Potential application of large language models in the financial field

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Abstract. Recent advancements in artificial intelligence have led to the research, development, and implementation of various new technologies. Large language models (LLMs) have emerged as a prominent research focus across multiple disciplines due to their remarkable capabilities in data collection, analysis, scenario simulation, and programming. These capabilities hold significant potential for applications in the financial sector. By leveraging these strengths, economic researchers, financial institutions, and individual investors can more effectively strike a balance between risk and return. The financial market contains vast amounts of information, ranging from essential data to peripheral materials, which can be challenging for humans to process comprehensively. Large language models can help financial professionals extract key insights from financial markets and make informed decisions.

Keywords: Large language model, Finance, Macroeconomics, Neural Network.

1. Introduction

In recent years, the powerful capabilities of LLMs have been demonstrated through versatile applications across various domains, and numerous researchers are investigating their potential applications within the financial domain. One of the key advantages of large language models is their powerful data capability for collecting messages and processing data. The heart of the financial market is unfiltered information, including direct information that will influence the market trajectory and indirect information that may cause market volatility. Researching potential related messages can be challenging for financial professionals, and even veteran financial analysts may overlook critical information at times. With the help of large language models, such as GPT and DeepSeek, financial practitioners may spend less time collecting messages and reduce the risk of making mistakes. Moreover, it is also complicated and time-consuming for professionals to process data; this process will be significantly streamlined by applying large language models.

Scenario simulation is another key advantage of large language models. To be more specific, large language models have the power to generate multiple possibilities rapidly. The biggest challenge for financial researchers is predicting future market trends. In other words, it is challenging for researchers to set all possible scenarios and make assumptions about future development without disregarding potential possibilities. According to Zhu et al., a graph neural network (GNN) can achieve a 27%-60% reduction in source consumption, resulting in a 42%-61% improvement in computational speed [7]. Applying a graph neural network (GNN) to large language models can support researchers in generating numerous ideas and significantly reduce the time required for this process.

This essay will outline the specialized models that can be systematically applied from the perspectives of financial professionals, companies, and private investors to better understand the potential applications of large language models in the financial field. This essay is more likely to provide a potential approach to generating a model designed in a manner similar to a neural network.

2. Literature Review

2.1 Fundamental construction of the neural network model

Sherstinsky highlights that recurrent neural network (RNN) and long short-term memory (LSTM) networks have remarkable performance across diverse sequential data applications, and their influence is particularly evident in areas such as language modeling, speech recognition, machine translation, and beyond [4]. As a result, constructing a neural network model offers a feasible strategy for investigation within the financial domain. The fundamental part of this "neural network "is calculation. The underlying logic of this section is based on formulas and conditional statements. From the perspective of financial professionals employed by a listed company, such as accountants, one of their primary tasks is to produce financial statements. Despite professionals recording each transaction clearly, it is still a high-volume process for humans to consider such considerable data.

To improve workflow productivity, train a model tailored for financial calculations. The most fundamental stage is inputting formulas to calculate key performance indicators (KPI), such as return on capital (ROC), return on equity (ROE), and trial balance. It is widely known that current models struggle with complex computations that require multi-step reasoning. More specifically, it is difficult for current models to filter and sort data from each transaction into the correct financial statement categories and then calculate relevant KPIs. Thus, we let the items of the financial statements, such as payable, receivable, inventory, and depreciation, be the most basic "Neuron". Based on that, we add conditional statements to filter for the corresponding data, which ensures that data for every transaction can be located. Sun states that knowledge embedding and neutral feature extraction greatly contribute to model improvement. After each data point is located, it will be sent to a larger neuron, which will be used to determine which formula applies to the calculation.[6]

To some extent, this model can mitigate errors caused by complex calculations, making it easier to identify the specific computational stage at which the error occurs. It is of great importance for machine learning engineers to set different trading scenarios to ensure the accuracy of data type recognition, as the process of tracing and validating incorrect data is time-consuming for accountants. Since the specialized model has been implemented, accountants will be able to more easily identify anomalous data and transactions and prepare the final financial statements. This model's most obvious effect is improving the efficiency and accuracy of routine tasks.

2.2 Incorporate the principles of microeconomics

The model requires additional functionality to address the demands of a broader user group, like analysts. To be more specific, the mentioned model is used solely for calculation and cannot analyze the underlying significance of the data. To handle this issue, a machine learning engineer must train the model to learn microeconomic theory. For instance, the model should assess a business's performance based on key performance indicators, such as net present value (NPV), return on equity (ROE), debt-to-asset ratio, and turnover ratio. However, the most challenging part of this stage is adding multiple conditional checks to capture all relevant key performance indicators. Typically, fulfilling these requirements necessitates iterative processing with branching logic. Thus, we add high-level conditional statements to classify calculated KPI based on the calculation stage. Once relevant data are classified, they will be sent to the comparison stage, where year-over-year (YoY) data will be analyzed to pinpoint change points. Subsequently, we can trace the issue back to its root cause in the calculation stage and analyze which segment of transactions had the most significant impact on financial and operational performance. This model makes it more convenient for analysts to thoroughly explore the company's financial and operational health and identify the KPIs driving the change.

2.3 Incorporate the principles of macroeconomics

To further improve the functionality of this model, we need to incorporate knowledge of macroeconomics into the training process. Since the model analyzes the company's financial and operational health, the next step is to develop a possible operational plan for the company's future. Liu points out that using a single type of data to establish linear and nonlinear dependencies among variables could reduce the accuracy of risk prediction [3]. First, we will consider the consumer factor. Specifically, we input the basic consumer-goods-producer models and the corresponding diagram, combined with the previously calculated data, to get consumer spending habits. According to the consumer spending habits, the model will set several different consumer preference scenarios and then return to the calculation stage to adjust variables (such as inventory, receivables, and expenses) and obtain corresponding results. After this simulation process, the model will display projected financial and operational performance under different simulation scenarios. To enhance the realism of the forecasts, we need to consider factors such as government policies and major social events. Moreover, competition within the industry is fierce, which significantly impacts the major strategic, financial, and operational choices that determine the company's future. Thus, a powerful and low-latency search engine is critical for this model to access the abovementioned data. Upon incorporating these new market variables, the model will repeat the previous simulation process and display corresponding projected financial and operational performance. According to Fazlija et al's research, Chain-of-Thought (CoT) and Tree-of-Thought (ToT) could increase the LLMs' accuracy in risk prediction [2]. However, the impact of all the above-mentioned factors is not absolute, which introduces varying degrees of bias into the simulation results and poses a risk of considerable loss to the company. Therefore, it becomes necessary to quantify and visualize the risks. Based on the existing simulation, we can run different scenarios by adjusting the probability of each risk factor occurring to obtain a series of risk coefficients that quantify the probability of each strategy. We can then plot the corresponding risk-reward gradient against the expected return. Following this process, we will increase simulation fidelity and create a comprehensive risk visualization.

2.4 Expand Applications

The next stage is to expand the applications of this model beyond company growth, and we aim to target the corresponding industry. If it were possible to procure the business data of leading industry enterprises, the model could provide a current analysis of the industry's development status through the analysis stage. However, the interplay of multiple uncertainties raises the risk of a potential event occurring. The above-mentioned risk assessment stage will formulate risk-adjusted recommendations based on probability assessments to address this issue. For instance, Chen's study on the Chinese carbon market indicates that LLMs improve approximately 30% of TSM forecasts across different regional markets [1]. The model simply increases the probability of event forecasting by optimizing input features. From the perspective of a private investor, the model provides an overview of the current state and future potential of various industries. Based on the analysis and simulation, a private investor can more easily formulate an investment strategy. More precisely, a private investor could select a company, then adjust the investment amount and run simulations to obtain projected returns and their corresponding risks. To determine a risk-appropriate asset allocation by running iterative simulations incorporating the investor's strategy. Moreover, it is also of great strategic importance to the company. Through the lens of the industry chain, the company could develop a subsequent strategy according to the evolving conditions of every industrial sector.

Meanwhile, for enterprises seeking to expand into new sectors or undergo a transformation, the model could identify potential barriers, calculate the associated costs, and estimate the corresponding risk of failure. For instance, New Energy Vehicles and Autonomous Driving have emerged as the most sought-after sectors in recent years. There is a strategic shift among traditional OEMs (Original Equipment Manufacturers) towards electrification, driven by policy and consumer demand. Leveraging the analytical output generated by this model, OEMs can initiate strategic collaborations with tier-one battery OEMs, contingent upon a thorough evaluation of their business viability and market stability. For enterprises outside the automotive industry targeting market entry into the electrified mobility domain, the model could display the essential prerequisites regarding technology, capital, and staffing, and quantify the risk-return pair for the investment. In summary, this model can provide forward-looking recommendations for developing companies and industries, while offering investment planning guidance for investors.

3. Limitations and Future Directions

3.1 Limitations

Despite the model's extensive functionality, considerable challenges persist in its development and training phases. One limitation is the complexities of setting up a fundamental computing network infrastructure. While neural network shape calculation significantly reduces the computational overhead and fragility of a single-threaded approach, this new model also introduces additional complexities. In other words, the initialization involving numerous fundamental variables and the configuration of intricate logic rules, as well as orchestrating core data through a directed acyclic graph (DAG) of conditional logic, will add significant overhead and iteration cycles to the foundational build-out, directly impacting time-to-market and initial capital outlay.

Similarly, for the simulation component, the iterative process of simulating complex scenarios with massive data volumes, followed by computation and visualization, imposes a significant computational burden on the application. Moreover, Zhuang states that these models are not robust to dynamically changing market conditions[8]. Their inability to detect subtle and context-sensitive sentiments in unstructured financial narratives fundamentally constrains their predictive efficacy and practical deployment. The resource implications of these technical limitations are currently unquantifiable, representing a significant unknown in our project planning.

An additional restricting factor is the availability and accessibility of relevant information. Strict authorization protocols usually govern access to a corporation's proprietary data. Consequently, ensuring the fidelity and reliability of the modeling and computational outputs becomes challenging. Leaving this data embedded in the model could result in data exposure or model inversion attacks. Therefore, security becomes the next issue that needs to be addressed. However, if a complete and debugged model is made public, the information leakage problem will persist indefinitely.

3.2 Future Directions

One possible approach is to build and open-source a basic framework for the simulation analysis, while allowing enterprises or individual investors to refine the specific problem analysis and scenario modeling on their own systems. This approach satisfies the need for customization while mitigating the information leakage risks associated with cloud connectivity. Paradoxically, this solution may lead to the emergence and aggravation of a separate challenge. Due to the information asymmetry between enterprises and investors, analyses of the same development status, recommendations for future strategy, and simulations of investment plans will yield drastically different results. This divergence creates market inefficiencies and can lead to the undervaluation of solid companies or the misallocation of capital. Suzuki suggests that it is necessary to establish domain-specified language models to process text documents to capture information from the financial market [5]. As such, while this model can drastically shorten processing time and reduce calculation errors, it cannot generate fully accurate predictions for future development simulations or investment plans. Its value lies more in exploring a wider range of potential scenarios and providing directional guidance. Consequently, it should be treated strictly as an auxiliary decision-support tool, not as the ultimate decision-maker. Unless the perennial problem of information security, which has long plagued AI and LLMs, is somehow solved in the future

4. Conclusion

In summary, this essay proposes the potential application of building an artificial neural network computation model in financial calculation. Building upon this foundation, the model will be enhanced by integrating microeconomics and macroeconomics. It will incorporate additional critical factors such as policy shifts and major social events. The platform significantly enriches the current situational analysis by manipulating these diverse variables to run comprehensive scenario simulations. This powerful functionality enables it to provide robust future development strategies, proactive risk management, and tailored investment planning tools, thereby meeting the diverse needs of a broad user base. However, data acquisition and information security protocol limitations require only a foundational simulation module framework to be made public. As a result, this model is intended strictly as a decision-support aid, not as a source of definitive conclusions. This essay puts forward a preliminary conjecture regarding its feasibility. It is anticipated that continued technological progress, particularly in resolving information security challenges, will pave the way for more robust and viable theories and models.

References

[1] Chen, R. et al. (2025) 'Can Large Language Models forecast carbon price movements? Evidence from Chinese carbon markets', Research in International Business and Finance,77. doi.org/10.1016/j.ribaf.2025.102951

[2] Fazlija, B. et al. (2025) 'Reasoning with financial regulatory texts via Large Language Models', Journal of Behavioral and Experimental Finance, 47. doi:10.1016/j.jbef.2025.101067.

[3] Liu, Y. et al. (2025) 'AT-FinGPT: Financial risk prediction via an audio-text large language model', Finance Research Letters, 77. doi:10.1016/j.frl.2025.106967.

[4] Sherstinsky, A. (2020) 'Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network', Physica D: Nonlinear Phenomena, 404. doi:10.1016/j.physd.2019.132306.

[5] Suzuki, M. et al. (2023) 'Constructing and analyzing domain-specific language model for financial text mining', Information Processing and Management, 60(2). doi:10.1016/j.ipm.2022.103194.

[6] Yongyong Sun, Haiping Yuan, and Fei Xu (2025). Financial sentiment analysis for pre-trained language models incorporating dictionary knowledge and neutral features. Natural Language Processing Journal, 11(100148-). doi:10.1016/j.nlp.2025.100148.

[7] Zhu, X. et al. (2026) 'Interactive simulation on generalized large-scale scenarios with GNN', Expert Systems With Applications, 296(Part C). doi:10.1016/j.eswa.2025.129095.

[8] Zhuang, Y. et al. (2025) 'Leveraging large language models to examine the interaction between investor sentiment and stock performance', Engineering Applications of Artificial Intelligence, 150. doi:10.1016/j.engappai.2025.110602.