Taxi demand prediction in New York City

```
#Importing Libraries
!pip3 install graphviz
!pip3 install dask
!pip install "dask[complete]"
!pip3 install toolz
!pip3 install cloudpickle
# https://www.youtube.com/watch?v=ieW3G7ZzRZ0
# https://github.com/dask/dask-tutorial
# please do go through this python notebook:
https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ipynb
import dask.dataframe as dd#similar to pandas

import pandas as pd#pandas to create small dataframes

!pip3 install folium
# if this doesnt work refere install_folium.JPG in drive
import folium #open street map

# unix time: https://www.unixtimestamp.com/
import datetime #Convert to unix time

import time #Convert to unix time

# if numpy is not installed already : pip3 install numpy
import numpy as np#Do aritmetic operations on arrays

# matplotlib: used to plot graphs
import matplotlib
# matplotlib.use('nbagg') : matplotlib uses this protocall which makes
plots more user intractive like zoom in and zoom out
matplotlib.use('nbagg')
import matplotlib.pylab as plt
import seaborn as sns#Plots
from matplotlib import rcParams#Size of plots

# this lib is used while we calculate the stight line distance between
two (lat,lon) pairs in miles
!pip install gpxpy
import gpxpy.geo #Get the haversine distance

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

```
import os

# download migwin: https://mingw-w64.org/doku.php/download/mingw-builds
# install it in your system and keep the path, migw_path ='installed path'
mingw_path = 'C:\\Program Files\\mingw-w64\\x86_64-5.3.0-posix-seh-rt_v4-rev0\\mingw64\\bin'
os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']

# to install xgboost: pip3 install xgboost
# if it didnt happen check install_xgboost.JPG
import xgboost as xgb

# to install sklearn: pip install -U scikit-learn
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import warnings
warnings.filterwarnings("ignore")
```

```
Requirement already satisfied: graphviz in
/usr/local/lib/python3.7/dist-packages (0.10.1)
Requirement already satisfied: dask in /usr/local/lib/python3.7/dist-
packages (2.12.0)
Requirement already satisfied: dask[complete] in
/usr/local/lib/python3.7/dist-packages (2.12.0)
Requirement already satisfied: PyYaml in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (3.13)
Requirement already satisfied: bokeh>=1.0.0 in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (2.3.3)
Requirement already satisfied: cloudpickle>=0.2.1 in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (1.3.0)
Requirement already satisfied: toolz>=0.7.3 in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (0.11.1)
Requirement already satisfied: pandas>=0.23.0 in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (1.1.5)
Collecting partd>=0.3.10
  Downloading partd-1.2.0-py3-none-any.whl (19 kB)
Requirement already satisfied: numpy>=1.13.0 in
/usr/local/lib/python3.7/dist-packages (from dask[complete]) (1.19.5)
Collecting fsspec>=0.6.0
  Downloading fsspec-2021.8.1-py3-none-any.whl (119 kB)
ent already satisfied: packaging>=16.8 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (21.0)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (5.1.1)
```

```
Requirement already satisfied: typing-extensions>=3.7.4 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (3.7.4.3)
Requirement already satisfied: pillow>=7.1.0 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (7.1.2)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (2.8.2)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.7/dist-packages (from bokeh>=1.0.0-
>dask[complete]) (2.11.3)
Requirement already satisfied: tblib>=1.6.0 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (1.7.0)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (57.4.0)
Requirement already satisfied: msgpack>=0.6.0 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (1.0.2)
Collecting cloudpickle>=0.2.1
  Downloading cloudpickle-1.6.0-py3-none-any.whl (23 kB)
Requirement already satisfied: click>=6.6 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (7.1.2)
Requirement already satisfied: psutil>=5.0 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (5.4.8)
Requirement already satisfied: zict>=0.1.3 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (2.0.0)
Collecting distributed>=2.0
  Downloading distributed-2021.8.1-py3-none-any.whl (778 kB)
ent already satisfied: sortedcontainers!=2.0.0,!=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from distributed>=2.0-
>dask[complete]) (2.4.0)
  Downloading distributed-2021.6.1-py3-none-any.whl (722 kB)
ent already satisfied: MarkupSafe>=0.23 in
/usr/local/lib/python3.7/dist-packages (from Jinja2>=2.9-
>bokeh>=1.0.0->dask[complete]) (2.0.1)
Requirement already satisfied: pyparsing>=2.0.2 in
/usr/local/lib/python3.7/dist-packages (from packaging>=16.8-
>bokeh>=1.0.0->dask[complete]) (2.4.7)
Requirement already satisfied: pytz>=2017.2 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.23.0-
>dask[complete]) (2018.9)
Collecting locket
  Downloading locket-0.2.1-py2.py3-none-any.whl (4.1 kB)
Requirement already satisfied: six>=1.5 in
```

```
/usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1-
>bokeh>=1.0.0->dask[complete]) (1.15.0)
Requirement already satisfied: heapdict in
/usr/local/lib/python3.7/dist-packages (from zict>=0.1.3-
>distributed>=2.0->dask[complete]) (1.0.1)
Installing collected packages: locket, cloudpickle, partd, fsspec,
distributed
  Attempting uninstall: cloudpickle
    Found existing installation: cloudpickle 1.3.0
    Uninstalling cloudpickle-1.3.0:
      Successfully uninstalled cloudpickle-1.3.0
  Attempting uninstall: distributed
    Found existing installation: distributed 1.25.3
    Uninstalling distributed-1.25.3:
      Successfully uninstalled distributed-1.25.3
Successfully installed cloudpickle-1.6.0 distributed-2.30.1 fsspec-
2021.8.1 locket-0.2.1 partd-1.2.0
Requirement already satisfied: toolz in /usr/local/lib/python3.7/dist-
packages (0.11.1)
Requirement already satisfied: cloudpickle in
/usr/local/lib/python3.7/dist-packages (1.6.0)
Requirement already satisfied: folium in
/usr/local/lib/python3.7/dist-packages (0.8.3)
Requirement already satisfied: branca>=0.3.0 in
/usr/local/lib/python3.7/dist-packages (from folium) (0.4.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.7/dist-packages (from folium) (2.23.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-
packages (from folium) (1.15.0)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.7/dist-packages (from folium) (2.11.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-
packages (from folium) (1.19.5)
Requirement already satisfied: MarkupSafe>=0.23 in
/usr/local/lib/python3.7/dist-packages (from jinja2->folium) (2.0.1)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from requests->folium)
(2021.5.30)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from requests->folium) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1
in /usr/local/lib/python3.7/dist-packages (from requests->folium)
(1.24.3)
Requirement already satisfied: idna<3,>=2.5 in
/usr/local/lib/python3.7/dist-packages (from requests->folium) (2.10)
Collecting gpxpy
  Downloading gpxpy-1.4.2.tar.gz (105 kB)
e=gpxpy-1.4.2-py3-none-any.whl size=42562
sha256=aa9e6b3079306fcc8f5b85475946cdb9c7c9a4eb69b1dd448acb1f3f29b3675
1
```

```
  Stored in directory:
/root/.cache/pip/wheels/e9/1b/e8/1e95d95fb1af470b278323a5564f4508f64c2
aa476e4547f63
Successfully built gpxpy
Installing collected packages: gpxpy
Successfully installed gpxpy-1.4.2
```

Data Information

Information on taxis:

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

Data Collection

We Have collected all yellow taxi trips data from jan-2015 to dec-2016(Will be using only 2015 data)   file name   file name size number of records   number of features   yellow_tripdata_2016-01   1. 59G   10906858   19

```
#Looking at the features
# dask dataframe  : #
https://github.com/dask/dask-tutorial/blob/master/07_dataframe.ipynb
```

```
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')
```

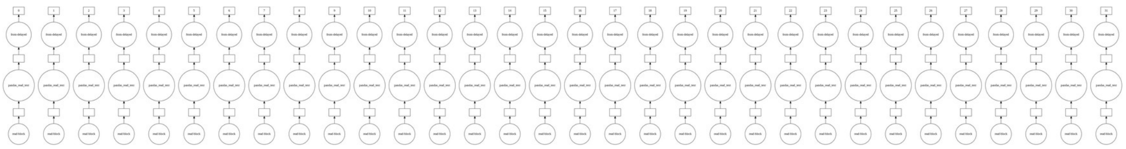
```
# !gdown --id 1kcIZlf-LQiQhqfSCZb719Nh6Rqkp2zKK
```

