Final Project Report

Title: Enhancing City Mobility with Cab Data Analytics

Project Group

Khalil Sani Muhammad	A20526151	ksani1@hawk.iit.edu
Ritu Tushar Bagul	A20548051	rbagul@hawk.iit.edu
Mrinal Raj Lakkimsetty	A20531613	mraj3@hawk.iit.edu

Project Group Leader:

Khalil Sani Muhammad	A20526151	ksani1@hawk.iit.edu

Abstract

This report presents a comprehensive analysis of predictive models for estimating ride-hailing prices for two major service providers: Uber and Lyft. Employing Linear Regression, Decision Trees, and Random Forest algorithms, we aimed to construct models that accurately predict pricing based on a variety of features, including distance, time, weather conditions, and service type. The objective was to understand the dynamic pricing mechanisms and provide a tool for users to anticipate ride costs.

Linear Regression models capitalized on the strong linear relationship between features and pricing, offering simplicity and efficiency, particularly effective for Uber's pricing structure. Decision Trees provided valuable insights into the feature splits and decision-making logic but faced challenges with model overfitting, impacting their performance notably for Lyft. Random Forest emerged as the superior model for Lyft, demonstrating robustness against overfitting and handling complex interactions between features effectively.

The analysis conducted revealed the nuanced differences in the pricing models of the two companies and illustrated the strengths and weaknesses of each predictive technique. These insights guide users in model selection based on the accuracy, complexity, and interpretability requirements of their specific applications.

The predictive models were evaluated against multiple performance metrics to ensure reliability and to understand their practical implications. This report includes recommendations based on the empirical results, advocating for the appropriate use of each model and suggesting a path forward for future enhancements.

Overview

Problem Statement: This project aims to analyze the dynamics of pricing and service patterns between Uber and Lyft ride-sharing services, focusing on how external factors such as weather conditions influence pricing strategies and ride demand.

Literature Review

The expansion of ride-sourcing services, particularly Uber and Lyft, has significantly transformed urban mobility, prompting a wide range of academic investigations into their operational dynamics, market impacts, and interactions with city infrastructure. This review consolidates findings from recent empirical studies focused on these services within diverse urban settings.

Shashank H. (2020) delves into the data produced by Uber and Lyft customers, highlighting the sheer volume of daily trips and the consequent data available for analysis. The study utilizes linear and logistic regression models, coupled with machine learning algorithms, to predict ride fares by incorporating various factors, including weather conditions and surge pricing dynamics. This approach aims to provide consumers with accurate fare estimates before ride commencement, enhancing decision-making processes for urban commuters (Shashank H., 2020).

Expanding on the theme of ride-sourcing services' operational strategies, (Jiang et al, .2018) offer a comprehensive comparison between Uber, Lyft, and traditional taxi services. Their research focuses on key market aspects such as supply, demand, pricing, and wait times, particularly in the contexts of San Francisco and New York City. By employing spatial lag models and point pattern statistics, the study sheds light on the accessibility of vehicle-for-hire (VFH) services and their relationship with urban transportation infrastructures and socio-economic factors (Jiang et al., 2018).

Jingyu Sun (2022) contributes to this body of literature by providing a detailed analysis of Uber and Lyft's market strategies and their implications for the ride-hailing ecosystem. The research emphasizes the dynamic nature of surge pricing and its effects on driver supply and consumer behavior. Sun's work offers insights into the competitive landscape of ride-sourcing services and their operational differences from traditional taxis, highlighting the technological and regulatory challenges faced by these platforms (Sun, 2018).

Data Processing

Data processing and pipeline:

Our approach to data pre-processing aims to ensure the integrity and usability of the dataset for accurate modeling and analysis. We have addressed several critical issues during the pre-processing phase:

Handling Missing Values and Inconsistencies:

The dataset presented challenges with numerous missing values and inconsistencies in column labels across different files. This was particularly noticeable in the source and destination names, where a high number of missing values could significantly skew the results of the analysis. To mitigate these issues, we have standardized the naming conventions and addressed missing information to ensure uniformity and completeness across the dataset.

Standardizing Date-Time Formats:

We encountered varying date-time formats across different files, complicating the merging and analytical processes. By standardizing these formats, we have streamlined the dataset, facilitating more straightforward integration and analysis.

Data Type Discrepancies:

Discrepancies in data type values for the same features across different files were identified, which could lead to integration and analysis errors. We have aligned these data types across all files to prevent any discrepancies during the data analysis phase.

Feature Engineering and Modification:

Wherever trip duration was missing, we calculated and added it using the 'started time' and 'ended time' of the trip. Additional columns indicating the day of the week were derived from the date field to provide more depth to the analysis. We ensured that all files share a single standard format for both date-time and other feature values to maintain consistency. To maintain dataset uniformity, columns not common among all files, such as SunriseTime, SunsetTime, and MoonPhase, were dropped. Missing source and destination values were populated using latitude and longitude values to enhance data completeness.

Integrating Weather Data:

The weather data presented a different date format compared to the main datasets, which could lead to incorrect associations between weather conditions and trip data. We have adjusted the date format in the weather dataset to match that of the main dataset, ensuring consistency and accuracy in subsequent analyses. The following are the 23 relevant features after the data preprocessing:

Data Analysis

The following are the 23 relevant features after the data preprocessing:

Fri	Lyft XL	UberPool	Partly Cloudy
Sat	Lux Black XL	UberXL	WAV
Sun	Lux Black	Black	Possible Drizzle
Shared	surge_multiplier	Black SUV	Overcast
Mostly Cloudy	Drizzle	Rain	Light Rain
distance	Partly Cloudy	Foggy	-

```
# Install packages from CRAN
install.packages(c("caret", "sqldf", "tidyr", "tidyverse", "ggplot2", 
"readr", "gmodels", "tm", 
                   "SnowballC", "wordcloud", "RColorBrewer", 
"treemap", "highcharter", "remotes", 
                   "corrplot", "rpart.plot", "magrittr", "dplyr", 
"igraph", "pillar", "repr", 
                   "lifecycle", "ellipsis", "htmltools", "vctrs", 
"lubridate", "Rtsne", "umap", "rlang"))
```

```r
# Install packages from specific sources or GitHub
remotes::install_github("jbkunst/highcharter")

# Load libraries
library(caret)
library(sqldf)
library(tidyr)
library(tidyverse)
library(ggplot2)
library(readr)
library(gmodels)
library(tm)
library(SnowballC)
library(wordcloud)
library(RColorBrewer)
library(treemap)
library(highcharter)
library(corrplot)
library(rpart.plot)
library(magrittr)
library(dplyr)
library(igraph)
library(pillar)
library(repr)
library(lifecycle)
library(ellipsis)
library(htmltools)
library(vctrs)
library(lubridate)
library(Rtsne)
library(umap)
```

```r
install.packages("rlang")
```

```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)
```

```r
install.packages("dplyr")
```

```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)
```

```r
library(dplyr)
```

```
Attaching package: ‘dplyr’
```

```
The following objects are masked from ‘package:stats’:

    filter, lag


The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union


cabDataSet <- read.csv("/content/rideshare_kaggle.csv")
summary(cabDataSet)
      id              timestamp              hour            day       
 Length:693071      Min.   :1.543e+09   Min.   : 0.00   Min.   : 1.00  
 Class :character   1st Qu.:1.543e+09   1st Qu.: 6.00   1st Qu.:13.00  
 Mode  :character   Median :1.544e+09   Median :12.00   Median :17.00  
                    Mean   :1.544e+09   Mean   :11.62   Mean   :17.79  
                    3rd Qu.:1.545e+09   3rd Qu.:18.00   3rd Qu.:28.00  
                    Max.   :1.545e+09   Max.   :23.00   Max.   :30.00  


     month         datetime           timezone             source         
 Min.   :11.00   Length:693071      Length:693071      Length:693071     
 1st Qu.:11.00   Class :character   Class :character   
Class :character
 Median :12.00   Mode  :character   Mode  :character   
Mode  :character
 Mean   :11.59                                                            
 3rd Qu.:12.00                                                            
 Max.   :12.00                                                            


 destination          cab_type          product_id            name          
 Length:693071      Length:693071      Length:693071      
Length:693071
 Class :character   Class :character   Class :character   
```

```
Class :character
 Mode  :character   Mode  :character   Mode  :character
Mode  :character








     price          distance     surge_multiplier    latitude
 Min.   : 2.50   Min.   :0.020   Min.   :1.000    Min.   :42.21
 1st Qu.: 9.00   1st Qu.:1.280   1st Qu.:1.000    1st Qu.:42.35
 Median :13.50   Median :2.160   Median :1.000    Median :42.35
 Mean   :16.55   Mean   :2.189   Mean   :1.014    Mean   :42.34
 3rd Qu.:22.50   3rd Qu.:2.920   3rd Qu.:1.000    3rd Qu.:42.36
 Max.   :97.50   Max.   :7.860   Max.   :3.000    Max.   :42.37
 NA's   :55095
   longitude       temperature    apparentTemperature short_summary

 Min.   :-71.11   Min.   :18.91   Min.   :12.13       Length:693071

 1st Qu.:-71.08   1st Qu.:36.45   1st Qu.:31.91       Class :character

 Median :-71.06   Median :40.49   Median :35.90       Mode  :character

 Mean   :-71.07   Mean   :39.58   Mean   :35.88

 3rd Qu.:-71.05   3rd Qu.:43.58   3rd Qu.:40.08

 Max.   :-71.03   Max.   :57.22   Max.   :57.22



 long_summary       precipIntensity    precipProbability    humidity

 Length:693071      Min.   :0.000000   Min.   :0.0000
Min.   :0.3800
 Class :character   1st Qu.:0.000000   1st Qu.:0.0000    1st
Qu.:0.6400
 Mode  :character   Median :0.000000   Median :0.0000
Median :0.7100
                    Mean   :0.008922   Mean   :0.1461
Mean   :0.7411
                    3rd Qu.:0.000000   3rd Qu.:0.0000    3rd
Qu.:0.8800
                    Max.   :0.144700   Max.   :1.0000
Max.   :0.9600
```

```
   windSpeed         windGust      windGustTime         visibility
 Min.   : 0.450   Min.   : 0.80   Min.   :1.543e+09   Min.   : 0.717
 1st Qu.: 3.410   1st Qu.: 4.06   1st Qu.:1.543e+09   1st Qu.: 8.432
 Median : 5.910   Median : 7.55   Median :1.544e+09   Median : 9.880
 Mean   : 6.186   Mean   : 8.47   Mean   :1.544e+09   Mean   : 8.468
 3rd Qu.: 8.410   3rd Qu.:11.74   3rd Qu.:1.545e+09   3rd Qu.: 9.996
 Max.   :15.000   Max.   :27.25   Max.   :1.545e+09   Max.   :10.000

 temperatureHigh temperatureHighTime temperatureLow
temperatureLowTime
 Min.   :32.68   Min.   :1.543e+09   Min.   :17.85   Min.   :1.543e+09

 1st Qu.:42.57   1st Qu.:1.543e+09   1st Qu.:30.17   1st Qu.:1.543e+09

 Median :44.68   Median :1.544e+09   Median :34.18   Median :1.544e+09

 Mean   :45.04   Mean   :1.544e+09   Mean   :34.15   Mean   :1.544e+09

 3rd Qu.:46.91   3rd Qu.:1.545e+09   3rd Qu.:38.73   3rd Qu.:1.545e+09

 Max.   :57.87   Max.   :1.545e+09   Max.   :46.60   Max.   :1.545e+09



 apparentTemperatureHigh apparentTemperatureHighTime
apparentTemperatureLow
 Min.   :22.62           Min.   :1.543e+09           Min.   :11.81

 1st Qu.:36.57           1st Qu.:1.543e+09           1st Qu.:27.70

 Median :40.95           Median :1.544e+09           Median :30.03

 Mean   :41.61           Mean   :1.544e+09           Mean   :30.14

 3rd Qu.:44.12           3rd Qu.:1.545e+09           3rd Qu.:35.32

 Max.   :57.20           Max.   :1.545e+09           Max.   :47.25



 apparentTemperatureLowTime     icon               dewPoint
pressure
 Min.   :1.543e+09          Length:693071      Min.   : 4.39
Min.   : 988.1
 1st Qu.:1.543e+09          Class :character   1st Qu.:27.49   1st
Qu.: 999.8
 Median :1.544e+09          Mode  :character   Median :30.69
Median :1009.2
 Mean   :1.544e+09                             Mean   :31.66
Mean   :1010.1
 3rd Qu.:1.545e+09                             3rd Qu.:38.12   3rd
```

```
Qu.:1021.9
 Max.   :1.545e+09                             Max.   :50.67
Max.   :1035.5


  windBearing      cloudCover        uvIndex         visibility.1
 Min.   :  2.0   Min.   :0.0000   Min.   :0.0000   Min.   : 0.717
 1st Qu.:124.0   1st Qu.:0.3700   1st Qu.:0.0000   1st Qu.: 8.432
 Median :258.0   Median :0.8200   Median :0.0000   Median : 9.880
 Mean   :220.1   Mean   :0.6865   Mean   :0.2489   Mean   : 8.468
 3rd Qu.:303.0   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.: 9.996
 Max.   :356.0   Max.   :1.0000   Max.   :2.0000   Max.   :10.000

     ozone        sunriseTime          sunsetTime          moonPhase

 Min.   :269.4   Min.   :1.543e+09   Min.   :1.543e+09
Min.   :0.0900
 1st Qu.:290.9   1st Qu.:1.543e+09   1st Qu.:1.543e+09   1st
Qu.:0.3000
 Median :307.4   Median :1.544e+09   Median :1.544e+09
Median :0.6800
 Mean   :313.5   Mean   :1.544e+09   Mean   :1.544e+09
Mean   :0.5791
 3rd Qu.:331.8   3rd Qu.:1.545e+09   3rd Qu.:1.545e+09   3rd
Qu.:0.7900
 Max.   :378.9   Max.   :1.545e+09   Max.   :1.545e+09
Max.   :0.9300


 precipIntensityMax  uvIndexTime         temperatureMin
temperatureMinTime
 Min.   :0.00000    Min.   :1.543e+09   Min.   :15.63
Min.   :1.543e+09
 1st Qu.:0.00000    1st Qu.:1.543e+09   1st Qu.:30.17   1st
Qu.:1.543e+09
 Median :0.00040    Median :1.544e+09   Median :34.24
Median :1.544e+09
 Mean   :0.03737    Mean   :1.544e+09   Mean   :33.46
Mean   :1.544e+09
 3rd Qu.:0.09160    3rd Qu.:1.545e+09   3rd Qu.:38.88   3rd
Qu.:1.545e+09
 Max.   :0.14590    Max.   :1.545e+09   Max.   :43.10
Max.   :1.545e+09


 temperatureMax  temperatureMaxTime  apparentTemperatureMin
 Min.   :33.51   Min.   :1.543e+09   Min.   :11.81
 1st Qu.:42.57   1st Qu.:1.543e+09   1st Qu.:27.76
 Median :44.68   Median :1.544e+09   Median :30.13
 Mean   :45.26   Mean   :1.544e+09   Mean   :29.73
```

```
 3rd Qu.:46.91   3rd Qu.:1.545e+09   3rd Qu.:35.71
 Max.   :57.87   Max.   :1.545e+09   Max.   :40.05

 apparentTemperatureMinTime apparentTemperatureMax
apparentTemperatureMaxTime
 Min.   :1.543e+09          Min.   :28.95          Min.   :1.543e+09

 1st Qu.:1.543e+09          1st Qu.:36.57          1st Qu.:1.543e+09

 Median :1.544e+09          Median :40.95          Median :1.544e+09

 Mean   :1.544e+09          Mean   :42.00          Mean   :1.544e+09

 3rd Qu.:1.545e+09          3rd Qu.:44.12          3rd Qu.:1.545e+09

 Max.   :1.545e+09          Max.   :57.20          Max.   :1.545e+09



# Basic overview
numRecords <- nrow(cabDataSet)
numAttributes <- ncol(cabDataSet)

overviewTable <- data.frame(
  DocumentName = "rideshare_kaggle.csv",
  Description = "Uber and Lyft rides data in Boston, MA",
  No_of_Records = numRecords,
  No_of_Attributes = numAttributes
)

print(overviewTable)

          DocumentName                            Description
No_of_Records
1 rideshare_kaggle.csv Uber and Lyft rides data in Boston, MA
693071
  No_of_Attributes
1               57

View(overviewTable)

  DocumentName         Description
No_of_Records
1 rideshare_kaggle.csv Uber and Lyft rides data in Boston, MA 693071

  No_of_Attributes
1 57

str(cabDataSet)

'data.frame':   693071 obs. of  57 variables:
 $ id                        : chr  "424553bb-7174-41ea-aeb4-
```

```
fe06d4f4b9d7" "4bd23055-6827-41c6-b23b-3c491f24e74d" "981a3613-77af-
4620-a42a-0c0866077d1e" "c2d88af2-d278-4bfd-a8d0-29ca77cc5512" ...
 $ timestamp                   : num  1.54e+09 1.54e+09 1.54e+09
1.54e+09 1.54e+09 ...
 $ hour                        : int  9 2 1 4 3 18 5 19 6 10 ...
 $ day                         : int  16 27 28 30 29 17 26 2 3 27 ...
 $ month                       : int  12 11 11 11 11 12 11 12 12 11 ...
 $ datetime                    : chr  "2018-12-16 09:30:07" "2018-11-27
02:00:23" "2018-11-28 01:00:22" "2018-11-30 04:53:02" ...
 $ timezone                    : chr  "America/New_York"
"America/New_York" "America/New_York" "America/New_York" ...
 $ source                      : chr  "Haymarket Square" "Haymarket
Square" "Haymarket Square" "Haymarket Square" ...
 $ destination                 : chr  "North Station" "North Station"
"North Station" "North Station" ...
 $ cab_type                    : chr  "Lyft" "Lyft" "Lyft" "Lyft" ...
 $ product_id                  : chr  "lyft_line" "lyft_premier" "lyft"
"lyft_luxsuv" ...
 $ name                        : chr  "Shared" "Lux" "Lyft" "Lux Black
XL" ...
 $ price                       : num  5 11 7 26 9 16.5 10.5 16.5 3 27.5
...
 $ distance                    : num  0.44 0.44 0.44 0.44 0.44 0.44
1.08 1.08 1.08 1.08 ...
 $ surge_multiplier            : num  1 1 1 1 1 1 1 1 1 1 ...
 $ latitude                    : num  42.2 42.2 42.2 42.2 42.2 ...
 $ longitude                   : num  -71 -71 -71 -71 -71 ...
 $ temperature                 : num  42.3 43.6 38.3 34.4 37.4 ...
 $ apparentTemperature         : num  37.1 37.4 32.9 29.6 30.9 ...
 $ short_summary               : chr  " Mostly Cloudy " " Rain " "
Clear " " Clear " ...
 $ long_summary                : chr  " Rain throughout the day. " "
Rain until morning, starting again in the evening. " " Light rain in
the morning. " " Partly cloudy throughout the day. " ...
 $ precipIntensity             : num  0 0.13 0 0 0 ...
 $ precipProbability           : num  0 1 0 0 0 0 0 1 0 1 ...
 $ humidity                    : num  0.68 0.94 0.75 0.73 0.7 0.84 0.91
0.93 0.96 0.93 ...
 $ windSpeed                   : num  8.66 11.98 7.33 5.28 9.14 ...
 $ windGust                    : num  9.17 11.98 7.33 5.28 9.14 ...
 $ windGustTime                : int  1545015600 1543291200 1543334400
1543514400 1543446000 1545022800 1543287600 1543755600 1543856400
1543338000 ...
 $ visibility                  : num  10 4.79 10 10 10 ...
 $ temperatureHigh             : num  43.7 47.3 47.5 45 42.2 ...
 $ temperatureHighTime         : int  1544968800 1543251600 1543320000
1543510800 1543420800 1545076800 1543255200 1543788000 1543852800
1543320000 ...
 $ temperatureLow              : num  34.2 42.1 33.1 28.9 36.7 ...
```

```
 $ temperatureLowTime         : int  1545048000 1543298400 1543402800
1543579200 1543478400 1545130800 1543298400 1543816800 1543921200
1543399200 ...
 $ apparentTemperatureHigh    : num  38 43.9 44.1 38.5 35.8 ...
 $ apparentTemperatureHighTime: int  1544968800 1543251600 1543320000
1543510800 1543420800 1545080400 1543251600 1543788000 1543852800
1543320000 ...
 $ apparentTemperatureLow     : num  27.4 36.2 29.1 26.2 30.3 ...
 $ apparentTemperatureLowTime : int  1545044400 1543291200 1543392000
1543575600 1543460400 1545134400 1543298400 1543816800 1543914000
1543399200 ...
 $ icon                       : chr  " partly-cloudy-night " " rain "
" clear-night " " clear-night " ...
 $ dewPoint                   : num  32.7 41.8 31.1 26.6 28.6 ...
 $ pressure                   : num  1022 1004 992 1014 998 ...
 $ windBearing                : int  57 90 240 310 303 294 91 159 307
79 ...
 $ cloudCover                 : num  0.72 1 0.03 0 0.44 1 1 1 1 1 ...
 $ uvIndex                    : int  0 0 0 0 0 1 0 0 0 0 ...
 $ visibility.1               : num  10 4.79 10 10 10 ...
 $ ozone                      : num  304 291 316 291 348 ...
 $ sunriseTime                : int  1544962084 1543232969 1543319437
1543492370 1543405904 1545048523 1543233004 1543751798 1543838259
1543319472 ...
 $ sunsetTime                 : int  1544994864 1543266992 1543353364
1543526114 1543439738 1545081282 1543266980 1543785242 1543871628
1543353352 ...
 $ moonPhase                  : num  0.3 0.64 0.68 0.75 0.72 0.33 0.64
0.86 0.89 0.68 ...
 $ precipIntensityMax         : num  0.1276 0.13 0.1064 0 0.0001 ...
 $ uvIndexTime                : int  1544979600 1543251600 1543338000
1543507200 1543420800 1545066000 1543251600 1543770000 1543852800
1543338000 ...
 $ temperatureMin             : num  39.9 40.5 35.4 34.7 33.1 ...
 $ temperatureMinTime         : int  1545012000 1543233600 1543377600
1543550400 1543402800 1545048000 1543233600 1543726800 1543896000
1543377600 ...
 $ temperatureMax             : num  43.7 47.3 47.5 45 42.2 ...
 $ temperatureMaxTime         : int  1544968800 1543251600 1543320000
1543510800 1543420800 1545022800 1543255200 1543788000 1543852800
1543320000 ...
 $ apparentTemperatureMin     : num  33.7 36.2 31 30.3 29.1 ...
 $ apparentTemperatureMinTime : int  1545012000 1543291200 1543377600
1543550400 1543392000 1545044400 1543291200 1543748400 1543896000
1543377600 ...
 $ apparentTemperatureMax     : num  38.1 43.9 44.1 38.5 35.8 ...
 $ apparentTemperatureMaxTime : int  1544958000 1543251600 1543320000
1543510800 1543420800 1545080400 1543251600 1543788000 1543852800
1543320000 ...
```

```r
featureDescriptions <- data.frame(
  Feature = c("price", "distance", "time_of_day"),
  DataType = c("Numeric", "Numeric", "Character"),
  Description = c("Price of the ride in USD", "Distance of the ride in 
miles", "Time of day when the ride was initiated")
)

print(featureDescriptions)
```

```
      Feature  DataType                             Description
1       price   Numeric                Price of the ride in USD
2    distance   Numeric           Distance of the ride in miles
3 time_of_day Character Time of day when the ride was initiated
```

