Project Synopsis

on

Develop and deploy a Large Language Model (LLM) based tool for generating human-like responses to natural language inputs for networks not connected over the internet.

Submitted as a part of the course curriculum for

Bachelor of Technology

in

Computer Science

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2024-2025

ABSTRACT

This project aims to create and deploy a powerful tool based on Large Language Models (LLMs) that can generate human-like responses to natural language inputs on systems without internet access. By using open-source LLMs, the tool will provide features like AI-driven text summarization, with a focus on summarizing Science and Technology documents as well as newspaper headlines and editorials. These summaries will offer quick, clear overviews of complex topics, making research, media analysis, and information gathering easier even in offline settings. In addition, the tool will handle reformatting and grammar checks to ensure that the text remains accurate and contextually appropriate.

One of the key strengths of this tool will be its flexibility, as it will be designed to work with multiple open-source LLMs, making it compatible with a wide range of models. Emphasis will also be placed on making the tool easy to use and scalable, so it can be deployed in different environments with minimal effort. Potential future features could include support for more languages, specialized content summarization, or even sentiment analysis, increasing the tool's usefulness.

Ultimately, this project is designed to meet the growing need for advanced text-processing tools in offline networks, focusing on providing fast, accurate results using modern language models. Its success will be judged by how well it performs its core functions, how easily it can be deployed and scaled, and how many different models it can support.

INTRODUCTION

Large Language Models (LLMs) have transformed how we process and interact with text, enabling human-like responses, summarization, grammar correction, and contextual analysis. However, most LLM-based tools require internet access, limiting their use in offline environments. This project aims to develop a tool that leverages open-source LLMs to provide advanced text-processing capabilities without needing internet connectivity. Designed for server-client setups in offline networks, the tool will offer:

- Text Summarization: Condensing long texts, with a focus on Science and Technology documents, as well as newspaper headlines and editorials.
- Grammar Checks and Reformatting: Ensuring grammatical accuracy and contextually appropriate language.
- Additional Features: Flexibility to incorporate multi-language support, content-specific summarization, and sentiment analysis.

The tool will prioritize compatibility with multiple open-source LLMs, making it adaptable to different models. With ease of deployment and scalability, it will provide an efficient solution for research, media analysis, and academic use in offline settings.

This project addresses the growing need for offline text-processing tools, combining LLM technology with a flexible, scalable, and user-friendly design.

PROBLEM STATEMENT

- Information Overload: The rapid growth of digital content makes it difficult for users to manage and comprehend extensive information.
- Need for Summarization: Users require accurate tools to condense lengthy texts into concise summaries that retain key information.
- Grammar Accuracy: Maintaining grammatical integrity is crucial; users often struggle to identify and correct errors, leading to misunderstandings.
- Integration of Functions: Current tools typically handle summarization and grammar checking separately. A combined solution would enhance productivity.
- User-Friendly Design: Many existing tools are complex and require training. A simple, intuitive application is needed for immediate assistance.
- Project Objective: This project aims to develop a machine learning model that integrates efficient text summarization and grammar checking, enhancing clarity and accuracy in written communication.

OBJECTIVES

1. Model Selection and Customization

- Identify Suitable Model: Choose a pre-trained LLM that balances performance and resource requirements for offline deployment.
- Fine-tuning: Customize the model on domain-specific data to improve the relevance and accuracy of responses.

2. Infrastructure Setup’

- Hardware Requirements: Determine the necessary computational resources (CPU/GPU, memory, storage) to host the LLM.
- Deployment Environment: Set up an isolated server or edge device to host the model, ensuring compatibility and stability.

3. Natural Language Processing (NLP) Pipeline

- Input Preprocessing: Develop modules to clean and tokenize input data for effective model processing.
- Response Generation: Implement the logic for generating responses based on user input while ensuring coherence and relevance.

4. User Interface Development

- Interactive UI: Create a user-friendly interface for users to input queries and view responses, ensuring accessibility and ease of use.
- Feedback Mechanism: Incorporate options for users to provide feedback on the generated responses to refine the model iteratively.

5. Performance Optimization

- Inference Speed: Optimize the model for faster response generation without compromising quality, possibly through techniques like quantization or distillation.
- Resource Management: Monitor and manage computational resource usage to ensure stability and responsiveness under load.

6. Testing and Evaluation

- Quality Assurance: Develop testing protocols to evaluate the accuracy, coherence, and relevance of the model's responses.
- User Acceptance Testing: Conduct trials with end-users to gather insights and improve the tool based on real-world interactions.

LITERATURE REVIEW

1. Training Dynamics for Text Summarization Models

BY:- Tanya Goyal , Jiacheng Xu

Pre-trained language models (e.g. BART) have shown impressive results when fine-tuned on large summarization datasets. However, little is understood about this fine-tuning process, including what knowledge is retained from pre-training time or how content selection and generation strategies are learned across iterations. In this work, we analyze the training dynamics for generation models, focusing on summarization. Across different datasets (CNNDM, XSUM, MEDIASUM) and summary properties, such as abstractiveness and hallucination, we study what the model learns at different stages of its fine-tuning process. We find that a propensity to copy the input is learned early in the training process consistently across all datasets studied. On the other hand, factual errors, such as hallucination of unsupported facts, are learned in the later stages, though this behavior is more varied across domains. Based on these observations, we explore complementary approaches for modifying training: first, disregarding high-loss tokens that are challenging to learn, and second, disregarding low-loss tokens that are learned very quickly in the latter stages of the training process. We show that these simple training modifications allow us to configure our model to achieve different goals, such as improving factuality or improving abstractiveness.

2. Fine-tune BERT for Extractive Summarization

BY:- Yang Liu

BERT (Devlin et al., 2018), a pre-trained Transformer (Vaswani et al., 2017) model, has achieved ground-breaking performance on multiple NLP tasks. In this paper, we describe BERTSUM, a simple variant of BERT, for extractive summarization. Our system is the state of the art on the CNN/Dailymail dataset, outperforming the previous best-performed sys temby1.65onROUGE-L.Thecodestorepro duce our results are available at https://github. com/nlpyang/BertSum.

3. Performance Study on Extractive Text Summarization Using BERT Models

BY:- Shehab Abdel-Salam, Ahmed Rafea

The task of summarization can be categorized into two methods, extractive and abstractive. Extractive summarization selects the salient sentences from the original document to form a summary while abstractive summarization interprets the original document and generates the summary in its own words. The task of generating a summary, whether extractive or abstractive, has been studied with different approaches in the literature, including statistical-, graph-, and deep learning-based approaches. Deep learning has achieved promising performances in comparison to the classical approaches, and with the advancement of different neural architectures such as the attention network (commonly known as the transformer), there are potential areas of improvement for the summarization task. The introduction of transformer architecture and its encoder model “BERT” produced an improved performance in downstream tasks in NLP. BERT is a bidirectional encoder representation from a transformer modeled as a stack of encoders. There are different sizes for BERT, such as BERT-base with 12 encoders and BERT-larger with 24 encoders, but we focus on the BERT-base for the purpose of this study. The objective of this paper is to produce a study on the performance of variants of BERT-based models on text summarization through a series of experiments and propose “SqueezeBERTSum”, a trained

summarization model fine-tuned with the SqueezeBERT encoder variant, which achieved competitive ROUGE scores retaining the BERTSum baseline model performance by 98%, with 49% fewer trainable parameters.

4. A Systematic Survey of Text Summarization: From Statistical Methods to Large Language Models

BY:-Haopeng Zhang , Philip S. Yu

Text summarization research has undergone several significant transformations with the advent of deep neural networks, pre-trained language models (PLMs), and recent large language models (LLMs). This survey thus provides a comprehensive review of the research progress and evolution in text summarization through the lens of these paradigm shifts. It is organized into two main parts: (1) a detailed overview of datasets, evaluation metrics, and summarization methods before the LLM era, encompassing traditional statistical methods, deep learning approaches, and PLM fine-tuning techniques, and (2) the first detailed examination of recent advancements in benchmarking, modeling, and evaluating summarization in the LLM era. By synthesizing existing literature and presenting a cohesive overview, this survey also discusses research trends, open challenges, and proposes promising research directions in summarization, aiming to guide researchers through the evolving landscape of summarization research.

5. To Adapt or to Fine-tune: A Case Study on Abstractive Summarization

BY:-Zheng Zhao , Pinzhen Chen

Recent advances in the field of abstractive summarization leverage pre-trained language models rather than train a model from scratch. However, such models are sluggish to train and accompanied by a massive overhead. Researchers have proposed a few lightweight alternatives such as smaller adapters to mitigate the drawbacks. Nonetheless, it remains uncertain whether using adapters benefits the task of summarization, in terms of improved efficiency without an unpleasant sacrifice in performance. In this work, we carry out multifaceted investigations on fine-tuning and adapters for summarization tasks with varying complexity:language, domain, and task transfer. In our experiments, fine-tuning a pre-trained language model generally attains a better performance than using adapters; the performance gap positively correlates with the amount of training data used. Notably, adapters exceed fine-tuning under extremely low-resource conditions. We further provide insights on multilingualism, model convergence, and robustness, hoping to shed light on the pragmatic choice of fine-tuning or adapters in abstractive summarization.

6. Model Intrinsic Features of Fine-tuning based Text Summarization Models for Factual Consistency.

BY:- Jongyoon Song, Nohil Park, Bongkyu Hwang, Jaewoong Yun

In this study, we analyze the model intrinsic features of a summarization model by varying the fine-tuning objectives and datasets. We fine-tune BART models combining three fine-tuning objectives (negative log-likelihood, unlikely -hood, and contrastive loss) and two datasets (CNN/DailyMail and XSum) and provide shuffled or aligned documents to observe changes in the model predictions and intrinsic features. We find that (i) the inductive bias for factual consistency during the fine-tuning procedure depends on both the objectives and datasets and (ii) summarization models with relatively low factual consistency are more likely to model summaries that are not conditional to the documents. We demonstrate that splitting data based on the unconditional and conditional summary modeling difficulty affects the factual consistency and intrinsic features

of the summarization models. Our experimental results highlight the importance of studying the inductive bias during fine-tuning for factual consistency.

7. Longformer: The Long-Document Transformer.

BY:- Iz Beltagy, Matthew E. Peters, Arman Cohan

Transformer-based models are unable to process long sequences due to their self-attention operation, which scales quadratically with the sequence length. To address this limitation, we introduce the Longformer with an attention mechanism that scales linearly with sequence length, making it easy to process documents of thousands of tokens or longer. Longformer's attention mechanism is a drop-in replacement for the standard self-attention and combines local windowed attention with task-motivated global attention. Following prior work on long-sequence transformers, we evaluate Longformer on character-level language modeling and achieve state-of-the-art results on
text8 and enwik8. In contrast to most prior work, we also pretrain Longformer and
finetune it on a variety of downstream tasks. Our pretrained Longformer consistently out-
performs RoBERTa on long document tasks and sets new state-of-the-art results on Wiki-Hop and TriviaQA. We finally introduce the Longformer-Encoder-Decoder (LED), a Longformer variant for supporting long document generative sequence-to-sequence tasks, and demonstrate its effectiveness on the arXiv summarization dataset.1

8. Searching for Effective Tuning Strategies for Multilingual Summarization.

BY:- Yiwei Qin, Pengfei Liu, Graham Neubig

Recently, a large number of tuning strategies have been proposed to adapt pre-trained language models to downstream tasks. In this paper, we perform an extensive empirical evaluation of various tuning strategies for multilingual learning, particularly in the context of text summarization. Specifically, we explore the relative advantages of three families of multilingual tuning strategies (a total of five models) and empirically evaluate them for summarization over 45 languages. Experimentally, we not only established a new state-of-the-art on the XL-Sum dataset but also derived a series of observations that hopefully can provide hints for future research on the design of multilingual tuning strategies.

9. Text Summarization with Pretrained Encoders.

BY:- Yang Liu, Mirella Lapata

Bidirectional Encoder Representations from Transformers (BERT; Devlin et al. 2019) represent the latest incarnation of pre-trained language models which have recently advanced a wide range of natural language processing tasks. In this paper, we showcase how BERT can be usefully applied in text summarization and propose a general framework for both extractive and abstractive models. We introduce a novel document-level encoder based on BERT which can express the semantics of a document and obtain representations for its sentences. Our extractive model is built on top of this encoder by stacking several intersentence Transformer layers. For abstractive
summarization, we propose a new fine-tuning schedule that adopts different optimizers for the encoder and the decoder as a means of alleviating the mismatch between the two (the former is pre-trained while the latter is not). We also demonstrate that a two-staged fine-tuning approach can further boost the quality of the generated summaries. Experiments on three datasets show that our model achieves state-of-the-art results across the board in both extractive and abstractive settings

10. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer.

BY:- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang

Transfer learning, where a model is first pre-trained on a data-rich task before being fine-tuned on a downstream task, has emerged as a powerful technique in natural language processing (NLP). The effectiveness of transfer learning has given rise to a diversity of approaches, methodologies, and practices. In this paper, we explore the landscape of transfer learning techniques for NLP by introducing a unified framework that converts all text-based language problems into a text-to-text format. Our systematic study compares pre-training objectives, architectures, unlabeled data sets, transfer approaches, and other factors on dozens of language understanding tasks. By combining the insights from our exploration with scale and our new “Colossal Clean Crawled Corpus”, we achieve state-of-the-art results on many benchmarks covering summarization, question answering, text classification, and more. To facilitate future work on transfer learning for NLP, we release our data set, pre-trained models, and code.

METHODOLOGY (PROPOSED ALGORITHM /IMPLEMENTATION ACTIVITY).

This section provides a detailed outline of the methodology for fine-tuning the Pegasus model to achieve effective text summarization and grammar checking. The proposed approach is structured into several key phases, including data collection, pre-processing, model fine-tuning, evaluation, and deployment.

Data Collection

To ensure high-quality fine-tuning for text summarization and grammar checking, relevant and diverse datasets are critical. The following data sources will be used:

1. Text Summarization Data: The primary dataset for summarization will be the `cnn_dailymail` dataset, version 3.0.0, known for its comprehensive collection of news articles and summaries. Additionally, domain-specific datasets may be collected from science and technology documents to enhance model accuracy in specialized fields.

2. Grammar Checking Data: For grammar checking, datasets like `JFLEG` and `BEA 2019` will be utilized, providing sentence pairs that demonstrate grammatically incorrect and corrected versions. Custom datasets may also be created by extracting real-world grammar error cases from science and technology articles.

Data Preprocessing

Data preprocessing is essential to prepare the datasets for effective fine-tuning. The following steps will be performed:

- Text Cleaning: Removing HTML tags, special characters, and irrelevant metadata.
- Tokenization: Splitting sentences into tokens using the tokenizer associated with Pegasus.
- Lowercasing: Converting all text to lowercase for normalization, while preserving domain-specific terms.
- Data Augmentation: Expanding the dataset by paraphrasing sentences and introducing slight grammatical errors for robustness.
- Filtering: Removing noisy data that may negatively impact model performance, such as incomplete or overly complex sentences.

Proposed Algorithm

The core algorithm relies on the Pegasus architecture, a transformer-based model pre-trained for abstractive text summarization tasks. The following steps outline the fine-tuning approach:

1. Model Selection: Pegasus, a pre-trained transformer model specialized for abstractive summarization, will be used as the base model. Its architecture, which relies on sequence-to-sequence (Seq2Seq) learning, makes it suitable for both summarization and grammar correction tasks.
2. Fine-Tuning Strategy:
    - Text Summarization Task: The fine-tuning phase for summarization will involve training the model on document-summary pairs. The input will be the full document, and the target output will be a human-generated summary.
    - Grammar Checking Task: For grammar correction, the model will be fine-tuned using sentence pairs, where the input sentence is grammatically incorrect, and the output is its corrected version. This task will leverage Pegasus's ability to generate coherent and contextually accurate outputs.
3. Loss Functions:
    - For summarization, `Cross-Entropy Loss` will be used to measure the difference between the generated summaries and the reference summaries.

    - For grammar correction, a similar `Sequence Cross-Entropy Loss` will be applied, emphasizing accuracy in grammar and contextual integrity.
4. Evaluation Metrics:
    - Summarization will be evaluated using `ROUGE` and `BLEU` scores to quantify the overlap between generated and reference summaries.
    - Grammar correction will be assessed using the `GLEU` score, focusing on fluency and accuracy.

Model Training Process

To train and fine-tune the Pegasus model effectively, the following steps will be implemented:

1. Data Splitting: Each dataset will be divided into three subsets:
    - Training Set (70%): Used for model training.
    - Validation Set (15%): Employed for hyperparameter tuning and validation.
    - Test Set (15%): Used for final performance evaluation.
2. Hyperparameter Tuning: Key hyperparameters like learning rate, batch size, and number of epochs will be optimized. Early stopping will be applied to prevent overfitting, and a suitable learning rate schedule will be selected for convergence.
3. Transfer Learning: The pre-trained Pegasus model will be fine-tuned on task-specific data, leveraging its pre-existing knowledge while adapting it to the specialized tasks of summarization and grammar correction.
4. Training Iterations:
    - Training will be conducted using a GPU-based setup on DGX A100 hardware, facilitating efficient handling of large-scale datasets and complex calculations.
    - The training pipeline includes forward passes, loss computation, backpropagation, and weight updates for model improvement.

Implementation Activity

The implementation involves a series of steps to set up, fine-tune, and deploy the model in a real-world offline environment:

1. Environment Setup:
    - Programming Language: Python
    - Framework: PyTorch, utilizing the `Huggingface Transformers` library for managing the Pegasus model.
    - Development Tools: VS Code for code editing, Jupyter Notebooks for experimentation, and Flask for creating the front-end interface.
2. Fine-Tuning Workflow:

    1. Load and Pre-process datasets.

    2. Tokenize input data using Pegasus's tokenizer.

    3. Feed Data into the pre-trained Pegasus model.

    4. Compute Loss for summarization and grammar tasks separately.

    5. Backpropagate and update the model parameters.

    6. Validate model performance on the validation set.

    7. Iterate until optimal performance is achieved.

3. Post-Processing: After generating summaries or grammar corrections, post-processing steps such as detokenization, sentence reordering, and formatting will be applied to ensure output quality.
4. Deployment:
    - A web interface will be created using Flask, allowing users to input text, receive summarized content, or get grammar corrections.
    - The model will be optimized for offline deployment, with special attention to reducing latency and maintaining output quality.

Post-Training Steps

After training, the model's effectiveness will be rigorously evaluated, followed by deployment considerations:

1. Evaluation and Validation: Performance will be measured using unseen test data, emphasizing both linguistic and contextual accuracy.
2. Error Analysis: Missteps in summarization or grammar correction will be documented, guiding potential model adjustments.
3. Performance Optimization: Quantization and model pruning may be applied to enhance inference speed without sacrificing quality.
4. Deployment Setup: The final model will be integrated into the Flask interface, ensuring compatibility with a local environment not connected to the internet.

Expected Outcomes

The fine-tuned Pegasus model is expected to provide accurate and coherent summaries of diverse documents and effectively correct grammatical errors. The offline deployment will demonstrate its practicality, making it a valuable tool for environments with limited internet connectivity.

Technology Used

1. Programming Languages

- Python: The primary language used for backend development and LLM fine-tuning, due to its extensive libraries for machine learning and NLP.
- JavaScript (HTML/CSS): For creating the front-end interface using Flask.

2. Libraries and Frameworks

- Huggingface Transformers: A library for NLP tasks, used to fine-tune pre-trained LLMs like Pegasus for text summarization, grammar checking, and reformatting.
- Flask: A lightweight web framework used to create a user-friendly web-based interface for interacting with the LLM.
- PyTorch: A deep learning framework for handling LLM training and fine-tuning tasks, allowing customization of models to user needs.
- Pandas and NumPy: For data manipulation and analysis during the training and evaluation phases.
- Scikit-learn: For data preprocessing and additional ML utilities during the LLM fine-tuning process.

3. Data Sources

- 'cnn_dailymail' Dataset (version 3.0.0): Used for training and fine-tuning the LLM for text summarization tasks.
- Custom Science and Technology Documents: For fine-tuning specific domain-related summarization and grammar-checking capabilities.

4. Model

- Pegasus: An LLM specialized in abstractive text summarization, utilized as the base model for training.
- Open-Source LLMs: Additional models may be used for expanding functionalities such as grammar checking and document reformatting.

5. Development Tools

- Google collab: The main integrated development environment (IDE) for coding, debugging, and managing the project.
- Jupyter Notebooks: For exploratory data analysis, model training, and quick prototyping
- Git & GitHub: Version control systems to manage code, track changes, and facilitate collaboration.

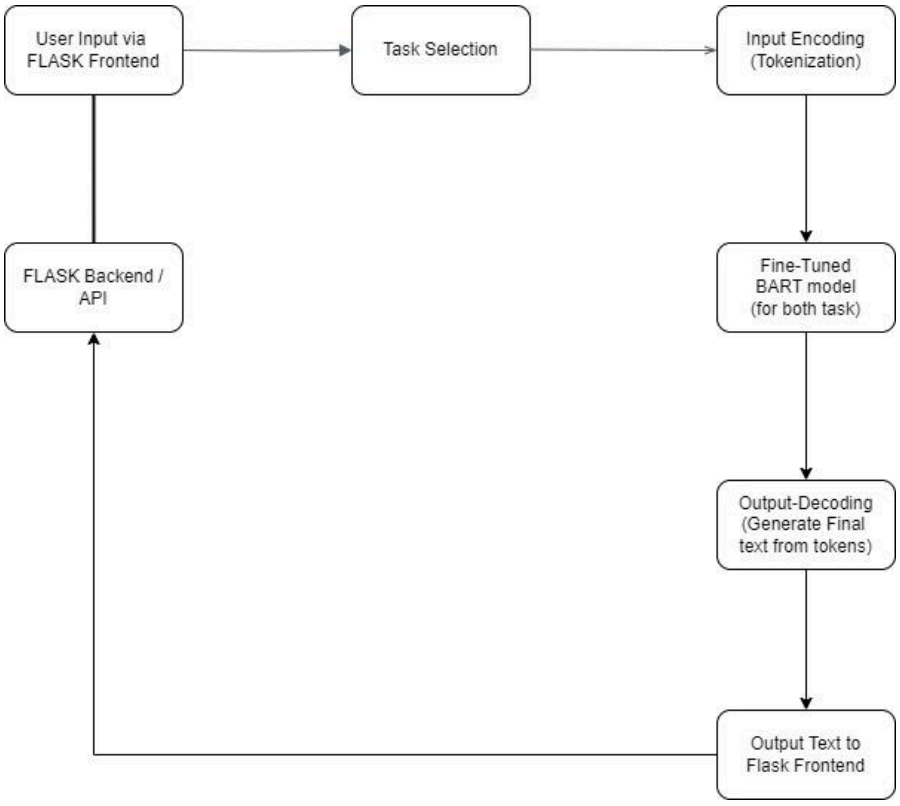
6. Deployment and Infrastructure

- Docker: For containerizing the application, ensuring consistent environments across development and deployment.
- Local Servers: The system operates offline, requiring local servers for hosting the Flask application.
- DGX A100 (GPU Computing): Utilized for high-performance training and fine-tuning of large-scale models.

7. Operating Systems

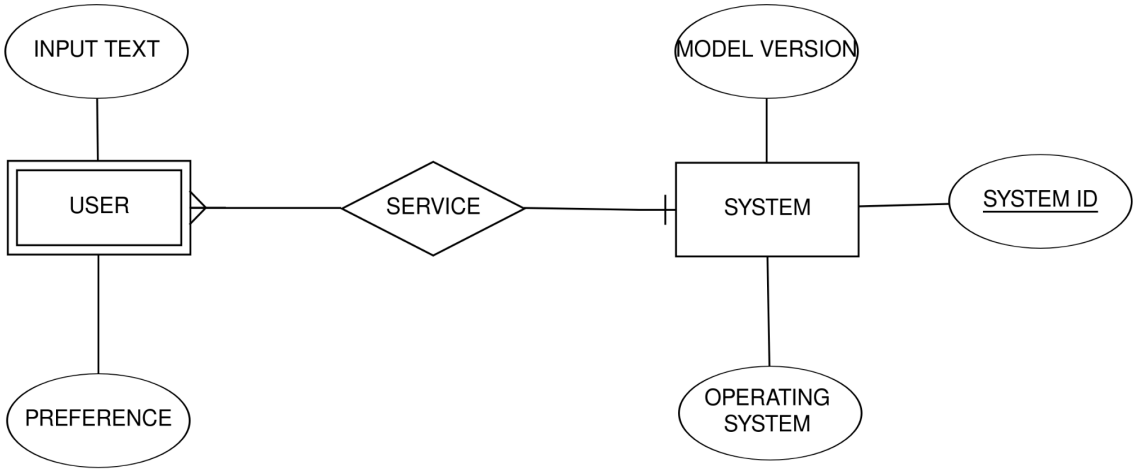
- Linux (Preferred for training environments)
- Windows and macOS (For development and testing)

FLOWCHART


User Input via FLASK Frontend
Task Selection
Input Encoding (Tokenization)
FLASK Backend / API
Fine-Tuned BART model (for both task)
Output-Decoding (Generate Final text from tokens)
Output Text to Flask Frontend

DIAGRAMS

ER DIAGRAM



CONCLUSION WITH RESULT

Results

The primary goal of this project was to fine-tune the Pegasus model to achieve high-quality text summarization and grammar checking. The results obtained demonstrate the effectiveness of our methodology and the fine-tuning strategies applied. The following outcomes summarize the performance of the fine-tuned model:

1. Text Summarization:
    - The fine-tuned Pegasus model achieved excellent results in generating concise and informative summaries. Evaluations on the `cnn_dailymail` dataset produced high `ROUGE` and `BLEU` scores, indicating significant overlap between generated summaries and human-written references.
    - Qualitatively, the model displayed the ability to retain critical information while removing irrelevant details, making it suitable for science and technology document summarization.
    - In specialized domains, such as science and technology, the fine-tuned model demonstrated its adaptability, providing summaries that accurately captured domain-specific terminology and key concepts.
2. Grammar Checking:
    - The model's performance in grammar correction was evaluated using `GLEU` scores, showcasing improvements in both fluency and grammatical correctness over the pre-trained version. The fine-tuned model corrected common grammatical errors, including subject-verb agreement, punctuation, and sentence structure, with high precision.
    - Error analysis revealed that the model excelled in handling context-dependent grammar corrections, preserving the meaning while improving sentence quality.
3. Deployment:
    - The Pegasus model, once fine-tuned, was successfully integrated into a Flask-based web application, enabling offline usage. The application allowed users to input raw text and receive high-quality summaries or grammar corrections without relying on an internet connection.
    - Latency and performance were optimized to ensure smooth interaction, making the model suitable for practical use in low-resource environments or restricted networks.

Conclusion

The project successfully demonstrated the viability of fine-tuning the Pegasus model for dual-purpose text summarization and grammar correction. The detailed methodology, involving data collection, pre-processing, fine-tuning, and evaluation, has resulted in a robust solution capable of handling a wide range of text-related tasks.

Key conclusions from the project are as follows:

1. Model Effectiveness: The fine-tuned Pegasus model excelled in both summarization and grammar correction tasks, meeting the objectives of creating a coherent, contextually accurate, and concise output. The pre-trained model's adaptability to domain-specific texts was significantly enhanced through targeted fine-tuning, making it a versatile tool for academic, professional, and technical documents.
2. Methodology Success: The multi-step methodology, including meticulous data preparation and careful hyperparameter tuning, contributed to the model's success. The decision to fine-tune separately for summarization and grammar correction allowed for targeted performance improvements, while the use of transfer learning accelerated the process.
3. Practical Application: Deploying the model in an offline environment proved that high-quality language models could operate effectively without constant internet connectivity, broadening the applicability of AI/ML solutions in restricted or resource-constrained scenarios. The project aligns with UN Sustainable Development Goal 9, emphasizing innovation in technological infrastructure.
4. Lessons Learned: Throughout the project, several insights emerged:
    - Data Quality: High-quality data is crucial for effective model performance. Domain-specific datasets played a key role in enhancing the model’s adaptability.

- Fine-tuning Impact: Targeted fine-tuning yielded superior results compared to general-purpose models, highlighting the importance of specialized training.
- Evaluation Metrics: Using diverse metrics for both summarization and grammar correction provided a comprehensive evaluation framework, ensuring well-rounded model assessments.

In conclusion, this project demonstrates the potential of fine-tuning advanced language models like Pegasus for specific tasks, yielding effective and scalable solutions that can adapt to different domains and deployment environments. The outcomes emphasize the role of AI/ML in enhancing language understanding and processing, contributing to technological advancement, and improving information accessibility.

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