Group B: Machine Learning

```
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```

Predict the price of the Uber ride from a given pickup point to the agreed drop-off location. Perform following tasks:

1. Pre-process the dataset.
2. Identify outliers.
3. Check the correlation.
4. Implement linear regression and random forest regression models.
5. Evaluate the models and compare their respective scores like R2, RMSE, etc. Dataset link: [https://www.kaggle.com/datasets/yasserh/uber-fares-dataset (https://www.kaggle.com/datasets/yasserh/uber-fares-dataset)](https://www.kaggle.com/datasets/yasserh/uber-fares-dataset)

In [1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
from datetime import datetime
import matplotlib.pyplot as plt
```

In [2]:
```python
# pd.set_option('display.max_columns',None)
# pd.set_option('display.max_rows',None)
```

In [3]:
```python
df = pd.read_csv("uber.csv")
df.head()
```

Out[3]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085

In [5]:
```python
df.columns
```

In [4]:
```python
df.shape
```

Out[4]:
```
(200000, 9)
```

Out[5]:
```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

Data preprocessing

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
  0 Unnamed: 0         200000 non-null  int64
  1 key                200000 non-null  object
  2 fare_amount        200000 non-null  float64
  3 pickup_datetime    200000 non-null  object
  4 pickup_longitude   200000 non-null  float64
  5 pickup_latitude    200000 non-null  float64
  6 dropoff_longitude  199999 non-null  float64
  7 dropoff_latitude   199999 non-null  float64
  8 passenger_count    200000 non-null  int64  dtypes: float64(5), int64(2),
 object(2) memory usage: 13.7+ MB
```

In [7]:
```
df['key'].value_counts()
```

Out[7]:
```
2015-05-07 19:52:06.0000003      1 2012-10-14
22:58:00.00000051     1
2013-09-06 10:59:00.00000086     1
2013-12-27 20:23:50.0000001      1
2010-07-22 18:55:00.000000151    1
                                ..
2010-06-28 11:17:41.0000005      1
2010-12-01 12:58:32.0000001      1
2013-05-12 21:10:21.0000003      1
2014-08-09 16:03:54.0000002      1
2010-05-15 04:08:00.00000076     1
Name: key, Length: 200000, dtype: int64
```

In [8]:
```
df['pickup_datetime'].value_counts()
```

Out[8]:
```
2014-04-13 18:19:00 UTC    4

2010-03-14 12:00:00 UTC    4

2009-02-12 12:46:00 UTC    4
```

```
2011-
02-18
18:55:00 UTC    3

2009-03-12 17:12:00 UTC    3

                          ..

2013-03-08 07:16:00 UTC    1

2013-05-17 21:33:31 UTC    1

2009-10-24 04:05:00 UTC    1

2013-05-16 16:12:00 UTC    1

2010-05-15 04:08:00 UTC    1

Name: pickup_datetime, Length: 196629, dtype: int64
```

In [9]:
```
df["Unnamed: 0"].value_counts()
```

Out[9]:
```
24238194    1 23286231
1
45197665    1
30631497    1
7869264     1
  ..
53467014    1
15557161    1
11971041    1
6135974     1
11951496    1
Name: Unnamed: 0, Length: 200000, dtype: int64
```

In [10]:
```
# df1 = df.drop(["Unnamed: 0","key","pickup_datetime"],axis=1)
df1 = df.drop(["Unnamed: 0","key"],axis=1)
df1.head()
```

Out[10]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitu
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.7232
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.7503
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.7726

3	2009-06-26 08:22:21 UTC	5.3	-73.976124	40.790844	-73.965316	40.8033
4	2014-08-28 17:47:00 UTC	16.0	-73.925023	40.744085	-73.973082	40.7612

In

[11]:
```
df1.isnull().sum()
```

Out[11]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1

passenger_count      0 dtype: int64
```

Out[12]:

In [12]:
```
df1.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passen
count	200000.000000	200000.000000	200000.000000	199999.000000	199999.000000	2000
mean	11.359955	-72.527638	39.935885	-72.525292	39.923890	
std	9.901776	11.437787	7.720539	13.117408	6.794829	
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.985513	
25%	6.000000	-73.992065	40.734796	-73.991407	40.733823	
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	
75%	12.500000	-73.967154	40.767158	-73.963658	40.768001	
max	499.000000	57.418457	1644.421482	1153.572603	872.697628	2

In [13]:
```
df1.fillna(df1.median(),inplace = True)
```

```
C:\Users\SIT\AppData\Local\Temp/ipykernel_6136/3299596212.py:1: FutureWarning:
Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None')
is deprecated; in a future version this will raise TypeError.  Select only vali
d columns before calling the reduction.
  df1.fillna(df1.median(),inplace = True)
```

In [14]:
```
df1.isnull().sum()
```

Out[14]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0 dtype:
int64
```

[15]:
```
df1.dtypes
```

In

Out[15]:
```
fare_amount           float64
pickup_datetime        object
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
passenger_count         int64 dtype:
object
```

In [16]:
```
for i in df1.columns:
    print(df1.value_counts(i))
```

```
fare_amount
6.50      9684
4.50      8247
8.50      7521
5.70      5858
5.30      5838
          ...
26.94        1
56.90        1
56.83        1
27.25        1
499.00       1
Length: 1244, dtype: int64
pickup_datetime
2009-02-12 12:46:00 UTC    4
2014-04-13 18:19:00 UTC    4
2010-03-14 12:00:00 UTC    4
2013-11-23 19:51:00 UTC    3
2009-04-11 23:57:00 UTC    3
```

In [17]:
```
df1.duplicated().count()
```

Out[17]: 200000

In [18]:
```
df1.duplicated().sum()
```

Out[18]: 0

[19]:
```
df1.describe()
```

Out[19]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passen
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	2000
mean	11.359955	-72.527638	39.935885	-72.525299	39.923895	
std	9.901776	11.437787	7.720539	13.117375	6.794812	
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.985513	

In

25%	6.000000	-73.992065	40.734796	-73.991407	40.733824	
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	
75%	12.500000	-73.967154	40.767158	-73.963659	40.768001	
max	499.000000	57.418457	1644.421482	1153.572603	872.697628	2

In [60]:
```python
import pandas as pd

data = [[10, 18, 11],
        [13, 15, 8,4],
        [9, 20, 3,5]]

df = pd.DataFrame(data)

print(df.describe())
```

```
               0          1          2         3
count   3.000000   3.000000   3.000000  2.000000
mean   10.666667  17.666667   7.333333  4.500000
std     2.081666   2.516611   4.041452  0.707107
min     9.000000  15.000000   3.000000  4.000000
25%     9.500000  16.500000   5.500000  4.250000
50%    10.000000  18.000000   8.000000  4.500000
75%    11.500000  19.000000   9.500000  4.750000
max    13.000000  20.000000  11.000000  5.000000
```

In [69]:
```python
mn
mn = 32/3
```

Out[69]: 10.666666666666666

In [71]:
```python
df.std()
```

Out[71]:
```
0    2.081666 1
2.516611
2    4.041452 3
0.707107 dtype:
float64  [70]:
np.sqrt(((10-
mn)**2+(13-
mn)**2+(9-
mn)**2)/2)
```

Out[70]: 2.081665999466133

In
In

[73]:
```
32*0.25
```

Out[73]: 8.0

In [20]:
```
df1.pickup_datetime
```

Out[20]:
```
0         2015-05-07 19:52:06 UTC 1
 2009-07-17 20:04:56 UTC
2         2009-08-24 21:45:00 UTC
3         2009-06-26 08:22:21 UTC
4         2014-08-28 17:47:00 UTC                ...
199995    2012-10-28 10:49:00 UTC
199996    2014-03-14 01:09:00 UTC
199997    2009-06-29 00:42:00 UTC
199998    2015-05-20 14:56:25 UTC
199999    2010-05-15 04:08:00 UTC
Name: pickup_datetime, Length: 200000, dtype: object
```

In [21]:
```
df1.pickup_datetime.dtypes
```

Out[21]: dtype('O')

In [22]:
```
df1.pickup_datetime = pd.to_datetime(df1.pickup_datetime, errors='coerce')
```

In [23]:
```
df1.pickup_datetime.dtypes
```

Out[23]: datetime64[ns, UTC]

In [24]:
```
# df1['pickup_datetime']=df1['pickup_datetime'].str.replace(' UTC','')
```

In [25]:
```
# df1['pickup_datetime']
```

In [26]:
```
# for i in df1['pickup_datetime']:
#     df1[i] = datetime.strptime(i,"%Y-%m-%d %H:%M:%S")
```

In [27]:
```
df1 = df1.assign(hour = df1.pickup_datetime.dt.hour,
             day= df1.pickup_datetime.dt.day,
             month = df1.pickup_datetime.dt.month,
             year = df1.pickup_datetime.dt.year,
             dayofweek = df1.pickup_datetime.dt.dayofweek)
```

In [28]:
```
df1.pickup_datetime.dt
```

Out[28]: <pandas.core.indexes.accessors.DatetimeProperties object at 0x0000007FC1AD0160>

[29]:
```
df1.head()
```

Out[29]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitu

In

0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.7232
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.7503
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.7726
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.8033
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.7612

Heversine formula to calculate the distance between two points and journey, using the longitude and latitude values.

In [30]:
```
from math import *
```

In [31]:
```
# function to calculate the travel distance from the longitudes and latitudes
def distance_transform(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []
        for pos in
range(len(longitude1)):
        long1,lati1,long2,lati2 = map(radians,[longitude1[pos],latitude1[pos],lon
dist_long = long2 - long1        dist_lati = lati2 - lati1
        a = sin(dist_lati/2)**2 + cos(lati1) * cos(lati2) * sin(dist_long/2)**2
c = 2 * asin(sqrt(a))*6371         travel_dist.append(c)
           return
travel_dist
```

In [32]:
```
df1['dist_travel_km'] = distance_transform(df1['pickup_longitude'],
df1['pickup_latitude'],
df1['dropoff_longitude'],
df1['dropoff_latitude']
                                              )
```

In [33]:
```
df1['dist_travel_km'] = distance_transform(df1['pickup_longitude'].to_numpy(),
df1['pickup_latitude'].to_numpy()
df1['dropoff_longitude'].to_numpy
df1['dropoff_latitude'].to_numpy(                                                )
```

[34]:
```
df1.head()
```

Out[34]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitu
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.7232

In

1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.7503
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.7726
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.8033
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.7612

In [35]:
```
# drop the column 'pickup_daetime' using drop()
# 'axis = 1' drops the specified column

df1 = df1.drop('pickup_datetime',axis=1)
```

In [36]:
```
df1.info()
```

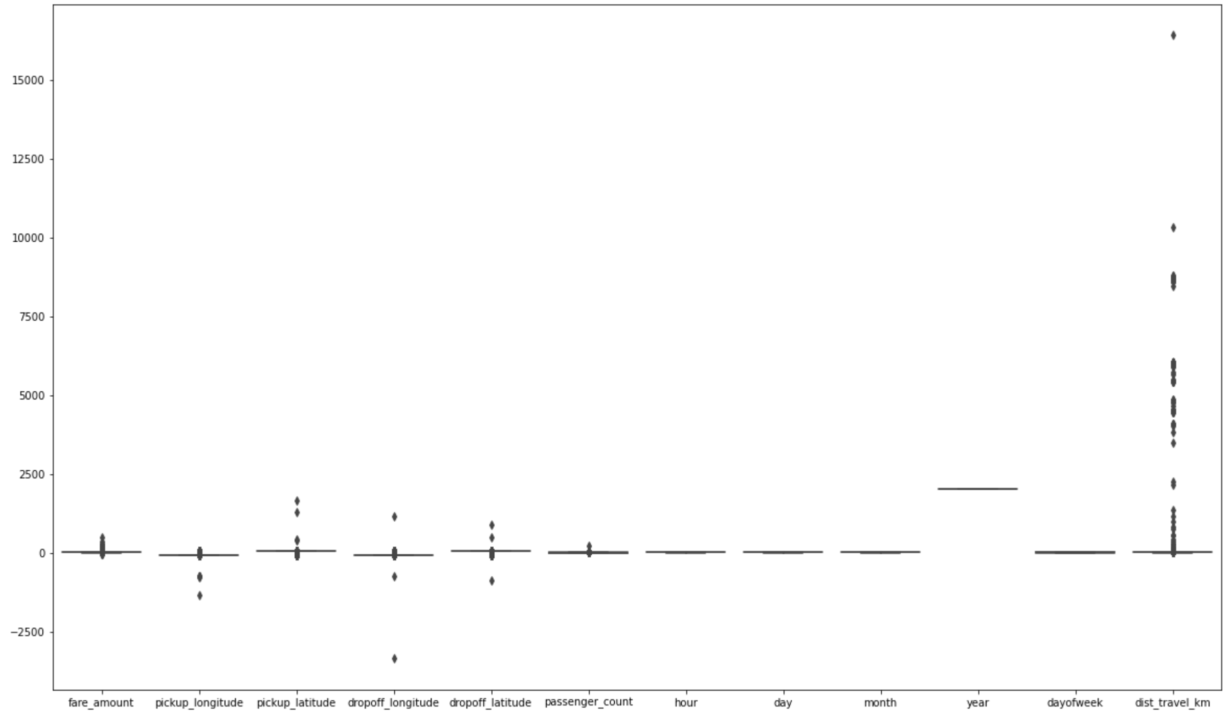
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
  0fare_amount        200000 non-null  float64
  1pickup_longitude   200000 non-null  float64
  2pickup_latitude    200000 non-null  float64
  3dropoff_longitude  200000 non-null  float64
  4dropoff_latitude   200000 non-null  float64
  5passenger_count    200000 non-null  int64
  6hour               200000 non-null  int64
  7day                200000 non-null  int64
  8month              200000 non-null  int64
  9year               200000 non-null  int64
  10      dayofweek        200000 non-null  int64
  11      dist_travel_km     200000 non-null  float64 dtypes: float64(6),
 int64(6) memory usage: 18.3 MB
```

