sy3420_HW04

December 5, 2022

Homework - build toy trading system

This version: 11-15-2022

Background

0.1 0.1 Business context

You are back on the trading desk, working with the trader from HW02. The trader is now interested in exploring whether you can use your expert knowledge of data science work to improve your predictions by including some technical indicators that traders use, instead of just using the raw variables used in HW02. But this time she is interested in trading silver. She asks you to mine (ha ha!) some silver data to come up with a model that she can use for trading silver futures.

This time, instead of simply evaluating how accurate your directional predictions are, the trader would like to get a more realistic sense of how the model would perform if she were to actually trade it. She asks you to show how your model gets turned into a trading system, and to show how the system would have performed over the past year. She now requires that you to you perform a basic *backtest* of the rules you discover.

0.2 0.2 ** Mandate

You are being asked to build four candidate models, to convert these into trading signal generators, and to backtest these on historical data and out-of-sample data.

0.3 0.3 Requirements

- Packages:
  - Please use the `talib` package (installation following talib installation) to create your market indicators.
  - Please use the `bt` package (installation following bt installation) to perform your backtesting.
- Dataset:

- Please use the raw data named 'HW04_silver_CM_sorted.csv' (under "Homework 04" on Brightspace) for your modeling and backtests.
- Please treat any data in the year of 2022 as out-of-sample, and any data before the year of 2022 as in-sample.

- Please assume that you will know the prior trading day's closing price before the next day's market open.
- Please ignore the effects of weekends and holidays on the returns and volatities.
- Please assume a 365 day convention for anualization if you require it.

0.4 0.4 Imports

[2362]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import talib
import bt
import talib
```

[2363]:
```
data = pd.read_csv("HW04_silver_CM_sorted.csv")
```

0.5 0.5 Helper functions and class definitions

0.5.1 SelectWhere

This subclass of bt.Algo lets you easily to take an set of (boolean) trading signals in dataframe and pull out the corresponding trading days. It can be used with other Algos to construt a AlgoStack.

[2364]:
```
class SelectWhere(bt.Algo):

    """
    Selects securities where the value is True on the current date (target.now).

    Args:
        * signal: DataFrame containing the signal (boolean DataFrame)


    """
    def __init__(self, signal):
        self.signal = signal

    # - - - - - - - - - - -

    def __call__(self, target):
        # get signal on target.now
        if target.now in self.signal.index:
```

```
            sig = self.signal.loc[target.now]

            # get indices where true as list
            selected = list(sig.index[sig])

            # save in temp - this will be used by the weighing algo
            target.temp['selected'] = selected

        # return True because we want to keep on moving down the stack
        return True
```

1. Data Understanding, Data Prep and Transformations

1 1.1 Understanding

1.1.0.1 Plot the time series of the closing price of silver futures prior to the year of 2022 with appropriate title, axes and readable labelings.

[2365]:
```
data['Date'] = pd.to_datetime(data['Date'], format='%m/%d/%y')
```

[2366]:
```
in_sample = data[:1063]
out_of_sample = data[1064:]
```

[2367]:
```
close_price = in_sample["Close"]
dates = in_sample["Date"]
```

[2368]:
```
%matplotlib inline
plt.plot(dates, close_price, label = "closing price")
plt.title("Price of silver futures prior to the year of 2022")
plt.xlabel("Dates prior to 2022")
plt.legend()
plt.ylabel("Price")
plt.show()
```

1.1.0.2 What do you observe in the trend of the prices? Are there any steep increase of decrease? If so, around which time did they occur? There is a huge drop in the price of silver in 2020. But it makes a huge jump and increases after a short period of time. This implies that the price was volatile. Around 2021, this huge increase reaches it's peak.

2 1.2 Preprocessing

2.1 1.2.1 Dependent variable (target feature)

1.2.1.1 Please create a new column in your dataframe for the log returns of the `Close` (price) in the data.

[2369]:
```
data["Log_Return"] = (np.log(data["Close"]/data["Close"].shift(1)))
```

[2370]:
```
data.head()
```

[2370]:
```
         Date    Open    High     Low   Close  Log_Return
0  2017-10-11  17.150  17.265  17.085  17.133         NaN
```

```
1 2017-10-12  17.190  17.290  17.135  17.266    0.007733
2 2017-10-13  17.275  17.450  17.200  17.411    0.008363
3 2017-10-16  17.425  17.495  17.135  17.369   -0.002415
4 2017-10-17  17.260  17.280  16.985  17.041   -0.019065
```

1.2.1.2 Please create a new column in your dataframe called `positive_return_dummy` that takes the value `1` if the return for the day is greater than 0 and `0` otherwise. This will be your dependent variable for data mining.

[2371]:
```
data['positive_return_dummy'] = np.where(data['Log_Return'] > 0, 1, 0)
```

[2372]:
```
data.head()
```

[2372]:
```
         Date    Open    High     Low   Close  Log_Return  \
0 2017-10-11  17.150  17.265  17.085  17.133         NaN
1 2017-10-12  17.190  17.290  17.135  17.266    0.007733
2 2017-10-13  17.275  17.450  17.200  17.411    0.008363
3 2017-10-16  17.425  17.495  17.135  17.369   -0.002415
4 2017-10-17  17.260  17.280  16.985  17.041   -0.019065

   positive_return_dummy
0                      0
1                      1
2                      1
3                      0
4                      0
```

2.2 1.2.2 Independent variables

In this section, we will calculate and work with several common following technical indicators from the `talib` package:

2.2.1 1.2.2.1 Historical Volatility

1.2.2.1.1 Please create new columns in your dataframe for historical (return) volatility using windows $[5, 10, 20, 30, 60, 120]$ and add them to your dataframe

[2373]:
```
log = data["Log_Return"]
window = [5,10,20,30,60,120]
windows = []
for i in window:
    result = talib.STDDEV(log, timeperiod=i)
    windows.append(result)
```

[2374]:
```
data["return_vol_5"] = windows[0]
data["return_vol_10"] = windows[1]
```

```
data["return_vol_20"] = windows[2]
data["return_vol_30"] = windows[3]
data["return_vol_60"] = windows[4]
data["return_vol_120"] = windows[5]
```

[2375]:
```
data.tail()
```

[2375]:

	Date	Open	High	Low	Close	Log_Return
1274	2022-11-02	19.230	19.255	19.090	19.594	-0.003719
1275	2022-11-03	19.500	19.515	19.455	19.430	-0.008405
1276	2022-11-04	20.784	20.965	20.784	20.784	0.067365
1277	2022-11-07	20.850	20.945	20.785	20.919	0.006474
1278	2022-11-08	21.425	21.540	21.380	21.502	0.027488

	positive_return_dummy	return_vol_5	return_vol_10	return_vol_20
1274	0	0.015041	0.012609	0.019706
1275	0	0.015528	0.012711	0.019659
1276	1	0.028556	0.022719	0.024526
1277	1	0.027727	0.022719	0.023311
1278	1	0.027672	0.023410	0.023774

	return_vol_30	return_vol_60	return_vol_120
1274	0.024853	0.021422	0.019764
1275	0.024866	0.021372	0.019749
1276	0.026737	0.022964	0.020557
1277	0.026296	0.022877	0.020548
1278	0.026525	0.022974	0.020685

2.2.2 1.2.2.2 SMA (simple moving average):

SMA is the average closing prices within a specified window.

1.2.2.2.1 Please create new columns in your dataframe for SMA using windows $[5, 10, 20, 30, 60, 120]$.

[2376]:
```
close = data["Close"]
window = [5,10,20,30,60,120]
windows1 = []
for i in window:
    result = talib.SMA(close, timeperiod=i)
    windows1.append(result)
```

[2377]:
```
data["sma_5"] = windows1[0]
data["sma_10"] = windows1[1]
data["sma_20"] = windows1[2]
data["sma_30"] = windows1[3]
```

```
data["sma_60"] = windows1[4]
data["sma_120"] = windows1[5]
```

[2378]:
```
windows_5 = windows1[0]
windows_10 = windows1[1]
windows_30 = windows1[3]
windows_120 = windows1[5]
```

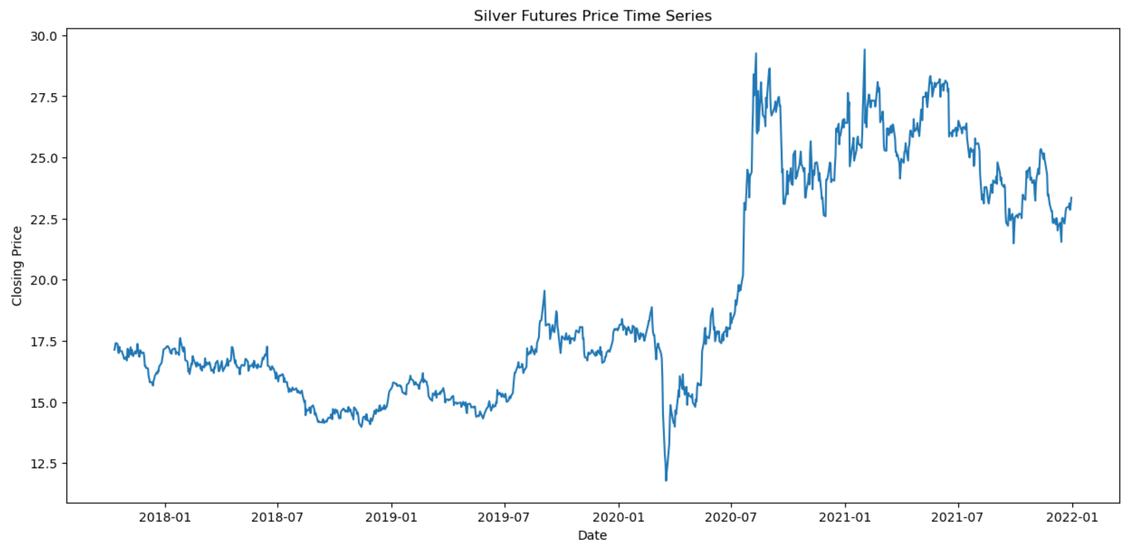
[2379]:
```
data.tail()
```

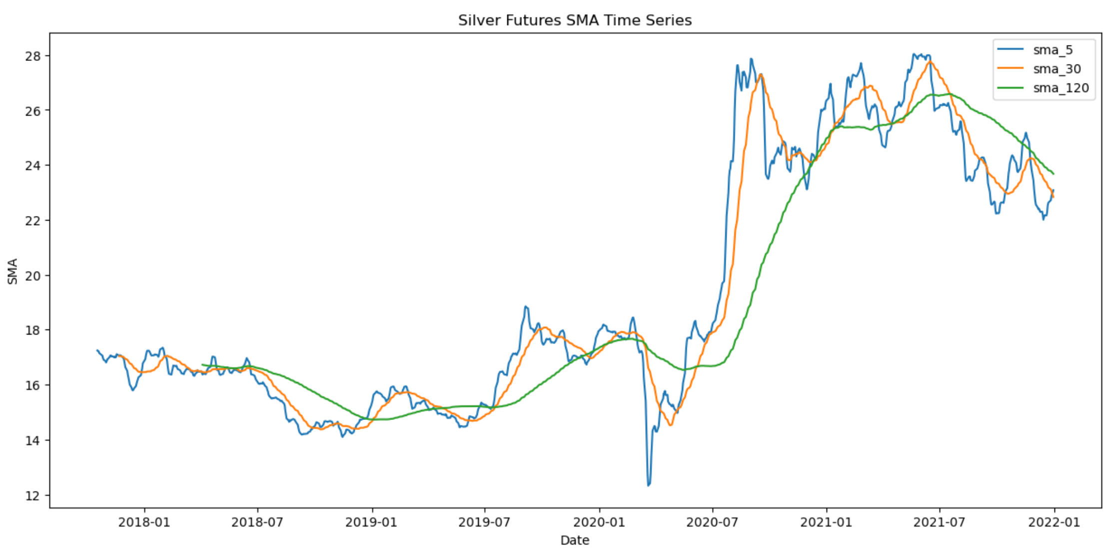
[2379]:
```
            Date    Open    High     Low   Close  Log_Return  \
1274  2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275  2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276  2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277  2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278  2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  \
1274                      0      0.015041       0.012609       0.019706
1275                      0      0.015528       0.012711       0.019659
1276                      1      0.028556       0.022719       0.024526
1277                      1      0.027727       0.022719       0.023311
1278                      1      0.027672       0.023410       0.023774

      return_vol_30  return_vol_60  return_vol_120    sma_5   sma_10  \
1274       0.024853       0.021422        0.019764  19.4042  19.2800
1275       0.024866       0.021372        0.019749  19.3914  19.3541
1276       0.026737       0.022964        0.020557  19.7188  19.5259
1277       0.026296       0.022877        0.020548  20.0788  19.6989
1278       0.026525       0.022974        0.020685  20.4458  19.9142

        sma_20     sma_30     sma_60    sma_120
1274  19.22110  19.287633  19.215950  19.887208
1275  19.15960  19.281400  19.194083  19.874117
1276  19.18605  19.343867  19.201333  19.867725
1277  19.25125  19.425167  19.205017  19.860800
1278  19.35200  19.530667  19.225517  19.860450
```

1.2.2.2.2 Please plot the following time series (before 2022) in two panels with Panel (1) above Panel (2): (1) the closing prices of silver future; (2) the SMA with windows $5, 30$ **and** 120**.**

[2380]:
```
in_sample = data[data['Date'] < '2022-01-01']

