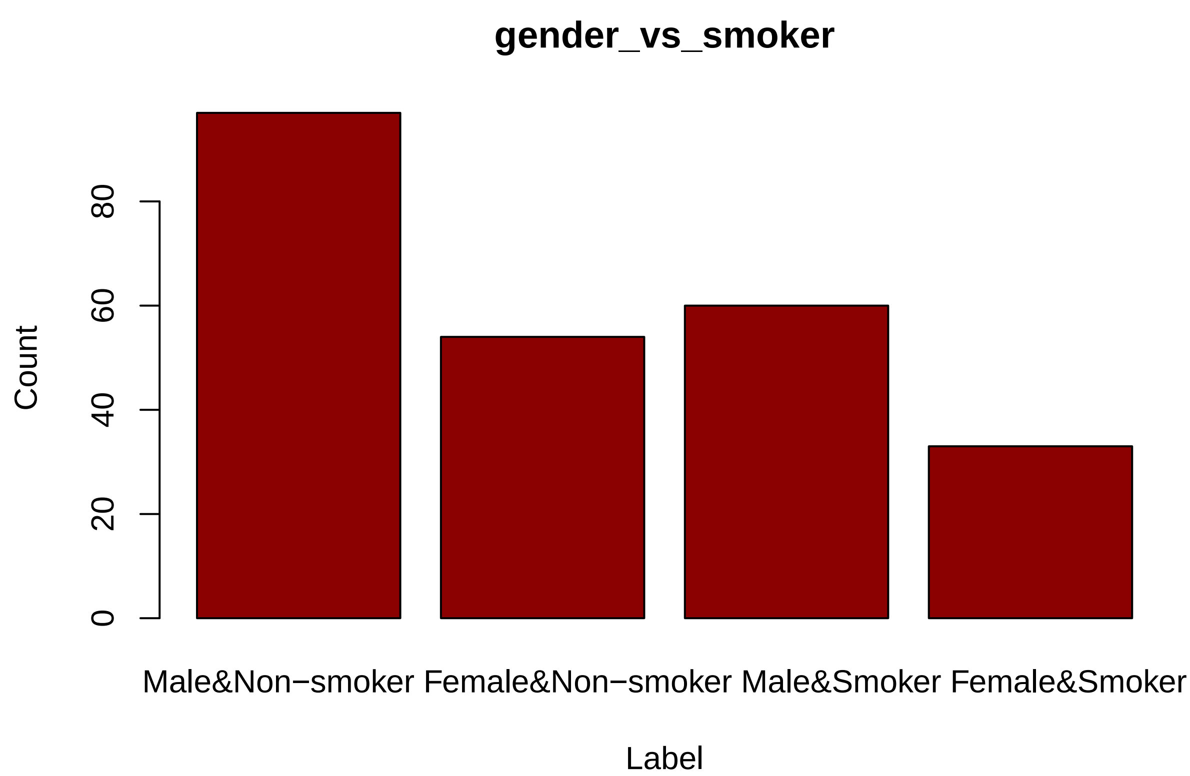

Figure 10: Plot10: Barplot of Gender vs Smoker

```r
head(tips_df)
```

```
##   total_bill  tip    sex smoker day   time size
## 1      16.99 1.01 Female     No Sun Dinner    2
## 2      10.34 1.66   Male     No Sun Dinner    3
## 3      21.01 3.50   Male     No Sun Dinner    3
## 4      23.68 3.31   Male     No Sun Dinner    2
## 5      24.59 3.61 Female     No Sun Dinner    4
## 6      25.29 4.71   Male     No Sun Dinner    4
```

```r
#subsetting the data
tips_df3 <- subset(tips_df, select = c(sex,smoker,day,time))

head(tips_df3)
```

```
##      sex smoker day   time
## 1 Female     No Sun Dinner
## 2   Male     No Sun Dinner
## 3   Male     No Sun Dinner
## 4   Male     No Sun Dinner
## 5 Female     No Sun Dinner
## 6   Male     No Sun Dinner
```

```r
#converting the sex column to categorical variables.
#Code
tips_df4 <- as.data.frame(apply(tips_df3,2,function(x) {x<-as.numeric(factor(x,levels = unique(x)))}))
```

```r
head(tips_df4)
```

```
##   sex smoker day time
## 1   1      1   1    1
## 2   2      1   1    1
## 3   2      1   1    1
## 4   2      1   1    1
## 5   1      1   1    1
## 6   2      1   1    1
```

```r
#confirming that we have the right number of unique values.

#Code
#how many unique items are in the sex column
length(unique(unlist(tips_df4[c("sex")])))
```

```
## [1] 2
```

```r
#how many unique items are in the smoker column
length(unique(unlist(tips_df4[c("smoker")])))
```

```
## [1] 2
```

```r
#hoe many unique items are in the day column
length(unique(unlist(tips_df4[c("day")])))
```

```
## [1] 4
```

```r
#hoe many unique items are in the time column
length(unique(unlist(tips_df4[c("time")])))
```

```
## [1] 2
```

```r
# horizontal merge
d <- merge(tips_df2, tips_df4, all="true")
head(d)
```

```
##   total_bill  tip size sex smoker day time
## 1      16.99 1.01    2   1      1   1    1
## 2      10.34 1.66    3   1      1   1    1
## 3      21.01 3.50    3   1      1   1    1
## 4      23.68 3.31    2   1      1   1    1
## 5      24.59 3.61    4   1      1   1    1
## 6      25.29 4.71    4   1      1   1    1
```