Identify outliers

In [37]:
```
import seaborn as sns
```

In [38]:
```
plt.figure(figsize=(20,12))
sns.boxplot(data= df1)
```

Out[38]: <AxesSubplot:>



Treat outliers

In [ ]:
```
err
```

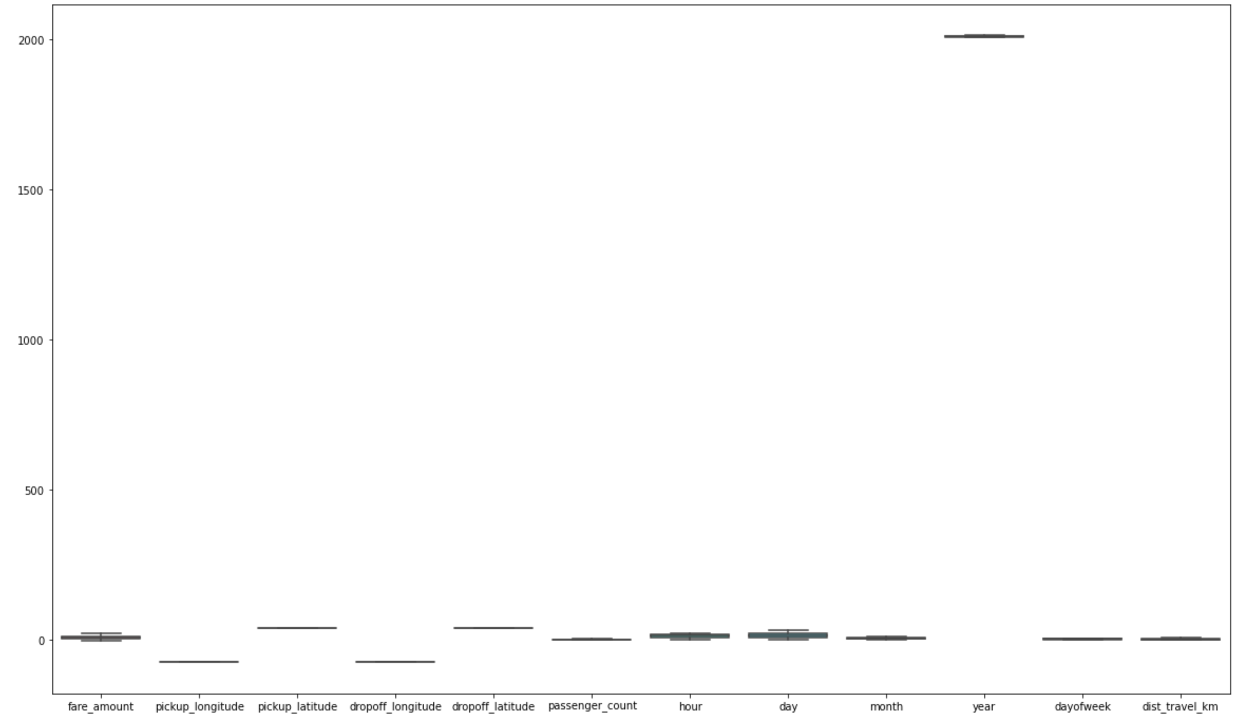
In [39]:
```
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df1[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df1 , c)
    return df1
```

