Taxi demand prediction in New York City

In [1]:
```
# Running in Google Colab
from google.colab import drive
drive.mount('/gdrive')
%cd /gdrive/My\ Drive/Data_Notebooks
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code (https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code)

Enter your authorization code:
··········
Mounted at /gdrive
/gdrive/My Drive/Data_Notebooks
```

Removing all EDA Cells and plotting cells and directly adding features and cleaning the data.

In [2]:

```
!pip install gpxpy
import dask.dataframe as dd

import pandas as pd

import folium

import datetime

import time

import numpy as np

import matplotlib
matplotlib.use('nbagg')
import matplotlib.pylab as plt
import seaborn as sns
from matplotlib import rcParams

import gpxpy.geo

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

import xgboost as xgb

from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import warnings
warnings.filterwarnings("ignore")
```

```
Collecting gpxpy
  Downloading https://files.pythonhosted.org/packages/6e/d3/ce52e67771929de455e76655365a4935a2f369f76dfb0d70c20a308ec463/gpxpy-1.3.5.tar.gz (https://files.pythonhosted.org/packages/6e/d3/ce52e67771929de455e76655365a4935a2f369f76dfb0d70c20a308ec463/gpxpy-1.3.5.tar.gz) (105kB)
     |████████████████████████████████| 112kB 2.8MB/s
Building wheels for collected packages: gpxpy
  Building wheel for gpxpy (setup.py) ... done
  Created wheel for gpxpy: filename=gpxpy-1.3.5-cp36-none-any.whl size=40315 sha256=b18a631aa6b0a64fdc3971423d8aeb804f5297db5667627654801c7c90519a65
  Stored in directory: /root/.cache/pip/wheels/d2/f0/5e/b8e85979e66efec3eaa0e47fbc5274db99fd1a07befd1b2aa4
Successfully built gpxpy
Installing collected packages: gpxpy
Successfully installed gpxpy-1.3.5
```

In [3]:

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

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

Trip Durations:

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

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

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

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

Remove all outliers/erronous points.

Outliers are removed based on the EDA done in original notebook.

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


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

```
                        (new_frame.pickup_longitude <= -73.7004) & (new_frame.pickup_latitud

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

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

In [6]:

```
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_d
```

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

Data-preperation

Clustering/Segmentation

In [0]:

```
#trying different cluster sizes to choose the right K in K-means
coords = frame_with_durations_outliers_removed[['pickup_latitude', 'pickup_longitude']].val
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_cent
                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 t

def find_clusters(increment):
    kmeans = MiniBatchKMeans(n_clusters=increment, batch_size=10000,random_state=42).fit(co
    frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_dur
    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)
```

Getting clusters for k=30

In [0]:
```
# Getting 30 clusters using the kmeans
kmeans = MiniBatchKMeans(n_clusters=30, batch_size=10000,random_state=0).fit(coords)
frame_with_durations_outliers_removed['pickup_cluster'] = kmeans.predict(frame_with_duratio
```

Time-binning

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

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

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

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

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

In [11]:
```
# hear the trip_distance represents the number of pickups that are happend in that particul
# 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*60/1
jan_2015_groupby.head()
```

Out[11]:

		trip_distance
pickup_cluster	**pickup_bins**	
0	**33**	138
	34	262
	35	311
	36	325
	37	381

In [12]:
```
# 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_dur
    #frame_with_durations_outliers_removed_2016['pickup_cluster'] = kmeans.predict(frame_wi

    print ("Final groupbying..")
    final_updated_frame = add_pickup_bins(frame_with_durations_outliers_removed,month_no,ye
    final_groupby_frame = final_updated_frame[['pickup_cluster','pickup_bins','trip_distanc

    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

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

# for each cluster region we will collect all the indices of 10min intravels in which the p
# 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(0,30):
        new = frame[frame['pickup_cluster'] == i]
        list_unq = list(set(new['pickup_bins']))
        list_unq.sort()
        values.append(list_unq)
    return values
```

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

#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)
```

there are two ways to fill up these values

- Fill the missing value with 0's
- Fill the missing values with the avg values
    - Case 1:(values missing at the start)
      Ex1: _ _ _ x =>ceil(x/4), ceil(x/4), ceil(x/4), ceil(x/4)
      Ex2: _ _ x => ceil(x/3), ceil(x/3), ceil(x/3)
    - Case 2:(values missing in middle)
      Ex1: x _ _ y => ceil((x+y)/4), ceil((x+y)/4), ceil((x+y)/4), ceil((x+y)/4)
      Ex2: x _ _ _ y => ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5), ceil((x+y)/5)
    - Case 3:(values missing at the end)
      Ex1: x _ _ _ => ceil(x/4), ceil(x/4), ceil(x/4), ceil(x/4)
      Ex2: x _ => ceil(x/2), ceil(x/2)

In [0]:
```
# Fills a value of zero for every bin where no pickup data is present
# the count_values: number pickps that are happened in each region for each 10min 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(0,30):
        smoothed_bins=[]
        for i in range(4464):
            if i in values[r]:
                smoothed_bins.append(count_values[ind])
                ind+=1
            else:
                smoothed_bins.append(0)
        smoothed_regions.extend(smoothed_bins)
    return smoothed_regions
```

In [0]:
```
# Fills a value of zero for every bin where no pickup data is present
# the count_values: number 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
# 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(0,30):
        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/resolve
                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 b
            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-
                            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,
                        smoothed_value=count_values[ind-1]*1.0/((4463-i)+2)*1.0
```

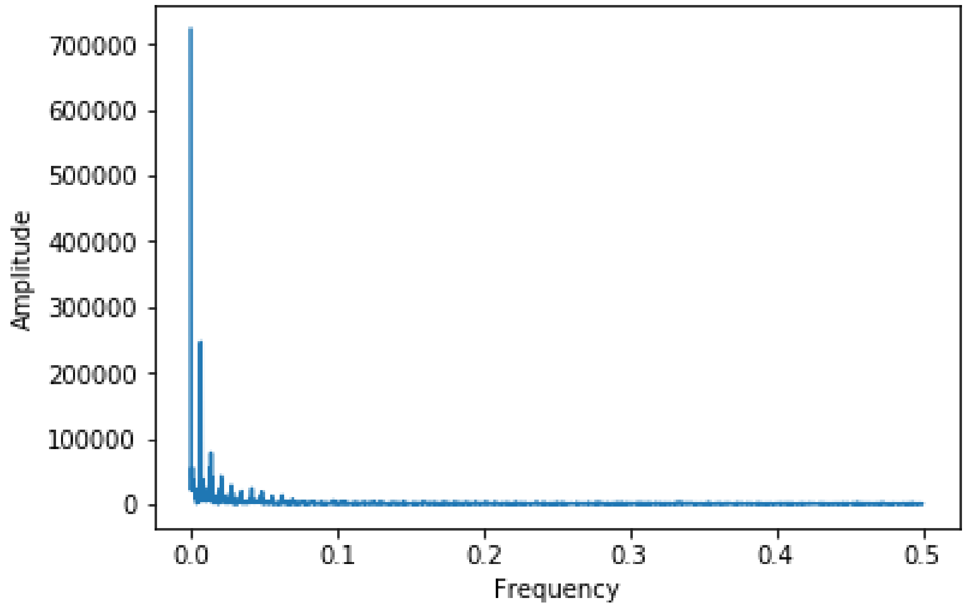
```
                    for j in range(i,4464):
                        smoothed_bins.append(math.ceil(smoothed_value))
                    smoothed_bins[i-1] = math.ceil(smoothed_value)
                    repeat=(4463-i)
                    ind-=1
                else:
                #Case 2: When we have the missing values between two known values
                    smoothed_value=(count_values[ind-1]+count_values[ind])*1.0/((right_
                    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 missin
                right_hand_limit=0
                for j in range(i,4464):
                    if  j not in values[r]:
                        continue
                    else:
                        right_hand_limit=j
                        break
                smoothed_value=count_values[ind]*1.0/((right_hand_limit-i)+1)*1.0
                for j in range(i,right_hand_limit+1):
                        smoothed_bins.append(math.ceil(smoothed_value))
                repeat=(right_hand_limit-i)
        ind+=1
    smoothed_regions.extend(smoothed_bins)
return smoothed_regions
```

In [0]:
```
# 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 st
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
# that are happened for three months in 2016 data

for i in range(0,30):
    regions_cum.append(jan_2016_smooth[4464*i:4464*(i+1)]+feb_2016_smooth[4176*i:4176*(i+1)

# print(len(regions_cum))
# 30
# print(len(regions_cum[0]))
# 13104
```

Time series and Fourier Transforms

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

In [19]:
```
# 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
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.f
freq = np.fft.fftfreq(4460, 1)
n = len(freq)
plt.figure()
plt.plot( freq[:int(n/2)], np.abs(Y)[:int(n/2)] )
plt.xlabel("Frequency")
plt.ylabel("Amplitude")
plt.show()
```



In [20]:
```
freq_amp_df = pd.DataFrame(np.array([np.abs(np.real(freq)), np.abs(Y)]).T, columns=['freq',
freq_amp_df.drop_duplicates(inplace=True)
freq_amp_df.sort_values('amp', ascending=False, inplace=True)
freq_amp_df.head()
```

Out[20]:

	freq	amp
0	0.000000	722007.000000
31	0.006951	246726.577980
4398	0.013901	78143.938628
62	0.013901	78143.938628
4402	0.013004	55749.451715

In [21]:
```
freq_amp_df = freq_amp_df.head()
print(freq_amp_df)
```

```
          freq            amp
0     0.000000  722007.000000
31    0.006951  246726.577980
4398  0.013901   78143.938628
62    0.013901   78143.938628
4402  0.013004   55749.451715
```

Calculating Fourier data for every 10-min interval

For each 10-min interval I take prev 7 days data = 1000 rows (~10080 minutes) and find fft values to add fourier features at that 10-min interval. I will take top 5 frequencies and amplitudes and add them to the matrix. So my final `fft_data` matrix size will be 30 * DF(13104 * 10)

In [22]:

```
freq_amp_cols = []
for i in range(5):
  freq_amp_cols.append('freq_'+str(i))
  freq_amp_cols.append('amp_'+str(i))

print(freq_amp_cols)
```

```
['freq_0', 'amp_0', 'freq_1', 'amp_1', 'freq_2', 'amp_2', 'freq_3', 'amp_3', 'freq_4', 'a
mp_4']
```

In [23]:

```
fft_data = []
ind = 0
for reg in regions_cum:
  print(f'cluster {ind} started..')
  fft_data_reg = pd.DataFrame(columns = freq_amp_cols)
  fft_data_reg.loc[0] = [0]*10
  for i in range(1, 13104):
    left_ind = max(0, i-1000)
    Y    = np.fft.fft(np.array(reg)[left_ind:i])
    freq = np.fft.fftfreq(len(Y), 1)
    freq_amp_df = pd.DataFrame(np.array([np.abs(np.real(freq)), np.abs(Y)]).T, columns=['fr
    freq_amp_df.drop_duplicates(inplace=True)
    freq_amp_df.sort_values('amp', ascending=False, inplace=True)
    freq_amp_df = freq_amp_df.head()
    freq_amp_df = freq_amp_df.values.flatten()
    if len(freq_amp_df)<10:
      extra_zeros = [0]*(10-len(freq_amp_df))
      freq_amp_df = np.append(freq_amp_df, [extra_zeros])
    fft_data_reg.loc[i] = freq_amp_df
  fft_data.append(fft_data_reg)
  print(f'cluster {ind} ended..')
  ind = ind+1
```

...

In [24]:
```
print(len(fft_data))
print(fft_data[0].shape)
```

```
30
(13104, 10)
```

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

Not Running baseline models except exponential weighted average because it is used in the final model and not using ratios in the final model as they are not providing as good results as previous day`s values.

Regression Models

Train-Test Split

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

In [0]:
```
# Preparing data to be split into train and test, The below prepares data in cumulative for
# 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
# 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 th
# 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 10
# 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(0,30):
    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
    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..x1
    tsne_feature = np.vstack((tsne_feature, [regions_cum[i][r:r+number_of_time_stamps] for
    output.append(regions_cum[i][5:])
tsne_feature = tsne_feature[1:]
```

In [27]:
```
len(tsne_lat[0])*len(tsne_lat) == tsne_feature.shape[0] == len(tsne_weekday)*len(tsne_weekd
```

Out[27]:
```
True
```

Exponential moving averages

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

# 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 bes
# we will try to add the same exponential weighted moving avarage at t as a feature to our
# 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 int
# 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..x1310
predict_list = []
tsne_flat_exp_avg = []
for r in range(0,30):
    for i in range(0,13104):
        if i==0:
            predicted_value= regions_cum[r][0]
            predicted_values.append(0)
            continue
        predicted_values.append(predicted_value)
        predicted_value =int((alpha*predicted_value) + (1-alpha)*(regions_cum[r][i]))
```

```
    predict_list.append(predicted_values[5:])
    predicted_values=[]
```

In [29]:
```
for i in range(30):
  fft_data[i] = fft_data[i][5:]
print(len(fft_data))
print(fft_data[0].shape)
```

```
30
(13099, 10)
```

In [30]:
```
# train, test split : 70% 30% split
# Before we start predictions using the tree based regression models we take 3 months of 20
# and split it such that for every region we have 70% data in train and 30% in test,
# ordered date-wise for every region
print("size of train data :", int(13099*0.7))
print("size of test data :", int(13099*0.3))
```

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

In [0]:
```
# extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) for our traini
train_features =  [tsne_feature[i*13099:(13099*i+9169)] for i in range(0,30)]
# temp = [0]*(12955 - 9068)
test_features = [tsne_feature[(13099*(i))+9169:13099*(i+1)] for i in range(0,30)]
```

In [32]:
```
print("Number of data clusters",len(train_features), "Number of data points in trian data",
print("Number of data clusters",len(train_features), "Number of data points in test data",
```

```
Number of data clusters 30 Number of data points in trian data 9169 Each data point conta
ins 5 features
Number of data clusters 30 Number of data points in test data 3930 Each data point contai
ns 5 features
```

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

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

In [0]:
```
fft_train_data = [i[:9169] for i in fft_data]
fft_test_data = [i[9169:] for i in fft_data]
```

In [0]:

```
# the above contains values in the form of list of lists (i.e. list of values of each regio
train_new_features = []
for i in range(0,30):
    train_new_features.extend(train_features[i])
test_new_features = []
for i in range(0,30):
    test_new_features.extend(test_features[i])
```

In [37]:

```
fft_train_data = pd.concat(fft_train_data, ignore_index=True)
fft_test_data = pd.concat(fft_test_data, ignore_index=True)
print(fft_train_data.shape)
print(fft_test_data.shape)
```

```
(275070, 10)
(117900, 10)
```

In [0]:

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

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

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

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

In [40]:
```
columns = ['ft_5','ft_4','ft_3','ft_2','ft_1']
df_train = pd.DataFrame(data=train_new_features, columns=columns)
sum(df_train.index == fft_train_data.index)
```

Out[40]:
```
275070
```

In [0]:
```
df_train_clusters = np.array([[i]*9169 for i in range(30)]).flatten()
df_test_clusters = np.array([[i]*3930 for i in range(30)]).flatten()
```

In [42]:
```
# 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 = pd.concat([df_train, fft_train_data], axis=1)
df_train['lat'] = tsne_train_lat
df_train['lon'] = tsne_train_lon
df_train['weekday'] = tsne_train_weekday
df_train['exp_avg'] = tsne_train_exp_avg
df_train['cluster_id'] = df_train_clusters

print(df_train.shape)
```

```
(275070, 20)
```

In [43]:
```
# Preparing the data frame for our train data
df_test = pd.DataFrame(data=test_new_features, columns=columns)
df_test = pd.concat([df_test, fft_test_data], axis=1)
df_test['lat'] = tsne_test_lat
df_test['lon'] = tsne_test_lon
df_test['weekday'] = tsne_test_weekday
df_test['exp_avg'] = tsne_test_exp_avg
df_test['cluster_id'] = df_test_clusters

print(df_test.shape)
```

```
(117900, 20)
```

In [44]:
```
df_test.head()
```

Out[44]:

	ft_5	ft_4	ft_3	ft_2	ft_1	freq_0	amp_0	freq_1	amp_1	freq_2	amp_2	freq_3	amp_3	freq_4	amp_
0	271	270	238	269	260	0	178108	0.007	64807.8	0.014	24480.6	0.014	24480.6	0.021	16455.
1	270	238	269	260	281	0	178150	0.007	64845.1	0.007	64845.1	0.014	24469	0.021	16418.
2	238	269	260	281	264	0	178190	0.007	64881.4	0.014	24454.6	0.021	16380.7	0.001	14849.
3	269	260	281	264	286	0	178228	0.007	64916.5	0.007	64916.5	0.014	24437.9	0.021	16343.
4	260	281	264	286	280	0	178249	0.007	64936.3	0.014	24427.1	0.021	16322.7	0.021	16322.

Assignments

In [45]:
```
'''
Task 1: Incorporate Fourier features as features into Regression models and measure MAPE. <

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%
'''
```

...

As fourier features are included in data in above code blocks, we can go ahead and do second Task.

Using Linear Regression

Before Running linear regression we can see some columns are not linearly related to the output values. Those are cluster_id, weekday, and even latitude and longitude. So it makes sense to encode them before running. We can remove latitude, longitude and cluster id and replace them with one-hot encoding of cluster id. And we can onehot encode the weekday column as well. As our model is Linear regression we can have more dimensions which will not affect our performance. For other tree based models we can neglect encoding for such features.

Creating new dataframe for training linear regression and adding onehot encoded data into it.

In [0]:
```
from sklearn.preprocessing import OneHotEncoder
```

In [47]:
```
onehotcoder = OneHotEncoder()
onehotcoder.fit(df_train[['weekday', 'cluster_id']])
# should be 30+7 = 37
print(len(onehotcoder.get_feature_names()))
```

```
37
```

In [0]:
```
df_ohe_train = onehotcoder.transform(df_train[['weekday', 'cluster_id']])
df_ohe_test = onehotcoder.transform(df_test[['weekday', 'cluster_id']])
```

In [0]:
```
from scipy import sparse
```

In [0]:
```
for i in df_train.columns:
  df_train[i] = pd.to_numeric(df_train[i])
  df_test[i] = pd.to_numeric(df_test[i])
```

In [51]:
```
df_lr_train = df_train.drop(['weekday', 'lat', 'lon', 'cluster_id'], axis=1)
df_lr_test = df_test.drop(['weekday', 'lat', 'lon', 'cluster_id'], axis=1)

df_lr_train = sparse.hstack([df_lr_train.values, df_ohe_train])
df_lr_test = sparse.hstack([df_lr_test.values, df_ohe_test])
# number of columns = 20-4+37 = 53
print(df_lr_train.shape)
print(df_lr_test.shape)
```

```
(275070, 53)
(117900, 53)
```

In [0]:
```
def calc_MAPE(y_true, y_predict):
  return mean_absolute_error(y_true, y_predict)/(sum(y_true)/len(y_true))
```

In [53]:
```
# find more about LinearRegression function here http://scikit-learn.org/stable/modules/gen
# -------------------------
# default paramters
# sklearn.linear_model.LinearRegression(fit_intercept=True, normalize=False, copy_X=True, n

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

from sklearn.linear_model import LinearRegression

print("With normalize = False:")
lr_reg=LinearRegression()
print(lr_reg.get_params())
lr_reg.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]

print(f'train MAPE: {calc_MAPE(tsne_train_output, lr_train_predictions)}')
print(f'test MAPE: {calc_MAPE(tsne_test_output, lr_test_predictions)}')

print("\n\nWith normalize = True:")
lr_reg=LinearRegression(normalize=True)
print(lr_reg.get_params())
lr_reg.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]

print(f'train MAPE: {calc_MAPE(tsne_train_output, lr_train_predictions)}')
print(f'test MAPE: {calc_MAPE(tsne_test_output, lr_test_predictions)}')
```

```
With normalize = False:
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize': False}
train MAPE: 0.12530635199192275
test MAPE: 0.11904826253585739


With normalize = True:
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize': True}
train MAPE: 0.12530635199192275
test MAPE: 0.11904826253585739
```

Input for linear regression is changed. The features which are meant to be categorical are changed to onehot encodings, as increase in dimensions is not a problem for linear regression. I didnt find any hyper-parameters for sklearn's LinearRegression .For both "with normalize" and "without normalize" the MAPE values are same. And the test MAPE value dropped below 12% for this model which is very good.

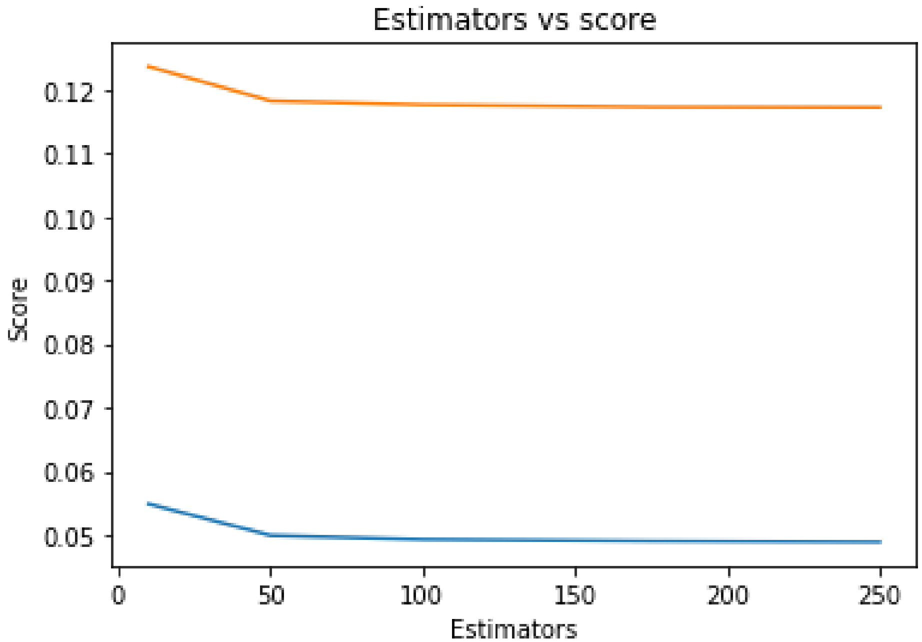
Using Random Forest Regressor

In [0]:
```
from scipy.stats import randint as sp_randint
from scipy.stats import uniform
```

In [55]:
```
estimators = [10,50,100,175,250]
train_scores = []
test_scores = []
for i in estimators:
  clf = RandomForestRegressor(n_estimators=i, min_samples_split=4, n_jobs=-1)
  clf.fit(df_train, tsne_train_output)
  train_sc = calc_MAPE(tsne_train_output,clf.predict(df_train))
  test_sc = calc_MAPE(tsne_test_output,clf.predict(df_test))
  test_scores.append(test_sc)
  train_scores.append(train_sc)
  print('Estimators = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(estimators,train_scores,label='Train Score')
plt.plot(estimators,test_scores,label='Test Score')
plt.xlabel('Estimators')
plt.ylabel('Score')
plt.title('Estimators vs score')
```

```
Estimators =  10 Train Score 0.054882891508404835 test Score 0.12356400094386034
Estimators =  50 Train Score 0.04996592943741556 test Score 0.11817462886896045
Estimators =  100 Train Score 0.04933770553814925 test Score 0.11756832532532893
Estimators =  175 Train Score 0.04908163876495708 test Score 0.1172080135892906
Estimators =  250 Train Score 0.04893984310310891 test Score 0.11714684101278983
```

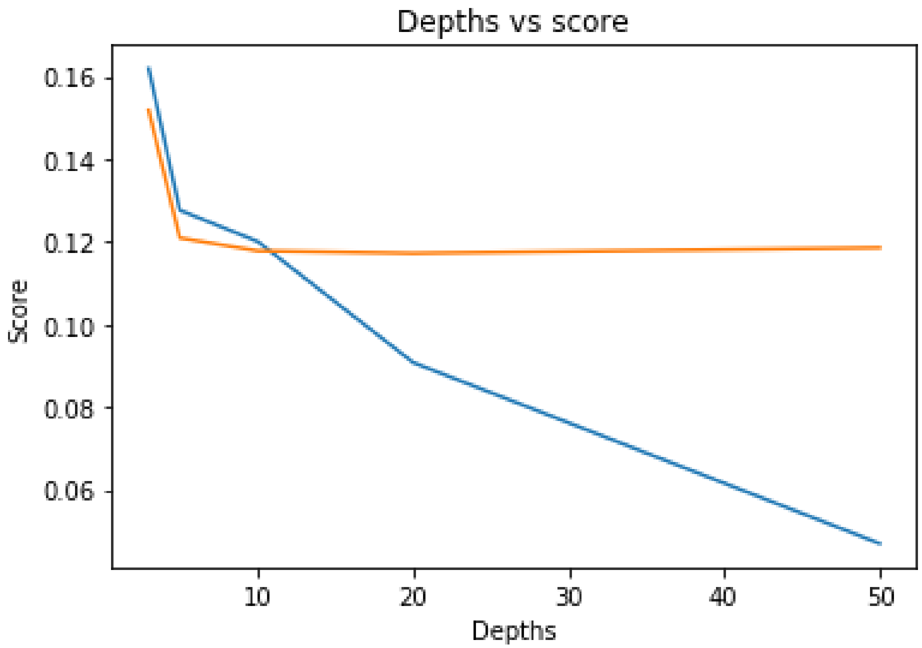
Out[55]:
```
Text(0.5, 1.0, 'Estimators vs score')
```


Estimators vs score
Score
0.12
0.11
0.10
0.09
0.08
0.07
0.06
0.05
0
50
100
150
200
250
Estimators

In [56]:
```
depths = [3,5,10,20, 50]
train_scores = []
test_scores = []
for i in depths:
  clf = RandomForestRegressor(n_estimators=40, max_depth=i, n_jobs=-1)
  clf.fit(df_train, tsne_train_output)
  train_sc = calc_MAPE(tsne_train_output,clf.predict(df_train))
  test_sc = calc_MAPE(tsne_test_output,clf.predict(df_test))
  test_scores.append(test_sc)
  train_scores.append(train_sc)
  print('Depths = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(depths,train_scores,label='Train Score')
plt.plot(depths,test_scores,label='Test Score')
plt.xlabel('Depths')
plt.ylabel('Score')
plt.title('Depths vs score')
```

```
Depths =  3 Train Score 0.16192714763533733 test Score 0.15180177439393988
Depths =  5 Train Score 0.12766156602817486 test Score 0.12095851757449985
Depths =  10 Train Score 0.12012001274781052 test Score 0.11783028051823466
Depths =  20 Train Score 0.09084533224337613 test Score 0.11726011269961327
Depths =  50 Train Score 0.04706327217774408 test Score 0.11855205833363403
```

Out[56]:
```
Text(0.5, 1.0, 'Depths vs score')
```



Taking `max_depth` and `n_estimators` values around the elbows of the graph. So, `max_depth` around 5, and `n_estimators` around 50.

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

In [60]:
```
param_dist = {"n_estimators":sp_randint(40,70),
    "max_depth": sp_randint(4,7),
    "min_samples_split": sp_randint(2, 5)}

clf = RandomForestRegressor(n_jobs=-1)
rf_random = RandomizedSearchCV(clf, param_distributions=param_dist,n_iter=5,scoring='neg_me
rf_random.fit(df_train, tsne_train_output)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])

clf = rf_random.best_estimator_

print('Best Estimator: ', clf)

clf.fit(df_train, tsne_train_output)
y_train_pred = clf.predict(df_train)
y_test_pred = clf.predict(df_test)

print("Train MAPE: ", calc_MAPE(tsne_train_output,y_train_pred))
print("Test MAPE: ", calc_MAPE(tsne_test_output,y_test_pred))
```

```
mean test scores [-325.37889565 -284.00989898 -326.23933216 -326.21787578 -326.22011626]
mean train scores [-306.47715345 -278.59774775 -306.47150171 -306.26970892 -306.49969652]
Best Estimator:  RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=5,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=41, n_jobs=-1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
Train MAPE:  0.12775629785820566
Test MAPE:  0.12092945844983294
```

In [64]:
```
#feature importances based on analysis using random forest
print (df_train.columns)
print (clf.feature_importances_)

inds = np.argsort(clf.feature_importances_)
imp_cols = df_train.columns[inds[None:-10:-1]]
print(imp_cols)
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'freq_0', 'amp_0', 'freq_1',
       'amp_1', 'freq_2', 'amp_2', 'freq_3', 'amp_3', 'freq_4', 'amp_4', 'lat',
       'lon', 'weekday', 'exp_avg', 'cluster_id'],
      dtype='object')
[2.74692769e-06 4.47063949e-05 7.34611639e-06 3.88654669e-06
 6.60703543e-03 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 9.93334279e-01 0.00000000e+00]
Index(['exp_avg', 'ft_1', 'ft_4', 'ft_3', 'ft_2', 'ft_5', 'freq_0', 'amp_0',
       'freq_1'],
      dtype='object')
```

Using XgBoost Regressor

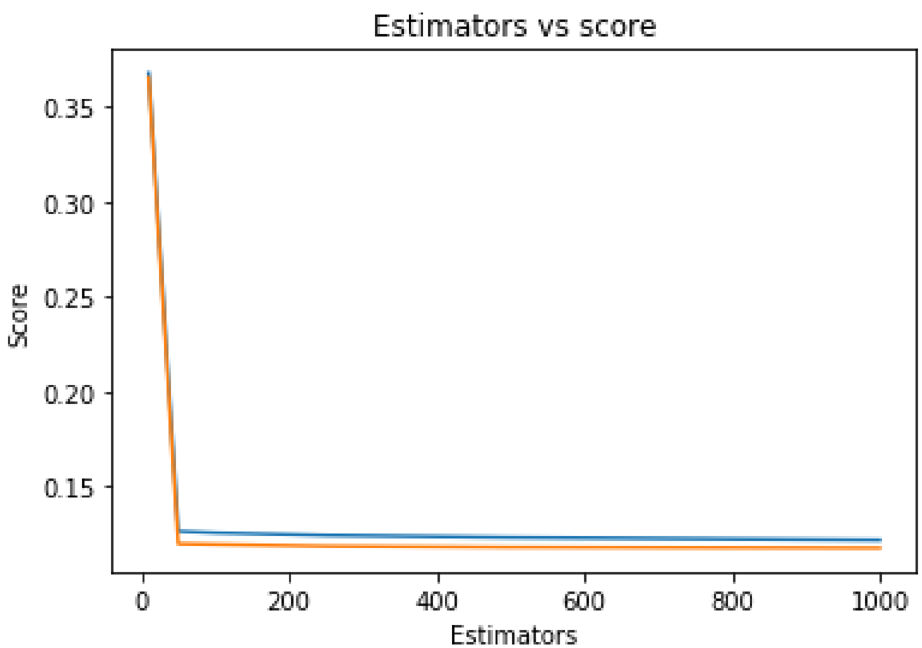
In [65]:
```
estimators = [10,50,100,250, 500, 1000]
train_scores = []
test_scores = []
for i in estimators:
  clf = xgb.XGBRegressor(
   learning_rate =0.1,
   n_estimators=i,
   max_depth=3,
   min_child_weight=3,
   gamma=0,
   subsample=0.8,
   reg_alpha=200, reg_lambda=200,
   colsample_bytree=0.8,nthread=4)
  clf.fit(df_train, tsne_train_output)
  train_sc = calc_MAPE(tsne_train_output,clf.predict(df_train))
  test_sc = calc_MAPE(tsne_test_output,clf.predict(df_test))
  test_scores.append(test_sc)
  train_scores.append(train_sc)
  print('Estimators = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(estimators,train_scores,label='Train Score')
plt.plot(estimators,test_scores,label='Test Score')
plt.xlabel('Estimators')
plt.ylabel('Score')
plt.title('Estimators vs score')
```

```
[20:26:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Estimators =  10 Train Score 0.36788927885816347 test Score 0.3654381200688201
[20:26:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Estimators =  50 Train Score 0.12608815449389313 test Score 0.11959402341755858
[20:26:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Estimators =  100 Train Score 0.125303446022751 test Score 0.11925624463497128
[20:26:49] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
```

```
recated in favor of reg:squarederror.
Estimators =  250 Train Score 0.12394196743860231 test Score 0.11829708356340835
[20:27:22] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Estimators =  500 Train Score 0.12282390984398615 test Score 0.11772948576887897
[20:28:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Estimators =  1000 Train Score 0.12150400946304023 test Score 0.11731681419788702
```

Out[65]:

```
Text(0.5, 1.0, 'Estimators vs score')
```



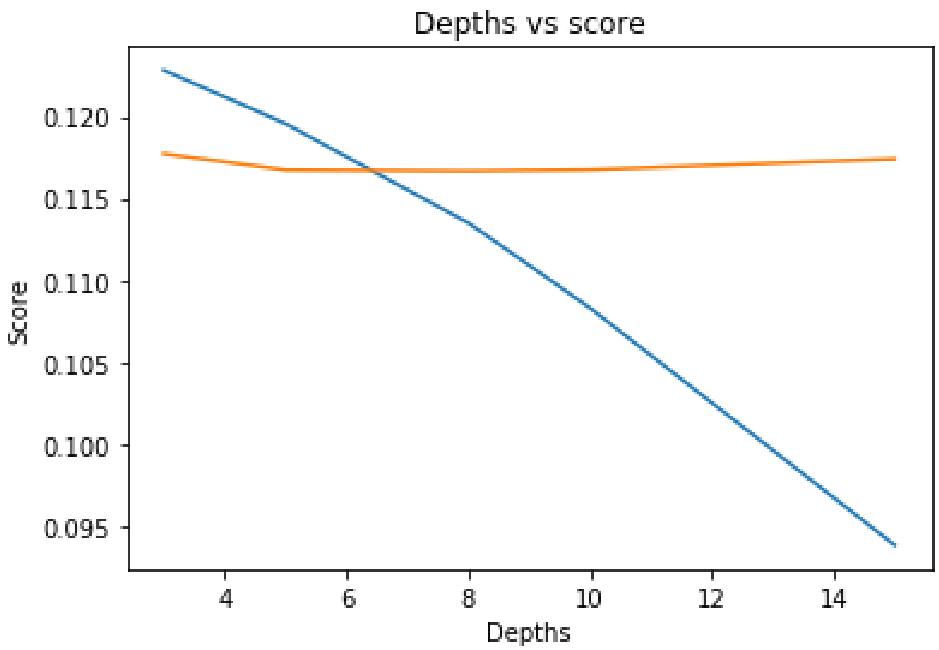
In [66]:
```
depths = [3, 5, 8, 10, 15]
train_scores = []
test_scores = []
for i in depths:
  clf = xgb.XGBRegressor(
   learning_rate =0.1,
   n_estimators=500,
   max_depth=i,
   min_child_weight=3,
   gamma=0,
   subsample=0.8,
   reg_alpha=200, reg_lambda=200,
   colsample_bytree=0.8,nthread=4)
  clf.fit(df_train, tsne_train_output)
  train_sc = calc_MAPE(tsne_train_output,clf.predict(df_train))
  test_sc = calc_MAPE(tsne_test_output,clf.predict(df_test))
  test_scores.append(test_sc)
  train_scores.append(train_sc)
  print('Depths = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(depths,train_scores,label='Train Score')
plt.plot(depths,test_scores,label='Test Score')
plt.xlabel('Depths')
plt.ylabel('Score')
plt.title('Depths vs score')
```

```
[20:30:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Depths =  3 Train Score 0.12282390984398615 test Score 0.11772948576887897
[20:31:45] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Depths =  5 Train Score 0.1195645236886165 test Score 0.11674756069142395
[20:33:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Depths =  8 Train Score 0.11351458624880534 test Score 0.11668544898648527
[20:36:47] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
```

```
recated in favor of reg:squarederror.
Depths =  10 Train Score 0.1083196457458951 test Score 0.11676210601079251
[20:41:05] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Depths =  15 Train Score 0.09386031458921193 test Score 0.1174185924862408
```

Out[66]:

```
Text(0.5, 1.0, 'Depths vs score')
```



In [68]:
```
param_dist = {"n_estimators":sp_randint(40,70),
    "max_depth": sp_randint(5,9),
   "learning_rate": uniform(0.08, 0.12)}

clf = xgb.XGBRegressor(
   min_child_weight=3,
   gamma=0,
   subsample=0.8,
   reg_alpha=200, reg_lambda=200,
   colsample_bytree=0.8,nthread=4)
rf_random = RandomizedSearchCV(clf, param_distributions=param_dist,n_iter=5,scoring='neg_me
rf_random.fit(df_train, tsne_train_output)
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])

clf = rf_random.best_estimator_

print('Best Estimator: ', clf)

clf.fit(df_train, tsne_train_output)
y_train_pred = clf.predict(df_train)
y_test_pred = clf.predict(df_test)

print("Train MAPE: ", calc_MAPE(tsne_train_output,y_train_pred))
print("Test MAPE: ", calc_MAPE(tsne_test_output,y_test_pred))
```

...

Previous code cell's output is copied to markdown cell below as there are lot of deprecated warnings which are printed before the main output.

mean test scores [-356.7389414 -373.01542058 -357.75932091 -371.91452142 -336.10340613]

mean train scores [-255.30896492 -247.72946075 -249.17872772 -267.54641259 -259.16311609]

Best Estimator: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.8, gamma=0, importance_type='gain', learning_rate=0.1865401918732345, max_delta_step=0, max_depth=5, min_child_weight=3, missing=None, n_estimators=55, n_jobs=1, nthread=4, objective='reg:linear', random_state=0, reg_alpha=200, reg_lambda=200, scale_pos_weight=1, seed=None, silent=None, subsample=0.8, verbosity=1)

Train MAPE: 0.12342634088042077

Test MAPE: 0.11810948813003048

In [75]:
```
clf.feature_importances_
```

Out[75]:
```
array([5.98805782e-04, 4.98338020e-04, 3.75492312e-03, 1.88882221e-02,
       2.63216078e-01, 0.00000000e+00, 4.86344274e-04, 1.41845565e-04,
       3.44068947e-04, 1.80868126e-04, 1.74489905e-04, 4.80664239e-05,
       1.16007854e-04, 2.16440938e-04, 1.88977196e-04, 4.30918386e-04,
       5.04031486e-04, 1.84068573e-04, 7.09724247e-01, 3.03326320e-04],
      dtype=float32)
```

In [76]:
```
#feature importances based on analysis using random forest
print (df_train.columns)
print (clf.feature_importances_)

inds = np.argsort(clf.feature_importances_)
imp_cols = df_train.columns[inds[None:-10:-1]]
print(imp_cols)
# inds = np.argsort(clf.feature_importances_)
# imp_cols = clf.columns[inds[None:-5:-1]]
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'freq_0', 'amp_0', 'freq_1',
       'amp_1', 'freq_2', 'amp_2', 'freq_3', 'amp_3', 'freq_4', 'amp_4', 'lat',
       'lon', 'weekday', 'exp_avg', 'cluster_id'],
      dtype='object')
[5.98805782e-04 4.98338020e-04 3.75492312e-03 1.88882221e-02
 2.63216078e-01 0.00000000e+00 4.86344274e-04 1.41845565e-04
 3.44068947e-04 1.80868126e-04 1.74489905e-04 4.80664239e-05
 1.16007854e-04 2.16440938e-04 1.88977196e-04 4.30918386e-04
 5.04031486e-04 1.84068573e-04 7.09724247e-01 3.03326320e-04]
Index(['exp_avg', 'ft_1', 'ft_2', 'ft_3', 'ft_5', 'lon', 'ft_4', 'amp_0',
       'lat'],
      dtype='object')
```

Conclusion

Printing a Table with MAPE values.

In [3]:
```
from prettytable import PrettyTable
table = PrettyTable()

table.field_names = ['Model', 'hyper-parameters', 'Train MAPE', 'Test MAPE']
table.add_row(['Linear Regression', 'None', '12.5306 %', '11.9048 %'])
table.add_row(['Random Forest', 'n_estimators: 250, min_sample_slit: 4', '4.894 %', '11.714
table.add_row(['Random Forest', 'n_estimators: 40, max_depth: 20', '9.0845 %', '11.726 %'])
table.add_row(['Random Forest', 'n_estimators: 41, max_depth: 5, min_sample_split: 2', '12.
table.add_row(['XGBoost', 'n_estimators: 1000, max_depth: 3', '12.1504 %', '11.7317 %'])
table.add_row(['XGBoost', 'n_estimators: 500, max_depth: 8', '11.3514 %', '11.6685 %'])
table.add_row(['XGBoost', 'n_estimators: 55, max_depth: 5, learning_rate: 0.1865', '12.3426

print(table)
```

```
+-------------------+--------------------------------------------------------+------------
+-----------+
|       Model       |                    hyper-parameters                    | Train MAPE
| Test MAPE |
+-------------------+--------------------------------------------------------+------------
+-----------+
| Linear Regression |                          None                          | 12.5306 %
| 11.9048 % |
|   Random Forest   |          n_estimators: 250, min_sample_slit: 4          |  4.894 %
| 11.7147 % |
|   Random Forest   |             n_estimators: 40, max_depth: 20             |  9.0845 %
|  11.726 % |
|   Random Forest   |  n_estimators: 41, max_depth: 5, min_sample_split: 2  | 12.7756 %
|  12.093 % |
|      XGBoost      |            n_estimators: 1000, max_depth: 3            | 12.1504 %
| 11.7317 % |
|      XGBoost      |             n_estimators: 500, max_depth: 8             | 11.3514 %
| 11.6685 % |
|      XGBoost      | n_estimators: 55, max_depth: 5, learning_rate: 0.1865 | 12.3426 %
| 11.8109 % |
```

```
+-----------------+-----------------------------------------------+-----------
+-----------+
```

In above models, sklearn's LinearRegression doesnt have any hyper-parameters to tune so there are None. For Random Forest, remaining hyper-parameters which are not mentioned here are default values of the sklearn's Random Forest. For XGBoost, remaining hyper-parameters which are not mentioned here are taken from the original notebook's XGBoost model. Hyper-parameters of third Random Forest model and XGBoost model are tuned using sklearn's RandomSearchCV.

Conclusion:

- **Among all models XGBoost with n_estimators: 500 and max_depth: 8 gave very good results. And also Random Forest model with n_estimators: 40 and max_depth: 20 gave good results.**
- **The training data is one-hot encoded before passing it to Linear regression model as the cluster centers and weekday are not linearly dependent on the output i.e. number of cabs booked. For tree based models encoding is not done as they can handle non-linear relation between input and output and also tree based models will not perform good with high-dimentional data and sparse data.**
- **Random Forest models for which max-depth is not tuned are overfitting a lot.**
- **When important features observed in both Random forest and XGBoost exponential moving average output and previous 10-min intervals data seems to be very important. And in XGBoost we can see latitude data and longitude data and a fourier data (amplitude of highest frequency) seems to be important. Below I print top features for both models.**

Important features for Random Forest: ['exp_avg', 'ft_1', 'ft_4', 'ft_3', 'ft_2', 'ft_5']

Important features for XGBoost: ['exp_avg', 'ft_1', 'ft_2', 'ft_3', 'ft_5', 'lon', 'ft_4', 'amp_0', 'lat']

In [ ]: