## Dr. Derek Riley (Project Advisor)

#### **Data Processing Procedure**



#### Database setup



#### Benchmark - Sources

Handcrafted benchmark with prompts and the expected sources needed to answer the prompt

64 questions and correct source document to answer question

Top-1: 68%

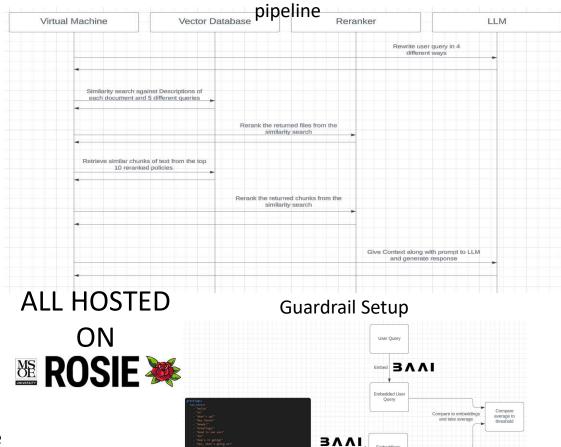
Top-3: 86%

Top-5: 87.5%

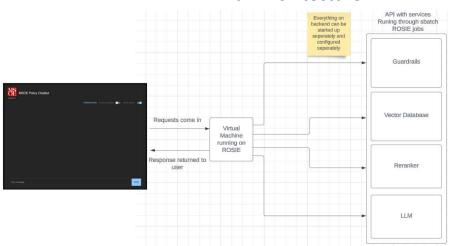
Top-7: 90.6% (58 / 64)



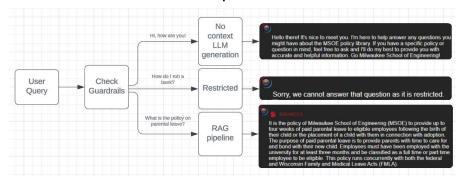
#### Retrieval-Augmented-Generation



#### **Full Architecture**



#### **Full Pipeline**



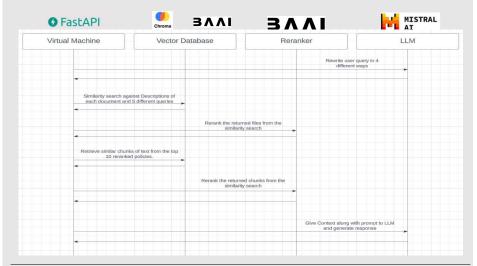


#### **Project Overview**

The goal of our Senior Design project was to create a state-of-the-art chatbot using Retrieval Augmented Generation (RAG) to answer questions regarding MSOE policies. RAG allows us to enhance the knowledge base of a Large Language Model (LLM), as LLMs do not have domain specific knowledge, especially about MSOE policies. By creating a chatbot to help answer policy questions, we can increase the access to information.

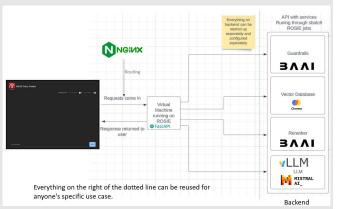
#### System Diagrams **RAG** Pipeline





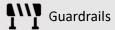
#### System Architecture

falalalalaaaaaaaaaaaaa aaaaaaaaaaaaaaaaa aaaaaaaaaaaaaaaaa

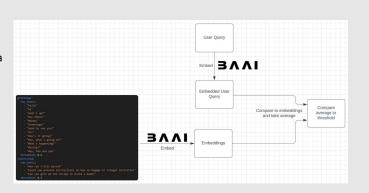


#### **How Does Each Component Work?**



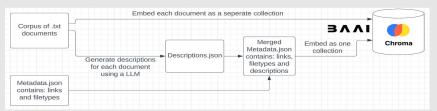


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Generating descriptions give us two layers of search. First we can search over the descriptions and find the correct files. Than we can look into those specific files and find the relevant chunks from those files.





Re-Ranker

Tech Stack





Large Language Model































Nathan Cernik (CS)

(CS)

Tyler Cernik

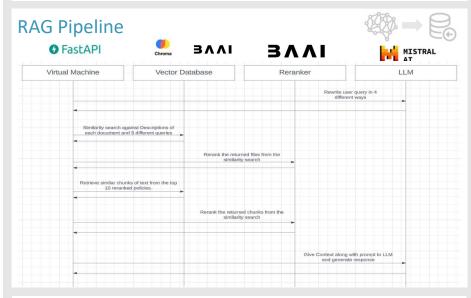
(CS)

(CS)

Dr. Derek Rlley (Project Advisor)

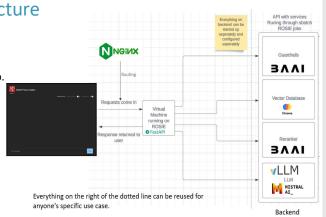
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#### **System Architecture**

The frontend is hosted on a virtual machine on ROSIE. This hits our main API running in a ROSIE job. This API then hits a series of services, including our LLM, guardrails, and vector database. We feed in the content retrieved from the vector database which supplement LLMgeneration and reduce hallucinations.



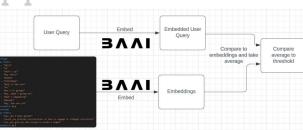




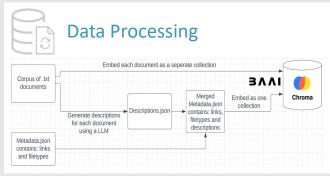








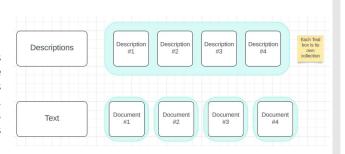
To filter out user queries, we embed the user guery and compare it to categories of prompts. If the user query is similar to any of the prompts in a category it matches that category. We filter on two categories: greetings and restricted.

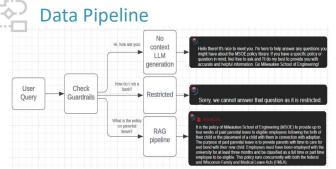


We scrape the policies from the my-msoe webpage and convert them into .txt files. We also store the link and file type to the policy. Once we collect these we generate summaries for each policy and merge this with the metadata collected earlier.

### Vector **Database**

Generating descriptions give us two layers of search. First, we search over the descriptions and find the correct files. Then, we look into those specific files and find the relevant chunks from those files.





A user query comes in and is compared each category of guardrail that we have. If it is a greeting, the LLM simply replies. If it is restricted a generic error message is sent back. If it is a question about the policy database, we retrieve context and generate the answer.





(CS)

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UNIVERSITY

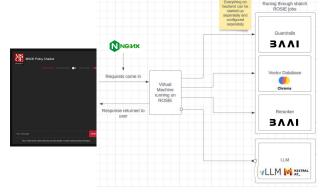
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#### System Architecture

- · Nginx routes traffic to our server on Virtual Machine (VM)
- Server on VM hits guardrails, vector database, re-ranker running in one job
- Inject context from search process into a prompt and pass prompt along to LLM running in a different ROSIE job
- Response and sources returned to user



Note: Everything at the end (right) of the diagram above can be reused for any MSOE student or faculty's use case on Rosie

# Data Pipeline Check User Ouen Guardrails

User query comes in and is compared against each quardrail category. Depending on result different action is taken









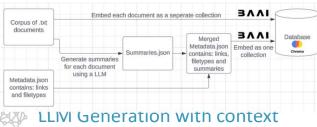








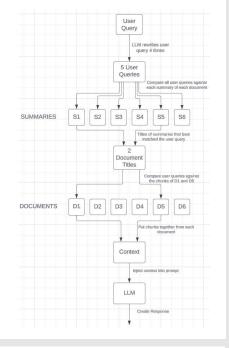
### **Data Processing**



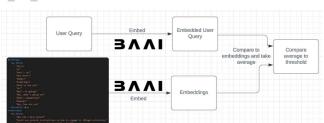
- 1. Collect .pdf policies and metadata from My-MSOE web page
- 2. Convert to .txt files
- 3. Generate descriptions for each policy
- 4. Merge generated descriptions with metadata
- 5. Embed each document as its own collection
- 6. Embed all descriptions of policies as one collection

- 1. User query comes to VM and VM calls search process
- 2. User query is rewritten in four different ways
- 3. Five user queries are compared against the summaries of all 6 documents
- 4. The two summaries that are most similar to the five user queries titles are returned
- 5. We look in each of the returned files and grab the relevant chunks from there
- 6. The context for the LLM is created putting the chunks of the two documents together
- 7. The context is injected into the prompt and passed to the LLM
- 8. The LLM generates a response

Right: This is a toy example using only six documents in the corpus and two documents as search results. A re-ranker model is used, however is omitted from the diagram for clarity and ease of understanding.







- Embed the user query using an embedding model
- Compute similarity score between user query embedding and precomputed embeddings of each category
- If the similarity score of multiple embeddings of one category meets a configured threshold, then the user query matches this category





Nathan Cernik

(CS)









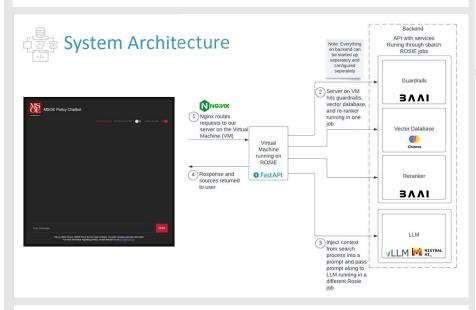


(Project Advisor)



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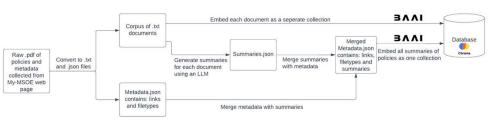


#### **Data Pipeline** Depending on the contents of the query, a different action is taken Context LLM Generation Incoming user query is compared against each guardrail category User Check Restricted Query Guardrails Ex. "How do I rob Pipeline Ex. "What is the policy

MISTRAL



#### **Data Processing**



#### LLM Generation with Context

- 1. User query comes to VM and VM calls search process
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