In [40]:
```
 df1 = treat_outliers_all(df1 , df1.columns)
```

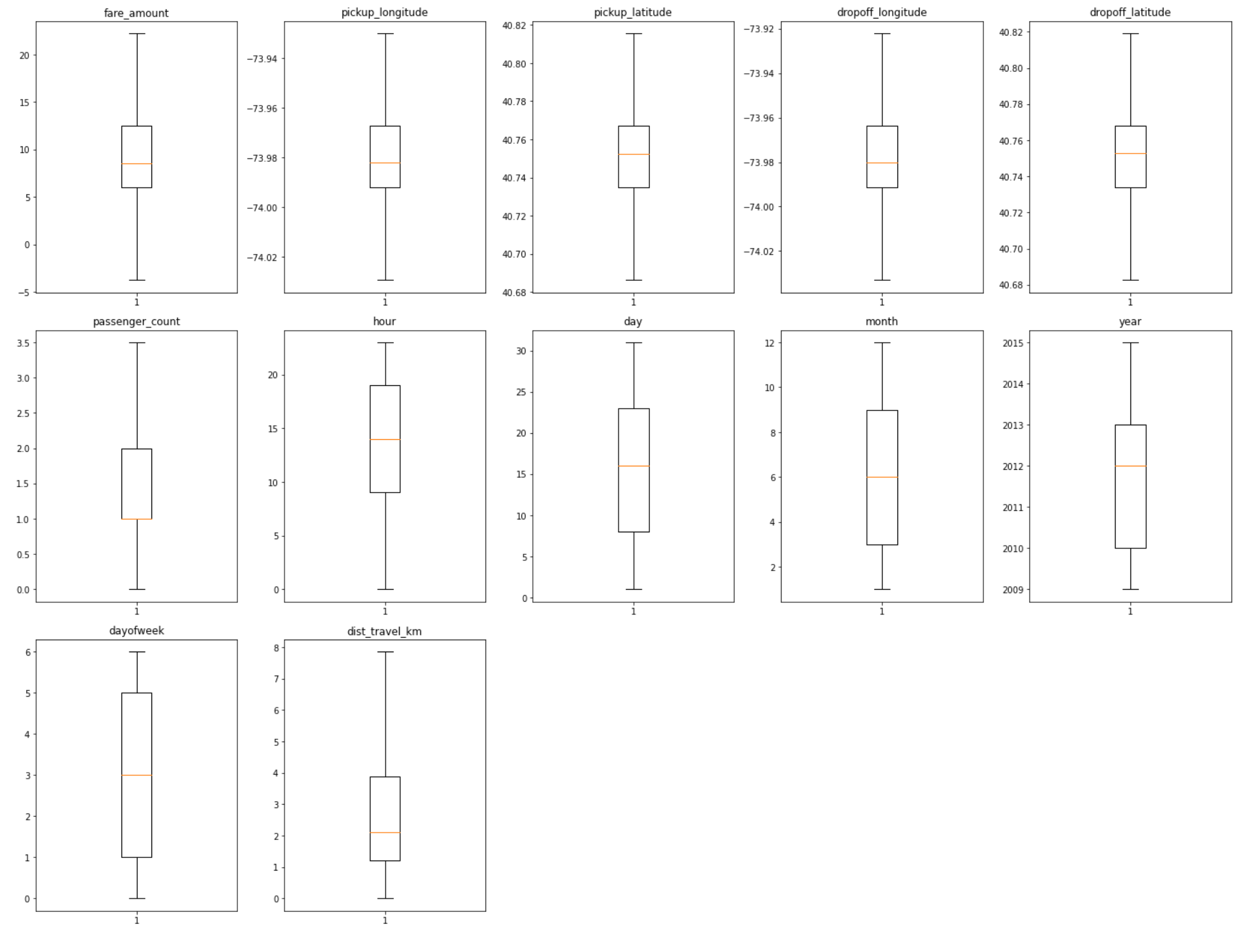
Out[41]: <AxesSubplot:>

In


2000
1500
1000
500
0
fare_amount
pickup_longitude
pickup_latitude
dropoff_longitude
dropoff_latitude
passenger_count
hour
day
month
year
dayofweek
dist_travel_km

In [42]:

```
plt.figure(figsize=(20,30))
for i , variable in enumerate(df1.iloc[: , 0::]):
    plt.subplot(6,5,i+1)
    plt.boxplot(df1[variable] , whis = 1.5)
    plt.tight_layout()
    plt.title(variable)
plt.show()
```



In [43]:
```
df1.shape
```

Out[43]:
```
(200000, 12)
```

In [74]:
```
df1.describe()
```

Out[74]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passen
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	2000
mean	10.081121	-73.978310	40.750196	-73.976193	40.750151	
std	5.440253	0.020508	0.025659	0.022879	0.028660	
min	-3.750000	-74.029432	40.686252	-74.033029	40.682558	
25%	6.000000	-73.992065	40.734796	-73.991407	40.733824	
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	
75%	12.500000	-73.967154	40.767158	-73.963659	40.768001	
max	22.250000	-73.929786	40.815701	-73.922036	40.819267	

In [44]:
```
df1.iloc[: , 0:]
```

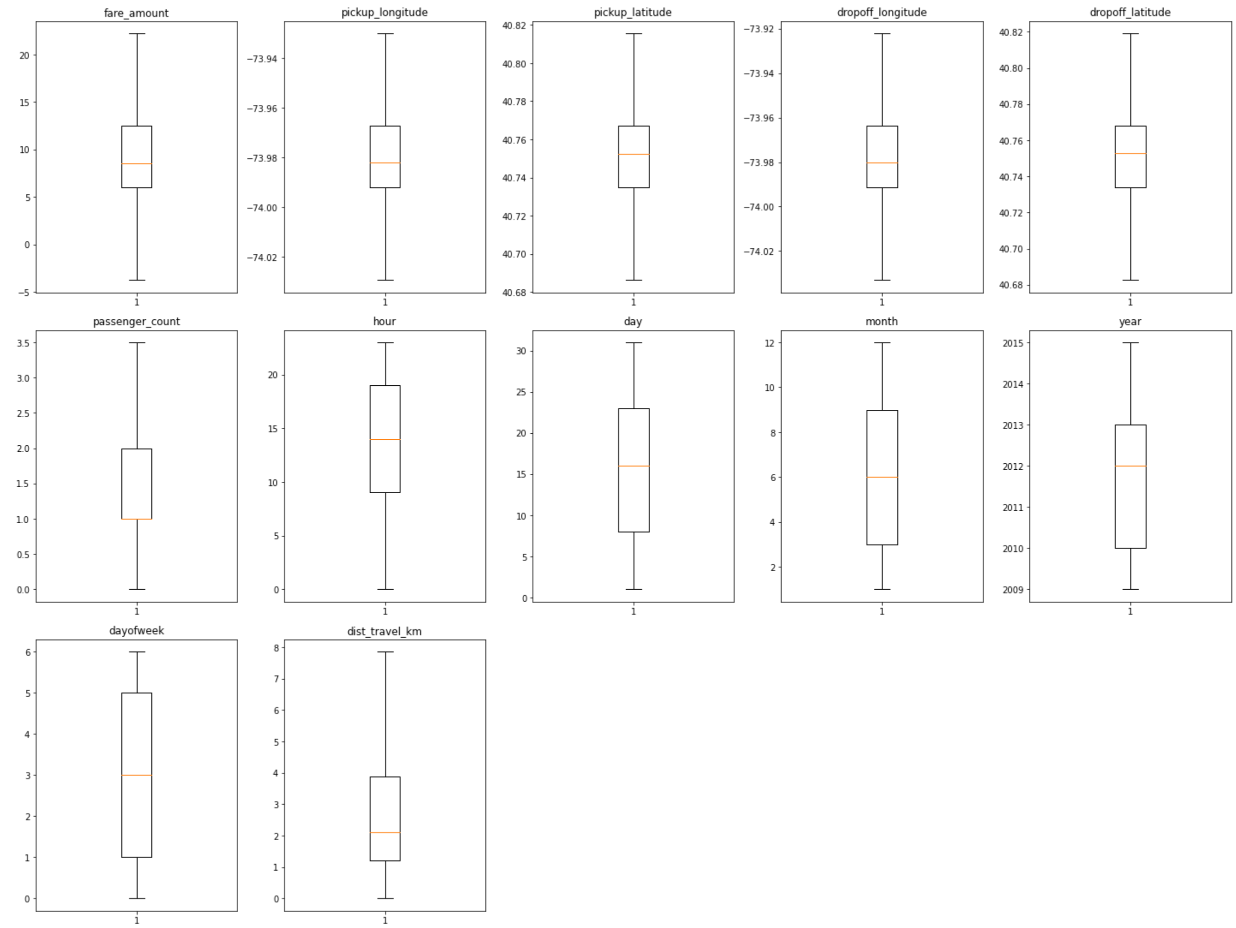
Out[44]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passeng
0	7.50	-73.999817	40.738354	-73.999512	40.723217	
1	7.70	-73.994355	40.728225	-73.994710	40.750325	
2	12.90	-74.005043	40.740770	-73.962565	40.772647	
3	5.30	-73.976124	40.790844	-73.965316	40.803349	
4	16.00	-73.929786	40.744085	-73.973082	40.761247	
...	...	...	...	...	...	
199995	3.00	-73.987042	40.739367	-73.986525	40.740297	
199996	7.50	-73.984722	40.736837	-74.006672	40.739620	
199997	22.25	-73.986017	40.756487	-73.922036	40.692588	
199998	14.50	-73.997124	40.725452	-73.983215	40.695415	
199999	14.10	-73.984395	40.720077	-73.985508	40.768793	

