Taxi demand prediction in New York City

In [1]:
```
#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_datafram
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 zoo
matplotlib.use('nbagg')
import matplotlib.pylab 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
#!pip install gpxpy
import gpxpy.geo #Get the haversine distance

from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering
import math
import pickle
import os

# download migwin: https://mingw-w64.org/doku.php/download/mingw-builds
# install it in your system and keep the path, migw_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")
```

Data Information

Ge the data from : 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 (FHVs)

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 [13]:

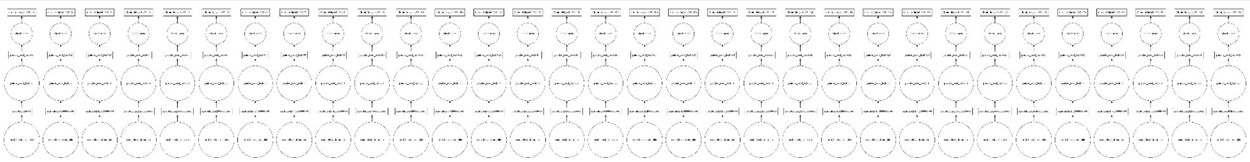
```
#Looking at the features
# dask dataframe  : # https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ipynb
month = dd.read_csv('C:/Users/PareshBhatia/Downloads/Learning/Data Science/analytics vidya/yellow_tripdata_
print(month.columns)
```

```
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 [14]:

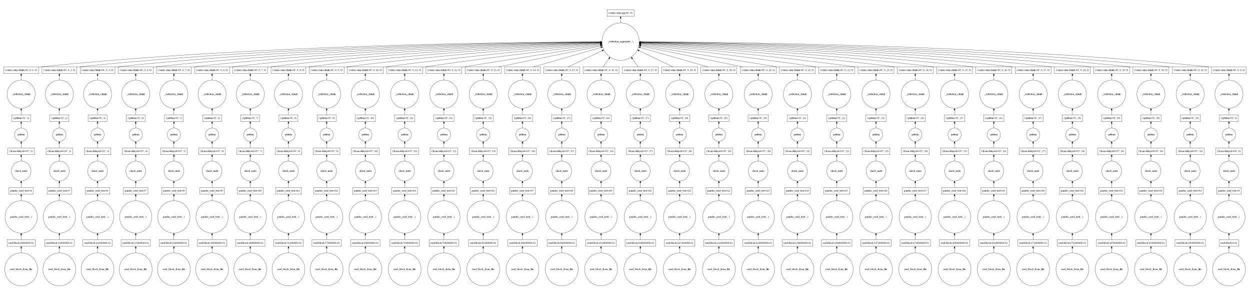
```
# However unlike Pandas, operations on dask.dataframes don't trigger immediate computation,
# instead they add key-value pairs to an underlying Dask graph. Recall that in the diagram below,
# circles are operations and rectangles are results.

# to see the visulaization you need to install graphviz
# pip3 install graphviz if this doesnt work please check the install_graphviz.jpg in the drive
```

Out[14]:



In [15]:

Out[15]:



Features in the dataset:

```
<tr>
    <td>Dropoff_longitude</td>
    <td>Longitude where the meter was disengaged.</td>
</tr>
<tr>
    <td>Dropoff_ latitude</td>
    <td>Latitude where the meter was disengaged.</td>
</tr>
<tr>
    <td>Payment_type</td>
    <td>A numeric code signifying how the passenger paid for the trip.
    <ol>
        <li> Credit card </li>
        <li> Cash </li>
        <li> No charge </li>
        <li> Dispute</li>
        <li> Unknown </li>
        <li> Voided trip</li>
    </ol>
    </td>
</tr>
<tr>
    <td>Fare_amount</td>
    <td>The time-and-distance fare calculated by the meter.</td>
</tr>
<tr>
    <td>Extra</td>
    <td>Miscellaneous extras and surcharges. Currently, this only includes. the $0.50 and $1 rush hour
and overnight charges.</td>
</tr>
<tr>
    <td>MTA_tax</td>
    <td>0.50 MTA tax that is automatically triggered based on the metered rate in use.</td>
</tr>
<tr>
    <td>Improvement_surcharge</td>
    <td>0.30 improvement surcharge assessed trips at the flag drop. the improvement surcharge began be
ing levied in 2015.</td>
</tr>
<tr>
    <td>Tip_amount</td>
    <td>Tip amount – This field is automatically populated for credit card tips.Cash tips are not incl
uded.</td>
</tr>
<tr>
    <td>Tolls_amount</td>
    <td>Total amount of all tolls paid in trip.</td>
</tr>
<tr>
    <td>Total_amount</td>
    <td>The total amount charged to passengers. Does not include cash tips.</td>
</tr>
```

Field Name	Description
VendorID	A code indicating the TPEP provider that provided the record. 1. Creative Mobile Technologies 2. 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.

ML Problem Formulation

Time-series forecasting and Regression

- To find number of pickups, given location cordinates(latitude and longitude) and time, in the query reigion 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 [16]:

```
#table below shows few datapoints along with all our features
```

Out[16]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	pickup_longitude	pickup_latitude	RateCodeID	store_
0	2	2015-01-15 19:05:39	2015-01-15 19:23:42	1	1.59	-73.993896	40.750111	1	
1	1	2015-01-10 20:33:38	2015-01-10 20:53:28	1	3.30	-74.001648	40.724243	1	
2	1	2015-01-10 20:33:38	2015-01-10 20:43:41	1	1.80	-73.963341	40.802788	1	
3	1	2015-01-10 20:33:39	2015-01-10 20:35:31	1	0.50	-74.009087	40.713818	1	
4	1	2015-01-10 20:33:39	2015-01-10 20:52:58	1	3.00	-73.971176	40.762428	1	

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 cordinates(lat,long) - (40.5774, -74.15) & (40.9176,-73.7004) so hence any cordinates not within these cordinates are not considered by us as we are only concerned with pickups which originate within New York.

In [17]:

```
# Plotting pickup cordinates 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)
```

Out[17]:

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

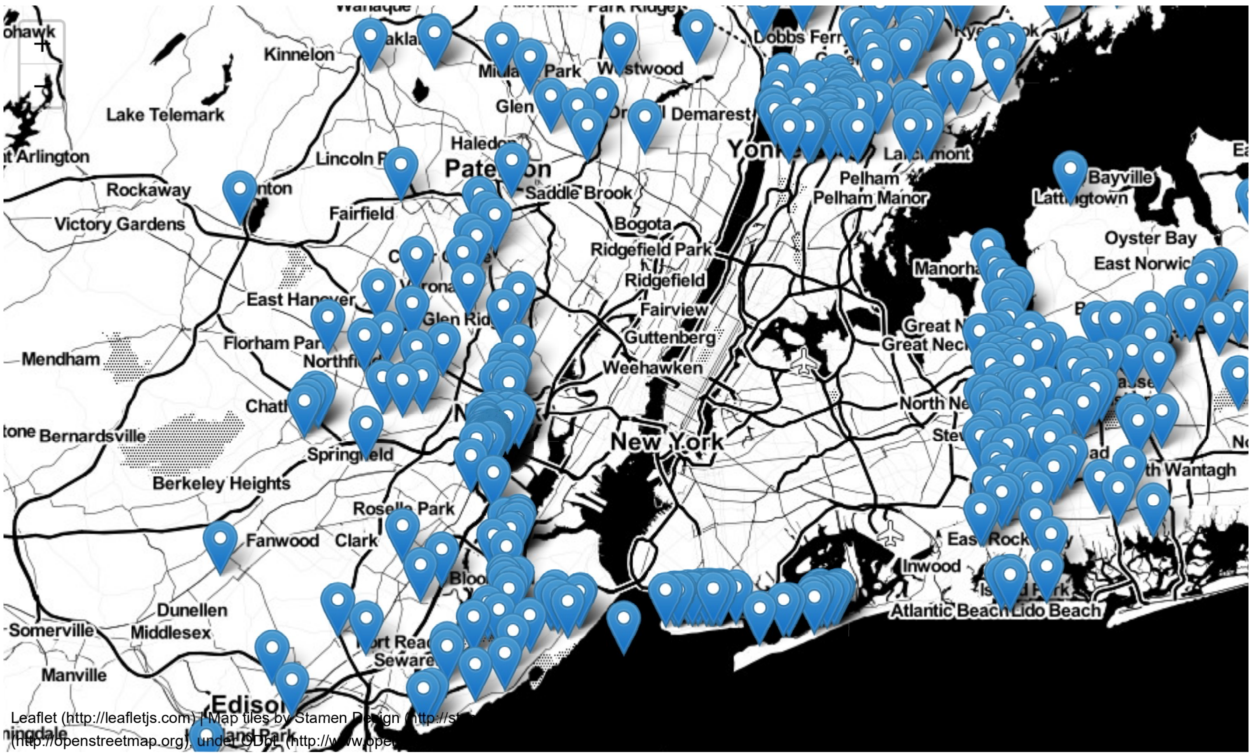
2. Dropoff Latitude & Dropoff Longitude

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

In [18]:

```
# Plotting dropoff cordinates 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)
```

Out[18]:



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

3. Trip Durations:

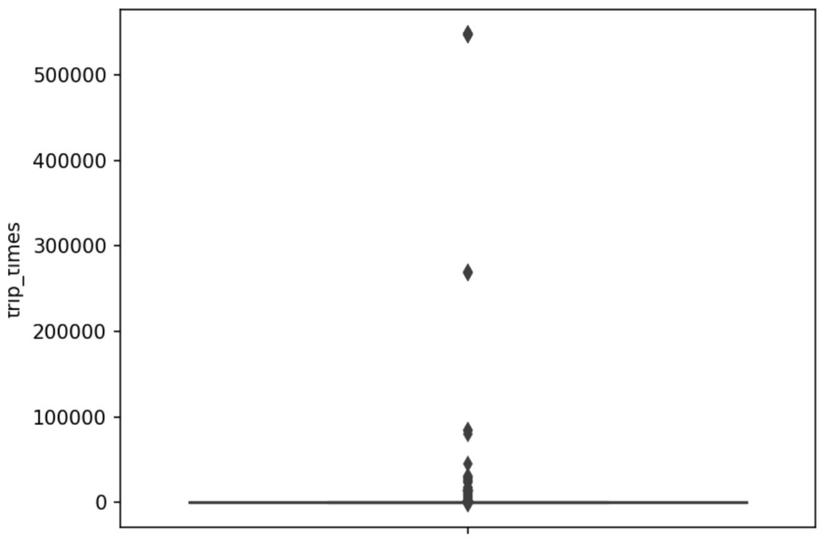
According to NYC Taxi & Limousine Commision Regulations **the maximum allowed trip duration in a 24 hour interval is 12 hours.**

In [19]:

