	mean 1.535403 1.662055 -73.973513 40.750919 -73.973422 40.751775 9.522291e+02 std 0.498745 1.312446 0.069754 0.033594 0.069588 0.036037 3.864626e+03 min 1.000000 0.000000 -121.933342 34.712234 -121.933304 32.181141 1.000000e+00 25% 1.000000 1.000000 -73.991859 40.737335 -73.991318 40.735931 3.970000e+02 50% 2.000000 1.000000 -73.981758 40.754070 -73.979759 40.754509 6.630000e+02 75% 2.000000 2.000000 -73.967361 40.768314 -73.963036 40.769741 1.075000e+03 max 2.000000 9.00000 -65.897385 51.881084 -65.897385 43.921028 1.939736e+06	
i v pd ppdddst	df.isna().sum() 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 dropoff_latitude 0 store_and_fwd_flag 0 trip_duration 0	
7 (R D	<pre># there are no null values in our dataset. df.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 729322 entries, 0 to 729321 Data columns (total 11 columns): # Column Non-Null Count Dtype</class></pre>	
d	1 vendor_id 729322 non-null inted object 729322 non-null object 3 dropoff_datetime 729322 non-null object 4 passenger_count 729322 non-null inted 5 pickup_longitude 729322 non-null floated 6 pickup_latitude 729322 non-null floated 7 dropoff_longitude 729322 non-null floated 7 dropoff_latitude 729322 non-null floated 729322 non-null object 10 trip_duration 729322 non-null object 10 trip_duration 729322 non-null floated 10 trip_duration 729322 non-null object 10 trip_duration 729322 non-null	
(************************************	<pre>df['trip_duration'].median() , df['trip_duration'].mean() (663.0, 952.2291333594764) # median is less than meanthis means that there are larger number of smaller values but some larger outliers present in the far end. Vendor_id = pd.get_dummies(df['vendor_id'] , prefix = 'vendor_id') df = pd.concat([df , Vendor_id] , axis = 1)</pre>	
(# Creating dummy variables for vendor Id. Similarly doing so for store and fwd flag variable. Store_and_fwd_Flag = pd.get_dummies(df['store_and_fwd_flag'] , prefix = 'store_and_fwd_flag') df = pd.concat([df , Store_and_fwd_Flag] , axis = 1) df.head() id vendor_id pickup_datetime dropoff_datetime passenger_count pickup_longitude pickup_latitude dropoff_longitude store_and_fwd_flag trip_duration vendor_id_1 vendor_id_2 vendor_id_3 vendor_id_4 vendor_id_5 vendor_id_5 vendor_id_6 v	id_2 st
1 2	1 id0889885 1 2016-03-11 2016-03-11 23:35:37 23:53:57 2 -73.988312 40.731743 -73.994751 40.694931 N 1100 1 2 id0887912 2 2016-02-21 17:59:33 18:26:48 2 -73.997314 40.721458 -73.948029 40.774918 N 1635 0 3 id3744273 2 2016-01-05 09:44:31 10:03:32 6 -73.961670 40.759720 -73.956779 40.780628 N 1141 0 4 id0232939 1 2016-02-17 06:42:23 06:56:31 1 -74.017120 40.708469 -73.988182 40.740631 N 848 1	1 0 1 1 0
	<pre># Now working with datetime features to extract features from pickup_datetime and dropoff_datetime variables. import datetime df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime']) df['dropoff_datetime'] = pd.to_datetime(df['dropoff_datetime']) df['weekday'] = df['pickup_datetime'].dt.weekday df['hour_of_day'] = df['pickup_datetime'].dt.hour df['month'] = df['pickup_datetime'].dt.month</pre>	
0	df.head() id vendor_id pickup_datetime dropoff_datetime passenger_count pickup_longitude pickup_latitude dropoff_longitude dropoff_latitude store_and_fwd_flag trip_duration vendor_id_1 vendor_id_2 id vendor_id 2 2016-02-29 2016-02-29 16:47:01 1 -73.953918 40.778873 -73.963875 40.771164 N 400 0 1 id vendor_id 2 2016-03-11 2016-03-1	id_2 st 1 0
3 4	# We have extracted the necessary features that might help us in our model. # Here weekday starts from 0 - Monday to 6 - Sunday # Similarly for month 1 - January and 12 - December.	1 0
0	df.drop(['id' , 'vendor_id' , 'pickup_datetime' , 'dropoff_datetime' , 'store_and_fwd_flag'] , axis = 1 , inplace = True) df.head() passenger_count pickup_longitude pickup_latitude dropoff_longitude dropoff_latitude trip_duration vendor_id_1 vendor_id_2 store_and_fwd_flag_N store_and_fwd_flag_Y weekday hour_of_day mor_of_day mor_of_day	nth 2 3 2
3	3 6 -73.961670 40.759720 -73.956779 40.780628 1141 0 1 0 1 1 0 1 9 4 1 -74.017120 40.708469 -73.988182 40.740631 848 1 0 1 0 2 6 df.to_csv('cleaned_df.csv' , index = False) x = df.drop(['trip_duration'] , axis = 1) y = df['trip_duration']	1 2
(<pre>x.shape , y.shape ((729322, 12), (729322,)) from sklearn.model_selection import train_test_split train_x , test_x , train_y , test_y = train_test_split(x , y , test_size = 0.25 , random_state = 100) # Importing the random forest regressor module</pre>	
11	<pre>from sklearn.ensemble import RandomForestRegressor clf = RandomForestRegressor(random_state = 100 , n_estimators = 100 , n_jobs = 1) from pprint import pprint print('Parameters currently in use:\n') pprint(clf.get_params()) Parameters currently in use: ('bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'mse', 'max_depth': None, 'max_features': 'auto', 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_impurity_decrease': 0.0, 'min_impurity_derease': 0.0, 'min_impurity_split': None, 'min_impurity_split': None, 'min_impurity_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_jobs': 1, 'oob_score': False, 'random_state': 100, }</pre>	
?	<pre>'verbose': 0, 'warm_start': False} clf.fit(train_x , train_y) RandomForestRegressor(n_jobs=1, random_state=100) clf.score(train_x , train_y) 0.8485352228031487</pre>	
7	clf.score(test_x , test_y) -0.026220339786820812 # Okk we are getting a very worse score for our model. # we will try to improve it later.	
	# Now scaling and preprocessing the data for knn and linear regression from sklearn.preprocessing import StandardScaler scaler = StandardScaler() x_scaled = scaler.fit_transform(x)	
) 1 2	x = pd.DataFrame (x_scaled , columns = x.columns) x = pd.DataFrame (x_scaled , columns) x = pd.D	
	4 -0.504444 -0.625160 -1.263600 -0.212103 -0.309245 1.073500 -1.073500 0.074634 -0.074634 -0.536760 -1.188799 -0.903461	
1	<pre>from sklearn.neighbors import KNeighborsRegressor as KNN from sklearn.metrics import mean_absolute_error as mae knn = KNN(n_neighbors = 380)</pre>	
K	train_x , test_x , train_y , test_y = train_test_split(x , y , test_size = 0.25 , random_state = 100) from sklearn.neighbors import KNeighborsRegressor as KNN from sklearn.metrics import mean_absolute_error as mae knn = KNN(n_neighbors = 380)	
1 1 1 1 K	<pre>from sklearn.neighbors import KNeighborsRegressor as KNN from sklearn.metrics import mean_absolute_error as mae knn = KNN(n_neighbors = 380) knn.fit(train_x , train_y) KNeighborsRegressor(n_neighbors=380) # predicting over train data #train_pred = knn.predict(train_x) #k = mse(train_pred , train_y) #print(k)</pre>	
1 1 1 1 KK 7 7 7 7 1 1 1 1 1 4 7 1 1 1 1 1 1 1 1 1	<pre>from sklearn.neighbors import KNeighborsRegressor as KNN from sklearn.metrics import mean_absolute_error as mae knn = KNN(n_neighbors = 380) knn.fit(train_x , train_y) KNeighborsRegressor(n_neighbors=380) # predicting over train data #train_pred = knn.predict(train_x) #k = mse(train_pred , train_y) #print(k) # predicting over test data test_pred = knn.predict(test_x) k = mse(train_pred , test_y) print(k) 437.9923462794242 # creating an elbow curve def elbow(K):</pre>	
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	from sklearn.meighbors import KNeighborsRegressor as KNW from sklearn.metrics import mean_absolute_error as mee knn = KNN(n_neighbors = 380) knn.fit(train x , train y) kneighborsRegressor(n_neighbors=380) # predicting over train data #train_pred = knn.predict(train_x) # predicting over test data # set_men(test_men d, train_y) # predicting over test data test_pred = knn.predict(test_x) k = meg(train_pred , test_y) print(k) # creating an elbow curve def elbow(k): test_mae = [] for i in K: # instance of knn knn = KOM(n_neighbors = i) knn fit(train x , train y) tops = man(train y , train y) tops = man(train y , train y) tops = man(train x , train y) tops = man(train x , train x , train y) tops = man(train x , train x , train y) tops = man(train x , train x , train x , train y) tops = man(train x , train x , train x , train x , train	
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