451 Multi-Level Algorithmic Trading: Programming Assignment 3

Prepared by Albert Lee

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Background

With the immense volume of trades going back and forth on an average daily basis, it's more important than ever to leverage technology to optimize portfolio management. According to FINRA, on average, there are ~74.1 million transactions for an average dollar volume of $516.5 billion being exchanged daily back in 2023. The volume has increased from 2020 when it was ~58.7 million transactions and $481.1 billion dollar in volume. Not only is there significant number of transactions and $ volume at play, there are also a significant volume of assets to monitor as well. According to the NYSE, in the US markets alone, there are ~8,000 US securities listed. The sheer number of assets also makes it difficult for companies to be able to track without leveraging technology.

Algorithmic trading history dates back to 1949 when Richard Donchian developed the Donchian Channels. The Donchian Channels uses model-based technical analysis trading strategy to identify potential breakouts (a rise above a resistance level or a drop below a level of support) and retracements. According to the Corporate Finance Institute (CFI) a retracement is when the price of a security starts to move back towards its previous price after a significant change. This foundation and model has named him the father of "trend following". Then in 1952, Harry Markwotiz introduced the Modern Portfolio Theory or MPT and is known as the father of quantitative analysis. MPT introduces portfolio allocation theory based on two factors – risk and return. Portfolio diversification can reduce risk to a portfolio.

As the internet gained wide usage in the 1980's and 1990's, so did applications in the market. In 1993, Interactive Brokers were known to be the pioneers in digital trading. The company leveraged technology from Timber Hill and developed an electronic network and trade execution services to customers. In 1996, the launch of island-ECN an electronic communication network allowing subscribed traders to receive real-time price and volume information on stocks. This electronic network provided the pathway to the present-day algorithmic trading.

Present Day

Algorithmic trading increased rapidly in the late 2000's with ~70% of captured orders were done through algorithmic trading by the end of 2009. Algorithmic trading doesn't always mean increased profits. The article titled *Moore's Law versus Murphy's Law: Algorithmic Trading and Its Discontents* by Andrei A. Kirilenko and Andrew W. Lo and published in Journal of Economic Perspectives. The authors of this article discusses the rise of high frequency trading (HFT) and algorithmic trading along with the impact on the financial markets. While algorithmic trading has improved efficiencies and lowered costs but have introduced new risks to the modern day financial markets. The article highlighted several notable examples of technology errors that resulted in companies losing millions of dollars. One example was in August 2012, Knight Capital Group suffered a devastating software malfunction during the NYSE market open, which caused the firm to flood the market with erroneous orders. Within just 30 minutes, these mistakes triggered wild price swings across nearly 150 stocks. Because most trades could not be canceled as “erroneous,” Knight was forced to liquidate the unintended positions on the open market, incurring a staggering loss of $457.6 million.

With more data and information available, algorithmic trading extends beyond just traditional stock prices. It now includes macroeconomic trends around various economic indicators, social media, news sentiment, earnings call, and/or reviews / surveys. Alternative data usage in trading and investments have formulated their own various type of strategies such as buying stocks based on brand value factor. In recent years, we’ve seen lots of this through the “meme stocks” momentum.

Now with the recent AI boom, many banks and investment firms are now using AI within their algorithmic trading models. According to the International Monetary Fund (IMF), patents relating to AI/LLM models within algorithmic trading has risen to 50% each year since 2020. While there has been an increase in AI/LLM models in the industry, it’s also creating portfolios that have a higher turnover rate than non-AI driven portfolios. Again, according to the IMF, AI-driven ETF’s have a 11.62x turnover rate vs other active ETFs of 0.26x in 2023. The frequent rebalancing could lead to market instability and/or higher fees for investors.

Data Preparation and Pipeline

The Python notebook developed uses automated, algorithmic trading based on multi-level prediction and future returns. The cutoffs in the multi-level prediction are based on the trading actions listed in the assignment:

Tolerance for Risk

Trading Actions:	Low	Moderate	High
Buy	5	15	25
Hold	90	70	50
Sell	5	15	25

Buy: Take a long position, purchase a call option
Hold: Keep current positions, do nothing
Sell: Take a short position, purchase a put option

The data preparation of the notebook begins by constructing a reproducible data pipeline to support systematic trading analysis. A **config** dataclass is introduced to consolidate the defined parameters such as ticker symbol, lookback horizon, strategy type (mean reversion or momentum), and risk profile (as shown above). The asset price history is retrieved through yfinance, and exploratory data analysis (EDA) is conducted to understand the statistical properties of the asset. The asset chosen initially was Apple or AAPL. The initial strategy used was a mean-reversion trading strategy. Mean-reversion signal measures the tendency of short-term losses to reverse, while the momentum signal captures the persistence of cumulative returns. Since I wanted flexibility in the model to be able to easier change the ticker symbol, risk profile, or strategy, I developed an in-notebook python widget that uses is based on ipywidgets. The second asset chosen for this assignment was Microsoft or MSFT. I was also hoping that this model can be potentially used for my own personal investment decisions as well.

Scores are standardized and then mapped into discrete trading actions using multi-level quantile cutoffs tied to the chosen risk profile. This process yields BUY, HOLD, or SELL designations that reflect both the direction and confidence of the signal. The data model also enforces safeguards against look-ahead bias by shifting positions to ensure only past information is used for trading decisions. To validate the accuracy of the model, I then developed train/test splits and applied it to partition historical data. To review the accuracy based on the train/test splits, a walk-forward framework is implemented to recalibrate and evaluate strategy performance across different regimes. The walk-forward strategy takes the historical data and is divided into sequential segments. At the end of each segment, the model is then recalibrated using only information available up to that date, and then tested on the next block of unseen data. Once the test period concludes, the window expands to include it, and the process repeats. By stitching together the returns from each rolling out-of-sample test period, the notebook constructs a walk-forward equity curve.

Programming

The programming component of the notebook includes the trading logic, performance evaluation, and diagnostics. The core engine is backtest_singnals, which simulates the daily equity curve by combining positions with realized returns, and deducting slippage. This backtester produces both a detailed trade-level record and an equity time series, which are then summarized into standard metrics including compound annual growth rate (CAGR), annualized volatility, Sharpe ratio, maximum drawdown, and Calmar ratio. The model also outputs the latest trading recommendation and decision evidence, reinforcing the link between predictive signals and actionable strategy outputs.

Using AAPL, the model is outputting the following latest recommendation:

```
{'date': '2025-08-29', 'ticker': 'AAPL', 'score': 0.5932, 'action': 'HOLD',
'position': 0.0, 'price': 232.13999938964844}

CAGR: None
AnnVol:  0.2677
Sharpe: -0.0399
MaxDD: -0.7850
```

	Ticker	Price	Score	Position	Ret	StratRet	Equity	Action
Date								
2025-08-14	AAPL	232.7800	0.4765	-1.0000	-0.0024	0.0024	0.3489	HOLD

	Ticker	Price	Score	Position	Ret	StratRet	Equity	Action
Date								
2025-08-15	AAPL	231.5900	0.4993	0.0000	-0.0051	0.0049	0.3507	HOLD
2025-08-18	AAPL	230.8900	0.5240	0.0000	-0.0030	-0.0000	0.3507	HOLD
2025-08-19	AAPL	230.5600	0.5189	0.0000	-0.0014	-0.0000	0.3507	HOLD
2025-08-20	AAPL	226.0100	0.5505	0.0000	-0.0197	-0.0000	0.3507	HOLD
2025-08-21	AAPL	224.9000	0.5528	0.0000	-0.0049	-0.0000	0.3507	HOLD
2025-08-22	AAPL	227.7600	0.5672	0.0000	0.0127	0.0000	0.3507	HOLD
2025-08-25	AAPL	227.1600	0.5720	0.0000	-0.0026	-0.0000	0.3507	HOLD
2025-08-26	AAPL	229.3100	0.5848	0.0000	0.0095	0.0000	0.3507	HOLD
2025-08-27	AAPL	230.4900	0.5778	0.0000	0.0051	0.0000	0.3507	HOLD
2025-08-28	AAPL	232.5600	0.5915	0.0000	0.0090	0.0000	0.3507	HOLD
2025-08-29	AAPL	232.1400	0.5932	0.0000	-0.0018	-0.0000	0.3507	HOLD

The signal strength is driven by the “score” and it’s currently 0.5932 which sits between the BUY and SELL cutoffs for the chosen risk profile or a HOLD.

For MSFT, the model is outputting the following latest recommendation:

```
{'date': '2025-08-29', 'ticker': 'MSFT', 'score': 0.6231, 'action': 'BUY',
'position': 1.0, 'price': 506.69000244140625}

CAGR: None
AnnVol:  0.1737
Sharpe: -0.0149
MaxDD: -0.7528
```

	Ticker	Price	Score	Position	Ret	StratRet	Equity	Action
Date								
2025-08-14	MSFT	521.6225	0.5730	0.0000	0.0036	0.0000	0.8152	HOLD
2025-08-15	MSFT	519.3163	0.5933	0.0000	-0.0044	-0.0000	0.8152	HOLD
2025-08-18	MSFT	516.2513	0.6140	0.0000	-0.0059	-0.0000	0.8152	BUY
2025-08-19	MSFT	508.9333	0.6755	0.0000	-0.0142	-0.0000	0.8152	BUY
2025-08-20	MSFT	504.8900	0.7056	0.0000	-0.0079	-0.0000	0.8152	BUY
2025-08-21	MSFT	504.2400	0.7038	0.0000	-0.0013	-0.0000	0.8152	BUY
2025-08-22	MSFT	507.2300	0.6699	1.0000	0.0059	-0.0002	0.8151	BUY
2025-08-25	MSFT	504.2600	0.6713	1.0000	-0.0059	-0.0059	0.8103	BUY

	Ticker	Price	Score	Position	Ret	StratRet	Equity	Action
Date								
2025-08-26	MSFT	502.0400	0.6818	1.0000	-0.0044	-0.0044	0.8067	BUY
2025-08-27	MSFT	506.7400	0.6377	1.0000	0.0094	0.0094	0.8143	BUY
2025-08-28	MSFT	509.6400	0.6143	1.0000	0.0057	0.0057	0.8189	BUY
2025-08-29	MSFT	506.6900	0.6231	1.0000	-0.0058	-0.0058	0.8142	BUY

Using the score signal again, MSFT is indicating as a BUY based on the model. The strategy delivered similarly weak outcomes when applied to both Apple (AAPL) and Microsoft (MSFT), though with slightly different risk profiles. For AAPL, the model produced no compounding growth, an annualized volatility of 26.8%, a negative Sharpe ratio (−0.04), and an extreme maximum drawdown of −78.5%. For MSFT, results were marginally less volatile but no more profitable: annualized volatility of 17.4%, a near-zero Sharpe ratio (−0.02), and a maximum drawdown of −75.3%. Trade logs for MSFT from August 2025 illustrate the mechanism of underperformance which resulted in scores drifting into the BUY territory.

For the algorithmic trading, an important portion of any model is it's accuracy. In the model, I reviewed two different types. One of the methods is to review the hit rate or the win rate. The hit rate is taking the number of predicted winning trades / total number of trades * 100. The other measure to review the accuracy of the model is AUC (Area Under Curve) and a Confusion Matrix.

For both AAPL and MSFT, predictive diagnostics showed little directional skill (ROC-AUC = 0.49–0.52, accuracy 50–55%), but the trading outcomes and action-level diagnostics diverged. The ROC-AUC of 0.49 – 0.52 indicates that the prediction probability is mostly 50-50 and at best a coin flip. While not the best, this indicates that the model can be further improved upon. AAPL's results were weak within the train/test data with a Sharpe ratio of only 0.28, a maximum drawdown of −27%, and extremely low BUY and SELL hit rates (~8%), indicating the model was wrong most of the time. MSFT, by contrast, achieved a modestly positive Sharpe ratio of 0.67 and a smaller drawdown of −20%. Its BUY hit rate (~7.5%) was similarly poor, but its SELL hit rate was slightly higher at 8.7%, and its BUY signals delivered larger average returns (+0.72% vs. +0.25% for AAPL). This suggests that while both stock tickers showed weak predictive accuracy and low directional hit rates. As a result, we would need to continue to fine tune the model for it to compete with the likes of those at banks or investment firms. According to Nastja Bethke and Ed Tricker from Graham Capital Management, a hit rate of above 50% can lead to satisfactory performance.

Exposition

While the algorithmic trading model did not produce the most accurate results for an investor, it did provide valuable lessons in developing these types of models. This model is currently based on single tickers and in most cases an algorithmic trading model would likely include multi-asset ticker options to help balance an overall portfolio. The empirical results highlight both the strengths and limitations of this framework.

The exploratory data analysis of both Apple (AAPL) and Microsoft (MSFT) showed that they both had some similarities and differences. For similarities, both have had strong compounding returns since 1999, with Apple seeing a 33% annualized return vs. Microsoft's 16.5%. While Apple's growth was higher, Apple also experienced higher volatility with a 39.7% vs. Microsoft's 30.5%. Apple did experience a far deeper drawdown compared to Microsoft. A drawdown is the difference between the peak and a following trough. Based on the exploratory data analysis, Apple tends to have better returns if investors can tolerate the higher volatility and severe drawdowns. Microsoft is better suited for investors with a more moderate risk appetite while generating a stable return performance.

Predictive diagnostics, however, showed that the signals had a decent predictive skill with a 50-50-coin flip chance for predicting. This at best case would be random. Future improvements to enhance the model could lead to a potentially better hit rate or ROC-AUC. That includes but not limited to multi-ticker portfolio composition, dynamic risk-profile cutoffs, rebalancing, and machine learning applied to multiple signals instead of just one. This model is a functioning prototype that allows me to go from data gathering, preparation, modeling, and predictive output. It also includes a lightweight in notebook front-end allowing flexibility for a user such as myself.

As discussed earlier, while algorithmic trading are seeing an uptick within the Finance industry, it doesn't always produce accurate results. It needs to be fine-tuned and in my opinion, a human should always check the model / output to ensure that million-to-billion-dollar errors don't occur such as the one highlighted above at Knight Capital Group. Henry Booth highlighted in a Medium article that banks / investment firms could employ anywhere from 100 to 5,000 Quantitative Finance professionals in the respective companies. While it would have been nice to have created an algorithm that could have a much more improved hit rate, it was insightful to be able to just build a functioning prototype.

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