Predictive_Models

April 21, 2022

1 Building Basic Predictive Models using Linear Regression, KNN, Decision Tree over NYC Taxi Trip Dataset

1.0.1 Importing Libraries

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

1.0.2 Importing Data

[3]:
```
data = pd.read_csv('nyc_taxi_trip_duration.csv')
```

[4]:
```
data.shape
```

[4]:
```
(729322, 11)
```

[5]:
```
data.columns
```

[5]:
```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration'],
      dtype='object')
```

In the Dataset, we have 729322 rows and 11 columns

2 Dataset Variables

Dataset Variables are as follows : vendor_id - code indicating provider associated with the trip record id - unique identifier for each trip pickup_datetime - date and time when the trip started dropoff_datetime - date and time when the trip ended passenger_count - number of passengers present during the trip   pickup_longitude - the longitude where the trip was started   pickup_latitude - the latitude where the trip was started   dropoff_longitude - the longitude where the trip was ended   dropoff_latitude - the latitude where the trip was ended   store_and_fwd_flag - The flag indicates that whether the connection during the trip with vehicle and vendor was lost due to any technical issue or not   trip_duration - duration of trip in seconds

[6]:
```
data.dtypes
```

[6]:
```
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
```

[7]:
```
#sample of first 5 rows
data.head()
```

[7]:
```
          id  vendor_id      pickup_datetime     dropoff_datetime  \
0  id1080784          2  2016-02-29 16:40:21  2016-02-29 16:47:01
1  id0889885          1  2016-03-11 23:35:37  2016-03-11 23:53:57
2  id0857912          2  2016-02-21 17:59:33  2016-02-21 18:26:48
3  id3744273          2  2016-01-05 09:44:31  2016-01-05 10:03:32
4  id0232939          1  2016-02-17 06:42:23  2016-02-17 06:56:31

   passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                1        -73.953918        40.778873         -73.963875
1                2        -73.988312        40.731743         -73.994751
2                2        -73.997314        40.721458         -73.948029
3                6        -73.961670        40.759720         -73.956779
4                1        -74.017120        40.708469         -73.988182

   dropoff_latitude store_and_fwd_flag  trip_duration
0         40.771164                  N            400
1         40.694931                  N           1100
2         40.774918                  N           1635
3         40.780628                  N           1141
4         40.740631                  N            848
```

[8]:
```
#sample of last 5 rows
data.tail()
```

[8]:
```
                   id  vendor_id      pickup_datetime     dropoff_datetime  \
729317  id3905982          2  2016-05-21 13:29:38  2016-05-21 13:34:34
729318  id0102861          1  2016-02-22 00:43:11  2016-02-22 00:48:26
729319  id0439699          1  2016-04-15 18:56:48  2016-04-15 19:08:01
729320  id2078912          1  2016-06-19 09:50:47  2016-06-19 09:58:14
729321  id1053441          2  2016-01-01 17:24:16  2016-01-01 17:44:40

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
729317                2        -73.965919        40.789780         -73.952637
729318                1        -73.996666        40.737434         -74.001320
729319                1        -73.997849        40.761696         -74.001488
729320                1        -74.006706        40.708244         -74.013550
729321                4        -74.003342        40.743839         -73.945847

        dropoff_latitude store_and_fwd_flag  trip_duration
729317         40.789181                  N            296
729318         40.731911                  N            315
729319         40.741207                  N            673
729320         40.713814                  N            447
729321         40.712841                  N           1224
```

2.0.1 Checking for null values

[9]:
```python
data.isnull().sum()
```

[9]:
```
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
```

In this dataset, we have 0 missing values and it's good to go further and work on each datatype of the dataset.

[10]:
```python
# Converting store_and_fwd_flag to category
data['store_and_fwd_flag'] = data['store_and_fwd_flag'].astype('category')
```

[11]:
```python
# Converting pickup and dropoff datetime from object to datetime
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data['dropoff_datetime'] = pd.to_datetime(data['dropoff_datetime'])
```

[12]:
```python
data.describe()
```

[12]:
```
          vendor_id  passenger_count  pickup_longitude  pickup_latitude  \
count  729322.000000    729322.000000     729322.000000    729322.000000
mean        1.535403         1.662055        -73.973513        40.750919
std         0.498745         1.312446          0.069754         0.033594
min         1.000000         0.000000       -121.933342        34.712234
25%         1.000000         1.000000        -73.991859        40.737335
50%         2.000000         1.000000        -73.981758        40.754070
75%         2.000000         2.000000        -73.967361        40.768314
max         2.000000         9.000000        -65.897385        51.881084

       dropoff_longitude  dropoff_latitude  trip_duration
count      729322.000000     729322.000000   7.293220e+05
mean          -73.973422         40.751775   9.522291e+02
std             0.069588          0.036037   3.864626e+03
min          -121.933304         32.181141   1.000000e+00
25%           -73.991318         40.735931   3.970000e+02
50%           -73.979759         40.754509   6.630000e+02
75%           -73.963036         40.769741   1.075000e+03
max           -65.897385         43.921028   1.939736e+06
```

