Final Project: Building Basic predictive models over the NYC Taxi Trip dataset.

Firstly Import All The Libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#import data from library

data = pd.read_csv('/Users/goura/Downloads/nyc_taxi_trip_duration.csv')
```

In [3]:
```
data.head()
```

Out[3]:

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

In [4]:
```
#Knowing about missing values is important

data.isnull().sum()
```

Out[4]:
```
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
```

Finding total Length / Shape / Data types.

In [5]:
```
len(data)
```

Out[5]: 729322

In [6]:
```
data.shape
```

Out[6]:
```
(729322, 11)
```

In [7]:
```
print (data.dtypes)
```

```
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       object
trip_duration             int64
dtype: object
```

In [8]:
```
# converting strings to datetime features

data['pickup_datetime'] = pd.to_datetime(data.pickup_datetime)
data['dropoff_datetime'] = pd.to_datetime(data.dropoff_datetime)
```

In [9]:
```
data['day_of_week'] = data['pickup_datetime'].dt.weekday
data['hour_of_day'] = data['pickup_datetime'].dt.hour
```

In [10]:
```
data.describe()
```

Out[10]:

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	tri
count	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	729322.000000	7.2
mean	1.535403	1.662055	-73.973513	40.750919	-73.973422	40.751775	9.5
std	0.498745	1.312446	0.069754	0.033594	0.069588	0.036037	3.8
min	1.000000	0.000000	-121.933342	34.712234	-121.933304	32.181141	1.0
25%	1.000000	1.000000	-73.991859	40.737335	-73.991318	40.735931	3.9
50%	2.000000	1.000000	-73.981758	40.754070	-73.979759	40.754509	6.6
75%	2.000000	2.000000	-73.967361	40.768314	-73.963036	40.769741	1.0
max	2.000000	9.000000	-65.897385	51.881084	-65.897385	43.921028	1.9

The tasks for this project are listed below & complete them and submit them in a.zip file.

Ques 1. Choose the most suitable evaluation metric and state why you chose it.?

Mean Squared Error is the best evaluation metric for the provided dataset. Since the square of the difference between the predicted value and the actual value of the target variable makes up the mean squared error formula. which will increase the error value and make it easier for us to find small errors.

Ques 2. Build a benchmark model for the given dataset.

In [11]:
```
from sklearn.utils import shuffle

# Shuffling the Dataset
data = shuffle(data, random_state = 42)

#creating 4 divisions
div = int(data.shape[0]/4)

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

In [12]:
```
train.head()
```

Out[12]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latit
469114	id2380741	2	2016-05-21 10:40:14	2016-05-21 10:51:11	1	-73.981796	40.762
694852	id3946961	2	2016-01-08 18:49:27	2016-01-08 18:52:42	5	-73.980965	40.747
696324	id0833913	1	2016-05-22 00:54:10	2016-05-22 01:08:10	1	-73.951065	40.782
356496	id1336849	1	2016-06-11 10:32:12	2016-06-11 10:38:50	1	-73.987625	40.762
645318	id1610858	1	2016-04-03 10:45:51	2016-04-03 10:57:13	3	-73.964333	40.792

In [13]:
```
test.head()
```

Out[13]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latit
546991	id2240736	1	2016-05-25 07:59:16	2016-05-25 08:05:02	1	-73.991364	40.732
43126	id1423404	1	2016-01-18 12:17:13	2016-01-18 12:21:13	2	-73.966225	40.768
641450	id1317268	2	2016-03-02 18:39:01	2016-03-02 18:50:12	1	-73.994926	40.766
611380	id3335546	1	2016-04-06 19:17:20	2016-04-06 19:18:03	1	-73.974388	40.793
62690	id2174190	2	2016-06-21 18:35:31	2016-06-21 18:40:56	3	-73.963440	40.798

Simple Mean (mean of trip_duration)

In [14]:
```
# 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[14]:
```
546991    951.586402
43126     951.586402
641450    951.586402
611380    951.586402
62690     951.586402
             ...
259178    951.586402
365838    951.586402
131932    951.586402
671155    951.586402
121958    951.586402
Name: simple_mean, Length: 139872, dtype: float64
```

In [15]:
```
#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[15]:
```
621.9954570969938
```

Mean Trip Duration with respect to Day of Week

In [16]:
```
day_of_week = pd.pivot_table(train, values='trip_duration', index = ['day_of_week'], agg
day_of_week
```

Out[16]:

day_of_week	trip_duration
0	890.012810
1	984.251885
2	973.047004
3	1005.146720
4	989.699815
5	918.067036
6	888.431043

In [17]:
```
# initializing new column to zero
test['day_of_week_mean'] = 0

# For every unique entry in Outlet_Identifier
for i in train['day_of_week'].unique():

  # Assign the mean value corresponding to unique entry
  test['day_of_week_mean'][test['day_of_week'] == i] = train['trip_duration'][train['day
```

In [18]:
```
#calculating mean absolute error
day_of_week_error = MAE(test['trip_duration'] , test['day_of_week_mean'] )
day_of_week_error
```

Out[18]:
```
620.6622607467708
```

Mean Trip Duration with respect to Hour of Day

In [19]:
```
hour_of_day = pd.pivot_table(train, values='trip_duration', index = ['hour_of_day'], agg
hour_of_day
```

Out[19]:

hour_of_day	trip_duration
0	982.268516
1	915.598624
2	853.385638
3	886.535977
4	890.512498
5	829.845634
6	726.336661
7	812.179002
8	937.732130
9	930.980245
10	951.272356
11	950.944420
12	979.790870
13	1014.624609
14	1084.491606
15	1117.583598
16	1093.067599
17	1041.374211
18	981.165605
19	895.084902
20	848.850640
21	889.002788
22	938.585268
23	916.715693

In [20]:
```
# initializing new column to zero
test['hour_of_day_mean'] = 0

# For every unique entry in Outlet_Identifier
for i in train['hour_of_day'].unique():
  # Assign the mean value corresponding to unique entry
  test['hour_of_day_mean'][test['hour_of_day'] == i] = train['trip_duration'][train['hou
```

In [21]:
```
#calculating mean absolute error
hour_of_day_error = MAE(test['trip_duration'] , test['hour_of_day_mean'] )
hour_of_day_error
```

Out[21]:
```
620.3242746375885
```

Let's check the data files! According to the data description we should find the following columns:

>>id - a unique identifier for each trip >>vendor_id - a code indicating the provider associated with the trip record >>pickup_datetime - date and time when the meter was engaged >>dropoff_datetime - date and time when the meter was disengaged >>passenger_count - the number of passengers in the vehicle (driver entered value) >>pickup_longitude - the longitude where the meter was engaged >>pickup_latitude - the latitude where the meter was engaged >>dropoff_longitude - the longitude where the meter was disengaged >>dropoff_latitude - the latitude where the meter was disengaged >>store_and_fwd_flag - This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server (Y=store and forward; N=not a store and forward trip) >>trip_duration - (target) duration of the trip in seconds Here, we have 2 variables dropoff_datetime and store_and_fwd_flag which are not available before the trip starts and hence will not be used as features to the model.

Mean Trip Duration with respect to Vendor ID

In [22]:
```
vendor = pd.pivot_table(train, values='trip_duration', index = ['vendor_id'], aggfunc=np
vendor
```

Out[22]:

vendor_id	trip_duration
1	838.174354
2	1049.946134

In [23]:
```
# initializing new column to zero
test['vendor_id_mean'] = 0

# For every unique entry in Outlet_Identifier
for i in train['vendor_id'].unique():
  # Assign the mean value corresponding to unique entry
  test['vendor_id_mean'][test['vendor_id'] == i] = train['trip_duration'][train['vendor_

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

Out[23]:
```
627.1274504364544
```

Mean Trip Duration with respect to Passenger Count

In [24]:
```
passenger = pd.pivot_table(train, values='trip_duration', index = ['passenger_count'], a
passenger
```

Out[24]:

passenger_count	trip_duration
0	334.733333
1	919.236280
2	1000.159939
3	1034.393923
4	1028.731304
5	1078.708147

6	1080.694100

In [25]:

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

# For every unique entry in Outlet_Identifier
for i in train['passenger_count'].unique():
  # Assign the mean value corresponding to unique entry
  test['passenger_count_mean'][test['passenger_count'] == i] = train['trip_duration'][tr

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

Out[25]:

```
622.5222915139927
```

Mean Trip Duration with respect to both Vendor Id and Passenger Count

In [26]:

```
combo = pd.pivot_table(train, values = 'trip_duration', index = ['vendor_id','passenger_
combo
```

Out[26]:

		trip_duration
vendor_id	**passenger_count**	
1	**0**	514.625000
	1	815.544883
	2	932.030630
	3	935.655634
	4	966.265018
	5	936.784722
	6	1133.650000
2	**0**	129.142857
	1	1037.136612
	2	1053.281189
	3	1095.370941
	4	1074.578032
	5	1079.358240
	6	1080.531284

In [27]:

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

# Assigning variables to strings ( to shorten code length)
s1 = 'passenger_count'
s2 = 'vendor_id'
# 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
    test['Super_mean'][(test[s1] == i) & (test[s2]==str(j))] = train['trip_duration'][(t

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

Out[27]:

```
954.9334105467856
```

Q3. Build a K-Nearest neighbours model for the given dataset and find the best value of K.

In [28]:

```
data = pd.read_csv('/Users/goura/Downloads/nyc_taxi_trip_duration.csv')
data.head()
```

Out[28]:

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

In [29]:

```
data.dtypes
```

Out[29]:

```
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     object
trip_duration           int64
dtype: object
```

In [30]:

```
# converting strings to datetime features

data['pickup_datetime'] = pd.to_datetime(data.pickup_datetime)
data['dropoff_datetime'] = pd.to_datetime(data.dropoff_datetime)

data['day_of_week'] = data['pickup_datetime'].dt.weekday
data['hour_of_day'] = data['pickup_datetime'].dt.hour
```

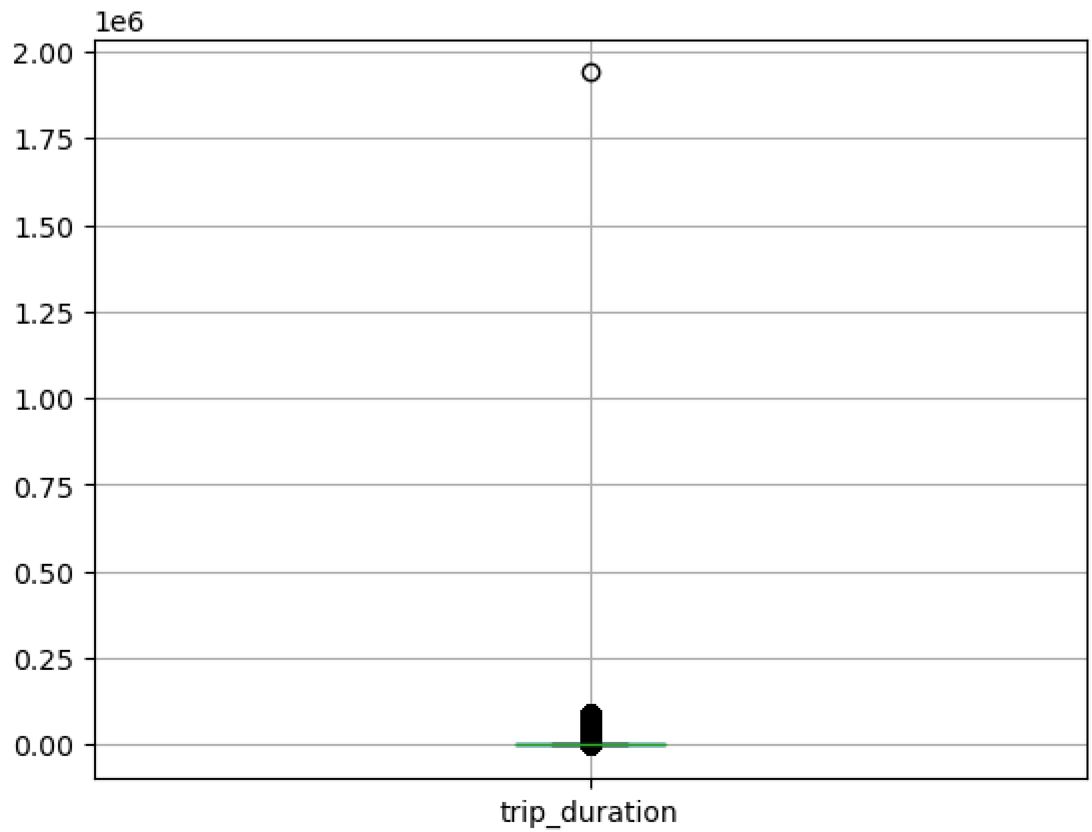
In [31]:

```
data['vendor_id'] = data['vendor_id'].astype('category')
```

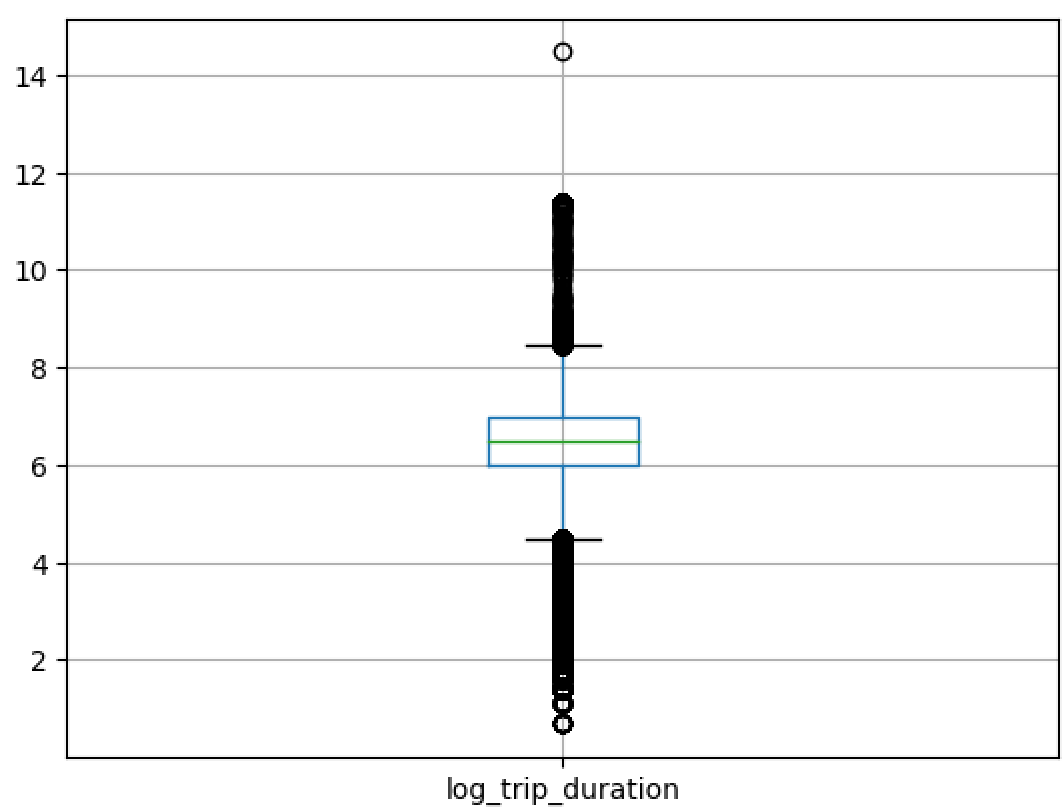
Outlier Detection and Removal

A. trip_duration

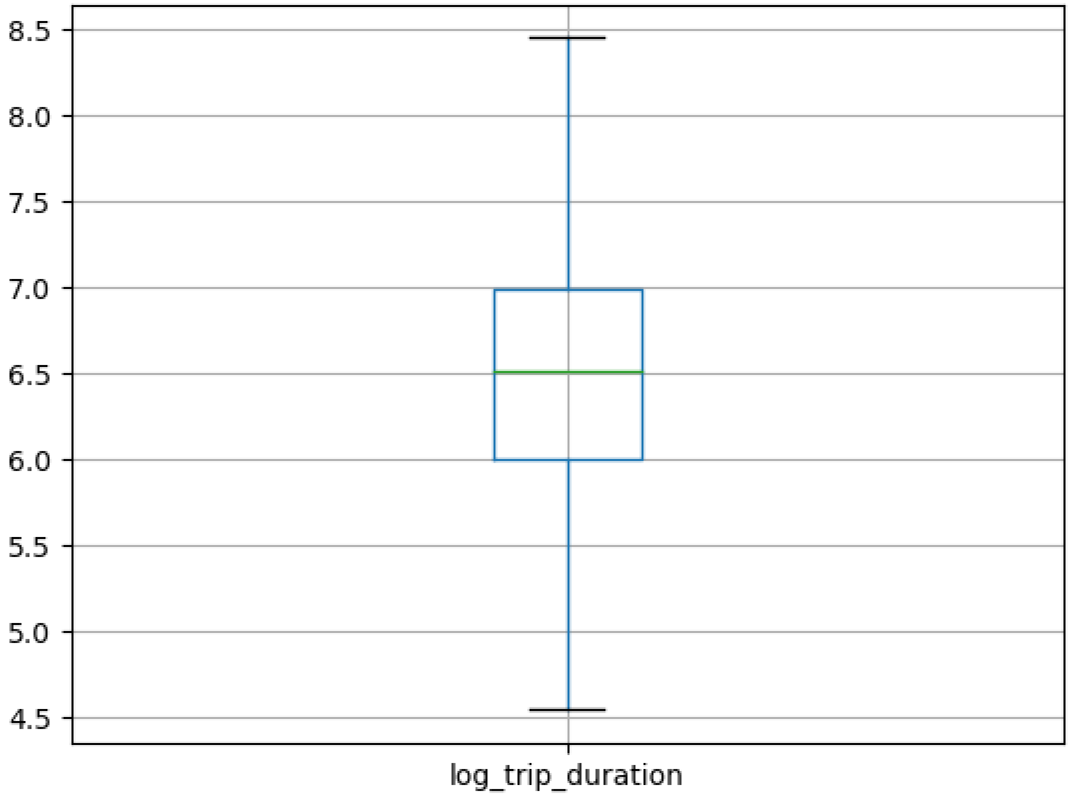
In [32]:
```
data.boxplot(column = ['trip_duration'])
plt.show()
```



In [33]:
```
data['log_trip_duration'] = np.log(data['trip_duration'].values + 1)
data['log_trip_duration'] = data['log_trip_duration'].astype('float16')

data.boxplot(column = ['log_trip_duration'])
plt.show()
```



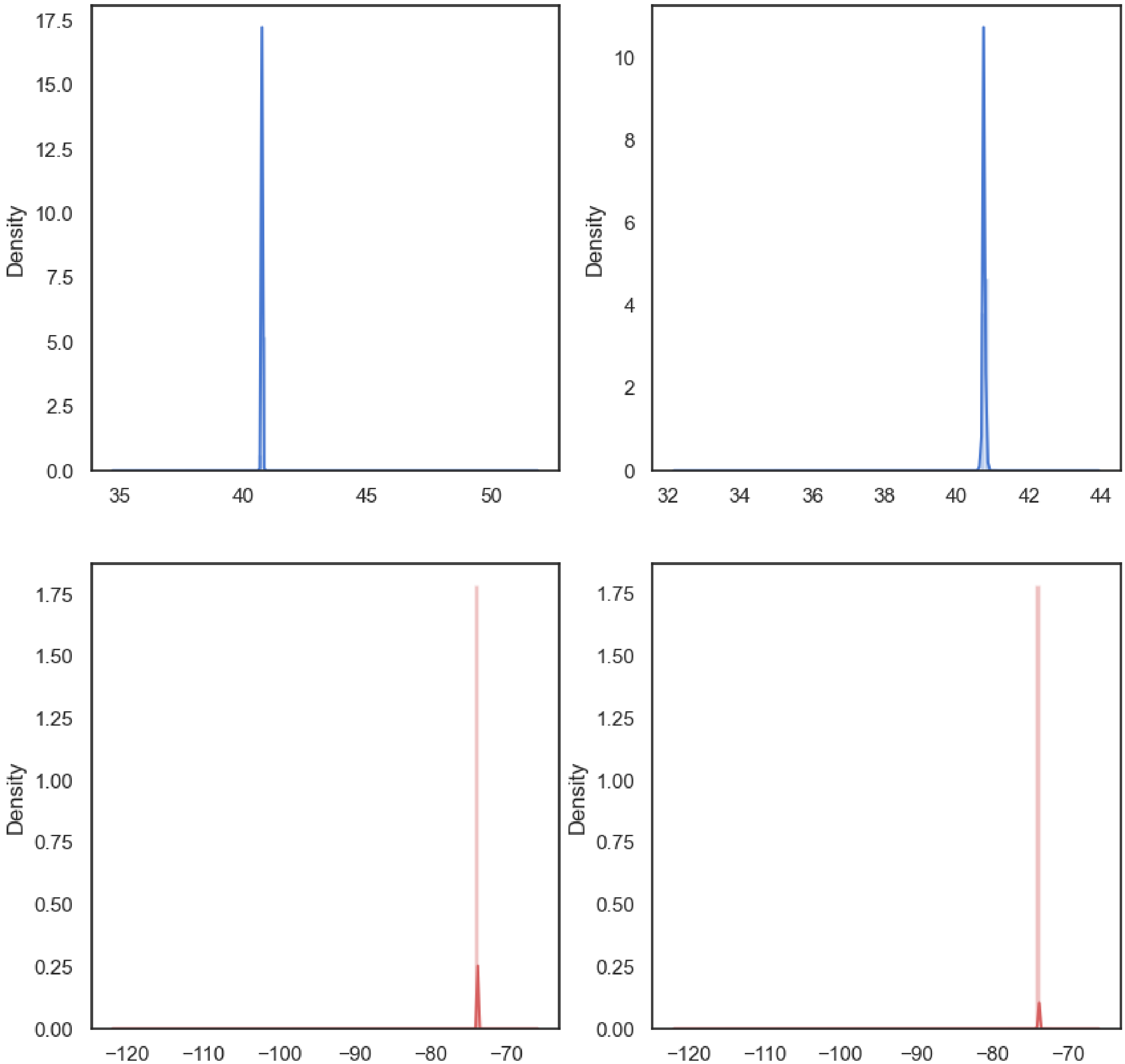
In [34]:
```
data = data.loc[(data.log_trip_duration > 4.53) & (data.log_trip_duration < 8.45)]
data.boxplot(column = ['log_trip_duration'])
plt.show()
```



B. pickup_latitude, pickup_longitude, dropoff_latitude & dropoff_longitude

Analysing Longitudes and Latitudes of the trips.

In [35]:
```
sns.set(style="white", palette="muted")
f, axes = plt.subplots(nrows = 2, ncols = 2, figsize=(10, 10), sharex = False, sharey =
sns.distplot(data['pickup_latitude'].values, label = 'pickup_latitude', color="b", bins
sns.distplot(data['pickup_longitude'].values, label = 'pickup_longitude', color="r", bin
sns.distplot(data['dropoff_latitude'].values, label = 'dropoff_latitude', color="b", bin
sns.distplot(data['dropoff_longitude'].values, label = 'dropoff_longitude', color="r", b
plt.show()
```

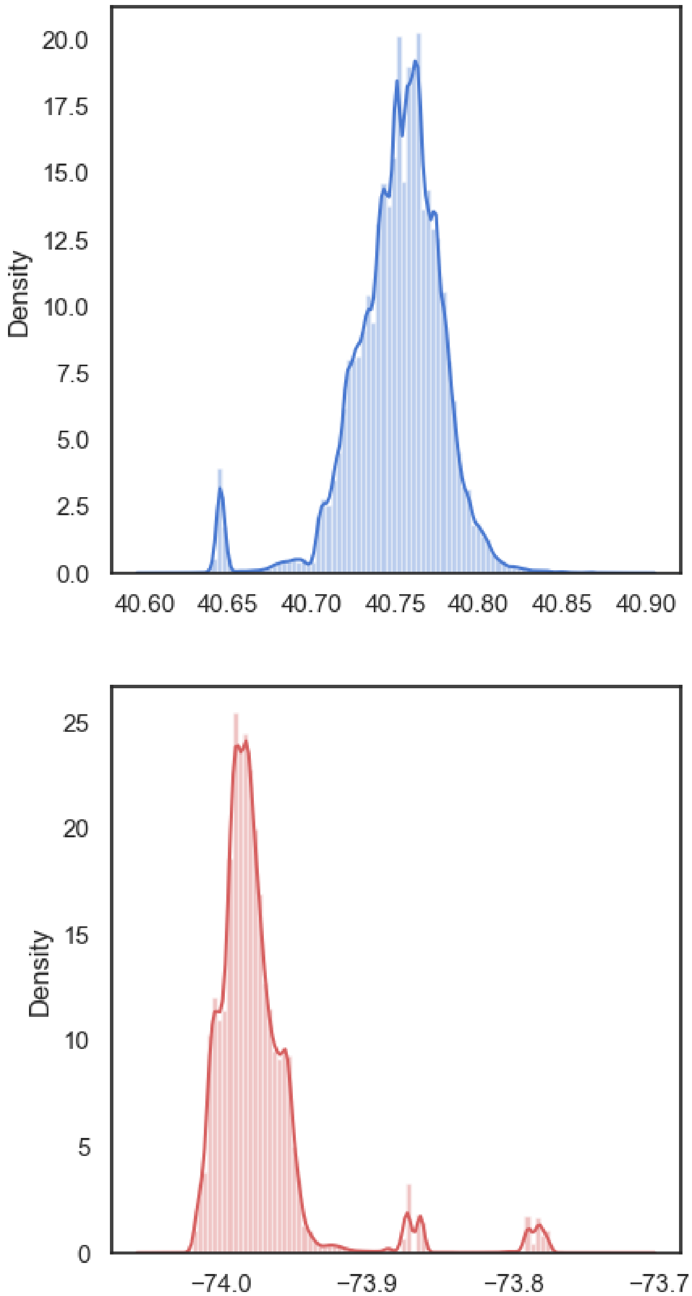


In [36]:

```
# Removing Outliers

data = data.loc[(data.pickup_latitude > 40.6) & (data.pickup_latitude < 40.9)]
data = data.loc[(data.dropoff_latitude>40.6) & (data.dropoff_latitude < 40.9)]
data = data.loc[(data.dropoff_longitude > -74.05) & (data.dropoff_longitude < -73.7)]
data = data.loc[(data.pickup_longitude > -74.05) & (data.pickup_longitude < -73.7)]
```

In [37]:

```
# Visualisation after removing outliers

sns.set(style="white", palette="muted")
f, axes = plt.subplots(2,2,figsize=(10, 10), sharex=False, sharey = False)
sns.distplot(data['pickup_latitude'].values, label = 'pickup_latitude',color="b",bins =
sns.distplot(data['pickup_longitude'].values, label = 'pickup_longitude',color="r",bins
sns.distplot(data['dropoff_latitude'].values, label = 'dropoff_latitude',color="b",bins
sns.distplot(data['dropoff_longitude'].values, label = 'dropoff_longitude',color="r",bin
plt.show()
```




```
In [38]: data = pd.get_dummies(data.drop(['trip_duration', 'pickup_datetime', 'dropoff_datetime',
data.head()
```

Out[38]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	day_of_week	hour_of_
0	1	-73.953918	40.778873	-73.963875	40.771164	0	
1	2	-73.988312	40.731743	-73.994751	40.694931	4	
2	2	-73.997314	40.721458	-73.948029	40.774918	6	
3	6	-73.961670	40.759720	-73.956779	40.780628	1	
4	1	-74.017120	40.708469	-73.988182	40.740631	2	

Segregating variables: Independent and Dependent Variables

seperating independent and dependent variables

In [39]:
```
#features
x = data.drop(['log_trip_duration'], axis=1)

#target
y = data['log_trip_duration']

x.shape, y.shape
```

Out[39]:
```
((715982, 11), (715982,))
```

Scaling the data (Using MinMax Scaler)

Importing the MinMax Scaler

In [40]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x)
x = pd.DataFrame(x_scaled, columns = x.columns)
x.head()
```

Out[40]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	day_of_week	hour_of_
0	0.111111	0.282868	0.596506	0.246491	0.570696	0.000000	0.695
1	0.222222	0.181487	0.438738	0.158009	0.316460	0.666667	1.000
2	0.222222	0.154950	0.404311	0.291902	0.583215	1.000000	0.739
3	0.666667	0.260019	0.532390	0.266824	0.602259	0.166667	0.391
4	0.111111	0.096568	0.360831	0.176833	0.468869	0.333333	0.260

Q4. Build a Linear model for the given dataset with regularisation. Attempt to interpret the variable coefficients of the Linear Model.

In [41]:
```
# As the dataset is already loaded and cleaned, we don't need to do preprocessing here.

data.head()
```

Out[41]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	day_of_week	hour_of_
0	1	-73.953918	40.778873	-73.963875	40.771164	0	
1	2	-73.988312	40.731743	-73.994751	40.694931	4	
2	2	-73.997314	40.721458	-73.948029	40.774918	6	
3	6	-73.961670	40.759720	-73.956779	40.780628	1	
4	1	-74.017120	40.708469	-73.988182	40.740631	2	

Segregating variables: Independent and Dependent Variables

In [42]:
```
# seperating independent and dependent variables

# Features
x = data.drop(['log_trip_duration'], axis=1)

# Target
y = data['log_trip_duration']

x.shape, y.shape
```

Out[42]:
```
((715982, 11), (715982,))
```

Splitting the data into train set and the test set

In [43]:
```
# Importing the train test split function
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(x,y, random_state = 56)
```

Implementing Linear Regression

In [44]:
```
from sklearn.linear_model import LinearRegression
```

In [45]:
```
train_error_reg = []
test_error_reg = []

lr = LinearRegression(normalize=True)

train_x_array = np.array(train_x)
train_y_array = np.array(train_y)
test_x_array = np.array(test_x)
test_y_array = np.array(test_y)

for i in range(1, 12):
    lr.fit(train_x_array[:, 0:i], train_y)
    train_y_pred = lr.predict(train_x_array[:, 0:i])
    test_y_pred = lr.predict(test_x_array[:, 0:i])

    mrss_train = sum((train_y_pred-train_y)**2)/train_x_array[:, 0:i].shape[0]
    mrss_test = sum((test_y_pred-test_y)**2)/test_x_array[:, 0:i].shape[0]

    train_error_reg.append(mrss_train)
    test_error_reg.append(mrss_test)
```

In [46]:
```
# Initializing the dataframe to store error

col = ['train_error_reg','test_error_reg']
ind = ['Number_of_variable_%d'%i for i in range(1, train_x.shape[1]+1)]
matrix_reg = pd.DataFrame(index=ind, columns=col)
```

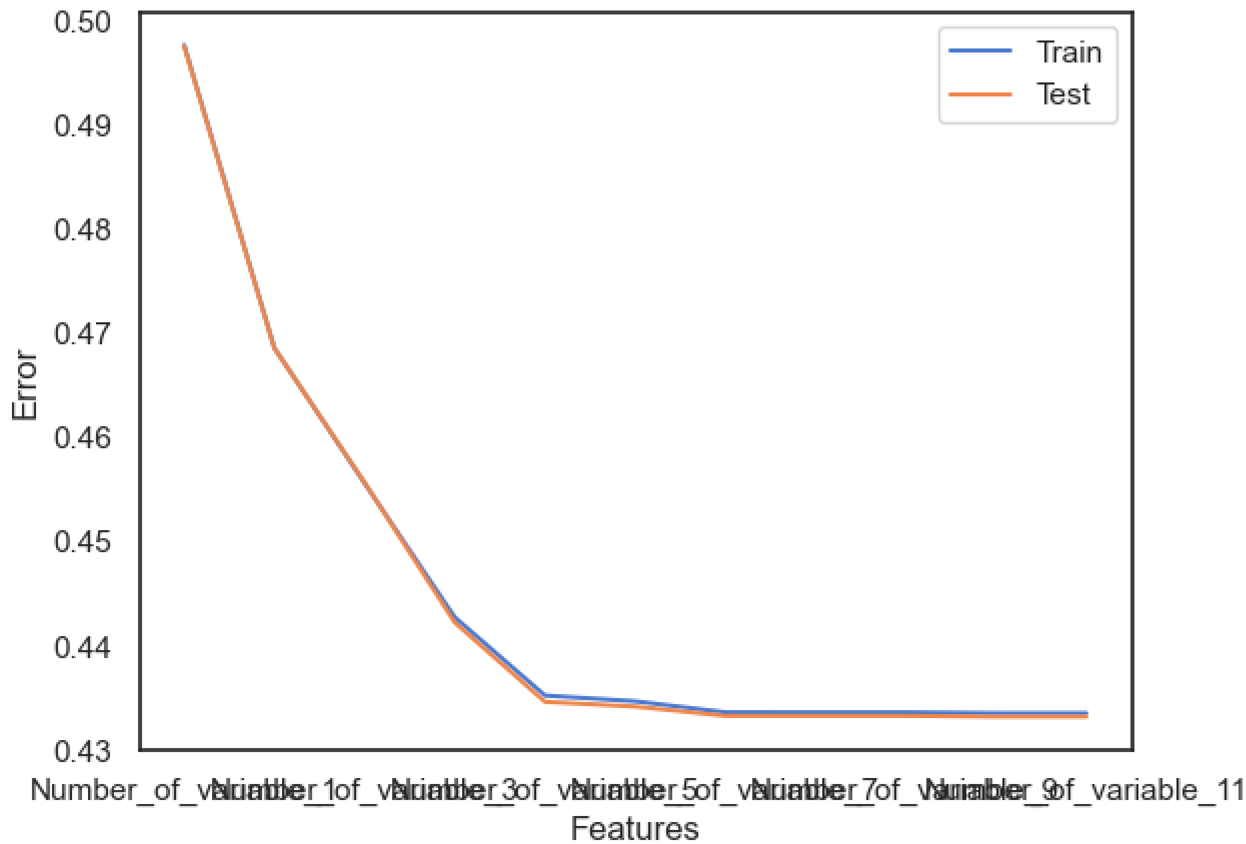
In [47]:
```
matrix_reg['train_error_reg'] = train_error_reg
matrix_reg['test_error_reg'] = test_error_reg
matrix_reg
```

Out[47]:

	train_error_reg	test_error_reg
Number_of_variable_1	0.497651	0.497568
Number_of_variable_2	0.468567	0.468540
Number_of_variable_3	0.455572	0.455662

Number_of_variable_4	0.442698	0.442191
Number_of_variable_5	0.435190	0.434580
Number_of_variable_6	0.434636	0.434131
Number_of_variable_7	0.433576	0.433239
Number_of_variable_8	0.433573	0.433239
Number_of_variable_9	0.433573	0.433239
Number_of_variable_10	0.433496	0.433154
Number_of_variable_11	0.433496	0.433154

In [48]:
```
# Plotting the Features VS Error curve

matrix_reg[['train_error_reg','test_error_reg']].plot()
plt.xlabel('Features')
plt.ylabel('Error')
plt.legend(['Train', 'Test'])
plt.show()
```



Parameters of Linear Regression

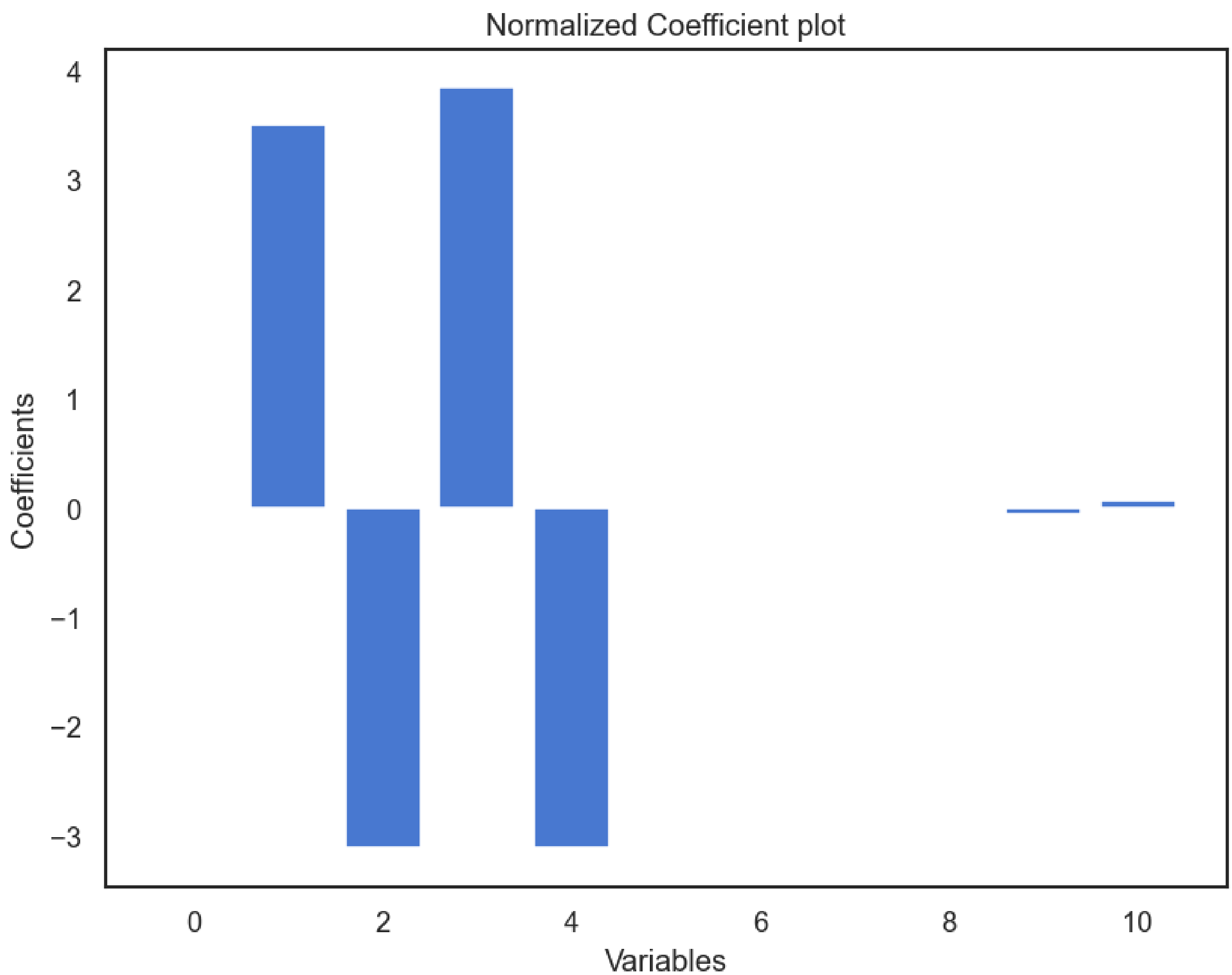
In [49]:
```
lr.coef_
```

Out[49]:
```
array([ 6.52460337e-03,  3.49826641e+00, -3.11621353e+00,  3.84410953e+00,
       -3.11608826e+00, -1.07123182e-02,  5.11803484e-03,  9.73216911e-04,
       -9.73216911e-04, -5.99991486e-02,  5.99991486e-02])
```

Plotting the coefficients

In [50]:
```
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('Coefficients')
plt.title('Normalized Coefficient plot')
plt.show()
```



Creating new subsets of data

In [51]:
```
# Seperating independent and dependent variables
x = data.drop(['log_trip_duration'], axis=1)
y = data['log_trip_duration']
x.shape, y.shape
```

Out[51]:
```
((715982, 11), (715982,))
```

Arranging coefficients with features

In [52]:
```
Coefficients = pd.DataFrame({
    'Variable'    : x.columns,
    'coefficient' : lr.coef_
})
Coefficients.head()
```

Out[52]:

	Variable	coefficient

0	passenger_count	0.006525
1	pickup_longitude	3.498266
2	pickup_latitude	-3.116214
3	dropoff_longitude	3.844110
4	dropoff_latitude	-3.116088

Choosing variables with sigificance greater than 0.5 (Filtering Significant Features)

In [53]:
```
sig_var = Coefficients[Coefficients.coefficient > 0.5]
```

Extracting the significant subset do independent Variables

In [54]:
```
subset = data[sig_var['Variable'].values]
subset.head()
```

Out[54]:

	pickup_longitude	dropoff_longitude
0	-73.953918	-73.963875
1	-73.988312	-73.994751
2	-73.997314	-73.948029
3	-73.961670	-73.956779
4	-74.017120	-73.988182

In [55]:
```
# Importing the train test split function
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(subset, y , random_state = 56)
```

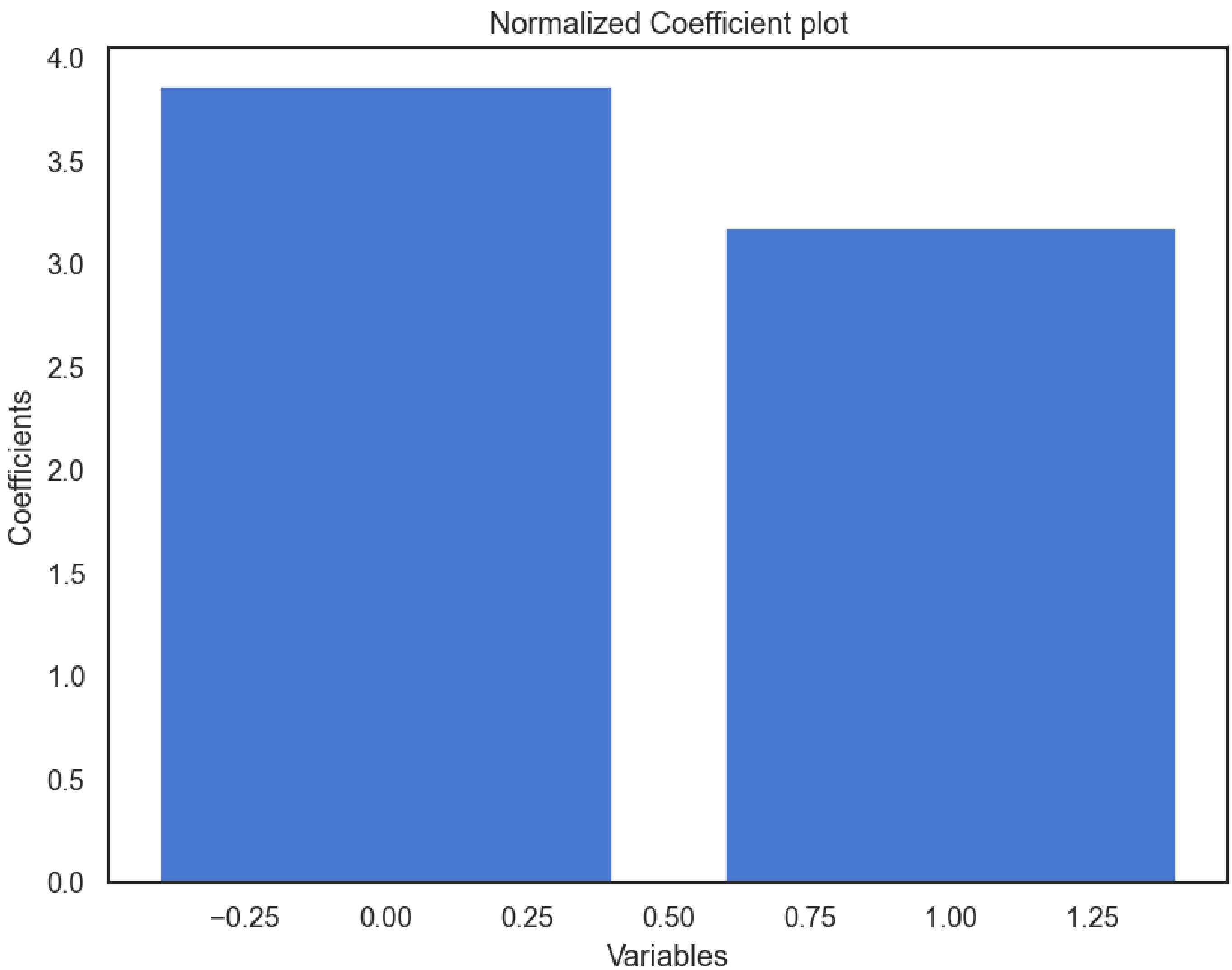
In [56]:
```
# Importing Linear Regression and metric mean square error
from sklearn.linear_model import LinearRegression as LR
from sklearn.metrics import mean_absolute_error as mae

# Creating instance of Linear Regresssion with Normalised Data
lr = LR(normalize = True)

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

Out[56]:
```
LinearRegression(normalize=True)
```

In [57]:
```
train_y_pred = lr.predict(train_x)
test_y_pred = lr.predict(test_x)

mrss_train_regression = sum((train_y_pred-train_y)**2)/train_x.shape[0]
mrss_test_regression = sum((test_y_pred-test_y)**2)/test_x.shape[0]

print('Train Error : ', mrss_train_regression)
print('Test Error  : ', mrss_test_regression)
```

