

# LLM Wrapper for Legal Documents: GraphRAG System Documentation

Technical Documentation

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# 1 System Overview

This document describes a **Graph Retrieval-Augmented Generation (GraphRAG)** system designed to process PDF documents, extract knowledge graphs, and enable intelligent question-answering. The system combines:

- **Neo4j** – Graph database for storing entities and relationships
- **Vector Stores** – For semantic similarity search
- **Multiple LLMs** – OpenAI, Claude, and Gemini for different tasks
- **LangChain** – Orchestration framework for LLM pipelines

## 2 Core Module: PDFGraphRAG

The PDFGraphRAG class (in `pdf_graphrag.py`) is the main entry point for processing documents and querying the knowledge graph.

### 2.1 Constructor and Initialization

Listing 1: Constructor signature

```
1 def __init__(self, vector_store_chunk_name, vector_store_nodes_name,
2               vector_store_relationships_name, neo4j_uri, neo4j_user,
3               neo4j_password, openai_api_key, google_api_key,
4               claude_api_key, advanced_search=False)
```

The constructor initializes:

1. **Neo4j Graph Connection** – Connects to the graph database
2. **OpenAI Embeddings** – Uses `text-embedding-3-large` model
3. **Vector Stores** – Three separate stores for chunks, nodes, and relationships
4. **LLM Clients**:
  - `openai_client` – GPT for question processing
  - `claude_client` – Claude Sonnet for graph transformation
  - `gemini_client` – Gemini Flash for general tasks
5. **Graph Transformer** – `LLMGraphTransformer` using Claude for entity extraction

### 2.2 PDF Processing Pipeline

#### 2.2.1 Loading PDFs

Listing 2: PDF loading function

```
1 def load_pdf(self, pdf_path: str):
2     loader = PyPDFLoader(pdf_path)
3     return loader.load()
```

Uses LangChain's `PyPDFLoader` to extract text content from PDF files.

### 2.2.2 Processing Pipeline

The `process_pdf()` method executes the following pipeline:

1. **Load PDF** – Extract raw text from document
2. **Chunk Text** – Split using `SpacyTextSplitter` for sentence-aware chunking
3. **For each chunk:**
  - Generate embedding vector
  - Create a **Chunk** node with text, embedding, and page metadata
  - Transform chunk into graph documents using `LLMGraphTransformer`
  - Create HAS relationships between chunks and extracted entities
4. **Store in Neo4j** – Add all graph documents to the database
5. **Update Vector Stores** – Index nodes and relationships for similarity search

Listing 3: Chunk node creation

```
1 chunk_node = Node(  
2     id=chunk_id,  
3     type="Chunk",  
4     properties={  
5         "text": document.page_content,  
6         "embedding": chunk_embedding,  
7         "page": document.metadata.get("page", 0)  
8     }  
9 )
```

## 2.3 Querying Functions

### 2.3.1 Graph Database Query

`query_graph_database(question)` converts natural language to Cypher queries using an LLM agent:

1. Retrieves graph schema (node labels, relationship types, sample data)
2. Creates an agent with a `search_database` tool
3. Agent iteratively explores the database with Cypher queries
4. Returns structured response with query, explanation, and data
5. Formats results into natural language answer

The agent uses a structured output schema:

Listing 4: Response schema structure

```
1 response_schema = {  
2     "cypher_query": "Final_Cypher_query",  
3     "explanation": "Query_strategy_explanation",  
4     "data": "JSON_string_of_results",  
5     "nodes_found": ["list", "of", "node", "ids"],  
6     "relationships_found": ["nodeA-[REL]->nodeB"]  
7 }
```

### 2.3.2 Vector Database Query

Listing 5: Vector similarity search

```
1 def query_vector_database(self, database: Neo4jVector,
2     question: str, k: int = 5):
3     return database.similarity_search(query=question, k=k)
```

Performs semantic similarity search on vector stores to find relevant nodes or relationships.

### 2.3.3 Chunk Similarity Query

Listing 6: Cosine similarity search on chunks

```
1 def query_chunks_by_similarity(self, question: str, k: int = 5):
2     question_embedding = self.embeddings.embed_query(question)
3     result = self.graph.query("""
4     MATCH (c:Chunk)
5     WITH c, gds.similarity.cosine(c.embedding, $embedding) AS score
6     ORDER BY score DESC
7     LIMIT $k
8     RETURN c.text AS text, c.page AS page, score
9     """, {"embedding": question_embedding, "k": k})
10    return result
```

Uses Neo4j's Graph Data Science library for cosine similarity computation directly in the database.

## 2.4 Answer Generation

### 2.4.1 Validation and Final Answer

`validate_and_answer()` combines results from multiple sources:

- Node vector search results
- Relationship vector search results
- Chunk vector search results
- Graph query results
- Optional advanced search results

All results are formatted into a prompt, and the LLM generates a comprehensive natural language answer.

### 2.4.2 Interactive Question Interface

`invoke_question()` provides an interactive CLI:

- `-h` – Display help instructions
- `-s` – Show graph schema
- `exit` – Exit the interface
- Any other input – Process as a question

The function orchestrates:

1. Vector searches on nodes, relationships, and chunks
2. Graph query via `GraphCypherQChain`
3. Optional advanced search (if enabled)
4. Final answer validation and generation

### 3 Testing Module: `RomeoJulietGraphTester`

The `test_romeo_juliet_graph.py` module validates knowledge graph accuracy by comparing graph query results against authoritative sources.

#### 3.1 Test Pipeline Overview

The test suite executes a 4-step process for each test iteration:

1. **Generate Question** – LLM creates varied test questions
2. **Query Graph** – Execute question against Neo4j
3. **Get Ground Truth** – Search web for authoritative answer
4. **Compare & Score** – Evaluate accuracy (0-100 scale)

#### 3.2 Question Generation

Listing 7: Question generation with schema constraints

```
1 def generate_test_question(self, iteration: int) -> Dict[str, Any]:  
2     # Returns: question, question_type, expected_nodes,  
3     #         expected_relationships
```

The function:

- Rotates through question categories (relationships, attributes, events, locations, multi-hop)
- Uses graph schema to constrain expected node/relationship types
- Tracks previous questions to avoid duplicates
- Returns structured output with validation constraints

Question types:

- `relationship` – Character relationships
- `character_attribute` – Traits, roles, affiliations
- `event` – Plot events and connections
- `location` – Settings and places
- `multi_hop` – Complex traversal queries

### 3.3 Graph Querying with Agent

The `query_graph_database()` method uses an LLM agent with tool access:

Listing 8: Database search tool

```
1 @tool
2 def search_database(cypher_query: str) -> str:
3     """Execute a Cypher query against Neo4j.
4     Returns JSON string of results or error message."""
5     # Handles Neo4j object serialization
6     # Returns JSON-formatted results
```

The agent follows this strategy:

1. Analyze question to identify relevant nodes/relationships
2. Start with exploration queries
3. Refine iteratively based on results
4. Return best Cypher query with found data

### 3.4 Comparison and Scoring

`compare_and_score()` evaluates graph accuracy:

Listing 9: Scoring rubric

```
1 Scoring Rubric:
2 - 100: Perfect match, all information correct
3 - 80-99: Mostly accurate, minor details missing
4 - 60-79: Partially accurate, some key info missing
5 - 40-59: Significantly inaccurate or incomplete
6 - 0-39: Mostly incorrect or no useful data
```

Output includes:

- `score` – Numeric accuracy score (0-100)
- `accuracy_assessment` – Detailed explanation
- `discrepancies` – Specific errors found
- `missing_data` – Information gaps
- `correct_elements` – What the graph got right
- `recommendations` – Improvement suggestions

### 3.5 Report Generation

`generate_final_report()` produces:

- JSON file with all test results
- Statistics: average, min, max scores
- Aggregated recommendations and issues
- Letter grade (A-F) based on average score

## 4 Utility Functions

### 4.1 JSON Serialization

`serialize_for_json()` handles Neo4j object conversion:

Listing 10: Object type handling

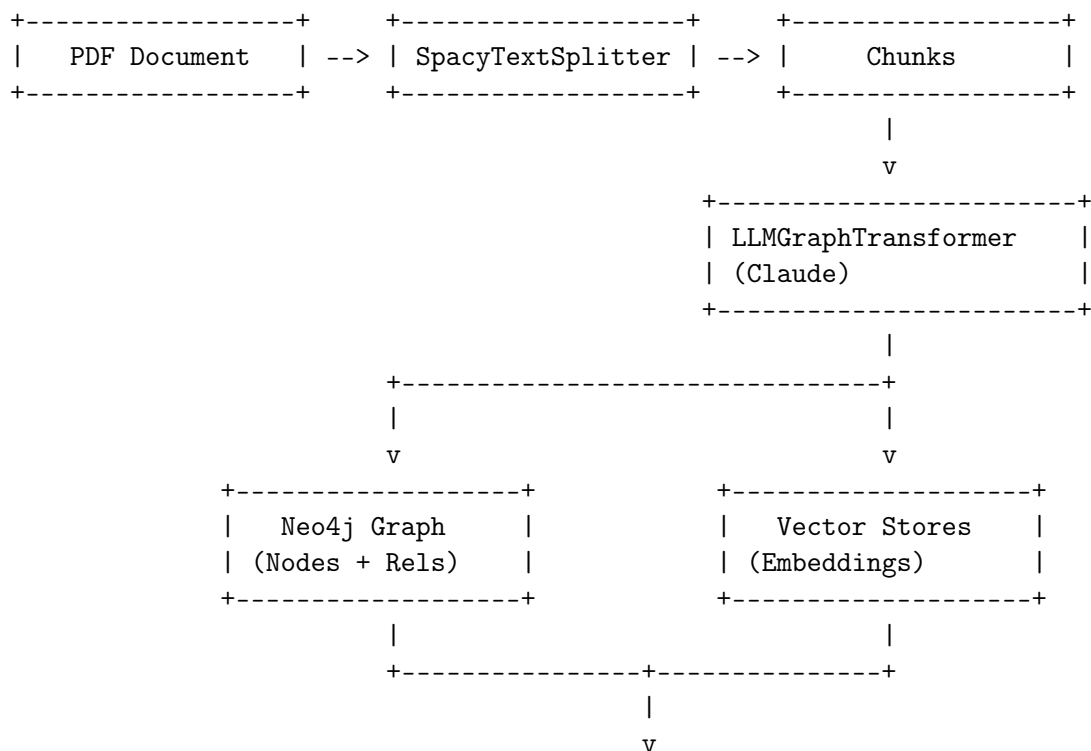
```
1 Supported types:
2 - Neo4j Node      -> {_type, labels, properties}
3 - Neo4j Relationship -> {_type, type, properties}
4 - Neo4j Path      -> {_type, nodes[], relationships[]}
5 - datetime        -> ISO format string
6 - dict/list       -> Recursive serialization
7 - primitives      -> Pass through
8 - other           -> String representation
```

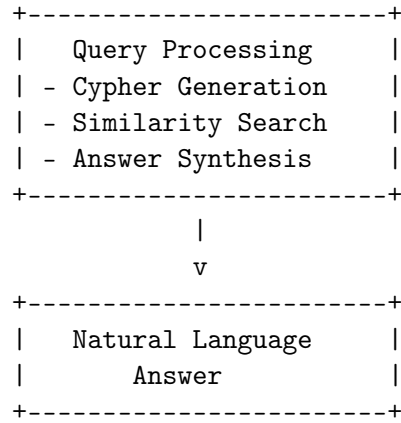
### 4.2 SpaCy Graph Extraction

`spacy_to_graph_document()` extracts knowledge from text:

1. **Entity Extraction** – Named entities become nodes
2. **SVO Triple Extraction** – Subject-Verb-Object patterns
  - Find ROOT verbs in dependency parse
  - Extract subjects (nsubj, nsubjpass)
  - Extract objects (dobj, pobj, attr)
  - Create relationships with verb lemma as type

## 5 Architecture Diagram





## 6 Key Dependencies

- `langchain-neo4j` – Neo4j integration with LangChain
- `langchain-experimental` – Graph transformers
- `langchain-openai` – OpenAI models and embeddings
- `langchain-anthropic` – Claude models
- `langchain-google-genai` – Gemini models
- `spacy` – NLP and text splitting
- `neo4j` – Python driver for Neo4j
- `python-dotenv` – Environment variable management