Have my arguments been replied to? Argument Pair Extraction as Machine Reading Comprehension

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Abstract

Argument pair extraction (APE) aims to automatically mine argument pairs from two interrelated argumentative documents. Existing studies typically identify argument pairs indirectly by predicting sentence-level relations between two documents, neglecting the modeling of the holistic argument-level interactions. Towards this issue, we propose to address APE via a machine reading comprehension (MRC) framework with two phases. The first phase employs an argument mining (AM) query to identify all arguments in two documents. The second phase considers each identified argument as an APE query to extract its paired arguments from another document, allowing to better capture the argument-level interactions. Also, this framework enables these two phases to be jointly trained in a single MRC model, thereby maximizing the mutual benefits of them. Experimental results demonstrate that our approach achieves the best performance, outperforming the state-of-the-art method by 7.11\% in F\(_1\) score.

1 Introduction

As a salient part of argument mining (AM), the analysis of dialogical argumentation has received increasing research attention (Morio and Fujita, 2018; Chakrabarty et al., 2019; Ji et al., 2021; Cheng et al., 2021; Yuan et al., 2021). Argument pair extraction (APE), proposed by Cheng et al. (2020), is a new task within this field that focuses on extracting interactive argument pairs from two interrelated documents (e.g., peer reviewer and rebuttal). Figure 1 presents an example of APE where two interrelated documents are segmented into arguments and non-arguments at sentence level. Two arguments from different documents that discuss the same issues are regarded as an argument pair.

![Figure 1: A simplified example of APE task, where each dashed line in the two documents denotes a sentence. \(s_i^j\) is the \(j\)-th sentence in document \(i\), and \(arg_i^j\) is an argument in the \(j\)-th argument pair from document \(i\). Sentences without colors indicate non-arguments, while sentences covered by colors form arguments. Two arguments with the same color are regarded as an argument pair.](image)

Previous works (Cheng et al., 2020, 2021) commonly address APE by decomposing it into two sentence-level subtasks, i.e., a sequence labeling task and a sentence relation classification task. These methods identify arguments by sentence-level sequence labeling and determine whether two sentences belong to the same argument pair by sentence relation classification. Afterwards, the argument pairs are inferred indirectly by certain rules combining the results of the two subtasks. However, such a paradigm only considers sentence-level relations, while the holistic argument-level relations can not be well modeled.

In this paper, we argue that APE can be considered as a multi-turn machine reading comprehension (MRC) task with two phases, i.e., an AM phase and an APE phase. Specifically, in the first turn, a special AM query is employed to identify all the arguments in the first document (AM phase). Afterwards, in each subsequent turn, every identified argument is treated as an APE query to extract its paired arguments from the second document (APE phase). Similarly, this process can also be performed in another direction, that is, using the
arguments identified in the second document as queries to extract the paired arguments from the first document. We train these two phases jointly in a single MRC model, allowing them to benefit each other. By considering arguments as queries, our proposed MRC framework can better capture the interactions between each query argument and the queried document, thus extracting the argument pairs at the argument level. In addition, considering the long length of the documents, we utilize Longformer (Beltagy et al., 2020) to model longer contexts.

We evaluate our method on the large benchmark dataset (Cheng et al., 2020). Results show that our proposed method significantly outperforms the current state-of-the-art method by 7.11% in F$_1$ score.

2 Related Work

2.1 Argument Mining

Argument mining aims to analyze the structure of argumentation, and it contains various subtasks, such as argument component identification (Moens et al., 2007; Goudas et al., 2015; Ajjour et al., 2017; Jo et al., 2019), argument relation prediction (Nguyen and Litman, 2016; Cocarascu et al., 2020; Jo et al., 2021), argumentation structure parsing (Stab and Gurevych, 2017; Kuribayashi et al., 2019; Morio et al., 2020; Bao et al., 2021), argumentation strategy analysis (Khatib et al., 2018; Morio et al., 2019), etc.

Most previous works mainly focus on monological argumentation, while dialogical argumentation (Morio and Fujita, 2018; Chakrabarty et al., 2019) is relatively less emphasized. Recently, the analysis of dialogical argumentation has attracted increasing attention in the field of argument mining. Cheng et al. (2020) propose the APE task which involves identifying arguments and extracting argument pairs in peer review and rebuttal. Ji et al. (2021) identify interactive argument pairs in online debate forums based on the discrete variational autoencoders. Cheng et al. (2021) address the APE task based on a table-filling approach. Yuan et al. (2021) construct a dialogical argumentation knowledge graph for identifying argument pairs.

