New York City Taxi Fare Prediction

image.png

In this assignment, we will foresee the passage sum for a taxi ride in New York City, surrendered the pick, drop off areas and the date season of the get. We will begin from making an easiest model after some essential information cleaning, this straightforward model isn't Machine Learning, at that point we will move to more complex models. We should begin.

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Environment setup for python

At first, we have to import the python libraries which will be used in this project. Then we have to lead the tarin and test data. But our train data has almost 55M rows and it's quite impossible for us to use the whole dataset. That's why we'll a part of the dataset.

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # for plotting
import seaborn as sns # high quality image
sns.set()  # use Seaborn styles
from collections import Counter
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/new-york-city-taxi-fare-prediction/GCP-Coupons-Instructions.rtf
/kaggle/input/new-york-city-taxi-fare-prediction/train.csv
/kaggle/input/new-york-city-taxi-fare-prediction/test.csv
/kaggle/input/new-york-city-taxi-fare-prediction/sample_submission.csv
```

```
#Here we're keeping out train dataset in "train_df" data frame and test dataset in "test_df" data frame.
train_df = pd.read_csv('/kaggle/input/new-york-city-taxi-fare-prediction/train.csv', nrows = 10_000_000)
test_df = pd.read_csv('/kaggle/input/new-york-city-taxi-fare-prediction/test.csv')
```

dataset observations

Now our 1st task is to carefully observe the test and train dataset using python's built in function.

> 1. At first, we're trying to find out the column's name & info of the train and test dataset

```
train_df.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73.841610	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
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73.991242	40.750562
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73.991567	40.758092
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73.956655	40.783762

```
test_df.head()
```

	key	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_coun
0	2015-01-27 13:08:24.0000002	2015-01-27 13:08:24 UTC	-73.973320	40.763805	-73.981430	40.743835	1
1	2015-01-27 13:08:24.0000003	2015-01-27 13:08:24 UTC	-73.986862	40.719383	-73.998886	40.739201	1
2	2011-10-08 11:53:44.0000002	2011-10-08 11:53:44 UTC	-73.982524	40.751260	-73.979654	40.746139	1
3	2012-12-01 21:12:12.0000002	2012-12-01 21:12:12 UTC	-73.981160	40.767807	-73.990448	40.751635	1
4	2012-12-01 21:12:12.0000003	2012-12-01 21:12:12 UTC	-73.966046	40.789775	-73.988565	40.744427	1

2. Now the datetype of the train and test dataset are shown

```
train_df.dtypes
```

```
key                   object
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

```
test_df.dtypes
```

```
key                   object
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

3. here the dimension of the dataset is shown

```
print('train_df: ' + str(train_df.shape))
print('test_df: ' + str(test_df.shape))
```

```
train_df: (10000000, 8)
test_df: (9914, 7)
```

4. It's time to know some statistical information about the train and test dataset

```
train_df.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	1.000000e+07	1.000000e+07	1.000000e+07	9.999931e+06	9.999931e+06	1.000000e+07
mean	1.133854e+01	-7.250775e+01	3.991934e+01	-7.250897e+01	3.991913e+01	1.684793e+00
std	9.799930e+00	1.299421e+01	9.322539e+00	1.287532e+01	9.237280e+00	1.323423e+00
min	-1.077500e+02	-3.439245e+03	-3.492264e+03	-3.426601e+03	-3.488080e+03	0.000000e+00
25%	6.000000e+00	-7.399207e+01	4.073491e+01	-7.399139e+01	4.073403e+01	1.000000e+00
50%	8.500000e+00	-7.398181e+01	4.075263e+01	-7.398016e+01	4.075316e+01	1.000000e+00
75%	1.250000e+01	-7.396710e+01	4.076712e+01	-7.396367e+01	4.076810e+01	2.000000e+00
max	1.273310e+03	3.457626e+03	3.344459e+03	3.457622e+03	3.351403e+03	2.080000e+02

```
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	-73.974722	40.751041	-73.973657	40.751743	1.671273
std	0.042774	0.033541	0.039072	0.035435	1.278747
min	-74.252193	40.573143	-74.263242	40.568973	1.000000
25%	-73.992501	40.736125	-73.991247	40.735254	1.000000
50%	-73.982326	40.753051	-73.980015	40.754065	1.000000
75%	-73.968013	40.767113	-73.964059	40.768757	2.000000
max	-72.986532	41.709555	-72.990963	41.696683	6.000000

Data cleaning

In Machine Learning world data cleaning is the most important part of ML project. We on avg spend 85% of time on cleaning dataset because our ML model's result is going to extremely depends on data cleaning.

Data cleaning will be applied on train data only

1. Missig values: At first, we are going to resolve the missing values. Since out train dataset is huge so we're not going to generate missing value. We'll drop the missing rows.

```
print(train_df.isnull().sum())
```

```
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude    69
dropoff_latitude     69
passenger_count       0
dtype: int64
```

```python
print('Old size: %d' % len(train_df))
train_df = train_df.dropna(how = 'any', axis = 'rows')
print('New size: %d' % len(train_df))
```

```
Old size: 10000000
New size: 9999931
```

```python
print(train_df.isnull().sum())
```

```
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

2. Valied fare: A valied fare is always positive number. So we have to remove the fare which are less than or equal to Zero.

```python
# count how many negative and Zero values are here
Counter(train_df['fare_amount'] <= 0)
```

```
Counter({False: 9999242, True: 689})
```

```python
train_df['fare_amount'].describe()
```

```
count    9.999931e+06
mean     1.133849e+01
std      9.799845e+00
min     -1.077500e+02
25%      6.000000e+00
50%      8.500000e+00
75%      1.250000e+01
max      1.273310e+03
Name: fare_amount, dtype: float64
```

```python
print('before: ' + str(train_df.shape))
train_df = train_df.drop(train_df[train_df['fare_amount'] <= 0].index, axis = 0)
print('after: ' + str(train_df.shape))
```

```
before: (9999931, 8)
after: (9999242, 8)
```

```python
train_df['fare_amount'].describe()
```

```
count    9.999242e+06
mean     1.133966e+01
std      9.798609e+00
min      1.000000e-02
25%      6.000000e+00
50%      8.500000e+00
75%      1.250000e+01
max      1.273310e+03
Name: fare_amount, dtype: float64
```

3. passenger_count: This value is always greater than or equal to one. On the other hand, a standard size taxi can carry max 6 people. So we are assuming that a valied passenger_count is greater tnan equal to One and less than or equal to Six.

```
train_df['passenger_count'].describe()
```

```
count    9.999242e+06
mean     1.684807e+00
std      1.323424e+00
min      0.000000e+00
25%      1.000000e+00
50%      1.000000e+00
75%      2.000000e+00
max      2.080000e+02
Name: passenger_count, dtype: float64
```

```
print('before: ' + str(train_df.shape))
train_df = train_df.drop(train_df[train_df['passenger_count'] <= 0].index, axis = 0) # remove numbers less or equal 0
train_df = train_df.drop(train_df[train_df['passenger_count'] > 6].index, axis = 0) # remove numbers greater or equal 0
print('after: ' + str(train_df.shape))
```

```
before: (9999242, 8)
after: (9963965, 8)
```

```
train_df['passenger_count'].describe()
```

```
count    9.963965e+06
mean     1.690557e+00
std      1.306525e+00
min      1.000000e+00
25%      1.000000e+00
50%      1.000000e+00
75%      2.000000e+00
max      6.000000e+00
Name: passenger_count, dtype: float64
```

Feature Engineering

1. Time: Taxi fare heavily depends on time. For example: in holydays, people do visit a lot. On the other hand during reany season people hardy go outside. Moreover, in the mid night people don't go outside without important reason. On the other hand, people go outside during festival eg: xmas days. So time plays an important role in taxi fare. That's why we'll do categories the data base on time(hour, weekday, month, year).

```
def add_time_features(df):
    df['pickup_datetime'] = df['pickup_datetime'].str.replace(" UTC", "")
    df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'], format='%Y-%m-%d %H:%M:%S')
    df['hour'] = df.pickup_datetime.dt.hour
    #df['week'] = df.pickup_datetime.dt.week
    df['weekday'] = df.pickup_datetime.dt.weekday
    df['month'] = df.pickup_datetime.dt.month
    df['year'] = df.pickup_datetime.dt.year

    return df
```

```
train_df = add_time_features(train_df) # adding some columns to train dataset
```

```
train_df.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21	-73.844311	40.721319	-73.841610	40.712278
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.782004
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.750562
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.758092
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.783762

2. Location: Let's build two new features in our training set that represent the "travel vector" in both longitude and latitude coordinates between the start and end points of the taxi trip. As we're just interested in the distance travelled, we'll take the absolute value. Using a helper feature so later on we may want to do the same thing with the test collection.

```
def add_travel_vector_features(df):
    df['abs_diff_longitude'] = (df.dropoff_longitude - df.pickup_longitude).abs()
    df['abs_diff_latitude'] = (df.dropoff_latitude - df.pickup_latitude).abs()
```

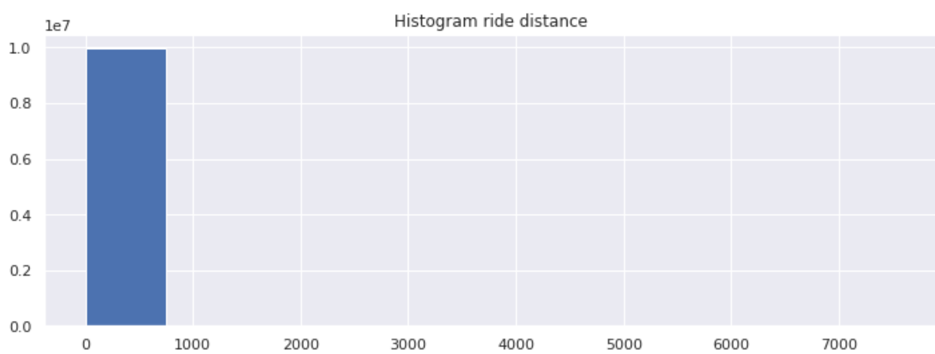
```
add_travel_vector_features(train_df)
```

```
# calculate straight distance and add as feature

def calculate_add_distance_feature(df):
    df['distance'] = (df['abs_diff_longitude'] ** 2 + df['abs_diff_latitude'] ** 2) ** .5
    return df

train_df = calculate_add_distance_feature(train_df)
```

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




```
train_df['distance'].describe()
```

```
count    9.963965e+06
mean     2.547027e-01
std      1.399081e+01
min      0.000000e+00
25%      1.239305e-02
50%      2.143539e-02
75%      3.835107e-02
max      7.548848e+03
Name: distance, dtype: float64
```

We expect most of these values to be very small (likely between 0 and 1) since it should all be differences between GPS coordinates within one city. For reference, one degree of latitude is about 69 miles. However, we can see the dataset has extreme values which do not make sense. Let's remove those values from our training set. Based on the scatterplot, it looks like we can safely exclude values above 5 (though remember the scatterplot is only showing the first 2000 rows...)

```
print('Old size: %d' % len(train_df))
train_df = train_df[(train_df.abs_diff_longitude < 5.0) & (train_df.abs_diff_latitude < 5.0)]
print('New size: %d' % len(train_df))
```

```
Old size: 9963965
New size: 9943523
```

```
train_df.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21	-73.844311	40.721319	-73.841610	40.712278
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.782004
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.750562
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.758092
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.783762

```
train_df.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour
count	9.943523e+06	9.943523e+06	9.943523e+06	9.943523e+06	9.943523e+06	9.943523e+06	9.943523e+06
mean	1.134003e+01	-7.256882e+01	3.995091e+01	-7.256796e+01	3.995125e+01	1.690605e+00	1.351120e+01
std	9.780789e+00	1.075765e+01	6.592764e+00	1.075754e+01	6.592813e+00	1.306535e+00	6.517226e+00
min	1.000000e-02	-3.348349e+03	-3.488080e+03	-3.348349e+03	-3.488080e+03	1.000000e+00	0.000000e+00
25%	6.000000e+00	-7.399209e+01	4.073497e+01	-7.399140e+01	4.073409e+01	1.000000e+00	9.000000e+00
50%	8.500000e+00	-7.398183e+01	4.075266e+01	-7.398018e+01	4.075318e+01	1.000000e+00	1.400000e+01
75%	1.250000e+01	-7.396717e+01	4.076714e+01	-7.396375e+01	4.076812e+01	2.000000e+00	1.900000e+01
max	1.273310e+03	3.442185e+03	2.973980e+03	3.442185e+03	2.973980e+03	6.000000e+00	2.300000e+01

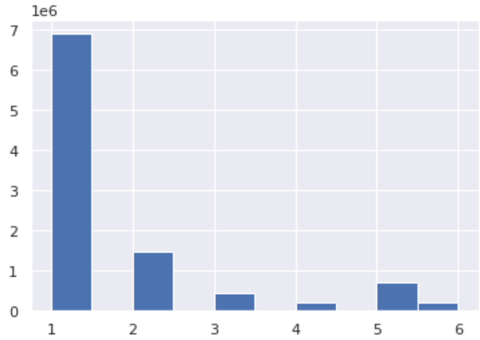
data visualization

a picture is worth a thousand words

In this part well do plot the data so that we can see the real picture. This will give us clear idea about the dataset and problem as well.

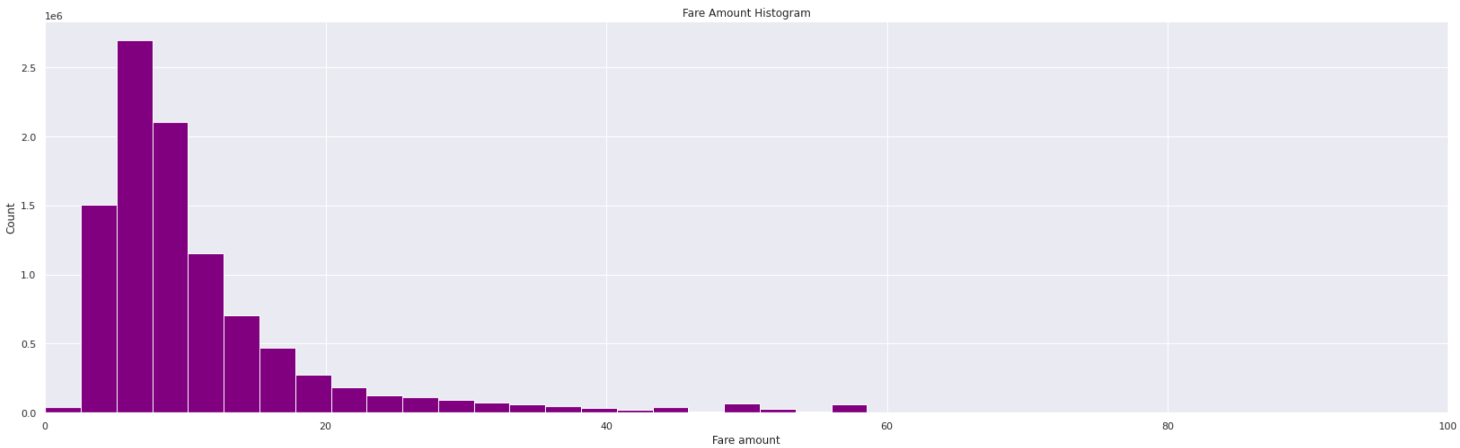
```
train_df.passenger_count.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb0fa476c50>
```



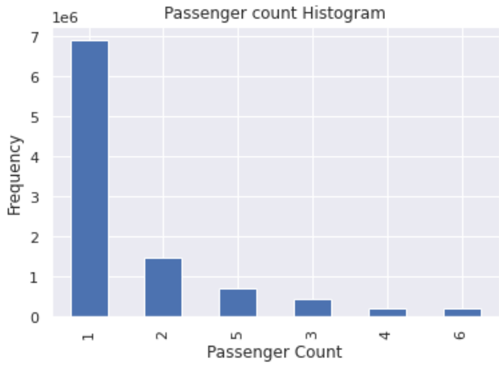

```
plt.figure(figsize=(28,8))
plt.hist(train_df["fare_amount"], 500, facecolor="purple")
plt.xlabel("Fare amount")
plt.ylabel("Count")
plt.title("Fare Amount Histogram")
plt.xlim(0,100)
```

```
(0.0, 100.0)
```




```
train_df["passenger_count"].value_counts().plot.bar()
plt.title("Passenger count Histogram")
plt.xlabel("Passenger Count")
plt.ylabel("Frequency")
```

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




```
def drop_unrealistic_distance(df):
    print('before: ' + str(df.shape))
    df = df.drop(df[train_df['distance'] < 0.01].index, axis = 0)
    print('after: ' + str(df.shape))
    return df

train_df = drop_unrealistic_distance(train_df)
```

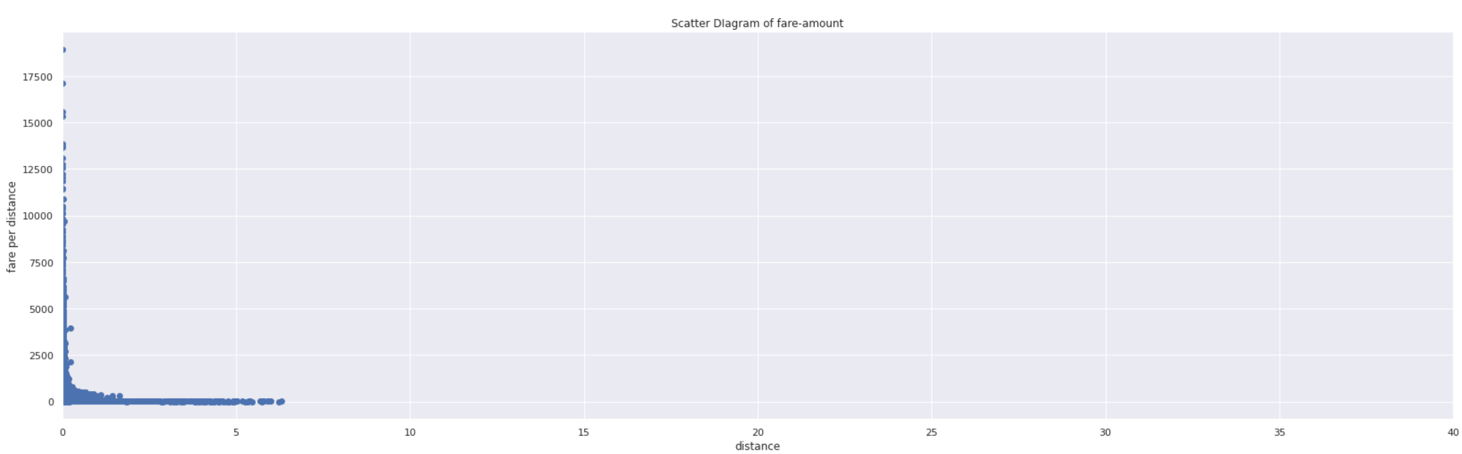
```
before: (9943523, 15)
after: (8203939, 15)
```

```
train_df["fare_per_distance"] = train_df["fare_amount"] / train_df["distance"]
train_df["fare_per_distance"].describe()
```

```
count    8.203939e+06
mean     3.754881e+02
std      1.517397e+02
min      4.715623e-02
25%      2.835819e+02
50%      3.513208e+02
75%      4.350787e+02
max      1.891399e+04
Name: fare_per_distance, dtype: float64
```

```
plt.figure(figsize=(28,8))
plt.scatter(train_df["distance"], train_df["fare_per_distance"])
plt.xlabel("distance")
plt.ylabel("fare per distance")
plt.xlim(0,40)
plt.title("Scatter DIagram of fare-amount")
```

```
Text(0.5, 1.0, 'Scatter DIagram of fare-amount')
```

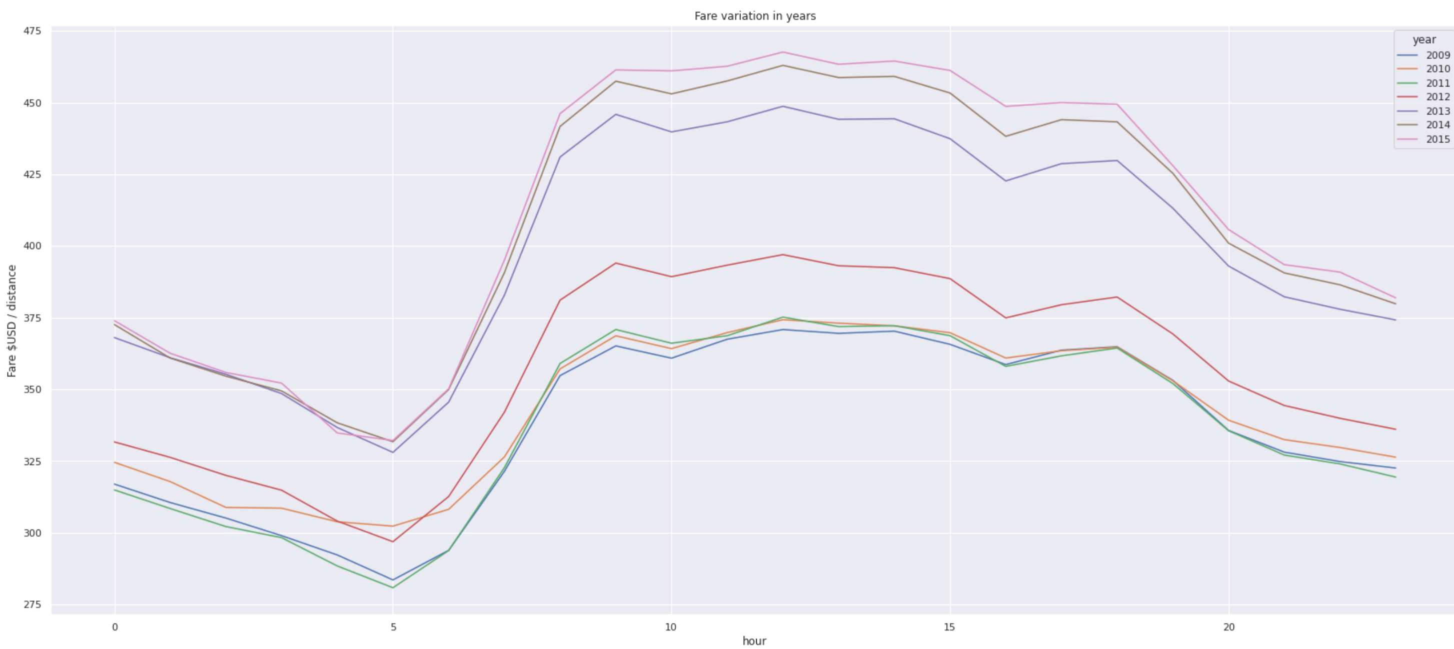



```
train_df.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.782004
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.750562
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.758092
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.783762
5	2011-01-06 09:50:45.0000002	12.1	2011-01-06 09:50:45	-74.000964	40.731630	-73.972892	40.758233

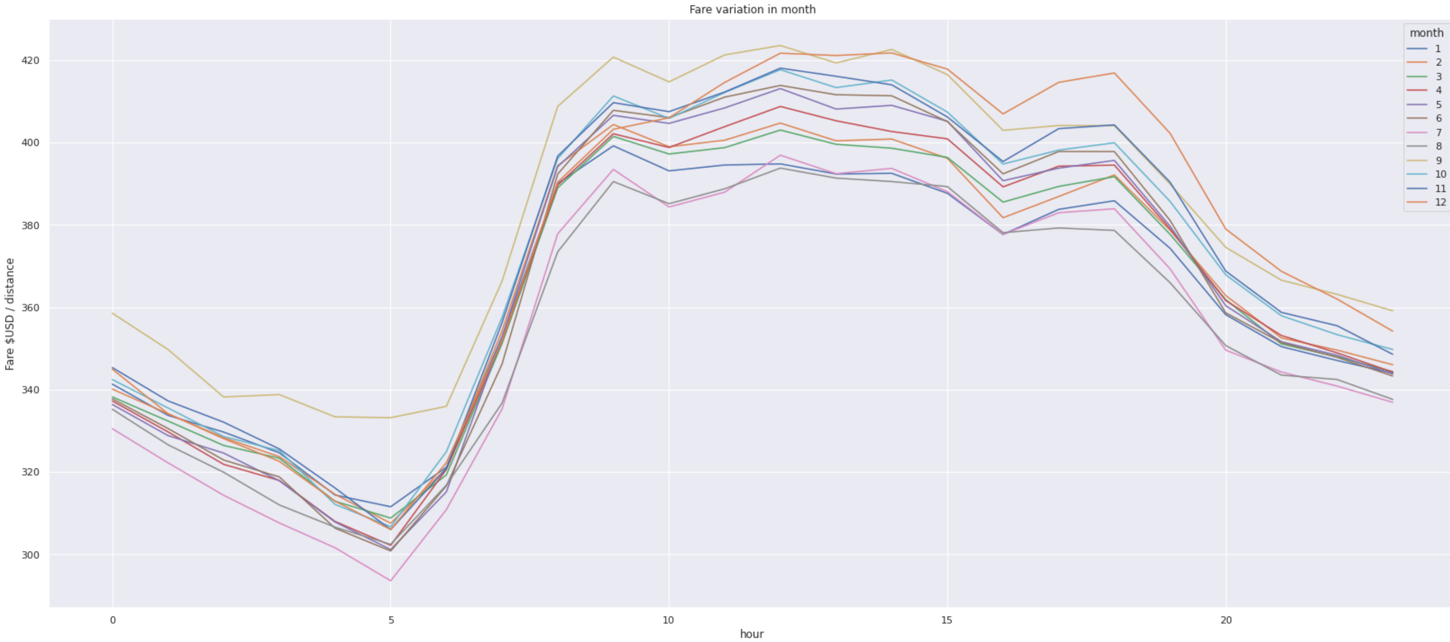
```
train_df.pivot_table('fare_per_distance', index='hour', columns='year').plot(figsize=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in years")
```

```
Text(0.5, 1.0, 'Fare variation in years')
```



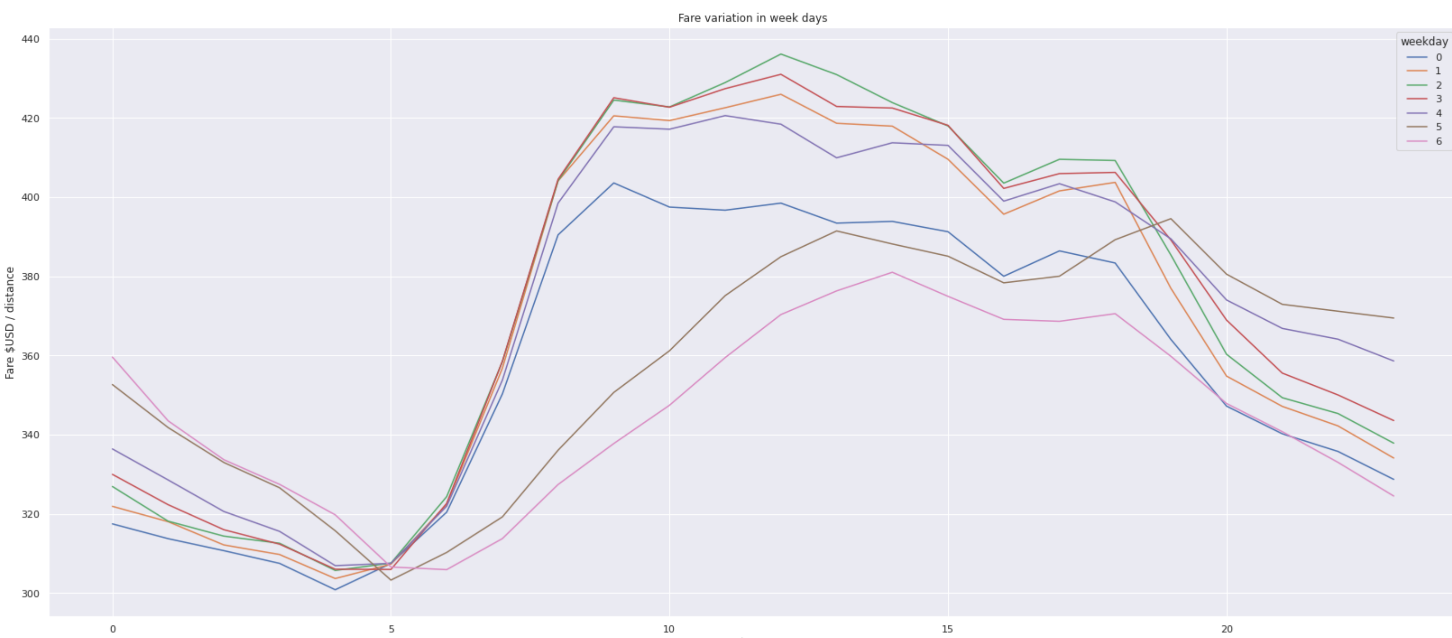

```
train_df.pivot_table("fare_per_distance", index="hour", columns="month").plot(figsize=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in month")
```

```
Text(0.5, 1.0, 'Fare variation in month')
```




```
train_df.pivot_table("fare_per_distance", index="hour", columns="weekday").plot(figsize=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in week days")
```

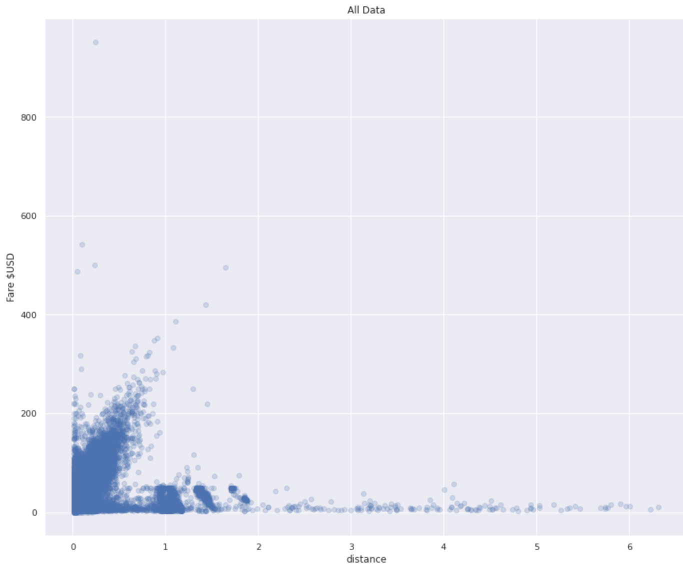
```
Text(0.5, 1.0, 'Fare variation in week days')
```

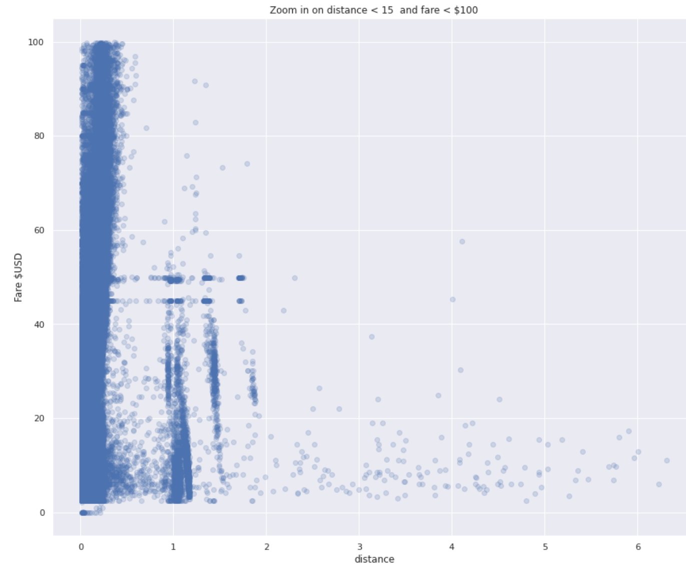



```
fig, axs = plt.subplots(1, 2, figsize=(32,12))
axs[0].scatter(train_df["distance"], train_df["fare_amount"], alpha=0.2)
axs[0].set_xlabel("distance")
axs[0].set_ylabel("Fare $USD")
axs[0].set_title("All Data")

idx = ((train_df['distance'] < 15) & (train_df["fare_amount"] < 100))
axs[1].scatter(train_df[idx]["distance"], train_df[idx]["fare_amount"], alpha=0.2)
axs[1].set_xlabel("distance")
axs[1].set_ylabel("Fare $USD")
axs[1].set_title("Zoom in on distance < 15  and fare < $100")
```

```
Text(0.5, 1.0, 'Zoom in on distance < 15  and fare < $100')
```





Fare Prediction

So far, we have cleaned up our dataset, have done feature engineering and done visualization. Now it's time to predict the fare.

At the very 1st time, we had only 8 columns in out train dataset. But after doing a lots of operation now our tarin data set has some new columns. Mainly we'll use theose columns to predict the fare.

```
train_df.dtypes
```

```
key                          object
fare_amount                 float64
pickup_datetime      datetime64[ns]
pickup_longitude            float64
pickup_latitude             float64
dropoff_longitude           float64
dropoff_latitude            float64
passenger_count               int64
hour                          int64
weekday                       int64
month                         int64
year                          int64
abs_diff_longitude          float64
abs_diff_latitude           float64
distance                    float64
fare_per_distance           float64
dtype: object
```

```
train_df.shape
```

```
(8203939, 16)
```

```
train_df.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.782004
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.750562
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.758092

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.783762
5	2011-01-06 09:50:45.0000002	12.1	2011-01-06 09:50:45	-74.000964	40.731630	-73.972892	40.758233

Here,

Our model is: X * m = Y

where, X = a matrix of input feature

Y = target variable (fare)

and m = weight

So, in our training session, model will learn some weight that will be kept in m.

Now, we have to decide which columns form train value are going to feed as X.

Here we'll use:

passenger_count, hour, weekday, month, year, abs_diff_longitude, abs_diff_latitude from train dataset and also will be added 1 as bias.

And then numpy's lstsq library function will be used to find the optimal weight column m.

```
def get_input_matrix(df):
    return np.column_stack((df.passenger_count, df.hour, df.weekday, df.month, df.year, df.abs_diff_longitude, df.abs_diff_latitude,

train_X = get_input_matrix(train_df)
train_y = np.array(train_df['fare_amount'])

print(train_X.shape)
print(train_y.shape)
```

```
(8203939, 8)
(8203939,)
```

```
(m, _, _, _) = np.linalg.lstsq(train_X, train_y, rcond = None)
print(m)
```

```
[ 7.22998460e-02  1.68596349e-03 -2.58805752e-02  9.46214495e-02
  6.52325783e-01  1.45891991e+02  7.60138750e+01 -1.30638699e+03]
```

Finally it's time to predict the fare using test date but before that we have to make a matrix same as X and to do that we are reusing:

add_time_features

add_travel_vector_features

function

```
test_df = add_time_features(test_df)
add_travel_vector_features(test_df)
test_df.head()
```

	key	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_coun
0	2015-01-27 13:08:24.0000002	2015-01-27 13:08:24	-73.973320	40.763805	-73.981430	40.743835	1

	key	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_coun
1	2015-01-27 13:08:24.0000003	2015-01-27 13:08:24	-73.986862	40.719383	-73.998886	40.739201	1
2	2011-10-08 11:53:44.0000002	2011-10-08 11:53:44	-73.982524	40.751260	-73.979654	40.746139	1
3	2012-12-01 21:12:12.0000002	2012-12-01 21:12:12	-73.981160	40.767807	-73.990448	40.751635	1
4	2012-12-01 21:12:12.0000003	2012-12-01 21:12:12	-73.966046	40.789775	-73.988565	40.744427	1

```
test_X = get_input_matrix(test_df)
print(test_X.shape)
```

```
(9914, 8)
```

Now we have,

test_X, m from train section. So it's time to find the test_Y

```
test_y_predictions = np.matmul(test_X, m).round(decimals = 2)
```

This will generate a CSV file to submit result in kaggle

```
submission = pd.DataFrame(
    {'key': test_df.key, 'fare_amount': test_y_predictions},
    columns = ['key', 'fare_amount'])
submission.to_csv('submission.csv', index = False)

print(os.listdir('.'))
```

```
['__notebook__.ipynb', 'submission.csv']
```

Now we have our submission.csv file that contains the predicted fare.

```
result_df = pd.read_csv('./submission.csv')
result_df.head()
```

	key	fare_amount
0	2015-01-27 13:08:24.0000002	10.91
1	2015-01-27 13:08:24.0000003	11.47
2	2011-10-08 11:53:44.0000002	7.16
3	2012-12-01 21:12:12.0000002	9.79
4	2012-12-01 21:12:12.0000003	13.94

Result Evaluation:

The evaluation metric for this project 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:

image.png

where yi is the ith observation and ^yi is the prediction for that observation.

Example 1. Suppose we have one observation, with an actual value of 12.5 and a prediction of 12.5 (good job!). The RMSE will be:

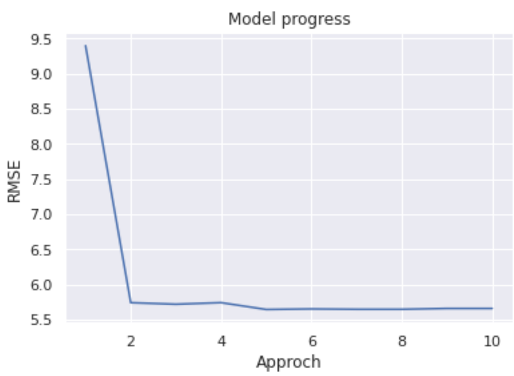
image.png

Example 2. We'll add another data point. Your prediction for the second data point is 11.0 and the actual value is 14.0. The RMSE will be:

image.png

```
approch = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
RMSE = [9.39599, 5.74184, 5.72030, 5.74240, 5.64520, 5.65298, 5.64798, 5.64792, 5.66021, 5.66021]
plt.plot(approch, RMSE)
plt.ylabel("RMSE");
plt.xlabel("Approch");
plt.title("Model progress")
```

```
Text(0.5, 1.0, 'Model progress')
```



conclusion:

New York City Taxi Fare Prediction is a very interesting real life problem to solve. By solving this problem one can get in to ML world.

Further Improvement:

New York City Taxi Fare Prediction has a very lagre dataset. A small part of that is used here. So by using large amount of rows can imporve the result. We also have used a linear model. Using a complex and non-linear model can also improve the result as well.

reference:

- NumPy
- Matplotlib
- pandas
- An Introduction to Linear Regression Analysis
- Kernels Starter Tutorial
- Easy to use map and GPS tool
- Calculate distance between locations