Lay It On Me. Generating Easy-to-Read Summaries for Non-Experts

Ahmed Soliman and **Marc Wenzlawski** and **Vladislav Yotkov**

Abstract

In this study, we present an extractive-abstractive lay summarization pipeline for biomedical papers aimed at generating accessible summaries for non-experts. To achieve this, we construct a sentence-level dataset optimized for maximizing ROUGE scores, utilizing both lay summaries and full articles. We employ a BERT-based classifier for identifying the most important sentences within each article. The extracted summaries are then input into two abstractive models, Clinical-Longformer and GPT-2, which paraphrase the summaries to enhance readability. We evaluate the performance of our models using the ROUGE metric, along with readability metrics such as Flesch-Kincaid Grade Level (FKGL), Gunning Fog Score, and Automated Readability Index (ARI). We find that a ROUGE-maximizing extractive summarization approach is effective for generating extractive summaries, with the Clinical-Longformer model achieving the best results for combined ROUGE and readability scores. Our approach demonstrates the potential for generating lay-friendly summaries of biomedical papers, bridging the gap between expert knowledge and public understanding.

1 Introduction

It can be challenging for individuals without expertise to comprehend scientific publications, particularly in biomedicine, where inaccuracies can directly impact health decisions (Islam et al. 2020). A possible remedy for this situation is to provide lay summaries, i.e., summaries in simpler terms, which are currently uncommon. Prior research on Automatic Text Summarisation (ATS) has neglected the biomedical domain owing to the absence of data (Chandrasekaran et al. 2020); however, two recently introduced datasets (PLOS and eLife) have emerged to tackle this issue (Goldsack et al. 2022).

2 Methods and Datasets

2.1 Dataset

The data we used is sourced from biomedical research articles in English published in the Public Library of Science (PLOS) and eLife (Goldsack et al. 2022). The datasets (Tables 1 and 2) contain technical abstracts and lay summaries written by experts, which are part of BioLaySumm2023 shared task (Goldsack et al. 2023).

Dataset	Training	Validation
PLOS	$24,773$	$1,376$
eLife	$4,346$	241

Table 1: PLOS and eLife: number of articles

Dataset	Avg. Sentences	Avg. Tokens
PLOS	300	$9,000$
eLife	600	$14,000$

Table 2: PLOS and eLife: Dataset statistics

2.2 Extractor Network

Due to the extreme length of medical articles (e.g., eLife has an average of 600 sentences per article), it is not feasible to pass them directly as input to the abstractive models due to their limited maximum input size:

i. **GPT-2** (Radford et al. 2019a): $1,024$ tokens, and
ii. **Clinical-Longformer** (Li et al. 2023): $4,096$ tokens

To overcome this limitation, we use the BioClinicalBERT (Alsentzer et al. 2019) model, pre-trained on the MIMIC-III dataset (Johnson et al. 2016), to extract the most important sentences from the articles. For that purpose, we cast the extraction summarisation problem as supervised binary classification where the input is a sentence s and the output is a binary label indicating whether the sentence should be included in the summary c or not (i.e., 1 and 0, respectively). Due to the nature of the provided gold summaries (i.e., abstractive and lay), we generate our own sentence-level dataset by applying the ROUGE-maximisation technique (Zmandar et al. 2021; Nallapati, Zhai, and Zhou 2017) on the gold summaries and the whole articles. More formally, for each gold summary sentence s_i^k, we find the sentence s_j^k in article a_k that maximises the ROUGE-2 score between them. We then label s_j^k as 1 and the rest of the sentences in a_k as 0. Because the number of sentences in the articles is much larger than the number of sentences in the gold summaries:

i. We base our extractive binary dataset on both eLife and PLOS data to maximise the number of training samples;

ii. We further resolve the class imbalance problem by random under-sampling the majority class (i.e., 0) to match the number of samples in the minority class (i.e., 1);

