Bert-Text Abstractive Summarization

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Abstract

Text summarization is a process/technique to shorten an extended text such as books, news articles, blog posts, research papers, emails, and tweets in a coherent, fluent summary. It is one of the Natural Language Processing applications, which significantly impacts our lives with a spiking demand every day. With growing digital media and publishing, text summarization helps with deciding on whether an article/ document/ book is valuable or not. With the availability of textual data, it has become easier to train a model for text summarization. This paper discusses Text Abstractive Summarization using Bert to create a model that produces results comparable to Google's massive Pegasus model they developed and released back in June of 2020. We used the English language for our project as it's a language we can speak and understand. We also used the datasets to train our model consist of only English entries. We have used the CNN/Daily Main, SAMSum Corpus, and BillSum Corpus as our datasets.

I. Introduction

Text Summarization summaries extended text while keeping coherent context. The increasing amount of unstructured data needs to be extracted in relevant summaries. There are different types of text summarization: Extractive and Abstractive. Extractive summarization generates a summary by selecting salient sentences or phrases from the source text, while abstractive methods paraphrase and restructure sentences to compose the summary. We focus on abstractive summarization in our work. There are many abstractive approaches based on a sequence-to-sequence model with a copy mechanism. However, some there are issues with these abstractive methods are: 1) because these methods use a left-context decoder while predicting each word, these methods do not have complete context. 2) as they do not use pre-trained contextualized language models on the decoder, the decoded does learn summary representation, context interactions, and language modeling together. BERT, which stands for Bidirectional Encoder Representations from Transformation, is designed to pre-train deep bidirectional representations from the unlabeled text by jointly conditioning both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 points absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 points absolute improvement).[1].

Bert has been very successful in textual entailment, name entity recognition, and machine reading comprehension. We have used the Bert-base-uncased pre-trained model for both the encoder and decoder, with the goal in mind of creating a model that resembles to Google's massive Pegasus model.

II. Background

i. Works Cited

We have used [1], [2] as reference. In the [1] paper, the text summarization model is based on the Transformer architecture. The architecture adopts the original model of Vaswami et al. (2017). On top of the decoder, they used a Pointer-Generator to increase the extractive capabilities of the network. In Paper [2], proposed 1. A natural language generation model based on BERT, making good use of the pre-trained language model in the encoder and decoder process, and the model can be trained end-to-end without handcrafted features. 2. A design a two-stage decoder process. In this architecture, our model can generate each word of the summary considering both sides' context information. 3. To conduct experiments on the benchmark datasets CNN/Daily Mail and New York Times. Our model achieves a 33.33 average of ROUGE-1, ROUGE-2 and ROUGE-L on the CNN/Daily Mail, which is state-of-the-art. On the New York Times dataset, our model achieves about 5.6% relative improvement over ROUGE-1. Our work doesn't differ much from the papers we referenced here [1], [2]. As BERT can't process sequences with more than 512 tokens, to deal with that our model is using overlapping subsection text of length 512 words and generating summaries for each of the individual subsections. In the end, a final summary across all those summaries. In the case of summaries, we didn't use a pre-trained summary model until the end.

[1] See "Computation and Language", arXiv:1810.04805

ii. Datasets

Our project used three datasets: **1) CNN/Dailymail, 2) SAMSum corpus, and 3) Billum corpus**. There are different datasets for text summarization. We tried to find datasets with "gold" summaries to compare our generated summaries with the "gold" summaries for our approach.

The **CNN/Dailymail** is an English-language dataset containing just over 300k unique news articles written by journalists at CNN and the Daily Mail. We have used version 3.0.0, which can be used to train both abstractive and extractive summarization.

The data consists of news articles and highlight sentences. In the question answering setting of the data, the articles are used as the context and entities are hidden one at a time in the highlight sentences, producing Cloze style questions where the goal of the model is to correctly guess which entity in the context has been hidden in the highlight. In the summarization setting, the highlight sentences are concatenated to form a summary of the article. The CNN articles were written between April 2007 and April 2015. The Daily Mail articles were written between June 2010 and April 2015. The model performance is measured by how high the output summary's ROUGE score for a given article is compared to the highlight written by the original article author. Zhong et al. (2020) report a ROUGE-1 score of 44.41 when testing a model trained for extractive summarization. See the Papers With Code leaderboard for more models.[2]. There is a string for the article for each instance, a string for the highlights, and a string for the id. The train set has 287,113, the validation set has 13,368, and the Test set has 11,490 instances in Split.

The **SAMSum** dataset contains about 16k messenger-like conversations with summaries. Conversations were created and written down by linguists fluent in English. The dataset reflects the proportion of topics of real-life

[2] See "Get To The Point: Summarization with Pointer-Generator Networks", https://www.aclweb.org/anthology/P17-1099

messenger conversations. It has 16369 conversations distributed uniformly into 4 groups. Each instance contains an id string, a summary string, and a dialogue string. The train set has 14,732, the validation set has 818, and the test set has 819 instances in Split. The summaries are annotated and assume they should 1) be short, 2) extract important pieces of information, 3)include names of interlocutors, and 4)be written in the third person. Each dialogue has only one reference of summary.[3]

The **BillSum** dataset summarizes the state bills of US Congressional and California states. It has several features: 1)text: bill text, 2) summary: summary of the bills, 3)title: title of the bills, 4)text_len: number of chars in text, 5)sum_len: number of chars in summary. The data field has a text string, a [1] summary string, and a title string. The train set has 18,949, the ca_test set has 1237, and the test set has 3269 instances in Split.[4]

III. Model and Approach

In the encoding and generation process, the attention mechanism is used to concentrate on the most important positions of text. The learning objective of most sequence-to-sequence models is to minimize the negative log likelihood of the generated sequence as shown in following equation, where y_t^* is the t-th ground-truth summary token.

$$Loss = -\log \sum_{t=1}^{|y|} P(y_t^* | y_{<t}^*, X) \tag{1}$$

We used BERT and tried to fine tune it. BERT consists of several layers. In each layer, there is a first multi-head self-attention sub-layer and then a linear sub layer with residual connection. In each self-attention sub-layer the attention scores e_{ij} are first calculated as Eq. (2), (3), in which d_e is output dimension, and W^Q, W^K, W^V are parameter matrices.

[3]See "SAMSum Corpus: A Human-annotated Dialogue Dataset for Abstractive Summarization", https://www.aclweb.org/anthology/D19-5409

[4]See "BillSum: A Corpus for Automatic Summarization of US Legislation", 1910.00523

$$a_{ij} = \frac{(h_i W_Q)(h_j W_K)^T}{\sqrt{d_e}} \tag{2}$$

$$e_{ij} = \frac{\exp e_{ij}}{\sum_{k=1}^{N} \exp e_{ik}} \tag{3}$$

Then the output is calculated as Eq. (4), which is the weighted sum of previous outputs h added by previous out-put h_i. The last layer outputs are context encoding of input sequence.

$$o_i = h_i + \sum_{j=1}^{N} e_{ij}(h_j W_V) \tag{4}$$

Despite the wide usage and huge success, there is also a mismatch problem between these pre-trained context encoders and sequence-to-sequence models. The issue is that while using a pre-trained context encoder like BERT, they model token-level representations by conditioning on both direction context. During pre-training, they are fed with complete sequences. However, with a left-context-only decoder, these pre-trained language models will suffer from incomplete and inconsistent context and thus cannot generate good enough context-aware word representations, especially during the inference process.

Based on the sequence-to-sequence framework built on top of BERT, we first followed the design mentioned in [2], which is a refine decoder at word-level to tackle the two problems described in the above section. We also introduce a discrete objective for the refine decoders to reduce the exposure bias problem.

i. Pre Trained Model Comparison

In order to gain a better understanding of BERT abstract text summarization, several pre-trained BERT summarizers to compare with one another and with our fine tuned BERT model. The models chosen were gathered from hugging face and are google/pegasus-cnn-dailymail, t5-base, sshleifer/distilbart-cnn-12-6, facebook/bart-large-cnn, nsi319/legal-led-base-16384, google/pegasus-newsroom, google/pegasus-wikihow, and ml6team/mt5-small-german-finetune-mlsum. These models were chosen by exploring the hugging face website and looking through the abstractive text summarization models while looking at which ones would provide interesting comparisions to our fine tuned BERT model. For example, two google pegasus models were chosen, google/pegasus-cnn-dailymail and google/pegasus-wikihow. Each of these models was trained on a different collection of text articles, providing a more complete view of the various pre-trained models, rather than just looking for ones trained on the same set of data.

In order to effectively compare these these classifiers they were first all initialized and loaded into a python dicitonary for access later, as shown below.

```
summarizers = {}
for name in tqdm(sum_list):
    summarizers[name] =
      pipeline(
        "summarization",
        model=name, tokenizer=name)
```

Once the models were all loaded into the dictionary they were then all given the same 200 articles from the **1) CNN/Dailymail, 2) SAMSum corpus, and 3) Billum corpus** datasets. However the pre trained models have character limits on the text they will summarize. This causes errors when trying to just generate summaries for every single article in the datasets. In order to rectify this issue, a BERT extractive summarizer that can be installed via pip. The extractive summarizer shortens an article that is to long by removing all but what it views as the critical sentences. Once the article is shortened it can be through the pre trained models and have an abstractive summary generated.

IV. Evaluation

Once all the articles are summarized through by the 6 pre trained models the summaries are evaluated using two metrics. The first is rouge, which calculates the precision, recall, and fmeasure for each model when comparing the generated summaries to the "gold" summaries used for evaluation, precision, recall, and fmeasure are defined below.

- Precision = $\frac{TP}{TP+FP}$
- Recall = $\frac{TP}{TP+FN}$
- Fmeasure = 2 * $\frac{Precision*Recall}{Precision+Recall}$

The second metric used was the SequenceMatcher simmilarity metric imported from the python difflib library. This library calculates a similarity score for two strings and returns a score as to how similar they are. When looking at the articles, we determined that a similarity score of 0.1 between the generated summary, and the "gold" summary shared the same main ideas. This similarity score was used to calculate a basic accuracy for each model, where if a generated summary had a similarity score > 0.1 it was considered "good". This was then used to compute an accuracy score where the number of good summaries is divided by the total number of generated summaries. The code below shows the model evaluations.

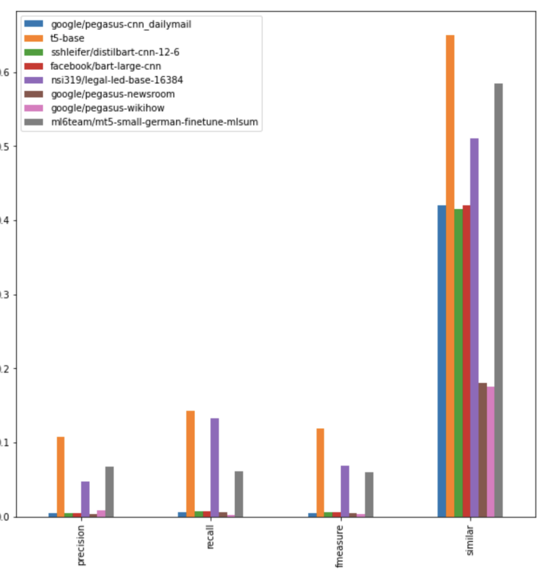
```
sum_scores = {}
for model_name in tqdm(sum_preds):
    sum_scores[model_name] = {}
    good_score = 0
        pred = []
        gold = []
        for text_sum in range(
          len(sum_preds[model_name])):
            pred.append(sum_preds[model_name]
                [text_sum])
            gold.append(clean_sum[text_sum])
            score=similar(sum_preds[model_name]
                [text_sum], clean_sum[text_sum])
            if score > .1:
                good_score += 1
        try:
            good = rouge.compute(
                predictions=pred,
                references=gold,
                rouge_types=
                  ["rouge2"])["rouge2"].mid
        except:
```

```
        good = [0.0, 0.0, 0.0]
    sum_scores[model_name]
      ['rouge'] = good
    sum_scores[model_name]
      ['similar']=
        good_score/len(summary)
```

This code takes into account the possibility that a model might not have generated any summaries for a given article. If this is the case then the precision, recall, and fmeasure are set to 0.0 as to not interfere with later comparisons.

Once these metrics were calculated we were able to look at how each model did at summarizing the data. Unfortunatly due to the how long our fine tuned model was taking to train due to the limitations of our personal machines, and online GPU's no data was able to be collected to compare to the pre-trained models. However all six of the pre-trained models were able to be evaluated and compared.

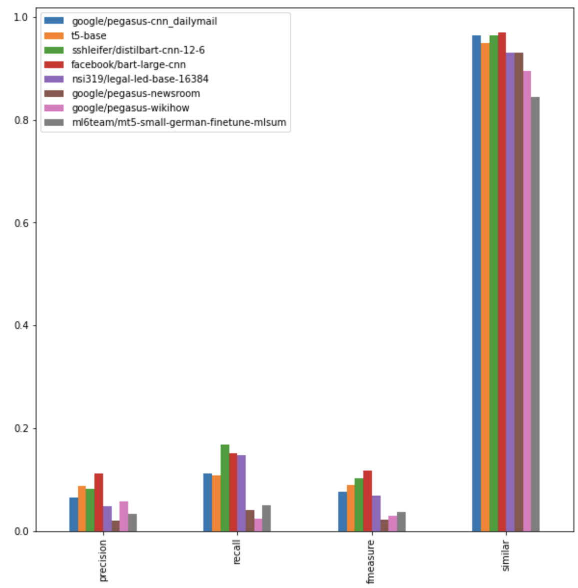
```
google/pegasus-cnn_dailymail:
Precision: 0.004057214480304053
Recall: 0.005905264789728774
Fmeasure: 0.004581924668642785
Similar: 0.42

t5-base:
Precision: 0.1073388727069371
Recall: 0.14239013214035595
Fmeasure: 0.1183132141131514
Similar: 0.65

sshleifer/distilbart-cnn-12-6:
Precision: 0.004520071790974368
Recall: 0.007408451371538898 5
Fmeasure: 0.005479731712023811
Similar: 0.415

facebook/bart-large-cnn:
Precision: 0.005140301159330723
Recall: 0.00741847862673695
Fmeasure: 0.00584081807500133
Similar: 0.42

nsi319/legal-led-base-16384:
Precision: 0.047713374623433426
Recall: 0.13309086083714433
Fmeasure: 0.06875642452398892
Similar: 0.51

google/pegasus-newsroom:
Precision: 0.0032018573368585773
Recall: 0.0057494030307497805
Fmeasure: 0.003990393536896979
Similar: 0.18

google/pegasus-wikihow:
Precision: 0.00826023391812865 5
Recall: 0.001940067674312532
Fmeasure: 0.002754875848317157
Similar: 0.175

ml6team/mt5-small-german-finetune-mlsum:
Precision: 0.06754566523757385
Recall: 0.060843013592276354
Fmeasure: 0.05992201390563309
Similar: 0.585
```



Above shows how each pre-trained model did classifying the CNN/Dailymail dataset. As shown, t5-base, nsi319/legal-led-base-16384, and ml6team/mt5-small-german-finetune-mlsum had the best similarity metrics, and high metrics accross the board. Interestingly the pre-trained models trained on the CNN/-Dailymail datasets such as google/pegasus-cnn-dailymail and facebook/bart-large-cnn struggled to have good metrics. Specifically their precision and recall were really low, signalling that these models generated a lot of false positives and false negatives. These metrics can be interpreted as more confusion being introduced due to the models being trained on the same data that is being used for evaluation.

The next dataset to be evaluated is the SAMSum corpus.

```
google/pegasus-cnn_dailymail:
Precision: 0.06570140791970662
Recall: 0.11194645893608307
Fmeasure: 0.07676660531430701
Similar: 0.965

t5-base:
Precision: 0.0871608200405255
Recall: 0.10878196145394188
Fmeasure: 0.08892795374747745
Similar: 0.95

sshleifer/distilbart-cnn-12-6:
Precision: 0.08222619140159643
Recall: 0.16857389607260176
Fmeasure: 0.10307547627520189
Similar: 0.965

facebook/bart-large-cnn:
Precision: 0.1109204418673014
Recall: 0.1506222918019447
Fmeasure: 0.11705913865658535
Similar: 0.97

nsi319/legal-led-base-16384:
Precision: 0.048056536636149755
Recall: 0.14721559364633643
Fmeasure: 0.06862347378183611
Similar: 0.93

google/pegasus-newsroom:
Precision: 0.01969416070376323
Recall: 0.04029707519377925
Fmeasure: 0.02146641285892842
Similar: 0.93

google/pegasus-wikihow:
Precision: 0.05703333158776708
Recall: 0.02338537494249275
Fmeasure: 0.02896930473234471
Similar: 0.895

ml6team/mt5-small-german-finetune-mlsum:
Precision: 0.032227086778997535
Recall: 0.05069437127612212
Fmeasure: 0.03666129567374895
Similar: 0.845
```

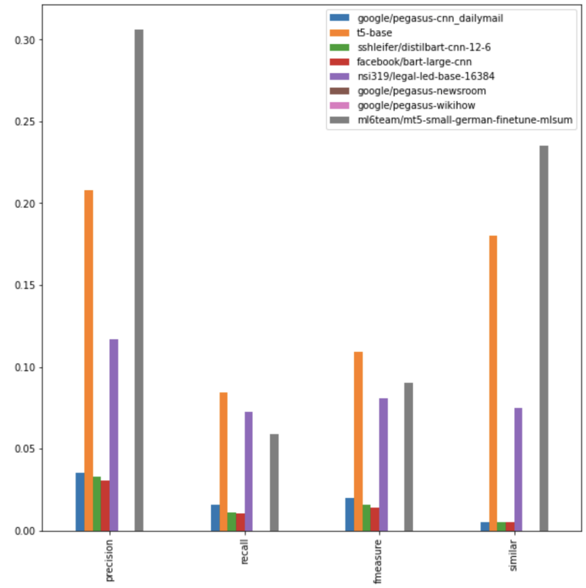


Here we see more parity between the models with facebook/bart-large-cnn and sshleifer/distilbart-cnn-12-6 preforming the best. Having the highest similarity scores, and the highest precision, recall, and fmeasure, two pre-trained models which were both trained using the CNN/Dailymail dataset interestingly preformed the best on a dataset seperate from what they were trained on.

The final dataset we looked at was the Billum corpus.

```
google/pegasus-cnn_dailymail:
Precision: 0.034997246400968116
Recall: 0.01585152779285387
Fmeasure: 0.020187958372424764
Similar: 0.005

t5-base:
Precision: 0.2080614656568488
Recall: 0.0842456195521589
Fmeasure: 0.10906555198486713
```

```
Similar: 0.18

sshleifer/distilbart-cnn-12-6:
Precision: 0.0328451080507806
Recall: 0.011291149429687435
Fmeasure: 0.015812224174392167
Similar: 0.005

facebook/bart-large-cnn:
Precision: 0.030416521070095112
Recall: 0.010306199164564775
Fmeasure: 0.014132734541054626
Similar: 0.005

nsi319/legal-led-base-16384:
Precision: 0.11671223384360122
Recall: 0.07259274110511799
Fmeasure: 0.08094988869337535
Similar: 0.075

google/pegasus-newsroom:
Precision: 0.0
Recall: 0.0
Fmeasure: 0.0
Similar: 0.0

google/pegasus-wikihow:
Precision: 0.0
Recall: 0.0
Fmeasure: 0.0
Similar: 0.0

ml6team/mt5-small-german-finetune-mlsum:
Precision: 0.30615950365348016
Recall: 0.05901749267334537
Fmeasure: 0.08999198010632611
Similar: 0.235
```



On this data we once again see the t5-base, nsi319/legal-led-base-16384, and ml6team/mt5-small-german-finetune-mlsum models out preforming the others. Once again having high similarity, precision, recall, and fmeasure scores. However two of the models, google/pegasus-newsroom and google/pegasus-wikihow, have scores of 0.0 across the board. This means that these models were not even able to generate summaries for this dataset.

V. Implications

When considering that for two out of the three data sets the same three models preformed the best. Leading to the interpretation that t5-base, nsi319/legal-led-base-16384, and ml6team/mt5-small-german-finetune-mlsum are more well suited for general text summarizaiton than the other models in this experiment. This is important to note in the future event that one wishes to preform abstract text summarization using pre-trained BERT models. Given the data collected one would be better to use t5-base, nsi319/legal-led-base-16384, or ml6team/mt5-small-german-finetune-mlsum rather than use google/pegasus-wikihow, google/pegasus-newsroom, google/pegasus-cnn-dailymail, facebook/bart-large-cnn, or sshleifer/distilbart-cnn-12-6.

VI. Conclusion

References

[1] Dmitrii Aksenov et al. "Abstractive Text Summarization based on Language Model Conditioning and Locality Modeling". In: *arXiv preprint arXiv:2003.13027* (2020).

[2] Haoyu Zhang, Jianjun Xu, and Ji Wang. "Pretraining-based natural language generation for text summarization". In: *arXiv preprint arXiv:1902.09243* (2019).