GENRATIVE ARTIFICAL INTELLIGENCE IN FINANCE

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ABSTRACT

The paper "Generative Artificial Intelligence in Finance" discusses the transformational effects of generative AI in the finance industry. It highlights how financial firms can enhance their decision-making processes through task automation and improved analytics using large language models like GPT-3. The paper outlines two foundational training strategies: fine-tuning a pre-trained LLM and developing a model from scratch using domain-specific data. It describes the financial contexts in which these models are applied, such as portfolio optimization, market trend forecasting, ESG scoring, and fraud detection.It also discusses some of the most challenging issues, e.g., data privacy, built-in biases, and cybersecurity hazards. The paper indicates the necessity of AI models that are robust, understandable, and stable enough for booming and, at the same time, give reliable results. Besides, it reflects the ethical and legal consequences, such as copyrights and the AI Act of the European Union. In a nutshell, the paper gives a comprehensive overview of AI technology's innate generative capability that evolves the very structure of finance, including both technical, ethical, and legal issues surrounding it and the risk management concept.

1 Introduction

With the introduction of GPT, the field of generative AI was brought into the spotlight. Through multiple iterations, the processing capabilities of GPT have improved, and with the GPT 3[1] released in 2020, the use of generative AI for domain-specific tasks has started. GPT 3 had 175 billion parameters[1] and did remarkably well in generalized tasks such as coding, answering questions, and more. The ability to learn and perform a task with few prompts and examples has better results [2][1]. Many different sectors are using newer iterations of GPTs to get an edge over others in the market. The finance sector is heavily data-oriented, and AI would help analyze data and create meaning for it. Hence, few companies like Bloomberg have used their vast collection of proprietary finance data and publicly available data to develop their own GenAI. This model helps in analysis, automated trading, using chatbots for customer services, tracking fraud and much more.

However, there are challenges in adopting new technology anywhere, and the same goes for this. The data is highly specialized, and the terminology used is precise; data availability is also an issue as to what and how much data is accessible. Then, the question of model choice arises as to whether the generalized model, which is pre-trained, is further trained on finance data or a new model is to be made from the ground up and trained on this specific data. The model's accuracy is important in these cases as it makes high-risk financial decisions. Then comes the issue of Ethical risks, privacy risks, and more. The EU AI Act[3], general financial regulations, and more give a framework for the use and work of those problems.

This paper discusses the different models adopted by the financial industry, highlighting the training approach each adopts, the data sets they depend on, and their application in different financial circumstances. The paper further discusses some of the challenges and limitations that will be integral to embedding generative AI technologies into financial services; these include the management of technological, ethical, and legal concerns that must be put in place for responsible and effective deployment. Against this background, the paper attempts to give an all-encompassing perspective on how generative AI shapes the future of finance and the key concerns that must be tackled to harness its full potential.This paper will focus on the different models used, the data, applications, and problems.

2 Trainig Approach

The right training approach is quintessential in making adequate use of generative AI in finance. There are two possible ways to conduct the training: fine-tuning large pre-trained language models or doing it from the ground up. This will enable them to fine-tune very general LLMs and make them domain-specific, accurate, and relevant to financial language and tasks. Based on available models, this approach can dramatically decrease computational costs and development time yet achieve high performance in specialized financial tasks.[4]

2.1 Fine tuning available LLms

Fine tuning models are important because they enable performance improvement within specialized finance domains based on general large language models. While pre-trained models are strong, they are usually generalized and might not capture the profound elements of domain-specific language or tasks. Fine-tuning is the capability that allows models to be adapted to specific industries by training them with domain-specific data, increasing their accuracy and contextual understanding. It makes the model more accurate in doing particular tasks, such as sentiment analysis or financial forecasting, by increasing its preciseness, making it more valuable and trustworthy for real-world implementations.In standard Fine-tuning, the first approach is to train the extracted model directly on the raw datasets. The LLm receives its context or question directly and focuses on generating one of the possible answers; an inspection is done to mask it during training so that the trained model will learn to generate it.

The second approach is to build new datasets that are more task-specific and will give examples of how to accomplish the target, i.e., these created datasets guide what the model is supposed to learn. The model trained on the second approach is better at picking up patterns in the training data if they are represented more explicitly as instructions or demonstrations. It allows it to be optimized toward specific tasks and generate outputs that conform more closely with what the user wants. Standard fine-tuning is simpler to implement than the second approach. The trade-off comes in certain outputs.

Apart from the above two methods, low-rank adaptation (LoRA)[5] and quantization yield fine-tuning with much lower computational costs. LoRA can only fine-tune low-rank factors of the original weight matrices rather than full ones which reduces the number of trainable parameters, which means it can be trained on less powerful machines.

