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# 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/
import warnings
warnings.filterwarnings("ignore")
import dask.dataframe as dd#similar to pandas

import pandas as pd#pandas to create small dataframes

# pip3 install foliun
# 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
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) pa
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\
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
```

# Data Information

Ge the data from : [http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml (http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml)](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 [2]:

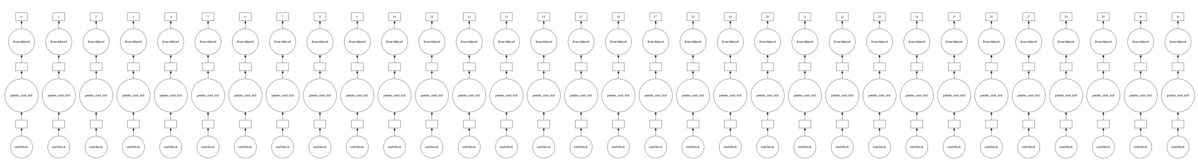
```
#Looking at the features
# dask dataframe  : # https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ip
month = dd.read_csv('yellow_tripdata_2015-01.csv')
print(month.columns)
```

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

In [3]:

```
# However unlike Pandas, operations on dask.dataframes don't trigger immediate computat
# instead they add key-value pairs to an underlying Dask graph. Recall that in the diag
# 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 th
month.visualize()
```

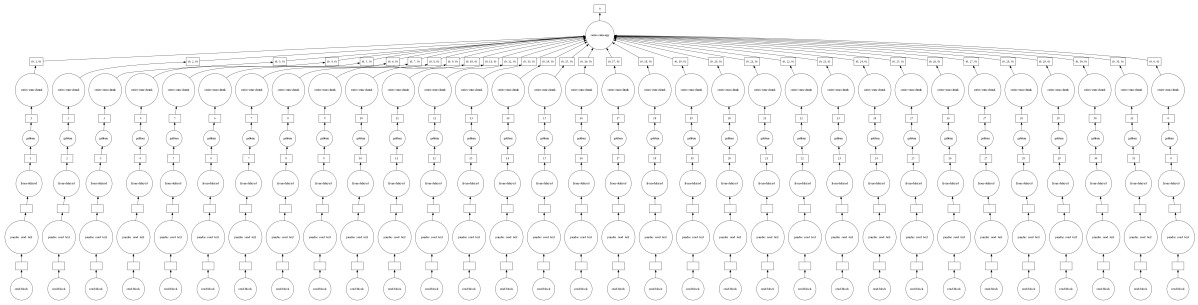
Out[3]:



In [4]:

```
month.fare_amount.sum().visualize()
```

Out[4]:



# Features in the dataset:

| Field Name | Description |
| --- | --- |
| VendorID | A code indicating the TPEP provider that provided the record.<br>1. Creative Mobile Technologies<br>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. |
| RateCodeID | The final rate code in effect at the end of the trip.<br>1. Standard rate<br>2. JFK<br>3. Newark<br>4. Nassau or Westchester<br>5. Negotiated fare<br>6. Group ride |
| Store_and_fwd_flag | This flag indicates whether the trip record was held in vehicle memory before sending to the vendor,<br> aka “store and forward,” because the vehicle did not have a connection to the server. <br>Y= store and forward trip <br>N= not a store and forward trip |
| Dropoff_longitude | Longitude where the meter was disengaged. |
| Dropoff_ latitude | Latitude where the meter was disengaged. |
| Payment_type | A numeric code signifying how the passenger paid for the trip.<br>1. Credit card<br>2. Cash<br>3. No charge<br>4. Dispute<br>5. Unknown<br>6. Voided trip |
| Fare_amount | The time-and-distance fare calculated by the meter. |

| | |
|---|---|
| Extra | Miscellaneous extras and surcharges. Currently, this only includes. the $0.50 and 1$ rush hour and overnight charges. |
| MTA_tax | 0.50 MTA tax that is automatically triggered based on the metered rate in use. |
| Improvement_surcharge | 0.30 improvement surcharge assessed trips at the flag drop. the improvement surcharge began being levied in 2015. |
| Tip_amount | Tip amount – This field is automatically populated for credit card tips.Cash tips are not included. |
| Tolls_amount | Total amount of all tolls paid in trip. |
| Total_amount | The total amount charged to passengers. Does not include cash tips. |

# ML Problem Formulation

**Time-series forecasting and Regression**

- *To find number of pickups, given location 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 [5]:

```
#table below shows few datapoints along with all our features
month.head(5)
```

Out[5]:

| | VendorID | tpep_pickup_datetime | tpep_dropoff_datetime | passenger_count | trip_distance | picku |
|---|---|---|---|---|---|---|
| 0 | 2 | 2015-01-15 19:05:39 | 2015-01-15 19:23:42 | 1 | 1.59 | |
| 1 | 1 | 2015-01-10 20:33:38 | 2015-01-10 20:53:28 | 1 | 3.30 | |
| 2 | 1 | 2015-01-10 20:33:38 | 2015-01-10 20:43:41 | 1 | 1.80 | |
| 3 | 1 | 2015-01-10 20:33:39 | 2015-01-10 20:35:31 | 1 | 0.50 | |
| 4 | 1 | 2015-01-10 20:33:39 | 2015-01-10 20:52:58 | 1 | 3.00 | |

### 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 [6]:

```
# 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_lo
outlier_locations = month[((month.pickup_longitude <= -74.15) | (month.pickup_latitude 
                   (month.pickup_longitude >= -73.7004) | (month.pickup_latitude >= 40.

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

# note: you dont need to remember any of these, you dont need indeepth knowledge on the

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 
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_os
map_osm
```

Out[6]:

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

## 2. Dropoff Latitude & Dropoff Longitude

It is inferred from the source https://www.flickr.com/places/info/2459115 (https://www.flickr.com/places/info/2459115) that New York is bounded by the location 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 [7]:

```
# 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_lo
outlier_locations = month[((month.dropoff_longitude <= -74.15) | (month.dropoff_latitud
                    (month.dropoff_longitude >= -73.7004) | (month.dropoff_latitude >= 4

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

# note: you dont need to remember any of these, you dont need indeepth knowledge on the

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 
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_
map_osm
```

Out[7]:

**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.**

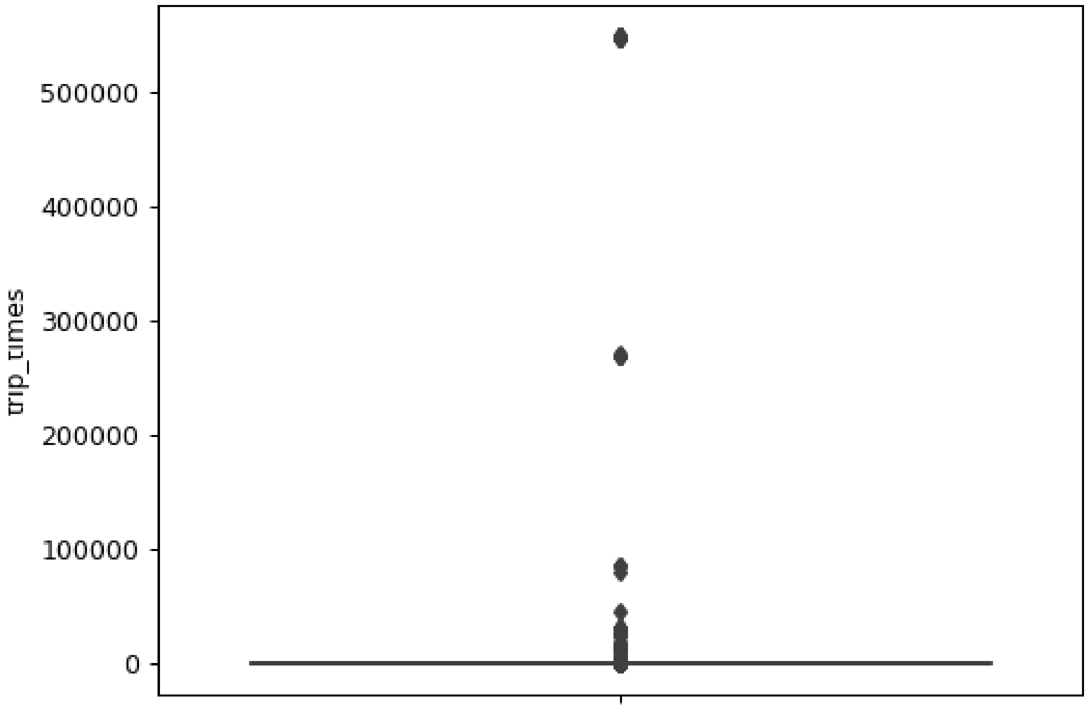
In [8]:

```
#The time stamps are converted to unix so as to get duration(trip-time) & speed also pi

# in out data we have time in the formate "YYYY-MM-DD HH:MM:SS" we convert thiss sting 
# 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'].val
    duration_drop = [convert_to_unix(x) for x in duration['tpep_dropoff_datetime'].valu
    #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_lat

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

In [9]:

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

<IPython.core.display.Javascript object>



In [10]:

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

```
0 percentile value is -1211.0166666666667
10 percentile value is 3.8333333333333335
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 [11]:

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

