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# How to Create a RAG Evaluation Dataset From Documents

Automatically create domain-specific datasets in any language using LLMs



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context	question	answer	source_doc	score	eval
string	string	string	string	int64	string
Official Journal of the European Union...	What is the date on which Regulation (EU)...	13 June 2024	documents/OJ_L_202401689_EN_TXT.pdf	4	The question can be answered from the give...
Having regard to the opinion of the...	What is the purpose of the proposed...	To improve the functioning of the...	documents/OJ_L_202401689_EN_TXT.pdf	4	The question is grounded in the contex...
At the same time, depending on the...	What type of AI systems require commo...	High-risk AI systems.	documents/OJ_L_202401689_EN_TXT.pdf	4	The question is grounded in the contex...
A Union legal framework laying down harmonised...	What is the main objective of laying...	To foster the development, use and...	documents/OJ_L_202401689_EN_TXT.pdf	4	The question is grounded in the contex...
Harmonised rules applicable to the...	What EU regulations are the harmonised...	Regulation (EC) No 765/2008 of the...	documents/OJ_L_202401689_EN_TXT.pdf	4	The question can be answered from the give...
. This Regulation should not affect the...	What is the purpose of this Regulation...	This Regulation aims to strengthen the...	documents/OJ_L_202401689_EN_TXT.pdf	4	- Groundedness: The question can be...
Regulation (EC) No 765/2008 of the...	What is the name of the European Union...	Regulation (EC) No 765/2008	documents/OJ_L_202401689_EN_TXT.pdf	4	The question is grounded in the contex...

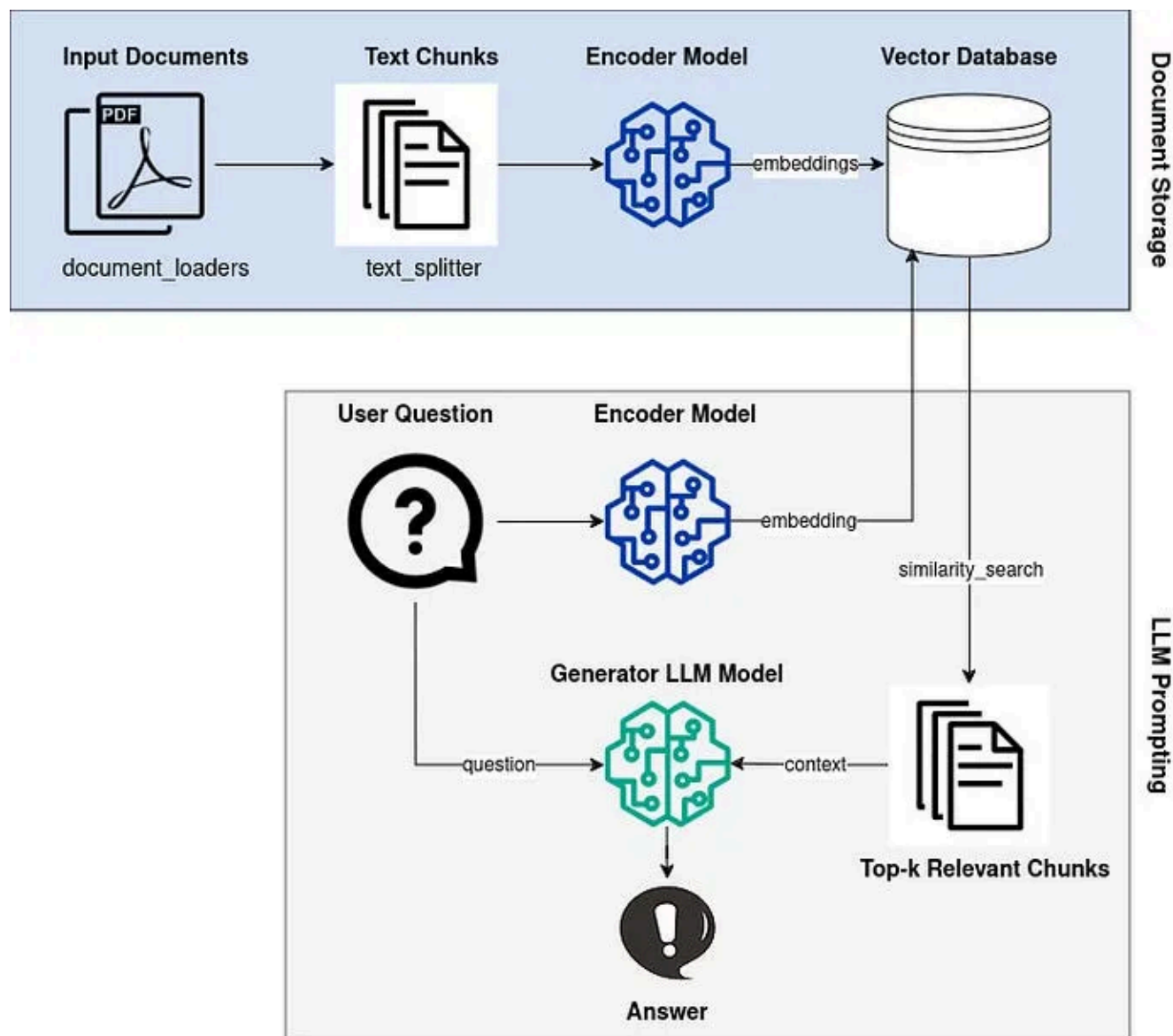
Our automatically generated RAG evaluation dataset on the Hugging Face Hub ([PDF input file](#) from the European Union licensed under [CC BY 4.0](#)). Image by the author

In this article I will show you how to create your own RAG dataset consisting of contexts, questions, and answers from documents in any language.

Retrieval-Augmented Generation (RAG) [1] is a technique that allows LLMs to access an external knowledge base.

By uploading PDF files and storing them in a vector database, we can retrieve this knowledge via a vector similarity search and then insert the retrieved text into the LLM prompt as additional context.

This provides the LLM with new knowledge and reduces the possibility of the LLM making up facts (hallucinations).



The basic RAG pipeline. Image by the author from the article [“How to Build a Local Open-Source LLM Chatbot With RAG”](#)

However, there are many parameters we need to set in a RAG pipeline, and researchers are always suggesting new improvements. How do we know which parameters to choose and which methods will really improve performance for our particular use case?

This is why we need a validation/dev/test dataset to evaluate our RAG pipeline. The dataset should be from the domain we are interested in and in the language we want to use.

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## Deploying a Local LLM With VLLM

First, we get a local LLM up and running.

I used [VLLM](#) to set up an **OpenAI-compatible LLM server** with a quantized [Llama-3.2-3B-Instruct](#). Make sure you use an LLM that has been trained on the language you want to use.

Deploying a local LLM with Docker and VLLM is quite simple:

With **Docker**:

```
docker run --runtime nvidia --gpus all \  
  -v ~/.cache/huggingface:/root/.cache/huggingface \  
  --env "HUGGING_FACE_HUB_TOKEN=<secret>" \  
  -p 8000:8000 \  
  --ipc=host \  
  vllm/vllm-openai:latest \  
  --model AMead10/Llama-3.2-3B-Instruct-AWQ \  
  --quantization awq \  
  --max-model-len 2048
```

## With Docker Compose:

```
services:
  vllm:
    image: vllm/vllm-openai:latest
    command: ["--model", "AMead10/Llama-3.2-3B-Instruct-AWQ", "--max-model-len"]
    ports:
      - 8000:8000
    volumes:
      - ~/.cache/huggingface:/root/.cache/huggingface
    environment:
      - "HUGGING_FACE_HUB_TOKEN=<secret>"
    deploy:
      resources:
        reservations:
          devices:
            - driver: nvidia
              count: 1
              capabilities: [gpu]
```

Now we can use our local LLM with the official OpenAI Python SDK.

If you want to use the official OpenAI models, just change the `base_url`, `api_key`, and `model` variables.

```
%pip install openai

from openai import OpenAI

# use local VLLM server
client = OpenAI(
    base_url="http://localhost:8000/v1",
    api_key="None",
)

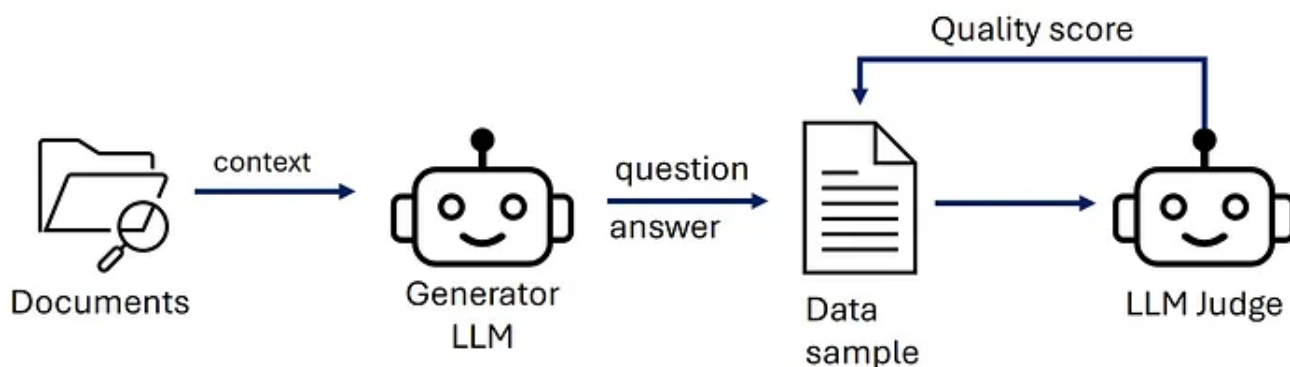
chat_completion = client.chat.completions.create(
    messages=[
        {
            "role": "user",
            "content": "Say this is a test",
        }
    ],
```

```
model="AMead10/Llama-3.2-3B-Instruct-AWQ",  
)
```

Let's perform a quick sanity check to see that everything works as expected:

```
print(chat_completion.choices[0].message.content)  
>> "This appears to be a test. Is there anything specific you'd like to test or
```

## Creating a RAG Evaluation Dataset



Workflow to automatically generate RAG evaluation data samples from documents. Image by the author

The basic workflow for automatically generating a RAG dataset starts with reading our knowledge base from documents, such as PDF files.

Then we ask a **generator LLM** to generate question-answer pairs from the given document context.

Finally, we use a **judge LLM** to perform quality control. The LLM will give each question-answer-context sample a score, which we can use to filter out bad samples.

Why not use a framework like Ragas to generate a synthetic test set for RAG?

Because Ragas uses English LLM prompts under the hood. Using Ragas with non-English documents does not work at the moment.

I used the OpenAI cookbook “RAG Evaluation” [2] as the basis for my code in this article. However, I tried to simplify their sample code and changed the evaluation based on a few research findings [3, 4, 5].

## Read Files

We will use LangChain to read a folder with all our files.

First, we need to install all the necessary packages. LangChain's DirectoryLoader uses the unstructured library to read all kinds of file types. In this article, I will only be reading PDFs so we can install a smaller version of `unstructured`.

```
pip install langchain==0.3.6 langchain-community==0.3.4 unstructured[pdf]==0.16
```

Now we can read our data folder to get the LangChain documents. The following code first loads all the PDF files from a folder and then chunks them into relatively large chunks of size 2000.

```
from langchain_text_splitters.character import RecursiveCharacterTextSplitter
from langchain_community.document_loaders.directory import DirectoryLoader

loader = DirectoryLoader("/path/to/data/folder", glob="**/*.pdf", show_progress=True)
docs = loader.load()

text_splitter = RecursiveCharacterTextSplitter(
    chunk_size=2000,
    chunk_overlap=200,
    add_start_index=True,
    separators=["\n\n", "\n", ".", " ", ""],
)

docs_processed = []
for doc in docs:
    docs_processed.extend(text_splitter.split_documents([doc]))
```

The result is a list `docs_processed` with items of the type `Document`. Each document has some `metadata` and the actual `page_content`.

This list of documents is our knowledge base from which we will create question-answer pairs based on the context of the `page_content`.

## Generating Question-Answer-Context Samples

Using the OpenAI client and the model we created earlier, we first write a generator function to create questions and answers from our documents.

```
def qa_generator_llm(context: str, client: OpenAI, model: str = "Amead10/Llama-
    generation_prompt = """
    Your task is to write a factoid question and an answer given a context.
    Your factoid question should be answerable with a specific, concise piece of fa
    Your factoid question should be formulated in the same style as questions users
    This means that your factoid question MUST NOT mention something like "accordin

    Provide your answer as follows:

    Output:::
    Factoid question: (your factoid question)
    Answer: (your answer to the factoid question)

    Now here is the context.

    Context: {context}\n
    Output:::"""

    chat_completion = client.chat.completions.create(
        messages=[
            {
                "role": "system",
                "content": "You are a question-answer pair generator."
            },
            {
                "role": "user",
                "content": generation_prompt.format(context=context),
            }
        ],
        model=model,
        temperature=0.5,
        top_p=0.99,
        max_tokens=500
    )

    return chat_completion.choices[0].message.content
```

If you want to use a language other than English, you will need to translate the `generation_prompt` (and the system instruction).

Next, we simply loop through all of our document chunks in our knowledge base and generate a question and an answer for each chunk.

```

from tqdm.auto import tqdm

outputs = []
for doc in tqdm(docs_processed):
    # Generate QA couple
    output_QA = qa_generator_llm(doc.page_content, client)
    try:
        question = output_QA.split("Factoid question: ")[-1].split("Answer: ")[0]
        answer = output_QA.split("Answer: ")[-1]
        assert len(answer) < 500, "Answer is too long"
        outputs.append(
            {
                "context": doc.page_content,
                "question": question,
                "answer": answer,
                "source_doc": doc.metadata["source"],
            }
        )
    except Exception as e:
        print(e)

```

Depending on how many PDF files you have, this may take a while. Don't forget to translate the strings in `output_QA.split` if necessary.

To generate a RAG evaluation dataset, I used a [PDF about the regulation of the EU AI Act](#) from the European Union (licensed under [CC BY 4.0](#)). Here is my generated raw `outputs` dataset:

```

[{'context': 'Official Journal of the European Union\n\n2024/1689\n\nREGULATION',
  'question': 'What is the date on which Regulation (EU) 2024/1689 of the Europ',
  'answer': '13 June 2024',
  'source_doc': 'documents/OJ_L_202401689_EN_TXT.pdf'},
 {'context': 'Having regard to the opinion of the Committee of the Regions (3),',
  'question': 'What is the purpose of the proposed Regulation on the developmen',
  'answer': 'To improve the functioning of the internal market by laying down a',
  'source_doc': 'documents/OJ_L_202401689_EN_TXT.pdf'},
 {'context': '(3)\n\nAI systems can be easily deployed in a large variety of se',
  'question': 'What is the official journal number for the regulation related t',
  'answer': '(4)',
  'source_doc': 'documents/OJ_L_202401689_EN_TXT.pdf'},
 ...
]

```



## Filtering out Bad Question-Answer Pairs

Next, we use an LLM as a **judge** to automatically filter out bad samples.

When using an LLM as a judge to evaluate the quality of a sample, it is best practice to use a different model than the one that was used to generate it because of a **self-preference bias** [6] — you wouldn't grade your own paper, would you?

When it comes to judging our generated questions and answers, there are a lot of possible prompts we could use.

To build our prompt, there is a structure we can use from the **G-Eval** paper [3]:

- We start with the **task introduction**
- We present our **evaluation criteria**
- We want the model to perform **chain-of-thought (CoT)** reasoning [7] to improve its performance
- We ask for the **total score** at the end

For the evaluation criteria, we can use a list where each criterion adds one point if it is fulfilled [4].

The evaluation criteria should ensure that the question, the answer, and the context all fit together and make sense.

Here are two evaluation criteria from the OpenAI RAG evaluation cookbook [2]:

- **Groundedness:** can the question be answered from the given context?
- **Stand-alone:** is the question understandable without any context? (To avoid a question like "What is the name of the function used in this guide?" )

And two more evaluation criteria from the RAGAS paper [5]:

- **Faithfulness:** the answer should be grounded in the given context
- **Answer Relevance:** the answer should address the actual question posed

You can try to add more criteria or change the text for the ones that I used.

Here is the `judge_llm()` function, which critiques a question, answer, and context sample and produces a total rating score at the end:

```
def judge_llm(
    context: str,
    question: str,
    answer: str,
    client: OpenAI,
    model: str = "AMead10/Llama-3.2-3B-Instruct-AWQ",
):
    critique_prompt = """
You will be given a question, answer, and a context.
Your task is to provide a total rating using the additive point scoring system
Points start at 0 and are accumulated based on the satisfaction of each evaluation criterion.

Evaluation Criteria:
- Groundedness: Can the question be answered from the given context? Add 1 point if yes, 0 if no.
- Stand-alone: Is the question understandable free of any context, for someone not familiar with the context? Add 1 point if yes, 0 if no.
- Faithfulness: The answer should be grounded in the given context. Add 1 point if yes, 0 if no.
- Answer Relevance: The generated answer should address the actual question that was asked. Add 1 point if yes, 0 if no.

Provide your answer as follows:

Answer::
Evaluation: (your rationale for the rating, as a text)
Total rating: (your rating, as a number between 0 and 4)

You MUST provide values for 'Evaluation:' and 'Total rating:' in your answer.

Now here are the question, answer, and context.

Question: {question}\n
Answer: {answer}\n
Context: {context}\n
Answer:: """

    chat_completion = client.chat.completions.create(
        messages=[
            {"role": "system", "content": "You are a neutral judge."},
            {
                "role": "user",
                "content": critique_prompt.format(
                    question=question, answer=answer, context=context
                ),
            },
        ],
        model=model,
        temperature=0.1,
        top_p=0.99,
        max_tokens=800
    )
```

```
)  
  
return chat_completion.choices[0].message.content
```

Now we loop through our generated dataset and critique each sample:

```
for output in tqdm(outputs):  
    try:  
        evaluation = judge_llm(  
            context=output["context"],  
            question=output["question"],  
            answer=output["answer"],  
            client=client,  
        )  
        score, eval = (  
            int(evaluation.split("Total rating: ")[-1].strip()),  
            evaluation.split("Total rating: ")[-2].split("Evaluation: ")[1],  
        )  
        output.update(  
            {  
                "score": score,  
                "eval": eval  
            }  
        )  
    except Exception as e:  
        print(e)
```

Let's filter out all the bad samples.

Since the generated dataset will be the ground truth for evaluation purposes, we should only allow very high-quality data samples. That's why I decided to keep only samples with the highest possible score.

```
dataset = [doc for doc in outputs if doc["score"] >= 4]
```

And here is our final RAG evaluation dataset as a Pandas DataFrame:

```
import pandas as pd

pd.set_option("display.max_colwidth", 200)

df = pd.DataFrame(dataset)
display(df)
```

	context	question	answer	source_doc	score	eval
0	Official Journal of the European Union\n2024/1689\nREGULATION (EU) 2024/1689 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL\n13 June 2024\nlaying down harmonised rules on artificial inte...	What is the date on which Regulation (EU) 2024/1689 of the European Parliament and of the Council was laid down?\n	13 June 2024	documents/OJ_L_202401689_EN_TXT.pdf	4	The question can be answered from the given context as it directly mentions the date of the regulation. The question is also understandable without any context, as it is a factual question that ca...
1	Having regard to the opinion of the Committee of the Regions (3),\nActing in accordance with the ordinary legislative procedure (4),\n\nWhereas:\n\n(1)\n\nThe purpose of this Regulation is to im...	What is the purpose of the proposed Regulation on the development, placing on the market, putting into service, and use of artificial intelligence systems in the Union?\n	To improve the functioning of the internal market by laying down a uniform legal framework for the development, placing on the market, putting into service, and use of artificial intelligence syst...	documents/OJ_L_202401689_EN_TXT.pdf	4	\n\nThe question is grounded in the context as it can be answered from the given text. The question is also stand-alone and understandable without any context, as it is a clear and concise inquiry. ...
2	At the same time, depending on the circumstances regarding its specific application, use, and level of technological development, AI may generate risks and cause harm to public interests and funda...	What type of AI systems require common rules for protection of public interests as regards health, safety and fundamental rights?\n	High-risk AI systems.	documents/OJ_L_202401689_EN_TXT.pdf	4	\n\nThe question is grounded in the context as it can be answered from the provided information. However, the question's stand-alone quality is limited due to its dependence on the context. The answ...
3	A Union legal framework laying down harmonised rules on AI is therefore needed to foster the development, use and uptake of AI in the internal market that at the same time meets a high level of pr...	What is the main objective of laying down rules regulating the placing on the market, the putting into service and the use of AI systems in the European Union?\n	To foster the development, use and uptake of AI in the internal market while meeting a high level of protection of public interests.	documents/OJ_L_202401689_EN_TXT.pdf	4	\n\nThe question is grounded in the context as it directly refers to the main objective of laying down rules regulating the placing on the market, the putting into service and the use of AI systems ...

The filtered RAG evaluation dataset in English ([PDF file](#) licensed under [CC BY 4.0](#)). Image by the author

## Saving The Dataset

We can convert our Pandas DataFrame into a Hugging Face dataset. Then, we can save it to disk and load it later when needed.

```
%pip install datasets==3.0.2

# save
from datasets import Dataset
dataset = Dataset.from_pandas(df, split="test")
dataset.save_to_disk("path/to/dataset/directory")

# load
from datasets import load_dataset
dataset = load_dataset("path/to/dataset/directory")
```

We can also upload the dataset to the [Hugging Face Hub](#).

## Creating a RAG Dataset in Another Language

I don't speak Spanish. However, I downloaded a [Spanish legal document](#) from the European Union law (licensed under [CC BY 4.0](#)) and converted my prompts using

This is what the filtered RAG dataset looks like after replacing the input document and translating the prompts from English to Spanish:

	context	question	answer	source_doc	score	eval
0	(3)\nLa Recomendación del Parlamento Europeo y del Consejo, de 23 de abril de 2008, relativa a la creación del Marco Europeo de Cualificaciones para el aprendizaje permanente (1) estableció un m...	¿Cuál es el título oficial de la Recomendación del Parlamento Europeo y del Consejo de 23 de abril de 2008?\n	Recomendación del Parlamento Europeo y del Consejo de 23 de abril de 2008.	documents/Legal text-ES.pdf	4	\n-Fundamentación: 1 punto, ya que la pregunta puede responderse a partir del contexto dado.\n-Independiente: 1 punto, ya que la pregunta es comprensible sin ningún contexto, para alguien con co...
1	(13)\nLos marcos y los sistemas nacionales de cualificaciones cambian a lo largo del tiempo, por lo que su correlación con el MEC debe revisarse y actualizarse cuando proceda.\n(14)\nLa conf...	¿Cuál fue el año en que la Recomendación del Parlamento Europeo y del Consejo relativa a la creación del Marco Europeo de Cualificaciones para el aprendizaje permanente se adoptó?\n	2008.	documents/Legal text-ES.pdf	4	\nLa pregunta puede responderse a partir del contexto dado, ya que la respuesta proporcionada (2008) se menciona explícitamente en el contexto. Además, la pregunta es independiente y puede respond...
2	(18) Aunque el acervo de la Unión en materia de migración legal y asilo establece la igualdad de trato con los nacionales en términos de reconocimiento de las cualificaciones e incluso de medida...	¿Cuántos países han establecido vínculos más estrechos entre sus marcos de cualificaciones y el MEC?\n	Un número creciente de terceros países y regiones buscan vínculos más estrechos entre sus marcos de cualificaciones y el MEC.	documents/Legal text-ES.pdf	4	\n-Fundamentación: 1 punto, ya que la pregunta puede responderse a partir del contexto dado, ya que el contexto proporciona información sobre el MEC y su enfoque en los resultados del aprendizaje...
3	(25) Debe haber coherencia, complementariedad y sinergias a escala nacional y de la Unión entre la aplicación del MEC, los marcos o los sistemas nacionales de cualificaciones y las herramientas so...	¿Cuál es el título del documento de 31 de diciembre de 2004, por el cual se establece un marco comunitario único para la transparencia de las cualificaciones y competencias?\n	Decisión n.º 2241/2004/CE del Parlamento Europeo y del Consejo, de 15 de diciembre de 2004, relativa a un marco comunitario único para la transparencia de las cualificaciones y competencias (Europ...	documents/Legal text-ES.pdf	4	\n-Fundamentación: 1 punto, ya que la pregunta puede responderse a partir del contexto dado.\n-Independiente: 1 punto, ya que la pregunta es comprensible sin ningún contexto, para alguien con co...
4	Por el Consejo\n(El Presidente)\nE. BARTOLOMEO\n189/19\n(El Consejo)\nEl título oficial de la Unión Europea\n(El Consejo)\nDefiniciones\n(El Consejo)\nEfectos de la presente Recomendación, se entenderá...	¿Qué es una "cualificación internacional" según la Recomendación del Consejo?\n	Una cualificación internacional es una cualificación otorgada por un organismo internacional establecido legalmente o por un organismo nacional que actúe en nombre de un organismo internacional.	documents/Legal text-ES.pdf	4	\nLa pregunta es independiente, ya que puede responderse por sí sola sin necesidad de contexto. La respuesta también se basa en el contexto dado, ya que se menciona explícitamente en el contexto q...
5	e)\n(El Consejo)\nResultados del aprendizaje: declaraciones respecto de lo que una persona sabe, comprende y es capaz de hacer al culminar un proceso de aprendizaje; se define en términos de conocimientos, ...	¿Cuál es la definición de "resultados del aprendizaje" según el contexto del MEC?\n	Resultados del aprendizaje se definen como declaraciones respecto de lo que una persona sabe, comprende y es capaz de hacer al culminar un proceso de aprendizaje.	documents/Legal text-ES.pdf	4	\n-Fundamentación: 1 punto, ya que la pregunta puede responderse a partir del contexto dado.\n-Independiente: 1 punto, ya que la pregunta es comprensible sin ningún contexto, para alguien con co...

By using our own dataset generation code, we can adapt it to any language and domain we want.

Automatically creating a RAG evaluation dataset from a collection of documents is easy. All we needed was a prompt for the LLM generator, a prompt for the LLM judge, and a little Python code in between.

To change the domain of our RAG evaluation dataset, we simply exchange the documents that we feed to the `DirectoryLoader`. The documents do not have to be PDF files, they can be CSV files, markdown files, etc.

To change the language of our RAG evaluation dataset, we simply translate the LLM prompts from English to another language.

If the generated data samples are not good enough for your use case, you can try to modify the prompts. Also, using bigger and better LLMs will increase the quality of the dataset.

## References

- [1] P. Lewis et al. (2021), Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks, arXiv:2005.11401
- [2] A. Roucher (2024), RAG Evaluation, Hugging Face AI Cookbook, accessed on 11-01-2024
- [3] Y. Liu et al. (2023), G-Eval: NLG Evaluation using GPT-4 with Better Human Alignment, arXiv:2303.16634
- [4] W. Yuan et al (2024), Self-Rewarding Language Models, arXiv:2401.10020
- [5] S. Es et al. (2023), RAGAS: Automated Evaluation of Retrieval Augmented Generation, arXiv:2309.15217
- [6] K. Wataoka, T. Takahashi, and R. Ri (2024), Self-Preference Bias in LLM-as-a-Judge, arXiv:2410.21819
- [7] J. Wei et al. (2022), Chain-of-Thought Prompting Elicits Reasoning in Large Language Models, arXiv:2201.11903

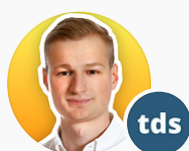
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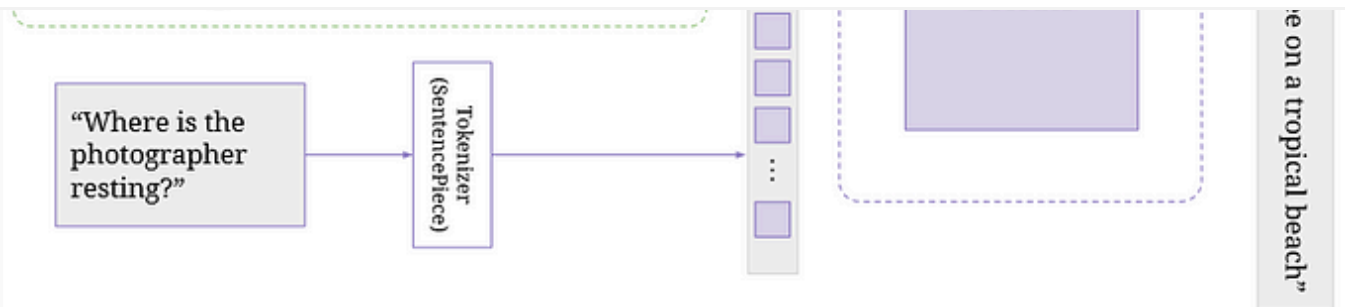
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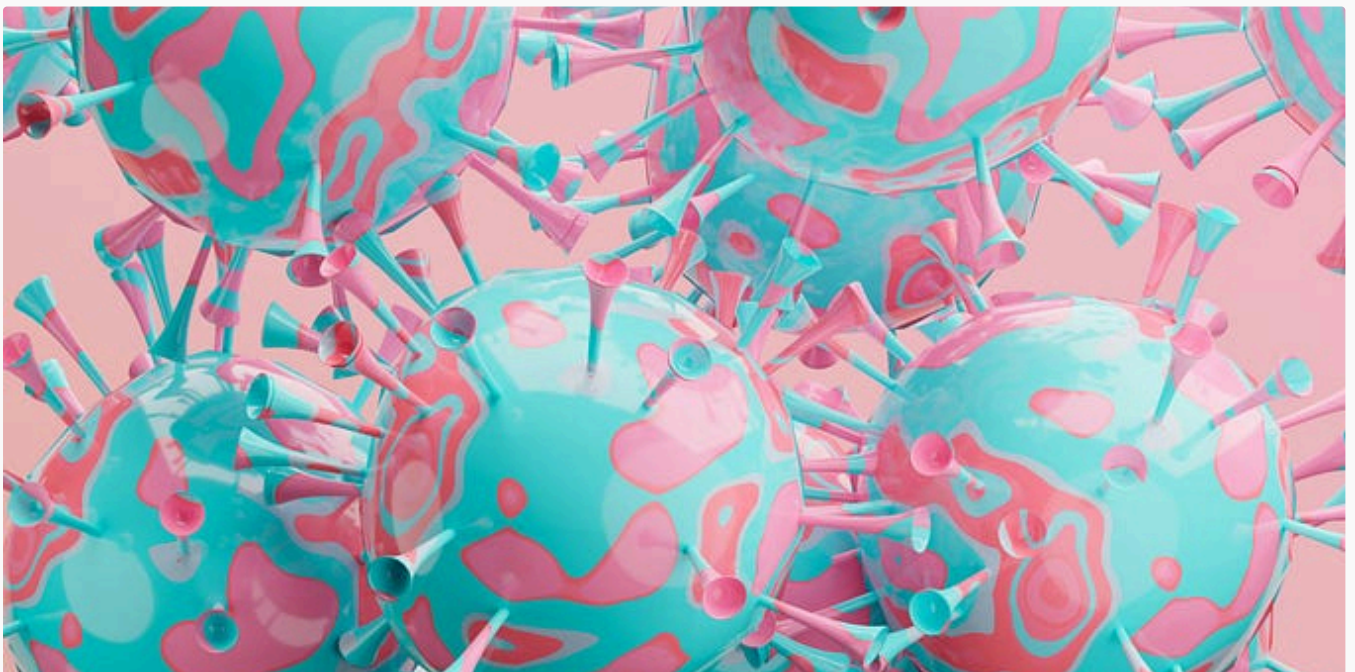
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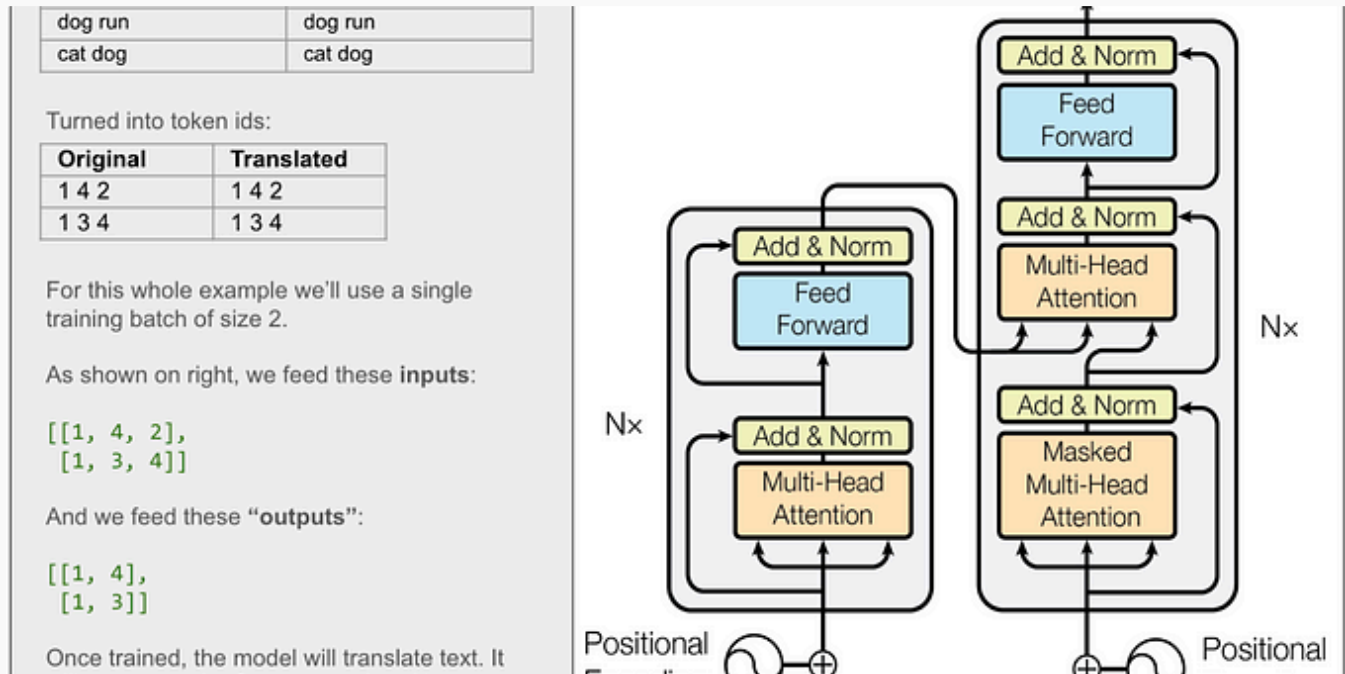


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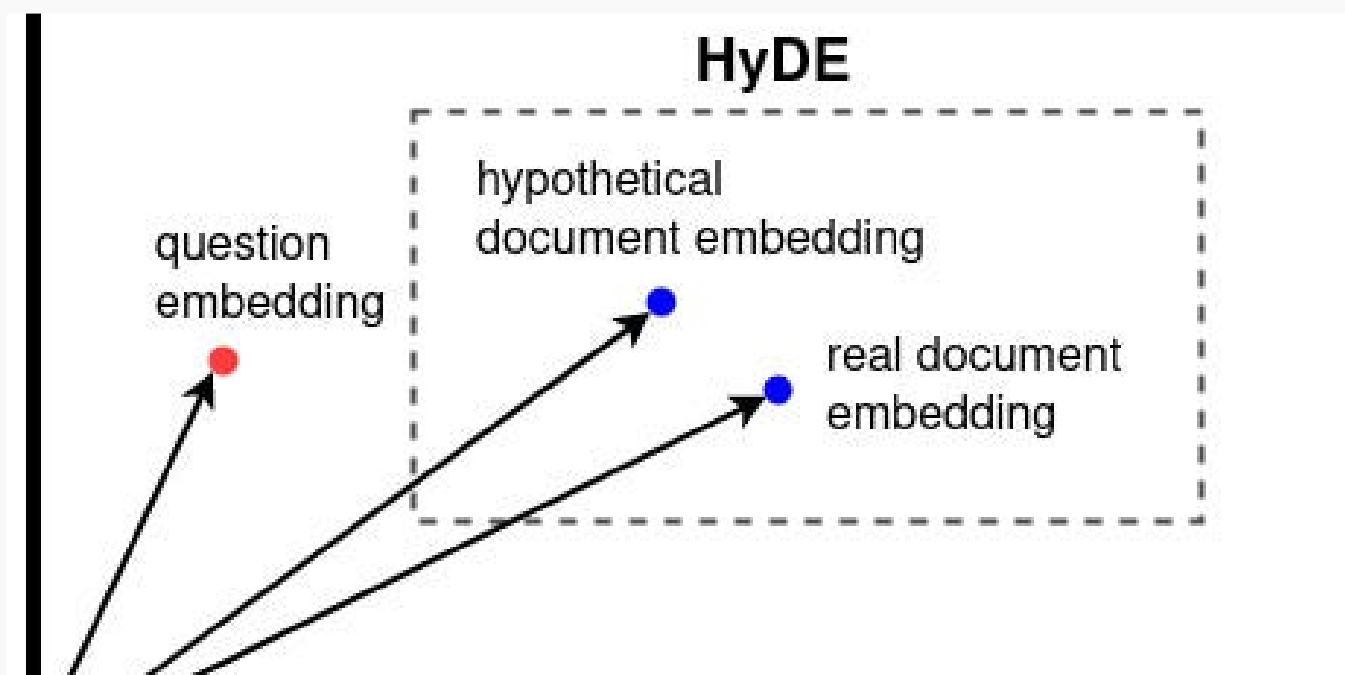


Eric Silberstein in Towards Data Science


## Tracing the Transformer in Diagrams

What exactly do you put in, what exactly do you get out, and how do you generate text with it?

1d ago 176 1





 Dr. Leon Eversberg in Towards Data Science

How to Use HyDE for Better LLM RAG Retrieval

Building an advanced local LLM RAG pipeline with hypothetical document embeddings

★ Oct 4

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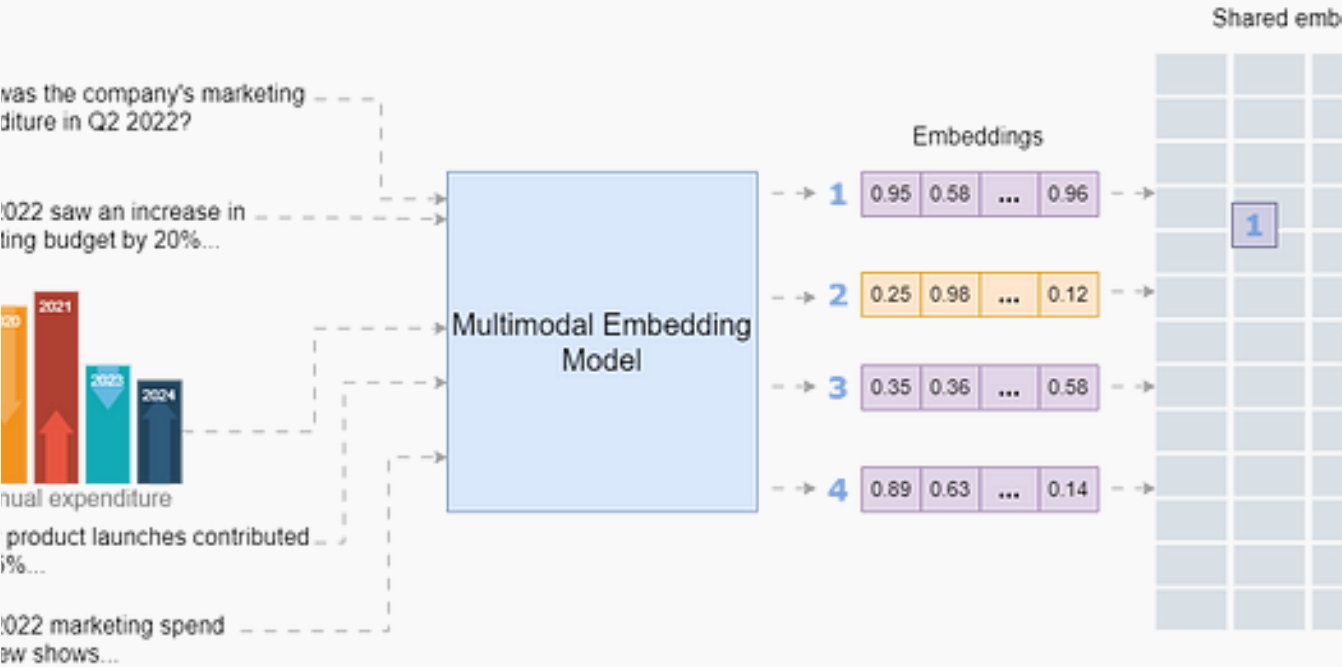
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- See all from Dr. Leon Eversberg
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
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(as a data scientist with no web dev experience)

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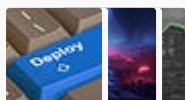


### Lists



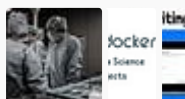
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Harendra

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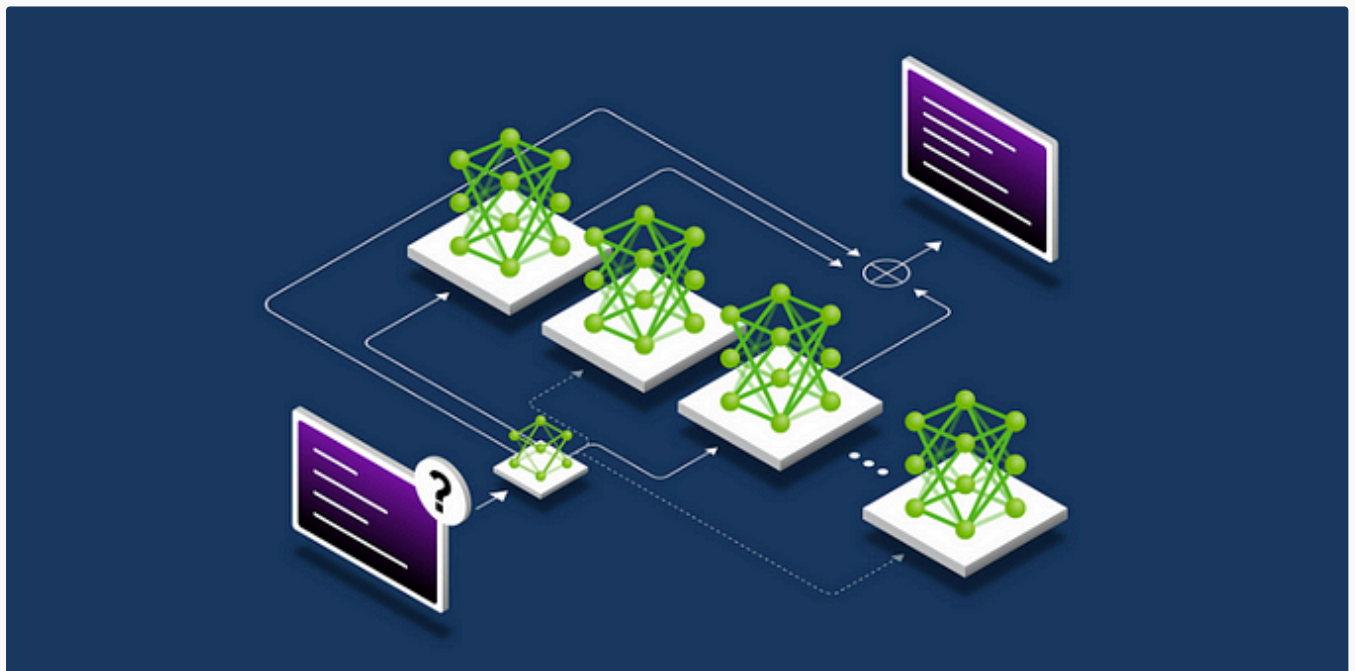
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34


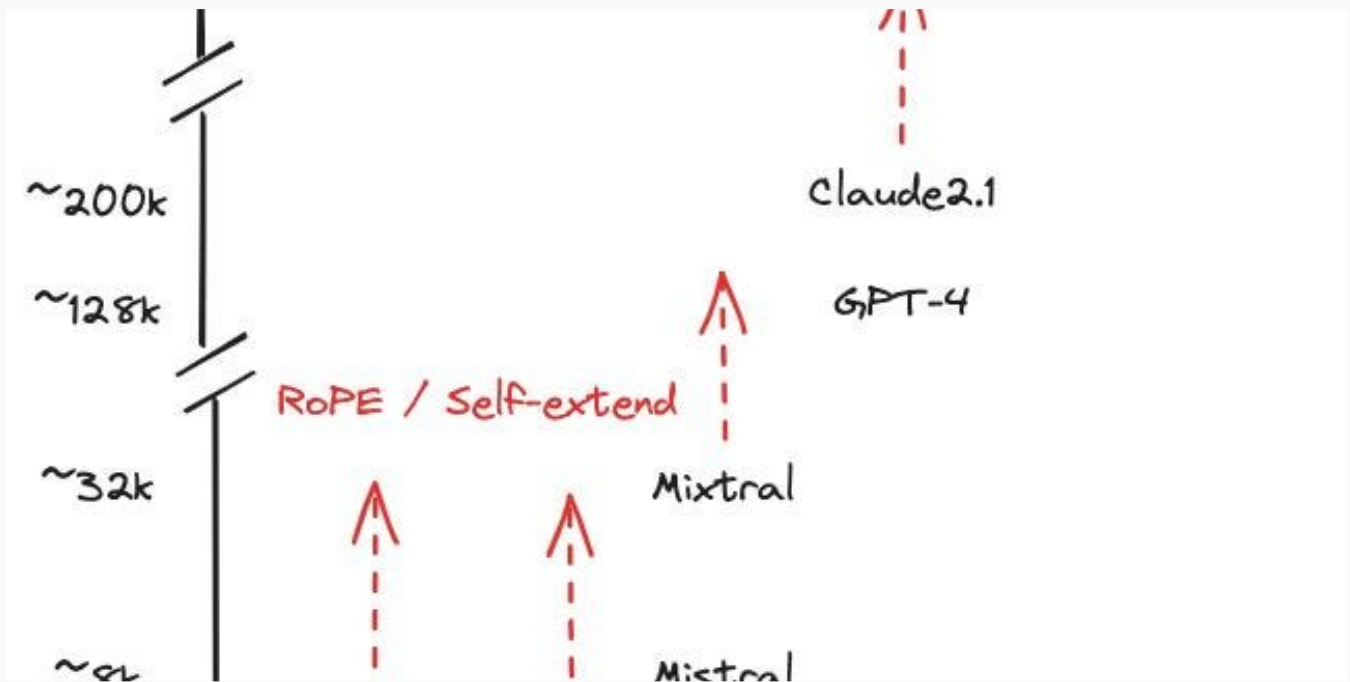


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
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## RAG From Scratch

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