200000 rows × 12 columns

In [45]:
```
df2 = treat_outliers_all(df1 , df1.iloc[: , 0:])
```

In [46]:
```
plt.figure(figsize=(20,30))
for i , variable in enumerate(df2.iloc[: , 0::]):
    plt.subplot(6,5,i+1)
    plt.boxplot(df2[variable] , whis = 1.5)
    plt.tight_layout()
    plt.title(variable)
plt.show()
```



In [47]:
```
df1.head()
```

Out[47]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_co
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	

In [48]:
```
df2.head()
```

Out[48]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_co
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	

Corelation

In [75]:
```
# use the corr() function to generate the correlation matrix of the numeric varia
co = df1.corr()

# print the correlation matrix
display(co,type(co))
```

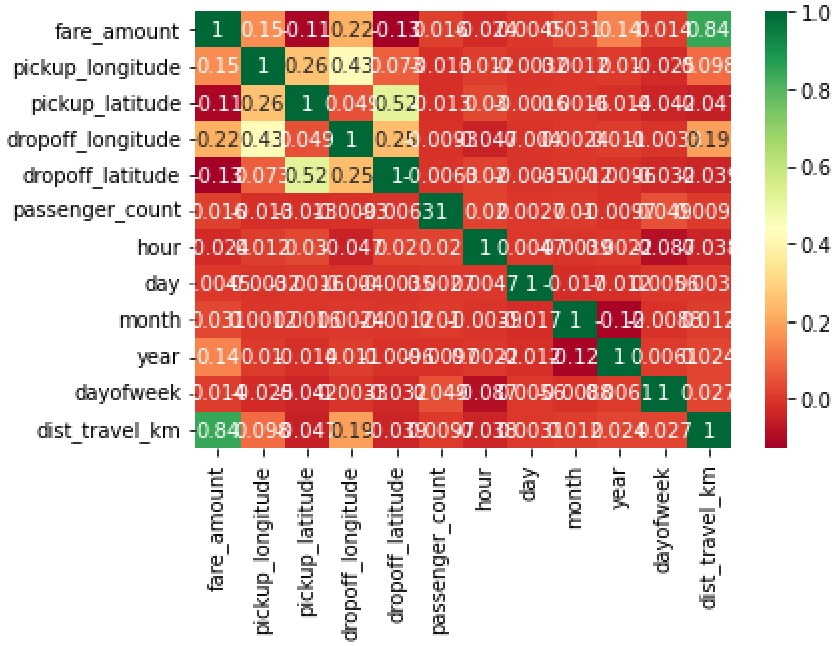
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitud
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.12587
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.07331
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.51573
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.24567
dropoff_latitude	-0.125871	0.073311	0.515735	0.245674	1.00000
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.00632
hour	-0.023623	0.011579	0.029681	-0.046558	0.01976
day	0.004534	-0.003204	-0.001553	-0.004007	-0.00349
month	0.030817	0.001169	0.001562	0.002391	-0.00119
year	0.141277	0.010198	-0.014243	0.011346	-0.00959
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.03193
dist_travel_km	0.844363	0.098078	-0.046821	0.186531	-0.03887

```
pandas.core.frame.DataFrame
```

In [77]:

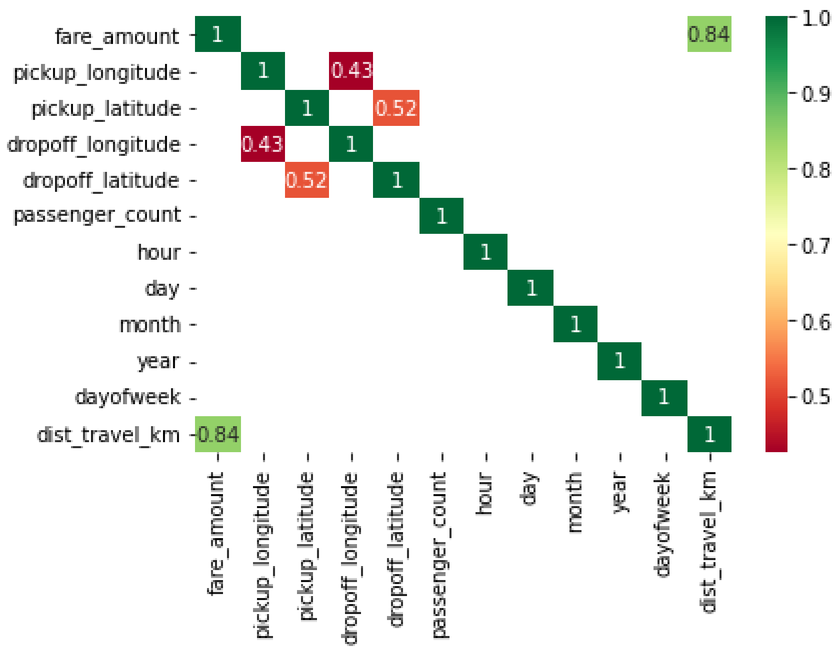
```python
# plot heatmap to visualize the null values in each column
# 'cbar = False' does not show the color axis
sns.heatmap(df1.corr(),cmap = 'RdYlGn',annot=True)

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



In [79]:
```
# plot heatmap to visualize the null values in each column
# 'cbar = False' does not show the color axis
sns.heatmap(co[(co >= 0.4) | (co <= -0.4)],cmap = 'RdYlGn',annot=True)

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



Implement linear regression and random forest regression models.

