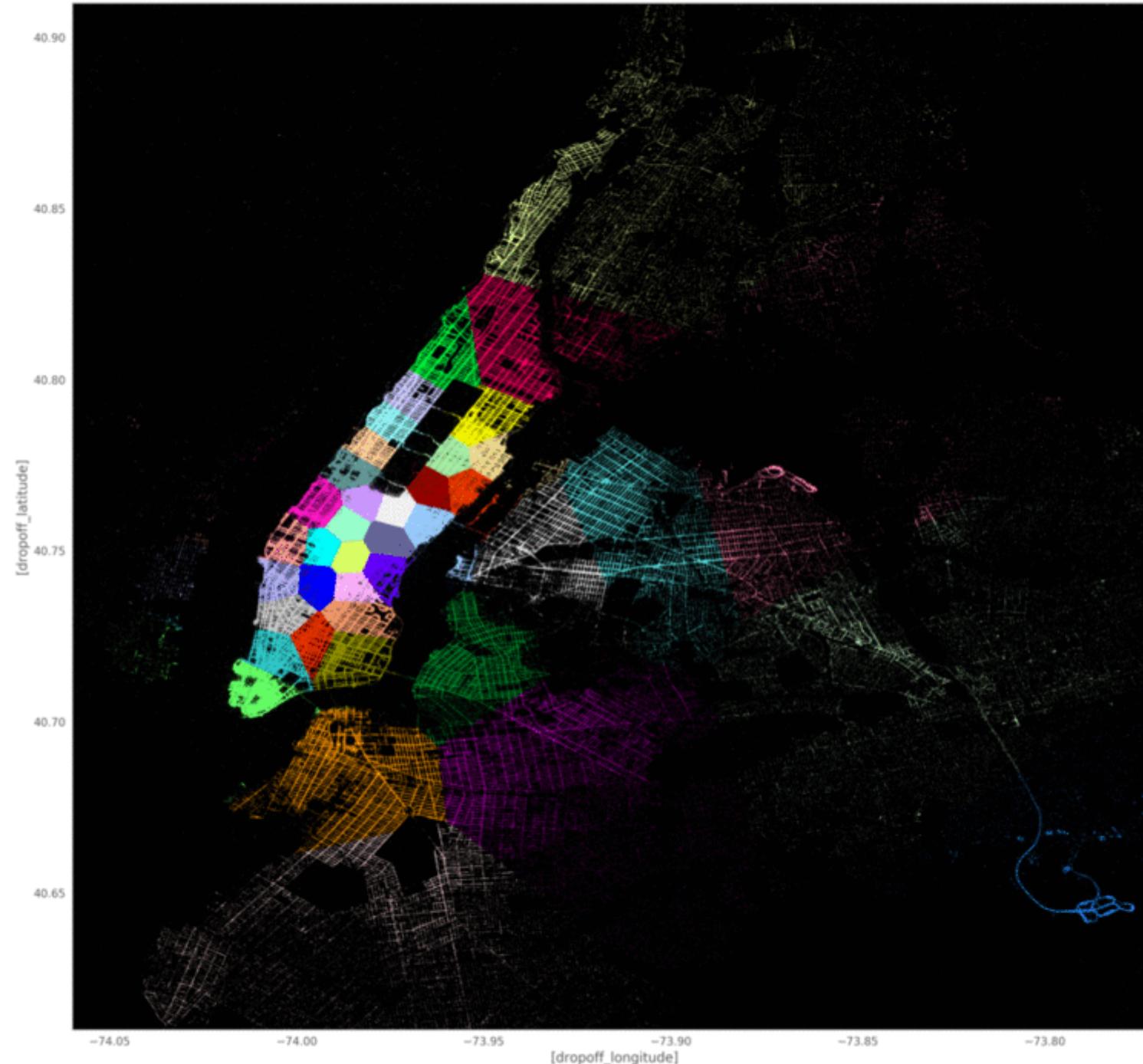


# Taxi demand prediction in New York City



```
In [1]: !pip install gpxpy
```

```
Requirement already satisfied: gpxpy in /usr/local/lib/python3.6/dist-packages (1.3.5)
```

```
In [2]: from google.colab import drive  
drive.mount('/content/drive')  
  
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
In [0]: %matplotlib inline
```

```
In [0]: #Importing Libraries  
# pip3 install graphviz  
#pip3 install dask  
#pip3 install toolz  
#pip3 install cloudpickle  
# https://www.youtube.com/watch?v=ieW3G7ZzRZ0  
# https://github.com/dask/dask-tutorial  
# please do go through this python notebook: https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ipynb  
import dask.dataframe as dd#similar to pandas  
  
import pandas as pd#pandas to create small dataframes  
  
# pip3 install folium  
# if this doesnt work refere install_folium.JPG in drive  
import folium #open street map  
  
# unix time: https://www.unixtimestamp.com/  
import datetime #Convert to unix time  
  
import time #Convert to unix time  
  
# if numpy is not installed already : pip3 install numpy  
import numpy as np#Do aritmetic operations on arrays  
  
# matplotlib: used to plot graphs  
import matplotlib  
# matplotlib.use('nbagg') : matplotlib uses this protocall which makes plots more user intractive like zoom in and zoom out  
matplotlib.use('nbagg')  
import matplotlib.pyplot as plt  
import seaborn as sns#Plots  
from matplotlib import rcParams#Size of plots  
  
# this lib is used while we calculate the stight line distance between two (lat,lon) pairs in miles  
import gpxpy.geo #Get the haversine distance  
  
from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering  
import math  
import pickle  
import os  
import scipy  
  
# download mingw: https://mingw-w64.org/doku.php/download/mingw-builds  
# install it in your system and keep the path, mingw_path ='installed path'  
# mingw_path = 'C:\\\\Program Files\\\\mingw-w64\\\\x86_64-5.3.0-posix-seh-rt_v4-rev0\\\\mingw64\\\\bin'  
# os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']  
  
# to install xgboost: pip3 install xgboost  
# if it didnt happen check install_xgboost.JPG  
import xgboost as xgb  
  
# to install sklearn: pip install -U scikit-learn  
from sklearn.ensemble import RandomForestRegressor  
from sklearn.metrics import mean_squared_error  
from sklearn.metrics import mean_absolute_error  
import warnings  
warnings.filterwarnings("ignore")
```

```
In [0]: dir_path="/content/drive/My Drive/Colab Notebooks/AppliedAI/NY_Taxi_Demand_Prediction/"
```

## Data Information

Get the data from : [http://www.nyc.gov/html/tlc/html/about/trip\\_record\\_data.shtml](http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml) (2016 data) The data used in the attached datasets were collected and provided to the NYC Taxi and Limousine Commission (TLC)

### Information on taxis:

#### ***Yellow Taxi: Yellow Medallion Taxicabs***

These are the famous NYC yellow taxis that provide transportation exclusively through street-hails. The number of taxicabs is limited by a finite number of medallions issued by the TLC. You access this mode of transportation by standing in the street and hailing an available taxi with your hand. The pickups are not pre-arranged.

#### ***For Hire Vehicles (FHV)s***

FHV transportation is accessed by a pre-arrangement with a dispatcher or limo company. These FHVs are not permitted to pick up passengers via street hails, as those rides are not considered pre-arranged.

#### ***Green Taxi: Street Hail Livery (SHL)***

The SHL program will allow livery vehicle owners to license and outfit their vehicles with green borough taxi branding, meters, credit card machines, and ultimately the right to accept street hails in addition to pre-arranged rides.

Credits: Quora

#### ***Footnote:***

In the given notebook we are considering only the yellow taxis for the time period between Jan - Mar 2015 & Jan - Mar 2016

# Data Collection

We Have collected all yellow taxi trips data from jan-2015 to dec-2016(Will be using only 2015 data)

file name	file name size	number of records	number of features
yellow_tripdata_2016-01	1. 59G	10906858	19
yellow_tripdata_2016-02	1. 66G	11382049	19
yellow_tripdata_2016-03	1. 78G	12210952	19
yellow_tripdata_2016-04	1. 74G	11934338	19
yellow_tripdata_2016-05	1. 73G	11836853	19
yellow_tripdata_2016-06	1. 62G	11135470	19
yellow_tripdata_2016-07	884Mb	10294080	17
yellow_tripdata_2016-08	854Mb	9942263	17
yellow_tripdata_2016-09	870Mb	10116018	17
yellow_tripdata_2016-10	933Mb	10854626	17
yellow_tripdata_2016-11	868Mb	10102128	17
yellow_tripdata_2016-12	897Mb	10449408	17
yellow_tripdata_2015-01	1.84Gb	12748986	19
yellow_tripdata_2015-02	1.81Gb	12450521	19
yellow_tripdata_2015-03	1.94Gb	13351609	19
yellow_tripdata_2015-04	1.90Gb	13071789	19
yellow_tripdata_2015-05	1.91Gb	13158262	19
yellow_tripdata_2015-06	1.79Gb	12324935	19
yellow_tripdata_2015-07	1.68Gb	11562783	19
yellow_tripdata_2015-08	1.62Gb	11130304	19
yellow_tripdata_2015-09	1.63Gb	11225063	19
yellow_tripdata_2015-10	1.79Gb	12315488	19
yellow_tripdata_2015-11	1.65Gb	11312676	19
yellow_tripdata_2015-12	1.67Gb	11460573	19

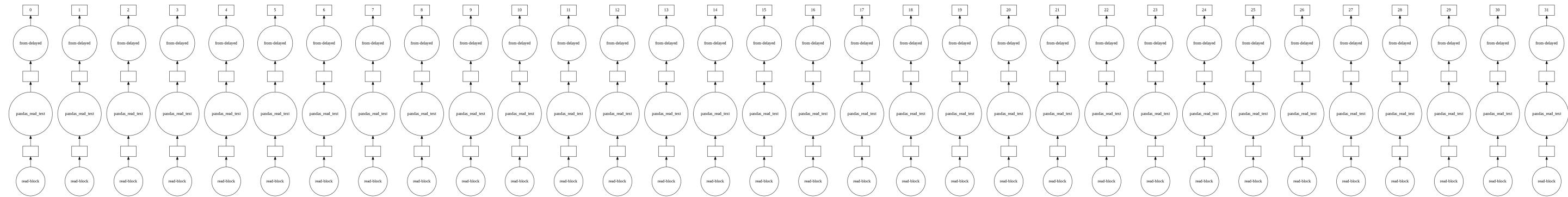
```
In [6]: #Looking at the features
# dask dataframe : # https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ipynb
month = dd.read_csv(dir_path+'yellow_tripdata_2015-01.csv')
print(month.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'pickup_longitude',
       'pickup_latitude', 'RateCodeID', 'store_and_fwd_flag',
       'dropoff_longitude', 'dropoff_latitude', 'payment_type', 'fare_amount',
       'extra', 'mta_tax', 'tip_amount', 'tolls_amount',
       'improvement_surcharge', 'total_amount'],
      dtype='object')
```

```
In [0]: # However unlike Pandas, operations on dask.dataframes don't trigger immediate computation,  
# instead they add key-value pairs to an underlying Dask graph. Recall that in the diagram below,  
# circles are operations and rectangles are results.
```

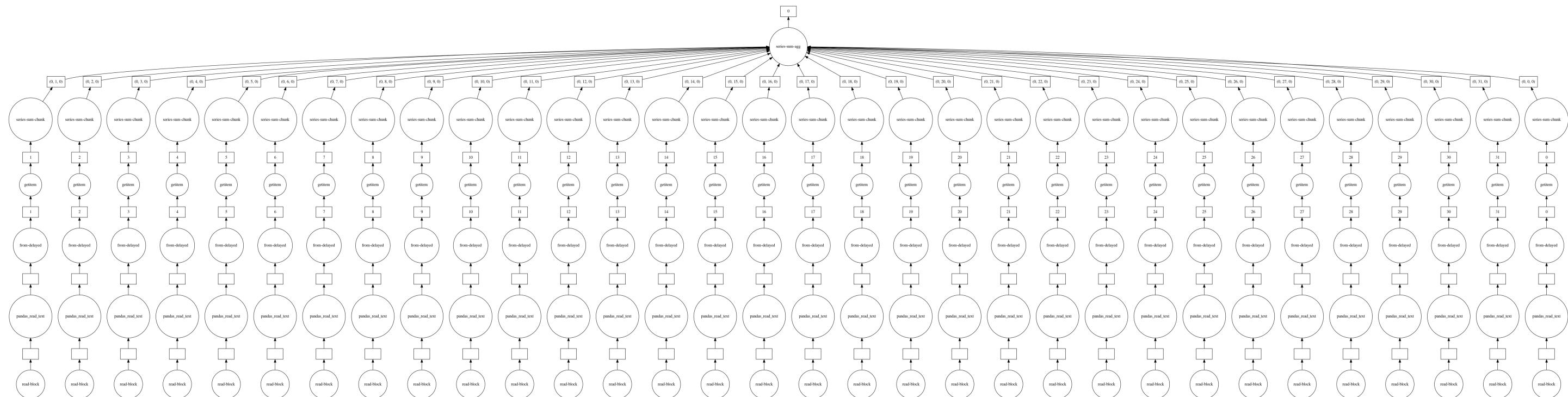
```
# to see the visualization you need to install graphviz  
# pip3 install graphviz if this doesnt work please check the install_graphviz.jpg in the drive  
month.visualize()
```

Out[0]:



```
In [0]: month.fare_amount.sum().visualize()
```

Out[0]:



## Features in the dataset:

Field Name		Description
VendorID	1. 2.	A code indicating the TPEP provider that provided the record. Creative Mobile Technologies VeriFone Inc.
tpep_pickup_datetime		The date and time when the meter was engaged.
tpep_dropoff_datetime		The date and time when the meter was disengaged.
Passenger_count		The number of passengers in the vehicle. This is a driver-entered value.
Trip_distance		The elapsed trip distance in miles reported by the taximeter.
Pickup_longitude		Longitude where the meter was engaged.
Pickup_latitude		Latitude where the meter was engaged.
RateCodeID	1. 2. 3. 4. 5. 6.	The final rate code in effect at the end of the trip. Standard rate JFK Newark Nassau or Westchester Negotiated fare Group ride
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka "store and forward," because the vehicle did not have a connection to the server. Y= store and forward trip N= not a store and forward trip	
Dropoff_longitude		Longitude where the meter was disengaged.
Dropoff_latitude		Latitude where the meter was disengaged.
Payment_type	1. 2. 3. 4. 5. 6.	A numeric code signifying how the passenger paid for the trip. Credit card Cash No charge Dispute Unknown Voided trip
Fare_amount		The time-and-distance fare calculated by the meter.
Extra		Miscellaneous extras and surcharges. Currently, this only includes. the 0.50 and 1 rush hour and overnight charges.
MTA_tax		0.50 MTA tax that is automatically triggered based on the metered rate in use.
Improvement_surcharge		0.30 improvement surcharge assessed trips at the flag drop. the improvement surcharge began being levied in 2015.
Tip_amount		Tip amount – This field is automatically populated for credit card tips.Cash tips are not included.
Tolls_amount		Total amount of all tolls paid in trip.
Total_amount		The total amount charged to passengers. Does not include cash tips.

## ML Problem Formulation

### Time-series forecasting and Regression

- To find number of pickups, given location coordinates(latitude and longitude) and time, in the query region and surrounding regions.

To solve the above we would be using data collected in Jan - Mar 2015 to predict the pickups in Jan - Mar 2016.

## Performance metrics

1. Mean Absolute percentage error.
2. Mean Squared error.

## Data Cleaning

In this section we will be doing univariate analysis and removing outlier/illegitimate values which may be caused due to some error

```
In [0]: #table below shows few datapoints along with all our features  
month.head(5)
```

Out[0]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	pickup_longitude	pickup_latitude	RateCodeID	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type	fare_amount	extra	mt
0	2	2015-01-15 19:05:39	2015-01-15 19:23:42	1	1.59	-73.993896	40.750111	1	N	-73.974785	40.750618	1	12.0	1.0	
1	1	2015-01-10 20:33:38	2015-01-10 20:53:28	1	3.30	-74.001648	40.724243	1	N	-73.994415	40.759109	1	14.5	0.5	
2	1	2015-01-10 20:33:38	2015-01-10 20:43:41	1	1.80	-73.963341	40.802788	1	N	-73.951820	40.824413	2	9.5	0.5	
3	1	2015-01-10 20:33:39	2015-01-10 20:35:31	1	0.50	-74.009087	40.713818	1	N	-74.004326	40.719986	2	3.5	0.5	
4	1	2015-01-10 20:33:39	2015-01-10 20:52:58	1	3.00	-73.971176	40.762428	1	N	-74.004181	40.742653	2	15.0	0.5	

### 1. Pickup Latitude and Pickup Longitude

It is inferred from the source <https://www.flickr.com/places/info/2459115> (<https://www.flickr.com/places/info/2459115>) that New York is bounded by the location coordinates(lat,long) - (40.5774, -74.15) & (40.9176,-73.7004) so hence any coordinates not within these coordinates are not considered by us as we are only concerned with pickups which originate within New York.

```
In [0]: # Plotting pickup coordinates which are outside the bounding box of New-York
# we will collect all the points outside the bounding box of newyork city to outlier_locations
outlier_locations = month[((month.pickup_longitude <= -74.15) | (month.pickup_latitude <= 40.5774)| \
                           (month.pickup_longitude >= -73.7004) | (month.pickup_latitude >= 40.9176))]

# creating a map with the a base location
# read more about the folium here: http://folium.readthedocs.io/en/latest/quickstart.html

# note: you dont need to remember any of these, you dont need indeepth knowledge on these maps and plots

map_osm = folium.Map(location=[40.734695, -73.990372], tiles='Stamen Toner')

# we will spot only first 100 outliers on the map, plotting all the outliers will take more time
sample_locations = outlier_locations.head(10000)
for i,j in sample_locations.iterrows():
    if int(j['pickup_latitude']) != 0:
        folium.Marker(list((j['pickup_latitude'],j['pickup_longitude']))).add_to(map_osm)
map_osm
```

Out[0]:

+  
-



Leaflet (<http://leafletjs.com>)

**Observation:-** As you can see above that there are some points just outside the boundary but there are a few that are in either South America, Mexico or Canada

## 2. Dropoff Latitude & Dropoff Longitude

It is inferred from the source <https://www.flickr.com/places/info/2459115> (<https://www.flickr.com/places/info/2459115>) that New York is bounded by the location coordinates(lat,long) - (40.5774, -74.15) & (40.9176,-73.7004) so hence any coordinates not within these coordinates are not considered by us as we are only concerned with dropoffs which are within New York.

```
In [0]: # Plotting dropoff coordinates which are outside the bounding box of New-York
# we will collect all the points outside the bounding box of newyork city to outlier_locations
outlier_locations = month[((month.dropoff_longitude <= -74.15) | (month.dropoff_latitude <= 40.5774) | \
                           (month.dropoff_longitude >= -73.7004) | (month.dropoff_latitude >= 40.9176))]

# creating a map with the a base location
# read more about the folium here: http://folium.readthedocs.io/en/latest/quickstart.html

# note: you dont need to remember any of these, you dont need indeepth knowledge on these maps and plots

map_osm = folium.Map(location=[40.734695, -73.990372], tiles='Stamen Toner')

# we will spot only first 100 outliers on the map, plotting all the outliers will take more time
sample_locations = outlier_locations.head(10000)
for i,j in sample_locations.iterrows():
    if int(j['pickup_latitude']) != 0:
        folium.Marker(list((j['dropoff_latitude'],j['dropoff_longitude']))).add_to(map_osm)
map_osm
```

Out[0]:

+

-



Leaflet (<http://leafletjs.com>)

**Observation:-** The observations here are similar to those obtained while analysing pickup latitude and longitude

### 3. Trip Durations:

According to NYC Taxi & Limousine Commission Regulations **the maximum allowed trip duration in a 24 hour interval is 12 hours.**

```
In [0]: #The timestamps are converted to unix so as to get duration(trip-time) & speed also pickup-times in unix are used while binning

# in out data we have time in the formate "YYYY-MM-DD HH:MM:SS" we convert thiss sting to python time formate and then into unix time stamp
# https://stackoverflow.com/a/27914405
def convert_to_unix(s):
    return time.mktime(datetime.datetime.strptime(s, "%Y-%m-%d %H:%M:%S").timetuple())

# we return a data frame which contains the columns
# 1. 'passenger_count' : self explanatory
# 2. 'trip_distance' : self explanatory
# 3. 'pickup_longitude' : self explanatory
# 4. 'pickup_latitude' : self explanatory
# 5. 'dropoff_longitude' : self explanatory
# 6. 'dropoff_latitude' : self explanatory
# 7. 'total_amount' : total fair that was paid
# 8. 'trip_times' : duration of each trip
# 9. 'pickup_times' : pickup time converted into unix time
# 10. 'Speed' : velocity of each trip
def return_with_trip_times(month):
    duration = month[['tpep_pickup_datetime', 'tpep_dropoff_datetime']].compute()
    #pickups and dropoffs to unix time
    duration_pickup = [convert_to_unix(x) for x in duration['tpep_pickup_datetime'].values]
    duration_drop = [convert_to_unix(x) for x in duration['tpep_dropoff_datetime'].values]
    #calculate duration of trips
    durations = (np.array(duration_drop) - np.array(duration_pickup))/float(60)

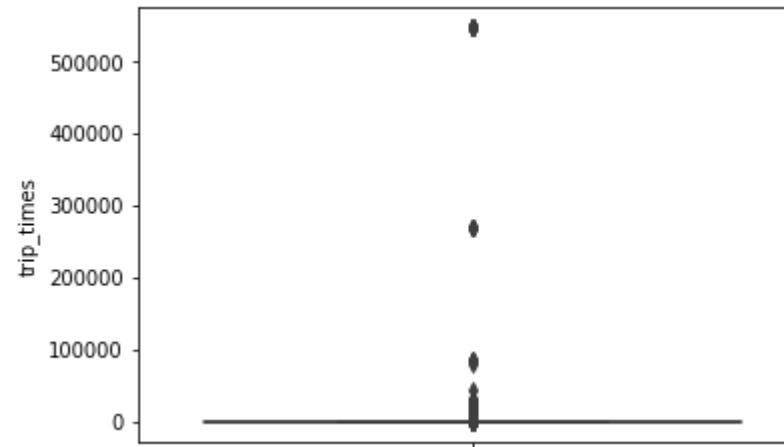
    #append durations of trips and speed in miles/hr to a new dataframe
    new_frame = month[['passenger_count', 'trip_distance', 'pickup_longitude', 'pickup_latitude',
                       'dropoff_longitude', 'dropoff_latitude', 'total_amount']].compute()

    new_frame['trip_times'] = durations
    new_frame['pickup_times'] = duration_pickup
    new_frame['Speed'] = 60*(new_frame['trip_distance']/new_frame['trip_times'])

    return new_frame

# print(frame_with_durations.head())
#   passenger_count      trip_distance     pickup_longitude     pickup_latitude     dropoff_longitude     dropoff_latitude    total_amount    trip_times    pickup_time
#   mes Speed
# 1  1.59      -73.993896      40.750111      -73.974785      40.750618      17.05      18.050000  1.421329e+09
# 5.285319
# 1  3.30      -74.001648      40.724243      -73.994415      40.759109      17.80      19.833333  1.420902e
# +9  9.983193
# 1  1.80      -73.963341      40.802788      -73.951820      40.824413      10.80      10.050000  1.420902e
# +9  10.746269
# 1  0.50      -74.009087      40.713818      -74.004326      40.719986      4.80      1.866667  1.420902e
# +9  16.071429
# 1  3.00      -73.971176      40.762428      -74.004181      40.742653      16.30      19.316667  1.420902e
# +9  9.318378
frame_with_durations = return_with_trip_times(month)
```

```
In [0]: # the skewed box plot shows us the presence of outliers  
sns.boxplot(y="trip_times", data =frame_with_durations)  
plt.show()
```



```
In [0]: #calculating 0-100th percentile to find a the correct percentile value for removal of outliers  
for i in range(0,100,10):  
    var =frame_with_durations["trip_times"].values  
    var = np.sort(var, axis = None)  
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))  
print ("100 percentile value is ",var[-1])
```

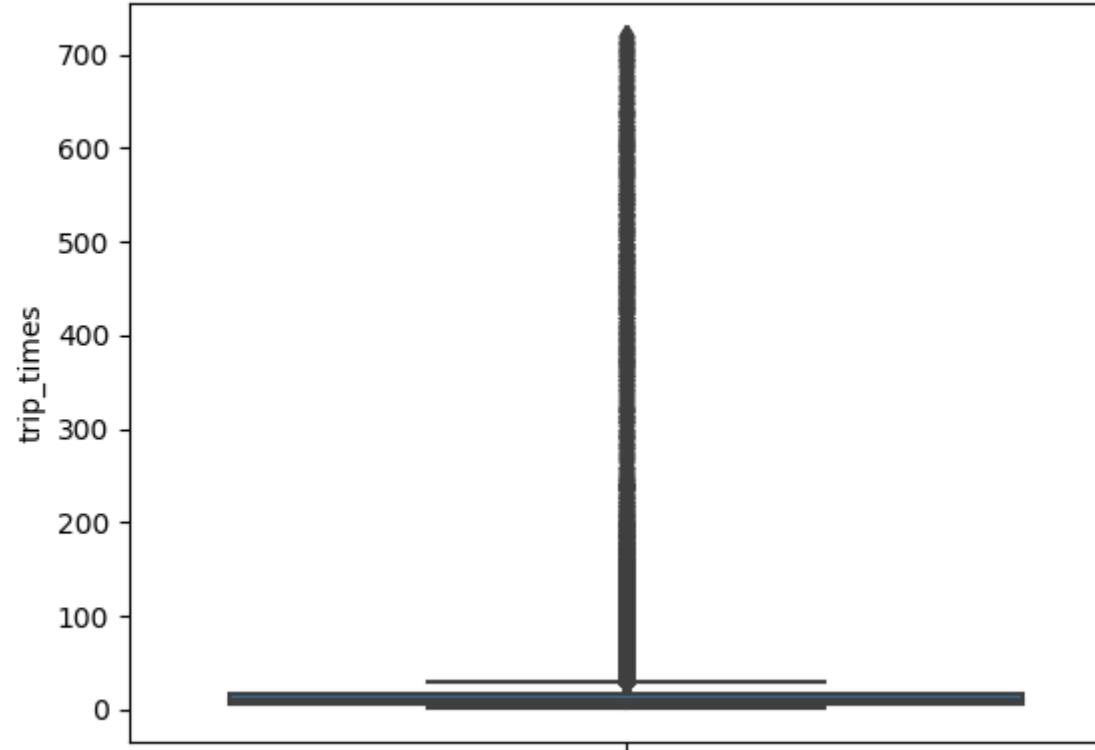
```
0 percentile value is -1211.0166666666667  
10 percentile value is 3.833333333333335  
20 percentile value is 5.38333333333334  
30 percentile value is 6.816666666666666  
40 percentile value is 8.3  
50 percentile value is 9.95  
60 percentile value is 11.866666666666667  
70 percentile value is 14.28333333333333  
80 percentile value is 17.63333333333333  
90 percentile value is 23.45  
100 percentile value is 548555.633333
```

```
In [0]: #looking further from the 99th percecntile  
for i in range(90,100):  
    var =frame_with_durations["trip_times"].values  
    var = np.sort(var, axis = None)  
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))  
print ("100 percentile value is ",var[-1])
```

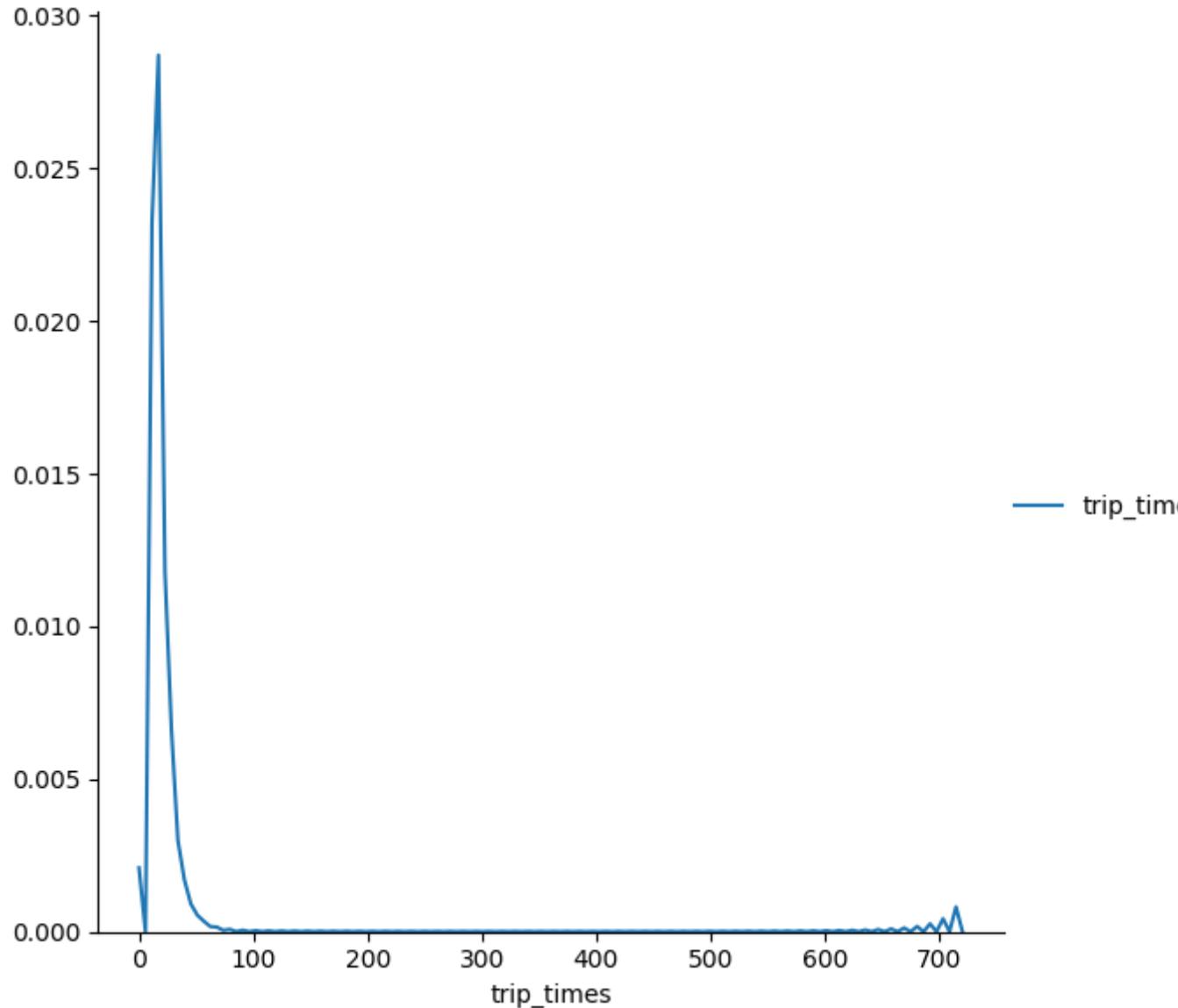
```
90 percentile value is 23.45  
91 percentile value is 24.35  
92 percentile value is 25.38333333333333  
93 percentile value is 26.55  
94 percentile value is 27.93333333333334  
95 percentile value is 29.58333333333332  
96 percentile value is 31.68333333333334  
97 percentile value is 34.46666666666667  
98 percentile value is 38.71666666666667  
99 percentile value is 46.75  
100 percentile value is 548555.633333
```

```
In [0]: #removing data based on our analysis and TLC regulations  
frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_times>1) & \  
                                                 (frame_with_durations.trip_times<720)]
```

```
In [0]: #box-plot after removal of outliers  
sns.boxplot(y="trip_times", data =frame_with_durations_modified)  
plt.show()
```



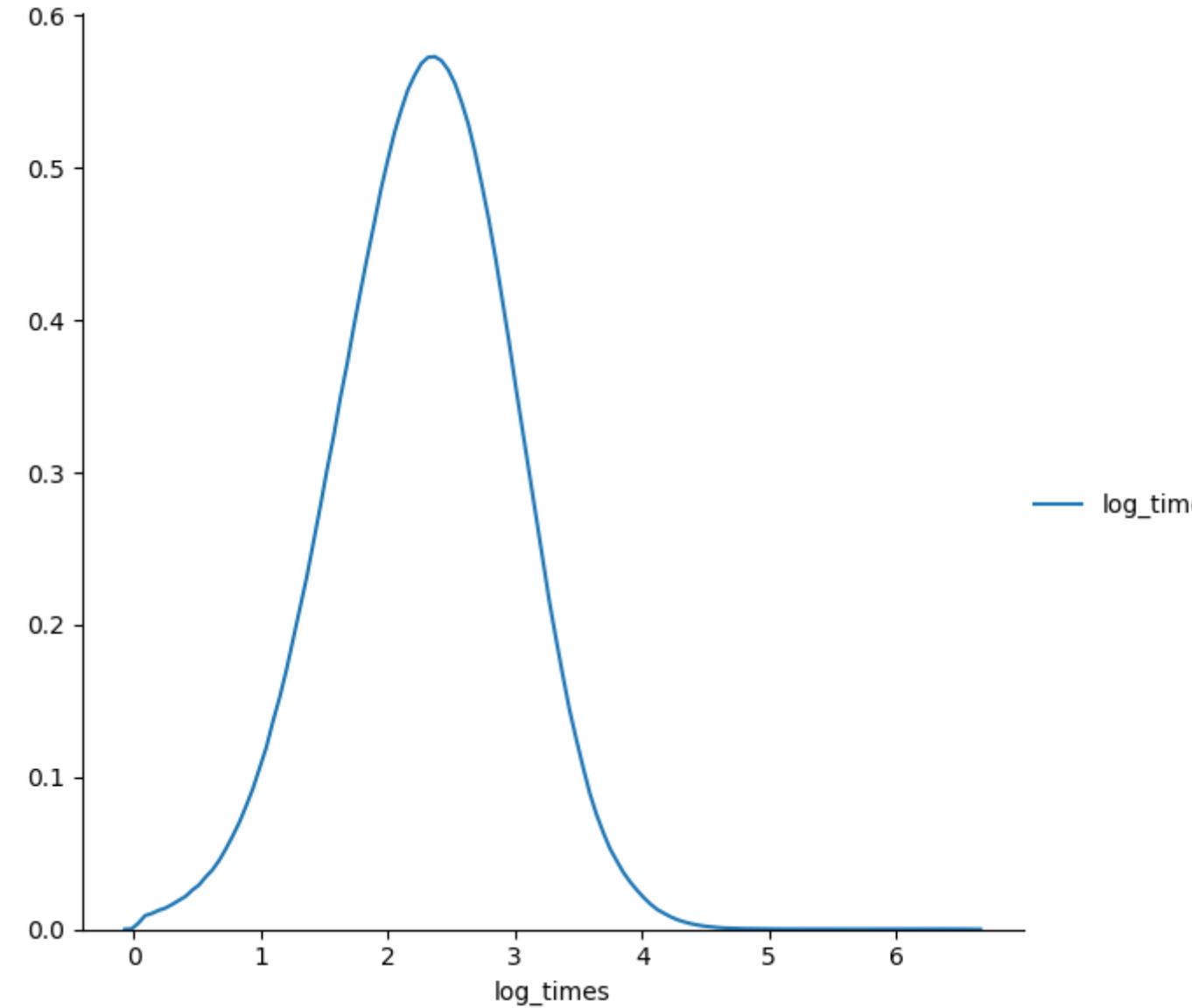
```
In [0]: #pdf of trip-times after removing the outliers  
sns.FacetGrid(frame_with_durations_modified,size=6) \  
    .map(sns.kdeplot,"trip_times") \  
    .add_legend();  
plt.show();
```



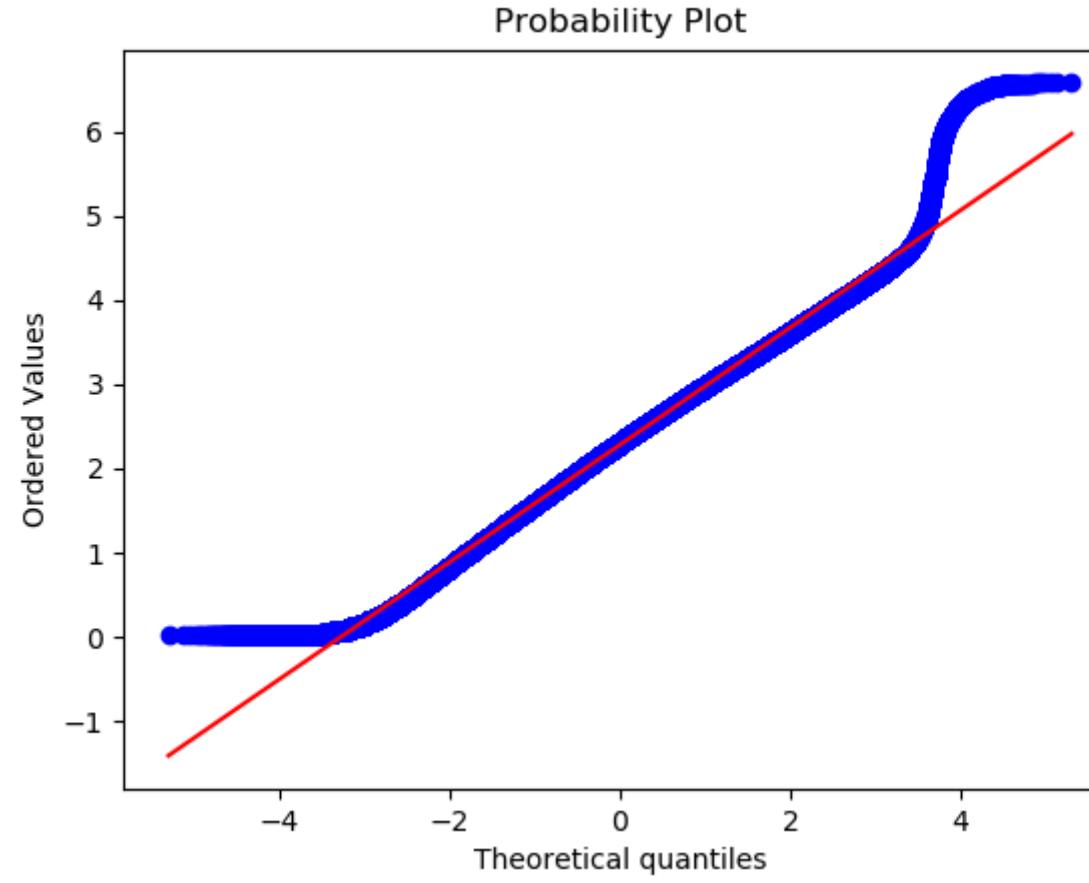
```
In [0]: #converting the values to log-values to chec for log-normal  
import math  
frame_with_durations_modified['log_times']=[math.log(i) for i in \  
    frame_with_durations_modified['trip_times'].values]
```

In [0]: #pdf of log-values

```
sns.FacetGrid(frame_with_durations_modified,size=6) \
    .map(sns.kdeplot,"log_times") \
    .add_legend();
plt.show();
```



```
In [0]: #Q-Q plot for checking if trip-times is log-normal  
scipy.stats.probplot(frame_with_durations_modified['log_times'].values, plot=plt)  
plt.show()
```



#### 4. Speed

```
In [11]: # check for any outliers in the data after trip duration outliers removed  
# box-plot for speeds with outliers  
frame_with_durations_modified['Speed'] = \  
    60*(frame_with_durations_modified['trip_distance']/frame_with_durations_modified['trip_times'])  
sns.boxplot(y="Speed", data =frame_with_durations_modified)  
plt.show()
```

```
In [0]: #calculating speed values at each percentile 0,10,20,30,40,50,60,70,80,90,100
for i in range(0,100,10):
    var = frame_with_durations_modified["Speed"].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var))*(float(i)/100)]))
print("100 percentile value is ",var[-1])
```

0 percentile value is 0.0  
10 percentile value is 6.409495548961425  
20 percentile value is 7.80952380952381  
30 percentile value is 8.929133858267717  
40 percentile value is 9.98019801980198  
50 percentile value is 11.06865671641791  
60 percentile value is 12.286689419795222  
70 percentile value is 13.796407185628745  
80 percentile value is 15.963224893917962  
90 percentile value is 20.186915887850468  
100 percentile value is 192857142.857

```
In [0]: #calculating speed values at each percentile 90,91,92,93,94,95,96,97,98,99,100
for i in range(90,100):
    var = frame_with_durations_modified[ "Speed" ].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print("100 percentile value is ",var[-1])

90 percentile value is 20.186915887850468
91 percentile value is 20.91645569620253
92 percentile value is 21.752988047808763
93 percentile value is 22.721893491124263
94 percentile value is 23.844155844155843
95 percentile value is 25.182552504038775
96 percentile value is 26.80851063829787
97 percentile value is 28.84304932735426
98 percentile value is 31.591128254580514
99 percentile value is 35.7513566847558
100 percentile value is 192857142.857
```

```
In [0]: #calculating speed values at each percentile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9
for i in np.arange(0.0, 1.0, 0.1):
    var = frame_with_durations_modified["Speed"].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var))*(float(99+i)/100))]))
print("100 percentile value is ",var[-1])
```

99.0 percentile value is 35.7513566847558  
99.1 percentile value is 36.31084727468969  
99.2 percentile value is 36.91470054446461  
99.3 percentile value is 37.588235294117645  
99.4 percentile value is 38.33035714285714  
99.5 percentile value is 39.17580340264651  
99.6 percentile value is 40.15384615384615  
99.7 percentile value is 41.338301043219076  
99.8 percentile value is 42.86631016042781  
99.9 percentile value is 45.3107822410148  
100 percentile value is 192857142.857

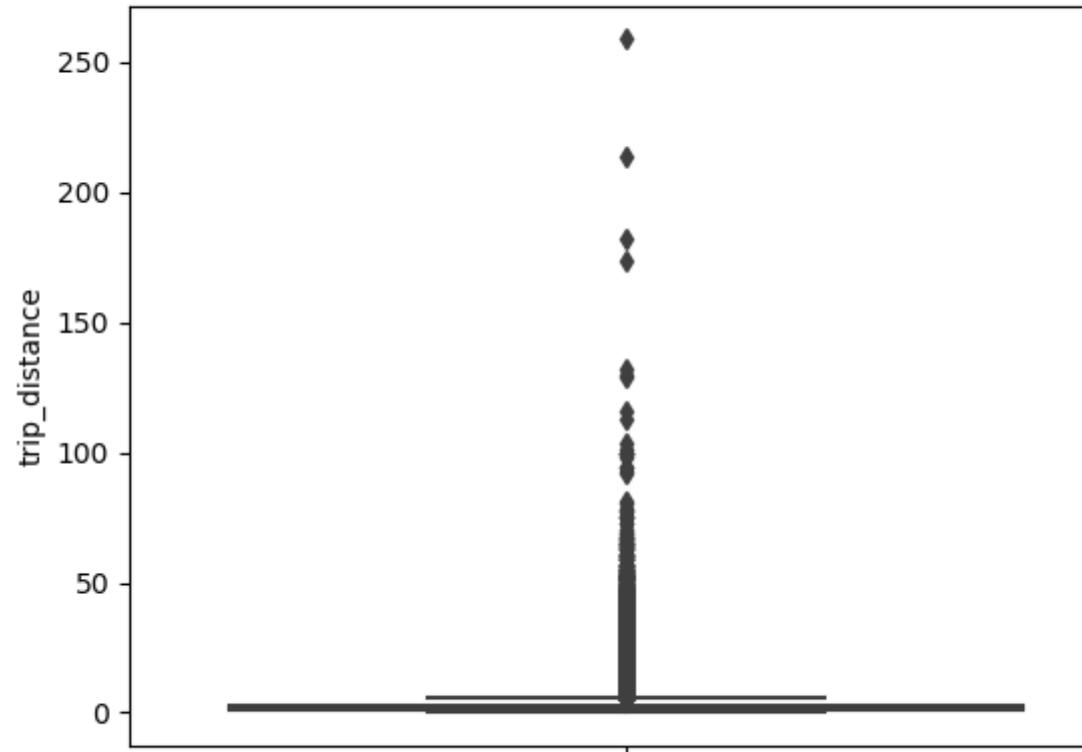
```
In [13]: #avg.speed of cabs in New-York  
sum(frame_with_durations_modified["Speed"]) / float(len(frame_with_durations_modified["Speed"]))
```

```
Out[13]: 12.450173996027528
```

The avg speed in Newyork speed is 12.45miles/hr, so a cab driver can travel 2 miles per 10min on avg.

#### 4. Trip Distance

```
In [0]: # up to now we have removed the outliers based on trip durations and cab speeds  
# lets try if there are any outliers in trip distances  
# box-plot showing outliers in trip-distance values  
sns.boxplot(y="trip_distance", data =frame_with_durations_modified)  
plt.show()
```



```
In [0]: #calculating trip distance values at each percentile 0,10,20,30,40,50,60,70,80,90,100
for i in range(0,100,10):
    var =frame_with_durations_modified["trip_distance"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))])))
print("100 percentile value is ",var[-1])
```

```
0 percentile value is 0.01
10 percentile value is 0.66
20 percentile value is 0.9
30 percentile value is 1.1
40 percentile value is 1.39
50 percentile value is 1.69
60 percentile value is 2.07
70 percentile value is 2.6
80 percentile value is 3.6
90 percentile value is 5.97
100 percentile value is 258.9
```

```
In [0]: #calculating trip distance values at each percentile 90,91,92,93,94,95,96,97,98,99,100
for i in range(90,100):
    var =frame_with_durations_modified["trip_distance"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print("100 percentile value is ",var[-1])
```

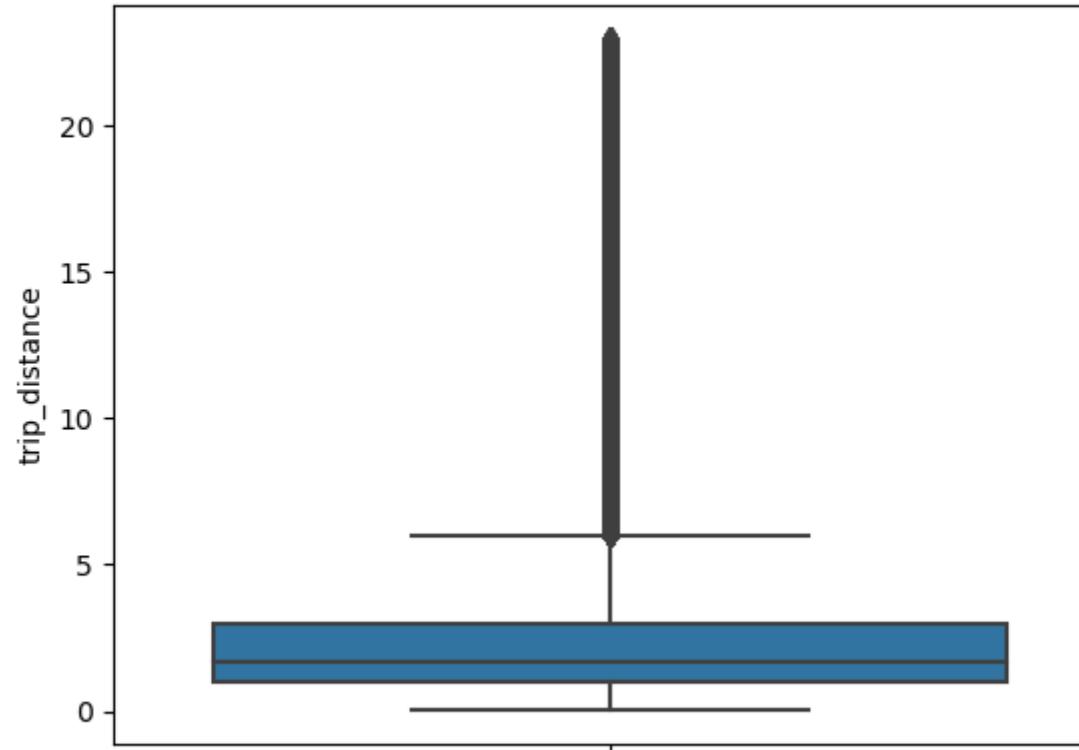
```
90 percentile value is 5.97
91 percentile value is 6.45
92 percentile value is 7.07
93 percentile value is 7.85
94 percentile value is 8.72
95 percentile value is 9.6
96 percentile value is 10.6
97 percentile value is 12.1
98 percentile value is 16.03
99 percentile value is 18.17
100 percentile value is 258.9
```

```
In [0]: #calculating trip distance values at each percentile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100
for i in np.arange(0.0, 1.0, 0.1):
    var =frame_with_durations_modified["trip_distance"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]))
print("100 percentile value is ",var[-1])
```

```
99.0 percentile value is 18.17
99.1 percentile value is 18.37
99.2 percentile value is 18.6
99.3 percentile value is 18.83
99.4 percentile value is 19.13
99.5 percentile value is 19.5
99.6 percentile value is 19.96
99.7 percentile value is 20.5
99.8 percentile value is 21.22
99.9 percentile value is 22.57
100 percentile value is 258.9
```

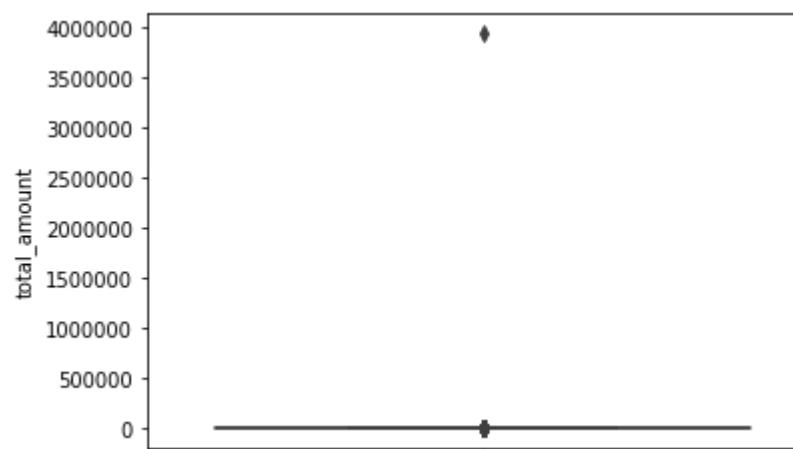
```
In [0]: #removing further outliers based on the 99.9th percentile value
frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_distance>0) & \
(frame_with_durations.trip_distance<23)]
```

```
In [0]: #box-plot after removal of outliers  
sns.boxplot(y="trip_distance", data = frame_with_durations_modified)  
plt.show()
```



## 5. Total Fare

```
In [0]: # up to now we have removed the outliers based on trip durations, cab speeds, and trip distances  
# lets try if there are any outliers in based on the total_amount  
# box-plot showing outliers in fare  
%matplotlib inline  
sns.boxplot(y="total_amount", data =frame_with_durations_modified)  
plt.show()
```



```
In [0]: #calculating total fare amount values at each percentile 0,10,20,30,40,50,60,70,80,90,100
for i in range(0,100,10):
    var = frame_with_durations_modified["total_amount"].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))])))
print("100 percentile value is ",var[-1])
```

```
0 percentile value is -242.55
10 percentile value is 6.3
20 percentile value is 7.8
30 percentile value is 8.8
40 percentile value is 9.8
50 percentile value is 11.16
60 percentile value is 12.8
70 percentile value is 14.8
80 percentile value is 18.3
90 percentile value is 25.8
100 percentile value is 3950611.6
```

```
In [0]: #calculating total fare amount values at each percentile 90,91,92,93,94,95,96,97,98,99,100
for i in range(90,100):
    var = frame_with_durations_modified["total_amount"].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))])))
print("100 percentile value is ",var[-1])
```

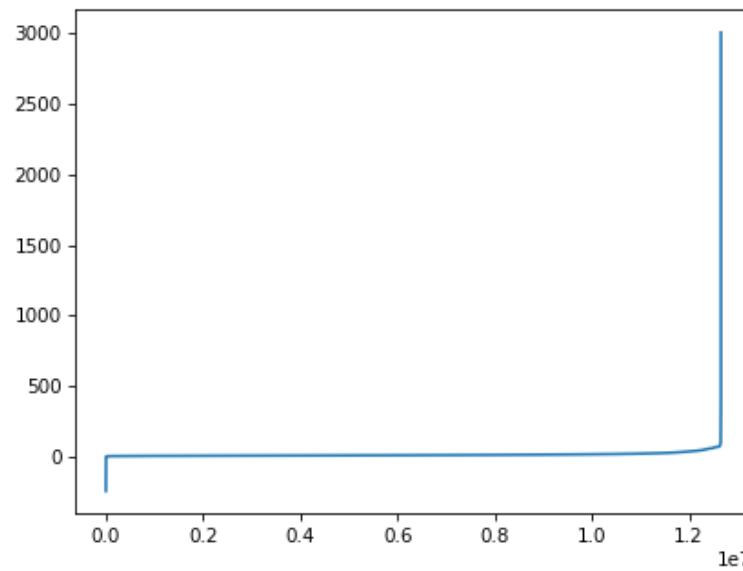
```
90 percentile value is 25.8
91 percentile value is 27.3
92 percentile value is 29.3
93 percentile value is 31.8
94 percentile value is 34.8
95 percentile value is 38.53
96 percentile value is 42.6
97 percentile value is 48.13
98 percentile value is 58.13
99 percentile value is 66.13
100 percentile value is 3950611.6
```

```
In [0]: #calculating total fare amount values at each percentile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100
for i in np.arange(0.0, 1.0, 0.1):
    var = frame_with_durations_modified["total_amount"].values
    var = np.sort(var, axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))])))
print("100 percentile value is ",var[-1])
```

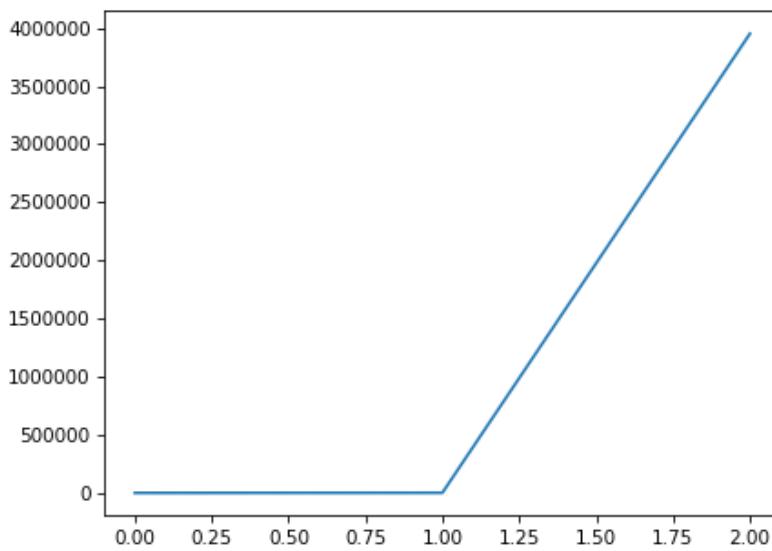
```
99.0 percentile value is 68.13
99.1 percentile value is 69.13
99.2 percentile value is 69.6
99.3 percentile value is 69.73
99.4 percentile value is 69.73
99.5 percentile value is 69.76
99.6 percentile value is 72.46
99.7 percentile value is 72.73
99.8 percentile value is 80.05
99.9 percentile value is 95.55
100 percentile value is 3950611.6
```

**Observation:-** As even the 99.9th percentile value doesn't look like an outlier, as there is not much difference between the 99.8th percentile and 99.9th percentile, we move on to do graphical analysis

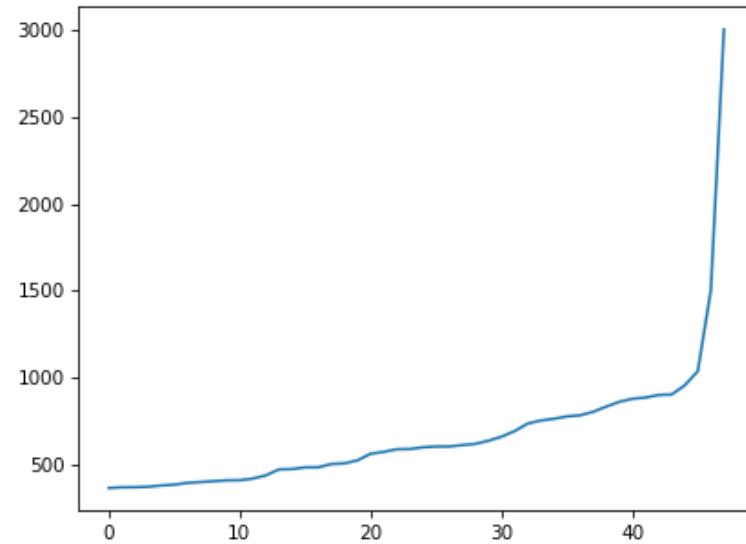
```
In [0]: #below plot shows us the fare values(sorted) to find a sharp increase to remove those values as outliers  
# plot the fare amount excluding last two values in sorted data  
plt.plot(var[:-2])  
plt.show()
```



```
In [0]: # a very sharp increase in fare values can be seen  
# plotting last three total fare values, and we can observe there is share increase in the values  
plt.plot(var[-3:])  
plt.show()
```



```
In [0]: #now looking at values not including the last two points we again find a drastic increase at around 1000 fare value  
# we plot last 50 values excluding last two values  
plt.plot(var[-50:-2])  
plt.show()
```



**Remove all outliers/errorous points.**

```
In [0]: #removing all outliers based on our univariate analysis above
def remove_outliers(new_frame):
    a = new_frame.shape[0]
    print ("Number of pickup records = ",a)
    temp_frame = new_frame[((new_frame.dropoff_longitude >= -74.15) & (new_frame.dropoff_longitude <= -73.7004) & \
                           (new_frame.dropoff_latitude >= 40.5774) & (new_frame.dropoff_latitude <= 40.9176)) & \
                           ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_latitude >= 40.5774)& \
                           (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_latitude <= 40.9176))]
    b = temp_frame.shape[0]
    print ("Number of outlier coordinates lying outside NY boundaries:",(a-b))

    temp_frame = new_frame[(new_frame.trip_times > 0) & (new_frame.trip_times < 720)]
    c = temp_frame.shape[0]
    print ("Number of outliers from trip times analysis:",(a-c))

    temp_frame = new_frame[(new_frame.trip_distance > 0) & (new_frame.trip_distance < 23)]
    d = temp_frame.shape[0]
    print ("Number of outliers from trip distance analysis:",(a-d))

    temp_frame = new_frame[(new_frame.Speed <= 65) & (new_frame.Speed >= 0)]
    e = temp_frame.shape[0]
    print ("Number of outliers from speed analysis:",(a-e))

    temp_frame = new_frame[(new_frame.total_amount <1000) & (new_frame.total_amount >0)]
    f = temp_frame.shape[0]
    print ("Number of outliers from fare analysis:",(a-f))

    new_frame = new_frame[((new_frame.dropoff_longitude >= -74.15) & (new_frame.dropoff_longitude <= -73.7004) & \
                           (new_frame.dropoff_latitude >= 40.5774) & (new_frame.dropoff_latitude <= 40.9176)) & \
                           ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_latitude >= 40.5774)& \
                           (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_latitude <= 40.9176))]

    new_frame = new_frame[(new_frame.trip_times > 0) & (new_frame.trip_times < 720)]
    new_frame = new_frame[(new_frame.trip_distance > 0) & (new_frame.trip_distance < 23)]
    new_frame = new_frame[(new_frame.Speed < 45.31) & (new_frame.Speed > 0)]
    new_frame = new_frame[(new_frame.total_amount <1000) & (new_frame.total_amount >0)]

    print ("Total outliers removed",a - new_frame.shape[0])
    print ("---")
    return new_frame
```

```
In [16]: print ("Removing outliers in the month of Jan-2015")
print ("----")
frame_with_durations_outliers_removed = remove_outliers(frame_with_durations)
print("fraction of data points that remain after removing outliers", float(len(frame_with_durations_outliers_removed))/len(frame_with_durations))
```

Removing outliers in the month of Jan-2015

---

Number of pickup records = 12748986  
 Number of outlier coordinates lying outside NY boundaries: 293919  
 Number of outliers from trip times analysis: 23889  
 Number of outliers from trip distance analysis: 92597  
 Number of outliers from speed analysis: 24473  
 Number of outliers from fare analysis: 5275  
 Total outliers removed 377910

---

fraction of data points that remain after removing outliers 0.9703576425607495

**Data-preperation**

**Clustering/Segmentation**

```
In [17]: #trying different cluster sizes to choose the right K in K-means
coords = frame_with_durations_outliers_removed[['pickup_latitude', 'pickup_longitude']].values
neighbours=[]

def find_min_distance(cluster_centers, cluster_len):
    nice_points = 0
    wrong_points = 0
    less2 = []
    more2 = []
    min_dist=1000
    for i in range(0, cluster_len):
        nice_points = 0
        wrong_points = 0
        for j in range(0, cluster_len):
            if j!=i:
                distance = gpxpy.geo.haversine_distance(cluster_centers[i][0], cluster_centers[i][1],
                                              cluster_centers[j][0], cluster_centers[j][1])
                min_dist = min(min_dist,distance/(1.60934*1000))
                if (distance/(1.60934*1000)) <= 2:
                    nice_points +=1
                else:
                    wrong_points += 1
        less2.append(nice_points)
        more2.append(wrong_points)
    neighbours.append(less2)
    print ("On choosing a cluster size of ",cluster_len,"Avg. Number of Clusters within the vicinity "+\
          "(i.e. intercluster-distance < 2):", np.ceil(sum(less2)/len(less2)), "\nAvg. Number of Clusters"+\
          " outside the vicinity (i.e. intercluster-distance > 2):", np.ceil(sum(more2)/len(more2)),\
          "\nMin inter-cluster distance = ",min_dist,"---")

def find_clusters(increment):
    kmeans = MiniBatchKMeans(n_clusters=increment, batch_size=10000,random_state=42).fit(coords)
    frame_with_durations_outliers_removed['pickup_cluster'] = \
        kmeans.predict(frame_with_durations_outliers_removed[['pickup_latitude',
                                                               'pickup_longitude']])
    cluster_centers = kmeans.cluster_centers_
    cluster_len = len(cluster_centers)
    return cluster_centers, cluster_len

# we need to choose number of clusters so that, there are more number of cluster regions
# that are close to any cluster center
# and make sure that the minimum inter cluster should not be very less
for increment in range(10, 100, 10):
    cluster_centers, cluster_len = find_clusters(increment)
    find_min_distance(cluster_centers, cluster_len)
```

On choosing a cluster size of 10  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 2.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 8.0  
Min inter-cluster distance = 1.0945442325142543  
---  
On choosing a cluster size of 20  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 4.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 16.0  
Min inter-cluster distance = 0.7131298007387813  
---  
On choosing a cluster size of 30  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 8.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 22.0  
Min inter-cluster distance = 0.5185088176172206  
---  
On choosing a cluster size of 40  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 8.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 32.0  
Min inter-cluster distance = 0.5069768450363973  
---  
On choosing a cluster size of 50  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 12.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 38.0  
Min inter-cluster distance = 0.365363025983595  
---  
On choosing a cluster size of 60  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 14.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 46.0  
Min inter-cluster distance = 0.34704283494187155  
---  
On choosing a cluster size of 70  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 16.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 54.0  
Min inter-cluster distance = 0.30502203163244707  
---  
On choosing a cluster size of 80  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 18.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 62.0  
Min inter-cluster distance = 0.29220324531738534  
---  
On choosing a cluster size of 90  
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance < 2): 21.0  
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance > 2): 69.0  
Min inter-cluster distance = 0.18257992857034985  
---

## Inference:

- The main objective was to find a optimal min. distance (Which roughly estimates to the radius of a cluster) between the clusters which we got was 4.

```
In [0]: # if check for the 50 clusters you can observe that there are two clusters with only 0.3 miles apart from  
# each other so we choose 40 clusters for solve the further problem  
  
# Getting 40 clusters using the kmeans  
kmeans = MiniBatchKMeans(n_clusters=40, batch_size=10000, random_state=0).fit(coords)  
frame_with_durations_outliers_removed['pickup_cluster'] = \  
    kmeans.predict(frame_with_durations_outliers_removed[['pickup_latitude',  
        'pickup_longitude']])
```

## Plotting the cluster centers:

```
In [19]: # Plotting the cluster centers on OSM
cluster_centers = kmeans.cluster_centers_
cluster_len = len(cluster_centers)
map_osm = folium.Map(location=[40.734695, -73.990372], tiles='Stamen Toner')
for i in range(cluster_len):
    folium.Marker(list((cluster_centers[i][0],cluster_centers[i][1])),
                 popup=(str(cluster_centers[i][0])+str(cluster_centers[i][1]))).add_to(map_osm)
map_osm
```

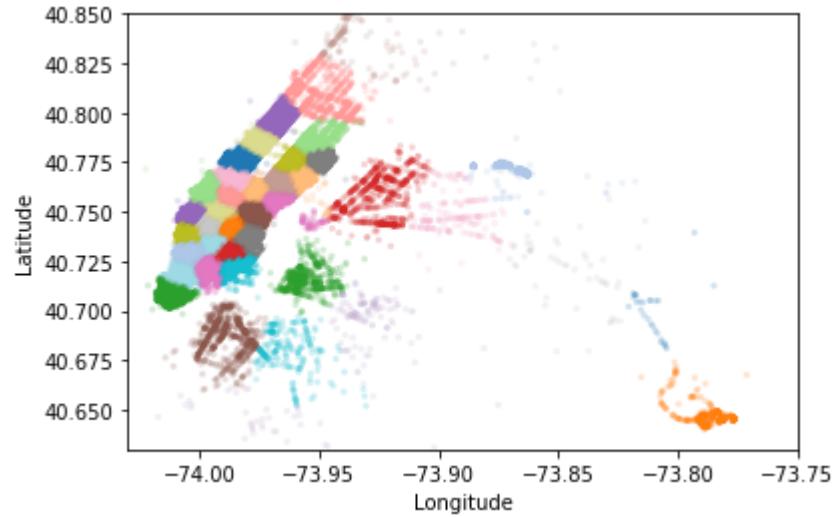
Out[19]:



## Plotting the clusters:

```
In [0]: #Visualising the clusters on a map
def plot_clusters(frame):
    city_long_border = (-74.03, -73.75)
    city_lat_border = (40.63, 40.85)
    fig, ax = plt.subplots(ncols=1, nrows=1)
    ax.scatter(frame.pickup_longitude.values[:100000], frame.pickup_latitude.values[:100000], s=10, lw=0,
               c=frame.pickup_cluster.values[:100000], cmap='tab20', alpha=0.2)
    ax.set_xlim(city_long_border)
    ax.set_ylim(city_lat_border)
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')
    plt.show()

plot_clusters(frame_with_durations_outliers_removed)
```



## Time-binning

```
In [0]: #Refer:https://www.unixtimestamp.com/
# 1420070400 : 2015-01-01 00:00:00
# 1422748800 : 2015-02-01 00:00:00
# 1425168000 : 2015-03-01 00:00:00
# 1427846400 : 2015-04-01 00:00:00
# 1430438400 : 2015-05-01 00:00:00
# 1433116800 : 2015-06-01 00:00:00

# 1451606400 : 2016-01-01 00:00:00
# 1454284800 : 2016-02-01 00:00:00
# 1456790400 : 2016-03-01 00:00:00
# 1459468800 : 2016-04-01 00:00:00
# 1462060800 : 2016-05-01 00:00:00
# 1464739200 : 2016-06-01 00:00:00

def add_pickup_bins(frame,month,year):
    unix_pickup_times=[i for i in frame['pickup_times'].values]
    unix_times = [[1420070400,1422748800,1425168000,1427846400,1430438400,1433116800],\
                  [1451606400,1454284800,1456790400,1459468800,1462060800,1464739200]]

    start_pickup_unix=unix_times[year-2015][month-1]
    # https://www.timeanddate.com/time/zones/est
    # (int((i-start_pickup_unix)/600)+33) : our unix time is in gmt to we are converting it to est
    tenminutewise_binned_unix_pickup_times=[(int((i-start_pickup_unix)/600)+33) for i in unix_pickup_times]
    frame['pickup_bins'] = np.array(tenminutewise_binned_unix_pickup_times)
    return frame
```

```
In [0]: # clustering, making pickup bins and grouping by pickup cluster and pickup bins
frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(\n                           frame_with_durations_outliers_removed[['pickup_latitude',\n                                         'pickup_longitude']])
jan_2015_frame = add_pickup_bins(frame_with_durations_outliers_removed,1,2015)
jan_2015_groupby = jan_2015_frame[['pickup_cluster','pickup_bins',\n                                     'trip_distance']].groupby(['pickup_cluster','pickup_bins']).count()
```

```
In [0]: # we add two more columns 'pickup_cluster'(to which cluster it belongs to)
# and 'pickup_bins' (to which 10min intravel the trip belongs to)
jan_2015_frame.head()
```

Out[0]:

	passenger_count	trip_distance	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	total_amount	trip_times	pickup_times	Speed	pickup_cluster	pickup_bins
0	1	1.59	-73.993896	40.750111	-73.974785	40.750618	17.05	18.050000	1.421349e+09	5.285319	34	2163
1	1	3.30	-74.001648	40.724243	-73.994415	40.759109	17.80	19.833333	1.420922e+09	9.983193	2	1452
2	1	1.80	-73.963341	40.802788	-73.951820	40.824413	10.80	10.050000	1.420922e+09	10.746269	16	1452
3	1	0.50	-74.009087	40.713818	-74.004326	40.719986	4.80	1.866667	1.420922e+09	16.071429	38	1452
4	1	3.00	-73.971176	40.762428	-74.004181	40.742653	16.30	19.316667	1.420922e+09	9.318378	22	1452

```
In [0]: # hear the trip_distance represents the number of pickups that are happend in that particular 10min intravel  
# this data frame has two indices  
# primary index: pickup_cluster (cluster number)  
# secondary index : pickup_bins (we divide whole months time into 10min intravels 24*31*60/10 =4464bins)  
jan_2015_groupby.head()
```

Out[0]:

	trip_distance	
	pickup_cluster	pickup_bins
0	33	104
	34	200
	35	208
	36	141
	37	155

In [22]: # upto now we cleaned data and prepared data for the month 2015,

```
# now do the same operations for months Jan, Feb, March of 2016
# 1. get the dataframe which includes only required columns
# 2. adding trip times, speed, unix time stamp of pickup_time
# 4. remove the outliers based on trip_times, speed, trip_duration, total_amount
# 5. add pickup_cluster to each data point
# 6. add pickup_bin (index of 10min intravel to which that trip belongs to)
# 7. group by data, based on 'pickup_cluster' and 'pickup_bin'

# Data Preparation for the months of Jan, Feb and March 2016
def datapreparation(month,kmeans,month_no,year_no):

    print ("Return with trip times..")

    frame_with_durations = return_with_trip_times(month)

    print ("Remove outliers..")
    frame_with_durations_outliers_removed = remove_outliers(frame_with_durations)

    print ("Estimating clusters..")
    frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_durations_outliers_removed[['pickup_latitude', 'pickup_longitude']])
#frame_with_durations_outliers_removed_2016['pickup_cluster'] = kmeans.predict(frame_with_durations_outliers_removed_2016[['pickup_latitude', 'pickup_longitude']])

    print ("Final groupbying..")
    final_updated_frame = add_pickup_bins(frame_with_durations_outliers_removed,month_no,year_no)
    final_groupby_frame = final_updated_frame[['pickup_cluster','pickup_bins','trip_distance']].groupby(['pickup_cluster','pickup_bins']).count()

    return final_updated_frame,final_groupby_frame

month_jan_2016 = dd.read_csv(dir_path+'yellow_tripdata_2016-01.csv')
month_feb_2016 = dd.read_csv(dir_path+'yellow_tripdata_2016-02.csv')
month_mar_2016 = dd.read_csv(dir_path+'yellow_tripdata_2016-03.csv')

jan_2016_frame,jan_2016_groupby = datapreparation(month_jan_2016,kmeans,1,2016)
feb_2016_frame,feb_2016_groupby = datapreparation(month_feb_2016,kmeans,2,2016)
mar_2016_frame,mar_2016_groupby = datapreparation(month_mar_2016,kmeans,3,2016)
```

```

Return with trip times..
Remove outliers..
Number of pickup records = 10906858
Number of outlier coordinates lying outside NY boundaries: 214677
Number of outliers from trip times analysis: 27190
Number of outliers from trip distance analysis: 79742
Number of outliers from speed analysis: 21047
Number of outliers from fare analysis: 4991
Total outliers removed 297784
---
Estimating clusters..
Final groupbying..
Return with trip times..
Remove outliers..
Number of pickup records = 11382049
Number of outlier coordinates lying outside NY boundaries: 223161
Number of outliers from trip times analysis: 27670
Number of outliers from trip distance analysis: 81902
Number of outliers from speed analysis: 22437
Number of outliers from fare analysis: 5476
Total outliers removed 308177
---
Estimating clusters..
Final groupbying..
Return with trip times..
Remove outliers..
Number of pickup records = 12210952
Number of outlier coordinates lying outside NY boundaries: 232444
Number of outliers from trip times analysis: 30868
Number of outliers from trip distance analysis: 87318
Number of outliers from speed analysis: 23889
Number of outliers from fare analysis: 5859
Total outliers removed 324635
---
Estimating clusters..
Final groupbying..

```

## Smoothing

```
In [0]: # Gets the unique bins where pickup values are present for each each region

# for each cluster region we will collect all the indices of 10min intravels in
# which the pickups happened and we got an observation that there are some pickup
# bins that dont have any pickups
def return_unq_pickup_bins(frame):
    values = []
    for i in range(0,40):
        new = frame[frame['pickup_cluster'] == i]
        list_unq = list(set(new['pickup_bins']))
        list_unq.sort()
        values.append(list_unq)
    return values
```

```
In [0]: # for every month we get all indices of 10min intravels in which atleast one  
# pickup got happened
```

```
#jan  
jan_2015_unique = return_unq_pickup_bins(jan_2015_frame)  
jan_2016_unique = return_unq_pickup_bins(jan_2016_frame)  
  
#feb  
feb_2016_unique = return_unq_pickup_bins(feb_2016_frame)  
  
#march  
mar_2016_unique = return_unq_pickup_bins(mar_2016_frame)
```

```
In [0]: # for each cluster number of 10min intavels with 0 pickups
for i in range(40):
    print("for the ",i,"th cluster number of 10min intavels with zero pickups: ",4464 - len(set(jan_2015_unique[i])))
    print('-'*60)
```

```
for the 0 th cluster number of 10min intavels with zero pickups: 40
-----
for the 1 th cluster number of 10min intavels with zero pickups: 1985
-----
for the 2 th cluster number of 10min intavels with zero pickups: 29
-----
for the 3 th cluster number of 10min intavels with zero pickups: 354
-----
for the 4 th cluster number of 10min intavels with zero pickups: 37
-----
for the 5 th cluster number of 10min intavels with zero pickups: 153
-----
for the 6 th cluster number of 10min intavels with zero pickups: 34
-----
for the 7 th cluster number of 10min intavels with zero pickups: 34
-----
for the 8 th cluster number of 10min intavels with zero pickups: 117
-----
for the 9 th cluster number of 10min intavels with zero pickups: 40
-----
for the 10 th cluster number of 10min intavels with zero pickups: 25
-----
for the 11 th cluster number of 10min intavels with zero pickups: 44
-----
for the 12 th cluster number of 10min intavels with zero pickups: 42
-----
for the 13 th cluster number of 10min intavels with zero pickups: 28
-----
for the 14 th cluster number of 10min intavels with zero pickups: 26
-----
for the 15 th cluster number of 10min intavels with zero pickups: 31
-----
for the 16 th cluster number of 10min intavels with zero pickups: 40
-----
for the 17 th cluster number of 10min intavels with zero pickups: 58
-----
for the 18 th cluster number of 10min intavels with zero pickups: 1190
-----
for the 19 th cluster number of 10min intavels with zero pickups: 1357
-----
for the 20 th cluster number of 10min intavels with zero pickups: 53
-----
for the 21 th cluster number of 10min intavels with zero pickups: 29
-----
for the 22 th cluster number of 10min intavels with zero pickups: 29
-----
for the 23 th cluster number of 10min intavels with zero pickups: 163
-----
for the 24 th cluster number of 10min intavels with zero pickups: 35
-----
for the 25 th cluster number of 10min intavels with zero pickups: 41
-----
for the 26 th cluster number of 10min intavels with zero pickups: 31
-----
for the 27 th cluster number of 10min intavels with zero pickups: 214
-----
for the 28 th cluster number of 10min intavels with zero pickups: 36
-----
for the 29 th cluster number of 10min intavels with zero pickups: 41
-----
for the 30 th cluster number of 10min intavels with zero pickups: 1180
-----
for the 31 th cluster number of 10min intavels with zero pickups: 42
-----
for the 32 th cluster number of 10min intavels with zero pickups: 44
```

```

for the 33 th cluster number of 10min intavels with zero pickups: 43
-----
for the 34 th cluster number of 10min intavels with zero pickups: 39
-----
for the 35 th cluster number of 10min intavels with zero pickups: 42
-----
for the 36 th cluster number of 10min intavels with zero pickups: 36
-----
for the 37 th cluster number of 10min intavels with zero pickups: 321
-----
for the 38 th cluster number of 10min intavels with zero pickups: 36
-----
for the 39 th cluster number of 10min intavels with zero pickups: 43
-----
```

there are two ways to fill up these values

- Fill the missing value with 0's
- Fill the missing values with the avg values
  - Case 1:(values missing at the start)  
 Ex1:  $\lfloor \frac{x}{4} \rfloor \Rightarrow \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4})$   
 Ex2:  $\lfloor \frac{x}{3} \rfloor \Rightarrow \text{ceil}(\frac{x}{3}), \text{ceil}(\frac{x}{3}), \text{ceil}(\frac{x}{3})$
  - Case 2:(values missing in middle)  
 Ex1:  $\lfloor \frac{x+y}{4} \rfloor \Rightarrow \text{ceil}(\frac{x+y}{4}), \text{ceil}(\frac{x+y}{4}), \text{ceil}(\frac{x+y}{4}), \text{ceil}(\frac{x+y}{4})$   
 Ex2:  $\lfloor \frac{x+y}{5} \rfloor \Rightarrow \text{ceil}(\frac{x+y}{5}), \text{ceil}(\frac{x+y}{5}), \text{ceil}(\frac{x+y}{5}), \text{ceil}(\frac{x+y}{5}), \text{ceil}(\frac{x+y}{5})$
  - Case 3:(values missing at the end)  
 Ex1:  $\lfloor \frac{x}{4} \rfloor \Rightarrow \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4}), \text{ceil}(\frac{x}{4})$   
 Ex2:  $\lfloor \frac{x}{2} \rfloor \Rightarrow \text{ceil}(\frac{x}{2}), \text{ceil}(\frac{x}{2})$

```
In [0]: # Fills a value of zero for every bin where no pickup data is present
# the count_values: number pickps that are happened in each region for each 10min
# interval there wont be any value if there are no pickups.
# values: number of unique bins

# for every 10min intravel(pickup_bin) we will check it is there in our unique bin,
# if it is there we will add the count_values[index] to smoothed data
# if not we add 0 to the smoothed data
# we finally return smoothed data
def fill_missing(count_values,values):
    smoothed_regions=[]
    ind=0
    for r in range(0,40):
        smoothed_bins=[]
        for i in range(4464):
            if i in values[r]:
                smoothed_bins.append(count_values[ind])
                ind+=1
            else:
                smoothed_bins.append(0)
        smoothed_regions.extend(smoothed_bins)
    return smoothed_regions
```

```
In [0]: # Fills a value of zero for every bin where no pickup data is present
# the count_values: number pickups that have happened in each region for each 10min
# interval there wont be any value if there are no pickups.
# values: number of unique bins

# for every 10min intravel(pickup_bin) we will check it is there in our unique bin,
# if it is there we will add the count_values[index] to smoothed data
# if not we add smoothed data (which is calculated based on the methods that are discussed in the above markdown cell)
# we finally return smoothed data
def smoothing(count_values,values):
    smoothed_regions=[] # stores list of final smoothed values of each region
    ind=0
    repeat=0
    smoothed_value=0
    for r in range(0,40):
        smoothed_bins=[] #stores the final smoothed values
        repeat=0
        for i in range(4464):
            if repeat!=0: # prevents iteration for a value which is already visited/resolved
                repeat-=1
                continue
            if i in values[r]: #checks if the pickup-bin exists
                smoothed_bins.append(count_values[ind]) # appends the value of the pickup bin if it exists
            else:
                if i!=0:
                    right_hand_limit=0
                    for j in range(i,4464):
                        if j not in values[r]: #searches for the left-limit or the pickup-bin value which has a pickup value
                            continue
                        else:
                            right_hand_limit=j
                            break
                    if right_hand_limit==0:
                        #Case 1: When we have the last/last few values are found to be missing,hence we have no right-limit here
                        smoothed_value=count_values[ind-1]*1.0/((4463-i)+2)*1.0
                        for j in range(i,4464):
                            smoothed_bins.append(math.ceil(smoothed_value))
                        smoothed_bins[i-1] = math.ceil(smoothed_value)
                        repeat=(4463-i)
                        ind-=1
                else:
                    #Case 2: When we have the missing values between two known values
                    smoothed_value=(count_values[ind-1]+count_values[ind])*1.0/((right_hand_limit-i)+2)*1.0
                    for j in range(i,right_hand_limit+1):
                        smoothed_bins.append(math.ceil(smoothed_value))
                    smoothed_bins[i-1] = math.ceil(smoothed_value)
                    repeat=(right_hand_limit-i)
            else:
                #Case 3: When we have the first/first few values are found to be missing,hence we have no left-limit here
                right_hand_limit=0
                for j in range(i,4464):
                    if j not in values[r]:
                        continue
                    else:
                        right_hand_limit=j
                        break
                smoothed_value=count_values[ind]*1.0/((right_hand_limit-i)+1)*1.0
                for j in range(i,right_hand_limit+1):
                    smoothed_bins.append(math.ceil(smoothed_value))
                repeat=(right_hand_limit-i)
            ind+=1
        smoothed_regions.extend(smoothed_bins)
    return smoothed_regions
```

```
In [0]: # Filling Missing values of Jan-2015 with 0
# here in jan_2015_groupby dataframe the trip_distance represents the number of pickups that are happened
jan_2015_fill = fill_missing(jan_2015_groupby['trip_distance'].values,jan_2015_unique)

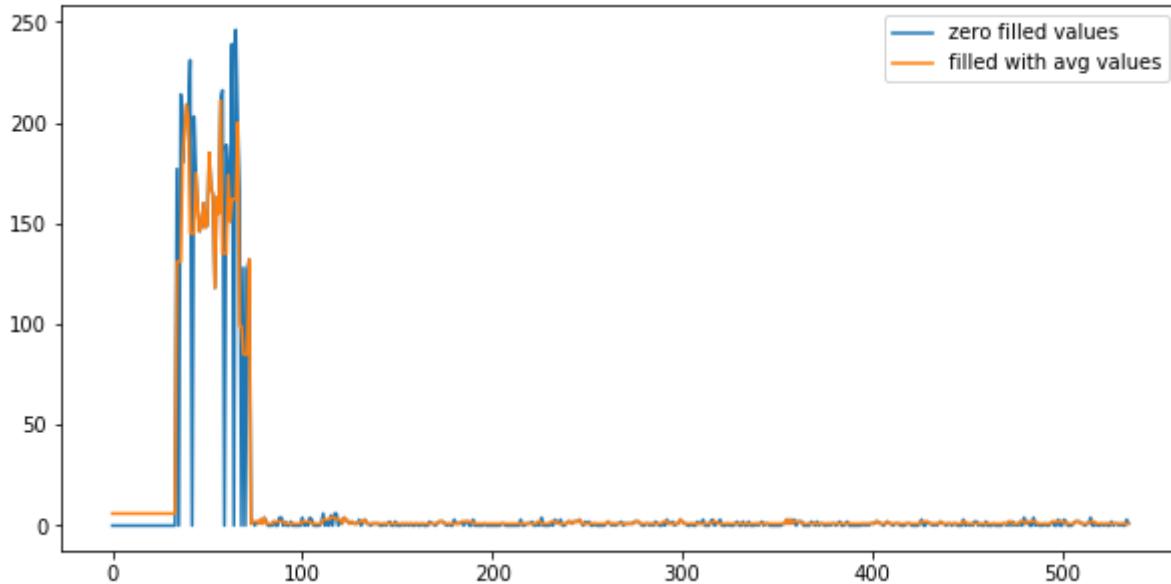
#Smoothing Missing values of Jan-2015
jan_2015_smooth = smoothing(jan_2015_groupby['trip_distance'].values,jan_2015_unique)
```

```
In [28]: # number of 10min indices for jan 2015= 24*31*60/10 = 4464
# number of 10min indices for jan 2016 = 24*31*60/10 = 4464
# number of 10min indices for feb 2016 = 24*29*60/10 = 4176
# number of 10min indices for march 2016 = 24*30*60/10 = 4320
# for each cluster we will have 4464 values, therefore 40*4464 = 178560 (length of the jan_2015_fill)
print("number of 10min intravels among all the clusters ",len(jan_2015_fill))

number of 10min intravels among all the clusters 178560
```

```
In [0]: %matplotlib inline
```

```
In [30]: # Smoothing vs Filling
# sample plot that shows two variations of filling missing values
# we have taken the number of pickups for cluster region 2
plt.figure(figsize=(10,5))
plt.plot(jan_2015_fill[4464:5000], label="zero filled values")      # 8920
plt.plot(jan_2015_smooth[4464:5000], label="filled with avg values")
plt.legend()
plt.show()
```



```
In [0]: # why we choose, these methods and which method is used for which data?

# Ans: consider we have data of some month in 2015 jan 1st, 10 _ _ 20, i.e there are 10 pickups that are happened in 1st
# 1st 10min intravel, 0 pickups happened in 2nd 10mins intravel, 0 pickups happened in 3rd 10min intravel
# and 20 pickups happened in 4th 10min intravel.
# in fill_missing method we replace these values like 10, 0, 0, 20
# where as in smoothing method we replace these values as 6,6,6,6,6, if you can check the number of pickups
# that are happened in the first 40min are same in both cases, but if you can observe that we looking at the future values
# when you are using smoothing we are looking at the future number of pickups which might cause a data leakage.

# so we use smoothing for jan 2015th data since it acts as our training data
# and we use simple fill_missing method for 2016th data.
```

```
In [0]: # Jan-2015 data is smoothed, Jan, Feb & March 2016 data missing values are filled with zero
jan_2015_smooth = smoothing(jan_2015_groupby['trip_distance'].values,jan_2015_unique)
jan_2016_smooth = fill_missing(jan_2016_groupby['trip_distance'].values,jan_2016_unique)
feb_2016_smooth = fill_missing(feb_2016_groupby['trip_distance'].values,feb_2016_unique)
mar_2016_smooth = fill_missing(mar_2016_groupby['trip_distance'].values,mar_2016_unique)

# Making list of all the values of pickup data in every bin for a period of 3 months and storing them region-wise
regions_cum = []

# a =[1,2,3]
# b = [2,3,4]
# a+b = [1, 2, 3, 2, 3, 4]

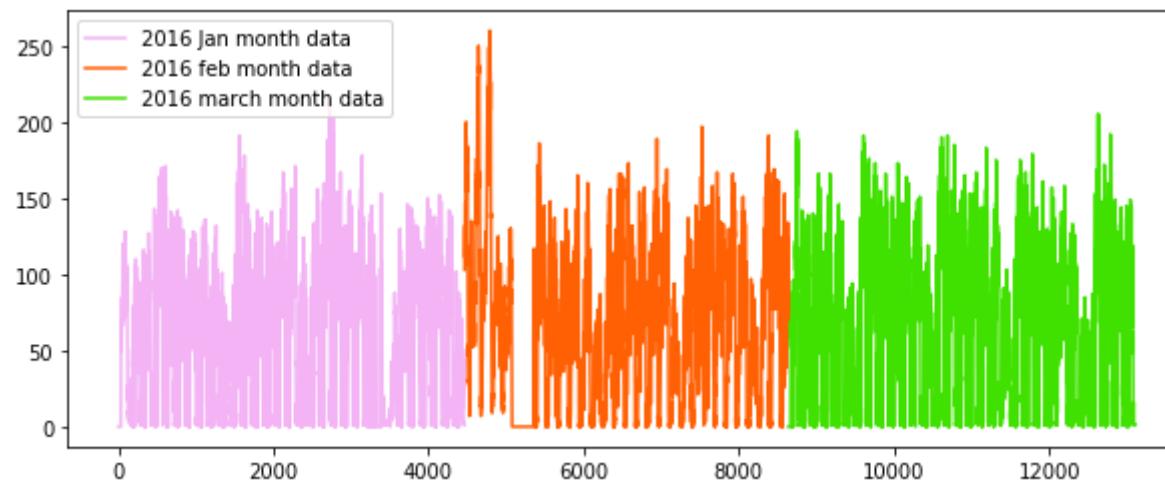
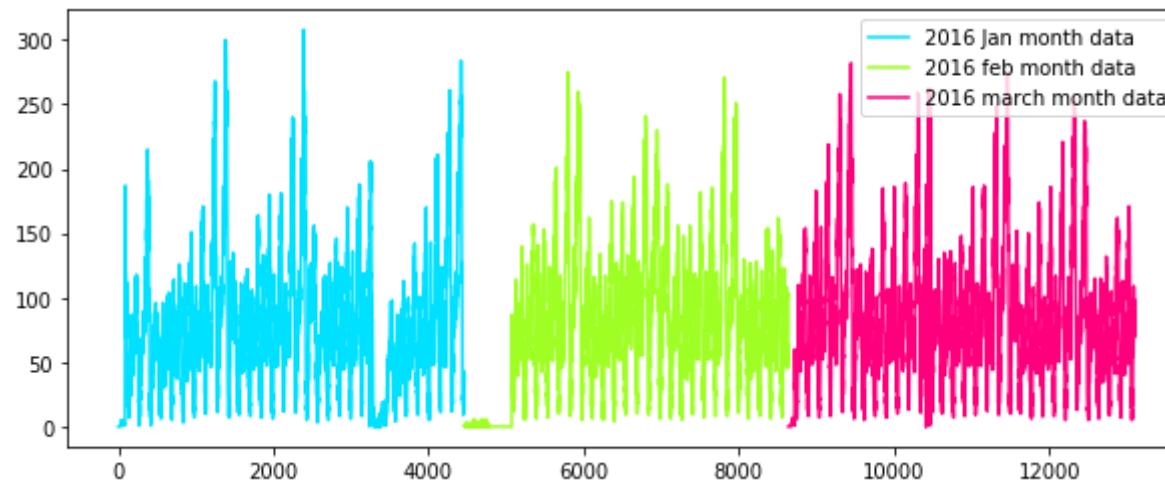
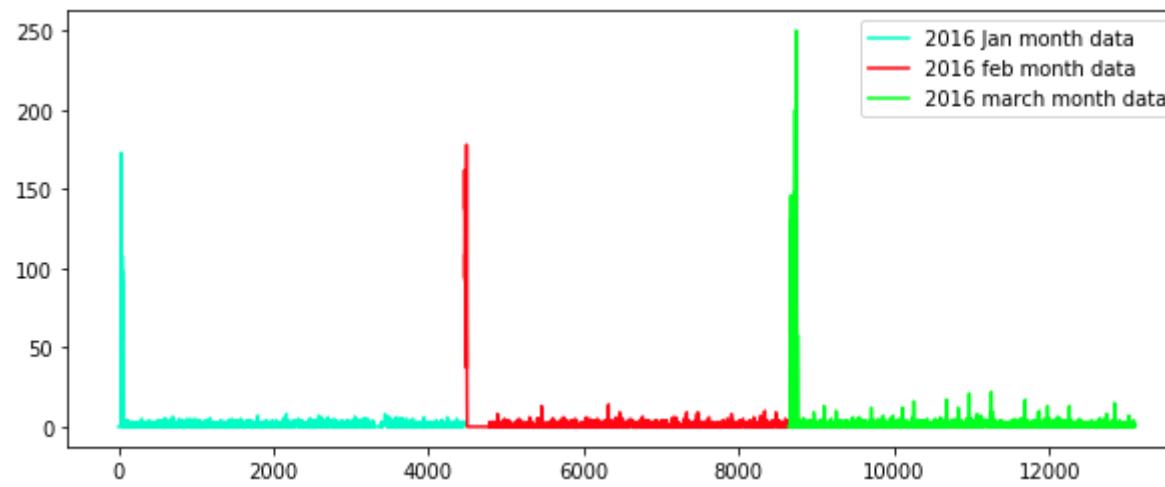
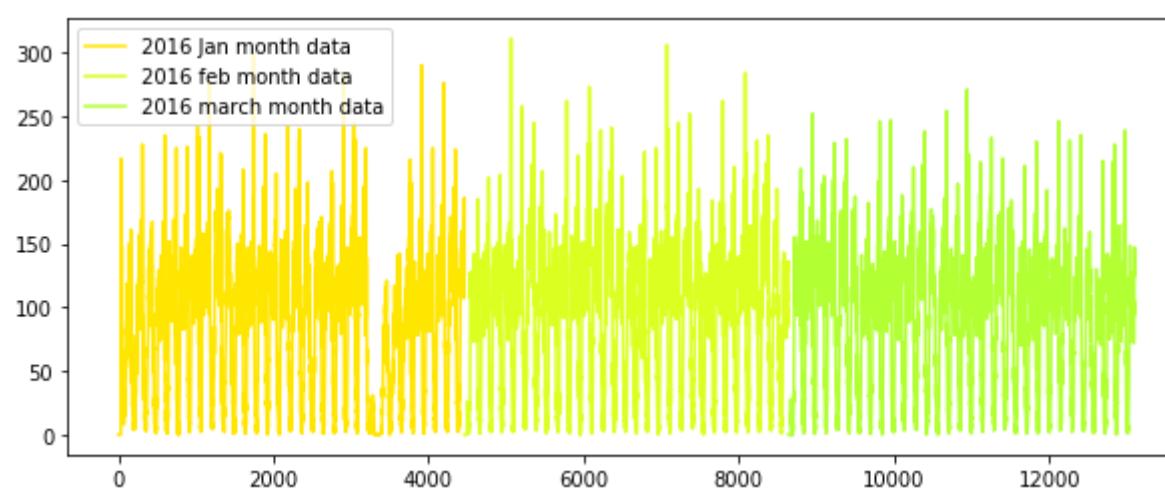
# number of 10min indices for jan 2015= 24*31*60/10 = 4464
# number of 10min indices for jan 2016 = 24*31*60/10 = 4464
# number of 10min indices for feb 2016 = 24*29*60/10 = 4176
# number of 10min indices for march 2016 = 24*31*60/10 = 4464
# regions_cum: it will contain 40 lists, each list will contain 4464+4176+4464 values which represents the number of pickups
# that are happened for three months in 2016 data

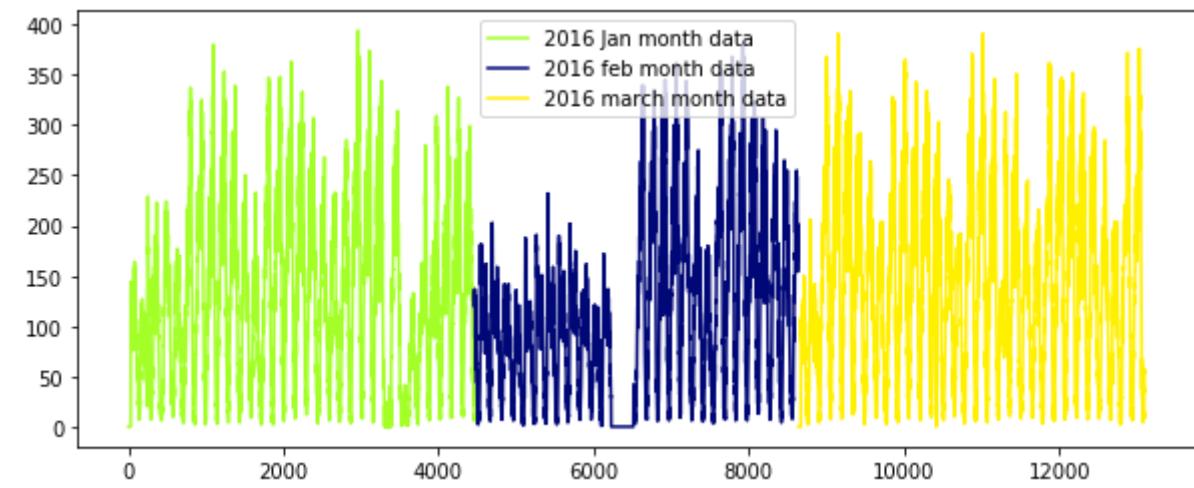
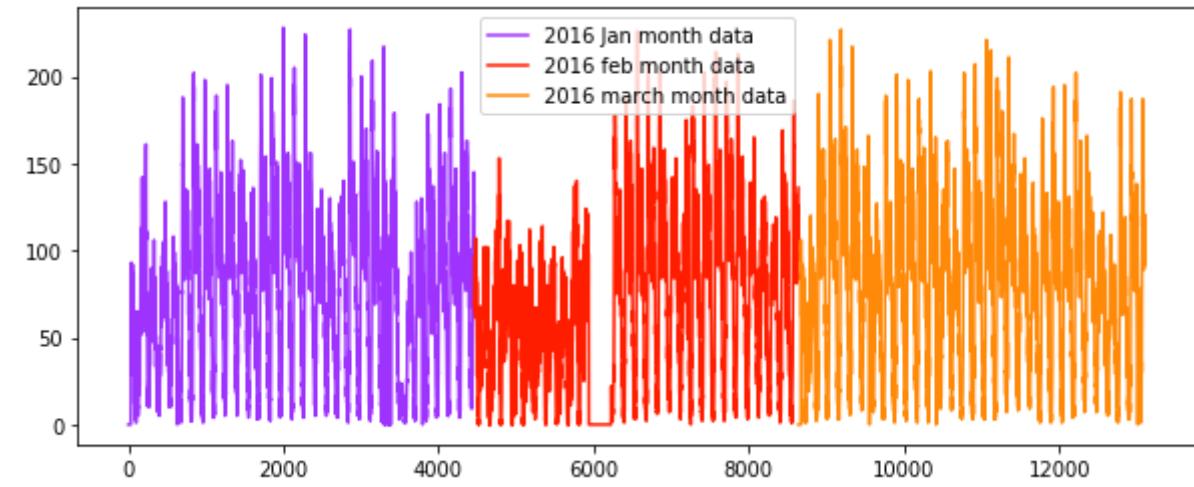
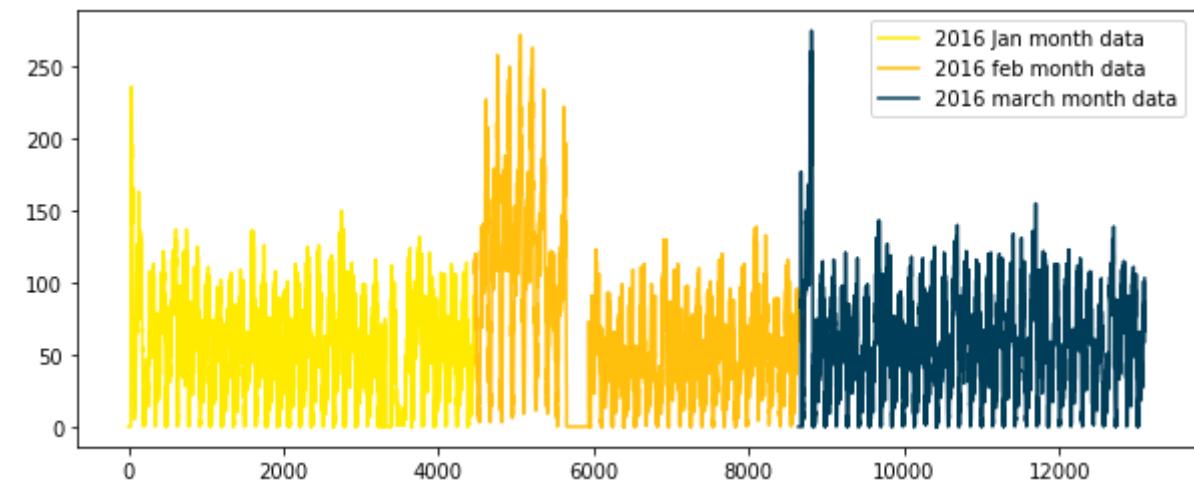
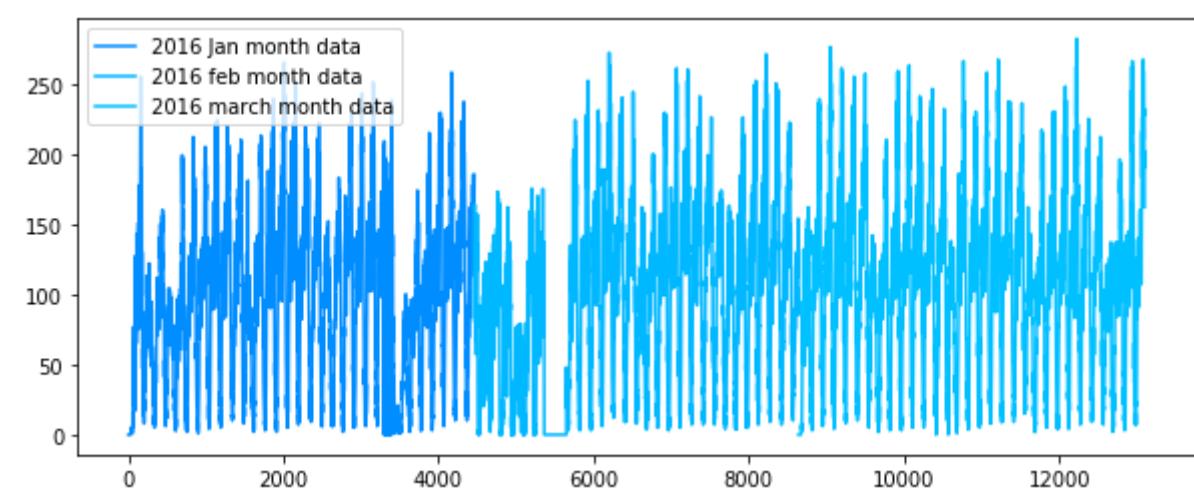
for i in range(0,40):
    regions_cum.append(jan_2016_smooth[4464*i:4464*(i+1)]+feb_2016_smooth[4176*i:4176*(i+1)]+mar_2016_smooth[4464*i:4464*(i+1)])

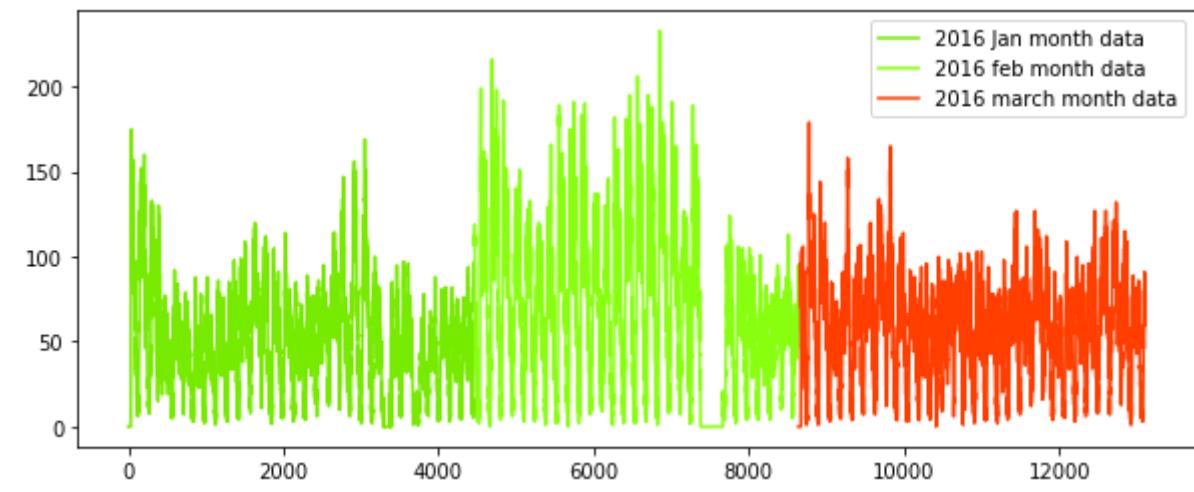
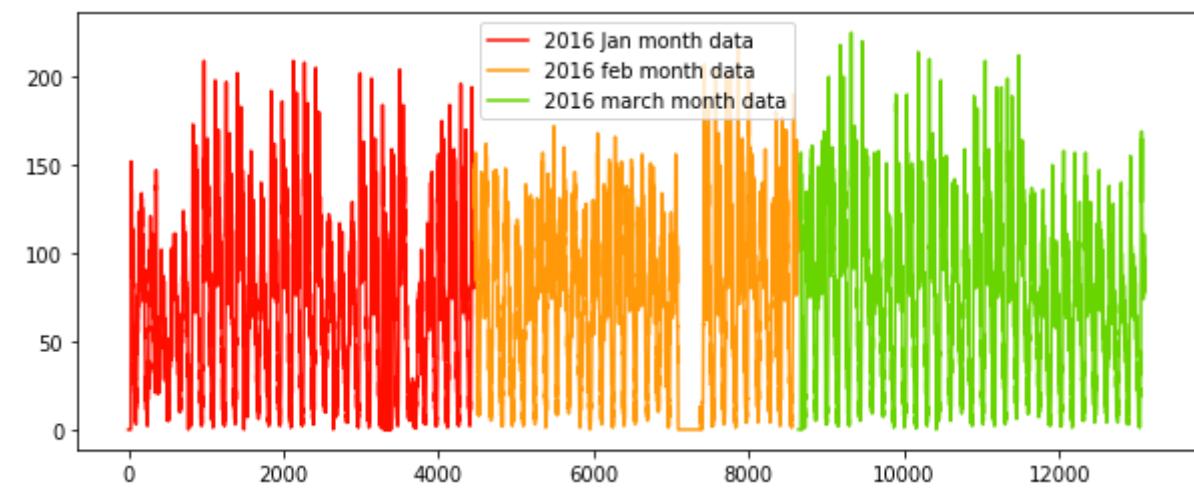
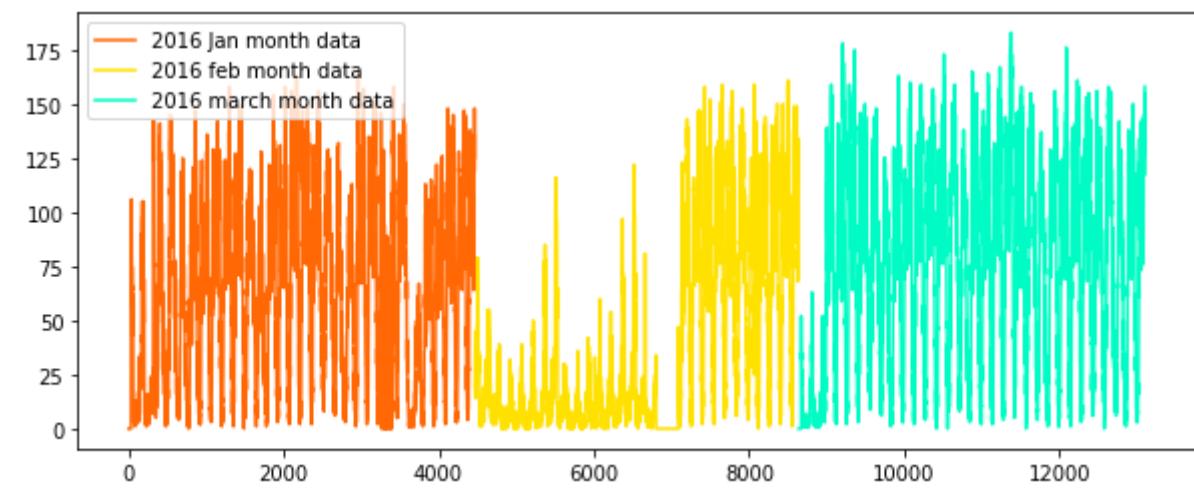
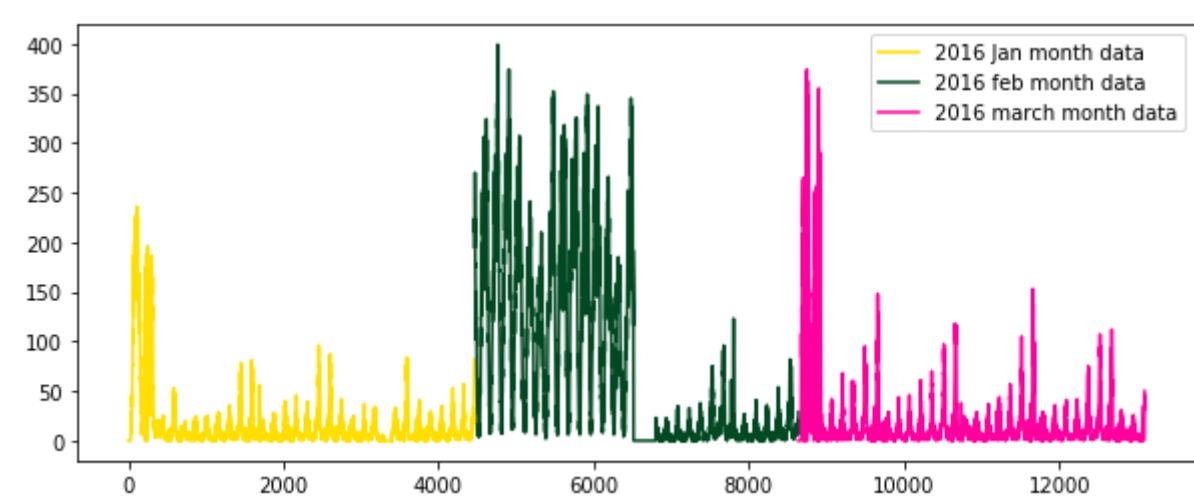
# print(len(regions_cum))
# 40
# print(len(regions_cum[0]))
# 13104
```

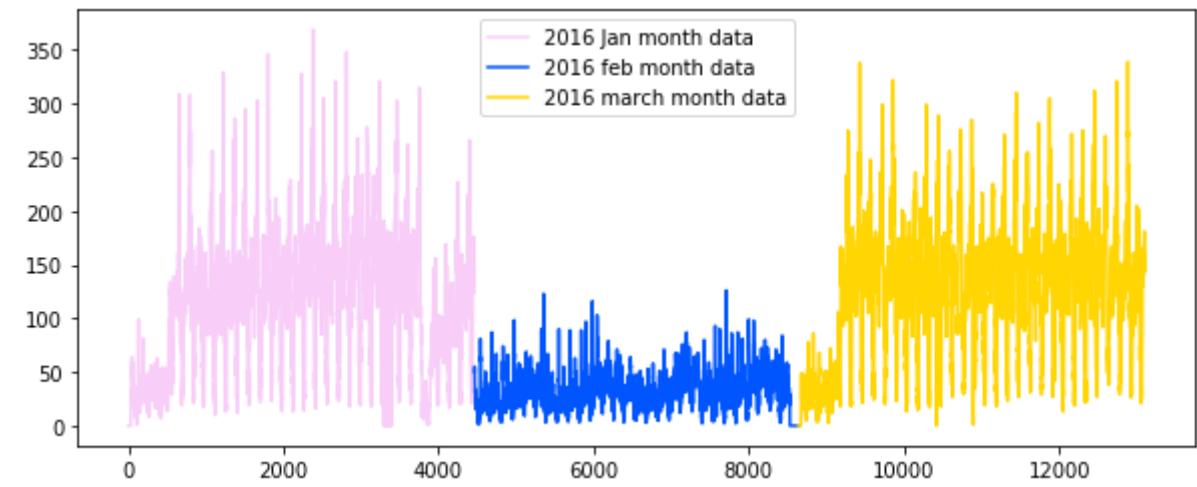
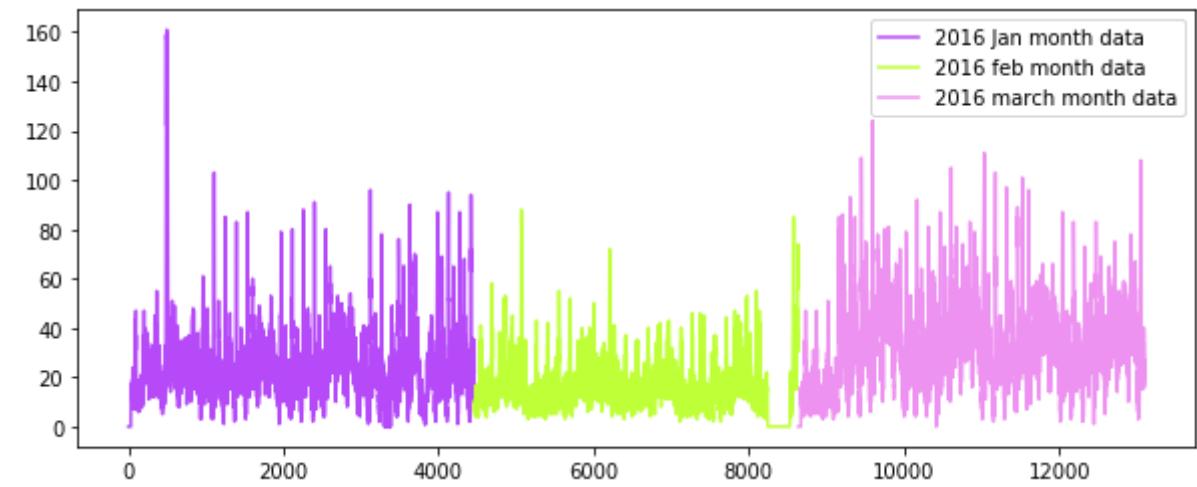
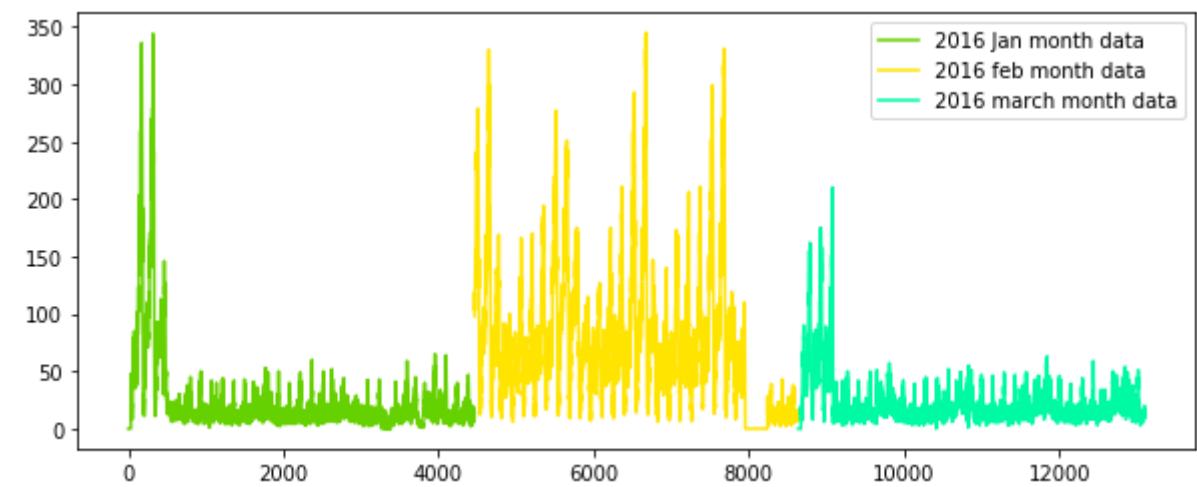
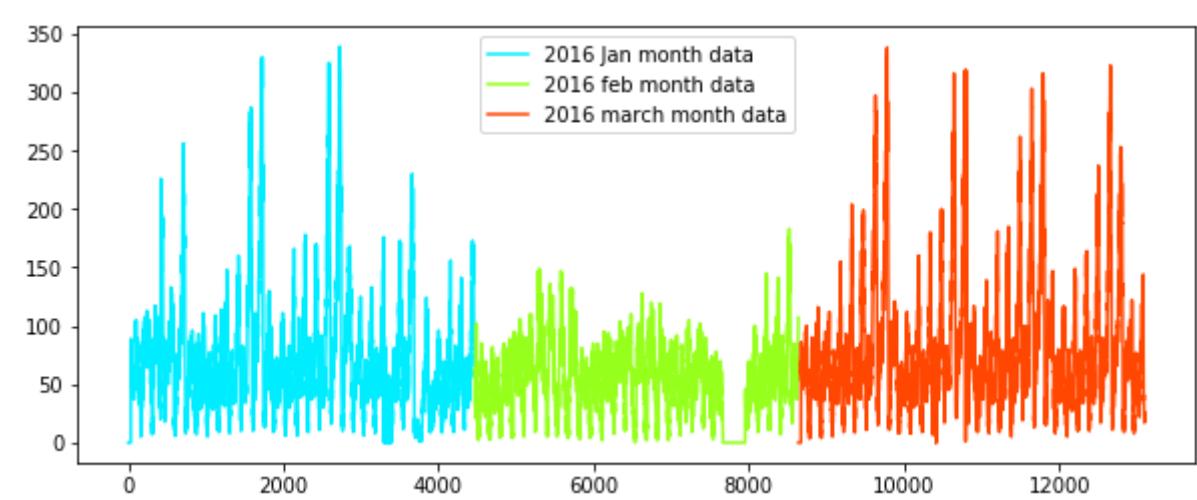
## Time series and Fourier Transforms

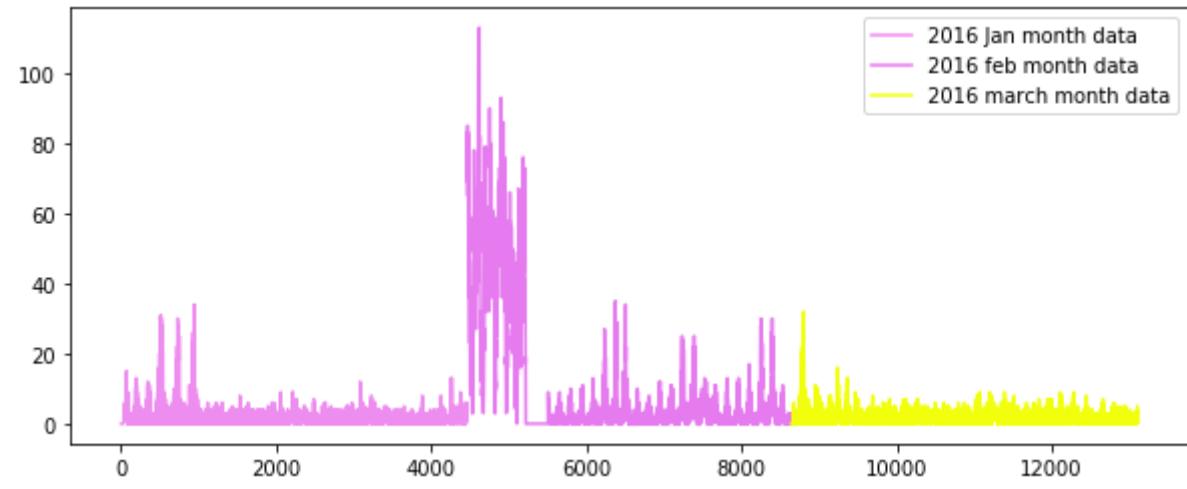
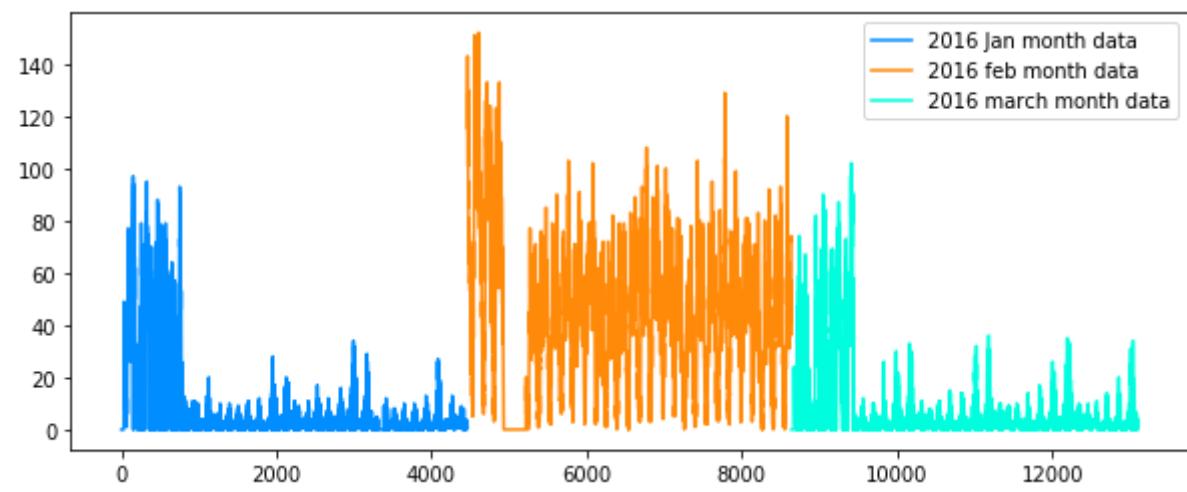
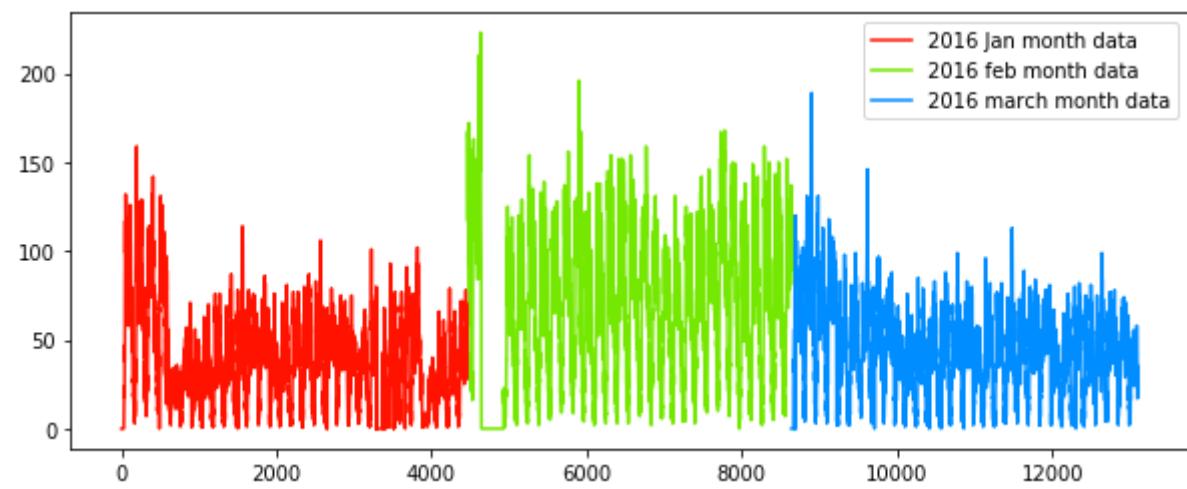
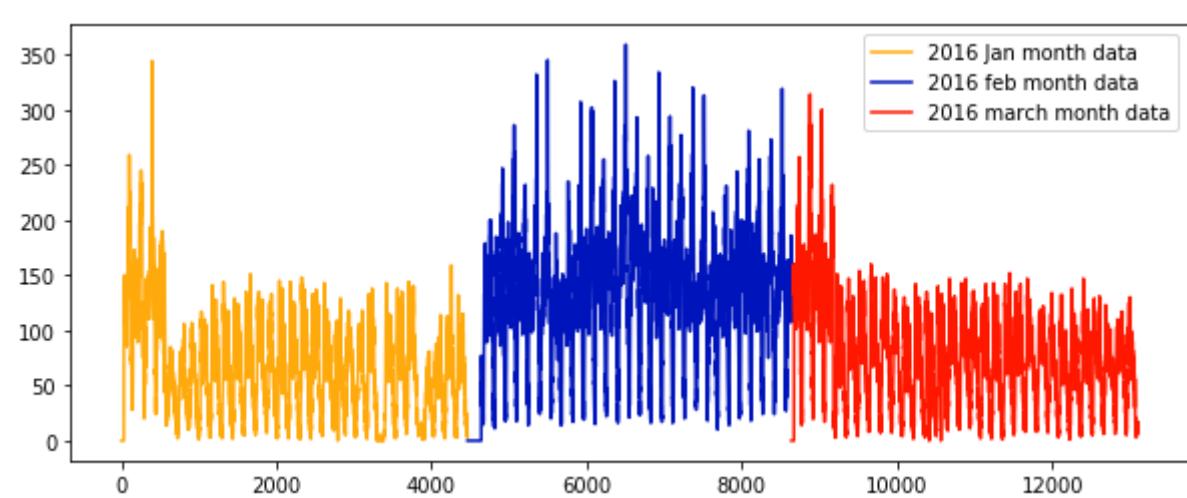
```
In [0]: def uniqueish_color():
    """There're better ways to generate unique colors, but this isn't awful."""
    return plt.cm.gist_ncar(np.random.random())
first_x = list(range(0,4464))
second_x = list(range(4464,8640))
third_x = list(range(8640,13104))
for i in range(40):
    plt.figure(figsize=(10,4))
    plt.plot(first_x,regions_cum[i][:4464], color=uniqueish_color(), label='2016 Jan month data')
    plt.plot(second_x,regions_cum[i][4464:8640], color=uniqueish_color(), label='2016 feb month data')
    plt.plot(third_x,regions_cum[i][8640:], color=uniqueish_color(), label='2016 march month data')
    plt.legend()
    plt.show()
```

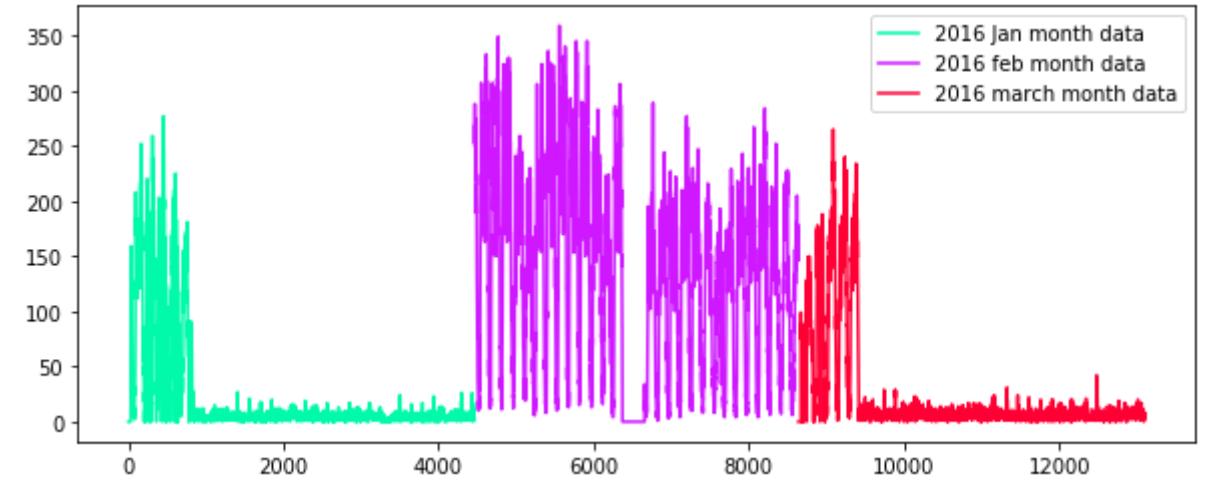
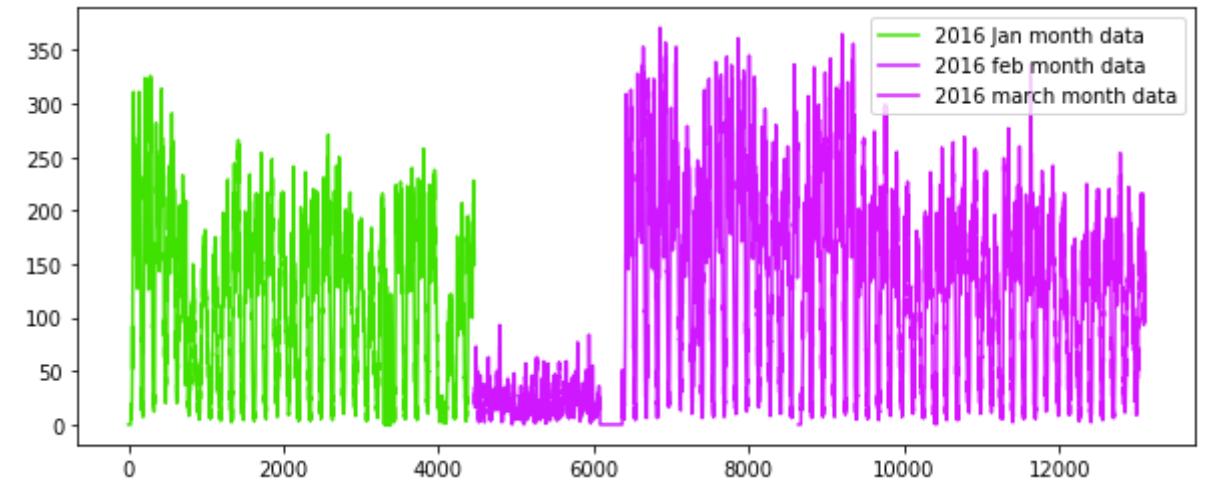
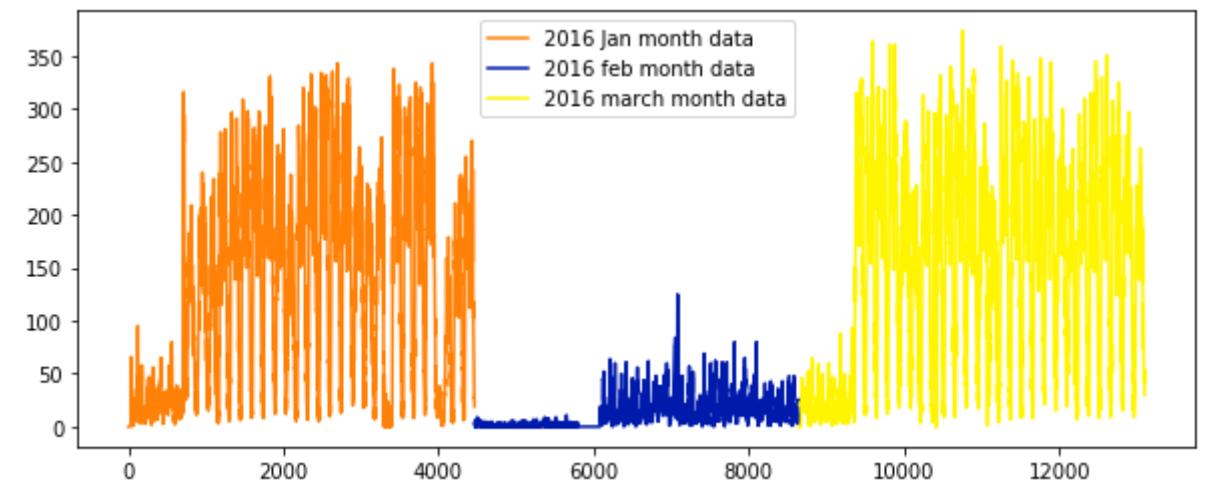
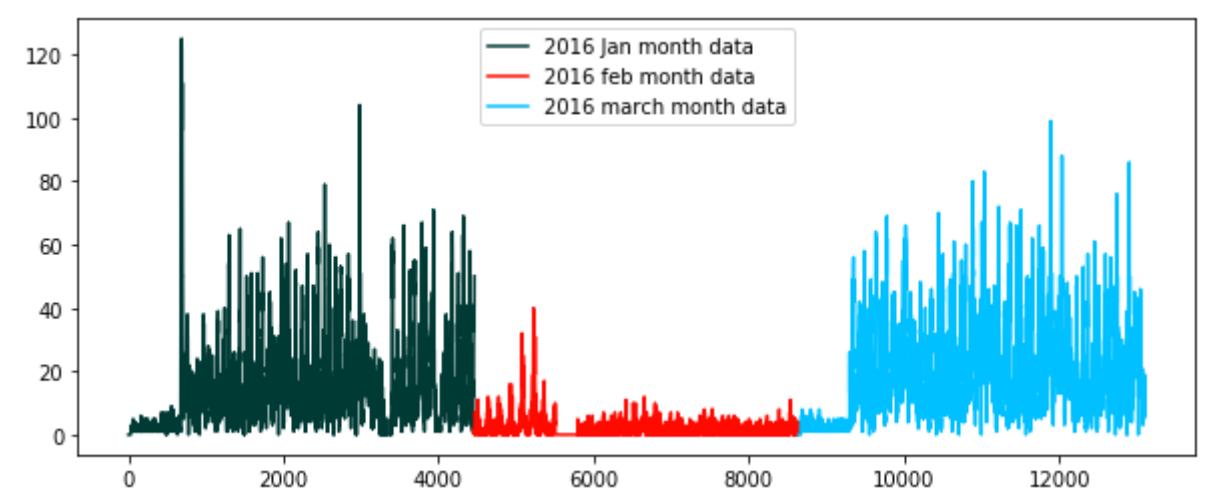


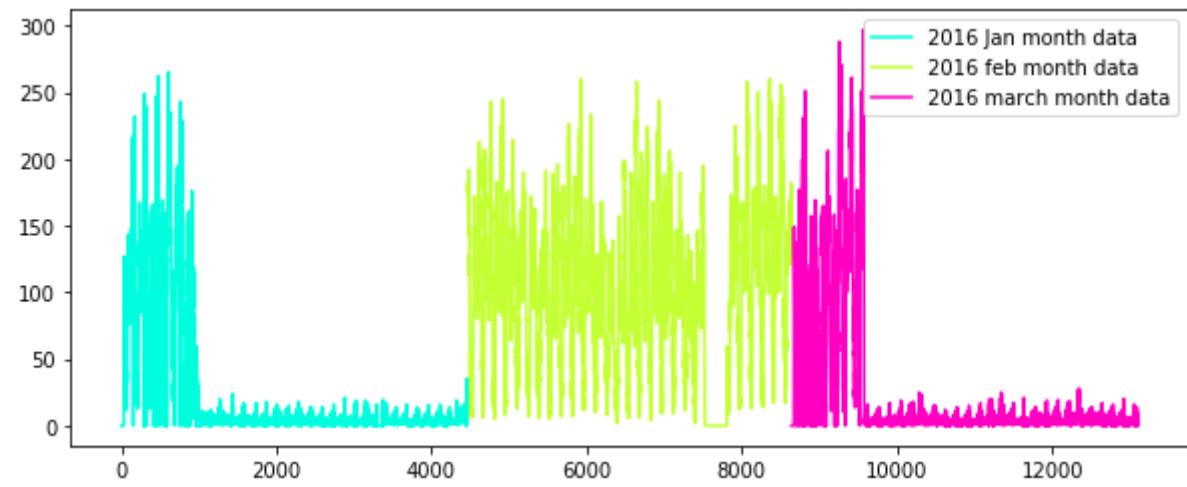
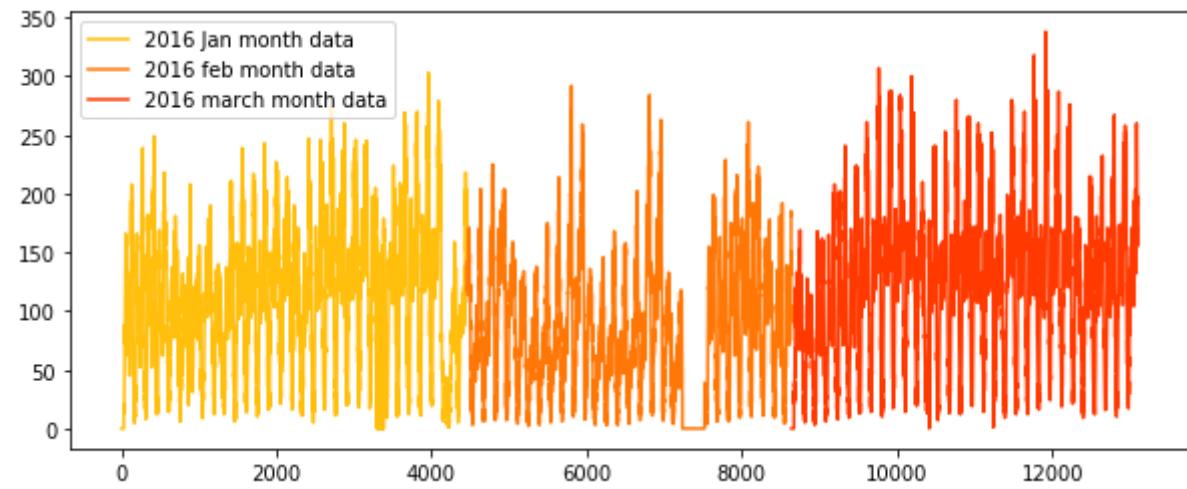
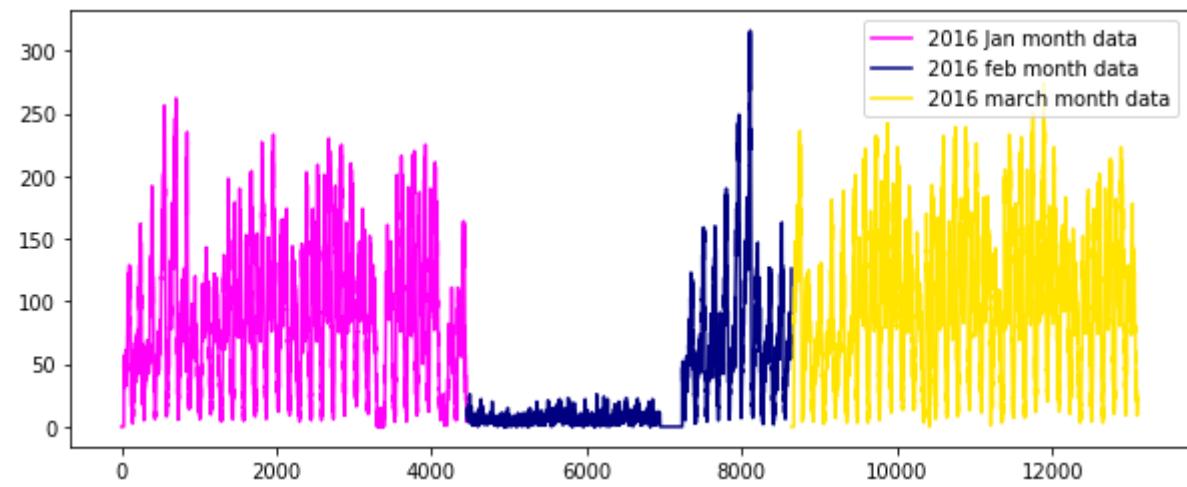
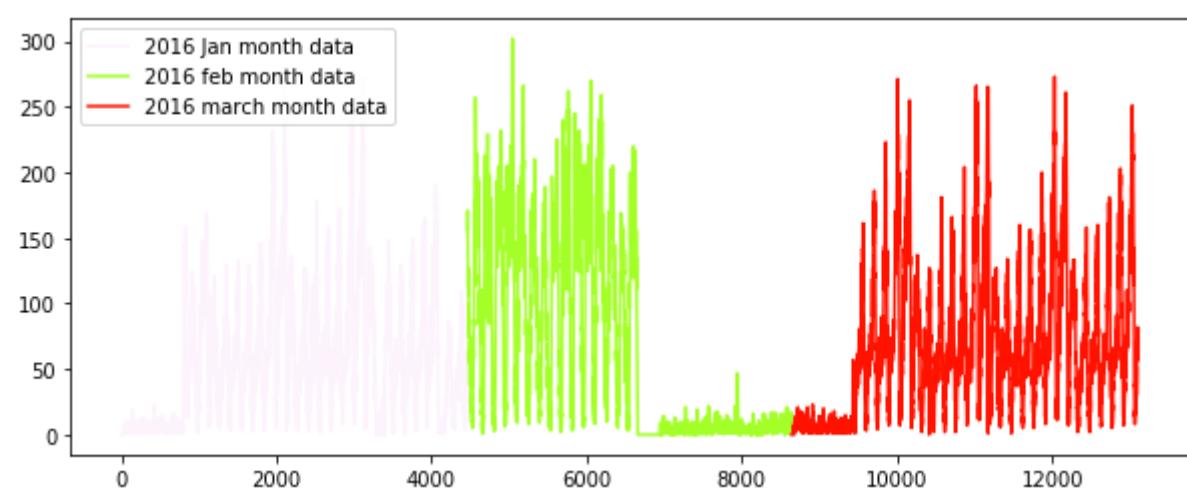


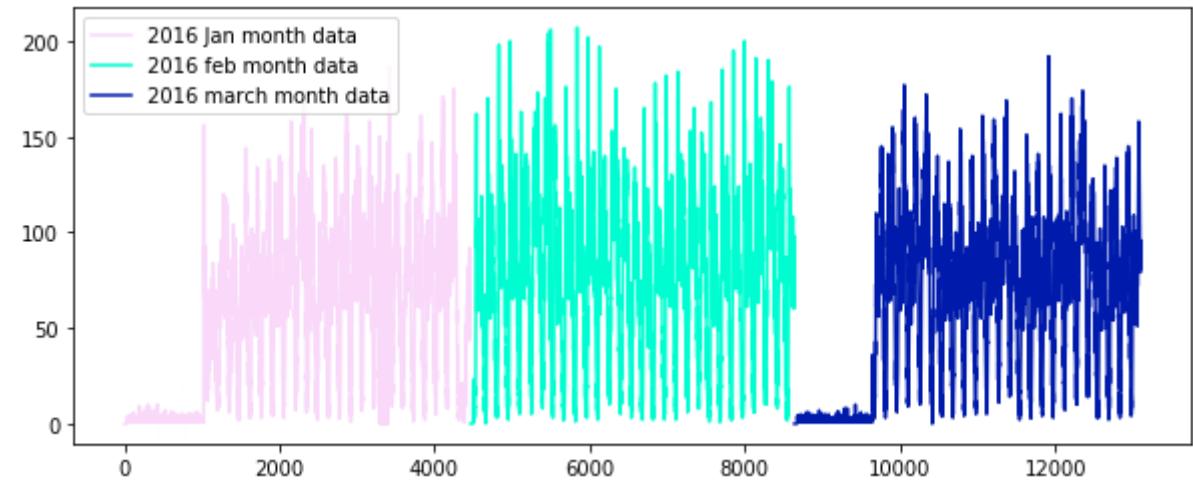
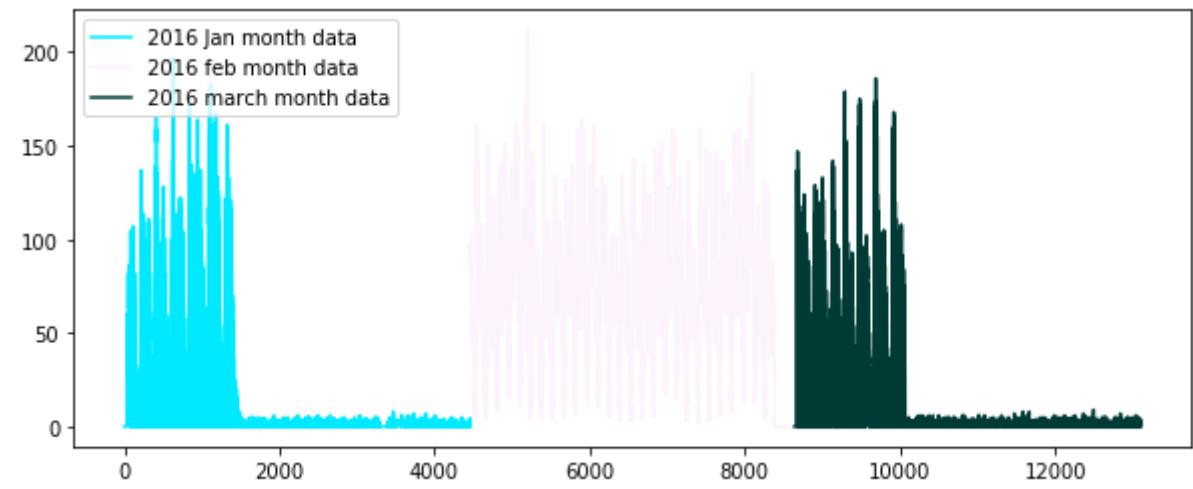
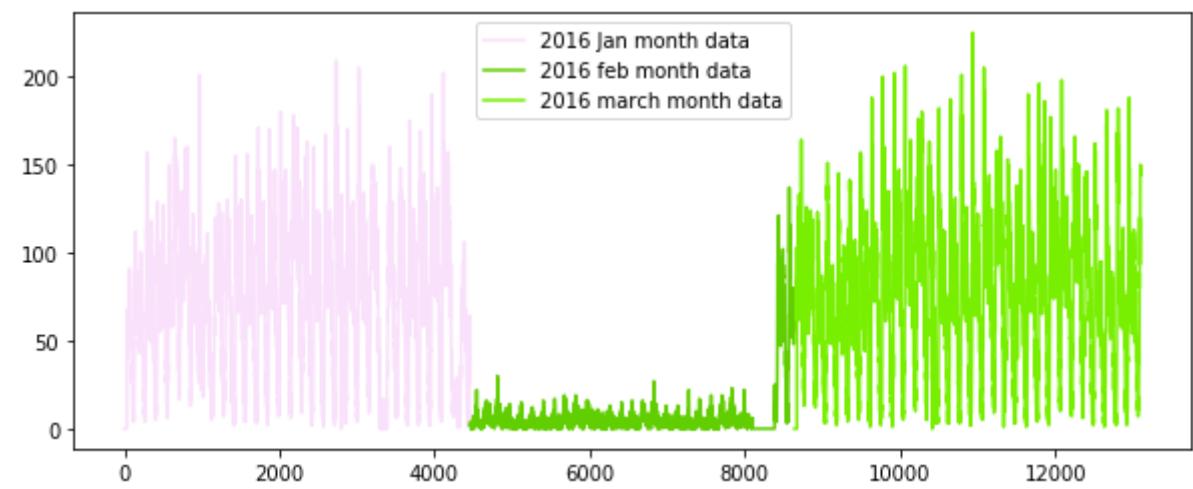
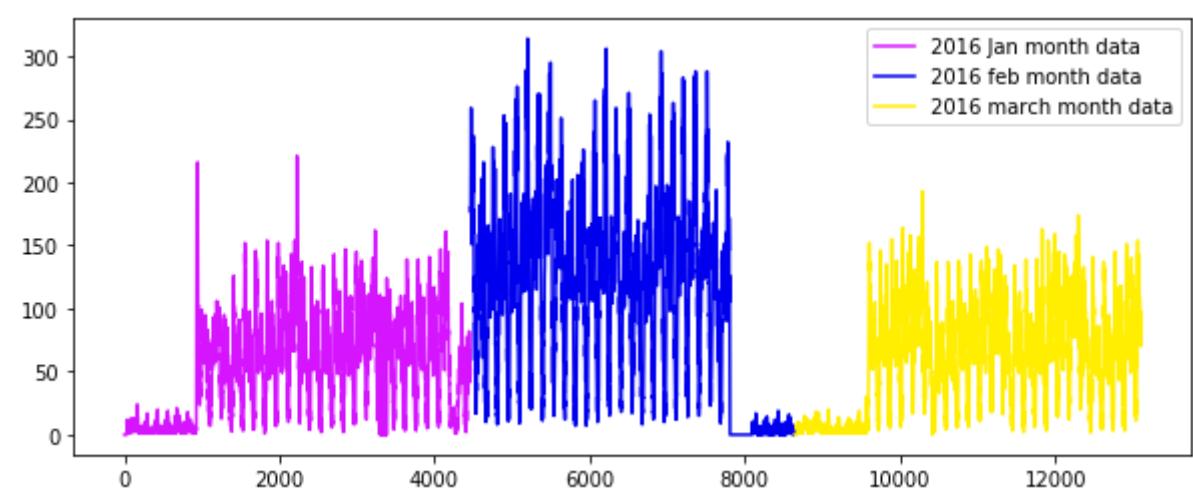


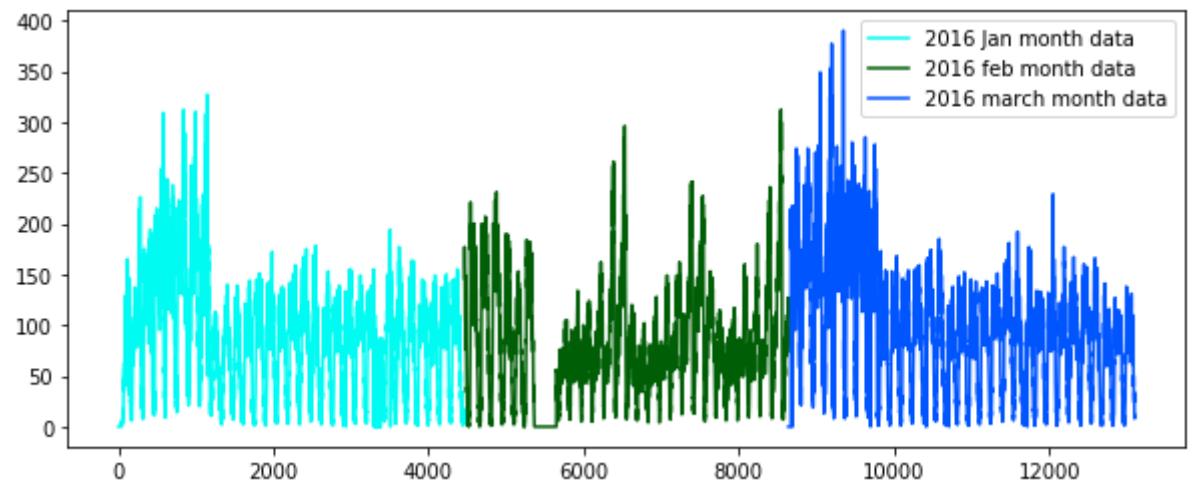
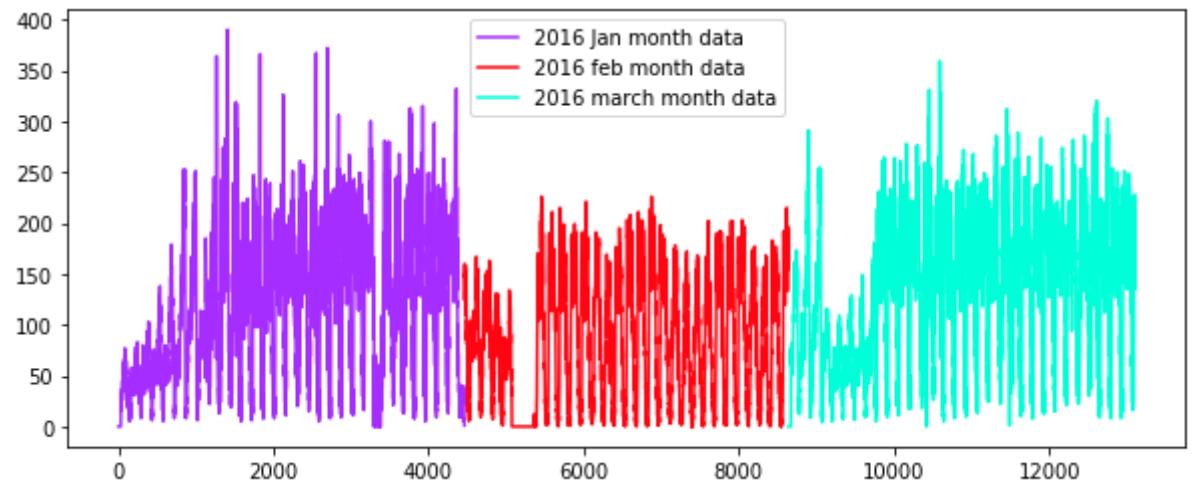
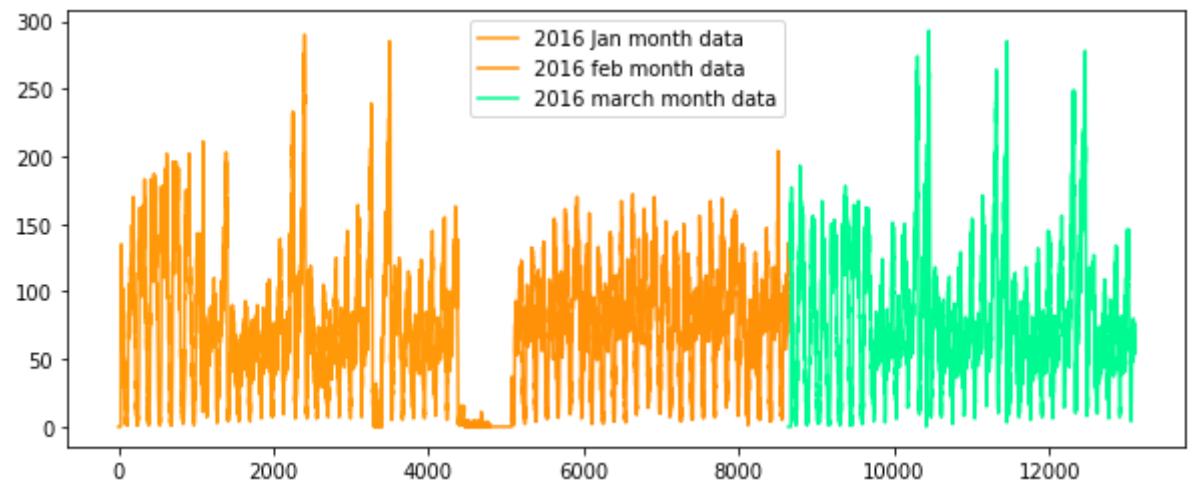
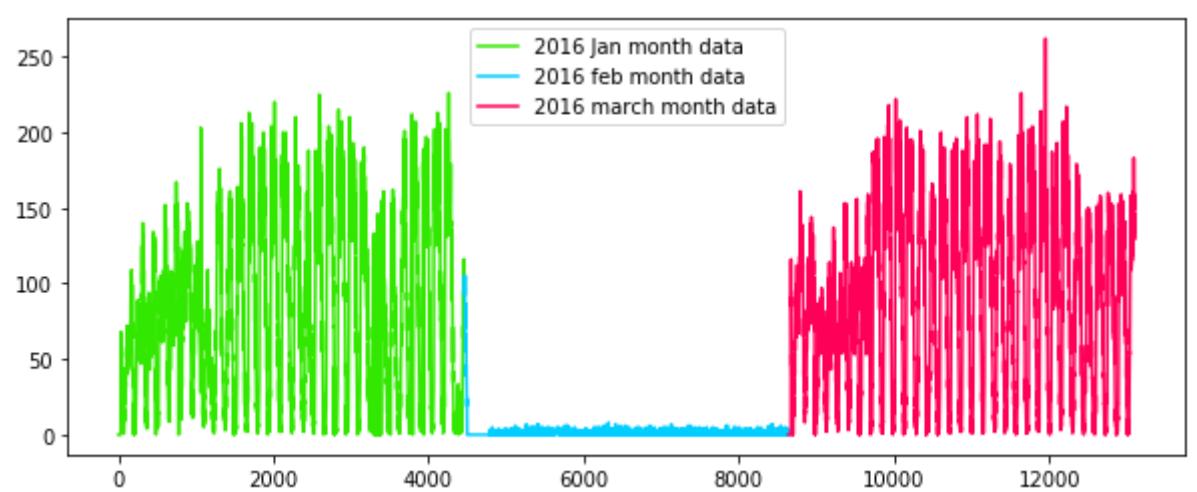


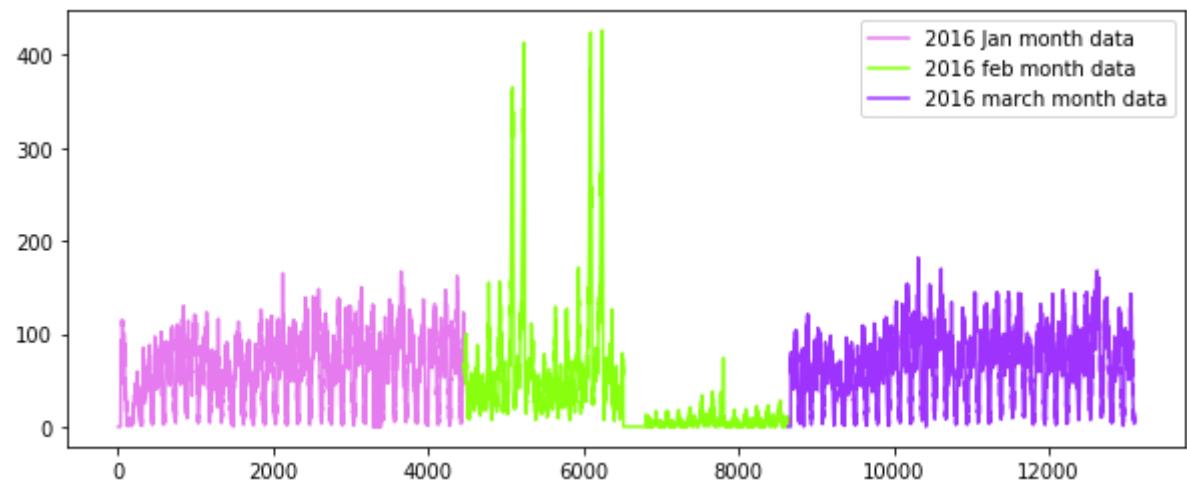
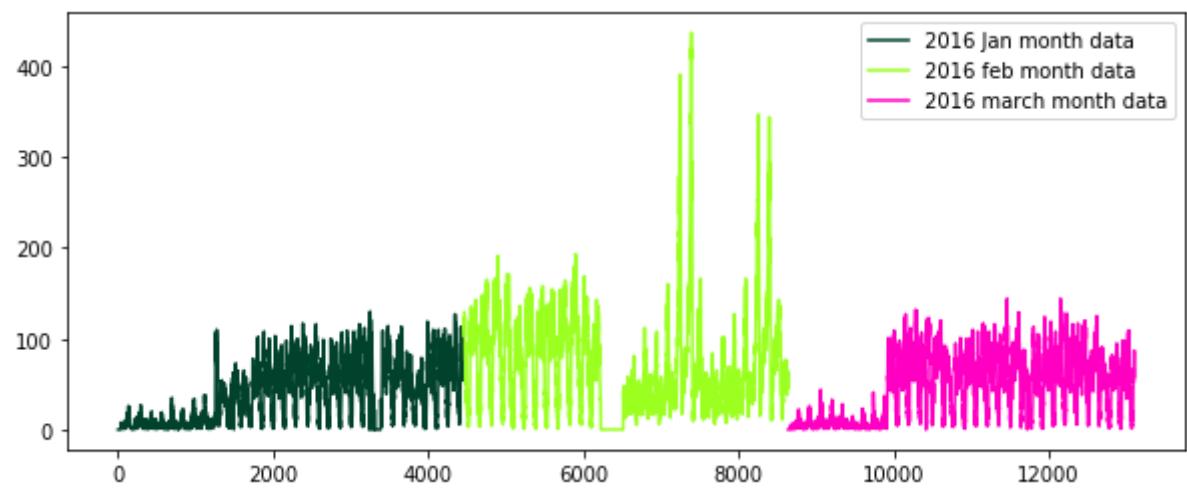
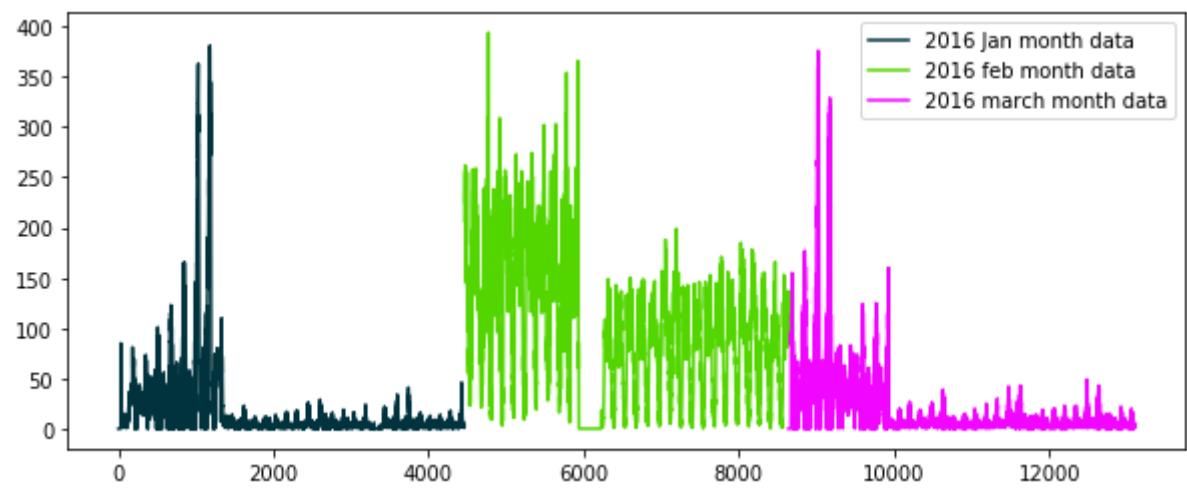
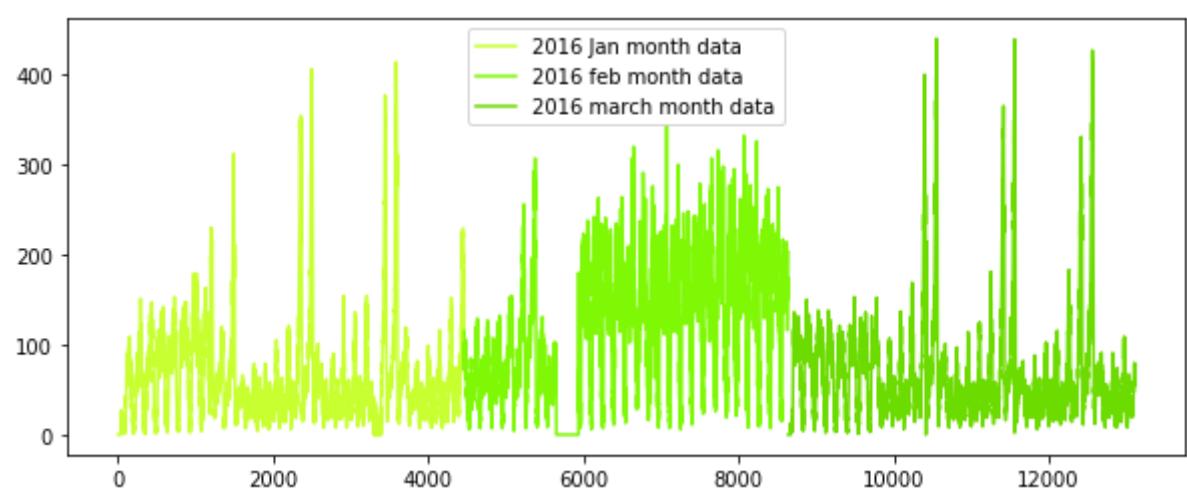




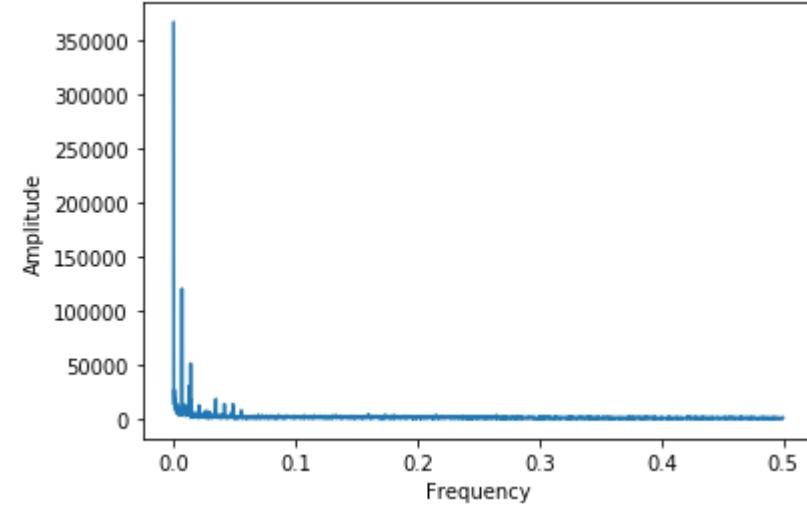








```
In [0]: # getting peaks: https://blog.ytotech.com/2015/11/01/findpeaks-in-python/
# read more about fft function : https://docs.scipy.org/doc/numpy/reference/generated/numpy.fft.fft.html
Y = np.fft.fft(np.array(jan_2016_smooth)[0:4460])
# read more about the fftfreq: https://docs.scipy.org/doc/numpy/reference/generated/numpy.fft.fftfreq.html
freq = np.fft.fftfreq(4460, 1)
n = len(freq)
plt.figure()
plt.plot( freq[:int(n/2)], np.abs(Y)[:int(n/2)] )
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.show()
```



```
In [0]: #Preparing the Dataframe only with x(i) values as jan-2015 data and y(i) values as jan-2016
ratios_jan = pd.DataFrame()
ratios_jan['Given']=jan_2015_smooth
ratios_jan['Prediction']=jan_2016_smooth
ratios_jan['Ratios']=ratios_jan['Prediction']*1.0/ratios_jan['Given']*1.0
```

## Modelling: Baseline Models

Now we get into modelling in order to forecast the pickup densities for the months of Jan, Feb and March of 2016 for which we are using multiple models with two variations

1. Using Ratios of the 2016 data to the 2015 data i.e  $R_t = P_t^{2016} / P_t^{2015}$
2. Using Previous known values of the 2016 data itself to predict the future values

## Simple Moving Averages

The First Model used is the Moving Averages Model which uses the previous n values in order to predict the next value

Using Ratio Values -  $R_t = (R_{t-1} + R_{t-2} + R_{t-3} \dots + R_{t-n})/n$

```
In [0]: def MA_R_Predictions(ratios,month):
    predicted_ratio=(ratios['Ratios'].values)[0]
    error=[]
    predicted_values=[]
    window_size=3
    predicted_ratio_values=[]
    for i in range(0,4464*40):
        if i%4464==0:
            predicted_ratio_values.append(0)
            predicted_values.append(0)
            error.append(0)
            continue
        predicted_ratio_values.append(predicted_ratio)
        predicted_values.append(int(((ratios['Given'].values)[i])*predicted_ratio))
        error.append(abs((math.pow(int(((ratios['Given'].values)[i])*predicted_ratio)-(ratios['Prediction'].values)[i],1))))
        if i+1>=window_size:
            predicted_ratio=sum((ratios['Ratios'].values)[(i+1)-window_size:(i+1)])/(window_size)
        else:
            predicted_ratio=sum((ratios['Ratios'].values)[0:(i+1)])/(i+1)

    ratios['MA_R_Predicted'] = predicted_values
    ratios['MA_R_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

For the above the Hyperparameter is the window-size (n) which is tuned manually and it is found that the window-size of 3 is optimal for getting the best results using Moving Averages using previous Ratio values therefore we get  $R_t = (R_{t-1} + R_{t-2} + R_{t-3})/3$

Next we use the Moving averages of the 2016 values itself to predict the future value using  $P_t = (P_{t-1} + P_{t-2} + P_{t-3} \dots + P_{t-n})/n$

```
In [0]: def MA_P_Predictions(ratios,month):
    predicted_value=(ratios['Prediction'].values)[0]
    error=[]
    predicted_values=[]
    window_size=1
    predicted_ratio_values=[]
    for i in range(0,4464*40):
        predicted_values.append(predicted_value)
        error.append(abs((predicted_value-(ratios['Prediction'].values)[i],1)))
        if i+1>=window_size:
            predicted_value=int(sum((ratios['Prediction'].values)[(i+1)-window_size:(i+1)])) / window_size
        else:
            predicted_value=int(sum((ratios['Prediction'].values)[0:(i+1)])) / (i+1)

    ratios['MA_P_Predicted'] = predicted_values
    ratios['MA_P_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

For the above the Hyperparameter is the window-size (n) which is tuned manually and it is found that the window-size of 1 is optimal for getting the best results using Moving Averages using previous 2016 values therefore we get  $P_t = P_{t-1}$

## Weighted Moving Averages

The Moving Average Model used gave equal importance to all the values in the window used, but we know intuitively that the future is more likely to be similar to the latest values and less similar to the older values. Weighted Averages converts this analogy into a mathematical relationship giving the highest weight while computing the averages to the latest previous value and decreasing weights to the subsequent older ones.

Weighted Moving Averages using Ratio Values -  $R_t = (N * R_{t-1} + (N - 1) * R_{t-2} + (N - 2) * R_{t-3} \dots 1 * R_{t-n}) / (N * (N + 1) / 2)$

```
In [0]: def WA_R_Predictions(ratios,month):
    predicted_ratio=(ratios['Ratios'].values)[0]
    alpha=0.5
    error=[]
    predicted_values=[]
    window_size=5
    predicted_ratio_values=[]
    for i in range(0,4464*40):
        if i%4464==0:
            predicted_ratio_values.append(0)
            predicted_values.append(0)
            error.append(0)
            continue
        predicted_ratio_values.append(predicted_ratio)
        predicted_values.append(int(((ratios['Given'].values)[i])*predicted_ratio))
        error.append(abs((math.pow(int(((ratios['Given'].values)[i])*predicted_ratio)-(ratios['Prediction'].values)[i],1))))
        if i+1>=window_size:
            sum_values=0
            sum_of_coeff=0
            for j in range(window_size,0,-1):
                sum_values += j*(ratios['Ratios'].values)[i-window_size+j]
                sum_of_coeff+=j
            predicted_ratio=sum_values/sum_of_coeff
        else:
            sum_values=0
            sum_of_coeff=0
            for j in range(i+1,0,-1):
                sum_values += j*(ratios['Ratios'].values)[j-1]
                sum_of_coeff+=j
            predicted_ratio=sum_values/sum_of_coeff

    ratios['WA_R_Predicted'] = predicted_values
    ratios['WA_R_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

For the above the Hyperparameter is the window-size (n) which is tuned manually and it is found that the window-size of 5 is optimal for getting the best results using Weighted Moving Averages using previous Ratio values therefore we get  $R_t = (5 * R_{t-1} + 4 * R_{t-2} + 3 * R_{t-3} + 2 * R_{t-4} + R_{t-5}) / 15$

Weighted Moving Averages using Previous 2016 Values -  $P_t = (N * P_{t-1} + (N - 1) * P_{t-2} + (N - 2) * P_{t-3} \dots 1 * P_{t-n}) / (N * (N + 1) / 2)$

```
In [0]: def WA_P_Predictions(ratios,month):
    predicted_value=(ratios['Prediction'].values)[0]
    error=[]
    predicted_values=[]
    window_size=2
    for i in range(0,4464*40):
        predicted_values.append(predicted_value)
        error.append(abs((math.pow(predicted_value-(ratios['Prediction'].values)[i],1))))
        if i+1>=window_size:
            sum_values=0
            sum_of_coeff=0
            for j in range(window_size,0,-1):
                sum_values += j*(ratios['Prediction'].values)[i-window_size+j]
                sum_of_coeff+=j
            predicted_value=int(sum_values/sum_of_coeff)

    else:
        sum_values=0
        sum_of_coeff=0
        for j in range(i+1,0,-1):
            sum_values += j*(ratios['Prediction'].values)[j-1]
            sum_of_coeff+=j
        predicted_value=int(sum_values/sum_of_coeff)

    ratios['WA_P_Predicted'] = predicted_values
    ratios['WA_P_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

For the above the Hyperparameter is the window-size (n) which is tuned manually and it is found that the window-size of 2 is optimal for getting the best results using Weighted Moving Averages using previous 2016 values therefore we get  $P_t = (2 * P_{t-1} + P_{t-2})/3$

## Exponential Weighted Moving Averages

[https://en.wikipedia.org/wiki/Moving\\_average#Exponential\\_moving\\_average](https://en.wikipedia.org/wiki/Moving_average#Exponential_moving_average) ([https://en.wikipedia.org/wiki/Moving\\_average#Exponential\\_moving\\_average](https://en.wikipedia.org/wiki/Moving_average#Exponential_moving_average)). Through weighted averaged we have satisfied the analogy of giving higher weights to the latest value and decreasing weights to the subsequent ones but we still do not know which is the correct weighting scheme as there are infinitely many possibilities in which we can assign weights in a non-increasing order and tune the the hyperparameter window-size. To simplify this process we use Exponential Moving Averages which is a more logical way towards assigning weights and at the same time also using an optimal window-size.

In exponential moving averages we use a single hyperparameter alpha ( $\alpha$ ) which is a value between 0 & 1 and based on the value of the hyperparameter alpha the weights and the window sizes are configured.

For eg. If  $\alpha = 0.9$  then the number of days on which the value of the current iteration is based is~  $1/(1 - \alpha) = 10$  i.e. we consider values 10 days prior before we predict the value for the current iteration. Also the weights are assigned using  $2/(N + 1) = 0.18$ , where N = number of prior values being considered, hence from this it is implied that the first or latest value is assigned a weight of 0.18 which keeps exponentially decreasing for the subsequent values.

$$R'_t = \alpha * R'_{t-1} + (1 - \alpha) * R'_{t-1}$$

```
In [0]: def EA_R1_Predictions(ratios,month):
    predicted_ratio=(ratios['Ratios'].values)[0]
    alpha=0.6
    error=[]
    predicted_values=[]
    predicted_ratio_values=[]
    for i in range(0,4464*40):
        if i%4464==0:
            predicted_ratio_values.append(0)
            predicted_values.append(0)
            error.append(0)
            continue
        predicted_ratio_values.append(predicted_ratio)
        predicted_values.append(int(((ratios['Given'].values)[i])*predicted_ratio))
        error.append(abs((math.pow(int(((ratios['Given'].values)[i])*predicted_ratio)-(ratios['Prediction'].values)[i],1))))
        predicted_ratio = (alpha*predicted_ratio) + (1-alpha)*((ratios['Ratios'].values)[i])

    ratios['EA_R1_Predicted'] = predicted_values
    ratios['EA_R1_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

$$P'_t = \alpha * P_{t-1} + (1 - \alpha) * P'_{t-1}$$

```
In [0]: def EA_P1_Predictions(ratios,month):
    predicted_value= (ratios['Prediction'].values)[0]
    alpha=0.3
    error=[]
    predicted_values=[]
    for i in range(0,4464*40):
        if i%4464==0:
            predicted_values.append(0)
            error.append(0)
            continue
        predicted_values.append(predicted_value)
        error.append(abs((math.pow(predicted_value-(ratios['Prediction'].values)[i],1))))
        predicted_value =int((alpha*predicted_value) + (1-alpha)*((ratios['Prediction'].values)[i]))

    ratios['EA_P1_Predicted'] = predicted_values
    ratios['EA_P1_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Prediction'].values))
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

```
In [0]: mean_err=[0]*10
median_err=[0]*10
ratios_jan,mean_err[0],median_err[0]=MA_R_Predictions(ratios_jan,'jan')
ratios_jan,mean_err[1],median_err[1]=MA_P_Predictions(ratios_jan,'jan')
ratios_jan,mean_err[2],median_err[2]=WA_R_Predictions(ratios_jan,'jan')
ratios_jan,mean_err[3],median_err[3]=WA_P_Predictions(ratios_jan,'jan')
ratios_jan,mean_err[4],median_err[4]=EA_R1_Predictions(ratios_jan,'jan')
ratios_jan,mean_err[5],median_err[5]=EA_P1_Predictions(ratios_jan,'jan')
```

## Comparison between baseline models

We have chosen our error metric for comparison between models as **MAPE (Mean Absolute Percentage Error)** so that we can know that on an average how good is our model with predictions and **MSE (Mean Squared Error)** is also used so that we have a clearer understanding as to how well our forecasting model performs with outliers so that we make sure that there is not much of a error margin between our prediction and the actual value

```
In [40]: print ("Error Metric Matrix (Forecasting Methods) - MAPE & MSE")
print ("-----")
print ("Moving Averages (Ratios) - MAPE: ",mean_err[0]," MSE: ",median_err[0])
print ("Moving Averages (2016 Values) - MAPE: ",mean_err[1]," MSE: ",median_err[1])
print ("-----")
print ("Weighted Moving Averages (Ratios) - MAPE: ",mean_err[2]," MSE: ",median_err[2])
print ("Weighted Moving Averages (2016 Values) - MAPE: ",mean_err[3]," MSE: ",median_err[3])
print ("-----")
print ("Exponential Moving Averages (Ratios) - MAPE: ",mean_err[4]," MSE: ",median_err[4])
print ("Exponential Moving Averages (2016 Values) - MAPE: ",mean_err[5]," MSE: ",median_err[5])
```

Error Metric Matrix (Forecasting Methods) - MAPE & MSE

Moving Averages (Ratios) -	MAPE: 0.22785156353133512	MSE: 1196.2953853046595
Moving Averages (2016 Values) -	MAPE: 0.15583458712025738	MSE: 254.66309363799283
-----		
Weighted Moving Averages (Ratios) -	MAPE: 0.22706529144871415	MSE: 1053.083529345878
Weighted Moving Averages (2016 Values) -	MAPE: 0.1479482182992932	MSE: 224.81054547491038
-----		
Exponential Moving Averages (Ratios) -	MAPE: 0.2275474636148534	MSE: 1019.3071012544802
Exponential Moving Averages (2016 Values) -	MAPE: 0.1475381297798153	MSE: 222.35159610215055

Please Note:- The above comparisons are made using Jan 2015 and Jan 2016 only

From the above matrix it is inferred that the best forecasting model for our prediction would be:-  $P'_t = \alpha * P_{t-1} + (1 - \alpha) * P'_{t-1}$  i.e Exponential Moving Averages using 2016 Values

## Regression Models

```
In [41]: len(regions_cum[19])
```

```
Out[41]: 13104
```

```
In [0]: first_x = list(range(0,4464))
second_x = list(range(4464,8640))
third_x = list(range(8640,13104))
```

```
In [0]: # At first we tried with 10 features each of amplitude and frequency, but that
# didn't work out well, so we are reverting back to 5 features each of amplitude
# and frequency
col_names = ['Amp_'+str(i) if i<6 else 'Freq_'+str(i-5) for i in range(1,11)]
```

In [43]: # Working on the fourier features

```
fourier_features = np.array([])

# iterating over the clusters #40
for i in range(0,40):
    # Calculate freq and amplitude using the regions_cum data from above
    # Also sort the freq and amplitude values and take only the top 5 values
    fft_JanAmp = sorted(np.fft.fft(regions_cum[i][:4464]), reverse=True)[:5]
    fft_JanFreq = sorted(np.fft.fftfreq(4464, 1), reverse=True)[:5]

    fft_FebAmp = sorted(np.fft.fft(regions_cum[i][4464:8640]), reverse=True)[:5]
    fft_FebFreq = sorted(np.fft.fftfreq(4176, 1), reverse=True)[:5]

    fft_MarAmp = sorted(np.fft.fft(regions_cum[i][8640:]), reverse=True)[:5]
    fft_MarFreq = sorted(np.fft.fftfreq(4464, 1), reverse=True)[:5]

    for topFreq in range(5):
        fft_JanAmp[topFreq] = [fft_JanAmp[topFreq]] * 4464
        fft_JanFreq[topFreq] = [fft_JanFreq[topFreq]] * 4464

        fft_FebAmp[topFreq] = [fft_FebAmp[topFreq]] * 4176
        fft_FebFreq[topFreq] = [fft_FebFreq[topFreq]] * 4176

        fft_MarAmp[topFreq] = [fft_MarAmp[topFreq]] * 4464
        fft_MarFreq[topFreq] = [fft_MarFreq[topFreq]] * 4464

# Transposing for dimensions
fft_JanAmp = np.array(fft_JanAmp).T
fft_JanFreq = np.array(fft_JanFreq).T
fft_FebAmp = np.array(fft_FebAmp).T
fft_FebFreq = np.array(fft_FebFreq).T
fft_MarAmp = np.array(fft_MarAmp).T
fft_MarFreq = np.array(fft_MarFreq).T

jan_feats = np.hstack((fft_JanAmp, fft_JanFreq))
feb_feats = np.hstack((fft_JanAmp, fft_JanFreq))
mar_feats = np.hstack((fft_JanAmp, fft_JanFreq))
all_feats = np.vstack((jan_feats, feb_feats, mar_feats))

# print("All Feats: ", all_feats.shape)
# print("Fourier Features: ", fourier_features.shape)
fourier_features = all_feats[:] if fourier_features.shape[0]==0 else \
                  np.append(fourier_features, all_feats, axis=0)

# print(fft_JanAmp.shape)
# print(fft_JanFreq.shape)
# print(fft_FebAmp.shape)
# print(fft_FebFreq.shape)
# print(fft_MarAmp.shape)
# print(fft_MarFreq.shape)
# print(jan_feats.shape)
# print(feb_feats.shape)
# print(mar_feats.shape)
# print(all_feats.shape)
# print(fft_JanAmp[0][:3])
# print('*10')
# print(fft_JanFreq[0][:3])
# print('*10')
# print(all_feats[0])

print("All Feats: ", all_feats.shape)
print("Fourier Features: ", fourier_features.shape)
fourier_features_df = pd.DataFrame(np.array(fourier_features),
```

```
columns=col_names, dtype=np.float)
fourier_features_df = fourier_features_df.fillna(0)
All Feats: (13392, 10)
Fourier Features: (535680, 10)
```

## Train-Test Split

Before we start predictions using the tree based regression models we take 3 months of 2016 pickup data and split it such that for every region we have 70% data in train and 30% in test, ordered date-wise for every region

```
In [0]: # Preparing data to be split into train and test, The below prepares data in cumulative form which will be later split into test and train
# number of 10min indices for jan 2015= 24*31*60/10 = 4464
# number of 10min indices for jan 2016 = 24*31*60/10 = 4464
# number of 10min indices for feb 2016 = 24*29*60/10 = 4176
# number of 10min indices for march 2016 = 24*31*60/10 = 4464
# regions_cum: it will contain 40 lists, each list will contain 4464+4176+4464 values which represents the number of pickups
# that are happened for three months in 2016 data

# print(len(regions_cum))
# 40
# print(len(regions_cum[0]))
# 13104

# we take number of pickups that are happened in last 5 10min intravels
number_of_time_stamps = 5

# output varaiable
# it is list of lists
# it will contain number of pickups 13099 for each cluster
output = []

# tsne_lat will contain 13104-5=13099 times lattitude of cluster center for every cluster
# Ex: [[cent_lat 13099times], [cent_lat 13099times], [cent_lat 13099times].... 40 lists]
# it is list of lists
tsne_lat = []

# tsne_lon will contain 13104-5=13099 times logitude of cluster center for every cluster
# Ex: [[cent_long 13099times], [cent_long 13099times], [cent_long 13099times].... 40 lists]
# it is list of lists
tsne_lon = []

# we will code each day
# sunday = 0, monday=1, tue = 2, wed=3, thur=4, fri=5,sat=6
# for every cluster we will be adding 13099 values, each value represent to which day of the week that pickup bin belongs to
# it is list of lists
tsne_weekday = []

# its an numpy array, of shape (523960, 5)
# each row corresponds to an entry in out data
# for the first row we will have [f0,f1,f2,f3,f4] fi=number of pickups happened in i+1th 10min intravel(bin)
# the second row will have [f1,f2,f3,f4,f5]
# the third row will have [f2,f3,f4,f5,f6]
# and so on...
tsne_feature = []

tsne_feature = [0]*number_of_time_stamps
for i in range(0,40):
    tsne_lat.append([kmeans.cluster_centers_[i][0]]*13099)
    tsne_lon.append([kmeans.cluster_centers_[i][1]]*13099)
    # jan 1st 2016 is thursday, so we start our day from 4: "(int(k/144))%7+4"
    # our prediction start from 5th 10min intravel since we need to have number of pickups that are happened in last 5 pickup bins
    tsne_weekday.append([int(((int(k/144))%7+4)%7) for k in range(5,4464+4176+4464)])
    # regions_cum is a list of lists [[x1,x2,x3..x13104], [x1,x2,x3..x13104], [x1,x2,x3..x13104], [x1,x2,x3..x13104], .. 40 lsits]
    tsne_feature = np.vstack((tsne_feature, [regions_cum[i][r:r+number_of_time_stamps] for r in range(0,len(regions_cum[i])-number_of_time_stamps)]))
    output.append(regions_cum[i][5:])
tsne_feature = tsne_feature[1:]
```

```
In [45]: len(tsne_lat[0])*len(tsne_lat) == tsne_feature.shape[0] == len(tsne_weekday)*len(tsne_weekday[0]) == 40*13099 == len(output)*len(output[0])
```

```
Out[45]: True
```

```
In [0]: # Getting the predictions of exponential moving averages to be used as a
# feature in cumulative form

# upto now we computed 8 features for every data point that starts from 50th
# min of the day
# 1. cluster center latitude
# 2. cluster center longitude
# 3. day of the week
# 4. f_t_1: number of pickups that are happened previous t-1th 10min intravel
# 5. f_t_2: number of pickups that are happened previous t-2th 10min intravel
# 6. f_t_3: number of pickups that are happened previous t-3th 10min intravel
# 7. f_t_4: number of pickups that are happened previous t-4th 10min intravel
# 8. f_t_5: number of pickups that are happened previous t-5th 10min intravel

# from the baseline models we said the exponential weighted moving avarage gives
# us the best error we will try to add the same exponential weighted moving
# avarage at t as a feature to our data exponential weighted moving
# avarage => p'(t) = alpha*p'(t-1) + (1-alpha)*P(t-1)
alpha=0.3

# it is a temporary array that store exponential weighted moving avarage for each 10min intravel,
# for each cluster it will get reset
# for every cluster it contains 13104 values
predicted_values=[]

# it is similar like tsne_lat
# it is list of lists
# predict_list is a list of lists [[x5,x6,x7..x13104], [x5,x6,x7..x13104], [x5,x6,x7..x13104], [x5,x6,x7..x13104], [x5,x6,x7..x13104], .. 40 lsits]
predict_list = []
tsne_flat_exp_avg = []
for r in range(0,40):
    for i in range(0,13104):
        if i==0:
            predicted_value= regions_cum[r][0]
            predicted_values.append(0)
            continue
        predicted_values.append(predicted_value)
        predicted_value =int((alpha*predicted_value) + (1-alpha)*(regions_cum[r][i]))
    predict_list.append(predicted_values[5:])
    predicted_values=[]
```

```
In [0]: # Code from :
# https://grisha.org/blog/2016/02/17/triple-exponential-smoothing-forecasting-part-iii/

def initial_trend(series, slen):
    #
    sum = 0.0
    for i in range(slen):
        sum += float(series[i+slen] - series[i]) / slen
    return sum / slen

def initial_seasonal_components(series, slen):
    # this code is for the seasonal components
    seasonals = {}
    season_averages = []
    n_seasons = int(len(series)/slen)
    # compute season averages
    for j in range(n_seasons):
        season_averages.append(sum(series[slen*j:slen*j+slen])/float(slen))
    # compute initial values
    for i in range(slen):
        sum_of_vals_over_avg = 0.0
        for j in range(n_seasons):
            sum_of_vals_over_avg += series[slen*j+i]-season_averages[j]
        seasonals[i] = sum_of_vals_over_avg/n_seasons
    return seasonals

def triple_exponential_smoothing(series, slen, alpha, beta, gamma, n_preds):
    result = []
    seasonals = initial_seasonal_components(series, slen)
    for i in range(len(series)+n_preds):
        if i == 0: # initial values
            smooth = series[0]
            trend = initial_trend(series, slen)
            result.append(series[0])
            continue
        if i >= len(series): # we are forecasting
            m = i - len(series) + 1
            result.append((smooth + m*trend) + seasonals[i%slen])
        else:
            val = series[i]
            last_smooth, smooth = smooth, alpha*(val-seasonals[i%slen]) + (1-alpha)*(smooth+trend)
            trend = beta * (smooth-last_smooth) + (1-beta)*trend
            seasonals[i%slen] = gamma*(val-smooth) + (1-gamma)*seasonals[i%slen]
            result.append(smooth+trend+seasonals[i%slen])
    return result
```

```
In [0]: # 0.716, 0.029 and 0.993
# alpha = 0.2
# beta = 0.15
# gamma = 0.2
# season_len = 24

predict_list_tes = []
tsne_flat_exp_avg = []
for r in range(0,40):
    # for i in range(0,13104):
    temp = triple_exponential_smoothing(regions_cum[r],slen=24,alpha=0.716,
                                         beta=0.029,gamma=0.993,n_preds=0)
    predict_list_tes.append(temp[5:])
```

```
In [49]: # train, test split : 70% 30% split
# Before we start predictions using the tree based regression models we take 3 months of 2016 pickup data
# and split it such that for every region we have 70% data in train and 30% in test,
# ordered date-wise for every region
print("size of train data :", int(13099*0.7))
print("size of test data :", int(13099*0.3))
```

```
size of train data : 9169
size of test data : 3929
```

```
In [0]: # extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our training data
train_features = [tsne_feature[i*13099:(13099*i+9169)] for i in range(0,40)]
# temp = [0]*(12955 - 9068)
test_features = [tsne_feature[(13099*(i))+9169:13099*(i+1)] for i in range(0,40)]
```

```
In [0]: ffeatures_train = pd.DataFrame(columns=col_names)
ffeatures_test = pd.DataFrame(columns=col_names)

for i in range(40):
    ffeatures_train = ffeatures_train.append(fourier_features_df[i*13099 : 13099*i + 9169])

ffeatures_train.reset_index(inplace = True, drop=True)

for i in range(40):
    ffeatures_test = ffeatures_test.append(fourier_features_df[i*13099 + 9169 : 13099*(i+1)])

ffeatures_test.reset_index(inplace = True, drop=True)
```

```
In [0]: print("Number of data clusters",len(train_features), "Number of data points in trian data", len(train_features[0]), "Each data point contains", len(train_features[0][0]), "features")
print("Number of data clusters",len(train_features), "Number of data points in test data", len(test_features[0]), "Each data point contains", len(test_features[0][0]), "features")
```

```
Number of data clusters 40 Number of data points in trian data 9169 Each data point contains 5 features
Number of data clusters 40 Number of data points in test data 3930 Each data point contains 5 features
```

```
In [0]: # extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our training data
tsne_train_flat_lat = [i[:9169] for i in tsne_lat]
tsne_train_flat_lon = [i[:9169] for i in tsne_lon]
tsne_train_flat_weekday = [i[:9169] for i in tsne_weekday]
tsne_train_flat_output = [i[:9169] for i in output]
tsne_train_flat_exp_avg = [i[:9169] for i in predict_list]
tsne_train_flat_triple_exp_avg = [i[:9169] for i in predict_list_tes]
```

```
In [0]: # extracting the rest of the timestamp values i.e 30% of 12956 (total timestamps) for our test data
tsne_test_flat_lat = [i[9169:] for i in tsne_lat]
tsne_test_flat_lon = [i[9169:] for i in tsne_lon]
tsne_test_flat_weekday = [i[9169:] for i in tsne_weekday]
tsne_test_flat_output = [i[9169:] for i in output]
tsne_test_flat_exp_avg = [i[9169:] for i in predict_list]
tsne_test_flat_triple_exp_avg = [i[9169:] for i in predict_list_tes]
```

```
In [0]: # the above contains values in the form of list of lists (i.e. list of values of each region), here we make all of them in one list
train_new_features = []
for i in range(0,40):
    train_new_features.extend(train_features[i])
test_new_features = []
for i in range(0,40):
    test_new_features.extend(test_features[i])
```

```
In [0]: # converting lists of lists into sinle list i.e flatten  
# a = [[1,2,3,4],[4,6,7,8]]  
# print(sum(a,[]))  
# [1, 2, 3, 4, 4, 6, 7, 8]
```

```
tsne_train_lat = sum(tsne_train_flat_lat, [])  
tsne_train_lon = sum(tsne_train_flat_lon, [])  
tsne_train_weekday = sum(tsne_train_flat_weekday, [])  
tsne_train_output = sum(tsne_train_flat_output, [])  
tsne_train_exp_avg = sum(tsne_train_flat_exp_avg, [])  
tsne_train_triple_exp_avg = sum(tsne_train_flat_triple_exp_avg, [])
```

```
In [0]: # converting lists of lists into sinle list i.e flatten  
# a = [[1,2,3,4],[4,6,7,8]]  
# print(sum(a,[]))  
# [1, 2, 3, 4, 4, 6, 7, 8]
```

```
tsne_test_lat = sum(tsne_test_flat_lat, [])  
tsne_test_lon = sum(tsne_test_flat_lon, [])  
tsne_test_weekday = sum(tsne_test_flat_weekday, [])  
tsne_test_output = sum(tsne_test_flat_output, [])  
tsne_test_exp_avg = sum(tsne_test_flat_exp_avg, [])  
tsne_test_triple_exp_avg = sum(tsne_test_flat_triple_exp_avg, [])
```

```
In [57]: # Preparing the data frame for our train data  
columns = ['ft_5','ft_4','ft_3','ft_2','ft_1']  
df_train = pd.DataFrame(data=train_new_features, columns=columns)  
df_train['lat'] = tsne_train_lat  
df_train['lon'] = tsne_train_lon  
df_train['weekday'] = tsne_train_weekday  
df_train['exp_avg'] = tsne_train_exp_avg  
df_train['3exp_avg'] = tsne_train_triple_exp_avg  
print(df_train.shape)
```

```
(366760, 10)
```

```
In [58]: # Preparing the data frame for our train data  
df_test = pd.DataFrame(data=test_new_features, columns=columns)  
df_test['lat'] = tsne_test_lat  
df_test['lon'] = tsne_test_lon  
df_test['weekday'] = tsne_test_weekday  
df_test['exp_avg'] = tsne_test_exp_avg  
df_test['3exp_avg'] = tsne_test_triple_exp_avg  
print(df_test.shape)
```

```
(157200, 10)
```

```
In [59]: df_test.head()
```

Out[59]:

	ft_5	ft_4	ft_3	ft_2	ft_1	lat	lon	weekday	exp_avg	3exp_avg
0	143	145	119	113	124	40.776228	-73.982119	4	121	121.733089
1	145	119	113	124	121	40.776228	-73.982119	4	120	132.227291
2	119	113	124	121	131	40.776228	-73.982119	4	127	111.115106
3	113	124	121	131	110	40.776228	-73.982119	4	115	117.089100
4	124	121	131	110	116	40.776228	-73.982119	4	115	141.465559

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

Out[0]:

	Amp_1	Amp_2	Amp_3	Amp_4	Amp_5	Freq_1	Freq_2	Freq_3	Freq_4	Freq_5
0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101	0.499776	0.499552	0.499328	0.499104	0.49888
1	367173.0	94490.188858	94490.188858	14349.849101	14349.849101	0.499776	0.499552	0.499328	0.499104	0.49888
2	367173.0	94490.188858	94490.188858	14349.849101	14349.849101	0.499776	0.499552	0.499328	0.499104	0.49888
3	367173.0	94490.188858	94490.188858	14349.849101	14349.849101	0.499776	0.499552	0.499328	0.499104	0.49888
4	367173.0	94490.188858	94490.188858	14349.849101	14349.849101	0.499776	0.499552	0.499328	0.499104	0.49888

```
In [60]: # Adding fourier features also
```

```
print(ffeatures_train.shape)
print(df_train.shape)
df_train = pd.concat([df_train, ffeatures_train], axis=1)
df_test = pd.concat([df_test, ffeatures_test], axis=1)
print("Shape of data after concatenation : ", df_train.shape)

(366760, 10)
(366760, 10)
Shape of data after concatenation : (366760, 20)
```

```
In [61]: df_train.shape
```

Out[61]: (366760, 20)

```
In [0]: from prettytable import PrettyTable
```

```
In [63]: table = PrettyTable(field_names=['Features & Models', 'Train MAPE', 'Test MAPE'])
print(table)

+-----+-----+-----+
| Features & Models | Train MAPE | Test MAPE |
+-----+-----+-----+
```

## Using Linear Regression

```
In [0]: def mean_absolute_percentage_error(y_true, y_pred):
# https://stackoverflow.com/questions/47648133/mape-calculation-in-python
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

```
In [0]: from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics.scorer import make_scorer
```

```
In [0]: # find more about LinearRegression function here http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html
# -----
# default paramters
# sklearn.linear_model.LinearRegression(fit_intercept=True, normalize=False, copy_X=True, n_jobs=1)

# some of methods of LinearRegression()
# fit(X, y[, sample_weight]) Fit linear model.
# get_params([deep]) Get parameters for this estimator.
# predict(X) Predict using the linear model
# score(X, y[, sample_weight]) Returns the coefficient of determination R^2 of the prediction.
# set_params(**params) Set the parameters of this estimator.
# -----
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/geometric-intuition-1-2-copy-8/
# -----


search_Params = {'fit_intercept':[True, False], 'normalize':[True, False],
                  'copy_X':[True, False]}

# since MAPE is not directly available we will use custom scorer
# Reverting back to 'mean_absolute_error' as custom scorer slows down
# the process and mean_absolute_error is almost same (just without percentage)
mape_scorer = make_scorer(mean_absolute_percentage_error,
                           greater_is_better=False)

# lr_reg=LinearRegression().fit(df_train, tsne_train_output)
lr_reg = LinearRegression(n_jobs = -1)

grid = GridSearchCV( lr_reg, search_Params, scoring='neg_mean_absolute_error',
                     cv=5, n_jobs=-1)
grid.fit(df_train, tsne_train_output)

print(grid.best_estimator_)
print(grid.best_params_)
print(grid.best_score_)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=-1, normalize=False)
{'copy_X': True, 'fit_intercept': True, 'normalize': False}
-8.670592954565864
```

```
In [0]: import sklearn
sklearn.metrics.SCORERS.keys()
```

```
Out[0]: dict_keys(['explained_variance', 'r2', 'max_error', 'neg_median_absolute_error', 'neg_mean_absolute_error', 'neg_mean_squared_error', 'neg_mean_squared_log_error', 'accuracy', 'roc_auc', 'balanced_accuracy', 'average_precision', 'neg_log_loss', 'brier_score_loss', 'adjusted_rand_score', 'homogeneity_score', 'completeness_score', 'v_measure_score', 'mutual_info_score', 'adjusted_mutual_info_score', 'normalized_mutual_info_score', 'fowlkes_mallows_score', 'precision', 'precision_macro', 'precision_micro', 'precision_samples', 'precision_weighted', 'recall', 'recall_macro', 'recall_micro', 'recall_samples', 'recall_weighted', 'f1', 'f1_macro', 'f1_micro', 'f1_samples', 'f1_weighted', 'jaccard', 'jaccard_macro', 'jaccard_micro', 'jaccard_samples', 'jaccard_weighted'])
```

```
In [0]: lr_reg_opt = LinearRegression(fit_intercept=True, normalize=False,
                                   copy_X=True, n_jobs=-1).fit(df_train, tsne_train_output)

y_pred = lr_reg_opt.predict(df_test)
lr_test_predictions = [round(value) for value in y_pred]
y_pred = lr_reg_opt.predict(df_train)
lr_train_predictions = [round(value) for value in y_pred]
```

## Using Random Forest Regressor

```
In [0]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [0]: # Training a hyper-parameter tuned random forest regressor on our train data
# find more about LinearRegression function here http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html
# -----
# default paramters
# sklearn.ensemble.RandomForestRegressor(n_estimators=10, criterion='mse', max_depth=None, min_samples_split=2,
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0,
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False)

# some of methods of RandomForestRegressor()
# apply(X)      Apply trees in the forest to X, return leaf indices.
# decision_path(X)    Return the decision path in the forest
# fit(X, y[, sample_weight])   Build a forest of trees from the training set (X, y).
# get_params([deep])   Get parameters for this estimator.
# predict(X)     Predict regression target for X.
# score(X, y[, sample_weight]) Returns the coefficient of determination R^2 of the prediction.
# -----
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# -----


search_Params = {'max_depth': [3,7,13,19,None],
                 'min_samples_split': [3,7,11,17], 'max_features': ['sqrt','log2'],
                 'min_samples_leaf': [5,10,20,50], 'n_estimators':[10,20,40,60,100]}

# regr1 = RandomForestRegressor(max_features='sqrt',min_samples_leaf=4,min_samples_split=3,n_estimators=40, n_jobs=-1)
# regr1.fit(df_train, tsne_train_output)

reg_RF = RandomForestRegressor(n_jobs=-1)
randomSearch = RandomizedSearchCV(reg_RF, search_Params,
                                   scoring='neg_mean_absolute_error', cv=5, n_jobs=-1)
randomSearch.fit(df_train, tsne_train_output)

print(randomSearch.best_estimator_)
print(randomSearch.best_params_)
print(randomSearch.best_score_)

RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=50, min_samples_split=11,
                      min_weight_fraction_leaf=0.0, n_estimators=60, n_jobs=-1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
{'n_estimators': 60, 'min_samples_split': 11, 'min_samples_leaf': 50, 'max_features': 'sqrt', 'max_depth': None}
-8.8054514253159
```

```
In [0]: # Predicting on test data using our trained random forest model

# the models reg_RF is already hyper parameter tuned
# the parameters that we got above are found using grid search

reg_RF_opt = RandomForestRegressor(max_depth=None, n_jobs=-1,
                                   max_features='sqrt', min_samples_split=11, min_samples_leaf=50,
                                   n_estimators=60).fit(df_train, tsne_train_output)

y_pred = reg_RF_opt.predict(df_test)
rndf_test_predictions = [round(value) for value in y_pred]
y_pred = reg_RF_opt.predict(df_train)
rndf_train_predictions = [round(value) for value in y_pred]
```

```
In [68]: #feature importances based on analysis using random forest
```

```
print (df_train.columns)
print (reg_RF_opt.feature_importances_)
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'lat', 'lon', 'weekday',
       'exp_avg', '3exp_avg', 'Amp_1', 'Amp_2', 'Amp_3', 'Amp_4', 'Amp_5',
       'Freq_1', 'Freq_2', 'Freq_3', 'Freq_4', 'Freq_5'],
      dtype='object')
[5.01672190e-02 5.58445944e-02 1.21471979e-01 1.21458333e-01
 1.18686126e-01 5.50495053e-03 4.44954597e-04 4.08100025e-05
 1.86545694e-01 3.34663649e-01 9.72091893e-04 1.65604537e-03
 5.11144426e-04 1.61977781e-03 4.12631545e-04 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00]
```

## Using XgBoost Regressor

```
In [0]: # Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBRegressor function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#module-xgboost.sklearn
# -----
# default paramters
# xgboost.XGBRegressor(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True, objective='reg:linear',
# booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1, max_delta_step=0, subsample=1, colsample_bytree=1,
# colsample_bylevel=1, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, base_score=0.5, random_state=0, seed=None,
# missing=None, **kwargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep]) Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
# -----
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# -----


# x_model = xgb.XGBRegressor(
#   learning_rate =0.1,
#   n_estimators=1000,
#   max_depth=3,
#   min_child_weight=3,
#   gamma=0,
#   subsample=0.8,
#   reg_alpha=200, reg_lambda=200,
#   colsample_bytree=0.8,nthread=4)
# x_model.fit(df_train, tsne_train_output)

search_Params = {
    'max_depth' : [3,7,13,19],
    'subsample':[0.7, 0.8, 0.9],
    'min_child_weight':[3, 5, 7, 9],
    'n_estimators':[10,20,40,60,100],
    'reg_lambda':[50,100,200,300],
}

# regr1 = RandomForestRegressor(max_features='sqrt',min_samples_leaf=4,min_samples_split=3,n_estimators=40, n_jobs=-1)
# regr1.fit(df_train, tsne_train_output)

reg_XGB = xgb.XGBRegressor(n_jobs=-1)
randomSearch = RandomizedSearchCV(reg_XGB, search_Params,
                                  scoring='neg_mean_absolute_error',cv=5,n_jobs=-1)
randomSearch.fit(df_train, tsne_train_output)

print(randomSearch.best_estimator_)
print(randomSearch.best_params_)
print(randomSearch.best_score_)

[13:50:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
            colsample_bynode=1, colsample_bytree=1, gamma=0,
            importance_type='gain', learning_rate=0.1, max_delta_step=0,
            max_depth=7, min_child_weight=7, missing=None, n_estimators=60,
            n_jobs=-1, nthread=None, objective='reg:linear', random_state=0,
            reg_alpha=0, reg_lambda=100, scale_pos_weight=1, seed=None,
            silent=None, subsample=0.8, verbosity=1)
{'subsample': 0.8, 'reg_lambda': 100, 'n_estimators': 60, 'min_child_weight': 7, 'max_depth': 7}
-8.636649718237656
```

```
In [69]: #predicting with our trained Xg-Boost regressor
# the models reg_XGB_opt is already hyper parameter tuned
# the parameters that we got above are found using grid search

reg_XGB_opt = xgb.XGBRegressor(subsample=0.8, reg_lambda=100, n_estimators=60,
                                min_child_weight=7, max_depth=7, n_jobs=-1).fit(df_train, tsne_train_output)

y_pred = reg_XGB_opt.predict(df_test)
xgb_test_predictions = [round(value) for value in y_pred]
y_pred = reg_XGB_opt.predict(df_train)
xgb_train_predictions = [round(value) for value in y_pred]
```

[21:37:36] WARNING: /workspace/src/objective/regression\_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

```
In [0]: #feature importances
# reg_XGB_opt.booster().get_score(importance_type='weight')
# This causes error
```

## Calculating the error metric values for various models

```
In [0]: train_mape=[]
test_mape=[]

train_mape.append((mean_absolute_error(tsne_train_output, df_train['ft_1'].values))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output, df_train['exp_avg'].values))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output, rndf_train_predictions))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output, xgb_train_predictions))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output, lr_train_predictions))/(sum(tsne_train_output)/len(tsne_train_output)))

test_mape.append((mean_absolute_error(tsne_test_output, df_test['ft_1'].values))/(sum(tsne_test_output)/len(tsne_test_output)))
test_mape.append((mean_absolute_error(tsne_test_output, df_test['exp_avg'].values))/(sum(tsne_test_output)/len(tsne_test_output)))
test_mape.append((mean_absolute_error(tsne_test_output, rndf_test_predictions))/(sum(tsne_test_output)/len(tsne_test_output)))
test_mape.append((mean_absolute_error(tsne_test_output, xgb_test_predictions))/(sum(tsne_test_output)/len(tsne_test_output)))
test_mape.append((mean_absolute_error(tsne_test_output, lr_test_predictions))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
In [73]: # My results
print ("Error Metric Matrix (Tree Based Regression Methods) - MAPE")
print ("-----")
print ("Baseline Model - Train: ",train_mape[0], " Test: ",test_mape[0])
print ("Exponential Averages Forecasting - Train: ",train_mape[1], " Test: ",test_mape[1])
print ("Linear Regression - Train: ",train_mape[4], " Test: ",test_mape[4])
print ("Random Forest Regression - Train: ",train_mape[2], " Test: ",test_mape[2])
print ("XgBoost Regression - Train: ",train_mape[3], " Test: ",test_mape[3])

# These results are before adding triple exponential smoothing features
# Error Metric Matrix (Tree Based Regression Methods) - MAPE
#
# -----
# Baseline Model - Train: 0.14870666996426116 Test: 0.14225522601041551
# Exponential Averages Forecasting - Train: 0.14121603560900353 Test: 0.13490049942819257
# Linear Regression - Train: 0.13802301026329256 Test: 0.13245145619313087
# Random Forest Regression - Train: 0.13579086250656994 Test: 0.13372383813599986
```

	Train:	Test:
Baseline Model -	0.14870666996426116	0.14225522601041551
Exponential Averages Forecasting -	0.14121603560900353	0.13490049942819257
Linear Regression -	0.008715182130203348	0.007313798407181784
Random Forest Regression -	0.031058117057109234	0.030828032058441257
XgBoost Regression -	0.0070961145917974745	0.00751691990698004

```
In [0]: table.add_row(['Baseline Model',round(0.14870666996426116,3),round(0.14225522601041551,3)])
table.add_row(['Exponential Averages Forecasting',round(0.14121603560900353,3),round(0.13490049942819257,3)])
table.add_row(['Linear Regression',round(0.008715182130203348,3),round(0.007313798407181784,3)])
table.add_row(['Random Forest Regression',round(0.031058117057109234,3),round(0.030828032058441257,3)])
table.add_row(['XgBoost Regression',round(0.0070961145917974745,3),round(0.00751691990698004,3)])
# print(table)
```

```
In [0]: # AAIC Results
print ("Error Metric Matrix (Tree Based Regression Methods) - MAPE")
print ("-----")
print ("Baseline Model - Train: ",train_mape[0]," Test: ",test_mape[0])
print ("Exponential Averages Forecasting - Train: ",train_mape[1]," Test: ",test_mape[1])
print ("Linear Regression - Train: ",train_mape[3]," Test: ",test_mape[3])
print ("Random Forest Regression - Train: ",train_mape[2]," Test: ",test_mape[2])
```

Error Metric Matrix (Tree Based Regression Methods) - MAPE

	Train:	Test:
Baseline Model -	0.140052758787	0.136531257048
Exponential Averages Forecasting -	0.13289968436	0.129361804204
Linear Regression -	0.13331572016	0.129120299401
Random Forest Regression -	0.0918514693197	0.127141622928

## Error Metric Matrix

```
In [77]: # My results
print ("Error Metric Matrix (Tree Based Regression Methods) - MAPE")
print ("-----")
print ("Baseline Model - Train: ",train_mape[0]," Test: ",test_mape[0])
print ("Exponential Averages Forecasting - Train: ",train_mape[1]," Test: ",test_mape[1])
print ("Linear Regression - Train: ",train_mape[4]," Test: ",test_mape[4])
print ("Random Forest Regression - Train: ",train_mape[2]," Test: ",test_mape[2])
print ("XgBoost Regression - Train: ",train_mape[3]," Test: ",test_mape[3])
print ("-----")
```

# These results are before adding triple exponential smoothing features  
# Error Metric Matrix (Tree Based Regression Methods) - MAPE  
# -----  
# Baseline Model - Train: 0.14870666996426116 Test: 0.14225522601041551  
# Exponential Averages Forecasting - Train: 0.14121603560900353 Test: 0.13490049942819257  
# Linear Regression - Train: 0.142064026879845 Test: 0.13475084095054785  
# Random Forest Regression - Train: 0.13579086250656994 Test: 0.13372383813599986  
# XgBoost Regression - Train: 0.13802301026329256 Test: 0.13245145619313087  
# -----

Error Metric Matrix (Tree Based Regression Methods) - MAPE

	Train:	Test:
Baseline Model -	0.14870666996426116	0.14225522601041551
Exponential Averages Forecasting -	0.14121603560900353	0.13490049942819257
Linear Regression -	0.008715182130203348	0.007313798407181784
Random Forest Regression -	0.031058117057109234	0.030828032058441257
XgBoost Regression -	0.0070961145917974745	0.00751691990698004

```
In [0]: # AAIC Code
print ("Error Metric Matrix (Tree Based Regression Methods) - MAPE")
print ("-----")
print ("Baseline Model - Train: ",train_mape[0]," Test: ",test_mape[0])
print ("Exponential Averages Forecasting - Train: ",train_mape[1]," Test: ",test_mape[1])
print ("Linear Regression - Train: ",train_mape[4]," Test: ",test_mape[4])
print ("Random Forest Regression - Train: ",train_mape[2]," Test: ",test_mape[2])
print ("XgBoost Regression - Train: ",train_mape[3]," Test: ",test_mape[3])
print ("-----")
```

```
Error Metric Matrix (Tree Based Regression Methods) - MAPE
-----
Baseline Model - Train: 0.140052758787 Test: 0.136531257048
Exponential Averages Forecasting - Train: 0.13289968436 Test: 0.129361804204
Linear Regression - Train: 0.13331572016 Test: 0.129120299401
Random Forest Regression - Train: 0.0917619544199 Test: 0.127244647137
XgBoost Regression - Train: 0.129387355679 Test: 0.126861699078
-----
```

## Assignments

```
In [0]: '''
Task 1: Incorporate Fourier features as features into Regression models and measure MAPE. <br>
Task 2: Perform hyper-parameter tuning for Regression models.
2a. Linear Regression: Grid Search
2b. Random Forest: Random Search
2c. Xgboost: Random Search
Task 3: Explore more time-series features using Google search/Quora/Stackoverflow
to reduce the MAPE to < 12%
'''
```

```
In [0]: # So we see a huge improvement in the MAPE after adding the triple exponential smoothing
# features. For the benefit of time we didn't go for hyperparameter tuning after adding
# these additional features but used the old hyperparams which we had got on the previous
# 29 features. Another change is to drop the Amplitude and Frequency features from 10
# each to 5 each, as they are not adding much value and increasing the data
```

```
In [76]: print(table)
```

Features & Models	Train MAPE	Test MAPE
Baseline Model	0.149	0.142
Exponential Averages Forecasting	0.141	0.135
Linear Regression	0.009	0.007
Random Forest Regression	0.031	0.031
XgBoost Regression	0.007	0.008

```
In [0]: 
```