```
90 percentile value is 23.45
91 percentile value is 24.35
92 percentile value is 25.383333333333333
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
```

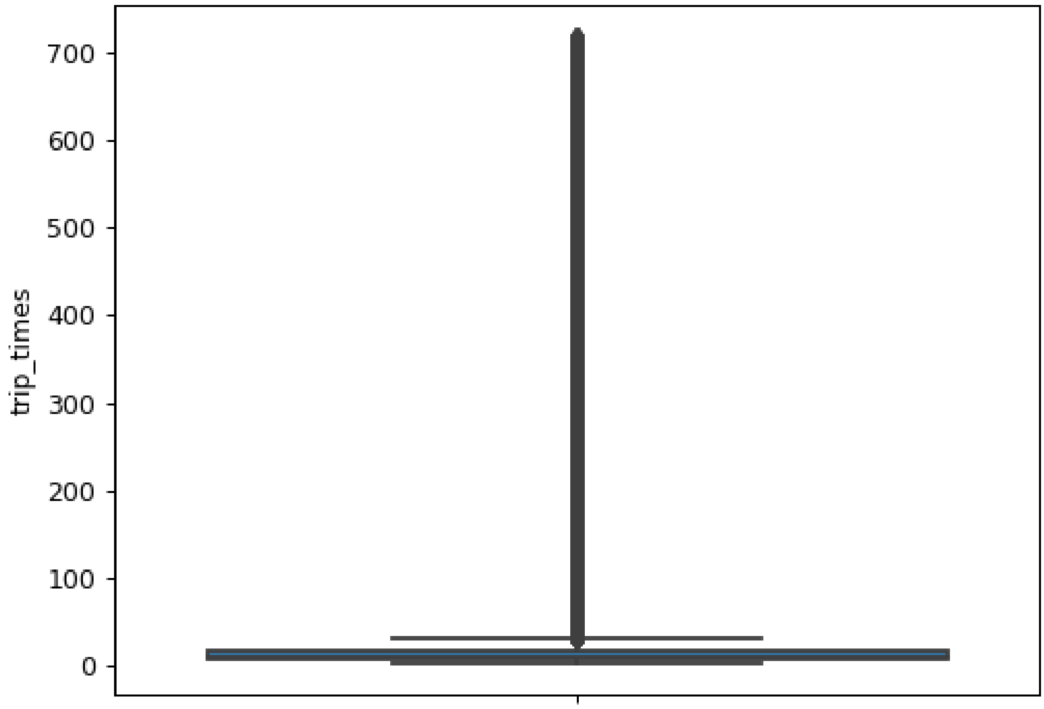
In [12]:

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

In [13]:

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

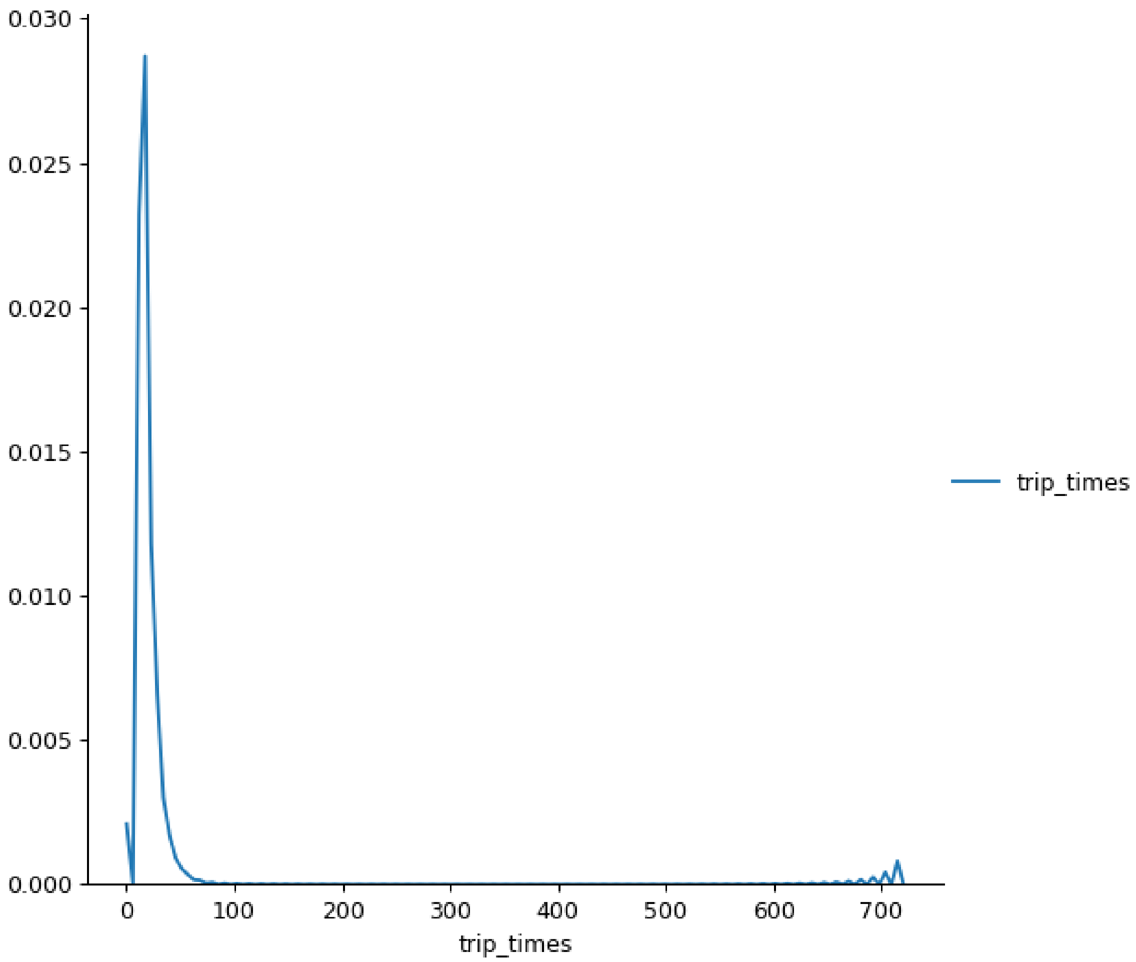
<IPython.core.display.Javascript object>



In [14]:

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

<IPython.core.display.Javascript object>



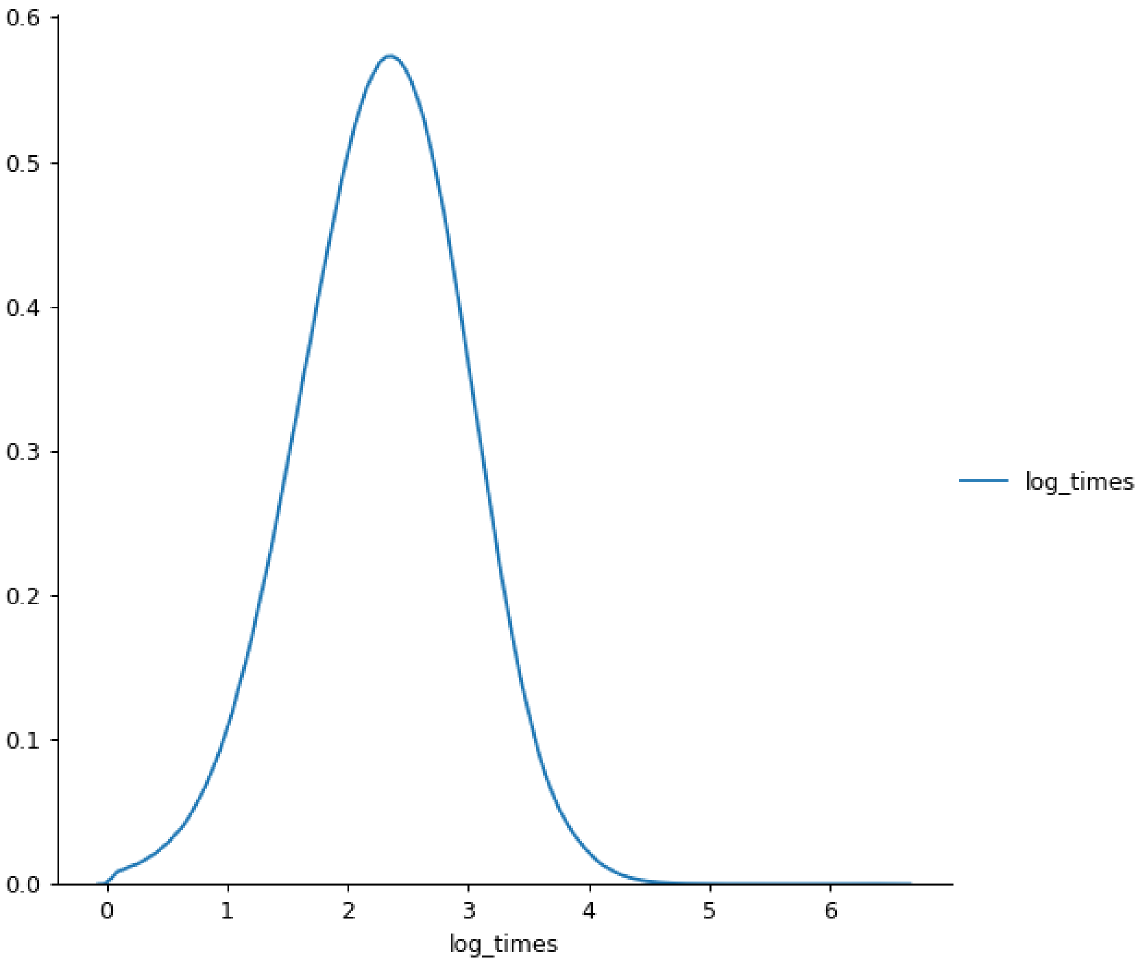

In [15]:

```
#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_m
```

In [16]:

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

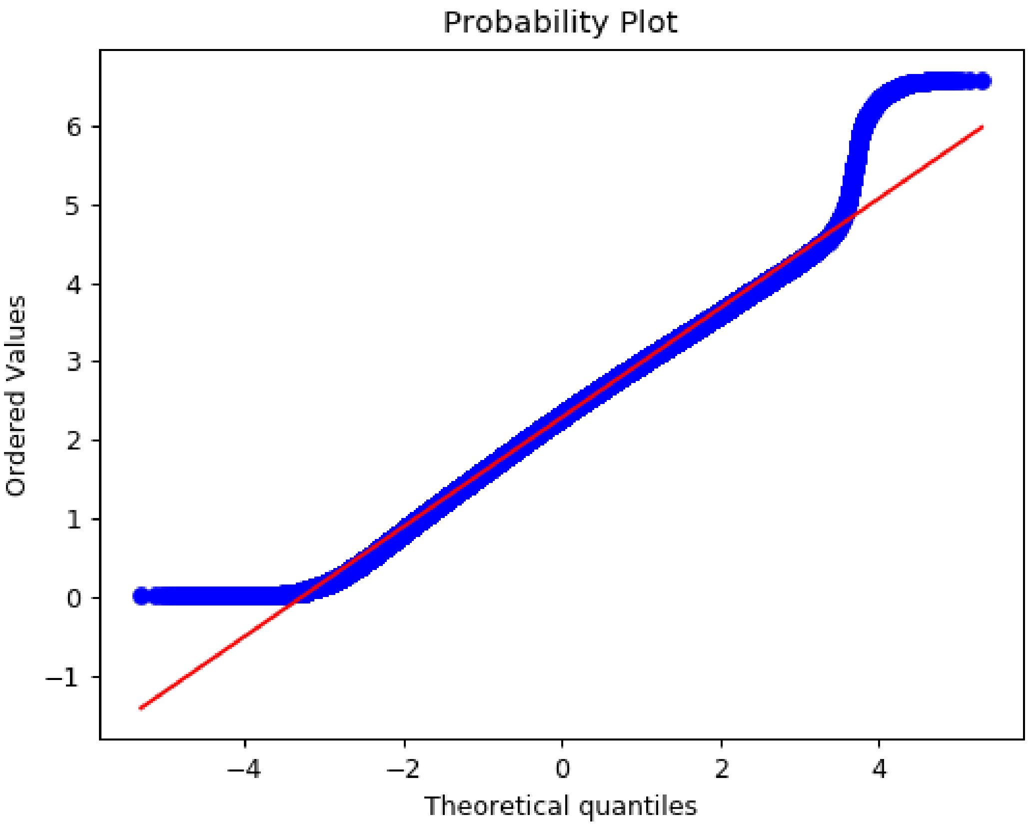
<IPython.core.display.Javascript object>



In [17]:

```
#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)
plt.show()
```

<IPython.core.display.Javascript object>

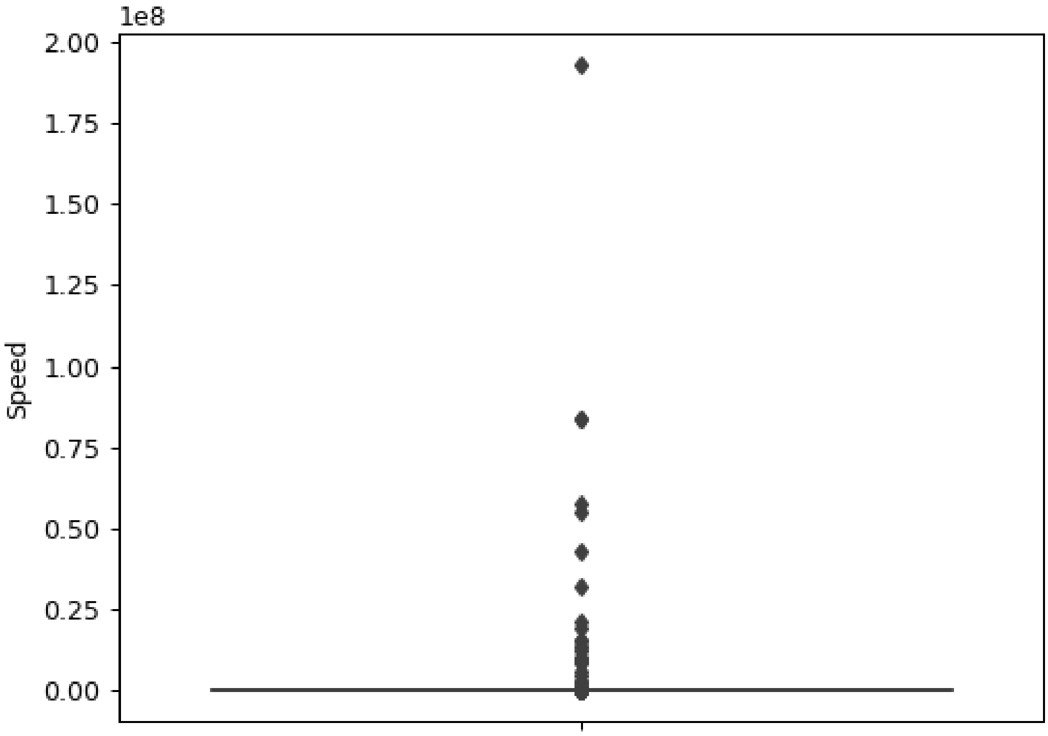



## 4. Speed

In [18]:

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

<IPython.core.display.Javascript object>



In [19]:

```
#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))]))
print("100 percentile value is ",var[-1])
```

```
0 percentile value is 0.0
10 percentile value is 6.409495548961425
20 percentile value is 7.80952380952381
30 percentile value is 8.929133858267717
40 percentile value is 9.98019801980198
50 percentile value is 11.06865671641791
60 percentile value is 12.286689419795222
70 percentile value is 13.796407185628745
80 percentile value is 15.963224893917962
90 percentile value is 20.186915887850468
100 percentile value is  192857142.85714284
```

In [20]:

```
#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))]))
print("100 percentile value is ",var[-1])
```

```
90 percentile value is 20.186915887850468
91 percentile value is 20.91645569620253
92 percentile value is 21.752988047808763
93 percentile value is 22.721893491124263
94 percentile value is 23.844155844155843
95 percentile value is 25.182552504038775
96 percentile value is 26.80851063829787
97 percentile value is 28.84304932735426
98 percentile value is 31.591128254580514
99 percentile value is 35.7513566847558
100 percentile value is  192857142.85714284
```

In [21]:

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

```
99.0 percentile value is 35.7513566847558
99.1 percentile value is 36.31084727468969
99.2 percentile value is 36.91470054446461
99.3 percentile value is 37.588235294117645
99.4 percentile value is 38.33035714285714
99.5 percentile value is 39.17580340264651
99.6 percentile value is 40.15384615384615
99.7 percentile value is 41.338301043219076
99.8 percentile value is 42.86631016042781
99.9 percentile value is 45.3107822410148
100 percentile value is  192857142.85714284
```

In [22]:

```
#removing further outliers based on the 99.9th percentile value
frame_with_durations_modified=frame_with_durations[(frame_with_durations.Speed>0) & (fr
```

In [23]:

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

Out[23]:

```
12.450173996027528
```

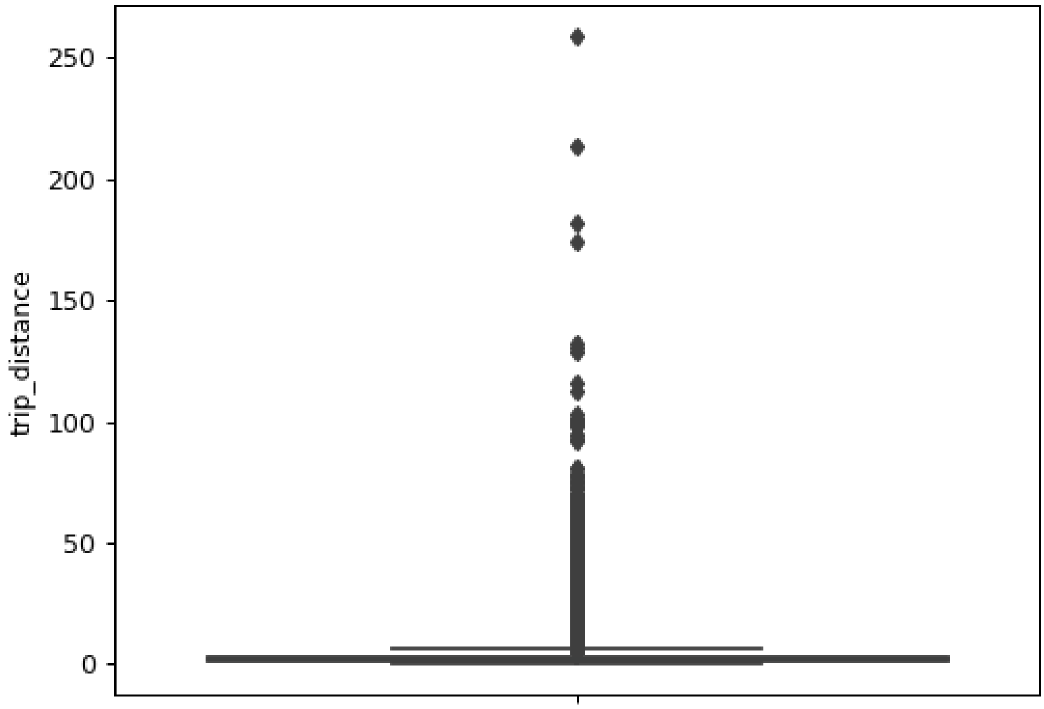
**The avg speed in Newyork speed is 12.45miles/hr, so a cab driver can travel 2 miles per 10min on avg.**

## 4. Trip Distance

In [24]:

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

<IPython.core.display.Javascript object>



In [25]:

```
#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))]))
print("100 percentile value is ",var[-1])
```

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

In [26]:

```
#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))]))
print("100 percentile value is ",var[-1])
```

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

In [27]:

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

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

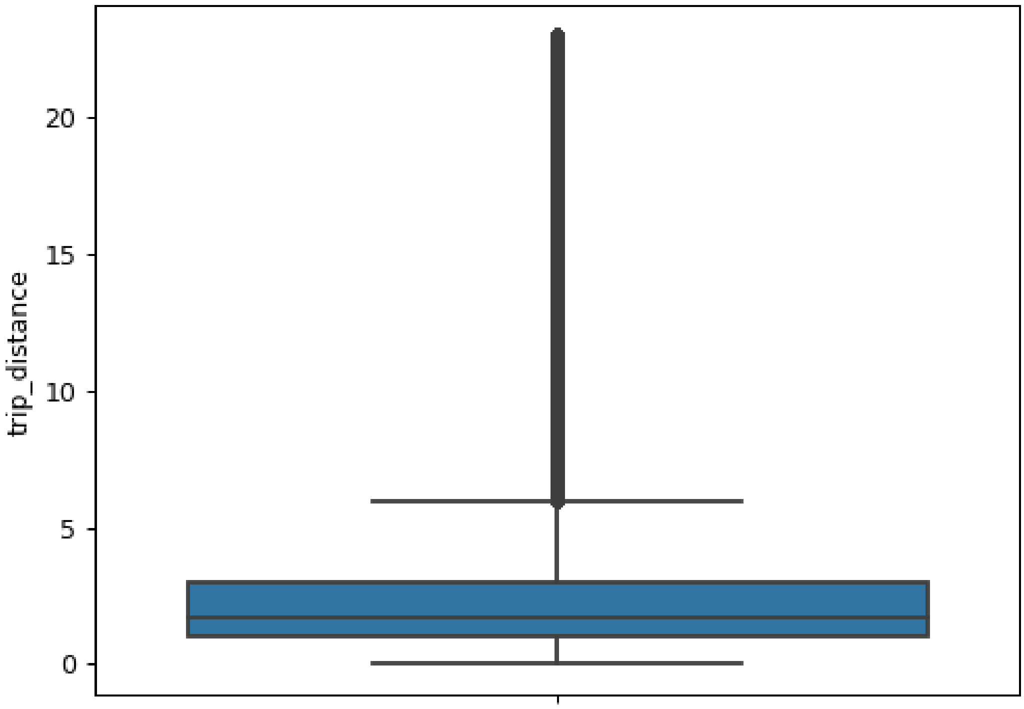
In [28]:

```
#removing further outliers based on the 99.9th percentile value
frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_distance>
```

In [29]:

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

<IPython.core.display.Javascript object>

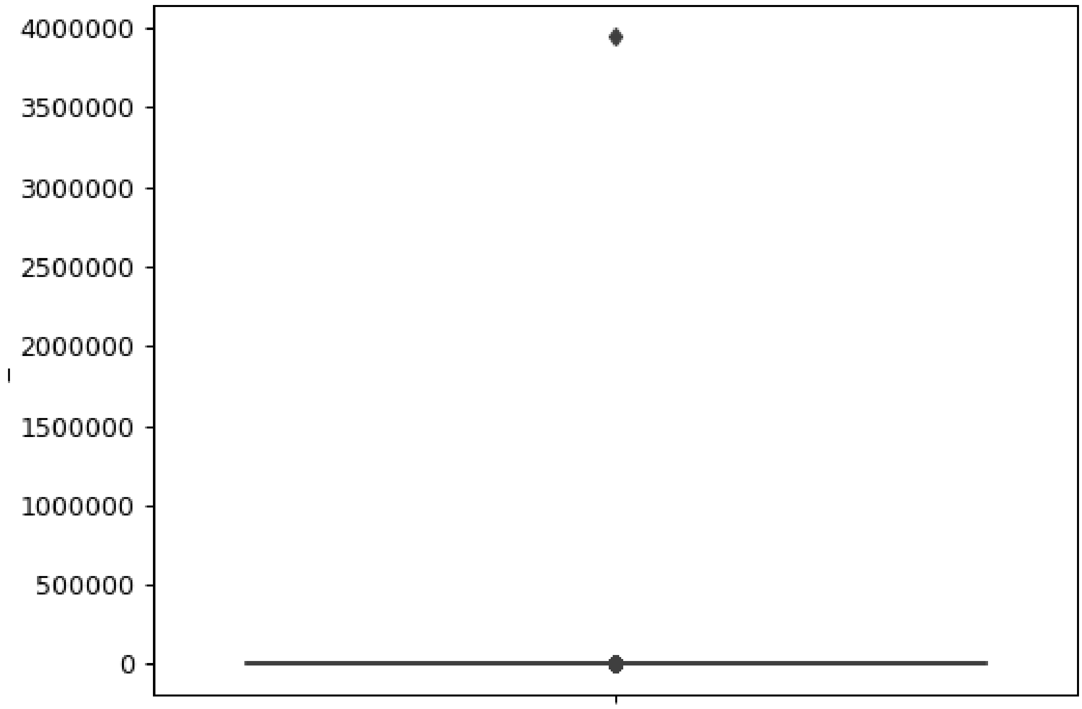



### 5. Total Fare

In [30]:

```
# up to now we have removed the outliers based on trip durations, cab speeds, and trip d
# 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)
plt.show()
```

```
<IPython.core.display.Javascript object>
```



In [31]:

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

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

In [32]:

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

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

In [33]:

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

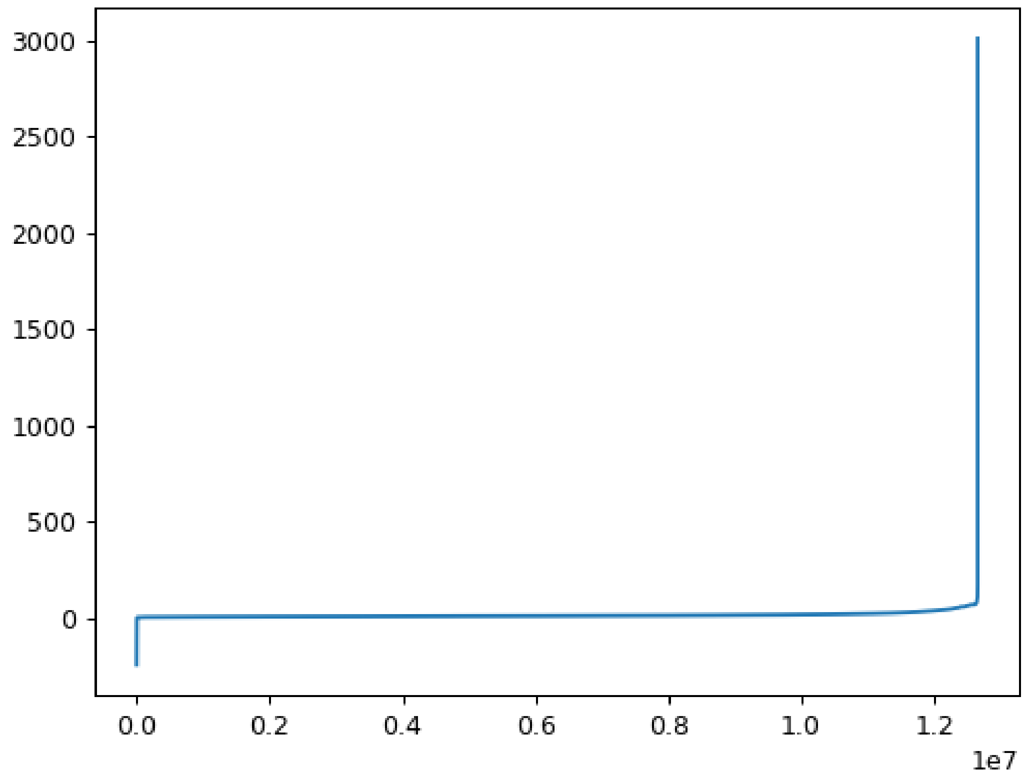
```
99.0 percentile value is 66.13
99.1 percentile value is 68.13
99.2 percentile value is 69.6
99.3 percentile value is 69.6
99.4 percentile value is 69.73
99.5 percentile value is 69.75
99.6 percentile value is 69.76
99.7 percentile value is 72.58
99.8 percentile value is 75.35
99.9 percentile value 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 [34]:

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

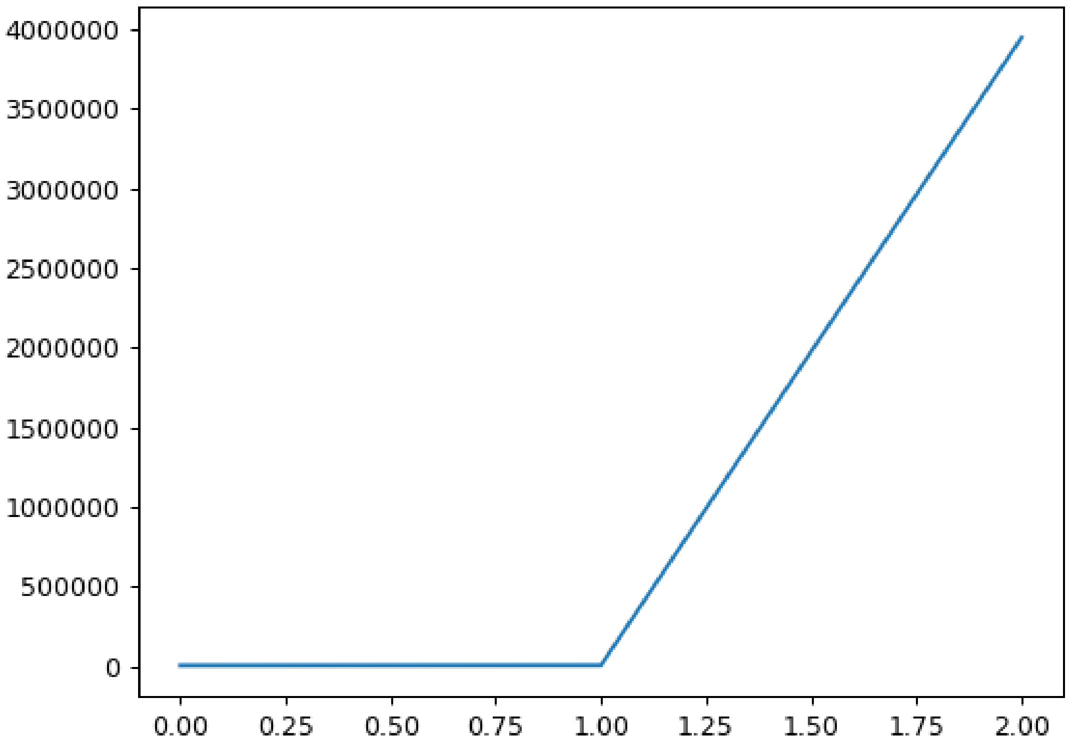
```
<IPython.core.display.Javascript object>
```



