Weaver Of Tasks

Vincent Tu

Disclaimer

I apologize: unfortunately, I was unable to dedicate as much time as I would've liked to this Challenge. Because of this, my submission isn't up to par with my standards. Despite this, I believe/hope my submission offers a unique direction and insights for future work. In Discussion & Limitations, I will discuss current limitation and future directions.

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Preliminaries

Dataset: U.S. Wildfires (Tabular; SQLite)

Method Part 1: Develop a Python Data Analyst Agent

Method Part 2: Develop a SQL Agent

Method Part 3: Develop a Search-augmented Agent

Rules:

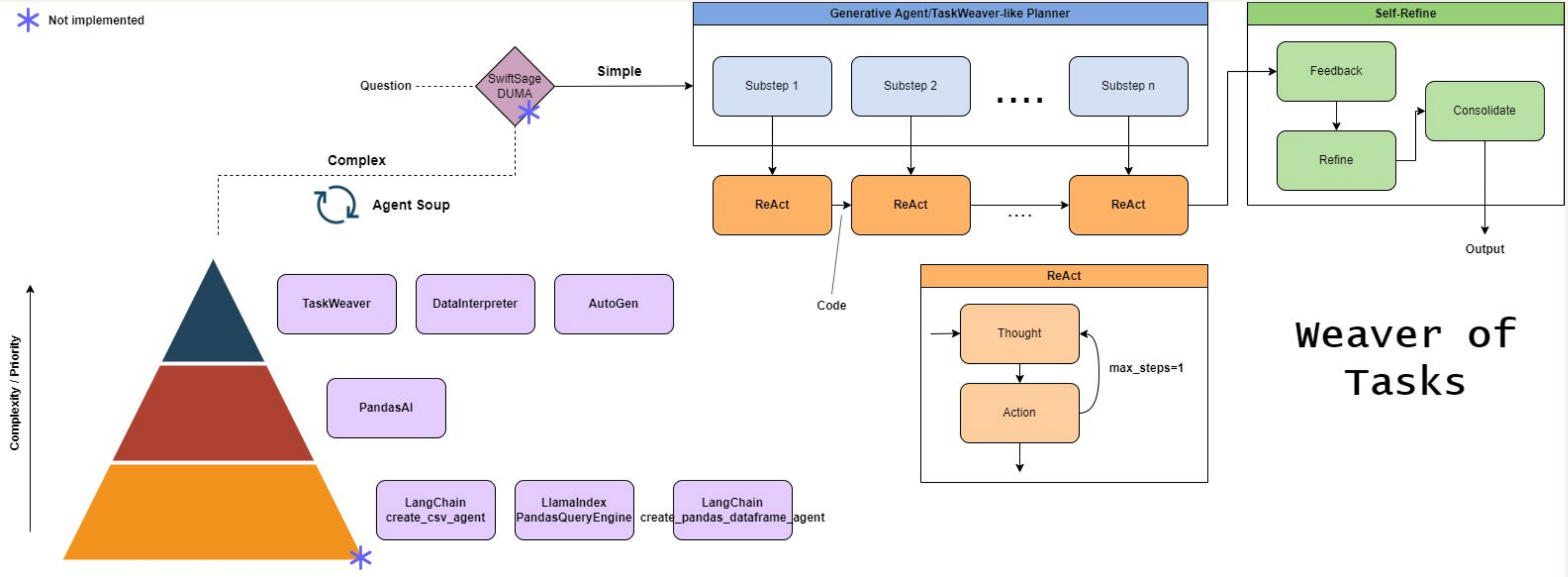
- Any LLM
- Any LLM Framework

Method: Part 1

Data Analyst Agent

- Similar to Generative Agents and TaskWeaver [1, 5], I use a question decomposition that breaks a question down into subtasks/planning steps
- I adopt the ReAct [2] structure for thinking/acting (reasoning)
- Inspired by Reflexion and Self-Refine [3, 4], I incorporate a refinement mechanism at the end of generation

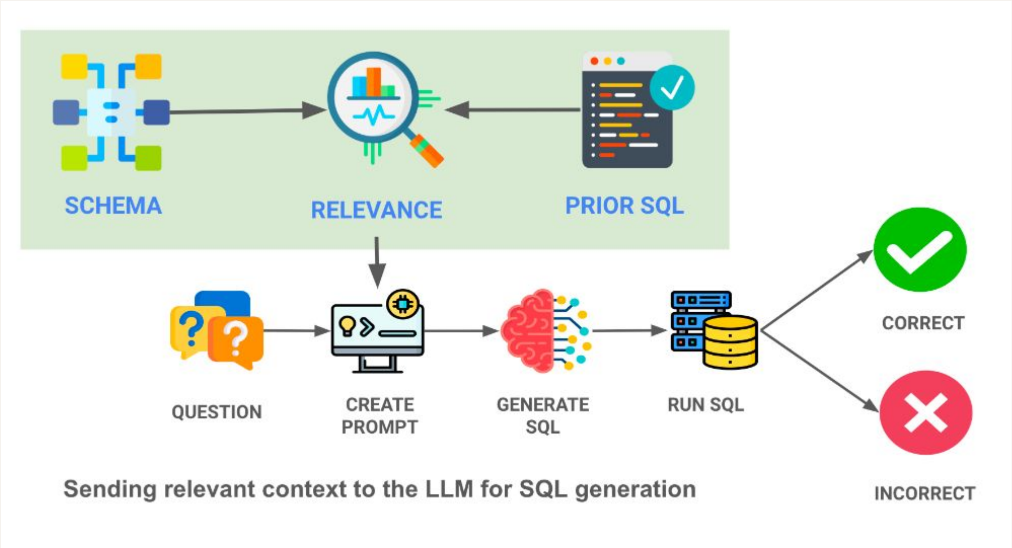
Data Analyst Agent



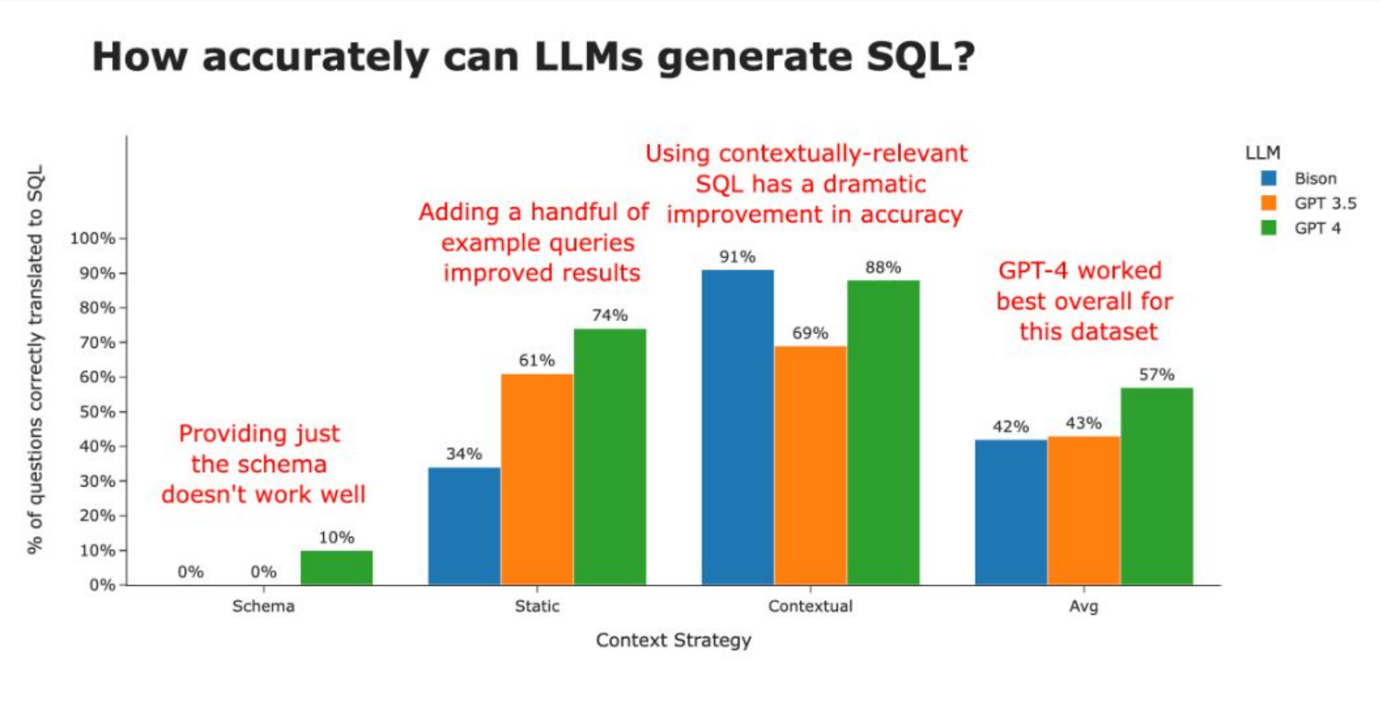
Method: Part 2

SQL Agent

- Due to time constraints, I used Vanna.AI's RAG-augmented, trainable text2SQL agent [7]



SQL Agent



How accurately can LLMs generate SQL?
% of questions correctly translated to SQL
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Providing just the schema doesn't work well
Adding a handful of example queries improved results
Using contextually-relevant SQL has a dramatic improvement in accuracy
GPT-4 worked best overall for this dataset
0%
0%
10%
34%
61%
74%
91%
69%
88%
42%
43%
57%
Schema
Static
Contextual
Avg
Context Strategy
LLM
Bison
GPT 3.5
GPT 4

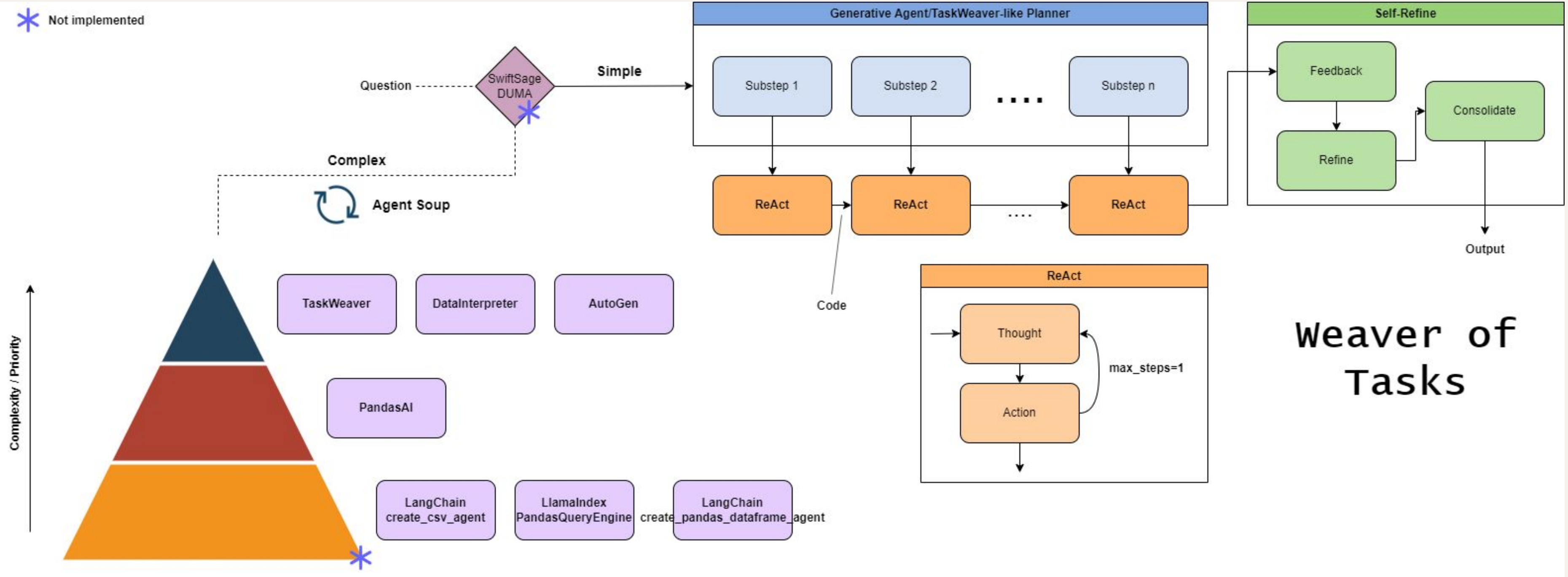
Method: Part 3

Search Agent

- Due to time constraints, I opted for LangChain's create_csv_agent augmented with You.com search and OpenWeatherMap APIs

Discussion & Limitations

Method: Part 1



Method: Part 1 Cont.

Limitations

- Custom-crafted agent derived from a mix of literature
- Not benchmarked and tested
- Lacks complexity/performance of more complex agents like TaskWeaver, DataInterpreter, and AutoGen [5, 6, 10]

Future Directions

- Adopt SwiftSage/DUMA [8, 9] Fast-mind/Slow-mind architecture; Slow-mind utilizes a complex agent like TaskWeaver, DataInterpreter, and AutoGen [5, 6, 10] (refer to previous slide)
- Thoroughly benchmark agent on Python data analysis/code generation benchmarks like HumanEval, MBPP, DataScienceProblems (DSP) [12, 13, 14]
- Experiment with open-source LLMs fine-tuned on code generation/data analysis as fast-thinkers (compute-efficient) like StarCoder [15]
- Experiment with agent fine-tuning methods like AgentTuning, FireAct, etc [16, 17]

Method: Part 2

Limitations

- High-level, abstracted, and managed Text2SQL agent separate from Method: Part 1
- Not benchmarked and tested on SQL generation and SQL-instruction-following tasks

Future Directions

- Refer to recent works in LLM-based agent SQL systems like AutoGen [10], MAC-SQL [11], and [20]
- Thoroughly benchmark Text2SQL agent on SQL-instruction-following generation benchmarks like WikiSQL [18] and [19]
- Experiment with compute-efficient open-source alternatives like StarCoder [15] fine-tuned on instruction-following SQL generation
- Tinker with a monolithic agent system (Part 1 and Part 2) or a distributed system

Method: Part 3

Limitations

- High-level, abstracted, and managed search agent separate from Method: Part 1 and Part 2
- Not benchmarked and tested on tool-use and retrieval-based tasks

Future Directions

- Refer to recent works in LLM-based agent SQL systems like AutoGen [10]
- Thoroughly benchmark search aspects of the agent on tool-use and retrieval task benchmarks like RoTBench [21], ToolQA [22], and RGB [23]
- Experiment with compute-efficient open-source alternatives like StarCoder [15] fine-tuned on retrieval-related tasks and tool-use
- Tinker with a monolithic agent system (Part 1 and Part 2) or a distributed system

In summary…

- Thoroughly explore current novel methods along multiple dimensions (code generation, Text2SQL, tool-use, and retrieval)
- Comprehensively benchmark along all relevant dimensions with popular benchmarks
- Tinker with open source alternatives as a more compute-efficient strategy
- Along any particular dimension, ablate existing state-of-the-art methods

Conclusion

Ideas for Future Work

- Dynamic Plan Generation/Updating like in Data Interpreter [6]
- Code generation verification/refinement and extensible plugins like in TaskWeaver [5]
- Synthesize & implement findings from Vanna.AI
  - RAG-based fewshot examples
  - Experiment with performant domain-specific instruction-following LLMs
- Incorporate Experiential/Continual Learning like the ExpeL Agent
- Though cost-inefficient, it would be interesting to try an Agent Soup/Ensemble (like a Model Soup) like More Agents Is All You Need [25] possibly with smart ensembling (model merging methods?)
- Leveraging agentic fine-tuning methods to further optimize compute-efficient open source LLM alternatives like AgentTuning and FireAct [16, 17] and many more [26, 27, 28, 29, 30]
- Investigate the impacts of developing a multi-agent system vs. single agent systems
  - How does a multi-agent system compare to a single agent for tool-use, retrieval, and code generation?
  - Explore into different language models and alternative architectures like RWKV or Mamba [31, 32] (underexplored for agentic tasks)
- Develop a UI with Streamlit/Chainlit/Flask 😔

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