[13]:
```python
# Using datetime to create new columns - day_name, day_number, month,␣
↪pickup_hour

data['day_name'] = data.pickup_datetime.dt.day_name
data['month'] = data.pickup_datetime.dt.month
data['day_number'] = data.pickup_datetime.dt.weekday
data['pickup_hour'] = data.pickup_datetime.dt.hour
```

[14]:
```python
# Converting day_number, month, pickup_hour to category

data['month'] = data['month'].astype('category')
data['day_number'] = data['day_number'].astype('category')
data['pickup_hour'] = data['pickup_hour'].astype('category')
```

[15]:
```python
data.dtypes
```

[15]:
```
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          category
trip_duration                  int64
day_name                      object
month                       category
day_number                  category
pickup_hour                 category
dtype: object
```

Looking at the dataset, we come to a point that the dataset is time and distance related. So, we can calculate the distance travelled for each and every trip.

[16]:
```python
# Importing geopy which can be used for distance calculation
import geopy.distance

def calc_dist(df):
    pickup = (df['pickup_latitude'], df['pickup_longitude'])
    dropoff = (df['dropoff_latitude'], df['dropoff_longitude'])
    return geopy.distance.distance(pickup, dropoff).km
```

[17]:
```python
# Adding the distance column in our dataframe

data['distance'] = data.apply(lambda x: calc_dist(x), axis=1)
```

We can calculate the speed of the vehicle at each trip by the distance and the trip duration.

[18]:
```python
data['speed'] = (data.distance/(data.trip_duration/3600))
```

[19]:
```python
# Considering only upto 6 passenger count to prevent any of the outlier

data = data[(data['passenger_count'] <= 6) & (data['passenger_count'] >0)]
```

[20]:
```python
# Converting all the categorical variables to numerical

dummy = pd.get_dummies(data.store_and_fwd_flag, prefix = 'flag')
data = pd.concat([data, dummy], axis =1)

dummy = pd.get_dummies(data.vendor_id, prefix = 'vendor_id')
data = pd.concat([data, dummy], axis =1)

dummy = pd.get_dummies(data.month, prefix = 'month')
data = pd.concat([data, dummy], axis = 1)

dummy = pd.get_dummies(data.day_number, prefix = 'day_number')
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.pickup_hour, prefix = 'pickup_hour')
data = pd.concat([data, dummy], axis = 1)
```

```
dummy = pd.get_dummies(data.passenger_count, prefix = 'passenger_count')
data = pd.concat([data, dummy], axis = 1)
```

[21]:
```
data.head()
```

[21]:
```
          id  vendor_id     pickup_datetime    dropoff_datetime  \
0  id1080784          2 2016-02-29 16:40:21 2016-02-29 16:47:01
1  id0889885          1 2016-03-11 23:35:37 2016-03-11 23:53:57
2  id0857912          2 2016-02-21 17:59:33 2016-02-21 18:26:48
3  id3744273          2 2016-01-05 09:44:31 2016-01-05 10:03:32
4  id0232939          1 2016-02-17 06:42:23 2016-02-17 06:56:31

   passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                1        -73.953918        40.778873         -73.963875
1                2        -73.988312        40.731743         -73.994751
2                2        -73.997314        40.721458         -73.948029
3                6        -73.961670        40.759720         -73.956779
4                1        -74.017120        40.708469         -73.988182

   dropoff_latitude store_and_fwd_flag  …  pickup_hour_20 pickup_hour_21  \
0         40.771164                  N  …               0              0
1         40.694931                  N  …               0              0
2         40.774918                  N  …               0              0
3         40.780628                  N  …               0              0
4         40.740631                  N  …               0              0

  pickup_hour_22 pickup_hour_23 passenger_count_1  passenger_count_2  \
0              0              0                 1                  0
1              0              1                 0                  1
2              0              0                 0                  1
3              0              0                 0                  0
4              0              0                 1                  0

   passenger_count_3  passenger_count_4  passenger_count_5  passenger_count_6
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  1
4                  0                  0                  0                  0

[5 rows x 64 columns]
```

Droping out the unwanted columns from the dataframe.

