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.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split

df = pd.read_csv('uber.csv')
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
```

1. Pre-process the dataset.

```
df.shape
```

```
(200000, 9)
```

```
df.head()
```

```
   Unnamed: 0                            key  fare_amount  \
0    24238194    2015-05-07 19:52:06.0000003          7.5   
1    27835199    2009-07-17 20:04:56.0000002          7.7   
2    44984355   2009-08-24 21:45:00.00000061         12.9   
3    25894730    2009-06-26 08:22:21.0000001          5.3   
4    17610152  2014-08-28 17:47:00.000000188         16.0   
```

```
           pickup_datetime  pickup_longitude  pickup_latitude  \
0  2015-05-07 19:52:06 UTC        -73.999817        40.738354
1  2009-07-17 20:04:56 UTC        -73.994355        40.728225
2  2009-08-24 21:45:00 UTC        -74.005043        40.740770
3  2009-06-26 08:22:21 UTC        -73.976124        40.790844
4  2014-08-28 17:47:00 UTC        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count
0         -73.999512         40.723217                1
1         -73.994710         40.750325                1
2         -73.962565         40.772647                1
3         -73.965316         40.803349                3
4         -73.973082         40.761247                5

df.isnull()

        Unnamed: 0    key  fare_amount  pickup_datetime
pickup_longitude  \
0            False  False        False            False
False
1            False  False        False            False
False
2            False  False        False            False
False
3            False  False        False            False
False
4            False  False        False            False
False
...            ...    ...          ...              ...
...
199995       False  False        False            False
False
199996       False  False        False            False
False
199997       False  False        False            False
False
199998       False  False        False            False
False
199999       False  False        False            False
False

        pickup_latitude  dropoff_longitude  dropoff_latitude
passenger_count
0                 False              False             False
False
1                 False              False             False
False
2                 False              False             False
False
3                 False              False             False
```

```
False
4                  False              False              False
False
...                  ...                ...                ...
...
199995             False              False              False
False
199996             False              False              False
False
199997             False              False              False
False
199998             False              False              False
False
199999             False              False              False
False

[200000 rows x 9 columns]
```

```
df.drop(columns=["Unnamed: 0", "key"], inplace=True)
df.head()
```

```
   fare_amount          pickup_datetime  pickup_longitude
pickup_latitude  \
0          7.5  2015-05-07 19:52:06 UTC        -73.999817
40.738354
1          7.7  2009-07-17 20:04:56 UTC        -73.994355
40.728225
2         12.9  2009-08-24 21:45:00 UTC        -74.005043
40.740770
3          5.3  2009-06-26 08:22:21 UTC        -73.976124
40.790844
4         16.0  2014-08-28 17:47:00 UTC        -73.925023
40.744085

   dropoff_longitude  dropoff_latitude  passenger_count
0         -73.999512         40.723217                1
1         -73.994710         40.750325                1
2         -73.962565         40.772647                1
3         -73.965316         40.803349                3
4         -73.973082         40.761247                5
```

```
df.isnull().sum()
```

```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
```

```
passenger_count      0
dtype: int64
```

```
df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inpl
ace = True)
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),
inplace = True)
```

```
df.dtypes
```

```
fare_amount           float64
pickup_datetime        object
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
passenger_count         int64
dtype: object
```

```
# From the above output, we see that the data type of
'pickup_datetime' is 'object
# But 'pickup_datetime'is a date time stamp variable, which is wrongly
interpreted as 'object', so we will convert this variable data type to
'datetime'.
```

```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime)
df.dtypes
```

```
fare_amount                         float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                    float64
pickup_latitude                     float64
dropoff_longitude                   float64
dropoff_latitude                    float64
passenger_count                       int64
dtype: object
```

```
# we will extract time feature from the 'pickup_datetime'
# we will add a variable which measures the distance between pickup
and drop
```

