



Text Summarization

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Group: 4



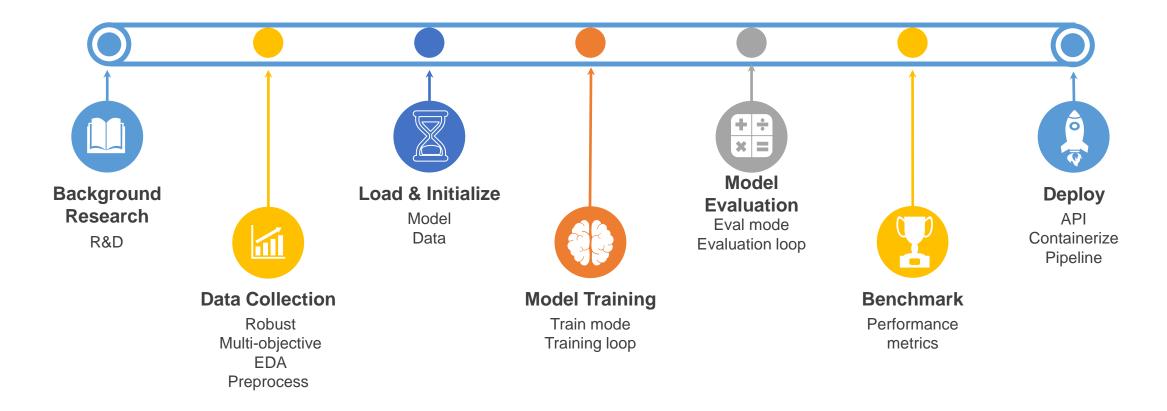
Introduction

Problem Statement & Planning

Introduction Problem Statement

- Developing an automated text summarization system that can accurately and efficiently condense large bodies of text into concise summaries is essential for enhancing business operations.
- This project aims to deploy NLP techniques to create a robust text summarization tool capable of handling various types of documents across different domains.
- The system should deliver high-quality summaries that retain the core information and contextual meaning of the original text.

INTENDED PLAN



Literature Review & Findings

Literature Review

S. No	Use-Case	Paper Title	Year	Method	Dataset	Results	Limitations
1	General text summarizatio n	Text Summarization Using Deep Learning Techniques: A Review	2023	Deep Learning (Seq2Seq, Attention, Transformers)	CNN/Daily Mail, XSum	Improved performanc e in capturing semantic relationship s, better coherence	Computatio nally expensive, requires large datasets

[1] Saiyyad, M.M.; Patil, N.N. "Text Summarization Using Deep Learning Techniques: A Review". Eng. Proc. 2023, 59, 194.

Literature Review

S. No	Use-Case	Paper Title	Year	Method	Dataset	Results	Limitations
2.	Implementati on of the Transformer architecture	Attention is all you need	2023	Transformer	WMT 2014 English- German, WMT 2014 English- French	Introduced the Transformer architecture, significantly improving the performance of text summarizati on tasks.	Requires large datasets and computatio nal resources for training.

[2] A. Vaswani, L. Jones, N. Shazeer, N. Parmar, A. N. Gomez, J. Uszkoreit, Ł. Kaiser, and I. Polosukhin, "Attention Is All You Need," arXiv:1706.03762v7 [cs.CL], Aug. 2, 2023.

Literature Review

S. No	Use-Case	Paper Title	Year	Method	Dataset	Results	Limitations
3.	Multi- document summarizatio n	Surveying the Landscape of Text Summarization with Deep Learning	2023	Deep learning methods. Various techniques like RBMs and fuzzy logic employed for summarization.	CNN/Daily Mail	Incorporati ng transfer learning enhances summary quality and reduces data demand.	Complex models, high computatio nal resources

[3] G. Wang and W. Wu, "Surveying the Landscape of Text Summarization with Deep Learning: A Comprehensive Review," arXiv:2310.09411v1 [cs.CL], Oct. 13, 2023.

Literature Review

S. No	U4se-Case	Paper Title	Year	Method	Dataset	Results	Limitations
4.	Abstractive summarization	Pegasus: Pre- training with gap- sentences for abstractive summarization	2020	Transformer (Pegasus)	XSum, CNN/Daily Mail, and Reddit TIFU	Significant improveme nts in abstractive summarizat ion quality	Resource- intensive

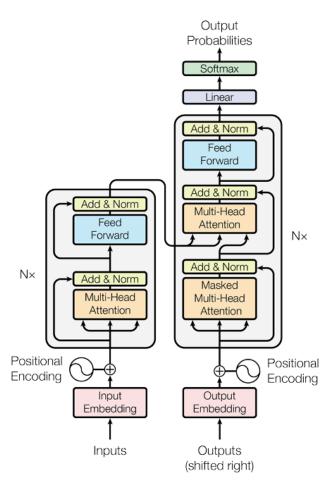
[4] J. Zhang, Y. Zhao, M. Saleh, and P. J. Liu, "PEGASUS: Pre-training with Extracted Gap-sentences for Abstractive Summarization," arXiv:1912.08777v3 [cs.CL], Jul. 10, 2020.

Literature Review

S. No	Use-Case	Paper Title	Year	Method	Dataset	Results	Limitations
5.	Extractive summarizatio n	Text Summarization with Pretrained Encoders	2019	Intersentence Transformer layers for summarizatio n	CNN/Daily Mail, NYT, Xsum, DailyMail	BERT-based models outperform ed other approaches in abstractive summarizat ion.	High computatio nal resources required

[5] Y. Liu and M. Lapata, "Text Summarization with Pretrained Encoders," arXiv:1908.08345v2 [cs.CL], Sep. 5, 2019.

Research Architecture



[2] Fig. :Transformer architecture:

Implementation methods:

- From Scratch
 - Build Model
 - NN
 - Initialize normalized W&B
 - Train model with extensive data
 - Hence,
 - Computationally Intensive
 - Sub-Optimal usage of resources
 - Out-of-scope
- Using Pre-trained model
 - Load Model & its parameters
 - Re-Train with specific dataset
 - Evaluate
 - Hence,
 - Innovation can be done at intended tasks
 - Optimal utilization of resources

Proposal

Architecture, Findings & Team Details

Proposal Workflow

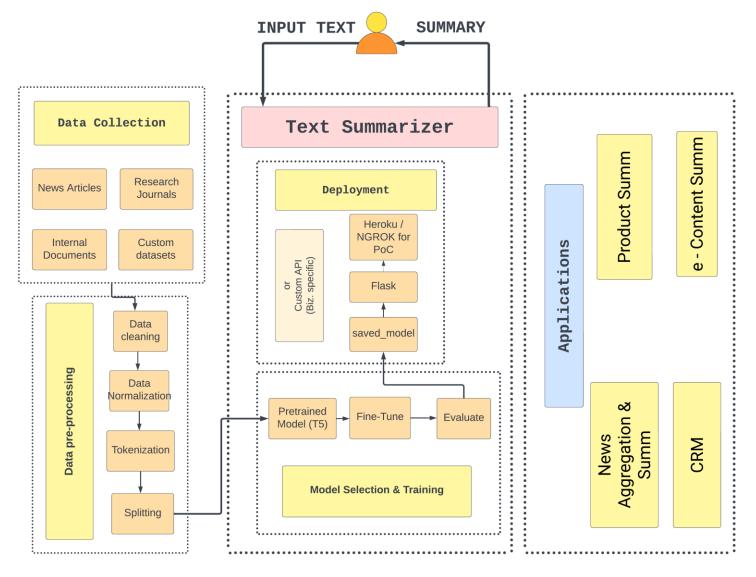


Fig.: Proposed Workflow

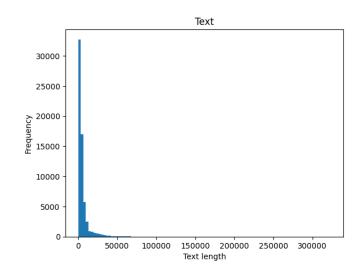
Proposal

Dataset

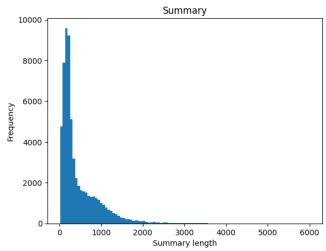
- Merged selective dataset from
 - CNN, Daily Mail: News,
 - BillSum: Legal,
 - ArXiv : Scientific
 - Dialoguesum
- Completed data preprocessing
 - Removed
 - NULL records, punctation, stop-words
 - Lowercasing, lemmatization.

	text	summary				
0	section 1 liability business entity providing	shield business entity civil liability relatin				
1	section 1 short title act may cited human righ	human right information act requires certain f				
2	section 1 short title act may cited jackie rob	jackie robinson commemorative coin act directs				
3	section 1 nonrecognition gain rollover small b	amends internal revenue code provide temporari				
4	section 1 short title act may cited native ame	native american energy act sec 3 amends energy				
2702	person1 excuse mr green manchester arent perso	tan ling pick mr green easily recognized white				
52703	person1 mister ewing said show conference cent	person1 person2 plan take underground together				
2704	person1 help today person2 would like rent car	person2 rent small car 5 day help person1				
2705	person1 look bit unhappy today whats person2 w	person2s mom lost job person2 hope mom wont fe				
62706	person1 mom im flying visit uncle lee family n	person1 asks person2s idea packing bag visitin				
62707 rows × 2 columns						

count	62707.000000
mean	5211.270975
std	7794.860686
min	83.000000
25%	1275.000000
50%	3176.000000
75%	5684.500000
max	323742.000000
Name:	text, dtype: floate



count	62707	. 000000	
mean	448	.081937	
std	459	.087443	
min	16	.000000	
25%	154	. 000000	
50%	255	.000000	
75%	618	. 000000	
max	6014	.000000	
Name:	summary,	dtype:	float64



* In characters.

https://drive.google.com/drive/folders/1yH89iZmARdc-R7QY6pwfE8tbOJI_n9K8?usp=sharing Infosys Text-Summarization/src/data preprocessing.ipynb at main · MohanKrishnaGR/Infosys Text-Summarization (github.com)

Proposal Model Training

- Load pre-trained transformer
 - Facebook/bart
 - (or) Google/T5
- OOP implementation of Dataset
 - Feature, Target
 - Tokenize
 - Padding, Truncate
 - Convert to Tensor
 - Pass to: DataLoader with batch size
- **Training Loop**
 - Adam optimizer
 - Forward pass & compute loss
 - Backward pass
 - Update params compute gradient
 - Update LR
 - Zero the gradients
 - Update total loss





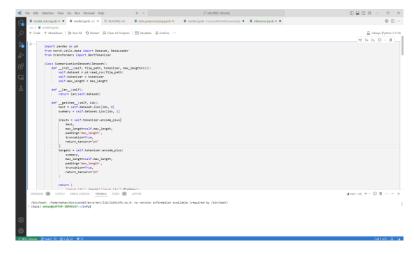


Fig.: Screenshot



Fig.: Fine-Tunning Overview

ProposalModel Validation

- Performance metrics ROUGE (Recall-Oriented Understudy for Gisting Evaluation)
 - Overlap between generated summary and reference summary.
 - Best suited: evaluating 'Text Summarization' tasks.
 - Other options : BLEU.
- Aimed to: implement custom evaluation function.
 - Calc.: ROUGE based on model's inference.
- Implementation:
 - Use: same Data loading methods OOP.
 - Load the saved model & tokenizer.
 - Use 'ROUGE' metric from the Hugging Face's 'datasets' library.
 - To evaluate.
 - Calculates for all in dataloader



