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

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## 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.

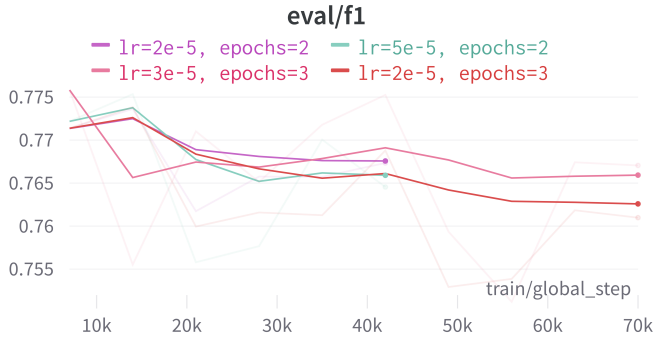


Figure 1: BioClinicalBERT: Evaluation F1

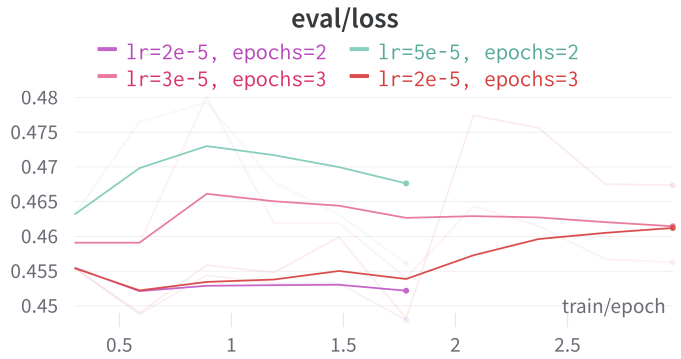


Figure 2: BioClinicalBERT: Evaluation Loss

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.

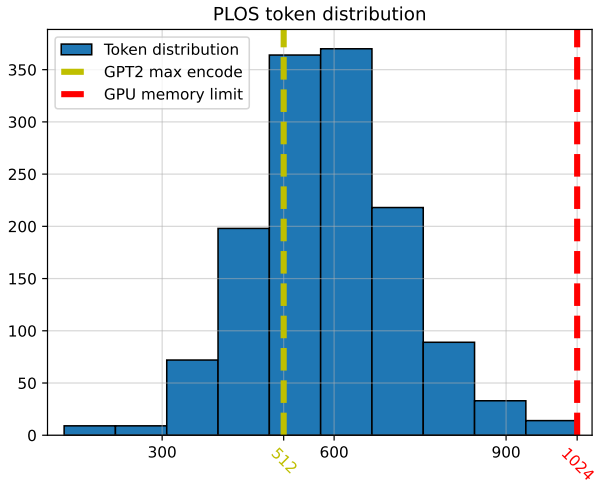


Figure 3: Token Distribution of Extracted Summaries

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,

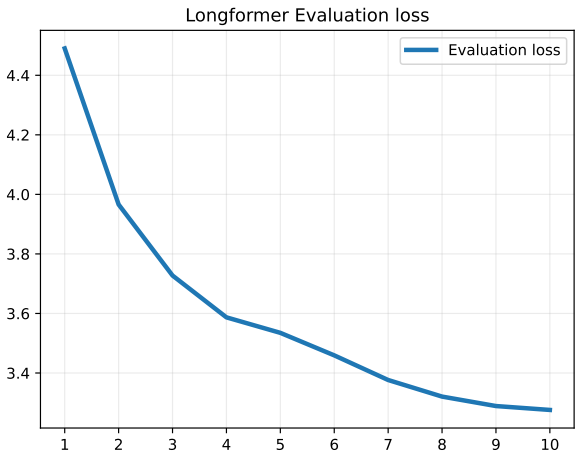


Figure 4: Longformer evaluation loss

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.

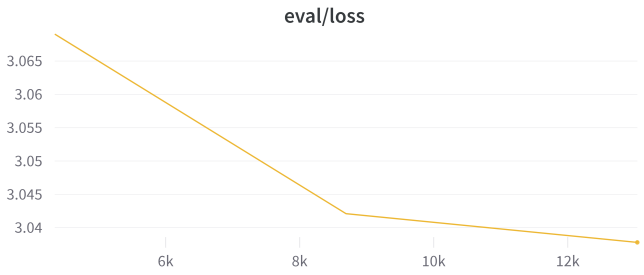


Figure 5: GPT 2 Evaluation Loss

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

# 4 Discussion and Conclusion

## 4.1 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.

## 4.2 Future Work

1. **Text-to-text (T5) experimentation** (Lehman and Johnson 2023): In light of the limitations discussed, we propose multiple venues for future work. The first involves training and evaluating the Clinical T5 model as a domain-specific alternative to the Clinical Longformer. The T5 is a transformer-based model with unique advantages, we are specifically interested in the denoising autoencoder present in its pretraining objective which it learns to reconstruct corrupted input text. This would be particularly useful with our extractive model which extracts sentences from disjoint sections of the article. Due to time constraints, we were unable to integrate the Clinical T5 model's inference in the current study. However, future work would perform rigourouss evalutation and comparison to the Clinical Longformer. Another primary objective is to expand the Clinical Longformer's maximum token length by leveraging better hardware resources. This would enable us to experiment with larger input sizes and train the model accordingly, potentially leading to better summarization performance and more accurate lay summaries. Additionally, we propose integrating readability and factual correctness rewards using reinforcement learning techniques to further enhance the performance of our summarization pipeline. This approach could encourage the model to generate summaries that are not only more readable for non-experts but also more accurate in conveying the content of the original articles. By incorporating these rewards, we hope to strike a better balance between generating lay summaries that are both accessible and factually correct.

| Model | Rouge1 | Rouge2 | RougeL |
|---|---|---|---|
| Lexrank | 0.334 | 0.085 | 0.164 |
| Extractive | 0.329 | 0.0998 | 0.163 |
| GPT2 | 0 | 0 | 0 |
| Longformer | 0.289 | 0.062 | 0.143 |

Table 3: ROUGE metrics.

| 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-10 sents) | 27.33 | 16.89 | 18.44 |
| Longformer (top-15 sents) | 23.84 | 19.62 | 20.62 |

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

### 4.3 Conclusion

## Bibliography


Alsentzer, Emily, John Murphy, William Boag, Wei-Hung Weng, Di Jin, Tristan Naumann, and Matthew McDermott. 2019. "Publicly Available Clinical BERT Embeddings." In *Proceedings of the 2nd Clinical Natural Language Processing Workshop*, 72–78. Minneapolis, Minnesota, USA: Association for Computational Linguistics. https://doi.org/10.18653/v1/W19-1909.

Chandrasekaran, Muthu Kumar, Guy Feigenblat, Eduard Hovy, Abhilasha Ravichander, Michal Shmueli-Scheuer, and Anita de Waard. 2020. "Overview and Insights from the Shared Tasks at Scholarly Document Processing 2020: CL-SciSumm, LaySumm and LongSumm." In *Proceedings of the First Workshop on Scholarly Document Processing*, 214–24. Online: Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.sdp-1.24.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. "BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding." *ArXiv* abs/1810.04805.

Goldsack, Tomas, Zheheng Luo, Qianqian Xie, Carolina Scarton, Matthew Shardlow, Sophia Ananiadou, and Chenghua Lin. 2023. "Overview of the BioLaySumm 2023 Shared Task on Lay Summarization of Biomedical Research Articles." In *Proceedings of the 22st Workshop on Biomedical Language Processing*. Toronto, Canada: Association for Computational Linguistics.

Goldsack, Tomas, Zhihao Zhang, Chenghua Lin, and Carolina Scarton. 2022. "Making Science Simple: Corpora for the Lay Summarisation of Scientific Literature." In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, 10589–604. Abu Dhabi, United Arab Emirates: Association for Computational Linguistics. https://aclanthology.org/2022.emnlp-main.724.

Gunning, Robert. 1952. *The Technique of Clear Writing*. New York: McGraw-Hill.

Islam, Md Saiful, Tonmoy Sarkar, Sazzad Hossain Khan, Abu-Hena Mostofa Kamal, Sarkar Mohammad Murshid Hasan, Alamgir Kabir, Dalia Yeasmin, et al. 2020. "COVID-19–Related Infodemic and Its Impact on Public Health: A Global Social Media Analysis." *The American Journal of Tropical Medicine and Hygiene* 103 (4). https://doi.org/https://doi.org/10.4269/ajtmh.20-0812.

Johnson, A. E. W., T. J. Pollard, L. Shen, L. W. Lehman, M. Feng, M. Ghassemi, B. Moody, P. Szolovits, L. A. Celi, and R. G. Mark. 2016. "MIMIC-III, a Freely Accessible Critical Care Database." *Scientific Data* 3: 160035. https://doi.org/10.1038/sdata.2016.35.

Kincaid, J. Peter, Robert P. Fishburne, Richard L. Rogers, and Brad S. Chissom. 1975. "Derivation of New Readability Formulas (Automated Readability Index, Fog Count and Flesch Reading Ease Formula) for Navy Enlisted Personnel." In.

Lehman, Eric, and Alistair Johnson. 2023. "Clinical-T5: Large Language Models Built Using MIMIC Clinical Text V1.0.0." *Physionet.org*. https://physionet.org/content/clinical-t5/1.0.0/.

Li, Yikuan, Ramsey M. Wehbe, Faraz S. Ahmad, Hanyin Wang, and Yuan Luo. 2022. "Clinical-Longformer and Clinical-BigBird: Transformers for Long Clinical Sequences." https://arxiv.org/abs/2201.11838.

Li, Yikuan, Ramsey M Wehbe, Faraz S Ahmad, Hanyin Wang, and Yuan Luo. 2023. "A Comparative Study of Pretrained Language Models for Long Clinical Text." *Journal of the American Medical Informatics Association* 30 (2): 340–47.

Lin, Jimmy. 2009. "Summarization." In *Encyclopedia of Database Systems*, 2906–10. Heidelberg, Germany: Springer.

Luo, Zheheng, Qianqian Xie, and Sophia Ananiadou. 2022. "Readability Controllable Biomedical Document Summarization." In *Findings of the Association for Computational Linguistics: EMNLP 2022*, 4667–80. Abu Dhabi, United Arab Emirates: Association for Computational Linguistics. https://aclanthology.org/2022.findings-emnlp.343.

Martinc, Matej, Senja Pollak, and Marko Robnik-Šikonja.

2021. “Supervised and Unsupervised Neural Approaches to Text Readability.” *Computational Linguistics* 47 (1): 141–79. https://doi.org/10.1162/coli_a_00398.

Nallapati, Ramesh, Feifei Zhai, and Bowen Zhou. 2017. “SummaRuNNer: A Recurrent Neural Network Based Sequence Model for Extractive Summarization of Documents.” In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, 3075–81. AAAI’17. San Francisco, California, USA: AAAI Press.

Orzhenovskii, Mikhail. 2021. “T5-LONG-EXTRACT at FNS-2021 Shared Task.” In *Proceedings of the 3rd Financial Narrative Processing Workshop*, 67–69. Lancaster, United Kingdom: Association for Computational Linguistics. https://aclanthology.org/2021.fnp-1.12.

Radford, Alec, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019a. “Language Models Are Unsupervised Multitask Learners.”

Radford, Alec, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019b. *Language Models Are Unsupervised Multitask Learners*. https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.

Senter, R J, and E A Smith. 1967. “Automated Readability Index.” AMRL-TR-6620. Wright-Patterson Air Force Base: Aerospace Medical Research Laboratories (U.S.).

Zmandar, Nadhem, Abhishek Singh, Mahmoud El-Haj, and Paul Rayson. 2021. “Joint Abstractive and Extractive Method for Long Financial Document Summarization.” In *Proceedings of the 3rd Financial Narrative Processing Workshop*, 99–105. Lancaster, United Kingdom: Association for Computational Linguistics. https://aclanthology.org/2021.fnp-1.19.