1. Split the data into features and target dataframes

In [80]:
```
# select only the target variable 'amount' and store it in dataframe 'y'
y = pd.DataFrame(df1['fare_amount'])
```

In [81]:
```
# use 'drop()' to remove the variable 'amount' from df_taxi
# 'axis = 1' drops the corresponding column(s)
x = df1.drop('fare_amount',axis = 1)
```

2. Split the data into training and test sets

In [82]:
```
from sklearn.model_selection import train_test_split
```

[83]:
```
# split data into train subset and test subset for predictor and target variables
# 'test_size' returns the proportion of data to be included in the test set
# set 'random_state' to generate the same dataset each time you run the code
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random
# check the dimensions of the train & test subset for
```

In

```
# print dimension of predictors train set
print("The shape of X_train is:",x_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",x_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (160000, 11)
The shape of X_test is: (40000, 11)
The shape of y_train is: (160000, 1)
The shape of y_test is: (40000, 1)
```

Linear Regression

```
Ordinary Least Squares regression (OLS) is a common technique for estimating
coefficients of linear regression equations which describe the relationship
between one or more independent quantitative variables and a dependent variable
```

In [84]:

```
import statsmodels.api as sm
```

[85]:

```
# build a full model using OLS()
# consider the log of sales price as the target variable
# use fit() to fit the model on train data
linreg_full = sm.OLS(y_train, x_train).fit()

# print the summary output
print(linreg_full.summary())
```

```
                            OLS Regression Results
==============================================================================
==========
Dep. Variable:            fare_amount   R-squared (uncentered):
0.941
Model:                            OLS   Adj. R-squared (uncentered):
0.941
Method:                 Least Squares   F-statistic:
2.316e+05
Date:                Thu, 18 Aug 2022   Prob (F-statistic):                0.00
Time:                        16:10:51   Log-Likelihood:
3.9082e+05
No. Observations:              160000   AIC:
7.817e+05
Df Residuals:                  159989   BIC:
7.818e+05
Df Model:                          11
Covariance Type:            nonrobust
```

In

In [ ]:
```
# build a full model using OLS()
# consider the log of sales price as the target variable
# use fit() to fit the model on train data
# linreg_full = sm.OLS(x_train,y_train).fit()

# print the summary output
# print(linreg_full.summary())
```

In [86]:
```
linreg_full_predictions = linreg_full.predict(x_test)
linreg_full_predictions
```

Out[86]:
```
49673      6.603748 171551
5.392594
5506       9.556585
38370      6.120355
36930      5.898148
             ...
63840      8.868155
128107     2.604096
108940    11.022542
199933    12.126706
22902     12.005790
Length: 40000, dtype: float64
```

[87]:
```
actual_fare = y_test["fare_amount"]
actual_fare
```

Out[87]:
```
49673      4.0
171551     6.1
5506       8.5
38370      4.9
36930      6.5
          ...
63840     10.7
128107     2.5
108940    10.0
199933    11.3
22902     12.5
Name: fare_amount, Length: 40000, dtype: float64
```

In [88]:
```
from statsmodels.tools.eval_measures import rmse
```

In [89]:
```
# calculate rmse using rmse()
linreg_full_rmse = rmse(actual_fare,linreg_full_predictions )

# calculate R-squared using rsquared
linreg_full_rsquared = linreg_full.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_full_rsquared_adj = linreg_full.rsquared_adj
```

[90]:
```
# create the result table for all accuracy scores
# accuracy measures considered for model comparision are RMSE, R-squared value an
```

In

```
# create a list of column names
cols = ['Model', 'RMSE', 'R-Squared', 'Adj. R-Squared']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)

# compile the required information
linreg_full_metrics = pd.Series({'Model': "Linreg full model ",
                     'RMSE':linreg_full_rmse,
                     'R-Squared': linreg_full_rsquared,
                     'Adj. R-Squared': linreg_full_rsquared_adj
                   })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a nam
result_tabulation = result_tabulation.append(linreg_full_metrics, ignore_index =
# print the result table
result_tabulation
```

Out[90]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model	2.759165	0.940922	0.940918

Decision Tree

In [91]:

```
from sklearn import tree from
sklearn.tree import export_graphviz
from sklearn import metrics
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
```

In [92]:

```
# instantiate the 'DecisionTreeRegressor' object using 'mse' criterion
# pass the 'random_state' to obtain the same samples for each time you run the co
decision_tree = DecisionTreeRegressor(criterion = 'mse', random_state = 10) #Max
# fit the model using fit() on train data decision_tree_model =
decision_tree.fit(x_train, y_train) #fit() method is define
```

```
C:\Users\SIT\anaconda3\lib\site-packages\sklearn\tree\_classes.py:397: FutureWa
rning: Criterion 'mse' was deprecated in v1.0 and will be removed in version 1.
2. Use `criterion='squared_error'` which is equivalent.
  warnings.warn(
```

In [93]:

```
y_pred_DT=decision_tree_model.predict(x_test)
y_pred_DT
```

Out[93]:

```
array([ 6. ,  6.5,  8.5, ..., 10. , 10.9, 12. ])
```

In [94]:
```
y_test
```

Out[94]:

	fare_amount
49673	4.0
171551	6.1
5506	8.5
38370	4.9
36930	6.5
...	...
63840	10.7
128107	2.5
108940	10.0
199933	11.3
22902	12.5

40000 rows × 1 columns

In [95]:
```
r_squared_DT=decision_tree_model.score(x_test,y_test)
# Number of observation or sample size
n = 159999

# No of independent variables
p = 11

#Compute Adj-R-Squared
Adj_r_squared_DT = 1 - (1-r_squared_DT)*(n-1)/(n-p-1)
Adj_r_squared_DT
```

Out[95]: 0.6052778859187499

In [96]:
```
# Compute RMSE
rmse_DT = sqrt(mean_squared_error(y_test, y_pred_DT))
```

[97]:
```
# compile the required information linreg_full_metrics =
pd.Series({'Model': "Decision Tree Model ",
                     'RMSE':rmse_DT,
                     'R-Squared': r_squared_DT,
                     'Adj. R-Squared': Adj_r_squared_DT
                   })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a nam
result_tabulation = result_tabulation.append(linreg_full_metrics, ignore_index =
# print the result table
result_tabulation
```

In
Out[97]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model	2.759165	0.940922	0.940918
1	Decision Tree Model	3.424367	0.605305	0.605278

Decision Tree with pruning

In [98]:

```
# instantiate the 'DecisionTreeRegressor' object
# max_depth: maximum depth of the tree
# max_leaf_nodes: maximum number of leaf nodes in the tree
# pass the 'random_state' to obtain the same samples for each time you run the co
prune = DecisionTreeRegressor(max_depth = 10, max_leaf_nodes = 32 , random_state

# fit the model using fit() on train data
decision_tree_prune = prune.fit(x_train, y_train)
```

In [99]:

```
y_pred_DT_prune=decision_tree_prune.predict(x_test)
y_pred_DT_prune
```

Out[99]:

```
array([ 4.99914948,  5.67888429,  9.75156665, ..., 11.96624034,
       11.08746429, 11.08746429])
```

In [100]:
```
r_squared_DT_prune=decision_tree_prune.score(x_test,y_test)
# Number of observation or sample size
n = 159999

# No of independent variables
p = 11

#Compute Adj-R-Squared
Adj_r_squared_DT_prune = 1 - (1-r_squared_DT_prune)*(n-1)/(n-p-1)
Adj_r_squared_DT_prune
# Compute RMSE rmse_DT_prune = sqrt(mean_squared_error(y_test,
y_pred_DT_prune))
```

In [101]:
```
# compile the required information linreg_full_metrics = pd.Series({'Model':
"Decision Tree Model after pruning ",
                     'RMSE':rmse_DT_prune,
                     'R-Squared': r_squared_DT_prune,
                     'Adj. R-Squared': Adj_r_squared_DT_prune
                   })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a
nam result_tabulation = result_tabulation.append(linreg_full_metrics,
ignore_index =
# print the result table
result_tabulation
```

Out[101]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model	2.759165	0.940922	0.940918
1	Decision Tree Model	3.424367	0.605305	0.605278
2	Decision Tree Model after pruning	2.583026	0.775426	0.775411

Random Forest

In [102]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics from sklearn import
preprocessing
from sklearn.model_selection import GridSearchCV
```

[103]:
```
#intantiate the regressor
rf_reg = RandomForestRegressor(n_estimators=100, random_state=10)

# fit the regressor with training dataset
rf_reg.fit(x_train, y_train)
```

In

```
C:\Users\SIT\AppData\Local\Temp/ipykernel_6136/854013030.py:5:
DataConversionWa rning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example using
ravel().  rf_reg.fit(x_train, y_train)
```

Out[103]:
```
RandomForestRegressor(random_state=10)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [104]:
```
# predict the values on test dataset using predict()
y_pred_RF = rf_reg.predict(x_test)
y_pred_RF
```

Out[104]:
```
array([ 4.791 ,  6.73  ,  8.98  , ..., 11.0875, 11.808 , 13.855 ])
```

In [105]:
```
r_squared_RF = rf_reg.score(x_test,y_test)
# Number of observation or sample size
n = 159999

# No of independent variables
p = 11

#Compute Adj-R-Squared
Adj_r_squared_RF = 1 - (1-r_squared_RF)*(n-1)/(n-p-1)
Adj_r_squared_RF
# Compute RMSE
rmse_RF = sqrt(mean_squared_error(y_test, y_pred_RF))
```

In [106]:
```
# Calculate MAE
rf_reg_MAE = metrics.mean_absolute_error(y_test, y_pred_RF)
print('Mean Absolute Error (MAE):', rf_reg_MAE)

# Calculate MSE
rf_reg_MSE = metrics.mean_squared_error(y_test, y_pred_RF)
print('Mean Squared Error (MSE):', rf_reg_MSE)

# Calculate RMSE
rf_reg_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_RF))
print('Root Mean Squared Error (RMSE):', rf_reg_RMSE)
```

```
Mean Absolute Error (MAE): 1.4891101490773808
Mean Squared Error (MSE): 5.579342779120985
Root Mean Squared Error (RMSE): 2.362063246215263
```

[107]:
```
# compile the required information linreg_full_metrics =
pd.Series({'Model': "Random Forest ",
                     'RMSE':rf_reg_RMSE,
                     'R-Squared': r_squared_RF,
                     'Adj. R-Squared': Adj_r_squared_RF
```

In

```
                   })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a
nam result_tabulation = result_tabulation.append(linreg_full_metrics,
ignore_index =
# print the result table
result_tabulation
```

Out[107]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model	2.759165	0.940922	0.940918
1	Decision Tree Model	3.424367	0.605305	0.605278
2	Decision Tree Model after pruning	2.583026	0.775426	0.775411
3	Random Forest	2.362063	0.812205	0.812192

------ End ------

In [ ]:

In [ ]:

```
str = "abc UTC "
str.strip('UTC ')
# df1['pickup_datetime'].strip('UTC ')
# df1.head()
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In

In [ ]:

In [ ]:
```
# Formatting the Format the datetime column "pickup_datetime" and only keep the d
date_st = [dates.strip

           ("UTC ") for dates in df1['pickup_datetime']]
df1['pickup_datetime'] = [datetime.strptime(dates, '%Y-%m-%d %H:%M:%S') for dates
df1['pickup_datetime'] = df1['pickup_datetime'].dt.date
```

In [ ]:
```
# Formatting the Format the datetime column "pickup_datetime" and only keep the d
date_st = [dates.strip("UTC ") for dates in df1['pickup_datetime']]
df1['pickup_datetime'] = [datetime.strptime(dates, '%Y-%m-%d %H:%M:%S') for dates
df1['pickup_datetime'] = df1['pickup_datetime'].dt.date
```

In [ ]:
```
# final print
df1
```

In [ ]:
```
# sorting the dataframe 'df1' based on the pickup_datetime date ascending and pr
df1.sort_values(by='pickup_datetime', ascending=True, inplace=True, ignore_index=
df1.head(10)
```

In [ ]:
```
#Calculating distances between the pick-up and drop-off locations.
from math import sqrt

lat1 = df1['pickup_latitude']
lon1 = df1['pickup_longitude']
lat2 = df1['dropoff_latitude']
lon2 = df1['dropoff_longitude']
```

In [ ]:
```
# df1['distance'] = np.sqrt((lat1 - lat2)**2 + (lon1 - lon2)**2)
# df1.tail(10)
```

In [ ]:
```
# p = pi/180
# a = 0.5 - cos((lat2-lat1)*p)/2 + cos(lat1*p) * cos(lat2*p) * (1-cos((lon2-lon1)
# df1['distance'] = 12742 * asin(sqrt(a)) #2*R*asin
```

In [ ]:
```
from math import cos, asin, sqrt, pi

def distance(lat1, lon1, lat2, lon2):
    p = pi/180
    a = []
    for i in range(len(lat1)):
        a.append(0.5 - cos((lat2[i]-lat1[i])*p)/2 + cos(lat1[i]*p) * cos(lat2[i]*
    return 12742 * asin(sqrt(a[i])) #2*R*asin...
```

In [ ]:
```
df1['distance'] = distance(lat1,lon1,lat2,lon2)
```

In [ ]:
```
df1.tail(10)
```

In [ ]:
```
# Selecting all the records in January 2014 and store it in a variable called 'tr
# Finally print your dataframe that must look like the one below. start =
pd.to_datetime("2014-01-01").date() end = pd.to_datetime("2014-01-31").date()
df_jan14 = df1.loc[(df1['pickup_datetime'] >= start) & (df1['pickup_datetime']
<=
# your final print
df_jan14
```

In [ ]:
```
#excluding rows from the variable 'trip_jan14' that will be considered outliers.
# The outliers in this task are considered the values below quantile 5% and
above # Therefore, selecting all rows that are within the range 5% and 95% of
this two fare_low = df_jan14['fare_amount'].quantile(0.05) fare_hi =
df_jan14['fare_amount'].quantile(0.95) dist_low =
df_jan14['distance'].quantile(0.05) dist_hi =
df_jan14['distance'].quantile(0.95)

outliers_list = df_jan14[(df_jan14["distance"] < dist_hi) &
(df_jan14["distance"] filtered = outliers_list # your final print filtered
```

In [ ]:
```
#Data Visualization
#Creating two scatter plots for the fare amount in y-axis and trip distances in
x # without the outliers (i.e., stored in variable 'filtered') and with the
outlier fig, ax1 = plt.subplots(1,2, figsize=(20,8))
filtered.plot.scatter(x='distance', y='fare_amount', s=5, ax=ax1[0],
title="Outli                                        xlabel="Distance", ylabel="Fare amount
(USD)") df_jan14.plot.scatter(x='distance', y='fare_amount', s=5, ax=ax1[1],
title="With                                         xlabel="Distance", ylabel="Fare amount
(USD)") plt.suptitle("Fare amount vs. Travel distance", fontsize=14) plt.show()
```

In [ ]:
```
err
#sns.pairplot(df1)
```

In [ ]:
```
plt.figure(figsize=(15,15))
df1.boxplot()
```

In [ ]:
```
sns.boxplot(df1['fare_amount'],data = df1)
```

In [ ]:
```
df1_sample = df1.loc[:10000,:]
df1_sample.shape
```

In [ ]:

Detecting outliers

```
df1_sample
```

In [ ]:
```
df1_sample.describe()
```

In [ ]:
```
df1_sample.boxplot()
```

Z-score

In [ ]:
```
def ZScore(dataFrame):
    outliers = []
    for i in dataFrame.columns:
        for val in dataFrame[i]:
            z = (val - dataFrame[i].mean())/dataFrame[i].std()
            if z > 3 or z < -3:
                outliers.append(i)
                break
    return outliers
```

In [ ]:
```
outliers_list = ZScore(df1_sample)
outliers_list
```

In [ ]:
```
def ZScore_detect(dataFrame):
    outliers = []
    for i in dataFrame.columns:
#         for val in dataFrame[i]:
            upper = dataFrame[i].mean() + (3 * dataFrame[i].std())
            lower = dataFrame[i].mean() - (3 * dataFrame[i].std())

            if any((dataFrame[i]>upper) | (dataFrame[i]<lower)):
                outliers.append(i)
                break
    return outliers
```

In [ ]:
```
outliers_list1 = ZScore_detect(df1_sample)
outliers_list1
```

In [ ]:
```
err
```

In [ ]:

```
def ZScore_treat(dataFrame,outliers):
   for i in outliers:
       upper_limit = dataFrame[i].mean() + (3 * dataFrame[i].std())
       lower_limit = dataFrame[i].mean() - (3 * dataFrame[i].std())
       for val in dataFrame[i]:
           z = (val - dataFrame[i].mean())/dataFrame[i].std()
           if z > 3:
               val = upper_limit
               print("UL")
           if z < -3:
               val = lower_limit

   return dataFrame
```

In [ ]:

```
df1_sample = ZScore_treat(df1_sample,outliers_list)
```

In [ ]:

```
outliers_list = ZScore(df1_sample)
outliers_list
```

In [ ]:

```
df1_sample.boxplot()
```

In [ ]:

```
df1.corr()
```

Outlier detection using IQR

In [ ]:

In [ ]:
```
df1_sample = df1.loc[:10000,:]
df1_sample.shape
```

In [ ]:
```
def outlier_IQR(dataFrame):
    outliers = []
    for i in dataFrame.columns:
        q1 = np.percentile(dataFrame[i],25)
        q3 = np.percentile(dataFrame[i],75)
        iqr = q3 - q1

        l_bound = q1 - (1.5 * iqr)
        u_bound = q3 + (1.5 * iqr)

        print(i,l_bound,u_bound)

        if any((dataFrame[i] < l_bound) | (dataFrame[i] > u_bound)):
            outliers.append(i)
            pass

    return outliers
```

In [ ]:
```
outliers_list = outlier_IQR(df1_sample)
outliers_list
```

Outlier treatment

In [ ]:
```
def outlier_treat_IQR(dataFrame):
    outliers = []
    for i in dataFrame.columns:
        q1 = np.percentile(dataFrame[i],25)
        q3 = np.percentile(dataFrame[i],75)
        iqr = q3 - q1

        l_bound = q1 - (1.5 * iqr)
        u_bound = q3 + (1.5 * iqr)

        print(i,l_bound,u_bound)

        np.where(dataFrame[i] > u_bound,u_bound,dataFrame[i])
        if i == 'fare_'
        np.where(dataFrame[i] < l_bound,l_bound)

    return dataFrame
```

In [ ]:
```
df1_sample = outlier_treat_IQR(df1_sample)
outliers_list = outlier_IQR(df1_sample)
outliers_list
```

In [ ]: