A Knowledge Graph-Based RAG Approach for Question Answering

A case study on EmPULIA Regulations

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July 14, 2025

The Challenge with LLMs in Specialized Domains

Critical Limitations in Public Administration

Large Language Models face significant challenges when applied to specialized fields:

- Hallucinations: Generating plausible but factually incorrect information
- Outdated Knowledge: Lack of access to current, domain-specific information
- Poor Verifiability: Difficulty tracing sources - crucial for accountability
- Opacity: Internal decision-making processes make verification challenging

Why This Matters

In public administration, accessing accurate and up-to-date information is **critical**.

Our Solution: Knowledge Graph-Enhanced RAG

Knowledge Graphs (KGs)

- Represent structured, interconnected knowledge
- Excel at complex relationship representation
- Enable structured, connected knowledge representation

Retrieval-Augmented Generation (RAG)

- Grounds LLM responses in retrieved, relevant data
- Mitigates hallucinations and improves accuracy
- Enhances LLMs with factual, domain-specific information

Goal: Create an accurate, verifiable, and context-aware QA system for **EmPULIA** e-procurement platform regulations.

Related Work: The Evolution of RAG

Standard RAG Limitations

Standard RAG approaches have limitations:

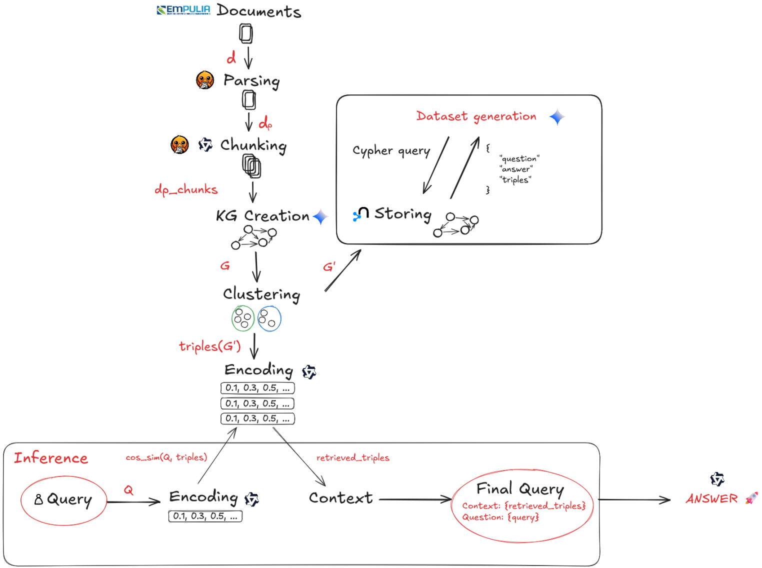
- Struggle with complex queries requiring relationship understanding
- Limited ability to navigate interconnected information
- Difficulty with multi-hop reasoning tasks
- Insufficient for intricate regulatory document analysis

Knowledge Graph Integration

Recent advances integrate KGs with RAG:

- **GraphRAG**: Leverages graph-based index for relationship navigation
- Better handling of complex questions requiring relationship understanding

High-Level Pipeline Overview



Document Processing Pipeline

Document Collection & Parsing

- Official regulatory texts from `EmPULIA` platform
- Parse PDFs using `Docling` with `HybridChunker`
- The `HybridChunker` ensures semantically coherent segments while maintaining tokenization awareness for better downstream processing.
- Uses `Qwen3-Embedding-0.6B` tokenizer for consistent boundaries
- Aggregate every three consecutive chunks for optimal granularity

Knowledge Graph Construction: Technical Details

Triple Extraction Process

- `Gemini-2.5-Flash` with structured output
- **Parameters:** `temperature=0`, `thinking_budget=0`
- Extract format: `(entity1, relation, entity2, source)`
- Merge all triples across chunks into unified KG

Graph Refinement & Clustering

- Cluster relation labels using `DBSCAN`
- **Parameters:** $\epsilon = 0.05$ for high similarity clustering
- Results in more cohesive and compact graph structure

Triple Encoding and Storage Strategy

Embedding Strategy

- Embed triples using `Qwen3-Embedding-0.6B`
- **Format:** `entity1 relation entity2: source`
- Alternative: embed only core triple `entity1 relation entity2`

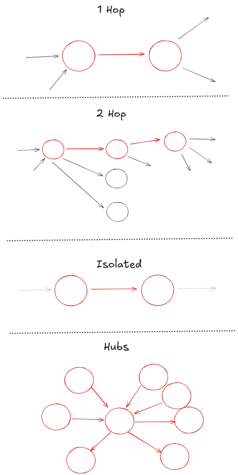
Retrieval Configuration

- **Search parameters:** `cosine_threshold=0.6`, `top_k=546`
- High k-value (size of largest connected component) tests model's filtering ability
- Two embedding strategies evaluated: with/without source information

EmPULIA-QA Dataset Construction

Systematic Difficulty Levels

- **Isolated Nodes**: Simple fact retrieval from single entities (8 questions)
- **Single Hop**: Questions requiring one relationship traversal (8 questions)
- **Two Hops**: Multi-step reasoning across two relationships (8 questions)
- **Hubs**: Queries about highly connected entities (6 questions)
- **Out-of-Domain**: Irrelevant questions (6 questions)



Answer Generation: Technical Implementation

Qwen3-4B Configuration

- **Core parameters:** `temperature=0`, `contextlength=8192`
- **Sampling:** `top_p=0.95`, `top_k=20` (Ollama default)
- **Quantization:** `Q4_K_M` (Ollama base quantization)

Structured Response Format

Each generated response contains three components:

- **Answer**: Direct reply to the user's query, grounded in context
- **Analysis**: Explanation of reasoning process and context usage
- **Sources**: Specific KG triples cited, ensuring full verifiability

Comprehensive Evaluation Metrics

Retrieval Component

- **Context Precision**:

$$CP = \frac{\sum(Precision@k)}{\text{No. relevant items in top K}}$$

- **Context Recall**:

$$CR = \frac{\sum(Recall@k)}{\text{No. relevant items in top K}}$$

Generation Component

- **Context Faithfulness**: Can generated answer be inferred from context?
- **Analysis Faithfulness**: Is reasoning explanation supported by context AND answer?
- **Answer Accuracy**: agreement between a model's response and the ground truth. LLM jury evaluation with perspective swapping (0-4 scale, then normalized)

Results - Retrieval Component

EmPULIA-QA						
Category	**Precision**			**Recall**		
	Source	w/out Source	Δ	Source	w/out Source	Δ
Single Hop	**0.539**	0.394	↓ 0.145	0.875	0.875	– 0.000
Two Hop	**0.659**	0.520	↓ 0.139	**1.000**	0.750	↓ 0.250
Isolated	0.567	**0.660**	↑ 0.093	**1.000**	**1.000**	– 0.000
Hubs	**0.463**	0.415	↓ 0.048	**0.108**	0.061	↓ 0.047
Out of Domain	1.000	1.000	– 0.000	1.000	1.000	– 0.000

Table: Retrieval Evaluation on `EmPULIA-QA` dataset. Precision and recall for each category, comparing *source* vs *nosource*. Best values in bold. Arrows indicate variation (nosource - source).

Results - Generation Component

EmPULIA-QA									
Category	**Context Faithfulness**			**Analysis Faithfulness**			**Answer Accuracy**		
	Source	w/out Source	Δ	Source	w/out Source	Δ	Source	w/out Source	Δ
Single Hop	0.288	**0.438**	↑ 0.150	0.625	**0.740**	↑ 0.115	0.250	0.250	- 0.000
Two Hop	**0.769**	0.583	↓ 0.186	**0.924**	0.913	↓ 0.011	0.375	**0.406**	↑ 0.031
Isolated	**0.627**	0.552	↓ 0.075	0.862	**0.958**	↑ 0.096	0.531	**0.594**	↑ 0.063
Hubs	0.565	**0.644**	↑ 0.079	0.844	**0.921**	↑ 0.077	0.333	**0.500**	↑ 0.167
Out of Domain	1.000	1.000	− 0.000	1.000	1.000	- 0.000	1.000	1.000	- 0.000

Table: Generation Evaluation on `EmPULIA-QA` dataset. Faithfulness and answer accuracy per category. Best source values in bold. Arrows indicate variation (nosource - source).

Source

Answer: L'ammontare a base d'asta che definisce gli appalti di sola esecuzione è di 100 milioni di euro, come stabilito nell'Articolo 129, comma 3 del dPR 5 ottobre 2010.
Analysis: Il contesto specifica che gli appalti di sola esecuzione hanno una base d'asta superiore a 100 milioni di euro, con riferimento all'Articolo 129, comma 3 del dPR 5 ottobre 2010. Questo articolo è citato come fonte per la definizione dell'importo minimo.
Sources:

- Fonte: dPR 5 ottobre 2010_207_agg_DM_infrastrutture_24apr2014, Art. 129, comma 3: «...di ammontare a base d'asta superiore a 100 milioni di euro.»

No Source

Answer: Il limite di base d'asta per gli appalti di sola esecuzione è di 100 milioni di euro, come stabilito nell'articolo 129, comma 3 del dPR 5 ottobre 2010. Questo è confermato dal riferimento al testo dPR 5 ottobre 2010_207_agg_DM_infrastrutture_24apr2014, art. 129, comma 3.

Analysis: La domanda chiede il limite di base d'asta. Il contesto specifica che gli appalti di sola esecuzione hanno una base d'asta superiore a 100 milioni di euro, riferendosi all'articolo 129, comma 3 del dPR 5 ottobre 2010_207_agg_DM_infrastrutture_24apr2014. Questo articolo è citato come fonte per il limite. Non ci sono altre informazioni aggiuntive nel contesto.

Sources:

- Fonte: dPR 5 ottobre 2010_207_agg_DM_infrastrutture_24apr2014, Art. 129, comma 3: «...di ammontare a base d'asta superiore a 100 milioni di euro.»

Question

Question: Quali sono le disposizioni relative ai materiali non accettati e ai magazzini secondo l'Art. 109, comma 6 del D.Lgs. 50/2016?

Answer Accuracy Evaluation

- Score 2: La risposta generata è parzialmente allineata alla ground truth, ma omette una delle due disposizioni chiave relative ai magazzini a disposizione della Stazione Appaltante.
- Score 0: La risposta generata non corrisponde alla ground truth. La ground truth indica solo la rimozione dei materiali non accettati, **mentre la risposta generata aggiunge una seconda disposizione non presente nella ground truth.**

Generated Response

Answer: Il comma 6 dell'art. 109 del D.Lgs. 50/2016 prevede che l'appaltatore deve rimuovere dai magazzini e dai cantieri i materiali non accettati dal direttore dei lavori. **Inoltre, deve mettere i magazzini a disposizione della stazione appaltante.**

Analysis: Il comma 6 dell'art. 109 stabilisce due obblighi principali per l'appaltatore:

1. Rimuovere i materiali non accettati dai magazzini e dai cantieri.
2. Mettere i magazzini a disposizione della stazione appaltante.

Sources:

... L'appaltatore deve rimuovere dai magazzini e dai cantieri i materiali non accettati dal direttore dei lavori.

... Deve mettere i magazzini a disposizione della stazione appaltante.

Some Insights

1. Data Preprocessing (Still) Matters

- Throwing LLMs at problems doesn't guarantee good results
- Quality of input data and preprocessing steps are **crucial**
- Careful document parsing and chunking significantly impact performance

2. Knowledge Graphs Are Powerful (If Carefully Crafted)

- Well-designed KGs significantly enhance retrieval and generation
- Structured, domain-specific context provides substantial benefits

3. Small Language Models Are Not Enough (Yet)

- Even with proper context, smaller models struggle with effective utilization
- Context filtering and relevance assessment remain challenging
- Needle in the Haystack problem persists

Current Limitations

Limitations

- **Graph topology**: Current embedding treats triples independently
- **Source validation**: Citation generation not rigorously evaluated
- **Dataset coverage**: Some regulatory facts may lie outside current scope
- Limited to EmPULIA domain - generalization needs exploration

Future Work

- **Prompt refinement**: Leverage model's instruction-following capabilities
- **Graph enhancement**: Utilize Neo4j's node/relation property capabilities
- **User feedback**

Thank You for the softmax $\left(\frac{QK^T}{\sqrt{d_k}}\right) V$

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