Trading strategies implemented on python Equity II

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Abstract

In this paper, we continue our previous paper on implementation of various trading strategies applied commonly on equities, these strategies were back tested with real data from Yahoo Finance and each strategy is accompanied by a graph with high lightened long and short signals and the return calculated. You can find the Python implementation on: Chenjie's Github Trading strategies or Maxime's Github Trading strategies.

Introduction

Overview

Stock trading strategies are systematic approaches employed by traders and investors to maximize returns and manage risks in the financial markets. These strategies are based on various principles and can range from simple to complex, utilizing technical, fundamental, and quantitative analyses. Understanding these strategies is crucial for anyone looking to navigate the stock market effectively.
Having a well-defined trading strategy is essential for success in the stock market. It provides a clear framework for making decisions, helps manage emotions, and ensures consistency in approach. A robust strategy incorporates risk management techniques, such as stop-loss orders and position sizing, to protect against significant losses.
Developing and understanding various stock trading strategies is vital for navigating the complexities of the financial markets. Whether you're a novice trader or an experienced investor, a well-crafted strategy can enhance your ability to achieve your financial goals. By leveraging different approaches, traders can adapt to changing market conditions and improve their chances of success in the stock market.
For each strategy, we'll explain its mechanics, rationale, and how to backtest and optimize it. However, our main goal is to implement it in Python to enhance our knowledge and skills. While we may not apply all backtesting and optimization techniques to every strategy, we hope you find the process enjoyable nonetheless.

Contents

1 Conventional notation of our paper

1.1 variable used

- σ_i is the annualized volatility for a stock i.
- R_i is the average return of a stock.
- R_f is the risk-free rate.
- R_m is the average return of the market.
- $\text{Var}(R_i)$ is the variance of a stock i.
- $\text{Cov}(R_i, R_m)$ is the co-variance between a stock i and the market m.
- ϵ_i is the error term.

1.2 Metric used in our paper

- *Alpha* : Represents the excess return of an investment relative to the return of a benchmark index.
  - Formula: $\alpha = R_i - (R_f + \beta(R_m - R_f))$
  - $\alpha > 0$: Indicates that the investment has outperformed its benchmark, suggesting that the investment manager's strategy has added value.
  - $\alpha < 0$: Indicates that the investment has under-performed its benchmark, suggesting that the investment manager's strategy has detracted value.
  - $\alpha = 0$: Indicates that the investment has performed in line with its benchmark, suggesting that the investment manager's strategy has neither added nor detracted value.

- *Beta* : Measures the volatility or systematic risk of an investment relative to the overall market.
  - Formula: $\beta = \frac{\text{Cov}(R_i, R_m)}{\text{Var}(R_m)}$
  - $\beta > 1$: Indicates that the investment is more volatile than the market, suggesting higher risk and potentially higher returns.
  - $\beta < 1$: Indicates that the investment is less volatile than the market, suggesting lower risk and potentially lower returns.
  - $\beta = 1$: Indicates that the investment's volatility is in line with the market, suggesting average market risk.

- *Correlation* : Measures the degree to which two securities move in relation to each other.
  - Formula: $\rho = \frac{\text{Cov}(R_i, R_m)}{\sigma_i \sigma_m}$
  - $\rho = 1$: Indicates a perfect positive correlation, suggesting that the two securities move in the same direction.
  - $\rho = -1$: Indicates a perfect negative correlation, suggesting that the two securities move in opposite directions.
  - $\rho = 0$: Indicates no correlation, suggesting that the movements of the two securities are unrelated.

- *SharpeRatio* : Measures the risk-adjusted return of an investment.
  - Formula: $\text{Sharpe Ratio} = \frac{R_i - R_f}{\sigma_i}$
  - Higher Sharpe Ratio: Indicates better risk-adjusted returns.
  - Lower Sharpe Ratio: Indicates worse risk-adjusted returns.

- $SortinoRatio$: Measures the risk-adjusted return of an investment, similar to the Sharpe Ratio, but only considers downside risk.
  - Formula: Sortino Ratio = $\frac{R_i - R_f}{\sigma_d}$
  - Higher Sortino Ratio: Indicates better risk-adjusted returns with respect to downside risk.
  - Lower Sortino Ratio: Indicates worse risk-adjusted returns with respect to downside risk.

- $UpsideCapture$: Measures a portfolio's performance in up markets relative to a benchmark.
  - Formula: Upside Capture = $\frac{\text{Portfolio Return in Up Markets}}{\text{Benchmark Return in Up Markets}} \times 100$
  - Upside Capture ¿ 100: Indicates the portfolio has outperformed the benchmark in up markets.
  - Upside Capture ¡ 100: Indicates the portfolio has under-performed the benchmark in up markets.

- $DownsideCapture$: Measures a portfolio's performance in down markets relative to a benchmark.
  - Formula: Downside Capture = $\frac{\text{Portfolio Return in Down Markets}}{\text{Benchmark Return in Down Markets}} \times 100$
  - Downside Capture ¡ 100: Indicates the portfolio has outperformed the benchmark in down markets.
  - Downside Capture ¿ 100: Indicates the portfolio has under-performed the benchmark in down markets.

- $AnnualizedReturn$: Measures the geometric average amount of money earned by an investment each year over a given time period.
  - Formula: Annualized Return = $\left(\prod_{t=1}^{T}(1+R_t)\right)^{\frac{252}{T}} - 1$
  - Higher Annualized Return: Indicates better performance.
  - Lower Annualized Return: Indicates worse performance.

- $CumulativeReturn$: Measures the total change in the value of an investment over a set time period.
  - Formula: Cumulative Return = $\prod_{t=1}^{T}(1+R_t) - 1$
  - Higher Cumulative Return: Indicates better performance.
  - Lower Cumulative Return: Indicates worse performance.

- $AnnualizedRisk$: Measures the annualized standard deviation of returns, representing the investment's volatility.
  - Formula: Annualized Risk = $\sigma_i \times \sqrt{252}$
  - Higher Annualized Risk: Indicates higher volatility and potential risk.
  - Lower Annualized Risk: Indicates lower volatility and potential risk.

- $MaximumDrawdown$: Measures the largest drop from a peak to a trough of an investment before a new peak is attained.
  - Formula: Maximum Drawdown = min $\left(\frac{C_t - P_t}{P_t}\right)$ where C_t is the cumulative return at time t and P_t is the peak return before t.
  - Lower Maximum Drawdown: Indicates better performance in avoiding large losses.
  - Higher Maximum Drawdown: Indicates worse performance in avoiding large losses.

2 Global challenges for our trading strategies

All our strategies implemented and back tested with real data from Yahoo Finance face similar challenges listed and each strategy represents specific risks and will be detailed on each section.

1. **Data Quality Issues:**
   - *Incomplete or Incorrect Data*: Stock volatility data from sources like Yahoo Finance or Bloomberg may be incomplete or incorrect, which can affect the accuracy of the low and high volatility portfolios.
2. **Market Efficiency:**
   - *Efficient Market Hypothesis*: According to the efficient market hypothesis, stock prices already reflect all available information. This could limit the effectiveness of the low volatility anomaly strategy, or quaterly published earning as market efficiency might diminish the potential advantage of investing in low volatility stocks.
3. **Market Conditions:**
   - *Market Trends*: Market trends and macroeconomic conditions can affect stock volatility and thereby impact the performance of the low and high volatility portfolios. For example, during periods of high market stress, the performance of low volatility stocks may not align with historical trends.
   - *Sector Rotation*: Shifts in sector performance may influence the volatility of stocks and affect the strategy's effectiveness.
4. **Stock-Specific Factors:**
   - *Company-Specific Events*: Earnings reports, management changes, or other significant company-specific events can cause abrupt changes in stock volatility, affecting portfolio stability.
   - *Sector-Specific Volatility*: Stocks within certain sectors may exhibit higher or lower volatility due to sector-specific factors, which could impact the results of the low volatility strategy.
5. **Behavioral Biases:**
   - *Investor Behavior*: Investor biases, such as overreacting to short-term market movements or news, can affect stock volatility and potentially distort the outcomes of the strategy.
   - *Herding Effect*: The tendency for investors to follow market trends or other investors can impact the volatility and performance of the stocks in the portfolio.

3 Stocks Trading Strategies

3.1 Support and Resistance

Concept

This strategy utilizes "support" (S) and "resistance" (R) levels to identify potential entry and exit points for trades. The key levels are determined using the "pivot point" (also known as the "center") C, calculated from the previous day's high, low, and closing prices.

Construction

- **Pivot Point Calculation:**
  - Calculate the pivot point (C) using the formula:

$$C = \frac{P_H + P_L + P_C}{3} \tag{1}$$

  - Where:
    * P_H is the previous day's high price.
    * P_L is the previous day's low price.
    * P_C is the previous day's closing price.

- **Resistance and Support Levels:**
  - Calculate the resistance level (R) as:

$$R = 2 \times C - P_L \tag{2}$$

  - Calculate the support level (S) as:

$$S = 2 \times C - P_H \tag{3}$$

- **Trading Signals:**
  - Generate trading signals based on the current price (P) in relation to the pivot point, resistance, and support levels:

$$\text{Signal} = \begin{cases} \text{Establish long position if } P > C \\ \text{Liquidate long position if } P \geq R \\ \text{Establish short position if } P < C \\ \text{Liquidate short position if } P \leq S \end{cases}$$

Expected Performance

The Support and Resistance Trading Strategy based on pivot points aims to identify potential reversal levels and capitalize on market movements around these levels.

- **Clear Signals:** This strategy provides clear and actionable trading signals based on the calculated levels.
- **Risk Management:** By defining support and resistance levels, traders can set stop-loss and take-profit orders to manage risk effectively.
- **Adaptability:** The strategy can be applied to various time frames and asset classes, making it versatile.

Practical Considerations

While the Support and Resistance strategy offers clear advantages, there are also challenges to consider:

- **False Breakouts:** Prices may break through support or resistance levels temporarily, leading to potential false signals.
- **Market Volatility:** High volatility can cause rapid price movements that make it difficult to determine accurate levels.
- **Time Sensitivity:** The effectiveness of the strategy can depend on the time frame chosen for the pivot point calculation.

Backtesting and Optimization

Backtesting this strategy involves simulating trades based on historical data to assess the performance. Metrics such as win/loss ratio, average return per trade, and maximum drawdown are commonly used. Optimization may involve adjusting the time frame for pivot point calculations or the thresholds for entering/exiting trades.

Our Implementation

Ticker	Total Return (%)	Annualized Volatility	Sharpe Ratio
AI.PA	19.03	0.289	-0.027
AIR.PA	18.43	0.309	-0.026
STMPA.PA	-15.47	0.462	-0.025

Table 1: Performance Metrics for Support and Resistance Strategy

AI.PA

- **Total Return (%):** The AI.PA ticker shows a positive total return of 19.03%, indicating that the support and resistance strategy resulted in a gain over the period.
- **Annualized Volatility:** With an annualized volatility of 0.289, the asset exhibits moderate price fluctuations, suggesting a relatively stable investment compared to more volatile assets.
- **Sharpe Ratio:** The negative Sharpe ratio (-0.027) indicates that the returns generated were not sufficient to justify the risk taken, as the returns are less than the risk-free rate when adjusted for volatility.

AIR.PA

- **Total Return (%):** AIR.PA also yielded a positive return of 18.43%, slightly lower than AI.PA, but still indicative of a profitable strategy.
- **Annualized Volatility:** The volatility is slightly higher at 0.309, which implies more variability in returns compared to AI.PA.
- **Sharpe Ratio:** Similar to AI.PA, the negative Sharpe ratio (-0.026) indicates that the strategy underperformed on a risk-adjusted basis, failing to exceed the risk-free rate after accounting for volatility.

STMPA.PA

- **Total Return (%):** Unlike AI.PA and AIR.PA, STMPA.PA experienced a significant loss of -15.47%. This negative return suggests that the support and resistance strategy did not perform well for this asset during the analyzed period.
- **Annualized Volatility:** The volatility is notably higher at 0.462, indicating substantial fluctuations in price, which may have contributed to the strategy's poor performance.
- **Sharpe Ratio:** The negative Sharpe ratio (-0.025) further underscores the poor risk-adjusted performance, as the strategy failed to deliver returns that justify the associated risk.

Limitations of this Model

1. **False Breakouts:** Temporary price movements beyond support or resistance levels can generate misleading signals, leading to potential losses when the breakout fails to sustain.
2. **Market Conditions:** The strategy may struggle in strongly trending markets where prices continuously break through support or resistance levels without significant reversals, making it less effective in capturing sustained trends.
3. **Time Frame Sensitivity:** The effectiveness of the strategy can vary with different time frames. A time frame mismatch may result in suboptimal entry and exit points, affecting overall performance.
4. **Subjectivity:** Identifying support and resistance levels can be subjective, leading to inconsistent signals and potential variability in the strategy's application across different traders.
5. **Fundamental Ignorance:** The strategy focuses solely on technical analysis, potentially overlooking fundamental factors like earnings reports or economic data that can impact price movements significantly.

3.2 Channel Strategy

Concept

The Channel Strategy involves buying and selling a stock when it reaches the floor (support) or ceiling (resistance) of a price channel. A channel is a range or band within which the stock price fluctuates. The trader's expectation is that when the price hits the floor or ceiling, it will reverse direction. However, if the price breaks through these levels, it may signal the beginning of a new trend.

Construction

- **Selection Criteria:**
  - Identify a security or asset with a well-defined trading range.
  - Determine the look-back period (T) to calculate the upper (B_{up}) and lower (B_{down}) bounds of the channel.
- **Channel Calculation:**
  - Calculate the upper boundary of the channel:

$$B_{up} = \max(P(1), P(2), \ldots, P(T))$$

  - Calculate the lower boundary of the channel:

$$B_{down} = \min(P(1), P(2), \ldots, P(T))$$

  - Where $P(1), P(2), \ldots, P(T)$ are the prices over the look-back period T.
- **Trading Signals:**
  - **Long Position:** Establish a long position or liquidate a short position when the price hits the lower boundary (B_{down}).
  - **Short Position:** Establish a short position or liquidate a long position when the price reaches the upper boundary (B_{up}).
- **Portfolio Formation:**
  - Positions are typically entered at the boundaries of the channel and exited either when the price reaches the opposite boundary or breaks out of the channel.
- **Rebalancing:**
  - Rebalancing is not typically required unless the channel's boundaries are recalculated regularly based on an updated look-back period.

Expected Performance

The Channel Strategy aims to capitalize on the range-bound nature of asset prices. It is expected to perform well in sideways markets, where prices oscillate within a defined range, but may struggle in trending markets where prices break through the channel's boundaries.

- **Capitalizing on Range-Bound Markets:** The strategy is particularly effective in markets where prices are stable and fluctuate within a predictable range.
- **Defined Risk and Reward:** By buying at support and selling at resistance, the strategy provides clear entry and exit points, with defined potential losses if the price breaks out of the channel.

Practical Considerations

While the Channel Strategy is straightforward, it comes with several challenges:

- **False Breakouts:** The strategy may suffer from false breakouts, where the price temporarily moves outside the channel only to return, potentially triggering premature exits or entries.
- **Trend Identification:** The strategy may underperform in trending markets, as it is designed for range-bound conditions. Identifying when the market has transitioned from range-bound to trending is crucial.
- **Time Frame Sensitivity:** The effectiveness of the strategy depends on the chosen time frame. A channel that works well on a daily chart may not be effective on an intraday or weekly chart.

Mathematical Formula

- **Upper Boundary (Resistance):**

$$B_{up} = \max(P(1), P(2), \ldots, P(T))$$

- **Lower Boundary (Support):**

$$B_{down} = \min(P(1), P(2), \ldots, P(T))$$

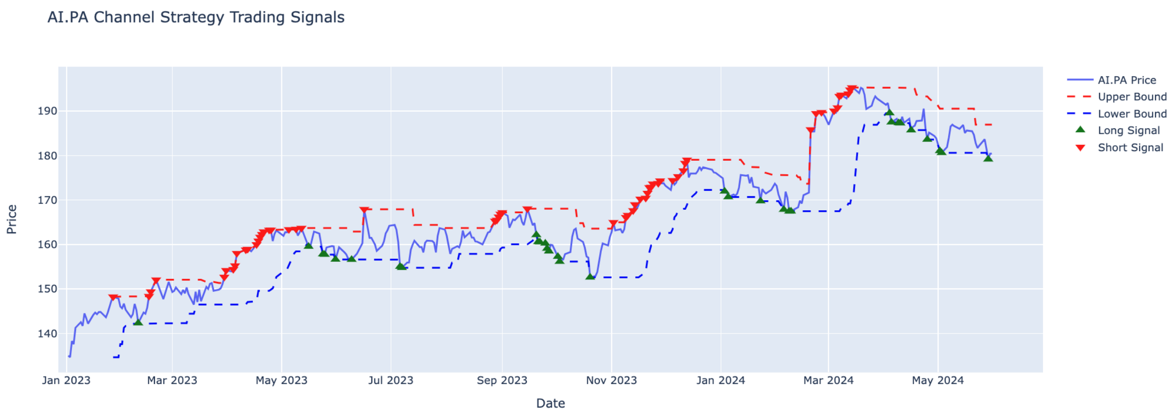
- **Trading Signal:**

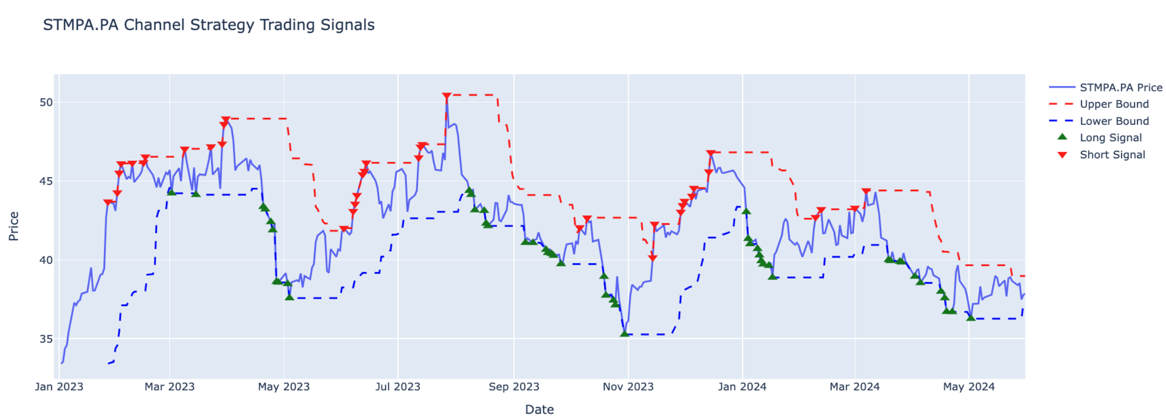
$$\text{Signal} = \begin{cases} \text{Establish long/liquidate short position if } P = B_{down} \\ \text{Establish short/liquidate long position if } P = B_{up} \end{cases}$$

Backtesting and Optimization

Backtesting this strategy involves applying it to historical data to evaluate its performance in different market conditions. Optimization can involve adjusting the look-back period (T) to find the optimal channel width that maximizes returns while minimizing false breakouts.

Our Implementation





Ticker	Total Return (%)	Annualized Volatility	Sharpe Ratio
AI.PA	21.17	0.668	0.038
AIR.PA	28.21	0.705	0.043
STMPA.PA	1.88	0.770	-0.010

Table 2: Performance Metrics for Channel Strategy

AI.PA

- **Total Return (%):** AI.PA generated a positive total return of 21.17%, indicating that the Channel Strategy was profitable for this ticker.
- **Annualized Volatility:** The annualized volatility of 0.668 suggests that AI.PA experienced moderate price fluctuations during the period. This level of volatility is typical for assets that show a balance between risk and reward.
- **Sharpe Ratio:** The Sharpe ratio of 0.038 is positive, albeit low, indicating that while the strategy provided returns above the risk-free rate, the risk-adjusted return is modest. The result suggests that the strategy was slightly effective in generating returns relative to the level of risk taken.

AIR.PA

- **Total Return (%):** AIR.PA showed the highest total return at 28.21%, suggesting that the Channel Strategy was most effective for this ticker. The strategy appears to have captured favorable price movements within the channel.
- **Annualized Volatility:** With an annualized volatility of 0.705, AIR.PA exhibited higher price fluctuations compared to AI.PA. The elevated volatility might have contributed to the higher returns.
- **Sharpe Ratio:** The Sharpe ratio of 0.043, while still modest, is the highest among the three tickers. This indicates that the Channel Strategy provided a slightly better risk-adjusted return for AIR.PA, though it still suggests room for improvement.

STMPA.PA

- **Total Return (%):** STMPA.PA delivered a minimal return of 1.88%, indicating that the Channel Strategy was barely profitable or only marginally effective for this asset.
- **Annualized Volatility:** The highest annualized volatility at 0.770 among the three tickers indicates that STMPA.PA experienced significant price fluctuations, which likely contributed to the strategy's limited success.
- **Sharpe Ratio:** The negative Sharpe ratio of -0.010 suggests that the strategy underperformed relative to the risk-free rate, failing to generate sufficient returns to justify the risk. This result implies that the strategy was not effective in capturing the price movements of STMPA.PA within the channel, leading to a poor risk-adjusted return.

Limitations of the Channel Strategy

1. **False Breakouts:** The strategy can be susceptible to false breakouts, where the price temporarily moves beyond the channel's boundaries only to revert back. These false signals can lead to premature entries or exits, resulting in potential losses.

2. **Trend Markets:** The Channel Strategy tends to underperform in strongly trending markets. When prices consistently break through the upper or lower bounds of the channel, the strategy may fail to capture sustained trends, leading to missed opportunities or losses.

3. **Time Frame Sensitivity:** The effectiveness of the Channel Strategy is highly dependent on the chosen time frame. A channel that works well on a daily chart may not be suitable for an intraday or weekly chart. Traders must carefully select the time frame that aligns with their trading style.

4. **Range-Bound Assumption:** The strategy assumes that prices will remain range-bound within the channel. In markets that are highly volatile or where new trends are emerging, this assumption may not hold, leading to reduced strategy effectiveness.

5. **Subjectivity in Channel Definition:** Defining the upper and lower bounds of the channel can be somewhat subjective, depending on the look-back period and the method used. Different traders may define the channel differently, leading to variability in trading signals.

3.3 Statistical arbitrage – optimization

Concept

Statistical arbitrage is a strategy that uses quantitative techniques to exploit pricing inefficiencies in financial markets. The core idea is to construct a portfolio of stocks that maximizes returns while controlling for risk. This involves using a covariance matrix to understand how stocks' returns move together, and then determining the optimal allocation of investments to balance risk and return. Key metrics such as expected profit and loss, portfolio volatility, and the Sharpe ratio help evaluate and refine the portfolio. By working with dimensionless weights rather than dollar amounts, the optimization process becomes more manageable, aiming to achieve the highest risk-adjusted return.

Construction

- **Selection Criteria:**
  - Select a set of N stocks for the portfolio.
  - Define the dollar holdings D_i for each stock i in the portfolio.
- **Predictor Variables:**
  - Define the expected stock returns E_i for each stock i in the portfolio.
  - Use the sample or model covariance matrix C_{ij} to understand the relationships between stock returns.
- **Normalization:**
  - Convert dollar holdings D_i into dimensionless holding weights w_i:

    $$w_i = \frac{D_i}{I}$$

    where I is the total investment amount.
  - The holding weights satisfy the condition:

    $$\sum_{i=1}^{N} |w_i| = 1$$

- **Distance Metric:**
  - This step is not directly applicable in the statistical arbitrage context but is used in nearest neighbors-based strategies. Instead, focus on using covariance matrix for portfolio optimization.
- **Prediction:**
  - Compute the expected portfolio profit and loss P:

    $$P = \sum_{i=1}^{N} E_i D_i$$

  - Calculate the portfolio volatility V:

    $$V^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij} D_i D_j$$

  - Determine the Sharpe ratio S:

    $$S = \frac{P}{V}$$

- **Trading Signal:**
  - Optimize the number of nearest neighbors k using a backtest if applying KNN. Otherwise, focus on optimizing weights for maximum Sharpe ratio.
  - To maximize the Sharpe ratio, solve the optimization problem:

$$w_i = \gamma \left(\sum_{j=1}^{N} C_{ij}^{-1} E_j \right)$$

    where C_{ij}^{-1} is the inverse of the covariance matrix C, and γ is a normalization coefficient determined from:

$$\sum_{i=1}^{N} |w_i| = 1$$

- **Optimization:**
  - Optimize the weights w_i to maximize the Sharpe ratio subject to constraints.
  - Ensure the solution provides a dollar-neutral portfolio, which may involve adjusting weights to satisfy:

$$\sum_{i=1}^{N} w_i = 0$$

Expected Performance

The statistical optimization strategy implemented involves recalculating portfolio weights over rolling 6-month periods to maximize the Sharpe ratio. This approach is designed to adjust the portfolio's allocation based on the latest available data, thereby capturing evolving market conditions. The strategy's performance depends on the accuracy of historical return data and the precision of the covariance matrix used for optimization. By using rolling windows, it dynamically adapts to changes in market volatility and return patterns. However, the effectiveness of this strategy relies on the assumption that past return patterns and volatility are predictive of future performance. Regular recalibration ensures that the portfolio remains aligned with current market dynamics, potentially enhancing risk-adjusted returns.

Practical Considerations

While the statistical optimization strategy offers a robust framework for portfolio management, it has several practical considerations:

- **Data Quality and Frequency:** The accuracy of the optimal weights relies heavily on the quality of historical return data and the covariance matrix. Inaccurate or incomplete data can lead to suboptimal portfolio decisions.

- **Window Size Sensitivity:** The performance of the rolling window optimization depends on the chosen window size. A window too short may result in high turnover and overfitting, while a window too long may not adapt quickly to changing market conditions.

- **Model Assumptions:** The strategy assumes that historical return patterns and volatilities are predictive of future performance. This assumption may not hold in highly volatile or anomalous market conditions, potentially impacting the strategy's effectiveness.

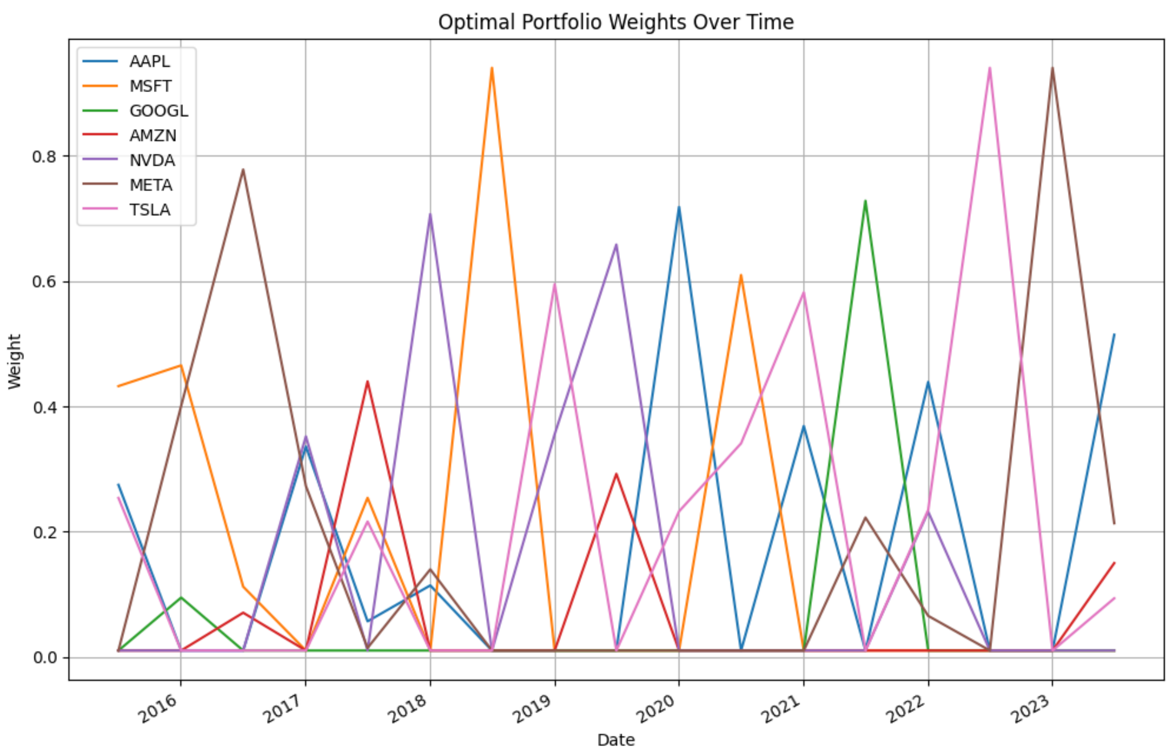
- **Rebalancing Costs:** Frequent rebalancing due to rolling window updates can incur transaction costs, which may erode the strategy's returns. Managing these costs is crucial for maintaining net profitability.

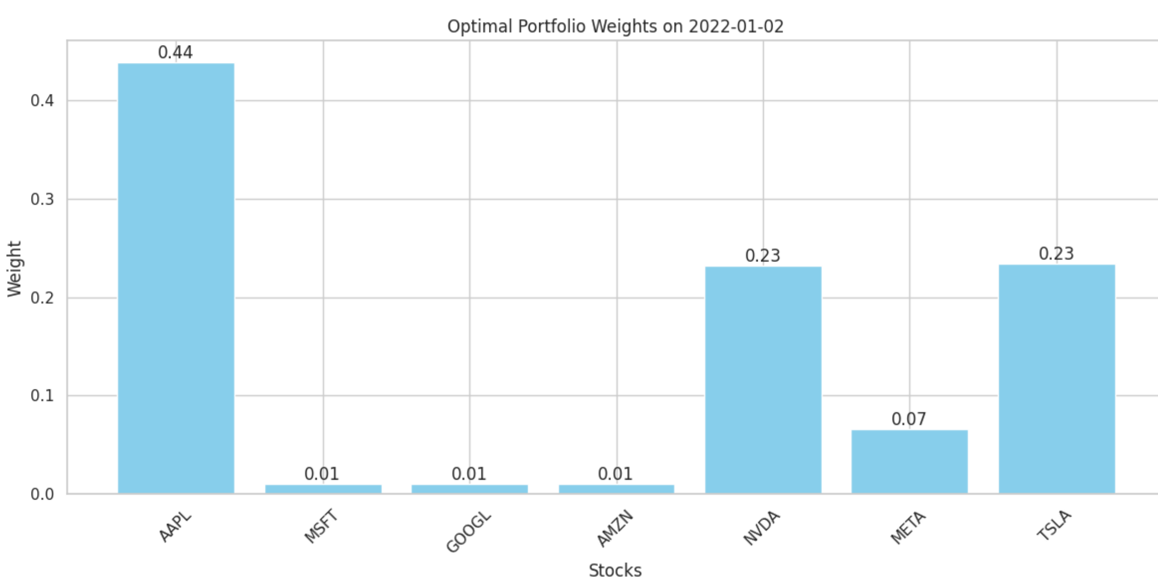
- **Optimization Constraints:** The strategy's constraints, such as minimum weight thresholds, can impact portfolio diversification. Balancing between practical constraints and theoretical optimization is essential for effective implementation.

Backtesting and Optimization

Backtesting this statistical optimization strategy involves applying it to historical data to assess its performance across various market conditions. The optimization process includes adjusting parameters such as the rolling window size and the frequency of rebalancing to find the settings that maximize the Sharpe ratio while managing transaction costs. Additionally, it is crucial to evaluate the strategy's sensitivity to changes in data quality and the covariance matrix to ensure robustness. Proper backtesting and optimization help in identifying the most effective configuration, ensuring that the strategy performs well in both stable and volatile market environments.

Our Implementation





Limitations of the Statistical Optimization Strategy

1. **Data Quality Dependence:** The effectiveness of the strategy heavily relies on the accuracy and completeness of historical price data. Inaccurate or missing data can lead to flawed covariance matrices and unreliable optimal weights, potentially impacting portfolio performance.

2. **Window Size Sensitivity:** The choice of rolling window size is crucial. A window that is too short may lead to excessive trading and overfitting, while a window that is too long may not capture recent market changes effectively. Finding the right balance is essential for optimal results.

3. **Market Conditions Adaptability:** The strategy assumes that past return patterns and volatilities are indicative of future performance. In highly volatile or unusual market conditions, these assumptions may not hold, reducing the strategy's effectiveness and potentially leading to poor performance.

4. **Transaction Costs:** Frequent rebalancing, driven by rolling window updates, can incur significant transaction costs. These costs can erode the strategy's returns, making it important to account for them when assessing overall performance.

5. **Constraint Impact on Diversification:** Constraints such as minimum weight thresholds can impact portfolio diversification. While they ensure practical investment constraints, they may limit the strategy's ability to fully optimize the portfolio for risk and return, affecting overall performance.

3.4 Market-making

This strategy revolves around capitalizing on the bid-ask spread in stock trading. Here's a breakdown of the concept:

Basic Strategy

- **Buy at the Bid**: Purchase shares at the price sellers are willing to accept (the bid price).
- **Sell at the Ask**: Sell shares at the price buyers are willing to pay (the ask price).

This simple strategy aims to profit from the difference between the bid and ask prices, known as the bid-ask spread.

Challenges in Different Market Conditions

- **"Dumb" vs. "Smart" Order Flow**:
  - In a market where most trades are executed by uninformed or *"dumb"* traders, this strategy could be very effective as it captures the bid-ask spread reliably.
  - In contrast, if most order flow is from informed or *"smart"* traders (those who have valuable information about future price movements), the strategy becomes less effective. In such markets, smart traders might trade through the bid and ask prices, causing adverse selection—where the trades are less profitable or even result in losses.
- **Adverse Selection**:
  - When the market price moves past your bid or ask price due to smart order flow, your orders may not be filled, or if filled, they might be filled at unfavorable prices, leading to potential losses.

Improving the Strategy

- **Short-Horizon Signals**:
  - To improve the strategy, traders can use short-term signals to predict the market direction. If these signals suggest the market is trending up, traders might place limit orders to buy at the bid price in anticipation of a price increase. Conversely, if the signal indicates a downward trend, they might sell at the ask price.
  - The key challenge is being among the first to place orders (high-frequency trading), requiring advanced technology and infrastructure to achieve speed and efficiency.
- **Longer-Horizon Signals**:
  - Integrating longer-term signals into the strategy can help mitigate the risks associated with adverse selection. For example, a longer-term signal might indicate that despite short-term fluctuations, the market trend is upward.
  - Using this information, traders could place limit orders that might initially experience adverse selection but become profitable over the longer term. This requires balancing between passive limit orders and more aggressive market orders based on the strength of the signals.
- **Balancing Passive and Aggressive Orders**:
  - If the longer-term signal strongly supports a particular direction and the short-term signal aligns, it might be more effective to place aggressive orders rather than waiting for limit orders to be filled.
  - Aggressive orders, which involve buying or selling immediately at the current market price, might better align with smart order flow and capitalize on favorable conditions.

Limitations of the Market-Making Strategy

1. **Adverse Selection Risk:** In markets dominated by informed traders, the strategy can suffer from adverse selection. This occurs when trades are executed at less favorable prices due to the informed nature of other market participants, potentially leading to losses.

2. **Order Fill Challenges:** The effectiveness of placing limit orders at the bid and ask prices is contingent upon getting these orders filled. In rapidly changing markets, orders might not be filled at the desired prices, or may not be filled at all if the price moves away from the bid or ask.

3. **Signal Accuracy Dependency:** The success of the strategy heavily relies on the accuracy of both short-term and long-term signals. If these signals are not reliable, the strategy may misjudge market direction and end up executing trades that result in losses.

4. **High-Frequency Trading Infrastructure:** Implementing this strategy efficiently requires advanced technology and high-frequency trading infrastructure. The need for speed in placing, canceling, and replacing orders can entail significant costs and technical challenges.

5. **Market Impact Costs:** Aggressive trading to align with short-term signals may incur market impact costs. These costs arise when large trades move the market price, which can erode the benefits of capturing the bid-ask spread.

6. **Competition and Queue Position:** In highly competitive markets, securing a favorable queue position for limit orders is crucial. Being among the first in line is not guaranteed, and other traders may execute trades before your orders are filled, impacting strategy performance.

7. **Integration of Signals:** Combining short-term and long-term signals adds complexity to the strategy. Misalignment between these signals or incorrect weighting can affect decision-making, potentially reducing the effectiveness of the strategy.

Summary

In essence, the strategy involves exploiting the bid-ask spread by buying at the bid price and selling at the ask price. Success depends on the nature of the order flow—whether it is dominated by uninformed or informed traders. To enhance effectiveness, traders use short-term and long-term signals to navigate market movements and decide between passive and aggressive order placements. High-frequency trading technology plays a crucial role in executing these strategies effectively by improving speed and order placement accuracy.

We will not implement this strategy because we used few API's on our differents projects and the number of API's call is limited when you have the free version. We hope that you fully understand this strategy which is not the most complicated and a simple implementation can show you the effect of this one.

3.5 Alpha combos

Concept

The alpha combos strategy leverages advances in technology and machine learning to analyze vast datasets and uncover numerous trading signals, or "alphas," which indicate potential returns. Unlike traditional alpha, these signals are practical trading indicators derived from various data sources such as price-volume, market capitalization, and sentiment. Due to their typically weak and fleeting nature, individual alphas alone are not highly profitable and may be undermined by trading costs. To counteract this, the strategy combines multiple alphas into a single, composite "mega-alpha." This aggregation aims to enhance predictive accuracy and create more robust trading opportunities by mitigating the limitations of single signals.

Construction

- **Selection Criteria:**
  - Start with a time series of realized alpha returns R_{is}, where $i = 1, \ldots, N$ and $s = 1, \ldots, M+1$.
  - Calculate the expected alpha returns E_i using moving averages or other methods.
- **Preprocessing:**
  - Demean the returns: $X_{is} = R_{is} - \frac{1}{M+1}\sum_{s=1}^{M+1} R_{is}$.
  - Compute sample variances of the alpha returns: $\sigma_i^2 = \frac{1}{M}\sum_{s=1}^{M+1} X_{is}^2$.
  - Normalize the demeaned returns: $Y_{is} = \frac{X_{is}}{\sigma_i}$.
  - Keep only the first M columns in Y_{is}: $s = 1, \ldots, M$.
  - Cross-sectionally demean Y_{is}: $\Lambda_{is} = Y_{is} - \frac{1}{N}\sum_{j=1}^{N} Y_{js}$.
  - Keep only the first $M-1$ columns in Λ_{is}: $s = 1, \ldots, M-1$.
- **Prediction:**
  - Normalize the expected alpha returns: $\tilde{E}_{ei} = \frac{E_i}{\sigma_i}$.
  - Calculate the residuals ϵ_{ei} from the regression of $\tilde{E}_{ei}$ over Λ_{is} (without the intercept and with unit weights).
- **Weight Assignment:**
  - Set the alpha portfolio weights to $w_i = \eta\frac{\epsilon_{ei}}{\sigma_i}$.
  - Determine the normalization coefficient η such that:

$$\sum_{i=1}^{N} |w_i| = 1$$

Expected Performance

The alpha combos strategy utilizes a combination of numerous alpha signals derived from extensive data mining and machine learning techniques. This strategy aims to construct a composite "mega-alpha" by aggregating individual alphas, which are then used to optimize portfolio weights. The expected performance of this strategy hinges on the quality and relevance of the alpha signals, which are based on various factors including price-volume data, market capitalization, and sentiment indicators.
The effectiveness of the alpha combos strategy depends on the accuracy of the expected alpha returns and the precision of the normalization and weighting processes. By combining multiple alphas, the strategy seeks to capture profitable trading opportunities while mitigating the risks associated with individual signals. Regular updates and recalibration of the alpha signals ensure the portfolio adapts to the latest market conditions. However, the strategy's performance is contingent upon the assumption that historical alpha signals remain informative about future returns. The success of the alpha combos approach is thus influenced by its ability to integrate and leverage diverse alpha sources while managing transaction costs and maintaining a balanced portfolio.

Practical Considerations

The alpha combos strategy, while powerful in combining multiple trading signals, involves several practical considerations:

- **Alpha Signal Quality:** The effectiveness of the strategy heavily depends on the quality and accuracy of the alpha signals. Weak or noisy signals may lead to suboptimal portfolio construction and reduced profitability.
- **Data Integration:** Integrating diverse data sources—such as price-volume, sentiment, and fundamental data—requires sophisticated data management and processing. Ensuring the consistency and relevance of this data is crucial for reliable alpha generation.
- **Transaction Costs:** Frequent adjustments based on alpha signals can result in significant transaction costs. Managing these costs is essential to ensure that the alpha-generated profits are not eroded by trading expenses.
- **Signal Overfitting:** There is a risk of overfitting when using complex machine learning methods to derive alphas. This can lead to alpha signals that perform well historically but fail to generalize to new market conditions.
- **Portfolio Diversification:** The combination of multiple alphas needs to be carefully managed to ensure adequate diversification. Concentrating too heavily on certain signals or sectors may increase risk and reduce the strategy's robustness.

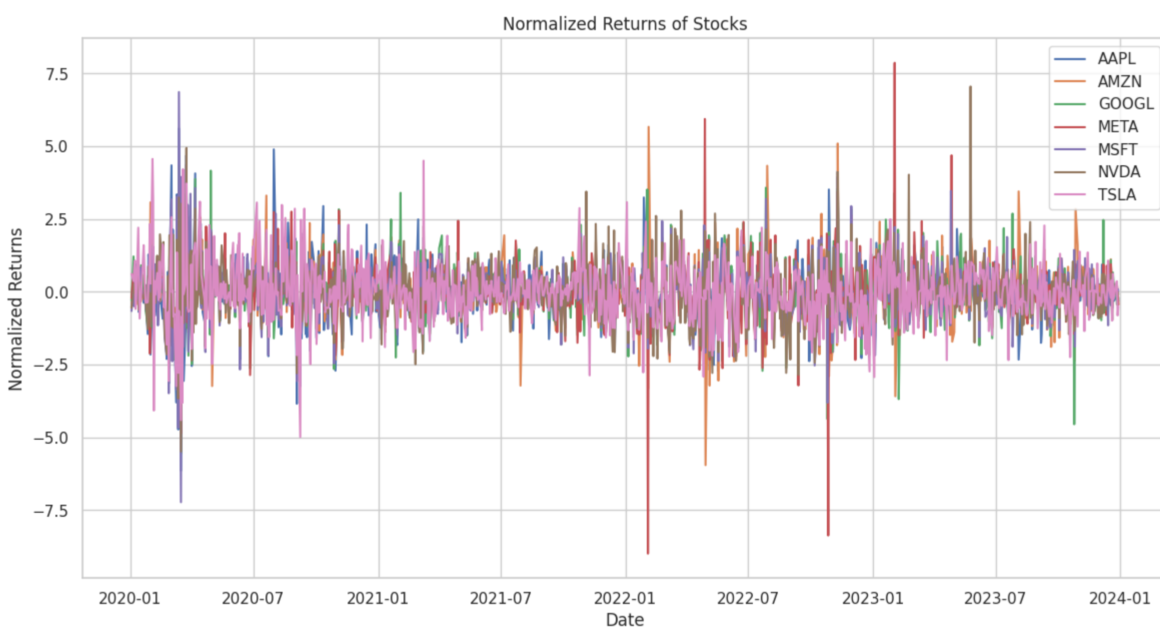
Backtesting and Optimization

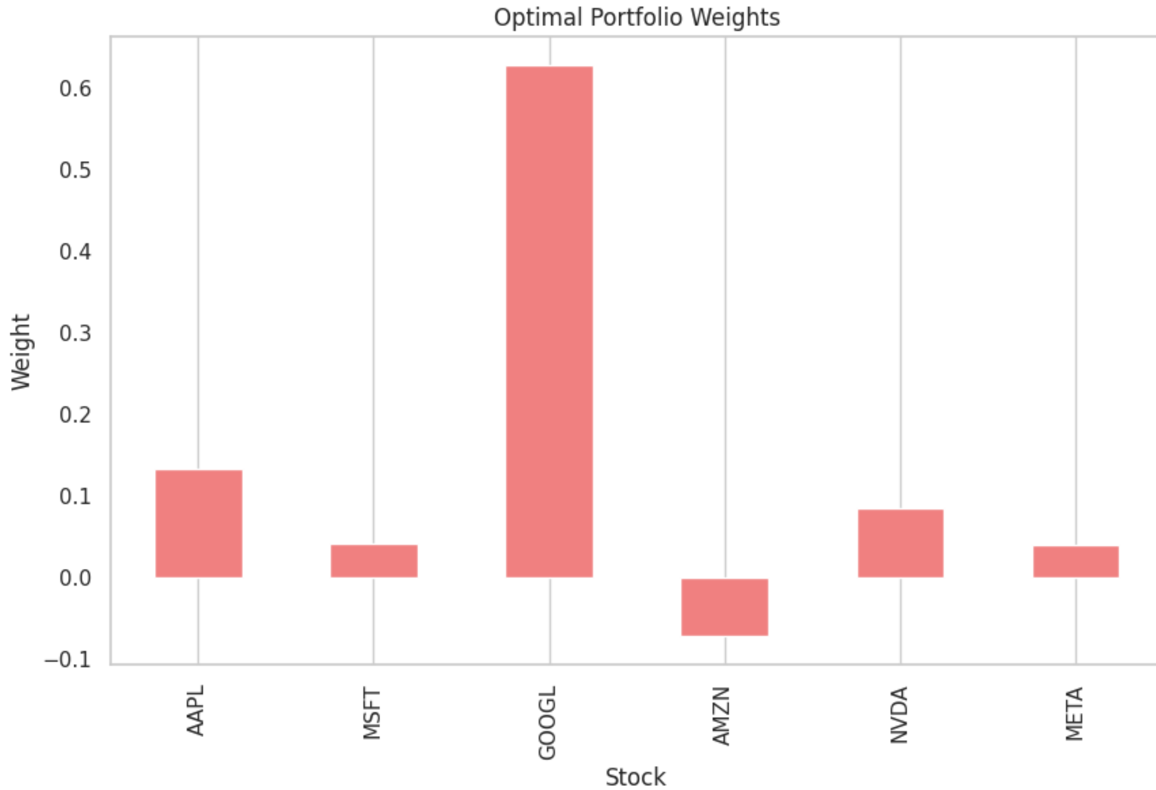
Backtesting the alpha combos strategy involves applying the approach to historical data to evaluate its performance and robustness across different market conditions. This process includes several key steps:

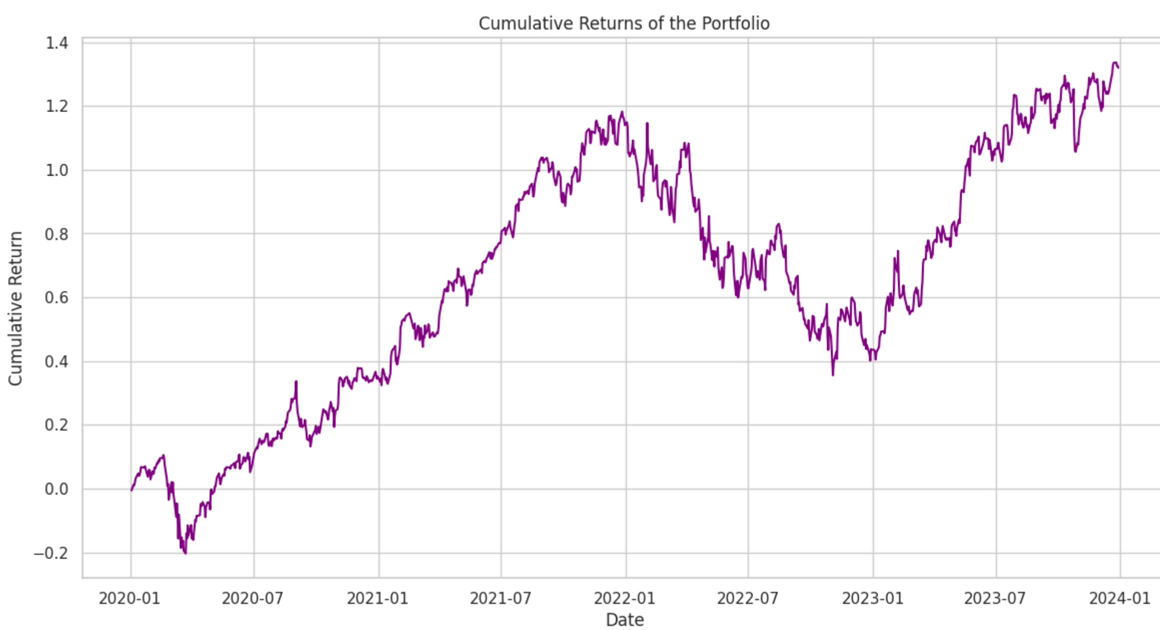
- **Alpha Signal Evaluation:** Assess the effectiveness of the alpha signals by applying them to historical returns and analyzing their predictive power. This helps in identifying which signals contribute most to the overall portfolio performance.
- **Parameter Tuning:** Optimize parameters such as the number of alphas included, the normalization techniques, and the weighting schemes. Adjustments to these parameters can help maximize the portfolio's risk-adjusted returns while controlling for overfitting.
- **Sensitivity Analysis:** Evaluate how changes in data quality, signal accuracy, and transaction costs impact the strategy's performance. This involves testing the strategy under various scenarios to ensure robustness and reliability.
- **Transaction Cost Management:** Incorporate realistic transaction costs into the backtesting process to assess their impact on net returns. This helps in fine-tuning the strategy to balance alpha generation with trading expenses.
- **Performance Metrics:** Analyze performance metrics such as the Sharpe ratio, alpha, and beta to gauge the strategy's effectiveness. This includes assessing performance across different market phases to ensure consistency and adaptability.

Effective backtesting and optimization are crucial for refining the alpha combos strategy, ensuring it performs well under diverse market conditions and is resilient to potential pitfalls.

Our Implementation







Our alpha combos strategy implementation does not include individual alpha signals due to data constraints. Effective use of the alpha combos approach usually requires analyzing hundreds of thousands or millions of stocks to identify and combine multiple alpha signals. However, due to limitations in available tools and data sources—such as restricted API access and data constraints from platforms like Yahoo Finance—we are limited in the number of stocks and signals we can analyze. Consequently, our implementation is based on the data and tools at hand, which may affect the strategy's depth and effectiveness.

Limitations of the Alpha Combos Strategy

1. **Alpha Quality and Stability:** The effectiveness of the Alpha Combos strategy depends heavily on the quality and stability of the individual alphas used. Since alphas are derived from historical data and models, they may be unstable or unreliable if the underlying data or model assumptions change. Variability in alpha quality can lead to inconsistent performance.

2. **Dimensionality Issues:** The strategy involves regression techniques on high-dimensional data. If the number of alphas (features) is high relative to the number of observations, it may lead to overfitting. This can result in poor generalization to unseen data and reduced effectiveness in real-world scenarios.

3. **Alpha Decay:** Alphas identified through historical data may lose their predictive power over time, a phenomenon known as alpha decay. This can be particularly problematic in rapidly changing markets or when the historical relationships used to generate alphas no longer hold.

4. **Data Overfitting:** The process of generating and selecting alphas can be prone to overfitting, especially when using sophisticated machine learning models. Overfitting occurs when the model fits the historical data too closely, capturing noise rather than true signals, which can diminish out-of-sample performance.

5. **Transaction Costs and Liquidity:** Combining multiple alphas and trading on them can lead to high turnover, resulting in significant transaction costs. Additionally, the liquidity of the stocks being traded can impact the execution of the strategy, especially if the stocks are not sufficiently liquid or if trading volumes are low.