[22]:
```
data = data.drop(['id'], axis = 1)
```

[23]:
```
data = data.drop(['store_and_fwd_flag'], axis = 1)
```

[24]:
```
data = data.drop(['vendor_id'], axis = 1)
```

[25]:
```
data = data.drop(['pickup_datetime'], axis = 1)
```

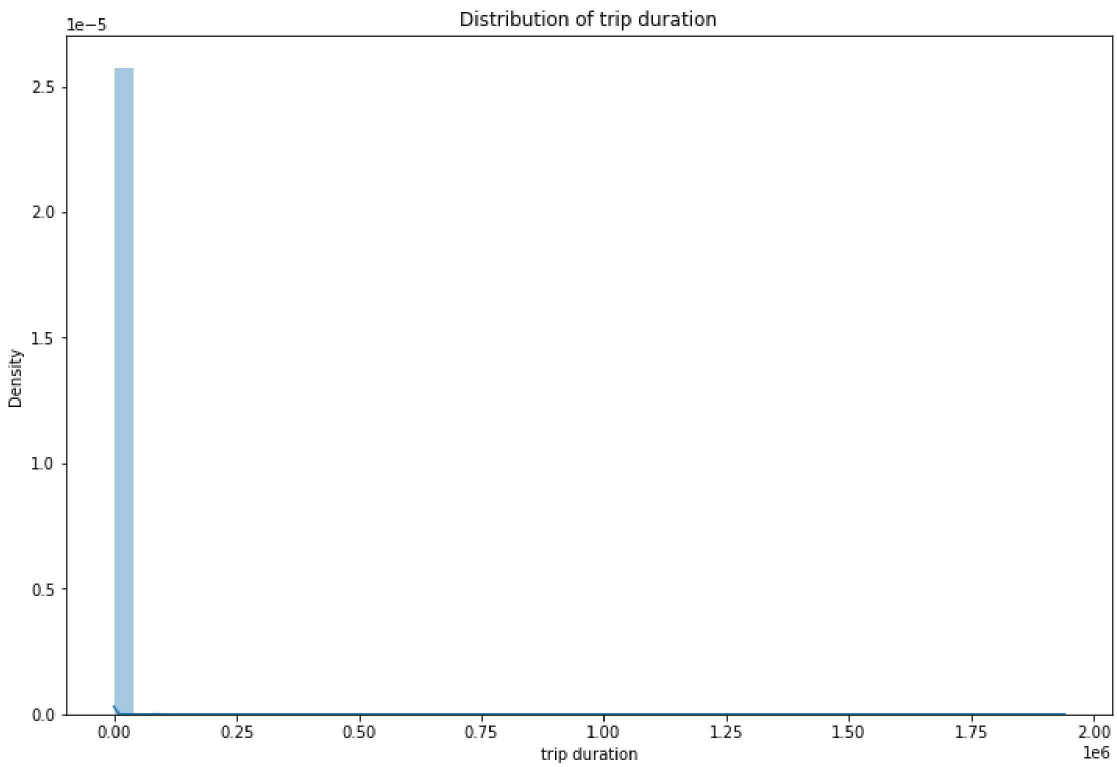
[26]:
```
data = data.drop(['dropoff_datetime'], axis = 1)
```

[27]:
```
data = data.drop(['day_name'], axis = 1)
```

Plotting distribution of trip duration and distance for checking outliers.

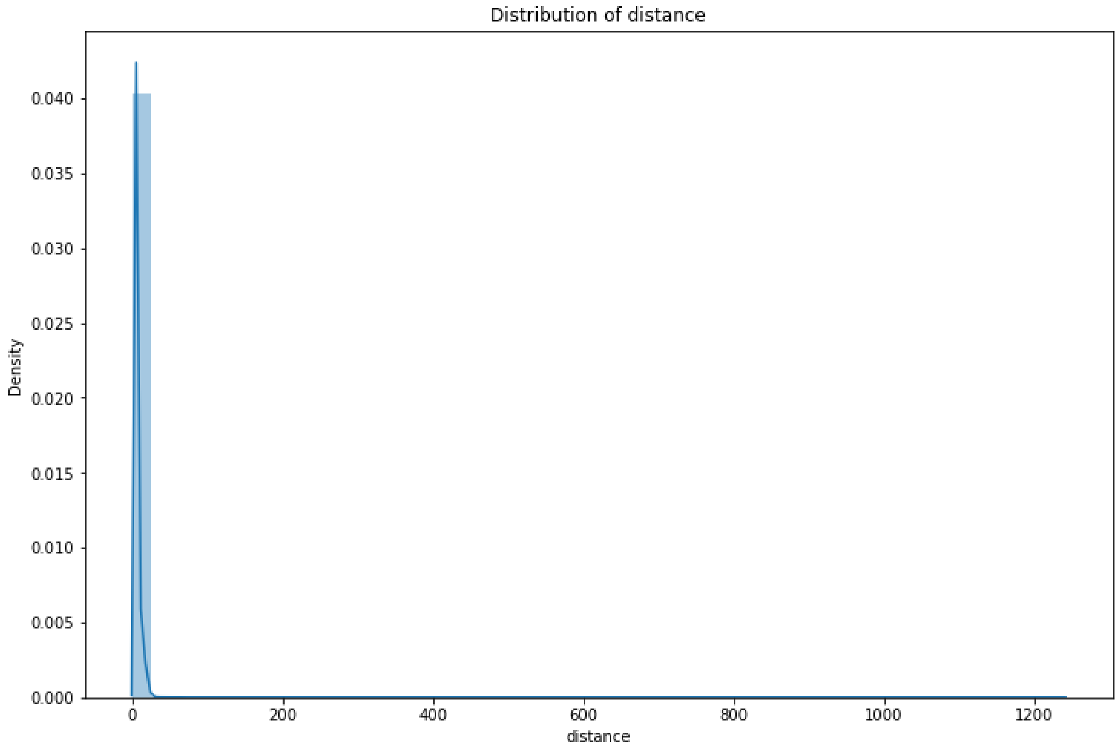
[28]:
```
plt.figure(figsize=(12, 8))
sns.distplot(data['trip_duration'])
plt.xlabel('trip duration')
plt.title('Distribution of trip duration')
```

[28]: Text(0.5, 1.0, 'Distribution of trip duration')



[29]:
```
plt.figure(figsize=(12, 8))
sns.distplot(data['distance'])
plt.xlabel('distance')
plt.title('Distribution of distance')
```

[29]: Text(0.5, 1.0, 'Distribution of distance')



We have to remove the potential outliers from distance and trip duration. Here, we have chosen the trip duration part normally greater than 10 seconds and less than 0.5 day.

[30]:
```
# Removing potential distance outlier

data = data[(data['distance'] < data['distance'].quantile(0.95)) &␣
↪(data['distance'] > data['distance'].quantile(0.05))]

# Removing potential trip duration outlier

data = data[(data['trip_duration'] < 3*3600) & (data['trip_duration'] > 10)]
data = data[(data['trip_duration'] < data['trip_duration'].quantile(0.95)) &␣
↪(data['trip_duration'] > data['trip_duration'].quantile(0.05))]
```

3 Selecting Metric for Evaluation and Building Simple Model

[31]:
```
# Creating a raw data copy
data_copy  = data
```

[32]:
```
from sklearn.utils import shuffle

# Shuffling the dataset
```

```
data_copy = shuffle(data_copy, random_state = 30)

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

# We will divide the 4 division - 3 for training part and 1 for testing

train = data_copy.loc[:3*div+1,:]
test = data_copy.loc[3*div+1:]
```

3.0.1 Calculating Mean of trip duration

[33]:
```
# storing mean in the test set as a new column
test['mean'] = train['trip_duration'].mean()

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

mean_error = MAE(test['trip_duration'], test['mean'])
mean_error
```

[33]: 302.9729421962103

3.0.2 I chosed the most appropriate Evaluation metric for this dataset - Mean Absolute Error because I have used the distance and speed variable concept which is related to time duration also most of the outliers in the data are removed and so mean squared or root mean squared error will not be felt required

4 Linear Regression with Regularization

[34]:
```
# separating independent and dependent variables
x5 = data.drop(['trip_duration'], axis =1)
y5 = data['trip_duration']
x5.shape, y5.shape
```

[34]: ((589827, 57), (589827,))

[35]:
```
# Importing the train test split function
from sklearn.model_selection import train_test_split
train_x5, test_x5, train_y5, test_y5 = train_test_split(x5, y5, random_state =␣
↪65)
```

[36]:
```
from sklearn.linear_model import LinearRegression as LR
from sklearn.metrics import mean_absolute_error as Mae
```

[37]:
```
# Creating instance of Linear Regression
lin_reg = LR(normalize = True)
```

```
# Fitting the model
lin_reg.fit(train_x5, train_y5)
```

[37]: LinearRegression(normalize=True)

[38]:
```
# Predicting over the train set and calculating the errors
train_pred = lin_reg.predict(train_x5)
k1 = Mae(train_pred, train_y5)
print('Training Mean Absolute Error is- ', k1)
```

```
Training Mean Absolute Error is-  106.55902525035604
```

[39]:
```
# Predicting over the test set and calculating the errors
test_pred = lin_reg.predict(test_x5)
k1 = Mae(test_pred, test_y5)
print('Test Mean Absolute Error is- ', k1)
```

```
Test Mean Absolute Error is-  106.45726550791078
```

[40]:
```
# Importing Ridge from sklearn
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
```

[41]:
```
# Creating Ridge Regression with alpha values
reg_cv = RidgeCV(alphas = [0.1, 0.5, 1.0, 10.0])
```

[42]:
```
#fitting the model into ridge cv
model_cv = reg_cv.fit(x5, y5)
```

[43]:
```
#finding the best value of alpha
model_cv.alpha_
```

[43]: 0.5

[44]:
```
#Selecting alpha=0.5 for ridge regression
rid_reg = Ridge(alpha = 0.5)
```

[45]:
```
# fitting the model on the training set
rid_reg.fit(train_x5,train_y5)
```

