```
In [3]: import pandas as pd
import numpy as np
import yfinance as yf

In [53]: """ Data """

sp500 = yf.Ticker("^GSPC").history(period="10y")
px_sp_s = sp500['Close']
px_sp_s.index = px_sp_s.index.date

In [52]: jpy = yf.Ticker("JPY=X").history(period="10y")
px_jpy_s = jpy['Close']
px_jpy_s.index = px_jpy_s.index.date

In [117... # Normally we pull data using some pd.read_csv(".datal.csv") etc...
```

Task 1

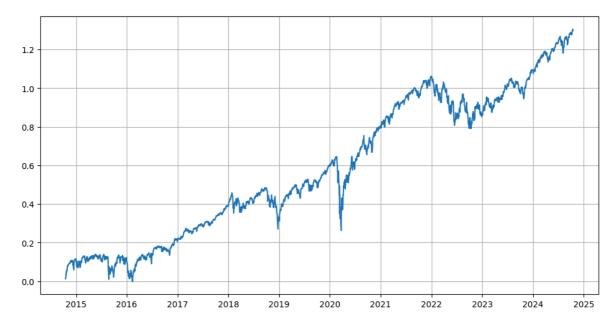
ret_s = px_sp_s.pct_change()

Out[48]: <AxesSubplot: >

ret_s.cumsum().plot(figsize=(12,6), grid=True)

Problem: What is the sharp ratio of buy-and-hold strategy for SP500 for the last 10Y?

```
In [47]: px_sp_s.plot(figsize=(12,6), grid=True)
Out[47]: <AxesSubplot: >
         6000
         5500
         5000
         4500
         4000
         3500
         3000
         2500
         2000
                                       2018
                                                      2020
                                                                     2022
                                                                                    2024
In [48]: # Converting prices to daily returns
```



```
In [36]: # Calculating average daily return
daily_ret = ret_s.mean()
```

```
In [35]: # Calculating daily STD
    daily_std = ret_s.std()
    daily_std
```

Out[35]: 0.011226050390846495

```
In [37]: # Daily SR (not meaningful before annualizing)
   daily_sr = daily_ret/daily_std
   daily_sr
```

Out[37]: 0.046130453769770714

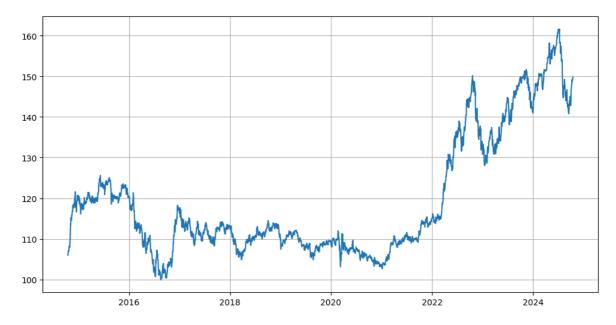
```
In [42]: # Annual SR (returns grow linearly with time, standard deviation with squ
trading_day_per_year = 252
annual_sharp_ratio = (daily_ret * trading_day_per_year) / (daily_std * np
annual_sharp_ratio
```

Out[42]: 0.7322982512482521

Task 2

Problem: Please build a strategy to trade a momentum signal for USDJPY.

```
In [55]: px_jpy_s.plot(figsize=(12,6), grid=True)
Out[55]: <AxesSubplot: >
```

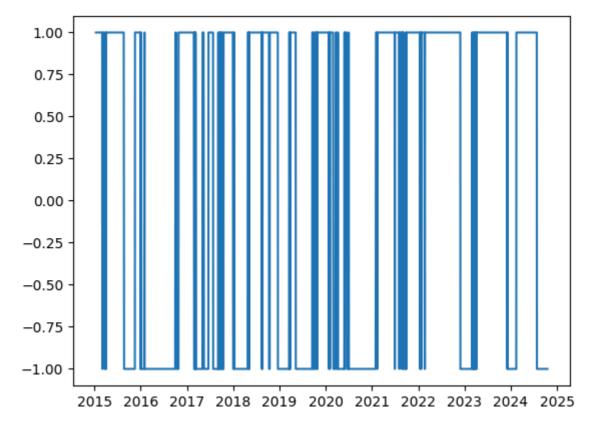


```
In [89]: """ Momentum indicator: sum of returns of last 63 days > 0 -> buy, < 0 ->
    window = 63

ret_jpy_s = px_jpy_s.pct_change()
    momentum = ret_jpy_s.rolling(window).sum()
```

```
In [91]: signal_mom = momentum.dropna().apply(lambda x: 1 if x > 0 else -1)
signal_mom.plot()
```

Out[91]: <AxesSubplot: >



```
in [92]: jpy_mom_returns = (ret_jpy_s * signal_mom.shift(1)).dropna()
jpy_mom_returns.cumsum().plot(figsize=(12,6), grid=True, title="63D Momen
```

Out[92]: <AxesSubplot: title={'center': '63D Momentum USDJPY'}>



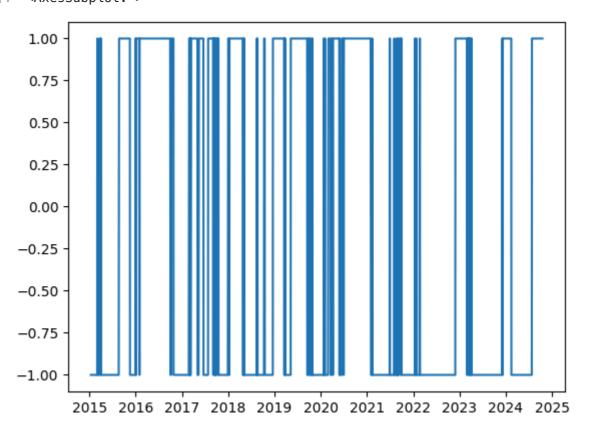
Task 3

Problem: Now make it a mean-reversion strategy

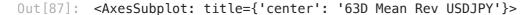
Piotr comment: This is actually as easy as replacing 1 with -1. If symbol was going up recently we assume it should start going down.

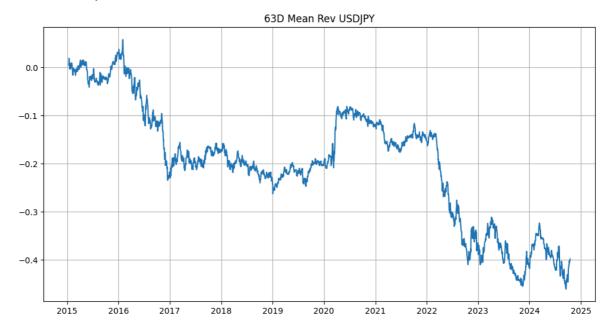
```
In [85]: signal_mr = momentum.dropna().apply(lambda x: -1 if x > 0 else 1)
    signal_mr.plot()
```

Out[85]: <AxesSubplot: >



```
In [87]: strategy_returns = (ret_s * signal_mr.shift(1)).dropna()
    strategy_returns.cumsum().plot(figsize=(12,6), grid=True, title="63D Mean
```





Task 4

Problem: Combine USDJPY momentum and SP500 buy and hold strategies into one portfolio, with equal / reasonably close weights.

Piotr comment: The key is the weighting. You achieve that by making sure that on average they have returns of simmilar scale. This is the difficult part of the interview that only people with real Quant Researcher experience usually get to.

You do this by **Vol Weighting**, meaning that you give higher weight to strategy with lower volatility and lower weight to strategy with higher volatility, so that on average they will contribute simmilar \$ to your daily PnL.

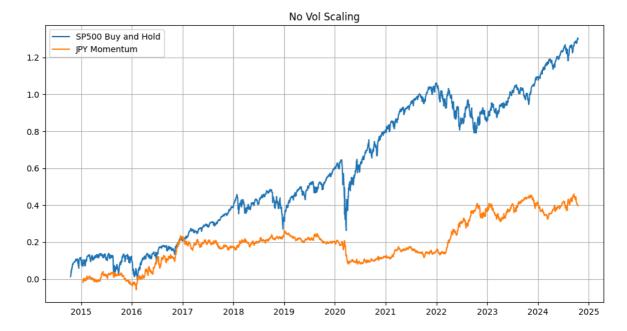
```
In [93]: ret_sp = px_sp_s.pct_change() # SP500 buy and hold (ret * 1)
    jpy_mom_returns = (ret_jpy_s * signal_mom.shift(1)).dropna()

In [114... # Weighted
    ret_sp_weighted = (ret_sp / (ret_sp.rolling(63).std() * 100))
    jpy_mom_weighted = (jpy_mom_returns / (jpy_mom_returns.rolling(63).std())
```

Comparison

```
In [108... # Without vol scaling - note how USDJPY momentum strategy contributes muc
ret_sp.cumsum().plot(figsize=(12,6), title="No Vol Scaling", label="SP500
jpy_mom_returns.cumsum().plot(label="JPY Momentum", legend=True, grid=Tru

Out[108... <AxesSubplot: title={'center': 'No Vol Scaling'}>
```



In [116... # With vol scaling
 ret_sp_weighted.cumsum().plot(figsize=(12,6), title="No Vol Scaling", lab
 jpy_mom_weighted.cumsum().plot(label="JPY Momentum", legend=True, grid=Tr



Conclusion

By dividing returns by rolling std I am adjusting for the fact that USDJPY has much lower volatility. Hence both strategies contribute more or less the same to the portfolio in risk terms. SP500 is still much better strategy but what can you do if Jerome Powell goes brrr....

In	[]:	
In	[]:	
In	[]:	