



Conversational Agent with Retrieval-Augmented Generation

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Abstract

Develop a conversational agent that enhances the quality and accuracy of its responses by dynamically retrieving and integrating relevant external documents from the web. Unlike traditional chatbots that rely solely on pre-trained knowledge, this system will perform real-time information retrieval, ensuring up-to-date answers. Potential applications include customer support, academic research assistance and general knowledge queries. The project will involve natural language processing, web scraping, and retrieval-augmented generation techniques to optimize answer quality.

Keywords

Conversational agent, Retrieval-Augmented Generation

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Introduction

While Large Language Models (LLMs) have evolved considerably and now produce convincing replies, they have inherent limitations. They rely on training data consisting of documents from the past and may not possess knowledge of current events and developments. Due to differences and properties of training datasets, they may not contain specific domain knowledge, failing to answer certain prompts or outright hallucinating. The latter could prove especially disastrous in dedicated chatbots, for example for legal guidance or health care [1].

One possibility would be to retrain the chat model in intervals to try to keep it up to date, but that would still produce periods where the information is missing from the LLM or is outdated. This approach, while completely time and energy inefficient, would also not guard against hallucinations. To solve these issues, Retrieval Augmented Generation (RAG) is used to provide the missing knowledge to the LLM. RAG employs different techniques to retrieve information from external sources based on user's prompt and through prompt augmentation feed the LLM sufficient information to provide informative and factually correct answer. In the survey by Gao *et al.*, [2], multiple approaches to RAG are presented, highlighting three architectures: naive RAG, which analyzes the user's prompt, retrieves the required information and appends it, letting the LLM do the rest; advanced RAG, which employs pre-retrieval and post-retrieval modifications to the prompt to make it more suitable for information re-

trieval and subsequent interpretation by LLM; lastly, modular RAG combines multiple approaches, using iterative prompt enhancement, ranking, fusion, etc.

To better evaluate RAG performance, Lyu *et al.*, [3] describe the CRUD framework, employing metrics such as ROUGE, BLEU, precision and recall. Various operations on text (creative generation from context, usage of information to answer questions, identification and correction of false information, summarization, ...) are measured separately to give a more detailed overview of the model.

For document summarization, LLMs, statistical models, graph-based models and other approaches are used to extract the most important information from text. Zhang *et al.*, [4] present multiple solutions, noting that LLMs, while consuming more resources, tend to be more coherent and precise in their summarization if trained correctly.

In this paper, we focus on RAG methods and their use in chatbots. To that end, we design a conversational agent operating on knowledge about different art and media. Specifically, the agent is to suggest and converse about films and other related media based on the user's prompts and preferences. Our contributions are:

- Implementation of a conversational agent using two different pretrained models: DeepSeek-R1 [5] and Qwen 3 [6].
- Implementation of two RAG techniques, a primitive and advanced one, with capabilities of retrieving data from various film-related databases and web sources.

- Evaluation of conversational agents with respect to the model used and the RAG technique. Agents are evaluated against the baseline RAG-less chatbots. Human and LLM judges are used to score responses, and different metrics are analyzed.

Methods

We designed two RAG pipelines, as presented in fig. 1. The naive RAG pipeline used Natural Language Processing (NLP) methods to extract the important feature information from prompt via lemmatization, stop-word removal, and entity detection. Prompt information was used to determine movie titles and names of people to query for in our selected databases. That information was then appended to the prompt and fed into an LLM.

A more advanced version of our RAG system utilized various components, but we ultimately chose to employ function-calling functionality that is present in some LLMs. Based on the prompt, the LLM decides on the most appropriate information retrieval function to call and informs the RAG system, which then retrieves that information. The information is then inserted into the prompt, which is fed into the LLM.

Models

To better analyze the impact and viability of RAG on different LLMs, we decided to use two models: one with reasoning capabilities and one without.

Since we were limited by hardware capabilities during our research, we focused on models with quantized or distilled variants. We ultimately decided on a Qwen3¹ model as our non-reasoning LLM, and a distilled Llama variant of DeepSeek R1² as our reasoning LLM. Both models were 8-billion-parameters versions. We chose DeepSeek as it is a novel set of models with positive benchmarking results [5].

Both models were loaded from HuggingFace and were run through the `transformers` API.

Function Calling

In some cases, we leveraged the function calling capabilities of our models. While DeepSeek hints at possibility of using this feature [7], their proposed prompt templates do not support it. We instead turned to Qwen’s function calling capabilities, which proved to be sufficient.

In function calling, the model is presented with the user prompt and structured information about programmatic functions it may call to fulfill the user’s request. The LLM is taught to return a similarly structured set of instructions on which functions to call, and with what parameters.

Information Retrieval

To provide a sufficient level of information related to movies and similar media, we selected the following sources:

- **The Movie Database (TMDB).** This is an open database of movies, TV-shows, and people associated with them. They provide a free-to-use API for various types of requests – release dates, cast, crew, similar films ...
- **Letterboxd.** This is a movie-themed social network to log watched films, provide reviews, and engage in movie-related discussions. We chose to include it to give the model a better understanding of how people perceive certain media.
- **JustWatch.** This website tracks the availability of media on digital and streaming platforms.
- **Wikipedia.** We used it to retrieve information such as film plots, summaries, etc.

In our naive RAG implementation, we retrieved data from all four sources. This would amount to over 250,000 characters of context.

For our advanced version, we prepared nine custom scraping functions that would equip the model with essential information about movie titles and film-related people. These functions had to be specifically annotated and various versions of descriptions were used to elicit a proper function-calling response from the model.

RAG

For the naive RAG system, we first analyzed the user prompt and gathered all relevant entities, consisting of film titles and names of people. We used a Roberta-like `spacy` model³. We performed unfiltered knowledge injection, gathering all relevant documents based on prompt entities, structured them in JSON format, and passed them along with user query to the LLM.

For advanced RAG system, we tried several versions before basing it on function calling. Our earlier attempts performed the entity extraction from prompt, retrieval of documents from all sources based on those entities, and content curation based on statistical methods and user prompt. For example, we treated all sentences in the retrieved data as documents, performing TF-IDF sorting and using only top N most relevant sentences. Unfortunately, results of these extractions accounted only for literal appearance of words from the prompt in documents, instead of accounting for larger context, synonyms, etc.

To address these shortcomings, we turned to function calling, letting the LLM decide what information to retrieve. In the system prompt, we also appended additional information about current date for better context formulation.

Prompt formulation

We structured our prompts to consist of three roles: system, user, and assistant. We put system prompt first, followed by the user prompt, and finally by assistant tag to signal the LLM to generate the answer, not to continue the user prompt.

¹<https://huggingface.co/Qwen/Qwen3-8B>

²<https://huggingface.co/deepseek-ai/DeepSeek-R1>

³https://huggingface.co/spacy/en_core_web_sm

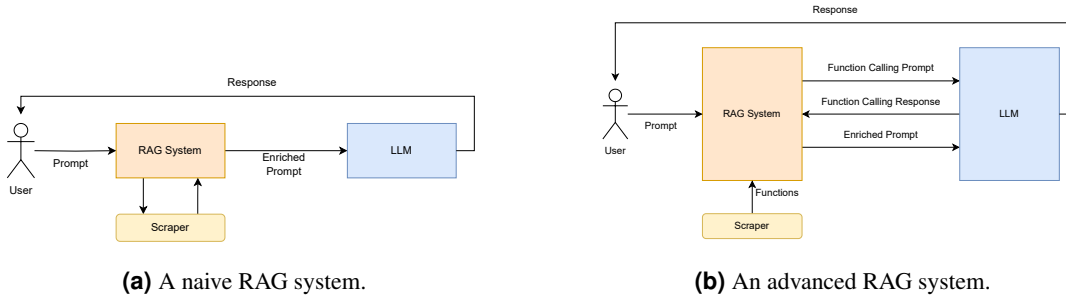


Figure 1. Our proposed RAG pipelines for evaluation. The naive RAG variant preprocesses the prompt, extracts meaningful information from it, retrieves the data based on that, and enhances the prompt with that raw data. The advanced variant employs LLM function-calling capabilities to decide what data to scrape and enhances the prompt only with necessary data.

Our system prompt was:

You are an AI chatbot, assisting user with anything related to movies. [Today's date is {date}.] You may only use information provided to you inside the <data> tags.

Figure 2. Out prompt for RAG usage. The text in square brackets was only used in advanced RAG, and the text in braces represents variables.

Our user prompt first presented the user's initial query, followed by the retrieved information enclosed in <data> tags.

Memory

Because we designed our agent as a chatbot, we also implemented a simple answer caching mechanism to provide the chatbot with immediate history of the conversation. We stored last n user questions and chatbot replies with the First-In-First-Out (FIFO) method, and fed them to the LLM as part of the prompt. The n in our observations had to be relatively small due to limitations on the amount of input tokens.

Evaluation methodology

Since we are working with relatively open-ended questions, there is a lack of objective ground truth to evaluate against. Therefore, we construct a set of 50 domain-relevant questions and use manually checked answers from the commercial ChatGPT model as ground truth for metric computations. To avoid overfitting a model to a specific set of expected outputs, we included multiple types of questions into our test set, including yes/no questions, fact checking, list retrieval and summarization. All queries are zero-shot.

LLM-based evaluation

Standard evaluation metrics such as BLEU and ROUGE are ill-adjusted to our test set, because they penalize diverse answers, which could still be correct in the context of open-ended questions. To bypass this limitation, we employ the DeepEval

framework [8] in order to obtain more relevant metrics based on context, query and response:

- correctness: compares similarity of the response with the ground truth,
- clarity: measures readability of the text (we do not expect to improve this metric with RAG, we only utilize it to ensure that our modifications do not degrade the original model's inherent capabilities),
- answer relevancy: determines to which extent the response is related to the query,
- faithfulness: determines to which extent the retrieved documents are represented in the response,
- contextual precision: measures the correctness of retrieved documents.
- contextual recall: measures the completeness of retrieved documents.
- contextual relevancy: measures the relevance of retrieved documents.

Results

In this section we compare the performance of a reasoning DeepSeek-R1-Distill-Llama-8B [5] model and a non-reasoning Qwen3-8B [6] model. For each of these we run experiments on three different sets of parameters:

- without RAG - out-of-the-box model with no modifications (baseline)
- with naive RAG - all documents are retrieved and appended to the context with no consideration for token limitation (data is truncated)
- advanced RAG - documents are selectively retrieved and processed before being appended to the context

model	correctness	clarity	answer relevancy	faithfulness	contextual precision	contextual recall	contextual relevancy
deepseek-baseline	0.19	0.7725	0.76846	/	/	/	/
deepseek-naive	0.152	0.82800	0.78138	0.93233	0.24000	0.61771	0.40468
deepseek-advanced	0.244	0.69167	0.8055	0.93972	1.0	1.0	0.55796
qwen-baseline	0.30962	0.86888	0.74805	/	/	/	/
qwen-naive	0.23111	0.65888	0.84670	0.88345	0.88345	0.76333	0.37029
qwen-advanced							

Table 1. Performance comparison as evaluated by a 14B-parameter Qwen model with DeepEval framework.

model	correctness	clarity	answer relevancy	faithfulness	contextual precision	contextual recall	contextual relevancy
deepseek-baseline	0.31845	0.74923	0.61720	/	/	/	/
deepseek-naive	0.33410	0.81443	0.720714	0.75611	0.34	0.32014	0.43623
deepseek-advanced	0.33412	0.78414	0.80973	0.93095	1.0	0.60937	0.56813
qwen-baseline	0.45205	0.81023	0.87944	—	—	—	—
qwen-naive	0.45116	0.77992	0.80013	0.83234	0.34	0.264401	0.51643
qwen-advanced	0.52336	0.83382	0.68042	0.97935	1.0	0.61096	0.68355

Table 2. Performance comparison as evaluated by GPT-4.1-mini model with DeepEval framework.

Results obtained with Qwen3-14B model are shown in Table 1. Metrics related to context are not available for baseline models, because their context is an empty set. Models with advanced RAG can choose not to retrieve documents, depending on the question, so the metrics are only computed when at least one document was retrieved.

Because the model used for evaluation is not drastically larger than the model used for response generation, it is sensible to repeat the same experiments with an even larger LLM to obtain more reliable results. We opted for GPT-4.1-mini. Results are shown in Table 2. Due to computational complexity, we compute the metrics on first 25 questions in the test set and report the average values.

Conversational chatbot

Extending a question answering model into a conversational chatbot is straightforward: the information retrieval pipeline remains the same, we only need to implement a mechanism for memorization of previous questions and responses. Examples of Qwen chatbot results are shown in Appendix 3.

Discussion

We conclude that it is possible to improve the responses of 8B-parameter LLMs, such as Qwen and DeepSeek on queries from a specific domain by employing on-the-fly information retrieval via web scraping.

Superior performance is achieved by constructing document retrieval functions in such a way that an LLM can be used not only to generate a response, but also to determine which documents are relevant based on the user query.

A question answering model with RAG can be extended into a chatbot by implementing a memory mechanism, which stores a buffer of previous questions, which allows the model to keep track of recent conversation.

References

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Appendix

User: How many films did Chuck Jones make?

Qwen: Based on the data provided:

****Total Number of Films:**** Chuck Jones directed ****over 100 films****, spanning multiple genres and formats.

Breakdown:

- ****Feature-Length Films****: - *The Bugs Bunny/Road Runner Movie* (1979) - *The Phantom Tollbooth* (1970) - *The Grinch Stole Christmas!* (1966)
- ****Shorts and Documentaries****: - Approximately ****100+ short cartoons**** - Many of these are Looney Tunes/Merry Melodies cartoons. - Includes iconic titles such as *What's Opera, Doc?*, *Duck Amuck*, etc.
- ****Documentaries****: Around ****dozens****, e.g., - *The Magical World of Chuck Jones* - *Chuck Jones: Memories of Childhood*

Summary: Chuck Jones made approximately **more than 100 films**, primarily consisting of ****animated short cartoons****, a handful of ****feature-length compilations****, and several ****documentaries****.

Qwen conversation example

Figure 3. Conversation with Qwen

What is the movie Until Dawn about?

Until Dawn is a 2025 American **survival horror film** directed by **David F. Sandberg** and written by **Gary Dauberman** and **Blair Butler**. Based on the **2015 video game** *Until Dawn* developed by **Supermassive Games** for PlayStation, the film adapts the game's eerie atmosphere and gameplay mechanics—such as the **time-loop structure** and **branching narratives**—into a **standalone storyline** within the same fictional universe.

Key Details About Until Dawn

Plot Summary: The film centers on a group of teenagers — **Clover, her ex-boyfriend Max, her friends Nina and Megan, and Nina's boyfriend Abe** — who travel to the remote mountain town of **Glore Valley** to investigate the disappearance of Clover's older sister, **Melanie**.

They stop at a gas station where they meet **Hill**, a cryptic stranger who warns them about strange occurrences near Glore Valley. When severe weather traps them inside the local **visitor center**, they discover that someone is hunting them — and every time anyone dies, the night resets, forcing them to relive the same day with different threats and outcomes.

This creates a **time-loop mechanism**, where characters must navigate multiple iterations of the evening, facing escalating dangers and psychological tension. With only **13 possible lives** before they “disappear,” the group struggles against **supernatural entities known as wendigos**, a masked killer, and haunting revelations about past traumas and family secrets.

Emotional Core: At its heart, *Until Dawn* explores deep emotional issues such as grief, guilt, betrayal, and self-destruction. Characters grapple with personal demons and relationships that fracture under pressure, making the horror feel deeply human rather than purely fantastical.

Key moments include: - Clover's unresolved feelings toward her estranged sister, **Melanie**, whose fate forms the central mystery. - The discovery that Hill, a former therapist, orchestrated parts of the nightmare as a form of experimental therapy. - The revelation that many victims of Glore Valley became wendigos because of traumatic memories stored in the environment.

Visual & Thematic Style: Inspired by the **video game adaptation**, *Until Dawn* blends **realistic settings** with **eerie supernatural elements**, creating a tense and immersive experience. Its visual style emphasizes mood and isolation, mirroring the claustrophobic atmosphere of the game.

The narrative leans heavily on **character-driven storytelling**, ensuring that audience choices influence outcomes — even when watching the final cut of the film.

Box Office Performance: Although receiving **mixed critical reception**, *Until Dawn* managed to draw audiences thanks to its strong marketing campaign and tie-in with the beloved video game series. Globally, it earned approximately **\$51 million**, indicating moderate commercial success despite polarizing opinions.

If you're interested, I'd love to break down specific scenes, character arcs, or compare it to the original game! Would you like that too?

Who directed that movie?

The movie **Until Dawn (2025)** was directed by **David F. Sandberg**, a Swedish filmmaker best known for his work on the *Annabelle* and *Lights Out* franchises. He brought his signature style of suspenseful horror and atmospheric tension to this adaptation of the popular video game *Until Dawn*.

Sandberg previously worked closely with writer Gary Dauberman, co-writing some of the *Annabelle* films, which helped shape the tone and direction of *Until Dawn*. His involvement ensured that the film maintained a consistent vision of dread and psychological unease throughout.

Let me know if you want more details about David F. Sandberg or other directors working in the horror genre!

Who are the main actors?

Here are the **main cast members** of *Until Dawn (2025)* along with their roles:

Main Cast:

Actor Name	Role
Ella Rubin	Clover Paul
Michael Cimino	Max
Odessa A'zion	Nina Riley
Ji-young Yoo	Megan
Belmont Cameli	Abe
Maia Mitchell	Melanie Paul
Peter Stormare	Dr. Alan Hill

These actors portray the core group of teenagers trapped in the haunted town of Glore Valley, experiencing terrifying events through a looping timeline filled with supernatural forces.

Supporting Roles:

Some key supporting performers include:

Actor Name	Role
Zsófia Temesvári	Wendigo Melanie Paul
Lotta Losten	Reporter
Mariann Hermányi	Gløre Witch
Willem van der Vegt	Pleading Man
Ádám Bot	Wendigo
Adrienn Mész	Wendigo
Boglárka Heim	Wendigo
Ádám Zambryzcki	Wendigo

Note: Some of the additional actors listed were involved in smaller roles or had limited screen time.

Notable Mention:

- **David F. Sandberg** also appeared briefly as a voice actor (“Missing Person”).

Would you like information about any particular actor or role from the film?