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Professor Li

CS427

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Project 2

First step is to import Python Modules

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import numpy as np

from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import robust_scale
from sklearn import preprocessing
from sklearn.preprocessing import OneHotEncoder
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn import datasets, linear_model
import scipy.stats as stats
import statistics
from fastai.imports import * # requires fastai library installation. pleas
# from fastai.structured import * -- not required
#from pandas_summary import DataFrameSummary
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from IPython.display import display

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

!pip install pandas-summary
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Requirement already satisfied: pandas-summary in /usr/local/lib/python3.9/dist-p
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: datatile in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: traceml<1.1 in /usr/local/lib/python3.9/dist-pack
```

```
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-package
```

```
import platform
print("Python version:", platform.python_version())
```

```
Python version: 3.9.16
```

```
! pip install fastai -- to install the fastai library
! xcode-select --install -- to overcome clang dependencies on mac os.
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Requirement already satisfied: fastai in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: to in /usr/local/lib/python3.9/dist-packages (0.3
Requirement already satisfied: install in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: the in /usr/local/lib/python3.9/dist-packages (0.
Requirement already satisfied: library in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: fastcore<1.6,>=1.5.29 in /usr/local/lib/python3.9
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: fastprogress>=0.2.4 in /usr/local/lib/python3.9/d
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: spacy<4 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: pip in /usr/local/lib/python3.9/dist-packages (fr
Requirement already satisfied: pyyaml in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: torch<2.1,>=1.7 in /usr/local/lib/python3.9/dist-
Requirement already satisfied: fastdownload<2,>=0.0.5 in /usr/local/lib/python3.
Requirement already satisfied: torchvision>=0.8.2 in /usr/local/lib/python3.9/di
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: pillow>6.0.0 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: pydantic!=1.8,!=1.8.1,<1.11.0,>=1.7.4 in /usr/loc
Requirement already satisfied: setuptools in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in /usr/local/lib/pyt
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/pythc
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.9/d
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in /usr/local/lib/python3.9/
Requirement already satisfied: pathy>=0.10.0 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in /usr/local/lib/pyt
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in /usr/local/lib/python3
Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in /usr/local/lib/python3
Requirement already satisfied: typer<0.8.0,>=0.3.0 in /usr/local/lib/python3.9/d
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.9/d
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in /usr/local/lib/python3.9/d
Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in /usr/local/lib/python
Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.9
Requirement already satisfied: thinc<8.2.0,>=8.1.8 in /usr/local/lib/python3.9/d
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/pythc
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/di
```

```
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.9/dis
Requirement already satisfied: networkx in /usr/local/lib/python3.9/dist-package
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Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: sympy in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: cmake in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: lit in /usr/local/lib/python3.9/dist-packages (fr
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dis
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dis
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.9/dist
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.9/dist
Requirement already satisfied: importlib-resources>=3.2.0 in /usr/local/lib/pyth
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-pac
```

```
import pyarrow as pa
import pyarrow.parquet as pq
```

```
import datetime
```

Question 1

a) Programmatically Download and load into your favorite analytical tool the trip data for September 2017

```
file_path = '/content/sample_data/green_tripdata_2017-09.parquet' # local file path
```

```
df_raw = pq.read_table(file_path).to_pandas() # read data into a pandas dataframe
```

```
def display_data(df):
    with pd.option_context("display.max_rows", 20, "display.max_columns", 22):
        display(df)
# This function will help us display our data. Max_rows and Max_columns can be altere
```

```
display_data(df_raw.tail()) # display last 5 rows of our data.
```

	VendorID	lpep_pickup_datetime	lpep_dropoff_datetime	store_and_fwd_flag
882459	2	2017-09-30 23:42:33	2017-09-30 23:45:24	N
882460	2	2017-09-30 23:48:34	2017-09-30 23:55:25	N

```
df_raw.columns # data columns
```

```
Index(['VendorID', 'lpep_pickup_datetime', 'lpep_dropoff_datetime',
       'store_and_fwd_flag', 'RatecodeID', 'PULocationID', 'DOLocationID',
       'passenger_count', 'trip_distance', 'fare_amount', 'extra', 'mta_tax',
       'tip_amount', 'tolls_amount', 'ehail_fee', 'improvement_surcharge',
       'total_amount', 'payment_type', 'trip_type', 'congestion_surcharge'],
      dtype='object')
```

```
df_raw.info() # data info. ex: datatypes, size etc..
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 882464 entries, 0 to 882463
Data columns (total 20 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   VendorID               882464 non-null  int64
 1   lpep_pickup_datetime   882464 non-null  datetime64[ns]
 2   lpep_dropoff_datetime  882464 non-null  datetime64[ns]
 3   store_and_fwd_flag     882464 non-null  object
 4   RatecodeID             882464 non-null  int64
 5   PULocationID           882464 non-null  int64
 6   DOLocationID           882464 non-null  int64
 7   passenger_count        882464 non-null  int64
 8   trip_distance          882464 non-null  float64
 9   fare_amount            882464 non-null  float64
 10  extra                  882464 non-null  float64
 11  mta_tax                882464 non-null  float64
 12  tip_amount             882464 non-null  float64
 13  tolls_amount           882464 non-null  float64
 14  ehail_fee              0 non-null       object
 15  improvement_surcharge  882464 non-null  float64
 16  total_amount           882464 non-null  float64
 17  payment_type           882464 non-null  int64
 18  trip_type              882464 non-null  int64
 19  congestion_surcharge   0 non-null       object
dtypes: datetime64[ns](2), float64(8), int64(7), object(3)
memory usage: 134.7+ MB
```

b) Report how many rows and columns of data you have loaded

```
row_count = df_raw.shape[0] # 0 for row
column_count = df_raw.shape[1] # 1 for column
```

```
print("Number of rows:", row_count)
print("Number of columns:", column_count)
```

```
Number of rows: 882464
Number of columns: 20
```

There are 882464 rows and 20 columns.

Question 2

a) Plot a histogram of the number of the trip distance ("Trip Distance").

```
display_data(df_raw.trip_distance.head()) # use the display_data helper function to v
```

```
0    0.00
1    1.74
2    0.93
3    5.85
4    1.15
Name: trip_distance, dtype: float64
```

```
minimum_trip_distance = df_raw['trip_distance'].min() # minimum trip distance
maximum_trip_distance = df_raw['trip_distance'].max() # maximum trip distance


print("Minimum trip distance:", minimum_trip_distance, "miles")
print("Maximum trip distance:", maximum_trip_distance, "miles")
```

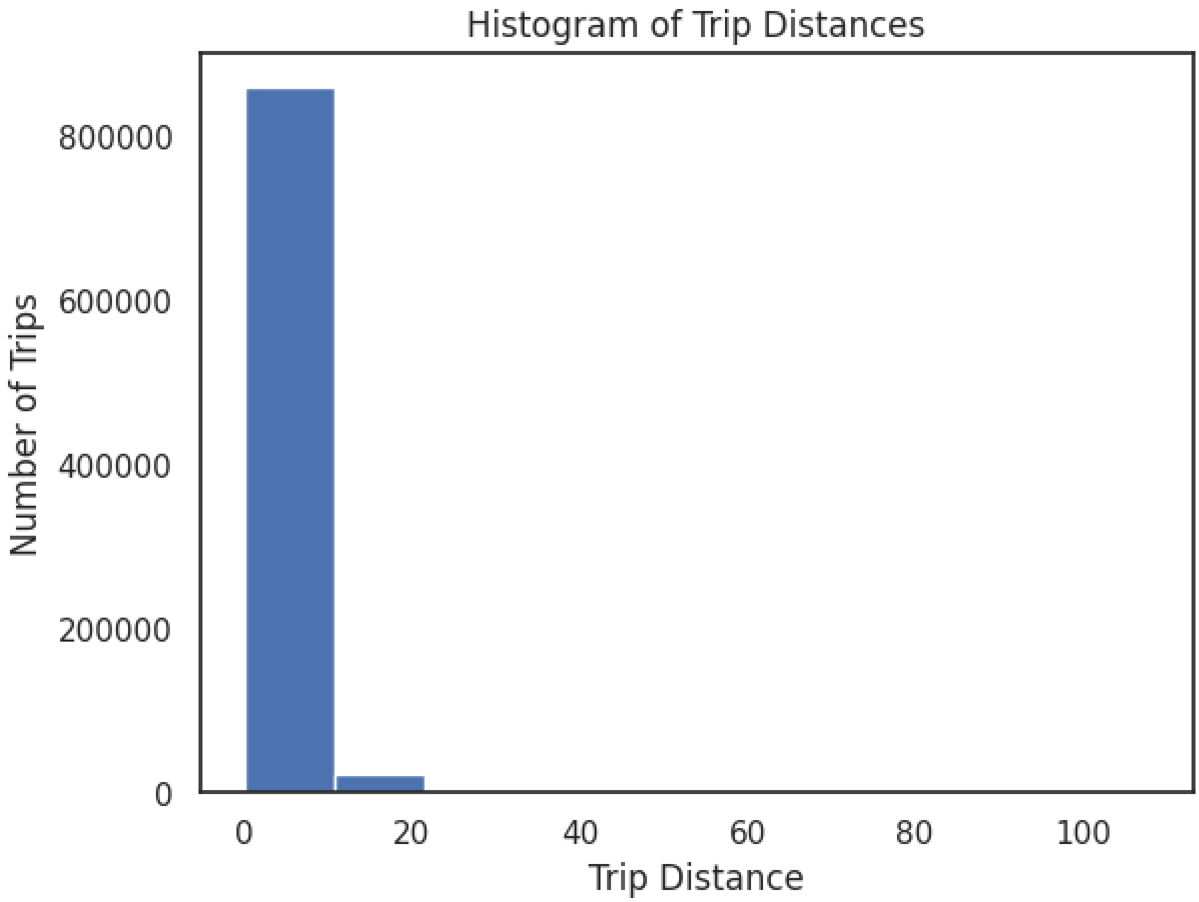
```
Minimum trip distance: 0.0 miles
Maximum trip distance: 107.7 miles
```

```
trip_distance_value_count = df_raw['trip_distance'].value_counts() # trip distance va
trip_distance_value_count.head()
```

```
1.0    10108
0.9    10029
0.8     9842
0.0     9439
1.1     9365
Name: trip_distance, dtype: int64
```

```
# This is Histogram A
# bin_edges = [0,2.5,5,7.5,10,12.5,15,17.5,20,22.5,25,27.5,30] -- not required to bin
```

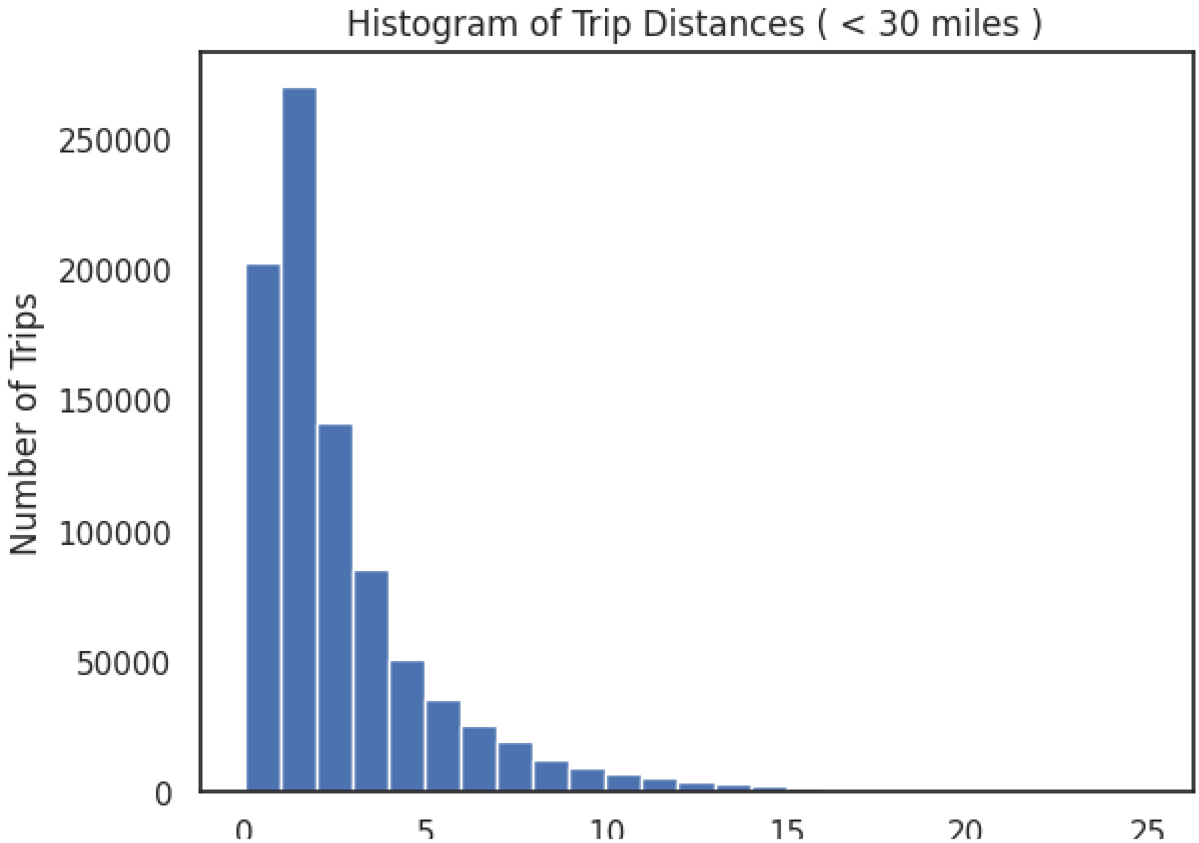
```
_ = plt.hist(df_raw['trip_distance'])
_ = plt.title('Histogram of Trip Distances')
_ = plt.xlabel('Trip Distance')
_ = plt.ylabel('Number of Trips')
plt.show()
```



Filtered Histogram below:

Filtered on rides with a trip distance ("trip_Distance") less than 25 miles due to higher frequency, Histogram B presents data that has been divided into 25 evenly spaced intervals or bins. In this process, original data values falling within each bin are replaced by a representative value, usually the central value of that interval.

