

ImpressionGPT: An Iterative Optimizing Framework for Radiology Report Summarization with ChatGPT

Chong Ma¹, Zihao Wu³, Jiaqi Wang², Shaochen Xu³, Yaonai Wei¹, Zhengliang Liu³, Lei Guo¹, Xiaoyan Cai¹, Shu Zhang², Tuo Zhang¹, Dajiang Zhu⁵, Dinggang Shen^{6,7,8}, Tianming Liu³, and Xiang Li⁴

¹*School of Automation, Northwestern Polytechnical University, Xi'an 710072, China*

²*School of Computer Science, Northwestern Polytechnical University, Xi'an 710072, China*

³*School of Computing, The University of Georgia, Athens 30602, USA*

⁴*Department of Radiology, Massachusetts General Hospital and Harvard Medical School, Boston 02114, USA*

⁵*Department of Computer Science and Engineering, The University of Texas at Arlington, Arlington 76019, USA*

⁶*School of Biomedical Engineering, ShanghaiTech University, Shanghai 201210, China*

⁷*Shanghai United Imaging Intelligence Co., Ltd., Shanghai 200230, China*

⁸*Shanghai Clinical Research and Trial Center, Shanghai, 201210, China*

Abstract

The 'Impression' section of a radiology report is a critical basis for communication between radiologists and other physicians, and it is typically written by radiologists based on the 'Findings' section. However, writing numerous impressions can be laborious and error-prone for radiologists. Although recent studies have achieved promising results in automatic impression generation using large-scale medical text data for pre-training and fine-tuning pre-trained language models, such models often require substantial amounts of medical text data and have poor generalization performance. While large language models (LLMs) like ChatGPT have shown strong generalization capabilities and performance, their performance in specific domains, such as radiology, remains under-investigated and potentially limited. To address this limitation, we propose ImpressionGPT, which leverages the in-context learning capability of LLMs by constructing dynamic contexts using domain-specific, individualized data. This dynamic prompt approach enables the model to learn contextual knowledge from semantically similar examples from existing data. Additionally, we design an iterative optimization algorithm that performs automatic evaluation on the generated impression results and composes the corresponding instruction prompts to further optimize the model. The

proposed ImpressionGPT model achieves state-of-the-art performance on both MIMIC-CXR and OpenI datasets without requiring additional training data or fine-tuning the LLMs. This work presents a paradigm for localizing LLMs that can be applied in a wide range of similar application scenarios, bridging the gap between general-purpose LLMs and the specific language processing needs of various domains.

1 Introduction

Text summarization is the process of compressing a large amount of text data into a shorter summary while maintaining its coherence and informative properties [23]. It has long been a critical and well-studied research area within the field of Natural Language Processing (NLP). As the volume of digital textual information is growing at an extraordinary rate in both the general and medical domains, the need for efficient and accurate text summarization models grows correspondingly [1]. In earlier studies, Luhn [61] proposed the first automatic summarization algorithm based on statistical methods. Later, a variety of alternative approaches have been proposed, such as rule-based methods [68], latent semantic analysis [27], and graph-based techniques [20]. Although traditional methods significantly advanced the research and application of text summarization, they often lack the ability to capture complex semantics and contextual information to generate human-level summarization performance [19].

The introduction of neural networks and deep learning methods [4], especially the sequence-to-sequence models that employ encoder-decoder architectures for generating summaries [10, 83] conveyed promising results. These approaches enabled the creation of more fluent and contextually relevant summaries compared with rule-based and statistical methods. Recently, the field of NLP, including text summarization, has experienced drastic changes with the emergence of large-scale, pre-trained foundational models, such as BERT [43] and GPT [74]. These models are trained on massive volumes of text data, which enables them to learn rich contextual representations and generate human-like languages [50, 76]. Studies [56, 57, 90] have been conducted to demonstrate that fine-tuning these foundational models on text summarization tasks can lead to state-of-the-art performance, outperforming earlier models by a wide margin.

Radiology reports are pivotal in clinical decision-making since they can provide crucial diagnostic and prognostic information to healthcare professionals [8]. The volume of imaging studies and the complexity of radiology data are both growing at an increasing rate, thus raising an urgent need for efficient language processing, including extracting key information from radiology reports. Text summarization can address this challenge by automatically generating concise, informative, and relevant summaries of radiology reports [59], thus can significantly enhance clinical workflows, reduce the workload of healthcare professionals, and improve patient care [71]. With the help of automatic text summarization methods, healthcare professionals can efficiently identify essential information, which leads to faster decision-making, optimized resource

allocation, and improved communication among multidisciplinary teams [72]. In addition, the efficient processing of large volumes of radiology reports can aid data-driven research, quality assurance, and the development of clinical guidelines [30].

Compared with general NLP tasks, radiology report summarization has its own unique challenges. It would be difficult for general-purpose NLP models to accurately capture the key information due to the highly specialized and technical nature of the language used, the frequent use of abbreviations, and the presence of ambiguous or inconsistent terminologies commonly found in radiology reports [13]. In addition, the demand for a high level of precision within clinical settings, the potential risks associated with misinterpretation of crucial findings, and the significance of maintaining the contextual and relational aspects of such findings further complicate the task [25]. In response, multiple specialized language processing methods have been developed for medical text summarization, which can be broadly categorized into three groups: traditional, deep learning-based, and LLM-based. Rule-based extraction [22] and keyword-based summarization [30] are both examples of traditional methods that provided a foundation for text summarization research. However, they often lacked the ability to capture complex semantics and contextual information. The introduction of deep learning techniques, such as convolutional neural networks (CNNs) [45], demonstrated superior performance in capturing the unique language features and context of radiology reports [25]. However, these techniques often require large volumes of annotated data for training and are limited to specific tasks and/or domains. More recently, BERT [43] and GPT [74] brought the emergence of LLMs and opened new possibilities for radiology report summarization. Fine-tuning BERT on domain-specific data, such as chest radiology reports, demonstrating better capability in capturing clinical context and generating high-quality summaries [7]. Nonetheless, utilizing pre-trained language models such as BERT [43] still needs a significant volume of annotated data for the downstream tasks (e.g., text summarization). On the other hand, recent LLMs such as GPT-4, LLaMA, and BloomZ adopt the frameworks of in-context learning, enabling fine-tuning of the models without a large amount of annotated data [33]. Thus, identifying the optimized schemes for in-context learning by designing corresponding prompts becomes an important component in developing specific-purposed LLMs [92].

In this study, we utilized and fine-tuned ChatGPT for radiology report summarization. An iterative optimization algorithm is designed and implemented via prompt engineering to take advantage of ChatGPT’s in-context learning ability while also continuously improving it through interaction. Specifically, we use similarity search techniques to construct a dynamic prompt to include semantically- and clinically-similar existing reports. These similar reports are used as examples to help ChatGPT learn the text descriptions and summarizations of similar imaging manifestations in a dynamic context. We also develop an iterative optimization method to further enhance the performance of the model by performing automated evaluation on the response generated by ChatGPT and integrating the generated text and the evaluation results to compose

the iterative prompt. In this way, the generated response from ChatGPT is continually updated for optimized results under pre-defined guidance. We evaluate our ImpressionGPT on two public radiology report datasets: MIMIC-CXR [40] and OpenI [17]. Our experimental results show that ImpressionGPT performs substantially better than the current methods in radiology report summarization, with only a small dataset (5-20 samples) used for fine-tuning. Overall, the main contributions of this work are:

- In-context learning of Language Model (LLM) with limited samples is achieved by similarity search. Through the identification of the most similar examples in the corpus, a dynamic prompt is created that encompasses the most useful information for LLM.
- An iterative optimization algorithm is developed with a dynamic prompt scheme. The iterative prompt provides feedback on the responses generated by LLM and the corresponding evaluation, followed by further instructions to iteratively update the prompts.
- A new paradigm for fine-tuning LLMs using domain-specific data. The proposed framework can be applied to any scenarios involving the development of domain-specific models from an existing LLM in an effective and resource-efficient approach.

