Load the Libraries

In [1]:

```
#importing all the required libraries
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline

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

Importing the Dataset

In [2]:

```
data = pd.read_csv('Datasets/nyc_taxi_trip_duration.csv')
```

In [3]:

```
#checking the size of the dataset
data.shape
```

Out[3]:

```
(729322, 11)
```

In [4]:

```
#checking the dataset by examining the top 5 rows
data.head()
```

Out[4]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitud
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.95391
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.98831
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.99731
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.96167
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.01712

In [5]:

```
#checking the datatypes of all the columns
data.dtypes
```

Out[5]:

```
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 [6]:

```
#Trip duration in hours
data['trip_duration_hours'] = data['trip_duration'].apply(lambda x : x/3600)
```

In [7]:

```
data.head()
```

Out[7]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitud
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.95391
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.98831
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.99731
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.96167
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.01712

In [8]:

```
data['passenger_count'].value_counts()
```

Out[8]:

```
1    517415
2    105097
5     38926
3     29692
6     24107
4     14050
0        33
7         1
9         1
Name: passenger_count, dtype: int64
```

In [9]:

```
# Removing outliers

mean = data['passenger_count'].mean()
std = data['passenger_count'].std()

data['z_score'] = (data['passenger_count']-mean)/std

thresh = 4

data = data[data['z_score'].abs() < thresh]

data=data[data.passenger_count!=0]
```

In [10]:

```
data['passenger_count'].value_counts()
```

Out[10]:

```
1    517415
2    105097
5     38926
3     29692
6     24107
4     14050
Name: passenger_count, dtype: int64
```

Checking for Null Values

In [11]:

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

Out[11]:

```
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
trip_duration_hours   0
z_score               0
dtype: int64
```

Evaluation Metrics

Here the Target variable is continuous in nature hence it is a Regression model. The most commonly used Evaluation metric for Regression problem is RMSE(Root Mean Squared Error) as it makes sure the unit does not change.

Benchmark Model

In [12]:

```
bench_data = data
bench_data.head()
```

Out[12]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitud
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.95391
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.98831
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.99731
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.96167
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.01712

In [13]:

```
# Storing simple mean in a new column
bench_data['simple_mean'] = bench_data['trip_duration_hours'].mean()
bench_data['simple_mean'].head()
```

Out[13]:

```
0    0.264515
1    0.264515
2    0.264515
3    0.264515
4    0.264515
Name: simple_mean, dtype: float64
```

In [14]:

```
# importing shuffle from sklearn
from sklearn.utils import shuffle
```

In [15]:

```
# Shuffling and creating train and test set

bench_data = shuffle(bench_data,random_state = 92)

# Creating 4 divisions
div = int(bench_data.shape[0]/4)

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

In [16]:

```
# Calculating root mean squared error
from sklearn.metrics import mean_squared_error as MSE
from math import sqrt

simple_mean_error = sqrt(MSE(test['trip_duration_hours'],test['simple_mean']))
simple_mean_error
```

Out[16]:

```
0.8381327484275816
```

In [17]:

```
# Mean by passenger_count to reduce error
pd.pivot_table(train,values = 'trip_duration_hours', index = ['passenger_count'], aggfu
nc = np.mean)
```

Out[17]:

passenger_count	trip_duration_hours
1	0.259248
2	0.279963
3	0.284530
4	0.286704
5	0.304356
6	0.293813

In [18]:

```
# initializing new column
test['passen_count_mean'] = 0

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

In [19]:

```
# Calculating root mean squared error

passen_count_error = sqrt(MSE(test['trip_duration_hours'],test['passen_count_mean']))
passen_count_error
```

Out[19]:

```
0.8779464516234601
```

In [20]:

```
# Mean by vendor_id to reduce the error

pd.pivot_table(train, values ='trip_duration_hours', index = ['vendor_id'], aggfunc = n
p.mean)
```

Out[20]:

vendor_id	trip_duration_hours
1	0.233965
2	0.296296

In [21]:

```
# initializing new column
test['vendor_id_mean'] = 0

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

In [22]:

```
# Calculating root mean squared error

vendor_id_error = np.sqrt(MSE(test['trip_duration_hours'],test['vendor_id_mean']))
vendor_id_error
```

Out[22]:

0.8779464516234601

In [23]:

```
# Mean by vendor_id and passenger_count to reduce the error

pd.pivot_table(train, values ='trip_duration_hours', index = ['vendor_id','passenger_co
unt'], aggfunc = np.mean)
```

Out[23]:

		trip_duration_hours
vendor_id	**passenger_count**	
1	**1**	0.228101
	2	0.257770
	3	0.259417
	4	0.271155
	5	0.280703
	6	0.295503
2	**1**	0.294643
	2	0.297304
	3	0.300028
	4	0.298240
	5	0.304452
	6	0.293809

In [24]:

```
test['super_mean'] = 0

s1 = 'vendor_id'
s2 = 'passenger_count'

for i in test[s1].unique():
    for j in test[s2].unique():
        test['super_mean'][(test[s1]==str(i)) & (test[s2]==str(j))] = train['trip_durat
ion_hours'][(train[s1]==str(i)) & (train[s2]==str(j))].mean()
```

In [25]:

```
super_mean_error = sqrt(MSE(test['trip_duration_hours'],test['super_mean']))
super_mean_error
```

Out[25]:

```
0.8779464516234601
```

- The Root Mean Square error (RMSE) for the simple mean is 0.83813.
- The RMSE for passenger count and vendor id is slightly higher which came out to be 0.87794.

KNN Model

In [26]:

```
sample_data = data.sample(100000)
```

In [27]:

```
sample_data.dtypes
```

Out[27]:

```
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
trip_duration_hours   float64
z_score               float64
simple_mean           float64
dtype: object
```

In [28]:

```
# one hot encoding
Filtered_data= pd.concat([sample_data, pd.get_dummies(sample_data[['passenger_count']].
astype('str'))], axis=1)
Filtered_data.head()
```

Out[28]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_lo
109900	id1464947	1	2016-03-02 15:58:20	2016-03-02 16:13:39	1	-73.
422826	id0168623	2	2016-04-24 01:24:11	2016-04-24 01:34:04	1	-73.
639792	id2548616	1	2016-06-18 00:59:40	2016-06-18 01:47:18	4	-73.
230145	id0945231	2	2016-04-18 15:44:01	2016-04-18 15:47:09	1	-73.
266042	id1349451	2	2016-05-11 14:42:42	2016-05-11 14:51:38	1	-73.

In [29]:

```
Filtered_data=Filtered_data.drop(['id','vendor_id','trip_duration_hours','pickup_dateti
me','dropoff_datetime','store_and_fwd_flag','passenger_count','trip_duration','z_scor
e'],axis=1)
Filtered_data.head()
```

Out[29]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	simple_mean	p
109900	-73.961990	40.800743	-73.941673	40.843407	0.264515	
422826	-73.987541	40.720112	-73.982407	40.735432	0.264515	
639792	-73.983910	40.721645	-73.976341	40.785683	0.264515	
230145	-73.975052	40.745998	-73.979347	40.744377	0.264515	
266042	-73.954102	40.774731	-73.967491	40.763199	0.264515	

In [30]:

```
# Separating independent and dependent variables

x = Filtered_data
y = sample_data['trip_duration_hours']
x.shape,y.shape
```

Out[30]:

```
((100000, 11), (100000,))
```

In [31]:

```
# Scaling the data

from sklearn.preprocessing import MinMaxScaler
Scaler = MinMaxScaler()
x_scaled = Scaler.fit_transform(x)
x = pd.DataFrame(x_scaled,columns=x.columns)
x.head()
```

Out[31]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	simple_mean	passen
0	0.086612	0.732077	0.082304	0.755336	0.0	
1	0.083718	0.688120	0.077657	0.696472	0.0	
2	0.084129	0.688956	0.078349	0.723867	0.0	
3	0.085133	0.702232	0.078006	0.701349	0.0	
4	0.087505	0.717896	0.079359	0.711610	0.0	

In [32]:

