Taxi demand prediction in New York City

```
%matplotlib inline

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

import pandas as pd#pandas to create small dataframes

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

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

import time #Convert to unix time

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

# matplotlib: used to plot graphs
import matplotlib
# matplotlib.use('nbagg') : matplotlib uses this protocall which makes plots mo
re 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 (la
t,lon) pairs in miles
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'
```

```python
os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']

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

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

Data Information

Ge the data from : http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml (2016 data) The data used in the attached datasets were collected and provided to the NYC Taxi and Limousine Commission (TLC)

Information on taxis:

Yellow Taxi: Yellow Medallion Taxicabs

These are the famous NYC yellow taxis that provide transportation exclusively through street-hails. The number of taxicabs is limited by a finite number of medallions issued by the TLC. You access this mode of transportation by standing in the street and hailing an available taxi with your hand. The pickups are not pre-arranged.

For Hire Vehicles (FHVs)

FHV transportation is accessed by a pre-arrangement with a dispatcher or limo company. These FHVs are not permitted to pick up passengers via street hails, as those rides are not considered pre-arranged.

Green Taxi: Street Hail Livery (SHL)

The SHL program will allow livery vehicle owners to license and outfit their vehicles with green borough taxi branding, meters, credit card machines, and ultimately the right to accept street hails in addition to pre-arranged rides.

Credits: Quora

Footnote:

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

Data Collection

We Have collected all yellow taxi trips data from jan-2015 to dec-2016(Will be using only 2015 data)

file name	file name size	number of records	number of features
yellow_tripdata_2016-01	1. 59G	10906858	19
yellow_tripdata_2016-02	1. 66G	11382049	19
yellow_tripdata_2016-03	1. 78G	12210952	19
yellow_tripdata_2016-04	1. 74G	11934338	19
yellow_tripdata_2016-05	1. 73G	11836853	19
yellow_tripdata_2016-06	1. 62G	11135470	19

yellow_tripdata_2016-07	884Mb	10294080	17
yellow_tripdata_2016-08	854Mb	9942263	17
yellow_tripdata_2016-09	870Mb	10116018	17
yellow_tripdata_2016-10	933Mb	10854626	17
yellow_tripdata_2016-11	868Mb	10102128	17
yellow_tripdata_2016-12	897Mb	10449408	17
yellow_tripdata_2015-01	1.84Gb	12748986	19
yellow_tripdata_2015-02	1.81Gb	12450521	19
yellow_tripdata_2015-03	1.94Gb	13351609	19
yellow_tripdata_2015-04	1.90Gb	13071789	19
yellow_tripdata_2015-05	1.91Gb	13158262	19
yellow_tripdata_2015-06	1.79Gb	12324935	19
yellow_tripdata_2015-07	1.68Gb	11562783	19
yellow_tripdata_2015-08	1.62Gb	11130304	19
yellow_tripdata_2015-09	1.63Gb	11225063	19
yellow_tripdata_2015-10	1.79Gb	12315488	19
yellow_tripdata_2015-11	1.65Gb	11312676	19
yellow_tripdata_2015-12	1.67Gb	11460573	19

Assignment

```
'''
Task 1: Incorporate Fourier features as features into Regression models and mea
sure 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/Stackoverfl
ow
to reduce the MAPE to < 12%
'''
```

```
'\nTask 1: Incorporate Fourier features as features into Regression models and measure MAP
E. <br>\n\nTask 2: Perform hyper-parameter tuning for Regression models.\n        2a. Line
ar Regression: Grid Search\n        2b. Random Forest: Random Search \n        2c. Xgboos
t: Random Search\nTask 3: Explore more time-series features using Google search/Quora/Stac
koverflow\nto reduce the MAPE to < 12%\n'
```

Task 1 and 2 : Incorporate Fourier features as features into Regression models and measure and hyper parameter tuning

```
from scipy import vstack,hstack

# top 5 amplitute of each month of each cluster/region
# features---> 'A1' , 'A2' , 'A3' , 'A4' , 'A5' , 'F1' , 'F2' , 'F3' , 'F4' ,
```

```
 'F5'
fourier_feature = []
for i in range(40):

        jan_fft_amp_top5_feat= sorted(np.fft.fft(np.array(regions_cum[i][:4464
])), reverse=True)[:5]
        jan_fft_freq_top5_feat = sorted(np.fft.fftfreq(4464), reverse=True)[:5]
        clust_jan_frq_amp = [np.hstack([jan_fft_amp_top5_feat,jan_fft_freq_top5
_feat]).astype(np.float)] * (4464 - 5) # removing first five 10_min_bins(50 min
s)


        feb_fft_amp_top5_feat = sorted(np.fft.fft(np.array(regions_cum[i][4464:
4464+4176])), reverse=True)[:5]
        feb_fft_freq_top5_feat = sorted(np.fft.fftfreq(4176), reverse=True)[:5]
        clust_feb_frq_amp = [np.hstack([feb_fft_amp_top5_feat,feb_fft_freq_top5
_feat]).astype(np.float)] * 4176


        mar_fft_amp_top5_feat = sorted(np.fft.fft(np.array(regions_cum[i][4464+
4176: ])), reverse=True)[:5]
        mar_fft_freq_top5_feat = sorted(np.fft.fftfreq(4176), reverse=True)[:5]
        clust_mar_frq_amp = [np.hstack([mar_fft_amp_top5_feat,mar_fft_freq_top5
_feat]).astype(np.float)] * 4464

        fourier_feature.extend(np.vstack([clust_jan_frq_amp, clust_feb_frq_amp,
clust_mar_frq_amp]))
```

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

```
# 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) fo
r 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_fea
tures[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_featur
es[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
```

```
# train and test split of fourier transform feature
# extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) fo
r our training data
train_fft_features =  [fourier_feature[i*13099:(13099*i+9169)] for i in range(0
,40)]
# temp = [0]*(12955 - 9068)
test_fft_features = [fourier_feature[(13099*(i))+9169:13099*(i+1)] for i in ran
ge(0,40)]
```

```
# extracting first 9169 timestamp values i.e 70% of 13099 (total timestamps) fo
r 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 timestamp
s) 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 o
f 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])

# fourier transformed feature
# the above contains values in the form of list of lists (i.e. list of values o
f each region), here we make all of them in one list for fourier transformed fe
ature
train_new_fft_features = []
for i in range(0,40):
```

```
    train_new_fft_features.extend(train_fft_features[i])
test_new_fft_features = []
for i in range(0,40):
    test_new_fft_features.extend(test_fft_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',"amp1", "amp2", "amp3", "amp4",
"amp5", "freq1", "freq2", "freq3", "freq4", "freq5"]
df_train = pd.DataFrame(data=np.hstack([train_new_features,train_new_fft_featur
es]), 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)
df_train.head()
```

```
(366760, 19)
```

	ft_5	ft_4	ft_3	ft_2	ft_1	amp1	amp2	amp3	amp4	amp5
0	0.0	0.0	0.0	0.0	0.0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101
1	0.0	0.0	0.0	0.0	0.0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101
2	0.0	0.0	0.0	0.0	0.0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101
3	0.0	0.0	0.0	0.0	0.0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101
4	0.0	0.0	0.0	0.0	0.0	367173.0	94490.188858	94490.188858	14349.849101	14349.849101

```
# Preparing the data frame for our train data
df_test = pd.DataFrame(data=np.hstack([test_new_features,test_new_fft_features
```