```
df = df.assign(hour = df.pickup_datetime.dt.hour,
               day = df.pickup_datetime.dt.day,
               month = df.pickup_datetime.dt.month,
               year = df.pickup_datetime.dt.year,
               dayofweek = df.pickup_datetime.dt.dayofweek)
```

```
df
```

```
        fare_amount           pickup_datetime  pickup_longitude  \
0               7.5 2015-05-07 19:52:06+00:00        -73.999817
```

```
1                7.7 2009-07-17 20:04:56+00:00        -73.994355
2               12.9 2009-08-24 21:45:00+00:00        -74.005043
3                5.3 2009-06-26 08:22:21+00:00        -73.976124
4               16.0 2014-08-28 17:47:00+00:00        -73.925023
...              ...                       ...               ...
199995           3.0 2012-10-28 10:49:00+00:00        -73.987042
199996           7.5 2014-03-14 01:09:00+00:00        -73.984722
199997          30.9 2009-06-29 00:42:00+00:00        -73.986017
199998          14.5 2015-05-20 14:56:25+00:00        -73.997124
199999          14.1 2010-05-15 04:08:00+00:00        -73.984395

        pickup_latitude  dropoff_longitude  dropoff_latitude
passenger_count  \
0             40.738354         -73.999512         40.723217
1
1             40.728225         -73.994710         40.750325
1
2             40.740770         -73.962565         40.772647
1
3             40.790844         -73.965316         40.803349
3
4             40.744085         -73.973082         40.761247
5
...                 ...                ...               ...
...
199995        40.739367         -73.986525         40.740297
1
199996        40.736837         -74.006672         40.739620
1
199997        40.756487         -73.858957         40.692588
2
199998        40.725452         -73.983215         40.695415
1
199999        40.720077         -73.985508         40.768793
1

        hour  day  month  year  dayofweek
0         19    7      5  2015          3
1         20   17      7  2009          4
2         21   24      8  2009          0
3          8   26      6  2009          4
4         17   28      8  2014          3
...      ...  ...    ...   ...        ...
199995    10   28     10  2012          6
199996     1   14      3  2014          4
199997     0   29      6  2009          0
199998    14   20      5  2015          2
199999     4   15      5  2010          5

[200000 rows x 12 columns]
```

```
df = df.drop(["pickup_datetime"], axis =1)
df
```

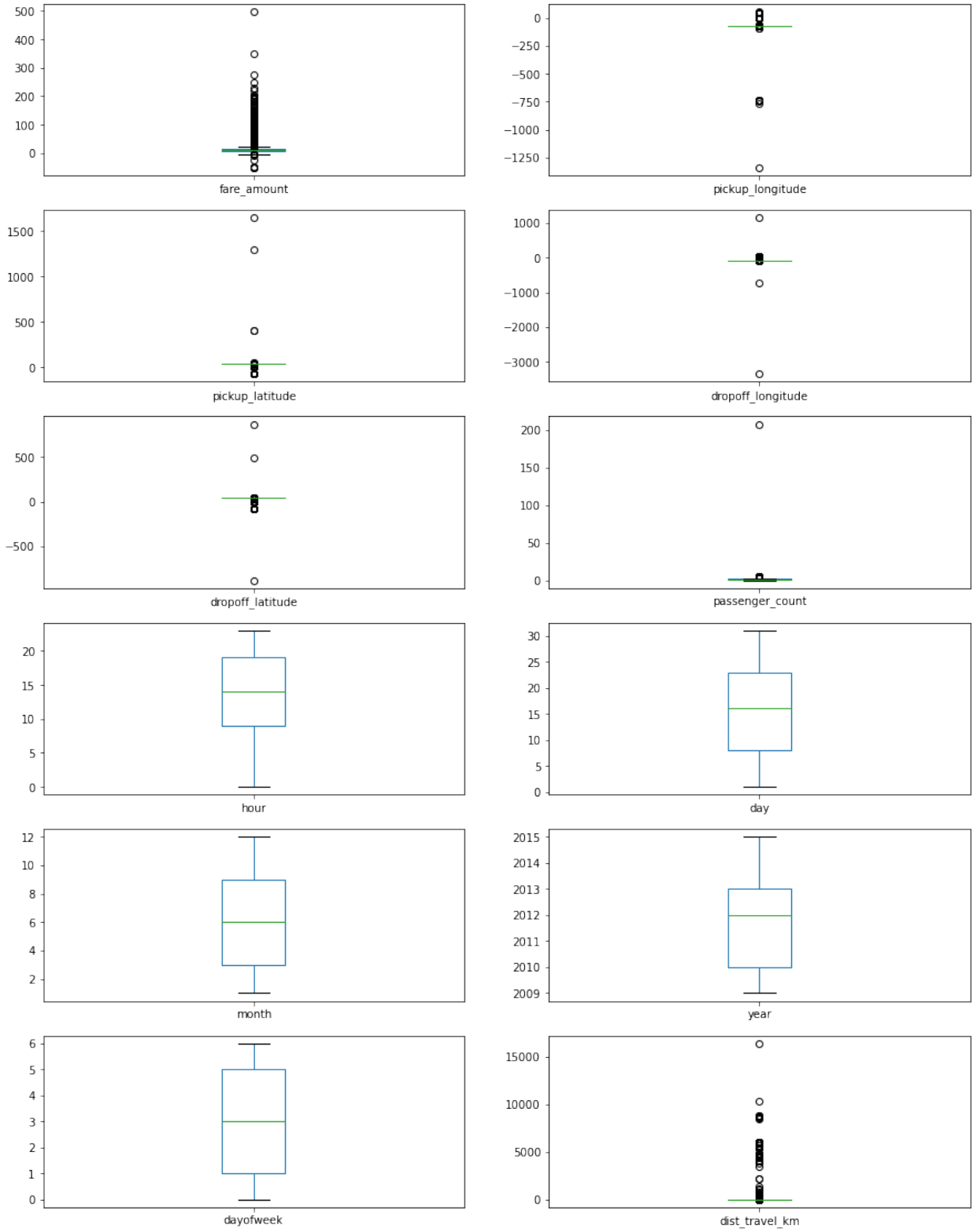
```
        fare_amount  pickup_longitude  pickup_latitude
dropoff_longitude  \
0               7.5        -73.999817        40.738354         -
73.999512
1               7.7        -73.994355        40.728225         -
73.994710
2              12.9        -74.005043        40.740770         -
73.962565
3               5.3        -73.976124        40.790844         -
73.965316
4              16.0        -73.925023        40.744085         -
73.973082
...             ...               ...              ...
...
199995          3.0        -73.987042        40.739367         -
73.986525
199996          7.5        -73.984722        40.736837         -
74.006672
199997         30.9        -73.986017        40.756487         -
73.858957
199998         14.5        -73.997124        40.725452         -
73.983215
199999         14.1        -73.984395        40.720077         -
73.985508

        dropoff_latitude  passenger_count  hour  day  month  year
dayofweek
0              40.723217                1    19    7      5  2015
3
1              40.750325                1    20   17      7  2009
4
2              40.772647                1    21   24      8  2009
0
3              40.803349                3     8   26      6  2009
4
4              40.761247                5    17   28      8  2014
3
...                  ...              ...   ...  ...    ...   ...
...
199995         40.740297                1    10   28     10  2012
6
199996         40.739620                1     1   14      3  2014
4
199997         40.692588                2     0   29      6  2009
0
199998         40.695415                1    14   20      5  2015
2
```

```
199999         40.768793                1     4   15      5  2010
5

[200000 rows x 11 columns]
```

```
# function to calculate the travel distance from the longitudes and
latitudes
from math import *

def distance_formula(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []

    for pos in range (len(longitude1)):
        lon1, lan1, lon2, lan2 = map(radians, [longitude1[pos],
latitude1[pos], longitude2[pos], latitude2[pos]])
        dist_lon = lon2 - lon1
        dist_lan = lan2 - lan1

        a = sin(dist_lan/2)**2 + cos(lan1) * cos(lan2) *
sin(dist_lon/2)**2

        #radius of earth = 6371
        c = 2 * asin(sqrt(a)) * 6371
        travel_dist.append(c)

    return  travel_dist

df['dist_travel_km'] =
distance_formula(df.pickup_longitude.to_numpy(),
df.pickup_latitude.to_numpy(), df.dropoff_longitude.to_numpy(),
df.dropoff_latitude.to_numpy())
```

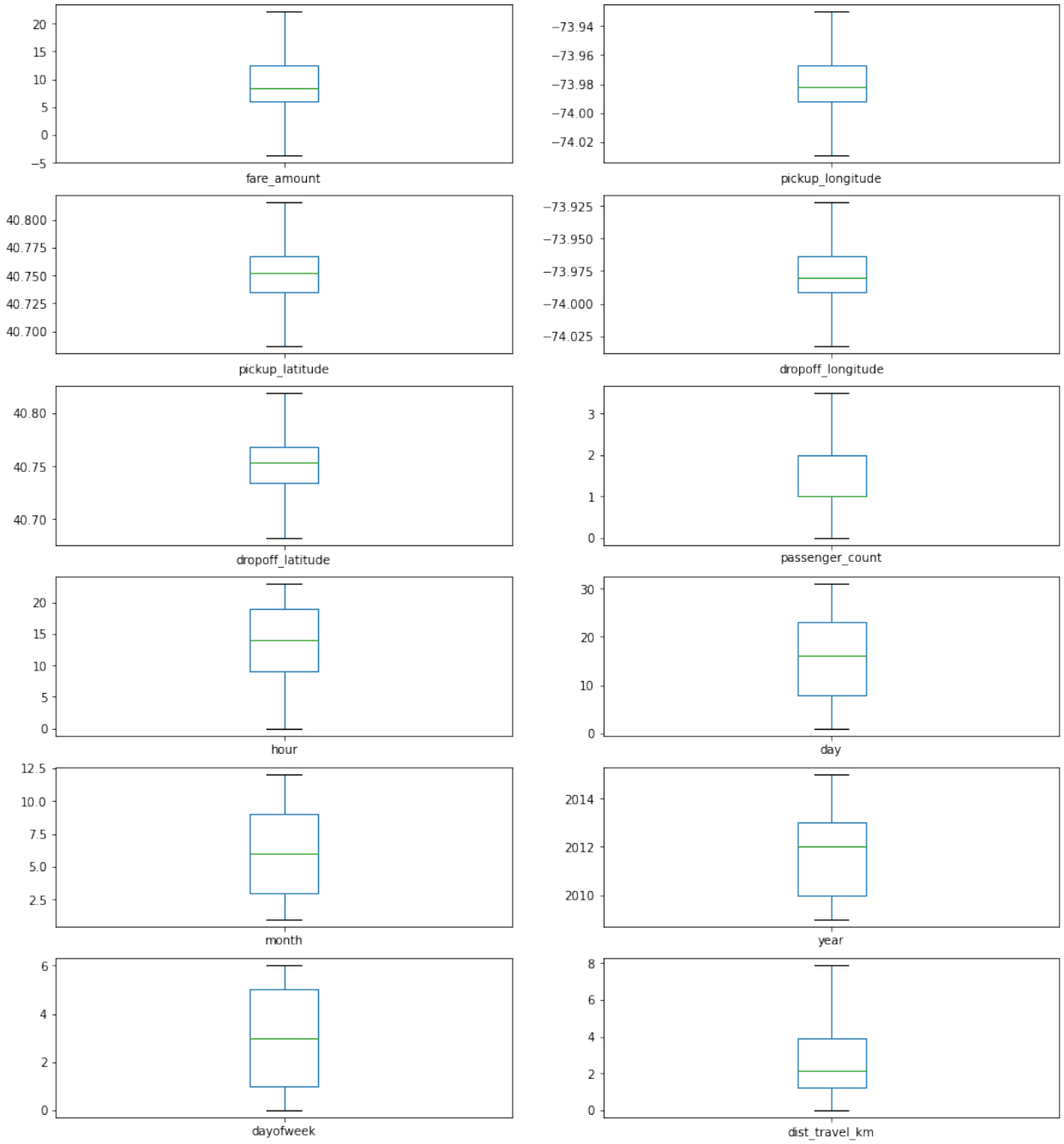
2. Identify outliers.

```
df.plot(kind = "box",subplots = True,layout = (6,2),figsize=(15,20))
#Boxplot to check the outliers
plt.show()
```




```
#Using the InterQuartile Range to fill the values
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
    df[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(df , c)
    return df1

df = treat_outliers_all(df , df.iloc[: , 0::])

#Boxplot shows that dataset is free from outliers
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20))
plt.show()
```



3. Check the correlation.

```
#Function to find the correlation
corr = df.corr()
corr
```

```
                   fare_amount  pickup_longitude  pickup_latitude  \
fare_amount           1.000000          0.154069        -0.110842
pickup_longitude      0.154069          1.000000         0.259497
pickup_latitude      -0.110842          0.259497         1.000000
```

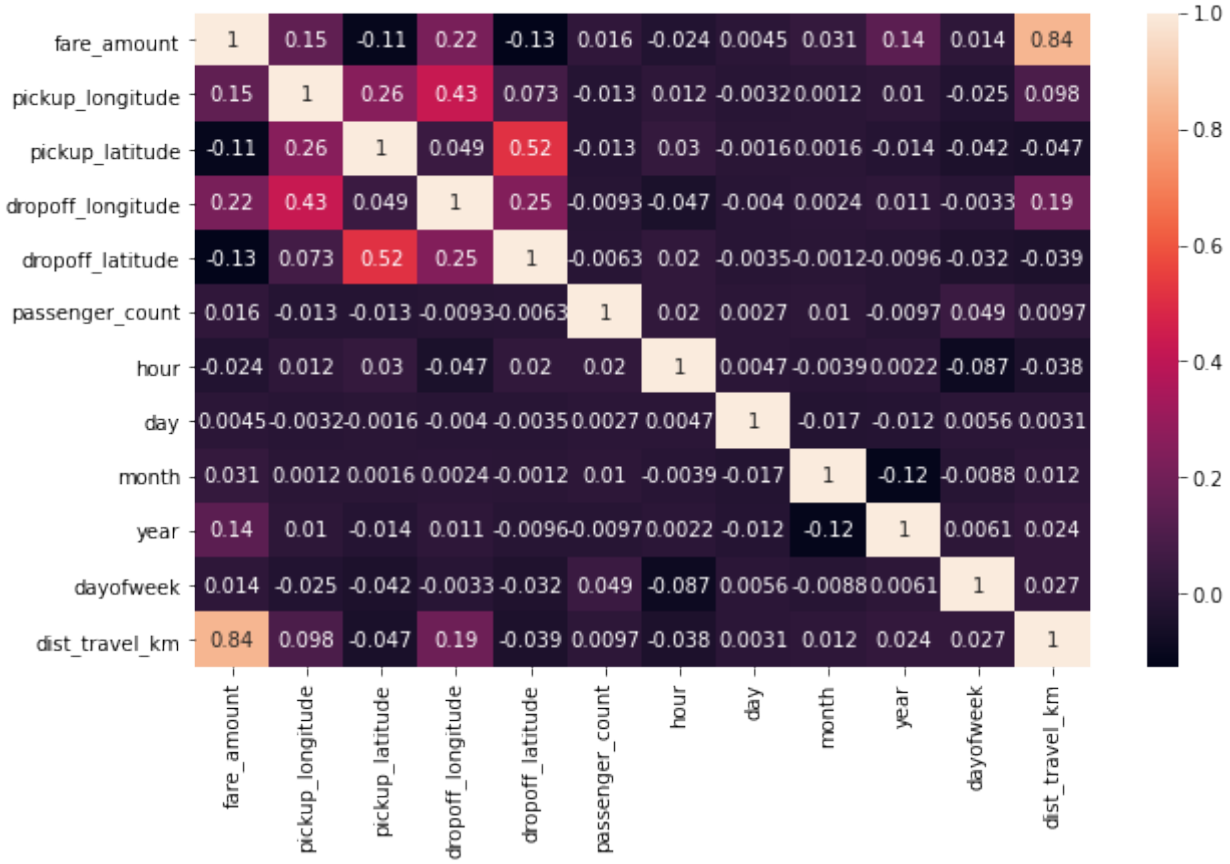
```
dropoff_longitude     0.218675           0.425619          0.048889
dropoff_latitude     -0.125898           0.073290          0.515714
passenger_count       0.015778          -0.013213         -0.012889
hour                 -0.023623           0.011579          0.029681
day                   0.004534          -0.003204         -0.001553
month                 0.030817           0.001169          0.001562
year                  0.141277           0.010198         -0.014243
dayofweek             0.013652          -0.024652         -0.042310
dist_travel_km        0.844374           0.098094         -0.046812

