Automating Financial Statement Audits with Large Language Models

Rushi Wang[1], Jiateng Liu[1], Weijie Zhao[2], Shenglan Li[2], Denghui Zhang[2]

[1]University of Illinois Urbana-Champaign, [2]Stevens Institute of Technology

{rushiw2, jiateng5}@illinois.edu, dzhang42@syevens.edu.

Abstract

Auditing financial statements is crucial for ensuring stakeholders have a transparent understanding of a company's financial health. However, the current auditing process is neither efficient nor accurate. Despite extensive manual verification efforts, certain errors in financial statements can go undetected during the auditing process. As a result, finalized financial statements may contain inaccuracies, undermining users' expectations regarding the transparency of a company's financial condition and the overall accuracy of the reports. To mitigate this problem, we propose to utilize the strong prior knowledge and reasoning capabilities of large language models (LLMs) to automate financial statement auditing. We created the benchmark for automatic financial statements auditing by manually curating a dataset from real-world financial tables and synthesizing the corresponding transaction data. By correlating the errors within these financial tables with the violation of specific accounting standards, our benchmark involves the tables similar to real-world financial tables which need further auditing. We also propose a five-stage systematic evaluation framework for evaluating the auditing capabilities of LLMs. We also verified that current state-of-the-art LLMs are sufficient for identifying errors in financial statements given historical transaction data. However, they still need to improve on generating a clear explanation of the error and providing evidence for accounting standards. Even with the best LLMs, it is very difficult for them to complete the full auditing process and revise the financial statements. This result calls for future research on further improving the domain-specific knowledge of LLMs in the auditing area. We believe that this task, which highlights challenges in auditing low-level financial statements, will be crucial for improved accuracy and efficiency in real-world auditing practices.

Introduction

In today's interconnected global financial market, auditing financial statements is essential to ensure that stakeholders have a transparent understanding and accurate information on a company's financial health (Popović et al. 2015). However, the current workflow for auditing financial statements is neither efficient nor accurate. Despite the transformative impact of information technologies like auditing software (Debreceny et al. 2005) and big data analytics (Cao, Chychyla, and Stewart 2015; Stewart 2015) on the auditing industry, most audit work remains heavily reliant on human labor (Byrnes et al. 2018) and the process is characterized by extensive labor, inefficiency, and less-than-optimal accuracy (Cho 2022; Li and Sun 2023). Meanwhile, auditors in the current workflow may only focus their efforts on areas that are more likely to have material misstatements or fraud, potentially neglecting less granular or lower-priority details, which may result in audited financial statements inaccuracy while failing to meet user expectations (Toumeh, Yahya, and Siam 2018). Furthermore, the exponential growth in data volume and complexity intensifies these challenges (Sun et al. 2024), underscoring the urgent need for intelligent agents to enhance both the accuracy and efficiency of financial statement audits.

Previous works for simplifying the auditing processes mostly focused on better sampling techniques (Elder et al. 2013; Nigrini 2017) or efficient data extraction approaches (Sirikulvadhana 2002; Vinatoru and Domnisoru 2016), which address only specific aspects of the auditing workflow. However, recent advancements centered on Large Language Models (LLMs) have pushed the boundaries of automation in auditing financial statements. Their strong prior knowledge (Hu et al. 2023) and capability in reasoning (Wei et al. 2022) enable improvements in tasks such as identifying inconsistencies in financial narratives through text matching (Hillebrand et al. 2023) and ensuring adherence to complex regulatory frameworks through automated compliance verification (Berger et al. 2023). **Nevertheless, these approaches still fail to address low-level auditing challenges, such as the labor-intensive cross-verification of transaction data against financial disclosures. Additionally, it is crucial that the auditing model understands and strictly follows accounting standards. The model should also provide justifications to ensure the trustworthiness of the output financial statements.** Our work is to tackle this foundational issue, offering a solution that systematically evaluates the LLM's abilities in auditing financial statements, particularly focusing on tasks such as identifying and cross-verifying transaction data with financial disclosures to address critical low-level auditing challenges.

This paper explores enhancing LLMs for automated financial statement auditing. As illustrated in Figure 1, the model analyzes historical transaction data and a generated financial table, which may be accurate or contain errors. Its objec-

Copyright © 2025, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

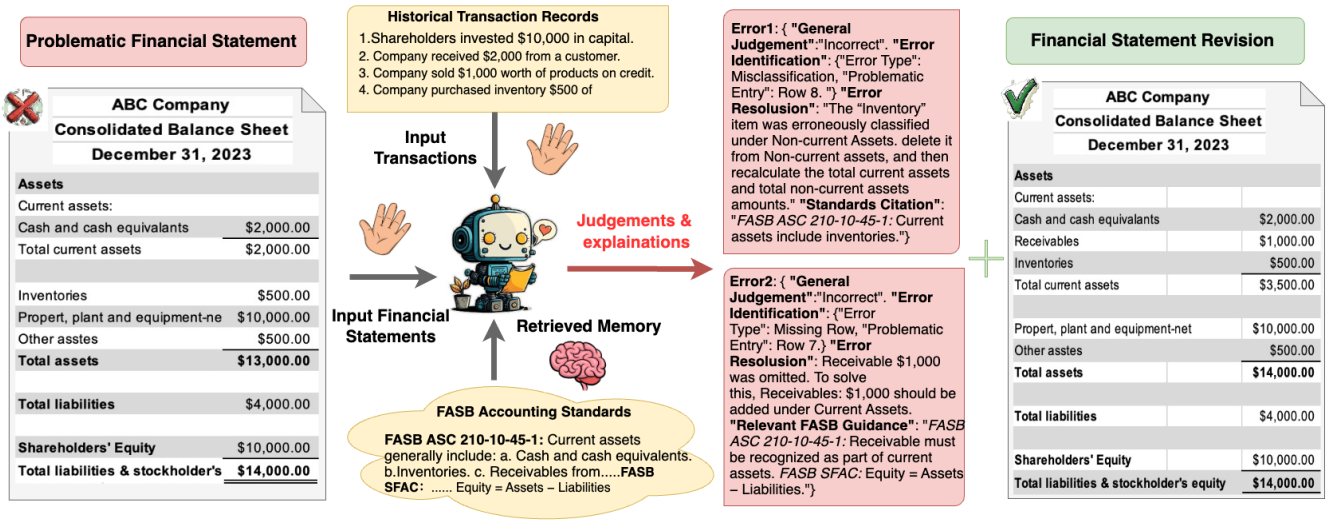

Figure 1: Our Automated Financial Statement Auditing pipeline: An LLM-based agent is provided with (a) The history transaction data of a company. (b) Financial statements prepared by accountants which may potentially contain errors. The LLM-based agent needs to (1) **Retrieve** the accounting standards provided by **FASB** (Financial Accounting Standards Board). (2) **Compare** the transaction data with the financial statements and check whether they align with accounting standards. (3) **Generate** a judgment of the financial statement. **Explain** the errors and concerns to the current financial statements, and further suggest a revision. (4) **Revise** the problematic financial statements and ensure compliance with accounting standards.

tive is to verify the table's accuracy, assess alignment with transaction data, identify discrepancies, and provide detailed justifications. Recognizing the critical role of financial auditing, we propose a systematic five-stage diagnostic framework to evaluate the model's performance.

