

# The need for retrieval in generative models

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## What's the Problem?

Generative models like GPT or T5 are trained on **huge static datasets**.

They learn to **generate** text from patterns in training data — but **they don't "know" anything beyond what they've seen**.

So they have 3 main **limitations**:

1. **Outdated Knowledge** – once trained, they can't access new facts or events.
  2. **Memory Constraints** – model parameters can't store every detail from training.
  3. **Hallucinations** – they might "make up" facts when unsure, because generation relies on learned probabilities, not direct retrieval.
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## The Core Need for Retrieval

To overcome these limitations, researchers introduced the idea of **retrieval in generative models** — that is, **augmenting generation with access to external knowledge** (like documents, databases, or the web).

This approach is known as:

| Retrieval-Augmented Generation (RAG)

The goal:

Combine **information retrieval** (from a knowledge source) + **text generation** (from the model).

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## How Retrieval Helps

Challenge	Without Retrieval	With Retrieval
<b>Knowledge limitation</b>	Model relies only on what it memorized	Model fetches relevant info from an external corpus
<b>Outdated data</b>	Model can't know recent events	Retrieval can include up-to-date documents
<b>Factual accuracy</b>	Often hallucinates details	Reduces hallucinations by grounding outputs in real text
<b>Explainability</b>	Hard to trace where info came from	Easier to show sources retrieved

## Example

### Without retrieval:

Prompt: "Who won the FIFA World Cup in 2022?"

Model (trained before 2022): "I think Germany won." ❌

### With retrieval:

The system retrieves a snippet from Wikipedia:

"Argentina won the 2022 FIFA World Cup after defeating France."

Then the generator outputs:

✅ "Argentina won the 2022 FIFA World Cup after defeating France in the final."

Here, retrieval provides *factual grounding* before generation.

## How Retrieval-Augmented Generation (RAG) Works

### 1. Query Encoder

- Takes the user query and converts it into a vector (embedding).

### 2. Retriever

- Searches a document database (using embeddings similarity) for the **top-k relevant documents**.

### 3. Generator

- Feeds both the **query** and **retrieved documents** into a **generative model** (e.g., GPT, T5, BART) to produce a contextually accurate response.

User Query → [Retriever] → Relevant Docs  
↓  
[Generator] → Final Answer

### Why Retrieval is Important (Summarized)



Benefit	Explanation
<b>Grounded responses</b>	Reduces hallucinations by basing answers on real data
<b>Fresh knowledge</b>	Keeps models up to date without full retraining
<b>Transparency</b>	Allows source attribution
<b>Efficiency</b>	Avoids cramming all facts into model weights
<b>Adaptability</b>	Model can specialize to new domains quickly by changing retrieval corpus

### Example Systems

Model	Type	Key Idea
<b>RAG (Facebook)</b>	Encoder-decoder (BERT + BART)	Retrieves top documents and conditions generation
<b>REALM (Google)</b>	Pretraining with retrieval	Learns to retrieve during pretraining
<b>RETRO (DeepMind)</b>	Retrieval during training	Enhances transformer with retrieval memory
<b>GPT + Vector DB (e.g., using LangChain)</b>	Post-hoc retrieval	Combines LLM with external database like FAISS, Pinecone, or Chroma

## Analogy

Think of a **retrieval-augmented model** as:

 A smart student (the generator) who has learned language deeply  
 but keeps a library (retriever) nearby to look up factual information when answering.

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## In Short

Retrieval in generative models bridges the gap between language fluency and factual grounding by allowing models to access external knowledge instead of relying solely on internal memory.

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