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From Documents to Dialogue: A Question-Answering System for Geoportale Nazionale Archeologia with Retrieval-Augmented Generation

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Contents

Abstract

This dissertation presents the design and development of a question-answering (QA) system tailored to the Geoportale Nazionale Archeologia (GNA). The research addresses the challenge of extracting relevant information from archaeological documentation using Retrieval-augmented generation (RAG) amd natural language processing (NLP) techniques. The methodology combines transformer-based language models with domain-specific information extraction to enable intuitive, natural language querying of technical documentation related to archaeological data.

Keywords: Digital Humanities · Information Retrieval · Question-Answering Systems · Retrieval-Augmented Generation · Natural Language Processing · AI · Cultural Heritage.

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Chapter 1

Introduction

At the swiftly evolving intersection of artificial intelligence (AI) and digital humanities (DH), computational methods have profoundly transformed access to and interpretation of cultural heritage resources. Question-answering systems (QASs), driven by advances in natural language processing (NLP) and retrieval-augmented generation (RAG), have become increasingly significant tools, offering new possibilities for engaging with extensive documentation and complex cultural repositories. This thesis emerges directly from an applied research experience conducted during an internship at BUP Solutions, aimed at exploring the realistic feasibility and effectiveness of these AI technologies in the context of cultural heritage. Specifically, the project focused on developing a specialised QAS for the Geoportale Nazionale Archeologia (GNA), Italy's primary repository for archaeological data.

The motivation for this study initially arose from a concrete, practical challenge: enabling efficient, intuitive, and contextually accurate access to the extensive and often fragmented archaeological documentation hosted by GNA. Archaeologists, heritage managers, and scholars regularly face difficulties in navigating vast volumes of technical reports, field notes, operational procedures, and geospatial data. In response, this project experimented with applying cutting-edge NLP and machine learning (ML) techniques – primarily transformer-based language models and advanced information retrieval methods – to dynamically retrieve and synthesise relevant information based on user queries expressed in natural language.

Central to the chosen methodology is retrieval-augmented generation (RAG), an approach that significantly enhances traditional QASs through the dynamic retrieval of domain-specific content, which augments the generative capabilities of language models. Instead of relying solely on internal model knowledge, RAG-based systems integrate external document retrieval with generative text production, resulting in greater reliability and contextually grounded responses – crucial qualities for scholarly and professional uses. While this approach inherently promises increased accuracy and reduced hallucinations compared to purely generative methods, it also involves several complexities and uncertainties, which were encountered firsthand during the development and evaluation phases, as will be discussed in the following chapters.

Rather than adopting a narrowly theoretical or idealised perspective, this study reflects the exploratory and evolving nature of hands-on experimentation, shaped by iterative cycles of trial-and-error, heuristic adjustments, and pragmatic responses to practical constraints such as computational limits, the absence of standardised evaluation benchmarks, and the linguistic complexity of the domain. This process brought to light the persistent tension between the ambitions of AI-driven solutions and the realities of applying them in intricate cultural contexts. In systems like the GNA's AI assistant, the focus necessarily shifts from abstract notions of understanding to measurable outcomes: the true test is not whether the system comprehends archaeology in any human sense, but whether it efficiently retrieves relevant information, handles the complexities of the domain, and supports users in making informed decisions. Against such backdrop, one might ask: how far can technical ingenuity take us before we run up against the unique subtleties of human knowledge and practice? It's in this spirit that I recall McDermott's classic essay, *Artificial Intelligence Meets Natural Stupidity*, which cautions against the lure of *wishful mnemonics* in AI and urges us to resist the temptation to label what our systems do with grand terms like "understand". Instead, McDermott advocates for a clear-eyed assessment and communication of what these systems actually accomplish – and where their true limits lie (McDermott, 1976).

In light of this reality, this study deliberately avoids overstating the system's semantic or interpretive capabilities. Instead, it foregrounds the project's exploratory nature, acknowledging both methodological achievements and encountered limitations. The outcome represents a pragmatic effort toward applying AI in the digital humanities, offering insights into the real-world challenges and possibilities of using retrieval-augmented generation in cultural heritage contexts.

This project remains, at its core, fundamentally hopeful. It demonstrates that even in the face of inherent methodological challenges, AI-driven tools such as RAG-based QAS hold substantial promise for enhancing access to cultural heritage information. Through a transparent presentation of both the strengths and shortcomings discovered during this internship experiment, this thesis seeks to contribute realistically yet optimistically to the ongoing dialogue between artificial intelligence and humanistic inquiry, offering a vision of AI's evolving role in supporting cultural heritage scholarship.

Chapter 2

The Evolution of Question-Answering Systems

This chapter introduces the foundations of question answering (QA) as both a computer science discipline and an applied technology. Before the emergence of large language models (LLMs),[1] Transformers,[2] and modern generative AI,[3] question-answering systems (QAS) progressed through distinct paradigms: from symbolic and rule-based architectures to classic information retrieval (IR) models and early neural networks approaches (Jurafsky and Martin, 2024; Antoniou and Bassiliades, 2022). Early systems depended on domain-specific adaptations, manually curated knowledge bases, keyword retrieval, and engineered features. In recent years, transformer-based language models such as BERT and GPT have significantly advanced the capabilities of QA systems by enabling both answer extraction and text generation. Unlike their predecessors, these models can generate or extract responses using deep contextual understanding derived from large-scale pretraining (Kaplan et al., 2020). However, they tend to exhibit factual inaccuracies, shallow contextual understanding in certain scenarios, and limited adaptability to new or evolving information. They also frequently hallucinate or generate outdated responses, constrained by their static training corpora (Harsh and Shobha, 2024).

The main stages in the evolution of QA systems, along with representative approaches and landmark examples, are summarised in Tab. 1 below.

[1] Large Language Models (LLMs) are advanced AI systems trained on massive text datasets to generate and understand human language. For an accessible overview, see *A Very Gentle Introduction to Large Language Models without the Hype* (Riedl, 2023).

[2] The Transformer is a neural network architecture introduced in 2017 that efficiently models sequential data using a self-attention mechanism. The original paper, *Attention Is All You Need* by Vaswani et al. (2017), provides a foundational outline.

[3] Generative AI refers to systems capable of producing new content, such as text, images, or audio, based on learned patterns. For more, see the *Stanford AI Index 2025 Report* (Maslej et al., 2025).

Models	**QA Approach**	**Examples / Results**
Symbolic / Rule-based (1960s–1980s)	Rule-based, domain-specific, handcrafted knowledge base	BASEBALL, LUNAR, SHRDLU
Early IR Approaches (1990s–mid-2010s)	Keyword retrieval, TF-IDF, BM25, open-domain ranking	TREC QA
Statistical / Seq2Seq (2000s–2018)	N-gram, embeddings, RNN/LSTM, statistical IR	Early neural QA, Reading comprehension in 2010s
Transformer-based	Pre-training, fine-tuning, self-attention	BERT (93% F1 on SQuAD), XLNet
Generative LLMs and agents	Prompting, retrieval-augmented generation, agentic reasoning	GPT-3, RAG pipelines

Table 1: Evolution of question-answering systems

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2.1 Pre-Transformer Era: Symbolic and Statistical Systems

The development of QAS prior to the rise of Transformers was shaped by several key methodological shifts and technological milestones. These earliest efforts prioritised manually curated knowledge bases and rules-based systems for precise but limited question matching. As the scope of QA expanded, techniques evolved to incorporate large-scale information retrieval methods, statistical modeling, and increasingly complex approaches to feature engineering and answer extraction. This trajectory ultimately set the stage for early neural models that leveraged word embeddings and sequence modeling, gradually moving the discipline toward data-driven architectures and deeper semantic representation. The following paragraphs trace these major trends, illustrating how each contributed to the capabilities and limitations of pre-Transformer QA systems.

2.1.1 Rule-Based Systems (1960s–1980s)

Early QAS relied on highly constrained, domain-specific approaches built around manually constructed knowledge bases. These systems operated within carefully delineated boundaries, matching user questions to a limited set of predefined templates and answer patterns. While this design enabled highly precise responses in their target domains, it also rendered the systems brittle and inflexible – minor variations in user queries or topics outside the encoded scope often resulted in failure to provide meaningful answers.

Expert systems from this era encoded explicit inference rules and logical representations of knowledge, enabling a form of automated reasoning that was fundamentally deterministic. However, these approaches struggled to address ambiguity or generalise beyond the hand-curated domain, and could not scale to larger, more dynamic information environments (*Question answering*, 2025; Jurafsky and Martin, 2024).

Seminal examples of early domain-specific QA systems include:

- **BASEBALL** (1960s): Hand-coded rules and database logic for Major League Baseball[4] questions (Green et al., 1961).
- **LUNAR** (1971): Pattern matching and restricted knowledge base for geological questions about Moon rocks (Woods et al., 1972).
- **SHRDLU**[5] (late 1960s): Symbolic reasoning for a blocks-world robot in a toy domain (Winograd, 1971).
- **Unix Consultant (UC)**[6] and **LILOG**[7] (1980s): Domain-specific QA via linguistic rules and expert knowledge; though both projects remained at the demonstration stage, they contributed to advanced research in computational linguistics.

These early QA systems demonstrated the potential of automated question answering but highlighted the central challenge of balancing precision with generality and scalability. Their

[4] Major League Baseball (MLB) is the leading professional baseball league in North America. It is regarded as the world's premier baseball competition.

[5] SHRDLU was developed at the MIT Computer Science and Artificial Intelligence Laboratory (CSAIL) between 1968–70. The software allowed users to interact conversationally with a program that could manipulate, describe, and answer questions about objects in a virtual `blocks world´, a simplified environment containing various movable blocks. Read more about SHRDLU program here: https://hci.stanford.edu/winograd/shrdlu/.

[6] UC (QA) system, created at U.C. Berkeley (CA), answered queries about the Unix operating system using a hand-crafted knowledge base and could tailor responses to different user types (Wilensky et al., 1988).

[7] LILOG project was as a text-understanding system designed for tourism information in a German city (*Question answering*, 2025).

evolution would motivate the subsequent shift toward statistical and data-driven approaches (Jurafsky and Martin, 2024; Antoniou and Bassiliades, 2022).

2.1.2 Classic Information Retrieval Strategies (1990s–mid-2010s)

As the volume of unstructured web data grew, QA moved toward ranking text passages with IR techniques like TF-IDF[8] and BM25,[9] to locate relevant content within large text collections. Open-domain QA systems – such as those in TREC QA[10] (Hirschman and Gaizauskas, 2001) – shifted the focus from structured fact retrieval to returning ranked sentences or extracting answer spans from retrieved passages. These approaches made it possible to scale QA to a broad range of topics and data sources, yet they also introduced notable challenges. Lacking deep understanding of natural language, IR-based QA systems often failed to interpret nuances, synonyms, or complex phrasing, and frequently missed correct answers that did not explicitly match the user's query terms (Antoniou and Bassiliades, 2022; Caballero, 2021).

2.1.3 Statistical Models and Feature Engineering (2000s–2018)

During the 2000s and 2010s, the adoption of n-gram models and statistical IR approaches (cf. TF-IDF, BM25, probabilistic models[11]) enabled reasoning over large corpora, moving beyond hand-crafted rules and enabling automated extraction of candidate answers from vast, unstructured datasets (Manning et al., 2008). The introduction of word embeddings – e.g., Word2Vec, GloVe – marked a significant advancement by capturing semantic similarities between words, thereby allowing models to generalise beyond simple keyword matching. These dense vector representations supported the emergence of recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), which facilitated more accurate modeling of sequence and context in reading comprehension and retrieval-based QA tasks (Jurafsky and Martin, 2024).

A major milestone in this era was IBM's *Watson* system, which achieved notable success by

[8] TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical method for ranking how important a word is to a document in a collection.

[9] BM25 is a ranking function that improves information retrieval by considering term frequency, document length, and saturation effects.
For more details on TF-IDF and BM25, read *Introduction to Information Retrieval* (Manning et al., 2008).

[10] TREC QA refers to the Question Answering track of the Text REtrieval Conference (TREC), a long-running evaluation series that has set benchmarks for open-domain QA research since 1999. See https://trec.nist.gov/data/qa.html

[11] Language Models for IR (LMIR) – such as n-gram models – estimate the probability of a query being generated by a document's language model. They capture local word dependencies and were widely used in early QA, speech recognition, and spelling correction, (Ponte and Croft, 1998) but were later outperformed by models like RNNs, LSTMs, and Transformers due to their limited handling of long-range context.

winning the *Jeopardy!* challenge in 2011.[12] Watson's *DeepQA* architecture integrated hundreds of NLP, IR and ranking components, employing sophisticated pipelines to analyse and combine evidence from diverse sources (Ferrucci et al., 2011). However, despite its advanced design, *Watson* relied on non-generative methods; it synthesised and ranked candidate answers but did not generate free-form responses from scratch.

Simultaneously, semantic QA systems began to emerge, mapping natural language (NL) questions to structured queries (e.g. using SPARQL language) executed over knowledge bases like Freebase and DBpedia. These systems required advanced components for entity recognition, relation extraction, and reasoning over symbolic representations. Typical architectures included steps like question analysis, sentence mapping, disambiguation, and query building, enabling automatic translation of natural language into formal queries over RDF data sources. Thanks to the usage of ontology-mapping and linguistic resources – e.g., WordNet –, these approaches further bridged the gap between unstructured text and structured knowledge bases (Franco et al., 2020).

Throughout this period, feature engineering played a central role. Techniques such as conditional random fields (CRFs) and support vector machines (SVMs) enabled models to exploit hand-crafted features – including lexical overlap, question type, and answer patterns—to enhance answer extraction from retrieved texts. Hybrid QA systems appeared, combining keywords-based information retrieval methods for unstructured sources with knowledge-base querying for fact-based answers, thereby improving both coverage and precision (Antoniou and Bassiliades, 2022).

This period laid essential groundwork for the deep learning and neural approaches that would soon transform the QA landscape, highlighting the importance of both statistical modeling and intelligent feature design.

2.1.4 Early Neural and Generative Models (Late 2010s)

The late 2010s witnessed the adoption of neural architectures in question answering, building upon the foundational use of word embeddings and recurrent neural networks (RNNs). Embedding methods such as Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014)

[12] The *Jeopardy! challenge* was a high-profile test where IBM *Watson* competed on the American television quiz show *Jeopardy!* against two of the show's greatest human champions. Watson's victory demonstrated significant progress in machine comprehension and open-domain question answering (Wikipedia IBM Watson). In February 2013, IBM announced that *Watson*'s first commercial deployment would assist with utilization management decisions for lung cancer treatment at Memorial Sloan Kettering Cancer Center in New York City, in partnership with WellPoint (now Elevance Health) (Upbin, 2013).

allowed systems to capture deeper semantic relationships between words, providing a richer representation of both questions and candidate answers. RNNs, and their improved variants like long short-term memory networks (LSTMs) and gated recurrent units (GRUs), facilitated sequential modeling of language, enabling systems to better process and compare question and answer pairs based on their context within a sentence or passage.

Despite these advancements, early neural QA models still faced significant limitations. The reliance on RNNs restricted their ability to effectively model long-range dependencies in text, often resulting in incomplete understanding when questions required reasoning across multiple sentences or broader contexts. While neural models improved matching between questions and answers, their performance remained constrained by the size and variety of the training data.

Around this time, encoder-decoder architectures began to appear in QA research, drawing inspiration from their success in machine translation. These generative models aimed to produce answers by generating sequences of text, rather than simply extracting passages from a source document. However, early generative QA systems often struggled with factual consistency: they had a tendency to copy or paraphrase the input text instead of synthesising novel, precise answers. Additionally, these models sometimes hallucinated information or failed to maintain logical coherence in their generated responses, limiting their reliability in open-domain settings (Caballero, 2021).

These developments set the stage for the subsequent breakthroughs brought about by attention mechanisms and transformer-based architectures, which dramatically improved the handling of context and factuality in generative QA.

2.2 Blind Spots and Bottlenecks: The Shortcomings of Early Approaches

Earlier approaches to question answering were hindered by several fundamental limitations. Most notably, symbolic and rule-based systems suffered from severe domain restrictions, as their performance relied on hand-crafted knowledge bases and rigid rules that did not generalise well to new or broader topics (Alqifari, 2019). The brittleness of these systems was further exposed by their heavy dependence on template matching, which frequently led to failures when users phrased questions in unanticipated ways or employed linguistic variations (Hirschman and Gaizauskas, 2001). Information retrieval (IR) and statistical models, while more scalable, continued to struggle with true semantic understanding and contextual reasoning, often retrieving only superficially relevant snippets in place of synthesising comprehensive or contextually rich answers (Alanazi et al., 2021; Diefenbach et al., 2018). The answers these systems produced were typically shallow, extracted verbatim from source texts rather than generated or adapted to the user's specific information need (Hirschman and Gaizauskas, 2001; Alqifari, 2019).

Substantial manual effort was required to design, maintain, and update rules, features, and parsers, creating significant bottlenecks and making adaptation to new domains costly and time-consuming (Alanazi et al., 2021). In addition, IR and knowledge base (KB) approaches frequently exhibited incomplete coverage, missing relevant answers due to differences in phrasing or limitations in their underlying datasets (Diefenbach et al., 2018). Early neural models, despite improvements, were generally confined to handling short text spans and struggled with complex or multi-sentence reasoning tasks. Finally, all these methods exhibited a strong dependence on the quantity and quality of available training data and engineered features, resulting in inconsistent performance across different domains and question types (L. Liu et al., 2022; Alanazi et al., 2021; Alqifari, 2019; Diefenbach et al., 2018; Hirschman and Gaizauskas, 2001).

These cumulative factors left pre-generative QA systems largely inflexible and brittle, with limited ability to provide context-aware, nuanced, or creative responses to user queries.

2.3 Deep Learning Breakthroughs

The advent of the Transformer architecture fundamentally reshaped the field of deep learning and revolutionised neural QAS. Introduced by Vaswani et al. in 2017, Transformers replaced RNNs and LSTMs with a self-attention mechanism that could model relationships between words regardless of their distance in the input sequence. This innovation allowed for efficient parallelization during training and inference, dramatically improving the scalability and performance of language models on a range of NLP tasks, including QA.

One of the earliest and most influential transformer-based models was BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019). BERT employs a bidirectional attention mechanism and is pre-trained using a masked language modeling objective, allowing it to capture complex context from both directions in a sentence. When fine-tuned for QA benchmarks, such as SQuAD (Rajpurkar et al., 2016), BERT achieved unprecedented accuracy – reaching Exact Match and F1 scores above 85% and 87% respectively on the SQuAD 2.0 leaderboard –, surpassing previous neural models and establishing a new standard for QA (Li and Zhang, 2024).

Building on this foundation, subsequent models explored variations and enhancements of the Transformer paradigm. XLNet, for example, employed a permutation-based language modeling objective, enabling it to better capture bidirectional context and achieve state-of-the-art results on several QA benchmarks (Z. Yang et al., 2020). In specialised domains, models such as BioBERT extended the BERT architecture with additional pre-training on biomedical texts, achieving top performance on domain-specific challenges like the BioASQ question answering competition (Yoon et al., 2019). Parallel research into model architectures also produced frameworks such as Dynamic Coattention Networks (DCN), which fused question and context representations through attention mechanisms and iterative decoding, further improving accuracy on reading comprehension tasks (Xiong et al., 2018).

Surveys in literature underscore a pronounced move toward both extractive and generative QA pipelines, with each stage – tokenisation, embedding, retrieval, and answer generation – now being explicitly modeled and systematically optimised (Farea and Emmert-Streib, 2025). At the same time, interest in conversational and multi-turn QA has grown rapidly, as Transformers demonstrate substantial ability to manage dialogue context and maintain coherent, context-aware interactions with users (Yue, 2025; Antoniou and Bassiliades, 2022). Together, these advances have laid the foundation for generative AI systems and retrieval-augmented approaches that now dominate state-of-the-art QA research.

2.4 Large Language Models, Agents and Modular Pipelines

A clear distinction now emerges between "traditional" QA systems, primarily built upon general-purpose pretrained language models – such as GPT, Llama, T5, etc. – and the new wave of modular approaches that dynamically retrieve external information sources. Traditional QA encompasses both extractive and generative paradigms, each defined by how they use the model's internal knowledge. Extractive QA models are designed to identify and extract exact answer spans directly from a provided text or document, making them highly effective for fact-based questions and reading comprehension tasks. Generative QA models, in contrast, use natural language generation (NLG) to produce answers, typically synthesising or paraphrasing responses in ways that may not appear verbatim in the original text. However, despite their success, both of these paradigms are fundamentally limited by the static nature of their training data: they may struggle with rare, fast-changing, or domain-specific queries, and are prone to hallucinations and outdated information (Farea and Emmert-Streib, 2025).

Recent advances in question answering are characterised by the emergence of retrieval-augmented generation (RAG). In these pipelines, a retriever component dynamically accesses external knowledge bases, while a generator conditions on the retrieved information to produce grounded answers. This approach addresses many of the shortcomings of earlier transformer-based models and significantly enhances factual accuracy, contextual relevance, and system adaptability. Generative LLMs within the RAG pipeline are able to incorporate real-time knowledge, thereby reducing hallucinated content and providing up-to-date responses, even as external data sources evolve (Yue, 2025; Lewis et al., 2020). Benchmarks show that RAG-enhanced models significantly outperform standard LLMs in factual QA, particularly in domains demanding precise recall or up-to-date knowledge. For instance, enterprise evaluations demonstrate up to 30-40% improvement in incorporating domain-specific terminology compared to standalone models, while user trust increases substantially when source citations are included (Vaibhav, 2025).

Furthermore, RAG-based QA systems offer practical advantages for scalability. Rather than requiring full model re-training to accommodate new information, they can simply update or expand the external KB. This design allows for the integration of vast and dynamic data resources, enabling high coverage across domains and rapid adaptation to new information needs. However, these benefits come with trade-offs. RAG architectures require more complex infrastructures, including document indexing and retrieval pipelines, which increase operational overhead and latency compared to traditional, static QA systems. As a result, deploying and maintaining RAG-based systems can be more challenging, especially at scale.

Beyond RAG, a parallel evolution is visible in the emergence of LLM-based agents. Unlike monolithic models, these agents operate as orchestrators of multi-stage reasoning, combining planning, question understanding, retrieval, reasoning, and answer generation in an iterative loop. Architectures typically integrate memory to retain conversational context, planning modules to decide on next actions, and reasoning modules to balance internal “thinking” with external interactions, such as calling APIs, querying databases, or consulting humans (Yue, 2025). It overcomes the rigidity of earlier pipelines, which relied on static submodules trained in isolation, and the limitations of naive LLM QA, which lacked external grounding and dynamic adaptability. Agents thus introduce a form of controlled autonomy: they not only retrieve information but also decide *when* and *how* to engage tools, creating more flexible and resilient QA systems.

Current research highlights that these modular and agentic pipelines offer more than incremental improvements. They introduce transparency through source attribution, factual grounding, and explainability – qualities increasingly demanded in high-stakes domains such as law, medicine, and cultural heritage. At the same time, promising directions include multimodal modes – retrieving from text, images, or audio; though cross-modal alignment remains an open challenge (Vaibhav, 2025) –, hybrid retrieval that combines sparse lexical methods and dense search, and adaptive systems that dynamically tune retrieval and reasoning strategies based on query type and context (Yue, 2025; Vaibhav, 2025). Taken together, these advances point toward a decisive shift: from static models locked within their parametric memory to dynamic, agentic systems capable of interacting with and reasoning over the evolving universe of human knowledge.

Tab. 2 summarises the functional differences between traditional and RAG-based QA systems, highlighting the shift toward dynamic, retrieval-augmented, and generative approaches that characterise the current state of the discipline.

Feature	**Traditional QAS** *(e.g., BERT, GPT-2/3)*	**RAG QAS** *(Retriever + Generator)*
Knowledge source	Fixed (training data)	Dynamic (external docs/databases)
Answer type	Extracted or generated	Retrieved + generated (synthesised)
Factual accuracy	Limited (can hallucinate or be outdated)	High (grounded in retrieved, up-to-date information)
Contextual depth	Limited	Comprehensive, nuanced
Scalability	Moderate	High (can update external data sources)
Computational cost	Lower	Higher (due to retrieval/generation)
Latency	Lower (faster for simple queries)	Higher (retrieval step adds time)
Complexity of setup	Simpler	More complex to maintain
Adaptability	Less adaptable to new domains	Highly adaptable via updated document index

Table 2: Comparison of traditional vs. retrieval-augmented generation question-answering systems.
Adapted from https://www.geeksforgeeks.org/nlp/rag-vs-traditional-qa/

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Chapter 3

State of the Art in Retrieval-Augmented Generation

In the landscape of AI, large language models (LLMs) have demonstrated remarkable results in text generation and understanding. Yet, when applied to real-world tasks such as question answering, these models still face significant limitations. As discussed in Chap. 2, LLMs are prone to hallucinations,[13] rely on static and often outdated training data, and offer limited transparency or traceability in their outputs. Additionally, they may struggle to incorporate domain-specific context or organisational knowledge (Vaibhav, 2025), posing challenges for domains like cultural heritage, GLAM (Galleries, Libraries, Archives and Museums) and archaeology, where reliability, provenance, and interpretive consistency are fundamental requirements (Di Marcantonio, 2024).

To address these concerns, retrieval-augmented generation (RAG)[14] has emerged as a crucial methodological advance. It improves the factual grounding and contextual relevance of generated answers, through the integration of external and verifiable knowledge at inference time, thereby reducing the risk of generating fabricated or distorted information (Martineau, 2023). This approach marks a clear progression beyond both traditional information retrieval and earlier neural QA models, which were often brittle, domain-dependent, or struggled to adapt to evolving information needs.

Although initially conceived for open-domain question answering and enterprise search (Akkiraju et al., 2024; Jiang et al., 2024; Packowski et al., 2024; R. Yang et al., 2025; Zhou et al., 2025), RAG pipelines are are now finding growing resonance in the humanities

[13] In the context of LLMs, hallucinations refer to outputs that are plausible-sounding but factually incorrect, fabricated, or unsupported by the underlying data or external sources (Harsh and Shobha, 2024).

[14] The terminology "retrieval-augmented generation" was introduced by Lewis et al. (2020) in their influential paper *Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks*. Since then, the term has come to designate a broad family of methods and design patterns that combine retrieval with generative techniques, unifying diverse approaches to knowledge-grounded text generation.
For more information about RAG technique, see https://en.wikipedia.org/wiki/Retrieval-augmented_generation.

and cultural heritage domains. In these settings, where interpretive rigour, provenance, and reliability of information are critical, they serve as valuable instruments to support scholars and professionals in navigating vast, fragmented knowledge repositories. Recent initiatives have begun to experiment with RAG for the analysis of sensitive historical materials (Callaghan and Vieira, 2025; Ciletti, 2025; Sergeev et al., 2025; Fan et al., 2025), underscoring its potential to support critical scholarly practices. However, the present work explores a distinct application: improving access to procedural and technical documentation, where clarity, consistency, and actionable guidance are the primary objectives.

This chapter provides a comprehensive account of the state of the art in retrieval-augmented generation, situating it within the broader research landscape, clarifying its core mechanisms, and tracing its emerging applications in the digital humanities.

3.1 Foundations of the Technique

Retrieval-augmented generation (RAG) has emerged as a hybrid paradigm tackles some of the most persistent shortcomings of LLMs, such as knowledge staleness, narrow scope of their context windows, and difficulty of tracing outputs back to their sources (Vaibhav, 2025; Y. Gao et al., 2024; Gupta et al., 2024). Although LLMs excel at producing fluent, human-like text, they often falter when facing domain-specific queries or requests for information that falls beyond their training cutoff. RAG directly addresses these challenges by integrating external information retrieval within the generation process, allowing outputs to be more factual, up-to-date, and grounded in verifiable sources (X. Wang et al., 2024).

At its core, a typical RAG pipeline consists of two main stages: **retrieval** and **generation** (ODSC-Community, 2024). The process begins with preprocessing and indexing, where raw data is cleaned, extracted, segmented into manageable "chunks", and encoded into vector representations. These embeddings are then stored in a vector database (e.g., Milvus, Faiss, Qdrant)[15] to facilitate efficient similarity searches. When a user submits a query, it is encoded in the same vector space, and the system retrieves the top-k most relevant chunks from the indexed knowledge base. In the subsequent stage, these retrieved documents are passed as context to a generative language model – often based on Transformer architectures (Vaswani et al., 2017) – which synthesises a response that blends the original query with external evidence, producing answers that are both coherent and contextually appropriate (Arslan et al., 2024).

[15] Cf. Glossary in Appendix B.

This modular design (Fig. 1) enables the continuous incorporation of domain-specific and current information, overcoming the constraints of static model parameters. Recent contributions have helped to formally systematise the RAG pipeline, with frameworks delineating specific interdependent modules such as query classification, retrieval, reranking, and generation (X. Wang et al., 2024; Y. Gao et al., 2024).

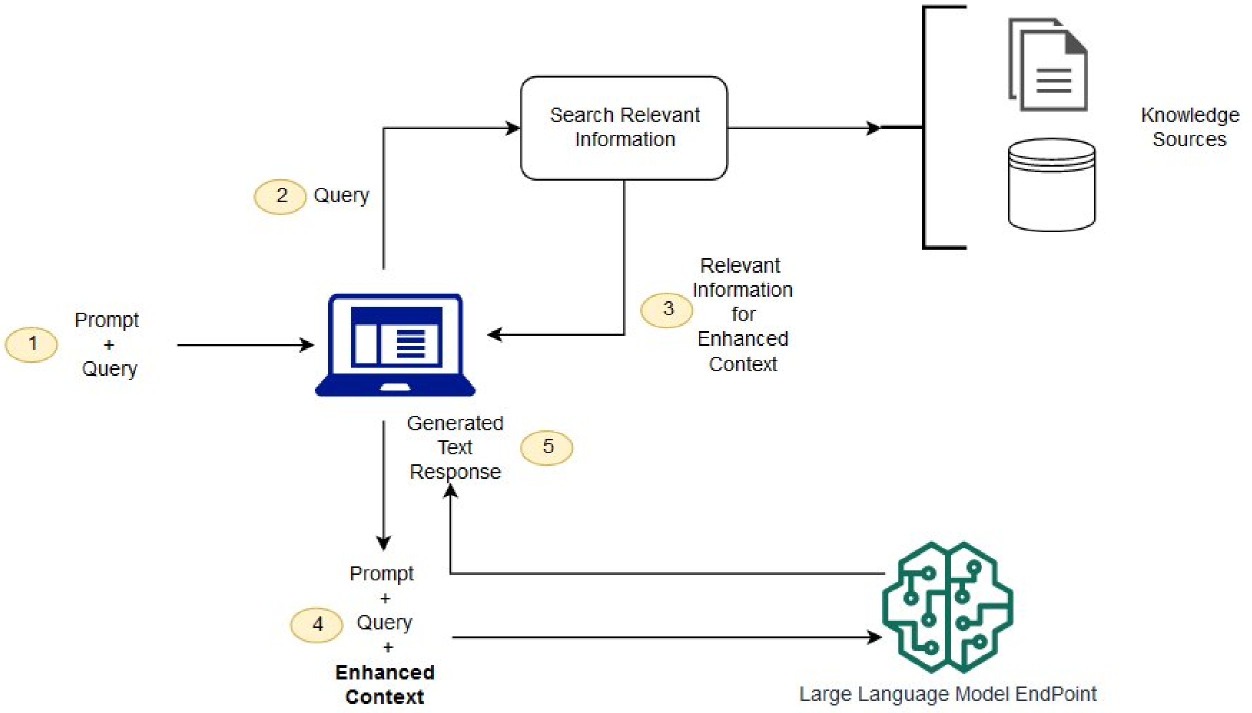
Search Relevant Information
Knowledge Sources
2
Query
Relevant Information for Enhanced Context
3
1
Prompt + Query
Generated Text Response
5
Prompt + Query + Enhanced Context
4
Large Language Model EndPoint

Figure 1: Typical retrieval-augmented generation (RAG) pipeline.
Source: https://aws.amazon.com/de/what-is/retrieval-augmented-generation/.

3.1.1 Pipeline Components and Common Practices

The design of RAG pipelines can vary considerably depending on the specific use case, domain of application, and resources available. Still, a number of recurring practices have gradually crystallised into what can be regarded as the current state of the art in retrieval-augmented generation (Vaibhav, 2025; X. Wang et al., 2024; Arslan et al., 2024; Y. Gao et al., 2024; Gupta et al., 2024). These practices often serve as reference blueprints rather than rigid prescriptions, since not every component needs to be implemented in every system. Instead, they represent a modular design space, where specific strategies can be combined, adapted or omitted to suit particular tasks.

In their most typical configuration, RAG pipelines comprise the following elements:

- **Query understanding and classification.** Not all queries require retrieval from external sources. Advanced systems first analyse and classify incoming queries to determine whether retrieval is necessary or if the LLM alone suffices. This step relies on natural language understanding (NLU) techniques to extract key entities, relationships, and user intent, thereby improving efficiency and reducing unnecessary retrieval latency.

- **Document indexing and chunking.** Raw data from source documents is preprocessed: cleaned, segmented into manageable chunks at token, sentence, or semantic level, and converted into dense vector representations (embeddings). Recent studies recommend dynamic or semantic chunking over simple fixed-size splitting, as it better preserves context and improves retrieval quality – especially in heterogeneous domains.

- **Embedding and Vector Database.** Both document chunks and user queries are embedded into a shared vector space using models fine-tuned for semantic similarity (e.g., BAAI/bge, LLM-Embedder, intfloat/e5). These vectors are stored in efficient vector databases (e.g., Milvus, Faiss, Qdrant), selected based on scalability, indexing strategies, and support for hybrid (vector plus keyword) search capabilities.

- **Retrieval and query transformation.** When a user submits a query, it is first encoded into a vector representation and used to retrieve the top-k relevant chunks from the indexed KB via similarity search. To make it more robust, the pipeline can adopt a hybrid approach based on dense retrieval – embedding-based methods such as DPR or Contriever – combined with sparse retrieval – lexical methods such as BM25. Retrieval can be further improved through query transformation strategies, including rewriting, decomposition, or the generation of hypothetical supporting documents (e.g., HyDE).

- **Reranking.** the initial candidate set can be reordered to emphasise relevance to the original query. This is frequently achieved with cross-encoder models such as monoT5, monoBERT, or RankLLaMA, which jointly consider the query and each candidate, or with more sophisticated algorithms through heuristics. This contextualization ensures that the most pertinent information is prioritised for the generative model.
  See Tab. 3 for a summary on reranking techniques.

- **Repacking and summarization.** In some cases, retrieved passages may be reorganised or summarised to distil key information, especially when dealing with lengthy corpora. This step can involve extractive summarization or abstractive (e.g., with Pegasus or T5) techniques to condense information and fit within the context window of the generator model.

- **Generation.** The generative model – usually a transformer-based LLM such as T5, BART, or GPT – synthesises a response conditioned on both the original query and the retrieved context, integrating intrinsic model knowledge with external evidence to produce a coherent, accurate, and contextually grounded answer.

Tab. 4 presents an overview of the methods most consistently reported as high-performing for each module of a RAG pipeline. When aiming for balanced efficiency – i.e., reducing latency while maintaining good, but not maximal, accuracy – adjustments are typically made at the retrieval and reranking stages. In practice, this involves replacing the Hybrid + HyDE retrieval method with a standard Hybrid search approach, which combines BM25 and dense retrieval without pseudo-document generation, and substituting monoT5 with TILDEv2 for reranking, which delivers faster processing at the cost of a modest reduction in answer quality (X. Wang et al., 2024).

Algorithm	Rationale
Cross-encoder rerankers	Jointly encode concatenated query-document pairs to produce fine-grained relevance scores. These models – e.g., monoT5, monoBERT, RankLLaMA – are fine-tuned to classify relevance as "true" or "false", and at inference, documents are ranked by the predicted probability of the "true" label (X. Wang et al., 2024).
TILDE (Zhuang and Zuccon, 2021)	Token-level likelihoods for queries across a collection, allowing fast reranking by summing the probabilities of query tokens given each candidate passage.
Learning-to-Rank (LTR) (Gupta et al., 2024)	Traditional machine learning ranking approaches: **a) Point wise:** predicts relevance score for each document independently; **b) Pair wise:** compares pairs of documents to learn relative relevance; **c) List wise:** considers the entire ranked list at once.
HyDe (L. Gao et al., 2022)	Generates hypothetical documents from queries for dense retrieval.
Hybrid Search (sparse + dense scoring)	Blends scores from dense retrievers (semantic similarity – e.g., DPR, Contriever) and sparse methods (lexical overlap – e.g., BM25, TF-IDF) for robust ranking. Sometimes uses learnable weighting (X. Wang et al., 2024).
HyDE + Hybrid Search (2024)	Combines HyDE's hypothetical document generation with hybrid search for retrieval.
Graph-based (Han et al., 2025)	Constructs a graph of candidates (nodes) based on relationships (semantic, citation, or knowledge graph edges), then uses graph algorithms (e.g., PageRank, label propagation) to identify central passages.
Self-RAG (LLM-enhanced reranking) (Asai et al., 2023)	Uses LLMs directly to score or select the most relevant passages, sometimes via few-shot prompting or chain-of-thought reasoning.

Table 3: Algorithms for document retrieval and reranking in RAG pipelines

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Module	Method(s)	Functionality
Retrieval	Hybrid with HyDE	Combines Hybrid Search (BM25 + dense) and HyDE pseudo-documents.
Reranking	DLM w/ monoT5	Deep LLM-based reranker (good balance of quality and speed).
Chunking	Small2big / Sliding Windows	Organising chunk block relationships for context preservation.
Embedding	LLM-Embedder	Dense supervised retriever, best trade-off performance/size.
Vector Database	Milvus	Best coverage of index type, scalability, hybrid search, cloud-native.
Repacking	Reverse	Puts most relevant context close to the query.
Summarization	Recomp	Both extractive and abstractive methods tested; Recomp performs best.

Table 4: Best-performing RAG pipeline selections for maximising performance w.r.t. answer quality and accuracy.

Fig. 2 provides a broader overview of the RAG ecosystem. The paradigm evolves from naive to modular RAG, incorporating techniques for improving retrieval and generation – e.g., chunk optimization, adaptive retrieval, dual fine-tuning –, as well as the key issues of when, what, and how to retrieve. RAG also faces open challenges, including robustness, scaling laws, production readiness, alongside modality extensions to image, audio, video, code, and ecosystem directions like customization, specialization. Finally, current evaluation targets and frameworks distinguish between retrieval quality and generation quality, together with their assessment aspects such as answer relevance, context relevance, faithfulness, robustness, and integration (Y. Gao et al., 2024).

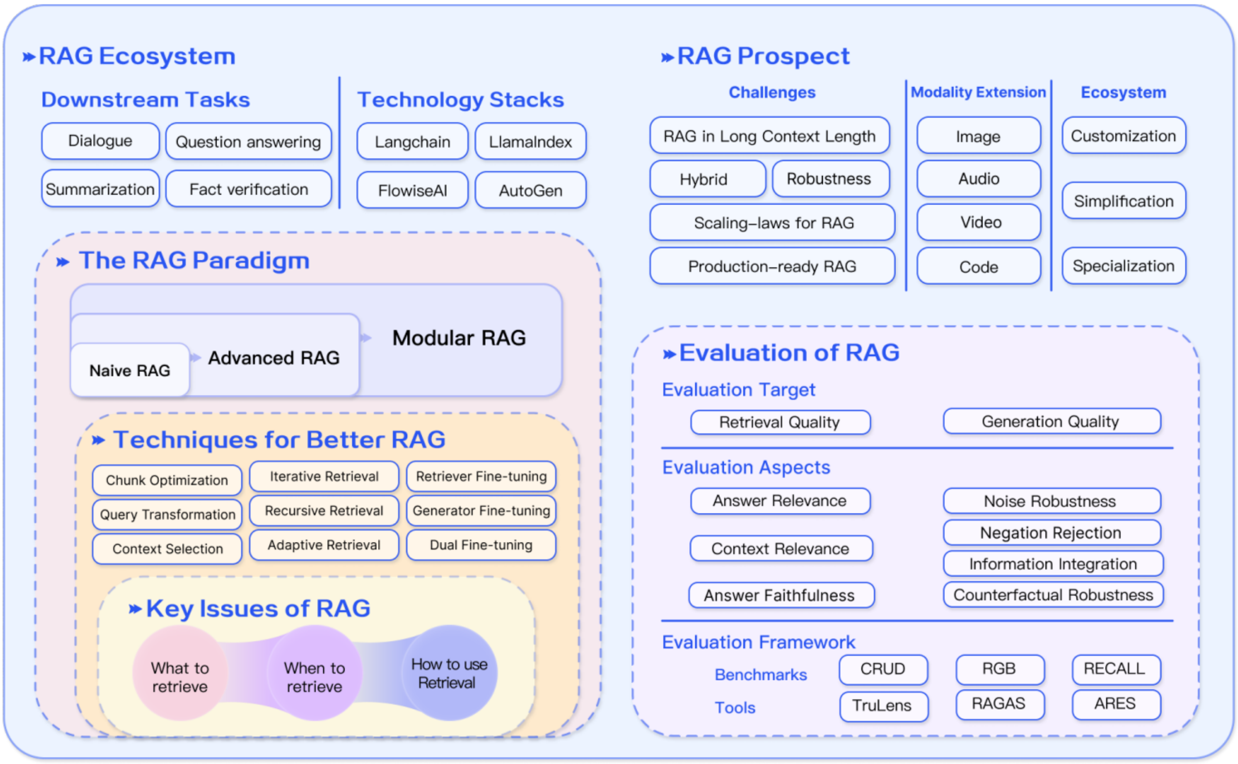


Figure 2: Summary overview of the RAG ecosystem.
Source: Y. Gao et al., 2024.

