Trading Strategy for Commodities (OIL)

TEAM 5	PROJECT
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Executive Summary

The United States Oil Fund (USO) Exchange Traded Fund is a security whose shares trade on the New York Stock Exchange. The ETF invests primarily in listed crude oil futures contracts and aims to mirror changes to the price of the oil commodities indices. The energy sector, and crude oil in particular, is well known for its volatility which presents an exciting opportunity for a disciplined and data-driven day trading strategy. The trading strategy we have applied to the USO ETF involves day trading with a one-day investment horizon. The objective is to capitalize on intraday price movements through the analysis of market indicators and machine learning. Using Machine Learning, we predict the daily High and Low of the ETF and use these predictions to enter or abstain from trading in a day. Beginning with a fixed capital of $10,000, our strategy dynamically adjusts the volume of trades and establishes entry and exit points of contracts, allowing for the creation of sustained returns. Applying a variety of strategies and then ensembling them to create a unified long-short strategy has allowed us to produce good returns within the validation and test sets.

Key components of our strategy are the creation of a robust and generalizable algorithm to enter and exit trades, the management of risk by optimizing for Sharpe ratio, the use of extensive backtesting and optimization to achieve strong alpha and the dynamic adaptation of strategy to suit varying market conditions. Going beyond simple buy/sell mechanics to include thresholds for friction (the cost of trading), long and short trades, stop-losses and take-profits, our project demonstrates the ability to be profitable, mitigate risk, and adapt to market circumstances. Furthermore, actionable steps for future work suggested in this report can build upon our efforts to improve the models, strategy and returns while allowing for more realistic benchmarking against the real-world.

Link to codebase: https://github.com/VibhuKrovvidi/USO_ETF_Day_Trading

Introduction

The USO ETF (United States Oil Fund), is an exchange traded fund which tracks the daily price movements of West Texas Intermediate (WTI) light sweet crude oil. Launched in 2006, USO is a popular investment vehicle for individuals and institutional investors seeking exposure to the fluctuations in oil prices without directly trading futures contracts. USO achieves its objective by investing in short-term oil futures contracts, allowing investors to gain or mitigate exposure to the energy market (USCF, n.d.). The fund aims to reflect the performance of the spot price of WTI crude oil, a key benchmark for oil pricing globally. With a market capitalization of over US$880 million and daily volumes of trades exceeding 4 million, it is liquid and presents low bid-ask spreads, making it suitable for a day trading strategy at a small scale.

Day trading is a short-term trading strategy where individuals trade securities within the same trading day. The aim is to profit from intraday price movements of these securities. Day trading has a number of attributes that affect the nature of the strategies applied:

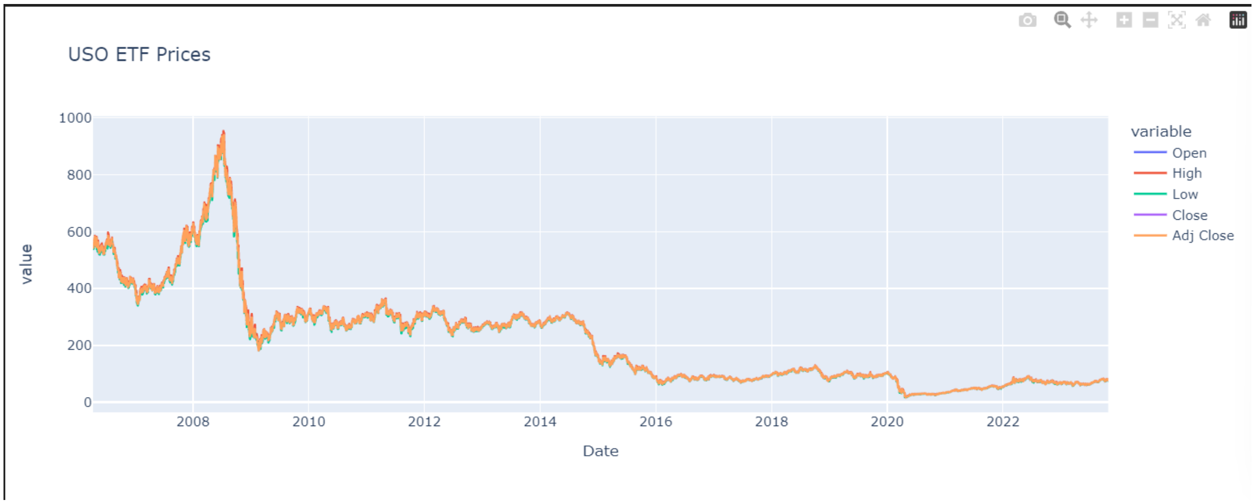
- **Investment Horizon:** Day trading is usually very short term and aims to capture fluctuations in the market by leveraging volatility of the security's price. Positions are never held overnight, and are usually closed by the end of the trading day.
- **Risk and Reward:** Day trading inherently exploits the volatility of the markets, thus meaning that the investor is exposed to considerable risk. Day trading therefore requires very careful management and monitoring of risk.
- **Market Knowledge:** Successful traders tend to possess a solid understanding of the fundamentals. In our case, we are not experts in the commodities market and thus rely on signals generated purely from the data to trade.
- **Capital Requirements:** Most securities do not have large volatility meaning that margins are slim. Thus, large capital is required for meaningful returns. Often, leverage is introduced, which adds to both return and risk.
- **Fees and Costs:** Large volumes of transactions in a single day may be expensive since brokers can deduct fees for buying and selling securities. Thus, depending on the market, friction introduced by fees is a serious consideration when calculating the expected profits from a trade.

Understanding the nature of day trading allows us to design meaningful strategies that can be applied to generate returns from the USO ETF. Our fundamental task can be broken down as follows:

1. Given a variable `delta`, if the expected profit from a day's trade exceeds `delta` then we enter the trade by buying a stock at the opening price.
2. We then predict the High or Low of the day and use that prediction to create take-profits to exit our position. If no profit is achieved, we exit at the day's close.
3. To make the predictions, we leverage Machine Learning trained on historical data from the ETF's inception in 2006.

