Diversity Aware Relevance Learning for Argument Search

Michael Fromm¹, Max Berrendorf¹, Sandra Obermeier¹, Thomas Seidl¹, and Evgeniy Faerman¹

Database Systems and Data Mining, LMU Munich, Germany
fromm@dbs.ifi.lmu.de

Abstract. In this work, we focus on the problem of retrieving relevant arguments for a query claim covering diverse aspects. State-of-the-art methods rely on explicit mappings between claims and premises, and thus are unable to utilize large available collections of premises without laborious and costly manual annotation. Their diversity approach relies on removing duplicates via clustering which does not directly ensure that the selected premises cover all aspects. This work introduces a new multi-step approach for the argument retrieval problem. Rather than relying on ground-truth assignments, our approach employs a machine learning model to capture semantic relationships between arguments. Beyond that, it aims to cover diverse facets of the query, instead of trying to identify duplicates explicitly. Our empirical evaluation demonstrates that our approach leads to a significant improvement in the argument retrieval task even though it requires less data.

Keywords: Argument Similarity · Argument Clustering · Argument Retrieval

1 Introduction

Argumentation is a paramount process in society, and debating on socially important topics requires arguments of high quality and relevance. In this work, we deal with the problem of argument search which is also known as argument retrieval. The goal is to develop an [Argument Retrieval System] (ARS) which organizes arguments, previously extracted from various sources [4, 8, 15, 17], in an accessible form. Users then formulate a query to access relevant arguments, which are retrieved by the [ARS]. The query can be defined as a topic, e.g. Energy in which case the [ARS] retrieves all possible arguments without further specification [10][15][17]. Our work deals with a more advanced case, where a query is formulated in form of a claim and the user expects premises attacking or supporting this query claim. An example of a claim related to the topic Energy could be "We should abandon Nuclear Energy" and a supporting premise e.g. "Accidents caused by Nuclear Energy have longstanding negative impacts". A popular search methodology to find relevant premises is a similarity search, where the representations of the retrieved premises are similar to the representation of the
(augmented) query claim \[1, 3, 16\]. However, as noted by \[4, 7\], the relevance of a premise does not necessarily coincide with pure text similarity. Therefore, the authors of \[4\] advocate for the utilization of the similarity between the query claim and other claims in an \textit{ARS} database and retrieve the premises assigned to the most similar claims. However, such \textit{ARS} requires ground truth information about the premise to claim assignments and therefore has limited applicability: Either, the information sources are restricted to those sources where such information is already available or can automatically be inferred, or expensive human annotations are required. To mitigate this problem and keep the advantages of the original system, we propose to use a machine learning model to learn the relevance between premises and claims. Using this model, we can omit the (noisy) claim-claim matching step and evaluate the importance of (preselected) candidate premises directly for the query claim. This also reduces the loss of information through multiple (approximate) matching steps. Since the relevance is defined on the semantic level, we have to design an appropriate training task to enable the model to learn semantic differences between relevant and non-relevant premises. Furthermore, an important subtask for an \textit{ARS} is to ensure, that the retrieved premises do not repeat the same ideas. Previous approaches \[6\] employ clustering to eliminate duplicates. However, clustering approaches often group data instances by other criteria than expected by the users \[12\], which was also observed for Argument Mining (AM) applications \[13\]. For our method, we thus propose an alternative to clustering based on the idea of core-sets \[14\], where the goal is to cover the space of relevant premises as well as possible.

2 Preliminaries

In our setting, the query comes in the form of a claim, and an answer is a sorted list of relevant premises from the \textit{ARS} database. A premise is considered to be of relevance if it attacks or supports the idea expressed in the claim \[11, 19\]. We denote the query claim by \(c_{\text{query}}\) and the list of premises retrieved by \textit{ARS} by \(A\), with the length being fixed to \(|A| = k\). Besides relevance, another important requirement for the \textit{ARS} is that premises in \(A\) should have diverse semantic meaning. We consider a two-step retrieval process. In the first step, the pre-filtering, the system selects a set of candidate premises \(T\) with \(|T| > k\). The pre-filtering step should have a relatively high recall, i.e. find most of the relevant premises. For a fair comparison to previously proposed approaches, we leave the pre-filtering step from \[6\] unchanged. We note that the current version of pre-filtering requires ground-truth matchings of premises to claims restricting its applicability and leave an improvement of it for future work. The pre-filtering process described in \[6\] has several steps. When a query claim arrives, the system first determines \textit{claims} from the database which have the highest Divergence from Randomness \[2\] similarity to the query claim. Next, the system receives the corresponding claim clusters of the claims found in the previous step and all premises assigned to all claims from these clusters are collected in a candidate seed set \(T_{\text{seed}}\). Each premise \(p \in T_{\text{seed}}\) is then used as a query to obtain the most
similar premises using the BM25 score, which are accumulated in a set $T_{\text{sim}}$. The complete candidate set is then given as the union $T = T_{\text{seed}} \cup T_{\text{sim}}$.

