LSTM-Based Dynamic Portfolio Allocation with Sentiment Analysis: Trading Strategy for NASDAQ Equities

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1 Introduction and Motivation

This strategy aims to capture short-term momentum while incorporating market sentiment. Most quantitative strategies fail to integrate technical patterns with investor sentiment effectively. Hence, this trading strategy aims to combine LSTM neural networks with sentiment analysis to create a dynamic portfolio allocation system.

The motivation stems from wanting to create a trading strategy that could withstand market volatility, given light of the unpredictability of the current market in 2025. The hypothesis is that combining LSTM predictions with sentiment-adjusted returns, implemented through Sharpe ratio-based allocation, will provide superior risk-adjusted performance compared to equal-weight benchmarks.

2 Methodology

My strategy consists of training an LSTM on the closing prices of NASDAQ stocks over a 6 year time period (Jan 2018 – Dec 2024). The trained LSTM, using 30-day rolling windows, then predicts the next day's percentage change daily throughout the period January 1st to May 1st of 2025.

These expected percentage changes are then enhanced based on the sentiment surrounding that equity to create an adjusted percentage change.

A CNN was trained on sentiment data. This was used to give each equity an overall sentiment score, ranging from 0 to 1, calculated from yfinance data using the headlines from the top related news articles.

The adjusted price is calculated using the formula:

$$\text{adjusted\_next\_pct\_change} = \text{next\_pct\_change} \times (1 + \alpha \times (\text{sentiment\_scores[ticker]} - 0.5)) \quad (1)$$

The daily expected excess returns are then calculated for each equity by subtracting the daily risk free rate (sourced from yfinance) from the expected adjusted percentage change for the next day. Volatility was also calculated for each day for each equity based on the standard deviation of the percentage change in the closing prices for the past 30 days.

For each equity, each day, a Sharpe ratio was then calculated by dividing the expected daily excess returns by the volatility.

2.1 Portfolio Allocation

Each day, the next day's portfolio allocation was calculated. The portfolio was weighted such that each equity's portfolio weight was proportional to its Sharpe score. The portfolio was rebalanced daily.

$$\text{Weight} = \frac{\text{sharpe\_score}}{\sum(\text{all\_sharpe\_scores})} \quad (2)$$

2.2 Signal Generation

Signals were generated each day with a buy signal being generated if that equity's portfolio weighting increased from the previous day. If it decreased, or if there was no change in allocation, a sell signal and a hold signal were generated respectively.

2.3 Backtesting

The value of the portfolio each day was multiplying each equity's portfolio weighting (calculated the previous day) with the percentage change in the closing price of the equity and summing them.

Based on these daily portfolio values, the maximum drawdown as well as annualized Sharpe ratio was also calculated.

To evaluate the performance of the strategy, a benchmark was created weighting all equities equally in the portfolio. The max drawdown, annualized Sharpe ratio as well as the daily value of the portfolio are also shown in the results.

$$\text{daily\_return} = \sum(\text{weight}_i \times \text{actual\_return}_i) \tag{3}$$

Note: My strategy does not use short selling.

3 Results

Table 1: Performance Comparison: Dynamic Allocation vs. Equally-weighted Benchmark

Metric	Dynamic Allocation	Equally-weighted Benchmark	Difference
Total return	-0.0765	-0.0848	+0.0083
Max Drawdown	-0.180	-0.205	0.025
Sharpe Ratio	-1.16	-1.09	-0.07
Volatility	0.331	0.379	-0.048

Win Rate (times dynamic portfolio allocation beats the benchmark): 56.9%

The strategy experienced a +0.83% advantage in total returns over the period, representing a relatively small total return advantage. Also, there were significant risk benefits, including lower maximum drawdown and reduced volatility that provided downside protection during bear markets. The strategy demonstrated outperformed the equally weighted benchmark with a 56.9% win rate, meaning it beat the benchmark on more than half of all trading days throughout the period.

It must be remembered that although the strategy closely tracks the benchmark on most days (often coming slightly under), it offers more downside protection during dips in the market and far outperforms the benchmark here.

During the February to March period, Figure 2 and 3 show that both strategies performed similarly during this phase, experiencing modest declines from peak levels. The dynamic allocation showed no significant advantage during these normal market conditions.

During the late March to early April period, while the benchmark experienced its full maximum drawdown of 20.46%, the dynamic strategy limited its losses to 17.97%, preserving an additional 2.49% of capital. Although daily return volatility spiked to extreme levels, the strategy effectively reduced the impact of these volatile conditions.

While the markets recovered during the mid-April to May period, the strategy experienced a slight lag in absolute returns during this recovery phase. Due to the earlier crash and subsequent rise, equities experiencing greater volatility and upside potential were still allocated proportionally less capital. Since allocation depends on the Sharpe ratio, despite higher predicted expected returns, the elevated volatility from the price spike reduced the risk-adjusted attractiveness, resulting in decreased allocation to these equities. This suggests that the strategy sacrifices returns during booms for downside protection. This volatility-adjusted allocation approach explains why the strategy provided good downside protection during the crash but underperformed slightly during recovery, as it reduces exposure to high-volatility equities regardless of return direction.

The negative total returns and Sharpe ratios could be attributed to the fact that the first half of 2025 was heavily impacted by the effects of Trump's tariff policies. Following Trump's liberation day announcement on April 2nd, many indices, including the NASDAQ, entered a bear market, which can be seen in the results through a sudden dip in daily returns.

4 Discussion

The strategy somewhat achieved its primary risk management objective during the volatile 2025 market period. The 2.49% reduction in maximum drawdown and 4.8% volatility reduction provided meaningful risk management. The 56.9% win rate demonstrates an outperformance over the benchmark, keeping in mind that the dynamic allocation mostly followed the benchmark closely (lagging behind slightly) except for in highly volatile periods during which it mostly outperformed the benchmark.

The LSTM successfully captured momentum patterns given a previous 30-day window, and the sentiment scores provided some enhancement without overthrowing the LSTM signals. The Sharpe ratio-based allocation did manage risk to an extent but also stunted returns when the market was recovering, again highlighting the trade-off between risk management and return maximization.

Some implementation challenges include transaction costs from daily rebalancing and the need for regular model retraining. Limitations include the short testing period, lack of short-selling, as well as the arbitrary weighting of the sentiment score (currently 0.05) when it comes to adjusting the predicting return from the LSTM.

5 Conclusion and Future Work

This paper demonstrates that combining LSTMs with sentiment adjustment can provide meaningful value during volatile markets, especially with risk reduction. The strategy proved most effective during volatile markets where adopting a more defensive stance provides clear value, while tracking the benchmark during normal conditions.

Future work could focus on optimizing the sentiment parameter (currently at 0.05) and incorporating fundamental metrics. Moreover, to consider the costs of reallocating the portfolio, a sell/buy signal should only be generated if the portfolio weighting changes considerably.

The strategy achieved its objectives by demonstrating that quantitative techniques can provide risk-adjusted performance during challenging, volatile conditions.

The value of alpha in the adjusted percentage change formula should be optimized and backtested. Considering company fundamentals would be better. To consider the costs of reallocating the portfolio, a sell/buy signal should only be generated if the portfolio weighting changes considerably. However, the threshold for this needs to be explored more.