Introduction to Large Language Models and Retrieval-Augmented Generation

1. Overview

Large Language Models (LLMs) are a class of deep learning models designed to understand and generate human-like text.
They are trained on massive text corpora and can perform a wide range of natural language processing tasks such as question answering, summarization, translation, and text generation.

Popular examples of LLMs include GPT, BERT, T5, and LLaMA.

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2. Limitations of Large Language Models

Despite their capabilities, LLMs have several limitations:

- They rely on information seen during training and may produce outdated answers.
- They can hallucinate facts that are not grounded in real data.
- They do not have direct access to private or domain-specific documents.

Because of these limitations, using LLMs alone is often insufficient for real-world enterprise applications.

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3. What is Retrieval-Augmented Generation (RAG)?

Retrieval-Augmented Generation (RAG) is a technique that combines information retrieval with text generation.

Instead of relying only on the LLM’s internal knowledge, RAG systems retrieve relevant documents or text chunks from an external knowledge base and provide them as context to the model.

This approach improves factual accuracy and allows LLMs to answer questions based on custom or private data.

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4. RAG Architecture

A typical RAG pipeline consists of the following steps:

1. Document Ingestion
   Documents such as PDFs or text files are loaded and preprocessed.

2. Chunking
   Long documents are split into smaller overlapping chunks to preserve context.

3. Embedding Generation
   Each chunk is converted into a vector representation using an embedding model.

4. Vector Storage
   Embeddings are stored in a vector database such as FAISS or ChromaDB.

5. Retrieval
   When a user asks a question, the most relevant chunks are retrieved based on similarity.

6. Generation
   The retrieved chunks are passed to the LLM as context to generate the final answer.

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5. Advantages of RAG Systems

Using RAG provides several benefits:

- Improved accuracy and reduced hallucinations
- Ability to use up-to-date or private data
- Modular and scalable architecture
- Better control over model outputs

For these reasons, RAG has become a common design pattern in modern LLM-powered applications.

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6. Use Cases

Common use cases of RAG include:

- Document-based question answering
- Enterprise knowledge assistants
- Customer support automation
- Legal and medical document analysis

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7. Conclusion

Retrieval-Augmented Generation bridges the gap between static language models and dynamic knowledge sources.
By combining vector search with generative models, RAG systems enable more reliable and context-aware AI applications.