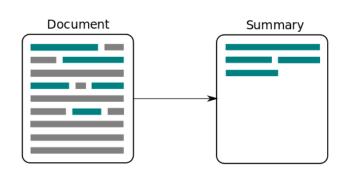


NLP Summarization Techniques

Abstract Text Summarization: Let Transformers Summarize for You!

DATA606: Capstone in Data Science Final Project, Fall 2022 Lee Whieldon







What is the value of abstract text summarization?

- Time Saving Summarization of Long Meeting Transcripts
- Consistency Summarize complex corpus of text like contracts
- Customer Satisfaction Distilling collection of dialogue into an actionable summary



Summary: Elizabeth was hospitalized after attending a party with Peter.



Data - SAMsum Corpus

Features:

Dialogues

Summaries

Ids – unique identifier

Data Splits:

• Train: 14,732 records

Validation: 818 records

Test: 819 records

16,369 dialogues in total

Dialogue:

Hannah: Hey, do you have Betty's number?

Amanda: Lemme check
Hannah: <file_gif>

Amanda: Sorry, can't find it.

Amanda: Ask Larry

Amanda: He called her last time we were at the park together

Hannah: I don't know him well

Hannah: <file_gif>

Amanda: Don't be shy, he's very nice

Hannah: If you say so..

Hannah: I'd rather you texted him

Amanda: Just text him (1)
Hannah: Urgh.. Alright

Hannah: Bye Amanda: Bye bye

Summary:

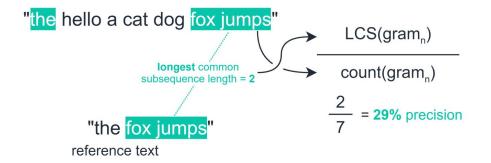
Hannah needs Betty's number but Amanda doesn't have it. She needs to contact Larry.



Scoring Metrics

<u>Recall-Oriented Understudy for Gisting</u> Evaluation – ROUGE!

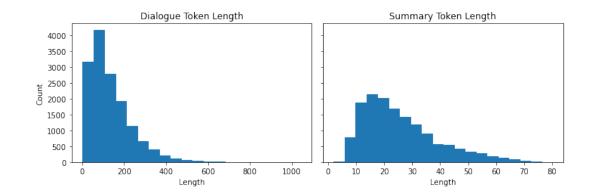
- Developed for automatic summarization and machine translation software
- High recall is more important than precision scoring alone
- Longest common subsequence (LCS): Help calculate the score per sentence and averages it for the summaries
- We also calculate the score over the whole summary (ROUGE L-Sum)





Pretraining Analysis

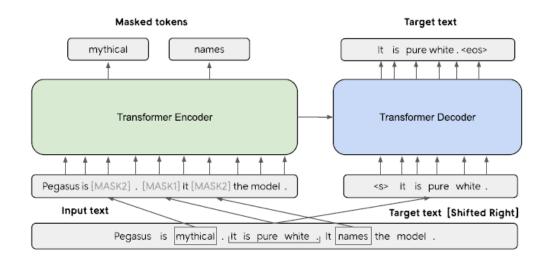
- Length of distribution:
 - Each Dialogue records contain 100-200 tokens (a.k.a. words)
 - Summaries are shorter, with around 20-40 tokens





Model - PEGASUS

- Encoder-decoder transformer
- Pretraining objective is to predict masked sentences in multisentence texts
- Applying Gap Sentence Generation (GSG)
- Applying Masked Language Modelling (MLM)





Training & Evaluation

Google's Pegasus-CNN_DailyMail

• Transfer learning from google/pegasus-cnn dailymail.

Training hyperparameters

Learning rate: 5e-05Train batch size: 1Eval batch size: 1

•seed: 42

• Gradient accumulation steps: 16

•Total train batch size: 16

• optimizer: Adam with betas=(0.9,0.999) and epsilon=1e-08

•Lr scheduler type: linear

•Lr scheduler warmup steps: 500

•Number of epochs: 1

Training results

• Training Loss: 1.6776

• Epoch: 0.54 • Step: 500

•Validation Loss: 1.4919

	rouge1		rouge2		rougeL		rougeLsum	
р	re-training score	after training score	pre-training score	after training score	pre-training score	after training score	pre-training score	after training score
	0.29614	0.431695	0.087609	0.201628	0.229381	0.346877	0.229379	0.347153



Conclusions & Limitations

- Not applicable for long corpus
 - Most models today can handle up to 1,000 characters
 - Research is actively being done today to account for this limitation
- Expedited processing with greater GPU clusters





Demo!



Thank you!

Looking forward to seeing everyone's projects!