Automatic Summarization for Academic Articles using Deep Learning and Reinforcement Learning with Viewpoints

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Abstract

The purpose of this research is to develop a Viewpoint Refinement in Automatic Summarization (VPRAS) system for research articles. The system will reflect viewpoints of survey to support surveys stage for researchers and students. We collect academic articles using web scraping technology and construct training data by combining sections and sentences through analysis of the article's PDF structure. We use machine learning techniques to classify sentences in Japanese articles into viewpoints. In addition to supervised learning, we introduce reinforcement learning and Dynamic Programming (DP) to extract important sentences for each viewpoint. Finally, we implemented an agent to automatically extract summary sentences based on a reward function.

Introduction

At the start of a new research project, keeping up with the-state-of-art science and technology is essential for accomplishing research objectives. With the rapid progress of information science in recent years, comprehending where particular fields are headed has grown increasingly important (Wu et al. 2022). However, novice researchers can find it arduous to catch valuable knowledge from numerous papers during their survey stage which may lead to inefficiencies. With the spread of the Internet, automatic summarization is a technology for grasping valuable knowledge from massive data. Sefid et al. propose a method for automatically generating abstractive slides for presentations based on section information from academic articles (Sefid et al. 2021). However, extracting important sentences using only the corresponding sentences for section information makes it difficult to reflect why these sentences are important during surveys. Additionally, *ChatPDF*(Mathis Lichtenberger und Moritz Lage GbR, n.d.) is a recently developed summarization tool that is based on the ChatGPT model, capable of generating highly readable and concise abstract summaries. However, since the model has not undergone advanced academic training, it may occasionally provide incorrect information. Therefore, it's necessary to confirm the veracity of the information, which can be time-consuming. To tackle these issues, In this research, we focus on the contents of an academic article that reflect viewpoints such as including background of field, Issues to be solved, research hypotheses, techniques employed etc. Identifying the contents that reflect these viewpoints and recognizing important sentences from each can improve the effectiveness of research activities.

Our Approach

Firstly, As a database construction for running machine learning models, we perform web-scraping to gather Japanese articles from Japan link center and then preprocess the collected articles in PDF format automatically.To reflect the structure of the article, we combine article content, meta information and hierarchize data down to sentence level. For each normalized sentence, a Japanese research expert assigned main-viewpoint class and sub-viewpoint class for labeling this sentence based on Table 1. Secondly, deep learning is applied to classify the text of the article according to the main-viewpoints. Finally, to extract important sentences for sub-viewpoints in each viewpoint, we conduct reinforcement learning by using the important information of each sentence provided by experts. In addition, we combine optimization technique for summary length control during the learning procedure.

Viewpoints Classification By Deep Learning

Based on the dataset we built, we use deep learning to classify sentences into main-viewpoint classes. We conduct morphological analysis using the tool *mecab*[1] and vectorize the words using the Skip-Gram-based Word2vec(Goldberg et al. 2014) for word embedding and PV-DM (Le et al. 2014) for document embedding. For the word-based Word2vec, we adopt LSTM model that can reflect the sequence information, and for the document-based PV-DM, we use SVM that has a high generalization performance as the classifier. The classifier outputs the prediction probability of each main-viewpoint for each sentence. Furthermore, to reflect the different features of the word-based and document-based models, we build a hybrid-model that determines the classification result based on the maximum value of the outputs from both models.

Important Sentence Extraction By Reinforcement Learning

In this part, We use the group of sentences classified by each main-viewpoint class as input for important sentence extrac-

[1]https://github.com/SamuraiT/mecab-python3

Table 1: Detail of viewpoints

	Background	**Objective**	**Method**	**Experiment**	**Evaluation**	**Conclusion**	**Related work**
Sub1	Background of field	Purpose of this research	Approach	Goal	Result	Work has done	Author's previous work
Sub2	Background based on related research	Research sub-goal	Function, architecture	Targets	Explanation	Knowledge as a result	Introduction of related research
Sub3	Issues	The ultimate goal of research	Features, effects	Setting	Interpretation	Conventional knowledge	Issues in related research and fields
Sub4	Definition of terms	Research hypotheses	Design, Development	Condition	Analysis	Future prospect	Comparison with related research

tion. The necessary state transition policies and expected rewards for reinforcement learning are set based on the annotations assigned by research experts. The proposed reinforcement learning model sets up 5 memories.

(1)Candidate Sentence Memory: The selected sentence based on sentence value is added as an action to the knapsack DP system.The candidate sentence with the highest sentence value in the viewpoint class is certainly extracted by deep learning described in the previous section.

(2)Summary Memory: Summary extracted at state **s**.

(3)Value Memory: Store each sentence value at state **s**.

(4)Penalty Memory: Storage of penalty information for sentence transition to eliminate redundancy.

(5)Q Memory: The optimization results are updated in the Q memory as the objective function.

***Summary extraction:** If the summary's permissible range is exceeded during the process, the value of the selected sentences will be reset,and the next loop will begin with the next candidate sentence. The final summary is extracted from the combination result corresponding to the maximum Q value in the Q memory after traversing all sentences in the candidate memory.

Experiment, Evaluation

We set the training-to-testing ratio to 5:1 for a total of 10,311 sentences. Table 2 presents the precision, recall, and F1 scores obtained using Word2vec/LSTM, PV-DV/SVM, and the hybrid model. The results reveal that the hybrid method slightly improved accuracy. Table 3 shows the results of the extraction of important sentences for each viewpoint class using *ROUGE-1*[2].Table 4 shows a sample summary and compares it with Chatpdf's output. According to the results from Chatpdf, the ***research purpose*** was incorrectly extracted as a summary of the ***research background***. The extraction of the summary for a complex viewpoint, such as ***the background based on related research***, has failed. In comparison, Our approach enables to extract a summary of the ***research background*** as a whole and generate summaries for each sub-viewpoint within the ***research background*** which can guide users in their research direction.

Table 2: Result of deep learning

Method	Precision	Recall	F1 score
Word2vec	0.742	0.751	0.746
PV-DM	0.765	0.770	0.767
Hybrid-model	0.770	0.778	0.774

[2]https://github.com/kavgan/ROUGE-2.0

Future Work

It is hoped to apply the **(1)**Navigator-style summaries reflecting the viewpoints of academic articles. **(2)**Automatic Summarization system that reflects the differential information from related research during survey stage. **(3)**Develop an extension corresponding to English articles. **(4)**Expand the dataset to increase stability.

Table 3: Result of Important Sentence Extraction

Viewpoint	**Deep learning in Hybrid method**	**Hitting the importance label%**	**ROUGE-1**
Background	0.746	0.514	0.633
Objective	0.421	0.492	0.659
Method	0.894	0.256	0.717
Experiment	0.754	0.488	0.563
Evaluation	0.807	0.287	0.401
Conclusion	0.649	0.272	0.505
Related work	0.493	0.223	0.562

Table 4: Sample summary of article (Li et al. 2023)

Method	Output Summary
Chatpdf ***Evaluation:*** *The summary is incorrect and does not fit within the sub-viewpoint.*	***Research background :*** *the aim is to develop a system that collects and preprocesses data from academic literature, and automatically generates a hierarchical dataset of paper structures.**(obj)*** *Background based on related research: I'm sorry, but the information you requested...**(Not Successful)***
Our approach ***Evaluation:*** *It is possible to extract sentences that reflects a certain sub-viewpoint.*	***The summary of research background:*** ***(1)****With a vast amount of information readily available, it has become an important skill to be able to extract and comprehend important information from large amounts of text data.* ***(Background of field)*** ***(2)****As a web scraping technology targeting Japanese literature,Nakachi et al. developed a web scraping web API that automatically extracts table data from web.* ***(Background based on related research)*** ***(3)****In the above study, the data included in academic papers, which are generally published in PDF format, was not targeted.**(Issue)***

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