```
# This is te filtered Histogram
_ = plt.hist(df_raw['trip_distance'][df_raw['trip_distance']<25],bins = 25)
_ = plt.title('Histogram of Trip Distances ( < 30 miles )')
_ = plt.xlabel('Trip Distance')
_ = plt.ylabel('Number of Trips')
plt.show()
```



b) Report any structure you find and any hypotheses you have about that structure

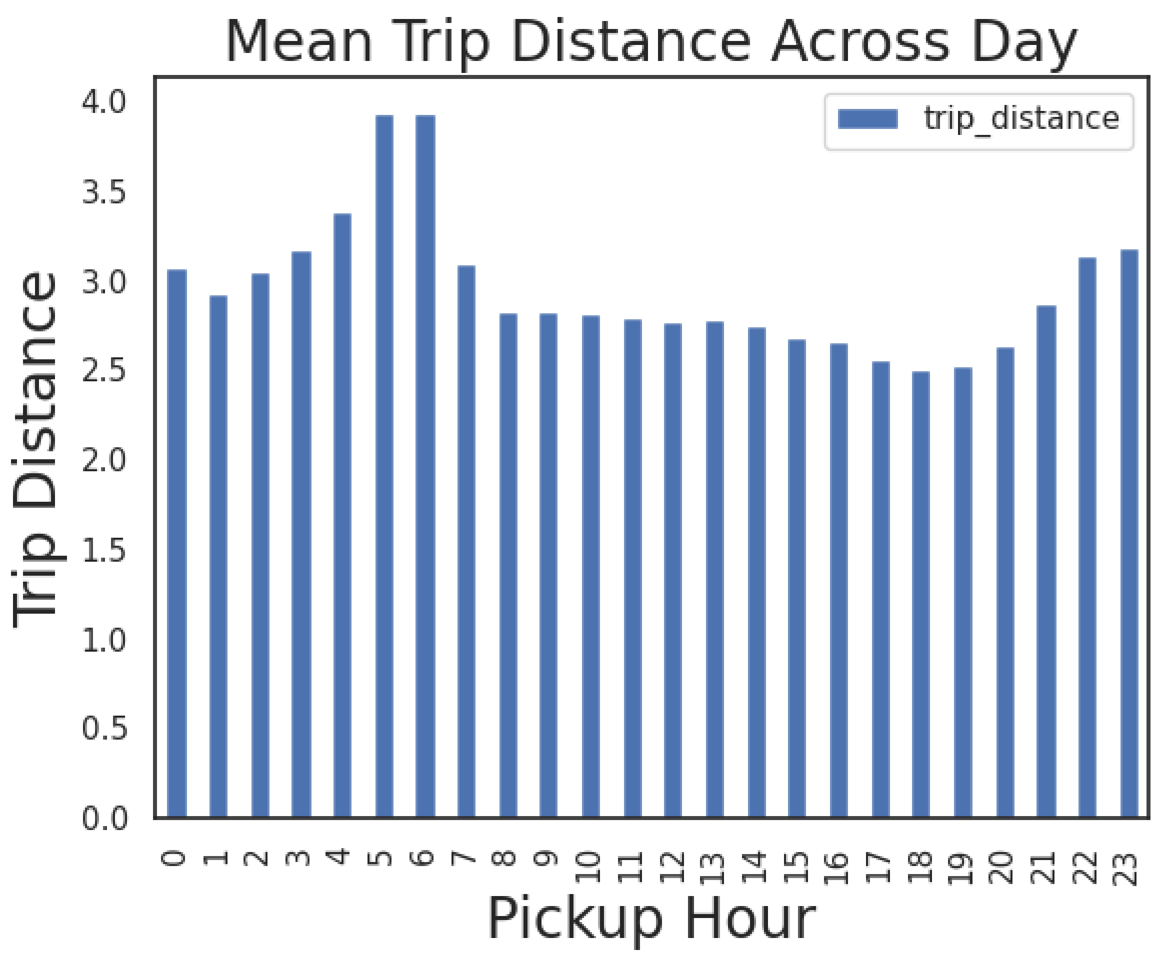
Before filtering, the Histogram looks more like a tall bar and show less data, but we could conclude that the graph suggests there are fewer trips with longer trip distances, while the majority of trips are clustered towards shorter distances.

After filtering, the Histogram looks more right-skewed, also known as a positively skewed histogram, typically shows a long tail extending towards higher values on the right-hand side of the graph. As for the unfiltered Histogram, this suggests that there are fewer trips with longer trip distances, while the majority of trips are clustered towards shorter distances. Most of the trips were within the range of 0 to 5 miles. A few trips were within the range of 5 to 10 miles, and a few trips in the dataset had trip distances greater than 10 miles.

Question 3

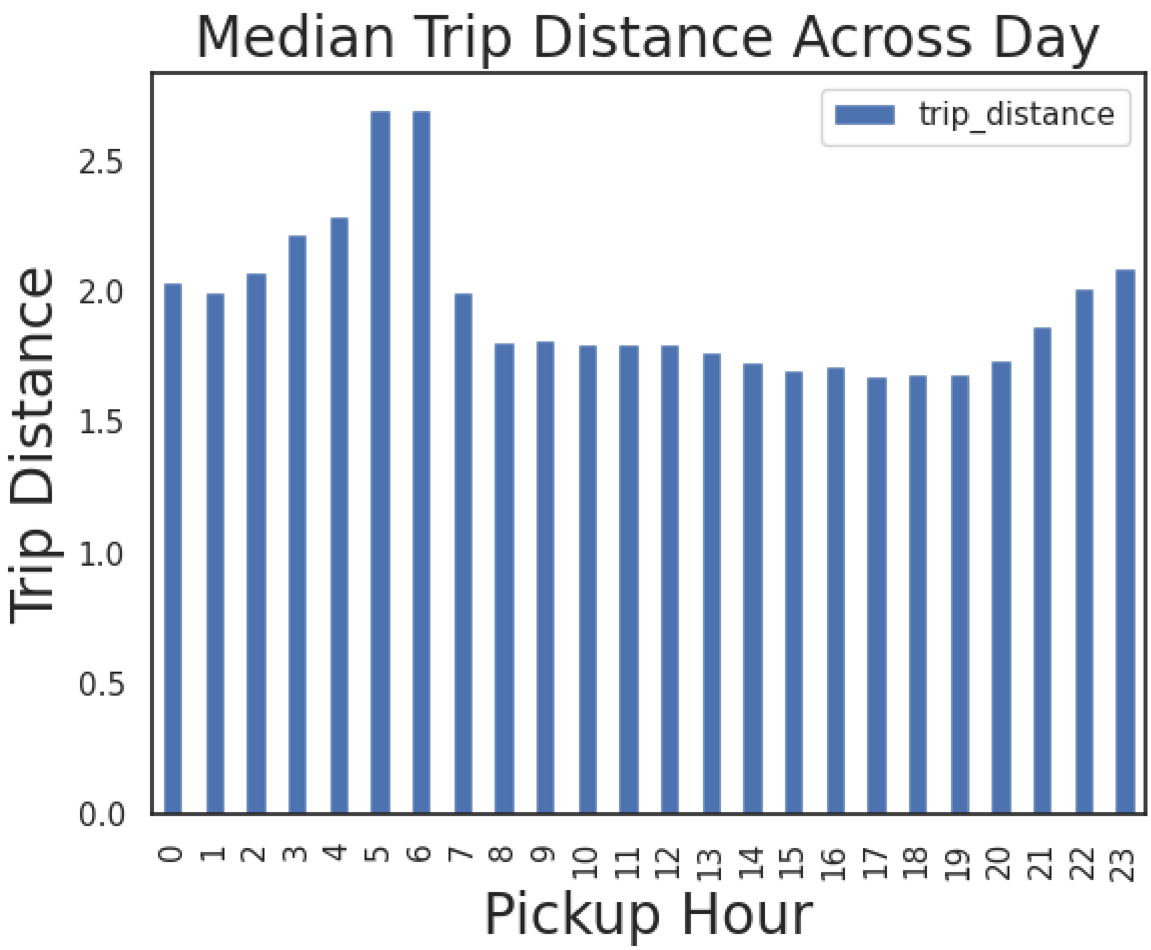
a) Report mean and median trip distance grouped by hour of day.

```
# we're stripping the hour field from the pickup_datetime field to create a new field
df_raw['pickup'] = pd.to_datetime(df_raw['lpep_pickup_datetime'], format='%Y-%m-%d %H
df_raw['pickup_hour'] = df_raw['pickup'].apply(lambda x: x.hour) # this is a new fiel


# we're stripping the hour field from the dropoff_datetime field to create a new fiel
df_raw['dropoff'] = pd.to_datetime(df_raw['lpep_dropoff_datetime'], format='%Y-%m-%d
df_raw['dropoff_hour'] = df_raw['dropoff'].apply(lambda x: x.hour)# this is a new fie


_ = df_raw[['trip_distance','pickup_hour']].groupby('pickup_hour').mean().plot.bar()
_ = plt.title('Mean Trip Distance Across Day', fontsize = 20)
_ = plt.xlabel('Pickup Hour', fontsize = 20)
_ = plt.ylabel('Trip Distance', fontsize = 20)
plt.show()
```



Based on this graph, we can conclude that the average trip distance covered by the "Green" cabs is relatively higher during the early hours as for 4AM to 7 AM. The more, the average trip distance covered by the "Green" cabs is relatively lower around 4PM to 8 PM.

```
_= df_raw[['trip_distance','pickup_hour']].groupby('pickup_hour').median().plot.bar()
_ = plt.title('Median Trip Distance Across Day', fontsize = 20)
_ = plt.xlabel('Pickup Hour', fontsize = 20)
_ = plt.ylabel('Trip Distance', fontsize = 20)
plt.show()
```



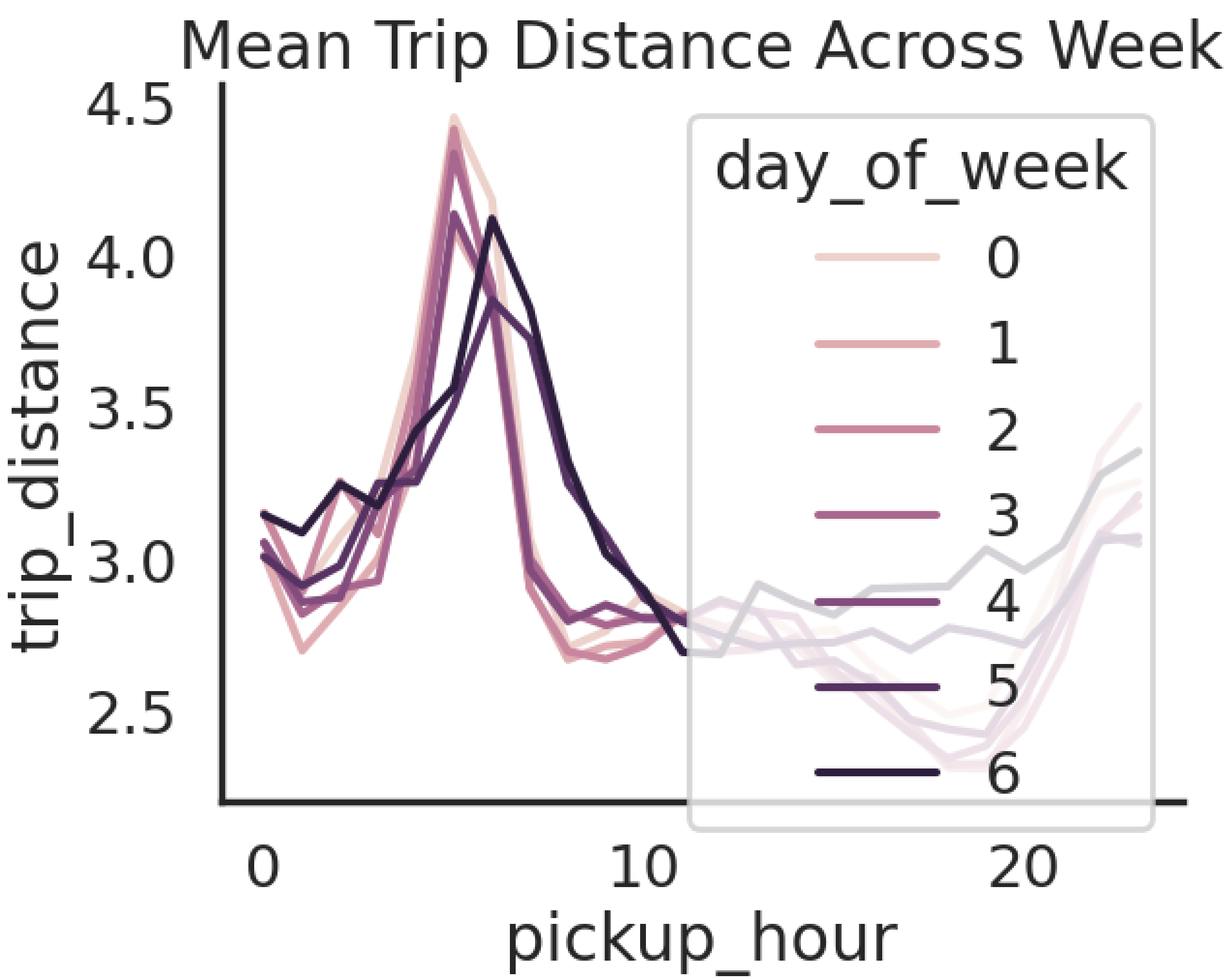
Based on this graph, we can conclude that the median trip distance covered by the "Green" cabs is relatively higher between 3AM to 6 AM. In addition, the median trip distance covered by the "Green" cabs is relatively lower around 3PM to 7 PM.

```
df_raw['lpep_pickup_datetime'] = pd.to_datetime(df_raw.lpep_pickup_datetime) # conver
df_raw.loc[:, 'day_of_week'] = df_raw['lpep_pickup_datetime'].dt.dayofweek # extract
```

Going deeper using Line-plots

```
# code block for mean trip distance

# Groupby day of week and pickup hour, calculate mean trip distance
summary_wdays_avg_duration = pd.DataFrame(df_raw.groupby(['day_of_week','pickup_hour'
```

```
# Reset index to convert group labels to columns
summary_wdays_avg_duration.reset_index(inplace = True)

# Set seaborn style and context
sns.set(style="white", palette="muted", color_codes=True)
sns.set_context("poster")

# Create time series plot with lineplot
sns.lineplot(data=summary_wdays_avg_duration, x="pickup_hour", y="trip_distance", hue

# Remove spines from the plot
sns.despine(bottom = False)

# Add title to the plot
_ = plt.title('Mean Trip Distance Across Week')

# Show the plot
plt.show()
```



Compared to the other week days, the graph shows that day 5 and 6, which are Saturday and Sunday, have a lowest average trip distance covered by the "Green" cabs between 4AM to 7 AM.

However, the graph also shows that day 5 and 6, have a highest average trip distance covered by the "Green" cabs between 4PM to 8 PM.

```
# Groupby day of week and pickup hour, calculate median trip distance
summary_wdays_avg_duration = pd.DataFrame(df_raw.groupby(['day_of_week','pickup_hour'

# Reset index to convert group labels to columns
summary_wdays_avg_duration.reset_index(inplace = True)

# Set seaborn style and context
sns.set(style="white", palette="muted", color_codes=True)
sns.set_context("poster")

# Create time series plot with lineplot
sns.lineplot(data=summary_wdays_avg_duration, x="pickup_hour", y="trip_distance", hue

# Remove spines from the plot
sns.despine(bottom = False)

# Add title to the plot
_ = plt.title('Median Trip Distance Across Week')

# Show the plot
plt.show()
```

Compared to the other week days, the graph shows that day 5 and 6, which are Saturday and Sunday, have a lowest median trip distance covered by the "Green" cabs between 4AM to 7 AM. However, the graph also shows that day 5 and 6, have a highest median trip distance covered by the "Green" cabs between 4PM to 8 PM.

b) We’d like to get a rough sense of identifying trips that originate or terminate at one of the NYC area airports. Can you provide a count of how many transactions fit this criteria, the average fare, and any other interesting characteristics of these trips.

```
def which_nyairport(row):
    if (
        (row['PULocationID'] == 132) or  # PULocationID 132 corresponds to JFK airpor
        (row['DOLocationID'] == 132)     # DOLocationID 132 corresponds to JFK airpor
    ):
        return 'JFK'  # John F. Kennedy International Airport

    if (
        (row['PULocationID'] == 138) or  # PULocationID 138 corresponds to LAG airpor
        (row['DOLocationID'] == 138)     # DOLocationID 138 corresponds to LAG airpor
    ):
        return 'LAG'  # LaGuardia Airport

    return 'NOT'  # Not an Airport pickup/dropoff


df_raw['Airport'] = df_raw.apply(which_nyairport, axis=1)
# this is to create a new field in the dataframe based on the helper function written


df_raw['Airport'].value_counts() # what's the distribution of the rides
```

```
NOT    865545
LAG     10981
JFK      5938
Name: Airport, dtype: int64
```

```
print('average fair for airport trips',df_raw[df_raw['Airport']!= 'NOT']['fare_amount
print('number of trips satisfying the criteria:',df_raw[df_raw['Airport']!='NOT']['fa
```

```
average fair for airport trips 27.013637330811513
number of trips satisfying the criteria: 16919
```

```
print('average fair for non-airport trips',df_raw[df_raw['Airport']=='NOT']['fare_amo
```

```
average fair for non-airport trips 12.04185989174451
```

```
df_raw_airports = df_raw[df_raw['Airport']!= 'NOT'] # display the non-aiport data.
display_data(df_raw_airports.head())
```

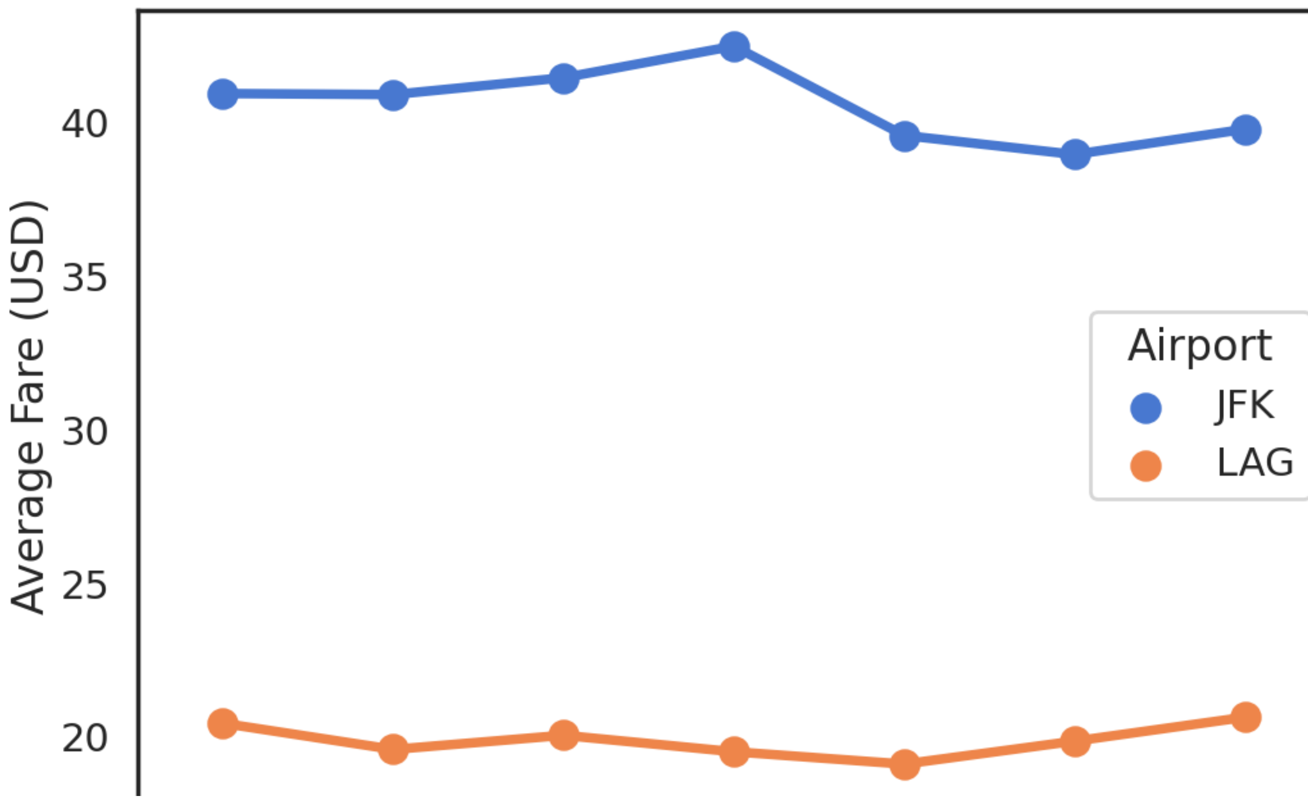
	VendorID	lpep_pickup_datetime	lpep_dropoff_datetime	store_and_fwd_flag
96	2	2017-09-01 01:00:06	2017-09-02 00:18:33	N
258	2	2017-09-01 00:30:06	2017-09-01 01:05:21	N
360	2	2017-09-01 00:55:36	2017-09-01 01:01:04	N
497	2	2017-09-01 00:47:30	2017-09-01 01:10:10	N
1837	2	2017-09-01 03:01:52	2017-09-01 03:11:28	N

5 rows × 26 columns

Points-Plots

- Simple point plots can explain how the average fare is changing with different days of week at JFK and LAG

```
grouped_df = df_raw_airports.groupby(['day_of_week', 'Airport'])['fare_amc
plt.figure(figsize=(12, 8))
sns.pointplot(x=grouped_df.day_of_week, y=grouped_df.fare_amount, hue=grou
plt.ylabel('Average Fare (USD)')
plt.xlabel('Day of Week')
plt.xticks(rotation='horizontal')
plt.show()
```



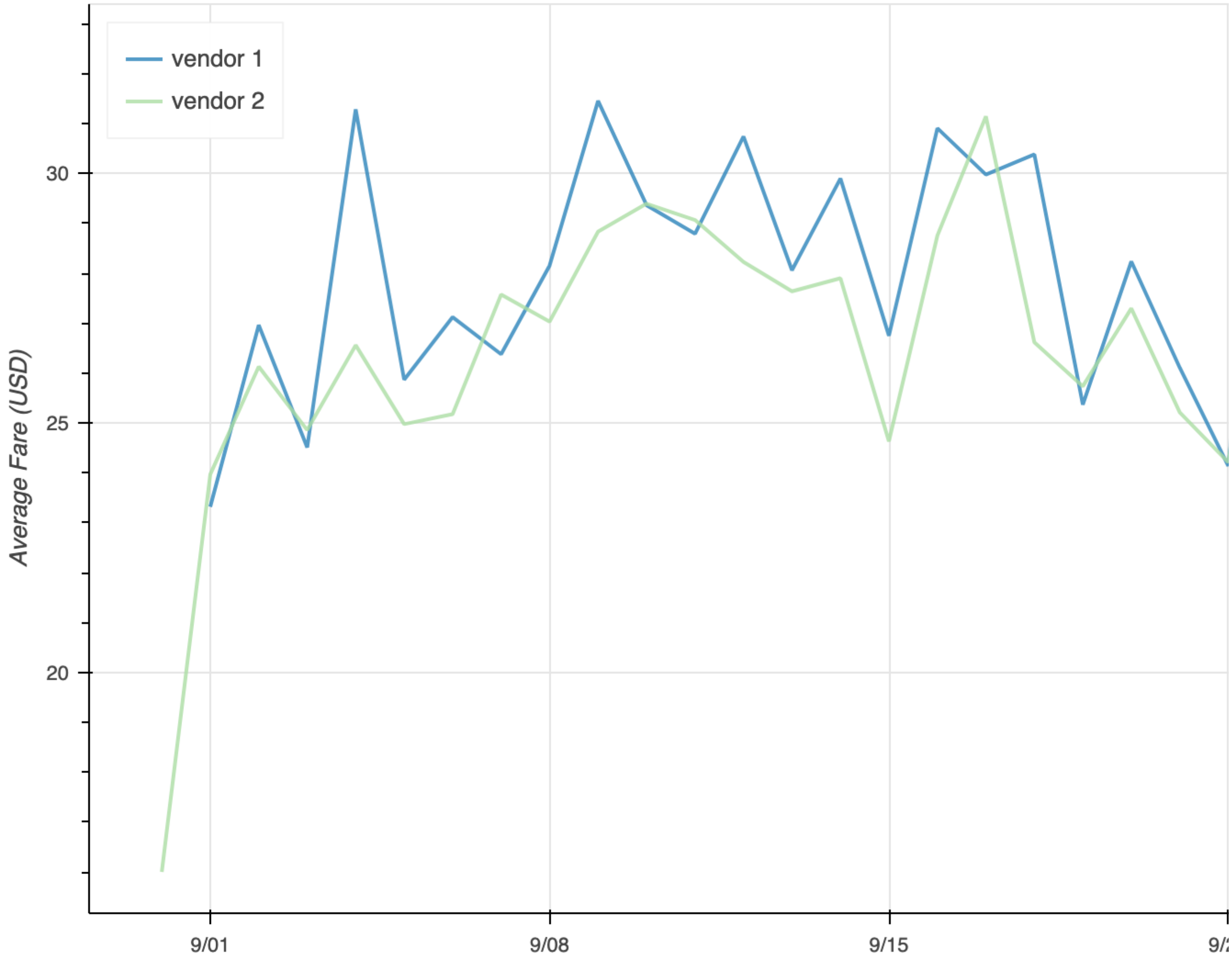

```
grouped_df = df_raw_airports.groupby(['pickup_hour', 'Airport'])['fare_amo
plt.figure(figsize=(12, 8))
sns.pointplot(x=grouped_df.pickup_hour, y=grouped_df.fare_amount, hue=grou
plt.ylabel('Average Fare (USD)')
plt.xlabel('Pick Up Hour')
plt.xticks(rotation='horizontal')
plt.show()
```

Findings

The data depicted in the point plots above clearly indicate that trips to/from JFK exhibit an average fare that is nearly twice as high as that of LAG. Additionally, it is notable that on Mondays (day 0) and Sundays (day 6), the average fare is higher compared to the weekdays. Interestingly, the average fare appears to peak in the afternoon, only to sharply decline by a significant margin later in the day.

Vendor-level analysis on Airport data

```
temp = df_raw_airports.copy()
df_raw_airports['pickup_datetime'] = pd.to_datetime(df_raw_airports.lpep_pickup_datet
df_raw_airports.loc[:, 'pickup_date'] = df_raw_airports['pickup_datetime'].dt.date

# get the average fare for vendor 1
ts_v1 = pd.DataFrame(df_raw_airports.loc[df_raw_airports['VendorID']==1].groupby('pic
ts_v1.reset_index(inplace = True)
# get the average fare for vendor 2
ts_v2 = pd.DataFrame(df_raw_airports.loc[df_raw_airports.VendorID==2].groupby('pickup
ts_v2.reset_index(inplace = True)

from bokeh.palettes import Spectral4 # import spectral plot module
from bokeh.plotting import figure, output_notebook, show
output_notebook()
p = figure(plot_width=950, plot_height=550, x_axis_type="datetime", tools="zoom_in, z
p.toolbar.active_scroll = "auto"
p.title.text = ''

for data, name, color in zip([ts_v1, ts_v2], ["vendor 1", "vendor 2"], Spectral4): #
    df = data
    p.line(df['pickup_date'], df['fare_amount'], line_width=2, color=color, alpha=0.8

p.legend.location = "top_left"
p.xaxis.axis_label = "Pickup Date"
p.yaxis.axis_label = "Average Fare (USD)"
show(p)
df_raw_airports = temp

import warnings
warnings.filterwarnings("ignore")
```



Findings

It's interesting to observe that Vendor 1 had a significantly higher average fare in the month of September. This disparity could possibly be explained by the fact that Vendor 1 tends to provide more rides compared to Vendor 2, or it could be due to Vendor 1 implementing dynamic or higher pricing strategies. However, it's worth noting that Vendor 2 managed to surpass Vendor 1 in terms of average fares on September 7th, September 9th, and September 18th.

Question 4

a) Build a derived variable for tip as a percentage of the total fare.

```
df_raw.columns # column info
```

```
Index(['VendorID', 'lpep_pickup_datetime', 'lpep_dropoff_datetime',
       'store_and_fwd_flag', 'RatecodeID', 'PULocationID', 'DOLocationID',
       'passenger_count', 'trip_distance', 'fare_amount', 'extra', 'mta_tax',
       'tip_amount', 'tolls_amount', 'ehail_fee', 'improvement_surcharge',
       'total_amount', 'payment_type', 'trip_type', 'congestion_surcharge',
       'pickup', 'pickup_hour', 'dropoff', 'dropoff_hour', 'day_of_week',
       'Airport'],
      dtype='object')
```

```
df_raw['tip_percent'] = df_raw['tip_amount']/df_raw['total_amount'] # calculate tip p
df_raw['tip_percent'] = df_raw['tip_percent'].apply(lambda x: x * 100) # multiply by
```

Analysis on the tip data

Below is the analysis on average tip across day.

```
# Grouping and aggregating data
grouped_df = df_raw.groupby(['pickup_hour', 'Airport'])['tip_percent'].mean().reset_i

# Creating a point plot
plt.figure(figsize=(12, 8))
sns.pointplot(x='pickup_hour', y='tip_percent', hue='Airport', data=grouped_df)
plt.ylabel('Average Tip (% of the fare amount)')
plt.xlabel('Pick up hour')
plt.xticks(rotation='vertical')
plt.show()
```

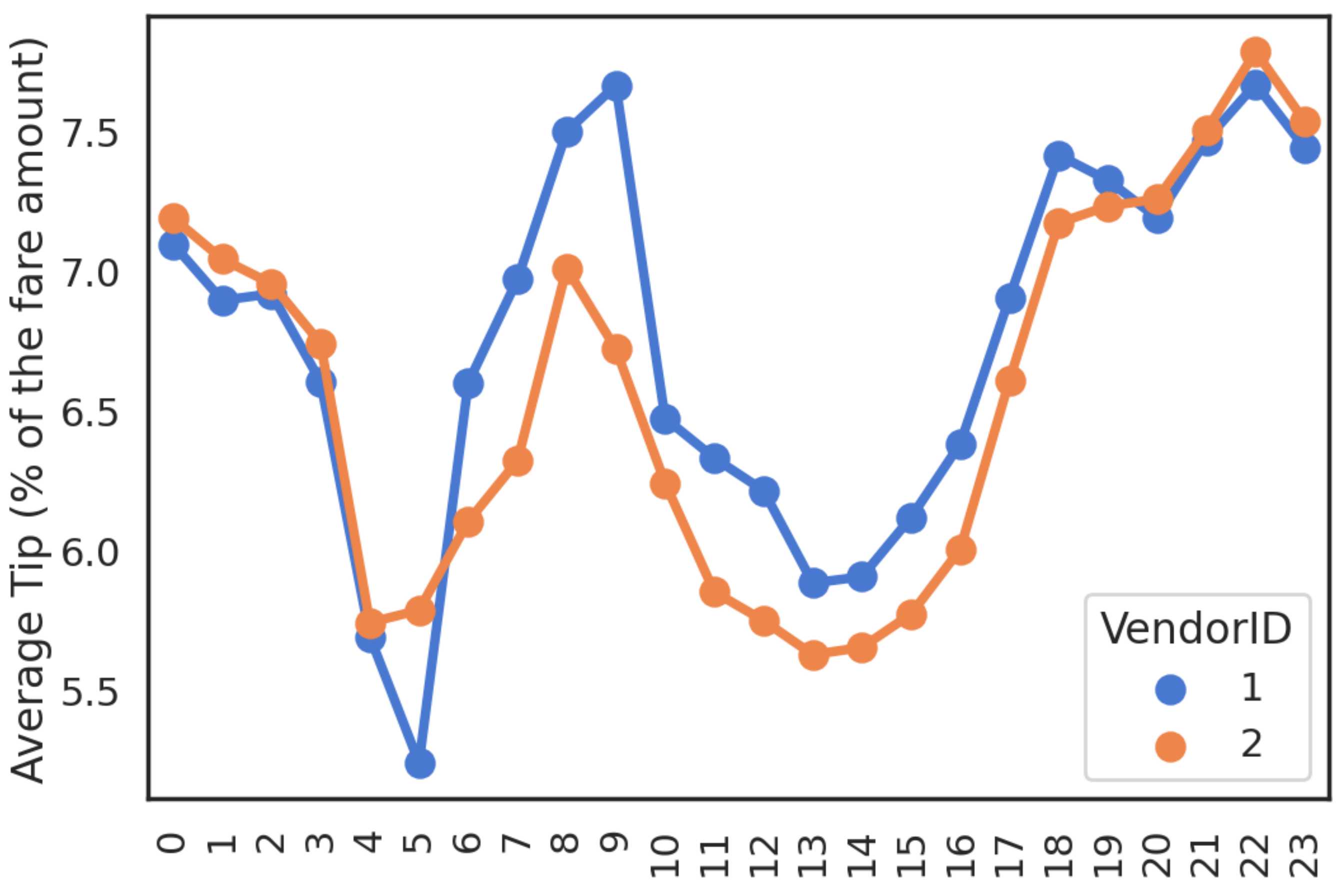
Findings

The average tip tends to be higher for trips to/from LGA Airport, as the average fare for these trips is relatively higher compared to JFK or non-airport rides.

Vendor-level Tip Analysis

1 - Vendor 1 ; 2 - Vendor 2

```
grouped_df = df_raw.groupby(['pickup_hour', 'VendorID'])['tip_percent'].mean().reset_
plt.figure(figsize=(12,8))
sns.pointplot(x='pickup_hour', y='tip_percent', hue='VendorID', data=grouped_df)
plt.ylabel('Average Tip (% of the fare amount)')
plt.xlabel('Pick up hour')
plt.xticks(rotation='vertical')
plt.show()
```



Findings:

According to the data, on average, Vendor 1 has a higher average tip percentage compared to Vendor 2. Furthermore, Vendor 1 tends to earn higher average tip percentages between 6am to 7pm, whereas Vendor 2 tends to receive more tips from 8pm to 5am. However, Vendor 2 holds the highest average tip percentage of 7.9 dollars at the pick-up hour of 10pm, whereas Vendor 1's highest average tip percentage is 7.8 dollars at the pick-up hour of 9am.

b) Build a predictive model for tip as a percentage of the total fare. Use as much of the data as you like (or all of it). Provide an estimate of performance using an appropriate sample, and show your work.

Predictive Model

```
import xgboost as xgb # please install xgboost before running this script.
import lightgbm as lgb # please install lightgbm before running this script.


# load the data into a new pandas dataframe.
df_model = pq.read_table(file_path).to_pandas() # read data into a pandas



df_model = df_model.reset_index() # reset the index of our dataframe.


#rename our columns.
df_model = df_model.rename(columns={'index': 'ID', 'lpep_pickup_datetime': 'pickup_da



df_model.drop(['ehail_fee', 'RatecodeID', 'extra', 'congestion_surcharge',], axis=1,



display_data(df_model.tail()) # let's see how our data looks like.
```

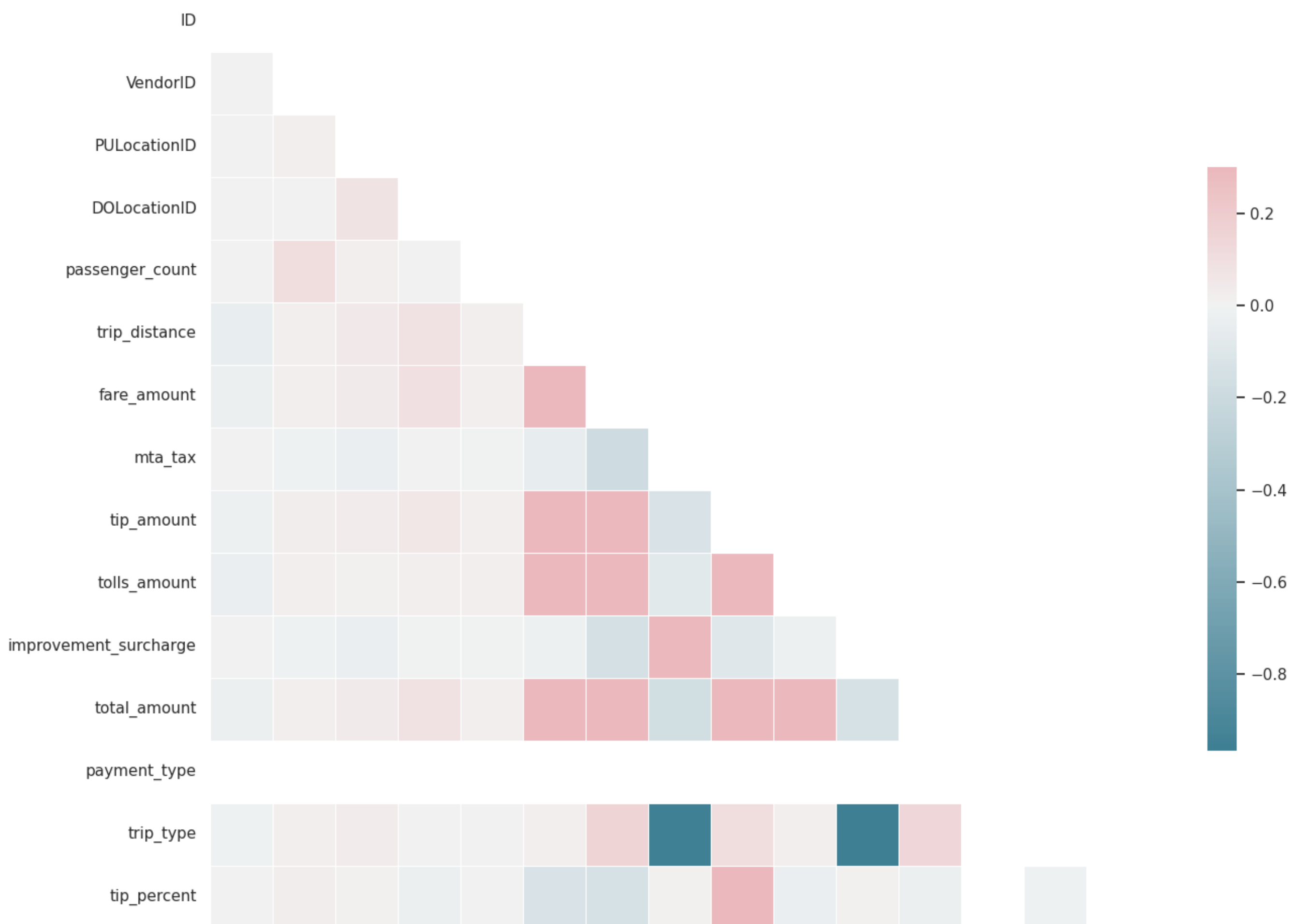
	ID	VendorID	pickup_datetime	dropoff_datetime	store_and_fwd_flag	P
882459	882459	2	2017-09-30 23:42:33	2017-09-30 23:45:24	N	
882460	882460	2	2017-09-30 23:48:34	2017-09-30 23:55:25	N	
882461	882461	2	2017-09-30 23:59:25	2017-10-01 00:12:47	N	

```
df_model['tip_percent'] = df_model['tip_amount']/df_model['total_amount'] # calculate
df_model['tip_percent'] = df_model['tip_percent'].apply(lambda x: x * 100) # multiply
df_model = df_model[df_model['tip_amount'] > 0] # make sure the tip is greater than z
df_model = df_model[df_model['fare_amount'] > 0] # make sure the fare amount is great
```

Feature Correlation Analysis:

Let's identify correlation using a heatmap and check how the features are correlated

```
sns.set(style="white")

# Generate a large random dataset
temp3 = df_model.copy() # our dataframe

# Compute the correlation matrix
corr = temp3.corr() # corr calculation

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(15, 15))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



Findings:

Variables such as total_amount, tolls_amount, and trip_type are of significant importance and demonstrate strong relationships with other variables.

Variables such as payment_type, trip_distance, and pickup_longitude are of relatively low importance and do not seem to have strong relationships with other variables.

On the other hand, total_amount is crucial, with a high correlation coefficient of 0.8.

Although strong correlations are observed among various independent variables (IDVs), we will be using a tree-based model, so there may not be a need to remove variables that are highly correlated. However, for the robustness of the model, it could be worth considering removing them. Additionally, tip_percent appears to be moderately correlated with several IDVs.

Train-test split

```
y = df_model.tip_percent # tip_percent is our target variable
X = df_model # predictor varibles


X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.2) # test size =
print ( "\nX_train:\n")
print (X_train.shape)
print ("\nX_test:\n")
print (X_test.shape)
```

```
X_train:

(288209, 18)

X_test:

(72053, 18)
```

```
X_train.head() # this is our training data
```

	ID	VendorID	pickup_datetime	dropoff_datetime	store_and_fwd_flag	P
865817	865817	2	2017-09-30 16:58:26	2017-09-30 17:01:07	N	
98237	98237	2	2017-09-04 19:00:16	2017-09-04 19:18:47	N	
800423	800423	2	2017-09-28 17:08:09	2017-09-28 17:17:05	N	
179829	179829	2	2017-09-07 18:34:34	2017-09-07 18:37:09	N	
543113	543113	2	2017-09-19 18:45:42	2017-09-19 18:59:33	N	

```
X_test = X_test.iloc[:, :-1] # exclude the target variable(tip_percent) from our test
```

```
X_test.shape # test data shape
```

```
(72053, 17)
```

```
X_test.head() # test data
```

	ID	VendorID	pickup_datetime	dropoff_datetime	store_and_fwd_flag	P
570990	570990	2	2017-09-20 18:24:16	2017-09-20 18:33:15	N	
824300	824300	2	2017-09-29 13:47:14	2017-09-29 14:08:54	N	
658354	658354	2	2017-09-23 17:03:41	2017-09-23 17:23:05	N	
354943	354943	1	2017-09-13 16:08:54	2017-09-13 16:12:46	N	
211882	211882	2	2017-09-08 19:05:26	2017-09-08 19:26:44	N	

```
X_test.drop(['tip_amount'], axis=1, inplace=True)
# Drop the tip_amount, because then it'd be easy for the model to identify the percen
# of tip by just dividing it with the total fare.
```

```
X_train['log_tip_percent'] = np.log1p(X_train['tip_percent'].values) # logarithm of t

plt.figure(figsize=(8,6))
plt.scatter(range(X_train.shape[0]), np.sort(X_train.tip_percent.values))
plt.xlabel('index', fontsize=12)
plt.ylabel('log_tip_percent', fontsize=12)
plt.show()
```

Check to see if there are any null values in the data

```
null_count_df = X_train.isnull().sum(axis=0).reset_index() # training set
null_count_df.columns = ['col_name', 'null_count']
null_count_df
```

	col_name	null_count
0	ID	0
1	VendorID	0
2	pickup_datetime	0
3	dropoff_datetime	0
4	store_and_fwd_flag	0
5	PULocationID	0
6	DOLocationID	0
7	passenger_count	0
8	trip_distance	0
9	fare_amount	0
10	mta_tax	0
11	tip_amount	0
12	tolls_amount	0
13	improvement_surcharge	0
14	total_amount	0
15	payment_type	0
16	trip_type	0
17	tip_percent	0
18	log_tip_percent	0

```
null_count_df = X_test.isnull().sum(axis=0).reset_index() # test set
null_count_df.columns = ['col_name', 'null_count']
null_count_df
```

	col_name	null_count
0	ID	0
1	VendorID	0
2	pickup_datetime	0
3	dropoff_datetime	0
4	store_and_fwd_flag	0
5	PULocationID	0
6	DOLocationID	0
7	passenger_count	0
8	trip_distance	0
9	fare_amount	0
10	mta_tax	0
11	tolls_amount	0
12	improvement_surcharge	0
13	total_amount	0
14	payment_type	0
15	trip_type	0

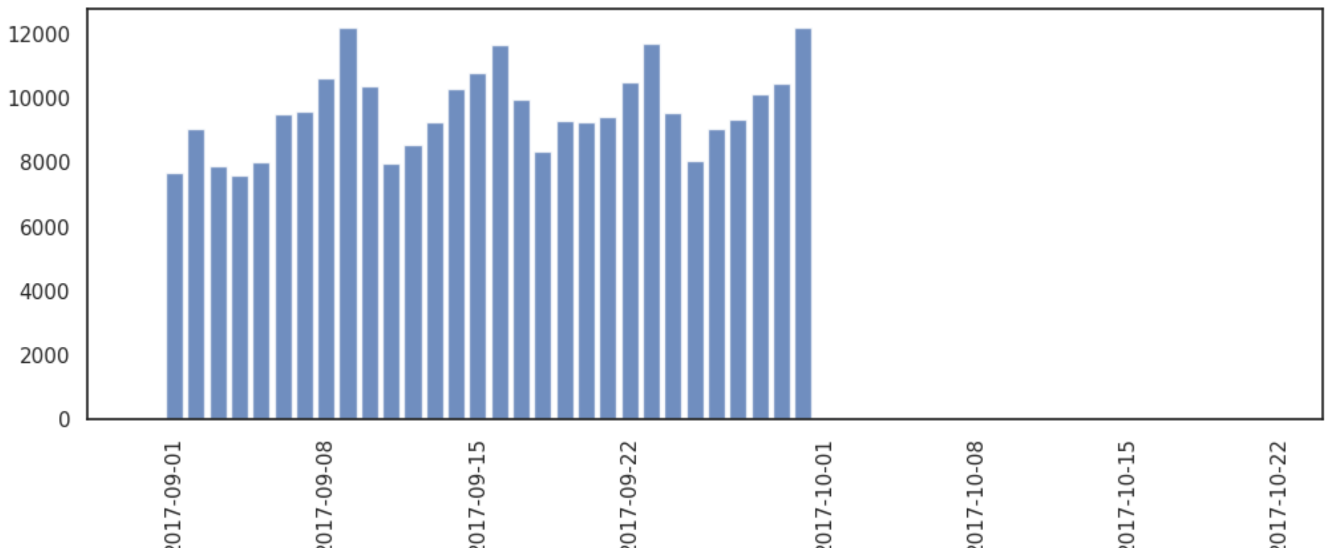
There are no missing values.

Validation Strategy:

- A well-defined validation strategy is crucial as it allows for effective model evaluation and comparison. Without proper validation, it can be challenging to accurately assess the performance of different models against each other.
- Given that dates are included in the dataset, it is imperative to verify whether the train and test datasets are sourced from the same time period or distinct time periods. This ensures that the model is evaluated on relevant and comparable data.

X TRAIN

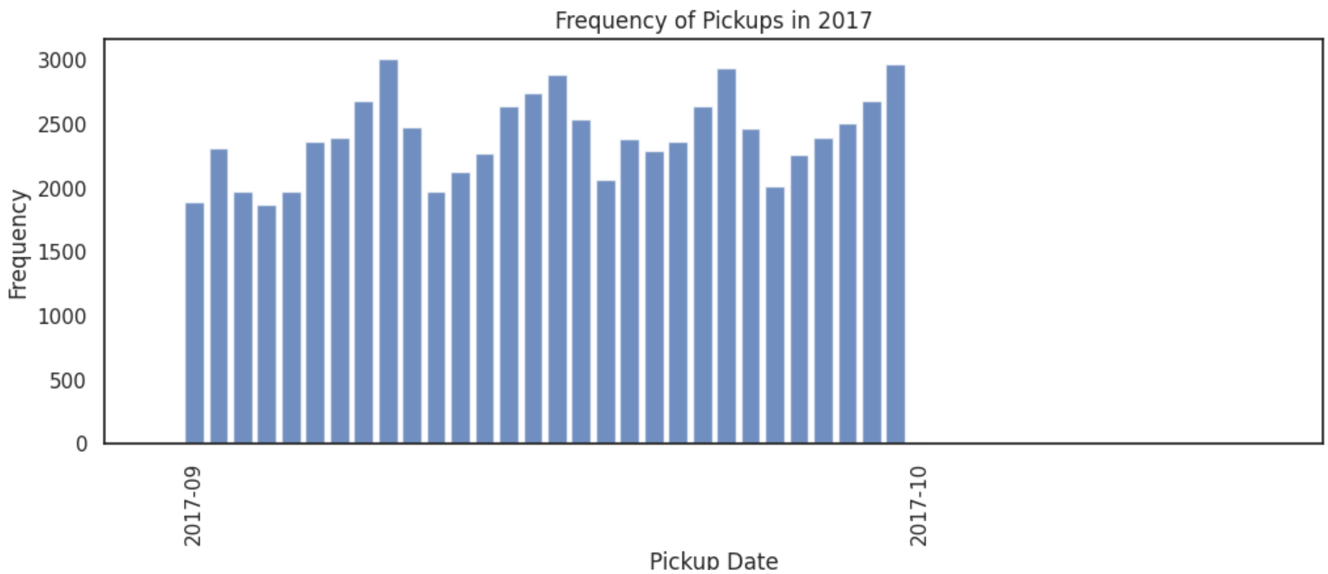
```
# Convert 'pickup_date' to datetime type
X_train['pickup_date'] = pd.to_datetime(X_train['pickup_date'])

# Filter pickup dates to include only dates from 2017
pickup_date_filtered = X_train[X_train['pickup_date'].dt.year == 2017]

# Get frequency counts of pickup dates in filtered DataFrame
cnt_srs = pickup_date_filtered['pickup_date'].value_counts()

# Create bar chart
plt.figure(figsize=(12,4))
ax = plt.subplot(111)
ax.bar(cnt_srs.index, cnt_srs.values, alpha=0.8)
ax.xaxis_date()
plt.xticks(rotation='vertical')
plt.show()
```



X TEST

```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# Convert 'pickup_datetime' column to datetime type
X_test['pickup_datetime'] = pd.to_datetime(X_test['pickup_datetime'])

# Extract 'pickup_date' from 'pickup_datetime' column
X_test['pickup_date'] = X_test['pickup_datetime'].dt.date

# Filter pickup dates to include only dates from 2017
pickup_date_filtered2 = X_test[X_test['pickup_datetime'].dt.year == 2017]

# Get frequency counts of pickup dates in filtered DataFrame
cnt_srs = pickup_date_filtered2['pickup_date'].value_counts()
```

```
# Create bar chart
plt.figure(figsize=(12, 4))
ax = plt.subplot(111)
ax.bar(cnt_srs.index, cnt_srs.values, alpha=0.8)
ax.xaxis.set_major_locator(mdates.MonthLocator())
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m'))
plt.xticks(rotation='vertical')
plt.xlabel('Pickup Date')
plt.ylabel('Frequency')
plt.title('Frequency of Pickups in 2017')
plt.show()
```



Findings

Given the close resemblance between the distributions, it appears feasible to employ K-fold cross-validation on our dataset. However, it's crucial to keep in mind that if the training and testing datasets are derived from disparate time periods, time-based validation would be necessary.

Baseline Model

- Once we have gained an understanding of the dataset, we can proceed to construct a baseline model employing the XGBoost algorithm, and assess its performance.
- To enhance the dataset, we can derive some fundamental variables from the datetime column and transform the store_and_forward_flag into a numeric format.

```
# day of the month
X_train['pickup_day'] = X_train['pickup_datetime'].dt.day
```

```
X_test['pickup_day'] = X_test['pickup_datetime'].dt.day

# month of the year
X_train['pickup_month'] = X_train['pickup_datetime'].dt.month
X_test['pickup_month'] = X_test['pickup_datetime'].dt.month

# hour of the day
X_train['pickup_hour'] = X_train['pickup_datetime'].dt.hour
X_test['pickup_hour'] = X_test['pickup_datetime'].dt.hour

# Week of year
X_train["week_of_year"] = X_train["pickup_datetime"].dt.weekofyear
X_test["week_of_year"] = X_test["pickup_datetime"].dt.weekofyear

# Day of week
X_train["day_of_week"] = X_train["pickup_datetime"].dt.weekday
X_test["day_of_week"] = X_test["pickup_datetime"].dt.weekday

# Convert to numeric
map_dict = {'N':0, 'Y':1}
X_train['store_and_fwd_flag'] = X_train['store_and_fwd_flag'].map(map_dict)
X_test['store_and_fwd_flag'] = X_test['store_and_fwd_flag'].map(map_dict)


# drop off the variables which are not needed
cols_to_drop = ['ID', 'pickup_datetime', 'pickup_date', 'dropoff_datetime']
train_id = X_train['ID'].values
test_id = X_test['ID'].values
train_y = X_train.log_tip_percent.values
train_X = X_train.drop(cols_to_drop + ['tip_amount', 'tip_percent', 'log_tip_percent'
test_X = X_test.drop(cols_to_drop, axis=1)
```

LightGBM distinguishes itself from other tree-based algorithms by adopting a vertical tree growth strategy, where trees are constructed leaf-wise rather than level-wise. This means that LightGBM selects the leaf with the maximum delta loss for growth, resulting in more effective reduction of loss during tree construction compared to level-wise algorithms. As a result, the leaf-wise approach of LightGBM can yield higher performance by reducing loss more efficiently during tree growth.

Helper function to run the xgboost model and light gbm model

```
def runXGB(train_X, train_y, val_X, val_y, test_X, eta=0.05, max_depth=5, min_child_w
    params = {}
    params["objective"] = "reg:linear"
    params['eval_metric'] = "rmse"
    params["eta"] = eta
    params["min_child_weight"] = min_child_weight
    params["subsample"] = subsample
    params["colsample_bytree"] = colsample
```

```
    params["silent"] = 1
    params["max_depth"] = max_depth
    params["seed"] = seed_val
    params["nthread"] = -1

    plst = list(params.items())
    xgtrain = xgb.DMatrix(train_X, label=train_y)
    xgval = xgb.DMatrix(val_X, label = val_y)
    xgtest = xgb.DMatrix(test_X)
    watchlist = [ (xgtrain,'train'), (xgval, 'test') ]
    model = xgb.train(plst, xgtrain, num_rounds, watchlist, early_stopping_rounds=ear

    pred_val = model.predict(xgval, ntree_limit=model.best_ntree_limit)
    pred_test = model.predict(xgtest, ntree_limit=model.best_ntree_limit)

    return pred_val, pred_test

def runLGB(train_X, train_y, val_X, val_y, test_X, eta=0.05, num_leaves=10, max_depth
    params = {}
    params["objective"] = "regression"
    params['metric'] = "l2_root"
    params["learning_rate"] = eta
    params["min_child_weight"] = min_child_weight
    params["bagging_fraction"] = subsample
    params["bagging_seed"] = seed_val
    params["feature_fraction"] = colsample
    params["verbosity"] = 0
    params["max_depth"] = max_depth
    params["num_leaves"] = num_leaves
    params["nthread"] = -1

    lgtrain = lgb.Dataset(train_X, label=train_y)
    lgval = lgb.Dataset(val_X, label = val_y)
    model = lgb.train(params, lgtrain, num_rounds, valid_sets=lgval, early_stopping_r

    pred_val = model.predict(val_X, num_iteration=model.best_iteration)
    pred_test = model.predict(test_X, num_iteration=model.best_iteration)

    return pred_val, pred_test, model
```

```
from sklearn import model_selection, preprocessing, metrics # import a few other modu
```

```
# SKIP THIS -- NOT NECESSARY ON EVERY MACHINE -- ONLY FOR macOS---

! import os

! os.environ['KMP_DUPLICATE_LIB_OK']='True' # this is only to overcome the dependenci

# SKIP THIS -- NOT NECESSARY ON EVERY MACHINE -- ONLY FOR macOS--
```

```
/bin/bash: import: command not found
/bin/bash: os.environ[KMP_DUPLICATE_LIB_OK]=True: command not found
```

```
kf = model_selection.KFold(n_splits=10, shuffle=True, random_state=2017)
cv_scores = []
pred_test_full = 0
pred_val_full = np.zeros(X_train.shape[0])
for dev_index, val_index in kf.split(train_X):
    dev_X, val_X = train_X.iloc[dev_index], train_X.iloc[val_index]
    dev_y, val_y = train_y[dev_index], train_y[val_index]
    pred_val, pred_test, model = runLGB(dev_X, dev_y, val_X, val_y, test_X, num_round
    pred_val_full[val_index] = pred_val
    pred_test_full += pred_test
    cv_scores.append(np.sqrt(metrics.mean_squared_error(val_y, pred_val)))
print(cv_scores)
print("Mean RMSE score : ",np.mean(cv_scores))

pred_test_full = pred_test_full / 5.
pred_test_full = np.expm1(pred_test_full)
pred_val_full = np.expm1(pred_val_full)

# saving train predictions for ensemble #
train_pred_df = pd.DataFrame({'ID':train_id})
train_pred_df['tip_percent'] = pred_val_full
train_pred_df.to_csv("train_preds_lgb_baseline.csv", index=False)

# saving test predictions for ensemble #
test_pred_df = pd.DataFrame({'ID':test_id})
test_pred_df['tip_percent'] = pred_test_full
test_pred_df.to_csv("test_preds_lgb_baseline.csv", index=False)
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of tes
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
Training until validation scores don't improve for 100 rounds
[20]	valid_0's rmse: 0.270832
[40]	valid_0's rmse: 0.232273
[60]	valid_0's rmse: 0.208615
[80]	valid_0's rmse: 0.191277
[100]	valid_0's rmse: 0.17995
[120]	valid_0's rmse: 0.172357
[140]	valid_0's rmse: 0.166506
[160]	valid_0's rmse: 0.158944
[180]	valid_0's rmse: 0.152952
[200]	valid_0's rmse: 0.148266
[220]	valid_0's rmse: 0.14484
[240]	valid_0's rmse: 0.142304
[260]	valid_0's rmse: 0.140017
[280]	valid_0's rmse: 0.137683
[300]	valid_0's rmse: 0.136396
[320]	valid_0's rmse: 0.134962
```

```
[340]	valid_0's rmse: 0.13379
[360]	valid_0's rmse: 0.132517
[380]	valid_0's rmse: 0.131446
[400]	valid_0's rmse: 0.130952
[420]	valid_0's rmse: 0.129485
[440]	valid_0's rmse: 0.128351
[460]	valid_0's rmse: 0.12702
[480]	valid_0's rmse: 0.126031
[500]	valid_0's rmse: 0.125358
[520]	valid_0's rmse: 0.124921
[540]	valid_0's rmse: 0.124474
[560]	valid_0's rmse: 0.12394
[580]	valid_0's rmse: 0.12357
[600]	valid_0's rmse: 0.123225
[620]	valid_0's rmse: 0.122465
[640]	valid_0's rmse: 0.121798
[660]	valid_0's rmse: 0.121109
[680]	valid_0's rmse: 0.120826
[700]	valid_0's rmse: 0.120439
[720]	valid_0's rmse: 0.120274
[740]	valid_0's rmse: 0.119849
[760]	valid_0's rmse: 0.119612
[780]	valid_0's rmse: 0.119201
[800]	valid_0's rmse: 0.118974
[820]	valid_0's rmse: 0.118801
[840]	valid_0's rmse: 0.11872
[860]	valid_0's rmse: 0.11841
[880]	valid_0's rmse: 0.11821
[900]	valid_0's rmse: 0.117919
[920]	valid_0's rmse: 0.117659
[940]	valid_0's rmse: 0.117342
[960]	valid_0's rmse: 0.11724
[980]	valid_0's rmse: 0.116848
[1000]	valid_0's rmse: 0.116676
Did not meet early stopping. Best iteration is:
[995]	valid_0's rmse: 0.116665
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of tes
You can set `force_col_wise=true` to remove the overhead.
```

LightGBM model gave us a RMSE score of 0.117

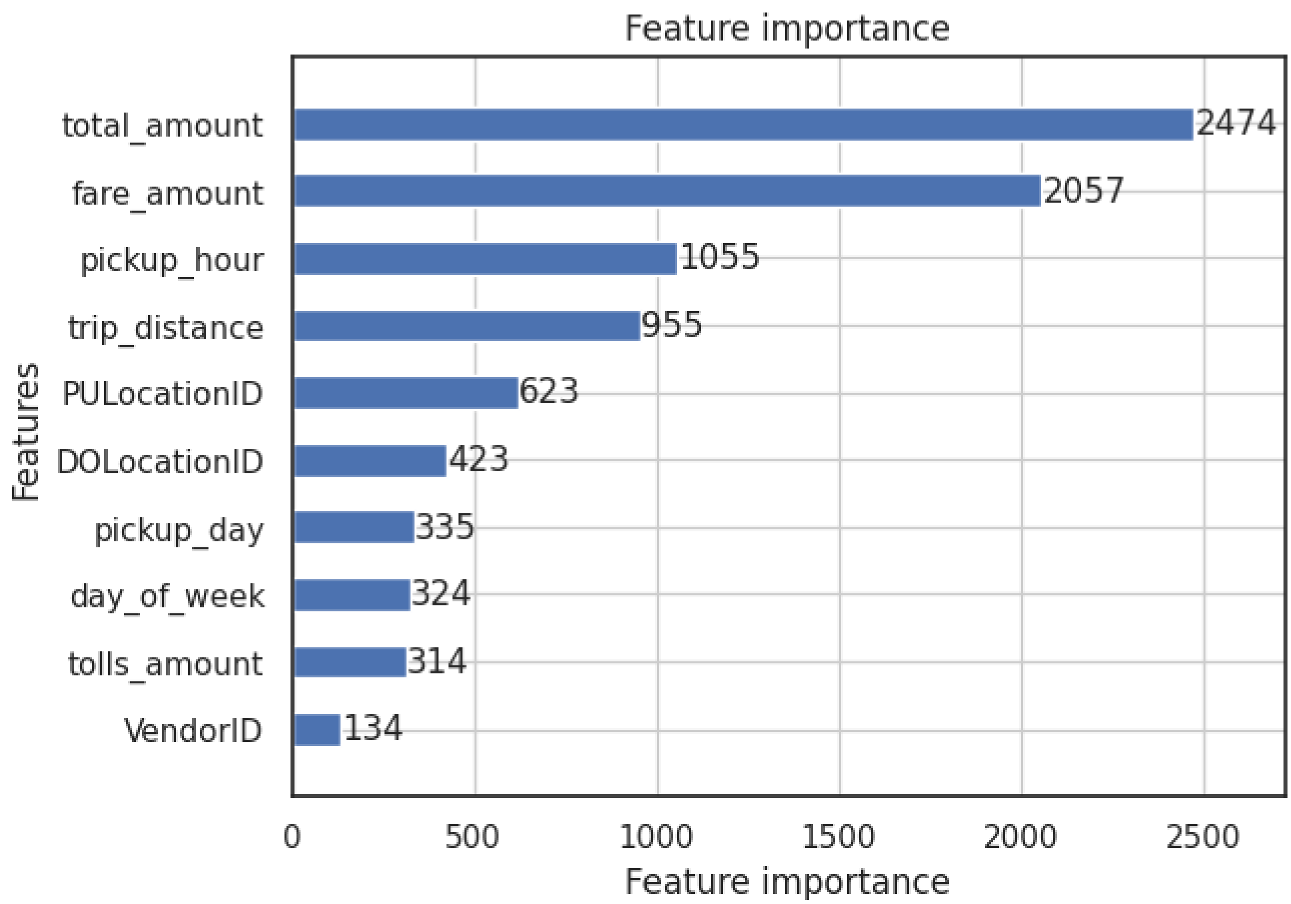
RMSE, or Root Mean Square Error, is a measure used to evaluate the accuracy of a regression model. It quantifies the difference between the predicted values of the model and the observed data values. A lower RMSE indicates a better fit of the model to the data, meaning that the predicted values are closer to the observed data points.

A good RMSE score depends on the context and the specific application of the model. In general, lower RMSE values indicate better prediction accuracy. A RMSE score of 0.117 is good.

Plot the most feature importance chart to identify the features which were really useful in our prediction step

```
print('Plot feature importances...')
ax = lgb.plot_importance(model, max_num_features=10, height = 0.5)
plt.show()
```

```
Plot feature importances...
```



Question 5

Option A: Distributions

```
df_raw.head()
```

	VendorID	lpep_pickup_datetime	lpep_dropoff_datetime	store_and_fwd_flag	Rat
0	2	2017-09-01 00:56:15	2017-09-01 00:56:18	N	
1	2	2017-09-01 00:40:55	2017-09-01 00:49:22	N	
2	2	2017-09-01 00:17:11	2017-09-01 00:20:40	N	
3	2	2017-09-01 00:46:31	2017-09-01 01:04:31	N	
4	2	2017-09-01 00:02:04	2017-09-01 00:07:03	N	

5 rows × 27 columns

```
ans_t = (df_raw['dropoff'] - df_raw['pickup']).apply(lambda x: x.total_seconds()) # e
```

```
print('Percentage of entries with travel time less than a minute: ',100 * df[ans_t <
```

```
Percentage of entries with travel time less than a minute:  3.225806451612903 %
```

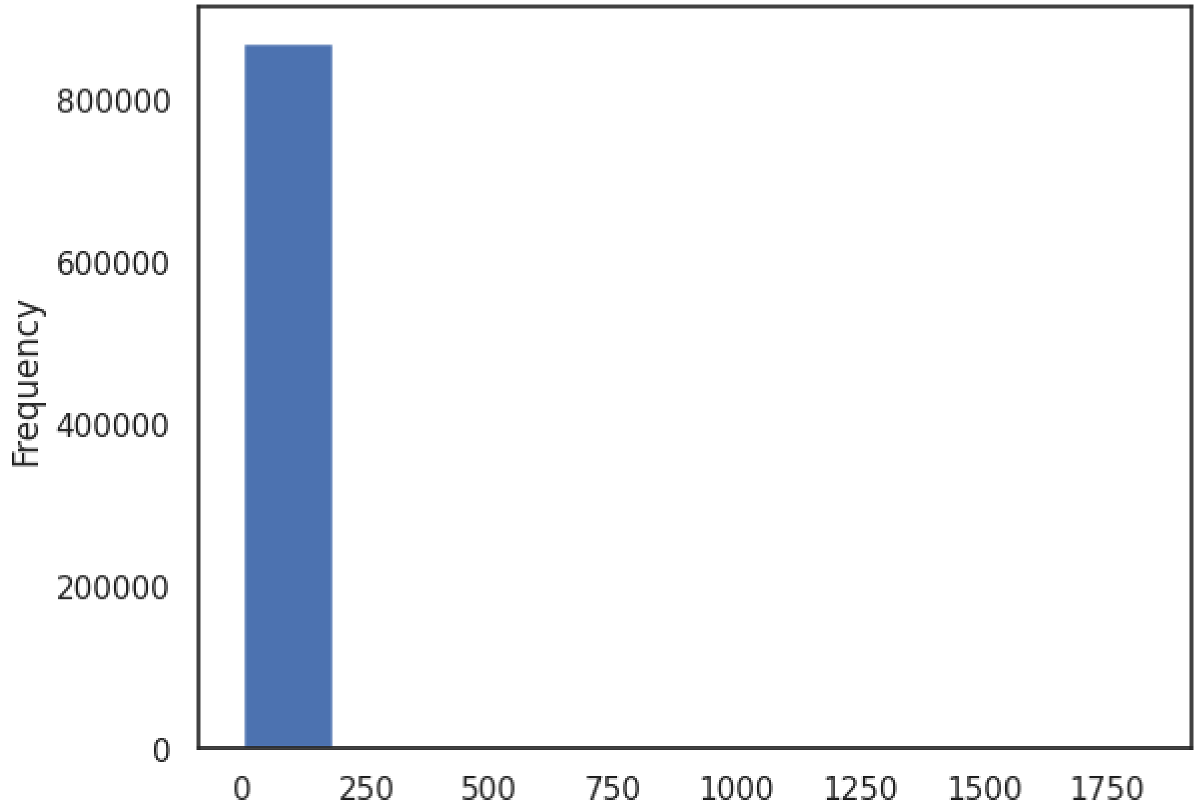
Trips with durations of less than 60 seconds are unlikely to be accurate, so we exclude these entries from our analysis to avoid potential bias. There are approximately 4000 such entries, which account for about 3.23% of the entire dataset. After removing this portion of data, we can proceed with our analysis

a) Build a derived variable representing the average speed over the course of a trip.

```
df_raw['travel_time'] = (df_raw['dropoff'] - df_raw['pickup']).apply(lambda x: x.tota
df_raw = df_raw[df_raw['travel_time'] > 60] # travel time greater than 60 seconds
df_raw['average_speed'] = 3600*(df_raw['trip_distance']/df_raw['travel_time'])
```

```
df_raw['average_speed'].plot.hist(bins=10)
```

```
<Axes: ylabel='Frequency'>
```




```
print('No of entries with average speed over 100 miles per hour: ',(df_raw['average_s
df_raw = df_raw[df_raw['average_speed']<100]
```

```
No of entries with average speed over 100 miles per hour:  75
```

We filter away the 75 entries with over 100 miles per hour of average speed as it is unreasonable and must have been a result of some erroneous data collection process or later in the pipeline.

b) Can you perform a test to determine if the average trip speeds are materially the same in all weeks of September? If you decide they are not the same, can you form a hypothesis regarding why they differ?

```
df_raw['week'] = df_raw['dropoff'].apply(lambda x: x.week) # extract week of year
```

```
df_raw['week'].value_counts() # week count
```

```
37    205508
36    203782
38    202097
```

```
39    177995
35     80030
40        44
42        16
41        12
1          3
44         3
48         3
43         2
46         2
45         2
Name: week, dtype: int64
```

```
week_1 = df_raw['average_speed'][df_raw['week']==36].values # reassign week=36 to wee
week_2 = df_raw['average_speed'][df_raw['week']==37].values # reassign week=37 to wee
week_3 = df_raw['average_speed'][df_raw['week']==38].values # reassign week=38 to wee
week_4 = df_raw['average_speed'][df_raw['week']==39].values # reassign week=39 to wee
week_5 = df_raw['average_speed'][df_raw['week']==40].values # reassign week=40 to wee
```

```
stats.f_oneway(week_1,week_2, week_3,week_4, week_5)
```

```
F_onewayResult(statistic=549.0952242559998, pvalue=0.0)
```

Hypotheses test

Based on the ANOVA test results, we observed a significant F-value and a small p-value. Therefore, we reject the null hypothesis, and it can be concluded that there are statistically significant differences between the groups. This suggests that the week of the month is indeed related to the average speed. To further substantiate our findings, we also calculated the mean, median, and histogram for each group

```
print(week_1.mean(),week_2.mean(),week_3.mean(),week_4.mean(),week_5.mean())
```

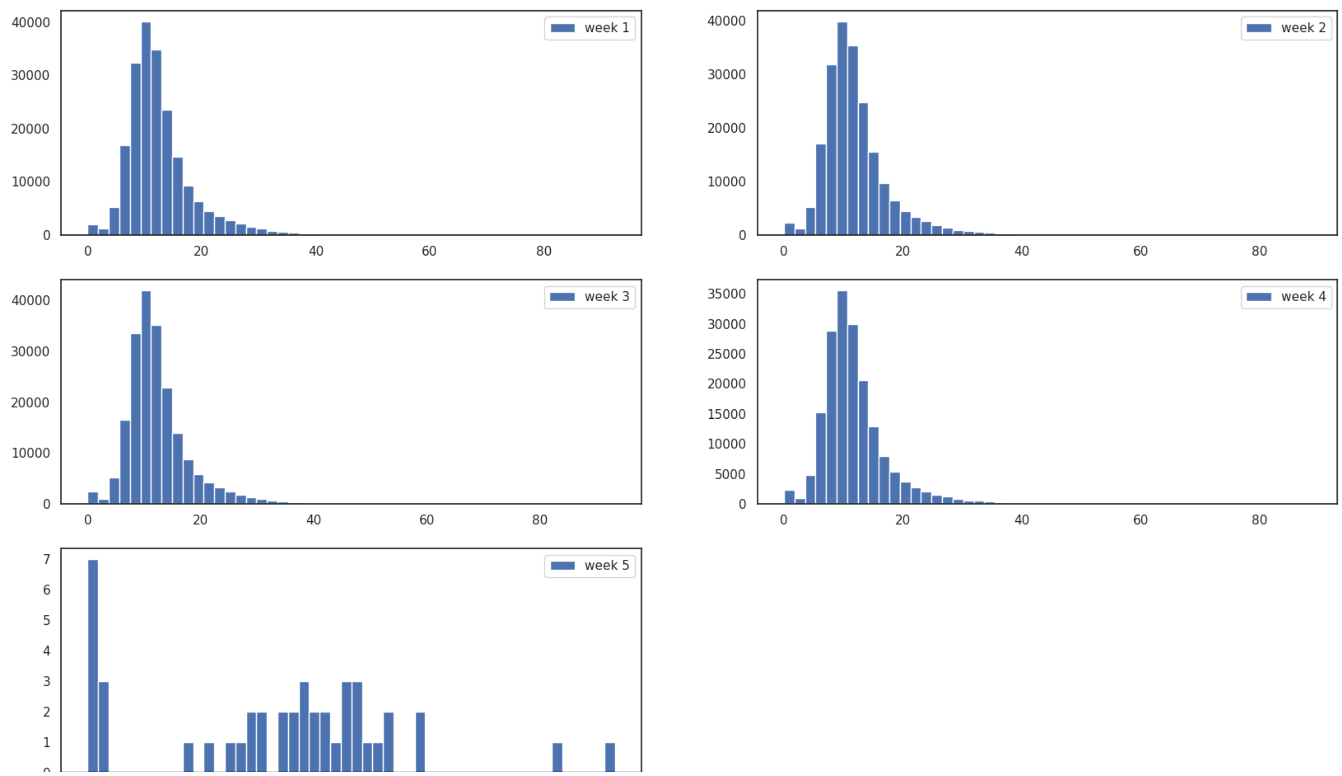
```
12.443903516475336 11.892298231546622 12.275733207598712 11.717498646620344 9.00
```

```
print(statistics.median(week_1),statistics.median(week_2),statistics.median(week_3),s
      statistics.median(week_5))
```

```
11.294727744165947 10.895486355389343 11.224334600760455 10.715008431703204 10.0
```

```
plt.rcParams["figure.figsize"] = [20,12]
plt.subplot(3,2,1)
plt.hist(week_1,bins = 50,label = 'week 1')
plt.legend()
```

```
plt.subplot(3,2,2)
plt.hist(week_2,bins = 50,label = 'week 2')
plt.legend()
plt.subplot(3,2,3)
plt.hist(week_3,bins = 50,label = 'week 3')
plt.legend()
plt.subplot(3,2,4)
plt.hist(week_4,bins = 50,label = 'week 4')
plt.legend()
plt.subplot(3,2,5)
plt.hist(week_5,bins = 50,label = 'week 5')
plt.legend()
plt.legend()
plt.savefig('task5')
plt.show()
```




```
grouped = df_raw.groupby('pickup_hour') # group by the hour
samples = []

for name,group in grouped:
    samples.append(group['average_speed']) # append the avg speed data



sample = samples
stats.f_oneway(sample[0],sample[1],sample[2],sample[3], sample[4],sample[5],sample[6]
              sample[10],sample[11],sample[12],sample[13],sample[14],sample[15],sampl
               sample[19],
              sample[20],sample[21],sample[22],sample[23])
```

```
F_onewayResult(statistic=3962.603957847265, pvalue=0.0)
```

Hpotheses test

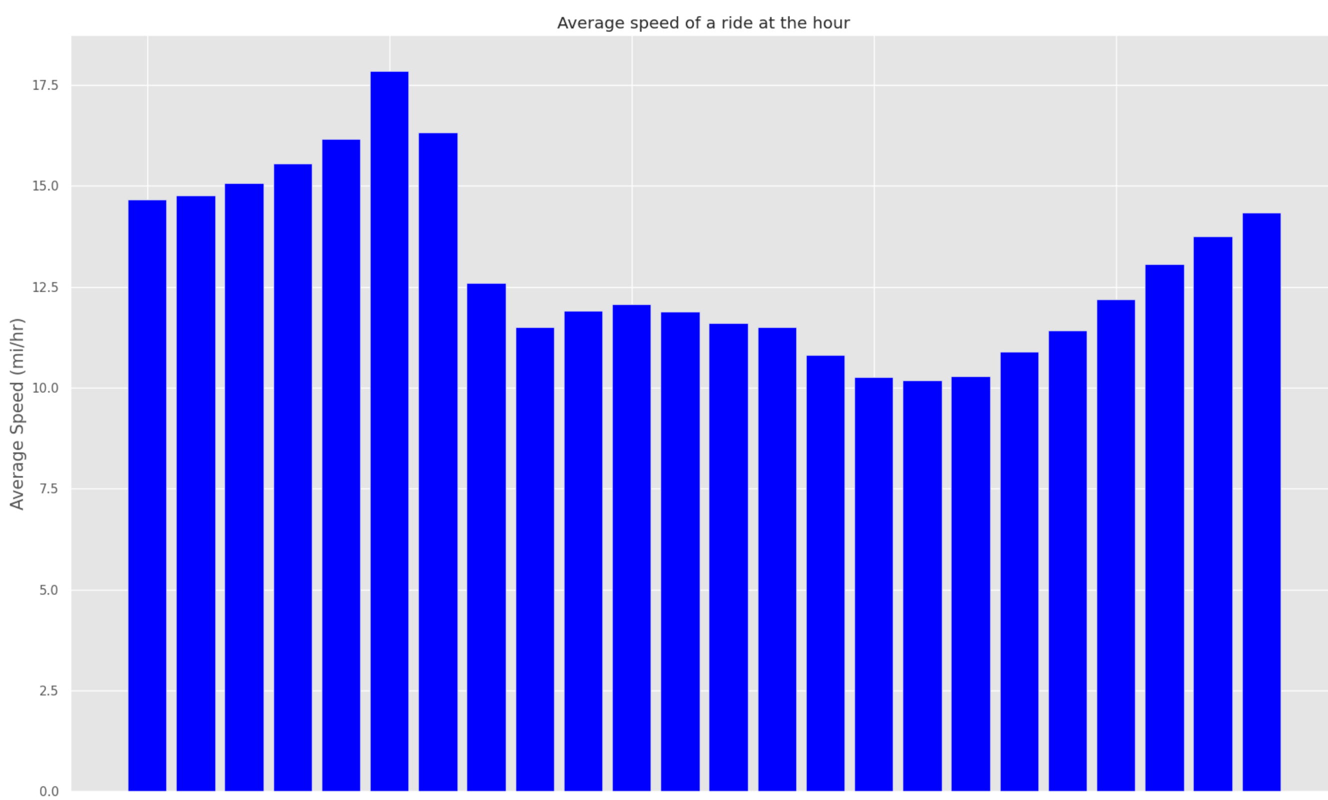
The ANOVA test conducted on the sets partitioned by the hour of the journey also yielded a high F-value and a p-value of 0, indicating that there are statistically significant differences among the data sets being considered.

```
means = [] # empty list for storing the mean info
medians = [] # empty list for storing the median info
for hour in range(24):
    means.append(statistics.mean(sample[hour]))
    print('Mean:',statistics.mean(sample[hour]))
    medians.append(statistics.median(sample[hour]))
    print('Median:',statistics.median(sample[hour]))
```

```
Mean: 14.659922614540353
Median: 13.257790368271955
Mean: 14.757639988707787
Median: 13.479195606180411
Mean: 15.06900692147735
Median: 13.846153846153845
Mean: 15.559455869532826
Median: 14.234588318085855
Mean: 16.153038806910125
Median: 14.462680459247471
Mean: 17.836077469911125
Median: 15.964056179159735
Mean: 16.31687440405793
Median: 14.623424369747898
Mean: 12.598420232776437
Median: 11.208791208791208
Mean: 11.49087285524742
Median: 10.344827586206897
Mean: 11.895365828770883
Median: 10.746268656716419
Mean: 12.068143090047396
Median: 10.885900216919739
Mean: 11.876901640564517
Median: 10.721003134796238
Mean: 11.602464380717336
Median: 10.552763819095476
Mean: 11.50004697715361
Median: 10.438883464794893
Mean: 10.814330508674816
Median: 9.915632754342433
Mean: 10.267961623781401
Median: 9.543741905098317
Mean: 10.189049423514998
Median: 9.527272727272727
```

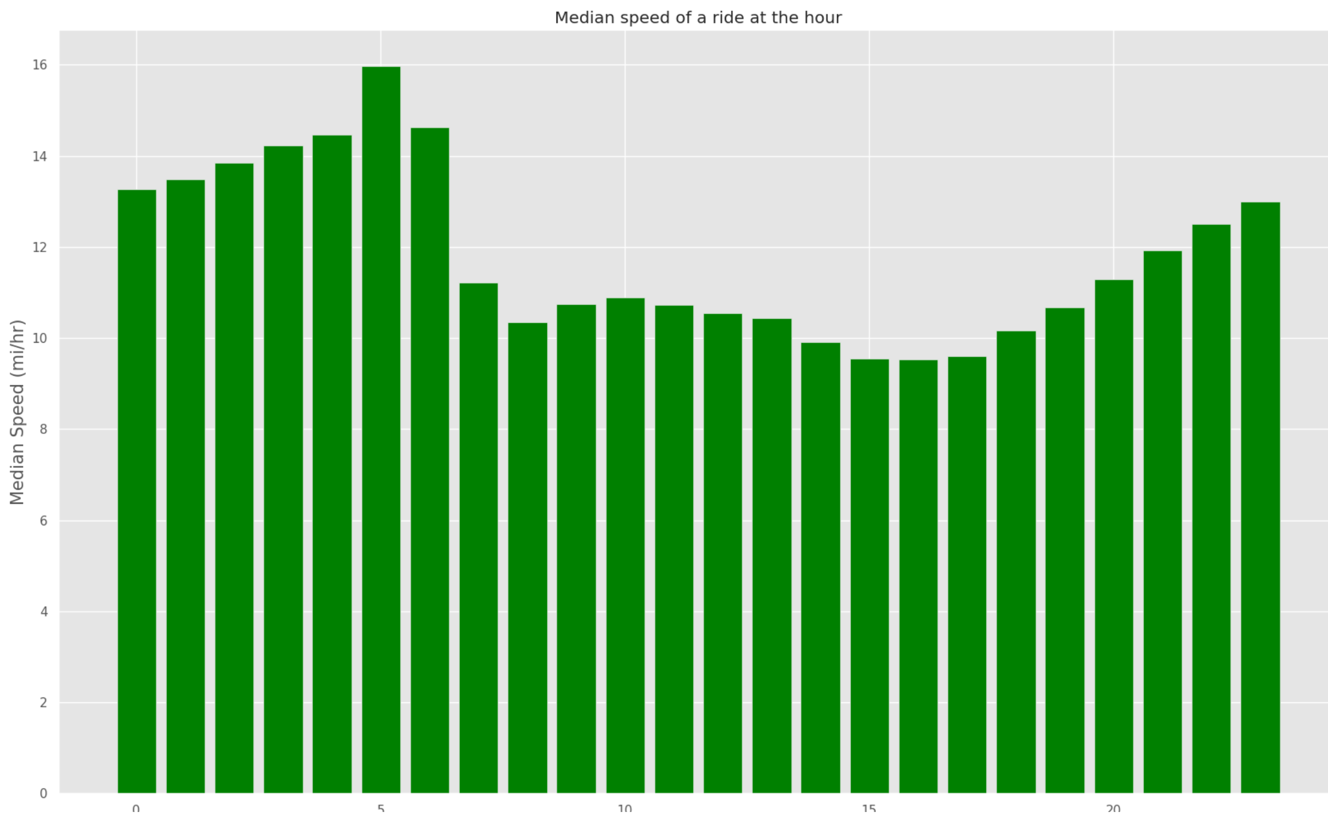
```
Mean: 10.279147988379538
Median: 9.6
Mean: 10.884686308834548
Median: 10.169491525423728
Mean: 11.415055838472076
Median: 10.672566371681416
Mean: 12.187529577078893
Median: 11.294117647058824
Mean: 13.058323545261178
Median: 11.924433249370276
Mean: 13.75673673556456
Median: 12.497323447742822
Mean: 14.33822878089494
Median: 13.000000000000002
```

```
# Define values for the x-axis (hour of day)
index = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21

plt.style.use('ggplot')

plt.bar(index, means, color='blue')
plt.xlabel("Hour of Day", fontsize = 15)
plt.ylabel("Average Speed (mi/hr)", fontsize = 15)
plt.title("Average speed of a ride at the hour")

plt.show()
```




```
# Define values for the x-axis (hour of day)
index = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21
```

```
plt.style.use('ggplot')

plt.bar(index, medians, color='green')
plt.xlabel("Hour of Day", fontsize = 15)
plt.ylabel("Median Speed (mi/hr)", fontsize = 15)
plt.title("Median speed of a ride at the hour")

plt.show()
```



Findings

Based on the findings, it appears that the average speed is higher in the early morning hours, specifically between 4-6 AM, possibly due to minimal traffic on the road.