

# Optimizing a Retrieval-Augmented QA Chatbot for HR Support using LLMs

Alexander Kowsik, 20.11.2023, Kick-off Presentation

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# Outline

- 1 Motivation & Problem Statement
- 2 Solution Proposal: Tech Stack & Data
- 3 Research Questions
- 4 Approaches & Timeline

# High HR workloads result in extensive manual labor and long delays



## **Problem 1: Large volumes of HR inquiries**

- HR departments deal with *large quantities of daily tasks* and queries from employees
- *More than 330.000 HR tickets* per year are created at SAP
- To effectively manage this, *a substantial number of HR experts* are needed

## **Problem 2: Manual and time-consuming process**

- Employee *questions must be manually processed and responded to* in accordance with HR rules and policies
- The result is *long waiting times*, ranging from hours to days or even weeks

# QA chatbots reduce HR workloads by processing inquiries significantly more efficiently

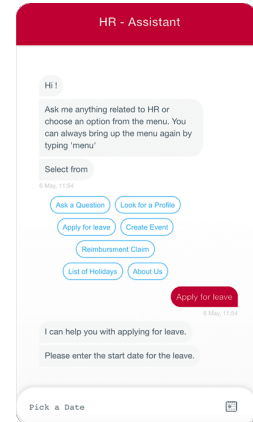


## Benefit 1: Save time for both employees and the HR domain experts

- QA chatbots provide *immediate responses*, effectively eliminating any answer delays
- *Reduction of HR workload* allows the HR experts to focus on more important tasks
- Goal: *Replace 30% of HR tickets* with chatbot functionalities

## Benefit 2: Automation of (mundane) manual tasks

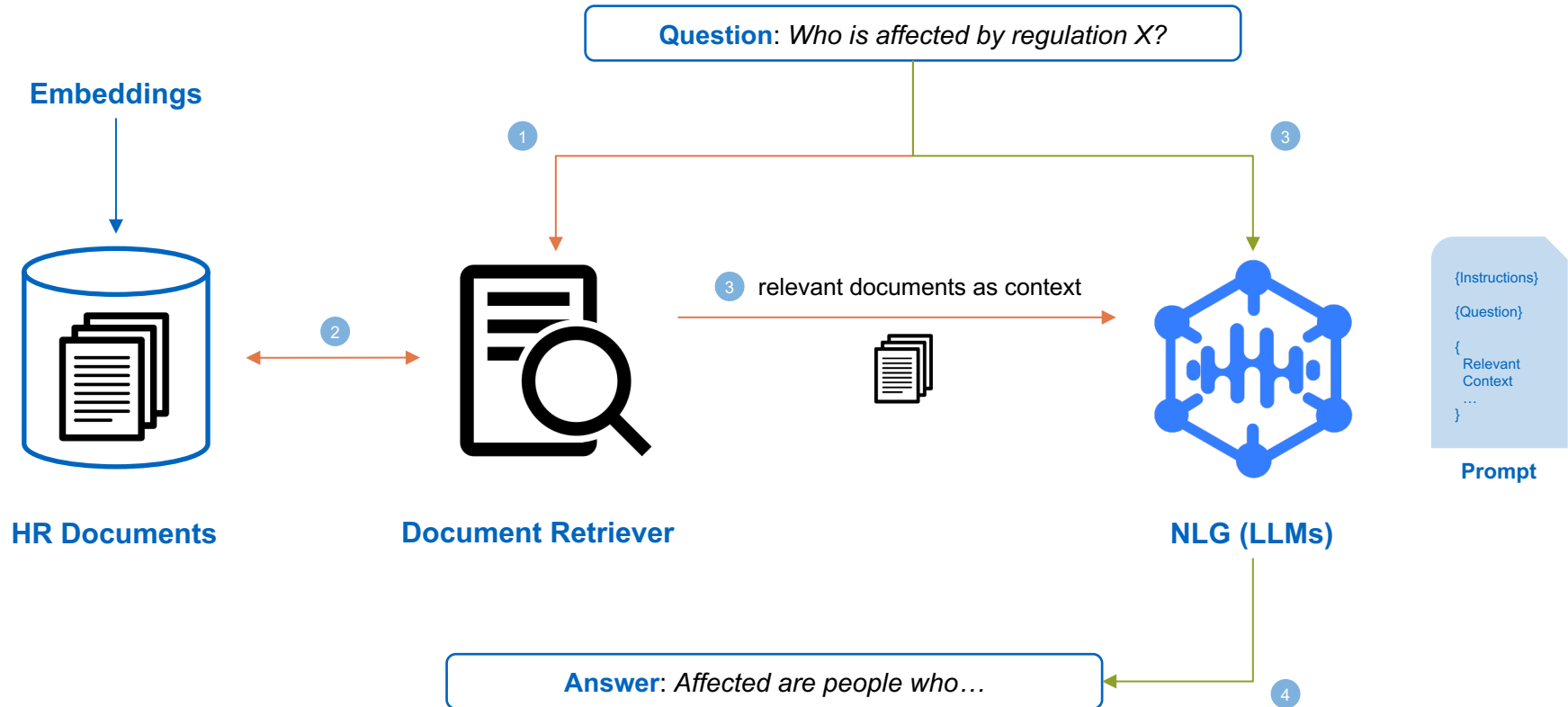
- The process of answering employee questions based on HR policies is *highly automatable using SOTA NLP models* (e.g., LLMs)
- Chatbots utilize the *HR rules and policies as grounding* for their responses



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# Retrieval-augmented Generation using LLMs – Most flexible and least limiting solution



# Retrieval-augmented Generation using LLMs – Most flexible and least limiting solution



## Document Retriever

Current solution:



**haystack**  
by deepset

Haystack DPR  
Fine-tuned

Proposed solution:



**OpenAI Embeddings + Vector Search**  
Better embeddings → better performance

Goal: Higher retrieval accuracy + better performance

- Removes need for [fine-tuning](#) DPR
- [Embed new documents](#) → include in vector search
- [Better embeddings](#) lead to better context retrieval
- [Vector Database](#): Scalability, Hybrid Search
- [Advanced retrieval methods](#): Query Transformations (Intended Topics, HyDE), Reranking, ...



## NLG (LLMs)

Current solution:



**T5 / LongT5**  
Fine-tuned

Proposed solution:



**LLMs**: APIs (OpenAI) / Open-source  
[Prompting](#) → flexible, more powerful  
Conversational capabilities

Challenge: Get desired outputs

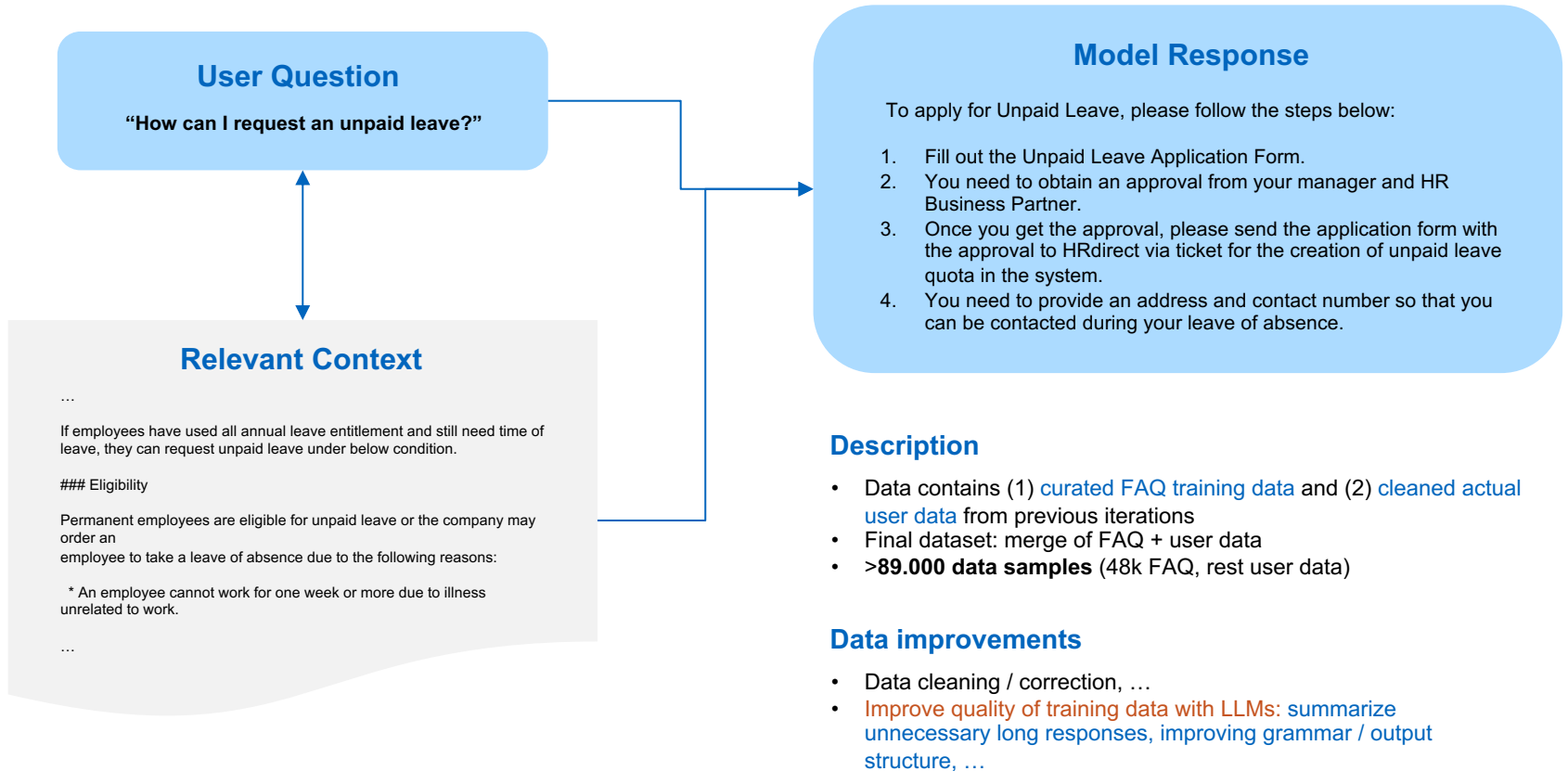
- Removes need for [fine-tuning](#) custom model
- Instruct LLM to return desired output
  - [Prompt engineering](#) / tuning
  - [In-context learning](#)
- Attach relevant context to [ground responses](#)
  - Prevent hallucinations

```
{Instructions}
```

```
{Question}
```

```
{  
  Relevant  
  Context  
  ...  
}
```

**Prompt**





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1

For domain-specific use-cases, are **LLM Chatbot Systems** able to **address the user queries as effectively as humans**?

2

Can direct inference yield adequate results *without the need for fine-tuning*, and what **prompt-tuning techniques** can be used to **improve the quality of the responses**?

3

What methods can be used to optimize the **retrieval** when using **LLM embeddings** and a **vector database** in comparison to the current **DPR module**?

4

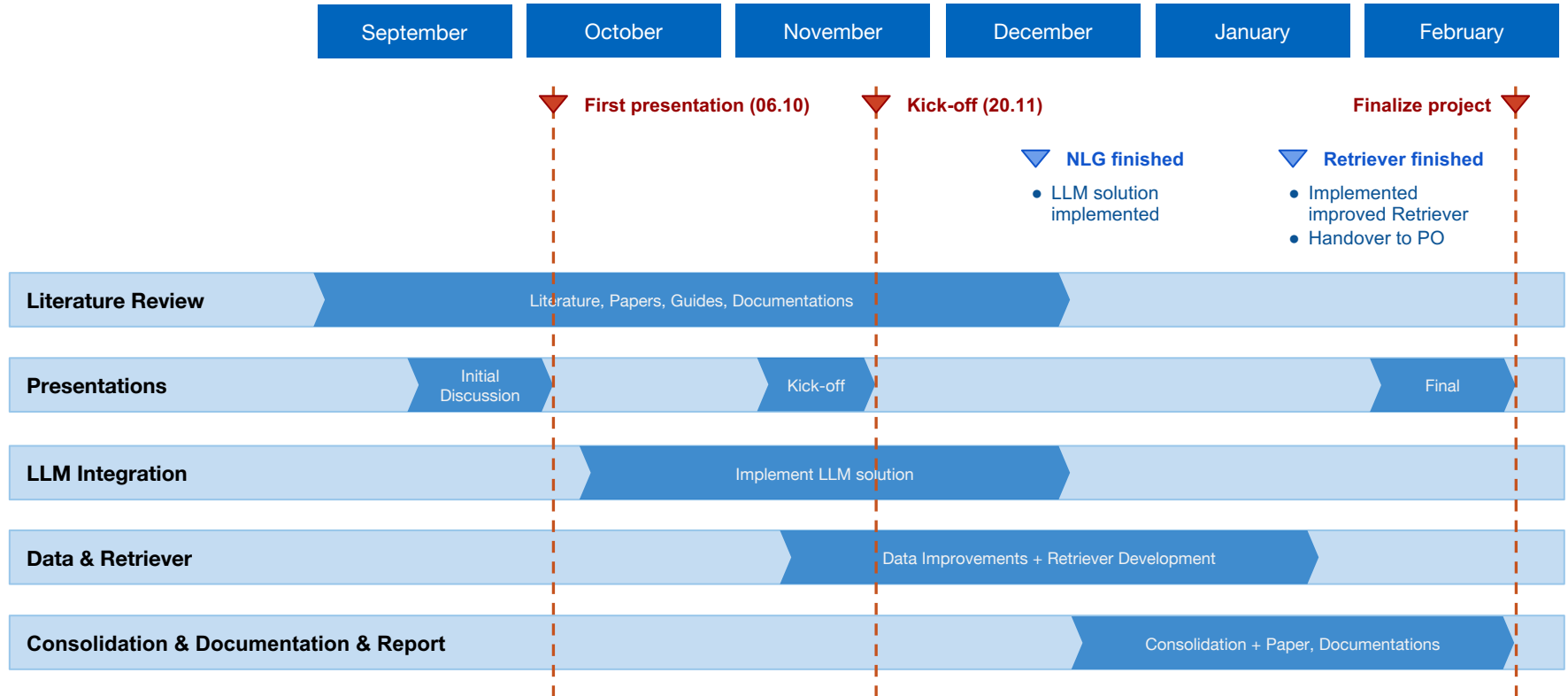
How can **LLMs** be utilized to **improve the quality of the training data**?

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1	Literature Review	Literature, Papers, Guides, Documentations, ...
2	Improve data with LLMs	Summarizations, ...
3	Replace DPR System	OpenAI <b>Embeddings</b> , <b>Vector Search</b> , Optimizations, ...
4	Implement the <b>LLM-NLG</b> module	<b>Prompt-Engineering/-tuning</b> , Model / APIs Benchmarks, ...
5	Evaluation (w/ Rajna)	Evaluate <b>components</b> and the <b>whole pipeline end-to-end</b>
6	Consolidation	Combine all components into a <b>deployable system</b> , <b>Documentation</b> , <b>Handover</b> , <b>Report Paper</b> , ...

# Project Timeline





Prof. Dr.

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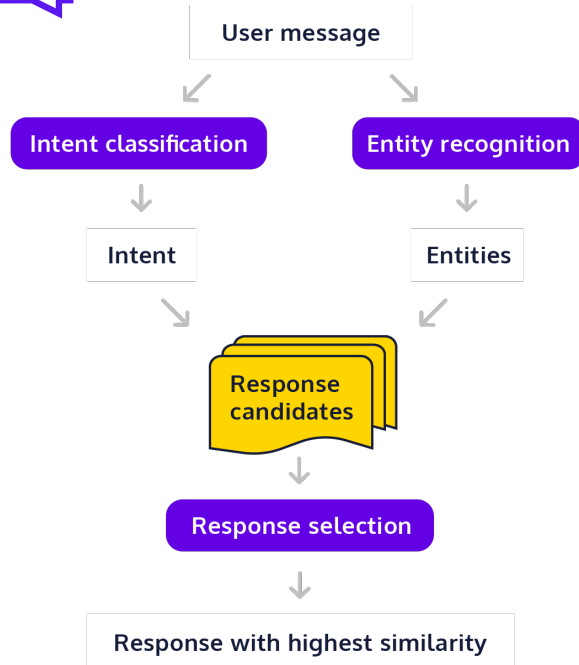
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**Thank you!**

Any questions?

# Traditional/Retrieval-based chatbots are limited and require extensive manual effort



<https://www.codecademy.com/learn/retrieval-based-chatbots/modules/retrieval-based-chatbots/cheatsheet>

**Goal:** Answer questions based on documents

**Functionalities**  
=  
**Intents**

## Problems

- Manually designed, limited intents
- Not manageable and scalable
- Limited understanding of complex queries

**Response**  
**Generation**

## Problems

- Rule-based and pre-defined responses
- No abstractive summarization of results