3.1.2 Evaluation and Benchmarking

Evaluating RAG systems poses unique challenges, as traditional metrics like BLEU, ROUGE or METEOR may not fully capture the quality of generated responses, particularly in terms of factual accuracy and contextual relevance. In conversational QA research, this limitation has long been acknowledged: multi-turn settings require models not only to answer a single query but also to maintain consistency, resolve co-references, and adapt to evolving conversational context (Zaib et al., 2022). Consequently, evaluation must go beyond surface level overlap and incorporate measures that reflect contextual appropriateness and understanding at discourse level. Moreover, assessing RAG systems requires attention to both retrieval and generation quality, since failures in either stage directly impact the final response (Abeysinghe and Circi, 2024).

Surveys of the field have increasingly highlighted the need for frameworks capable of measuring multiple dimensions of RAG. Despite the rapid systems' advancements in retrieval, generation, and augmentation, evaluation methods remain underdeveloped, with persistent challenges in capturing retrieval quality, hallucination rates, and faithfulness of generated content in a systematic way (Y. Gao et al., 2024). Large-scale benchmarks such as BEIR (Thakur et al.,

2021) and TREC (Voorhees et al., 2005) continue to be standard for retrieval, but generation quality requires different approaches. Newer frameworks like the Retrieval-Augmented Generation Assessment System (RAGAS) have therefore been introduced to capture aspects such as contextual alignment, answer faithfulness, and pipeline-level performance (Es et al., 2023).

Experimental studies of RAG pipelines within LLM-based applications further demonstrate the complexity of the task. For example, a recent work compares automated metrics, human evaluation, and LLM-based evaluation in the context of *EdTalk*, a RAG-powered chatbot built to navigate educational reports. Their findings show that automated metrics such as BLEURT are useful for rapid iteration but often misalign with human judgments, while factored human evaluation – structured around criteria including correctness, informativeness, relevance, clarity, and hallucination – provides richer insights into system performance. At the same time, LLM-based evaluators show promise for scalable assessment but risk inflating scores, especially when the same model is used for both generation and evaluation. This stresses the need for hybrid and carefully designed evaluation pipelines when deploying RAG in real-world contexts (Abeysinghe and Circi, 2024).

Human-in-the-loop evaluation continues to be critical, with expert judges assessing criteria such as factual accuracy, coherence, and domain relevance – offering richer and often more reliable quality assessments than quantitative metrics alone. In conversational contexts, this is especially important: metrics must reflect user satisfaction and interaction quality rather than isolated response correctness (Gupta et al., 2024).

Alongside automated and human-centred metrics, evaluation taxonomies are moving toward a more fine-grained view of system quality. Dimensions such as answer relevance, context relevance, and faithfulness directly address hallucination and grounding, while robustness dimensions – including resilience to noise, negation, counterfactual scenarios, and multi-source information integration – test whether systems remain reliable under real-world conditions. To operationalise these dimensions, new benchmarks such as CRUD, RGB, and RECALL extend beyond traditional IR settings by jointly assessing retrieval and generation. Complementary tools make evaluation continuous and developer-friendly: RAGAS targets faithfulness and contextual alignment, ARES offers flexible automated pipelines, and TruLens integrates performance monitoring into deployed workflows. Together, these resources enable evaluations that move beyond static accuracy to capture robustness and reliability under dynamic conditions (Y. Gao et al., 2024).

Furthermore, ethical considerations must be embedded throughout the lifecycle of RAG pipelines. Protecting data privacy, mitigating algorithmic bias, and complying with regulations such as GDPR are fundamental. This means adopting technical measures like privacy by design, data minimization, and access control, in addition to committing to broader ethical principles widely recognised in international guidelines: transparency, justice and fairness, non-maleficence and responsibility (Jobin et al., 2019). Ongoing audits, stakeholder involvement, and mechanisms for accountability, including whistleblowing and legal clarity, help bridge the gap between abstract principles and operational practice, ensuring systems remain trustworthy and socially beneficial (Ashery et al., 2025).

Overall, the trajectory of RAG systems points toward increasingly sophisticated applications that are deeply integrated into the workflows of research, industry, and cultural institutions. Innovations in evaluation frameworks, user interaction, and system scalability are steadily pushing the boundaries of what these models can achieve. As these technologies continue to mature, success will depend on the ability to combine robust benchmarking, user-centred feedback mechanisms, and adaptive optimization strategies. Addressing challenges related to factuality, scalability, and responsible deployment will be essential for building trustworthy systems capable of delivering high-quality information in context-sensitive settings. With continued progress, RAG systems are set to play a pivotal role in shaping the future of digital knowledge access and discovery. (Zaib et al., 2022; X. Wang et al., 2024; Y. Gao et al., 2024).

3.2 New Frontiers Applications

RAG systems are increasingly deployed across a wide spectrum of contexts – spanning academic research, enterprise infrastructures, and real-world product environments – where they serve to enhance data accessibility, support decision-making, and facilitate natural language interaction with complex knowledge bases. Recent surveys and empirical studies trace a rapidly expanding set of scholarly applications. In the field of academic support, for instance, retrieval-augmented pipelines power automated literature review tools and citation management platforms such as *LitLLM* (Agarwal et al., 2025), and *KNIMEZoBot* (Alshammari et al., 2023). In conversational AI, retrieval enables grounded multi-turn dialogue, exemplified by *Wizard of Wikipedia (WoW)* (Dinan et al., 2019), which can be read as an early instantiation of what is now formalised as RAG-based dialogue modelling.The paradigm is also leveraged for large-scale summarisation, distilling insights across vast corpora of scholarly papers, and for fact verification tasks, as in resources like *PubHealth*, increasingly adopted to counter misinformation in sensitive domains such as health communication (Kotonya and Toni, 2020). In this regard, RAG has proven especially valuable in domain-specific knowledge extraction, most notably in biomedical and legal research, where retrieval mechanisms act as an extension of expert knowledge.

In one experiment, a RAG system was developed to assist data scientists through a combination of GROBID library[16] for structured bibliographic extraction, fine-tuned embeddings, semantic chunking, and an abstract-first retrieval strategy. The system's performance, assessed using the *Retrieval-augmented generation Assessment System (RAGAS)*, demonstrated improved faithfulness and context relevance in response generation (Aytar et al., 2024). A similar approach was explored in the context of academic library systems, where RAG was applied to improve contextual retrieval through semantic indexing of structured metadata (e.g., MARC/RDA standards) and multimodal resources. Additionally, the framework introduced conversational querying via a natural language interface, supporting complex interdisciplinary searches and significantly improving document discoverability by synthesising citation-backed responses from diverse scholarly sources – including journals, datasets, and videos. This solution also addressed challenges such as copyright compliance and ethical AI transparency (Bevara et al., 2025). Collectively, these studies affirm RAG systems' efficacy in alleviating information overload and improving research workflow discoverability.

In parallel, the work of (Soman and Roychowdhury, 2024) provides further critical insights into the design of RAG systems for domain-specific and technical content, closely aligning with the methodological framework adopted in the GNA question-answering system. Using IEEE telecommunications engineering corpora (i.e., wireless LAN specifications and battery glossaries) as testbeds, their analysis highlights key factors influencing retrieval quality, which include chunk size, sentence-level similarity, and the strategic placement of domain-specific terms. These aspects are similarly addressed in the GNA RAG pipeline (Pograri, 2025), which applies customised chunking, semantic preprocessing, and contextual embedding strategies. Both studies advocate for more nuanced, context-aware approaches to enhance precision in technical and highly structured domains.

Numerous recent graduate-level research projects have provided substantive input into the implementation and evaluation of RAG systems:

- Antolini (2025) developed a custom RAG system for open-domain question answering using both traditional (BM25, PRF) and advanced retrieval strategies, integrated with local LLMs. A novel Parametric RAG (PRAG) approach was also explored, embedding context into model parameters for performance gains;

- Caramanna (2024) investigated conversational agent architectures, comparing various

[16] GROBID is a machine learning library designed to extract, parse, and convert raw documents, like PDFs, structured XML/TEI encoded documents (*GROBID*, 2008–2025).

LLM types and retrieval configurations;

- Florio (2024) implemented a LangChain-based RAG chatbot for corporate documentation, evaluating multiple vector database technologies.
- Salcuni (2025) applied RAG to the medical domain, improving LLM responses in hypertension care. The study used RAGAS to assess quality and relevance, focusing on personalization and accuracy;
- Nicoletti (2025) developed Essence Coach, a chatbot that integrates LLMs with the Essence software engineering standard. This system significantly outperformed generic LLMs like GPT-4o in domain-specific reasoning tasks.

3.3 Retrieval-Augmented Generation in the Digital Humanities

A growing body of research is exploring RAG applications within the digital humanities. One such example is the *iREAL* project, which applied RAG to interpret archival records from Aboriginal schools in Australia, demonstrating a careful balance between cultural sensitivity and historical accuracy (Callaghan and Vieira, 2025). Another initiative, *ValuesRAG*, focuses on cultural alignment in LLMs by integrating societal and demographic knowledge through retrieval-augmented contextual learning, experimenting with the *World Values Survey* dataset (Seo et al., 2025). In another case, the *Foggia Occupator Dataset* project applied a RAG model to post-WWII Italian periodicals, extracting information on political figures and stylistic traits (Ciletti, 2025).

Among the technical approaches explored in recent experiments on generative AI for digital scholarly editions, RAG emerges as a promising method for addressing challenges such as entity linking (EL) and the integration of external knowledge sources. Notably, RAG is recognised for its ability to mitigate hallucinations in named entity recognition (NER) and to enable the enrichment of text with information from structured databases or knowledge graphs (Pollin et al., 2025). For example, an experiment with the Regesta Imperii project demonstrates how knowledge bases, including Neo4j graph databases, are leveraged within RAG pipelines to improve accuracy in information extraction, entity normalization, and semantic annotation (Kuczera and Armbruster, 2024). Similarly, the editorial workflow developed for the Hugo Schuchardt Archive outlines a process that combines prompt engineering, human-in-the-loop oversight, and RAG tool chains to enhance the generation of TEI-compliant XML, supporting more explainable and modular processing pipelines (Pollin et al., 2023). These and other experiments underscore the need for standardised workflows, robust evaluation protocols, and systematic research into both the strengths and weaknesses of LLMs and related tools in the editorial process, while also advocating for thoughtful engagement with advanced computational methods in the humanities (Pollin et al., 2024). As digital editions become increasingly complex and interconnected with broader knowledge infrastructures, the relevance and application of AI technologies – such as RAG – are both expected and desirable to grow accordingly.

RAG methodologies are being adopted within the GLAM sector as well. In archival contexts, a smart assistant developed for querying the *Prozhito* digital archive of personal diaries combines text-to-SQL filtering, hybrid search, and automatic query reformulation, proving especially effective for historians and anthropologists without prior knowledge of database query languages (Sergeev et al., 2025). Meanwhile, in museum settings, a comparative evaluation of RAG techniques versus direct large-context input approaches – i.e., feeding the entire context at once to a language model – for answering multimodal questions about artworks demonstrated that large-context models generally give more accurate answers than RAG, at least for this task and dataset. However, RAG remains useful when information exceeds context window limits or when efficiency is important (Ramos-Varela et al., 2025).

Innovations in graph-based retrieval are also gaining momentum. Techniques combining structured supervision and chain-of-thought prompting have been used to map character relationships in early modern English historiography, thereby reducing the manual workload typically associated with historical data annotation (Fan et al., 2025). Related directions are being explored within cultural heritage institutions, as seen in the *CAT-IA* initiative, which integrates ArCo knowledge graph (Carriero et al., 2019) within a RAG system for provenance tracking, AI explainability (XAI), and structured metadata extraction (Barbato, 2025). Designed to streamline and enrich user interactions with the General Catalogue of Cultural Heritage *(Catalogo generale dei beni culturali)*, *CAT-IA* marks a notable stride in applying advanced digital technologies to promote accessibility and valorization of cultural assets.

A complementary, conceptual perspective emerges in a critical mapping of the theoretical contours of RAG within the broader landscape of archives, libraries, and cultural heritage – articulating not only the potential for RAG-augmented LLMs to enhance the precision, accessibility, and contextualization of information retrieval, but also foregrounding the social and infrastructural challenges inherent in such integration. This viewpoint encourages the field to reflect on both the affordances and the epistemic and ethical complexities introduced by RAG systems in digital humanities contexts (Di Marcantonio, 2024).

Finally, efforts to advance access to fragmented digital repositories – such as web archives – have increasingly adopted RAG methodologies. An illustrative bespoke prototype transforms keyword-based search into semantically guided question answering (Davis, 2025), sharing architectural parallels with the GNA QA system presented in the context of this thesis. Both systems prioritise semantic retrieval over lexical matching using dense embeddings – e.g., *E5* variants (L. Wang et al., 2024) – to interpret queries in context, employ structured text processing pipelines to reduce noise in source materials, and apply optimised chunking strategies for retrieval accuracy. Crucially, these studies highlight RAG's potential to transform scattered and heterogeneous resources – whether web archives or catalographic procedures – into coherent, accessible knowledge through context-aware synthesis.

3.4 Future Directions

Ongoing research is rapidly pushing the frontiers of RAG, opening up new avenues that extend well beyond traditional information retrieval into domains such as scientific research and the digital humanities. Among the most promising innovations is the use of synthetic corpora to bolster the robustness and generalizability of RAG systems, particularly in low-resource or specialised domains where annotated data is scarce (Bor-Woei, 2024). This strategy improves retrieval accuracy while addressing longstanding issues of bias, coverage, and representativity in humanities corpora.

RAG is also at the core of a new wave of applications that automate and enhance scholarly practices. In scientific research, advanced RAG frameworks – including agentic systems like *PaperQA* (Lála et al., 2023) – are being leveraged to conduct systematic literature reviews, automate evidence synthesis, summarise emerging trends, and provide transparent citation recommendations. Particularly, these multi-stage architectures enable recursive reasoning and dynamic tool usage, often surpassing human-level performance in both retrieval and summary tasks (Skarlinski et al., 2024).

Despite these advances, several critical research challenges remain. There is an urgent need to develop domain-adapted and multilingual LLMs that can process not just text, but also multimodal data such as images, tables, and audiovisual materials – a key requirement for both scientific and cultural heritage applications. Future RAG systems should be able to retrieve and reason over heterogeneous, cross-domain sources, necessitating robust mechanisms for source evaluation, multimodal fusion, and trust calibration. The ongoing development of benchmarks and evaluation datasets, tailored to the peculiar needs of fields such as the digital humanities, is essential to guide progress and ensure methodological rigour (Yue, 2025).

Another major direction is the semantic enrichment of RAG pipelines through the integration of ontologies and knowledge graphs. Ontologies, as formal domain knowledge models, provide structured frameworks that enable more precise and explainable retrieval semantic coherence, and the inclusion of ethical dimensions in generative AI. Complementing this, knowledge graphs capture complex relationships and support context-aware multi-hop reasoning, improving accuracy, explainability, and cultural sensitivity of outputs. Current research and practical applications in this direction span a range of initiatives, from ontology-guided entity typing to the grounding of AI in explicit ethical and procedural knowledge, demonstrating that these semantic tools are essential for creating robust and transparent RAG systems, addressing challenges in fields as diverse as healthcare, engineering, scientific discovery, and enterprise knowledge management (Tiwari et al., 2025; Ludwig et al., 2025; Bran et al., 2024; Sharma et al., 2024; Xiao et al., 2024; Park et al., 2024; DeBellis, 2024; Franco et al., 2020).

In the specific context of the digital humanities, the accelerated adoption of AI is shaping a transformative future for scholarship, curation, and access to cultural heritage. The diverse case studies and technical innovations, discussed in Sec. 3.3, illustrate both the breadth of RAG's impact and the field's growing ambition. Across applications, from digital scholarly editions, to archival assistance and museum information systems, RAG is emerging as a pivotal enabler for addressing the limitations of traditional search and annotation by supporting context-aware, semantically rich, and explainable information access.

Looking forward, several converging trends and open challenges will define the evolution of RAG in the digital humanities. First, technical advances such as the integration of knowledge graphs, graph-based retrieval, and multimodal pipelines are driving improvements in semantic linking and annotation of historical, literary, and artistic materials. Second, the increasing complexity of digital scholarly editions and GLAM infrastructures is catalysing demand for standardised, reproducible workflows, robust evaluation protocols, and domain-adapted benchmarks, ensuring that RAG methods are critically assessed and tuned for the nuanced needs of humanistic research.

At the same time, as digital repositories become ever more fragmented, the promise of RAG lies in its ability to synthesise heterogeneous, dispersed data – transforming scattered web archives, periodicals, and catalogues into knowledge spaces that are accessible and meaningfully structured. Yet, this evolution also foregrounds critical conceptual and ethical questions. As highlighted by recent critical perspectives, it is essential to position RAG as an augmentative technology: one that enhances, but does not replace, established cataloguing, metadata, and interpretive practices. Human interpretive oversight, transparency, and cultural sensitivity must remain central, particularly as RAG systems are increasingly relied upon for knowledge production and mediation in complex social and historical domains (Di Marcantonio, 2024).

In sum, the next phase of RAG's development in the digital humanities will require sustained interdisciplinary collaboration and critical reflection. Researchers and practitioners must continue to experiment with new strategies, but also engage deeply with the epistemic, social, and infrastructural complexities of integrating advanced AI into cultural knowledge management. Ultimately, RAG applications stand poised not only to offer improved access to information, but they also invite a reimagining of the relationship between artificial intelligence and cultural knowledge production, fostering tools that augment – not displace – human creativity and understanding.

Chapter 4

Case Study: A Question-Answering System for GNA

4.1 Geoportale Nazionale per l'Archeologia (GNA)

Geoportale Nazionale per l'Archeologia (GNA) (Mic, 2019) serves as the central online hub for the collection, management, and dissemination of data generated by archaeological investigations carried out across Italy (Acconcia, 2023). Developed under the auspices of the Ministry of Culture (MiC), the project's primary goal is the creation of a dynamic archaeological map of the national territory, which is easily updatable over time, openly accessible, and designed for reuse and integration across multiple institutional and disciplinary contexts (Falcone et al., 2023).

The inception of the GNA traces back to a 2014 *Memorandum of Understanding* signed by the Ministero dei Beni e delle Attività Culturali e del Turismo (MiBACT) – specifically the Segretariato Generale, the Direzione Generale per le Antichità (DG-Ant), and the Consiglio Nazionale delle Ricerche (CNR). This agreement laid the groundwork for a national platform dedicated to the safeguarding and enhancement of cultural heritage through integrated digital infrastructure. However, it was the establishment of the Istituto Centrale per l'Archeologia (ICA) in 2016 that provided the structural and institutional foundation for the GNA. The ICA's mandate to define standards and promote digital archaeological databases gave renewed potential to the initiative, which culminated in the launch and formal presentation of the GNA at a ministerial venue in 2019 (Calandra, 2023).

Beyond being a data aggregator, the GNA serves as a dynamic knowledge base, collecting digital content from professional archaeologists – especially those engaged in preventive archaeology –, research groups, universities, and concession-holders. The platform also accommodates a variety of outputs, from QGIS-based vector data to reports, documentation packages, and datasets from academic and research contexts. Data publication in the GNA is managed with attention to quality standards, intellectual property, and open-access principles, supported by the assignment of DOIs and the use of Creative Commons licensing (CC-BY 4.0), ensuring both traceability and reusability (Acconcia, 2023; Falcone et al., 2023; Boi, 2023).

4.1.1 Purpose and Scope

As the official repository for all research activities in archaeology – particularly those related to public infrastructure projects – the GNA platform was established to provide a unified national access point to essential archaeological data gathered nationwide. This includes the interventions listed in Tab. 5, all conducted under the scientific supervision of the Italian Ministry of Culture (MiC) (Acconcia, 2023; Falcone et al., 2023).

Archaeological interventions	**Description**
Preventive archaeology reports	Data from excavations and surveys carried out ahead of construction projects (e.g., highways, railways, pipelines), often submitted by private firms or cultural heritage consultants.
Assisted scientific excavations records	Results from academic digs by universities or research institutions, including documentation of stratigraphy, finds, and site interpretation.
Accidental discoveries	Locations of fortuitous archaeological finds, such as during agricultural work or construction, reported to local heritage authorities. Typically include preliminary spatial data and descriptive reports.
Scheduled excavations	Long-term planned investigations, often at known heritage sites, including geospatial boundaries, uncovered structures, and findings.
Archaeological surveys	Surface survey data with GPS-tracked locations of finds, artifact scatters, and site features.
Cultural heritage GIS layers	External datasets from institutions (regional superintendencies, local governments, ICCD), e.g., maps of protected zones, risk maps, or site inventories.
Legacy data and digitised archives	Georeferenced digitizations of paper maps, notebooks, and archival records previously stored in non-digital formats, essential for integrating historical with current data.
Depository locations	Georeferenced storage locations of archaeological finds (museums, storerooms) associated with sites or interventions.
Remote sensing and aerial surveys	Drone imagery, LiDAR scans, or satellite data used to identify and map archaeological features not visible at ground level.
Paleontological sites	A specific level dedicated to paleontological sites is currently under study for future inclusion, aiming to protect this fragile heritage.

Table 5: Types of archaeological data sources integrated into Geoportale Nazionale per l'Archeologia.

These sources, once georeferenced and structured, are integrated into the GNA using standardised metadata and visualization protocols, to allow users to view, search, and analyse information in a spatially accurate and coherent manner (Boi, 2023; Acconcia, 2023).

4.1.2 Stakeholders and Intended Users

The development of the GNA saw significant acceleration during the COVID-19 pandemic, which provided both the urgency and institutional impetus toward the creation of a unified digital platform for managing archaeological data nationwide. This initiative built upon years of prior collaboration between key stakeholders, including the Istituto Centrale per l'Archeologia (ICA) and the Istituto Centrale per il Catalogo e la Documentazione (ICCD), who had already developed a cataloging structure to document archaeological assessments and identified sites within the Sistema Informativo Generale del Catalogo (SiGECweb) (Calandra, 2023; Boi, 2023). The pandemic underscored the limitations of purely textual cataloguing and catalysed a shift toward a more dynamic and geospatially grounded approach, leading to the adoption of a GIS-based framework better suited for preventive archaeology and territorial planning. The result was a consolidated national infrastructure designed not only to support compliance with cultural heritage protection regulations but also to enable data harmonization across previously fragmented practices (Acconcia, 2023).

The GNA is primarily intended for use by:

- Public administrators and government officials;
- Professional archaeologists and cultural heritage consultants;
- Stakeholders involved in public works, such as national infrastructure planners.

For instance, major entities like TERNA (the national electricity grid operator), RFI (the Italian railway network), or the Milan Metro rely on the platform to assess archaeological constraints before launching construction projects. The platform helps them identify archaeological sites, deposits, and or protected areas that must be preserved. The GNA also supports compliance with European and Italian open data and transparency regulations, guaranteeing both civic access and the protection of intellectual property, as per national FOIA and EU directives[17] (Falcone et al., 2023).

Central to the system is a QGIS[18] template that standardises data entry and visualization. This tool supports collaborative integration of local information into the national infrastructure,

[17] The FOIA (Freedom of Information Act) Guidelines are documents issued by the Italian National Anti-Corruption Authority (ANAC) to clarify and guide the implementation of the right to generalised civic access in Italy. The guidelines – especially those from 2016 – define the limits and exclusions to access, as well as specify the publication and transparency obligations for public administrations.
Read more at https://foia.gov.it/normativa.

[18] QGIS is a free, open-source Geographic Information System (GIS) software used for creating, managing, and analysing geospatial data.

offering users a unified territorial overview. It enables the comparison of diverse archaeological records, improves the quality of evaluations, and promotes transparency across institutional workflows. Thanks to its open-source foundation and modular structure, the GNA continues to evolve based on user feedback, maintaining a shared national standard while accommodating diverse local contributions (Calandra, 2023; Boi, 2023).

4.1.3 User Manual and Operational Support

To guide users in correctly navigating the system, a collaboratively maintained user manual (*manuale operativo*) is made available online through a MediaWiki environment hosted on the GNA server (GNA, 2024). This living document offers structured instructions on all aspects of data input, visualization, and management within the GNA platform.

The manual offers step-by-step instructions for compiling and submitting data using the QGIS template, including the creation and editing of project modules (MOPR), the documentation of archaeological sites and events (MOSI), and the proper use of supporting layers such as risk maps or thematic overlays. Each section of the manual is designed to be accessible both to GIS beginners and to experienced professionals, offering annotated screenshots, workflow examples, and direct links to downloadable resources. A notable feature of the operational manual is its integration with the GNA QGIS plugin, which allows users to directly download standardised data layers – such as archaeological risk assessments, site boundaries, or previous project records – into their local GIS environment (Gabucci, 2023).

In addition to the written documentation, the GNA provides ongoing operational support through a dedicated Help Desk service, coordinated by Ada Gabucci.[19] Users encountering technical challenges or seeking clarification on data entry procedures can contact the Help Desk for personalised assistance. This direct support, together with the collaborative and evolving nature of the manual, fosters a strong community of practice, encouraging the sharing of expertise and continual improvement of the platform's tools and resources.

[19] Ada Gabucci is a specialist in Roman-period archaeology, with expertise in stratigraphic methods, northern Italian material culture, and the structuring of archaeological data. She has over thirty years of experience consulting for public institutions, including the Italian Ministry of Culture (ICCD, ICA, DG-ABAP), its regional branches, the Veneto Region, and several universities, including Trieste, Venice, Verona, Bologna, Genova, and Pisa. Her work also encompasses cultural heritage cataloguing, ministerial regulations, and the design of complex Geographic Information Systems.
Source: https://web.archive.org/web/20250724081422/https://conf24.garr.it/it/speaker/ada-gabucci.

4.2 Proof of Concept

In response to the challenges users face in quickly locating relevant information when accessing and navigating the GNA operative manual, as well as the high volume of inquiries received by the Help Desk, a need emerged for a smarter and more efficient support solution. To address this, we developed an information system in the form of a question-answering system designed to assist users directly and reduce the Help Desk's workload. Based on the current state of AI, ML and DH methodologies – as discussed in Chap. 3 and especially Sec. 3.2 – RAG combined with NLP was chosen as the most effective approach. This technology enables the chatbot to dynamically retrieve relevant information, which serves as an augmented knowledge base, allowing it to generate precise, context-aware, and up-to-date answers tailored to user queries.

4.2.1 Functional Requirements

Functional requirements define what the system must do to deliver value to users and stakeholders:

- **Natural language understanding (NLU):** the system must interpret user queries phrased in natural language, supporting diverse question types (factoid, list, explanatory, etc.) and handling both simple and complex multipart queries.

- **Information retrieval:** the system must retrieve relevant passages or document segments from the GNA knowledge base, using vector similarity search over chunked content.

- **Context-aware answer generation:** the system must synthesise coherent, context-aware answers using RAG, drawing from retrieved passages and maintaining reference to original sources.

- **Source attribution and citation:** answers must include traceable citations (e.g., URLs) to ensure transparency and support verification.

- **Conversational memory:** the system must retain context from previous exchanges to handle follow-up questions and maintain dialogue continuity within a session.

- **Multilingual support:** the chatbot must process and generate responses in Italian, with potential extensibility to other languages.

- **User feedback collection:** the system must provide mechanisms for users to rate responses and submit qualitative feedback, enabling ongoing evaluation and improvement.
- **Interactive user interface:** users must be able to input queries and view answers through an accessible web interface, including features such as clickable citations, feedback buttons, and session management.

4.2.2 Non-Functional Requirements

Non-functional requirements define how the system should operate to ensure quality, usability, and maintainability:

- **Accuracy and relevance:** answers must be factually correct, directly address user queries, and reference up-to-date information.
- **Performance and scalability:** the system must deliver responses with low latency (target average retrieval and response time inferior to 1 second per query) and scale to support multiple concurrent users.
- **Robustness and reliability:** the system should gracefully handle invalid queries, errors, and resource constraints without crashing.
- **Transparency and traceability:** every generated answer must cite its sources clearly. The underlying process for retrieval should be auditable.
- **Security and privacy:** the system must securely handle sensitive data. User interactions should be anonymised, and no personally identifiable information should be stored.
- **Maintainability and extensibility:** The architecture must support modular updates (e.g., changing retrieval strategies), and facilitate maintenance, debugging, and future enhancements.
- **Resource efficiency:** the solution must operate efficiently within the limits of available hardware, minimising memory and compute consumption, especially for cloud deployment scenarios without GPU access.
- **User accessibility:** the web interface must be usable by non-technical users and meet accessibility standards (e.g., clear labelling, visual feedback, keyboard navigation).

- **Continuous evaluation:** the system must support automated and human-in-the-loop evaluation methodologies, generating reports on retrieval accuracy, answer quality, and user satisfaction over time.

(Abu Shawar and Atwell, 2007; Arslan et al., 2024; Gupta et al., 2024)

The following chapter details the methodological framework and practical steps undertaken during the development of the system, providing in-depth explanation of the design choices, technical architecture, data preparation, implementation and evaluation processes.

Chapter 5

Methodology

This chapter details the methodological workflow for designing and implementing the GNA QA system. The system leverages a RAG pipeline tailored to the Geoportale Nazionale per l'Archeologia (GNA) knowledge base (KB). It comprises modular components for data acquisition, preprocessing, retrieval, generation, feedback collection, and evaluation. The methodology evolved through iterative development: beginning with a prototype, built using LangChain, and advancing to a full-scale system with custom components optimised for resource efficiency.

5.1 Prototype

The initial prototype served as a proof-of-concept, developed to validate the feasibility of applying RAG to the case study and to identify early challenges. The system integrated a minimal pipeline built with LangChain[20] – an off-the-shelf tool widely adopted for coordinating retrieval and generation tasks (Mishra, 2024; Akkiraju et al., 2024) – to combine vector-based retrieval and LLM generation within an interactive environment.

5.1.1 System Design

The prototype architecture (Fig. 3) consisted of:

- **knowledge base**: a CSV dataset created from the web-based operational manual of the Geoportale Nazionale dell'Archeologia (GNA). Content was pre-processed into document chunks enriched with metadata (titles, URLs, descriptions);
- **vector store**: semantic embeddings of chunks were computed using MistralAI API and then stored in a FAISS database;

[20] LangChain is an open-source and Python-centric framework designed to simplify the development of applications powered by LLMs. For further details and practical examples, consult the official documentation at https://python.langchain.com/docs/introduction/.

- **generation language model**: the Mistral *NeMo* LLM was accessed via the same Mistral API for answer generation;
- **retrieval mechanism**: queries were embedded and matched against FAISS; all retrieved chunks were concatenated into a single context and passed to the Mistral model;
- **user interface**: a front-end implemented via Streamlit (Fig. 4) allowed users to input queries in natural language and visualise answers in a clean, accessible format.

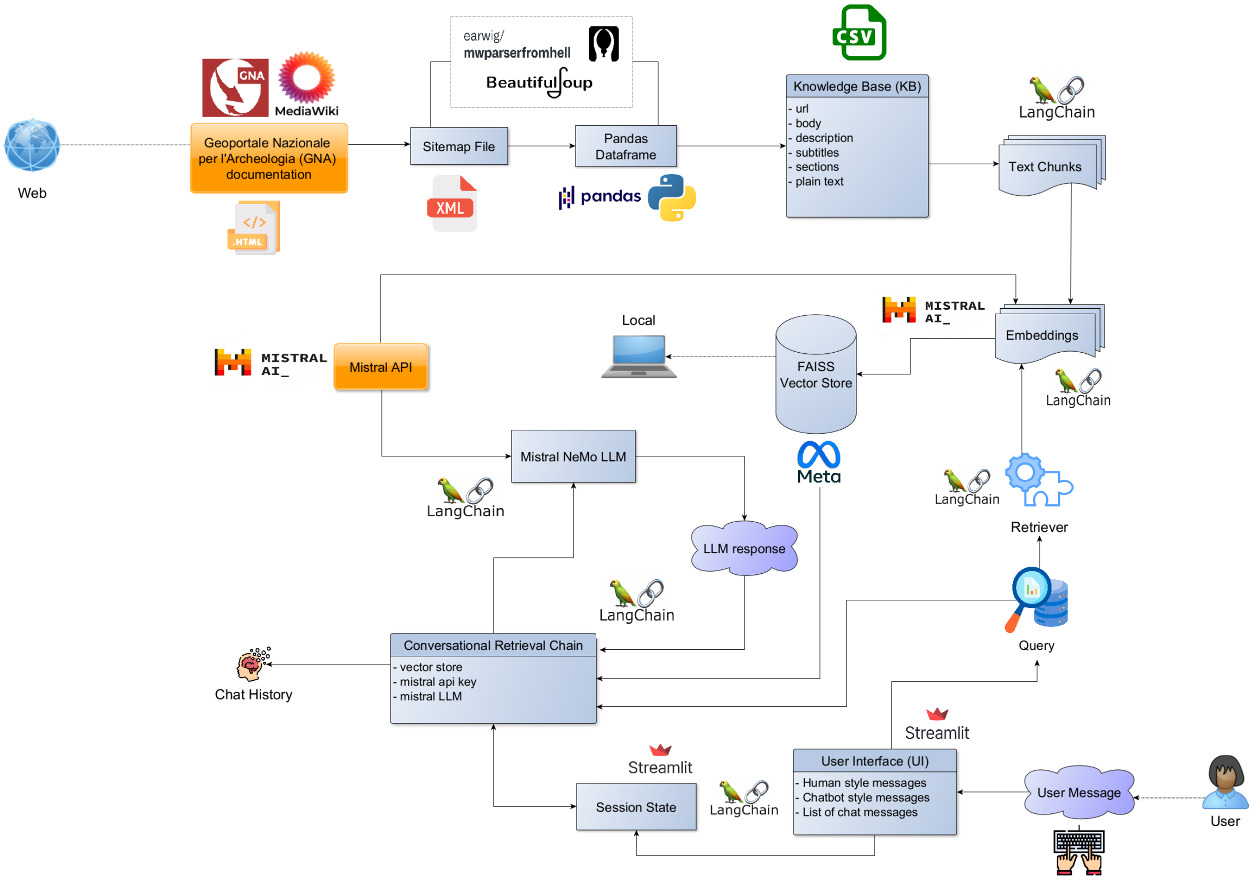
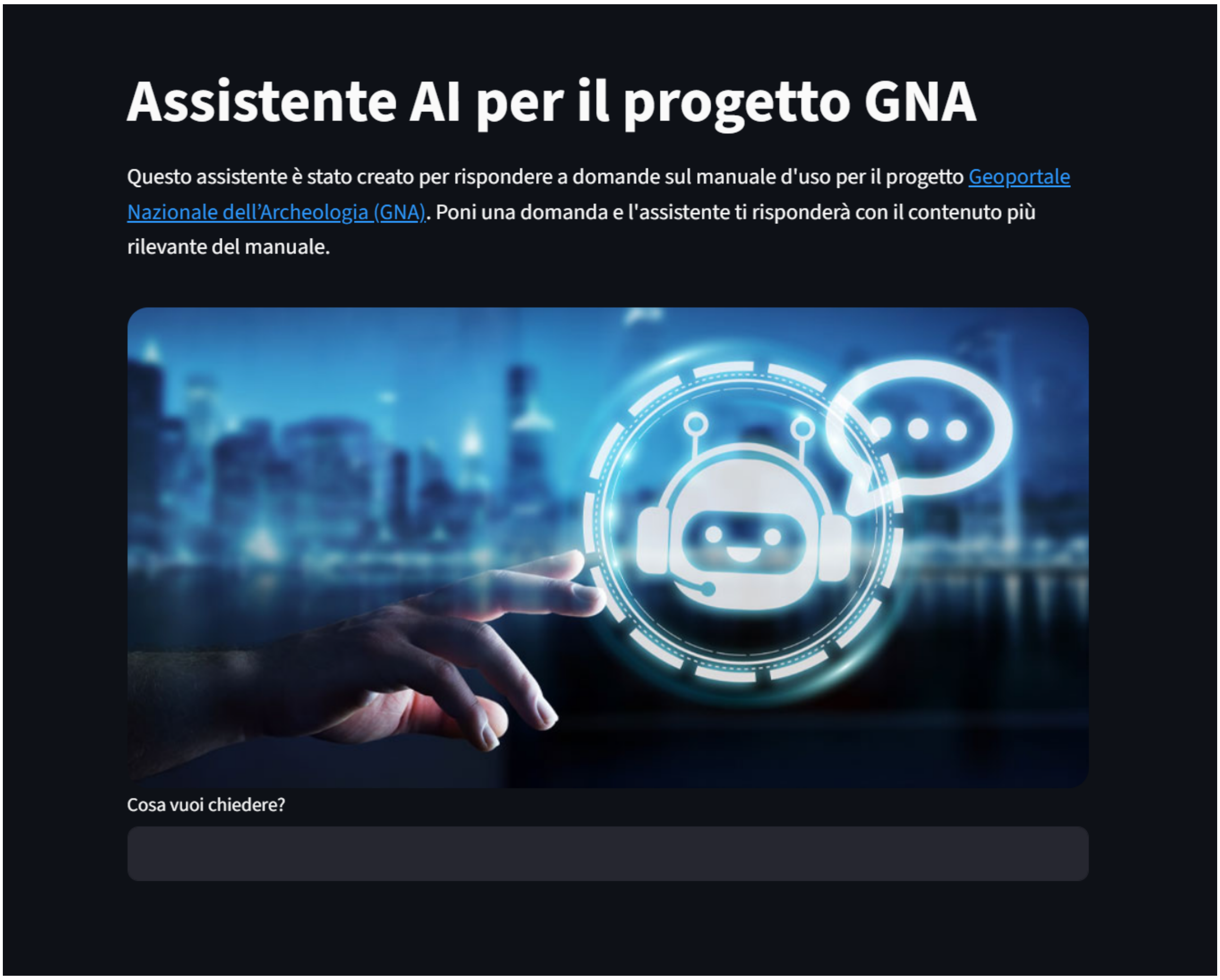


Figure 3: Prototype system architecture.



Assistente AI per il progetto GNA

Questo assistente è stato creato per rispondere a domande sul manuale d'uso per il progetto Geoportale Nazionale dell'Archeologia (GNA). Poni una domanda e l'assistente ti risponderà con il contenuto più rilevante del manuale.

Figure 4: Prototype user interface deployed on Streamlit Community Cloud.

LangChain served as the orchestration layer, providing ready-made abstractions that connected data ingestion, retrieval, and generation into a single workflow (Fig. 5). Concretely, it handled prompt templating for the Mistral *NeMo* model, mediated the `Conversational Retrieval` flow, and maintained short-term dialogue state through `ConversationBufferMemory`. The retriever was based on a FAISS vector store, which indexed chunked representations of documents and returned the top-k semantically similar chunks given a user query. Retrieved chunks were then combined using LangChain's *stuff* method[21] (Listing 5.1), in which all documents are concatenated into a single prompt template and passed to the LLM.

[21] In LangChain, the stuff method is a particular abstraction for context packing. It concatenates the top-k retrieved documents and inserts the combined block into a single prompt template passed to the LLM. While computationally lightweight, it is limited by the model's context window. LangChain also provides alternative strategies such as *map-reduce*, *refine*, and *map-rerank* (Topsakal and Akinci, 2023).

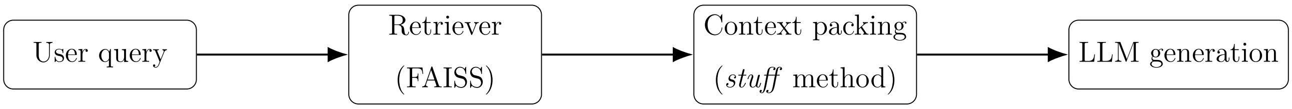


Figure 5: Prototype retrieval pipeline: from user query to generation via retrieval and context packing.

The appeal, methodologically, privileged rapid deployment over optimisation, with the primary aim of validating the pipeline: a single Pythonic framework glued together embedding creation, vector search, prompt assembly, and LLM calls, enabling a minimal viable product that validated feasibility before investing efforts in bespoke infrastructure.

```
from mistralai import Mistral
from langchain_mistralai import ChatMistralAI
from langchain.memory import ConversationBufferMemory
from langchain.chains import ConversationalRetrievalChain
from langchain.prompts import (
    ChatPromptTemplate,
    HumanMessagePromptTemplate,
    SystemMessagePromptTemplate,
)

def get_conversation_chain(vector_store, api_key: str, model_name:
    str, system_message:str, human_message:str):
    """
    Create a conversational retrieval chain with a Mistral LLM.

    The chain uses LangChain's ConversationalRetrievalChain with
       the
    default "stuff" document combination strategy, concatenating
       the
    retrieved chunks into a prompt template. A
       ConversationBufferMemory
    maintains chat history across turns, enabling stateful
       interaction.

      Args:
        vector_store: The vector database wrapper (FAISS) used for
            retrieval.
        api_key (str): API key for the Mistral LLM.
        model_name (str): Identifier of the Mistral model to be
           used.
        system_message (str): The system-level instruction in the
           prompt.
        human_message (str): The user-facing prompt template.

      Returns:
        conversation_chain: A ConversationalRetrievalChain
           instance ready
        for query-answering with memory support.
      """

    llm = create_mistral_llm(api_key, model_name)

    # Configure memory for conversation history
    memory = ConversationBufferMemory(memory_key="chat_history",
       return_messages=True)

    conversation_chain = ConversationalRetrievalChain.from_llm(
        llm=llm,
        retriever=vector_store.as_retriever(),
        memory=memory,
        rephrase_question=False,
        combine_docs_chain_kwargs={
            "prompt": ChatPromptTemplate.from_messages(
                [
                    system_message,
                    human_message,
                ]
            ),
        },
    )
    return conversation_chain
```

Listing 5.1: Usage example of the stuff method from LangChain.

At the same time, the prototyping phase exposed several framework frictions that informed the later redesign. One issue concerned redundant model calls within the LangChain stack – most notably the automatic query rephrasing in `ConversationalRetrievalChain` – which doubled LLM invocations and increased the risk of hitting API rate limits. This was mitigated through a simple rate-limiting guard with a one-second delay, but the solution remained suboptimal. A second problem arose with the retry logic in `MistralAIEmbeddings`, which failed to handle `HTTP 429` *Too Many Requests*[22] responses correctly due to a bug in LangChain's client error handling. This reduced robustness under bursty traffic until an upstream patch was introduced later on,[23] but the episode highlighted the limited control over low-level failure modes. Finally, reliance on predefined chains restricted experimentability by limiting chunk-level metadata control and constraining the ability to vary context-packing strategies or introduce custom pre- and post-processing filters without abandoning the abstraction layer altogether.

These findings, which emerged during implementation and debugging, motivated a shift toward a more modular pipeline. In this redesign, chunking, vectorisation, and retrieval, were configured and evaluated explicitly, avoiding reliance on predefined chains and granting finer control over performance-critical components.

5.1.2 Evaluation

The evaluation of the system's prototype followed a pronged path:

1. **Human assessment**: responses were manually annotated on a 5-point Likert scale for consistency, fluency, completeness, and relevance, following best practices in human-centred evaluation of dialogue systems (Abeysinghe and Circi, 2024; Lee et al., 2021);

2. **LLM-as-a-judge**: an external model – namely, OpenAI's GPT-3.5 – was prompted in a few-shot setting to automatically score responses across the same criteria, producing an additional layer of intrinsic evaluation (Svikhnushina and Pu, 2023).

This custom approach reflected the broader methodological challenges in evaluating RAG systems, where automatic metrics – e.g., BLEU, ROUGE, METEOR, etc. – have shown limited reliability in dialogue contexts (Deriu et al., 2020; C.-W. Liu et al., 2016).

[22] The HTTP 429 *Too Many Requests* status code signals that the client has exceeded the allowable number of requests within a specified timeframe. This response enforces what is commonly known as *rate limiting*, instructing the client to reduce its request frequency.

[23] Pull request addressing the incorrect exception handling for rate limiting in `MistralAIEmbeddings` emerged in LangChain PR#29242 and it was released in the subsequent version (January 2025).

5.1.3 Insights for System Redesign

Prototyping revealed several challenges that guided the design of the subsequent system:

- **Scalability:** reliance on CSV storage and naive concatenation of retrieved chunks limited efficiency and made the system unsuitable for larger-scale deployments.
- **Resource efficiency:** redundant LLM calls (e.g., for query rephrasing in LangChain) caused unnecessary latency and risked exceeding API rate limits.
- **Metadata control:** the absence of fine-grained chunk-level metadata management constrained retrieval flexibility.
- **Evaluation scope:** intrinsic evaluation without a gold standard or baseline system restricted comparability with other solutions; user and domain-expert feedback was absent at this stage.
- **Dependency on third-party frameworks:** reliance on LangChain introduced constraints in terms of customization and debugging transparency, limiting the control over specific components.
- **Limited multilingual support:** initial prototype focused primarily on Italian, with limited capabilities for handling cross-lingual queries or documents.
- **Simplistic retrieval:** the use of basic dense retrieval without exploring hybrid or advanced reranking techniques may have constrained retrieval effectiveness.
- **Lack of user feedback integration:** the prototype did not incorporate mechanisms for collecting and utilising user feedback to iteratively improve system performance.
- **Narrow evaluation metrics:** assessment relied mainly on subjective human ratings and LLM-based scoring, without the inclusion of broader quantitative measures.
- **Absence of real-world testing:** the prototype was not deployed in a live environment, preventing the observation of actual user interaction patterns and limiting insights into robustness under realistic conditions.

These limitations underscored the need for a more scalable and systematically evaluated architecture, motivating the full system design presented in Sec. 5.2. In parallel, the prototype confirmed the viability of the RAG approach, offering crucial insights into system bottlenecks that directly informed the subsequent design.

5.2 Full-Scale Implementation

The full system was re-engineered from scratch to support dynamic, scalable document ingestion, contextual retrieval, and answer generation using open-source language models. All LangChain dependencies were removed in favour of custom Python implementations to improve modularity, debugging transparency, and flexibility in processing. The final architecture (fig. xx) includes:

- a custom KB construction module, which integrates sitemap generation and web-crawling,
- semantic chunking and metadata enrichment,
- MistralAI-based vector embeddings,
- a FAISS vector store for retrieval,
- a generation module with open-source Mistral *NeMo* model,
- generative responses with inline citation handling,
- a reactive front-end Streamlit interface,
- and a feedback management system.

5.3 Data Acquisition and Preprocessing

5.3.1 Sitemap Generation

The sitemap is constructed via a focused breadth-first crawler targeting the MediaWiki documentation (https://gna.cultura.gov.it/wiki) which constitutes the user manual of the GNA (Mic, 2019).

The crawler:

- starts at the root node (`Pagina_principale`);
- follows internal links matching `/wiki/index.php/`, excluding namespaces such as `Special:`, `User:`, or `Talk:`;
- removes query parameters to avoid duplicates;
- applies a polite crawling policy (1-second delay and custom user-agent header);

- imposes crawl depth[24] (max 10) and page limits[25] (max 200 pages);
- and outputs a structured sitemap serialised into an XML file (`GNA__sitemap.xml`) with last-modified timestamps, priority, and change frequency.

This sitemap serves as the foundation for subsequent document harvesting.

5.3.2 Document Crawling

The next stage systematically collects the contents of all URLs listed in the sitemap to ensure comprehensive coverage of the manual. Pages are fetched asynchronously with retry logic, exponential backoff, and controlled concurrency to withstand transient network issues or throttling. Requests are interleaved with pauses to avoid overwhelming the server and failed URLs are logged for reprocessing.

Once retrieved, the raw HTML is parsed using BeautifulSoup, focusing on the main content (`deiv#mw-content-text`) and stripped of extraneous elements such as navigation bars, footers, and other layout components that do not contribute semantic content. The remaining material is processed preserving the logical reading order. Structural features are carefully retained: section headers (`h1-h6`) are used to reconstruct a hierarchical outline of the page; paragraphs, tables, lists, and images are preserved as discrete items, each linked back to its contextual breadcrumb trail. This ensures that the captured content is situated within its original navigational hierarchy, which later supports more precise retrieval.

The outcome of this step is a collection of structured representations of the user manual's pages, where meaningful content is disentangled from noise and the logical organisation of the source is preserved.

5.3.3 Chunking

After parsing, documents are segmented into smaller and more manageable units. To this end, the system employs a sliding-window strategy with a maximum span of 512 characters and an overlap of 128, a configuration recommended to favour dense retrieval while mitigating excessive fragmentation of context (X. Wang et al., 2024).

[24] Crawl depth is intended as the maximum number of link "level" away from the starting url that the crawler will follow.

[25] Page limit parameter refers to the maximum number of pages the crawler will visit and include in the sitemap, regardless of depth.

Chunks are not treated as inert slices of text, but as semantically enriched units that carry a set of contextual signals. Each one is assigned a unique identifier – a SHA-256 hash of its source and position – and is accompanied by the source URL, page title, and the chain of section headers that serve as navigational breadcrumbs. Content is further annotated with keywords extracted through the *KeyBERT* method[26] and named entities identified with the model *it_core_news_md* from spaCy. The metadata also records the content type – whether a passage of text, a table, a list, or an image – ensuring that the heterogeneous nature of the original source remains visible at retrieval time.

Tables. Tables are preserved as autonomous chunks formatted in Markdown, maintaining both their structure and interpretability.

Lists. Lists are likewise extracted as discrete units, safeguarding their enumerative character.

Images. Images are handled with particular care, since they frequently consist of illustrative diagrams, tables embedded as graphics, or screenshots of the GNA QGIS plugin (cf. Sec. 4.1.2) that can be of value for the retrieval and answer generation stages. To unlock this layer of information, the system applies an OCR pipeline built on Tesseract, enhanced with a series of pre-processing steps. Each image is first converted to greyscale and rescaled through bicubic interpolation to sharpen textual contours, then contrast-limited adaptive histogram equalisation (CLAHE) is applied to reduce noise and improve legibility across varied backgrounds. The processed image is passed to Tesseract with a configuration optimised for Italian language recognition and extended character support, allowing the extraction of structured textual surrogates. These OCR outputs are integrated into the retrieval space as additional content, making usable otherwise inaccessible visual information.

The overarching principle guiding this design is that chunking must adapt to the structure of the document rather than obey a rigid, uniform rule (cf. Fig. 6). Accordingly, the approach combines sentence-based splitting for textual passages – ensuring units remain compact and well-suited for dense retrieval – with boundary-based segmentation for structural elements such as tables, lists, and images, which act as natural delimiters. This custom strategy avoids the weaknesses of relying exclusively on one paradigm: purely sentence-driven methods risk breaking semantic continuity, while purely boundary-driven approaches tend to produce uneven or oversized segments (Microsoft Learn, 2025).

[26] *KeyBERT* is a keyword extraction technique which uses BERT embeddings to generate the keywords and keyphrases most closely aligned with a document.

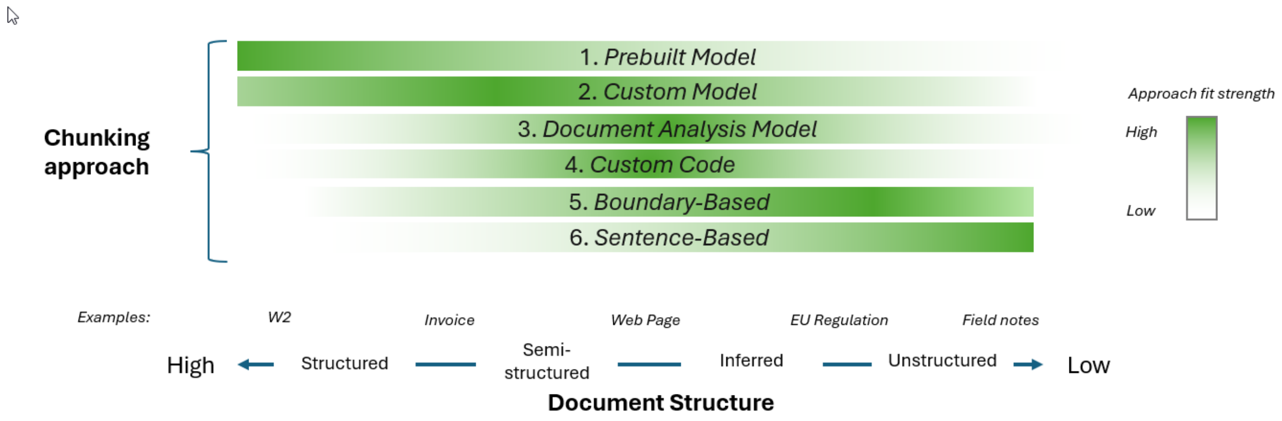


Figure 6: Different chunking strategies according to document structure.
Source: Microsot Learn.

Such tailoring proves especially important in the archaeological domain, where textual exposition often coexists with structured metadata, tabular references, and visual documentation. The resulting knowledge base is one that strikes a careful balance: granular enough to be tractable for retrieval, yet faithful enough to preserve the integrity of the original material. In practice, this balance enhances retrieval precision and ensures that the content of the GNA user manual – complex, layered, and semi-structured – remains interpretable in downstream processings.

Finally, all enriched chunks are serialised into a JSON file,[27] which constitutes the data source for embedding, retrieval, and generation tasks. This modular format ensures transparency and traceability of the preprocessing pipeline and enables flexibility to experiment with alternative retrievers, query rewriting techniques, and reranking strategies as outlined in Sec. 5.4.1.

5.3.4 Vector Embeddings

Document chunks are converted into dense vector representations using the *intfloatmultilingual-e5-large* model from Sentence Transformers. This model was selected for its multilingual encoding capabilities and strong performance in semantic retrieval tasks, making it suitable for the predominantly Italian KB while allowing also cross-lingual queries.

Text chunks are processed in batches and transformed into L2-normalised embeddings to ensure vector magnitudes are uniform. Embeddings are cached locally to avoid redundant computation across runs. The normalised vectors are stored in a FAISS `IndexFlatIP` index, which performs brute-force nearest neighbor search using the inner product (dot product) as

[27] Output: 835 structured chunks saved in `data/chunks_memory.json`.

metric. Alongside the vector index, a separate metadata store is maintained, linking each embedding to its corresponding chunk through a unique identifier. This separation enables efficient similarity search in FAISS while preserving quick access to rich metadata such as source URL, document structure, and content type for downstream processing.[28]

These embeddings and their associated metadata form the foundation for the retrieval stage, where user queries – also encoded with the same *multilingual-e5-large* model, to guarantee that both queries and documents share the same normalised vector space – are matched against the stored vectors to identify the most semantically relevant chunks for answer generation.

5.4 Candidates Retrieval

When a user submits a query, it is embedded using the same encoder to ensure vector space consistency. The FAISS index, configured for inner-product similarity, is queried to return the top-k candidate chunks.[29] Retrieval is executed entirely within the vector space to maximise speed and maintain consistent scoring across CPU-based deployments. The retrieved results are enriched with their stored metadata, which includes source URL, document title from the original web section, hierarchical section headings, and content type (text, table, image). Candidates are then grouped by provenance, ensuring that related chunks from the same source URL are passed together into the generation stage, thus improving contextual coherence, supporting inline citation, and reducing redundancy.

To further improve factual density, a lightweight filtering heuristic is applied to penalise very short or contextless chunks, deprioritising fragments that lack substantive information. The grouped and filtered candidates are returned as structured context objects, ready to be consumed by the answer generation module.

This retrieval framework serves as the baseline for subsequent ablation studies described in the evaluation phase (cf. Sec. 5.4.1), where alternative retrieval strategies and scoring variations are tested against this reference implementation.

5.4.1 Experimental Setup for Ablation Studies

To systematically evaluate the contribution of different retrieval strategies. we conducted a series of ablation experiments. In this context, *ablation* refers to the systematic removal,

[28] Output: FAISS index stored in `.faiss_db`, linked with its metadata.

[29] The default value of `k=5` was determined empirically to balance response quality and token constraints.

isolation, or modification of system components in order to evaluate their specific effect on overall performance. Importantly, none of the tested approaches was permanently integrated into the main pipeline; instead, each configuration was evaluated independently to allow for a broader performance comparison, as detailed in Sec. 5.6. The results were then compared to the baseline retrieval outcomes.

The following retrieval configurations were implemented and evaluated:

- **Dense retrieval.**

  This method employs dense vector embeddings for document representation and similarity search. It relies on FAISS as the underlying vector database, wrapped via the `VectorDatabaseWrapper` module. Queries are encoded into embeddings and compared with pre-computed document embeddings, returning the top-k results ranked by inner-product similarity. Query embeddings are cached using a normalised MD5 hash to avoid redundant computations, and batch querying is supported.

- **BM25 retrieval.**

  A traditional sparse retriever based on the BM25 algorithm. The index was constructed over concatenated metadata fields – `title`, `keywords`, `headers_context`, and `document` – from the same chunks metadata store. Preprocessing was applied specifically for Italian, including stopword removal, stemming, and handling of clitics and apocope forms. The tokenised corpus was then indexed for lexical matching. As with dense retrieval, a batch mode was implemented. The default cutoff parameter (k = 5) was selected empirically to balance response quality against tokenisation and latency constraints.

- **Hybrid retrieval.**

  To combine semantic similarity with lexical matching, hybrid retrieval strategies were explored. Two fusion techniques were implemented:

  - **Weighted Reciprocal Rank Fusion (RRF):** ranks from dense and sparse retrievers are aggregated using RRF. The fusion score for document d is computed as:

    $$\frac{w_{\text{dense}}}{k + \text{rank}_{\text{dense}}} + \frac{w_{\text{sparse}}}{k + \text{rank}_{\text{sparse}}};$$

    where the default weights parameters were $w_{\text{dense}} = w_{\text{sparse}} = 1.0$, candidates set size = 50, and `k` = 60.

  - **Score-blend fusion:** here, normalised scores from the two retrievers are merged using a custom blending function that allows for fine-tuning the influence of each method:

$$S_{\text{norm},d} = \frac{S_d - \min(S_d)}{\max(S_d) - \min(S_d)}, \quad S_{\text{norm},s} = \frac{S_s - \min(S_s)}{\max(S_s) - \min(S_s)};$$

$$S_h = S_{\text{norm},d} + \alpha \cdot S_{\text{norm},s};$$

where $S_{\text{norm},d}$ and $S_{\text{norm},s}$ are the min-max normalised scores of the dense and sparse retrievers, respectively, and α controls the relative weight of the sparse component ($w_d = w_s = 1$, $k = 60$) (2024). Unlike RRF, this approach requires that scores from different retrievers are defined on comparable scales.

What to pick?

The choice between RRF and Score-blend depends on the specific retrieval context. RRF is particularly suitable when score scales between retrievers are incompatible or unstable, as its rank-based aggregation is less sensitive to scale differences and prioritises consensus across retrieval methods. Conversely, Score-blend is more appropriate when per-query scores are reliable, as it allows finer control over the relative influence of dense and sparse components. Edge-case behaviours include:

(a) *Document appears in only one list*: RRF ranks it lower, while Score-blend assigns it a normalised score from the contributing retriever;

(b) *All scores equal in a list*: Score-blend reduces the contribution of that retriever, whereas RRF still differentiates documents by rank.

Query Rewrite

To sharpen retrieval quality, we experimented with *query rewriting*, i.e. reformulating user queries to increase the likelihood of retrieving relevant documents. Within these experiments, query rewriting was conceived as a multi-strategy process that generates alternative query variants through complementary transformations, each targeting different aspects of query understanding and manipulation (Li et al., 2024). Specifically, the approach integrates:

- **Core Content Extraction (CCE):** a sequence-to-sequence transformation using the *it5-small* model, that rewrites the query to capture its essential informational content while removing peripheral terms.

- **Keyword Expansion (QE):** extraction of key terms with KeyBERT, followed by enrichment through n-gram combinations and synonym substitutions to introduce semantically related expressions.

- **General Query Rewriting (GQR):** linguistic normalisation based on spaCy lemmatisation and stop word removal, yielding canonical query forms.

- **Pseudo-Relevance Feedback (PRF):** top-ranked documents from an initial retrieval pass are analysed to extract additional high-frequency terms not present in the original query, which are then appended to the original query to form an expanded version.

- **Query Decomposition:** conjunctive or disjunctive queries are split into simpler subqueries, each addressing a distinct semantic aspect.

These strategies can be applied individually or in combination (`strategy="all"`), producing a set of reformulated queries submitted to the base retriever (Dense, BM25, or Hybrid).

Reranking

Finally, a *reranking* stage was introduced to refine retrieval outcomes.[30] In our implementation, it operates as a wrapper around a base retriever (Dense, BM25, or Hybrid) and uses a transformer-based cross-encoder model (*cross-encoder/ms-marco-MiniLM-L-6-v2*) to jointly encode the query and each candidate document, assigning a contextual relevance score. Unlike the base retriever, which typically evaluates query-document similarity using independent embeddings or lexical term matching, the cross-encoder considers full cross-attention between query and document tokens, thereby capturing finer semantic relationships.

At runtime, the reranker receives the top-N candidates (with $N = 50$) from the base retriever, tokenises each query-document pair, and performs inference in batches with mixed-precision support when available. The final output consists of a top-k ranked list reordered by cross-encoder scores. This stage provided a more precise estimation of relevance, compensating for weaknesses in both dense and sparse retrieval alone.

[30] Reranking is a post-retrieval process that reorders an initial set of candidate documents based on a more precise estimation of their relevance.

5.5 Generation

The generation phase employs Mistral *NeMo*,[31] an open-source LLM accessible via a dedicated API and hosted independently. Its selection was guided by a convergence of methodological and practical requirements. First, open-source availability and a permissive licence ensured transparency, reproducibility, and the possibility of adaptation without the restrictions of proprietary services. Second, the model's strong performance on multilingual benchmarks, including robust handling of Italian, made it particularly suitable for a system intended to operate in a cultural heritage setting where linguistic specificity is paramount. Third, Mistral *NeMo* demonstrated competitive efficiency, with low latency and high throughput even when deployed on modest hardware, a quality that enabled real-time responsiveness without requiring more powerful computing infrastructures. In addition, the availability of an official API greatly facilitated seamless integration into the retrieval-augmented generation pipeline, while its ability to support extended context windows – up to 128k tokens – allowed the system to process multiple retrieved passages in a single prompt without truncation or loss of coherence.

While different open-source alternatives were considered too – such as *LLaMA 3*, *Falcon*, and *OpenAI* models –, none aligned as closely with the system's combined requirements. *LLaMA 3*, for instance, offers state-of-the-art performance and strong community support, but its licensing terms restrict certain deployment scenarios and its context window is more limited in practice. *Falcon* models, though efficient, have shown more variability in multilingual performance, particularly outside English. Proprietary APIs, while powerful, introduce cost barriers and potential vendor lock-in, compromising the long-term reproducibility of the research workflow. By contrast, Mistral *NeMo* offered a balanced compromise: multilingual coverage, scalable deployment options, and infrastructure for fine-tuning embeddings, made it a natural fit for both the prototyping stage and the full-scale system.[32]

The generation module itself is designed to deliver fluent, context-aware answers with inline citations, ensuring that responses remain both interpretable and verifiable. Prompts are constructed through a structured template combining system-level instructions (see Sec. 5.5.1), the user query, top-k retrieved grouped chunks, and the conversational history maintained in memory to sustain continuity across follow-ups. API calls are issued with a combination of

[31] https://web.archive.org/web/20250803120348/https://mistral.ai/news/mistral-nemo.

[32] For an overview between open-source and proprietary models, read *Open Source vs. Proprietary LLMs: A Comprehensive Comparison* (2025).

decoding parameters: a temperature of 0.3[33] to prioritise factual accuracy, a top-*p* of 0.9[34] to maintain lexical diversity without drifting off-topic, and a maximum of 512 tokens to keep answers concise. Finally, responses undergo lightweight post-processing to enforce inline citation formatting, guarantee Italian output, and preserve readability through numbered references and paragraph boundaries.

5.5.1 Prompt Engineering Techniques

The system uses structured prompt engineering to ensure accurate, traceable, and contextually coherent answers. The prompt template is dynamically generated with the following components:

System Instructions, Boundaries and Constraints

A custom system message (Listing 5.2) is injected at the top of the prompt to guide the model's behaviour. This message instructs the system to enforce neutrality in its answers, prioritise relevant and verifiable information, and include inline citations that correspond to metadata entries. It also explicitly discourages hallucinations and speculative responses.

```
system_content = """
    Sei un assistente virtuale incaricato di rispondere a
       domande sul manuale operativo del Geoportale Nazionale
       per l'Archeologia (GNA), gestito dall'Istituto Centrale
       per il Catalogo e la Documentazione (ICCD).

    Segui sempre queste regole:
    1. Non rispondere a una domanda con un'altra domanda.
    2. Rispondi **sempre** in italiano, indipendentemente dalla
        lingua della domanda, a meno che l'utente non richieda
       esplicitamente un'altra lingua.
    3. Cita le fonti utilizzando la notazione [numero] dove:
        - Le fonti sono fornite nel contesto della domanda e
           sono numerate in ordine crescente;
```

[33] The parameter temperature set to 0.3 sharpens the model's probability distribution, favouring high-likelihood tokens and suppressing unlikely alternatives, thereby producing more deterministic and factual outputs.

[34] The parameter top-*p*, also called *nucleus sampling*, restricts generation to the smallest set of candidate tokens whose combined probability mass reaches a chosen threshold (here 90%), ensuring that the model considers diverse but still plausible continuations while discarding unlikely options.

```
            - Usa numeri diversi per fonti diverse;
            - Non includere mai l'URL nel corpo della risposta;
        4. Alla fine della risposta, aggiungi un elenco di
           riferimenti con il seguente formato, su righe separate:
            [ID] URL completo
        5. Se non hai informazioni sufficienti per rispondere,
           rispondi "Non ho informazioni sufficienti".

        Le tue risposte devono essere sempre:
        - Disponibili, professionali e naturali
        - Grammaticalmente corrette e coerenti
        - Espresse con frasi semplici, evitando formulazioni
           complesse o frammentate
        - Complete e chiare, evitando di lasciare domande senza
           risposta
    """
```

Listing 5.2: System prompt specifying assistant constraints and response instructions.

Each chunk passed to the LLM is numbered and grouped with its metadata (title, URL). When generating a response, Mistral is instructed to cite only the chunks used, ensuring traceability. Post-processing checks for unmatched citations or unreferenced metadata.

5.6 Evaluation Protocol

Evaluation was conducted across two complementary dimensions:

- **Quantitative**, focusing on retrieval performance through metrics such as Recall (R@), Mean Reciprocal Rank (MRR@), Normalised Discounted Cumulative Gain (nDCG@), Average Precision (AP@), and Latency to assess retrieval performance;
- **Qualitative**, assessing the perceived quality and usability of responses through human feedback.

This dual perspective reflects the understanding that effective RAG-based QASs require not only accurate retrieval and generation but also operational efficiency and adaptability in real-world contexts (Akkiraju et al., 2024). To support continuous refinement, the evaluation was designed as an iterative process, with quantitative results informing system optimisation and qualitative insights guiding user-centred adjustments.

All retrieval configurations (Dense, BM25, Hybrid, Query Rewriting, and Reranking variants) were evaluated under the same protocol, ensuring comparability of results across ablation studies. While this framework provided a coherent structure for assessment, its application also revealed several limitations inherent to the experimental setting and the available resources. These included:

- **Absence of a gold standard:** there was no authoritative or verified set of annotated responses to serve as a benchmark of correctness.
- **No baseline system:** internal institutional tasks had no legacy solutions or established benchmarks for direct comparison in the archaeological domain.
- **Limited availability of domain experts:** during the early phases, development was conducted without input from real users or expert annotators; human feedback was integrated only at a later stage.
- **Limited applicability of automated generation metrics:** common algorithmic measures, although widely applied in text generation, have been shown to be ineffective for dialogue and QA evaluation (Deriu et al., 2020; C.-W. Liu et al., 2016).

These constraints mirror challenges identified in recent RAG evaluation literature, which emphasises the lack of standardised protocols and the importance of balancing intrinsic metrics with human-centred evaluation (Abeysinghe and Circi, 2024), as noted in Sec. 3.1.2. Akkiraju et al. (2024) further highlight the need to assess both accuracy and efficiency, pointing to critical control points in the RAG pipeline where trade-offs between retrieval quality and latency emerge.

5.6.1 Datasets

Widely used QA benchmarks such as SQuAD, Natural Questions (Kwiatkowski et al., 2019), or multi-hop datasets like HotpotQA (Z. Yang et al., 2018) and 2WikiMultiHopQA (Ho et al., 2020) are indispensable for advancing general-domain research but are misaligned with the objectives of this study. These datasets are predominantly built around encyclopaedic or factoid queries in English, often centred on entity recognition and short-span extraction. By contrast, the GNA QA system targets procedural, explanatory, and domain-specific questions expressed in Italian, where answers are not simple factual snippets but often involve step-by-step guidance, cross-references to interface components, or the interpretation of heterogeneous content.

Equally important, while KBs such as Wikipedia do consists of text that coexists with tables and lists, their role is largely illustrative or descriptive. In the GNA manual, instead, such structures are integral to the semantics of the documentation. Tables encode data entry examples or parameter constraints, lists enumerate workflows, and images – often screenshots – embody key instructional content. These formats are not ancillary but essential to the information needs of end-users, requiring reasoning that goes beyond the scope of existing benchmarks.

Evaluating on standard datasets would therefore risk producing misleadingly inflated scores that fail to capture the genuine challenges of domain-specific, multimodal documentation. Given these considerations, a custom evaluation set was constructed and sampled directly from the GNA KB. This ensured ecological validity, testing the QA system on the exact materials and information needs it is designed to serve.

To support systematic analysis, two synthetic evaluation sets were created:

- **Single-hop dataset:** containing 508 queries designed to elicit single-document answers, each with a single gold document (cf. Listing 5.3). This dataset tested the system's ability to retrieve and generate answers based on isolated chunks of information.
- **Combined dataset:** containing 400 additional queries that require multi-hop reasoning, where answers are derived from multiple documents (2-4 chunks), for a total of 908 queries entries (cf. Listing 5.4). This dataset assessed the system's capacity to integrate information from various sources and generate coherent contextual responses.

```
{
  "question": "<Italian question>",
  "relevant_docs": ["<chunk_id>"],
  "document_content": "<chunk text>"
}
```

Listing 5.3: JSON output format for single-hop dataset items.

```
{
  "question": "<Italian question>",
        "relevant_docs": ["<chunk_id_1>", "<chunk_id_2>", "..."],
        "document_content": ["<text_1>", "<text_2>", "..."],
        "is_multihop": false|true,
        "num_docs": 1|2|3|4
    }
```

Listing 5.4: JSON output format for combined dataset items, including single-hop and multi-hop questions.

Together, these custom test sets provided balanced coverage of both simple and complex retrieval scenarios. In both cases, questions were generated directly from the chunk corpus using Mistral *NeMo* (cf. Sec. 5.5). For the single-hop dataset, each question was elicited from an individual chunk through a prompt that constrained the model to formulate queries strictly grounded in the given text, ensuring that answers could only be retrieved from the associated gold document. In contrast, the multi-hop dataset required a more demanding construction: subsets of two to four chunks were sampled at random, concatenated, and provided as input to the LLM with explicit instructions to generate questions resolvable only by combining information across all documents in the set. To avoid superficial overlaps, in this case the prompt enforced specificity and disallowed formulations answerable from a single source.

5.6.2 Metrics

To evaluate retrieval in a consistent and transparent manner, the system was assessed using a set of standard IR metrics, complemented by latency measurements to capture operational performance (X. Wang et al., 2024):

- R@5 (Recall at 5): proportion of relevant documents successfully retrieved within the top 5 results, reflecting coverage of the retrieval step;
- MRR (Mean Reciprocal Rank): average of reciprocal ranks of the first relevant document retrieved, rewarding systems that place the correct answer as early as possible;
- nDCG@5 (Normalised Discounted Cumulative Gain at 5): evaluates ranking quality by weighting relevant documents higher when they appear near the top of the result list;
- AP@5 (Average Precision at 5): computes the average of precision values at each point a relevant document is retrieved within the top 5, providing a balance of recall and precision across ranks;

- Latency: mean retrieval time per query (in seconds).

Each evaluation run stores a machine-readable report (JSON) capturing dataset name (single-hop / multi-hop), creation timestamp (UTC), orchestrator and model identifiers (Mistral API model name), retrieval parameters (top-k and candidate-k), batch size, and device configuration. These artefacts ensure precise traceability of conditions across ablation experiments (cf. Sec. 6.2).

5.6.3 Qualitative Assessment

To complement intrinsic metrics, qualitative evaluation focused on dimensions more directly linked to user experience:

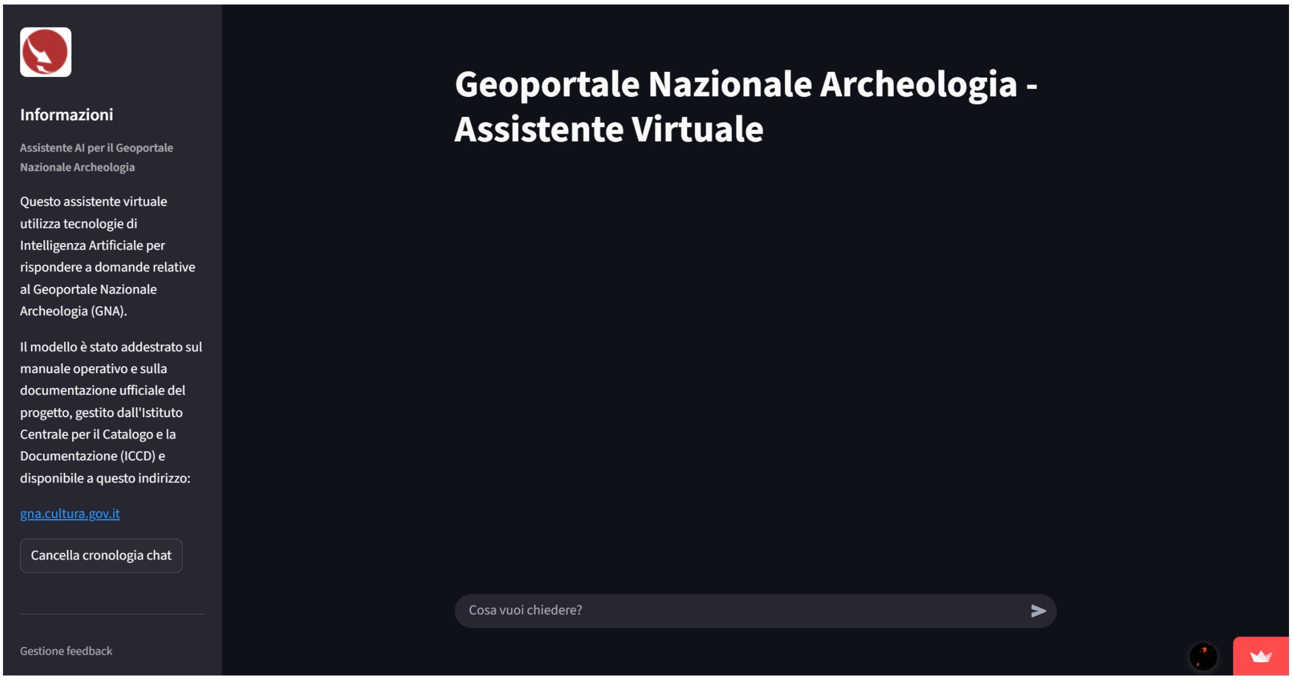
- **Relevance:** Whether the generated answer addressed the query meaningfully.
- **Fluency:** Linguistic naturalness and readability of responses.
- **Completeness:** Coverage of the key information needed to satisfy the query.
- **Usability:** Perceived usefulness of the system as an interactive tool.

Human feedback was collected using a lightweight rating approach (3-point Likert-scale scoring), later exported as structured datasets for analysis. Although limited in scale, this qualitative perspective provided insights into aspects of response quality that purely algorithmic metrics could not capture, particularly in relation to user trust and system transparency.

5.7 User Interface

The user interface (UI) was developed using Streamlit, chosen for its ability to support rapid prototyping and its native integration with Python NLP pipelines. Streamlit also offers built-in handling of asynchronous processes, making it well suited for a RAG system where retrieval and generation stages can vary in latency. Within the system, the UI serves as the primary interaction layer between users and the GNA QA service. Through a simple and accessible design (Fig. 7), users are able to submit queries in natural language, receive answers, and inspect the underlying evidence via inline citations linked to the retrieved documents.

Beyond serving as a functional entry point to the system, the UI assumes a crucial methodological role. It provides a framework for integrating explicit user feedback, thereby enabling the collection of qualitative evaluations that complement quantitative retrieval metrics. Through the interface, users can annotate responses in terms of perceived relevance, fluency, completeness, and usability by selecting an option on a three-point Likert scale. These annotations generate valuable data that can be used to iteratively refine the system. As previously discussed, this human-centred dimension is particularly important in dialogue and QA contexts, where conventional automated metrics often fail to capture the subtleties of interaction quality. The interface therefore does more than display outputs: it functions as an evaluation instrument in its own right, supporting the triangulation of system performance across computational measures and human judgements.



Informazioni

Assistente AI per il Geoportale Nazionale Archeologia

Questo assistente virtuale utilizza tecnologie di Intelligenza Artificiale per rispondere a domande relative al Geoportale Nazionale Archeologia (GNA).

Il modello è stato addestrato sul manuale operativo e sulla documentazione ufficiale del progetto, gestito dall'Istituto Centrale per il Catalogo e la Documentazione (ICCD) e disponibile a questo indirizzo:

gna.cultura.gov.it

Geoportale Nazionale Archeologia - Assistente Virtuale

Figure 7: Streamlit user interface of GNA QA system.

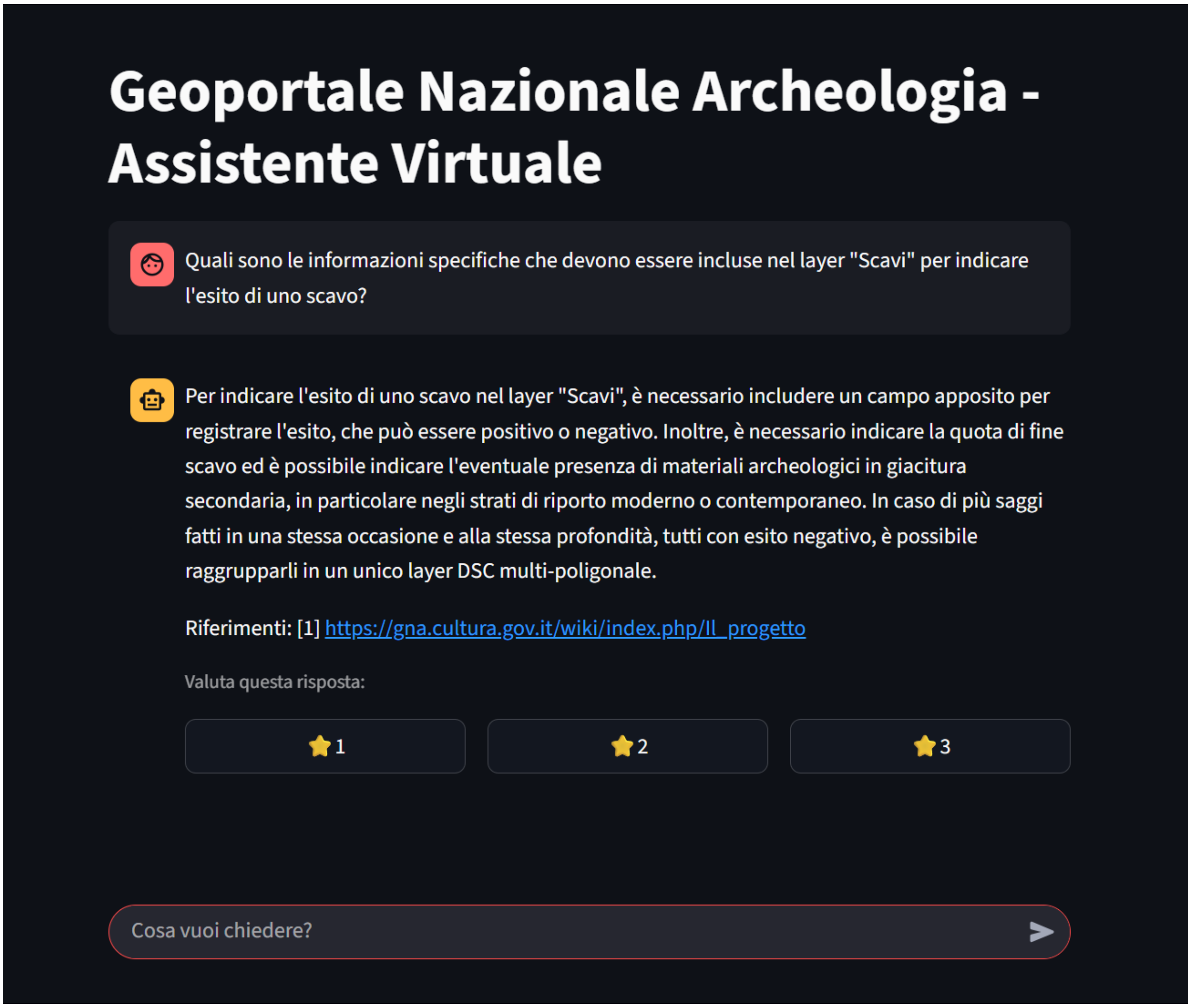
The application interface is organised into three main areas:

1. **Sidebar:** contains MiC reference, institutional links to the GNA documentation, and contextual help describing the assistant's capabilities. It also provides functional controls including a *Clear chat history* button ("*Cancella cronologia chat*") to reset the Streamlit session (`st.session_state.chat_history`) and a "*Download Feedback*" button for exporting user queries and system's responses.

2. **Main interface:** provides a natural language input field for querying the assistant. It displays the chat history, including user messages, assistant responses and feedback buttons for each assistant reply (Fig. 11).

3. **Session features**:

   - Chat history is limited to the most recent ten exchanges, which are stored and updated in the session state;
   - Feedback from individual message indexes is stored as a set (`st.session_state.feedback_given`), allowing the system to prevent duplicate ratings and dynamically update UI.



Geoportale Nazionale Archeologia - Assistente Virtuale

Quali sono le informazioni specifiche che devono essere incluse nel layer "Scavi" per indicare l'esito di uno scavo?

Per indicare l'esito di uno scavo nel layer "Scavi", è necessario includere un campo apposito per registrare l'esito, che può essere positivo o negativo. Inoltre, è necessario indicare la quota di fine scavo ed è possibile indicare l'eventuale presenza di materiali archeologici in giacitura secondaria, in particolare negli strati di riporto moderno o contemporaneo. In caso di più saggi fatti in una stessa occasione e alla stessa profondità, tutti con esito negativo, è possibile raggrupparli in un unico layer DSC multi-poligonale.

Riferimenti: [1] https://gna.cultura.gov.it/wiki/index.php/Il_progetto

Valuta questa risposta:

Figure 8: Rating mechanism embedded in the user interface.

To guarantee smooth interactions and to minimise computational overhead, the system makes extensive use of `st.session_state`, a built-in Streamlit object designed for persisting variables across user interactions. Unlike ordinary Python variables, which are re-initialised each time Streamlit re-runs a script, `st.session_state` retains values for the duration of a session. This functionality is critical in a conversational application, as it allows chat memory to persist between turns. Both user queries and model responses are stored, so that continuity is preserved across multi-turn dialogues.[35]

Beyond the bounds of memory management, `st.session_state` is also used to cache API outcomings, including responses generated by Mistral and their associated citation mappings. This prevents redundant API calls when users revisit or re-evaluate queries, at the advantage of efficiency and costs mitigation. In addition, the same mechanism is employed to track user feedback, linking annotations directly to the relevant conversational context.

To ensure a responsive user experience, the system integrates Python's `asyncio` and `concurrent.futures` modules. Each call to the language model is executed within a new event loop, ensuring compatibility with Streamlit's execution environment, while a `ThreadPoolExecutor` provides thread-safe parallel execution. This design enables non-blocking retrieval and generation: the interface remains responsive even under conditions of high latency or slow API responses, thus preserving a fluid user experience.

5.8 Feedback Loop

To support iterative improvement of the assistant and promote user engagement, the system integrates an interactive feedback module that allows users to rate each answer directly within the Streamlit interface. This design is intended to support continuous quality assessment and transparent evaluation of LLM-generated content.

5.8.1 Collection

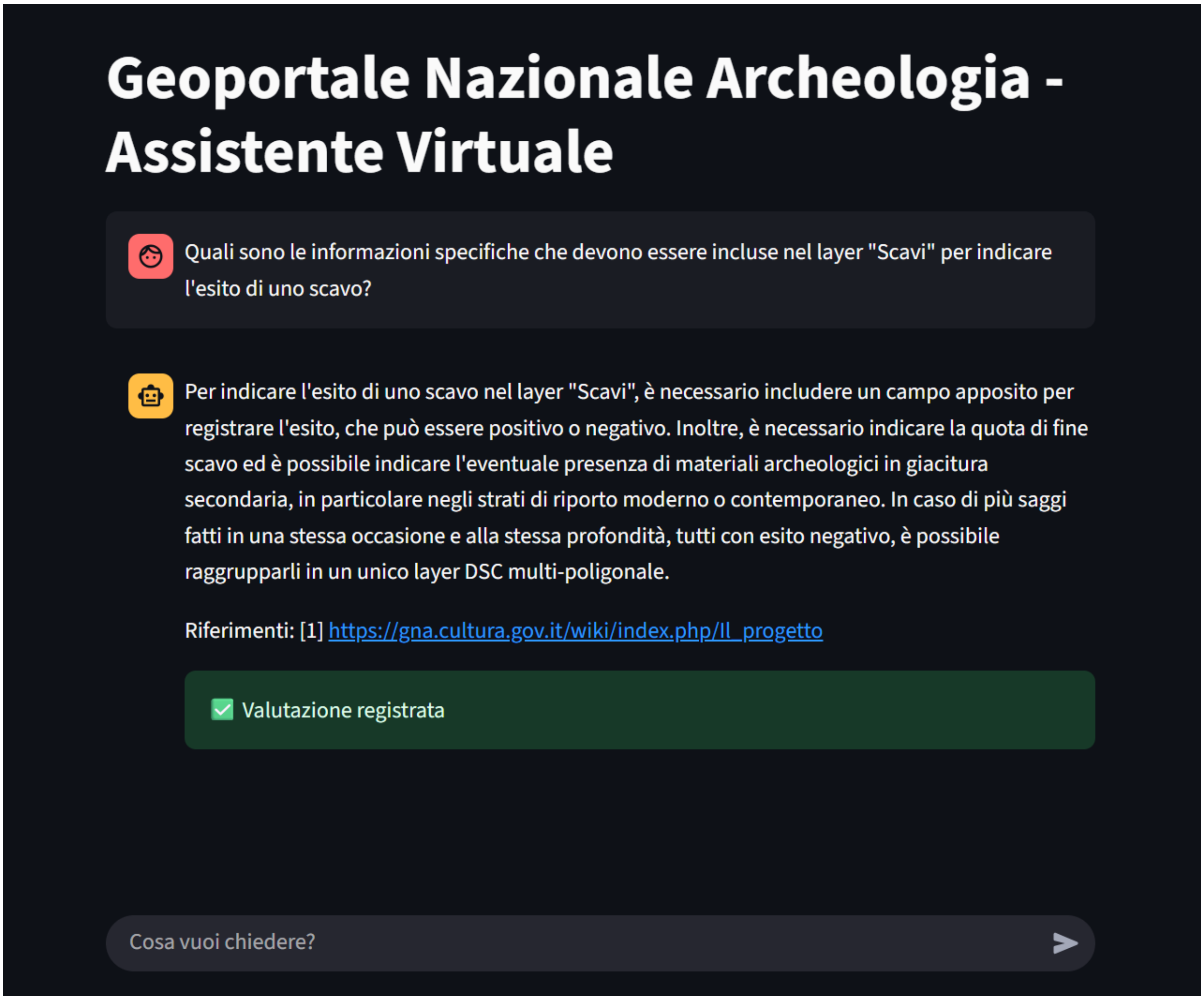
As noted earlier, each assistant response is immediately followed by three clickable UI buttons based on a 3-point Likert scale:

- 1 point - Poor: the answer is incorrect, incomplete, or irrelevant.
- 2 points - Fair: the answer is partially correct but lacks clarity or depth.
- 3 points - Good: the answer is accurate, complete, and well-structured.

This mechanism is implemented using Streamlit's interactive widgets. Once a rating is submitted, the system prevents duplicate feedback using an in-memory tracking set

[35] For more details on Streamlit session state management, see the official API documentation at https://docs.streamlit.io/.

(`st.session_state.feedback_given`). The interface then displays a confirmation message (“*Valutazione registrata*”, Fig. 9), improving transparency.



Geoportale Nazionale Archeologia - Assistente Virtuale

Quali sono le informazioni specifiche che devono essere incluse nel layer "Scavi" per indicare l'esito di uno scavo?

Per indicare l'esito di uno scavo nel layer "Scavi", è necessario includere un campo apposito per registrare l'esito, che può essere positivo o negativo. Inoltre, è necessario indicare la quota di fine scavo ed è possibile indicare l'eventuale presenza di materiali archeologici in giacitura secondaria, in particolare negli strati di riporto moderno o contemporaneo. In caso di più saggi fatti in una stessa occasione e alla stessa profondità, tutti con esito negativo, è possibile raggrupparli in un unico layer DSC multi-poligonale.

Riferimenti: [1] https://gna.cultura.gov.it/wiki/index.php/Il_progetto

✅ Valutazione registrata

Figure 9: Confirmation message of registered user’s feedback.

5.8.2 Storage and Export

Feedback is stored locally in a SQLite database (`feedback.db`) with the schema specified in Listing 5.5. Each record captures:

```
CREATE TABLE feedback (
    id INTEGER PRIMARY KEY AUTOINCREMENT,
    timestamp TEXT NOT NULL,
    message_index INTEGER NOT NULL,
    question TEXT NOT NULL,
    answer TEXT NOT NULL,
    rating INTEGER NOT NULL
```

```
                );
```

Listing 5.5: SQL schema of the feedback database.

This structure supports reproducibility and traceability by maintaining a clear mapping between: the user's query string, the generated response, the rating score (1-3) and the associated timestamp (i.e., time of submission). All records are saved with minimal overhead, using parameterised SQL insertions and transaction-safe commits.

To ensure long-term preservation and collaborative accessibility of user feedback, the system implements a mechanism for periodic synchronization of collected feedback with a persistent repository. This setup enables version control over user interaction logs, supports iterative evaluation by external reviewers, and enables rollback and comparison across model updates.[36]

From the sidebar, users can export all feedback as a `.csv` file using the *"Esporta feedback"* functionality. This latter is powered by the `export_feedbacks()` function, which queries the database and converts it to a downloadable format using Pandas.

Feedback data can be used by researchers, developers, or project coordinators to assess the assistant's performance over time.

5.9 Resources and Deployment

The GNA QA system is deployed on Streamlit Community Cloud, a platform that allows developers to openly host interactive Python applications directly from a linked GitHub repository. The service abstracts most of the infrastructure overhead: each push to the repository automatically triggers a build and deployment, packaging dependencies specified in configuration files and exposing the application as a live web service. This solution enabled rapid iteration and made the system easily accessible to stakeholders without local installation.

However, long-running RAG pipelines are not trivial to host within such constrained environments. Indeed, early deployments surfaced memory leaks: object references from retrieval and generation modules, especially cached embeddings and session state artefacts, were not consistently released, leading to a progressive increase in memory usage during extended interactions. Identifying these leaking objects required targeted profiling, after which caching decorators and object reinitialisation strategies were introduced to reduce overhead. Although these optimisations improved stability, the underlying workload still proved too heavy for the

[36] This implementation is intended for controlled research use only. For production environments, sounder alternatives such as authenticated APIs and hardened database infrastructures are recommended to ensure data safety and compliance with privacy standards.

default configuration availabilities of Streamlit Cloud.

To mitigate this, we contacted the Streamlit team directly and requested additional resources. As a result, the hosting environment was scaled up to 8 gibibytes (GiB), a critical increase that allowed the application to sustain concurrent sessions and longer conversational histories without interruption.

This experience underlines a broader methodological point: deploying RAG systems is not merely a matter of algorithmic optimisation but also of infrastructure alignment, where careful monitoring, memory management, and resource planning or negotiation are essential to ensure reliability and usability under real-world usage conditions.

5.9.1 Memory Management

As discussed above, deploying a RAG workflow with multiple NLP resources integrated into a single pipeline poses considerable challenges for environments lacking access to GPUs or large memory allocations, such as free hosting platforms like Streamlit Community Cloud. To keep the system sustainable under these constraints, several optimisation strategies were adopted in terms of memory management:

- **Garbage collection routines:** explicit calls to Python's garbage collector (`gc.collect()`) were introduced to free unused memory between embedding and response generation steps;

- **Batch processing:** document chunks are processed in batches to minimise memory overhead, especially during retrieval;

- **Lazy loading:** all embeddings are computed once and stored persistently. At application startup, only the metadata is loaded into memory, and the FAISS index is accessed through memory-mapping to reduce RAM footprint;

- **Asynchronous processing:** Streamlit's async capabilities are leveraged to keep the UI responsive while background tasks run in parallel, preventing memory spikes during long-running operations;

- **Cache clearing policies:** `st.session_state` objects are pruned after each session or upon manual reset by the user to prevent memory bloating during prolonged use.

5.9.2 Computational Constraints Mitigation

To counterbalance the limitations of operating under strict computational constraints and preserve system responsiveness, the following strategies were introduced:

- **Model selection:** the use of *intfloat/multilingual-e5-large* for embedding provides a trade-off between semantic accuracy and compute efficiency, even without GPU acceleration;
- **API offloading:** offloading generative tasks to the external Mistral API prevents the local system from being overloaded and allows scaling independently of front-end performance;
- **Timeout and fallback handlers:** if the generation request exceeds 10 seconds or fails (e.g., due to API rate limits), the interface returns a graceful fallback response, allowing users to retry without crashing the app;
- **Asynchronous I/O:** for embedding, retrieval, and response generation, asynchronous requests reduce UI freezing and ensure smoother user experience even under high latency conditions.

5.10 Ethics and Data Governance

The GNA QA system has been developed with sustained attention to ethical considerations and data governance, particularly in the context of cultural heritage and public information. Transparency is pursued through open release of the source code and documentation of the pipeline – covering models, prompts, parameters –, together with versioned configurations, and machine-readable evaluation artefacts; per-run JSON logs record dataset IDs, model identifiers, and retrieval settings, all of which are made accessible through the project's GitHub repository. Privacy is safeguarded by design, as the system processes no personally identifiable information and relies exclusively on publicly available or openly licensed materials. Licensing constraints are respected, as all resources – from the knowledge base to the language models and software libraries – are drawn from projects distributed under permissive terms that guarantee lawful reuse in research and educational contexts. Auditability is ensured through persistent logging of system performance and user feedback on Streamlit Community Cloud.

On the whole, these practices turn abstract commitments – provenance, privacy, licensing, and auditability – into concrete safeguards, allowing the GNA QA system to remain technically reliable and also a responsible instrument for public engagement.

Chapter 6

Results

This chapter presents the results with regards to the evaluation of the retrieval methods applied to the test datasets. We compare various configurations, including query rewriting and reranking, across single-hop and combined datasets.

Briefly restate the test dataset size (400 queries) and the methodology adopted (automatic question generation, retrieval evaluation). Note the dual evaluation approach (intrinsic retrieval metrics + qualitative)

compare prototype vs. full-scale implementation but HOW???? because their methodologies are not the same thus results do not align

We conducted a series of experiments to evaluate the performance of different retrieval methods, including dense, BM25, and hybrid approaches. The results are summarized in Tab. 6, which shows the retrieval effectiveness measured by Recall@5 (R@5), Mean Reciprocal Rank (MRR), Normalised Discounted Cumulative Gain at 5 (nDCG@5), Average Precision at 5 (AP@5), and latency per query.

6.1 Prototyping Phase

A radar plot of the evaluation dimensions in Fig. 10 highlights this profile: strong alignment and topical accuracy, yet with opportunities for improvement in richness and expressivity.

The prototype implementation offered an initial validation of the feasibility of a RAG-based QA system for the Geoportale Nazionale dell'Archeologia. Although limited in scope, it demonstrated that the architecture could effectively combine retrieval and generation within an interactive interface.

The evaluation outcomes (Fig. 10) indicate a high level of consistency (mean score close to 5) and strong topical relevance (≈ 4.7). Fluency was also rated positively (≈ 4.9), showing that the system could produce linguistically natural answers. By contrast, completeness achieved slightly lower scores (≈ 4.6), suggesting that responses occasionally lacked sufficient depth or coverage of the available information. Overall, the radar profile highlights a system capable of producing reliable and coherent answers, while leaving room for improvement in expressivity and informational richness.

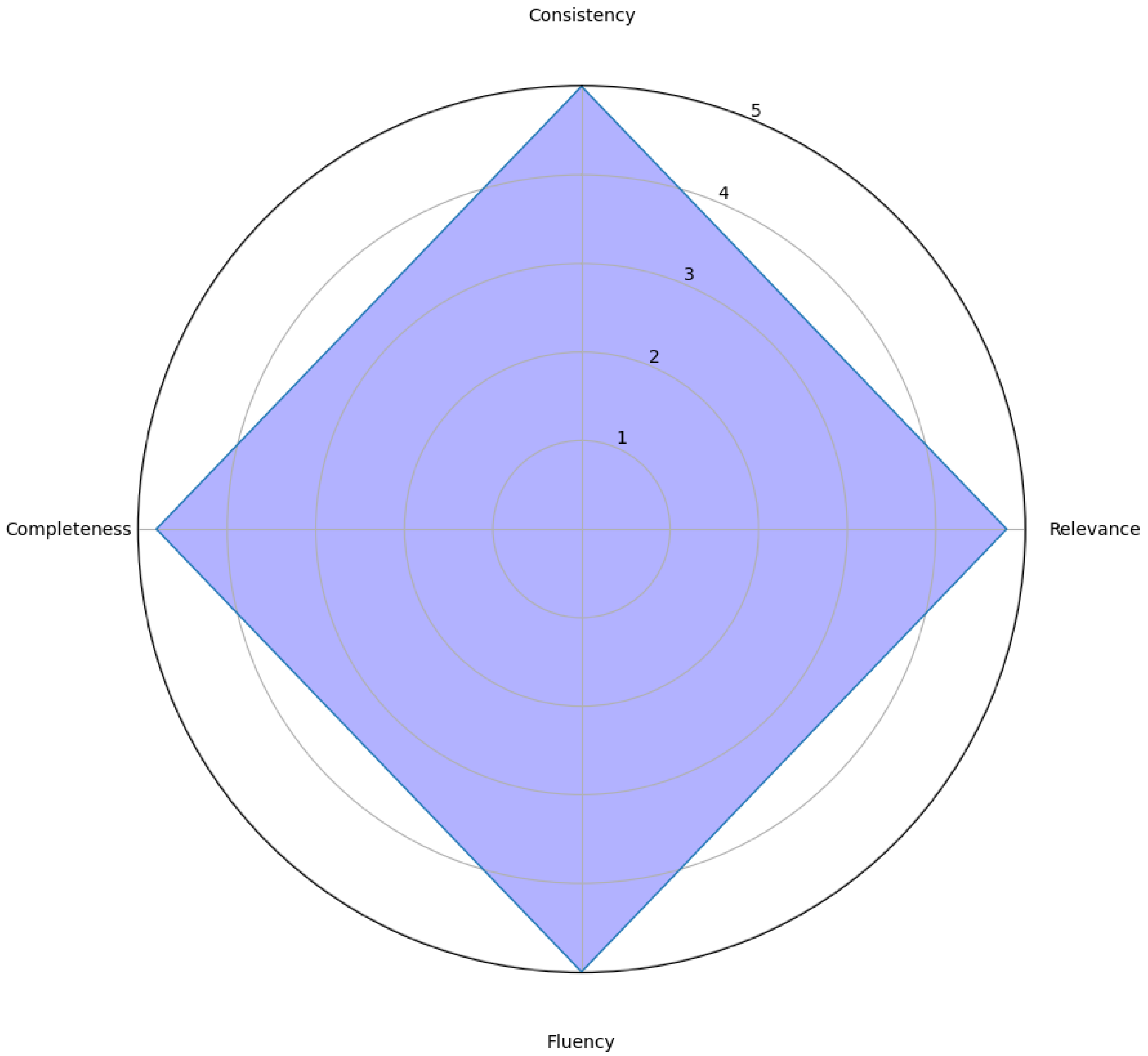


Figure 10: Evaluation results for prototype version of GNA QA system.

Performance testing showed that embedding generation required an average of 31.2 seconds, while query response times averaged 1.26 seconds. Although the latter figure is acceptable for interactive applications, efficiency remains suboptimal compared to production-ready systems, and response delays may accumulate under higher traffic conditions.

6.2 Retrieval Performance and Ablation Studies

			SINGLE-HOP					COMBINED (single+multi-hop)				
Method	**Query rewrite**	**Rerank**	R@5	MRR	nDCG@5	AP@5	Latency	R@5	MRR	nDCG@5	AP@5	Latency
Dense	✗	✗	67.51	47.04	52.18	47.04	0.29	50.78	48.21	53.70	34.98	0.19
	✓	✗	58.07	36.76	42.09	36.76	5.98	42.64	35.41	41.32	26.24	3.10
	✗	✓	45.47	25.41	30.36	25.41	1.30	34.57	27.71	32.90	19.48	0.82
	✓	✓	52.55	31.66	36.87	31.66	4.76	38.16	30.45	36.0	22.51	3.46
BM25	✗	✗	65.15	43.56	48.98	43.56	**0.001**	53.09	**51.23**	**57.13**	35.50	**0.001**
	✓	✗	57.87	37.37	42.50	37.37	1.98	46.65	42.15	48.33	29.38	1.20
	✗	✓	45.47	25.41	30.36	25.41	1.30	34.57	27.71	32.90	19.48	0.82
	✓	✓	43.89	25.87	30.35	25.87	10.02	35.18	30.33	35.68	20.59	4.96
Hybrid												
+ Weighted RRF	✗	✗	69.68	46.72	52.49	46.72	0.33	**53.98**	50.93	56.92	36.15	0.32
	✓	✗	57.48	37.48	42.48	37.48	4.38	43.52	38.41	44.10	27.68	3.21
	✗	✓	43.50	24.70	29.33	24.70	1.67	33.06	26.36	31.26	18.70	0.87
	✓	✓	38.58	21.14	25.47	21.14	6.51	29.98	23.95	28.66	16.44	6.75
+ Score-blend	✗	✗	**70.27**	**48.59**	**54.02**	**48.59**	0.55	53.35	50.84	56.48	**36.69**	0.45
	✓	✗	57.67	37.17	42.31	37.17	4.57	43.61	38.16	43.87	27.52	3.99
	✗	✓	43.70	24.89	29.53	24.89	2.64	33.14	26.21	31.14	18.70	1.22
	✓	✓	38.58	21.47	25.72	21.47	6.44	30.13	23.98	28.82	16.55	4.8

Table 6: Results for different retrieval methods on the test datasets. Best per column is bold and the second-best is underlined. Latency is measured in seconds per query. Reranking is performed using the *cross-encoder/ms-marco-MiniLM-L-6-v2* model.

Provide a short interpretation — e.g., which configuration excels in which scenario, trade-offs between speed and accuracy, and performance differences between single-hop and combined datasets.

Highlight consistency (or not) in performance with growing dataset size.

6.3 Qualitative Analysis

Results showed that:

65% of answers were rated as “Relevant”,

25% as “Partially relevant”,

10% as “Not relevant”.

Feedback indicated that relevance dropped when:

the query used ambiguous phrasing,

or too few document chunks were retrieved due to vector sparsity.

Users appreciated:

the traceability of answers via citations,

the lightweight UI,

and the multilingual support.

Edge Cases to Test: Queries with no relevant chunks Queries matching multiple chunks Out-of-domain queries Short vs. long queries discuss answers to Out-of-domain queries (system correctly adress these)

Include observations about citation traceability, coherence of generated answers.

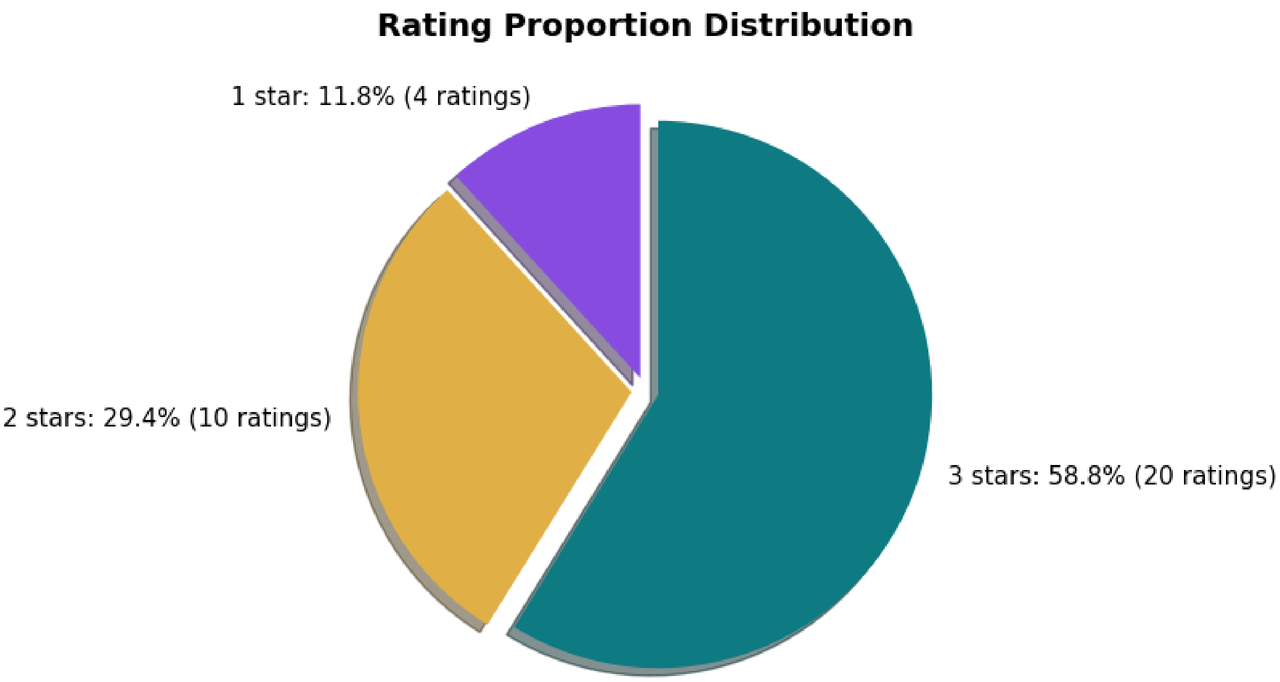


Figure 11: Information visualisation of users feedback.

Chapter 7

Discussion

Explain what metrics values % indicate for the GNA QA system.

Discuss trade-offs: precision vs. recall in heritage QA; speed vs. accuracy; LLM hallucination vs. retrieval grounding.

PROTOTYPE.

Overall, the prototype established:

the technical feasibility of combining dense retrieval with generative models for Italian-language queries;

the practical utility of combining human and LLM-based evaluation in the absence of gold standards;

the main bottlenecks, namely limited scalability, lack of chunk-level metadata control, and inefficiencies introduced by LangChain's orchestration.

LangChain was invaluable as scaffolding: it accelerated prototyping, unified stateful conversation with retrieval-augmented prompts, and smoothed integration with Mistral and Streamlit. Yet the same abstractions that sped up early development also hid critical details (error handling, call scheduling, metadata routing). Recognising this trade-off helped you carve out clearer module boundaries in the subsequent architecture and design an evaluation-first workflow that is easier to profile, ablate, and optimise.

7.1 Strengths

Scalable crawling and chunking pipeline.

Transparent retrieval with source citations.

Lightweight implementation (CPU-friendly, deployable on Streamlit).

7.2 Weaknesses

Limited adaptability to domain shifts, Maintenance and update strategy: the system is not designed to easily adapt to changes in the domain or knowledge base, which could affect its performance as the underlying information evolves.

EVALUATION PROTOCOL. This methodology introduces its own limitations. Since questions were generated with the help of an LLM directly from document chunks, there is a risk of lexical leakage: wording and uncommon tokens in the question often mirror those of the gold chunk. This can unintentionally bias the retrieval stage, making the task easier for dense retrievers, which rely on semantic embeddings, while disadvantaging lexical retrievers, which benefit less from surface similarity. Moreover, the resulting queries may not faithfully reflect real user behaviour, which typically involves synonyms, abbreviations, typos, ellipses, or more implicit forms of reasoning. As such, while the synthetic datasets provided a controlled and reproducible environment for system evaluation, they should be interpreted as diagnostic tools rather than as complete proxies for deployment scenarios.

Security and privacy considerations: the prototype does not address potential security vulnerabilities or data privacy concerns associated with handling user queries and sensitive information.

the tension between system ambition and infrastructural limits (e.g., RAG deployed on Streamlit poses deployment and computational challenges)

CITATIONS OF SOURCES (CHUNKS, URLS). A user-facing provenance display (inline citations to retrieved chunks or sources e.g. URLs) have been drafted as a functionality and its improvement is on the roadmap; an experimental mechanism exists but is not yet reliable

7.3 Relation to Previous Work

Compare findings with studies in the bibliography; Show how this project aligns with or diverges from existing QA and RAG applications.

7.4 Implications for Digital Humanities

Value of RAG systems for cultural heritage platforms (accessibility, democratising archaeology knowledge).

Tension between automation and scholarly authority (machine-generated vs. curated responses).

Potential role as support tool for researchers, students, and the public.

Chapter 8

Conclusion

further development and future work

Summary of Contributions.

State what you built (end-to-end QA system for GNA).

Emphasise technical and scholarly contributions (pipeline, evaluation framework, deployment).

Reconnect to the thesis questions/objectives (e.g., “Can RAG improve access to archaeological knowledge?”).

Show how these results answer them.

FUTURE DIRECTIONS.

Technical improvements: advanced retrieval (re-ranking, hybrid search), larger/more specialised LLMs, multilingual expansion.

Evaluation: collaboration with domain experts for annotated datasets, user studies.

Digital Humanities applications: integration into museum/archives portals, scholalry editions, educational tools, comparison with traditional catalogues.

specializzazione sul dominio archeologia

Final Reflections.

Situate your work as a bridge between AI techniques and DH practices.

Emphasise the potential of RAG systems to enrich cultural heritage accessibility, while noting the importance of critical human oversight.

End on a hopeful note: your project shows a feasible, scalable, and adaptable model for future DH knowledge infrastructures.

Appendices

Appendix A

Implementation details

In this study, all the experiments have been executed in Python 3.11.9 on a system equipped with an Intel Core i7-1185G7 CPU at 3.00 GHz, 16 GB of RAM, and integrated Intel Iris Xe Graphics with 128 MB of VRAM.

The ablation studies were conducted on the *singlehop* dataset, comprising 508 queries, and on the *combined* dataset, comprising 908 queries in total (singlehop plus multi-hop questions). The retrieval index, implemented using FAISS, contained 801 document chunks with a length of 687 words (average: 91.83 words). Evaluation was carried out in batch mode with a batch size of 32, retrieving up to `candidate_k` = 50 documents per query before applying top-k selection ($k = 5$). For hybrid retrieval configurations, the RRF parameter was set to $k = 60$, with dense and sparse weights both equal to 1.0, while $\alpha = 0.3$.

Additionally, the proposed approach was implemented using the following libraries: PyTorch, Hugging Face Transformers, SentenceTransformers, PEFT, spaCy, KeyBERT, NLTK, FAISS, Rank-BM25, and scikit-learn. These were complemented by supporting and utility packages such as NumPy, Pandas, Matplotlib, Streamlit, Pillow (PIL), BeautifulSoup (bs4), httpx, and the MistralAI API, as well as standard Python libraries including asyncio, concurrent.futures, collections, functools, and urllib.

Appendix B

Abbreviations and Glossary

Table 7: Abbreviations and acronyms with their full forms and definitions used in this thesis.

Term	Full form	Glossary definition
AI	Artificial intelligence	The field of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, and problem-solving.
DH	Digital humanities	An interdisciplinary field that applies computational methods and tools to humanities research, analysis, and dissemination.
IR	Information retrieval	The field of computer science that focuses on finding relevant information in large collections of data, typically unstructured text (like documents, web pages, or articles).
NLP	Natural language processing	The area of AI focused on enabling computers to understand, interpret, and generate human language.
NLG	Natural language generation	The process of automatically generating human-like text from structured data or models, often used in chatbots and content creation.
NL	Natural language	The everyday language used by humans for communication, which NLP systems aim to understand and generate.
QA	Question answering	A task in NLP and IR that focuses on building systems capable of automatically answering questions posed in natural language.
QAS	Question-answering system	A system designed to answer questions automatically by processing natural language input, often using methods from IR and NLP.
RAG	Retrieval-augmented generation	An approach combining information retrieval with generative models, allowing AI to reference external data sources when generating answers.
LLM	Large language model	A type of neural network trained on massive text corpora to understand and generate human language.
API	Application programming interface	A set of protocols and tools that allow different software applications to communicate and interact with each other.

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Term	Full form	Glossary definition
GNA	Geoportale Nazionale Archeologia	Italy's institutional repository for archaeological data, hosting extensive documentation and resources related to the country's cultural heritage.
MiC	Ministero della Cultura	The Italian Ministry of Culture, responsible for the preservation and promotion of Italy's cultural heritage.
MiBACT	Ministero dei Beni e delle Attività Culturali e del Turismo	The former name of the Italian Ministry of Culture, which was responsible for cultural heritage and tourism before its reorganization in 2021.
CNR	Consiglio Nazionale delle Ricerche	The Italian National Research Council, a major public research institution that conducts scientific research across various disciplines, including cultural heritage.
DG-Ant	Direzione Generale Archeologia, Belle Arti e Paesaggio	The Directorate General for Archaeology, Fine Arts, and Landscape within the Italian Ministry of Culture, overseeing archaeological heritage and cultural sites.
ICA	Istituto Centrale per l'Archeologia	The Central Institute for Archaeology in Italy, established in 2016 as part of the Ministry of Culture, responsible for archaeological research and documentation.
ICCD	Istituto Centrale per il Catalogo e la Documentazione	The Central Institute for Cataloging and Documentation, part of the Italian Ministry of Culture, responsible for cataloging cultural heritage assets and proposing best practices.
SiGECweb	Sistema Informativo Generale del Catalogo	A web platform that handles every stage of cultural heritage cataloguing, from standard creation and code assignment to cataloguing diverse assets and publishing records online for public access.
GIS	Geographic information system	A computer system, including software and hardware, designed to capture, store, manipulate, analyse, manage, and present spatial or geographic data, often used in archaeology for mapping and spatial analysis.
QGIS	Quantum GIS	A particular GIS software that is free and open-source.
GLAM	Galleries, Libraries, Archives and Museums	A collective term for institutions that preserve and provide access to cultural heritage in the public interest.
KB	Knowledge base	A structured collection of information or data, often used to support reasoning, search, or retrieval in AI systems.
ML	Machine learning	A subset of AI that involves training algorithms to recognise patterns and make decisions based on data.
NER	Named entity recognition	A subtask of NLP that identifies and classifies named entities (e.g., people, organizations, locations) in text.
EL	Entity linking	The process of connecting named entities in text to their corresponding entries in a knowledge base, enhancing understanding and retrieval.
TF-IDF	Term Frequency-Inverse Document Frequency	A statistical measure used in IR to evaluate how important a word is to a document relative to a corpus, balancing term frequency and document rarity.
BM25	Best match 25	A ranking function used in IR to estimate the relevance of documents to a given search query, based on term frequency and document length normalization.

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Term	Full form	Glossary definition
PRF	Precision-Recall-F1	Metrics used to evaluate the performance of classification models, where precision measures the accuracy of positive predictions, recall measures the ability to find all relevant instances, and F1 is the harmonic mean of precision and recall.
RDF	Resource Description Framework	A standard model for data interchange on the web, allowing structured representation of information about resources in a machine-readable format.
SQL	Structured Query Language	A standard programming language used for managing and manipulating relational databases, allowing users to query, insert, update, and delete data.
SPARQL	SPARQL Protocol and RDF Query Language	A query language and protocol used to retrieve and manipulate data stored in RDF format, commonly used for querying knowledge graphs.
Ontology		A formal representation of a set of concepts within a domain and the relationships between those concepts, used to enable knowledge extraction, sharing and reuse.
JSON	JavaScript Object Notation	A lightweight data interchange format that is easy for humans to read and write, and easy for machines to parse and generate, often used for data exchange in web applications.
CSV	Comma-Separated Values	A text file format used to store tabular data (numbers and text) where each row represents a record, and each column (field) is separated by a comma.
TREC	Text REtrieval Conference	An ongoing series of workshops and evaluations focused on advancing research in text retrieval and related tasks.
LMIR	Language model information retrieval	A method of using language models to improve the effectiveness of information retrieval systems by leveraging their understanding of language and context.
RNN	Recurrent Neural Network	A type of neural network architecture designed to process sequential data by maintaining a form of memory of previous inputs.
LSTM	Long Short-Term Memory	A special kind of RNN capable of learning long-range dependencies, often used for tasks like language modeling or time series prediction.
CRF	Conditional Random Field	A probabilistic graphical model used for structured prediction, especially in NLP tasks such as sequence labelling.
SVM	Support Vector Machine	A supervised machine learning algorithm used for classification and regression, which finds the optimal boundary between classes in the feature space.
Word2Vec	Word to Vector	A technique for representing words as vectors in a continuous vector space, capturing semantic relationships between words based on their context in large text corpora.
GloVe	Global Vectors for Word Representation	An unsupervised learning algorithm for obtaining vector representations of words, which captures global statistical information from a corpus.
BERT	Bidirectional Encoder Representations from Transformers	A pre-trained language model that uses the Transformer architecture to understand the context of words in a sentence by considering both left and right contexts simultaneously.

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Term	Full form	Glossary definition
OpenAI		An artificial intelligence research and deployment company based in San Francisco (USA).
GPT	Generative Pre-Trained Transformer	A family of LLMs developed by OpenAI.
ChatGPT	Generative Pre-trained Transformer	An application of the GPT architecture developed by OpenAI, fine-tuned for conversational interaction and instruction following, and released to the public in November 2022.
T5	Text-to-Text Transfer Transformer	T5 is a series of LLMs developed by Google AI and introduced in 2019.
KeyBERT		A keyword extraction technique using BERT embeddings to generate the keywords and keyphrases most similar to a document.
BAAI	Beijing Academy of Artificial Intelligence	A Chinese research institute that develops and releases cutting-edge AI models. BAAI is the organization behind BGE, and also known for other large-scale AI projects.
BGE	BAAI General Embedding	A family of embedding models designed for dense retrieval and semantic search.
Intfloat	Intelligent Floating Point	A research group and organization that develops open-source AI models for NLP.
E5	Embedding from Explicitly-Explained Supervision	A family of text embedding models developed by the research group Intfloat.
Intfloat/e5		A family of models available on Hugging Face and based on the implementation of *E5*.
LLM-embedder		A model designed to generate embeddings for text using large language models, enhancing the quality of semantic representations for retrieval tasks.
Embeddings		Dense vector representations of text that capture semantic meaning, used in various NLP tasks including retrieval and classification.
Chunking		The process of breaking down text into smaller, manageable pieces or “chunks” to facilitate processing and analysis in NLP tasks.
Vector database		A specialised database designed to store and retrieve high-dimensional vectors efficiently, often used in RAG systems for managing embeddings.
Retriever		A component of a system responsible for searching and retrieving relevant documents or information from a database or corpus based on user queries.
Ranking function		A mathematical function used to score and order documents based on their relevance to a given query, often employed in IR systems.
XML	eXtensible Markup Language	A markup language used to encode documents in a format that is both human-readable and machine-readable, often used for data interchange.

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Term	Full form	Glossary definition
TEI	Text Encoding Initiative	A set of guidelines for encoding literary and linguistic texts in XML, providing a standardised way to represent complex textual structures.
MARC/RDA	Machine-Readable Cataloging / Resource Description and Access	Standards for encoding bibliographic information in a machine-readable format, widely used in libraries and information systems.
GROBID	GeneRation Of BIbliographic Data	A machine learning library for extracting and structuring bibliographic information from scholarly documents, often used in academic publishing and research.
Milvus	Milvus Vector Database	An open-source vector database designed for efficient storage, indexing, and retrieval of high-dimensional vectors, commonly used in RAG systems.
Faiss	Facebook AI Similarity Search	A library for efficient similarity search and clustering of dense vectors, widely used in RAG systems for indexing and searching large datasets.
Qdrant	Qdrant Vector Database	An open-source vector database that provides efficient storage and retrieval of high-dimensional vectors, supporting hybrid search capabilities.
DLM reranking	Deep language model reranking	Deep language model-based reranking uses fine-tuned models that jointly encode query-document pairs and classify their relevance as “true” or “false”. At inference, documents are ranked by the probability of being labeled “true”.
HyDE	Hypothetical Document Embeddings	A method that generates a brief, plausible answer to the query first, then embeds that “hypothetical doc” for retrieval. This richer proxy query improves vector search recall/precision in RAG context, especially for vague or underspecified queries.
Hybrid Search		A search approach that combines vector-based retrieval with traditional keyword search, allowing for more comprehensive and context-aware results in RAG systems.
TILDE		A framework designed to facilitate the development and deployment of RAG systems, providing tools for data preparation, indexing, and retrieval.
TILDEv2		An updated version of the TILDE framework, incorporating improvements in efficiency and performance.
LTR	Learning-to-Rank	A machine learning approach used to optimise the ranking of search results based on user interactions and relevance feedback, improving the quality of retrieved documents in RAG systems.
Self-RAG	Self-Retrieval-Augmented Generation	A variant of RAG where the system retrieves relevant information from its own generated content, enhancing the context and accuracy of responses.
RAGAS	Retrieval-Augmented Generation with Adaptive Sampling	An advanced RAG approach that dynamically selects and retrieves the most relevant information based on the context of the query, improving the efficiency and accuracy of responses.

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Term	Full form	Glossary definition
AHE	Adaptive histogram equalization	A computer image processing technique designed to enhance contrast in pictures. Unlike standard histogram equalization, the adaptive approach divides the image into multiple regions, generates a separate histogram for each, and then redistributes the lightness values based on these localized histograms.
CLAHE	Contrast limited AHE	A variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce the problem of noise amplification.
XAI	Explainable Artificial Intelligence	A field of AI focused on rendering the decision-making processes of AI systems transparent and understandable to humans, often used to build trust and accountability in AI applications.
RAG-chain	Retrieval-Augmented Generation Chain	A method that links multiple RAG components in a sequence.
ArCo	Italian Cultural Heritage Knowledge Graph	A knowledge graph representing Italian cultural heritage, providing structured information about historical sites, artifacts, and related entities.

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