Making LLMs Work for Enterprise Data Tasks

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Background

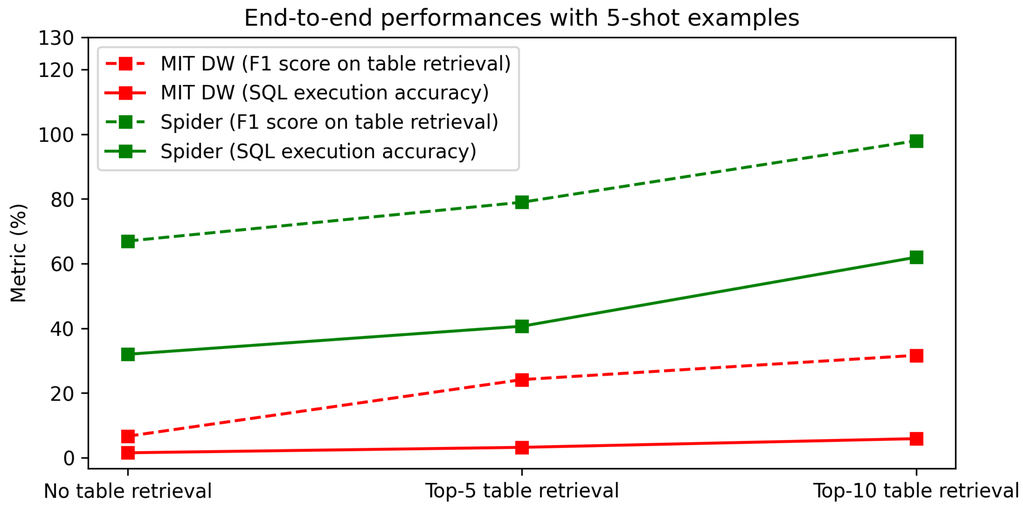
Large language models (LLMs) have shown strong performances on natural language (NL) comprehension tasks, from summarization to question-answering. To expand the scope of what LLMs can achieve, there are recent efforts that try to apply LLMs to data-related tasks, such as question-answering over tables, data cleaning, and data integration. Among these, the task of automatically translating natural language questions into SQL statements (text-to-SQL) for query purposes is a popular and challenging task. Given the complexity of databases, text-to-SQL can greatly empower non-technical users to perform data tasks without relying on experts, boosts SQL user productivity, and improves the usability of the data systems at large: jump start & use any tool.

Problem

Existing open-source datasets on text-to-SQL, Spider[1] and Bird[2], are criticized for their over-simplicity in terms of table structures and queries, which leads to unrealistic assumptions of solutions based on these datasets. An enterprise database, on the other hand, can have

- **Thousands of tables** instead of tens of tables in one database, which makes it impossible to fit all tables in one context and requires an intelligent retrieval system[3]
- **Domain-specific knowledge** (e.g., MIT buildings are numbered) and **non-obvious schema names** (FCLT, which stands for facility) which require external knowledge and additional schema understanding beyond simple semantic matching
- **Complicated queries** that involve joining 5 or more tables, compared to at most 4 joins in open-source datasets, which requires a more sophisticated SQL-generation strategy

While LLMs can achieve 60-70% accuracies on open-source datasets, their performances on enterprise datasets have not yet been explored and the task is far from being solved.



Experimental setup

- Data: 50 queries from the MIT Datawarehouse (DW) that involves 99 tables; 50 queries sampled from Spider that involves 11 tables
- Retrieval-augmented generation (RAG): retrieve top-k most relevant tables in terms of the cosine similarities of the question and table embeddings
- Model: GPT-3.5-turbo-16k with 5-shot examples and up to top-10 tables from RAG
- Metrics: F1 score on tables used in the gold and predicted SQL statements; exact-match execution accuracy between the outputs of the gold and predicted SQL statements

Results

- **Low performances on enterprise data compared to open-source data**: Under the setting of providing 5-shot examples and the top-10 most relevant table in the prompt, execution accuracy is 5.9%, and table retrieval F1 is 32.5% on the MIT DW and 62% and 63% on the Spider dataset. **Execution accuracy and retrieval F1 on MIT DW is 52% and 62% lower than the Spider dataset.**
- **Retrieval-augmented generation (RAG) helps with performances**: Compared to the setting without retrieval, providing the top-10 most relevant tables increases the performances of both metrics on the MIT DW by 325% (execution accuracy) and 284% (table F1). Additionally, the Spider data experienced similar behavior, where the accuracy increased by 97% and the F1 score by 41%.

Conclusion & Next steps

- Our results demonstrate that LLMs cannot generalize to enterprise datasets due to scale, domain-specific knowledge, and query complexity.
- Our project aims to open-source a benchmark dataset from various enterprise sources and explore solutions to improve LLMs' performances on these more complicated datasets.

References

[1] Yu, Tao, et al. "Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task." arXiv preprint arXiv:1809.08887 (2018).

[2] Li, Jinyang, et al. "Can llm already serve as a database interface? a big bench for large-scale database grounded text-to-sqls." Advances in Neural Information Processing Systems 36 (2024).

[3] Chen, Peter Baile, Yi Zhang, and Dan Roth. "Is Table Retrieval a Solved Problem? Join-Aware Multi-Table Retrieval." ACL 2024.