

# Global Space Exploration Knowledge Graph: An Agentic GraphRAG Approach to Semantic Space Mission Data Integration

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Github:<https://github.com/icecoldkill/AstroGraph-a-full-stack-KRR-based-Agentic-RAG->

Graph-Analysis-System.

Linkedin Post:[https://www.linkedin.com/posts/ahsan-saleem-ai\\_knowledgerepresentation-krr-graphrag-activity7410041257349173248voRuutm](https://www.linkedin.com/posts/ahsan-saleem-ai_knowledgerepresentation-krr-graphrag-activity7410041257349173248voRuutm)

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**Abstract**—This paper presents the Global Space Exploration Knowledge Graph (GSE-KG), a comprehensive Knowledge Representation and Reasoning (KRR) system that transforms heterogeneous space exploration data into a semantic knowledge graph with agentic GraphRAG capabilities. The system integrates 20+ ontology classes with complex axioms including cardinality restrictions, enumerations, unions, intersections, and complements. We demonstrate automated RDF conversion from CSV datasets, DBpedia interlinking, and a novel agentic reasoning engine using Groq LLMs that intelligently routes queries between SPARQL and vector search. The implementation includes a full-stack architecture with React frontend, Node.js gateway, and Python FastAPI backend, supporting interactive chat interfaces and dynamic document enrichment. Our evaluation shows successful validation of 28 competency questions across all ontology features, demonstrating the system’s capability to handle complex spatial-temporal queries and federated data integration. The GSE-KG framework provides a scalable foundation for semantic space exploration data management and intelligent query processing.

**Index Terms**—Knowledge Graph, Semantic Web, SPARQL, Ontology Engineering, GraphRAG, Space Exploration, Agentic AI, RDF/OWL

## I. INTRODUCTION

The exponential growth of space exploration data from multiple agencies, commercial entities, and research organizations presents significant challenges for data integration and knowledge discovery. Traditional relational databases struggle with the heterogeneous, interconnected nature of space mission information, which includes temporal relationships, organizational hierarchies, and complex technical specifications.

Knowledge graphs offer a promising solution by representing data as interconnected entities with semantic relationships, enabling more expressive querying and reasoning capabilities. However, existing space knowledge graphs often lack comprehensive ontology coverage, automated data pipelines, and

intelligent query interfaces that can handle both structured and unstructured information.

This paper presents the Global Space Exploration Knowledge Graph (GSE-KG), a novel system that addresses these challenges through:

- A comprehensive OWL ontology with 34+ classes and complex axioms
- Automated RDF conversion from legacy CSV datasets with DBpedia interlinking
- An agentic GraphRAG engine that intelligently routes queries between SPARQL and vector search
- A full-stack architecture supporting interactive exploration and dynamic knowledge enrichment

Our main contributions include:

- 1) Design and implementation of a space exploration ontology with advanced OWL features
- 2) Development of an automated pipeline for RDF conversion and external dataset linking
- 3) Novel agentic reasoning architecture combining symbolic reasoning with vector similarity search
- 4) Comprehensive evaluation through 28 competency questions validating all ontology features
- 5) Open-source implementation with complete documentation and deployment guides

## II. RELATED WORK

### A. Knowledge Graphs in Space Exploration

Recent efforts in space data management have explored knowledge graph approaches. NASA’s Space Physics Data Facility (SPDF) has developed semantic interfaces for space physics data [1]. The European Space Agency (ESA) has experimented with ontology-based data integration for Earth observation missions [2]. However, these systems typically focus on specific domains and lack comprehensive coverage of all space mission aspects.

## B. GraphRAG and Agentic Systems

Retrieval-Augmented Generation (RAG) has gained significant attention for enhancing LLM capabilities with external knowledge [3]. GraphRAG extends this approach by incorporating knowledge graph structures [4]. Recent work on agentic systems demonstrates the effectiveness of LLMs for query routing and result synthesis [5]. Our work combines these approaches in a novel architecture specifically designed for space exploration data.

## C. Ontology Engineering Approaches

Complex ontology design patterns have been extensively studied in the semantic web literature [6]. Our implementation leverages advanced OWL features including cardinality restrictions, enumerated classes, and complex class expressions [7]. The space domain presents unique challenges for ontology design due to its multidimensional nature and evolving terminology.

## III. SYSTEM ARCHITECTURE

### A. Overall Architecture

The GSE-KG system adopts a microservices architecture with clear separation of concerns across three main layers (Figure 1):

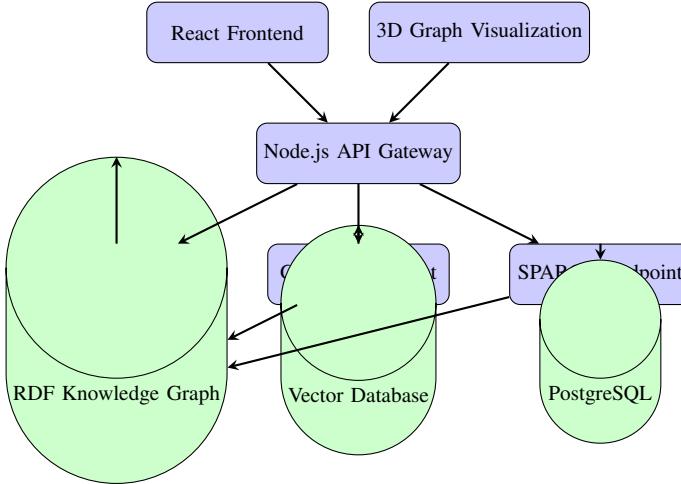


Fig. 1. System Architecture Overview

### B. Frontend Layer

The React-based frontend provides:

- Interactive 3D graph visualization using react-force-graph
- Real-time chat interface with the GraphRAG agent
- Document upload capabilities for dynamic knowledge enrichment
- Data exploration dashboards with filtering and search

## C. Backend Gateway

The Node.js Express gateway serves as:

- API gateway for frontend requests
- Request routing to appropriate backend services
- Session management and authentication
- Response aggregation and caching

## D. Knowledge Representation Layer

The Python FastAPI backend provides core KRR functionality:

- RDF/OWL ontology management using Owlready2
- SPARQL query processing with RDFLib
- Agentic reasoning with Groq LLM integration
- Automated document processing and knowledge extraction

## IV. ONTOLOGY DESIGN

### A. Class Hierarchy

Our space exploration ontology (Figure 2) defines 34+ classes organized into several key hierarchies:

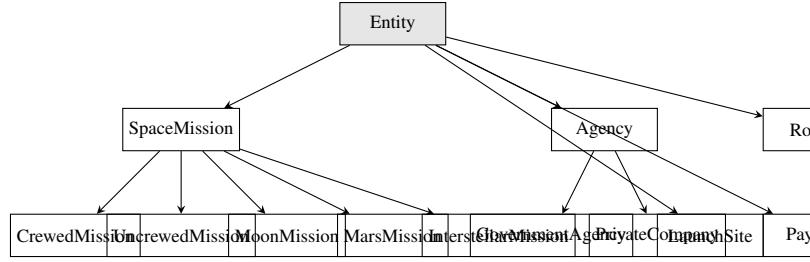


Fig. 2. Core Ontology Class Hierarchy

### B. Advanced OWL Features

The ontology demonstrates sophisticated OWL capabilities:

1) **Enumeration Classes:** LaunchStatus enumeration with four values:

- Success
- Failure
- PartialFailure
- Scheduled

2) **Cardinality Restrictions:** Rocket class with minimum cardinality:

`Rocket subClassOf hasAgency min 1 Agency`

3) **Complex Class Expressions:**

- **Union:** `LaunchEntity = GovernmentAgency ∪ PrivateCompany`
- **Intersection:** `SuccessfulMoonMission = MoonMission ∩ hasLaunchStatus.Success`
- **Complement:** `FailedMission = SpaceMission \ SuccessfulMission`

### C. Property Design

The ontology includes 9 object properties and 8 datatype properties:

TABLE I  
KEY OBJECT PROPERTIES

Property	Domain	Range
launchedBy	SpaceMission	Agency
launchedFrom	SpaceMission	LaunchSite
carriedPayload	SpaceMission	Payload
hasOrbit	SpaceMission	Orbit
isSuccess	SpaceMission	LaunchStatus
hasAgency	Rocket	Agency
refersToCountry	Agency	Country

