portfolio_optimizer

September 20, 2017

0.0.1 Import all required packages

```
In [1]: from pandas_datareader import data
        import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        import pickle
        import copy
        import json
        import os
        import glob
        import time
        import datetime
        from IPython.display import display                 # Allows the use of display() for 

        from sklearn.tree import DecisionTreeClassifier
        from sklearn.metrics import accuracy_score, fbeta_score, make_scorer, f1_score
        from sklearn.naive_bayes import GaussianNB
        from sklearn import cross_validation
        from sklearn.svm import SVC
        from sklearn.ensemble import AdaBoostClassifier
        from sklearn.grid_search import GridSearchCV

        from keras.models import Sequential
        from keras.layers import Dense
        from keras.models import model_from_json
        from keras.utils import np_utils
        from sklearn.preprocessing import LabelEncoder
        from keras import optimizers
        from keras import regularizers

        import multiprocessing as mp

        from mpl_toolkits.mplot3d import Axes3D

        # Pretty display for notebooks
        %matplotlib inline
```

```
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/cross_validation.py:44: DeprecationWarn
  "This module will be removed in 0.20.", DeprecationWarning)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/grid_search.py:43: DeprecationWarning:
  DeprecationWarning)
Using TensorFlow backend.
```

0.0.2 Updateable Parameters

```
In [2]: ## Start time.  Used to measure execution time.
        START = time.clock()

        ## Yahoo's API has changed, so we'll use google as our source
        #DATA_SOURCE = 'google'
        DATA_SOURCE = 'yahoo'

        ## Date range used for training data
        #TRAINING_START_DATE = '2010-01-01'
        #TRAINING_END_DATE = '2017-7-31'
        TRAINING_START_DATE = datetime.datetime(2014, 4, 1)
        TRAINING_END_DATE = datetime.datetime(2016, 5, 31)

        ## Date range used for testing data
        #TEST_START_DATE = '2016-06-01'
        #TEST_END_DATE = '2017-7-31'
        TEST_START_DATE = datetime.datetime(2016, 6, 1)
        TEST_END_DATE = datetime.datetime(2017, 7, 31)

        # ## Stock tickers for training data
        TRAINING_TICKERS = ['AAPL','GOOG','T','IMAX','IBM','NFLX','SIRI','S','PLUG','C',\
                            'ZNGA','WMS','BAC','AMZN','FB','P','WM','NOK','DDD','XME','XONE','S
                            'TSLA','SSYS','TXN','F','GS','LQMT','HTZ','BAH','GLW','SPWR',\
                            'BIDU','SRPT','YGE','CNX','URRE','VJET','RAD','NQ',\
                            'KORS','TWTR','HLF','ORCL','WLL','BLDP','PEG','MJNA','CBIS',\
                            'TM','SBUX','MBLY','MRK','DBO','PFE','CAMP','TRXC',\
                            'BMY','FE','VTR','UHT','MVO','KF','RACE','STOR','MU','RTN']
        # TRAINING_TICKERS = ['AAPL', 'GOOG', 'YHOO', 'T', 'IMAX', 'IBM', 'NFLX', 'SIRI', 'S',
        #             'C', 'BAC', 'P', 'NOK', 'XONE', 'SSYS', 'TSLA', 'AMZN', 'SDRL', 'DDD', \
        #             'DBO', 'SRPT', 'SPWR', 'SCTY', 'FB', 'URRE', 'NQ', 'TWTR', 'F', 'BAH', \
        #             'MZDAY','FSYS', 'BIDU', 'KORS', 'HLF', 'ORCL', 'MBLY']
                   ## SOME NETWORK CAUSES MZDAY AND FSYS TO HAVE SOME NaN FOR SOME REASON

        ## Stock tickers for testing data
        ## unable to read SHOP,HEMP,LMT
        # TESTING_TICKERS = ['BA','OLED', 'HON','MA','TPLM', 'SD', 'FCEL', 'CHK', 'CMG','UHT',
        #                        'UHT','BMY','FE','VTR','UHT','MVO','KF','RACE','MU','RTN']
        #TESTING_TICKERS = ['BA','OLED', 'HON','MA','TPLM', 'SD', 'FCEL', 'CHK', 'CMG']
        TESTING_TICKERS = ['BA', 'HON','MA','TPLM', 'SD', 'FCEL', 'CHK', 'CMG']
```

```python
#TESTING_TICKERS = ['BA', 'HON','MA']
#TESTING_TICKERS = ['SD', 'FCEL', 'CHK', 'CMG']

## Initial money to be invested
MONEY = 10000

## Commision rate when buying/selling stocks
COMM_RATE = 4.95

## Long term capital gain tax rate (percentage)
GAIN_LONG = 0.15

## Short term capital gain tax rate (percentage).
## Also used for losses, assuming its the individuals tax bracket
GAIN_SHORT = 0.25

## Models predict the ratio base on these targets
#TARGET_RATIOS = ['vr15','vr25','vr40']
TARGET_RATIOS = ['vClose','vr2','vr3','vr5','vr10','vr15','vr25','vr40']
## New target ratio, will not just be relative to close
#TARGET_RATIOS = ['Close_pc','r2_p2','r3_p3','r5_p5','r10_p10','r15_p15','r25_p25','r4

## Used to determine when predictions will be a buy/sell
#SELL_BUY_VALUES = [(1,1)]
SELL_BUY_VALUES = [(0.985,0.985),(0.99,0.99),(0.995,0.995), (1,1),(1.005,1.005),\
                   (1.01,1.01),(1.015,1.015), \
                   (0.985,1.015),(0.99,1.01),(0.995,1.005),\
                   (0.995,1.00),(1.00,1.005),(1.005,1.01), \
                   (1.00,1.015),(1.00,1.01)]

## Set to True if we are reading existing models
## Set to False to generate new models
READ_EXISTING_MODELS = True

## Set True if using multiprocessing
MULTIPROCESSOR = True

## Number of processes for multiprocessing pool
NUM_PROCESSES = 8

## Set True to read existing training stocks
## If training tickers have been updated, set this to False
READ_EXISTING_TRAINING_STOCKS = True

## Set True to read existing testing stocks
## If testing tickers have been updated, set this to False
READ_EXISTING_TESTING_STOCKS = True
```

0.0.3 Get all the stocks data. Save data as pickle files

In [3]:
```
def gather_training_data():
    all_weekdays = pd.date_range(start=TRAINING_START_DATE,end=TRAINING_END_DATE,freq=
    ## panel type
    panel_data = data.DataReader(TRAINING_TICKERS,DATA_SOURCE,TRAINING_START_DATE,\
                                 TRAINING_END_DATE)

    if DATA_SOURCE == 'yahoo':
        ## Yahoo has extra column
        panel_data.drop('Adj Close', inplace=True)

    panel_data.drop('Volume', inplace=True)

    ## save to pickle
    panel_data.to_pickle('training_stocks.pkl')

def gather_testing_data():
    all_weekdays = pd.date_range(start=TEST_START_DATE,end=TEST_END_DATE,freq='B')
    panel_data = data.DataReader(TESTING_TICKERS,DATA_SOURCE,TEST_START_DATE,TEST_END_I

    if DATA_SOURCE == 'yahoo':
        ## Yahoo has extra column
        panel_data.drop('Adj Close', inplace=True)

    panel_data.drop('Volume', inplace=True)

    panel_data.to_pickle('testing_stocks.pkl')

## Read existing data
if READ_EXISTING_TRAINING_STOCKS == False:
    gather_training_data()

if READ_EXISTING_TESTING_STOCKS == False:
    gather_testing_data()
```

0.0.4 Helper function to get the rolling averages. 2, 3, 5, 10, 15, 25 and 40-day moving averages.

In [4]:
```
def get_rolling(df):
    stock = df['Close']
    r2 = stock.rolling(window=2).mean()
    r3 = stock.rolling(window=3).mean()
    r5 = stock.rolling(window=5).mean()
    r10 = stock.rolling(window=10).mean()
    r15 = stock.rolling(window=15).mean()
    r25 = stock.rolling(window=25).mean()
    r40 = stock.rolling(window=40).mean()
```

```
        return r2, r3, r5, r10, r15, r25, r40
```

0.0.5 Helper function to plot stocks data, with rolling averages

```
In [5]: def plot_stock(tick, df):
            print("Plotting: ", tick)
            close = df['vClose']
            r2 = df['vr2']
            r3 = df['vr3']
            r5 = df['vr5']
            r10 = df['vr10']
            r15 = df['vr15']
            r25 = df['vr25']
            r40 = df['vr40']

            fig = plt.figure()
            ax = fig.add_subplot(1,1,1)
            ax.plot(close.index,close,label=tick)
            ax.plot(r2.index, r2, label='2 days rolling')
            ax.plot(r3.index, r3, label='3 days rolling')
            ax.plot(r5.index, r5, label='5 days rolling')
            ax.plot(r10.index, r10, label='10 days rolling')
            ax.plot(r15.index, r15, label='15 days rolling')
            ax.plot(r25.index, r25, label='25 days rolling')
            ax.plot(r40.index, r40, label='40 days rolling')
            ax.set_xlabel('Date')
            ax.set_ylabel('Closing prices ($)')
            ax.legend()

            #plt.show()
            #fig.savefig("figures/"+tick+'.png')
            fig.savefig("figures/"+tick+'.svg', format='svg', dpi=1200)
            plt.close(fig)
```

0.0.6 Helper function to statistics of the training data

```
In [6]: def describe_data():
            df = pd.DataFrame.from_csv("training_data/all_raw_data.csv")
            df = df.describe()
            df.to_csv("training_data/all_raw_data_description.csv")
            print("\nRaw training data description:\n",df)

            df = pd.DataFrame.from_csv("training_data/all_processed_data.csv")
            df = df.describe()
            df.to_csv("training_data/all_processed_data_description.csv")
            print("\nProcessed training data description:\n",df)
```

0.0.7 Get each DataFrame of the entire list of stocks for training, from the pickle file

In [7]:
```
def get_training_stocks_df(filename):
    processed_df = pd.DataFrame()
    raw_inputs_df = pd.DataFrame()
    raws = []
    processed = []
    panel_data = pd.read_pickle(filename)                          ## read saved stocks d

    for tick in TRAINING_TICKERS:
        ## Extract single stock from panel_data
        df = panel_data[:,:,tick]                                  ## becomes df type, fr
        df.to_csv("training_data/"+tick+".csv")                    ## raw input

        raws.append(df)                                            ## gather all the raw

        ## Get full df with 109 columns
        df = get_stock_df(df,tick)

        ## Save df
        df.to_csv("training_data/"+tick+"_processed.csv")

        ## Plot stock
        plot_stock(tick,df)

        #processed_df = processed_dfmain_df.append(df)
        processed.append(df)                               ## faster to append once, with

    ## append all raw input to one df, then save
    raw_inputs_df = raw_inputs_df.append(raws)
    raw_inputs_df.to_csv("training_data/all_raw_data.csv")

    ## append all processed input to on df, then save
    processed_df = processed_df.append(processed)         ## faster to append once, with
    processed_df.to_csv("training_data/all_processed_data.csv")

    return processed_df
```

0.0.8 Helper function to get DataFrame of individual stocks. Generates 108 columns, 20 columns will be removed later

In [8]:
```
"""
Columns generated:

#predict, prev_close, prev_r2, prev_r3, prev_r5, prev_r10, prev_r15, prev_r25, prev_r4
predict, prev_close, prev_r2, prev_r3, prev_r5, prev_r10, prev_r15, prev_r25, prev_r40
vOpen, vHigh, vLow, vClose, vr2, vr3, vr5, vr10, vr15, vr25, vr40,
Open_pc, High_pc, Low_pc, Close_pc, r2_pc, r3_pc, r5_pc, r10_pc, r15_pc, r25_pc, r40_p
```

```
Open_p2, High_p2, Low_p2, Close_p2, r2_p2, r3_p2, r5_p2, r10_p2, r15_p2, r25_p2, r40_p
Open_p3, High_p3, Low_p3, Close_p3, r2_p3, r3_p3, r5_p3, r10_p3, r15_p3, r25_p3, r40_p
Open_p5, High_p5, Low_p5, Close_p5, r2_p5, r3_p5, r5_p5, r10_p5, r15_p5, r25_p5, r40_p
Open_p10, High_p10, Low_p10, Close_p10, r2_p10, r3_p10, r5_p10, r10_p10, r15_p10, r25_
Open_p15, High_p15, Low_p15, Close_p15, r2_p15, r3_p15, r5_p15, r10_p15, r15_p15, r25_
Open_p25, High_p25, Low_p25, Close_p25, r2_p25, r3_p25, r5_p25, r10_p25, r15_p25, r25_
Open_p40, High_p40, Low_p40, Close_p40, r2_p40, r3_p40, r5_p40, r10_p40, r15_p40, r25_

"""
def get_stock_df(df,tick):
    ## Yahoo and Google data source returns different orders, ## make sure its this or
    #df = df.reindex_axis(['Open','High','Low','Close','Volume'], axis=1)
    df = df.reindex_axis(['Open','High','Low','Close'], axis=1)

    r2, r3, r5, r10, r15, r25, r40 = get_rolling(df)        ## get moving averages

    ## Rename Volume column then remove it
#     vol = df['Volume']
#     vol = vol.to_frame()
#     vol.columns = ['Vol']
#     df = df.drop('Volume', 1)                               ## 1 for axis 1, which i

    ## Rename columns
    df_r2= r2.to_frame()                                    ## from series to df
    df_r2.columns = ['r2']                                  ## change column title

    df_r3= r3.to_frame()
    df_r3.columns = ['r3']

    df_r5= r5.to_frame()
    df_r5.columns = ['r5']

    df_r10= r10.to_frame()
    df_r10.columns = ['r10']

    df_r15= r15.to_frame()
    df_r15.columns = ['r15']

    df_r25= r25.to_frame()
    df_r25.columns = ['r25']

    df_r40= r40.to_frame()
    df_r40.columns = ['r40']

    ## Shift rows to generate next/previous values
    #predict = df['Close'].copy()
    predict = df['Close'].shift(-1)                                  ## a seri
    predict = predict.to_frame()
```

```python
    predict.columns = ['predict']

    prev_close = df['Close'].shift(1)
    prev_close = prev_close.to_frame()
    prev_close.columns = ['prev_close']

    prev_r2 = df_r2['r2'].shift(1)
    prev_r2 = prev_r2.to_frame()
    prev_r2.columns = ['prev_r2']

    prev_r3 = df_r3['r3'].shift(1)
    prev_r3 = prev_r3.to_frame()
    prev_r3.columns = ['prev_r3']

    prev_r5 = df_r5['r5'].shift(1)
    prev_r5 = prev_r5.to_frame()
    prev_r5.columns = ['prev_r5']

    prev_r10 = df_r10['r10'].shift(1)
    prev_r10 = prev_r10.to_frame()
    prev_r10.columns = ['prev_r10']

    prev_r15 = df_r15['r15'].shift(1)
    prev_r15 = prev_r15.to_frame()
    prev_r15.columns = ['prev_r15']

    prev_r25 = df_r25['r25'].shift(1)
    prev_r25 = prev_r25.to_frame()
    prev_r25.columns = ['prev_r25']

    prev_r40 = df_r40['r40'].shift(1)
    prev_r40 = prev_r40.to_frame()
    prev_r40.columns = ['prev_r40']

    ## Generate entire dataframe
    ## encapsulate in a list for multiple df
#     df1 = predict.join([prev_close,prev_r2,prev_r3,prev_r5,prev_r10,prev_r15,\
#                         prev_r25,prev_r40,vol])
    df1 = predict.join([prev_close,prev_r2,prev_r3,prev_r5,prev_r10,prev_r15,\
                        prev_r25,prev_r40])
    df2 = df.join([df_r2,df_r3,df_r5,df_r10,df_r15, df_r25, df_r40])
    df3 = df2.copy()
    df4 = df2.copy()
    df5 = df2.copy()
    df6 = df2.copy()
    df6 = df2.copy()
    df7 = df2.copy()
    df8 = df2.copy()
```

```
df9 = df2.copy()
df10 = df2.copy()
## will have original value (not percentage)
df10.columns = ['vOpen','vHigh','vLow','vClose','vr2','vr3',\
                'vr5','vr10','vr15','vr25','vr40']
## will be with respect to prev_close
df2.columns = ['Open_pc','High_pc','Low_pc','Close_pc','r2_pc','r3_pc','r5_pc',\
               'r10_pc','r15_pc','r25_pc','r40_pc']
## will be with respect to prev_r2
df3.columns = ['Open_p2','High_p2','Low_p2','Close_p2','r2_p2','r3_p2','r5_p2',\
               'r10_p2','r15_p2','r25_p2','r40_p2']
## will be with respect to prev_r3
df4.columns = ['Open_p3','High_p3','Low_p3','Close_p3','r2_p3','r3_p3','r5_p3',\
               'r10_p3','r15_p3','r25_p3','r40_p3']
## will be with respect to prev_r5
df5.columns = ['Open_p5','High_p5','Low_p5','Close_p5','r2_p5','r3_p5','r5_p5',\
               'r10_p5','r15_p5','r25_p5','r40_p5']
## will be with respect to prev_r10
df6.columns = ['Open_p10','High_p10','Low_p10','Close_p10','r2_p10','r3_p10',\
               'r5_p10','r10_p10','r15_p10','r25_p10','r40_p10']
## will be with respect to prev_r15
df7.columns = ['Open_p15','High_p15','Low_p15','Close_p15','r2_p15','r3_p15',\
               'r5_p15','r10_p15','r15_p15','r25_p15','r40_p15']
## will be with respect to prev_r25
df8.columns = ['Open_p25','High_p25','Low_p25','Close_p25','r2_p25','r3_p25',\
               'r5_p25','r10_p25','r15_p25','r25_p25','r40_p25']
## will be with respect to prev_r40
df9.columns = ['Open_p40','High_p40','Low_p40','Close_p40','r2_p40','r3_p40',\
               'r5_p40','r10_p40','r15_p40','r25_p40','r40_p40']

## Combine all to one dataframe
df = df1.join([df10,df2,df3,df4,df5,df6,df7,df8,df9])

## Drop N/A
df = df.dropna(axis=0,how='any')                    ## drop rows containing at lea

## Normalize columns, base on previous values.  Get ratios/percentage
#df[columns_to_divide] = df[columns_to_divide] / df['prev_close']   ## having size

cols_to_divide = ['Open_pc','High_pc','Low_pc','Close_pc','r2_pc','r3_pc','r5_pc',
                  'r10_pc','r15_pc','r25_pc','r40_pc']
df[cols_to_divide] = df[cols_to_divide].div(df['prev_close'].values,axis=0)

cols_to_divide = ['Open_p2','High_p2','Low_p2','Close_p2','r2_p2','r3_p2','r5_p2',
                  'r10_p2','r15_p2','r25_p2','r40_p2']
df[cols_to_divide] = df[cols_to_divide].div(df['prev_r2'].values,axis=0)

cols_to_divide = ['Open_p3','High_p3','Low_p3','Close_p3','r2_p3','r3_p3','r5_p3',
```

```
                      'r10_p3','r15_p3','r25_p3','r40_p3']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r3'].values,axis=0)

    cols_to_divide = ['Open_p5','High_p5','Low_p5','Close_p5','r2_p5','r3_p5','r5_p5',\
                      'r10_p5','r15_p5','r25_p5','r40_p5']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r5'].values,axis=0)

    cols_to_divide = ['Open_p10','High_p10','Low_p10','Close_p10','r2_p10','r3_p10',\
                      'r5_p10','r10_p10','r15_p10','r25_p10','r40_p10']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r10'].values,axis=0)

    cols_to_divide = ['Open_p15','High_p15','Low_p15','Close_p15','r2_p15','r3_p15',\
                      'r5_p15','r10_p15','r15_p15','r25_p15','r40_p15']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r15'].values,axis=0)

    cols_to_divide = ['Open_p25','High_p25','Low_p25','Close_p25','r2_p25','r3_p25',\
                      'r5_p25','r10_p25','r15_p25','r25_p25','r40_p25']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r25'].values,axis=0)

    cols_to_divide = ['Open_p40','High_p40','Low_p40','Close_p40','r2_p40','r3_p40',\
                      'r5_p40','r10_p40','r15_p40','r25_p40','r40_p40']
    df[cols_to_divide] = df[cols_to_divide].div(df['prev_r40'].values,axis=0)

    return df
```

0.0.9 Update target, base on target ratio

```
In [9]: def get_target(X,target_ratio):
            ## update predict base on target_ratio
            ## All these are base on predict (relative to close only)
            cols_to_divide = ['predict']
            X[cols_to_divide] = X[cols_to_divide].div(X[target_ratio].values,axis=0)

            ## New targets: prev target_ratio/current target ratio
            ## Shift rows to generate next values
            #target = X[target_ratio].shift(-1)
            ##target = X[target_ratio].copy()
            #X['predict'] = target
            ### Drop N/A
            #X = X.dropna(axis=0,how='any')

            ## Convert target base on sell/buy prices thats provided
            y = convert_target_value(X['predict'],sell_below,buy_above)

            ## Delete unneccesary columns
            del X['predict'],X['prev_close'],X['prev_r2'],X['prev_r3'],X['prev_r5']
            del X['prev_r10'],X['prev_r15'],X['prev_r25'],X['prev_r40']
            ## Delete columns with actual price
```

```
        del X['vOpen'],X['vHigh'],X['vLow'],X['vClose'],X['vr2']
        del X['vr3'],X['vr5'],X['vr10'],X['vr15'],X['vr25'],X['vr40']

        return X, y
```

0.0.10 Helper function to convert target. Buy (1), Sell (-1), or Neutral (0). Base on sell/buy prices

```
In [10]: def convert_target_value(arr,sell_below,buy_above):
             ans = []

             for x in arr:
                 if x <= sell_below:
                     ans.append(-1)
                 elif x >= buy_above:
                     ans.append(1)
                 else:
                     ans.append(0)

             return ans
```

0.0.11 Create Neural Network Model

```
In [11]: def neural_network_model():
             ## create model
             model = Sequential()
             model.add(Dense(300,input_dim=88,activation='tanh',kernel_regularizer=regularizers
             model.add(Dense(150,activation='tanh'))
             model.add(Dense(3,activation='softmax'))

             ## for binary classifier
             #model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
             #model.compile(loss='mean_squared_error',optimizer='adam',metrics=['accuracy'])
             #model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy
             #model.compile(loss='categorical_crossentropy',optimizer='adamax',metrics=['accura
             #model.compile(loss='categorical_crossentropy',optimizer='nadam',metrics=['accura
             #model.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accu
             #model.compile(loss='categorical_crossentropy',optimizer='adagrad',metrics=['accu
             #model.compile(loss='categorical_crossentropy',optimizer='adadelta',metrics=['acc
             #model.compile(loss='categorical_crossentropy',optimizer='tfoptimizer',metrics=['

             opt = optimizers.SGD(lr=0.001,momentum=0.9,decay=1e-6,nesterov=True)
             model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])

             return model
```

0.0.12 Helper function to get encoding, for 'target' in Neural Network

In [12]:
```
"""
Returns a (XXX,3) from (XXX,1), for the input of the neural network
Didnt use np_utils.to_categorical() since output could be -1,1 or
-1,0,1 depending on sell/buy values
"""
def myEncoder(arr):
    s = (len(arr),3)
    numpy_arr = np.zeros(s)

    for i,num in enumerate(arr):
        if num == -1:
            numpy_arr[i] = np.array([1,0,0])
        elif num == 1:
            numpy_arr[i] = np.array([0,0,1])
        else:
            numpy_arr[i] = np.array([0,1,0])

    return numpy_arr
```

0.0.13 Helper function to decode, as 1 dimensional target

In [13]:
```
"""
Returns a (XXX,1) from (XXX,3), from predict of the neural network
"""
def myDecoder(numpy_arr):
    arr = []
    ## Models predictions are ndarray, percentages per category
    for i,a in enumerate(numpy_arr):
        if np.argmax(a) == 0:
            arr.append(-1)
        elif np.argmax(a) == 2:
            arr.append(1)
        else:
            arr.append(0)

    ## Convert the arr list to an ndarray.
    return np.array(arr)
```

0.0.14 Helpter function to scale input data for neural network

In [14]:
```
def rescale_input(arr):
    """
    Scales data to be between a - b
    """
    ## Function below is not used.  Initially thought arr was a df
    def scaler(x):
```

```
        new_x = (((highest_scale-lowest_scale)*(x-min_input))/(max_input-min_input))+l
        return new_x

    ## Tried -1 to 1 before
    lowest_scale = -1
    highest_scale = 1
    max_input = 1.15
    min_input = 0.85

    #result = arr.applymap(scaler)    ## if its a df, use applymap

    ## arr is an ndarray.  Use vectorize instead of applymap
    scaler = lambda x: (((highest_scale-lowest_scale)*(x-min_input))/(max_input-min_in
                       + lowest_scale
    func = np.vectorize(scaler)                          ## vectorize scaler function
    result = func(arr)                                   ## pass arr to vectorized fun

    return result
```

0.0.15 Get the metrics of the models

```
In [15]: def get_model_metrics(target_ratio,sell_below,buy_above,X):
    temp_result = {}
    temp_result['target_ratio'] = target_ratio
    temp_result['sell_below'] = sell_below
    temp_result['buy_above'] = buy_above

    X,y = get_target(X,target_ratio)
    #print("Input shape: {} Target shape: {}".format(X.shape,len(y)))
    #print("Target found are: {}".format(set(y)))

    ## Perform cross validation.  95% to have as much training data as possible.
    ## Also, performance will be base on totally different set of stocks
    try: X_train, X_test, y_train, y_test \
        = cross_validation.train_test_split(X,y,train_size=0.90,stratify=y)
    ## error sometimes: The least populated class in y has only 1 member, which is to
    ## The minimum number of labels for any class cannot be less than 2.
    except: X_train, X_test, y_train, y_test \
        = cross_validation.train_test_split(X,y,train_size=0.90)

    #print("Sample of training data:")
    #print("Number of rows: {}. Number of columns: {}.".format(len(X_train),len(X_tra
    #print(X_train.head())

    beta = 0.5

    ## Initialize Models
    ## entropy for exploratory analysis, gini (default) to minimize misclassification
```

```
## max_features default None
#clf1 = DecisionTreeClassifier(criterion="entropy",random_state=0,max_features=No
clf1 = DecisionTreeClassifier()
clf2 = GaussianNB()
## kernel 'rbf' default, others are linear, poly, sigmoid, C is penalty parameter
#clf3 = SVC()                         ## <-- makes execution time 20x longer
## defaults are 1 for learning rate and 50 for n_estimators
#clf4 = AdaBoostClassifier(random_state=0,learning_rate=0.7,n_estimators=50)
clf4 = AdaBoostClassifier()
clf5 = neural_network_model()

if READ_EXISTING_MODELS == True:
    ## Read existing models

    ## For DecisionTree
    with open("models/DecisionTree_"+target_ratio+"_"+str(sell_below)\
              +"_"+str(buy_above)+".pkl", 'rb') as f:
        clf1 = pickle.load(f)

    ## For GaussianNB
    with open("models/GaussianNB_"+target_ratio+"_"+str(sell_below)\
              +"_"+str(buy_above)+".pkl", 'rb') as f:
        clf2 = pickle.load(f)

    ## For SVC model
    #with open("models/SVC_"+target_ratio+"_"+str(sell_below)\
    #          +"_"+str(buy_above)+".pkl", 'rb') as f:
    #    clf3 = pickle.load(f)

    ## For Adaboost
    with open("models/Adaboost_"+target_ratio+"_"+str(sell_below)\
              +"_"+str(buy_above)+".pkl", 'rb') as f:
        clf4 = pickle.load(f)

    ## For Neural Network
    ## Load json and create model
    json_file = open("models/NN_"+target_ratio+"_"+str(sell_below)\
                     +"_"+str(buy_above)+".json","r")
    loaded_model_json = json_file.read()
    json_file.close()
    clf5 = model_from_json(loaded_model_json)
    ## Load weights into new model
    clf5.load_weights("models/NN_"+target_ratio+"_"+str(sell_below)+"_"+str(buy_al
    ## Compile, make sure its the same as above
    opt = optimizers.SGD(lr=0.001,momentum=0.9,decay=1e-6,nesterov=True)
    clf5.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy

else:
```

```
## Generate new models

## Fit Data to DecisionTree Model
clf1.fit(X_train,y_train)
## Save model to a file
with open("models/DecisionTree_"+target_ratio+"_"+str(sell_below)\
          +"_"+str(buy_above)+".pkl", 'wb') as f:
    pickle.dump(clf1, f)

# Fit Data to GaussianNB Model
clf2.fit(X_train,y_train)
## Save model to a file
with open("models/GaussianNB_"+target_ratio+"_"+str(sell_below)\
          +"_"+str(buy_above)+".pkl", 'wb') as f:
    pickle.dump(clf2, f)

# Fit Data to SVC Model
#clf3.fit(X_train,y_train)
## Save model to a file
#with open("models/SVC_"+target_ratio+"_"+str(sell_below)\
#          +"_"+str(buy_above)+".pkl", 'wb') as f:
#    pickle.dump(clf3, f)

# Fit Data to Adaboost Model
clf4.fit(X_train,y_train)
## Save model to a file
with open("models/Adaboost_"+target_ratio+"_"+str(sell_below)\
          +"_"+str(buy_above)+".pkl", 'wb') as f:
    pickle.dump(clf4, f)

## Fit Data to Neural Model
input_train = X_train.as_matrix(columns=None)               ## convert df to 
#np.savetxt("test1.csv",input_train,delimiter=",")
input_train = rescale_input(input_train)
#print("Input_train:",input_train[np.r_[0:5]])              ## print first 5

### encode class values as integers
#encoder = LabelEncoder()
#encoder.fit(y_train)
#encoded_y = encoder.transform(y_train)
### convert integers to dummy variables (i.e one hot encoded)
#dummy_y = np_utils.to_categorical(encoded_y)
#print(dummy_y)
dummy_y = myEncoder(y_train)
clf5.fit(input_train,dummy_y,epochs=20,batch_size=100)
## Serialize model to JSON
model_json = clf5.to_json()
with open("models/NN_"+target_ratio+"_"+str(sell_below)\
```

```
            +"_"+str(buy_above)+".json","w") as json_file:
        json_file.write(model_json)
    ## Serialize weights to HDF5
    clf5.save_weights("models/NN_"+target_ratio+"_"+str(sell_below)+"_"+str(buy_al

## Get accuracy and fscore of the models
temp_result['DecisionTree Accuracy'] = accuracy_score(y_test, clf1.predict(X_test
temp_result['DecisionTree Fscore'] = fbeta_score(y_test, clf1.predict(X_test),\
                                                 beta,average='weighted')

temp_result['GaussianNB Accuracy'] = accuracy_score(y_test,clf2.predict(X_test))
temp_result['GaussianNB Fscore'] = fbeta_score(y_test, clf2.predict(X_test),\
                                               beta,average='weighted')

#temp_result['SVC Accuracy'] = accuracy_score(y_test,clf3.predict(X_test))
#temp_result['SVC Fscore'] = fbeta_score(y_test, clf3.predict(X_test),\
#                                         beta,average='weighted')

temp_result['Adaboost Accuracy'] = accuracy_score(y_test,clf4.predict(X_test))
temp_result['Adaboost Fscore'] = fbeta_score(y_test,clf4.predict(X_test),\
                                             beta,average='weighted')

input_test = X_test.as_matrix(columns=None)
input_test = rescale_input(input_test)
dummy_y = myEncoder(y_test)
#scores = clf5.evaluate(input_test, dummy_y)
#temp_result['NN Accuracy'] = scores[1]*100
temp_result['NN Accuracy'] = accuracy_score(y_test,myDecoder(clf5.predict(input_te
temp_result['NN Fscore'] = fbeta_score(y_test, \
                              myDecoder(clf5.predict(input_test)),beta,average='we

## Determine performance of the portfolio on each model
#models = [('DecisionTree',clf1),('GaussianNB',clf2),('Adaboost',clf4),\
#              ('SVC',clf3),('NN',clf5)]
## No SVC model
models = [('DecisionTree',clf1),('GaussianNB',clf2),('Adaboost',clf4),('NN',clf5)]
test_model_performance(models,temp_result,target_ratio,sell_below,buy_above)

## Check if multiprocessor is set
if MULTIPROCESSOR == False:
    ## Result will contain all the result from each combination of the models
    result.append(temp_result)
else:
    ## To support multiprocessing, will have to save for later
    ## temp_result is a dict, not df
    #temp_result.to_csv("temp_results/"+str(time.clock())+".csv")
    with open("temp_results/"+str(time.clock())+".json", 'w') as fp:
        json.dump(temp_result, fp)
```

0.0.16 Calculate model performance

```
In [16]: def test_model_performance(models,temp_result,target_ratio,sell_below,buy_above):
             panel_data = pd.read_pickle('testing_stocks.pkl')          ## read saved stocks

             ## Initialize total to be 0 across all models
             total = {'benchmark':0}
             for model_name,_ in models:
                 total[model_name] = 0                          ## will hold total money for that
                 total[model_name+"_transactions"] = 0          ## will hold total transactions f

             ## Go through each stock
             for tick in TESTING_TICKERS:
                 ## Extract single stock from panel_data
                 #df = panel_data[:,:,tick]
                 #X = get_stock_df(df,tick)
                 ## We will now just read the test stocks, generated before
                 X = pd.DataFrame.from_csv("testing_data/"+tick+'_processed.csv')

                 ## Delete unnecessary columns
                 del X['predict'],X['prev_close'],X['prev_r2'],X['prev_r3'],X['prev_r5']
                 del X['prev_r10'],X['prev_r15'],X['prev_r25'],X['prev_r40']
                 ## Delete columns with actual price
                 del X['vOpen'],X['vHigh'],X['vLow'],X['vClose'],X['vr2']
                 del X['vr3'],X['vr5'],X['vr10'],X['vr15'],X['vr25'],X['vr40']

                 ## Get predictions base on each models
                 for model_name, model in models:
                     ## predictions will be an ndarray
                     if model_name == 'NN':
                         input_test = X.as_matrix(columns=None)
                         input_test = rescale_input(input_test)
                         predictions = model.predict(input_test)
                         predictions = myDecoder(predictions)
                     else:
                         predictions = model.predict(X)

                     ## Add predictions to the dataframe
                     pred = pd.DataFrame(predictions.flatten(),index=X.index,columns=['Predicti
                     S = X.join(pred)
                     S['Transactions'] = 0                        ## will contain number of tra
                     S['Money'] = 0                               ## will contain total current

                     ## Calculate transactions (NOT COMPLETE)
                     #temp_df = pd.DataFrame(X['Close_pc'].values,columns=['Close_pc'])
                     #temp_df = temp_df.join(pd.DataFrame(predictions.flatten(),columns=['Pred
                     #temp_df['playing'] = temp_df['Predictions'].shift().eq(1)
                     ### cumprod of 'Close_pc' where 'playing' is True.  Then multiple with in
```

```
        #temp_df['Money'] = \
        #     temp_df['Close_pc'].where(temp_df['playing'],1).cumprod().mul(MONEY
        ### get just last value from 'Money'
        #temp_result[tick+'_'+model_name] = float(format(temp_df['Money'].iloc[-1
        #total[model_name] += float(format(temp_df['Money'].iloc[-1], '.2f'))

        ## Calculate transactions. SLOWER? BUT COMPLETE
        playing = False                     ## used to determine if currently in
        money = copy.copy(MONEY)
        transactions = 0
        i = 0
        for index, row in S.iterrows():
            ## Update money
            if i > 0 and playing == True:
                money = float(format(money*row['Close_pc'],'.2f'))

            ## Buy/Sell
            if row['Predictions'] == 1:
                if playing == False:
                    playing = True          ## Buy, playing after this
                    transactions += 1       ## increment transaction number for t
            elif row['Predictions'] == -1:
                if playing == True:
                    playing = False         ## Sell, not playing after this
                    transactions += 1       ## increment transaction number for t
            i += 1

            ## Change value in sample data S in index and column provided,
            ## with value/data provided
            S.set_value(index,'Money',money)
            S.set_value(index,'Transactions',transactions)

        ## Save dataframe for testing purposes
        S.to_csv("model_predictions/"+tick+"_"+model_name+"_"\
                 +target_ratio+"_"+str(sell_below)+"_"+str(buy_above)+".csv")

        ## If still playing at the end, we'll sell, thus increment number of tran
        transactions = transactions + 1 if playing == True else transactions
        ## Will contain total money for this stock and model
        temp_result[tick+'_'+model_name] = money
        ## Will contain total number of transactions for this stock and model
        temp_result[tick+'_'+model_name+"_transactions"] = transactions
        ## Will contain total money for this model, including all stocks
        total[model_name] += money
        ## total transactions for the model, including all stocks
        total[model_name+"_transactions"] += transactions

    ## Calculate benchmark portfolio for current stock (NOT COMPLETE)
```

```
        #temp_df = X['Close_pc'].to_frame()
        #temp_df['Close_pc'].iloc[0] = 1       ## since first one is not played
        #temp_df['Money'] = temp_df['Close_pc'].cumprod().mul(MONEY)
        ### total money in benchmark, for that stock
        #temp_result[tick+'_benchmark'] = float(format(temp_df['Money'].iloc[-1], '.2
        #total['benchmark'] += float(format(temp_df['Money'].iloc[-1], '.2f'))

        ## Calculate benchmark portfolio for current stock. SLOWER? BUT COMPLETE
        money = copy.copy(MONEY)
        for i,r in enumerate(X['Close_pc']):
            if i > 0:
                money = float(format(money*r,'.2f'))
        temp_result[tick+'_benchmark'] = money      ## total money in benchmark, for
        total['benchmark'] += money          ## will contain total money in benchmark
        total['benchmark_transcations'] = 2         ## Initial buy and the sell at th

    ## Determine Total values of each portfolio
    temp_result['total_benchmark'] = total['benchmark']   ## total money in benchmark

    ## Get total money and transactions per each model.  Each including all stocks
    for model_name,_ in models:
        temp_result['total_'+model_name] = total[model_name]
        temp_result['total_'+model_name+"_transactions"] = total[model_name+"_transac
```

0.0.17 Helper function to save each of the testing stocks as csv

```
In [17]: def save_testing_stocks(filename):
             panel_data = pd.read_pickle(filename)                   ## read saved stocks data

             ## Go through each stock
             for tick in TESTING_TICKERS:
                 ## Extract single stock from panel_data
                 df = panel_data[:,:,tick]

                 ## save raw stock data
                 df.to_csv("testing_data/"+tick+".csv")

                 ## process data
                 df = get_stock_df(df,tick)

                 ## Plot stock
                 plot_stock(tick,df)

                 ## Save to csv
                 df.to_csv("testing_data/"+tick+"_processed.csv")
```

0.0.18 Helper function to delete all the old data from previous runs

```
In [18]: def cleanup_contents():
             filelist = glob.glob("temp_results/*.json")
             for f in filelist:
                 os.remove(f)

             filelist = glob.glob("model_predictions/*.csv")
             for f in filelist:
                 os.remove(f)

             filelist = glob.glob("figures/*")
             for f in filelist:
                 if "README.md" not in f:
                     os.remove(f)

             filelist = glob.glob("training_data/*.csv")
             for f in filelist:
                 os.remove(f)

             filelist = glob.glob("testing_data/*.csv")
             for f in filelist:
                 os.remove(f)

             if READ_EXISTING_MODELS == False:
                 filelist = glob.glob("models/*")
                 for f in filelist:
                     if "README.md" not in f:
                         os.remove(f)
```

0.0.19 Main()

```
In [19]: %%time


         result = []

         ## Remove all existing .json files in temp folder and remove old csv files in data fol
         cleanup_contents()

         filename = 'training_stocks.pkl'
         ## Generate data to be inputted to the models
         X = get_training_stocks_df(filename)

         ## Describe training data
         describe_data()
```

```
        filename = 'testing_stocks.pkl'
        ## Generate data of test stocks and save to csv files
        save_testing_stocks(filename)

        ## Check if multiprocessor is set
        if MULTIPROCESSOR == False:
            ## For single processing
            # Get performance of different types of models
            for sell_below, buy_above in SELL_BUY_VALUES:
                for target_ratio in TARGET_RATIOS:
                    ## copy to prevent updating
                    get_model_metrics(target_ratio,sell_below,buy_above,X.copy())
                    print("Completed target ratio: {} with sell: {} and buy: {}"\
                          .format(target_ratio,sell_below,buy_above))
        else:
            ## For multiprocessing
            ## Get the arguments for the pool
            args = []
            for sell_below, buy_above in SELL_BUY_VALUES:
                for target_ratio in TARGET_RATIOS:
                    arg = (target_ratio,sell_below,buy_above,X.copy())
                    args.append(arg)

            ## With multiprocessing
            pool = mp.Pool(processes=NUM_PROCESSES)
            pool.starmap(get_model_metrics,args)
            pool.close()
            pool.join()
```

```
Plotting:  AAPL
Plotting:  GOOG
Plotting:  T
Plotting:  IMAX
Plotting:  IBM
Plotting:  NFLX
Plotting:  SIRI
Plotting:  S
Plotting:  PLUG
Plotting:  C
Plotting:  ZNGA
Plotting:  WMS
Plotting:  BAC
Plotting:  AMZN
Plotting:  FB
Plotting:  P
Plotting:  WM
Plotting:  NOK
Plotting:  DDD
```

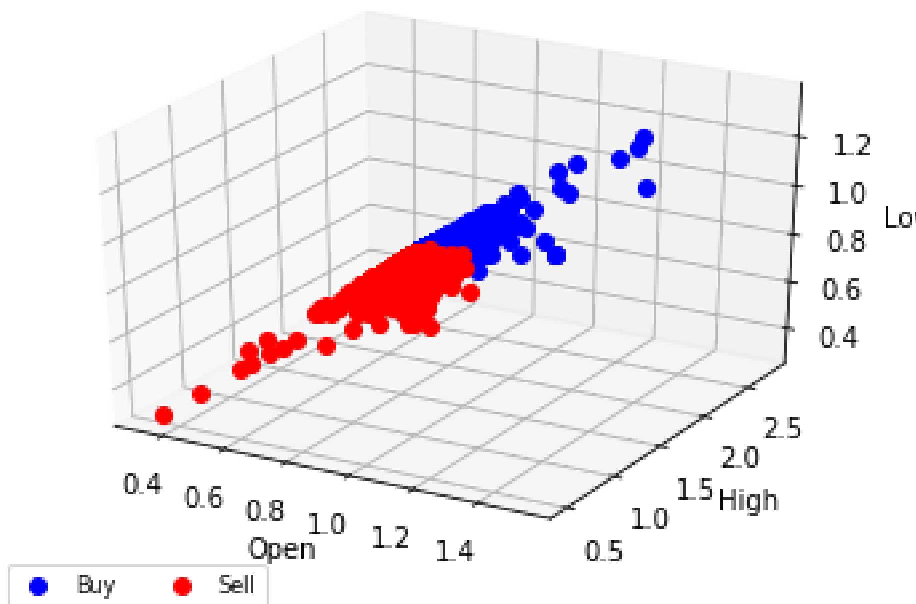
```
Plotting:  XME
Plotting:  XONE
Plotting:  SDRL
Plotting:  TSLA
Plotting:  SSYS
Plotting:  TXN
Plotting:  F
Plotting:  GS
Plotting:  LQMT
Plotting:  HTZ
Plotting:  BAH
Plotting:  GLW
Plotting:  SPWR
Plotting:  BIDU
Plotting:  SRPT
Plotting:  YGE
Plotting:  CNX
Plotting:  URRE
Plotting:  VJET
Plotting:  RAD
Plotting:  NQ
Plotting:  KORS
Plotting:  TWTR
Plotting:  HLF
Plotting:  ORCL
Plotting:  WLL
Plotting:  BLDP
Plotting:  PEG
Plotting:  MJNA
Plotting:  CBIS
Plotting:  TM
Plotting:  SBUX
Plotting:  MBLY
Plotting:  MRK
Plotting:  DBO
Plotting:  PFE
Plotting:  CAMP
Plotting:  TRXC
Plotting:  BMY
Plotting:  FE
Plotting:  VTR
Plotting:  UHT
Plotting:  MVO
Plotting:  KF
Plotting:  RACE
Plotting:  STOR
Plotting:  MU
Plotting:  RTN
```

```
Raw training data description:
              Close          High           Low          Open
count  35863.000000  35863.000000  35863.000000  35863.000000
mean      57.492626     58.181523     56.792067     57.509487
std       98.580690     99.558195     97.533216     98.600096
min        0.011000      0.011000      0.010000      0.011000
25%       11.600000     11.960000     11.300000     11.670000
50%       30.750000     31.250000     30.270000     30.790001
75%       54.279999     54.880001     53.740002     54.340000
max      776.599976    789.869995    766.900024    784.500000

Processed training data description:
            predict    prev_close       prev_r2       prev_r3       prev_r5  \
count  33116.000000  33116.000000  33116.000000  33116.000000  33116.000000
mean      57.650932     57.637520     57.634570     57.631384     57.625151
std      100.020293     99.834763     99.784070     99.734307     99.636152
min        0.011000      0.011000      0.011000      0.011000      0.011000
25%       10.937500     11.007500     11.045000     11.040000     11.111000
50%       30.270000     30.320000     30.320000     30.313334     30.319000
75%       54.340000     54.340000     54.335000     54.336666     54.328000
max      776.599976    776.599976    773.799988    770.036662    763.478003

           prev_r10      prev_r15      prev_r25      prev_r40         vOpen  \
count  33116.000000  33116.000000  33116.000000  33116.000000  33116.000000
mean      57.608467     57.590755     57.557355     57.505788     57.655950
std       99.392219     99.143964     98.668996     97.983877     99.939926
min        0.011200      0.011467      0.012200      0.012275      0.011000
25%       11.131500     11.207667     11.433800     11.601563     11.000000
50%       30.374500     30.423333     30.618000     30.815375     30.299999
75%       54.333500     54.259167     54.133000     53.965500     54.369999
max      756.831995    754.413330    754.352402    747.968002    784.500000

           ...          High_p40       Low_p40     Close_p40        r2_p40  \
count      ...      33116.000000  33116.000000  33116.000000  33116.000000
mean       ...          1.003903      0.969174      0.986053      0.986247
std        ...          0.114326      0.110338      0.113037      0.109736
min        ...          0.375742      0.295510      0.343568      0.350964
25%        ...          0.954380      0.921143      0.936566      0.938189
50%        ...          1.006872      0.983364      0.994662      0.995022
75%        ...          1.051578      1.026764      1.039941      1.038682
max        ...          3.582875      2.254823      2.855776      2.779254

             r3_p40        r5_p40       r10_p40       r15_p40       r25_p40  \
count  33116.000000  33116.000000  33116.000000  33116.000000  33116.000000
mean       0.986453      0.986874      0.988081      0.989481      0.992811
std        0.106759      0.101113      0.087536      0.073997      0.046771
min        0.357857      0.371710      0.399461      0.440318      0.566140
```

```
25%        0.939784      0.942944      0.950446      0.958205      0.973870
50%        0.995284      0.995688      0.996419      0.996939      0.998050
75%        1.037749      1.035906      1.030854      1.026081      1.016421
max        2.504456      2.095218      1.732265      1.502319      1.271795

            r40_p40
count  33116.000000
mean       0.999160
std        0.004857
min        0.965386
25%        0.997213
50%        0.999780
75%        1.001645
max        1.036849

[8 rows x 108 columns]
Plotting:  BA
Plotting:  HON
Plotting:  MA
Plotting:  TPLM
Plotting:  SD
Plotting:  FCEL
Plotting:  CHK
Plotting:  CMG


/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)
/Users/Gio/anaconda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefi
  'precision', 'predicted', average, warn_for)


CPU times: user 47.3 s, sys: 5.94 s, total: 53.2 s
Wall time: 2min 44s
```

0.0.20 Graph 3D plot for Close_pc, with respect with Open_pc, High_pc, and Low_pc

```
In [20]: df_res = pd.DataFrame.from_csv("training_data/all_processed_data.csv")

         x1 = df_res["Open_pc"].where(df_res["Close_pc"] > 1)
         x1 = x1.dropna(axis=0, how='all')

         y1 = df_res["High_pc"].where(df_res["Close_pc"] > 1)
         y1 = y1.dropna(axis=0, how='all')

         z1 = df_res["Low_pc"].where(df_res["Close_pc"] > 1)
         z1 = z1.dropna(axis=0, how='all')

         x0 = df_res["Open_pc"].where(df_res["Close_pc"] < 1)
         x0 = x0.dropna(axis=0, how='all')

         y0 = df_res["High_pc"].where(df_res["Close_pc"] < 1)
         y0 = y0.dropna(axis=0, how='all')

         z0 = df_res["Low_pc"].where(df_res["Close_pc"] < 1)
         z0 = z0.dropna(axis=0, how='all')

         colors=['b', 'r']

         ax = plt.subplot(111, projection='3d')

         ax.plot(x1, y1, z1, 'o', color=colors[0], label='Buy')
         ax.plot(x0, y0, z0, 'o', color=colors[1], label='Sell')

         ax.set_xlabel('Open')
         ax.set_ylabel('High')
         ax.set_zlabel('Low')

         plt.legend(loc='upper left', numpoints=1, ncol=3, fontsize=8, bbox_to_anchor=(0, 0))
         plt.savefig("figures/input.svg", format='svg', dpi=1200)
         plt.show()
```



0.0.21 Read all json in temp folder and append to result (used for multiprocessing)

In [21]:
```
if MULTIPROCESSOR == True:
    result = []

    directory = "temp_results/"
    for filename in os.listdir(directory):
        if filename.endswith(".json"):
            js = open(directory+filename).read()
            temp_dict = json.loads(js)
            result.append(temp_dict)
```

0.0.22 Print Results of the models

In [22]:
```
result_df = pd.DataFrame(result)
print(result_df)
```

```
    Adaboost Accuracy  Adaboost Fscore  BA_Adaboost  \
0            0.566123         0.540336     10819.24
1            0.885266         0.847715     16960.51
2            0.886473         0.851341     16657.76
3            0.677536         0.641591     13386.15
4            0.681159         0.637764     14010.03
5            0.884964         0.849340     16466.70
6            0.677536         0.641591     13386.15
```

7	0.816727	0.773385	15652.32
8	0.623792	0.600917	13027.33
9	0.566123	0.540336	10819.24
10	0.816727	0.773385	15652.32
11	0.566123	0.540336	10819.24
12	0.816727	0.773385	15652.32
13	0.841184	0.792480	16455.14
14	0.623792	0.600917	13027.33
15	0.841184	0.792480	16455.14
16	0.675725	0.646505	13928.51
17	0.623792	0.600917	13027.33
18	0.623792	0.600917	13027.33
19	0.841184	0.792480	16455.14
20	0.841184	0.792480	16455.14
21	0.886775	0.849813	17090.62
22	0.675725	0.646505	13928.51
23	0.886775	0.849813	17090.62
24	0.675725	0.646505	13928.51
25	0.675725	0.646505	13928.51
26	0.886775	0.849813	17090.62
27	0.886775	0.849813	17090.62
28	0.522645	0.351298	10000.00
29	0.757246	0.706535	14708.86
..	...	...	...
90	0.850242	0.811005	16447.50
91	0.888889	0.847373	17090.62
92	0.679952	0.644279	13550.79
93	0.679952	0.644279	13550.79
94	0.889795	0.848054	16721.16
95	0.681461	0.643762	13429.85
96	0.679952	0.644279	13550.79
97	0.566123	0.540336	10819.24
98	0.772343	0.737797	14768.38
99	0.889795	0.848054	16721.16
100	0.890399	0.851732	16656.12
101	0.530797	0.347789	10000.00
102	0.773853	0.733195	14582.51
103	0.530797	0.347789	10000.00
104	0.773249	0.720688	14834.16
105	0.525060	0.349880	10000.00
106	0.773249	0.731688	14458.21
107	0.565217	0.537384	10966.00
108	0.816727	0.773385	15652.32
109	0.803442	0.762763	15726.71
110	0.565217	0.537384	10966.00
111	0.803442	0.753740	15990.51
112	0.804650	0.762921	15728.18
113	0.562802	0.531948	10970.40

114	0.629227	0.607595	13396.57
115	0.854167	0.804483	16544.40
116	0.854167	0.806186	16438.43
117	0.629227	0.607595	13396.57
118	0.628925	0.605614	12993.82
119	0.854167	0.805247	16438.43

	BA_Adaboost_transactions	BA_DecisionTree	BA_DecisionTree_transactions	\
0	28	11362.73	64	
1	18	16228.10	16	
2	16	16201.26	26	
3	52	12708.60	58	
4	58	13350.19	70	
5	18	16201.26	26	
6	52	14254.24	60	
7	34	16244.51	42	
8	46	12283.55	76	
9	28	11362.73	64	
10	34	16244.51	42	
11	28	11362.73	64	
12	34	16244.51	42	
13	20	16714.52	32	
14	46	12283.55	76	
15	20	16714.52	32	
16	52	11464.95	64	
17	46	12283.55	76	
18	46	12283.55	76	
19	20	16714.52	32	
20	20	16714.52	32	
21	16	16863.94	22	
22	52	11464.95	64	
23	16	16863.94	22	
24	52	11464.95	64	
25	52	11464.95	64	
26	16	16863.94	22	
27	16	16863.94	22	
28	0	11801.10	60	
29	40	15088.91	46	
..	...	...	...	
90	20	17925.32	24	
91	16	16415.20	26	
92	60	14220.86	62	
93	60	12710.69	72	
94	20	16802.22	18	
95	56	14220.86	62	
96	60	12710.69	72	
97	28	11362.73	64	
98	32	12310.48	52	

99	20	16802.22	18
100	20	16802.22	18
101	0	11472.35	52
102	34	14762.57	48
103	0	11597.25	72
104	40	14797.87	56
105	0	11062.07	68
106	38	15068.73	56
107	30	13063.17	84
108	34	16244.51	42
109	28	15898.11	38
110	30	11898.72	68
111	32	15709.38	42
112	28	15433.70	30
113	30	11951.63	72
114	58	11186.95	82
115	18	16230.78	34
116	22	16189.45	34
117	58	13513.65	64
118	58	12314.89	70
119	22	16959.71	30

	BA_GaussianNB	BA_GaussianNB_transactions	BA_NN	BA_NN_transactions \
0	10334.98	2	10326.56	10
1	16577.61	2	17037.26	14
2	16577.61	2	17123.13	14
3	16577.61	2	12316.68	62
4	16577.61	2	14193.64	58
5	16577.61	2	17123.13	14
6	16577.61	2	12316.68	62
7	16577.61	2	15691.99	34
8	16577.61	2	11038.13	56
9	10334.98	2	10326.56	10
10	16577.61	2	15691.99	34
11	10334.98	2	10326.56	10
12	16577.61	2	15691.99	34
13	16577.61	2	16444.62	20
14	16577.61	2	11038.13	56
15	16577.61	2	16444.62	20
16	16577.61	2	12829.09	62
17	16577.61	2	11038.13	56
18	16577.61	2	11038.13	56
19	16577.61	2	16444.62	20
20	16577.61	2	16444.62	20
21	16577.61	2	17020.63	14
22	16577.61	2	12829.09	62
23	16577.61	2	17020.63	14
24	16577.61	2	12829.09	62

25	16577.61	2	12829.09	62
26	16577.61	2	17020.63	14
27	16577.61	2	17020.63	14
28	10334.98	2	10000.00	0
29	16577.61	2	14355.48	42
..	...	...	...	...
90	16577.61	2	16692.48	20
91	16577.61	2	17020.63	14
92	16577.61	2	14101.76	58
93	16577.61	2	14101.76	58
94	16577.61	2	17037.26	14
95	16577.61	2	12310.20	60
96	16577.61	2	14101.76	58
97	10334.98	2	10326.56	10
98	16577.61	2	14588.03	40
99	16577.61	2	17037.26	14
100	16577.61	2	17123.13	14
101	10334.98	2	10000.00	0
102	16577.61	2	14648.65	42
103	10334.98	2	10000.00	0
104	16577.61	2	14648.65	42
105	10334.98	2	10000.00	0
106	16577.61	2	14833.46	40
107	10334.98	2	10517.79	14
108	16577.61	2	15691.99	34
109	16577.61	2	15617.80	36
110	10334.98	2	10517.79	14
111	16577.61	2	16077.98	28
112	16577.61	2	15707.85	38
113	10334.98	2	10517.79	14
114	16577.61	2	11172.91	60
115	16577.61	2	16884.75	18
116	16577.61	2	16793.74	20
117	16577.61	2	11172.91	60
118	16577.61	2	11244.13	58
119	16577.61	2	16793.74	20

	...	target_ratio	total_Adaboost	\
0	...	vr2	59765.96	
1	...	vr40	76612.10	
2	...	vr40	77254.12	
3	...	vr5	70617.86	
4	...	vr5	72031.89	
5	...	vr40	76761.01	
6	...	vr5	70617.86	
7	...	vr15	81043.92	
8	...	vr3	66142.60	
9	...	vr2	59765.96	

10	...	vr15	81043.92
11	...	vr2	59765.96
12	...	vr15	81043.92
13	...	vr25	75812.47
14	...	vr3	66142.60
15	...	vr25	75812.47
16	...	vr5	71664.07
17	...	vr3	66142.60
18	...	vr3	66142.60
19	...	vr25	75812.47
20	...	vr25	75812.47
21	...	vr40	77857.79
22	...	vr5	71664.07
23	...	vr40	77857.79
24	...	vr5	71664.07
25	...	vr5	71664.07
26	...	vr40	77857.79
27	...	vr40	77857.79
28	...	vClose	83363.26
29	...	vr10	72114.89
..	...	...	...
90	...	vr25	75777.64
91	...	vr40	77293.08
92	...	vr5	69477.77
93	...	vr5	69477.77
94	...	vr40	76747.22
95	...	vr5	71971.39
96	...	vr5	69477.77
97	...	vr2	59765.96
98	...	vr10	72366.03
99	...	vr40	76747.22
100	...	vr40	77169.35
101	...	vClose	86962.55
102	...	vr10	71362.06
103	...	vClose	86962.55
104	...	vr10	73162.54
105	...	vClose	80525.35
106	...	vr10	71935.62
107	...	vr2	60653.77
108	...	vr15	81043.92
109	...	vr15	76210.15
110	...	vr2	60653.77
111	...	vr15	79227.53
112	...	vr15	79766.38
113	...	vr2	60577.61
114	...	vr3	65545.02
115	...	vr25	76107.41
116	...	vr25	75468.25

```
117       ...                  vr3        65545.02
118       ...                  vr3        66566.11
119       ...                 vr25        75496.54

     total_Adaboost_transactions  total_DecisionTree  \
0                            550            64345.57
1                            166            77875.34
2                            158            75210.90
3                            408            69447.27
4                            436            75173.05
5                            160            75210.90
6                            408            71889.11
7                            264            77143.57
8                            524            68409.68
9                            550            64345.57
10                           264            77143.57
11                           550            64345.57
12                           264            77143.57
13                           214            76273.80
14                           524            68409.68
15                           214            76273.80
16                           406            68359.70
17                           524            68409.68
18                           524            68409.68
19                           214            76273.80
20                           214            76273.80
21                           168            80889.81
22                           406            68359.70
23                           168            80889.81
24                           406            68359.70
25                           406            68359.70
26                           168            80889.81
27                           168            80889.81
28                           128            79745.34
29                           326            77700.76
..                           ...                 ...
90                           204            81857.08
91                           168            75351.72
92                           440            69357.59
93                           440            64750.35
94                           168            73026.53
95                           424            69357.59
96                           440            64750.35
97                           550            64345.57
98                           300            75164.14
99                           168            73026.53
100                          168            73026.53
101                           78            98477.43
```

102	304	77009.80
103	78	68085.64
104	316	73990.25
105	106	79582.96
106	322	72520.42
107	582	75524.06
108	264	77143.57
109	258	80076.66
110	582	72567.45
111	266	76941.56
112	258	71774.25
113	580	73779.90
114	536	73238.46
115	212	76356.85
116	214	77590.62
117	536	75766.59
118	512	80268.48
119	218	77635.51

	total_DecisionTree_transactions	total_GaussianNB \
0	624	62234.79
1	230	76606.62
2	248	76606.62
3	556	69942.73
4	542	69375.30
5	248	76606.62
6	548	69942.73
7	354	71651.71
8	608	67110.88
9	624	62234.79
10	354	71651.71
11	624	62234.79
12	354	71651.71
13	306	73744.83
14	608	67110.88
15	306	73744.83
16	556	69893.21
17	608	67110.88
18	608	67110.88
19	306	73744.83
20	306	73744.83
21	256	76386.58
22	556	69893.21
23	256	76386.58
24	556	69893.21
25	556	69893.21
26	256	76386.58
27	256	76386.58

28	598	71583.00
29	420	71372.60
..	...	...
90	278	74506.69
91	236	73259.61
92	566	69301.98
93	572	69301.98
94	238	73645.78
95	566	69228.59
96	572	69301.98
97	624	62234.79
98	428	71372.60
99	238	73645.78
100	238	76323.88
101	632	71762.17
102	426	71024.09
103	624	71762.17
104	424	72286.02
105	604	71422.87
106	454	71502.80
107	640	62438.38
108	354	71651.71
109	372	71761.09
110	622	62438.38
111	342	72030.06
112	372	72141.38
113	632	61737.31
114	610	66564.88
115	310	73848.41
116	320	73744.83
117	582	66564.88
118	596	67219.68
119	286	73744.83

	total_GaussianNB_transactions	total_NN	total_NN_transactions	\
0	138	67412.39	426	
1	60	76987.90	162	
2	62	75660.41	162	
3	124	70437.85	436	
4	124	70913.04	428	
5	62	75532.20	168	
6	124	70437.85	436	
7	88	74075.27	276	
8	146	66547.47	482	
9	138	67412.39	426	
10	88	74075.27	276	
11	138	67412.39	426	
12	88	74075.27	276	

13	68	77505.77	208
14	146	66547.47	482
15	68	77505.77	208
16	124	70046.18	438
17	146	66547.47	482
18	146	66547.47	482
19	68	77505.77	208
20	68	77505.77	208
21	60	76505.30	160
22	124	70046.18	438
23	60	76505.30	160
24	124	70046.18	438
25	124	70046.18	438
26	60	76505.30	160
27	60	76505.30	160
28	90	76350.15	52
29	94	73366.95	324
..	...	...	...
90	68	76887.32	206
91	62	76505.30	162
92	122	71519.51	446
93	122	71519.51	446
94	64	76498.13	162
95	122	69339.79	438
96	122	71519.51	446
97	138	67412.39	426
98	96	74035.62	318
99	64	76498.13	162
100	62	75732.33	166
101	90	91098.91	38
102	96	73231.91	334
103	90	91098.91	38
104	96	72871.88	330
105	86	90704.68	44
106	96	73232.51	318
107	138	67131.81	450
108	88	74075.27	276
109	88	74208.37	278
110	138	67131.81	450
111	88	78448.76	258
112	86	74127.82	284
113	142	69437.54	436
114	136	67803.96	488
115	70	78530.02	204
116	68	77681.49	210
117	136	67803.96	488
118	144	68393.86	488
119	68	78494.64	208

```
     total_benchmark
0           74037.88
1           74037.88
2           74037.88
3           74037.88
4           74037.88
5           74037.88
6           74037.88
7           74037.88
8           74037.88
9           74037.88
10          74037.88
11          74037.88
12          74037.88
13          74037.88
14          74037.88
15          74037.88
16          74037.88
17          74037.88
18          74037.88
19          74037.88
20          74037.88
21          74037.88
22          74037.88
23          74037.88
24          74037.88
25          74037.88
26          74037.88
27          74037.88
28          74037.88
29          74037.88
..               ...
90          74037.88
91          74037.88
92          74037.88
93          74037.88
94          74037.88
95          74037.88
96          74037.88
97          74037.88
98          74037.88
99          74037.88
100         74037.88
101         74037.88
102         74037.88
103         74037.88
104         74037.88
```

```
105         74037.88
106         74037.88
107         74037.88
108         74037.88
109         74037.88
110         74037.88
111         74037.88
112         74037.88
113         74037.88
114         74037.88
115         74037.88
116         74037.88
117         74037.88
118         74037.88
119         74037.88

[120 rows x 92 columns]
```

0.0.23 Add a column FinalValue per model. Which takes taxes and commisions into account

```
In [23]: ## Go through each row
         for index, row in result_df.iterrows():
             ## Initialize params
             benchmark = {'value':0,'loss':0,'gain':0,'transactions':len(TESTING_TICKERS)*2.0}
             decisiontree = {'value':0,'loss':0,'gain':0,'transactions':0}
             gaussiannb = {'value':0,'loss':0,'gain':0,'transactions':0}
             adaboost = {'value':0,'loss':0,'gain':0,'transactions':0}
             svc = {'value':0,'loss':0,'gain':0,'transactions':0}
             nn = {'value':0,'loss':0,'gain':0,'transactions':0}

             #models_dict = {'benchmark':benchmark,'DecisionTree':decisiontree,\
             #                'GaussianNB':gaussiannb,'Adaboost':adaboost, 'SVC':svc, 'NN':nn}
             ## No SVC model
             models_dict = {'benchmark':benchmark,'DecisionTree':decisiontree,\
                            'GaussianNB':gaussiannb,'Adaboost':adaboost, 'NN':nn}

             ## Gather each stock information
             for tick in TESTING_TICKERS:
                 ## update each models
                 for key, model in models_dict.items():
                     stock_value = row[tick+"_"+key]
                     if stock_value > MONEY:                         ## capital gain
                         model['gain'] += stock_value-MONEY
                     else:                                           ## loss
                         model['loss'] += MONEY-stock_value

                     if key != 'benchmark':
```

```
                    model['transactions'] += row[tick+"_"+key+"_transactions"]


        ## Get Final Values
        for key, model in models_dict.items():
            ## more gains than loss
            if model['gain'] > model['loss']:
                if key == 'benchmark':
                    model['value'] = float(format(row['total_'+key] \
                                      - COMM_RATE*model['transactions'] \
                                      - GAIN_LONG*(model['gain']-model['loss']),'.2f')
                else:
                    model['value'] = float(format(row['total_'+key] \
                                      - COMM_RATE*model['transactions'] \
                                      - GAIN_SHORT*(model['gain']-model['loss']),'.2f
            ## more loss than gain
            else:
                ## All model gains GAIN_LONG (assuming its on 25% tax bracket)
                model['value'] = float(format(row['total_'+key] - COMM_RATE*model['transac
                                + GAIN_LONG*(model['loss']-model['gain']),'.2f')) ## add


            result_df.set_value(index,key+"_FinalValue",model['value'])
```

In [24]:
```
print(result_df)
result_df.to_csv('Results.csv')  ## can use parameters: mode='a', header=False, if mem
```

```
    Adaboost Accuracy  Adaboost Fscore  BA_Adaboost  \
0            0.566123         0.540336     10819.24
1            0.885266         0.847715     16960.51
2            0.886473         0.851341     16657.76
3            0.677536         0.641591     13386.15
4            0.681159         0.637764     14010.03
5            0.884964         0.849340     16466.70
6            0.677536         0.641591     13386.15
7            0.816727         0.773385     15652.32
8            0.623792         0.600917     13027.33
9            0.566123         0.540336     10819.24
10           0.816727         0.773385     15652.32
11           0.566123         0.540336     10819.24
12           0.816727         0.773385     15652.32
13           0.841184         0.792480     16455.14
14           0.623792         0.600917     13027.33
15           0.841184         0.792480     16455.14
16           0.675725         0.646505     13928.51
17           0.623792         0.600917     13027.33
```

18	0.623792	0.600917	13027.33
19	0.841184	0.792480	16455.14
20	0.841184	0.792480	16455.14
21	0.886775	0.849813	17090.62
22	0.675725	0.646505	13928.51
23	0.886775	0.849813	17090.62
24	0.675725	0.646505	13928.51
25	0.675725	0.646505	13928.51
26	0.886775	0.849813	17090.62
27	0.886775	0.849813	17090.62
28	0.522645	0.351298	10000.00
29	0.757246	0.706535	14708.86
..	...	...	...
90	0.850242	0.811005	16447.50
91	0.888889	0.847373	17090.62
92	0.679952	0.644279	13550.79
93	0.679952	0.644279	13550.79
94	0.889795	0.848054	16721.16
95	0.681461	0.643762	13429.85
96	0.679952	0.644279	13550.79
97	0.566123	0.540336	10819.24
98	0.772343	0.737797	14768.38
99	0.889795	0.848054	16721.16
100	0.890399	0.851732	16656.12
101	0.530797	0.347789	10000.00
102	0.773853	0.733195	14582.51
103	0.530797	0.347789	10000.00
104	0.773249	0.720688	14834.16
105	0.525060	0.349880	10000.00
106	0.773249	0.731688	14458.21
107	0.565217	0.537384	10966.00
108	0.816727	0.773385	15652.32
109	0.803442	0.762763	15726.71
110	0.565217	0.537384	10966.00
111	0.803442	0.753740	15990.51
112	0.804650	0.762921	15728.18
113	0.562802	0.531948	10970.40
114	0.629227	0.607595	13396.57
115	0.854167	0.804483	16544.40
116	0.854167	0.806186	16438.43
117	0.629227	0.607595	13396.57
118	0.628925	0.605614	12993.82
119	0.854167	0.805247	16438.43

	BA_Adaboost_transactions	BA_DecisionTree	BA_DecisionTree_transactions	\
0	28	11362.73	64	
1	18	16228.10	16	
2	16	16201.26	26	

3	52	12708.60	58
4	58	13350.19	70
5	18	16201.26	26
6	52	14254.24	60
7	34	16244.51	42
8	46	12283.55	76
9	28	11362.73	64
10	34	16244.51	42
11	28	11362.73	64
12	34	16244.51	42
13	20	16714.52	32
14	46	12283.55	76
15	20	16714.52	32
16	52	11464.95	64
17	46	12283.55	76
18	46	12283.55	76
19	20	16714.52	32
20	20	16714.52	32
21	16	16863.94	22
22	52	11464.95	64
23	16	16863.94	22
24	52	11464.95	64
25	52	11464.95	64
26	16	16863.94	22
27	16	16863.94	22
28	0	11801.10	60
29	40	15088.91	46
..	...	...	...
90	20	17925.32	24
91	16	16415.20	26
92	60	14220.86	62
93	60	12710.69	72
94	20	16802.22	18
95	56	14220.86	62
96	60	12710.69	72
97	28	11362.73	64
98	32	12310.48	52
99	20	16802.22	18
100	20	16802.22	18
101	0	11472.35	52
102	34	14762.57	48
103	0	11597.25	72
104	40	14797.87	56
105	0	11062.07	68
106	38	15068.73	56
107	30	13063.17	84
108	34	16244.51	42
109	28	15898.11	38

110	30	11898.72	68
111	32	15709.38	42
112	28	15433.70	30
113	30	11951.63	72
114	58	11186.95	82
115	18	16230.78	34
116	22	16189.45	34
117	58	13513.65	64
118	58	12314.89	70
119	22	16959.71	30

	BA_GaussianNB	BA_GaussianNB_transactions	BA_NN	BA_NN_transactions	\
0	10334.98	2	10326.56	10	
1	16577.61	2	17037.26	14	
2	16577.61	2	17123.13	14	
3	16577.61	2	12316.68	62	
4	16577.61	2	14193.64	58	
5	16577.61	2	17123.13	14	
6	16577.61	2	12316.68	62	
7	16577.61	2	15691.99	34	
8	16577.61	2	11038.13	56	
9	10334.98	2	10326.56	10	
10	16577.61	2	15691.99	34	
11	10334.98	2	10326.56	10	
12	16577.61	2	15691.99	34	
13	16577.61	2	16444.62	20	
14	16577.61	2	11038.13	56	
15	16577.61	2	16444.62	20	
16	16577.61	2	12829.09	62	
17	16577.61	2	11038.13	56	
18	16577.61	2	11038.13	56	
19	16577.61	2	16444.62	20	
20	16577.61	2	16444.62	20	
21	16577.61	2	17020.63	14	
22	16577.61	2	12829.09	62	
23	16577.61	2	17020.63	14	
24	16577.61	2	12829.09	62	
25	16577.61	2	12829.09	62	
26	16577.61	2	17020.63	14	
27	16577.61	2	17020.63	14	
28	10334.98	2	10000.00	0	
29	16577.61	2	14355.48	42	
..	...	...	...	...	
90	16577.61	2	16692.48	20	
91	16577.61	2	17020.63	14	
92	16577.61	2	14101.76	58	
93	16577.61	2	14101.76	58	
94	16577.61	2	17037.26	14	

95	16577.61	2	12310.20	60
96	16577.61	2	14101.76	58
97	10334.98	2	10326.56	10
98	16577.61	2	14588.03	40
99	16577.61	2	17037.26	14
100	16577.61	2	17123.13	14
101	10334.98	2	10000.00	0
102	16577.61	2	14648.65	42
103	10334.98	2	10000.00	0
104	16577.61	2	14648.65	42
105	10334.98	2	10000.00	0
106	16577.61	2	14833.46	40
107	10334.98	2	10517.79	14
108	16577.61	2	15691.99	34
109	16577.61	2	15617.80	36
110	10334.98	2	10517.79	14
111	16577.61	2	16077.98	28
112	16577.61	2	15707.85	38
113	10334.98	2	10517.79	14
114	16577.61	2	11172.91	60
115	16577.61	2	16884.75	18
116	16577.61	2	16793.74	20
117	16577.61	2	11172.91	60
118	16577.61	2	11244.13	58
119	16577.61	2	16793.74	20

	...	total_GaussianNB	total_GaussianNB_transactions	\
0	...	62234.79	138	
1	...	76606.62	60	
2	...	76606.62	62	
3	...	69942.73	124	
4	...	69375.30	124	
5	...	76606.62	62	
6	...	69942.73	124	
7	...	71651.71	88	
8	...	67110.88	146	
9	...	62234.79	138	
10	...	71651.71	88	
11	...	62234.79	138	
12	...	71651.71	88	
13	...	73744.83	68	
14	...	67110.88	146	
15	...	73744.83	68	
16	...	69893.21	124	
17	...	67110.88	146	
18	...	67110.88	146	
19	...	73744.83	68	
20	...	73744.83	68	

21	...	76386.58	60
22	...	69893.21	124
23	...	76386.58	60
24	...	69893.21	124
25	...	69893.21	124
26	...	76386.58	60
27	...	76386.58	60
28	...	71583.00	90
29	...	71372.60	94
..	...	...	...
90	...	74506.69	68
91	...	73259.61	62
92	...	69301.98	122
93	...	69301.98	122
94	...	73645.78	64
95	...	69228.59	122
96	...	69301.98	122
97	...	62234.79	138
98	...	71372.60	96
99	...	73645.78	64
100	...	76323.88	62
101	...	71762.17	90
102	...	71024.09	96
103	...	71762.17	90
104	...	72286.02	96
105	...	71422.87	86
106	...	71502.80	96
107	...	62438.38	138
108	...	71651.71	88
109	...	71761.09	88
110	...	62438.38	138
111	...	72030.06	88
112	...	72141.38	86
113	...	61737.31	142
114	...	66564.88	136
115	...	73848.41	70
116	...	73744.83	68
117	...	66564.88	136
118	...	67219.68	144
119	...	73744.83	68

	total_NN	total_NN_transactions	total_benchmark	\
0	67412.39	426	74037.88	
1	76987.90	162	74037.88	
2	75660.41	162	74037.88	
3	70437.85	436	74037.88	
4	70913.04	428	74037.88	
5	75532.20	168	74037.88	

6	70437.85	436	74037.88
7	74075.27	276	74037.88
8	66547.47	482	74037.88
9	67412.39	426	74037.88
10	74075.27	276	74037.88
11	67412.39	426	74037.88
12	74075.27	276	74037.88
13	77505.77	208	74037.88
14	66547.47	482	74037.88
15	77505.77	208	74037.88
16	70046.18	438	74037.88
17	66547.47	482	74037.88
18	66547.47	482	74037.88
19	77505.77	208	74037.88
20	77505.77	208	74037.88
21	76505.30	160	74037.88
22	70046.18	438	74037.88
23	76505.30	160	74037.88
24	70046.18	438	74037.88
25	70046.18	438	74037.88
26	76505.30	160	74037.88
27	76505.30	160	74037.88
28	76350.15	52	74037.88
29	73366.95	324	74037.88
..	...	...	...
90	76887.32	206	74037.88
91	76505.30	162	74037.88
92	71519.51	446	74037.88
93	71519.51	446	74037.88
94	76498.13	162	74037.88
95	69339.79	438	74037.88
96	71519.51	446	74037.88
97	67412.39	426	74037.88
98	74035.62	318	74037.88
99	76498.13	162	74037.88
100	75732.33	166	74037.88
101	91098.91	38	74037.88
102	73231.91	334	74037.88
103	91098.91	38	74037.88
104	72871.88	330	74037.88
105	90704.68	44	74037.88
106	73232.51	318	74037.88
107	67131.81	450	74037.88
108	74075.27	276	74037.88
109	74208.37	278	74037.88
110	67131.81	450	74037.88
111	78448.76	258	74037.88
112	74127.82	284	74037.88

113	69437.54	436	74037.88
114	67803.96	488	74037.88
115	78530.02	204	74037.88
116	77681.49	210	74037.88
117	67803.96	488	74037.88
118	68393.86	488	74037.88
119	78494.64	208	74037.88

	DecisionTree_FinalValue	Adaboost_FinalValue	NN_FinalValue	\
0	63604.93	60078.57	67191.83	
1	77055.54	76298.59	76637.82	
2	74701.66	76883.90	75509.45	
3	68277.98	70005.58	69713.97	
4	73214.19	71068.91	70157.48	
5	74701.66	76454.86	75370.77	
6	70393.14	70005.58	69713.97	
7	75819.73	79476.14	73597.78	
8	67138.63	65627.41	66179.45	
9	63604.93	60078.57	67191.83	
10	75819.73	79476.14	73597.78	
11	63604.93	60078.57	67191.83	
12	75819.73	79476.14	73597.78	
13	75318.03	75381.30	76850.30	
14	67138.63	65627.41	66179.45	
15	75318.03	75381.30	76850.30	
16	67353.54	70904.76	69371.15	
17	67138.63	65627.41	66179.45	
18	67138.63	65627.41	66179.45	
19	75318.03	75381.30	76850.30	
20	75318.03	75381.30	76850.30	
21	79400.16	77347.52	76237.51	
22	67353.54	70904.76	69371.15	
23	79400.16	77347.52	76237.51	
24	67353.54	70904.76	69371.15	
25	67353.54	70904.76	69371.15	
26	79400.16	77347.52	76237.51	
27	79400.16	77347.52	76237.51	
28	76823.44	81888.85	76640.23	
29	75966.65	71683.96	72758.11	
..	...	...	...	
90	80016.71	75401.19	76334.52	
91	74880.76	76867.52	76227.61	
92	68152.25	68878.10	70583.88	
93	64206.40	68878.10	70583.88	
94	72894.45	76403.54	76221.51	
95	68152.25	71076.88	68770.72	
96	64206.40	68878.10	70583.88	
97	63604.93	60078.57	67191.83	

98	73770.92	72026.13	73356.18
99	72894.45	76403.54	76221.51
100	72894.45	76762.35	75550.78
101	90729.67	84835.81	88136.08
102	75349.63	71152.95	72593.82
103	66783.99	84835.81	88136.08
104	72792.91	72623.96	72307.60
105	76655.72	79869.31	87810.71
106	71395.06	71551.38	72673.53
107	73027.45	60674.80	66834.54
108	75819.73	79476.14	73597.78
109	78216.10	75501.53	73701.01
110	70603.43	60674.80	66834.54
111	75707.43	78026.70	77404.35
112	71166.71	78524.32	73602.85
113	71584.51	60619.97	68863.71
114	71233.19	65060.07	67217.77
115	75368.82	75641.90	77740.72
116	76368.03	75088.71	76989.77
117	73520.70	65060.07	67217.77
118	77251.16	66046.79	67719.18
119	76574.48	75092.96	77690.84

	benchmark_FinalValue	GaussianNB_FinalValue
0	74853.0	64216.47
1	74853.0	76818.63
2	74853.0	76808.73
3	74853.0	70837.52
4	74853.0	70355.21
5	74853.0	76808.73
6	74853.0	70837.52
7	74853.0	72468.35
8	74853.0	68321.55
9	74853.0	64216.47
10	74853.0	72468.35
11	74853.0	64216.47
12	74853.0	72468.35
13	74853.0	74346.51
14	74853.0	68321.55
15	74853.0	74346.51
16	74853.0	70795.43
17	74853.0	68321.55
18	74853.0	68321.55
19	74853.0	74346.51
20	74853.0	74346.51
21	74853.0	76631.59
22	74853.0	70795.43
23	74853.0	76631.59

```
24               74853.0             70795.43
25               74853.0             70795.43
26               74853.0             76631.59
27               74853.0             76631.59
28               74853.0             72400.05
29               74853.0             72201.41
..                   ...                  ...
90               74853.0             74994.09
91               74853.0             73963.77
92               74853.0             70302.78
93               74853.0             70302.78
94               74853.0             74282.11
95               74853.0             70240.40
96               74853.0             70302.78
97               74853.0             64216.47
98               74853.0             72191.51
99               74853.0             74282.11
100              74853.0             76568.40
101              74853.0             72552.34
102              74853.0             71895.28
103              74853.0             72552.34
104              74853.0             72967.92
105              74853.0             72283.74
106              74853.0             72302.18
107              74853.0             64389.52
108              74853.0             72468.35
109              74853.0             72561.33
110              74853.0             64389.52
111              74853.0             72789.95
112              74853.0             72894.47
113              74853.0             63773.81
114              74853.0             67906.95
115              74853.0             74424.65
116              74853.0             74346.51
117              74853.0             67906.95
118              74853.0             68423.93
119              74853.0             74346.51

[120 rows x 97 columns]
```

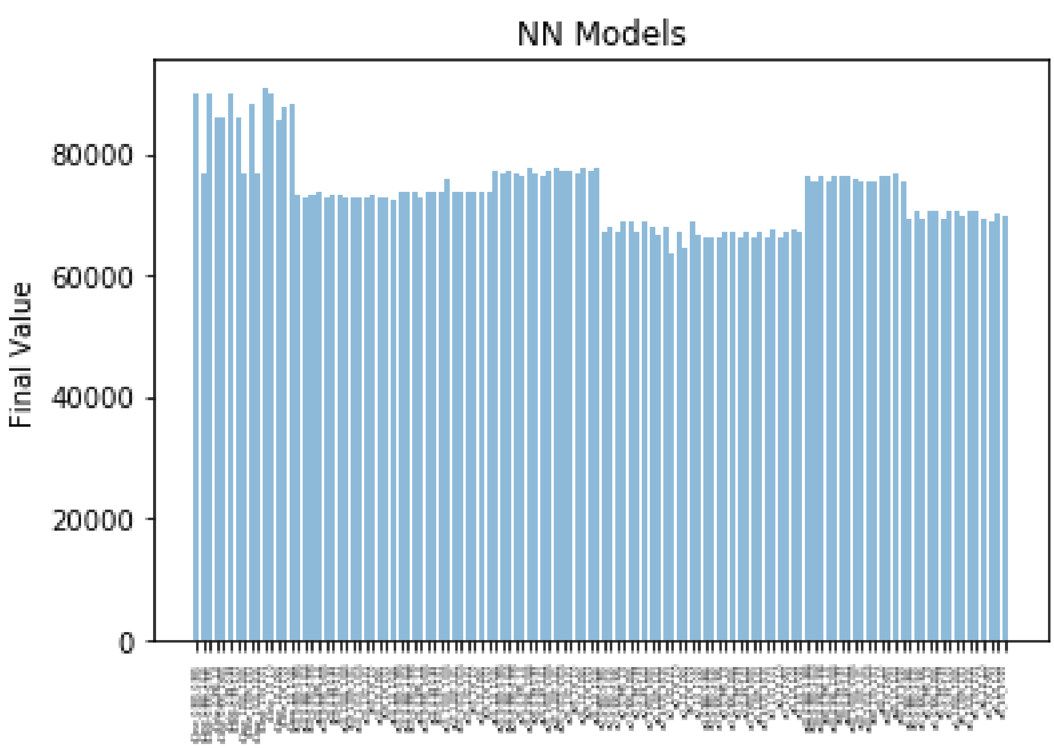
0.0.24 Graph entire results. All 480 models

```
In [25]: def graph_all_models(df,model_name,title,filename):
             y = df[model_name].values
             fnc = lambda i,j,k: str(i)+'_'+str(j)+'_'+str(k)
             x_ticks = list(map(fnc,df['target_ratio'],df['sell_below'],df['buy_above']))
             x = np.arange(len(x_ticks))
```

```
    graph_data = zip(x_ticks,y)
    graph_data = sorted(graph_data)    ## sort labels

    y = [ y for x, y in graph_data ]
    x_ticks = [ x for x, y in graph_data ]

    fig, ax = plt.subplots()
    opacity = 0.5
    plt.bar(x,y,align='center',alpha=opacity)
    plt.xticks(x,x_ticks,rotation=90,)
    plt.ylabel('Final Value')
    plt.title(title)
    plt.tick_params(axis='x',which='major',labelsize=3)
    plt.show()
    fig.savefig("figures/"+filename, format='svg', dpi=1200)

df_res = pd.DataFrame.from_csv("Results.csv")
```

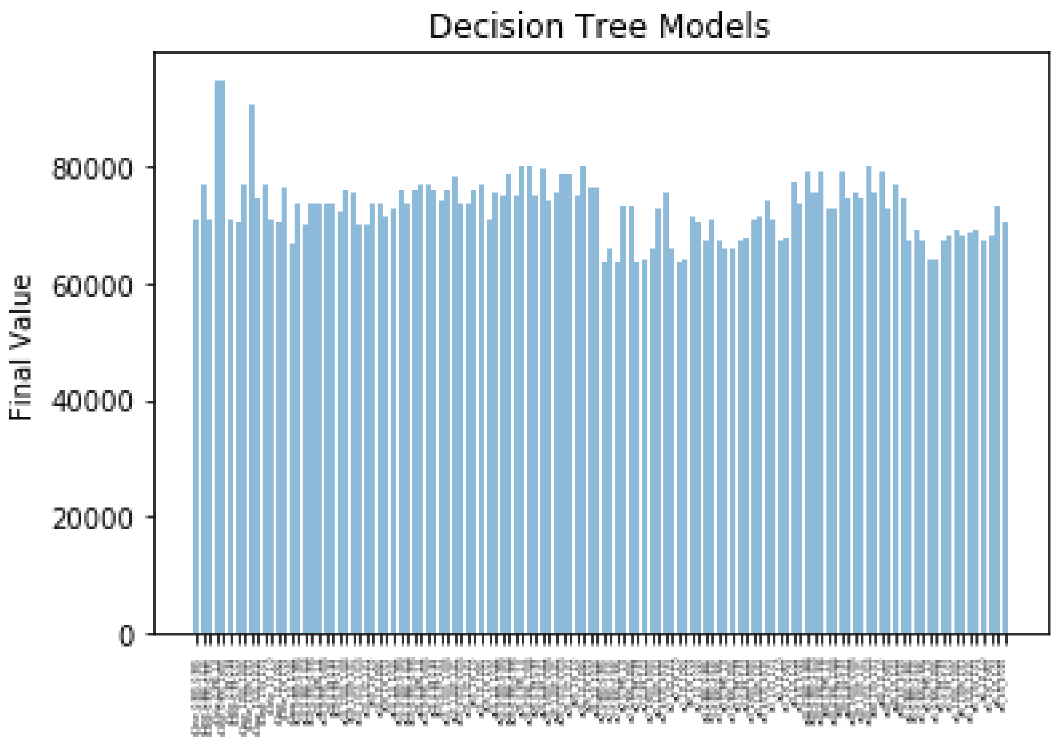
0.0.25 Graph of NN Models

In [26]:
```
graph_all_models(df = df_res, \
                 model_name = 'NN_FinalValue', \
                 title = 'NN Models', \
                 filename = 'NN_models.svg')
```



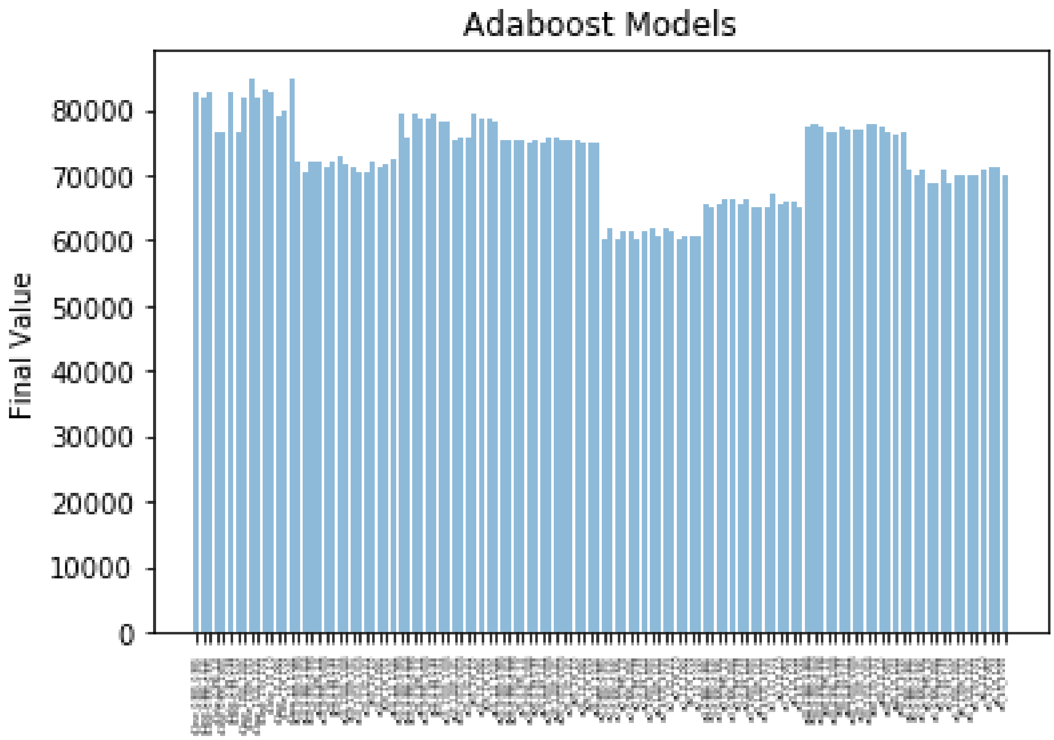
0.0.26 Graph of Decision Tree Models

```
In [27]: graph_all_models(df = df_res, \
                          model_name = 'DecisionTree_FinalValue', \
                          title = 'Decision Tree Models', \
                          filename = 'DT_models.svg')
```



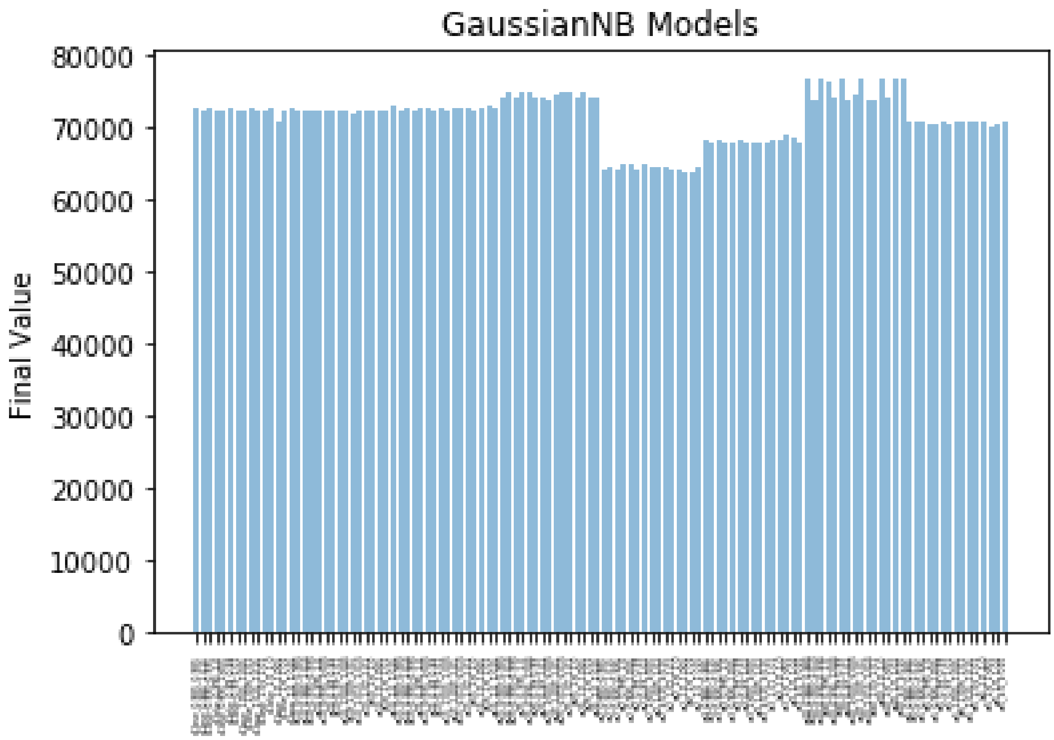
0.0.27 Graph of Adaboost Models

```
In [28]: graph_all_models(df = df_res, \
                          model_name = 'Adaboost_FinalValue', \
                          title = 'Adaboost Models', \
                          filename = 'Adaboost_models.svg')
```



0.0.28 Graph of GaussianNB Models

```
In [29]: graph_all_models(df = df_res, \
                          model_name = 'GaussianNB_FinalValue', \
                          title = 'GaussianNB Models', \
                          filename = 'GaussianNB_models.svg')
```



0.0.29 Get the top performing model of each model

```
In [30]: max_benchmark_FinalValue = result_df['benchmark_FinalValue'].iloc[0]
         max_NN_FinalValue = 0
         max_GaussianNB_FinalValue = 0
         max_Adaboost_FinalValue = 0
         max_DecisionTree_FinalValue = 0
         max_SVC_FinalValue = 0

         row_benchmark = result_df.iloc[0]
         row_NN = None
         row_GaussianNB = None
         row_Adaboost = None
         row_DecisionTree = None
         row_SVC = None

         for index, row in result_df.iterrows():
             if row['NN_FinalValue'] > max_NN_FinalValue:
                 row_NN = copy.deepcopy(row)
                 max_NN_FinalValue = row['NN_FinalValue']

             if row['GaussianNB_FinalValue'] > max_GaussianNB_FinalValue:
                 row_GaussianNB = copy.deepcopy(row)
```

```
                max_GaussianNB_FinalValue = row['GaussianNB_FinalValue']

            if row['Adaboost_FinalValue'] > max_Adaboost_FinalValue:
                row_Adaboost = copy.deepcopy(row)
                max_Adaboost_FinalValue = row['Adaboost_FinalValue']

            if row['DecisionTree_FinalValue'] > max_DecisionTree_FinalValue:
                row_DecisionTree = copy.deepcopy(row)
                max_DecisionTree_FinalValue = row['DecisionTree_FinalValue']

            #if row['SVC_FinalValue'] > max_SVC_FinalValue:
            #    row_SVC = copy.deepcopy(row)
            #    max_SVC_FinalValue = row['SVC_FinalValue']

        print("benchmark FinalValue: {}".format(max_benchmark_FinalValue))
        print("Max NN FinalValue: {}".format(max_NN_FinalValue))
        print("Max GaussianNB FinalValue: {}".format(max_GaussianNB_FinalValue))
        print("Max Adaboost FinalValue: {}".format(max_Adaboost_FinalValue))
        print("Max DecisionTree FinalValue: {}".format(max_DecisionTree_FinalValue))
        #print("Max SVC FinalValue: {}".format(max_SVC_FinalValue))
```

```
benchmark FinalValue: 74853.0
Max NN FinalValue: 90873.81
Max GaussianNB FinalValue: 76818.63
Max Adaboost FinalValue: 84835.81
Max DecisionTree FinalValue: 94896.15
```

0.0.30 Get summary of the top models

```
In [31]: #model_list = [('benchmark',row_benchmark),('NN',row_NN),('GaussianNB',row_GaussianNB
         #               ('SVC',row_SVC),('Adaboost',row_Adaboost),('DecisionTree',row_Decisio
         ## No SVC
         model_list = [('benchmark',row_benchmark),('NN',row_NN),('GaussianNB',row_GaussianNB)
                       ('Adaboost',row_Adaboost),('DecisionTree',row_DecisionTree)]

         best_model = None
         best_model_val = 0

         for name, model in model_list:
             ## Get all data relevant to each model
             for index_name in model.index:
                 if name not in index_name and index_name not in ["sell_below","buy_above","ta
                 #if name not in index_name:
                     del model[index_name]

             print("\n{} Data: \n{}".format(name,model))
```

```python
            if model[name+"_FinalValue"] > best_model_val:
                best_model_val = model[name+"_FinalValue"]
                best_model = name + "_" + model["target_ratio"] + "_" + str(model["sell_below"])
                                  + "_" + str(model["buy_above"])
```

```
benchmark Data:
BA_benchmark           18139.2
CHK_benchmark           9749.5
CMG_benchmark          8140.79
FCEL_benchmark         2896.68
HON_benchmark          11879.7
MA_benchmark           13322.6
SD_benchmark           8545.85
TPLM_benchmark         1363.63
buy_above                 0.99
sell_below                0.99
target_ratio               vr2
total_benchmark        74037.9
benchmark_FinalValue     74853
Name: 0, dtype: object

NN Data:
BA_NN                       10000
BA_NN_transactions              0
CHK_NN                      10000
CHK_NN_transactions             0
CMG_NN                      10000
CMG_NN_transactions             0
FCEL_NN                   9465.17
FCEL_NN_transactions           10
HON_NN                      10000
HON_NN_transactions             0
MA_NN                       10000
MA_NN_transactions              0
NN Accuracy              0.524155
NN Fscore                0.315765
SD_NN                       10000
SD_NN_transactions              0
TPLM_NN                   25402.8
TPLM_NN_transactions           46
buy_above                    1.01
sell_below                   1.01
target_ratio               vClose
total_NN                    94868
total_NN_transactions          56
NN_FinalValue             90873.8
Name: 30, dtype: object
```

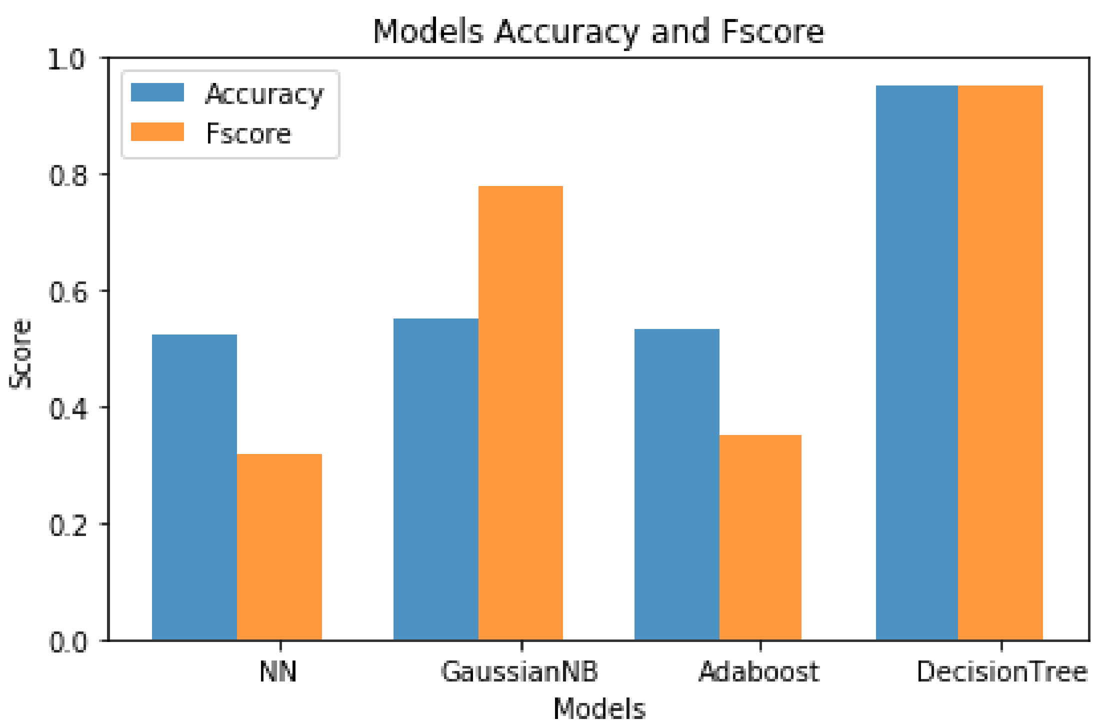
```
GaussianNB Data:
BA_GaussianNB                      16577.6
BA_GaussianNB_transactions               2
CHK_GaussianNB                     10001.8
CHK_GaussianNB_transactions             14
CMG_GaussianNB                      8169.4
CMG_GaussianNB_transactions              6
FCEL_GaussianNB                    9371.85
FCEL_GaussianNB_transactions             8
GaussianNB Accuracy               0.549517
GaussianNB Fscore                   0.7769
HON_GaussianNB                     10430.8
HON_GaussianNB_transactions              2
MA_GaussianNB                      10216.5
MA_GaussianNB_transactions               2
SD_GaussianNB                      8904.41
SD_GaussianNB_transactions               6
TPLM_GaussianNB                    2934.24
TPLM_GaussianNB_transactions            20
buy_above                             1.01
sell_below                               1
target_ratio                          vr40
total_GaussianNB                   76606.6
total_GaussianNB_transactions           60
GaussianNB_FinalValue              76818.6
Name: 1, dtype: object

Adaboost Data:
Adaboost Accuracy               0.530797
Adaboost Fscore                 0.347789
BA_Adaboost                        10000
BA_Adaboost_transactions               0
CHK_Adaboost                     9833.75
CHK_Adaboost_transactions             14
CMG_Adaboost                       10000
CMG_Adaboost_transactions              0
FCEL_Adaboost                    14118.2
FCEL_Adaboost_transactions            36
HON_Adaboost                       10000
HON_Adaboost_transactions              0
MA_Adaboost                        10000
MA_Adaboost_transactions               0
SD_Adaboost                      9588.21
SD_Adaboost_transactions               2
TPLM_Adaboost                    13422.4
TPLM_Adaboost_transactions            26
buy_above                           1.01
```

```
sell_below                        1.005
target_ratio                     vClose
total_Adaboost                  86962.6
total_Adaboost_transactions          78
Adaboost_FinalValue             84835.8
Name: 101, dtype: object

DecisionTree Data:
BA_DecisionTree                      10429.2
BA_DecisionTree_transactions              50
CHK_DecisionTree                     7711.18
CHK_DecisionTree_transactions             92
CMG_DecisionTree                     10909.2
CMG_DecisionTree_transactions             86
DecisionTree Accuracy               0.951087
DecisionTree Fscore                 0.951036
FCEL_DecisionTree                      12195
FCEL_DecisionTree_transactions           110
HON_DecisionTree                     10535.7
HON_DecisionTree_transactions             62
MA_DecisionTree                      11337.3
MA_DecisionTree_transactions              54
SD_DecisionTree                      10228.7
SD_DecisionTree_transactions              68
TPLM_DecisionTree                      30581
TPLM_DecisionTree_transactions            94
buy_above                              1.005
sell_below                             0.995
target_ratio                          vClose
total_DecisionTree                    103927
total_DecisionTree_transactions          616
DecisionTree_FinalValue              94896.1
Name: 66, dtype: object
```

0.0.31 Graph model's score

```
In [32]: accuracies = []
         fscores = []
         names = []

         for name, model in model_list:
             if name != "benchmark":
                 accuracies.append(model[name+" Accuracy"])
                 fscores.append(model[name+" Fscore"])
                 names.append(name)
```

```python
n_groups = len(model_list) - 1 ## subtract benchmark


## create plot
fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = 0.35
opacity = 0.8

# Bar features
rects1 = plt.bar(index, accuracies, bar_width,alpha=opacity,label="Accuracy")
rects2 = plt.bar(index+bar_width, fscores, bar_width,alpha=opacity,label="Fscore")

## Labels
plt.xlabel('Models')
plt.ylabel('Score')
plt.title('Models Accuracy and Fscore')
plt.xticks(index + bar_width, names)
plt.legend()

plt.tight_layout()
plt.show()
fig.savefig("figures/Scores.svg", format='svg', dpi=1200)
```



0.0.32 Graph each stocks performance of the best optimal model

```
In [33]: print(best_model)
```

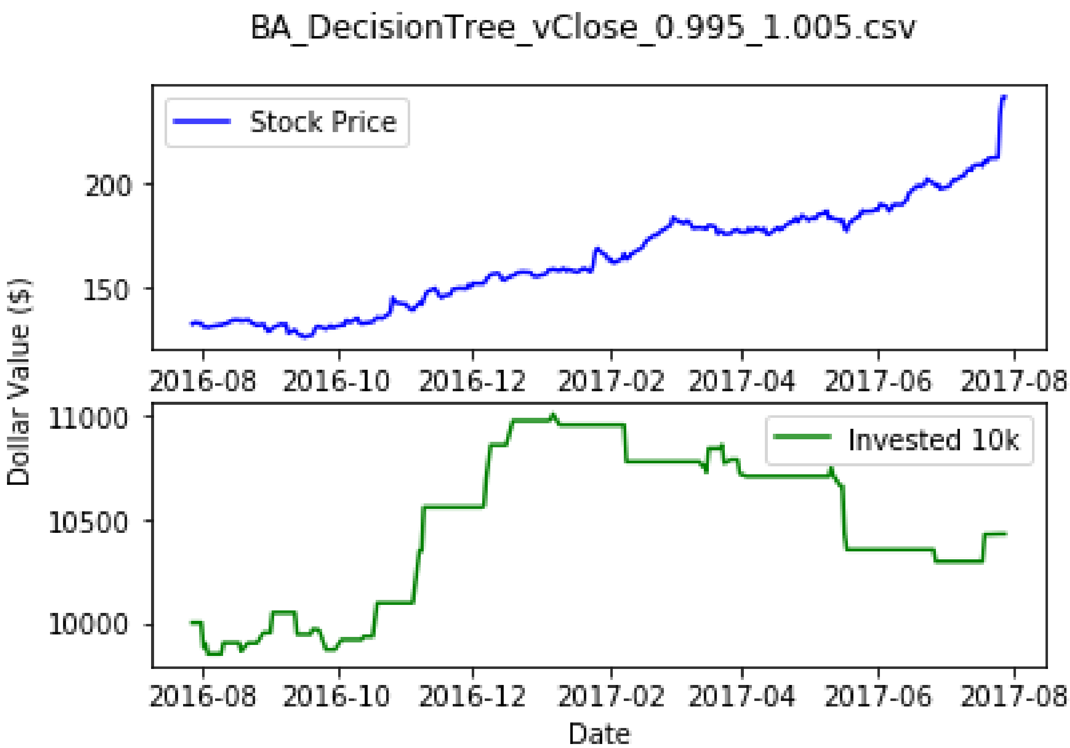
```
DecisionTree_vClose_0.995_1.005
```

```
In [34]: graph_data = []

         ## Get test data that used best model
         filelist = glob.glob("model_predictions/*")
         for f in filelist:
             if best_model+".csv" in f:
                 graph_data.append(f)

         print(graph_data)
```

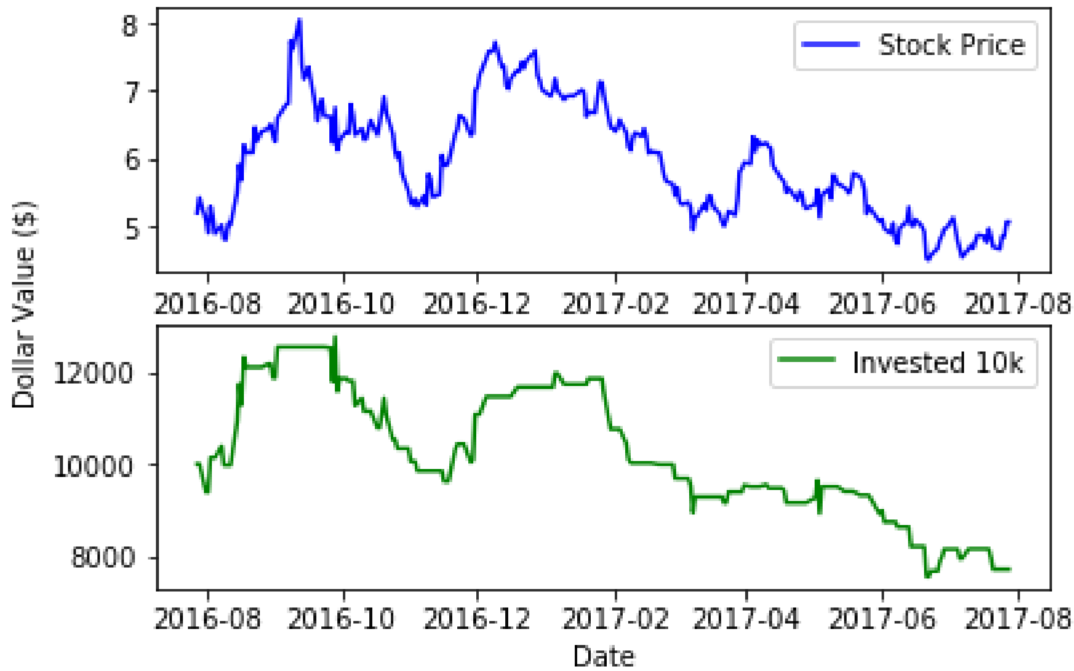
```
['model_predictions/BA_DecisionTree_vClose_0.995_1.005.csv', 'model_predictions/CHK_DecisionTre
```

```
In [35]: def plot_data(f,df):
             remove = len("model_predictions/")
             file = f[remove:]
             tick = file.split('_')[0]

             fig = plt.figure()
             ## Top plot
             df0 = pd.DataFrame.from_csv("testing_data/"+tick+"_processed.csv")
             price = df0['vClose']
             ax1 = fig.add_subplot(2,1,1)
             ax1.plot(price.index,price,label='Stock Price',color='b')
             ax1.legend()

             ## Bottom plot
             money = df['Money']
             ax2 = fig.add_subplot(2,1,2)
             ax2.plot(money.index,money,label='Invested 10k',color='g')
             ax2.set_xlabel('Date')
             ax2.legend()

             fig.text(0.00, 0.5, 'Dollar Value ($)', va='center', rotation='vertical')

             plt.suptitle(file)
             plt.show()
             #fig.savefig("figures/"+file+'.png')
             fig.savefig("figures/"+file+'.svg', format='svg', dpi=1200)
             plt.close(fig)
```

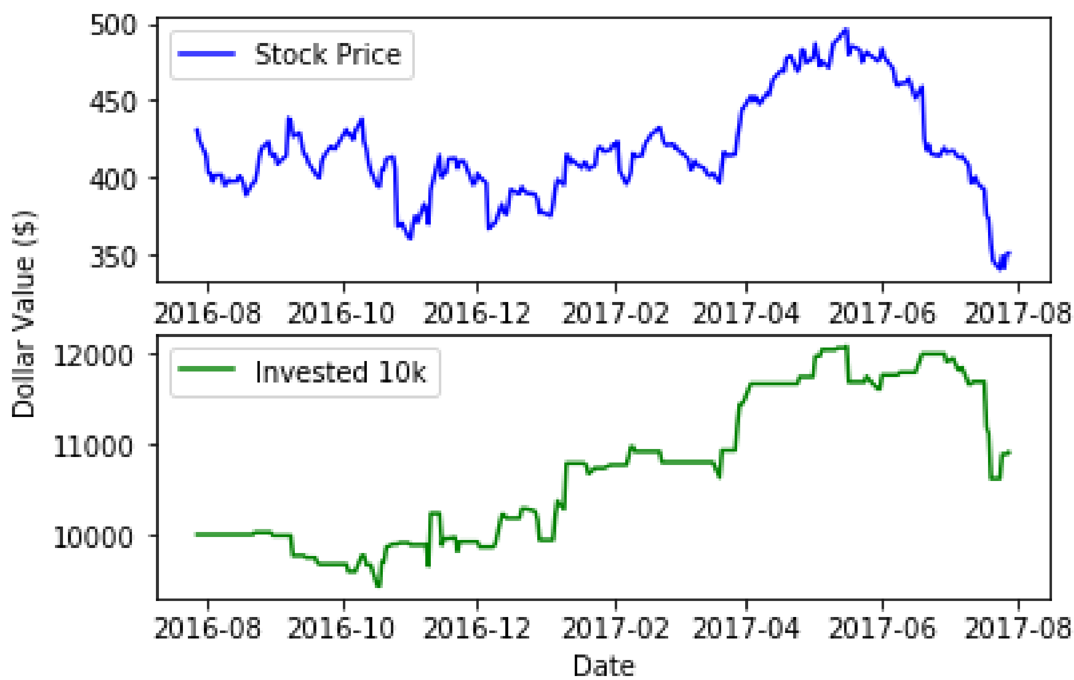
```
for f in graph_data:
    df = pd.DataFrame.from_csv(f)

    plot_data(f,df)
```

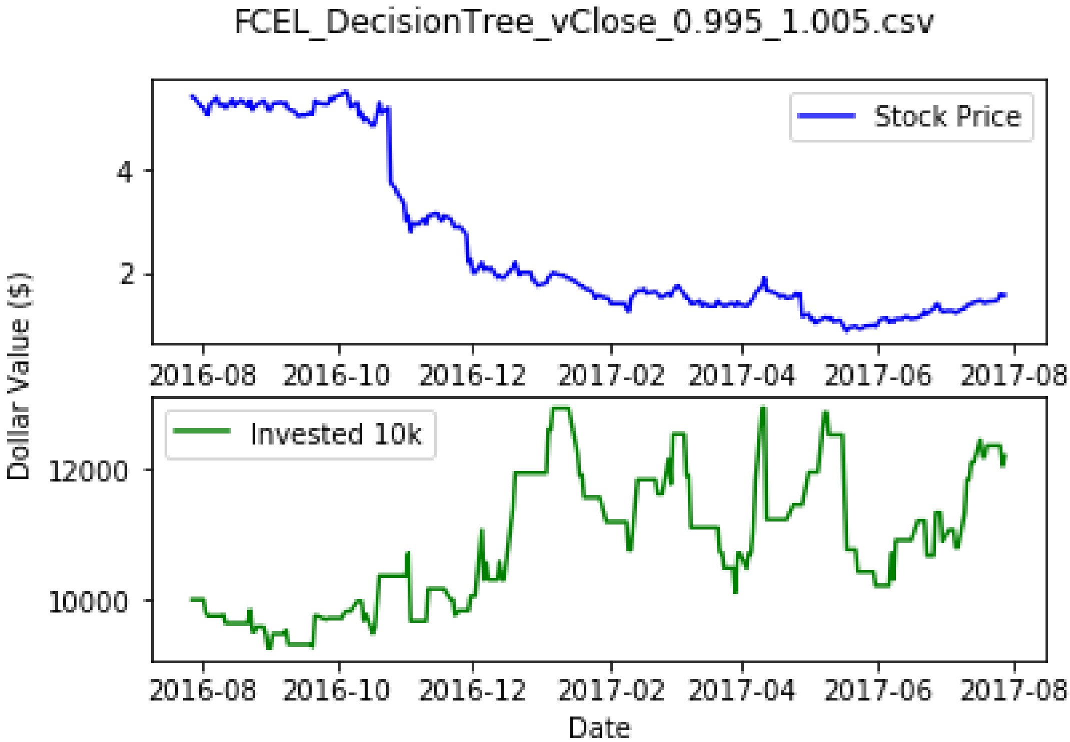


CHK_DecisionTree_vClose_0.995_1.005.csv

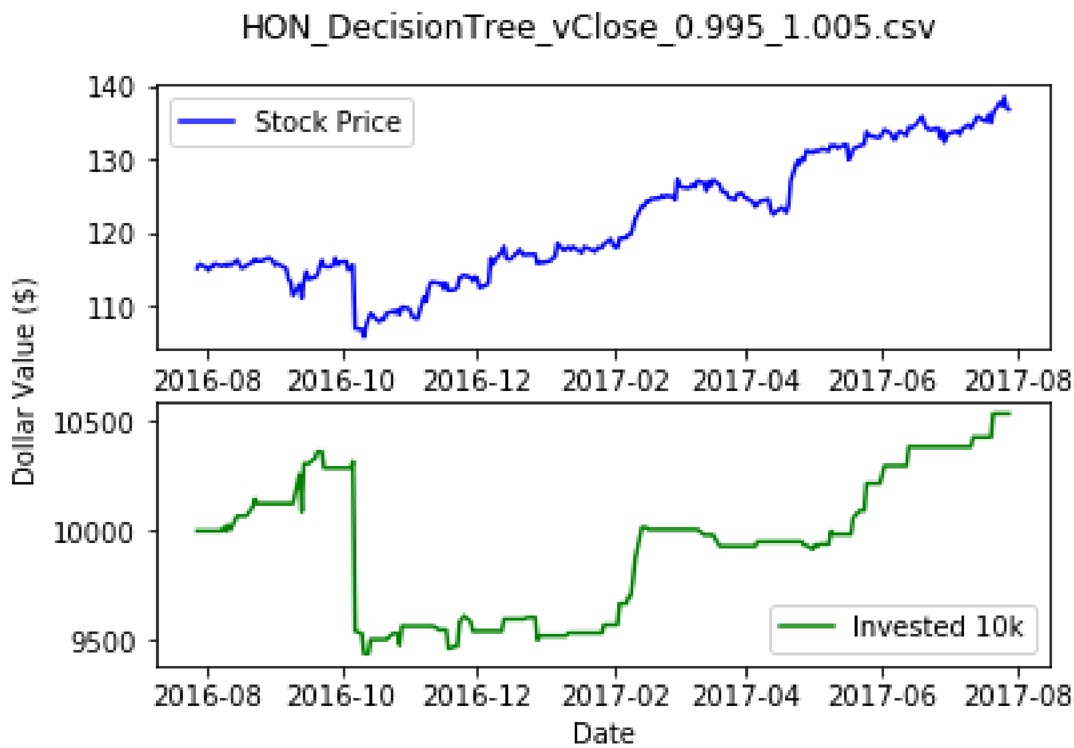


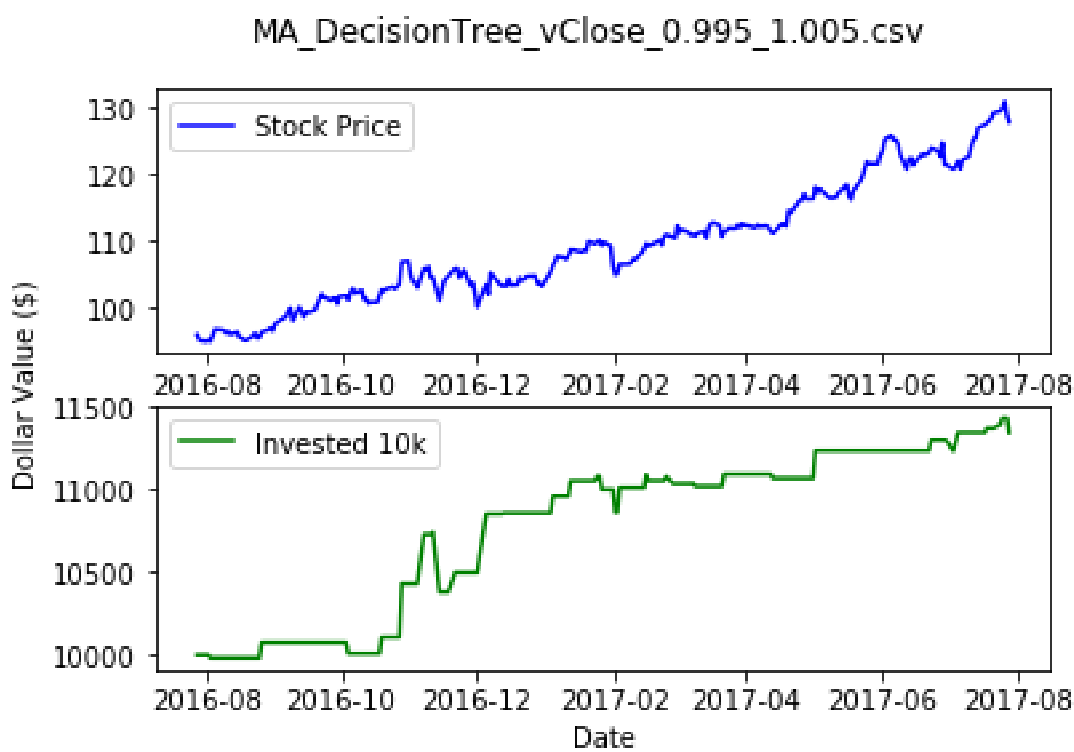
CMG_DecisionTree_vClose_0.995_1.005.csv



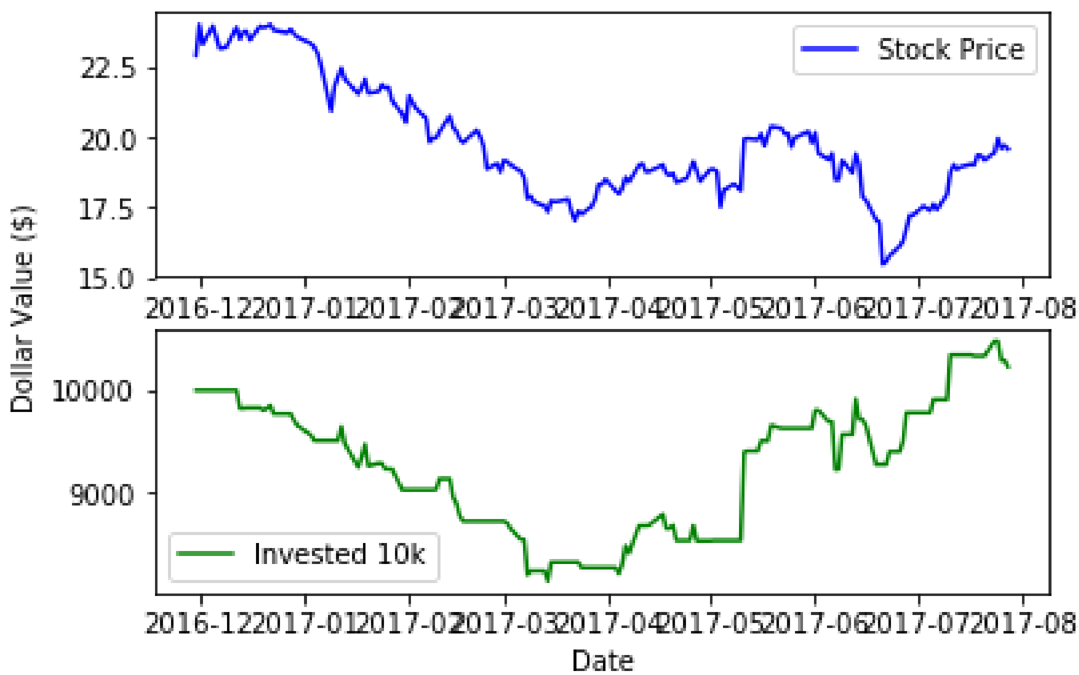


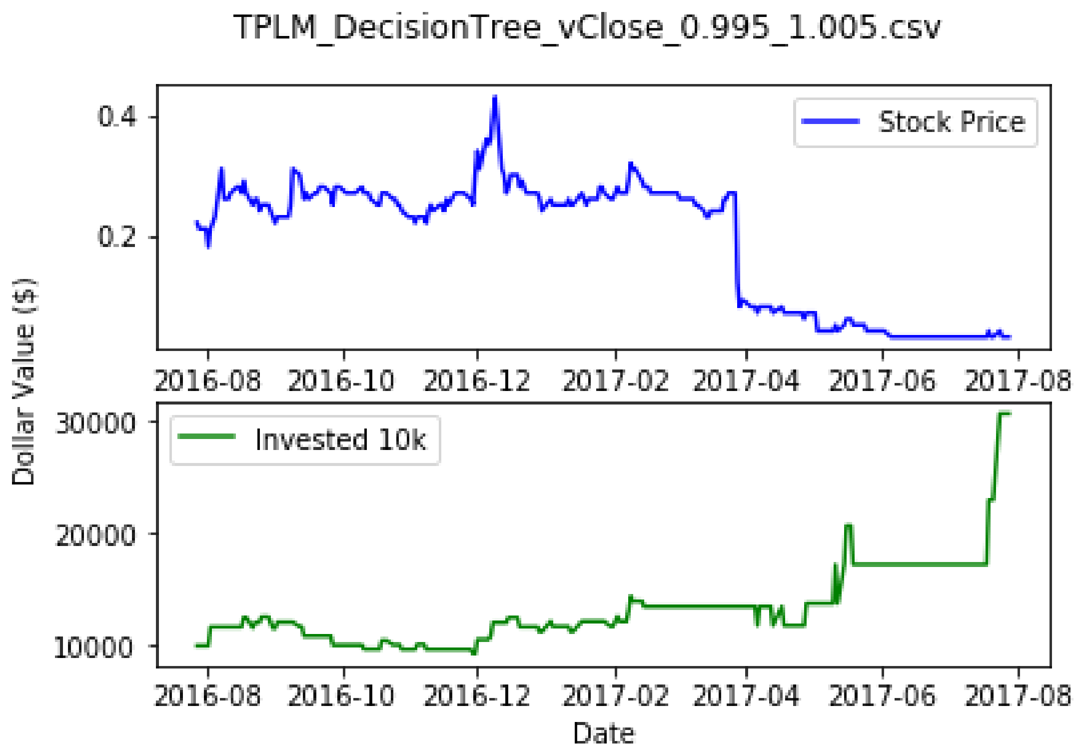
FCEL_DecisionTree_vClose_0.995_1.005.csv
Stock Price
Invested 10k
Dollar Value ($)
4
2
12000
10000
2016-08
2016-10
2016-12
2017-02
2017-04
2017-06
2017-08
Date


HON_DecisionTree_vClose_0.995_1.005.csv
Stock Price
Invested 10k
Dollar Value ($)
Date
140
130
120
110
10500
10000
9500
2016-08
2016-10
2016-12
2017-02
2017-04
2017-06
2017-08


MA_DecisionTree_vClose_0.995_1.005.csv
Stock Price
Invested 10k
Dollar Value ($)
Date
130
120
110
100
11500
11000
10500
10000
2016-08
2016-10
2016-12
2017-02
2017-04
2017-06
2017-08

SD_DecisionTree_vClose_0.995_1.005.csv





0.0.33 Helper function for create bar graph

In [36]:
```
def bar_graph(graph_data,number_of_groups, filename, xlabel, title, xticks):
    n_groups = number_of_groups

    ## create plot
    fig, ax = plt.subplots()
    index = np.arange(n_groups)
    bar_width = 0.167    ## each bar need 100%.  There are 5 models plus the space, so
    opacity = 0.8

    # Bar features
    rects = {}
    pos = 0
    for k, v in graph_data.items():
        ## pos moves the bar through x-axis
        rects[k] = plt.bar(index+pos, v, bar_width,alpha=opacity,label=k)
        pos += bar_width

    ## Labels
    plt.xlabel(xlabel)
    plt.ylabel('Value')
    plt.title(title)
```

```
        plt.xticks(index + bar_width, xticks)
        plt.legend()

        plt.tight_layout()
        plt.show()
        fig.savefig("figures/"+filename+".svg", format='svg', dpi=1200)
```

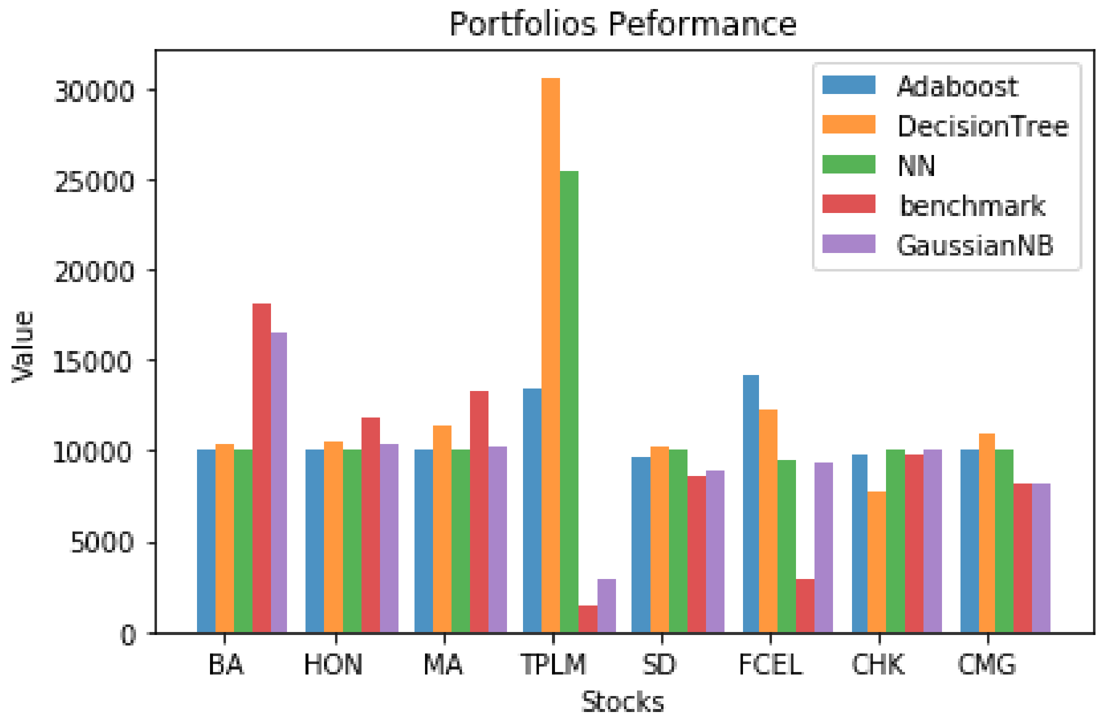
0.0.34 Gather data of each stock for each optimal models

```
In [37]: graph_data = {}

         for name, model in model_list:
             graph_data[name] = []

         for tick in TESTING_TICKERS:
             for name, model in model_list:
                 for index_name in model.index:
                     ## Get data about that ticker
                     if tick in index_name and 'transactions' not in index_name:
                         graph_data[name].append(model[index_name])


         print(graph_data)
```

```
{'Adaboost': [10000.0, 10000.0, 10000.0, 13422.42, 9588.21, 14118.17, 9833.75, 10000.0], 'Deci
```

0.0.35 Graph Models

```
In [38]: bar_graph(graph_data = graph_data, \
                   number_of_groups = len(TESTING_TICKERS),\
                   filename = 'Portfolio',\
                   xlabel = 'Stocks', \
                   title = 'Portfolios Peformance',\
                   xticks = TESTING_TICKERS)
```



0.0.36 Gather data of each optimal models

```
In [39]: graph_data = {}

         for name, model in model_list:
             graph_data[name] = []

         tick = 'FinalValue'
         for name, model in model_list:
             for index_name in model.index:
                 ## Get data about that ticker
                 if tick in index_name and 'transactions' not in index_name:
                     graph_data[name].append(model[index_name])

         print(graph_data)
```

```
{'Adaboost': [84835.81], 'DecisionTree': [94896.15], 'NN': [90873.81], 'benchmark': [74853.0],
```

0.0.37 Graph Total Final Value of the optimal models

```
In [40]: bar_graph(graph_data = graph_data, \
                   number_of_groups = 1,\
                   filename = 'Portfolios_Total',\
```

```
xlabel = 'Models',\
title = 'Portfolios Peformance',\
xticks = "")
```