#JCON2025
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# From ChatGPT User to RAG Implementer: A Developer's Journey

I’m Pasha

And this is my story

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Who is like me here?

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I will cross some T's in this talk

# Of course...

I heard about neural networks

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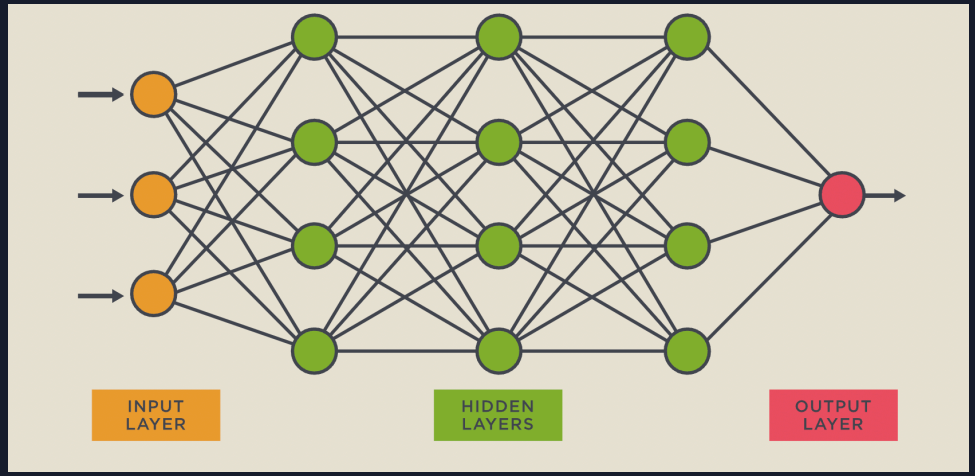

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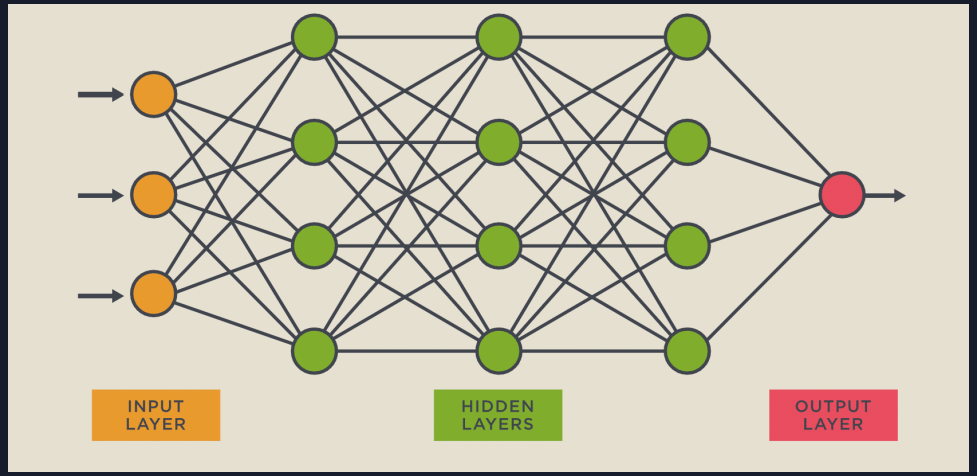
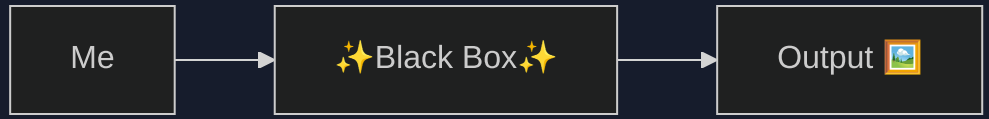



But what the heck is this?

# How I perceived LLMs



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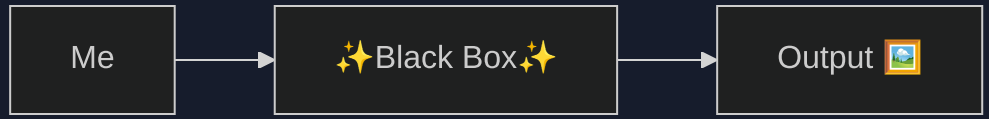


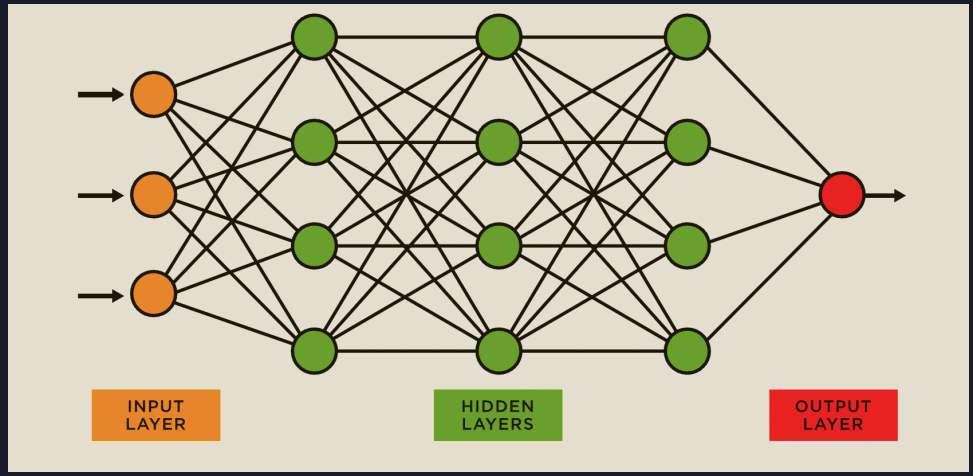

# Time to tell about me

1. I work with JVM languages for almost 15 years
2. I used to be a
    1. Backend developer
    2. Data engineer
    3. Engineering manager
3. Worked with data scientists, product managers, and other stakeholders
4. Usually did performance optimizations
5. Worked with Spring and without it

# And now...

1. Developer Advocate at BellSoft
2. Have a lot of time to experiment
3. Need to produce content for the community
4. Still love to code

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Follow me, BTW!

asm0dey

asm0di0

@asm0dey@fosstodon.org

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I found that we have A LOT of documents:

1. Blog posts
2. Documentation
3. Whitepapers

And I just can’t find my way through them

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So I decided to do something about it

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- Elasticsearch?

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- `grep`?


WHO ARE WE
DEVELOPERS!
WHAT SHOULD WE DO?
SOLVE PROBLEMS!
WHAT WILL WE DO?
YAK SHAVING!
imgflip.com

# Let’s use AI!

But how?

# Luckily I have a friend

Who I could ask stupid questions (thanks @shrimpsizemoose)

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I couldn't

# Embeddings

Here’s an embedding

```
[0.123, -0.456, 0.789, -0.234, 0.567, -0.890, 0.345, -0.678, 0.901, -0.432]
```

And one more:

```
[0.234, -0.567, 0.890, -0.123, 0.456, -0.789, 0.321, -0.654, 0.987, -0.345]
```

What do they mean?

We do not know. Nothing in this context

# What is an embedding?

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Embeddings tell us where things are in "meaning space" 🤯

Similar things should have similar coordinates:

- "cat" and "kitten" would be close together
- "cat" and "rocket" would be far apart

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These relationships emerge naturally when AI models learn from text!

# Word2Vec: A Breakthrough in Word Embeddings

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Word2Vec was introduced by Google researchers in 2013:

- First major breakthrough in creating meaningful word embeddings
- Made it practical to capture word relationships in vector space

# How Word2Vec Works

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- Predicts words that appear near each other
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For example:

- "cat" and "dog" often appear near words like:
  - "pet"
  - "food"
  - "vet"

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- Produced higher quality embeddings

Conceptual breakthrough:

- Showed that simple neural networks could capture complex meaning

# Word2Vec’s Impact

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Changed the field of NLP:

- Sparked a revolution in natural language processing
- Laid groundwork for modern language models
- Still used today in many applications

# Word2Vec Results

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Properties of the vectors:

- Typically 100-300 dimensions
- Enable measuring word similarity
- Can be visualized in lower dimensions

# Word2Vec’s Limitations

Technical limitations:

- Fixed context window misses broader document meaning
- Cannot handle polysemy (same word with different meanings)
- Requires pre-trained embeddings for each word

# Modern Alternatives

Superseded by newer architectures:

- BERT and other transformers learn contextual embeddings
- Large language models capture richer relationships
- Modern models handle multiple word meanings

# Text Embeddings

Similar concept, but for chunks of text:

Instead of: `"cat"` → `[0.1, 0.2, -0.3, ...]`

We get: `"The cat sat on the mat"` → `[0.4, -0.2, 0.1, ...]`

# Benefits

- Captures meaning of entire passages
- Similar texts get similar vectors
- Can compare documents, paragraphs, or sentences

# Use Cases

- Semantic search (find similar documents)
- Document clustering
- Question answering
- Text classification

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  - Pooling layers combine information

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- Combine token representations
- Output fixed-size vector

# Popular models

- OpenAI's `text-embedding-ada-003`
- Sentence-BERT
- Universal Sentence Encoder

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- Similar texts get similar vectors, enabling semantic search
- RAG workflow
- This is not only a search, but also summarization!

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No!

- The whole NN is a huge bunch of hardcoded weights
- NN can’t access anything directly, it’s not a program, more of a data structure

# And here I hear the magic word

## RAG (Retrieval Augmented Generation)

Essentially, the idea is to mix relevant data into prompt and make LLM use it

# How to implement RAG?

1. Convert documents to embeddings
2. Store them in a vector database
3. Convert user query to embedding
4. Find most similar document embeddings
5. Feed relevant documents to LLM as context

# 1. Convert documents to embeddings

- Not all documents can be converted to embeddings directly
  - Text needs to be split into chunks
  - Each chunk has a maximum token limit:
    - OpenAI ada-002: 8,191 tokens
    - Mistral-7B: 8,192 tokens
    - Claude: 8,000 tokens
  - Need to balance chunk size:
    - Too small → loses context
    - Too large → less precise matches
- Some information may be lost in the conversion process

# 2. Store them in a vector database

## Where?

Vector database is a specialized database for storing and searching vectors

Key features:

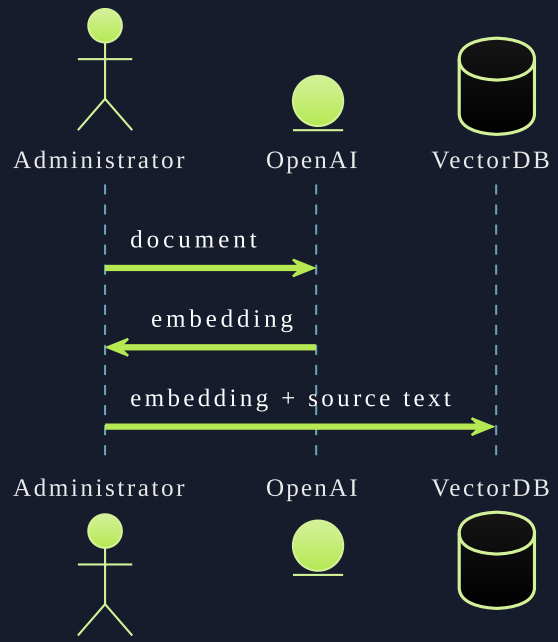
- Efficient similarity search:
  - Cosine similarity: $\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$
  - Euclidean distance: $\sqrt{\sum (a_i - b_i)^2}$
  - Dot product: $\sum_i a_i b_i$
- Optimized for high-dimensional data
- Can store metadata alongside vectors

# 2. Store them in a vector database

## For example

- Chroma
- Weaviate
- Pinecone
- Milvus
- pgvector (PostgreSQL extension)

# This is how it works



# 3. Convert user query to embedding

Same as with document.

Probably return an error if the query is too big.

# 4. Find most similar document embeddings

- Use vector database to find closest embeddings to query embedding
- Usually returns:
  - Distance/similarity score
  - Original text
  - Optional metadata
- Can limit number of results (e.g. top-k)
- Can filter by metadata (e.g. only search specific document types)

# 5. Feed relevant documents to LLM as context

- Take relevant documents from vector search
- Add them as context to LLM prompt
- Ask LLM to answer based on provided context
- LLM generates response using only provided context
- Response is more accurate and grounded in your documents

Demo!

# Summary

- RAG is simple
- You need to know embeddings to understand RAG
- Embeddings are not magic, they are just vectors
- You don’t need to know how LLM works to use RAG

Blog

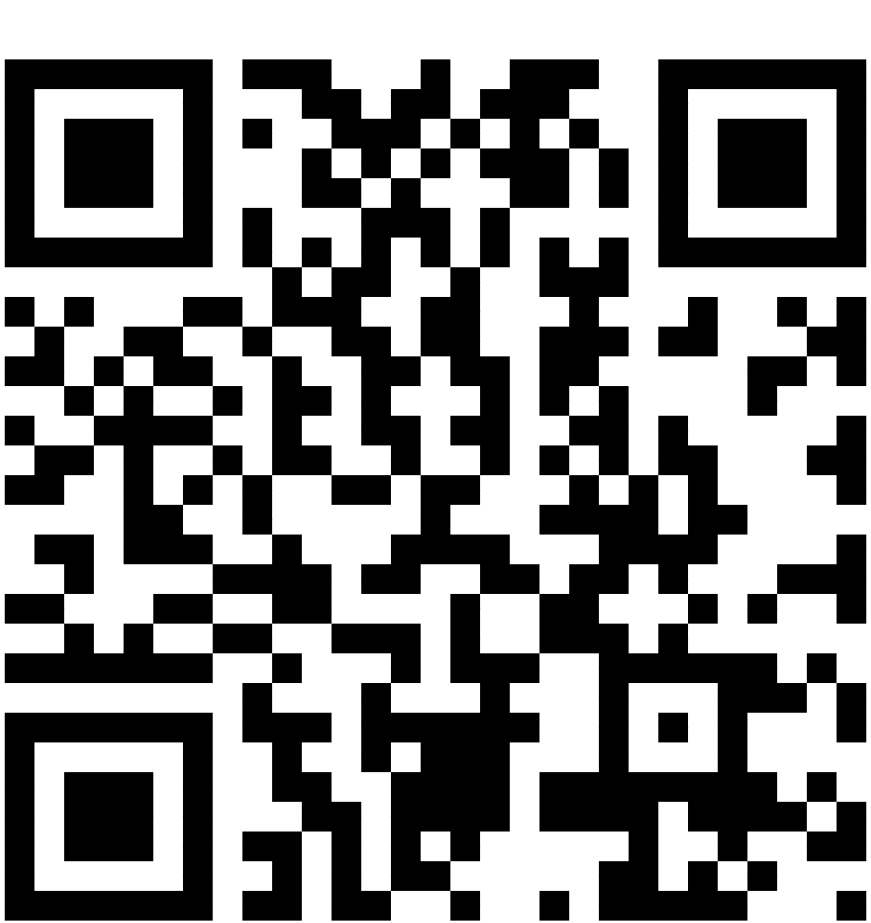
Source code

# Questions?

asm0dey

asm0di0

@asm0dey@fosstodon.org



END