CSE519_Homework2_Final

September 25, 2018

0.1 Imports

```
In [0]: import numpy as np                       #For NumPy arrays and mathematical functions
        import pandas as pd                      #For operations using DataFrames
        import matplotlib.pyplot as plt          #For plotting
        import seaborn as sns                    #For plotting
        import time
        import os
```

0.2 Mounting Google Drive on Colab

```
In [2]: from google.colab import drive
        drive.mount('gdrive')
```

```
Mounted at gdrive
```

Creating File and Directory paths

```
In [0]: dir_path = "gdrive/My Drive/Colab Notebooks/Datasets/NYC/"
        file_name = "train.feather"
```

0.2.1 Installing Feather locally for reading

```
In [0]: !pip install -U feather-format
```

0.3 Reading the dataset

```
In [4]: print("Reading Feather file...")
        df = pd.read_feather(dir_path+file_name)
        print("Reading completed")
        %time
```

```
Reading Feather file...


/usr/local/lib/python3.6/dist-packages/pandas/io/feather_format.py:112: FutureWarning: `nthreac
  return feather.read_dataframe(path, nthreads=nthreads)
```

```
Reading completed
CPU times: user 3 ţs, sys: 2 ţs, total: 5 ţs
Wall time: 14.5 ţs
```

0.3.1 Now let's examine the properties of dataset

```
In [0]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55423856 entries, 0 to 55423855
Data columns (total 7 columns):
fare_amount          float32
pickup_datetime      datetime64[ns, UTC]
pickup_longitude     float32
pickup_latitude      float32
dropoff_longitude    float32
dropoff_latitude     float32
passenger_count      uint8
dtypes: datetime64[ns, UTC](1), float32(5), uint8(1)
memory usage: 1.5 GB
```

```
In [6]: df.head()
```

```
Out[6]:    fare_amount           pickup_datetime  pickup_longitude  pickup_latitude  \
        0          4.5 2009-06-15 17:26:00+00:00        -73.844315        40.721317
        1         16.9 2010-01-05 16:52:00+00:00        -74.016045        40.711304
        2          5.7 2011-08-18 00:35:00+00:00        -73.982735        40.761269
        3          7.7 2012-04-21 04:30:00+00:00        -73.987129        40.733143
        4          5.3 2010-03-09 07:51:00+00:00        -73.968094        40.768009

           dropoff_longitude  dropoff_latitude  passenger_count
        0         -73.841614         40.712276                1
        1         -73.979271         40.782005                1
        2         -73.991241         40.750561                2
        3         -73.991570         40.758091                1
        4         -73.956657         40.783764                1
```

```
In [7]: df.describe()
```

```
Out[7]:         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
        count  5.542386e+07      5.542386e+07     5.542386e+07       5.542348e+07
        mean   1.134503e+01     -7.250972e+01     3.991985e+01      -7.251106e+01
        std    2.071083e+01      1.284888e+01     9.642353e+00       1.278220e+01
        min   -3.000000e+02     -3.442060e+03    -3.492264e+03      -3.442025e+03
        25%    6.000000e+00     -7.399207e+01     4.073493e+01      -7.399140e+01
        50%    8.500000e+00     -7.398180e+01     4.075265e+01      -7.398015e+01
        75%    1.250000e+01     -7.396708e+01     4.076713e+01      -7.396368e+01
```

```
max     9.396336e+04      3.457626e+03     3.408790e+03       3.457622e+03

       dropoff_latitude  passenger_count
count      5.542348e+07     5.542386e+07
mean       3.992067e+01     1.685380e+00
std        9.633346e+00     1.327664e+00
min       -3.547887e+03     0.000000e+00
25%        4.073403e+01     1.000000e+00
50%        4.075316e+01     1.000000e+00
75%        4.076810e+01     2.000000e+00
max        3.537133e+03     2.080000e+02
```

As we can see from the above description, our dataset contains a lot of anomalies and outliers. If a model is built without cleaning, it will be far from accurate. To build a good model, we will have to clean the data and add additional features

0.4 Data Cleaning and Exploration

1. Perform Initial Operations Check shape of data

In [0]:
```
df.shape
```

Out[0]:
```
(55423856, 7)
```

Check rows having NaN values

In [5]:
```
df.isnull().sum().sort_values(ascending=False)
```

Out[5]:
```
dropoff_latitude     376
dropoff_longitude    376
passenger_count        0
pickup_latitude        0
pickup_longitude       0
pickup_datetime        0
fare_amount            0
dtype: int64
```

Dropping rows having NaN values As only the first two columns contain NaN values, we choose a subset of column to check for dropping the rows and proceed with this to improve performance

In [0]:
```
df = df.dropna(axis='index', how='any', subset=['dropoff_latitude', 'dropoff_longitude
```

Now, after the rows are dropped, the shape will change

In [9]:
```
df.shape
```

Out[9]:
```
(55423480, 7)
```

After having dropped the null rows, let us focus on making data good The data contains a lot of issues - 1. Fare Amount is negative 2. Latitude and Longitude 3. Passenger Count

Step 1: Deleting rows having negative fare amount and fare above 95 dollars. The first task towards cleaning data would be removing rows having negative fare amount.

```
In [0]: #Removing rows with negative fare
        df = df[df.fare_amount > 0]
```

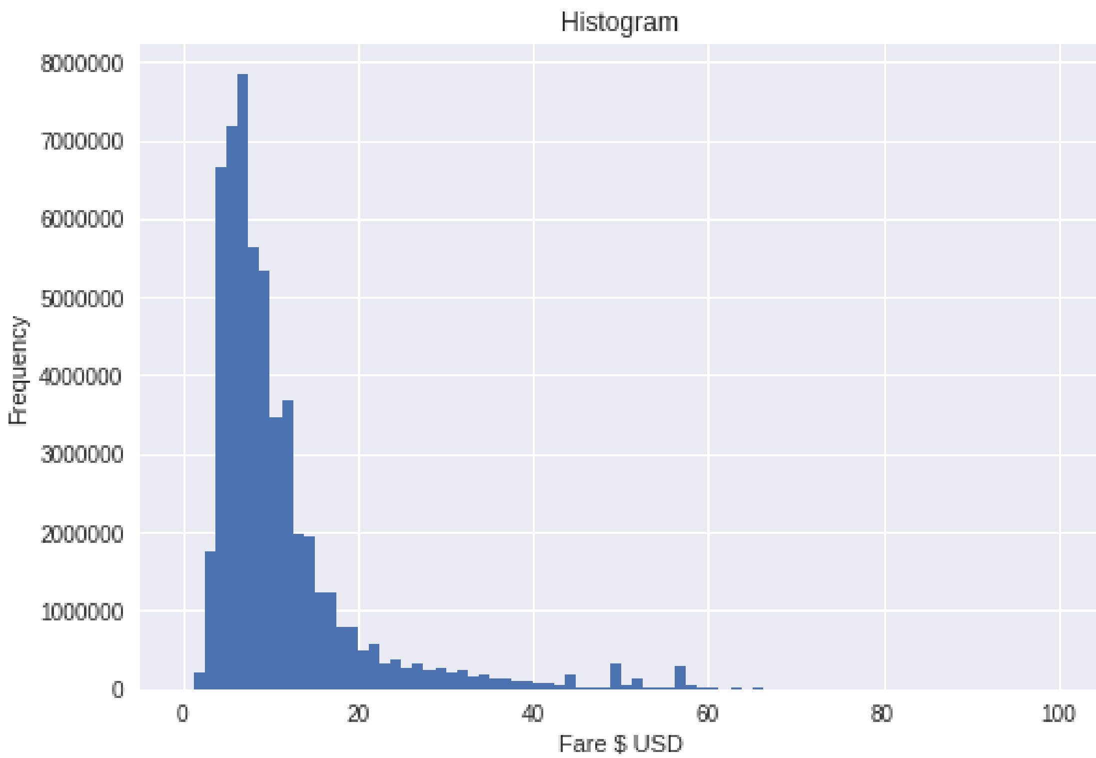
```
In [0]: df.shape
```

```
Out[0]: (55419646, 7)
```

Let's plot a histogram checking for the distribution of fare_amount

```
In [0]: df[df.fare_amount<100].fare_amount.hist(bins=80)
        plt.xlabel('Fare $ USD')
        plt.ylabel('Frequency')
        plt.title('Histogram')
```

```
Out[0]: Text(0.5,1,'Histogram')
```



This is a unimodal distribution. But even then, there exist fare amount greater than 150 dollars or so. A simple observation at the distribution reveals that the maximum fare amount lies between 5 to 15 dollars. In order to trim the outliers, let us check the quantiles.

```
In [0]: low =  0
        high = .99953       #3.5-standard deviation, that means covering 99.953% observations
        quantiles_df = df.quantile([low, high])
        print(quantiles_df)
```

```
         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
0.00000     0.010000      -3442.059570     -3492.263672       -3442.024658
0.99953    95.330002         40.701997        41.012809          40.687964

         dropoff_latitude  passenger_count
0.00000      -3547.886719              0.0
0.99953         40.989659              6.0
```

As we can see, for 3.5 sigma, fare_amount -> 95 dollars. This means that the 99.953% of the observations lie below 95 dollars. **So it is safe to remove the outliers, that is, 0.047% observations.**

```
In [8]: #Removing rows having having fare amount less than 3.5 sigma
        df = df[df.fare_amount <= 95]
        df.shape

Out[8]: (55393378, 7)

In [0]: df.fare_amount.describe()

Out[0]: count    5.539338e+07
        mean     1.128455e+01
        std      9.371513e+00
        min      1.000000e-02
        25%      6.000000e+00
        50%      8.500000e+00
        75%      1.250000e+01
        max      9.500000e+01
        Name: fare_amount, dtype: float64
```

Even now, we can see that the minimum fare is $0.01.

But looking online for the taxi fares during the years 2009-2015, we understand that the minimum fare was $ 2. So we should only keep those rows for which the fare was above 2 dollars

```
In [9]: #Removing rows with fare amount less than USD 2.
        df = df[df.fare_amount >= 2]
        df.shape

Out[9]: (55392531, 7)

In [0]: low =  0
        high = .9973          #3-standard deviation
        quantiles_df = df.quantile([low, high])
        print(quantiles_df)

        fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
0.0000         0.01       -3442.05957     -3492.263672       -3442.024658
0.9973        60.00           0.00000        40.828285           0.000000

        dropoff_latitude  passenger_count
0.0000      -3547.886719              0.0
0.9973         40.866947              6.0
```

Step 2: Delete passengers more than 6. We saw in the quantile plot above that 3 sigma as well as 3.5 sigma for passenger_count is 6.0, so let's drop rows having passenger_count > 6

```
In [10]: #Dropping rows
         df = df[df.passenger_count <= 6]
         df.shape
```

```
Out[10]: (55392419, 7)
```

Also, removing rows with 0 passengers as a taxi cannot operate with 0 passengers

```
In [0]: #Dropping rows
        df = df[df.passenger_count > 0]
```

```
In [12]: df.shape
```

```
Out[12]: (55197444, 7)
```

Step 3: Cleaning based on Coordinates Now we try to understand latitudes and longitudes and remove outliers in these fields.

From basic Geography, we know that **Latitude** lies between -90 to +90. And **Longitude** lies between -180 to +180.

But in our observation, we have a longitude of **-3446**, which clearly means that we need to remove outliers like these.

Leaving everything aside, I found out the bounding box coordinates for NYC as the cabs were in NYC. Reducing our observations to these bounding box coordinates would ensure that we have eliminated all outliers.

The coordinates for New York City are: -74.259087, 40.477398, -73.70018, 40.91618

```
In [15]: df = df[(df.pickup_longitude >=  -74.259087) & (df.dropoff_longitude <= -73.70018)
                   & (df.dropoff_longitude >= -74.259087) & (df.pickup_longitude <= -73.70018)
                   & (df.pickup_latitude >= 40.477398) & (df.dropoff_latitude <= 40.91618)
                   & (df.dropoff_latitude >= 40.477398) & (df.pickup_latitude <= 40.91618)]
         df.shape
```

```
Out[15]: (53979707, 7)
```

```
In [0]: df.describe()
```

Now we have sufficiently cleaned the data and it is free from outliers and looks uniform!

0.5 Creating a new feature for Time of Day

```
In [0]: df['time_of_day'] = df['pickup_datetime'].apply(lambda x:x.hour)
        #df.head()
```

0.6 Creating a new feature for Month of Year

```
In [0]: df['month_of_year'] = df['pickup_datetime'].apply(lambda x:x.month)
        #df.head()
```

0.7 Creating a new feature for Year

```
In [0]: df['year'] = df['pickup_datetime'].apply(lambda x:x.year)
        #df.head()
```

0.8 Creating a new feature for Day of Week

```
In [0]: df['day_of_week'] = pd.to_datetime(df['pickup_datetime']).dt.weekday.astype(np.int64)
```

```
In [0]: df.head()
```

```
In [26]: df.describe()
```

```
Out[26]:          fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
         count  5.397971e+07      5.397971e+07     5.397971e+07       5.397971e+07
         mean   1.126501e+01     -7.397079e+01     4.075009e+01      -7.397059e+01
         std    9.294146e+00      3.441382e-02     2.688210e-02       3.377897e-02
         min    2.000000e+00     -7.425903e+01     4.047759e+01      -7.425906e+01
         25%    6.000000e+00     -7.399229e+01     4.073658e+01      -7.399158e+01
         50%    8.500000e+00     -7.398210e+01     4.075336e+01      -7.398061e+01
         75%    1.250000e+01     -7.396835e+01     4.076752e+01      -7.396541e+01
         max    9.500000e+01     -7.370018e+01     4.091616e+01      -7.370018e+01

                dropoff_latitude  passenger_count   time_of_day  month_of_year  \
         count      5.397971e+07     5.397971e+07  5.397971e+07   5.397971e+07
         mean       4.075017e+01     1.691365e+00  1.351012e+01   6.269418e+00
         std        3.071281e-02     1.307223e+00  6.516493e+00   3.436574e+00
         min        4.047765e+01     1.000000e+00  0.000000e+00   1.000000e+00
         25%        4.073559e+01     1.000000e+00  9.000000e+00   3.000000e+00
         50%        4.075385e+01     1.000000e+00  1.400000e+01   6.000000e+00
         75%        4.076837e+01     2.000000e+00  1.900000e+01   9.000000e+00
         max        4.091618e+01     6.000000e+00  2.300000e+01   1.200000e+01

                        year   day_of_week
         count  5.397971e+07  5.397971e+07
         mean   2.011739e+03  3.041228e+00
         std    1.865315e+00  1.949146e+00
         min    2.009000e+03  0.000000e+00
         25%    2.010000e+03  1.000000e+00
         50%    2.012000e+03  3.000000e+00
         75%    2.013000e+03  5.000000e+00
         max    2.015000e+03  6.000000e+00
```

0.9 Calculating Euclidean Distance [Haversine Distance]

Referred this site: https://stackoverflow.com/questions/27928/calculate-distance-between-two-latitude-longitude-points-haversine-formula?rq=1

```
In [0]: from math import sin, cos, asin, sqrt, radians
```

```
def euclidean_dist(lon1, lat1, lon2, lat2):
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])
    # haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = (np.sin(dlat/2)**2
         + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2)
    c = 2 * np.arcsin(np.sqrt(a))
    miles = 3959 * c
    return miles
```

```
In [0]: df['euclidean_dist'] = euclidean_dist(df.loc[:,'pickup_longitude'].astype(float),
                                              df.loc[:,'pickup_latitude'].astype(float),
                                              df.loc[:,'dropoff_longitude'].astype(float),
                                              df.loc[:,'dropoff_latitude'].astype(float))
```

```
In [0]: df.head()
```

```
Out[0]:    fare_amount            pickup_datetime  pickup_longitude  pickup_latitude  \
        0          4.5 2009-06-15 17:26:00+00:00        -73.844315        40.721317
        1         16.9 2010-01-05 16:52:00+00:00        -74.016045        40.711304
        2          5.7 2011-08-18 00:35:00+00:00        -73.982735        40.761269
        3          7.7 2012-04-21 04:30:00+00:00        -73.987129        40.733143
        4          5.3 2010-03-09 07:51:00+00:00        -73.968094        40.768009

           dropoff_longitude  dropoff_latitude  passenger_count  time_of_day  \
        0         -73.841614         40.712276                1           17
        1         -73.979271         40.782005                1           16
        2         -73.991241         40.750561                2            0
        3         -73.991570         40.758091                1            4
        4         -73.956657         40.783764                1            7

           month_of_year  year  euclidean_dist
        0              6  2009        0.640513
        1              1  2010        5.250911
        2              8  2011        0.863531
        3              4  2012        1.739456
        4              3  2010        1.242248
```

```
In [0]: df.describe()
```

0.9.1 Data Cleaning after adding new features

After calculating Euclidean distance, there is an important parameter to work with. We now will **clean** the rows that have distance travelled less than 0.3 miles as most of the people do not use cabs for distances as short as this! There are almost 2 million such entries and they can spoil the model

```
In [22]: len(df[df.euclidean_dist <= 0.3 ])
```

```
Out[22]: 2093705
```

```
In [0]: #Removing rows having distance less than 0.3 miles
        df = df[df.euclidean_dist >= 0.3]
```

```
In [24]: df.shape
```

```
Out[24]: (51886002, 12)
```

1 Now let's export this cleaned file!

```
In [0]: #Creating a feather file
        import feather
        feather.write_dataframe(df,'gdrive/My Drive/Colab Notebooks/Datasets/NYC/train_cleaned
```

1.1 Creating a correlation DataFrame

```
In [0]: df_correlation = df.filter(['fare_amount', 'time_of_day', 'euclidean_dist'], axis=1)
```

2 Calculating Pearson Correlation Coefficient

```
In [27]: df_correlation.corr(method='pearson')
```

```
Out[27]:                 fare_amount  time_of_day  euclidean_dist
         fare_amount        1.000000    -0.018592        0.904927
         time_of_day       -0.018592     1.000000       -0.032418
         euclidean_dist     0.904927    -0.032418        1.000000
```

```
In [0]: sns.pairplot(df_correlation)
```

2.1 Converting to CSV File

```
In [0]: #df.to_csv(path="gdrive/My Drive/Colab Notebooks/Datasets/NYC/train_cleaned.csv")
        df.to_csv("gdrive/My Drive/Colab Notebooks/Datasets/NYC/train_cleaned.csv",encoding='u
```

2.2 Converting to Feather File

```
In [0]: df_1 = df
        df_1.reset_index()
        #df_1.head()
        #df_1.to_feather("gdrive/My Drive/Colab Notebooks/Datasets/NYC/train_cleaned.feather")
        df_1.to_feather("gdrive/My Drive/Colab Notebooks/Datasets/NYC/train_cleaned.feather")
```

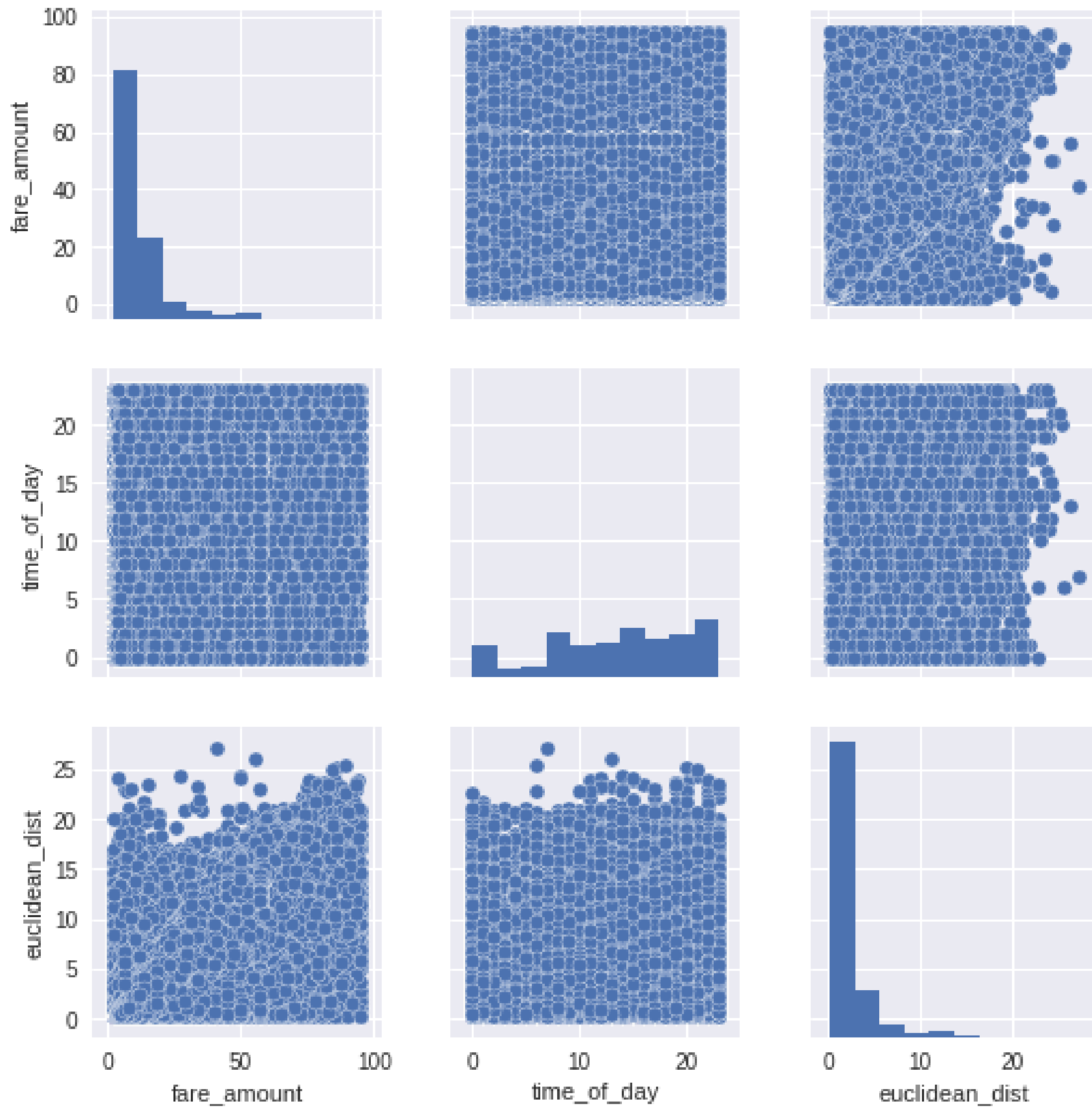
```
Out[0]:    fare_amount           pickup_datetime  pickup_longitude  pickup_latitude  \
        0          4.5 2009-06-15 17:26:00+00:00        -73.844315        40.721317
        1         16.9 2010-01-05 16:52:00+00:00        -74.016045        40.711304
        2          5.7 2011-08-18 00:35:00+00:00        -73.982735        40.761269
        3          7.7 2012-04-21 04:30:00+00:00        -73.987129        40.733143
```

```
4          5.3 2010-03-09 07:51:00+00:00        -73.968094        40.768009

   dropoff_longitude  dropoff_latitude  passenger_count  time_of_day  \
0         -73.841614         40.712276                1           17
1         -73.979271         40.782005                1           16
2         -73.991241         40.750561                2            0
3         -73.991570         40.758091                1            4
4         -73.956657         40.783764                1            7

   month_of_year  year  euclidean_dist
0              6  2009        0.640513
1              1  2010        5.250911
2              8  2011        0.863531
3              4  2012        1.739456
4              3  2010        1.242248
```

2.3 Plotting the relationship betweeen variables

In [0]:
```
sns.pairplot(df_correlation[:10000000])
```

Out[0]:
```
<seaborn.axisgrid.PairGrid at 0x7f23831a6198>
```

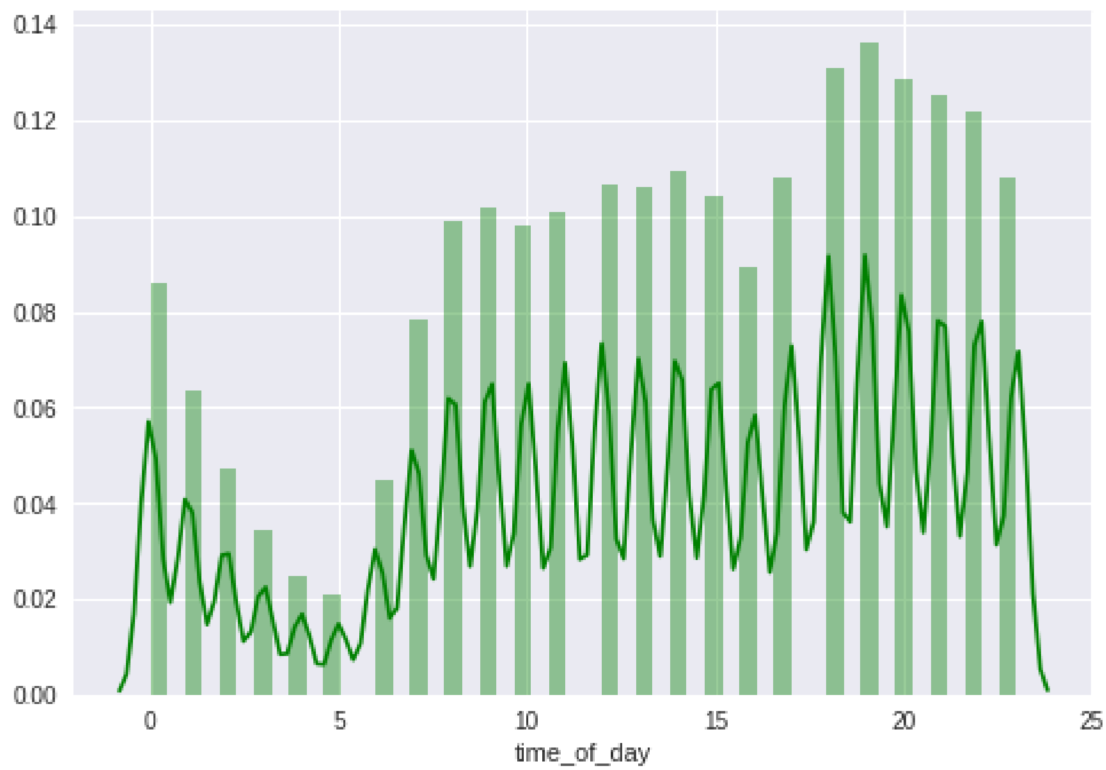


The plots do not show a very linear kind of relationship, but fare_amount and euclidean_dist are highly correlated

```
In [0]: df_reduced = df.sample(frac=0.2, random_state=42)
```

```
In [31]: #Creating a distribution plot to check the frequency of cab bookings according to the
         sns.distplot(df_reduced['time_of_day'], color="green")
```

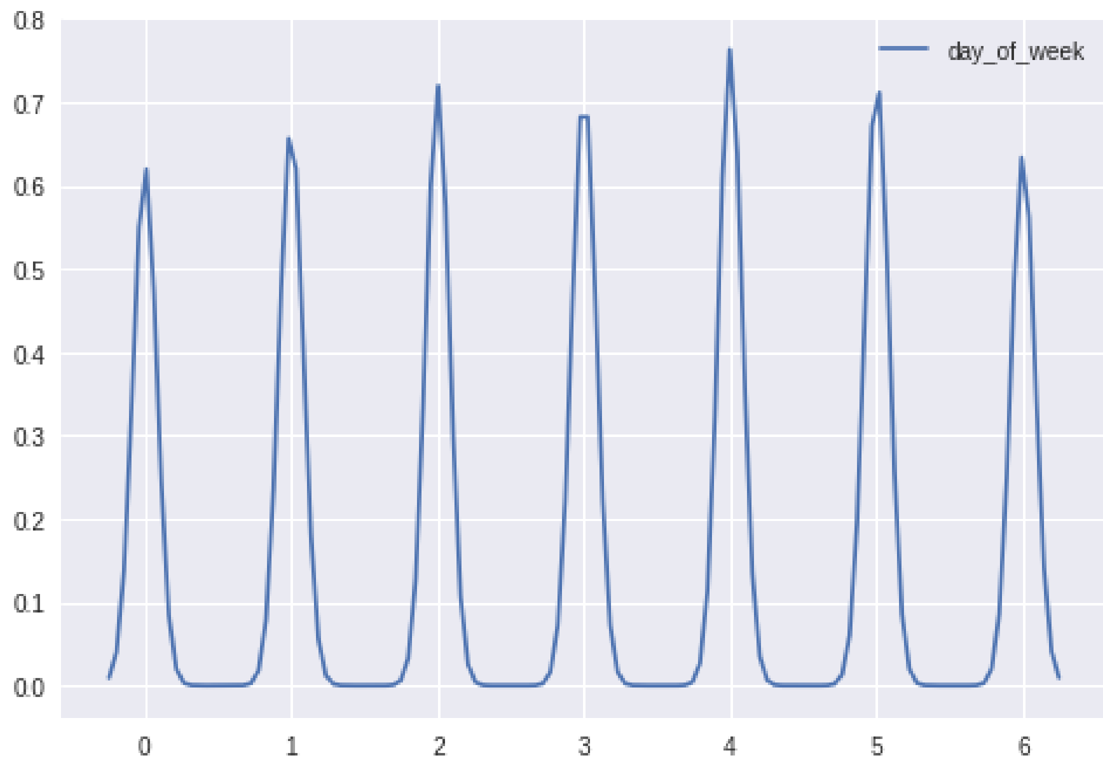
```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7fac4b58a780>
```



From this graph, it is evident that the highest number of cab bookings are done in between 6PM to 9PM, and this coincides with the closing time of offices in NYC. Also the bookings done at late night [12AM to 5AM] could be people travelling to/from airports!

```
In [30]: sns.kdeplot(df_reduced['day_of_week'])
```

```
Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7fac6c09a710>
```



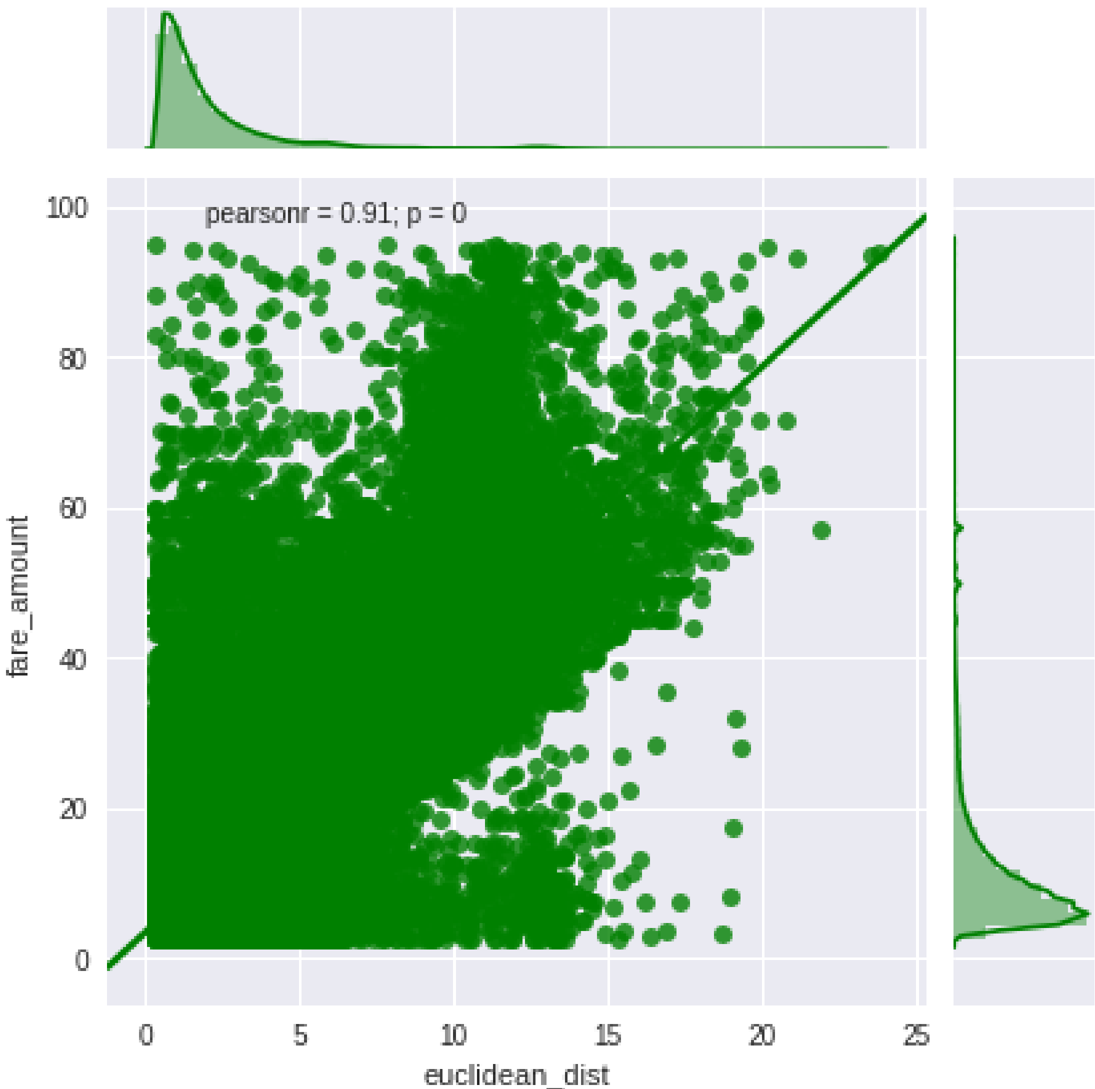
This plot shows that the distribution is more or less similar for every day I have drawn a Kernel Density Estimation plot here!

```
In [0]: sns.jointplot("euclidean_dist", "fare_amount", data=df_reduced, kind='hex')
```

```
In [0]: df_reduced = df_reduced[:1000000]
```

```
In [35]: sns.jointplot("euclidean_dist", "fare_amount", data=df_reduced,color='green', kind='re
```

```
Out[35]: <seaborn.axisgrid.JointGrid at 0x7fac4b36b7b8>
```



This plot also reveals an interesting insight into the data! The correlation is quite high and can be seen from the line!

3 Building Linear Regression Model based on the above features

```
In [0]: import numpy as np                  #For NumPy arrays and mathematical functions
        import pandas as pd                 #For operations using DataFrames
        import matplotlib.pyplot as plt     #For plotting
        import seaborn as sns               #For plotting
        import time
        import os
```

```
In [2]: dir_path = "gdrive/My Drive/Colab Notebooks/Datasets/NYC/"
        file_name = "train_cleaned.feather"
```

```
        df_lin = pd.read_feather(dir_path+file_name, nthreads=2)
        %time
```

```
/usr/local/lib/python3.6/dist-packages/pandas/io/feather_format.py:112: FutureWarning: `nthreac
  return feather.read_dataframe(path, nthreads=nthreads)


CPU times: user 1e+03 ns, sys: 2 ţs, total: 3 ţs
Wall time: 9.78 ţs
```

```
In [0]: print(df_lin.shape)
        df_lin.head()
```

```
In [0]: from sklearn.linear_model import LinearRegression
        from sklearn.cross_validation import train_test_split
        from sklearn.metrics import mean_squared_error
        from sklearn.preprocessing import PolynomialFeatures
        #from IPython.html import widgets
        #from IPython.html.widgets import interact
        #from IPython.display import display
```

```
In [0]: df_subset = df_lin.sample(frac=0.5, random_state=42)
```

```
In [14]: df_subset.shape
```

```
Out[14]: (25943001, 12)
```

```
In [0]: features = ['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitu

        X1 = df_subset[features].values

        Y = df_subset[['fare_amount']].values

        X1_train, X1_test, y_train, y_test = train_test_split(X1, Y, test_size=0.3, random_sta
```

```
In [16]: slr = LinearRegression()
         slr.fit(X1_train, y_train)
         y_train_pred = slr.predict(X1_train)
         y_test_pred = slr.predict(X1_test)
         slr.coef_
```

```
Out[16]: array([[ 1.26752508e+01,  8.25524376e+00, -5.74357322e+00,
                 -1.50032256e+01,  3.70326356e+00,  1.07440275e-02,
                 -4.96219671e-02]])
```

When frac=0.5 array([[1.26752508e+01, 8.25524376e+00, -5.74357322e+00, -1.50032256e+01, 3.70326356e+00, 1.07440275e-02, -4.96219671e-02]])

For frac=0.2array([[1.26912264e+01, 8.28425098e+00, -5.60640618e+00, -1.50239738e+01, 3.70220438e+00, 1.05555875e-02, -5.09145992e-02]])

In [17]:
```
from math import sqrt
import numpy as np
print ('Simple Linear Regression on Euclidean Distance Results:')
print ('Root Mean Squared Error Train: %.5f' % np.sqrt(mean_squared_error(y_train,y_t
print ('Root Mean Squared Error Test: %.5f' % np.sqrt(mean_squared_error(y_test,y_tes
```

```
Simple Linear Regression on Euclidean Distance Results:
Root Mean Squared Error Train: 3.87634
Root Mean Squared Error Test: 3.87814
```

Simple Linear Regression over 50% of dataset Results: Root Mean Squared Error Train: 3.87634 Root Mean Squared Error Test: 3.87814

Simple Linear Regression frac=0.2 Results: Root Mean Squared Error Train: 3.86948 Root Mean Squared Error Test: 3.87446

4 Checking results with the Test File

In [0]:
```
dir_path = "gdrive/My Drive/Colab Notebooks/Datasets/NYC/"
file_name = "test.csv"
```

In [0]:
```
df_test = pd.read_csv(dir_path+file_name)
```

In [0]:
```
df_test.head()
```

In [0]:
```
from math import sin, cos, asin, sqrt, radians

def euclidean_dist(lon1, lat1, lon2, lat2):
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])
    # haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = (np.sin(dlat/2)**2
         + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2)
    c = 2 * np.arcsin(np.sqrt(a))
    miles = 3959 * c
    return miles
```

In [0]:
```
df_test['euclidean_dist'] = euclidean_dist(df_test.loc[:,'pickup_longitude'].astype(fl
                                            df_test.loc[:,'pickup_latitude'].astype(float),
                                            df_test.loc[:,'dropoff_longitude'].astype(float)
                                            df_test.loc[:,'dropoff_latitude'].astype(float))
```

In [0]:
```
df_test['time_of_day'] = pd.to_datetime(df_test['pickup_datetime']).dt.hour
df_test['year'] = pd.to_datetime(df_test['pickup_datetime']).dt.year
df_test['day_of_week'] = pd.to_datetime(df_test['pickup_datetime']).dt.weekday.astype(
df_test['month_of_year'] = pd.to_datetime(df_test['pickup_datetime']).dt.month
```

In [10]:
```
df_test.shape
```

```
Out[10]: (9914, 12)
```

```
In [11]: features = ['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_lati

         X1_train = df_subset[features].values
         y_train  = df_subset[['fare_amount']].values
         X1_test  = df_test[features].values

         slr = LinearRegression()
         model = slr.fit(X1_train, y_train)
         pred = model.predict(X1_test)
         slr.coef_

         print(pred[:10])
```

```
[[ 9.23534548]
 [ 9.10376691]
 [ 4.82819657]
 [ 8.15740108]
 [16.50943335]
 [11.40557623]
 [ 5.77304848]
 [54.6477168 ]
 [11.84817396]
 [ 6.09650996]]
```

```
In [12]: df_submit = df_test[['key']]
         df_submit['fare_amount'] = pred
         df_submit.to_csv(dir_path+"linear_reg_2.csv", index=False)
         print("Done!")
```

```
Done!
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
In [0]: df_submit.shape
```

```
Out[0]: (9914, 2)
```

4.1 Kaggle RMSE for Linear Regression: 5.814, 5.912, 5.813

5 Random Forest

```
In [0]: import numpy as np                     #For NumPy arrays and mathematical functions
        import pandas as pd                    #For operations using DataFrames
        import matplotlib.pyplot as plt        #For plotting
        import seaborn as sns                  #For plotting
        import time
        import os
```

```
In [0]: from google.colab import drive
        drive.mount('gdrive')
```

```
In [0]: dir_path = "gdrive/My Drive/Colab Notebooks/Datasets/NYC/"
        file_name = "train_cleaned.feather"
```

```
In [0]: !pip install -U feather-format
```

```
In [0]: df = pd.read_feather(dir_path+file_name, nthreads=2)
```

```
/usr/local/lib/python3.6/dist-packages/pandas/io/feather_format.py:112: FutureWarning: `nthreac
  return feather.read_dataframe(path, nthreads=nthreads)
```

```
In [0]: # Loading 20% of the dataset
        df_subset = df.sample(frac=0.1, random_state=42)
        df_subset.head()
```

```
Out[0]:           fare_amount           pickup_datetime  pickup_longitude  \
        44976798         12.5 2011-02-15 11:29:00+00:00        -73.998558
        45538027          4.9 2009-09-26 04:04:00+00:00        -73.988586
        47711137         10.1 2012-07-28 10:09:00+00:00        -73.992920
        19321254          6.5 2012-05-09 22:24:00+00:00        -73.986252
        49976425         12.5 2012-02-08 20:05:00+00:00        -73.994736

                  pickup_latitude  dropoff_longitude  dropoff_latitude  \
        44976798        40.724583         -73.995834         40.767811
        45538027        40.733788         -73.976578         40.727203
        47711137        40.755295         -73.977371         40.784374
        19321254        40.726101         -73.981277         40.744148
        49976425        40.726070         -73.966980         40.758049

                  passenger_count  time_of_day  month_of_year  year  euclidean_dist  \
        44976798                1           11              2  2011        2.990362
        45538027                1            4              9  2009        0.776115
        47711137                4           10              7  2012        2.167814
        19321254                6           22              5  2012        1.273934
        49976425                1           20              2  2012        2.644608

                  day_of_week
```

```
44976798           1
45538027           5
47711137           5
19321254           2
49976425           2
```

```
In [0]: df_subset.shape

Out[0]: (518860, 12)

In [0]: features = ['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitu
                    'passenger_count', 'euclidean_dist', 'year', 'day_of_week', 'time_of_day']
        X = df_subset[features].values
        y = df_subset['fare_amount'].values

In [0]: # Using Skicit-learn to split data into training and testing sets
        from sklearn.model_selection import train_test_split
        # Split the data into training and testing sets
        X_train, X_test , y_train, y_test = train_test_split(X, y, test_size = 0.25, random_sta

In [0]: # Import the model we are using
        from sklearn.ensemble import RandomForestRegressor
        # Instantiate model with 10 decision trees
        rf = RandomForestRegressor(n_estimators = 50, random_state = 42)
        # Train the model on training data
        rf.fit(X_train, y_train)
        y_train_pred = rf.predict(X_train)
        y_test_pred = rf.predict(X_test)

In [0]: from math import sqrt
        import numpy as np
        from sklearn.metrics import mean_squared_error
        print ('Random Forest Results:')
        print ('Root Mean Squared Error Train: %.5f' % np.sqrt(mean_squared_error(y_train,y_tra
        print ('Root Mean Squared Error Test: %.5f' % np.sqrt(mean_squared_error(y_test,y_test_
```

6 Checking with Test File

```
In [0]: dir_path = "gdrive/My Drive/Colab Notebooks/Datasets/NYC/"
        file_name = "test.csv"

In [0]: df_test = pd.read_csv(dir_path+file_name)

In [0]: from math import sin, cos, asin, sqrt, radians

        def euclidean_dist(lon1, lat1, lon2, lat2):
            lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])
            # haversine formula
            dlon = lon2 - lon1
```

```
    dlat = lat2 - lat1
    a = (np.sin(dlat/2)**2
         + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2)
    c = 2 * np.arcsin(np.sqrt(a))
    miles = 3959 * c
    return miles
```

```
In [0]: df_test['euclidean_dist'] = euclidean_dist(df_test.loc[:,'pickup_longitude'].astype(fl
                                                    df_test.loc[:,'pickup_latitude'].astype(float),
                                                    df_test.loc[:,'dropoff_longitude'].astype(float)
                                                    df_test.loc[:,'dropoff_latitude'].astype(float))
```

```
In [0]: df_test['time_of_day'] = pd.to_datetime(df_test['pickup_datetime']).dt.hour
        df_test['year'] = pd.to_datetime(df_test['pickup_datetime']).dt.year
        df_test['day_of_week'] = pd.to_datetime(df_test['pickup_datetime']).dt.weekday.astype(i
        df_test['month_of_year'] = pd.to_datetime(df_test['pickup_datetime']).dt.month
```

```
In [0]: df_test.head()
```

```
In [0]: features = ['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitu
                    'passenger_count', 'euclidean_dist', 'year', 'day_of_week', 'time_of_day']
        X_train = df_subset[features].values
        y_train = df_subset['fare_amount'].values
        X_test = df_test[features].values
```

```
In [0]: # Import the model we are using
        from sklearn.ensemble import RandomForestRegressor
        # Instantiate model with 10 decision trees
        rf = RandomForestRegressor(n_estimators = 50, random_state = 42)
        # Train the model on training data
        rf.fit(X_train, y_train)
        y_train_pred = rf.predict(X_train)
        y_test_pred = rf.predict(X_test)

        print(y_test_pred[:10])
```

```
In [0]: from math import sqrt
        import numpy as np
        from sklearn.metrics import mean_squared_error
        print ('Random Forest Results:')
        print ('Root Mean Squared Error Train: %.5f' % np.sqrt(mean_squared_error(y_train,y_tra
        print ('Root Mean Squared Error Test: %.5f' % np.sqrt(mean_squared_error(y_test,y_test_
```

```
In [0]: df_submit = df_test[['key']]
        df_submit['fare_amount'] = y_test_pred
        df_submit.to_csv(dir_path+"rf_regressor_n100.csv", index=False)
        print("Done!")
```

```
Done!
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

7 Random Forest RMSE over Kaggle:

7.1 1. No. of rows = 1/100 * Cleaned Dataset [Around 520,000 rows] and n_estimators = 50 -> *RMSE: 3.45618*

7.2 2. No. of rows = 1/10 * Cleaned Dataset [Around 5.2 million rows] and n_estimators = 100 -> *RMSE: 3.43151*

7.3 END OF FILE