2.2 Machine Reading Comprehension

Machine reading comprehension (MRC) aims to extract answer spans from a passage according to a given query (Seo et al., 2017; Chen et al., 2017; Devlin et al., 2019; Wen et al., 2021). Formulating NLP tasks as MRC tasks has been a rising trend in recent years, such as dependency parsing (Gan et al., 2021), relation extraction (Levy et al., 2017), named entity recognition (Li et al., 2020), sentiment analysis (Chen et al., 2021; Mao et al., 2021). Unlike previous studies above, we employ a MRC framework to analyze the complex argumentative relations between two documents with excessively long length.

3 Methodology

3.1 Task Formulation

We assume that two interrelated documents $D_a = (s^a_1, s^a_2, ..., s^a_n)$ and $D_b = (s^b_1, s^b_2, ..., s^b_n)$ are given, where $s^a_j$ denotes the $j$-th sentence in document $i$. We need to extract the collection of argument pairs $P = \{(arg^a_i, arg^b_i)\}_{i=1}^{|P|}$, where $arg^a_i$ and $arg^b_i$ respectively represent the arguments in document $D_a$ and $D_b$, and they compose the $i$-th argument pair. Note that each argument consists of one or more consecutive sentences. For example, $arg^a_i = (s^a_{start}, s^a_{start+1}, ..., s^a_{end})$ where $start$ and $end$ denote the start and end sentence index.

To frame APE as a multi-turn MRC task, two types of queries are constructed, i.e., the argument mining (AM) query and the argument pair extraction (APE) query. Intuitively, we could consider the process of extracting argument pairs from the perspective of two directions, i.e., $D_a \rightarrow D_b$ and $D_b \rightarrow D_a$. For the $D_a \rightarrow D_b$ direction, we first construct an AM query using a special token whose corresponding answers are all the arguments in document $D_a$. After recognizing all arguments through the AM query, each recognized argument is considered as an APE query whose corresponding answers are its paired arguments in document $D_b$. Similarly, for the $D_b \rightarrow D_a$ direction, we first query document $D_b$ with the AM query, and then generate the APE queries for document $D_a$. Finally, the argument pairs can be derived by fusing the answer results of all APE queries.

3.2 MRC Framework

3.2.1 Encoder

Since APE is a document-level task with excessively long text, we adopt Longformer to capture contextual information over longer distances. For brevity, we only describe the MRC process in the $D_a \rightarrow D_b$ direction below, and the $D_b \rightarrow D_a$ direction can be performed similarly.
Formally, we use a special token “[AM]” to represent the AM query $q^{am}$, which aims to identify all the arguments $A^a = \{arg_k^a\}_{k=1}^n$ in document $D_a$ where $arg_k^a$ indicates the $k$-th argument in $D_a$. Then, each identified argument $arg_k^a$ is considered as an APE query $q_k^{a,ape}$, i.e., $q_k^{a,ape} = arg_k^a = (s_{\text{start}}^{a,k}, ..., s_{\text{end}}^{a,k})$. Note that we use gold arguments as APE queries during training.

With these queries, we first concatenate the AM query $q^{am}$ and the document $D_a$ as an input sequence for AM:

$$I^{am} = ([s], q^{am}, [/s], [s], s_1^a, s_2^a, ..., s_n^a, [/s])$$

(1)

Also, we concatenate each APE query $q_k^{a,ape}$ and the document $D_b$ to obtain multiple input sequences for APE:

$$I_k^{ape} = ([s], q_k^{a,ape}, [/s], [s], s_1^b, s_2^b, ..., s_n^b, [/s])$$

(2)

where $[s]$ and $[/s]$ are special tokens of Longformer.

Subsequently, for each sequence above, we feed it into Longformer to get the hidden representation of each token in the input document. Specifically, to enable Longformer to better learn argument-specific representations, we add global attention to the tokens of the query. Afterwards, we derive the hidden representation of each sentence through mean pooling on token representations in this sentence. Further, to better model the long-term dependency among sentences, the hidden representations of sentences are fed into LSTM to derive the contextual sentence representation matrix $H = (h_1, h_2, \ldots, h_n)$.

3.2.2 Answer Span Prediction

For each turn, one or more answer spans will be extracted as arguments. Note that, in each direction, the first turn aims to extract all arguments, while the following turns aim to extract arguments that can form pairs with the query argument.

Specifically, inspired by Li et al. (2020), we feed $H$ into two binary classifiers to predict the start and end sentence positions of arguments. After obtaining all start and end positions, we further employ another binary classifier to determine whether each start and end position pair (matched by Cartesian product) forms an answer span. Note that the input of this span classifier is the concatenation of the start and end sentence representations from $H$.

3.2.3 Training

During training, the three classifiers described in Section 3.2.2 yield three cross-entropy losses, i.e., a start loss, an end loss, and a span loss. We simply sum these losses up as the training objective of our model. In addition, the AM phrase and the APE phrase are trained jointly in a single MRC model.

