COMP 5313- ARTIFICIAL INTELLIGENCE PROJECT 2

Text Summarization Techniques in Python

Methodology:

I created one .py file in order to do text summarization techniques in python.

I used four techniques that are BART, T5, BERT and Pegasus to do text summarization.

Dataset:

Here I used ccdv/pubmed-summarization dataset from hugging face. This dataset has two columns article and abstract. Abstract is the summarization of the article which will be the baseline of our project.

This is the dataset.



Abstractive text summarization

Abstractive text summarization generates legible sentences from the entirety of the text provided. It rewrites large amounts of text by creating acceptable representations, which is further processed and summarized by natural language processing.

Then I created a sample text with first 1000 characters of the article

```
sample_text = dataset["train"][1]["article"][:1000]
sample_text
```

'it occurs in more than 50% of patients and may reach 90% in certain types of cancers , especially in patients undergoing chemotherapy and/or radiation therapy.1 anemia is defined as an inadequate circulating level of hemo globin (hb) (hb < 12 g / dl) and may arise as a result of the underlying disease , bleeding , poor nutritio n , chemotherapy , or radiation therapy . \n preliminary studies suggest that survival and loco - regional cont rol after radiation therapy , especially in head and neck cancers , may be compromised by anemia.24 anemia ofte n worsens symptoms such as fatigue , weakness , and dyspnea , and thus may have a negative effect on quality of life (qol) and performance status in patients with cancer . \n thus , to improve physical functioning , qol , and prognosis in patients with cancer , it would be reasonable to take a proactive approach in identifying populations who need treatment for cancer - associated anemia (caa) and provide timely management . \n blood tra

T5:

T5, or **Text-to-Text Transfer Transformer**, is a Transformer based architecture that uses a text-to-text approach. Every task – including translation, question answering, and classification – is cast as feeding the model text as input and training it to generate some target text.

```
# Initializing T5 pipeline
t5_pipeline = pipeline('summarization', model='t5-small')
t5_output = t5_pipeline(sample_text)
summaries['t5'] = '\n'.join(sent_tokenize(t5_output[0]['summary_text']))
```

I created a pipeline for the T5 model and passed sample_text through the model to generate summarization.

BART:

BART, or **Bidirectional and Auto-Regressive Transformers** is a denoising autoencoder for pretraining sequence-to-sequence models. It is trained by corrupting text with an arbitrary noising function, and learning a model to reconstruct the original text. It uses a standard Transformer-based neural machine translation architecture.

```
# Initialize BART pipeline
bart_pipeline = pipeline("summarization", model="facebook/bart-large-cnn")
bart_output = bart_pipeline(sample_text)
summaries['bart'] = '\n'.join(sent_tokenize(bart_output[0]['summary_text']))
```

Here, I created a pipeline for the BART and passed sample_text through the model to generate summarization.

PEGASUS:

PEGASUS proposes a transformer-based model for abstractive summarization. It uses a special self-supervised pre-training objective called gap-sentences generation (GSG) that's designed to perform well on summarization-related downstream tasks.

```
# Initialize PEGASUS pipeline
pegasus_tokenizer = AutoTokenizer.from_pretrained("google/pegasus-large")
pegasus_model = AutoModelForSeq2SeqLM.from_pretrained("google/pegasus-large")
pegasus_pipeline = pipeline("summarization", model=pegasus_model, tokenizer=pegasus_tokenizer)
pegasus_output = pegasus_pipeline(sample_text)
summaries['pegasus'] = '\n'.join(sent_tokenize(pegasus_output[0]['summary_text']))
```

First, I initialized the PEGASUS tokenizer using 'AutoTokenizer' from the Hugging Face Transformers library. Then, I created a pipeline for the PEGASUS and passed sample_text through the model to generate summarization.

BERT:

BERT, or **Bidirectional Encoder Representations from Transformers**, improves upon standard Transformers by removing the unidirectionality constraint by using a masked language model (MLM) pre-training objective.

```
# Initialize BERT model
bert_tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
bert_model = BertForNextSentencePrediction.from_pretrained("bert-base-uncased")
bert_pipeline = pipeline("feature-extraction", model=bert_model, tokenizer=bert_tokenizer)
bert_output = bert_pipeline(sample_text)
top_sentences = sorted(list(enumerate(bert_output[0])), key=lambda x: x[1], reverse=True)[:3]
summary_sentences = [sent_tokenize(sample_text)[index] for index, _ in top_sentences]
summaries['bert'] = '\n'.join(summary_sentences)
```

Here I initialized the BERT tokenizer with the pre-trained weights of the "bert-base-uncased" model. Initialized the BERT model for next sentence prediction task using the pre-trained weights. Then, I created a pipeline for the BERT and passed sample_text through the model to generate summarization.

This is what the summarized text looks like.

```
summaries

{'t5': 'anemia is defined as an inadequate circulating level of hemoglobin ( hb 12 g / dl ) and may arise as a result of the underlying disease .\npreliminary studies suggest survival and loco - regional control after radiation therapy may be compromised by anemia .', 'bart': 'Anemia is defined as an inadequate circulating level of hemoglobin ( hb) It occurs in more than 50% of patients and may reach 90% in certain types of cancers.\nAnemia often worsens symptoms such as fatigue and dyspnea.\nIt can have a negative effect on quality of life ( qol) and performance status in patients with cancer.'
'pegasus': 'preliminary studies suggest that survival and loco - regional control after radiation therapy , especially in head and neck cancers , may be compromised by anemia.24 anemia often worsens symptoms such as fatigue , weakness , and dyspnea , and thus may have a negative effect on quality of life ( qol ) and performance status in patients with cancer
```

"bert': 'it occurs in more than 56% of patients and may reach 96% in certain types of cancers , especially in patients undergoing chemotherapy and/or radiation therapy.1 anemia is defined as an inadequate circulating level of hemoglobin (hb) (hb < 12 g / dl) and may arise as a result of the underlying disease , bleeding , poor nutrition , chemotherapy , or radiation therapy .\text{Apreliminary studies suggest that survival and loco - regional control after radiation therapy , especially in head and neck cancers , may be compromised by amenia.24 anemia often worsens symptoms such as fatigue , weakness , and dyspnea , and thus may have a negative effect on quality of life (qol) and performance status in patients with cancer .')

```
T5 Summary:
anemia is defined as an inadequate circulating level of hemoglobin ( hb 12 g / dl ) and may arise as a result of the underlying disease .
preliminary studies suggest survival and loco - regional control after radiation therapy may be compromised by anemia .

Bart Summary:
Anemia is defined as an inadequate circulating level of hemoglobin ( hb) It occurs in more than 56% of patients and may reach 96% in certain types of cancers.
Anemia often worsens symptoms such as fatigue and dyspnea.
It can have a negative effect on quality of life ( qol) and performance status in patients with cancer.

Pegasus Summary:
preliminary studies suggest that survival and loco - regional control after radiation therapy , especially in head and neck cancers , may be compromised by anemia.24 anemia often worse

Bert Summary:
it occurs in more than 56% of patients and may reach 96% in certain types of cancers , especially in patients undergoing chemotherapy and/or radiation therapy.1 anemia is defined as an preliminary studies suggest that survival and loco - regional control after radiation therapy , especially in head and neck cancers , may be compromised by anemia.24 anemia often worse
```

Rouge Score:

ROUGE, or Recall-Oriented Understudy for Gisting Evaluation, is a set of metrics and a software package used for evaluating automatic summarization and machine translation software in natural language processing. The metrics compare an automatically produced summary or translation against a reference or a set of references (human-produced) summary or translation. ROUGE metrics range between 0 and 1, with higher scores indicating higher similarity between the automatically produced summary and the reference.

```
TS ROUGE Scores: {'rouge1': 0.11956521739130434, 'rouge2': 0.027322404371584695, 'rouge1': 0.69598260869565217, 'rouge1sum': 0.10869565217391303}

Bart ROUGE Scores: {'rouge1': 0.1671018276762402, 'rouge2': 0.07349081364829396, 'rouge1': 0.10443864229765014, 'rouge1sum': 0.1566579634464752}

Pegasus ROUGE Scores: {'rouge1': 0.15748031496062992, 'rouge2': 0.058047493403693924, 'rouge1': 0.09448818897637797, 'rouge1sum': 0.12073490813648294}

Bert ROUGE Scores: {'rouge1': 0.15748031496062992, 'rouge2': 0.058047493403693924, 'rouge1': 0.09448818897637797, 'rouge1sum': 0.12073490813648294}

Bert ROUGE Scores: {'rouge1': 0.1671018276762402, 'rouge1': 0.0580474934083693924, 'rouge1': 0.09448818897637797, 'rouge1sum': 0.12073490813648294}

Bert ROUGE Scores: {'rouge1': 0.1671018276762402, 'rouge1': 0.0580474934083693924, 'rouge1': 0.09448818897637797, 'rouge1sum': 0.12073490813648294}

TS 0.119565 0.027322 0.059783 0.108696

Bert ROUGE Scores: {'rouge1': 0.167102 0.073491 0.094488 0.120735}

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Bert ROUGE Scores: {'rouge1': 0.167102 0.07449 0.15667 0.094488 0.120735}

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Bert ROUGE Scores: {'rouge1': 0.157480 0.094488 0.120735}

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Bert ROUGE Scores: {'rouge1': 0.167102 0.094488 0.120735}
```

These are the rouge score for all the above models.

Conclusion:

As you can see above, after using all the four deep learning models for text summarization. B ERT model got the higher rouge score in all rouge1 has 0.268, rouge2 has 0.091, rougeL has 0.132 and rougeLsum has 0.223 which is the highest among all the other. Next comes BART m odel with rouge1 has 0.167, rouge2 has 0.073, rougeL has 0.104 and rougeLsum has 0.156. T hen comes PEGASUS and then T5. According to my model BERT is the best.

References:

- [1] https://paperswithcode.com/method/t5
- [2] https://paperswithcode.com/method/bart
- [3] https://paperswithcode.com/method/pegasus
- [4] https://paperswithcode.com/method/bert
- [5] https://en.wikipedia.org/wiki/ROUGE_(metric)
- [6] https://www.turing.com/kb/5-powerful-text-summarization-techniques-in-python
- [7] https://www.projectpro.io/article/text-summarization-python-nlp/546