1. **General Judgment**: Provide an overall assessment of the correctness of the financial statements, framed as a binary classification task (correct/incorrect).
2. **Error Identification**: Identify the error types in the statements and the specific erroneous entries within the financial table.
3. **Error Resolution**: Analyze the identified errors and propose amendments to address the identified issues using natural language explanations accordingly.
4. **Standards Citation**: Generate references to relevant accounting standards as evidence to substantiate findings.
5. **Financial Statement Revision**: Apply direct modifications to the table and generate a corrected version of the financial statements.

Based on our framework, we introduce the first benchmark for automatic financial statement auditing using real financial statements from S&P 500 companies globally. We carefully curate this data manually and produce high-quality synthetic historical transaction data. Our data generation process aims to maintain a balanced mix of correct and erroneous tables and to diversify the types of discrepancies between transaction data and financial statements. This approach enhances the realism and complexity of our benchmark, making it a robust tool for evaluating the efficacy of automated auditing systems.

With the created benchmark together with our evaluation framework, we conduct comprehensive experiments for evaluating the capabilities of State-of-The-Art LLMs on financial statement auditing. We first verified that current LLMs are sufficient for identifying errors in financial statements when provided with historical transaction data. However, they still need improvement in terms of generating a clear explanation of the error and providing accounting standards evidence. We draw valuable qualitative analyses and provide insights into how we can potentially improve the abilities of LLMs on this specific task, which should pave the way for further research in the related area and push it towards real-world applications.

Overall, our contributions are:

- We introduce a novel task for the automatic auditing of financial statements, highlighting critical low-level auditing challenges and laying the foundation for enhanced accuracy and efficiency in real-world auditing practices.
- We develop the first high-quality benchmark for the automatic auditing of financial statements, offering a valuable resource to drive future research in this domain.
- We conduct a systematic evaluation of LLMs' capabilities in automatic financial statement auditing, providing detailed qualitative analyses to inspire future advancements.

Automatic Auditing Benchmark

We release the first benchmark for evaluating LLMs' ability of Automatic Auditing of Financial Statements, aiming to advance research and applications in this domain. For each data piece, input data contains a pair of the generated financial statements and the company's historical transaction data. The

financial statements are labeled as either correct or incorrect based on their alignment with the transaction data. We also provide the ground truth five-stage evaluation results as part of the dataset. Additionally, we provide a curated knowledge base of accounting standards, serving as the agent's external memory. We have professional accounting practitioners manually summarize the accounting standards as a comparison to the original standards. While the original standards offer comprehensive details, the summaries are easier for model to understand.

Data Creation

Statements. For financial statements, we manually selected financial statements from consolidated income statement, consolidated balance sheet, consolidated statements of shareholders' equity, and consolidated statements of cash flows from randomly selected companies in the S&P 500. The table data are captured as screenshots and then transformed into structured text using predefined rules. Each table begins with a [Tab] token and a descriptive title, followed by year-specific data introduced by [Time] tokens. Rows are indexed as ([row n]), with columns separated by vertical bars |, and concluded with [SEP] tokens. We execute this process with GPT-4-vision while a notable number of errors occurred during the transformation. As a result, we manually check and modify a small set of tables and ensure the accuracy of the structured representations. An example of a transformed table is shown in the Appendix.

Transactions. Historical transaction data from real-world companies are hardly applicable, as the majority of such data are confidential. As a result, we asked accounting major students to write few-shot examples to prompt the GPT-4 models to generate diversified synthetic transaction data and then followed by a round of human verification. While we ensured the generated data is of high quality, the amount and truthfulness of the data were insufficient. These limitations are further discussed in the limitations section.

Errors and Explanations. To create erroneous tables, we first define the error types for financial statements. Comparing a wrong table with a right table, there are the following types of errors: **(1) Missing Row**: A row containing a specific account with values is missing. **(2) Numerical Error**: The value of a specific account is incorrectly computed. **(3) Redundant Row**: A redundant row with a logical account name and amount that fits the respective category **(4) Misclassification**: A wrong row from one category is written to another where it logically does not belong. (e.g., "Accounts Payable" from "Liabilities" is moved to "Assets"). Based on the error types, we ask GPT-4 to insert these errors into the original table. We take single errors and multiple errors into consideration. For multiple errors, we ask the GPT models to insert several errors from different categories into the original table and provide information for these errors sequentially. We manually verify the generated errors and make sure that the concrete errors are diverse. Along with the erroneous tables, we generate five-stage evaluation ground truth labels simultaneously. Since the GPT models are the generator of these errors, it is easy to ensure that the ground truth labels are aligned and accurate. Prompts for generating synthetic data are all provided in the Appendix.

Dataset Statistics

We manually collected 124 images form from the S&P500 Companies. Since each image may contain financial statements from different years, we manually curate them into 371 financial statements expressed in textual format. Among them, there are 101 consolidated balance sheets, 140 consolidated statements of income, and 130 consolidated statements of cash flows. We did not include the consolidated statements of shareholders' equity since they are hard to parse into text. We first insert only one type of error that is mentioned above in each of the tables, resulting in 1484 wrong tables. We also insert random multiple errors into the tables, resulting in 371 wrong tables which are more difficult for LLMs.

Experiments

Experimental Settings

We utilize state-of-the-art large language models GPT-3.5-turbo and GPT-4 to assist in auditing financial statements. Evaluations are conducted independently across financial statements that are correct, contain a single error, and contain multiple errors. Our experiments do not differentiate between various types of financial sheets.

Evaluation Metrics

We used the following metrics to evaluate the five stage's performance, besides, we also added an extra overall evaluation which synthesizes scores from all stages to generally judge the model performance.

- **Evaluate General Judgment**: The binary classification task is evaluated with an Exact Match Score (EM Score).
- **Evaluate Error Identification**: The type of the error and the entry position of the problematic table are independently evaluated with EM Score.
- **Evaluate Error Resolution**: As a generation-based task, error resolution is evaluated using BertScore, which assesses the semantic similarity between the generated results and the ground truth.
- **Evaluate Standards Citation**: For this stage, an external retriever extracts relevant accounting standards from our standards database. The evaluation compares the retrieved standard's index with the ground truth using the Top-K retrieval-based EM Score.
- **Evaluate Financial Statement Revision**: The modifications to table entries are compared to the ground truth using BLEU, which focuses on capturing low-level accuracy in the generation process.
- **Evaluate the Overall Auditing Process**: The complete auditing process is assessed with Success Rate (SR), which measures the model's ability to perform well in every auditing stage. We apply strict requirements to the output. We require all the EM-Score to be 1, the BertScore to be over 0.85, and the BLEU score to be over 0.99 to obtain a complete successful auditing.

Evaluation → **Model ↓**	**General Judgment** Avg. EM Score	**Error Type Identification** Avg. EM Score	**Error Entry Identification** Avg. EM Score	**Error Resolution** Avg. BertScore
GPT-3.5-Turbo	1.000	0.764	0.418	0.869
GPT-4	1.000	0.899	0.737	0.878
Evaluation → **Model ↓**	**Standards Citation(Top-1)** Avg. EM Score	**Standards Citation (Top-5)** Avg. EM Score	**Table Revision** Avg. BLEU	**Overall Evaluation** Avg. Success Rate
GPT-3.5-Turbo	0.137	0.360	0.707	0.025
GPT-4	0.262	0.515	0.783	0.041

Table 1: This table shows state-of-the-art LLMs' auditing performance on financial statements with a **single error**. **Up:** Model performance on General Judgment, Error Identification, and Error Resolution. **Down:** Model performance on Standards Citation, Table Revision, and Overall Evaluation. We report the average performance across 150 random samples in our dataset.

Evaluation → **Model ↓**	**General Judgment** Avg. EM Score	**Error Type Identification** Avg. EM Score	**Error Entry Identification** Avg. EM Score	**Error Resolution** Avg. BertScore
GPT-3.5-Turbo	1.000	0.482	0.349	0.637
GPT-4	1.000	0.752	0.587	0.792
Evaluation → **Model ↓**	**Standards Citation(Top-1)** Avg. EM Score	**Standards Citation (Top-5)** Avg. EM Score	**Table Revision** Avg. BLEU	**Overall Evaluation** Avg. Success Rate
GPT-3.5-Turbo	0.086	0.265	0.680	0.012
GPT-4	0.193	0.396	0.742	0.030

Table 2: This table shows state-of-the-art LLMs' auditing performance on financial statements with **multiple errors**. **Up:** Model performance on General Judgment, Error Identification, and Error Resolution. **Down:** Model performance on Standards Citation, Table Revision, and Overall Evaluation. We report the average performance across 150 random samples in our dataset.

Evaluation → **Model ↓**	**General Judgment** Avg. EM Score
GPT-3.5-Turbo	1.000
GPT-4	1.000

Table 3: This table shows state-of-the-art LLMs' performance on correct financial statements.

Results and Qualitative Analysis

We show the results in Table 1, Table 2 and Table 3. The results show that both GPT-3.5-turbo and GPT-4 excel in General Judgment tasks with perfect accuracy in identifying misalignments between transaction data and generated financial statements. However, their performance drops significantly with more complex tasks, such as identifying specific error types, where GPT-4 only achieves about 50% accuracy. To make matters worse, the accumulation of errors in 'Error Type Identification' and 'Error Entry Identification' makes it significantly hard for models to correctly revise the table into the right one. This limitation becomes pronounced in real-world audit scenarios, where we require auditors to not only report errors in existing financial statements but also provide new ones. The results generally show that current sota LLMs are insufficient for serving as responsible auditors in the workflow. To explain the poor performance, we identify two primary challenges contributing to this failure in applying LLMs in automatic financial statements auditing: (1) Despite their advancements in prior knowledge, state-of-the-art LLMs like GPT-4 lack domain-specific knowledge in accounting standards, which is crucial for addressing real-world problems. (2) The models face difficulties in performing extensive joint reasoning across tables and text, which is essential for these tasks. According to this, we propose two major suggestions for future research in this area: (1) Integrate domain-specific knowledge in Accounting and Finance. (2) Improve hybrid reasoning across tables and text.

Conclusion

Auditing financial statements is essential for financial transparency, yet current methods are often inefficient and error-prone. This work leverages the reasoning capabilities of large language models (LLMs) to automate and enhance the auditing process. We develop a benchmark dataset combining real-world financial tables with synthesized transaction data and systematically injected errors, showcasing LLMs' ability to detect discrepancies in alignment with accounting standards. A five-stage evaluation framework further assesses their performance, offering insights into integrating LLMs into auditing tasks.

Our experiments show that while LLMs effectively identify errors in financial statements when paired with historical data, they struggle to generate comprehensive explanations and align findings with specific accounting standards. Addressing these challenges will require enhancing LLMs' reasoning abilities, integrating domain-specific pretraining, and refining their capacity to produce evidence tied to structured standards. Expanding the dataset to include diverse error types and complex scenarios is also crucial. These advancements have the potential to transform financial auditing, delivering more accurate, efficient, and scalable solutions to meet public expectations.

Limitation

We reflect on the limitations of our work below:

1. While our proposed task setting is similar to the real-world auditing scenario, the transaction data provided in our benchmark is simplified and lacks scalability. In real-world applications, auditors are faced with large amounts of transaction data, and it's unlikely we can feed this large corpus directly into the context window of current large language models. This limitation is quite prevalent in data-sparse scenarios (Liu et al. 2024a) However, when combined with sampling-based auditing techniques, we believe that the proposed framework can still enhance the efficiency and reliability of the auditing process.
2. Another limitation of our study lies in its narrow focus on detecting errors in the primary financial statements using Large Language Models. In practice, auditors are required to assess a much broader range of reports, such as budget variance analyses, and segment disclosures, among others. These tasks involve additional layers of complexity, including inter-company adjustments, managerial estimates, and compliance with specialized reporting standards. Future research should investigate the capability of LLMs to handle these more diverse and complex auditing challenges to ensure practical applicability across a wider spectrum of audit responsibilities.
3. The evaluated LLMs on a sample of 300 financial statements instead of the full dataset, may introduce discrepancies compared to results on the complete dataset. While sampling reflects common auditing practices, it may not fully capture the model's overall performance. We neither incorporated more advanced prompting techniques like a multiple-interaction based (Wang et al. 2023) or code-based (Yang et al. 2024) agent setting to complete the task. It is worth exploring whether there prompting frameworks will bring extra benefit to the task. Also, it is possible that a LLM updated with domain-specific knowledge would be helpful. We would further consider updating or continuing pretraining LLMs with unstructured text (Liu et al. 2024b; Deng et al. 2024) to enhance its domain knowledge in accounting and finance.

References

Berger, A.; Hillebrand, L.; Leonhard, D.; Deußer, T.; De Oliveira, T. B. F.; Dilmaghani, T.; Khaled, M.; Kliem, B.; Loitz, R.; Bauckhage, C.; et al. 2023. Towards automated regulatory compliance verification in financial auditing with large language models. In *2023 IEEE International Conference on Big Data (BigData)*, 4626–4635. IEEE.

Byrnes, P. E.; Al-Awadhi, A.; Gullvist, B.; Brown-Liburd, H.; Teeter, R.; Warren Jr, J. D.; and Vasarhelyi, M. 2018. Evolution of auditing: From the traditional approach to the future audit. In *Continuous auditing: Theory and application*, 285–297. Emerald Publishing Limited.

Cao, M.; Chychyla, R.; and Stewart, T. 2015. Big data analytics in financial statement audits. *Accounting horizons*, 29(2): 423–429.

Cho, J. 2022. How Do Auditors Respond to Labor Investment Inefficiency? *The Journal of the Korea Contents Association*, 22(2): 593–604.

Debreceny, R.; Lee, S.-L.; Neo, W.; and Toh, J. S. 2005. Employing generalized audit software in the financial services sector: Challenges and opportunities. *Managerial Auditing Journal*, 20(6): 605–618.

Deng, J.; Wei, Z.; Pang, L.; Ding, H.; Shen, H.; and Cheng, X. 2024. UnKE: Unstructured Knowledge Editing in Large Language Models. *arXiv preprint arXiv:2405.15349*.

Elder, R. J.; Akresh, A. D.; Glover, S. M.; Higgs, J. L.; and Liljegren, J. 2013. Audit sampling research: A synthesis and implications for future research. *Auditing: A Journal of Practice & Theory*, 32(Supplement 1): 99–129.

Hillebrand, L.; Berger, A.; Deußer, T.; Dilmaghani, T.; Khaled, M.; Kliem, B.; Loitz, R.; Pielka, M.; Leonhard, D.; Bauckhage, C.; et al. 2023. Improving zero-shot text matching for financial auditing with large language models. In *Proceedings of the ACM Symposium on Document Engineering 2023*, 1–4.

Hu, L.; Liu, Z.; Zhao, Z.; Hou, L.; Nie, L.; and Li, J. 2023. A survey of knowledge enhanced pre-trained language models. *IEEE Transactions on Knowledge and Data Engineering*.

Li, J.; and Sun, Z. 2023. Government audit, employee efficiency and labor cost stickiness. *Plos one*, 18(9): e0291014.

Liu, J.; Ai, L.; Liu, Z.; Karisani, P.; Hui, Z.; Fung, M.; Nakov, P.; Hirschberg, J.; and Ji, H. 2024a. PropaInsight: Toward Deeper Understanding of Propaganda in Terms of Techniques, Appeals, and Intent. *arXiv preprint arXiv:2409.18997*.

Liu, J.; Yu, P.; Zhang, Y.; Li, S.; Zhang, Z.; Sarikaya, R.; Small, K.; and Ji, H. 2024b. EVEDIT: Event-based Knowledge Editing for Deterministic Knowledge Propagation. In Al-Onaizan, Y.; Bansal, M.; and Chen, Y.-N., eds., *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, 4907–4926. Miami, Florida, USA: Association for Computational Linguistics.

Nigrini, M. J. 2017. Audit sampling using Benford's Law: A review of the literature with some new perspectives. *Journal of emerging technologies in accounting*, 14(2): 29–46.

Popović, S.; Tošković, J.; Majstorović, A.; Brkanlić, S.; and Katić, A. 2015. THE IMPORTANCE OF CONTINUOUS AUDIT OF FINANCIAL STATEMENTS OF THE COMPANY OF COUNTRIES JOINING THE EU. *Annals of'Constantin Brancusi'University of Targu-Jiu. Economy Series/Analele Universităţii'Constantin Brâncuşi'din Târgu-Jiu Seria Economie*.

Sirikulvadhana, S. 2002. *Data mining as a financial auditing tool*. Ph.D. thesis, Citeseer.

Stewart, T. R. 2015. Data analytics for financial statement audits. *Audit Analytics*, 105.

Sun, Y.; Li, J.; Lu, M.; and Guo, Z. 2024. Study of the Impact of the Big Data Era on Accounting and Auditing. *arXiv preprint arXiv:2403.07180*.

Toumeh, A. A.; Yahya, S.; and Siam, W. Z. 2018. Expectations gap between auditors and user of financial statements

in the audit process: an auditors' perspective. *Asia-Pacific Management Accounting Journal (APMAJ)*, 13(3): 79–107.

Vinatoru, S.; and Domnisoru, S. 2016. USING DATA MINING IN FINANCIAL AUDIT. In *3rd International Multidisciplinary Scientific Conference on Social Sciences and Arts SGEM 2016*, 677–684.

Wang, X.; Wang, Z.; Liu, J.; Chen, Y.; Yuan, L.; Peng, H.; and Ji, H. 2023. Mint: Evaluating llms in multi-turn interaction with tools and language feedback. *arXiv preprint arXiv:2309.10691*.

Wei, J.; Wang, X.; Schuurmans, D.; Bosma, M.; Xia, F.; Chi, E.; Le, Q. V.; Zhou, D.; et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35: 24824–24837.

Yang, K.; Liu, J.; Wu, J.; Yang, C.; Fung, Y. R.; Li, S.; Huang, Z.; Cao, X.; Wang, X.; Wang, Y.; et al. 2024. If llm is the wizard, then code is the wand: A survey on how code empowers large language models to serve as intelligent agents. *arXiv preprint arXiv:2401.00812*.

Appendix

Prompting Templates

In this section, we provide all the templates we used to prompt GPT models to generate synthetic data. We also provide templates that we used to simulate LLMs as financial statement auditors.

Templates to Generate Textual Financial Statements

We use the following template to transform cropped financial statement images into textual table descriptions:

> You are a helpful assistant who can help transform table inputs into formmated text. Input a image which shows a table, you need to transform it into text obeying the following rules: (1) Start the table with [Tab], together with the title of the table, you can also add subtitle if necessary, summarize the table if the name is not provided. It should be one of Balance Sheet, Income Statement, Cash Flow Statement or Statement of Changes in Equity of the company. (2) The table contains data from multiple years, translate the table year by year, seperate the information of each year with a token. This means you should first focus on all the rows for a certain year (the year is usually in column) before looking at and transforming the next year. Use a [Time] together with the real time shown on table to show the specific time of the data. (3) For each row without actual data, input a row with the title, for example: just put 'oprating activities' in a row and then [SEP] (4) For data of each year, start each row with [row n], where n is the index of the row of the table. Then you sequentially output the content of each line, you should seperate columns with a 'l' and use a [SEP] token at the end of each line.
>
> For example, your output can be something like:
>
> [Tab] Consolidated Balance Sheets from Abbive Inc.
>
> [Time]: September 30, 2023 [SEP] [row 0]: Net sales [SEP] [row 1]: Products | $298,085 [SEP] [row 2]: Services | $85,200 [SEP] [row 3]: Total net sales | $383,285 [SEP]
>
> [Time]: September 30, 2024 [SEP] [row 0]: Net sales [SEP] [row 1]: Products | $236,085 [SEP] [row 2]: Services | $89,100 [SEP] [row 3]: Total net sales | $386,314 [SEP]
>
> [Time]: September 30, 2025 [SEP] [row 0]: Net sales [SEP] [row 1]: Products | $238,085 [SEP] [row 2]: Services | $92,100 [SEP] [row 3]: Total net sales | $389,235 [SEP]
>
> Now here is a table from the of the company , remember to directly generate your output. Now let's begin!

Templates to Generate Synthetic Transaction Data

Based on the textual financial statements obtained from the previous step, we simulate synthetic transactions to align with the financial entries. The following template is used to generate corresponding transaction data:

You are a financial data expert and a helpful assistant in generating synthetic transaction data from consolidated financial statements. Based on the input data from the following types of financial statements—Consolidated Income Statement, Consolidated Balance Sheet, Consolidated Statement of Cash Flow, and Consolidated Statement of Equity, you need to Generate Realistic Transactions that lead to the numbers in the table. The transaction data that you generate should follow the following rules: (1) Align logically with the type of financial statement (e.g., revenue and expense transactions for income statements, asset and liability transactions for balance sheets, etc.) (2) Incorporate relatively plausible amounts and reflect realistic business activities for the specific company. (3) Generate event descriptions for each row of the financial statement, there should be several different events which contributes to the final number. (4) Generate transaction data row by row, and make sure that the sum of the generated scattered transactions is equal to the sum of each item on the financial statements.

You need to generate the output in the following format (note that you must repeat the original input as part of your output): Input: Here is a [specific financial statements] from the [specific company] [The input of original financial table]

Output: Transactions: [List of realistic transactions generated based on the input]

A concrete example is given here for your reference:

Input: Here is a table from Meta Platforms

[Tab] Consolidated Balance Sheets from Meta Platforms, Inc. [Time]: December 31, 2023 [SEP] [row 0]: Assets [SEP] [row 1]: Cash and cash equivalents | $41,862 [SEP] [row 2]: Marketable securities | $23,541 [SEP] [row 3]: Accounts receivable, net | $16,169 [SEP] [row 4]: Prepaid expenses and other current assets | $3,793 [SEP] [row 5]: Total current assets | $85,365 [SEP] [row 6]: Non-marketable equity securities | $6,141 [SEP] [row 7]: Property and equipment, net | $96,587 [SEP] [row 8]: Operating lease right-of-use assets | $13,294 [SEP] [row 9]: Intangible assets, net | $788 [SEP] [row 10]: Goodwill | $20,654 [SEP] [row 11]: Other assets | $6,794 [SEP] [row 12]: Total assets | $229,623 [SEP] [Time]: December 31, 2022 [SEP] [row 0]: Assets [SEP] [row 1]: Cash and cash equivalents | $14,681 [SEP] [row 2]: Marketable securities | $26,057 [SEP] [row 3]: Accounts receivable, net | $13,466 [SEP] [row 4]: Prepaid expenses and other current assets | $5,345 [SEP] [row 5]: Total current assets | $59,549 [SEP] [row 6]: Non-marketable equity securities | $6,201 [SEP] [row 7]: Property and equipment, net | $79,518 [SEP] [row 8]: Operating lease right-of-use assets | $12,673 [SEP] [row 9]: Intangible assets, net | $897 [SEP] [row 10]: Goodwill | $20,306 [SEP] [row 11]: Other assets | $6,583 [SEP] [row 12]: Total assets | $185,727 [SEP] [Time]: December 31, 2023 [SEP] [row 0]: Liabilities and stockholders' equity [SEP] [row 1]: Accounts payable | $4,849 [SEP] [row 2]: Partners payable | $863 [SEP] [row 3]: Operating lease liabilities, current | $1,623 [SEP] [row 4]: Accrued expenses and other current liabilities | $24,625 [SEP] [row 5]: Total current liabilities | $31,960 [SEP] [row 6]: Operating lease liabilities, non-current | $17,226 [SEP] [row 7]: Long-term debt | $18,385 [SEP] [row 8]: Other liabilities | $8,884 [SEP] [row 9]: Total liabilities | $76,455 [SEP] [Time]: December 31, 2022 [SEP] [row 0]: Liabilities and stockholders' equity [SEP] [row 1]: Accounts payable | $4,990 [SEP] [row 2]: Partners payable | $1,117 [SEP] [row 3]: Operating lease liabilities, current | $1,367 [SEP] [row 4]: Accrued expenses and other current liabilities | $19,952 [SEP] [row 5]: Total current liabilities | $27,026 [SEP] [row 6]: Operating lease liabilities, non-current | $15,301 [SEP] [row 7]: Long-term debt | $9,923 [SEP] [row 8]: Other liabilities | $7,764 [SEP] [row 9]: Total liabilities | $60,014 [SEP] [Time]: December 31, 2023 [SEP] [row 0]: Stockholders' equity [SEP] [row 1]: Additional paid-in capital | $73,253 [SEP] [row 2]: Accumulated other comprehensive loss | ($2,155) [SEP] [row 3]: Retained earnings | $82,070 [SEP] [row 4]: Total stockholders' equity | $153,168 [SEP] [Time]: December 31, 2022 [SEP] [row 0]: Stockholders' equity [SEP] [row 1]: Additional paid-in capital | $64,444 [SEP] [row 2]: Accumulated other comprehensive loss | ($3,530) [SEP] [row 3]: Retained earnings | $64,799 [SEP] [row 4]: Total stockholders' equity | $125,713 [SEP] [Time]: December 31, 2023 [SEP] [row 0]: Total liabilities and stockholders' equity | $229,623 [SEP] [Time]: December 31, 2022 [SEP] [row 0]: Total liabilities and stockholders' equity | $185,727 [SEP]

Templates to Generate Synthetic Transaction Data

Your Output: Trasactons For 2023: [contributing to row 1]: Cash and cash equivalents | $41,862 [SEP] 1. Advertising revenue of $22,000 was collected from clients, with direct cash payment by the clients. 2.The sale of short-term investments generated $22,862 in cash income. 3.Employee wages resulted in a cash outflow of $3,000. [Explanation: 41,862 = 22,000 + 22,862 - 3,000]
[contributing to row 2]: Marketable securities 4.Purchase of short-term government securities $23,541. [Explanation: $23,541=$23,541]
[contributing to row 3]: Accounts receivable, net 5.Advertisers were invoiced for Q4 campaigns, totaling $18,000. 6.A write-off of uncollectible accounts was recorded, totaling $1,831. [Explanation: $16,169 = $18,000- $1,831]
[contributing to row 4]: Prepaid expenses and other current assets 7.$1,000 prepayment for upcoming marketing events. 8.Advance payment for annual cloud service subscriptions for $2,793. [Explanation:$3,793= $1,000 + $2,793]
[contributing to row 5]: Total current assets [Explanation: $85,365 = 41,862 + $23,541 + $16,169 + $3,793]
[contributing to row 6]: Non-marketable equity securities 9.There was no major change except for minor revaluations or adjustments, resulting in a net increase of $6,141. [Explanation:$6,141=$6,141]
[contributing to row 7]: Property and equipment, net 10.Capital expenditure on new data centers and office equipment totaled $95,000. 11.Brought property this year for $1,587. [Explanation:$96,587 = $95,000+$1,587]
[contributing to row 8]:Operating lease right-of-use assets 12.Recognized additional lease assets worth $14,000 from new agreements. 13.Amortization of existing lease assets reduced the value by $706. [Explanation: $13,294 = $14,000 - $706]
[contributing to row 9]: Intangible assets, net 14.Development costs that meet the capitalization criteria are included in intangible assets $788. [Explanation: $788 = $788]
[contributing to row 10]:Goodwill 15.Acquisition of a small tech firm increased goodwill to $20,654. [Explanation: $20,654 = $20,654]
[contributing to row 11]:Other assets 16.Other assets in the company totaled $6,794. [Explanation: $6,794 = $6,794]
[contributing to row 12]:Total assets [Explanation: $229,623 =$85,365 + $6,141 + $96,587 + $13,294 + $788+ $20,654 + $6,794]
[contributing to row 1]:Accounts payable 17.Payments to vendors reduced accounts payable by $151. 18.New purchases on credit added $5,000 to accounts payable. [Explanation: $4,849 = $5,000-$151]
[contributing to row 2]Partners payable 19.Partners payable for this year totaled $863. [Explanation: $863 = $863]
[contributing to row 3] Operating lease liabilities, current 20.Payments toward lease obligations totaled $1,623. [Explanation: $1,623 = $1,623]
[contributing to row 4]: Accrued expenses and other current liabilities 21.Additional accrued expenses for Q4 salaries and benefits amounted to $25,000. 22.Payment of $375 toward previously accrued liabilities. [Explanation: $24,625 = $25,000 - $375]
[contributing to row 5]: Total current liabilities [Explanation: $31,960= $4,849 + $863 + $1,623 + $24,625]
[contributing to row 6]: Operating lease liabilities, non-current 23.New lease agreements added $18,000. 24.Amortization of long-term liabilities reduced by $774. [Explanation: $17,226 = $18,000-$774]
[contributing to row 7]: Long-term debt 25.Issued new bonds worth $18,385 for business expansion. [Explanation: $18,385 = $18,385]
[contributing to row 8]: Other liabilities 26.Other liabilities for the company totaled 8,884. [Explanation: $8,884 = $8,884]
[row 9]: Total liabilities | $76,455 [Explanation: $76,455 = $31,960 + $17,226 + $18,385 + $8,884]
[contributing to row 1]: Additional paid-in capital 27.Stock issuance generated $73,253 in additional paid-in capital. [Explanation: $73,253 = $73,253]
[contributing to row 2]: Accumulated other comprehensive loss 28.Decrease due to foreign currency adjustments and revaluation of securities amounted to $2,155. [Explanation: ($2,155) = ($2,155)]
[contributing to row 3]: Retained earnings 29.Retained Earning for the company totaled 82,070. [Explanation: $82,070 = 82,070]
[contributing to row 4]: Total stockholders' equity [Explanation: $153,168 = $73,253 + ($2,155) + $82,070]
[contributing to row 0]: Total liabilities and stockholders' equity | $229,623 [Explanation: $229,623 = $76,455 + $153,168]
Now let's begin! Output your transactions which aligns with the table !
Input: { }

Templates for Error Injection in Financial Statements

We inject errors into textual financial statements and generate corresponding judgments and explanations for incorrect entries. The template is constructed as follows:

You will help generate modified financial statements with specific types of errors for financial auditing purposes. Based on the input data from the original financial statement, you need to create a version with deliberate errors, as well as identify and explain the errors and provide corrections. The error types are provided as below: <1> Missing Row: Delete a row containing a specific account with values (e.g., an account under "Operating Activities," "Investing Activities," or "Financing Activities" in the Consolidated Statements of Cash Flows) but avoid removing key totals like "Total Revenue," "Total Expenses," "Total Assets," "Total Liabilities," "Total Equity," or "Net Cash Provided by Operating/Investing/Financing Activities.". <2> Numerical Error: Modify the value of a specific account (e.g., "Accounts Receivable" under Assets) by changing it to an incorrect amount. <3> Redundant Row: Add a new row with a logical account name and amount that fits the respective category (e.g., adding "Software Licenses" under Assets or "Deferred Revenue" under Liabilities). <4> Misclassification: Move a row from one category to another where it logically does not belong (e.g., relocating "Accounts Payable" from Liabilities to Assets in the Balance Sheet, or shifting an expense item under Revenue in the Consolidated Statement of Income). The outputs should consist of the following components:

"Modified Financial Statement with Errors": Introduce one of the following errors into the financial statement and output the changed statement as a table similar to input. You can use any of the type of errors introduced above by deleting rows, change a number, add an extra row, or move a row to a wrong place.

"General Judgment": Always output 'Incorrect' as you are introducing errors to the right table.

"Error Identification": Output the error type you have introduced together with the problematic entry row index. Generate your results with "Error type"

"Error Resolution": Provide a detailed explanation of the specific error(s), including why it is incorrect. For example: "The 'Inventory' item was wrong; it should be $2000, and the calculation should be..", "The 'Accounts Liabilities' item was erroneously classified under Assets.", "Receivables (with the amount) was omitted." Then explain the error and suggest specific corrections to resolve the error(s). For example: "Accounts Liabilities does not belong under Assets; it should be moved to Liabilities." "Add 'Receivables' (with the amount) under Current Assets."

"Standards Citation": Cite the relevant Financial Accounting Standards Board (FASB) guidance related to the error, including specific references to sections, if applicable.

Your task is to generate outputs for each section described above in detail. Make sure the modifications are logical, align with accounting principles, and provide concise yet accurate error descriptions.

Here is an example output for your reference:

Input: "Input Table": [Time]: September 30, 2023 [SEP] [row 0]: Current assets: [SEP] [row 1]: Cash and cash equivalents | $29,965 [SEP] [row 2]: Marketable securities | $31,590 [SEP] [row 3]: Accounts receivable, net | $29,508 [SEP] [row 4]: Vendor non-trade receivables | $31,477 [SEP] [row 5]: Inventories | $6,331 [SEP] [row 6]: Other current assets | $14,695 [SEP] [row 7]: Total current assets | $143,566 [SEP] [row 8]: Non-current assets: [SEP] [row 9]: Marketable securities | $100,544 [SEP] [row 10]: Property, plant and equipment, net | $43,715 [SEP] [row 11]: Other non-current assets | $64,758 [SEP] [row 12]: Total non-current assets | $209,017 [SEP] [row 13]: Total assets | $352,583 [SEP] [row 14]: Current liabilities: [SEP] [row 15]: Accounts payable | $62,611 [SEP] [row 16]: Other current liabilities | $58,829 [SEP] [row 17]: Deferred revenue | $8,061 [SEP] [row 18]: Commercial paper | $5,985 [SEP] [row 19]: Term debt | $9,822 [SEP] [row 20]: Total current liabilities | $145,308 [SEP] [row 21]: Non-current liabilities: [SEP] [row 22]: Term debt | $95,281 [SEP] [row 23]: Other non-current liabilities | $49,848 [SEP] [row 24]: Total non-current liabilities | $145,129 [SEP] [row 25]: Total liabilities | $290,437 [SEP] [row 26]: Commitments and contingencies | [SEP] [row 27]: Shareholders' equity: [SEP] [row 28]: Common stock and additional paid-in capital | $73,812 [SEP] [row 29]: Accumulated deficit | $(214) [SEP] [row 30]: Accumulated other comprehensive loss | $(11,452) [SEP] [row 31]: Total shareholders' equity | $62,146 [SEP] [row 32]: Total liabilities and shareholders' equity | $352,583 [SEP]

Templates for Error Injection in Financial Statements

"Transaction data": Transactions for 20231a [contributing to row 1]: Cash and cash equivalents | $29,965 [SEP] 1. Apple launched a new iPhone model, generating revenue of $18,000, with direct cash payment by the customers. 2. The sale of short-term investments resulted in a cash income of $15,000. 3. Vendor payments and operational expenses resulted in a cash outflow of $3,035. [Explanation: $29,965 = $18,000 + $15,000 - $3,035] [contributing to row 2]: Marketable securities 4.The company purchased various securities totaling $31,590. [Explanation: $31,590=$31,590] [contributing to row 3]: Accounts receivable, net 5. Income from iPhone sales yet to be received, billed at $32,500. 6. A write-off of uncollectible accounts was done, amounting to $2,992. [Explanation: $29,508 = $32,500 - $2,992] [contributing to row 4]: Vendor non-trade receivables 7. Receivables from partners such as app developers on the App store, totaling $31,477. [Explanation: $31,477 = $31,477] [contributing to row 5]: Inventories 8. Production of new iPhone and Mac computers added $6,331 to inventories. [Explanation: $6,331= $6,331] [contributing to row 6]: Other current assets 9. Other current assets for the company, consisting of prepaid expenses and advances, totaling $14,695. [Explanation: $14,695 = $14,695] [contributing to row 7]: Total current assets [Explanation: $143,566 = 29,965 + $31,590 + $29,508 +6,331 +14,695] [contributing to row 9]: Marketable securities - non-current 10. The company made long-term investments totaling $100,544. [Explanation: $100,544 = $100,544] [contributing to row 10]: Property, plant and equipment, net 11. Capital expenditure on new retail stores and updating manufacturing equipment, totaling $43,715. [Explanation: $43,715 = $43,715] [contributing to row 11]: Other non-current assets 12. Other non-current assets for the company totaled $64,758. [Explanation: $64,758 = $64,758] [contributing to row 12]: Total non-current assets [Explanation: $209,017 = $100,544 + $43,715 + $64,758] [contributing to row 13]: Total assets [Explanation: $352,583 = $143,566 + $209,017] [contributing to row 15]: Accounts payable 13. Payments to vendors reduced accounts payable by $12,000. 14. New purchases on credit added $74,611 to accounts payable. [Explanation: $62,611 = $74,611 - $12,000] [contributing to row 16]: Other current liabilities 15. Accrued expenses and other outstanding payments for the company amounted to $58,829. [Explanation: $58,829 = $58,829] [contributing to row 17]: Deferred revenue 16. Revenue deferred for services to be provided in the future totaled $8,061. [contributing to row 18]: Commercial paper 17. Short-term debt issued by the company, totaling $5,985. [Explanation: $5,985 = $5,985] [contributing to row 19]: Term debt - current 18. Current portion of long-term term debt, amounting to $9,822. [Explanation: $9,822 = $9,822] [contributing to row 20]: Total current liabilities [Explanation: $145,308= $62,611+ $58,829 + $8,061 +$5,985 + $9,822] [contributing to row 22]: Term debt - non-current 19. The company issued long-term bonds worth $95,281 for business expansion. [Explanation: $95,281 = $95,281] [contributing to row 23]: Other non-current liabilities 20. Other long-term liabilities, including pension obligations, amounted to $49,848. [Explanation: $49,848 = $49,848] [contributing to row 24]: Total non-current liabilities [Explanation: $145,129 = $95,281 + $49,848] [contributing to row 25]: Total liabilities [Explanation: $290,437 = $145,308 + $145,129] [contributing to row 28]: Common stock and additional paid-in capital 21. Stock issuance generated an additional $73,812 in paid-in capital. [Explanation: $73,812 = $73,812] [contributing to row 29]: Accumulated deficit 22. There was a net loss for the company during this period, amounting to $214. [Explanation: ($214) = ($214)] [contributing to row 30]: Accumulated other comprehensive loss 23. This reflects an increase of loss from various sources such as foreign currency translation, totaling ($11,452) [Explanation: ($11,452) = ($11,452)] [contributing to row 31]: Total shareholders' equity [Explanation: $62,146 = $73,812 - $214 - $11,452] [contributing to row 32]: Total liabilities and shareholders' equity [Explanation: $352,583 = $290,437 + $62,146]

Templates for Error Injection in Financial Statements

You Ideal output in the json format: "Modified Financial Statement with Errors": "[Time]: September 30, 2023 [SEP] [row 0]: Current assets: [SEP] [row 1]: Cash and cash equivalents | $29,965 [SEP] [row 2]: Marketable securities | $31,590 [SEP] [row 3]: Vendor non-trade receivables | $31,477 [SEP] [row 4]: Inventories | $6,331 [SEP] [row 5]: Other current assets | $14,695 [SEP] [row 6]: Total current assets | $114,058 [SEP] [row 7]: Non-current assets: [SEP] [row 8]: Accounts receivable, net | $29,508 [SEP] [row 9]: Marketable securities | $100,544 [SEP] [row 10]: Property, plant and equipment, net | $43,715 [SEP] [row 11]: Other non-current assets | $64,758 [SEP] [row 12]: Total non-current assets | $238,525 [SEP] [row 13]: Total assets | $352,583 [SEP] [row 14]: Current liabilities: [SEP] [row 15]: Accounts payable | $62,611 [SEP] [row 16]: Other current liabilities | $58,829 [SEP] [row 17]: Deferred revenue | $8,061 [SEP] [row 18]: Commercial paper | $5,985 [SEP] [row 19]: Term debt | $9,822 [SEP] [row 20]: Total current liabilities | $145,308 [SEP] [row 21]: Non-current liabilities: [SEP] [row 22]: Term debt | $95,281 [SEP] [row 23]: Other non-current liabilities | $49,848 [SEP] [row 24]: Total non-current liabilities | $145,129 [SEP] [row 25]: Total liabilities | $290,437 [SEP] [row 26]: Commitments and contingencies | [SEP] [row 27]: Shareholders' equity: [SEP] [row 28]: Common stock and additional paid-in capital | $73,812 [SEP] [row 29]: Accumulated deficit | $(214) [SEP] [row 30]: Accumulated other comprehensive loss | $(11,452) [SEP] [row 31]: Total shareholders' equity | $62,146 [SEP] [row 32]: Total liabilities and shareholders' equity | $352,583 [SEP]", "General Judgement": "Incorrect", "Error Identification": "Error Type": Misclassification, "Problematic Entry": Row 8, "Error Resolution": "The Financial Statement mistakenly wrote accounts receivable, net into non-current assets. Move accounts receivable, net to the current assets item, delete it from Non-current assets, and then recalculate the total current assets and total non-current assets amounts.", "Standards Citation": "Current assets generally include: Receivables from officers, employees, affiliates, and others, if collectible in the ordinary course of business within a year."

Now, let's begin! Remember to follow the output format that is provided by the few-shot example. In this round, you need to generate the error of {Current error}

Input: "Input Table": {Current Table}

"Transaction data": {Current Transaction}

Templates for Prompting Sota LLMs to Serve as Auditors

We use the following prompt to evaluate the LLMs' ability to audit financial statements.

You will serve as a financial statement auditor helping to identify, explain, and correct intentional errors introduced into financial statements based on provided data. Your input will be an incorrect financial statement with corresponding transactions. The errors introduced into financial statements belong to one of the following types: <1> Missing Row: Delete a row containing a specific account with values (e.g., an account under "Operating Activities," "Investing Activities," or "Financing Activities" in the Consolidated Statements of Cash Flows) but avoid removing key totals like "Total Revenue," "Total Expenses," "Total Assets," "Total Liabilities," "Total Equity," or "Net Cash Provided by Operating/Investing/Financing Activities.". <2> Numerical Error: Modify the value of a specific account (e.g., "Accounts Receivable" under Assets) by changing it to an incorrect amount. <3> Redundant Row: Add a new row with a logical account name and amount that fits the respective category (e.g., adding "Software Licenses" under Assets or "Deferred Revenue" under Liabilities). <4> Misclassification: Move a row from one category to another where it logically does not belong (e.g., relocating "Accounts Payable" from Liabilities to Assets in the Balance Sheet, or shifting an expense item under Revenue in the Consolidated Statement of Income).

For each pair of input, you need to output your auditing results in the following format:

"General Judgment": Judge whether the table is problematic, output 'correct' if you believe that there is no errors, output 'incorrect' if you believe that there is errors. If you output 'correct', there is no need to output anything else. If you output 'incorrect', then you need to also output the following for each error you have identified. You should always use "Information for error 1" to wrap up your first identified error.

"Error Identification": Output the error type you have identified together with the problematic entry row index, for the row index, you should output in the form of 'Row N'.

"Error Resolution": Provide a detailed explanation of the specific error(s), including why it is incorrect.

"Standards Citation": Cite the relevant Financial Accounting Standards Board (FASB) guidance related to the error, including specific references to sections, if applicable.

"Corrected Statements": Provide the corrected financial statement after addressing the identified errors.

Your task is to generate outputs for each section described above in detail. Make sure the modifications are logical, align with accounting principles, and provide concise yet accurate error descriptions.

Here is an example output for your reference:

Input: "Input Table": "[Time]: September 30, 2023 [SEP] [row 0]: Current assets: [SEP] [row 1]: Cash and cash equivalents | $29,965 [SEP] [row 2]: Marketable securities | $31,590 [SEP] [row 3]: Vendor non-trade receivables | $31,477 [SEP] [row 4]: Inventories | $6,331 [SEP] [row 5]: Other current assets | $14,695 [SEP] [row 6]: Total current assets | $114,058 [SEP] [row 7]: Non-current assets: [SEP] [row 8]: Accounts receivable, net | $29,508 [SEP] [row 9]: Marketable securities | $100,544 [SEP] [row 10]: Property, plant and equipment, net | $43,715 [SEP] [row 11]: Other non-current assets | $64,758 [SEP] [row 12]: Total non-current assets | $238,525 [SEP] [row 13]: Total assets | $352,583 [SEP] [row 14]: Current liabilities: [SEP] [row 15]: Accounts payable | $62,611 [SEP] [row 16]: Other current liabilities | $58,829 [SEP] [row 17]: Deferred revenue | $8,061 [SEP] [row 18]: Commercial paper | $5,985 [SEP] [row 19]: Term debt | $9,822 [SEP] [row 20]: Total current liabilities | $145,308 [SEP] [row 21]: Non-current liabilities: [SEP] [row 22]: Term debt | $95,281 [SEP] [row 23]: Other non-current liabilities | $49,848 [SEP] [row 24]: Total non-current liabilities | $145,129 [SEP] [row 25]: Total liabilities | $290,437 [SEP] [row 26]: Commitments and contingencies | [SEP] [row 27]: Shareholders' equity: [SEP] [row 28]: Common stock and additional paid-in capital | $73,812 [SEP] [row 29]: Accumulated deficit | $(214) [SEP] [row 30]: Accumulated other comprehensive loss | $(11,452) [SEP] [row 31]: Total shareholders' equity | $62,146 [SEP] [row 32]: Total liabilities and shareholders' equity | $352,583 [SEP]",

"Transaction data": Transactions for 2023: 1. Apple launched a new iPhone model, generating revenue of $18,000, with direct cash payment by the customers. 2. The sale of short-term investments resulted in a cash income of $15,000. 3. Vendor payments and operational expenses resulted in a cash outflow of $3,035. 4.The company purchased various securities totaling $31,590 5. Income from iPhone sales yet to be received, billed at $32,500. 6. A write-off of uncollectible accounts was done, amounting to $2,992. 7. Receivables from partners such as app developers on the App store, totaling $31,477. 8. Production of new iPhone and Mac computers added $6,331 to inventories. 9. Other current assets for the company, consisting of prepaid expenses and advances, totaling $14,695 10. The company made long-term investments totaling $100,544. 11. Capital expenditure on new retail stores and updating manufacturing equipment, totaling $43,715. 12. Other non-current assets for the company totaled $64,758. 13. Payments to vendors reduced accounts payable by $12,000. 14. New purchases on credit added $74,611 to accounts payable. 15. Accrued expenses and other outstanding payments for the company amounted to $58,829. 16. Revenue deferred for services to be provided in the future totaled $8,061. 17. Short-term debt issued by the company, totaling $5,985. 18. Current portion of long-term term debt, amounting to $9,822. 19. The company issued long-term bonds worth $95,281 for business expansion. 20. Other long-term liabilities, including pension obligations, amounted to $49,848. 21. Stock issuance generated an additional $73,812 in paid-in capital. 22. There was a net loss for the company during this period, amounting to $214. 23. This reflects an increase of loss from various sources such as foreign currency translation, totaling $11,452

Templates for Prompting Sota LLMs to Serve as Auditors

You Ideal output in the json format:

"General Judgment": "Incorrect", "Information for error 1": "Error Identification": "Error Type": Misclassification, "Problematic Entry": Row 8 , "Error Resolution": "The Financial Statement mistakenly wrote accounts receivable, net into non-current assets. Move accounts receivable, net to the current assets item, delete it from Non-current assets, and then recalculate the total current assets and total non-current assets amounts.", "Standards Citation": "Current assets generally include: Receivables from officers, employees, affiliates, and others, if collectible in the ordinary course of business within a year.", "Corrected Statements": "[Time]: September 30, 2023 [SEP] [row 0]: Current assets: [SEP] [row 1]: Cash and cash equivalents | $29,965 [SEP] [row 2]: Marketable securities | $31,590 [SEP] [row 3]: Accounts receivable, net | $29,508 [SEP] [row 4]: Vendor non-trade receivables | $31,477 [SEP] [row 5]: Inventories | $6,331 [SEP] [row 6]: Other current assets | $14,695 [SEP] [row 7]: Total current assets | $143,566 [SEP] [row 8]: Non-current assets: [SEP] [row 9]: Marketable securities | $100,544 [SEP] [row 10]: Property, plant and equipment, net | $43,715 [SEP] [row 11]: Other non-current assets | $64,758 [SEP] [row 12]: Total non-current assets | $209,017 [SEP] [row 13]: Total assets | $352,583 [SEP] [row 14]: Current liabilities: [SEP] [row 15]: Accounts payable | $62,611 [SEP] [row 16]: Other current liabilities | $58,829 [SEP] [row 17]: Deferred revenue | $8,061 [SEP] [row 18]: Commercial paper | $5,985 [SEP] [row 19]: Term debt | $9,822 [SEP] [row 20]: Total current liabilities | $145,308 [SEP] [row 21]: Non-current liabilities: [SEP] [row 22]: Term debt | $95,281 [SEP] [row 23]: Other non-current liabilities | $49,848 [SEP] [row 24]: Total non-current liabilities | $145,129 [SEP] [row 25]: Total liabilities | $290,437 [SEP] [row 26]: Commitments and contingencies | [SEP] [row 27]: Shareholders' equity: [SEP] [row 28]: Common stock and additional paid-in capital | $73,812 [SEP] [row 29]: Accumulated deficit | $(214) [SEP] [row 30]: Accumulated other comprehensive loss | $(11,452) [SEP] [row 31]: Total shareholders' equity | $62,146 [SEP] [row 32]: Total liabilities and shareholders' equity | $352,583 [SEP] " "Information for error 2": .....

An example for correct tables: if your output is correct just output : "General Judgement": "Correct",

Now, let's begin! Remember to follow the output format directly as json format. Do not output anything else except the json output.

Input: "Input Table": { }

"Transaction data": { }