Investment Thesis
Xuan Duy Le
3/21/2025

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Optimizing Exponential Moving Average (EMA) Crossover Strategies Across Multiple Asset Classes

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Abstract:

“The goal is to optimize a simple EMA crossover strategy, and to see if it can outperform certain benchmarks. Historical data is collected over the past 10 years, and the strategy is back tested over the period. Optimizing EMA crossover strategy can easily lead to overfitting, but even then, will not be able to yield abnormal return compared to passive investing.”

Investment Thesis
Xuan Duy Le
3/21/2025

Introduction

Why EMA crossovers?

Before we dive into why we choose EMA crossovers, we will first discover what Simple Moving Average (SMA) is. SMA is an indicator that calculates the average price of an asset within a time frame. A 50-day SMA calculates the average price of the asset for the past 50 days. However, SMA is not just a number, but rather a smooth line that is created from dotting many averages over time.

Figure 1:

This graph shows the plotted 200 Period SMA, and the period can indicate one second, minute, hour, day, or week, depending on the time interval we are looking at. Each point on the SMA line represents the average of all prices in the last 200 periods.

EMA is just another version of SMA, but it gives more weight to more recent data compared to data that is dated further.

Investment Thesis
Xuan Duy Le
3/21/2025

Both SMA and EMA crossover strategies combine two indicators, one SMA/EMA with a fast window ranging from 10-50 periods, and one SMA/EMA with a slower window, ranging from 50-200 periods. This strategy is not new, and it has been used by a lot of traders. It capitalizes on the momentum factor and believes that the market is not 100% efficient. The reason why traders use this strategy when they don't think the market is inefficient is because of a delayed reaction in prices when news comes out. They believe that the market is not priced in immediately, and thus it is possible to gain abnormal returns by "riding the trends".

Hypothesis:

EMA Crossover strategy cannot outperform passive investing within one asset, even with optimization.

Methodology

1. Dataset
   This paper uses free data sources from Yahoo Finance.
   Data character:
   a. Time horizon: 10 years
   b. Frequency: 1 day
   c. Missing data is omitted
   d. Close price

   *Since Yahoo Finance recent update, there is no Adjusted Close price available.

   *Note that Yahoo Finance is a reliable data source for exploration and educational purposes, but not for serious investing/trading.

2. EMA pairs tested
   EMA fast window: 10, 15, 20, 25, 30, 35, 40, 45, 50
   EMA slow window: 50, 70, 90, 110, 130, 150, 170, 190, 210
   The way EMA pairs are tested is through all possible combinations. For example, 10-period EMA is tested against all possible EMA slow windows.

3. Backtest Framework
   Signal:
   Entry: If EMA fast windows cross above EMA slow windows
   Exit: If EMA fast windows cross below EMA slow windows
   Direction of the backtest is long only and will have no short positions

Investment Thesis
Xuan Duy Le
3/21/2025

Initial cash is 10,000 USD
Fees are 0.01% per trade
Size per trade is 100% of capital

Performance metrics:

1. Benchmark return: The return of the actual asset itself over 10 years
2. Win rate: Out of all trades, how many trades profit
3. Average winning trade: On average, what is the return for all winning trades
4. Average losing trade: On average, what is the return for all losing trades
5. Sharpe Ratio: Risk-adjusted return
6. Sortino Ratio: Risk-adjusted return, ignoring upside deviation

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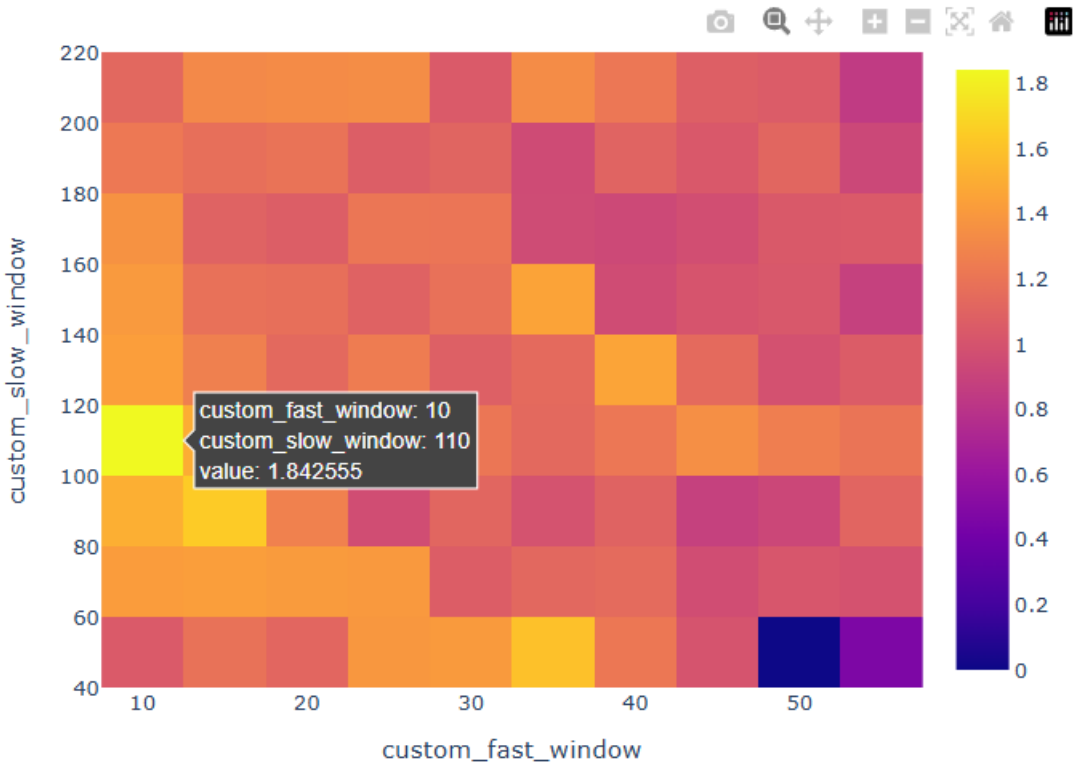
Results and Analysis

First we determine what is the best combination of EMA windows to choose from. By running the backtest and generating a heatmap that shows all possible combinations, we select the one with the highest return to analyze performance metrics.

Asset 1: SPY (S&P 500 ETF)

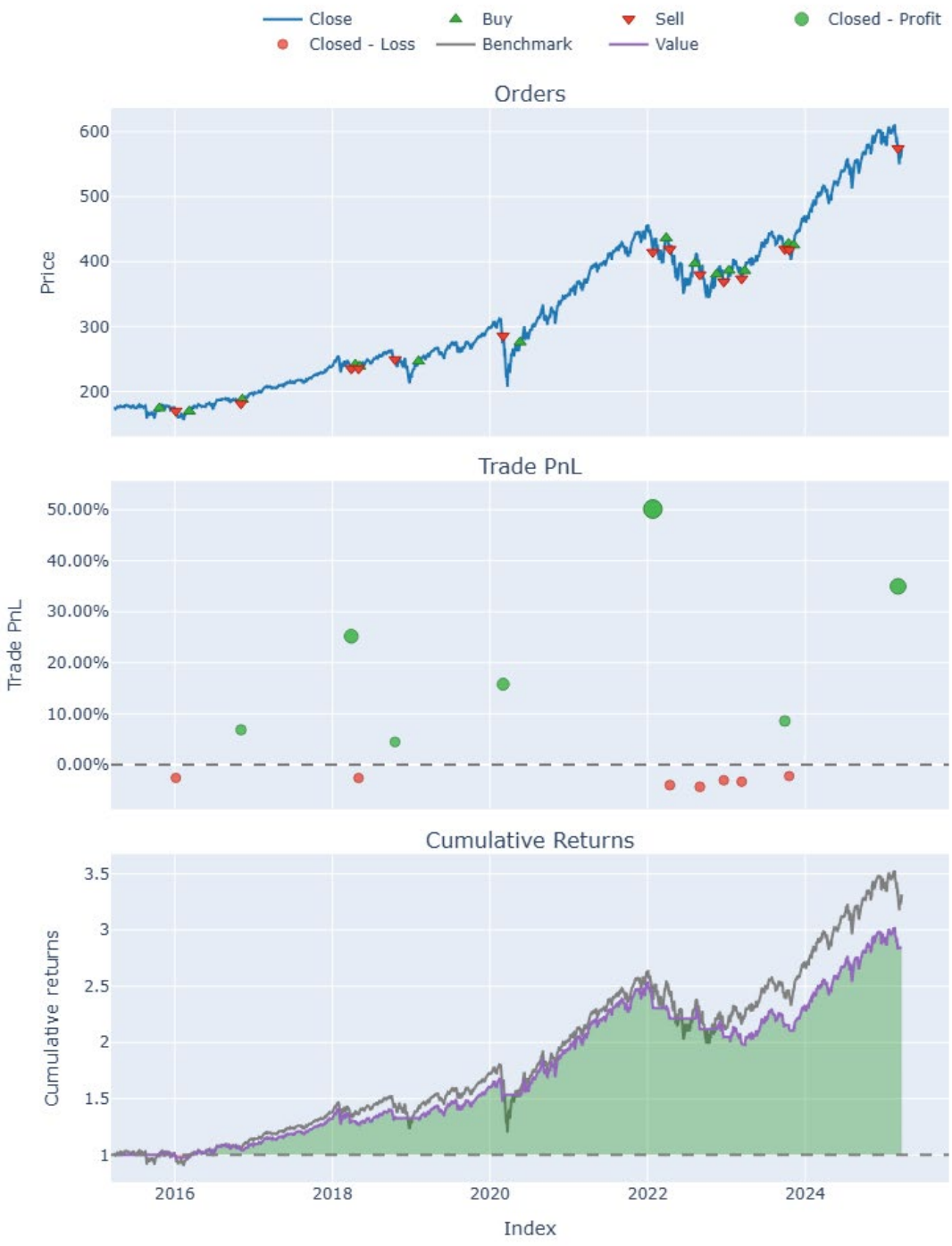


Investment Thesis
Xuan Duy Le
3/21/2025

From this map, we can see that the bright yellow square on the left represents the highest return of approximately 184.26% over 10 years, which is a combination of 10-day EMA and 110-day EMA.

Using this exact combination to run our portfolio:

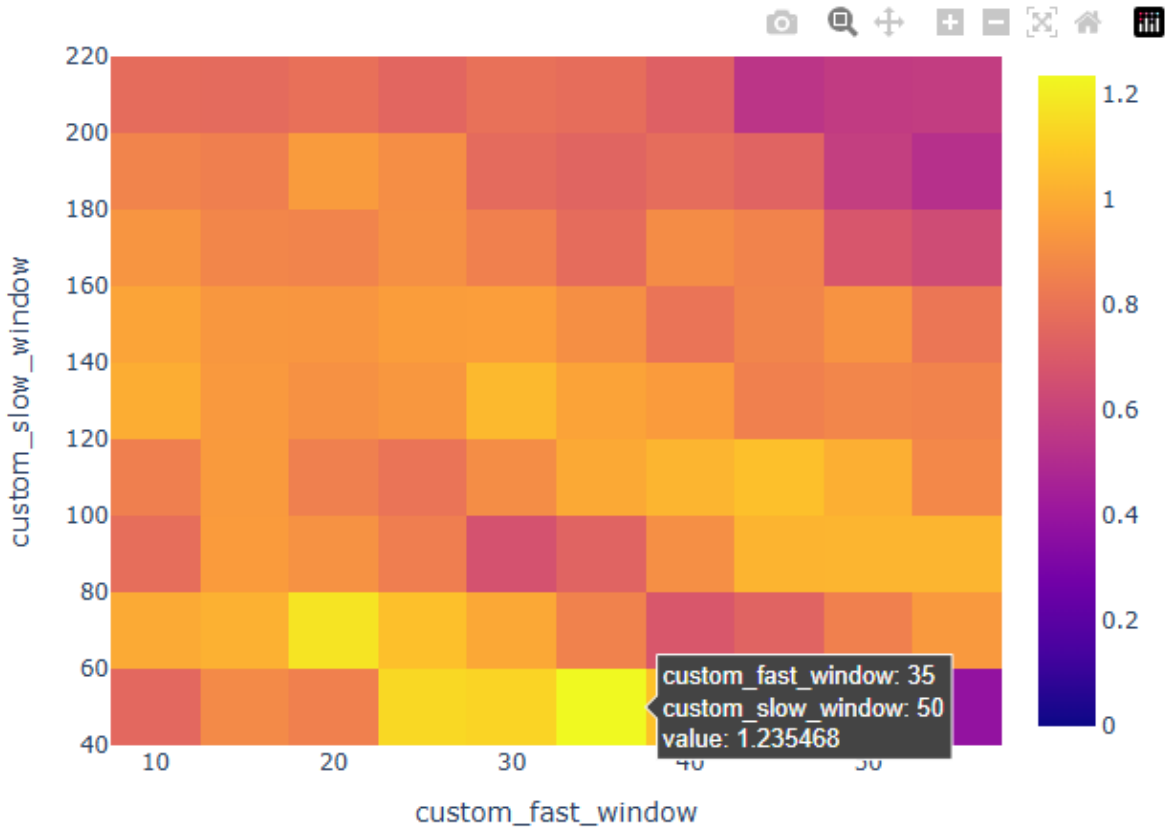
Performance Metrics:



