taxi-trip-duration-prediction

Use the "Run" button to execute the code.

```
!pip install jovian geopy --upgrade --quiet
```

```
import jovian
```

```

```

image.png

In this competition, Kaggle is challenging you to build a model that predicts the total ride duration of taxi trips in New York City. Your primary dataset is one released by the NYC Taxi and Limousine Commission, which includes pickup time, geo-coordinates, number of passengers, and several other variables.

Longtime Kagglers will recognize that this competition objective is similar to the ECML/PKDD trip time challenge we hosted in 2015. But, this challenge comes with a twist. Instead of awarding prizes to the top finishers on the leaderboard, this playground competition was created to reward collaboration and collective learning.

We are encouraging you (with cash prizes!) to publish additional training data that other participants can use for their predictions. We also have designated bi-weekly and final prizes to reward authors of kernels that are particularly insightful or valuable to the community.

Problem Statement

The competition dataset is based on the 2016 NYC Yellow Cab trip record data made available in Big Query on Google Cloud Platform. The data was originally published by the NYC Taxi and Limousine Commission (TLC). The data was sampled and cleaned for the purposes of this playground competition. Based on individual trip attributes, participants should predict the duration of each trip in the test set.

Importing the libraries

Before importing let's install all the libraries that are going to be used in the notebook.

```
pip install numpy pandas matplotlib seaborn sklearn opendatasets xgboost --quiet
```

```
import os
import opendatasets as od
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.simplefilter('ignore')
pd.set_option("display.max_columns", None)
```

Downloading the data

We can download the dataset from Kaggle directly within the Jupyter notebook using the opendatasets library.

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

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

```
Please provide your Kaggle credentials to download this dataset. Learn more:
http://bit.ly/kaggle-creds
Your Kaggle username: omkarhirugade
Your Kaggle Key: ··········
Downloading nyc-taxi-trip-duration.zip to ./nyc-taxi-trip-duration

100%|██████████| 85.8M/85.8M [00:04<00:00, 19.4MB/s]


Extracting archive ./nyc-taxi-trip-duration/nyc-taxi-trip-duration.zip to ./nyc-taxi-
trip-duration
```

```
os.listdir('nyc-taxi-trip-duration') # list of files in the nyc-taxi-trip-duration dire
```

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

```
import zipfile
with zipfile.ZipFile('./nyc-taxi-trip-duration/train.zip', 'r') as zip_ref:
    zip_ref.extractall('nyc-taxi-trip-duration')
```

```
with zipfile.ZipFile('./nyc-taxi-trip-duration/test.zip', 'r') as zip_ref:
    zip_ref.extractall('nyc-taxi-trip-duration')
```

```
with zipfile.ZipFile('./nyc-taxi-trip-duration/sample_submission.zip', 'r') as zip_ref:
    zip_ref.extractall('nyc-taxi-trip-duration')
```

Reading the dataset

```
train_df=pd.read_csv('./nyc-taxi-trip-duration/train.csv',nrows=100)
test_df=pd.read_csv('./nyc-taxi-trip-duration/test.csv',nrows=20)
```

```
train_df.head()
```

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropo
0	id2875421	2	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937	

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	dropo
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	

Feature Description:

id - a unique identifier for each trip

vendor_id - a code indicating the provider associated with the trip record

pickup_datetime - date and time when the meter was engaged

dropoff_datetime - date and time when the meter was disengaged

passenger_count - the number of passengers in the vehicle (driver entered value)

pickup_longitude - the longitude where the meter was engaged

pickup_latitude - the latitude where the meter was engaged

dropoff_longitude - the longitude where the meter was disengaged

dropoff_latitude - the latitude where the meter was disengaged

store_and_fwd_flag - This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server - Y=store and forward; N=not a store and forward trip

trip_duration - duration of the trip in seconds

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id                  100 non-null    object
 1   vendor_id           100 non-null    int64
 2   pickup_datetime     100 non-null    object
 3   dropoff_datetime    100 non-null    object
 4   passenger_count     100 non-null    int64
 5   pickup_longitude    100 non-null    float64
 6   pickup_latitude     100 non-null    float64
 7   dropoff_longitude   100 non-null    float64
```

```
 8   dropoff_latitude    100 non-null    float64
 9   store_and_fwd_flag  100 non-null    object
 10  trip_duration       100 non-null    int64
dtypes: float64(4), int64(3), object(4)
memory usage: 8.7+ KB
```

Here we have to convert the pickup and dropoff to datetime

```
train_df.describe() # descriptive statisitics of train data
```

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_durati
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.0000(
mean	1.480000	1.430000	-73.973521	40.748470	-73.969231	40.747412	984.9800(
std	0.502117	1.027451	0.040302	0.028275	0.043674	0.032011	685.8150
min	1.000000	1.000000	-74.016327	40.643559	-74.012268	40.641472	57.0000(
25%	1.000000	1.000000	-73.993574	40.737203	-73.995106	40.728586	466.2500(
50%	1.000000	1.000000	-73.981762	40.753716	-73.980652	40.748802	777.0000(
75%	2.000000	1.000000	-73.968266	40.767100	-73.961336	40.765676	1276.2500(
max	2.000000	6.000000	-73.782478	40.806606	-73.788750	40.864029	3528.0000(

Converting the Objects into datetime

```
train_df["pickup_datetime"]= pd.to_datetime(train_df["pickup_datetime"])
train_df["dropoff_datetime"]= pd.to_datetime(train_df["dropoff_datetime"])
```

```
train_df['pickup_day']= train_df["pickup_datetime"].dt.day_name()
train_df['dropoff_day']= train_df["dropoff_datetime"].dt.day_name()
```

```
train_df['pickup_month']= train_df["pickup_datetime"].dt.month_name()
train_df['dropoff_month']= train_df["dropoff_datetime"].dt.month_name()
```

```
train_df['pickup_day_no']=train_df['pickup_datetime'].dt.weekday
train_df['dropoff_day_no']=train_df['dropoff_datetime'].dt.weekday
```

```
train_df['pickup_hour']=train_df['pickup_datetime'].dt.hour
train_df['dropoff_hour']=train_df['dropoff_datetime'].dt.hour
```

We have created the following features:

pickup_day and dropoff_day which will contain the name of the day on which the ride was taken.

pickup_day_no and dropoff_day_no which will contain the day number instead of characters with Monday=0 and Sunday=6.

pickup_hour and dropoff_hour with an hour of the day in the 24-hour format.

pickup_month and dropoff_month with month number with January=1 and December=12.

Next, I have defined a function that lets us determine what time of the day the ride was taken. I have created 4 time zones 'Morning' (from 6:00 am to 11:59 pm), 'Afternoon' (from 12 noon to 3:59 pm), 'Evening' (from 4:00 pm to 9:59 pm), and 'Late Night' (from 10:00 pm to 5:59 am)

```
def time_of_day(x):
    if x in range(6,12):
        return 'Morning'
    elif x in range(12,16):
        return 'Afternoon'
    elif x in range(16,22):
        return 'Evening'
    else:
        return 'Late night'
```

```
train_df['pickup_timeofday']=train_df['pickup_hour'].apply(time_of_day)
train_df['dropoff_timeofday']=train_df['dropoff_hour'].apply(time_of_day)
```

We also saw during dataset exploration that we have coordinates in the form of longitude and latitude for pickup and dropoff. But, we can't really gather any insights or draw conclusions from that. So, the most obvious feature that we can extract from this is distance. Let us do that.

Importing the library which lets us calculate distance from geographical coordinates.

Defining a function to take coordinates as inputs and return us distance.

```
def distance(lat1, lon1, lat2, lon2):
  p = 0.017453292519943295 # Pi/180
  a = 0.5 - np.cos((lat2 - lat1) * p)/2 + np.cos(lat1 * p) * np.cos(lat2 * p) * (1 - np
  return 0.6213712 * 12742 * np.arcsin(np.sqrt(a))
```

Finally, applying the function to our dataset and creating the feature 'distance'.

```
train_df["distance_miles"] = distance(train_df["pickup_latitude"], train_df["pickup_lon
                                      train_df["dropoff_latitude"], train_df["dropoff_l
```

```
train_df
```

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drop
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	

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drop
...	...	...	...	...	...	...	...	
95	id3025098	2	2016-01-20 19:21:31	2016-01-20 19:31:27	1	-73.976982	40.750301	
96	id3333094	2	2016-06-02 23:34:00	2016-06-02 23:41:15	1	-73.973465	40.755230	
97	id2228940	1	2016-02-04 13:22:02	2016-02-04 13:40:30	1	-73.981865	40.758774	
98	id2102594	1	2016-03-30 16:14:29	2016-03-30 17:01:33	1	-73.789841	40.643559	
99	id0010677	1	2016-04-29 10:40:34	2016-04-29 10:53:23	2	-73.991974	40.749996	

100 rows × 22 columns

Locations of pickup and dropoff lats and longs

We use geopy to get the locations of pickup and dropoff points

```
from geopy.geocoders import Nominatim
from geopy.point import Point
```

```
geolocator = Nominatim(user_agent="geoapiExercises")
```

The function below gives the name of the road of pickup and dropoff location.

```
def city_state_country(lat,long):
    location = geolocator.reverse(Point(lat, long))
    address = location.raw['address']
    if 'road' in address:
        x=address['road']
    else:
        x='NA'
    return x
```

```
train_df["pickup_location"] = np.vectorize(city_state_country)(train_df["pickup_latituc
train_df["dropoff_location"] = np.vectorize(city_state_country)(train_df["dropoff_latit
```

```
pd.set_option("display.max_colwidth", -1)
```

```
train_df["pickup_location"]
```

```
0      Columbus Circle
1      2nd Avenue
2      West 56th Street
3      Greenwich Street
```

```
4       Broadway
          ...
95      Lexington Avenue
96      Madison Avenue
97      Rockefeller Plaza
98      NA
99      Pennsylvania Plaza
Name: pickup_location, Length: 100, dtype: object
```

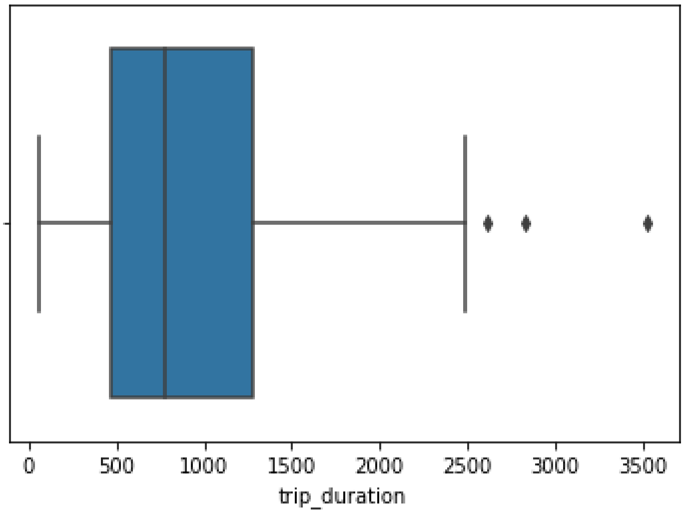
EDA

Target

Let us start by analyzing the target variable.

```
sns.boxplot(train_df['trip_duration'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f40fabc2f90>
```



We can clearly see an outlier.

```
train_df['trip_duration'].sort_values(ascending=False)
```

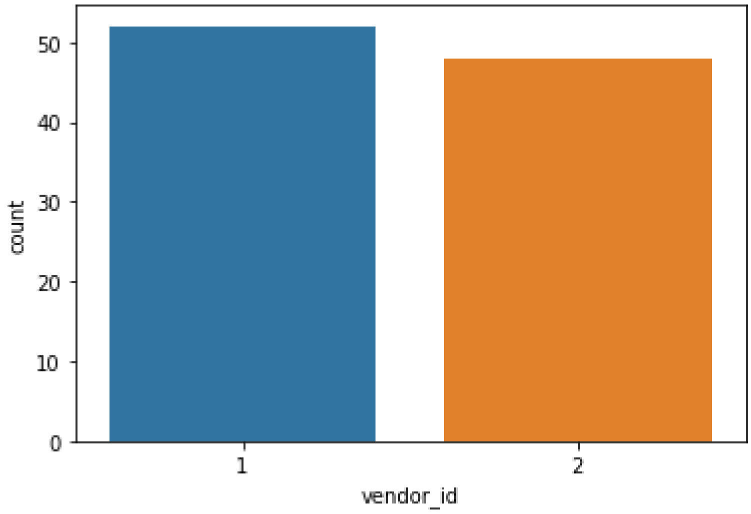
```
55      3528
98      2824
57      2607
24      2485
93      2341
        ...
83      218
68      215
15      211
64      174
72      57
Name: trip_duration, Length: 100, dtype: int64
```

We can see that there is an entry which is significantly different from others.

Vendor id

```
sns.countplot(x='vendor_id',data=train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f40fab2e5d0>
```



We see that there is not much difference between the trips taken by both vendors.

Passenger Count

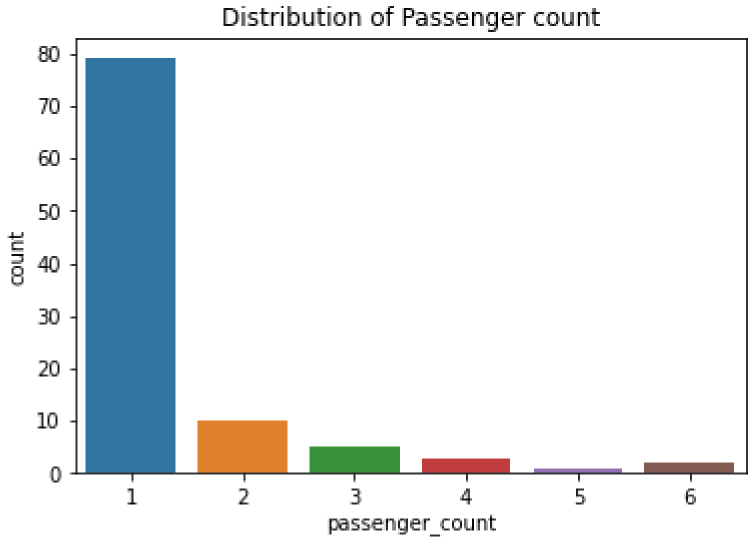
```
train_df.passenger_count.value_counts()
```

```
1    79
2    10
3     5
4     3
6     2
5     1
Name: passenger_count, dtype: int64
```

There are some trips with even 0 passenger count. There is only 1 trip each for 7 and 9 passengers.

