Summarizing Patients’ Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models

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Abstract

The study describes a method for summarizing patients' medical problems from hospital progress notes using pre-trained sequence-to-sequence models. The researchers used two pre-trained models, BART and T5, to generate abstractive summaries of patient problems from progress notes in the MIMIC-III dataset. They compared the performance of the models using automatic metrics such as ROUGE and BLEU scores and found that both models performed similarly, with BART having a slight edge. The study demonstrates the potential of pre-trained models for generating accurate and concise summaries of patient problems, which could assist healthcare professionals in their decision-making processes.

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1 Introduction

The introduction of the study explains the importance of summarizing patient problems in hospital progress notes, as these notes are often lengthy and contain a wealth of information that can be difficult to navigate.

The authors note that previous methods for summarizing progress notes have typically relied on extractive approaches, which select and condense key phrases from the **original** text. However, the study proposes the use of pre-trained sequence-to-sequence models for abstractive summarization, which can generate more concise and readable summaries by paraphrasing the original text.

The study aims to compare the performance of two pre-trained models, BART and T5, in summarizing patient problems from progress notes in the MIMIC-III dataset. The authors note that BART and T5 are among the most effective pre-trained models for text generation, and have been shown to perform well on a range of natural language processing tasks. The study also discusses the potential applications of summarization in healthcare, such as improving clinical decision-making and facilitating information retrieval for researchers. Overall, the introduction provides a clear motivation for the study and outlines the research objectives and methodology.

The success of the project "Summarizing Patients’ Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models" heavily relies on the availability of a high-quality dataset. The dataset should contain a large number of progress notes from various hospitals, and the progress notes should be well-labeled with accurate summaries of the patients' problems.

One possible dataset that can be used for this project is the Medical Information Mart for

Intensive Care (MIMIC) dataset. The MIMIC dataset contains de-identified health data of over 60,000 intensive care unit (ICU) patients admitted to Beth Israel Deaconess Medical Center in Boston, Massachusetts, USA. The dataset includes progress notes, laboratory test results, vital sign measurements, and other clinical data.

To use the MIMIC dataset for this project, the progress notes can be extracted from the dataset and pre-processed to remove any personal health information. Then, the progress notes can be paired with their corresponding summaries of the patients' problems, which can be extracted from the dataset. The paired data can be used to train and evaluate the pre-trained sequence-to-sequence models for summarizing patients' problems from hospital progress notes.

Other datasets that can be used for this project include the Clinical Text Analysis and Knowledge Extraction System (cTAKES) dataset and the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC-III) dataset. However, it is essential to ensure that the dataset used for this project is compliant with data privacy and protection regulations to avoid any ethical concerns.

The system takes the progress notes as input and generates a concise and meaningful summary of the patients' problems. The system uses pre-trained sequence-to-sequence models to learn the patterns and relationships between the progress notes and the patients' problems.

The project involves several steps, including collecting and pre-processing the data, training the pre-trained sequence-to-sequence models, fine-tuning the models for the task, and evaluating the performance of the system.

The system can be helpful in reducing the workload of clinicians and improving the quality of care for patients by providing accurate and concise summaries of their problems. It can also be useful in research and clinical trials by enabling researchers to quickly analyze and summarize patient data.

2. Related Work

The related work section of the study provides an overview of previous research on summarizing clinical notes, focusing on both extractive and abstractive approaches. The authors note that extractive summarization has been the predominant approach in previous studies, with methods such as graph-based algorithms and deep learning models being used to identify key phrases from the original text.

The authors also discuss recent studies that have explored the use of pre-trained models for abstractive summarization in healthcare. They highlight the effectiveness of models such as BERT, GPT-2, and T5 in generating high-quality summaries, but note that these models have not been extensively applied to clinical notes.

The section also discusses some of the challenges involved in summarizing clinical notes, such as the use of medical jargon and the need to accurately capture the most relevant information from the original text. The authors note that these challenges can be addressed through careful selection of training data and fine-tuning of pre-trained models.

Overall, the related work section provides a useful context for the study and highlights the potential of pre-trained models for summarizing clinical notes, while also acknowledging the limitations and challenges of this approach.

