EDA Project - NYC Taxi Trip

Evaluation Metric (MAE)

A suitable evaluation metric would be Mean Absolute Error (MAE). MAE is the average of the absolute differences between the predicted and actual values. This metric is preferred because it gives equal weightage to all errors and is less sensitive to outliers compared to other metrics such as Root Mean Squared Error (RMSE) and has the same scale as the target we are predicting.

In [4]:

```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
from datetime import timedelta
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [44]:

```
#importing and reading the file to check imported data is correct.
data= pd.read_csv("C:/Users/aitha/OneDrive/Desktop/EDA_NYC_Taxi (1)/nyc_taxi_trip_duration.csv")
data.head()
```

Out[44]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.953918	40.778873	-73.963875	40.771164
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.988312	40.731743	-73.994751	40.694931
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.997314	40.721458	-73.948029	40.774918
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.961670	40.759720	-73.956779	40.780628
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.017120	40.708469	-73.988182	40.740631

In [45]:

```
# finding out the rows and columns of data
data.shape
```

Out[45]:

```
(729322, 11)
```

In [46]:

```
# Coverting trip_duration from seconds to hours
data['trip_duration'] = data['trip_duration'].apply(lambda x: x/3600)
```

In [47]:

```
# Converting yes and no flag into 1 and 0
data['store_and_fwd_flag'] = 1 * (data.store_and_fwd_flag.values == 'Y')
```

In [48]:

```
# Checking the above codes are done correctly
data.head()
```

Out[48]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.953918	40.778873	-73.963875	40.771164
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.988312	40.731743	-73.994751	40.694931
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.997314	40.721458	-73.948029	40.774918
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.961670	40.759720	-73.956779	40.780628
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.017120	40.708469	-73.988182	40.740631

In [49]:

```
# checking datatypes of data
data.dtypes
```

Out[49]:

```
id                     object
vendor_id               int64
pickup_datetime        object
dropoff_datetime       object
passenger_count         int64
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
store_and_fwd_flag      int32
trip_duration         float64
dtype: object
```

In [50]:

```
#checking missing value
data.isnull().sum()
```

Out[50]:

```
id                    0
vendor_id             0
pickup_datetime       0
dropoff_datetime      0
passenger_count       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
store_and_fwd_flag    0
trip_duration         0
dtype: int64
```

From this we can conclude there is no missing values.

In [35]:

```
#Checking the statistics of data
data.describe()
```

Out[35]:

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	store_and_fwd_flag	trip_duration
count	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000
mean	1.535403	1.662055	-73.973513	40.750919	-73.973422	40.751775	0.005539	0.264508
std	0.498745	1.312446	0.069754	0.033594	0.069588	0.036037	0.074221	1.073507
min	1.000000	0.000000	-121.933342	34.712234	-121.933304	32.181141	0.000000	0.000278
25%	1.000000	1.000000	-73.991859	40.737335	-73.991318	40.735931	0.000000	0.110278
50%	2.000000	1.000000	-73.981758	40.754070	-73.979759	40.754509	0.000000	0.184167
75%	2.000000	2.000000	-73.967361	40.768314	-73.963036	40.769741	0.000000	0.298611
max	2.000000	9.000000	-65.897385	51.881084	-65.897385	43.921028	1.000000	538.815556

In [51]:

```
# Converting to datetime
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data['dropoff_datetime'] = pd.to_datetime(data['dropoff_datetime'])
```

In [52]:

```
# Creating a new column to get trip_duration
data['check_trip_duration'] = (data['dropoff_datetime'] - data['pickup_datetime']).map(lambda x: x.total_seconds())

duration_difference = data[np.abs(data['check_trip_duration'].values  - data['trip_duration'].values) > 1]
duration_difference.shape
```

Out[52]:

```
(729309, 12)
```

In [53]:

```
data.dtypes
```

Out[53]:

```
id                             object
vendor_id                       int64
pickup_datetime        datetime64[ns]
dropoff_datetime       datetime64[ns]
passenger_count                 int64
pickup_longitude              float64
pickup_latitude               float64
dropoff_longitude             float64
dropoff_latitude              float64
store_and_fwd_flag              int32
trip_duration                 float64
check_trip_duration           float64
dtype: object
```

In [38]:

```
data.shape
```

Out[38]:

```
(729322, 12)
```

In [59]:

```
# Extracting Information datetime from column and sepreating columns

data['pickup_hour'] = data['pickup_datetime'].dt.hour
data['day_of_week'] = data['pickup_datetime'].dt.weekday
data['pickup_date'] = data['pickup_datetime'].dt.date
data['dropoff_date'] = data['dropoff_datetime'].dt.date
data['dropoff_hour'] = data['dropoff_datetime'].dt.hour
```

In [60]:

```
#checking with head()function
data.head()
```

Out[60]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.953918	40.778873	-73.963875	40.771164
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.988312	40.731743	-73.994751	40.694931
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.997314	40.721458	-73.948029	40.774918
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.961670	40.759720	-73.956779	40.780628
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.017120	40.708469	-73.988182	40.740631

In [61]:

```
def time_of_day(x):
    # to calculate what time of it is now
    if x in range(6,12):
        return 'Morning'
    elif x in range(12,16):
        return 'Afternoon'
    elif x in range(16,22):
        return 'Evening'
    else:
        return 'Late night'

data['pickup_time_of_day'] = data['pickup_hour'].apply(time_of_day)
data['dropoff_time_of_day'] = data['dropoff_hour'].apply(time_of_day)
```

In [66]:

```
data.drop(columns=['pickup_hour','dropoff_hour'], inplace=True)
```

In [67]:

```
data.head()
```

Out[67]:

gitude	dropoff_latitude	store_and_fwd_flag	trip_duration	check_trip_duration	day_of_week	pickup_date	dropoff_date	pickup_time_of_day	dropoff_t
63875	40.771164	0	0.111111	400.0	0	2016-02-29	2016-02-29	Evening	
94751	40.694931	0	0.305556	1100.0	4	2016-03-11	2016-03-11	Late night	
48029	40.774918	0	0.454167	1635.0	6	2016-02-21	2016-02-21	Evening	
56779	40.780628	0	0.316944	1141.0	1	2016-01-05	2016-01-05	Morning	
88182	40.740631	0	0.235556	848.0	2	2016-02-17	2016-02-17	Morning	

In [68]:

```
data.shape
```

Out[68]:

```
(729322, 17)
```

Since we are asked for model buliding in problem we skip the univariate and bivariate analysis and go for model buliding part

Benchmark model

Shuffling and dividing data into Train and Test Set

In [197]:

```
from sklearn.utils import shuffle
# Shuffling the Dataset and putting random state becoz every time we shuffle the value remains same
data = shuffle(data, random_state = 42)
```

In [198]:

```
data.head()
```

Out[198]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	pic
247177	1	-73.992981	40.737129	-73.981178	40.781891	0.420556	1514.0	6	
41189	1	-73.962509	40.773117	-73.979301	40.755665	0.370000	1332.0	0	
441690	1	-73.999649	40.718616	-73.982681	40.774021	0.511111	1840.0	5	
246922	2	-73.972954	40.756306	-73.949081	40.775032	0.285278	1027.0	4	
202073	2	-74.003334	40.743763	-74.004105	40.751137	0.081944	295.0	5	

In [199]:

```
#Dividing the data into 4 parts
div = int(data.shape[0]/4)

#  Creating the test and train data by putting 3 parts to train set and 1 part to test set
train = data.loc[:3*div+1,:]
test = data.loc[3*div+1:]

train.head()
```

Out[199]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	pic
247177	1	-73.992981	40.737129	-73.981178	40.781891	0.420556	1514.0	6	
41189	1	-73.962509	40.773117	-73.979301	40.755665	0.370000	1332.0	0	
441690	1	-73.999649	40.718616	-73.982681	40.774021	0.511111	1840.0	5	
246922	2	-73.972954	40.756306	-73.949081	40.775032	0.285278	1027.0	4	
202073	2	-74.003334	40.743763	-74.004105	40.751137	0.081944	295.0	5	

In [200]:

```
test.head()
```

Out[200]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	pic
546991	1	-73.991364	40.732590	-74.000526	40.742283	0.096111	346.0	2	
115009	1	-73.966866	40.761665	-74.014481	40.708088	0.278611	1003.0	0	
127693	1	-73.991577	40.770470	-74.000137	40.730358	0.211389	761.0	6	
204591	2	-73.874580	40.774097	-73.960419	40.762299	0.364722	1313.0	0	
94205	1	-73.994789	40.750259	-73.999840	40.727032	0.224722	809.0	3	

since our target variable is trip duratation which is continuous variable we use mean , in first we just find mean of target variable the keep on adding variable to make our model better and robust.

Simple Mean (trip_duration)

In [201]:

```
# Creating and storing simple mean in a new column in the test set as "simple_mean"
test['simple_mean'] = train['trip_duration'].mean()
test['simple_mean']
```

Out[201]:

```
546991    0.26507
115009    0.26507
127693    0.26507
204591    0.26507
94205     0.26507
           ...
604610    0.26507
112278    0.26507
725627    0.26507
371399    0.26507
5948      0.26507
Name: simple_mean, Length: 426065, dtype: float64
```

In [203]:

```
#calculating mean absolute error
from sklearn.metrics import mean_absolute_error as MAE

simple_mean_error = MAE(test['trip_duration'] , test['simple_mean'])
simple_mean_error
```

Out[203]:

```
0.17207002339174687
```

```
#calculating mean absolute error
from sklearn.metrics import mean_squared_error as MSE

simple_mean_error_MSE = np.sqrt(MSE(test['trip_duration'] , test['simple_mean']))
```

```
simple_mean_error_MSE
```

Mean trip_duration with respect to dropoff_time_of_day

In [89]:

```
#trip_duration mean with respect to the mean of dropoff time of the day
dropoff =pd.pivot_table(train, values='trip_duration', index = ['dropoff_time_of_day'], aggfunc=np.mean)
dropoff
```

Out[89]:

	trip_duration
dropoff_time_of_day	
Afternoon	0.284258
Evening	0.269666
Late night	0.256343
Morning	0.247905

In [90]:

```
# initializing new column to zero
test['dropoff_mean'] = 0

# For every unique entry in dropoff longitude
for i in train['dropoff_time_of_day'].unique():
  # Assign the mean value corresponding to unique entry
  test['dropoff_mean'][test['dropoff_time_of_day'] == str(i)] = train['trip_duration'][train['dropoff_time_of_day'] == str(i)].mean(
```

In [86]:

```
#calculating mean absolute error
dropoff_error = MAE(test['trip_duration'] , test['dropoff_mean'] )
dropoff_error
```

Out[86]:

```
0.17263892934259387
```

In [93]:

```
#calculating mean absolute error
dropoff_error = np.sqrt(MSE(test['trip_duration'] , test['dropoff_mean'] ))
dropoff_error
```

Out[93]:

```
0.8903865469170373
```

Mean trip_duration with respect to pickup_time_of_day

In [95]:

```
#trip_duration mean with respect to the mean of pickup time of the day
pickup = pd.pivot_table(train, values='trip_duration', index = ['pickup_time_of_day'], aggfunc=np.mean)
pickup
```

Out[95]:

	trip_duration
pickup_time_of_day	
Afternoon	0.291531
Evening	0.264078
Late night	0.255589
Morning	0.250610

In [96]:

```
# initializing new column to zero
test['pickup_mean'] = 0

# For every unique entry in pickup longitude
for i in train['pickup_time_of_day'].unique():
  # Assign the mean value corresponding to unique entry
  test['pickup_mean'][test['pickup_time_of_day'] == str(i)] = train['trip_duration'][train['pickup_time_of_day'] == str(i)].mean()
```

In [98]:

```
#calculating mean absolute error
pickup_error = MAE(test['trip_duration'] , test['pickup_mean'] )
pickup_error
```

Out[98]:

```
0.17262796487353868
```

Mean trip_duration with respect to passenger_count

In [118]:

```
##trip_duration_hour mean with respect to the mean of passenger_count
pass_count = pd.pivot_table(train, values='trip_duration', index = ["passenger_count"], aggfunc=np.mean)
pass_count
```

Out[118]:

passenger_count	trip_duration
0	0.092981
1	0.255343
2	0.277822
3	0.287332
4	0.285759
5	0.299641
6	0.300193

In [120]:

```
# initializing new column to zero
test['pass_count'] = 0

# For every unique entry in passenger count
for i in train['passenger_count'].unique():
  # Assign the mean value corresponding to unique entry
  test['pass_count'][test['passenger_count'] == str(i)] = train['trip_duration'][train['passenger_count'] == str(i)].mean()

pass_count_error = MAE(test['trip_duration'] , test['pass_count'] )
pass_count_error
```

Out[120]:

```
0.2652592807074405
```

Mean trip_duration with respect store_and_fwd_flag

In [128]:

```
store_and_fwd = pd.pivot_table(train, values='trip_duration', index = ["store_and_fwd_flag"], aggfunc=np.mean)
store_and_fwd
```

Out[128]:

store_and_fwd_flag	trip_duration
0	0.264109
1	0.304058

In [130]:

```
# initializing new column to zero
test['store_and_fwd'] = 0

# For every unique entry in pickup latitude
for i in train['store_and_fwd_flag'].unique():
  # Assign the mean value corresponding to unique entry
  test['store_and_fwd'][test['store_and_fwd_flag'] == str(i)] = train['trip_duration'][train['store_and_fwd_flag'] == str(i)].mean()

str_and_fwd_error = MAE(test['store_and_fwd'] , test['trip_duration'] )
str_and_fwd_error
```

Out[130]:

```
0.26515595259657526
```

Mean trip_duration with respect to passenger_count, store_and_fwd_flag

In [113]:

```
##trip_duration mean with respect to the mean of passenger_count
pass_store = pd.pivot_table(train, values='trip_duration', index = ["passenger_count", "store_and_fwd_flag"], aggfunc=np.mean)
pass_store
```

Out[113]:

		trip_duration
passenger_count	**store_and_fwd_flag**	
0	**0**	0.098899
	1	0.010139
1	**0**	0.255153
	1	0.286368
2	**0**	0.277306
	1	0.364515
3	**0**	0.287040
	1	0.346985
4	**0**	0.284720
	1	0.421980
5	**0**	0.299639
	1	0.357778
6	**0**	0.300193

In [114]:

```
# initializing new column to zero
test['pass_store'] = 0
 # Assigning variables to strings ( to shorten code length)
s1 = 'passenger_count'
s2 = 'store_and_fwd_flag'

# For every Unique Value in s1
for i in test[s1].unique():
  # For every Unique Value in s2
  for j in test[s2].unique():
        # Calculate and Assign mean to new column, corresponding to both unique values of s1 and s2 simultaneously
       test['pass_store'][(test[s1] == i) & (test[s2] == str(j)) ] = train['trip_duration'][(train[s1] == i) & (train[s2] == str(j)
```

In [115]:

```
test.dropna(subset=['pass_store'], inplace=True)
```

In [116]:

```
pass_count_error = MAE(test['trip_duration'] , test['pass_store'] )
pass_count_error
```

Out[116]:

```
0.2652592807074405
```

Mean trip_duration with respect to passenger_count, pickup_time_of_day and dropoff_time_of_day

In [122]:

```
combo = pd.pivot_table(train, values = 'trip_duration', index = ['passenger_count','pickup_time_of_day','dropoff_time_of_day'], aggf
combo
```

Out[122]:

			trip_duration
passenger_count	**pickup_time_of_day**	**dropoff_time_of_day**	
0	**Afternoon**	**Afternoon**	0.305417
	Evening	**Evening**	0.054352
		Late night	0.106944
	Late night	**Late night**	0.023856
	Morning	**Afternoon**	0.432222
...	**...**	**...**	...
6	**Late night**	**Late night**	0.282054
		Morning	0.313738
	Morning	**Afternoon**	0.376369
		Late night	16.731944
		Morning	0.267228

75 rows × 1 columns

In [123]:

```
# Initiating new empty column
test['Super_mean'] = 0

# Assigning variables to strings ( to shorten code length)
s1 = 'passenger_count'
s2 = 'pickup_time_of_day'
s3 = 'dropoff_time_of_day'

# For every Unique Value in s1
for i in test[s1].unique():
  # For every Unique Value in s2
  for j in test[s2].unique():
    # For every Unique Value in s3
      for k in test[s3].unique():
    # Calculate and Assign mean to new column, corresponding to both unique values of s1 and s2 simultaneously
        test['Super_mean'][(test[s1] == i) & (test[s2] == str(j)) & (test[s3] == str(k))] = train['trip_duration'][(train[s1] == i) &
```

In [124]:

```
test.dropna(subset=['Super_mean'], inplace=True)
```

In [126]:

```
#calculating mean absolute error
super_mean_error = MAE(test['trip_duration'] , test['Super_mean'] )
super_mean_error
```

Out[126]:

```
0.16813712281281906
```

In [132]:

```
#calculating mean absolute error
super_mean_error = np.sqrt(MSE(test['trip_duration'] , test['Super_mean'] ))
super_mean_error
```

Out[132]:

```
0.8618719927438696
```

Conclusion

1. The error of simple mean of trip duration is 0.17277651586O276, 0.8899768861825853 which is also almost equal to MAE of dropoff time and pickup time of the day is 0.17263892934259387, 0.17262796487353868 respectively.
2. The Mean absolute error of trip duration with respect to str_fwd_error and passanger count error is almost i.e. 0.26515595259657526,
3. The Mean absolute error of trip duration with respect to passenger_count, store_and_fwd_flag is 0.2652592807074405.

4.The Mean absolute error of trip duration with respect to pickup_time_error , dropoff_time_error and pass_count error is 0.16813712281281906

KNN model

In [133]:

```
# top 5 rows of the dataset
data.head()
```

Out[133]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
469114	id2380741	2	2016-05-21 10:40:14	2016-05-21 10:51:11	1	-73.981796	40.762035	-73.972267	40.78
694852	id3946961	2	2016-01-08 18:49:27	2016-01-08 18:52:42	5	-73.980965	40.747677	-73.982704	40.74
696324	id0833913	1	2016-05-22 00:54:10	2016-05-22 01:08:10	1	-73.951065	40.782722	-73.867691	40.83
356496	id1336849	1	2016-06-11 10:32:12	2016-06-11 10:38:50	1	-73.987625	40.762791	-73.973518	40.76
645318	id1610858	1	2016-04-03 10:45:51	2016-04-03 10:57:13	3	-73.964333	40.792503	-73.988609	40.75

In [135]:

```
data.describe()
```

Out[135]:

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	store_and_fwd_flag	trip_duration	cl
count	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	
mean	1.535403	1.662055	-73.973513	40.750919	-73.973422	40.751775	0.005539	0.264508	
std	0.498745	1.312446	0.069754	0.033594	0.069588	0.036037	0.074221	1.073507	
min	1.000000	0.000000	-121.933342	34.712234	-121.933304	32.181141	0.000000	0.000278	
25%	1.000000	1.000000	-73.991859	40.737335	-73.991318	40.735931	0.000000	0.110278	
50%	2.000000	1.000000	-73.981758	40.754070	-73.979759	40.754509	0.000000	0.184167	
75%	2.000000	2.000000	-73.967361	40.768314	-73.963036	40.769741	0.000000	0.298611	
max	2.000000	9.000000	-65.897385	51.881084	-65.897385	43.921028	1.000000	538.815556	

In [136]:

```
data.columns
```

Out[136]:

```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'check_trip_duration', 'day_of_week', 'pickup_date',
       'dropoff_date', 'pickup_time_of_day', 'dropoff_time_of_day'],
      dtype='object')
```

In [138]:

```
data.drop(columns=['id','vendor_id','pickup_datetime','dropoff_datetime','store_and_fwd_flag','dropoff_date','pickup_date'],inplace=
```

In [139]:

```
data.dtypes
```

Out[139]:

```
passenger_count          int64
pickup_longitude       float64
pickup_latitude        float64
dropoff_longitude      float64
dropoff_latitude       float64
trip_duration          float64
check_trip_duration    float64
day_of_week              int64
pickup_time_of_day      object
dropoff_time_of_day     object
dtype: object
```

In [140]:

```
df = data.iloc[1:150001,]
cat_cols = ['pickup_time_of_day', 'dropoff_time_of_day']
df = pd.concat([df, pd.get_dummies(df[cat_cols].astype('str'))], axis=1)
df.drop(columns = ['pickup_time_of_day', 'dropoff_time_of_day'],inplace = True)
df
```

Out[140]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	picl
694852	5	-73.980965	40.747677	-73.982704	40.741161	0.054167	195.0	4	
696324	1	-73.951065	40.782722	-73.867691	40.833664	0.233333	840.0	6	
356496	1	-73.987625	40.762791	-73.973518	40.762909	0.110556	398.0	5	
645318	3	-73.964333	40.792503	-73.988609	40.758369	0.189444	682.0	6	
498463	1	-73.956047	40.781849	-73.977707	40.758499	0.210556	758.0	5	
...	...	...	...	...	...	...	...	...	
60847	1	-73.870895	40.773697	-73.982536	40.742413	0.276389	995.0	2	
219009	2	-73.959290	40.801121	-73.984360	40.769802	0.198889	716.0	0	
476363	5	-73.961182	40.777611	-73.972412	40.786308	0.173889	626.0	1	
554000	1	-73.954231	40.765156	-73.975334	40.752388	0.366667	1320.0	4	
674441	1	-73.979889	40.753960	-73.988953	40.742077	0.084167	303.0	3	

150000 rows × 16 columns

In [141]:

```
#seperate features variables and target variables or independent and dependent variables
x = df.drop(['trip_duration'], axis=1)
y = df["trip_duration"]
x.shape,y.shape
```

Out[141]:

```
((150000, 15), (150000,))
```

In [142]:

```
# Scaling up the data to get all in one particular scale by using MinMax Scaler
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x)
```

In [143]:

```
# Converting into dataframe
x = pd.DataFrame(x_scaled)
```

In [144]:

```
# Importing Train test split and applying random state
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(x,y, random_state = 56)
```

In [145]:

```
#Implementing and importing KNN regressor and metric
from sklearn.neighbors import KNeighborsRegressor as KNN
from sklearn.metrics import mean_absolute_error as MAE
```

In [206]:

```
# Creating instance of KNN
reg = KNN(n_neighbors = 5)
# Fitting the model
reg.fit(train_x, train_y)
# Predicting over the Train Set and calculating MSE
test_predict = reg.predict(test_x)
k = MAE(test_predict, test_y)
print('Test MAE     ', k )
```

```
Test MAE     0.1005912162962963
```

Finding K value using Elbow classifier

In [149]:

```
def Elbow(K):
  #initiating empty list
    test_MAE = []

  #training model for evey value of K
    for i in K:
        #Instance of KNN
        reg = KNN(n_neighbors = i)
        reg.fit(train_x, train_y)
        #Appending MAE value to empty list claculated using the predictions
        tmp = reg.predict(test_x)
        tmp = MAE(tmp,test_y)
        test_MAE.append(tmp)

    return test_MAE
```

In [164]:

```
#Defining K range
k = range(1,10)
```

In [165]:

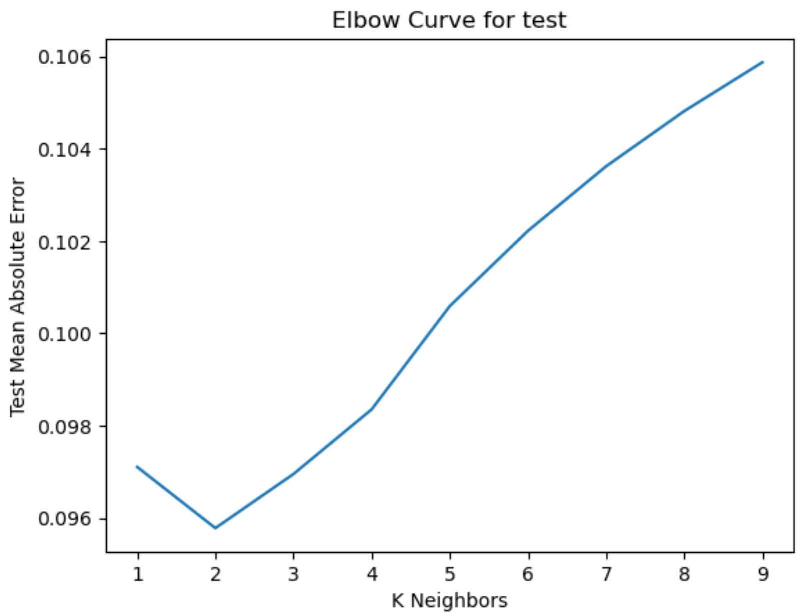
```
# calling above defined function
test = Elbow(k)
```

In [166]:

```
# plotting the Curves
plt.plot(k, test)
plt.xlabel('K Neighbors')
plt.ylabel('Test Mean Absolute Error')
plt.title('Elbow Curve for test')
```

Out[166]:

```
Text(0.5, 1.0, 'Elbow Curve for test')
```



In [207]:

```
# Creating instance of KNN
reg = KNN(n_neighbors = 2)

# Fitting the model
reg.fit(train_x, train_y)

# Predicting over the Train Set and calculating F1
test_predict = reg.predict(test_x)
k = MAE(test_predict, test_y)
print('Test MAE    ', k )
```

```
Test MAE     0.09577997037037037
```

For different values of k the Test MAE values are 1- 0.09710413333333333 2-0.09577997037037037 3- 0.09695288395061728

In [167]:

```
knn_train_score = reg.score(train_x,train_y)
knn_train_score*100
```

Out[167]:

```
23.577168212623857
```

In [168]:

```
knn_test_score = reg.score(test_x,test_y)
knn_test_score*100
```

Out[168]:

```
27.52035767562998
```

Conclusions

1.The Test MAE is when we took the value of k as 2. We used Elbow method in order to determine the value of k. On using Elbow method we found that at k = 2(0.029005723456790127) the test MAE is lesser than the MAE at K =5 (0.1005912162962963)

2.The train score is 23.577168212623857

3.The test score is 27.52035767562998

Linear model

In [169]:

```
#Importing data
data.head()
```

Out[169]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	pic
469114	1	-73.981796	40.762035	-73.972267	40.781265	0.182500	657.0	5	
694852	5	-73.980965	40.747677	-73.982704	40.741161	0.054167	195.0	4	
696324	1	-73.951065	40.782722	-73.867691	40.833664	0.233333	840.0	6	
356496	1	-73.987625	40.762791	-73.973518	40.762909	0.110556	398.0	5	
645318	3	-73.964333	40.792503	-73.988609	40.758369	0.189444	682.0	6	

In [170]:

```
df = data.iloc[1:150001,]
cat_cols = ['pickup_time_of_day', 'dropoff_time_of_day']
df = pd.concat([data, pd.get_dummies(df[cat_cols].astype('str'))], axis=1)
df.drop(columns = ['pickup_time_of_day', 'dropoff_time_of_day'],inplace = True)
df
```

Out[170]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_duration	check_trip_duration	day_of_week	pic
469114	1	-73.981796	40.762035	-73.972267	40.781265	0.182500	657.0	5	
694852	5	-73.980965	40.747677	-73.982704	40.741161	0.054167	195.0	4	
696324	1	-73.951065	40.782722	-73.867691	40.833664	0.233333	840.0	6	
356496	1	-73.987625	40.762791	-73.973518	40.762909	0.110556	398.0	5	
645318	3	-73.964333	40.792503	-73.988609	40.758369	0.189444	682.0	6	
...	...	...	...	...	...	...	...	...	
259178	1	-73.960854	40.811741	-73.960251	40.817940	0.139167	501.0	1	
365838	1	-73.984215	40.728931	-73.985313	40.738132	0.082778	298.0	1	
131932	1	-73.996338	40.723541	-73.994255	40.726402	0.036667	132.0	0	
671155	1	-73.961449	40.765327	-73.980003	40.745914	0.238889	860.0	3	
121958	5	-73.982208	40.763008	-74.004097	40.742710	0.208611	751.0	1	

729322 rows × 16 columns

In [171]:

```
# Performing the train test split function
train_x,test_x,train_y,test_y = train_test_split(x,y, random_state = 56)
```

In [172]:

```
#Implementing and importing Linear Regression
from sklearn.linear_model import LinearRegression as LR
```

In [173]:

```
# Creating instance of Linear Regresssion
lr = LR()

# Fitting the model
lr.fit(train_x, train_y)
```

Out[173]:

```
▸ LinearRegression
```

In [174]:

```
# Predicting over the Train Set and calculating error
train_predict = lr.predict(train_x)
k = MAE(train_predict, train_y)
print('Training Mean Absolute Error', k )
```

```
Training Mean Absolute Error 1.1216615220544882e-14
```

In [175]:

```
# Predicting over the Test Set and calculating error
test_predict = lr.predict(test_x)
k = MAE(test_predict, test_y)
print('Test Mean Absolute Error    ', k )
```

```
Test Mean Absolute Error     1.112948637474002e-14
```

Parameters of Linear Regression

In [176]:

```
lr.coef_
```

Out[176]:

```
array([-9.66507073e-16,  2.06334949e-13,  1.02053891e-13, -4.41454964e-13,
       -4.15677258e-13,  5.38815278e+02, -2.19269047e-15,  1.51894635e-01,
        1.51894635e-01,  1.51894635e-01,  1.51894635e-01, -9.15061330e-03,
       -9.15061330e-03, -9.15061330e-03, -9.15061330e-03])
```

Plotting the coefficients

In [177]:

```
range(len(train_x.columns))
```

Out[177]:

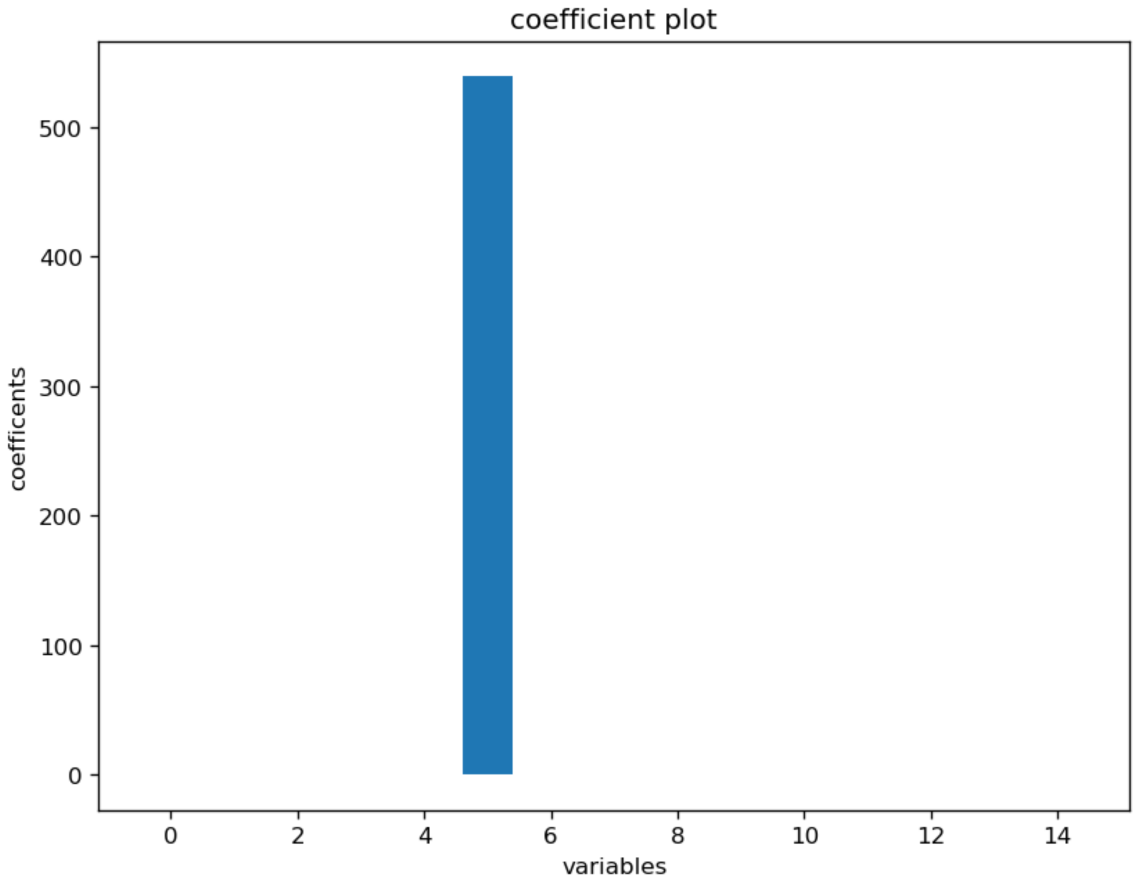
```
range(0, 15)
```

In [182]:

```
plt.figure(figsize=(8,6), dpi=120, facecolor="w", edgecolor="b")
x=range(len(train_x.columns))
y=lr.coef_
plt.bar(x,y)
plt.xlabel("variables")
plt.ylabel("coefficents")
plt.title("coefficient plot")
```

Out[182]:

```
Text(0.5, 1.0, 'coefficient plot')
```



In [189]:

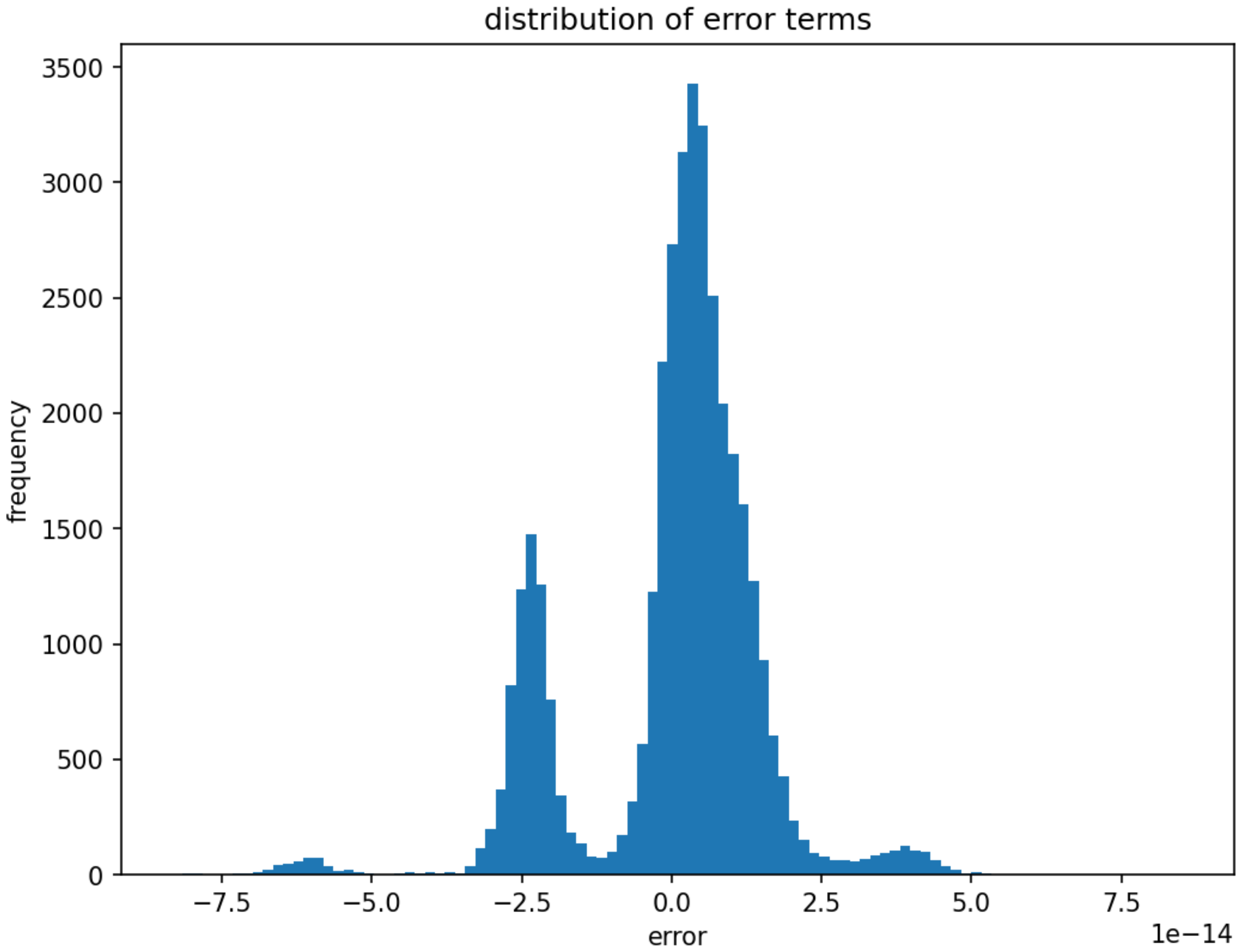
```
# Arranging and calculating the Residuals
residuals = pd.DataFrame({
    'fitted values' : test_y,
    'predicted values' : test_predict})

residuals['residuals'] = residuals['fitted values'] - residuals['predicted values']
residuals.head()
```

Out[189]:

	fitted values	predicted values	residuals
359019	0.147222	0.147222	5.356826e-15
609490	0.162500	0.162500	9.298118e-15
328509	0.208056	0.208056	-2.625677e-14
124487	0.125833	0.125833	1.137979e-15
116857	0.478611	0.478611	-2.703393e-14

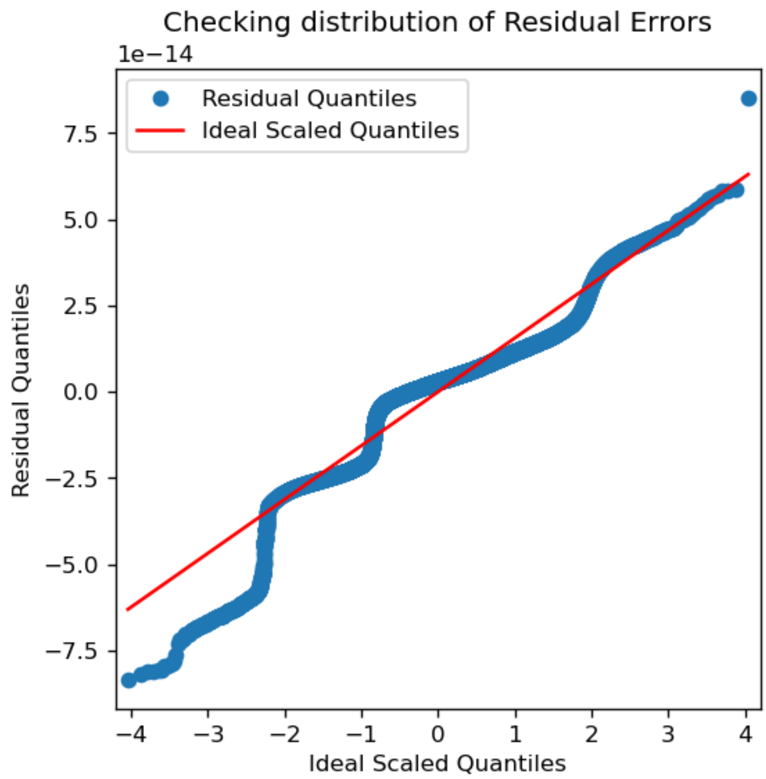
In [190]:

```
plt.figure(figsize=(8,6),dpi=150,facecolor="w",edgecolor="b")
plt.hist(residuals.residuals,bins=100)
plt.xlabel("error")
plt.ylabel("frequency")
plt.title("distribution of error terms")
plt.show()
```



In [191]:

```
# importing the QQ-plot from the from the statsmodels
from statsmodels.graphics.gofplots import qqplot

## Plotting the QQ plot
fig, ax = plt.subplots(figsize=(5,5) , dpi = 120)
qqplot(residuals.residuals, line = 's' , ax = ax)
plt.ylabel('Residual Quantiles')
plt.xlabel('Ideal Scaled Quantiles')
plt.legend(["Residual Quantiles","Ideal Scaled Quantiles"])
plt.title('Checking distribution of Residual Errors')
plt.show()
```



In [192]:

```
#calculating the train score

linear_train_score = lr.score(train_x,train_y)
linear_train_score*100
```

Out[192]:

```
100.0
```

In [193]:

```
#calculating the test score

linear_test_score = lr.score(test_x,test_y)
linear_test_score*100
```

Out[193]:

```
100.0
```

Conclusions

1. The training and test MAE has a huge difference as the training MAE is 1.1216615220544882e-14 and testing MAE is 1.112948637474002e-14
2. The coefficients we observed that there are some negative values as well and on plotting the qqplot we see that the residual quantile line doesn't fit over all ideal scaled quantiles.

Plotting Bar Graph

In [194]:

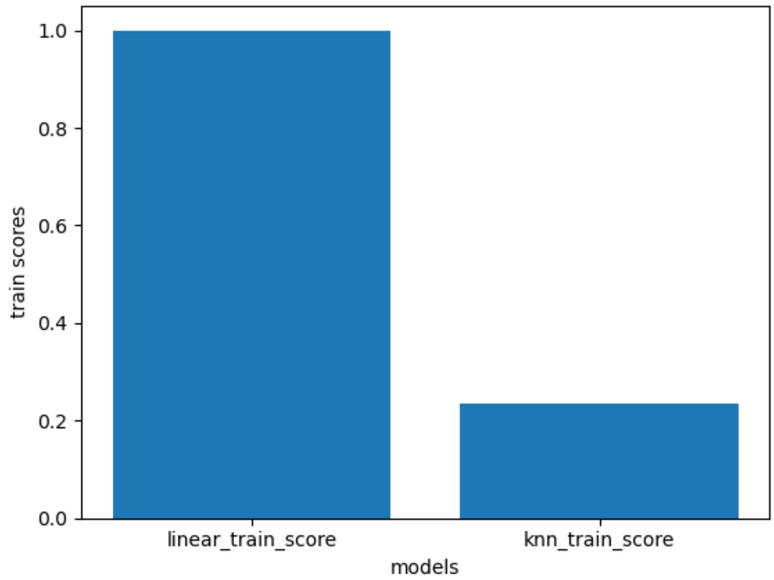
```
linear_train_score,knn_train_score
```

Out[194]:

```
(1.0, 0.23577168212623856)
```

In [195]:

```
#assining the train score values in x,y
x=["linear_train_score","knn_train_score"]
y=[1.0, 0.23577168212623856 ]
plt.figure(dpi=100)
plt.bar(x,y)
plt.xlabel("models")
plt.ylabel("train scores")
plt.show()
```



Test score

In [204]:

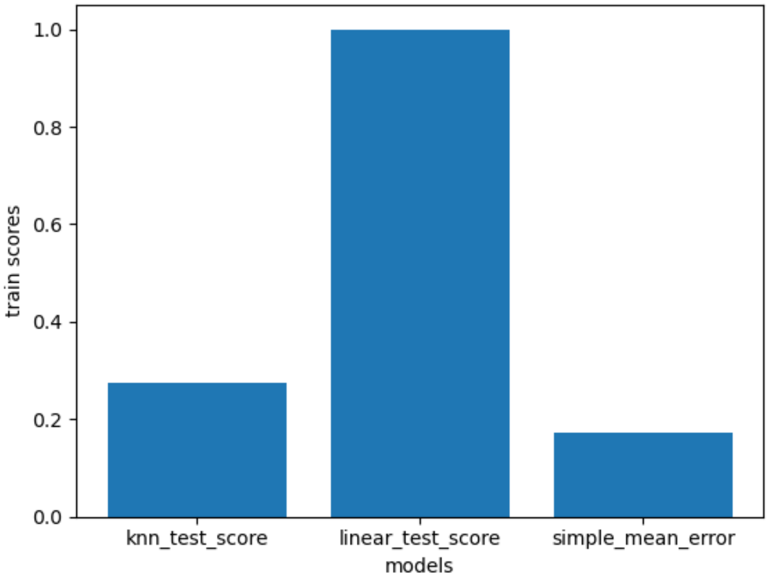
```
knn_test_score, linear_test_score,simple_mean_error
```

Out[204]:

```
(0.2752035767562998, 1.0, 0.17207002339174687)
```

In [205]:

```
#assining the test score value in x1,y1
x1=["knn_test_score","linear_test_score","simple_mean_error"]
y1=[0.2752035767562998, 1.0, 0.17207002339174687]
plt.figure(dpi=100)
plt.bar(x1,y1)
plt.xlabel("models")
plt.ylabel("train scores")
plt.show()
```



Conclusion

From the above bar graph for both train and test score i prefer linear model is the best.

In [ ]: