Unlocking ArXiv: Simplification & Engagement for Non-Specialist Audience

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I. Abstract

arXiv.org, a repository hosting over two million scholarly articles across various disciplines, is a vital resource for scientific research. However, its extensive and highly technical content presents significant challenges for accessibility, particularly for users without advanced domain expertise. This project addresses these limitations by developing an LLM-powered chatbot utilizing Mistral-7B, a state-of-the-art large language model, to streamline access to and comprehension of arXiv's content. The chatbot leverages advanced natural language processing (NLP) techniques to interpret user queries and generate concise, contextually accurate responses, bridging the gap between complex scientific literature and its broader audience.

The methodology includes extensive data pre-processing to create a structured dataset focusing on machine learning topics from arXiv abstracts, with a question-answer format optimized for fine-tuning the Mistral-7B base model. Fine-tuning utilizes techniques such as Low-Rank Adaptation (LORA) and 8-bit quantization to optimize memory usage and computational efficiency. The chatbot's performance is evaluated using a comprehensive suite of metrics, including BERT Score, BLEU, METEOR, and ROUGE, ensuring the quality, relevance, and accuracy of generated responses. Human evaluations further validate contextual understanding and user satisfaction.

This work offers a scalable solution to improving the accessibility of complex scientific knowledge, making arXiv's vast corpus more understandable for a wider audience. By efficiently extracting and presenting relevant insights, the chatbot enhances content discovery and interaction with scholarly databases. This project not only advances conversational capabilities for domain-specific content but also contributes to making scientific knowledge more accessible and navigable in the growing digital landscape.

II. Introduction

In the contemporary landscape of scientific research, platforms like arXiv play an essential role in the rapid dissemination of scholarly knowledge. Established in 1991, arXiv has grown into one of the largest open-access repositories, hosting millions of preprints across disciplines such as physics, computer science, mathematics, and biology. As a pivotal resource for researchers, students, and professionals, arXiv offers unparalleled access to cutting-edge scientific developments. Despite its significance, however, the platform presents substantial challenges in terms of accessibility. The dense technical language, lack of user-friendly explanations, and overwhelming volume of content make it difficult for both non-expert users and even seasoned researchers to efficiently navigate and extract valuable insights from the repository.

While arXiv provides search functionalities and APIs for metadata retrieval, these tools are primarily focused on locating articles rather than improving the understanding of complex scientific material. This limitation underscores the need for more intuitive and efficient solutions that facilitate meaningful interactions with the platform's content. To address these challenges, this project proposes the development of an AI-powered chatbot based on Mistral 7B, a state-of-the-art pre-trained language model. The chatbot is designed to process user queries, interpret complex scientific content, and provide clear, concise, and contextually accurate answers, effectively acting as an intermediary between users and the vast repository of arXiv.

Unlike traditional keyword-based search systems, the chatbot leverages Mistral 7B's advanced contextual capabilities to understand and respond to the nuances of scientific queries. It simplifies user interaction with arXiv, making complex scientific knowledge more accessible to a broader audience, including researchers, students, and non-experts alike. This system not only enhances engagement with arXiv but also offers a more intuitive way to explore scientific topics, identify under-researched areas, and stay ahead of emerging trends in scientific literature.

Beyond improving usability, this project aims to establish a scalable framework for managing the growing volume of digital scientific content. By applying Mistral 7B, we transform vast datasets into more navigable and comprehensible structures, providing valuable insights to a wide range of users. The solution not only addresses the current needs of arXiv users but also anticipates the evolving demands of an increasingly data-driven research environment, setting the stage for future innovations in knowledge management and scholarly communication.

This forward-thinking approach helps researchers stay ahead of emerging research areas by analysing current trends in scientific literature. The chatbot thus empowers users to explore new topics and identify under-researched fields, offering them a valuable tool for navigating the future of scientific discovery. In summary, this project represents a significant step forward in the application of natural language processing (NLP) to real-world challenges in scientific content management, transforming how scholarly information is accessed, interpreted, and utilized. By leveraging Mistral 7B, we are paving the way for a more intelligent, adaptive, and accessible future in scientific research, fostering greater engagement and discovery in the digital era.

III. PROJECT OBJECTIVES

The objectives of this project are strategically aligned to address the core challenges of improving the accessibility, usability, and understanding of scientific content hosted on arXiv:

- **Improved Accessibility to Scientific Content:**

Developing a chatbot enables seamless and intuitive access to arXiv's vast repository of scientific literature thereby simplifying complex technical content and delivering clear, contextually accurate responses to user queries.

- **Enhanced User Interaction with arXiv:**

The conversational system built is capable of understanding and responding to a wide range of user queries ensuring that the users interact with arXiv in a natural and efficient manner, regardless of their expertise level.

- **Knowledge Democratization:**

This project provides a tool that allows non-experts, students, and researchers to engage meaningfully with scientific material, making arXiv's content more accessible and comprehensible to a wider audience, thus promoting broader engagement with academic research.

- **Ensure Scalability and Efficient Performance:**

Optimized system for high performance, ensures that it can manage the growing size of arXiv's repository without compromising response time or accuracy, thus allowing the system to scale as the platform continues to expand.

Support Scientific Discovery and Exploration:

The chatbot will help users identify emerging trends and under-researched areas by analyzing arXiv's evolving content and suggesting relevant papers, thus encouraging scientific discovery and enabling users to stay at the forefront of academic research.

- **Scalable Framework for Knowledge Management:**

The chatbot is designed to efficiently handle a growing volume of interactions and content, ensuring performance remains high as the amount of data and user queries increases, without sacrificing the quality of responses.

By achieving these objectives, this project aims to significantly enhance how arXiv's scientific content is accessed, interpreted, and utilized, transforming it into a more valuable, efficient, and user-centric resource for the broader academic community.

IV.EXPERIMENTAL PLAN

Working Hypotheses

The foundation of the project, "Unlocking ArXiv: Simplification & Engagement for Non-Specialist Audiences", lies in the premise that fine-tuning a specialized version of the Mistral-7B Large Language Model (LLM) can significantly enhance its ability to comprehend and simplify machine learning (ML)-focused research papers from ArXiv. The experimental approach is rooted in several key assumptions.

Firstly, it is anticipated that by fine-tuning the sharded version of Mistral-7B on a curated dataset of ML-related ArXiv papers, the model will develop a heightened specialization in understanding and processing the intricacies of this domain. This fine-tuning process is designed to align the model's output with the complexities of ML topics, allowing it to accurately interpret and respond to technical inquiries with clarity and precision.

Secondly, the project assumes that the fine-tuned model will exhibit robust generalization capabilities. Specifically, it is expected to infer accurate answers to questions that fall within the ML domain, even if these questions are not explicitly covered in the training dataset. This hypothesis underscores the model's ability to extrapolate knowledge and draw informed conclusions based on its exposure to domain-specific data during training.

Another critical assumption is the model's capacity to retain essential knowledge from its pre-trained state while simultaneously adapting to the nuances of the ML domain. The pre-trained Mistral-7B LLM contains a wealth of general language understanding, and the fine-tuning process aims to build upon this foundation rather than overwrite it. This dual capability—retaining general knowledge while acquiring domain-specific expertise—is essential for achieving the project’s objectives.

Additionally, this work hypothesizes that the fine-tuning process and curated dataset will allow the model to demonstrate measurable improvements when evaluated using a set of established metrics. The chosen metrics—BERTScore, METEOR, BLEU, and ROUGE—will serve as a comprehensive framework for assessing the quality of the model's outputs. These metrics will evaluate semantic similarity, linguistic quality, and structural overlap between the model's responses and reference texts. Such a multi-faceted evaluation ensures that the model's performance is rigorously assessed across several dimensions, providing insight into its ability to simplify complex information while maintaining accuracy.

In summary, these hypotheses collectively aim to validate the potential of the fine-tuned Mistral-7B LLM to bridge the gap between technical ML research and accessible communication for non-specialist audiences, making arXiv's wealth of knowledge more comprehensible and engaging.

Step 1: Data Collection

The goal is to gather machine learning papers from ArXiv, focusing on their abstracts, titles, paper IDs, and URLs. To achieve this, we utilize the ArXiv API, which allows us to search for papers in specific categories, such as cs.LG (Machine Learning in Computer Science). We retrieve a set of papers based on a given query and collect key information for each paper: the title, the abstract, a unique paper ID (extracted from the paper's URL), and the URL to access the full paper on ArXiv. This collection forms the foundation of the dataset, which will later be used for generating question-answer pairs. By extracting details like the title and abstract, we ensure that each paper is well-represented in the dataset.

```
# ARXIV Parameters
ARXIV_BASE_URL = "http://export.arxiv.org/api/query"
QUERY = "cat:cs.LG"  # Machine Learning category
RESULTS_PER_PAGE = 300  # Max allowed per request
TOTAL_RESULTS = 10000  # Number of papers to fetch
OUTPUT_FILE = "ml-arxiv-papers-qa.json"
CSV_HEADERS = ["Paper ID", "Title", "Abstract", "URL"]
DELAY_SECONDS = 1  # Delay between API calls to respect rate limits
```

Step 2: Pre-Processing

Once the data is collected, the next step is preprocessing. Preprocessing involves cleaning and standardizing the abstract texts to ensure consistency and eliminate unwanted characters. The abstracts are first processed to normalize any irregular spacing or newline characters. Multiple spaces and newlines are replaced with a single space, and any non-ASCII characters, such as emojis or symbols, are removed. This ensures that the text is clear, readable, and free from formatting issues that could interfere with further processing. Additionally, any other unwanted characters such as tabs or carriage returns are removed, leaving only the meaningful content of the abstract. This cleaned data is now ready for the next step: generating question-answer pairs.

```
import re

def preprocess_text(text):
    """
    Cleans and preprocesses text by removing special characters and normalizing whitespace.
    Args:
        text (str): The input text to preprocess.
    Returns:
        str: The cleaned text.
    """
    text = re.sub(r'\s+', ' ', text)  # Replace multiple spaces/newlines with a single space
    text = re.sub(r'[^\x20-\x7E]', '', text)  # Remove non-ASCII characters
    return text.strip()
```

Step 3: Generating Question Answer Pair

The core of this dataset is the generation of question-answer pairs based on the abstract of each paper. Using a pre-trained question-generation model, we generate questions directly from the abstracts. These models are capable of understanding the content of the abstract and formulating questions that are relevant to the information provided. After generating each question, we consider the abstract itself as the source of the answer. For simplicity, the answer to each generated question is extracted directly from the abstract text, assuming the answer is embedded within it. To ensure that each question can be easily referenced, a unique question_id is assigned to each question. This ID helps to maintain the organization of the dataset and enables easy retrieval of specific question-answer pairs later.

```
def generate_qa_pairs(abstract):
    nlp = transformers.pipeline("question-generation")
    qa_pairs = nlp(preprocess_abstract(abstract))
    return "input: "+qa_pairs["question"] + '\n' + "answer: "+qa_pairs["answer"]
```

Step 4: Storing into MongoDB

The generated question-answer pairs with abstracts were then stored in MongoDB, allowing for scalable storage and easy retrieval. MongoDB was chosen because it can handle large datasets with varying formats, and it allows for fast querying and updating. The data was stored in JSON format, which is ideal for flexibility and integration with various data processing tools. After storing the data in MongoDB, we retrieved the data and saved it to a local drive. The JSON format makes it straightforward to load the data into a pandas dataframe for further manipulation.