We can see that the strategy performs better than expected, despite underperforming the benchmark return by a bit. With this strategy, there is a 50% win-rate, where the average return on all winning trades is 20.85% and the average return on all losing trades is only -4.33%. Sharpe ratio comes at around 1.16, which is better than 1 but not exceptional returns. Sortino ratio comes higher at 1.6, which means the strategy volatility comes mostly from upside potential rather than downside, which is good. Overall, the strategy performance is well, but not as well as passive investing.

Asset 2: GLD (Gold ETF)

From this heatmap, we can see the most optimal combination is an EMA fast and slow window of 35 and 50, respectively.



Using this exact combination to run our portfolio:

Performance Metrics:

The strategy has an overall return of 123.50%, which is less than the benchmark returns of 141.61%. This strategy has a win rate of 54%, where the average of all winning trades is 8.59%, and the average of all losing trades is -2.80%. Sharpe and Sortino come at 1.18 and 1.30, respectively. Overall, the strategy did not yield abnormal returns compared to passive investing.

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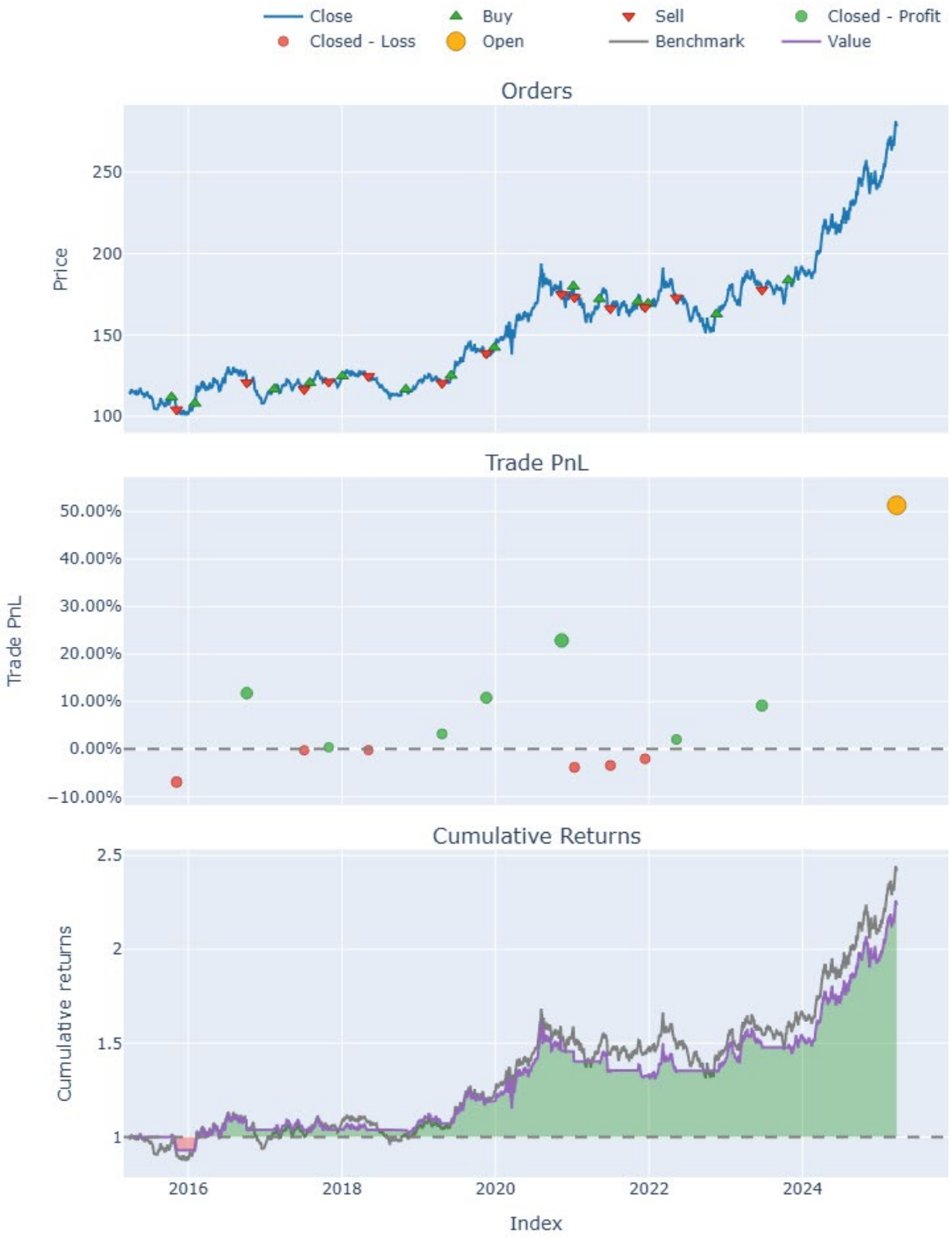
Xuan Duy Le
3/21/2025



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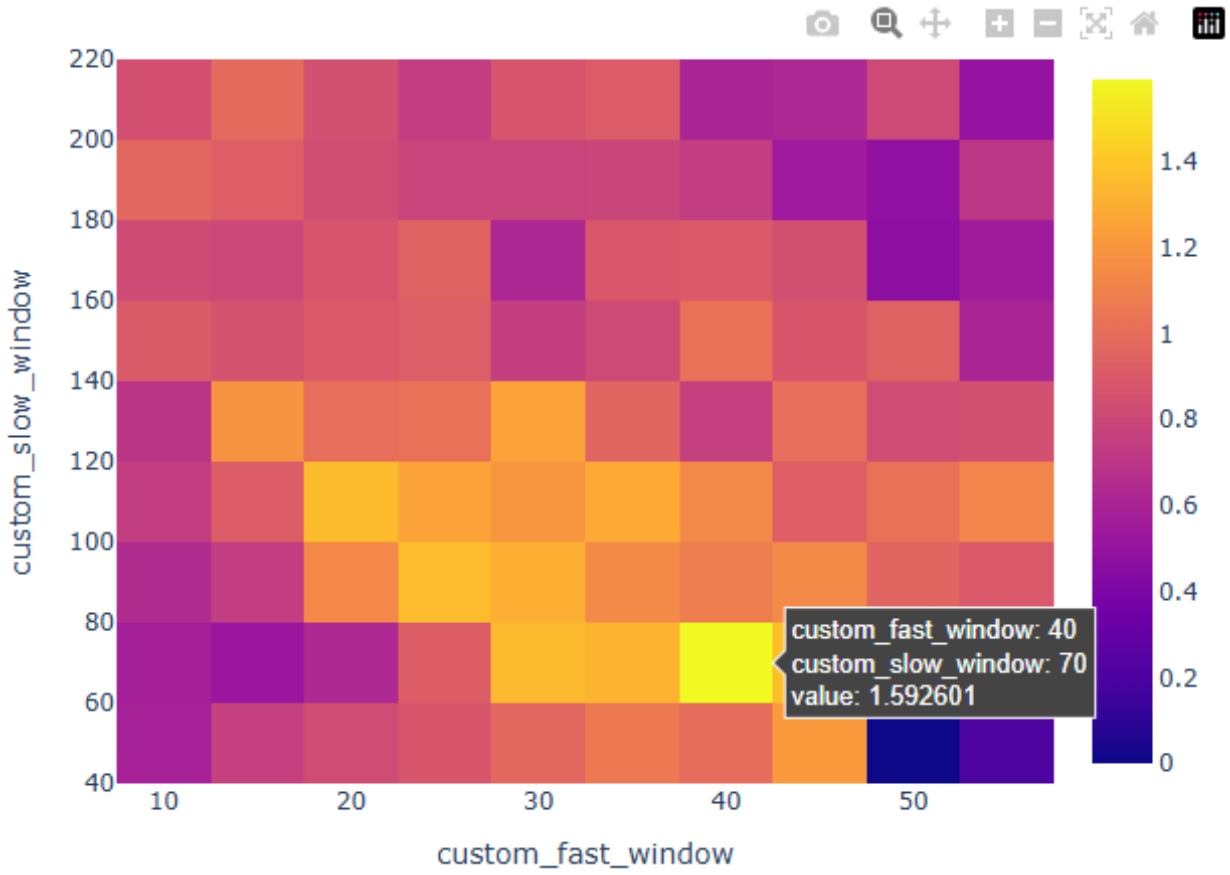
Xuan Duy Le
3/21/2025

Asset 3: XLF (Financial ETF)



Using 40-day EMA and 70-day EMA crossover, we can see the performance below:

This strategy yields a total return of 159.33%, compared to the benchmark return of 211.37%. The win rate is only 33%, but the average winning return is 37.47% compared to the average of losing return of -5.09%, which gives a positive expected return. Sharpe and Sortino come at around 0.87 and 1.16, respectively. Sharpe ratio indicates poor risk-adjusted return, but Sortino confirms that most trades volatility come from upside potential.

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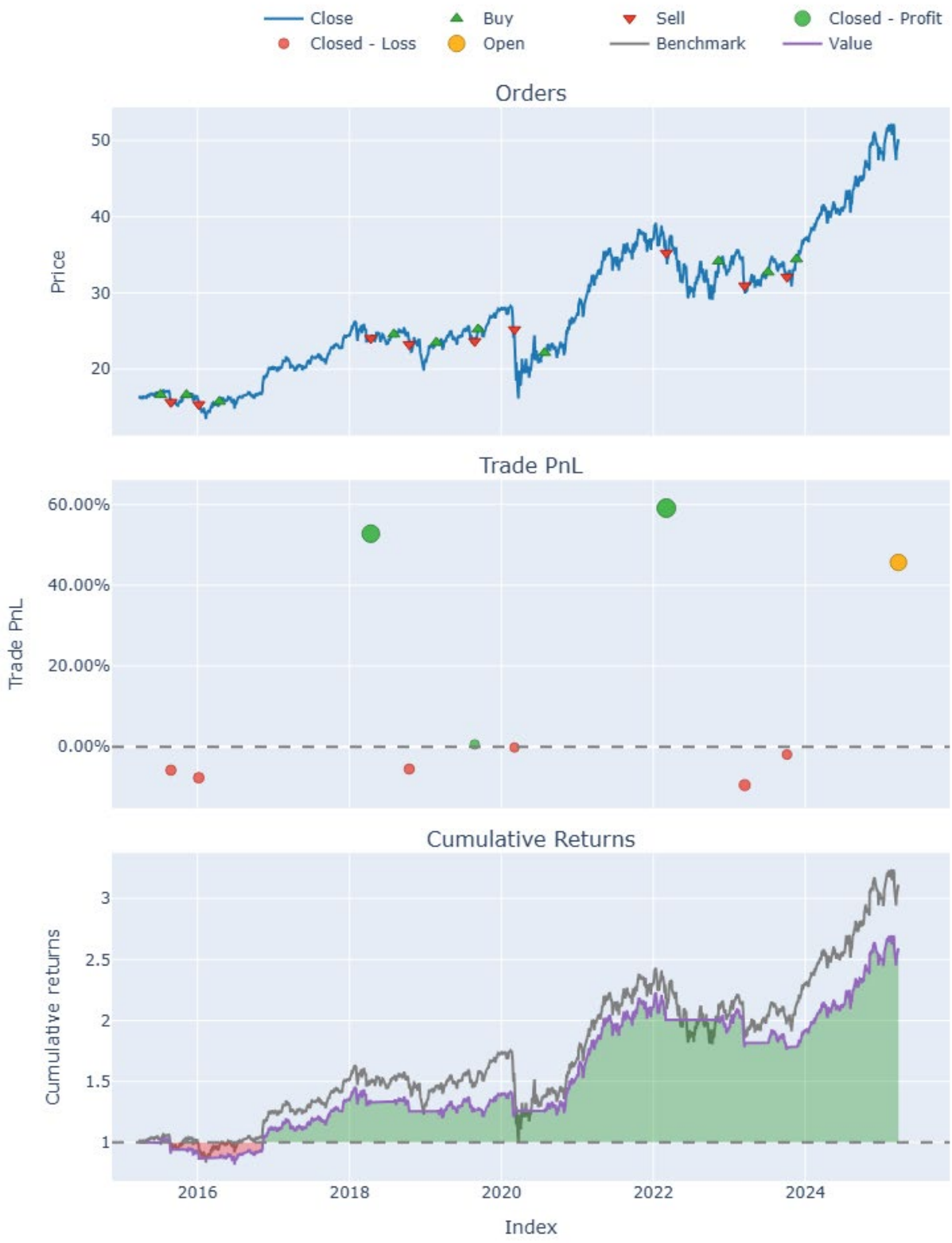
Xuan Duy Le
3/21/2025



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3/21/2025

General Findings

Tech Sector (SPY)

- Tech stocks exhibit strong, extended momentum due to growth and sentiment-driven rallies.
- A short, fast EMA (10) allows quick response to new trends, while very long EMA (110) prevents premature exits during pullbacks, especially in the volatile tech sector.
- Tech trends are longer-lasting, and capturing entry early is crucial.

Commodity Sector (GLD)

- Commodities react better to closely spaced EMA windows, suggesting choppier and shorter trends.
- Small EMA gap captures medium-term mean reversion or breakout swings without being too sensitive to noise.
- Commodity trends are range bound with occasional breakouts.

Financial Sector (XLF)

- Moderate EMA pair suggests a slower trend and exhibits cyclical behavior (interest rate, economic cycles, etc.)
- Requires patience to stay in trades.

Overfitting Risk

Optimizing EMA window combinations to find distinct optimal pairs can expose the test to overfitting risk, especially when testing a large number of EMA pairs, resulting in a very specific “superior” pair in comparison to the rest.

Overfitting occurs when there are excessive parameters tuning, resulting in a pair that might work best for historical data, but not for future data. This is because excessive tuning leads to parameters capturing minor short-term volatility (noise), instead of the underlying pattern.

Solution

Out-of-Sample Testing:

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Xuan Duy Le
3/21/2025

Split the dataset and test strategy on unseen data. For example, instead of using all 10-year data, we can use only 6-year data to optimize EMA windows, can test those windows on the 4-year unseen data.

Walk-Forward Analysis:

Recalibrate EMAs over rolling windows to simulate real-time re-optimization. For example, instead of using all data (10-year period), we can slice data into 10 different windows, each window equals 1 year. We begin testing for optimal EMA windows for the first window, use the optimal pair on the second window, and so on.

Limit Parameter Granularity:

Instead of testing EMA window in steps of 5, we can test in steps of 10 or 50 for fast and slow window respectively. This avoids cases there the best EMA window is something like 32 or 117.