Portfolio Optimization Using No-Regret Online Learning: A Case Study on US Stocks

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Abstract. This paper presents a portfolio optimization method using the Multiplicative Weight Update (MWU) algorithm combined with Long Short-Term Memory networks. Our approach aims to enhance investment strategies by dynamically adjusting portfolio weights based on past performance, thereby minimizing regret and optimizing returns over the long term. We demonstrate our methodology using a decade of stock data from prominent US companies, showing significant improvement over traditional fixed-weight strategies, especially during volatile market periods like the 2000 Dot-com bubble and the 2008 financial crisis.

Keywords: portfolio optimization, no-regret learning, MWU.

1 Introduction

Investment strategies that adapt to market conditions dynamically can significantly reduce risks and enhance returns. Traditional methods appear to be vulnerable and often fail during market downturns, as seen in the 2000 Dot-com bubble [3] and 2008 global financial crises derived due to subprime mortgages which targeted low-income buyers [4]. To address this, we resort to no-regret online learning algorithms, which have been extensively studied due to its robustness for online decision making when facing adversarial environment [6, 7]. We apply a no-regret learning algorithm, i.e., the Multiplicative Weight Update (MWU) algorithm (also known as the Hedge algorithm) [5], which adjusts investment weights based on their daily performance, and leverage a number of *experts* which can predict stock price movements. The experts herein are trained LSTM networks which has been known to be a competitive machine learning model for time series forecast.

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While similar methods using online learning algorithms like those discussed by Helmbold et al. [1] and reinforcement learning approaches as seen in [2] have been explored, our work with the MWU algorithm offers distinct advantages, in both the theoretical guarantee and practical applicability. Firstly, the MWU approach is inherently *no-regret*, meaning it performs as well as any fixed expert, determined offline in the hindsight, in average, hence the name "no-regret" is called. Additionally, MWU is *model-free* and is straightforward to implement. This benefit clearly enhances its practical applicability in financial scenarios.

Moreover, our project uniquely integrates MWU with a mechanism to determine buy/sell signals, a novel approach not seen in prior works. This integration allows for dynamic portfolio adjustments based on predictive analytics, further optimizing investment returns. Another significant benefit of MWU is its *model-free* nature, which eliminates the need for specialized training of its parameters, simplifying the implementation and reducing the computational overhead. This feature makes MWU particularly appealing for real-time financial applications where adaptability and computational efficiency are crucial.

2 Methodology

This project is structured into three main components: 1) Model training, 2) Portfolio management by adaptively rebalancing using MWU, and 3) GUI and visualization. The specifics of each component are delineated in the subsequent sections.

I. Model Training. This component trains an LSTM model for each US stock symbol to predict the next day's closing price. By comparing predictions with actual data, we compute stock movements (encoded as 1 for upward, -1 for downward, and 0 for flat), Profit and Loss (PnL), and returns. Training starts with US stock symbols from Yahoo Finance data (2009-present), enhanced with generally used technical indicators such as MACD, ADX, CCI, K, D, MFI and WILLR. Features are standardized to improve model convergence and stability. To ensure robustness, a Walk Forward strategy is used instead of training on the entire dataset. This acts as a form of cross-validation, training models on 5-year segments and testing on half-year segments, advancing until the present. Each model predicts the next day's price using a 10-day window, capturing temporal correlations and enhancing predictive accuracy. The system selects the model with the lowest RMSE for each set of hyperparameters, ensuring optimal performance.

II. Portfolio Management by Adaptively Rebalancing Using MWU. In this component, the goal is to use MWU, a no-regret learning algorithm, to design the investment strategy by portfolio weighting mechanism. The MWU algorithm is a fundamental method in the field of online learning and decision-making, especially suited for scenarios where decisions or predictions must be made sequentially without complete knowledge of the environment. MWU operates in environments where a decision-maker repeatedly chooses from a set of actions over a series of rounds. At each round, the algorithm updates the weights of all actions based on the loss incurred, favoring actions that performed well by assigning them higher probabilities. In our case, the MWU algorithm adjusts the portfolio's investment weights by decreasing the weights of underperforming assets. Our implementation uses these updates to choose the optimal strategy daily, balancing between exploiting known profitable strategies and exploring less certain ones. Note that the MWU algorithm never sets the weight of a model to be zero due to fact that the exp(price difference) is always positive in practical[‡]. Hence, the "overfitting-like" issue by following-the-leader type algorithm can be alleviated. Algorithm 1 shows the detail.

Algorithm 1: portfolio management by adaptively rebalancing using MWU

1: Maintain a vector of weights $\mathbf{w}_t = (\mathbf{w}_t(1), \ldots, \mathbf{w}_t(n))$ representing the ratios of investment for each stock where $\mathbf{w}_1 \leftarrow (1, 1, \ldots, 1)$.

2: Update the weights at time t by

(a) Derive the PnL $\ell_{t-1}(i)$ of the investment on stock i at time $t-1$ for each $i = 1, 2, \ldots, n$.

(b) $\mathbf{w}_t(i) \leftarrow \mathbf{w}_{t-1}(i) \cdot e^{-\beta \ell_{t-1}(i)}$. /* β: a constant parameter */

(c) $\mathbf{x}_t(i) \leftarrow \dfrac{\mathbf{w}_t(i)}{\sum_{j=1}^{n} \mathbf{w}_t(j)}$ for each $i = 1, 2, \ldots, n$,

/* $\mathbf{x}_t(i)$: the recommended proportion of investment on stock i at time t */

III. Graphical User Interfaces. The graphical user interfaces (GUIs) for both the training and analysis phases are designed to enhance user experience, featuring intuitive functionalities that allow seamless navigation between applications, model updates, and analysis execution. Fig. 1 displays the GUI for managing model training tasks. Subfigure 1 illustrates the interface where users can enter the stock symbol, select from two training modes, and update models with the latest data. Subfigure 2 presents a screenshot capturing the training procedure for AAPL from April 2019 to May 2024. This interface not only simplifies the operation of the training process but also enables effective monitoring of ongoing progress. Fig. 2 presents the GUI that displays analytics results. Subfigure 1 illustrates the interface used to obtain various analytics and visualization results. Subfigure 2 visualizes the predicted and actual closing prices for a single stock, derived from an LSTM model. Subfigure 3 displays multiple selected stocks, aiding users in understanding the behavior of investment combinations across different stocks. Finally, Subfigure 4 shows results from the MWU algorithm, including portfolio value, the weight of each strategy, changes in funds and weights relative to the previous day (where weight indicates the suggested proportion of funds for daily allocation and the change in funds represents the amount needed for trading), maximum drawdown, Sharpe ratio, and more.

[‡] $\exp(x) : \mathbb{R} \mapsto \mathbb{R}^+ \cup \{0\}$ is always nonnegative.

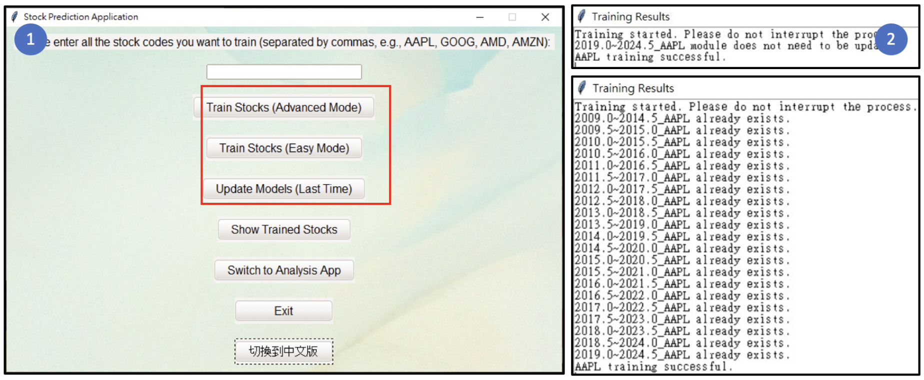

Fig. 1. GUI for executing model training.

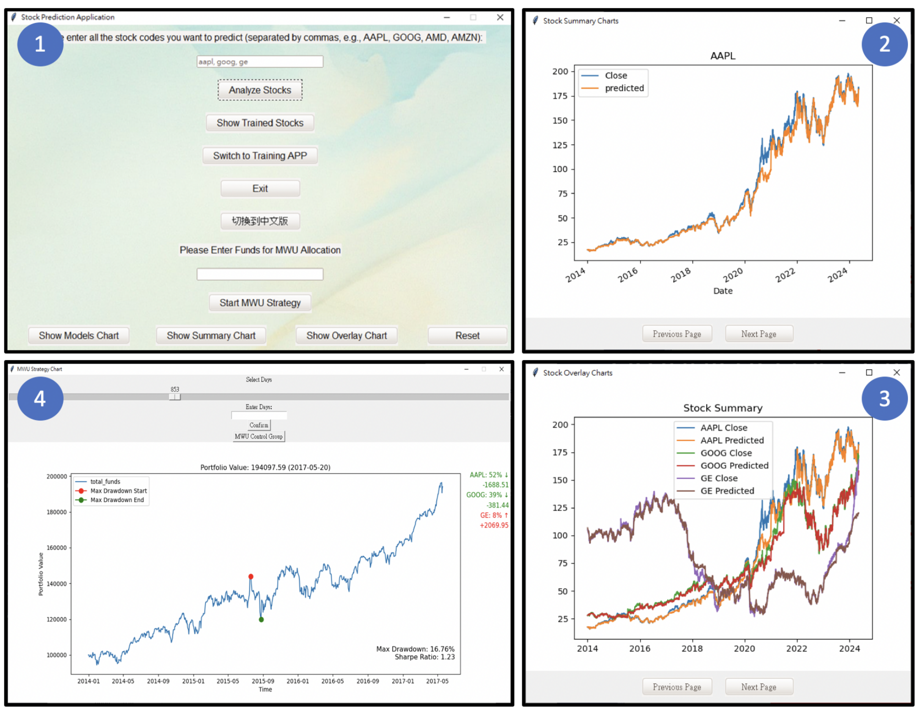

Fig. 2. GUI displaying analytics results and data visualizations.

3 Case Studies

Our experiments show that portfolios using the MWU strategy outperform those using fixed weights, especially in mixed-trend scenarios. For instance, when combining stocks with opposite trends like AAPL and GE[‡], MWU effectively reallocates weights to minimize risk and maximize returns.

Fig. 3 presents the experimental outcomes of implementing an investment strategy that considers AAPL and GE as the instruments of investment in the portfolio. Clearly, we can see that the price trends of the two stocks, one is rising while the other is falling, are quite different. The MWU algorithm can adaptively rebalance the portfolio weights of the two stocks to capitalize on these divergent movements. The case clearly illustrates that MWU showcases its ability of risk-

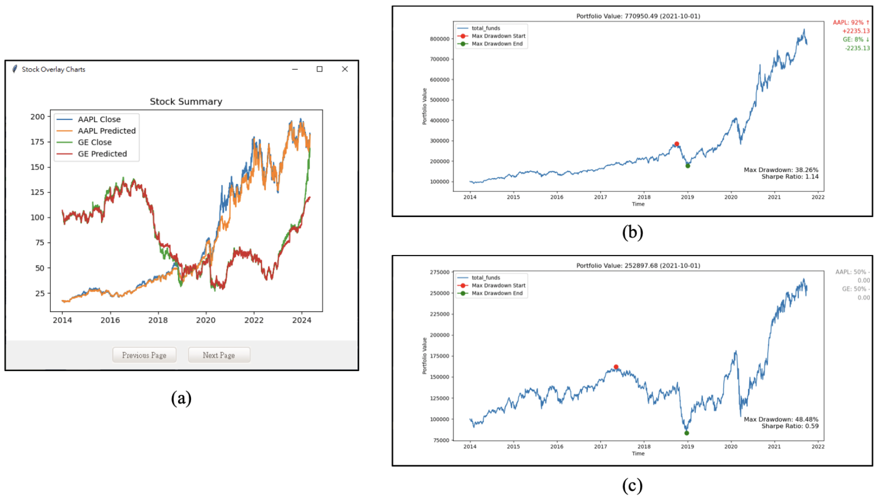

Fig. 3. Investment strategy combination: {AAPL, GE} (a) close price, (b) experimental group, (c) control group.

Fig. 4 presents the experimental outcomes of implementing an investment strategy that considers GE and APA[‡] as the instruments of investment in the portfolio. In this case, both stocks experienced a price decline, while the degree of decline of the two stocks differs. It is inevitable to suffer loss in any portfolio involving these two stocks. Nonetheless, the MWU algorithm can substantially mitigate the loss by adaptively adjusting fund allocations according the previous PnL. Compared to any conventional weight-fixed investment strategy (Fig 4 (b) and (c)), the MWU algorithm leads to less maximum drawdown percentage (84.87% vs. 85.43%) and incurs better Sharpe ratio (0.11 vs. 0.03). As highlighted in this case, even though the we are experiencing a bear market, MWU can still effectively adapt the trend and then mitigate loss in a investment portfolio.

4 Conclusion

Our work leverages the power of recurrent neural networks (i.e., LSTMs) and no-regret online learning (i.e., MWU) to optimize investment of US stocks. The

[‡] AAPL is the ticker of Apple Inc., and GE is the ticker of General Electric Company.

[‡] APA is the ticker of APA Corporation.

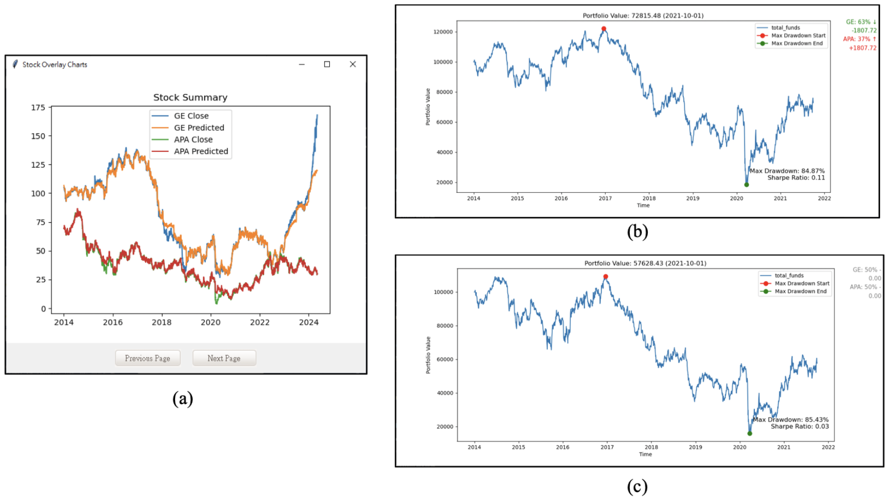

Fig. 4. Investment strategy combination: {GE, APA} (a) close price, (b) experimental group, (c) control group.

MWU algorithm is model-free and hence is easy to implement. The experimental results justify the effectiveness and robustness of our approach. Our GUIs facilitate the users to involve in the portfolio construction from scratch and provides interactive components. The illustration via the GUI provides detail financial information, such as portfolio weight of each stock, daily portfolio PnL, maximum drawdown, Sharpe ratio. We believe that this work demonstrates huge potential in future applications. For example, one can consider other state-of-the-art machine learning algorithms as the experts for the price prediction and then apply MWU for weight rebalancing.

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