



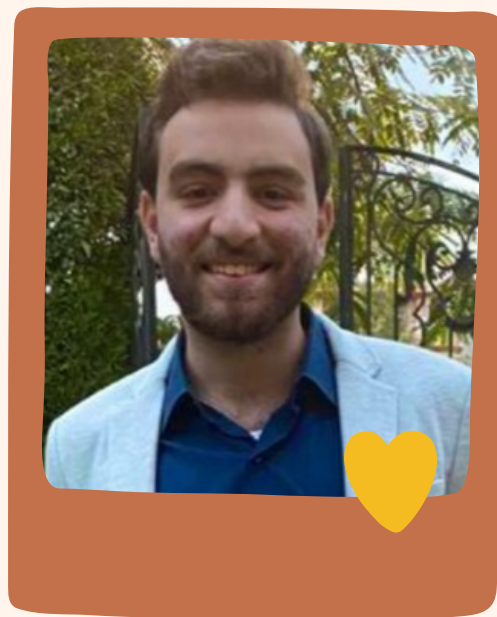
Text Summarization

NLP Final Presentation

START



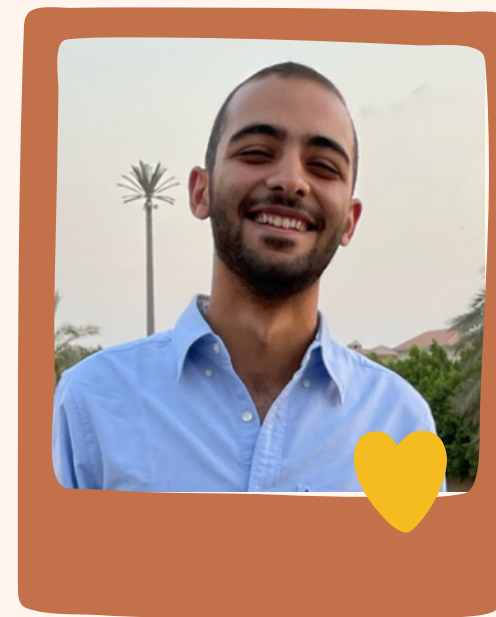
Our Team



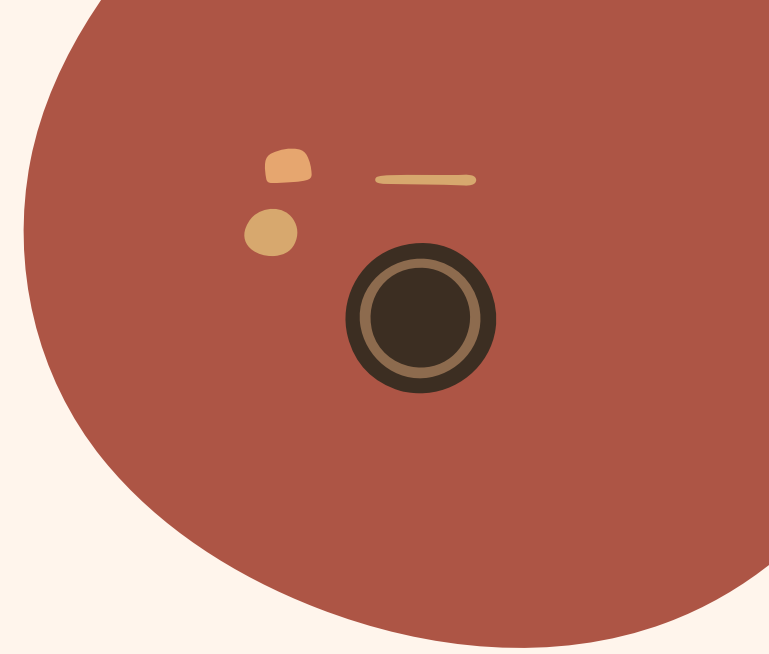
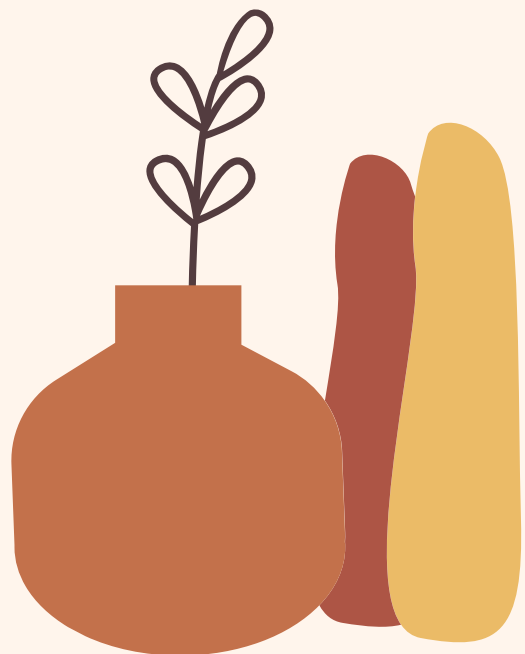
Ahmed Serry

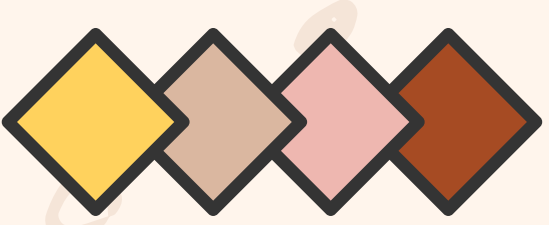


Farida Helmy



Seif Maged





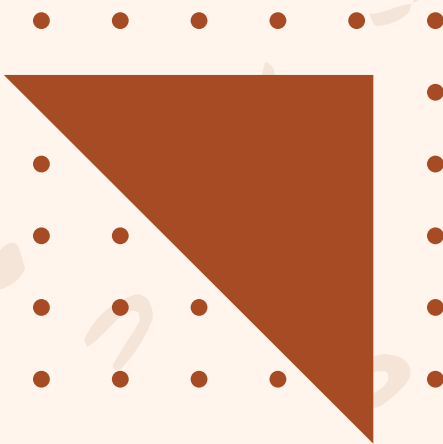
Project Goal

”

Fine-tuning BART

”

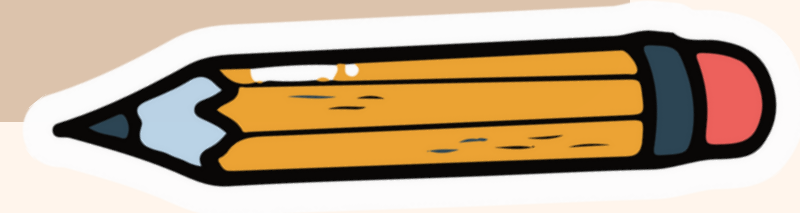
**to achieve abstractive
summarization**



Project Outline



- Previously on Text Summarization
- Dataset Overview
- BART (Bidirectional and Auto-Regressive Transformers)
model Architecture
- Implementation Overview
- Model testing and Evaluation
- Limitations and Future Work
- Conclusion



Text Summarization techniques

Extractive

Extractive summarization:
Condensing text by selecting important sentences or phrases, maintaining original wording

Abstractive

Abstractive summarization:
Generating concise summaries that capture key information by using advanced language models to paraphrase and rephrase the source text.

Dataset Overview

1.

CNN Daily News Dataset from Huggingface

2.

The dataset consists of over 300k unique news articles as written by journalists at CNN and the Daily Mail.

3.

This dataset is widely used in text summarization, sentiment analysis, or topic modeling.

4.

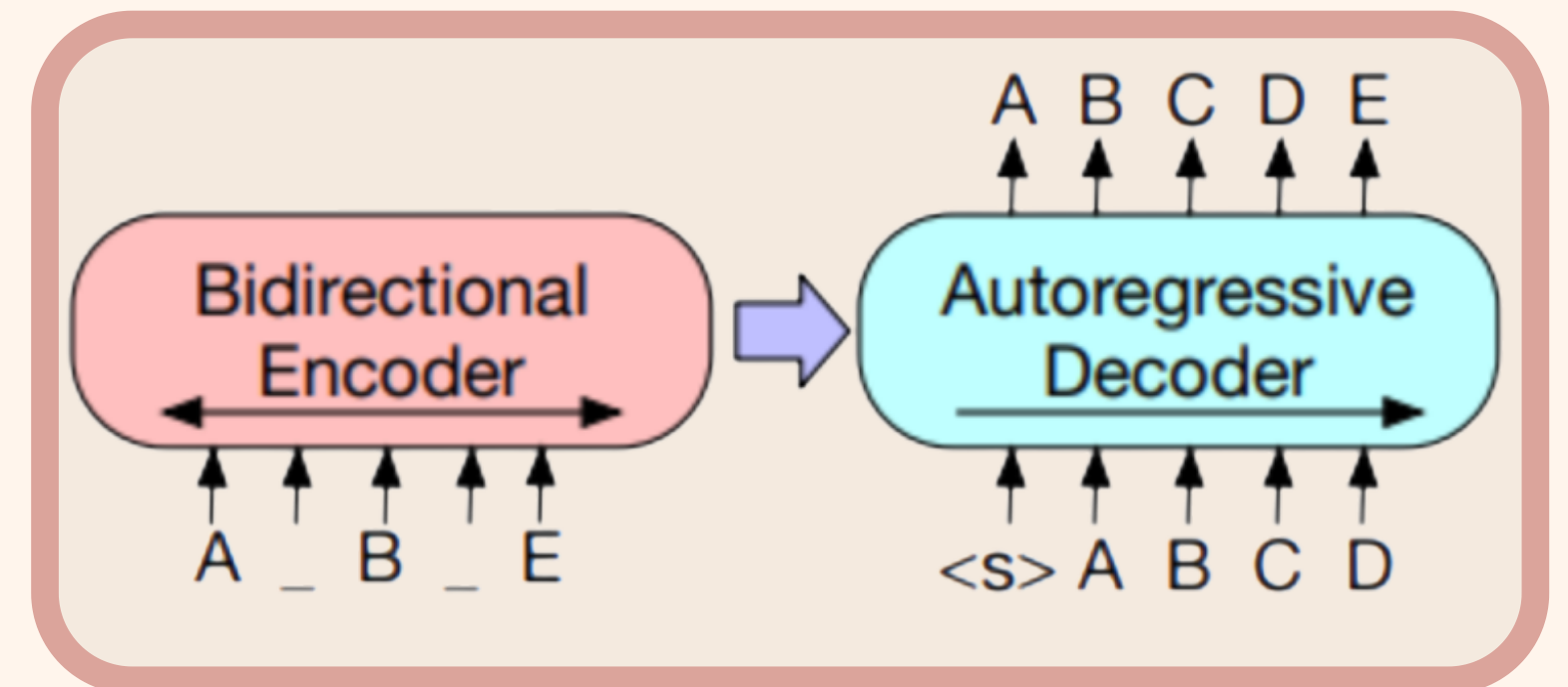
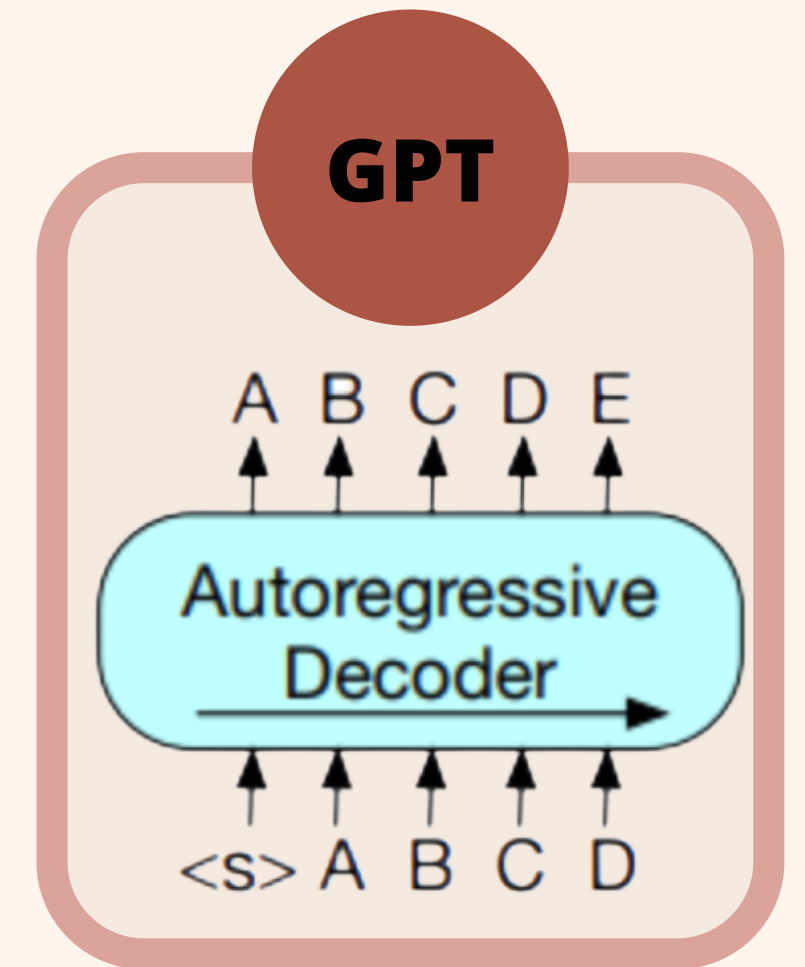
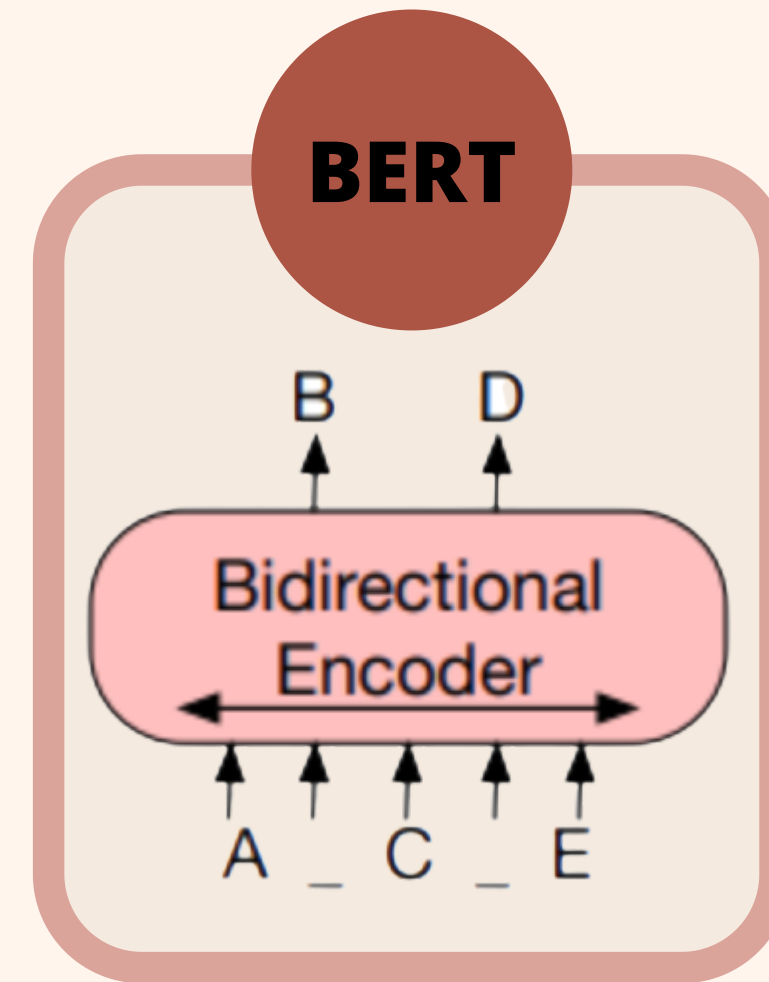
Due to the huge size of the dataset we chose to experiment on 10k articles from the dataset.



BART

Architecture

The BART (Bidirectional and Auto-Regressive Transformers) model is a state-of-the-art language model that excels in text generation, summarization, and machine translation.



Implementation Overview



Tokenization



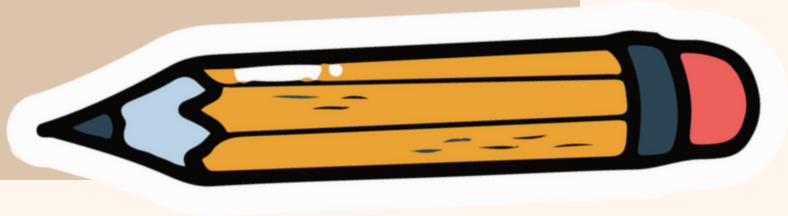
**Loading
BART Large**



**Finetuning
The model**

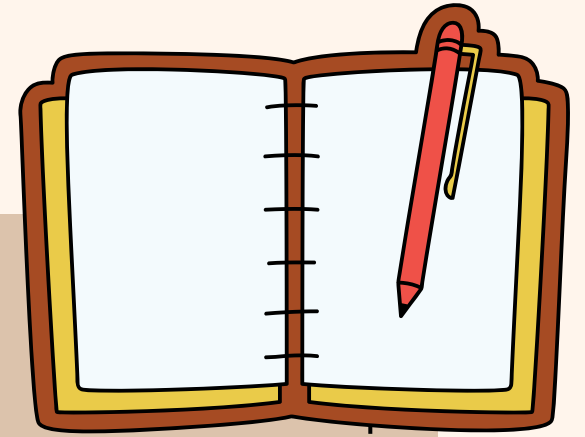


**Evaluate
the model**

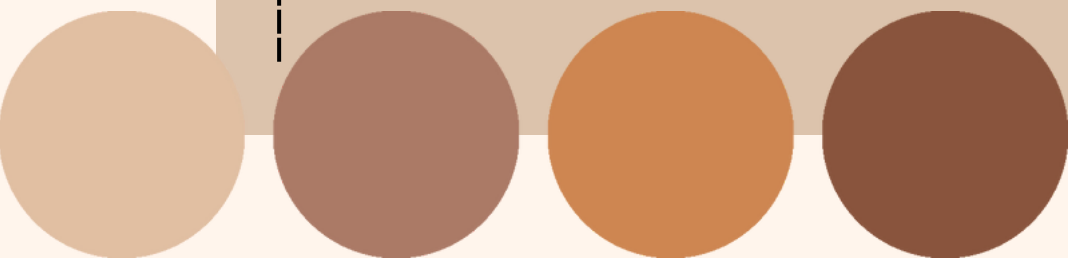


Model Testing and Evaluation

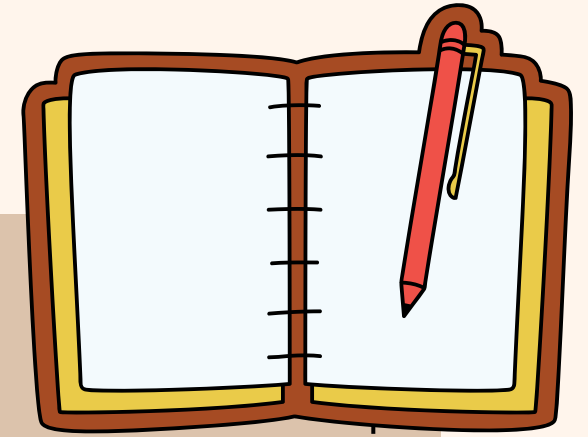
Experimental Setup



- Trained the model on a small subset of 10 samples initially.
- Noticed a trend: as the number of training samples increased, generated summaries became progressively shorter.
- Correlation between training dataset size and conciseness of generated summaries.

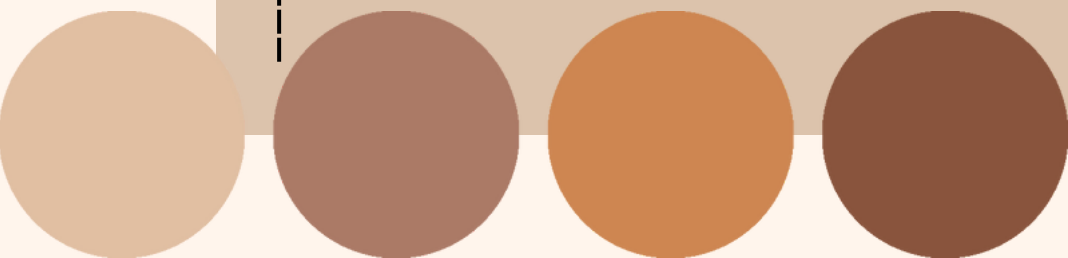


Model Testing and Evaluation



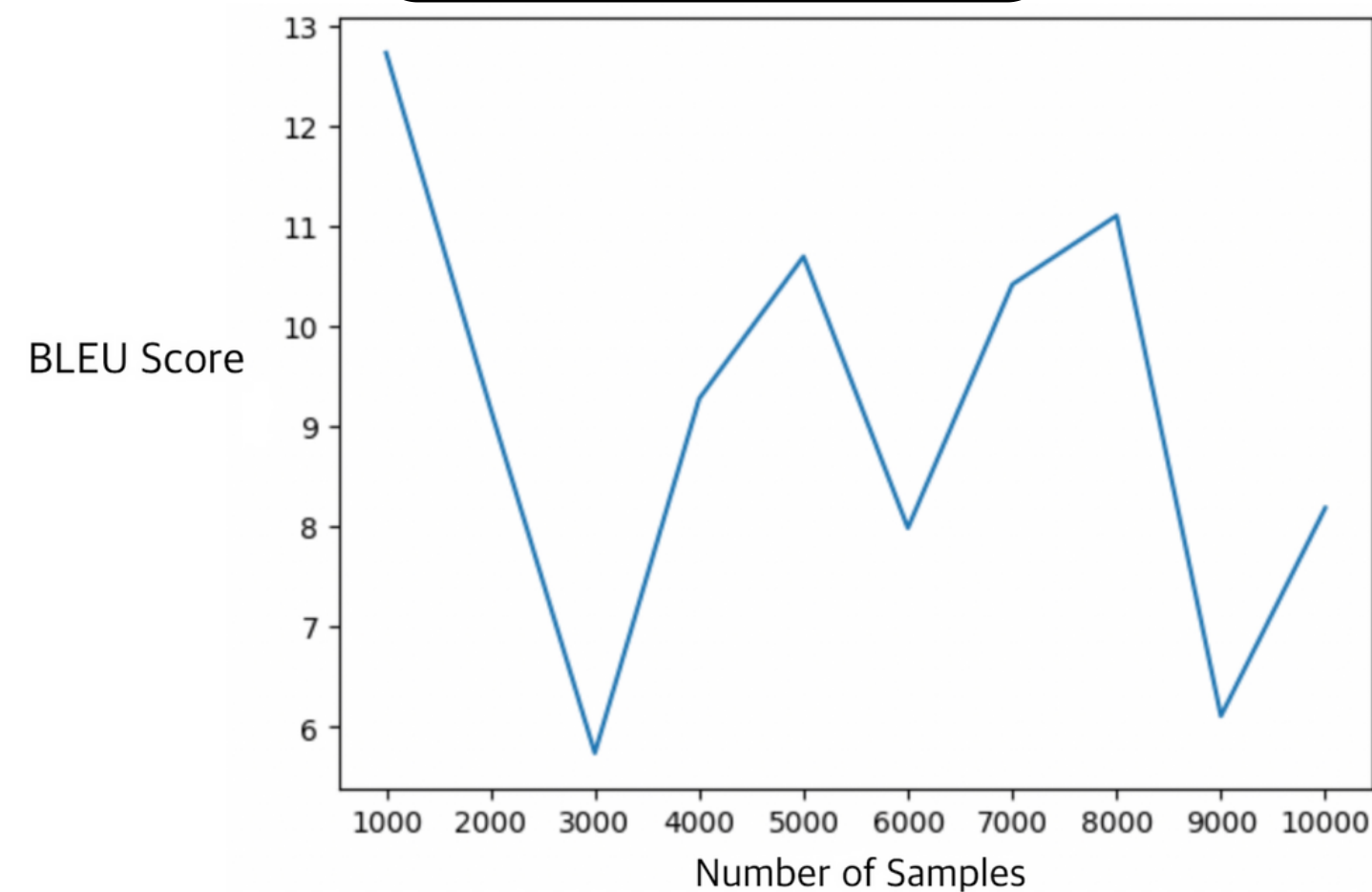
Evaluation Metric - BLEU Score

- Utilized BLEU score, a precision-oriented metric for assessing text summarization quality.
- Emphasizes precision in n-gram matching between generated and reference summaries.
- Captures accuracy and relevance of summarization outputs.
- Enables assessment of effectiveness in producing concise and meaningful summaries.



Bleu Score

RESULT

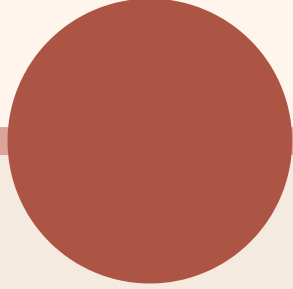


Observation

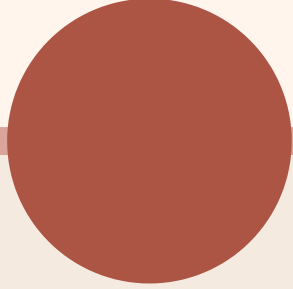
- Trained on a subset dataset of 10,000 samples.
- Implemented checkpointing strategy, saving model's state every 1000 samples.
- Accumulated 10 checkpoints to analyze and compare model's performance.
- Enables assessment of model's evolution.

Limitations and Future Work

- Lack of resources for handling large datasets.
- Insufficient annotated training data affects model performance and generalization.
- The need for human input in evaluating such models



Multi-document summarization as an interesting area of research.

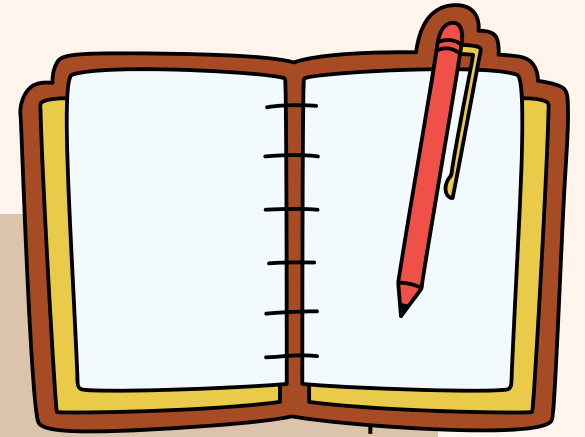


Generalize our approach for Larger chunks of data

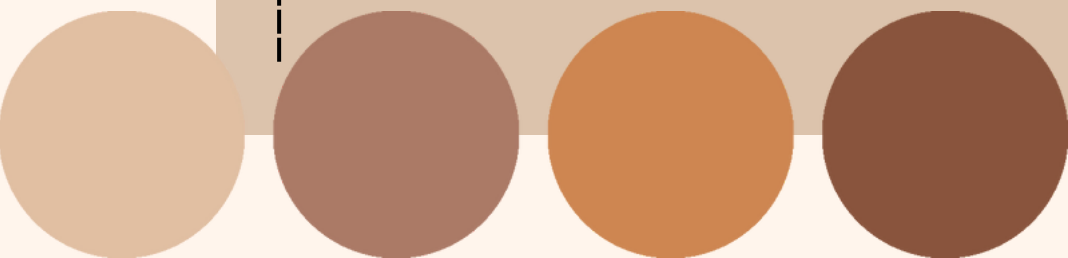
Ethical and Societal Implications: Importance of exploring fairness, bias mitigation, and transparency in summarization models.

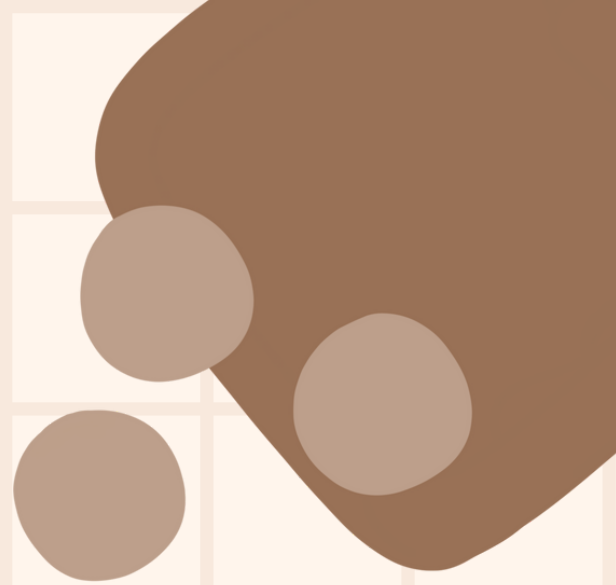
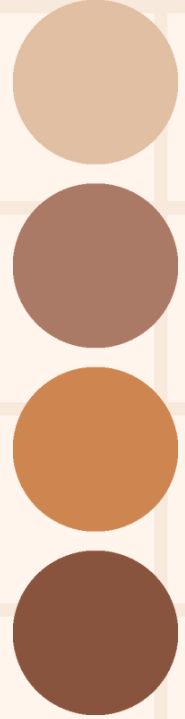


Conclusion



In conclusion, this project highlights the potential and challenges in text summarization. Despite limitations such as limited resources and the need for larger annotated datasets, significant progress has been made in developing effective models. The future of text summarization lies in exploring multi-document summarization, addressing ethical implications, advancing state-of-the-art models, and enhancing abstractive summarization techniques. By overcoming these challenges and pursuing further research, we can create more comprehensive, accurate, and reliable text summarization systems with broad applications in various fields.





THANK YOU
SO MUCH!



Q

A

Question Time