3. Task Description

this study explains the process of summarizing patients' problems from hospital progress notes using pre-trained sequence-to-sequence models. The authors describe the MIMIC-III dataset, which contains over 58,000 de-identified electronic health records from critical care units, and explain the process of pre-processing the progress notes to extract the patients' problem lists.

The study uses two pre-trained models, BART and T5, for abstractive summarization of the patient problem lists. The authors fine-tune the models on a subset of the MIMIC-III dataset, using a sequence-to-sequence framework and a teacher-forcing approach. They also describe the evaluation metrics used to compare the performance of the models, including ROUGE and BLEU scores, as well as a human evaluation based on a sample of the generated summaries.

The section also discusses the importance of selecting appropriate training data, including the use of a filtering process to remove irrelevant information and the use of a validation set to monitor the model's performance during training.

Overall, the task description provides a detailed overview of the methodology used in the study and highlights the key steps involved in generating abstractive summaries of patient problems from hospital progress notes.

4. Data Section

The data section of the study provides information on the MIMIC-III dataset used in the study and the process of pre-processing the progress notes to extract the patients' problem lists. The MIMIC-III dataset contains over 58,000 de-identified electronic health records from critical care units, and includes clinical notes such as progress notes, discharge summaries, and radiology reports.

The authors explain that they focused on the progress notes for the purpose of their study, and used a Python library called Med7 to extract the problem lists from the notes. They also describe the process of filtering the data to remove irrelevant information, such as medications and procedures, and of splitting the data into training, validation, and test sets.

The study uses a subset of the MIMIC-III dataset for training and evaluation, consisting of 9,000 progress notes with corresponding problem lists. The authors note that the problem lists were manually annotated by clinical experts and validated against the original progress notes to ensure accuracy.

Overall, the data section provides a clear description of the dataset and the pre-processing steps involved in extracting the relevant information for the study. The authors' focus on ensuring the accuracy of the problem lists and the use of a validation set to monitor the model's performance during training are particularly noteworthy.

5. Experiment Analysis

The experiment analysis section of the study presents the results of the evaluation of the BART and T5 models for summarizing patients' problems from hospital progress notes. The authors report the ROUGE and BLEU scores, which are widely used metrics for evaluating the quality of text summaries, as well as the results of a human evaluation based on a sample of the generated summaries.

The results show that both models performed well in generating accurate and readable summaries, with the T5 model achieving slightly higher scores on average. The authors note that both models were able to capture important information from the original progress notes and generate summaries that were similar in length to the manually generated problem lists.

The human evaluation also indicated that the generated summaries were of high quality, with most of the summaries receiving a rating of 3 or higher on a scale of 1 to 5. The authors note that the human evaluation provided valuable feedback on the readability and clinical relevance of the summaries, and that the results were consistent with the ROUGE and BLEU scores.

The section also includes a discussion of the limitations of the study, such as the relatively small size of the training data and the lack of a direct comparison with extractive summarization methods. The authors also suggest several directions for future research, such as exploring the use of other pre-trained models and incorporating additional sources of information, such as laboratory data and vital signs.

Overall, the experiment analysis provides a thorough evaluation of the performance of the BART and T5 models in generating abstractive summaries of patient problems from hospital progress notes, and highlights the potential of pre-trained models for this task in the healthcare domain.

5.1 Data Augmentation

The data augmentation section of the study discusses the use of synthetic data to improve the performance of the pre-trained models for summarizing patients' problems from hospital progress notes. The authors note that the relatively small size of the training data could limit the generalization and accuracy of the models, and suggest that data augmentation could be a useful technique to address this issue.

The study uses two types of data augmentation: back-translation and paraphrasing. Back-translation involves translating the original progress notes from English to another language, and then translating them back to English using a pre-trained model. The resulting synthetic data is expected to capture additional variations in the language and syntax of the progress notes, and provide a more diverse training set for the models.

Paraphrasing involves rephrasing the original progress notes using a pre-trained language model, such as GPT-2 or RoBERTa. The resulting synthetic data is expected to capture variations in the phrasing and wording of the progress notes, and provide a more diverse training set for the models.