```
#The timestamps are converted to unix so as to get duration(trip-time) & speed also pickup-times in unix a

# in out data we have time in the formate "YYYY-MM-DD HH:MM:SS" we convert thiss sting to python time form
# 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_lon

    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_latitu
#   1                  1.59       -73.993896          40.750111       -73.974785          40.750618
#   1                   3.30        -74.001648          40.724243       -73.994415          40.759109
#   1                   1.80        -73.963341          40.802788       -73.951820          40.824413
#   1                   0.50        -74.009087          40.713818       -74.004326          40.719986
#   1                   3.00        -73.971176          40.762428       -74.004181          40.742653
frame_with_durations = return_with_trip_times(month)
```

In [20]:
```
# the skewed box plot shows us the presence of outliers
sns.boxplot(y="trip_times", data =frame_with_durations)
```

Figure 1



In [21]:
```
#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))]))
```

```
0 percentile value is -1211.0166666666667
10 percentile value is 3.8333333333333335
20 percentile value is 5.383333333333334
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 14.283333333333333
80 percentile value is 17.633333333333333
90 percentile value is 23.45
100 percentile value is  548555.6333333333
```

In [22]:
```
#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))]))
```

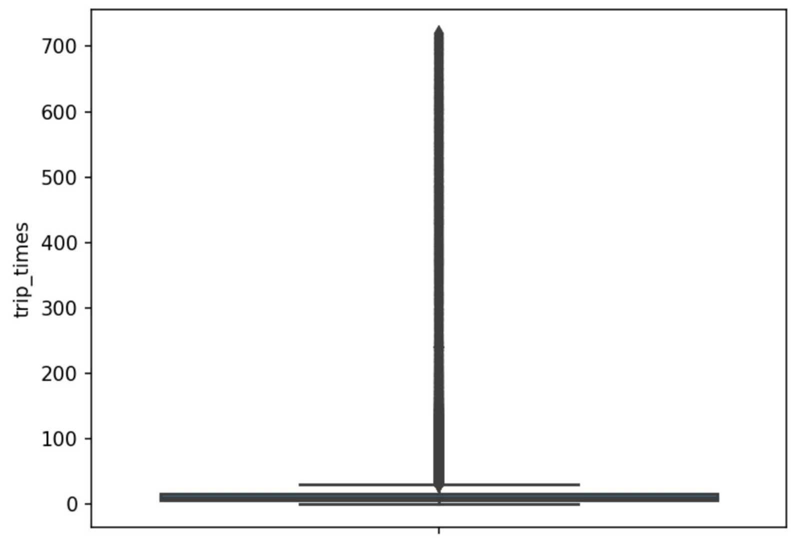
```
90 percentile value is 23.45
91 percentile value is 24.35
92 percentile value is 25.383333333333333
93 percentile value is 26.55
94 percentile value is 27.933333333333334
95 percentile value is 29.583333333333332
96 percentile value is 31.683333333333334
97 percentile value is 34.46666666666667
98 percentile value is 38.71666666666667
99 percentile value is 46.75
100 percentile value is  548555.6333333333
```

In [23]:
```
#removing data based on our analysis and TLC regulations
frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_times>1) & (frame_with_durat
```

In [24]:

```
#box-plot after removal of outliers
sns.boxplot(y="trip_times", data =frame_with_durations_modified)
```

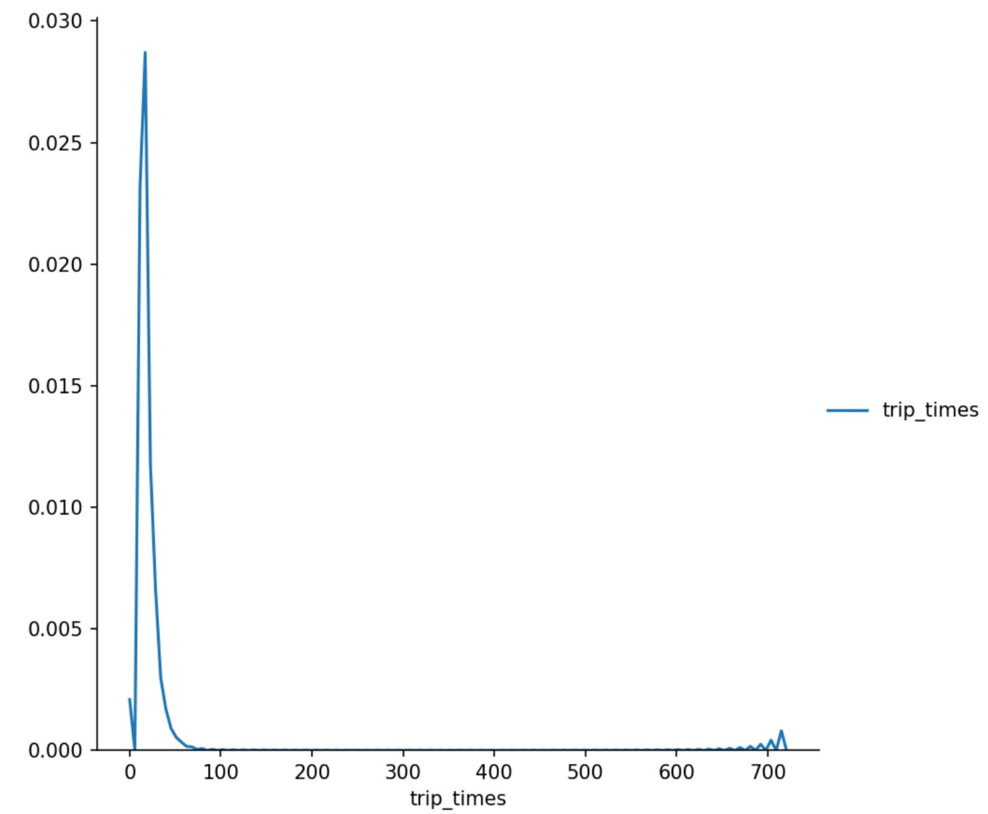
Figure 2



In [25]:

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

Figure 3



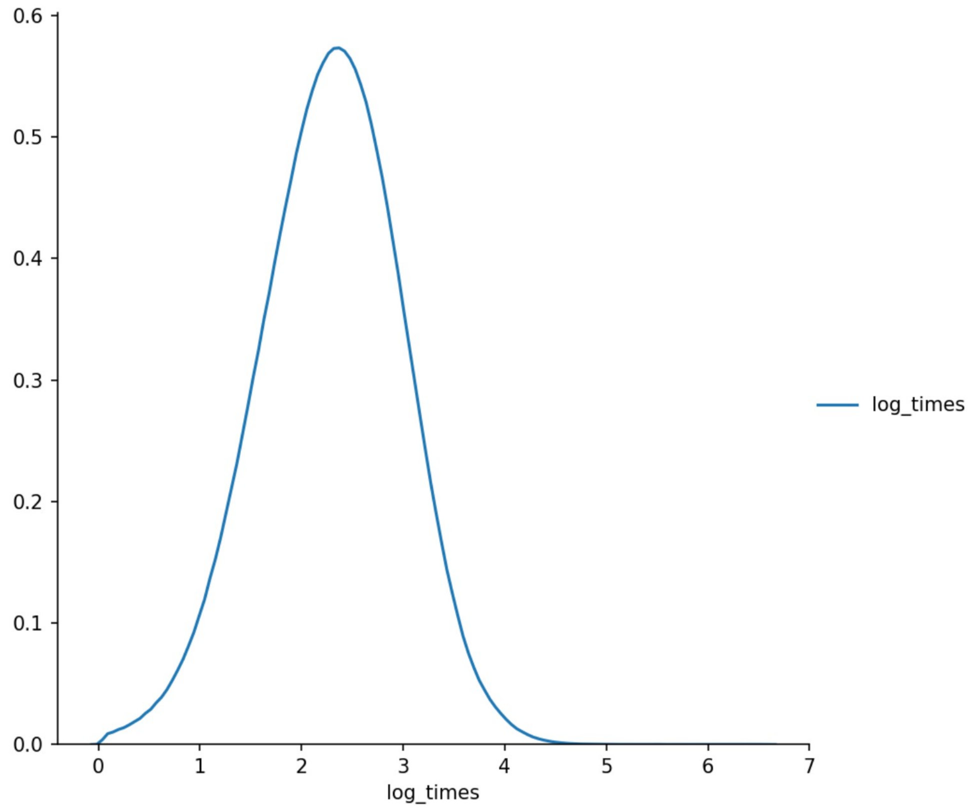
In [26]:

