Generating Character Relationship Maps for a Story

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Abstract

In this study, we propose a novel system that extracts characters from the narrative text of novels and generate a character-relationship map. By using the generated character-relationship maps when selecting a novel, the user can obtain an overview of the novel's content without having to read it, and can select only the novels that they like. In addition, if the user forgets the progression of a story, the system can also help the user to resume reading by providing an overall picture of the story up to that point. This system aims to eliminate factors that may cause stress when reading. The system extracts the names of people from the narrative text, creates a list of characters, replaces pronouns with the most appropriate words using GPT, outputs the relationships, and creates a relationship map. The results of the quantitative evaluation showed that the relationship map with the pronoun conversion had a higher percentage of correct character relationships.

1 Introduction

In recent years, increasingly many people have lost the habit of reading books. Among them, many, especially those in their 20s, do not read regularly, which is considered a problem. One of the reasons for this is that reading takes up a lot of time, and one cannot understand the content of a book until the user has read it. Today, there are many forms of entertainment, most of which can be enjoyed without spending much time. This situation has contributed to the decline in the reading population. In addition, when people forget the contents of a book, they need to go back to the previous page in order to recall it, which takes time. Although the number of young people who are no longer reading is growing, the market size of electronic publishing has been increasing in recent years due to the spread of smartphones and tablets. As a result, opportunities to read on electronic media such as smartphones and tablets have increased. We believe that reading on electronic media is one of the ways to make reading more accessible and to solve the problem of reading away from books. Unlike paper novels, reading on electronic media is not heavy, even if one owns multiple novels. Therefore, the number of people who read multiple books in parallel is expected to rise. When reading novels in parallel, it is expected that the number of people who forget the progress of a story will increase. However, in today's society, it is difficult to find time for reading, and many people read in their limited spare time, so spending time going back to the previous page is not effective. Therefore, we have developed a system that extracts characters from the narrative text of a novel and creates a character relationship map to help the reader recall the content of the book without needing to go back to the previous page.

2 Related Work

In their research, Kobayashi and his colleagues (Satoshi Kobayashi. 2007.) proposed a method for extracting place, time, and character candidates from a story using existing dictionaries and other resources, and then segmenting scenes based on the number of different words counted in each of these three categories. In addition, Yoneda et al 2012 (Yoneda et al. 2012.) proposed a method for extracting unknown character names from a story using local occurrence frequencies and co-occurring predicate information. In their research, Jindai et al. (Jindai et al. 2008.) proposed a method for identifying speakers and listeners by machine learning that uses the relative positions of speakers and sentences as features, and then learns a classifier that determines the existence of personal relationships by using personal expressions such as "Watakushime"(myself) as features to extract friendly, hostile, and superior/subordinate persons from conversational texts. Srivastava et al. (Srivastava et al.2016.) used sentiment analysis to exploit the contextual meaning of text and showed that polarity can be associated with interactions. Chu et al. (Chu et al. 2021.) showed that a method combining neural learning and text-passage summarization utilizing BERT is effective for relationship extraction. Shahsavari et al. (Shahsavari et al. 2020.) show that the use of reader reviews allows for the generation of a narrative framework.

2.1 Extraction and Systematization of Person Information

In the study by Baba et al. (Baba et al. 2007.), names of people are extracted based on the results of morphological analysis of detective story texts from English and American literature. The relevance between specific pairs is calculated using the co-occurrence frequency in scenes. As a result, it has been shown that it is possible to create a person correlation map. Figure 1 shows an overview of the method developed by Baba et al. The input is a novel text and the output is a person correlation map. Rectangles represent processes, and columns represent resources such as rules and dictionaries. Agata et al. (Agata et al. 2010.) also showed that judging presence status based on a pre-generated list of death expressions is effective in extracting information about a person.

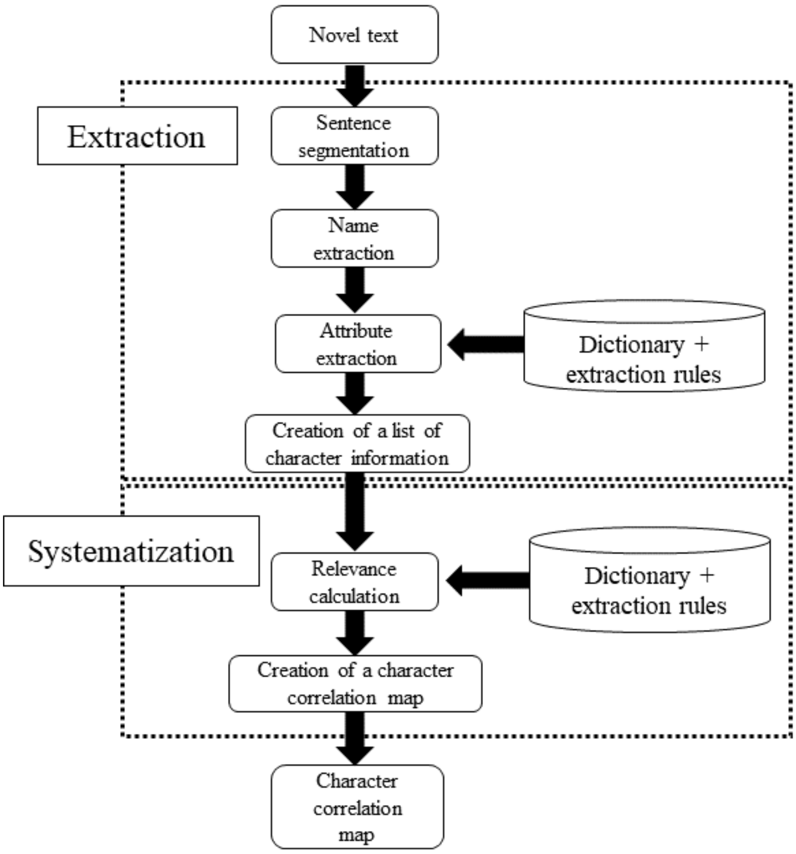

Figure 1:Extraction of a character map Overview (Baba et al. 2007.)

2.2 Improvement of pre-trained language models

In a study by Tianyu et al. (Tianyu et al. 2021.) an effective method for fine-tuning language models with a small number of examples was proposed for improvement of per-trained language models. In this study, templates with masked relations are inserted into novel texts, and the relations are outputted.

3 System Structure

In previous research, we could not find any method that focus on pronouns to clarify the relationships between characters. Therefore, in this study, we replace pronouns with character names to elucidate these relationships. First, we extract the names of characters from books in the Aozora Bunko (Aozora Bunko). To perform each process sentence by sentence, the text is divided accordingly. Next, based on the morphological analysis results, the names of the characters are extracted and a list of characters is created. Then, pronouns are converted based on this list. To determine the degree of association between personal names, a sentence-by-sentence noun list is created, and a dictionary object consisting of co-occurring word pairs and their frequency of occurrence is referenced. Finally, we use GPT (Ilya Sutskever. 2019.) to output the relationships.

3.1 Person name extraction.

In this study, morphological analysis is first performed using MeCab (Taku Kudo. "MeCab,") with reference to the method of Baba et al. (Baba et al. 2007.) The morphological analysis results show that morphemes parsed as "proper noun, person's name" are extracted as names of people, and a list of characters is created based on them. If morphemes parsed as "proper noun, person's name" appear consecutively in a sentence, it is likely that the words form a family name and a first name, so the two words are combined and treated as a single name. Additionally, to extract names of characters not registered as person's names, the part of speech of the morpheme parsed as "particle" is used to extract the previous word, provided it is not a "conjunctive particle".

3.2 Pronoun Conversion

Morphological analysis is performed using MeCab, and words with the parts of speech "pronoun, general" are converted into the token "[MASK]". Then, the words in the character list are inserted into the "[MASK]" token in order. Next, using GPT, we calculate the Perplexity score for each word in the character list and insert the word with the lowest Perplexity score into the sentence.

3.2.1 Perplexity Score

Perplexity is a transformed probability that a given sequence of tokens will occur naturally. In this study, the lower the Perplexity score, the more natural the sentence. Equation (1) shows the calculation for Perplexity. Here, "N" represents the number of data points, "n" denotes the nth word in the dataset, $t_{n,k}$ is the correct answer label for the nth word, and $P_{model}(y_{n,k})$ is the probability of predicting the correct word for the nth word.

$$ppl = \exp\left(-\frac{1}{N}\Sigma_n\Sigma_k t_{n,k} log p_{model}(y_{n,k})\right) \quad (1)$$

3.3 Relational Output

Referring to Tianyu et al. (Tianyu et al. 2021.), the novel text is divided into 600-character segments, and a template with "[MASK]" as the relationship is inserted at the end of the sentence. Then, a word representing the relationship is inserted into "[MASK]". The words used in this study as relationship words are shown in Table 1. Next, GPT is used to compute a Perplexity score for each word. The Perplexity score is then modified based on the frequency of occurrence of each relation, and the word with the lowest Perplexity score is inserted into the sentence. Table 2 shows the templates used in this study.

Table 1: Nouns used to describe relationships between characters.

Acquaintance (知人)	Sibling (きょうだい)	Cousin (いとこ)
Lover (恋人)	Same person (同一人物)	Parent and child (親子)
Married couple (夫婦)	Unrelated (無関係)	

Table 2: Templates.

[name1 and name2 have a [MASK] relationship.]
[name1 has a [MASK] relationship with name2.]
[name2 has a [MASK] relationship with name1.]

3.4 Creating a Relationship Map

In this study, we represent a character relationship map by using person names as nodes and relationships between people as edges. We use NetworkX (GitHub - networkx/networkx: Network Analysis in Python) to create the graph.

3.5 Evaluation

In this experiment, we calculated the percentage of correct answers based on the output results of each relationship, and confirmed the accuracy for each story and each relationship. In this study, the relationships considered correct answers are those selected by three men and three women in their early twenties who read the novel and made their selections. Let the relationship classes be fromL_1 to L_n. If the number of instances predicted to belong to class L_i and actually belonging to class L_j is denoted by C_{ij}, the accuracy A is expressed by the following equation (2).

$$A = \frac{\sum_{i=1}^{N} C_{ii}}{\sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij}} \quad (2)$$

4 Experiment

In this study, we used Ryunosuke Akutagawa's novels "Abababa," "Autumn," "Rashomon," "In a Grove," and "The Nose," Osamu Dazai's "Ritsuko and Sadako," and Rampo Edogawa's "Diary" among works included in the Aozora Bunko. The following two experiments were conducted.

4.1 Experiment 1

A personality map was created without pronoun conversion using GPT.

4.2 Experiment 2

Pronouns were converted using GPT and a character relationship map was created.

5 Result

5.1 Experiment 1

The results of generating the relationships using GPT are shown below. Figures 2 and 3 present an example of a relationship map generated from narrative text in Experiment 1, along with the corresponding correct answers for the character relationship map. Table 3 shows the percentage of correct answers for each story.

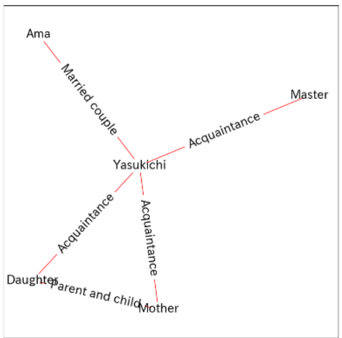

Figure 2: Character relationship map of "Abababa" in the experiment 1, Predicted result

*: "Ama" is the name of a product mentioned in the work, not a character.

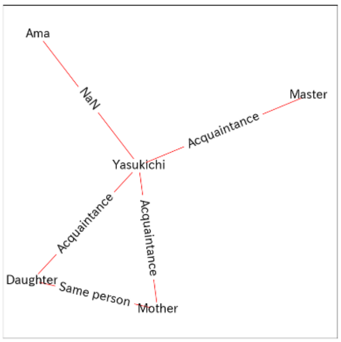

Figure 3: Character relationship map of "Abababaaba" in the experiment 1, Correct result

Table 3: Accuracy of Human relationship extraction for different stories in Experiment 1

Title of the novel	Accuracy(%)
Abababaaba	60.0
Autumn	100.0
Diary	50.0
Ritsuko and Sadako	50.0
Rashomon	14.3
In a Grove	42.9
The Nose	20.0

Figure 2 and 3 show that the word "ama," which is not a character in the story, was included in the list of characters as a name. In addition, Figure 3 shows that the correct output is "parent and child" instead of "same person," which is the correct output. One of the reasons for this output is thought to be that the preceding and following sentences contain conversations and descriptions related to the parent and child. Table 3 shows that the correct response rate was higher for "Autumn" than for "Abababaaba." The reason for this can be attributed to the fact that the sentences used in "Autumn" are similar to the modern kana usage that the GPT is trained.

5.2 Experiment 2

The results of generating the relationships using GPT are shown below. Figure 3 and 4 show an example of a relationship map generated when narrative text was input in Experiment 1, as well as an example of the correct answers for the generated character relationship map. Table 3 shows the percentage of correct answers for each story.

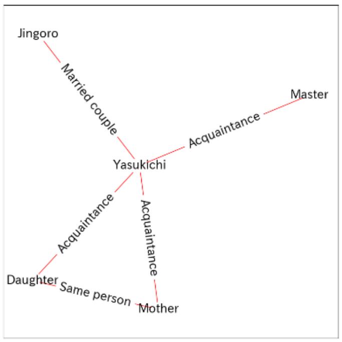

Figure 4: Character relationship map of "Abababaaba" in the experiment 2, Predicted result

**: "Jingoro" is the author of the novel mentioned in the work, not a character in it.

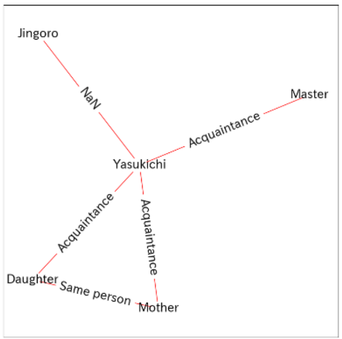

Figure 5: Character relationship map of "Abababaaba" in the experiment 2, Correct result

Table 4: Accuracy of Human relationship extraction for different stories in Experiment 2

Title of the novel	Accuracy(%)
Abababaaba	80.0
Autumn	100.0
Diary	75.0
Ritsuko and Sadako	75.5
Rashomon	66.7
In a Grove	88.9
The Nose	66.7

Figure 4 and 5 show that words that are not characters are included in the list of characters such as "Jingoro". Table 4 shows that the percentage of correct answers in Experiment 2 is higher than in Experiment 1 for all stories.

6 Discussions

The results of the quantitative evaluation showed that the relationship map with the pronoun conversion had a higher percentage of correct character relationships. Although the system performed well, there are some issues to be addressed. One contributing factor to this issue is that non-character names appeared in the character relationship map. For example, the term "irrelevant," which was considered as a potential relationship descriptor, was not generated even once. This indicates variability in the specificity of terms used to represent relationships in the study, which could be a contributing factor. Furthermore, the list of character names employed to generate the relationship map included not just character names but also the names of regions, locations, and authors referenced in the narrative. Consequently, it is important to account for nouns that serve dual purposes as personal and place names within the context of the narrative. Additionally, newly introduced characters in the narrative may initially be referred to by pronouns. Under the current methodology, this can lead to the erroneous insertion of incorrect character names. To mitigate this, the system must be configured to prevent conversions when perplexity score comparisons surpass a predefined threshold. Establishing precise threshold values is crucial to prevent incorrect pronoun conversions, necessitating further analysis to determine optimal thresholds in future research..

7 Conclusion

In this study, a list of characters was initially created by extracting the names of individuals from the narrative text. Next, GPT was used to replace pronouns with the corresponding names from the character list, selecting the words with the lowest perplexity scores to identify relationships and generate a relationship map. The performance evaluation demonstrated that pronoun replacement significantly improved the accuracy of the relationship map. Future research should focus on developing methods to enhance the precision of identifying relationships between characters.

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