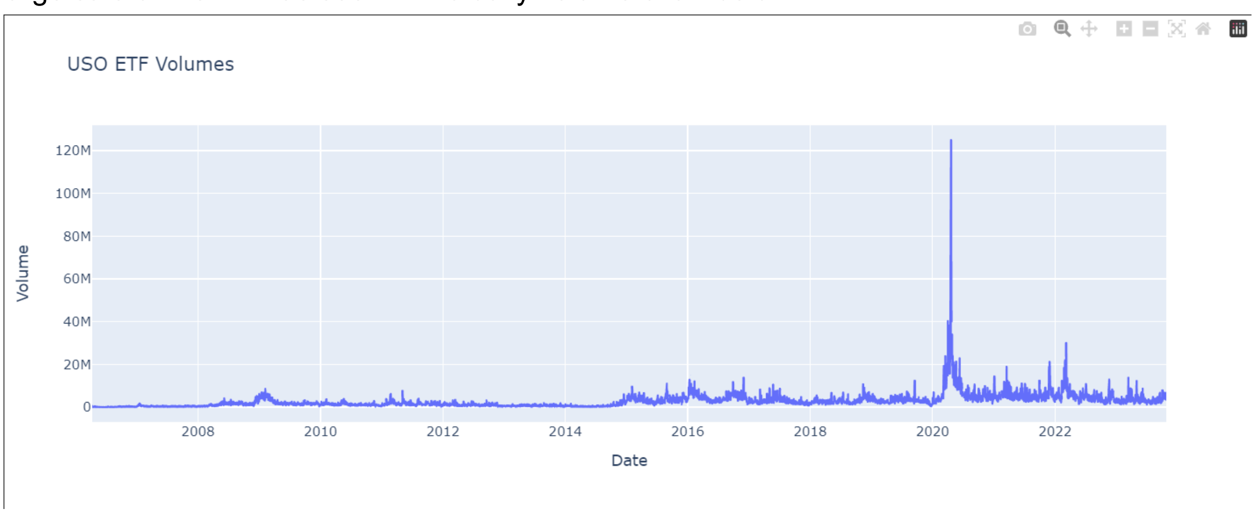
Exploratory Data Analysis

We began by pulling the historical data of the USO ETF from it's inception in 2006 to the 31st of October 2023. We obtained data for 4418 trading days across variables like Date, Open, High, Low, Close, Volume. We then visualized these in an interactive plot to understand the time series of the price of the ETF since inception:

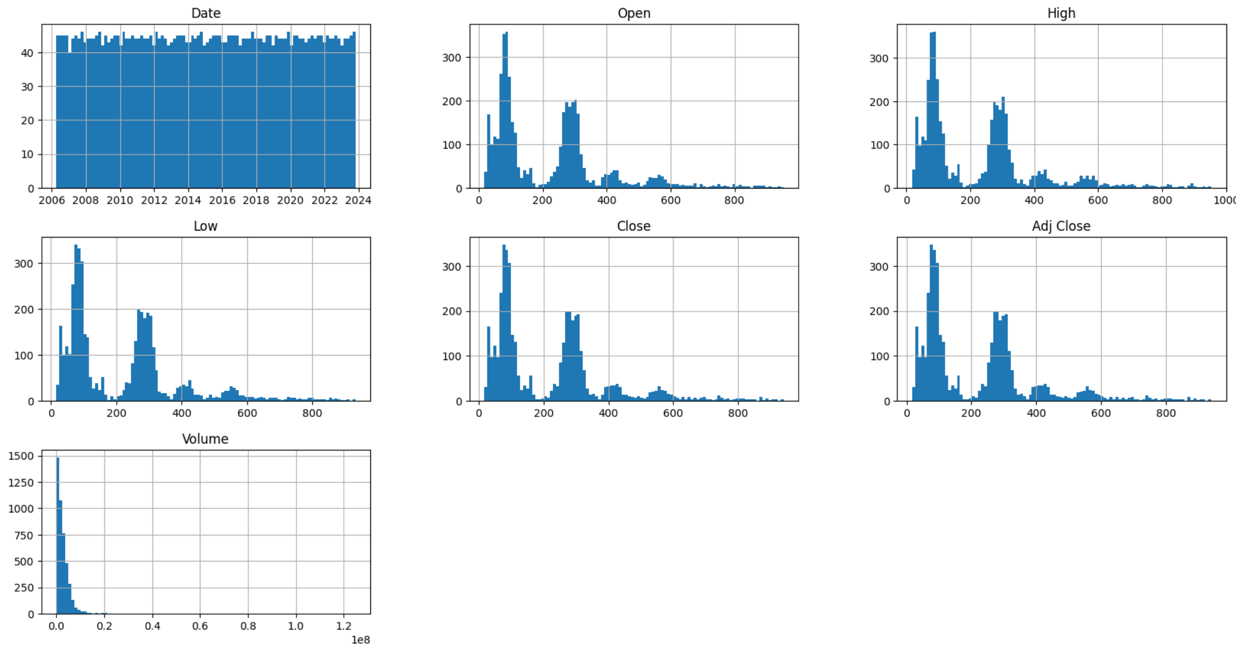


The ETF shows large changes in the first 3 years and then settles from 2010 to 2015 before facing a steady decline. Sharp declines are observed in 2014 and 2020 which correspond to the geopolitical events of the invasion of Crimea and COVID-19 pandemic.

Notably, in 2020 during the start of the pandemic, the price of oil became negative which led to a large sale of the ETF as seen in the daily volume chart below:

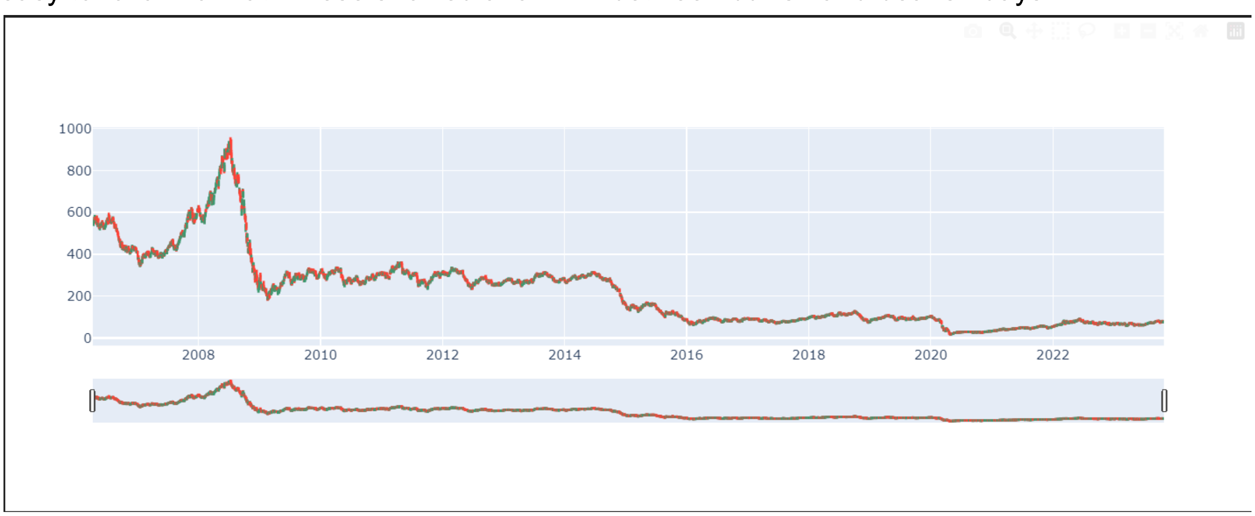


To better understand the distribution of the prices and the volumes, we plotted histograms as follows:



It is interesting to see that the distribution of values for the price are bimodal, having two peaks around $100 and $300. These are attributed to the large values of the ETF from 2006-2009 and then the stable but lower values from 2009-2015. The distribution of Volume is heavily skewed to the left, pointing to the equilibrium trading volumes for the ETF in all periods except the start of the pandemic.

We also created a candlestick chart that expressed the Open, High, Low, Close prices in a more easy to follow format. These showed a fair mix between bullish and bearish days:



The key takeaways from our EDA are:

- The bimodal distribution makes a normal distribution scaler unsuitable.
- There are a few distinct periods of large change/transition surrounded by long periods of stability. Thus, our model should learn to handle both the stable and transitionary periods to be successful.

Data Augmentation

To complement the raw dataset, we introduced several new variables and datasets that could add prediction power to the model. These are:

- **Ten Year Treasury Yield - Two Year Treasury Yield**
    - Treasury yields are ultimately a reflection of supply and demand because they showcase the cost of the U.S. government debt. The 10 year - 2 year Treasury yield spread is a measure of steepness of the yield curve, conveying market expectations of future interest rates. Oil prices are deeply connected with US treasury yield: over the last five years, crude oil and US treasury yields have moved in tandem because crude oil prices reflect world demand. Thus, including the 10-2 year spread is a valuable addition to our oil ETF price prediction model.
- **US Dollar Index (DXY)**
    - Crude oil and U.S. Dollar often have an inverse relationship: when the value of the U.S. dollar decreases, crude oil prices tend to increase and vice versa. This is because crude oil is priced in U.S. dollars, so a weaker dollar means it takes more dollars to buy the same amount of oil. As DXY is a measure of the U.S. Dollar relative to a basket of foreign currencies, its inclusion into our data could convey useful information to our oil ETF price prediction model.
- **Gold Index**
    - Changes and co-movement in gold and oil prices have always been the subject of worldwide attention. Research suggests that there has been a positive price correlation between gold and oil prices more than 80% of the time in the past 50 years. Interestingly, this relationship was briefly inverted during the COVID-19 pandemic, where the WTI crude oil prices plummeted, prompting investors to seek safer assets, particularly gold. Undeniably, there is a deep connection between these two assets, and to leverage that we introduce the Gold Index data into our model.
- **Swiss Franc Exchange Rates (CHF/USD)**
    - When observing multilateral relationship between currencies and oil, significant evidence was found that the Swiss Franc moves multilaterally AGAINST oil currencies and not against the global price of oil - this negative correlation could help in our model's predictions.
- **BNO ETF and USL ETF (Competing ETFs)**
    - The inclusion of quantitative data from competing ETFs could help catch early trends that the other ETFs react to early on compared to the USO ETF. Indeed, both funds own much fewer net assets than USO ETF (145M and 75M compared to 1B+) and have varying fund strategies, which could provide important complementary information when predicting oil prices.
- **S&P GSCI Index (A commodities index)**
    - The S&P GSCI® is a composite index of commodity sector returns. GSCI is heavily weighted towards energy commodities. As of 2021, energy commodities make up around 40% of the index. This means that any movement in the energy sector can have a significant impact on the overall performance of the GSCI. For

example, if oil prices rise, the GSCI is likely to increase as well. By including the GSCI index, we aim to capture this intricate connection between GSCI and oil.

We also added lagged variables so that the model has access to previous days' values. This helps supply some information about the past to the model while refraining from using leaked values that the true model would not have access to such as the present day's close, highs and lows.

Our final dataframe of raw data consisted of 4419 rows (including column titles) and 79 columns.

Modeling

Our objective is to predict the High and Low price of the ETF each day so that we can place orders to buy/sell. Since the target variables are both numerical, the modeling task is a regression problem. As seen in the EDA, the price of the ETF varies by a lot over time, hitting a high of $939.12 in July 2008 and a low of $20.56 in April 2020. This represents a very large change of scale which could be a challenge for regression models to handle. Thus, we opted to use the difference between the day's High/Low as the target variable. This helps us increase the resolution of our data which will in-turn help us get more representative metrics of model performance.

For the prediction of High - Open and Low - Open, we performed the following steps:

- Remove High, Low and Close for present day while maintaining the lagged values from previous days.
  - This ensures that there is no data leakage from the model's point of view.
- <u>Randomly</u> split the data into train, validation and test sets
  - We used a ratio of 56.25 : 18.75 : 25 to ensure that we have plenty of data to train and validate our models while still having a decent sized test set to compare against.
  - This translates to 2485 days, 829 days and 1105 days respectively.
- Perform forward piecewise variable selection using Linear Regression
  - Starting with no variables, we iteratively add variables and produce a regression model using the train data. We then observe the p-value of the added variable. If the p-value is less than 0.05, then we add the variable to the selected variable list else we move on.
  - The purpose of this is twofold:
    - Remove multicollinearity which would create bias in our model and cause overfitting.
    - Reduce the total amount of data to make the modeling and strategy tasks more computational efficient.
- We instantiated a pipeline that applies a MinMax Scaler to all columns in the train data and then performs Regression
  - This pipeline ensures that when we do hyperparameter tuning the scaler does not use data from the unseen test datasets.
  - We tested 4 Regression methods:
    - Linear Regression
      - Ridge and Lasso Regression
    - Random Forest
      - Random Forest Regression
    - XGBoost
      - XGBoost Regression
    - Neural Networks
      - Deep Neural Network
- We then perform a random search over a large parameter space to ensure that we find

the best hyperparameters for the models.
  - We fit 20 iterations using 5-fold cross validation for a total of 100 fits to find the best value.
  - The use of random search instead of grid search allows us to randomly traverse a large parameter space quickly, thereby improving the efficiency of the model tuning.
- Finally, we use the best model and apply it on the validation dataset to find the Mean Square Error and R^2 metric.
  - The MSE is a useful metric since it is direction agnostic (ie it is able to handle both positive and negative errors). Since our data is scaled, the mean square error is a good indicator of how well our model is able to predict the High/Low prices across various scenarios.
  - The R^2 metric is a measure of the amount of variability in the High/Low prices that our model is able to capture. This is a useful metric because it provides insight into how the model is able to learn correlations between the independent and dependent variables, indicating better generalization in unseen data.

Strategy

We employed three strategies using our predictions of daily High and Low pricing. For each, we supplied a delta which represented the minimum difference between Open and High/Low required for our model to consider trading. Based on this delta and our predictions, each strategy then has different mechanisms for entering and exiting trades within the day. Each strategy also takes a capital allocation limit parameter which represents the maximum percentage of capital that can be allocated to a trade in a given day. This can be changed to represent more conservative or aggressive risk profiles.

Since day trading is mostly carried out by small scale investors rather than large institutions, we instituted a scenario with $10,000 of starting capital to test on our different datasets. This provides an easy to follow measure of the model's long-term performance along with other measures of risk and return.

Each strategy is then tuned on the training dataset where hyperparameters such as the capital allocation ratio and the delta are tuned to optimize for a user supplied choice of:

- Sharpe Ratio
- Total Capital
- Average P&L
- Standard deviation of P&L

Each strategy caters to different strengths and scenarios. Some are more conservative while others are risky but offer opportunities for greater returns. The strategies are outlined below:

Blind Strategy

- If the predicted difference between High and Open is greater than the delta parameter supplied, enter a trade with a take-profit at our predicted High
- If we enter a trade, then:
    - Put an order to sell at our predicted High price
    - If the actual High of the day is equal or exceeds our prediction, we sell at our predicted high and take profit
    - Else, if the predicted High is not reached, we sell at Close

Stoploss Strategy

- If the predicted difference between High and Open is greater than the delta parameter supplied, enter a trade with a take-profit at our predicted High.
- We simultaneously put a stop-loss at the Open price so that in a day we would only ever end with a profit or no loss.
- If we enter the trade, then:
    - Put an order to sell at our predicted High price

    - If the actual High of the day is equal or exceeds our prediction, we sell at our predicted high and take profit
    - If price is at Open and about to dip below Open, sell the stock
    - Else, if the predicted High is not reached, we sell at Close

Ensemble Long-Short Strategy

- If the predicted difference between High and Open is greater than the delta parameter supplied, enter a trade with a take-profit at our predicted High. The amount of stock we go long is equal to the capital allocation ratio.
- We simultaneously short the stock with a take profit at the predicted Low price. The amount of stock we go short is equal to 1 - the capital allocation ratio.
- If we enter a long trade, then:
    - Put an order to sell at our predicted High price
    - If the actual High of the day is equal or exceeds our prediction, we sell at our predicted high and take profit
    - Else, if the predicted High is not reached, we sell at Close
- If we enter a short trade, then:
    - Put an order to buy back at our predicted Low price
    - If the actual Low of the day is equal or is lower than our prediction, we buy back at our predicted Low and take profit
    - Else, if the predicted Low is not reached, we buy back at Close

This strategy is ensembling our long and short strategies and allocating complete capital in each trade. It is risker since we could face unlimited downside with the short, but maximizes the opportunities for alpha too. Without a stop-loss in place, the goal of this strategy is to apply both our High - Open and Low - Open predictions to gain profits.

Results

Model Performance

To recall, we experimented with four different types of **regression** models:

1. Linear Regression
2. Random Forests
3. XGBoost
4. 2-layer Neural Network

For all above models, we mask the high, low and close features, as well as the “lag” features (which indicate difference with the previous trading day), to prevent **data leakage**.

Additionally, we performed **forward feature selection** and **random search hyperparameter tuning** using cross-validation to identify the best performing models. All models were implemented using **Scikit-Learn** and **XGBoost** libraries in Python. We used **Mean Squared Error (MSE)** and **R^2 Scores** to measure the performance of the regression models.

The following table summarizes the performance of all regressors for the **High - Open** daily price prediction:

Regressor	**Train MSE**	**Test MSE**	**Train R^2**	**Test R^2**
Linear Regression	7.677	**7.842**	0.506	**0.380**
Random Forest	4.396	8.373	0.717	0.338
XGBoost	0.0013	10.410	0.999	0.177
Neural Network	9.784	9.129	0.369	0.278

Similarly, the following table summarizes the performance of all regressors for the **Low - Open** daily price prediction:

Regressor	**Train MSE**	**Test MSE**	**Train R^2**	**Test R^2**
Linear Regression	8.261	**7.934**	0.542	**0.501**
Random Forest	3.481	8.718	0.807	0.451
XGBoost	0.354	8.403	0.980	0.471
Neural Network	9.428	8.763	0.477	0.449

MSE is in **red** as the lower the value, the better the model performance, and R^2 score is in **green** as the higher the value, the better the model performance.

From both tables, we observe that the **Linear Regression model** performs the best among all models. Our analysis reveals that:

1. Linear regression has sufficient and **appropriate model complexity** for this problem given the scarcity in data, compared to more complex models such as Random Forests or XGBoost.
2. Therefore, the linear regression model **avoids overfitting** on the training data: this can be observed by the fact that both Random Forests and XGBoost have much better training data scores but worse test data scores.
3. Neural networks don't perform well due to the **lack of data**: these models are particularly data hungry, and are underfitting our data. This is clear from the poor training and test scores of the 2 layer neural network model.

As the Linear Regression model achieves the best MSE and R^2 scores, we deploy its predictions for our Day Trading strategies.

Strategy Performance

For all day trading strategies we explored, this section presents tables and plots of results for the train and test datasets. Several values for the delta (threshold to enter the market) were explored, and the best delta value was tuned for the training data. The same value of delta was used on the test data.

Number of trading days in the training data: 3314, or 13.15 years
Number of trading days in the test data: 1105, or 4.38 years

We present results for two categories of tuning: to achieve the best Sharpe Ratio, and to achieve the best Final Capital. That is, we optimize for two different metrics in each case.

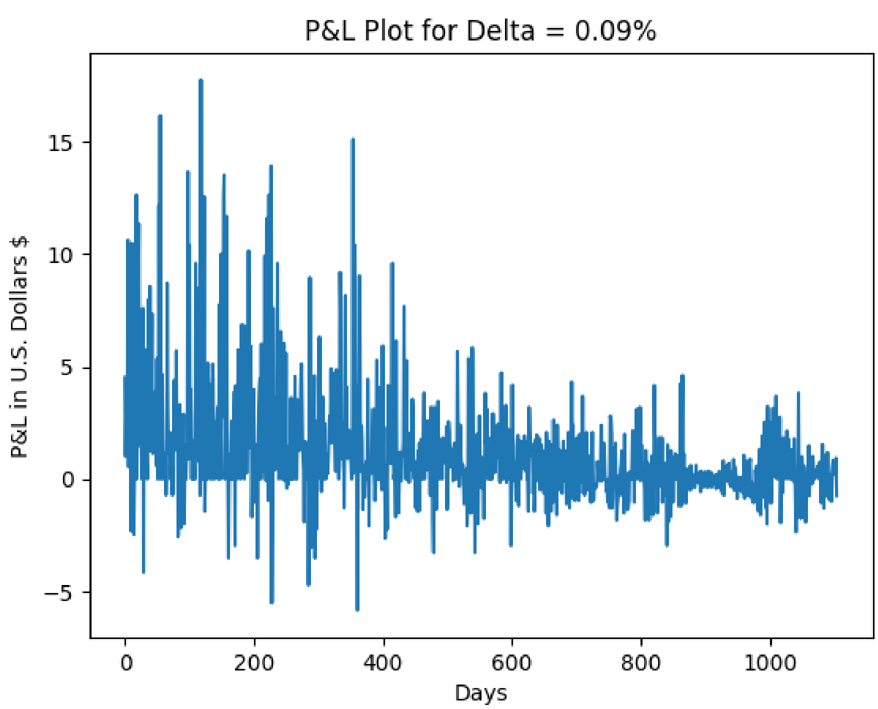
The initial capital chosen is 10,000 USD, with a limit to at maximum invest up to 50,000 USD. For Sharpe Ratio calculations, the risk-free rate is assumed to be at 4% based on approximate 10-year treasury yields data over the recent past.

Blind (Long Only) Strategy

i) **Optimizing Sharpe Ratio:**
The following table shows results for the Blind strategy, optimizing Sharpe Ratio. To get the Best Sharpe Ratio, the Best Delta = 0.09% of open price.

Metric	**Training**	**Test**
Sharpe Ratio	0.421	0.471
Annualized Return	36.781%	75.575%
Final Capital	614,950.672$	118,018.330$
Average P&L per share over all traded days	1.041$	1.119$
Risk: Standard Deviation of P&L per share over all traded days	2.470	2.375
% Profitable Trading Days	63.46%	63.17%
% Lossy Trading Days	22.51%	22.08%
% Neutral Trading Days	14.03%	14.75%

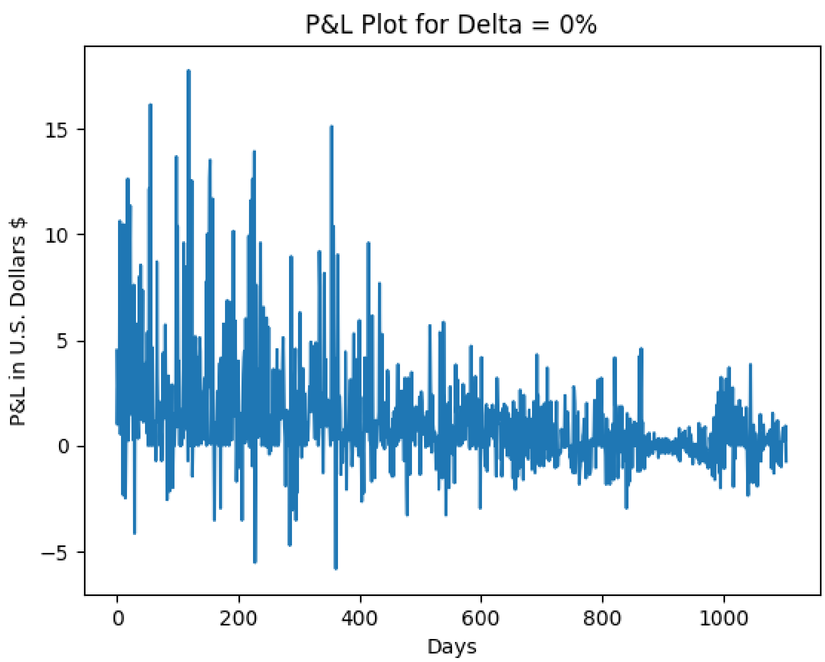
For test data, P&L per share plot (Blind Strat, Sharpe Ratio Optimization, 0.09% Delta):



ii) **Optimizing Final Capital/Annualized Return:**
The following table shows results for the Blind (Long Only) strategy, optimizing Final Capital. To get the Best Final Capital, the Best Delta = 0% of open price: that is, if the difference between high and open is positive, the trade is made.

Metric	**Training**	**Test**
Sharpe Ratio	0.415	0.474
Annualized Return	36.894%	75.863%
Final Capital	621,674.25$	118,869.97$
Average P&L per share over all traded days	1.067$	1.125$
Risk: Standard Deviation of P&L per share over all traded days	2.570	2.372
% Profitable Trading Days	65.87%	66.70%
% Lossy Trading Days	22.51%	22.08%
% Neutral Trading Days	11.62%	11.22%

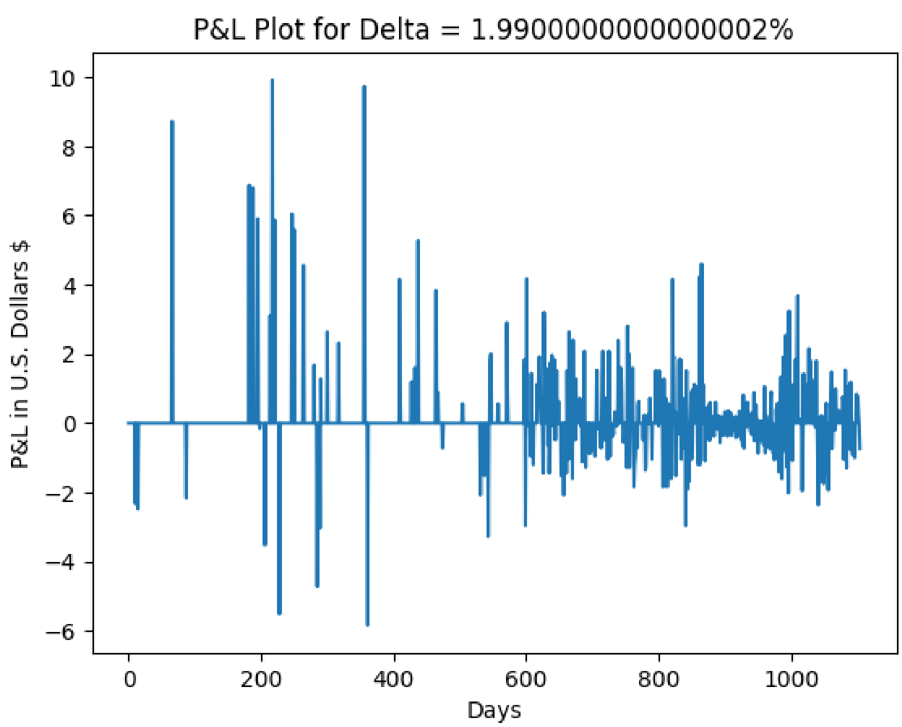
For test data, P&L per share plot (Blind Strat, Final Capital Optimization, 0% Delta):



ii) **Optimizing Standard Deviation:**
The following table shows results for the Blind (Long Only) strategy, optimizing Standard Deviation (minimizing risk). To get the Best Stdev, the Best Delta = 1.99% of open price.

Metric	**Training**	**Test**
Sharpe Ratio	0.104	0.100
Annualized Return	12.700%	9.203%
Final Capital	48178.14$	14711.44$
Average P&L per share over all traded days	0.109$	0.100$
Risk: Standard Deviation of P&L per share over all traded days	1.052	1.005
% Profitable Trading Days	17.29%	16.65%
% Lossy Trading Days	15.36%	15.20%
% Neutral Trading Days	67.35%	68.14%

For test data, P&L per share plot (Blind Strat, Standard Deviation Optimization, 1.99% Delta):

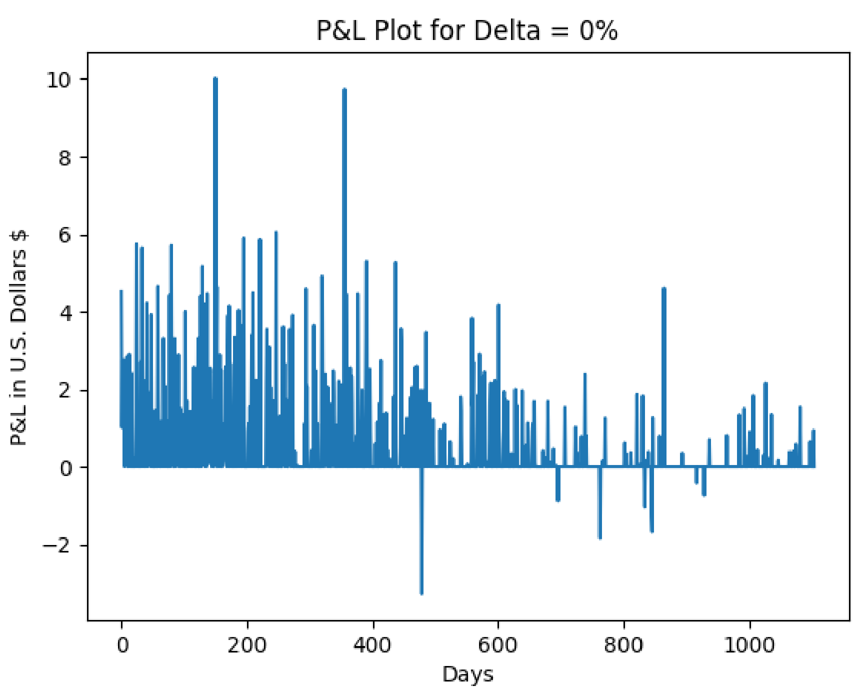


Stop Loss Strategy

i) **Optimizing Sharpe Ratio:**
The following table shows results for the Stop Loss strategy, optimizing Sharpe Ratio. To get the Best Sharpe Ratio, the Best Delta = 0% of open price: that is, if the difference between high and open is positive, the trade is made.

Metric	Training	Test
Sharpe Ratio	0.455	0.453
Annualized Return	27.709%	30.905%
Final Capital	249,393.74$	32,572.03$
Average P&L per share over all traded days	0.510$	0.494$
Risk: Standard Deviation of P&L per share over all traded days	1.120	1.091
% Profitable Trading Days	33.04%	32.22%
% Lossy Trading Days	0.91%	0.72%
% Neutral Trading Days	66.05%	67.06%

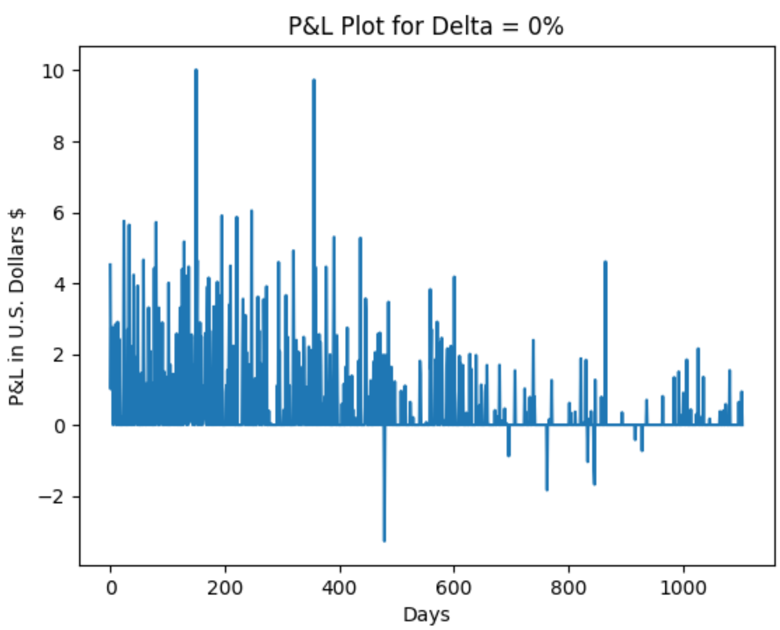
For test data, P&L per share plot (Stop Loss Strat, Sharpe Ratio Optimization, 0% Delta):



ii) **Optimizing Final Capital/Annualized Return:**
The following table shows results for the Stop Loss strategy, optimizing Final Capital. To get the Best Final Capital, the Best Delta = 0% of open price: that is, if the difference between high and open is positive, the trade is made. As this is the same delta as the Sharpe Ratio optimization case, the results match!

Metric	**Training**	**Test**
Sharpe Ratio	0.455	0.453
Annualized Return	27.709%	30.905%
Final Capital	249,393.74$	32,572.03$
Average P&L per share over all traded days	0.510$	0.494$
Risk: Standard Deviation of P&L per share over all traded days	1.120	1.091
% Profitable Trading Days	33.04%	32.22%
% Lossy Trading Days	0.91%	0.72%
% Neutral Trading Days	66.05%	67.06%

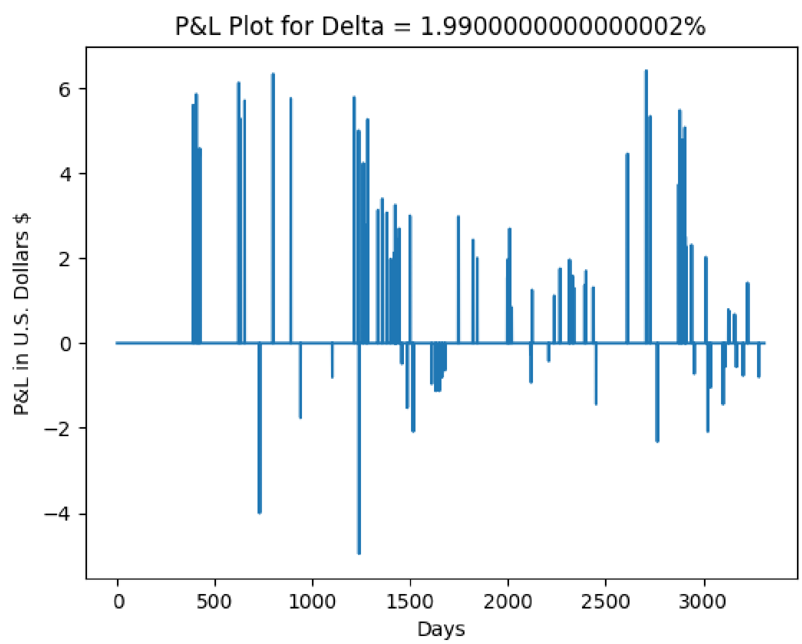
For test data, P&L per share plot (Stop Loss Strat, Sharpe Ratio Optimization, 0% Delta):



iii) **Optimizing Standard Deviation:**
The following table shows results for the Stop Loss strategy, optimizing Standard Deviation. To get the Best Standard Deviation, the Best Delta = 1.99% of open price

Metric	**Training**	**Test**
Sharpe Ratio	0.092	0.097
Annualized Return	6.173%	6.697%
Final Capital	21984.70$	13287.77$
Average P&L per share over all traded days	0.044$	0.051$
Risk: Standard Deviation of P&L per share over all traded days	0.480	0.519
% Profitable Trading Days	1.75%	1.81%
% Lossy Trading Days	0.75%	0.63%
% Neutral Trading Days	97.50%	97.56%

For test data, P&L per share plot (Stop Loss Strat, Standard Deviation Optimization, 1.99% Delta):

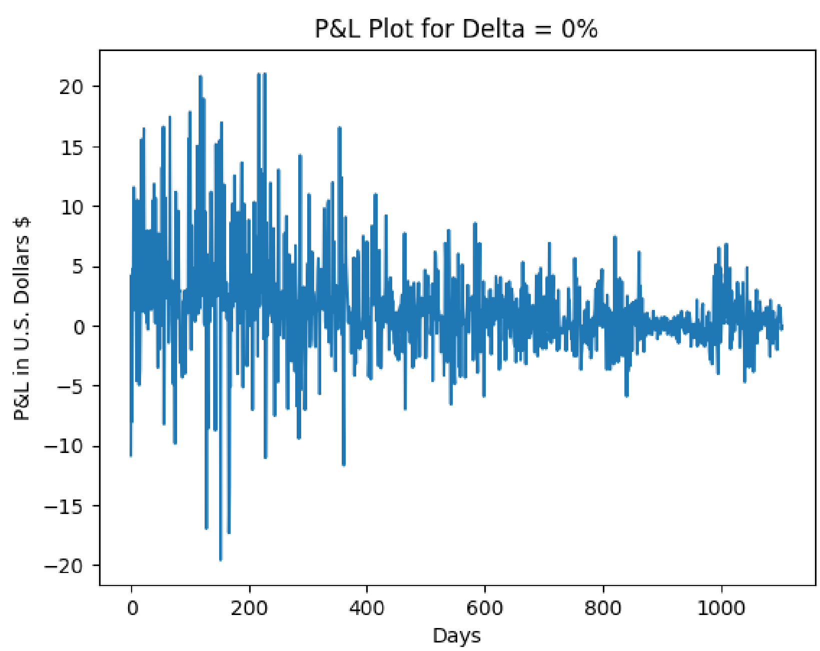


Ensemble Long-Short Combined Strategy

i) **Optimizing Sharpe Ratio:**
The following table shows results for the Long-Short strategy, optimizing Sharpe Ratio. To get the Best Sharpe Ratio, the Best Delta = 0% of open price: that is, if the difference between high and open is positive, the trade is made.

Metric	**Training**	**Test**
Sharpe Ratio	0.274	0.335
Annualized Return	40.354%	109.548%
Final Capital	1,395,404.16$	357,168.83$
Average P&L per share over all traded days	1.106$	1.273$
Risk: Standard Deviation of P&L per share over all traded days	4.031	3.796
% Profitable Trading Days	52.98%	52.79%
% Lossy Trading Days	6.29%	5.91%
% Neutral Trading Days	40.72%	41.30%

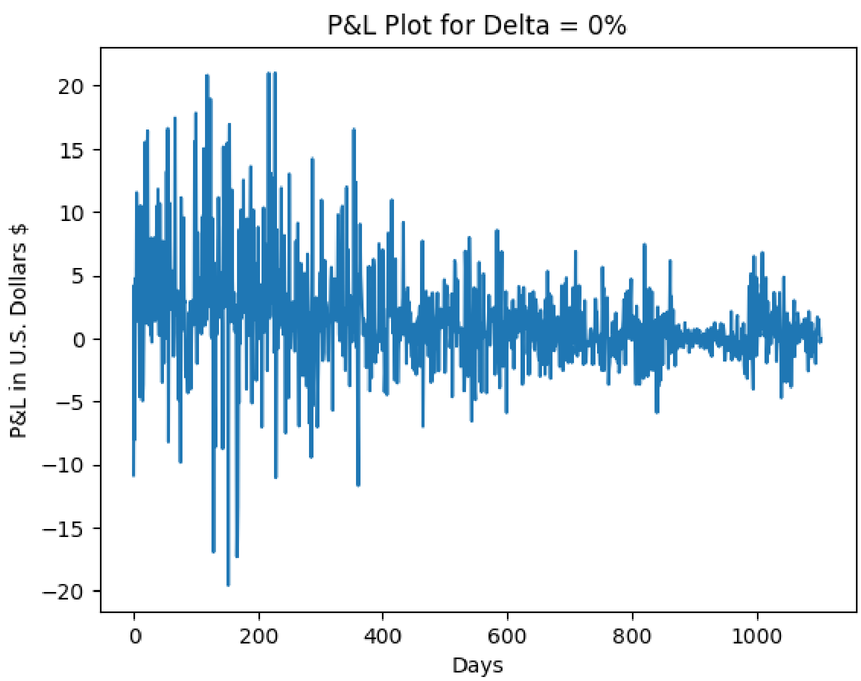
For test data, P&L per share plot (Long Short Strat, Sharpe Ratio Optimization, 0% Delta):



ii) **Optimizing Final Capital/Annualized Return:**
The following table shows results for the Long Short strategy, optimizing Final Capital. To get the Best Final Capital, the Best Delta = 0% of open price: that is, if the difference between high and open is positive, the trade is made. As this is the same delta as the Sharpe Ratio optimization case, the results match!

Metric	**Training**	**Test**
Sharpe Ratio	0.274	0.335
Annualized Return	40.354%	109.548%
Final Capital	1,395,404.16$	357,168.83$
Average P&L per share over all traded days	1.106$	1.273$
Risk: Standard Deviation of P&L per share over all traded days	4.031	3.796
% Profitable Trading Days	52.98%	52.79%
% Lossy Trading Days	6.29%	5.91%
% Neutral Trading Days	40.72%	41.30%

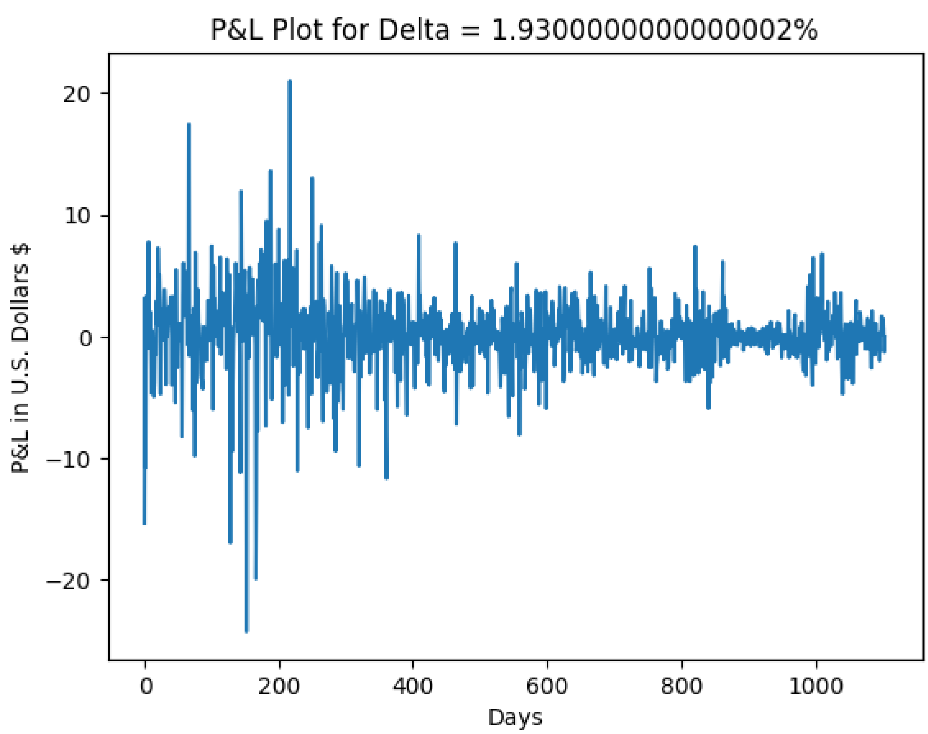
For test data, P&L per share plot (Long Short Strat, Sharpe Ratio Optimization, 0% Delta):



iii) **Optimizing Standard Deviation:**
The following table shows results for the Long Short strategy, optimizing Standard Deviation. To get the Best Standard Deviation, the Best Delta = 1.93% of open price

Metric	**Training**	**Test**
Sharpe Ratio	0.022	0.061
Annualized Return	21.539%	40.550%
Final Capital	707,915.60$	120,058.97$
Average P&L per share over all traded days	0.067$	0.175$
Risk: Standard Deviation of P&L per share over all traded days	3.041	2.895
% Profitable Trading Days	32.58%	32.39%
% Lossy Trading Days	12.97%	12.39%
% Neutral Trading Days	54.44%	55.22%

For test data, P&L per share plot (Stop Loss Strat, Standard Deviation Optimization, 1.93% Delta):



Discussion

Methodology

Our methodology is built around the nature of the dataset provided. Without more granular information about the price of the stock, we are unable to more surgically place trades, leading to loss of resolution and inflated alpha results. Furthermore, we take many liberties with the modeling, such as using random splitting of the dataset which assumes that the underlying mechanics of the ETF's price has remained the same since its inception in 2006. This may not necessarily be the case since geopolitical events, wars, economic cycles and environmental policies have fundamentally changed the landscape for oil as a commodity. We justify this choice of random splitting by considering our investment horizon as one day and ensuring that the data is normalized using a min-max scaler, making it easier and fairer to make an apples-to-apples comparison between any two dates in our dataset.

We also limit our model to fairly straightforward methods of trading such as going long and/or short and using take-profit and stop-loss. Through the implementation of more sophisticated approaches, such as the use of options/derivatives and the use of fractional share trading (offered by many retail brokers) we would be able to more effectively take advantage of the predictions to extract more profits or reduce losses further.

Finally, our choice of treating each day as independent is fundamentally flawed since the price of the ETF is inherently a time series. We apply the independence assumption since our investment horizon is one day, and since we are exploiting volatility within a day rather than trends over longer periods of time. We could have used ARIMA models, mixture models and other time series tools to better analyze the data and trends, however, this may not necessarily improve the accuracy of our predictions and the effectiveness of the strategy.

Metrics and Results

Our metrics and results are chosen to create profits and manage risk. The choice of Sharpe Ratio and Total Capital represent two goals: risk management and capital accumulation. Conventionally, day trading is carried out by smaller scale investors without access to large capital or leverage. Therefore, capital accumulation is tied closely to risk management to prevent sharp erosion of savings. Depending on perspective, different objectives could be optimized for. For instance, if servicing the needs of pension funds, low volatility and risk would be the focus, whereas for investors with a large basket of ETFs being selected, diversification of risk might be the focus.

Overall, our results are decent given the limited data and modeling assumptions made. They produce good returns and manage risk more effectively than the "best-case" model which would take profit as High - Low. Below, we outline future works which we think can enhance our models.

Future Work

A major area of future work is the use of further ensembling to allocate capital to different strategies with dynamic weights as opposed to the current weights to better manage risk while getting return. The exact ratio/breakdown of capital allocation to each strategy, the changing of this allocation based on seasonalities and market events and the inclusion of more sophisticated trading methods would undoubtedly build upon this work.

Currently, our selection of external datasets is limited to a few that are intuitively tied to the price of Crude Oil and therefore the USO ETF. These include prices for Swiss Francs (CHF), a safe-haven currency. In our exploration and through a literature review, we observed that rather than CHF, currencies such as the Canadian Dollar (CAD) or Australian Dollar (AUD) are more correlated with oil prices than the Japanese Yen (JPY) or the Swiss Franc (CHF). This could be because both Canada and Australia are large commodities exporters, with Canada exporting large quantities of Oil and Australia exporting rare earth metals, minerals and ores. It is reasonable to assume that commodities required for construction, transportation and manufacturing would be linked, and thus we could capture more variation in the price of the USO ETF if we included these currencies.

Another challenge that our strategy encountered was the snowball effect of compounding returns. Left unconstrained, our model would invest progressively larger amounts, even breaching the total market capitalization of the ETF. In the real world, we believe that at a sufficient capital allocation size and daily trade volume, our model would begin to influence the market, getting big enough to move the market. This would make it difficult for us to get the same prices as the ones in our dataset, would allow brokers to mark up their prices and remove any alpha generated. Large asset managers and investing institutions often avoid this by gradually placing orders. While this approach could help mitigate the effects of sharp price rises, the gradual increase in price as the orders come in would erode alpha steadily, making it harder to achieve the same kind of returns as our model makes at a much smaller scale.

To better model this behavior, we propose the inclusion of a function based on the exponential function which manages the relationship between the number of trades our model makes and increases in price. This function can then be tuned to adjust the prices and model the erosion of alpha. Through this, we will also be able to model friction, changes in market conditions and the model's influence on the market. A drawback of this is that it is very difficult to account for the universe of events that might affect the ways in which trading moves the market, making it difficult to effectively model the results.

Another future work is to perform analysis of our model at different initial capital levels. Essentially, by comparing the growth curves of capital with starting points of $1000, $10,000 and $100,000, we would like to see if the curves overlap once total capital hits each benchmark. If, for instance, the model performs a lot better with larger capital than with smaller capital at the same total capital amount, we can try to analyze the reasons for the disparity. Furthermore, we can even apply concepts in econometrics to carry out causal inference on the variables involved, providing more academic insight into the relationship between our independent and dependent variables.

Conclusion

The implementation of our day trading strategy for the USO ETF offers an interesting foundation for the development of a more nuanced model for oil commodity trading. The focus on short-term price fluctuations and intraday volatility allows us to effectively create alpha while managing risk. By optimizing for the Sharpe ratio and capital allocation, we are able to ensure that a balance between maximizing profits and safeguarding the capital is achieved. Through our extensive backtesting, we have shown the model to be adaptable and moderately profitable across a large number of trading days.

We have provided various optimizations such as for capital, Sharpe ratio, standard deviation and average P&L. These correspond to the different risk profiles and appetites that traders could have. Despite certain modeling assumptions and dataset limitations, the models and strategies thus represent meaningful work that can be built upon in future research.

With actionable steps to improve the model and the strategies, we also lay out a roadmap for the tuning and optimization of this project. These can be applied to inject more real-world scenarios and realistic benchmarking which can help productionize this code.

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