```
axis=sns.countplot(x=train_df['passenger_count'])
plt.title('Distribution of Passenger count')
```

```
Text(0.5, 1.0, 'Distribution of Passenger count')
```



Most of the passengers are single passengers

Let us remove the rows which have 0 or 7 or 9 passenger count.

Store and Forward Flag

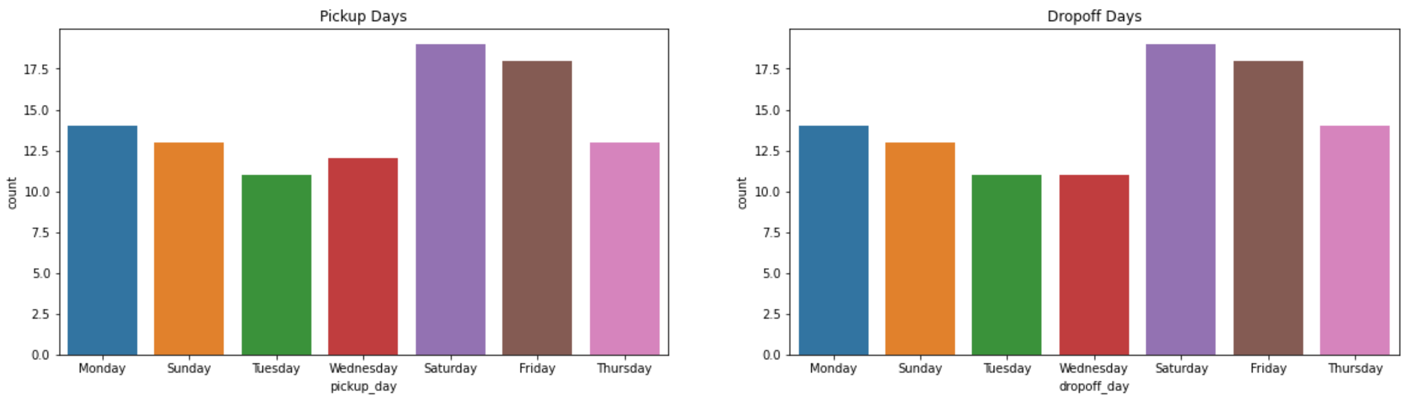
```
train_df['store_and_fwd_flag'].value_counts(normalize=True)
```

```
N    1.0
Name: store_and_fwd_flag, dtype: float64
```

We see there are less than 1% of trips that were stored before forwarding.

Trips per Day

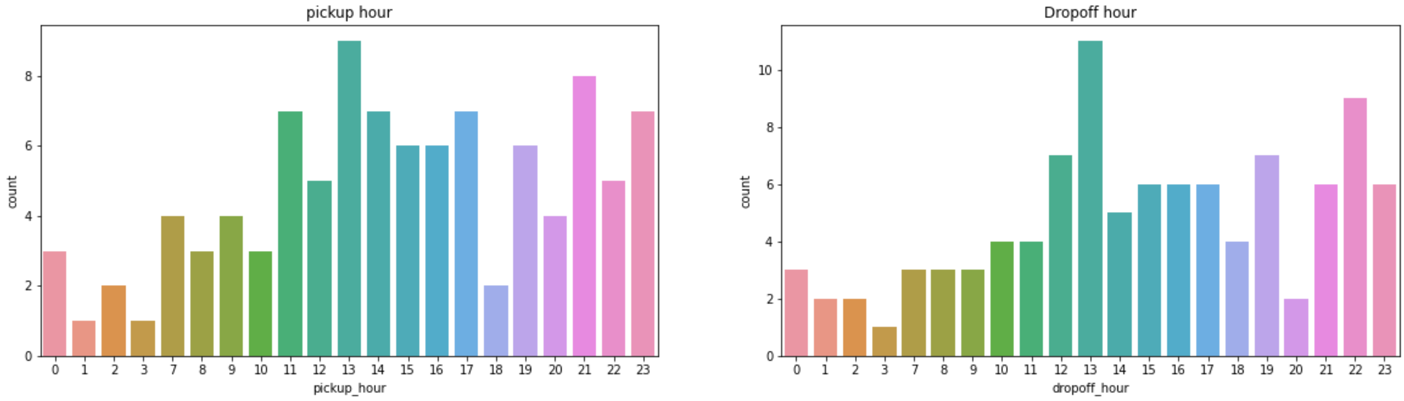
```
figure,(ax1,ax2)=plt.subplots(ncols=2,figsize=(20,5))
ax1.set_title('Pickup Days')
ax=sns.countplot(x="pickup_day",data=train_df,ax=ax1)
ax2.set_title('Dropoff Days')
ax=sns.countplot(x="dropoff_day",data=train_df,ax=ax2)
```



We see Fridays are the busiest days followed by Saturdays. That is probably because it’s weekend.

Trips per Hour

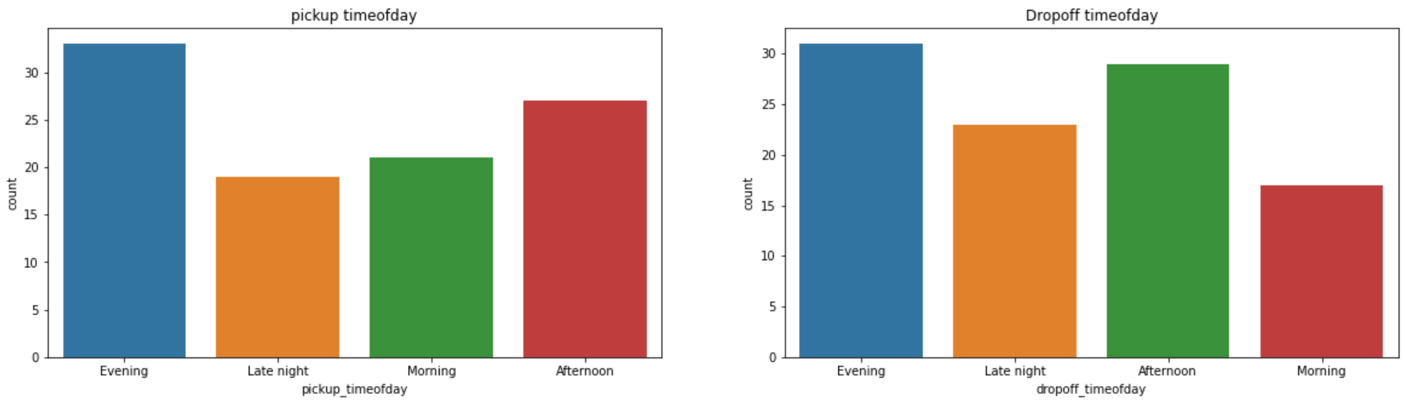
```
figure,(ax1,ax2)=plt.subplots(ncols=2,figsize=(20,5))
ax1.set_title('pickup hour')
ax=sns.countplot(x="pickup_hour",data=train_df,ax=ax1)
ax2.set_title('Dropoff hour')
ax=sns.countplot(x="dropoff_hour",data=train_df,ax=ax2)
```



We see the busiest hours are 6:00 pm to 7:00 pm and that makes sense as this is the time when people return from their offices.

Trips per Time of Day

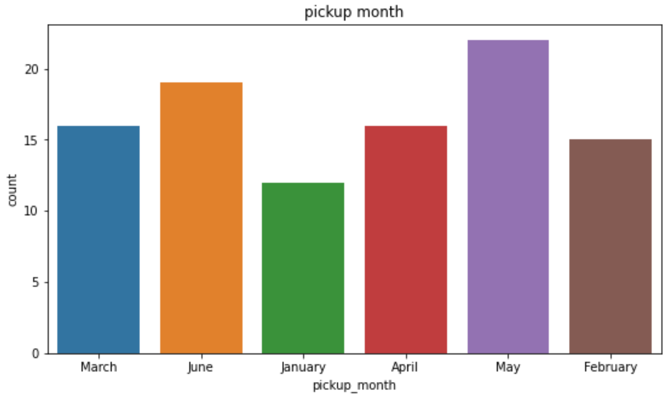
```
figure,(ax1,ax2)=plt.subplots(ncols=2,figsize=(20,5))
ax1.set_title('pickup timeofday')
ax=sns.countplot(x="pickup_timeofday",data=train_df,ax=ax1)
ax2.set_title('Dropoff timeofday')
ax=sns.countplot(x="dropoff_timeofday",data=train_df,ax=ax2)
```

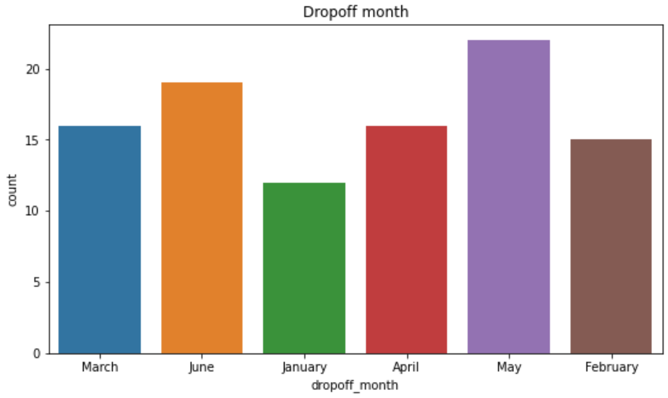


As we saw above, evenings are the busiest.

Trips per month

