

Tools for Understanding Taxicab and E-Hail Service Use in New York City

A Thesis

Presented to

The Division of

Smith College

In Partial Fulfillment

of the Requirements for the Degree

Bachelor of Arts

Wencong (Priscilla) Li

May 2018

Approved for the Division
(Statistical and Data Sciences)

Benjamin Baumer

Acknowledgements

I would love to thank my thesis advisor Benjamin Baumer, Assistant Professor of Statistical and Data Sciences at Smith College, for encouraging me to challenge myself and guiding me through this project. I want to thank Jordan Crouser for being my second reader and help me to revise my paper. I also want to thank all my friends and my roommates for their love and support.

Table of Contents

Chapter 1: Introduction	1
1.1 Motivation	1
1.2 Background	2
1.2.1 Yellow Taxi	2
1.2.2 Green Taxi	2
1.2.3 Uber	3
1.2.4 Lyft	3
1.3 Literature Review	3
1.3.1 New York City Traffic and Taxi	3
1.3.2 Competition between New York City taxi and e-hail services	5
1.3.3 etl R package	6
1.4 Contribution	7
1.4.1 ‘nyctaxi’ Package	7
1.4.2 Social Impact of NYC Taxi	8
1.4.3 Reproducible Research	8
Chapter 2: Data and nyctaxi Package	11
2.1 Data and Storage	11
2.1.1 Yellow Taxi	11
2.1.2 Green Taxi	12

2.1.3	TLC Summary Report	12
2.1.4	Uber	13
2.1.5	Lyft	14
2.1.6	Data Storage	14
2.2	ETL nyctaxi Package	15
2.2.1	Taxi zone shapefile attached to nyctaxi R package	17
2.3	Extract-Transform-Load	18
2.3.1	Extract	18
2.3.2	Transform	19
2.3.3	Load	21
2.3.4	SQL Database Initialization	22
2.4	New York City Taxicab and E-hail Services Summary	24
2.5	Source Code	25
2.5.1	ETL Extract	25
2.5.2	ETL Transform	29
2.5.3	ETL Load	37
2.5.4	ETL Init	42
Chapter 3: New York City Taxi Driver	49
3.1	Aggregated Zone-level Tip Amount	50
3.1.1	Pick-up Zone Percent Tip Amount	52
3.1.2	Which pick-up zones have the highest number of pick-ups? . .	54
3.1.3	Which pick-up zones have the highest percent tips?	55
3.2	What features of taxi trips increase the percent tip amount that passengers pay?	56
3.2.1	Does trip distance increase the percent tips paid by passengers?	57
3.2.2	Do passengers pay more tips during rush hours?	57

Chapter 4: New York City Taxi Passengers	61
4.1 How long does it take passengers to get to JFK, La Guardia, and Newark Airports from anywhere in New York City? When is the best time to travel in order to avoid the traffic?	61
4.1.1 Case Study: From Central Park, Manhattan to all three airport	63
4.1.2 A Shiny App: allowing users to choose a pick up zone of their interest, and output the best time to travel from that zone to all three airports in New York	65
4.2 How does weather affect the number of taxi and Lyft trips?	66
4.2.1 Case Study: March 14th, 2017 Snow Storm	67
4.2.2 Case Study: Impact of Precipitation on Taxi Rides	68
Chapter 5: New York City Taxi Fare & Limousine Commission . . .	73
5.1 Should there be a flat rate between Manhattan and John F. Kennedy International Airport?	73
5.2 Passengers departing from Manhattan benefit from the \$52 flat rate .	74
5.2.1 Trips from Manhattan to JFK Airport	75
5.2.2 Which taxi zones would pay more than \$52 without the flat rate?	76
5.3 Are taxi drivers happy when a passenger wants to go to JFK Airport from Manhattan?	78
5.3.1 How much on average would taxi driver make on their way back from JFK Airport?	79
Chapter 6: Conclusion	85
6.1 Future Research	86
Appendix A: Utility Function	87
Appendix B: Data Dictionary – Yellow Taxi	89

Appendix C: Freedom of Information Law Request	91
Appendix D: NOAA Climate Data Request	93
References	95

List of Tables

3.1	Ten taxi pick-up zones with the highest average tip in January, 2017	53
3.2	Ten taxi zones with the highest number of pick-ups	55
3.3	Ten taxi pick-up zones with the highest percent tip (taxi zones has at least 1 pick-up per hour)	55
3.4	Ten taxi pick-up zones with the highest percent tip (taxi zones has at least 1 pick-up per minute)	56
4.1	Average number of minutes it takes from Alphabet City, Manhattan to JFK Airport during different hours	62
4.2	Uber 2017 Weekly Total Dispatched Trips	66
4.3	Yellow Taxi 2017 Weekly Total Dispatched Trips	67
4.4	10 weeks that have the most rainfall in 2017	69
4.5	10 weeks that have the most rainfall in 2017 and the total number of dispatched yellow taxi trips in those weeks	69
4.6	10 weeks that have the most rainfall in 2017 and the total number of dispatched Uber trips in those weeks	70
4.7	The percentage change in total number of dispatched trips comparing to the previous weeks of yellow taxi and Uber	70
5.1	Ten pick-up zones with the highest avergae fare from Manhattan to JKF Airport	77

5.2	5 most popular destinations in Manhattan	79
5.3	10 most popular taxi drop-off zones from JFK Airport with the corresponding average fare amount	81

List of Figures

1.1	NYC Monthly Taxi Pickups	5
2.1	NYC Taxi Zone Map	18
2.2	MySQL View	23
2.3	Summary of Number of trips Made by 4 Types of Transportations between 2014 and 2016 in NYC	24
3.1	Percent Tip Paid by Passengers on Each Pick-up And Drop-off Pair in NYC	51
3.2	Tip Payment Page on New York City Touch Panel	52
3.3	Percent Tip Paid by Passengers on Each Pick-up Taxi Zone in NYC .	53
3.4	Number of Pick-ups in Each Taxi Zone	54
4.1	Average number of minutes it takes from Central Park, Manhattan to all three airports during different hours	63
5.1	Estimated fare amount from the each pick-up zone to JFK Airport .	76
5.2	Pick-up Zones that cost more than the 52 US Dollar flat rate	77
5.3	Zones that cost more than the 52 US Dollar flat rate	80
5.4	Zones that cost more than the 52 US Dollar flat rate	81
B.1	Data Dictionary – Yellow Taxi Trips Records	89

C.1	FOIL Request	92
D.1	NOAA Climate Data Request	93
D.2	NOAA Climate Data Order Compeleted	94

Abstract

Yellow Taxi Cabs are widely recognized as the icons of New York City. The New York City Taxi & Limousine Commission (TLC) provides publicly accessible yellow and green taxi trip records (N. T. staff, 2009a). Each taxi trip record is like a little piece of a gigantic puzzle, and all together they tell a story of what happens in New York City. This thesis presents a more efficient and easy-to-use way for users to retrieve trip records information of both New York City taxi and other ride-sharing services, such as Uber and Lyft, in New York City. By analyzing trip records of New York City's iconic yellow taxi, we seek answers to questions that are commonly asked by taxi drivers, passengers, and TLC officials to help all three parties to improve their services or experiences.

Chapter 1

Introduction

1.1 Motivation

When is the best time during a day to travel to JFK Airport from Brooklyn? How much tip do passengers usually pay to the taxi drivers? Is the \$52 flat rate from Manhattan to JFK Airport appropriate? Questions about New York City taxicabs are frequently asked by people travelling in taxis in New York City. New York City Taxi and Limousine Commission (TLC) provides taxi trip data on their website for people to study and answer these questions. However, it is not easy to work with taxi trip data provided by TLC, because there are more than 250,000 taxi trips happenning everyday in New York City (Whitford, 2017), which implies the large size of the datasets.

Working with medium data, such as the taxi TLC trips records, in **R** is not an easy task. Loading medium-sized data into the **R** environment takes a long time and might crash an **R** session. Creating a user-friendly platform that allows **R** users to easily work with medium data is my motivation. In my study, I focus on New York City taxicab data because there are a lot of interesting questions about New York City

taxicabs that I want to explore.

New York City taxi drivers, passengers, and New York City TLC are the three parties who are closely involved in the New York City taxi industry. Each party has its own needs. Better understanding the needs of the three parties and providing solutions to satisfy their needs is the goal of this thesis.

This work contains two main components. The first component is building the tool to work with the TLC taxi trip data, and the second component is using the tool we build to understand the taxicab and e-hail service use in New York City.

1.2 Background

1.2.1 Yellow Taxi

NYC Taxicabs are operated by private firms and licensed by the New York City Taxi and Limousine Commission (TLC). TLC issues medallions to taxicabs, and every taxicab must have a medallion to operate. There were 13,437 yellow medallion taxicabs licenses in 2014, and taxi patronage has declined since 2011 because of the competition caused by rideshare services (W. staff, 2018a).

1.2.2 Green Taxi

The apple green taxicabs in New York City are called Boro taxis and they are only allowed to pick up passengers in the outer boroughs and in Manhattan above East 96th and West 110th Streets. Historically, only the yellow medallion taxicabs were allowed to pick up passengers on the street. However, since 95% of yellow taxi pick-ups occurred in Manhattan to the South of 96th Street and at the two airports, the Five

Borough Taxi Plan was started to allow green taxis to fill in the gap in outer boroughs in the summer of 2013 (N. T. staff, 2009d).

1.2.3 Uber

Uber Technologies Inc. is an American technology company that operates private cars worldwide. Uber drivers use their own cars, instead of corporate-owned vehicles, to drive with Uber. In NYC, Uber uses ‘upfront pricing’, meaning that riders are informed about the fares that they will pay before requesting a ride, and gratuity is not required. Riders are given the opportunity to compare different transportation fares before making their decisions on which one to choose. Uber NYC was launched in May 2011 (Griswold, 2015).

1.2.4 Lyft

Similar to Uber, Lyft is also an on-demand transportation company, and it operates the Lyft car transportation mobile app. Lyft is the main competitor of Uber, and it came into market in July 2014 in New York City (Griswold, 2015).

1.3 Literature Review

1.3.1 New York City Traffic and Taxi

New York City is one of the most popular cities in the United States, and New York City taxicabs represent the image of New York City. New York City’s traffic is a popular topic in journalism, and different aspects of it has been studied by journalists, such as Patricia Reaney. New York City’s traffic is a nightmare, and the

city officials have long been trying to solve the congestion problem. In 2009, New York City was voted to be the U.S. city with the “angriest and most aggressive drivers”. (Reaney, 2009) The bad temper of drivers are exacerbated by New York City’s severe cogestion.

How bad is the cogestion? In a journal published by New York Post in 2016, New York City was described as “the city that never moves”. (Danielle Furfaro & Fears, 2016) What has led to the congestion in the city? A journal from New York Post tried to find an answer to this question: According to a former top NYPD official, “The city streets are being engineered to create traffic congestion, to slow traffic down, to favor bikers and pedestrians” so that drivers will have the incentive to leave their cars at home and turn to mass transit or bicycles (Sugar, 2017).

No matter how miserable the driving experiences are, taxi drivers have no luxury to choose alternative transportation, and instead thay have to consistently drive their cabs, which are usually surrounded by bad traffic, in order to make a living.

1.3.2 Competition between New York City taxi and e-hail services

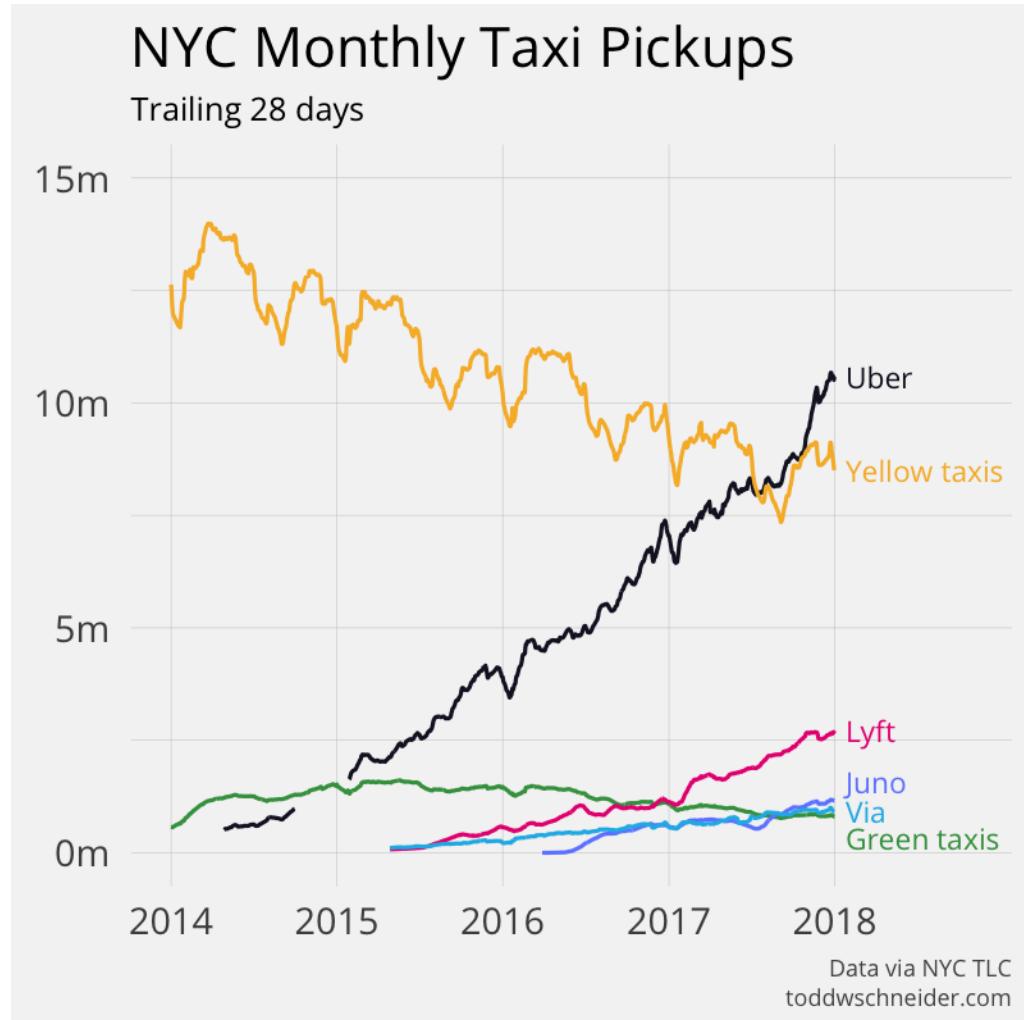


Figure 1.1: NYC Monthly Taxi Pickups

As shown in the visualization above (Schneider, 2015), the number of New York City yellow taxi trips has been consistently declining for about 4 years, and the numbers of Uber and Lyft trips keep increasing. In 2017, for the first time, the total number of monthly Uber trips exceeded the number of yellow taxi trips.

Some studies have shown how competitive Uber and Lyft are. In 2017, Uber and Lyft registered vehicles outnumbered NYC yellow cabs by 4 to 1. (Sugar, 2017) Even

though Yellow cab used to be the most popular street-hail transportation service in New York City, passengers nowadays tend to choose the more convenient options, ride-hailing apps.(Hu, 2017)

As reported in a journal from Forbes Tech, data scientists from the University of Cambridge in the UK and the University of Namur in Belgium found that yellow taxi rides are on average \$1.40 cheaper than Uber X, which is one type of economy ride service offered by Uber (H. staff, 2018). Moreover, uber appears more expensive for trips that are cheaper than \$35, and less expensive than yellow taxi ride for trips that are more expensive than \$35. Therefore, for short trips, taking a taxi is more affordable. (Guerrini, 2015)

Apps, such as Openstreetcab, that compares the price of Uber and taxi trips are designed to help customers to compare the fares of different transportations. (O. staff, 2015)

1.3.3 etl R package

In *R Markdown: Integrating A Reproducible Analysis Tool into Introductory Statistics*, the authors have presented experimental and statistical evidence that *R Markdown* replaced the antiquated and hard-to-reproduce *copy-and-paste workflow*, and makes creating fully-reproducible statistical analysis straight-forward (B. Baumer, Cetinkaya-Rundel, Bray, Loi, & Horton, 2014).

Work with taxi trip data is not an easy task, because of the large size of the taxi trip datasets (Whitford, 2017). Taxi trip datasets are classified as ‘medium data’. Loading medium-sized data into **R** environment takes a long time and might crush an **R** session. **etl R** package creates a user-friendly platform that allows **R** users to easily work with medium data with the extract, transform, load framework, which is

commonly known as ETL in computing (W. staff, 2018b). The ETL process has been set up (B. S. Baumer, 2017) in **R** to facilitate etl operations for medium data, and it is designed to work with any general data set. Packages that are specific to particular data sets are needed to be written in order to better work with complex medium-sized data sets.

1.4 Contribution

1.4.1 ‘nyctaxi’ Package

`nyctaxi` is an **R** package that help users to easily get access to New York City Taxi, Uber and Lyft trip data through Extract, Transform, and Load functions (ETL). (B. S. Baumer, 2017) This package facilitates ETL to deal with medium data that are too big to store in memory on a laptop. Users are given the option to choose specific years and months as the input parameters of the three ETL functions, and a connection to a populated SQL database will be returned as the output. Users do not need to learn SQL queries, since all user interaction is in **R**.

