Euro Dollar Future Trading Strategy

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Summary of Strategy

Short-Term Rates Trend Strategy, Step by Step:

1. For each futures contract, forecast the next day's volatility using a GARCH(1,1) with past three years' daily return.

2. Compare the forecast to the trailing three years' fitted GARCH volatility; if the forecast is above the median, use High Vol Regime; otherwise, use Low Vol Regime.

3. Compare the current contract price to the moving average price that corresponds to the current volatility regime (Low, use 66 days; High, use 252 days).

4. If the contract price is above the moving average price, the strategy generates a "Long" signal—buy the contract (or hold if already long) at the close on the next business day. If the contract is below the moving average price, the strategy generates a "Short" signal—sell the contract (or hold if already short).

5. Repeat process for each of the four contracts in each region, equally weighting the four contracts and weighting the regions proportionally to open interest.

Main functions

➢ **future_analyzing_contract:**

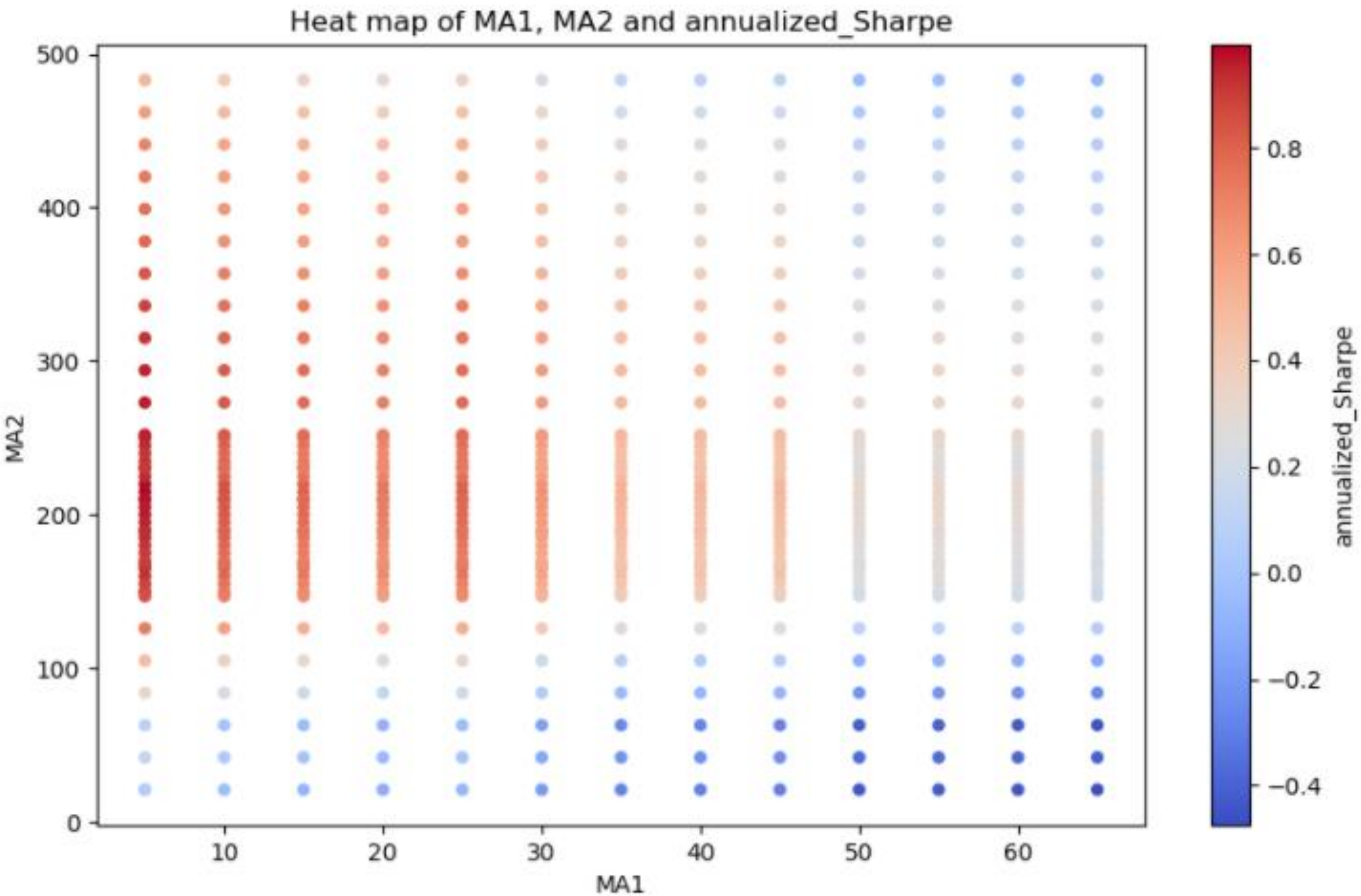
```
future_analyzing_contract(price,window = 252*3, MA1 = 66, MA2=262, forecast_horizon = 1, agg ='mean', update_regime = 5): # c
'''
This function is to calculate the return of a future constract with a trading strategy based of volatility regime and moving
(for low volatility regime) and 252 days (for high volatility regime)

Input
-----
    Price: a data frame with a Time column and Price column
    window: number of days to fit GARCH(1,1)
    forecast_horizon: horizon to forecast volatility regime
    update_regime: the frequency of regime update

Output
------
    price_minus_window: a dataframe with 10 columns including Time,price, log_ret,low66, high252, forecasted _variance, reali
    annualized_returns
    annualized_sharpe
    annualized_standard_deviation
    proportion_long_over_short
    max_draw_down
```

Main functions

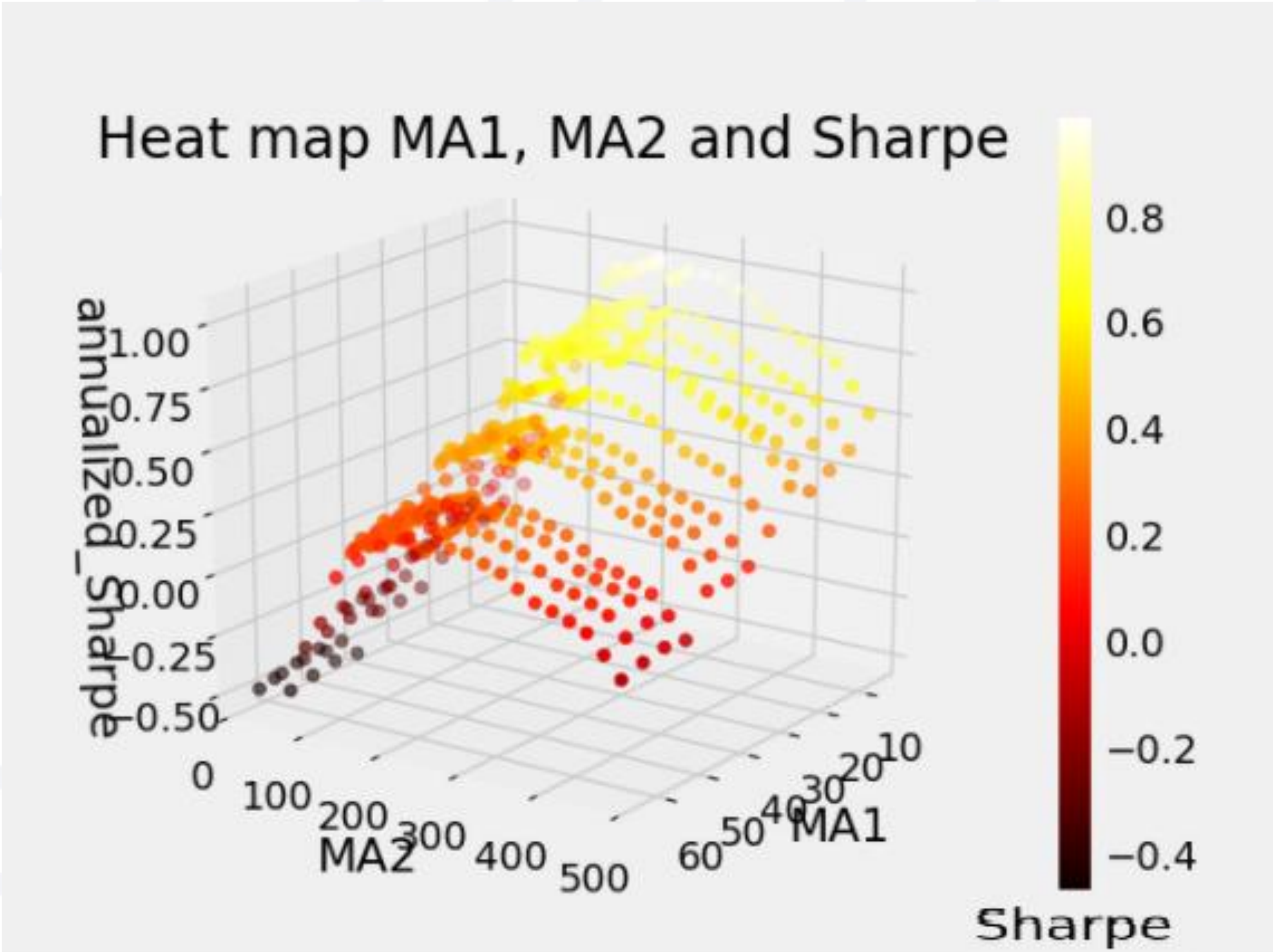
- **future_analyzing_port_baseline:**

```
future_analyzing_port_baseline(data, MA1 = 5, MA2=210, window = 3,  forecast_horizon = 5, update_regime = 5):
'''
This function is to calculate the return of a portfolio that include many future contracts

Input
-----
    data: a csv file cotaining columns. Each column provides price over time of 1 future contract
    window: number of years to fit GARCH(1,1), can be from 1-4, otherwise we can not have enough observations for strategy
    weight: for calcualting the portfolio return, can be 'max_sharpe', 'min_vol' or equal
    MA1: moving average window for low volatility regime
    MA2: moving average window for high volatility regime
    forecast_horizon: horizon to forecast volatility regime
    agg: the method to choose the calculate the volatility forecast if  forecast_horizon > 1, the method can be 'min', 'max',
    update_regime: the frequency of regime update

Output
------
    port_ret: a dataframe which includes Time and return of each contract
    port_ret1: similar to port_ret but with Time column is convereted to index
    summary_port: a data frame containing avg_annualized_return, annualized_standard_deviation and annualized_Sharpe of portf
    summary_contracts: annualized_ret, annualized_sharpe, standard_deviations, max_draw_downs of individual contracts.
    weights: optimal weights of portfolio in 3 cases: 'max_shape', 'min_volatility' and 'equal_weight'
    annualized_Sharpe, max_draw_down_port: annualized_sharpe and max_draw_down of portfolio
```

1. run grid-search with changes of MA1 (fast-moving window) and MA2 (slow-moving window) to see how these parameters affect the Sharpe ratio

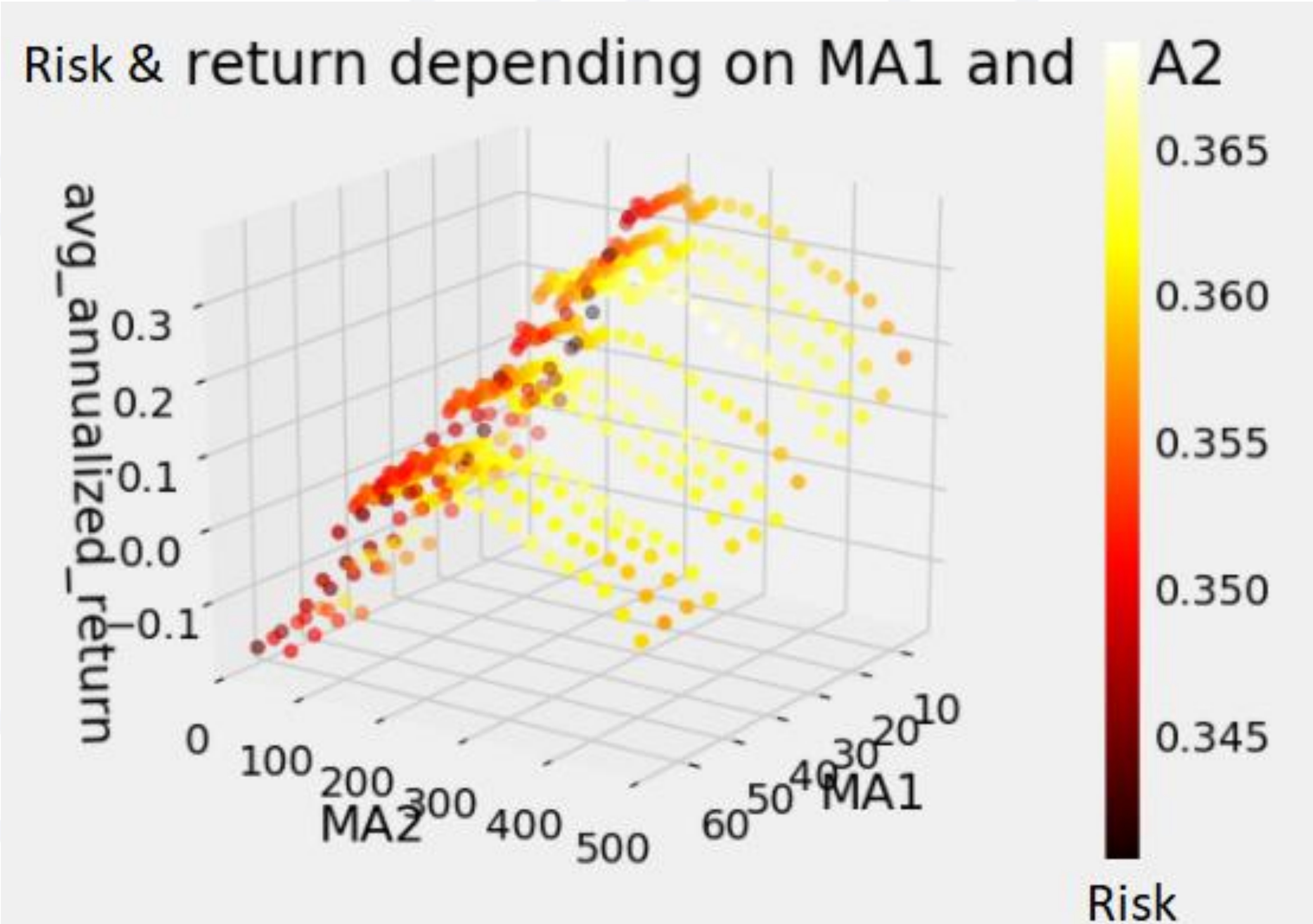


For easier to imagination, I created a 3d heat map



It can be seen that MA1 = 5 days and MA2 moves in a range from 200 - 300 days tends to produce highest Sharpe ratio

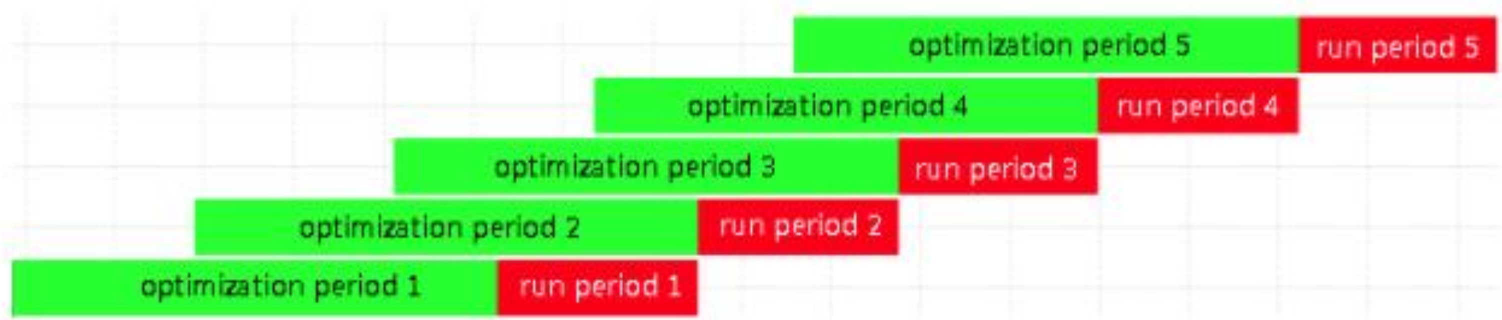
2. How changes in MA1 and MA2 affect risk and return profile?



3. To avoid overfitting, I run Walk Forward Analysis to see how the strategy works in out_of_sample context.

- The Walk Forward Analysis can be described as follows:

The picture below illustrates the walk forward analysis procedure. An optimization is performed over a longer period (the in-sample data), and then the optimized parameter set is tested over a subsequent shorter period (the out-of-sample data). The optimization and testing periods are shifted forward, and the process is repeated until a suitable sample size is achieved.