```
# Importing the train test split function

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=5
1)
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[32]:

```
((80000, 11), (20000, 11), (80000,), (20000,))
```

In [33]:

```
# Importing knn regressor and metric mse

from sklearn.neighbors import KNeighborsRegressor as KNN
from sklearn.metrics import mean_squared_error as MSE
```

In [34]:

```
# Creating instance of KNN
reg = KNN(n_neighbors=3)

# Fitting the model
reg.fit(x_train,y_train)

# Predicting over the train set and calculating rmse
test_predict = reg.predict(x_test)
k = sqrt(MSE(test_predict,y_test))
print('Test RMSE is',k)
```

```
Test RMSE is 1.596804859851506
```

ELBOW for classifier

In [35]:

```
def ELBOW(k):
    test_error = []
    # training model for every value of k
    for i in k:
        # instance of KNN
        reg = KNN(n_neighbors = i)
        reg.fit(x_train,y_train)
        # Appending RMSE scores to empty list calculated using the predictions
        test_predict = reg.predict(x_test)
        rmse = sqrt(MSE(test_predict,y_test))
        test_error.append(rmse)
    return test_error
```

In [45]:

```
# Defining K range

k= range(1,50,10)
```

In [46]:

```
# calling above defined function

score = ELBOW(k)
```

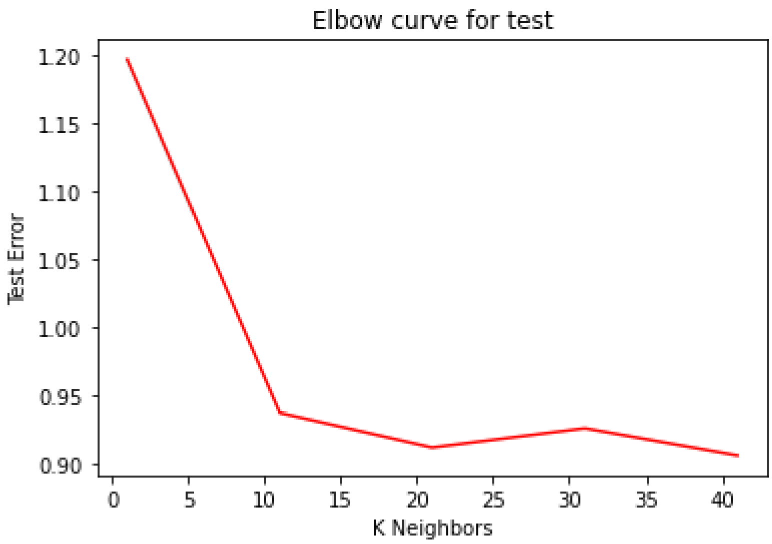
In [57]:

```
# plotting the curves

plt.plot(k,score,color = 'red')
plt.xlabel('K Neighbors')
plt.ylabel('Test Error')
plt.title('Elbow curve for test')
```

Out[57]:

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



We can see from the above ELBOW curve that the optimum value of k is around 21.

In [49]:

```
# Creating instance of KNN
reg = KNN(n_neighbors=21)

# Fitting the model
reg.fit(x_train,y_train)

# Predicting over the train set and calculating rmse
test_predict = reg.predict(x_test)
k_1 = sqrt(MSE(test_predict,y_test))
print('Test RMSE is',k_1)
```

```
Test RMSE is 0.9115394018508014
```

Linear Regression Model

In [50]:

```
# Separating independent and dependent variables

a = Filtered_data
b = sample_data['trip_duration_hours']
a.shape,b.shape
```

Out[50]:

```
((100000, 11), (100000,))
```

In [51]:

```
# Importing the train test split function

from sklearn.model_selection import train_test_split
a_train, a_test, b_train, b_test = train_test_split(a, b, test_size=0.2, random_state=
1)
a_train.shape,a_test.shape,b_train.shape,b_test.shape
```

Out[51]:

```
((80000, 11), (20000, 11), (80000,), (20000,))
```

In [52]:

```
#importing Linear Regression and metric mean square error
from sklearn.linear_model import LinearRegression as LR
from sklearn.metrics import mean_squared_error as MSE
```