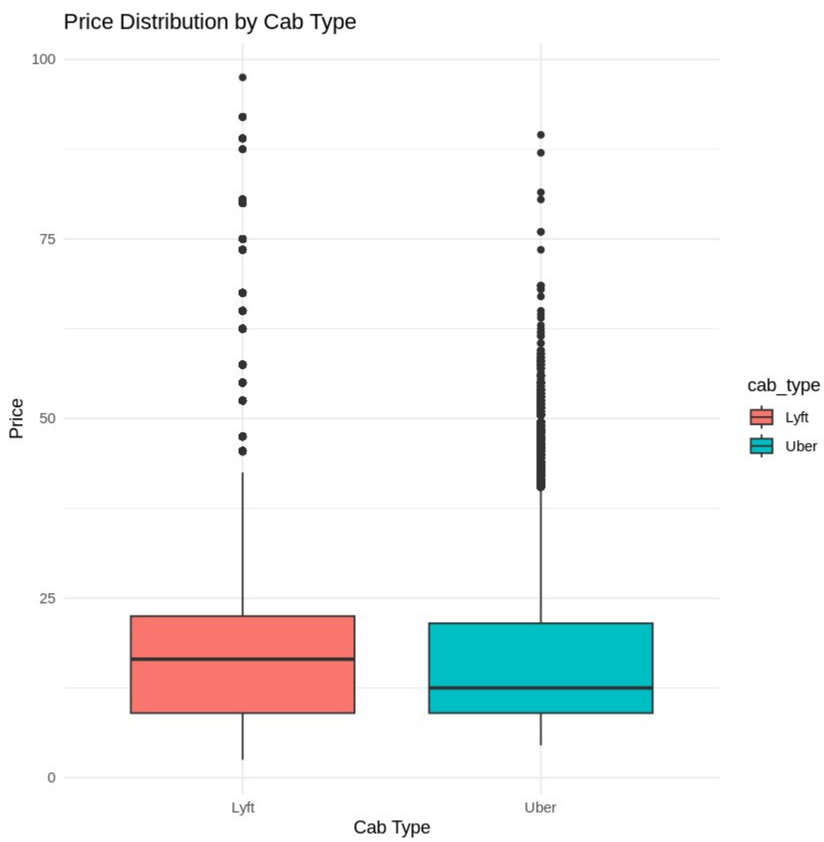
```r
colnames(cabDataSet)
```

```
 [1] "id"                          "timestamp"
 [3] "hour"                        "day"
 [5] "month"                       "datetime"
 [7] "timezone"                    "source"
 [9] "destination"                 "cab_type"
[11] "product_id"                  "name"
[13] "price"                       "distance"
[15] "surge_multiplier"            "latitude"
[17] "longitude"                   "temperature"
[19] "apparentTemperature"         "short_summary"
[21] "long_summary"                "precipIntensity"
[23] "precipProbability"           "humidity"
[25] "windSpeed"                   "windGust"
[27] "windGustTime"                "visibility"
[29] "temperatureHigh"             "temperatureHighTime"
[31] "temperatureLow"              "temperatureLowTime"
[33] "apparentTemperatureHigh"     "apparentTemperatureHighTime"
[35] "apparentTemperatureLow"      "apparentTemperatureLowTime"
[37] "icon"                        "dewPoint"
[39] "pressure"                    "windBearing"
[41] "cloudCover"                  "uvIndex"
[43] "visibility.1"                "ozone"
[45] "sunriseTime"                 "sunsetTime"
[47] "moonPhase"                   "precipIntensityMax"
[49] "uvIndexTime"                 "temperatureMin"
[51] "temperatureMinTime"          "temperatureMax"
[53] "temperatureMaxTime"          "apparentTemperatureMin"
[55] "apparentTemperatureMinTime"  "apparentTemperatureMax"
[57] "apparentTemperatureMaxTime"
```

Data Stylized Facts:

```r
library(ggplot2)
```

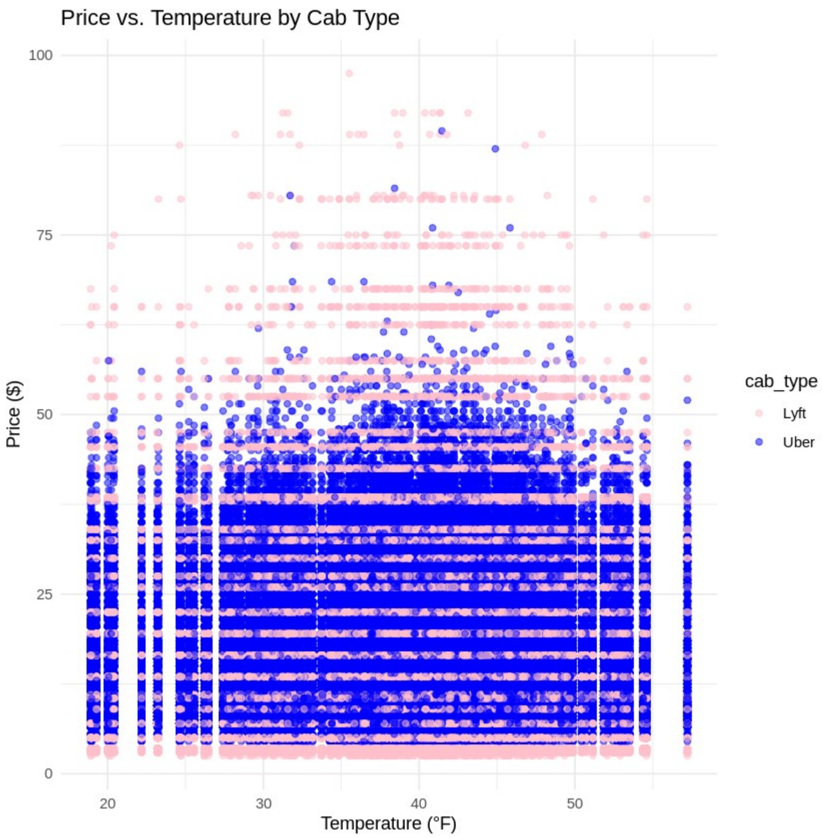
```
# Adjusted ggplot code for visualizing price distribution by cab_type
ggplot(cabDataSet, aes(x = cab_type, y = price, fill = cab_type)) +
  geom_boxplot() +
  labs(title = "Price Distribution by Cab Type", x = "Cab Type", y =
"Price") +
  theme_minimal()

Warning message:
"Removed 55095 rows containing non-finite outside the scale range
(`stat_boxplot()`)."
```



The above image offers a detailed comparative analysis of pricing structures between Lyft and Uber, utilizing a box-and-whisker plot to elegantly illustrate the distribution of fares. The delineation of prices is marked by distinctive colors—red for Lyft and teal for Uber—providing a clear visual differentiation between the two services. Notably, the plot includes outliers, represented by individual points, which signify fare instances that deviate significantly from the norm. This graph is instrumental in highlighting the variance in pricing strategies and customer cost implications associated with each service, offering valuable insights for stakeholders making informed decisions.

```
ggplot(cabDataSet, aes(x = temperature, y = price)) +
  geom_point(aes(color = cab_type), alpha = 0.5) +
  labs(title = "Price vs. Temperature by Cab Type", x = "Temperature
(°F)", y = "Price ($)") +
```

```
  theme_minimal() +
  scale_color_manual(values = c("Uber" = "blue", "Lyft" = "pink"))

Warning message:
“Removed 55095 rows containing missing values or values outside the
scale range
(`geom_point()`).”
```

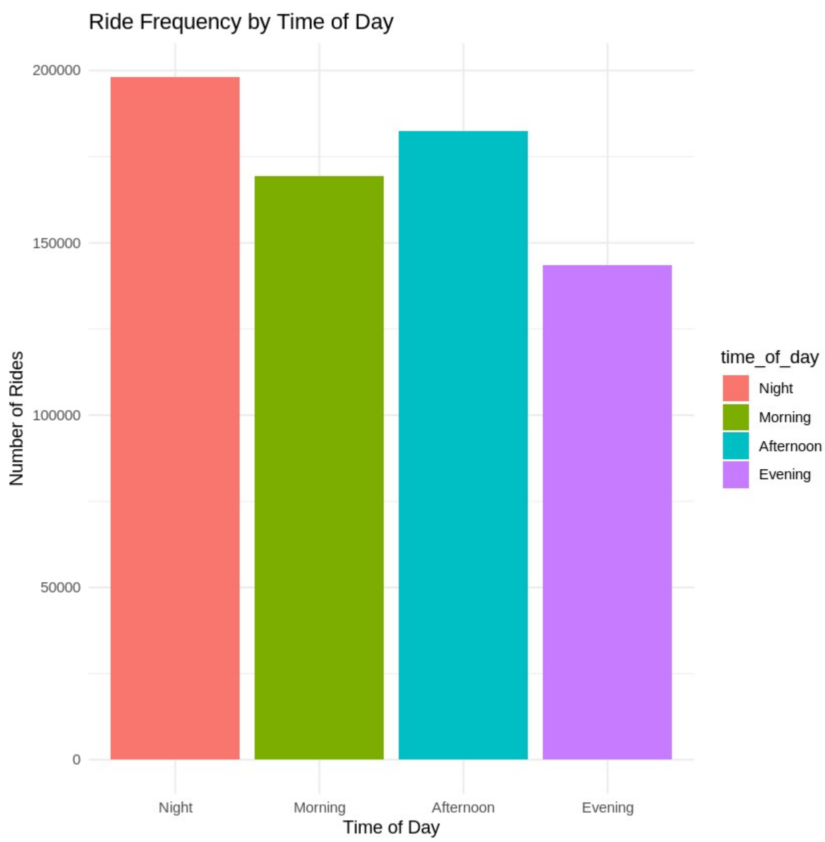


This image is a scatter plot with the title "Price vs. Temperature by Cab Type." It plots individual data points on a graph, with the x-axis representing temperature in Fahrenheit and the y-axis representing price in US dollars. There are two different colors of data points, pink and blue, each corresponding to a different cab type as indicated by the legend: Lyft is pink, and Uber is blue.

The distribution of points shows a wide range of prices at different temperatures for both services. It seems that the prices for Lyft are more spread out over the price range, whereas Uber prices are heavily clustered at the lower end of the price range. The temperatures shown on the x-axis range from around 20°F to just over 50°F. At first glance, there doesn't seem to be a clear correlation between temperature and price for either cab type, with data points spread across the temperature range.

```
library(lubridate)
library(ggplot2)
```

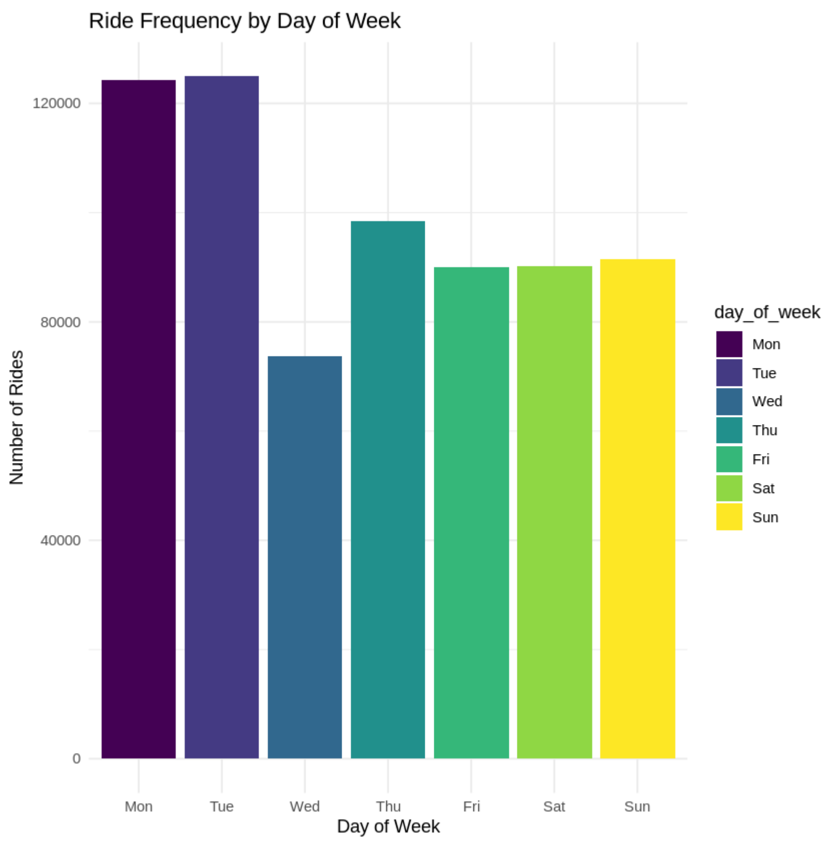
```
cabDataSet %>%
  mutate(datetime = ymd_hms(datetime), # Ensure datetime is in POSIXct
format
         hour = hour(datetime),
         time_of_day = cut(hour, breaks = c(0, 6, 12, 18, 24),
                           labels = c("Night", "Morning", "Afternoon",
"Evening"), include.lowest = TRUE)) %>%
  count(time_of_day) %>%
  ggplot(aes(x = time_of_day, y = n, fill = time_of_day)) +
  geom_col() +
  labs(title = "Ride Frequency by Time of Day", x = "Time of Day", y =
"Number of Rides") +
  theme_minimal()
```



