Generation of Objections Using Topic and Claim Information in Debate Dialogue System

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Abstract In recent years, systems with a dialogue interface are attracting wide attention [1, 2]. We propose a dialogue system that can debate with users about news broadcasts on TV or radio and help users to understand the meaning deeply. We previously reported a debate system that collected opinions from the Web [4], vectorized them, and finally selected the most appropriate supporting/opposing opinion among them for debating. In this paper, we propose a Neural Network Language Model that can generate objections instead selecting one opinion for debating. The model generates sentences by putting claim information (supporting/opposition) in the input layer of Long Short-Term Memory (LSTM) [3]. We conducted experiments by BLEU score and Human Evaluation, and both showed the effectiveness of our method.

1 Introduction

There are many systems that support users by answering their questions [1, 2], but in order to deal with even more complicated problems, we propose a debate dialogue system that supports users to be able to understand things deeply by providing new perspectives on topics of news broadcast on TV or radio. To this end, we already developed a system that could estimate a user's claim (supporting/opposing) on the topic as well as the reason behind the claim, and debate with a user by showing the appropriate opinions selected from the Web [4]. However, depending on the number and quality of opinions on the Web, we encountered the problem that the debate was

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not active in some cases. Therefore, in this paper, we propose a method to generate opinions or objections that are more appropriate to the user's opinion when there are no suitable candidate opinions found on the Web.

For generating objections, we employ a neural network language model using LSTM. Unlike the majority of seq2seq models, our model does not have the encoder of the input sentence but, rather, is trained to generate an objection to the user's opinion, by decoding the document vector created by Sparse Composite Document Vectors (SCDV) [6]. SCDV combines syntax and semantics learnt by word embedding models together with a latent topic model that can handle different senses of words, thus enhancing the expressive power of the document vectors. Specifically, we cluster distributed representations of all words using Gaussian Mixture Models, improve the word representation based on the probabilities belonging to each class, and use it for calculating the document vector. In addition, we control the claim of the sentences generated by the model by connecting a system claim vector (that is opposite to the user's claim) to the word embedding vector. We examined the performance of this model by BLEU score and a subjective evaluation experiment.

2 Debate management

In this section, we briefly explain the process of objection generation in our debate dialogue system, which has already been proposed in [4], (please see the upper part of Fig. 1). First, the Language Understanding module estimates the user's claim (supporting/opposing/neither) and reason (presence/absence). We use a Convolutional Neural Networks model proposed by Shi [5] to estimate them. In this module, when the user's claim is estimated to be "neither", or when the reason is estimated to be "absence", the system generates an utterance to ask the user for clarification.

Finally, after the system estimates the user's claim and reason, the system selects an opinion from the debate database, that is against the user's claim. For example, if the user's claim is estimated to be "supporting", the system utterance is selected from the opposite opinion stored in the debate database. As for the selection method, an opposite opinion with the highest cosine similarity to the user's utterance is selected.

However, because there are cases where it cannot be dealt with well, in this paper we propose an objection generation model, which is composed of a LSTM decoder and SCDV of the user opinion, as shown in the lower part of Fig. 1. This part is described in Section 4.

3 Debate database and motivation for generating objections

We employed Inoue's method [7] for collecting opinions from the Web, and created a database for debates. We collected 4 topics. The number of collected opinions is shown in Table 1.

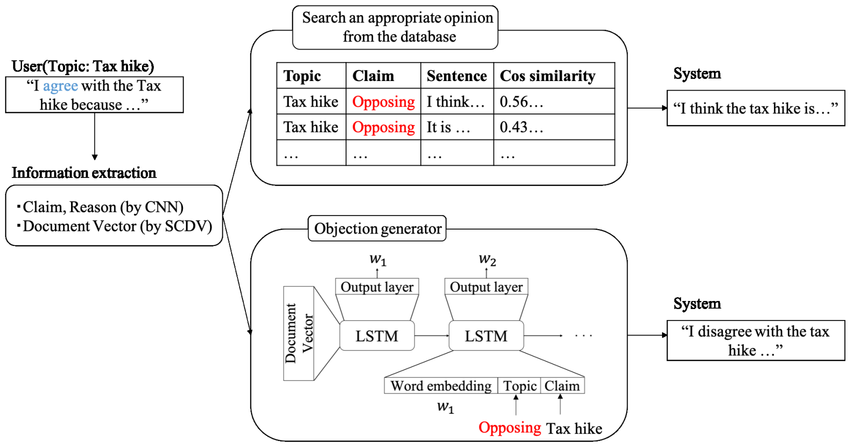

Fig. 1 Overview of the debate system

Table 1 Debate Database Information

Topics	Claims	Number of Opinions	Avg. Length of Words
Capital punishment	Supporting	228	60.84
	Opposing	283	64.19
Nuclear power plant	Supporting	124	64.06
	Opposing	320	80.68
Tax hike	Supporting	126	65.03
	Opposing	202	70.44
Casino bill	Supporting	52	57.40
	Opposing	141	87.20

Depending on the topic and claim, the number of opinions that can be collected is unbalanced in terms of supporting and opposing, as well as in terms of topics. Therefore, there is a possibility that the system cannot find the appropriate objection to the user's opinion because of the limited number of candidate opinions. In addition, even for a topic with a large number of collected opinions, the system may not be able to find the appropriate objection if there are no candidate objections that deal with the point being made in the argument. Hence, in such a case, we propose a language model to generate more appropriate objections to the users' claim instead of selecting the candidate objections.

4 Model of objection generator

The structure of the language model for our objection generator is shown in Fig. 2, which corresponds to the lower part of Fig. 1. In recent years, models have been proposed that concatenate additional information to the input layer and generate a characteristic response sentence [8, 9]. We applied these models to our objection generator and employed the topic and claim as additional information. Here, the "Topic" is capital punishment, a casino bill or the like, and the "Claim" is either supporting or opposing.

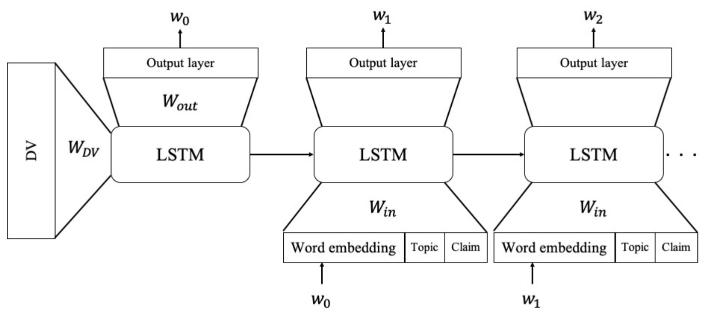

Fig. 2 Objection generator

In training the model, we encode a document (opinion) $D = \{w_0, w_1, ..., w_n\}$, into a vector representation *DV* created by SCDV (Due to space limitations, the SCDV explanation is omitted here. Please refer to [6] for an explanation.). Then, the original opinion sentence is reproduced by LSTM [3] from the *DV* as shown in Fig. 2. The values of hidden units in LSTM are obtained by combining the value of hidden units produced at the previous time step $t-1$, the word representations e_t at the current time step t, the topic vector t_i for topic $i(i \in [0,1,2,3])$, and the claim vector c_j for claim $j(j \in [0,1])$. An input gate, a memory gate, and an output gate, respectively denoted as i_t, f_t and o_t, are computed as follows:

$$\begin{bmatrix} i_0 \\ f_0 \\ o_0 \\ l_0 \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ tanh \end{bmatrix} W_{DV} \cdot SCDV(D) \tag{1}$$

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ l_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ tanh \end{bmatrix} W_{in} \cdot \begin{bmatrix} h_{t-1} \\ e_t \\ t_i \\ c_j \end{bmatrix} (t \geq 1) \tag{2}$$

Each value of the topic vector $t_i(i \in [0,1,2,3])$ and claim vector $c_j(j \in [0,1])$ is randomly initialized by the value drawn independently from Gaussian distribution $N(0,1)$. After training and generating an objection, the claim vector is replaced with the desired one, and the model predicts w_t by computing the following equation iteratively: $w_t = \texttt{softmax}(W_{out}(h_t))$. See the related work [9] for the computation of h_t.

5 Experiments

The human evaluation and BLEU were conducted using 90% of the collected opinions (Table 1) as training data and the rest as test data. We used 1-layer LSTM models with 180 hidden cells. The word embedding size, topic vector size, claim vector size, and vocabulary size were 256, 32, 50, and 7,557, respectively. The optimization method was Adam [10] and the Document Vector *DV* size was 2,000.

5.1 BLEU

In this experiment, we clarify the sentence generation ability from document vectors and the effect of the topic vector and claim vector. The BLEU score [12] was calculated between the original sentence and the sentence generated from the document vector, which was converted from the original sentence. The results are shown in Table 2. BLEU-1, BLEU-2, BLEU-3, and BLEU-4 are 1-gram, 2-gram, 3-gram, and 4-gram precision, respectively. “Objection Generator” is a model that does not use the claim vector or topic vector. “Objection Generator-T” is a model that only uses the topic vector, and “Objection Generator-T&C” is a model that uses both. “LSTM Encoder-Decoder” [11] was implemented for comparison. “Objection Generator”

Table 2 BLEU score

	BLEU-1	BLEU-2	BLEU-3	BLEU-4
LSTM Encoder-Decoder	3.71	1.07	0.31	0.00
Objection Generator	6.32	2.76	1.03	0.00
Objection Generator - T	9.52	3.70	1.36	0.46
Objection Generator - T&C	**10.01**	**3.94**	**1.51**	**0.63**

shows better performance than LSTM Encoder-Decoder. The reason is that it is difficult to train the encoder because of limited data and the number of words per sentence is large. On the other hand, our model uses SCDV to reduce the number of parameters related to encoding. Moreover, the topic vector proved to be effective. Since the opinion vectors are well divided into each topic, it seems that SCDV helps our model to discriminatively learn the vocabulary used in each topic.

5.2 Human Evaluation

A 5-point Likert scale evaluation was conducted using the top 30 generated sentences with the highest cosine similarity for each input sentence. Comparison with human opinion sentences selected by the method described in Section 2 was conducted, and the result is shown in Fig. 3.

Ten participants evaluated generated or selected sentences on “Naturalness” (whether the wording is natural), “Clarity” (whether the claim [supporting or op-

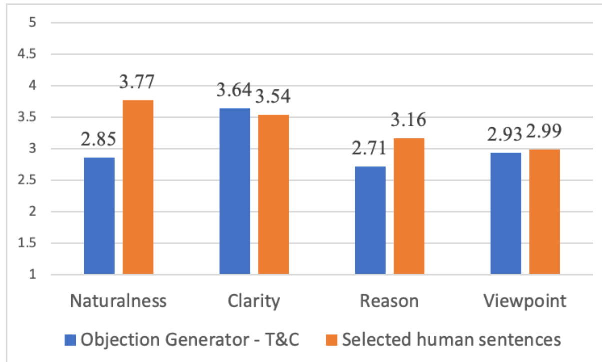

Fig. 3 Results on generated sentences having the highest cosine similarity

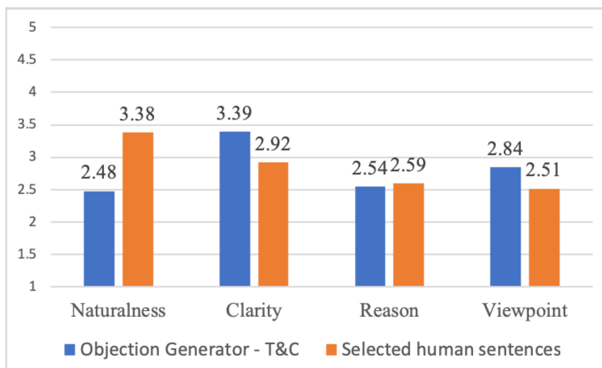

Fig. 4 Results on generated sentences having higher cosine similarity than selected human opinion

posing] is clear), “Reason” (whether appropriate reason is included), “Viewpoint” (Whether the point of view is the same as the point of view of the user opinion sentence), and then the scores were averaged. Although our model is superior in “clarity”, it cannot be said that our performance is better than the selected human opinion sentences. Here, the averaged results for only 13 sentences generated with higher cosine similarity than the selected human opinion sentences are shown in Fig. 4. Since problems remain in “naturalness”, our model is superior to selected human opinion sentences in “Clarity” and “Viewpoint”.

6 Conclusions

We proposed a model that can generate objections based on the topic and claim vectors when there were no suitable candidate sentences. Experiments showed the effectiveness of this model. In particular, the model shows good performance in "clarity", which is considered to be owing to the effect of the Topic Vector. However, at this time, from the viewpoint of "reason", the sentences generated by our model are inferior to selected opinion sentences created by humans. We will endeavor or improve our model in this regard in future research. In addition, there is also a problem regarding "naturalness", so that it is necessary to consider techniques (such as pre-training) using data other than opinions collected. Finally, regarding the human evaluation, examples of generated sentences that obtain good evaluation are shown in Table 3.

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Table 3 Examples of generated objections

Inputs	Generated Objections
「誰でも良かった」等と発言する犯罪者もいますが、それでも何らかの感情があるから殺しているんだと思います。更生する可能性があるのだとしたら、死刑制度には反対です。死刑にしなくても、刑務所の中で働いたりして反省するかもしれないので、殺人を犯した人は終身刑でもいいのではないかと思います。 (Some criminals say, "It doesn't matter who it was,", but I still think that they killed people because there was some motivation. If they could be rehabilitated, I would oppose the capital punishment. Since they may be rehabilitated by receiving punishment in the prison, I think that it is better for them to receive life imprisonment rather than the depth penalty.)	死刑に賛成です。親兄弟が皆殺しにされて、終身刑を最高刑にする事はおかしいと思います。殺された遺族の方は刑務所生活の生活費が税金とかなるの？ (I agree with capital punishment. I think that it is wrong that the punishment of the criminal who killed my family is, at most, only life imprisonment. How do the bereaved families feel about the fact that the cost of keeping the criminal in prison all that time is paid for by their taxes?)
私は死刑には大反対です。なぜなら、どんな理由があろうと、国家が殺人を犯すのはおかしいから。死刑という名で殺人を国家がしていいわけがない。 (I am very mush against capital punishment because, whatever the reason, it is wrong for the state to commit murder. Even the capital punishment system does not mean that the state can murder criminals.)	死刑に賛成です。死刑に値する罪を犯した人の世話を税金で養う事に疑問があるのです。犯人を奪ったんです。 (I agree with capital punishment. I question using tax money to take care of those who committed serious crimes. Capital punishment removes the criminal and the cost of imprisoning him/her.)
私は死刑制度に賛成します。人を何人殺しても警察に捕まり裁判にかけられても、命の保証はあります。また社会復帰の道もあります。 (I agree with the capital punishment system. If there is no capital punishment system, then even if a person kills many people, gets caught by the police and is tried and convicted, he will still live. He might even make it back into society one day.)	私は死刑制度に反対です。理由は、冤罪の可能性を減らすために。国家権力によって人を殺す権利があるだろうか。 (I disagree with capital punishment we need to reduce the possibility of false charges. The government has no right to kill people)
私は死刑制度には賛成です。罪に応じた刑罰が必要で、被害者の社会復帰無くして加害者の更生などは意味がないと考えているからです。... (長文のため省略) ... 人を殺めたらやはりそれは厳正な裁判の結果、死をもって償うべきであると思っています。 (I agree with the capital punishment system. This is because punishment is necessary for sin, and since the victim cannot return to society, it seems meaningless to rehabilitate the perpetrator. (An Omission) If you kill a person, I think you should be judged severely and pay for your crime with your death.)	私は死刑制度に反対です。理由は、冤罪の可能性を否定できるのですか。 (I disagree with capital punishment. The reason is, can the possibility of false charges be denied?)
実のところ、私もカジノには反対だ。カジノが日本人のためになるとは思えない。しかし、カジノは隔離された場所で行われるものである。 (Actually, I am against the casino as well. I do not think that casinos will benefit the Japanese. However, the casino is in an isolated place.)	実は、カジノ大賛成です。日本人の博打好きはたいへん多い。 (Actually, I am in favor of the casino. There are a lot of Japanese fans like gambling.)