

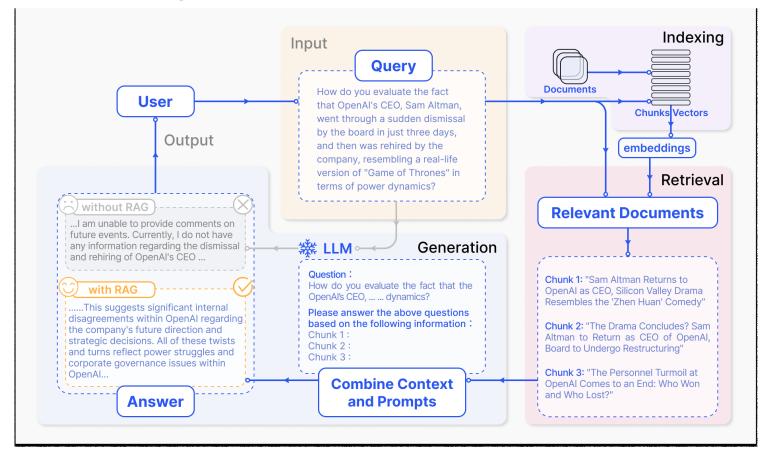
Retrieval Augmented Generation (RAG)

- Data used to trains LLMs often lags in timeliness and may not cover all domain knowledge
 - Hallucinations
 - Outdated Knowledge
 - Non-transparent and untraceable reasoning
- Data augmented LLMs can
 - exhibit domain expert-level capabilities like doctors, lawyers
 - generate responses based on real data minimizing the possibility of hallucinations
- Data augmented LLMs application primarily follows:
 - RAG
 - Fine-tuning



Retrieval Augmented Generation

- RAG enhances accuracy and credibility of the generation merging LLM's intrinsic knowledge (training data) with the vast, dynamic repo of external databases leveraging –
 - Vector database, Embeddings, Sentence transformers, Cosine distance





Retrieval Augmented Generation

- Naïve RAG The earliest RAG method, follows a "Retrieve-Read" framework involving indexing, retrieval, and generation
 - **Indexing Process:** Raw data from various formats (PDF, HTML, Word) is cleaned, segmented, and converted into vectors using an embedding model, stored in a vector database.
 - Retrieval Phase: The system encodes user queries into vectors, matches them against stored vectors, and retrieves the most relevant chunks for the expanded prompt context.
 - **Generation Phase:** The model generates responses by synthesizing the query and retrieved documents



Retrieval Augmented Generation

- Drawbacks
 - Retrieval Challenges: Precision and recall issues may lead to irrelevant or missing chunks.
 - **Generation Issues:** Hallucination, irrelevance, bias, or toxic content can arise in the generated responses.
 - **Augmentation Hurdles:** Combining retrieved information can be difficult, leading to redundancy, disjointed responses, and over-reliance on the retrieved content.