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The Development Research and Application Prospect of Large Language Model Technology in The Financial Field

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Abstract: With the continuous development and rapid progress of the information and computer age, large language model technology has been widely used in various fields and development operators, including, of course, the field of financial technology. In the financial field, large language model technology can promote the development and operation of finance from different angles, and make finance become a more intelligent new industry. Bring new development opportunities to finance. This paper focuses on the introduction of large language model, its development process in different development fields and stages, as well as its development principles and application status, and analyzes the development challenges and advantages of big language model in the application process in the financial field, and looks forward to the future development of big language model in the financial field.

Keywords: Large Language Model, The Financial Sector, Application and Development.

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1 INTRODUCTION

In recent years, large language models represented by AIGC have made great progress in both theory and practice. However, its application in financial markets is still in the early stages of exploration. This paper gives a systematic overview of the historical background and development of large-scale language models. Considering the special nature of financial markets, this paper summarizes the various potential application scenarios, technical challenges, and business advantages of large language models in this field. In addition, various problems arising from the application of large-scale language models in financial markets are summarized and discussed. Based on China's national conditions, this paper puts forward technical considerations and policy suggestions on the application of large-scale language models in financial markets. [1] A large language model is a computer program built using neural networks, which can learn language patterns and rules from a large amount of text data, and then realize the understanding and generation of natural language. With the continuous improvement of deep learning and large-scale computing power, large language models have become one of the research hotspots in [2] NLP and have achieved remarkable application results in many fields. The paper concludes that the application and exploration of techniques such as large language models in financial markets should be strengthened. At the same time, it is necessary to consider the specific requirements of the financial market and risk management, improve the process standards and institutional framework, and realize the digitalization of China's financial industry.

2 LARGE LANGUAGE MODEL IN THE FINANCIAL FIELD

[Publisher's note: The original manuscripts provided by the authors of this section are in German.]

Die verarbeitung natürlicher sprachen ist ein klassischer aspekt des bereichs der künstlichen intelligenz, der sich hauptsächlich auf die verarbeitung der beiden grundlegenden funktionen der sprache durch algorithmus bezieht: "semantische verständigung" und "spracherzeugung". Traditionell werden aufgaben der einfachen natürlichen sprachverarbeitung durch statistische modelle auf grundlage Von regeln Oder statistischen modellen erledigt. Was im bereich der natürlichen sprachverarbeitung einen durchbruch darstellt. [5] So haben google und OpenAI im jahr 2018 das große BERT und GPT entwickelt. Dennoch hat sich die anwendung Von tiefenlern-modellen in der natürlichen sprachverarbeitung im letzten jahrzehnt durch die eingehende forschung zu neuronetzwerken und die verbesserungen bei der hardware des computers erheblich verbessert. Second, large language model technology is also important in financial risk management. [6] Risk fluctuations in financial markets are often accompanied by a large amount of information flow, which may come from news reports, public

opinion analysis, market comments, etc.2017 lancierten Vaswani und andere transformatoren einen transformator, der eine kreative schnittstelle und integration Von informationen auf der ganzen welt ermöglicht und die genauigkeit Von neuronalen netzwerken mit text deutlich verbessert.

Zuvor konzentrierte man sich hauptsächlich auf die architektur des modells und erhöhte die leistungsqualität, indem man ein kodierer, ein kodierer und ein kodierer in seiner struktur ausloten würde. [7] Als die forschung 2019 anfing, auf methoden zu warten, die vor dem training verwendet wurden, um eindrücke zu erstellen, stiegen die wichtigen sprachmodelle explosionsartig an. Im jahr 2022 hat OpenAI programme Oder apps veröffentlicht, die den chatgpt-dienst Oder das protokoll zum dialog, das die öffentlichkeit auf bemerkenswerte weise interessiert, unterstützt.

3 THE DEVELOPMENT OF LARGE LANGUAGE MODEL TECHNOLOGY

The development of large language model technology can be traced back to early statistical language models, which were modeled based on word frequency and syntactic rules, but had shortcomings and shortcomings in handling semantic understanding and generation tasks [8]. With the rise of deep learning and neural networks, a new generation of large language model technologies has made breakthroughs, capable of generating fluent, coherent text and performing exceptionally well on multiple natural language processing tasks.

3.1 TRADITIONAL NLP TECHNOLOGY

Natural language processing (NLP), as an important branch of the field of artificial intelligence, aims to enable computers to understand and generate natural language, thereby facilitating communication and interaction between humans and machines. However, the traditional natural language processing technology faces a series of challenges, which are particularly prominent in practical applications.

The main problems of traditional NLP technology

1. Rules and templates basics

Traditional natural language processing techniques rely heavily on predefined rules and templates. These rules and templates are designed by language experts to handle specific language tasks. For example, syntax parsers and lexical analyzers often parse text based on hand-written rules. This approach, while effective when dealing with structured data, is inadequate for the complexity and diversity of natural language. The syntax and semantics of natural languages are complex and flexible, and different contexts and expressions may cause rules to not cover all situations, which in turn affects the accuracy of processing.

2. Difficult to deal with the complexity of the language

The complexity of natural language is mainly reflected in the following aspects:

Grammatical complexity: The grammatical rules of natural languages are rich and varied. The grammatical differences between different languages make the rules not universally applicable to all languages, leading to difficulties in translation and grammatical analysis.

Context dependency: The meaning of a language often depends on the context. Traditional rule-based methods are difficult to deal with long distance dependencies and multi-level context information.

Semantic ambiguity: The same word may have different meanings in different contexts, and this semantic ambiguity is difficult to accurately capture through simple rules.

3. Limitations of data processing

When dealing with large and diverse linguistic data, the limitations of traditional methods become more and more obvious:

Large-scale data processing: When working with large-scale data sets, rule-based approaches often require a lot of manual tuning and maintenance, which adds effort and complexity.

Data diversity: The diversity of linguistic data requires that the system can adapt to a variety of language habits and expressions. Traditional methods are often inflexible enough to handle this variety.

4. Labor input and time cost

Because traditional NLP techniques rely heavily on experts to manually design and adjust rules, rules need to be redesigned and adjusted whenever language rules or text structures change. This not only increases the maintenance cost of the system, but also limits the flexibility and scalability of the technology. For example:

Rule update: When new language phenomena emerge or grammatical rules change, existing rules may need to be rewritten or adjusted, which is a time-consuming work.

Expert dependence: The design and maintenance of the system relies on the knowledge and experience of language experts, which limits the popularization and application of the technology.

The response of modern technology

To overcome these limitations of traditional approaches, the modern field of natural language processing is increasingly turning to data-driven techniques such as deep learning and neural networks. Here are some of the key developments:

Deep learning models: Deep learning models, particularly neural network-based approaches such as

convolutional neural networks (CNNS) and recurrent neural networks (RNNS), are capable of automatically learning language features from large-scale data, reducing the reliance on manual rules.

Pre-trained language models: such as Bidirectional encoder Representations from Transformers and GPT (Generative pre-trained Transformers), through large-scale pre-training and fine-tuning, we can better understand and generate natural language, and improve processing effects.

Self-attention mechanism: The self-attention mechanism introduced by the Transformers model significantly improves the model's ability to understand and generate text through the interaction and integration of global information.

In general, advances in modern technology have provided the field of natural language processing with more powerful tools, allowing systems to better handle the complexity and diversity of languages. However, in the face of the evolving language environment and application needs, it is still an important direction to continue to study and optimize these technologies.

3.2 Breakthroughs in introducing deep learning

The rise of deep learning has opened up new possibilities to break the limitations of traditional NLP techniques. [13] Deep learning is a machine learning method that automates learning data characteristics and representations by building multi-layer neural networks. In contrast to traditional methods, deep learning does not require manual rules design but improves performance through learning patterns and regularities in large-scale data. The application of deep learning in the field of NLP has attracted wide attention, and the performance of NLP tasks has been significantly improved by introducing deep learning models. For example, convolutional neural networks and recurrent neural networks can be used to efficiently complete tasks such as text classification [14], sentiment analysis, and machine translation.

3.3 The continuous evolution of large language models

Big language model is another important breakthrough in deep learning in the field of NLP, which is a model based on neural networks with powerful language understanding and generation capabilities. Large language models can gain a deep understanding of language by training massive text data, and then achieve high-quality output for various natural language processing tasks. In the practical application of large language model technology, the most representative is the GPT series model launched by OpenAI[15]. Based on the Transformer architecture, GPT models can be optimized and upgraded through pre-training and fine-tuning to generate text with a high degree of coherence and semantic accuracy. In addition, large language models can not only complete traditional text generation tasks, but also be used for complex NLP [16] tasks such as question answering systems, conversation generation, text summarization, and machine translation. The continuous evolution of large language models marks a new milestone in the field of NLP, providing more powerful and efficient natural language processing methods for multi-technology fields such as artificial intelligence, and bringing great potential and opportunities to realize human-computer interaction, information retrieval and knowledge processing.

4 TECHNICAL PRINCIPLES OF LARGE LANGUAGE MODELS

Large language models are widely used in tasks related to natural language processing. The main goal is to train a model through large-scale text corpus to generate text with reasonable syntax and semantics and understand and reason relatively complex semantic relationships. Through neural network architecture, unsupervised learning, self-supervised learning [17], pre-training and fine-tuning, application of attention mechanism, generation, and inference, large language model technology can show good performance in natural language processing tasks.

4.1 Neural network architecture

Neural network architecture is a core component of large language models. Common neural network architectures are recurrent neural networks, variants (such as short-duration memory networks and gated loop units), and self-attention mechanisms. [18] These neural network architectures have good representation and memory ability, can capture contextual information and long-term dependencies, and therefore help improve models' generation and reasoning ability. [19][20] Self-supervised learning is a special unsupervised learning method that generates models' labels by predicting input transformations or filling in partial information. Unsupervised and self-supervised learning are the key methods for large language model training. Unsupervised learning means that the model only uses the input data without the corresponding label information in the training process.These methods enable large language models to learn rich language knowledge and semantic representation from large-scale unlabeled text.

4.2 Pre-training and fine-tuning

Pre-training and fine-tuning are two stages of large language model training. In the pre-training stage, text data of a large language scale is used for the initial training of the model, and the goal is to learn and get a good initial parameter [21]. enabling models to weigh combinations of information from different locations to better capture relationships between local and global contexts. This mechanism can improve the accuracy and consistency of model generation and reasoning.

The fine-tuning phase uses task-specific labeled data to optimize the pre-trained model further. Combining these two phases enables large language models to perform well on many different tasks.

The application of the attention mechanism plays an important role in large language models. Attention mechanisms can help models focus on key information during generation and inference tasks [22], Application status of large language model in the financial field.These fields have been more widely used to provide more and better facilitation and intelligent services for technological progress and industry development [23][24]. In the financial field, the large language model, with its powerful natural language processing capability and intelligent decision support system, has become the right-hand person for financial institutions to process industry big data and conduct complex financial analyses. [25] The application of large language models in the financial field shows a diversified and extensive trend. It plays an important role in text generation, dialogue systems, portfolio optimization, anti-fraud, and risk control.

4.3 TEXT GENERATION

In terms of text generation, financial institutions can apply the large language model to generate high-quality financial market reports, analyst comments and other articles and investment recommendations in the financial field, helping financial institutions to provide relevant financial information more efficiently and provide comprehensive and accurate financial investment guidance for investors. ChatGPT, released by OpenAI [26], has strong semantic understanding and text generation capabilities, and domestic technology companies such as iFlytek and Baidu have also released large language model applications such as "Spark cognition" and "Wenxin Word". On this basis, financial institutions can allocate relevant financial data and business resources, develop application models that meet the needs of the financial field, and improve the quality and efficiency of smart office capabilities and intelligent services.

4.4 DIALOGUE SYSTEM

Large language models can be used to build intelligent conversation systems to provide accurate customer service. Financial institutions can integrate the large language model into the internal dialogue system to provide financial customers with "7x24" [27] hours of business support and consulting services, which can improve customer satisfaction and reduce the operating costs of financial institutions. For example, KAI-GPT [28], a large language model for the banking industry launched by Kasisto, an artificial intelligence research and development company, can assist financial institutions to analyze and understand the consulting needs of customers and provide accurate dialogue services, greatly improve the efficiency of customer service response, and provide good technical support in improving the quality of business operations and customer satisfaction.

4.5 PORTFOLIO OPTIMIZATION

Large language models can be used for portfolio optimization. Through in-depth analysis of historical returns, risk indicators and other relevant factors, the big language model can provide investors with the best asset allocation scheme, so that investors can choose portfolios more scientifically, reduce risks and improve returns. At present, domestic institutions of higher learning and technology companies have achieved remarkable results in the research and development of large language models of financial retail, among which the "Zhihai-Jinpan" model released by Zhejiang University and science and Technology company is the first large language model developed in the field of vertical financial retail, which can be based on financial customers' investment needs, expected returns and other data [29]. Provide personalized and intelligent investment advice to help financial institutions improve the depth of financial services and customer satisfaction.

4.6 ANTI-FRAUD AND RISK CONTROL

Large language models can also be used for anti-fraud and risk control. By analyzing a large amount of transaction data, the large language model can identify potential fraud and risk events, provide risk early warning, and take appropriate measures to help financial institutions improve the security protection of customer funds and risk control level, as well as reduce losses. Domestic financial technology companies on the language model in applying intelligent financial risk control scene conducted in-depth research. For example, the Bank of China financial technology companies publishing a platform for intelligent risk control through the technology of language model for risk identification and management of the whole process of credit business is working to provide strong support, report generation, risk early warning monitoring and risk map analysis of automated processing, Improve the timeliness and accuracy of risk control management [30].

Large language models can quickly analyze massive financial data and provide accurate analysis and prediction results, thus supporting investment decision, risk management and market prediction. With the continuous progress of technology, the application prospect of large language models in the financial field will be broader, and it will positively impact the stability and development of the financial market.

5 CONCLUSION

With the continuous expansion of model scale and the continuous increase of training data, the ability to generate text and understand semantics of large language models has been significantly improved. It is expected to become an important engine to promote the digital and intelligent transformation of the financial industry. But at the same time, large language model technology also faces many challenges

regarding computing power and data security. The challenge of large language model technology is that large language model technology has a high demand for computing resources and power. With the continuous iteration and upgrading of the scale of large language models, the model requires more and more computing resources and computing power of hardware devices for training. Training and upgrading large models require deploying huge computing resources and high-performance training equipment, which is not a small challenge for most financial institutions and technology companies. The second is the accuracy and interpretability of applying large language model technology. The complexity and volatility of the financial market easily led to the prediction bias of the big language model, for example, when dealing with professional terms or specific scenarios in the financial field, there may be understanding errors or inaccurate content generation. At the same time, the explanation of the logic and motivation of investment decisions is also the focus of financial practitioners. Such potential problems need to be accurately corrected by financial professionals to ensure the correctness of the model's output content. Third, data privacy and security issues are also important challenges in the application process of large language model technology. Large language models require a large amount of training data, which may contain sensitive information, and once this important information or data is leaked, it will bring great risks. Therefore, it is critical to protect the security and privacy of financial customer data when applying large language model technology.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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