PREDICTING TAXI TRIP DURATION IN NYC

We are given historical data about taxi trips in NewYork City. The time duration of each trip is given along with the rest of the data like latitude/longitudinal coordinates, etc. We will try to build a machine learning model to predict the time duration each taxi trip is going to take in the test data file as accurately as possible. We will try different models and compare the errors and proceed with the one we think would be best suited to predict the duration of trips

course-project-taxi-trip-duration

Use the "Run" button to execute the code.

```
# Execute this to save new versions of the notebook
jovian.commit(project="course-project-taxi-trip-duration")
```

```
[jovian] Detected Colab notebook...
[jovian] Please enter your API key ( from https://jovian.ai/ ):
API KEY: ··········
[jovian] Uploading colab notebook to Jovian...
Committed successfully! https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration
```

```
'https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration'
```

First lets install all the required libraies/modules

```
!pip install pandas-profiling numpy matplotlib seaborn --quiet
!pip install opendatasets scikit-learn jovian --quiet --upgrade
```

```
import opendatasets as od
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib
import plotly.express as px
import jovian
import os
import zipfile
import math
%matplotlib inline

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 150)
sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (10, 6)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

Downloading the Dataset

The dataset is available on kaggle at https://www.kaggle.com/competitions/nyc-taxi-trip-duration

We will use the opendatasets library to download all the files inside this link. Then we will create dataframes for training and test sets respectively

```
od.download('https://www.kaggle.com/competitions/nyc-taxi-trip-duration')
```

```
Skipping, found downloaded files in "./nyc-taxi-trip-duration" (use force=True to force download)
```

```
os.listdir('nyc-taxi-trip-duration')
```

```
['train.zip', 'test.zip', 'sample_submission.zip']
```

Training dataframe

```
zf=zipfile.ZipFile('nyc-taxi-trip-duration/train.zip')
```

```
orig_df=pd.read_csv(zf.open('train.csv'))
train_df=orig_df.copy()
train_df
```

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude
0	id2875421	2	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	id2377394	1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	id3858529	2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	id3504673	2	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	id2181028	2	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209
...	...	...	...	...	...	...	...
1458639	id2376096	2	2016-04-08 13:31:04	2016-04-08 13:44:02	4	-73.982201	40.745522
1458640	id1049543	1	2016-01-10 07:35:15	2016-01-10 07:46:10	1	-74.000946	40.747379
1458641	id2304944	2	2016-04-22 06:57:41	2016-04-22 07:10:25	1	-73.959129	40.768799
1458642	id2714485	1	2016-01-05 15:56:26	2016-01-05 16:02:39	1	-73.982079	40.749062
1458643	id1209952	1	2016-04-05 14:44:25	2016-04-05 14:47:43	1	-73.979538	40.781750

1458644 rows × 11 columns

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458644 entries, 0 to 1458643
Data columns (total 11 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   id                  1458644 non-null  object
 1   vendor_id           1458644 non-null  int64
 2   pickup_datetime     1458644 non-null  object
 3   dropoff_datetime    1458644 non-null  object
 4   passenger_count     1458644 non-null  int64
 5   pickup_longitude    1458644 non-null  float64
 6   pickup_latitude     1458644 non-null  float64
 7   dropoff_longitude   1458644 non-null  float64
 8   dropoff_latitude    1458644 non-null  float64
 9   store_and_fwd_flag  1458644 non-null  object
 10  trip_duration       1458644 non-null  int64
dtypes: float64(4), int64(3), object(4)
memory usage: 122.4+ MB
```

```
train_df.shape
```

```
(1458644, 11)
```

```
train_df.describe()
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_du
count	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.45864
mean	1.534950e+00	1.664530e+00	-7.397349e+01	4.075092e+01	-7.397342e+01	4.075180e+01	9.59492
std	4.987772e-01	1.314242e+00	7.090186e-02	3.288119e-02	7.064327e-02	3.589056e-02	5.23743
min	1.000000e+00	0.000000e+00	-1.219333e+02	3.435970e+01	-1.219333e+02	3.218114e+01	1.00000
25%	1.000000e+00	1.000000e+00	-7.399187e+01	4.073735e+01	-7.399133e+01	4.073588e+01	3.97000
50%	2.000000e+00	1.000000e+00	-7.398174e+01	4.075410e+01	-7.397975e+01	4.075452e+01	6.62000
75%	2.000000e+00	2.000000e+00	-7.396733e+01	4.076836e+01	-7.396301e+01	4.076981e+01	1.07500
max	2.000000e+00	9.000000e+00	-6.133553e+01	5.188108e+01	-6.133553e+01	4.392103e+01	3.52628

Test dataframe

```
zf1=zipfile.ZipFile('nyc-taxi-trip-duration/test.zip')
orig_test_df=pd.read_csv(zf1.open('test.csv'))
test_df=orig_test_df.copy()
```

Submission dataframe

```
zf2=zipfile.ZipFile('nyc-taxi-trip-duration/sample_submission.zip')
orig_sub_df=pd.read_csv(zf2.open('sample_submission.csv'))
sub_df=orig_sub_df.copy()
```

Feature Engineering

We will try to add a few new columns to our training dataframe to better analyze the dataset with respect to the target column. For that case, we will be creating helper functions.

Log Time Duration

We all take natural log of the target column trip_duration since the evaluation criteria for this project is mean squared logarithmic error. Moreover, a few relationships would be visualized better by taking natural log of the target column trip_duration

This will also be our target column. At the end, we will convert the time back to seconds using the numpy exponent function