[45]: Ridge(alpha=0.5)

[46]:
```
#prediction on the training set
pred_reg_train = rid_reg.predict(train_x5)
linear_train = Mae(train_y5, pred_reg_train)
linear_train
```

[46]: 106.28311777605897

[47]:
```
Linear_training = 1 - (linear_train/mean_error)
Linear_training
```

[47]: 0.6491993080120393

[48]:
```
#prediction on the test set
pred_reg_test = rid_reg.predict(test_x5)
linear_test = Mae(test_y5, pred_reg_test)
linear_test
```

[48]: 106.18321271938494

[49]:
```
Linear_testing = 1 - (linear_test/mean_error)
Linear_testing
```

[49]: 0.64952905711752

[ ]:
```

```

5 Decision Tree Model

[50]:
```
data.columns
```

[50]:
```
Index(['passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'trip_duration', 'month',
       'day_number', 'pickup_hour', 'distance', 'speed', 'flag_N', 'flag_Y',
       'vendor_id_1', 'vendor_id_2', 'month_1', 'month_2', 'month_3',
       'month_4', 'month_5', 'month_6', 'day_number_0', 'day_number_1',
       'day_number_2', 'day_number_3', 'day_number_4', 'day_number_5',
       'day_number_6', 'pickup_hour_0', 'pickup_hour_1', 'pickup_hour_2',
       'pickup_hour_3', 'pickup_hour_4', 'pickup_hour_5', 'pickup_hour_6',
       'pickup_hour_7', 'pickup_hour_8', 'pickup_hour_9', 'pickup_hour_10',
       'pickup_hour_11', 'pickup_hour_12', 'pickup_hour_13', 'pickup_hour_14',
       'pickup_hour_15', 'pickup_hour_16', 'pickup_hour_17', 'pickup_hour_18',
       'pickup_hour_19', 'pickup_hour_20', 'pickup_hour_21', 'pickup_hour_22',
       'pickup_hour_23', 'passenger_count_1', 'passenger_count_2',
       'passenger_count_3', 'passenger_count_4', 'passenger_count_5',
       'passenger_count_6'],
      dtype='object')
```

[51]:
```
#Shuffling the dataset

from sklearn.utils import shuffle
data = shuffle(data, random_state = 42)
```

[52]:
```
#Separating the independent and dependent variables
```

```
x2 = data.drop(['trip_duration'], axis = 1)
y2 = data['trip_duration']
```

[53]:
```
#Importing library and creating the train and test set

from sklearn.model_selection import train_test_split
train_x6, test_x6, train_y6, test_y6 = train_test_split(x2, y2, random_state =␣
 ↪101, test_size = 0.20)
```

[54]:
```
#Creating the train and validation set

train_x7, valid_x6, train_y7, valid_y6 = train_test_split(train_x6, train_y6,␣
 ↪random_state = 101, test_size = 0.20)
```

[55]:
```
#Importing Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor
dec_mod = DecisionTreeRegressor(random_state = 10)
```

[56]:
```
dec_mod.fit(train_x7, train_y7)
```

[56]:
```
DecisionTreeRegressor(random_state=10)
```

[57]:
```
#Checking the train score

dec_mod.score(train_x7, train_y7)
```

[57]:
```
1.0
```

[58]:
```
#Checking the validation score

dec_mod.score(valid_x6, valid_y6)
```

[58]:
```
0.9998153525565519
```

We noticed that both train and validation have a good score and we need to check whether there's overfitting and to interpret that how different properties influence the tree. Next, interpreting accuracy relative to max depth

[59]:
```
train_acc = []
validation_acc = []
for dep in range(1, 15):
    dec_mod = DecisionTreeRegressor(max_depth = dep, min_impurity_split = 1000,␣
 ↪random_state=10)
    dec_mod.fit(train_x7, train_y7)
    train_acc.append(dec_mod.score(train_x7, train_y7))
    validation_acc.append(dec_mod.score(valid_x6, valid_y6))
```

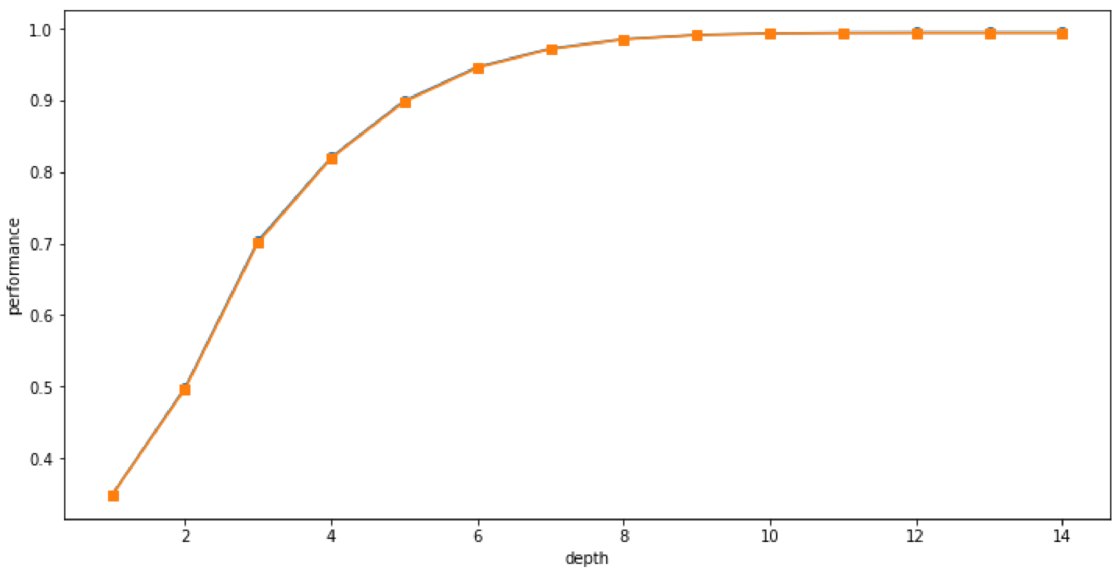
[60]:
```
#Collecting this data into a dataframe
df = pd.DataFrame({'max_depth' : range(1, 15), 'tr_acc' : train_acc,␣
↪'valid_acc' : validation_acc})
df.head()
```

[60]:

	max_depth	tr_acc	valid_acc
0	1	0.348427	0.347822
1	2	0.498316	0.496411
2	3	0.703810	0.701247
3	4	0.820469	0.819176
4	5	0.899602	0.898004

[61]:
```
#Plotting maxdepth relative
plt.figure(figsize = (12, 6))
plt.plot(df['max_depth'], df['tr_acc'], marker = 'o')
plt.plot(df['max_depth'], df['valid_acc'], marker = 's')
plt.xlabel('depth')
plt.ylabel('performance')
```

[61]: Text(0, 0.5, 'performance')



The best Maximum Depth is at 9 while further plot is constant and overfitting might be the reason for this.

[62]:
```
#Creating a function for iterating over different max features and finding␣
↪train and validation score

train_accura = []
validation_accura = []
```

```
for feat in range(1, 35):
    dec_mod = DecisionTreeRegressor(max_depth = 9, max_features = feat,␣
 ↪min_samples_leaf = 1000, random_state = 10)
    dec_mod.fit(train_x7, train_y7)
    train_accura.append(dec_mod.score(train_x7, train_y7))
    validation_accura.append(dec_mod.score(valid_x6, valid_y6))
```

[63]:

```
#Collecting the above data into a dataframe
df = pd.DataFrame({'max_features':range(1, 35), 'train_acc':train_accura,␣
 ↪'valid_acc':validation_accura})
df.head()
```

[63]:

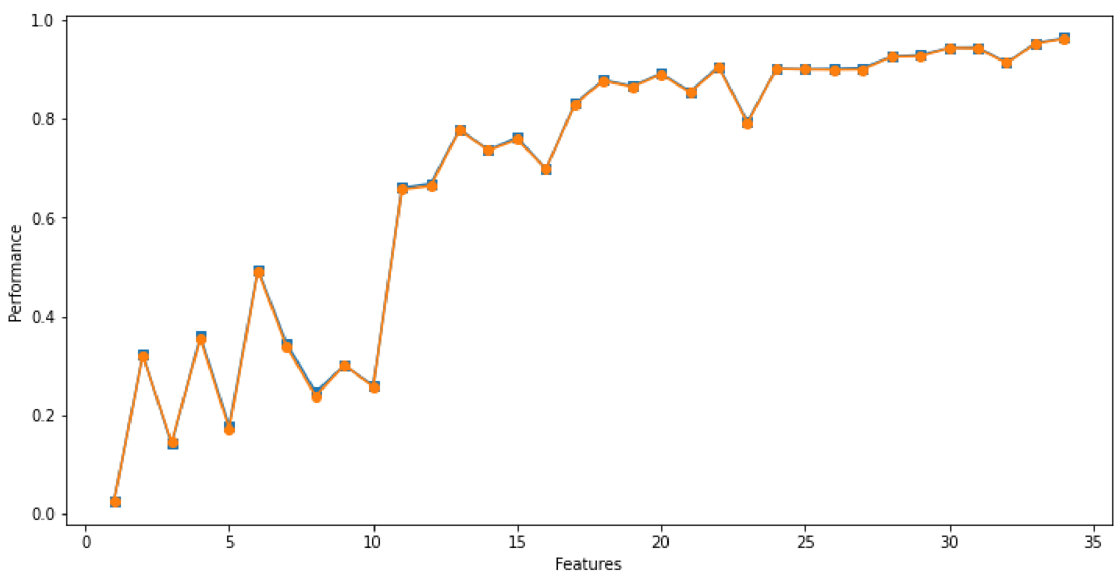
	max_features	train_acc	valid_acc
0	1	0.026221	0.025147
1	2	0.321571	0.319832
2	3	0.141577	0.144611
3	4	0.359889	0.354934
4	5	0.177230	0.171587

