**Social Media Analytics Assignment Report**

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**Summary Report: Evaluating Text Summarization with FLAN T5 using BERT Score, ROUGE Score, and BLEU Score**

# Dataset: Abstractive Text Summarization

**About this Dataset**

### Context

Global Vector or GloVe is an unsupervised learning algorithm for obtaining vector representations for words

### Content

Contains 4 files for 4 embedding representations.

1. glove.6B.50d.txt - 6 Billion token and 50 Features
2. glove.6B.100d.txt - 6 Billion token and 100 Features
3. glove.6B.200d.txt - 6 Billion token and 200 Features
4. glove.6B.300d.txt - 6 Billion token and 300 Features

### Acknowledgements

<https://nlp.stanford.edu/projects/glove/>

**NOTE: AS we have less computation power, we have generated summaries for 500 rows only.**

**Also as doesn’t have sufficient computational power for 3rd question we have taken the output file from a peer who has done it under your guidance where you have provided him with Google Colab Pro.**

**\*\*\*\*\* The jupyter source files for q1, q2 and q3 are attached in the zip file.**

**Procedure:**

Step 1: Initialization of Tokenizer and Model of Flan T5

Step 2: Loading Metric Functions

Step 3: Generating Summaries and Calculating Metrics

Step 4: Fine-tuning Flan T5/base

Step 5: Generating Summaries and Calculating Metrics with fine-tuned Flan T5

Step 6: Comparing Metrics Before and After Fine-Tuning

**Results**:

* **BERT Score before fine-tuning:**

A number on a white background

Description automatically generated

* **BERT Score before after-tuning:**

A number with black text

Description automatically generated with medium confidence

* **ROUGE Score before fine-tuning:**

A number on a white background

Description automatically generated

* **ROUGE Score after fine-tuning:**

A number on a white background

Description automatically generated

* **BLEU Score before fine-tuning:**

A screen shot of a computer

Description automatically generated

* **BLEU Score after fine-tuning:**



**Conclusion:**

In this project, we fine-tuned a large language model (LLM) on a dataset of <https://www.kaggle.com/code/akashsdas/abstractive-text-summarization/input?select=news_summary.csv> text and code. We evaluated the model's performance on a variety of tasks, including

Initialization of Tokenizer and Model of Flan T5

Generating Summaries and Calculating Metrics

And

Comparing Metrics Before and After Fine-Tuning.

Our results showed that fine-tuning significantly improved the model's performance on all tasks, even though we were only able to fine-tune the model on 500 rows of data due to limited computational resources. For example, on the Comparing Metrics Before and After Fine-Tuning. the model's accuracy increased.

These results demonstrate that fine-tuning can be used to improve the performance of LLMs on a variety of tasks, even with limited computational resources. This is especially useful for researchers and practitioners who do not have access to powerful computing hardware.

Our study also highlights the importance of data efficiency in fine-tuning LLMs. We were able to achieve significant improvements in model performance with only a small amount of fine-tuning data. This suggests that it is possible to fine-tune LLMs on limited datasets using a variety of techniques, such as transfer learning, low-rank adaptations, and few-shot learning.

**Directions for future work:**

One direction for future work is to explore the use of parameter-efficient fine-tuning methods, such as LoRA, to further improve the performance of LLMs on limited datasets. Another direction for future work is to investigate the use of synthetic data to generate additional training data for fine-tuning LLMs.

Overall, our study demonstrates that fine-tuning is a powerful technique for improving the performance of LLMs on a variety of tasks, even with limited computational resources and data. We believe that fine-tuning will continue to be an important tool for researchers and practitioners who are developing and using LLMs.