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(15, 15))

ax1.plot(in_sample['Date'], in_sample['Close'])
```

```
ax1.set_title('Silver Futures Price Time Series')
ax1.set_xlabel('Date')
ax1.set_ylabel('Closing Price')

ax2.plot(in_sample['Date'], in_sample['sma_5'], label='sma_5')
ax2.plot(in_sample['Date'], in_sample['sma_30'], label='sma_30')
ax2.plot(in_sample['Date'], in_sample['sma_120'], label='sma_120')
ax2.set_title('Silver Futures SMA Time Series')
ax2.set_xlabel('Date')
ax2.set_ylabel('SMA')
ax2.legend()

plt.show()
```





1.2.2.2.3 What do you notice about about these SMA series? Describe your observations. SMA is to establish the direction in which the price of a security is moving based on past prices. Since SMA is built using past closing prices, it is a lag indicator. This means that it simply displays a previous trend, but it is not predictive of future prices.

All three windows look similar to one another. Since they look similar, this is an indication that the direction of security price is not much different through the 3 windows.

Although SMA-120 seems to be smoother than the other 3 windows and the other two seems bumpy suggesting they could be a bit more volatile than SMA 120.

2.2.3 1.2.2.3 EWMA (exponentially weighted moving average):

EWMA is the weighted moving average that applies more weighting to more recent prices.

1.2.2.3.1 Please create new columns in your dataframe for EWMA using windows $[5, 10, 20, 30, 60, 120]$**.**

[2381]:
```
window = [5,10,20,30,60,120]
windows2 = []
for i in window:
    result  = talib.EMA(close, timeperiod=i)
    windows2.append(result)
```

[2382]:
```
data["ewma_5"] = windows2[0]
data["ewma_10"] = windows2[1]
data["ewma_20"] = windows2[2]
data["ewma_30"] = windows2[3]
data["ewma_60"] = windows2[4]
data["ewma_120"] = windows2[5]
```

[2383]:
```
data.tail()
```

[2383]:
```
           Date    Open    High     Low   Close  Log_Return  \
1274 2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275 2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276 2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277 2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278 2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  …  \
1274                      0      0.015041       0.012609       0.019706  …
1275                      0      0.015528       0.012711       0.019659  …
1276                      1      0.028556       0.022719       0.024526  …
1277                      1      0.027727       0.022719       0.023311  …
1278                      1      0.027672       0.023410       0.023774  …

        sma_20      sma_30      sma_60     sma_120      ewma_5     ewma_10  \
```

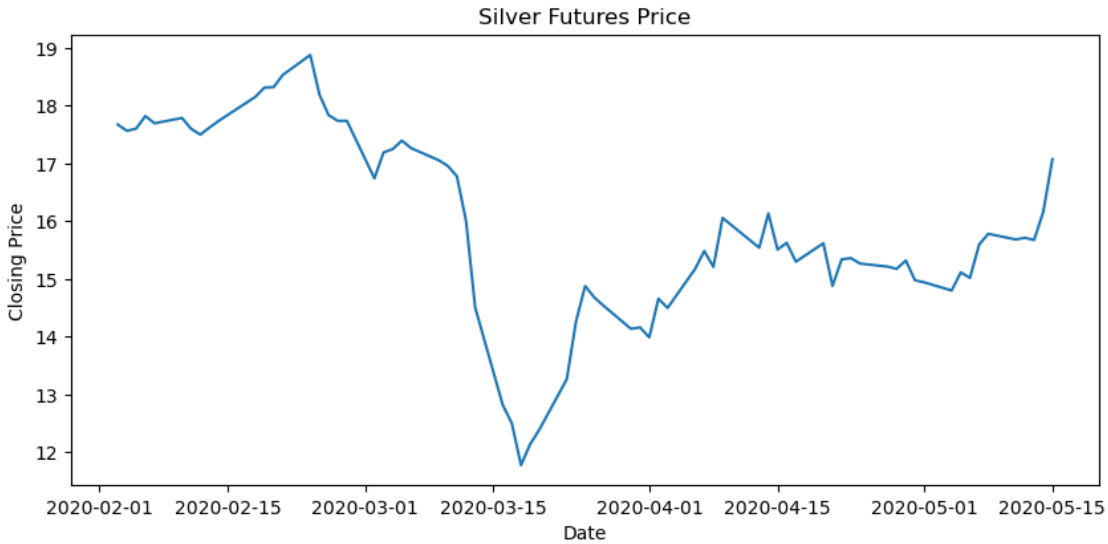
```
1274  19.22110  19.287633  19.215950  19.887208  19.437934  19.320930
1275  19.15960  19.281400  19.194083  19.874117  19.435289  19.340761
1276  19.18605  19.343867  19.201333  19.867725  19.884859  19.603168
1277  19.25125  19.425167  19.205017  19.860800  20.229573  19.842410
1278  19.35200  19.530667  19.225517  19.860450  20.653715  20.144154

        ewma_20    ewma_30    ewma_60   ewma_120
1274  19.262498  19.255472  19.406310  20.110127
1275  19.278451  19.266732  19.407086  20.098885
1276  19.421836  19.364620  19.452231  20.110209
1277  19.564423  19.464903  19.500322  20.123578
1278  19.748954  19.596328  19.565951  20.146362

[5 rows x 25 columns]
```

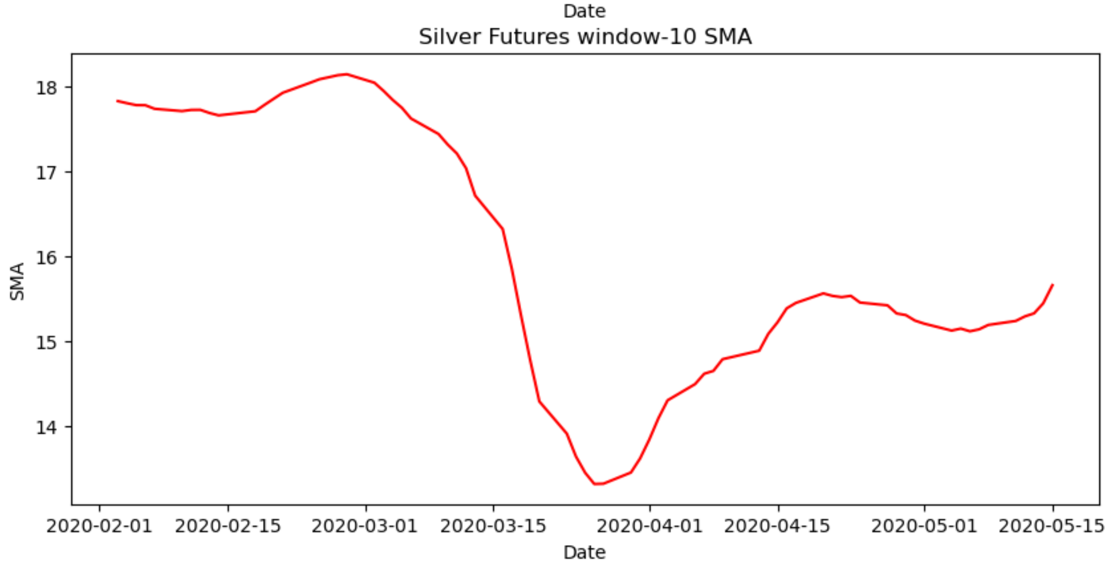
1.2.2.3.2 Please plot the window-10 EMA, window-10 SMA and the closing prices from 2020-02-01 to 2020-05-15.

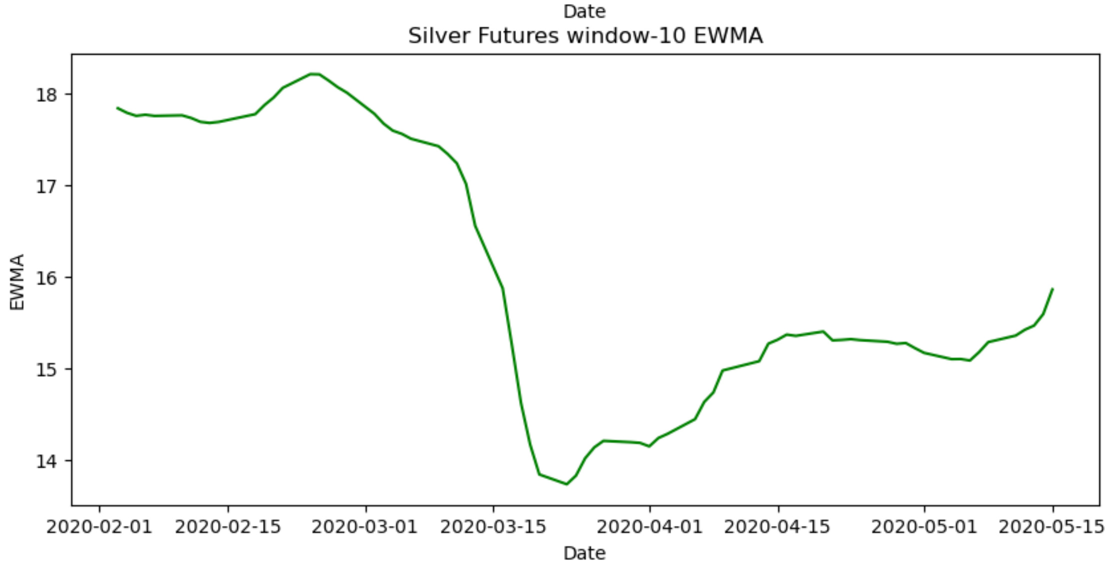
[2384]:
```
windows_10 = windows1[1]
windows2_10 = windows2[1]
```

[2385]:
```
mask = data[(data['Date'] >= '2020-02-01') & (data['Date'] <= '2020-05-15')]
```

[2386]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3, 1, figsize=(10, 15))

#Plot the closing price
ax1.plot(mask['Date'], mask['Close'])
ax1.set_title('Silver Futures Price')
ax1.set_xlabel('Date')
ax1.set_ylabel('Closing Price')

#Plot the 10d SMA
ax2.plot(mask['Date'], mask['sma_10'], color = "red")
ax2.set_title('Silver Futures window-10 SMA')
ax2.set_xlabel('Date')
ax2.set_ylabel('SMA')

#Plot the 10d EMA
ax3.plot(mask['Date'], mask['ewma_10'], color = "green")
ax3.set_title('Silver Futures window-10 EWMA')
ax3.set_xlabel('Date')
ax3.set_ylabel('EWMA')

plt.show()
```


Silver Futures Price
Closing Price
19
18
17
16
15
14
13
12
2020-02-01
2020-02-15
2020-03-01
2020-03-15
2020-04-01
2020-04-15
2020-05-01
2020-05-15
Date


Silver Futures window-10 SMA
SMA
18
17
16
15
14
2020-02-01
2020-02-15
2020-03-01
2020-03-15
2020-04-01
2020-04-15
2020-05-01
2020-05-15
Date


Silver Futures window-10 EWMA
EWMA
18
17
16
15
14
2020-02-01
2020-02-15
2020-03-01
2020-03-15
2020-04-01
2020-04-15
2020-05-01
2020-05-15
Date

1.2.2.3.3 What do you observe about the reactions of SMA and EMA to the price decrease in March? Briefly explain the underlying reason to this observation. We can see that in the month of march, there is a a huge dip. This means that the security price is decreasing for SMA and EMA

Calculations make EMA quicker to react to price changes.In the beginning, the prices seem pretty stable/ consistent, but there is a huge dip arond late Feb to early March. However, EWMA seems to be doing a bit better compared to other graphs. Although all three experienced something in March, the overal performance is likely due to the considered 10 day window.

2.2.4 1.2.2.4 MACD (moving average convergence/divergence):

MACD is a trend-following momentum indicator, which is the difference between a 26-day and 12-day exponential moving average.

1.2.2.4.1 Please create a new column in your dataframe for MACD.

[2387]:
```
macd, macdsignal, macdhist = talib.MACD(close, fastperiod=12, slowperiod=26)
```

[2388]:
```
data["macd"] = macd
data["macdsingal"] = macdsignal
data["macdhist"] = macdhist
```

[2389]:
```
data.tail()
```

[2389]:
```
           Date    Open    High     Low   Close  Log_Return  \
1274 2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275 2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276 2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277 2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278 2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  …  \
1274                      0      0.015041       0.012609       0.019706  …
1275                      0      0.015528       0.012711       0.019659  …
1276                      1      0.028556       0.022719       0.024526  …
1277                      1      0.027727       0.022719       0.023311  …
1278                      1      0.027672       0.023410       0.023774  …

        sma_120     ewma_5    ewma_10    ewma_20    ewma_30    ewma_60  \
1274  19.887208  19.437934  19.320930  19.262498  19.255472  19.406310
1275  19.874117  19.435289  19.340761  19.278451  19.266732  19.407086
1276  19.867725  19.884859  19.603168  19.421836  19.364620  19.452231
1277  19.860800  20.229573  19.842410  19.564423  19.464903  19.500322
1278  19.860450  20.653715  20.144154  19.748954  19.596328  19.565951
```

```
       ewma_120      macd  macdsingal  macdhist
1274  20.110127  0.043334   -0.019549  0.062883
1275  20.098885  0.050615   -0.005517  0.056131
1276  20.110209  0.163754    0.028337  0.135416
1277  20.123578  0.261298    0.074930  0.186369
1278  20.146362  0.381252    0.136194  0.245058

[5 rows x 28 columns]
```

1.2.2.4.2 Please print the dates on whihc your system would have bought or sold in the period from 2020-02-01 to 2020-05-15 as suggested by the basic MACD trading rule. The basic MACD trading rule is to sell when the MACD falls below its signal line. Similarly, a buy signal occurs when the MACD rises above its signal line. (Hint: MACD is calculated using the closing prices.)

[2390]:
```
buy = data[data["macd"] > data["macdsingal"]][["Close", "macd", "macdsingal",␣
↪"Date"]]
```

[2391]:
```
sell = data[data["macd"] < data["macdsingal"]][["Close", "macd", "macdsingal",␣
↪"Date"]]
```

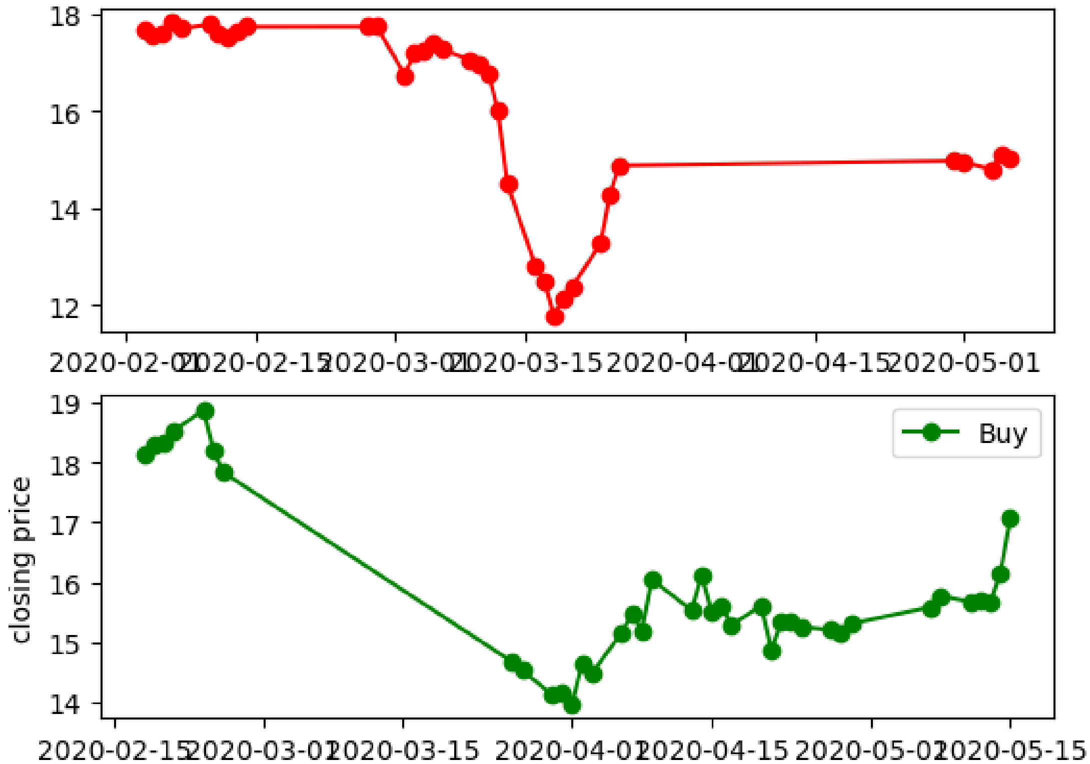
[2392]:
```
mask = (buy["Date"] >= "2020-02-03") & (buy["Date"] <= "2020-05-15" )
```

[2393]:
```
mask2 = (sell["Date"] >= "2020-02-03") & (sell["Date"] <= "2020-05-15" )
```

[2394]:
```
buy = buy.loc[mask]
sell = sell.loc[mask2]
```

1.2.2.5 Please plot the following time series (from 2020-02-01 to 2020-05-15) in two panels with Panel (1) above Panel (2): (1) the closing prices of silver future with selling dates in red dots and buying dates in green dots; 2) the MACD with the MACD signal line on top.

[2395]:
```
fig, ax = plt.subplots(2)
ax[0].plot(sell["Date"], sell["Close"], marker = 'o', color = "red", label =␣
↪"Sell")
ax[1].plot(buy["Date"], buy["Close"], marker='o', color = "green", label =␣
↪"Buy")
plt.ylabel("closing price")
plt.legend()
plt.show()
```



2.2.5 1.2.2.5 DX (directional movement index):

DX determines the trend direction of the asset price and the strength of this price movement by comparing the current price with previous lows and highs that lead to positive directional movement (+DI) and negative directional movement (-DI).

1.2.2.5.1 Please create new columns in your dataframe for DX using windows $[5, 10, 20, 30, 60, 120]$.

[2396]:
```
window = [5,10,20,30,60,120]
windows3 = []
for i in window:
    real = talib.DX(high, low, close, timeperiod=i)
    windows3.append(real)
```

[2397]:
```
data["dx_5"] = windows3[0]
data["dx_10"] = windows3[1]
data["dx_20"] = windows3[2]
data["dx_30"] = windows3[3]
data["dx_60"] = windows3[4]
data["dx_120"] = windows3[5]
```

[2398]:
```
data.tail()
```

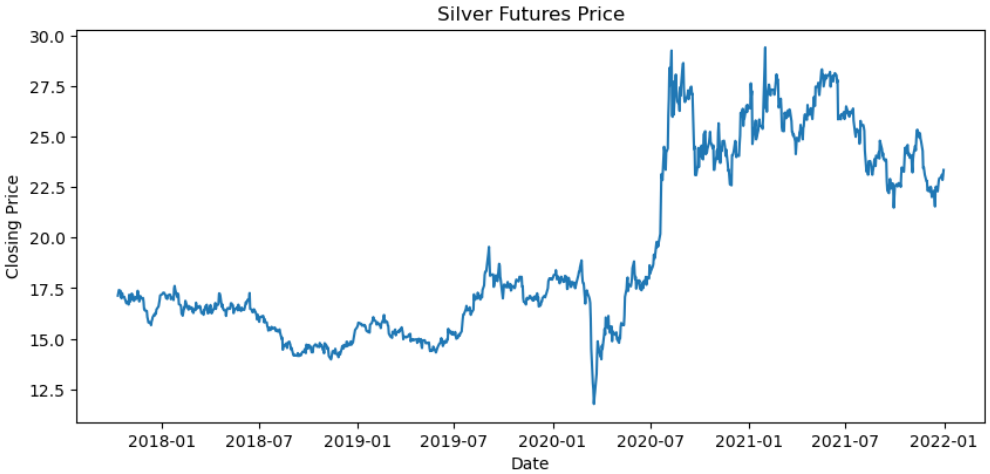
[2398]:
```
            Date    Open    High     Low   Close  Log_Return  \
1274  2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275  2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276  2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277  2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278  2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  …  \
1274                      0      0.015041       0.012609       0.019706  …
1275                      0      0.015528       0.012711       0.019659  …
1276                      1      0.028556       0.022719       0.024526  …
1277                      1      0.027727       0.022719       0.023311  …
1278                      1      0.027672       0.023410       0.023774  …

        ewma_120      macd  macdsingal  macdhist       dx_5      dx_10  \
1274  20.110127  0.043334   -0.019549  0.062883   8.766988   7.980343
1275  20.098885  0.050615   -0.005517  0.056131  10.195173   1.587200
1276  20.110209  0.163754    0.028337  0.135416  59.462160  36.468723
1277  20.123578  0.261298    0.074930  0.186369  59.462160  36.468723
1278  20.146362  0.381252    0.136194  0.245058  70.010688  46.139818

          dx_20      dx_30      dx_60     dx_120
1274   9.392356  10.331599  11.747334  10.683349
1275   4.594587   7.066255  10.036665   9.819272
1276  16.821279   8.548576   1.246392   5.200601
1277  16.821279   8.548576   1.246392   5.200601
1278  23.905341  14.052989   2.073416   3.386260

[5 rows x 34 columns]
```

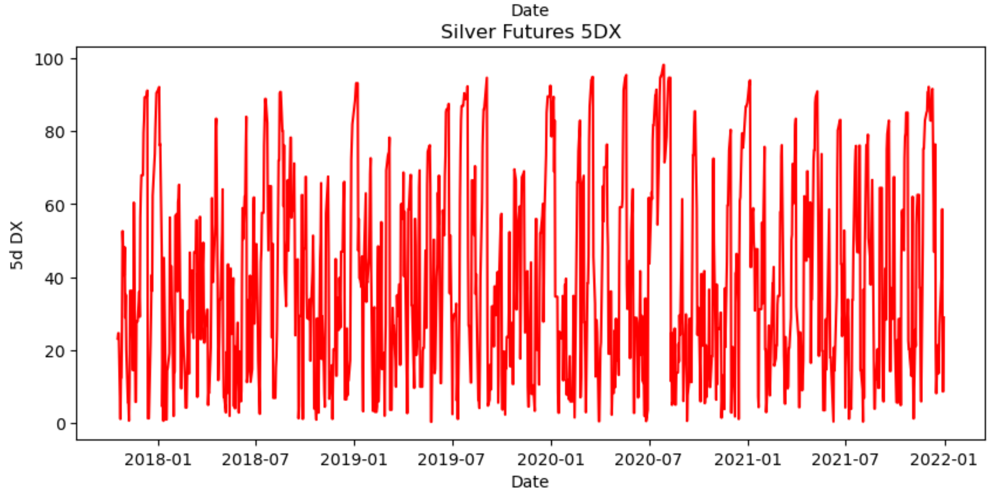
1.2.2.5.2 Please plot the following four time series (before 2022) in four panels: (1) the closing prices of silver future; (2) - (4) the directional movement indices with windows $5, 30$ and 120.

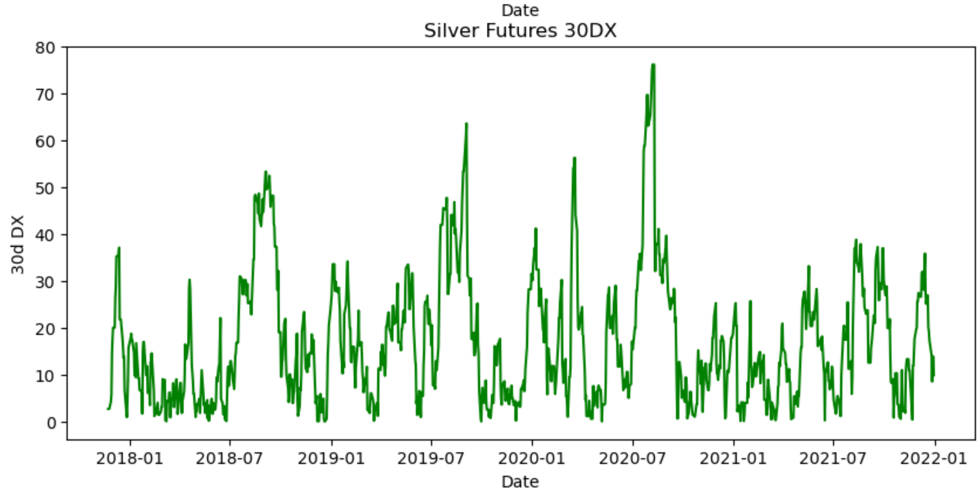
[2399]:
```
m_2022 = data[data["Date"] <= "2022-01-01"]
```

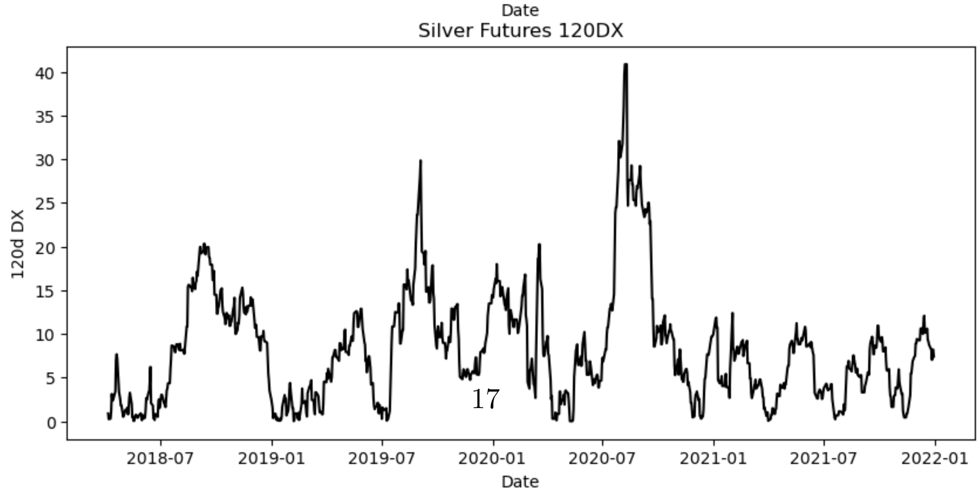
[2400]:
```
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(10, 20))

ax1.plot(m_2022['Date'], m_2022['Close'])
ax1.set_title('Silver Futures Price')
ax1.set_xlabel('Date')
ax1.set_ylabel('Closing Price')

ax2.plot(m_2022['Date'], m_2022['dx_5'], color = "red")
ax2.set_title('Silver Futures 5DX')
```

```
ax2.set_xlabel('Date')
ax2.set_ylabel('5d DX')

ax3.plot(m_2022['Date'], m_2022['dx_30'], color = "green")
ax3.set_title('Silver Futures 30DX')
ax3.set_xlabel('Date')
ax3.set_ylabel('30d DX')

ax4.plot(m_2022['Date'], m_2022['dx_120'], color = "black")
ax4.set_title('Silver Futures 120DX')
ax4.set_xlabel('Date')
ax4.set_ylabel('120d DX')

plt.show()
```


Silver Futures Price
Closing Price
Date


Silver Futures 5DX
5d DX
Date


Silver Futures 30DX
30d DX
Date


Silver Futures 120DX
120d DX
Date

2.2.6 1.2.2.6 ADX (average directional movement index):

ADX is the average of the values of the DX over the specified period. It measures the strength of the trend (regardless of direction) over time.

1.2.2.6.1 Please create new columns in your dataframe for ADX using windows $[5, 10, 20, 30, 60, 120]$.

[2401]:
```
window = [5,10,20,30,60,120]
windows4 = []
for i in window:
    real = talib.ADX(high, low, close, timeperiod=i)
    windows4.append(real)
```

[2402]:
```
data["adx_5"] = windows4[0]
data["adx_10"] = windows4[1]
data["adx_20"] = windows4[2]
data["adx_30"] = windows4[3]
data["adx_60"] = windows4[4]
data["adx_120"] = windows4[5]
```

[2403]:
```
data.tail()
```

[2403]:
```
            Date    Open    High     Low   Close  Log_Return  \
1274  2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275  2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276  2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277  2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278  2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  …  \
1274                      0      0.015041       0.012609       0.019706  …
1275                      0      0.015528       0.012711       0.019659  …
1276                      1      0.028556       0.022719       0.024526  …
1277                      1      0.027727       0.022719       0.023311  …
1278                      1      0.027672       0.023410       0.023774  …

          dx_20      dx_30      dx_60     dx_120      adx_5     adx_10  \
1274   9.392356  10.331599  11.747334  10.683349  20.773601  15.836958
1275   4.594587   7.066255  10.036665   9.819272  18.657916  14.411982
1276  16.821279   8.548576   1.246392   5.200601  26.818765  16.617656
1277  16.821279   8.548576   1.246392   5.200601  33.347444  18.602763
1278  23.905341  14.052989   2.073416   3.386260  40.680092  21.356468
```

```
         adx_20     adx_30     adx_60    adx_120
1274  13.772487  14.253200  13.541278  8.799837
1275  13.313592  14.013635  13.482868  8.808332
1276  13.488976  13.831467  13.278927  8.778268
1277  13.655591  13.655370  13.078385  8.748454
1278  14.168079  13.668624  12.894968  8.703769

[5 rows x 40 columns]
```

2.3 1.2.3 Time structure

1.2.3.1 Please shift your dependent variable by one day (as we did in previous HWs) so that the values of the independent variables, x_{t-1} , are associated (in the same row as) the values of y_t (the dependent variable).

[2404]:
```python
data['positive_return_dummy'] = data['positive_return_dummy'].shift(-1)
```

[2405]:
```python
data.tail()
```

[2405]:
```
            Date    Open    High     Low   Close  Log_Return  \
1274  2022-11-02  19.230  19.255  19.090  19.594   -0.003719
1275  2022-11-03  19.500  19.515  19.455  19.430   -0.008405
1276  2022-11-04  20.784  20.965  20.784  20.784    0.067365
1277  2022-11-07  20.850  20.945  20.785  20.919    0.006474
1278  2022-11-08  21.425  21.540  21.380  21.502    0.027488

      positive_return_dummy  return_vol_5  return_vol_10  return_vol_20  …  \
1274                    0.0      0.015041       0.012609       0.019706  …
1275                    1.0      0.015528       0.012711       0.019659  …
1276                    1.0      0.028556       0.022719       0.024526  …
1277                    1.0      0.027727       0.022719       0.023311  …
1278                    NaN      0.027672       0.023410       0.023774  …

          dx_20      dx_30      dx_60     dx_120      adx_5     adx_10  \
1274   9.392356  10.331599  11.747334  10.683349  20.773601  15.836958
1275   4.594587   7.066255  10.036665   9.819272  18.657916  14.411982
1276  16.821279   8.548576   1.246392   5.200601  26.818765  16.617656
1277  16.821279   8.548576   1.246392   5.200601  33.347444  18.602763
1278  23.905341  14.052989   2.073416   3.386260  40.680092  21.356468

         adx_20     adx_30     adx_60    adx_120
1274  13.772487  14.253200  13.541278  8.799837
1275  13.313592  14.013635  13.482868  8.808332
1276  13.488976  13.831467  13.278927  8.778268
1277  13.655591  13.655370  13.078385  8.748454
1278  14.168079  13.668624  12.894968  8.703769
```

```
[5 rows x 40 columns]
```

1.2.3.2 Now please relabel all of your independent variables `xxx_L01d`, where `xxx` is the original name of the variable (e.g., `Close` would become `Close_L01d`). This will help us remember which variables were shifted forward go with which dates (i.e., the `_L01d` suffix reminds us that that varaible represents the value as of the previous trading period.)

[2416]:
```
data = data.rename(columns = lambda col: f"{col}_L01d"
                                if col not in ('positive_return_dummy')
                                else col)
```

[2417]:
```
data.tail()
```

[2417]:
```
       Date_L01d  Open_L01d  High_L01d  Low_L01d  Close_L01d  Log_Return_L01d  \
1274  2022-11-02     19.230     19.255    19.090      19.594        -0.003719
1275  2022-11-03     19.500     19.515    19.455      19.430        -0.008405
1276  2022-11-04     20.784     20.965    20.784      20.784         0.067365
1277  2022-11-07     20.850     20.945    20.785      20.919         0.006474
1278  2022-11-08     21.425     21.540    21.380      21.502         0.027488

      positive_return_dummy  return_vol_5_L01d  return_vol_10_L01d  \
1274                    0.0           0.015041            0.012609
1275                    1.0           0.015528            0.012711
1276                    1.0           0.028556            0.022719
1277                    1.0           0.027727            0.022719
1278                    NaN           0.027672            0.023410

      return_vol_20_L01d  …  dx_20_L01d  dx_30_L01d  dx_60_L01d  \
1274            0.019706  …    9.392356   10.331599   11.747334
1275            0.019659  …    4.594587    7.066255   10.036665
1276            0.024526  …   16.821279    8.548576    1.246392
1277            0.023311  …   16.821279    8.548576    1.246392
1278            0.023774  …   23.905341   14.052989    2.073416

      dx_120_L01d  adx_5_L01d  adx_10_L01d  adx_20_L01d  adx_30_L01d  \
1274    10.683349   20.773601    15.836958    13.772487    14.253200
1275     9.819272   18.657916    14.411982    13.313592    14.013635
1276     5.200601   26.818765    16.617656    13.488976    13.831467
1277     5.200601   33.347444    18.602763    13.655591    13.655370
1278     3.386260   40.680092    21.356468    14.168079    13.668624

      adx_60_L01d  adx_120_L01d
1274    13.541278      8.799837
1275    13.482868      8.808332
1276    13.278927      8.778268
1277    13.078385      8.748454
```

```
1278    12.894968      8.703769

[5 rows x 40 columns]
```

1.2.3.3 Please print the head of your newly labeled dataframe. Make sure the dataframe only contains valid and useful rows.

[2418]:
```
last_date = data['Date_L01d'].dt.date.astype(str).iloc[-1]
data = data.dropna()

data.head()
```

[2418]:
```
      Date_L01d  Open_L01d  High_L01d  Low_L01d  Close_L01d  Log_Return_L01d  \
239  2018-09-24     14.325     14.420    14.220      14.341        -0.001254
240  2018-09-25     14.295     14.595    14.250      14.493         0.010543
241  2018-09-26     14.500     14.545    14.340      14.401        -0.006368
242  2018-09-27     14.375     14.480    14.195      14.290        -0.007738
243  2018-09-28     14.270     14.755    14.255      14.712         0.029103

     positive_return_dummy  return_vol_5_L01d  return_vol_10_L01d  \
239                    1.0           0.003373            0.005048
240                    0.0           0.004056            0.005642
241                    0.0           0.005591            0.005591
242                    1.0           0.006740            0.006044
243                    0.0           0.013727            0.010028

     return_vol_20_L01d  …  dx_20_L01d  dx_30_L01d  dx_60_L01d  dx_120_L01d  \
239            0.007942  …   35.881485   37.310103   28.797288    17.917223
240            0.008279  …   21.669577   28.130242   24.776605    16.159252
241            0.008297  …   21.669577   28.130242   24.776605    16.159252
242            0.008374  …   28.532130   32.152273   26.736396    17.199332
243            0.010121  …    9.398113   19.077970   20.672801    14.483191

     adx_5_L01d  adx_10_L01d  adx_20_L01d  adx_30_L01d  adx_60_L01d  \
239   31.377502    45.266917    46.373462    35.474286    16.140366
240   37.603560    41.792218    45.138267    35.229484    16.284303
241   42.584407    38.664988    43.964833    34.992843    16.425842
242   34.285022    35.822630    43.193198    34.898157    16.597684
243   36.994259    34.342602    41.503444    34.370818    16.665603

     adx_120_L01d
239      6.786362
240      6.864470
241      6.941926
242      7.027405
243      7.089536
```

```
[5 rows x 40 columns]
```

3 1.2 Building some basic to toy models

3.1 1.2.1 Take 1 - kitchen sink - linear model

1.2.1.1 Please estimate a logit model using the silver data, in which the dependent variable is `positive_return_dummy` and your lagged variables are *all* of the variables from 1.1.2, and print the summary of the model. (Hint, you will find it much easier to do linear model analysis if you use `statsmodels.api.formula` version of the API.)