```
figure,(ax1,ax2)=plt.subplots(ncols=2,figsize=(20,5))
ax1.set_title('pickup month')
ax=sns.countplot(x="pickup_month",data=train_df,ax=ax1)
ax2.set_title('Dropoff month')
ax=sns.countplot(x="dropoff_month",data=train_df,ax=ax2)
```



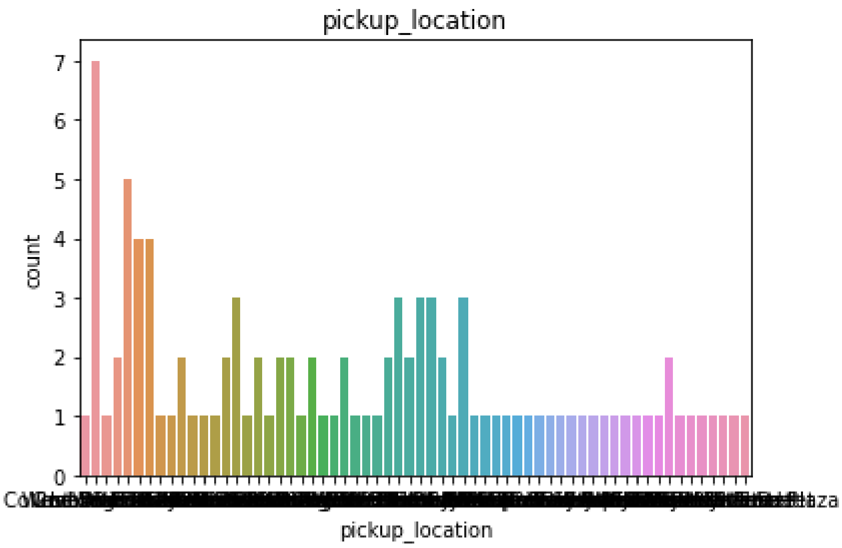


There is not much difference in the number of trips across months.

The pickup and dropoff locations

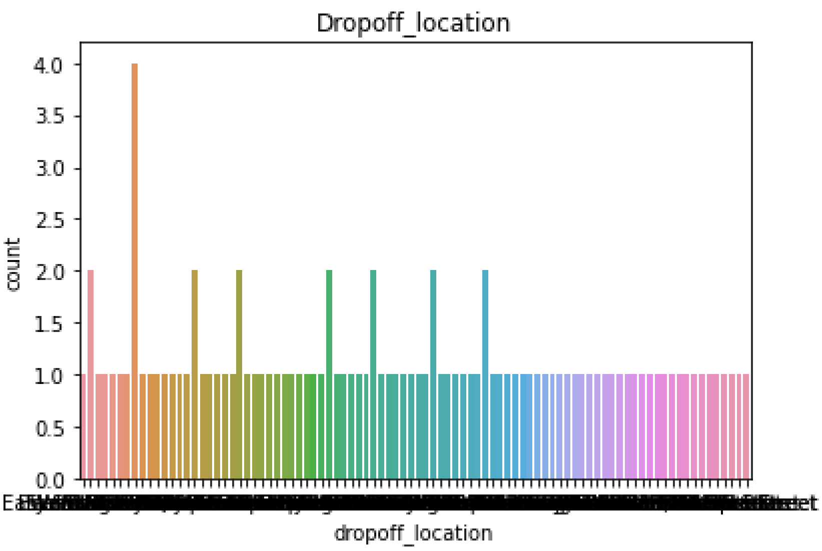
```
sns.countplot(x="pickup_location",data=train_df).set_title('pickup_location')
```

```
Text(0.5, 1.0, 'pickup_location')
```



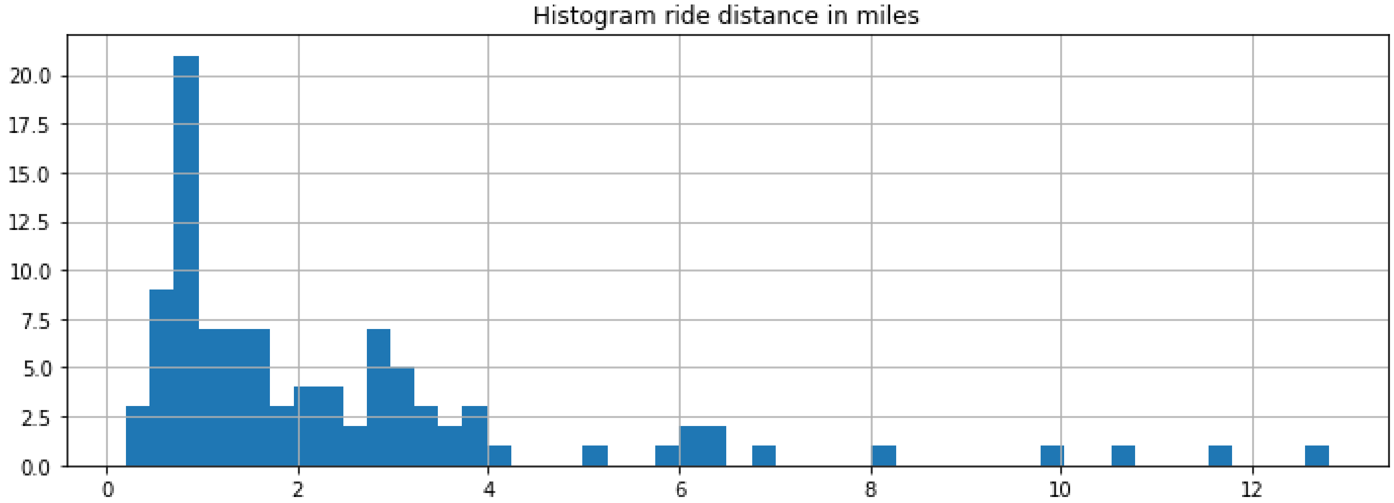

```
sns.countplot(x="dropoff_location",data=train_df).set_title('Dropoff_location')
```