```
def log_time(df):
  df['log_time_duration']=np.log(df.trip_duration)
```

Spliting Dates

We will split the pickup time date column into month, weekday, day, and hour. There could be a holiday someday or traffic could be more on some specific hours of the day. So these columns could prove useful

```
def split_dates(df):
  df['pickup_month']=pd.to_datetime(df.pickup_datetime).dt.month
  df['pickup_weekday']=pd.to_datetime(df.pickup_datetime).dt.weekday
  df['pickup_day']=pd.to_datetime(df.pickup_datetime).dt.day
  df['pickup_time_hour']=pd.to_datetime(df.pickup_datetime).dt.hour
```

Haversine Distance

We are given the pickup and dropoff latitude and longitude coordinates. Using them, we can calculate the distance between two points using the concept of Haversine Distance which is basically the distance between two points on a sphere. Since Earth is assumed to be an sphere, the distance calculated could be a good factor in designing our machine learning model later

The code below is based on the concept of haversine distance studied from an internet source mentioned at the end of the notebook

```
def cal_distance(df):
  earth_radius=6370
  df['pickup_latitude_radians']=np.radians(df.pickup_latitude)
  df['pickup_longitude_radians']=np.radians(df.pickup_longitude)
  df['dropoff_latitude_radians']=np.radians(df.dropoff_latitude)
  df['dropoff_longitude_radians']=np.radians(df.dropoff_longitude)
  df['dlon']=df.dropoff_longitude_radians - df.pickup_longitude_radians
```

```
    df['dlat']=df.dropoff_latitude_radians - df.pickup_latitude_radians
    df['a'] = np.sin(df.dlat / 2)**2 + np.cos(df.pickup_latitude_radians) * np.cos(df.drc
    df['c']=2 * np.arctan2(np.sqrt(df.a), np.sqrt(1 - df.a))
    df['Distance_km']=earth_radius*df.c
```

Although the above calculation does create a few columns, the Distance_km column is what we are interested in. It is the distance between pickup and dropoff coordinates in kilometers

```
train_df.columns
```

```
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')
```

The helper functions are called to add the new columns

```
log_time(train_df)
split_dates(train_df)
cal_distance(train_df)
```

```
train_df.columns
```

```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'log_time_duration', 'pickup_month', 'pickup_weekday',
       'pickup_day', 'pickup_time_hour', 'pickup_latitude_radians',
       'pickup_longitude_radians', 'dropoff_latitude_radians',
       'dropoff_longitude_radians', 'dlon', 'dlat', 'a', 'c', 'Distance_km'],
      dtype='object')
```

Exploratory Data Analysis

Lets see some trends and relationships for the target column with other columns

First lets see on which hours there are most taxi rides through a histogram

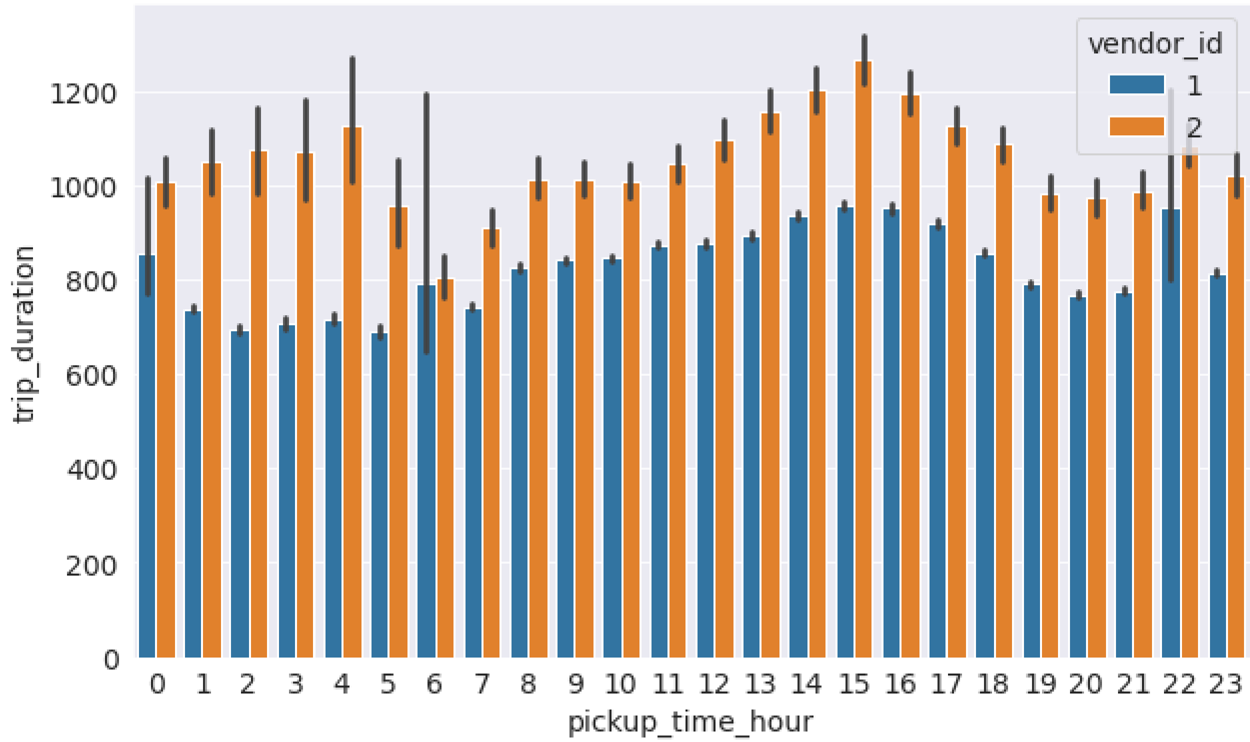
```
fig=px.histogram(train_df,
                 x='pickup_time_hour',
                 color='vendor_id',
                 color_discrete_sequence=['green','red'],
                 title='No. of Trips at different hours of the day')
fig.update_layout(bargap=0.1)
fig.show()
```

Output hidden; open in https://colab.research.google.com to view.

It seems that there are almost equal number of trips for both the vendors at all hours of the day. Moreover, at hours 18:00, 19:00 were recorded the most trips, hence these hours seem to be the busiest at New York City

```
sns.barplot(x='pickup_time_hour', y='trip_duration', hue='vendor_id', data=train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f83e021e310>
```



The trips from vendor 1 on average takes less time to travel to the destination at all times of the day. So passengers travelling through taxis of this vendor are highly likely to get a faster service

```
fig=px.scatter(train_df,
                 x='pickup_time_hour',
                 y='log_time_duration',
                 color='vendor_id',
                 opacity=0.8,
                 title='Log Trip time vs Hour of the day')
fig.update_traces(marker_size=5)
fig.show()
```

The scatter plot above doesn't show a linear relationship between the pickup time hour and log of time duration.

```
fig=px.scatter(train_df,
                 x='Distance_km',
                 y='log_time_duration',
                 color='vendor_id',
                 opacity=0.8,
                 title='Log Trip time vs Distance in Kilometer')
fig.update_traces(marker_size=5)
fig.show()
```

```
train_df.corr()
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lat
vendor_id	1.000000	0.287415	0.007820	0.001742	0.001528	0.00
passenger_count	0.287415	1.000000	0.002169	-0.005125	-0.000343	-0.00
pickup_longitude	0.007820	0.002169	1.000000	0.022568	0.783582	0.10
pickup_latitude	0.001742	-0.005125	0.022568	1.000000	0.114884	0.49
dropoff_longitude	0.001528	-0.000343	0.783582	0.114884	1.000000	0.12
dropoff_latitude	0.004496	-0.002762	0.100190	0.494038	0.124873	1.00
trip_duration	0.020304	0.008471	0.026542	-0.029204	0.014678	-0.02
log_time_duration	0.019833	0.021124	0.110344	-0.144149	0.071411	-0.12
pickup_month	-0.006221	-0.002143	0.004474	-0.001439	0.004758	-0.00
pickup_weekday	0.001311	0.025191	-0.016356	-0.028976	-0.001130	-0.02
pickup_day	0.000734	0.002014	-0.000874	-0.006495	-0.000456	-0.00
pickup_time_hour	0.009299	0.009101	0.010150	0.010603	-0.022455	0.01
pickup_latitude_radians	0.001742	-0.005125	0.022568	1.000000	0.114884	0.49
pickup_longitude_radians	0.007820	0.002169	1.000000	0.022568	0.783582	0.10
dropoff_latitude_radians	0.004496	-0.002762	0.100190	0.494038	0.124873	1.00
dropoff_longitude_radians	0.001528	-0.000343	0.783582	0.114884	1.000000	0.12
dlon	-0.009589	-0.003823	-0.333900	0.139935	0.323994	0.03
dlat	0.003001	0.002000	0.082270	-0.436748	0.020302	0.56
a	-0.000746	0.001047	0.036748	0.148908	-0.052441	-0.02
c	0.008109	0.010306	0.259780	-0.210354	0.134033	-0.14
Distance_km	0.008109	0.010306	0.259780	-0.210354	0.134033	-0.14

The distance column we created has the highest correlation coefficient with the target column 'log_time_duration' i.e. 0.572.

Relatively, The other columns don't seem to have a strong corelation coefficients as they are all close to 0

Preparing Dataset for Training

```
train_df.columns
```

```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'log_time_duration', 'pickup_month', 'pickup_weekday',
       'pickup_day', 'pickup_time_hour', 'pickup_latitude_radians',
       'pickup_longitude_radians', 'dropoff_latitude_radians',
       'dropoff_longitude_radians', 'dlon', 'dlat', 'a', 'c', 'Distance_km'],
      dtype='object')
```

Identifying Input and Target columns

```
input_cols=['vendor_id','passenger_count','pickup_longitude', 'pickup_latitude','dropof
           'pickup_day', 'pickup_time_hour', 'Distance_km', 'store_and_fwd_flag']
target_col=['log_time_duration']
```

```
inputs_df=train_df[input_cols].copy()
targets=train_df[target_col].copy()
```

```
numeric_cols=inputs_df[input_cols].select_dtypes(include=np.number).columns.tolist()
categorical_cols=['store_and_fwd_flag']
```

```
numeric_cols
```

```
['vendor_id',
 'passenger_count',
 'pickup_longitude',
 'pickup_latitude',
 'dropoff_longitude',
 'dropoff_latitude',
 'pickup_month',
 'pickup_weekday',
 'pickup_day',
 'pickup_time_hour',
 'Distance_km']
```

```
categorical_cols
```

```
['store_and_fwd_flag']
```

Imputing missing Values

```
inputs_df.isna().sum()
```

```
vendor_id             0
passenger_count       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
pickup_month          0
pickup_weekday        0
pickup_day            0
pickup_time_hour      0
Distance_km           0
store_and_fwd_flag    0
dtype: int64
```

There are no null values in the dataframe, hence no need to create an imputer for missing values

Encoding Categorical Columns

```
inputs_df.store_and_fwd_flag.value_counts()
```

```
N    1450599
Y       8045
Name: store_and_fwd_flag, dtype: int64
```

```
flag_codes={'N':0, 'Y':1}
inputs_df['flag_code']=inputs_df.store_and_fwd_flag.map(flag_codes)
encoded_cols=['flag_code']
```

Scaling Numeric Columns in the range (0,1)

```
from sklearn.preprocessing import MinMaxScaler
```

```
scaler=MinMaxScaler()
scaler.fit(inputs_df[numeric_cols])
```

```
MinMaxScaler()
```

```
inputs_df[numeric_cols] = scaler.transform(inputs_df[numeric_cols])
```

```
inputs_df[numeric_cols]
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pickup_mo
0	1.0	0.111111	0.791302	0.365738	0.791591	0.731222	
1	0.0	0.111111	0.791331	0.364062	0.791016	0.728287	
2	1.0	0.111111	0.791354	0.365510	0.790920	0.726493	
3	1.0	0.111111	0.790842	0.363001	0.790805	0.726206	
4	1.0	0.111111	0.791452	0.367181	0.791454	0.732663	
...	...	...	...	...	...	...	
1458639	1.0	0.444444	0.791302	0.364459	0.791092	0.729055	
1458640	0.0	0.111111	0.790992	0.364565	0.791500	0.733858	
1458641	1.0	0.111111	0.791682	0.365787	0.790935	0.726262	
1458642	0.0	0.111111	0.791304	0.364661	0.791426	0.730498	
1458643	0.0	0.111111	0.791345	0.366527	0.791456	0.733350	

1458644 rows × 11 columns

```
inputs_df[numeric_cols].describe()
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pickup_r
count	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.458644e+06	1.45864

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pickup_r
mean	5.349503e-01	1.849477e-01	7.914453e-01	3.647671e-01	7.914464e-01	7.300461e-01	5.03363
std	4.987772e-01	1.460269e-01	1.170040e-03	1.876631e-03	1.165773e-03	3.057147e-03	3.36207
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.00000(
25%	0.000000e+00	1.111111e-01	7.911420e-01	3.639923e-01	7.911508e-01	7.286905e-01	2.00000
50%	1.000000e+00	1.111111e-01	7.913091e-01	3.649485e-01	7.913418e-01	7.302782e-01	6.00000
75%	1.000000e+00	2.222222e-01	7.915469e-01	3.657624e-01	7.916180e-01	7.315802e-01	8.00000
max	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.00000(

```
inputs_df=inputs_df[numeric_cols+encoded_cols]
inputs_df
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pickup_mo
0	1.0	0.111111	0.791302	0.365738	0.791591	0.731222	
1	0.0	0.111111	0.791331	0.364062	0.791016	0.728287	
2	1.0	0.111111	0.791354	0.365510	0.790920	0.726493	
3	1.0	0.111111	0.790842	0.363001	0.790805	0.726206	
4	1.0	0.111111	0.791452	0.367181	0.791454	0.732663	
...	...	...	...	...	...	...	
1458639	1.0	0.444444	0.791302	0.364459	0.791092	0.729055	
1458640	0.0	0.111111	0.790992	0.364565	0.791500	0.733858	
1458641	1.0	0.111111	0.791682	0.365787	0.790935	0.726262	
1458642	0.0	0.111111	0.791304	0.364661	0.791426	0.730498	
1458643	0.0	0.111111	0.791345	0.366527	0.791456	0.733350	

1458644 rows × 12 columns

```
inputs_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458644 entries, 0 to 1458643
Data columns (total 13 columns):
 #   Column             Non-Null Count    Dtype
---  ------             --------------    -----
 0   vendor_id          1458644 non-null  float64
 1   passenger_count    1458644 non-null  float64
 2   pickup_longitude   1458644 non-null  float64
 3   pickup_latitude    1458644 non-null  float64
 4   dropoff_longitude  1458644 non-null  float64
 5   dropoff_latitude   1458644 non-null  float64
 6   pickup_month       1458644 non-null  float64
 7   pickup_weekday     1458644 non-null  float64
 8   pickup_day         1458644 non-null  float64
```

```
 9   pickup_time_hour    1458644 non-null  float64
 10  Distance_km         1458644 non-null  float64
 11  store_and_fwd_flag  1458644 non-null  object
 12  flag_code           1458644 non-null  int64
dtypes: float64(11), int64(1), object(1)
memory usage: 144.7+ MB
```

Splitting the datsets for Training & Validation

90% of the data would be used for training. The rest for validation

```
from sklearn.model_selection import train_test_split
```

```
train_inputs, val_inputs, train_targets, val_targets= train_test_split(inputs_df, targe
```

```
train_inputs.shape
```

```
(1312779, 13)
```

```
val_inputs
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pickup_mo
67250	1.0	0.111111	0.791245	0.363912	0.791332	0.730784	
1397036	1.0	0.111111	0.791364	0.365534	0.791146	0.729881	
1021087	1.0	0.555556	0.791188	0.364394	0.791447	0.729781	
951424	1.0	0.222222	0.791167	0.363638	0.791152	0.729801	
707882	0.0	0.444444	0.794482	0.358817	0.791220	0.730679	
...	...	...	...	...	...	...	
526279	1.0	0.111111	0.791400	0.365147	0.791449	0.731142	
80354	0.0	0.333333	0.791304	0.365490	0.791255	0.728972	
328645	1.0	0.333333	0.794594	0.358690	0.791145	0.729862	
657429	0.0	0.111111	0.791344	0.364821	0.791421	0.730600	
128732	1.0	0.111111	0.791563	0.365386	0.791514	0.730514	

145865 rows × 13 columns

Creating Machine Learning Models

Since its a Regression problem, We will be using RandomForest Regressor and the XGboost models to analyze and predict the data by calculating root mean squared error. Then we will try hyperparameter tuning to reduce the validation rmse. Eventually we will proceed with the model with the lowest validation rmse.

1: RandomForestRegressor

Training model & rmse loss

```python
from sklearn.ensemble import RandomForestRegressor
```

```python
model = RandomForestRegressor(n_estimators=10, n_jobs=-1, random_state=42)
```

```python
model.fit(train_inputs, train_targets)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  """Entry point for launching an IPython kernel.
```

```
RandomForestRegressor(n_estimators=10, n_jobs=-1, random_state=42)
```

```python
train_preds=model.predict(train_inputs)
train_preds
```

```
array([6.26888888, 6.19167906, 7.00879007, ..., 7.31451641, 5.9711587 ,
       7.36788556])
```

```python
val_preds=model.predict(val_inputs)
```

```python
train_targets
```

	log_time_duration
879655	6.329721
646838	6.186209
1138713	6.955593
864716	6.052089
434927	6.011267
...	...
259178	7.155396
1414414	6.725034
131932	7.158514
671155	5.963579
121958	7.358831

1312779 rows × 1 columns

```python
from sklearn.metrics import mean_squared_error
```

```python
train_rmse=mean_squared_error(train_preds, train_targets, squared=False)
val_rmse=mean_squared_error(val_preds, val_targets, squared=False)
```

```
train_rmse, val_rmse
```

```
(0.1803041895047248, 0.42728649444470673)
```

The training and validation errors have been calculated as above.

```
val_preds
```

```
array([6.63749101, 6.57875352, 5.91708045, ..., 7.73107684, 5.86113437,
       5.46503797])
```

```
val_targets
```

	log_time_duration
67250	6.946976
1397036	6.717805
1021087	6.419995
951424	6.765039
707882	8.510571
...	...
526279	5.978886
80354	6.658011
328645	7.759614
657429	5.973810
128732	6.638568

145865 rows × 1 columns

```
val_targets.mean()
```

```
log_time_duration    6.465028
dtype: float64
```

```
jovian.commit()
```

```
[jovian] Detected Colab notebook...
[jovian] Uploading colab notebook to Jovian...
Committed successfully! https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration
```

```
'https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration'
```

```
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
```

HyperParameter Tuning

Now we will try hyperparameter tuning to reduce the validation error on the overfitting curve for the RandomForestRegressor model we created

We will create a helper function test_params and pass to it different values of parameters and analyze the errors

```
def test_params(**params):
    model = RandomForestRegressor(random_state=42, n_jobs=-1, **params).fit(train_input
    train_rmse = mean_squared_error(model.predict(train_inputs), train_targets, squarec
    val_rmse = mean_squared_error(model.predict(val_inputs), val_targets, squared=False
    return train_rmse, val_rmse
```

n_estimators

```
test_params(n_estimators=5)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.20821658960877765, 0.44931706436269475)
```

```
test_params(n_estimators=15)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.1700276463481815, 0.419667826924148)
```

```
test_params(n_estimators=20)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.16454596102462402, 0.41593562272911627)
```

n_estimators=20 seems to be a better value as it gives the lowest validation error

Another helper fubction is defined with a n_estimators set at 20 and varying other parameters to see the errors

```
def test_params_const_n_est(**params):
    model = RandomForestRegressor(random_state=42, n_jobs=-1, n_estimators=20, **params
    train_rmse = mean_squared_error(model.predict(train_inputs), train_targets, squarec
    val_rmse = mean_squared_error(model.predict(val_inputs), val_targets, squared=False
    return train_rmse, val_rmse
```

max_depth

```
test_params_const_n_est(max_depth=5)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.5339011936126692, 0.5383776512083263)
```

```
test_params_const_n_est(max_depth=10)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.4583207679056237, 0.46780473876465506)
```

```
test_params_const_n_est(max_depth=20)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.3161938181285681, 0.4226642814059941)
```

```
test_params_const_n_est(max_depth=30)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.1863304363366188, 0.415743399978883)
```

The max_depth of 20 seems to give the lowest validation error

min_samples_leaf

```
test_params_const_n_est(min_samples_leaf=1)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.16454596102462402, 0.41593562272911627)
```

```
test_params_const_n_est(min_samples_leaf=3)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.24624714139194423, 0.4115908622267881)
```

```
test_params_const_n_est(min_samples_leaf=6)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.3021262139504197, 0.41006658001128465)
```

min_samples_leaf doesn't have a major effect on the errors

max_features

```
test_params_const_n_est(max_features=0.2)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.1688778313082322, 0.4254865645087845)
```

```
test_params_const_n_est(max_features=0.5)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.16304893393879588, 0.4123610643914954)
```

```
test_params_const_n_est(max_features=0.8)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples,), for example using ravel().
```

```
(0.16364586915573745, 0.4142369687079782)
```

Same goes for max_features (No such effect on error)

Putting it Together for RandomForestRegressor

```
test_params(n_estimators=20, max_depth=30, min_samples_leaf=6, max_features=0.5)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
```

```
(0.31313634322036143, 0.40678104656174835)
```

##2: XGBoost

Training model & rmse loss

```
from xgboost import XGBRegressor
```

```
model = XGBRegressor(random_state=42, n_jobs=-1, n_estimators=100, max_depth=20)
```

```
model.fit(train_inputs, train_targets)
```

```
[10:10:48] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
XGBRegressor(max_depth=20, n_jobs=-1, random_state=42)
```

```
train_preds2=model.predict(train_inputs)
val_preds2=model.predict(val_inputs)
```

```
train_rmse2=mean_squared_error(train_preds2, train_targets)
val_rmse2=mean_squared_error(val_preds2, val_targets)
```

```
train_rmse2, val_rmse2
```

```
(0.01823574690850151, 0.15667657496307597)
```

```
val_targets
```

	log_time_duration
67250	6.946976
1397036	6.717805
1021087	6.419995
951424	6.765039

	log_time_duration
707882	8.510571
...	...
526279	5.978886
80354	6.658011
328645	7.759614
657429	5.973810
128732	6.638568

145865 rows × 1 columns

```
val_preds2
```

```
array([6.6193085, 6.687004 , 6.103874 , ..., 7.808759 , 5.773875 ,
       5.6612706], dtype=float32)
```

HyperParameter Tuning

```
def test_params2(**params):
    model = XGBRegressor(random_state=42, n_jobs=-1, **params).fit(train_inputs, train_
    train_rmse2 = mean_squared_error(model.predict(train_inputs), train_targets, square
    val_rmse2 = mean_squared_error(model.predict(val_inputs), val_targets, squared=Fals
    return train_rmse2, val_rmse2
```

n_estimators

```
test_params2(n_estimators=10)
```

```
[10:28:23] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
```

```
(2.1516853007402297, 2.153699482815737)
```

```
test_params2(n_estimators=30)
```

```
[10:28:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
```

```
(0.5440560081946834, 0.5483471200969486)
```

```
test_params2(n_estimators=100)
```

```
[10:29:11] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
```

```
(0.4484664158436235, 0.4531734071902341)
```

max_depth

```
test_params2(n_estimators=100, max_depth=3)
```

[10:31:03] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4484664158436235, 0.4531734071902341)

```
test_params2(n_estimators=100, max_depth=6)
```

[10:33:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.41825372837975144, 0.42609603957679226)

```
test_params2(n_estimators=100, max_depth=10)
```

[10:37:55] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.36890508972046554, 0.403759845878455554)

```
test_params2(n_estimators=100, max_depth=20)
```

[10:46:18] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.13503979749874298, 0.39582391913965476)

learning_rate

```
test_params2(n_estimators=100, learning_rate=0.01)
```

[11:11:04] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(2.252986056264769, 2.254912270961598)

```
test_params2(n_estimators=100, learning_rate=0.1)
```

[11:13:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4484664158436235, 0.4531734071902341)

```
test_params2(n_estimators=100, learning_rate=0.3)
```

[11:16:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4333913931956763, 0.4393109150515189)

```
test_params2(n_estimators=100, learning_rate=0.5)
```

[11:19:17] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4278456859623037, 0.43379010140340823)

```
test_params2(n_estimators=100, learning_rate=0.7)
```

[11:22:02] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4250769016967997, 0.4313370836987829)

```
test_params2(n_estimators=100, learning_rate=0.9)
```

[11:24:19] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.42408398284768445, 0.43042398924728)

subsample

```
test_params2(n_estimators=100, subsample=0.1)
```

[11:26:24] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.44857706783617224, 0.45292728234450613)

```
test_params2(n_estimators=100, subsample=0.4)
```

[11:28:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.44866796509869067, 0.4532739190632897)

```
test_params2(n_estimators=100, subsample=0.7)
```

[11:30:48] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.4486530071804086, 0.4533789689115442)

colsample_bytree

```
test_params2(n_estimators=100, colsample_bytree=0.1)
```

[11:33:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

(0.5350412055134752, 0.5401606696729085)

```
test_params2(n_estimators=100, colsample_bytree=0.3)
```

```
[11:34:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
(0.46726612043359517, 0.4717266466861409)
```

```
test_params2(n_estimators=100, colsample_bytree=0.6)
```

```
[11:35:37] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
(0.4510318531766353, 0.4555485589818679)
```

```
test_params2(n_estimators=100, colsample_bytree=0.8)
```

```
[11:37:18] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
(0.448494915380476, 0.45327803622921403)
```

The subsample, colsample_bytree donot seem to have an effect on the validation rmse

Puting it Together for XGBoostRegreesor

So the max_depth of 20 with n_estimators equal to 100 and all other parameters at their default value gives the least validation rmse

```
jovian.commit()
```

Preparation of Test_df for testing with XGBoost

```
test_df
```

	id	vendor_id	pickup_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude
0	id3004672	1	2016-06-30 23:59:58	1	-73.988129	40.732029	-73.990173
1	id3505355	1	2016-06-30 23:59:53	1	-73.964203	40.679993	-73.959808
2	id1217141	1	2016-06-30 23:59:47	1	-73.997437	40.737583	-73.986160
3	id2150126	2	2016-06-30 23:59:41	1	-73.956070	40.771900	-73.986427
4	id1598245	1	2016-06-30 23:59:33	1	-73.970215	40.761475	-73.961510
...	...	...	...	...	...	...	...
625129	id3008929	1	2016-01-01 00:02:52	1	-74.003464	40.725105	-74.001251

	id	vendor_id	pickup_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude
625130	id3700764	1	2016-01-01 00:01:52	1	-74.006363	40.743782	-73.953407
625131	id2568735	1	2016-01-01 00:01:24	2	-73.972267	40.759865	-73.876602
625132	id1384355	1	2016-01-01 00:00:28	1	-73.976501	40.733562	-73.854263
625133	id0621643	2	2016-01-01 00:00:22	2	-73.981850	40.716881	-73.969330

625134 rows × 9 columns

```
split_dates(test_df)
cal_distance(test_df)
test_inputs_df=test_df[input_cols].copy()
test_numeric_cols=test_inputs_df[input_cols].select_dtypes(include=np.number).columns.t
test_categorical_cols=['store_and_fwd_flag']
flag_codes={'N':0, 'Y':1}
test_inputs_df['flag_code']=test_inputs_df.store_and_fwd_flag.map(flag_codes)
test_encoded_cols=['flag_code']
scaler.fit(test_inputs_df[test_numeric_cols])
test_inputs_df[test_numeric_cols] = scaler.transform(test_inputs_df[test_numeric_cols])
test_inputs_df=test_inputs_df[test_numeric_cols+test_encoded_cols]
```

```
test_numeric_cols
```

```
['vendor_id',
 'passenger_count',
 'pickup_longitude',
 'pickup_latitude',
 'dropoff_longitude',
 'dropoff_latitude',
 'pickup_month',
 'pickup_weekday',
 'pickup_day',
 'pickup_time_hour',
 'Distance_km']
```

```
test_inputs_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 625134 entries, 0 to 625133
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   vendor_id          625134 non-null  float64
 1   passenger_count    625134 non-null  float64
 2   pickup_longitude   625134 non-null  float64
 3   pickup_latitude    625134 non-null  float64
```

```
 4   dropoff_longitude  625134 non-null  float64
 5   dropoff_latitude   625134 non-null  float64
 6   pickup_month       625134 non-null  float64
 7   pickup_weekday     625134 non-null  float64
 8   pickup_day         625134 non-null  float64
 9   pickup_time_hour   625134 non-null  float64
 10  Distance_km        625134 non-null  float64
 11  flag_code          625134 non-null  int64
dtypes: float64(11), int64(1)
memory usage: 57.2 MB
```

```
test_inputs_df.shape
```

```
(625134, 12)
```

Final Model

Though there was not much of a difference in the validation errors between the two models, we will proceed with the XGboostRegressor as it had a slighlty less error as compared to the RandomForestRegressor model

```
model = XGBRegressor(random_state=42, n_jobs=-1, n_estimators=100, max_depth=20)
```

The model is trained through the train_inputs which is 90% of the data in training dataframe. So it would be good to go

```
model.fit(train_inputs, train_targets)
```

```
[12:37:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
XGBRegressor(max_depth=20, n_jobs=-1, random_state=42)
```

```
test_preds=model.predict(test_inputs_df)
test_preds
```

```
array([6.3063436, 6.27259  , 5.5327506, ..., 6.840295 , 7.5178547,
       7.0027347], dtype=float32)
```

```
model.predict(train_inputs)
```

```
array([6.255489 , 6.1759205, 7.1359553, ..., 7.2043743, 5.8884797,
       7.3309894], dtype=float32)
```

Feature Importances

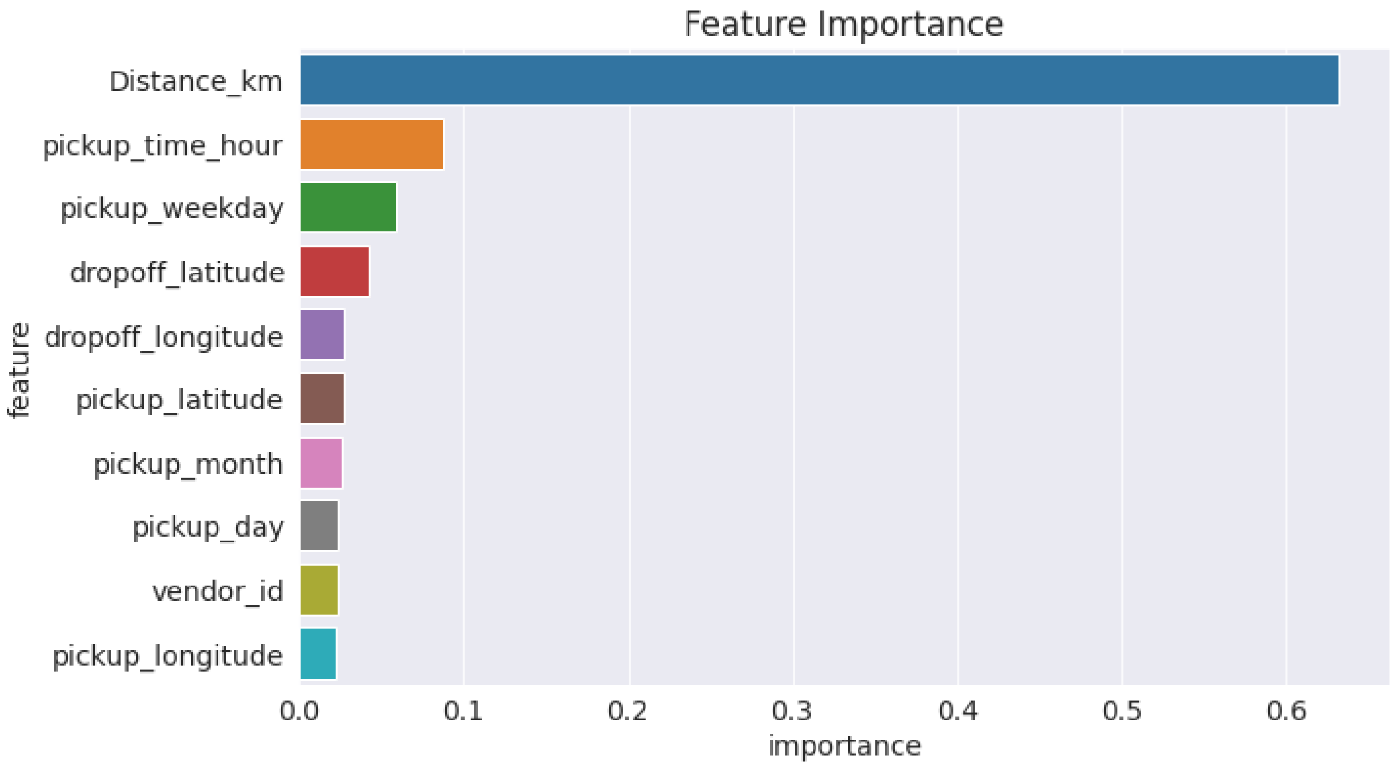
```
importance_df = pd.DataFrame({
    'feature': test_inputs_df.columns,
```

```
    'importance': model.feature_importances_
}).sort_values('importance', ascending=False)
```

```
importance_df.head(10)
```

	feature	importance
10	Distance_km	0.631457
9	pickup_time_hour	0.088267
7	pickup_weekday	0.058863
5	dropoff_latitude	0.042961
4	dropoff_longitude	0.027089
3	pickup_latitude	0.026540
6	pickup_month	0.026032
8	pickup_day	0.023743
0	vendor_id	0.022976
2	pickup_longitude	0.022075

```
plt.figure(figsize=(10,6))
plt.title('Feature Importance')
sns.barplot(data=importance_df.head(10), x='importance', y='feature');
```



It is evident that that the Distance_km column we created through feature engineering has the most weightage of 0.63 in determining the trip duration, followed by pickup_time_hour and pickup_weekday. (also created through feature engineering)

Prepartaion of Submission file from test predictions

```
sub_df
```

	id	trip_duration
0	id3004672	959
1	id3505355	959
2	id1217141	959
3	id2150126	959
4	id1598245	959
...	...	...
625129	id3008929	959
625130	id3700764	959
625131	id2568735	959
625132	id1384355	959
625133	id0621643	959

625134 rows × 2 columns

```
submission = pd.DataFrame({'id': sub_df.id, 'trip_duration':np.exp(test_preds)-1})
submission.to_csv('submission.csv', index=None)
submission.trip_duration
```

```
0          547.037354
1          528.847961
2          251.838425
3          753.931824
4          301.447815
              ...
625129     133.720215
625130     855.283936
625131     933.764709
625132    1839.614258
625133    1098.636230
Name: trip_duration, Length: 625134, dtype: float32
```

```
submission.head()
```

	id	trip_duration
0	id3004672	547.037354
1	id3505355	528.847961
2	id1217141	251.838425
3	id2150126	753.931824
4	id1598245	301.447815

```
from IPython.display import FileLink
FileLink('submission.csv')
```

submission.csv

Saving and Loading Final Trained Model

```
import joblib
```

```
nyc_taxi_trip_duartion = {
    'model': model,
    'scaler': scaler,
    'input_cols': input_cols,
    'target_col': target_col,
    'numeric_cols': numeric_cols,
    'categorical_cols': categorical_cols,
    'encoded_cols': encoded_cols,
    'feature_importance': importance_df
}
```

```
joblib.dump(nyc_taxi_trip_duartion, 'nyc_taxi_trip_duartion_weights')
```

```
['nyc_taxi_trip_duartion_weights']
```

Conclusion

We have finally trained the model to predict the time duration for taxi trips in test file. The model used was XGboost Regressor and the hyperparameters have been stated above. First the dataset was prepared for training by imputing missing values (if any), scaling numeric columns and creating encoded columns. Then it was split into two sets, one for training and the second for validation. We calculated the root mean squared error on the target column log_time_duration to train the model and then fit it in the test file. The Distance column ws created using the concept of Haversine distance and by looking at the feature importances, it had the major impact with the most weightage. Eventually, using exponent in numpy array, the log_time_duration column was converted back to the time duration in seconds.

References

Mentioned below are the links to sources I found useful for this project

https://www.kaggle.com/code/coreprinciple/taxi-cleaned-data

https://www.kaggle.com/code/mirhyun0508/2022-smarcle-ai-study-nyc-taxi-trip-duration-eda

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.haversine_distances.


```
jovian.commit()
```

```
[jovian] Detected Colab notebook...
[jovian] Uploading colab notebook to Jovian...
Committed successfully! https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration
```

```
'https://jovian.ai/noorullah-rizwann/course-project-taxi-trip-duration'
```