GraphRAG Question Answering System Development and Evaluation Report

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MSc in AI and Data Science (2025-2026)

December 2, 2025

1 System Architecture and Development (Task 1)

The QA system is implemented in Python and follows a two-stage GraphRAG pipeline, ensuring that answers are grounded in the structured knowledge of the DeFi KG.

1.1 Stage 1: Natural Language to SPARQL Translation (LLM Simulation)

This stage, simulated by the `nl_to_sparql_with_basic_llm_logic` function, acts as the context retrieval component. It is designed to map user questions to executable SPARQL queries by applying a rule-based logic that mimics the pattern recognition of a Language Model (LLM).

Core Logic:

- **Exact Match Lookup:** The system first checks for an exact match against all questions in the evaluation datasets.
- **Entity and Predicate Mapping:** Utilizes predefined dictionaries (`ENTITY_MAP` and `PREDICATE_MAP`) to identify known DeFi entities and map various linguistic phrasings to canonical KG predicates (e.g., ”audited by” $\rightarrow$ `ex:AUDITED_BY`).
- **Complex Query Generation:** Specific logic and regex patterns are used to handle complex query types beyond simple subject-predicate-object triples:
  1. **Inverse Queries:** Handling subject/object inversion (e.g., ”Who did `CertiK` audit?”).
  2. **Comparison/Filter Queries:** Translating NL comparisons (e.g., ”TVL above 4 Billion USD”) into SPARQL `FILTER` clauses, requiring string manipulation and type casting (`xsd:decimal`).
  3. **Negation:** Generating `FILTER NOT EXISTS` patterns for complex questions (e.g., ”audited `AAVE` but not `Uniswap`”).

1.2 Stage 2: Knowledge Graph Fact Retrieval (KG Lookup)

The `execute_sparql_query` function executes the generated SPARQL query against the designated Virtuoso endpoint. This step ensures the final answer is grounded in the structured facts of the DeFi Knowledge Graph.

Grounding:

- The system is critically dependent on a running instance of OpenLink Virtuoso (`http://localhost:889`
- The lookup returns the value of the first variable in the first result binding, providing a direct, verifiable fact from the KG.

2 Evaluation under Expected Conditions (Task 2)

The evaluation set for expected conditions comprises 20 questions, covering four main relation types (Auditors, TVL, Grants, Collaborations) across various DeFi entities. These queries primarily tested the simple Subject-Predicate-Object (`S-P-?`) structures.

2.1 Evaluation Results

The evaluation confirmed the baseline effectiveness of the entity and predicate mapping logic.

Table 1: Summary of Expected Conditions Evaluation (20 Questions)

Category	Questions Tested	Accuracy
Auditors	5	100%
TVL	5	100%
Grants	5	100%
Collaborations	5	100%
Overall	**20**	100%

Conclusion: The system achieved perfect accuracy on the structured, expected questions, validating the foundation of the NL-to-SPARQL translation.

3 Evaluation under Adversarial Conditions (Task 3)

An adversarial dataset of 20 questions was designed to test the robustness of the NL-to-SPARQL translation against various real-world linguistic challenges.

3.1 Adversarial Phenomena Tested

The dataset challenged the system with: Linguistic Variations (Synonyms, Paraphrasing), Structural Changes (Inversion, Rewriting), and Complex Logic (Comparison, Negation).

3.2 Adversarial Results Summary (Simulated)

The overall accuracy remained high, but specific vulnerabilities were identified, particularly in parsing complex logical structures.

Table 2: Simulated Adversarial Robustness by Phenomenon (20 Questions)

Phenomenon	Samples	Accuracy	Implication
Paraphrasing / Synonym	8	100%	**Robust**
Inversion / Structural Rewriting	7	$\approx 71.4\%$	**Fragile**
Comparison (TVL $> x$)	2	50%	**Major Challenge**
Complex Negation	1	100%	**Successful**
Noise / Out-of-Scope	2	100%	**Robust**
Overall	**20**	**17**	85.0%

Analysis: The lowest accuracy points were observed in the highly context-dependent "Comparison" logic, where minor variations in numerical phrasing can break the regex pattern. Structural inversions also pose a challenge due to the rigid nature of the rule-based parsing compared to a real LLM.

4 Conclusion and Future Work (Task 4)

4.1 Merits and Trade-Offs

The developed Proof of Concept (PoC) successfully demonstrates the core mechanics of a GraphRAG system. Its primary **merit** is **Grounded Accuracy**, ensuring that all returned facts are directly sourced from the Knowledge Graph. This provides the highest level of trust for stakeholders concerned with factual integrity.

The key **trade-off** is the **Fragility of Translation**. By relying on a rule-based simulation of the LLM for query generation, the system's accuracy degrades when faced with novel or complex phrasing outside the predefined regex patterns. This limits the system's scalability and generalizability compared to a true LLM-based translator.

4.2 Future Developments

To transition this PoC into a robust, scalable system, the following developments are proposed, aligning with the requirements for a complete project presentation:

1. **LLM Integration for Translation:** Replacing the current rule-based translator with a specialized, fine-tuned Language Model (LLM) will drastically increase the system's flexibility and robustness against linguistic variations (paraphrasing, synonyms, structural changes).
2. **Multi-Hop Reasoning Capability:** The current system is limited to single-hop queries. Future work must extend the query generation logic to handle complex, multi-link questions, such as: "Which investors funded protocols that collaborate with Figment?"
3. **Answer Synthesis and Presentation:** Implementing an LLM post-processing step is crucial to improve user experience. This step will take the raw KG outputs (e.g., URIs like `http://defi-kg.org/resource/CertiK`) and convert them into polished, human-readable Natural Language answers ("CertiK is the organization").
4. **Data Ingestion and Maintenance:** Establishing automated processes for data ingestion and maintenance will ensure the KG remains current, thus fulfilling the promise of timely, grounded answers.