[2419]:
```
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

[2420]:
```
train = data[data['Date_L01d'].dt.date.astype(str) < '2021-12-31']
test = data[data['Date_L01d'].dt.date.astype(str) >= '2021-12-31']


last_date_val = test['Date_L01d'].dt.date.astype(str).iloc[-1]
train1 = train.iloc[:int(.85*len(train))].dropna()
val = train.iloc[int(.85*len(train)):].dropna()
```

[2421]:
```
feat1.columns
```

[2421]:
```
Index(['return_vol_5_L01d', 'return_vol_10_L01d', 'return_vol_20_L01d',
       'return_vol_30_L01d', 'return_vol_60_L01d', 'return_vol_120_L01d',
       'sma_5_L01d', 'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d',
       'sma_60_L01d', 'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d',
       'ewma_20_L01d', 'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d',
       'macd_L01d', 'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d',
       'dx_10_L01d', 'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d',
       'adx_5_L01d', 'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d',
       'adx_60_L01d', 'adx_120_L01d'],
      dtype='object')
```

[2422]:
```
X1 = train1[['return_vol_5_L01d', 'return_vol_10_L01d', 'return_vol_20_L01d',
       'return_vol_30_L01d', 'return_vol_60_L01d', 'return_vol_120_L01d',
       'sma_5_L01d', 'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d',
       'sma_60_L01d', 'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d',
       'ewma_20_L01d', 'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d',
       'macd_L01d', 'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d',
       'dx_10_L01d', 'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d',
       'adx_5_L01d', 'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d',
       'adx_60_L01d', 'adx_120_L01d']]
```

```python
Y1 = train1['positive_return_dummy']
```

[2423]:
```python
log_reg = sm.Logit(Y1, X1)
result = log_reg.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.657737
         Iterations 13
```

[2424]:
```python
result.summary2()
```

[2424]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                                   Results: Logit
================================================================================
====
Model:                   Logit                       Pseudo R-squared:      0.048
Dependent Variable:      positive_return_dummy       AIC:
986.8312
Date:                    2022-12-05 16:06            BIC:
1137.0168
No. Observations:        700                         Log-Likelihood:
-460.42
Df Model:                32                          LL-Null:
-483.42
Df Residuals:            667                         LLR p-value:
0.051994
Converged:               1.0000                      Scale:
1.0000
No. Iterations:          13.0000
--------------------------------------------------------------------------------
----
                      Coef.     Std.Err.      z     P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
return_vol_5_L01d     22.9810      13.8198  1.6629 0.0963        -4.1054
50.0674
return_vol_10_L01d   -57.1688      19.5752 -2.9205 0.0035       -95.5355
-18.8022
return_vol_20_L01d    12.8424      28.5919  0.4492 0.6533       -43.1967
68.8816
return_vol_30_L01d     4.6595      32.3428  0.1441 0.8854       -58.7311
68.0502
return_vol_60_L01d    -1.6691      35.1498 -0.0475 0.9621       -70.5615
67.2232
return_vol_120_L01d   77.3100      46.7744  1.6528 0.0984       -14.3661
```

```
168.9860
sma_5_L01d             1.3777       1.7392  0.7922 0.4282       -2.0309
4.7864
sma_10_L01d            3.2207       1.8667  1.7253 0.0845       -0.4380
6.8793
sma_20_L01d           -1.1052       2.0056 -0.5510 0.5816       -5.0360
2.8257
sma_30_L01d            0.7643       2.4886  0.3071 0.7588       -4.1134
5.6419
sma_60_L01d            0.3304       1.3855  0.2385 0.8115       -2.3851
3.0458
sma_120_L01d           0.9759       0.9269  1.0529 0.2924       -0.8408
2.7927
ewma_5_L01d           -8.0347      17.0255 -0.4719 0.6370      -41.4041
25.3347
ewma_10_L01d        -477.8969     523.9978 -0.9120 0.3618    -1504.9137
549.1198
ewma_20_L01d         208.5166     288.2841  0.7233 0.4695     -356.5098
773.5430
ewma_30_L01d         288.2975     285.5504  1.0096 0.3127     -271.3710
847.9660
ewma_60_L01d         -18.3254      18.1974 -1.0070 0.3139      -53.9916
17.3408
ewma_120_L01d          1.8776       2.1881  0.8581 0.3908       -2.4109
6.1661
macd_L01d            395.1402 5076117.5581  0.0001 0.9999 -9948612.4550
9949402.7353
macdsingal_L01d      124.5305 5076117.7231  0.0000 1.0000 -9948883.3881
9949132.4491
macdhist_L01d        270.6098 5076117.7895  0.0001 1.0000 -9948737.4389
9949278.6586
dx_5_L01d              0.0094       0.0079  1.1813 0.2375       -0.0062
0.0249
dx_10_L01d            -0.0161       0.0192 -0.8406 0.4006       -0.0536
0.0214
dx_20_L01d            -0.0556       0.0480 -1.1578 0.2469       -0.1497
0.0385
dx_30_L01d             0.1178       0.0598  1.9692 0.0489        0.0006
0.2351
dx_60_L01d            -0.1265       0.0643 -1.9680 0.0491       -0.2524
-0.0005
dx_120_L01d            0.1043       0.0515  2.0264 0.0427        0.0034
0.2052
adx_5_L01d            -0.0002       0.0161 -0.0154 0.9877       -0.0318
0.0313
adx_10_L01d            0.0317       0.0385  0.8240 0.4099       -0.0437
0.1071
```

```
adx_20_L01d             0.0461        0.1174  0.3927 0.6945        -0.1841
0.2763
adx_30_L01d            -0.1379        0.1838 -0.7501 0.4532        -0.4980
0.2223
adx_60_L01d             0.1993        0.2487  0.8013 0.4229        -0.2882
0.6868
adx_120_L01d           -0.3308        0.3414 -0.9690 0.3326        -0.9998
0.3383
================================================================================
====

"""
```

1.2.1.2 Analyze the estimates of the model based on the output of 1.2.1.1

(Hint: evaluate both the coefficients and the marginal effects. Do you notice anything about the coefficients on similar variables like `SMA_05` and `SMA_10`? Why?)

[2425]:
```python
result.get_margeff().summary()
```

[2425]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
        Logit Marginal Effects
========================================
Dep. Variable:     positive_return_dummy
Method:                             dydx
At:                              overall
================================================================================
=======
                         dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
return_vol_5_L01d       5.3529      3.196      1.675      0.094      -0.911
11.617
return_vol_10_L01d    -13.3161      4.455     -2.989      0.003     -22.048
-4.584
return_vol_20_L01d      2.9913      6.656      0.449      0.653     -10.054
16.037
return_vol_30_L01d      1.0853      7.533      0.144      0.885     -13.679
15.850
return_vol_60_L01d     -0.3888      8.187     -0.047      0.962     -16.436
15.658
return_vol_120_L01d    18.0075     10.816      1.665      0.096      -3.191
39.206
sma_5_L01d              0.3209      0.404      0.794      0.427      -0.472
1.114
```

sma_10_L01d	0.7502	0.431	1.739	0.082	-0.095	1.596
sma_20_L01d	-0.2574	0.467	-0.551	0.581	-1.172	0.657
sma_30_L01d	0.1780	0.580	0.307	0.759	-0.958	1.314
sma_60_L01d	0.0770	0.323	0.238	0.811	-0.555	0.709
sma_120_L01d	0.2273	0.215	1.056	0.291	-0.195	0.649
ewma_5_L01d	-1.8715	3.963	-0.472	0.637	-9.639	5.896
ewma_10_L01d	-111.3145	121.775	-0.914	0.361	-349.989	127.360
ewma_20_L01d	48.5689	67.053	0.724	0.469	-82.853	179.991
ewma_30_L01d	67.1519	66.326	1.012	0.311	-62.844	197.148
ewma_60_L01d	-4.2685	4.227	-1.010	0.313	-12.553	4.016
ewma_120_L01d	0.4373	0.509	0.860	0.390	-0.560	1.434
macd_L01d	92.0383	1.18e+06	7.78e-05	1.000	-2.32e+06	2.32e+06
macdsingal_L01d	29.0064	1.18e+06	2.45e-05	1.000	-2.32e+06	2.32e+06
macdhist_L01d	63.0320	1.18e+06	5.33e-05	1.000	-2.32e+06	2.32e+06
dx_5_L01d	0.0022	0.002	1.186	0.236	-0.001	0.006
dx_10_L01d	-0.0037	0.004	-0.842	0.400	-0.012	0.005
dx_20_L01d	-0.0129	0.011	-1.162	0.245	-0.035	0.009
dx_30_L01d	0.0274	0.014	1.990	0.047	0.000	0.054
dx_60_L01d	-0.0295	0.015	-1.989	0.047	-0.058	-0.000
dx_120_L01d	0.0243	0.012	2.050	0.040	0.001	0.048
adx_5_L01d	-5.763e-05	0.004	-0.015	0.988	-0.007	0.007
adx_10_L01d	0.0074	0.009	0.826	0.409	-0.010	0.025
adx_20_L01d	0.0107	0.027	0.393	0.694	-0.043	0.064
adx_30_L01d	-0.0321	0.043	-0.751	0.452	-0.116	

```
0.052
adx_60_L01d              0.0464       0.058       0.803       0.422      -0.067
0.160
adx_120_L01d            -0.0770       0.079      -0.971       0.331      -0.232
0.078
================================================================================
=======
"""
```

The coef of sma 5 and sma 10 seems to be different but not similar or close in values. This could be because there was an influence in the 5 day difference window. This implies that during those windows, there was something like an event that influenced the performance.

3.2 1.2.2 Take 2 - Using variable selection

1.2.2.1 Please create four new columns in your dataframe, respectively, with the following indicators using the ratio of the its 20-window value and 120-day window value. For example, the SMA variable would be $SMA_{ratio} = \frac{SMA_{20}}{SMA_{120}}$.

- historical volatility
- MA (simple moving average)
- ADX (average directional movement index)
- DX (directional movement index)

[2426]:
```
train1['ratio_vol_L01d'] = train1['return_vol_20_L01d']/
 ↪train1['return_vol_120_L01d']
train1['ratio_sma_L01d'] = train1['sma_20_L01d']/train1['sma_120_L01d']
train1['ratio_adx_L01d'] = train1['adx_20_L01d']/train1['adx_120_L01d']
train1['ratio_dx_L01d'] = train1['dx_20_L01d']/train1['dx_120_L01d']

val['ratio_vol_L01d'] = val['return_vol_20_L01d']/val['return_vol_120_L01d']
val['ratio_sma_L01d'] = val['sma_20_L01d']/val['sma_120_L01d']
val['ratio_adx_L01d'] = val['adx_20_L01d']/val['adx_120_L01d']
val['ratio_dx_L01d'] = val['dx_20_L01d']/val['dx_120_L01d']
```

1.2.2.2 Now estimate a linear model using the four new varialbes, the values of the four indicators at 10-days window (e.g., `SMA_10`), MACD, along with yesterday's closing price. Print the summary.

[2427]:
```
feat2 = train1[['macd_L01d', 'sma_10_L01d', 'ewma_10_L01d', 'dx_10_L01d',␣
 ↪'adx_10_L01d', 'ratio_vol_L01d', 'ratio_sma_L01d', 'ratio_adx_L01d',␣
 ↪'ratio_dx_L01d', 'Close_L01d']]
feature_cols2 = feat2.columns
```

[2428]:
```
X = train1[feature_cols2]
Y = train1.positive_return_dummy
```

[2429]:
```
linear = sm.OLS(Y, X)
linear_results = linear.fit()
```

[2430]:
```
linear_results.summary()
```

[2430]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
================================================================================
==========
Dep. Variable:     positive_return_dummy   R-squared (uncentered):
0.539
Model:                               OLS   Adj. R-squared (uncentered):
0.533
Method:                    Least Squares   F-statistic:
80.79
Date:                   Mon, 05 Dec 2022   Prob (F-statistic):
3.81e-109
Time:                           16:06:52   Log-Likelihood:
-503.52
No. Observations:                    700   AIC:
1027.
Df Residuals:                        690   BIC:
1073.
Df Model:                             10
Covariance Type:               nonrobust
================================================================================
==
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--
macd_L01d         -0.1075      0.060     -1.783      0.075      -0.226
0.011
sma_10_L01d        0.1515      0.159      0.954      0.341      -0.160
0.463
ewma_10_L01d      -0.1098      0.196     -0.559      0.576      -0.496
0.276
dx_10_L01d        -0.0003      0.001     -0.269      0.788      -0.003
0.002
adx_10_L01d        0.0051      0.003      1.678      0.094      -0.001
0.011
ratio_vol_L01d    -0.0989      0.067     -1.481      0.139      -0.230
0.032
ratio_sma_L01d     0.5548      0.147      3.774      0.000       0.266
0.843
ratio_adx_L01d    -0.0055      0.027     -0.203      0.839      -0.059
```

```
0.048
ratio_dx_L01d     -0.0001      0.000     -0.538      0.591      -0.001
0.000
Close_L01d        -0.0446      0.051     -0.874      0.382      -0.145
0.056
==============================================================================
Omnibus:                     2981.453   Durbin-Watson:                   2.211
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              105.435
Skew:                          -0.139   Prob(JB):                     1.27e-23
Kurtosis:                       1.119   Cond. No.                     1.16e+03
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[3] The condition number is large, 1.16e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

1.2.2.3 Compare your results to those in 1.2.1.2. Discuss your conclusions briefy. Looking at the results, ratio_sma_L01d seems to have the biggest coef values indicating that this variable has the most influence in this model. The 10 day windows seem to have a lower coef than the previous model aboove. This could be because the model above suffered from multi-colinearity.

3.3 1.2.3 Take 3 - DecisionTree and Random Forest

1.2.3.1 Please use the silver data to estimate a tree model and a random forest model. Use `positive_return_dummy` as the dependent variable and your lagged variables are *all* of the variables from 1.1.2 and 1.2.2 as your independent variables.

[2431]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import RocCurveDisplay
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree␣
 ↪Classifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

[2432]:
```
X_train = train1[['Close_L01d', 'return_vol_5_L01d',
       'return_vol_10_L01d', 'return_vol_20_L01d', 'return_vol_30_L01d',
       'return_vol_60_L01d', 'return_vol_120_L01d', 'sma_5_L01d',
       'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d', 'sma_60_L01d',
       'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d', 'ewma_20_L01d',
       'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d', 'macd_L01d',
```

```
       'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d', 'dx_10_L01d',
       'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d', 'adx_5_L01d',
       'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d', 'adx_60_L01d',
       'adx_120_L01d', 'ratio_vol_L01d', 'ratio_sma_L01d', 'ratio_adx_L01d',
       'ratio_dx_L01d']]
Y_train = train1.positive_return_dummy
```

[2433]:
```
clf = RandomForestClassifier(n_estimators=100)
clf = clf.fit(X_train, Y_train)
```

[2434]:
```
# Decision Tree
dectree = DecisionTreeClassifier()
dectree = dectree.fit(X_train, Y_train)
```

4 1.3 Validating the models (a teeny bit)

4.1 1.3.1 Data prep

1.3.1.1 Please preprocess your test data so that it has the same form as your training data and print the head of the final test dataframe.

[2435]:
```
test['ratio_vol_L01d'] = test['return_vol_20_L01d']/test['return_vol_120_L01d']
test['ratio_sma_L01d'] = test['sma_20_L01d']/test['sma_120_L01d']
test['ratio_adx_L01d'] = test['adx_20_L01d']/test['adx_120_L01d']
test['ratio_dx_L01d'] = test['dx_20_L01d']/test['dx_120_L01d']

Y_test = test["positive_return_dummy"]
X_test = test[['Close_L01d', 'return_vol_5_L01d',
       'return_vol_10_L01d', 'return_vol_20_L01d', 'return_vol_30_L01d',
       'return_vol_60_L01d', 'return_vol_120_L01d', 'sma_5_L01d',
       'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d', 'sma_60_L01d',
       'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d', 'ewma_20_L01d',
       'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d', 'macd_L01d',
       'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d', 'dx_10_L01d',
       'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d', 'adx_5_L01d',
       'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d', 'adx_60_L01d',
       'adx_120_L01d', 'ratio_vol_L01d', 'ratio_sma_L01d', 'ratio_adx_L01d',
       'ratio_dx_L01d']]
```

```
/Users/seonhyeyang/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
  """Entry point for launching an IPython kernel.
/Users/seonhyeyang/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/Users/seonhyeyang/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
/Users/seonhyeyang/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

1.3.1.2 For each model in Section 1.2, please use the `xxx.predict(X)` method to produce a vector of predictions based on the out-of-sample data. Create new dataframes made up of a column of the actual value for the dependent variable, and a column for your model's predictions. Print the head of the new data frames.

[2436]:
```
predict_rf = clf.predict(X_test)
rf_df = pd.DataFrame({"Actual":Y_test, "Predicted":predict_rf})
```

[2437]:
```
# rf_df = rf_df.dropna()
rf_df.head()
```

[2437]:

	Actual	Predicted
1063	0.0	1.0
1064	1.0	1.0
1065	1.0	0.0
1066	0.0	0.0
1067	1.0	0.0

[2438]:
```
predict_dt = dectree.predict(X_test)
dt_df = pd.DataFrame({"Actual": Y_test, "Predicted": predict_dt})
```

[2439]:
```
dt_df.head()
```

[2439]:

	Actual	Predicted
1063	0.0	1.0
1064	1.0	0.0
1065	1.0	0.0
1066	0.0	1.0
1067	1.0	0.0

1.3.1.3 Calculate the area under the ROC for each model on the test data and print your results. Which model has the best area under the ROC?

[2440]:
```
from sklearn.metrics import roc_curve, auc, roc_auc_score, RocCurveDisplay,␣
↪confusion_matrix
```

[2441]:
```
tree_fpr, tree_tpr, tree_thresholds = roc_curve(dt_df['Actual'],␣
↪dt_df['Predicted'])
tree_auc = auc(tree_fpr, tree_tpr)
print('Decision Tree ROC AUC:', tree_auc)

forest_fpr, forest_tpr, forest_thresholds = roc_curve(rf_df['Actual'],␣
↪rf_df['Predicted'])
forest_auc = auc(forest_fpr, forest_tpr)
print('Random Forest ROC AUC:', forest_auc)
```

```
Decision Tree AUC: 0.4882744894427138
Random Forest AUC: 0.46897715472481827
```

Random forest seems to have a better ROC

2. Backtesting

5 2.1 In-Sample Testing

5.1 2.1.1 Data Prep

5.1.1 2.1.1.1 Creating signals

2.1.1.1.1 Please define new `signal` variables for each set of model *predictions*. Please assume that model predictions > 0.5 have a `signal` value of 1, and that the value is 0 otherwise. Construct four dataframes (or one dataframe with four columns) and date index, which can be later passed into the `SelectWhere()` function, each column being the boolean `signal` produced by one of the four models, with appropriate column names. Print the head of the dataframes. (Note that if we had more information about trading costs and profits, we could estimate the "optimal" cutoff value, but for simplicity, here, we will assume that we can use 0.5.)

[2442]:
```python
import bt
```

[2443]:
```python
x = val[['Close_L01d', 'return_vol_5_L01d',
        'return_vol_10_L01d', 'return_vol_20_L01d', 'return_vol_30_L01d',
        'return_vol_60_L01d', 'return_vol_120_L01d', 'sma_5_L01d',
        'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d', 'sma_60_L01d',
        'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d', 'ewma_20_L01d',
        'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d', 'macd_L01d',
        'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d', 'dx_10_L01d',
        'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d', 'adx_5_L01d',
        'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d', 'adx_60_L01d',
        'adx_120_L01d', 'ratio_vol_L01d', 'ratio_sma_L01d', 'ratio_adx_L01d',
        'ratio_dx_L01d']]
y = val["positive_return_dummy"]
```

[2444]:
```python
#decision tree, random forest, linear, and logit model prediction.

dt_val = dectree.predict(x)
rf_val = clf.predict(x)
ols = linear_results.predict(val[feature_cols2])
logit = result.predict(val[['return_vol_5_L01d', 'return_vol_10_L01d',␣
 ↪'return_vol_20_L01d',
        'return_vol_30_L01d', 'return_vol_60_L01d', 'return_vol_120_L01d',
        'sma_5_L01d', 'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d',
        'sma_60_L01d', 'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d',
        'ewma_20_L01d', 'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d',
        'macd_L01d', 'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d',
        'dx_10_L01d', 'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d',
        'adx_5_L01d', 'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d',
        'adx_60_L01d', 'adx_120_L01d']])
```

[2445]:
```python
#defining new signal variables for each set of model predictions.

signal_insample = pd.DataFrame({'tree': np.where(dt_val > 0.5, 1, 0)})
signal_insample['forest'] = np.where(rf_val > 0.5, 1, 0)
signal_insample['linear'] = np.where(ols > 0.5, 1, 0)
signal_insample['logit'] = np.where(logit > 0.5, 1, 0)
```

[2446]:
```python
signal_insample['Date'] = np.append(val['Date_L01d'].dt.date.astype(str).
 ↪values[1:], last_date_val)

signal_insample['Date'] = pd.to_datetime(signal_insample['Date'])
```

[2447]:
```python
signal_insample.set_index('Date', inplace=True)
```

[2448]:
```python
signal_insample.head()
```

[2448]:

	tree	forest	linear	logit
Date				
2021-07-08	0	0	1	1
2021-07-09	1	1	1	1
2021-07-12	0	0	1	1
2021-07-13	1	0	1	1
2021-07-14	0	0	1	1

[2449]:

```
signal_outsample = pd.DataFrame({'tree': np.where(dt_df['Predicted'] > 0.5, 1,␣
↪0)})
signal_outsample['forest'] = np.where(rf_df['Predicted'] > 0.5, 1, 0)
```

[2450]:

```
ols_pred = linear_results.predict(X_test[feature_cols2])
logit_pred = result.predict(X_test[['return_vol_5_L01d', 'return_vol_10_L01d',␣
↪'return_vol_20_L01d',
       'return_vol_30_L01d', 'return_vol_60_L01d', 'return_vol_120_L01d',
       'sma_5_L01d', 'sma_10_L01d', 'sma_20_L01d', 'sma_30_L01d',
       'sma_60_L01d', 'sma_120_L01d', 'ewma_5_L01d', 'ewma_10_L01d',
       'ewma_20_L01d', 'ewma_30_L01d', 'ewma_60_L01d', 'ewma_120_L01d',
       'macd_L01d', 'macdsingal_L01d', 'macdhist_L01d', 'dx_5_L01d',
       'dx_10_L01d', 'dx_20_L01d', 'dx_30_L01d', 'dx_60_L01d', 'dx_120_L01d',
       'adx_5_L01d', 'adx_10_L01d', 'adx_20_L01d', 'adx_30_L01d',
       'adx_60_L01d', 'adx_120_L01d']])

signal_outsample['ols'] = np.where(ols_pred > 0.5, 1, 0)
signal_outsample['logit'] = np.where(logit_pred > 0.5, 1, 0)
signal_outsample['Date'] = pd.to_datetime(np.append(test['Date_L01d'].dt.date.
↪astype(str).values[1:], last_date))

signal_outsample.set_index('Date', inplace=True)

signal_outsample.head()
```

[2450]:

	tree	forest	ols	logit
Date				
2022-01-03	1	1	0	1
2022-01-04	0	1	0	1
2022-01-05	0	0	0	1
2022-01-06	1	0	0	1
2022-01-07	0	0	0	1

5.1.2 2.1.1.2 Organizing price data

2.1.1.2.1 We also need our price data for our backtesting. Please create a new dataframe or four one-column dataframes (within the same time range as the signal dataframe) with four columns of closing prices of silver future, each with a *same*

column name of the signal dataframe, and date index. This dataframe will be later passed into `bt.Backtest()`. Print the head of the dataframes. (Note: pay careful attention to whether or not we need to lag the closing prices for backtesting)

[2451]:
```python
close_insample = pd.DataFrame({'tree': val['Close_L01d'], 'forest':␣
↪val['Close_L01d'], 'linear': val['Close_L01d'], 'logit': val['Close_L01d'],␣
↪'Date': np.append(val['Date_L01d'].dt.date.astype(str).values[1:],␣
↪last_date_val)
})

#convert dates to datetime
close_insample['Date'] = pd.to_datetime(close_insample['Date'])

close_insample.set_index('Date', inplace=True)

close_insample.head()
```

[2451]:
```
              tree  forest  linear   logit
Date
2021-07-08  26.129  26.129  26.129  26.129
2021-07-09  25.987  25.987  25.987  25.987
2021-07-12  26.234  26.234  26.234  26.234
2021-07-13  26.239  26.239  26.239  26.239
2021-07-14  26.140  26.140  26.140  26.140
```

[2452]:
```python
close_outsamp_df = pd.DataFrame({'tree': test['Close_L01d'], 'forest':␣
↪test['Close_L01d'], 'linear': test['Close_L01d'], 'logit':␣
↪test['Close_L01d'], 'Date': np.append(test['Date_L01d'].dt.date.astype(str).
↪values[1:], last_date)
})

#convert dates to datetime
close_outsamp_df['Date'] = pd.to_datetime(close_outsamp_df['Date'])

close_outsamp_df.set_index('Date', inplace=True)

close_outsamp_df
```

[2452]:
```
              tree  forest  linear   logit
Date
2022-01-03  23.352  23.352  23.352  23.352
2022-01-04  22.810  22.810  22.810  22.810
2022-01-05  23.056  23.056  23.056  23.056
2022-01-06  23.170  23.170  23.170  23.170
2022-01-07  22.190  22.190  22.190  22.190
…              …       …       …       …
2022-11-02  19.667  19.667  19.667  19.667
```

```
2022-11-03  19.594  19.594  19.594  19.594
2022-11-04  19.430  19.430  19.430  19.430
2022-11-07  20.784  20.784  20.784  20.784
2022-11-08  20.919  20.919  20.919  20.919

[215 rows x 4 columns]
```

5.2 2.1.2 Individual Backtests

In this section, you will be performing backtesting using the bt package.

`We can perform a backtesting following:`

```
algo_stack = [SelectWhere(signal), bt.algos.WeighEqually(), bt.algos.Rebalance()]
strategy = bt.Strategy(strategy_name, algo_stack)
bt_instance = bt.Backtest(strategy, closing_price)
res = bt.run(bt_instance)
```

`We can access the statistics of the backtest using`

`res.stats`

`We can view the equity curve using`

`res.plot()`

(Hint: To avoid unexpected bugs, the inputs into `SelectWhere()` and `bt.Backtest()` should be dataframes with the same column names)

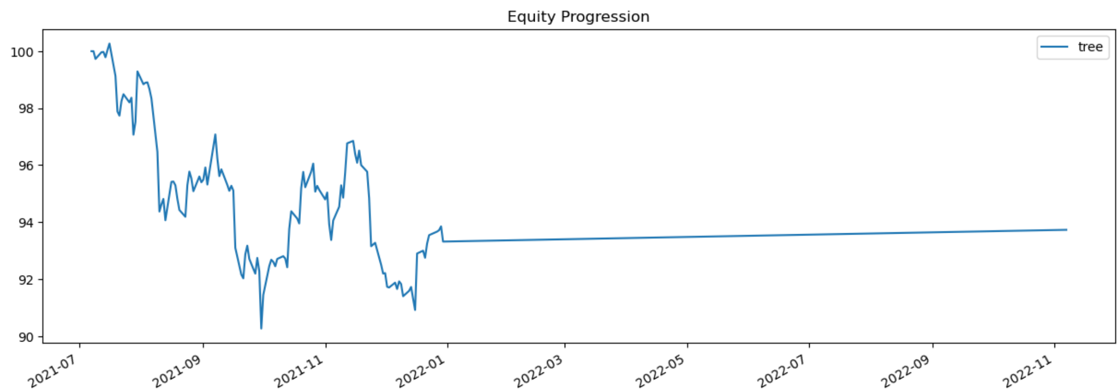
2.1.2.1 Using the above functions, please perform in-sample backtests for your four strategies. Plot the equity progression curves for all strategies, with take_1 and take_2 on the same plot, and take_3 and take_4 on the same plot.

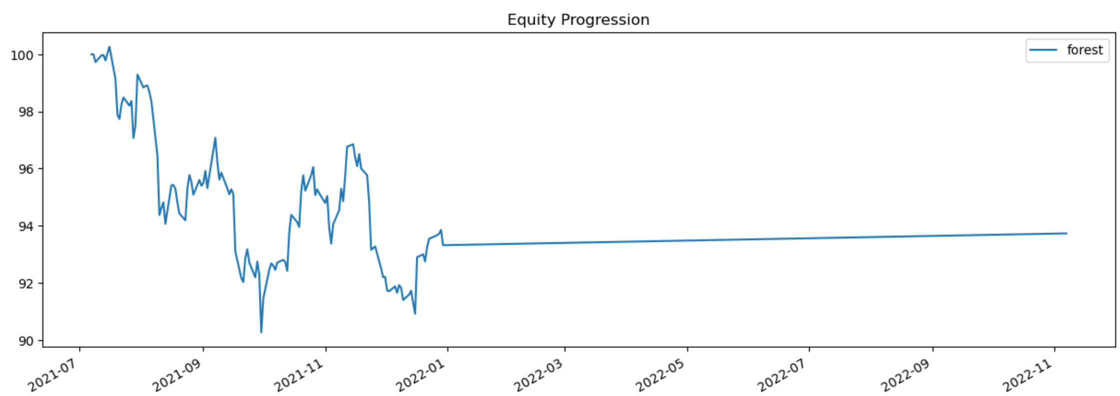
[2465]:
```
#tree
algo_stack = [SelectWhere(signal_insample), bt.algos.WeighEqually(), bt.algos.
 ↪Rebalance()]
strategy_tree = bt.Strategy('tree', algo_stack)
bt_instance_tree = bt.Backtest(strategy_tree, close_insamp_df)
res_tree = bt.run(bt_instance_tree)



#forest
strategy_forest = bt.Strategy('forest', algo_stack)
bt_instance_forest = bt.Backtest(strategy_forest, close_insamp_df)
res_forest = bt.run(bt_instance_forest)

#linear
strategy_ols = bt.Strategy('linear', algo_stack)
bt_instance_ols = bt.Backtest(strategy_ols, close_insamp_df)
res_ols = bt.run(bt_instance_ols)
```

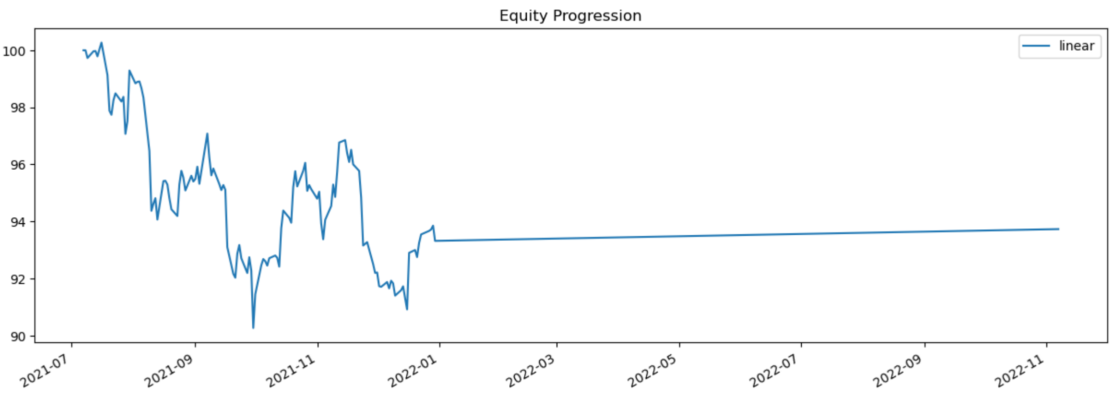
```
#logit
strategy_logit = bt.Strategy('logit', algo_stack)
bt_instance_logit = bt.Backtest(strategy_logit, close_insamp_df)
res_logit = bt.run(bt_instance_logit)
```

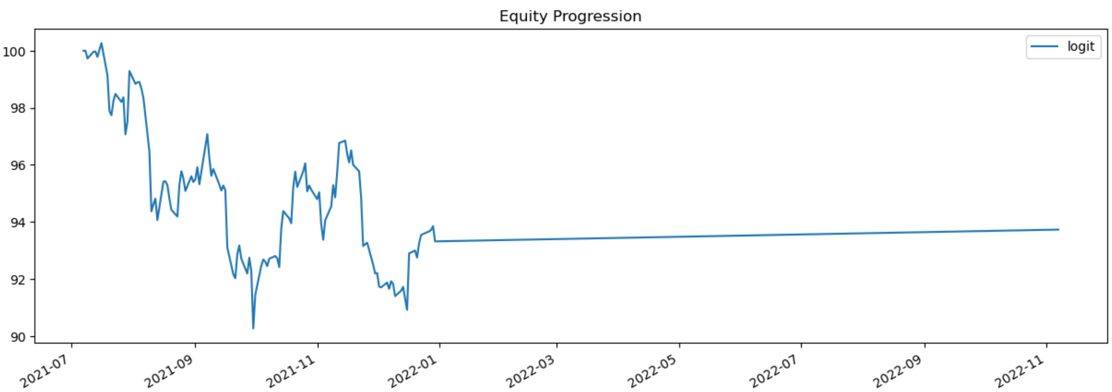
[2472]:
```
res_tree.plot()
res_forest.plot()

res_ols.plot()
res_logit.plot()
```

[2472]: <AxesSubplot:title={'center':'Equity Progression'}>









2.1.2.2 Please display the statistics of the backtests.

[2455]:
```python
stat = pd.DataFrame(res_tree.stats)

stat['forest'] = res_forest.stats
stat['ols'] = res_ols.stats
stat['logit'] = res_logit.stats

stat.head()
```

[2455]:
```
                             tree               forest                  ols  \
start         2021-07-07 00:00:00  2021-07-07 00:00:00  2021-07-07 00:00:00
end           2022-11-07 00:00:00  2022-11-07 00:00:00  2022-11-07 00:00:00
rf                            0.0                  0.0                  0.0
total_return            -0.062703            -0.062703            -0.062703
cagr                    -0.047311            -0.047311            -0.047311

                            logit
start         2021-07-07 00:00:00
```

```
end            2022-11-07 00:00:00
rf                             0.0
total_return             -0.062703
cagr                     -0.047311
```

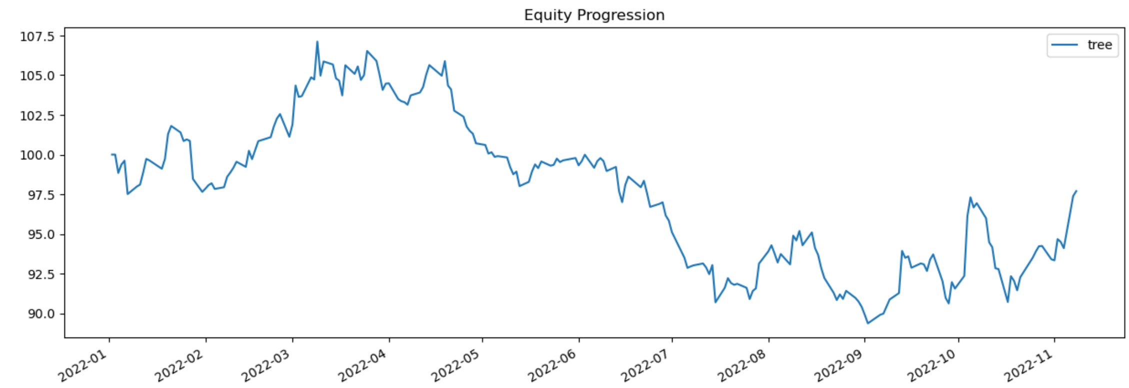
2.1.2.3 Write a short paragraph to report and analyze the pregression curves and the statistics.

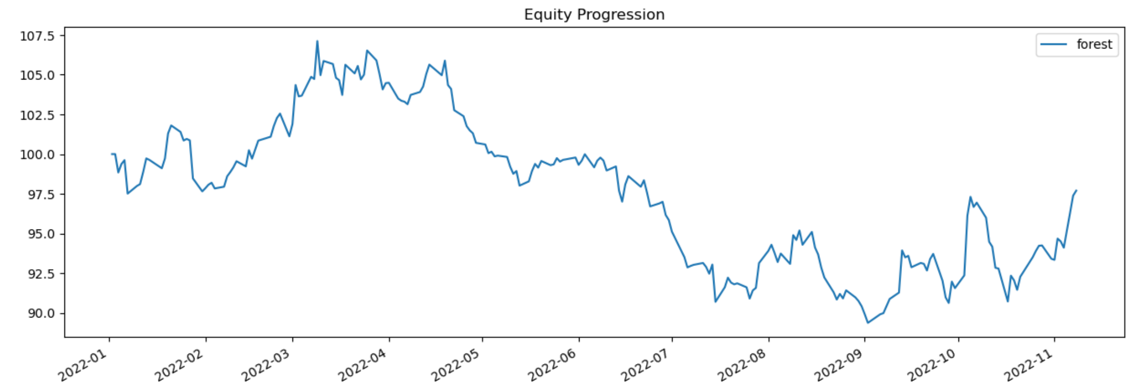
6 2.2 Out-of-Sample Testing

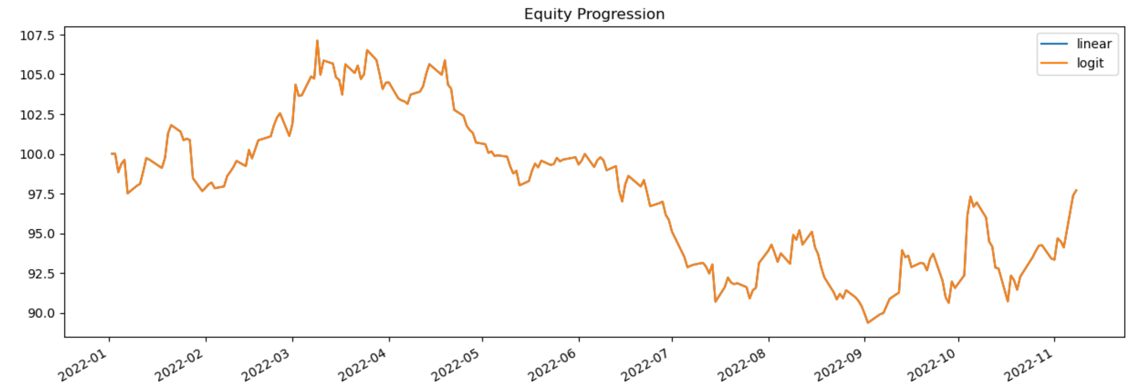
2.2.1 Please backtest your best model using the out-of-sample data, plot the results and stastics.

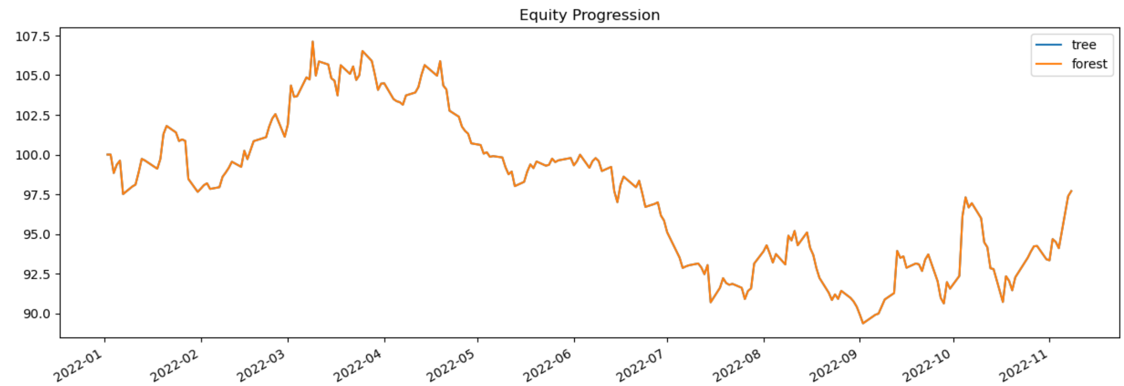
[2473]:
```
algo_stack_out = [SelectWhere(signal_outsample), bt.algos.WeighEqually(), bt.
↪algos.Rebalance()]
strategy_tree_out = bt.Strategy('tree', algo_stack_out)
bt_instance_tree_out = bt.Backtest(strategy_tree_out, close_outsamp_df)
res_tree_out = bt.run(bt_instance_tree_out)
res_tree_out.plot()

strategy_forest_out = bt.Strategy('forest', algo_stack_out)
bt_instance_forest_out = bt.Backtest(strategy_forest_out, close_outsamp_df)
res_forest_out = bt.run(bt_instance_forest_out)
res_forest_out.plot()

#linear
strategy_ols_out = bt.Strategy('linear', algo_stack_out)
bt_instance_ols_out = bt.Backtest(strategy_ols_out, close_outsamp_df)
res_ols_out = bt.run(bt_instance_ols_out)

#logit
strategy_logit_out = bt.Strategy('logit', algo_stack_out)
bt_instance_logit_out = bt.Backtest(strategy_logit_out, close_outsamp_df)
res_logit_out = bt.run(bt_instance_logit_out)

res_ols_logit_out = bt.run(bt_instance_ols_out, bt_instance_logit_out)
res_ols_logit_out.plot()

res_tree_forest_out = bt.run(bt_instance_tree_out, bt_instance_forest_out)
res_tree_forest_out.plot()
```

[2473]:
```
<AxesSubplot:title={'center':'Equity Progression'}>
```


Equity Progression
tree
107.5
105.0
102.5
100.0
97.5
95.0
92.5
90.0
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
2022-08
2022-09
2022-10
2022-11


Equity Progression
forest
107.5
105.0
102.5
100.0
97.5
95.0
92.5
90.0
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
2022-08
2022-09
2022-10
2022-11


Equity Progression
linear
logit
107.5
105.0
102.5
100.0
97.5
95.0
92.5
90.0
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
2022-08
2022-09
2022-10
2022-11



[2457]:
```
stats = pd.DataFrame(res_tree_out.stats)

stats['random'] = res_forest_out.stats
stats['linear'] = res_ols_out.stats
stats['logit'] = res_logit_out.stats
```

[2458]:
```
stats.head()
```

[2458]:
```
                             tree               random               linear  \
start         2022-01-02 00:00:00  2022-01-02 00:00:00  2022-01-02 00:00:00
end           2022-11-08 00:00:00  2022-11-08 00:00:00  2022-11-08 00:00:00
rf                            0.0                  0.0                  0.0
total_return            -0.022989            -0.022989            -0.022989
cagr                     -0.02703             -0.02703             -0.02703

                            logit
start         2022-01-02 00:00:00
end           2022-11-08 00:00:00
rf                            0.0
total_return            -0.022989
cagr                     -0.02703
```

2.2.2 Please interpret your result and compare it to the corresponding in-sample back-testing results. Outsample and insample on all same methods. Outsample seems to do better than insample. Although there is a dip starting on April 2022. Then it continues to decrease and stays pretty much volatile throughout. Whereas, insample seems to be more volatile as we can see by sudden dips and sudden ups.

3. One more thing…

In this short excercise you have had the opportunity to try to build a simple trading system. Please describe what you see as the major challenges you encountered and

what, if anything, you might do to address them (2-3 paragraphs only, please). One of the major challenges of building a trading system is that it's very hard to build a good trading system. Prices can get erratic and things can get unpredictable. One of the great things about backtesting is that it allows us to apply our ideas to historical data of the market.

One of the major challenges I encountered was building a backtesting system. This was challenging because I don't have the experience. But also, the model didn't perform as well as I wanted it to. If I could improve this model, I could do feature selection which can help reduce multicollinarity.

Extra Credit* (not required)

6.0.1 By leveraging what you've learned in HW01, can you build a model that leads to a strategy that performs better in backtesting than this model? Write a paragraph to explain your results.

[2459]:
```
#building tree model
X_train_extra = train1[['Log_Return_L01d', 'return_vol_5_L01d',
                        'return_vol_10_L01d', 'return_vol_20_L01d',␣
 ↪'return_vol_30_L01d',
                        'return_vol_60_L01d', 'return_vol_120_L01d',␣
 ↪'macdsingal_L01d', 'macdhist_L01d',
                        'macdsingal_L01d', 'macdhist_L01d']]
Y_train_extra = train1["positive_return_dummy"]

X_test_extra =  test[['Log_Return_L01d', 'return_vol_5_L01d',
                        'return_vol_10_L01d', 'return_vol_20_L01d',␣
 ↪'return_vol_30_L01d',
                        'return_vol_60_L01d', 'return_vol_120_L01d',␣
 ↪'macdsingal_L01d', 'macdhist_L01d',
                        'macdsingal_L01d', 'macdhist_L01d']]
Y_test_extra = test["positive_return_dummy"]

X_val_extra = val[['Log_Return_L01d', 'return_vol_5_L01d',
                        'return_vol_10_L01d', 'return_vol_20_L01d',␣
 ↪'return_vol_30_L01d',
                        'return_vol_60_L01d', 'return_vol_120_L01d',␣
 ↪'macdsingal_L01d', 'macdhist_L01d',
                        'macdsingal_L01d', 'macdhist_L01d']]
Y_val_extra = val['positive_return_dummy']
```

[2460]:
```
tree = DecisionTreeClassifier(max_depth=6, random_state=0, min_samples_leaf=5)
tree.fit(X_train_extra, Y_train_extra)

y_pred1 = tree.predict(X_val_extra)
insamp_ec_res = pd.DataFrame({'real': Y_val_extra, 'pred': y_pred1})
y_pred_test = random.predict(X_test_extra)
outsamp_ec_res = pd.DataFrame({'real': Y_test_extra, 'pred': y_pred_test})
```

[2475]:
```
fpr, tpr, thresholds = metrics.roc_curve(insamp_ec_res['real'],␣
    ↪insamp_ec_res['pred'])
print('In Sample AUC:', metrics.auc(fpr, tpr))

#out-of-sample
fpr, tpr, thresholds = metrics.roc_curve(outsamp_ec_res['real'],␣
    ↪outsamp_ec_res['pred'])
print('Out of Sample AUC:', metrics.auc(fpr, tpr))
```

```
In-Sample AUC: 0.5398126463700234
Out-of-Sample AUC: 0.5066632052613361
```

[2462]:
```
signal_insamp_extra = pd.DataFrame({'extra_tree': np.where(y_pred1 > 0.5, 1,␣
    ↪0), 'extra_tree1': np.where(y_pred1 > 0.5, 1, 0)})
signal_insamp_extra['Date'] = np.append(val['Date_L01d'].dt.date.astype(str).
    ↪values[1:], last_date_val)
signal_insamp_extra['Date'] = pd.to_datetime(signal_insamp_extra['Date'])
signal_insamp_extra.set_index('Date', inplace=True)
close_insamp_extra = pd.DataFrame({'extra_tree': val['Close_L01d'],␣
    ↪'extra_tree1': val['Close_L01d']})
close_insamp_extra['Date'] = np.append(val['Date_L01d'].dt.date.astype(str).
    ↪values[1:], last_date_val)
close_insamp_extra['Date'] = pd.to_datetime(close_insamp_extra['Date'])
close_insamp_extra.set_index('Date', inplace=True)
```

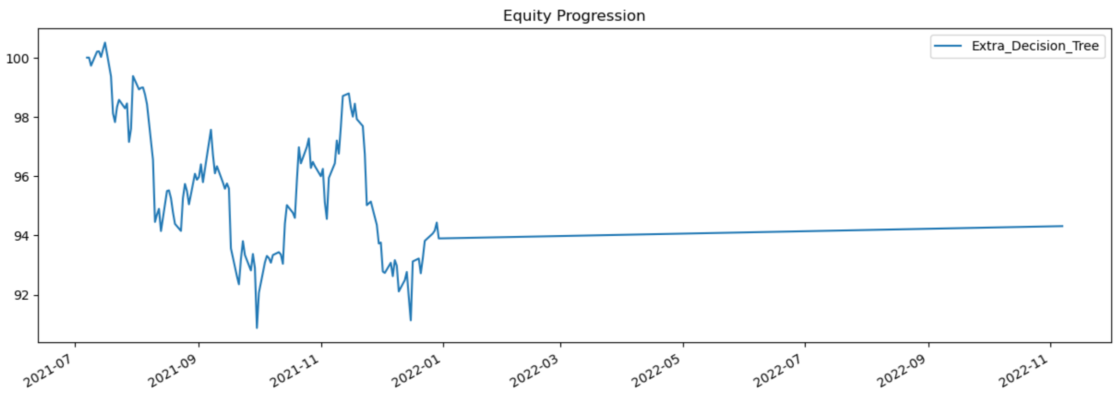
[2463]:
```
signal_outsamp_extra = pd.DataFrame({'extra_tree': np.where(y_pred_test > 0.5,␣
    ↪1, 0), 'extra_tree1': np.where(y_pred_test > 0.5, 1, 0)})
signal_outsamp_extra['Date'] = np.append(test['Date_L01d'].dt.date.astype(str).
    ↪values[1:], last_date)
signal_outsamp_extra['Date'] = pd.to_datetime(signal_outsamp_extra['Date'])
signal_outsamp_extra.set_index('Date', inplace=True)
close_outsamp_extra = pd.DataFrame({'extra_tree': test['Close_L01d'],␣
    ↪'extra_tree1': test['Close_L01d']})
close_outsamp_extra['Date'] = np.append(test['Date_L01d'].dt.date.astype(str).
    ↪values[1:], last_date)
close_outsamp_extra['Date'] = pd.to_datetime(close_outsamp_extra['Date'])
```

[2474]:
```
algo_stack_extra = [SelectWhere(signal_insamp_extra), bt.algos.WeighEqually(),␣
    ↪bt.algos.Rebalance()]
strategy_tree_extra = bt.Strategy('Extra_Decision_Tree', algo_stack_extra)
bt_instance_extra = bt.Backtest(strategy_tree_extra, close_insamp_extra)
res_extra = bt.run(bt_instance_extra)
print('In-Sample Backtest Results')
res_extra.plot()
res_extra.stats
```

```
In-Sample Backtest Results
```

[2474]:

	Extra_Decision_Tree
start	2021-07-07 00:00:00
end	2022-11-07 00:00:00
rf	0.0
total_return	-0.056871
cagr	-0.042877
max_drawdown	-0.095831
calmar	-0.447428
mtd	NaN
three_month	0.004418
six_month	0.004418
ytd	0.004418
one_year	-0.016964
three_year	NaN
five_year	NaN
ten_year	NaN
incep	-0.042877
daily_sharpe	-0.879481
daily_sortino	-1.432799
daily_mean	-0.11105
daily_vol	0.126268
daily_skew	-0.044848
daily_kurt	0.797116
best_day	0.021814
worst_day	-0.021854
monthly_sharpe	-0.826847
monthly_sortino	-1.599175
monthly_mean	-0.126177
monthly_vol	0.1526
monthly_skew	1.278451
monthly_kurt	1.416291
best_month	0.060115
worst_month	-0.052165
yearly_sharpe	NaN
yearly_sortino	NaN
yearly_mean	0.004418
yearly_vol	NaN
yearly_skew	NaN
yearly_kurt	NaN
best_year	0.004418
worst_year	0.004418
avg_drawdown	-0.033478
avg_drawdown_days	160.0
avg_up_month	0.030971
avg_down_month	-0.038172
win_year_perc	1.0
twelve_month_win_perc	0.166667



I suspect there was multicollinearity before the extra credit ones. This one reduces multicollinearity.

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[ ]: