Predicting interest rates from Federal Reserve documents

Baseline Definition (Vol. 5)

FE 690: Machine Learning in Finance

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Setup

Environment

```
# -*- coding: utf-8 -*-

# ENVIRONMENT CHECK:
import sys, os, inspect, site, pprint
# Check whether in Colab:
IN_COLAB = 'google.colab' in sys.modules
if IN_COLAB == True:
  print('YES, this is a Google Colaboratory environment.')
else:
  print('NO, this is not a Google Colaboratory environment.')
print(' ')

# Python installation files:
stdlib = os.path.dirname(inspect.getfile(os))
python_version = !python --version
print('Python Standard Library is located in:\n' + stdlib)
print(' ')
print('This environment is using {}'.format(str(python_version[0])))
print(' ')
print('Local system packages are located in:')
pprint.pprint(site.getsitepackages())
print(' ')
print('Local user packages are located in:\n' + site.getusersitepackages())

# Installed packages:
!pip list -v
!pip list --user -v
```

```
    pyviz-comms                   2.0.1          /usr/local/lib/python3.6/dist-packages pip
    PyWavelets                    1.1.1          /usr/local/lib/python3.6/dist-packages pip
    PyYAML                        3.13           /usr/local/lib/python3.6/dist-packages pip
    pyzmq                         20.0.0         /usr/local/lib/python3.6/dist-packages pip
    qdldl                         0.1.5.post0    /usr/local/lib/python3.6/dist-packages pip
    qtconsole                     5.0.1          /usr/local/lib/python3.6/dist-packages pip
    QtPy                          1.9.0          /usr/local/lib/python3.6/dist-packages pip
    Quandl                        3.5.3          /usr/local/lib/python3.6/dist-packages pip
    regex                         2019.12.20     /usr/local/lib/python3.6/dist-packages pip
```

```
requests                      2.24.0          /usr/local/lib/python3.6/dist-packages pip
requests-oauthlib             1.3.0           /usr/local/lib/python3.6/dist-packages pip
resampy                       0.2.2           /usr/local/lib/python3.6/dist-packages pip
retrying                      1.3.3           /usr/local/lib/python3.6/dist-packages pip
rpy2                          3.2.7           /usr/local/lib/python3.6/dist-packages pip
rsa                           4.6             /usr/local/lib/python3.6/dist-packages pip
sacremoses                    0.0.43          /usr/local/lib/python3.6/dist-packages pip
scikit-image                  0.16.2          /usr/local/lib/python3.6/dist-packages pip
scikit-learn                  0.22.2.post1    /usr/local/lib/python3.6/dist-packages pip
scikit-plot                   0.3.7           /usr/local/lib/python3.6/dist-packages pip
scipy                         1.4.1           /usr/local/lib/python3.6/dist-packages pip
screen-resolution-extra       0.0.0           /usr/lib/python3/dist-packages
scs                           2.1.2           /usr/local/lib/python3.6/dist-packages pip
seaborn                       0.11.0          /usr/local/lib/python3.6/dist-packages pip
Send2Trash                    1.5.0           /usr/local/lib/python3.6/dist-packages pip
sentencepiece                 0.1.91          /usr/local/lib/python3.6/dist-packages pip
setuptools                    51.3.3          /usr/local/lib/python3.6/dist-packages pip
setuptools-git                1.2             /usr/local/lib/python3.6/dist-packages pip
Shapely                       1.7.1           /usr/local/lib/python3.6/dist-packages pip
simplegeneric                 0.8.1           /usr/local/lib/python3.6/dist-packages pip
six                           1.12.0          /usr/local/lib/python3.6/dist-packages pip
sklearn                       0.0             /usr/local/lib/python3.6/dist-packages pip
sklearn-pandas                1.8.0           /usr/local/lib/python3.6/dist-packages pip
smart-open                    4.1.0           /usr/local/lib/python3.6/dist-packages pip
snowballstemmer               2.0.0           /usr/local/lib/python3.6/dist-packages pip
sortedcontainers              2.3.0           /usr/local/lib/python3.6/dist-packages pip
soupsieve                     2.1             /usr/local/lib/python3.6/dist-packages pip
spacy                         2.2.4           /usr/local/lib/python3.6/dist-packages pip
SpeechRecognition             3.8.1           /usr/local/lib/python3.6/dist-packages pip
Sphinx                        1.8.5           /usr/local/lib/python3.6/dist-packages pip
sphinxcontrib-serializinghtml 1.1.4           /usr/local/lib/python3.6/dist-packages pip
sphinxcontrib-websupport      1.2.4           /usr/local/lib/python3.6/dist-packages pip
SQLAlchemy                    1.3.22          /usr/local/lib/python3.6/dist-packages pip
sqlparse                      0.4.1           /usr/local/lib/python3.6/dist-packages pip
srsly                         1.0.5           /usr/local/lib/python3.6/dist-packages pip
statsmodels                   0.10.2          /usr/local/lib/python3.6/dist-packages pip
sympy                         1.1.1           /usr/local/lib/python3.6/dist-packages pip
tables                        3.4.4           /usr/local/lib/python3.6/dist-packages pip
tabulate                      0.8.7           /usr/local/lib/python3.6/dist-packages pip
tblib                         1.7.0           /usr/local/lib/python3.6/dist-packages pip
tensorboard                   2.4.0           /usr/local/lib/python3.6/dist-packages pip
tensorboard-plugin-wit        1.7.0           /usr/local/lib/python3.6/dist-packages pip
tensorboardcolab              0.0.22          /usr/local/lib/python3.6/dist-packages pip
tensorflow                    2.4.0           /usr/local/lib/python3.6/dist-packages pip
tensorflow-addons             0.8.3           /usr/local/lib/python3.6/dist-packages pip
tensorflow-datasets           4.0.1           /usr/local/lib/python3.6/dist-packages pip
tensorflow-estimator          2.4.0           /usr/local/lib/python3.6/dist-packages pip
tensorflow-gcs-config         2.4.0           /usr/local/lib/python3.6/dist-packages pip
tensorflow-hub                0.11.0          /usr/local/lib/python3.6/dist-packages pip
tensorflow-metadata           0.26.0          /usr/local/lib/python3.6/dist-packages pip
tensorflow-privacy            0.2.2           /usr/local/lib/python3.6/dist-packages pip
```

Mount Google Drive

```
# Mount Google Drive:
if IN_COLAB:
  from google.colab import drive
  drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

System Environment Variables

```
if IN_COLAB:
  employment_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/Employment/'
  cpi_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/CPI/'
  fed_rates_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/FEDRates/'
  fx_rates_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/FXRates/'
  gdp_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/GDP/'
  ism_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/ISM/'
  sales_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/Sales/'
  treasury_data_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/MarketData/Treasury/'
  fomc_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/FOMC/'
  preprocessed_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/preprocessed/'
  train_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/train_data/'
  output_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/result/'
  keyword_lm_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/LoughranMcDonald/'
  glove_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/GloVe/'
  model_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/models/'
  graph_dir = '/content/drive/My Drive/Colab Notebooks/proj2/src/data/graphs/'
else:
  employment_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/Employment/'
  cpi_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/CPI/'
  fed_rates_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/FEDRates/'
  fx_rates_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/FXRates/'
  gdp_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/GDP/'
  ism_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/ISM/'
  sales_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/Sales/'
  treasury_data_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/MarketData/Treasury/'
  fomc_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/FOMC/'
  preprocessed_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/preprocessed/'
  train_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/train_data/'
  output_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/result/'
  keyword_lm_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/LoughranMcDonald/'
  glove_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/GloVe/'
  model_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/models/'
  graph_dir = 'C:/Users/theon/GDrive/Colab Notebooks/proj2/src/data/graphs/'
```

Packages

Uninstall/Install Packages:

```
#if IN_COLAB:
#  # Uninstall existing versions:
#  !pip uninstall bs4 -y
#  !pip uninstall textract -y
#  !pip uninstall numpy -y
#  !pip uninstall pandas -y
#  !pip uninstall requests -y
#  !pip uninstall tqdm -y
#  !pip uninstall nltk -y
```

```
#  !pip uninstall quandl -y
#  !pip uninstall scikit-plot -y
#  !pip uninstall seaborn -y
#  !pip uninstall sklearn -y
#  !pip uninstall torch -y
#  !pip uninstall transformers -y
#  !pip uninstall wordcloud -y
#  !pip uninstall xgboost -y
#
#  # Install packages:
#  !pip install bs4==0.0.1
#  !pip install textract==1.6.3
#  !pip install numpy==1.19.4
#  !pip install pandas==1.1.4
#  !pip install requests==2.24.0
#  !pip install tqdm==4.51.0
#  !pip install nltk==3.5
#  !pip install quandl==3.5.3
#  !pip install scikit-plot==0.3.7
#  !pip install seaborn==0.11.0
#  !pip install sklearn==0.0
#  !pip install torch==1.7.1+cu101 torchvision==0.8.2+cu101 -f https://download.pytorch.org/whl/torch_stable.html
#  !pip install transformers==3.5.0
#  !pip install wordcloud==1.8.0
#  !pip install xgboost==1.2.1
#  os.kill(os.getpid(), 9)
```

Inspect Packages

```
!pip list -v
!pip list --user -v
```

```
PyDrive                  1.3.1            /usr/local/lib/python3.6/dist-packages pip
pyemd                    0.5.1            /usr/local/lib/python3.6/dist-packages pip
pyglet                   1.5.0            /usr/local/lib/python3.6/dist-packages pip
Pygments                 2.6.1            /usr/local/lib/python3.6/dist-packages pip
pygobject                3.26.1           /usr/lib/python3/dist-packages
pymc3                    3.7              /usr/local/lib/python3.6/dist-packages pip
PyMeeus                  0.3.7            /usr/local/lib/python3.6/dist-packages pip
pymongo                  3.11.2           /usr/local/lib/python3.6/dist-packages pip
pymystem3                0.2.0            /usr/local/lib/python3.6/dist-packages pip
PyOpenGL                 3.1.5            /usr/local/lib/python3.6/dist-packages pip
pyparsing                2.4.7            /usr/local/lib/python3.6/dist-packages pip
pyrsistent               0.17.3           /usr/local/lib/python3.6/dist-packages pip
pysndfile                1.3.8            /usr/local/lib/python3.6/dist-packages pip
PySocks                  1.7.1            /usr/local/lib/python3.6/dist-packages pip
pystan                   2.19.1.1         /usr/local/lib/python3.6/dist-packages pip
pytest                   3.6.4            /usr/local/lib/python3.6/dist-packages pip
python-apt               1.6.5+ubuntu0.5 /usr/lib/python3/dist-packages
python-chess             0.23.11          /usr/local/lib/python3.6/dist-packages pip
python-dateutil          2.8.1            /usr/local/lib/python3.6/dist-packages pip
python-louvain           0.15             /usr/local/lib/python3.6/dist-packages pip
python-pptx              0.6.18           /usr/local/lib/python3.6/dist-packages pip
python-slugify           4.0.1            /usr/local/lib/python3.6/dist-packages pip
python-utils             2.4.0            /usr/local/lib/python3.6/dist-packages pip
pytz                     2018.9           /usr/local/lib/python3.6/dist-packages pip
```

```
    pyviz-comms                2.0.1          /usr/local/lib/python3.6/dist-packages pip
    PyWavelets                 1.1.1          /usr/local/lib/python3.6/dist-packages pip
    PyYAML                     3.13           /usr/local/lib/python3.6/dist-packages pip
    pyzmq                      20.0.0         /usr/local/lib/python3.6/dist-packages pip
    qdldl                      0.1.5.post0    /usr/local/lib/python3.6/dist-packages pip
    qtconsole                  5.0.1          /usr/local/lib/python3.6/dist-packages pip
    QtPy                       1.9.0          /usr/local/lib/python3.6/dist-packages pip
    Quandl                     3.5.3          /usr/local/lib/python3.6/dist-packages pip
    regex                      2019.12.20     /usr/local/lib/python3.6/dist-packages pip
    requests                   2.24.0         /usr/local/lib/python3.6/dist-packages pip
    requests-oauthlib          1.3.0          /usr/local/lib/python3.6/dist-packages pip
    resampy                    0.2.2          /usr/local/lib/python3.6/dist-packages pip
    retrying                   1.3.3          /usr/local/lib/python3.6/dist-packages pip
    rpy2                       3.2.7          /usr/local/lib/python3.6/dist-packages pip
    rsa                        4.6            /usr/local/lib/python3.6/dist-packages pip
    sacremoses                 0.0.43         /usr/local/lib/python3.6/dist-packages pip
    scikit-image               0.16.2         /usr/local/lib/python3.6/dist-packages pip
    scikit-learn               0.22.2.post1   /usr/local/lib/python3.6/dist-packages pip
    scikit-plot                0.3.7          /usr/local/lib/python3.6/dist-packages pip
    scipy                      1.4.1          /usr/local/lib/python3.6/dist-packages pip
    screen-resolution-extra    0.0.0          /usr/lib/python3/dist-packages
    scs                        2.1.2          /usr/local/lib/python3.6/dist-packages pip
    seaborn                    0.11.0         /usr/local/lib/python3.6/dist-packages pip
    Send2Trash                 1.5.0          /usr/local/lib/python3.6/dist-packages pip
    sentencepiece              0.1.91         /usr/local/lib/python3.6/dist-packages pip
    setuptools                 51.3.3         /usr/local/lib/python3.6/dist-packages pip
    setuptools-git             1.2            /usr/local/lib/python3.6/dist-packages pip
    Shapely                    1.7.1          /usr/local/lib/python3.6/dist-packages pip
    simplegeneric              0.8.1          /usr/local/lib/python3.6/dist-packages pip
    six                        1.12.0         /usr/local/lib/python3.6/dist-packages pip
    sklearn                    0.0            /usr/local/lib/python3.6/dist-packages pip
    sklearn-pandas             1.8.0          /usr/local/lib/python3.6/dist-packages pip
    smart-open                 4.1.0          /usr/local/lib/python3.6/dist-packages pip
    snowballstemmer            2.0.0          /usr/local/lib/python3.6/dist-packages pip
    sortedcontainers           2.3.0          /usr/local/lib/python3.6/dist-packages pip
    soupsieve                  2.1            /usr/local/lib/python3.6/dist-packages pip
```

Import Packages:

```
# Python libraries
import pprint
import datetime as dt
import re
import pickle
from tqdm.notebook import tqdm
import time
import logging
import random
from collections import defaultdict, Counter
import xgboost as xgb

# Data Science modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
plt.style.use('ggplot')

# Import Scikit-learn models
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
```

```
from sklearn.metrics import accuracy_score, f1_score, plot_confusion_matrix
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier, ExtraTreesClassifier, VotingClassifier
from sklearn.linear_model import LogisticRegression, Perceptron, SGDClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn import model_selection
from sklearn.model_selection import GridSearchCV, cross_val_score, cross_validate, StratifiedKFold, learning_curve, RandomizedSearchCV
import scikitplot as skplt

# Import nltk modules and download dataset
import nltk
from nltk.corpus import stopwords
from nltk.util import ngrams
from nltk.tokenize import word_tokenize, sent_tokenize

# Import Pytorch modules
import torch
from torch import nn, optim
import torch.nn.functional as F
from torch.utils.data import (DataLoader, RandomSampler, SequentialSampler, TensorDataset)
from torch.autograd import Variable
from torch.optim import Adam, AdamW
```

Settings

```
# General:
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
get_ipython().run_line_magic('matplotlib', 'inline')



# Fiinalize nltk setup:
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

stop = set(stopwords.words('english'))

# Test pprint
pprint.pprint(sys.path)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
['',
```

```
     '/env/python',
     '/usr/lib/python36.zip',
     '/usr/lib/python3.6',
     '/usr/lib/python3.6/lib-dynload',
     '/usr/local/lib/python3.6/dist-packages',
     '/usr/lib/python3/dist-packages',
     '/usr/local/lib/python3.6/dist-packages/IPython/extensions',
     '/root/.ipython']


## Use TPU
#if IN_COLAB:
#  assert os.environ['COLAB_TPU_ADDR'], 'Select TPU: Runtime > Change runtime type > Hardware accelerator'
#  VERSION = "20200220"
#  !curl https://raw.githubusercontent.com/pytorch/xla/master/contrib/scripts/env-setup.py -o pytorch-xla-env-setup.py
#  !python pytorch-xla-env-setup.py --version $VERSION


## Use GPU Runtime:
if IN_COLAB:
  if torch.cuda.is_available():
    torch.cuda.get_device_name(0)
    gpu_info = !nvidia-smi
    gpu_info = '\n'.join(gpu_info)
    print(gpu_info)
  else:
    print('Select the Runtime > "Change runtime type" menu to enable a GPU accelerator, and then re-execute this cell.')
    os.kill(os.getpid(), 9)


     Mon Jan 25 12:27:54 2021
     +-----------------------------------------------------------------------------+
     | NVIDIA-SMI 460.32.03    Driver Version: 418.67       CUDA Version: 10.1     |
     |-------------------------------+----------------------+----------------------+
     | GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
     | Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
     |                               |                      |               MIG M. |
     |===============================+======================+======================|
     |   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
     | N/A   35C    P0    26W / 250W |     10MiB / 16280MiB |      0%      Default |
     |                               |                      |                 ERR! |
     +-------------------------------+----------------------+----------------------+

     +-----------------------------------------------------------------------------+
     | Processes:                                                                  |
     |  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
     |        ID   ID                                                   Usage      |
     |=============================================================================|
     |  No running processes found                                                 |
     +-----------------------------------------------------------------------------+


# Set logger
logger = logging.getLogger('mylogger')
logger.setLevel(logging.DEBUG)
timestamp = time.strftime("%Y.%m.%d_%H.%M.%S", time.localtime())
fh = logging.FileHandler('log_model.txt')
fh.setLevel(logging.DEBUG)
ch = logging.StreamHandler()
ch.setLevel(logging.DEBUG)
formatter = logging.Formatter('[%(asctime)s][%(levelname)s] ## %(message)s')
```

```
fh.setFormatter(formatter)
ch.setFormatter(formatter)
logger.addHandler(fh)
logger.addHandler(ch)


# Set Random Seed
random.seed(42)
np.random.seed(42)
torch.manual_seed(42)
torch.cuda.manual_seed(42)
rand_seed = 42


# Set Seaborn Style
sns.set(style='white', context='notebook', palette='deep')
```

Load preprocessed data

```
# Load data
file = open(train_dir + 'nontext_train_small.pickle', 'rb')
train_df = pickle.load(file)
file.close()
#train_df = pd.read_csv(train_dir + 'nontext_train_small.csv')
train_df
```

	target	prev_decision	GDP_diff_prev	PMI_value	Employ_diff_prev	Rsales_diff_year	Unemp_diff_prev	Inertia_diff	Hsales_diff_year	Balanced_diff
date										
1982-10-05	-1	0	0.456197	38.8	-169.0	1.807631	-0.166667	-0.018226	-15.485275	0.003723
1982-11-16	-1	-1	-0.382295	39.4	-228.0	1.807631	-0.200000	-0.018226	-9.537496	0.003723
1982-12-21	0	-1	-0.382295	39.2	-198.5	1.807631	-0.333333	-0.018226	-3.116275	0.003723
1983-01-14	0	0	-0.382295	42.8	-68.0	1.807631	-0.233333	-0.018226	-0.774432	0.003723
1983-01-21	0	0	-0.382295	42.8	-68.0	1.807631	-0.233333	-0.043785	-0.774432	0.003723
...	...	...	...	...	...	...	...	...	...	...
2020-03-15	-1	-1	0.527469	50.1	232.5	2.217385	0.000000	-0.058085	13.910886	0.004279
2020-03-19	0	-1	0.527469	50.1	232.5	2.217385	0.000000	-0.057139	13.910886	0.001426
2020-03-23	0	0	0.527469	50.1	232.5	2.217385	0.000000	-0.057139	13.910886	0.001426
2020-03-31	0	0	0.527469	50.1	232.5	2.217385	0.000000	-0.114279	13.910886	0.006092
2020-04-29	0	0	0.527469	49.1	-561.0	-2.491979	-0.300000	-0.431520	12.468252	0.040295

398 rows × 10 columns

Balancing the classes

```
# Percentage before the balancing
n_hold = sum(1 for each in train_df['target'] if each == 0)
```

```
n_hold = sum(1 for each in train_df['target'] if each == 0)
n_lower = sum(1 for each in train_df['target'] if each == -1)
n_raise = sum(1 for each in train_df['target'] if each == 1)
N_examples = len(train_df)

print('Hold: ', round(n_hold/N_examples, 2))
print('Lower:', round(n_lower/N_examples, 2))
print('Raise:', round(n_raise/N_examples, 2))
```

```
Hold:  0.66
Lower: 0.18
Raise: 0.16
```

Here, take random sampling approach to balance the data. Though it loses some data, easy to process and less prone to the bias.

_Update: Decided not to do this as we do not have a lot of data. Consider different approach to tackle this imbalanced data issue. Thus, set keep_prob = 1 (keep everything). _

```
# Too many Hold. Better to randomly pick to even the distribution
n_hold = sum(1 for each in train_df['target'] if each == 0)
N_examples = len(train_df)

# Keep probability (specify decimal value between 0 and 1)
# keep_prob = (N_examples - n_hold)/2/n_hold
keep_prob = 1

balanced = pd.concat([train_df.loc[train_df['target'] != 0], train_df.loc[train_df['target'] == 0].sample(frac=keep_prob, random_state=1)])
balanced.sort_index(ascending=True, inplace=True)

n_hold = sum(1 for each in balanced['target'] if each == 0)
n_lower = sum(1 for each in balanced['target'] if each == -1)
n_raise = sum(1 for each in balanced['target'] if each == 1)
N_examples = len(balanced['target'])
print('Hold: ', round(n_hold/N_examples, 2))
print('Lower:', round(n_lower/N_examples, 2))
print('Raise:', round(n_raise/N_examples, 2))
```

```
Hold:  0.66
Lower: 0.18
Raise: 0.16
```

```
def convert_class(x):
    if x == 1:
        return 3
    elif x == 0:
        return 2
    elif x == -1:
        return 1
```

```
Y_balanced = balanced['target'].map(convert_class)
X_balanced = balanced.drop(columns=['target'])
Y_balanced
X_balanced
```

date	prev_decision	GDP_diff_prev	PMI_value	Employ_diff_prev	Rsales_diff_year	Unemp_diff_prev	Inertia_diff	Hsales_diff_year	Balanced_diff
1982-10-05	0	0.456197	38.8	-169.0	1.807631	-0.166667	-0.018226	-15.485275	0.003723
1982-11-16	-1	-0.382295	39.4	-228.0	1.807631	-0.200000	-0.018226	-9.537496	0.003723
1982-12-21	-1	-0.382295	39.2	-198.5	1.807631	-0.333333	-0.018226	-3.116275	0.003723
1983-01-14	0	-0.382295	42.8	-68.0	1.807631	-0.233333	-0.018226	-0.774432	0.003723
1983-01-21	0	-0.382295	42.8	-68.0	1.807631	-0.233333	-0.043785	-0.774432	0.003723
...	...	...	...	...	...	...	...	...	...
2020-03-15	-1	0.527469	50.1	232.5	2.217385	0.000000	-0.058085	13.910886	0.004279
2020-03-19	-1	0.527469	50.1	232.5	2.217385	0.000000	-0.057139	13.910886	0.001426
2020-03-23	0	0.527469	50.1	232.5	2.217385	0.000000	-0.057139	13.910886	0.001426
2020-03-31	0	0.527469	50.1	232.5	2.217385	0.000000	-0.114279	13.910886	0.006092
2020-04-29	0	0.527469	49.1	-561.0	-2.491979	-0.300000	-0.431520	12.468252	0.040295

398 rows x 9 columns

```
# Because the prediction should be on the latest and should not look back, use shuffle=False
X_train, X_test, Y_train, Y_test = \
model_selection.train_test_split(X_balanced.values, Y_balanced.values, test_size=0.2, shuffle=False)


print("Training Data: Total {}, {}".format(len(Y_train), Counter(Y_train)))
print("Test Data: Total {}, {}".format(len(Y_test), Counter(Y_test)))
```

```
Training Data: Total 318, Counter({2: 203, 1: 63, 3: 52})
Test Data: Total 80, Counter({2: 58, 3: 13, 1: 9})
```

```
Y_balanced.head()
```

```
date
1982-10-05    1
1982-11-16    1
1982-12-21    2
1983-01-14    2
1983-01-21    2
Name: target, dtype: int64
```

Modeling and Training

Sanity checks

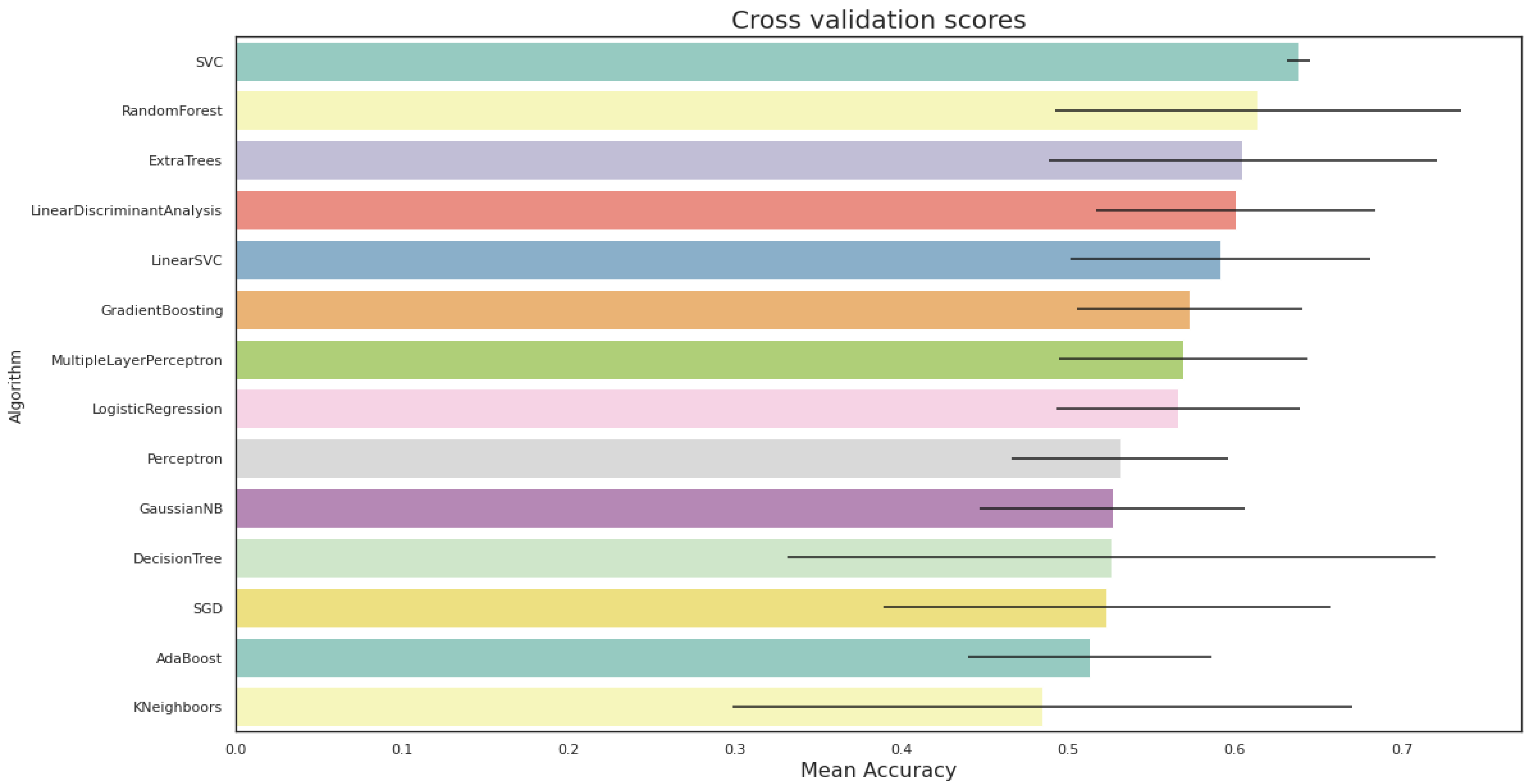
```
# Use Stratified KFold Cross Validation
n_fold = 7
kfold = StratifiedKFold(n_splits=n_fold)
kfold
```

```
     StratifiedKFold(n_splits=7, random_state=None, shuffle=False)

# Roughly check base classifiers without hyperparameter setting

random_state = 2
classifiers = []
classifiers.append(("SVC", SVC(random_state=random_state)))
classifiers.append(("DecisionTree", DecisionTreeClassifier(random_state=random_state)))
classifiers.append(("AdaBoost", AdaBoostClassifier(DecisionTreeClassifier(random_state=random_state),random_state=random_state,learning_rate=0.1)))
classifiers.append(("RandomForest", RandomForestClassifier(random_state=random_state, n_estimators=100)))
classifiers.append(("ExtraTrees", ExtraTreesClassifier(random_state=random_state)))
classifiers.append(("GradientBoosting", GradientBoostingClassifier(random_state=random_state)))
classifiers.append(("MultipleLayerPerceptron", MLPClassifier(random_state=random_state)))
classifiers.append(("KNeighboors", KNeighborsClassifier(n_neighbors=3)))
classifiers.append(("LogisticRegression", LogisticRegression(random_state = random_state)))
classifiers.append(("LinearDiscriminantAnalysis", LinearDiscriminantAnalysis()))
classifiers.append(("GaussianNB", GaussianNB()))
classifiers.append(("Perceptron", Perceptron()))
classifiers.append(("LinearSVC", LinearSVC()))
classifiers.append(("SGD", SGDClassifier()))

cv_results = []
classifier_name = []
for classifier in classifiers :
    cv_results.append(cross_validate(classifier[1], X_train, y = Y_train, scoring = ["accuracy", "f1_macro"], cv = kfold, n_jobs=4))
    classifier_name.append(classifier[0])

cv_acc_means = []
cv_acc_std = []
cv_f1_means = []
cv_f1_std = []
for cv_result in cv_results:
    cv_acc_means.append(cv_result['test_accuracy'].mean())
    cv_acc_std.append(cv_result['test_accuracy'].std())
    cv_f1_means.append(cv_result['test_f1_macro'].mean())
    cv_f1_std.append(cv_result['test_f1_macro'].std())

cv_res = pd.DataFrame({"Algorithm": classifier_name,
                       "CVAccMeans":cv_acc_means,
                       "CVAccErrors": cv_acc_std,
                       "CVf1Means":cv_f1_means,
                       "CVf1Errors": cv_f1_std})


cv_res.sort_values(by='CVAccMeans', ascending=False)
```

	Algorithm	CVAccMeans	CVAccErrors	CVf1Means	CVf1Errors
0	SVC	0.638440	0.006933	0.259768	0.001724
3	RandomForest	0.613872	0.084025	0.499901	0.133119
4	ExtraTrees	0.604555	0.089632	0.484787	0.129810
9	LinearDiscriminantAnalysis	0.600621	0.079205	0.441110	0.109036
12	LinearSVC	0.591235	0.073014	0.328765	0.076731
5	GradientBoosting	0.572740	0.067923	0.473122	0.093812
6	MultipleLayerPerceptron	0.569220	0.074575	0.366500	0.137015

```
plt.figure(figsize=(18,10))
ax = sns.barplot("CVAccMeans","Algorithm",data=cv_res.sort_values(by='CVAccMeans', ascending=False), palette="Set3", orient="h", **{'xerr':cv_acc_std})
ax.set_xlabel("Mean Accuracy", size=16)
ax.set_title("Cross validation scores", size=20)
```

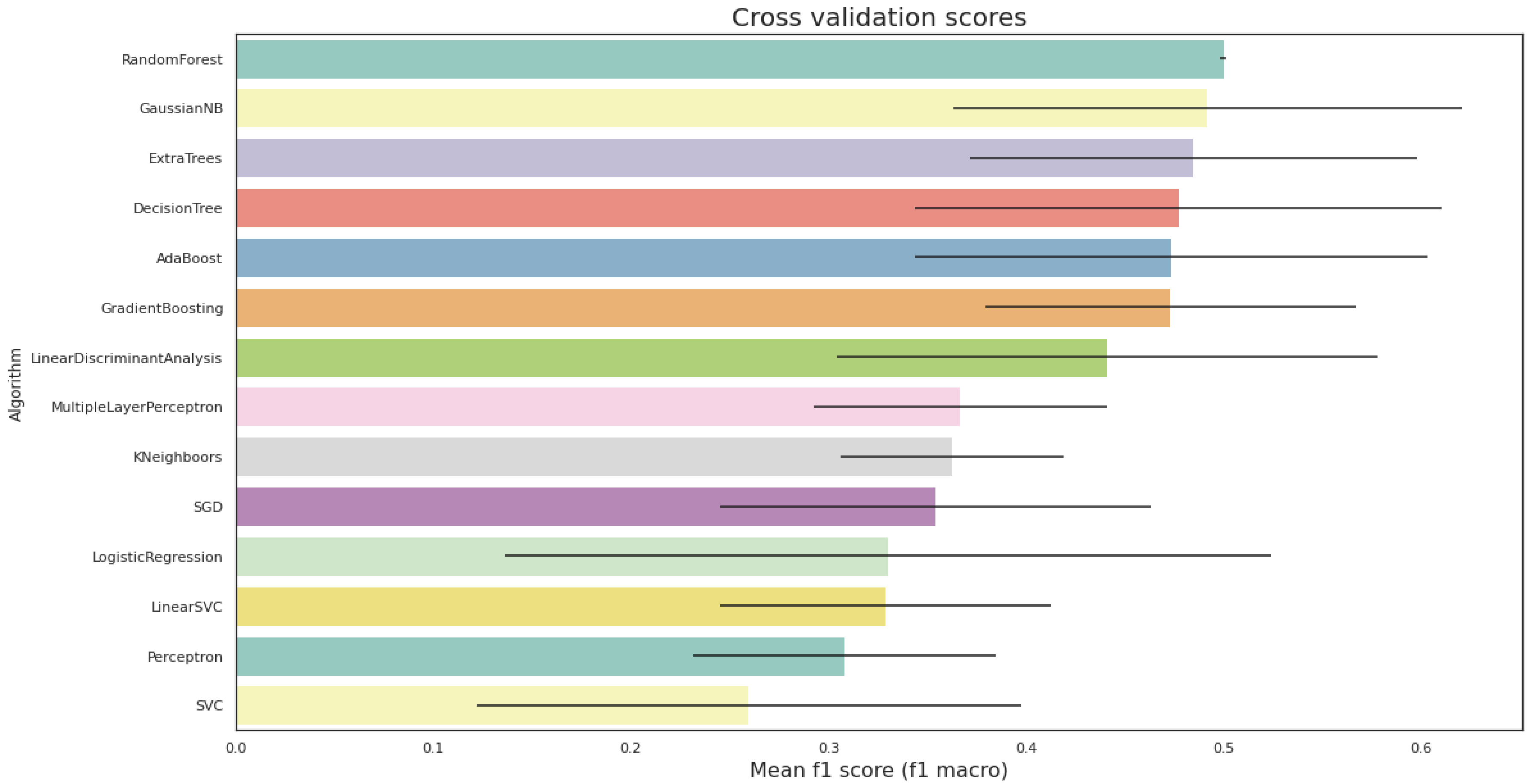
```
Text(0.5, 1.0, 'Cross validation scores')
```




```
plt.figure(figsize=(18,10))
ax = sns.barplot("CVf1Means","Algorithm",data=cv_res.sort_values(by='CVf1Means', ascending=False), palette="Set3", orient="h", **{'xerr':cv_f1_std})
ax.set_xlabel("Mean f1 score (f1_macro)", size=16)
```

```
ax.set_xlabel("Mean f1 score (f1 macro)", size=16)
ax.set_title("Cross validation scores", size=20)
```

```
Text(0.5, 1.0, 'Cross validation scores')
```



Hyperparameter Tuning

```
def metric(y_true, y_pred):
    acc = accuracy_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred, average='macro')
    return acc, f1

scoring = {'Accuracy': 'accuracy', 'F1': 'f1_macro'}
refit = 'F1'


def train_grid_search(estimator, param_grid, scoring, refit, cv=5, verbose=1, plot=True):
    model = GridSearchCV(estimator, param_grid=param_grid, cv=cv, scoring=scoring, verbose=verbose,
                         refit=refit, n_jobs=-1, return_train_score=True)
    model.fit(X_train, Y_train)

    results = model.cv_results_
    best_estimator = model.best_estimator_
```

```
train_scores = results['mean_train_' + refit]
test_scores = results['mean_test_' + refit]
train_time = results['mean_fit_time']

print("Best Score: ", model.best_score_)
print("Best Param: ", model.best_params_)

pred_train = best_estimator.predict(X_train)
pred_test = best_estimator.predict(X_test)

acc, f1 = metric(Y_train, pred_train)
logger.info('Training - acc: %.8f, f1: %.8f' % (acc, f1))
acc, f1 = metric(Y_test, pred_test)
logger.info('Test - acc: %.8f, f1: %.8f' % (acc, f1))

if plot:
    fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(15, 5))
    fig.suptitle("GridSearchCV Result", fontsize=20)

    ax1.plot(train_scores, test_scores, 'bo')
    ax1.set_title("Train Score v.s. Test Score", fontsize=16)
    ax1.set_xlabel("Train Score")
    ax1.set_ylabel("Test Score")
    ax1.set_xlim(0, 1)
    ax1.set_ylim(0, 1)
    ax1.grid(True)

    x_param = list(param_grid.keys())[0]
    x_param_min = np.min(list(param_grid.values())[0])
    x_param_max = np.max(list(param_grid.values())[0])

    ax2.set_title("Score over the first param", fontsize=16)
    ax2.set_xlabel(x_param)
    ax2.set_ylabel("Score")
    ax2.set_xlim(x_param_min, x_param_max)
    ax2.set_ylim(0, 1)

    X_axis = np.array(results['param_' + x_param].data, dtype=float)

    for scorer, color in zip(sorted(scoring), ['r', 'g']):
        for sample, style in (('train', '--'), ('test', '-')):
            sample_score_mean = results['mean_%s_%s' % (sample, scorer)]
            sample_score_std = results['std_%s_%s' % (sample, scorer)]
            ax2.fill_between(X_axis, sample_score_mean - sample_score_std,
                            sample_score_mean + sample_score_std,
                            alpha=0.1 if sample == 'test' else 0, color=color)
            ax2.plot(X_axis, sample_score_mean, style, color=color,
                    alpha=1 if sample == 'test' else 0.7,
                    label="%s (%s)" % (scorer, sample.capitalize()))

        best_index = np.nonzero(results['rank_test_%s' % scorer] == 1)[0][0]
        best_score = results['mean_test_%s' % scorer][best_index]

        ax2.plot([X_axis[best_index], ] * 2, [0, best_score],
                linestyle='-.', color=color, marker='x', markeredgewidth=3, ms=8)

        ax2.annotate("%0.2f" % best_score,
                    (X_axis[best_index], best_score + 0.005))
```

```
                (X_axis[best_index], best_score + 0.005))

ax2.legend(loc="best")
ax2.grid(False)

lc_acc_train_sizes, lc_acc_train_scores, lc_acc_test_scores = learning_curve(
    best_estimator, X_train, Y_train, cv=kfold, n_jobs=-1, scoring=scoring['Accuracy'],
    train_sizes=np.linspace(.1, 1.0, 5))
lc_acc_train_mean = np.mean(lc_acc_train_scores, axis=1)
lc_acc_train_std = np.std(lc_acc_train_scores, axis=1)
lc_acc_test_mean = np.mean(lc_acc_test_scores, axis=1)
lc_acc_test_std = np.std(lc_acc_test_scores, axis=1)

lc_f1_train_sizes, lc_f1_train_scores, lc_f1_test_scores = learning_curve(
    best_estimator, X_train, Y_train, cv=kfold, n_jobs=-1, scoring=scoring['F1'],
    train_sizes=np.linspace(.1, 1.0, 5))
lc_f1_train_mean = np.mean(lc_f1_train_scores, axis=1)
lc_f1_train_std = np.std(lc_f1_train_scores, axis=1)
lc_f1_test_mean = np.mean(lc_f1_test_scores, axis=1)
lc_f1_test_std = np.std(lc_f1_test_scores, axis=1)

ax3.set_title("Learning Curve", fontsize=16)
ax3.set_xlabel("Training examples")
ax3.set_ylabel("Score")

ax3.fill_between(lc_acc_train_sizes,
                 lc_acc_train_mean - lc_acc_train_std,
                 lc_acc_train_mean + lc_acc_train_std, alpha=0.1, color="r")
ax3.fill_between(lc_acc_train_sizes,
                 lc_acc_test_mean - lc_acc_test_std,
                 lc_acc_test_mean + lc_acc_test_std, alpha=0.1, color="r")
ax3.plot(lc_acc_train_sizes, lc_acc_train_mean, 'o--', color="r",
         label="Accuracy (Train)")
ax3.plot(lc_acc_train_sizes, lc_acc_test_mean, 'o-', color="r",
         label="Accuracy (Test)")

ax3.fill_between(lc_f1_train_sizes,
                 lc_f1_train_mean - lc_f1_train_std,
                 lc_f1_train_mean + lc_f1_train_std, alpha=0.1, color="g")
ax3.fill_between(lc_f1_train_sizes,
                 lc_f1_test_mean - lc_f1_test_std,
                 lc_f1_test_mean + lc_f1_test_std, alpha=0.1, color="g")
ax3.plot(lc_f1_train_sizes, lc_f1_train_mean, 'o--', color="g",
         label="F1 (Train)")
ax3.plot(lc_f1_train_sizes, lc_f1_test_mean, 'o-', color="g",
         label="F1 (Test)")

ax3.legend(loc="best")
ax3.grid(True)

plt.tight_layout(pad=3.0)
plt.show()

class_names = ['Lower', 'Hold', 'Raise']
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle("Confusion Matrix", fontsize=20)

plot_confusion_matrix(best_estimator, X_train, Y_train, display_labels=class_names,
```

```python
                         cmap=plt.cm.Blues, normalize=None, ax=ax1)
    ax1.set_title("Train Data: Actual Count")
    ax1.grid(False)

    plot_confusion_matrix(best_estimator, X_train, Y_train, display_labels=class_names,
                         cmap=plt.cm.Blues, normalize='all', ax=ax2)
    ax2.set_title=("Train Data: Normalized")
    ax2.grid(False)

    plot_confusion_matrix(best_estimator, X_test, Y_test, display_labels=class_names,
                         cmap=plt.cm.Blues, normalize=None, ax=ax3)
    ax3.set_title=("Test Data: Actual Count")
    ax3.grid(False)

    plot_confusion_matrix(best_estimator, X_test, Y_test, display_labels=class_names,
                         cmap=plt.cm.Blues, normalize='all', ax=ax4)
    ax4.set_title("Test Data: Normalized")
    ax4.grid(False)

    plt.tight_layout(pad=3.0)
    plt.show()

return model
```

ADA Boost (on Decision Tree)

```python
DTC = DecisionTreeClassifier()
ada_clf = AdaBoostClassifier(DTC, random_state=rand_seed)


rand_param_grid = {"base_estimator__criterion" : ["gini", "entropy"],
              "base_estimator__splitter" :   ["best", "random"],
              "algorithm" : ["SAMME","SAMME.R"],
              "n_estimators" : [10, 50, 100, 200, 500],
              "learning_rate":  [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.5, 1.0, 1.5]}

rand_model = RandomizedSearchCV(estimator=ada_clf, param_distributions=rand_param_grid,
                                n_iter=300, cv=kfold, scoring=scoring[refit], verbose=1,
                                random_state=rand_seed, n_jobs=-1)
rand_model.fit(X_train,Y_train)
print(rand_model.best_score_)
print(rand_model.best_params_)
```

```
Fitting 7 folds for each of 300 candidates, totalling 2100 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 312 tasks      | elapsed:    0.7s
0.48384574599440144
{'n_estimators': 500, 'learning_rate': 0.001, 'base_estimator__splitter': 'best', 'base_estimator__criterion': 'gini', 'algorithm': 'SAMME.R'}
[Parallel(n_jobs=-1)]: Done 2100 out of 2100 | elapsed:    3.5s finished
```

```python
param_grid = {'n_estimators': np.linspace(1, 500, 50, dtype=int),
              'base_estimator__criterion': ['gini'],
              'base_estimator__splitter': ['random'],
              'algorithm': ['SAMME.R'],
              'learning_rate': [0.01]}
```

```
ada_model = train_grid_search(ada_clf, param_grid, scoring, refit, cv=kfold, verbose=1, plot=True)
ada_best = ada_model.best_estimator_
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
Fitting 7 folds for each of 50 candidates, totalling 350 fits
[Parallel(n_jobs=-1)]: Done 238 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 350 out of 350 | elapsed:    0.7s finished
[2021-01-25 12:28:14,729][INFO] ## Training - acc: 1.00000000, f1: 1.00000000
[2021-01-25 12:28:14,731][INFO] ## Test - acc: 0.43750000, f1: 0.29121278
Best Score:  0.37360576621869923
Best Param:  {'algorithm': 'SAMME.R', 'base_estimator__criterion': 'gini', 'base_estimator__splitter': 'random', 'learning_rate': 0.01, 'n_estimators': 1}
```

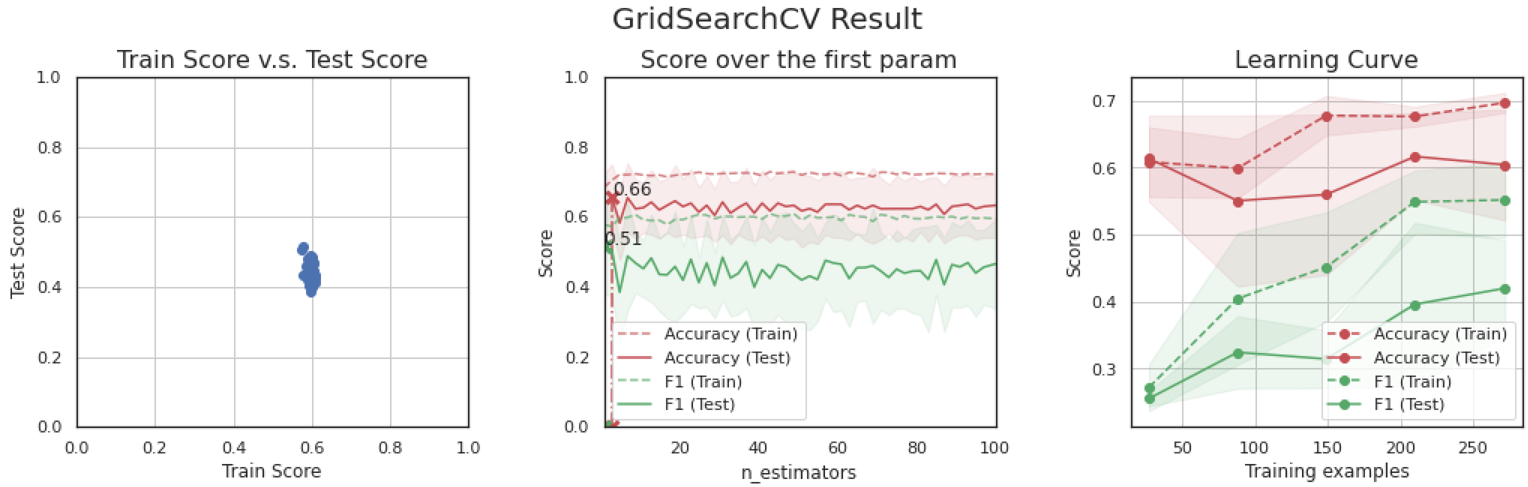
Extra Tree

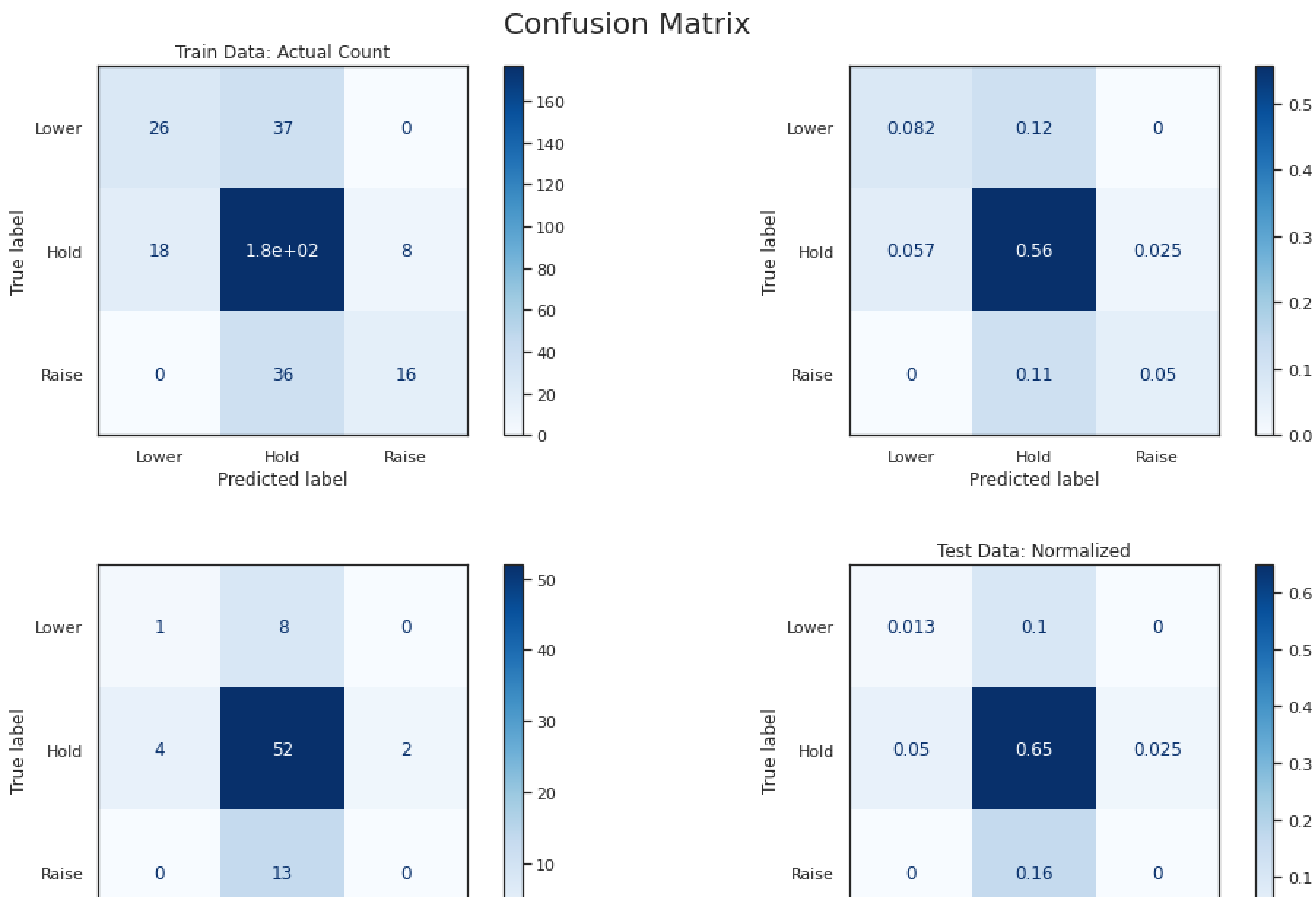

```
ext_clf = ExtraTreesClassifier()

rand_param_grid = {"max_depth": [None],
              "max_features": [1, 2, 3, 5],
              "min_samples_split": [2, 3, 5, 10, 20],
              "min_samples_leaf": [1, 3, 5, 7, 10],
              "bootstrap": [False],
              "n_estimators" : [1, 2, 5, 10, 20, 100, 200, 1000],
              "criterion": ["gini"]}

rand_model = RandomizedSearchCV(estimator=ext_clf,
                               param_distributions=rand_param_grid,
                               n_iter=300,
                               cv=kfold,
                               scoring=scoring[refit],
                               verbose=1,
                               random_state=rand_seed,
                               n_jobs=-1)
rand_model.fit(X_train,Y_train)
print(rand_model.best_score_)
print(rand_model.best_params_)
```

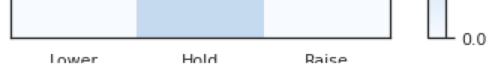
```
Fitting 7 folds for each of 300 candidates, totalling 2100 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  90 tasks      | elapsed:    3.5s
[Parallel(n_jobs=-1)]: Done 392 tasks      | elapsed:   25.5s
[Parallel(n_jobs=-1)]: Done 1109 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 1942 tasks      | elapsed:  1.9min
0.519764562959472
{'n_estimators': 5, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 2, 'max_depth': None, 'criterion': 'gini', 'bootstrap': False}
[Parallel(n_jobs=-1)]: Done 2100 out of 2100 | elapsed:  2.0min finished
```

```
param_grid = {'n_estimators': np.linspace(1, 100, 50, dtype=int),
              'min_samples_split': [5],
              'min_samples_leaf': [10],
              'max_features': [8],
              'max_depth': [None],
              'criterion': ['gini'],
              'bootstrap': [False]}

ext_model = train_grid_search(ext_clf, param_grid, scoring, refit, cv=kfold, verbose=1, plot=True)
ext_best = ext_model.best_estimator_
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
Fitting 7 folds for each of 50 candidates, totalling 350 fits
[Parallel(n_jobs=-1)]: Done 200 tasks      | elapsed:    2.9s
[Parallel(n_jobs=-1)]: Done 350 out of 350 | elapsed:    7.6s finished
[2021-01-25 12:30:25,724][INFO] ## Training - acc: 0.68867925, f1: 0.56283030
[2021-01-25 12:30:25,725][INFO] ## Test - acc: 0.66250000, f1: 0.31225009
Best Score:  0.5146332790798632
Best Param:  {'bootstrap': False, 'criterion': 'gini', 'max_depth': None, 'max_features': 8, 'min_samples_leaf': 10, 'min_samples_split': 5, 'n_estimators': 1}
```







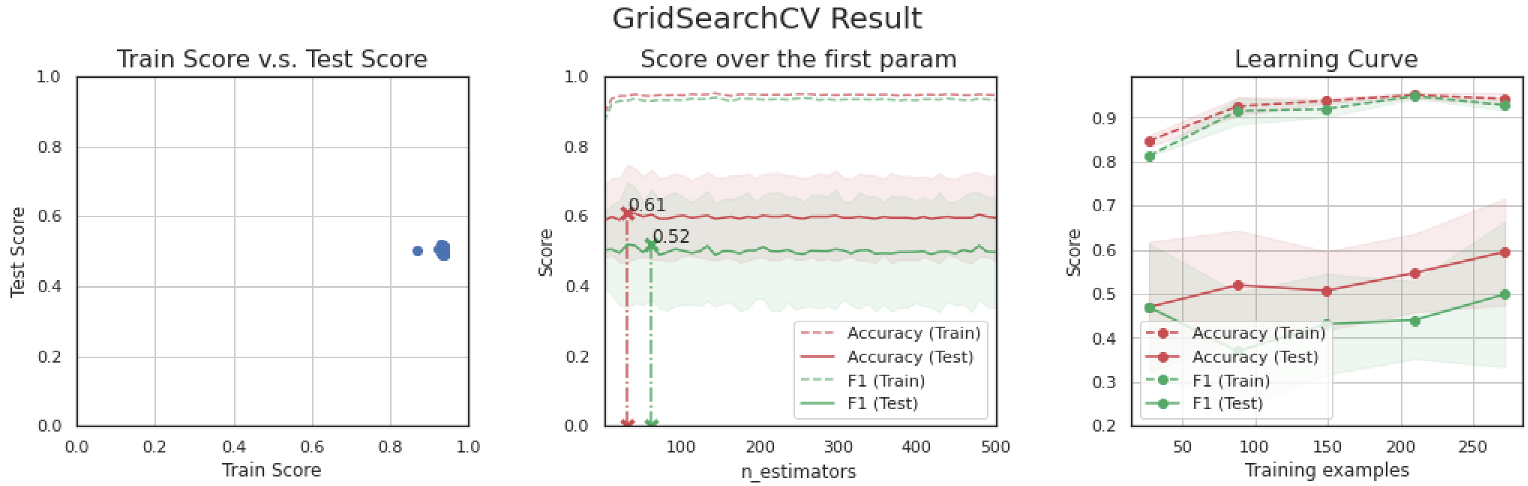
Random Forest

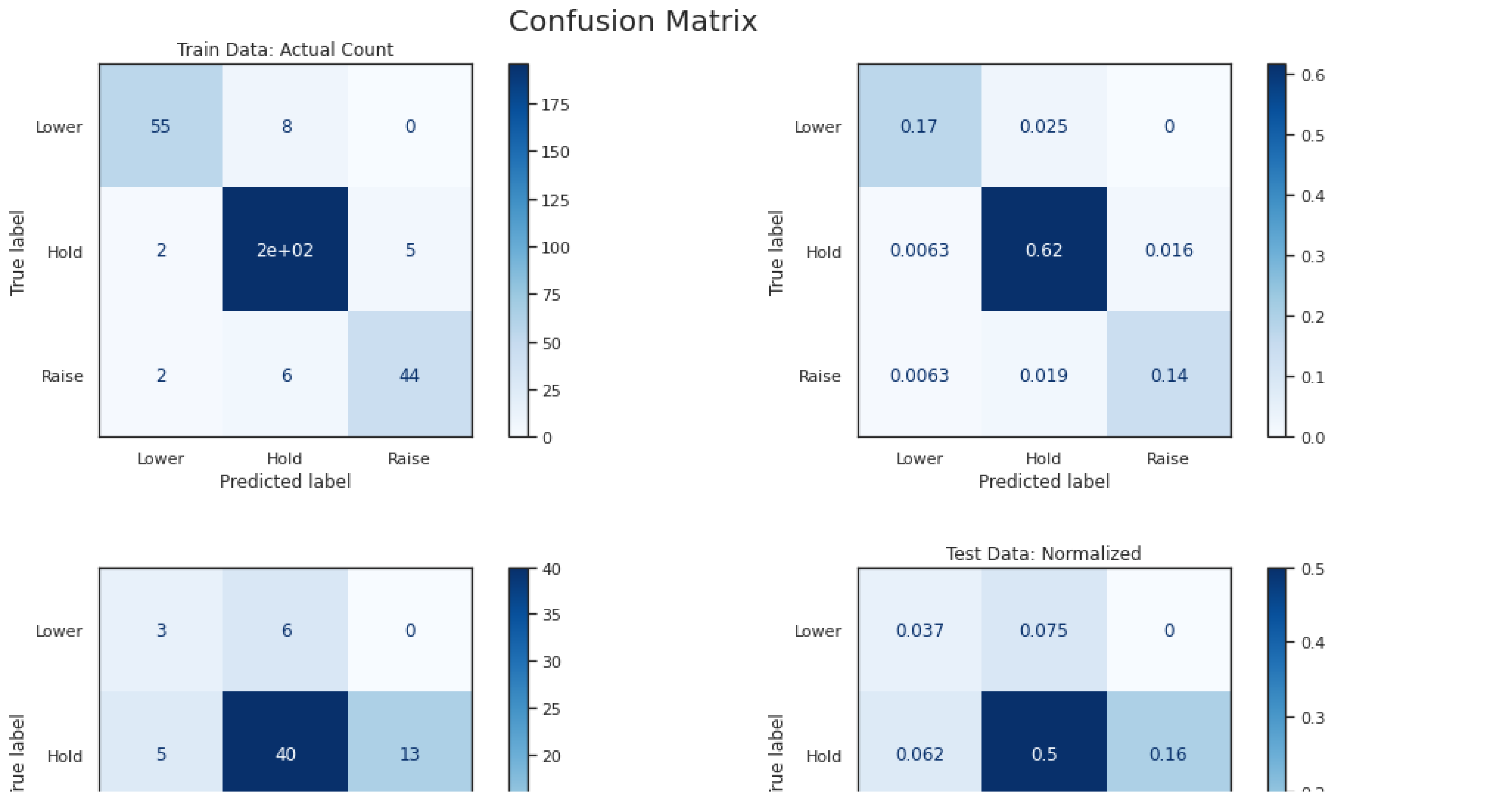
```
rf_clf = RandomForestClassifier()

rand_param_grid = {"max_depth": [None],
              "max_features": [1, 2, 3, 5],
              "min_samples_split": [2, 3, 5, 7, 10],
              "min_samples_leaf": [1, 3, 5, 7, 10, 15],
              "bootstrap": [False],
              "n_estimators" :[1, 2, 5, 10, 100, 200, 300, 500, 1000],
              "criterion": ["gini"]}

rand_model = RandomizedSearchCV(estimator=rf_clf,
                                param_distributions=rand_param_grid,
                                n_iter=300,
                                cv=kfold,
                                scoring=scoring[refit],
                                verbose=1,
                                 random_state=rand_seed, n_jobs=-1)
rand_model.fit(X_train,Y_train)
print(rand_model.best_score_)
print(rand_model.best_params_)
```

```
Fitting 7 folds for each of 300 candidates, totalling 2100 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  53 tasks      | elapsed:    5.5s
[Parallel(n_jobs=-1)]: Done 252 tasks      | elapsed:   23.8s
[Parallel(n_jobs=-1)]: Done 650 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 1261 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 1902 tasks      | elapsed:  3.3min
0.5653566171077676
{'n_estimators': 2, 'min_samples_split': 7, 'min_samples_leaf': 10, 'max_features': 1, 'max_depth': None, 'criterion': 'gini', 'bootstrap': False}
[Parallel(n_jobs=-1)]: Done 2100 out of 2100 | elapsed:  3.5min finished
```

```
param_grid = {'n_estimators': np.linspace(1, 500, 50, dtype=int),
              'min_samples_split': [2],
              'min_samples_leaf': [3],
              'max_features': [8],
              'max_depth': [None],
              'criterion': ['gini'],
              'bootstrap': [False]}

rf_model = train_grid_search(rf_clf, param_grid, scoring, refit, cv=kfold, verbose=1, plot=True)
rf_best = rf_model.best_estimator_
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
Fitting 7 folds for each of 50 candidates, totalling 350 fits
[Parallel(n_jobs=-1)]: Done 128 tasks      | elapsed:    8.5s
[Parallel(n_jobs=-1)]: Done 284 tasks      | elapsed:   39.3s
[Parallel(n_jobs=-1)]: Done 350 out of 350 | elapsed:   59.2s finished
[2021-01-25 12:34:55,180][INFO] ## Training - acc: 0.92767296, f1: 0.90735967
[2021-01-25 12:34:55,182][INFO] ## Test - acc: 0.62500000, f1: 0.50148544
Best Score:  0.5198793780563115
Best Param:  {'bootstrap': False, 'criterion': 'gini', 'max_depth': None, 'max_features': 8, 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 62}
```





Gradient Boosting

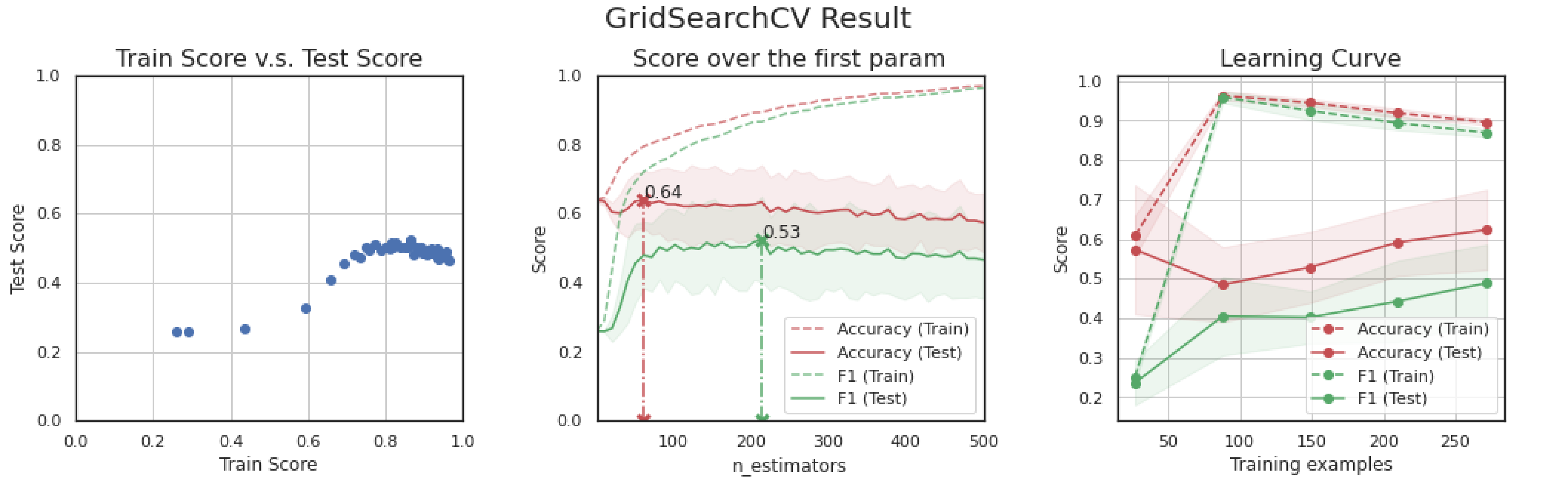
Raise 0 6 7 Raise 0 0.075 0.087

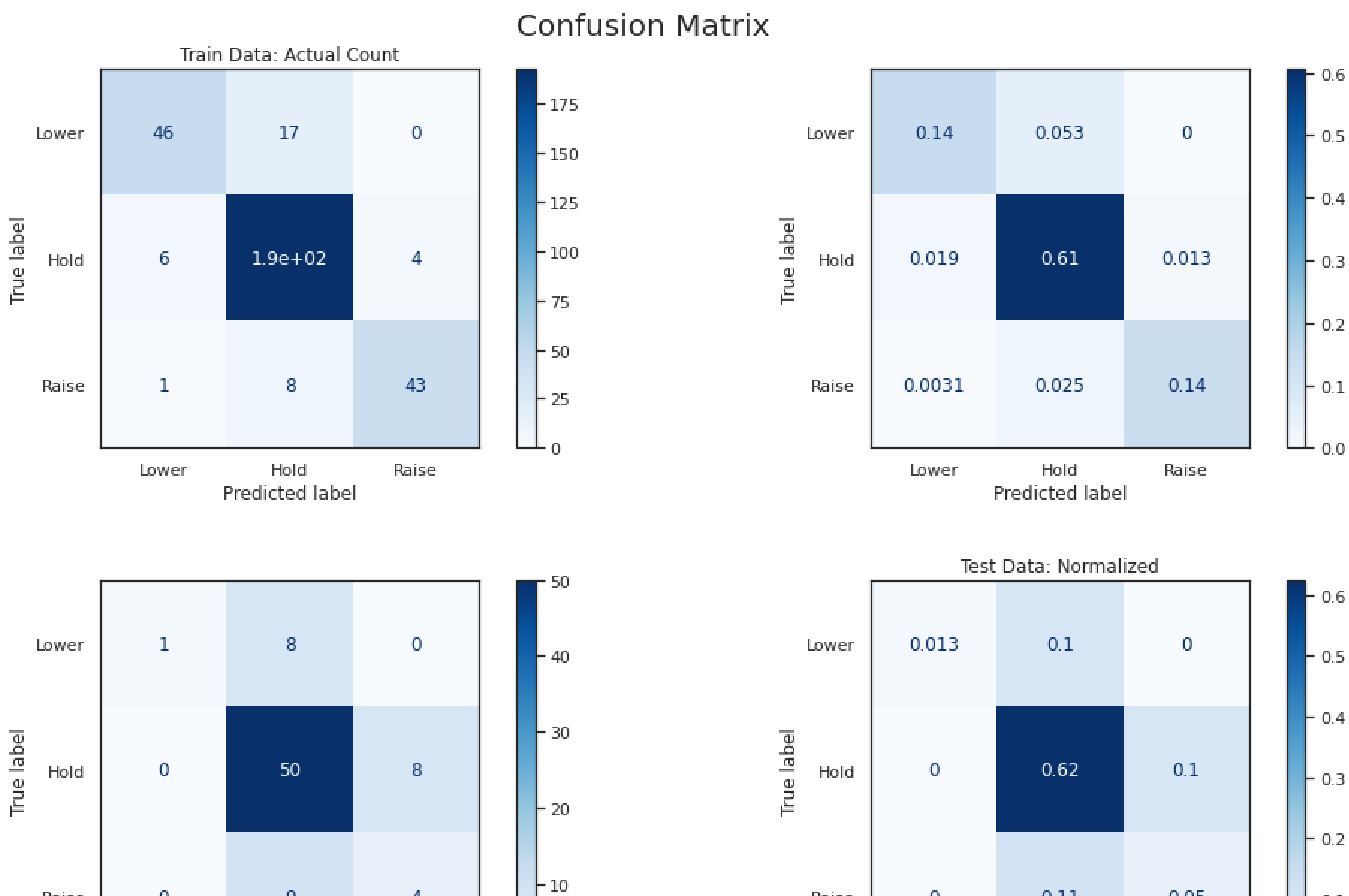
```
gb_clf = GradientBoostingClassifier()

rand_param_grid = {
    'loss' : ["deviance"],
    'n_estimators' : [1, 10, 100, 200, 300, 1000],
    'learning_rate': [0.1, 0.05, 0.01, 0.005],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_leaf': [2, 5, 10, 15, 20, 30, 50, 100, 200, 300],
    'max_features': [0.8, 0.6, 0.4, 0.2, 0.1]
    }

rand_model = RandomizedSearchCV(estimator=gb_clf,
                                param_distributions=rand_param_grid,
                                n_iter=300,
                                cv=kfold,
                                scoring=scoring[refit],
                                verbose=1,
                                random_state=rand_seed,
                                n_jobs=-1)

rand_model.fit(X_train,Y_train)
print(rand_model.best_score_)
print(rand_model.best_params_)
```

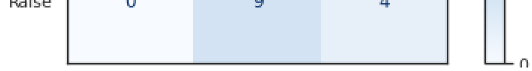
```
Fitting 7 folds for each of 300 candidates, totalling 2100 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  50 tasks      | elapsed:   28.5s
[Parallel(n_jobs=-1)]: Done 208 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 490 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 901 tasks      | elapsed:  4.1min
[Parallel(n_jobs=-1)]: Done 1430 tasks      | elapsed:  5.8min
[Parallel(n_jobs=-1)]: Done 2060 tasks      | elapsed:  8.3min
[Parallel(n_jobs=-1)]: Done 2093 out of 2100 | elapsed:  8.4min remaining:    1.7s
[Parallel(n_jobs=-1)]: Done 2100 out of 2100 | elapsed:  8.4min finished
0.5230603358290681
{'n_estimators': 1000, 'min_samples_leaf': 15, 'max_features': 0.4, 'max_depth': 2, 'loss': 'deviance', 'learning_rate': 0.01}
```

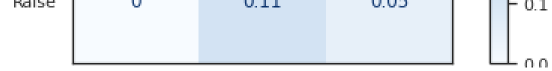
```
param_grid = {'n_estimators': np.linspace(1, 500, 50, dtype=int),
              'min_samples_leaf': [15],
              'max_features': [0.6],
              'max_depth': [2],
              'loss': ['deviance'],
              'learning_rate': [0.05]}

gb_model = train_grid_search(gb_clf,
                             param_grid,
                             scoring,
                             refit,
                             cv=kfold,
                             verbose=1,
                             plot=True)

gb_best = gb_model.best_estimator_
```

```
Fitting 7 folds for each of 50 candidates, totalling 350 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 119 tasks      | elapsed:    7.8s
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:   38.9s
[Parallel(n_jobs=-1)]: Done 350 out of 350 | elapsed:  1.1min finished
[2021-01-25 12:44:30,595][INFO] ## Training - acc: 0.88679245, f1: 0.85955164
[2021-01-25 12:44:30,597][INFO] ## Test - acc: 0.68750000, f1: 0.44000000
Best Score:  0.5256642087094295
Best Param:  {'learning_rate': 0.05, 'loss': 'deviance', 'max_depth': 2, 'max_features': 0.6, 'min_samples_leaf': 15, 'n_estimators': 214}
```









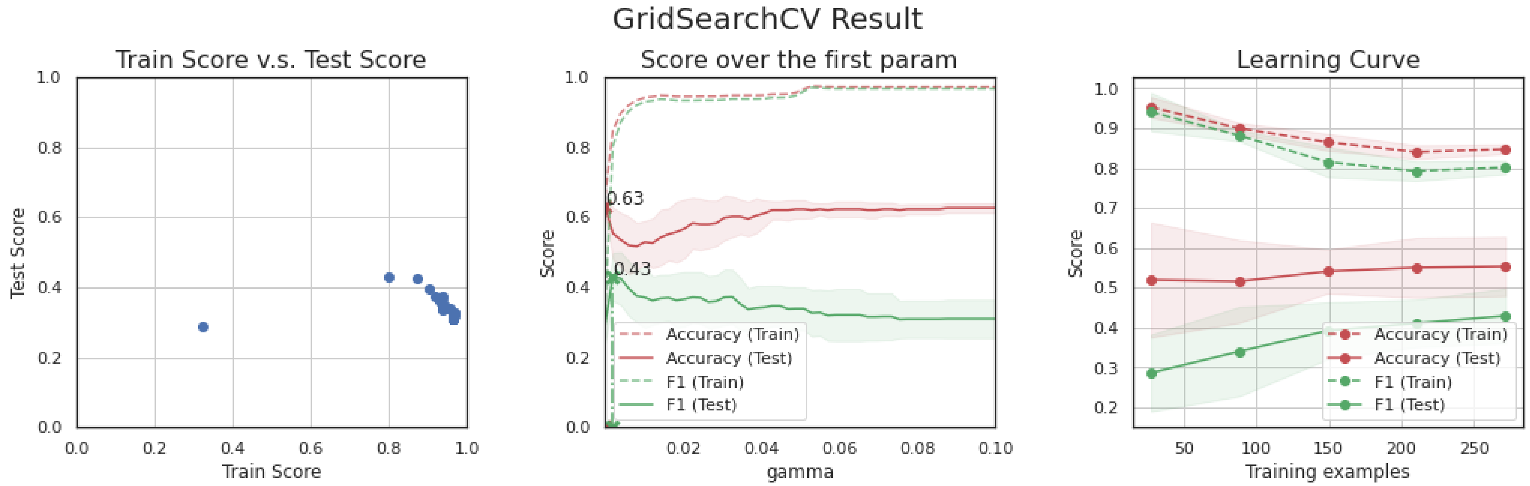
SVM

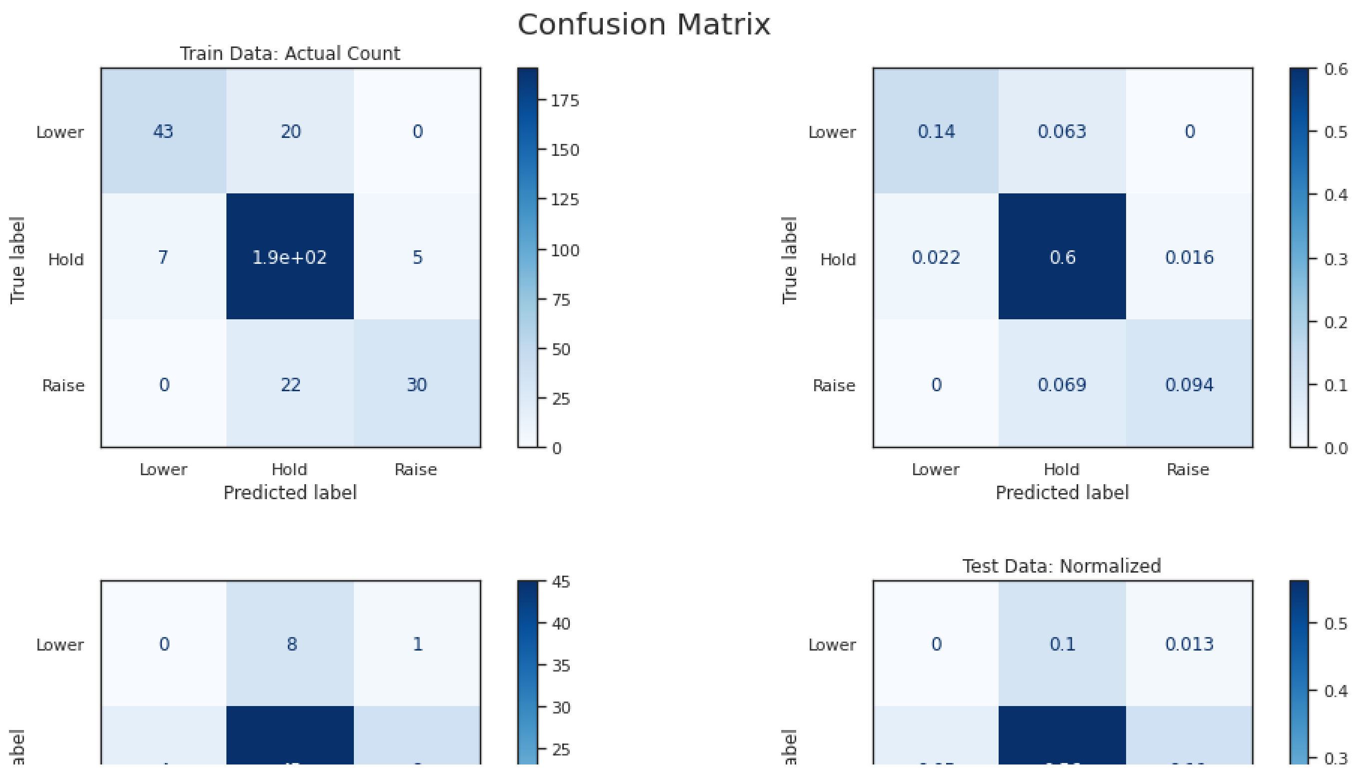
```
svm_clf = SVC(probability=True)

rand_param_grid = {'kernel': ['rbf'],
                  'gamma': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1],
                  'C': [1, 2, 3, 5, 8, 10, 50, 100, 200, 300, 500, 1000]}

rand_model = RandomizedSearchCV(estimator=svm_clf,
                                param_distributions=rand_param_grid,
                                n_iter=300,
                                cv=kfold,
                                scoring=scoring[refit],
                                verbose=1,
                                random_state=rand_seed,
                                n_jobs=-1)

rand_model.fit(X_train,Y_train)
print(rand_model.best_score_)
print(rand_model.best_params_)
```

```
Fitting 7 folds for each of 84 candidates, totalling 588 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 128 tasks      | elapsed:    1.3s
0.4645510437396955
{'kernel': 'rbf', 'gamma': 0.001, 'C': 100}
[Parallel(n_jobs=-1)]: Done 581 out of 588 | elapsed:    6.1s remaining:    0.1s
[Parallel(n_jobs=-1)]: Done 588 out of 588 | elapsed:    6.2s finished
```

```
param_grid = {'gamma': np.linspace(0.0001, 0.1, 50, dtype=float),
              'C': [10],
              'kernel': ['rbf']}

svm_model = train_grid_search(svm_clf,
                              param_grid,
                              scoring,
                              refit,
                              cv=kfold,
                              verbose=1,
                              plot=True)

svm_best = svm_model.best_estimator_
```

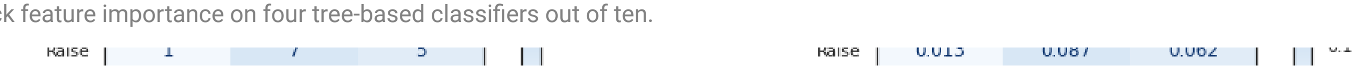
```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
Fitting 7 folds for each of 50 candidates, totalling 350 fits
[Parallel(n_jobs=-1)]: Done 128 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Done 350 out of 350 | elapsed:    4.1s finished
[2021-01-25 12:44:51,591][INFO] ## Training - acc: 0.83018868, f1: 0.77562130
[2021-01-25 12:44:51,593][INFO] ## Test - acc: 0.62500000, f1: 0.37328491
Best Score:  0.42960685147685435
Best Param:  {'C': 10, 'gamma': 0.0021387755102040816, 'kernel': 'rbf'}
```



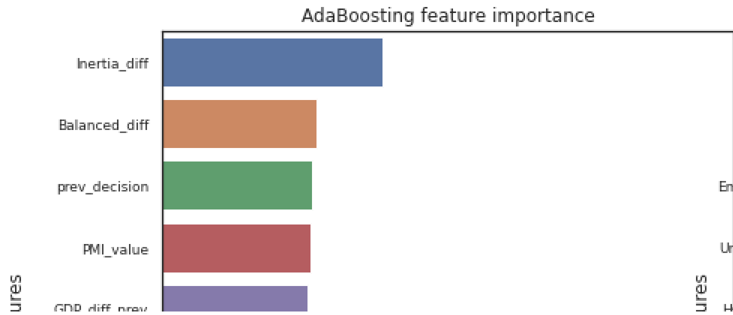


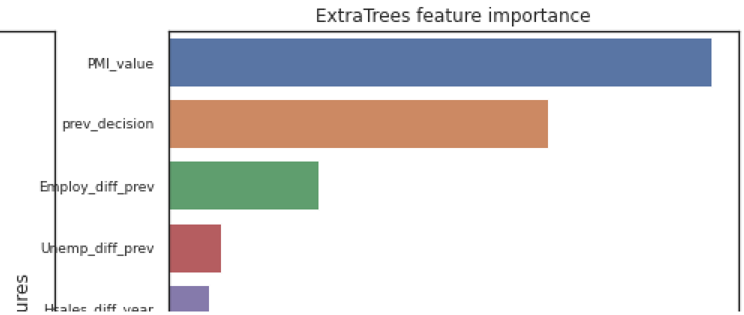
Feature Importance

Check feature importance on four tree-based classifiers out of ten.



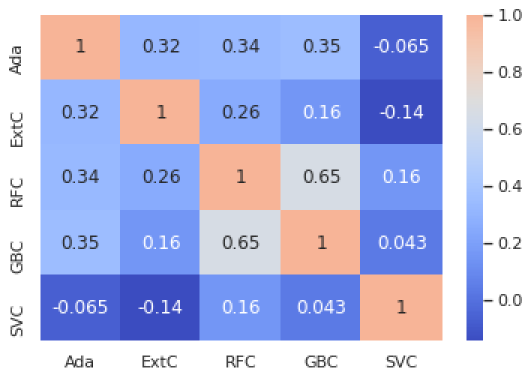
```python
nrows = ncols = 2
fig, axes = plt.subplots(nrows = nrows, ncols = ncols, sharex="all", figsize=(15,15))

names_classifiers = [("AdaBoosting", ada_best),
                     ("ExtraTrees", ext_best),
                     ("RandomForest", rf_best),
                     ("GradientBoosting",gb_best)]

nclassifier = 0
for row in range(nrows):
    for col in range(ncols):
        name = names_classifiers[nclassifier][0]
        classifier = names_classifiers[nclassifier][1]
        indices = np.argsort(classifier.feature_importances_)[::-1][:40]
        g = sns.barplot(y=X_balanced.columns[indices][:40], x=classifier.feature_importances_[indices][:40] , orient='h',ax=axes[row][col])
        g.set_xlabel("Relative importance",fontsize=12)
        g.set_ylabel("Features",fontsize=12)
        g.tick_params(labelsize=9)
        g.set_title(name + " feature importance")
        nclassifier += 1
```



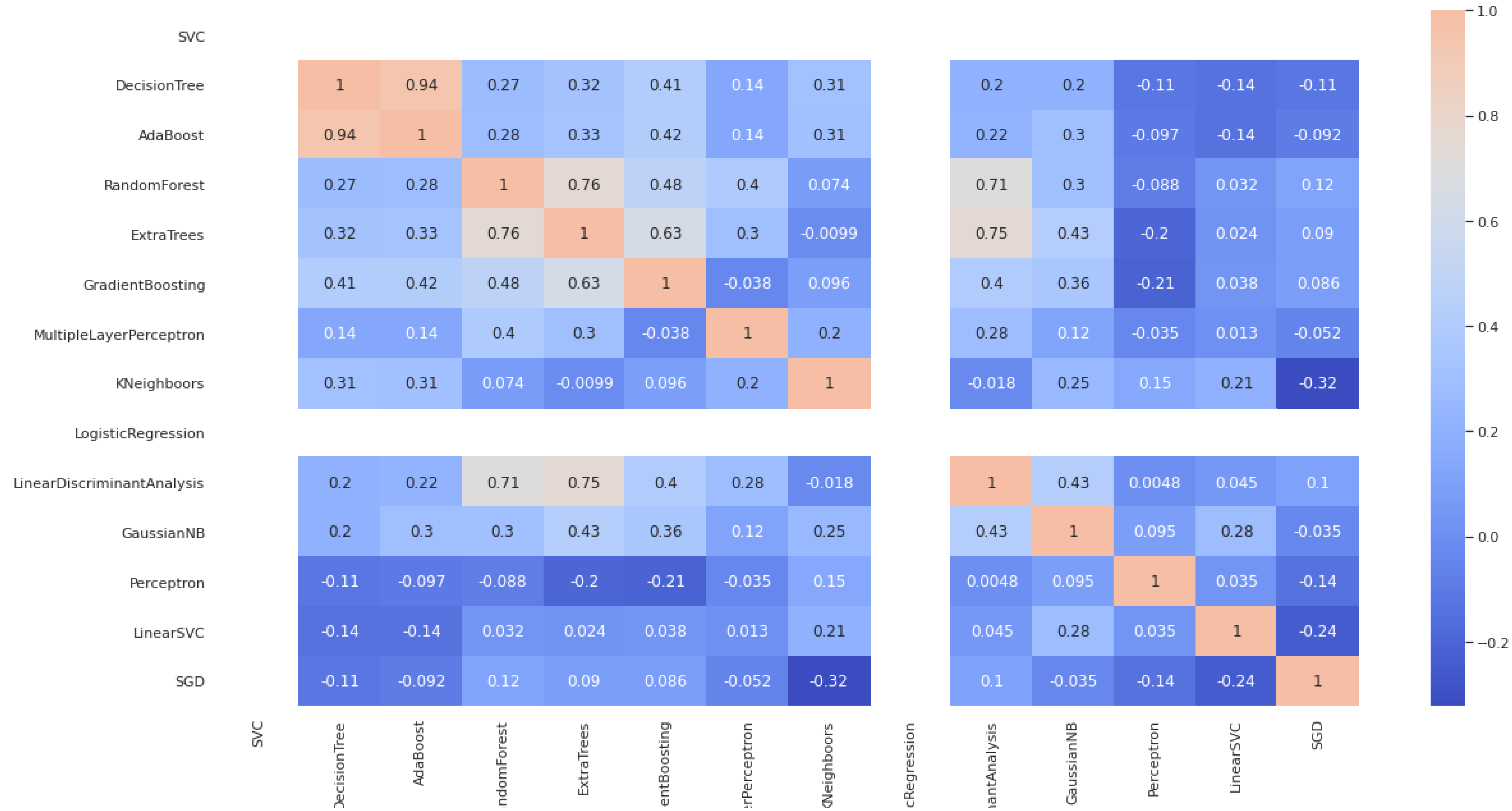


Ensembling

```
test_ada = pd.Series(ada_best.predict(X_test), name="Ada")
test_ext = pd.Series(ext_best.predict(X_test), name="ExtC")
test_rf = pd.Series(rf_best.predict(X_test), name="RFC")
test_gb = pd.Series(gb_best.predict(X_test), name="GBC")
test_svm = pd.Series(svm_best.predict(X_test), name="SVC")

ensemble_results = pd.concat([test_ada, test_ext, test_rf, test_gb, test_svm],axis=1)

g = sns.heatmap(ensemble_results.corr(),annot=True, cmap="coolwarm", center=0.7)
```




```
test_resuts = []

for classifier in classifiers:
    estimator = classifier[1].fit(X_train, Y_train)
    test_resuts.append(pd.Series(estimator.predict(X_test), name=classifier[0]))

base_results = pd.concat(test_resuts, axis=1)

plt.figure(figsize=(20,10))
g = sns.heatmap(base_results.corr(),annot=True, cmap="coolwarm", center=0.7)
```



Voting Classifier

```
voting_best = VotingClassifier(estimators=[('adac', ada_best),
                                           ('extc', ext_best),
                                           ('rfc', rf_best),
                                           ('gbc', gb_best),
                                           ('svmc', svm_best)], voting='soft', n_jobs=-1)

voting_best.fit(X_train, Y_train)
```

```
    VotingClassifier(estimators=[('adac',
                                  AdaBoostClassifier(algorithm='SAMME.R',
                                                     base_estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                                                                           class_weight=None,
                                                                                           criterion='gini',
                                                                                           max_depth=None,
                                                                                           max_features=None,
                                                                                           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,
                                                                             presort='depreca...
                                                  validation_fraction=0.1,
                                                  verbose=0,
                                                  warm_start=False)),
                              ('svmc',
                               SVC(C=10, break_ties=False, cache_size=200,
                                   class_weight=None, coef0=0.0,
                                   decision_function_shape='ovr', degree=3,
                                   gamma=0.0021387755102040816, kernel='rbf',
                                   max_iter=-1, probability=True,
                                   random_state=None, shrinking=True, tol=0.001,
                                   verbose=False))],
                 flatten_transform=True, n_jobs=-1, voting='soft',
                 weights=None)
```

```
voting_pred_train = voting_best.predict(X_train)
voting_pred_test = voting_best.predict(X_test)

acc, f1 = metric(Y_train, voting_pred_train)
logger.info('Training - acc: %.8f, f1: %.8f' % (acc, f1))

acc, f1 = metric(Y_test, voting_pred_test)
logger.info('Test - acc: %.8f, f1: %.8f' % (acc, f1))
```

```
[2021-01-25 12:44:57,156][INFO] ## Training - acc: 0.95597484, f1: 0.94641285
[2021-01-25 12:44:57,158][INFO] ## Test - acc: 0.62500000, f1: 0.31076389
```

Stacking by XGBoost

```
# Class to get out-of-fold predictions
def get_oof(clf, x_train, y_train, x_test):
    #Set parameters for ensembling
    n_train = x_train.shape[0]
    n_test = x_test.shape[0]
    oof_train = np.zeros((n_train,))
    oof_test = np.zeros((n_test,))
    oof_test_skf = np.empty((n_fold, n_test))

    for i, (train_index, test_index) in enumerate(kfold.split(y_train, y_train)):
        x_tr = x_train[train_index]
        y_tr = y_train[train_index]
        x_te = x_train[test_index]

        clf.fit(x_tr, y_tr)

        oof_train[test_index] = clf.predict(x_te)
        oof_test_skf[i, :] = clf.predict(x_test)

    oof_test[:] = oof_test_skf.mean(axis=0)
    return oof_train.reshape(-1,1), oof_test.reshape(-1, 1)
```

```
# Create OOF train and test predictions.
ada_oof_train, ada_oof_test = get_oof(ada_best, X_train, Y_train, X_test) # AdaBoost
ext_oof_train, ext_oof_test = get_oof(ext_best, X_train, Y_train, X_test) # Extra Trees
rf_oof_train, rf_oof_test = get_oof(rf_best, X_train, Y_train, X_test) # Random Forest
```

```
rf_oof_train, rf_oof_test = get_oof(rf_best, X_train, Y_train, X_test) # Random Forest
gb_oof_train, gb_oof_test = get_oof(gb_best, X_train, Y_train, X_test) # Gradient Boost
svmc_oof_train, svmc_oof_test = get_oof(svm_best, X_train, Y_train, X_test) # Support Vector Classifier


X_train_xgb = np.concatenate((ada_oof_train, ext_oof_train, rf_oof_train, gb_oof_train, svmc_oof_train), axis=1)
X_test_xgb = np.concatenate((ada_oof_test, ext_oof_test, rf_oof_test, gb_oof_test, svmc_oof_test), axis=1)


gbm = xgb.XGBClassifier(
    n_estimator=2000,
    max_depth=4,
    min_child_weight=2,
    gamma=0.9,
    subsample=0.8,
    colsample_bytree=0.8,
    objective='binary:logistic',
    nthread=-1,
    scale_pos_weight=1).fit(X_train_xgb, Y_train)

# Predict
gbm_pred_train = gbm.predict(X_train_xgb)
gbm_pred_test = gbm.predict(X_test_xgb)

xgb_acc_train, xgb_f1_train = metric(Y_train, gbm_pred_train)
logger.info('Train - acc: %.8f, f1: %.8f' % (xgb_acc_train, xgb_f1_train))

xgb_acc_test, xgb_f1_test = metric(Y_test, gbm_pred_test)
logger.info('Test - acc: %.8f, f1: %.8f' % (xgb_acc_test, xgb_f1_test))
```

```
[2021-01-25 12:45:00,981][INFO] ## Train - acc: 0.72641509, f1: 0.60388454
[2021-01-25 12:45:00,983][INFO] ## Test - acc: 0.75000000, f1: 0.46108140
[12:45:00] WARNING: ../src/learner.cc:516:
Parameters: { n_estimator, scale_pos_weight } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.
```

Result

```
result_clf = [('AdaDTC', ada_best),
              ('ExtraTree', ext_best),
              ('RandomForest', rf_best),
              ('GradientBoost', gb_best),
              ('SVM', svm_best),
              ('Voting', voting_best)]

results = []

for clf in result_clf:
    pred_train = clf[1].predict(pd.DataFrame(X_train))
    pred_test = clf[1].predict(pd.DataFrame(X_test))
    train_acc, train_f1 = metric(Y_train, pred_train)
    test_acc, test_f1 = metric(Y_test, pred_test)
```

```
    results.append((clf[0],
                    train_acc,
                    train_f1,
                    test_acc,
                    test_f1))

result_df = pd.DataFrame(results, columns=[
                                           'Classifier',
                                           'Train Accuracy',
                                           'Train F1',
                                           'Test Accuracy',
                                           'Test F1'
                                           ]
                         )
result_df
```

	Classifier	Train Accuracy	Train F1	Test Accuracy	Test F1
0	AdaDTC	0.896226	0.879437	0.4750	0.320101
1	ExtraTree	0.682390	0.554694	0.6125	0.253230
2	RandomForest	0.921384	0.906394	0.7125	0.417893
3	GradientBoost	0.864780	0.831184	0.7000	0.426677
4	SVM	0.808176	0.739655	0.6250	0.366667
5	Voting	0.955975	0.946413	0.6250	0.310764

```
# Set Random Forest as the baseline model (highest F1 score)
baseline_model = rf_best
pred_test = baseline_model.predict(pd.DataFrame(X_test))
prediction_df = pd.concat([pd.Series(balanced.index.values), pd.Series(pred_test, name="Predict")],axis=1)
```

Save the Data

```
if IN_COLAB:
  def save_data(df, file_name, dir_name = output_dir, index_csv=False):
    if not os.path.exists(dir_name):
      os.mkdir(dir_name)
    # Save results to a picke file
    file = open(dir_name + file_name + '.pickle', 'wb')
    pickle.dump(df, file)
    file.close()
    print('Successfully saved {}.pickle. in {}'.format(file_name, dir_name + file_name + '.pickle'))
    # Save results to a csv file
    df.to_csv(dir_name + file_name + '.csv', index=index_csv)
    print('Successfully saved {}.csv. in {}'.format(file_name, dir_name + file_name + '.csv'))

else:
  def save_data(df, file_name, dir_name=result_dir, index_csv=False):
    # Save results to a .picke file
    file = open(dir_name + file_name + '.pickle', 'wb')
    pickle.dump(df, file)
```

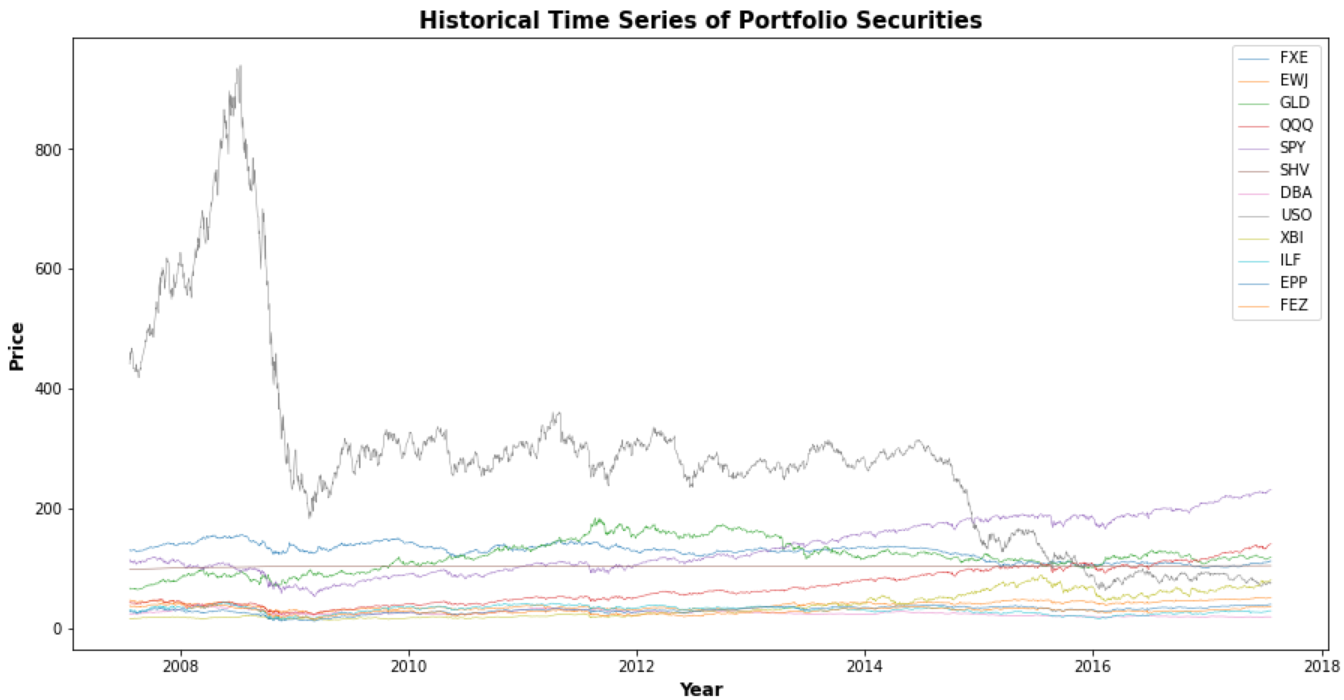
```
    file.close()
    print('Successfully saved {}.pickle. in {}'.format(file_name, dir_name + file_name + '.pickle'))
    # Save results to a .csv file
    df.to_csv(dir_name + file_name + '.csv', index=index_csv)
    print('Successfully saved {}.csv. in {}'.format(file_name, dir_name + file_name + '.csv'))
```

```
# Save result
save_data(result_df, "result_scores", output_dir)
save_data(prediction_df, "baseline_predictions")
save_data(X_balanced, "training_data", output_dir, index_csv=True)
```

```
Successfully saved result_scores.pickle. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/result_scores.pickle
Successfully saved result_scores.csv. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/result_scores.csv
Successfully saved baseline_predictions.pickle. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/baseline_predictions.pickle
Successfully saved baseline_predictions.csv. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/baseline_predictions.csv
Successfully saved training_data.pickle. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/training_data.pickle
Successfully saved training_data.csv. in /content/drive/My Drive/Colab Notebooks/proj2/src/data/result/training_data.csv
```

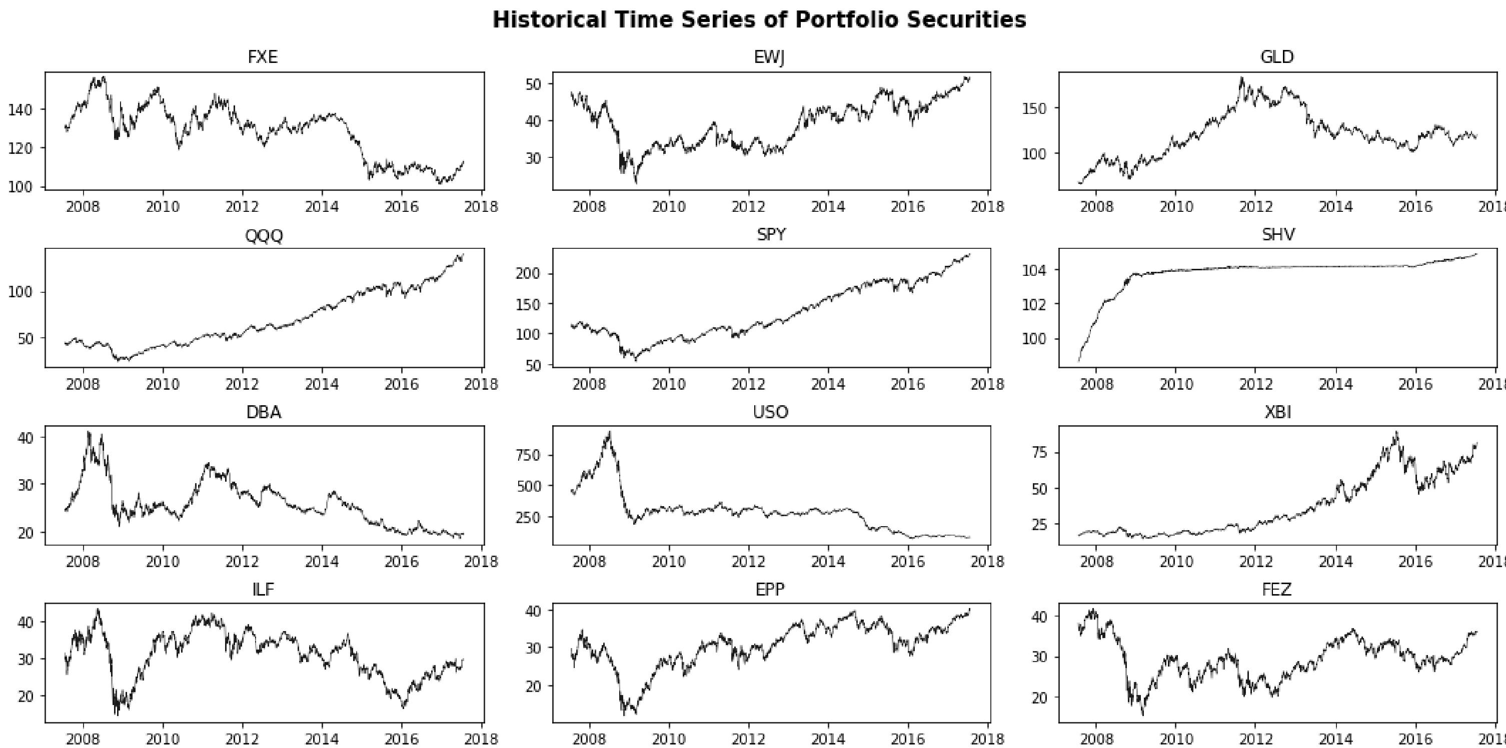
Good Plotting Practices

```
## Visualize ETF Price Time Series:
#fig = plt.figure(figsize=(15, 7.5))
#ts_u = fig.add_subplot(111)
#ts_u.plot(R_u['FXE'], linewidth=0.5, alpha=0.9, label='FXE')
#ts_u.plot(R_u['EWJ'], linewidth=0.5, alpha=0.9, label='EWJ')
#ts_u.plot(R_u['GLD'], linewidth=0.5, alpha=0.9, label='GLD')
#ts_u.plot(R_u['QQQ'], linewidth=0.5, alpha=0.9, label='QQQ')
#ts_u.plot(R_u['SPY'], linewidth=0.5, alpha=0.9, label='SPY')
#ts_u.plot(R_u['SHV'], linewidth=0.5, alpha=0.9, label='SHV')
#ts_u.plot(R_u['DBA'], linewidth=0.5, alpha=0.9, label='DBA')
#ts_u.plot(R_u['USO'], linewidth=0.5, alpha=0.9, label='USO')
#ts_u.plot(R_u['XBI'], linewidth=0.5, alpha=0.9, label='XBI')
#ts_u.plot(R_u['ILF'], linewidth=0.5, alpha=0.9, label='ILF')
#ts_u.plot(R_u['EPP'], linewidth=0.5, alpha=0.9, label='EPP')
#ts_u.plot(R_u['FEZ'], linewidth=0.5, alpha=0.9, label='FEZ')
#ts_u.set_xlabel('Year', fontweight='bold', fontsize=12)
#ts_u.set_ylabel('Price', fontweight='bold', fontsize=12)
#ts_u.set_title('Historical Time Series of Portfolio Securities', fontweight='bold', fontsize=15)
#ts_u.legend(loc='upper right', fontsize=10)
#plt.savefig(graphs_dir + 'rho_u.png', bbox_inches='tight')
```



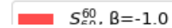

```
## Visualize ETF Price Time Series:
#R_u = p_u
#returns_u, axs = plt.subplots(4,3,figsize=(15, 7.5))
#returns_u.suptitle('Historical Time Series of Portfolio Securities', fontweight='bold', fontsize=15)
#axs[0,0].plot(R_u['FXE'], 'black', linewidth=0.5, alpha=0.9)
#axs[0,0].set_title('FXE')
#axs[0,1].plot(R_u['EWJ'], 'black', linewidth=0.5, alpha=0.9)
#axs[0,1].set_title('EWJ')
#axs[0,2].plot(R_u['GLD'], 'black', linewidth=0.5, alpha=0.9)
#axs[0,2].set_title('GLD')
#axs[1,0].plot(R_u['QQQ'], 'black', linewidth=0.5, alpha=0.9)
#axs[1,0].set_title('QQQ')
#axs[1,1].plot(R_u['SPY'], 'black', linewidth=0.5, alpha=0.9)
#axs[1,1].set_title('SPY')
#axs[1,2].plot(R_u['SHV'], 'black', linewidth=0.5, alpha=0.9)
#axs[1,2].set_title('SHV')
#axs[2,0].plot(R_u['DBA'], 'black', linewidth=0.5, alpha=0.9)
#axs[2,0].set_title('DBA')
#axs[2,1].plot(R_u['USO'], 'black', linewidth=0.5, alpha=0.9)
#axs[2,1].set_title('USO')
#axs[2,2].plot(R_u['XBI'], 'black', linewidth=0.5, alpha=0.9)
#axs[2,2].set_title('XBI')
#axs[3,0].plot(R_u['ILF'], 'black', linewidth=0.5, alpha=0.9)
#axs[3,0].set_title('ILF')
#axs[3,1].plot(R_u['EPP'], 'black', linewidth=0.5, alpha=0.9)
#axs[3,1].set_title('EPP')
#axs[3,2].plot(R_u['FEZ'], 'black', linewidth=0.5, alpha=0.9)
#axs[3,2].set_title('FEZ')
#plt.tight_layout()
```

```
#returns_u.subplots_adjust(top=0.9)
#plt.savefig(graphs_dir + 'prices_u_raw.png', bbox_inches='tight')
```




```
#fig = plt.figure(figsize=(20, 20))
#ax = fig.add_subplot(111, projection='3d')
#for i in range(6):
#  dt = pre_subprime_final.iloc[:,i]
#  col_name = pre_subprime_final.columns[i]
#  c =  ['r', 'g', 'b', 'y', 'm','orange'][i]
#  z =  [-1.0, -0.5, 0.5, 1.0, 1.5, 2.0][i]
#  x,y = np.histogram(dt,bins = 100)
#  x = x/len(dt)
#  y = (y[:-1]+y[1:])/2
#  cs = [c] * len(x)
#  ax.bar(y, x, zs=z, zdir='y', color=cs, alpha=0.7,width = 0.003,label = col_name[0]+', '+col_name[1])
#  ax.legend(loc='left', fontsize=13)
#
#  samples = np.asarray(dt).reshape(-1,1)
#  x_plot = np.linspace(-10,10,100).reshape(-1,1)
#  kde = KernelDensity(kernel='gaussian', bandwidth=0.9).fit(samples)
#  log_dens = kde.score_samples(x_plot)
#  dens = np.exp(log_dens)
#  ax.view_init(20, 50)
#  ax.plot(x_plot / 50, [z] * len(y), dens / 8, color = 'black', linewidth = 3.0)
#ax.set_xlabel('$ρ$', fontweight='bold', fontsize=15)
#ax.set_ylabel('$β$', fontweight='bold', fontsize=15)
#ax.set_zlabel('$f$', fontweight='bold', fontsize=15)
#ax.set_title('$S_{60}^{60}$ Returns Before the Subprime Crisis', fontweight='bold', fontsize=18)
```

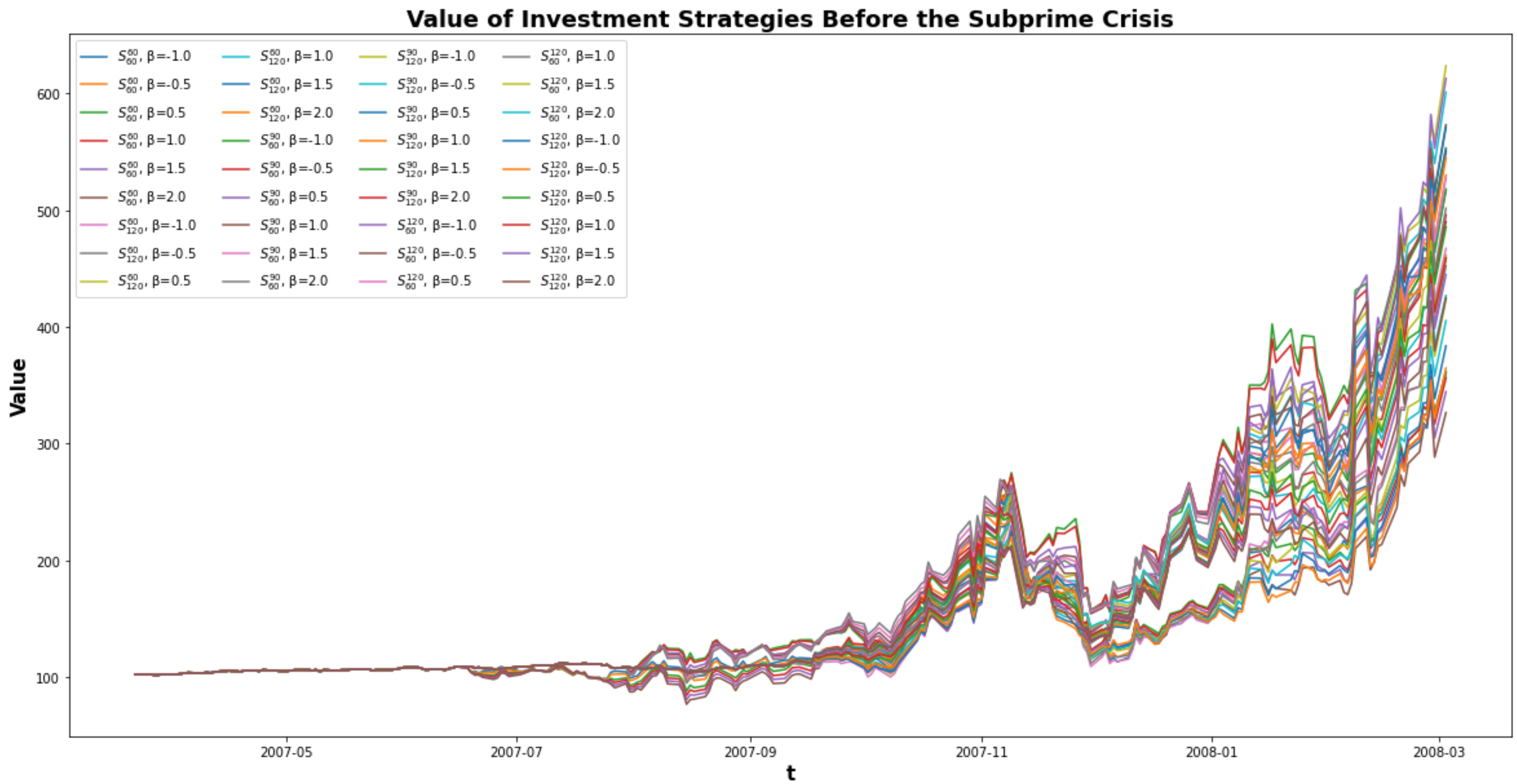
```
#ax.set_title('$S_{60}^{60}$ Returns Before the Subprime Crisis', fontweight='bold', fontsize=18)
#
#plt.savefig(graphs_dir + '01_pre_subprime_ret_distS6060.png', bbox_inches='tight')
```



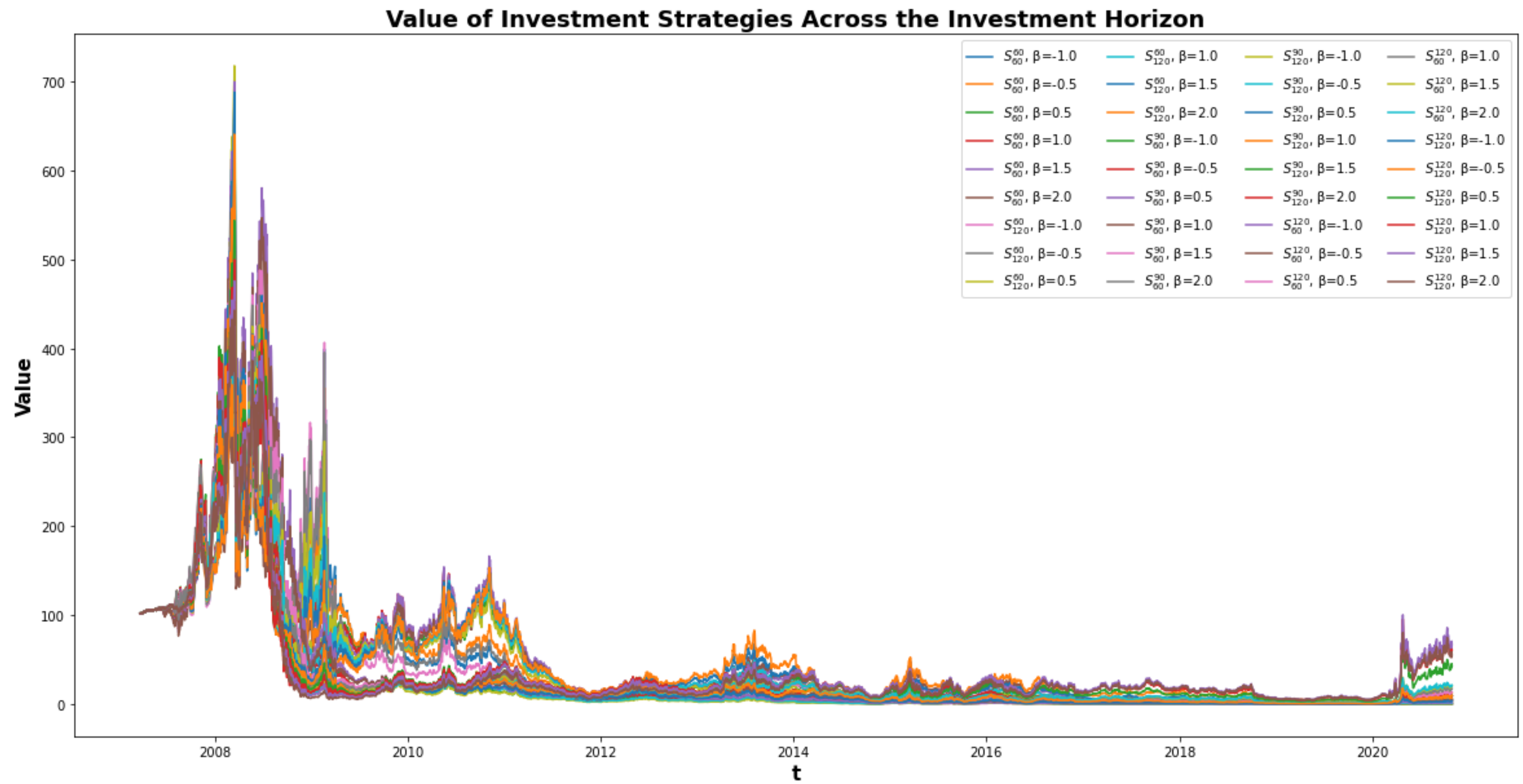
```
## Pre-Subprime Crisis:
#pre_subprime_R_u = R_etf.loc[:'3/3/2008',:'FEZ']
#pre_subprime_ff_factors = ff_3_daily.loc[:'3/3/2008','Mkt-RF':'RF']
#pre_subprime_lookbacks = [[60,60], [60,120], [90,60], [90,120], [120,60], [120,120]]
#pre_subprime_betas = [-1.0, -0.5, 0.5, 1.0, 1.5, 2.0]
#pre_subprime_exec = pd.DataFrame([])
#pre_subprime_final = pd.DataFrame([])
#omegas = []
#for lb in pre_subprime_lookbacks:
#    for bt in pre_subprime_betas:
#        res = backtesting(pre_subprime_R_u,
#                        pre_subprime_ff_factors,
#                        return_period = lb[0],
#                        variance_period = lb[1],
#                        lamb = 10,
#                        beta_tm = bt)
#        omegas.append(res[1])
#        res = pd.DataFrame(res[0],index = pd.to_datetime(pre_subprime_R_u.index))
#        res_perf = analytics(X = res,rf = 0.06, confidenceLevel = 0.95, position = 100)
#        pre_subprime_final = pd.concat([pre_subprime_final,res],axis = 1)
#        pre_subprime_exec = pd.concat([pre_subprime_exec,res_perf],axis = 1)
#
#pre_subprime_final = pd.concat([pre_subprime_final,pre_subprime_R_u['SPY']],axis = 1)
#
#pre_subprime_spy_performance = analytics(X = pd.DataFrame(pre_subprime_R_u.loc[:,'SPY']),rf = 0.06, confidenceLevel = 0.95, position = 100)
#pre_subprime_exec = pd.concat([pre_subprime_exec,pre_subprime_spy_performance],axis = 1)
#pre_subprime_exec.columns = [['$S^{60}_{60}$','$S^{60}_{60}$','$S^{60}_{60}$','$S^{60}_{60}$','$S^{60}_{60}$','$S^{60}_{60}$',
#                              '$S^{60}_{120}$','$S^{60}_{120}$','$S^{60}_{120}$','$S^{60}_{120}$','$S^{60}_{120}$','$S^{60}_{120}$',
#                              '$S^{90}_{60}$','$S^{90}_{60}$','$S^{90}_{60}$','$S^{90}_{60}$','$S^{90}_{60}$','$S^{90}_{60}$',
#                              '$S^{90}_{120}$','$S^{90}_{120}$','$S^{90}_{120}$','$S^{90}_{120}$','$S^{90}_{120}$','$S^{90}_{120}$',
#                              '$S^{120}_{60}$','$S^{120}_{60}$','$S^{120}_{60}$','$S^{120}_{60}$','$S^{120}_{60}$','$S^{120}_{60}$',
#                              '$S^{120}_{120}$','$S^{120}_{120}$','$S^{120}_{120}$','$S^{120}_{120}$','$S^{120}_{120}$','$S^{120}_{120}$','SPY'],
#                             ['β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0',
#                              'β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0',
#                              'β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0',
#                              'β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0',
#                              'β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0',
#                              'β=-1.0','β=-0.5','β=0.5','β=1.0','β=1.5','β=2.0','']]
#pre_subprime_final.columns = pre_subprime_exec.columns
#save_data(pre_subprime_exec, 'pre_subprime_exec')
```

β

```
## Total Value:
#fig = plt.figure(figsize=(20, 10))
#ax = fig.add_subplot(111)
#for i in range(36):
#  ax.plot(100*(np.cumprod(pre_subprime_final.iloc[:,i]+1)),label = pre_subprime_final.columns[i][0]+', '+pre_subprime_final.columns[i][1])
#  ax.legend(loc='best', ncol=4, fontsize=10)
#plt.xlabel('t', fontweight='bold', fontsize=15)
#plt.ylabel('Value', fontweight='bold', fontsize=15)
#plt.title('Value of Investment Strategies Before the Subprime Crisis', fontweight='bold', fontsize=18)
#plt.savefig(graphs_dir + '00_pre_subprime_strategy_val.png', bbox_inches='tight')
```




```
#fig = plt.figure(figsize=(20, 10))
#ax = fig.add_subplot(111)
#for i in range(36):
#  ax.plot(100*(np.cumprod(full_horizon_final.iloc[:,i]+1)),label = full_horizon_final.columns[i][0]+', '+full_horizon_final.columns[i][1])
#  ax.legend(loc='best', ncol=4, fontsize=10)
#plt.xlabel('t', fontweight='bold', fontsize=15)
#plt.ylabel('Value', fontweight='bold', fontsize=15)
#plt.title('Value of Investment Strategies Across the Investment Horizon', fontweight='bold', fontsize=18)
#plt.savefig(graphs_dir + '35_full_horizon_strategy_val.png', bbox_inches='tight')
```



Value of Investment Strategies Across the Investment Horizon
Value
t
0
100
200
300
400
500
600
700
2008
2010
2012
2014
2016
2018
2020
S^{60}_{60}, β=-1.0
S^{60}_{60}, β=-0.5
S^{60}_{60}, β=0.5
S^{60}_{60}, β=1.0
S^{60}_{60}, β=1.5
S^{60}_{60}, β=2.0
S^{60}_{120}, β=-1.0
S^{60}_{120}, β=-0.5
S^{60}_{120}, β=0.5
S^{60}_{120}, β=1.0
S^{60}_{120}, β=1.5
S^{60}_{120}, β=2.0
S^{90}_{60}, β=-1.0
S^{90}_{60}, β=-0.5
S^{90}_{60}, β=0.5
S^{90}_{60}, β=1.0
S^{90}_{60}, β=1.5
S^{90}_{60}, β=2.0
S^{90}_{120}, β=-1.0
S^{90}_{120}, β=-0.5
S^{90}_{120}, β=0.5
S^{90}_{120}, β=1.0
S^{90}_{120}, β=1.5
S^{90}_{120}, β=2.0
S^{120}_{60}, β=-1.0
S^{120}_{60}, β=-0.5
S^{120}_{60}, β=0.5
S^{120}_{60}, β=1.0
S^{120}_{60}, β=1.5
S^{120}_{60}, β=2.0
S^{120}_{120}, β=-1.0
S^{120}_{120}, β=-0.5
S^{120}_{120}, β=0.5
S^{120}_{120}, β=1.0
S^{120}_{120}, β=1.5
S^{120}_{120}, β=2.0