The screenshot shows the GitHub page for the `nyctaxi` package. At the top, there is a link to the `README.md` file. Below it, the title "New York City Taxi" is displayed in bold. Underneath the title, there are four small status indicators: "build failing", "CRAN 0.0.1", "downloads", and "216/month". The main content area is titled "nyctaxi" in bold. It describes the package as an R package to download NYC's Taxi and Limousine Commission (TLC) Trip Data. It states that NYC's [Taxi and Limousine Commission \(TLC\) Trip Data](#) is a collection of green and yellow taxi trip records including fields capturing pick-up and drop-off locations, times, trip distances, fares, rate types, and driver-reported passenger counts. The data was collected and provided to the NYC TLC by technology providers under the Taxicab & Livery Passenger Enhancement Programs.

1.4.2 Social Impact of NYC Taxi

NYC Taxi drivers wants to make the most profit. Taxi passengers want the cheapest and most convenient way of transportantion. Since Uber and Lyft launched their services in New York City, many consumers started to demand the cheaper e-hail services (Sugar, 2017). TLC wants to protect both taxi drivers and passengers, and it creates policies to make NYC taxi more accessible to consumers who really need this service. In these sections, we analyze what each party wants and try to find a way for them to be achieve their goals.

1.4.3 Reproducible Research

Reproducible research and open source are two main emphasis of this honors project. As scholars place more emphasis on the reproducibility of research studies, it is essential for us to make our data and code openly available for people to redo the analysis.

Knitr and Github are used in my project to make my study reproducible, ranging from the initial source to raw data to the package I wrote to utlize the raw data to the statistical data analysis. I used an **R** package called **thesisdown** to typeset this paper, this tool allows authors to create reproducible and dynamic technical report in **R** Markdown. It also allows users to embed **R** code and interactive applicationis, and output into PDF, Word, ePub, or gitbook doocuments. **thesisdown** helps users to efficiently put together any paper with similar format.

Github is used to store the scripts for **nyctaxi** and this thesis. **nyctaxi** is available on CRAN for people to download and install (W. P. Li, Baumer, & Trang Le, 2017), and the source code for data analysis in this thesis is available under the Github account of the author so that scholars can easily access the information that thery

are interested in. In terms of tables, figures, and anything included in the Appendix attached to this thesis, scripts that are used to generate them are included in the Github repository.

Chapter 2

Data and nyctaxi Package

2.1 Data and Storage

The `nyctaxi` R package allows users to download, clean, and load data into SQL databases. There are four types of data that are available for users to get access to: trip level yellow taxi data from 2009 to the most recent month, trip level green taxi data from August 2013 to the most recent month, Uber pick-up data from April to September 2014 and from January to June 2015, and weekly-aggregated Lyft trip data from 2016 to the most recent week (W. P. Li et al., 2017).

2.1.1 Yellow Taxi

The total size of all yellow taxi trip data csv files (from Jan 2010 to Dec 2016) is 191.38 GB, and NYC yellow taxi trip data from Jan 2009 to the most recent month can be found on the NYC Taxi & Limousine Commission (TLC) website (N. T. staff, 2009b). The data were collected and provided to the NYC TLC by technology providers authorized under the Taxicab & Livery Passenger Enhancement Programs

(TPEP/LPEP).

The yellow taxi trip records include the following fields: pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts.

2.1.2 Green Taxi

The total size of green taxi trip data `csv` files (from Aug 2013 to Dec 2016) is 7.8 GB, and green taxi trip data from Aug 2013 to the most recent month can be downloaded from NYC Taxi & Limousine Commission (TLC). (N. T. staff, 2009b) Green taxi trip records include the same variables as yellow taxi trip records.

2.1.3 TLC Summary Report

The New York City TLC publishes summary reports that include aggregate statistics about taxi, Uber, and Lyft usage. These are in addition to the trip-level data; although the summary reports contain much less detail, they're updated more frequently, which provides a more current glimpse into the state of the cutthroat NYC taxi market. (N. T. staff, 2009a)

In addition, the trip level NYC Uber data only covers two periods, from April to September 2014 and from January to June 2015. However, the summary reports cover weekly-aggregated data from 2015 to the most recent week.

The screenshot shows the official website of the NYC Taxi & Limousine Commission. At the top, there's a navigation bar with links to 'NYC Resources', '311', and 'Office of the Mayor'. Below the header, the 'NYC Taxi & Limousine Commission' logo is displayed. A search bar is located at the top right. A horizontal menu bar includes 'Online Transactions (LARS)', 'Printer Friendly', 'Newsletter Sign-up', 'Translate This Page', and 'Text Size' options. On the left, a sidebar menu lists various categories such as Home, About TLC, TLC Rules and Local Laws, Licensing/Industry Information, Passenger Information, Frequently Asked Questions, TLC News, TLC Site Map, and Contact/Visit TLC. Below this is a social media sharing section with icons for Facebook, Twitter, YouTube, Instagram, LinkedIn, and NextDoor. The main content area features a yellow header titled 'Aggregated Reports'. Under this, there's a section about monthly aggregated reports, followed by links to 'Yellow Taxi Monthly Indicators' (CSV file format, Data Dictionary) and 'Street Hail Livery Monthly Indicators' (CSV file format, Data Dictionary). Both links lead to monthly metrics containing average daily trips and fare collected. There's also a link to the 'FHV Base Aggregate Weekly Report' (Dataset on Open Data, Data Dictionary), which provides weekly total dispatched trips and unique dispatched vehicles by base. To the right of the main content is a yellow box titled 'Taxi News' containing a brief update about new rules and pilot programs for FHV bases. At the bottom right of the page, there are navigation arrows and a page number '1/7'.

The data can be accessed by using the following commands:

- Yellow taxi data

```
download.file("http://www.nyc.gov/html/tlc/downloads/csv/data_reports_monthly_indi
```

*Uber and Lyft data

```
download.file("http://data.cityofnewyork.us/api/views/2v9c-2k7f/rows.csv?accessType
```

2.1.4 Uber

The total size of Uber pick-up data (from Apr to Sep 2014 and from Jan to June 2015) is 900 MB, and thanks to FiveThirtyEight who obtained the data from NYC TLC by submitting a Freedom of Information Law (FOIL) request on July 20, 2015, these data are now open to public (N. T. staff, 2009c).

The 2014 Uber data contains 4 variables: **Date/Time** (the date and time of the Uber pick-up), **Lat** (the latitude of the Uber pick-up), **Lon** (the longitude of the Uber pick-up), and **Base** (the TLC base company code affiliated with the Uber pickup).

The 2015 Uber data contains 4 variables: **Dispatching_base_num** (the TLC base company code of the base that dispatched the Uber), **Pickup_date** (the date of the Uber pick-up), **Affiliated_base_num** (the TLC base company code affiliated with the Uber pickup), and **locationID** (the pick-up location ID affiliated with the Uber pickup).

NYC Open Data also provides weekly-aggregated Uber pick-up data from 2015 to the most recent month. (N. O. staff, 2015b)

2.1.5 Lyft

The total size of weekly-aggregated Lyft trip data (from Jan 2015 to Dec 2016) is 914.9 MB, and these data are open to public and weekly-aggregated Lyft data from 2015 to the most recent week can be found on NYC OpenData website. (N. O. staff, 2015a)

2.1.6 Data Storage

The total size of all **csv** files of the four services is about 200 GB, and a laptop usually has memory less than or equal to 8 GB. Limited memory constrains the amount of data that can be loaded by a personal computer at one time. When users load data into **R** environment, **R** keeps them in memory; when the amount of data loaded into **R** environment gets close to the limit of a computer's memory, **R** becomes unresponsive or force quit the current session. Therefore, better ways to work with data that takes more space than 8 GB is needed. According to Zhang (2016), comparing to RAM,

hard disk is often used to store medium-sized data, because it is affordable and are designed for storing large items permanently. However, retrieving data from hard drives is about 1,000,000 times slower.

2.2 ETL *nyctaxi* Package

etl is the parent package of **nyctaxi**. **etl** provides a framework that allows **R** users to work with medium data without any knowledge in SQL database. Users can run SQL queries by using **dplyr** commands in **R** and choose to only return the final result, which could be a summary table, from SQL database into **R** Environment in order to avoid **R** from crashing. The user interaction takes place solely within **R**.

etl framework has three operations -Extract, Transfer, and Load- which bring real-time data into local or remote SQL databases. Users can specify which type of SQL database they prefer to connect to. **etl**-dependent packages, such as **nyctaxi**, make medium data more accessible to a wider audience. (B. Baumer et al., 2014)

nyctaxi was initially designed to work with New York City taxi data, but later on Uber and Lyft data were added and the ETL functions are modified to be specialized in working with these data. This package compiles three major sources of hail service in New York City so that it is convenient for users to compare and contrast the performance of these three services. (W. P. Li et al., 2017)

This package inherits functions from many packages: **etl**, **dplyr**, **DBI**, **rlang**, and **stringr**.

Since SQL databases are good tools for medium data analysis, ETL functions build connection to a SQL database at the back end and convert **R** code automatically into SQL queries and send them to the SQL database to get data tables containing data of each hail service. Thus, users do not need to have any knowledge of SQL queries

and they can draw in any subsets of the data from the SQL database in **R**.

In general, `etl_extract.etl_nyctaxi()` function download data of the four types of hail service data (yellow taxi, green taxi, Uber, and Lyft) from the corresponding sources. `etl_transform.etl_nyctaxi()` uses different techniques to clean all four types of data to get then ready for the next step. `etl_load.etl_nyctaxi()` loads the data user selected to a SQL database.

The Comprehensive **R** Archive Network (CRAN) is a collection of sites that carry identical material, consisting of the **R** distributions, the contributed extensions, documentation for **R**, and binaries. (C. staff, n.d.) `nyctaxi` **R** package lives on CRAN, and it can be installed with the `install.packages()` function in **R**.

```
install.packages("nyctaxi")
```

Users need to create an `etl` object in order to apply the `etl` operations to it, and only the name of the SQL database, working directory, and type of SQL database need to be specified during initialization. If the type of SQL database is not specified, a local RSQLite database will be generated as default.

```
db <- src_mysql("nyctaxi", user = "username", host = "host", password = "pw")  
taxi <- etl("nyctaxi", dir = "~/Desktop/nyctaxi", db)
```

In the example above, a folder called `nyctaxi` is created on the desktop and a connection to a MySQL database is generated. In the process of initialization, a local folder contains two subfolders, `raw` and `load`, are also created under the directory the user specifies. `raw` folder stores data downloaded from online open sources, and `load` folder stores cleaned CSV data files that are ready to be loaded into SQL database. The ETL framework keeps data directly scraped from online data sources in their original forms. In this way, the original data is always available to users in case data corruption happens in later stages.

After an `etl` object is created (`nyctaxi` is the `etl` object in this case), four parameters are needed to specify the data that users want: (1) `obj`: an `etl` object; (2) `years`: a numeric vector giving the years, and the default is the most recent year; (3) `months`: a numeric vector giving the months, and the default is `1:12`; (4) `type`: a character variable giving the type of data the user wants to download. There are four types: `yellow`, `green`, `uber`, and `lyft`. The default is `yellow`.

2.2.1 Taxi zone shapefile attached to nyctaxi R package

Two datasets are attached to `nyctaxi`. The first one is called `taxi_zone_lookup`, and this dataset contains information, such as taxi zone location IDs, location names, and corresponding boroughs for each ID. (N. T. staff, 2009b) A shapefile containing the boundaries for the taxi zones, `taxi_zones`, is also included in the package for users to do spatial analysis. Visualizations similar to one shown below can be generated with the shapefile.

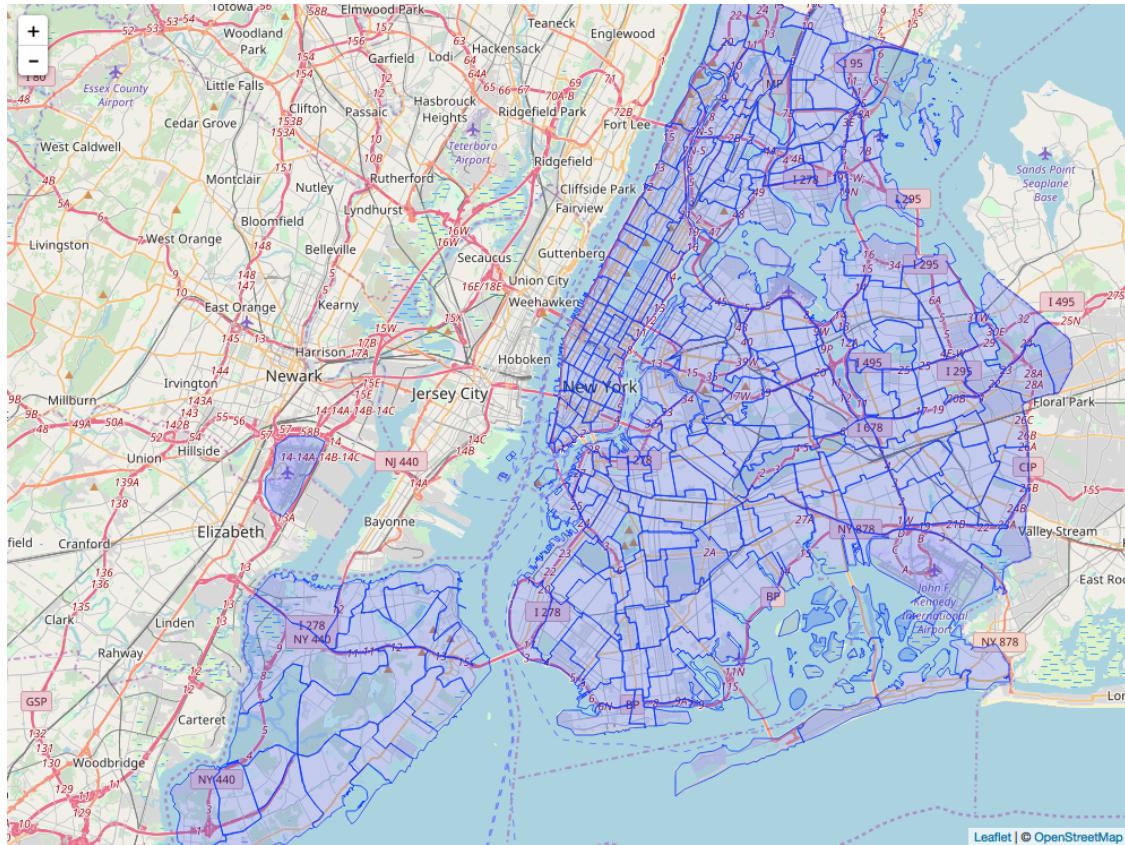


Figure 2.1: NYC Taxi Zone Map

2.3 Extract-Transform-Load

2.3.1 Extract

`etl_extract.etl_nyctaxi()` allows users to download New York City yellow taxi, green taxi, Uber, and Lyft data from the corresponding data sources. It takes the `years`, `months`, and `type` parameters and download the New York City taxi data specified by users. New York City Yellow and Green Taxi data are updated on NYC Taxi & Limousine Commission (TLC) website on a monthly basis.

```
taxi %>%
  etl_extract(years = 2014:2016, months = 1:12, type = c("yellow", "green"))
```

Uber trip record data is static and small, so we decided to only give users the options to either download all data from April to Sepetember, 2014 or download all Uber trip records from Janaury to June, 2015 at onc. Users do not have the ability to download Uber data from a specific month.

```
taxi %>%
  etl_extract(years = 2014:2016, months = 1:12, type = c("uber"))
```

Lyft data is updated on NYC Open Data webiste on a weekly basis. Since the weekly-aggregated data is tiny and only data later then 2014 is available, we decided to only allow users to download Lyft data by year.

```
taxi %>%
  etl_extract(years = 2014:2016, months = 1:12, type = c("lyft"))
```

The default `years` is the current year, and the default `months` are the all twelve months. The default type of transportation is `yellow`. When an invalid month is entered, warning message will suggest users to reconsider their choice and select a new set of month.

An utility function, `download_nyc_data()`, was written to be used in `etl_extract.etl_nyctaxi()` to make this function more condense (Appendix A).

2.3.2 Transform

`etl_transform.etl_nyctaxi()` allows users to transform New York City yellow taxi, green taxi, Uber, and Lyft data into cleaned formats, and it utlizes different data cleaning techniques when it transforms data for each transportation type. In general,

it cleans the data and creates a new `csv` file in the `load` directory to store the cleaned data. It helps us to retain and protect raw data from being modified or destroyed. Users are allowed to specify the month of interest in order to only transform the data that they are interested in. This functionality helps people to be more efficient with their use of time.

By default, it takes the current year Yellow taxi trip records data files, and save copies of them in the `load` directory. It skips the cleaning step, because the raw Yellow Taxi data downloaded from TLC is already in a desired format with all variables correctly labelled.

```
taxi %>%
  etl_transform(years = 2014:2016, months = 1:12, type = c("yellow", "green", "uber", "
```

There are a few main transformations that are done by this function:

Green Taxi – Extra Blank Row and Column

Green Taxi monthly data from August 2013 to the most recent month besides 2015 all have a blank second row in the `csv` files. Similar to this problem, Green Taxi data from 2013, 2014, and 2015 all have an extra blank columns attached to the right-most column. These blank rows and columns cause problems in the later stage when users want to load data into SQL database. In order to get Green Taxi data ready for the `load` phase, we used the `system()` function in **R** to invoke the Terminal command specified to remove the blank rows and columns.