2 Background and Related Works

2.1 Text Summarization in Natural Language Processing

Text summarization is to extract, summarize or refine the key information of the original text to obtain the main content or general meaning of the the original text. There are two major categories of text summarization: extractive summarization and abstractive summarization. Among them, extractive summarization [15, 20, 39, 51, 55, 64, 65, 67] is to take one or more sentences from a text or text set to construct a summary. An advantageous aspect of this approach lies in its simplicity, and its results exhibit a low tendency towards deviations from the essential message conveyed in the text. Before the emergence of artificial neural network, the practice of text summarization predominantly relied on the technique of extractive summarization. For example, Hongyan [39] developed filtering rules based on prior knowledge to remove unimportant parts of the text to obtain a summary. TextRank [64] and LexRanK [20] represented the words and sentences in a graph and search the text with the highest similarity in the graph. [15] used Bayesian query methods to search the corpus and generate summaries. [67] used algebraic statistics to extract latent semantic information from text and generates text summaries based on latent semantic similarities. After the emergence of artificial neural networks and deep learning, methods such as SummaRuNNer [65], which used the RNN [89] model, and BertSUM [55] and TransEXT [51] were training based on the BERT [43] model. However, extractive summarization suffers from incoherent generation

of summaries, uncontrollable length, and the quality of the results is severely dependent on the original text.

For the task of abstractive summarization [44, 52, 55, 56, 66, 69, 77, 79, 82], there is no issue as mentioned previously. Abstractive summarization task is an end-to-end generative task, and it is necessary to understand the meaning of the original text and generate a new summarization. Compared with extractive summarization, abstractive summarization is more challenging, but it is also more in line with the daily writing habits of human beings, so it has gradually become a significant research focus in the field of text summarization since the introduction of artificial neural networks and deep learning. For example, [77] first proposed an attentional encoder-decoder model for abstracting summaries to generate summaries from scratch. [66] adapted DeepMind’s question-answering dataset [32] to form the CNN/Daily Mail dataset and provided the first abstracted baseline. Later, PGN (LSTM) [79] used a pointer-generator network to copy words from the original text and also retains the ability to generate new words, thus improving the seq2seq+attention model architecture. Similarly, CGU [52] proposed a global encoding framework for summary generation, which uses a combination of CNN and self-attention to filter the global encoding of text, solving the alignment problem between source text and target summary. With the emergence of BERT [43], a milestone model within the NLP field, the previous training method was changed to use the strategy of pre-training + fine-tuning. Among others, BART [48] and PEGASUS [90] explored the use of pre-trained models to achieve advanced performance on text summarization task. TransABS [56] accomplished generative summarization based on the BertSUM [55] used a two-stage fine-tuning method and achieved optimality on three datasets. CAVC [82] used a Mask Language Modeling (MLM) strategy based on the BERT model to further improve the performance. There are also some approaches that try to use the pre-training model in the medical-related text processing, such as, [69] helped the scientific community to understand the rapidly flowing COVID-19 literature array based on the BERT model. [44] used the BERT and GPT [9] to generate text summaries of COVID-19 medical research articles.

2.2 Radiology Report Summarization

With the development of text summarization in NLP, text processing related to the medical field is also gaining attention. In the standard radiology report, the impression section is a summary of the entire report description. Therefore, automatic impression generation (AIG) has become the focus of NLP research in the medical field [7, 18, 26, 28, 34–36, 41, 46, 62, 63, 91]. Earlier studies have focused on the use of seq2seq methods. For example, [91] first employed a bi-directional LSTM for sequence-to-sequence generation and found that 30% of the generated radiology summaries had factual errors. [62] proposed a sequence-to-sequence abstract summary model complemented by domain-specific ontology information to enhance content selection and summary generation. [26] further extracted salient clinical ontology terms from the study results and

then incorporated them into a summarizer using a separate encoder. In addition, [28] proposed a template-based framework and weak supervision based on Recurrent-GAN for generating MRI diagnostic reports to address the problem of data limitation. [41] trained a bi-directional LSTM based model as a summary extractor using the method of Multi-agent Reinforcement Learning.

After the emergence of BERT [43], BioBERT [46] pre-trained BERT using large-scale biomedical corpora, surpassing previous methods in a variety of medical-related downstream tasks such as named entity recognition, relationship extraction, and question answering. This work explored the path of using pre-trained language models within the biomedical domain. Similar, Clinical BERT [36] pre-trained BERT using clinical notes and fine-tuned it for the task of predicting hospital readmission. And [18] pre-trained a domain-aware bi-directional language model on large-scale biomedical corpora, and fine-tuned it for extractive summarization tasks in the biomedical domain. UmlsBERT [63] proposed a contextual embedding model that integrates domain knowledge during the pre-training process via a novel knowledge augmentation strategy, and outperformed existing domain-specific methods on common named-entity recognition (NER) and clinical natural language inference tasks. WGSUM [34] constructed a word graph from the findings section of radiology report by identifying the salient words and their relations, and proposed a graph-based model WGSUM to generate impressions with the help of the word graph. ChestXray-BERT [7] pre-trained BERT using a radiology-related corpus and combined it as an encoder with a Transformer decoder [85] to perform the diagnostic report summarization task. [35] utilized a graph encoder to encode the word graph during pre-training to enhance the text extraction ability of the model, and introduced contrast learning to reduce the distance between keywords. Its results on AIG outperform the previous methods. All the above methods have achieved good results in the medical text domain based on the pre-trained language model, but still have the problem of poor generalization due to the low complexity of the model.

2.3 Large Language Model

With the advent of BERT [43] model based on Transformer [85] architecture, an increasing number of studies related to natural language processing (NLP) have incorporated pre-training + fine-tuning methodologies. The approach that first pre-training on a large amount of unlabeled data and then fine-tuning on a small portion of labeled data has proven to achieve more outstanding results. For example, before BERT, GPT-1 [54] with 117 million parameters has been initially trained using self-supervised pre-training + supervised fine-tuning. It directly used the Transformer decoder to achieve excellent results on natural language inference and question-and-answer tasks. Later, Google proposed the landmark model BERT [43], which introduced Transformer encoder and further improved the performance by using Mask Language Modeling and Next Sentence Prediction methods in the pre-training stage, where the number of parameters in BERT-Large has reached 340 million. Four months after the release

of BERT [43], GPT-2 [74] was introduced, which further extended the model parameters and training data set based on GPT-1 [54], with Extra Large of GPT-2 model reaching 1.5 billion parameters. In addition, the researchers [74] found that with the expanded training dataset, outstanding results of large language model could be achieved in downstream tasks without using fine-tuning. Later, the Google team released the T5 [75] model and proposed that all text-based language problems could be converted into text-generated-text form. GPT-3 [5] further expanded the data size and parameter size based on GPT-2 [74], and the maximum parameter reached 175 billion, and its performance on downstream tasks was significantly improved. And they first proposed a training paradigm of unsupervised pre-training + few-shot prompt. Recently, PaLM [11] used Pathways [2] to train a model with 540 billion parameters, and further refreshed the results using zero-shot, one-shot and few-shot in downstream tasks.

In comparison to small pre-trained language models (PLMs), large language models (LLMs) possess superior generalization capability. They can accurately learn potential features of input text and perform effectively across different downstream tasks, even without fine-tuning. One prominent example of a large language model is ChatGPT, based on the GPT-3.5 model, which employs training data in conversation mode to facilitate user-friendly human-machine interaction. ChatGPT has been widely integrated into various applications such as education and healthcare, and performs well in tasks such as text classification, data expansion, summarization, and other natural language processing. Although ChatGPT performs well in most tasks, its performance in specialized domains is still unsatisfactory. Hence, we propose ImpressionGPT, an iterative optimization algorithm that enables ChatGPT to achieve excellent performance on the radiology report summarization task.

2.4 Prompt Engineering

Prompt engineering is a burgeoning field that has garnered significant attention in recent years due to its potential to enhance the performance of large language models (LLMs). The fundamental idea behind prompt engineering is to utilize prompts as a means to program LLMs, which is a vital skill required for effective communication with these models [12], such as ChatGPT. Recent research has demonstrated that designing prompts to guide the model toward relevant aspects of input can lead to more precise and consistent outputs. This is particularly crucial in applications such as language translation and text summarization, where the quality of the output is paramount.

In general, prompt engineering is a new paradigm in the field of natural language processing, and although still in its early stages, has provided valuable insights into effective prompt patterns [53]. These patterns provide a wealth of inspiration, highlighting the importance of designing prompts to provide value beyond simple text or code generation. However, crafting prompts that are suitable for the model can be a delicate process. Even a minor variation in prompts could significantly impact the model’s performance. Therefore, finding the most suitable prompts remains an important challenge. Typically, there are

two main types of prompts: manual prompts and automated template prompts.

2.4.1 Manual Prompt

Manual prompts are designed manually to guide LLMs towards specific inputs. These prompts provide the model with explicit information about what type of data to focus on and how to approach the task at hand [53]. Manual prompts are particularly useful when the input data is well-defined and the output needs to adhere to a specific structure or format [5, 70, 78]. For example, in the medical field where interpretability is crucial, manually created prompts are often employed to guide the model toward focusing on specific aspects of the input data. In the area of medical text security, for instance, manual prompts were utilized to guide the model toward identifying and removing private information in medical texts, effectively solving the ethical issues associated with medical data [60]. also employed to augment data and mitigate the challenges posed by low-quality and scarce data in the target domain [14]. Overall, manual prompts play a vital role in improving model performance in various domains by providing the model with a more structured and focused approach to the task.

2.4.2 Automated Template Prompt

While manual prompts are a powerful tool for addressing many issues, they do have certain limitations. For example, creating prompts requires time and expertise, and even minor modifications to prompts can result in significant changes in model predictions, particularly for complex tasks where providing effective manual prompts is challenging [38, 80]. To address these issues, researchers have proposed various methods for automating the process of prompt design, different types of prompts can assist language models in performing specific tasks more effectively. Prompt mining involves extracting relevant prompts from a given dataset [38], while prompt paraphrasing improves model performance and robustness by increasing prompt diversity [38, 88]. Gradient-based search helps identify optimal prompts in a model’s parameter space [81, 86], and prompt generation can create new prompts using techniques such as generative models [3, 24]. Additionally, prompt scoring evaluates different prompts to select the best ones for a specific task [16]. These discrete prompts are typically automatically searched for in a discrete space of prompt templates, often corresponding to natural language phrases. Other types of prompts, such as continuous prompts that construct prompts in a model’s embedding space [47, 49, 84], static prompts that create fixed prompt templates for input [21], and dynamic prompts that generate custom templates for each input, can also aid in task performance [58].

These different prompt types can be used independently or in combination to help language models perform various tasks, including natural language understanding, generation, machine translation, and question-answering.

3 Method

In this section, we first illustrate the pipeline of our ImpressionGPT. Then we elaborate on the dynamic prompt generation in Sec. 3.1 and the iterative optimization in Sec. 3.2.

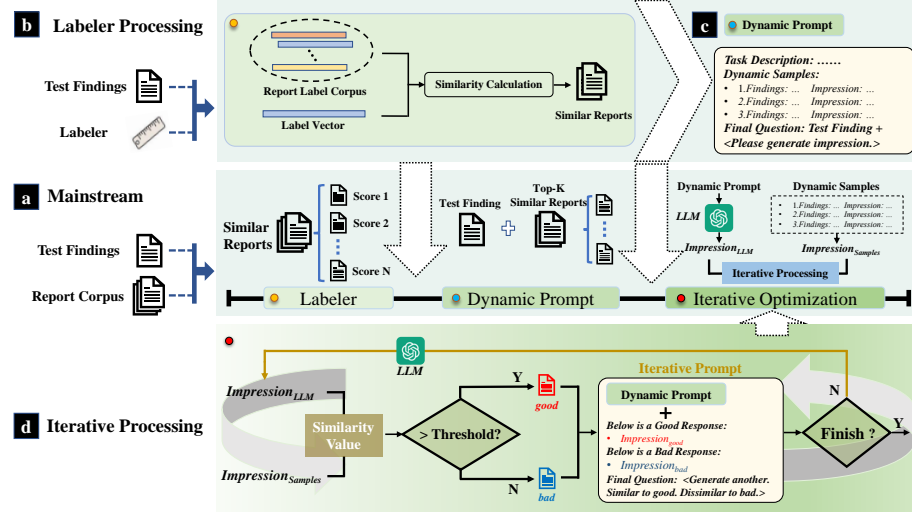


Figure 1: The pipeline of our ImpressionGPT. Part *a* in the middle is the mainstream of our method. We first use a labeler to categorize the diseases of test report and obtain the similar reports in the corpus (part *b*), and then construct a dynamic prompt in part *c*. Part *d* accomplishes the iterative optimization of LLM through interaction with positive (*good*) and negative (*bad*) responses.

In this work, we employed dynamic prompt and iterative optimization to enhance the adaptation of ChatGPT to radiology report summarization. Fig. 1 shows the pipeline of our ImpressionGPT. Firstly, as shown in the first step of mainstream in Fig. 1, we use a labeler to categorize the "Findings" section of the report and extract disease labels. Then, based on the disease category, we search for similar reports in the existing diagnostic report corpus, as shown in part *b* of Fig. 1. And we designed a dynamic prompt (shown in part *c* of Fig. 1) to construct a context environment with similar diagnostic reports, so that ChatGPT can learn to summarize diagnostic reports related to the current disease. We refer to this as "dynamic context". Based on the dynamic context, we utilized an iterative optimization method, as shown in the part *d* of Fig. 1, to optimized the response of ChatGPT. During the iterative optimization process, we compare the generated "Impression" from ChatGPT with examples in dynamic prompt to obtain good and bad responses. These are added to the dynamic prompt with further guidance to ensure that the next response is closer to the good response while avoiding the bad response. Overall, our

method requires a small number of examples, facilitating ChatGPT’s acquisition of excellent domain-specific processing capabilities. More details of dynamic prompt generation and iterative optimization can be found in the following subsections.

3.1 Dynamic Prompt Generation

In previous manual-designed prompts, fixed-form prompts were frequently employed for simple tasks that were easily generalized, such as translation, Q&A, and style rewriting [53]. However, these fixed-form prompts were found to be insufficient in providing prior knowledge for more intricate tasks and datasets that are peculiar to specific domains, like processing medical diagnosis reports, resulting in poor performance of ChatGPT. Consequently, we propose a hypothesis which suggests that constructing dynamic prompts by utilizing similar examples from relevant domain-specific corpora can enhance the model’s comprehension and perception.

3.1.1 Similarity Search

The process for generating dynamic prompts mainly encompasses two phases. Initially, a disease classifier is employed to extract the disease categories appearing in the input radiology report. Subsequently, relying on these categories, a similarity search is conducted on the report corpus to obtain examples similar to the input radiology report.

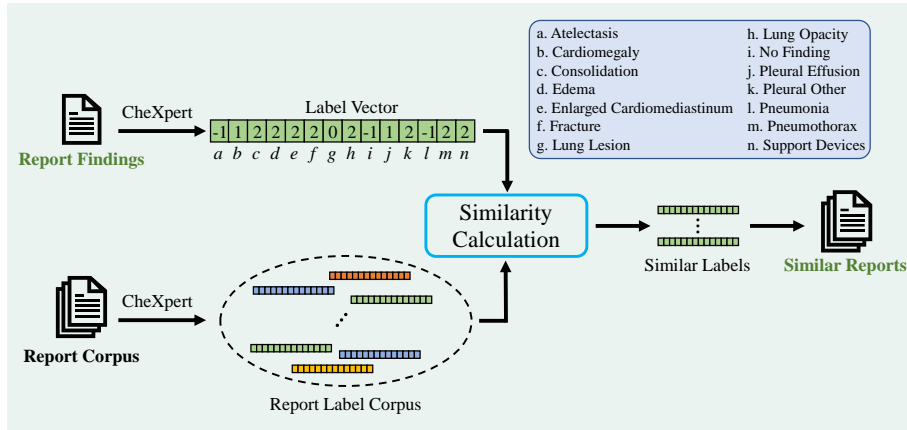


Figure 2: Details of similarity search process. CheXpert is initially employed to obtain the label vector for the radiology reports present in the corpus. Then the similarity between the label vector of the test report and the label corpus is calculated, allowing for the identification of the similar radiology reports.

Corpus search methods typically involve two approaches: text-based [42,

87] and feature-based [31, 73]. Text-based methods can be time-consuming and significantly increase search time, particularly with large corpora. Feature-based methods require feature extraction and storage of each sample, making it more space-demanding. In this study, we utilize diagnostic report labels for similarity search, requiring only prior identification and local label storage of the report sample. This approach substantially reduces time and space costs. Moreover, using tag values to calculate the similarity enables the identification of samples with similar diseases, which provides domain-specific and even sample-specific knowledge that can be leveraged by ChatGPT’s contextual processing capabilities.

Specifically, we use CheXpert labeler [37] as the disease classifier, which is a rule-based labeler to extract observations from the free text radiology reports. The observations contain 14 classes based on the prevalence in the chest radiology reports and clinical relevance conformed to [29]. As shown in Fig. 2, each observation is represented by a letter from ‘a’ to ‘n’, and each contains four categories. The categories correspond to the clearly presence (‘1’) or absence (‘0’) of the observation in the radiology report, the presence of uncertainty or ambiguous description (‘-1’), and the unmentioned observation (*blank*), which is replaced by the number ‘2’ to facilitate similarity calculation. The labels of each radiology report in the corpus are extracted and saved as a one-dimensional vector of scale 1×14 . The label vectors of test reports are then compared to those in the corpus using Euclidean distance, and the radiology reports that are closest to each other are selected to generate dynamic prompts. This method ensures reliable and accurate disease classification of radiology reports.

For the MIMIC-CXR [40] dataset, we use the officially split training set as a corpus and extract and preserve the corresponding disease labels. To minimize the time required for similarity computation in cases of particularly large corpora like MIMIC-CXR dataset, we employ a systematic random sampling technique to generate a subset of the original corpus. Specifically, 10,000 random radiology reports of the 220,000 training data from MIMIC-CXR are selected for the current similarity computation. On the other hand, since the OpenI [17] dataset is relatively small in volume, we directly use all available samples in its training set as the corpus.

3.1.2 Dynamic Prompt

Prior to introducing the dynamic prompt, it is necessary to provide an overview of the input format when utilizing the ChatGPT API. The message that is fed into ChatGPT is accessed through the API in the form of a string, which is categorized into three distinct roles: *System*, *User*, and *Assistant*, as illustrated in Fig. 3. These roles are represented by the colors red, green, and blue, respectively. The *System* message initiates the conversation and provides information regarding the task while constraining the behavior of the *Assistant*. The *User* message instructs the *Assistant* and serves as the input provided by the user. Lastly, the *Assistant* component represents the response that is generated by the model. Notably, as the *Assistant* message can be artificially set,

it enables the implementation of our dynamic prompt and facilitates iterative optimization.

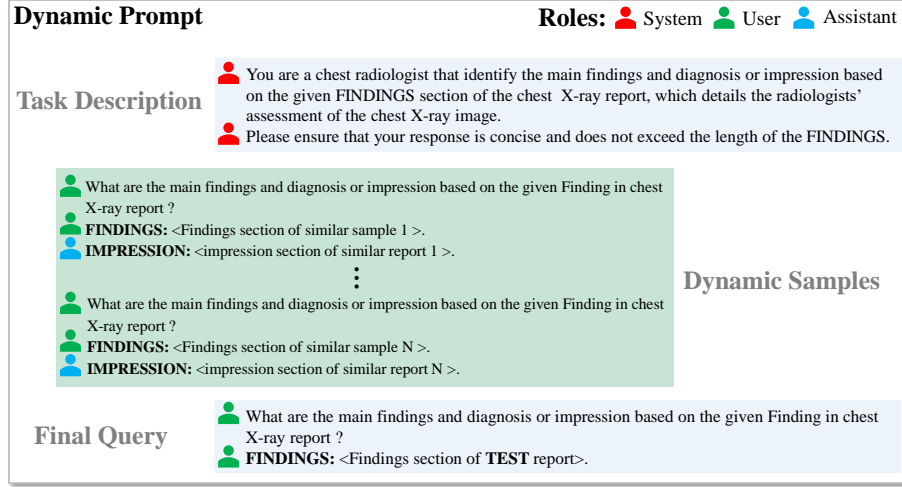


Figure 3: Details of dynamic prompt. The dynamic prompt is composed of task description, dynamic samples, and final query. Each component contains message of multiple roles. The flags in front of each sentence represent the role of the current message, red for System, green for User, and blue for Assistant.

In this work, we employ the prefix form for designing the dynamic prompt. The dynamic prompt consists of three modules: task description, dynamic samples, and final query, as illustrated in Fig. 3. The task description module specifies the role of the ChatGPT as a chest radiologist and provides a brief overview of the radiology report summary task along with a simple rule that serves as the foundation for the entire prompt. Subsequently, the dynamic prompt integrates similar reports obtained in Sec. 3.1.1. The dynamic samples module, depicted in the central part of Fig. 3, utilizes a question-and-answer format to provide the prompt in each sample. Specifically, the question part consists of a pre-defined question sentence and the "Findings" section of dynamic sample and is treated as the message of the *User* role. Then the "Impression" section of the dynamic sample is treated as the following message of the *Assistant* role. At the end of our dynamic prompt, the same pre-defined question is used as in the previous samples, and the "Findings" section of the test report is inserted. Overall, the resulting dynamic prompt uses a question-answering approach and provides multiple examples that have similar content to the target test sample, thus creating a data-specific dynamic context.

3.2 Iterative Optimization

In Sec. 3.1, we constructed a dynamic context within the prompt in order to facilitate the model learning relevant prior knowledge from semantically similar examples. However, the use of this fixed form of prompt on ChatGPT produced a one-off effect, as we cannot guarantee that the generated response is appropriate. Therefore, based on the dynamic prompt, we utilized an iterative optimization operation. The specific optimization process is presented in Algorithm 1. The first step is to input the dynamic prompt designed in Sec. 3.1 and N_s similar radiology reports we selected.

Algorithm 1 Iterative Optimization Algorithm

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1: Input: Dynamic prompt with  $N_s$  similar reports
2: Initialize:  $I$ =Iteration times,  $Thres$ =Threshold of evaluation score,
    $iter=0$ 
3: Definition:  $GPT$  means ChatGPT,  $Prompt_{Dy}$  means our dynamic
   prompt,  $Prompt_{Iter}$  means our iterative prompt,  $L$  means evaluate function,
    $M_{good}$  and  $M_{bad}$  represent prompt merging with good and bad response
4: while  $iter < I$  do
5:   if  $iter = 0$  then
6:      $response = GPT(Prompt_{Dy})$ 
7:   else
8:      $response = GPT(Prompt_{Iter})$ 
9:   end if
10:   $score = \frac{1}{N_s} \sum_{i=0}^{N_s} L(response, Impression_i)$ 
11:  if  $score > Thres$  then
12:     $Prompt_{Iter} = M_{good}(Prompt_{Dy}, response)$ 
13:  else
14:     $Prompt_{Iter} = M_{bad}(Prompt_{Dy}, response)$ 
15:  end if
16:   $iter++$ 
17: end while

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First, the input of the algorithm is the dynamic prompt designed in Sec. 3.1 and the N similar radiology reports we selected. In the initial iteration, the dynamic prompt is directly inputted into ChatGPT. After receiving the initial response, we evaluate it with a defined threshold. As described in lines 10-14 of Algorithm 1, if the evaluated score is higher than the previously defined threshold, it is considered acceptable and is merged into the prompt to generate the iterative prompt. Conversely, if the score is lower than the threshold, the response is considered unsatisfactory and also merged into the iterative prompt. The purpose of the iterative prompt is to enable ChatGPT to optimize its response during the iterative process, so that the responses are more similar to those considered good and avoid the ones that are considered bad. Through this method, ChatGPT becomes iterative and self-optimizing. A detailed description

of the evaluation method and iterative prompt design is described below.

3.2.1 Response Evaluation

During the process of iterative optimization, it is crucial to assess the quality of a response. In this study, we employ the Rouge-1 score [51], a prevalent metric for evaluating summarization models. The similarity between the generated results and ground-truth is measured on a word-by-word basis by the Rouge-1 score, thus enabling the evaluation of the outputs at a more refined scale. The dynamic prompt incorporates N radiology reports having the highest similarity in the corpus, with the impression section deemed of high reference value for the ChatGPT response evaluation. As depicted in line 10 of Algorithm 1, we calculate the Rouge-1 score of ChatGPT’s response with the impression section of each similar report in the dynamic prompt, and average it to get the final evaluation result. Subsequently, we derive ”good response” and ”bad response” based on the pre-defined threshold and merge the outcomes into the iterative prompt, and feed it again into ChatGPT. This process is repeated until the maximum number of iterations, following which the response with the highest evaluation score during the iteration is chosen as the final generated impression of input radiology report.

3.2.2 Iterative Prompt

The subsequent and crucial stage after identifying the positive and negative feedback is to utilize the evaluation results to instruct ChatGPT in generating enhanced responses. As shown in Fig. 4, the initial part of the iterative prompt is the dynamic prompt described in Sec. 3.1.2, which delivers the fundamental context for subsequent enhancement. For the responses evaluated in Sec. 3.2.1, a pair of *User* and *Assistant* roles are included in the iterative prompt. The *User* initiates the message with ”Below is an excellent impression of the FINDINGS above” for the positive feedback and ”Below is a negative impression of the FINDINGS above” for the negative feedback. The response produced by ChatGPT is positioned after the corresponding *User* message, adopting the ”Instruction + Response” form to enable ChatGPT to learn the relevant content from the good and bad samples. As shown in the bottom ”Final Query” in Fig. 4, the final query that concludes the iterative prompt provides specific optimization rules to regenerate a response that is consistent with the good response and avoids the bad response. Additionally, a length limit instruction is included to avoid ChatGPT from generating overly verbose responses. Note that after extensive experimental validation, we finally insert one good and one bad response in the iterative prompt. In the process of each iteration, good response or bad response will be updated, which enables our prompt to optimize ChatGPT’s responses in time.

To summarize, our approach involves utilizing a dynamic prompt to establish a contextual understanding that is highly relevant to the semantics of the given test case. This context is then fed into ChatGPT to obtain an initial response,

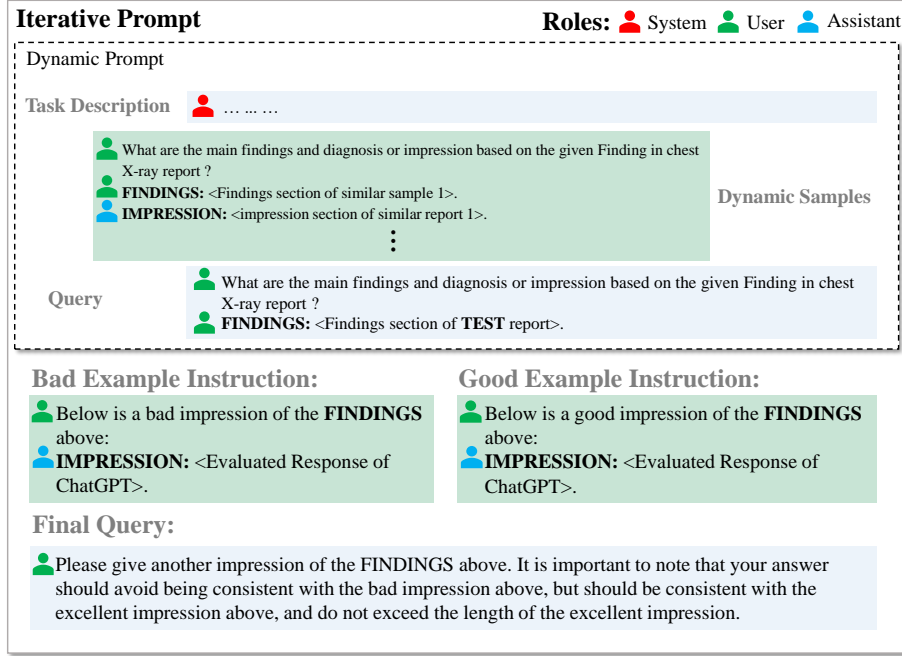


Figure 4: Details of iterative prompt. We construct our iterative prompt by including the bad and good example instructions along with the final query, in addition to applying a "Instruction + Response" approach in the example instruction for optimizing the response.

which is further evaluated and incorporated into an iterative prompt. The iterative prompt is used to elicit subsequent responses that are specific to the task domain, thereby enabling self-iterative updates of ChatGPT with limited examples. Our experimental results demonstrate that ImpressionGPT delivers superior results in the summarization of radiology reports, as elaborated in Sec. 4.2.

4 Experiment and Analysis

4.1 Dataset and Evaluation Metrics

We evaluated our ImpressionGPT on two public available chest X-ray datasets: MIMIC-CXR [40] and OpenI [17]. MIMIC-CXR [40] dataset contains of 227,835 radiology reports, which are amalgamated into our corpus after applying the official split that includes both the training and validation sets. The test set is reserved solely for evaluating the effectiveness of our ImpressionGPT. In line with the objective of medical report summarization, we excluded ineligible re-

ports by implementing the following criteria: (1) removal of incomplete reports without finding or impression sections, (2) removal of reports whose finding section contained less than 10 words, and (3) removal of reports whose impression section contained less than 3 words. Consequently, we filtered out 118,891 reports to construct our corpus and included 1,400 test reports. OpenI [17] dataset contains 3,955 reports, and since the official split is not provided, we randomly divided the dataset into training and testing sets in a 9:1 ratio. Similar to the MIMIC-CXR dataset, we use the training set to build our corpus, while the test set is reserved for evaluating the model. After applying the same inclusion criteria as above, we obtained 3079 reports as our corpus and 342 reports for evaluation. The code to process radiology reports is publicly available on GitHub¹.

In our experiments, we employ Rouge metrics [51] to evaluate the generated impression from our ImpressionGPT, and we reported F1 scores for Rouge-1 (R-1), Rouge-2 (R-2), and Rouge-L (R-L) that compare word-level unigram, bigram, and longest common sub-sequence overlap with the reference impression of the test report, respectively.

4.2 Comparison with Other Methods

Table 1 presents a comparison of our ImpressionGPT with other radiology report summarization methods on MIMIC-CXR [40] and OpenI [17] datasets, including rule-based [20], sequence-based [52, 79], and pre-trained language model-based methods [7, 34, 35, 56, 82]. The evaluation is based on the Rouge-1, Rouge-2, and Rouge-L metrics, comparing the impressions generated by our model with handwritten impressions. We also include a comparison with ChestXray-BERT [7], which used a combined dataset of MIMIC-CXR and OpenI. However, as their data processing method was not public, we use it as a weak reference. As shown in Table 1, our method outperforms other methods in all metrics except for the Rouge-2 score on the OpenI dataset, where it performs slightly lower than Jinpeng et al. [35]. Pre-trained language models perform better than earlier studies, as they are trained with a large amount of medical text data, enabling them to learn the prior knowledge of the medical domain adequately. And our method is even better than the pre-trained language models, with the ability to construct a smaller number of relevant samples in the prompt for the LLM to learn. Thus, we successfully transfer generic knowledge learned by LLMs in pre-training to domain-specific tasks, such as radiology report summarization, at a lower cost than previous pre-trained language models.

In summary, we conclude that incorporating semantically similar examples as context in prompt is beneficial in using LLMs in specific domains. Moreover, the generated output of LLMs can be optimized further with iterative interaction.

¹<https://github.com/MoMarky/radiology-report-extraction>

Table 1: Comparison results of impressionGPT with other prominent methods on MIMIC-CXR and OpenI dataset. **Bold** denotes the best result and Underline denotes the second-best result.

Method	MIMIC-CXR [40]			OpenI [17]		
	R-1↑	R-2↑	R-L↑	R-1↑	R-2↑	R-L↑
LexRank [20]	18.11	7.47	16.87	14.63	4.42	14.06
PGN [79]	46.41	32.33	44.76	63.71	54.23	63.38
CGU [52]	46.50	32.61	44.98	61.60	53.00	61.58
TransEXT [56]	31.00	16.55	27.49	15.58	5.28	14.42
TransAbs [56]	47.16	32.31	45.47	59.66	49.41	59.18
CAVC [82]	43.97	29.36	42.50	53.18	39.59	52.86
WGSUM (LSTM) [34]	47.48	33.03	45.43	64.32	55.48	63.97
WGSUM (Trans) [34]	48.37	33.34	46.68	61.63	50.98	61.73
Jinpeng et al. [35]	<u>49.13</u>	<u>33.76</u>	<u>47.12</u>	<u>64.97</u>	55.59	<u>64.45</u>
ChestXrayBERT [7]	41.3*	28.6*	41.5*	-	-	-
ImpressionGPT (Ours)	57.79	36.64	49.71	69.75	<u>54.61</u>	66.45

* denotes the results on a combined dataset of MIMIC-CXR and OpenI.

5 Discussion and Conclusion

In this work, we explore the applicability of Large Language Models (LLMs) in the task of radiology report summarization by optimizing the input prompts based on a few existing samples and an iterative scheme. Specifically, relevant examples are extracted from the corpus to create dynamic prompts that facilitate in-context learning of LLMs. Additionally, an iterative optimization method is employed to improve the generated results. The method involves providing automated evaluation feedback to the LLM, along with instructions for good and bad responses. Our approach has demonstrated state-of-the-art results, surpassing existing methods that employ large volumes of medical text data for pre-training. Furthermore, this work is a precursor to the development of other domain-specific language models in the current context of artificial general intelligence [92].

While developing the iterative scheme of ImpressionGPT, we noticed that evaluating the quality of responses generated by the model is a crucial yet challenging task. In this work, We employed the Rouge-1 score, a conventional metric for calculating text similarity, as the criterion for evaluating the results. We also compared the evaluation criteria using Rouge-1, Rouge-2, and Rouge-L scores and finally found that the performance is sensitive to the set threshold and achieved optimal results using the Rouge-1 score. We speculate that such differences caused by the scores used are caused by the fact that the expression of words or phrases in a specific domain differs greatly from the general-domain text used for training the LLMs. Thus, using fine-grained evaluation metrics (i.e., Rouge-1) is better for evaluating the details of the generated results. We also envision that better evaluation criteria that can capture higher-level se-

mantic information from the text will be highly needed with the advancement of LLMs.

In the future, we will continue to optimize the prompt design to better incorporate the domain-specific data from both public and local data sources while at the same time addressing the data privacy and safety concerns involved, especially in a multi-institution scenario. We are also investigating the utilization of Knowledge Graph [6] in the prompt design to make it more conformed to existing domain knowledge (e.g., the relationship among different diseases). Finally, we will introduce human experts, e.g., radiologists, into the prompt optimization iterations, adding human input to evaluate the generated results when adding them to the prompts. In such a human-in-the-loop approach, we can better fine-tune the LLMs with decisions and opinions from human experts interactively.

References

- [1] Afantenos, S., Karkaletsis, V., Stamatopoulos, P.: Summarization from medical documents: a survey. *Artificial intelligence in medicine* **33**(2), 157–177 (2005)
- [2] Barham, P., Chowdhery, A., Dean, J., Ghemawat, S., Hand, S., Hurt, D., Isard, M., Lim, H., Pang, R., Roy, S., et al.: Pathways: Asynchronous distributed dataflow for ml. *Proceedings of Machine Learning and Systems* **4**, 430–449 (2022)
- [3] Ben-David, E., Oved, N., Reichart, R.: Pada: A prompt-based autoregressive approach for adaptation to unseen domains. *arXiv preprint arXiv:2102.12206* (2021)
- [4] Bengio, Y., Courville, A., Vincent, P.: Representation learning: A review and new perspectives (2014)
- [5] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al.: Language models are few-shot learners. *Advances in neural information processing systems* **33**, 1877–1901 (2020)
- [6] Cai, H., Liao, W., Liu, Z., Huang, X., Zhang, Y., Ding, S., Li, S., Li, Q., Liu, T., Li, X.: Coarse-to-fine knowledge graph domain adaptation based on distantly-supervised iterative training. *arXiv preprint arXiv:2211.02849* (2022)
- [7] Cai, X., Liu, S., Han, J., Yang, L., Liu, Z., Liu, T.: Chestxraybert: A pretrained language model for chest radiology report summarization. *IEEE Transactions on Multimedia* (2021)
- [8] Casey, A., Davidson, E., Poon, M., Dong, H., Duma, D., Grivas, A., Grover, C., Suárez-Paniagua, V., Tobin, R., Whiteley, W., et al.: A systematic

- review of natural language processing applied to radiology reports. *BMC medical informatics and decision making* **21**(1), 179 (2021)
- [9] Chang, E., Demberg, V., Marin, A.: Jointly improving language understanding and generation with quality-weighted weak supervision of automatic labeling. In: *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. pp. 818–829 (2021)
 - [10] Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y.: Learning phrase representations using rnn encoder-decoder for statistical machine translation (2014)
 - [11] Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., Barham, P., Chung, H.W., Sutton, C., Gehrmann, S., et al.: Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311* (2022)
 - [12] Chuang, Y.N., Tang, R., Jiang, X., Hu, X.: Spec: A soft prompt-based calibration on mitigating performance variability in clinical notes summarization. *arXiv preprint arXiv:2303.13035* (2023)
 - [13] Cohen, R., Elhadad, M., Elhadad, N.: Redundancy in electronic health record corpora: analysis, impact on text mining performance and mitigation strategies. *BMC bioinformatics* **14**(1), 1–15 (2013)
 - [14] Dai, H., Liu, Z., Liao, W., Huang, X., Wu, Z., Zhao, L., Liu, W., Liu, N., Li, S., Zhu, D., et al.: Chataug: Leveraging chatgpt for text data augmentation. *arXiv preprint arXiv:2302.13007* (2023)
 - [15] Daumé III, H., Marcu, D.: Bayesian query-focused summarization. In: *Proceedings of the 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics*. pp. 305–312 (2006)
 - [16] Davison, J., Feldman, J., Rush, A.M.: Commonsense knowledge mining from pretrained models. In: *Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP)*. pp. 1173–1178 (2019)
 - [17] Demner-Fushman, D., Kohli, M.D., Rosenman, M.B., Shooshan, S.E., Rodriguez, L., Antani, S., Thoma, G.R., McDonald, C.J.: Preparing a collection of radiology examinations for distribution and retrieval. *Journal of the American Medical Informatics Association* **23**(2), 304–310 (2016)
 - [18] Du, Y., Li, Q., Wang, L., He, Y.: Biomedical-domain pre-trained language model for extractive summarization. *Knowledge-Based Systems* **199**, 105964 (2020)

- [19] El-Kassas, W.S., Salama, C.R., Rafea, A.A., Mohamed, H.K.: Automatic text summarization: A comprehensive survey. *Expert systems with applications* **165**, 113679 (2021)
- [20] Erkan, G., Radev, D.R.: Lexrank: Graph-based lexical centrality as salience in text summarization. *Journal of artificial intelligence research* **22**, 457–479 (2004)
- [21] Feng, W., Bu, X., Zhang, C., Li, X.: Beyond bounding box: Multimodal knowledge learning for object detection. *arXiv preprint arXiv:2205.04072* (2022)
- [22] Friedman, C., Shagina, L., Lussier, Y., Hripcsak, G.: Automated encoding of clinical documents based on natural language processing. *Journal of the American Medical Informatics Association* **11**(5), 392–402 (2004)
- [23] Gambhir, M., Gupta, V.: Recent automatic text summarization techniques: a survey. *Artificial Intelligence Review* **47**, 1–66 (2017)
- [24] Gao, T., Fisch, A., Chen, D.: Making pre-trained language models better few-shot learners. *arXiv preprint arXiv:2012.15723* (2020)
- [25] Gehrmann, S., Dernoncourt, F., Li, Y., Carlson, E.T., Wu, J.T., Welt, J., Foote Jr, J., Moseley, E.T., Grant, D.W., Tyler, P.D., et al.: Comparing deep learning and concept extraction based methods for patient phenotyping from clinical narratives. *PloS one* **13**(2), e0192360 (2018)
- [26] Gharebagh, S.S., Goharian, N., Filice, R.: Attend to medical ontologies: Content selection for clinical abstractive summarization. In: *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. pp. 1899–1905 (2020)
- [27] Gong, Y., Liu, X.: Generic text summarization using relevance measure and latent semantic analysis. In: *Proceedings of the 24th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*. p. 19–25. SIGIR '01, Association for Computing Machinery, New York, NY, USA (2001). <https://doi.org/10.1145/383952.383955>, <https://doi.org/10.1145/383952.383955>
- [28] Han, Z., Wei, B., Leung, S., Chung, J., Li, S.: Towards automatic report generation in spine radiology using weakly supervised framework. In: *Medical Image Computing and Computer Assisted Intervention–MICCAI 2018: 21st International Conference, Granada, Spain, September 16–20, 2018, Proceedings, Part IV* 11. pp. 185–193. Springer (2018)
- [29] Hansell, D.M., Bankier, A.A., MacMahon, H., McLoud, T.C., Muller, N.L., Remy, J.: Fleischner society: glossary of terms for thoracic imaging. *Radiology* **246**(3), 697–722 (2008)

- [30] Hassanpour, S., Langlotz, C.P.: Information extraction from multi-institutional radiology reports. *Artificial Intelligence in Medicine* **66**, 29–39 (2016). <https://doi.org/https://doi.org/10.1016/j.artmed.2015.09.007>, <https://www.sciencedirect.com/science/article/pii/S09333365715001244>
- [31] Helmers, L., Horn, F., Biegler, F., Oppermann, T., Müller, K.R.: Automating the search for a patent’s prior art with a full text similarity search. *PloS one* **14**(3), e0212103 (2019)
- [32] Hermann, K.M., Kocisky, T., Grefenstette, E., Espeholt, L., Kay, W., Suleyman, M., Blunsom, P.: Teaching machines to read and comprehend. *Advances in neural information processing systems* **28** (2015)
- [33] Holmes, J., Liu, Z., Zhang, L., Ding, Y., Sio, T.T., McGee, L.A., Ashman, J.B., Li, X., Liu, T., Shen, J., et al.: Evaluating large language models on a highly-specialized topic, radiation oncology physics. *arXiv preprint arXiv:2304.01938* (2023)
- [34] Hu, J., Li, J., Chen, Z., Shen, Y., Song, Y., Wan, X., Chang, T.H.: Word graph guided summarization for radiology findings. In: *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. pp. 4980–4990 (2021)
- [35] Hu, J., Li, Z., Chen, Z., Li, Z., Wan, X., Chang, T.H.: Graph enhanced contrastive learning for radiology findings summarization. In: *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. pp. 4677–4688 (2022)
- [36] Huang, K., Altosaar, J., Ranganath, R.: Clinicalbert: Modeling clinical notes and predicting hospital readmission. *arXiv preprint arXiv:1904.05342* (2019)
- [37] Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilcus, S., Chute, C., Marklund, H., Haghighi, B., Ball, R., Shpanskaya, K., et al.: Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In: *Proceedings of the AAAI conference on artificial intelligence*. vol. 33, pp. 590–597 (2019)
- [38] Jiang, Z., Xu, F.F., Araki, J., Neubig, G.: How can we know what language models know? *Transactions of the Association for Computational Linguistics* **8**, 423–438 (2020)
- [39] Jing, H.: Sentence reduction for automatic text summarization. In: *Sixth applied natural language processing conference*. pp. 310–315 (2000)
- [40] Johnson, A.E., Pollard, T.J., Berkowitz, S.J., Greenbaum, N.R., Lungren, M.P., Deng, C.y., Mark, R.G., Horng, S.: Mimic-cxr, a de-identified publicly available database of chest radiographs with free-text reports. *Scientific data* **6**(1), 317 (2019)

- [41] Karn, S.K., Liu, N., Schütze, H., Farri, O.: Differentiable multi-agent actor-critic for multi-step radiology report summarization. In: Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). pp. 1542–1553 (2022)
- [42] Karthiga, M., Sountharajan, S., Bazila Banu, A., Sankarananth, S., Suganya, E., Sathish Kumar, B.: Similarity analytics for semantic text using natural language processing. In: 3rd EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing. pp. 239–248. Springer (2022)
- [43] Kenton, J.D.M.W.C., Toutanova, L.K.: Bert: Pre-training of deep bidirectional transformers for language understanding. In: Proceedings of NAACL-HLT. pp. 4171–4186 (2019)
- [44] Kieuvongngam, V., Tan, B., Niu, Y.: Automatic text summarization of covid-19 medical research articles using bert and gpt-2. arXiv preprint arXiv:2006.01997 (2020)
- [45] Kim, Y.: Convolutional neural networks for sentence classification (2014)
- [46] Lee, J., Yoon, W., Kim, S., Kim, D., Kim, S., So, C.H., Kang, J.: Biobert: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics* **36**(4), 1234–1240 (2020)
- [47] Lester, B., Al-Rfou, R., Constant, N.: The power of scale for parameter-efficient prompt tuning. arXiv preprint arXiv:2104.08691 (2021)
- [48] Lewis, M., Liu, Y., Goyal, N., Ghazvininejad, M., Mohamed, A., Levy, O., Stoyanov, V., Zettlemoyer, L.: Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. pp. 7871–7880 (2020)
- [49] Li, X.L., Liang, P.: Prefix-tuning: Optimizing continuous prompts for generation. arXiv preprint arXiv:2101.00190 (2021)
- [50] Liao, W., Liu, Z., Dai, H., Wu, Z., Zhang, Y., Huang, X., Chen, Y., Jiang, X., Zhu, D., Liu, T., et al.: Mask-guided bert for few shot text classification. arXiv preprint arXiv:2302.10447 (2023)
- [51] Lin, C.Y.: Rouge: A package for automatic evaluation of summaries. In: Text summarization branches out. pp. 74–81 (2004)
- [52] Lin, J., Sun, X., Ma, S., Su, Q.: Global encoding for abstractive summarization. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). pp. 163–169 (2018)
- [53] Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., Neubig, G.: Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys* **55**(9), 1–35 (2023)

- [54] Liu, P.J., Saleh, M., Pot, E., Goodrich, B., Sepassi, R., Kaiser, L., Shazeer, N.: Generating wikipedia by summarizing long sequences. arXiv preprint arXiv:1801.10198 (2018)
- [55] Liu, Y.: Fine-tune bert for extractive summarization. arXiv preprint arXiv:1903.10318 (2019)
- [56] Liu, Y., Lapata, M.: Text summarization with pretrained encoders. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). pp. 3730–3740 (2019)
- [57] Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., et al.: Summary of chatgpt/gpt-4 research and perspective towards the future of large language models. arXiv preprint arXiv:2304.01852 (2023)
- [58] Liu, Y., Wei, W., Peng, D., Zhu, F.: Declaration-based prompt tuning for visual question answering. arXiv preprint arXiv:2205.02456 (2022)
- [59] Liu, Z., He, M., Jiang, Z., Wu, Z., Dai, H., Zhang, L., Luo, S., Han, T., Li, X., Jiang, X., et al.: Survey on natural language processing in medical image analysis. *Zhong nan da xue xue bao. Yi xue ban= Journal of Central South University. Medical Sciences* **47**(8), 981–993 (2022)
- [60] Liu, Z., Yu, X., Zhang, L., Wu, Z., Cao, C., Dai, H., Zhao, L., Liu, W., Shen, D., Li, Q., et al.: Deid-gpt: Zero-shot medical text de-identification by gpt-4. arXiv preprint arXiv:2303.11032 (2023)
- [61] Luhn, H.P.: The automatic creation of literature abstracts. *IBM Journal of Research and Development* **2**(2), 159–165 (1958). <https://doi.org/10.1147/rd.22.0159>
- [62] MacAvaney, S., Sotudeh, S., Cohan, A., Goharian, N., Talati, I., Filice, R.W.: Ontology-aware clinical abstractive summarization. In: Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. pp. 1013–1016 (2019)
- [63] Michalopoulos, G., Wang, Y., Kaka, H., Chen, H., Wong, A.: Umlsbert: Clinical domain knowledge augmentation of contextual embeddings using the unified medical language system metathesaurus. In: Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. pp. 1744–1753 (2021)
- [64] Mihalcea, R., Tarau, P.: Textrank: Bringing order into text. In: Proceedings of the 2004 conference on empirical methods in natural language processing. pp. 404–411 (2004)

- [65] Nallapati, R., Zhai, F., Zhou, B.: Summarunner: A recurrent neural network based sequence model for extractive summarization of documents. In: Proceedings of the AAAI conference on artificial intelligence. vol. 31 (2017)
- [66] Nallapati, R., Zhou, B., dos Santos, C., Gülçehre, Ç., Xiang, B.: Abstractive text summarization using sequence-to-sequence rnns and beyond. In: Proceedings of the 20th SIGNLL Conference on Computational Natural Language Learning. pp. 280–290 (2016)
- [67] Ozsoy, M.G., Alpaslan, F.N., Cicekli, I.: Text summarization using latent semantic analysis. *Journal of Information Science* **37**(4), 405–417 (2011)
- [68] Paice, C.D.: Constructing literature abstracts by computer: Techniques and prospects. *Inf. Process. Manage.* **26**(1), 171–186 (apr 1990). [https://doi.org/10.1016/0306-4573\(90\)90014-S](https://doi.org/10.1016/0306-4573(90)90014-S), [https://doi.org/10.1016/0306-4573\(90\)90014-S](https://doi.org/10.1016/0306-4573(90)90014-S)
- [69] Park, J.W.: Continual bert: Continual learning for adaptive extractive summarization of covid-19 literature. arXiv preprint arXiv:2007.03405 (2020)
- [70] Petroni, F., Rocktäschel, T., Lewis, P., Bakhtin, A., Wu, Y., Miller, A.H., Riedel, S.: Language models as knowledge bases? arXiv preprint arXiv:1909.01066 (2019)
- [71] Pons, E., Braun, L.M.M., Hunink, M.G.M., Kors, J.A.: Natural language processing in radiology: A systematic review. *Radiology* **279**(2), 329–343 (2016). <https://doi.org/10.1148/radiol.16142770>, <https://doi.org/10.1148/radiol.16142770>, pMID: 27089187
- [72] Pons, E., Braun, L.M., Hunink, M.M., Kors, J.A.: Natural language processing in radiology: a systematic review. *Radiology* **279**(2), 329–343 (2016)
- [73] Qurashi, A.W., Holmes, V., Johnson, A.P.: Document processing: Methods for semantic text similarity analysis. In: 2020 International Conference on INnovations in Intelligent SysTems and Applications (INISTA). pp. 1–6. IEEE (2020)
- [74] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., et al.: Language models are unsupervised multitask learners. *OpenAI blog* **1**(8), 9 (2019)
- [75] Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., Liu, P.J.: Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research* **21**(1), 5485–5551 (2020)

- [76] Rezayi, S., Dai, H., Liu, Z., Wu, Z., Hebbar, A., Burns, A.H., Zhao, L., Zhu, D., Li, Q., Liu, W., et al.: Clinicalradiobert: Knowledge-infused few shot learning for clinical notes named entity recognition. In: Machine Learning in Medical Imaging: 13th International Workshop, MLMI 2022, Held in Conjunction with MICCAI 2022, Singapore, September 18, 2022, Proceedings. pp. 269–278. Springer (2022)
- [77] Rush, A.M., Chopra, S., Weston, J.: A neural attention model for sentence summarization. In: Conference on Empirical Methods in Natural Language Processing, EMNLP 2015. pp. 379–389. Association for Computational Linguistics (ACL) (2015)
- [78] Schick, T., Schütze, H.: Few-shot text generation with pattern-exploiting training. arXiv preprint arXiv:2012.11926 (2020)
- [79] See, A., Liu, P.J., Manning, C.D.: Get to the point: Summarization with pointer-generator networks. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). pp. 1073–1083 (2017)
- [80] Shin, R., Lin, C.H., Thomson, S., Chen, C., Roy, S., Platanios, E.A., Pauls, A., Klein, D., Eisner, J., Van Durme, B.: Constrained language models yield few-shot semantic parsers. arXiv preprint arXiv:2104.08768 (2021)
- [81] Shin, T., Razeghi, Y., Logan IV, R.L., Wallace, E., Singh, S.: Autoprompt: Eliciting knowledge from language models with automatically generated prompts. arXiv preprint arXiv:2010.15980 (2020)
- [82] Song, K., Wang, B., Feng, Z., Liu, R., Liu, F.: Controlling the amount of verbatim copying in abstractive summarization. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 34, pp. 8902–8909 (2020)
- [83] Sutskever, I., Vinyals, O., Le, Q.V.: Sequence to sequence learning with neural networks (2014)
- [84] Tsimpoukelli, M., Menick, J.L., Cabi, S., Eslami, S., Vinyals, O., Hill, F.: Multimodal few-shot learning with frozen language models. *Advances in Neural Information Processing Systems* **34**, 200–212 (2021)
- [85] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is all you need. *Advances in neural information processing systems* **30** (2017)
- [86] Wallace, E., Feng, S., Kandpal, N., Gardner, M., Singh, S.: Universal adversarial triggers for attacking and analyzing nlp. arXiv preprint arXiv:1908.07125 (2019)
- [87] Yang, J., Li, Y., Gao, C., Zhang, Y.: Measuring the short text similarity based on semantic and syntactic information. *Future Generation Computer Systems* **114**, 169–180 (2021)

- [88] Yuan, W., Neubig, G., Liu, P.: Bartscore: Evaluating generated text as text generation. *Advances in Neural Information Processing Systems* **34**, 27263–27277 (2021)
- [89] Zaremba, W., Sutskever, I., Vinyals, O.: Recurrent neural network regularization. *arXiv preprint arXiv:1409.2329* (2014)
- [90] Zhang, J., Zhao, Y., Saleh, M., Liu, P.: Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In: *International Conference on Machine Learning*. pp. 11328–11339. PMLR (2020)
- [91] Zhang, Y., Ding, D.Y., Qian, T., Manning, C.D., Langlotz, C.P.: Learning to summarize radiology findings. In: *Proceedings of the Ninth International Workshop on Health Text Mining and Information Analysis*. pp. 204–213 (2018)
- [92] Zhao, L., Zhang, L., Wu, Z., Chen, Y., Dai, H., Yu, X., Liu, Z., Zhang, T., Hu, X., Jiang, X., et al.: When brain-inspired ai meets agi. *arXiv preprint arXiv:2303.15935* (2023)