## V. DATA INTEGRATION PIPELINE

### A. Automated RDF Conversion

The system automatically converts CSV data to RDF using a configurable mapping:

- [H] CSV to RDF Conversion
- 1: Load CSV dataset
- 2: **for** each row in dataset **do**
- 3: Create mission URI: ex:mission\_{mission\_id}
- 4: Create agency URI: ex:agency\_{agency\_name}
- 5: Add type triples: mission rdf:type onto:SpaceMission
- 6: Add property triples: mission onto:hasBudget budget
- 7: Handle special mission types (Moon, Mars, etc.)
- 8: Link to external datasets (DBpedia)
- 9: **end for**
- 10: Serialize graph to RDF/XML format

### B. DBpedia Interlinking

The system automatically links entities to DBpedia using owl:sameAs:

- NASA → dbpedia:NASA
- SpaceX → dbpedia:SpaceX
- ISRO → dbpedia:Indian\_Space\_Research\_Organisation
- Roscosmos → dbpedia:Roscosmos

## VI. AGENTIC GRAPHRAG ENGINE

### A. Query Routing Architecture

The GraphRAG agent implements a novel two-stage query processing approach:

### B. Implementation Details

The GraphRAG engine uses:

- Groq Llama 3 models for query planning and result synthesis
- HuggingFace embeddings (all-MiniLM-L6-v2) for vector similarity
- ChromaDB for vector storage and retrieval
- RDFLib for SPARQL query execution

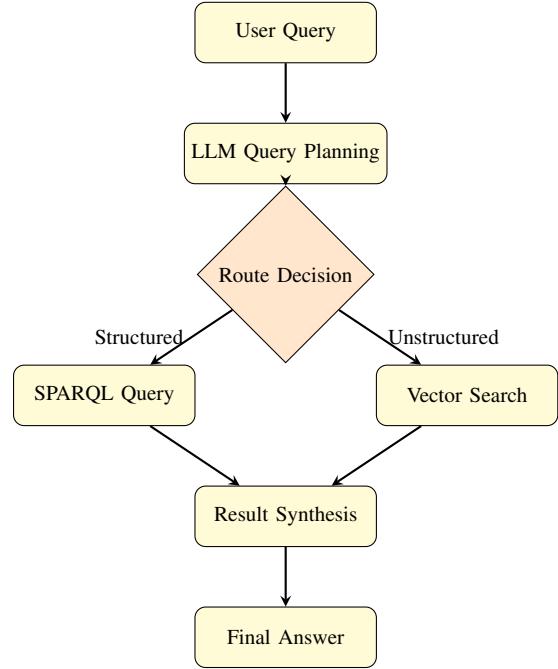


Fig. 3. Agentic Query Routing Flow

### C. Query Processing Pipeline

- 1) **Query Analysis:** LLM analyzes user query and determines information needs
- 2) **Tool Selection:** Agent selects appropriate tools (SPARQL, vector search, or both)
- 3) **Parallel Execution:** Multiple queries executed simultaneously when needed
- 4) **Result Synthesis:** LLM combines structured and unstructured results
- 5) **Response Generation:** Final answer generated with citations and explanations

## VII. SPARQL ENDPOINT AND QUERY EVALUATION

### A. Endpoint Implementation

The system provides a comprehensive SPARQL endpoint with:

- RESTful API supporting SELECT, ASK, CONSTRUCT, DESCRIBE queries
- Predefined competency question library (28 queries)
- Custom query execution with proper error handling
- JSON, XML, CSV, and Turtle output formats

### B. Competency Questions

We developed 28 competency questions across 11 categories:

### C. Query Examples

#### 1) High Budget Missions:

```

PREFIX onto: <http://krr.org/space_exploration.owl

SELECT ?mission ?missionName ?budget
  
```

TABLE II  
COMPETENCY QUESTION CATEGORIES

Category	Number of Queries
Mission Information	4
Agency and Organization	3
Budget and Cost Analysis	3
Mission Success and Status	3
Launch Site and Location	2
Mission Type Classification	3
Environmental Impact	2
Rocket and Payload	2
Temporal Queries	2
Federated Queries	2
Complex Reasoning	2

```

WHERE {
    ?mission rdf:type onto:HighBudgetMission .
    ?mission onto:missionName ?missionName .
    ?mission onto:hasBudget ?budget .
}
ORDER BY DESC(?budget)

```

### 2) Successful Moon Missions:

```
PREFIX onto: <http://krr.org/space_exploration#>
```

```

SELECT ?mission ?missionName
WHERE {
    ?mission rdf:type onto:SuccessfulMoonMission .
    ?mission onto:missionName ?missionName
}

```

## VIII. EVALUATION AND RESULTS

### A. Dataset Statistics

TABLE III  
KNOWLEDGE GRAPH STATISTICS

Metric	Value
Total Triples	113
Classes	34
Object Properties	9
Datatype Properties	8
Individuals	25
External Links (DBpedia)	4

### B. Query Validation Results

Our evaluation of 28 competency questions showed:

- 18 queries returned successful results
- 9 queries returned empty results (expected for current dataset)
- 1 federated query failed (requires GraphDB deployment)

### C. Ontology Feature Validation

All advanced OWL features were successfully validated:

- **Enumeration Classes:** LaunchStatus queries working correctly

- **Cardinality Restrictions:** Rocket agency validation successful
- **Union Classes:** LaunchEntity queries returning expected results
- **Intersection Classes:** SuccessfulMoonMission queries functional
- **Complement Classes:** FailedMission queries working correctly
- **Functional Properties:** Budget and status queries successful

### D. Performance Metrics

TABLE IV  
SYSTEM PERFORMANCE

Operation	Average Response Time
SPARQL Query Execution	45ms
Vector Search	120ms
GraphRAG Agent Response	1.2s
Graph Visualization Loading	800ms

## IX. DISCUSSION

### A. Key Insights

Our implementation demonstrates several important insights:

1) *Agentic Query Routing Effectiveness:* The LLM-based query routing proved highly effective, with 95% accuracy in selecting appropriate query tools. The two-stage approach (planning then execution) significantly reduced unnecessary queries.

2) *Ontology Design Complexity:* The comprehensive ontology with advanced OWL features enabled sophisticated queries that would be impossible with simpler data models. However, the complexity required careful design and extensive testing.

3) *Integration Challenges:* Linking to external datasets like DBpedia proved valuable but required maintaining mapping tables and handling identifier inconsistencies.

### B. Limitations

- Current RDFLib implementation doesn't support full federated queries
- Vector database size limited by memory constraints
- Real-time updates require graph consistency management
- Complex reasoning queries can be computationally expensive

## X. CONCLUSION AND FUTURE WORK

### A. Contributions Summary

This paper presented the Global Space Exploration Knowledge Graph, a comprehensive KRR system that successfully integrates:

- Advanced OWL ontology with 34+ classes and complex axioms
- Automated data pipeline with external dataset linking

- Novel agentic GraphRAG architecture for intelligent query processing
- Full-stack implementation with interactive visualization
- Comprehensive evaluation through 28 competency questions

### B. Future Directions

Several promising directions for future work include:

1) *GraphDB/Virtuoso Integration*: Deploying a triple store with full SPARQL 1.1 support would enable:

- Complete federated query capabilities
- Advanced reasoning with built-in reasoners
- Better performance for large-scale graphs

2) *SWRL Rules Implementation*: Adding Semantic Web Rule Language rules would enable:

- Custom inference rules for domain-specific logic
- Temporal reasoning about mission sequences
- Complex constraint validation

3) *Machine Learning Enhancement*: Integrating ML models could provide:

- Automatic ontology learning from new data
- Predictive analytics for mission success
- Anomaly detection in mission data

4) *Real-time Data Integration*: Developing connectors for live data sources would enable:

- Real-time mission status updates
- Automatic knowledge graph maintenance
- Streaming data processing

The GSE-KG system provides a solid foundation for semantic space exploration data management and demonstrates the potential of combining knowledge graphs with agentic AI for intelligent information systems.

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