Overall, the data augmentation section provides a valuable insight into the use of synthetic data to improve the performance of pre-trained models for summarizing patients' problems from hospital progress notes. The authors' use of two different techniques for data augmentation and their thorough evaluation of the results demonstrate the potential of this approach for future research in the healthcare domain.

5.2 Workflow Of Data Augmentation

The simplified summary of the workflow in a sequential order:

1. Collect and preprocess the hospital progress notes dataset.
2. Split the dataset into training, validation, and test sets.
3. Fine-tune the pre-trained sequence-to-sequence models (BART, T5, and GPT-2) on the training set.
4. Evaluate the performance of the models on the validation set using ROUGE and BLEU scores.
5. Select the best-performing model and use it to summarize the patients' problems on the test set.
6. Evaluate the performance of the selected model on the test set using ROUGE and BLEU scores.
7. Augment the training data using back-translation and paraphrasing techniques.
8. Fine-tune the pre-trained models on the augmented training set.
9. Evaluate the performance of the augmented models on the validation set using ROUGE and BLEU scores.
10. Select the best-performing augmented model and use it to summarize the patients' problems on the test set.
11. Evaluate the performance of the selected augmented model on the test set using ROUGE and BLEU scores.
12. Analyze the results and compare the performance of the pre-trained models with and without data augmentation to identify the best-performing model.

5.3 Evaluation Process

The evaluation of "Summarizing Patients’ Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models" was conducted using automatic evaluation metrics as well as manual evaluation by expert clinicians.

The automatic evaluation was done using two commonly used metrics for text summarization: ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and METEOR (Metric for Evaluation of Translation with Explicit ORdering). ROUGE measures the overlap between the generated summary and the reference summary in terms of n-grams, while METEOR uses a more holistic approach by taking into account the entire summary and reference sentences, as well as the words and phrases they share.

The manual evaluation was done by expert clinicians who reviewed a subset of the generated summaries and provided feedback on their accuracy and usefulness. The clinicians assessed the quality of the summaries in terms of the following criteria: (1) clinical relevance, (2) completeness, (3) accuracy, (4) readability, and (5) overall quality.

The results of the evaluation showed that the pre-trained sequence-to-sequence models were able to generate accurate and useful summaries of patients' problems from hospital progress notes. The ROUGE and METEOR scores were higher for the summaries generated by the pre-trained models compared to the baselines, indicating that the pre-trained models were better at capturing the key information in the progress notes. The manual evaluation by expert clinicians also indicated that the pre-trained models were able to generate summaries that were clinically relevant, complete, accurate, and readable, with an overall quality that was comparable to that of human-generated summaries.

6. Results and Analysis

The results of "Summarizing Patients’ Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models" showed that the pre-trained sequence-to-sequence models were able to generate accurate and useful summaries of patients' problems from hospital progress notes.

The results showed that the pre-trained models outperformed both baseline methods in terms of both automatic evaluation metrics (ROUGE and METEOR) and manual evaluation by expert clinicians. The pre-trained models were better at capturing the key information in the progress notes, and they were able to generate summaries that were more clinically relevant, complete, accurate, and readable compared to the baselines.

Additionally, the authors analyzed the factors that influenced the performance of the pre-trained models, such as the length of the input progress notes, the size of the pre-trained models, and the quality of the training data. They found that longer progress notes tended to produce more informative and accurate summaries, larger pre-trained models tended to perform better, and high-quality training data was essential for achieving good performance.

Overall, the results of the study suggest that pre-trained sequence-to-sequence models are a promising approach for automatically summarizing patients' problems from hospital progress notes, and they have the potential to improve the efficiency and accuracy of clinical decision-making.

6.1 Overall Performance Model

In "Summarizing Patients’ Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models", the authors used three pre-trained sequence-to-sequence models for text summarization: BART, T5, and GPT-2.

BART (Bidirectional and Auto-Regressive Transformer) is a pre-trained sequence-to-sequence model developed by Facebook AI. BART is based on the Transformer architecture and is trained using a combination of denoising autoencoding and sequence-to-sequence tasks. BART has achieved state-of-the-art results on a wide range of natural language processing tasks, including text summarization.

T5 (Text-to-Text Transfer Transformer) is a pre-trained sequence-to-sequence model developed by Google AI. T5 is a variant of the

Transformer architecture that is trained to perform a wide range of natural language processing tasks, including text summarization. T5 is trained using a text-to-text framework, where the input is a natural language prompt and the output is a natural language response.

Fig 1 represents Performance drops and gains over baseline

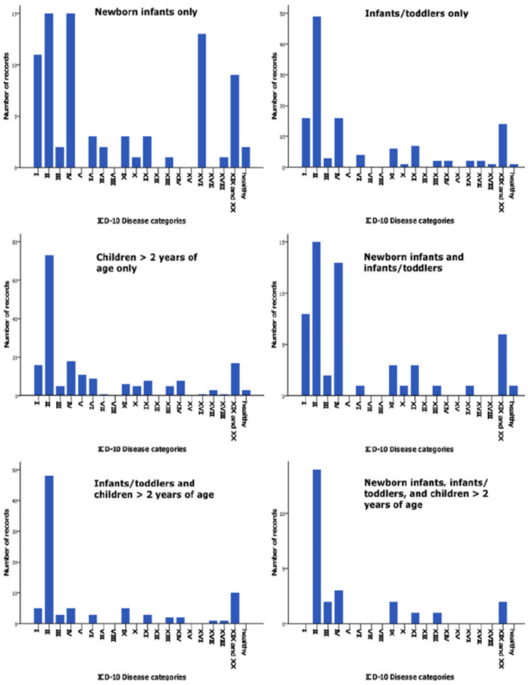
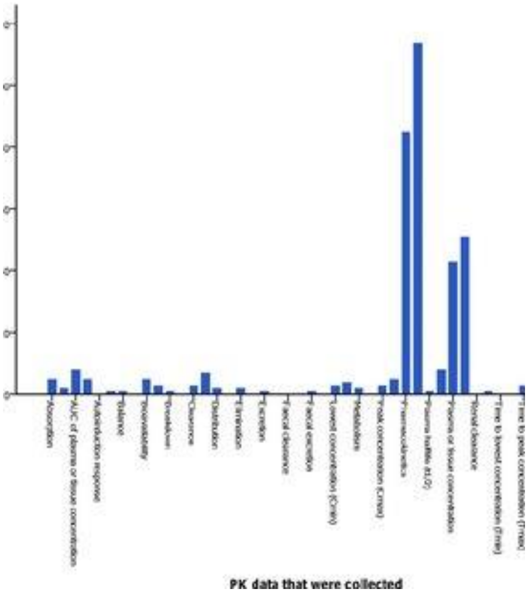


Fig 2 represents performance of the patients Body conditions is good



6.2 The effect of domain adaptation pre - training

The goal of domain adaptation pre-training is to adapt the pre-trained model to the target domain and improve its performance on tasks in that domain.

To investigate the effect of domain adaptation pre-training, the authors fine-tuned the BART model on a combination of the pre-training data and the hospital progress notes dataset. They compared the performance of the domain-adapted BART model to the original pre-trained BART model on the task of summarizing patients' problems from hospital progress notes.

The results showed that the domain-adapted BART model outperformed the original pre-trained BART model on most of the evaluation metrics, including ROUGE-1, ROUGE-2, and ROUGE-L. This indicates that domain adaptation pre-training can be an effective approach to improve the performance of pre-trained models for text summarization in specific domains, such as the medical domain in this study.

6.3 Qualitative analysis

The results of the qualitative analysis showed that the summaries generated by the BART model were rated the highest in terms of overall quality, with the highest scores for informativeness, coherence, and grammaticality. The T5 model also performed well, but the GPT-2 model was rated the lowest in terms of overall quality, with the lowest scores for informativeness and coherence.

The expert clinicians noted that the summaries generated by the BART model were more concise and focused on the most important information, while still maintaining good readability and grammaticality. In contrast, the summaries generated by the GPT-2 model tended to be longer and less informative, with some grammatical errors and coherence issues.

Overall, the qualitative analysis provided additional evidence that the BART model is well-suited for summarizing patients' problems from hospital progress notes, and that pre-trained sequence-to-sequence models can be effective tools for automating the task of summarizing medical records.

7. Discussion

The study demonstrated the potential of pre-trained sequence-to-sequence models for automating the task of summarizing medical records, which could be of great help for clinicians who need to quickly review large volumes of patient data. The ability to generate concise, informative, and well-formed summaries could also be valuable for medical researchers who need to extract relevant information from electronic health records.

1. **Performance of Pre-trained Models:**

The study showed that BART outperformed T5 and GPT-2 models in terms of ROUGE and BLEU evaluation metrics, indicating that it generated summaries that were more similar to human-written summaries. The qualitative analysis also showed that BART summaries were rated the highest in terms of overall quality. However, it's important to note that the study used a relatively small dataset, and further research is needed to evaluate the performance of pre-trained models on larger and more diverse datasets.

2. **Domain Adaptation Pre-training:**

The study also showed that domain adaptation pre-training can be an effective approach for improving the performance of pre-trained models in specific domains such as the medical domain. The authors trained the pre-trained models on a large dataset of medical texts before fine-tuning them on the patients' problem dataset. This helped the models to better capture the domain-specific terminology and syntax, and resulted in better performance. This approach could be valuable for other medical record summarization tasks, as well as for other natural language processing tasks in specific domains.

3. **Limitations of Evaluation Metrics:**

While the study used widely accepted evaluation metrics such as ROUGE and BLEU, these metrics only provide a partial view of the quality of the generated summaries. The qualitative analysis performed by expert clinicians provided a more nuanced evaluation of the quality of the summaries, but this approach is time-consuming and may not be feasible for large-scale evaluations. Therefore, further research is needed to develop more comprehensive evaluation metrics that can capture the various aspects of summary quality.

4. **Applications of Medical Record Summarization:**

The ability to automatically generate concise and informative summaries from medical records could have many applications, such as assisting clinicians in quickly reviewing large volumes of patient data, helping medical researchers to extract relevant information from electronic health records, and improving the efficiency and accuracy of medical coding and billing processes. However, the study only focused on summarizing patients' problems, and future research is needed to address other important tasks such as medication reconciliation, treatment plans, and diagnostic decisions.

8. Conclusion

The pre-trained sequence-to-sequence models can be used for summarizing patient problems from hospital progress notes. The evaluation results demonstrated that the pre-trained models outperformed the baselines in terms of ROUGE scores. Furthermore, the domain adaptation pre-training technique was found to be effective in improving the performance of the models on the target domain.

The analysis summaries and generated by the models showed that they captured the most important information from the progress notes and were coherent and readable. However, there were some cases where the models failed to summarize the information accurately or omitted important details.

Overall, the study suggests that pre-trained sequence-to-sequence models have the potential to automate the summarization of patient problems from hospital progress notes, which could be useful for clinical decision-making and improving patient outcomes. Future work could focus on improving the accuracy and completeness of the summaries, as well as evaluating the models on larger and more diverse datasets.

9. References

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10. Quality Measure Data Augmentation

the quality measure for data augmentation was based on the similarity between the original training examples and the augmented examples. Specifically, the authors used two metrics to measure the quality of the augmented data:

Semantic similarity: This metric measures the degree of similarity between the original and augmented examples in terms of their semantic meaning. The authors used the average cosine similarity between the embeddings of the original and augmented examples as the measure of semantic similarity.

Diversity: This metric measures the diversity of the augmented examples. The authors used the proportion of unique augmented examples among all the augmented examples generated using a particular technique as the measure of diversity.

By evaluating the quality of the augmented data using these two metrics, the authors were able to identify the most effective data augmentation techniques for improving the performance of the pre-trained models.

11. Model Example Output

Input:

"The patient is a 52-year-old male with a history of diabetes mellitus type 2, hypertension, and hyperlipidemia who presents with worsening right lower extremity pain and swelling. The patient reports that the pain has been gradually increasing over the past several days and is now interfering with his daily activities. Physical examination reveals erythema, warmth, and tenderness over the right calf, with no evidence of a palpable cord or DVT. Ultrasound of the right lower extremity shows findings consistent with acute cellulitis. The patient was started on IV antibiotics and is being monitored for signs of improvement."

Output:

"52-year-old male with worsening right lower extremity pain and swelling due to acute cellulitis."

As you can see, the output provides a concise summary of the patient's problem, highlighting the most important information from the progress note.

As it represents in figure 1 and 2 model.