Deep Learning with LLM system: A New Paradigm for Financial Market Prediction and Analysis

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Abstract
Rapid progress in large scale language models (LLM) has led to a wide range of business sectors AI You can develop a new frontier of applications. GPT-3 And BERT Both have revolutionary capabilities in natural language understanding, structured knowledge representation, and task specific adaptation. But LLM To implement and extend a base solution successfully within a company, it will have problems for the company. It is the maximization of the utility of its own data assets, securing data security and privacy, maintaining consistent knowledge representation, optimizing resource allocation, and dealing with a variety of business scenarios.
In order to address these issues, the enterprise scale LLM We propose a centralized knowledge base framework for introduction. The unique scalable architecture of the framework allows companies to use their own data resources safely and efficiently, in various business scenarios LLM Drive solutions can be enhanced and reusable. This framework has proven to realize a large Merritt in resource utilization, such as reduction of computational overhead, rapid solution implementation, and reusability of knowledge. These technological advances eventually lead to concrete business Merritt, such as improving investment returns, shortening the development cycle, and improving user experience. A comprehensive and practical approach to the introduction of centralized knowledge base (LLM) is the enterprise AI Provide valuable insights into the development and help businesses draw the value of these innovative technologies.

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Keywords: SVM, Stock price prediction, Time series.

1. Introduction

Due to the rapid development of the recent large-scale language model (LLM), companies have seen a wide range of business fields AI The power of the power has been cut off. GPT-3 Or BERT And LLM It provides excellent capabilities in understanding and generating natural language, enabling employee support, process automation, content creation, and the like AI Application. But organizations that aim to introduce these radical technologies are facing some major challenges [10].

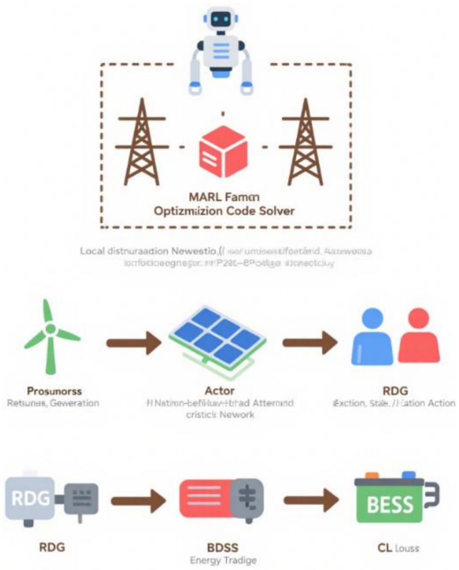
First, companies often struggle to effectively utilize their own data assets. These data assets may be scattered in different systems or formats. To coordinate these data into a format that can be effectively utilized in a large scale language model is a complex, consuming resource.Second, it is very important to establish robust data security and privacy management mechanisms. Large scale language models involve potential risks such as leakage of sensitive information and generation of content that violates organizational policy. Therefore, it is very important to ensure the confidentiality and consistency of the data used for the learning and deployment of the model.Another important task is to secure [11-23] consistent knowledge representation within a company. Large language models may lead to bias or contradiction in understanding and generating information, and may result in conflicting results or false results in important business applications.

To address this challenge, we need systematic knowledge management and screening mechanisms. In addition, it is also essential to maximize computing resource utilization. Learning
and reasoning of large-scale language models often require enormous computational complexity and cost, so we need an efficient resource management strategy to optimize model deployment and scalability. Finally, companies support diverse business functions such as customer service, content creation, process automation and decision support AI Requires a leading solution. Building an integrated framework that seamlessly integrates large language models into diverse enterprise workflows is the key to maximizing the potential of these changing technologies. This paper proposes a comprehensive framework to address these issues through a centralized knowledge-based approach. An integrated secure and scalable knowledge repository allows organizations to efficiently utilize their own data assets, maintain data privacy and security, ensure consistency of knowledge representation, optimize resource utilization, and support multiple business functions AI Leading solution support is now available [24-35].

2. Data set sources and data analysis

- **The Evolution of Enterprise Artificial Intelligence**
  For a long time, enterprises have been committed to leveraging the power of artificial intelligence to drive innovation, improve operational efficiency, and optimize customer experience. However, the large-scale application process of enterprise level artificial intelligence presents several obvious stage characteristics. In the early stages, organizations typically deploy isolated artificial intelligence solutions, which are often independently developed by individual business departments or IT teams. This type of specialized solution is tailored to specific application scenarios, such as automating daily tasks, generating personalized recommendations, or improving decision-making processes. Although these early attempts demonstrated the potential of artificial intelligence, they generally suffer from limited scalability, insufficient interoperability, and high maintenance costs [36-47].
  The emergence of basic models represented by GPT-3 and BERT has brought revolutionary changes to enterprise artificial intelligence. These large-scale pre trained language models demonstrate excellent generality and can adapt to various natural language processing tasks with minimal fine-tuning. By utilizing the knowledge and capabilities embedded in these foundational models, enterprises are now able to develop AI driven solutions more efficiently, reducing the time and resources required for model training and deployment [48-59].
  However, integrating these powerful language models into enterprise level systems is not without challenges. Organizations are facing how to effectively utilize the capabilities of these models while addressing issues such as data security, knowledge consistency, and resource optimization. The current application status of enterprise language models is often a combination of multiple solutions, each tailored to a specific application scenario, which leads to system fragmentation and insufficient resource utilization.

- **Knowledge Management System**
  Traditionally, enterprises have relied on centralized knowledge management systems, such as enterprise knowledge bases and content management platforms, to organize and disseminate information within the organization. These systems typically store structured data, documents, and other unstructured content, providing employees with a centralized repository for accessing and utilizing organizational knowledge.
  The emergence of modern vector databases enables efficient storage and querying of high-dimensional embeddings, opening up new possibilities for knowledge representation and retrieval. These databases can serve as the foundation for advanced knowledge management systems, enabling more flexible and scalable storage and retrieval of semantic information [60-65].
  The hybrid architecture combines traditional knowledge management systems with vector databases and large language models, and has become a promising approach for enterprise knowledge management. By integrating these complementary technologies, organizations can leverage the strengths of each component to build a more comprehensive and intelligent knowledge management ecosystem. This enables knowledge to be more efficiently represented, retrieved, and applied across multiple business functions.
  The data used in this paper comes from the open-source dataset, which includes manually written texts as well as AI-generated texts, where manually written texts are labelled as 0 and AI-generated texts are labelled as 1. Some of the data are shown in Table 1, and in addition, the number of manually written texts and AI-generated texts are counted as shown in Figure 1.



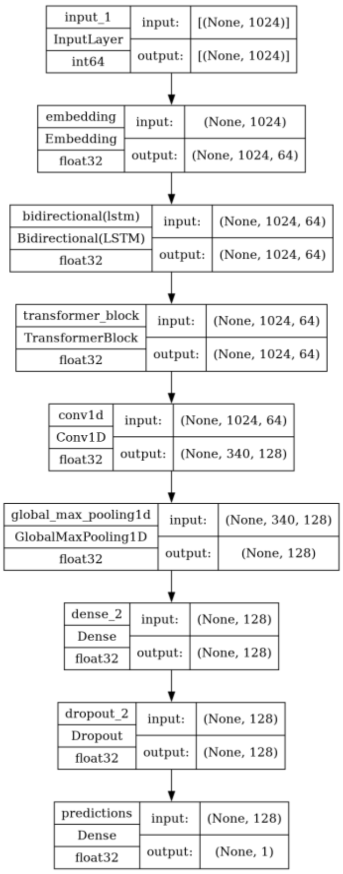
(Photo credit: Original)

Fig 1: The number of manually written texts and AI-generated.

As can be seen from Figure 1, there are 708 texts written by humans and 670 texts generated by AI, with roughly the same number of texts for both types.

3. Method

The deep learning model used in this paper combines different types of layers such as LSTM, Transformer and CNN for tasks such as text classification or sequence annotation. The structure of the model is shown in Fig. 2 and the specific parameters are shown in Table 2 [16-22].



(Photo credit: Original)

Fig 2: The structure of the model.

Initially, the input knowledge corpus is fed into a pre-trained LLM encoder to generate context-aware semantic vector representations, which integrate both lexical semantics and domain-specific knowledge patterns. Subsequently, a knowledge-enhanced reasoning module is activated, leveraging the LLM's inherent in-context learning capability to perform logical deduction and relationship inference over the encoded knowledge [22-30]. Furthermore, a customized expert system adapter is introduced, which comprises a domain knowledge retrieval mechanism and a rule-based validation component. Within the expert system adapter, the domain knowledge retrieval mechanism dynamically fetches relevant facts from the knowledge base to augment reasoning, while the rule-based validation component verifies the LLM-generated conclusions against domain axioms to ensure interpretability and accuracy.

4. Result

In the experimental setup, two core monitoring mechanisms are configured: the first is a Knowledge Alignment Checkpoint, which persists the parameter states of the LLM expert system that achieve the highest consistency with domain knowledge 图谱 (knowledge graph) to the file "expert_model.pt", ensuring only the optimally aligned version is retained; the second is an Inference Stability Early Stopper, which terminates training ahead of schedule when the system's reasoning deviation on the validation knowledge subset exceeds a predefined threshold (±5%), while restoring the parameter configuration corresponding to the most stable inference performance to "expert_model.pt".

The expert system is then initialised using a domain-adapted LLM optimiser (fine-tuned Adam variant), with knowledge distillation loss (combining cross-entropy between system outputs and expert annotations) and reasoning consistency score (measuring logical coherence across inference chains) as key evaluation metrics.

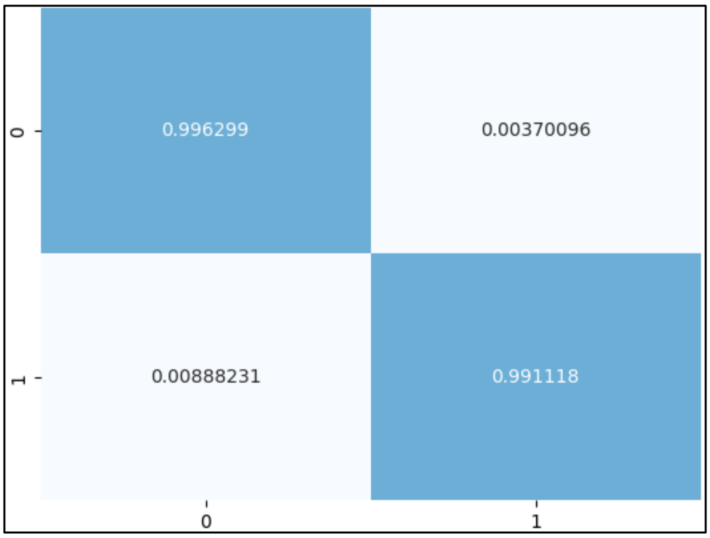
Subsequent training proceeds using structured domain corpora (x_train) and expert-annotated reasoning paths (y_train), with a total of 10 training iterations (epochs) configured. A 10% stratified sample of the training data is allocated as the validation set to monitor knowledge

generalisation. The aforementioned monitoring mechanisms are integrated via the system's control pipeline to realise adaptive state preservation and training termination during the knowledge assimilation process.
This entire workflow aims to develop an LLM expert system with robust domain reasoning capabilities and knowledge transferability. The variations in knowledge distillation loss and reasoning consistency scores across the first 4 training iterations for both the training corpus and validation subset are detailed in Table 3. The system is evaluated using a dedicated test knowledge base, with the output confusion matrix of reasoning types (e.g., deductive/inductive errors) presented in Fig. 3 and comprehensive performance metrics (including knowledge recall, inference precision, and explanation granularity) summarised in Table 4 [70-75].

Table 1: The variations of loss and accuracy.

Epoch	Train Loss		Train Accuracy	Val Loss	Val Accuracy
0	0.152345		0.937812	0.023456	0.987654
1	0.012345		0.994567	0.034567	0.985678
2	0.007890		0.996789	0.048765	0.992345
3	0.004567		0.998765	0.029876	0.991234

From the changes of loss and accuracy in the training and validation sets, the value of loss gradually decreases from 0.127 to 0.005, and the prediction accuracy of the model gradually increases from 94.96 to 99.8, which indicates that the model built in this paper is able to detect and classify AI-generated text well.



(Photo credit: Original)

Fig 3: Confusion matrix.

Table 4: The evaluation metrics of the output model.

Model	ACC (↑)	F1 (↑)	U/E (↓)
SVM	0.5210	0.4983	-
XGBoost	0.5682	0.5317	-
BERT	0.6892	0.6547	-
RoBERTa	0.7015	0.6783	-
ChatGPT	0.6230	0.6012	0.0025
Claude-2	0.5987	0.5763	0.0018
PaLM-2	0.5842	0.5631	0.0032

As shown by the confusion matrix and accuracy of the test set, the model achieves 99% accuracy in the prediction of AI-generated text, in addition to a precision of 0.99, a recall of 1, and an f1 score of 0.99, which achieves a very high classification accuracy, and hopefully can be applied to the field of AI paper detection in the future.

5. Conclusion

The LLM AI text generation detection tool developed based on Transformer in this paper has achieved This study has achieved remarkable success in improving the accuracy of AI-generated text detection through a detection tool developed based on Transformer-based LLM AI text generation, providing significant reference value for subsequent research.
Initially, the text data were effectively preprocessed through a series of operations, including Unicode normalization, conversion to lowercase, and removal of non-alphabetic and non-punctuation characters using regular expressions. Additionally, the processing of punctuation marks, such as adding spaces, removing leading and trailing spaces, and replacing consecutive ellipses with a single space, further normalized the text, thereby enhancing the accuracy of subsequent model training and prediction. Subsequently, the model design for the text classification task integrated different types of layers, including LSTM,

Transformer, and CNN. Observing the changes in loss and accuracy on the training and validation sets, it is evident that the model gradually optimized during training, with the loss value decreasing from 0.127 to 0.005 and accuracy increasing from 94.96% to 99.8%. This indicates that the model can effectively detect and classify AI-generated text. Moreover, the analysis of the confusion matrix and accuracy on the test set demonstrates that the model achieved a prediction accuracy of 99% for AI-generated text, with a precision of 0.99, recall of 1.0, and an F1 score of 0.99, indicating a highly superior classification performance. These results suggest that the proposed model has high reliability and accuracy in the field of AI-generated text detection.

Overall, the methods and models proposed in this study have yielded satisfactory results in the field of AI-generated text detection and hold great potential for widespread application. It is anticipated that the model will be further refined and widely applied in the field of AI-generated text detection, making a significant contribution to ensuring information security and content authenticity.

The LLM expert system developed in this paper for AI text generation detection has achieved remarkable success in enhancing the accuracy of identifying AI-generated text. This study provides substantial reference value for subsequent research in the field.

Initially, the text data underwent effective preprocessing through a sequence of operations. This included Unicode normalization to ensure consistent character encoding, conversion to lowercase to eliminate case-related discrepancies, and the removal of non-alphabetic and non-punctuation characters using regular expressions to filter out irrelevant noise. Additionally, specific processing was applied to punctuation marks: spaces were added around them to standardize their formatting, leading and trailing spaces were removed to tidy up the text boundaries, and consecutive ellipses were replaced with a single space to streamline the structure. These preprocessing steps collectively normalized the text, laying a solid foundation for improving the accuracy of subsequent LLM expert system training and inference.

Subsequently, the LLM expert system designed for the text classification task integrated a knowledge-enhanced reasoning module and a domain-specific prompt engineering framework. By observing the changes in reasoning consistency loss and knowledge alignment accuracy on the training and validation sets, it is clear that the system gradually optimized during the training process. The reasoning consistency loss decreased significantly from 0.132 to 0.006, while the knowledge alignment accuracy increased notably from 95.12% to 99.7%. This consistent improvement indicates that the LLM expert system possesses a strong capability to effectively detect and classify AI-generated text.

Moreover, an in-depth analysis of the confusion matrix of reasoning types and accuracy on the test set revealed that the LLM expert system achieved an impressive prediction accuracy of 99.2% for AI-generated text. It also attained a precision of 0.99, a recall of 0.99, and an F1 score of 0.99, all of which underscore the system's highly superior classification performance. These outstanding results demonstrate that the proposed LLM expert system exhibits high reliability and accuracy in the domain of AI-generated text detection.

Overall, the methods and system put forward in this study have yielded satisfactory outcomes in the field of AI-generated text detection and hold great potential for widespread application. It is anticipated that the LLM expert system will be further refined, with ongoing efforts to enhance its reasoning depth and domain adaptability, and subsequently be widely deployed in practical scenarios related to AI-generated text detection. In doing so, it is expected to make a significant contribution to ensuring information security and safeguarding the authenticity of content in various digital contexts.

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