Our final extractive dataset consists of $944,234$ sentences with a completely balanced class distribution. Data is further split into 80-training, 10-validation and 10-testing datasets in a random stratified manner. We then fine-tune the extractive model with a batch size of 32 and a learning rate of $2e-5$ following the guidance from BERT's authors (Devlin et al. 2019) and find that the model starts to over-fit beyond 2 epochs (see Figures 1 and 2). We also report high F1 scores of 0.767 and 0.765 on the validation and test sets, respectively.
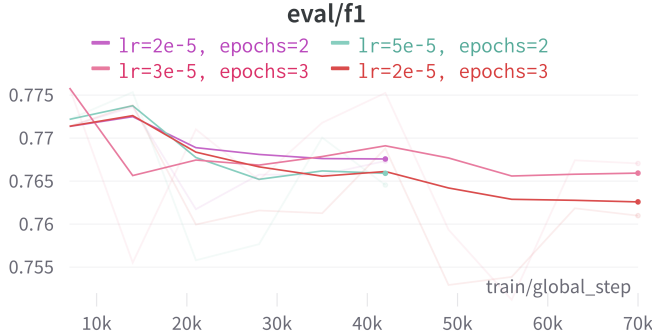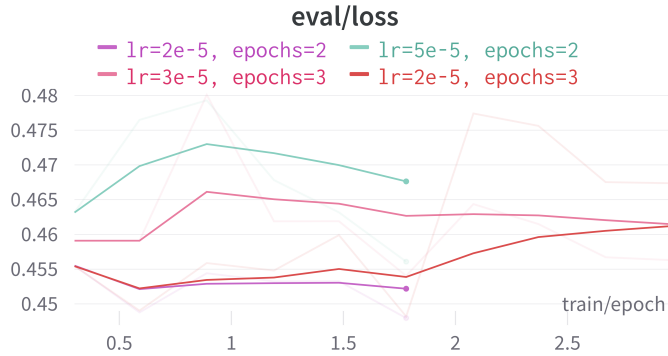

Figure 1: BioClinicalBERT: Evaluation F1

Figure 2: BioClinicalBERT: Evaluation Loss

We then use the BioClinicalBERT model to predict the probability of each sentence in the article being *summarising.* The top 10 sentences with the highest probability are selected and concatenated to produce the final extractive summary. We arrive at this number after analysing the token distribution and finding that 10 sentences is a reasonable number to fit within the maximum input size of the GPT-2 abstractive model (i.e., $1,024$ tokens split between the 10 sentences and their lay paraphrases). While we are aware that this can cause the *dangling anaphora phenomenon* (Lin 2009), we use the extracted text only as an intermediate step fed into the abstractive models which paraphrase it into lay language.

2.3 Abstractive Network

Once the extractive summary is generated, we train the abstractive models on the lay summaries and the extractive summaries. For this, we compare two models: GPT-2 (Radford et al. 2019a) and Clinical-Longformer (Li et al. 2022). We fine tune both models separately on eLife and PLOS. This is done due to the difference in structure and the average number of tokens in the lay summaries between the two datasets (i.e., 450 and 800 for PLOS and eLife, respectively). Hyperparameters are set based on widely used values in the literature (Li et al. 2022; Radford et al. 2019a; Devlin et al. 2019).

2.3.1 Clinical Longformer Abstractor

The Clinical Longformer (Li et al. 2023) is a transformer-based model that is pre-trained on the MIMIC-III dataset (Johnson et al. 2016) and can process up to $4,096$ tokens in a single input sequence. This is achieved by the implementation of a sparse attention mechanism that allows more computationally efficient processing of long-range dependencies. We fine-tune the Clinical Longformer as a sequence-to-sequence task on pairs of (a) gold lay summaries and (b) ROUGE-maximising training data described in Section 2.2.
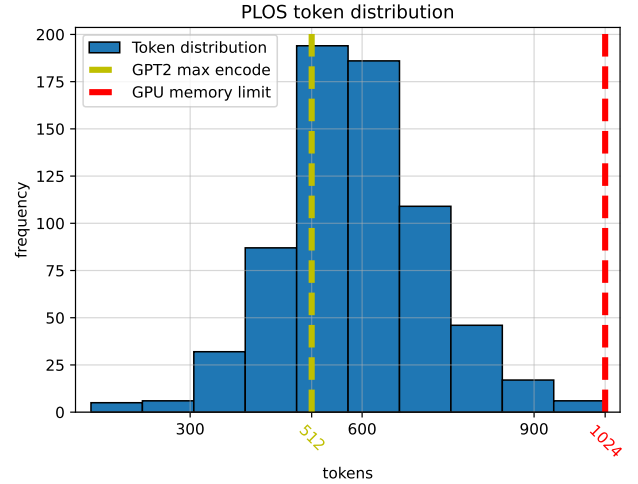

Figure 3: Token Distribution of Extracted Summaries

For the Longformer model, we experimented with window, batch, and input size to ensure that we would not run out of memory during training, as this is a common issue with such models (Orzhenovskii 2021). We found that a window size of 64, batch size of 1, and input size of $1,024$ worked best for our dataset, resulting in an evaluation loss of 3.4 (Figure 4).

2.3.2 GPT-2 Abstractor

The GPT-2 is an autoregressive language model that was trained using a casual language modeling objective (Radford et al. 2019b). Given its extensive exposure to diverse text sources and natural language patterns, we hypothesize that GPT-2 would be particularly adept at generating lay summaries, making it a promising candidate for the abstractive summarization task. To fine-tune GPT-2 for this purpose,
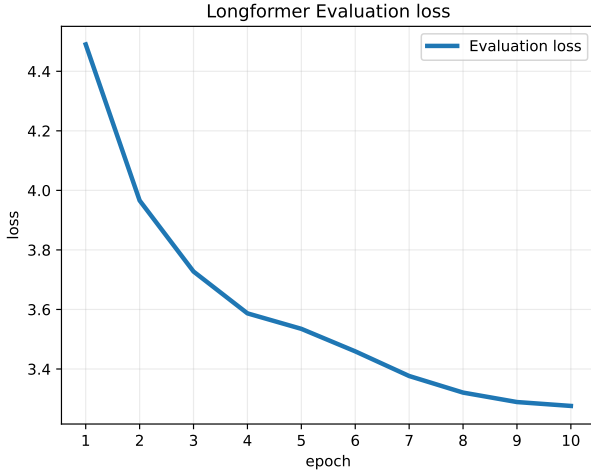
Figure 4: Longformer evaluation loss

we utilize a "TL;DR" prompt, instructing the model to generate concise and informative summaries.

Similar to the Longformer, we train GPT-2 on both eLife and PLOS datasets, adopting most hyperparameters from the existing literature to ensure optimal performance. Since GPT-2 can accommodate a total of 1024 tokens, we experimented with various splits between the number of tokens allocated for the extracted summary and the lay summary. Through experimentation, we determined that allocating 507 tokens for the article and 512 tokens for the summary, with 5 reserved for the "TL;DR" prompt, yielded the best results in terms of summary quality and model performance. The evaluation loss decrease during the fine-tuning process is illustrated in Figure 5.
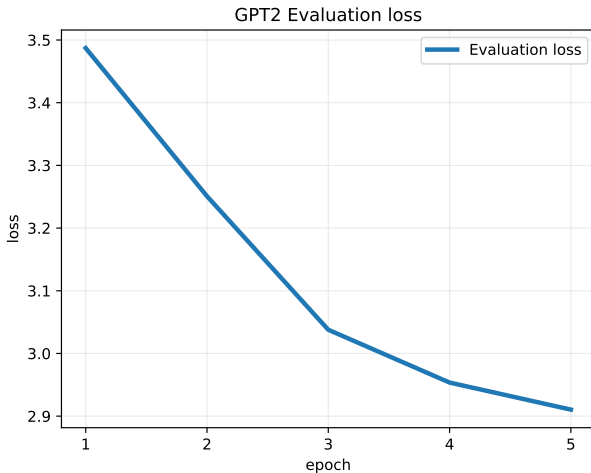

Figure 5: GPT 2 Evaluation Loss

In the evaluation phase, we compared the performance of the GPT-2 Abstractor against the Clinical Longformer Abstractor, as well as other summarization models. The results indicate that both models have their strengths and weaknesses, which we will discuss in further detail in the following sections.

3 Evaluation

In this section, we evaluate the performance of the summarization models described in Section 2. # Quantitative Evaluation {#sec:evaluation-quantitative}

Model	Rouge1	Rouge2	RougeL
Lexrank	0.34	0.09	0.16
Extractive	0.33	0.10	0.16
GPT2	0.18	0.02	0.09
Longformer (top-15)	0.28	0.07	0.15
Longformer (top-10)	0.29	0.06	0.14

Table 3: ROUGE F1 Scores.

Model	FKGL	ARI	Gunning
Lay	20.01	16.50	19.11
Lex (Baseline)	33.58	15.41	18.50
Extractive	10.60	25.01	26.22
GPT2	30.68	21.36	23.26
Longformer (top-15)	23.84	19.62	20.62
Longformer (top-10)	27.33	16.89	18.44

Table 4: Readability metrics.
FKGL - higher is better, ARI and Gunning - lower is better

4 Qualitative Evaluation

5 Discussion and Conclusion

5.1 Limitations

We identify the following limitations of our work:

1. **Readability Evaluation**: Although, we are evaluating our models with the traditional metrics: FKGL (Kincaid et al. 1975), ARI (Senter and Smith 1967), and Gunning (Gunning 1952), they are insufficient for the estimation of text readability in scientific writing. Instead, what some researchers propose is to leverage masked language models (Martinc, Pollak, and Robnik-Šikonja 2021) like the noun-phrase BERT-based metric (Luo, Xie, and Ananiadou 2022) that computes the probability of technical jargon. We appreciate that this method would have provided a more thorough evaluation of our models, and we leave it as future work.

2. **Limited input size**: Due to the limited available computational resources (i.e., Tesla V100-SXM2-16GB) we had to restrict the input size of the Longformer to $1,024$ tokens (i.e., 4 times less than the maximum size). Therefore, we could not make use of the full model capabilities in attending to long-range dependencies. This limitation propagates back to our extractor network, which produces only enough sentences to fit in the abstractor network. Thus, if we could increase the Longformer's input size, we could do the same for the Extractor model.

5.2 Future Work

In light of the limitations discussed, we propose multiple venues for future work:

1. **T5 Experimentation** (Lehman and Johnson 2023): We aim to develop and assess the Clinical T5 model as a specialized counterpart to the Clinical Longformer. The T5, a transformer-based model, boasts unique features like a denoising autoencoder in its pretraining objective, which is adept at reconstructing corrupted input text. This makes it suitable for our extractive approach, utilizing sentences from disparate article sections.

2. **Clinical Longformer Enhancement** (Li et al. 2022): Our goal is to augment the Clinical Longformer's maximum token capacity by employing advanced hardware resources. This would facilitate experimentation with larger input dimensions and model training, potentially leading to superior summarization performance and more precise lay summaries.

3. **Feedback Integration**: We suggest incorporating readability and factual correctness rewards into our summarization pipeline using reinforcement learning methods (Scialom et al. 2019). This can be achieved by the combination of the RNPTC metric (Luo, Xie, and Ananiadou 2022) and the factual accuracy (Zhang et al. 2020) into a single reward function, optimised via the Reinforce algorithm (Williams 1992).
   This approach aspires to promote the generation of summaries that are not only more comprehensible for non-experts but also more correct with respect to the input article.

5.3 Conclusion

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