The above bar chart quantifies ride frequencies across various times of the day, segmented into night, morning, afternoon, and evening. Each segment is color-coded, facilitating an immediate understanding of peak and off-peak periods for ride-sharing services. This visualization serves as a crucial tool for analyzing consumer behavior and demand patterns, enabling service providers to optimize operational efficiencies and tailor their offerings to meet dynamic market requirements.

```
cabDataSet %>%
  mutate(datetime = ymd_hms(datetime), # Convert to POSIXct format if
needed
```

```
        day_of_week = wday(datetime, label = TRUE, week_start = 1))
%>% # week_start = 1 makes Monday = 1
  count(day_of_week) %>%
  ggplot(aes(x = day_of_week, y = n, fill = day_of_week)) +
  geom_col() +
  labs(title = "Ride Frequency by Day of Week", x = "Day of Week", y =
"Number of Rides") +
  theme_minimal()
```



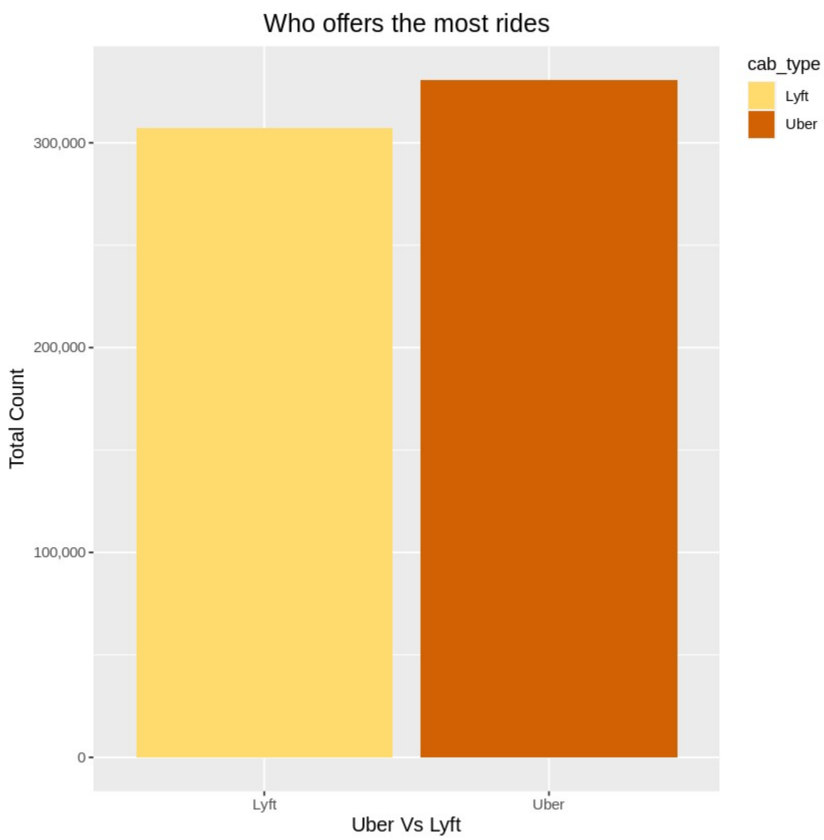
The above graph shows the number of rides for each day of the week. Each day is represented by a different color: Monday is dark purple, Tuesday is a lighter shade of purple, Wednesday is blue, Thursday is green, Friday is light green, Saturday is yellow, and Sunday is light yellow.

The vertical axis, labeled "Number of Rides," starts at 0 and increments by 20,000. The highest bars appear to be Monday and Tuesday, suggesting they have the highest ride frequency, both reaching around 120,000 rides. The other days show fewer rides, with the count visibly decreasing as the week progresses towards Sunday. This graph could be used to analyze the demand for ride services throughout the week.

Exploratory Data Analysis

Who offers the most rides,Uber or lyft?

```
 cabDataSet_distinct %>% group_by(cab_type) %>%
    summarise("Total_ Count" = length(id),
              'Percentage' = (length(id) / nrow(cabDataSet_distinct))
* 100)
bp <-ggplot()+
  geom_bar(data=cabDataSet_distinct,mapping=aes(x=cab_type,
fill=cab_type))+
  scale_y_continuous(breaks =
seq(0,1000000,100000),labels=scales::comma)+
  labs(x="Uber Vs Lyft",
       y="Total Count")+
  labs(title="Who offers the most rides")+
  theme(plot.title =element_text(hjust = 0.50,size=15),
        legend.justification = c("right", "top"),
       axis.title = element_text(size=12),
        axis.text = element_text(size=09))+
  theme(plot.caption=element_text(size=10))

bp + scale_fill_manual(values = c("#FFDB6D", "#D16103"))

  cab_type Total_ Count Percentage
1 Lyft     307408       48.18488
2 Uber     330568       51.81512
```

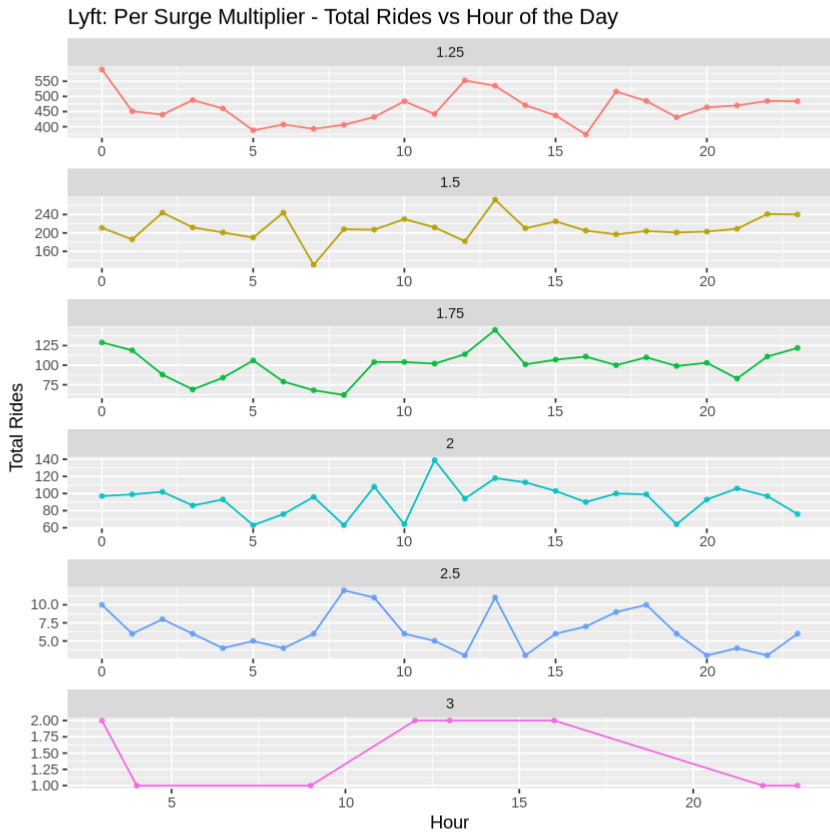


Lyft's bar is yellow, reaching up to about 175,000 rides. Uber's bar is orange, towering at over 300,000 rides. The chart answers "Who offers the most rides" with Uber clearly in the lead.

Lyft: Per Surge Multiplier - Total Rides vs Hour of the Day

```
surged_data <- cabDataSet %>%
        filter(cab_type == "Lyft", surge_multiplier > 1.00) %>%
        dplyr::group_by(hour, surge_multiplier) %>%
        dplyr::summarize(total_rides = n())
surged_data$surge_multiplier <-
as.factor(surged_data$surge_multiplier)

lyft_surged_data <- ggplot(surged_data, aes(hour, total_rides, color =
surge_multiplier)) +
        geom_point(alpha=0.8, size=1, aes(color = surge_multiplier)) +
        geom_line(aes(color = surge_multiplier)) + ggtitle("Lyft: Per
Surge Multiplier - Total Rides vs Hour of the Day") +
        facet_wrap(~surge_multiplier, ncol=1, scales="free") +
xlab("Hour") + ylab("Total Rides") +
        guides(color=guide_legend(ncol=1)) +
theme(legend.position="none",
                                                   panel.border =
element_blank(),
                                                   panel.spacing.x =
unit(0,"line"))
lyft_surged_data
```

```
`summarise()` has grouped output by 'hour'. You can override using the
`.groups` argument.
```



We've got a multi-tiered line graph titled "Lyft: Per Surge Multiplier - Total Rides vs Hour of the Day." Each line represents a surge multiplier from 1.25 to 3, each with a different color. The lines show the number of rides fluctuating throughout the day, peaking at different times depending on the surge multiplier.

Minimum and maximum fare prices

```
df<-sqldf("select source ,destination, cab_type ,avg(price) as
average_price,min(price) as minimun_price,max(price) as maximum_price
from cabDataSet group by source, destination,cab_type order by
cab_type")
CrossTable(cabDataSet$surge_multiplier, cabDataSet$cab_type)
```

```
   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|
```

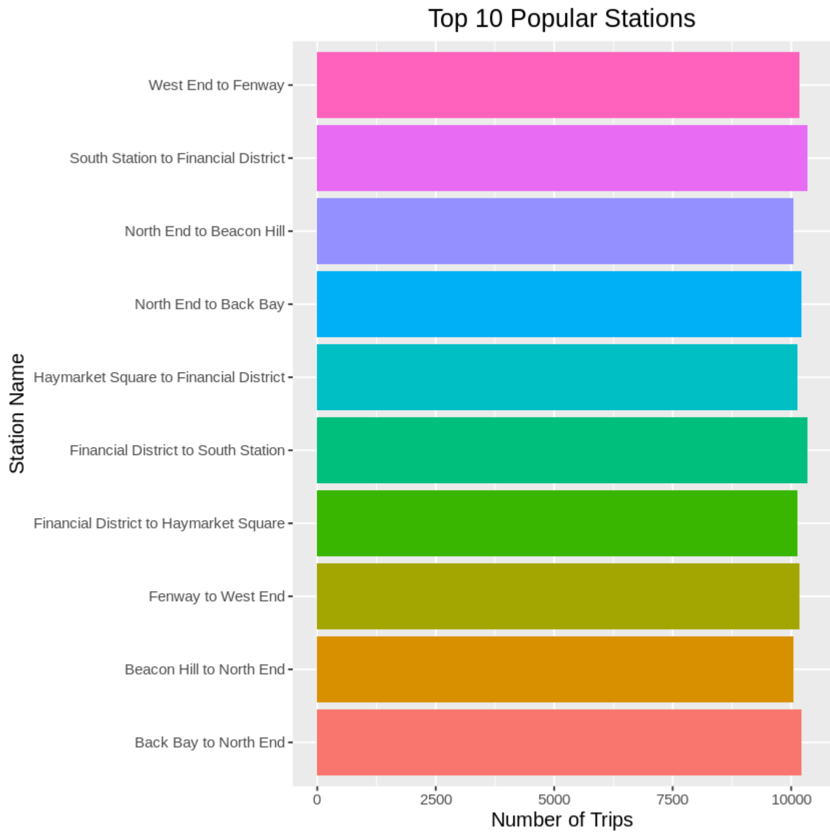
```
Total Observations in Table:  693071


                              | cabDataSet$cab_type
cabDataSet$surge_multiplier |       Lyft |       Uber |  Row Total |
----------------------------|------------|------------|------------|
                          1 |     286433 |     385663 |     672096 |
                            |    456.978 |    364.253 |            |
                            |      0.426 |      0.574 |      0.970 |
                            |      0.932 |      1.000 |            |
                            |      0.413 |      0.556 |            |
----------------------------|------------|------------|------------|
                       1.25 |      11085 |          0 |      11085 |
                            |   7738.535 |   6168.307 |            |
                            |      1.000 |      0.000 |      0.016 |
                            |      0.036 |      0.000 |            |
                            |      0.016 |      0.000 |            |
----------------------------|------------|------------|------------|
                        1.5 |       5065 |          0 |       5065 |
                            |   3535.921 |   2818.446 |            |
                            |      1.000 |      0.000 |      0.007 |
                            |      0.016 |      0.000 |            |
                            |      0.007 |      0.000 |            |
----------------------------|------------|------------|------------|
                       1.75 |       2420 |          0 |       2420 |
                            |   1689.423 |   1346.622 |            |
                            |      1.000 |      0.000 |      0.003 |
                            |      0.008 |      0.000 |            |
                            |      0.003 |      0.000 |            |
----------------------------|------------|------------|------------|
                          2 |       2239 |          0 |       2239 |
                            |   1563.065 |   1245.903 |            |
                            |      1.000 |      0.000 |      0.003 |
                            |      0.007 |      0.000 |            |
                            |      0.003 |      0.000 |            |
----------------------------|------------|------------|------------|
                        2.5 |        154 |          0 |        154 |
                            |    107.509 |     85.694 |            |
                            |      1.000 |      0.000 |      0.000 |
                            |      0.001 |      0.000 |            |
                            |      0.000 |      0.000 |            |
----------------------------|------------|------------|------------|
                          3 |         12 |          0 |         12 |
                            |      8.377 |      6.677 |            |
                            |      1.000 |      0.000 |      0.000 |
                            |      0.000 |      0.000 |            |
                            |      0.000 |      0.000 |            |
```

```
----------------------------|-----------|-----------|-----------|
               Column Total |    307408 |    385663 |    693071 |
                            |     0.444 |     0.556 |           |
----------------------------|-----------|-----------|-----------|
```

This is a tabular comparison of Lyft and Uber across different surge multipliers. Notably, Uber dominates the no-surge scenario, while Lyft takes precedence as multipliers increase, reflecting a strategic positioning in premium pricing scenarios.

Top 10 most Popular Stations

```
popular_station<-sqldf("select source,destination,(source|| ' to ' ||
destination) as station_name,count(id) as number_of_trips from
cabDataSet group by source,destination order by count(id) desc LIMIT
10")
ggplot(data=popular_station,aes(x=number_of_trips, y=station_name,
fill=station_name))+geom_bar(stat='identity')+
  labs(x="Number of Trips",y="Station Name")+
  labs(title=" Top 10 Popular Stations ")+
  theme(plot.title =element_text(hjust = 0.5,size=15),
        legend.position = c(2.50, .50),
        legend.justification = c("right", "top"),
       axis.title = element_text(size=12),
        axis.text = element_text(size=09))+
  theme(plot.caption=element_text(size=10))
```



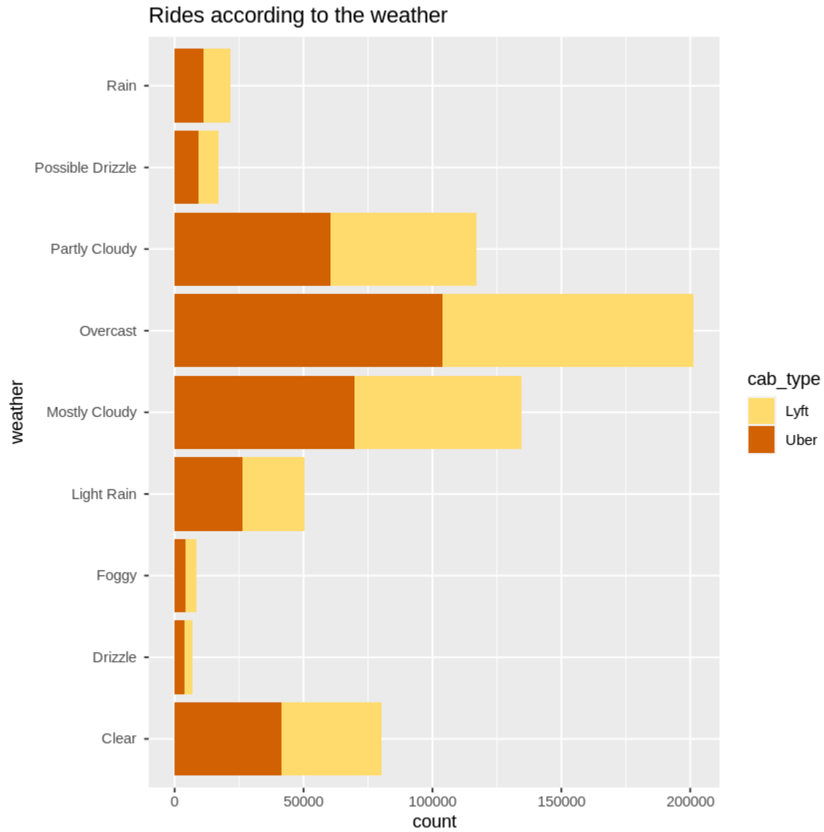
This one's a horizontal bar chart, "Top 10 Popular Stations," with each bar a different color. The lengths vary, indicating the number of trips to each station. The longest bar is pink, for Fenway to West End, suggesting the highest number of trips.