3.2.4 Inference

During inference, the $D_a \rightarrow D_b$ direction uses the trained MRC model to first identify all the arguments in $D_a$ by the AM query and then extract all the argument pairs in $D_b$ by the APE queries. Similarly, the $D_b \rightarrow D_a$ direction can be performed in the same manner by simply exchanging the order of $D_a$ and $D_b$. Each APE query in both directions yields one or more argument pairs, where each argument pair contains the query argument and one extracted argument. We simply merge all argument pairs extracted by all APE queries into a union set to obtain the final inference results.

4 Experiments

4.1 Experimental setup

4.1.1 Dataset

Our experiments are conducted on the large APE benchmark dataset, namely the Review-Rebuttal (RR) dataset (Cheng et al., 2020), which contains 4,764 pairs of review-rebuttal passages of ICLR. Following the setup of (Cheng et al., 2021), we also evaluate our method on two versions of the train/dev/test (8:1:1) split, i.e., RR-Passage-v1 and RR-Submission-v2. Note that in our method, we view review passage and rebuttal passage as document $D_a$ and document $D_b$, respectively.

4.1.2 Implementation Details

We adopt Longformer-base-4096 \(^1\) as base encoder, and we use sliding window attention with the window size of 512. We train our model 6 epochs with a batch size of 4. AdamW (Kingma and Ba, 2015) is used as the optimizer, and the learning rates for Longformer and other layers are 1e-5 and 1e-3.\(^2\)

The evaluation metrics contain two aspects, namely AM and APE. Different from (Cheng et al., 2021, 2020), sentence pairing is not included as a metric because we extract argument pairs directly.

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\(^1\)https://huggingface.co/allenai/longformer-base-4096

\(^2\)Our source code is available at https://github.com/HLT-HITSZ/MRC_APE
We select the best parameters based on the performance (i.e., average $F_1$ scores of AM and APE) on the dev set. All scores are averaged across 5 distinct trials using different random seeds.

### 4.1.3 Baselines

We compare our model with several baselines. **PL-H-LSTM-CRF** (Cheng et al., 2020) independently trains an argument mining task and a sentence pairing task, while **MT-H-LSTM-CRF** (Cheng et al., 2020) trains two subtasks in a multi-task framework. **MLMC** (Cheng et al., 2021) is an attention-guided model based on a table-filling approach, which is the current state-of-the-art method.

Furthermore, we implement two additional baselines. For a fair comparison with MLMC, **MRC-APE-Bert** replaces Longformer with Bert, where documents with excessively long length are split into several segments. Instead of jointly training AM and APE phases, **MRC-APE-Sep.** trains the two phases separately.

### 4.2 Results and Analysis

#### 4.2.1 Main Results

As shown in Table 1, our model achieves the best performance on both versions of the RR dataset. Concretely, on RR-Submission-v2, our model significantly outperforms the current state-of-the-art model MLMC by at least 7.11% in APE $F_1$ score. On RR-Passage-v1, our model obtains at least a 6.54% higher APE $F_1$ score than the MLMC. Also, our model achieves the best performance on AM. Furthermore, without applying Longformer as the base encoder, MRC-APE-Bert still outperforms MLMC in APE $F_1$ score, demonstrating that our improvement is not only brought by Longformer. However, for the AM task, MAC-APE-Bert achieves slightly lower $F_1$ score than MLMC. The reason may be that, in MLMC, the predictions of the AM task are influenced by the APE task through a complex attention interaction mechanism. However, our model does not require such a complex design and can achieve much better results on the APE task. Besides, our MRC-APE achieves better results than MRC-APE-Sep. on both AM and APE tasks, indicating that jointly training two phases in a single MRC model could maximize the mutual benefits of the two phases.

In addition, to analyze the error propagation from the first phase to the second phase, we use the true label of AM task to predict APE task. Under this setting, our model can achieve around 59.44% $F_1$ score for APE task, showing effectiveness in identifying argument pairs.

#### 4.2.2 Ablation Study

The ablation study results are shown in Table 2. It can be observed that using two directions contributes greatly to our method. Also, using the arguments recognized in $D_a$ to extract the paired arguments in $D_b$ is more critical in the RR dataset, removing it causes a 6.51% decrease in APE $F_1$ score. Without the LSTM to capture the long-
term dependency among sentences, the APE $F_1$ score decreases by 0.86%. Furthermore, the performance drops heavily without the global attention, because it enables more interactions between the query argument and the queried document, thus better argument-specific representations could be learned.

5 Conclusion

In this paper, we propose to frame the argument pair extraction (APE) task as a machine reading comprehension (MRC) task. Our MRC framework addresses APE through two phases with two types of queries, that is, argument mining (AM) query and argument pair extraction (APE) query. Our proposed method can better model the argument-level interactions, thus facilitating the extraction of argument pairs. Experimental results on a large benchmark dataset demonstrate that our proposed method achieves state-of-the-art performance.

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