

# RAG basics

JUNE 2025



There are no magic! It is simple REST API!

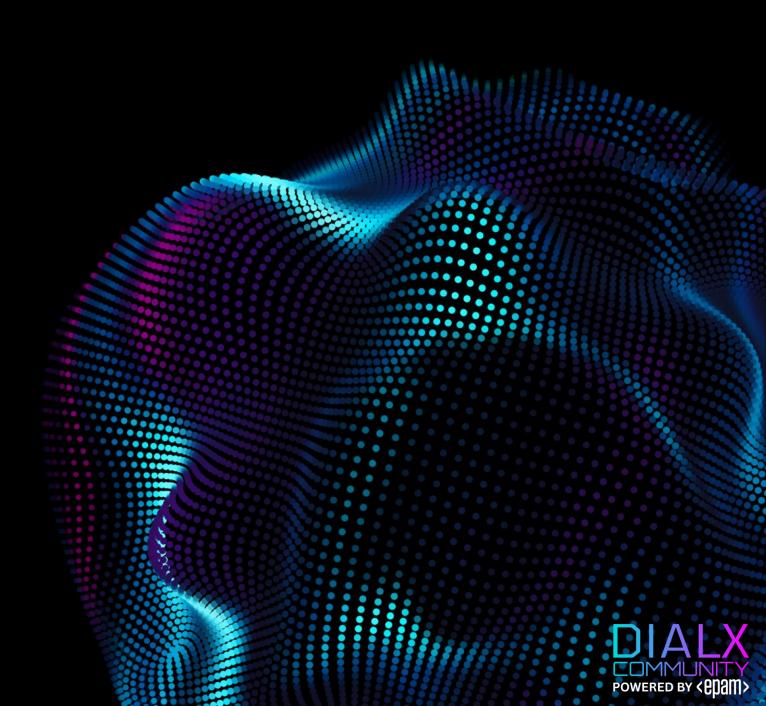
### **Before we start:**

- Raise your hand and ask questions if you have any
- It is better to ask questions when you have
- Also, type them in chat
- We will need DIAL API key for this session

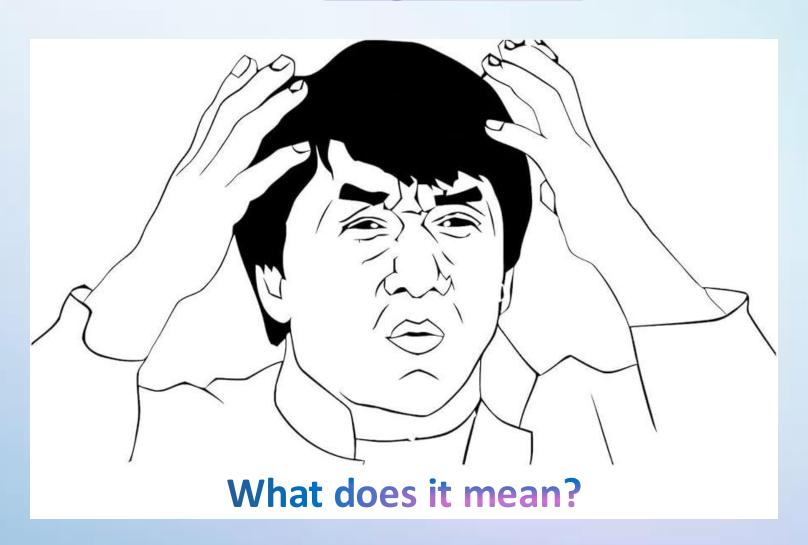
# Agenda:

- Presentation:
  - About RAG Concept
  - Real life sample
  - Application architecture and main components
- Workshop:
  - Create MicrowaveRAG application

# RAG Concept



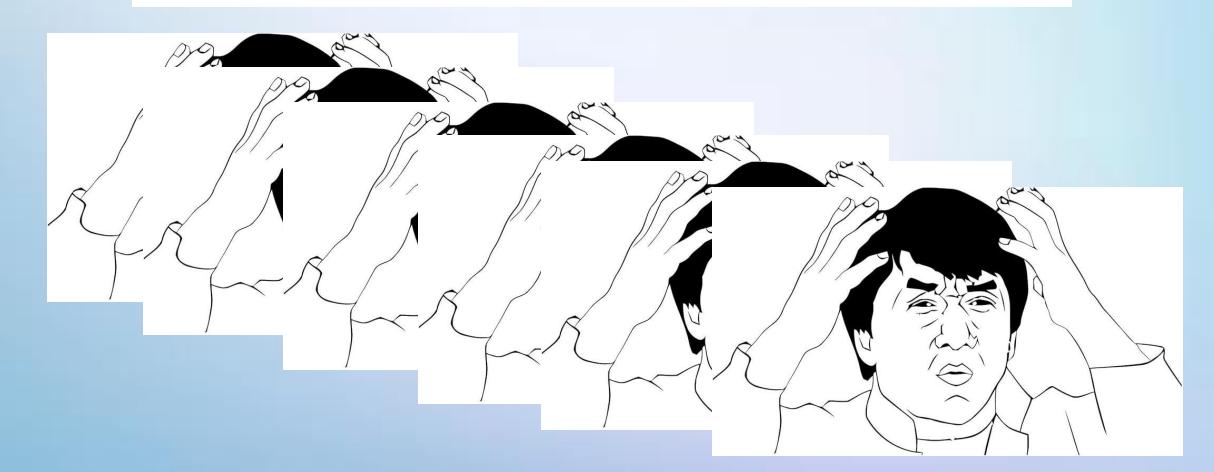
## **RAG** = Retrieval-Augmented Generation



Retrieval-augmented generation (RAG) is a technique that enables Gen AI models to retrieve and incorporate new information.

It modifies interactions with a LLM so that the model responds to user queries with reference to a specified set of documents, using this information to supplement information from its pre-existing training data.

This allows LLMs to use domain-specific and/or updated information. Use cases include providing chatbot access to internal company data or generating responses based on authoritative sources.

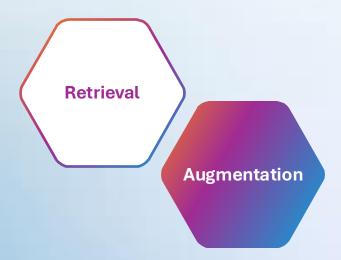


### R A G concept:



- The system searches through an external knowledge base (documents, databases, webpages, or vector stores) to find information relevant to the user query.
- Often, this is done using vector embeddings (semantic search) to find relevant documents based on similarity measures.

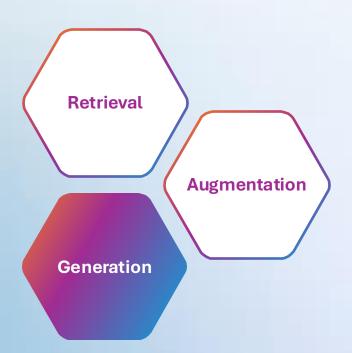
### R A G concept:



The retrieved information is then used to extend or "augment" the context provided to the language model.

«User input + Retrieved data»

### R A G concept:



The LLM generates response based on the provided information (user input + retrieved data)

# Retrieval-augmented generation (RAG) is a technique that helps us:





Provide the most relevant context data based on user request



**Reduces hallucinations** 



Enables up-to-date knowledge



**Enables domain specialization** 

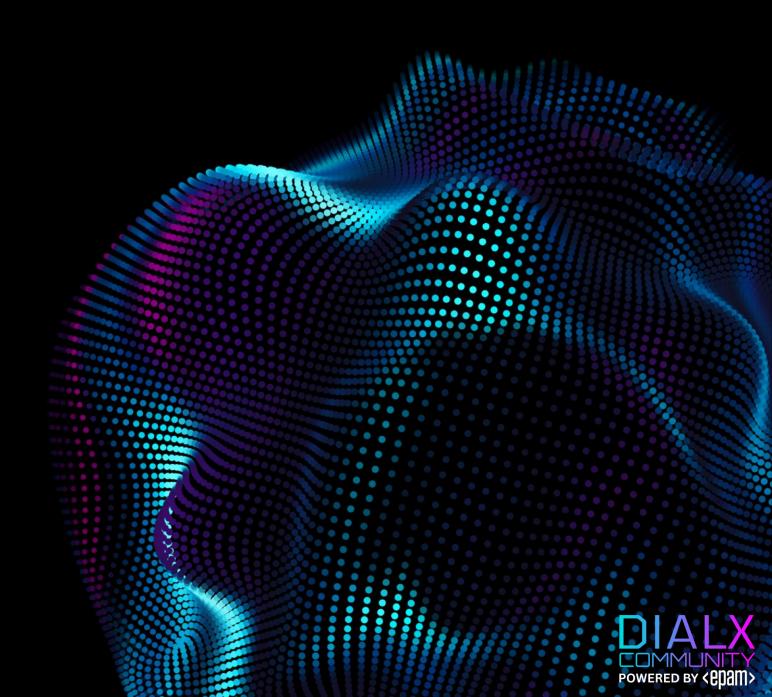


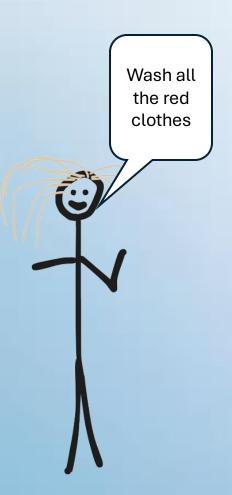
Reduces context window usage



Reduces costs (not always\*)

# Sample





Retrieval

Wash all the red clothes



Retrieval

Wash all the red clothes



Got it. Here are Now I'll all the red retrieve all clothes the red that I was clothes able to find from this bucket

Wash all the red clothes



Retrieval



Augmentation

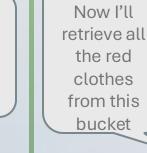


Retrieval

Augmentation

Generation

Wash all the red clothes



Got it.

Here are all the red clothes that I was able to find



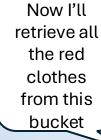


I've made the laundry with all the provided red stuff. There were a couple of rags and a pair of shoes. Any other instructions?



Retrieval

Wash all the red clothes



Got it.

Here are all the red clothes that I was able to find



**Augmentation** 

'Wash all the red clothes' + the clothes



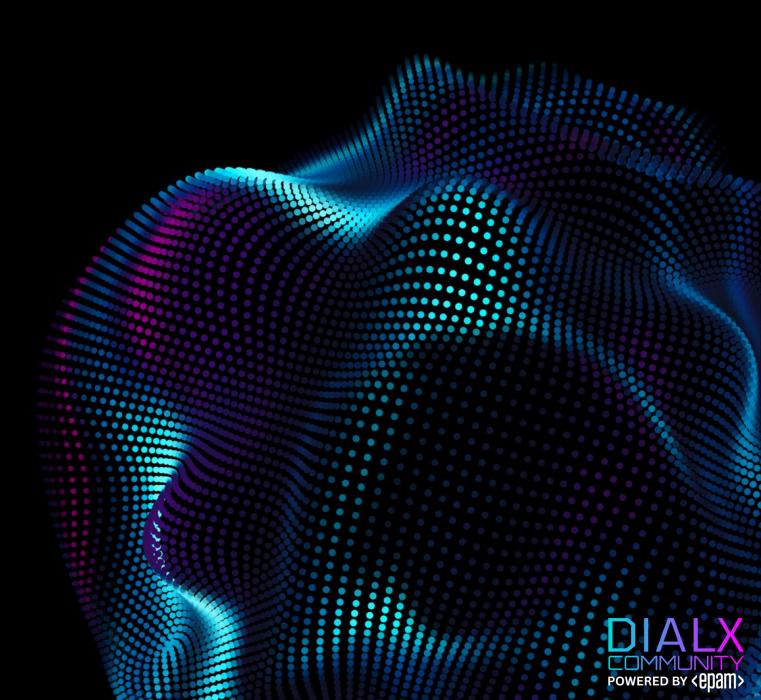
Generation

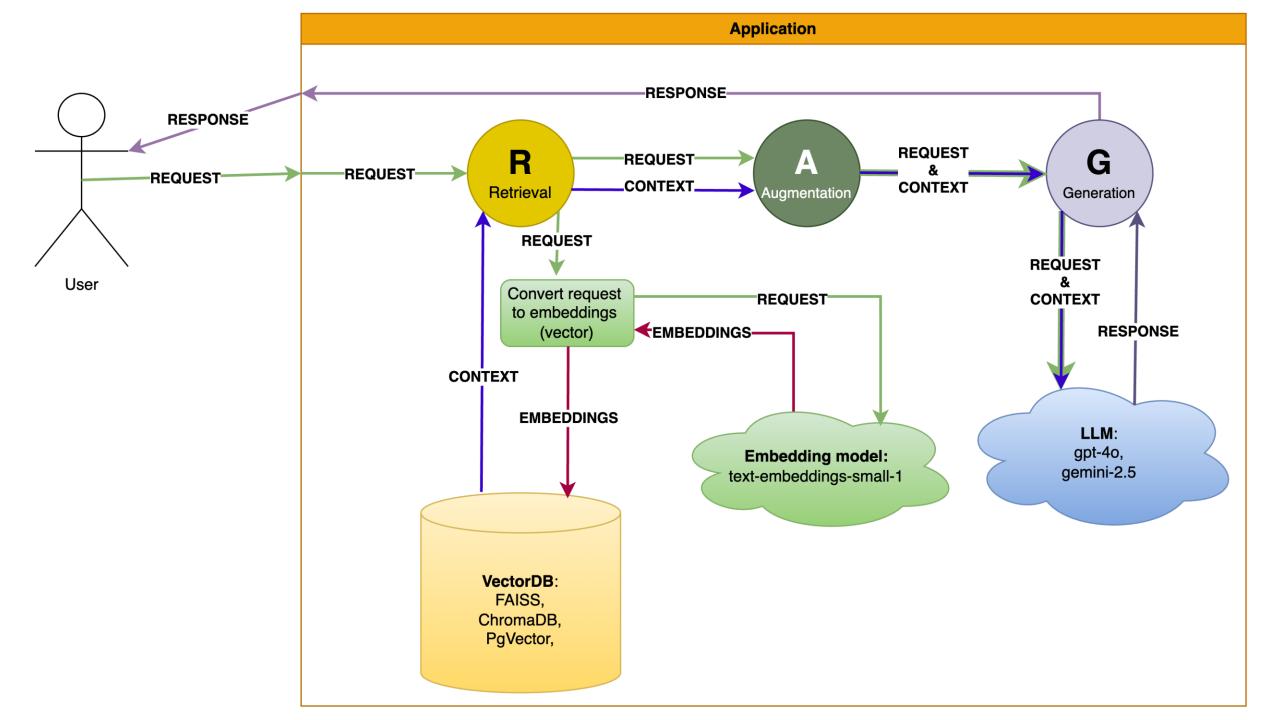
I've made the laundry with all the provided red stuff. There were a couple of rags and a pair of shoes. Any other instructions?





# Application





Client that is working with Embedding model. Via this client you will convert text chunks and user requests into embeddings. Embedding models:

- text-embedding-3-large-1
- text-embedding-3-smal-1

```
AzureOpenAlEmbeddings(
deployment='text-embedding-3-large-1',
azure_endpoint=DIAL_URL,
api_key=SecretStr(API_KEY),
)
```

#### Client to work with LLM:

- gpt-4o
- gemini-2.5
- sonnet-3.7

```
AzureChatOpenAI(
temperature=0.0,
azure_deployment='gpt-4o-2024-08-06',
azure_endpoint=DIAL_URL,
api_key=SecretStr(API_KEY),
api_version="2024-05-01-preview"
```

Via this API you will be able to load locally saved indexed FAISS Vector DB. This is needed to avoid creation new DB each time when Application is started

```
embeddings=self.embeddings,
allow_dangerous_deserialization=True,
```

FAISS.load local(

Will convert Chunks (documents) into embeddings and create FAISS Vector DB with them. Then you can locally save it.

FAISS.from\_documents(chunks, self.embeddings)

folder path='microwave faiss index',

Will convert Chunks (documents) into embeddings and create FAISS Vector DB with them. Then you can locally save it.

Via this API you can make similarity search relevant context to user request (query).

- k limit of results that we expect to get
- score\_threshold filter with similarity score. Range 0.0-1.0

```
vectorstore.similarity_search_with_relevance_scores(
    query,
    k=k,
    score_threshold=score
)
```



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