In [35]:

```
# 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 
plt.plot(var[-3:])
plt.show()
```

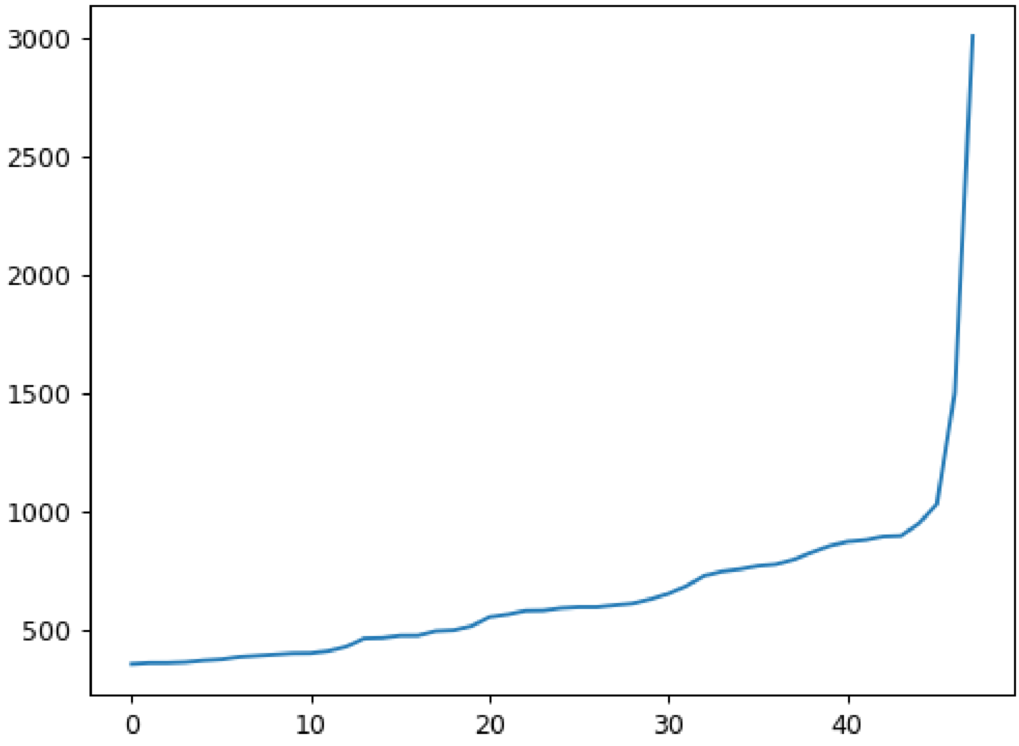
<IPython.core.display.Javascript object>



In [36]:

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

<IPython.core.display.Javascript object>



# Remove all outliers/erronous points.

In [37]:

```
#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.dropof
                       (new_frame.dropoff_latitude >= 40.5774) & (new_frame.dropoff_lat
                       ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_lati
                       (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_lat
    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 < 2
    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_
                       (new_frame.dropoff_latitude >= 40.5774) & (new_frame.dropoff_lat
                       ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_lati
                       (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_lat

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

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

In [38]:

```
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_wi
```

```
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 0.970357642560
7495
```

# Data-preperation

## Clustering/Segmentation

In [39]:

```
#trying different cluster sizes to choose the right K in K-means
coords = frame_with_durations_outliers_removed[['pickup_latitude', 'pickup_longitude']]
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_
                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 with

def find_clusters(increment):
    kmeans = MiniBatchKMeans(n_clusters=increment, batch_size=10000,random_state=42).fi
    frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_
    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 region
#that are close to any cluster center
# and make sure that the minimum inter cluster should not be very less
for increment in range(10, 100, 10):
    cluster_centers, cluster_len = find_clusters(increment)
    find_min_distance(cluster_centers, cluster_len)
```

```
On choosing a cluster size of  10
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance <
2): 2.0
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance >
2): 8.0
Min inter-cluster distance =  1.0945442325142543
---
On choosing a cluster size of  20
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance <
2): 4.0
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance >
2): 16.0
Min inter-cluster distance =  0.7131298007387813
---
On choosing a cluster size of  30
Avg. Number of Clusters within the vicinity (i.e. intercluster-distance <
2): 8.0
Avg. Number of Clusters outside the vicinity (i.e. intercluster-distance >
```

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

## Inference:

- The main objective was to find a optimal min. distance(Which roughly estimates to the radius of a cluster) between the clusters which we got was 40

In [40]:

```
# if check for the 50 clusters you can observe that there are two clusters with only 0..
# 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_dur.
```

## Plotting the cluster centers:

In [41]:

```
# 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(clust
map_osm
```

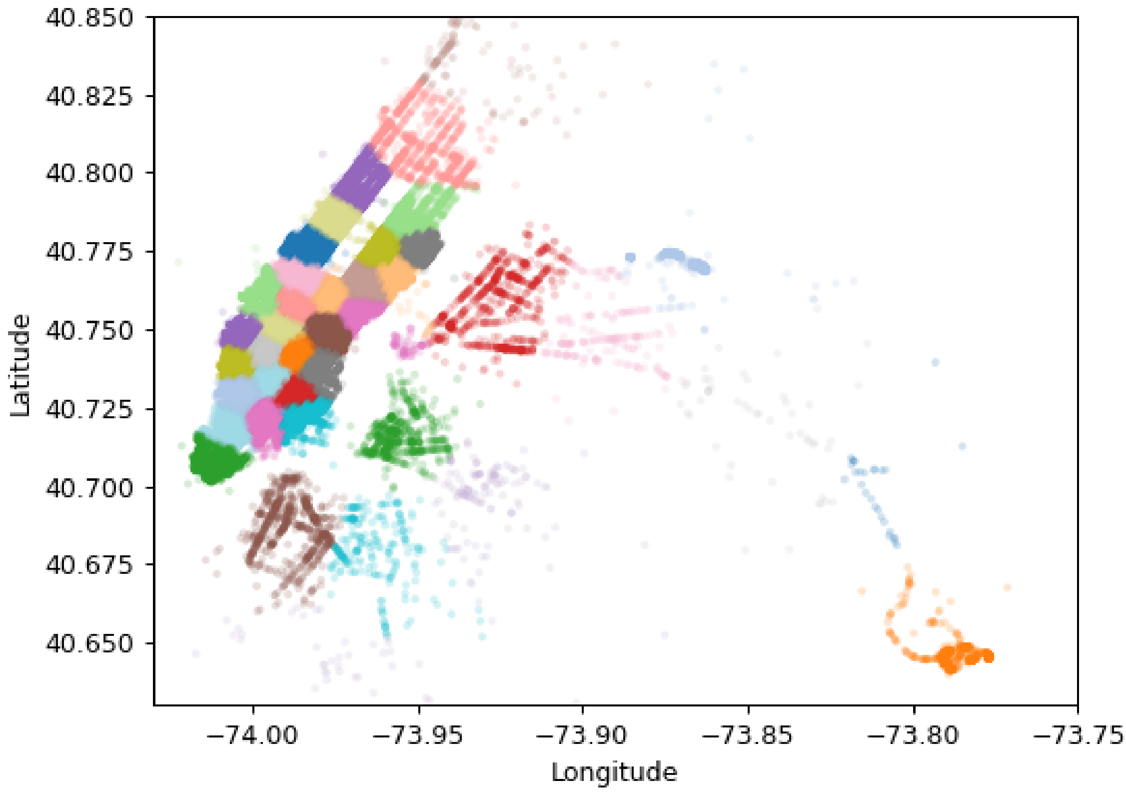
Out[41]:

## Plotting the clusters:

In [42]:

```
#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[:10
               c=frame.pickup_cluster.values[:100000], cmap='tab20', alpha=0.2)
    ax.set_xlim(city_long_border)
    ax.set_ylim(city_lat_border)
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')
    plt.show()

plot_clusters(frame_with_durations_outliers_removed)
```

<IPython.core.display.Javascript object>




## Time-binning

In [43]:

```
#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 convertin
    tenminutewise_binned_unix_pickup_times=[(int((i-start_pickup_unix)/600)+33) for i in
    frame['pickup_bins'] = np.array(tenminutewise_binned_unix_pickup_times)
    return frame
```

In [44]:

```
# clustering, making pickup bins and grouping by pickup cluster and pickup bins
frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_dur
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']].gro
```

In [45]:

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

Out[45]:

| | passenger_count | trip_distance | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_la |
|---|---|---|---|---|---|---|
| 0 | 1 | 1.59 | -73.993896 | 40.750111 | -73.974785 | 40.75 |
| 1 | 1 | 3.30 | -74.001648 | 40.724243 | -73.994415 | 40.75 |
| 2 | 1 | 1.80 | -73.963341 | 40.802788 | -73.951820 | 40.82 |
| 3 | 1 | 0.50 | -74.009087 | 40.713818 | -74.004326 | 40.7 |
| 4 | 1 | 3.00 | -73.971176 | 40.762428 | -74.004181 | 40.74 |

In [46]:

```
# hear the trip_distance represents the number of pickups that are happend in that part
# 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*
jan_2015_groupby.head()
```

Out[46]:

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

In [47]:

```
# 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_
    #frame_with_durations_outliers_removed_2016['pickup_cluster'] = kmeans.predict(fram

    print ("Final groupbying..")
    final_updated_frame = add_pickup_bins(frame_with_durations_outliers_removed,month_n
    final_groupby_frame = final_updated_frame[['pickup_cluster','pickup_bins','trip_dis

    return final_updated_frame,final_groupby_frame
```

In [48]:

```
month_jan_2016 = dd.read_csv('yellow_tripdata_2016-01.csv')
jan_2016_frame,jan_2016_groupby = datapreparation(month_jan_2016,kmeans,1,2016)
month_feb_2016 = dd.read_csv('yellow_tripdata_2016-02.csv')
feb_2016_frame,feb_2016_groupby = datapreparation(month_feb_2016,kmeans,2,2016)
month_mar_2016 = dd.read_csv('yellow_tripdata_2016-03.csv')
mar_2016_frame,mar_2016_groupby = datapreparation(month_mar_2016,kmeans,3,2016)
```

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

# Smoothing

In [49]:

```
# 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 t
# 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)
    return values
```

In [50]:

```
# for every month we get all indices of 10min intravels in which atleast one pickup got

#jan
jan_2015_unique = return_unq_pickup_bins(jan_2015_frame)
jan_2016_unique = return_unq_pickup_bins(jan_2016_frame)

#feb
feb_2016_unique = return_unq_pickup_bins(feb_2016_frame)

#march
mar_2016_unique = return_unq_pickup_bins(mar_2016_frame)
```

In [51]:

```
# 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 -
    print('-'*60)
```

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

```
for the  27 th cluster number of 10min intavels with zero pickups:  214
------------------------------------------------------------
for the  28 th cluster number of 10min intavels with zero pickups:  36
------------------------------------------------------------
for the  29 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  30 th cluster number of 10min intavels with zero pickups:  1180
------------------------------------------------------------
for the  31 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  32 th cluster number of 10min intavels with zero pickups:  44
------------------------------------------------------------
for the  33 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  34 th cluster number of 10min intavels with zero pickups:  39
------------------------------------------------------------
for the  35 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  36 th cluster number of 10min intavels with zero pickups:  36
------------------------------------------------------------
for the  37 th cluster number of 10min intavels with zero pickups:  321
------------------------------------------------------------
for the  38 th cluster number of 10min intavels with zero pickups:  36
------------------------------------------------------------
for the  39 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
```

there are two ways to fill up these values

- Fill the missing value with 0's
- Fill the missing values with the avg values
  - Case 1:(values missing at the start)
    Ex1: _ _ _ 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 [52]:

```
# 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 intra
# 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)
    return smoothed_regions
```

In [53]:

```
# 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 intra
# 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 discus
# 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/res
                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 pick
            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 pic
                            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 miss
                        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/((ri
                        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 mi
                    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 [54]:

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

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

In [55]:

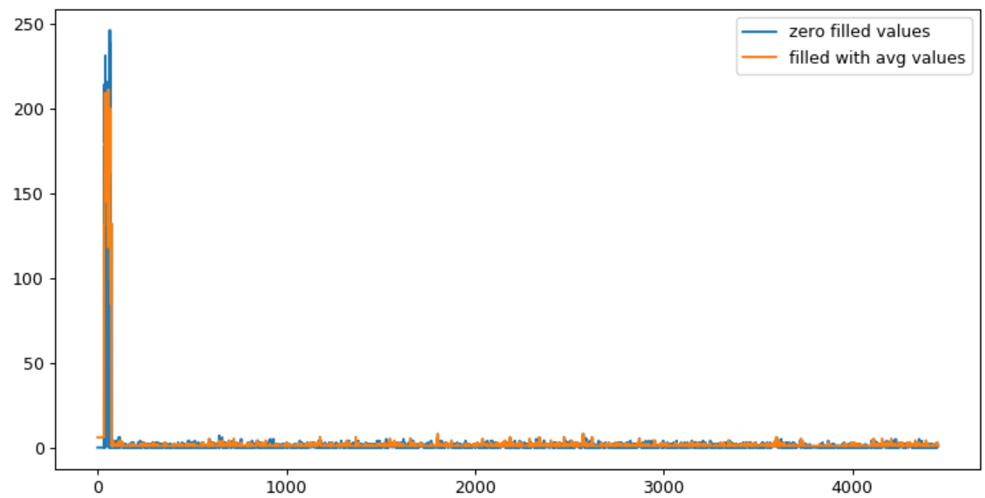
```
# number of 10min indices for jan 2015= 24*31*60/10 = 4464
# number of 10min indices for jan 2016 = 24*31*60/10 = 4464
# number of 10min indices for feb 2016 = 24*29*60/10 = 4176
# number of 10min indices for march 2016 = 24*30*60/10 = 4320
# for each cluster we will have 4464 values, therefore 40*4464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

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

In [56]:

```
# 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()
plt.show()
```

```
<IPython.core.display.Javascript object>
```



In [57]:

```
# 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 
# 10st 10min intravel, 0 pickups happened in 2nd 10mins intravel, 0 pickups happened in
# 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 t
# that are happened in the first 40min are same in both cases, but if you can observe t
# wheen you are using smoothing we are looking at the future number of pickups which mi

# 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 [58]:

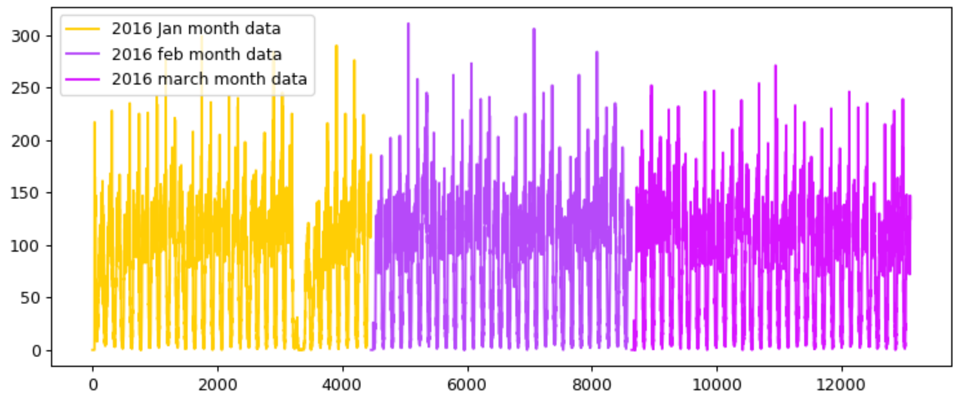
```
# Jan-2015 data is smoothed, Jan,Feb & March 2016 data missing values are filled with z
jan_2015_smooth = smoothing(jan_2015_groupby['trip_distance'].values,jan_2015_unique)
jan_2016_smooth = fill_missing(jan_2016_groupby['trip_distance'].values,jan_2016_unique
feb_2016_smooth = fill_missing(feb_2016_groupby['trip_distance'].values,feb_2016_unique
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 an
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 w
# 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*(

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

## Time series and Fourier Transforms

In [59]:

```
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 mo
    plt.plot(second_x,regions_cum[i][4464:8640], color=uniqueish_color(), label='2016 f
    plt.plot(third_x,regions_cum[i][8640:], color=uniqueish_color(), label='2016 march 
    plt.legend()
    plt.show()
```

<IPython.core.display.Javascript object>

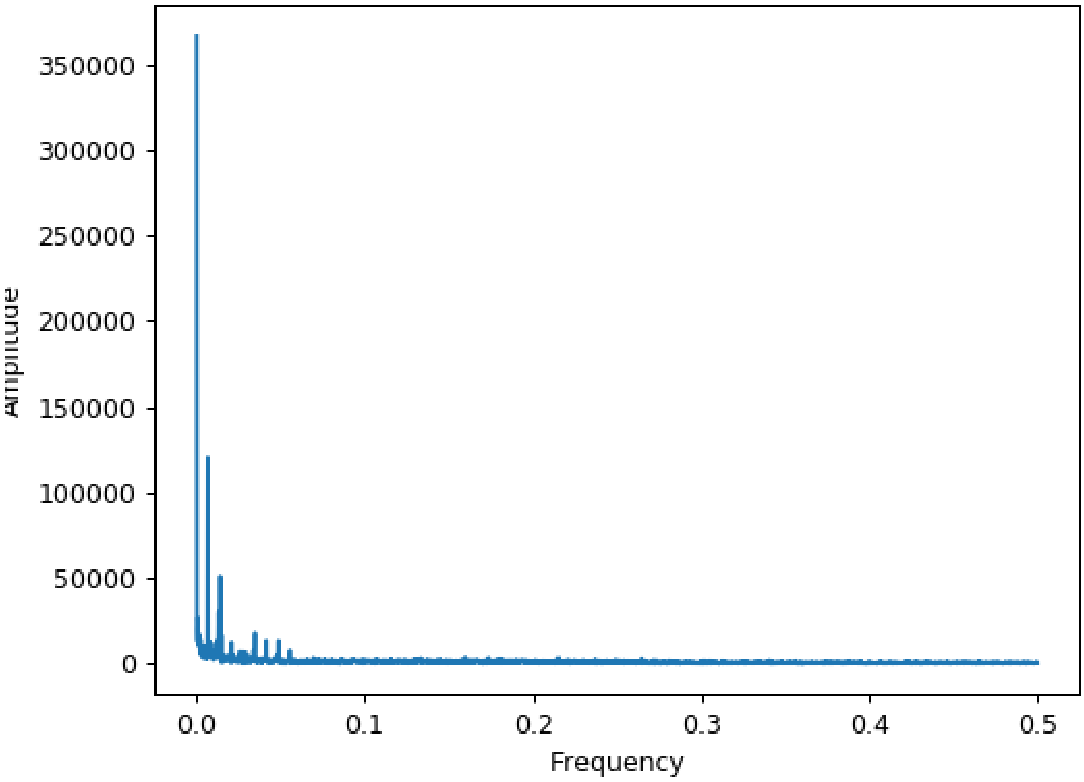



<IPython.core.display.Javascript object>

In [60]:

```
# 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/n
Y    = np.fft.fft(np.array(jan_2016_smooth)[0:4460])
# read more about the fftfreq: https://docs.scipy.org/doc/numpy/reference/generated/num
freq = np.fft.fftfreq(4460, 1)
n = len(freq)
plt.figure()
plt.plot( freq[:int(n/2)], np.abs(Y)[:int(n/2)] )
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.show()
```

<IPython.core.display.Javascript object>



In [61]:

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

# Modelling: Baseline Models

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

1. Using Ratios of the 2016 data to the 2015 data i.e $R_t = P^{2016}_t / P^{2015}_t$
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 [62]:

```
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)-(
        if i+1>=window_size:
            predicted_ratio=sum((ratios['Ratios'].values)[(i+1)-window_size:(i+1)])/win
        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['Pr
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

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

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

In [63]:

```
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+
        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['Pr
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

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

## Weighted Moving Averages

The Moving 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 [64]:

```
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)-(
        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['Pr
    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 [65]:

```
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['Pr
    mse_err = sum([e**2 for e in error])/len(error)
    return ratios,mape_err,mse_err
```

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

## Exponential Weighted Moving Averages

https://en.wikipedia.org/wiki/Moving_average#Exponential_moving_average (https://en.wikipedia.org/wiki/Moving_average#Exponential_moving_average) 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 $(\alpha)$ which is a value between 0 & 1 and based on the value of the hyperparameter alpha the weights and the window sizes are configured. For eg. If $\alpha = 0.9$ then the number of days on which the value of the current iteration is based is~ $1/(1-\alpha) = 10$ i.e. we consider values 10 days prior before we predict the value for the current iteration. Also the weights are assigned using $2/(N+1) = 0.18$ ,where N = number of prior values being considered, hence from this it is implied that the first or latest value is assigned a weight of 0.18 which keeps exponentially decreasing for the subsequent values.

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

In [66]:

```
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)-(
        predicted_ratio = (alpha*predicted_ratio) + (1-alpha)*((ratios['Ratios'].values

    ratios['EA_R1_Predicted'] = predicted_values
    ratios['EA_R1_Error'] = error
    mape_err = (sum(error)/len(error))/(sum(ratios['Prediction'].values)/len(ratios['Pr
    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 [67]:

```
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']

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

In [68]:

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

# Comparison between baseline models

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

In [69]:

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

```
Error Metric Matrix (Forecasting Methods) - MAPE & MSE
---------------------------------------------------------------------------
------------------------------
Moving Averages (Ratios) -                             MAPE:  0.2278515635
3133512       MSE:  1196.2953853046595
Moving Averages (2016 Values) -                        MAPE:  0.1558345871
2025738        MSE:  254.66309363799283
---------------------------------------------------------------------------
------------------------------
Weighted Moving Averages (Ratios) -                    MAPE:  0.2270652914
4871415       MSE:  1053.083529345878
Weighted Moving Averages (2016 Values) -               MAPE:  0.1479482182
992932       MSE:  224.81054547491038
---------------------------------------------------------------------------
------------------------------
Exponential Moving Averages (Ratios) -              MAPE:  0.2275474636148
534       MSE:  1019.3071012544802
Exponential Moving Averages (2016 Values) -         MAPE:  0.1475381297798
153       MSE:  222.35159610215055
```

**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 [70]:

```
# Preparing data to be split into train and test, The below prepares data in cumulative
# 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 w
# 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 clust
# 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 cluste
# Ex: [[cent_long 13099times],[cent_long 13099times], [cent_long 13099times].... 40 lis
# 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 o
# 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+1t
# 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 pick
    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
    tsne_feature = np.vstack((tsne_feature, [regions_cum[i][r:r+number_of_time_stamps] 
    output.append(regions_cum[i][5:])
tsne_feature = tsne_feature[1:]
```

In [71]:

```
len(tsne_lat[0])*len(tsne_lat) == tsne_feature.shape[0] == len(tsne_weekday)*len(tsne_w
```

Out[71]:

True

In [72]:

```
# Getting the predictions of exponential moving averages to be used as a feature in cum

# upto now we computed 8 features for every data point that starts from 50th min of the
# 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
# we will try to add the same exponential weighted moving avarage at t as a feature to
# 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
# 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..x
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 [73]:

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

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

In [74]:

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

In [75]:

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

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

In [76]:

```
# extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our tr
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 [77]:

```
# extracting the rest of the timestamp values i.e 30% of 12956 (total timestamps) for o
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 [78]:

```
# the above contains values in the form of list of lists (i.e. list of values of each r
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 [79]:

```
# 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 [80]:

```
# 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 [81]:

```
# 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

print(df_train.shape)
```

```
(366760, 9)
```

In [82]:

```
# 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
print(df_test.shape)
```

```
(157200, 9)
```

In [83]:

```
df_test.head()
```

Out[83]:

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

## Using Linear Regression

In [84]:

```
# find more about LinearRegression function here http://scikit-learn.org/stable/modules,
# -------------------------
# default paramters
# sklearn.linear_model.LinearRegression(fit_intercept=True, normalize=False, copy_X=Tru

# 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 pre
# set_params(**params)  Set the parameters of this estimator.
# -----------------------
# video link: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/g
# -----------------------

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 [85]:

```
# Training a hyper-parameter tuned random forest regressor on our train data
# find more about LinearRegression function here http://scikit-learn.org/stable/modules,
# -------------------------
# default paramters
# sklearn.ensemble.RandomForestRegressor(n_estimators=10, criterion='mse', max_depth=No
# min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes
# min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None

# 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 pre
# -----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/
# -----------------------

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

Out[85]:

```
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_job
s=-1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
```

In [86]:

```
# 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)
rndf_train_predictions = [round(value) for value in y_pred]
```

In [87]:

```
#feature importances based on analysis using random forest
print (df_train.columns)
print (regr1.feature_importances_)
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'lat', 'lon', 'weekday',
       'exp_avg'],
      dtype='object')
[0.02024173 0.05955837 0.07716413 0.20821812 0.28185245 0.00588304
 0.00338191 0.00196422 0.34173604]
```

### Using XgBoost Regressor

In [88]:

```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data

# find more about XGBRegressor function here http://xgboost.readthedocs.io/en/latest/py
# -------------------------
# default paramters
# xgboost.XGBRegressor(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True, o
# booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1, max_delta_step
# colsample_bylevel=1, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, base_score=0.5, r
# missing=None, **kwargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_rounds=
# get_params([deep])    Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: This fun
# get_score(importance_type='weight') -> get the feature importance
# -----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/
# -----------------------

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

```
[14:20:07] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/ob
jective/regression_obj.cu:152: reg:linear is now deprecated in favor of re
g:squarederror.
```

Out[88]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.8, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=3, missing=None, n_estimators=1
000,
             n_jobs=1, nthread=4, objective='reg:linear', random_state=0,
             reg_alpha=200, reg_lambda=200, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.8, verbosity=1)
```

In [89]:

```
#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)
xgb_train_predictions = [round(value) for value in y_pred]
```

In [90]:

```
#feature importances
# cite : https://github.com/TeamHG-Memex/eli5/issues/252#issuecomment-390088506
x_model.get_booster().get_score(importance_type='weight')
```

Out[90]:

```
{'ft_1': 1158,
 'ft_2': 1012,
 'exp_avg': 832,
 'ft_3': 793,
 'ft_4': 795,
 'ft_5': 1093,
 'lon': 546,
 'lat': 530,
 'weekday': 149}
```

## Calculating the error metric values for various models

In [91]:

```
train_mape=[]
test_mape=[]

train_mape.append((mean_absolute_error(tsne_train_output,df_train['ft_1'].values))/(sum
train_mape.append((mean_absolute_error(tsne_train_output,df_train['exp_avg'].values))/(
train_mape.append((mean_absolute_error(tsne_train_output,rndf_train_predictions))/(sum(
train_mape.append((mean_absolute_error(tsne_train_output, xgb_train_predictions))/(sum(
train_mape.append((mean_absolute_error(tsne_train_output, lr_train_predictions))/(sum(t

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

## Error Metric Matrix

In [93]:

```
print ("Error Metric Matrix (Tree Based Regression Methods) -  MAPE")
print (110*"*")
print ("Baseline Model -                             Train: ",train_mape[0],"      Test
print ("Exponential Averages Forecasting -           Train: ",train_mape[1],"      Test
print ("Linear Regression -                         Train: ",train_mape[4],"      Test:
print ("Random Forest Regression -                   Train: ",train_mape[2],"     Test:
print ("XgBoost Regression -                         Train: ",train_mape[3],"      Test
print (110*"*")
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
**************************************************************************
************************************
Baseline Model -                             Train:  0.14870666996426116
Test:  0.14225522601041551
Exponential Averages Forecasting -           Train:  0.14121603560900353
Test:  0.13490049942819257
Linear Regression -                         Train:  0.14212750303572363
Test:  0.1348928075901918
Random Forest Regression -                   Train:  0.09886538947146044
Test:  0.13328597313573348
XgBoost Regression -                         Train:  0.13853391044522317
Test:  0.13281686597864917
**************************************************************************
************************************
```

### Pretty Table - Regression baseline models

In [ ]:

```

```

# Assignments

In [94]:

```
'''
Task 1: Incorporate Fourier features as features into Regression models and measure MAP

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[94]:

```
'\nTask 1: Incorporate Fourier features as features into Regression models
and measure MAPE. <br>\n\nTask 2: Perform hyper-parameter tuning for Regre
ssion models.\n        2a. Linear Regression: Grid Search\n        2b. Ran
dom Forest: Random Search \n        2c. Xgboost: Random Search\nTask 3: Ex
plore more time-series features using Google search/Quora/Stackoverflow\nt
o reduce the MAPE to < 12%\n'
```

# Task1: Fourier feature into Regression model and measure MAPE

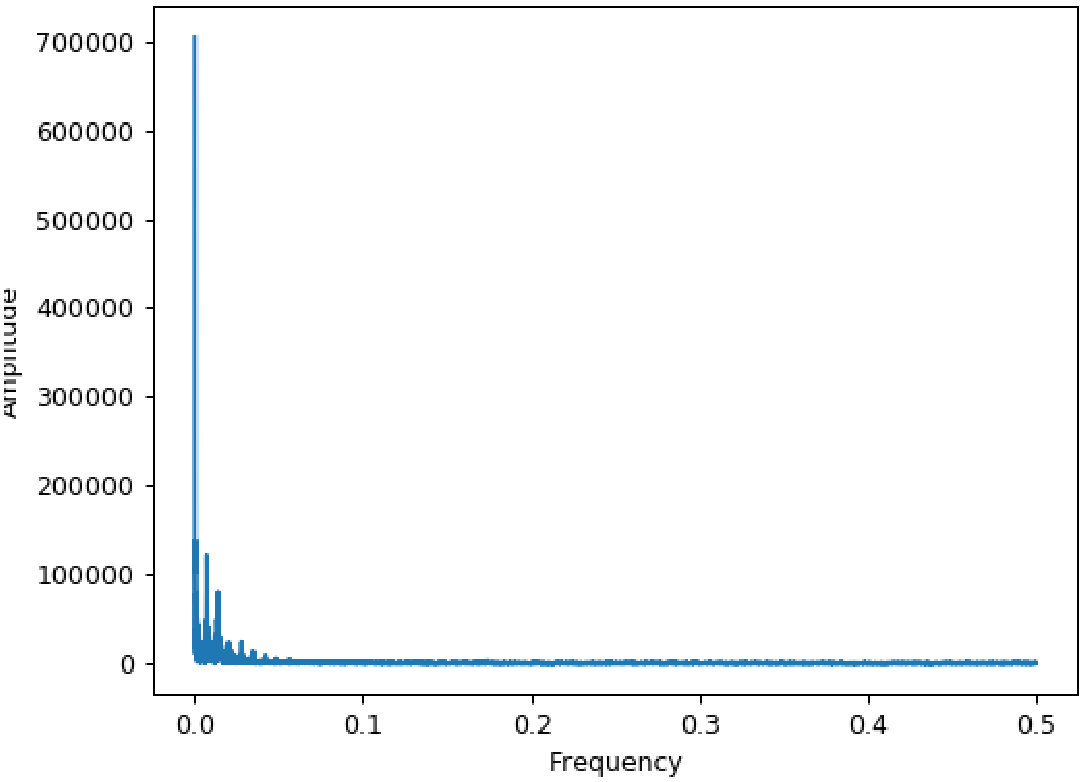
In [95]:

```
amplitude = []
frequency = []
for i in range(40):
    amps  = np.abs(np.fft.fft(regions_cum[i][0:13104]))
    freqs = np.abs(np.fft.fftfreq(13104, 1))
    amp_indices = np.argsort(-amps)[1:]
    amp_values = []
    freq_values = []
    for j in range(0, 9, 2):   #taking top five amplitudes and frequencies
        amp_values.append(amps[amp_indices[j]])
        freq_values.append(freqs[amp_indices[j]])
    for k in range(13104):    #those top 5 frequencies and amplitudes are same for all
        amplitude.append(amp_values)
        frequency.append(freq_values)
```

In [96]:

```
n = len(freqs)
plt.figure()
plt.plot( freqs[:int(n)], np.abs(amps)[:int(n)] )
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.show()
```

<IPython.core.display.Javascript object>



In [97]:

```
print("amp_indices:", amp_indices)
print("-amps :", -amps)
print(110*"-")
print("Length of regious :", len(regions_cum[34]))
print("Length of amplitude :", len(amplitude[:]))
print("lenth of regious_cum * 34 :", 13104*40)# lenth of regious_cum * 34
print(110*"-")
print("amplitude[13102:13105]:", amplitude[13100:13105])
```

```
amp_indices: [    2 13102    90 ...  9904 10321  2783]
-amps : [-703777.         -103667.50708037 -138645.49259443 ...  -62969.48
852339
 -138645.49259443 -103667.50708037]
---------------------------------------------------------------------------
-----------------------------------
Length of regious : 13104
Length of amplitude : 524160
lenth of regious_cum * 34 : 524160
---------------------------------------------------------------------------
-----------------------------------
amplitude[13102:13105]: [[364029.70303860103, 181600.69563522245, 83398.44
06755517, 67881.73381540622, 62607.923181729166], [364029.70303860103, 181
600.69563522245, 83398.4406755517, 67881.73381540622, 62607.923181729166],
[364029.70303860103, 181600.69563522245, 83398.4406755517, 67881.733815406
22, 62607.923181729166], [364029.70303860103, 181600.69563522245, 83398.44
06755517, 67881.73381540622, 62607.923181729166], [9047.531027454246, 885
0.75428739854, 8593.662502166022, 8505.457083606912, 8503.968972656718]]
```

In [98]:

```
train_frequencies = [frequency[i*13099:(13099*i+9169)] for i in range(0,40)]
test_frequencies = [frequency[(13099*(i))+9169:13099*(i+1)] for i in range(0,40)]

train_amplitudes = [amplitude[i*13099:(13099*i+9169)] for i in range(0,40)]
test_amplitudes = [amplitude[(13099*(i))+9169:13099*(i+1)] for i in range(0,40)]

train_features =  [tsne_feature[i*13099:(13099*i+9169)] for i in range(0,40)]
# temp = [0]*(12955 - 9068)
test_features = [tsne_feature[(13099*(i))+9169:13099*(i+1)] for i in range(0,40)]
```

In [99]:

```
# extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our tr
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 [100]:

```
# extracting the rest of the timestamp values i.e 30% of 12956 (total timestamps) for o
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 [101]:

```
print("length of tsne_test_flat_lat[25]:", len(tsne_test_flat_lat[25]))
```

```
length of tsne_test_flat_lat[25]: 3930
```

In [102]:

```
# the above contains values in the form of list of lists (i.e. list of values of each r
#here we make all of them in one list
train_new_features = []
for i in range(0,40):
    train_new_features.extend(train_features[i])
test_new_features = []
for i in range(0,40):
    test_new_features.extend(test_features[i])
train_freq=[]
test_freq=[]
train_amp=[]
test_amp=[]
for i in range(0,40):
    train_freq.extend(train_frequencies[i])
    test_freq.extend(test_frequencies[i])
    train_amp.extend(train_amplitudes[i])
    test_amp.extend(test_amplitudes[i])
```

In [103]:

```
train_neww_features=np.hstack((train_new_features,train_freq,train_amp))
test_neww_features=np.hstack((test_new_features,test_freq,test_amp))
print("train_neww_features :", train_neww_features)
print(110*"-")
print("test_neww_features :", test_neww_features)
```

```
train_neww_features : [[0.00000000e+00 0.00000000e+00 0.00000000e+00 ...
8.33984407e+04
  6.78817338e+04 6.26079232e+04]
 [0.00000000e+00 0.00000000e+00 0.00000000e+00 ... 8.33984407e+04
  6.78817338e+04 6.26079232e+04]
 [0.00000000e+00 0.00000000e+00 0.00000000e+00 ... 8.33984407e+04
  6.78817338e+04 6.26079232e+04]
 ...
 [6.70000000e+01 7.50000000e+01 7.70000000e+01 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]
 [7.50000000e+01 7.70000000e+01 6.50000000e+01 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]
 [7.70000000e+01 6.50000000e+01 6.60000000e+01 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]]
----------------------------------------------------------------------------
----------------------------------
test_neww_features : [[1.43000000e+02 1.45000000e+02 1.19000000e+02 ... 8.
33984407e+04
  6.78817338e+04 6.26079232e+04]
 [1.45000000e+02 1.19000000e+02 1.13000000e+02 ... 8.33984407e+04
  6.78817338e+04 6.26079232e+04]
 [1.19000000e+02 1.13000000e+02 1.24000000e+02 ... 8.33984407e+04
  6.78817338e+04 6.26079232e+04]
 ...
 [1.10000000e+01 7.00000000e+00 1.50000000e+01 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]
 [7.00000000e+00 1.50000000e+01 9.00000000e+00 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]
 [1.50000000e+01 9.00000000e+00 3.00000000e+00 ... 1.03667507e+05
  1.00397694e+05 8.76404546e+04]]
```

In [104]:

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

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

# TSNE_TEST
# 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 [105]:

```
# Preparing the data frame for our train data
columns = ['ft_5','ft_4','ft_3','ft_2','ft_1','freq1','freq2','freq3','freq4','freq5','A
           'Amp2','Amp3','Amp4','Amp5']
df_train = pd.DataFrame(data=train_neww_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

print("Shape of dataframe train :", df_train.shape)
```

```
Shape of dataframe train : (366760, 19)
```

In [106]:

```
df_train.head(5)
```

Out[106]:

| | ft_5 | ft_4 | ft_3 | ft_2 | ft_1 | freq1 | freq2 | freq3 | freq4 | freq5 | Amp1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029.703039 |
| 1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029.703039 |
| 2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029.703039 |
| 3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029.703039 |
| 4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029.703039 |

In [107]:

```
# Preparing the data frame for our test data
df_test = pd.DataFrame(data=test_neww_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
print("Shape of dataframe test :",df_test.shape)
```

```
Shape of dataframe test : (157200, 19)
```

In [108]:

```
df_test.head(3)
```

Out[108]:

| | ft_5 | ft_4 | ft_3 | ft_2 | ft_1 | freq1 | freq2 | freq3 | freq4 | freq5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 143.0 | 145.0 | 119.0 | 113.0 | 124.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029 |
| 1 | 145.0 | 119.0 | 113.0 | 124.0 | 121.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029 |
| 2 | 119.0 | 113.0 | 124.0 | 121.0 | 131.0 | 0.006944 | 0.013889 | 0.012897 | 0.034722 | 0.007937 | 364029 |

# Task 2 : Hyperparameter Tuning

## 2.1 Linear Regression :

In [109]:

```
from sklearn.linear_model import SGDRegressor
from sklearn.model_selection import GridSearchCV
model=SGDRegressor(loss='squared_loss',penalty='l2')
alpha=[10**-4,10**-3,10**-2,10**-1,1,10,100,500]
param_grid={"alpha":alpha}
clf = GridSearchCV(model,param_grid, scoring = "neg_mean_absolute_error", cv=3,n_jobs=-
clf.fit(df_train,tsne_train_output)
print("best parameters :",clf.best_params_)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  3.5min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  5.5min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  8.4min
[Parallel(n_jobs=-1)]: Done  20 out of  24 | elapsed:  9.8min remaining:
2.0min
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed: 11.2min finished

best parameters : {'alpha': 500}
```

In [110]:

```
from sklearn.linear_model import SGDRegressor
from sklearn.model_selection import GridSearchCV
model=SGDRegressor(loss='squared_loss',penalty='l2')
alpha=[10**-4,10**-3,10**-2,10**-1,1,10,100,500]
param_grid={"alpha":alpha}
clf = GridSearchCV(model,param_grid, scoring = "neg_mean_absolute_error", cv=5,n_jobs=-
clf.fit(df_train,tsne_train_output)
print("best parameters :",clf.best_params_)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  4.1min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  6.5min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed: 10.5min
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed: 13.8min
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed: 18.5min
[Parallel(n_jobs=-1)]: Done  38 out of  40 | elapsed: 21.4min remaining:
1.1min
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 22.1min finished


best parameters : {'alpha': 0.001}
```

In [111]:

```
lr_reg = SGDRegressor(loss='squared_loss', penalty='l2', alpha=0.01)
lr_reg.fit(df_train, tsne_train_output)

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

In [112]:

```
len(lr_train_predictions)
```

Out[112]:

```
366760
```

## 2.2 Random Forest - Hyperparameter Tuning

In [113]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform

param_dist = {"n_estimators":[10,20,50,100,150,200,250,300],
              "max_depth": [10,20,50,100,150,200,250,300],
              "min_samples_split": sp_randint(120,190),
              "min_samples_leaf": sp_randint(25,65)}

clf_rf = RandomForestRegressor(random_state=25,n_jobs=-1)

model_rf = RandomizedSearchCV(clf_rf, param_distributions=param_dist,n_iter=3,cv=3,
                                   scoring='neg_mean_absolute_error',random_state=3,n_j

model_rf.fit(df_train,tsne_train_output)
print("RF model best paramaters :",model_rf.best_estimator_)
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   3 out of   9 | elapsed:   35.6s remaining:
1.2min
[Parallel(n_jobs=-1)]: Done   4 out of   9 | elapsed:  4.3min remaining:
5.3min
[Parallel(n_jobs=-1)]: Done   5 out of   9 | elapsed:  5.3min remaining:
4.3min
[Parallel(n_jobs=-1)]: Done   6 out of   9 | elapsed:  6.2min remaining:
3.1min
[Parallel(n_jobs=-1)]: Done   7 out of   9 | elapsed:  6.4min remaining:
1.8min
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed:  6.6min remaining:
0.0s
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed:  6.6min finished

RF model best paramaters : RandomForestRegressor(bootstrap=True, criterion
='mse', max_depth=10,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=25, min_samples_split=141,
                      min_weight_fraction_leaf=0.0, n_estimators=200, n_jo
bs=-1,
                      oob_score=False, random_state=25, verbose=0,
                      warm_start=False)
```

In [114]:

```
RFReg = RandomForestRegressor(n_estimators=200, max_depth=10, min_samples_split=141,
                              min_samples_leaf=25, n_jobs=-1, random_state=25, verbose=1

RFReg.fit(df_train,tsne_train_output)
y_pred_test_rf = RFReg.predict(df_test)
rndf_test_predictions = [round(value) for value in y_pred_test_rf]
y_pred_train_rf = RFReg.predict(df_train)
rndf_train_predictions = [round(value) for value in y_pred_train_rf]
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   30.2s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed:  2.3min finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent wor
kers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.2s
[Parallel(n_jobs=4)]: Done 192 tasks      | elapsed:    1.2s
[Parallel(n_jobs=4)]: Done 200 out of 200 | elapsed:    1.2s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent wor
kers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.6s
[Parallel(n_jobs=4)]: Done 192 tasks      | elapsed:    2.8s
[Parallel(n_jobs=4)]: Done 200 out of 200 | elapsed:    2.9s finished
```

## 2.3 XGBoost - Hyperparameter Tuning

In [115]:

```
tsne_train_output_df = pd.DataFrame(tsne_train_output)
tsne_test_output_df = pd.DataFrame(tsne_test_output)
```

In [116]:

```
import pickle
df_train.to_pickle("df_train.txt")
with open('tsne_train_output.pkl', 'wb') as f:
    pickle.dump(tsne_train_output, f)

df_test.to_pickle("df_test.txt")
with open('tsne_test_output.pkl', 'wb') as f:
    pickle.dump(tsne_test_output, f)

df_train = pd.read_pickle("df_train.txt")
with open('tsne_train_output.pkl', 'rb') as f:
    tsne_train_output = pickle.load(f)

df_test = pd.read_pickle("df_test.txt")
with open('tsne_test_output.pkl', 'rb') as f:
    tsne_test_output = pickle.load(f)
```

In [117]:

```python
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
from scipy import stats

clf_xgb = xgb.XGBRegressor()
c_param={'learning_rate' :stats.uniform(0.01,0.2),
      'n_estimators':sp_randint(100,1000),
      'max_depth':sp_randint(1,10),
      'min_child_weight':sp_randint(1,8),
      'gamma':stats.uniform(0,0.02),
      'subsample':stats.uniform(0.6,0.4),
      'reg_alpha':sp_randint(0,200),
      'reg_lambda':stats.uniform(0,200),
      'colsample_bytree':stats.uniform(0.6,0.3)}
param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15)
              }
model_xgb = RandomizedSearchCV(clf_xgb
                               , param_distributions=c_param,
                                   n_iter=3,cv=3,scoring='neg_mean_absolute_error',rand
                               verbose=1)
model_xgb.fit(df_train,tsne_train_output)
model_xgb.best_estimator_
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed: 17.2min finished

[15:30:27] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/ob
jective/regression_obj.cu:152: reg:linear is now deprecated in favor of re
g:squarederror.
```

Out[117]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.6154401609902489,
             gamma=0.00881619687301273, importance_type='gain',
             learning_rate=0.015975242175713392, max_delta_step=0, max_dep
th=8,
             min_child_weight=7, missing=None, n_estimators=604, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alp
ha=26,
             reg_lambda=55.69745652959506, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.8705019607920526, verbosity=1)
```

In [118]:

```
xgb_model=xgb.XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.6154401609902489,
             gamma=0.00881619687301273, importance_type='gain',
             learning_rate=0.015975242175713392, max_delta_step=0, max_depth=8,
             min_child_weight=7, missing=None, n_estimators=604, n_jobs=-1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=26,
             reg_lambda=55.69745652959506, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.8705019607920526, verbosity=1)
xgb_model.fit(df_train,tsne_train_output)

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

```
[15:37:43] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/ob
jective/regression_obj.cu:152: reg:linear is now deprecated in favor of re
g:squarederror.
```

### 2.4 calculating the error metric values for various models

In [119]:

```
train_mape=[]
test_mape=[]

train_mape.append((mean_absolute_error(tsne_train_output, lr_train_predictions))/(sum(t
train_mape.append((mean_absolute_error(tsne_train_output,rndf_train_predictions))/(sum(
train_mape.append((mean_absolute_error(tsne_train_output, xgb_train_predictions))/(sum(

test_mape.append((mean_absolute_error(tsne_test_output, lr_test_predictions))/(sum(tsne
test_mape.append((mean_absolute_error(tsne_test_output, rndf_test_predictions))/(sum(ts
test_mape.append((mean_absolute_error(tsne_test_output, xgb_test_predictions))/(sum(tsn
```

### 2.5 Error Metric matrix

In [120]:

```
print ("Error Metric Matrix (Tree Based Regression Methods) -  MAPE")
print (110*"-")
print ("Linear Regression -                          Train: ",train_mape[0],"      Test:
print ("Random Forest Regression -                    Train: ",train_mape[1],"      Test:
print ("XgBoost Regression -                          Train: ",train_mape[2],"      Test
print (110*"-")
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
---------------------------------------------------------------------------
------------------------------------
Linear Regression -                          Train:  3.1691229754092896e+16
Test:  2.8789297178980316e+16
Random Forest Regression -                    Train:  0.1385681795060892
Test:  0.1328413659070961
XgBoost Regression -                          Train:  0.1362144549765687
Test:  0.1315665149791898
---------------------------------------------------------------------------
------------------------------------
```

### 2.7 Pretty Table - Treen based models

In [137]:

```
from prettytable import PrettyTable
p = PrettyTable()
p = PrettyTable(["Models", "MAPE train ", "MAPE test "])
p.add_row(['Linear Regression ','3.169','2.878'])
p.add_row(['Random Forest Regression','0.138','0.132'])
p.add_row(['XGBoost Regression', '0.136', '0.131'])
print(p)
```

```
+--------------------------+-------------+------------+
|          Models          | MAPE train  | MAPE test  |
+--------------------------+-------------+------------+
|    Linear Regression     |    3.169    |   2.878    |
| Random Forest Regression |    0.138    |   0.132    |
|    XGBoost Regression    |    0.136    |   0.131    |
+--------------------------+-------------+------------+
```

## 3. Reducing MAPE

In [121]:

```
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt
```

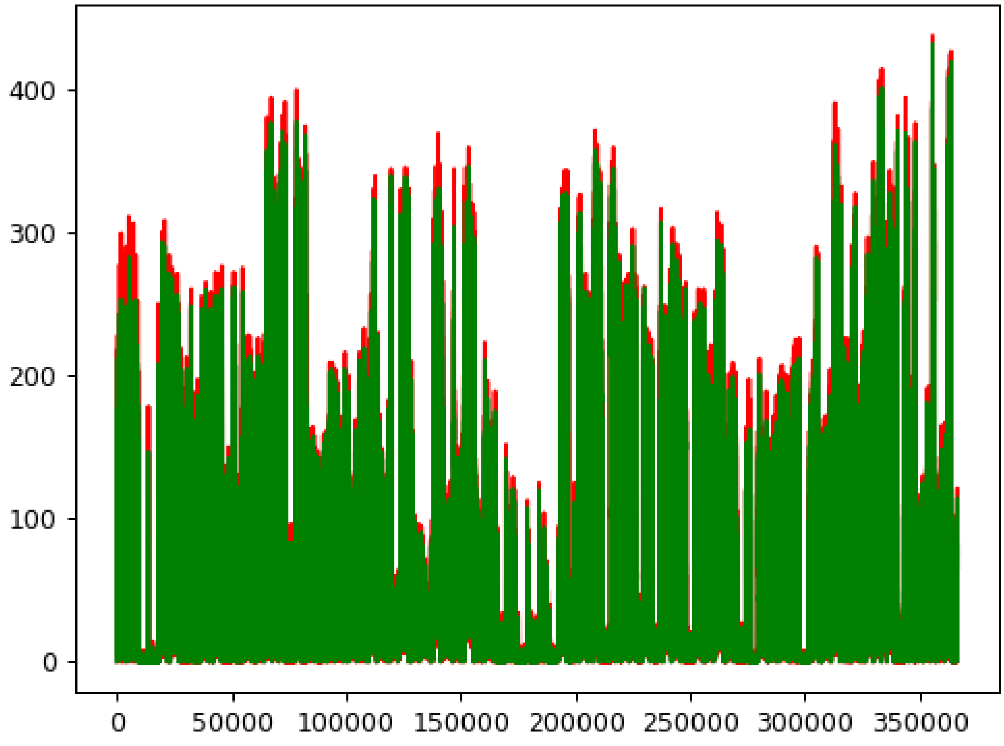
In [122]:

```
tsne_train_output1 = (tsne_train_output)[:]
tsne_test_output1 = tsne_test_output[:]
```

In [123]:

```
import time
start_time = time.time()

model = ExponentialSmoothing(tsne_train_output1,trend='add').fit()
pred_train_exp1 = model.predict(start=0, end=len(tsne_train_output1)-1)

ind = list(range(0,len(tsne_train_output1)))
# plt.plot(ind, tsne_train_output1, label='Train',color='blue')
plt.plot(ind, tsne_train_output1, label='Test',color='red')
plt.plot(ind, pred_train_exp1, label='Holt-Winters',color='green')
# plt.legend(loc='best')
print("--- %s seconds ---" % (time.time() - start_time))
plt.show()
```

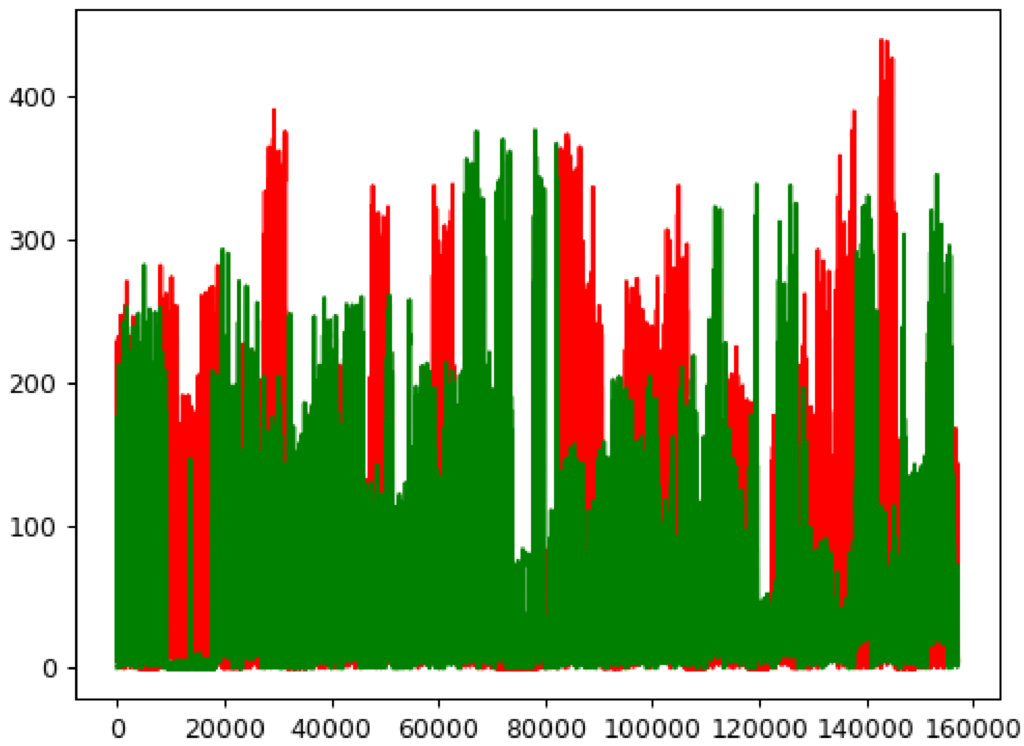
```
--- 10.009076118469238 seconds ---

<IPython.core.display.Javascript object>
```



In [124]:

```
import time
start_time = time.time()

model = ExponentialSmoothing(tsne_train_output1,trend='add').fit()
pred_test_exp1 = model.predict(start=0, end=len(tsne_test_output1)-1)

ind = list(range(0,len(tsne_test_output1)))
# plt.plot(ind, tsne_train_output1, label='Train',color='blue')
plt.plot(ind, tsne_test_output1, label='Test',color='red')
plt.plot(ind, pred_test_exp1, label='Holt-Winters',color='green')
# plt.legend(loc='best')
print("--- %s seconds ---" % (time.time() - start_time))
plt.show()
```

```
--- 9.776626586914062 seconds ---

<IPython.core.display.Javascript object>
```



In [125]:

```
print((mean_absolute_error(tsne_test_output1,pred_test_exp1))/(sum(tsne_test_output1)/l
```

```
1.0098063259037064
```

In [126]:

```
print((mean_absolute_error(tsne_train_output1,pred_train_exp1))/(sum(tsne_train_output1
```

```
0.14143645585635845
```

### 3.2 Manual checks to reduce below 0.12 MAPE

In [127]:

```
tsne_train_output1 = (tsne_train_output)[:]
tsne_test_output1 = tsne_test_output[:]
```

In [128]:

```
def exponential_smoothing(series, alpha):
    result = [series[0]] # first value is same as series
    for n in range(1, len(series)):
        result.append(alpha * series[n] + (1 - alpha) * result[n-1])
    return result
```

In [129]:

```
len(tsne_test_output)
```

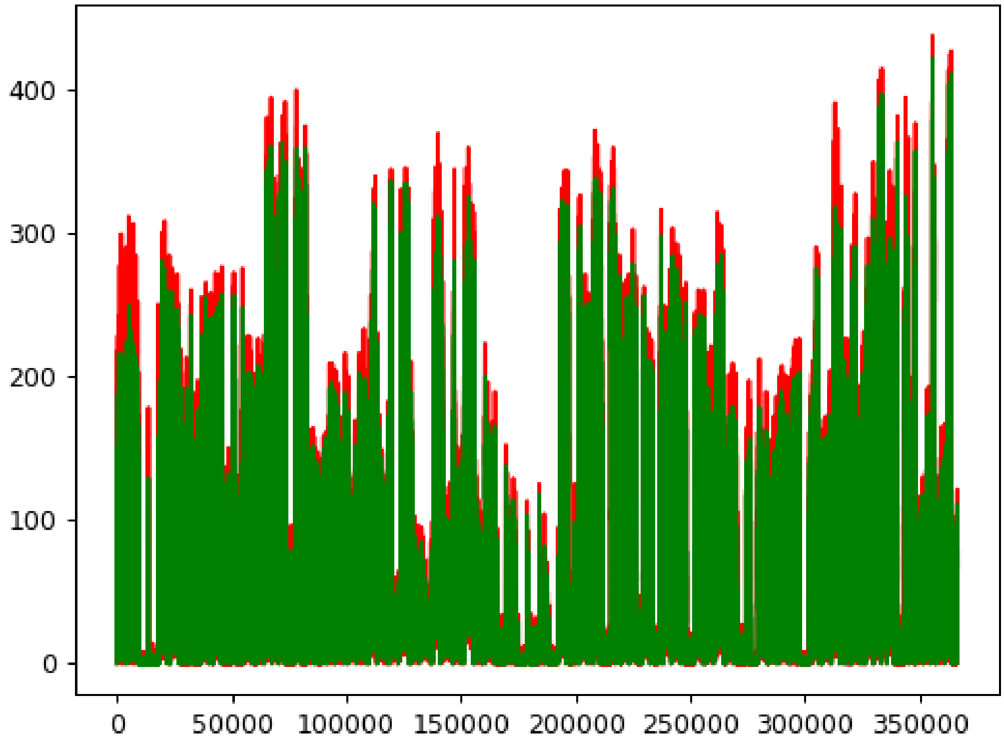
Out[129]:

```
157200
```

In [130]:

```
pred_train_exp2 = exponential_smoothing(tsne_train_output1,0.4)
ind = list(range(0,len(tsne_train_output1)))
# plt.plot(ind, tsne_train_output1, label='Train',color='blue')
plt.plot(ind, tsne_train_output1, label='Test',color='red')
plt.plot(ind, pred_train_exp2, label='Holt-Winters',color='green')
# plt.legend(loc='best')
# print("--- %s seconds ---" % (time.time() - start_time))
plt.show()
```

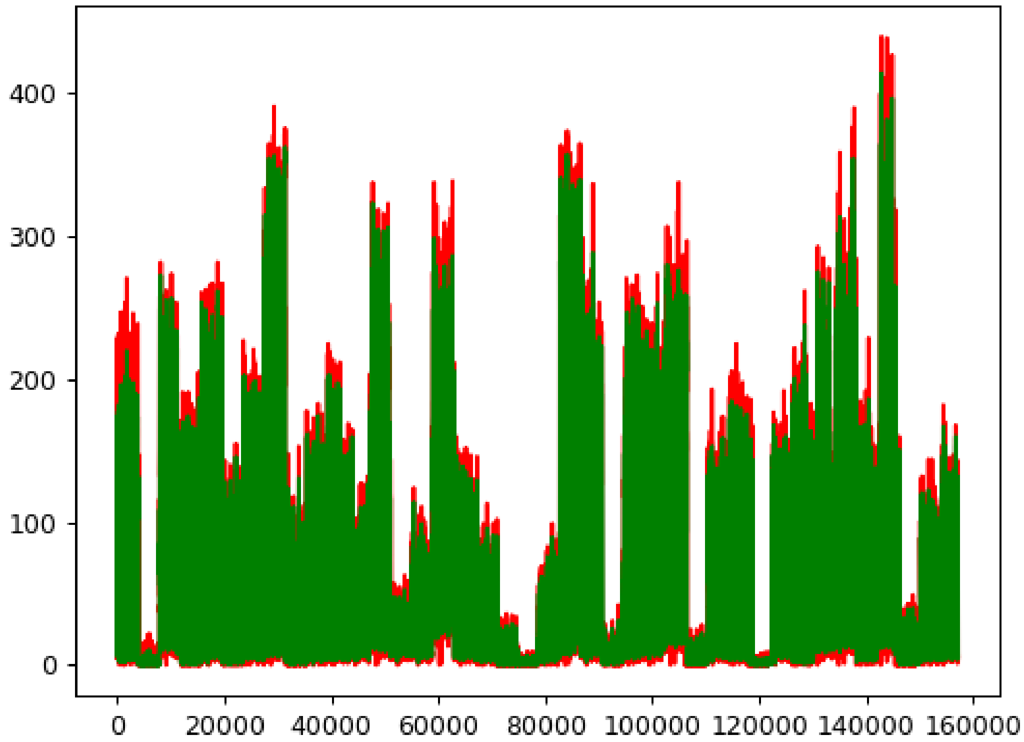
<IPython.core.display.Javascript object>



In [131]:

```
pred_test_exp2 = exponential_smoothing(tsne_test_output1,0.4)
ind = list(range(0,len(tsne_test_output1)))
# plt.plot(ind, tsne_train_output1, label='Train',color='blue')
plt.plot(ind, tsne_test_output1, label='Test',color='red')
plt.plot(ind, pred_test_exp2, label='Holt-Winters',color='green')
# plt.legend(loc='best')
# print("--- %s seconds ---" % (time.time() - start_time))
plt.show()
```

<IPython.core.display.Javascript object>




In [132]:

```
print((mean_absolute_error(tsne_test_output1,pred_test_exp2))/(sum(tsne_test_output1)/l
```

0.08678375578826916

In [133]:

```
print((mean_absolute_error(tsne_train_output1,pred_train_exp2))/(sum(tsne_train_output1
```

0.09079147963174913

### 3.3. Calculating error rating with various models

In [134]:

```
train_mape=[]
test_mape=[]

train_mape.append((mean_absolute_error(tsne_train_output1,pred_train_exp1))/(sum(tsne_t
                                                                              (tsne_trai
train_mape.append((mean_absolute_error(tsne_train_output1,pred_train_exp2))/(sum(tsne_t
                                                                              (tsne_trai

test_mape.append((mean_absolute_error(tsne_test_output1,pred_test_exp1))/(sum(tsne_test_
                                                                           (tsne_test_ou

test_mape.append((mean_absolute_error(tsne_test_output1,pred_test_exp2))/(sum(tsne_test_
                                                                           (tsne_test_ou
```

In [135]:

```
print ("Error Metric Matrix (Tree Based Regression Methods) -  MAPE")
print ("--------------------------------------------------------------------------------
print ("ExponentialSmoothing(LIBRARY)               - Train: ",train_mape[0],"      Tes
print ("ExponentialSmoothing(MANUAL IMPLEMENTATION) - Train: ",train_mape[1],"      Tes
print ("--------------------------------------------------------------------------------
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
--------------------------------------------------------------------------
------------------------------
ExponentialSmoothing(LIBRARY)               - Train:  0.14143645585635845
Test:  1.0098063259037064
ExponentialSmoothing(MANUAL IMPLEMENTATION) - Train:  0.09079147963174913
Test:  0.08678375578826916
--------------------------------------------------------------------------
------------------------------
```

### 3.4 Prettytable - Reduced to below 12%

In [136]:

```
from prettytable import PrettyTable
p = PrettyTable()
p = PrettyTable(["Models", "MAPE train ", "MAPE test "])
p.add_row(['ExponentialSmoothing(LIBRARY)','0.141','1.009'])
p.add_row(['ExponentialSmoothing(MANUAL IMPLEMENTATION)','0.090','0.086'])
print(p)
```

```
+---------------------------------------------+-------------+------------+
|                    Models                   | MAPE train  | MAPE test  |
+---------------------------------------------+-------------+------------+
|        ExponentialSmoothing(LIBRARY)        |    0.141    |   1.009    |
| ExponentialSmoothing(MANUAL IMPLEMENTATION) |    0.090    |   0.086    |
+---------------------------------------------+-------------+------------+
```

## 4. Step by step procedure

- Our main objective is to pridict number of pickups, given location cordinates(latitude and longitude) and time, in the query reigion and surrounding regions.And to solve this we used the data collected in Jan -

Mar 2015 to predict the pickups in Jan - Mar 2016.

- Now first we diid data cleaning and visualization so that we will able to remove the outliers from our data and also we will be able to know the most important feature in the data which help us to improve our model performance.
- After doing all above we did data-preparation in which using cordinates(latitude and longitude) we converted our dataset into clusters and distributing time into 10 min of interval, so that we pridict the number of pickups for the given region for the time interval.
- Our data is time series data so we split our dataset into train and test .
- And next we tried some Baseline model with
  1. Using Ratios of the 2016 data to the 2015 data
  2. Using Previous known values of the 2016 data itself to predict the future values
- And tried to get the performance of our baseline models
- we add up some more impoatant features like fourier transforms features in our dataset to reduce MAPE to below 12% .


**Sign Off RAMESH BATTU** (https://www.linkedin.com/in/rameshbattuai/)