

# Agentic RAG Using MCP

# Problem statement

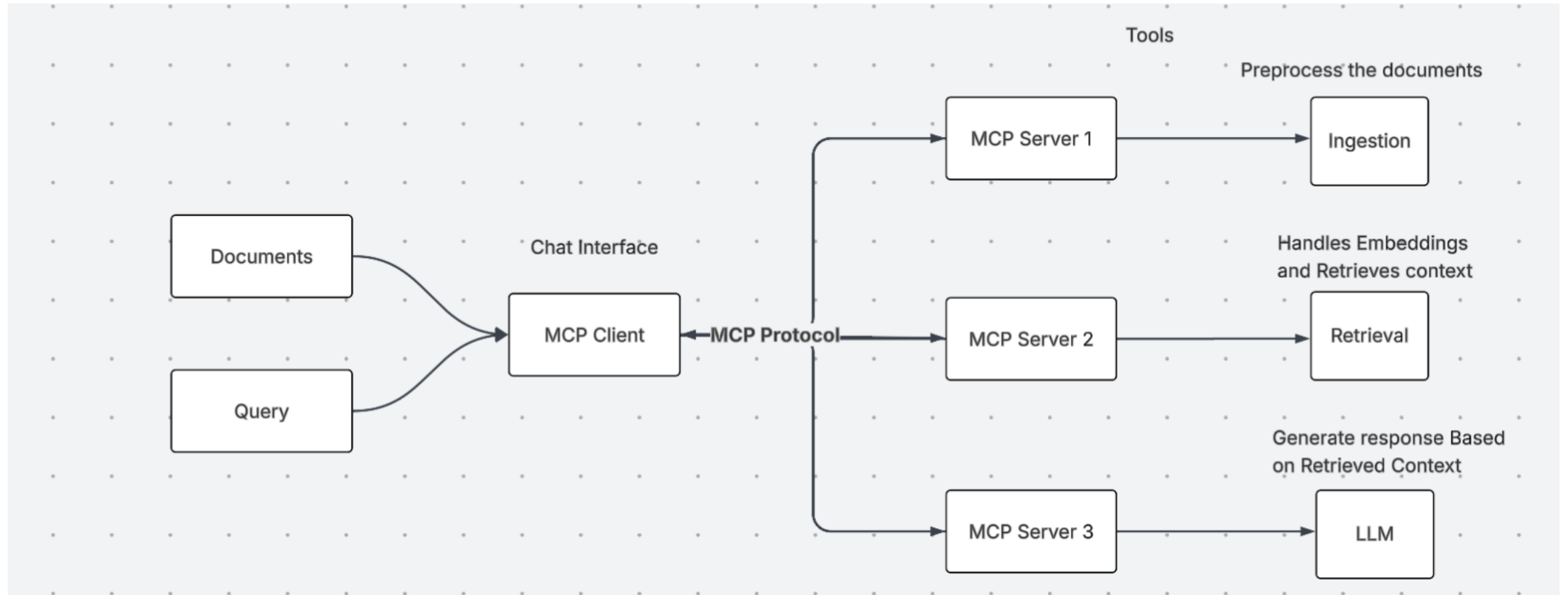
## The Problem:

- Valuable information is often trapped within various document formats like PDFs, presentations, and spreadsheets.
- Manually searching through these documents is time-consuming and inefficient.
- Standard chatbots lack knowledge of private, domain-specific data, leading to generic or incorrect answers.

## The Solution:

- Our goal is to build an agent-based chatbot that can read any document and provide factual, verifiable answers using RAG and the Model Context Protocol (MCP).

# Architecture




# Results

## 1. Document Setup

Upload your documents (PDF, DOCX, etc.)

Drag and drop files here  
Limit 200MB per file • PDF, DOCX, TXT, CSV, PPTX

Browse files

 NIPS-2017-att...  
0.5MB

Process Documents

## 2. System Status


✓ System Ready for Q&A

Deploy


# Agentic RAG Chatbot

Upload documents, ask questions, and get answers from your own data.

## Chat with your Documents



What is the diff bw encoder and decoder?



The key differences between the encoder and decoder in the Transformer architecture are:

1. **Number of Sub-layers:**
  - Encoder: Each layer has 2 sub-layers (multi-head self-attention + position-wise feed-forward network).
  - Decoder: Each layer has 3 sub-layers (adds a third sub-layer for multi-head attention over the encoder's output).

Ask a question about your documents...

>



What is encoder and decoder?



Based on the context:

**Encoder:** The encoder is a stack of 6 identical layers. Each layer has two sub-layers:


1. A multi-head self-attention mechanism.
2. A position-wise fully connected feed-forward network. Residual connections and layer normalization are applied around each sub-layer. The encoder maps an input sequence to a sequence of continuous representations.

**Decoder:** The decoder is also a stack of 6 identical layers. Each layer has three sub-layers:

1. A multi-head self-attention mechanism (modified to prevent positions from attending to subsequent positions).
2. A multi-head attention mechanism over the encoder's output.
3. A position-wise fully connected feed-forward network. Like the encoder, residual connections and layer normalization are applied around each sub-layer. The decoder generates an output sequence one element at a time,

# Retrieved contexts

Both share similarities like residual connections, layer normalization, and output dimensionality ( $d_{\text{model}} = 512$ ).

View Sources 

Source 1:

Here, the encoder maps an input sequence of symbol representations  $(x_1, \dots, x_n)$  to a sequence of continuous representations  $z = (z_1, \dots, z_n)$ . Given  $z$ , the decoder then generates an output sequence  $(y_1, \dots, y_m)$  of symbols one element at a time. At each step the model is auto-regressive [9], consuming the previously generated symbols as additional input when generating the next. The Transformer follows this overall architecture using stacked self-attention and point-wise, fully connected layers for both the encoder and decoder, shown in the left and right halves of Figure 1, respectively.

3.1 Encoder and Decoder Stacks

Encoder: The encoder is composed of a stack of  $N = 6$  identical layers. Each layer has two sub-layers. The first is a multi-head self-attention mechanism, and the second is a simple, position-wise fully connected feed-forward network. We employ a residual connection [10] around each of

# Tech stack used:

- Python
- Streamlit
- mcp
- DeepSeek model
- Sentence Transformers
- FAISS
- LangChain
- And some other python libraries

# Challenges faced

- Integrating asyncio-based MCP with Streamlit's synchronous script execution model.
- Debugging silent failures in agent subprocesses.