Uber Data – Reconciling Inconsistent Filenames

Uber only released over 4.5 million data records from April to September 2014 and 14.3 million records from January to June 2015. Information of different sets of variables

are released for 2014 and 2015, and variables have different naming convention. When users want to download data from both years, variables are renamed so that data from both years can be consolidated into one big dataset with consistent variable names.

Uber Data – Reconciling Inconsistent Data Formats

The data type of Date/Time variable in Uber datasets is originally encoded as **character**. In order to enable it to be recognized as **timestamp** by **R**, we use **ymd_hms** in **lubridate** (Grolemund & Wickham, 2011) to transform date time to **POSIXct** objects.

Optimizing I/O Process

Improving file input and output processes is an important part of **etl_transform**. **data.table** (Dowle & Srinivasan, 2017) only takes half of the time to read from and write into datasets comparing to **readr** (Wickham, Hester, & Francois, 2017). Therefore, **etl_transform** uses **fread()** and **fwrite()** from **data.table** instead of **read_csv** or **write_csv** from **readr** to reduce the data processing time (Zhang, 2017).

2.3.3 Load

etl_load.etl_nyctaxi() allows users to load New York City yellow taxi, green taxi, Uber, and Lyft data into different data tables in a SQL database. It populates a SQL database with data cleaned by **etl_transform**.

```
taxi %>%
  etl_load(years = 2014:2016, months = 1:12, type = c("yellow", "green", "uber", "lyft"))
```

2.3.4 SQL Database Initialization

`init.mysql()` is written under `nyctaxi` to help users to set up five basic table structures for MySQL database. `yellow_old` is created for Yellow Taxi data that are prior to August 2016, and `yellow` is created for data later than July 2016. `green`, `uber`, and `lyft` are also initiated for the three transportations.

`etl_init()` can be run after a database connection is built to process to `init.mysql()` to initialize a MySQL database, and default columns with the correct variable names and typed defined will be automatically generated.

```
taxi %>%
  etl_init()
```

In order to increase the query speed at the data analysis stage, KEYS are created for multiple variables for each transportation. Since there is no variable containing unique value for each observation, no primary variable is needed. Using KEYS in data analysis query can speed up the query process.

Due to the large size of Yellow Taxi datasets, `yellow_old` and `yellow` are partitioned into subgroups by `year`. When we need to run a query on data from a specific year, having partitions allows MySQL to directly find the data specified without filtering on every single row. It speeds up the query process. A VIEW called `yellow_old_sum` is also created to generate a summary table for the number of Yellow Taxi trips in each month.

```
CREATE
  ALGORITHM = UNDEFINED
  DEFINER = 'wiz7'@'%'
  SQL SECURITY DEFINER
VIEW nyctaxi`.`yellow_old_sum` AS
SELECT
  YEAR(`nyctaxi`.`yellow_old`.`tpep_pickup_datetime`) AS `the_year`,
  MONTH(`nyctaxi`.`yellow_old`.`tpep_pickup_datetime`) AS `the_month`,
  COUNT(1) AS `num_trips`
FROM
  `nyctaxi`.`yellow_old`
GROUP BY YEAR(`nyctaxi`.`yellow_old`.`tpep_pickup_datetime`), MONTH(`nyctaxi`.`yellow_old`.`tpep_pickup_datetime`)
```

The screenshot shows the MySQL Workbench interface. On the left, the schema browser displays the 'nyctaxi' database with tables like green, lyft, uber, yellow, and yellow.old, and a view named yellow.old_sum. The central pane shows the SQL code for creating the view. Below the code, the 'Object Info' tab is selected, showing the view's columns: the_year (int(4)), the_month (int(2)), and num_trips (bigint(21)). The bottom pane shows the query history with one entry: a SELECT * from nyctaxi.yellow.old_sum limit 0,100 query that returned 0 rows in 0.284 seconds.

Figure 2.2: MySQL View

2.4 New York City Taxicab and E-hail Services Summary

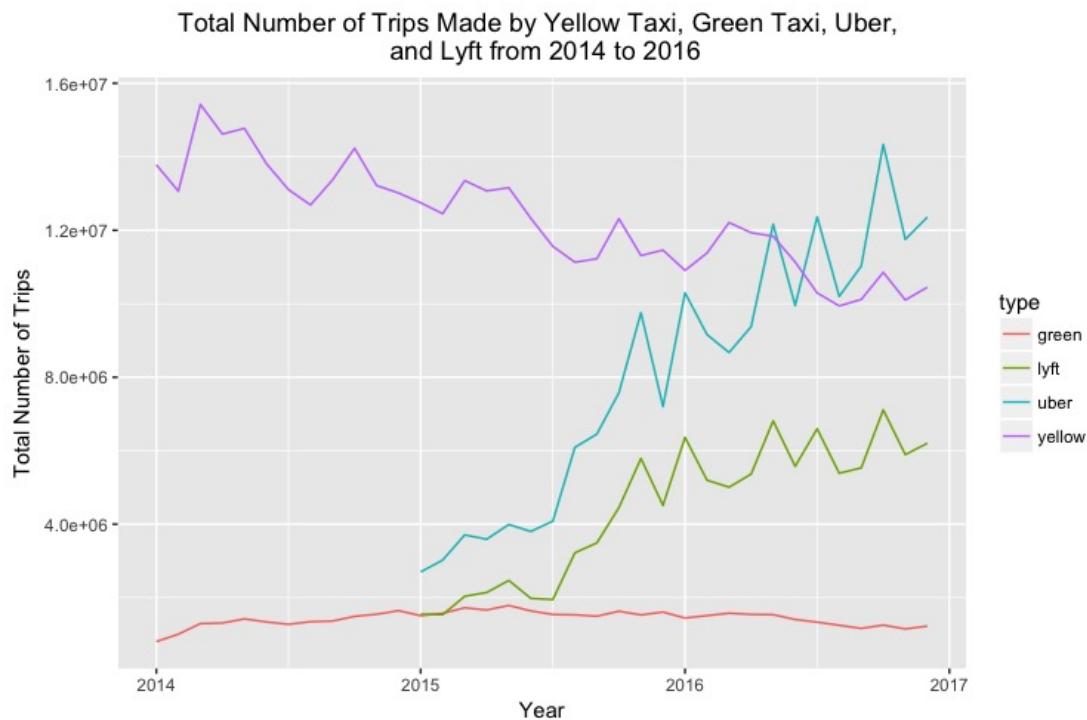


Figure 2.3: Summary of Number of trips Made by 4 Types of Transporations between 2014 and 2016 in NYC

Figure 2.3 is a summary of total number of trips made by all 4 types of transporations that are available to users from 2014 to 2016. In order to generate this summary, I combined trip-level yellow and green taxi data from TLC trip data website and weekly Uber and Lyft data from NYC OpenData. Data used in Figure 2.3 can be accessed by running the code below:

- Yellow taxi monthly data

```
download.file("http://www.nyc.gov/html/tlc/downloads/csv/data_reports_monthly_indicators
```

- Uber weekly data

```
download.file("https://data.cityofnewyork.us/resource/gt3n-7ri6.csv", destfile = "
```

- Lyft weekly data

```
download.file("https://data.cityofnewyork.us/resource/juxc-sutg.csv", destfile = "
```

2.5 Source Code

2.5.1 ETL Extract

```
etl_extract.etl_nytaxi <-
  function(obj,
years = as.numeric(format(Sys.Date(), '%Y')),
                         months = 1:12,
                         type   = "yellow",...) {
#TAXI YELLOW-----
taxi_yellow <- function(obj, years, months,...) {
  message("Extracting raw yellow taxi data...")
  remote <- etl::valid_year_month(years, months,
begin = "2009-01-01") %>%
  mutate_(src =
~file.path("https://s3.amazonaws.com/nyc-tlc/trip+data",
                         paste0("yellow", "_tripdata_", year, "-",
stringr::str_pad(month, 2, "left", "0"), ".csv")))
tryCatch(expr = etl::smart_download(obj, remote$src, ...),
error = function(e){warning(e)},
finally = warning("Only the following data are available on
```

```

TLC: Yellow taxi data: 2009 Jan -
      last month))}

#TAXI GREEN-----
taxi_green <- function(obj, years, months,...) {
  message("Extracting raw green taxi data...")
  remote <- etl::valid_year_month(years, months, begin = "2013-08-01") %>%
    mutate_(src =
      file.path("https://s3.amazonaws.com/nyc-tlc/trip+data",
                paste0("green", "_tripdata_", year, "-",
                       stringr::str_pad(month, 2, "left", "0"), ".csv")))
  tryCatch(expr = etl::smart_download(obj, remote$src, ...),
           error = function(e){warning(e)},
           finally = warning("Only the following data are availabel on TLC:
                             Green taxi data: 2013 Aug - last month"))
}

#UBER-----
uber <- function(obj, years, months,...) {
  message("Extracting raw uber data...")
  raw_month_2014 <- etl::valid_year_month(years = 2014, months = 4:9)
  raw_month_2015 <- etl::valid_year_month(years = 2015, months = 1:6)
  raw_month <- bind_rows(raw_month_2014, raw_month_2015)
  path = "https://raw.githubusercontent.com/
fivethirtyeight/uber-tlc-foil-response/master/uber-trip-data"
  remote <- etl::valid_year_month(years, months)
  remote_small <- intersect(raw_month, remote)
  if (2015 %in% remote_small$year && !(2014 %in% remote_small$year)){
    #download 2015 data
    message("Downloading Uber 2015 data...")
```

```
    etl::smart_download(obj, "https://github.com/fivethirtyeight/
                                uber-foil-response/raw/master/
                                uber-trip-data/uber-raw-data-jan-june-15.csv.zip",...)}
else if (2015 %in% remote_small$year && 2014 %in% remote_small$year) {
  #download 2015 data
  message("Downloading Uber 2015 data...")
  etl::smart_download(obj, "https://github.com/fivethirtyeight/
                                uber-foil-response/raw/master/uber-trip-data/
                                /uber-raw-data-jan-june-15.csv.zip",...)
  #download 2014 data
  small <- remote_small %>%
    filter_(~year == 2014) %>%
    mutate_(month_abb = ~tolower(month.abb[month])),
    src = ~file.path(path,
      paste0("uber-raw-data-", month_abb,
      substr(year, 3, 4), ".csv")))
  message("Downloading Uber 2014 data...")
  etl::smart_download(obj, small$src,...)
} else if (2014 %in% remote_small$year &&
! (2015 %in% remote_small$year)) {
  message("Downloading Uber 2014 data...")
  #file paths
  small <- remote_small %>%
    mutate_(month_abb =
      ~tolower(month.abb[month]),
      src = ~file.path(path,
      paste0("uber-raw-data-", month_abb,
```

```
        substr(year,3,4), ".csv")))

etl::smart_download(obj, small$src,...)}

else {warning("The Uber data you requested are

not currently available. Only data

from 2014/04-2014/09 and 2015/01-

2015/06 are available...")}

}

#LYFT-----

lyft <- function(obj, years, months,...){

  message("Extracting raw lyft data...")

  #check if the week is valid

  valid_months <- etl::valid_year_month(years, months,
  begin = "2015-01-01")

  base_url = "https://data.cityofnewyork.us/
  resource/edp9-qgv4.csv"

  valid_months <- valid_months %>%
    mutate_(new_filenames =
      ~paste0("lyft-", year, ".csv")) %>%
    mutate_(drop = TRUE)

  #only keep one data set per year

  year <- valid_months[1,1]

  n <- nrow(valid_months)

  for (i in 2:n) {

    if(year == valid_months[i-1,1]) {

      valid_months[i,6] <- FALSE

      year <- valid_months[i+1,1]

    } else {
```

```
    valid_months[i,6] <- TRUE  
    year <- valid_months[i+1,1]}  
  
}  
  
row_to_keep = valid_months$drop  
valid_months <- valid_months[row_to_keep,]  
  
#download lyft files, try two different methods  
first_try<-tryCatch(  
  download_nyc_data(obj, base_url, valid_months$year,  
  n = 50000, names = valid_months$new_filenames),  
  error = function(e){warning(e)},  
  finally = 'method = "libcurl" fails')  
  
}  
  
  
if (type == "yellow"){taxi_yellow(obj, years, months,...)}  
else if (type == "green"){taxi_green(obj, years, months,...)}  
else if (type == "uber"){uber(obj, years, months,...)}  
else if (type == "lyft"){lyft(obj, years, months,...)}  
else {message("The type you chose does not exist...")}  
  
invisible(obj)  
}
```

2.5.2 ETL Transform

```
opts_chunk$set(tidy.opts=list(width.cutoff=60))

etl_transform.etl_nyctaxi <- function(obj,
                                       years = as.numeric(format(Sys.Date(), '%Y')),
                                       months = 1:12,
                                       type   = "yellow", ...){

#TAXI YELLOW-----
taxi_yellow <- function(obj, years, months) {

  message("Transforming yellow taxi data from raw to
          load directory...")

#create a df of file path of the files that the user wants to transform
remote <- etl::valid_year_month(years, months,
begin = "2009-01-01") %>%
  mutate_(src = ~file.path(attr(obj, "raw_dir")),
         paste0("yellow", "_tripdata_", year, "-",
                stringr::str_pad(month, 2, "left", "0"), ".csv")))
#create a df of file path of the files that are in the raw directory
src <- list.files(attr(obj, "raw_dir"), "yellow", full.names = TRUE)
src_small <- intersect(src, remote$src)

#Move the files
in_raw <- basename(src_small)
in_load <- basename(list.files(attr(obj, "load_dir"), "yellow",
                               full.names = TRUE))
file_remian <- setdiff(in_raw,in_load)
file.copy(file.path(attr(obj, "raw_dir")),file_remian,
          file.path(attr(obj, "load_dir"),file_remian) )}

#TAXI GREEN-----
```

```
taxi_green <- function(obj, years, months) {  
  
  message("Transforming green taxi data from raw  
  to load directory...")  
  
  #create a df of file path of the files that the user wants to transform  
  remote <- etl::valid_year_month(years, months,  
  begin = "2013-08-01") %>%  
  
  mutate_(src = ~file.path(attr(obj, "raw_dir"),  
  paste0("green", "_tripdata_", year, "-",  
  stringr::str_pad(month, 2, "left", "0"), ".csv")))  
  
  #create a df of file path of the files that are in the raw directory  
  src <- list.files(attr(obj, "raw_dir"), "green", full.names = TRUE)  
  src_small <- intersect(src, remote$src)  
  
  #Clean the green taxi data files  
  
  #get rid of 2nd blank row  
  
  if (length(src_small) == 0){  
  
    message("The files you requested are not available  
    in the raw directory.")  
  
  } else{  
  
    #a list of the ones that have a 2nd blank row  
  
    remote_green_1 <- remote %>% filter_(~year != 2015)  
    src_small_green_1 <- intersect(src, remote_green_1$src)  
  
    # check that the sys support command line,  
  
    #and then remove the blank 2nd row  
  
    if(length(src_small_green_1) != 0) {  
  
      if (.Platform$OS.type == "unix"){  
  
        cmds_1 <- paste("sed -i -e '2d'", src_small_green_1)  
        lapply(cmds_1, system)
```

```
    } else {

      message("Windows system does not
              currently support removing the 2nd blank row
              in the green taxi datasets. This might affect
              loading data into SQL...")}

    } else {

      "You did not request for any
      green taxi data, or all the green
      taxi data you requested are cleaned."}

#fix column number

remote_green_2 <- remote %>%
  filter_(~year %in% c(2013, 2014, 2015)) %>%
  mutate_(keep =
    ~ifelse(year %in% c(2013, 2014), 20, 21),
    new_file =
    ~paste0("green_tripdata_", year, "_",
           stringr::str_pad(month, 2, "left", "0"),
           ".csv"))

src_small_green_2 <- intersect(src, remote_green_2$src)
src_small_green_2_df <- data.frame(src_small_green_2)
names(src_small_green_2_df) <- "src"
src_small_green_2_df <- inner_join(src_small_green_2_df,
                                    remote_green_2, by = "src")
src_small_green_2_df <- src_small_green_2_df %>%
  mutate(cmds_2 = paste("cut -d, -f1-", keep, " ", src, " > ",
                       attr(obj, "raw_dir"), "/green_tripdata_",
                       year, "_", stringr::str_pad(month, 2, "left", "0"), ".csv",
                       sep = ""))
```

```
sep = ""))

#remove the extra column

if(length(src_small_green_2) != 0) {

  if (.Platform$OS.type == "unix"){

    lapply(src_small_green_2_df$cmds_2, system)}

  else {

    message("Windows system does not currently

support removing the 2nd blank row

in the green taxi datasets. This might

affect loading data into SQL...")

  }else {

    "All the green taxi data you

requested are in cleaned formats."}

#Find the files paths of the files that need to be transformed

file.rename(file.path(dirname(src_small_green_2_df$src) ,

                     src_small_green_2_df$new_file) ,

            file.path(attr(obj, "load_dir") ,

                      basename(src_small_green_2_df$src)))}

#Move the files

in_raw <- basename(src_small)

in_load <- basename(list.files(attr(obj, "load_dir") ,

                                "green", full.names = TRUE))

file_remian <- setdiff(in_raw,in_load)

file.copy(file.path(attr(obj, "raw_dir"),file_remian) ,

          file.path(attr(obj, "load_dir"),file_remian) )}

#UBER-----

uber <- function(obj) {
```

```

message("Transforming uber data from raw to load directory...")

#creat a list of 2014 uber data file directory

uber14_list <- list.files(path = attr(obj, "raw_dir"),
pattern = "14.csv")

uber14_list <- data.frame(uber14_list)

uber14_list <- uber14_list %>% mutate_(file_path =
~file.path(attr(obj, "raw_dir"), uber14_list))

uber14file <- lapply(uber14_list$file_path, readr::read_csv)

n <- length(uber14file)

if (n == 1) {

  uber14 <- data.frame(uber14file[1])

} else if (n == 2) {

  uber14 <- bind_rows(uber14file[1], uber14file[2])

} else if (n > 2) {

  uber14 <- bind_rows(uber14file[1], uber14file[2])

  for (i in 3:n){uber14 <- bind_rows(uber14, uber14file[i])}

}

substrRight <- function(x, n){substr(x, nchar(x)-n+1, nchar(x))}

uber14_datetime <- uber14 %>%
  mutate(date = gsub( ".*$", "", `Date/Time`),
len_date = nchar(date),
time = sub('.*\\" ', '', `Date/Time`))

uber14_datetime <- uber14_datetime %>%
  mutate(month =
substr(`Date/Time`, 1, 1),
day = ifelse(len_date == 8,
substr(`Date/Time`, 3,3), substr(`Date/Time`, 3,4)),
```

```
pickup_date =  
    lubridate::ymd_hms(paste0("2014-", month, "-",
                                day, " ", time)))  
  
uber14_df <- uber14_datetime[-c(1,5:9)]  
  
#2015  
  
zipped_uberfileURL <- file.path(attr(obj, "raw_dir"),  
    "uber-raw-data-janjune-15.csv.zip")  
  
raw_month_2015 <- etl::valid_year_month(years = 2015, months = 1:6)  
  
remote_2015 <- etl::valid_year_month(years, months)  
  
remote_small_2015 <- inner_join(raw_month_2015, remote_2015)  
  
if(file.exists(zipped_uberfileURL) &&  
    nrow(remote_small_2015) != 0){  
    utils::unzip(zipfile = zipped_uberfileURL, unzip = "internal",  
                exdir = file.path(tempdir(), "uber-raw-data-janjune-15.csv.zip"))  
    uber15 <- readr::read_csv(file.path(tempdir(),  
                                    "uber-raw-data-janjune-15.csv.zip",  
                                    "uber-raw-data-janjune-15.csv"))}  
  
  
names(uber14_df) <- c("lat", "lon", "affiliated_base_num",  
                      "pickup_date")  
  
names(uber15) <- tolower(names(uber15))  
  
uber <- bind_rows(uber14_df, uber15)  
  
utils::write.csv(uber, file.path(tempdir(), "uber.csv"))  
  
if(nrow(uber) != 0) {  
    if (.Platform$OS.type == "unix"){cmds_3 <-  
        paste("cut -d, -f2-7", file.path(tempdir(), "uber.csv"), " > ",
```

```
file.path(attr(obj, "load_dir"), "uber.csv"))

lapply(cmds_3, system)

} else {

  message("Windows system does not currently
support removing the 2nd blank row
in the green taxi datasets. This might
affect loading data into SQL...")}

else {

  "You did not request for any
green taxi data, or all the green
taxi data you requested are cleaned."}

}

#LYFT-----
lyft <- function(obj, years, months){

  valid_months <- etl::valid_year_month(years, months = 1,
begin = "2015-01-01")

  message("Transforming lyft data from raw to load directory...")

  src <- list.files(attr(obj, "raw_dir"), "lyft", full.names = TRUE)
  src_year <- valid_months %>% distinct_(~year)
  remote <- data_frame(src)

  remote <- remote %>%
    mutate_(lcl = ~file.path(attr(obj, "load_dir"), basename(src)),
           basename = ~basename(src), year = ~substr(basename, 6, 9))
  class(remote$year) <- "numeric"
  remote <- inner_join(remote, src_year, by = "year" )
  for(i in 1:nrow(remote)) {

    datafile <- readr::read_csv(remote$src[i])
```

```

    readr::write_delim(datafile, path = remote$lcl[i],
    delim = "|", na = "")}

#transform the data from raw to load

if (type == "yellow"){taxi_yellow(obj, years, months)}

else if (type == "green"){taxi_green(obj, years, months)}

else if (type == "uber"){uber(obj)}

else if (type == "lyft"){lyft(obj, years, months)}

else {message("The type you chose does not exist...")}

invisible(obj)
}

```

2.5.3 ETL Load

```

opts_chunk$set(tidy.opts=list(width.cutoff=60))

etl_load.etl_nyctaxi <- function(obj,
  years = as.numeric(format(Sys.Date(), '%Y')),
  months = 1:12,
  type   = "yellow", ...){

#TAXI YELLOW-----
taxi_yellow <- function(obj, years, months,...) {

  #create a df of file path of the files that are in the load directory
  src <- list.files(attr(obj, "load_dir"), "yellow",
  full.names = TRUE)

  src <- data.frame(src)
}

```

```
#files before 2016-07

remote_old <- etl::valid_year_month(years, months,
begin = "2009-01-01", end = "2016-06-30") %>%
  mutate_(src = ~file.path(attr(obj, "load_dir")),
  paste0("yellow", "_tripdata_", year, "-",
  stringr::str_pad(month, 2, "left", "0"), ".csv")))
src_small_old <- inner_join(remote_old, src, by = "src")

#files later then 2017-06

remote_new <- etl::valid_year_month(years, months,
begin = "2016-07-01") %>%
  mutate_(src = ~file.path(attr(obj, "load_dir")),
  paste0("yellow", "_tripdata_", year, "-",
  stringr::str_pad(month, 2, "left", "0"), ".csv")))
src_small_new <- inner_join(remote_new, src, by = "src")

#data earlier than 2016-07

if(nrow(src_small_old) == 0) {
  message("The taxi files (earlier than 2016-07)
    you requested are not available in
    the load directory...")
} else {
  message("Loading taxi data from
    load directory to a sql database...")
  mapply(DBI::dbWriteTable,
    name = "yellow_old", value = src_small_old$src,
    MoreArgs =
      list(conn = obj$con, append = TRUE))}
```

```
#data later than 2016-06

if(nrow(src_small_new) == 0) {

  message("The new taxi files (later than 2016-06)

    you requested are not available in the

    load directory...")

} else {

  message("Loading taxi data from load

  directory to a sql database...")

  mapply(DBI::dbWriteTable,

    name = "yellow", value = src_small_new$src,

    MoreArgs =

      list(conn = obj$con, append = TRUE))}

}

#TAXI GREEN-----

taxi_green <- function(obj, years, months, ...) {

  #create a list of file that the user wants to load

  remote <- etl::valid_year_month(years, months,

  begin = "2013-08-01") %>%

    mutate_(src = ~file.path(attr(obj, "load_dir")),

    paste0("green", "_tripdata_", year, "-",

    stringr::str_pad(month, 2, "left", "0"), ".csv")))

  #create a df of file path of the files that are in the load directory

  src <- list.files(attr(obj, "load_dir"), "tripdata",

  full.names = TRUE)

  src <- data.frame(src)

  #only keep the files thst the user wants to transform
```

```
src_small <- inner_join(remote, src, by = "src")

if(nrow(src_small) == 0) {
  message("The taxi files you requested
    are not available in the
    load directory...")

} else {
  message("Loading taxi data from
    load directory to a sql database...")

  mapply(DBI::dbWriteTable,
    name = "green", value = src_small$src,
    MoreArgs =
      list(conn = obj$con, append = TRUE, ... = ...))}

#UBER-----
uber <- function(obj,...) {

  uberfileURL <- file.path(attr(obj, "load_dir"), "uber.csv")

  if(file.exists(uberfileURL)) {
    message("Loading uber data from
      load directory to a sql database...")

    DBI::dbWriteTable(conn = obj$con, name = "uber",
      value = uberfileURL, append = TRUE, ... = ...)

  } else {
    message("There is no uber data
      in the load directory...")}

#LYFT-----
lyft <- function(obj, years, months,...){

  message("Loading lyft data from
    load directory to a sql database...")
```

```
#create a list of file that the user wants to load

valid_months <- etl::valid_year_month(years, months,
begin = "2015-01-01")

src <- list.files(attr(obj, "load_dir"), "lyft",
full.names = TRUE)

src_year <- valid_months %>% distinct_(~year)

remote <- data_frame(src)

remote <- remote %>% mutate_(tablename = ~"lyft",
year = ~substr(basename(src), 6, 9))

class(remote$year) <- "numeric"

remote <- inner_join(remote, src_year, by = "year" )

if(nrow(remote) != 0) {

  write_data <- function(...) {

    lapply(remote$src, FUN = DBI::dbWriteTable,
    conn = obj$con, name = "lyft", append = TRUE,
    sep = "|", ... = ...)

    write_data(...)

  } else {

    message("The lyft files you requested
    are not available in the
    load directory...")}

}

if (type == "yellow"){taxi_yellow(obj, years, months,...)
}else if (type == "green"){taxi_green(obj, years, months,...)
}else if (type == "uber"){uber(obj,...)
}else if (type == "lyft"){lyft(obj, years, months,...)
}else {message("The type you chose does not exist...")}
```

```
    }

invisible(obj)
}
```

2.5.4 ETL Init

```
DROP TABLE IF EXISTS `yellow_old`;
```

```
CREATE TABLE `yellow_old` (
  `VendorID` tinyint DEFAULT NULL,
  `tpep_pickup_datetime` DATETIME NOT NULL,
  `tpep_dropoff_datetime` DATETIME NOT NULL,
  `passenger_count` tinyint DEFAULT NULL,
  `trip_distance` float(10,2) DEFAULT NULL,
  `pickup_longitude` double(7,5) DEFAULT NULL,
  `pickup_latitude` double(7,5) DEFAULT NULL,
  `RatecodeID` tinyint DEFAULT NULL,
  `store_and_fwd_flag` varchar(10) COLLATE latin1_general_ci DEFAULT NULL,
  `dropoff_longitude` double(7,5) DEFAULT NULL,
  `dropoff_latitude` double(7,5) DEFAULT NULL,
  `payment_type` tinyint DEFAULT NULL,
  `fare_amount` decimal(5,3) DEFAULT NULL,
  `extra` decimal(5,3) DEFAULT NULL,
  `mta_tax` decimal(5,3) DEFAULT NULL,
  `tip_amount` decimal(5,3) DEFAULT NULL,
  `tolls_amount` decimal(5,3) DEFAULT NULL,
```

```
`improvement_surcharge` decimal(5,3) DEFAULT NULL,  
 `total_amount` decimal(5,3) DEFAULT NULL,  
 KEY `VendorID` (`VendorID`),  
 KEY `pickup_datetime` (`tpep_pickup_datetime`),  
 KEY `dropoff_datetime` (`tpep_dropoff_datetime`),  
 KEY `pickup_longitude` (`pickup_longitude`),  
 KEY `pickup_latitude` (`pickup_latitude`),  
 KEY `dropoff_longitude` (`dropoff_longitude`),  
 KEY `dropoff_latitude` (`dropoff_latitude`)  
)  
PARTITION BY RANGE( YEAR(tpep_pickup_datetime) ) (  
    PARTITION p09 VALUES LESS THAN (2010),  
    PARTITION p10 VALUES LESS THAN (2011),  
    PARTITION p11 VALUES LESS THAN (2012),  
    PARTITION p12 VALUES LESS THAN (2013),  
    PARTITION p13 VALUES LESS THAN (2014),  
    PARTITION p14 VALUES LESS THAN (2015),  
    PARTITION p15 VALUES LESS THAN (2016),  
    PARTITION p16 VALUES LESS THAN (2017)  
);  
  
DROP TABLE IF EXISTS `yellow`;  
  
CREATE TABLE `yellow` (  
 `VendorID` tinyint DEFAULT NULL,  
 `tpep_pickup_datetime` DATETIME NOT NULL,  
 `tpep_dropoff_datetime` DATETIME NOT NULL,
```

```
`passenger_count` tinyint DEFAULT NULL,  
 `trip_distance` float(10,2) DEFAULT NULL,  
 `RatecodeID` tinyint DEFAULT NULL,  
 `store_and_fwd_flag` varchar(10) COLLATE latin1_general_ci DEFAULT NULL,  
 `PULocationID` tinyint DEFAULT NULL,  
 `DOLocationID` tinyint DEFAULT NULL,  
 `payment_type` tinyint DEFAULT NULL,  
 `fare_amount` decimal(5,3) DEFAULT NULL,  
 `extra` decimal(5,3) DEFAULT NULL,  
 `mta_tax` decimal(5,3) DEFAULT NULL,  
 `tip_amount` decimal(5,3) DEFAULT NULL,  
 `tolls_amount` decimal(5,3) DEFAULT NULL,  
 `improvement_surcharge` decimal(5,3) DEFAULT NULL,  
 `total_amount` decimal(5,3) DEFAULT NULL,  
 KEY `VendorID` (`VendorID`),  
 KEY `pickup_datetime` (`tpep_pickup_datetime`),  
 KEY `dropoff_datetime` (`tpep_dropoff_datetime`),  
 KEY `PULocationID` (`PULocationID`),  
 KEY `DOLocationID` (`DOLocationID`)  
)  
PARTITION BY RANGE( YEAR(tpep_pickup_datetime) ) (  
    PARTITION p16 VALUES LESS THAN (2017),  
    PARTITION p17 VALUES LESS THAN (2018)  
);
```

```
DROP TABLE IF EXISTS `green`;
```

```
CREATE TABLE `green` (
    `VendorID` tinyint DEFAULT NULL,
    `lpep_pickup_datetime` DATETIME NOT NULL,
    `Lpep_dropoff_datetime` DATETIME NOT NULL,
    `Store_and_fwd_flag` varchar(10) COLLATE latin1_general_ci DEFAULT NULL,
    `RatecodeID` tinyint DEFAULT NULL,
    `Pickup_longitude` double(7,5) DEFAULT NULL,
    `Pickup_latitude` double(7,5) DEFAULT NULL,
    `Dropoff_longitude` double(7,5) DEFAULT NULL,
    `Dropoff_latitude` double(7,5) DEFAULT NULL,
    `Passenger_count` tinyint DEFAULT NULL,
    `Trip_distance` float(10,2) DEFAULT NULL,
    `Fare_amount` decimal(5,3) DEFAULT NULL,
    `Extra` decimal(5,3) DEFAULT NULL,
    `MTA_tax` decimal(5,3) DEFAULT NULL,
    `Tip_amount` decimal(5,3) DEFAULT NULL,
    `Tolls_amount` decimal(5,3) DEFAULT NULL,
    `improvement_surcharge` decimal(5,3) DEFAULT NULL,
    `Total_amount` decimal(5,3) DEFAULT NULL,
    `Payment_type` tinyint DEFAULT NULL,
    `Trip_type` tinyint DEFAULT NULL,
    KEY `VendorID` (`VendorID`),
    KEY `pickup_datetime` (`lpep_pickup_datetime`),
    KEY `dropoff_datetime` (`Lpep_dropoff_datetime`)
);
```

```
DROP TABLE IF EXISTS `lyft`;

CREATE TABLE `lyft` (
  `base_license_number` varchar(15) COLLATE latin1_general_ci DEFAULT NULL,
  `base_name` varchar(40) COLLATE latin1_general_ci DEFAULT NULL,
  `dba` varchar(40) COLLATE latin1_general_ci DEFAULT NULL,
  `pickup_end_date` DATE NOT NULL,
  `pickup_start_date` DATE NOT NULL,
  `total_dispatched_trips` smallint DEFAULT NULL,
  `unique_dispatched_vehicle` smallint DEFAULT NULL,
  `wave_number` tinyint DEFAULT NULL,
  `week_number` tinyint DEFAULT NULL,
  `years` smallint DEFAULT NULL,
  KEY `base_name` (`base_name`),
  KEY `pickup_end_date` (`pickup_end_date`),
  KEY `pickup_start_date` (`pickup_start_date`)
);
```

```
DROP TABLE IF EXISTS `uber`;
```

```
CREATE TABLE `uber` (
  `lat` double(7,5) DEFAULT NULL,
  `lon` double(7,5) DEFAULT NULL,
  `dispatching_base_num` varchar(15) COLLATE latin1_general_ci DEFAULT NULL,
  `pickup_date` DATETIME NOT NULL,
```

```
`affiliated_base_num` varchar(15) COLLATE latin1_general_ci DEFAULT NULL,  
`locationid` tinyint DEFAULT NULL,  
KEY `pickup_date` (`pickup_date`),  
KEY `locationid` (`locationid`)  
);  
  
CREATE VIEW yellow_old_sum AS SELECT YEAR(tpipep_pickup_datetime) as the_year, MONTH(tpipep_pickup_datetime) as the_month  
FROM yellow_old  
GROUP BY the_year, the_month;  
);
```


Chapter 3

New York City Taxi Driver

The income of Taxi drivers in New York City has two parts: taxi fare and tips. Taxi fare is usually calculated by the meters installed in the taxis, and the rate of fare cannot be changed by taxi drivers. Therefore, in order to make more profit, taxi drivers prefer to pick up passengers who offer big amount of tips. What are the regions that provide the most tips to yellow taxicab drivers?