```
Downloading...
From: https://drive.google.com/uc?id=1kcIZlf-LQiQhqfSCZb719Nh6Rqkp2zKK
To: /content/yellow_tripdata_2015-01.csv
1.99GB [00:32, 61.8MB/s]
```

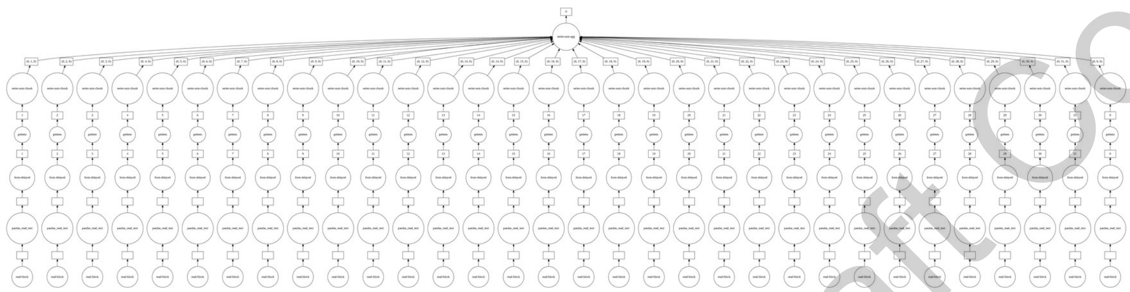
```
# However unlike Pandas, operations on dask.dataframes don't trigger
immediate computation,
# instead they add key-value pairs to an underlying Dask graph. Recall
that in the diagram below,
# circles are operations and rectangles are results.

# to see the visulaization you need to install graphviz
# pip3 install graphviz if this doesnt work please check the
```

```
install_graphviz.jpg in the drive
month.visualize()
```



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



Features in the dataset:

ML Problem Formulation

- To find number of pickups, given location cordinates(latitude and longitude) and time, in the query reigion and surrounding regions. To solve the above we would be using data collected in Jan - Mar 2015 to predict the pickups in Jan - Mar 2016.

Performance metrics

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

Data Cleaning

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

```
#table below shows few datapoints along with all our features
month = dd.read_csv('yellow_tripdata_2015-01.csv')
print(month.columns)
month.head(5)
```

```
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')

   VendorID tpep_pickup_datetime  ... improvement_surcharge
total_amount
0         2  2015-01-15 19:05:39  ...                   0.3
17.05
1         1  2015-01-10 20:33:38  ...                   0.3
17.80
2         1  2015-01-10 20:33:38  ...                   0.3
10.80
3         1  2015-01-10 20:33:39  ...                   0.3
4.80
4         1  2015-01-10 20:33:39  ...                   0.3
16.30

[5 rows x 19 columns]
```

1. Pickup Latitude and Pickup Longitude

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

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

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

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

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

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

```
folium.Marker(list((j['pickup_latitude'],j['pickup_longitude']))).add_
to(map_osm)
map_osm
```

```
<folium.folium.Map at 0x7f1f4c6484d0>
```

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

2. Dropoff Latitude & Dropoff Longitude

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

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

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

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

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

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

folium.Marker(list((j['dropoff_latitude'],j['dropoff_longitude']))).ad
d_to(map_osm)
map_osm
```

```
<folium.folium.Map at 0x7f1f43fdab10>
```

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

3. Trip Durations:

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

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



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

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

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

```
    return new_frame

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

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

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

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

0 percentile value is -1211.0166666666667
10 percentile value is 3.8333333333333335
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
```

```
#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
```

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

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

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

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

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

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

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

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

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

```
#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()
```

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

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

4. Speed

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

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

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

```
#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  192857142.857
```

```
#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  192857142.857
```

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

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

```
#removing further outliers based on the 99.9th percentile value
frame_with_durations_modified=frame_with_durations[(frame_with_duratio
ns.Speed>0) & (frame_with_durations.Speed<45.31)]
```

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

```
12.450173996027528
```

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

4. Trip Distance

```
# up to now we have removed the outliers based on trip durations and 
cab speeds
# lets try if there are any outliers in trip distances
# box-plot showing outliers in trip-distance values
```

```
sns.boxplot(y="trip_distance", data =frame_with_durations_modified)
plt.show()
```

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

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

```
#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
```

```
#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
```

```
#calculating trip distance values at each percntile
99.0,99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100
for i in np.arange(0.0, 1.0, 0.1):
```

```
    var =frame_with_durations_modified["trip_distance"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is
{}".format(99+i,var[int(len(var)*(float(99+i)/100))]))
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
```

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

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

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

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

5. Total Fare

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

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

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

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

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

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

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

```
99.9 percentile value is 95.55
100 percentile value is  3950611.6
```

Observation:- As even the 99.9th percentile value 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

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

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

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

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

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

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

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

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

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

Remove all outliers/erronous points.

```python
#removing all outliers based on our univariate analysis above
def remove_outliers(new_frame):


    a = new_frame.shape[0]
    print ("Number of pickup records = ",a)
    temp_frame = new_frame[((new_frame.dropoff_longitude >= -74.15) & 
(new_frame.dropoff_longitude <= -73.7004) &\
                       (new_frame.dropoff_latitude >= 40.5774) & 
(new_frame.dropoff_latitude <= 40.9176)) & \
                       ((new_frame.pickup_longitude >= -74.15) & 
(new_frame.pickup_latitude >= 40.5774)& \
                       (new_frame.pickup_longitude <= -73.7004) & 
(new_frame.pickup_latitude <= 40.9176))]
```

```
    b = temp_frame.shape[0]
    print ("Number of outlier coordinates lying outside NY 
boundaries:",(a-b))


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


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

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

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


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

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

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

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

```
Removing outliers in the month of Jan-2015
----
Number of pickup records =  12748986
Number of outlier coordinates lying outside NY boundaries: 293919
Number of outliers from trip times analysis: 23889
Number of outliers from trip distance analysis: 92597
Number of outliers from speed analysis: 24473
Number of outliers from fare analysis: 5275
Total outliers removed 377910
---
fraction of data points that remain after removing outliers
0.9703576425607495
```

Data-preperation

Clustering/Segmentation

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

def find_min_distance(cluster_centers, cluster_len):
    nice_points = 0
    wrong_points = 0
    less2 = []
    more2 = []
    min_dist=1000
    for i in range(0, cluster_len):
        nice_points = 0
        wrong_points = 0
        for j in range(0, cluster_len):
            if j!=i:
                distance =
gpxpy.geo.haversine_distance(cluster_centers[i][0], cluster_centers[i]
[1],cluster_centers[j][0], cluster_centers[j][1])
                min_dist = min(min_dist,distance/(1.60934*1000))
                if (distance/(1.60934*1000)) <= 2:
                    nice_points +=1
                else:
                    wrong_points += 1
        less2.append(nice_points)
```

```
        more2.append(wrong_points)
    neighbours.append(less2)
    print ("On choosing a cluster size of ",cluster_len,"\nAvg. Number
of Clusters within the vicinity (i.e. intercluster-distance < 2):",
np.ceil(sum(less2)/len(less2)), "\nAvg. Number of Clusters outside the
vicinity (i.e. intercluster-distance > 2):",
np.ceil(sum(more2)/len(more2)),"\nMin inter-cluster distance =
",min_dist,"\n---")

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

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

```
On choosing a cluster size of  10
Avg. Number of Clusters within the vicinity (i.e. intercluster-
distance < 2): 2.0
Avg. Number of Clusters outside the vicinity (i.e. intercluster-
distance > 2): 8.0
Min inter-cluster distance =  1.0933194607372518
---
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 =  0.7123318236197774
---
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 =  0.5179286172497254
---
On choosing a cluster size of  40
Avg. Number of Clusters within the vicinity (i.e. intercluster-
```

```
distance < 2): 9.0
Avg. Number of Clusters outside the vicinity (i.e. intercluster-
distance > 2): 31.0
Min inter-cluster distance =  0.5064095487015858
---
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 =  0.36495419250817024
---
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 =  0.346654501371586
---
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 =  0.30468071844965394
---
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 =  0.29187627608454664
---
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 =  0.18237562550345013
---
```

Inference:

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

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

# Getting 40 clusters using the kmeans
kmeans = MiniBatchKMeans(n_clusters=40,
```

```
batch_size=10000,random_state=0).fit(coords)
frame_with_durations_outliers_removed['pickup_cluster'] =
kmeans.predict(frame_with_durations_outliers_removed[['pickup_latitude
', 'pickup_longitude']])
```

Plotting the cluster centers:

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

```
<folium.folium.Map at 0x1128295c0>
```

Plotting the clusters:

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

plot_clusters(frame_with_durations_outliers_removed)
```

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

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

Time-binning

```
#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
```

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

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

[1451606400,1454284800,1456790400,1459468800,1462060800,1464739200]]

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

# clustering, making pickup bins and grouping by pickup cluster and
pickup bins
frame_with_durations_outliers_removed['pickup_cluster'] =
kmeans.predict(frame_with_durations_outliers_removed[['pickup_latitude
', 'pickup_longitude']])
jan_2015_frame =
add_pickup_bins(frame_with_durations_outliers_removed,1,2015)
jan_2015_groupby =
jan_2015_frame[['pickup_cluster','pickup_bins','trip_distance']].group
by(['pickup_cluster','pickup_bins']).count()

# 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()
```

```
   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  1.421329e+09   5.285319              34         2130
1  1.420902e+09   9.983193               2         1419
2  1.420902e+09  10.746269              16         1419
3  1.420902e+09  16.071429              38         1419
4  1.420902e+09   9.318378              22         1419

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

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

# upto now we cleaned data and prepared data for the month 2015,

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

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

    print ("Return with trip times..")

    frame_with_durations = return_with_trip_times(month)
```

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

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

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

    return final_updated_frame,final_groupby_frame

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

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

```
Return with trip times..
Remove outliers..
Number of pickup records =  10906858
Number of outlier coordinates lying outside NY boundaries: 214677
Number of outliers from trip times analysis: 27190
Number of outliers from trip distance analysis: 79742
Number of outliers from speed analysis: 21047
Number of outliers from fare analysis: 4991
Total outliers removed 297784
---
Estimating clusters..
Final groupbying..
Return with trip times..
Remove outliers..
Number of pickup records =  11382049
Number of outlier coordinates lying outside NY boundaries: 223161
```

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

Smoothing

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

# for each cluster region we will collect all the indices of 10min intravels in which the pickups are happened
# 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

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

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

#feb
feb_2016_unique = return_unq_pickup_bins(feb_2016_frame)

#march
mar_2016_unique = return_unq_pickup_bins(mar_2016_frame)
```

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

```
for the  0 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  1 th cluster number of 10min intavels with zero pickups:
1986
------------------------------------------------------------
for the  2 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  3 th cluster number of 10min intavels with zero pickups:  355
------------------------------------------------------------
for the  4 th cluster number of 10min intavels with zero pickups:  38
------------------------------------------------------------
for the  5 th cluster number of 10min intavels with zero pickups:  154
------------------------------------------------------------
for the  6 th cluster number of 10min intavels with zero pickups:  35
------------------------------------------------------------
for the  7 th cluster number of 10min intavels with zero pickups:  34
------------------------------------------------------------
for the  8 th cluster number of 10min intavels with zero pickups:  118
------------------------------------------------------------
for the  9 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  10 th cluster number of 10min intavels with zero pickups:  26
------------------------------------------------------------
for the  11 th cluster number of 10min intavels with zero pickups:  45
------------------------------------------------------------
for the  12 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  13 th cluster number of 10min intavels with zero pickups:  29
------------------------------------------------------------
for the  14 th cluster number of 10min intavels with zero pickups:  27
------------------------------------------------------------
for the  15 th cluster number of 10min intavels with zero pickups:  32
------------------------------------------------------------
for the  16 th cluster number of 10min intavels with zero pickups:  41
------------------------------------------------------------
for the  17 th cluster number of 10min intavels with zero pickups:  59
------------------------------------------------------------
for the  18 th cluster number of 10min intavels with zero pickups:
1191
------------------------------------------------------------
for the  19 th cluster number of 10min intavels with zero pickups:
1358
------------------------------------------------------------
for the  20 th cluster number of 10min intavels with zero pickups:  54
```

```
------------------------------------------------------------
for the  21 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  22 th cluster number of 10min intavels with zero pickups:  30
------------------------------------------------------------
for the  23 th cluster number of 10min intavels with zero pickups:  
164
------------------------------------------------------------
for the  24 th cluster number of 10min intavels with zero pickups:  36
------------------------------------------------------------
for the  25 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  26 th cluster number of 10min intavels with zero pickups:  32
------------------------------------------------------------
for the  27 th cluster number of 10min intavels with zero pickups:  
215
------------------------------------------------------------
for the  28 th cluster number of 10min intavels with zero pickups:  37
------------------------------------------------------------
for the  29 th cluster number of 10min intavels with zero pickups:  42
------------------------------------------------------------
for the  30 th cluster number of 10min intavels with zero pickups:  
1181
------------------------------------------------------------
for the  31 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  32 th cluster number of 10min intavels with zero pickups:  45
------------------------------------------------------------
for the  33 th cluster number of 10min intavels with zero pickups:  44
------------------------------------------------------------
for the  34 th cluster number of 10min intavels with zero pickups:  40
------------------------------------------------------------
for the  35 th cluster number of 10min intavels with zero pickups:  43
------------------------------------------------------------
for the  36 th cluster number of 10min intavels with zero pickups:  37
------------------------------------------------------------
for the  37 th cluster number of 10min intavels with zero pickups:  
322
------------------------------------------------------------
for the  38 th cluster number of 10min intavels with zero pickups:  37
------------------------------------------------------------
for the  39 th cluster number of 10min intavels with zero pickups:  44
------------------------------------------------------------
```

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)

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

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

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

# for every 10min intravel(pickup_bin) we will check it is there in our unique bin,
# if it is there we will add the count_values[index] to smoothed data
# if not we add smoothed data (which is calculated based on the methods that are discussed in the above markdown cell)
# we finally return smoothed data
def smoothing(count_values,values):
    smoothed_regions=[] # stores list of final smoothed values of each reigion
    ind=0
    repeat=0
    smoothed_value=0
    for r in range(0,40):
        smoothed_bins=[] #stores the final smoothed values
        repeat=0
        for i in range(4464):
```

```
            if repeat!=0: # prevents iteration for a value which is 
already visited/resolved
                repeat-=1
                continue
            if i in values[r]: #checks if the pickup-bin exists
                smoothed_bins.append(count_values[ind]) # appends the 
value of the pickup bin if it exists
            else:
                if i!=0:
                    right_hand_limit=0
                    for j in range(i,4464):
                        if  j not in values[r]: #searches for the 
left-limit or the pickup-bin value which has a pickup value
                            continue
                        else:
                            right_hand_limit=j
                            break
                    if right_hand_limit==0:
                    #Case 1: When we have the last/last few values are 
found to be missing,hence we have no right-limit here
                        smoothed_value=count_values[ind-1]*1.0/((4463-
i)+2)*1.0
                        for j in range(i,4464):
                            
smoothed_bins.append(math.ceil(smoothed_value))
                        smoothed_bins[i-1] = math.ceil(smoothed_value)
                        repeat=(4463-i)
                        ind-=1
                    else:
                    #Case 2: When we have the missing values between 
two known values
                        smoothed_value=(count_values[ind-
1]+count_values[ind])*1.0/((right_hand_limit-i)+2)*1.0
                        for j in range(i,right_hand_limit+1):
                            
smoothed_bins.append(math.ceil(smoothed_value))
                        smoothed_bins[i-1] = math.ceil(smoothed_value)
                        repeat=(right_hand_limit-i)
                else:
                    #Case 3: When we have the first/first few values 
are found to be missing,hence we have no left-limit here
                    right_hand_limit=0
                    for j in range(i,4464):
                        if  j not in values[r]:
                            continue
                        else:
                            right_hand_limit=j
                            break
```

```
smoothed_value=count_values[ind]*1.0/((right_hand_limit-i)+1)*1.0
                    for j in range(i,right_hand_limit+1):

smoothed_bins.append(math.ceil(smoothed_value))
                    repeat=(right_hand_limit-i)
            ind+=1
        smoothed_regions.extend(smoothed_bins)
    return smoothed_regions

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

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

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

number of 10min intravels among all the clusters  178560

# 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()

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# why we choose, these methods and which method is used for which
data?

# Ans: consider we have data of some month in 2015 jan 1st, 10 _ _ _
20, i.e there are 10 pickups that are happened in 1st
# 10st 10min intravel, 0 pickups happened in 2nd 10mins intravel, 0
pickups happened in 3rd 10min intravel
# and 20 pickups happened in 4th 10min intravel.
```

```
# in fill_missing method we replace these values like 10, 0, 0, 20
# where as in smoothing method we replace these values as 6,6,6,6,6,
if you can check the number of pickups
# that are happened in the first 40min are same in both cases, but if
you can observe that we looking at the future values
# wheen you are using smoothing we are looking at the future number of
pickups which might cause a data leakage.

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

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

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

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

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

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

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

Time series and Fourier Transforms

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

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

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

Modelling: Baseline Models

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

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

Simple Moving Averages

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

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

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


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

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

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

```
def MA_P_Predictions(ratios,month):
    predicted_value=(ratios['Prediction'].values)[0]
    error=[]
```

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

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

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

Weighted Moving Averages

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

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

```
def WA_R_Predictions(ratios,month):
    predicted_ratio=(ratios['Ratios'].values)[0]
    alpha=0.5
    error=[]
    predicted_values=[]
    window_size=5
    predicted_ratio_values=[]
    for i in range(0,4464*40):
        if i%4464==0:
            predicted_ratio_values.append(0)
            predicted_values.append(0)
            error.append(0)
            continue
```

```
        predicted_ratio_values.append(predicted_ratio)
        predicted_values.append(int(((ratios['Given'].values)
[i])*predicted_ratio))
        error.append(abs((math.pow(int(((ratios['Given'].values)
[i])*predicted_ratio)-(ratios['Prediction'].values)[i],1))))
        if i+1>=window_size:
            sum_values=0
            sum_of_coeff=0
            for j in range(window_size,0,-1):
                sum_values += j*(ratios['Ratios'].values)[i-
window_size+j]
                sum_of_coeff+=j
            predicted_ratio=sum_values/sum_of_coeff
        else:
            sum_values=0
            sum_of_coeff=0
            for j in range(i+1,0,-1):
                sum_values += j*(ratios['Ratios'].values)[j-1]
                sum_of_coeff+=j
            predicted_ratio=sum_values/sum_of_coeff

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

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

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

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

```
                sum_values += j*(ratios['Prediction'].values)[i-window_size+j]
                sum_of_coeff+=j
            predicted_value=int(sum_values/sum_of_coeff)

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

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

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

Exponential Weighted Moving Averages

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

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

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

```
def EA_R1_Predictions(ratios,month):
    predicted_ratio=(ratios['Ratios'].values)[0]
    alpha=0.6
```

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

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

$$P_t^{'}=\alpha*P_{t-1}+(1-\alpha)*P_{t-1}^{'}$$

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

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

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

Comparison between baseline models

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

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

```
Error Metric Matrix (Forecasting Methods) - MAPE & MSE
----------------------------------------------------------------------
----------------------------------
```

```
Moving Averages (Ratios) -                              MAPE:
0.182115517339       MSE:  400.0625504032258
Moving Averages (2016 Values) -                         MAPE:
0.14292849687        MSE:  174.84901993727598
----------------------------------------------------------------------
---------------------------------
Weighted Moving Averages (Ratios) -                     MAPE:
0.178486925438       MSE:  384.01578741039424
Weighted Moving Averages (2016 Values) -                MAPE:
0.135510884362       MSE:  162.46707549283155
----------------------------------------------------------------------
---------------------------------
Exponential Moving Averages (Ratios) -               MAPE:
0.177835501949       MSE:  378.34610215053766
Exponential Moving Averages (2016 Values) -          MAPE:
0.135091526367       MSE:  159.73614471326164
```

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

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

Regression Models

Train-Test Split

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

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

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

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

# output varaible
```

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


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


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

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

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


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

```
[x1,x2,x3..x13104], .. 40 lsits]
    tsne_feature = np.vstack((tsne_feature, [regions_cum[i]
[r:r+number_of_time_stamps] for r in range(0,len(regions_cum[i])-
number_of_time_stamps)]))
    output.append(regions_cum[i][5:])
tsne_feature = tsne_feature[1:]

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

True

# Getting the predictions of exponential moving averages to be used as
a feature in cumulative form

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

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

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

# it is similar like tsne_lat
# it is list of lists
# predict_list is a list of lists [[x5,x6,x7..x13104],
[x5,x6,x7..x13104], [x5,x6,x7..x13104], [x5,x6,x7..x13104],
```

```
[x5,x6,x7..x13104], .. 40 lsits]
predict_list = []
tsne_flat_exp_avg = []
for r in range(0,40):
    for i in range(0,13104):
        if i==0:
            predicted_value= regions_cum[r][0]
            predicted_values.append(0)
            continue
        predicted_values.append(predicted_value)
        predicted_value =int((alpha*predicted_value) + (1-
alpha)*(regions_cum[r][i]))
    predict_list.append(predicted_values[5:])
    predicted_values=[]
```

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

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

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

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

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

```
# extracting first 9169 timestamp values i.e 70% of 13099 (total
timestamps) for our training data
tsne_train_flat_lat = [i[:9169] for i in tsne_lat]
```

```
tsne_train_flat_lon = [i[:9169] for i in tsne_lon]
tsne_train_flat_weekday = [i[:9169] for i in tsne_weekday]
tsne_train_flat_output = [i[:9169] for i in output]
tsne_train_flat_exp_avg = [i[:9169] for i in predict_list]

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

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

# 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,[])

# 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,[])

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

```
print(df_train.shape)
```

```
(366760, 9)
```

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

```
(157200, 9)
```

```
df_test.head()
```

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

Using Linear Regression

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

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

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

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

Using Random Forest Regressor

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

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

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

RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='sqrt', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=4, min_samples_split=3,
           min_weight_fraction_leaf=0.0, n_estimators=40, n_jobs=-1,
```

```
           oob_score=False, random_state=None, verbose=0,
warm_start=False)

# Predicting on test data using our trained random forest model

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

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

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

Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'lat', 'lon',
'weekday',
       'exp_avg'],
      dtype='object')
[ 0.00477243  0.07614745  0.14289548  0.1857027   0.23859285
0.00227886
  0.00261956  0.00162121  0.34536947]
```

Using XgBoost Regressor

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

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

# colsample_bylevel=1, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
base_score=0.5, random_state=0, seed=None,
# missing=None, **kwargs)

# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None,
early_stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep]) Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with
data. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
```

```python
# ----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
# ----------------------

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

```
XGBRegressor(base_score=0.5, colsample_bylevel=1,
colsample_bytree=0.8,
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=3, missing=None, n_estimators=1000, nthread=4,
       objective='reg:linear', reg_alpha=200, reg_lambda=200,
       scale_pos_weight=1, seed=0, silent=True, subsample=0.8)
```

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

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

```python
#feature importances
x_model.booster().get_score(importance_type='weight')
```

```
{'exp_avg': 806,
 'ft_1': 1008,
 'ft_2': 1016,
 'ft_3': 863,
 'ft_4': 746,
 'ft_5': 1053,
 'lat': 602,
 'lon': 612,
 'weekday': 195}
```

Calculating the error metric values for various models

```python
train_mape=[]
test_mape=[]
```

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

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

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

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
--------------------------------------------------------------------------------------------------------
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
```

Error Metric Matrix

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

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

Assignments

```
'''
Task 1: Incorporate Fourier features as features into Regression
models and measure MAPE. <br>

Task 2: Perform hyper-parameter tuning for Regression models.
        2a. Linear Regression: Grid Search
        2b. Random Forest: Random Search
        2c. Xgboost: Random Search
Task 3: Explore more time-series features using Google
search/Quora/Stackoverflow
to reduce the MAPE to < 12%
'''
```

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