In [53]:

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

# Fitting the model
lr.fit(a_train,b_train)
```

Out[53]:

```
LinearRegression()
```

In [54]:

```
# Predicting over the Test Set and calculating error
test_predict_2 = lr.predict(a_test)
k_2 = sqrt(MSE(test_predict_2, b_test))
print('Test RMSE    ', k_2 )
```

```
Test RMSE     0.722378006063582
```

In [55]:

```
# Parameters of Linear Regression
lr.coef_
```

Out[55]:

```
array([ 1.50441719e+00, -1.63442067e+00, -2.59422442e-02, -2.04529442e-01,
       -3.43957856e+11, -1.33186477e+12, -1.33186477e+12, -1.33186477e+12,
       -1.33186477e+12, -1.33186477e+12, -1.33186477e+12])
```

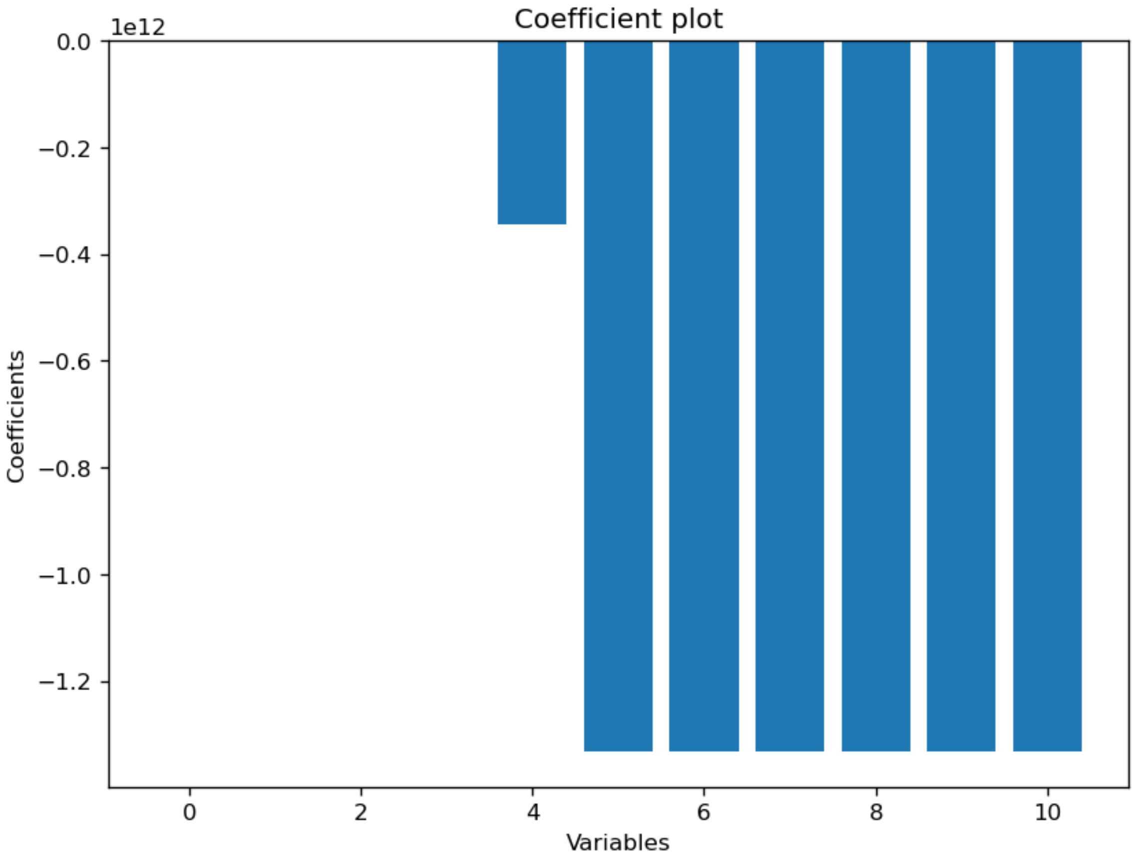
Plotting the coefficients

In [56]:

```
plt.figure(figsize=(8, 6), dpi=120, facecolor='w', edgecolor='r')
x = range(len(a_train.columns))
y = lr.coef_
plt.bar( x, y )
plt.xlabel( "Variables")
plt.ylabel('Coefficients')
plt.title('Coefficient plot')
```

Out[56]:

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



Here we can see that the model depends upon some Independent variables toos much, But these coefficients are not suitable for interpretation because these are not scaled

Checking the assumptions of linear model

In [58]:

```
# Arranging and calculating the Residuals
residuals = pd.DataFrame({
    'fitted values' : b_test,
    'predicted values' : test_predict_2,
})

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

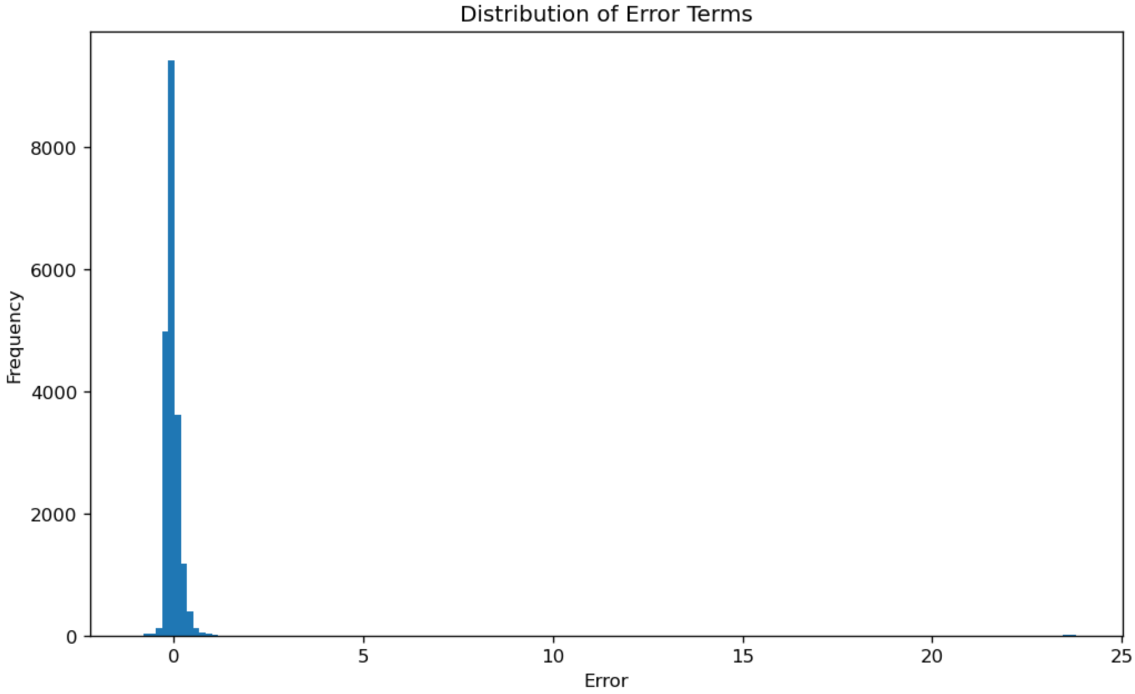
Out[58]:

	fitted values	predicted values	residuals
176562	0.231111	0.257568	-0.026457
479297	0.426389	0.276611	0.149778
554524	0.001667	0.744873	-0.743206
494240	0.165278	0.286621	-0.121343
653052	0.138333	0.257080	-0.118747

Checking Distribution of residuals

In [59]:

