

NoxTrader: LSTM-Based Stock Return Momentum Prediction

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Abstract— We introduce NoxTrader, which is designed for portfolio construction and trading execution, aims at generating profitable outcomes. The primary focus of NoxTrader is on stock market trading with an emphasis on cultivating moderate to long-term profits. The underlying learning process of NoxTrader hinges on the assimilation of insights gleaned from historical trading data, primarily hinging on time-series analysis due to the inherent nature of the employed dataset. We delineate the sequential progression encompassing data acquisition, feature engineering, predictive modeling, parameter configuration, establishment of a rigorous backtesting framework, and ultimately position NoxTrader as a testament to the prospective viability of algorithmic trading models within real-world trading scenarios.

I. INTRODUCTION

In an era characterized by rapid advancements in algorithmic and machine learning-based trading, the landscape of financial markets is undergoing a profound transformation. While manual trading approaches have traditionally held sway, the emergence of model-based trading methodologies represents a pivotal shift. Despite this evolving landscape, literature dedicated to the discourse of model-based trading remains relatively scarce. Existing works, such as "Quantitative Trading using Deep Q Learning" [Soumyadip Sarkar, 2023][1] and "Reinforcement Learning for Quantitative Trading" [SHUO SUN, RUNDONG WANG, and BO AN, 2023][2], have explored reinforcement learning (RL)-based strategies that interact with the market environment.

In contrast, NoxTrader introduces a distinctive paradigm that sets it apart from its contemporaries. Unlike prevailing RL-focused methodologies, NoxTrader harnesses the predictive power of Long Short-Term Memory (LSTM) networks and supervised learning techniques to discern intricate patterns within historical data, effectively capturing the nuanced fluctuations in market prices. This departure from conventional RL-centric approaches is a hallmark of NoxTrader's innovation, underpinning its ability to navigate the dynamic intricacies of financial markets.

Of particular note is NoxTrader's novel employment of time-series data for predictive purposes, a facet that differentiates it from prevalent trading models. Moreover, NoxTrader introduces a unique perspective on label generation by adopting the concept of "return momentum", which is the difference of return between two consecutive days, as a predictive label with appropriate filter, as opposed to the more customary use of raw returns. This nuanced

approach to label formulation adds an additional layer of sophistication to NoxTrader's predictive capabilities.

The subsequent sections of this paper are carefully structured to provide a comprehensive exposition of NoxTrader's inner workings. We delve into the intricacies of each constituent unit, meticulously detailing the process of feature generation, predictive modeling, and the creation of a robust backtest environment. Our narrative is further enriched by a diverse array of empirical experiments, designed to showcase the results garnered from NoxTrader's operational deployment and substantiate its potential profitability. Finally, we make a complete discussion and conclude it with some possible future improvements we're going to make.

II. METHODS

NoxTrader's implementation consists of three primary components. The initial component, termed "Feature Generation," assumes the role of crafting distinct facets of features and subsequently conveying them to the model. The subsequent component, denoted as the "Prediction" module, bears the responsibility of harnessing the previously generated features. It assigns scores to individual stocks within our screener based on these features. Following the evaluation of all stocks, a mechanism for portfolio construction and strategy backtesting becomes imperative. This function, referred to as "Backtest," facilitates the process of portfolio assembly and strategy evaluation. In the subsequent sections, a comprehensive exposition of each of these three components is presented.

A. Feature Generation

The historical data supplied by the yfinance platform embodies a set of fundamental raw metrics, encompassing the opening, closing, highest, and lowest values of each individual stocks. Notably, these initial data points, while serving as a foundational basis, lack the requisite depth to facilitate effective learning and precise predictive outcomes within the model. As such, a compelling imperative exists to undertake a transformative process on this raw dataset, thereby bringing in some enlightening features that are primed to empower the model's learning capacity.

In the spirit of holistic pattern recognition, NoxTrader undertakes a multifaceted approach to feature engineering, drawing upon a rich spectrum of insights that collectively enhance the model's ability. The subsequent enumeration

explain the diverse array of features meticulously integrated into the NoxTrader framework:

- **Returns:** A crucial measure is "Returns," which shows how much the closing price has grown compared to its previous value, usually from the day before. This measure helps the model understand the changes in stock values over time more effectively.
- **ReturnMomentum:** Building upon the Returns paradigm, ReturnMomentum augments the model's insight by quantifying the differential between the current day's Returns and the Returns observed on the preceding day. This parameter encapsulates the intraday dynamics that could potentially exert influence on future stock performance.
- **ReturnAcceleration:** Delving deeper into the temporal dynamics, ReturnAcceleration discerns the variance in ReturnMomentum from one day to the next, thereby encapsulating the intricate curvature of the stock valuation trajectory. This higher-order derivative augments the model's ability to capture evolving trends.
- **WeekPriceMomentum:** Harnessing a broader temporal horizon, WeekPriceMomentum appraises the growth rate of the closing price compared to its state a week prior. This temporal frame of reference imparts a long-range perspective on valuation trends, arming the model with insights into sustained momentum. [3]
- **MonthPriceMomentum:** Extending the purview even further, MonthPriceMomentum represents the growth rate of the closing price in relation to its value a month preceding. This elongated temporal context serves as a harbinger of extended trends, enriching the model's predictive prowess. [3]
- **VolumeVelocity:** Recognizing the pivotal role of trading volume, VolumeVelocity indexes the growth rate of trading volume in comparison to the preceding day. This feature offers insights into market sentiment and potential shifts in supply-demand dynamics.[4]

These intricate features collaboratively contribute to the enhancement of NoxTrader's learning efficacy. By seamlessly integrating these multifaceted metrics, the model is able to glean a more profound comprehension of market nuances, thereby enhancing its predictive power and heightening the precision of its projections.

B. Prediction Method

In this section, we detail the methodology employed for predicting stock price changes using a Long Short-Term Memory (LSTM) network. The dataset, feature extraction, model architecture, loss function, performance evaluation, and the rationale behind the chosen approach are discussed.

- **Dataset:** The dataset comprises individual data instances, each consisting of two main components: features and labels. The features encapsulate information from the stock market for the past 10 days, which include the stock's daily data and technical indicators. Notably, the features

incorporate data from the current day as well as the preceding 9 days. The labels represent the difference between tomorrow's stock price return and today's stock price return, effectively representing the difference in price fluctuations. A training set of 240 such instances is constructed, chosen based on utilizing historical data from the past year. Since stock market only opens 5 days a week, approximately 20 trading days correspond to a month.

- **Model Architecture:** Our approach employs the Long Short-Term Memory (LSTM) network as the primary model architecture. The LSTM's inherent ability to capture temporal dependencies makes it suitable for modeling stock price patterns. By recognizing the analogy between stock prices and language, which both exhibit temporal sequences, the LSTM aims to capture intricate patterns in stock price fluctuations.
- **Loss Function:** The Mean Squared Error (MSE) is chosen as the loss function for the LSTM model. This selection aligns with the objective of minimizing the discrepancy between predicted and actual stock return momentum. The MSE quantifies the average squared difference between predicted and actual values, enabling the model to learn optimal parameters that minimize this error.
- **Performance Evaluation:** To assess the performance of the model, we not only employ the MSE loss function but also calculate the correlation between our predictions and the true labels. This correlation metric ranges predominantly between 0.65 and 0.75, signifying a meaningful correspondence between predicted and actual trends. Importantly, considering the temporal nature of stock data, retraining the model is necessary every 10 days to ensure its adaptability to evolving market patterns.
- **Model Generalization:** While a predictive horizon beyond 10 days might be appealing, we observed a decline in correlation beyond this point. Specifically, if we use the same model to make predictions for 40 days, the correlation for the initial 20 days significantly surpasses the latter 20 days, implying reduced accuracy for longer prediction horizons. Consequently, forecasting stock prices over an entire year would necessitate the training of 24 separate models, each specialized for a specific 10-day prediction window.

C. BackTest Environment

The presented backtesting framework is designed with the intention of harnessing the outcomes generated by our model. This is accomplished through the conversion of model-generated labels into corresponding stock positions, followed by the simulation of trading activities under conditions resembling those of the real market. The outlined system comprises two sections: label-to-position conversion and performance evaluation.

- i. **Label-to-position Conversion:** This section consists of a two-fold procedure, involving filtration and capital allocation.

- **Filtration:** Stocks whose predicted labels fall within a predetermined range are classified as "no-trade" due to our observation of heightened correlation between predicted and actual labels when the predicted label magnitudes are large. Additionally, it has come to our attention that a strong concordance exists between the polarity of returns velocity and returns, particularly evident in scenarios where the magnitude of returns velocity are large. Following the identification of "no-trade" entities, the remaining candidates will undergo an adjustment process, involving a subtraction by a constant if the value is positive, and an addition by a constant if the value is negative.
- **Capital Allocation:** The remaining candidates will partake in a weighted average computation. On a daily basis, each candidate will be allocated a position value. The position value is determined by multiplying the total equity by their respective weighted average.
- ii. **Performance Evaluation:** The computation of portfolio gains and losses entails the multiplication of positions with actual market returns. The subsequent benchmarks are introduced to provide enhanced comprehension of the portfolio's performance.
 - **In the market days:** The ratio of the number of days in the market to the total number of days
 - **Position Qualified:** The ratio of the number of position in the market to the total number of position
 - **Annual Returns:** the total returns earned by an investment in a year, considering compounding effects
 - **Win Rate:** the percentage of successful trades among all position
 - **Max Drawdown:** the largest percentage decline in an investment's value from its peak to the lowest point

III. EXPERIMENT RESULT

The following experiment will demonstrate our approach to selecting model labels, establishing evaluation criteria, and ultimately formulating a comprehensive strategy.

A. Initial Returns Prediction

During the first stage of our research, a noteworthy discovery was made. Despite our efforts, the correlation between predicted results (returns) and actual outcomes had become nearly negligible. This puzzling development extended to post-hoc testing, where the model's performance remained far from satisfactory. Although the overall correlation stood at around 0, it was intriguing to observe that the predicted trends of upward and downward movements exhibited some semblance to the true labels. To probe deeper, an analysis was conducted by computing the correlation between the predicted return differential and corresponding true label differentials, yielding an improved but modest correlation coefficient of 0.2. Please refer to Figure 1.

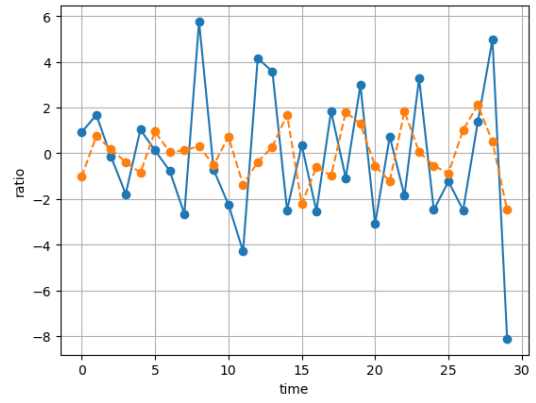


Fig. 1. Correlation between the Predicted Returns Differential and the Corresponding Return Momentum

B. Refining Label Representation

Upon entering this stage, a pivotal change was introduced in the way we represented the true labels. Shifting from the initial approach of using stock returns, we adopted their differentials, namely "return momentum" as the new label representation. This alteration yielded remarkable results as the correlation coefficient surged to an impressive 0.6. Please refer to Figure 2. This change reaffirmed the importance of label representation in the predictive accuracy of the model. However, a concerning pattern emerged when the predicted results were inversely transformed to the original returns. The correlation plummeted back to negligible levels, puzzling us further.

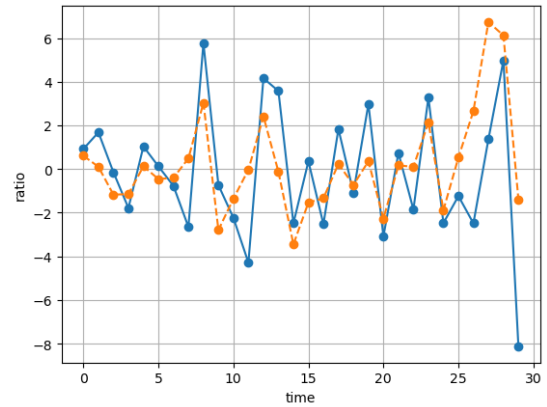


Fig. 2. Correlation between Predicted Return Momentum and True Labels

C. Return Momentum Backtesting

Our focus shifted towards understanding the stark discrepancy observed during the transformation from differentials to actual price changes. Intriguingly, employing the true return momentum as inputs for backtesting proved highly effective. Please refer to Figure 3. This unexpected success hinted at an inherent capability of return momentum to profit effectively without transforming back to return. Despite this, using the predicted return momentum for backtesting yielded disappointing results, indicating a major discrepancy between the model's predictive power and its application to the actual data. Please refer to Figure 4.

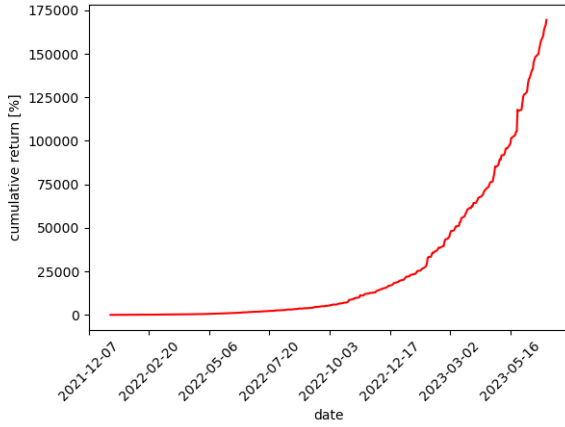


Fig. 3. True Label of Return Momentum as Inputs for Backtesting



Fig. 4. Predicted Return Momentum as Inputs for Backtesting

D. Correlation Viability Assessment

To evaluate the viability of the correlation between predicted and true labels, stocks exhibiting a correlation exceeding 0.7 within each group are selected for a backtesting exercise. Each group represents a four-month testing period. The findings reveal that the observed correlation is indeed viable, substantiated by an annual return of 122.95% and a maximum drawdown of 11.14%. The comprehensive results of this analysis are illustrated through Figure 5.

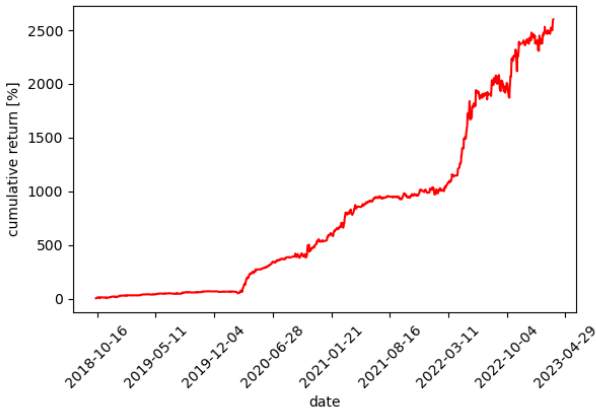


Fig. 5. Cumulative Return Chart of Candidates with High Correlation

E. Correlation-Label Relationship

Our investigation delves into establishing the connection between labels and correlation, building on the understanding

that high correlation signifies superior performance. During this analysis, we incorporate the standard deviation of labels within each distinct group. It reveals a discernible pattern: instances of heightened standard deviation correlate with relatively high correlation. For an in-depth visual representation, please refer to Figure 6.

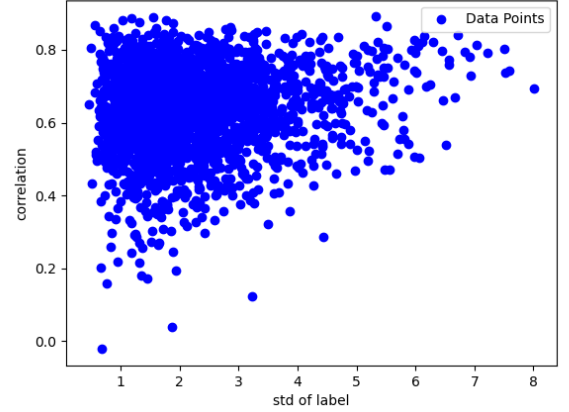


Fig. 6. Relation between Standard Deviation of Labels and Correlation

F. Final Strategy

The investigation into the Correlation-Label Relationship has bestowed insights that guide our strategic decisions. Labels characterized by little absolute values have been deemed less conducive to our strategy and therefore discarded in the strategy. Furthermore, the remaining labels are subjected to an adjustment process, aligning their values closer to zero in a standardizing approach. The empirical outcomes are striking: a cumulative return of 325.38% over a span of six years, an annual return of 37.72%, and a maximum drawdown of 23.84%. The visual representation of a gracefully undulating curve, akin to an exponential curve, serves as compelling evidence of the pronounced positive impact of our filtration approach. A comprehensive tabulation can be found in Table I, while Figure 7 visually reinforces these outcomes.

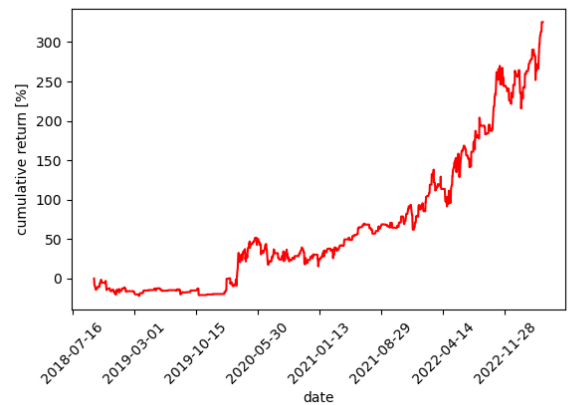


Fig. 7. Cumulative Return Chart of Final Strategy

TABLE I. RESULT DATA OF FINAL STRATEGY

Property	Value
Start Date	2018-10-04
End Date	2023-04-17
Market Days	1140
In the Market Days	41.491228 %
Position Qualified	2.353445 %
Commission	0.01 %
Equity Initial	1000000
Equity Final	4253800
Return	325.380000 %
Ann. Return	37.718672 %
Win Rate	61.090909 %
Max. Drawdown	23.837605 %

IV. CONCLUSION

In conclusion, this paper has introduced and expounded upon NoxTrader, a holistic trading system meticulously devised to orchestrate the complete lifecycle of trading operations, from inception to realization. With a paramount focus on stock market trading, NoxTrader's core objective centers on the cultivation of sustained moderate to long-term profits. Rooted in an intricate learning process, NoxTrader derives its insights from historical trading data through a steadfast reliance on time-series analysis, harmonizing seamlessly with the intrinsic characteristics of the employed dataset. The narrative has unfolded a systematic journey encompassing data acquisition, feature engineering, predictive modeling, parameter configuration, and the establishment of a rigorous backtesting framework. In contrast to conventional methodologies, NoxTrader diverges by introducing an innovative approach to label generation. This entails the incorporation of the "return momentum" concept as a predictive label combined with filters. This distinctive strategy yields notable outcomes that underscore its significance and efficacy.

In envisioning the future, there lie exciting avenues for further refinement and expansion. The pursuit of more robust predictive metrics, such as incorporating measures like standard deviation, promises to enhance the model's correlation with true labels, bolstering the effectiveness of its predictions. Moreover, our commitment extends towards researching and formulating a more sophisticated trading strategy, one that can maximize the actionable signals furnished by our model. Our present allocation approach, while serving as a foundational framework, is acknowledged as a simplification. By delving into advanced trading strategies, NoxTrader can harness its predictive power more astutely, culminating in a formidable tool capable of navigating complex real-world trading dynamics.

In closing, NoxTrader stands as a testament to the potential within algorithmic trading models. Through this comprehensive exposition, it is evident that NoxTrader's journey is just beginning, with the horizon teeming with opportunities for innovation, refinement, and ever-greater achievements in the realm of model trading.

REFERENCES

- [1] S. Sarkar, "Quantitative Trading using Deep Q Learning", April 2023.
- [2] S. Sun, R. Wang, and B. An, "Reinforcement Learning for Quantitative Trading," *ACM Trans. Intell. Syst. Technol.*, vol. 14, no. 3, Article 44, pp. 1-29, Mar. 2023.
- [3] Z. Kakushadze, "101 Formulaic Alphas," Quantigic Solutions LLC, 1127 High Ridge Road, #135, Stamford, CT 06905, and Free University of Tbilisi, Business School & School of Physics, 240, David Agmashenebeli Alley, Tbilisi, 0159, Georgia, Dec. 2015.
- [4] C. M. C. Lee and B. Swaminathan, "Price Momentum and Trading Volume," *The Journal of Finance*, vol. 55, no. 5, pp. 2017-2069, Oct. 2000.
- [5] C. S. Asness, T. J. Moskowitz, and L. H. Pedersen, "Value and Momentum Everywhere," *The Journal of Finance*, vol. 68, no. 3, pp. 929-985, Jun. 2013.