```
Text(0.5, 1.0, 'Dropoff_location')
```

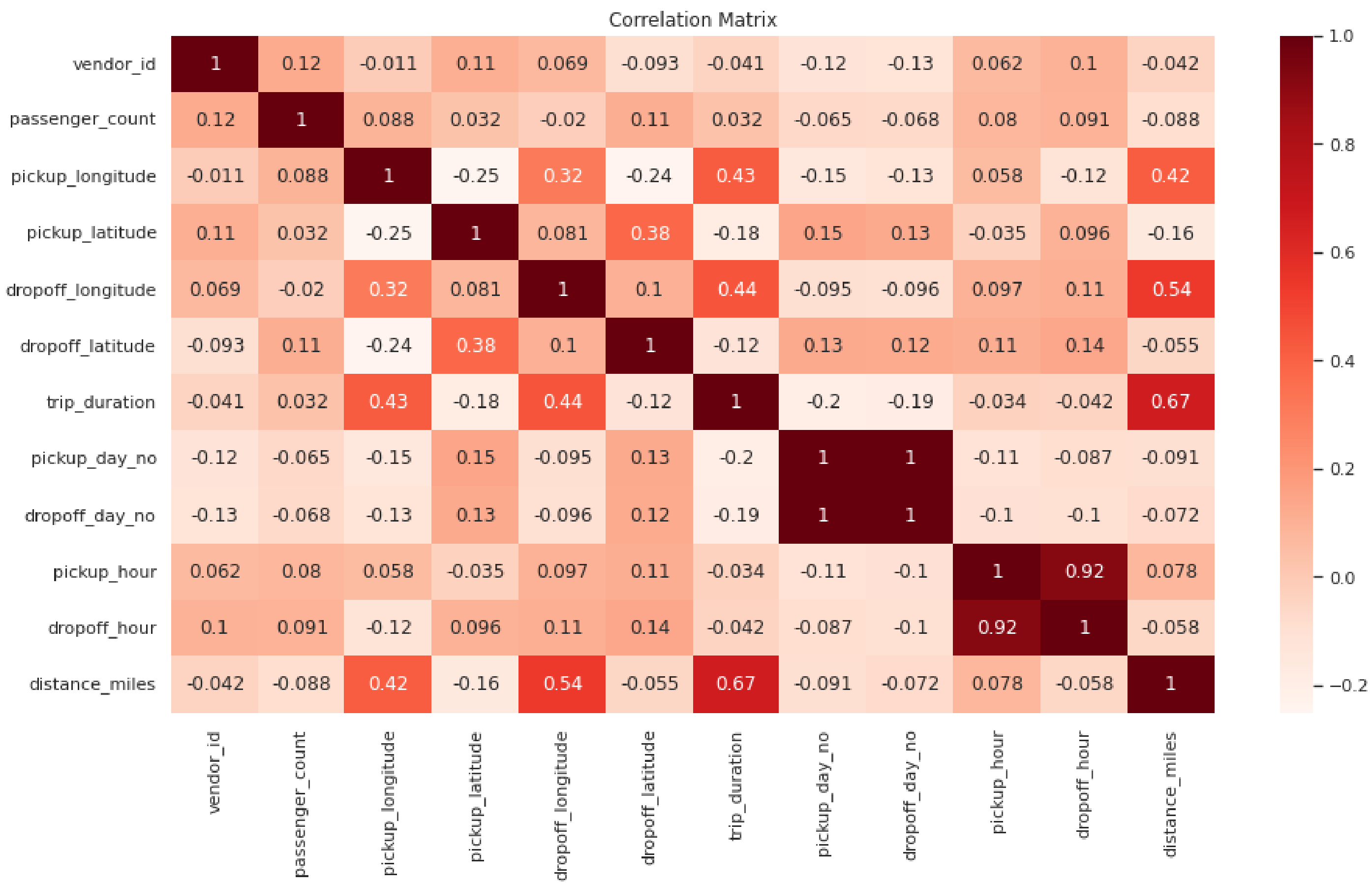


distance_miles

```
train_df["distance_miles"].hist(bins=50, figsize=(12,4))
plt.title("Histogram ride distance in miles");
```




```
sns.set(rc = {'figure.figsize':(15,8)})
sns.heatmap(train_df.corr(), cmap='Reds', annot=True)
plt.title('Correlation Matrix');
```



Data Preprocessing

Here we are finalizing and sorting the features into two dataframes(categorical and numerical) for further encoding and processing

```
catogorical_df=train_df[['id','store_and_fwd_flag','pickup_day','pickup_month','pickup_
numerical_df=train_df[['id','passenger_count','distance_miles','pickup_hour']].copy()
```

Defining the targets dataframe

```
targets=train_df[['trip_duration']].copy()
```

One-hot encode categorical columns

Since ML models cannot process categorical data we need to tranform those data to numerical data.

```
from sklearn.preprocessing import  LabelEncoder
```

```
encoder = LabelEncoder()
```

```
catogorical_df['store_and_fwd_flag']=encoder.fit_transform(train_df['store_and_fwd_flag
catogorical_df['pickup_day']=encoder.fit_transform(train_df['pickup_day'])
catogorical_df['pickup_month']=encoder.fit_transform(train_df['pickup_month'])
catogorical_df['pickup_location']=encoder.fit_transform(train_df['pickup_location'])
catogorical_df['dropoff_location']=encoder.fit_transform(train_df['dropoff_location'])
```

Merging the numerical and categorical columns on the basis of 'id'

```
inputs_df=numerical_df.merge(catogorical_df,left_on='id', right_on='id')
```

Droppping the 'id' column as there is no use to the model

```
inputs_df=inputs_df.drop(['id'],axis='columns')
```

```
inputs_df
```

	passenger_count	distance_miles	pickup_hour	store_and_fwd_flag	pickup_day	pickup_month	pickup_location	dro
0	1	0.931138	17	0	1	4	17	
1	1	1.121890	0	0	3	3	3	
2	1	3.967516	11	0	5	2	58	
3	1	0.923046	19	0	6	0	32	
4	1	0.738555	13	0	2	4	12	
...	...	...	...	...	...	...	...	
95	1	1.378121	19	0	6	2	37	
96	1	0.881344	23	0	4	3	38	
97	1	1.855594	13	0	4	1	46	
98	1	9.946651	16	0	6	4	41	
99	2	0.811495	10	0	0	0	44	

100 rows × 8 columns

Create training and validation sets

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

```
train_inputs, val_inputs, train_targets, val_targets = train_test_split(
    inputs_df, targets, test_size=0.20, random_state=42)
```

Model 1 Decision Tree

The first model that I am going to train is a Decision Tree

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
```

```
tree = DecisionTreeRegressor(random_state=42)
```

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

```
DecisionTreeRegressor(random_state=42)
```

```
train_targets_pred=tree.predict(train_inputs)
```

```
train_loss = mean_squared_error(train_targets, train_targets_pred)
```

```
train_loss
```

```
0.0
```

```
tree.score(train_inputs,train_targets)
```

```
1.0
```

```
val_targets_pred=tree.predict(val_inputs)
```

```
val_loss= mean_squared_error(val_targets, val_targets_pred)
```

```
val_loss
```

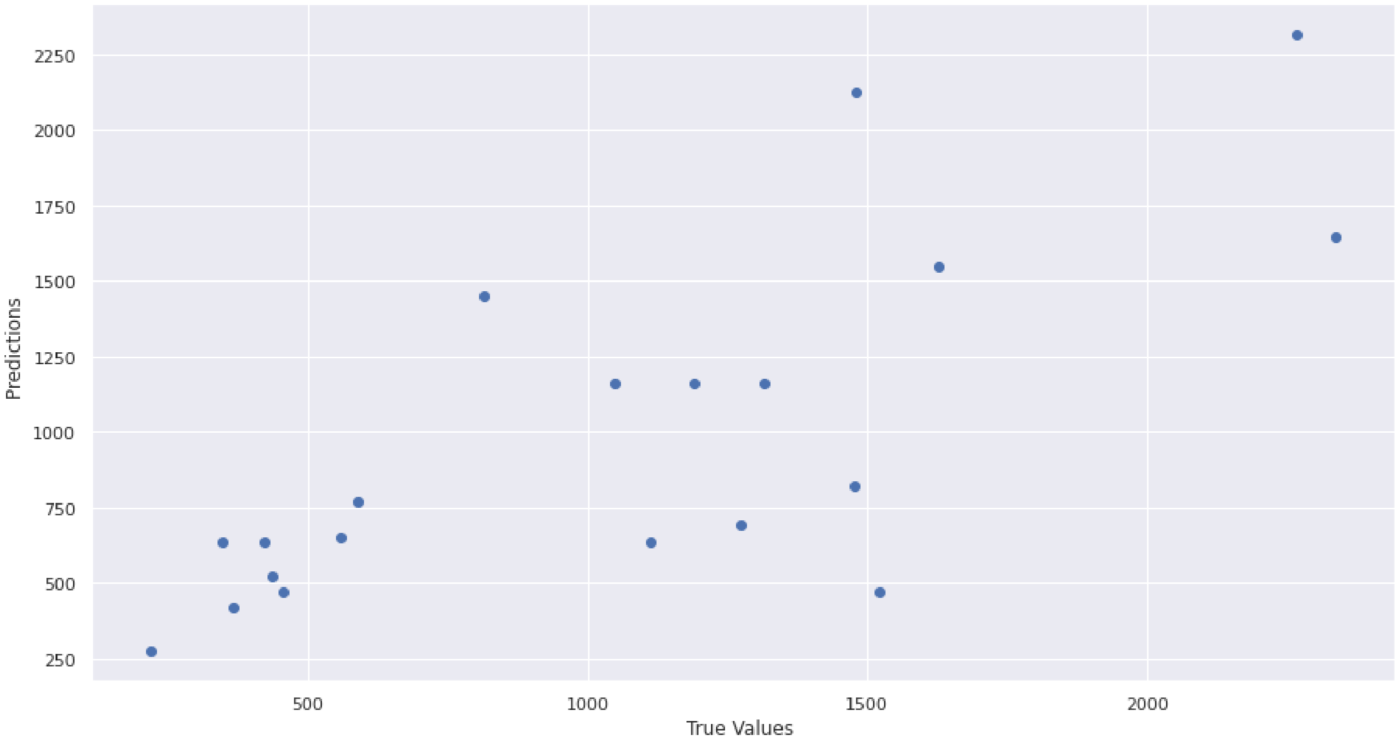
```
181823.6
```

```
tree.score(val_inputs,val_targets)
```

```
0.5153699346439373
```

```python
plt.scatter(val_targets, val_targets_pred);
plt.xlabel('True Values ')
plt.ylabel('Predictions ')
```

```
Text(0, 0.5, 'Predictions ')
```



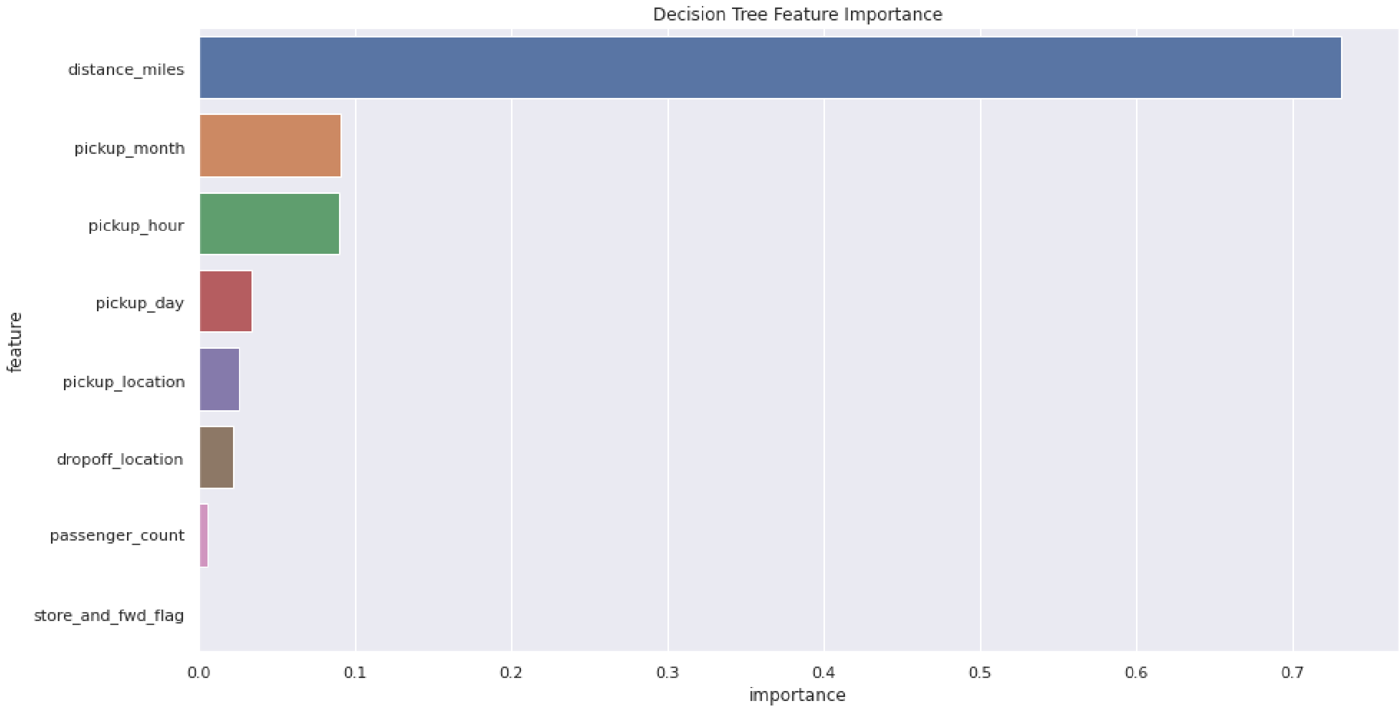

```python
tree_importances = tree.feature_importances_
```

```python
tree_importance_df = pd.DataFrame({
    'feature': train_inputs.columns,
    'importance': tree_importances
}).sort_values('importance', ascending=False)
```

```python
tree_importance_df
```

	feature	importance
1	distance_miles	0.730924
5	pickup_month	0.090654
2	pickup_hour	0.090028
4	pickup_day	0.034112
6	pickup_location	0.026386
7	dropoff_location	0.022179
0	passenger_count	0.005717
3	store_and_fwd_flag	0.000000

```
plt.title('Decision Tree Feature Importance')
sns.barplot(data=tree_importance_df.head(10), x='importance', y='feature');
```



Model 2 RandomForestRegressor

The second model that I am going to train is a RandomForestRegressor

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

```
rf1 = RandomForestRegressor(n_jobs=-1, random_state=42)
```

```
rf1.fit(train_inputs,train_targets)
```

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

```
train_targets_pred=rf1.predict(train_inputs)
```

```
train_loss = mean_squared_error(train_targets, train_targets_pred)
```

```
train_loss
```

```
34426.958423749995
```

```
rf1.score(train_inputs,train_targets)
```

```
0.929336819184423
```

```
rf1_val_preds = rf1.predict(val_inputs)
```

```
val_targets_pred=tree.predict(val_inputs)
```

```
val_loss= mean_squared_error(val_targets, val_targets_pred)
```

```
val_loss
```

```
181823.6
```

```
rf1.score(val_inputs,val_targets)
```

```
0.6424299007364969
```

Model 3 LinearRegression

The third model that I am going to train is a LinearRegression

```
model=LinearRegression()
```

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

# Generate predictions
predictions = model.predict(train_inputs)
```

```
train_loss = mean_squared_error(train_targets, predictions)
```

```
train_loss
```

```
248083.7221201105
```

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

```
0.4907948388062916
```

```
val_predictions= model.predict(val_inputs)
```

```
val_loss = mean_squared_error(train_targets, predictions)
```

```
val_loss
```

```
248083.7221201105
```

```
model.score(val_inputs,val_targets)
```

```
0.3348218669604104
```

Model 4 XGBRegressor

The fourth model that I am going to train is a XGBRegressor

```
from xgboost import XGBRegressor
```

```
model = XGBRegressor(random_state=42, n_jobs=-1, n_estimators=20, max_depth=4)
```

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

```
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
XGBRegressor(max_depth=4, n_estimators=20, n_jobs=-1, random_state=42)
```

```
preds = model.predict(train_inputs)
```

```
train_loss = mean_squared_error(train_targets, preds)
```

```
train_loss
```

```
70570.93574427768
```

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

```
0.8551493648831273
```

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

```
val_loss = mean_squared_error(val_targets, val_preds)
```

```
val_loss
```

```
202980.0431881786
```

```
model.score(val_inputs,val_targets)
```

```
0.4589798486210622
```

Feature importance

XGBoost also provides a feature importance score for each column in the input.

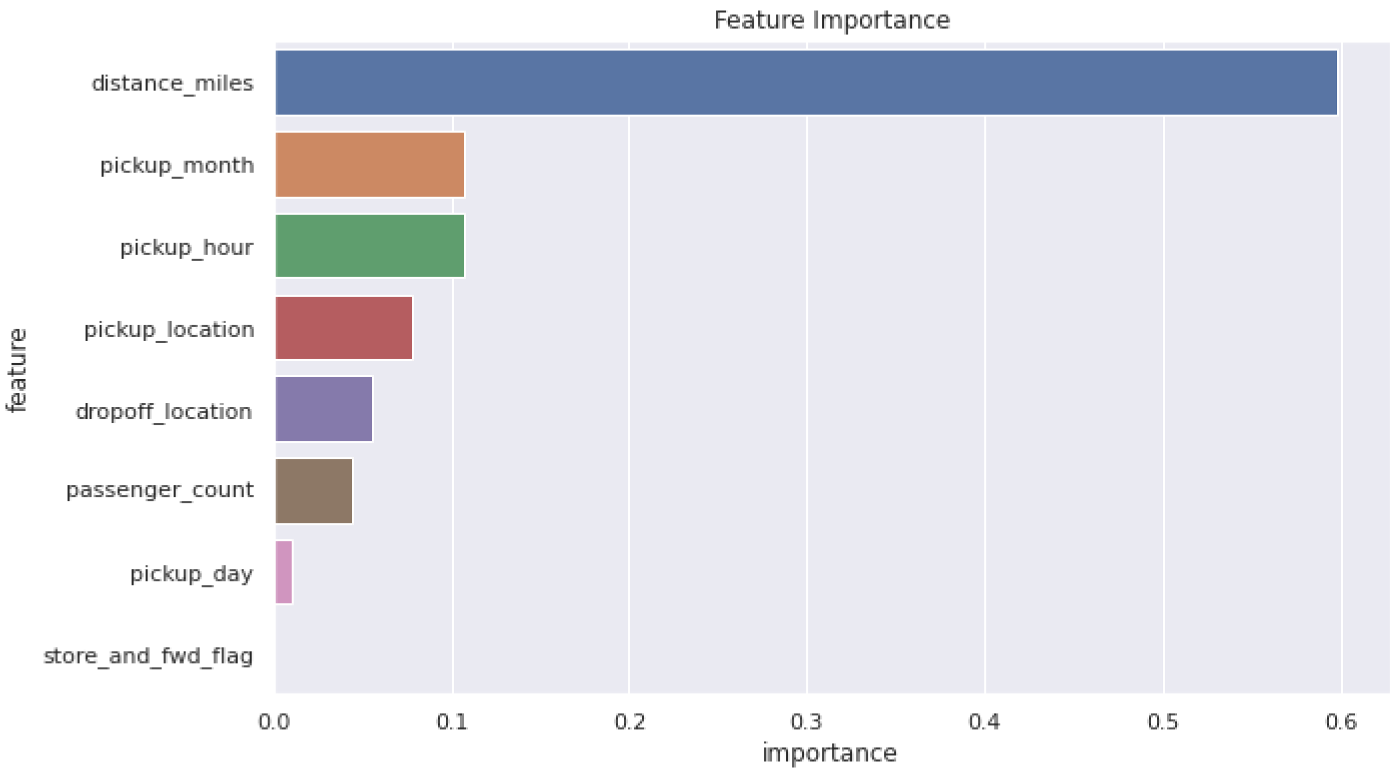
```
importance_df = pd.DataFrame({
    'feature': val_inputs.columns,
```

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

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

	feature	importance
1	distance_miles	0.598005
5	pickup_month	0.107259
2	pickup_hour	0.107026
6	pickup_location	0.077638
7	dropoff_location	0.055364
0	passenger_count	0.044058
4	pickup_day	0.010650
3	store_and_fwd_flag	0.000000

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



K Fold Cross Validation

We'll use a different validation strategy this time, called K-fold cross validation

```
from sklearn.model_selection import KFold
```

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

```python
def rmse(a, b):
    return mean_squared_error(a, b, squared=False)
```

```python
def train_and_evaluate(X_train, train_targets, X_val, val_targets, **params):
    model = XGBRegressor(random_state=42, n_jobs=-1, **params)
    model.fit(X_train, train_targets)
    train_rmse = rmse(model.predict(X_train), train_targets)
    val_rmse = rmse(model.predict(X_val), val_targets)
    return model, train_rmse, val_rmse
```

```python
kfold = KFold(n_splits=5)
```

```python
models = []

for train_idxs, val_idxs in kfold.split(inputs_df):
    train_inputs, train_targets = inputs_df.iloc[train_idxs], targets.iloc[train_idxs]
    val_inputs, val_targets = inputs_df.iloc[val_idxs], targets.iloc[val_idxs]
    model, train_rmse, val_rmse = train_and_evaluate(train_inputs,
                                                     train_targets,
                                                     val_inputs,
                                                     val_targets,
                                                     max_depth=4,
                                                     n_estimators=20)
    models.append(model)
    print('Train RMSE: {}, Validation RMSE: {}'.format(train_rmse, val_rmse))
```

```
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 282.9215051224088, Validation RMSE: 501.4156581336584
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 278.22975382381924, Validation RMSE: 458.46521675074945
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 231.19437246750803, Validation RMSE: 790.7074920143757
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 270.69066862959744, Validation RMSE: 449.3663101969354
[13:41:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 283.9057607652019, Validation RMSE: 447.46522033337374
```

```python
import numpy as np

def predict_avg(models, inputs):
    return np.mean([model.predict(inputs) for model in models], axis=0)
```

```
preds = predict_avg(models, inputs_df)
```

```
preds
```

```
array([ 487.68994,  496.79517, 1609.2585 ,  426.6065 ,  349.3278 ,
        383.84268,  296.38428, 1190.5608 ,  317.67694, 1034.845  ,
        985.0438 ,  898.847  ,  733.6171 ,  240.02946, 1193.6575 ,
        202.29036, 1598.4222 ,  604.6256 , 1221.9454 ,  313.09448,
        490.92188,  601.9355 ,  427.7914 , 1182.4935 , 1714.7451 ,
       1207.0936 , 1018.16766,  692.3186 ,  774.5682 , 1934.6641 ,
       1276.5127 , 1170.0583 ,  936.3299 , 1869.3105 ,  506.79095,
        424.90887,  470.26328,  232.0968 ,  948.18787,  913.62177,
       1160.4991 ,  866.4492 ,  841.0752 ,  295.7038 ,  493.36914,
       1434.8666 ,  303.71686,  401.85263, 1024.1326 ,  826.0461 ,
       1371.4812 , 1197.4877 ,  593.7135 ,  337.99985, 1162.6428 ,
       1991.7571 ,  872.77716, 1896.8451 ,  625.7919 ,  982.2028 ,
        648.7958 ,  643.31464,  574.6368 ,  775.06946,  241.36174,
        364.79105,  689.91113,  939.53125,  197.94351,  883.51184,
        848.41223,  452.05707,  106.64122,  489.59674, 1848.4427 ,
        640.652  , 1258.8445 , 1442.809  ,  811.29333, 1084.5432 ,
       1163.426  ,  559.453  ,  375.49332,  232.69199,  204.14432,
       1011.12726, 1370.9229 ,  815.78546,  249.9082 ,  550.17395,
        407.34418,  449.48047, 1470.1667 , 1795.2279 ,  389.21222,
        649.08887,  421.33057,  874.68567, 1954.7695 ,  546.8163 ],
      dtype=float32)
```

```python
def test_params_kfold(n_splits, **params):
    train_rmses, val_rmses, models = [], [], []
    kfold = KFold(n_splits)
    for train_idxs, val_idxs in kfold.split(X):
        train_inputs, train_targets = X.iloc[train_idxs], targets.iloc[train_idxs]
        val_inputs, val_targets = X.iloc[val_idxs], targets.iloc[val_idxs]
        model, train_rmse, val_rmse = train_and_evaluate(train_inputs, train_targets, v
        models.append(model)
        train_rmses.append(train_rmse)
        val_rmses.append(val_rmse)
    print('Train RMSE: {}, Validation RMSE: {}'.format(np.mean(train_rmses), np.mean(va
    return models
```

Hyper-Parameter Tuning

In machine learning, hyperparameter optimization or tuning is the problem of choosing a set of optimal hyperparameters for a learning algorithm.

A hyperparameter is a parameter whose value is used to control the learning process.

```
def test_params(**params):
    model = XGBRegressor(n_jobs=-1, random_state=42, **params)
    model.fit(train_inputs, train_targets)
    train_rmse = rmse(model.predict(train_inputs), train_targets)
    val_rmse = rmse(model.predict(val_inputs), val_targets)
    print('Train RMSE: {}, Validation RMSE: {}'.format(train_rmse, val_rmse))
```

n_estimators

The number of trees to be created. More trees = greater capacity of the model.

```
test_params(n_estimators=10)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 555.076982957697, Validation RMSE: 667.3867650110902
```

```
test_params(n_estimators=10)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 555.076982957697, Validation RMSE: 667.3867650110902
```

```
test_params(n_estimators=100)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 82.86420482105146, Validation RMSE: 291.1980033418279
```

```
test_params(n_estimators=400)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 4.355110353837723, Validation RMSE: 280.1441550930396
```

max_depth

As you increase the max depth of each tree, the capacity of the tree increases and it can capture more information about the training set.

```
test_params(max_depth=2)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 222.97147756445986, Validation RMSE: 254.79416917024287
```

```
test_params(max_depth=6)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 3.7408298727217693, Validation RMSE: 391.127638453683
```

```
test_params(max_depth=4)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 24.71443566110006, Validation RMSE: 281.64159352630554
```

learning_rate

The scaling factor to be applied to the prediction of each tree. A very high learning rate (close to 1) will lead to overfitting, and a low learning rate (close to 0) will lead to underfitting.

```
test_params(n_estimators=400, learning_rate=0.01)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 212.2565168087213, Validation RMSE: 336.9555346497022
```

```
test_params(n_estimators=400, learning_rate=0.1)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 4.355110353837723, Validation RMSE: 280.1441550930396
```

```
test_params(n_estimators=400, learning_rate=0.3)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 0.0018741037840345962, Validation RMSE: 252.9114086943572
```

```
test_params(n_estimators=400, learning_rate=0.15)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 0.47060580365575916, Validation RMSE: 236.4991747520863
```

```
test_params(subsample=0.9)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Train RMSE: 70.92869247343457, Validation RMSE: 274.446345198172
```

```
test_params(subsample=0.7)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
Train RMSE: 75.48992939665729, Validation RMSE: 266.43904313598347
```

```
test_params(subsample=1)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
Train RMSE: 82.86420482105146, Validation RMSE: 291.1980033418279
```

```
test_params(colsample_bytree=0.7)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
Train RMSE: 113.41234352756027, Validation RMSE: 317.3723478111917
```

```
test_params(colsample_bytree=0.5)
```

```
[13:41:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
Train RMSE: 107.40429638834046, Validation RMSE: 362.66460585941564
```

```
test_params(colsample_bytree=0.9)
```

```
[13:41:35] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
Train RMSE: 90.32690164722128, Validation RMSE: 274.15343085778
```

Putting it Together and Making Predictions

Let's train a final model on the entire training set with custom hyperparameters.

```
model = XGBRegressor(n_jobs=-1, random_state=42, n_estimators=100,
                     learning_rate=0.3, max_depth=2, subsample=0.7,
                     colsample_bytree=0.9)
```

```
model.fit(inputs_df, targets)
```

```
[13:41:35] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

```
XGBRegressor(colsample_bytree=0.9, learning_rate=0.3, max_depth=2, n_jobs=-1,
             random_state=42, subsample=0.7)
```

Preparing Test_df

```
test_df
```

	id	vendor_id	pickup_datetime	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dro
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	
5	id0668992	1	2016-06-30 23:59:30	1	-73.991302	40.749798	-73.980515	
6	id1765014	1	2016-06-30 23:59:15	1	-73.978310	40.741550	-73.952072	
7	id0898117	1	2016-06-30 23:59:09	2	-74.012711	40.701527	-73.986481	
8	id3905224	2	2016-06-30 23:58:55	2	-73.992332	40.730511	-73.875618	
9	id1543102	2	2016-06-30 23:58:46	1	-73.993179	40.748760	-73.979309	
10	id3024712	1	2016-06-30 23:58:32	4	-73.968529	40.678432	-73.966591	
11	id3665810	2	2016-06-30 23:58:05	1	-73.982773	40.756908	-73.974693	
12	id1836461	1	2016-06-30 23:58:01	1	-73.921104	40.767292	-73.936859	
13	id3457080	2	2016-06-30 23:57:57	1	-73.986801	40.734917	-73.975899	
14	id3376065	1	2016-06-30 23:57:25	1	-73.996346	40.748161	-73.950829	
15	id3008739	1	2016-06-30 23:57:22	1	-73.968025	40.762283	-73.934792	
16	id0902216	2	2016-06-30 23:56:44	1	-74.007713	40.740681	-73.968811	
17	id3564824	2	2016-06-30 23:55:36	5	-73.984299	40.724983	-73.981819	
18	id0820280	2	2016-06-30 23:55:28	1	-73.952599	40.768322	-73.948555	
19	id0775088	2	2016-06-30 23:55:20	1	-73.966690	40.794090	-73.920776	

```
test_df["pickup_datetime"]= pd.to_datetime(test_df["pickup_datetime"])
test_df['pickup_day']= test_df["pickup_datetime"].dt.day_name()
test_df['pickup_month']= test_df["pickup_datetime"].dt.month_name()
```

```
test_df['pickup_day_no']=test_df['pickup_datetime'].dt.weekday
test_df['pickup_hour']=test_df['pickup_datetime'].dt.hour
```

```
test_df['pickup_timeofday']=test_df['pickup_hour'].apply(time_of_day)
```

```
test_df["distance_miles"] = distance(test_df["pickup_latitude"], test_df["pickup_longit
                                      test_df["dropoff_latitude"], test_df["dropoff_lon
```

```
test_df["pickup_location"] = np.vectorize(city_state_country)(test_df["pickup_latitude"
test_df["dropoff_location"] = np.vectorize(city_state_country)(test_df["dropoff_latituc
```

```
catogorical_df=test_df[['id','store_and_fwd_flag','pickup_day','pickup_month','pickup_l
numerical_df=test_df[['id','passenger_count','distance_miles','pickup_hour']].copy()
```

```
from sklearn.preprocessing import  LabelEncoder
encoder = LabelEncoder()
catogorical_df['store_and_fwd_flag']=encoder.fit_transform(test_df['store_and_fwd_flag'
catogorical_df['pickup_day']=encoder.fit_transform(test_df['pickup_day'])
catogorical_df['pickup_month']=encoder.fit_transform(test_df['pickup_month'])
catogorical_df['pickup_location']=encoder.fit_transform(test_df['pickup_location'])
catogorical_df['dropoff_location']=encoder.fit_transform(test_df['dropoff_location'])
```

```
test_input_df=numerical_df.merge(catogorical_df,left_on='id', right_on='id')
test_input_df=test_input_df.drop(['id'],axis='columns')
```

Making predictions on the test data

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

```
submission_df=test_df[['id']].copy()
```

```
submission_df['trip_duration']=test_preds
```

```
submission_df
```

	id	trip_duration
0	id3004672	812.557007
1	id3505355	1256.600952
2	id1217141	404.700470
3	id2150126	1601.774536
4	id1598245	448.065613

	id	trip_duration
5	id0668992	1154.280151
6	id1765014	1172.125122
7	id0898117	1433.855469
8	id3905224	2100.426270
9	id1543102	847.526062
10	id3024712	1599.662720
11	id3665810	464.000885
12	id1836461	651.148743
13	id3457080	990.777466
14	id3376065	1541.920898
15	id3008739	1823.985840
16	id0902216	1360.143677
17	id3564824	411.500122
18	id0820280	357.685608
19	id0775088	1850.080566

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

```
[jovian] Detected Colab notebook...
[jovian] Please enter your API key ( from https://jovian.ai/ ):
API KEY:
```