[64]:

```
#Plotting the max features according to the model score

plt.figure(figsize =(12, 6))
plt.plot(df['max_features'], df['train_acc'], marker = 's')
plt.plot(df['max_features'], df['valid_acc'], marker = 'o')
plt.xlabel('Features')
plt.ylabel('Performance')
```

[64]: Text(0, 0.5, 'Performance')



The best no. of feature from the plot is 31. Moving on selecting the max feature and depth and finding train and test score.

[65]:
```
DecisionTreeRegressor(max_depth = 9, max_features = 31, min_samples_leaf =␣
↪1000, random_state =10)
```

[65]:
```
DecisionTreeRegressor(max_depth=9, max_features=31, min_samples_leaf=1000,
                      random_state=10)
```

[66]:
```
#Fitting this model

dec_mod.fit(train_x7, train_y7)
```

[66]:
```
DecisionTreeRegressor(max_depth=9, max_features=34, min_samples_leaf=1000,
                      random_state=10)
```

[67]:
```
#Training Score
dec_train = dec_mod.score(train_x7, train_y7)
dec_train
```

[67]:
```
0.9636017176508239
```

[68]:
```
#Validation Score
dec_mod.score(valid_x6, valid_y6)
```

[68]:
```
0.9620747110819923
```

5.0.1 Finally, at last we see how this model performs on the test data

[69]:
```
dec_test = dec_mod.score(test_x6, test_y6)
dec_test
```

[69]:
```
0.9620526513788826
```

5.0.2 We get to see that the data didn't overfit and a good test score is obtained.

5.0.3 Drawing Decision Tree

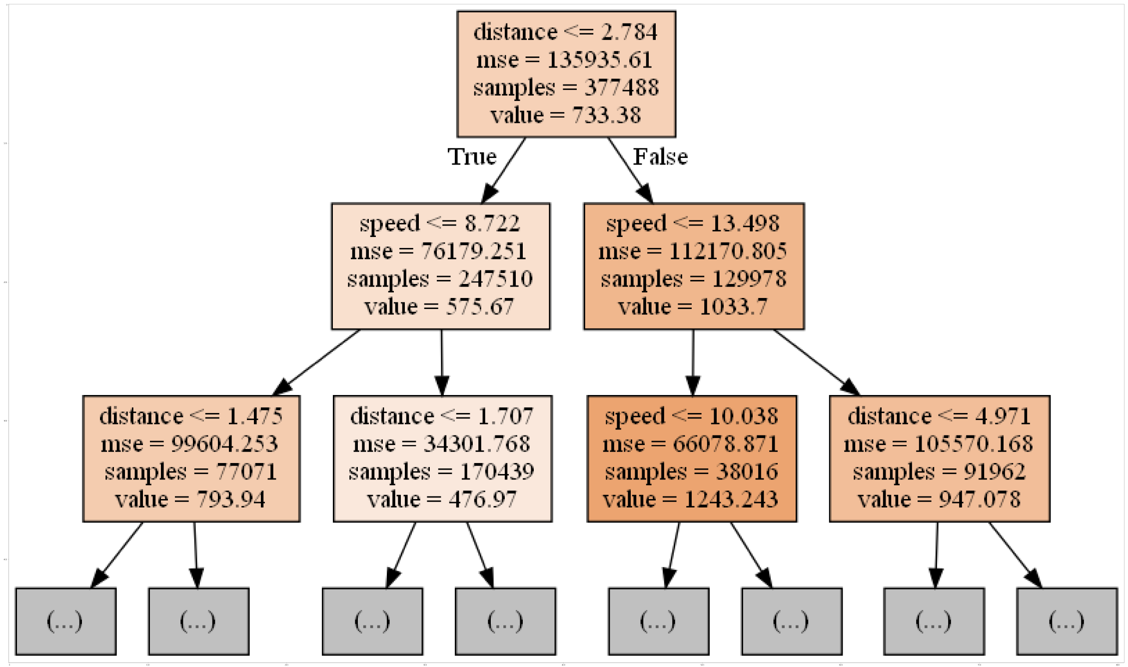
[70]:
```
from sklearn import tree
```

[71]:
```
deci_tree = tree.export_graphviz(dec_mod, out_file = 'decision_tree.dot',␣
↪feature_names = train_x6.columns, max_depth = 2, filled = True)
```

[72]:
```
!dot -Tpng decision_tree.dot -o decision_tree.png
```

[73]:
```
img = plt.imread('decision_tree.png')
plt.figure(figsize = (100, 100))
plt.imshow(img)
```

[73]: <matplotlib.image.AxesImage at 0x1e6bf8940d0>



In the decision tree plot, we can see that the distance and speed variables takes precedence and predictions that are accurate is based on these two.

6 K-Nearest Neighbour Model

[74]:
```
#Separating dependent and independent variables

x = data.drop(['trip_duration'], axis =1)
y = data['trip_duration']
```

[75]:
```
#Importing MinMax Scaler

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_scale = scaler.fit_transform(x)
```

[76]:
```
frame = pd.DataFrame(x_scale, columns= x.columns)
```

[77]:
```
#Creating train and test sets
from sklearn.model_selection import train_test_split
train_x3, test_x3, train_y3, test_y3 = train_test_split(frame,y, random_state =␣
↪65)
```

[78]:
```python
# Importing KNN Regressor and Evaluation Metric MAE
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.metrics import mean_absolute_error as mae
```

[83]:
```python
# Creating instance of KNN
regr = knn(n_neighbors = 2)

# Fitting the model
regr.fit(train_x3, train_y3)
```

[83]:
```
KNeighborsRegressor(n_neighbors=2)
```

[ ]:
```python
train_pred = regr.predict(train_x3)
k2 = mae(train_y3, train_pred)
KNN_train = 1 - (k2/mean_error)
print('Train MAE score is -', KNN_train)
```

[ ]:
```python
test_pred = regr.predict(test_x3)
k4 = MAE(test_pred, test_y3)
KNN_Test = 1 - (k4/mean_error)
print('Test MAE score is -', KNN_Test)
```

6.0.1 With respect to KNN model, after trying over different values of n neighbors and using predict for the training dataset, there is a failure of the output due to lack of computational capacity or the system freezes. With this model, there is no particular conclusion. Even after trying the concept of k values, still the same problem arises. It is better not to use KNN for this dataset.

6.1 Comparing Models

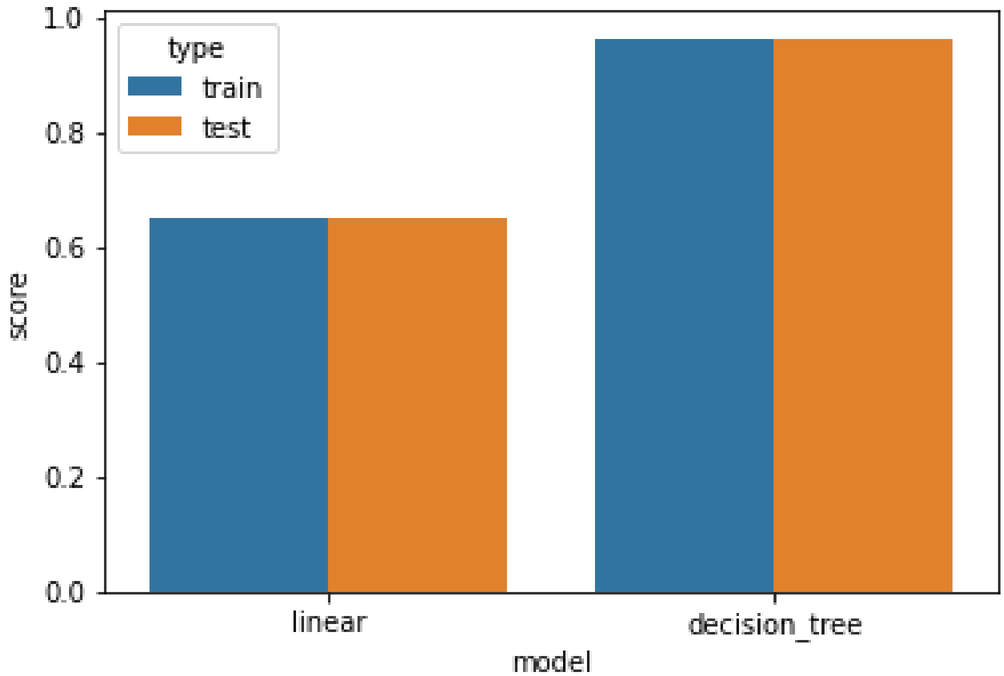
[85]:
```python
p = {'type':['train','test','train','test'],
     'model': ['linear','linear','decision_tree','decision_tree'],
     'score': [Linear_training, Linear_testing,dec_train,dec_test]
    }



df = pd.DataFrame(p)
```

[86]:
```python
sns.barplot(data = df,x = 'model' ,y = 'score',hue = 'type',ci = None )
```

[86]:
```
<AxesSubplot:xlabel='model', ylabel='score'>
```



6.1.1 Looking at the plot, it is clear that the Decision tree is giving best output for prediction of data.

```
[ ]:
```