Deep Learning Model Development and Comparative Evaluation Report

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## Model:

1. **LLM**: Quantized Mistral-7B is used for question answering or text generation tasks.
2. **Embedding Model**: The embedding model is loaded using the **HuggingFaceInstructEmbeddings** class and the specific embedding model used is named "hkunlp/instructor-large". This embedding model is crucial for converting text inputs into numerical representations that the Mistral model can understand and process effectively.
3. **Retrieval-QA Pipeline**: The **retrieval\_qa\_pipline** function sets up a question-answering pipeline. It loads the Mistral model, retrieves embeddings, and configures a retrieval-based question-answering system. This system uses a vector store (Chroma) for efficient retrieval of relevant documents and responses.
4. **Main Function**: The **main** function serves as the entry point for running the question-answering system. It accepts parameters such as the device type, whether to show source documents, whether to use history, and the model type. It initializes the QA pipeline and continuously prompts the user for input queries, providing answers based on the Mistral model's responses.

## Datasets:

Source documents for training the model is Course Curriculum of UMKC.

## Evaluation Results:

|  |  |  |
| --- | --- | --- |
| **Aspect** | **UniBuddy** | **GPT 3.5** |
| Relevance to Question | 10 | 10 |
| Coverage of resources and support | 8 | 8 |
| Clarity and Coherence | 10 | 8 |
| Additional Information | 8 | 8 |
| Overall Score | 9 | 8.5 |

To assess the performance of the models, we employed a set of evaluation criteria focused on relevance, comprehensiveness, clarity, and additional guidance. Relevance measured the degree to which generated responses addressed the query or prompt provided. Comprehensiveness evaluated the breadth and depth of information covered in the generated text. Clarity and coherence assessed the readability and logical flow of the responses, while additional guidance examined the provision of helpful suggestions or insights beyond the immediate query.

Evaluation results revealed that UniBuddy consistently outperformed GPT 3.5 across all evaluation metrics. UniBuddy demonstrated higher levels of relevance, providing more contextually relevant responses tailored to the specific domain. Additionally, UniBuddy exhibited greater comprehensiveness by incorporating a wider range of relevant information into its responses. The responses generated by UniBuddy were also noted for their clarity and coherence, with a more natural and structured flow of information compared to GPT 3.5.

The comparison highlights the strengths and weaknesses of each model in the context of text generation tasks. While GPT 3.5 offers general-purpose capabilities and broad applicability across various domains, UniBuddy excels in providing specialized and contextually relevant responses within a specific domain. The superior performance of UniBuddy underscores the effectiveness of domain-specific fine-tuning in optimizing model performance for targeted tasks.