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Extraction of Online Discussion Structures for Automated Facilitation Agent

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This paper proposes an approach that aims to extract the discussion structure from large-scale text-based online discussions. The ultimate goal is to develop an automated facilitation agent that is able to extract discussion structures from large-scale online discussions. To support this facilitation agent, an extraction approach is needed. Towards this end, we adopt the issue-based information system (IBIS), as a suitable format for structuring online discussions. In this context, we model the task of extracting an IBIS structure as it consists of node extraction and link extraction. Towards this end, a deep neural network based approach is employed in order to perform these two extraction subtasks. In order to evaluate the proposed approach, a set of experiments has been conducted on the data collected from the discussions in the online discussion support system called D-Agree. The experimental results show that the proposed approach is efficient for extracting online discussion structures.

1. Introduction

Several research attempts have been proposed in order to build intelligent online discussion forums because they are the cornerstone of the next-generation open and public deliberative democracy. Towards this end, an intelligent crowd decision support system that has facilitator functions was developed and deployed for several real-world online discussion forums [Ito 14, Ito 15, Sengoku 16, Takahashi 16]. This facilitator-mediated online discussion model leads online discussions to better directions. In this regard, human facilitators play an important role to coordinate, lead, integrate, classify, and summarize discussions in order to reach an acceptable consensus. Therefore, our ultimate goal becomes to create intelligent software agents that can function as automated facilitators.

In this regard, when an automated agent facilitates online discussions, extracting discussion structures is required because this facilitation agent needs to analyze the structure during these online discussions. As a result, this automated facilitation agent will be able to understand whether a discussion topic is positive or negative, what words are being focused on, and which words are important. Towards this end, we adopt the issue-based information system (IBIS) [Kunz 70] as an approach for structuring online discussions. The elements of IBIS are "issues" that need to be answered, "ideas" that are possible answers, "arguments" that support or object to a given idea. In this study, we use the term "pros" to refer to the arguments that support an idea and "cons" to refer to the arguments that oppose an idea. We also use the term "nodes" in order to refer to the issues, ideas, pros, and cons, and "links" in order to refer to the relationships amongst these nodes. As a result, our goal becomes to extract this "IBIS structure" from large-scale online discussions.

In order to achieve this goal, we propose an approach that includes two steps which are node extraction and link extraction. In this context, extracting nodes means classifying sentences which composes the submissions in online discussions into the elements of IBIS. On the other hand, extracting links means extracting the relationships amongst these nodes. Eventually, we construct a tree-like discussion structure that consists of the nodes and their relationships in IBIS. Towards this end, we employ bidirectional long short-term memory (Bi-LSTM) for both of node extraction and link extraction.

The results of the experiments that are conducted on the data collected from the discussion support system called D-Agree demonstrate that the proposed approach is efficient for extracting discussion structures. Therefore, we conclude that extracting discussion structures is efficient with the proposed deep learning approach.

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2. Extracting IBIS Structure with Deep Learning

The problem of extracting nodes from online discussions can be formulated as follows. Given a data thread in the form of natural language $X = \{x_1, x_2, \ldots, x_n\}$, where x_i is the i^{th} submission. Each submission consists of sentences $x_i = \{x_{i1}, x_{i2}, \ldots, x_{im}\}$, where x_{ij} is the j^{th} sentence. The proposed model classify sentences into four types of issues, ideas, pros, and cons which are the elements of IBIS. Figure 1 shows the sentence about "Let's discuss town development with IoT and AI." is classified into issues, the sentence about "I propose signs that provide information." is classified into ideas, and the sentence about "It is nice idea because the signs are easy to understand." is classified into pros. In order to support node extraction, we employ Bi-LSTM which is a type of RNN model that aims at classifying time series data. The input is the embedding of each

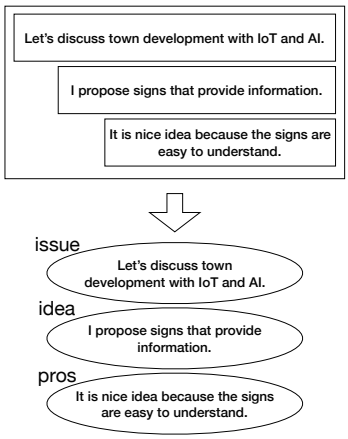

Figure 1: Node-extraction

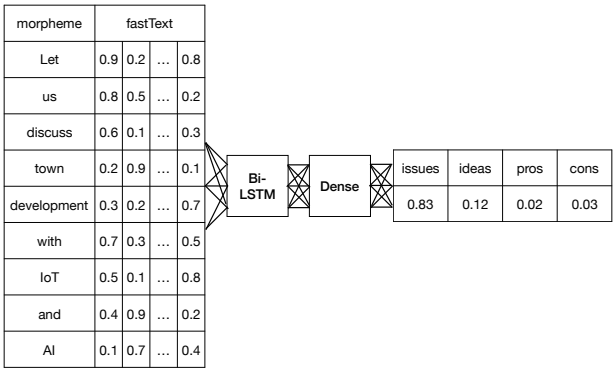

Figure 2: Node-extraction architecture

word by fastText [Bojanowski 16, Joulin 16] and the output is a normalized probability. Then, we consider a sentence as the type of the node that acquires the highest probability. This node-extraction architecture is shown in Figure 2.

On the other hand, the problem of link extraction can be formulated as follows. Given the extracted nodes in the form of natural language $S_1, S_2, \ldots, S_n$ and $T_1, T_2, \ldots, T_m$. Note that $S_k (1 \leq k \leq n)$ has a relation with $T_l (l \in \{1, 2, \ldots, m\})$. For example, the idea node about "I propose signs that provide information." has a relation with the issue node about "Let's discuss town development with IoT and AI.". Therefore, in order to address the link extraction challenge, we model it as a prediction of the head of the arrow. It should be noted that this prediction model adopts a regression technique. Towards this end, we calculate the cosine similarities between the prediction model output and the embedded candidate nodes in order to find an adequate link from these candidate nodes. In this context, we consider that the input node points to the nearest node, among these candidate nodes, to the output. In addition, we limit the space of candidate nodes using the structure of the discussion support system. Please note that

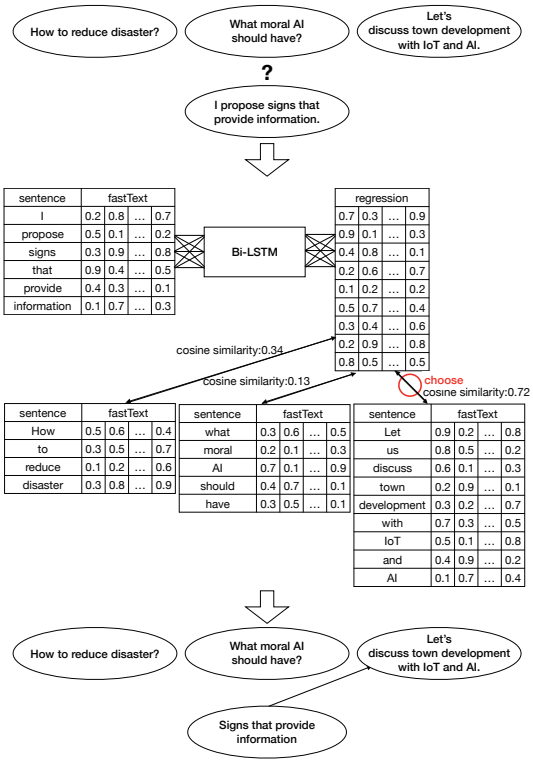

Figure 3: Link-extraction architecture

we also use Bi-LSTM as in the node extraction step. This link-extraction architecture is shown in Figure 3.

3. Experiments and Discussions

3.1 Experiment settings

D-Agree is an intelligent crowd decision support system that is developed by AI research center at Nagoya Institute of Technology (NIT). We gathered the experimental data from a number of online discussions (19 discussions) that were created in D-Agree. The themes of these discussions were chosen from the topics which are relevant to Nagoya, AI, IoT, and city development. In addition, we chose topics about which participates can easily think. Furthermore, we set a threshold of at least five participates per discussion. During these online discussions in D-Agree, one person acted as facilitator in accordance with IBIS structure. Those who have facilitated the online discussions in D-Agree did also annotate the experimental data.

3.2 Results

We conducted a set of experiments in order to evaluate the node-extraction performance of the proposed approach using Bi-LSTM. The results of these experiments are demonstrated in Figure 4. The results in Figure 4 represent the values of precision, recall, and F1 score for sentence classification. Please note that each value is the average of leave-one-out cross-validation. The results in Figure 1 show that the proposed approach achieved an F1 score value of 0.887 in issues/node extraction, 0.761 in ideas/node extrac-

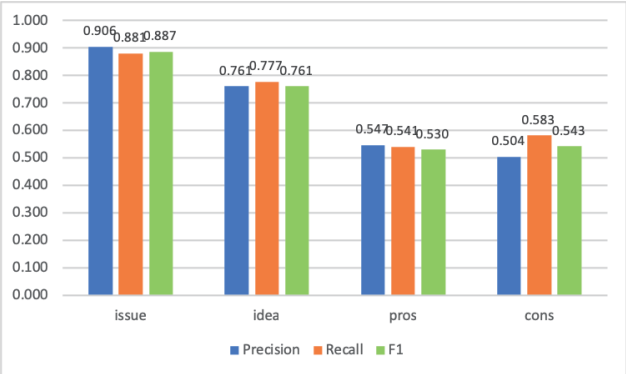

Figure 4: Experimental results of node extraction

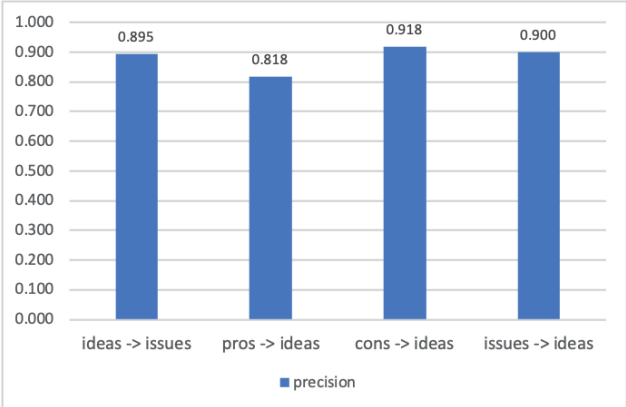

Figure 5: Experimental results of link extraction

tion, 0.530 in pros/node extraction and 0.543 in cons/node extraction.

In addition, we conducted a second set of experiments in order to evaluate the link-extraction performance of the proposed approach. The results of these experiments are demonstrated in Figure 5, which represent the precision values for link extraction using Bi-LSTM. Please note that we did not calculate the recall and F1 score values because the proposed approach aims to predict the point of the link (head of the arrow), not to classify it. As demonstrated in Figure 5, the proposed approach obtained a precision value of 0.895 when extracting the links from ideas nodes to issues nodes, 0.818 when extracting the links from pros nodes to ideas nodes, 0.918 when extracting the links from cons nodes to ideas nodes, and 0.900 when extracting the links from issues nodes to ideas nodes. These high precision values are competitive amongst the state of art technologies in the field of argumentation mining [Stab 14]. Therefor, it becomes promising that the availability of more data will increase the precision values when extracting other links.

3.3 Discussions

To summarize, the experimental results demonstrate the efficiency of the proposed approach in extracting IBIS structures from online discussions. In specific, the results of link-extraction express high precision values in predicting all types of links. In this regard, it is worth mentioning that the precision value of extracting the link from pros to ideas is slightly less than other precision values. This result is attributed to the fact that similar ideas are extracted from a single discussion domain/topic where the range of ideas is narrow. On the other hand, the results of node-extraction show lower F1 scores when extracting pros and cons. These results are attributed to the existence of certain sentences which are classified with dependencies on their context. A number of sentences is sometimes classified into pros, sometimes into cons by its context. It is, therefore, concluded that the proposed approach that is not use context as features is not able to classify into pros and cons. An approach which regards context as a feature to classify is expected to improve the results.

4. Conclusions and Future Work

This paper proposes a novel approach that aims to promote automated facilitation in large-scale online discussion platforms. The proposed approach employs deep learning in order to extract the IBIS structure from online discussions. Towards this end, the proposed approach employs a novel two-step method, that involves node extraction and link extraction, that aims to construct IBIS structures. In order to evaluate the performance of the proposed approach, a set of experiments are conducted using the discussion that are created in D-Agree system. The experimental results demonstrate the ability of the proposed approach to extract the IBIS structures efficiently. Future work is planned to involve improving the accuracy of the extraction of IBIS structures. Another direction will be developing an automated facilitation agent that promotes large-scale online discussions. This agent needs the abilities of questioning and making remarks to facilitate online discussions.

Acknowledgement

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