Chameleon Concierge: Retrieval-Augmented Generation (RAG) To Enhance Open Testbed Documentation

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References

Good Infrastructure Demands Good Documentation

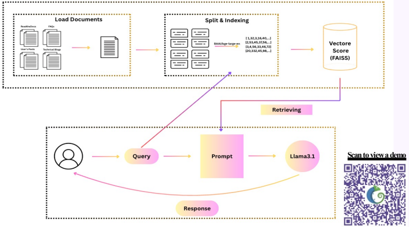
- ❖ Computing infrastructure for open science enables complex, large-scale experiments in computer and domain sciences
- ❖ Experimental design and methodology selection for testbeds requires expertise across multiple technical resource types
- ❖ Researchers need guidance to match their experimental hypotheses with appropriate infrastructure resources, configurations, and methodologies

Where Do Researchers Struggle?

- ❖ **Searching for comprehensive technical solutions** across multiple, disparate documentation sources is a challenge
- ❖ Leads to opening a support ticket or project abandonment**, redirecting infrastructure operators away from other key operations and reducing research impacts**
- ❖ **Solution**: implement a custom **LLM search service** for documentation to generate **accurate and cited responses to natural language queries**

How Can Advances in LLMs and RAG Help?

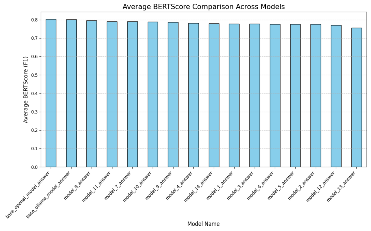
- ❖ Combine conventional (ReadtheDocs) and non-convention (usage data; user tickets) docs for efficient information search to user queries
- ❖ Pull relevant "slices" of information from diverse sources that respond most comprehensively to the user's question
- ❖ Pass along context and sources with question to an LLM to generate a robust response with direct links to sources and up-to-date info



Scan to view a demo

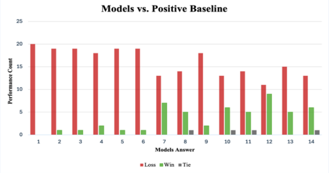
Grading the System's Answers

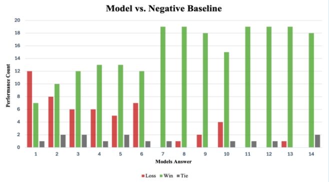
Statistical metrics for textual distances to evaluate quality:



- ❖ Compared RAG model with 20 reference answers to common questions
- ❖ Calculated statistical similarity to compare answers, i.e., BERTScore, but metrics were of limited value for evaluating the system
- ❖ Utilized LLM as a Judge (Claude 3.5 Sonnet) to compare positive baseline (expected best performance), negative baseline (expected to perform worst), and RAG answers (see images on the right)
- ❖ LLM Judge score winning answers by "win", "loss", and "tie" between the baselines and the RAG answers

LLM-as-a-Judge to compare pairwise and select best answer of each match-up:





Insights

Summary:

- ❖ RAG models generated **accurate and cited answers to a variety of user queries**
- ❖ The similarity metrics were not sufficient to determine compare performance; **Judge method provides more meaning evaluation results to determine system quality**
- ❖ Top RAG performance is higher than that of a generic LLM and **comparable to a free-tier proprietary LLM**
- ❖ RAG systems designed around high-quality documentation sources can fill the gap between the researchers' knowledge and limitations of static documentation
- ❖ RAG is not a guaranteed replacement for existing proprietary models, but optimized correctly, one can yield definite benefits

Future work:

- ❖ Enhance data sources by including specialized data (i.e., user ticket data sanitized to remove private data)
- ❖ Explore new generation designs and other evaluation methods through user-provided rankings of answers

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