I'll break down the code **step by step**, explain **each concept**, provide **theoretical background**, and include **an architectural diagram**.

📌 Overview of the Code

The provided code implements **efficient document reranking** and **retrieval-augmented generation (RAG)** using **FlashRank**, **FAISS**, and **LangChain**.
It focuses on:

1. **FlashRanker-based Reranking**: Reorders retrieved documents based on relevance.
2. **Embedding-based Retrieval with FAISS**: Uses vector search to fetch relevant documents.
3. **Contextual Compression with FlashRankRerank**: Compresses retrieved data before passing it to an LLM.
4. **Retrieval-Augmented Generation (RAG)**: Uses retrieved documents to enhance LLM responses.

📌 Step-by-Step Code Explanation

Step 1: Install Required Libraries

```
python
CopyEdit
!pip install flashrank langchain_community langchain_openai faiss-cpu
```

✅ **Installs necessary libraries**:

- `flashrank` → Lightweight reranking model.
- `langchain_community` → LangChain utilities.
- `langchain_openai` → OpenAI integration for embeddings & chat models.
- `faiss-cpu` → Efficient vector database for retrieval.

Step 2: Helper Function to Print Documents

```
python
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def pretty_print_docs(docs):
    print(
        f"\n{'-' * 100}\n".join(
            [
                f"Document {i+1}:\n\n{d.page_content}\nMetadata:
{d.metadata}"
                for i, d in enumerate(docs)
            ]
        )
    )
```

✅ **Formats retrieved documents for display**.

Step 3: Define Query and Passages

```
python
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query = "How to speedup LLMs?"
passages = [
   {"id":1, "text":"Introduce *lookahead decoding*...", "meta":
{"additional": "info1"}},
   {"id":2, "text":"LLM inference efficiency...", "meta":
{"additional": "info2"}},
   {"id":3, "text":"There are many ways to increase LLM inference
throughput...", "meta": {"additional": "info3"}},
   {"id":4, "text":"Ever want to make your LLM inference go
brrrrr...", "meta": {"additional": "info4"}},
   {"id":5, "text":"vLLM is a fast and easy-to-use library...",
"meta": {"additional": "info5"}}
]
```

✅ Defines **sample text passages** that describe different LLM speed-up techniques.
✅ **Each passage has metadata** for additional context.

Step 4: Define the FlashRanker Function

```
python
CopyEdit
from flashrank.Ranker import Ranker, RerankRequest

def get_result(query, passages, choice):
  if choice == "Nano":
    ranker = Ranker()
  elif choice == "Small":
    ranker = Ranker(model_name="ms-marco-MiniLM-L-12-v2",
cache_dir="/opt")
  elif choice == "Medium":
    ranker = Ranker(model_name="rank-T5-flan", cache_dir="/opt")
  elif choice == "Large":
    ranker = Ranker(model_name="ms-marco-MultiBERT-L-12",
cache_dir="/opt")

  rerankrequest = RerankRequest(query=query, passages=passages)
  results = ranker.rerank(rerankrequest)
  print(results)

  return results
```

✅ Defines a function `get_result()` that uses **FlashRanker to reorder documents**.
✅ **Chooses between different ranking models** based on user selection:

- **Nano** → Fastest (~4MB)
- **Small** → More accurate (~34MB)
- **Medium** → Best zero-shot ranking (~110MB)
- **Large** → Supports **100+ languages** (~150MB) ✅ Uses `RerankRequest()` to **rank documents based on relevance to the query**.

Step 5: Execute FlashRanker with Different Models

```
python
CopyEdit
%%time
get_result(query, passages, "Nano")

%%time
get_result(query, passages, "Small")

%%time
get_result(query, passages, "Medium")
```

✅ **Runs reranking for different models** and measures execution time.

Step 6: Load Documents & Split for Processing

```
python
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from langchain_community.document_loaders import TextLoader
from langchain_text_splitters import RecursiveCharacterTextSplitter

documents = TextLoader("/content/state_of_the_union.txt").load()
text_splitter = RecursiveCharacterTextSplitter(chunk_size=500,
chunk_overlap=100)
texts = text_splitter.split_documents(documents)
```

✅ **Loads a large document (`state_of_the_union.txt`)** and splits it into smaller chunks (**500 characters, with 100 overlapping characters**) using **RecursiveCharacterTextSplitter**.

Step 7: Assign Metadata to Documents

```
python
```

```
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for id, text in enumerate(texts):
    text.metadata["id"] = id
```

✅ **Assigns unique IDs** to each document chunk.

Step 8: Generate Embeddings & Store in FAISS

```python
python
CopyEdit
from langchain_community.embeddings import OpenAIEmbeddings
from langchain_community.vectorstores import FAISS

embedding = OpenAIEmbeddings(model="text-embedding-ada-002")
retriever = FAISS.from_documents(texts,
embedding).as_retriever(search_kwargs={"k": 10})
```

✅ **Creates embeddings** for document chunks using **OpenAI's text-embedding-ada-002** model.

✅ **Stores embeddings in FAISS**, enabling **fast similarity search**.

✅ Retrieves **top-10** relevant documents for a query.

Step 9: Retrieve Documents Based on Query

```python
python
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query = "What did the president say about Ketanji Brown Jackson"
docs = retriever.invoke(query)
pretty_print_docs(docs)
```

✅ **Searches FAISS** for relevant **State of the Union** speech snippets.

✅ Prints retrieved results.

Step 10: Compress Retrieved Documents with FlashRank

```
python
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from langchain.retrievers import ContextualCompressionRetriever
from langchain.retrievers.document_compressors import FlashrankRerank
from langchain_openai import ChatOpenAI

llm = ChatOpenAI(temperature=0)
compressor = FlashrankRerank()
compression_retriever =
ContextualCompressionRetriever(base_compressor=compressor,
base_retriever=retriever)

compressed_docs = compression_retriever.invoke("What did the president
say about Ketanji Jackson Brown")
pretty_print_docs(compressed_docs)
```

✅ Uses `FlashrankRerank()` **to further filter** retrieved documents.

✅ **Reduces hallucinations** by ensuring only highly relevant documents are passed to the LLM.

Step 11: Generate Final Answer with Retrieval-Augmented Generation (RAG)

```
python
CopyEdit
from langchain.chains import RetrievalQA

chain = RetrievalQA.from_chain_type(llm=llm,
retriever=compression_retriever)
chain.invoke(query)
```

✅ Uses **retrieved and compressed documents** as context for **LLM-generated responses**.
✅ **Ensures factual accuracy** by limiting model output to **retrieved context**.

📌 Architecture Diagram

graphql
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```
┌─────────────────────────────┐
│         User Query          │
└─────────────┬───────────────┘
              │
┌─────────────▼───────────────┐
│       FAISS Vector DB       │
└─────────────┬───────────────┘
              │
┌─────────────▼───────────────┐
│     FlashRank Reranker      │
└─────────────┬───────────────┘
              │
┌─────────────▼───────────────┐
│   Contextual Compression    │
└─────────────┬───────────────┘
              │
┌─────────────▼───────────────┐
│  OpenAI Chat Model (RAG)    │
└─────────────────────────────┘
```

📌 Missing Concepts (Improvements)

✅ **Use Hybrid Retrieval** (BM25 + Embeddings).
✅ **Experiment with Other Rerankers** (ColBERT, RankT5).
✅ **Implement Query Expansion** for better search results.

📌 Final Thoughts

This code **efficiently retrieves, ranks, and filters** documents before feeding them to an LLM, ensuring **speed, accuracy, and factual correctness**. 🚀

#################DeepSeek#######################################

1. **Line-by-Line Explanation**

Installation & Setup

python
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```
!pip install flashrank
```

- Installs the `flashrank` library for lightweight re-ranking of search results.

Helper Function

python
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```
def pretty_print_docs(docs):
    print(
        f"\n{'-' * 100}\n".join(
            [
                f"Document {i+1}:\n\n{d.page_content}\nMetadata:
{d.metadata}"
                for i, d in enumerate(docs)
            ]
        )
    )
```

- **Purpose**: Formats and prints documents with their metadata.
- **Mechanics**:
    - Iterates over a list of documents.
    - Separates documents with `---` lines.
    - Includes page content and metadata for each document.

Query & Passages

python
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```
query = "How to speedup LLMs?"
passages = [ ... ]
```

- **Query**: A question about speeding up large language models (LLMs).
- **Passages**: A list of 5 example documents (with `id`, `text`, and `metadata`) to be re-ranked.

FlashRank Initialization

python
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```
from flashrank.Ranker import Ranker, RerankRequest

def get_result(query, passages, choice):
    if choice == "Nano":
```

```
        ranker = Ranker()  # Uses default model (ms-marco-TinyBERT-L-
2-v2)
    elif choice == "Small":
        ranker = Ranker(model_name="ms-marco-MiniLM-L-12-v2",
cache_dir="/opt")
    elif choice == "Medium":
        ranker = Ranker(model_name="rank-T5-flan", cache_dir="/opt")
    elif choice == "Large":
        ranker = Ranker(model_name="ms-marco-MultiBERT-L-12",
cache_dir="/opt")

    rerankrequest = RerankRequest(query=query, passages=passages)
    results = ranker.rerank(rerankrequest)
    print(results)
    return results
```

- **Purpose**: Reranks passages using a selected FlashRank model.
- **Mechanics**:
  - Initializes a `Ranker` with a model based on the `choice` (Nano/Small/Medium/Large).
  - Creates a `RerankRequest` object with the query and passages.
  - Executes reranking and returns results.

Timing Execution

python
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```
%%time
get_result(query, passages, "Nano")
```

- **Purpose**: Measures the execution time of reranking with the Nano model.

LangChain Integration

python
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```
!pip install langchain_community langchain_openai
from google.colab import userdata
```

```
OPENAI_API_KEY = userdata.get('OPENAI_API_KEY')
os.environ["OPENAI_API_KEY"] = OPENAI_API_KEY
```

- Installs LangChain libraries and sets up OpenAI API key.

Document Loading & Splitting

python
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```python
from langchain_community.document_loaders import TextLoader
from langchain_text_splitters import RecursiveCharacterTextSplitter

documents = TextLoader("/content/state_of_the_union.txt").load()
text_splitter = RecursiveCharacterTextSplitter(chunk_size=500,
chunk_overlap=100)
texts = text_splitter.split_documents(documents)
for id, text in enumerate(texts):
    text.metadata["id"] = id
```

- **Purpose**: Loads a text file and splits it into chunks for processing.
- **Mechanics**:
  - Uses `TextLoader` to load a document.
  - Splits text into 500-token chunks with 100-token overlap.
  - Adds an `id` to each chunk's metadata.

Vector Store & Retriever

python
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```python
from langchain_community.embeddings import OpenAIEmbeddings
from langchain_community.vectorstores import FAISS

embedding = OpenAIEmbeddings(model="text-embedding-ada-002")
retriever = FAISS.from_documents(texts,
embedding).as_retriever(search_kwargs={"k": 10})
```

- **Purpose**: Creates a vector store for semantic search.
- **Mechanics**:

- Uses OpenAI embeddings (`text-embedding-ada-002`) to convert text to vectors.
- Builds a FAISS index for efficient similarity search.
- Retriever fetches the top 10 documents for a query.

Re-Ranking with FlashRank

python
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```python
from langchain.retrievers import ContextualCompressionRetriever
from langchain.retrievers.document_compressors import FlashrankRerank

compressor = FlashrankRerank()
compression_retriever = ContextualCompressionRetriever(
    base_compressor=compressor, base_retriever=retriever
)
compressed_docs = compression_retriever.invoke("What did the president
say about Ketanji Jackson Brown")
```

- **Purpose**: Combines retrieval and re-ranking to improve result quality.
- **Mechanics**:
  - `FlashrankRerank` reorders documents based on relevance.
  - `ContextualCompressionRetriever` wraps the retriever and compressor.

Question Answering

python
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```python
from langchain.chains import RetrievalQA

chain = RetrievalQA.from_chain_type(llm=llm,
retriever=compression_retriever)
chain.invoke(query)
```

- **Purpose**: Answers questions using the compressed/reranked documents.
- **Mechanics**:
  - Uses `ChatOpenAI` (LLM) to generate answers.
  - Combines retrieval, re-ranking, and LLM inference.

2. **Key Concepts**

Re-Ranking

- **What**: Reordering search results to prioritize relevance.
- **Why**: Initial retrievers (e.g., FAISS) use vector similarity, which may miss contextual relevance.
- **FlashRank**: Uses lightweight cross-encoder models to score query-passage pairs.

Cross-Encoders

- **Mechanism**: Process the query and document together (unlike bi-encoders).
- **Advantage**: Higher accuracy but slower than bi-encoders.
- **Models**:
    - **Nano**: TinyBERT (4MB, fastest).
    - **Small**: MiniLM (34MB, best accuracy).
    - **Medium**: T5-FLAN (110MB, zero-shot).
    - **Large**: MultiBERT (150MB, multilingual).

LangChain Components

- **Retriever**: Fetches documents (FAISS here).
- **Compressor**: Improves results (FlashrankRerank here).
- **Chain**: Combines retrieval, compression, and LLM (RetrievalQA).

3. **Architecture Diagram**

Copy

```
[User Query]
    │
    ▼
[FAISS Retriever] → Retrieves top 10 documents
    │
    ▼
[FlashRankRerank] → Re-orders documents by relevance
    │
    ▼
[ChatOpenAI] → Generates final answer
```

4. **Missing Points**

1. **Model Details**:
    a. FlashRank models are based on **cross-encoders**, which are slower but more accurate than bi-encoders.
    b. `rank-T5-flan` (Medium) is a text-to-text model, while others are BERT-based.
2. **Use Case**:
    a. Designed for serverless deployments (AWS Lambda, Vercel) due to low memory usage.
3. **Performance Tradeoffs**:
    a. Nano is 4MB but less accurate; Small is 34MB with best accuracy.
4. **Alternatives**:
    a. Compare with other rerankers (Cohere, SentenceTransformers).
5. **Quantitative Results**:
    a. Missing benchmarks (e.g., latency vs. accuracy for each model).
6. **Error Handling**:
    a. No code for handling API failures or model loading errors.
7. **Cache Directory**:
    a. `cache_dir="/opt"` is specific to deployment environments (e.g., Docker/cloud VMs).