```
Train Error :  0.4583871514331174
Test Error  :  0.45798488009889277
```

In [58]:
```
plt.figure(figsize=(8, 6), dpi=120, facecolor='w', edgecolor='b')
columns = range(len(train_x.columns))
coef = lr.coef_
plt.bar(columns, coef)
plt.xlabel("Variables")
plt.ylabel('Coefficients')
plt.title('Normalized Coefficient plot')
plt.show()
```



Interpretation from the linear variable Coefficients -

The above coefficient is normalized which can be used for making final inferences out of it.

From the above coefficient plot, we can observe that most of the variables aren't contributing in the linear model, only 2 variables are mostly contributing in the linear regression model.

Regularisation :-

Ridge

In [59]:
```
# Importing ridge from sklearn's linear_model module
from sklearn.linear_model import Ridge
# Setting the different values of alpha to be tested
alpha_ridge = [0, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20, 25]
```

In [60]:
```
train_error_ridge = []
test_error_ridge = []

for i in alpha_ridge:

    R = Ridge(alpha = i, normalize=True)
    R.fit(train_x, train_y)
    train_y_pred = R.predict(train_x)
    test_y_pred = R.predict(test_x)

    mrss_train = sum((train_y_pred-train_y)**2)/train_x.shape[0]
    mrss_test = sum((test_y_pred-test_y)**2)/test_x.shape[0]

    train_error_ridge.append(mrss_train)
    test_error_ridge.append(mrss_test)
```

In [61]:
```
R.coef_
```

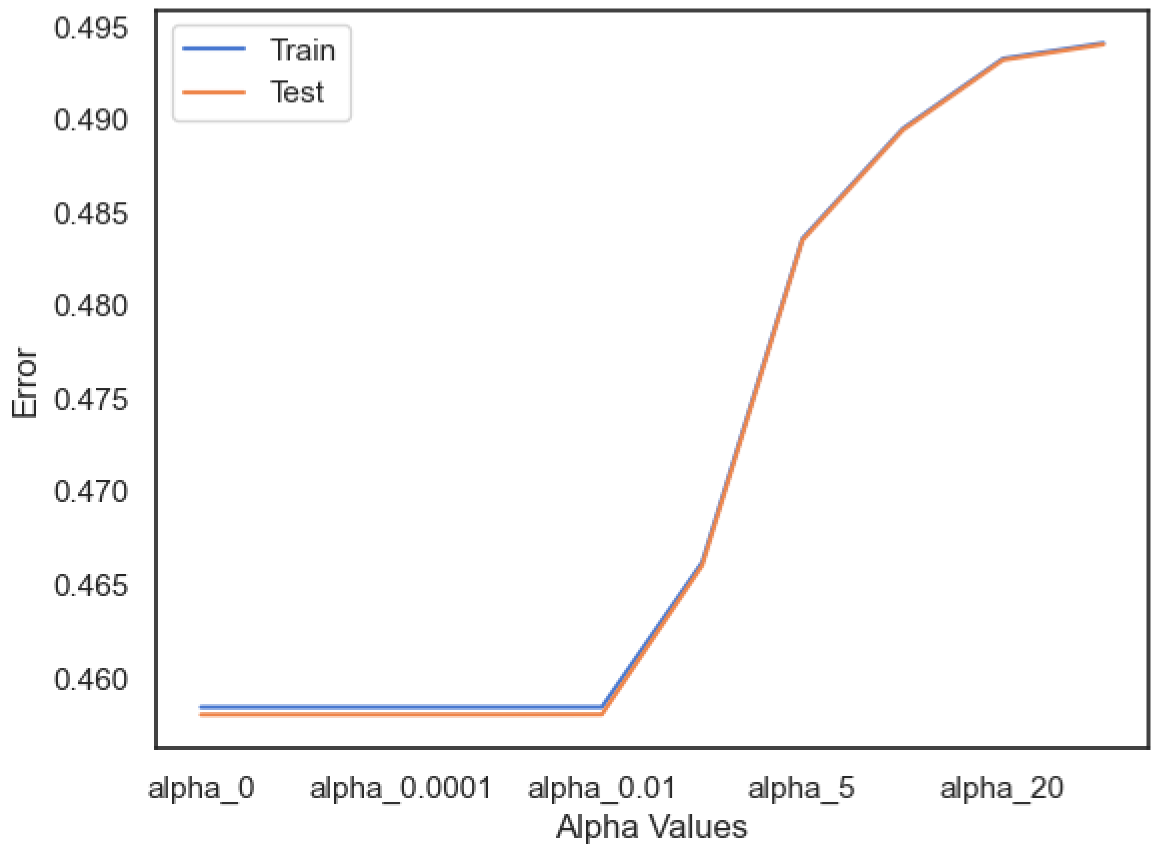
Out[61]:
```
array([0.1750103 , 0.16345732])
```

In [62]:
```
# Initializing the dataframe to store error

col = ['train_error_ridge','test_error_ridge']
ind = ['alpha_%.2g'%alpha_ridge[i] for i in range(0,10)]
matrix_ridge = pd.DataFrame(index=ind, columns=col)


matrix_ridge['train_error_ridge'] = train_error_ridge
matrix_ridge['test_error_ridge'] = test_error_ridge
matrix_ridge
```

Out[62]:

	train_error_ridge	test_error_ridge
alpha_0	0.458387	0.457985
alpha_1e-08	0.458387	0.457985
alpha_0.0001	0.458387	0.457985
alpha_0.001	0.458387	0.457985
alpha_0.01	0.458390	0.457993
alpha_1	0.466161	0.465995
alpha_5	0.483552	0.483471
alpha_10	0.489463	0.489389
alpha_20	0.493234	0.493161
alpha_25	0.494071	0.493998

In [63]:
```
# Plotting the Alpha Values VS Error graph

matrix_ridge[['train_error_ridge','test_error_ridge']].plot()
plt.xlabel('Alpha Values')
plt.ylabel('Error')
plt.legend(['Train', 'Test'])
plt.show()
```



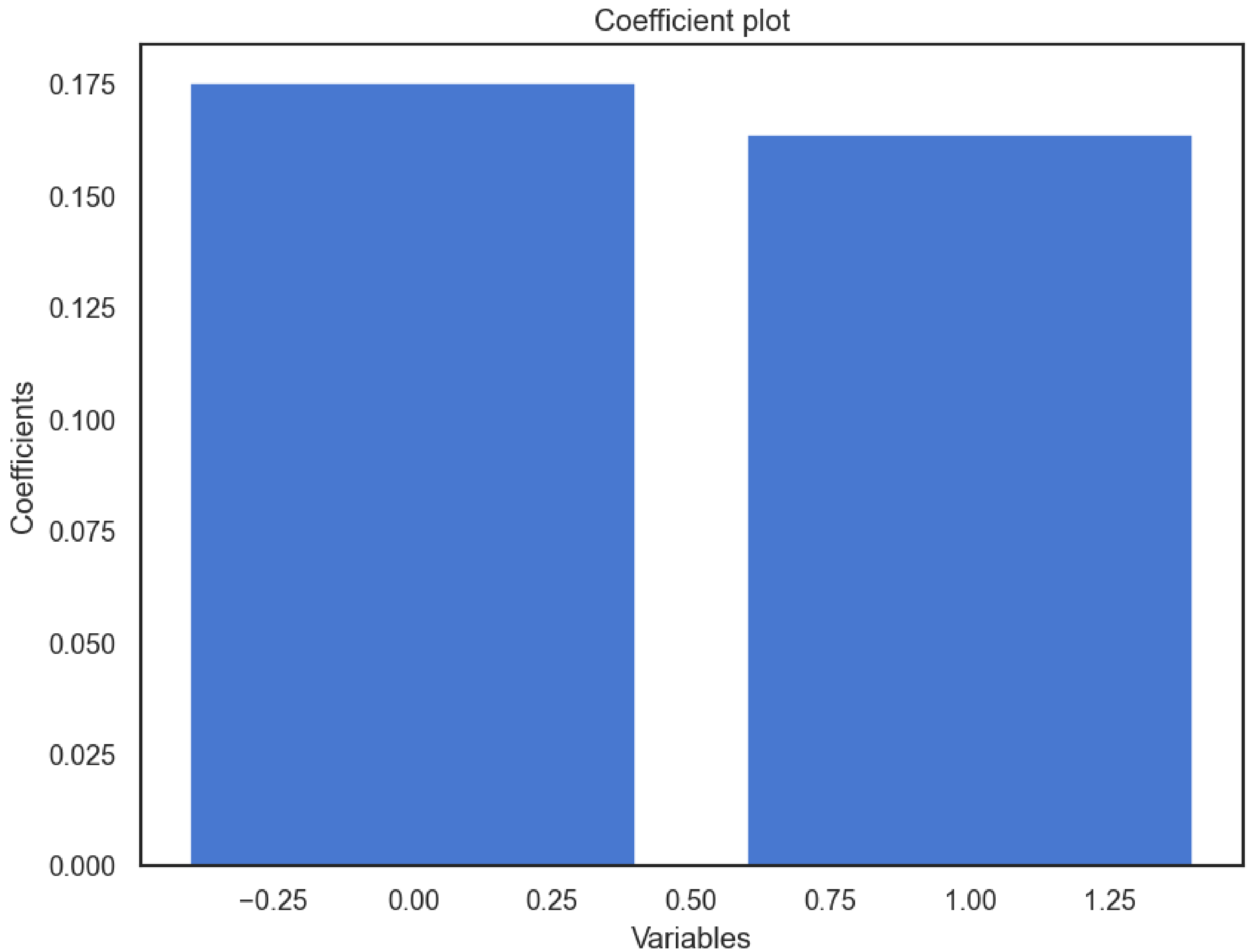
From the above plot, we can observe that the least error we can get is at alpha_0.001.

In [64]:
```
matrix_ridge.min()[0]
```

Out[64]:
```
0.45838715143311665
```

Interpreting the coefficients

In [65]:
```
plt.figure(figsize=(8, 6), dpi=120, facecolor='w', edgecolor='b')
x = range(len(train_x.columns))
y = R.coef_
plt.bar( x, y )
plt.xlabel( "Variables")
plt.ylabel('Coefficients')
plt.title('Coefficient plot')
plt.show()
```



Interpretation from the linear variable Coefficients -

The above coefficient is normalized which can be used for making final inferences out of it From the above coefficient plot, we can interpret that 2 of the variables are mostly contributing in the linear model while rest a=do not have any major impact on the ridge regression model.

Lasso

In [66]:
```
# Importing Lasso model from sklearn's linear_model module
from sklearn.linear_model import Lasso

# Definining the alpha values to test
alpha_lasso = [0, 1e-10, 1e-8, 1e-5,1e-4, 1e-3,1e-2, 1, 5, 10]
```

In [67]:
```
train_error_lasso = []
test_error_lasso = []

for i in alpha_lasso:

    L = Lasso(alpha = i, normalize=True)
    L.fit(train_x, train_y)
    train_y_pred = L.predict(train_x)
    test_y_pred = L.predict(test_x)

    mrss_train = sum((train_y_pred-train_y)**2)/train_x.shape[0]
    mrss_test = sum((test_y_pred-test_y)**2)/test_x.shape[0]
```

```
    train_error_lasso.append(mrss_train)
    test_error_lasso.append(mrss_test)
```

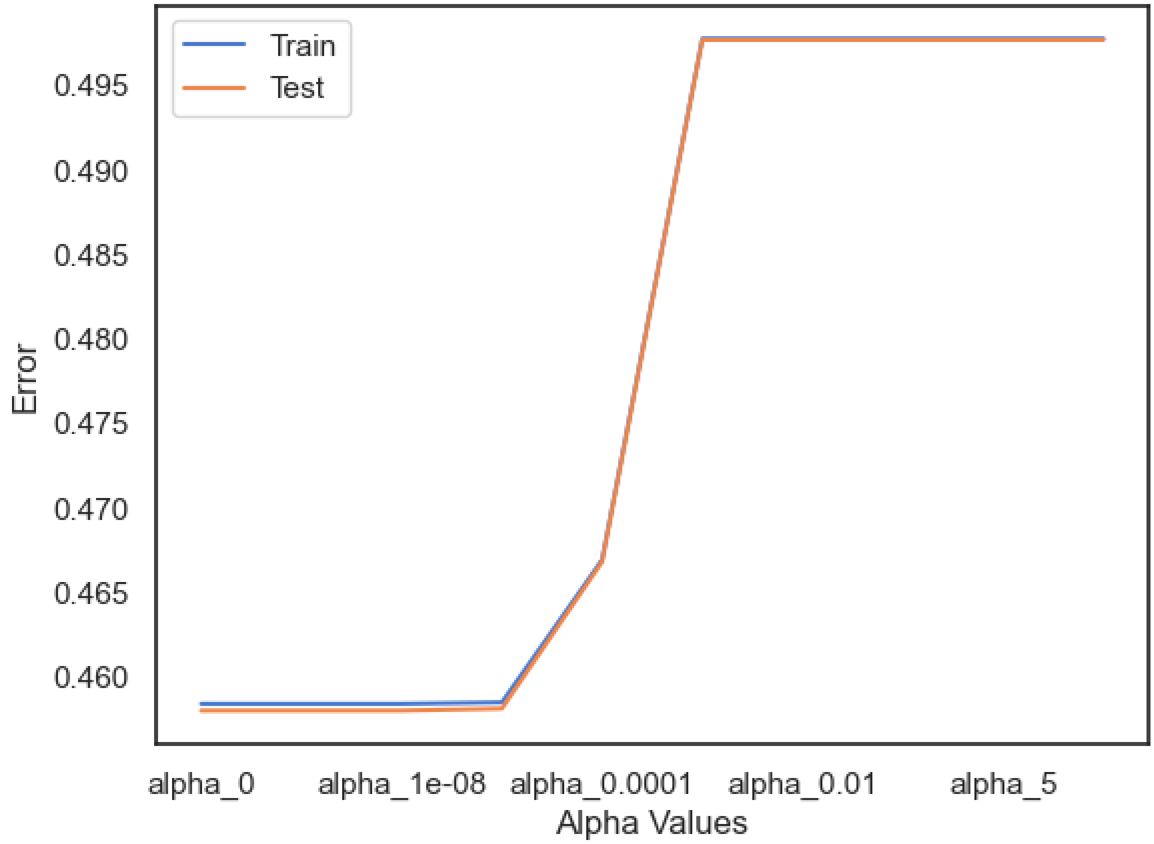
In [68]:
```
# Initializing the dataframe to store error

col = ['train_error_lasso','test_error_lasso']
ind = ['alpha_%.2g'%alpha_lasso[i] for i in range(0,10)]
matrix_lasso = pd.DataFrame(index=ind, columns=col)
```

In [69]:
```
matrix_lasso['train_error_lasso'] = train_error_lasso
matrix_lasso['test_error_lasso'] = test_error_lasso
matrix_lasso
```

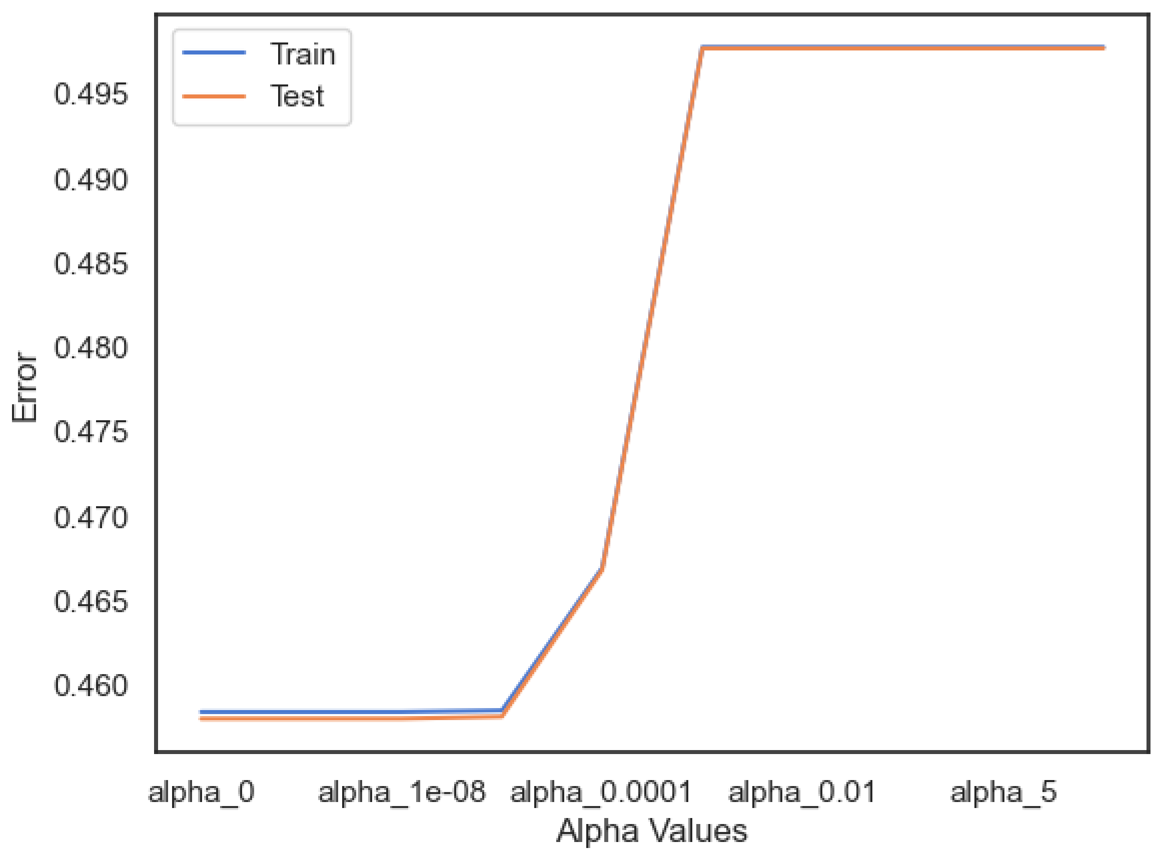
Out[69]:

	train_error_lasso	test_error_lasso
alpha_0	0.458387	0.457985
alpha_1e-10	0.458387	0.457985
alpha_1e-08	0.458387	0.457985
alpha_1e-05	0.458472	0.458105
alpha_0.0001	0.466907	0.466783
alpha_0.001	0.497738	0.497664
alpha_0.01	0.497738	0.497664
alpha_1	0.497738	0.497664
alpha_5	0.497738	0.497664
alpha_10	0.497738	0.497664

In [70]:
```
# Plotting the Alpha Values VS Error graph

matrix_lasso[['train_error_lasso','test_error_lasso']].plot()
plt.xlabel('Alpha Values')
plt.ylabel('Error')
plt.legend(['Train', 'Test'])
plt.show()
```



In [71]:
```
# Plotting the Alpha Values VS Error graph

matrix_lasso[['train_error_lasso','test_error_lasso']].plot()
plt.xlabel('Alpha Values')
plt.ylabel('Error')
plt.legend(['Train', 'Test'])
plt.show()
```



From the above plot, we can observe that the least error we can get is at alpha_1e-08.

In [72]:
```
matrix_lasso.min()
```

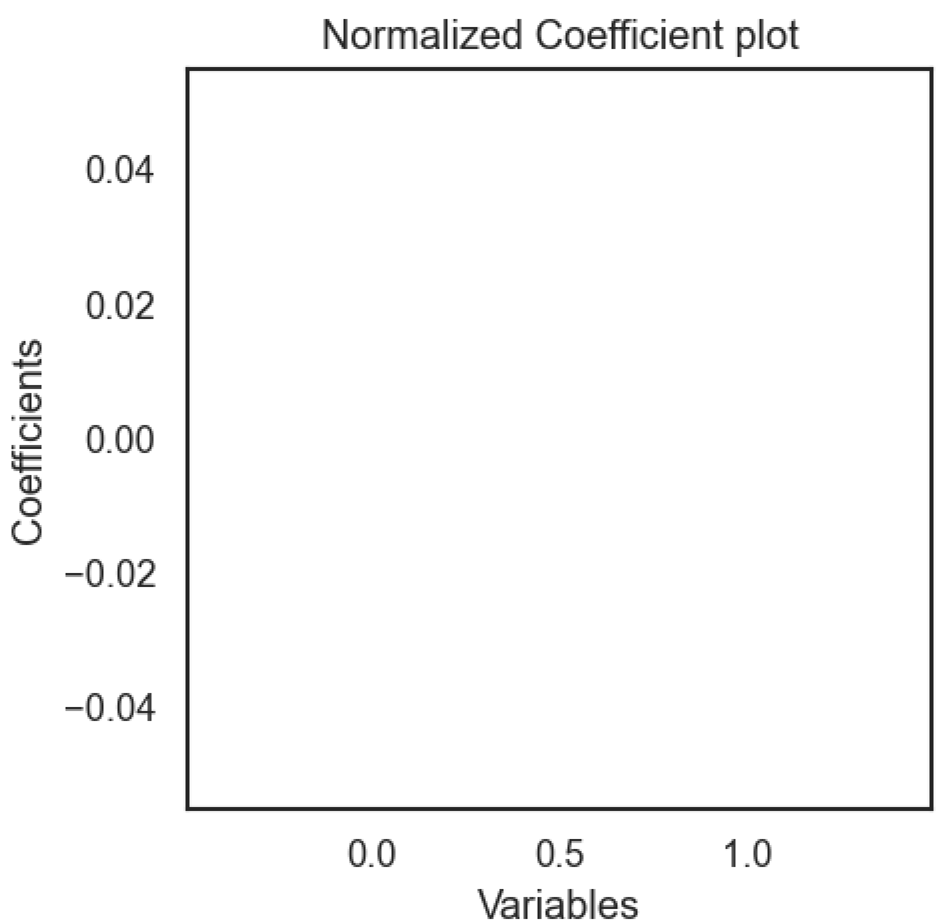
Out[72]:
```
train_error_lasso     0.458387
test_error_lasso      0.457985
dtype: float64
```

Plotting the coefficients

In [73]:
```
L.coef_
```

Out[73]:
```
array([0., 0.])
```

In [74]:
```
plt.figure(figsize=(4, 4), dpi=120, facecolor='w', edgecolor='b')
x = range(len(train_x.columns))
y = L.coef_
plt.bar( x, y )
plt.xlabel( "Variables")
plt.ylabel('Coefficients')
plt.title('Normalized Coefficient plot')
plt.show()
```



Interpretation from the linear variable Coefficients -

The above coefficient is normalized which can be used for making final inferences out of it.

From the above coefficient plot, we can interpret that none of the variables are contributing in the lasso modeling.

Q5. Build a Decision tree model for the given dataset. Attempt to interpret the variable importance.

Segregating variables: Independent and Dependent Variables

In [75]:
```
# Seperating independent and dependent variables
# Features
x = data.drop(['log_trip_duration'], axis=1)

# Target
y = data['log_trip_duration']

x.shape, y.shape
```

Out[75]:
```
((715982, 11), (715982,))
```

Splitting the data into train set and the test set

In [76]:
```
# Importing the train test split function
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(x,y, random_state = 56, test_size = 0.2
```

Implementing Decision Tree Regressor

In [77]:
```
# Importing decision tree regressor
from sklearn.tree import DecisionTreeRegressor
```

In [78]:
```
# Creating the decision tree function
dt_model = DecisionTreeRegressor(random_state=10)
```

In [79]:
```
# Fitting the model
dt_model.fit(train_x, train_y)
```

Out[79]:
```
DecisionTreeRegressor(random_state=10)
```

In [80]:
```
# Checking the training score
dt_model.score(train_x, train_y)
```

Out[80]:
```
0.9999950762507785
```

In [81]:
```
# Checking the test score
dt_model.score(test_x, test_y)
```

Out[81]:
```
0.5684601912091733
```

In [82]:
```
# Predictions on test set
y_pred = dt_model.predict(test_x)
```

Changing the max_depth

In [83]:
```
train_accuracy = []
test_accuracy = []
for depth in range(1,30):
    dt_model = DecisionTreeRegressor(max_depth=depth, random_state=10)
    dt_model.fit(train_x, train_y)
    train_accuracy.append(dt_model.score(train_x, train_y))
    test_accuracy.append(dt_model.score(test_x, test_y))
```

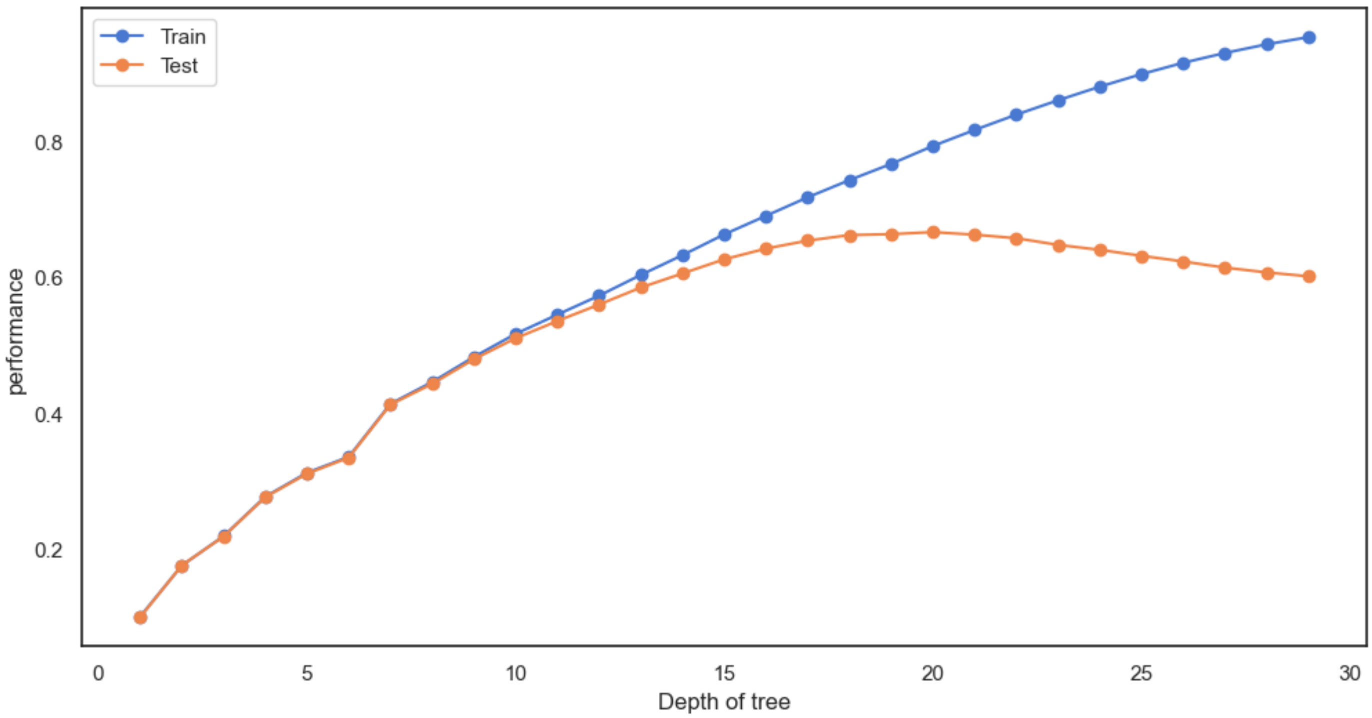
In [84]:
```
frame = pd.DataFrame({'max_depth':range(1,30), 'train_acc':train_accuracy, 'test_acc':te
frame
```

Out[84]:

	max_depth	train_acc	test_acc
0	1	0.099740	0.098872
1	2	0.175118	0.175315
2	3	0.218434	0.217927
3	4	0.276628	0.275836
4	5	0.311894	0.310457
5	6	0.335355	0.334237
6	7	0.413576	0.412425
7	8	0.445711	0.442968
8	9	0.482716	0.479353
9	10	0.516750	0.510261
10	11	0.545103	0.535723
11	12	0.573062	0.559962
12	13	0.603688	0.585108
13	14	0.632835	0.605839
14	15	0.663497	0.626675
15	16	0.690829	0.642543
16	17	0.718147	0.654311
17	18	0.743503	0.662427
18	19	0.767453	0.663841
19	20	0.793828	0.666830
20	21	0.817485	0.663071
21	22	0.840064	0.657833
22	23	0.861236	0.648065
23	24	0.881348	0.640681
24	25	0.899855	0.631894
25	26	0.916578	0.623548
26	27	0.931018	0.614480
27	28	0.943812	0.607398

28	29	0.954408	0.601644

In [85]:
```
plt.figure(figsize=(12,6))
plt.plot(frame['max_depth'], frame['train_acc'], marker='o')
plt.plot(frame['max_depth'], frame['test_acc'], marker='o')
plt.xlabel('Depth of tree')
plt.ylabel('performance')
plt.legend(['Train', 'Test'])
plt.show()
```



In [86]:
```
dt_model = DecisionTreeRegressor(max_depth=18, max_leaf_nodes=80, random_state=10)
```

In [87]:
```
# Fitting the model
dt_model.fit(train_x, train_y)
```

Out[87]:
```
DecisionTreeRegressor(max_depth=18, max_leaf_nodes=80, random_state=10)
```

In [88]:
```
# Training score
dt_model.score(train_x, train_y)
```

Out[88]:
```
0.5246615145105771
```

In [89]:
```
# Test score
dt_model.score(test_x, test_y)
```

Out[89]:
```
0.521722466581197
```

In [90]:
```
from sklearn import tree
```

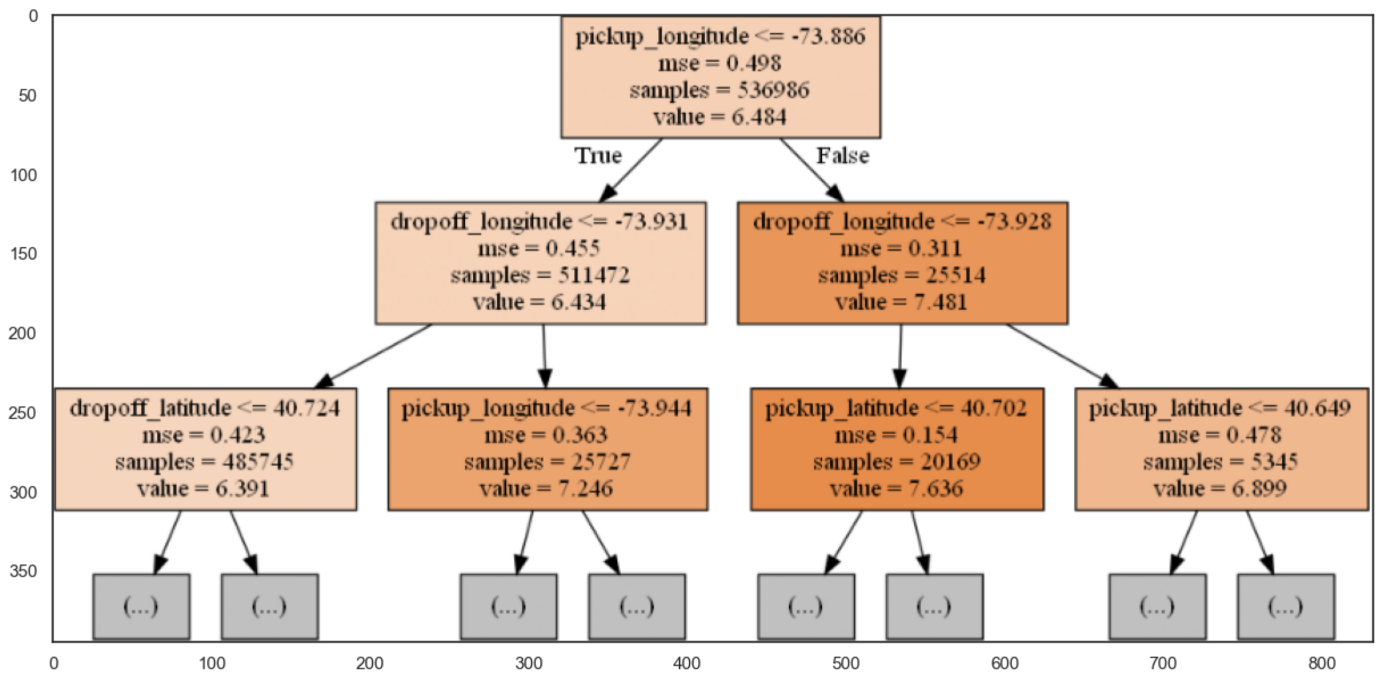
In [91]:
```
decision_tree = tree.export_graphviz(dt_model,out_file='tree.dot',feature_names=train_x.
```

In [92]:
```
!dot -Tpng tree.dot -o tree.png
```

```
'dot' is not recognized as an internal or external command,
operable program or batch file.
```

In [93]:
```
image = plt.imread('/Users/goura/Downloads/download.png')
plt.figure(figsize=(15, 40))
```

```
plt.imshow(image)
plt.show()
```



Variable Importance -

From the above decision tree model, it can be interpreted that the variable pickup_longitude is the most suitable root node because after splitting, reduction in varience, i.e., MSE, of the child nodes is least compared to other variables after the split.

Q6. Plot the following Barplots:

a. train score of all the above models.

b. test (not validation!) score of all the above models.

c. Attempt to explain the observations from the plots (optional).

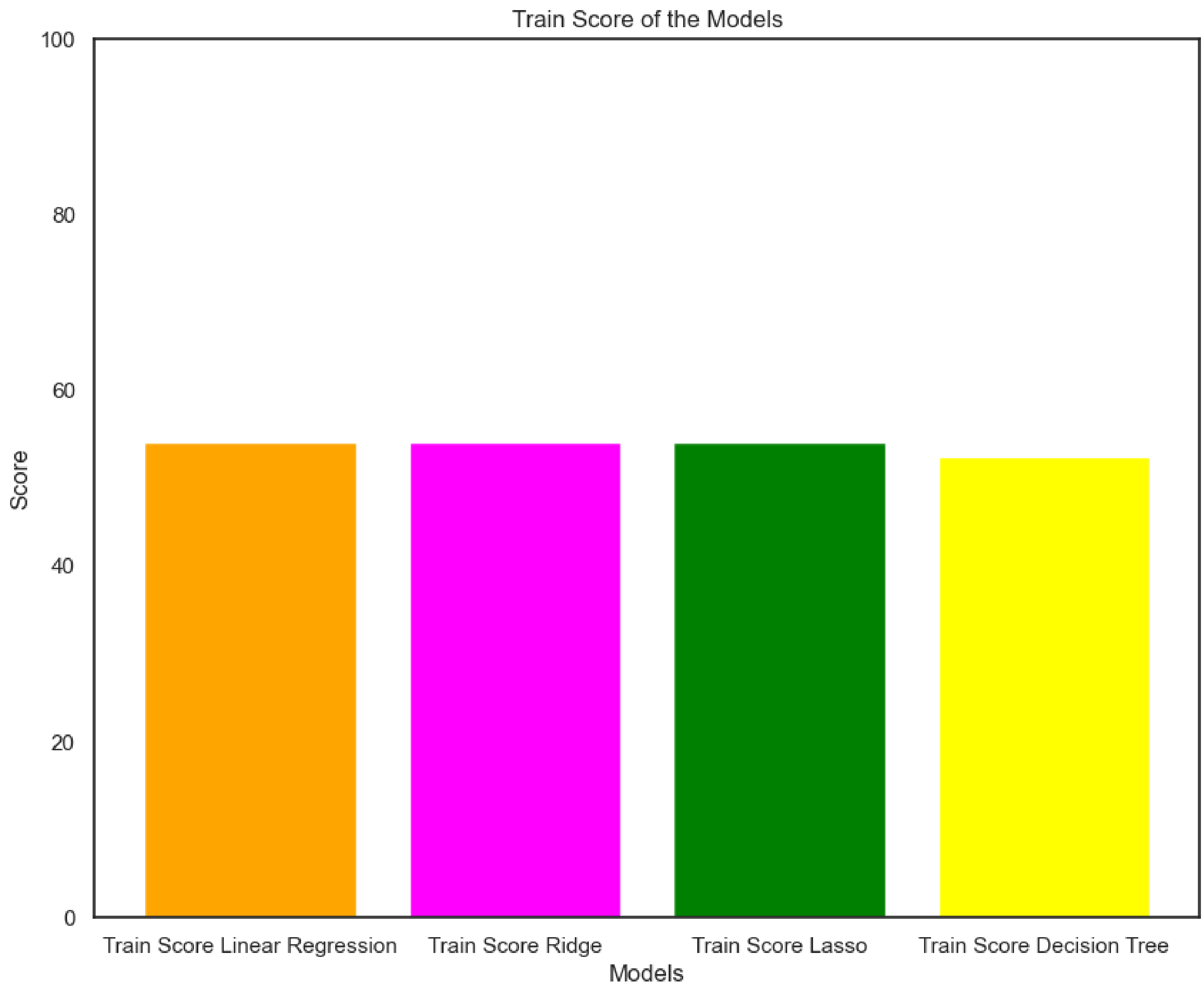
In [94]:

```
# Collecting scores from the models and putting them in respective variables.

# Linear Regression
c = (1 - mrss_train_regression)*100
d = (1 - mrss_test_regression)*100

# Ridge Regression
e = (1 - matrix_ridge.min()[0])*100
f = (1 - matrix_ridge.min()[1])*100

# Lasso Regression
g = (1 - matrix_lasso.min()[0])*100
h = (1 - matrix_lasso.min()[1])*100

# Decision Tree
i = (dt_model.score(train_x, train_y))*100
j = (dt_model.score(test_x, test_y))*100
```

Train Error Bar plot

In [99]:
```
train_error_name = ['Train Score Linear Regression',
                    'Train Score Ridge',
                    'Train Score Lasso',
                    'Train Score Decision Tree']
score_train = [c, e, g, i]
```

In [100…
```
plt.figure(figsize = (10, 8))
plt.ylim(0, 100)
plt.bar(train_error_name, score_train, color=['orange', 'magenta', 'green', 'yellow'])
plt.xlabel('Models')
plt.ylabel('Score')
plt.title('Train Score of the Models');
```



Observation -

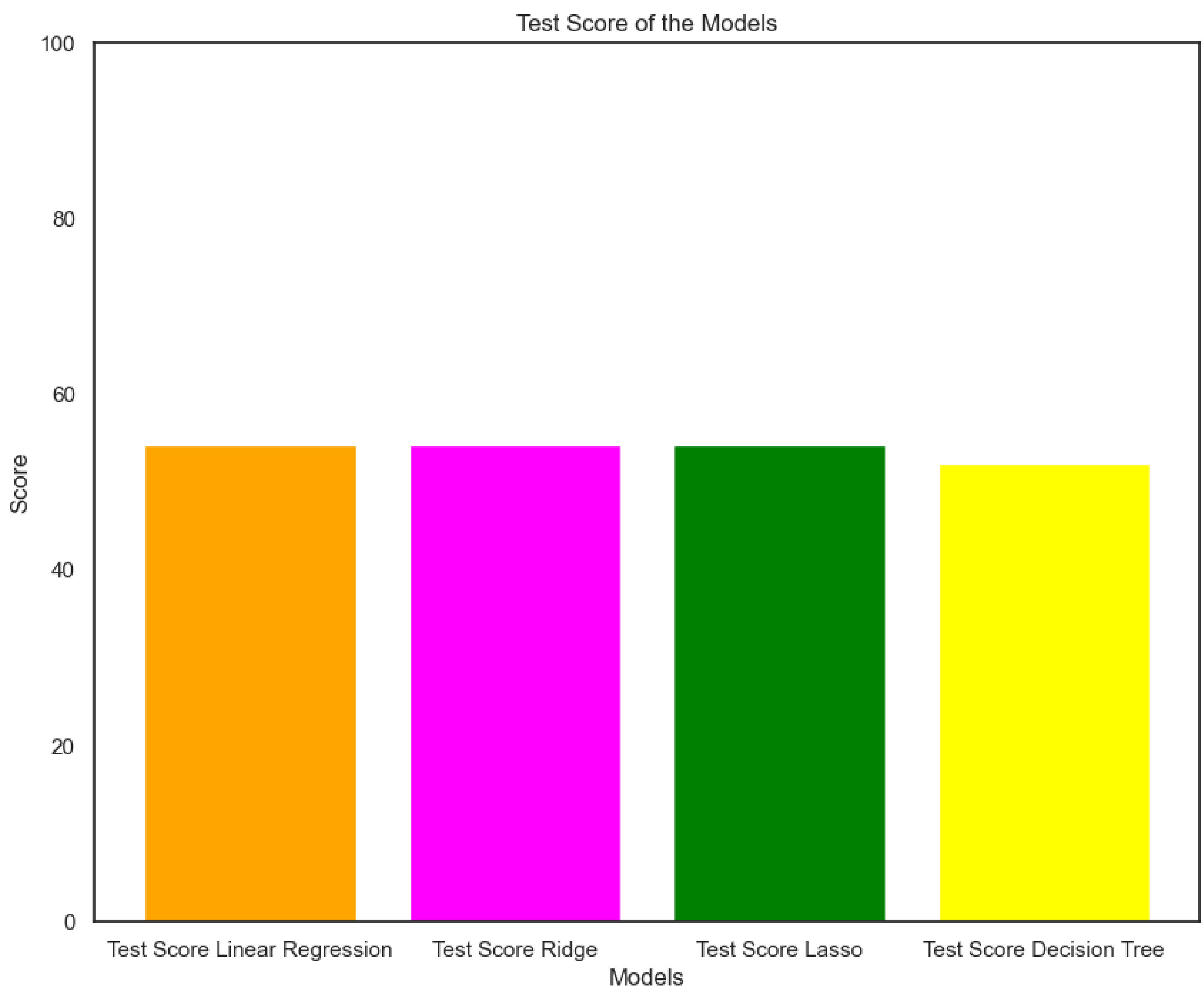
From the above bar plot it can be observed that the train score of KNN model has the best score among all of the other models.

Test error Bar plot

```
test_error_name = ['Test Score Linear Regression',
```

```
In [97]:                     'Test Score Ridge',
                             'Test Score Lasso',
                             'Test Score Decision Tree']
        score_test = [d, f, h, j]
```

```
In [98]: plt.figure(figsize = (10, 8))
        plt.ylim(0, 100)
        plt.bar(test_error_name, score_test, color=['orange', 'magenta', 'green', 'yellow'])
        plt.xlabel('Models')
        plt.ylabel('Score')
        plt.title('Test Score of the Models');
```



Observation -

From the above test score bar plot, KNN model is performing best with least test error and better score among all the other models.

Overall observation -

From the above bar plots, it can be seen that both the train and test score of all models are in sync with each other and out of all these models, K-Nearest Neighbor model is performing better than the other models.