In this analysis, we will focus on trip data collected in 2017. Descriptions of variables mentioned in the following chapters can be found in Appendix B.

In order to answer questions regarding to taxi trips' tips, we filter out trips that are not paid by credit or debit card, because taxi drivers usually do not correctly record the amount of tips paid by cash or check (Appendix C) (W. Li, 2018).

As mentioned in the previous chapter, that we can utilize the connection to a MySQL database to run data analysis in MySQL for medium-sized data. Since we are using all 12 month data from 2017 in this analysis, it is impractical to load all data needed into **R** environment. Instead, we want to only load a fraction of the 2017 Yellow Taxi data from MySQL database.

In this section, we only want to load trip records with payment type equals to 1, which represents credit card. Only trip records with payment type credit card have accurate information on tip amount. Let's load the 2017 trip record into **R** environment by using the MySQL connection we just generated, **taxi**.

```
yellow_2017 <- taxi %>%
 tbl("yellow") %>%
  filter(payment_type == 1) %>%
  collect(n = Inf)
```

3.1 Aggregated Zone-level Tip Amount

Instead of the nominal amount of tips, we want to focus on the percentage of tips that passengers pay in addition to the total fare amount. Therefore, we use tip amount over fare amount to calculate the percent tip. We then calculated the mean percent tip, mean distances travelled, mean number of minutes spent travelling, and total number of trips of each pick-up and drop-off pair in 2017 to get the aggregated zone-level information in order to compare the percent tip passengers pay in each zone.

```
yellow_2017_summary <- yellow_2017 %>%
  mutate(year = year(tpep_pickup_datetime),
         month = month(tpep_pickup_datetime),
         tip_perct = tip_amount/fare_amount) %>%
  group_by(year, month, PULocationID, DOLocationID) %>%
  summarise(avg_tip = mean(tip_perct),
            trips = n(),
            avg_dis = mean(trip_distance),
            avg_duration = mean(duration))
```

Each taxi trip has pick-up and drop-off locations associated with it, and there are 263 known taxi zones and 2 taxi zones that are labelled as “Unknown”. We only want to include trips coming from and going to known taxi zones in this analysis.

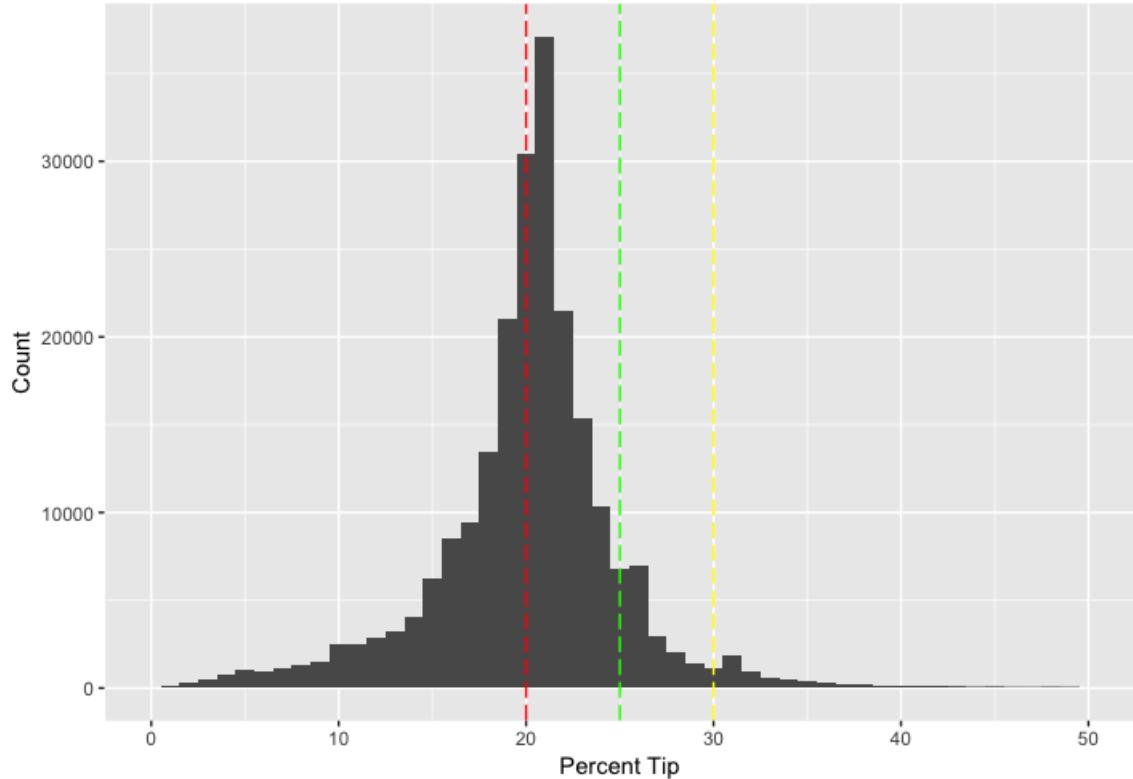


Figure 3.1: Percent Tip Paid by Passengers on Each Pick-up And Drop-off Pair in NYC

Figure 3.1 is a histogram of mean tip percents for all known pick-up and drop-off zone pairs. The red, green, and yellow dash lines are drawn at 20%, 25%, and 30%, which are the default percentage of tips that are shown on the touch panel for credit and debit car payments.

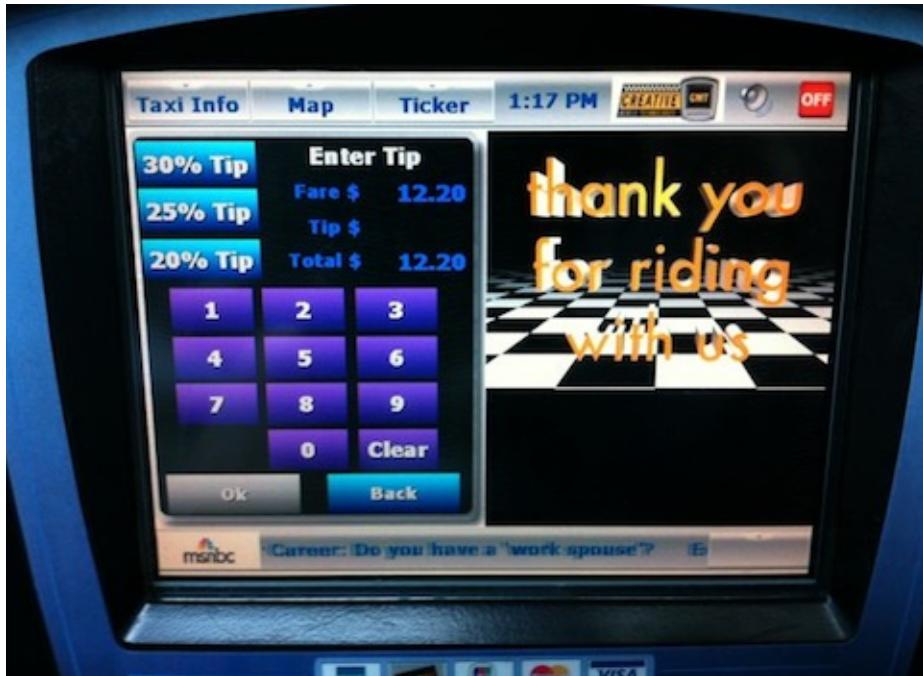


Figure 3.2: Tip Payment Page on New York City Touch Panel

3.1.1 Pick-up Zone Percent Tip Amount

Taxi drivers are required to be indifferent to where passengers are going. It is illegal for New York city taxi drivers to refuse service because of passengers' race, ethnicity, cultural background, disability, gender, or destination (Harshbarger, 2015). Taxi drivers cannot choose where the passengers want to go, and instead they can only choose which pick-up zone they would prefer to drive around to get hailed. Therefore, it makes sense to investigate the average amount of tips paid by passengers departed from each pick-up zone. What are the taxi pick-up zones that have the highest percent tips paid by passengers?

We first calculate the average percent tip paid for each pick-up zone. Table 3.1 is a list of pick-up zones with their average percent tips.

We created a histogram to visualize the distribution of average percent tips paid for all pick-up zones.

Table 3.1: Ten taxi pick-up zones with the highest average tip in January, 2017

avg_tip	avg_dis	avg_duration	Borough	Zone
29	7.37	15.74	Queens	Douglas
29	7.05	20.78	Bronx	East Tremont
29	10.40	17.87	Queens	Oakland Gardens
28	7.97	22.29	Queens	Glendale
28	8.33	25.23	Queens	Saint Michaels Cemetery/Woodside
27	7.60	19.70	Queens	Bayside
27	9.56	24.35	Brooklyn	Coney Island
27	10.63	25.94	Queens	Howard Beach
27	11.20	23.28	Brooklyn	Marine Park/Mill Basin
26	6.22	18.80	Bronx	Norwood

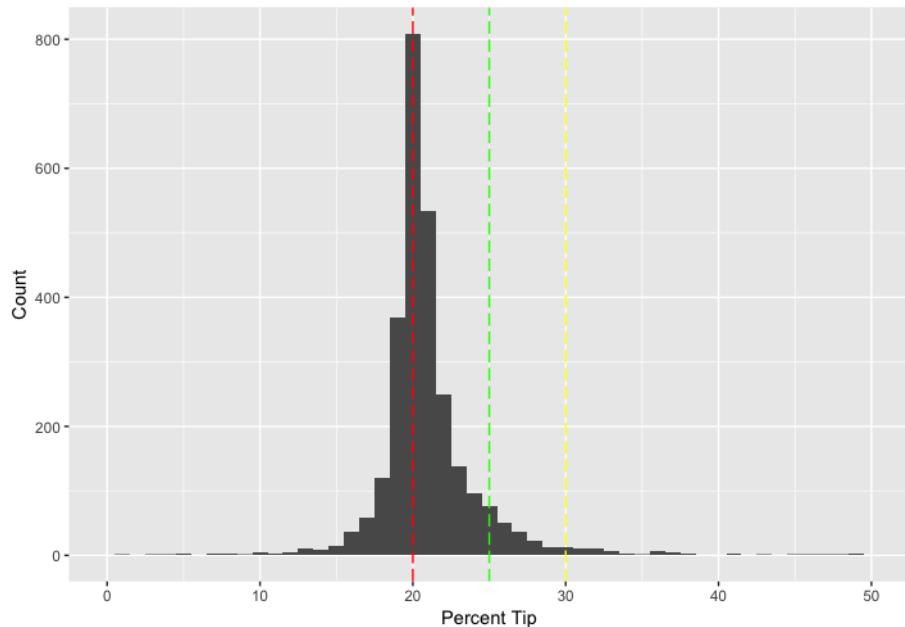


Figure 3.3: Percent Tip Paid by Passengers on Each Pick-up Taxi Zone in NYC

As shown in Figure 3.3, the first peak is around 20%, which is the cheapest default option on the touch panel for passengers to choose.

3.1.2 Which pick-up zones have the highest number of pick-ups?

Which pick-up zones have the highest number of taxi trip pick-ups? We can create a heat map to visualizae the number of trips for each pick-up zones on a map of New York City Taxi Zones.



Figure 3.4: Number of Pick-ups in Each Taxi Zone

According to Figure 3.4, it's obvious that Upper East Side Manhattan, Midtown Manhattan, and La Guardia Airport are the most popular location for pick-ups. Table 3.2 gives you a better idea of which taxi zones have the highest number of pick-ups.

Table 3.2: Ten taxi zones with the highest number of pick-ups

avg_tip	avg_dis	avg_duration	Borough	Zone
19.64	9.21	33.32	Manhattan	Upper East Side South
20.82	10.04	34.48	Manhattan	Midtown Center
20.18	9.63	33.22	Manhattan	Union Sq
19.73	9.21	31.94	Manhattan	Upper East Side North
20.55	9.70	32.83	Manhattan	Midtown East
20.55	9.66	31.90	Manhattan	Murray Hill
20.55	9.99	36.77	Manhattan	Penn Station/Madison Sq West
20.00	9.48	30.39	Manhattan	East Village
21.00	11.90	36.10	Queens	LaGuardia Airport
20.36	10.32	35.97	Manhattan	Times Sq/Theatre District

Table 3.3: Ten taxi pick-up zones with the highest percent tip (taxi zones has at least 1 pick-up per hour)

avg_tip	avg_dis	avg_duration	Borough	Zone
21.55	14.27	42.94	Queens	Baisley Park
21.45	6.89	24.04	Brooklyn	Gowanus
21.36	8.18	26.10	Queens	Steinway
21.18	7.11	25.85	Brooklyn	Carroll Gardens
21.00	11.90	36.10	Queens	LaGuardia Airport
21.00	6.74	25.06	Brooklyn	Greenpoint
21.00	6.45	25.44	Brooklyn	Prospect Heights
20.82	10.04	34.48	Manhattan	Midtown Center
20.82	6.91	26.12	Brooklyn	Cobble Hill
20.82	6.83	23.07	Brooklyn	East Williamsburg

3.1.3 Which pick-up zones have the highest percent tips?

Most yellow cab pick-ups occur in Manhattan. If we focus on the pick-up zones that have at least 24 trips per day or 8760 per year, we will observe that many taxi pick-up zones with the highest percent tips are not necessarily the ones with the highest number of pick-ups. People might think it is more reasonable to see a list that is populated with Zones in Manhattan, since that's where most of the wealthy people live. However, Table @ref(tab:pickup_zone_30) shows that passengers who get on taxis from certain zones in Brooklyn and Queens also pay a lot of tips. Taxi drivers

Table 3.4: Ten taxi pick-up zones with the highest percent tip (taxi zones has at least 1 pick-up per minute)

avg_tip	avg_dis	avg_duration	Borough	Zone
21.00	11.90	36.10	Queens	LaGuardia Airport
20.82	10.04	34.48	Manhattan	Midtown Center
20.73	10.22	32.82	Manhattan	Battery Park City
20.55	9.70	32.83	Manhattan	Midtown East
20.55	9.66	31.90	Manhattan	Murray Hill
20.55	9.99	36.77	Manhattan	Penn Station/Madison Sq West
20.45	9.07	30.18	Manhattan	UN/Turtle Bay South
20.36	10.32	35.97	Manhattan	Times Sq/Theatre District
20.18	9.63	33.22	Manhattan	Union Sq
20.18	9.84	35.49	Manhattan	Midtown North

who would love to get more tips compensation can drive to the zones listed above to pick-up passengers.

If we focus on the pick-up zones that have more than 2400 trips per day, then we observe that all pick-up zones that have the highest percent tips are in Manhattan besides La Guardia Airport. There are more than 100 times more yellow cab pick-ups that happen in Manhattan everyday than in Brooklyn. By comparing the average tip percent in Table 3.2 and Table 3.3, we can observe that percent tips paid in taxi zones with low pick-up numbers seem to be higher than percent tips paid in taxi zones with high pick-up numbers.

3.2 What features of taxi trips increase the percent tip amount that passengers pay?

So far, we have learned what pick-up zones offer the highest percent tip. Now, we want to dig into the relationships between percent tip and taxi-zone-specific variables.

3.2.1 Does trip distance increase the percent tips paid by passengers?

Will longer trips result in higher tip percent. It takes taxi drivers more time to complete longer trips, so passengers might want to compensate taxi drivers more. I personally pay higher percent of tips for longer rides, so I believe trip distance has an impact on percentage of tips paid.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.211325482	3.733048e-04	566.09360	0
avg_dis	-0.001052903	2.105014e-05	-50.01881	0

According to the simple linear regression result, trip distance does have a negative significant impact on the percent of tips paid, controlling for both pick-up and drop-off locations. This could be caused by a psychological reason. Long trips cost more than short trips. For a constant tip percent, the nominal value of tip amount cost more for longer trips. For example, for a \$100 trip, 20% tip costs \$20; for a \$50 trip, 20% tip costs \$10. Even though consumers are paying the same percent amount of tips, \$20 is more expensive than \$10. Therefore, consumers might decide to pay less percent tip for longer trips.

3.2.2 Do passengers pay more tips during rush hours?

New York City Taxi Fare & Limousine Commission has information on how New York City taxi fare amount is calculated on their official website.

Metered Fare Information

- Onscreen rate is ‘Rate #01 – Standard City Rate.’

- The initial charge is \$2.50.
- Plus 50 cents per 1/5 mile or 50 cents per 60 seconds in slow traffic or when the vehicle is stopped.
- In moving traffic on Manhattan streets, the meter should “click” approximately every four downtown blocks, or one block going cross-town (East-West).
- There is a 50-cent MTA State Surcharge for all trips that end in New York City or Nassau, Suffolk, Westchester, Rockland, Dutchess, Orange or Putnam Counties.
- There is a 30-cent Improvement Surcharge.
- There is a daily 50-cent surcharge from 8pm to 6am.
- There is a \$1 surcharge from 4pm to 8pm on weekdays, excluding holidays.
- Passengers must pay all bridge and tunnel tolls.
- Your receipt will show your total fare including tolls. Please take your receipt.
- The driver is not required to accept bills over \$20.
- Please tip your driver for safety and good service.
- There are no charges for extra passengers or bags.

The metered fare rate information is collected from TLC rate of fare webpage (N. T. staff, n.d.).

In taxi fare calculation, the only unknown variable is slow-traffic time, and all other variables were collected by the meters installed on each medallion taxi for each trip. It is reasonable to assume that for trips with the same pick-up and drop-off locations, the longer the total slow traffic time is, the longer the trip would take. Taxi drivers are compensated for both the normal-speed trip distance and the time spent in slow-traffic. According to the fare calculation algorithm, in moving traffic on Manhattan streets, the meter should “click” approximately every four downtown blocks, or one block going cross-town (East-West); in slow traffic, the meter should “click” every 60 seconds.

3.2. What features of taxi trips increase the percent tip amount that passengers pay?

Therefore, slow traffic increases the minute per mile ratio.

New York City has the worst traffic jams, and it has overtaken Miami to be voted the U.S. city with the angriest and most aggressive drivers in 2009, according to a survey on road rage released on Tuesday. Bad traffic also causes slow-traffic, and taxi drivers tend to get stuck in traffic during rush hours (Reaney, 2009). Does minute per mile ratio have an impact on the percent tip that passengers pay? Do passengers compensate taxi drivers more during rush hours? Are passengers sympathetic to taxi drivers for the time they spend in slow traffic?

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.193453599	1.870711e-04	1034.1180	0
min_per_mile	0.002841351	3.134322e-05	90.6528	0

As shown in the regression result, `min_per_mile` ratio does have an positive impact on percent tips. Since trips with slow traffic can be depicted by high minute per mile ratio, passengers do pay more tips during rush hours.

Our analysis has proved that taxi passengers are sympathetic with the drivers who have to suffer the cogestion in New York City, and taxi drivers do get compensated more during rush hours.

Chapter 4

New York City Taxi Passengers

4.1 How long does it take passengers to get to JFK, La Guardia, and Newark Airports from anywhere in New York City? When is the best time to travel in order to avoid the traffic?

We want to calculate the average number of minutes it takes to go to all three airport from a specific taxi zone at every hour. First, we want to focus on trips going to any of the three airports, JFK, LaGuardia, or Newark Airport. We need to load trip records with destination as one of the three airports from the MySQL connection we built.

```
to_jfk_trip <- taxi %>%
 tbl("yellow") %>%
  filter(DOLocationID == 132) %>%
  collect(n = Inf)
```

Table 4.1: Average number of minutes it takes from Alphabet City, Manhattan to JFK Airport during different hours

	PULocationID	hour	avg_min	airport
10	4	0	45.37000	JFK
11	4	1	36.77500	JFK
12	4	2	28.66000	JFK
13	4	3	27.83350	JFK
14	4	4	27.19490	JFK
15	4	5	28.68889	JFK
16	4	6	34.25271	JFK
17	4	7	38.13817	JFK
18	4	8	41.59687	JFK
19	4	9	35.39226	JFK
20	4	10	36.22867	JFK

```
to_lg_trip <- taxi %>%
 tbl("yellow") %>%
  filter(DOLocationID == 138) %>%
  collect(n = Inf)

to_newark_trip <- taxi %>%
 tbl("yellow") %>%
  filter(DOLocationID == 1) %>%
  collect(n = Inf)
```

Now we want to calculate the average amount of time it take from each zone to one of the three airports during each hour.

So far, we have created three tables summarising the average number of minutes it takes to go to all three airports for every hour from different taxi zones. It would be easier if we combine all three tables and put information related to trip duration to all three airports in the same table. Table 4.1 displays the average number of minutes

4.1. How long does it take passengers to get to JFK, La Guardia, and Newark Airports from anywhere in New York City? When is the best time to travel in order to avoid the traffic?
it takes from Alphabet City, Manhattan to JFK Airport during different hours. 63

4.1.1 Case Study: From Central Park, Manhattan to all three airport

Alphabet City, Manhattan has pick-up zone ID number 4. Let's take a look at how much time is needed to travel to all three airports from taxi zone No.4.

```
alphabet <- three_air%>%  
  filter(PULocationID ==43)
```

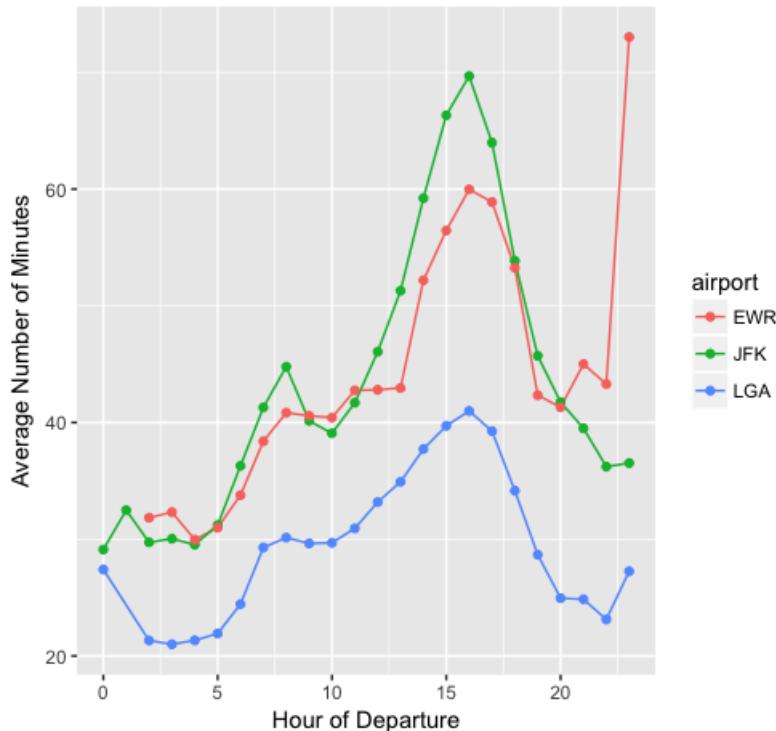


Figure 4.1: Average number of minutes it takes from Central Park, Manhattan to all three airports during different hours

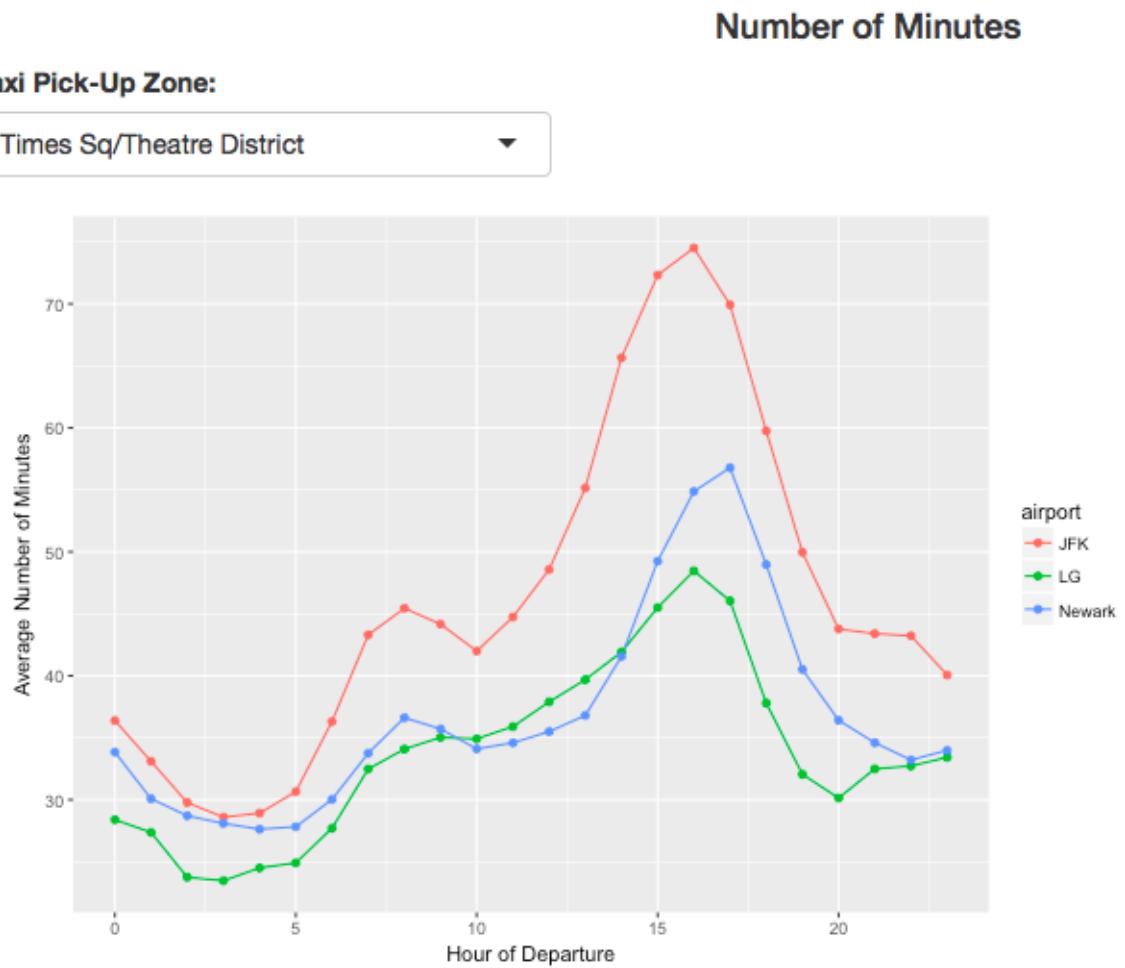
According to the red line Figure 4.1, it takes the least time, less than 30 minutes, to travel from Central Park, Manhattan to Newark Airport around 4 AM in the morning and it takes more than 70 minutes around 11 PM at night.

According to the green line, it only takes about 30 minutes to travel to JFK Airport around 4 AM in the morning, and it takes the most time, about 70 minutes, around 4 PM in the afternoon.

As shown by the blue line, it takes the least time, about 20 minutes, to travel to La Guardia Airport at 1 AM at midnight, and it takes a little more than 40 minutes around 4 PM in the evening.

Being able to know the average time it takes to go to one of the airports ahead, passengers can buy their flight tickets accordingly.

4.1.2 A Shiny App: allowing users to choose a pick up zone of their interest, and output the best time to travel from that zone to all three airports in New York



This Shiny App helps passengers to estimate the amount of time that is needed for them to travel to any one of the these three airports from any New York City taxi zones.

Table 4.2: Uber 2017 Weekly Total Dispatched Trips

Pickup Start Date	Pickup End Date	Uber Total Dispatched Trips
2017-01-01	01/07/2017	2866569
2017-01-08	01/14/2017	3114792
2017-01-15	01/21/2017	3089595
2017-01-22	01/28/2017	3299763
2017-01-29	02/04/2017	3224451
2017-02-05	02/11/2017	3310481
2017-02-12	02/18/2017	3456042
2017-02-19	02/25/2017	3194805
2017-02-26	03/04/2017	3533347
2017-03-05	03/11/2017	3614559

4.2 How does weather affect the number of taxi and Lyft trips?

On a snowy or rainy day, it is hard for passengers to find a yellow cab on the street. Taxi drivers get paid at the same rate no matter how bad the weather gets, so they tend to stay at home instead of going out to work when the weather is bad. Uber drivers, however, get paid more on a snowy or rainy day, since Uber uses a pricing model that takes the number of Uber vehicles available on the street into account. When weather is bad, fewer Uber vehicles are available on the street, so Uber fare rate increases. Uber's pricing model gives Uber drivers an incentive to keep working on ugly days. Lyft has a similar pricing model to the one that Uber uses.

In this section, we want to study the number of pickups of yellow cab, Uber, and Lyft. We compare number of pick-ups in each taxi zone in the weeks of bad weather with previous weeks' total number of pick-ups to see whether Uber drivers have an incentive to drive around the city more when weather gets bad.

Uber Weekly Data

Table 4.3: Yellow Taxi 2017 Weekly Total Dispatched Trips

Pickup Start Date	Pickup End Date	Yellow Total Dispatched Trips
2017-01-01	01/07/2017	2044643
2017-01-08	01/14/2017	2230950
2017-01-15	01/21/2017	2219214
2017-01-22	01/28/2017	2307122
2017-01-29	02/04/2017	2331749
2017-02-05	02/11/2017	2181622
2017-02-12	02/18/2017	2387399
2017-02-19	02/25/2017	2225850
2017-02-26	03/04/2017	2464800
2017-03-05	03/11/2017	2456285

Yellow Cab Weekly Data

In this section, we use New York City Yellow Taxi and Uber data to calculate the number of trips occurred in each week.

4.2.1 Case Study: March 14th, 2017 Snow Storm

There are two commonly known bad weather conditions, rainy and snowy days. Let's first focus on snowstorm. On March 14th, 2017, a snow storm brought seven inches of snow to New York City. **Yellow Taxi**

	Pickup Start Date	Yellow Total Dispatched Trips	Pickup End Date
1	2017-03-05	2456285	03/11/2017
2	2017-03-12	2066285	03/18/2017
$(2066285 - 2456285) / 2456285$			

[1] -0.1587764

Uber

```
# A tibble: 0 x 3
```

```
# Groups:  Pickup Start Date [0]
# ... with 3 variables: Pickup Start Date <chr>, Pickup End Date <chr>,
#   Uber Total Dispatched Trips <int>
(3430189-3614559)/3614559
```

[1] -0.05100761

In this case, we observe that the percent decline in Uber's total number of pick-ups is 10% less than the percent decline in Yellow Taxi's total number of drop-off. Even though the total number of Uber pick-ups did not increase, Uber's pricing model definitely was able to keep more drivers in the market on a snowy day.

4.2.2 Case Study: Impact of Precipitation on Taxi Rides

People living in New York might have noticed that it is hard to find a taxi on the street when it rains. Economists have studied this phenomena for a long time, and an analysis studied the correlation between taxi movement and hourly rainfall data in Central Park from 2009 to 2013 has found that there is no significant correlation between a driver's hourly wage and rain in the city, which implies that drivers don't earn more when it's raining (Jaffe, 2014).

I got access to the 2017 daily Central Park weather data from the National Climatic Data Center by submitting a Climate Data Online request (Appendix D) to National Centers for Environmental Information (Environmental Information staff, n.d.), and joined it to the 2017 taxi data to study relationship between rainfall and taxi rides.

First, we generate a list of total amount of daily rainfall in New York City and we pick the 10 weeks that have the most rainfall in 2017. We then find the weekly total number of dispatched yellow taxi trips of the 10 weeks with the srtat date listed

Table 4.4: 10 weeks that have the most rainfall in 2017

Pickup Start Date	Pickup End Date	Weekly Rainfall
2017-06-18	2017-06-25	7.00
2017-04-30	2017-05-07	6.71
2017-10-29	2017-11-05	6.16
2017-07-02	2017-07-09	5.56
2017-03-26	2017-04-02	5.11
2017-01-22	2017-01-29	3.99
2017-08-13	2017-08-20	3.95
2017-06-11	2017-06-18	3.91
2017-04-02	2017-04-09	3.17
2017-04-23	2017-04-30	2.88

Table 4.5: 10 weeks that have the most rainfall in 2017 and the total number of dispatched yellow taxi trips in those weeks

Pickup Date	Dispatched Trips	Last Week Date	Last Week Trips	%Change Trips
2017-06-18	2231205	2017-06-11	2285958	-2.3951884
2017-04-30	2386559	2017-04-23	2394329	-0.3245168
2017-10-29	2266196	2017-10-22	2267693	-0.0660142
2017-07-02	1664159	2017-06-25	2038406	-18.3597870
2017-03-26	2341096	2017-03-19	2272369	3.0244648
2017-01-22	2307122	2017-01-15	2219214	3.9612223
2017-08-13	1871668	2017-08-06	1929860	-3.0153483
2017-06-11	2285958	2017-06-04	2313236	-1.1792139
2017-04-02	2414700	2017-03-26	2341096	3.1439975
2017-04-23	2394329	2017-04-16	2337161	2.4460446

above. We also need to add the weekly total number of dispatched Uber trips of the 10 weeks with the most rainfall. We combine the percentage change in total number of dispatched trips of yellow taxi and Uber, and we compare the result. Besides the week of April 30th, 2017, all other weeks have higher increases in the number of total dispatched trips of Uber or lower declines in the number of weekly Uber trips. Therefore, on rainy days, Uber drivers tend to increase the number of trips they drive at a higher rate.

Uber passengers have to pay higher rate of fare on rainy days because of Uber's pricing

Table 4.6: 10 weeks that have the most rainfall in 2017 and the total number of dispatched Uber trips in those weeks

Pickup Date	Dispatched Trips	Last Week Date	Last Week Trips	%Change Trips
2017-06-18	3654932	2017-06-11	3658220	-0.0898798
2017-04-30	3546893	2017-04-23	3606408	-1.6502570
2017-10-29	4317572	2017-10-22	4193611	2.9559489
2017-07-02	3212582	2017-06-25	3406814	-5.7012798
2017-03-26	3541624	2017-03-19	3425475	3.3907414
2017-01-22	3299763	2017-01-15	3089595	6.8024450
2017-08-13	3599772	2017-08-06	3584023	0.4394224
2017-06-11	3658220	2017-06-04	3622252	0.9929734
2017-04-02	3443444	2017-03-26	3541624	-2.7721746
2017-04-23	3606408	2017-04-16	3427564	5.2178165

Table 4.7: The percentage change in total number of dispatched trips comparing to the previous weeks of yellow taxi and Uber

Pickup Start Date	Weekly Rainfall	Last Week Date	uber	yellow
2017-06-18	7.00	2017-06-11	-0.0898798	-2.3951884
2017-04-30	6.71	2017-04-23	-1.6502570	-0.3245168
2017-10-29	6.16	2017-10-22	2.9559489	-0.0660142
2017-07-02	5.56	2017-06-25	-5.7012798	-18.3597870
2017-03-26	5.11	2017-03-19	3.3907414	3.0244648
2017-01-22	3.99	2017-01-15	6.8024450	3.9612223
2017-08-13	3.95	2017-08-06	0.4394224	-3.0153483
2017-06-11	3.91	2017-06-04	0.9929734	-1.1792139
2017-04-02	3.17	2017-03-26	-2.7721746	3.1439975
2017-04-23	2.88	2017-04-16	5.2178165	2.4460446

model. Since taxi drivers do not get paid more on rainy days, they tend to work less than Uber drivers, which limits the options for passengers. Passengers sometimes have to choose the more costly Uber instead. New York City TLC could modify the rate of fare on rainy or snowy days to incentive taxicab drivers to pick up more trips in order to make taking a street hail vechle on average more affordable on rainy days for passengers.

Chapter 5

New York City Taxi Fare & Limousine Commission

5.1 Should there be a flat rate between Manhattan and John F. Kennedy International Airport?

Why is there a flat rate to and from JFK airport and any location in Manhattan? Why is the flat rate \$52? Does TLC make profit from the \$52 flat rate? Does \$52 reduce the congestion on the road to JFK airport and make taking a train a more preferable choice? The New York City taxi trip records can reveal the answers to these questions.

Imagine it's your first time travelling to New York City, and you decided to live in a hotel in Manhattan. Since you might not know much about the city, the \$52 flat rate is nice for you, and it incentivizes you to take taxi to the JFK Airport. If there is no flat rate, there is uncertainty in how much someone needs to pay to take a taxi to

JFK, and tourists might instead choose to take the train, even though taking a train would cost them more time and inconvenience.

Additionally, people living in most parts of Manhattan would have paid more than \$52 to take a taxi to go to the JFK Airport. The higher the taxi fare is, the less the demand for taxi will be. Therefore, having a flat rate might help taxi drivers to get more trips from Manhattan to JFK Airport.

5.2 Passengers departing from Manhattan benefit from the \$52 flat rate

If there is no flat rate between JFK and Manhattan, how much would passengers pay for the distance they travelled between JFK Airport AND Manhattan? And how much more or less should they have paid comparing to the \$52 flat rate?

In this study, we are only interested in yellow taxi trip between Manhattan and JFK Airport.

```
to_jkf <- taxi %>%  
 tbl("yellow") %>%  
  filter(DOLocationID == 132) %>%  
  collect(n = Inf)  
  
from_jfk <- taxi %>%  
  tbl("yellow") %>%  
  filter(PULocationID == 132) %>%  
  collect(n = Inf)
```

Read 81.3% of 577783 rows

Read 577783 rows and 20 (of 20) columns from 0.064 GB file in 00:00:03

Read 4.0% of 1491842 rows

Read 35.5% of 1491842 rows

Read 53.0% of 1491842 rows

Read 57.0% of 1491842 rows

Read 85.1% of 1491842 rows

Read 87.8% of 1491842 rows

Read 1491842 rows and 20 (of 20) columns from 0.164 GB file in 00:00:10

5.2.1 Trips from Manhattan to JFK Airport

We first focus on all the trips that departed in Manhattan and went to JFK Airport, and then we calculate the estimated fare amount that the passengers should have paid based on the distance travelled from each pick-up point to JFK Airport based on the fare rate suggested by TLC for each pick-up zone.

Here is a map of estimated fare amount calculated by taking the average of all estimated fare amounts from the same pick-up zone to JFK Airport based on the fare rate suggested by TLC for each pick-up zone.

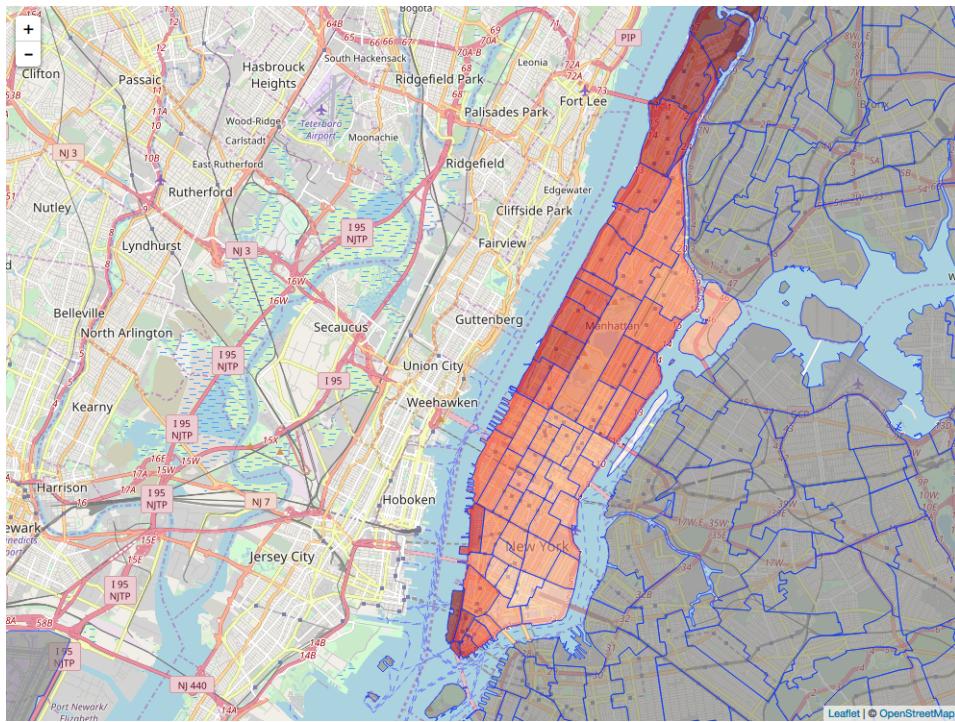


Figure 5.1: Estimated fare amount from each pick-up zone to JFK Airport

According to the map, trips from Midtown on average cost less than trips from other taxi zones in Manhattan.

5.2.2 Which taxi zones would pay more than \$52 without the flat rate?

We computed the average fare paid by passengers for trips going from each taxi zone in Manhattan to JFK Airport in Table @ref(tab:to_jkf_zone_above).

Let's visualize the taxi zones that would have costed more than the \$52 flat rate.

Table 5.1: Ten pick-up zones with the highest average fare from Manhattan to JFK Airport

avg_est_fare	avg_est_diff	Borough	Zone
64.03150	11.844558	Manhattan	Battery Park City
63.98256	9.970366	Manhattan	Inwood
62.97567	10.892992	Manhattan	Washington Heights North
61.99327	9.889636	Manhattan	Battery Park
60.49388	8.278941	Manhattan	Washington Heights South
60.18006	8.107309	Manhattan	Upper West Side South
59.74384	7.511991	Manhattan	World Trade Center
59.31411	7.058534	Manhattan	Meatpacking/West Village West
59.24692	7.200516	Manhattan	Lincoln Square West
59.13439	7.083517	Manhattan	Upper West Side North

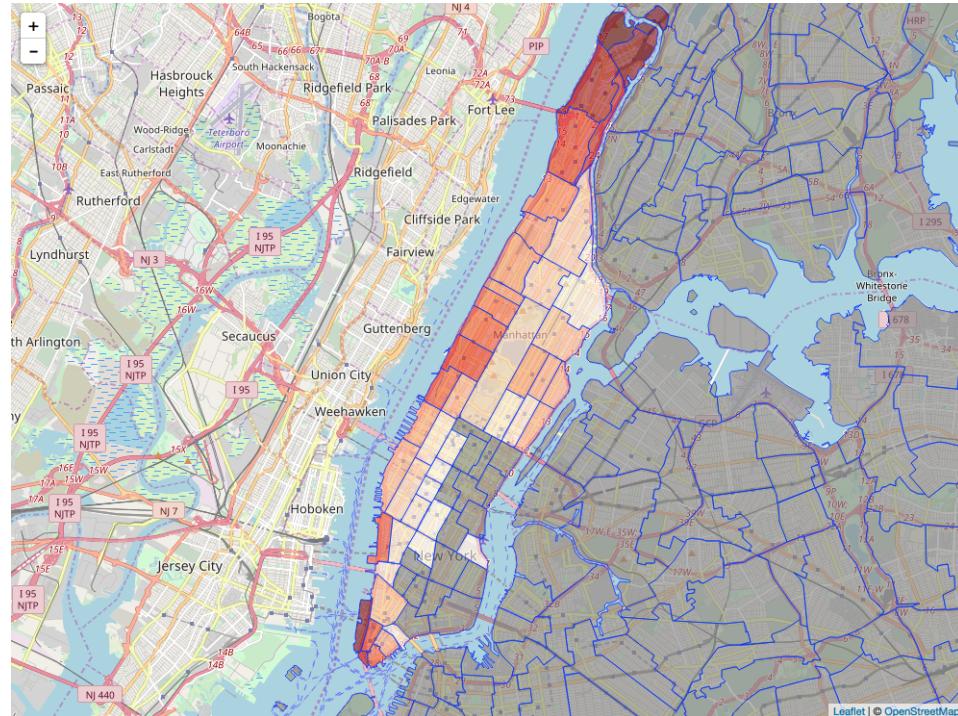


Figure 5.2: Pick-up Zones that cost more than the 52 US Dollar flat rate

Therefore, passengers from places in Manhattan besides Midtown, East Village, and some parts of Lower Manhattan benefit from the \$52 flat rate. However, people living in Midtown, East Village, and some parts of Lower Manhattan might be relatively

more indifferent to the price of taxi. Instead, they probably put more emphasis on convenience and time.

[1] 2.825257

On average people travel from Manhattan pay `meanfare` less with the \$52 flat rate policy. Therefore, passengers overall benefit from the \$52 flat rate policy.

5.3 Are taxi drivers happy when a passenger wants to go to JFK Airport from Manhattan?

Everytime I travel to New York City, I always take Yellow cabs to go around the city. It seemed to me that the cab drivers were always happy when they heard me telling them that I needed to go to the JFK Airport from Manhattan. Are taxi drivers happy when their passengers want to go to JFK Airport from Manhattan? In this section, we study the hourly wage of taxi drivers for different trips they completed, and we investigate whether taxi driver hourly wage from Manhattan to JFK Airport is higher than other trips.

[1] 63.29116

The average hourly wage of taxi drivers calculated by using all trips excluding the ones going from Manhattan to JFK Airport is `mean_overall`.

[1] 69.05252

The average hourly wage of taxi drivers calculated by using trips going from Manhattan to JFK Airport is `mean_jfk`. `mean_jfk` dollar per hour is higher than `mean_overall` dollar per hour, which means that on average taxi drivers driving from Manhattan to JFK Airport have an hourly wage that is about \$6 higher than the hourly wage of

Table 5.2: 5 most popular destinations in Manhattan

Borough	Zone	num_trips	avg_fare	avg_duration
Manhattan	Times Sq/Theatre District	59419	69.80599	55.92389
Manhattan	Midtown East	40513	69.40195	47.42096
Manhattan	Murray Hill	40071	69.91174	43.66998
Manhattan	Midtown South	38890	70.11065	48.34342
Manhattan	Midtown Center	36405	69.64272	52.62410

taxis drivers doing other trips.

5.3.1 How much on average would taxi driver make on their way back from JFK Airport?

Since a taxi driver waiting in line to pickup passengers at JFK Airport could be directed back to anywhere in the city. We calculate the average taxi fare amount that a taxi driver would get paid for a trip from JFK Airport to any part of the city.

What are the most popular drop-off locations for passengers departing from JFK Airport?

Table @ref(tab:from_jkf_zone) shows that Times Square is the most popular destination for passengers coming from the JFK Airport in 2017!

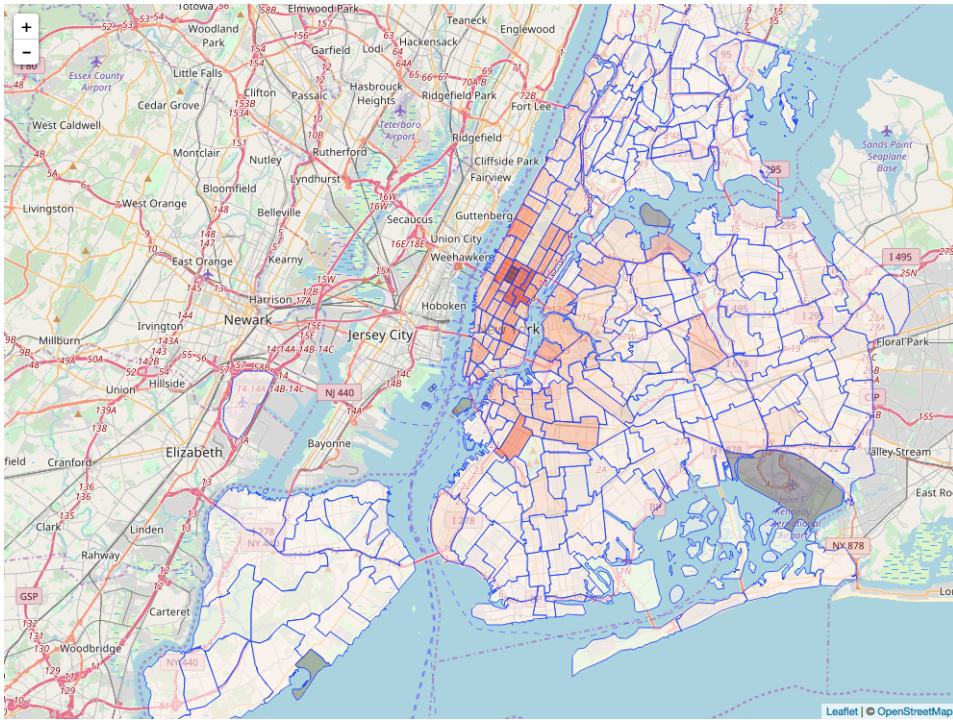


Figure 5.3: Zones that cost more than the 52 US Dollar flat rate

According to the Figure @??fig:from-jkf-num-trips), Manhattan is the most popular destination for passengers departing from JFK Airport.

```
# A tibble: 2 x 2
```

```
Manhattan all_trips
```

	<dbl>	<int>
1	0	521476
2	1	970366

According to the summary, the total amount of trips from JFK Airport to Manhattan is about `total_trip%` of the total number of trips travelling from JFK Airport to all other Borough. Therefore, it is very likely for taxi drivers to get passengers who want to go to Manhattan with a flat rate of \$52. In this case, a round trip to and from JFK Airport is worthwhile. Therefore, taxi drivers should be pretty happy when their passengers are going to JFK Airport from Manhattan.

Table 5.3: 10 most popular taxi drop-off zones from JFK Airport with the corresponding average fare amount

Borough	Zone	num_trips	avg_fare	avg_duration
Manhattan	Times Sq/Theatre District	59419	69.80599	55.92389
Manhattan	Midtown East	40513	69.40195	47.42096
Manhattan	Murray Hill	40071	69.91174	43.66998
Manhattan	Midtown South	38890	70.11065	48.34342
Manhattan	Midtown Center	36405	69.64272	52.62410
Manhattan	Clinton East	35297	69.20170	55.78806
Manhattan	Midtown North	34538	68.30039	55.80455
Brooklyn	Park Slope	27219	60.96428	45.75234
Manhattan	East Village	26595	66.98102	45.45684
Manhattan	Upper West Side South	24723	69.94912	50.87777

What's the average fare to each drop-off zone from JFK Airport?

We can use a map to visualize the distribution of average fare amount needed to travel from JFK Airport to any taxi zone in New York City.

