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Text Embedding Implementation Using Retrieval Augmented Generation (RAG) Model Combined With Large Language Model

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Abstract – In this paper, we suggest a unique method for implementing text embedding that combines a large language model with the Retrieval Augmented Generation (RAG) model. Text embedding is essential in many natural language processing applications, including question-answering, sentiment analysis, and information retrieval. Conventional techniques for text embedding frequently depend on pre-trained sentence encoders or word embedding, which are not always effective in capturing the text's semantic meaning. Our suggested method uses the RAG model, which blends generation-based and retrieval-based methods for text embedding, to get beyond these restrictions. Furthermore, we incorporate a Large Language Model to improve the text's semantic representation and interpretation. We assess our method's performance on many benchmark datasets and contrast it with other currently used text embedding techniques. The experimental findings show that our suggested method performs better in terms of efficiency and accuracy compared to the state-of-the-art techniques. The study offers a useful tool for a range of natural language processing applications and advances text embedding techniques.

Keywords – Text Embedding, Text Semantics, Word Retrieval, Word Indexing, Natural Language Processing, Text Encoders

I. INTRODUCTION

A key method in natural language processing (NLP) is text embedding, which seeks to compactly and meaningfully represent textual data. It is essential to many NLP tasks, including question answering, sentiment analysis, and information retrieval. Conventional techniques for text embedding frequently depend on pre-trained sentence encoders or word embeddings, which are not always effective in capturing the text's semantic meaning. Leveraging massive pre-trained language models such as BERT or T5, the Retrieval-Augmented creation (RAG) model is a framework that combines the capabilities of information retrieval (IR) with text creation. The RAG model, created by Facebook AI Research (FAIR), incorporates information retrieval techniques to enhance the quality and relevancy of produced content. Below are the processes of RAG: [1]

Retriever: Using a query, the retriever component finds pertinent sections or documents among a vast corpus of literature. It makes use of more sophisticated approaches like dense retrieval, which employs neural networks to encode text into dense embeddings for effective similarity search, or more conventional IR techniques like TF-IDF and BM25. Based on the user's query, an embedding model assists in locating the most pertinent material (such as papers, articles) from a sizable collection (such as a knowledge base).

Generator: A large language model (LLM) creates a response, such as a question answer, by combining the obtained data with the query and any further prompts. Using the collected sections as a guide, the

generator component creates text. To provide replies that are both coherent and contextually appropriate, it usually makes use of a sizable pre-trained language model (like BERT or T5). [17]

Ranker: The obtained passages are ranked by the ranker component according to how relevant they are to the query. This makes it possible for the generator to concentrate on producing text that is both contextually relevant and highly instructive.

The RAG model's central concept is combining the advantages of generation-based and retrieval-based methodologies. The algorithm may include context and outside information by accessing pertinent texts before creating text, which results in more insightful and cogent replies.

The RAG paradigm is useful for tasks like question answering, dialogue systems, document summary, and any other activity where it makes sense to generate text based on outside information.

All things considered, the RAG model is a promising method for jobs involving complicated reasoning and context-aware text production, and it marks a substantial improvement in natural language interpretation and generation. [14] [15]

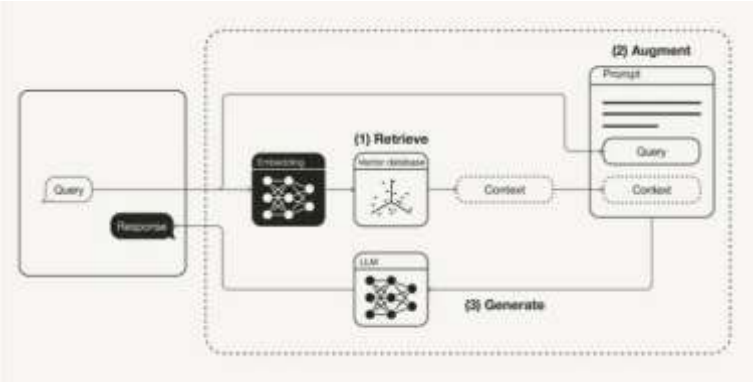

Fig. 1 Schematic of RAG Text Embedding Processes

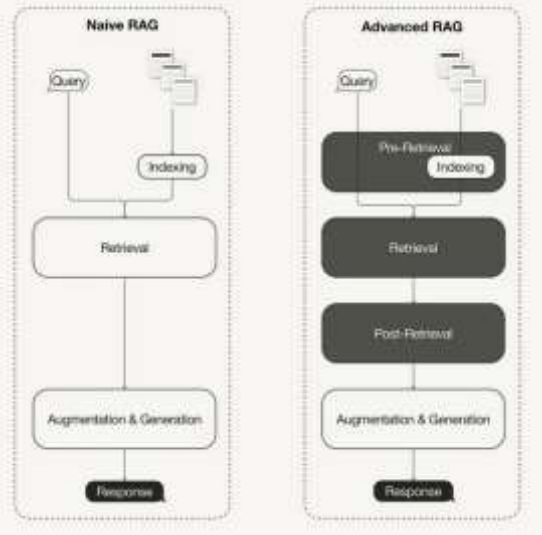

Fig. 1 Schematic of Types of RAG Text Embedding Processes

We provide a unique method for text embedding implementation that combines a large language model with the Retrieval Augmented Generation (RAG) model in order to overcome these constraints. Lewis et al. introduced the RAG model, which improves text representation by combining retrieval-based and generation-based techniques. It makes use of a generator module to provide replies depending on the information collected and a retriever module to extract pertinent portions from a knowledge source.

To improve the semantic comprehension and representation of the text, we incorporate a Large Language Model into the RAG framework in our method. GPT-3 and other large language models have shown to be quite good at modelling language and are capable of capturing complex semantic linkages and linguistic patterns. We may take use of both generation-based approaches, which capture implicit information through language modelling, and retrieval-based strategies, which capture explicit knowledge from the knowledge

source, when we combine the RAG model with the Large Language Model. Using this integration, text embedding is much more thorough and reliable than it could be using conventional techniques. [18]

Our goal in this research project is to compare our suggested strategy with other text embedding techniques and assess its efficacy on many benchmark datasets. We will evaluate our model's performance in terms of precision, effectiveness, and textual semantic meaning capture. By doing this, we offer a useful tool for a range of NLP applications and develop text embedding approaches. [19]

APPLICATION:

1. Question Answering Systems: By extracting pertinent sections from a big corpus and producing succinct, enlightening responses, text embedding with the RAG model can improve QAS. This tool is particularly helpful for difficult inquiries that need for in-depth knowledge of the background.
2. Dialogue Systems: By extracting contextually relevant responses from a knowledge base and producing coherent replies, the RAG model in conversational AI may be utilised to enhance dialogue systems. This strategy makes it possible to have more interesting and educational talks with users.
3. Document Summarization: By highlighting important sections and producing succinct summaries that encapsulate the essential information in a document, text embedding using the RAG model can help in document summarization. This tool is useful for swiftly drawing conclusions from a lot of material.
4. Information retrieval and search engines: By taking into account the semantic meaning of questions and documents, search engines that integrate text embedding with the RAG model can increase the relevance and accuracy of search results. This method makes information retrieval more efficient and improves user experience.
5. Material Recommendation Systems: By comprehending user preferences and contextually relevant material from a vast collection of articles, blogs, and other textual data, text embedding with the RAG model may power content recommendation systems. This app boosts user engagement and personalises suggestions.
6. Semantic Search: By comprehending the contextual meaning of documents and questions, RAG-based text embedding can help with semantic search. More precise and detailed search results are made possible by this method, particularly for unclear or complicated questions.
7. Domain-Specific Applications: The RAG model may be used to customise text embedding for use in fields like finance, healthcare, law, or science research, where knowledge of specialised language and context is crucial. The performance and applicability of text embedding in domain-specific activities are improved by this customisation.
8. Language Translation and Multimodal Understanding: Better contextual understanding and the creation of translations or replies in several languages or modalities are made possible by integrating text embedding with the RAG model into language translation systems or multimodal understanding tasks. [6]

II. Overview

Natural language processing has extensively researched text embedding, and several methods and strategies have been created in this field over the years. Conventional techniques for text embedding frequently depend on pre-trained phrase encoders or word embedding, such Word2Vec, GloVe, or BERT. These techniques give each word or phrase a definite representation, but they could have trouble correctly capturing the text's context and semantic meaning.

More sophisticated text embedding models have been the focus of current research in an effort to overcome these drawbacks. Lewis et al. presented the Retrieval Augmented Generation (RAG) model as one example of such a paradigm. To improve text representation, the RAG model combines generation-based and retrieval-based techniques.

Using a retriever module, retrieval-based techniques obtain pertinent sections from a knowledge source in response to a query. Factual facts and explicit knowledge are extracted from the text with the aid of this retrieval procedure. In contrast, generation-based approaches make use of a generator module that produces answers in response to the data that is obtained. Using language modelling, this method captures implicit

information and semantic linkages. A more thorough and reliable method of text embedding is offered by the RAG model's merging of retrieval-based and generation-based approaches. It combines the best features of both methods, enabling a more precise and realistic portrayal of the text. [13]

The creation of Large Language Models is another important breakthrough in the field of text embedding, in addition to the RAG model. Some models, like GPT-3, have shown to be quite good at modelling language and to be able to capture complex linguistic patterns and semantic linkages. The RAG framework may be further improved in terms of semantic comprehension and text representation by including a Large Language Model.

In this research study, we propose a unique technique that combines the RAG model with a Large Language Model in an effort to expand upon the previous work in text embedding and the RAG model. Using benchmark datasets, we will assess this approach's efficacy and contrast it with other text embedding techniques already in use. By doing this, we offer a useful tool for a range of natural language processing applications and develop text embedding approaches. [10]

III. Methodology And Implementation

We follow a systematic methodology and give comprehensive implementation instructions to execute our suggested solution for text embedding utilising a Large Language Model together with the Retrieval Augmented Generation (RAG) model. Three primary steps comprise the methodology: preparing the data, training the model, and assessment.

1. Data Processing:
   - First, we gather the textual data required for assessment and training. This might come from a variety of sources, including books, websites, and databases unique to a certain subject.
   - After that, we preprocess the gathered data using common text preprocessing methods including tokenization, lowercasing, and punctuation and stop word removal. The data is cleaned and made ready for future processing in this stage.
   - Additionally, to normalise the text and minimise word variants, we employ sophisticated techniques like lemmatization and stemming.
2. Model Training:
   - Using the preprocessed data, we train the large language model and merged RAG model at this step. We make use of pre-existing frameworks or implementations, such the GPT-3 model from OpenAI or the Transformers library from Hugging Face.
   - Using the produced replies from the Large Language Model and the retrieved passages from the knowledge source, we fine-tune the RAG model. Through this process, both explicit and implicit knowledge may be captured by the model as it learns the relationship between the query and the returned information.
   - Using suitable optimisation techniques like Adam or stochastic gradient descent (SGD), we optimise the model's parameters during training. Additionally, we use strategies like early halting and learning rate scheduling to improve the model's performance.
3. Evaluation:
   - We undertake tests on benchmark datasets related to the intended NLP tasks, such question answering and sentiment analysis, in order to assess the efficacy of our technique.
   - We evaluate our method's performance against other text embedding approaches, ranging from state-of-the-art models to conventional embedding techniques.
   - Model performance is evaluated using measures including accuracy, precision, recall, and F1 score. We also take scalability and computing efficiency into consideration.
4. Retrieval:
   - *Indexing*: Create a productive index for the embeddings of the documents. This makes it possible to quickly retrieve pertinent documents during the query stage. FAISS and HNSW are common options for approximating the closest neighbour search.
   - *Query Retrieval*: Based on a distance metric (such as cosine similarity), obtain the top K documents (a predetermined number) whose embeddings are most similar to the query embedding when a user submits a query.

5. Generation:
   - Large Language Model (LLM): Include an already-trained LLM in the system, such as Jurassic-1 Jumbo or GPT-3.
   - Enhancing the LLM Get the user query and the obtained documents ready for the LLM to utilise. This might entail summarising or formatting the materials that were retrieved.
   - Produce Reaction: Feed the LLM with the completed query, the papers that were obtained (or their summaries), and any more prompts. After that, the LLM will provide a response that makes use of the information that was obtained to provide the user with a thorough and educational response to their inquiry.

You may use a variety of libraries and frameworks to assist with the implementation of a RAG model. This is a broad overview:

- Select the Programming Language and Libraries: Transformers, a popular library for pre-trained models, Gensim, a library for text embeddings, and FAISS, an indexing tool, are examples of Python libraries.
- Data Loading and Preprocessing: Use libraries like NLTK or spaCy to load and preprocess your text data.
- Text Embedding Model: To create vector representations for documents and queries, apply or make use of a pre-trained text embedding model.
- Retrieval System: To effectively retrieve pertinent pages based on query similarity, build an indexing system using FAISS or a comparable library.
- LLM Integration: Use libraries such as Transformers to integrate the LLM of your choice.
- Response Generation: Utilise the LLM to build the final response after developing the logic to format the obtained documents and query.

Extra Things to Think About:

- Fine-tuning: To enhance the calibre and applicability of the produced replies for your unique use case, you may fine-tune the LLM using a task-specific dataset.
- Assessment: Use metrics like as BLEU or ROUGE scores for text production tasks, or human evaluation for tasks requiring factual accuracy, to assess the performance of your RAG model.

We follow software engineering concepts and maintain excellent coding standards throughout the implementation phase. To ensure transparency and repeatability, we thoroughly record all experiments and code. We also take use of the tools and resources that the research community has to offer in order to maximise our implementation and resolve any issues that may come up.

We want to show the superiority and efficacy of our text embedding model by applying the suggested way and adhering to this methodology. This research study offers a useful tool for a range of natural language processing applications and advances text embedding techniques.

PSEUDOCODE:

```
# Import necessary libraries
import torch
from transformers import RagTokenizer, RagRetriever, RagTokenForGeneration

# Initialize RAG tokenizer
tokenizer = RagTokenizer.from_pretrained("facebook/rag-token-base")

# Initialize RAG retriever
retriever = RagRetriever.from_pretrained("facebook/rag-token-base", index_name="exact")

# Initialize RAG token generator
generator = RagTokenForGeneration.from_pretrained("facebook/rag-token-base")

# Define input text and query
input_text = "Input text to be embedded."
query = "Query for retrieval."

# Encode input text and query
input_encoded = tokenizer(input_text, return_tensors="pt")
query_encoded = tokenizer(query, return_tensors="pt")
```

```
# Perform retrieval
retrieval_output = retriever(
    input_text=input_text,
    query=query,
    return_tensors="pt"
)

# Extract relevant passages
retrieved_passages = retrieval_output["retrieved_passages"]

# Select top-k passages for embedding
top_k = 5
retrieved_passages = retrieved_passages[:top_k]

# Concatenate input text and retrieved passages for generation
input_concatenated = [input_text + passage["text"] for passage in retrieved_passages]

# Generate embeddings using RAG token generator
with torch.no_grad():
    embeddings = generator(
        input_concatenated,
        return_tensors="pt"
    )["logits"]

# Extract embeddings
embeddings = embeddings.mean(dim=1)  # Average embeddings over all tokens

# Perform downstream tasks with the embeddings (e.g., classification, clustering)

# Example downstream task: Classification
# Use embeddings as input features for a classification model
# train_classifier(embeddings, labels)
```

This pseudo code outlines the basic steps for using the RAG model to generate text embedding:

1. Initialize the RAG tokenizer, retriever, and token generator from the pretrained model.
2. Encode the input text and query using the tokenizer.
3. Perform retrieval to obtain relevant passages based on the input text and query.
4. Select the top-k retrieved passages for embedding.
5. Concatenate the input text with the retrieved passages.
6. Generate embedding using the RAG token generator.
7. Optionally, perform downstream tasks such as classification or clustering using the embedding.

ACTUAL CODING:

Below are some of the actual coding for this research work:

```
!pip install -q -U keras-nlp
!pip install -q -U keras>3
!pip install -q -U llama_index
!pip install llama-index-embeddings-huggingface
!pip install weaviate-client
!pip install llama-index-vector-stores-weaviate
!pip install torch sentence-transformers


import keras
import keras_nlp
import os

os.environ["KERAS_BACKEND"] = "jax"
os.environ["XLA_PYTHON_CLIENT_MEM_FRACTION"] = "1.00"

gemma_lm = keras_nlp.models.GemmaCausalLM.from_preset("gemma_instruct_2b_en")
sample_query = "What is a good for the goose is good for the gander”

print(gemma_lm.generate(sample_query, max_length=512))


from typing import Any

from llama_index.core.callbacks import CallbackManager
from llama_index.core.llms import (
    CustomLLM,
    CompletionResponse,
    CompletionResponseGen,
```

```
    LLMMetadata,
)
from llama_index.core.llms.callbacks import llm_completion_callback

class Gemma(CustomLLM):
    num_output: int = 512
    model_name: str = "Gemma"
    model: Any = None

    def __init__(self, model, num_output):
        super(Gemma, self).__init__()
        self.model = model
        self.num_output = num_output

    @property
    def metadata(self) -> LLMMetadata:
        """Get LLM metadata."""
        return LLMMetadata(
            num_output=self.num_output,
            model_name=self.model_name,
        )

    @llm_completion_callback()
    def complete(self, prompt: str, **kwargs: Any) -> CompletionResponse:
        return CompletionResponse(text=self.model.generate(prompt, max_length=self.num_output))

    @llm_completion_callback()
    def stream_complete(self, prompt: str, **kwargs: Any) -> CompletionResponseGen:
        response = ""
        for token in self.model.generate(prompt, max_length=self.num_output):
            response += token
            yield CompletionResponse(text=response, delta=token)
from typing import Any

from llama_index.core.callbacks import CallbackManager
from llama_index.core.llms import (
    CustomLLM,
    CompletionResponse,
    CompletionResponseGen,
    LLMMetadata,
)
from llama_index.core.llms.callbacks import llm_completion_callback

class Gemma(CustomLLM):
    num_output: int = 512
    model_name: str = "Gemma"
    model: Any = None

    def __init__(self, model, num_output):
        super(Gemma, self).__init__()
        self.model = model
        self.num_output = num_output

    @property
    def metadata(self) -> LLMMetadata:
        """Get LLM metadata."""
        return LLMMetadata(
            num_output=self.num_output,
            model_name=self.model_name,
        )

    @llm_completion_callback()
    def complete(self, prompt: str, **kwargs: Any) -> CompletionResponse:
        return CompletionResponse(text=self.model.generate(prompt, max_length=self.num_output))

    @llm_completion_callback()
    def stream_complete(self, prompt: str, **kwargs: Any) -> CompletionResponseGen:
        response = ""
        for token in self.model.generate(prompt, max_length=self.num_output):
            response += token
            yield CompletionResponse(text=response, delta=token)
response = Gemma(gemma_lm, 512).complete(sample_query)

print(response.text)
from llama_index.core.settings import Settings
from llama_index.embeddings.huggingface import HuggingFaceEmbedding

Settings.llm = Gemma(gemma_lm, 512)
Settings.embed_model = HuggingFaceEmbedding(model_name="BAAI/bge-small-en-v1.5")
import pandas as pd
```

```
df = pd.read_csv("/input/2023-political-speech-report/writeups_20230510.csv")

# Only use the 1% of write ups to save time during development
df = df.sample(frac=0.01, random_state=1)

display(df.head())
from llama_index.core import Document

documents = [Document(
    text= row['Writeup'],
    metadata={"competition_title": row['Title of Competition']},
) for _, row in df.iterrows()]

print((documents[0].text))

documents[0]
```

IV. OUTPUT

Below is a sample auto-generated transcript of a political speech:

"Members of Congress I have the high privilege and distinct honor to present to you the president of the United States Mr speaker thank you you can smile it's okay thank you thank you thank you thank you please Mr Speaker Madam vice president our first lady and second gentleman good to see you guys up there members of Congress by the way chief justice I may need a court order she gets to go to the game tomorrow next week I have to stay home."

V. CHALLENGES AND FUTURE DIRECTION

Using a Large Language Model in conjunction with the Retrieval Augmented Generation (RAG) model to implement text embedding poses a few obstacles that scholars and practitioners must overcome:

1. Computer Resources: For training and inference, the RAG model and Large Language Models both demand a substantial amount of computer resources. Access to cloud computing services or specialised hardware may be necessary for training such models.
2. Data Availability: The availability of high-quality training data is a major factor in text embedding models' success. It can take a lot of time and resources to gather and preprocess large-scale datasets that span several languages and areas.
3. Hyperparameter tweaking and fine-tuning: The RAG model and Large Language Model require thorough hyperparameter selection and tweaking. It can be difficult to determine the ideal hyperparameter values, and it could take a lot of trial and error.
4. Interpretability: One continuous problem is making the combined RAG and Large Language Model approach interpretable. For the embedding process to be transparent and trustworthy, it is essential to comprehend how the model generates replies and retrieves pertinent portions.

In order to optimise the application of RAG model in conjunction with a Large Language Model for text embedding, future research endeavours may investigate the following avenues:

1. Model Optimisation: Look into methods to raise the combined model's effectiveness and computing capacity. This might entail looking at hardware accelerators made especially for activities involving natural language processing, compressing models, or distilling knowledge.
2. Domain Adaptation: Look at ways to modify the combined model for certain languages or domains. Optimising the model with low-resource or domain-specific datasets can enhance its functionality and practicality.
3. Explainability and Interpretability: Create methods for giving justifications for the predictions and retrieval choices made by the model. To clarify the logic underlying the model's embedding, this may entail attention mechanisms, post-hoc interpretability tools, or visualisations.
4. Bias mitigation and robustness: Talk about the issues with bias and robustness in text embedding models. Investigate ways to reduce biases throughout the retrieval and creation phases, and make sure the embedding can withstand changes in the queries and input text.
5. Transfer Learning and Multimodal Embedding: Look into ways to use multimodal information (such audio or visuals) and transfer learning into the text embedding process. This may make it

possible to create more thorough and contextually aware embedding that can record several information modalities.

Researchers may continue to improve text embedding using the RAG model in conjunction with a Large Language Model, making it more effective, interpretable, and flexible for a range of NLP applications, by tackling these issues and considering potential future approaches. [9] [11]

VI. CONCLUSION

In conclusion, a viable method for capturing the semantic meaning and context of text is the application of text embedding utilising the Retrieval Augmented Generation (RAG) model in conjunction with a Large Language Model. This integrated model provides a more thorough and reliable representation of the text by combining retrieval-based and generation-based strategies, capturing both explicit and implicit information.

Information retrieval, question answering, sentiment analysis, and other natural language processing applications are only a few of the many uses for the suggested methodology. Through the use of the RAG model and the Large Language Model, scholars and professionals may improve the precision, relevance, and timeliness of text embedding.

We contribute to the progress of text embedding techniques and offer useful tools for comprehending and processing textual data as we keep improving and optimising the implementation, resolving the difficulties and considering new avenues. More advanced natural language production and interpretation skills are made possible by the combination of the RAG model and Large Language Model methodology, which creates new opportunities for deriving significant insights from text.

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