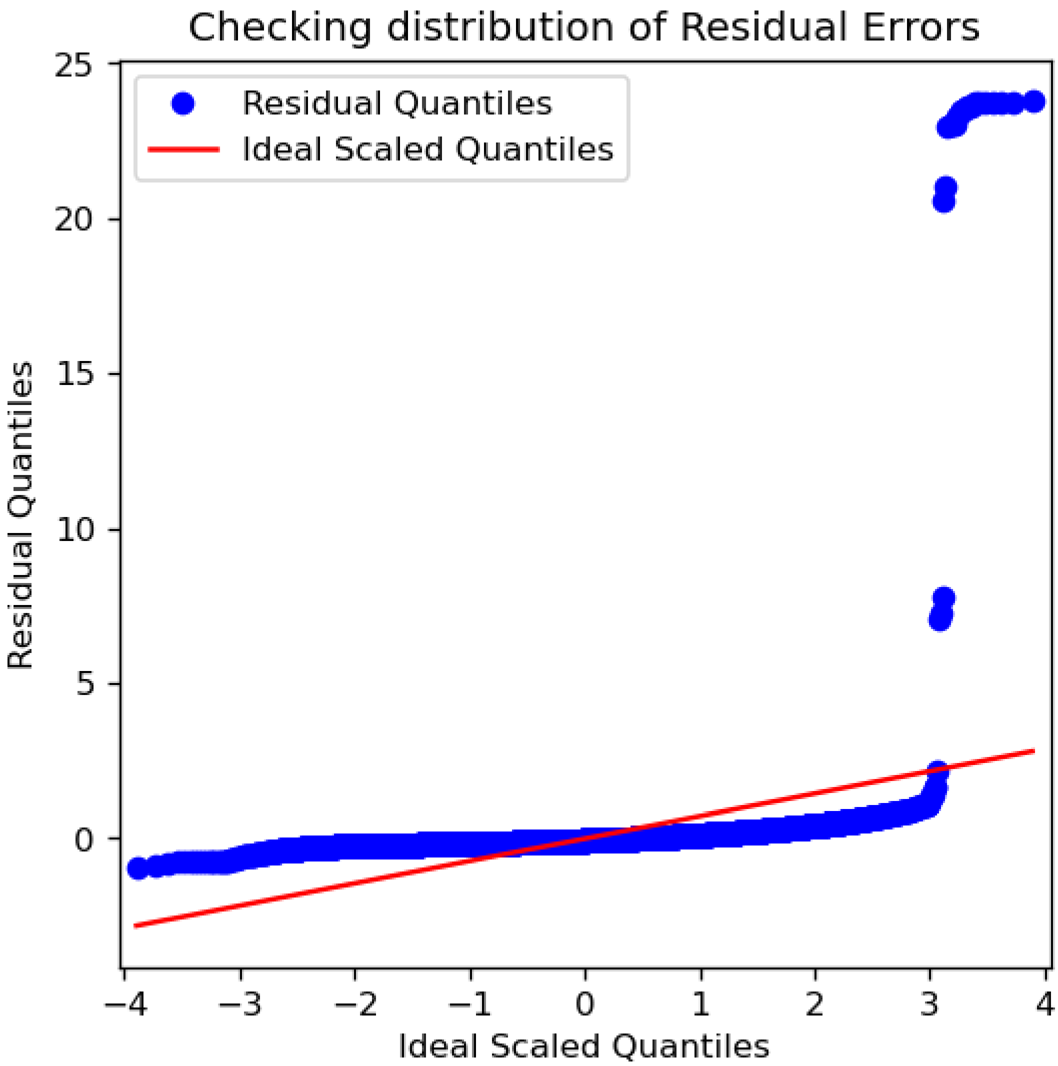
```
# Histogram for distribution
plt.figure(figsize=(10, 6), dpi=120, facecolor='w', edgecolor='b')
plt.hist(residuals.residuals, bins = 150)
plt.xlabel('Error')
plt.ylabel('Frequency')
plt.title('Distribution of Error Terms')
plt.show()
```



In [75]:

```
# 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.title('Checking distribution of Residual Errors')
plt.legend(['Residual Quantiles','Ideal Scaled Quantiles'])
plt.show()
```



- On computing the coefficients we observed there are some negative values as well.
- On plotting the qq plot we see that the residual quantile line does'nt fit over all ideal scaled Quantiles.

Decision Tree Model

In [61]:

```
# Separating independent and dependent variables

p = Filtered_data
q = sample_data['trip_duration_hours']
p.shape,q.shape
```

Out[61]:

```
((100000, 11), (100000,))
```

In [62]:

```
# Importing the train test split function

from sklearn.model_selection import train_test_split
p_train,p_test,q_train,q_test = train_test_split(p,q,random_state=25)
```

In [63]:

```
#importing Decision Tree Regressor and metric mean square error
from sklearn.tree import DecisionTreeRegressor as tree
from sklearn.metrics import mean_squared_error as MSE
```

In [64]:

```
# Creating instance of Decision Tree Regressor
tree = tree()

# Fitting the model
tree.fit(p,q)
```

Out[64]:

```
DecisionTreeRegressor()
```

In [65]:

```
# Predicting over the Test Set and calculating error
test_predict_3 = tree.predict(p_test)
k_3 = sqrt(MSE(test_predict_3, q_test))
print('Test RMSE     ', k_3 )
```

```
Test RMSE     0.0013194192980059893
```

Scores of all Models

In [66]:

```
#Calculating train scores of each model
knn_train_score = reg.score(x_train,y_train)
linear_train_score = lr.score(a_train,b_train)
decision_train_score = tree.score(p_train,q_train)
```

In [67]:

```
knn_train_score,linear_train_score,decision_train_score
```

Out[67]:

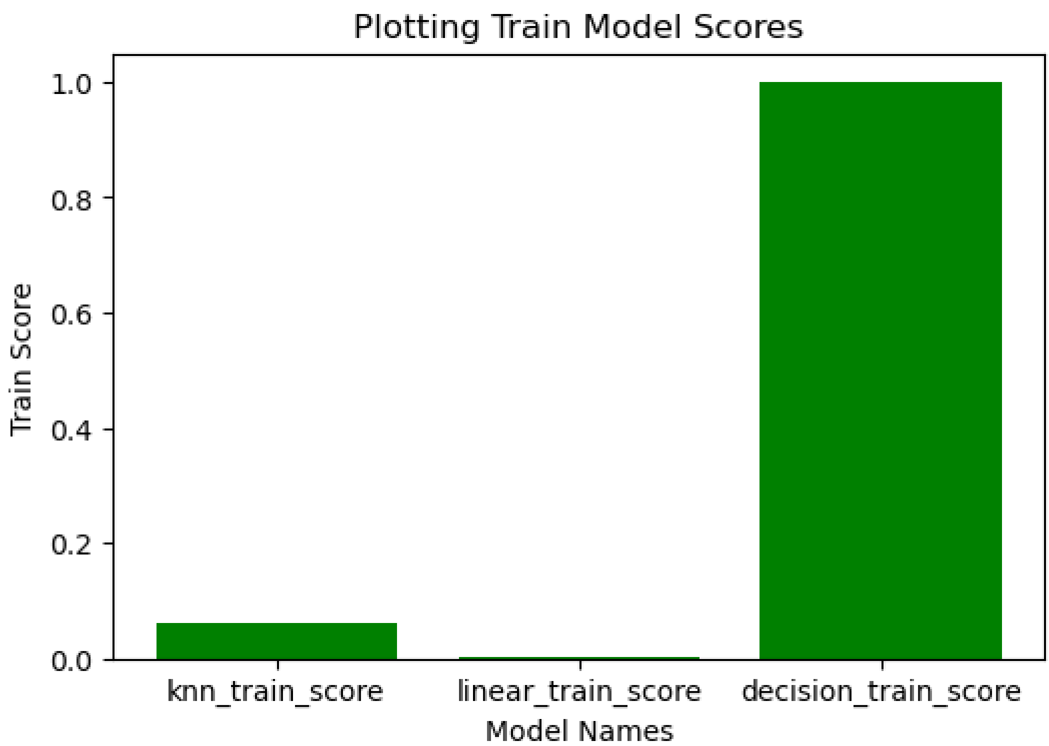
```
(0.06218552282987655, 0.0020427439432741945, 0.9999999342713259)
```

In [68]:

```
#Plotting Model Scores
x=['knn_train_score','linear_train_score','decision_train_score']
y=[0.06218552282987655, 0.0020427439432741945, 0.9999999342713259]
```

In [69]:

```
plt.figure(dpi=100)
plt.bar(x,y,color ='green',width = 0.8)
plt.xlabel('Model Names')
plt.ylabel("Train Score")
plt.title('Plotting Train Model Scores')
plt.show()
```



In [70]:

```
#Calculating test scores of each model
knn_test_score = reg.score(x_test,y_test)
linear_test_score = lr.score(a_test,b_test)
decision_test_score = tree.score(p_test,q_test)
```

In [71]:

```
knn_test_score,linear_test_score,decision_test_score
```

Out[71]:

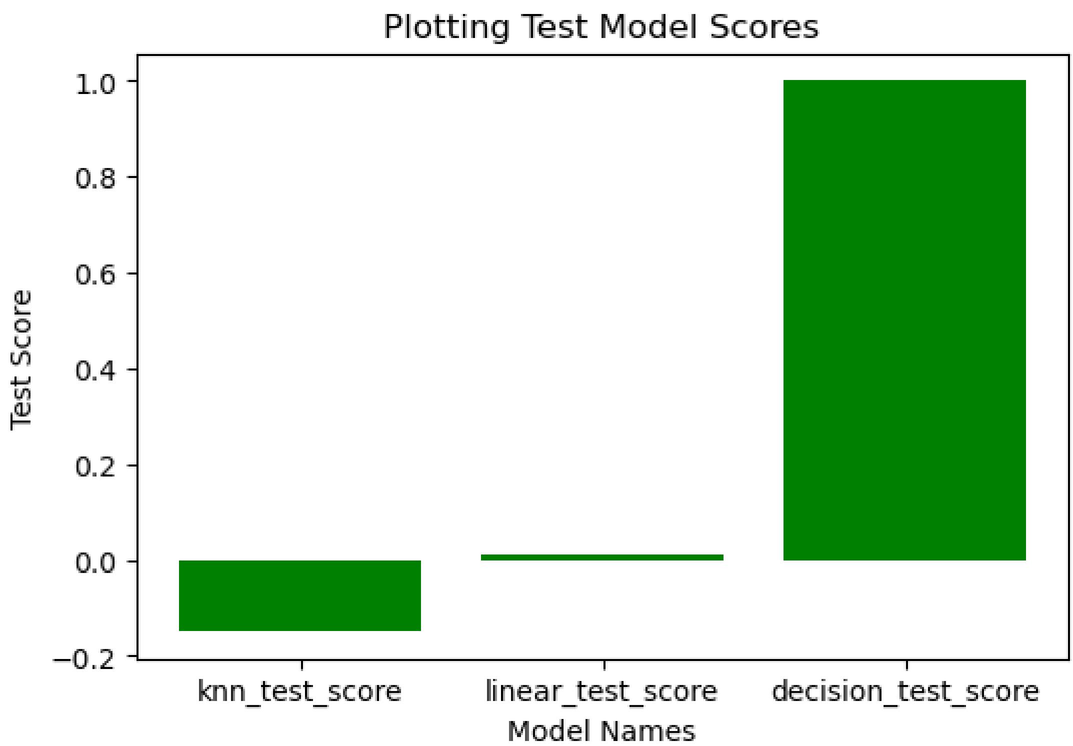
```
(-0.14739887868126256, 0.010485708309207586, 0.9999979543731345)
```

In [72]:

```
#Plotting Model Scores
x=['knn_test_score','linear_test_score','decision_test_score']
y=[-0.14739887868126256, 0.010485708309207586, 0.9999979543731345]
```

In [73]:

```
plt.figure(dpi=100)
plt.bar(x,y,color ='green',width = 0.8)
plt.xlabel('Model Names')
plt.ylabel("Test Score")
plt.title('Plotting Test Model Scores')
plt.show()
```



In [74]:

```
k_1,k_2,k_3
```

Out[74]:

```
(0.9115394018508014, 0.722378006063582, 0.0013194192980059893)
```

- **From the 3 models (KNN,LR,Decision Tree) the train score and test score for Decision Tree is around 0.999 and hence it is the best model for predicting the Trip duration.**
- **Also the RMSE for Decision Tree model is lowest (k_3 = 0.0013194192980059893)**