```
]), columns=columns)
df_test['lat'] = tsne_test_lat
df_test['lon'] = tsne_test_lon
df_test['weekday'] = tsne_test_weekday
df_test['exp_avg'] = tsne_test_exp_avg
print(df_test.shape)
```

```
(157200, 19)
```

```
df_test.head()
```

	ft_5	ft_4	ft_3	ft_2	ft_1	amp1	amp2	amp3	amp4	am
0	143.0	145.0	119.0	113.0	124.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
1	145.0	119.0	113.0	124.0	121.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
2	119.0	113.0	124.0	121.0	131.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
3	113.0	124.0	121.0	131.0	110.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
4	124.0	121.0	131.0	110.0	116.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351

Using Linear Regression

```
## Hyper Parameter tuning
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso

clf_lin_reg = Lasso(alpha=1.0)

param={'alpha':[0.001,0.01,0.1,1,10]}
gscv=GridSearchCV(estimator=clf_lin_reg, param_grid = param, scoring='neg_mean_
absolute_error', n_jobs=-1,verbose=10)
gscv.fit(df_train, tsne_train_output)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 out of  15 | elapsed:   22.2s remaining:  2.4min
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed:   32.0s remaining:  1.5min
[Parallel(n_jobs=-1)]: Done   6 out of  15 | elapsed:   41.6s remaining:  1.0min
[Parallel(n_jobs=-1)]: Done   8 out of  15 | elapsed:   50.9s remaining:   44.5s
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed:   55.0s remaining:   27.5s
[Parallel(n_jobs=-1)]: Done  12 out of  15 | elapsed:  1.1min remaining:   16.2s
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed:  1.3min finished


GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=1000, normalize=False, positive=False,
                             precompute=False, random_state=None,
                             selection='cyclic', tol=0.0001, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': [0.001, 0.01, 0.1, 1, 10]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=10)
```

```
print("Best Param: ",gscv.best_params_)
print("\nBest Score: ",-gscv.best_score_)
```

```
Best Param:  {'alpha': 0.001}

Best Score:  8.673587450397548
```

```
# Traning Using Optimal Parameter
from sklearn.linear_model import LinearRegression
lr_reg=Lasso(alpha=0.001).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("Test MAPE : ",(mean_absolute_error(tsne_test_output, lr_test_predictions
))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
Test MAPE :  0.1346818043304668
```

Using Random Forest Regressor

```
## Hyper Parameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV

clf_rf = RandomForestRegressor(max_features='sqrt',max_depth=None, n_estimators
=40, n_jobs=-1)
param={'max_depth':[3,5,10,15,30],"n_estimators":[20,50,100,200,500]}

rscv= RandomizedSearchCV(estimator = clf_rf, param_distributions = param, scori
ng='neg_mean_absolute_error', n_jobs=-1,verbose=10)
rscv.fit(df_train, tsne_train_output)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:   22.0s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:   57.4s
[Parallel(n_jobs=-1)]: Done  19 out of  30 | elapsed:  1.8min remaining:  1.1min
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  2.4min remaining:   44.0s
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  2.7min remaining:   18.3s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  3.1min finished
```

```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
                   estimator=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=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_leaf=0.0,
```

```
                                                       n_estimators=40, n_jobs=-1,
                                                       oob_score=False,
                                                       random_state=None, verbose=0,
                                                       warm_start=False),
                            iid='warn', n_iter=10, n_jobs=-1,
                            param_distributions={'max_depth': [3, 5, 10, 15, 30],
                                                 'n_estimators': [20, 50, 100, 200,
                                                                  500]},
                            pre_dispatch='2*n_jobs', random_state=None, refit=True,
                            return_train_score=False, scoring='neg_mean_absolute_error',
                            verbose=10)
```

```
print("Best Param: ",rscv.best_params_)
print("\nBest Score: ",-rscv.best_score_)
```

```
Best Param:  {'n_estimators': 200, 'max_depth': 10}

Best Score:  8.707279030116073
```

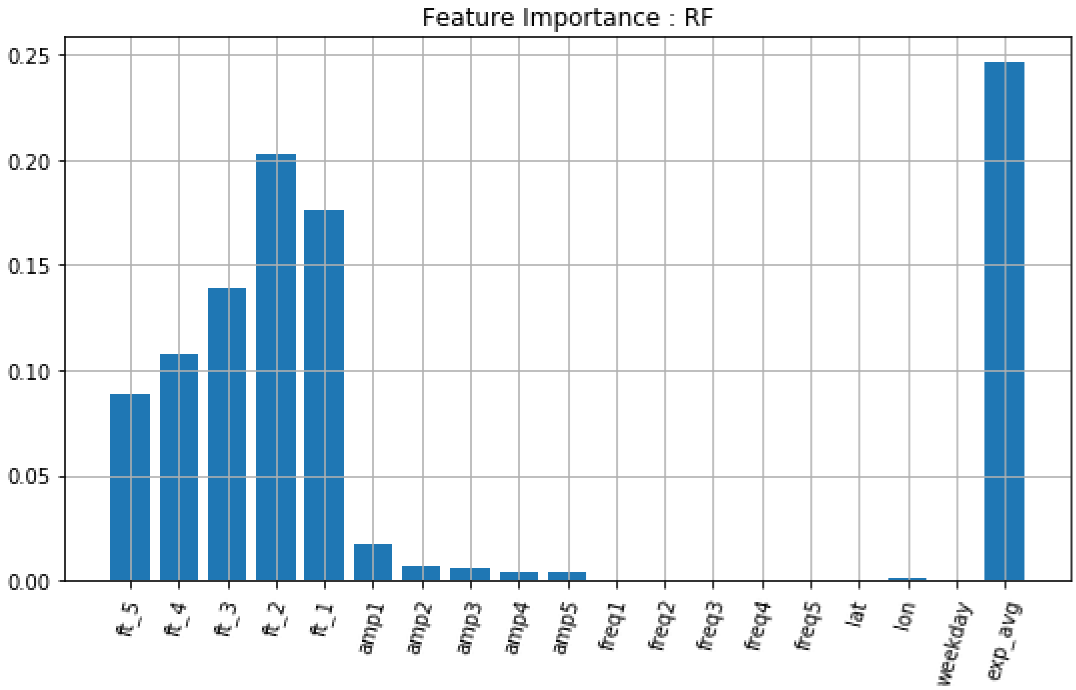
```
#Traning Using Optimal Hyperparameter
regr1 = RandomForestRegressor(max_features='sqrt',max_depth=10, n_estimators=20
0, n_jobs=-1)
regr1.fit(df_train, tsne_train_output)

# 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]


print("Train MAPE : ",(mean_absolute_error(tsne_train_output, rndf_train_predic
tions))/(sum(tsne_train_output)/len(tsne_train_output)))
print("Test MAPE : ",(mean_absolute_error(tsne_test_output, rndf_test_predictio
ns))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
Train MAPE :  0.1368512323624647
Test MAPE :  0.1345528473427501
```

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

plt.figure(figsize=(9,5))
plt.title("Feature Importance : RF")
plt.bar(df_train.columns,regr1.feature_importances_)
plt.xticks(np.arange(len(df_train.columns)),df_train.columns,rotation=75)
plt.grid()
plt.show()
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'amp1', 'amp2', 'amp3', 'amp4',
       'amp5', 'freq1', 'freq2', 'freq3', 'freq4', 'freq5', 'lat', 'lon',
       'weekday', 'exp_avg'],
```

```
       dtype='object')
[8.86960207e-02 1.07706847e-01 1.38791168e-01 2.02615824e-01
 1.76294874e-01 1.70238361e-02 6.54180559e-03 6.29633501e-03
 4.27791512e-03 4.23602924e-03 3.66332410e-05 3.21296205e-05
 3.49534810e-05 2.95853407e-05 2.67832446e-05 4.44513356e-04
 7.20698144e-04 1.67374390e-04 2.46026674e-01]
```



Using XgBoost Regressor

```python
## Hyper Parameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV

clf_xgb = xgb.XGBRegressor(learning_rate =0.1,n_estimators=1000,max_depth=3, nt
hread=-1)

param={'max_depth':[3,5,10,15,30],"n_estimators":[100,200,500,1000],"learning_r
ate":[1,0.1,0.01]}

rscv= RandomizedSearchCV(estimator = clf_xgb, param_distributions = param, scor
ing='neg_mean_absolute_error', n_jobs=1,verbose=10)
rscv.fit(df_train, tsne_train_output)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[CV] n_estimators=200, max_depth=10, learning_rate=1 .................
[06:53:02] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.


[CV]  n_estimators=200, max_depth=10, learning_rate=1, score=-13.310, total=  25.6s
[CV] n_estimators=200, max_depth=10, learning_rate=1 .................
[06:53:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   25.6s remaining:    0.0s


[CV]  n_estimators=200, max_depth=10, learning_rate=1, score=-11.170, total=  26.1s
[CV] n_estimators=200, max_depth=10, learning_rate=1 ................
[06:53:54] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   51.7s remaining:    0.0s


[CV]  n_estimators=200, max_depth=10, learning_rate=1, score=-12.260, total=  25.7s
[CV] n_estimators=1000, max_depth=5, learning_rate=0.1 ..............
[06:54:20] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:  1.3min remaining:    0.0s


[CV]  n_estimators=1000, max_depth=5, learning_rate=0.1, score=-9.384, total=  54.1s
[CV] n_estimators=1000, max_depth=5, learning_rate=0.1 ..............
[06:55:14] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:  2.2min remaining:    0.0s


[CV]  n_estimators=1000, max_depth=5, learning_rate=0.1, score=-7.661, total=  55.5s
[CV] n_estimators=1000, max_depth=5, learning_rate=0.1 ..............
[06:56:09] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  3.1min remaining:    0.0s


[CV]  n_estimators=1000, max_depth=5, learning_rate=0.1, score=-9.207, total=  55.0s
[CV] n_estimators=200, max_depth=15, learning_rate=1 ................
[06:57:04] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:  4.0min remaining:    0.0s


[CV]  n_estimators=200, max_depth=15, learning_rate=1, score=-13.210, total=  44.7s
[CV] n_estimators=200, max_depth=15, learning_rate=1 ................
[06:57:49] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:  4.8min remaining:    0.0s


[CV]  n_estimators=200, max_depth=15, learning_rate=1, score=-11.520, total=  45.4s
[CV] n_estimators=200, max_depth=15, learning_rate=1 ................
[06:58:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:  5.5min remaining:    0.0s
```

```
[CV]  n_estimators=200, max_depth=15, learning_rate=1, score=-12.466, total=  44.2s
[CV] n_estimators=1000, max_depth=3, learning_rate=0.1 ..............
[06:59:19] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:  6.3min remaining:    0.0s


[CV]  n_estimators=1000, max_depth=3, learning_rate=0.1, score=-9.296, total=  34.5s
[CV] n_estimators=1000, max_depth=3, learning_rate=0.1 ..............
[06:59:53] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=1000, max_depth=3, learning_rate=0.1, score=-7.618, total=  35.1s
[CV] n_estimators=1000, max_depth=3, learning_rate=0.1 ..............
[07:00:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=1000, max_depth=3, learning_rate=0.1, score=-9.163, total=  34.5s
[CV] n_estimators=500, max_depth=30, learning_rate=1 ................
[07:01:03] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=500, max_depth=30, learning_rate=1, score=-12.971, total=  22.6s
[CV] n_estimators=500, max_depth=30, learning_rate=1 ................
[07:01:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=500, max_depth=30, learning_rate=1, score=-10.845, total=  22.5s
[CV] n_estimators=500, max_depth=30, learning_rate=1 ................
[07:01:48] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=500, max_depth=30, learning_rate=1, score=-12.509, total=  24.0s
[CV] n_estimators=200, max_depth=10, learning_rate=0.1 ..............
[07:02:12] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=10, learning_rate=0.1, score=-9.471, total=  24.3s
[CV] n_estimators=200, max_depth=10, learning_rate=0.1 ..............
[07:02:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=10, learning_rate=0.1, score=-7.843, total=  25.2s
[CV] n_estimators=200, max_depth=10, learning_rate=0.1 ..............
[07:03:01] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=10, learning_rate=0.1, score=-9.306, total=  24.6s
[CV] n_estimators=100, max_depth=30, learning_rate=1 ................
[07:03:26] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=30, learning_rate=1, score=-12.971, total=  16.4s
[CV] n_estimators=100, max_depth=30, learning_rate=1 ................
[07:03:42] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=30, learning_rate=1, score=-10.845, total=  16.3s
[CV] n_estimators=100, max_depth=30, learning_rate=1 ................
[07:03:59] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=30, learning_rate=1, score=-12.509, total=  17.6s
[CV] n_estimators=100, max_depth=10, learning_rate=0.01 .............
[07:04:16] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=10, learning_rate=0.01, score=-24.290, total=  13.1s
[CV] n_estimators=100, max_depth=10, learning_rate=0.01 .............
[07:04:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=10, learning_rate=0.01, score=-21.091, total=  13.3s
```

```
[CV] n_estimators=100, max_depth=10, learning_rate=0.01 ..............
[07:04:43] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=100, max_depth=10, learning_rate=0.01, score=-23.913, total=  13.0s
[CV] n_estimators=200, max_depth=30, learning_rate=0.1 ...............
[07:04:56] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=30, learning_rate=0.1, score=-10.220, total= 2.2min
[CV] n_estimators=200, max_depth=30, learning_rate=0.1 ...............
[07:07:06] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=30, learning_rate=0.1, score=-8.612, total= 2.1min
[CV] n_estimators=200, max_depth=30, learning_rate=0.1 ...............
[07:09:15] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=30, learning_rate=0.1, score=-10.070, total= 2.1min
[CV] n_estimators=200, max_depth=5, learning_rate=0.1 ................
[07:11:22] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=5, learning_rate=0.1, score=-9.203, total=  11.0s
[CV] n_estimators=200, max_depth=5, learning_rate=0.1 ................
[07:11:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=5, learning_rate=0.1, score=-7.540, total=  11.3s
[CV] n_estimators=200, max_depth=5, learning_rate=0.1 ................
[07:11:44] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
[CV]  n_estimators=200, max_depth=5, learning_rate=0.1, score=-9.139, total=  11.2s
[07:11:55] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.


[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed: 18.9min finished
```

```
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
                   estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                          colsample_bylevel=1,
                                          colsample_bynode=1,
                                          colsample_bytree=1, gamma=0,
                                          importance_type='gain',
                                          learning_rate=0.1, max_delta_step=0,
                                          max_depth=3, min_child_weight=1,
                                          missing=None, n_estimators=1000,
                                          n_jobs=1, nthread=-1,
                                          objective='reg:linear',
                                          rando...pha=0,
                                          reg_lambda=1, scale_pos_weight=1,
                                          seed=None, silent=None, subsample=1,
                                          verbosity=1),
                   iid='warn', n_iter=10, n_jobs=1,
                   param_distributions={'learning_rate': [1, 0.1, 0.01],
                                        'max_depth': [3, 5, 10, 15, 30],
                                        'n_estimators': [100, 200, 500, 1000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring='neg_mean_absolute_error',
                   verbose=10)
```

```python
print("Best Param: ",rscv.best_params_)
print("\nBest Score: ",-rscv.best_score_)
```

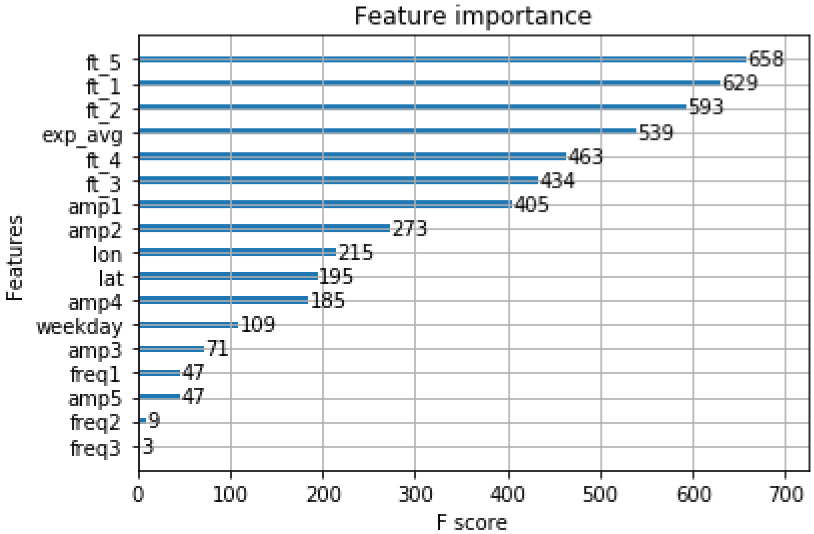
```
Best Param:  {'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.1}

Best Score:  8.627213474899476
```

```python
# Traninng with optimal Hyperparameter

x_model = xgb.XGBRegressor(
 learning_rate =0.1,
 n_estimators=200,
 max_depth=5,
 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)

#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]


print("Train MAPE : ",(mean_absolute_error(tsne_train_output, xgb_train_predict
ions))/(sum(tsne_train_output)/len(tsne_train_output)))
print("Test MAPE : ",(mean_absolute_error(tsne_test_output, xgb_test_prediction
s))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
[07:13:19] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
Train MAPE :  0.13838850211637208
Test MAPE :  0.13360181329858015
```

```python
# Feature Importance of XGBoost Regressor
from xgboost import plot_importance
plt.figure(figsize=(9,5))
plot_importance(x_model,height=0.3)
plt.show()
```

```
<Figure size 648x360 with 0 Axes>
```



Calculating the error metric values for various models

```
train_mape=[]
test_mape=[]

train_mape.append((mean_absolute_error(tsne_train_output,df_train['ft_1'].value
s))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output,df_train['exp_avg'].va
lues))/(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)))
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)))


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'].valu
es))/(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)))
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)))
```

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[2],"
```

```
Test: ",test_mape[2])
print ("Random Forest Regression -                    Train: ",train_mape[3],"
Test: ",test_mape[3])
print ("XgBoost Regression -                          Train: ",train_mape[4],"
Test: ",test_mape[4])
print ("--------------------------------------------------------------------------------
---------------------------------")
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
--------------------------------------------------------------------------------------------
------------
Baseline Model -                          Train:  0.14870666996426116       Test:  0.1422
5522601041551
Exponential Averages Forecasting -        Train:  0.14121603560900353       Test:  0.1349
0049942819257
Linear Regression -                      Train:  0.14219263664944806       Test:  0.13468
18043304668
Random Forest Regression -                Train:  0.1368512323624647      Test:  0.134552
8473427501
XgBoost Regression -                      Train:  0.13838850211637208       Test:  0.1336
0181329858015
--------------------------------------------------------------------------------------------
------------
```

Task 3: Explore more time-series features using Google search/Quora/Stackoverflow to reduce the MAPE to < 12%

Reference

https://www.youtube.com/watch?v=DUyZl-abnNM -- Holt double exponential smooting

https://www.youtube.com/watch?v=mrLiC1biciY -- Holt winter tripple exponential smooting

https://grisha.org/blog/2016/01/29/triple-exponential-smoothing-forecasting/ --- Code reference

https://grisha.org/blog/2016/02/16/triple-exponential-smoothing-forecasting-part-ii/ --- Code reference

https://grisha.org/blog/2016/02/17/triple-exponential-smoothing-forecasting-part-iii/ --- Code reference

https://medium.com/datadriveninvestor/how-to-build-exponential-smoothing-models-using-python-simple-exponential-smoothing-holt-and-da371189e1a1

3.1 Holt double exponential smoothing

https://grisha.org/blog/2016/02/16/triple-exponential-smoothing-forecasting-part-ii/ --- Code reference

```
# Holt double exponential averaging
# given a series and alpha, return series of smoothed points
def double_exponential_smoothing(series, alpha, beta):
    result = [series[0]]
    for n in range(1, len(series)+1):
        if n == 1:
            level, trend = series[0], series[1] - series[0]
```

```python
        if n >= len(series): # we are forecasting
            value = result[-1]
        else:
            value = series[n]
        last_level, level = level, alpha*value + (1-alpha)*(level+trend)
        trend = beta*(level-last_level) + (1-beta)*trend
        result.append(level+trend)
    return result
```

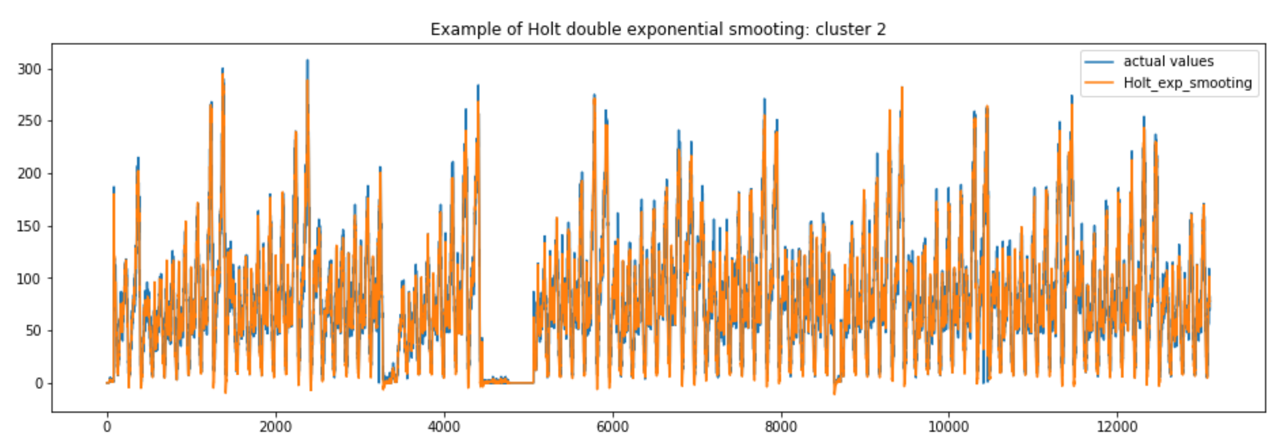
```python
# hyperparameter tuning

# removing top 5 values from each cluster for calculating MAPE and MSE
cumulative_test = [ regions_cum[i][5:] for i in range(40) ]

# Parameter initialisation
alpha = [0.1, 0.2, 0.3, 0.4, 0.5]
beta = [0.1, 0.12, 0.15, 0.20, 0.3]

# Storing all the results
result_double_exp = []

for al in alpha:
    for b in beta:

        double_exp_smooth_feat = []
        for r in range(0,40):
            smoothing_feat = double_exponential_smoothing(regions_cum[r][0:13104], alpha=al, beta=b)
            double_exp_smooth_feat.append(smoothing_feat[6:])

        # calculating MAPE
        error = (sum(abs(np.subtract(np.array(cumulative_test).flatten(), np.array(double_exp_smooth_feat).flatten()))))/len(np.array(double_exp_smooth_feat).flatten())
        y_ = sum(np.array(cumulative_test).flatten())/len(np.array(double_exp_smooth_feat).flatten())
        mape_2_exp = error/y_

        # calculating MSE
        mse_2_exp = sum((np.subtract(np.array(cumulative_test).flatten(), np.array(double_exp_smooth_feat).flatten()))**2.0) / len(np.array(double_exp_smooth_feat).flatten())

        # Storing results
        result_double_exp.append(([al, b],(mape_2_exp, mse_2_exp)))
```

```python
# Finding Optimal hyperparameter
mape_res_2_exp=[]
for i in range(len(result_double_exp)):
    mape_res_2_exp.append(result_double_exp[i][1][0])

result_dataframe_2_exp = pd.DataFrame(result_double_exp, columns=["_alpha  ,_beta ","_MAPE   ,_MSE"])
print("Optimal_hyperparameter: \n")
print(result_dataframe_2_exp.iloc[np.argmin(mape_res_2_exp)])
```

```
Optimal_hyperparameter:

_alpha  ,_beta                                  [0.4, 0.1]
_MAPE   ,_MSE      (0.10268183636675085, 104.46471317931922)
Name: 15, dtype: object
```

```
alpha = 0.4
beta = 0.1

double_exp_smooth_feat = []

for r in range(0,40):
    smoothing_feat = double_exponential_smoothing(regions_cum[r][0:13104], alph
a, beta)
    double_exp_smooth_feat.append(smoothing_feat[6:])

# calculating MAPE
error = (sum(abs(np.subtract(np.array(cumulative_test).flatten(), np.array(doub
le_exp_smooth_feat).flatten()))))/len(np.array(double_exp_smooth_feat).flatten
())
y_ = sum(np.array(cumulative_test).flatten())/len(np.array(double_exp_smooth_fe
at).flatten())
mape_2_exp = error/y_

# calculating MSE
mse_2_exp = sum((np.subtract(np.array(cumulative_test).flatten(), np.array(doub
le_exp_smooth_feat).flatten()))**2.0) / len(np.array(double_exp_smooth_feat).fl
atten())
```

```
i=2
plt.figure(figsize=(16,5))
# traning plot for cluste 'i'
plt.plot(np.arange(len(cumulative_test[i])), (cumulative_test[i]), label='actua
l values')
plt.plot(np.arange(len(double_exp_smooth_feat[i])), double_exp_smooth_feat[i],
label='Holt_exp_smooting')
plt.title(f"Example of Holt double exponential smooting: cluster {i}")
plt.legend(loc='best')
plt.show()
```



3.2 Holt-Winter tripple exponential averaging

https://grisha.org/blog/2016/02/17/triple-exponential-smoothing-forecasting-part-iii/ --- Code reference

```
# Holt-Winter tripple exponential

def initial_trend(series, slen):
    sum = 0.0
    for i in range(slen):
        sum += float(series[i+slen] - series[i]) / slen
    return sum / slen

def initial_seasonal_components(series, slen):
    seasonals = {}
    season_averages = []
    n_seasons = int(len(series)/slen)
    # compute season averages
    for j in range(n_seasons):
        season_averages.append(sum(series[slen*j:slen*j+slen])/float(slen))
    # compute initial values
    for i in range(slen):
        sum_of_vals_over_avg = 0.0
        for j in range(n_seasons):
            sum_of_vals_over_avg += series[slen*j+i]-season_averages[j]
        seasonals[i] = sum_of_vals_over_avg/n_seasons
    return seasonals


def triple_exponential_smoothing(series, slen, alpha, beta, gamma, n_preds):
    result = []
    seasonals = initial_seasonal_components(series, slen)
    for i in range(len(series)+n_preds):
        if i == 0: # initial values
            smooth = series[0]
            trend = initial_trend(series, slen)
            result.append(series[0])
            continue
        if i >= len(series): # we are forecasting
            m = i - len(series) + 1
            result.append((smooth + m*trend) + seasonals[i%slen])
        else:
            val = series[i]
            last_smooth, smooth = smooth, alpha*(val-seasonals[i%slen]) + (1-al
pha)*(smooth+trend)
            trend = beta * (smooth-last_smooth) + (1-beta)*trend
            seasonals[i%slen] = gamma*(val-smooth) + (1-gamma)*seasonals[i%sle
n]
            result.append(smooth+trend+seasonals[i%slen])
    return result
```

```
# hyperparameter tuning

# removing top 5 values from each cluster for calculating MAPE and MSE
cumulative_test = [ regions_cum[i][5:] for i in range(40) ]
```

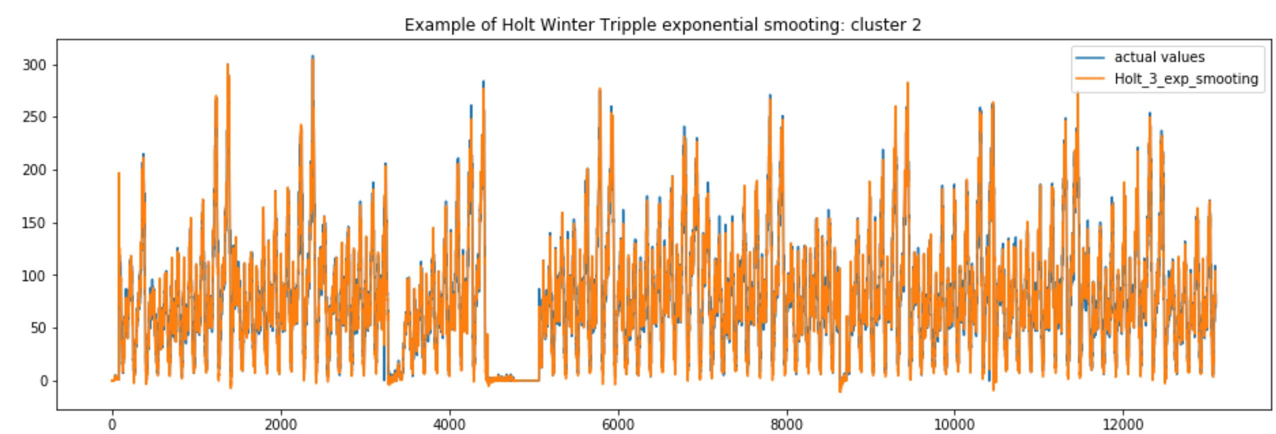
```
# Parameter initialisation
alpha = [0.1, 0.2, 0.3, 0.4, 0.5]
beta = [0.1, 0.12, 0.15, 0.20, 0.3]
gamma = [0.1,0.2,0.3,0.4]
season_len = [10,20,25]

# Storing all the results
result = []

for al in alpha:
    for b in beta:
        for g in gamma:
            for season in season_len:

                holt_winter_3_exp_smooth_feat = []

                # Holt winter feature for each cluster wise
                for r in range(0,40):
                    holt_wint_exp = triple_exponential_smoothing(regions_cum[r]
[0:13104], season, al, b, g, 0)
                    holt_winter_3_exp_smooth_feat.append(holt_wint_exp[5:])

                # calculating MAPE
                error = (sum(abs(np.subtract(np.array(cumulative_test).flatten
(), np.array(holt_winter_3_exp_smooth_feat).flatten()))))/len(np.array(holt_win
ter_3_exp_smooth_feat).flatten())
                y_ = sum(np.array(cumulative_test).flatten())/len(np.array(holt
_winter_3_exp_smooth_feat).flatten())
                mape_3_exp = error/y_

                # calculating MSE
                mse_3_exp = sum((np.subtract(np.array(cumulative_test).flatten
(), np.array(holt_winter_3_exp_smooth_feat).flatten()))**2.0) / len(np.array(ho
lt_winter_3_exp_smooth_feat).flatten())

                # Storing results
                result.append(([al, b, g, season],(mape_3_exp, mse_3_exp)))
```

```
# Finding Optimal hyperparameter
mape_res=[]
for i in range(len(result)):
    mape_res.append(result[i][1][0])

result_dataframe = pd.DataFrame(result, columns=["_alpha   ,_beta   ,_gamma   ,_se
ason_len","_MAPE    ,_MSE"])
print("Optimal_hyperparameter: \n")
print(result_dataframe.iloc[np.argmin(mape_res)])
```

```
Optimal_hyperparameter:

_alpha   ,_beta   ,_gamma   ,_season_len                           [0.5, 0.1, 0.4, 10]
_MAPE    ,_MSE                          (0.05073852849780103, 24.983657477980596)
Name: 249, dtype: object
```

```
# Using Optimal hyperparameter for holt-winter feature transform
alpha = 0.5
beta = 0.1
gamma = 0.4
season_len = 10


holt_winter_3_exp_smooth_feat = []

for r in range(0,40):
    holt_wint_exp = triple_exponential_smoothing(regions_cum[r][0:13104], seaso
n_len, alpha, beta, gamma, 0)
    holt_winter_3_exp_smooth_feat.append(holt_wint_exp[5:])

# calculating MAPE
error = (sum(abs(np.subtract(np.array(cumulative_test).flatten(), np.array(holt
_winter_3_exp_smooth_feat).flatten()))))/len(np.array(holt_winter_3_exp_smooth_
feat).flatten())
y_ = sum(np.array(cumulative_test).flatten())/len(np.array(holt_winter_3_exp_sm
ooth_feat).flatten())
mape_3_exp = error/y_

# calculating MSE
mse_3_exp = sum((np.subtract(np.array(cumulative_test).flatten(), np.array(holt
_winter_3_exp_smooth_feat).flatten()))**2.0) / len(np.array(holt_winter_3_exp_s
mooth_feat).flatten())
```

```
i=2
plt.figure(figsize=(16,5))
# traning plot for cluste 'i'
plt.plot(np.arange(len(cumulative_test[i])), (cumulative_test[i]), label='actua
l values')
plt.plot(np.arange(len(holt_winter_3_exp_smooth_feat[i])), holt_winter_3_exp_sm
ooth_feat[i], label='Holt_3_exp_smooting')
plt.title(f"Example of Holt Winter Tripple exponential smooting: cluster {i}")
plt.legend(loc='best')
plt.show()
```




```
print ("Error Metric Matrix (Forecasting Methods) - MAPE & MSE")
print ("--------------------------------------------------------------------
---------------------------------")
print ("holt-winter tripple exponential Averages (Values) -      MAPE: ",mape_3
```

```
_exp,"        MSE: ",mse_3_exp)
print ("holt double exponential Averages (Values) -              MAPE: ",mape_2
_exp,"        MSE: ",mse_2_exp)
```

```
Error Metric Matrix (Forecasting Methods) - MAPE & MSE
--------------------------------------------------------------------------------------------
------------
holt-winter tripple exponential Averages (Values) -      MAPE:  0.05073852849780103       MS
E:  24.983657477980596
holt double exponential Averages (Values) -              MAPE:  0.10268183636675085        M
SE:  104.46471317931922
```

3.3 Train Test Split of Additional feature

```
# Train Test Split of Holt Double Exponential Averages
train_holt_2_exp_smooth_feat = [(double_exp_smooth_feat)[i][:9169] for i in ran
ge(40)]
test_holt_2_exp_smooth_feat = [(double_exp_smooth_feat)[i][9169:] for i in rang
e(40)]

# 'holtz double exponential'
# the above contains values in the form of list of lists (i.e. list of values o
f each region), here we make all of them in one list for 'holtz double exponent
ial' feture
train_new_holt_2_exp_features = []
for i in range(0,40):
    train_new_holt_2_exp_features.extend(train_holt_2_exp_smooth_feat[i])
test_new_holt_2_exp_features = []
for i in range(0,40):
    test_new_holt_2_exp_features.extend(test_holt_2_exp_smooth_feat[i])
```

```
# train and test split of holtz winter tripple exponential feature
train_holt_winter_3_exp = [(holt_winter_3_exp_smooth_feat)[i][:9169] for i in r
ange(40)]
test_holt_winter_3_exp = [(holt_winter_3_exp_smooth_feat)[i][9169:] for i in ra
nge(40)]

#holtz winter 3  exponential
# the above contains values in the form of list of lists (i.e. list of values o
f each region), here we make all of them in one list for 'holtz winter exponent
ial' feture
train_new_holtz_wint_3_exp_features = []
for i in range(0,40):
    train_new_holtz_wint_3_exp_features.extend(train_holt_winter_3_exp[i])
test_new_holtz_wint_3_exp_features = []
for i in range(0,40):
    test_new_holtz_wint_3_exp_features.extend(test_holt_winter_3_exp[i])
```

```
# Adding additional feature into dataframe
df_train['holt_2exp_feature'] = train_new_holt_2_exp_features
df_train['holt_winter_3exp_feature'] = train_new_holtz_wint_3_exp_features
print("Train dataframe shape: ",df_train.shape)

df_test['holt_2exp_feature'] = test_new_holt_2_exp_features
```

```
df_test['holt_winter_3exp_feature'] = test_new_holtz_wint_3_exp_features
print("Test dataframe shape: ",df_test.shape)
df_test.head()
```

```
Train dataframe shape:  (366760, 21)
Test dataframe shape:  (157200, 21)
```

	ft_5	ft_4	ft_3	ft_2	ft_1	amp1	amp2	amp3	amp4	am
0	143.0	145.0	119.0	113.0	124.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
1	145.0	119.0	113.0	124.0	121.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
2	119.0	113.0	124.0	121.0	131.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
3	113.0	124.0	121.0	131.0	110.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351
4	124.0	121.0	131.0	110.0	116.0	387761.0	91160.781939	91160.781939	17509.351171	17509.351

5 rows × 21 columns

3.4 Modeling: After adding additional feature

Using Linear Regression

```
## Hyper Parameter tuning
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso

clf_lin_reg = Lasso(alpha=1.0)

param={'alpha':[0.001,0.01,0.1,1,10]}
gscv=GridSearchCV(estimator=clf_lin_reg, param_grid = param, scoring='neg_mean_
absolute_error', n_jobs=-1,verbose=10)
gscv.fit(df_train, tsne_train_output)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 out of  15 | elapsed:   23.2s remaining:  2.5min
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed:   32.9s remaining:  1.5min
[Parallel(n_jobs=-1)]: Done   6 out of  15 | elapsed:   42.8s remaining:  1.1min
[Parallel(n_jobs=-1)]: Done   8 out of  15 | elapsed:   52.3s remaining:   45.8s
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed:   58.1s remaining:   29.1s
[Parallel(n_jobs=-1)]: Done  12 out of  15 | elapsed:  1.1min remaining:   16.0s
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed:  1.3min finished
```

```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=1000, normalize=False, positive=False,
                             precompute=False, random_state=None,
                             selection='cyclic', tol=0.0001, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': [0.001, 0.01, 0.1, 1, 10]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=10)
```

```
print("Best Param: ",gscv.best_params_)
print("\nBest Score: ",-gscv.best_score_)
```

```
Best Param:  {'alpha': 0.1}

Best Score:  2.3855348430384375
```

```
# Traning Using Optimal Parameter
from sklearn.linear_model import Lasso
lr_reg=Lasso(alpha=0.1).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("Train MAPE : ",(mean_absolute_error(tsne_train_output, lr_train_predicti
ons))/(sum(tsne_train_output)/len(tsne_train_output)))
print("Test MAPE : ",(mean_absolute_error(tsne_test_output, lr_test_predictions
))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
Train MAPE :  0.0387738969024487
Test MAPE :  0.03493433401929968
```

Using Random Forest Regressor

```
## Hyper Parameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV

clf_rf = RandomForestRegressor(max_features='sqrt',max_depth=None, n_estimators
=40, n_jobs=-1)
param={'max_depth':[3,5,10,15,30],"n_estimators":[20,50,100,200,500]}

rscv= RandomizedSearchCV(estimator = clf_rf, param_distributions = param, scori
ng='neg_mean_absolute_error', n_jobs=-1,verbose=10)
rscv.fit(df_train, tsne_train_output)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:   25.0s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  4.0min
[Parallel(n_jobs=-1)]: Done  19 out of  30 | elapsed:  6.4min remaining:  3.7min
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  6.8min remaining:  2.1min
[Parallel(n_jobs=-1)]: Done  27 out of  30 | elapsed:  7.3min remaining:   48.4s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  7.6min finished


   RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
                      estimator=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=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n_estimators=40, n_jobs=-1,
                                                  oob_score=False,
                                                  random_state=None, verbose=0,
                                                  warm_start=False),
                   iid='warn', n_iter=10, n_jobs=-1,
                   param_distributions={'max_depth': [3, 5, 10, 15, 30],
                                        'n_estimators': [20, 50, 100, 200,
                                                         500]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring='neg_mean_absolute_error',
                   verbose=10)
```

```python
print("Best Param: ",rscv.best_params_)
print("\nBest Score: ",-rscv.best_score_)
```

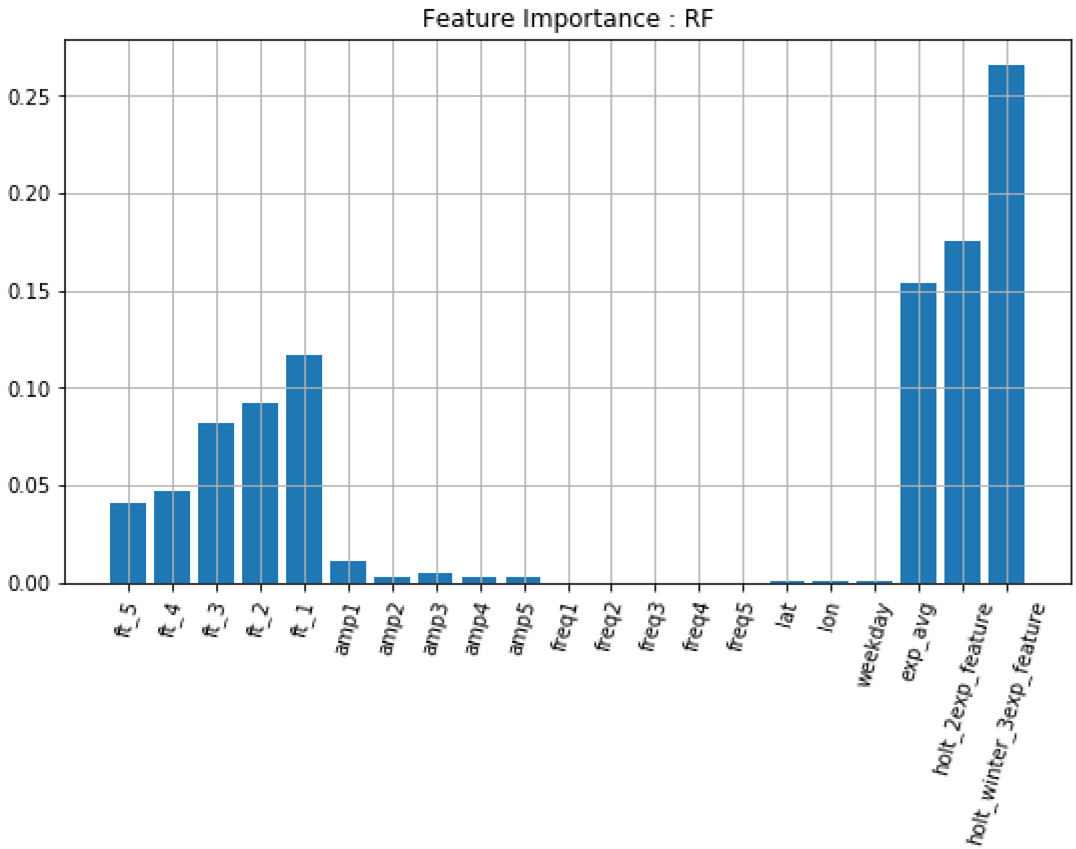
```
Best Param:  {'n_estimators': 500, 'max_depth': 30}

Best Score:  2.6191153166237626
```

```python
#Traning Using Optimal Hyperparameter
regr1 = RandomForestRegressor(max_features='sqrt',max_depth=30, n_estimators=50
0, n_jobs=-1)
regr1.fit(df_train, tsne_train_output)

# 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]


print("Train MAPE : ",(mean_absolute_error(tsne_train_output, rndf_train_predic
tions))/(sum(tsne_train_output)/len(tsne_train_output)))
print("Test MAPE : ",(mean_absolute_error(tsne_test_output, rndf_test_predictio
ns))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
Train MAPE :  0.013369995703600486
Test MAPE :  0.037977358077754604
```

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

plt.figure(figsize=(9,5))
plt.title("Feature Importance : RF")
plt.bar(df_train.columns,regr1.feature_importances_)
plt.xticks(np.arange(len(df_train.columns)),df_train.columns,rotation=75)
plt.grid()
plt.show()
```

```
Index(['ft_5', 'ft_4', 'ft_3', 'ft_2', 'ft_1', 'amp1', 'amp2', 'amp3', 'amp4',
       'amp5', 'freq1', 'freq2', 'freq3', 'freq4', 'freq5', 'lat', 'lon',
       'weekday', 'exp_avg', 'holt_2exp_feature', 'holt_winter_3exp_feature'],
      dtype='object')
[4.10266989e-02 4.68910421e-02 8.16174639e-02 9.21024551e-02
 1.16445305e-01 1.07856249e-02 3.35777926e-03 4.87201869e-03
 3.03248110e-03 2.87230813e-03 3.90639136e-05 3.98205440e-05
 4.18543337e-05 3.97779159e-05 4.17126466e-05 5.06493314e-04
 5.51738386e-04 3.55574382e-04 1.54004671e-01 1.75515509e-01
 2.65860607e-01]
```



Using XgBoost Regressor

```
## Hyper Parameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV

clf_xgb = xgb.XGBRegressor(learning_rate =0.1,n_estimators=1000,max_depth=3, nt
hread=-1)

param={'max_depth':[3,5,10,15,30],"n_estimators":[100,200,500,1000],"learning_r
ate":[1,0.1,0.01]}

rscv= RandomizedSearchCV(estimator = clf_xgb, param_distributions = param, scor
ing='neg_mean_absolute_error', n_jobs=1,verbose=10)
rscv.fit(df_train, tsne_train_output)
```

```
## Hyper Parameter tuning using random search
from sklearn.model_selection import RandomizedSearchCV

clf_xgb = xgb.XGBRegressor(learning_rate =0.1,n_estimators=1000,max_depth=3, nt
```

```python
hread=-1)

param={'max_depth':[3,5,10,15,30],"n_estimators":[100,200,500,1000],"learning_r
ate":[1,0.1,0.01]}

rscv= RandomizedSearchCV(estimator = clf_xgb, param_distributions = param, scor
ing='neg_mean_absolute_error', n_jobs=1,verbose=10)
rscv.fit(df_train, tsne_train_output)
```

```python
print("Best Param: ",rscv.best_params_)
print("\nBest Score: ",-rscv.best_score_)
```

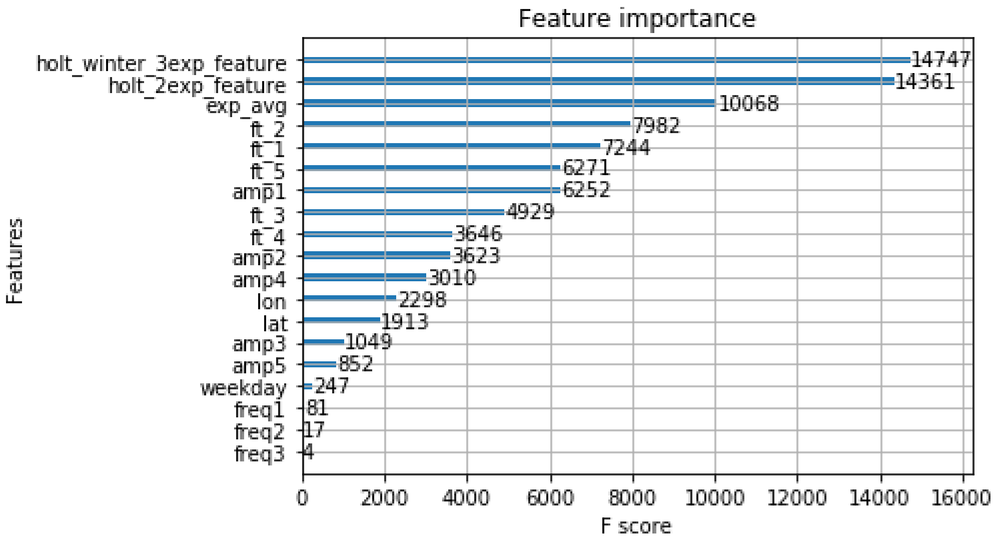
```
Best Param:  {'n_estimators': 500, 'max_depth': 10, 'learning_rate': 0.01}

Best Score:  2.218369189599684
```

```python
# Traninng with optimal Hyperparameter

x_model = xgb.XGBRegressor(
 learning_rate =0.01,
 n_estimators=500,
 max_depth=10,
 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)

#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]


print("Train MAPE : ",(mean_absolute_error(tsne_train_output, xgb_train_predict
ions))/(sum(tsne_train_output)/len(tsne_train_output)))
print("Test MAPE : ",(mean_absolute_error(tsne_test_output, xgb_test_prediction
s))/(sum(tsne_test_output)/len(tsne_test_output)))
```

```
[16:32:56] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprec
ated in favor of reg:squarederror.
Train MAPE :  0.03919242740659407
Test MAPE :  0.03906713008882744
```

```python
# Feature Importance of XGBoost Regressor
from xgboost import plot_importance
plt.figure(figsize=(9,5))
plot_importance(x_model,height=0.3)
plt.show()
```

```
<Figure size 648x360 with 0 Axes>
```



Result

```
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,df_train['holt_2exp_feature'].values))/(sum(tsne_train_output)/len(tsne_train_output)))
train_mape.append((mean_absolute_error(tsne_train_output,df_train['holt_winter_3exp_feature'].values))/(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)))
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)))



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, df_test['holt_2exp_feature'].values))/(sum(tsne_test_output)/len(tsne_test_output)))
test_mape.append((mean_absolute_error(tsne_test_output, df_test['holt_winter_3exp_feature'].values))/(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)))
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)))
```

Error Metric Matrix

```
# include onle 3 exp
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 ("Holt Double Exponential Averages Forecasting -           Train: ",train
_mape[2],"      Test: ",test_mape[2])
print ("Holt Wint Tripple Exponential Averages Forecasting -     Train: ",train
_mape[3],"      Test: ",test_mape[3])
print ("Linear Regression + Feature Eng.-                       Train: ",train_
mape[4],"      Test: ",test_mape[4])
print ("Random Forest Regression + Feature Eng.-                 Train: ",train
_mape[5],"      Test: ",test_mape[5])
print ("XgBoost Regression + Feature Eng.-                       Train: ",train
_mape[6],"      Test: ",test_mape[6])
print ("-------------------------------------------------------------------------------
---------------------------------")
```

```
Error Metric Matrix (Tree Based Regression Methods) -  MAPE
---------------------------------------------------------------------------------------------
------------
Baseline Model -                                         Train:  0.14870666996426116       T
est:  0.14225522601041551
Exponential Averages Forecasting -                       Train:  0.14121603560900353       T
est:  0.13490049942819257
Holt Double Exponential Averages Forecasting -           Train:  0.10413810004833247       T
est:  0.09959478141081789
Holt Wint Tripple Exponential Averages Forecasting -     Train:  0.05160889036066572       T
est:  0.04889349525540393
Linear Regression + Feature Eng.-                       Train:  0.0387738969024487       Tes
t:  0.03493433401929968
Random Forest Regression + Feature Eng.-                 Train:  0.013369995703600486
Test:  0.037977358077754604
XgBoost Regression + Feature Eng.-                       Train:  0.03919242740659407       T
est:  0.03906713008882744
---------------------------------------------------------------------------------------------
------------
```

Conclusion

Best MAPE score is 0.034 using Linear regression on all the features.

Adding Holt double and triple Exponential smoothing feaure is definitely improved the model in the great way.

END :)