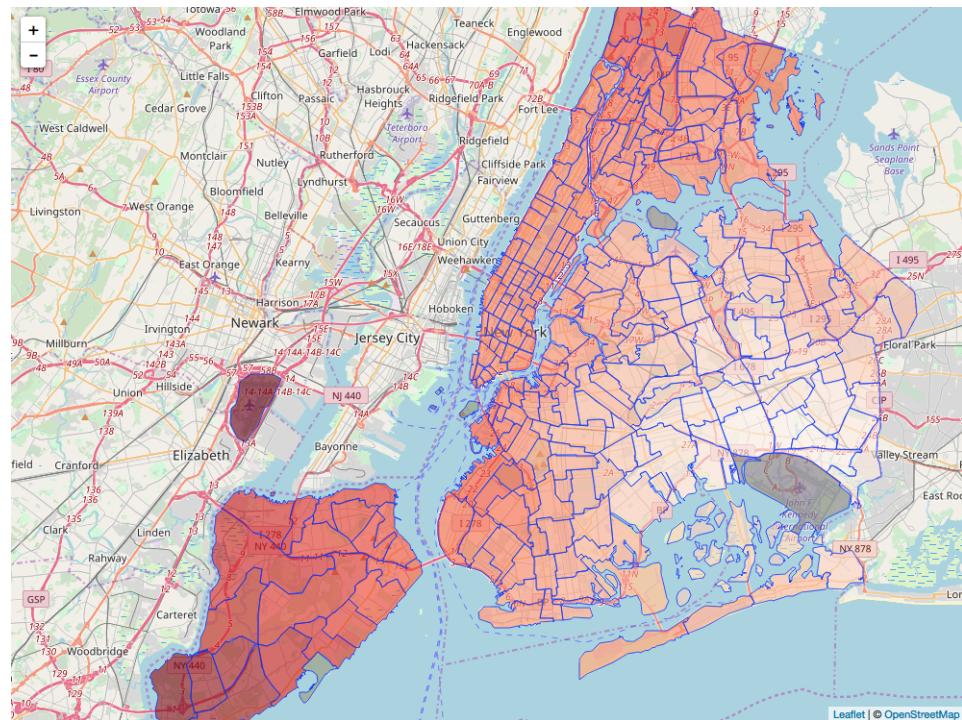


Figure 5.4: Zones that cost more than the 52 US Dollar flat rate

As we expected, the red shades are smoothly distributed, since taxi zones that are further away should cost more to get there.

How much on average would taxi driver make on their way back from JFK Airport?

[1] 62.69673

On average, taxi drivers would get paid for `mean_fare` for a trip from the JFK Airport to any taxi zone in New York City.

[1] 63.14558

The average hourly wage of taxi drivers calculated by using all trips excluding the ones departing from JFK Airport is `mean_no_jfk`.

[1] 94.65196

The average hourly wage of taxi drivers calculated by using trips departing from JFK Airport is `mean_from_jfk_wage` dollar per hour. `mean_from_jfk_wage` dollar per hour is higher than `mean_no_jfk` dollar per hour, which means that on average taxi drivers going from JFK Airport to any taxi zones in New York City have an hourly wage that is more than \$30 higher than the hourly wage of taxi drivers doing other trips.

In conclusion, taxi drivers' hourly wages are higher when they drive from Manhattan to JFK Airport. On their way back, they make on average `mean_from_jfk_wage` dollar per hour, which is much higher than the average hourly wage of yellow cab drivers. Taxicab drivers feel happy when they pick up passengers who want to go to JFK Airport in Manhattan. Even though \$52 is lower than the average amount of fare that taxi drivers would have made without the flat rate, it still induces an higher than average hourly wage, so it does not disincentive drivers. Therefore, the \$52 flat

rate is appropriate.

Chapter 6

Conclusion

In this Honors thesis, we present a more efficient and easy-to-use way for users to retrieve trip records information of both New York City taxi and other ride-sharing services, such as Uber and Lyft, in New York City.

By analyzing trip records of New York City's yellow taxi, we found answers to questions that are commonly asked by taxi drivers, passengers, and TLC officials.

We found which taxi zones have passengers who offer the highest percent of tips, and we proved that taxi drivers do get compensated more during rush hours. We are able to help passengers to know the average time it takes to go to one of the three airports in New York City so that passengers can plan their trips accordingly. We also found that the \$52 flat rate between Manhattan and JFK Airport is beneficial for the passengers, because it is cheaper than the average amount of fare that passenger would need to pay without the flat rate. We have also shown that the flat rate does not disencourage drivers. Therefore, the \$52 flat rate is appropriate.

6.1 Future Research

For future study, we would love to investigate the sharp decline in the consumption of NYC yellow cab after e-hail services were introduced into the NYC ride-hail market. We also want to study what the impact of introducing new GPS and entertainment system is on the number of rides. The global product and marketing at Verifone, Jason Gross, said that, “We like to say that we provide what Uber says it provides.” With the raised expectation among rides caused by Uber and Lyft, yellow taxi industry need to respond quickly (Hawkins, 2016). How does the market react to the newly installed entertainment system? Has the market share of yellow cab rebounded since 2016? By looking into the patterns in market shares, it might be possible for me to predict the future market share distribution and find out what features of ride-hail transportation are the ones that affect market share distribution the most.

Appendix A

Utility Function

This utility function was written to shortened the source code in ETL `etl_extract.etl_nyctaxi()` function.

```
download_nyc_data <- function(obj, url, years, n, names, ...) {  
  url <- paste0(url, "?years=", years, "&$limit=", n)  
  lcl <- file.path(attr(obj, "raw"), names)  
  downloader::download(url, destfile = lcl, ...)  
  lcl  
}
```


Appendix B

Data Dictionary – Yellow Taxi

Data Dictionary – Yellow Taxi Trip Records September 28, 2015 Page 1 of 1

This data dictionary describes yellow taxi trip data. For dictionaries describing green taxi and FHV data, please visit http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml.

Field Name	Description
VendorID	A code indicating the TPEP provider that provided the record. 1= Creative Mobile Technologies, LLC; 2= VeriFone Inc.
tpep_pickup_datetime	The date and time when the meter was engaged.
tpep_dropoff_datetime	The date and time when the meter was disengaged.
Passenger_count	The number of passengers in the vehicle. This is a driver-entered value.
Trip_distance	The elapsed trip distance in miles reported by the taximeter.
Pickup_longitude	Longitude where the meter was engaged.
Pickup_latitude	Latitude where the meter was engaged.
RateCodeID	The final rate code in effect at the end of the trip. 1= Standard rate 2=FK 3=Newark 4=Nassau or Westchester 5=Negotiated fare 6=Group ride
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka “store and forward,” because the vehicle did not have a connection to the server. Y= store and forward trip N= not a store and forward trip
Dropoff_longitude	Longitude where the meter was disengaged.
Dropoff_latitude	Latitude where the meter was disengaged.
Payment_type	A numeric code signifying how the passenger paid for the trip. 1= Credit card 2= Cash 3= No charge 4= Dispute 5= Unknown 6= Voided trip
Fare_amount	The time-and-distance fare calculated by the meter.
Extra	Miscellaneous extras and surcharges. Currently, this only includes the \$0.50 and \$1 rush hour and overnight charges.
MTA_tax	\$0.50 MTA tax that is automatically triggered based on the metered rate in use.
Improvement_surcharge	\$0.30 improvement surcharge assessed trips at the flag drop. The improvement surcharge began being levied in 2015.
Tip_amount	Tip amount – This field is automatically populated for credit card tips. Cash tips are not included.
Tolls_amount	Total amount of all tolls paid in trip.
Total_amount	The total amount charged to passengers. Does not include cash tips.

Figure B.1: Data Dictionary – Yellow Taxi Trips Records

Appendix C

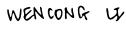
Freedom of Information Law Request

NYC
Taxi & Limousine
Commission

Meera Joshi
Commissioner

Christopher Wilson
Deputy Commissioner/General Counsel
Office of Legal Affairs
33 Beaver Street, 22nd Floor
New York, NY 10004

+1 212 676 1102 fax

FOIL REQUEST FORM	
Taxi and Limousine Commission Office of Legal Affairs 33 Beaver Street, 22 nd Floor New York, New York 10004 Attn: Records Access Officer	FROM: (Please print your name, address, telephone # and email address)
<input mailto:foil@tlc.nyc.gov"="" type="text" value="Our email address: FOIL@tlc.nyc.gov"/> <input type="text" value="Your email address: _____"/>	
<p>I request the following record(s) under the Freedom of Information Law: Please reasonably describe the record(s) you are requesting to allow us to identify any responsive document(s).</p> <hr/> <hr/> <hr/>	
<p>Please state the reason for your request: (optional)</p> <hr/> <hr/> <hr/>	
 Signature	Date _____

This is a Freedom of Information Law ("FOIL") request. As such, your request will be considered under the Public Officer's Law, Article 6, Section 84 et seq. Subject to the provisions of this article, the Taxi and Limousine Commission, within five business days of the receipt of a written request for a record reasonably described, shall furnish a written acknowledgement of the receipt of such request.

Figure C.1: FOIL Request

Appendix D

NOAA Climate Data Request

Smith College Mail - Climate Data Online request 1313559 submitted. 4/14/18, 11:21 PM



Wencong Li <wli37@smith.edu>

Climate Data Online request 1313559 submitted.

1 message

NCDC CDO <noreply@noaa.gov>
To: wli37@smith.edu

Sat, Apr 14, 2018 at 11:00 PM



Order submitted

Getting started

Thank you for using the NCEI data ordering services. Your order has been successfully submitted and will begin processing shortly. This is the first step of getting your data order processed. Once the data is added to the processing queue it will be processed as soon as possible and then an email will be sent when processing is complete.

Order details

Order #1313559 (LCD CSV)

Order # 1313559

Date Submitted 2018-04-14 11:00

Order Summary [View Summary](#)

Documentation [View Documentation](#)

What's next?

Most orders only take a very short while to process, but larger orders do take more time and are affected by the number of orders in the data request queue.

While you are waiting for your order to complete, you may find it helpful to find out more about the dataset from which you ordered the data or certification.

Other questions you may have may also be answered in our Help/Frequently Asked Questions section. Use the links below to find this information.

If you still have questions, use the Contact Us link below to contact one of our Customer Service representatives for further assistance.

Want to manage your order online?

https://mail.google.com/mail/u/0/?ui=2&ik=b9ce5d19c1&jsver=z8_jB6...&view=pt&search=inbox&th=162c73f4ed5ab6c0&siml=162c73f4ed5ab6c0 Page 1 of 2

Figure D.1: NOAA Climate Data Request

Smith College Mail - Climate Data Online request 1313559 complete 4/14/18, 11:23 PM

 Wencong Li <wli37@smith.edu>

Climate Data Online request 1313559 complete
1 message

NCDC CDO <noreply@noaa.gov>
To: wli37@smith.edu Sat, Apr 14, 2018 at 11:03 PM



Order Complete

Your order has been processed and is ready for download. Use the links below to download the individual orders.

If any part of your order has certifiable data, a link will be supplied that will help you with the certification process.

Documentation for each dataset is linked from within the order for your convenience.

Order Details

Order #1313559 (LCD CSV)

File	Download (Available until 2018-Apr-21)
Order ID	1313559
Date Submitted	2018-04-14 11:00
Order Summary	View Summary
Documentation	View Documentation

Want to manage your previous orders online?

If you want to check or resubmit an older order, please visit our [order status page](#).

 Order Certification  Help  Contact Us

https://mail.google.com/mail/u/0/?ui=2&k=b9ce5d19c1&jsver=z8_jB6_n.&view=pt&search=inbox&th=162c7417c23ed7a1&siml=162c7417c23ed7a1 Page 1 of 2

Figure D.2: NOAA Climate Data Order Compeleted

References

- Baumer, B. S. (2017). A grammar for reproducible and painless extract-transform-load operations on medium data. *arXiv*, 8(23), 1–24. Retrieved from <https://arxiv.org/abs/1708.07073>
- Baumer, B., Cetinkaya-Rundel, M., Bray, A., Loi, L., & Horton, N. J. (2014). R markdown: Integrating a reproducible analysis tool into introductory statistics. *TISE*.
- Danielle Furfaro, S. C., & Fears, D. (2016, December). NYC is already tired of Christmas and Donald Trump. New York Post. Retrieved from <https://nypost.com/2016/12/01/nyc-is-already-tired-of-christmas-and-donald-trump/>
- Dowle, M., & Srinivasan, A. (2017). *Data.table: Extension of ‘data.frame’*. Retrieved from <https://CRAN.R-project.org/package=data.table>
- Environmental Information staff, N. C. for. (n.d.). Climate Data Online. National Centers for Environmental Information. Retrieved from <https://www.ncdc.noaa.gov/cdo-web/>
- Griswold, A. (2015, November). Uber Won New York. Slate Business. Retrieved from http://www.slate.com/articles/business/moneybox/2015/11/uber_

- won_new_york_city_it_only_took_five_years.html
- Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, 40(3), 1–25. Retrieved from <http://www.jstatsoft.org/v40/i03/>
- Guerrini, F. (2015, April). Which Is Cheaper To Use In NYC: Uber Or A Taxi? Big Data Will Solve The Dilemma. Forbes Tech. Retrieved from <https://www.forbes.com/sites/federicoguerrini/2015/04/09/living-in-new-york-this-app-will-tell-you-which-is-cheaper-uber-or-a-taxi/#26bc29904023>
- Harshbarger, R. (2015, June). City puts biased drivers who refuse rides on notice with new video. New York Post. Retrieved from <https://nypost.com/2015/06/09/city-puts-biased-taxi-drivers-on-notice/>
- Hawkins, A. J. (2016, September). Yellow taxis have a new weapon in their war against uber: Gadgets. The Verge. Retrieved from <https://www.theverge.com/2016/9/26/13035642/nyc-taxi-cab-android-touchscreen-tablet-verifone>
- Hu, W. (2017, January). Yellow Cab, Long a Fixture of City Life, Is for Many a Thing of the Past. The New York Times. Retrieved from <https://www.nytimes.com/2017/01/15/nyregion/yellow-cab-long-a-fixture-of-city-life-is-for-many-a-thing-of-the-past.html>
- Jaffe, E. (2014, October). Why New Yorkers Can't Find a Taxi When It Rains. CITYLAB. Retrieved from <https://www.citylab.com/environment/2014/10/why-new-yorkers-cant-find-a-taxi-when-it-rains/381652/>
- Li, W. (2018, February). FOIL request. NYC TLC.
- Li, W. P., Baumer, B., & Trang Le. (2017). *Nyctaxi: Accessing new york city taxi*

- data.* Retrieved from <http://github.com/beanumber/nyctaxi>
- Reaney, P. (2009, June). New York Drivers Named Most Aggressive, Angry in U.S. Reuters. Retrieved from <https://www.reuters.com/article/us-driving-roadrage-life/new-york-drivers-named-most-aggressive-angry-in-u-s-idUSTRE55F1J720090616>
- Schneider, T. W. (2015, November). Analyzing 1.1 Billion NYC Taxi and Uber Trips, with a Vengeance. Todd W. Schneider. Retrieved from <http://toddwschneider.com/posts/analyzing-1-1-billion-nyc-taxi-and-uber-trips-with-a-vengeance/>
- staff, C. (n.d.). The Comprehensive R Archive Network. Retrieved from <https://cran.r-project.org/index.html>
- staff, H. (2018, January). Uber's 4 Basic Level of Service. HyreCar. Retrieved from <https://hyrecar.com/blog/difference-between-uber-cars/>
- staff, N. O. (2015a). LYFT Data. NYC OpenData. Retrieved from <https://data.cityofnewyork.us/Transportation/LYFT-Data/juxc-sutg/data>
- staff, N. O. (2015b). Uber Trips NYC 2016. NYC OpenData. Retrieved from <https://data.cityofnewyork.us/Transportation/Uber-Trips-NYC-2016/gt3n-7ri6/data>
- staff, N. T. (2009a). TLC Aggregated Reports. NYC Taxi & Limousine Commission. Retrieved from http://www.nyc.gov/html/tlc/html/technology/aggregated_data.shtml
- staff, N. T. (2009b). TLC Trip Record Data. NYC Taxi & Limousine Commission. Retrieved from http://www.nyc.gov/html/tlc/html/about/trip_record_

- data.shtml
- staff, N. T. (2009c). TLC Trip Record Data. NYC Taxi & Limousine Commission. Retrieved from http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml
- staff, N. T. (2009d). Your guide to Boro Taxis. NYC Taxi & Limousine Commission. Retrieved from http://www.nyc.gov/html/tlc/html/passenger/shl_passenger.shtml
- staff, N. T. (n.d.). NYC tlc Taxicab Rate of Fare. NYC TLC. Retrieved from http://www.nyc.gov/html/tlc/html/passenger/taxicab_rate.shtml
- staff, O. (2015). OpenStreetCab. University of Cambridge UK Computer Laboratory, University of Namur Belgium, Complexity; Networks group. Retrieved from <https://www.openstreetcab.com>
- staff, W. (2018a, April). Taxicabs of New York City. *Wikipedia*. Wikimedia Foundation. Retrieved from https://en.wikipedia.org/wiki/Taxicabs_of_New_York_City
- staff, W. (2018b, March). Extract, transform, load. *Wikipedia*. Wikimedia Foundation. Retrieved from https://en.wikipedia.org/wiki/Extract,_transform,_load
- Sugar, R. (2017, January). Uber and Lyft cars now outnumber yellow cabs in NYC 4 to 1. Curbed New York. Retrieved from <https://ny.curbed.com/2017/1/17/14296892/yellow-taxi-nyc-uber-lyft-via-numbers>
- Whitford, E. (2017, October). Daily Uber Trips Have Officially Outstripped Taxi Trips. Gothamist. Retrieved from http://gothamist.com/2017/10/13/uber_

taxis_nyc.php

Wickham, H., Hester, J., & Francois, R. (2017). *Readr: Read rectangular text data.*

Retrieved from <https://CRAN.R-project.org/package=readr>

Zhang, W. (2017, May). Improving access to open-source data about the nyc bike sharing system (Citi Bike). Smith College.