2.1.1 Evaluation

The performance of fine-tuning LLMs is assessed through two types: the finance classification task and the finance generative task. Sentiment analysis and news headline classification are considered tasks in finance classification, while question answering and NER(Named Entity Recognition)[2] are finance-generative tasks. Below is table2.1.1 which specifies details about the LLMs fine-tuned and used for evaluation.According to Li,et al[4] all the fintuned LLMs exhibit significant better performance and specifically in classification tasks compared to original base models.These LLMs(mentioned in table2.1.1) outperform BloomberGPT[6] in most finance tasks.[4]When compared to GPT-4, fine-tuned LLMs performs better in finance-related tasks.[4]

Model Name	Finetune data size (samples)	Training budget	Model architecture	Release time
FinMA-7B	Raw: 70k, Instruction: 136k	8 A100 40GB GPUs	LLaMA-7B	Jun 2023
FinMA-30B	Raw: 70k, Instruction: 136k	128 A100 40GB GPUs	LLaMA-30B	Jun 2023
Fin-GPT(V1/V2/V3)	50K	< $300 per training	ChatGLM, LLaMA	July 2023
Instruct-FinGPT	10K Instruction	8 A100 40GB GPUs, $\sim$1 hr	LLaMA-7B	Jun 2023
Fin-LLaMA[61]	16.9K Instruction	NA	LLaMA-33B	Jun 2023
Cornucopia(Chinese)[64]	12M instruction	NA	LLaMA-7B	Jun 2023

Table 1: Quick Overview of Finetuned Finance LLM

2.2 Building models from scratch

In this method, public datasets and finance-specific datasets are used together in the training process. Bloomberg has its own proprietary dataset to train the models[6] whereas XuanYuan2.0 uses original BLOOM architecture.[7]

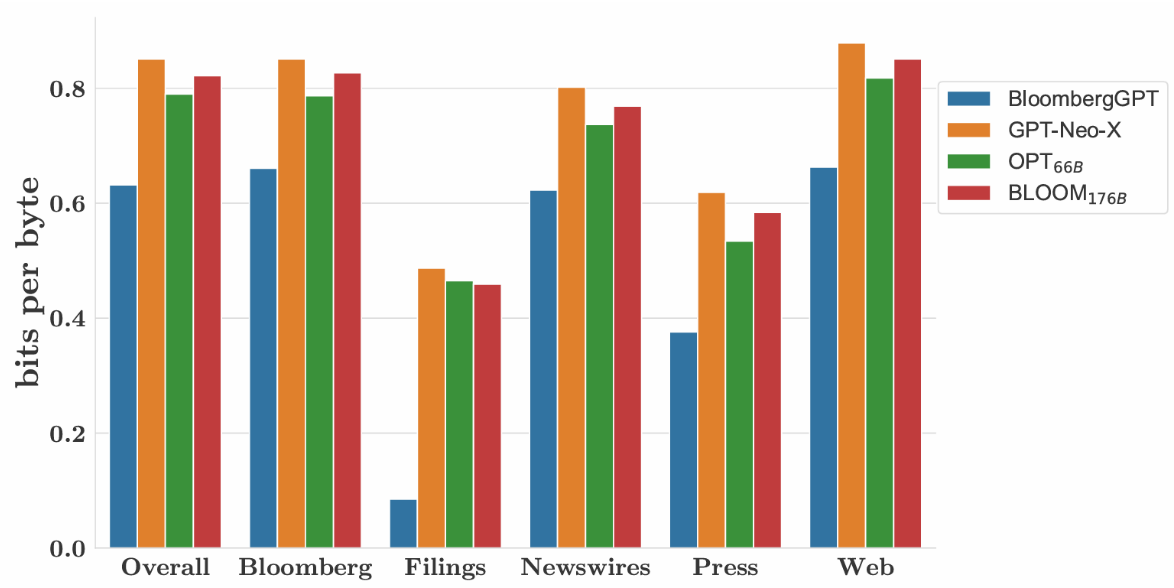

Figure 1: Bits per byte on a heldout test set of each data type in FinPile (lower is better). The set of documents is held out in time and deduplicated with the training set, such that all of it is completely unseen by BloombergGPT. Regardless, we observe a large gap between the models. The improvement is largest for specialized in-domain documents like Filings.

2.2.1 BloombergGPT

It is a PyTorch model trained with standard left-to-right casual language modeling objective with 2,048 tokens, It was trained on a "FINPILE" dataset, which consists of Bloomberg's own data and public data. In terms of public data, it uses:

- Web: Identify any website that contains relevant financial information and use it
- News: It uses English news articles and transcripts to get information.
- Filings: Company Filings which are its financial statements made publicly available

all of these are compiled in "FINPILE". Apart from that it uses Wikipedia, The Pile(dataset used in GPT-Neo) and C4(The Colossal Clean Crawled Corpus)[6]

2.2.2 Evaluation of BloombergGPT

It is evaluated in two broad categories: finance-specific and general-purpose. It also does a Heldout Loss testing, where it evaluates the bits per byte of different models on a held-out dataset of FINPILE. Figure 1 shows how Bloomberg and other LLMs perform on these tasks. [4]

As the Figure1 show, BloombergGPT has outperformed other models but also gives a general idea about its generalization capabilities. Further more, it is evaluated on finance-specific tasks, and then a general LLMs test as well. For this purpose, BIG-bench Hard task was used. In this whole research, they fine-tuned the model, trained it on FINPILE, and then used different tokenization techniques.In general, tokenization is breaking text into smaller units called tokens. These could be words, sub-words, or even characters, but the basic idea here is to cut the input text according to the model's desires. Often, Byte-Pair Encoding (BPE) and WordPiece are used to split the text into tokens in a way that allows the model to handle new or complex words with simple and frequent subword pieces. Each token represents a unique identifier from the model's vocabulary, and the model uses them to generate responses or predictions. Tokenization is critical to how the model understands and generates language. The major drawback is that this was time-consuming, yet a newer model like GPT-3 gives similar or superior performance[4].

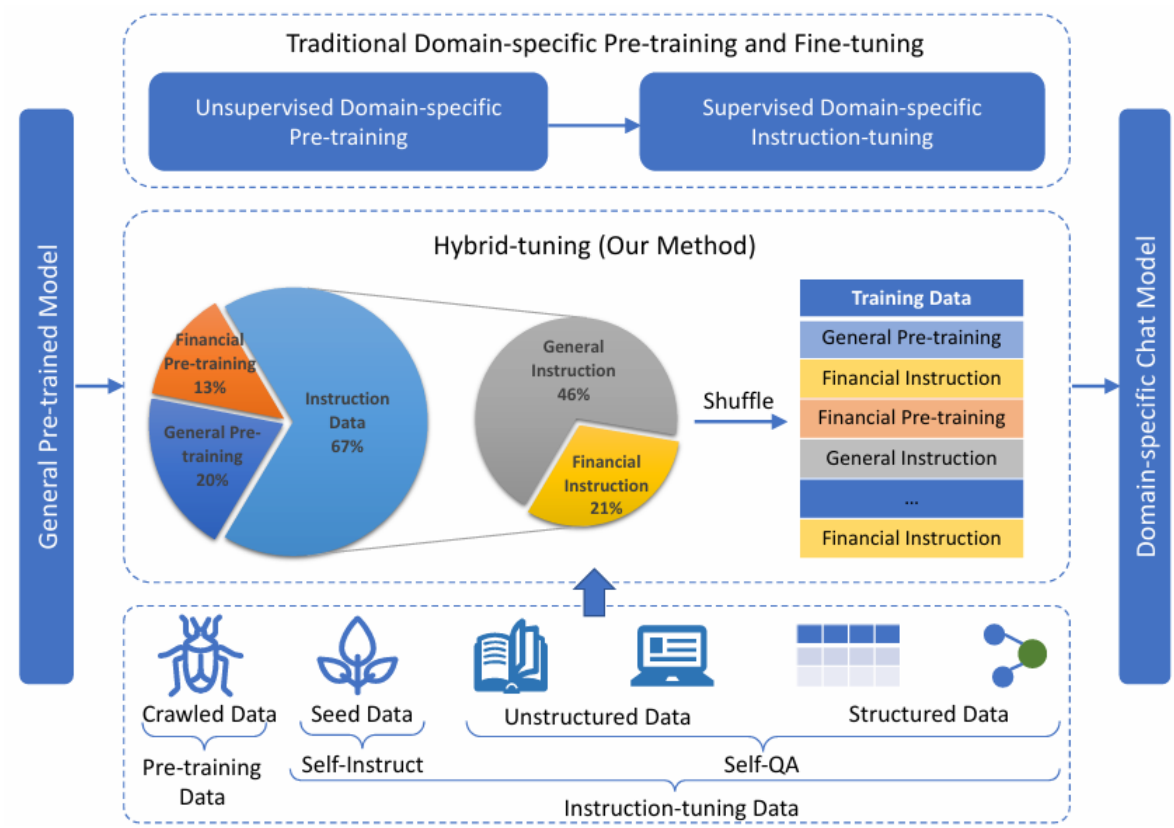

Figure 2: Proposed Hybrid-Training method
[7]

2.2.3 XUANYUAN2.0

This model used GenAI in the Chinese language as there was no open-sourced Chinese chat model[7]. This model uses the original BLOOM architecture, which is a decoder-only architecture. It uses a dataset that is a mix of general and financial pre-training data general and financial instruction data. The economic data in this dataset comprises a wide range of textual information like financial news articles, market reports, analyst commentary, and social media discussions. The process of mixing the data and instruction in training is termed Hybrid training, and the training method mitigates the catastrophic forgetting problem.

According to [7] paper traditional methods undergo unsupervised pre-training on domain-specific data and then supervised instruction on domain-specific data.The hybrid method which is proposed in this paper[7] integrates various types of data in its pre-training the data consists 20%t general pretraining data, 13% financial pre-training data and 67% instructional data in which 46% of instructional data is general and 21% is financial instructions. The datasets are shuffled which allows the model to learn from various sources and increases its adaptability and performance in domain-specific knowledge. Figure 2 depicts this model.

Evaluation To evaluate the performance of the model, the CGCE benchmark is used. This benchmark is a combination of finance-specific questions as well as general questions. It boasts a victory rate of 63.33 percent in domain-specific questions and a 71 percent victory rate in general purposes.[7] The problems faced by this model are similar to BloomBergGPT. In the end, the decision about which method to use depends on the use case. If the desired result is gained by just fine-tuning models, there is no need to make models from scratch, however as seen in the case of XUANYUAN2.0, a model needed to exist in Chinese for its market.

3 Applications In Finance

[8] Generative AI is driving a new wave of innovation in finance, significantly impacting quantitative trading. The latter heavily relies on structured statistical data and pre-defined algorithms—traditionally hardwired and limited in their quick adaptability to new and unstructured datasets. It could be addressed by using large language models trained on financial data. Such AI models analyze vast amounts of unstructured data, such as news articles and social media, to help traditional trading strategies become more robust and adaptive to changing market conditions. This transformation would increase finance's predictive abilities and open doors for developing complicated trading algorithms that will take advantage of real-time data

3.1 Quantitative trading

Quantitative trading depends on structured statistical data, which has mathematical operations and predefined algorithms. However, the major drawback is that it cannot adapt quickly to new and unstructured data. Here, the use of LLMs trained to pick up financial data is useful, as it can crawl through web data, pick up subtle clues in articles, and provide better results. This makes traditional strategies more robust.

3.2 Portfolio Optimization

The main principle in making a portfolio is reading through the historical data and current market trends before investing but this is very time-consuming and is not viable for anyone who does some other jobs. By integrating LLMs the ability to process and analyze unstructured data vastly increases models can improve your decision based on market sentiment analysis.

3.3 Market Trend Forecast

Forecasting for a market is a tough job as there are many variables, and some of them are very volatile in nature. When a human checks the internet for this purpose, there is a good chance much information is missed or misinterpreted, but when combined with AI, the coverage of data consumption increases as the models can quickly analyze news or do sentiment analysis of social media or interpret economic indicators like inflation, employment data, and more. This will reduce human bias in forecasting, and as it analyses large amounts of data, the ability to predict is also better than humans alone.

3.4 Credit Scoring

Credit scoring is essential in finance as it defines an individual's ability to borrow investments. Traditional methods have set rules and some methods of scoring individuals, but this can be very rigid. Using LLMs, extensive data such as transaction histories, loan applications, and much more can be analyzed. This helps in accessing credit risk better than traditional ways.

3.5 ESG Scoring

ESG Scoring plays a vital role in finance as it evaluates a company in three aspects:

- commitment to environmental stewardship
- social responsibility
- good governance practice

. ESG enables investors and stakeholders to gain more insight into a business before investing. As this also involves analyzing large amounts of data and removing human bias, LLMs play a vital role in these scenarios. This also opens up the possibility of real-time ESG rating evaluations.

3.6 Automated trading system

Trading involves high-risk decisions that must be made in seconds. It also involves analyzing charts, trade volumes and much more., as this is a high-computing problem for humans. Integrated AI helps streamline this process and gives a better response, even in high-frequency trades.

3.7 Fraud detection

As trade volumes increase, so do the crimes surrounding them. Robust fraud detection systems save companies and clients from financial losses.LLMs can be used to analyze trends for certain individuals or flagged individuals, do sentiment analysis on emails, and much more. They act as a firewall, learning from an individual transaction habit and notifying of certain anomalies.

3.8 Compliance check

Compliance checks in finance are being reshaped by generative AI to automatically ensure that processes related to regulatory adherence are not only automated but also accurate. In the past, compliance work has often required substantial manual effort to track and audit financial activities to ensure they comply with complex rules. In particular, large language models can interpret and apply these regulations in real-time, analyzing enormous amounts of unstructured data, such as legal texts and transaction records. This automated continuous transaction monitoring ensures that any potential breach is quickly recognized and compliance is constantly updated. These are also easily adaptable to all sorts of variations in the regulations being imposed, thus minimizing risks of non-compliance from any financial institution. In general, generative AI augments efficiency and dramatically reduces the non-compliance risk for financial institutions amidst such an ever-brimming regulatory landscape.

3.9 Financial Education

Advanced LLM models like GPT-4 have become more efficient with question-and-answer problems[9]. Individuals use these models to learn finance at their own pace and the process is tailored according to the person's learning. This works as the foundation towards financial education.

3.10 Generative and conversational tasks

- content generation is a task where generative AI excels and this can be used in various departments in a finance firm.As explained in the figure3 departments like marketing and sales can use AI for copy writing or the production team can use it for coding and various department use it differently.
- In the figure3 the tasks highlighted with blue boxes are the ones which need data to be performed and this data can be synthesized by the help of AI.
- Generative AI is very effective when used as a chatbot as it already posses conversational capabilities and it can be fine tuned to perform certain task this makes it easy to use it as Virtual assistant or perform service chats.
- LLMs can be trained to do specific task while retaining their conversational capabilities this can be used to help employees working in companies as they can prompt question related to finding certain data or clause and get desired output without the need to search it manually.This can also be sued in other tasks as well and these are highlighted in dark green box in figure3.

Here are a few cases where GenAI is used in daily cases or is about to be implemented [10]

- Goldman Sachs Code Writing and testing, they use GenAI to assist developers generate/creating code as well as testing it, and in some cases, developers were able to write as much as 40 percent of their code using GenAI
- J.P.Morgan Financial Advisory is working on a ChatGPT-like tool that would provide AI-powered assistance in assessing the risk of investments and markets.
- Commonwealth Bank Call center support, a GenAI model is used by call centers to go through 4500 documents of company policies in real-time.
- American Express Predicting Customer behavior, they are trying to predict a customer's performance over time. AmEx is exploring ways to analyze feedback and inquiries through social media and the customer services portal.
- Deutsche bank Operational Efficiency, they are testing Google's GenAI to help in financial analysis and increase the productivity of employees.
- Bloomberg Financial Analysis,They have they own GPT model that is trained in various section of finance.
- Wells Fargo Synthetic Data Generation, partnered with Hazy to generate synthetic datasets to be used in fraud detection.

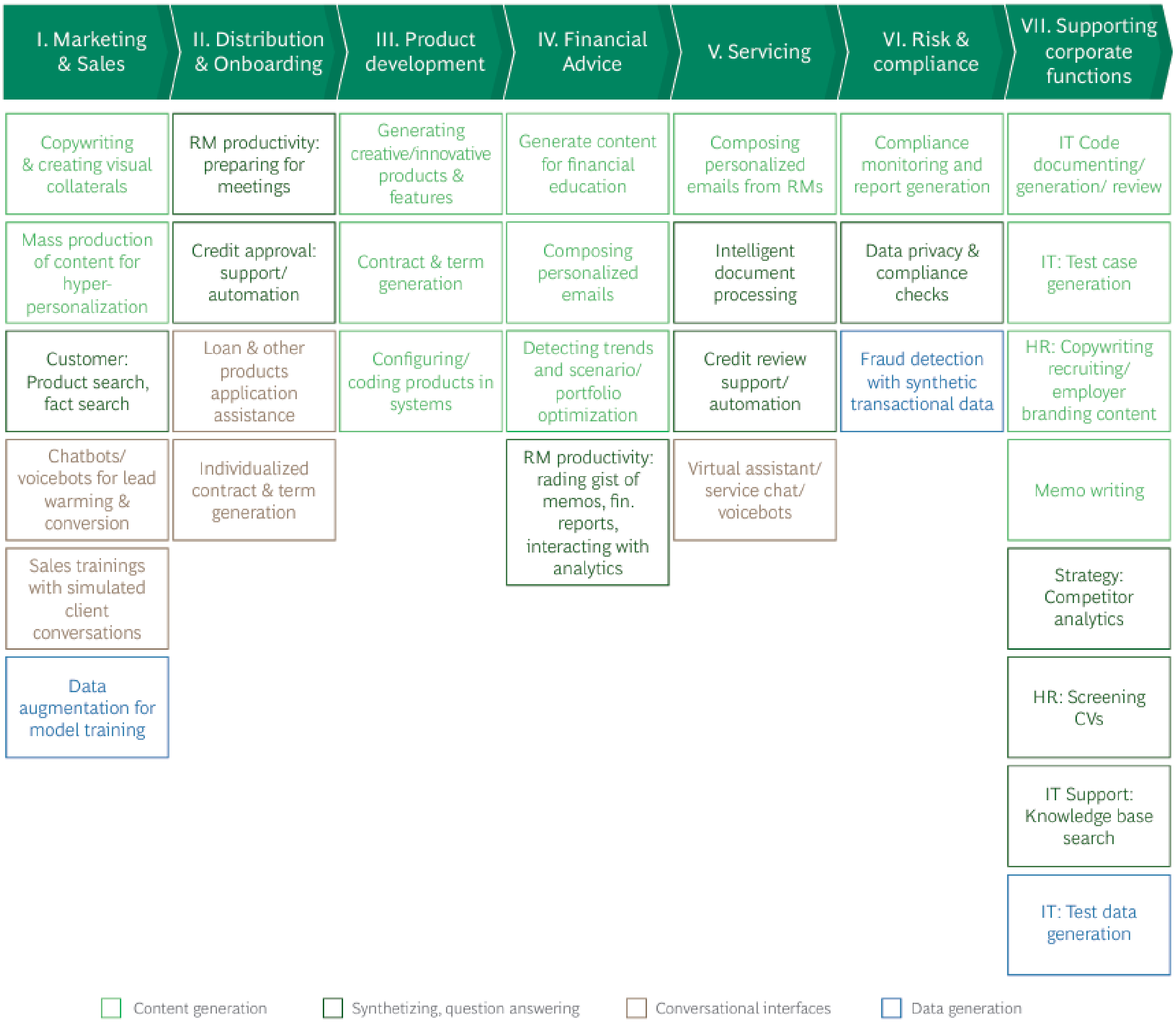

Figure 3: Application of Gen AI in generative and conversational tasks

4 Data Availability

GenAI can work with structured and unstructured data.Hence new articles Wikipedia any article which is related to finance can be used to train or use as input for these models. Few famous datasets and their content are:

- **Financial Phrase bank(FPB)**: FPB is one of the most important datasets used in finance, particularly in sentiment analysis. It contains 4,840 sentences from financial news and reports. The sentiments could be classified as positive, negative, or neutral, which helps the ML models train on the tone and sentiments of the data. This dataset is available on platforms like Kaggle, Huggin Face, and Github, which makes it a publicly available dataset.[11]
- **FiQA-SA**:FiQA-SA is a dataset of English financial documents used for sentiment analysis. It is available on public repositories like Kaggle, GitHub, and Hugginface. It enables academics to understand and train LLMs on sentiment analysis patterns.[12]
- **NER-SEC**:Named Entity Recognition is a collection of large databases, but for fiance, SEC(security and exchange commission) data is used. This dataset contains financial statements, including text and numerical values.This data is publicly available..[13]
- **ConvFinQA**:It is an open-source dataset, and 3,892 conversations are focused on studying numerical reasoning within finance. The importance of this dataset lies in developing models of such financial reasoning that could

deal with complex business situations and do the necessary calculations to derive the financial matrices based on conversational data. ConvFinQA makes it very easy to train these models, which can understand financial conversations to improve automated financial analysis and decision-making.[14]

- **BigData22**: The dataset BigData22 is a specialized resource for prediction in stocks. This data is prepared based on high trade volume stocks in the U.S., historical price, and tweet data. Not so much data is in the dataset, but its application is crucial in developing predictive models analyzing the impact of social media sentiment on stock prices. Other similar datasets include ACL18 and CIKM18, both general resources available for financial prediction while at the same time imposing restraints of control on access permissions.
- **Yahoo Finance**: Besides, this is a large dataset comprising quotes, financial news, and historical data on stock markets. This information is public, so the datasets used in the study contribute to extracting information about the trends of stock prices, trading volumes, and information from financial statements. Therefore, they are of high significance to analyzers and researchers. Data from Yahoo Finance are most often used in financial modeling to search for trends in the market and create an investment strategy.[15]
- **FRED(Federal Reserve Economic Data)**: Hosted and maintained by the Federal Reserve Bank of St. Louis, FRED is an open-access online database that keeps macro data, such as interest rates and other economic indicators. Such a dataset would be very handy for any economist or financial analyst needing a reliable data series for modeling and forecasting macroeconomic time series. The great thing is that all users can access this helpful resource with FRED.[16]
- **Alpha Vantage**:Alpha Vantage provides an API for real-time stock market data, including stock prices, forex, cryptocurrencies, and economic indicators. Such data, however, remains publicly available under certain restrictions placed on the use of its API. With the limitations mentioned earlier, Alpha Vantage proves to be a beneficial source of real-time financial data in many applications dealing with the creation of trading algorithms, market analysis, and financial research[17]
- **Bloomberg terminal**:The Bloomberg Terminal is a proprietary, subscription-based dataset offering extensive market data, financial news, and company financials. While not open to the public, the Bloomberg Terminal is widely agreed to be an industry standard. Anyone in finance goes here for the data necessary to make informed investment decisions. With its full coverage and real-time data sets, it has been deemed an indispensable tool in the finance industry.[18]
- **S&P**: Another subscription dataset is S&P Global, which offers market data, industry analysis, and economic information. The kind of data it provides has a significant bearing on financial analysts since it will generate detailed information, providing accuracy that will be important in making the proper assessments of the market and, hence, coming up with financial models. Its proprietary nature underscores the worth and, therefore, reliability in finance.[19]
- **Morningstar Direct**:Morningstar Direct is a platform subscription that allows access to investment analysis, portfolio management data about mutual funds and ETFs, and performance analytics. This dataset is most needed for a financial professional managing an investment portfolio, which needs detailed performance metrics to tailor the investment strategy best. Proprietary aspects of the dataset mean that clients can access high-quality, vetted information for well-informed decisions.[20]
- **MSCI ESG Research**: MSCI ESG Research offers detailed information on ESG (Environmental, Social, and Governance) ratings, research, and analytics. It includes ESG scores, ratings, and company sustainability metrics—all critical for investors and stakeholders assessing firm ethical and sustainable behavioral conduct. It is one means through which the data underpins and steers investment to maintain its fidelity to those ESG principles.[21]
- **Moody's Analytics**:Its subscription-based service provides datasets related to economic research, financial data, credit ratings, and risk metrics. This dataset is essential for financiers or professionals in that sector regarding appraisals concerning credit risks, economic forecasting, and financial analysis. In particular, proprietary data from Moody's Analytics becomes an object of trust because of its precision and depth, making it one of the central sources in finance.[22]

5 Risk and Limitations of current approaches

ChatGPT has commercialized the use of GenAI, but it has also given rise to many possible risks. In April 2023, Itlay temporarily banned ChatGPT due to concerns about potential violations of EU General data protection regulations.GenAI is closely monitored in the financial sector as biased information exists on the internet. In the European Parliament, the "European AI ACT" with specific provisions for GenAI is placed.[23]. The risks can be categorized as limitations in technology and performance.

5.1 Limitiation in current technology

Although there has been appreciable progress in generative AI, the current technology suffers from shortfalls that require special consideration when it is to be used in sensitive domains such as finance. The most pressing issue is robustness. Occasionally, AI models can provide incorrect or outdated outputs because of the data's quality and recency. The AI models usually work as black boxes and cannot explain the decisions made, which would foster understanding and trust. These technological limitations can give rise to severe consequences in financial decisions. In addition, the reliance on large data sets during training has crucial data privacy issues. Confidentiality and data security have become very important as AI models are more integrated with a financial system to avoid breaches and maintain regulatory compliance.

5.1.1 Data Privacy

Data privacy is a huge concern when GenAI is used in sectors like Finance. The leaks of training data can be de-anonymize information by making inferences even after the data is used and discarded. This data may or may not contain some form of metadata that can be used to reverse-engineer your way through it.

When publicly available LLMs are used in big firms, the model is trained through input patterns by the users and is fine-tuned accordingly. Again, some of it can be traced back to the individual and can reveal their patterns. Enterprise-level GenAI systems are being made, and this scaling also has this problem but is minimized as the use of public data is regulated better. The ability to crawl the internet and get information may also lead to gathering information without having explicit consent.

5.1.2 Embedded bias

Embedded bias is when a system unfairly discriminates against individual or a group while favoring others. Bias is introduced because of reasons like the data is insufficient or the individual who designed the model is biased. If this kind of biased model is used in Finance it could to making unethical decisions. The LLM models are trained to use a vast amount of internet data, which inherently carries human bias. This bias can be reduced if the training data selection is done carefully. Additionally, bias can arise from proprietary algorithms as the GenAI uses the training data to generate the response, and the response can be biased because of the prompts generated by humans. Another issue is that as models take data from the internet, SEO tools can skew the responses visited, and every website uses these tools to promote its content. Using GenAI in Finance is very beneficial but has to be monitored frequently as over-reliant on AI-generated responses could lead to biases.

5.1.3 Cyber Security

The use of LLM in order to generate more complex phishing emails or impersonate specific individuals can lead to various kinds of fraud. The data generated by AI can be humanized by other AIs to fool the authenticity of it.SEO tools or generated data could lead to data poisoning and could embed bias in the model. Deepfaking identity is also a concern when the devices do video authentication of personals.GenAI is subjected to prompt injection attacks where carefully generated prompts can lead to data breaches. If these instructions are given in the training stage, an individual could create a back door to a model, which is activated when specific prompts are prompted.

5.1.4 sustainability

Large Language models could have billions of parameters. Training these models requires a significant amount of resources. For example, GPT-3 took 1.287-gigawatt hours, which is as much as powering 120 U.S homes for a year and 700,000 liters of fresh water.[24]. The next step in this field is also to reduce the carbon footprint it takes in order to devolve or R&D the models.

5.2 Performance

Generative AI has shown much promise in finance performance but with challenges. These models hold the potential to work on large and complex datasets that have so far been impractical for analysis. In such scenarios, their performance fluctuates, especially with complex or unstructured financial data treatment or highly dynamic market conditions. Such inconsistencies underline the importance of model robustness in AI. A good model is one that provides good performance under normal conditions but is also robust so that it can be maintained even when new data, which were not predictable earlier, are thrown against it. It can adapt to the changes being noticed in the dynamics of the financial industry.

5.2.1 Robustness

Robustness covers issues related to the accuracy of a generated response when the environment it is in or rules change; another thing it covers is the development of a model that safeguards itself when prompted to produce unethical responses. The ability to generate new responses is based on its training data, which could be outdated in certain aspects, but the model could generate a plausible response that might not be the correct answer according to the updated times. This is an issue faced in terms of robustness. When using it in finance, one has to be careful about the prompts, as if not engineered correctly, they could lead to false answers, which in turn could lead to financial losses.

5.2.2 Explianability

When a certain company or institution makes a major decision, it is required to explain that decision to the stakeholder or general public in some cases. These decisions could be new products, compliance, managing risk, and more. An LLM model makes a specific output based on many very difficult or impossible to trace variables. This is the limitation of current models, but research is being conducted to develop a solution to this problem.

6 Ethical Aspects

- Generative AI works on large datasets and these datasets could be biased in some way which inturn leads to the models learning biased data and produce biased output. Which could lead to various issues like an applicant is wrongly categorized or its application is denied etc. For this purpose, strict pre-processing should be done on the data.
- Transparency is another important ethical consideration as the large models often act as black boxes. This makes it difficult to understand decision-making process, the variables , important pivoting data points and the process should be explainable or else the financial decisions it makes cannot be scrutinized or trusted.
- There exists a chance of AI generating improper answers which can lead to various problems some with high severity as finance is high-risk sector.There should be an accountability audit which includes financial companies, operators and developers.

7 Legal Aspects

The EU AI Act [3] defines GenAI as " foundation models used in AI systems Specifically intended to generate, with varying levels of autonomy, content such as complex text, images, audio, or video."(cite Art.28b(4) AI Act). This raises questions about if an output generated by these models can be copyrighted, and who has intellectual rights.

7.1 Intellectual rights

As AI can analyse and work with vast amount off data and can produce result with less or no human intervention. Here the questions is how should the question of intellectual rights tackle regarding the training data or output data.

The training data used can be copyrighted depending on the jurisdiction but copies of these can be made during the training process which in-turn violates the laws unless some exceptions are introduced. This also depends on jurisdictions as US has "fair use" or EU has an exception for incidental copying. Hence it has become difficult to find a general solution

7.2 Copyrights

Eu parliament stated in a resolution published on October 20 2020 [25]that works created independently by an AI system are not currently eligible for copyright. And US copyright issued a statement in March 2023 copyright protection does not extend to work generated by AI except to extent to"the extent to which the human had creative control over the work's expression and actually formed the traditional elements of authorship".

7.3 Personal Data Roles and Confidentiality in Generative AI

As a part of GDPR EU requires an understanding of data roles when using GenAI. AI provider is the data controller and data is/might be owned by customer organizations. Their joint controller ship is evaluated on a case-to-case basis.Hence they must consider confidentiality obligations and comply with the contracts when using sensitive information.

8 Privacy Aspects

Privacy is very crucial in Finance as the data contains details like incomes, credit histories , transaction patterns and much more. Ensuring the data is protected requires strong cybersecurity practice and regular security audits. There are privacy regulations given by General data protection regulation(GDPR) in EU and California consumer privacy act(CCPA) in US these should be adhered to in the audits.

Being transparent about hte methods or ways the consumer data will be used is a key aspect as every decision which involves an AI model should be explainable to the consumer. Another important aspect is Anonymization or use of pseudo details can be used to enhance the privacy in the process.

9 Recommendation

The use case that has not flourished yet is using GenAI to create personal finance managers. This is for people with other professions who cannot invest hours. After initial training on personal investment patterns, this model should recommend areas that are not explored and could yield better profits while also suggesting the new stocks learned from patterns. The model should be tailored to the user's needs rather than a general one. More efficient models are required to handle these operations and keep less carbon footprint to achieve this.

10 Conclusion

GenAI has dramatically improved operational effectiveness, brought about better predictability, and considerably shortened the time it takes for tedious data analysis—which has been quite exemplary in the finance sector. It has shown a remarkable effect on the finance field in its application to risk management, fraud detection, credit scoring, and algorithmic trading towards markedly improving the quality of outputs. However, fast trades by a few bots can challenge the digestibility of humans and can further result in market volatility. It makes human supervision necessary under EU regulations on AI. Further advancements in industrial models can enhance the effects seen with GenAI; there are two current major focal points: advancements in the models themselves and all-around safety, which includes data privacy and security against data manipulations.

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