taxiassignmentfinal

April 15, 2019

0.1 taxi demand prediction in new york city

0.1.1 problem statement is to predict the number of pickup values in the next 10 minute minutes in particular bin .

In [0]:
```
!pip3 install gpxpy
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) p
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
import warnings
warnings.filterwarnings("ignore")
```

```
Collecting gpxpy
  Downloading https://files.pythonhosted.org/packages/6e/d3/ce52e67771929de455e76655365a4935a2
    100% || 112kB 2.8MB/s
Building wheels for collected packages: gpxpy
  Building wheel for gpxpy (setup.py) ... done
  Stored in directory: /root/.cache/pip/wheels/d2/f0/5e/b8e85979e66efec3eaa0e47fbc5274db99fd1a
Successfully built gpxpy
Installing collected packages: gpxpy
Successfully installed gpxpy-1.3.5
```

In [0]:
```
!pip3 install graphviz
!pip3 install dask
!pip3 install toolz
!pip3 install cloudpickle
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (0.10.1)
Requirement already satisfied: dask in /usr/local/lib/python3.6/dist-packages (0.20.2)
Requirement already satisfied: toolz in /usr/local/lib/python3.6/dist-packages (0.9.0)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.6/dist-packages (0.6.1)
```

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
    100% || 993kB 20.5MB/s
  Building wheel for PyDrive (setup.py) ... done
```

```
In [0]: link = 'https://drive.google.com/open?id=1kcIZlf-LQiQhqfSCZb719Nh6Rqkp2zKK' # The shar
```

```
In [0]: fluff, id = link.split('=')
        print (id) # Verify that you have everything after '='
```

```
1kcIZlf-LQiQhqfSCZb719Nh6Rqkp2zKK
```

```
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('yellow_tripdata_2015-01.csv')
```

```
In [0]: #Looking at the features
        # dask dataframe  : # https://github.com/dask/dask-tutorial/blob/master/07_dataframe.i
        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_amount',
       'extra', 'mta_tax', 'tip_amount', 'tolls_amount',
       'improvement_surcharge', 'total_amount'],
      dtype='object')
```

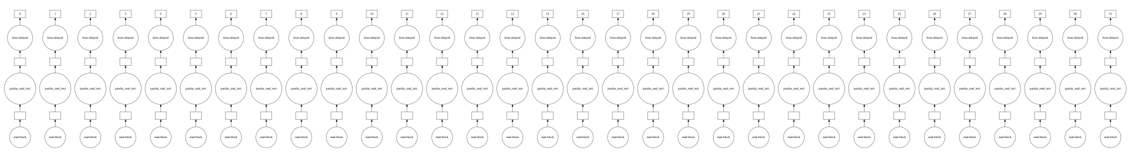
```
In [0]: month.head(5)
```

```
Out[0]:    VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
        0         2  2015-01-15 19:05:39   2015-01-15 19:23:42                1
        1         1  2015-01-10 20:33:38   2015-01-10 20:53:28                1
        2         1  2015-01-10 20:33:38   2015-01-10 20:43:41                1
        3         1  2015-01-10 20:33:39   2015-01-10 20:35:31                1
        4         1  2015-01-10 20:33:39   2015-01-10 20:52:58                1

           trip_distance  pickup_longitude  pickup_latitude  RateCodeID  \
        0           1.59        -73.993896        40.750111           1
        1           3.30        -74.001648        40.724243           1
        2           1.80        -73.963341        40.802788           1
        3           0.50        -74.009087        40.713818           1
        4           3.00        -73.971176        40.762428           1

          store_and_fwd_flag  dropoff_longitude  dropoff_latitude  payment_type  \
        0                  N         -73.974785         40.750618             1
        1                  N         -73.994415         40.759109             1
        2                  N         -73.951820         40.824413             2
```

```
3                    N          -74.004326         40.719986              2
4                    N          -74.004181         40.742653              2

   fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0         12.0    1.0      0.5        3.25           0.0
1         14.5    0.5      0.5        2.00           0.0
2          9.5    0.5      0.5        0.00           0.0
3          3.5    0.5      0.5        0.00           0.0
4         15.0    0.5      0.5        0.00           0.0

   improvement_surcharge  total_amount
0                    0.3         17.05
1                    0.3         17.80
2                    0.3         10.80
3                    0.3          4.80
4                    0.3         16.30
```

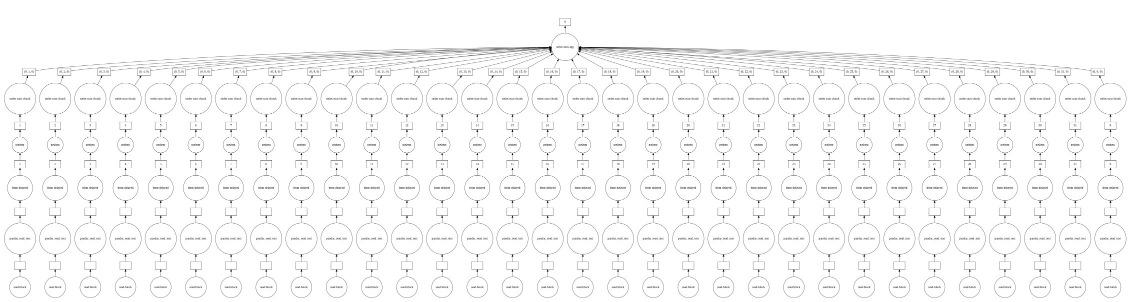
In [0]:
```
# pip3 install graphviz if this doesnt work please check the install_graphviz.jpg in th
month.visualize()
```

Out[0]:



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

Out[0]:



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

```
Out[0]:    VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0         2  2015-01-15 19:05:39   2015-01-15 19:23:42                1
1         1  2015-01-10 20:33:38   2015-01-10 20:53:28                1
2         1  2015-01-10 20:33:38   2015-01-10 20:43:41                1
3         1  2015-01-10 20:33:39   2015-01-10 20:35:31                1
4         1  2015-01-10 20:33:39   2015-01-10 20:52:58                1

   trip_distance  pickup_longitude  pickup_latitude  RateCodeID  \
0           1.59        -73.993896        40.750111           1
1           3.30        -74.001648        40.724243           1
2           1.80        -73.963341        40.802788           1
3           0.50        -74.009087        40.713818           1
4           3.00        -73.971176        40.762428           1

  store_and_fwd_flag  dropoff_longitude  dropoff_latitude  payment_type  \
0                  N         -73.974785         40.750618             1
1                  N         -73.994415         40.759109             1
2                  N         -73.951820         40.824413             2
3                  N         -74.004326         40.719986             2
4                  N         -74.004181         40.742653             2

   fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0         12.0    1.0      0.5        3.25           0.0
1         14.5    0.5      0.5        2.00           0.0
2          9.5    0.5      0.5        0.00           0.0
3          3.5    0.5      0.5        0.00           0.0
4         15.0    0.5      0.5        0.00           0.0

   improvement_surcharge  total_amount
0                    0.3         17.05
1                    0.3         17.80
2                    0.3         10.80
3                    0.3          4.80
4                    0.3         16.30
```

```
In [0]: # 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_l
        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.h

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

        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_o
map_osm
```

Out[0]: <folium.folium.Map at 0x7f9edfc392b0>

0.1.2 3. Trip Durations:

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

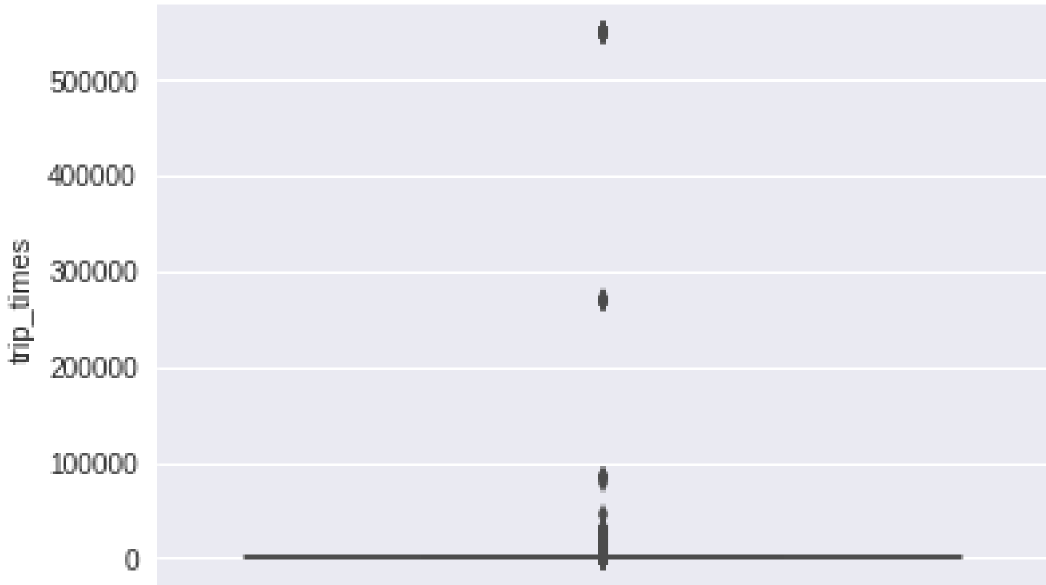
In [0]:
```
#The timestamps are converted to unix so as to get duration(trip-time) & speed also pi

# 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'].va
    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_la

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

In [0]:
```
frame_with_durations.head(5)
```

Out[0]:
```
   passenger_count  trip_distance  pickup_longitude  pickup_latitude  \
0                1           1.59        -73.993896        40.750111
1                1           3.30        -74.001648        40.724243
2                1           1.80        -73.963341        40.802788
3                1           0.50        -74.009087        40.713818
4                1           3.00        -73.971176        40.762428

   dropoff_longitude  dropoff_latitude  total_amount  trip_times  \
0         -73.974785         40.750618         17.05   18.050000
1         -73.994415         40.759109         17.80   19.833333
2         -73.951820         40.824413         10.80   10.050000
3         -74.004326         40.719986          4.80    1.866667
4         -74.004181         40.742653         16.30   19.316667

   pickup_times      Speed
0  1.421349e+09   5.285319
1  1.420922e+09   9.983193
2  1.420922e+09  10.746269
3  1.420922e+09  16.071429
4  1.420922e+09   9.318378
```

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




```
In [0]: #calculating 0-100th percentile to find a the correct percentile value for removal of 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 [0]: import matplotlib.pyplot as plt
        %matplotlib inline
        #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
```

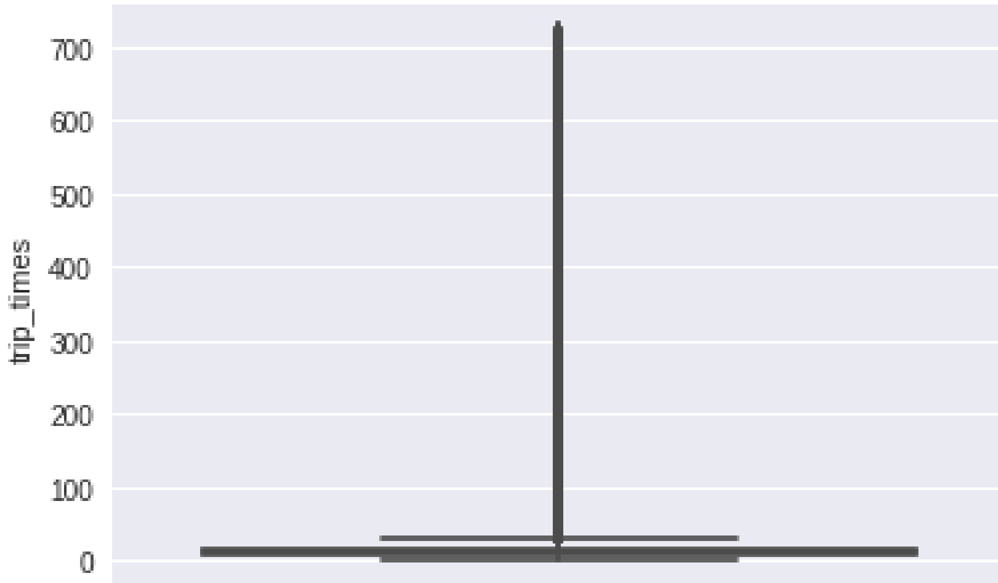
In [0]:
```
#removing data based on our analysis and TLC regulations
frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_times>1)
```

1 after removing the outliers of trip times we got the dataframe frame_with_durations_modified

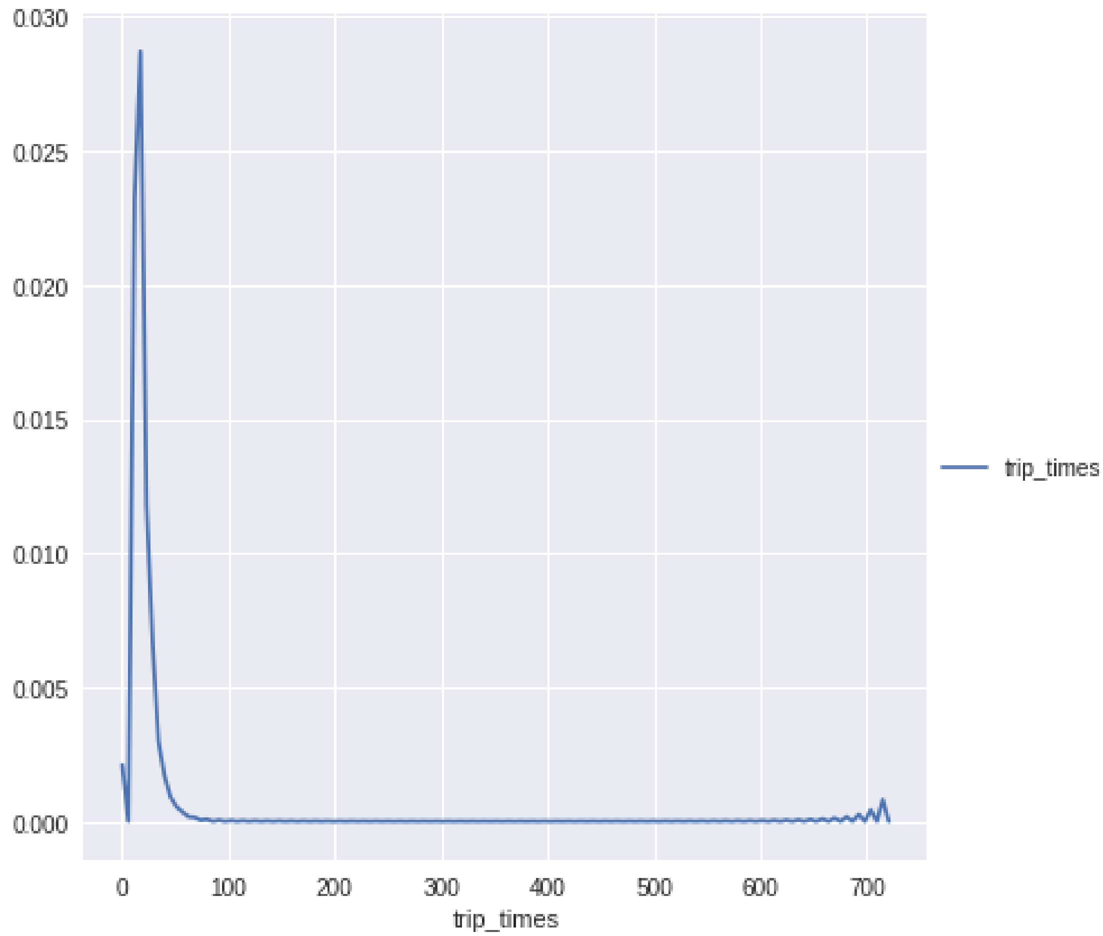
In [0]:
```
frame_with_durations_modified.head(5)
```

Out[0]:
```
   passenger_count  trip_distance  pickup_longitude  pickup_latitude  \
0                1           1.59        -73.993896        40.750111
1                1           3.30        -74.001648        40.724243
2                1           1.80        -73.963341        40.802788
3                1           0.50        -74.009087        40.713818
4                1           3.00        -73.971176        40.762428

   dropoff_longitude  dropoff_latitude  total_amount  trip_times  \
0         -73.974785         40.750618         17.05   18.050000
1         -73.994415         40.759109         17.80   19.833333
2         -73.951820         40.824413         10.80   10.050000
3         -74.004326         40.719986          4.80    1.866667
4         -74.004181         40.742653         16.30   19.316667

   pickup_times      Speed
0  1.421349e+09   5.285319
1  1.420922e+09   9.983193
2  1.420922e+09  10.746269
3  1.420922e+09  16.071429
4  1.420922e+09   9.318378
```

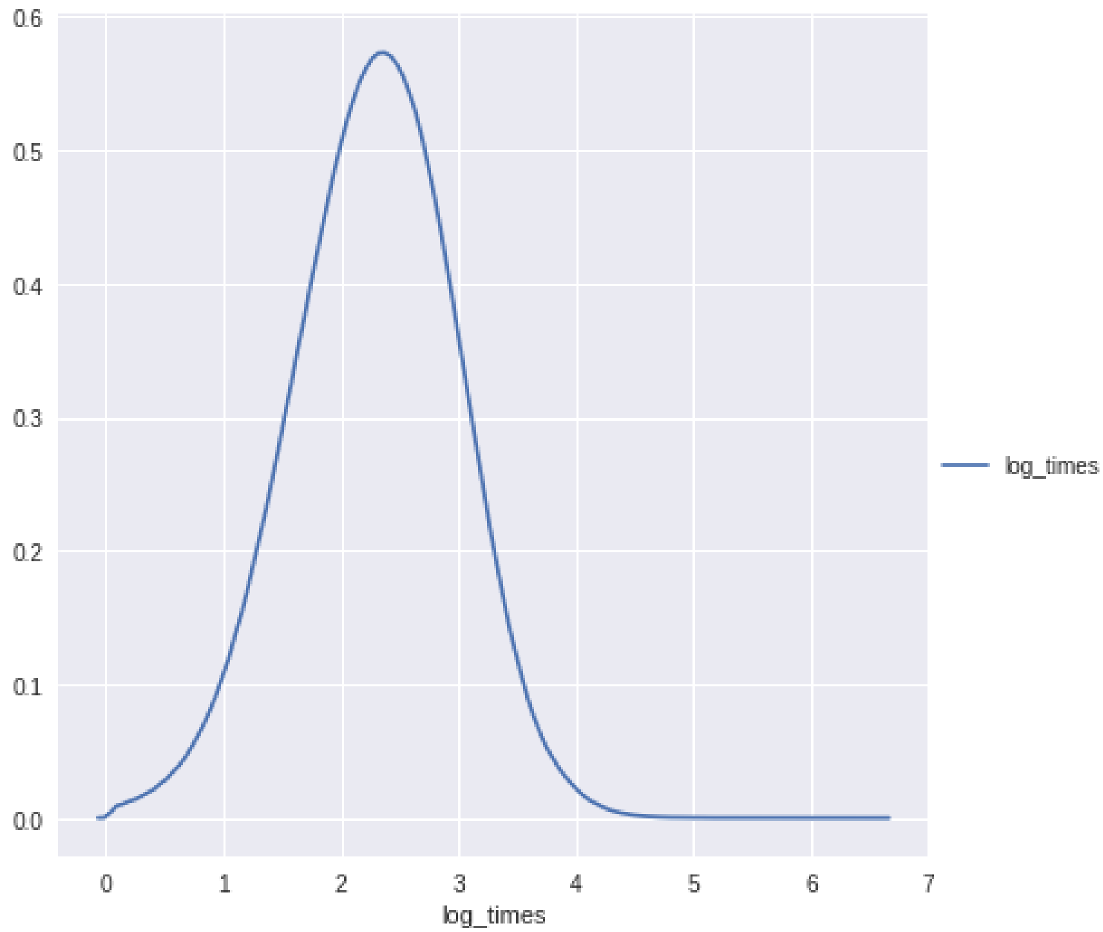
In [0]:
```
#box-plot after removal of outliers
sns.boxplot(y="trip_times", data =frame_with_durations_modified)
plt.show()
```



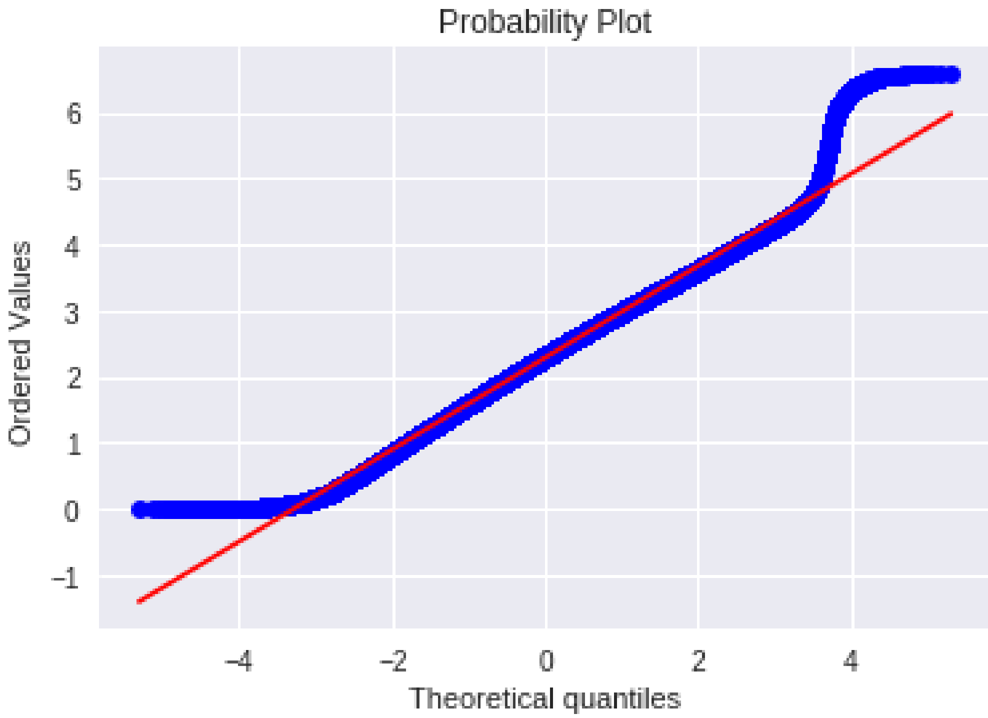
In [0]:
```
#pdf of trip-times after removing the outliers
sns.FacetGrid(frame_with_durations_modified,size=6) \
      .map(sns.kdeplot,"trip_times") \
      .add_legend();
plt.show();
```




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

In [0]: #pdf of log-values
        sns.FacetGrid(frame_with_durations_modified,size=6) \
              .map(sns.kdeplot,"log_times") \
              .add_legend();
        plt.show();
```




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



1.0.1 4. Speed

```
In [0]: # 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>


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

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

```
In [0]: #avg.speed of cabs in New-York
        sum(frame_with_durations_modified["Speed"]) / float(len(frame_with_durations_modified[
```

```
Out[0]: 12.450173996027528
```

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

1.0.2 4. Trip Distance

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

```
In [0]: #calculating trip distance values at each 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 [0]: #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 [0]: #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])
```

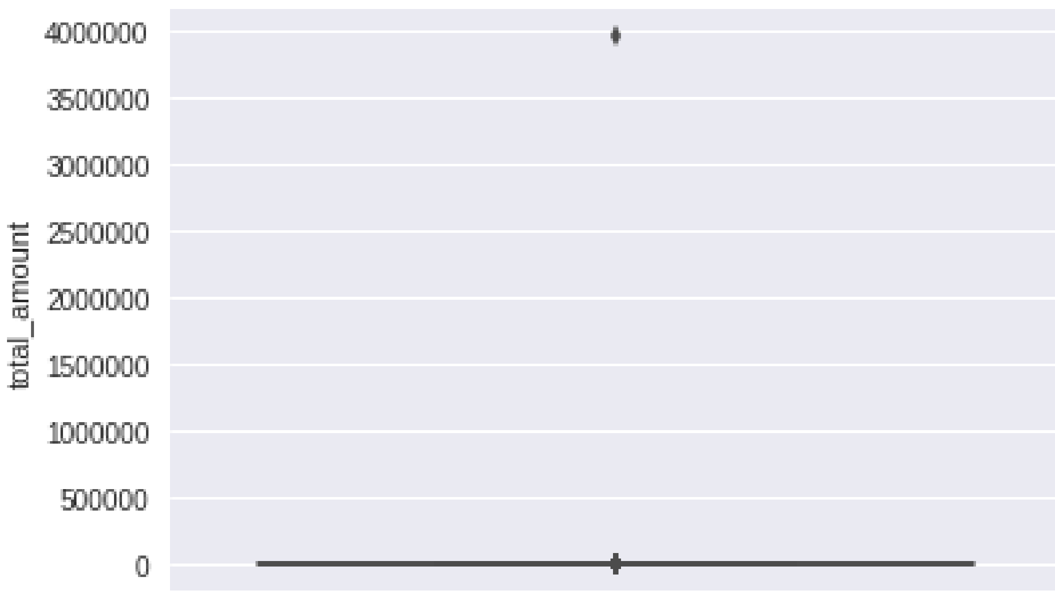
```
99.0 percentile value is 18.17
99.1 percentile value is 18.37
99.2 percentile value is 18.6
99.3 percentile value is 18.83
99.4 percentile value is 19.13
99.5 percentile value is 19.5
99.6 percentile value is 19.96
99.7 percentile value is 20.5
99.8 percentile value is 21.22
99.9 percentile value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

```
In [0]: #removing further outliers based on the 99.9th percentile value
        frame_with_durations_modified=frame_with_durations[(frame_with_durations.trip_distance
```

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

1.0.3 5. Total Fare

```
In [0]: # up to now we have removed the outliers based on trip durations, cab speeds, and trip
        # 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()
```




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

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

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

```
90 percentile value is 25.8
91 percentile value is 27.3
```

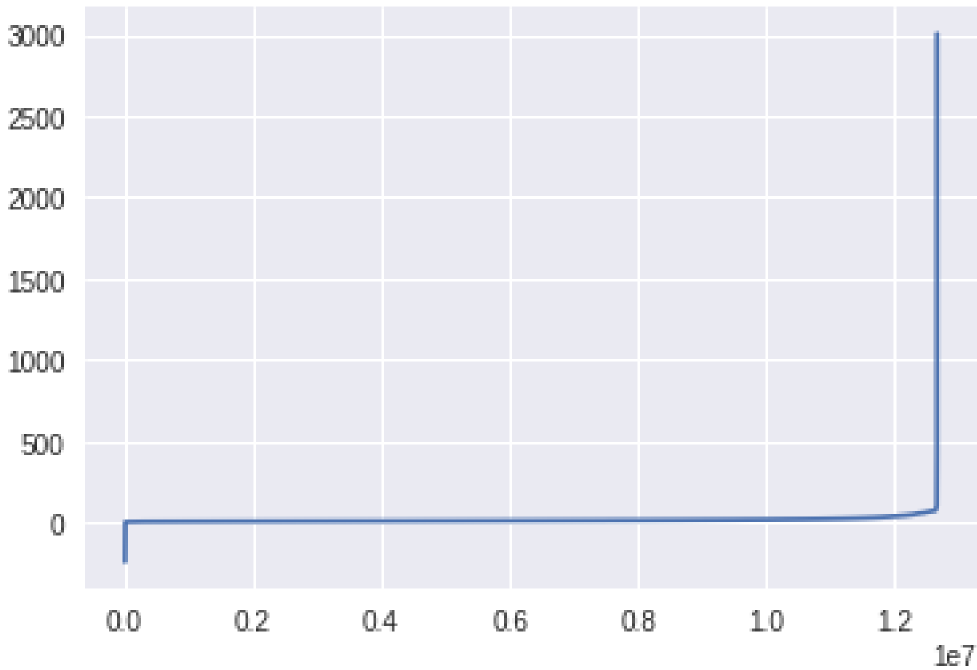
```
92 percentile value is 29.3
93 percentile value is 31.8
94 percentile value is 34.8
95 percentile value is 38.53
96 percentile value is 42.6
97 percentile value is 48.13
98 percentile value is 58.13
99 percentile value is 66.13
100 percentile value is  3950611.6
```

```
In [0]: #calculating total fare amount values at each percntile 99.0,99.1,99.2,99.3,99.4,99.5,
        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])
```

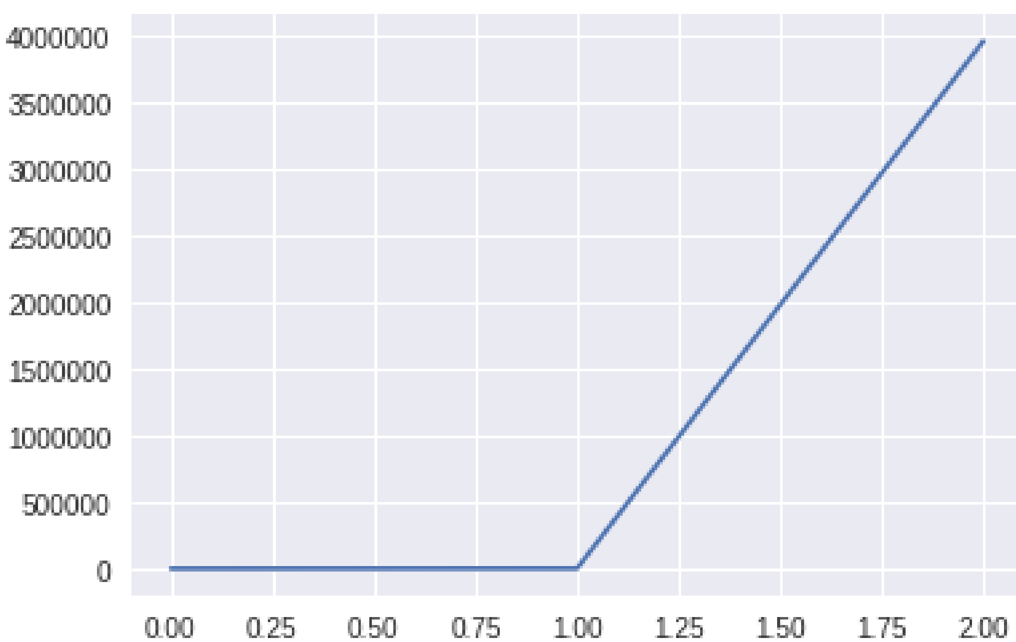
```
99.0 percentile value is 66.13
99.1 percentile value is 68.13
99.2 percentile value is 69.6
99.3 percentile value is 69.6
99.4 percentile value is 69.73
99.5 percentile value is 69.75
99.6 percentile value is 69.76
99.7 percentile value is 72.58
99.8 percentile value is 75.35
99.9 percentile value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

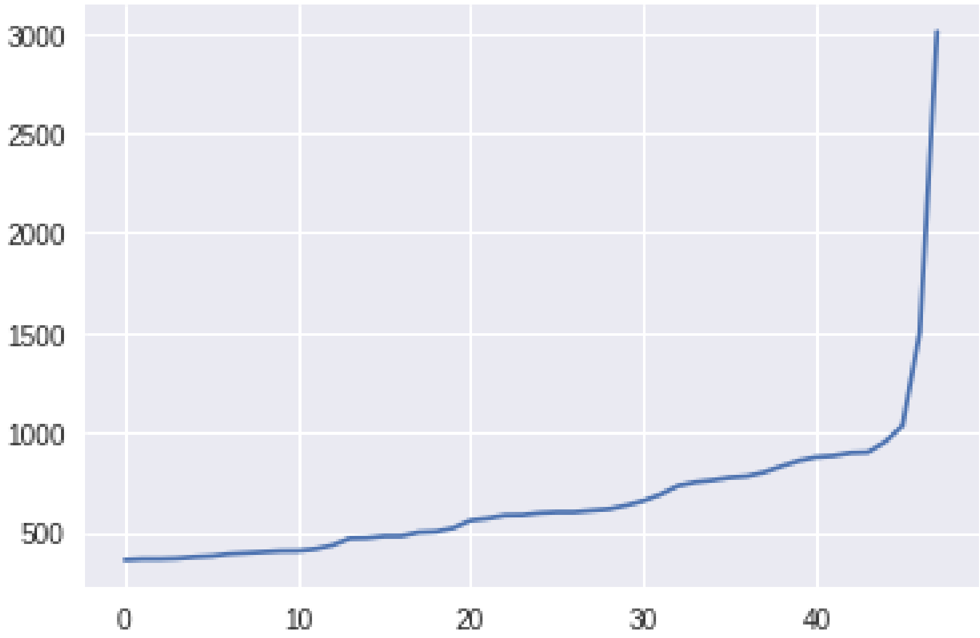
```
In [0]: #below plot shows us the fare values(sorted) to find a sharp increase to remove those
        # plot the fare amount excluding last two values in sorted data
        plt.plot(var[:-2])
        plt.show()
```




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



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



1.1 Remove all outliers/erronous points.

In [0]:
```
#removing all outliers based on our univariate analysis above
def remove_outliers(new_frame):


    a = new_frame.shape[0]
    print ("Number of pickup records = ",a)
    temp_frame = new_frame[((new_frame.dropoff_longitude >= -74.15) & (new_frame.dropo
                       (new_frame.dropoff_latitude >= 40.5774) & (new_frame.dropoff_la
                       ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_lat
                       (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_la
    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_la
                                   ((new_frame.pickup_longitude >= -74.15) & (new_frame.pickup_lat
                                   (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_la

            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 [0]: 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 0.9703576425607495
```

2 finally we have extractes the features after removing the outliers of jan 2015 dataframe

- now we assign cluster for each data point based on its location of latitude and longtitude
- we add pickup bin to the each data point based on the pickup time of that particular point claibrated to 10 min time interval
- we will consider 2 mile for making the clusters
- we will consider 10 min interval for bin
- using all these features we our class label gonna be the number of pickups

3 Data-preperation

3.1 Clustering/Segmentation

In [0]:
```
#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 wit

def find_clusters(increment):
    kmeans = MiniBatchKMeans(n_clusters=increment, batch_size=10000,random_state=42).f
    frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_wit
    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 regio
#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
---
```

```
In [0]: # 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_du
```

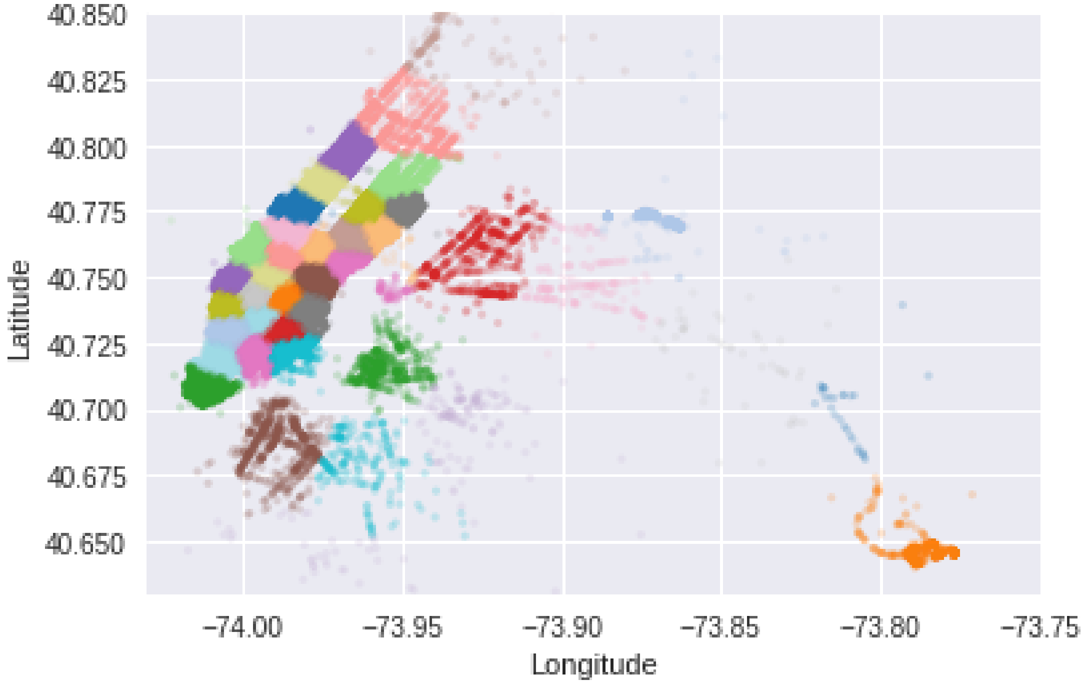
3.1.1 Plotting the cluster centers:

```
In [0]: # 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(clus
        map_osm
```

```
Out[0]: <folium.folium.Map at 0x7f9edd613898>
```

3.1.2 Plotting the clusters:

```
In [0]: #Visualising the clusters on a map
        def plot_clusters(frame):
            city_long_border = (-74.03, -73.75)
            city_lat_border = (40.63, 40.85)
            fig, ax = plt.subplots(ncols=1, nrows=1)
            ax.scatter(frame.pickup_longitude.values[:100000], frame.pickup_latitude.values[:1
                       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)
```



3.2 Time-binning

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

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

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

    start_pickup_unix=unix_times[year-2015][month-1]
    # https://www.timeanddate.com/time/zones/est
```

```
    # (int((i-start_pickup_unix)/600)+33) : our unix time is in gmt to we are converti
    tenminutewise_binned_unix_pickup_times=[(int((i-start_pickup_unix)/600)+33) for i i
    frame['pickup_bins'] = np.array(tenminutewise_binned_unix_pickup_times)
    return frame
```

In [0]:
```
# clustering, making pickup bins and grouping by pickup cluster and pickup bins
frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_du
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']].gr
```

- finally we draw the various features from the 2015 year january datframe

In [0]:
```
# 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(5)
```

Out[0]:
```
   passenger_count  trip_distance  pickup_longitude  pickup_latitude  \
0                1           1.59        -73.993896        40.750111
1                1           3.30        -74.001648        40.724243
2                1           1.80        -73.963341        40.802788
3                1           0.50        -74.009087        40.713818
4                1           3.00        -73.971176        40.762428

   dropoff_longitude  dropoff_latitude  total_amount  trip_times  \
0         -73.974785         40.750618         17.05   18.050000
1         -73.994415         40.759109         17.80   19.833333
2         -73.951820         40.824413         10.80   10.050000
3         -74.004326         40.719986          4.80    1.866667
4         -74.004181         40.742653         16.30   19.316667

   pickup_times      Speed  pickup_cluster  pickup_bins
0  1.421349e+09   5.285319              34         2163
1  1.420922e+09   9.983193               2         1452
2  1.420922e+09  10.746269              16         1452
3  1.420922e+09  16.071429              38         1452
4  1.420922e+09   9.318378              22         1452
```

In [0]:
```
jan_2015_groupby
```

Out[0]:
```
                            trip_distance
pickup_cluster pickup_bins
0              33                     104
               34                     200
               35                     208
               36                     141
               37                     155
               38                     139
               39                     181
               40                     166
```

	41	167
	42	160
	43	154
	44	167
	45	118
	46	137
	47	134
	48	145
	49	150
	50	136
	51	94
	52	108
	53	89
	54	78
	55	73
	56	54
	57	54
	58	47
	59	35
	60	27
	61	32
	62	25
...		...
39	4467	191
	4468	189
	4469	193
	4470	184
	4471	201
	4472	217
	4473	182
	4474	200
	4475	195
	4476	178
	4477	192
	4478	176
	4479	174
	4480	178
	4481	179
	4482	178
	4483	177
	4484	169
	4485	185
	4486	202
	4487	182
	4488	171
	4489	185
	4490	186
	4491	145

```
4492                     154
4493                     178
4494                     154
4495                     157
4496                     156

[170398 rows x 1 columns]
```

In [0]:
```
#number of features that we contrain in the january 2015 dataframe
jan_2015_frame.columns
```

Out[0]:
```
Index(['passenger_count', 'trip_distance', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'total_amount', 'trip_times', 'pickup_times', 'Speed', 'pickup_cluster',
       'pickup_bins'],
      dtype='object')
```

- now we take the data from the 2016 year january february and march data frames
- using the 2016 datas we extract he features after performing the methods of feature extraction
- which involvec the removal of outliers
- we also perform the feature engineering methods to get the features like pickup cluster and pickup bins

In [0]:
```
# hear the trip_distance represents the number of pickups that are happend in that par
# 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[0]:
```
                             trip_distance
pickup_cluster pickup_bins
0              33                      104
               34                      200
               35                      208
               36                      141
               37                      155
```

4 we perform smoothing only on 2015 not on jan,feb,march of 2016 data which are out train and test data

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
```

```
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [0]:
```
link = 'https://drive.google.com/open?id=1zfDwQmNyZUzkVhRys5j09uVk9Fwyv3if' # The shar
```

In [0]:
```
fluff, id = link.split('=')
print (id) # Verify that you have everything after '='
```

```
1zfDwQmNyZUzkVhRys5j09uVk9Fwyv3if
```

In [0]:
```
downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('yellow_tripdata_2016-01.csv')
month_jan_2016 = dd.read_csv('yellow_tripdata_2016-01.csv')
```

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [0]:
```
link = 'https://drive.google.com/open?id=1bWdNt9F3ZakZ1-ZPzGUA7QCGzBS49yBL' # The shar
```

In [0]:
```
fluff, id = link.split('=')
print (id) # Verify that you have everything after '='
```

```
1bWdNt9F3ZakZ1-ZPzGUA7QCGzBS49yBL
```

In [0]:
```
downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('yellow_tripdata_2016-02.csv')
month_feb_2016 = dd.read_csv('yellow_tripdata_2016-02.csv')
```

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
In [0]: link = 'https://drive.google.com/open?id=12hFPRHhGAFZk8eF-WssicyX6OPUriSYR' # The shar
```

```
In [0]: fluff, id = link.split('=')
        print (id) # Verify that you have everything after '='
```

```
12hFPRHhGAFZk8eF-WssicyX6OPUriSYR
```

```
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('yellow_tripdata_2016-03.csv')
        month_mar_2016 = dd.read_csv('yellow_tripdata_2016-03.csv')
```

- for 2016 data we add the features and preprocess the few features
- we add pickup cluster and pickup bin
- what is the difference between pickup cluster and pickup bin
- picup cluster is the cluster from the which the pickup point is there after getting the cluster to each point based on the latitude and longtitude
- pickup bin is the time when the pickup is happening.

```
In [0]: # upto now we cleaned data and prepared data for the month 2015,
        from sklearn.cluster import KMeans
        # 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_wit
            #frame_with_durations_outliers_removed_2016['pickup_cluster'] = kmeans.predict(fra

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

            return final_updated_frame,final_groupby_frame
```

```
In [0]: jan_2016_frame,jan_2016_groupby = datapreparation(month_jan_2016,kmeans,1,2016)
```

```
In [0]: feb_2016_frame,feb_2016_groupby = datapreparation(month_feb_2016,kmeans,2,2016)
```

```
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..
```

```
In [0]: mar_2016_frame,mar_2016_groupby = datapreparation(month_mar_2016,kmeans,3,2016)
```

```
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..
```

4.1 Smoothing

5 actually for the january month of 2015, 4464 number of unique pickups should present but we are not having in each cluster

6 similarly in other clusters due to reason of all bins not presenting we will use the process of smoothing so that all the bins are present with average value

- so what we do is we take the cluster and find the number of missing pickup bins.
- we will fill the values with zeros.
- similarly we do this to january,febrauary and march dataframes of 2016 also.

- for the models the output class labels are the number of pickups

- we should calculate the number of pickups and set it as a class label for the data point

```
In [0]: # 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
        # 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
```

7 the above output clearly states that bins are missing so we compensate all the bins with the values.

```
In [0]: jan_2015_unique = return_unq_pickup_bins(jan_2015_frame)
```

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

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


        #march
        #since we are not taking march data due to computation limits
        #mar_2016_unique = return_unq_pickup_bins(mar_2016_frame)
```

```
In [0]: #feb
        feb_2016_unique = return_unq_pickup_bins(feb_2016_frame)
```

```
In [0]: mar_2016_unique = return_unq_pickup_bins(mar_2016_frame)
```

```
In [0]: # 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)
```

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)

8 we are doing two things

- fill missing with zero
- perform smoothing
- but what we are filling?
- number of pickups.
- we have number of pickups in trip_distance column after performing the groupby and count.
- we put all the 4464 bins (or else what ever the maximum number of bins in that particular month(4176 in case of february)) and the number of pickups in each bin.
- since each cluster doesnot have all the bins, if particular bin is present in the cluster put the value of number of pickups
- if the particular bin is not present in the cluster then number of pickups also not present so fill it with zero in case of 2015
- fill that based on the avewrage of previous values in case of 2016 data which i s called smoothing. **we will finally have cluster and every time bin in that particular cluster and pickup value of time bin of that particular cluster**

```
In [0]: # Fills a value of zero for every bin where no pickup data is present
        # the count_values: number pickps that are happened in each region for each 10min intr
        # 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 [0]: def fill_missing1(count_values,values):
            smoothed_regions=[]
```

```
        ind=0
        for r in range(0,40):
            smoothed_bins=[]
            for i in range(4176):
                if i in values[r]:
                    smoothed_bins.append(count_values[ind])
                    ind+=1
                else:
                    smoothed_bins.append(0)
            smoothed_regions.extend(smoothed_bins)
        return smoothed_regions
```

In [0]:
```
# Fills a value of zero for every bin where no pickup data is present
# the count_values: number 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 discu
# 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/re
                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 pic
            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 pi
                            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 mis
                        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/((r
                    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 m
                right_hand_limit=0
                for j in range(i,4464):
                    if  j not in values[r]:
                        continue
                    else:
                        right_hand_limit=j
                        break
                smoothed_value=count_values[ind]*1.0/((right_hand_limit-i)+1)*1.0
                for j in range(i,right_hand_limit+1):
                        smoothed_bins.append(math.ceil(smoothed_value))
                repeat=(right_hand_limit-i)
        ind+=1
    smoothed_regions.extend(smoothed_bins)
return smoothed_regions
```

In [0]:
```
#Filling Missing values of Jan-2015 with 0
# here in jan_2015_groupby dataframe the trip_distance represents the number of pickup
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 [0]:
```
jan_2016_smooth=fill_missing(jan_2016_groupby['trip_distance'].values,jan_2016_unique)
```

In [0]:
```
feb_2016_smooth=fill_missing1(feb_2016_groupby['trip_distance'].values,feb_2016_unique
```

In [0]:
```
mar_2016_smooth=fill_missing(mar_2016_groupby['trip_distance'].values,mar_2016_unique)
```

In [0]:
```
print(len(mar_2016_smooth))
print(len(feb_2016_smooth))
```

```
178560
167040
```

In [0]:
```
print(np.array(jan_2016_smooth).shape)
print(np.array(feb_2016_smooth).shape)
```

```
(178560,)
(178560,)
```

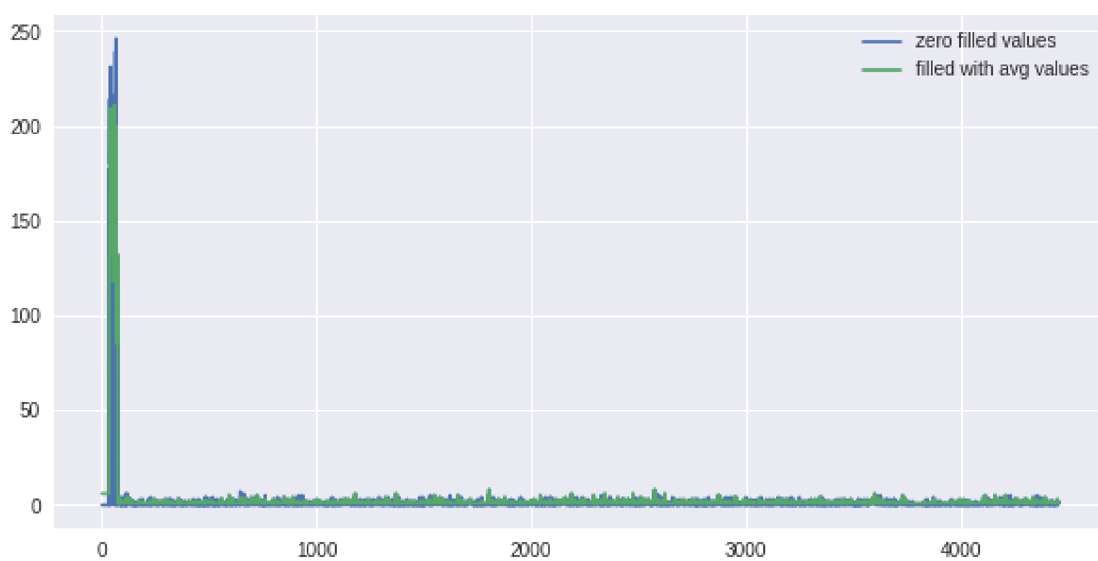
9 below cloumn shows the entire crux of story

- we 4464 ten minute time bins in each cluster (4176 in case of febraury)
- 4464 pickup values should present in each cluster.
- there are 40 clusters
- for every bin each cluster we calculated thh number of pickups which can be average value or zero or actual value

In [0]:
```
# 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 [0]:
```
# 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()
```



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

# Ans: consider we have data of some month in 2015 jan 1st, 10 _ _ _ 20, i.e there are
# 10st 10min intravel, 0 pickups happened in 2nd 10mins intravel, 0 pickups happened i
# 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
# that are happened in the first 40min are same in both cases, but if you can observe
# wheen you are using smoothing we are looking at the future number of pickups which m

# 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 [0]:
```
# Jan-2015 data is smoothed, Jan,Feb & March 2016 data missing values are filled with
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_uniqu
feb_2016_smooth = fill_missing(feb_2016_groupby['trip_distance'].values,feb_2016_uniqu

print(len(jan_2015_smooth))
print(len(jan_2016_smooth))
print(len(feb_2016_smooth))
```

```
178560
178560
178560
```

In [0]:
```
mar_2016_smooth = fill_missing(mar_2016_groupby['trip_distance'].values,mar_2016_uniqu
```

In [0]:
```
print(february_2016_smooth)
```

In [0]:
```
print(march_2016_smooth)
```

In [0]:
```
jan2015smoothingdata=pd.DataFrame(jan_2015_smooth)
jan2015smoothingdata.to_csv('jan2015smoothingdata.csv')
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
# This only needs to be done once in a notebook.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
```

```
drive = GoogleDrive(gauth)

# Create & upload a file.
uploaded = drive.CreateFile({'title': 'jan2015smoothingdata.csv'})
uploaded.SetContentFile('jan2015smoothingdata.csv')
uploaded.Upload()
print('Uploaded file with ID {}'.format(uploaded.get('id')))
```

In [0]:
```
jan2015smoothingdata=pd.DataFrame(feb_2016_smooth)
jan2015smoothingdata.to_csv('feb2016smoothingdataactual.csv')
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
# This only needs to be done once in a notebook.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

# Create & upload a file.
uploaded = drive.CreateFile({'title': 'feb2016smoothingdataactual.csv'})
uploaded.SetContentFile('feb2016smoothingdataactual.csv')
uploaded.Upload()
print('Uploaded file with ID {}'.format(uploaded.get('id')))
```

In [0]:
```
jan2015smoothingdata=pd.DataFrame(jan_2016_smooth)
jan2015smoothingdata.to_csv('jan2016smoothingdata.csv')
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
# This only needs to be done once in a notebook.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

# Create & upload a file.
uploaded = drive.CreateFile({'title': 'jan2016smoothingdata.csv'})
uploaded.SetContentFile('jan2016smoothingdata.csv')
uploaded.Upload()
print('Uploaded file with ID {}'.format(uploaded.get('id')))
```

```
In [0]: mar2016smoothingdata=pd.DataFrame(mar_2016_smooth)
        mar2016smoothingdata.to_csv('mar2016smoothingdata.csv')
        !pip install -U -q PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials

        # Authenticate and create the PyDrive client.
        # This only needs to be done once in a notebook.
        auth.authenticate_user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get_application_default()
        drive = GoogleDrive(gauth)

        # Create & upload a file.
        uploaded = drive.CreateFile({'title': 'mar2016smoothingdata.csv'})
        uploaded.SetContentFile('mar2016smoothingdata.csv')
        uploaded.Upload()
        print('Uploaded file with ID {}'.format(uploaded.get('id')))
```

due to limited computational power we ahve converted the data into csv file we can use these files to generate the train and test data january smoothing data sharable link https://drive.google.com/open?id=1L9gyWu4ppFSOnjdHOdiaUJzsW9KTMeIj february smoothing data sharable link https://drive.google.com/open?id=1IIxSzvekOzyWjpa7x8YbdkSTOlpHi2BA for march https://drive.google.com/open?id=1UudETdZQbfV5voowjk_28lY8Op4k6SFa we take the list of the datas

10 to overcome memory error these lists are stored in the form of csv files

- we can retrieve them back and perform feature engineering and modelise them.

```
In [0]: # Code to read csv file into Colaboratory:
        !pip install -U -q PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials
        # Authenticate and create the PyDrive client.

        auth.authenticate_user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get_application_default()
        drive = GoogleDrive(gauth)
```

```
In [0]: link = 'https://drive.google.com/open?id=1L9gyWu4ppFSOnjdHOdiaUJzsW9KTMeIj' # The shar
```

In [0]:
```
fluff, id = link.split('=')
print (id) # Verify that you have everything after '='
```

```
1L9gyWu4ppFSOnjdHOdiaUJzsW9KTMeIj
```

In [0]:
```
downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('jan2016smoothingdata.csv')
```

In [0]:
```
jan2016smooth=pd.read_csv('jan2016smoothingdata.csv',names=['a'])
```

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [0]:
```
link = 'https://drive.google.com/open?id=1IIxSzvekOzyWjpa7x8YbdkSTOlpHi2BA' # The shar
```

In [0]:
```
fluff, id = link.split('=')
print (id) # Verify that you have everything after '='
```

```
1IIxSzvekOzyWjpa7x8YbdkSTOlpHi2BA
```

In [0]:
```
downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('feb2016smoothingdataactual.csv')
```

In [0]:
```
feb2016smooth=pd.read_csv('feb2016smoothingdataactual.csv',names=['a'])
```

In [0]:
```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [0]:
```
link = 'https://drive.google.com/open?id=1UudETdZQbfV5voowjk_28lY8Op4k6SFa' # The shar
```

```
In [0]: fluff, id = link.split('=')
        print (id) # Verify that you have everything after '='
```

```
1UudETdZQbfV5voowjk_28lY8Op4k6SFa
```

```
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('mar2016smoothingdata.csv')
```

```
In [0]: march2016smooth=pd.read_csv('mar2016smoothingdata.csv',names=['a'])
```

```
In [0]: mar_2016_smooth=list(march2016smooth['a'])
        feb_2016_smooth=list(feb2016smooth['a'])
        jan_2016_smooth=list(jan2016smooth['a'])
```

11 we are appending 2016 january and february data into list of regions_cum serirs of bins forming 4464+4176+4464=13104

12 this means each regions_cum will contain each cluster with 13099 pickup values.

13 then for each cluster we divide the data into train and test data.and each cluster.

```
In [0]: print(jan_2016_smooth)
        print(feb_2016_smooth)
        print(mar_2016_smooth)
```

```
Output hidden; open in https://colab.research.google.com to view.
```

- these are the values of the total bins of total cluster.
- january and march consisting of data of (40*4464)
- february consisting of the data of 40*4176
- each cluster will consist of 4464 from the january data ,4464 from the march data and 4176 from the february data as pickupvalues in that particular bins.

```
In [0]: regionscumulative=[]
        for i in range(0,40):
          regionscumulative.append(jan_2016_smooth[4464*i:4464*(i+1)]+feb_2016_smooth[4176*i:4
        print(len(regionscumulative))
        print(len(regionscumulative[0]))
        print(4464+4176+4464)
```

```
40
13104
13104
```

14 As per the tasks of assignment

14.0.1 1. include frequency and amplitude features

14.0.2 2.perform the different hyperparameter tunuing for the different models.

14.0.3 3.perform with more time features .

```
In [0]: %matplotlib inline
        def uniqueish_color():
          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):
            print('for the cluster ',i)
            plt.figure(figsize=(10,4))
            plt.plot(first_x,regionscumulative[i][:4464], color=uniqueish_color(), label='2016
            plt.plot(second_x,regionscumulative[i][4464:8640], color=uniqueish_color(), label=
            plt.plot(third_x,regionscumulative[i][8640:13104], color=uniqueish_color(), label=
            plt.legend()
            plt.show()
```

```
Output hidden; open in https://colab.research.google.com to view.
```

we have seen the graph of the time bins vs the number of pickup values these timebin values will vary over 3 months.

This is a time series data in which we can see the sinusoidal behavior in the waves.

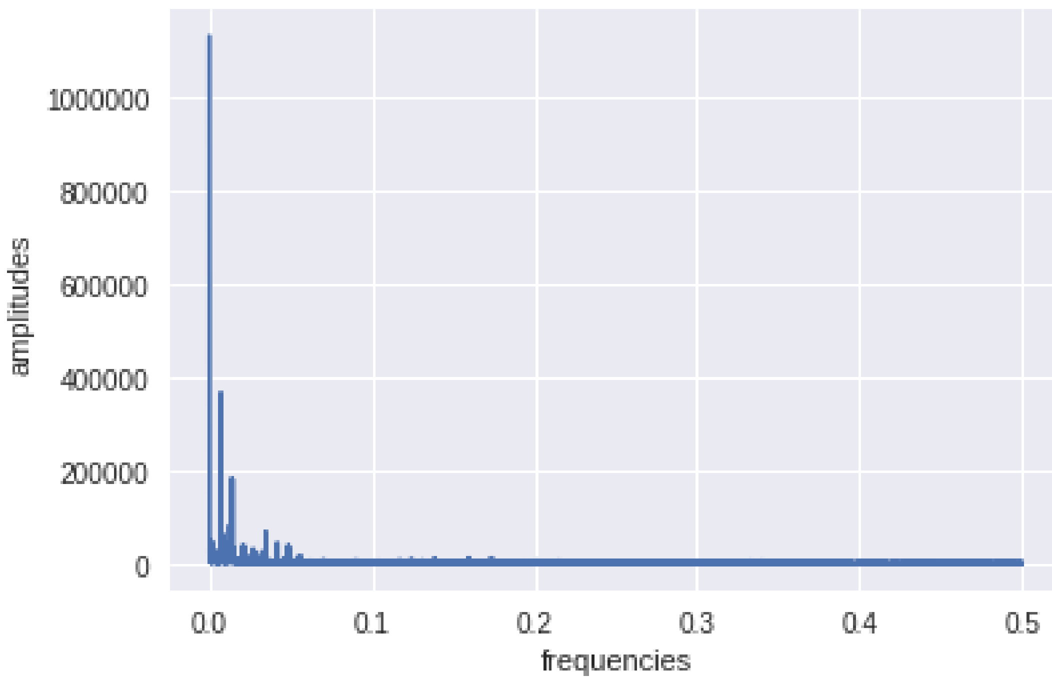
we gonna featurise this data by considering the previos pickup values.

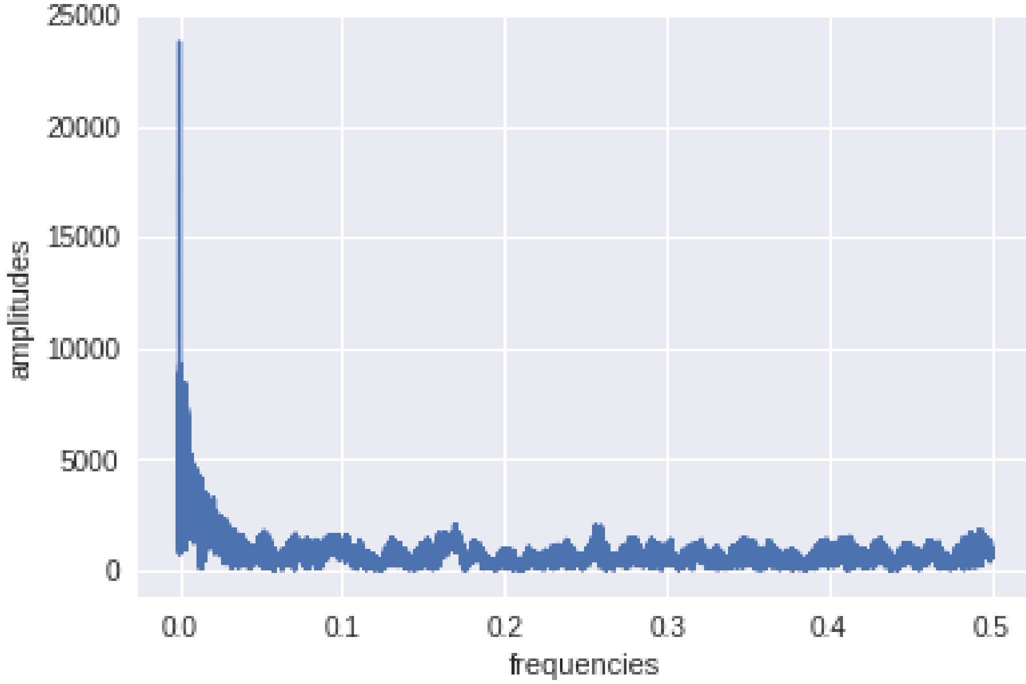
if we see the frequency behavior of the pickup vlaues of cluster

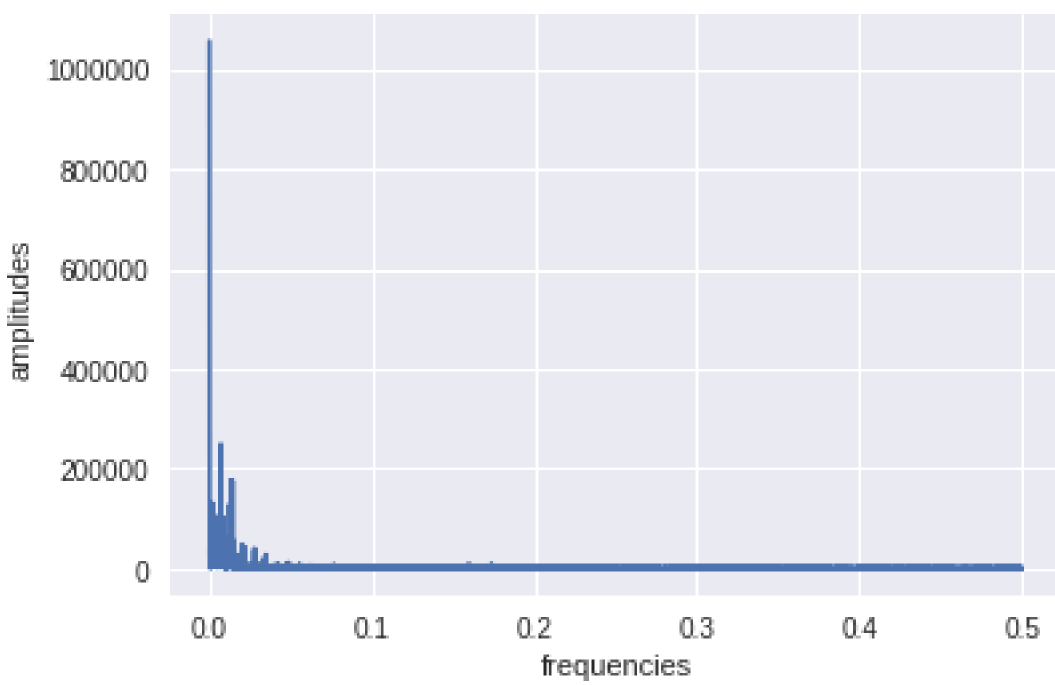
In using frequencies as the features we plot the frequencies vs the amplitudes where we plot the frequencies on x axis and amplitudes on y axis. where we take the time samples and convert them into frequencies.in ur case time samples are bins and the amplitudes are values present in the bins.

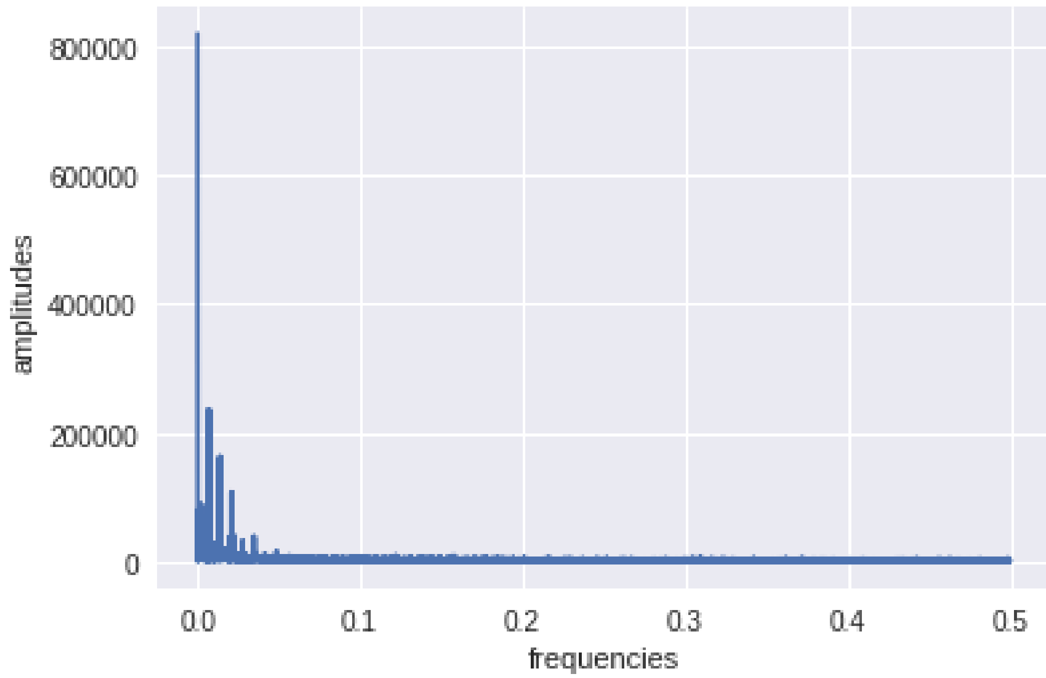
- we take the maximum frequencies and maximum samples form each cluster and apped as the features for that particualr cluster.
- to get the amplitudes amplitudes=numpy.fft.fft(binvalues)
- frequencies =numpy.fftfreq(number_of_bins,timeperiod)
- timeperiod is one in our case in which the differnce between two bins #### plotting the fft plot of every cluster

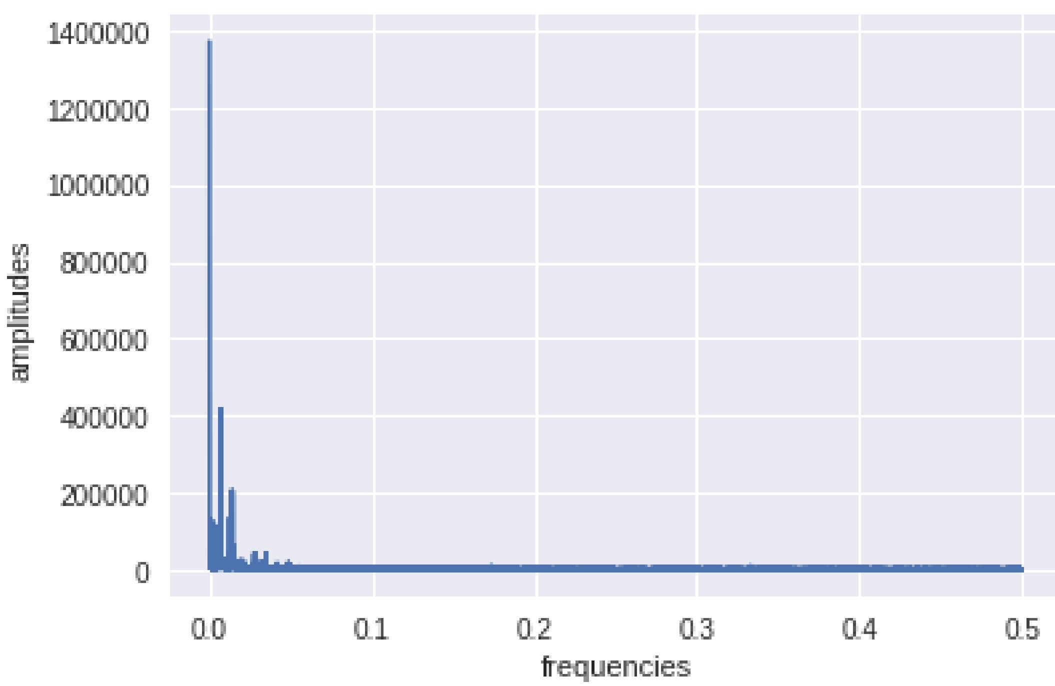
In [0]:
```
maximumamplitudes=[]
for i in range(0,40):
  amplitudes=np.abs(np.fft.fft(regionscumulative[i][0:13104]))
  frequencies=np.abs(np.fft.fftfreq(13104,1))
  plt.plot(frequencies,amplitudes)
  plt.xlabel('frequencies')
  plt.ylabel('amplitudes')
  plt.show()
```




25000
20000
15000
10000
5000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1400000
1200000
1000000
800000
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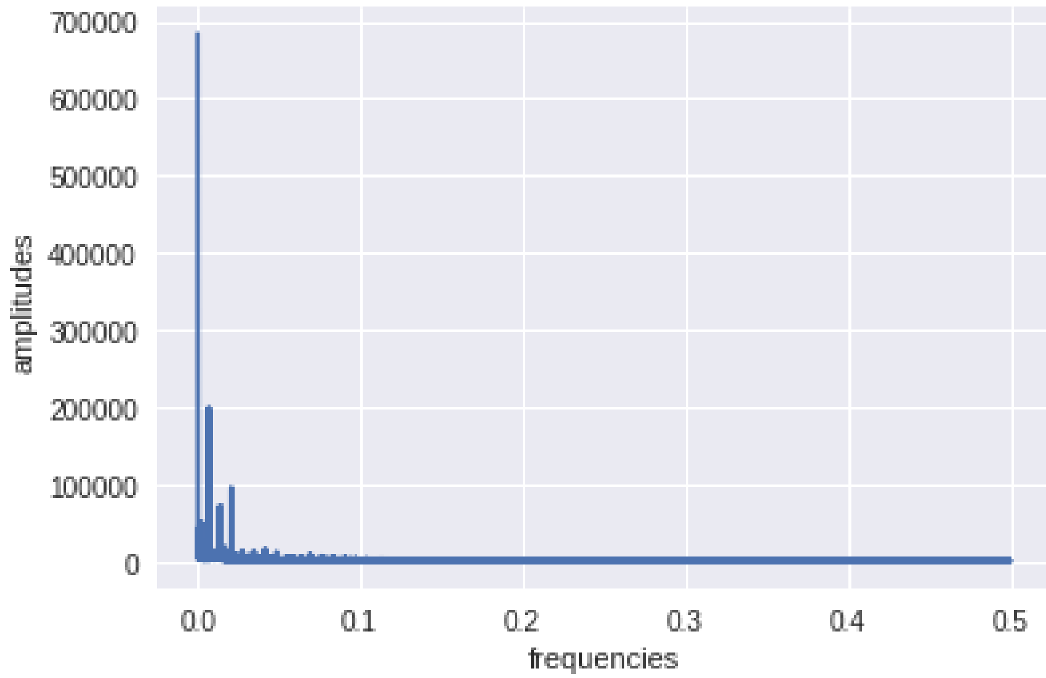
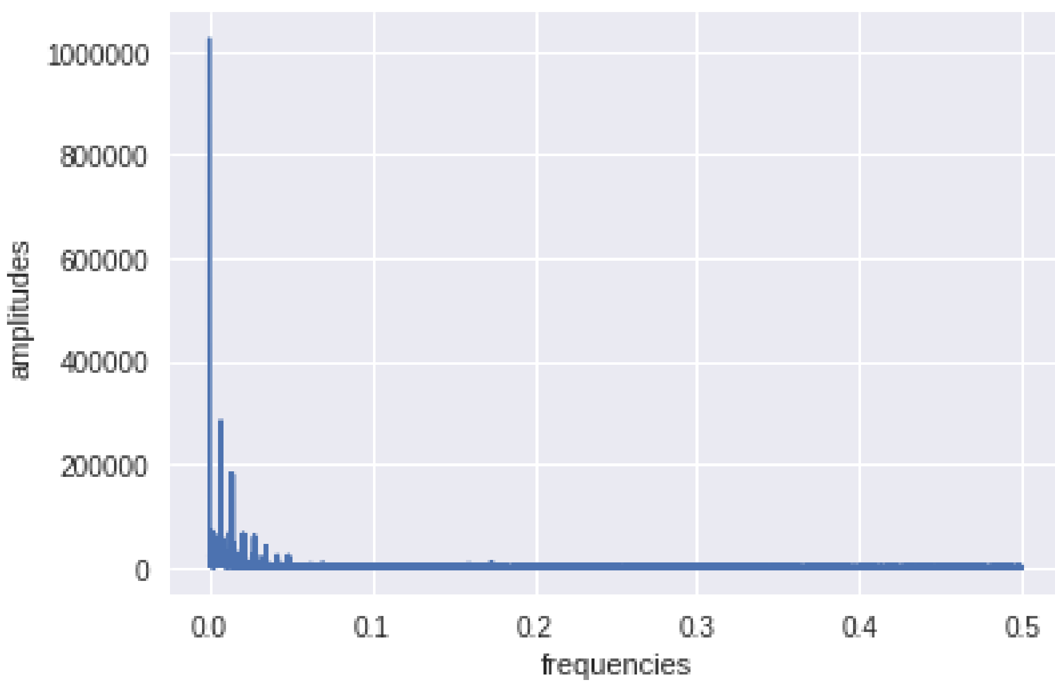
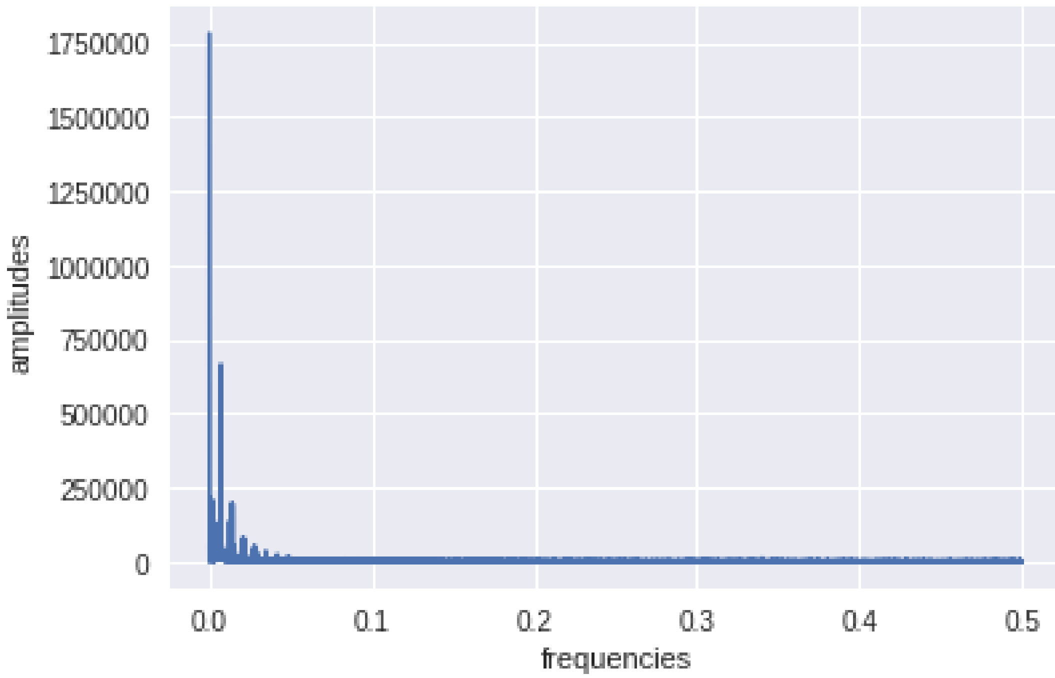
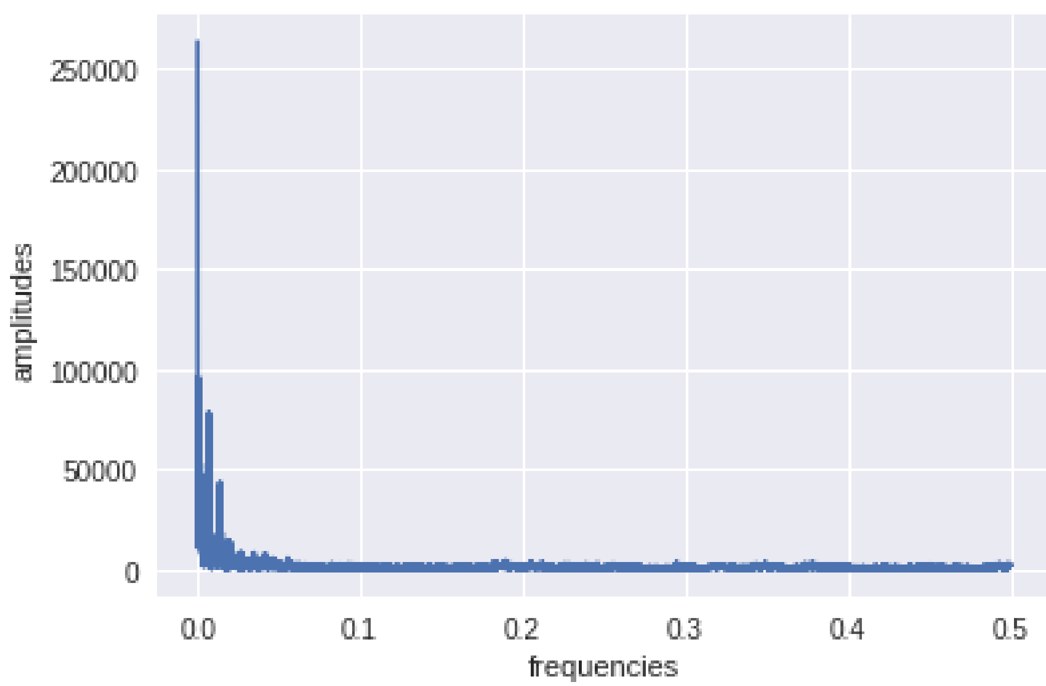
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


700000
600000
500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1750000
1500000
1250000
1000000
750000
500000
250000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


250000
200000
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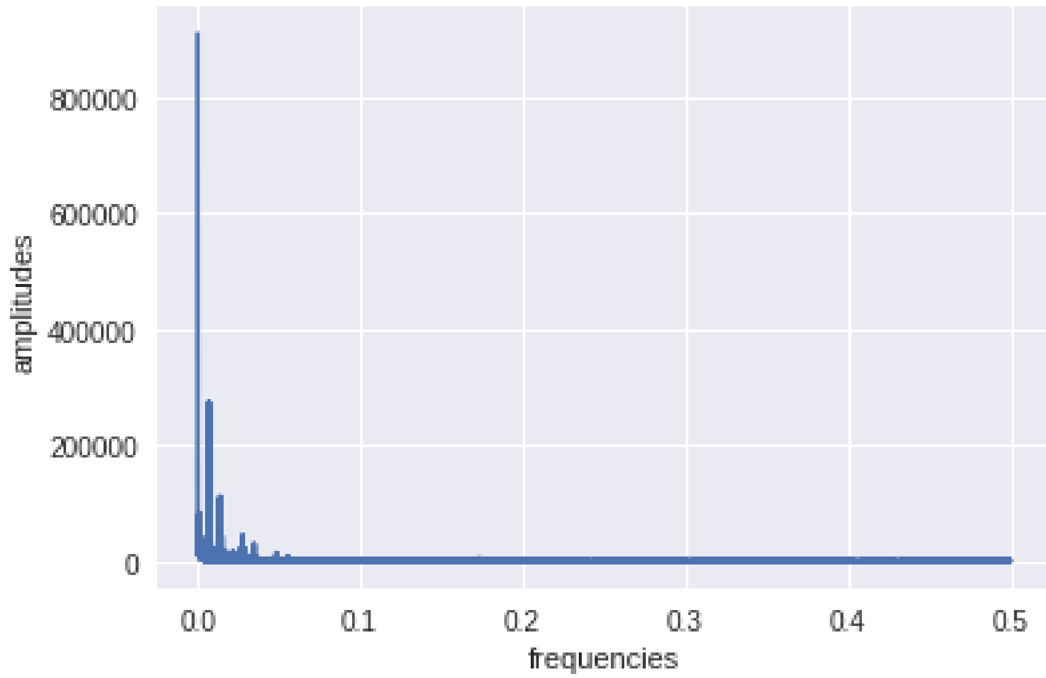
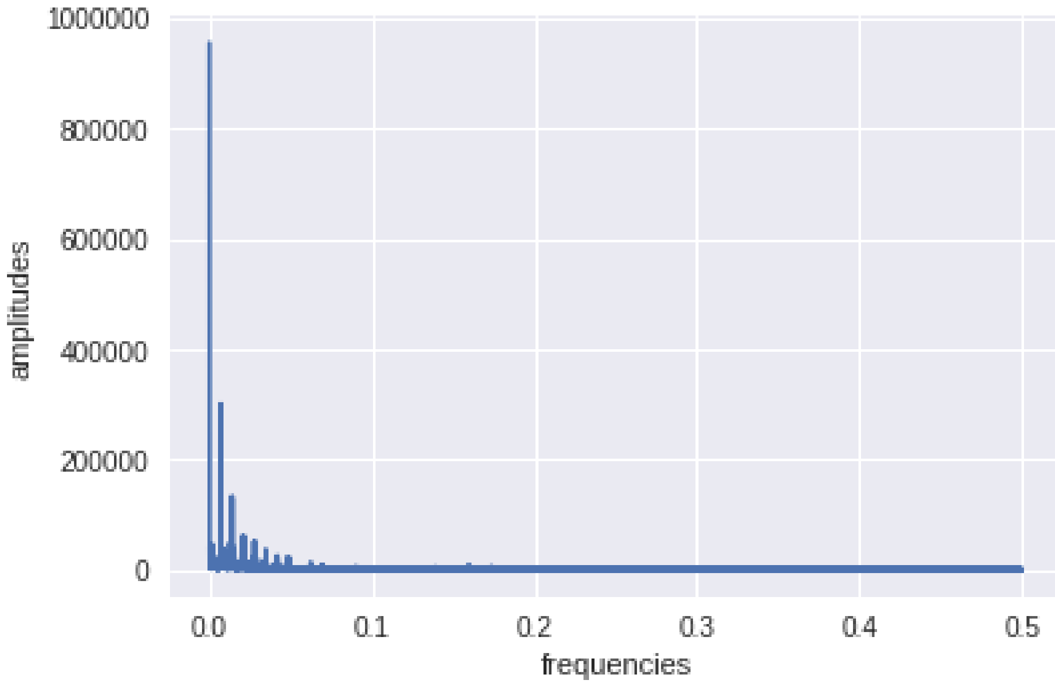
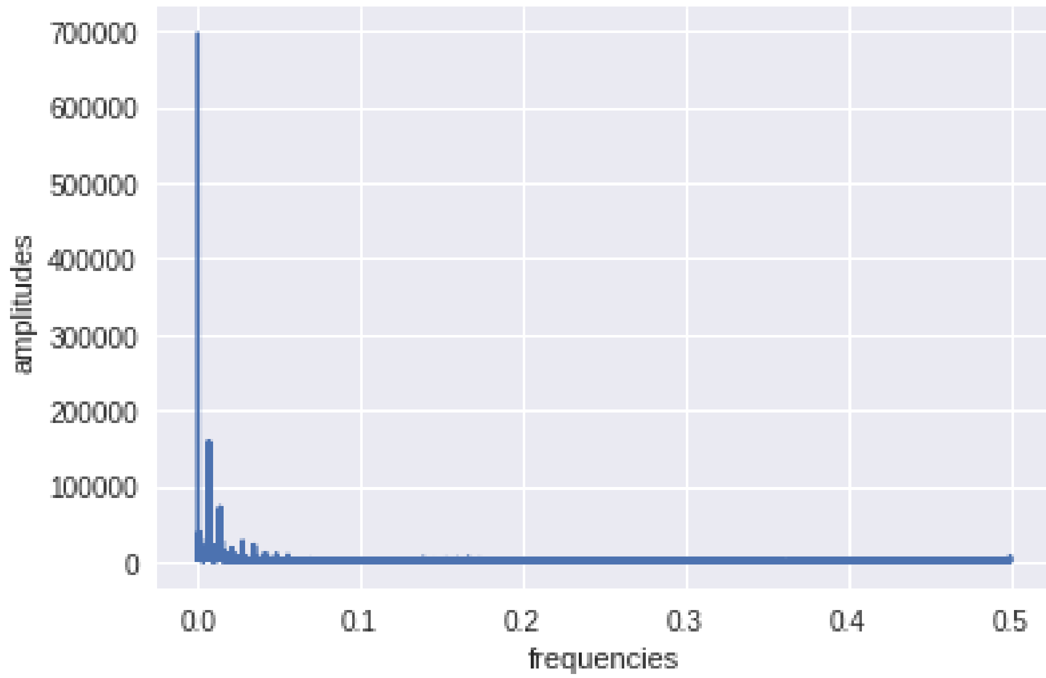
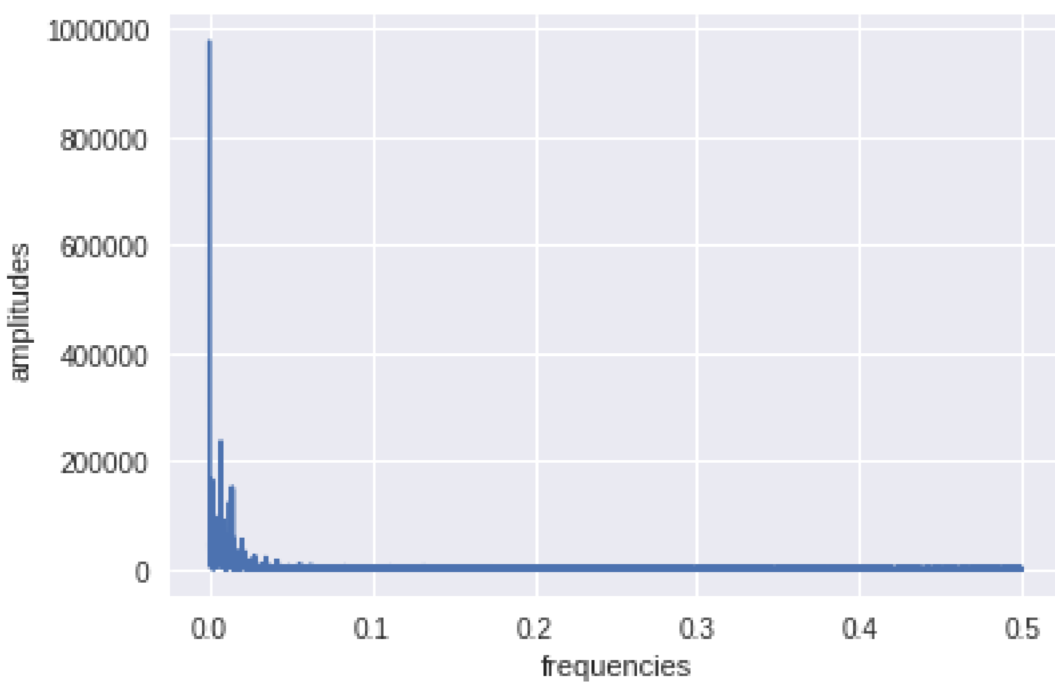
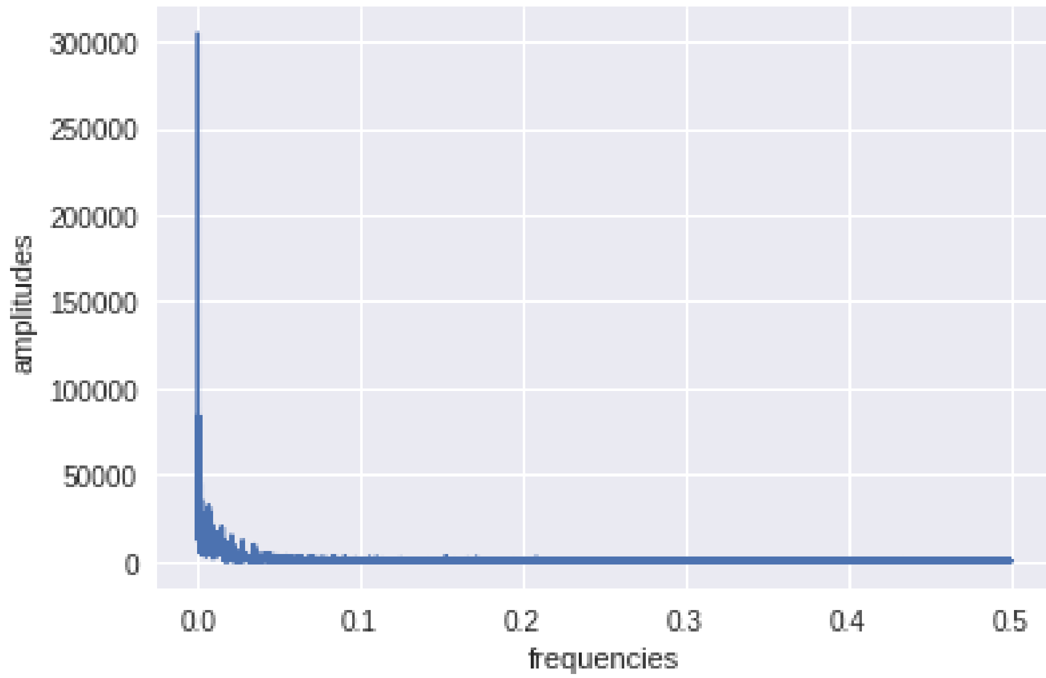
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

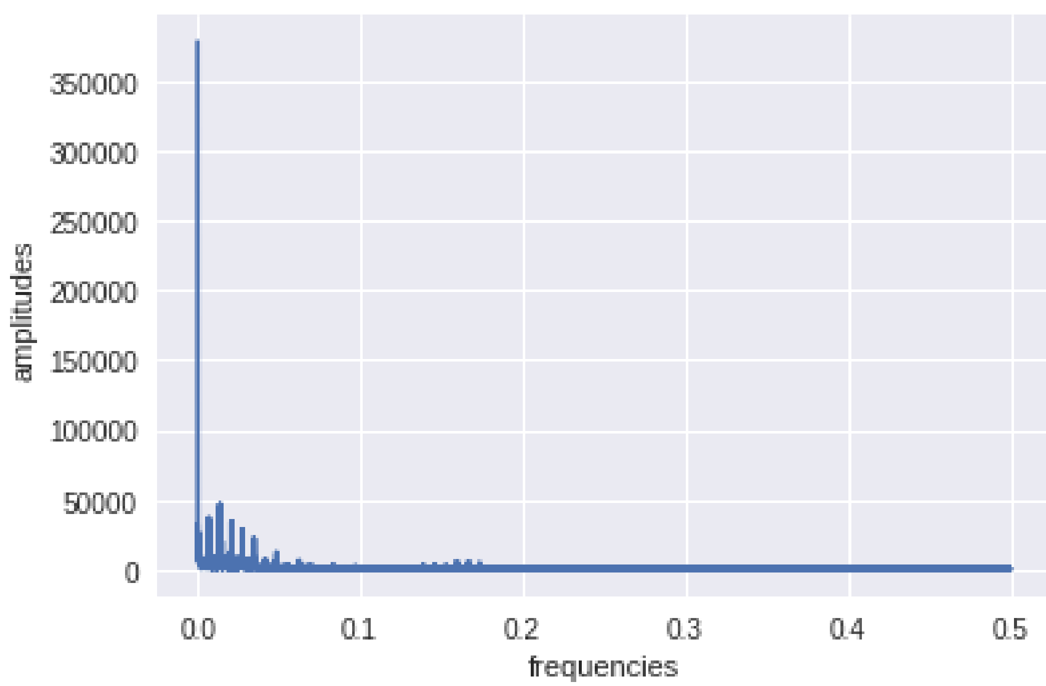

800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

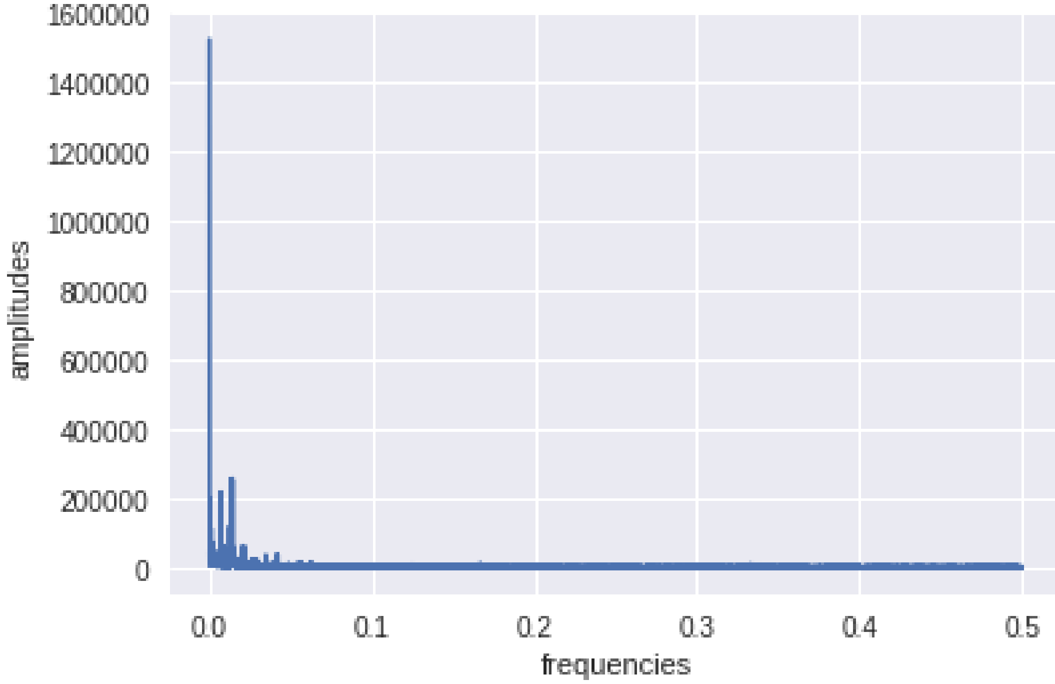

1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

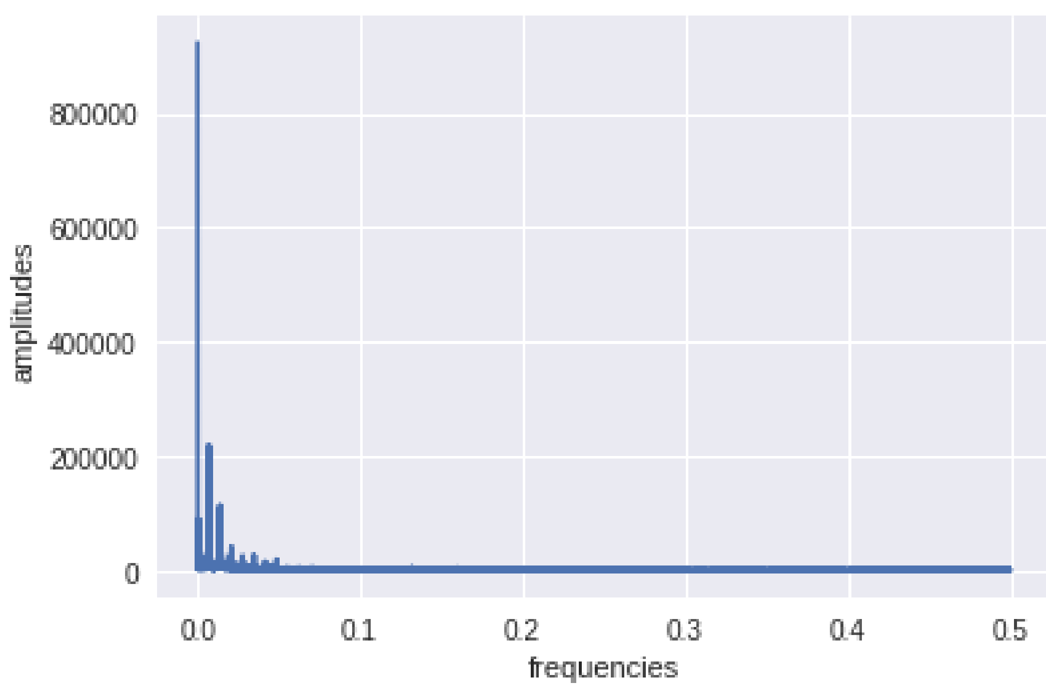

700000
600000
500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

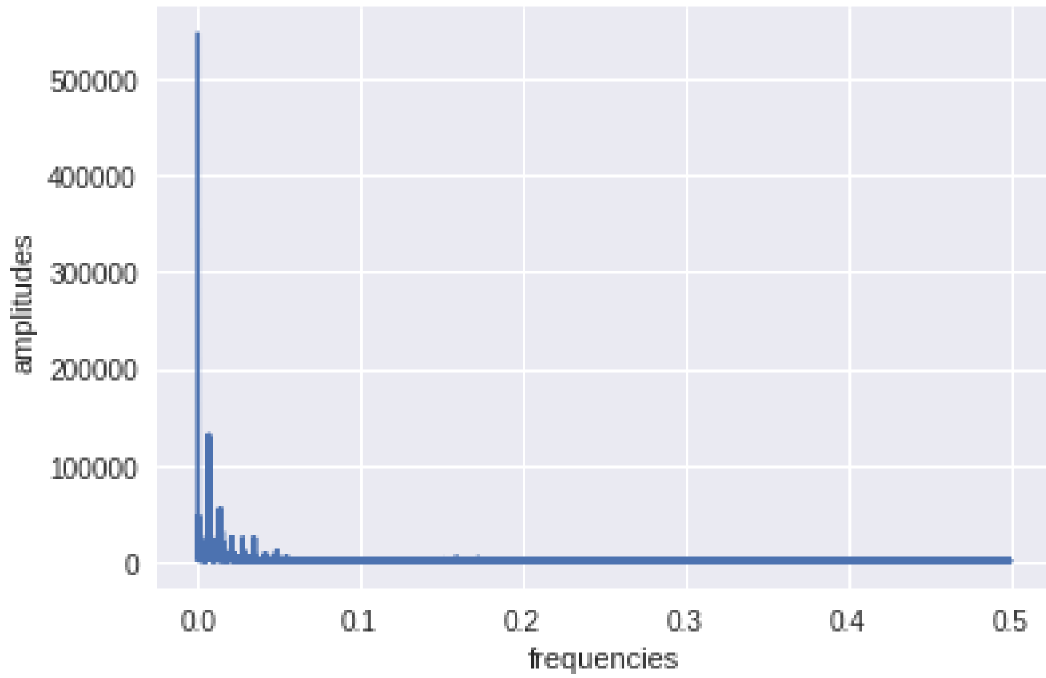

1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


300000
250000
200000
150000
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

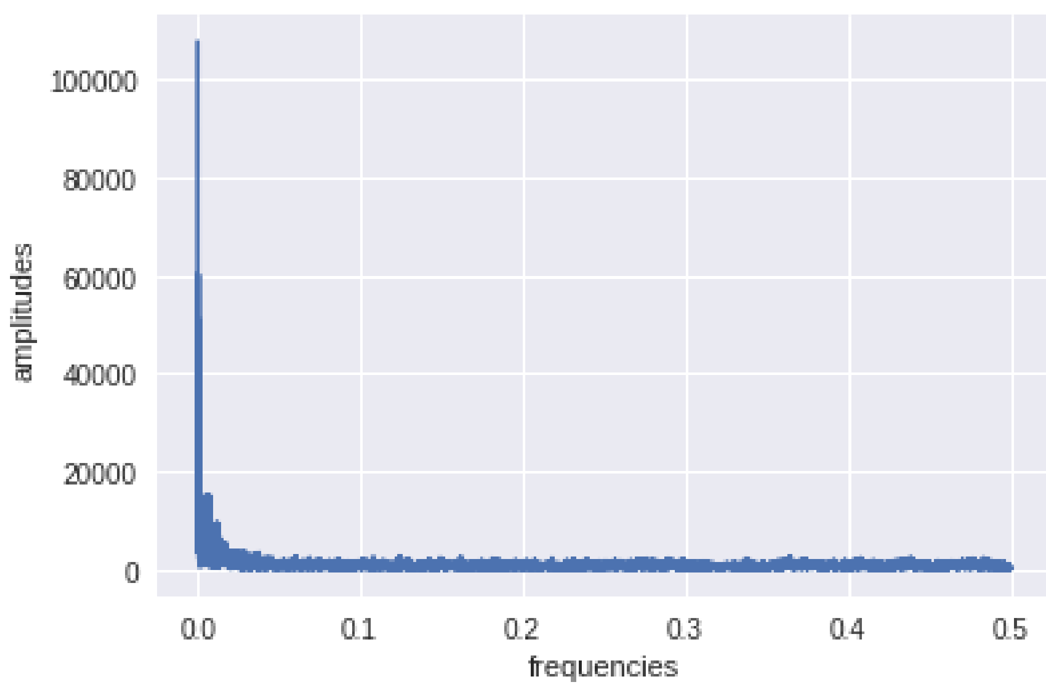

350000
300000
250000
200000
150000
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1600000
1400000
1200000
1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

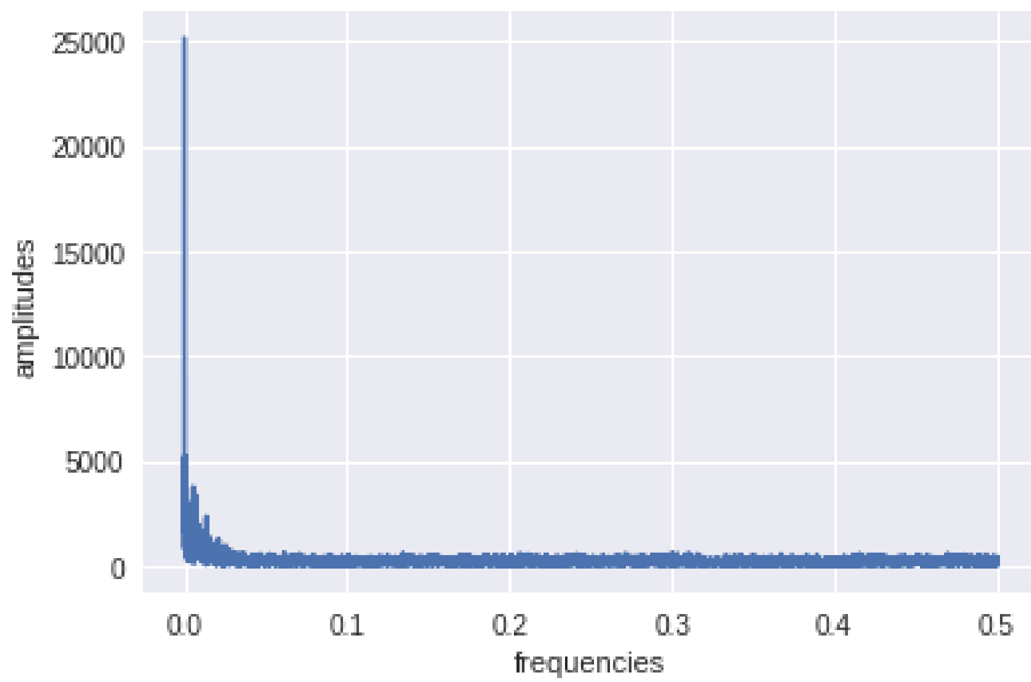

800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies

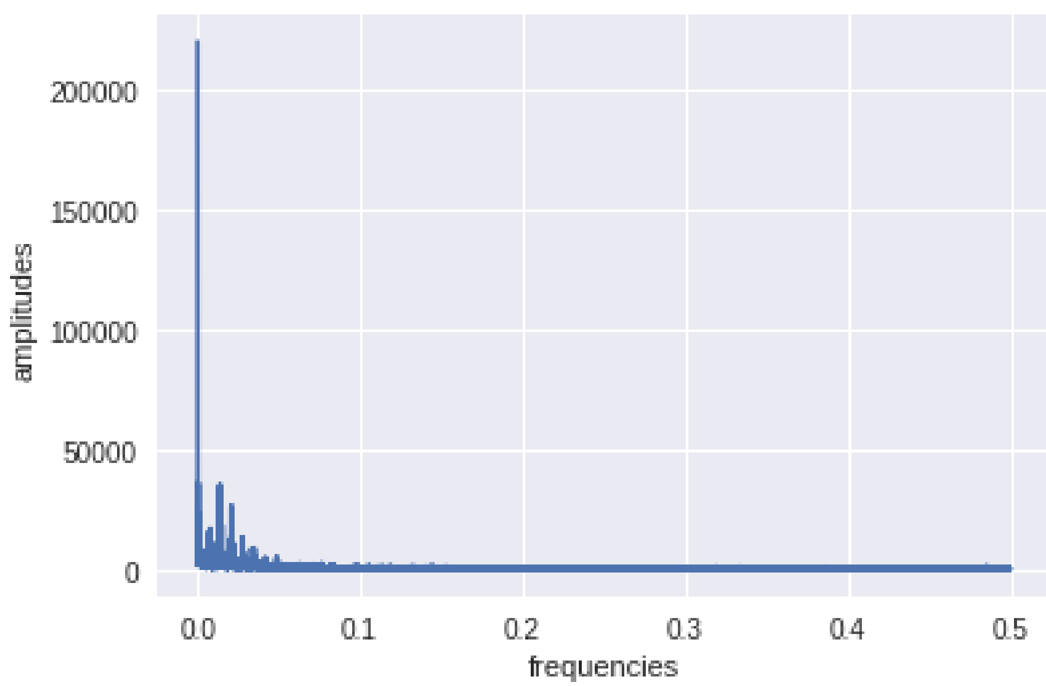


500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



100000
80000
60000
40000
20000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


25000
20000
15000
10000
5000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


200000
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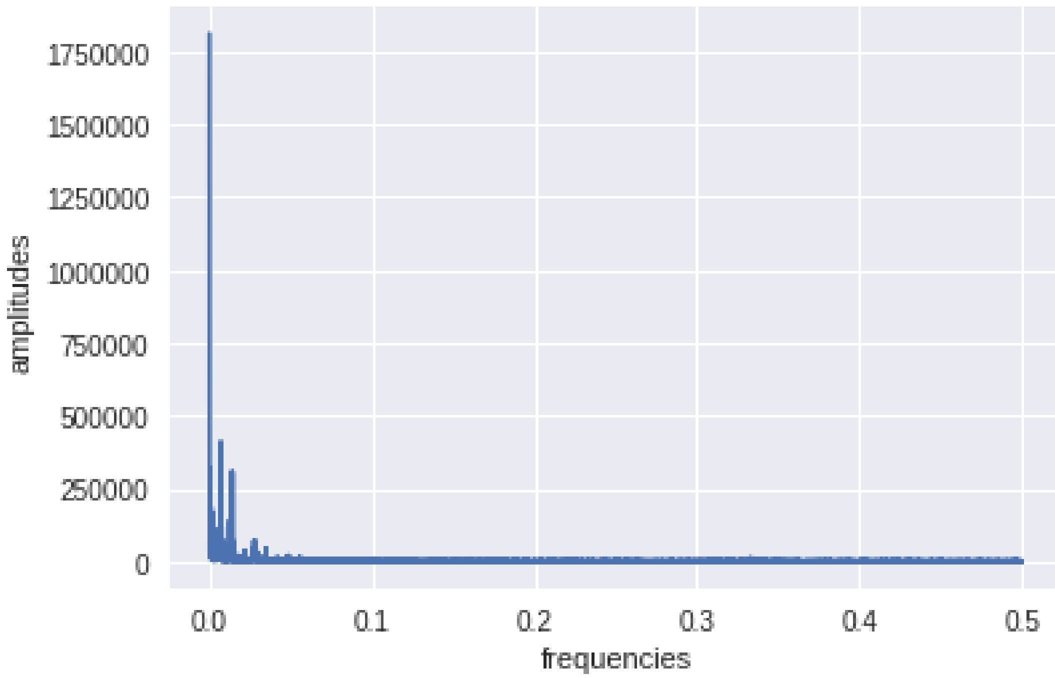
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1750000
1500000
1250000
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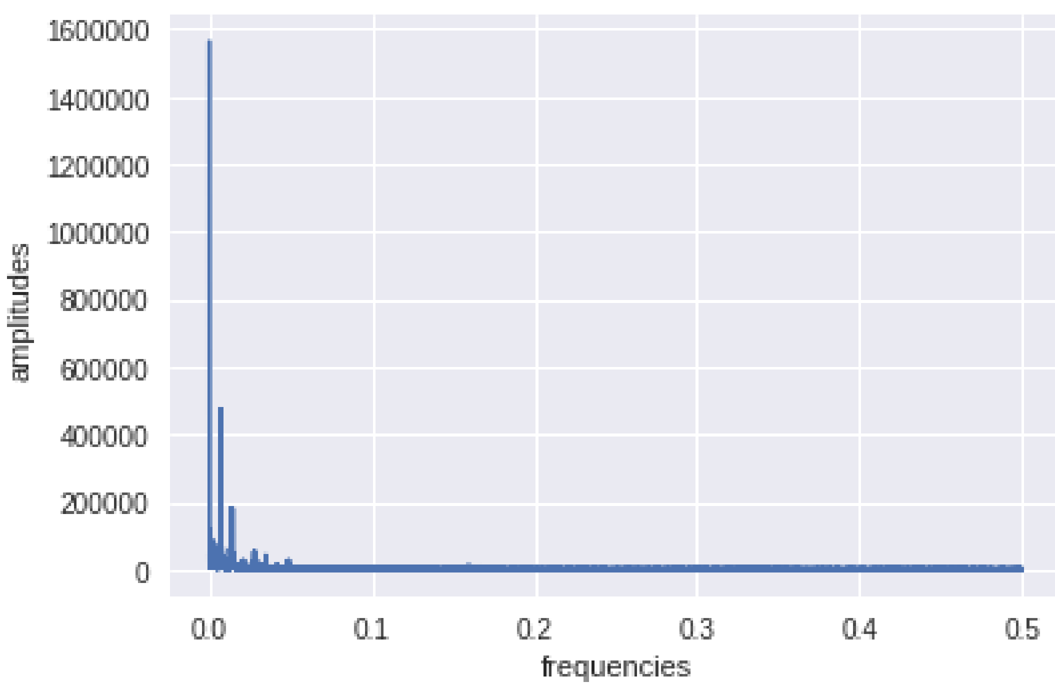
500000
250000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1600000
1400000
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200000
0
amplitudes
0.0
0.1
0.2
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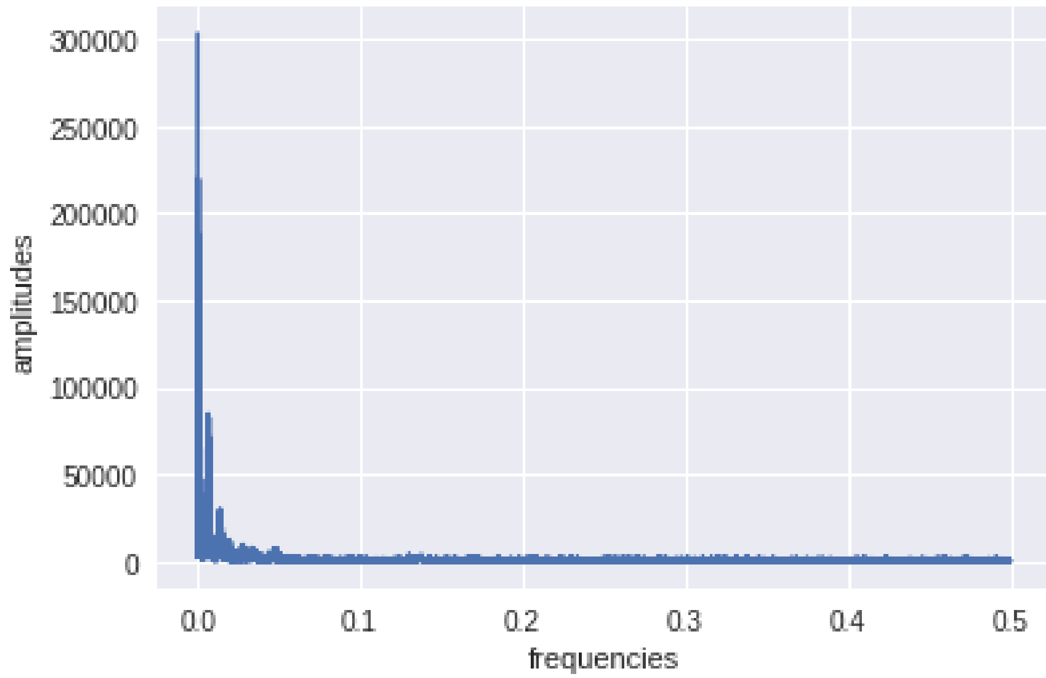
0.4
0.5
frequencies


300000
250000
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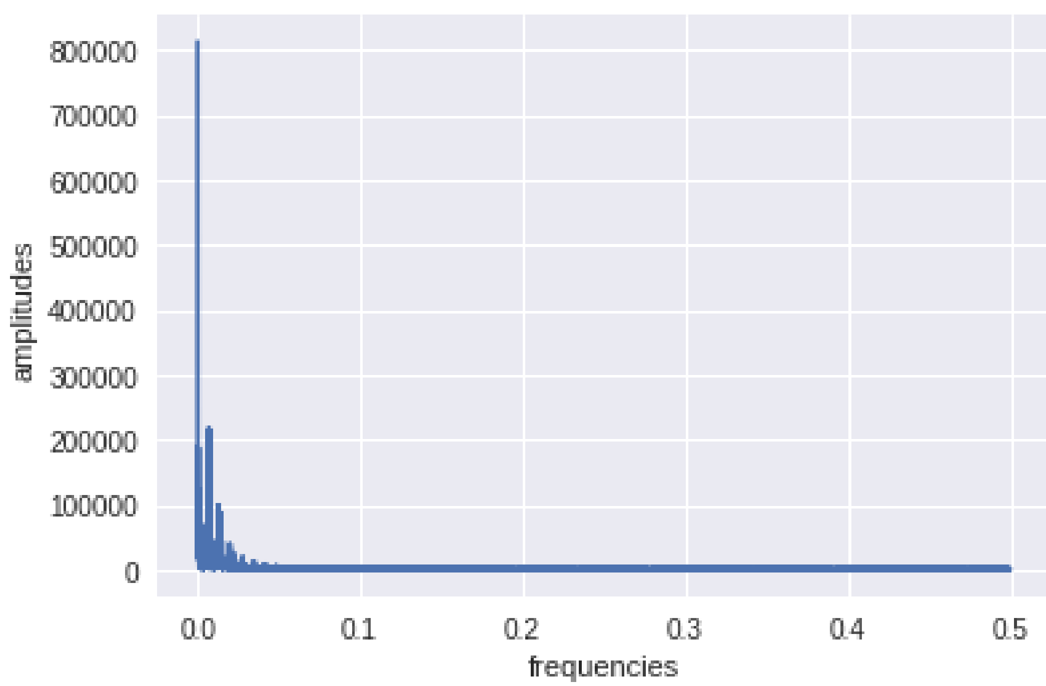
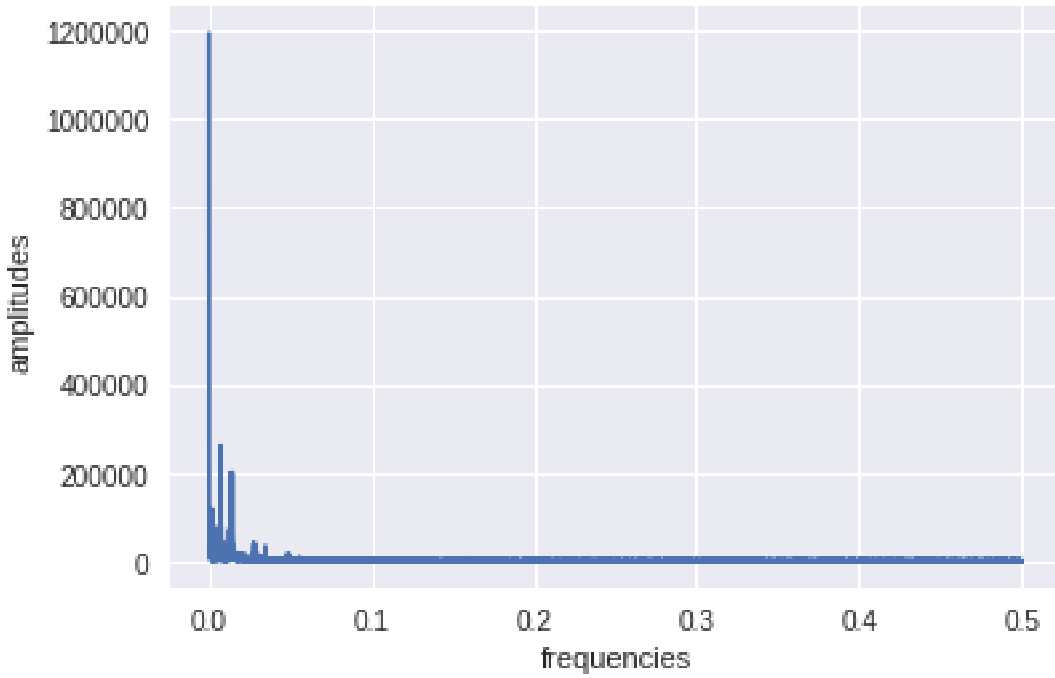
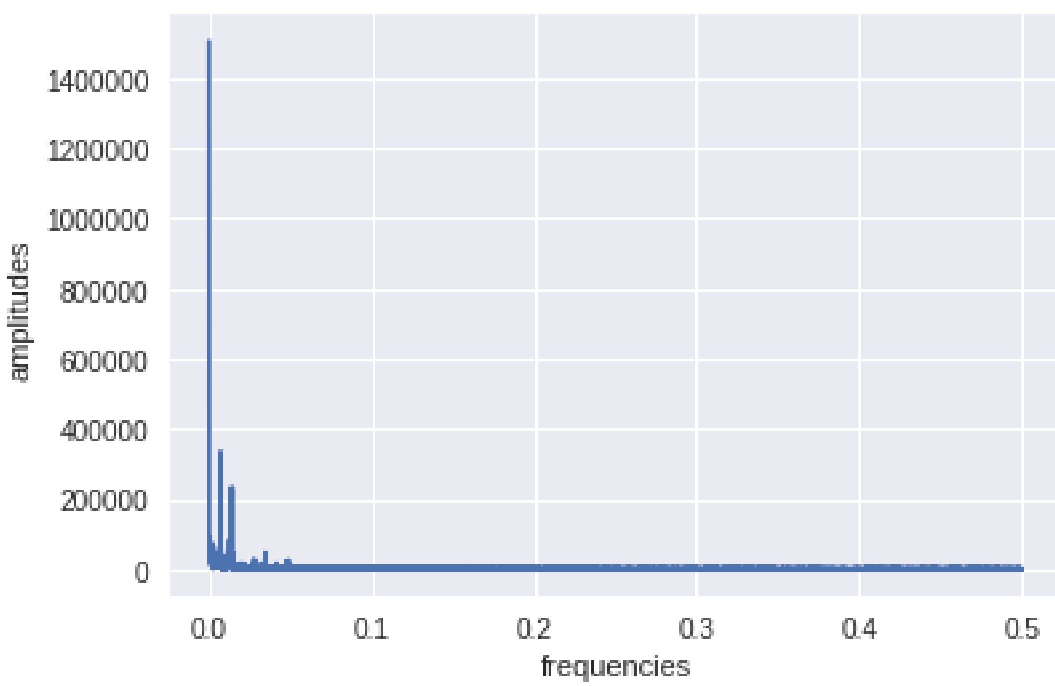
150000
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


800000
700000
600000
500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



1200000
1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



1400000
1200000
1000000
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0
amplitudes
0.0
0.1
0.2
0.3
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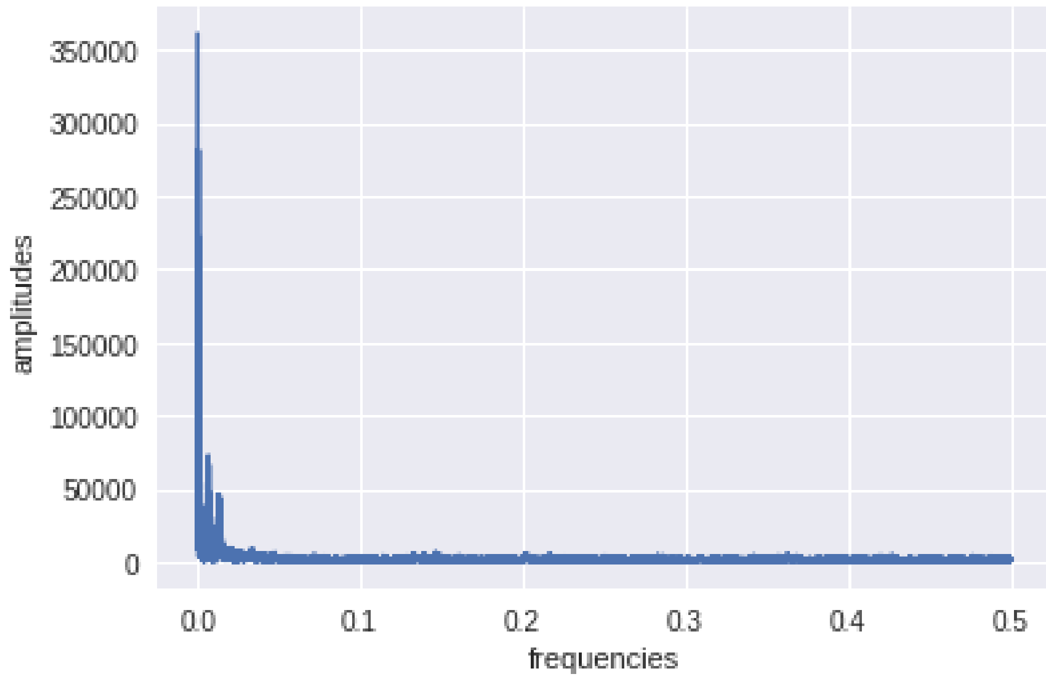
frequencies


amplitudes
350000
300000
250000
200000
150000
100000
50000
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0.1
0.2
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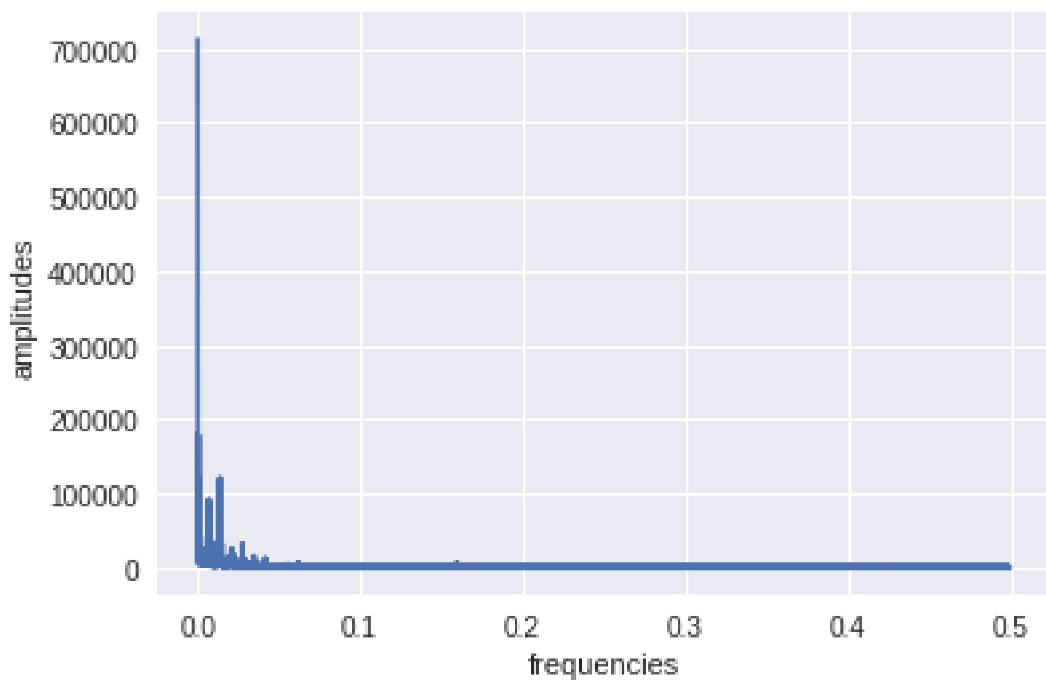
0.5
frequencies


amplitudes
700000
600000
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100000
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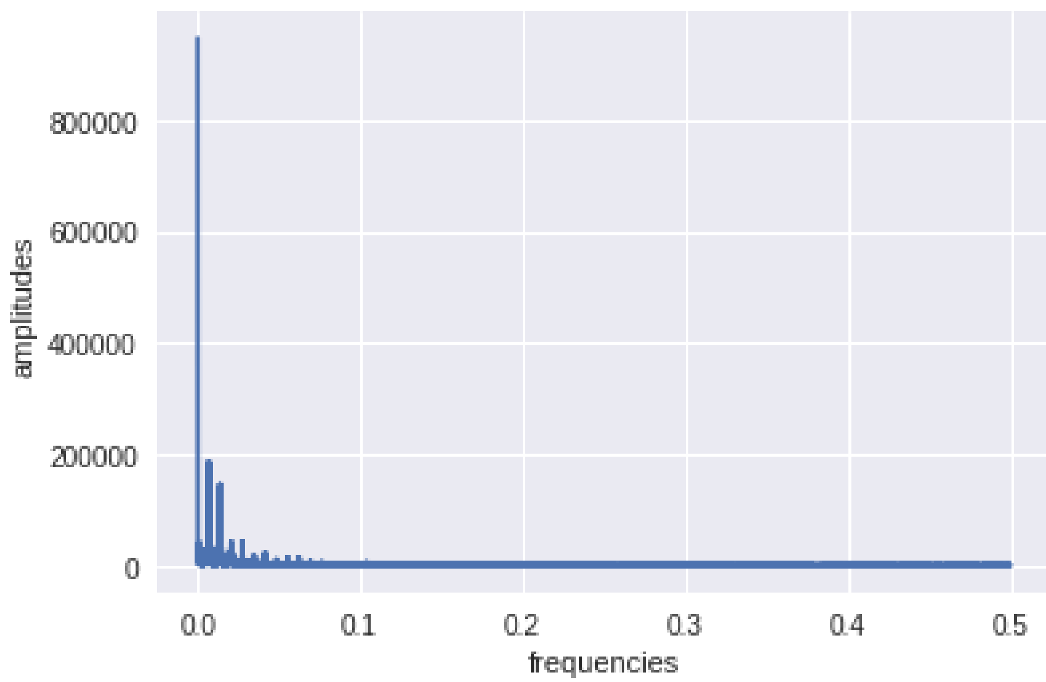
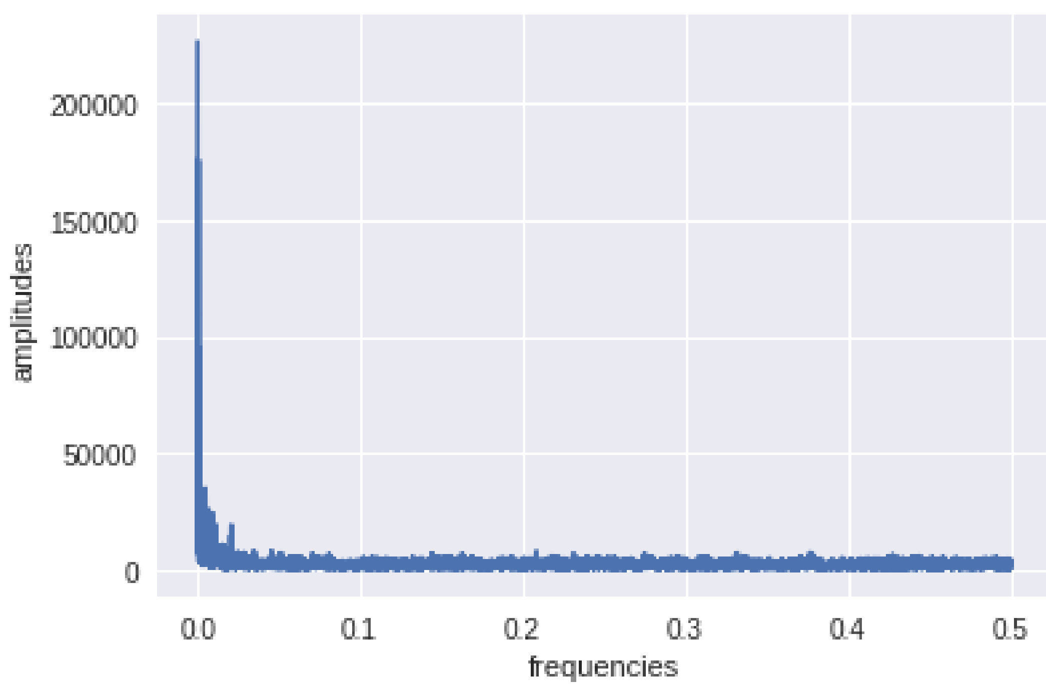
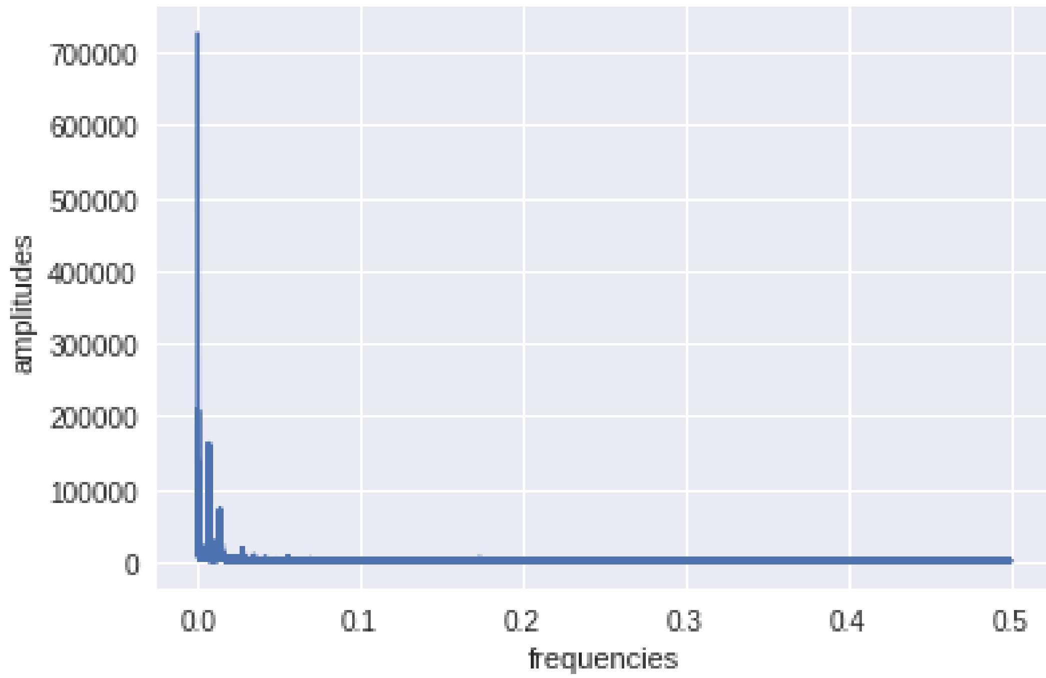
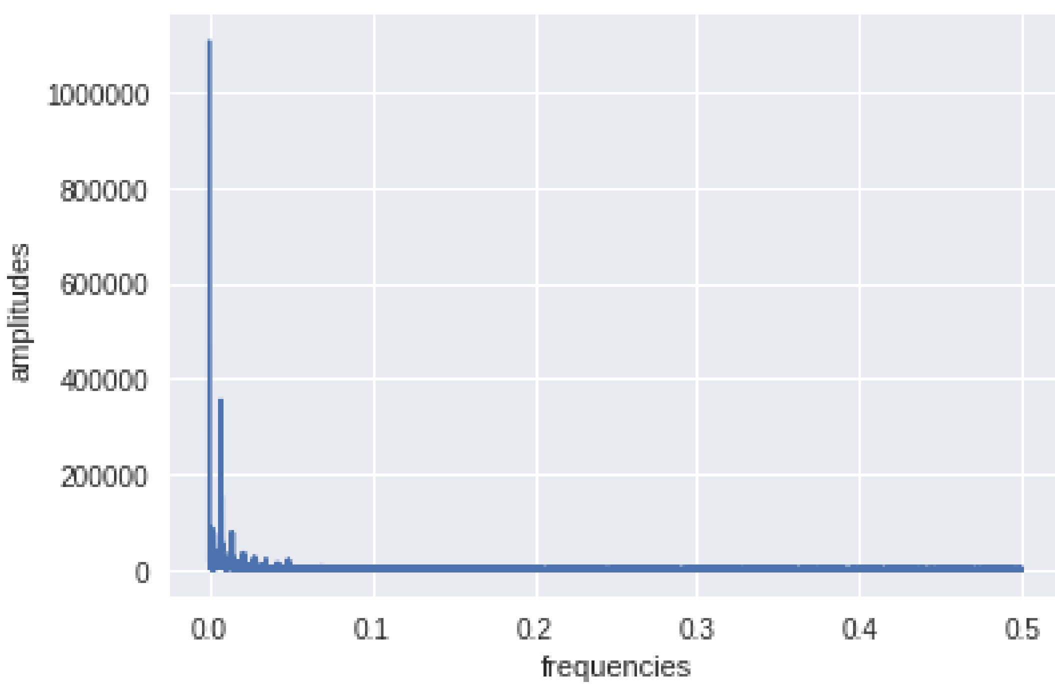
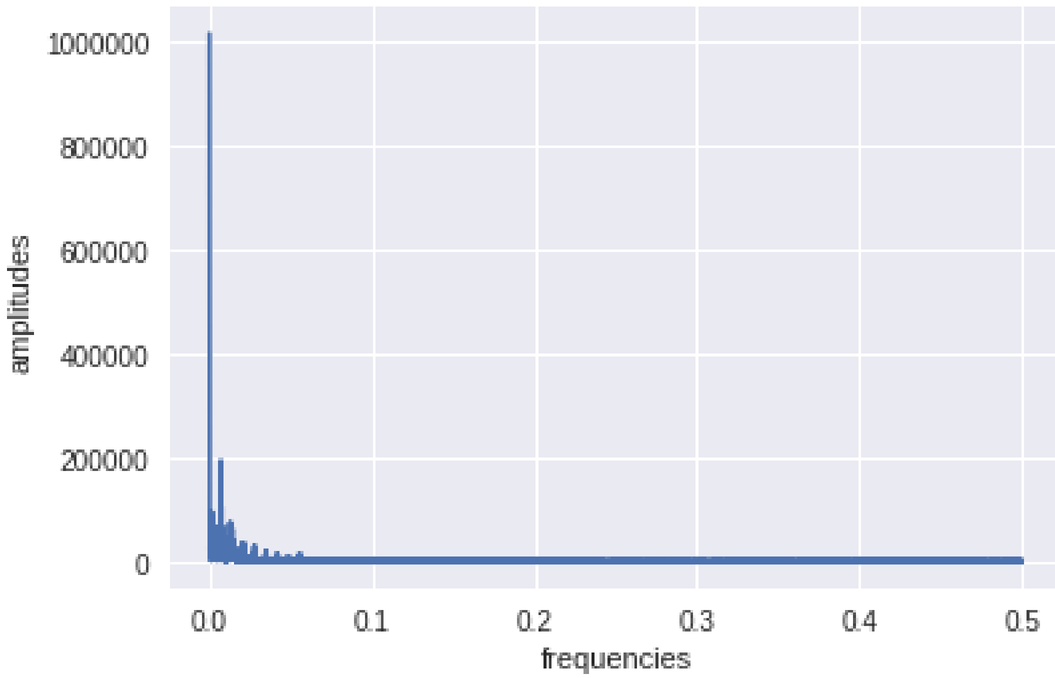
0.1
0.2
0.3
0.4
0.5
frequencies


800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


200000
150000
100000
50000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


700000
600000
500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



1000000
800000
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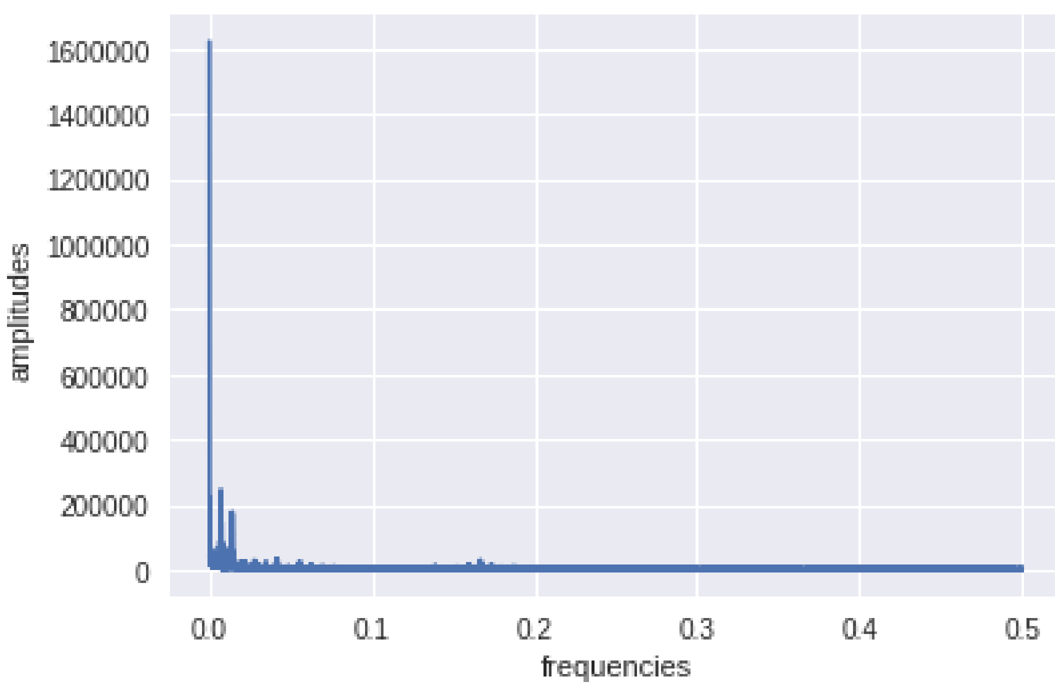
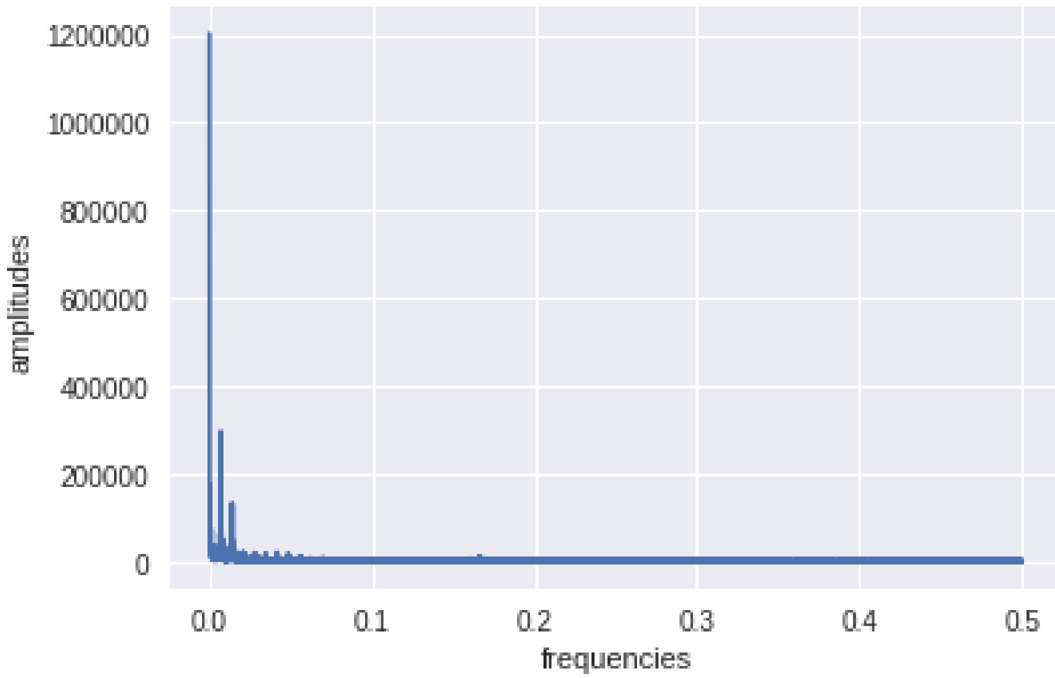
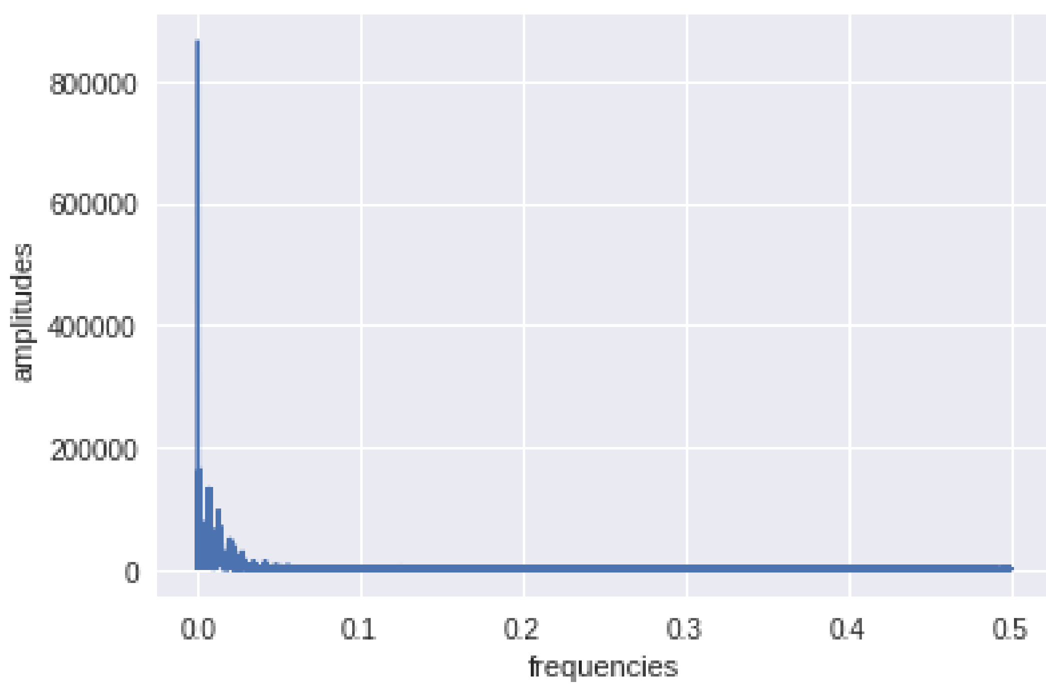
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



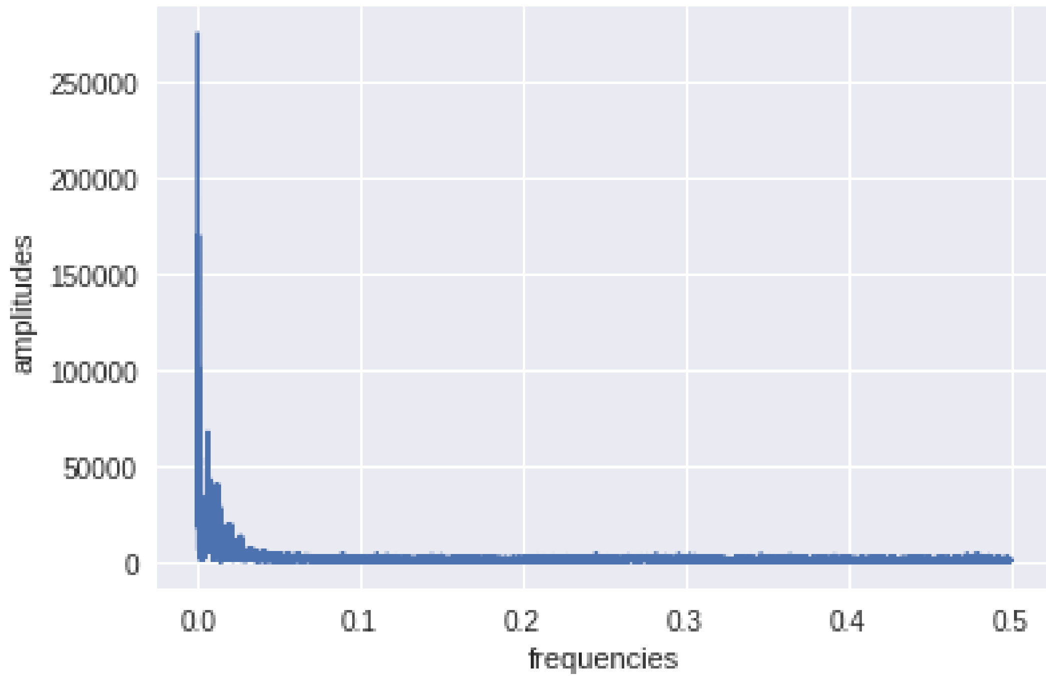
1600000
1400000
1200000
1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



1200000
1000000
800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies



800000
600000
400000
200000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies


250000
200000
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100000
50000
0
amplitudes
0.0
0.1
0.2
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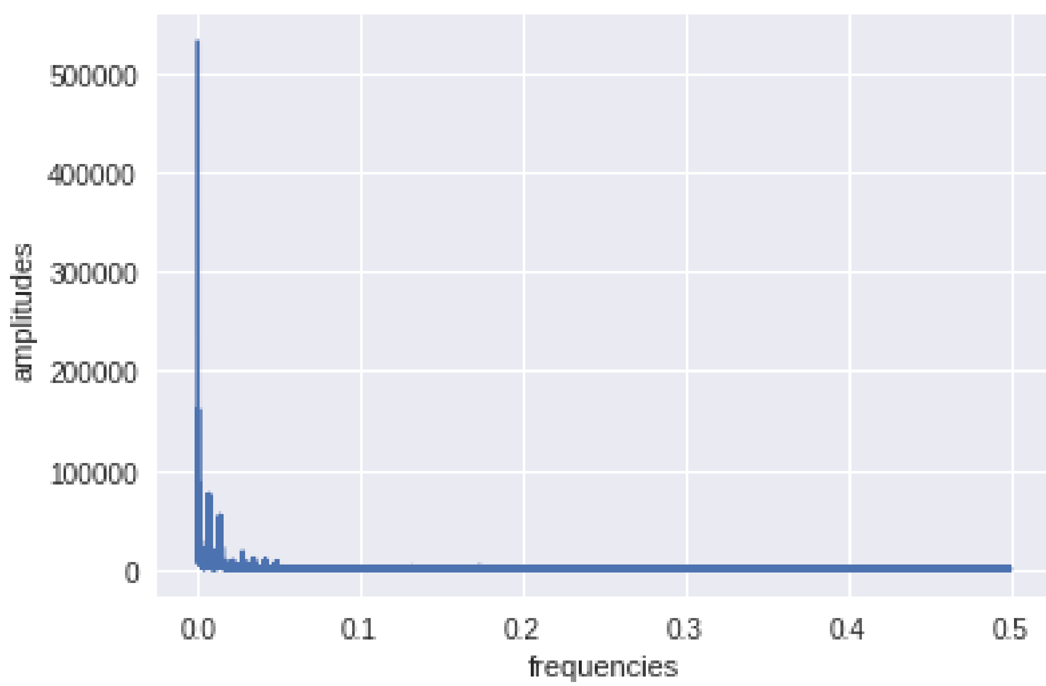
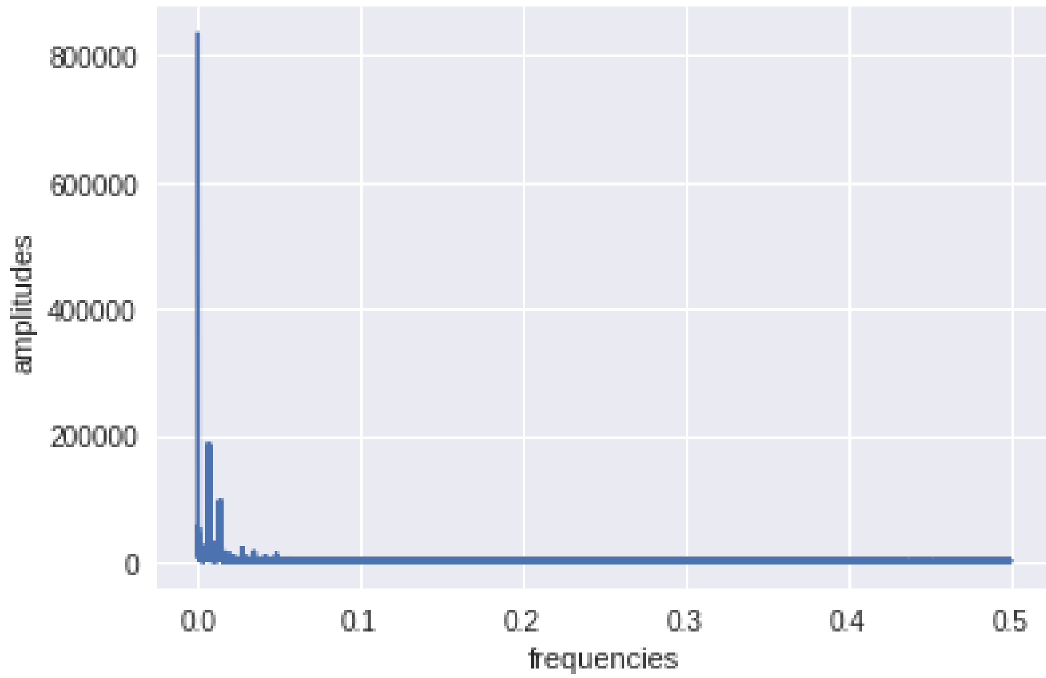
0.4
0.5
frequencies


500000
400000
300000
200000
100000
0
amplitudes
0.0
0.1
0.2
0.3
0.4
0.5
frequencies




```
In [0]: print(len(amplitudes))
        print(len(frequencies))
```

```
13104
13104
```

now we have to find the top 3 amplitudes of each cluster and the frequencies of that particular amplitudes and add them as the features to that particualr cluster.

```
In [0]: featureamplitudes=[]
        featurefrequencies=[]
        feature_amplitude_frequencies=[]
        for i in range(0,40):
          amplitudes=np.abs(np.fft.fft(regionscumulative[i][0:13104]))
          amplitudes=amplitudes.astype(int)
          maximumamplitudesindices=np.argsort(amplitudes)[::-1][:5]
          amplitude_as_features=list(amplitudes[maximumamplitudesindices])
          frequencies=np.abs(np.fft.fftfreq(13104,1))
          frequencies_as_features=list(frequencies[maximumamplitudesindices])
          for j in range(13099):
            feature_amplitude_frequencies.append(amplitude_as_features+frequencies_as_features)
```

```
In [0]: print(len(feature_amplitude_frequencies))
        print(13099*40)
```

```
523960
523960
```

14.1 Regression Models

we are having the total bins of 4464+4176+4464=13104 bins . wea re taking the last 5 pickup points as features . hence we will be having the 13104-5=12099 bins.now our training data is latitude and longtitude of each bin,pickups in the last 5 bins. weekday and exponential average of that particular bin.number of pickups on the present bin.

14.1.1 Train-Test Split

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

```
In [0]: #brilliant code
        number_of_time_stamps = 5
        outputpickupvalue= []
        latitudeinfo = []
        longtitudeinfo= []
        weekdayinfo = []
        lastpickupfeature = []
        lastpickupfeature= [0]*number_of_time_stamps
        for i in range(0,40):
            latitudeinfo.append([kmeans.cluster_centers_[i][0]]*13099)
            longtitudeinfo.append([kmeans.cluster_centers_[i][1]]*13099)
            weekdayinfo.append([int(((int(k/144))%7+4)%7) for k in range(5,4464+4176+4464)])
            lastpickupfeature = np.vstack((lastpickupfeature,[regionscumulative[i][r:r+number_o
            outputpickupvalue.append(regionscumulative[i][5:])
            #print(outputpickupvalue)
            #print(len(outputpickupvalue[0]))
            #13099
```

```
In [0]: alpha=0.3

        # it is a temporary array that store exponential weighted moving avarage for each 10mi
        # 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..
        predict_list = []
```

```
    tsne_flat_exp_avg = []
    for r in range(0,40):
        for i in range(0,13104):
            if i==0:
                predicted_value= regionscumulative[r][0]
                predicted_values.append(0)
                continue
            predicted_values.append(predicted_value)
            predicted_value =int((alpha*predicted_value) + (1-alpha)*(regionscumulative[r]
        predict_list.append(predicted_values[5:])
        predicted_values=[]
```

```
In [0]: # train, test split : 70% 30% split
        # Before we start predictions using the tree based regression models we take 3 months
        # and split it such that for every region we have 70% data in train and 30% in test,
        # ordered date-wise for every region
        print("size of train data :", int(13099*0.7))
        print("size of test data :", int(13099*0.3))
```

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

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

        test_features = [lastpickupfeature[(13099*(i))+9169:13099*(i+1)] for i in range(0,40)]
```

```
In [0]: # extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our t
        train_features1 =  [feature_amplitude_frequencies[i*13099:(13099*i+9169)] for i in rang
        # temp = [0]*(12955 - 9068)
        test_features1 = [feature_amplitude_frequencies[(13099*(i))+9169:13099*(i+1)] for i in
```

```
In [0]: 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 data point contains 5
Number of data clusters 40 Number of data points in test data 3930 Each data point contains 5 i
```

```
In [0]: print("Number of data clusters",len(train_features1), "Number of data points in trian d
        print("Number of data clusters",len(train_features1), "Number of data points in test da
```

```
Number of data clusters 40 Number of data points in trian data 9169 Each data point contains 10
Number of data clusters 40 Number of data points in test data 3930 Each data point contains 10
```

```
In [0]: # extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our t
        tsne_train_flat_lat = [i[:9169] for i in latitudeinfo]
```

```
tsne_train_flat_lon = [i[:9169] for i in longtitudeinfo]
tsne_train_flat_weekday = [i[:9169] for i in weekdayinfo]
tsne_train_flat_output = [i[:9169] for i in outputpickupvalue]
tsne_train_flat_exp_avg = [i[:9169] for i in predict_list]
```

In [0]:
```
# extracting the rest of the timestamp values i.e 30% of 12956 (total timestamps) for 
tsne_test_flat_lat = [i[9169:] for i in latitudeinfo]
tsne_test_flat_lon = [i[9169:] for i in longtitudeinfo]
tsne_test_flat_weekday = [i[9169:] for i in weekdayinfo]
tsne_test_flat_output = [i[9169:] for i in outputpickupvalue]
tsne_test_flat_exp_avg = [i[9169:] for i in predict_list]
```

In [0]:
```
# the above contains values in the form of list of lists (i.e. list of values of each 
train_new_features = []
for i in range(0,40):
    train_new_features.extend(np.hstack((train_features[i],train_features1[i])))
test_new_features = []
for i in range(0,40):
   test_new_features.extend(np.hstack((test_features[i],test_features1[i])))
```

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

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

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

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

In [0]:
```
# Preparing the data frame for our train data
columns = ['ft_5','ft_4','ft_3','ft_2','ft_1','amplitude1','amplitude2','amplitude3','a
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, 19)
```

```
In [0]: # 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, 19)
```

```
In [0]: df_test.head(5)
```

```
Out[0]:    ft_5   ft_4   ft_3   ft_2   ft_1  amplitude1  amplitude2  amplitude3  \
        0  121.0  105.0  143.0  145.0  119.0   1128411.0    363730.0    363730.0
        1  105.0  143.0  145.0  119.0  113.0   1128411.0    363730.0    363730.0
        2  143.0  145.0  119.0  113.0  124.0   1128411.0    363730.0    363730.0
        3  145.0  119.0  113.0  124.0  121.0   1128411.0    363730.0    363730.0
        4  119.0  113.0  124.0  121.0  131.0   1128411.0    363730.0    363730.0

           amplitude4  amplitude5  freq.amplitude1  freq.amplitude2  freq.amplitude3  \
        0    181588.0    181588.0              0.0         0.006944         0.006944
        1    181588.0    181588.0              0.0         0.006944         0.006944
        2    181588.0    181588.0              0.0         0.006944         0.006944
        3    181588.0    181588.0              0.0         0.006944         0.006944
        4    181588.0    181588.0              0.0         0.006944         0.006944

           freq.amplitude4  freq.amplitude5        lat        lon  weekday  exp_avg
        0         0.013889         0.013889  40.776228 -73.982119        4      116
        1         0.013889         0.013889  40.776228 -73.982119        4      121
        2         0.013889         0.013889  40.776228 -73.982119        4      120
        3         0.013889         0.013889  40.776228 -73.982119        4      127
        4         0.013889         0.013889  40.776228 -73.982119        4      115
```

```
In [0]: print(df_train.shape)
```

```
(366760, 19)
```

14.1.2 standardising the data is very important it reduced my mape from 22 to 9. i got 22 without standardising

```
In [0]: from sklearn.preprocessing import StandardScaler
        scale=StandardScaler()
```

```
df_train=scale.fit_transform(df_train)
scale1=StandardScaler()
df_test=scale1.fit_transform(df_test)
```

14.1.3 Using Linear Regression

In [0]:
```
from sklearn.linear_model import SGDRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
params={
    'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]
    }
model=SGDRegressor(loss='squared_loss',penalty='l2')
#model=LinearRegression()

sigmamodel=GridSearchCV(model,param_grid=params,scoring='neg_mean_absolute_error',cv=4)
sigmamodel.fit(df_train,tsne_train_output)
print(sigmamodel.best_params_)
print(sigmamodel.cv_results_)
```

```
{'alpha': 0.0001}
{'mean_fit_time': array([0.54988891, 0.58651382, 0.57441312, 0.58622676, 0.58235532,
       0.59289598, 0.5798614 , 0.59354156, 0.60202742]), 'std_fit_time': array([0.00318173, 0.0
       0.00836906, 0.00300694, 0.01269465, 0.00497848]), 'mean_score_time': array([0.01092231,
       0.01332724, 0.01328737, 0.01332784, 0.01330686]), 'std_score_time': array([1.39655921e-0
       2.16825608e-04, 1.09776481e-04, 2.32155577e-04, 6.84080615e-05,
       1.67734545e-04]), 'param_alpha': masked_array(data=[0.0001, 0.001, 0.01, 0.1, 1, 10, 100
             mask=[False, False, False, False, False, False, False, False,
                   False],
       fill_value='?',
            dtype=object), 'params': [{'alpha': 0.0001}, {'alpha': 0.001}, {'alpha': 0.01}, {'a
       -15.13231666, -32.58978464, -50.04685055, -52.04961383,
       -52.23580222]), 'split1_test_score': array([ -7.33239509,  -7.41562802,  -7.48666096,  -
       -10.21171612, -25.19169546, -43.34534172, -45.29803766,
       -45.17354021]), 'split2_test_score': array([ -9.21141073,  -9.33568283,  -9.43251265, -1
       -15.76286725, -38.10385839, -54.14295139, -56.84234445,
       -57.55602759]), 'split3_test_score': array([ -9.92711264,  -9.94434868, -10.11149616, -1
       -15.0439548 , -31.72182072, -45.69309379, -47.81662678,
       -48.07948195]), 'mean_test_score': array([ -9.14499738,  -9.30804211,  -9.4119774 , -10
       -14.03771371, -31.9017898 , -48.30705936, -50.50165568,
       -50.76121299]), 'std_test_score': array([1.09898591, 1.17217872, 1.18840745, 1.29245031
       4.58248695, 4.13932262, 4.38427672, 4.65719033]), 'rank_test_score': array([1, 2, 3, 4,
       -13.20645498, -30.98946864, -47.31478581, -49.34313594,
       -49.52708601]), 'split1_train_score': array([ -9.72470949,  -9.79097574,  -9.97523022,  -
       -14.45588273, -32.15799085, -50.8702069 , -52.96046524,
       -53.05232824]), 'split2_train_score': array([ -9.2181421 ,  -9.26208481,  -9.37939677,  -
       -13.492832  , -30.53851237, -44.66166524, -46.86842048,
       -47.51621535]), 'split3_train_score': array([ -8.85371901,  -8.84709749,  -9.07352879,  -
```

```
       -14.26597615, -31.98502878, -48.51676287, -51.13771061,
       -51.5085431 ]), 'mean_train_score': array([ -9.15120209,  -9.23662901,  -9.36829769, -10
       -13.85528646, -31.41775016, -47.8408552 , -50.07743307,
       -50.40104317]), 'std_train_score': array([0.36725755, 0.35209592, 0.37412491, 0.39297348
       0.67569325, 2.23706396, 2.25127836, 2.08218043])}
```

```
In [0]: mod=SGDRegressor(loss='squared_loss',alpha=0.0001)
        mod.fit(df_train,tsne_train_output)
        y_pred = mod.predict(df_test)
        lr_test_predictions = [round(value) for value in y_pred]
        print(mean_absolute_error(tsne_test_output,lr_test_predictions))
        y_pred =mod.predict(df_train)
        lr_train_predictions = [round(value) for value in y_pred]
        print(mean_absolute_error(tsne_train_output,lr_train_predictions))
```

```
9.719968193384224
9.211304395244847
```

14.1.4 Using Random Forest Regressor

```
In [0]: from sklearn.ensemble import RandomForestRegressor
        from sklearn.model_selection import RandomizedSearchCV
        params={'bootstrap': [True, False],
         'max_depth': [10, 30, 50,75 ],
         'min_samples_leaf': [1, 2, 4],
         'min_samples_split': [2, 5, 10],
         'n_estimators': [50, 100, 300, 500, 1000]}
        regr1 = RandomForestRegressor()
        sigmamodel=RandomizedSearchCV(regr1,param_distributions=params,scoring='neg_mean_absolu
        sigmamodel.fit(df_train,tsne_train_output)
        print(sigmamodel.best_params_)
        print(sigmamodel.cv_results_)
```

```
{'n_estimators': 50, 'min_samples_split': 5, 'min_samples_leaf': 2, 'max_depth': 10, 'bootstrap
{'mean_fit_time': array([  77.40287334,  313.62021458,   49.16944385,  169.10775602,
        742.06496155,  103.58275604,  111.60486788, 1010.09953618,
        616.10138834, 1655.69479495]), 'std_fit_time': array([ 1.23023355,  6.73882852,  0.5089
        1.91329749,  2.08840495, 15.33481577,  9.22982887, 28.26123332]), 'mean_score_time': ar
        1.32920706,  1.44931376,  9.67181599,  7.1847617 , 15.52460432]), 'std_score_time': arr
       0.03379656, 0.05636963, 0.48416826, 0.16954761, 0.78378478]), 'param_n_estimators': mask
             mask=[False, False, False, False, False, False, False, False,
                   False, False],
       fill_value='?',
            dtype=object), 'param_min_samples_split': masked_array(data=[10, 2, 5, 10, 5, 2, 2
             mask=[False, False, False, False, False, False, False, False,
                   False, False],
       fill_value='?',
```

```
     dtype=object), 'param_min_samples_leaf': masked_array(data=[2, 4, 2, 1, 2, 4, 2, 2
      mask=[False, False, False, False, False, False, False, False,
            False, False],
fill_value='?',
     dtype=object), 'param_max_depth': masked_array(data=[10, 30, 10, 50, 10, 50, 30, 30
      mask=[False, False, False, False, False, False, False, False,
            False, False],
fill_value='?',
     dtype=object), 'param_bootstrap': masked_array(data=[False, False, True, False, Fal
            True, False],
      mask=[False, False, False, False, False, False, False, False,
            False, False],
fill_value='?',
     dtype=object), 'params': [{'n_estimators': 50, 'min_samples_split': 10, 'min_sample
-10.60230449, -10.25968425, -10.32196701, -13.50802157,
-10.22991526, -13.46132157]), 'split1_test_score': array([-7.45322494, -9.32831539, -7.3
-7.42298881, -7.45501791, -9.75614372, -7.37351128, -9.70325413]), 'split2_test_score':
 -9.32747223,  -9.24478876,  -9.34932034, -12.22822957,
 -9.23516717, -12.17195275]), 'split3_test_score': array([-10.15788011, -12.1078895 ,  -
-10.1486099 , -10.00547944, -10.06464763, -12.68210992,
 -9.98221383, -12.61856792]), 'mean_test_score': array([ -9.37943272, -11.43642034,  -9
 -9.38376728,  -9.23323532,  -9.29773822, -12.04362619,
 -9.20520188, -11.98877409]), 'std_test_score': array([1.20537213, 1.28621724, 1.104606
1.10985183, 1.12199304, 1.39810316, 1.11912616, 1.39840912]), 'rank_test_score': array(
-5.36507926, -4.24432389, -3.38803561, -5.28359253, -3.76005499]), 'split1_train_score'
-5.902742  , -4.84900339, -3.99922623, -5.93201948, -4.39061637]), 'split2_train_score'
-5.60976121, -4.62509179, -3.97887496, -5.63761814, -4.32361547]), 'split3_train_score'
-5.40635828, -4.32774398, -3.57787982, -5.36259067, -3.94544928]), 'mean_train_score': a
-5.57098519, -4.51154076, -3.73600416, -5.55395521, -4.10493403]), 'std_train_score': ar
0.21275892, 0.24081164, 0.26189573, 0.25477855, 0.26163568])}
```

In [0]:
```python
mod= RandomForestRegressor(n_estimators= 50, min_samples_split= 5, min_samples_leaf= 2
mod.fit(df_train,tsne_train_output)
y_pred = mod.predict(df_test)
lr_test_predictions = [round(value) for value in y_pred]
print(mean_absolute_error(tsne_test_output,lr_test_predictions))
y_pred =mod.predict(df_train)
lr_train_predictions = [round(value) for value in y_pred]
print(mean_absolute_error(tsne_train_output,lr_train_predictions))
```

```
9.583784987277353
8.759722979605192
```

In [0]:
```python
#feature importances based on analysis using random forest
print (mod.feature_importances_)
```

```
[1.43865373e-03 1.51737866e-03 1.27874108e-03 1.62610365e-03
 2.97272632e-03 9.56057453e-04 1.41923338e-04 1.39090571e-04
```

```
 1.14054314e-04 1.07526275e-04 0.00000000e+00 4.47368538e-05
 5.30442470e-05 4.14955947e-05 4.47575991e-05 2.19156521e-04
 5.50598188e-04 3.36503978e-04 9.88417452e-01]
```

14.1.5 Using XgBoost Regressor

```
In [0]: hyper_parameter = {"max_depth":[1,5,10,20], "n_estimators":[40, 80, 150, 600]}
        clf = xgb.XGBRegressor()
        best_parameter = RandomizedSearchCV(clf, hyper_parameter, scoring = "neg_mean_absolute_
        best_parameter.fit(df_train, tsne_train_output)
        estimators = best_parameter.best_params_["n_estimators"]
        depth = best_parameter.best_params_["max_depth"]
```

```
In [0]: print(best_parameter.best_params_)
```

```
{'n_estimators': 80, 'max_depth': 10}
```

```
In [0]: mod= xgb.XGBRegressor(n_estimators=80,max_depth=10)
        mod.fit(df_train,tsne_train_output)
        y_pred = mod.predict(df_test)
        lr_test_predictions = [round(value) for value in y_pred]
        print(mean_absolute_error(tsne_test_output,lr_test_predictions))
        y_pred =mod.predict(df_train)
        lr_train_predictions = [round(value) for value in y_pred]
        print(mean_absolute_error(tsne_train_output,lr_train_predictions))
```

```
9.386393129770992
7.939246373650343
```

14.1.6 Calculating the error metric values for various models

14.2 ERROR METRIC VALUES BEFORE USING THE FREQUNCIES AS FEATURES

```
In [0]: 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(

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

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

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
----------------------------------------------------------------------------------
Baseline Model -                            Train:  0.140052758787       Test:  0.136531257048
Exponential Averages Forecasting -          Train:  0.13289968436      Test:  0.129361804204
Linear Regression -                        Train:  0.13331572016      Test:  0.129120299401
Random Forest Regression -                  Train:  0.0918514693197      Test:  0.127141622928
```

14.3 USING THE FREQUENCIES AS FEATURES THE ERROR METRICS IN MAPE IS

```
In [2]: import pandas as pd
        dta = [['LINEAR REGRESSION',9.2,9.7],['RANDOM FOREST REGRESSOR',8.75,9.58],['xgb REGRES
        aa=pd.DataFrame(dta, columns=['model',"MAPE_FOR TRAIN DATA",'MAPE FOR TEST DATA'])
        aa
```

```
Out[2]:                                   model  MAPE_FOR TRAIN DATA  \
        0                     LINEAR REGRESSION                 9.20
        1               RANDOM FOREST REGRESSOR                 8.75
        2  xgb REGRESSOR WITH RANDOM SEARCH CV                 7.93

           MAPE FOR TEST DATA
        0                9.70
        1                9.58
        2                9.38
```

14.3.1 DOCUMENTATION CONCLUSION AND KEYTAKEAWAYS OF TAXI DEMAND PREDICTION

*** IN TAXI DEMAND PREDICTION ASSIGNMENT WE TAKEN THE DATA OUR PEOBLEM STATEMENT IS WE HAVE TO PREDICT THE NUMBER OF PICKUPS IN THE PARTICULAR CLUSTER IN ANOTHER MINUTES.**

*** WE HAVE THE DATA OF FOUR MONTHS WITH VARIOUS FEATURES SUCH AS PICKUP LATITUDE,LONGTITUDE,SPED,FARE.**

*** IT IS US TO PERFORM THE FEATURE ENGINEERING AND 0OBTAIN THE RIGT FEATURE AND PREDICT THE REQUIREMENT FROM THE DATA WE HAVE.** AS A PART OF DATA PREPROCESSING WE SELECTES THE COLUMNS THAT ARE MORE IMPORTANT THAT CAN BE USED FOR PREDICTION OF FUTURE PICKUPS. * WE HAVE PERFORMED

EXPLORATORY DATA ANALYSIS AND VISUALISED THE FEATURES HOW THEY ARE PERFORMING. * we have used box plots and violin plots to find the outliers presence and used the percentilevalues to detect hte thresholds * we removed the outliers form the data based on the outliers detected. * as a part of feature engineering we ahve extracted the features like trip times from the already existing features. * then we applied strategy of feature engineering technique we divided the area into variou clusters based on the longitudes and latitudes. * uisng the kmeans clustering divided the area into various clusters uniformly based on the number of pickups. * we found the optimal number o9f clusters by condition of 10 minute time bins we founfd te optimal number of clusters uising the threshold as 2 miles. * we assumed that it takes 10 minutes for a cab driver to travel 2 miles. * using the unix time we have divided the january,feb,march data into tome bins which are discrete varying y 10 minutes which is 600 seconds. * we have to predict the number of pickups based on the number of trip times we have taken the number of pickups in particular cluster. * we have added pickup bins in each cluster but the every cluster is not having the all pickupbins hence we have done the preocess of smoothing with average vallues or fill the missing bins with null values. * in january 2016 we have 4464 bins feb 2016 we ave 4176 bins mar 2016 we have 4464 bins are present. * totally we have 13104 bins present by the way we have 13104 bins in each cluster and we have the 40 clusters present . * so totally we have the 524160 bins present which is (13104*40)* for featurisation we have considerd the previous 5 time bin values as features so we are left with 13099 bins. * observing the amplitudes of the time bis of each cluster it follows a sinusoidal path. * this is a key take away from the analysis the reason consider the previous pickup values as the features. * we have also considerd the top frequencies and top ampltudes of the frequencies as the features for each cluster. * we have taken the top 3 frequencies and top 3 amplitudes of that frequencies for each cluster. * we have taken centroid which is the cluster center instead of taking the pickup point coordinates. * now we have 13099 bins.we have divided the train data and test data. * traindata consists of 9169 points as train data for each cluster. * we have 9169*40 points as train points=366760* we have 3929 points as test data points in each cluster * we have 3929*40 points as the test data points.* extreemly important thing before applying the model is data standardisation (it reduces my mape from 22 to 9) #### we applied our machine learning models like * linear regression with grid search cv. * random forest regressor random searchcv. * xgb regressor with random search cv * conclusion are displayed above.

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In [0]:
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