Requirement Discovery Using Embedded Knowledge Graph with ChatGPT

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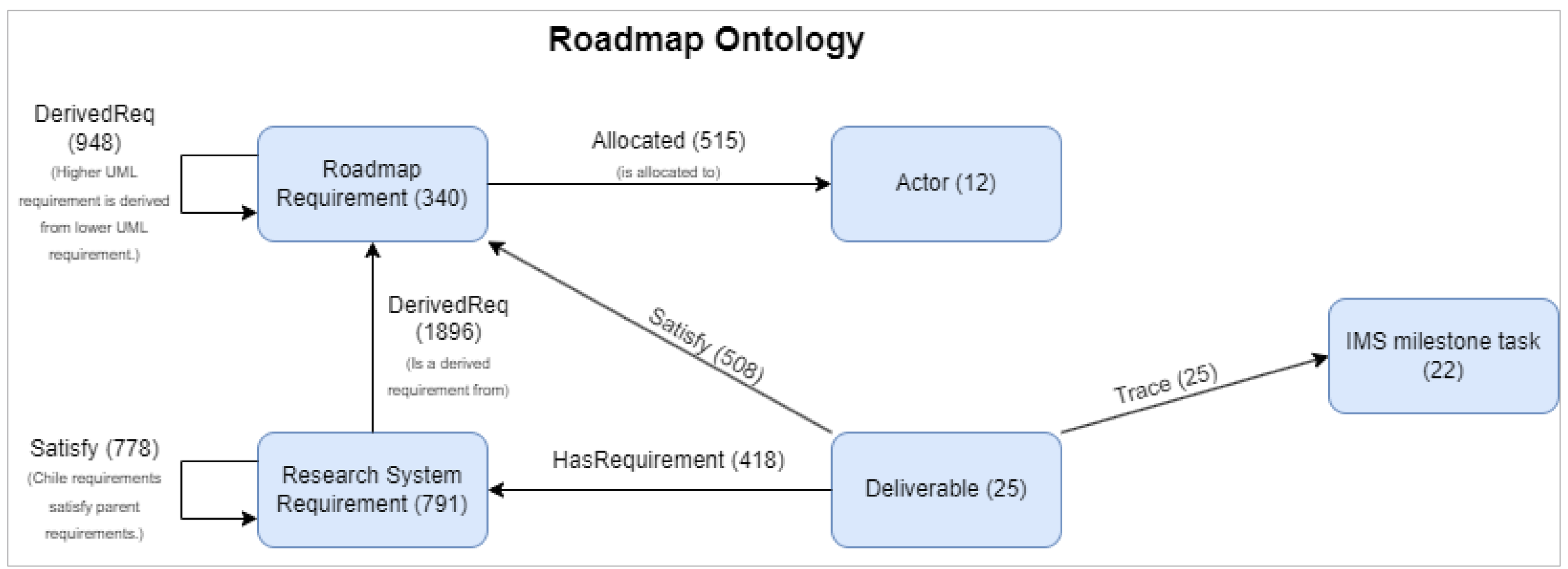
PURPOSE / PROBLEM

- NASA's Air Traffic Management-Exploration (ATM-X) project is conducting research that evolves the Urban Air Mobility (UAM) air traffic management system towards a highly automated and operationally flexible system of the future.
- The UAM airspace system research roadmap, or just roadmap, is a system engineering methodology to manage what is known, what is developed, and what is planned in NASA's UAM airspace research & development (R&D) lifecycle. The roadmap can be seen below, node / relationship counts are in parentheses.



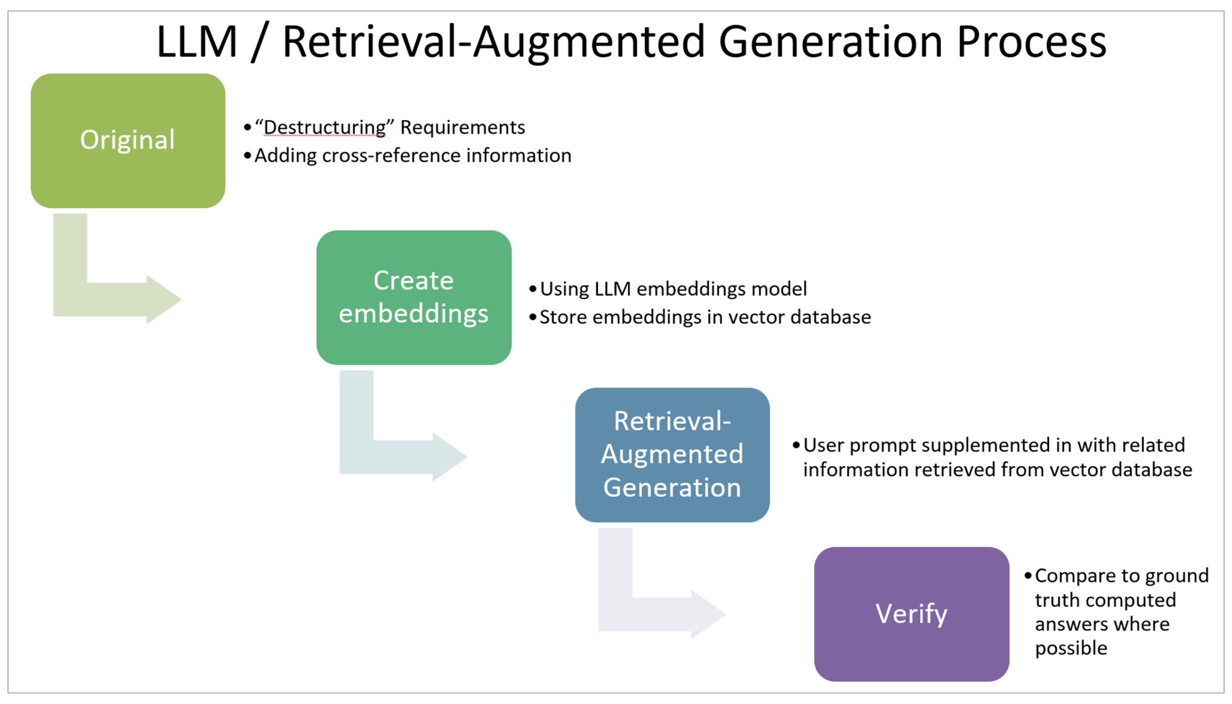
- System Engineers (SEs) are worried that they might miss dependencies when developing the UAM roadmap. SEs have limited bandwidth to perform requirement analysis, so we need to find a way to lighten the workload by providing a system that can analyze the roadmap for missing requirements and links.

OBJECTIVES / GOALS

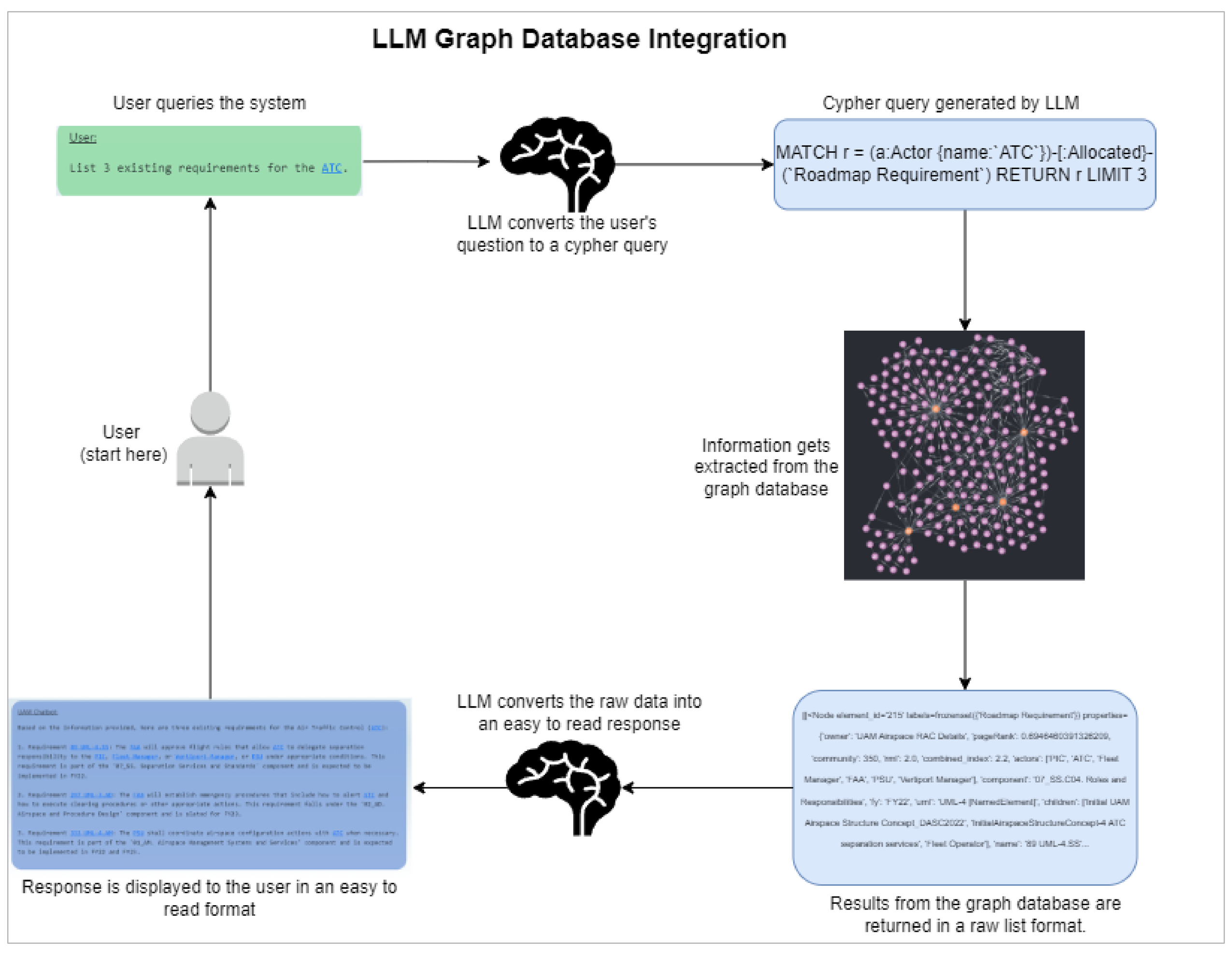
- This research introduces the utilization of Large Language Models (LLMs), such as OpenAI's GPT-4, to enhance the UAM Requirement discovery process.

METHODS / DESCRIPTION

- Two approaches were investigated:
- **Approach 1:** Utilize a vector store to provide relevant information to the LLM based on the user's question, a process known as Retrieval Augmented Generation (RAG).



- **Approach 2**: Integrate the LLM with a graph database. The LLM acts as an intermediary between the user and the graph database, translating user questions into cypher queries for the database and database responses into human-readable answers for the user.



DATA / RESULTS

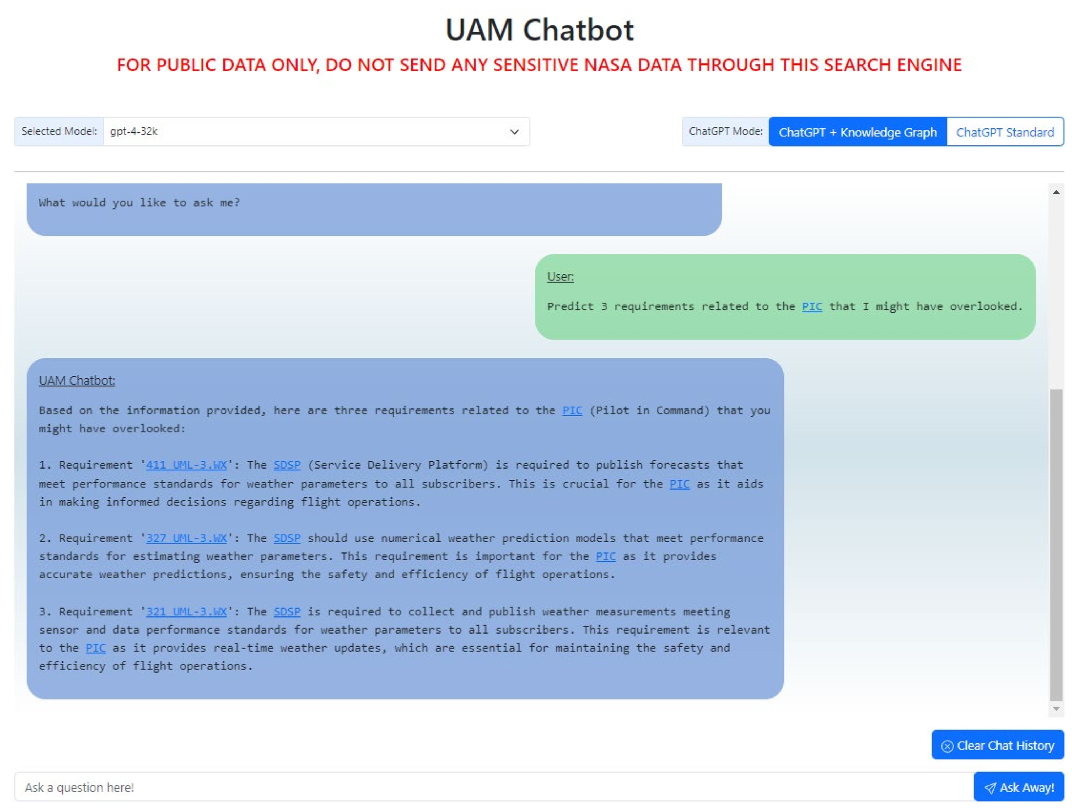
- **Approach 1, LLM with RAG (Azure OpenAI GPT-4) -** More capable of answering generalized questions, however, fell short when it came to numerical analysis, finding existing links, or questions that required advanced graph analysis techniques such as requirement generation using link prediction.
- **Approach 2, Graph Database / Data Science + LLM (Azure OpenAI GPT-4) –** Requires additional setup, cost, and on-going maintenance, but proved to be the better solution for our specific use-case. Approach 2 was able to answer all questions from our test set as seen in the table below.

Approach response comparisons

User Question	Approach 1: LLM with RAG (Azure OpenAI GPT-4)	Approach 2: Graph Database / Data Science + LLM (Azure OpenAI GPT-4)
How many unique requirements do we have for the System?	Capable of answering	Capable of answering
How many unique system actors do we have?	Capable of answering	Capable of answering
Please list the unique system actors	Capable of answering	Capable of answering
Give me 5 requirements with multiple actors.	Capable of answering	Capable of answering
Find all requirements where one actor is UAM Aircraft	Only Finds 4 of 6	Capable of answering
Predict five requirements for UAM Aircraft that I may have missed	Not able to answer	Capable of answering
Create five new requirements for UAM Aircraft	Capable of answering	Capable of answering
Summarize the responsibilities of the UAM Operator	Capable of answering	Capable of answering, requires two separate questions from the user.

Color Key: Acceptable Answer - | Partially Acceptable Answer - | Unacceptable Answer -

- Approach 2 was deployed internally as a web-application, the interface for the web application can be seen below.



CONCLUSIONS

- Observed 7x improvement in the speed of which SEs navigate the UAM roadmap and in some cases the LLM exhibited more creativity than human user when generating requirements.
- Allows users to access powerful graph data algorithms, like link prediction, without having to know the complex cypher query language needed to access those methods traditionally.
- Reduces the likelihood of hallucinations from the LLM by coupling it with an authoritative data source (graph database).

CONTACTS / REFERENCES

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