

Who are Tembo?



- Cloud Services <u>cloud.tembo.io</u>
- Trunk (Extensions) pat.dev
- pg_vectorize
- pgmq
- pg_tier
- pg_timeseries
- And more!



Who am I?

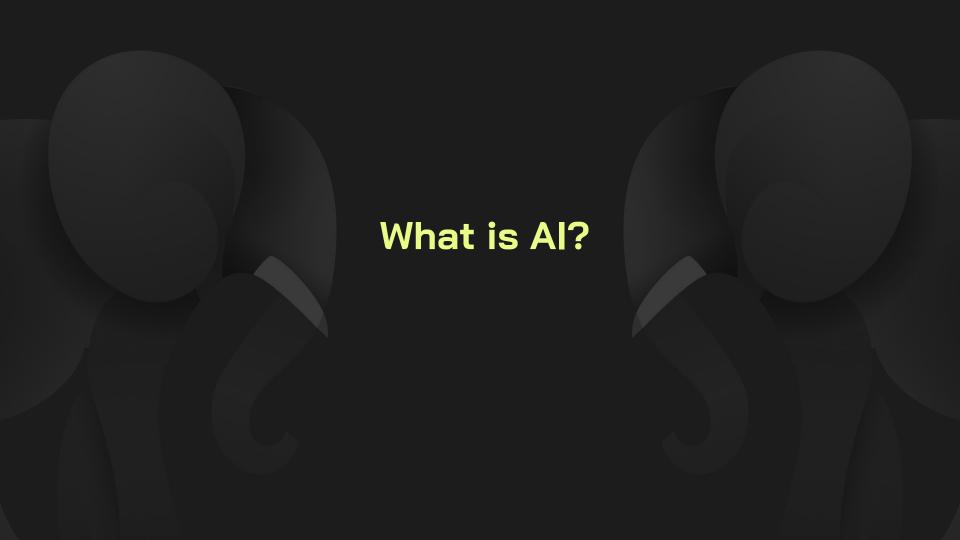


- Author
- Speaker
- Blogger
- Mentor
- Dev

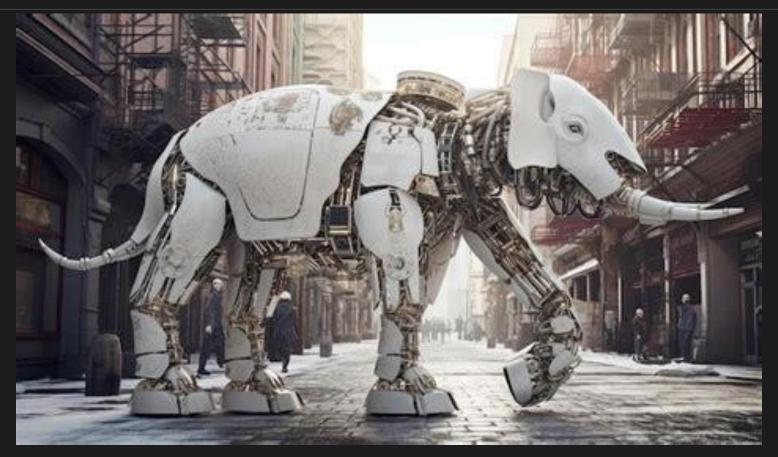
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Not This!





What it Really is





LLM

Large Language Model



RAG

Retrieval Augmented Generation



Token

Word Chunk



Embedding

Big-Ass Array



Embedding

Big-Ass Array



Embedding

Vector to Token Coordinates



Transformer

Translates Text into Embeddings



Coordinates Where?







Transform Individual Phrases

- Easily transform a prompt or search terms into compatible vectors
- Output is compatible with pgvector vector search



Create and Maintain Embeddings

Embeddings are maintained by pg_cron job, or pgmq live updates



Important Latency Note!

Writes can spawn embeddings via queue



Natural Language Search

Consider this like Full Text Search, but better



Bootstrap a RAG Stack

Realtime embeddings are queued to avoid write latency



Perform a RAG Request

```
SELECT vectorize.rag(
    agent_name => 'blog_chat',
    query => 'Is Postgres the best database?',
    chat_model => 'ollama/llama3.1'
) -> 'chat response';
```

The result is a JSON object that includes context if we need it



Works with OpenAl

Just supply your OpenAl token:

ALTER SYSTEM SET vectorize.openai_key TO '<your api key>';



Or Roll Your Own

Search using Ollama or vLLM instead:

```
ALTER SYSTEM SET vectorize.openai_service_url
TO 'https://api.myserver.com/v1';
```

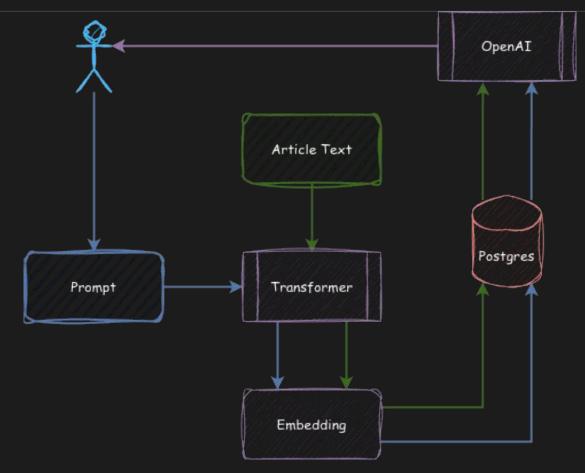
Use a custom transformer service:

```
ALTER SYSTEM SET vectorize.embedding_service_url
TO 'https://api.myserver.com/v1';
```





Anatomy of a RAG App





How it Works

Data Side

- 1. Gather content
- 2. Pass through transformer
- 3. Store vector in database

User Side

- 1. Asks a question
- 2. Pass through transformer
- 3. Match against stored vectors
- 4. Question + Results sent to Al
- 5. Send answer to user



The Full Monty

To build a RAG app, we need to:

- 1. Parse and load the content and metadata into Postgres
- 2. Generate the embeddings
- 3. Transform user input into an embedding
- 4. Match results from user search vector
- 5. Build new prompt from results and user search
- 6. Send full instructions to OpenAI
- 7. Return results to user



From the Perspective of pg_vectorize

Or if we're using pg_vectorize:

- 1. Parse and load the content and metadata into Postgres
- 2. Call vectorize.init_rag(...)
- 3. Call vectorize.rag(...)

Which would you rather do?



A Place for Blogs



Chunky Style

- Embeddings are usually "fuzzy" (only 384 coordinates)
- We need chunks for sharper context



More than Meets the Eye

Look familiar? Now we're indexing chunks rather than full articles.



Slice and Dice

Here's a closer look at a chunk splitter in Python:

```
from langchain_text_splitters import RecursiveCharacterTextSplitter

splitter = RecursiveCharacterTextSplitter(
    separators = ["\n\n", "\n", ' ', '.', '```'],
    chunk_size = 500,
    chunk_overlap = 20,
    length_function = len,
    is_separator_regex = False
)

def chunk_content(content):
    return splitter.split text(content)
```



A Pleasing Result

Now we can finally figure out which database is best:

```
SELECT vectorize.rag(
    agent_name => 'blog_chat',
    query => 'Is Postgres the best database engine?',
    chat_model => 'ollama/llama3.1'
) -> 'chat_response';
"Four times since 2017, it has won the DB-Engines \"DBMS of the Year\"
award."
```



Conclusion!

If you can write queries You can build AI apps with Postgres





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Want to experiment? Use the Tembo free trial!

- Two weeks to test
- \$300 USD credit
- Reverts to Hobby tier instance after trial ends



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Easily deploy one of our Postgres stacks

- AI / RAG
- Geospatial
- Analytics
- Timeseries



Other ways to extend / focus slides