Modelling

```r
head(d)
```

```
##   total_bill  tip size sex smoker day time
## 1      16.99 1.01    2   1      1   1    1
## 2      10.34 1.66    3   1      1   1    1
## 3      21.01 3.50    3   1      1   1    1
## 4      23.68 3.31    2   1      1   1    1
## 5      24.59 3.61    4   1      1   1    1
## 6      25.29 4.71    4   1      1   1    1
```

Linear Regression

Create Training and Test data

```r
model <- lm(tip ~ total_bill+size+sex+smoker+day+time, data = d)
summary(model)
```

```
##
## Call:
## lm(formula = tip ~ total_bill + size + sex + smoker + day + time,
##     data = d)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9279 -0.5547 -0.0852  0.5095  4.0425
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.689e-01  2.711e-02   24.67   <2e-16 ***
## total_bill   9.271e-02  5.799e-04  159.87   <2e-16 ***
## size         1.926e-01  5.428e-03   35.48   <2e-16 ***
## sex         -3.507e-14  8.860e-03    0.00        1
## smoker      -1.446e-14  8.871e-03    0.00        1
## day         -1.723e-14  6.261e-03    0.00        1
## time         8.902e-15  1.280e-02    0.00        1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.007 on 59529 degrees of freedom
## Multiple R-squared:  0.4679, Adjusted R-squared:  0.4678
## F-statistic:  8723 on 6 and 59529 DF,  p-value: < 2.2e-16
```

The p-value is lower than the significance level which means that the model is statistically significant.

Next, we examine the coefficients table to obtain the estimate of regression beta coefficients and the associated t-statitic p-values

```r
summary(model)$coefficient
```

```
##                  Estimate   Std. Error       t value      Pr(>|t|)
## (Intercept)  6.689447e-01 0.0271112043  2.467411e+01 9.569756e-134
## total_bill   9.271334e-02 0.0005799436  1.598661e+02  0.000000e+00
## size         1.925978e-01 0.0054283441  3.548003e+01 7.149936e-273
## sex         -3.506477e-14 0.0088596104 -3.957823e-12  1.000000e+00
## smoker      -1.446117e-14 0.0088708869 -1.630183e-12  1.000000e+00
## day         -1.722720e-14 0.0062613841 -2.751340e-12  1.000000e+00
## time         8.901614e-15 0.0127954921  6.956836e-13  1.000000e+00
```

The coefficients show us that total bill, time and size affect the size of the tip given while sex, smoker and day do not affect tip amounts

```r
model2  <- lm(tip ~total_bill+size+time, data = d)
summary(model2)
```

```
##
## Call:
## lm(formula = tip ~ total_bill + size + time, data = d)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9279 -0.5547 -0.0852  0.5095  4.0425
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.689e-01  1.704e-02   39.26   <2e-16 ***
## total_bill   9.271e-02  5.799e-04  159.87   <2e-16 ***
## size         1.926e-01  5.428e-03   35.48   <2e-16 ***
## time        -6.531e-15  9.208e-03    0.00        1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.007 on 59532 degrees of freedom
## Multiple R-squared:  0.4679, Adjusted R-squared:  0.4678
## F-statistic: 1.745e+04 on 3 and 59532 DF,  p-value: < 2.2e-16
```

```r
confint(model2)
```

```
##                   2.5 %     97.5 %
## (Intercept)  0.63554615 0.70234333
## total_bill   0.09157667 0.09385000
## size         0.18195849 0.20323710
## time        -0.01804682 0.01804682
```

```r
sigma(model2)/mean(d$tip)
```

```
## [1] 0.3359561
```

Our model has a 33% error rate

The value for R2 indicates the level of accuracy of the model. The R2 value is 46.79 for both models.

To increase the level of accuracy, we can train using more data, use a more robust algorithm such as gradient boost.

Discussion

Our analysis indicates that it is possible to predict a waiters with 67% accuracy. The factors that influence the amount of tip the most are the total bill, size of the group and the time when the meal was taken. The average tipping rate is 7.048% of the total bill. Tips are an acceptable secondary source of income for servers thus one can calculate their earnings if the total bill is known. 67% is the confidence level and it is abit low. Therefore, some enhancements are necessary to increase the level of accuracy.

Conclusions:

The analysis was completed successfully. A multiple Linear regression was used to predict a waiters tip amount using other dependent variables. The coefficients of sex is -3.653905e-14 , that of being a smoker is -1.493559e-14 and for the day of week is -1.779964e-14. All the three coefficients are negative meaning that they do not affect the dependent variable(Amount of tip in dollars). The t-statistic for sex is -4.124228e-12, for that of smoker is -1.683664e-12 and day is -2.842765e-12 which further supports previous findings that the three variables have a negative relationship with the dependent variable.

Weaknesses of the analysis. The dataset had 244 records which means that the data may be insuffucient for modelling.

Some of the variables sucha as sex, smoker and day do not influence tipping decisions.

Future steps of the analysis. using a larger dataset

Using variables that with a positive correlation towards the dependent variable.

References:

Data: https://www.kaggle.com/jsphyg/tipping

Bryant, P. G. and Smith, M (1995) Practical Data Analysis: Case Studies in Business Statistics. Homewood, IL: Richard D. Irwin Publishing

Introduction: The promise of collaborative public service delivery. (2019). Collaboration in Public Service Delivery, 1-1. https://doi.org/10.4337/9781788978583.00008

Rathore, S. (2015). Capturing, analyzing, and managing word-of-Mouth in the digital marketplace. IGI Global.

Toporek, A. (2015). Be your customer's hero: Real-world tips and techniques for the service front lines. AMACOM.