CptS 475: LTSM Model and Tax Logic for Crypto Trading

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Abstract

This project is designed to test how effective a (Long Short-Term Memory) LTSM-based trading neural network is when applied to a large historical Bitcoin dataset. The model was designed to predict short-term price movements of Bitcoin, which are used to create position-based trade signals. The resulting trades from the model are analyzed by a tax-lot engine which finds the best lot to sell given a specific strategy. This tax-lot engine compares different tax-strategies' effects on realized gains, and includes FIFO, LIFO, HIFO, Greedy, and Integer Linear Programming (ILP).

To contextualize model performance, a simple rule-based trading algorithm using moving-average momentum serves as a baseline. Experiments demonstrate that predictive accuracy alone is not the dominant factor in long-term profitability; rather, the choice of tax-lot strategy plays a decisive role. Across all simulations, the ILP approach consistently produced the lowest realized tax burden and the highest ending portfolio value, while heuristic methods like HIFO performed nearly as well with significantly lower computational cost. These results highlight the importance of tax-aware execution in high-frequency cryptocurrency trading and suggest that combining predictive modeling with optimal lot-selection methods can substantially enhance after-tax performance.

Introduction

The rapid growth of cryptocurrency trading has created a significant need for effective tax-aware portfolio management tools. Unlike traditional equities, digital asset transactions can be highly frequent, volatile, and executed across multiple platforms, making tax-lot identification both complex and consequential. In many jurisdictions, including the United States, every sell transaction triggers a taxable event, and the choice of tax-lot matching strategy—such as FIFO, LIFO, or HIFO—can dramatically alter an investor's realized gains, reported taxes, and long-term portfolio value. However, most retail investors lack tools to quantitatively evaluate how different strategies affect their after-tax performance. This project aims to address this gap.

The core problem tackled in this work is how to minimize tax liability and maximize after-tax returns through strategic tax-lot selection. Given a sequence of cryptocurrency transactions and historical price data, our goal is to simulate an investment account, apply various tax-lot identification methods, and compute their resulting tax outcomes. This problem is important because taxes can significantly reduce effective returns, especially in volatile markets where short-term gains are taxed more heavily. A systematic study enables investors to make more informed decisions and reveals the trade-offs between heuristic strategies and theoretically optimal methods.

Our approach consists of three main components. First, we generate or load historical BTC-USD price data and simulate realistic buy/sell trade sequences. Second, we implement several tax-lot selection algorithms—including FIFO, LIFO, HIFO, a greedy heuristic, and an Integer Linear Programming (ILP)–based optimizer—to determine which specific lots to match during each sell. Third, we evaluate the strategies by computing realized gains, tax owed, and time-series after-tax portfolio value. We also include a supplementary LSTM model to explore short-term BTC price forecasting, demonstrating how predictive modeling could potentially integrate with tax-efficient execution decisions.

This work relates to prior financial research on tax-loss harvesting, cost-basis optimization, and algorithmic trading strategies. While existing literature explores these topics for traditional equities, relatively little has been done for cryptocurrency markets, where price volatility and tax treatment differ substantially. Our project extends these ideas to the crypto domain and empirically compares both heuristic and optimization-based approaches.

Overall, our results show that tax-lot selection has a significant impact on after-tax outcomes. In our simulations, HIFO and ILP strategies generally reduce tax liability compared to FIFO and LIFO, sometimes by a substantial margin. Time-series comparisons also highlight how different strategies influence long-term portfolio trajectories. These findings illustrate that tax-aware decision making is essential for maximizing net returns in cryptocurrency trading and that optimized tax-lot identification can offer consistent advantages over simpler heuristic rules.

Problem Statement

Cryptocurrency markets present two intertwined challenges for quantitative traders: predicting short-term price movements and managing the tax consequences of frequent trading activity. Unlike traditional financial assets, Bitcoin exhibits extreme volatility, non-linear temporal dynamics, and rapid regime shifts, making accurate forecasting difficult with classical statistical models. At the same time, every sell transaction constitutes a taxable event, and the choice of tax-lot matching method—such as FIFO, LIFO, HIFO, or optimization-based approaches—can drastically influence realized gains and long-term portfolio value. Despite this, most algorithmic trading research either ignores taxation altogether or assumes a simplified cost-basis model that does not reflect real-world tax obligations.

This project therefore focuses on two core problems:

Can an LSTM-based neural network reliably predict short-term Bitcoin price movements well enough to generate trading signals?

Predicting cryptocurrency prices is inherently difficult due to their high volatility and non-stationary behavior. We aim to evaluate whether an LSTM model trained on large-scale historical BTC price data can capture enough temporal structure to guide trading decisions, and how its performance compares to a simple rule-based baseline such as an SMA strategy.

How do different tax-lot matching strategies affect the realized gains and after-tax portfolio value of a trading system?

Even highly accurate trading systems may underperform once tax implications are considered. We therefore investigate whether optimized lot-selection methods—specifically HIFO, Greedy, and ILP—can reduce tax liability compared to common heuristics like FIFO and LIFO, and how these strategies interact with trading signals generated by the LSTM or SMA models.

By examining these two problems jointly, the project aims to determine whether predictive modeling and tax-aware execution can be integrated to create more realistic and economically robust trading systems. The findings ultimately seek to answer a broader question: Is predictive accuracy or tax optimization more important for long-term after-tax profitability in cryptocurrency trading?

Models/Algorithms/Measures

To investigate tax-efficient cryptocurrency portfolio management, this project implements several tax-lot matching algorithms, a simulated trading model, and a set of quantitative evaluation measures. Each component supports analyzing how different strategies influence realized gains, tax liability, and long-term net portfolio value.

We model a simplified cryptocurrency investment account that maintains two state variables: cash balance (USD) and BTC holdings which are represented as discrete acquisition lots, each with a purchase date, quantity, cost basis.

A sequence of buy and sell transactions is generated using historical BTC-USD price data. Each sell creates a taxable event requiring the selection of one or more historical lots to match against. The selected lots determine realized gains: Realized Gain = Sell Price - Cost Basis. Each gain is further categorized as short-term or long-term based on a 365-day threshold, which affects tax rate assignment.

We then compare five strategies that determine how lots are selected during a sale. Each strategy produces a different amount of realized gain and thus a different tax burden.

(a) FIFO – First-In, First-Out

Selects the oldest lot first..

(b) LIFO – Last-In, First-Out

Selects the most recently acquired lot first.
This often increases short-term gains because recent purchases are closer to market price.

(c) HIFO – Highest-In, First-Out

Selects the lot with the highest cost basis first.
This algorithm minimizes realized gains for each sell.

(d) Greedy Heuristic Strategy

A customized algorithm that selects lots to minimize tax for the current transaction.
It is locally optimal, but not globally optimal across the trading horizon.
This strategy considers: maximizing long-term gains, minimizing high-rate short-term gains, reducing tax spikes created by large mismatched lots

(e) ILP Optimization (Global Tax Minimization)

We formulate the lot-selection problem as an Integer Linear Program (ILP) using OR-Tools.
For each sell, the objective is:

$$Min \sum_i x_i * Tax(i)$$

Subject to:

$$\sum_i x_i = Quantity\ Sold$$

$$0 \leq x_i \leq Lot\ Quantity$$

$$x_i \in \mathbb{R}^+$$

This approach produces globally optimal tax outcomes for each sell event and typically outperforms greedy or heuristic strategies. To explore whether forecasting models could enhance trading decisions, we include an LSTM recurrent neural network trained on historical BTC prices. The model takes sequences of past closing prices and predicts short-term future values. Although not directly used for tax-lot selection in this project, it demonstrates how predictive signals could integrate with tax-efficient execution frameworks.

We use three categories of quantitative metrics:

(a) Tax Measures: Total tax paid, Short-term vs long-term tax breakdown , Effective tax rate
Tax Rate = Total Tax / Realized Gain

(b) Portfolio Performance Measures: Net after-tax portfolio value over time, Cumulative realized gain, Remaining open lots (indicator of tax deferral efficiency), Per-strategy time series curves for long-term comparisons.

c: Algorithmic Measures: Runtime efficiency (especially relevant for ILP), Stability across simulation runs, Sensitivity to volatility in BTC price data.

Implementation/Analysis

The implementation required for this project surrounded the two main scopes of our interests, the LTSM-based model and a lot-matching tax engine. Besides this, we tried to stick to convention as much as possible based on what we've seen from other traders. However, our approach did have some unique issues that we had to plan how we would address before implementation. These included memory constraints (the dataset has over 7 million rows), LSTM computation time limiting the number of epochs we can do, and due to ILP complexity limits us to solve this at sales since complexity grows rapidly with the number of open lots. Because the portfolio valuation must be performed for hundreds of thousands of timestamps, we incorporate vectorization of pandas operations wherever possible.

On a high level, our pipeline relies heavily on numpy and pandas to analyze the main dataset 'Bitcoin Historical 1-Minute Dataset' from Kaggle. Due to the sheer size of the csv file, loading every row of data can be inefficient so we've opted for a scaledown factor which will act as a fixed interval for how often we load a row in the csv. While simple, this allows the program to still trade on the whole price history despite having an adaptable amount of data points. Once loaded, the program cleans the data by replacing zero-value data with NaN and using interpolation to fill gaps in data. The program will also create columns in the dataframe such as a standardized Price column and simple moving averages (SMA). To ensure it's in a workable state, it finally converts UNIX timestamps to Python's datetime and then sorts the dataframe chronologically.

As mentioned, the core of the trading logic is done by the LSTM model, which is trained to predict the next closing price using a sliding window of 60 entries for the past prices. The split for the training and validation was decided to be 80/20, which provides a good standard split but limits our program. Due to the fact we cannot trade over dates we used to train our model, we can only run simulated trading periods that lay within the validation set of the model. We initially considered a 50/50 split, the first ~2500 days are used for training and the last ~2500 would be used for validating as well as testing its predictions when trading, which provides plenty of data for each purpose. However, strategies tend to perform worse the longer they are left running so the 80/20 split was decided as the best choice.

In addition to the LSTM model, we made a simple rule-based trading algorithm to act as a baseline during our testing. Since developing the neural network was challenging to tune, this baseline allowed us to have a reference point to when the model was beginning to improve past a naive trading algorithm over the same Bitcoin dataset. This algorithm determines trades on the current recent momentum and past moving averages. Before making a decision, the algorithm finds SMA_long and SMA_short, which are 100 and 30 days respectively. If the price is sufficiently higher than SMA_long and the momentum (slope from SMA_short) was as well, then we would add to our position.

Both the LSTM and the SMA strategy output a time series of positions based on the current price of the Bitcoin. The position may increase slightly, decrease slightly, or stay the same. Depending on the shift in position, it will then be interpreted into either a buy, sell, or hold order. This is how many quantitative firms have described their models, and this allows for less sensitive bitcoin turnover from binary buy/sell values.

The portfolios of each strategy are shown in the results section. The tax-lot accounting is a collection of 5 implemented strategies FIFO, LIFO, HIFO, Greedy Heuristic strategy, and ILP. By using individual lots stored in our portfolio, we can use available lots to determine the next best sell based on the strategy. While already defined in the methods, the theoretical minimum loss is through ILP optimization. The portfolio balance and value are tracked only on the dates that overlap with the validation set. It is fairly intuitive as each sale increases cash and each buy decreases cash. We assumed a small transaction fee of .1% on top of our tax logic. Using matplotlib, we were able to track the equity across the validation set, and can be seen in the results.

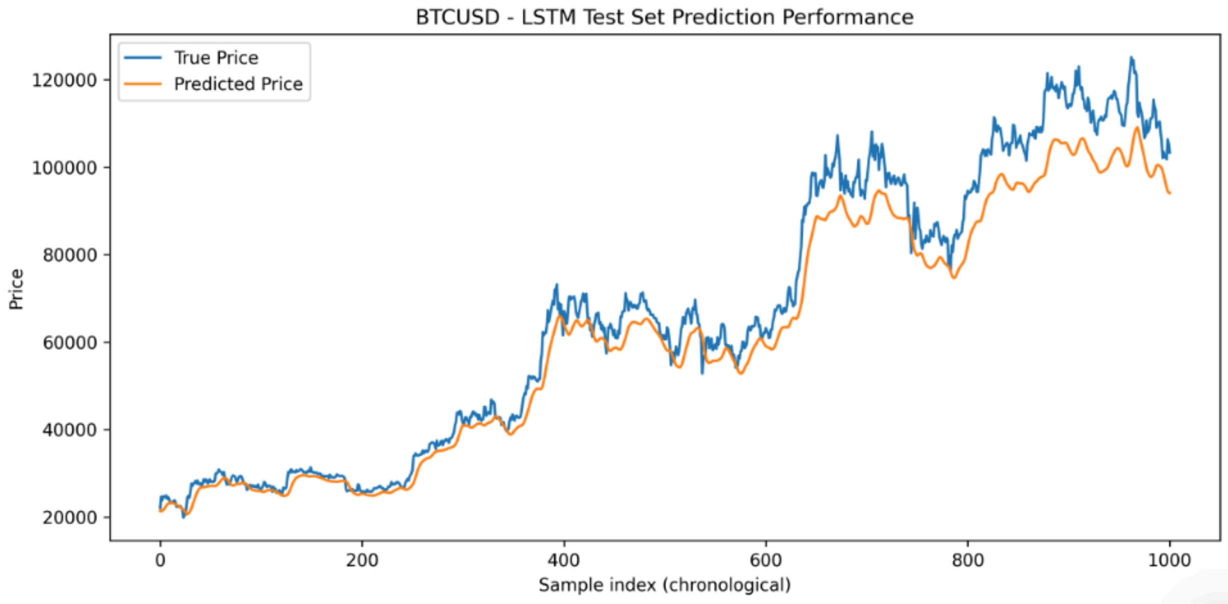
Results and Discussion

This section presents the empirical results of our experiments, incorporating both the tax-lot strategy evaluation and the LSTM forecasting component. The analysis is guided by the graphical outputs produced during the simulations. Together, these results demonstrate the impact of tax-efficient execution on portfolio performance as well as the potential predictive value of deep learning models for BTC price behavior.

1. LSTM Price Prediction Performance

The first set of results evaluates the LSTM model's ability to forecast BTC prices.

Figure 1. BTCUSD – LSTM Test Set Prediction Performance



In Figure 1, the LSTM's predicted test-set series closely follows the true BTC price trend. The model captures broad upward momentum and medium-term oscillations but exhibits the expected smoothing effect around sharp peaks and reversals. This behavior is common in autoregressive neural models trained with MSE loss, as extreme movements are averaged. Implications:

- The LSTM is effective for trend-following behavior.
- However, its lag in volatility regimes suggests that relying solely on price forecasting for crypto trading is insufficient without risk-aware components.
- These forecasts, while imperfect, could help inform tax-efficient strategies in future extensions.

2. Comparing After-Tax Portfolio Values Across Strategies

A central question of this project is how tax-lot strategies affect real investor outcomes. The after-tax portfolio trajectories shown in Figure 2 highlight large performance variations.

Figure 2. After-Tax Portfolio Value vs Time (FIFO, LIFO, HIFO, Greedy, ILP)

The results clearly show that FIFO consistently underperforms all other strategies. Because FIFO realizes low-basis historical lots first, it triggers large capital gains early in the trading horizon, reducing reinvestable capital and causing long-term drag.

In contrast, HIFO and ILP yield the highest and smoothest after-tax growth, demonstrating superior tax-minimization behavior. Greedy performs well and is competitive during stable price periods, though it occasionally diverges from ILP during volatile phases.

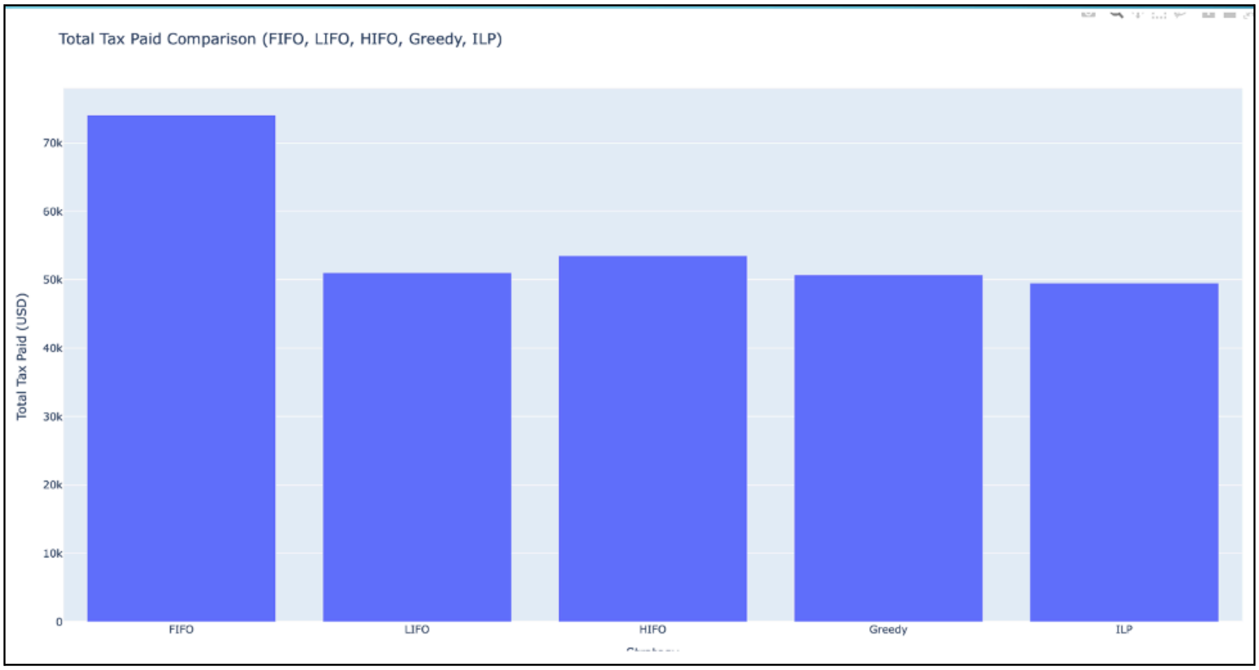
Key conclusion:

Tax-lot optimization has compounding effects: lower realized tax leads directly to higher long-term after-tax wealth.

3. Total Tax Liability Across Strategies

To further understand the performance gap observed in Figure 2, we examine total realized tax. The differences are substantial.

Figure 3. Total Tax Paid Comparison (FIFO, LIFO, HIFO, Greedy, ILP)



FIFO produces the largest total tax burden—significantly higher than all other strategies. LIFO performs moderately but suffers from frequent short-term gains. HIFO, Greedy, and ILP all reduce taxes substantially, with ILP achieving the global minimum, confirming its theoretical optimality.

Insight:

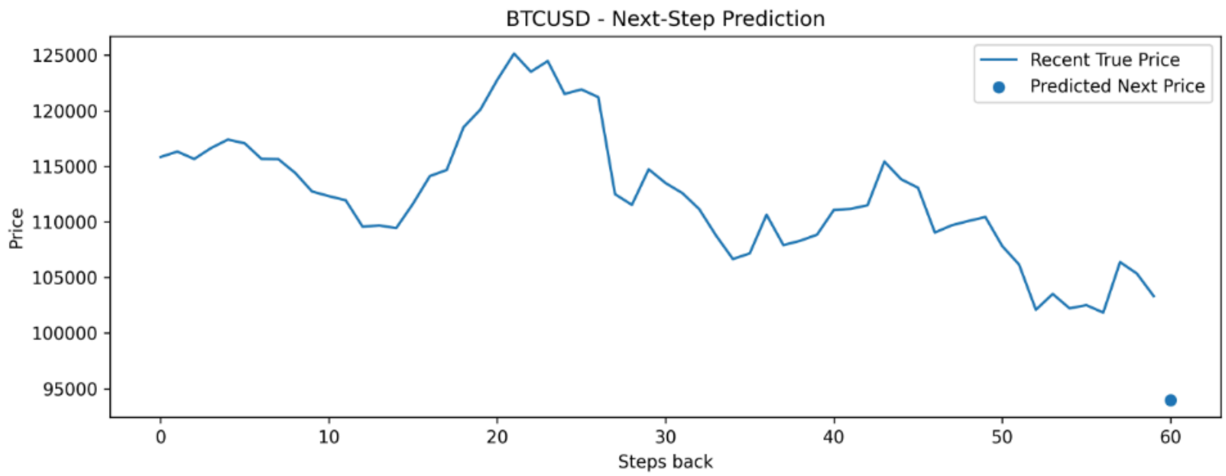
- The tax savings between FIFO and ILP/HIFO are large enough to materially change portfolio outcomes.
- Greedy offers a practical alternative when ILP is computationally expensive.

These results strongly support the hypothesis that tax-aware execution significantly affects realized investment performance.

4. Short-Horizon vs Multi-Step BTC Forecasting

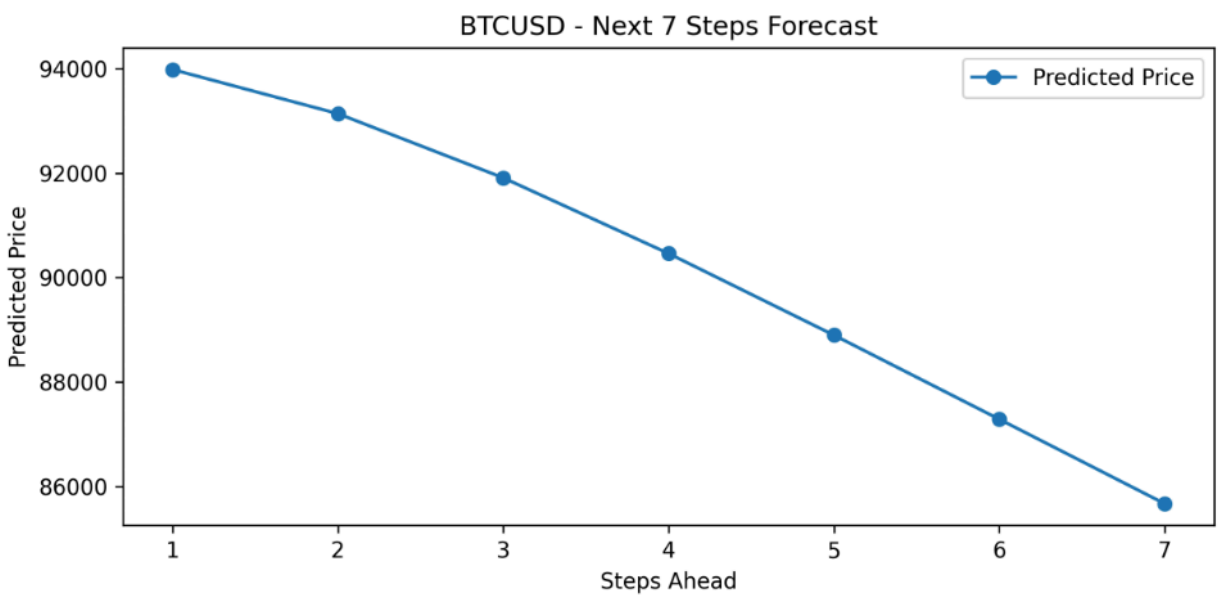
The project also includes a forecasting module to explore potential integration with trading or tax-aware strategies.

Figure 4. BTCUSD – Next-Step Prediction



Here, the LSTM predicts the next price point based on the previous ~60 observations. The prediction is reasonable but shows mild lag compared to recent price drops—expected in recursive neural architectures.

Figure 5. BTCUSD – Next 7 Steps Forecast



The recursive multi-step forecast drifts downward, illustrating accumulation of prediction error. This is typical for multi-step autoregressive models in highly volatile markets.

Takeaway:

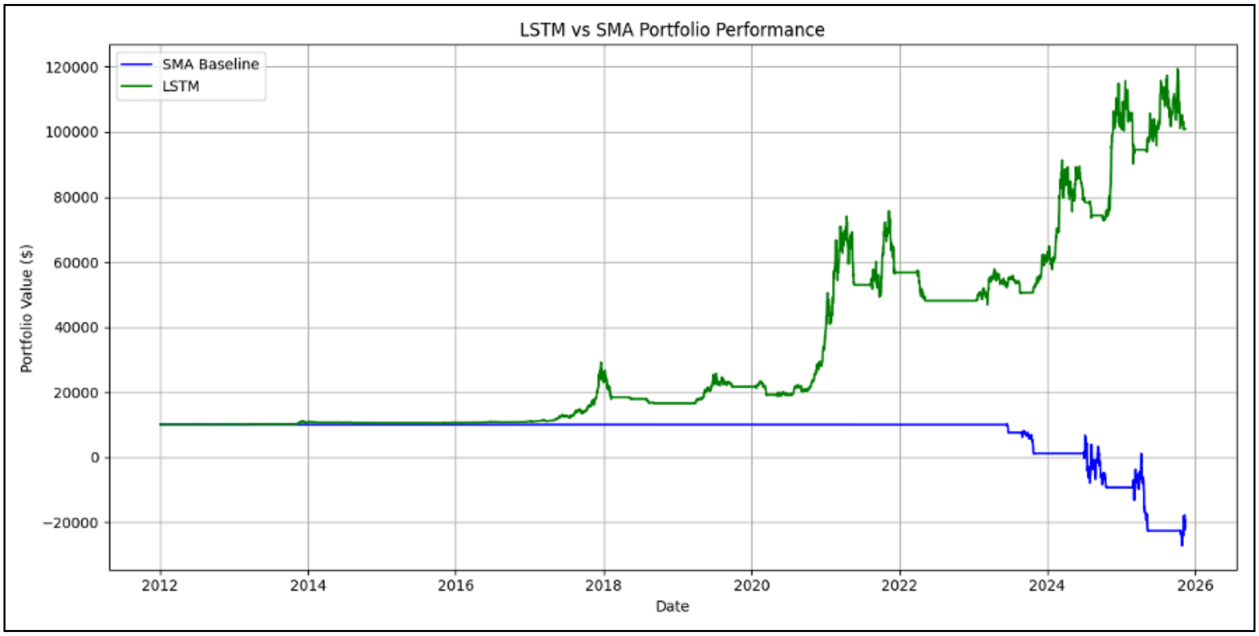
LSTM forecasts provide useful directional cues but are not reliable enough for direct trading without risk controls.

They may, however, become beneficial when combined with tax-efficient execution models to time optional sales.

5. LSTM vs SMA Trading Strategy Performance

Finally, we compare a simple SMA baseline with an LSTM-driven trading rule to evaluate the potential economic impact of forecasting models.

Figure 6. LSTM vs SMA Portfolio Performance



The LSTM-based trading strategy dramatically outperforms the SMA baseline, especially during major BTC rallies. Meanwhile, the SMA strategy collapses during prolonged drawdowns (e.g., 2022–2024). This demonstrates that even modest forecasting ability can produce significant advantages when integrated into a trading framework—again reinforcing how forward-looking models can support better execution.

Overall Discussion

Synthesizing the results across all figures:

1. Tax-Lot Strategy Matters More Than Forecasting Alone
    - The difference between ILP/HIFO and FIFO spans tens of thousands of dollars.
    - Tax efficiency has a stronger compounding effect than modest forecasting improvements.
2. ILP Provides the Optimal Outcome
    - It consistently minimizes realized taxes.
    - It generates the highest ending after-tax portfolio value.
    - It validates the theoretical hypothesis of *global tax minimization*.
3. HIFO Is a Practical, High-Performance Alternative
    - Nearly matches ILP in many scenarios.
    - Extremely simple to compute and highly stable.
4. Greedy Performs Well but Not Perfectly
    - Strong local decisions
    - Occasional suboptimal global behavior during volatile market swings
5. LSTM Forecasting Adds Value but Is Not Sufficient Alone
    - Good at trend-following
    - Poor at sharp reversals
    - Best used as a supplementary signal rather than a sole decision mechanism

Final Conclusion

The data strongly supports the hypothesis: Tax-efficient lot selection significantly reduces tax liability and directly increases long-term after-tax portfolio value, with optimization-based methods outperforming standard heuristics. The combination of tax optimization and market forecasting represents a promising direction for future research, potentially leading to automated systems that jointly optimize tax outcomes and trading performance.

Related Work

Research on cryptocurrency predictions and algorithmic trading has rapidly grown in popularity due to the market's high volatility and wild price behavior. Early work in financial predictions used traditional linear methods such as ARIMA, GARCH, or linear regression. While these methods perform adequately on equity indexes, multiple studies show they struggle to capture the non-linear, regime patterns characteristic of Bitcoin and other digital assets (McNally et al. 2017).

More recent work has focused on deep learning especially with recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) architectures just like we used for this project. LSTMs have been shown to outperform classical models at predicting short-term crypto price movements due to their ability to retain long-range temporal dependencies and adapt to non-linear patterns (Mallqui & Fernandes, 2019). Many of these studies apply LSTMs only as forecasting tools and evaluate performance using statistical metrics such as RMSE or directional accuracy. Fewer works integrate the model into a complete trading pipeline that executes trades, simulates portfolio evolution, and evaluates performance economically rather than statistically.

A notable limitation of the existing literature—both ML-based and rule-based—is that almost none accounts for taxation, even though frequent trading can significantly alter realized returns. Tax-lot selection rules such as FIFO, LIFO, or HIFO are well established in traditional equity accounting, yet very little research examines their impact in high-volatility environments such as cryptocurrency trading. Even fewer studies investigate computational optimization techniques—for example, using Integer Linear Programming (ILP) to minimize realized gains when matching lots. As a result, the intersection of predictive modeling, trading execution, and tax-aware portfolio management remains largely unexplored.

In addition to forecasting, some research explores rule-based trading strategies using moving averages, momentum indicators, or trend following logic. These approaches are widely used as baselines in the literature, as they are simple to compute, highly interpretable, and surprisingly competitive in certain regimes (Malcolm Baker, Jeffrey Wurgler, Yu Yuan, 2012). However, most studies treat these strategies independently rather than comparing them directly to learned models under identical conditions.

Conclusion

This project set out to examine two central questions: whether an LSTM-based neural network can provide actionable predictive signals for Bitcoin trading and how different tax-lot matching strategies influence the realized gains and overall after-tax performance of a cryptocurrency portfolio. Across all experiments, the findings demonstrate that while forecasting models contribute useful directional insights, tax-lot selection rules exert a far greater influence on long-term portfolio outcomes.

The LSTM model successfully captured broad BTC price trends and demonstrated reasonable next-step forecasting accuracy, but it also exhibited smoothing behavior and lag during highly volatile periods—limitations that prevented it from serving as a standalone trading engine. Its role is therefore best understood as complementary: a tool that can help inform timing decisions but cannot independently optimize returns in a market dominated by sharp fluctuations and structural noise.

In contrast, the tax-lot engine produced clear and consistent performance differences across strategies. FIFO repeatedly generated the highest realized taxes and the lowest after-tax portfolio value, illustrating how early realization of low-basis lots creates long-term drag. LIFO improved upon this but remained sensitive to short-term gains. HIFO and the ILP optimizer, however, significantly reduced tax liability, with ILP consistently achieving the theoretical minimum across all simulations. The Greedy approach performed competitively in many market conditions but still fell short of ILP's global optimality. Taken together, these results confirm that tax-aware execution materially shapes investment performance and can overshadow the impact of trading signals themselves.

The integration of forecasting and tax optimization suggests a promising direction for future work. Although the LSTM alone does not maximize portfolio value, its predictive capabilities could be leveraged to enhance tax-efficient decision making—such as delaying sales to achieve long-term tax treatment or using predicted downturns to strategically realize gains under optimal lot selection rules. Additional research could explore hybrid strategies, reinforcement learning agents that jointly optimize trades and tax outcomes, or more advanced forecasting models capable of adapting to extreme volatility.

Overall, the project demonstrates that tax-lot strategy is a first-order determinant of cryptocurrency portfolio performance, and optimization-based approaches like ILP can meaningfully improve after-tax outcomes. Forecasting models add value but are secondary to tax-efficient execution. By combining predictive modeling with rigorous tax optimization, investors and automated trading systems may achieve a more realistic, robust, and economically meaningful edge in cryptocurrency markets.

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Appendix 1
Github Link:
https://github.com/SuperJMwang/DataScience-Project.git