The Kyutech corpus and topic segmentation using a combined method

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Abstract

Summarization of multi-party conversation is one of the important tasks in natural language processing. In this paper, we explain a Japanese corpus and a topic segmentation task. To the best of our knowledge, the corpus is the first Japanese corpus annotated for summarization tasks and freely available to anyone. We call it “the Kyutech corpus.” The task of the corpus is a decision-making task with four participants and it contains utterances with time information, topic segmentation and reference summaries. As a case study for the corpus, we describe a method combined with LCSeg and TopicTiling for a topic segmentation task. We discuss the effectiveness and the problems of the combined method through the experiment with the Kyutech corpus.

1 Introduction

In collaborative work, people share information, discuss it, and then make decisions through multi-party conversations, such as meetings. Therefore, understanding such conversations and meetings is one of the most important tasks in natural language processing. Conversation summarization is useful to understand the content of conversations for both participants and non-participants. Many researchers have studied meeting and conversation summarization (Banerjee et al., 2015; Mehdad et al., 2014; Oya et al., 2014).

For the summarization tasks, corpora are very important to analyze characteristics of conversations and to construct a method for summary generation. There are some corpora in English, such as the AMI corpus (Carletta, 2007) and the ICSI corpus (Janin et al., 2003). In contrast, there is no corpus for conversation summarization tasks in Japanese. In this study, we construct a Japanese conversation corpus about a decision-making task with four participants. We call it “the Kyutech corpus.” To the best of our knowledge, the Kyutech corpus is the first Japanese corpus annotated for summarization tasks and freely available to anyone.

The final goal of our study is to generate a summary from a multi-party conversation. Topic segmentation has often been used as the first process in summarization (Banerjee et al., 2015; Oya et al., 2014). In a similar way, we apply topic segmentation to the Kyutech corpus. In this paper, we combine two different text segmentation methods; LCSeg (Galley et al., 2003) and TopicTiling (Riedl and Biemann, 2012). We evaluate the effectiveness of the methods on the Kyutech corpus.

The contributions of this paper are as follows:

- We open the Kyutech corpus, a freely available Japanese conversation corpus for a decision-making task, on the web. This is the first Japanese corpus for summarization.

- As a case study, we examine a combined method based on LCSeg and TopicTiling for topic segmentation with the Kyutech corpus. This is the first step of our conversation summarization.

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¹http://www.pluto.ai.kyutech.ac.jp/-shimada/resources.html
2 Related work

The AMI (Carletta, 2007) and the ICSI (Janin et al., 2003) are very famous meeting corpora and contain numerous annotations, such as dialogue acts and summaries. These corpora are useful and freely available. In addition, they contain a variety of resources, such as speech information in the AMI and ICSI and Powerpoint slides in the AMI corpus. In this paper, we, however, focus on Japanese corpora. Some discussion and conversation corpora in Japanese have been collected on the basis of different task settings; a chat corpus for a detection task of dialogue breakdown (Higashinaka and Funakoshi, 2014) and a multi-modal corpus for three discussion tasks, such as travel planning for foreign friends (Nihei et al., 2014). On the other hand, our task is summarization and our corpus is annotated for the task. The current version contains topic tags of each utterance and reference summaries. In addition, the corpus is freely available to anyone.

For the topic segmentation, some methods have been proposed. The methods were generally based on lexical cohesion for the topic segmentation. TextTiling proposed by (Hearst, 1994) is one of the most famous approaches using a cosine similarity in word vector space. Galley et al. (2003) have proposed a topic segmentation method, LCSeg. It is also a domain-independent discourse segmentation method based on lexical cohesion. It considered the more sophisticated notion of lexical chains as compared with TextTiling. Eisenstein and Barzilay (2008) have proposed an unsupervised approach to topic segmentation based on lexical cohesion modeled by a Bayesian framework. Banerjee et al. (2015) reported that LCSeg tended to outperform the Bayesian segmentation in the summarization. Therefore, we employ LCSeg as a segmentation method. Riedl and Biemann (2012) have proposed a topic segmentation method using the Latent Dirichlet Allocation (LDA) topic model. It was not based on words, but on the topic IDs assigned by the Bayesian Inference method of LDA. Since the topic model alleviated the problem of the sparsity of word vectors, it led to the improvement of the segmentation accuracy. TopicTiling is essentially different from LCSeg because of the use of the topic model. Therefore, we also employ TopicTiling as another method for the topic segmentation. Since the characteristics of the two methods are different, they have a potential to improve the accuracy by a complementary style. Therefore, in this paper, we combine the two methods with a weight factor.

3 Kyutech corpus

In this section, we explain the Kyutech corpus and the annotation for summarization.

3.1 Task

The Kyutech corpus contains multi-party conversations with four participants. The conversations are a decision-making task. The participants pretend managers of a virtual shopping mall in a virtual city, and then determine a new restaurant from three candidates, as an alternative to a closed restaurant. Before the discussion, the participants read a 10-pages document including information about the three candidates, the closed restaurant and the existing restaurants in the mall, the city information, statistics information about the shopping mall, and so on. Figure 1 is a part of the document for the discussion.

The environment of the discussion is shown in Figure 2. The participants are seated around a 1.8m × 1.8m table in a meeting room. We record the discussion by using a four-direction camera and a video camera. They read the document for 10 minutes, then discuss the candidates for 20 minutes and finally determine one restaurant as a new restaurant opening. We prepared four scenarios with different settings, e.g., different candidates. The participants for each discussion were selected from 20 students consisting of 16 males and 4 females. The current Kyutech corpus consists of nine conversations. After discussion, the participants answer a questionnaire about the satisfaction for the decision, and so on.

3.2 Annotation

We transcribe and annotate the conversations. We annotate topic tags for each utterance and generate summaries for each conversation. The working time for the topic annotation was two hours on average.

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2 The original document is written in Japanese because the corpus is Japanese. This is English translation of the document.

3 KingJim MR360. http://www.kingjim.co.jp/sp/mr360/
The restaurant "Japanese WAYA" in the shopping mall UBC was closed. Please select one restaurant from three candidates on the basis of the following information:

| Name          | Menu                                                                 | Price range       | Seats | Business hours |
|---------------|----------------------------------------------------------------------|-------------------|-------|----------------|
| Taiwan Noodles| Beef noodles: ¥ 880, Zhajiangmian: ¥ 980                           | ¥ 800 - ¥ 1,200   | 25    | 11:00 - 23:00 |
| Chinese Shisen| Mabo tofu: ¥ 720, Chukadon: ¥ 900                                | ¥ 900 - ¥ 1,500   | 25    | 11:00 - 23:00 |
| Ramen Fu - Jin| Ramen: ¥ 700, Dumpling: ¥ 200                                      | ¥ 700 - ¥ 1,000   | 30    | 11:00 - 23:00 |

- Taiwan Noodles: A famous local noodle restaurant in the area. Strong smell but good taste.
- Chinese Shisen: A famous Chinese chain restaurant. There are 300 restaurants in Japan.
- Ramen Fu - Jin: A popular Ramen noodle restaurant in Japan. There is no same restaurant in the U city.

For one conversation. Besides, the time for the summary generation by an annotator was 30 minutes on average for one conversation. In this sub-section, we explain the way for the corpus construction and report the results.

### 3.2.1 Transcription

We transcribed the conversations by using ELAN\(^4\). The transcription rules were based on the construction manual of Corpus of Spontaneous Japanese (CSJ) by (National Institute for Japanese Language and Linguistics, 2006). More properly, we separated utterances by 0.2-sec interval on the basis of the manual and annotated some tags shown in Table 1. As a result, the corpus consists of 4509 utterances.

Each utterance is not always sentence-level because it depends on the 0.2-sec interval rule. Other researchers that want to use this corpus might need sentence-level segmentation for their purpose. Therefore, we added another tags, +, / and *, to the end of each utterance for sentence-level identification\(^5\).

Here “+” denotes that the current utterance links to the next utterance. “/” denotes the actual end of a sentence. “*” has an intermediate meaning between + and /.

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\(^4\)https://tla.mpi.nl/tools/tla-tools/elan/

\(^5\)This is just a subjective annotation for other users. Note that we do not use this annotation in the latter part of this paper, namely topic segmentation.
| Topic  | Description                                       | Topic     | Description                                       |
|--------|---------------------------------------------------|-----------|---------------------------------------------------|
| CandX  | Topic about the candidate 1                       | Location  | Topic about the positional relation               |
| CandY  | Topic about the candidate 2                       | Area      | among restaurants                                  |
| CandZ  | Topic about the candidate 3                       | People    | Topic about the target customers                  |
| CandS  | Topic about the candidates                        | Price     | Topic about the price                              |
| Closed | Topic about the closed restaurant                  | Menu      | Topic about the menu                               |
| Exist1 | Topic about the existing restaurant 1             | Atomsos   | Topic about the atmosphere                         |
| Exist2 | Topic about the existing restaurant 2             | Time      | Topic about the business hours                     |
| Exist3 | Topic about the existing restaurant 3             | Seat      | Topic about the number of seats                    |
| Exist4 | Topic about the existing restaurant 4             | Sell      | Topic about the sales                              |
| Exist5 | Topic about the existing restaurant 5             | Access    | Topic about the access to the shopping mall        |
| Exist6 | Topic about the existing restaurant 6             | Meeting   | Topic about the proceedings and final decision     |
| ClEx   | Topic about the existing restaurants and the closed restaurant | Chat | Chats that not related to the task |
| Mall   | Topic about the shopping mall                      | Vague     | Others and unknown                                 |
| OtherMall | Topic about other shopping malls                  |           |                                                   |

Table 2: Topic tags in the Kyutech corpus.

An example

A: ahh, in this condition +
A: which one is suitable (Q) /
C: I think the ramen is better /
B: me too /

In this example, the first and the second utterances by the participant A are connected by the tag +. The process is as follows:

**Step1:** The worker of the transcription subjectively judges whether the end of each utterance should be + or /.

**Step2:** After that, we check the worker’s results with some conditions. If a condition is satisfied, replace + with /. The following is a condition.

**Condition:** the next utterance begins with “conjunction”, “filter” or “adverb”.

**Step3:** Replace + with * if we subjectively judge that the current utterance links to the next one although the condition in **Step2** is not satisfied.

3.2.2  Topic annotation

There are a wide variety of tags that should be annotated to utterances; e.g., communicative functions such as INFORM and REQUEST. Here we focus on a summarization task. In general, topic segmentation has an important role as the first step in the meeting summarization (Banerjee et al., 2015; Oya et al., 2014). Therefore, we manually annotated the topics of each utterance in the Kyutech corpus, as the first annotation.

First, we examined the conversations in the Kyutech corpus by four annotators including the authors. We repeated this process twice, and then created a topic tag set consisting of 28 tags. Table 2 shows the tag names and the descriptions.

Next, six annotators who included persons not related to this study annotated topic tags to each utterance, on the basis of the tag set. We applied two annotators into one conversation and the annotation was independently executed. In this process, each annotator annotated at least one tag to one utterance as the main tag of the utterance. In addition, we allowed adding the second-tag if an annotator wanted to add it. The annotators checked the document in Section 3.1 during the annotation process and considered the context in the conversation to select suitable topic tags. Although we allowed creating a new tag if an annotator wanted to create it, no new tags were generated in this process. After the annotation with two...
Annotator1 | Addition | Annotator2 | Addition | Final tags | Addition1 | Addition2 | Utterance
--- | --- | --- | --- | --- | --- | --- | ---
D | Closed | Sell | Closed | Sell | Closed | Sell | the closed restaurant was (D not profitable) unprofitable /
A | Closed | Sell | Closed | Sell | Closed | Sell | yes /
A | Closed | Sell | Closed | Sell | Closed | Sell | if unprofitable restaurant must be closed, profitability is +
D | Closed | Sell | Closed | Sell | Closed | Sell | <\\(E\\)> /
A | Closed | Sell | Closed | Sell | Closed | Sell | the most important thing, isn’t it /
D | Closed | Sell | Closed | Sell | Closed | Sell | <\\(E\\)> /
A | Exist4 | Sell | Exist4 | Sell | Exist4 | Sell | "FamilyPlate" made the biggest sale in the restaurants +
D | Exist4 | Sell | Exist4 | Sell | Exist4 | Sell | (L, uhn) /
A | Exist4 | Sell | Meeting | Exist4 | Sell | and the restaurant is ... +
A | Exist4 | Sell | Meeting | Exist4 | Sell | the reason, what is the reason (Q) /
D | Exist4 | Menu | People | Exist4 | Menu | People | many menus and branches (? maybe) /
C | Exist4 | People | People | Exist4 | Menu | People | in addition +
C | Exist4 | People | People | Exist4 | Menu | People | families +
C | Exist4 | People | People | Exist4 | Menu | People | visit in the restaurant, the document says, many menus +
A | Exist4 | People | People | Exist4 | Menu | People | Ummm /
A | Exist4 | People | People | Exist4 | Menu | People | (? ) families are /
C | Exist4 | People | People | Exist4 | Menu | People | might contribute to getting customers /
D | Exist4 | People | People | Exist4 | Menu | People | Ah /
D | People | People | People | Mail | People | the document says low buying motivation on holidays, for couples and families/

Figure 3: Topic tags by two annotators and final tags with utterances.

Annotators, we computed an agreement between tags of the annotators. The agreement score was based on a partial match scheme ($AS_p$) as follows:

$$AS_p(A_1, A_2) = \frac{\sum_{i \in U} PM_i(A_1, A_2)}{U_N}$$  \hspace{1cm} (1)

where $PM_i$ is the partial match scheme between tag sets of annotators, $A_1$ and $A_2$, for an utterance $i$. In other words, $PM_i$ is true if a tag of an annotator for an utterance is the same as at least one tag of another annotator. For example, $PM_i(A_1, A_2)$ is 1 in the case that $A_1 = \{\text{Cand}X, \text{People}\}$ and $A_2 = \{\text{People}\}$ for an utterance $i$. $U$ is the set of utterances and $U_N$ is the number of utterances, namely 4509. The agreement score $AS_p$ was 0.879.

After that, we checked the tags of two annotators in each conversation. Here we extended the number of tags for one utterance; 2 to 3, namely one main tag and two additional tags. We discussed each tag from annotators, and then determined the final tags of each utterance. After the discussion and the determination of the final tags, we also computed an agreement score of them. Here the agreement score was also based on a partial match scheme between the final tag that the authors created ($F$) and the tag set from two annotators ($A_{all}$). For example, assume $F = \{\text{People}\}$, $A_1 = \{\text{People}, \text{Mall}\}$ and $A_2 = \{\text{Mall}, \text{Menu}\}$. Here $A_{all}$ is $\{\text{People}, \text{Mall}, \text{Menu}\}$ and $A_{all}$ contains $F = \{\text{People}\}$. Therefore, $PM_i(F, A_{all})$ in this situation is 1. The partial agreement score between the final tags and the tags by two annotators, namely $AS_p(F, A_{all})$, was 0.965. Thus, we obtained a corpus with the high agreement topic tag set. Figure 3 shows an example of the annotation result. In the Kyutech corpus, assuming that the main tag sequence is one topic, one topic sequence usually consists of approximately 10 utterances.

### 3.2.3 Reference summary

Next, each annotator generated a summary of the conversation. The size of a summary is from 250 characters to 500 characters. The summary generation complied with the guidelines of abstractive hand summaries of the AMI corpus. Based on the guideline, the generation carried out after the process in

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7The working time for the final tag determination was approximately two hours for each conversation.
8The number of words was approximately 150 content words on average. The number of unique words was 80 words on average.
9[http://groups.inf.ed.ac.uk/ami/corpus/guidelines.shtml](http://groups.inf.ed.ac.uk/ami/corpus/guidelines.shtml)
At the beginning of the discussion, a targeted customer segment and various menus were the important evaluation points to obtain the high sales for the new restaurant because the closed restaurant was almost unprofitable. From the viewpoints, "The Ramen Kaibutsu" was rejected in the early stage of the discussion because the main target of the restaurant differs from the target that they want and the restaurant probably acquires limited customers. After that, they discussed the advantages and disadvantages of the remaining candidates, "The Tsukemen Fujin" and "BonoPasta". The advantages of "BonoPasta" were ...
Table 3: The number of utterances and segments of each conversation in the Kyutech corpus.

| ConvID | Utterances | Segments |
|--------|------------|----------|
| Conv1  | 505        | 52       |
| Conv2  | 637        | 77       |
| Conv3  | 324        | 33       |
| Conv4  | 502        | 36       |
| Conv5  | 566        | 48       |
| Conv6  | 487        | 51       |
| Conv7  | 284        | 31       |
| Conv8  | 445        | 42       |
| Conv9 (dev) | 759    | 48       |

computed with

$$cos_L(A, B) = \frac{\sum_i w_{i,A} \cdot w_{i,B}}{\sqrt{\sum_i w_{i,A}^2 \sum_i w_{i,B}^2}}$$  

where

$$w_{i,□} = \begin{cases} tfidf(R_i) & \text{if } R_i \text{ overlaps } \Gamma \in \{A, B\} \\ 0 & \text{otherwise} \end{cases}$$

4.2 TopicTiling

TopicTiling is a text segmentation method with the Latent Dirichlet Allocation (LDA) topic model (Riedl and Biemann, 2012). It uses topic IDs obtained from the LDA inference method, instead of words. The method first estimates a topic distribution from the Kyutech corpus. Then, it generates a vector space based on topic IDs in the LDA model. The calculation of the similarity is similar to LCSeg. The similarity $cos_T$ between windows (A and B) is also computed as follows:

$$cos_T(A, B) = \frac{\sum_n t_{p_n,A} \cdot t_{p_n,B}}{\sqrt{\sum_n t_{p_n,A}^2 \sum_n t_{p_n,B}^2}}$$

where $tp$ denotes the probabilistic distribution from LDA.

4.3 Combined method

Since the characteristics of the two methods are different, they have a potential to improve the accuracy by a complementary style. Therefore, in this paper, we combine the two methods with a weight factor $wf$. The similarity $cos_C$ between windows (A and B) is computed as follows:

$$cos_C(A, B) = wf \times cos_L(A, B) + (1 - wf) \times cos_T(A, B)$$

The weight factor $wf$ is a trade-off parameter.

4.4 Experiment for topic segmentation

We evaluated these methods with the Kyutech corpus. The details of the Kyutech corpus are shown in Table 3. In the experiment, we used the main tags as the topic sequence. In other words, a changing point of the main tags is a border of two topics, e.g., the 7th utterance in Figure 3.

We used one conversation (Conv9) as the development data for the method. Hence we evaluated the methods with eight conversations without Conv9. In the experiment, we compared two weight factors $wf = 0.3$ and $wf = 0.7$. For the LDA, we compared three types of the number of topics, 10, 20 and 30. Parameters on LCSeg, such as the window size, were based on (Galley et al., 2003).
Table 4: The F-measure on complete match and partial match.

| Method          | Comp | Partial |
|-----------------|------|---------|
| LCseg           | 0.195| 0.396   |
| Topic(10)       | 0.142| 0.394   |
| Topic(20)       | 0.148| 0.345   |
| Topic(30)       | 0.100| 0.299   |
| Comb(10,0.3)    | 0.155| 0.401   |
| Comb(10,0.7)    | 0.182| 0.399   |
| Comb(20,0.3)    | 0.168| 0.367   |
| Comb(20,0.7)    | 0.184| 0.391   |
| Comb(30,0.3)    | 0.132| 0.308   |
| Comb(30,0.7)    | 0.172| 0.362   |

We evaluated these methods with two criteria; complete matching and partial matching that were used in (Tajima, 2013). We computed the F-measure from the recall and precision rates for the complete and partial matching. The values are computed as follows:

\[ p_{\text{comp}} = \frac{|B_r \cap B_h|}{|B_h|}, \quad r_{\text{comp}} = \frac{|(B_r \cap B_h)|}{|B_r|} \]  \hspace{1cm} (7)

where \( B_r \) is the set of the sentence IDs before each topic change. \( B_h \) is the set of the outputs from each method.

\[ p_{\text{part}} = \frac{|B'_r \cap B_h|}{|B_h|}, \quad r_{\text{part}} = \frac{|(B_r \cap B'_h)|}{|B_r|} \]  \hspace{1cm} (8)

where \( B'_r = \bigcup_{i \in B_r} i - 1, i, i + 1 \) and \( B'_h = \bigcup_{i \in B_h} i - 1, i, i + 1 \). The F-measure is the harmonic mean between the recall and precision rates.

Table 4 shows the experimental result about the complete match and the partial match. Topic and Comb are the methods with TopicTiling and the combined methods, respectively. Topic(\( \beta \)) in the table denotes the number of topics in LDA and \( \beta = \{10, 20, 30\} \). \( \beta \) and \( wf \) in Comb(\( \beta, wf \)) denote the number of topics and the value of the weight factor (\( wf \in \{0.3, 0.7\} \)). For the complete matching, LCSeg produced the best performance. For the partial matching, Comb(10,0.3) obtained the highest F-measure value although there is no dramatic improvement as compared with the single methods, LCSeg and TopicTiling. TopicTiling-based methods were low accuracy on the whole. This is one reason that the combined methods did not improve the accuracy. The size of the Kyutech corpus is not always sufficient for the statistical methods, as compared with the AMI corpus. For the TopicTiling-based methods, we need a larger dataset. Moreover, the values on the F-measure were not high (0.401 even on the partial match scheme). Galley et al. (2003) reported that a feature-based segmentation method outperformed LCSeg. Applying a supervised method into our task leads to the improvement of the accuracy of the topic segmentation. In general, machine learning methods need a large dataset to generate a strong classifier. Therefore, scaling up the Kyutech corpus is the most important future work.

5 Discussion and Conclusions

In this paper, we explained the Kyutech corpus and a topic segmentation task for the corpus as the first step of multi-party conversation summarization. The Kyutech corpus consists of conversations about a decision-making task with four participants. The corpus contained utterances with time information, topic annotation and reference summaries.

For the topic annotation, we prepared 28 topic tags, and generated the annotated corpus in the two steps; (1) annotation by two annotators and (2) final judgment of each tag by three annotators. The partial agreement score \( AS_p \) between annotators was 0.879. In addition, the \( AS_p \) between final tags...
that the authors created and tag sets from two annotators was 0.965. In a similar way, we generated three summaries; two summaries by annotators and a consensus summary of the two summaries. The ROUGE-1 score among them was 0.564 on average. To the best of our knowledge, the Kyutech corpus is the first Japanese corpus annotated for summarization tasks and freely available to anyone.

As a case study of the corpus, we evaluated some topic segmentation methods. We compared LCSeg, TopicTiling and a combined method on the Kyutech corpus. However, there is no dramatic improvement of the accuracy. One reason was that TopicTiling was not effective in our experiment. It was caused by the size of the Kyutech corpus. Therefore, scaling up the Kyutech corpus is the most important future work.

The Kyutech corpus contains the topic tags and summaries. On the other hand, the AMI corpus contains numerous annotations, such as extractive summaries and dialogue-acts. Our topic tags focused on semantic contents of each utterance because of our purpose, namely summarization. However, communicative functions (Bunt, 2000), such as INFORM and Auto-Feedback, are also an important role as a conversation corpus. We are currently developing the Kyutech corpus with communicative functions, and then are going to open the new corpus in the next phase. In addition, hierarchical topic tag definition, such as (Ohtake et al., 2009), might be appropriate for our summarization task because each utterance often contained some topic tags. Other annotation to the Kyutech corpus is also future work. In addition, an extension of the Kyutech corpus to a multi-modal corpus with audio-visual data, such as (Sanchez-Cortes et al., 2013) and (Nihei et al., 2014), is important future work. In this paper, we just dealt with a topic segmentation task. However, the main purpose is to summarize a multi-party conversation. Abstractive summarization using the segmented topics is also the important future work.

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