```
#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
```

In [27]:

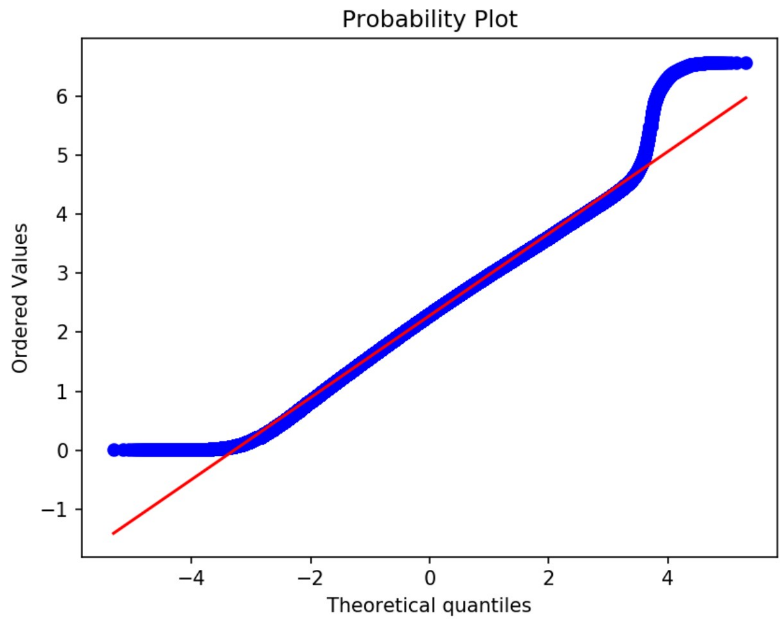
```
#pdf of log-values
sns.FacetGrid(frame_with_durations_modified,size=6) \
      .map(sns.kdeplot,"log_times") \
      .add_legend();
```

Figure 4



In [28]:
```
#Q-Q plot for checking if trip-times is log-normal
import scipy
scipy.stats.probplot(frame_with_durations_modified['log_times'].values, plot=plt)
```

Figure 5

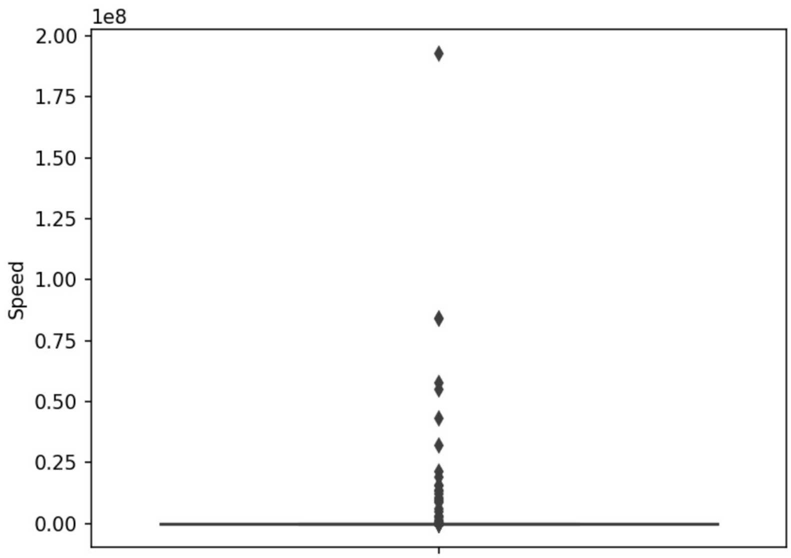


4. Speed

In [29]:

```
# 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_dur
sns.boxplot(y="Speed", data =frame_with_durations_modified)
plt.show()
```

Figure 6



In [30]:

```
#calculating speed values at each percntile 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))]))
```

```
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  192857142.85714284
```

In [31]:

```
#calculating speed values at each percntile 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))]))
```

```
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  192857142.85714284
```

In [32]:
```
#calculating speed values at each percntile 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["Speed"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]))
```

```
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  192857142.85714284
```

In [33]:
```
#removing further outliers based on the 99.9th percentile value
frame_with_durations_modified=frame_with_durations[(frame_with_durations.Speed>0) & (frame_with_durations.S
```

In [34]:
```
#avg.speed of cabs in New-York
```

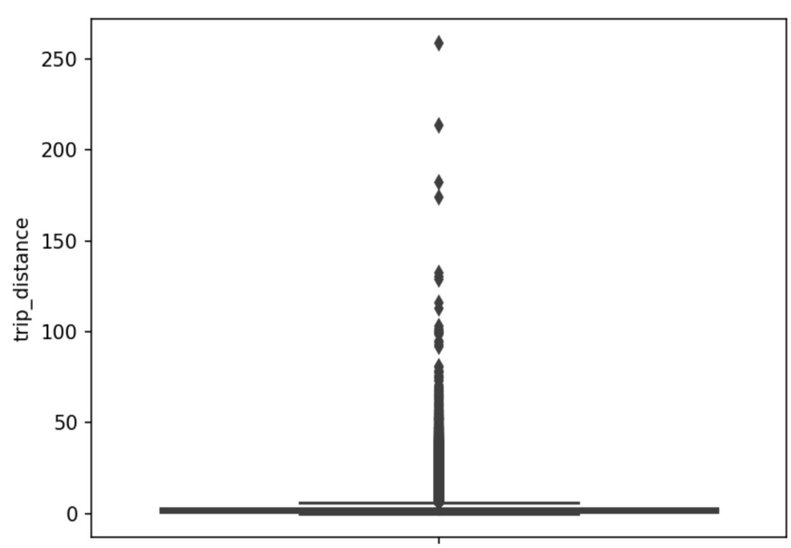
Out[34]: 12.450173996027528

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 [35]:
```
# 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)
```

Figure 7



In [36]:
```
#calculating trip distance values at each percntile 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))]))
```

```
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 [37]:
```
#calculating trip distance values at each percntile 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))]))
```

```
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
```

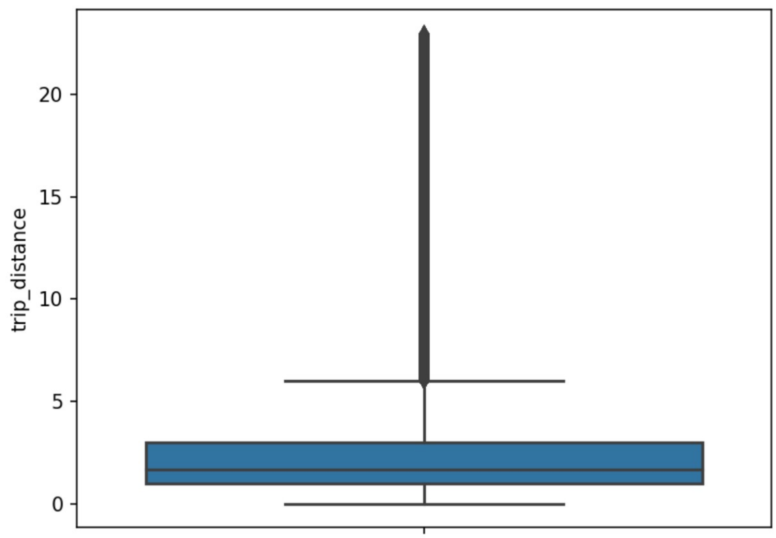
In [38]:
```
#calculating trip distance values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100
for i in np.arange(0.0, 1.0, 0.1):
    var =frame_with_durations_modified["trip_distance"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]))
```

```
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 [39]:
```
#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_du
```

In [40]:
```
#box-plot after removal of outliers
sns.boxplot(y="trip_distance", data = frame_with_durations_modified)
```

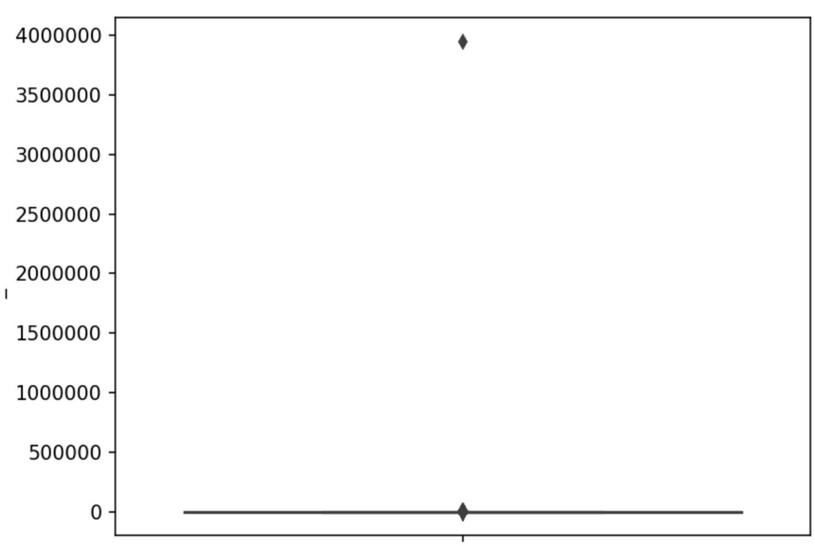
Figure 8



5. Total Fare

In [41]:
```
# 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
sns.boxplot(y="total_amount", data =frame_with_durations_modified)
```

Figure 9



In [42]:
```
#calculating total fare amount values at each percntile 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))]))
```

```
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 [43]:
```
#calculating total fare amount values at each percntile 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))]))
```

```
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
```

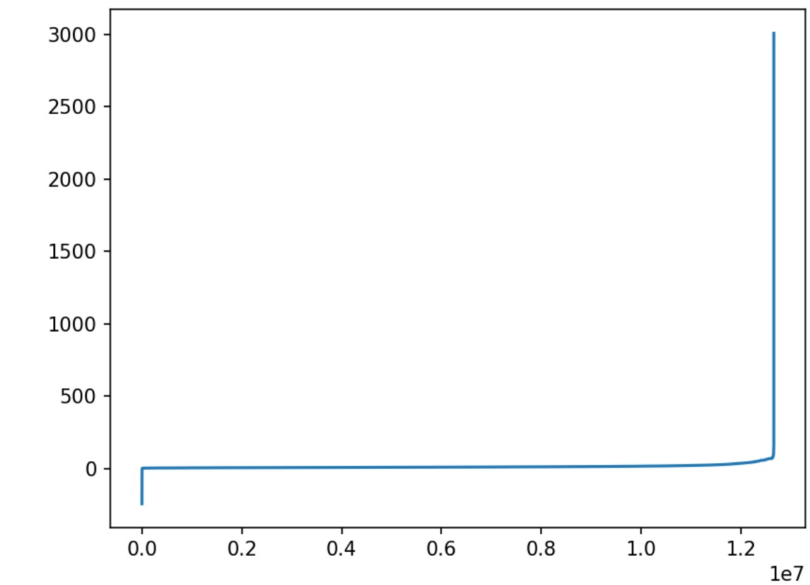
In [44]:
```
#calculating total fare amount values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,
for i in np.arange(0.0, 1.0, 0.1):
    var = frame_with_durations_modified["total_amount"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(99+i,var[int(len(var)*(float(99+i)/100))]))
```

```
99.0 percentile value is 66.13
99.1 percentile value is 68.13
99.2 percentile value is 69.6
99.3 percentile value is 69.6
99.4 percentile value is 69.73
99.5 percentile value is 69.75
99.6 percentile value is 69.76
99.7 percentile value is 72.58
99.8 percentile value is 75.35
99.9 percentile value is 88.28
100 percentile value is  3950611.6
```

Observation:- As even the 99.9th percentile value doesnt 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 analyis

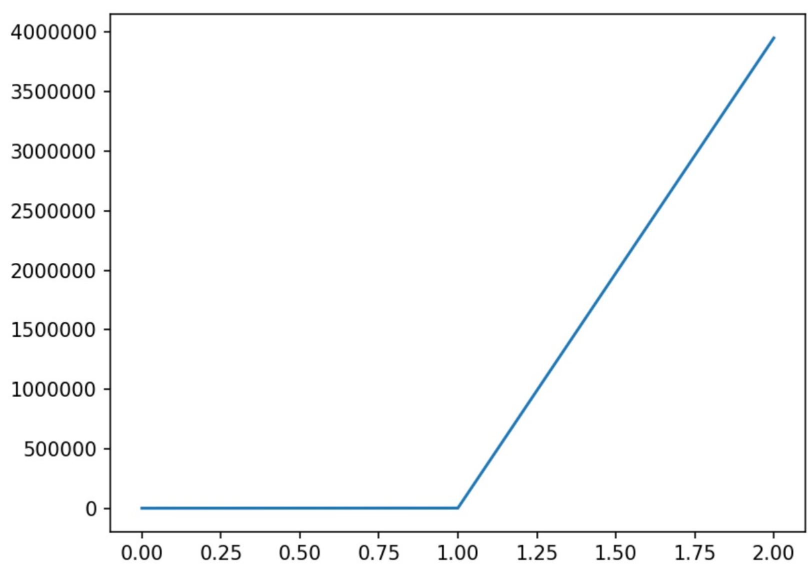
In [45]:
```
#below plot shows us the fare values(sorted) to find a sharp increase to remove those values as outliers
# plot the fare amount excluding last two values in sorted data
plt.plot(var[:-2])
```

Figure 10



In [46]:
```
# 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:])
```

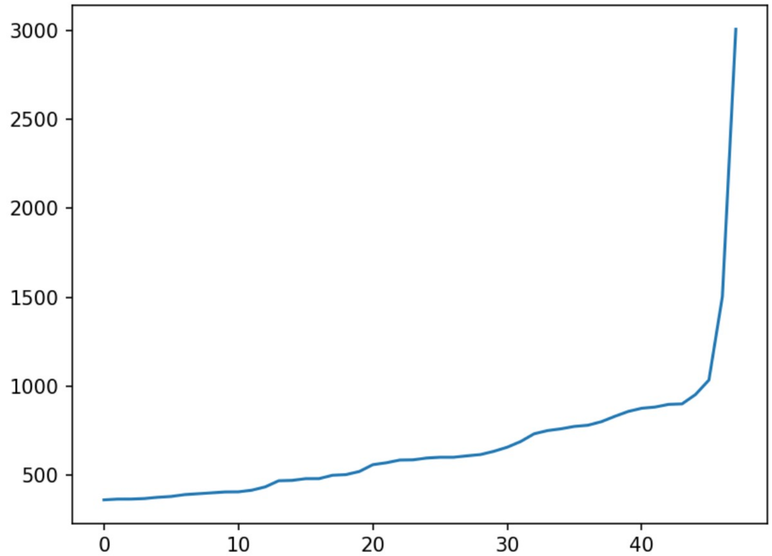
Figure 11



In [47]:

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

Figure 12



Remove all outliers/erronous points.

In [48]:
```
#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.
                       (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 <= -73.7
                       (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 ("---")
```

In [49]:
```
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_outlie
```

```
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 [50]:

```
#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],clust
                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,"\nAvg. Number of Clusters within the vicinity (i.

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_
    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
---
```

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 40

In [51]:

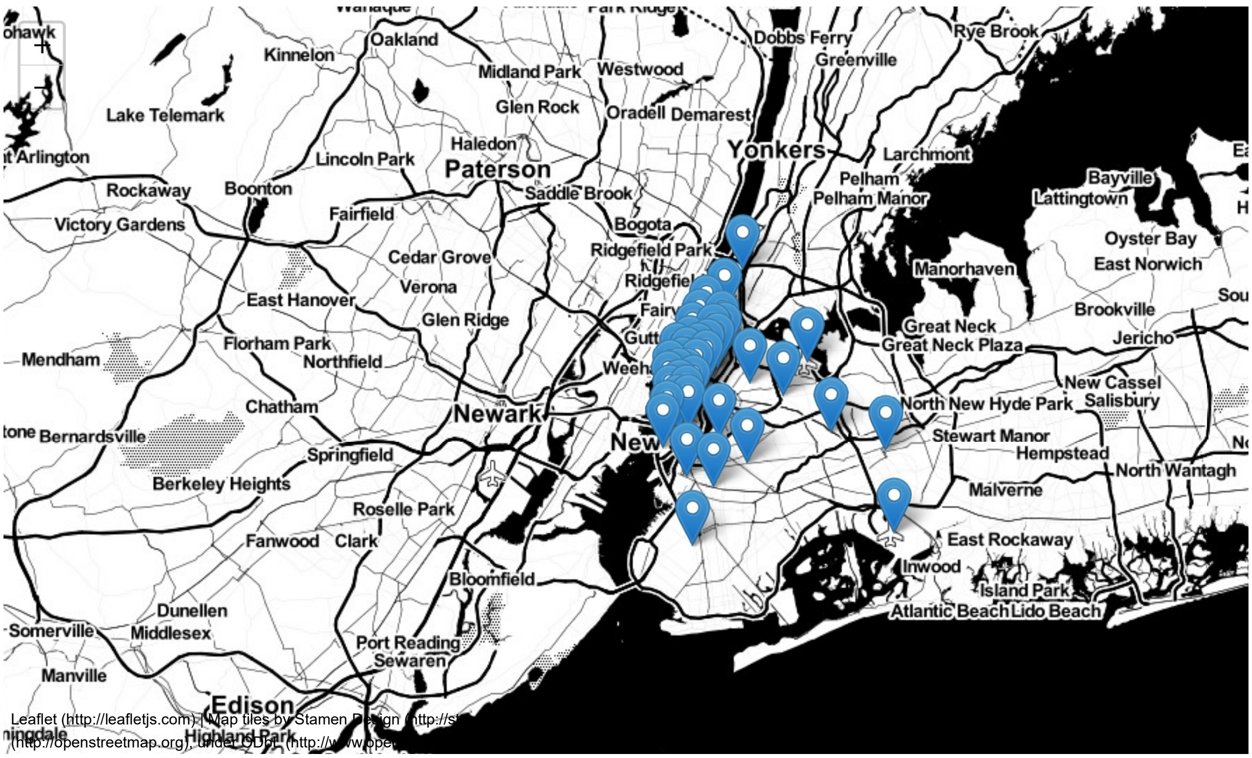
```
# if check for the 50 clusters you can observe that there are two clusters with only 0.3 miles apart from 
# so we choose 40 clusters for solve the further problem

# 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_rem
```

Plotting the cluster centers:

In [52]:

```
# 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])+s
map_osm
```

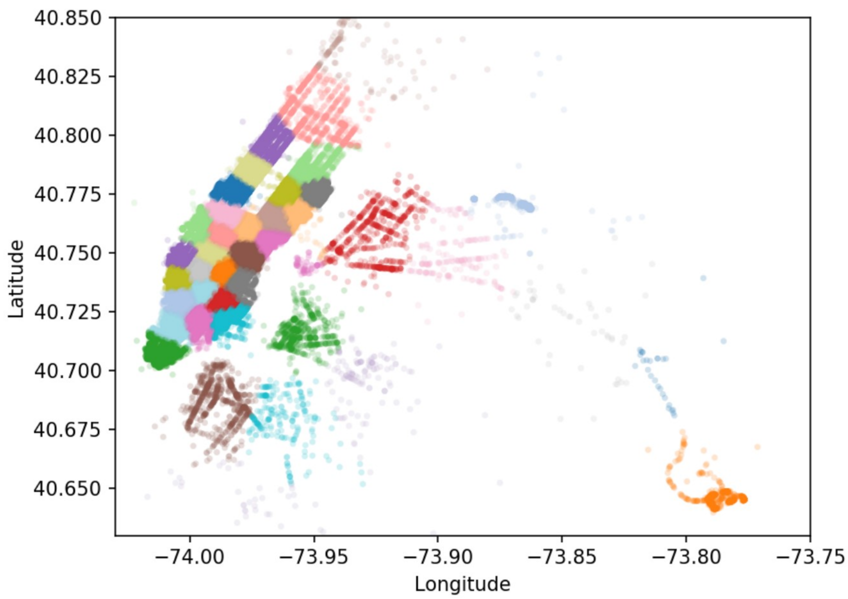
Out[52]:



Plotting the clusters:

In [53]:
```python
#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()
```

Figure 13



Time-binning

In [54]:
```python
#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)
```

In [55]:
```
# clustering, making pickup bins and grouping by pickup cluster and pickup bins
frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_durations_outliers_remo
jan_2015_frame = add_pickup_bins(frame_with_durations_outliers_removed,1,2015)
jan_2015_groupby = jan_2015_frame[['pickup_cluster','pickup_bins','trip_distance']].groupby(['pickup_clust
```

In [56]:
```
# we add two more columns 'pickup_cluster'(to which cluster it belogns to)
# and 'pickup_bins' (to which 10min intravel the trip belongs to)
```

Out[56]:

	passenger_count	trip_distance	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	total_amount	trip_times	pickup_times
0	1	1.59	-73.993896	40.750111	-73.974785	40.750618	17.05	18.050000	1.421329e+09
1	1	3.30	-74.001648	40.724243	-73.994415	40.759109	17.80	19.833333	1.420902e+09
2	1	1.80	-73.963341	40.802788	-73.951820	40.824413	10.80	10.050000	1.420902e+09
3	1	0.50	-74.009087	40.713818	-74.004326	40.719986	4.80	1.866667	1.420902e+09
4	1	3.00	-73.971176	40.762428	-74.004181	40.742653	16.30	19.316667	1.420902e+09

In [57]:
```
# hear the trip_distance represents the number of pickups that are happend in that particular 10min intrave
# this data frame has two indices
# primary index: pickup_cluster (cluster number)
# secondary index : pickup_bins (we devid whole months time into 10min intravels 24*31*60/10 =4464bins)
```

Out[57]:

		trip_distance
pickup_cluster	**pickup_bins**	
0	**1**	105
	2	199
	3	208
	4	141
	5	155

In [58]:

```
# 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 inlcudes only required colums
# 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 'pickuo_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_
    #frame_with_durations_outliers_removed_2016['pickup_cluster'] = kmeans.predict(frame_with_durations_ou

    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(['

    return final_updated_frame,final_groupby_frame

month_jan_2016 = dd.read_csv('C:/Users/PareshBhatia/Downloads/Learning/Data Science/analytics vidya/yellow_
month_feb_2016 = dd.read_csv('C:/Users/PareshBhatia/Downloads/Learning/Data Science/analytics vidya/yellow_
month_mar_2016 = dd.read_csv('C:/Users/PareshBhatia/Downloads/Learning/Data Science/analytics vidya/yellow_

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
```

Smoothing

In [59]:

```
# Gets the unique bins where pickup values are present for each each reigion

# for each cluster region we will collect all the indices of 10min intravels in which the pickups are happ
# we got an observation that there are some pickpbins that doesnt 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)
```

In [60]:
```
# 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
```

In [61]:

```
# for each cluster number of 10min intravels 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_u
    print('-'*60)
```

```
for the  0 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  1 th cluster number of 10min intavels with zero pickups:  1986
------------------------------------------------------------
for the  2 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  3 th cluster number of 10min intavels with zero pickups:  355
------------------------------------------------------------
for the  4 th cluster number of 10min intavels with zero pickups:  38
------------------------------------------------------------
for the  5 th cluster number of 10min intavels with zero pickups:  154
------------------------------------------------------------
for the  6 th cluster number of 10min intavels with zero pickups:  35
------------------------------------------------------------
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:  118
------------------------------------------------------------
for the  9 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  10 th cluster number of 10min intavels with zero pickups:  26
------------------------------------------------------------
for the  11 th cluster number of 10min intavels with zero pickups:  45
------------------------------------------------------------
for the  12 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  13 th cluster number of 10min intavels with zero pickups:  29
------------------------------------------------------------
for the  14 th cluster number of 10min intavels with zero pickups:  27
------------------------------------------------------------
for the  15 th cluster number of 10min intavels with zero pickups:  32
------------------------------------------------------------
for the  16 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  17 th cluster number of 10min intavels with zero pickups:  59
------------------------------------------------------------
for the  18 th cluster number of 10min intavels with zero pickups:  1191
------------------------------------------------------------
for the  19 th cluster number of 10min intavels with zero pickups:  1358
------------------------------------------------------------
for the  20 th cluster number of 10min intavels with zero pickups:  54
------------------------------------------------------------
for the  21 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  22 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  23 th cluster number of 10min intavels with zero pickups:  164
------------------------------------------------------------
for the  24 th cluster number of 10min intavels with zero pickups:  36
------------------------------------------------------------
for the  25 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  26 th cluster number of 10min intavels with zero pickups:  32
------------------------------------------------------------
for the  27 th cluster number of 10min intavels with zero pickups:  215
------------------------------------------------------------
for the  28 th cluster number of 10min intavels with zero pickups:  37
------------------------------------------------------------
for the  29 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  30 th cluster number of 10min intavels with zero pickups:  1181
------------------------------------------------------------
for the  31 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  32 th cluster number of 10min intavels with zero pickups:  45
------------------------------------------------------------
for the  33 th cluster number of 10min intavels with zero pickups:  44
------------------------------------------------------------
for the  34 th cluster number of 10min intavels with zero pickups:  40
------------------------------------------------------------
for the  35 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  36 th cluster number of 10min intavels with zero pickups:  37
------------------------------------------------------------
for the  37 th cluster number of 10min intavels with zero pickups:  322
```

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: _ _ _ x =>ceil(x/4), ceil(x/4), ceil(x/4), ceil(x/4)
    Ex2: _ _ x => ceil(x/3), ceil(x/3), ceil(x/3)
  - Case 2:(values missing in middle)
    Ex1: x _ _ y => ceil((x+y)/4), ceil((x+y)/4), ceil((x+y)/4), ceil((x+y)/4)
    Ex2: x _ _ _ y => ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5)
  - Case 3:(values missing at the end)
    Ex1: x _ _ _ => ceil(x/4), ceil(x/4), ceil(x/4), ceil(x/4)
    Ex2: x _ => ceil(x/2), ceil(x/2)

In [62]:

```python
# 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 intravel
# there wont be any value if there are no picksups.
# 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)
```

In [63]:

```
# 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 intravel
# there wont be any value if there are no picksups.
# 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 ma
# we finally return smoothed data
def smoothing(count_values,values):
    smoothed_regions=[] # stores list of final smoothed values of each reigion
    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
                            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 n
                        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
                        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
                    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 [64]:

```
#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
```

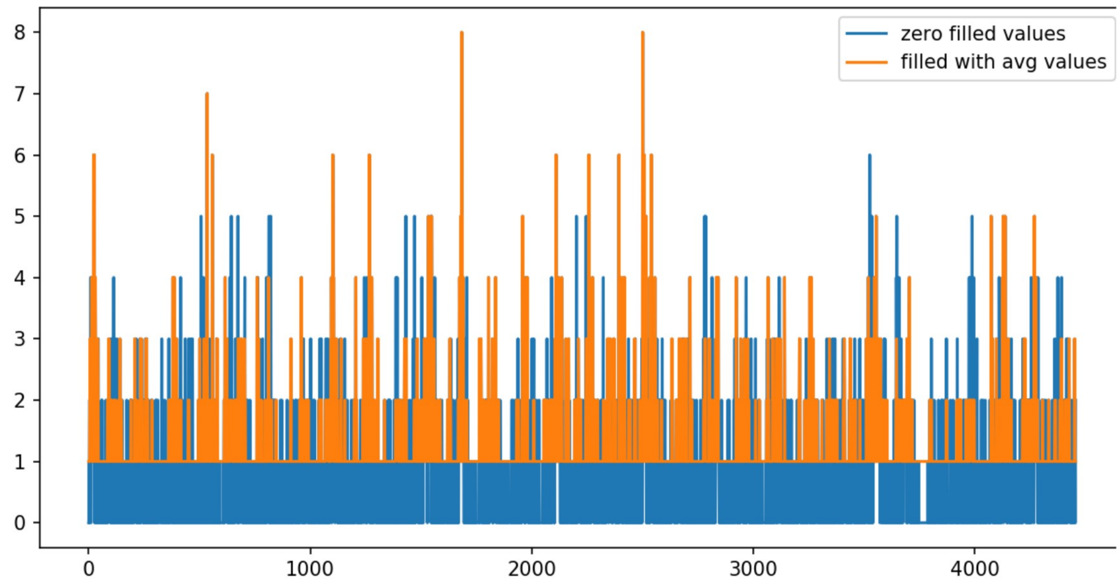
In [65]:

```
# 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)
```

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

In [66]:
```
# 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[4464:8920], label="zero filled values")
plt.plot(jan_2015_smooth[4464:8920], label="filled with avg values")
plt.legend()
```

Figure 14



In [67]:
```
# 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
# 10st 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 pickup.
# that are happened in the first 40min are same in both cases, but if you can observe that we looking at t.
# wheen you are using smoothing we are looking at the future number of pickups which might cause a data le.

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

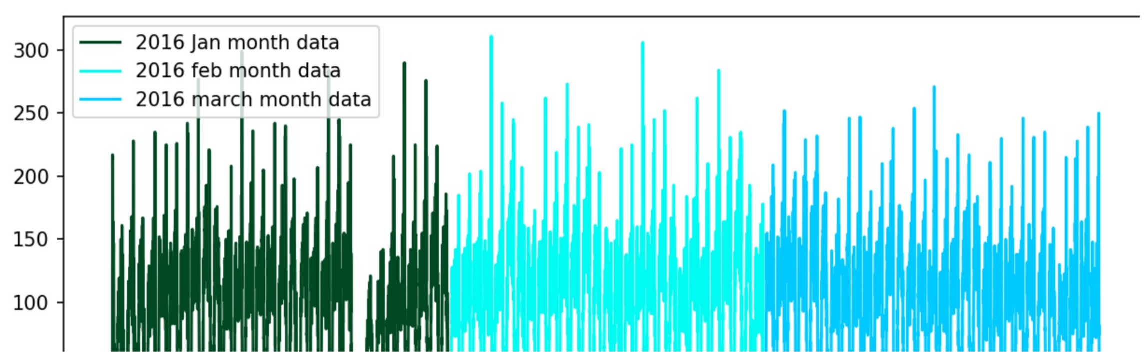
In [68]:
```
# Jan-2015 data is smoothed, Jan,Feb & March 2016 data missing values are filled with zero
jan_2015_smooth = smoothing(jan_2015_groupby['trip_distance'].values,jan_2015_unique)
jan_2016_smooth = fill_missing(jan_2016_groupby['trip_distance'].values,jan_2016_unique)
feb_2016_smooth = fill_missing(feb_2016_groupby['trip_distance'].values,feb_2016_unique)
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 regi
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
# 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_smoo

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

In [69]:
```
import pickle
with open('regions_cum.pkl','wb') as f:
```

Time series and Fourier Transforms

In [70]:
```
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()
```

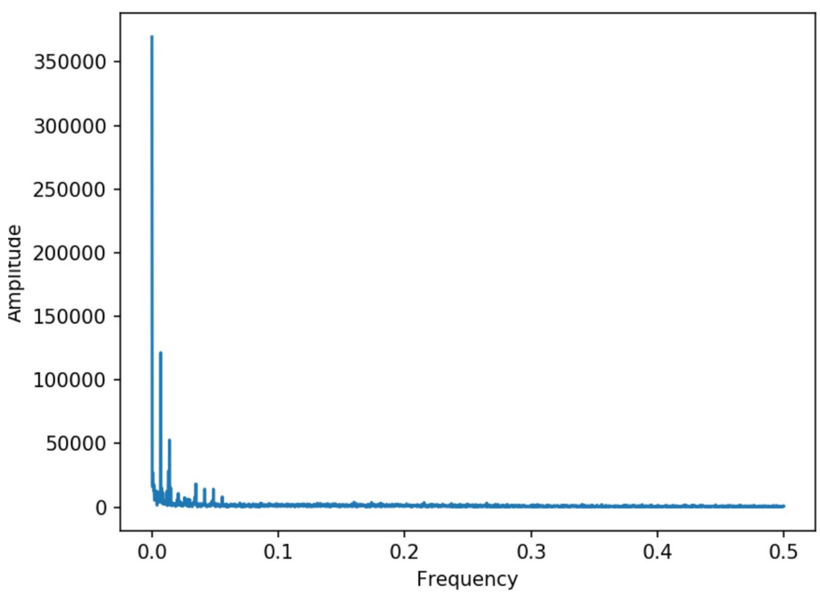
Figure 15



In [71]:

```
# 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")
```

Figure 55



In [72]:

```
#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
```

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 - $R_t = (R_{t-1} + R_{t-2} + R_{t-3} \ldots . R_{t-n})/n$

In [73]:
```
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'
        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 $P_t = (P_{t-1} + P_{t-2} + P_{t-3} \ldots . P_{t-n})/n$

In [74]:
```
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((math.pow(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)
```

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 Avergaes 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 - $R_t = (N * R_{t-1} + (N-1) * R_{t-2} + (N-2) * R_{t-3} \ldots . 1 * R_{t-n})/(N * (N+1)/2)$

In [75]:

```
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'
        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 -
$P_t = (N * P_{t-1} + (N-1) * P_{t-2} + (N-2) * P_{t-3} \ldots 1 * P_{t-n})/(N * (N+1)/2)$

In [76]:

```
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)
```

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) 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 infinetly 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 (α) 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 [77]:

```
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'
        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 [78]:

```
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)
```

In [79]:

```
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')
```

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 [80]:

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

```
Error Metric Matrix (Forecasting Methods) - MAPE & MSE
--------------------------------------------------------------------------------------------------------
Moving Averages (Ratios) -                              MAPE:  0.1821155173392136       MSE:  400.06255040
32258
Moving Averages (2016 Values) -                         MAPE:  0.14292849686975506       MSE:  174.849019
93727598
--------------------------------------------------------------------------------------------------------
Weighted Moving Averages (Ratios) -                     MAPE:  0.1784869254376018       MSE:  384.01578741
039424
Weighted Moving Averages (2016 Values) -                MAPE:  0.13551088436182082       MSE:  162.4670754
9283155
--------------------------------------------------------------------------------------------------------
Exponential Moving Averages (Ratios) -              MAPE:  0.17783550194861494       MSE:  378.3461021505
3766
Exponential Moving Averages (2016 Values) -         MAPE:  0.1350915263669572       MSE:  159.73614471326
164
```

Plese 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

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 [81]:
```
# Preparing data to be split into train and test, The below prepares data in cumulative form which will be
# 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
# that are happened for three months in 2016 data

# print(len(regions_cum))
# 40
# print(len(regions_cum[0]))
# 12960

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

# output varaible
# 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 pic
# it is list of lists
tsne_weekday = []

# its an numbpy 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(bi
# 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 happen
    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,x
    tsne_feature = np.vstack((tsne_feature, [regions_cum[i][r:r+number_of_time_stamps] for r in range(0,len
    output.append(regions_cum[i][5:])
tsne_feature = tsne_feature[1:]
```

In [82]:
```
len(tsne_lat[0])*len(tsne_lat) == tsne_feature.shape[0] == len(tsne_weekday)*len(tsne_weekday[0]) == 40*13
```

Out[82]: True

In [83]:

```
# 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 lattitude
# 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..
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 [ ]:

In [84]:

```
# 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))
```

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

In [85]:

```
# 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)
```

In [86]:

```
print("Number of data clusters",len(train_features), "Number of data points in trian data", len(train_featu
print("Number of data clusters",len(train_features), "Number of data points in test data", len(test_feature
```

```
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 [87]:

```
# # using double exponential smoothing with holt-winter's
# from statsmodels.tsa.holtwinters import ExponentialSmoothing
# from datetime import datetime
# holt_exp = []

# for r in range(0,40):
#     start = datetime.now()

#     predicted_value = ExponentialSmoothing(regions_cum[r], seasonal_periods=4, trend='add', seasonal='ad

#     holt_exp.append(predicted_value.astype(np.int64)[5:])

#     print('{} : {}'.format(r, datetime.now()-start))
```

In [88]:

In [89]:
```
# 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]
```

In [90]:
```
# 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]
```

In [91]:
```
# the above contains values in the form of list of lists (i.e. list of values of each region), here we mak
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 [92]:
```
# 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,[])
```

In [93]:
```
# 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,[])
```

In [94]:

```
366760
```

In [95]:
```
# 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['holt'] = tsne_train_holt
```

```
(366760, 9)
```

In [96]:
```
# 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['holt'] = tsne_test_holt
```

```
(157200, 9)
```

In [97]:
```
# with open('df_train.pkl','wb') as f:
#     pickle.dump(df_train,f)

with open('df_test.pkl','wb') as f:
    pickle.dump(df_test,f)
```

In [98]:
```
df_test.head()
```

Out[98]:

	ft_5	ft_4	ft_3	ft_2	ft_1	lat	lon	weekday	exp_avg
0	118	106	104	93	102	40.776228	-73.982119	4	100
1	106	104	93	102	101	40.776228	-73.982119	4	100
2	104	93	102	101	120	40.776228	-73.982119	4	114
3	93	102	101	120	131	40.776228	-73.982119	4	125
4	102	101	120	131	164	40.776228	-73.982119	4	152

Using Linear Regression

In [99]:
```
# find more about LinearRegression function here http://scikit-learn.org/stable/modules/generated/sklearn.
# -------------------------
# 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-
# -----------------------

from sklearn.linear_model import LinearRegression
lr_reg=LinearRegression().fit(df_train, tsne_train_output)

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

Using Random Forest Regressor

In [86]:
```
# 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.
# -------------------------
# default paramters
# sklearn.ensemble.RandomForestRegressor(n_estimators=10, criterion='mse', max_depth=None, min_samples_spl
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_s

# 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-de
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# -----------------------

regr1 = RandomForestRegressor(max_features='sqrt',min_samples_leaf=4,min_samples_split=3,n_estimators=40, 
regr1.fit(df_train, tsne_train_output)
```

Out[86]:
```
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=4, min_samples_split=3,
                      min_weight_fraction_leaf=0.0, n_estimators=40, n_jobs=-1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
```

In [87]:
```
# Predicting on test data using our trained random forest model

# the models regr1 is already hyper parameter tuned
# the parameters that we got above are found using grid search

y_pred = regr1.predict(df_test)
rndf_test_predictions = [round(value) for value in y_pred]
y_pred = regr1.predict(df_train)
```

In [88]:
```
#feature importances based on analysis using random forest
print (df_train.columns)
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'lat', 'lon', 'weekday',
       'exp_avg'],
      dtype='object')
[0.05653407 0.04967482 0.13617875 0.23053264 0.21779969 0.00409651
 0.00257052 0.00165312 0.3009599 ]
```

Using XgBoost Regressor

In [89]:
```
# 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.htm
# -------------------------
# default paramters
# xgboost.XGBRegressor(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True, objective='reg:linea
# booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1, max_delta_step=0, subsample=1, co
# colsample_bylevel=1, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, base_score=0.5, random_state=0, seed
# 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,
# 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
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-de
# 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=3)
x_model.fit(df_train, tsne_train_output)
```

Out[89]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=0.8, gamma=0, learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=3, missing=None, n_estimators=1000,
             n_jobs=1, nthread=3, objective='reg:linear', random_state=0,
             reg_alpha=200, reg_lambda=200, scale_pos_weight=1, seed=None,
             silent=True, subsample=0.8)
```

In [90]:
```
#predicting with our trained Xg-Boost regressor
# the models x_model is already hyper parameter tuned
# the parameters that we got above are found using grid search

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

In [91]:
```
#feature importances
```

Out[91]:
```
array([0.15286624, 0.10694712, 0.12738854, 0.15153311, 0.14486742,
       0.0865057 , 0.08783884, 0.02532958, 0.11672345], dtype=float32)
```

Calculating the error metric values for various models

In [92]:
```
train_mape=[]
test_mape=[]

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

test_mape.append((mean_absolute_error(tsne_test_output, df_test['ft_1'].values))/(sum(tsne_test_output)/len
test_mape.append((mean_absolute_error(tsne_test_output, df_test['exp_avg'].values))/(sum(tsne_test_output)/
test_mape.append((mean_absolute_error(tsne_test_output, rndf_test_predictions))/(sum(tsne_test_output)/len
test_mape.append((mean_absolute_error(tsne_test_output, xgb_test_predictions))/(sum(tsne_test_output)/len(t
test_mape.append((mean_absolute_error(tsne_test_output, lr_test_predictions))/(sum(tsne_test_output)/len(ts
```

In [93]:
```
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])
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
--------------------------------------------------------------------------------------------------------
Baseline Model -                             Train:  0.14005275878666593       Test:  0.13653125704827038
Exponential Averages Forecasting -           Train:  0.13289968436017227       Test:  0.12936180420430524
Linear Regression -                         Train:  0.12939582809998681       Test:  0.12686179464732844
Random Forest Regression -                   Train:  0.09174527572696145      Test:  0.12722524647443126
```

Error Metric Matrix

In [94]:
```
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])
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
--------------------------------------------------------------------------------------------------------
Baseline Model -                             Train:  0.14005275878666593       Test:  0.13653125704827038
Exponential Averages Forecasting -           Train:  0.13289968436017227       Test:  0.12936180420430524
Linear Regression -                         Train:  0.13331572016045437       Test:  0.1291202994009687
Random Forest Regression -                   Train:  0.09174527572696145      Test:  0.12722524647443126
XgBoost Regression -                         Train:  0.12939582809998681       Test:  0.12686179464732844
--------------------------------------------------------------------------------------------------------
```

Assignments

In [206]:
```
'''
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%
```

Out[206]:
```
'\nTask 1: Incorporate Fourier features as features into Regression models and measure MAPE. <br>\n\nTask
2: Perform hyper-parameter tuning for Regression models.\n        2a. Linear Regression: Grid Search\n
2b. Random Forest: Random Search \n        2c. Xgboost: Random Search\nTask 3: Explore more time-series f
eatures using Google search/Quora/Stackoverflow\nto reduce the MAPE to < 12%\n'
```

Fourier Features

In [2]:
```
import pickle
train = open('df_train.pkl','rb')
```

In [4]:
```
test = open('df_test.pkl','rb')
```

In [6]:
```
region = open('regions_cum.pkl','rb')
```

In [100]:
```
# incorporate fourier feautures - 5 frequencies and amplitudes
final_df = pd.DataFrame(columns=['f_1','a_1','f_2','a_2','f_3','a_3','f_4','a_4','f_5','a_5'])

for i in range(40):
    ampli_jan = np.abs(np.fft.fft(regions_cum[i][:4464]))
    freq_jan = np.abs(np.fft.fftfreq(4464,1))

    ampli_feb = np.abs(np.fft.fft(regions_cum[i][4464:8640]))
    freq_feb = np.abs(np.fft.fftfreq(4176,1))

    ampli_mar = np.abs(np.fft.fft(regions_cum[i][8640:]))
    freq_mar = np.abs(np.fft.fftfreq(4464,1))

    #create dataframe for all three months
    df_jan = pd.DataFrame()
    df_feb = pd.DataFrame()
    df_mar = pd.DataFrame()

    #add values to Dataframe
    df_jan['freq'] = freq_jan
    df_jan['amp'] = ampli_jan
    jan_sorted = df_jan.sort_values(by='amp',ascending = False)[:5].reset_index(drop=True).T

    df_feb['freq'] = freq_feb
    df_feb['amp'] = ampli_feb
    feb_sorted = df_feb.sort_values(by='amp',ascending = False)[:5].reset_index(drop=True).T

    df_mar['freq'] =freq_mar
    df_mar['amp'] = ampli_mar
    mar_sorted = df_mar.sort_values(by='amp',ascending = False)[:5].reset_index(drop=True).T

    jan =[]
    feb =[]
    mar =[]
    for i in range(5):
        jan.append(jan_sorted[i]['freq'])
        jan.append(jan_sorted[i]['amp'])
        feb.append(feb_sorted[i]['freq'])
        feb.append(feb_sorted[i]['amp'])
        mar.append(mar_sorted[i]['freq'])
        mar.append(mar_sorted[i]['amp'])
    columns= ['f_1','a_1','f_2','a_2','f_3','a_3','f_4','a_4','f_5','a_5']
    #create jan,feb and mar data frame of actual size
    new_jan = pd.DataFrame([jan]*4464)
    new_feb = pd.DataFrame([feb]*4176)
    new_mar = pd.DataFrame([mar]*4464)

    new_jan.columns = columns
    new_feb.columns = columns
    new_mar.columns = columns
    final_df = final_df.append(new_jan,ignore_index = True)
    final_df = final_df.append(new_feb,ignore_index = True)
```

In [101]:

In [102]:

In [103]:
```
final_df_ =final_df[366761:].reset_index()
test = pd.concat([df_test,final_df_],axis=1,sort=False)
test = test.dropna()
test.drop('index',axis=1,inplace=True)
print('training dataset shape :',train.shape)
```

```
training dataset shape : (366760, 19)
test dataset shape : (157200, 19)
```

In [104]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression

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

lrReg = LinearRegression()
grid_search = GridSearchCV(lrReg,param_grid = param,n_jobs = -1)
grid_search.fit(df_train,tsne_train_output)
```

Out[104]:
```
{'copy_X': True, 'fit_intercept': True, 'normalize': False}
```

In [100]:

```
lrReg = LinearRegression(fit_intercept=True,normalize=False,copy_X=True)
lrReg.fit(train,tsne_train_output)

pred_y = lrReg.predict(test)
lr_test_predictions_hpt = [round(value) for value in pred_y]

pred_y = lrReg.predict(train)
lr_train_predictions_hpt = [round(value) for value in pred_y]
print("MAPE for train data:",(mean_absolute_error(tsne_train_output,lr_train_predictions_hpt))/(sum(tsne_t

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,lr_test_predictions_hpt))/(sum(tsne_test_
```

```
MAPE for train data: 0.1333141232643236
MAPE for test data: 0.12915738047089137
```

RandomForest Regressor

In [101]:

```
import pickle
# nyctrain_fname = 'nyctrain.pkl'
# # Open the file to save as pkl file
# nyctrain_pkl = open(nyctrain_fname, 'wb')
# pickle.dump(train, nyctrain_pkl)
# # Close the pickle instances
```

In [102]:

```
# nyctest_fname = 'nyctest.pkl'
# # Open the file to save as pkl file
# nyctest_pkl = open(nyctest_fname, 'wb')
# pickle.dump(test, nyctest_pkl)
# # Close the pickle instances
# nyctest_pkl.close()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 366760 entries, 0 to 366759
Data columns (total 19 columns):
ft_5       366760 non-null int64
ft_4       366760 non-null int64
ft_3       366760 non-null int64
ft_2       366760 non-null int64
ft_1       366760 non-null int64
lat        366760 non-null float64
lon        366760 non-null float64
weekday    366760 non-null int64
exp_avg    366760 non-null int64
f_1        366760 non-null float64
a_1        366760 non-null float64
f_2        366760 non-null float64
a_2        366760 non-null float64
f_3        366760 non-null float64
a_3        366760 non-null float64
f_4        366760 non-null float64
a_4        366760 non-null float64
f_5        366760 non-null float64
a_5        366760 non-null float64
dtypes: float64(12), int64(7)
memory usage: 53.2 MB
```

In [104]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor

param = {'n_estimators':[40,50,70],'max_depth':[3,6],'min_samples_split':[2,3,6]}
random_reg = RandomForestRegressor()
random_search = RandomizedSearchCV(random_reg,param_distributions=param,n_jobs=-1,random_state = 2091)
random_search.fit(train,tsne_train_output)
```

Out[104]:

```
{'max_depth': 6, 'min_samples_split': 2, 'n_estimators': 70}
```

In [105]:

```
random_reg = RandomForestRegressor(n_estimators=70,max_depth=6,min_samples_split=2)
random_reg.fit(df_train,tsne_train_output)

pred_y = random_reg.predict(df_test)
random_reg_test_predictions_hpt = [round(value) for value in pred_y]

pred_y = random_reg.predict(df_train)
random_reg_train_predictions_hpt = [round(value) for value in pred_y]
print("MAPE for train data:",(mean_absolute_error(tsne_train_output,random_reg_train_predictions_hpt))/(sur

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,random_reg_test_predictions_hpt))/(sum(t:
```

```
MAPE for train data: 0.13294812354280455
MAPE for test data: 0.12904317459832026
```

XGboost

In [106]:

```
from xgboost import XGBRegressor

param = {'learning_rate':[0.1,0.2,0.3],
 'n_estimators':[500,600, 1000],
 'max_depth':[2,3,5,6],
 'min_child_weight':[3,5,7],
 'gamma':[0,0.1,0.2],
 }
xgb_reg = XGBRegressor()
xgb_search = RandomizedSearchCV(xgb_reg,param_distributions=param,n_jobs=-1,random_state = 2019)
xgb_search.fit(df_train,tsne_train_output)
```

Out[106]:

```
{'gamma': 0.2,
 'learning_rate': 0.1,
 'max_depth': 2,
 'min_child_weight': 3,
 'n_estimators': 600}
```

In [107]:

```
xgb_reg_new = XGBRegressor(learning_rate=0.1,n_estimators=600,max_depth=2,min_child_weight=3,gamma=0.2)
xgb_reg_new.fit(df_train,tsne_train_output)

pred_y = xgb_reg_new.predict(df_test)
xgb_reg_test_predictions_new = [round(value) for value in pred_y]

pred_y = xgb_reg_new.predict(df_train)
xgb_reg_train_predictions_new = [round(value) for value in pred_y]

print("MAPE for train data:",(mean_absolute_error(tsne_train_output,xgb_reg_train_predictions_new))/(sum(t:

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,xgb_reg_test_predictions_new))/(sum(tsne_
```

```
MAPE for train data: 0.1310378809046399
MAPE for test data: 0.12797413117524056
```

In [108]:

Out[108]:

```
array([0.15286624, 0.10694712, 0.12738854, 0.15153311, 0.14486742,
       0.0865057 , 0.08783884, 0.02532958, 0.11672345], dtype=float32)
```

In [109]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 366760 entries, 0 to 366759
Data columns (total 19 columns):
ft_5       366760 non-null int64
ft_4       366760 non-null int64
ft_3       366760 non-null int64
ft_2       366760 non-null int64
ft_1       366760 non-null int64
lat        366760 non-null float64
lon        366760 non-null float64
weekday    366760 non-null int64
exp_avg    366760 non-null int64
f_1        366760 non-null float64
a_1        366760 non-null float64
f_2        366760 non-null float64
a_2        366760 non-null float64
f_3        366760 non-null float64
a_3        366760 non-null float64
f_4        366760 non-null float64
a_4        366760 non-null float64
f_5        366760 non-null float64
a_5        366760 non-null float64
dtypes: float64(12), int64(7)
memory usage: 53.2 MB
```

In [110]:

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 171888 entries, (0, 1) to (39, 4463)
Data columns (total 1 columns):
trip_distance    171888 non-null int64
dtypes: int64(1)
memory usage: 1.8 MB
```

Add more features to reduce MAPE

Double exponential Smoothing

Double exponential smoothing is given by the formulas

$$s_1 = x_1$$
$$b_1 = x_1 - x_0$$

And for t > 1 by

$$s_t = \alpha x_t + (1-\alpha)(s_{t-1} + b_{t-1})$$

$$b_t = \beta(s_t - s_{t-1}) + (1-\beta)b_{t-1}$$

where α is the data smoothing factor, 0 < α < 1, and β is the trend smoothing factor, 0 < β < 1. (sourced from wikipedia)

In [90]:

```
#https://en.wikipedia.org/wiki/Exponential_smoothing
alpha= 0.3
beta = 0.3

predicted_values = []
predict_list = []
double_exp_avg = []
for r in range(0,40):
    s = []
    b = []
    for i in range(1,13104):
        if i == 0:
            s.append(0)
            continue
        if i == 1:
            s1 = regions_cum[r][1]
            b1 = regions_cum[r][1]-regions_cum[r][0]
            s.append(s1)
            b.append(b1)
            continue
        st = int((alpha*regions_cum[r][i])+ ((1-alpha)*(s[-1]+b[-1])))
        bt = int((beta*(st-s[-1]))+((1-beta)*b[-1]))
        s.append(st)
        b.append(bt)
```

In [91]:
```
double_exp_tr = [i[:9169] for i in double_exp_avg]
```

In [ ]:

In [96]:
```
# add more features for mean, median, standard deviation, max ,min values and their feature interactions
# of pickups in last 5 bins features
df_train['mean'] = df_train.apply(lambda row:np.mean(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1
df_test['mean'] = df_test.apply(lambda row:np.mean(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)

df_train['median'] = df_train.apply(lambda row:np.median(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),ax
df_test['median'] = df_test.apply(lambda row:np.median(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis

df_train['std'] = df_train.apply(lambda row:np.std(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)
df_test['std'] = df_test.apply(lambda row:np.std(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)

df_train['max'] = df_train.apply(lambda row:np.max(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)
df_test['max'] = df_test.apply(lambda row:np.max(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)

df_train['min'] = df_train.apply(lambda row:np.min(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)
df_test['min'] = df_test.apply(lambda row:np.min(row[['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1']]),axis=1)

df_train['max-min'] = df_train.apply(lambda row:row['max'] - row['min'],axis=1)
df_test['max-min'] = df_test.apply(lambda row:row['max'] - row['min'],axis=1)

df_train['double_exp'] = sum(double_exp_tr,[])
df_test['double_exp'] = sum(double_exp_te,[])

df_train = df_train.fillna(0)
```

In [97]:

Out[97]:

	ft_5	ft_4	ft_3	ft_2	ft_1	lat	lon	weekday	exp_avg	mean	median	std	max	min	max-min	double_exp
0	0	63	217	189	137	40.776228	-73.982119	4	150	121.2	137.0	80.125901	217.0	0.0	217.0	39
1	63	217	189	137	135	40.776228	-73.982119	4	139	148.2	137.0	52.833323	217.0	63.0	154.0	24
2	217	189	137	135	129	40.776228	-73.982119	4	132	161.4	137.0	35.200000	217.0	129.0	88.0	14
3	189	137	135	129	150	40.776228	-73.982119	4	144	148.0	137.0	21.614810	189.0	129.0	60.0	6
4	137	135	129	150	164	40.776228	-73.982119	4	158	143.0	137.0	12.537942	164.0	129.0	35.0	0

Linear Regression

In [98]:
```
# hyperparameter tuning using random search
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression

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

lrReg = LinearRegression()
grid_search = GridSearchCV(lrReg,param_grid = param,n_jobs = -1)
grid_search.fit(df_train,tsne_train_output)
```

Out[98]: {'copy_X': True, 'fit_intercept': False, 'normalize': True}

In [99]:
```
lrReg = LinearRegression(fit_intercept=True,normalize=False,copy_X=True)
lrReg.fit(df_train,tsne_train_output)

pred_y = lrReg.predict(df_test)
lr_test_predictions_hpt = [round(value) for value in pred_y]

pred_y = lrReg.predict(df_train)
lr_train_predictions_hpt = [round(value) for value in pred_y]
print("MAPE for train data:",(mean_absolute_error(tsne_train_output,lr_train_predictions_hpt))/(sum(tsne_t

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,lr_test_predictions_hpt))/(sum(tsne_test_
```

```
MAPE for train data: 0.11108661551305633
MAPE for test data: 0.1061297493396129
```

Random Forest

In [100]:
```
# hyperparameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor

param = {'n_estimators':[40,50,70],'max_depth':[3,6],'min_samples_split':[2,3,6]}
random_reg = RandomForestRegressor()
random_search = RandomizedSearchCV(random_reg,param_distributions=param,n_jobs=-1,random_state = 2091)
random_search.fit(df_train,tsne_train_output)
```

Out[100]:
```
{'max_depth': 6, 'min_samples_split': 2, 'n_estimators': 70}
```

In [101]:
```
random_reg = RandomForestRegressor(n_estimators=70,max_depth=6,min_samples_split=2)
random_reg.fit(df_train,tsne_train_output)

pred_y = random_reg.predict(df_test)
random_reg_test_predictions_hpt = [round(value) for value in pred_y]

pred_y = random_reg.predict(df_train)
random_reg_train_predictions_hpt = [round(value) for value in pred_y]
print("MAPE for train data:",(mean_absolute_error(tsne_train_output,random_reg_train_predictions_hpt))/(sum

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,random_reg_test_predictions_hpt))/(sum(t
```

```
MAPE for train data: 0.12033747915662416
MAPE for test data: 0.11697424203617124
```

XGBoost

In [103]:
```
# hyperparameter tuning using random search
from xgboost import XGBRegressor
param = {'learning_rate':[0.1,0.2,0.3],
 'n_estimators':[500,600, 1000],
 'max_depth':[2,3,5,6],
 'min_child_weight':[3,5,7],
 'gamma':[0,0.1,0.2],
 }
xgb_reg = XGBRegressor()
xgb_search = RandomizedSearchCV(xgb_reg,param_distributions=param,n_jobs=-1,random_state = 2019)
xgb_search.fit(df_train,tsne_train_output)
```

Out[103]:
```
{'gamma': 0,
 'learning_rate': 0.1,
 'max_depth': 2,
 'min_child_weight': 5,
 'n_estimators': 1000}
```

In [104]:
```
xgb_reg_new = XGBRegressor(learning_rate=0.1,n_estimators=1000,max_depth=2,min_child_weight=5,gamma=0)
xgb_reg_new.fit(df_train,tsne_train_output)

pred_y = xgb_reg_new.predict(df_test)
xgb_reg_test_predictions_new = [round(value) for value in pred_y]

pred_y = xgb_reg_new.predict(df_train)
xgb_reg_train_predictions_new = [round(value) for value in pred_y]

print("MAPE for train data:",(mean_absolute_error(tsne_train_output,xgb_reg_train_predictions_new))/(sum(t

print("MAPE for test data:",(mean_absolute_error(tsne_test_output,xgb_reg_test_predictions_new))/(sum(tsne_
```

```
MAPE for train data: 0.09770795280444458
MAPE for test data: 0.09542383280642534
```

In [105]:
```
# with open('tsne_train_output.pkl','wb') as f:
#     pickle.dump(tsne_train_output,f)

# with open('tsne_test_output.pkl','wb') as f:
```

Conclusion

In [111]:

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Feature engineering","Model","HyperParameters","MAPE"]
x.add_row(['Fourier Features','Linear Regression','copy_X:True,fit_intercept:True,normalize:False',.1291])
x.add_row(['Fourier Features','Random Forest','max_depth: 6,min_samples_split:2,n_estimators:70',.1290])
x.add_row(['Fourier Features','XgBoost','learning_rate:0.1,n_estimators:600,max_depth:2, \n min_child_weig

x.add_row(['Double Exponential Smoothing \n & Other features','Linear Regression','copy_X:True,fit_interce
x.add_row(['Double Exponential Smoothing \n & Other features','Random Forest','max_depth: 6,min_samples_sp
x.add_row(['Double Exponential Smoothing \n & Other features','XgBoost','learning_rate:0.1,n_estimators:10
#x.add_row(['TFIDF Weighted W2V','Decision Tree',5,500,.605])
print(x)
```

```
+------------------------------+-------------------+---------------------------------------------------+
--------+
|      Feature engineering      |       Model       |                  HyperParameters                   |
MAPE  |
+------------------------------+-------------------+---------------------------------------------------+
--------+
|        Fourier Features       | Linear Regression |   copy_X:True,fit_intercept:True,normalize:False   |
0.1291 |
|        Fourier Features       |   Random Forest   |  max_depth: 6,min_samples_split:2,n_estimators:70  |
0.129  |
|        Fourier Features       |      XgBoost      |  learning_rate:0.1,n_estimators:600,max_depth:2,   |
0.1279 |
|                               |                   |           min_child_weight:3,gamma:0.2             |
|
| Double Exponential Smoothing  | Linear Regression |   copy_X:True,fit_intercept:True,normalize:False   |
0.1061 |
|        & Other features       |                   |                                                    |
|
| Double Exponential Smoothing  |   Random Forest   |  max_depth: 6,min_samples_split:2,n_estimators:70  |
0.1169 |
|        & Other features       |                   |                                                    |
|
| Double Exponential Smoothing  |      XgBoost      | learning_rate:0.1,n_estimators:1000,max_depth:2,   |
0.0954 |
|        & Other features       |                   |             min_child_weight:5,gamma:0             |
|
+------------------------------+-------------------+---------------------------------------------------+
--------+
```

1. Models perform worse with fourier features!
2. Overall XgBoost models perform best.
3. We were able to reduce MAPE to 0.095 with double exponential smoothing and mean/median/max/min features.
4. With Double exponetial smoothing and other features, Linear regression perform better than random forest.

In [ ]: