British Journal of Computer, Networking and Information Technology
ISSN: 2689-5315
Volume 7, Issue 3, 2024 (pp. 85-93) www.abjournals.org

COMPREHENSIVE REVIEW ON NATURAL LANGUAGE GENERATION FOR AUTOMATED REPORT WRITING IN FINANCE

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Cite this article:

S. Abbas, B. L. Pal, Ajay S., Faisal R., Asifa S., Haruna U., B. Mua'az, Abdulgaffar A. Y. (2024), Comprehensive Review on Natural Language Generation for Automated Report Writing in Finance. British Journal of Computer, Networking and Information Technology 7(3), 85-93. DOI: 10.52589/BJCNIT-ELBOL7TY

Manuscript History

Received: 12 Jun 2024

Accepted: 14 Aug 2024

Published: 16 Aug 2024

ABSTRACT: *The financial industry is transforming with the advent of Natural Language Generation (NLG), a subset of Natural Language Processing (NLP), which automates data conversion into coherent and contextually relevant narratives. This paper presents a comprehensive review of NLG's application in financial report automation, tracing its evolution from template-based methods to advanced deep learning and knowledge graph techniques. We discuss the relevance of NLG in automating report generation, its role in enhancing data analysis and decision-making, and its potential to improve investor communications and compliance with regulations. The paper identifies research gaps, including the need for optimization, accuracy improvement, and the integration of machine learning models for better classification and prediction. A proposed methodology for structured report generation is outlined, leveraging deep learning architectures such as RNNs and LSTMs. Future work aims to address these gaps and further integrate NLG into financial reporting, promising to streamline processes, reduce costs, and provide more personalized and insightful financial narratives.*

KEYWORDS: Natural language processing, Natural language generation, Machine learning, deep learning, RNN, LSTM, Report Generation, Automated report writing, Financial Report Generation.

INTRODUCTION

Natural language processing (NLP) is a machine-learning technology that allows computers to interpret, manipulate, and comprehend human language. NLP is a broader field encompassing both NLU and NLG, as well as other subfields like sentiment analysis, entity recognition, and text summarization. Natural Language Generation (NLG) is widely used in intelligent writing, human-computer dialogue, and other fields, which is one of the signs of the maturity of artificial intelligence. It requires machines to sort out the meaning of inputted data, text and/or numbers, and automatically generate understandable natural language using accurate language models or statistical models.

NLG generates new text based on a given dataset; it uses a combination of machine learning, deep learning, and knowledge representation techniques to generate a new comprehensive text that is often more natural and coherent (Martinez, 2024). Natural Language Generation is a field that evolved from computational linguistics, the discipline concerned with understanding written and spoken words and building artifacts that usually process and produce language. The emphasis of NLG is on computer systems that can produce understandable texts in human languages. It is one of the fastest growing applications of Artificial Intelligence as it articulately communicates ideas from data at remarkable scale and accuracy. NLG includes a variety of application areas, such as Healthcare, Finance, Human Resources, Legal, Marketing, Sales, Operations, Strategy, and Supply Chain. The field of NLG has changed drastically in the last few years with the emergence of successful deep learning methods. (Bisen & Agrawal, 2022).

The applications of NLG are diverse and continue to grow, with potential uses in areas like chatbots, business intelligence, and content creation.

Relevance of NLG in to automate report generation

Here are some key aspects of NLG's relevance to automated report generation in finance:

- Automation of Report Writing: NLG automates the writing of financial reports, removing the risk of error and manual intervention. This ensures that reports are generated quickly, accurately, and consistently, freeing up resources for more strategic tasks.

- Data Analysis and Insights: NLG technology can analyze large datasets and generate insights, enabling finance professionals to make informed decisions. It can also identify errors and issues, reducing the risk of financial mismanagement.

- Compliance and Regulation: NLG ensures compliance with regulatory requirements by generating reports that meet specific formatting and content standards. This reduces the risk of non-compliance and associated penalties.

- Scalability and Flexibility: NLG solutions can handle large volumes of data and generate reports in multiple formats, making them suitable for various financial institutions and industries.

- Improved Decision-Making: NLG-generated reports provide actionable insights, enabling finance professionals to make data-driven decisions. This leads to better financial planning, risk management, and strategic decision-making.

Article DOI: 10.52589/BJCNIT-ELBOL7TY
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- Cost Savings: Automated report generation using NLG reduces the need for manual reporting, freeing up resources and minimizing costs associated with data analysis and reporting.
- Enhanced Collaboration: NLG-generated reports can be easily shared and collaborated on, facilitating communication among finance professionals, stakeholders, and clients.

IMPORTANCE OF FOCUSING ON NLG IN FINANCIAL DOMAIN

Natural Language Generation (NLG) is gaining traction in the financial industry, revolutionizing the way financial institutions communicate complex data insights to clients and stakeholders. By automating the process of converting data into human-readable reports, NLG enables financial experts to focus on higher-value tasks, such as strategy development and client interactions.

Focusing on NLG in the financial domain is crucial for unlocking efficiency, insight, and innovation. By automating the process of data reporting, NLG enables financial experts to focus on higher-value tasks, improves investor communications, and enhances transparency. As the financial industry continues to evolve, NLG will play a vital role in shaping the future of financial reporting and decision-making.

- Time and Cost Efficiency: NLG reduces the time and effort spent on manual report creation, freeing up financial experts to focus on more strategic tasks. This leads to increased productivity and cost savings, allowing institutions to allocate resources more effectively.
- Accessibility and Personalization: NLG-generated reports are more accessible to a broader audience, enabling clients with varying levels of financial literacy to better understand and make informed decisions. Additionally, NLG can tailor financial insights and recommendations to individual investors based on their portfolios and goals, providing a more personalized investment experience.
- Improved Investor Communications: NLG can transform raw data into insightful narratives, improving investor communications and enhancing transparency. This is particularly useful for public relations or financial news outlets, ensuring timely and consistent reporting.
- Domain-Specific Capabilities: Techniques like fine-tuning and transfer learning, bolstered by NLU, will be employed to enhance NLG's domain-specific capabilities, tailoring it to various industries such as finance, healthcare, and marketing. This fusion of NLG with data visualization and storytelling tools will enable the creation of informative and engaging visual narratives from raw data.

BACKGROUND AND MOTIVATION

Organizations today have large volumes of voice and text data from various communication channels like emails, text messages, social media news feeds, video, audio, and more. They use NLP software to automatically process this data, analyze the intent or sentiment in the message, and respond in real time to human communication.

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With organizations' continuous advancement in increasing volume of data, the amount of enterprise data has shown an explosive growth trend. Business managers need to turn the phenomena or trends into effective resources for business management to make more accurate decisions. In this process, a good report can assist decision-makers to make accurate decisions and improve work efficiency.

TRADITIONAL METHODS OF FINANCIAL REPORT GENERATION AND THEIR LIMITATIONS

Traditional methods of financial report generation involve the use of financial statements such as the Balance Sheet, Income Statement, and Cash Flow Statement, to provide stakeholders with information about a company's financial performance and position. These statements are typically generated using historical cost accounting and may not accurately reflect the company's current financial situation.

Limitations of Traditional Methods

The traditional methods of financial report generation have several limitations, including:

- Historical Cost Accounting: Traditional financial reports are based on historical cost accounting, which may not accurately reflect the current market value of assets and liabilities. This can lead to inaccurate financial statements and poor decision-making.
- Lack of Transparency: Traditional financial reports may not provide sufficient transparency into a company's financial activities, making it difficult for stakeholders to make informed decisions.
- Inadequate Disclosure: Traditional financial reports may not provide adequate disclosure of important information, such as off-balance-sheet transactions and contingent liabilities.
- Dependence on Historical Costs: Traditional financial reports are based on historical costs, which may not reflect the current market value of assets and liabilities.
- Limited Information: Traditional financial reports may not provide sufficient information about a company's financial performance and position, making it difficult for stakeholders to make informed decisions.
- No Consideration of Non-Financial Factors: Traditional financial reports do not consider non-financial factors, such as environmental and social impacts, which are increasingly important to stakeholders.
- Auditor Dependence: Traditional financial reports rely heavily on auditors, who may not always provide accurate and reliable opinions.
- Limited Usefulness: Traditional financial reports may not be useful for decision-making, as they do not provide timely and relevant information about a company's financial performance and position.

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www.abjournals.org

Hence, traditional methods of financial report generation have several limitations as mentioned above. These limitations can lead to inaccurate financial statements and poor decision-making. As a result, there is a need for more transparent and timely financial reporting that provides stakeholders with relevant and reliable information about a company's financial performance and position.

POTENTIAL OF NLG IN TRANSFORMING FINANCIAL REPORTING PROCESSES

Natural Language Generation (NLG) has the potential to revolutionize financial reporting processes by automating the creation of financial reports, improving data analysis, and enhancing transparency as mentioned earlier.

By leveraging on NLG, financial institutions can improve efficiency, reduce costs, and make better decisions. As the technology continues to evolve, in the near future we can expect to see even more innovative applications of NLG in financial reporting.

Real-World Applications of NLG in Financial Reporting

- Automated Business Unit Performance Summaries: NLG can generate automated business unit performance summaries, enabling CFOs to monitor organizational health more frequently and in less time.
- Financial Report Automation: NLG can automate the generation of financial reports, reducing the time and effort required to create reports.
- Data Analysis and Insights: NLG can analyze large amounts of data and identify trends, anomalies, and patterns, providing valuable insights for financial decision-making.
- Narrative Reporting: NLG can create clear and concise reports that are easy to understand, improving transparency and accountability in financial reporting.

LITERATURE REVIEW

Canrui et al. (2022), in their paper titled ‘Review on Automated Report Generation Methods for Enterprises’, traced the evolution of report generation from simple templates to advanced deep learning and knowledge graph techniques. Future Direction: It suggests that combining templates with intelligent methods will be the mainstream direction for future research in this field. The paper provides a comprehensive overview of the current state and potential advancements in automated report generation technology.

Wen et al. (2015) in their paper on ‘Context-aware Natural Language Generation with Recurrent Neural Networks’ proposed model aimed to generate not only semantically and syntactically coherent sentences, but also the sentences that are reasonable at particular contexts. Indeed, contexts have been proved to be very useful for various natural language processing tasks such as topic extraction, text classification and language modeling. They have

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proposed two novel approaches for context-aware natural language generation, which map a set of contexts to text sequences. They have evaluated the approaches on the user reviews data.

Yang et al. (2024) in 'Financial Statement Analysis with Large Language Models' investigated whether an LLM can successfully perform financial statement analysis in a way similar to a professional human analyst. They provided standardized and anonymous financial statements to GPT4 and instructed the model to analyze them to determine the direction of future earnings. Even without any narrative or industry specific information, the LLM outperforms financial analysts in its ability to predict earnings changes. The LLM exhibits a relative advantage over human analysts in situations when the analysts tend to struggle. Furthermore, it is found that the prediction accuracy of the LLM is on par with the performance of a narrowly trained state-of-the-art ML model. LLM prediction does not stem from its training memory. Instead, the LLM generated useful narrative insights about a company's future performance. Lastly, the trading strategies based on GPT's predictions yielded a higher Sharpe ratio and alphas than strategies based on other models. Taken together, the results suggested that LLMs may take a central role in decision-making.

Zhao et al. (2024) on the paper 'Revolutionizing Finance with LLMs: An Overview of Applications and Insights' Stated that In recent years, Large Language Models (LLMs) like ChatGPT have seen considerable advancements and have been applied in diverse fields. Built on the Transformer architecture, these models are trained on extensive datasets, enabling them to understand and generate human language effectively. In the financial domain, the deployment of LLMs is gaining momentum. These models are being utilized for automating financial report generation, forecasting market trends, analyzing investor sentiment, and offering personalized financial advice. Leveraging their natural language processing capabilities, LLMs can distill key insights from vast financial data, aiding institutions in making informed investment choices and enhancing both operational efficiency and customer satisfaction. In this study, we provide a comprehensive overview of the emerging integration of LLMs into various financial tasks. Additionally, we conducted holistic tests on multiple financial tasks through the combination of natural language instructions. Our findings show that GPT-4 effectively follows prompt instructions across various financial tasks. This survey and evaluation of LLMs in the financial domain aim to deepen the understanding of LLMs' current role in finance for both financial practitioners and LLM researchers, identify new research and application prospects, and highlight how these technologies can be leveraged to solve practical challenges in the finance industry. The paper addresses challenges such as computational limitations and ethical compliance. The challenges are being gradually overcome as technology advances, and the future prospects of using LLMs in the financial sector are expected to open up more innovations and opportunities.

Wu et al. (2023) in their paper 'BloombergGPT: A Large Language Model for Finance' argued that the use of NLP in the realm of financial technology is broad and complex, with applications ranging from sentiment analysis and named entity recognition to question answering. Large Language Models (LLMs) have been shown to be effective on a variety of tasks; however, no LLM specialized for the financial domain has been reported in literature stated that In this work, we present BloombergGPT, a 50 billion parameter language model that is trained on a wide range of financial data. We constructed a 363 billion token dataset based on Bloomberg's extensive data sources, perhaps the largest domain-specific dataset yet, augmented with 345 billion tokens from general purpose datasets. We validate BloombergGPT on standard LLM benchmarks, open financial benchmarks, and a suite of internal benchmarks that most

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accurately reflect our intended usage. Our mixed dataset training leads to a model that outperforms existing models on financial tasks by significant margins without sacrificing performance on general LLM benchmarks. Additionally, we explain our modeling choices, training process, and evaluation methodology. The model trained on datasets that cover a broad range of topics and domains. While these have included some datasets for specialized domains.

As an important branch of natural language processing (NLP), natural language generation (NLG) is widely used in intelligent writing, human-computer dialogue, and other fields, which is one of the signs of the maturity of artificial intelligence. (Lauriola et al., 2022). In today's world, NLG technology of course has great research value and is widely used. In 1994, Goldberg et al. developed the FoG system, which automatically converts meteorological concepts into meteorological texts; since 2011, StatSheet has developed software to replace editors to automate news writing (Day, 2018). Similarly, in 2018, Jing et al. (2018) introduced deep learning methods to help generate medical diagnosis reports and reduce the workload of medical professionals. In the field of human-computer dialogue, the classic chatbots were the first (Xiong et al., 2019), and in recent years, instant messaging platforms such as wechat and customer service have gradually emerged in order to achieve more intelligent and convenient human-computer interaction.

METHODOLOGY

Reports are generally used by subordinates to report to their superiors, reflect the situation and make suggestions. Common types of reports include enterprise development reports (daily, weekly, monthly, quarterly, annual reports, etc.), government development reports, industry development reports, and work summary reports (Canrui, Jianye & Zhiyong, 2022).

At present, most of the reports are written manually, which requires a lot of repetitive work, and the quality of the reports depends on the writing level and personal experience of the writers. Manual report writing is time-consuming and labor-intensive, and it usually takes a day to two days to complete a short report, which can actually be automated, so automating the generation of reports is especially important in the era of rapid development of artificial intelligence technology. NLG technology can interpret the data and automatically output a comprehensive and targeted in-depth analysis report according to the rules presented by the data, so as to meet the increasingly refined management needs of enterprises.

According to the different types of data sources, report generation can be divided into data-to-report generation, text-to-report generation, and image-to-report generation. Among them, the generation of data-to-reports has a wide range of application scenarios in people's lives, such as BI (Business Intelligence) reports, sports competition reports, and weather forecasts. Text-to-report generation also has attractive business value in the industry, such as keyword news writing, topic essays, and email generation. Commonly used areas of image-to-report generation include pathology report generation, children's education, picture reading, and storytelling, among others. This paper focuses on the method and progress of generating financial reports from data (numerical and textual) generated in the process of enterprise work.

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COMMON METHOD OF REPORT GENERATION

The report generation method based on data merging is similar to fill-in-the-blank and is the simplest way to generate reports, and this method is often used in fixed-format scenarios, such as batch production of business cards, transcripts, letter covers, and notices, among others. The template-based report generation method is one of the earliest report generation technologies adopted by people, and it has a wide range of application scenarios, but the scope of application of this string-based operation is limited and the generalizability is poor. The automated generation of intelligent reports is more flexible, with the text being understood and contextualized while presenting the final result in a language that can be understood. The following is an introduction to report generation methods based on data merging, templates, intelligence, and a mix of templates and intelligence.

Report generation methods based on data consolidation

Natural language generation technology is not the only way to generate text in computers, and mail merge technology in Microsoft Word can also enable simple report generation capabilities. Mail Merge is an important feature of Office, which can be used to generate documents in word format, as well as document generation in pdf format and to direct mail. The simplest mail merge system simply inserts the input data into a predefined slot in the template document [9], inserts the data where it is needed and generates reports in batches.

Mail merge technology makes it easy to create a large number of files with essentially the same content, improving office efficiency. However, in applications where the output text changes greatly, mail merge technology is not suitable.

Template-based report generation methods

Template-based report generation methods have the advantages of standardization and process in structured knowledge acquisition, but they are inflexible in complex research questions, and most of the templates are coarse-grained. In specific fields, in order to ensure that the template can fully cover the content involved, users need to fill in too much content, and the user experience is poor.

Intelligent report automatic generation method

With the improvement of computer hardware processing power, report generation has developed more intelligently from the initial template generation. The intelligent report automatic generation method is based on NLG technology, which tries to generate text on the basis of understanding the text. The automatic report generation method based on deep learning has become a research hotspot, the most classic of which is the sequence generation model, and then some scholars have gradually introduced external knowledge to guide report generation. The following is mainly based on the sequence generation model and knowledge graph, and introduces the automatic generation method of intelligent reports.

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www.abjournals.org

Table 1 summarizes the common models used in the above report generation methods.

Model	Features and Limitation
RNN	Timing sequence can be handled efficiently, but long-term dependencies are difficult to handle
LSTM	Solve the problem of short-time memory of RNNs
BRNN, BI-LSTM	Introduce the ability to leverage both past and feature information
Attention	Solve the problem of information overload and improve the efficiency and accuracy of task processing
Transformer	Build a model with a pure attention mechanism to solve the parallelism problem
BERT	Bidirectional encoding

Thanks to the large-scale labeled data, the deep learning algorithm can learn enough hierarchical feature representations to achieve better results. The limitation of deep learning is that it relies on large-scale labeled data, and it is difficult to effectively use prior knowledge to ensure the correctness of the results [44]. In addition, the text generated by deep learning methods is usually mainly short text, which is difficult to generate logical and smooth long text, and the application scenarios are limited in practical applications.

CONCLUSION

In this review paper, we have tried to understand the work done in the field of Natural Language Generation related to finance. We have tried to uncover all the research gaps which can be filled further by integrating the deep learning models such as RNN, LSTM, Bi-directional LSTM and also evaluating the output with the report template to generate the structured report. the best model amongst others which is suitable for classification, analysis and prediction is identifies and chosen. We conclude that a hybrid model is the best approach to generate structured reports from unstructured input data both in text and numeric. Those result in achieving highest accuracy and performance by saving time and cost spent in financial activities.

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Future Scope

In future we will try to fill the entire Research gap. The structured and templated report can be used to generate automatic financial records to facilitate customer outcomes and streamline the treatment of the customer by industries. These reports can also be useful to share financial records for the further studies which help to promote methodological research shared for the further studies which helps to promote methodological research.

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