- To run Walk Forward Analysis, first I run a for loop to find an training window and testing out-of-sample window

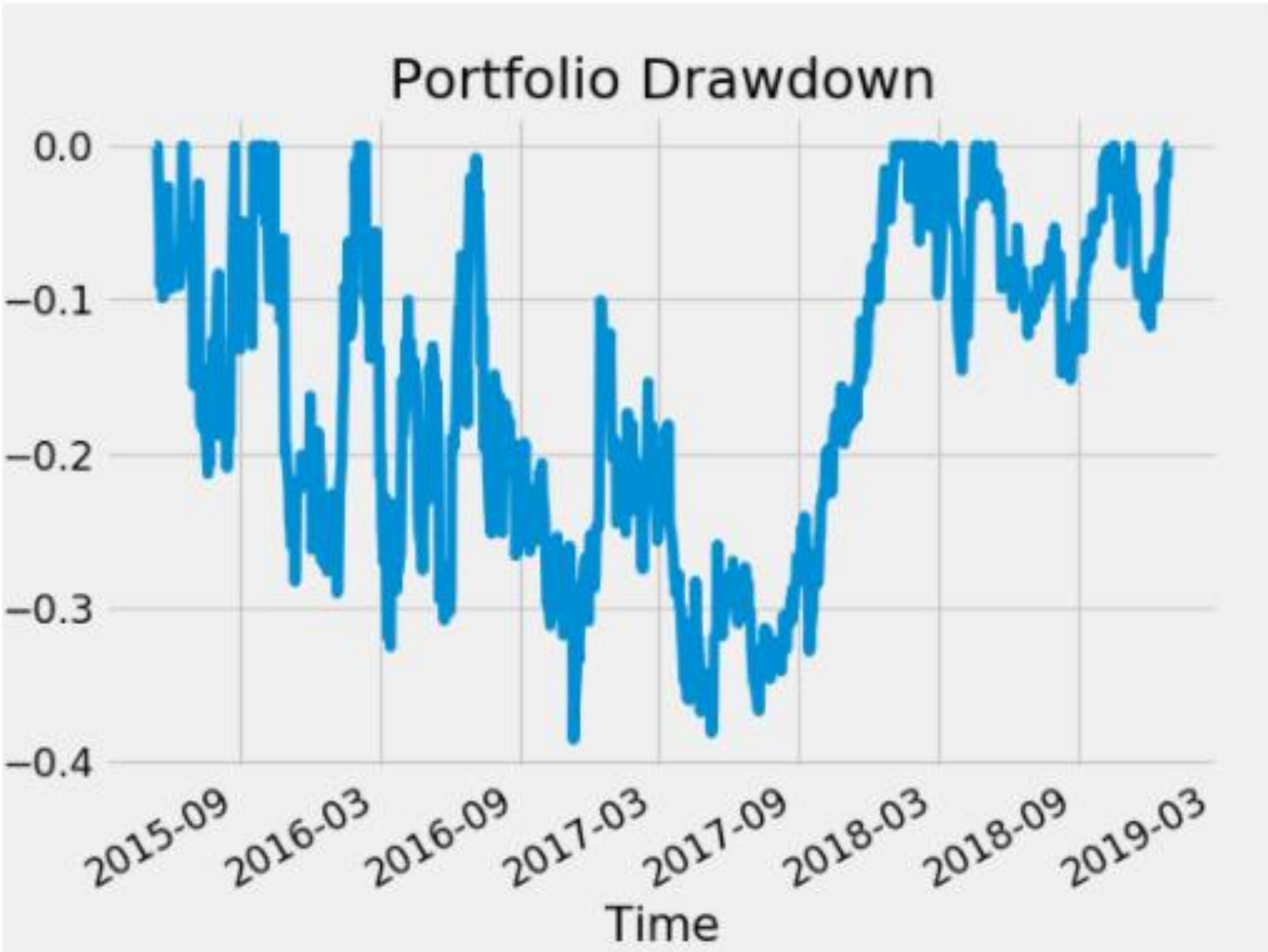
```
# We got the results like this:
      train_period  valid_period  mean_valid_sharpe
 0         6.375         0.125           3.331654
 0             7         0.125           0.112202
 0             7         0.25            1.228202
 0           7.5         0.25            0.277203
 0           8.0         0.25           -0.103875
```

- From the above results I choose 1606 days (6.375*252) for training period from that we got optimal MA1 and MA2 & then apply these MA1, MA2 into testing period of 31 days (0.125*252). The the out-of-sample results over the 4 years (2015-2019) are as follows:

index	Start	Finish	MA1	MA2	annualized_return	annualized_sd	annualized_Sharpe	max_draw_down	winning_percentage
1	2015-05-12	2015-06-29	5	273	1.205105	0.496489	2.427253	0.098972	0.588235
2	2015-06-26	2015-08-14	25	210	-0.517570	0.686469	-0.753960	0.193396	0.428571
3	2015-08-11	2015-09-28	60	210	6.778134	0.697462	9.718281	0.132557	0.500000
4	2015-09-25	2015-11-13	60	252	-0.190740	0.658533	-0.289643	0.259746	0.500000
5	2015-11-10	2015-12-29	20	210	-0.473486	0.511561	-0.925570	0.184890	0.441176
6	2015-12-28	2016-02-12	30	42	33.056746	0.655367	50.440041	0.097649	0.636364
7	2016-02-09	2016-03-29	30	273	-0.653102	0.712658	-0.916431	0.325741	0.470588
8	2016-03-29	2016-05-13	5	294	0.745190	0.506713	1.470635	0.195182	0.470588
9	2016-05-11	2016-06-28	15	252	1.432937	0.704742	2.033278	0.198417	0.500000
10	2016-06-28	2016-08-12	25	252	-0.789390	0.573439	-1.376590	0.246269	0.424242
11	2016-08-11	2016-09-27	30	252	-0.066693	0.441926	-0.150914	0.118516	0.454545
12	2016-09-27	2016-11-11	65	295	-0.772266	0.421546	-1.831983	0.225865	0.470588
13	2016-11-10	2016-12-28	65	294	10.567245	0.505084	20.921773	0.059112	0.666667
14	2016-12-28	2017-02-10	35	147	-0.536519	0.523899	-1.024090	0.143666	0.354839
15	2017-02-10	2017-03-29	20	63	-0.518708	0.400004	-1.296759	0.173177	0.363636
16	2017-03-30	2017-05-12	60	105	-0.209228	0.424462	-0.492925	0.137665	0.419355
17	2017-05-12	2017-06-28	30	84	0.205265	0.364754	0.562749	0.079983	0.484848
18	2017-06-29	2017-08-11	25	84	-0.020898	0.288320	-0.072480	0.091859	0.451613
19	2017-08-14	2017-09-27	60	42	0.754365	0.362501	2.081001	0.115567	0.593750
20	2017-09-28	2017-11-10	15	105	1.578413	0.264159	5.975250	0.044146	0.625000
21	2017-11-13	2017-12-28	65	105	1.915169	0.288565	6.636867	0.043076	0.656250
22	2017-12-28	2018-02-09	50	105	4.656074	0.345322	13.483280	0.062257	0.766667
23	2018-02-12	2018-03-29	5	21	0.544175	0.481380	1.130450	0.125270	0.545455
24	2018-03-29	2018-05-11	35	147	2.011034	0.299715	6.709824	0.036736	0.548387
25	2018-05-15	2018-06-28	35	147	-0.490205	0.235682	-2.079939	0.106642	0.406250
26	2018-06-29	2018-08-13	35	147	-0.219582	0.249365	-0.880565	0.100350	0.451613
27	2018-08-15	2018-09-27	5	294	1.278299	0.254070	5.031276	0.038469	0.516129
28	2018-09-28	2018-11-12	5	126	0.713387	0.281664	2.532759	0.076817	0.531250
29	2018-11-14	2018-12-28	5	147	0.577714	0.292356	1.976063	0.087119	0.516129

4. After the above analysis, I concatenated returns of small pe check the performance of the whole out-of-sample testing per results are as follows:

```
Average annualized daily return of porfolio is 36.56 %
Annualized standard deviation return of portfolio is 47.0 %
Annualized Sharpe of portfolio is 0.7774
Max drawdown of portfolio is 39.0 %
```


Portfolio Drawdown
0.0
−0.1
−0.2
−0.3
−0.4
2015-09
2016-03
2016-09
2017-03
2017-09
2018-03
2018-09
2019-03
Time

Out of sample performance summary

	Year	Annualize_return	Annualize_volatility	Annualize_sharpe	MaxDrawdown
0	2015	0.237705	0.609526	0.389983	0.283233
1	2016	0.341594	0.574650	0.594437	0.385868
2	2017	0.195010	0.370295	0.526634	0.269274
3	2018	0.697870	0.315292	2.213411	0.151955