                    dropoff_longitude  dropoff_latitude
passenger_count  \
fare_amount                  0.218675         -0.125898
0.015778
pickup_longitude             0.425619          0.073290         -
0.013213
pickup_latitude              0.048889          0.515714         -
0.012889
dropoff_longitude            1.000000          0.245667         -
0.009303
dropoff_latitude             0.245667          1.000000         -
0.006308
passenger_count             -0.009303         -0.006308
1.000000
hour                        -0.046558          0.019783
0.020274
day                         -0.004007         -0.003479
0.002712
month                        0.002391         -0.001193
0.010351
year                         0.011346         -0.009603         -
0.009749
dayofweek                   -0.003336         -0.031919
0.048550
dist_travel_km               0.186531         -0.038900
0.009709

                         hour       day     month      year
dayofweek  \
fare_amount       -0.023623  0.004534  0.030817  0.141277   0.013652

pickup_longitude   0.011579 -0.003204  0.001169  0.010198  -0.024652

pickup_latitude    0.029681 -0.001553  0.001562 -0.014243  -0.042310

dropoff_longitude -0.046558 -0.004007  0.002391  0.011346  -0.003336

dropoff_latitude   0.019783 -0.003479 -0.001193 -0.009603  -0.031919

passenger_count    0.020274  0.002712  0.010351 -0.009749   0.048550
```

```
hour                1.000000  0.004677 -0.003926  0.002156  -0.086947

day                 0.004677  1.000000 -0.017360 -0.012170   0.005617

month              -0.003926 -0.017360  1.000000 -0.115859  -0.008786

year                0.002156 -0.012170 -0.115859  1.000000   0.006113

dayofweek          -0.086947  0.005617 -0.008786  0.006113   1.000000

dist_travel_km     -0.038366  0.003062  0.011628  0.024278   0.027053
```

```
                   dist_travel_km
fare_amount              0.844374
pickup_longitude         0.098094
pickup_latitude         -0.046812
dropoff_longitude        0.186531
dropoff_latitude        -0.038900
passenger_count          0.009709
hour                    -0.038366
day                      0.003062
month                    0.011628
year                     0.024278
dayofweek                0.027053
dist_travel_km           1.000000
```

```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values
means highly correlated)
```

```
<AxesSubplot:>
```



4. Implement linear regression and random forest regression models.

```
# Dividing the dataset into feature and target values
df_x =
df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_
latitude','passenger_count','hour','day','month','year','dayofweek','d
ist_travel_km']]
df_y = df['fare_amount']

# Dividing the dataset into training and testing dataset
x_train, x_test, y_train, y_test = train_test_split(df_x, df_y,
test_size=0.2, random_state=1)

df
```

```
        fare_amount  pickup_longitude  pickup_latitude
dropoff_longitude  \
0              7.50        -73.999817        40.738354          -
73.999512
1              7.70        -73.994355        40.728225          -
73.994710
2             12.90        -74.005043        40.740770          -
```

```
73.962565
3              5.30        -73.976124        40.790844         -
73.965316
4             16.00        -73.929786        40.744085         -
73.973082
...             ...               ...              ...
...
199995         3.00        -73.987042        40.739367         -
73.986525
199996         7.50        -73.984722        40.736837         -
74.006672
199997        22.25        -73.986017        40.756487         -
73.922036
199998        14.50        -73.997124        40.725452         -
73.983215
199999        14.10        -73.984395        40.720077         -
73.985508

        dropoff_latitude  passenger_count  hour  day  month  year
dayofweek  \
0              40.723217              1.0    19    7      5  2015
3
1              40.750325              1.0    20   17      7  2009
4
2              40.772647              1.0    21   24      8  2009
0
3              40.803349              3.0     8   26      6  2009
4
4              40.761247              3.5    17   28      8  2014
3
...                  ...              ...   ...  ...    ...   ...
...
199995         40.740297              1.0    10   28     10  2012
6
199996         40.739620              1.0     1   14      3  2014
4
199997         40.692588              2.0     0   29      6  2009
0
199998         40.695415              1.0    14   20      5  2015
2
199999         40.768793              1.0     4   15      5  2010
5

        dist_travel_km
0             1.683323
1             2.457590
2             5.036377
3             1.661683
4             4.475450
```

```
...                 ...
199995         0.112210
199996         1.875050
199997         7.865286
199998         3.539715
199999         5.417783

[200000 rows x 12 columns]
```

```
from sklearn.linear_model import LinearRegression

# initialize the linear regression model
reg = LinearRegression()

# Train the model with our training data
reg.fit(x_train, y_train)
```

```
LinearRegression()
```

```
y_pred_lin = reg.predict(x_test)
print(y_pred_lin)
```

```
[ 6.27615184  5.09986098  9.43641238 ... 11.07663949 12.15392248
 11.41496075]
```

```
from sklearn.ensemble import RandomForestRegressor

#Here n_estimators means number of trees you want to build before
making the prediction
rf = RandomForestRegressor(n_estimators=100)
rf.fit(x_train,y_train)
```

```
RandomForestRegressor()
```

```
y_pred_rf = rf.predict(x_test)
print(y_pred_rf)
```

```
[ 5.197   6.591   9.395  ... 11.3375 11.608  13.642 ]
```

5. Evaluate the models and compare their respective scores like R2, RMSE, etc

```
cols = ['Model', 'RMSE', 'R-Squared']

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

from sklearn import metrics
from sklearn.metrics import r2_score
```

```
reg_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_lin))
reg_squared = r2_score(y_test, y_pred_lin)

full_metrics = pd.Series({'Model': "Linear Regression", 'RMSE' :
reg_RMSE, 'R-Squared' : reg_squared})

# 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 name
result_tabulation = result_tabulation.append(full_metrics,
ignore_index = True)

# print the result table
result_tabulation
```

```
                Model      RMSE  R-Squared
0  Linear Regression  2.703957   0.753906
```

```
rf_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_rf))
rf_squared = r2_score(y_test, y_pred_rf)


full_metrics = pd.Series({'Model': "Random Forest ", 'RMSE':rf_RMSE,
'R-Squared': rf_squared})
# 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 name
result_tabulation = result_tabulation.append(full_metrics,
ignore_index = True)

# print the result table
result_tabulation
```

```
                Model      RMSE  R-Squared
0  Linear Regression  2.703957   0.753906
1     Random Forest   2.363869   0.811918
```