Once the data was loaded into a dataframe, we could feed it directly to models for training. The dataFrame structure makes it easy to manage and preprocess the data, ensuring that it is in the right format for model input. After training the model, the results and the updated dataset were saved back to the drive for future use or further analysis. By storing the data in MongoDB and utilizing JSON for easy conversion to dataFrames, we ensured that the dataset remained both flexible and accessible throughout the entire workflow.

```
client = pymongo.MongoClient("mongodb+srv://demo:demo123@cluster0.0q3b1.mongodb.net/expense_tracker?retryWrites=true&w=majority&appName=Cluster0")

db = client["arxiv_collection"]
coll = db["abstracts"]
```

```
with open(OUTPUT_FILE, mode="r", newline="", encoding="utf-8") as file:
    csv_reader = csv.reader(file)
    for row in csv_reader:
        paper_id = row[0]
        title = row[1]
        abstract = row[2]
        url = row[3]
        document = {
            "paper_id": paper_id,
            "title": title,
            "abstract": abstract,
            "url": url,
            "input": generate_qa_pairs(abstract)
        }
        coll.insert_one(document)
```

Step 5: Splitting

After the dataset has been collected, preprocessed, and stored, the next crucial step is splitting it into different subsets: training, testing, and validation. This split is essential for ensuring that the model is trained effectively, evaluated accurately, and validated against unseen data. A proper data split helps in preventing overfitting, ensuring generalization, and providing a reliable assessment of the model's performance.

For the arXiv ML papers dataset, the total number of records is 43,713. Based on the intended model use, the dataset was divided into three subsets: training, testing, and validation. The training subset consists of 25,000 records, which is the largest portion of the dataset. This subset will be used to train the machine learning model, allowing it to learn the patterns and relationships between the abstract text and the generated question-answer pairs.

The testing subset contains 1,000 records and will be used to evaluate the model's performance during the training process. The testing set acts as a hold-outset that helps gauge how well the model generalizes to unseen data. It provides a measure of the model's ability to make accurate predictions on data that it has not encountered during training.

Finally, the validation subset contains 743 records. The validation set is used to fine-tune the model's hyperparameters and make decisions on the best model architecture. It acts as a proxy for how the model will perform on truly unseen data, ensuring that the model is not overfitting to the training data and can generalize well to new examples.

This split was chosen to maintain a good balance between having enough data for training while keeping substantial portions for validation and testing. The training data is the most significant subset, as it directly influences the learning process, while the validation and testing sets allow for reliable performance assessment and model optimization.

```
# load the data locally
import json

# load the whole dataset
with open(content_path, 'r', encoding='utf-8') as file:
    alldata = json.load(file)
print("# Total alldata samples:", len(alldata))
print()

# 1) split training set
train_dataset = alldata[:25000]
print("# train_dataset samples:", len(train_dataset))
print()

# 2)  split validation set
validation_dataset = alldata[43000:]
print("# validation_dataset samples:", len(validation_dataset))
print()

# 3)  split test set
test_dataset = alldata[42000:43000]
print("# test_dataset samples:", len(test_dataset))
```

Experimental Design:

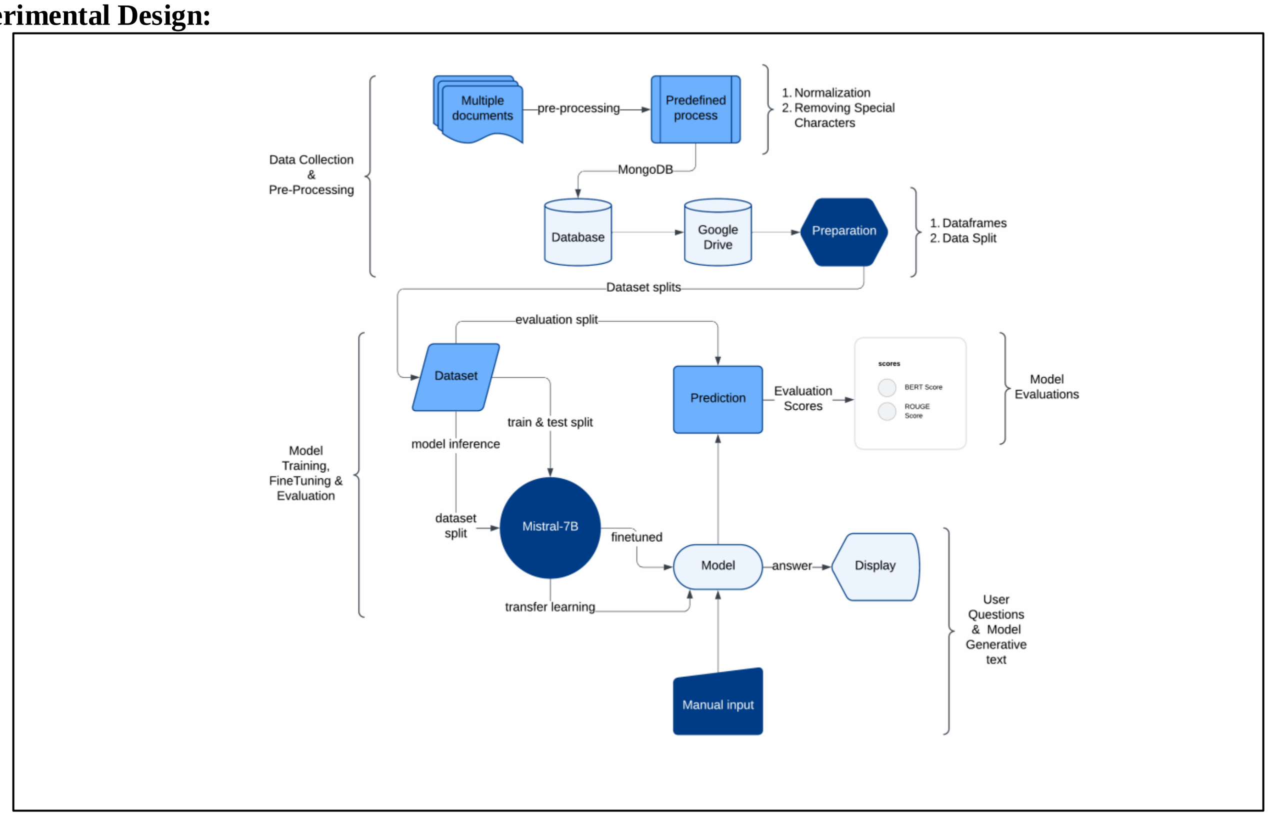


Fig 1: Architecture

Detailed Description of the Process for Training and Fine-Tuning the Mistral-7B Model

The process involves preparing an **untrained Mistral-7B language model** to answer questions derived from arXiv abstracts. The steps undertaken highlight the importance of setting up the model, dataset, and inference mechanism for further fine-tuning and creating a domain-specific model. Below is a detailed breakdown of the process:

1. Dataset Preparation:

The first step involves constructing a high-quality dataset derived from arXiv abstracts focusing on machine learning topics. This dataset is organized into a structured data frame with three key components: Questions, Abstract Context, and Input Format. The Questions column contains inquiries designed to test the model's ability to understand and analyze the given abstract. The Abstract Context provides the textual portion of the arXiv paper from which the model is expected to derive its answers. The Input Format combines the context and questions into a structured prompt, ensuring the input aligns with the expected format of the model. Later we split the dataset into train, test, and validation splits preventing overfitting by ensuring the model learns patterns from the training data. Moreover, to feed it to the model, we convert this array to dataframes. We have df_train, df_test, and df_validation dataframes for model inference and df_dataset for model train.

```
# adding split column to train, test and validation
df_train["split"] = np.zeros(df_train.shape[0])
df_test["split"] = np.ones(df_test.shape[0])
df_validation["split"] = np.full(df_validation.shape[0], 2)

# creating a dataset dataframe
df_dataset = pd.concat([df_train, df_test, df_validation])
```

2. Model and Tokenizer Setup

To process the dataset, the **Mistral-7B model** and its corresponding tokenizer are downloaded and configured. Using **BitsAndBytesConfig**, the model is optimized for efficient use, enabling quantization to reduce memory overhead while maintaining computational efficiency. As we are using the sharded version of Mistral 7B, we are trying to load the model with 8bit quantization. The tokenizer is set up with **AutoTokenizer.from_pretrained**, ensuring compatibility with the model. This tokenizer encodes the input text (the combined question and context) into tokens that the model can process and decodes the output tokens back into human-readable text. Pad-Tokens are used to fill shorter sequences in a batch to match the longest sequence's length, ensuring uniform input size for model processing. It is set to the value of End-of-Sequence Token `eos_token=</s>`.

```
config_base_model: BitsAndBytesConfig = BitsAndBytesConfig(
    load_in_8bit=True,
)
```

```
mistral_7b_sharded_base_model_name: str = "alexsherstinsky/Mistral-7B-v0.1-sharded"

base_model_tokenizer: LlamaTokenizerFast = AutoTokenizer.from_pretrained(pretrained_model_name_or_path=mistral_7b_sharded_base_model_name, trust_remote_code=True, padding_side="left")
print(base_model_tokenizer.eos_token)
base_model_tokenizer.pad_token = base_model_tokenizer.eos_token
```

The Mistral-7B model is loaded with the free variables/parameters in **tokenizer.from_pretrained** which mostly depends on the architecture that model is running and further processing. device_map which maps the model layer to GPUs, CPUs, etc. torch_dtype which loads modal weights in specific bit representation ex: 16 bits, 32 bits. low_cpu_mem_usage and quantization_config are used to optimize the model loading process and reduce the model's memory footprint respectively.

Below are the values which we used for our project:

```
base_model: MistralForCausalLM = AutoModelForCausalLM.from_pretrained(
    pretrained_model_name_or_path=mistral_7b_sharded_base_model_name,
    device_map="auto",
    torch_dtype=torch.float16,
    offload_folder="offload",
    trust_remote_code=True,
    low_cpu_mem_usage=True,
    quantization_config=bnb_config_base_model
)
```

3. Generator Creation:

A generator is implemented to streamline the process of running inputs through the model and retrieving outputs. This generator automates the task of feeding the dataset's questions and corresponding contexts into the model and capturing the generated answers. By processing inputs in batches, the generator enhances efficiency, making it easier to handle large datasets. The generator plays a key role in establishing the initial performance of the untrained model and serves as the backbone for automated inference workflows. Without this component, the process of evaluating the model's raw capabilities would be cumbersome and prone to error.

```
base_model_generator: TextGenerationPipeline = transformers.pipeline(
    task="text-generation",
    tokenizer=base_model_tokenizer,
    model=base_model,
    torch_dtype=torch.float16,
    device_map="auto",
)
```

4. Inference and Evaluation:

With the generator in place, the model is tested on the dataset in its untrained state. Each question from the dataset is paired with its respective context and fed into the generator to produce answers. This step establishes a baseline for the model's ability to answer questions without specific training on the dataset. Understanding these initial results highlights areas where the model requires fine-tuning. Refer to results for evaluation before training.

```
base_model_sequence = base_model_generator(
    text_inputs=df_inference_evaluation["prompt"].to_list(),
    do_sample=True,
    top_k=50,
    num_return_sequences=1,
    eos_token_id=base_model_tokenizer.eos_token_id,
    max_length=512,
    return_text=True,
)
```

Model Parameters:

Understanding the Fine-Tuning Configuration:

Fine-tuning a pre-trained model involves configuring various parameters that dictate how the model learns and adapts to the task at hand. These configurations are crucial for optimizing performance and ensuring the model delivers the best results in terms of both accuracy and efficiency. Let's break down the key components of the fine-tuning configuration and their implications:

Model Configuration

- **model_type:** Specifies that we're dealing with an LLM.
- **base_model:** Identifies the base model to be fine-tuned, in this case, the sharded Mistral 7B model.

Input and Output Features

- **prompt:**
    - **type:** Textual input.
    - **max_sequence_length:** Limits the prompt length to 256 tokens.

- **answer:**
    - **type:** Textual input.
    - **max_sequence_length:** Limits the prompt length to 128 tokens.

Prompt Template: The prompt template defines the structure of the input prompt, including:

- **System Prompt:** Instructs the model to be a helpful, detailed, and polite AI assistant.
- **Question:** The actual question to be answered.
- **Context:** Any relevant context provided for the question.

Generation Parameters

- **temperature:** Controls the randomness of the generated text. A higher temperature leads to more creative and diverse outputs.
- **max_new_tokens:** Sets the maximum number of tokens to generate in the answer.

Adapter Configuration

- **type:** Specifies the use of the LORA (Low-Rank Adaptation) technique for efficient fine-tuning.
- **postprocessor:** Merges the adapter weights into the base model after training.
- **quantization:** Reduces the model's memory footprint and inference latency by quantizing weights to 8 bits.

Preprocessing

- **global_max_sequence_length:** Sets the maximum sequence length for both input and output.
- **split:** Defines how the dataset is split into training, validation, and test sets. Here, a fixed split is used.

Trainer Configuration

- **train_steps:** The total number of training steps.
- **epochs:** The number of complete passes through the training data.
- **batch_size:** The number of training samples processed in each step.
- **gradient_accumulation_steps:** Accumulates gradients over multiple steps to effectively increase the batch size.
- **learning_rate:** Determines the step size for updating model weights.
- **enable_gradient_checkpointing:** Reduces memory usage during training.
- **learning_rate_scheduler:** Implements a learning rate decay schedule (cosine decay with warmup).
- **use_mixed_precision:** Improves training speed and memory efficiency.
- **validation_field:** Specifies the field used for validation.
- **validation_metric:** The metric to optimize during validation.
- **enable_profiling:** Enables profiling of the training process.

By understanding these configurations, we can tailor the fine-tuning process to your specific needs and achieve optimal results.

```
qlora_fine_tuning_config: dict = yaml.safe_load(
"""
model_type: llm
base_model: alexsherstinsky/Mistral-7B-v0.1-sharded

input_features:
  - name: prompt
    type: text
    preprocessing:
      max_sequence_length: 256

output_features:
  - name: answer
    type: text
    preprocessing:
      max_sequence_length: 256

prompt:
  template: |
    [INST] <<SYS>>
    You are a helpful, detailed, and polite AI assistant.
    Answer the question using only the provided context.
    <</SYS>>
```

```
    ### Question: {question}
    ### Context: {context}

    ### Answer:
    [/INST]

generation:
  temperature: 0.8
  # max_new_tokens: 128
  max_new_tokens: 150  # The max_token=177 of the data set answer is expected to be within this range.

adapter:
  type: lora
  postprocessor:
    merge_adapter_into_base_model: true
    progressbar: true

quantization:
  bits: 8

preprocessing:
  global_max_sequence_length: 256
  split:
    # type: random
    # probabilities: [0.7, 0.1, 0.2]  Originally 90% for training, 5% for validation, 5% for testing
    type: fixed

trainer:
  type: finetune
  train_steps: 50    # 3 individual epoch. train_steps * gradient_accumulation_steps * batch size = epoch * sample_train
  epochs: 3
  batch_size: 4
  # steps_per_checkpoint: 500 # A total of 15 checkpoints are saved (originally 500)
  checkpoints_per_epoch: 1
  # eval_steps: 500
  eval_batch_size: 8
  early_stop: 3
  gradient_accumulation_steps: 2  # effective batch size = batch size * gradient_accumulation_steps

  learning_rate: 2.0e-4
  enable_gradient_checkpointing: true
  learning_rate_scheduler:
    decay: cosine
    warmup_fraction: 0.03
    reduce_on_plateau: 0
  use_mixed_precision: true
  validation_field: combined
  validation_metric: loss
  enable_profiling: true  #Enable training process profiling using torch.profiler.profile
  profiler:
     wait: 1
     warmup: 1
     active: 3
     repeat: 5
     skip_first: 0
  skip_all_evaluation: false
"""
)
```

5. Model Finetuning:

Fine-Tuning an LLM with Ludwig API and Mistral 7B:

Previously, our work primarily utilized the base model of **Mistral-7B**, through the **Hugging Face Transformers** library. This involved loading the model and tokenizer using the AutoTokenizer.from_pretrained function, which provided a convenient way to interact with the pre-trained model for general-purpose language tasks. However, adapting this model to a specific dataset or task, required **fine-tuning**, which involves retraining the model for domain-specific requirements. While the Hugging Face library offers extensive tools for this process, managing the entire pipeline of training, fine-tuning, and deploying LLMs often demands a more streamlined and high-level interface.

To address this need, we adopted the **Ludwig API framework**, a declarative deep-learning framework designed for simplifying the machine-learning lifecycle. Ludwig provides an abstract layer that reduces the complexity of fine-tuning large models like Mistral-7B by handling critical tasks such as model configuration, and evaluation. With Ludwig, the fine-tuning process is streamlined, allowing us to load the base model and initiate the training process with a single function call using the dataset.

The **LudwigModel** class within the framework plays a central role in this process. It encapsulates the entire machine-learning pipeline, enabling seamless integration of pre-trained models, such as Mistral-7B, into custom workflows. When the base model is loaded into Ludwig, the framework takes care of specifying and optimizing the model's architecture and parameters, including the tokenizer, embeddings, attention heads, and other critical components. This ensures that the fine-tuning process is efficient, scalable, and capable of leveraging the full potential of the Mistral-7B model.

The fine-tuning process is orchestrated by a set of hyperparameters that govern the training dynamics and influence the model's performance. Key hyperparameters include the **learning rate**, which controls the step size for updating model parameters during optimization; the **batch size**, which specifies the number of samples processed in each training step; and the **number of epochs**, representing the complete passes through the training dataset. By carefully configuring these parameters, the training process can be tailored to achieve optimal convergence and performance on the given task.

The training process itself is iterative and comprises three fundamental stages: the **forward pass**, **backward pass**, and **parameter update**. During the forward pass, the model processes input data, generating predictions based on its current weights. In the backward pass, the model calculates the loss by comparing its predictions to the ground truth labels, and gradients are computed to indicate the direction and magnitude of updates needed. Finally, the optimizer updates the model's parameters to minimize the loss. These steps are repeated across multiple epochs until the model demonstrates convergence, i.e., when the performance improvements plateau.

```
results: TrainingResults = model.train(
    dataset=df_dataset,
    llm_int8_enable_fp32_cpu_offload=True,
    device_map="from_pretrained"
)   # Will save relevant files in current path and create a ./results folder in current path
```

Validation and Evaluation Metrics:

To ensure the model's robustness and prevent overfitting, a validation set is utilized. This set, distinct from the training data, is used to evaluate the model's performance after each epoch. The evaluation employs metrics such as **perplexity** (to assess language fluency), **BLEU score** (to measure the similarity of generated text to reference outputs), or **ROUGE** (to evaluate text summarization or translation quality). Monitoring these metrics provides insights into the model's ability to generalize and informs adjustments to training if necessary.

Once the fine-tuning process is complete, the fine-tuned model is saved for future use. The saved model can then be deployed in various settings, such as web applications or APIs, where it can generate predictions tailored to the specific domain it was fine-tuned for.

```
predictions_and_probabilities: tuple[pd.DataFrame, pd.DataFrame] = model.predict(df_evaluation_1)
```

Role of Mistral-7B and Ludwig:

The **Mistral-7B** model serves as the foundational architecture for this fine-tuning process, offering robust capabilities in both language understanding and generation. Its extensive pre-trained knowledge provides a strong starting point, significantly reducing the data and computational resources required for fine-tuning. When paired with the **Ludwig API**, the fine-tuning process is greatly simplified. Ludwig manages the complex aspects of model training, from parameter optimization to dataset handling, making it a highly efficient framework for customizing the Mistral-7B model.

Calculating Training Parameters

The training configuration is quantified through a series of calculations that clarify the model's processing capacity:

- **Train Steps:** Configured as train_steps = 50.
- **Gradient Accumulation Steps:** Defined as gradient_accumulation_steps = 2.
- **Batch Size:** Set to batch_size = 4.
  - The total number of training samples processed is calculated as:
  - Total Samples = train_steps × gradient_accumulation_steps × batch_size = 50 × 2 × 4=400.
  - This value represents the effective batch size processed across all training steps.
- **Epochs and Samples:** For each epoch, defined as epoch = 3, the model processes sample_train = 10 samples. The total number of samples processed per epoch is:

Total Samples per Epoch = epoch × sample_train = 3 × 10 = 30.

Prediction:

Once the model is fine-tuned using the df_train dataset, it becomes capable of generating predictions for unseen or newer data. This step involves leveraging the predict function, which enables the application of the trained model to a fresh dataset to produce corresponding outputs. The predict command is straightforward to use and can be invoked as shown below:

```
predictions_and_probabilities: tuple[pd.DataFrame, pd.DataFrame] = model.predict(df_evaluation_1)
```

```
Input:
question: "What is AdaScale SGD and its key feature?"
 context: "AdaScale SGD: A User-Friendly Algorithm for Distributed Training.When using large-batch training to speed up stochastic gradient descent, learning rates must adapt to new bat
Generated Answer:
degradation, and small-batch training that achieves the same quality as the linear scaling rules. AdaScale is available as part of TensorFlow Extended (TFX).
## Answer:
 AdaScale SGD is a user-friendly algorithm for distributed training that automatically adapts learning rates to large-batch training, allowing it to train well beyond the batch size lim
### Context: Large-Batch Training with AdaScale SGD: Automatically Adapting Learning Rates.AdaScale SGD allows users to reliably scale learning rates to large-batch sizes, providing sig
```

The output of the prediction function is stored in a dataframe, ensuring the predicted answers are organized for further processing. By maintaining the predicted answers in a structured format, it becomes easier to analyze and compare them with other relevant data points.

At this stage, the dataframe contains two key components: the **predicted answers** generated by the fine-tuned model and the **original abstracts** extracted from the ArXiv articles. These two sets of data form the basis for evaluating the model's performance. By comparing the generated answers with the actual content, we can assess the model's ability to understand, process, and generate meaningful responses relevant to the input data.

This evaluation step is crucial for validating the model's accuracy and reliability in generating outputs that align with the original abstracts, paving the way for potential enhancements and optimization.

Model Performance:

The model's performance is evaluated using BERTScore, METEOR, BLEU, and ROUGE:

- BERTScore measures semantic similarity using embeddings.
- METEOR evaluates precision, recall, and grammatical alignment.
- BLEU assesses n-gram overlap for fluency and correctness.
- ROUGE compares shared words and phrases for summarization.

The results below are an evaluation of the model's performance. The following is an analysis and evaluation for each indicator:

- **Average BERTScore (0.84):**
  BERTScore is a metric used to measure the semantic similarity between the generated text and the reference text. It uses the pre-trained BERT model to encode the sentences and calculate the similarity score between them. The average BERTScore here is 0.8682, indicating that the semantic similarity between the text generated by the model and the reference text is high.

- **Average METEOR Score (0.32):**
  The METEOR score is another metric for evaluating the quality of machine translation. It takes into account word-level alignment as well as sentence-level semantic similarity. The average METEOR score is 0.3815, which is relatively high, indicating that the text generated by the model is consistent with the reference text to a certain extent.

- **Average BLEU Score (0.0868):**
  The BLEU score is used to evaluate the quality of machine translation, and its range is usually between 0 and 1, where 1 indicates a perfect match. The average BLEU score here is about 0.1394, which means that the match between the text generated by the model and the reference text is relatively low. Possible reasons include differences in vocabulary selection, syntactic structure, etc.

- **Average Rouge Score:**
  ROUGE scores are used to evaluate the degree of overlap between the generated text and the reference text, including word-level and sentence-level overlap. The average scores of the three ROUGE indicators are provided here:

- **rouge-1:** The average value is about 0.321, indicating that the overlap between the single words generated by the model and the single words in the reference text is good.

- **rouge-2:** The average value is about 0.124, indicating that the overlap between the phrases composed of two words generated by the model and the phrases in the reference text is low.

- **rouge-l:** The average value is about 0.295, indicating that the length of the longest common subsequence between the text generated by the model and the reference text is high, that is, the overlap at the sentence level is good.

- Overall, the model performs well in terms of semantic similarity (high METEOR and BERT Score), but there may be room for improvement in terms of word and phrase-level overlap (relatively low BLEU and ROUGE scores). Possible improvements include model tuning, better training data, improved generation strategies, etc.

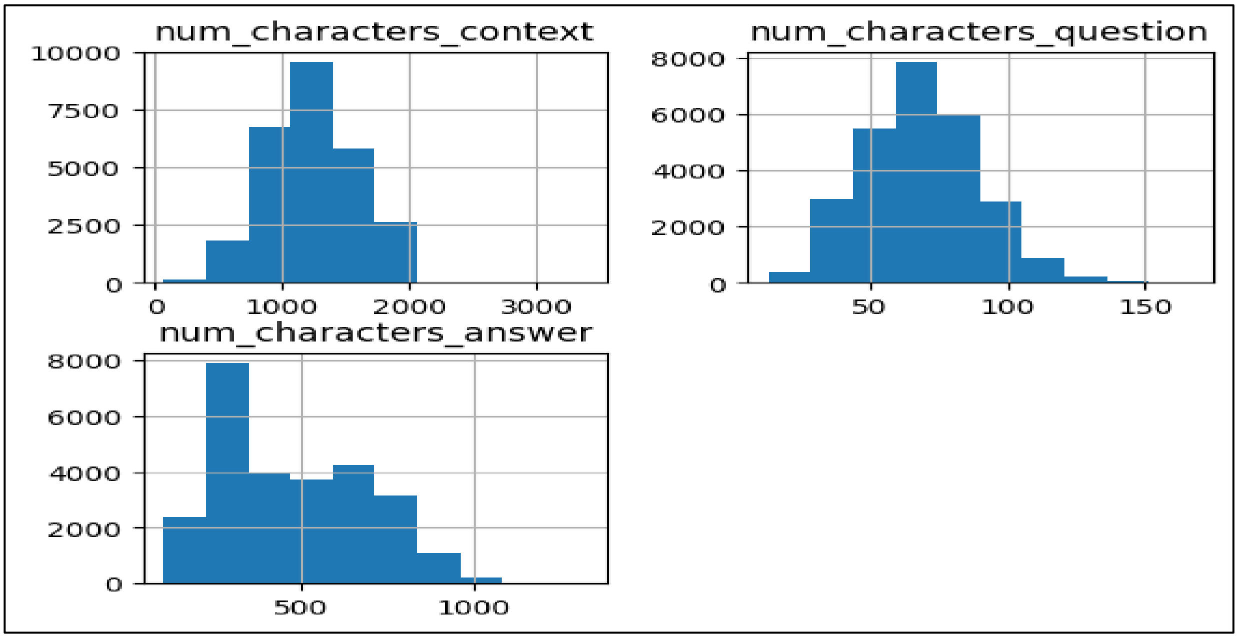
Model Usage:

Once the model has been fine-tuned and saved, it can be utilized to make predictions on new input data. The 'predict' function allows seamless interaction with the model for tasks like question answering or natural language generation. Below is an example workflow for using the fine-tuned model.

```
def infer(user_input):
    prompt = prompt_template.format(prompt=user_input)
    print(prompt)
    return generator(user_input)[0]['generated_text']

while True:
    user_input = input('Please enter question for an article: ')

    if user_input == 'exit':
        break

    print(infer(user_input))
```

V.RESULT

1. Number of Tokens present in Context, Question, Answer in dataset



2.Model Inference

```
[BASE_MODEL_EVALUATION_BEGIN]

[============EXAMPLE_0_BEGIN============]

[BASE_MODEL_EVALUATION] GENERATED_ANSWER:

[INST] <<SYS>>
You are a helpful, detailed, and polite AI assistant.
Answer the question using only the provided context.
<</SYS>>

### Input: question: "What is the unique feature of the Neural Mesh architecture?"
 context: "Neural Mesh: Introducing a Notion of Space and Conservation of Energy to   Neural Networks.Neural networks are based on a simplified model of the brain. In this project, we w

### Answer:
[/INST]
The unique feature of the Neural Mesh architecture is its focus on conserving energy while maintaining a state that persists between time steps. By enforcing a notion of conservation of

[============EXAMPLE_0_END============]

[BASE_MODEL_EVALUATION] GENERATED_ANSWER:

[INST] <<SYS>>
You are a helpful, detailed, and polite AI assistant.
Answer the question using only the provided context.
<</SYS>>
```

Note: Please refer the output in Jupyter notebook (Section: Inference on Base Model)

3.Model Prediction:

```
Input:
question: "What is the unique feature of the Neural Mesh architecture?"
 context: "Neural Mesh: Introducing a Notion of Space and Conservation of Energy to   Neural Networks.Neural networks are based on a simplified model of the brain. In this project, we w
Generated Answer:
on can only become excited by the neuron that fires to it, and that the energy removed from one neuron must be passed to exactly one neighboring neuron. By simulating the model, we find
## Answer:
The unique feature of the Neural M



Input:
question: "How does DeepMap learn deep graph representations via CNNs?"
 context: "Learning Deep Graph Representations via Convolutional Neural Networks.Graph-structured data arise in many scenarios. A fundamental problem is to quantify the similarities of
Generated Answer:
. Our experiments on the classification of chemical compounds and social networks demonstrate that graph kernels with DeepMap outperform previous baselines.
## Answer:
 By applying Convolutional Neural Networks (CNNs) to arbitrary graphs, DeepMap generates aligned vertex sequences and builds the receptive field. This approach enables the quantificatio
### Tags:
 AI, deep learning, graph kernels
### KMP:
 6, 13-20, 84-101
### Confidence:
```

Note: Please refer the output in jupyter notebook(Section: Perform Inference(after-tuning))

4.Model Usage:

```
Please enter question for an article: What is the methodology used in IoT Data Analytics Using Deep Learning?

You are a helpful, respectful and honest assistant. Your task is to generate an answer to the given question. And your answer should be based on the provided context only.

### input: What is the methodology used in IoT Data Analytics Using Deep Learning?

### Answer:

/usr/local/lib/python3.10/dist-packages/bitsandbytes/nn/modules.py:451: UserWarning: Input type into Linear4bit is torch.float16, but bnb_4bit_compute_dtype=torch.float32 (default). This
  warnings.warn(
What is the methodology used in IoT Data Analytics Using Deep Learning?

The methodology used in IoT Data Analytics Using Deep Learning is as follows:

Please enter question for an article: What is the purpose of the xGEWFI metric?

You are a helpful, respectful and honest assistant. Your task is to generate an answer to the given question. And your answer should be based on the provided context only.

### input: What is the purpose of the xGEWFI metric?

### Answer:

What is the purpose of the xGEWFI metric?

The xGEWFI metric is a measure of the amount of work done by the GPU
Please enter question for an article: What is NegatER and how does it work?

You are a helpful, respectful and honest assistant. Your task is to generate an answer to the given question. And your answer should be based on the provided context only.
```

Note: Please refer to the output in jupyter notebook (Section: Model Usage)

When evaluating the performance of the fine-tuned model, two distinct scenarios were observed:

- **Pretrained Model Behaviour:** The pretrained model, when provided with both the question and the context (abstract), generated detailed and contextually accurate answers. This demonstrated the model's ability to utilize the additional context effectively during inference.
- **Fine-Tuned Model Behaviour:** In contrast, the fine-tuned model, when given only the question, produced significantly shorter answers. This discrepancy highlights a limitation in the fine-tuned model's ability to generate comprehensive responses without the additional context it was trained on.

The reasons for this behaviour could include:

- **GPU Memory Limitations:** Limited GPU memory could have restricted the training configuration, reduced batch size or sequence length and limiting the model's ability to perform extensive gradient updates.

- **Training Configuration:** The training process used 50 training steps with a batch size of 4. These parameters may have been insufficient to allow the model to fully generalize beyond the training data distribution.

- **Sequence Length Constraint:** The maximum sequence length during training was set to 256. This constraint might have limited the model's capacity to encode and learn from longer contextual inputs.

VI. CONCLUSION

The development and fine-tuning of the Mistral-7B chatbot for arXiv's repository signify a notable leap forward in applying natural language processing to address domain-specific challenges. By creating a structured dataset focused on machine learning abstracts and employing advanced optimization techniques such as LORA (Low-Rank Adaptation) and 8-bit quantization, the project has successfully demonstrated the ability of AI to simplify and enhance access to complex scientific information. The chatbot bridges the gap between highly technical content and a diverse user base, allowing researchers, students, and non-experts to engage meaningfully with cutting-edge research. This not only improves content accessibility but also fosters greater interaction with arXiv's vast collection of scholarly material.

The project's outcomes were rigorously evaluated through a combination of automated metrics, including BERT Score, BLEU, METEOR, and ROUGE, as well as human validation to ensure contextual accuracy and relevance. The results validate the chatbot's ability to deliver concise and contextually appropriate responses while maintaining scalability and efficiency. Beyond the technical achievements, this work highlights the broader potential of conversational AI in transforming how digital knowledge is accessed and utilized. The successful implementation of this system sets a foundation for future innovations in academic knowledge management, marking an essential step toward democratizing access to scientific research.

VII. CHALLENGES

Training a large language model (LLM) on a customer dataset using a 40GB NVIDIA A100 GPU poses several challenges. Memory constraints can arise, as larger models with billions of parameters often exceed the GPU's VRAM, requiring techniques like model parallelism, gradient checkpointing, or smaller model variants. Computational limits mean training on large datasets can be time-intensive, necessitating strategies like fine-tuning specific layers or lightweight approaches like LoRA. Efficient dataset management is crucial to handle tokenization, batching, and storage without bottlenecks. Training may face instability due to exploding or vanishing gradients, mitigated by mixed-precision training, learning rate schedulers, and gradient accumulation. Continuous GPU usage raises heat and power concerns, requiring proper cooling and monitoring. Over-parameterized models also lead to inefficiencies, solved by pruning or task-specific adapters. Dataset bias and privacy must be addressed with anonymization and differential privacy. Limited checkpointing and logging can risk training progress, while scalability challenges demand modular workflows and cloud resources for future adaptability. Adopting pre-trained models, efficient frameworks like Hugging Face, and optimized workflows can alleviate these issues.

VIII. FUTURE WORK

Looking ahead, this project offers numerous opportunities for enhancement and expansion. A key area for future work is the broadening of the dataset to include abstracts from disciplines beyond machine learning. Expanding the chatbot's scope to cover physics, biology, mathematics, and other fields will increase its versatility and utility for a wider audience. Automating the data ingestion pipeline, including preprocessing steps such as formatting and special character removal, will also streamline the dataset creation process, making the system more efficient and adaptable to new domains of content.

Another promising direction involves incorporating multimodal capabilities to enrich user interaction. This could include processing and generating visual elements, such as diagrams or graphs, alongside textual summaries to provide a more comprehensive understanding of complex scientific materials. Adding dynamic feedback loops, where the chatbot learns from user corrections or preferences, can further refine its performance over time. These enhancements will create a more interactive and adaptive system, tailored to the needs of its users.

From a technical perspective, experimenting with more advanced language models, including future iterations of Mistral or other architectures, could improve response accuracy and contextual comprehension. Reinforcement learning from human feedback (RLHF) offers another opportunity to refine the chatbot's output by tailoring it more closely to user expectations. Additionally, exploring fine-tuning methodologies that combine domain-specific training with broader generalization capabilities will enhance the system's ability to handle diverse queries effectively.

Finally, deploying the chatbot as a web-based application or integrating it with arXiv's existing infrastructure will enable broader accessibility and adoption. Addressing challenges such as ensuring low latency, managing concurrent user requests, and maintaining high performance on a large scale will be critical for successful deployment. Such developments would transform the chatbot from a proof of concept into a practical tool for researchers and non-experts alike, driving greater engagement with scholarly repositories and paving the way for further innovations in scientific communication.

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