

Five Techniques for Improving RAG Chatbots

Improving Retrievers to Build High-Quality Conversational Assistants

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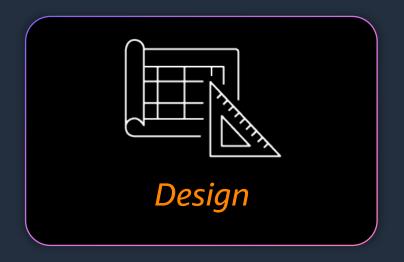
About Me



https://kozodoi.me

- Applied Scientist at Amazon Web Services
- Building Generative AI solutions across industries
- Working on the frontier of research & business
- Earned PhD in ML for Credit Risk Analytics
- Won 18 Kaggle competition medals

My Team: Generative Al Innovation Center

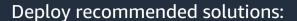






Design guidance:

- Select the GenAl use case with the highest business impact
- Design how to develop, train, and deploy it to production



 Develop and fine-tune a GenAl solution to meet your business objectives and demonstrate what's possible



 Accelerate stickiness and adoption with a path to production for your GenAI solution integrated into your application.

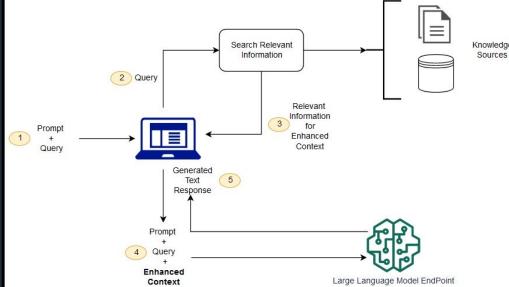
https://aws.amazon.com/generative-ai/innovation-center/



Agenda

- Intro to RAG Chatbots
- Techniques to Improve Retrieval
 - #1: Small-to-Big Retrieval
 - #2: Leveraging Meta-Data
 - #3: Hybrid Search
 - #4: Query Rewriting & Expansion
 - #5: Document Reranking







Intro to RAG Chatbots

(RAG = Retrieval Augmented Generation)



Search vs Q&A Assistant

What is self-attention?

Send

[1] Attention is all you need

Attention mechanisms have become an integral part of compelling sequence modeling...

[2] Mistral 7B

The number of operations in vanilla attention is quadratic in the sequence length...

Search

What is self-attention?

Send

Self-attention is a mechanism used in DL models to capture dependencies and relationships within input sequences [1].

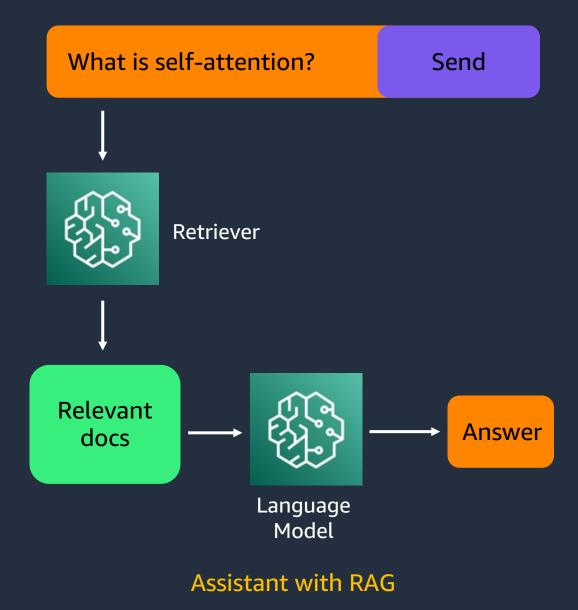
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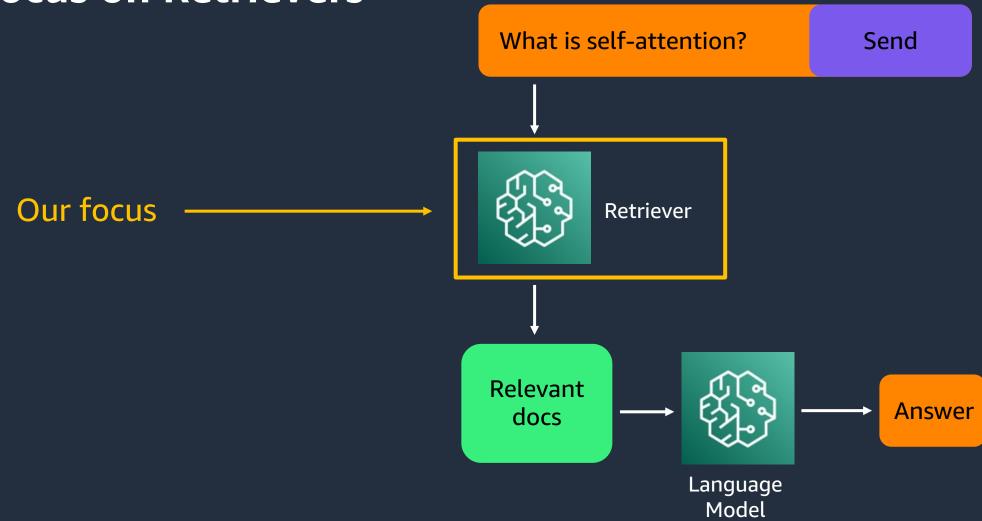
Q&A Assistant

Assistant with/without RAG :

What is self-attention? Send Answer Language Model Assistant with no RAG



Let's Focus on Retrievers

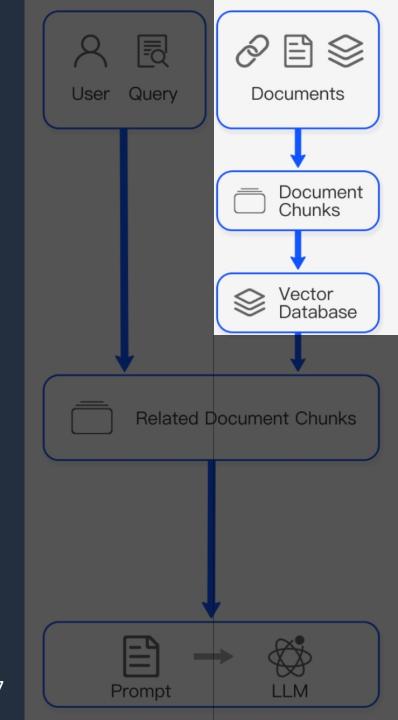




RAG Chatbot Architecture

1. Indexing stage:

- Each document is parsed into text
- Texts are split into chunks (e.g. paragraphs)
- Each chunk is embedded into a vector
- Vectors and text chunks are stored in a database

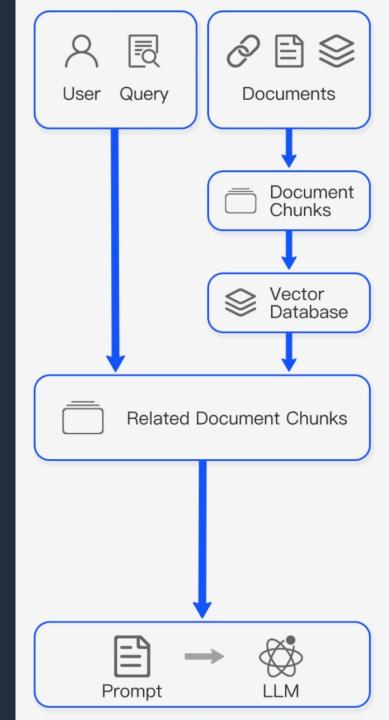




RAG Chatbot Architecture

2. Q&A stage:

- User question is embedded into a vector
- Top-K closest chunks are fetched from the database
- User question and chunks are shown to LLM
- LLM provides a response to the user





Techniques to Improve Retrievers

#1. Small-to-Big Retrieval



Idea: use small chunk size on embedding stage and large size on Q&A stage Why:

- Embedding very large chunks adds too much noise => poor recall
- Embedding small chunks leads to very limited context => incomplete answers

Attention mechanisms have become an integral part of compelling sequence modeling and transduction models in various tasks, allowing modeling of dependencies without regard to their distance in the input or output sequences [2, 16]. In all but a few cases [22], however, such attention mechanisms are used in conjunction with a recurrent network. In this work we propose the Transformer, a model architecture eschewing recurrence and instead relying entirely on an attention mechanism to draw global dependencies between input and output. The Transformer allows for significantly more parallelization and can reach a new state...

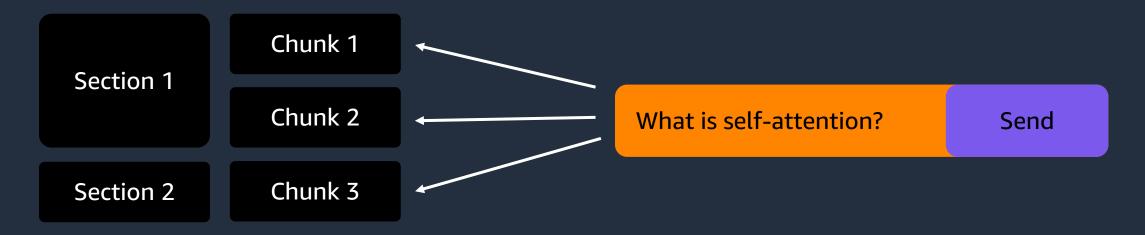
VS

Attention mechanisms have become an integral part of compelling sequence modeling...



Solution:

- Use a smaller chunk size on the embedding stage
- Append "neighbor" chunks to extend the chunk before feeding to LLM





Solution:

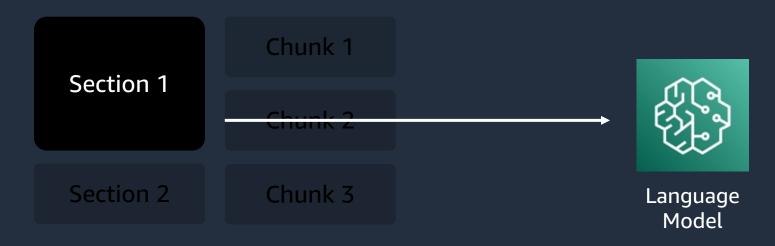
- Use a smaller chunk size on the embedding stage
- Append "neighbor" chunks to extend the chunk before feeding to LLM





Solution:

- Use a smaller chunk size on the embedding stage
- Append "neighbor" chunks to extend the chunk before feeding to LLM



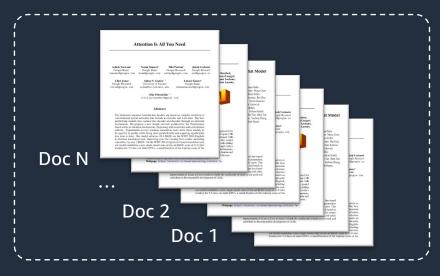


Techniques to Improve Retrievers

#2. Leveraging Meta-Data



2. Leveraging Document Meta-Data



Documents

doc	author	year	•••	title
1	Ashish Vaswani	2017	•••	Attention is
2	Albert Q. Jiang	2023		Mistral 7B
•••				
N	Hugo Touvron	2023		LLAMA 2:

Meta-Data



2. Leveraging Document Meta-Data



doc	author	year	•••	title
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Meta-Data

- Meta-data can start as simple as the file name and path
- You can also use LLM to generate meta-data



Documents

2.1. Use Filters Based on Meta-Data

Idea: let user specify filters before asking the question

Why: filters reduce the search space, leading to more precise retrieval

What is self-attention?

Send

Year: 2017 Title: Attention is all you need



2.2. Include Meta-Data in Chunk Text

Idea: append document meta-data as a string to chunks before embedding

Why: relevant meta-data text improves search in the embedding space

Attention mechanisms have become an integral part of compelling sequence modeling...

Year: 2017

Title: Attention is all you need

Attention mechanisms have become an integral part of compelling sequence modeling...

Chunk (Before)

Chunk (After)



Techniques to Improve Retrievers

#3. Hybrid Search



3. Hybrid Search

Idea: combine vector-based search and keyword-based search

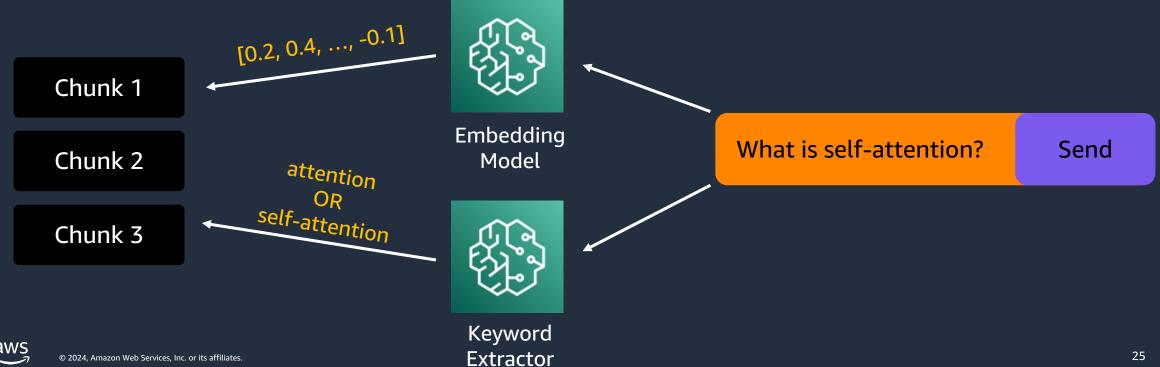
Why:

- Consider docs with domain-specific syntax and abbreviations
- Such texts may not be poorly represented in the embedding model data
- Including a few docs from keyword-based search helps to address this gap



3. Hybrid Search

Idea: combine vector-based search and keyword-based search



Techniques to Improve Retrievers

#4. Query Rewriting & Expansion



4. User Query Rewriting

Idea: reformulate user question into a better-structured search query

Why:

- Users are not always very good at formulating specific questions
- Especially relevant for follow-up conversations that assume certain context

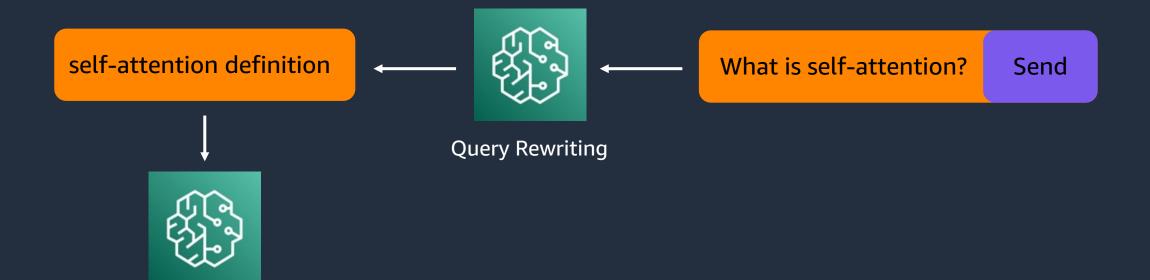
Hey, can you tell me about self-attention please? I am struggling to understand it...

Send



4.1. Simple Rewriting

Idea: reformulate user question into a better-structured search query

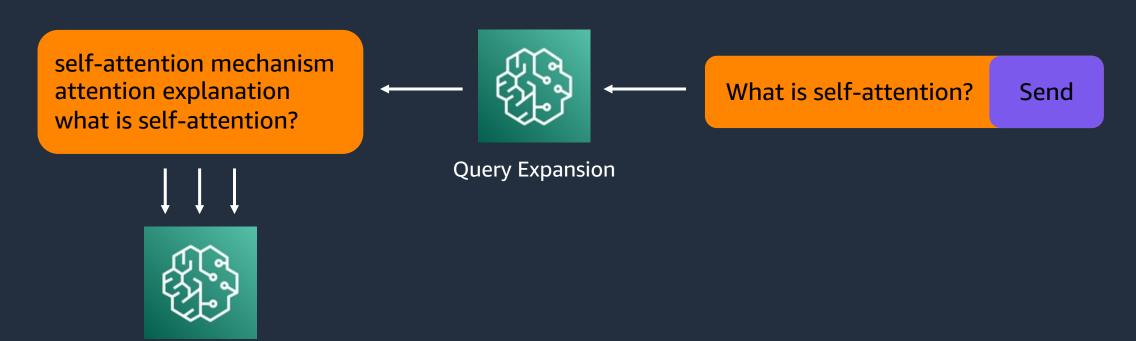




Embedding Model

4.2. Query Expansion

Idea: reformulate user question into MULTIPLE search queries





Embedding Model

Techniques to Improve Retrievers

#5. Document Reranking



5. Document Reranking

Idea: rerank retrieved documents (e.g., using LLM)

Why:

- Documents with the highest embedding similarity may not be most relevant
- LLM can rerank document chunks to better match the user query

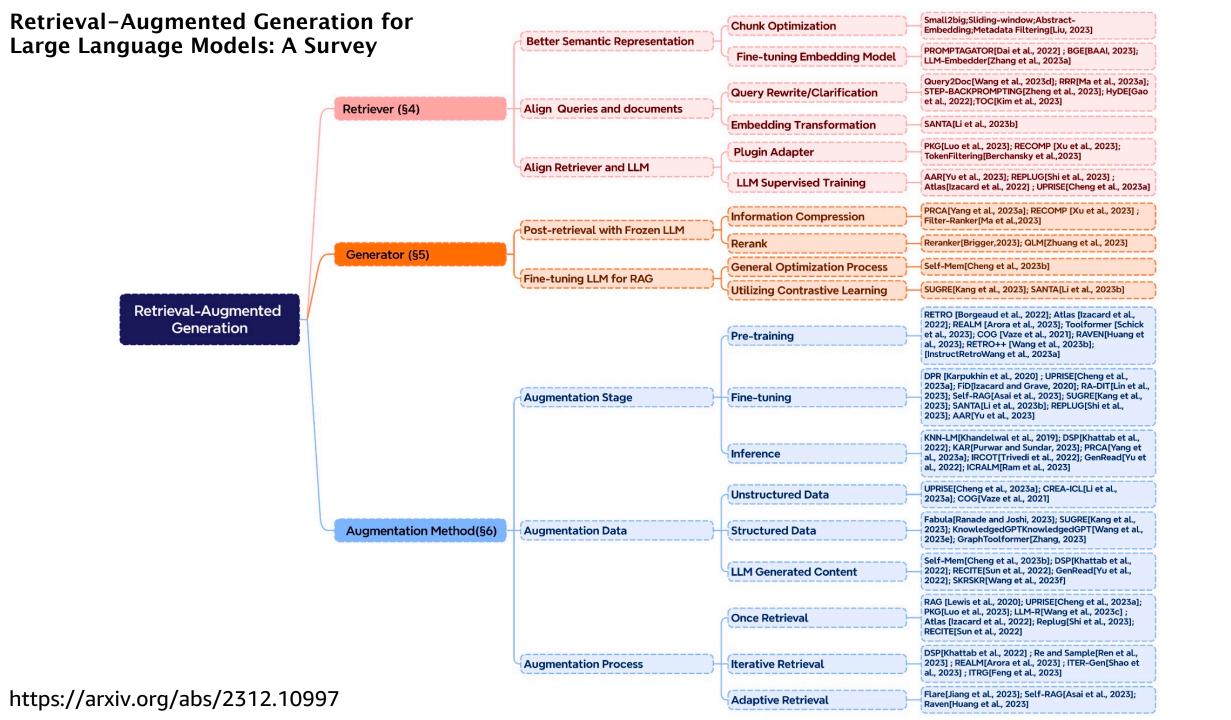
Chunk 1 Chunk 2 Chunk 3

5. Document Reranking

Idea: rerank retrieved documents (e.g., using LLM)









Thank You!

- #1: Small-to-Big Retrieval
- #2: Leveraging Meta-Data
- #3: Hybrid Search
- #4: Query Rewriting
- #5: Document Reranking

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