New York City Taxi Fare Prediction

Problem Statement:

The New York City Taxi Fare Prediction challenge is a regression problem where the goal is to predict the fare amount (in USD) that a passenger will have to pay for a taxi ride in New York City, based on certain information available at the start of the ride.

Historical dataset that includes:

- Pickup date and time
- Pickup location (latitude and longitude)
- Drop-off location (latitude and longitude)
- Passenger count

The task is to use this information to accurately predict the taxi fare for each trip.

Key Features Typically Available in the Dataset:

- pickup_datetime: When the taxi ride started (timestamp).
- pickup_longitude, pickup_latitude: The pickup location's GPS coordinates.
- dropoff_longitude, dropoff_latitude: The drop-off location's GPS coordinates.
- passenger_count: Number of passengers.
- fare_amount: The target variable (how much the trip cost).

We'll train a machine learning model to predict the fare for a taxi ride in New York city given information like pickup date & time, pickup location, drop location and no. of passengers.

Dataset Link: https://www.kaggle.com/c/new-york-city-taxi-fare-prediction

Download the Dataset

- Install required libraries
- Download data from Kaggle
- View dataset files
- Load training set with Pandas
- Load test set with Pandas

```
Start coding or generate with AI.
```

```
!pip install opendatasets
```

```
Requirement already satisfied: opendatasets in /usr/local/lib/python3.11/dist-packages (0.1.22)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from opendatasets) (4.67.1)
Requirement already satisfied: kaggle in /usr/local/lib/python3.11/dist-packages (from opendatasets) (1.7.4.2)
Requirement already satisfied: click in /usr/local/lib/python3.11/dist-packages (from opendatasets) (8.1.8)
Requirement already satisfied: bleach in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (6.2.0)
Requirement already satisfied: certifi>=14.05.14 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2025.1.31)
Requirement already satisfied: charset-normalizer in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (3.4.1)
Requirement already satisfied: idna in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (3.10)
Requirement already satisfied: protobuf in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (5.29.4)
Requirement already satisfied: python-dateutil>=2.5.3 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2.9.0
Requirement already satisfied: python-slugify in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (8.0.4)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2.32.3)
Requirement already satisfied: setuptools>=21.0.0 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (75.2.0)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (1.17.0)
Requirement already satisfied: text-unidecode in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (1.3)
Requirement already satisfied: urllib3>=1.15.1 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2.4.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (0.5.1)
```

```
import opendatasets as od
url = "https://www.kaggle.com/competitions/new-york-city-taxi-fare-prediction/data"
```

```
od.download(url)
```

```
data_dir = "/content/new-york-city-taxi-fare-prediction"
```

View Dataset Files

```
# List of fils with size
!ls -lh {data_dir}
```

```
total 5.4G
-rw-r--r-- 1 root root  486 Apr 28 17:32 GCP-Coupons-Instructions.rtf
-rw-r--r-- 1 root root 336K Apr 28 17:32 sample_submission.csv
-rw-r--r-- 1 root root 960K Apr 28 17:32 test.csv
-rw-r--r-- 1 root root 5.4G Apr 28 17:34 train.csv
```

```
# Training data
!wc -l {data_dir}/train.csv
```

```
55423856 /content/new-york-city-taxi-fare-prediction/train.csv
```

```
# Test data
!wc -l {data_dir}/test.csv
```

```
9914 /content/new-york-city-taxi-fare-prediction/test.csv
```

```
!wc -l {data_dir}/sample_submission.csv
```

```
9915 /content/new-york-city-taxi-fare-prediction/sample_submission.csv
```

```
!head {data_dir}/train.csv
```

```
key,fare_amount,pickup_datetime,pickup_longitude,pickup_latitude,dropoff_longitude,dropoff_latitude,passenger_count
2009-06-15 17:26:21.0000001,4.5,2009-06-15 17:26:21 UTC,-73.844311,40.721319,-73.84161,40.712278,1
2010-01-05 16:52:16.0000002,16.9,2010-01-05 16:52:16 UTC,-74.016048,40.711303,-73.979268,40.782004,1
2011-08-18 00:35:00.00000049,5.7,2011-08-18 00:35:00 UTC,-73.982738,40.76127,-73.991242,40.750562,2
2012-04-21 04:30:42.0000001,7.7,2012-04-21 04:30:42 UTC,-73.98713,40.733143,-73.991567,40.758092,1
2010-03-09 07:51:00.000000135,5.3,2010-03-09 07:51:00 UTC,-73.968095,40.768008,-73.956655,40.783762,1
2011-01-06 09:50:45.0000002,12.1,2011-01-06 09:50:45 UTC,-74.000964,40.73163,-73.972892,40.758233,1
2012-11-20 20:35:00.0000001,7.5,2012-11-20 20:35:00 UTC,-73.980002,40.751662,-73.973802,40.764842,1
2012-01-04 17:22:00.00000081,16.5,2012-01-04 17:22:00 UTC,-73.9513,40.774138,-73.990095,40.751048,1
2012-12-03 13:10:00.000000125,9,2012-12-03 13:10:00 UTC,-74.006462,40.726713,-73.993078,40.731628,1
```

```
!head {data_dir}/test.csv
```

```
key,pickup_datetime,pickup_longitude,pickup_latitude,dropoff_longitude,dropoff_latitude,passenger_count
2015-01-27 13:08:24.0000002,2015-01-27 13:08:24 UTC,-73.973320007324219,40.7638053894043,-73.981430053710938,40.74383544921875,1
2015-01-27 13:08:24.0000003,2015-01-27 13:08:24 UTC,-73.986862182617188,40.719383239746094,-73.998886108398438,40.739200592041016,1
2011-10-08 11:53:44.0000002,2011-10-08 11:53:44 UTC,-73.982524,40.75126,-73.979654,40.746139,1
2012-12-01 21:12:12.0000002,2012-12-01 21:12:12 UTC,-73.98116,40.767807,-73.990448,40.751635,1
2012-12-01 21:12:12.0000003,2012-12-01 21:12:12 UTC,-73.966046,40.789775,-73.988565,40.744427,1
2012-12-01 21:12:12.0000005,2012-12-01 21:12:12 UTC,-73.960983,40.765547,-73.979177,40.740053,1
2011-10-06 12:10:20.0000001,2011-10-06 12:10:20 UTC,-73.949013,40.773204,-73.959622,40.770893,1
2011-10-06 12:10:20.0000003,2011-10-06 12:10:20 UTC,-73.777282,40.646636,-73.985083,40.759368,1
2011-10-06 12:10:20.0000002,2011-10-06 12:10:20 UTC,-74.014099,40.709638,-73.995106,40.741365,1
```

```
!head {data_dir}/sample_submission.csv
```

```
key,fare_amount
2015-01-27 13:08:24.0000002,11.35
2015-01-27 13:08:24.0000003,11.35
2011-10-08 11:53:44.0000002,11.35
2012-12-01 21:12:12.0000002,11.35
2012-12-01 21:12:12.0000003,11.35
2012-12-01 21:12:12.0000005,11.35
2011-10-06 12:10:20.0000001,11.35
2011-10-06 12:10:20.0000003,11.35
2011-10-06 12:10:20.0000002,11.35
```

Observations:

- This is a supervised learning regression problem
- Training data is 5.5 GB in size
- Training data has 5.5 million rows
- Test set is much smaller (< 10,000 rows)
- The training set has 8 columns:
    - `key` (a unique identifier)
    - `fare_amount` (target column)
    - `pickup_datetime`
    - `pickup_longitude`
    - `pickup_latitude`

    - `dropoff_longitude`
    - `dropoff_latitude`
    - `passenger_count`
- The test set has all columns except the target column `fare_amount`.
- The submission file should contain the `key` and `fare_amount` for each test sample.

Loading Training Set

Loading the entire dataset into Pandas is going to be slow, so we can use the following optimizations:

- Ignore the `key` column
- Parse pickup datetime while loading data
- Specify data types for other columns
    - `float32` for geo coordinates
    - `float32` for fare amount
    - `uint8` for passenger count
- Work with a 1% sample of the data (~500k rows)

```
import pandas as pd
import random
```

```
sample_frac = 0.01
```

```
%%time
selected_cols = "fare_amount,pickup_datetime,pickup_longitude,pickup_latitude,dropoff_longitude,dropoff_latitude,passenger_count".split(
dtypes = {
    'fare_amount': 'float32',
    'pickup_longitude': 'float32',
    'pickup_latitude': 'float32',
    'dropoff_longitude': 'float32',
    'passenger_count': 'float32'
}

def skip_row(row_idx):
  if row_idx == 0:
    return False
  return random.random() > sample_frac

df = pd.read_csv(data_dir + "/train.csv" ,
                 usecols= selected_cols,
                 dtype=dtypes,
                 parse_dates=["pickup_datetime"],
                 skiprows=skip_row
                  )
```

```
CPU times: user 1min 6s, sys: 1.92 s, total: 1min 8s
Wall time: 1min 18s
```

```
df
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	58.000000	2015-01-11 03:15:38+00:00	-73.983330	40.738720	-73.933197	40.847225	1.0
1	9.000000	2012-12-06 18:05:00+00:00	-73.960831	40.773079	-73.978371	40.774907	1.0
2	42.500000	2011-01-10 16:07:00+00:00	-73.795677	40.807720	-73.978683	40.724365	2.0
3	10.900000	2010-06-30 06:15:00+00:00	-73.953941	40.781300	-73.994423	40.750140	5.0
4	5.500000	2012-09-09 10:24:15+00:00	-73.999435	40.749065	-73.995079	40.738264	1.0
...	...	...	...	...	...	...	...
554405	2.500000	2010-11-20 20:35:00+00:00	-73.999672	40.733284	-73.999634	40.733375	1.0
554406	7.300000	2009-10-29 09:05:00+00:00	-73.961517	40.771206	-73.968811	40.759417	5.0

```
test_df = pd.read_csv(data_dir + "/test.csv" , dtype=dtypes , parse_dates=["pickup_datetime"])
```

```
test_df
```

	key	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	2015-01-27 13:08:24.0000002	2015-01-27 13:08:24+00:00	-73.973320	40.763805	-73.981430	40.743835	1.0
1	2015-01-27 13:08:24.0000003	2015-01-27 13:08:24+00:00	-73.986862	40.719383	-73.998886	40.739201	1.0
2	2011-10-08 11:53:44.0000002	2011-10-08 11:53:44+00:00	-73.982521	40.751259	-73.979652	40.746139	1.0
3	2012-12-01 21:12:12.0000002	2012-12-01 21:12:12+00:00	-73.981163	40.767807	-73.990448	40.751635	1.0
4	2012-12-01 21:12:12.0000003	2012-12-01 21:12:12+00:00	-73.966049	40.789776	-73.988564	40.744427	1.0
...	...	...	...	...	...	...	...
9909	2015-05-10 12:37:51.0000002	2015-05-10 12:37:51+00:00	-73.968124	40.796997	-73.955643	40.780388	6.0
9910	2015-01-12 17:05:51.0000001	2015-01-12 17:05:51+00:00	-73.945511	40.803600	-73.960213	40.776371	6.0
9911	2015-04-19 20:44:15.0000001	2015-04-19 20:44:15+00:00	-73.991600	40.726608	-73.789742	40.647011	6.0
9912	2015-01-31 01:05:19.0000005	2015-01-31 01:05:19+00:00	-73.985573	40.735432	-73.939178	40.801731	6.0
9913	2015-01-18 14:06:23.0000006	2015-01-18 14:06:23+00:00	-73.988022	40.754070	-74.000282	40.759220	6.0

9914 rows × 7 columns

Explore the Dataset

- Basic info about training set
- Basic info about test set
- Exploratory data analysis & visualization

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 554410 entries, 0 to 554409
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   fare_amount        554410 non-null  float32
 1   pickup_datetime    554410 non-null  datetime64[ns, UTC]
 2   pickup_longitude   554410 non-null  float32
 3   pickup_latitude    554410 non-null  float32
 4   dropoff_longitude  554407 non-null  float32
 5   dropoff_latitude   554407 non-null  float64
 6   passenger_count    554410 non-null  float32
dtypes: datetime64[ns, UTC](1), float32(5), float64(1)
memory usage: 19.0 MB
```

```
df.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	554410.000000	554410.000000	554410.000000	554407.000000	554407.000000	554410.000000
mean	11.335371	-72.506813	39.920559	-72.484795	39.908954	1.686679
std	9.798096	14.617648	10.655162	12.561418	11.311485	1.343792
min	-63.000000	-3344.155273	-2099.729248	-3047.750000	-3114.419380	0.000000
25%	6.000000	-73.992058	40.734921	-73.991379	40.734033	1.000000
50%	8.500000	-73.981796	40.752666	-73.980133	40.753193	1.000000
75%	12.500000	-73.967056	40.767123	-73.963676	40.768082	2.000000
max	400.000000	2080.490234	3347.260498	1326.914673	3306.705933	208.000000

```
df.pickup_datetime.min() , df.pickup_datetime.max()
```

```
(Timestamp('2009-01-01 00:06:17+0000', tz='UTC'),
 Timestamp('2015-06-30 23:55:12+0000', tz='UTC'))
```

Observations about training data:

- 550k+ rows, as expected
- No missing data (in the sample)
- `fare_amount` ranges from $-52.0 to $499.0
- `passenger_count` ranges from 0 to 208
- There seem to be some errors in the latitude & longitude values
- Dates range from 1st Jan 2009 to 30th June 2015
- The dataset takes up ~19 MB of space in the RAM

We may need to deal with outliers and data entry errors before we train our model.

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9914 entries, 0 to 9913
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   key                9914 non-null   object
 1   pickup_datetime    9914 non-null   datetime64[ns, UTC]
 2   pickup_longitude   9914 non-null   float32
 3   pickup_latitude    9914 non-null   float32
 4   dropoff_longitude  9914 non-null   float32
 5   dropoff_latitude   9914 non-null   float64
 6   passenger_count    9914 non-null   float32
dtypes: datetime64[ns, UTC](1), float32(4), float64(1), object(1)
memory usage: 387.4+ KB
```

```
test_df.describe()
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	9914.000000	9914.000000	9914.000000	9914.000000	9914.000000
mean	-73.974716	40.751041	-73.973656	40.751743	1.671273
std	0.042799	0.033542	0.039093	0.035435	1.278756
min	-74.252190	40.573143	-74.263245	40.568973	1.000000
25%	-73.992500	40.736125	-73.991249	40.735254	1.000000
50%	-73.982327	40.753052	-73.980015	40.754065	1.000000
75%	-73.968012	40.767113	-73.964062	40.768757	2.000000
max	-72.986534	41.709557	-72.990967	41.696683	6.000000

Some observations about the test set:

- 9914 rows of data
- No missing values
- No obvious data entry errors
- 1 to 6 passengers (we can limit training data to this range)
- Latitudes lie between 40 and 42
- Longitudes lie between -75 and -72
- Pickup dates range from Jan 1st 2009 to Jun 30th 2015 (same as training set)

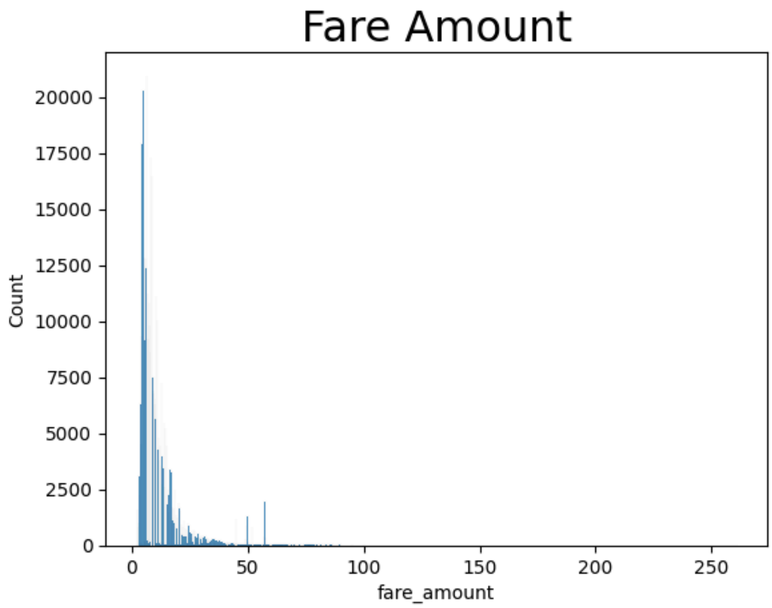
We can use the ranges of the test set to drop outliers/invalid data from the training set.

Exploratory Data Analysis and Visualization

```
import seaborn as sns
```

```
sns.histplot(train_df , x = "fare_amount" )
plt.title("Fare Amount" , color = "Black" , size = 23)
```

```
Text(0.5, 1.0, 'Fare Amount')
```



What is the busiest day of the week?

```
train_df["pickup_datetime_weekday"].value_counts().sort_values(ascending = False)
```

pickup_datetime_weekday	count
4	66613
5	65530
3	64887
2	62539
1	60576
6	56669
0	55649

dtype: int64

What is the busiest time of the day?

- Highest time is around 19th hour

```
train_df["pickup_datetime_hour"].value_counts().sort_values(ascending = False)
```

pickup_datetime_hour	count
19	27241
18	25872
20	25537
21	24582
22	24144
14	21905
23	21397
13	21287
17	21226
12	21200
15	20793
9	20203
11	20164
8	19629
10	19365
16	17874
0	17126
7	15782
1	12597
2	9512
6	8997
3	6861
4	4961
5	4208

dtype: int64

In which month are fares the highest?

- In the Month of 5th fare amount is highest

```
train_df.groupby("pickup_datetime_month")["fare_amount"].sum().sort_values(ascending = False)
```

pickup_datetime_month	fare_amount
5	474170.25000
4	452513.34375
3	447959.50000
6	445795.68750
1	412085.46875
10	405111.59375
2	393834.31250
12	389207.75000
9	388029.68750
11	377153.18750
7	364826.37500
8	351812.96875

dtype: float32

What is the average ride distance?

- Seeem like average ride distance is around 3.3KM

```
train_df["trip_distance"].mean()
```

```
np.float64(3.328505957524262)
```

```
train_df
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	picku
241935	12.0	2012-09-28 13:03:00+00:00	-73.955757	40.781963	-73.972527	40.758938	1.0	
110152	6.5	2010-10-03 08:51:55+00:00	-73.973610	40.789894	-73.955612	40.773519	1.0	
471274	15.5	2013-07-31 22:30:00+00:00	-73.949165	40.773338	-73.989326	40.740577	1.0	
50645	4.5	2009-10-06 08:56:27+00:00	-73.965927	40.758778	-73.974403	40.750485	1.0	
461753	11.7	2009-02-06 15:14:00+00:00	-73.983681	40.776676	-73.973343	40.754727	1.0	
...	...	...	...	...	...	...	...	
110268	14.9	2010-12-17 21:02:00+00:00	-73.967117	40.759018	-74.003250	40.740143	3.0	
259178	4.9	2011-10-07 21:58:11+00:00	-73.999046	40.734234	-73.986984	40.729487	1.0	
365838	22.5	2013-12-27 13:26:45+00:00	-73.965874	40.773830	-74.000473	40.717472	1.0	
131932	7.7	2011-08-17 00:08:00+00:00	-73.978043	40.783016	-73.963554	40.761622	5.0	
121958	5.0	2013-04-10 17:24:00+00:00	-74.006561	40.709591	-74.013451	40.704617	6.0	

432463 rows × 18 columns

Prepare Dataset for Training

- Split Training & Validation Set
- Fill/Remove Missing Values
- Extract Inputs & Outputs
  - Training
  - Validation
  - Test

Split Training & Validation Set

We'll set aside 20% of the training data as the validation set, to evaluate the models we train on previously unseen data.

Since the test set and training set have the same date ranges, we can pick a random 20% fraction.

```
from sklearn.model_selection import train_test_split
train_df , val_df =  train_test_split(df , test_size = 0.2 , random_state=42)
```

```
len(train_df) , len(val_df)
```

```
(443528, 110882)
```

Fill/Remove Missing Values

There are no missing values in our sample, but if there were, we could simply drop the rows with missing values instead of trying to fill them (since we have a lot of training data)

```
train_df = train_df.dropna()
val_df = val_df.dropna()
```

Extract Inputs and Outputs

```
df.columns
```

```
Index(['fare_amount', 'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

```
input_cols = ['pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count']
target_col = "fare_amount"
```

Training

```
train_inputs = train_df[input_cols]
train_target= train_df[target_col]
```

```
train_inputs
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
241935	-73.955757	40.781963	-73.972527	40.758938	1.0
110152	-73.973610	40.789894	-73.955612	40.773519	1.0
471274	-73.949165	40.773338	-73.989326	40.740577	1.0
50645	-73.965927	40.758778	-73.974403	40.750485	1.0
461753	-73.983681	40.776676	-73.973343	40.754727	1.0
...	...	...	...	...	...
110268	-73.967117	40.759018	-74.003250	40.740143	3.0
259178	-73.999046	40.734234	-73.986984	40.729487	1.0
365838	-73.965874	40.773830	-74.000473	40.717472	1.0
131932	-73.978043	40.783016	-73.963554	40.761622	5.0
121958	-74.006561	40.709591	-74.013451	40.704617	6.0

443525 rows × 5 columns

```
train_target
```

	fare_amount
241935	12.0
110152	6.5
471274	15.5
50645	4.5
461753	11.7
...	...
110268	14.9
259178	4.9
365838	22.5
131932	7.7
121958	5.0

443525 rows × 1 columns

dtype: float32

Validation

```
val_inputs = val_df[input_cols]
val_target = val_df[target_col]
```

```
val_inputs
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
491808	-73.984535	40.759209	-73.984535	40.759210	1.0
458930	-73.972641	40.743565	-73.976166	40.788377	1.0
388483	-73.964836	40.758568	-73.990288	40.748342	3.0
63343	-73.977982	40.746166	-73.908623	40.774917	1.0
181534	-73.952782	40.786564	-73.947510	40.775588	2.0
...	...	...	...	...	...
125284	-73.964569	40.760635	-73.975075	40.759573	1.0
133620	-73.980934	40.763363	-73.985123	40.760926	1.0
373155	-73.977760	40.761826	-73.988441	40.754262	2.0
474921	-73.981651	40.778988	-73.953613	40.785122	1.0
352091	-74.015381	40.715843	-73.981407	40.766112	6.0

110882 rows × 5 columns

```
val_target
```

	fare_amount
491808	5.3
458930	12.5
388483	9.5
63343	20.5
181534	5.3
...	...
125284	7.0
133620	4.5
373155	9.3
474921	9.7
352091	15.0

110882 rows × 1 columns

dtype: float32

Test

```
test_inputs = test_df[input_cols]
test_inputs
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	-73.973320	40.763805	-73.981430	40.743835	1.0
1	-73.986862	40.719383	-73.998886	40.739201	1.0
2	-73.982521	40.751259	-73.979652	40.746139	1.0
3	-73.981163	40.767807	-73.990448	40.751635	1.0
4	-73.966049	40.789776	-73.988564	40.744427	1.0
...	...	...	...	...	...
9909	-73.968124	40.796997	-73.955643	40.780388	6.0
9910	-73.945511	40.803600	-73.960213	40.776371	6.0
9911	-73.991600	40.726608	-73.789742	40.647011	6.0
9912	-73.985573	40.735432	-73.939178	40.801731	6.0
9913	-73.988022	40.754070	-74.000282	40.759220	6.0

9914 rows × 5 columns

Train Baseline Models

Train & Evaluate Hardcoded Model

Let's create a simple model that always predicts the average.

```
import numpy as np
class MeanRegressor():
  def fit(self , inputs , targets):
    self.mean = targets.mean()

  def predict(self , inputs):
    return np.full(inputs.shape[0] , self.mean)
```

```
mean_model = MeanRegressor()
```

```
mean_model.fit(train_inputs , train_target)
```

```
train_preds = mean_model.predict(train_inputs)
train_preds
```

```
array([11.344462, 11.344462, 11.344462, ..., 11.344462, 11.344462,
       11.344462], dtype=float32)
```

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

```
array([11.344462, 11.344462, 11.344462, ..., 11.344462, 11.344462,
       11.344462], dtype=float32)
```

The evaluation metric for this competition is the root mean-squared error or RMSE. RMSE measures the difference between the predictions of a model, and the corresponding ground truth. A large RMSE is equivalent to a large average error, so smaller values of RMSE are better. One nice property of RMSE is that the error is given in the units being measured, so you can tell very directly how incorrect the model might be on unseen data.

RMSE is given by:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}$$

```
from sklearn.metrics import mean_squared_error , root_mean_squared_error
train_rmse = root_mean_squared_error(train_target, train_preds)
```

```
train_rmse
```

```
9.809823989868164
```

```
val_rmse = root_mean_squared_error(val_target , val_preds )
val_rmse
```

```
9.7508544921875
```

Train & Evaluate Baseline Model

We'll traina linear regression model as our baseline, which tries to express the target as a weighted sum of the inputs.

```
from sklearn.linear_model import LinearRegression
```

```
linreg_model = LinearRegression()
```

```
linreg_model.fit(train_inputs , train_target)
```

```
▾ LinearRegression
LinearRegression()
```

```
train_preds = linreg_model.predict(train_inputs)
train_preds
```

```
array([11.27214011, 11.27213302, 11.27215506, ..., 11.27216867,
       11.628133  , 11.71729138])
```

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

```
array([11.27214362, 11.27214246, 11.45015319, ..., 11.36113332,
       11.27213461, 11.71721794])
```

```
train_rmse = root_mean_squared_error(train_target , train_preds)
train_rmse
```

```
9.808675432238369
```

```
val_rmse = root_mean_squared_error(val_target , val_preds)
val_rmse
```

```
9.74977764118121
```

The linear regression model is off by $9.79, which isn't much better than simply predicting the average.

This is mainly because the training data is not in a format that's useful for the model, and we're not using one of the most important columns: pickup date & time.

However, now we have a baseline that our other models should ideally beat.

Make Prediction

```
test_inputs
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	-73.973320	40.763805	-73.981430	40.743835	1.0
1	-73.986862	40.719383	-73.998886	40.739201	1.0
2	-73.982521	40.751259	-73.979652	40.746139	1.0
3	-73.981163	40.767807	-73.990448	40.751635	1.0
4	-73.966049	40.789776	-73.988564	40.744427	1.0
...	...	...	...	...	...
9909	-73.968124	40.796997	-73.955643	40.780388	6.0
9910	-73.945511	40.803600	-73.960213	40.776371	6.0
9911	-73.991600	40.726608	-73.789742	40.647011	6.0
9912	-73.985573	40.735432	-73.939178	40.801731	6.0
9913	-73.988022	40.754070	-74.000282	40.759220	6.0

9914 rows × 5 columns

```
test_preds = linreg_model.predict(test_inputs)
test_preds
```

```
array([11.27219171, 11.27225642, 11.27222302, ..., 11.71827683,
       11.71723808, 11.71707   ])
```

```
submission_df = pd.read_csv(data_dir+ "/sample_submission.csv")
```

```
submission_df
```

	key	fare_amount
0	2015-01-27 13:08:24.0000002	11.35
1	2015-01-27 13:08:24.0000003	11.35
2	2011-10-08 11:53:44.0000002	11.35
3	2012-12-01 21:12:12.0000002	11.35
4	2012-12-01 21:12:12.0000003	11.35
...	...	...
9909	2015-05-10 12:37:51.0000002	11.35
9910	2015-01-12 17:05:51.0000001	11.35
9911	2015-04-19 20:44:15.0000001	11.35
9912	2015-01-31 01:05:19.0000005	11.35
9913	2015-01-18 14:06:23.0000006	11.35

9914 rows × 2 columns

```
def generate_submission(test_preds , fname):
  sub_df = pd.read_csv(data_dir + "/sample_submission.csv")
  sub_df["fare_amount"] = test_preds
  sub_df.to_csv(fname , index = None)
```

```
generate_submission(test_preds , "sub2.csv")
```

Feature Engineering

- Extract parts of date
- Remove outliers & invalid data
- Add distance between pickup & drop
- Add distance from landmarks

Extract Parts of Date

- Year
- Month
- Day
- Weekday
- Hour

```
def add_dateparst(df , col):
  df[col + "_year"] = df[col].dt.year
  df[col + "_month"] = df[col].dt.month
  df[col + "_day"] = df[col].dt.day
  df[col + "_weekday"] = df[col].dt.weekday
  df[col + "_hour"] = df[col].dt.hour
```

```
add_dateparst(train_df ,"pickup_datetime")
```

```
add_dateparst(val_df ,"pickup_datetime")
```

```
add_dateparst(test_df ,"pickup_datetime")
```

```
train_df
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	picku
241935	12.0	2012-09-28 13:03:00+00:00	-73.955757	40.781963	-73.972527	40.758938	1.0	
110152	6.5	2010-10-03 08:51:55+00:00	-73.973610	40.789894	-73.955612	40.773519	1.0	
471274	15.5	2013-07-31 22:30:00+00:00	-73.949165	40.773338	-73.989326	40.740577	1.0	
50645	4.5	2009-10-06 08:56:27+00:00	-73.965927	40.758778	-73.974403	40.750485	1.0	
461753	11.7	2009-02-06 15:14:00+00:00	-73.983681	40.776676	-73.973343	40.754727	1.0	
...	...	...	...	...	...	...	...	
110268	14.9	2010-12-17 21:02:00+00:00	-73.967117	40.759018	-74.003250	40.740143	3.0	
259178	4.9	2011-10-07 21:58:11+00:00	-73.999046	40.734234	-73.986984	40.729487	1.0	
365838	22.5	2013-12-27 13:26:45+00:00	-73.965874	40.773830	-74.000473	40.717472	1.0	
131932	7.7	2011-08-17 00:08:00+00:00	-73.978043	40.783016	-73.963554	40.761622	5.0	
121958	5.0	2013-04-10 17:24:00+00:00	-74.006561	40.709591	-74.013451	40.704617	6.0	

443525 rows × 12 columns

Add Distance Between Pickup and Drop

We can use the haversine distance:

- https://en.wikipedia.org/wiki/Haversine_formula

```
def haversine_np(lon1 , lat1 , lon2 , lat2):

  lon1 , lat1 , lon2 , lat2 = map(np.radians , [lon1 , lat1 , lon2 , lat2])

  dlon = lon2 - lon1
  dlat = lat2 - lat1
  a = np.sin(dlat/2.0)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2.0)**2

  c = 2 * np.arcsin(np.sqrt(a))
  km = 6367 * c
  return km
```

```
def add_trip_distance(df):
    df['trip_distance'] = haversine_np(df['pickup_longitude'], df['pickup_latitude'], df['dropoff_longitude'], df['dropoff_latitude'])
```

```
add_trip_distance(train_df)
```

```
add_trip_distance(val_df)
```

```
add_trip_distance(test_df)
```

```
train_df
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	picku
241935	12.0	2012-09-28 13:03:00+00:00	-73.955757	40.781963	-73.972527	40.758938	1.0	
110152	6.5	2010-10-03 08:51:55+00:00	-73.973610	40.789894	-73.955612	40.773519	1.0	
471274	15.5	2013-07-31 22:30:00+00:00	-73.949165	40.773338	-73.989326	40.740577	1.0	
50645	4.5	2009-10-06 08:56:27+00:00	-73.965927	40.758778	-73.974403	40.750485	1.0	
461753	11.7	2009-02-06 15:14:00+00:00	-73.983681	40.776676	-73.973343	40.754727	1.0	
...	...	...	...	...	...	...	...	
110268	14.9	2010-12-17 21:02:00+00:00	-73.967117	40.759018	-74.003250	40.740143	3.0	
259178	4.9	2011-10-07 21:58:11+00:00	-73.999046	40.734234	-73.986984	40.729487	1.0	
365838	22.5	2013-12-27 13:26:45+00:00	-73.965874	40.773830	-74.000473	40.717472	1.0	
131932	7.7	2011-08-17 00:08:00+00:00	-73.978043	40.783016	-73.963554	40.761622	5.0	
121958	5.0	2013-04-10 17:24:00+00:00	-74.006561	40.709591	-74.013451	40.704617	6.0	

443525 rows × 13 columns

Add Distance From Popular Landmarks

- JFK Airport
- LGA Airport
- EWR Airport
- Times Square
- Met Meuseum
- World Trade Center

```
jfk_lonlat = -73.7781, 40.6413
lga_lonlat = -73.8740, 40.7769
ewr_lonlat = -74.1745, 40.6895
met_lonlat = -73.9632, 40.7794
wtc_lonlat = -74.0099, 40.7126
```

```
def add_landmark_dropoff_distance(df, landmark_name, landmark_lonlat):
    lon, lat = landmark_lonlat
    df[landmark_name + '_drop_distance'] = haversine_np(lon, lat, df['dropoff_longitude'], df['dropoff_latitude'])
```

```
%%time
for a_df in [train_df, val_df, test_df]:
    for name, lonlat in [('jfk', jfk_lonlat), ('lga', lga_lonlat), ('ewr', ewr_lonlat), ('met', met_lonlat), ('wtc', wtc_lonlat)]:
        add_landmark_dropoff_distance(a_df, name, lonlat)
```

```
CPU times: user 309 ms, sys: 3.71 ms, total: 313 ms
Wall time: 334 ms
```

```
train_df.sample(5)
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	picku
466636	4.1	2011-04-29 07:55:26+00:00	-74.002060	40.750896	-74.001961	40.745706	2.0	
394279	23.5	2012-10-07 00:17:00+00:00	-73.989998	40.772583	-73.996719	40.726032	1.0	
48881	8.5	2011-04-07 22:10:10+00:00	-74.005653	40.741016	-73.975403	40.758353	2.0	
349775	4.5	2013-11-17 09:25:00+00:00	-73.968788	40.764210	-73.966423	40.770552	2.0	
130631	6.1	2010-11-30 09:05:31+00:00	-73.991615	40.759750	-73.988960	40.753764	1.0	

Remove Outliers and Invalid Data

There seems to be some invalide data in each of the following columns:

- Fare amount
- Passenger count
- Pickup latitude & longitude
- Drop latitude & longitude

```
train_df.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	pickup_datetime_year
count	443525.000000	443525.000000	443525.000000	443525.000000	443525.000000	443525.000000	443525.000000
mean	11.344462	-72.512596	39.929352	-72.490334	39.906149	1.686527	2011.742702
std	9.808430	14.648813	11.421376	13.006611	11.823192	1.314302	1.862331
min	-63.000000	-3344.155273	-2099.729248	-3047.750000	-3114.419380	0.000000	2009.000000
25%	6.000000	-73.992073	40.734924	-73.991394	40.733987	1.000000	2010.000000
50%	8.500000	-73.981819	40.752632	-73.980164	40.753188	1.000000	2012.000000
75%	12.500000	-73.967079	40.767113	-73.963654	40.768096	2.000000	2013.000000
max	400.000000	2080.490234	3347.260498	1326.914673	3306.705933	6.000000	2015.000000

We'll use the following ranges:

- `fare_amount` : $1 to $500
- `longitudes` : -75 to -72
- `latitudes` : 40 to 42
- `passenger_count` : 1 to 6

```
def remove_outliers(df):
    return df[(df['fare_amount'] >= 1.) &
              (df['fare_amount'] <= 500.) &
              (df['pickup_longitude'] >= -75) &
              (df['pickup_longitude'] <= -72) &
              (df['dropoff_longitude'] >= -75) &
              (df['dropoff_longitude'] <= -72) &
              (df['pickup_latitude'] >= 40) &
              (df['pickup_latitude'] <= 42) &
              (df['dropoff_latitude'] >=40) &
              (df['dropoff_latitude'] <= 42) &
              (df['passenger_count'] >= 1) &
              (df['passenger_count'] <= 6)]
```

```
train_df = remove_outliers(train_df)
```

```
val_df = remove_outliers(val_df)
```

```
Start coding or generate with AI.
```

Train & Evaluate Different Models

We'll train each of the following & submit predictions to Kaggle:

- Ridge Regression
- Random Forests
- Gradient Boosting
- Decision Tree

Split Inputs and Targets

```
train_df.columns
```

```
Index(['fare_amount', 'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
       'pickup_datetime_year', 'pickup_datetime_month', 'pickup_datetime_day',
       'pickup_datetime_weekday', 'pickup_datetime_hour', 'trip_distance',
       'jfk_drop_distance', 'lga_drop_distance', 'ewr_drop_distance',
       'met_drop_distance', 'wtc_drop_distance'],
      dtype='object')
```

```
input_cols = ['pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
       'pickup_datetime_year', 'pickup_datetime_month', 'pickup_datetime_day',
       'pickup_datetime_weekday', 'pickup_datetime_hour', 'trip_distance',
       'jfk_drop_distance', 'lga_drop_distance', 'ewr_drop_distance',
       'met_drop_distance', 'wtc_drop_distance']
```

```
target_col = "fare_amount"
```

```
train_inputs = train_df[input_cols]
train_target = train_df[target_col]
```

```
val_inputs = val_df[input_cols]
val_target = val_df[target_col]
```

```
test_inputs = test_df[input_cols]
```

```
test_inputs
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	pickup_datetime_year	pickup_datetime
0	-73.973320	40.763805	-73.981430	40.743835	1.0	2015	
1	-73.986862	40.719383	-73.998886	40.739201	1.0	2015	
2	-73.982521	40.751259	-73.979652	40.746139	1.0	2011	
3	-73.981163	40.767807	-73.990448	40.751635	1.0	2012	
4	-73.966049	40.789776	-73.988564	40.744427	1.0	2012	
...	...	...	...	...	...	...	
9909	-73.968124	40.796997	-73.955643	40.780388	6.0	2015	
9910	-73.945511	40.803600	-73.960213	40.776371	6.0	2015	
9911	-73.991600	40.726608	-73.789742	40.647011	6.0	2015	
9912	-73.985573	40.735432	-73.939178	40.801731	6.0	2015	
9913	-73.988022	40.754070	-74.000282	40.759220	6.0	2015	

9914 rows × 16 columns

Let's define fucntion to evalute model and generate test predictions

```
def evaluate(model):
    train_preds = model.predict(train_inputs)
    train_rmse = root_mean_squared_error(train_target, train_preds)
    val_preds = model.predict(val_inputs)
    val_rmse = root_mean_squared_error(val_target, val_preds)
    return train_rmse, val_rmse, train_preds, val_preds
```

```
def predict_and_submit(model, fname):
    test_preds = model.predict(test_inputs)
    sub_df = pd.read_csv(data_dir+'/sample_submission.csv')
    sub_df['fare_amount'] = test_preds
```

```
    sub_df.to_csv(fname, index=None)
    return sub_df
```

Ridge Regression

```
from sklearn.linear_model import Ridge
```

```
model1 = Ridge(random_state=42 , alpha=0.9)
```

```
%%time
model1.fit(train_inputs , train_target)
```

```
CPU times: user 135 ms, sys: 0 ns, total: 135 ms
Wall time: 155 ms
```

```
Ridge
Ridge(alpha=0.9, random_state=42)
```

```
evaluate(model1)
```

```
(5.10927939051802,
 5.060686737738835,
 array([ 9.85466698,  6.8942935 , 14.7013476 , ..., 17.45302083,
         8.19749924,  8.68315597]),
 array([ 4.56747632, 14.08666821, 10.77678217, ...,  6.65587044,
         8.08507296, 17.34923927]))
```

```
predict_and_submit(model1 , "ridge_submission.csv")
```

	key	fare_amount
0	2015-01-27 13:08:24.0000002	10.170917
1	2015-01-27 13:08:24.0000003	11.447528
2	2011-10-08 11:53:44.0000002	5.491039
3	2012-12-01 21:12:12.0000002	8.730576
4	2012-12-01 21:12:12.0000003	14.348684
...	...	...
9909	2015-05-10 12:37:51.0000002	9.048474
9910	2015-01-12 17:05:51.0000001	11.232310
9911	2015-04-19 20:44:15.0000001	47.906543
9912	2015-01-31 01:05:19.0000005	22.304240
9913	2015-01-18 14:06:23.0000006	9.026694

9914 rows × 2 columns

Random Forest

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

```
model2 = RandomForestRegressor(max_depth=10 , n_jobs=-1 , random_state=42 , n_estimators=50)
```

```
%%time
model2.fit(train_inputs  , train_target)
```

```
CPU times: user 9min, sys: 1.51 s, total: 9min 2s
Wall time: 5min 58s
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=10, n_estimators=50, n_jobs=-1, random_state=42)
```

```
evaluate(model2)
```

```
(3.576403310293266,
 3.9976308205081637,
 array([10.69908611,  8.31743559, 15.45023897, ..., 21.28401067,
         8.18991948,  5.18916252]),
 array([ 9.24303814, 12.04465764, 10.63059751, ...,  6.21539827,
         8.26499006, 17.83043807]))
```

```
predict_and_submit(model2 , "rf_submission.csv")
```

	key	fare_amount
0	2015-01-27 13:08:24.0000002	10.607184
1	2015-01-27 13:08:24.0000003	10.630598
2	2011-10-08 11:53:44.0000002	5.121043
3	2012-12-01 21:12:12.0000002	8.403312
4	2012-12-01 21:12:12.0000003	13.816892
...	...	...
9909	2015-05-10 12:37:51.0000002	8.961535
9910	2015-01-12 17:05:51.0000001	12.131915
9911	2015-04-19 20:44:15.0000001	55.583641
9912	2015-01-31 01:05:19.0000005	22.445715
9913	2015-01-18 14:06:23.0000006	6.878608

9914 rows × 2 columns

Gradient Boosting

```
from xgboost import XGBRegressor
```

```
model3 = XGBRegressor(random_state=42, n_jobs=-1, objective='reg:squarederror' , n_estimator = 100)
```

```
%%time
model3.fit(train_inputs , train_target)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [17:41:32] WARNING: /workspace/src/learner.cc:740:
Parameters: { "n_estimator" } are not used.

  warnings.warn(smsg, UserWarning)
CPU times: user 8.86 s, sys: 59.5 ms, total: 8.92 s
Wall time: 4.71 s
```

```
XGBRegressor

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimator=100, n_estimators=None, n_jobs=-1,
             num_parallel_tree=None, ...)
```

```
evaluate(model3)
```

```
(3.161956310272217,
 3.9021904468536377,
 array([11.992061 ,  7.9727583, 13.984547 , ..., 22.252626 ,  8.32993   ,
         5.7389045], dtype=float32),
 array([ 9.652845 , 12.966296 , 12.792313 , ...,  6.9353213,  9.407492 ,
        16.26467  ], dtype=float32))
```

```
predict_and_submit(model3 ,"xgb_submission.csv")
```

	key	fare_amount
0	2015-01-27 13:08:24.0000002	11.579693
1	2015-01-27 13:08:24.0000003	11.815858
2	2011-10-08 11:53:44.0000002	4.852398
3	2012-12-01 21:12:12.0000002	8.503675
4	2012-12-01 21:12:12.0000003	16.544617
...	...	...
9909	2015-05-10 12:37:51.0000002	8.849944
9910	2015-01-12 17:05:51.0000001	11.092917
9911	2015-04-19 20:44:15.0000001	55.118965
9912	2015-01-31 01:05:19.0000005	19.550594
9913	2015-01-18 14:06:23.0000006	6.802860

9914 rows × 2 columns

Decission Tree

```
from sklearn.tree import DecisionTreeRegressor
```

```
# ?DecisionTreeRegressor
```

```
model4 = DecisionTreeRegressor(
        random_state=42 ,
        max_depth=20,
        max_leaf_nodes=10,
        criterion="squared_error",
        min_samples_split=10,
        max_features=10



                              )
```

```
model4.fit(train_inputs , train_target)
```

```
DecisionTreeRegressor

DecisionTreeRegressor(max_depth=20, max_features=10, max_leaf_nodes=10,
                      min_samples_split=10, random_state=42)
```

```
evaluate(model4)
```

```
(5.117178092384083,
 5.284806414687044,
 array([ 8.75215215,  8.75215215, 13.46688619, ..., 13.46688619,
         8.75215215,  6.2345112 ]),
 array([ 6.2345112 , 13.46688619,  8.75215215, ...,  6.2345112 ,
         8.75215215, 13.46688619]))
```

Tune Hyperparmeters

We'll train parameters for the XGBoost model. Here's a strategy for tuning hyperparameters:

- Tune the most important/impactful hyperparameter first e.g. n_estimators , max_depth m learning_rate
- With the best value of the first hyperparameter, tune the next most impactful hyperparameter

Let's define a helper function for trying different hyperparameters.

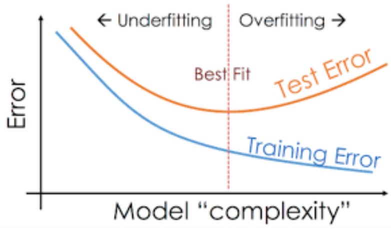
```
import matplotlib.pyplot as plt
def test_params(modelclass , **params):
  model = modelclass(**params).fit(train_inputs , train_target)
  train_rmse = root_mean_squared_error(model.predict(train_inputs) , train_target)
  val_rmse = root_mean_squared_error(model.predict(val_inputs) , val_target)
  return train_rmse , val_rmse

def test_param_and_plot(ModelClass, param_name, param_values, **other_params):
```

```
    train_errors, val_errors = [], []
    for value in param_values:
        params = dict(other_params)
        params[param_name] = value
        train_rmse, val_rmse = test_params(ModelClass, **params)
        train_errors.append(train_rmse)
        val_errors.append(val_rmse)

    plt.figure(figsize=(10,6))
    plt.title('Overfitting curve: ' + param_name)
    plt.plot(param_values, train_errors, 'b-o')
    plt.plot(param_values, val_errors, 'r-o')
    plt.xlabel(param_name)
    plt.ylabel('RMSE')
    plt.legend(['Training', 'Validation'])
```

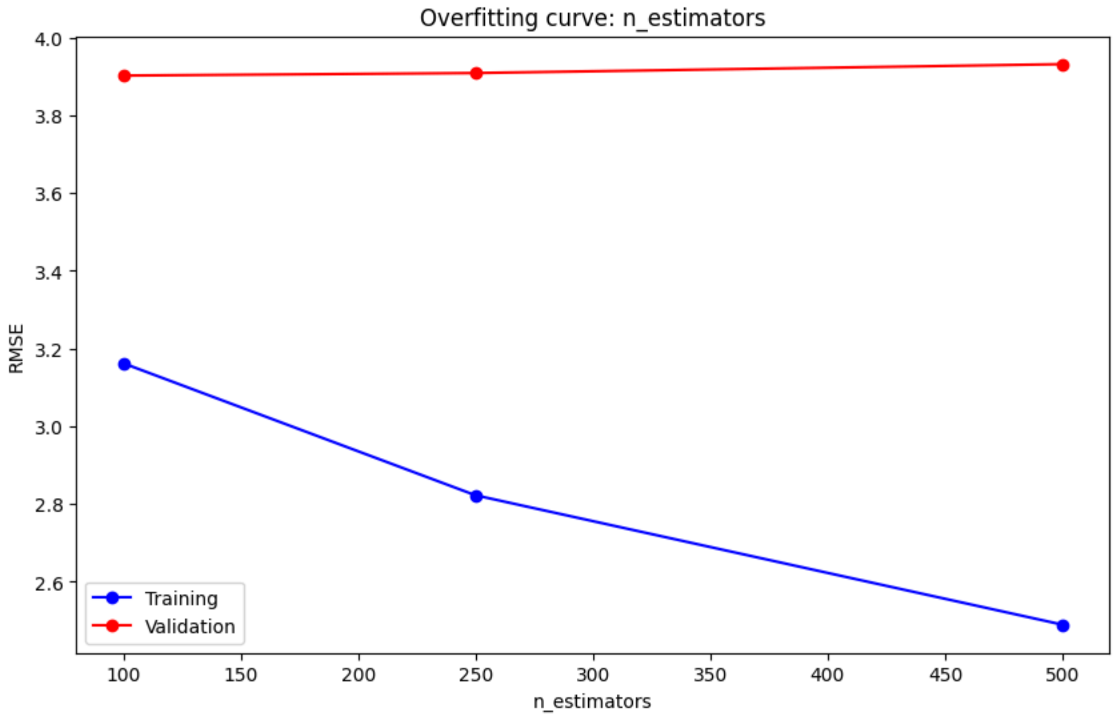
```
best_params = {
    "random_state" : 42,
    "n_jobs":-1,
    "objective": "reg:squarederror"
}
```



Number of trees

```
%%time
test_param_and_plot(XGBRegressor , "n_estimators" , [100 , 250 , 500] , **best_params)
```

```
CPU times: user 1min 31s, sys: 307 ms, total: 1min 31s
Wall time: 60 s
```



Seems like 500 estimators has the lowest validation loss. However, it also takes a long time. Let's stick with 250 for now.

```
best_params["n_estimators"] = 250
```

Max Depth

```
%%time
test_param_and_plot(XGBRegressor , "max_depth" , [3,4,5] , **best_params)
```

```
CPU times: user 1min, sys: 210 ms, total: 1min
Wall time: 38.8 s
```