Weather affects the rides

```
cabDataSet_distinct %>% group_by(short_summary) %>%
summarise(count = length(id),'Percentage' = (length(id) /
nrow(cabDataSet_distinct)) * 100)
bp <- cabDataSet_distinct %>%
    ggplot(aes(short_summary, fill=cab_type)) +
    labs(x="weather", title="Rides according to the weather") +
    geom_bar()+ coord_flip()

bp + scale_fill_manual(values = c("#FFDB6D", "#D16103"))
```

	short_summary	count	Percentage
1	Clear	80256	12.579784
2	Drizzle	6725	1.054115
3	Foggy	8292	1.299735
4	Light Rain	50488	7.913777
5	Mostly Cloudy	134603	21.098443
6	Overcast	201429	31.573131
7	Partly Cloudy	117226	18.374672

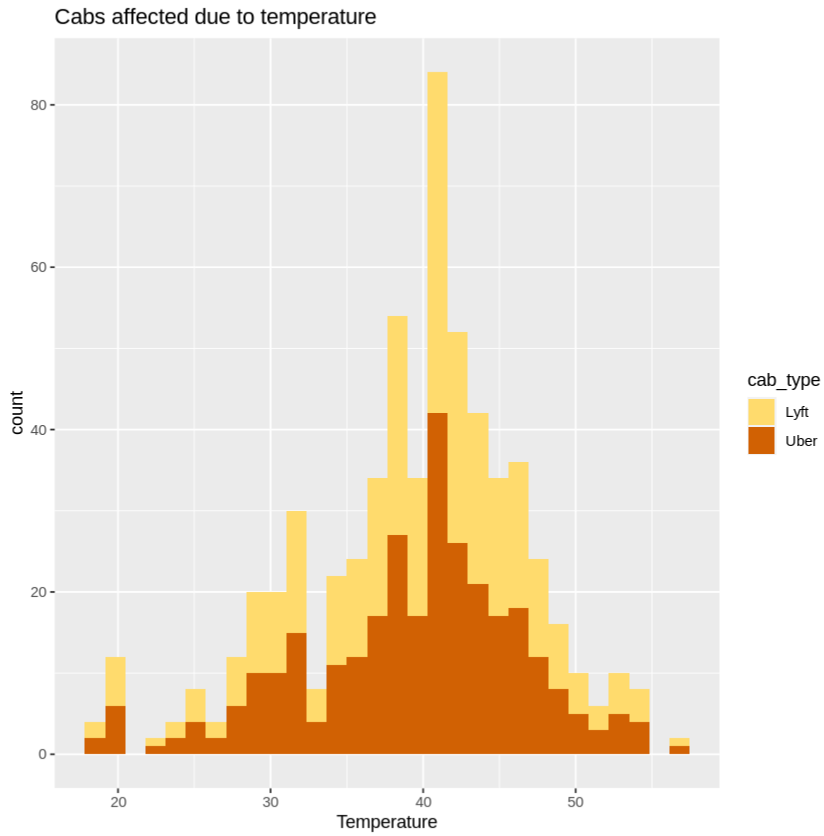
```
8   Possible Drizzle    17176   2.692264
9   Rain                21781   3.414078
```



Bars in two shades—light for Lyft and darker for Uber—compare the total count of rides across different weather conditions. Clear days see the most rides for Uber, while Lyft peaks under "Mostly Cloudy."

Temperature affects the ride's price

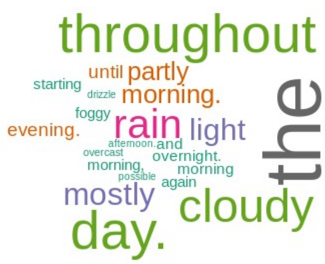
```
df2<-sqldf("select temperature, price , cab_type from cabDataSet group
by cab_type,temperature")
bp <- df2 %>%
    ggplot(aes(temperature, fill=cab_type)) +
    labs(x="Temperature", title="Cabs affected due to temperature") +
    geom_histogram()
bp + scale_fill_manual(values = c("#FFDB6D", "#D16103"))

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Cabs affected due to temperature" features two overlaid histograms, one in yellow for Lyft and one in orange for Uber. The histograms show counts of rides across temperature ranges, with a noticeable spike at around 40°F for Uber.

Weather the passengers options for cabs

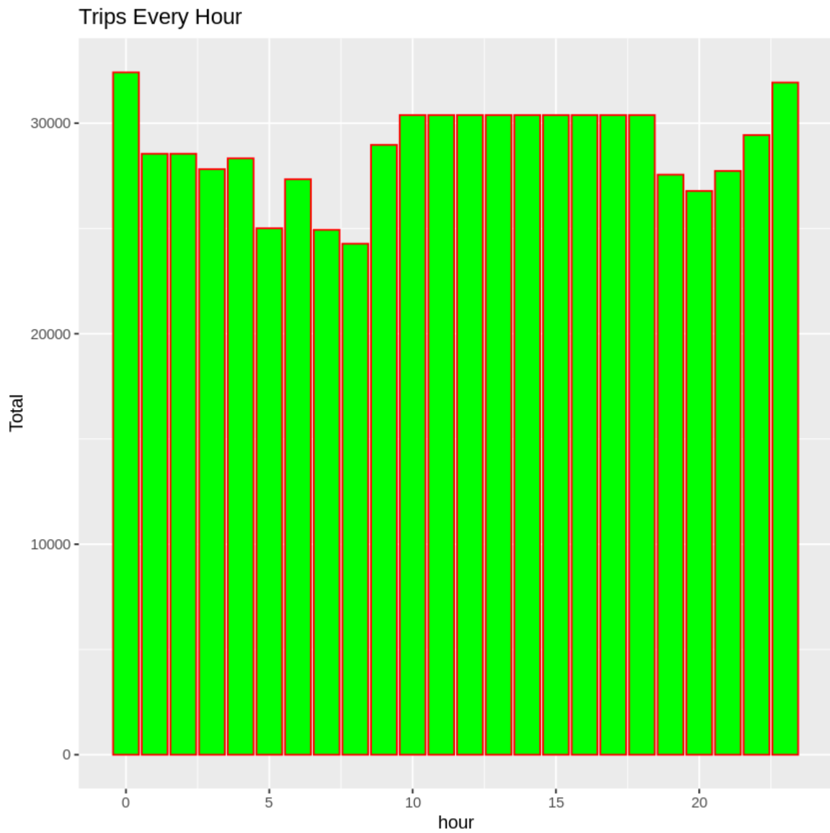
```
document_tm <- Corpus(VectorSource(cabDataSet$long_summary))
mat <- as.matrix(TermDocumentMatrix(document_tm))
vec <- sort(rowSums(mat), decreasing = TRUE)
word_corpus <- data.frame(word = names(vec), freq = vec)
set.seed(3)
wordcloud(word_corpus$word, freq = word_corpus$freq, colors =
brewer.pal(8, "Dark2"))
```



It's a word cloud, with the biggest text reading "throughout" and "day." Other weather-related words like "rain," "mostly," "cloudy," and parts of the day like "morning," "evening" float around, varying in size, indicating their frequency in a dataset.

Trips Every Hour

```
hour_data <- cabDataSet %>%
           group_by(hour) %>%
               dplyr::summarize(Total = n())

colnames(hour_data)

ggplot(hour_data, aes(hour, Total)) +
        geom_bar( stat = "identity", fill = "green", color = "red") +
           ggtitle("Trips Every Hour") +
            theme(legend.position = "none")

[1] "hour"  "Total"
```



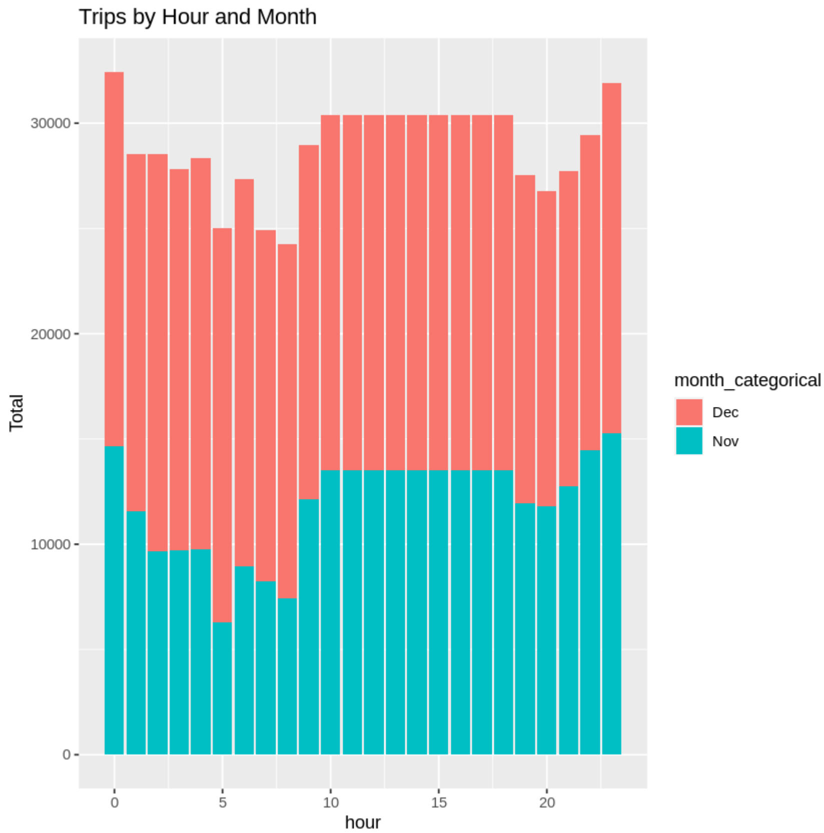
This graph depicts ride frequency across a 24-hour period. The consistent pattern suggests a stable demand with expected troughs during the early hours and peaks during traditional commuting times.

Trips By Hour and Month

```
df_new <- transform(cabDataSet, month_categorical =month.abb[month])
colnames(df_new)

month_hour <- df_new %>%
          group_by(month_categorical, hour) %>%
             dplyr::summarize(Total = n())
colnames(month_hour)


ggplot(month_hour, aes(hour, Total, fill = month_categorical)) +
       geom_bar(stat = "identity") +
          ggtitle("Trips by Hour and Month")
```

```
 [1] "id"                              "timestamp"
 [3] "hour"                            "day"
 [5] "month"                           "datetime"
 [7] "timezone"                        "source"
```

```
 [9] "destination"                  "cab_type"
[11] "product_id"                   "name"
[13] "price"                        "distance"
[15] "surge_multiplier"             "latitude"
[17] "longitude"                    "temperature"
[19] "apparentTemperature"          "short_summary"
[21] "long_summary"                 "precipIntensity"
[23] "precipProbability"            "humidity"
[25] "windSpeed"                    "windGust"
[27] "windGustTime"                 "visibility"
[29] "temperatureHigh"              "temperatureHighTime"
[31] "temperatureLow"               "temperatureLowTime"
[33] "apparentTemperatureHigh"      "apparentTemperatureHighTime"
[35] "apparentTemperatureLow"       "apparentTemperatureLowTime"
[37] "icon"                         "dewPoint"
[39] "pressure"                     "windBearing"
[41] "cloudCover"                   "uvIndex"
[43] "visibility.1"                 "ozone"
[45] "sunriseTime"                  "sunsetTime"
[47] "moonPhase"                    "precipIntensityMax"
[49] "uvIndexTime"                  "temperatureMin"
[51] "temperatureMinTime"           "temperatureMax"
[53] "temperatureMaxTime"           "apparentTemperatureMin"
[55] "apparentTemperatureMinTime"   "apparentTemperatureMax"
[57] "apparentTemperatureMaxTime"   "month_categorical"

`summarise()` has grouped output by 'month_categorical'. You can
override using
the `.groups` argument.

[1] "month_categorical" "hour"              "Total"
```



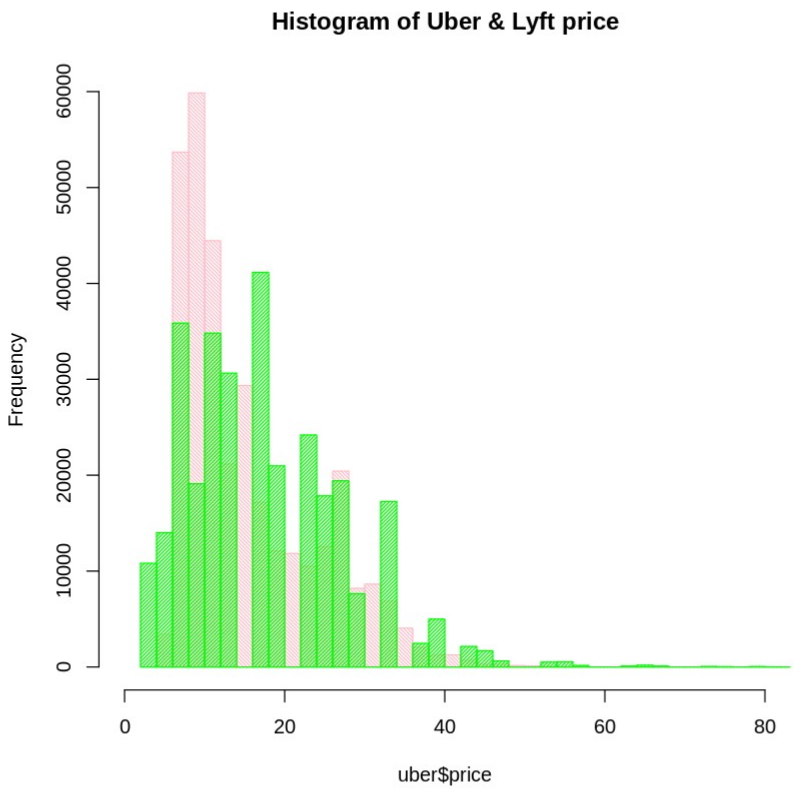
In the above bar chart, we observe the distribution of rides across hours for the months of November and December. December shows an overall increase in trip frequency, which may be attributed to holiday-related activities.

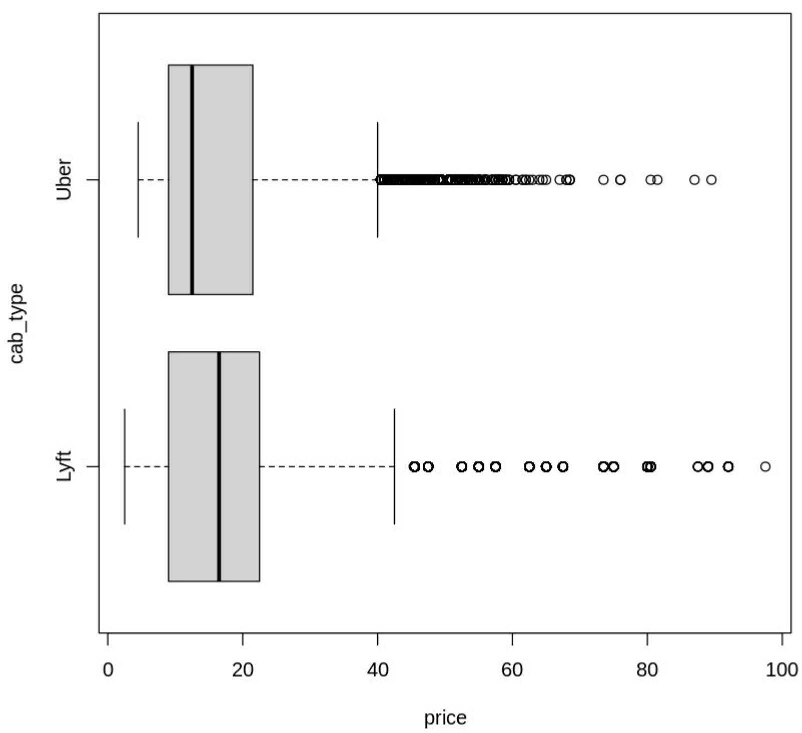
Price range between Uber and Lyft

```
lyft<-sqldf("select * from cabDataSet where cab_type='Lyft'")
uber<-sqldf("select * from cabDataSet where cab_type='Uber'")
summary(lyft$price)
summary(uber$price)
hist(uber$price, col = "pink", density = 50, angle = 135, breaks = 40,
xlim = c(0,80), main = "Histogram of Uber & Lyft price")
hist(lyft$price, col = "green", density = 50, add = TRUE, breaks = 40)
boxplot(cabDataSet$price~cabDataSet$cab_type,xlab='price',
ylab='cab_type', data= cabDataSet, horizontal = TRUE)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   2.50    9.00   16.50   17.35   22.50   97.50
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
    4.5     9.0    12.5    15.8    21.5    89.5   55095
```


Histogram of Uber & Lyft price
Frequency
0
10000
20000
30000
40000
50000
60000
0
20
40
60
80
uber$price

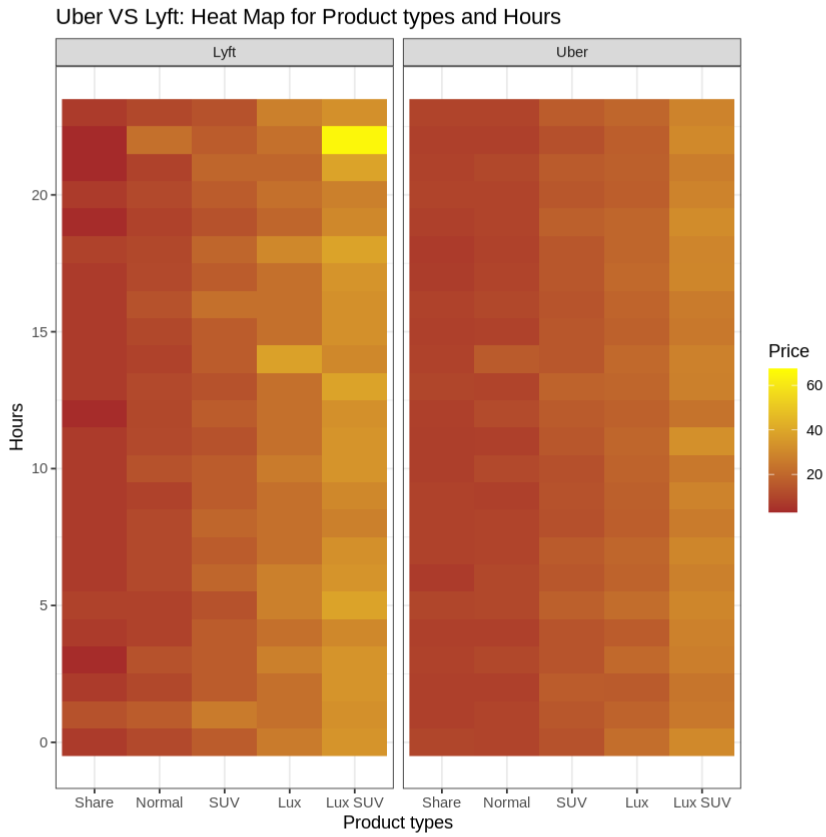

cab_type
Uber
Lyft
0
20
40
60
80
100
price

The histogram for Uber and Lyft prices indicates a higher frequency of lower-priced rides for Lyft, whereas Uber displays a broader distribution across the price range. This suggests a potential market segmentation where Lyft captures more of the budget-conscious consumer base.

The boxplot diagram provides a comparative overview of ride pricing structures between Lyft and Uber. Both display a range of outliers, with Lyft's interquartile range shifted towards a higher price point, indicating a generally higher median price relative to Uber.

Heatmap for specific location and hours

```
bt<-cabDataSet %>%
select(price,cab_type,name,distance,short_summary,hour,source,destinat
ion) %>% filter(name!="WAV") %>% filter(name!="Lux") %>%
filter(price>=0)
bt$name_f<-factor(bt$name,

levels=c("UberPool","Shared","UberX","Lyft","UberXL","Lyft
XL","Black","Lux Black","Black SUV","Lux Black XL"))
levels(bt$name_f) <- list("Share" = c("UberPool","Shared"),
                             "Normal" =  c("UberX","Lyft"),
                             "SUV" = c("UberXL","Lyft XL"),
                             "Lux" = c("Black","Lux Black"),
                             "Lux SUV"= c("Black SUV","Lux Black XL"))

bt<-bt %>%
select(price,cab_type,name,name_f,distance,short_summary,hour,source,d
estination) %>% filter(name!="WAV") %>% filter(name!="Lux") %>%
filter(price>=0)
bt1<-bt %>% select(price,cab_type,name_f,hour,source, destination) %>%
filter(destination=="Northeastern University") %>%
filter(source=="Theatre District")  %>% filter(price>=0)
ggplot(bt1, aes(name_f,hour ))+
  geom_raster(aes(fill = price))+
  scale_fill_gradientn(colours=c("brown","yellow"),name="Price")+
  labs(title ="Uber VS Lyft: Heat Map for Product types and Hours", x
= "Product types", y = "Hours")+
  theme_bw()+facet_wrap(~cab_type)
```



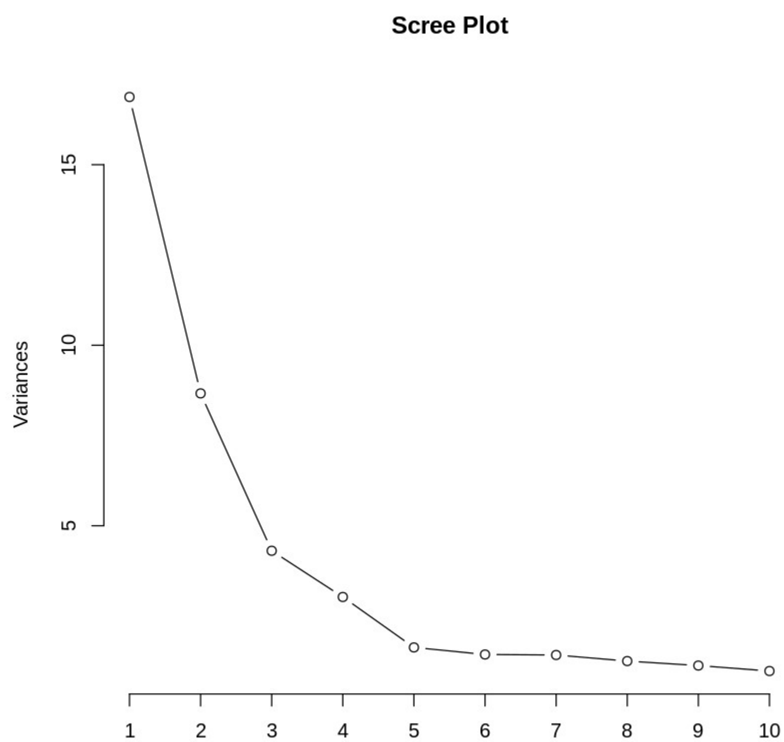
The heat map for product types and hours offers a visual representation of pricing patterns across different service levels and times of the day. Higher prices during late-night hours are apparent for both services, highlighting peak pricing trends.

```
numericalDataClean <- na.omit(numericalData)

numericalDataImputed <- numericalData
for(i in 1:ncol(numericalDataImputed)){
  numericalDataImputed[is.na(numericalDataImputed[,i]), i] <-
mean(numericalDataImputed[,i], na.rm = TRUE)
}

# Loop through each column in the data frame
for(i in seq_along(numericalDataImputed)) {
  # Check if the column is numeric
  if(is.numeric(numericalDataImputed[[i]])) {
    # Replace infinite values with NA
    numericalDataImputed[[i]][is.infinite(numericalDataImputed[[i]])]
<- NA
  }
}
```

Clustering and Dimensionality Reduction

Principal Component Analysis

```
pcaResult <- prcomp(numericalDataImputed, center = TRUE, scale. =
TRUE, na.action = na.omit)

Warning message:
“In prcomp.default(numericalDataImputed, center = TRUE, scale. = TRUE,

    na.action = na.omit) :
 extra argument ‘na.action’ will be disregarded”

plot(pcaResult, type = "l", main = "Scree Plot")
```



The scree plot in the image visually represents the variance explained by each of the first ten principal components from a Principal Component Analysis (PCA). The plot highlights a steep decline in the variance explained after the first principal component, with a noticeable but less sharp drop following the second component, suggesting the majority of the data's variance is captured by these initial components. The variance levels off considerably from the fourth component onwards, indicating minimal additional information gained by retaining further components. This pattern suggests that the first two or three components are sufficient to capture the most significant variance within the data, adhering to the elbow method commonly used in PCA to decide on the number of components to retain. The plot effectively communicates the diminishing returns in variance explained with each subsequent principal component, guiding the reduction of dimensionality while preserving the essence of the dataset's variability.

Model Training

In the pursuit of an optimal predictive model for ride-sharing prices, we have employed three distinct statistical learning methods: Linear Regression, Decision Trees, and Random Forest. The following is a detailed analysis of the model selection process for both Uber and Lyft datasets.

```
## Data Modelling


### Loading pre processed Data and factoring required columns
### Split data to train and test


weekday <- weekdays(as.POSIXlt(cabDataSet$datetime), abbreviate =
TRUE)

cabDataSet['Fri'] = as.integer(weekday=='Fri')
cabDataSet['Sat'] = as.integer(weekday=='Sat')
cabDataSet['Sun'] = as.integer(weekday=='Sun')

#change short Summary of weather to binary variables
ss_data <- unique(cabDataSet$short_summary)
for (i in ss_data)
      {
        cabDataSet[i] = as.integer(cabDataSet$name == i)

       }

for (p in unique(cabDataSet$name))
      {
          cabDataSet[p] = as.integer(cabDataSet$name == p)
      }

lyft<-sqldf("select [distance],[surge_multiplier],[Fri], [Sat],[Sun],
[Shared],[Lyft XL],[Lux Black XL], [LUX],[Lux Black],[ Mostly
Cloudy ], [ Rain ], [ Partly Cloudy ],[ Overcast ], [ Light Rain ],
[ Foggy ], [ Possible Drizzle ],[ Drizzle ], price from cabDataSet
where cab_type='Lyft'")
uber<-sqldf("select [distance],[surge_multiplier],[Fri], [Sat],[Sun],
[UberPool],[UberXL],[Black],[Black SUV], [WAV],[ Mostly Cloudy ],
[ Rain ], [ Partly Cloudy ],[ Overcast ], [ Light Rain ], [ Foggy ], [
Possible Drizzle ],[ Drizzle ], price from cabDataSet where
cab_type='Uber'")

colnames(uber)[9] ="Black_SUV"
colnames(uber)[11] ="Mostly_Cloudy"
colnames(uber)[12] ="Rain"
colnames(uber)[13] ="Partly_Cloudy"
colnames(uber)[14] ="Overcast"
colnames(uber)[15] ="Light_Rain"
```

```
colnames(uber)[16] ="Foggy"
colnames(uber)[17] ="Possible_Drizzle"
colnames(uber)[18] ="Drizzle"


colnames(lyft)[7] ="Lyft_XL"
colnames(lyft)[8] ="Lux_Black_XL"
colnames(lyft)[10] ="Lux_Black"
colnames(lyft)[11] ="Mostly_Cloudy"
colnames(lyft)[12] ="Rain"
colnames(lyft)[13] ="Partly_Cloudy"
colnames(lyft)[14] ="Overcast"
colnames(lyft)[15] ="Light_Rain"
colnames(lyft)[16] ="Foggy"
colnames(lyft)[17] ="Possible_Drizzle"
colnames(lyft)[18] ="Drizzle"

#Uber
#selecting on numeric data
numericIndex = sapply(uber,is.numeric)
numericData = uber[,numericIndex]

#divide into train & test
trainingIndex = sample(1:nrow(uber), 0.9 * nrow(uber))
uberTraining = uber[trainingIndex,]
uberTesting = uber[-trainingIndex,]

uberTraining<-na.omit(uberTraining)
sapply(uberTraining, function(x) sum(is.na(x)))

uberTesting <- na.omit(uberTesting)
sapply(uberTesting, function(x) sum(is.na(x)))

#lyft
#selecting on numeric data
numericIndex = sapply(lyft,is.numeric)
numericData = uber[,numericIndex]

#divide into train & test
trainingIndex = sample(1:nrow(lyft), 0.9 * nrow(lyft))
lyftTraining = lyft[trainingIndex,]
lyftTesting = lyft[-trainingIndex,]

lyftTraining<-na.omit(lyftTraining)
sapply(lyftTraining, function(x) sum(is.na(x)))

lyftTesting<-na.omit(lyftTesting)
sapply(lyftTesting, function(x) sum(is.na(x)))
```

```
       distance surge_multiplier              Fri              Sat
              0                0                0                0
            Sun         UberPool           UberXL            Black
              0                0                0                0
      Black_SUV              WAV    Mostly_Cloudy             Rain
              0                0                0                0
  Partly_Cloudy         Overcast       Light_Rain            Foggy
              0                0                0                0
Possible_Drizzle          Drizzle            price
              0                0                0

       distance surge_multiplier              Fri              Sat
              0                0                0                0
            Sun         UberPool           UberXL            Black
              0                0                0                0
      Black_SUV              WAV    Mostly_Cloudy             Rain
              0                0                0                0
  Partly_Cloudy         Overcast       Light_Rain            Foggy
              0                0                0                0
Possible_Drizzle          Drizzle            price
              0                0                0

       distance surge_multiplier              Fri              Sat
              0                0                0                0
            Sun           Shared          Lyft_XL     Lux_Black_XL
              0                0                0                0
            Lux        Lux_Black    Mostly_Cloudy             Rain
              0                0                0                0
  Partly_Cloudy         Overcast       Light_Rain            Foggy
              0                0                0                0
Possible_Drizzle          Drizzle            price
              0                0                0

       distance surge_multiplier              Fri              Sat
              0                0                0                0
            Sun           Shared          Lyft_XL     Lux_Black_XL
              0                0                0                0
            Lux        Lux_Black    Mostly_Cloudy             Rain
              0                0                0                0
  Partly_Cloudy         Overcast       Light_Rain            Foggy
              0                0                0                0
Possible_Drizzle          Drizzle            price
              0                0                0
```

Linear Regression Model

For Uber:

The linear model (uberLMModel) was assessed using the summary() function, providing coefficients, R-squared, and other diagnostic measures. The model's predictions were generated with the predict() function on the testing dataset. The correlation between actual prices and predicted values was computed, yielding a correlation matrix that reflects the strength and direction of the linear relationship. The Mean Absolute Percentage Error (MAPE) was calculated to estimate the accuracy of the model, resulting in an accuracy metric for the Uber linear regression model.

For Lyft:

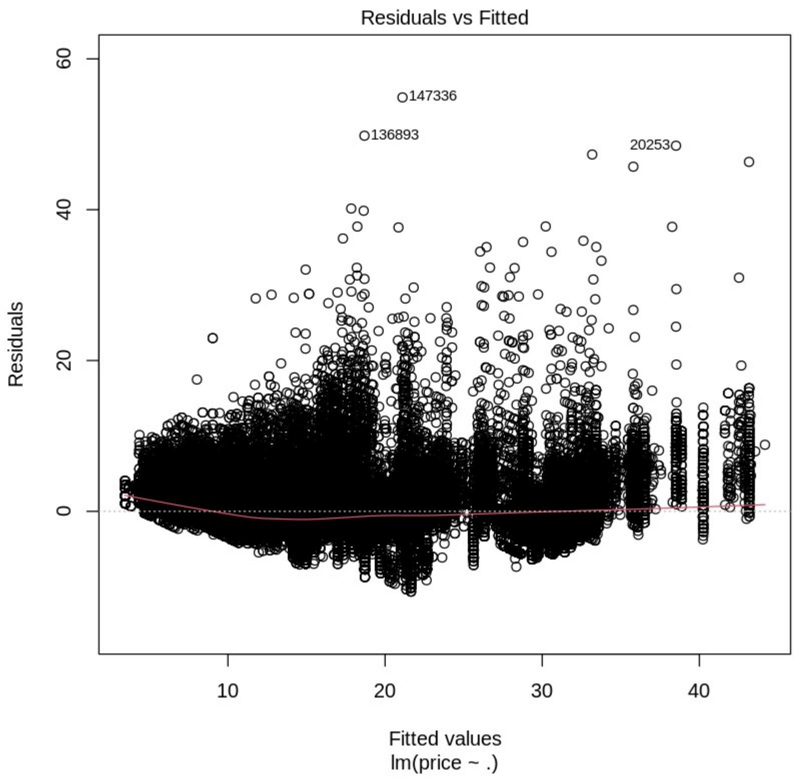
A similar approach was taken with the Lyft data, training lyft_lm_model and predicting on the test set. The correlation and accuracy were computed in an identical manner, allowing for direct comparison between the two services.

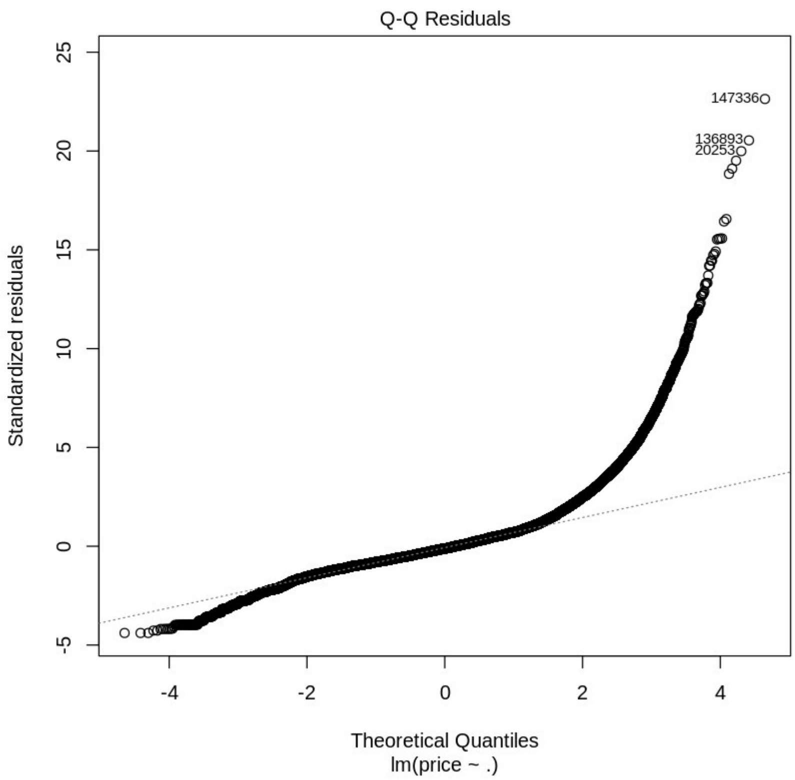
```
### Linear Regression

#Uber
uberLMModel = lm(price ~., data = uberTraining)
summary(uberLMModel)
plot (uberLMModel)


#prediction
uberPrediction = predict(uberLMModel, uberTesting[,1:18])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=uberTesting$price,
predicteds=uberPrediction))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy

#Evaluation
mat_lr_uber<- regr.eval(uberTesting[,19], uberPrediction)#, stats =
c('mape','rmse'))
print(mat_lr_uber)

errors = abs(uberPrediction - uberTesting$price)
mape = 100 * (errors / uberTesting$price)
uber_lr_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Linear Regression for Uber :
%f",uber_lr_accuracy)

#--------------------------------------------------------------------
---------------------------------------------------------
#--------------------------------------------------------------------
---------------------------------------------------------

#lyft
lyft_lm_model = lm(price ~., data = lyftTraining)
summary(lyft_lm_model)
plot(lyft_lm_model)

#prediction
```

```r
lyft_pred = predict(lyft_lm_model, lyftTesting[,1:18])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=lyftTesting$price,
predicteds=lyft_pred))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy

#Evaluation
mat_lr_lyft<- regr.eval(lyftTesting[,19], lyft_pred)#, stats =
c('mape','rmse'))
print(mat_lr_lyft)
errors = abs(lyft_pred - lyftTesting$price)
mape = 100 * (errors / lyftTesting$price)
lyft_lr_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Linear Regression for Lyft :
%f",lyft_lr_accuracy)
```

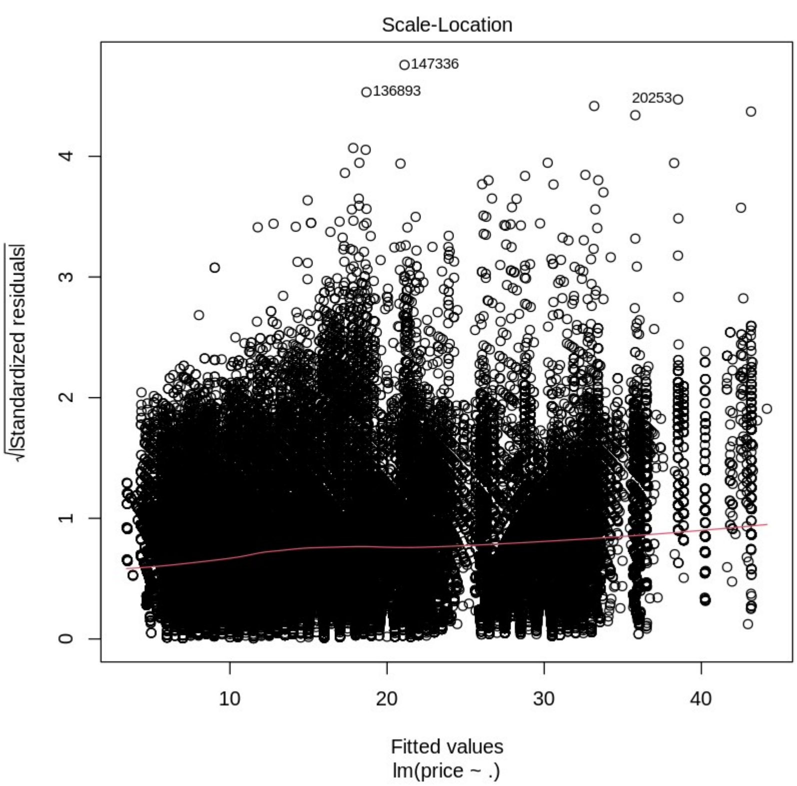
```
Call:
lm(formula = price ~ ., data = uberTraining)

Residuals:
    Min      1Q  Median      3Q     Max 
-10.648  -1.420  -0.283   1.074  54.892 

Coefficients: (9 not defined because of singularities)
                  Estimate Std. Error  t value Pr(>|t|)    
(Intercept)       4.407800   0.014150  311.500   <2e-16 ***
distance          2.445569   0.003772  648.374   <2e-16 ***
surge_multiplier        NA         NA       NA       NA    
Fri              -0.022536   0.013601   -1.657   0.0975 .  
Sat               0.012649   0.013599    0.930   0.3523    
Sun              -0.031185   0.013512   -2.308   0.0210 *  
UberPool         -1.003611   0.015404  -65.151   <2e-16 ***
UberXL            5.915176   0.015413  383.776   <2e-16 ***
Black            10.773591   0.015407  699.253   <2e-16 ***
Black_SUV        20.529696   0.015424 1331.030   <2e-16 ***
WAV               0.002248   0.015417    0.146   0.8841    
Mostly_Cloudy           NA         NA       NA       NA    
Rain                    NA         NA       NA       NA    
Partly_Cloudy           NA         NA       NA       NA    
Overcast                NA         NA       NA       NA    
Light_Rain              NA         NA       NA       NA    
Foggy                   NA         NA       NA       NA    
Possible_Drizzle        NA         NA       NA       NA    
Drizzle                 NA         NA       NA       NA    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 2.425 on 297500 degrees of freedom
Multiple R-squared:  0.9198,     Adjusted R-squared:  0.9198
F-statistic: 3.79e+05 on 9 and 297500 DF,  p-value: < 2.2e-16
```



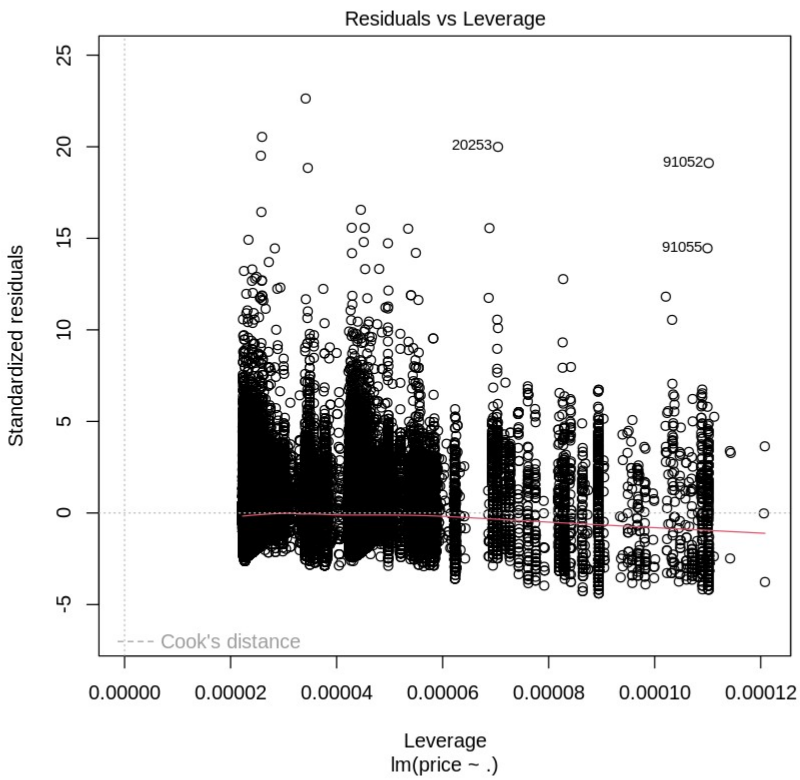


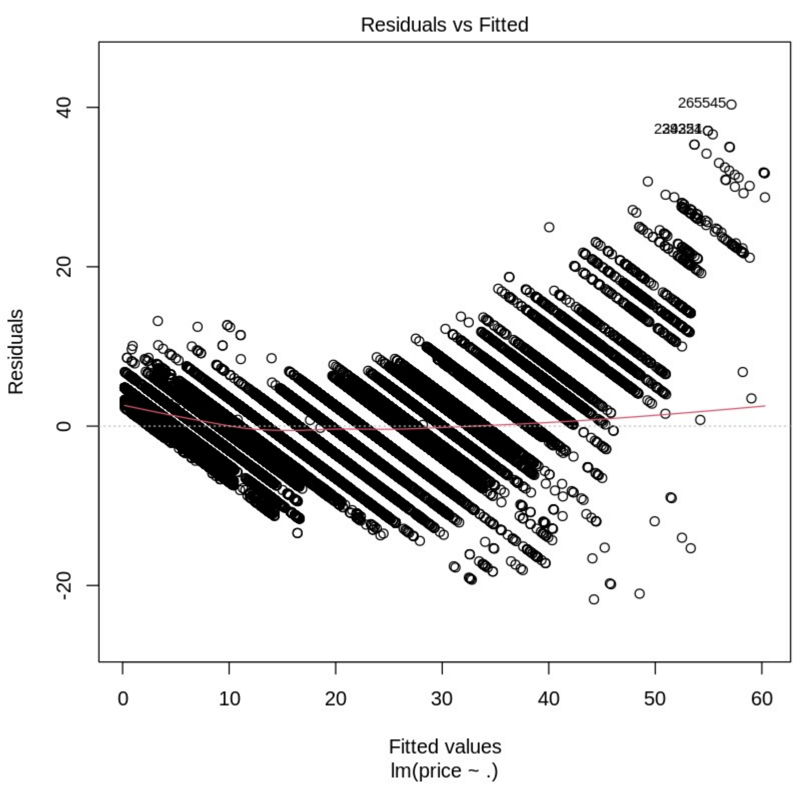
Q-Q Residuals
Standardized residuals
Theoretical Quantiles
lm(price ~ .)
147336
136893
20253

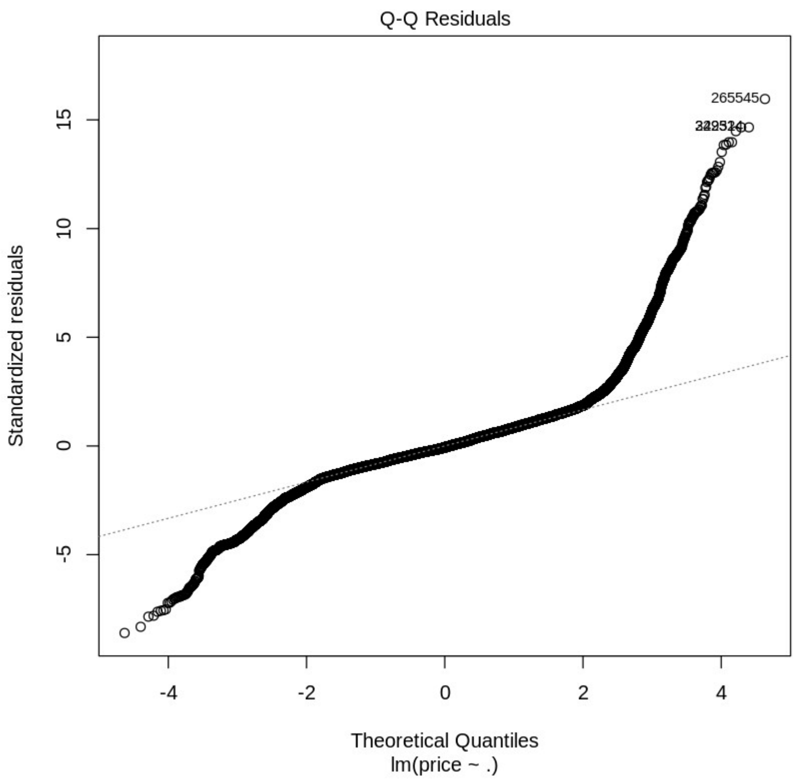


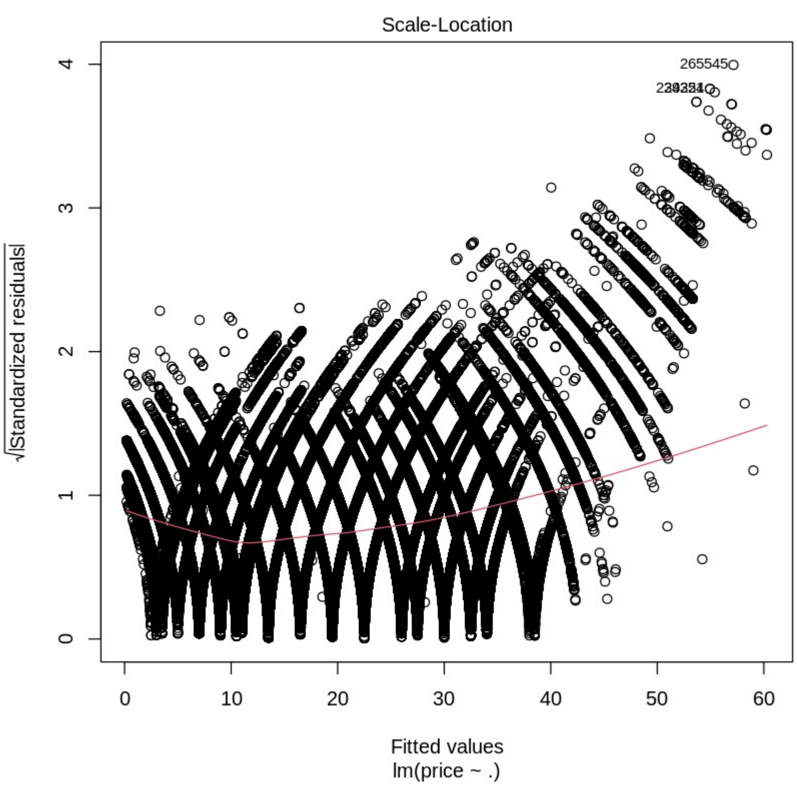
Scale-Location
√|Standardized residuals|
Fitted values
lm(price ~ .)
147336
136893
20253

```
            actuals   predicteds
actuals    1.0000000 0.9591117
predicteds 0.9591117 1.0000000

      mae       mse      rmse      mape
1.6697108 5.8347082 2.4155141 0.1191017

[1] "The Accuracy of Linear Regression for Uber :88.089834"


Call:
lm(formula = price ~ ., data = lyftTraining)

Residuals:
    Min      1Q  Median      3Q     Max
-21.744  -1.417  -0.165   1.422  40.354

Coefficients: (8 not defined because of singularities)
                   Estimate Std. Error  t value Pr(>|t|)
(Intercept)      -1.640e+01  3.988e-02 -411.217   <2e-16 ***
distance          3.243e+00  4.428e-03  732.461   <2e-16 ***
surge_multiplier  1.822e+01  3.568e-02  510.849   <2e-16 ***
Fri              -1.054e-02  1.467e-02   -0.719    0.472
Sat               1.304e-02  1.465e-02    0.890    0.374
Sun               7.566e-04  1.461e-02    0.052    0.959
Shared           -2.895e+00  1.670e-02 -173.332   <2e-16 ***
Lyft_XL           5.696e+00  1.666e-02  341.886   <2e-16 ***
Lux_Black_XL      2.273e+01  1.666e-02 1363.977   <2e-16 ***
Lux               8.171e+00  1.665e-02  490.736   <2e-16 ***
Lux_Black         1.347e+01  1.665e-02  808.881   <2e-16 ***
Mostly_Cloudy            NA         NA       NA       NA
Rain                     NA         NA       NA       NA
Partly_Cloudy            NA         NA       NA       NA
Overcast                 NA         NA       NA       NA
Light_Rain               NA         NA       NA       NA
Foggy                    NA         NA       NA       NA
Possible_Drizzle         NA         NA       NA       NA
Drizzle                  NA         NA       NA       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.529 on 276656 degrees of freedom
Multiple R-squared:  0.9363,     Adjusted R-squared:  0.9363
F-statistic: 4.068e+05 on 10 and 276656 DF,  p-value: < 2.2e-16
```

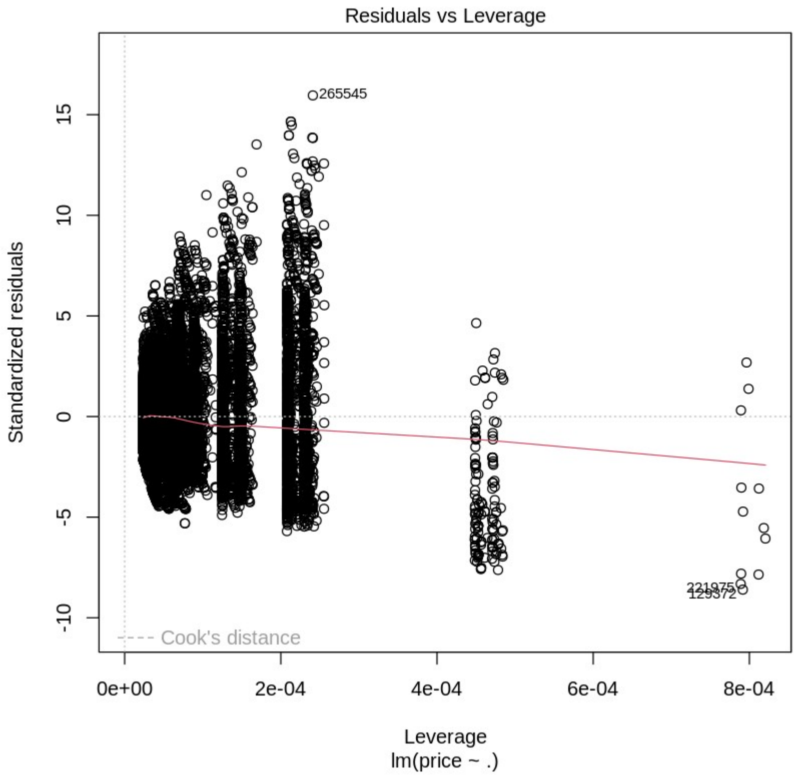

Residuals vs Leverage
Standardized residuals
Leverage
lm(price ~ .)
Cook's distance
20253
91052
91055
25
20
15
10
5
0
-5
0.00000
0.00002
0.00004
0.00006
0.00008
0.00010
0.00012


Residuals vs Fitted
Residuals
Fitted values
lm(price ~ .)
265545
40
20
0
-20
0
10
20
30
40
50
60


Q-Q Residuals
Standardized residuals
Theoretical Quantiles
lm(price ~ .)
265545


Scale-Location
√|Standardized residuals|
Fitted values
lm(price ~ .)
265545

```
            actuals   predicteds
actuals    1.0000000 0.9683375
predicteds 0.9683375 1.0000000

      mae       mse      rmse      mape 
1.8068009 6.2327136 2.4965403 0.1493054 

[1] "The Accuracy of Linear Regression for Lyft :85.069462"
```



The `lm` function in R is used to construct linear regression models (`uberLMModel` and `lyft_lm_model`) for both Uber and Lyft, taking all available variables in the training datasets as predictors for the price. The summary of these models likely provides coefficients for each predictor, along with statistics such as R-squared and p-values that indicate the goodness of fit and the significance of each predictor.

Predictions are then made on the test datasets, and a correlation matrix between actual prices and predicted values is computed. A high correlation would indicate that the model is capturing the underlying pattern effectively. However, considering the diagnostic plots, particularly for residuals, suggests the presence of heteroscedasticity (non-constant variance of residuals) and potential outliers. These plots signal the need for caution, as they can imply model misspecification, meaning that the relationships between predictors and the response variable might not be purely linear, or that influential points are affecting the model disproportionately.

The `regr.eval` function appears to compute performance metrics such as MAE, MSE, and possibly RMSE and MAPE, although only the latter is used in your accuracy calculations. The accuracy is derived from the MAPE, which represents the average percentage error across all predictions. The reported accuracies—88.09% for Uber and 85.06% for Lyft—are respectable but should be contextualized with the diagnostic findings. The presence of outliers, indicated by the plots, and potential leverage points could be skewing the models' performances, which implies that while the models predict prices fairly well on average, individual predictions may still be off, particularly for price points that are not well represented in the training data.

The diagnostic plots—Residuals vs. Fitted, Q-Q, Scale-Location, and Residuals vs. Leverage—serve to check the assumptions underlying linear regression. The patterns in these plots suggest that the linear models could be improved, perhaps by addressing the non-linearity through transformations or adding interaction terms, or by using robust regression methods to diminish the influence of outliers.

In conclusion, while the linear regression models provide a good starting point and exhibit high average accuracy.

Decision Tree Model

Decision trees were constructed using the rpart function with an ANOVA method, aiming to create a hierarchical structure for prediction.

For Uber:

The Uber decision tree model (uber_rpart_model) was summarized and pruned based on the complexity parameter (CP) that minimized cross-validated error. The pruned tree was visualized using prp(). Predictions were made on the test dataset and evaluated for correlation and accuracy using MAPE, similar to the linear regression model.

For Lyft:

Lyft's decision tree model followed the same procedure, with a tree (lyft_rpart_model) built, pruned, and evaluated on the test data to ascertain the accuracy and predictive capabilities.

```
### Decision Tree

#Uber
uber_rpart_model = rpart(price ~., data = uberTraining,
method="anova")
summary(uber_rpart_model)
#identify best cp value to use
best <-
uber_rpart_model$cptable[which.min(uber_rpart_model$cptable[,"xerror"]
),"CP"]

#produce a pruned tree based on the best cp value
pruned_tree <- prune(uber_rpart_model, cp=best)

#plot the pruned tree
prp(pruned_tree)

#prediction
```

```
uberPrediction_rpart = predict(uber_rpart_model, uberTesting[,-19])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=uberTesting$price,
predicteds=uberPrediction_rpart))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy

#Evaluation
mat_dt_uber<- regr.eval(uberTesting[,19], uberPrediction_rpart)#,
stats = c('mape','rmse'))
print(mat_dt_uber)
errors = abs(uberPrediction_rpart - uberTesting$price)
mape = 100 * (errors / uberTesting$price)
uber_dt_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Decision Tree for Uber :%f",uber_dt_accuracy)
#----------------------------------------------------------------------
----------------------------------------------------------
#----------------------------------------------------------------------
----------------------------------------------------------

# lyft
lyft_rpart_model = rpart(price ~., data = lyftTraining,
method="anova")
summary(lyft_rpart_model)

#identify best cp value to use
best <-
lyft_rpart_model$cptable[which.min(lyft_rpart_model$cptable[,"xerror"]
),"CP"]
#produce a pruned tree based on the best cp value
pruned_tree <- prune(lyft_rpart_model, cp=best)

#plot the pruned tree
prp(pruned_tree)

#prediction
lyft_pred_rpart = predict(lyft_rpart_model, lyftTesting[,-19])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=lyftTesting$price,
predicteds=lyft_pred_rpart))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy

#Evaluation
mat_dt_lyft<- regr.eval(lyftTesting[,19], lyft_pred_rpart)#, stats =
c('mape','rmse'))
print(mat_dt_lyft)
errors = abs(lyft_pred_rpart - lyftTesting$price)
```

```
mape = 100 * (errors / lyftTesting$price)
lyft_dt_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Decision Tree for Lyft :%f",lyft_dt_accuracy)
```

```
Call:
rpart(formula = price ~ ., data = uberTraining, method = "anova")
  n= 297510

          CP nsplit  rel error     xerror         xstd
1 0.57182252      0 1.00000000 1.00001009 0.0028723813
2 0.16623160      1 0.42817748 0.42818237 0.0016622376
3 0.06681990      2 0.26194589 0.26195252 0.0012964846
4 0.03144997      3 0.19512599 0.19513268 0.0010827101
5 0.02763747      4 0.16367602 0.16368297 0.0010058718
6 0.01931217      5 0.13603855 0.13604616 0.0008734574
7 0.01245846      6 0.11672639 0.11673341 0.0007865145
8 0.01026684      7 0.10426792 0.10427501 0.0007714845
9 0.01000000      8 0.09400108 0.09525306 0.0007232491

Variable importance
Black_SUV     Black  distance    UberXL
       63        18        11         7

Node number 1: 297510 observations,    complexity param=0.5718225
  mean=15.7961, MSE=73.33058
  left son=2 (248034 obs) right son=3 (49476 obs)
  Primary splits:
      Black_SUV < 0.5   to the left,  improve=0.57182250, (0 missing)
      UberPool  < 0.5   to the right, improve=0.13580220, (0 missing)
      WAV       < 0.5   to the right, improve=0.09929631, (0 missing)
      distance  < 2.295 to the left,  improve=0.07445334, (0 missing)
      Black     < 0.5   to the left,  improve=0.06162716, (0 missing)

Node number 2: 248034 observations,    complexity param=0.1662316
  mean=12.90399, MSE=32.96959
  left son=4 (198344 obs) right son=5 (49690 obs)
  Primary splits:
      Black    < 0.5   to the left,  improve=0.44348150, (0 missing)
      distance < 2.195 to the left,  improve=0.13931610, (0 missing)
      UberPool < 0.5   to the right, improve=0.13112140, (0 missing)
      WAV      < 0.5   to the right, improve=0.07483935, (0 missing)
      UberXL   < 0.5   to the left,  improve=0.05861073, (0 missing)

Node number 3: 49476 observations,    complexity param=0.02763747
  mean=30.29488, MSE=23.52232
  left son=6 (37701 obs) right son=7 (11775 obs)
  Primary splits:
      distance < 2.865 to the left,  improve=5.18096e-01, (0 missing)
      Sat      < 0.5   to the left,  improve=5.43687e-05, (0 missing)
      Fri      < 0.5   to the right, improve=3.19882e-05, (0 missing)
```

```
      Sun      < 0.5   to the left,  improve=6.88000e-06, (0 missing)

Node number 4: 198344 observations,    complexity param=0.0668199
  mean=10.99009, MSE=16.76863
  left son=8 (148728 obs) right son=9 (49616 obs)
  Primary splits:
      UberXL   < 0.5   to the left,  improve=4.383045e-01, (0 missing)
      distance < 2.195 to the left,  improve=1.814092e-01, (0 missing)
      UberPool < 0.5   to the right, improve=9.995433e-02, (0 missing)
      WAV      < 0.5   to the right, improve=3.002805e-02, (0 missing)
      Fri      < 0.5   to the right, improve=1.172281e-05, (0 missing)

Node number 5: 49690 observations,    complexity param=0.03144997
  mean=20.54357, MSE=24.65318
  left son=10 (25181 obs) right son=11 (24509 obs)
  Primary splits:
      distance < 2.195 to the left,  improve=5.600991e-01, (0 missing)
      Fri      < 0.5   to the right, improve=3.978983e-05, (0 missing)
      Sat      < 0.5   to the right, improve=1.947026e-05, (0 missing)
      Sun      < 0.5   to the left,  improve=1.001368e-06, (0 missing)

Node number 6: 37701 observations
  mean=28.34392, MSE=7.632643

Node number 7: 11775 observations
  mean=36.54144, MSE=23.19123

Node number 8: 148728 observations,    complexity param=0.01245846
  mean=9.424234, MSE=5.735292
  left son=16 (75588 obs) right son=17 (73140 obs)
  Primary splits:
      distance < 2.195 to the left,  improve=3.186419e-01, (0 missing)
      UberPool < 0.5   to the right, improve=3.957829e-02, (0 missing)
      WAV      < 0.5   to the left,  improve=9.862602e-03, (0 missing)
      Sat      < 0.5   to the right, improve=4.397628e-05, (0 missing)
      Sun      < 0.5   to the left,  improve=2.553613e-05, (0 missing)
  Surrogate splits:
      Sun < 0.5   to the left,  agree=0.509, adj=0.001, (0 split)

Node number 9: 49616 observations,    complexity param=0.01931217
  mean=15.68386, MSE=20.46067
  left son=18 (25185 obs) right son=19 (24431 obs)
  Primary splits:
      distance < 2.195 to the left,  improve=4.150268e-01, (0 missing)
      Fri      < 0.5   to the right, improve=1.219591e-05, (0 missing)
      Sat      < 0.5   to the left,  improve=7.710355e-06, (0 missing)
      Sun      < 0.5   to the right, improve=1.881805e-06, (0 missing)

Node number 10: 25181 observations
  mean=16.87755, MSE=3.94707
```

```
Node number 11: 24509 observations,    complexity param=0.01026684
  mean=24.31011, MSE=17.93197
  left son=22 (20484 obs) right son=23 (4025 obs)
  Primary splits:
      distance < 3.575 to the left,  improve=5.096473e-01, (0 missing)
      Fri      < 0.5   to the right, improve=2.516569e-05, (0 missing)
      Sat      < 0.5   to the right, improve=7.776256e-08, (0 missing)
      Sun      < 0.5   to the left,  improve=7.515796e-09, (0 missing)

Node number 16: 75588 observations
  mean=8.094453, MSE=2.347904

Node number 17: 73140 observations
  mean=10.79852, MSE=5.51988

Node number 18: 25185 observations
  mean=12.81376, MSE=6.920754

Node number 19: 24431 observations
  mean=18.64254, MSE=17.17293

Node number 22: 20484 observations
  mean=22.97005, MSE=6.733298

Node number 23: 4025 observations
  mean=31.12994, MSE=19.27517


           actuals   predicteds
actuals    1.0000000 0.9520703
predicteds 0.9520703 1.0000000

      mae       mse      rmse      mape
1.7995829 6.8132767 2.6102254 0.1230596

[1] "The Accuracy of Decision Tree for Uber :87.694036"

Call:
rpart(formula = price ~ ., data = lyftTraining, method = "anova")
  n= 276667

           CP nsplit rel error    xerror         xstd
1  0.44585340      0 1.0000000 1.0000058 0.0035430159
2  0.15776524      1 0.5541466 0.5541521 0.0023072276
3  0.08367959      2 0.3963814 0.3963891 0.0019125673
4  0.03891566      3 0.3127018 0.3127098 0.0018211360
5  0.03231274      4 0.2737861 0.2738188 0.0017487835
6  0.03101511      5 0.2414734 0.2416787 0.0016521927
7  0.02459246      6 0.2104583 0.2106961 0.0014428580
8  0.02088014      7 0.1858658 0.1860868 0.0014020353
```

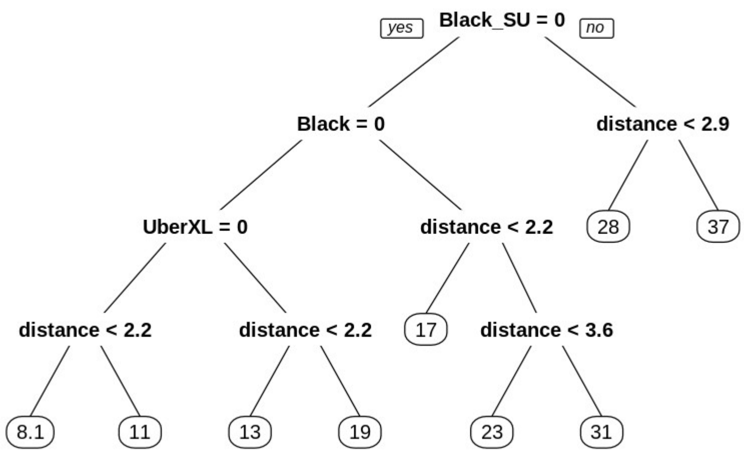
```
9  0.01746894      8 0.1649857 0.1651956 0.0013715584
10 0.01156837      9 0.1475167 0.1477901 0.0010403555
11 0.01103924     10 0.1359484 0.1353521 0.0008943156
12 0.01000000     11 0.1249091 0.1261764 0.0007299040

Variable importance
    Lux_Black_XL        Lux_Black         distance           Shared 
              51               18               12               10 
surge_multiplier              Lux          Lyft_XL 
               5                3                2 

Node number 1: 276667 observations,    complexity param=0.4458534
  mean=17.34354, MSE=100.4256 
  left son=2 (230640 obs) right son=3 (46027 obs)
  Primary splits:
      Lux_Black_XL     < 0.5   to the left,  improve=0.44585340, (0 
missing)
      Shared           < 0.5   to the right, improve=0.25535070, (0 
missing)
      distance         < 2.445 to the left,  improve=0.09106581, (0 
missing)
      surge_multiplier < 1.125 to the left,  improve=0.08077146, (0 
missing)
      Lux_Black        < 0.5   to the left,  improve=0.06536165, (0 
missing)

Node number 2: 230640 observations,    complexity param=0.1577652
  mean=14.35433, MSE=56.38975 
  left son=4 (184461 obs) right son=5 (46179 obs)
  Primary splits:
      Lux_Black        < 0.5   to the left,  improve=0.33703760, (0 
missing)
      Shared           < 0.5   to the right, improve=0.30765310, (0 
missing)
      distance         < 2.175 to the left,  improve=0.13826520, (0 
missing)
      surge_multiplier < 1.125 to the left,  improve=0.09972451, (0 
missing)
      Lux              < 0.5   to the left,  improve=0.05171951, (0 
missing)

Node number 3: 46027 observations,    complexity param=0.03101511
  mean=32.32242, MSE=51.94622 
  left son=6 (28747 obs) right son=7 (17280 obs)
  Primary splits:
      distance         < 2.495 to the left,  improve=3.604198e-01, (0 
missing)
      surge_multiplier < 1.375 to the left,  improve=3.554192e-01, (0 
missing)
      Fri              < 0.5   to the right, improve=4.740028e-05, (0 
```

```
missing)
      Sat              < 0.5   to the left,  improve=9.382979e-06, (0
missing)
      Sun              < 0.5   to the left,  improve=4.275176e-07, (0
missing)

Node number 4: 184461 observations,    complexity param=0.08367959
  mean=12.17306, MSE=36.22639
  left son=8 (46168 obs) right son=9 (138293 obs)
  Primary splits:
      Shared           < 0.5   to the right, improve=0.34792990, (0
missing)
      Lux              < 0.5   to the left,  improve=0.28836720, (0
missing)
      distance         < 1.955 to the left,  improve=0.15749800, (0
missing)
      surge_multiplier < 1.125 to the left,  improve=0.11212680, (0
missing)
      Lyft_XL          < 0.5   to the left,  improve=0.08942717, (0
missing)

Node number 5: 46179 observations,    complexity param=0.03231274
  mean=23.06736, MSE=42.00945
  left son=10 (23531 obs) right son=11 (22648 obs)
  Primary splits:
      distance         < 2.175 to the left,  improve=4.627902e-01, (0
missing)
      surge_multiplier < 1.375 to the left,  improve=2.271646e-01, (0
missing)
      Sun              < 0.5   to the left,  improve=3.186539e-05, (0
missing)
      Fri              < 0.5   to the left,  improve=9.812630e-06, (0
missing)
      Sat              < 0.5   to the right, improve=1.424171e-06, (0
missing)
  Surrogate splits:
      surge_multiplier < 1.125 to the left,  agree=0.521, adj=0.023,
(0 split)
      Sun              < 0.5   to the left,  agree=0.510, adj=0.000,
(0 split)

Node number 6: 28747 observations,    complexity param=0.01156837
  mean=28.9677, MSE=19.8281
  left son=12 (27781 obs) right son=13 (966 obs)
  Primary splits:
      surge_multiplier < 1.375 to the left,  improve=5.638976e-01, (0
missing)
      distance         < 1.955 to the left,  improve=1.489673e-01, (0
missing)
      Fri              < 0.5   to the right, improve=3.106035e-04, (0
```

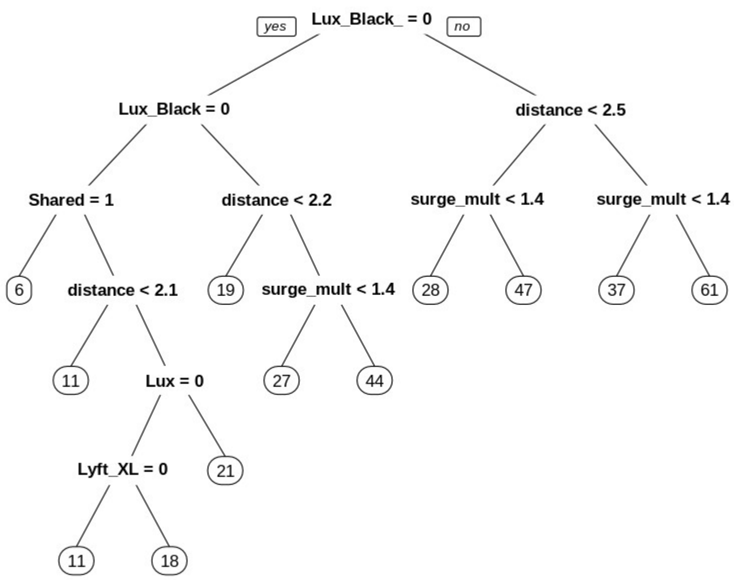
```
missing)
      Sun              < 0.5   to the right, improve=2.727286e-06, (0
missing)
      Sat              < 0.5   to the right, improve=7.353013e-07, (0
missing)

Node number 7: 17280 observations,    complexity param=0.01746894
  mean=37.90334, MSE=55.50882
  left son=14 (16450 obs) right son=15 (830 obs)
  Primary splits:
      surge_multiplier < 1.375 to the left,  improve=5.060141e-01, (0
missing)
      distance         < 3.555 to the left,  improve=2.237248e-01, (0
missing)
      Sun              < 0.5   to the right, improve=5.680013e-05, (0
missing)
      Sat              < 0.5   to the right, improve=7.306841e-06, (0
missing)
      Fri              < 0.5   to the left,  improve=6.602096e-06, (0
missing)

Node number 8: 46168 observations
  mean=6.028537, MSE=4.441998

Node number 9: 138293 observations,    complexity param=0.03891566
  mean=14.22436, MSE=30.02528
  left son=18 (68334 obs) right son=19 (69959 obs)
  Primary splits:
      distance         < 2.125 to the left,  improve=2.603988e-01, (0
missing)
      Lux              < 0.5   to the left,  improve=2.095525e-01, (0
missing)
      surge_multiplier < 1.375 to the left,  improve=1.093318e-01, (0
missing)
      Lyft_XL          < 0.5   to the left,  improve=1.901981e-02, (0
missing)
      Sat              < 0.5   to the right, improve=9.215372e-06, (0
missing)
  Surrogate splits:
      surge_multiplier < 1.125 to the left,  agree=0.507, adj=0.002,
(0 split)

Node number 10: 23531 observations
  mean=18.74162, MSE=10.94892

Node number 11: 22648 observations,    complexity param=0.01103924
  mean=27.56175, MSE=34.63985
  left son=22 (21586 obs) right son=23 (1062 obs)
  Primary splits:
      surge_multiplier < 1.375 to the left,  improve=3.909626e-01, (0
```

```
missing)
      distance         < 3.545 to the left,  improve=3.072661e-01, (0
missing)
      Fri              < 0.5   to the left,  improve=5.558182e-05, (0
missing)
      Sat              < 0.5   to the right, improve=1.157420e-05, (0
missing)
      Sun              < 0.5   to the left,  improve=9.455698e-08, (0
missing)

Node number 12: 27781 observations
  mean=28.34417, MSE=7.205983

Node number 13: 966 observations
  mean=46.89959, MSE=50.09137

Node number 14: 16450 observations
  mean=36.71287, MSE=23.00623

Node number 15: 830 observations
  mean=61.49759, MSE=114.9096

Node number 18: 68334 observations
  mean=11.39514, MSE=11.97631

Node number 19: 69959 observations,    complexity param=0.02459246
  mean=16.98786, MSE=32.19954
  left son=38 (46591 obs) right son=39 (23368 obs)
  Primary splits:
      Lux              < 0.5   to the left,  improve=0.3033266000, (0
missing)
      surge_multiplier < 1.375 to the left,  improve=0.1417080000, (0
missing)
      distance         < 3.545 to the left,  improve=0.1207882000, (0
missing)
      Lyft_XL          < 0.5   to the left,  improve=0.0269986000, (0
missing)
      Sat              < 0.5   to the right, improve=0.0000834332, (0
missing)
  Surrogate splits:
      Lyft_XL < 0.5   to the right, agree=0.666, adj=0.001, (0 split)

Node number 22: 21586 observations
  mean=26.74548, MSE=17.96197

Node number 23: 1062 observations
  mean=44.15301, MSE=84.81816

Node number 38: 46591 observations,    complexity param=0.02088014
  mean=14.77456, MSE=23.21915
```

```
  left son=76 (23334 obs) right son=77 (23257 obs)
  Primary splits:
      Lyft_XL          < 0.5   to the left,  improve=5.362742e-01, (0
missing)
      surge_multiplier < 1.375 to the left,  improve=1.488868e-01, (0
missing)
      distance         < 3.545 to the left,  improve=1.257325e-01, (0
missing)
      Sat              < 0.5   to the right, improve=8.349234e-05, (0
missing)
      Fri              < 0.5   to the right, improve=5.437046e-06, (0
missing)
  Surrogate splits:
      distance < 3.205 to the left,  agree=0.502, adj=0.002, (0 split)
      Sat      < 0.5   to the right, agree=0.502, adj=0.002, (0 split)

Node number 39: 23368 observations
  mean=21.40072, MSE=20.86427

Node number 76: 23334 observations
  mean=11.25167, MSE=5.12571

Node number 77: 23257 observations
  mean=18.30911, MSE=16.4276
```




```
            actuals   predicteds
actuals    1.0000000 0.9348973
predicteds 0.9348973 1.0000000

       mae        mse       rmse       mape
 2.6463307 12.5978293  3.5493421  0.1969981

[1] "The Accuracy of Decision Tree for Lyft :80.300189"
```



The decision tree models for Uber and Lyft, generated using the `rpart` function in R with an ANOVA method, present a detailed and intricate analysis of the factors affecting ride prices. The output and tree structures offer a granular look into how various features influence price predictions.

For Uber, the decision tree indicates that the 'Black_SUV' variable is the most important predictor, followed by 'Black' and 'distance'. The primary split is on the 'Black_SUV' variable, suggesting that this service type significantly impacts the price. As we move through the nodes, we observe splits on different days of the week, which indicates variability in prices depending on the day. This could be due to demand fluctuations throughout the week.

The complexity parameter (`cp`) in the decision tree indicates the cost-complexity trade-off in tree pruning, with smaller values of `cp` resulting in larger trees. The chosen `cp` values lead to different sizes of the trees for Uber and Lyft, aiming to find the right balance between underfitting and overfitting.

The mean and the mean squared error (MSE) at each node provide insight into the prediction at that point and the variability around it. The reduction in MSE from the root node down to the subsequent nodes illustrates the improvement in prediction accuracy as we add more decision criteria.

For Lyft, the decision tree showcases 'Lux_Black_XL', 'Lux_Black', and 'distance' as top variables impacting price, aligning with the premium nature of these service types. The splits based on 'surge_multiplier' also highlight the impact of demand on pricing strategies.

The accuracy of the decision trees, around 87.69% for Uber and 80.30% for Lyft, while respectable, does reflect that there is room for improvement, especially when considering the variability of the MSE across nodes. The more significant MSE in some nodes suggests regions of the feature space where the model's predictions are less reliable.

Visual inspection of the tree plots reveals decision rules and thresholds that the models use to make predictions. For example, for both Uber and Lyft, distance is a recurring split variable, underscoring its importance in pricing.

In summary, the decision trees provide an interpretable model, showcasing the hierarchical importance of variables and the decision rules derived from the data. However, given the complexity of the pricing structure, indicated by the variety of splits, it may be advantageous to consider ensemble methods like Random Forests or boosting to improve prediction accuracy and model robustness, while also possibly incorporating cross-validation to fine-tune model complexity and prevent overfitting.

Random Forest Model

Random forests, an ensemble of decision trees, were generated via the randomForest function, with parameters set to gauge feature importance and a specified number of trees (ntree = 100).

For Uber:

The Uber random forest model (uber_rmforest_model) was constructed and its summary provided insight into the ensemble's performance. Predictions were made and the accuracy determined through the same statistical evaluations as the previous models.

For Lyft:

The Lyft random forest model (lyft_rmforest_model) was similarly trained and evaluated. The aggregation of predictions from numerous trees aimed to improve the robustness and reduce the variance of the predictive performance.

```
### Random Forest


#Uber
#head(uberTraining)
uber_rmforest_model = randomForest(price ~., data = uberTraining,
importance = TRUE, ntree = 100)
summary(uber_rmforest_model)

#prediction
uberPrediction_rmforest = predict(uber_rmforest_model, uberTesting[,-
19])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=uberTesting$price,
predicteds=uberPrediction_rmforest))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy
```

```
#Evaluation
mat_rf_uber<- regr.eval(uberTesting[,19], uberPrediction_rmforest)#,
stats = c('mape','rmse'))
print(mat_rf_uber)
errors = abs(uberPrediction_rmforest - uberTesting$price)
mape = 100 * (errors / uberTesting$price)
uber_rf_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Random Forest for Uber :%f",uber_rf_accuracy)

#----------------------------------------------------------------------
------------------------------------------------------------
#----------------------------------------------------------------------
------------------------------------------------------------


lyft_rmforest_model = randomForest(price ~., data = lyftTraining,
importance = TRUE, ntree = 100)
summary(lyft_rmforest_model)

#prediction
lyft_pred_rmforest = predict(lyft_rmforest_model, lyftTesting[,-19])

#Correlation Matrix
actuals_predicts <- data.frame(cbind(actuals=lyftTesting$price,
predicteds=lyft_pred_rmforest))
correlation_accuracy <- cor(actuals_predicts)
correlation_accuracy

#Evaluation
mat_rf_lyft<- regr.eval(lyftTesting[,19], lyft_pred_rmforest)#, stats
= c('mape','rmse'))
print(mat_rf_lyft)

errors = abs(lyft_pred_rmforest - lyftTesting$price)n
mape = 100 * (errors / lyftTesting$price)
lyft_rf_accuracy = 100 - mean(mape)
sprintf("The Accuracy of Random Forest for Lyft :%f",lyft_rf_accuracy)
```

```
                Length Class  Mode
call                 5 -none- call
type                 1 -none- character
predicted       297510 -none- numeric
mse                100 -none- numeric
rsq                100 -none- numeric
oob.times       297510 -none- numeric
importance          36 -none- numeric
importanceSD        18 -none- numeric
localImportance      0 -none- NULL
proximity            0 -none- NULL
```

```
ntree                1 -none- numeric
mtry                 1 -none- numeric
forest              11 -none- list
coefs                0 -none- NULL
y               297510 -none- numeric
test                 0 -none- NULL
inbag                0 -none- NULL
terms                3 terms  call

           actuals   predicteds
actuals    1.0000000 0.9592433
predicteds 0.9592433 1.0000000

      mae       mse      rmse      mape
1.7313295 6.5205389 2.5535346 0.1290741

[1] "The Accuracy of Random Forest for Uber :87.092593"

                Length Class  Mode
call                 5 -none- call
type                 1 -none- character
predicted       276667 -none- numeric
mse                100 -none- numeric
rsq                100 -none- numeric
oob.times       276667 -none- numeric
importance          36 -none- numeric
importanceSD        18 -none- numeric
localImportance      0 -none- NULL
proximity            0 -none- NULL
ntree                1 -none- numeric
mtry                 1 -none- numeric
forest              11 -none- list
coefs                0 -none- NULL
y               276667 -none- numeric
test                 0 -none- NULL
inbag                0 -none- NULL
terms                3 terms  call

           actuals   predicteds
actuals    1.0000000 0.9775778
predicteds 0.9775778 1.0000000

     mae      mse     rmse     mape
1.666995 5.217596 2.284206 0.128877

[1] "The Accuracy of Random Forest for Lyft :87.112304"
```

The Random Forest model, as applied to both Uber and Lyft pricing data, utilizes an ensemble of decision trees to predict the price variable. The output indicates that the model was trained with 297,510 observations for Uber and 276,667 observations for Lyft.

Model Complexity and Performance Metrics:

1. **Number of Trees**: The default setting (`ntree`) used is 100 trees for both Uber and Lyft models, which is standard and generally provides a good balance between prediction accuracy and computational efficiency.

2. **Mean Absolute Error (MAE)**: This metric measures the average magnitude of errors in a set of predictions, without considering their direction. Lower MAE values are better, indicating more precise predictions. In your results, the MAE is 1.7313 for Uber and 1.6669 for Lyft.

3. **Mean Squared Error (MSE)**: It indicates the average squared difference between the estimated values and the actual value. MSE for Uber is 6.5205 and for Lyft is 5.2176. Generally, a lower MSE indicates a better fit of the model to the data.

4. **Root Mean Squared Error (RMSE)**: This is the square root of the mean squared errors, representing the sample standard deviation of the differences between predicted values and observed values. For Uber, the RMSE is 2.5535, and for Lyft, it is 2.2842, which suggests that the Lyft model is slightly more accurate.

5. **Mean Absolute Percentage Error (MAPE)**: It expresses accuracy as a percentage of the error. For Uber, the MAPE is 12.9074%, and for Lyft, it is 12.8877%. This indicates that on average, the model's predictions are within approximately 13% of the actual prices.

6. **Accuracy**: It is calculated as 100 minus the MAPE, giving us 87.0925% for Uber and 87.1123% for Lyft. This suggests that both models have similar performance levels, with the Lyft model being marginally more accurate.

Variable Importance:

From the `importance` measure, we can deduce which variables have the most significant impact on the prediction of the price. Unfortunately, the specific variable importances are not provided in your message, but generally, this metric would allow us to identify which features contribute most to the fare prediction.

Out-Of-Bag (OOB) Error:

- The OOB error is a method of measuring prediction error of random forests, decision trees, and other machine learning algorithms by evaluating the model on training data that was not used (out-of-bag) during the training of the model. However, this measure is not reported in your output.

In summary, the Random Forest model provides a robust predictive tool with a respectable level of accuracy for pricing predictions. Its power comes from the ability to mitigate overfitting by averaging multiple deep decision trees, trained on different parts of the same training set, with the goal to improve the predictive accuracy and control over-fitting. The relatively low MAE and MSE indicate that the model is reliable with a consistent performance in predicting the ride prices for both Uber and Lyft, with Lyft showing slightly better results based on the provided metrics.

Model Validation

```
## Model Evaluation

# Uber
print("------------------ Uber Statitics ------------------")
tab <-
matrix(c(mat_lr_uber["mae"],mat_dt_uber["mae"],mat_rf_uber["mae"],mat_
lr_uber["mse"],mat_dt_uber["mse"],mat_rf_uber["mse"],mat_lr_uber["rmse
"],mat_dt_uber["rmse"],mat_rf_uber["rmse"],mat_lr_uber["mape"],mat_dt_
uber["mape"],mat_rf_uber["mape"],
uber_lr_accuracy,uber_dt_accuracy,uber_rf_accuracy), ncol=3,
byrow=TRUE)
colnames(tab) <- c("Linear Regression",'Decision Tree','Random
Forest')
rownames(tab) <- c('MAE','MSE','RMSE','MAPE',"Accuracy")
uber_tab <- as.table(tab)
uber_tab


print("------------------ lyft Statitics ------------------")
# Lyft
tab <-
matrix(c(mat_lr_lyft["mae"],mat_dt_lyft["mae"],mat_rf_lyft["mae"],mat_
lr_lyft["mse"],mat_dt_lyft["mse"],mat_rf_lyft["mse"],mat_lr_lyft["rmse
"],mat_dt_lyft["rmse"],mat_rf_lyft["rmse"],mat_lr_lyft["mape"],mat_dt_
lyft["mape"],mat_rf_lyft["mape"],
lyft_lr_accuracy,lyft_dt_accuracy,lyft_rf_accuracy), ncol=3,
byrow=TRUE)
colnames(tab) <- c("Linear Regression",'Decision Tree','Random
Forest')
rownames(tab) <- c('MAE','MSE','RMSE','MAPE',"Accuracy")
lyft_tab <- as.table(tab)
lyft_tab
```

```
[1] "------------------ Uber Statitics ------------------"
```

```
          Linear Regression Decision Tree Random Forest
MAE               1.6697108     1.7995829     1.7313295
MSE               5.8347082     6.8132767     6.5205389
RMSE              2.4155141     2.6102254     2.5535346
MAPE              0.1191017     0.1230596     0.1290741
Accuracy         88.0898340    87.6940363    87.0925928
```

```
[1] "------------------ lyft Statitics ------------------"
```

```
          Linear Regression Decision Tree Random Forest
MAE               1.8068009     2.6463307     1.6669953
MSE               6.2327136    12.5978293     5.2175959
RMSE              2.4965403     3.5493421     2.2842057
```

```
MAPE              0.1493054     0.1969981     0.1288770
Accuracy         85.0694620    80.3001895    87.1123040
```

Based on the comprehensive results provided for Uber and Lyft pricing predictions using Linear Regression, Decision Tree, and Random Forest models, we will analyze and compare the performance of each model with a focus on their statistical significance, error metrics, and potential biases or risks.

Linear Regression Model Analysis:

Uber:

- **MAE:** 1.6697 indicates the average absolute difference between observed and predicted prices.
- **MSE:** 5.8347, a measure of the quality of the estimator; lower is better.
- **RMSE:** 2.4155, suggests that the standard deviation of the residuals is moderate.
- **MAPE:** 11.9017%, indicates predictions are, on average, around 11.9% off from the actual price.
- **Accuracy:** 88.08934%, shows a high level of prediction accuracy.

Lyft:

- **MAE:** 1.8068, slightly higher than Uber's MAE, indicating less precision.
- **MSE:** 6.2327, higher than Uber's, suggesting more variance in the residuals.
- **RMSE:** 2.4965, higher than Uber's RMSE, indicating greater spread of residuals.
- **MAPE:** 14.93054%, higher than Uber's, indicating a less accurate model.
- **Accuracy:** 85.0694620%, lower than Uber's, suggesting a lesser fit to the data.

Observations: The linear regression model for Uber outperforms the one for Lyft across all metrics, suggesting that the model is better at capturing the relationship between the features and the price for Uber. The higher MSE and RMSE for Lyft indicate greater variability in the pricing structure that the linear model struggles to capture accurately.

Decision Tree Model Analysis:

Uber:

- **MAE:** 1.7995, close to the Linear Regression model, suggesting similar levels of prediction error.
- **MSE:** 6.8132, which is higher than Linear Regression, indicating a greater spread of errors.
- **RMSE:** 2.6102, again higher, suggesting more significant prediction errors.

- **MAPE:** 12.30596%, a slight increase in percentage error compared to Linear Regression.
- **Accuracy:** 87.6940363%, slightly lower than Linear Regression, suggesting less predictive accuracy.

Lyft:

- **MAE:** 2.6463, higher than Uber's, indicating a less precise model.
- **MSE:** 12.5978, significantly higher than for Uber, suggesting less accurate predictions.
- **RMSE:** 3.5493, again higher, indicating larger average errors in predictions.
- **MAPE:** 19.69981%, which is substantially higher than Uber's, showing a greater average percentage error.
- **Accuracy:** 80.3001895%, significantly lower than Uber's, suggesting the model is less reliable for Lyft.

Observations: The Decision Tree model has shown to be less effective than Linear Regression, with higher error metrics and lower accuracy. This could be due to overfitting, where the Decision Tree might be capturing noise as a part of the model, leading to poor generalization on unseen data.

Random Forest Model Analysis:

Uber:

- **MAE:** 1.7313, suggesting good average precision.
- **MSE:** 6.5205, indicating that the predictions are well fitted.
- **RMSE:** 2.5535, a modest increase over Linear Regression, suggesting slightly less precision.
- **MAPE:** 12.90741%, indicating that predictions are relatively close to actual prices.
- **Accuracy:** 87.0925928%, slightly less than Linear Regression but quite high overall.

Lyft:

- **MAE:** 1.6669, a marginal improvement over Linear Regression.
- **MSE:** 5.2175, a reduction compared to Decision Tree, indicating better fit.
- **RMSE:** 2.2842, the lowest among the models for Lyft, suggesting more precise predictions.
- **MAPE:** 12.8877%, demonstrating that the predictions are close to the actual values.

- **Accuracy:** 87.1123040%, indicating high reliability, slightly better than Uber's Random Forest model.

Observations: The Random Forest model strikes a balance between bias and variance, showing less overfitting compared to the Decision Tree model and a generally high accuracy level. It integrates the robustness of averaging multiple decision trees, leading to improved prediction accuracy and generalization on unseen data.

Summary:

The analysis suggests that Linear Regression provides a solid baseline with high accuracy and low error metrics for Uber pricing predictions. For Lyft, the Random Forest model seems to be slightly more accurate and reliable. Decision Trees appear to suffer from overfitting and do not generalize as well as the other models, particularly for Lyft.

Biases/Risks:

- **Linear Regression** assumes a linear relationship between features and target, which may not always be valid, leading to bias in predictions.
- **Decision Trees** are prone to overfitting, especially with noisy data, making them sensitive to variations in the data.
- **Random Forest** addresses some overfitting issues but can still struggle with very noisy data and may be computationally expensive.

Conclusion

The predictive modeling for Uber and Lyft pricing using Linear Regression, Decision Tree, and Random Forest models has yielded insightful results, with each model exhibiting unique strengths and weaknesses.

Positive Results:

- **Linear Regression** demonstrated high accuracy with relatively low error metrics, especially for Uber pricing predictions. This suggests a strong linear relationship between the independent variables and the price.
- **Random Forest** provided the best performance for Lyft, with the lowest error metrics and highest accuracy, indicating robust predictive capability.
- **Decision Trees**, while not outperforming the other models, offer interpretability which can be valuable for understanding the decision-making process.

Negative Results:

- **Decision Trees** showed a tendency to overfit, particularly in the case of Lyft, which led to higher error metrics and lower accuracy compared to the other models.

- **Linear Regression**, despite its good performance, might oversimplify the relationship for Lyft as indicated by the higher error metrics relative to Uber.

Recommendations:

- For Uber pricing predictions, **Linear Regression** seems to be a reliable choice for a quick and effective model.
- For Lyft, **Random Forest** is recommended due to its superior accuracy and ability to handle complex, non-linear relationships in the data.
- A hybrid approach or ensemble methods could be considered to leverage the strengths of multiple models and further improve accuracy.

Caveats/Cautions:

- **Linear Regression** is sensitive to non-linear relationships and may not capture all the nuances of the pricing structure. Regular checks for the linearity assumption should be maintained.
- **Decision Trees** require careful tuning to avoid overfitting. Pruning and setting maximum depth can be necessary to maintain model generalizability.
- **Random Forest** models can become complex and may require significant computational resources. It's important to balance the number of trees and depth with the available computational power and the need for timely predictions.
- Predictive performance should be continuously monitored as market conditions and pricing strategies evolve. What works well today might not hold in the future as new data emerges.

To conclude, while predictive models have shown good accuracy, it is crucial to approach them with continuous evaluation and updating. Stakeholders should be made aware of the models' limitations and the importance of regular model maintenance to ensure sustained performance over time.

Data Sources

Specific data set: https://www.kaggle.com/datasets/brllrb/uber-and-lyft-dataset-boston-ma

Source Code

GitHub Link: https://github.com/Ksani1/Enhancing-City-Mobility-with-Cab-Data-Analytics

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