3 Our Approach for Candidate Refinement

The main focus of our work is the second step in the retrieval process or the candidate refinement/ranking procedure. In the refinement step, the candidates are analyzed more thoroughly and non-relevant or redundant premises are discarded. Our refinement process comprises two components. The relevance filter component determines the relevance of each premise from the candidate set $T$ using an advanced machine learning model that keeps only the most relevant ones. The relevance filter thus maps the candidate set $T$ to a subset thereof, denoted by $T_{\text{filtered}} \subseteq T$. The subsequent premise ranker selects and orders $k$ premises from $T_{\text{filtered}}$ to the result list $A$. An important requirement for the premise ranker is that $A$ does not contain semantically redundant premises. In the following, we describe both components in more detail.

3.1 Relevance Filter

*Inference* Given a set of candidate premises $T$ and the query claim $c_{\text{query}}$, the relevance filter determines the relevance score of each candidate $p \in T$ denoted as $r(p \mid c_{\text{query}})$. We keep only the most relevant candidates in the filtered candidate set $T_{\text{filtered}} = \{ p \in T \mid r(p \mid c_{\text{query}}) > \tau \}$ with a relevance threshold $\tau$. We interpret the relevance prediction as a binary classification problem and train a Transformer \cite{Vaswani2017} model to solve this classification task given the concatenation of the candidate premise and the query claim. At inference time, we use the predicted likelihood as the relevance score and evaluate the model on the concatenation of each candidate premise with the query claim.

*Training Task* For the training part, we assume that we have access to a (separate) dataset $D = (P', C', R^+)$ containing a set of premises $P'$, a set of claims $C'$ and a set of relevant premise-claim pairs $R^+ \subseteq P' \times C'$. In fact, several datasets fulfill this requirement e.g. \cite{Hendrickx2020, Wang2020}. Since the relevance filter receives as input the remaining candidate premises after the pre-filtering, we assume that the non-relevant premises appear similar to the relevant ones. Therefore, the training task has to be designed very carefully to enable the model to learn semantic differences between relevant and non-relevant premises. We use the ground truth premise-claim pairs $R^+$ as instances of the positive class (i.e. an instance of matching pairs). For each positive instance $(p^+, c) \in R^+$, we generate $L$ instances of the negative class $(p^-_i, c) \in R^-$. For $p^-_i$, we choose the $L$ most similar premises according to a premise similarity $p_{\text{sim}}$ which do not co-occur with $c$ in the database. We use the cosine similarity $p_{\text{sim}}(p, p') = \cos(\phi(p), \phi(p'))$ between the premise representations $\phi(p)$ obtained from a pre-trained BERT model without any fine-tuning as premise similarity.$^1$ The transformer model which predicts

$^1$ Using average pooling of the second-to-last hidden layer over all tokens
the premise-claim relevance is initialized with weights from a pre-trained BERT model \[5\].

### 3.2 Premise Ranker

**Algorithm 1: Biased Coreset**

**Data:** candidates \( T \), relevances \( R \), similarity \( psim \), \( k \in \mathbb{N} \), \( \alpha \in [0,1] \)

**Result:** premise list \( A \)

for \( i = 1 \) to \( k \) do

if \(|A| = 0\) then \( a = \operatorname{argmax}_{p \in T} \alpha \cdot R[p]\);

else \( a = \operatorname{argmax}_{p \in T} \alpha \cdot R[p] - (1 - \alpha) \cdot \max_{a \in A} psim(a, p)\);

\( A\).append(a); \( T = T \setminus \{a\} \)

end

The premise ranker receives a set of relevant premises with the corresponding relevance scores and makes the final decision about the premises and the order in which they are returned to the user. Since the two relevance filtering steps have been applied, we assume that the majority of remaining candidates are relevant such that the main task of this component is to avoid semantic duplicates. While related approaches \[6\] advocate for the utilization of clustering for the detection of duplicates and expect that premises with the same meaning end up in the same clusters, we pursue a different idea. Instead of explicitly detecting the duplicates we aim to identify \( k \) premises that adequately represent all premises in \( T_{\text{filtered}} \). Therefore, we borrow the idea of core-sets from \[14\] and aim to select \( k \) premises from the final candidate set \( T_{\text{filtered}} \) such that for each candidate premise \( p \in T_{\text{filtered}} \) there is a similar premise in the result \( A \). More formally, we denote \( Q(p, A) = \max_{a \in A} psim(p, a) \) as a measure of how well \( p \) is represented by \( A \), using the premise similarity \( psim \). Thus, \( \bar{Q}(A) = \min_{p \in T_{\text{filtered}}} Q(p, A) \) denotes the worst representation of any premise \( p \in T_{\text{filtered}} \) by \( A \). Hence, we aim to maximize \( \bar{Q} \) such that every premise \( p \) is well represented. This min-max objective ensures that every premise is well-represented at not only the majority of premises. To solve the selection problem we adapt the greedy approach from \[14\]. Since our goal is not only that the selected premises represent the remaining candidates well, but also that the selected premises have high relevance, we start with the most relevant premise and also consider the relevance score \( r \) for the next assignments, with a weighting parameter \( \alpha \in [0,1] \). \( \alpha = 0 \) scores only according to the coreset criterion, while \( \alpha = 1 \) uses only the relevance. The full algorithm is presented in Algorithm \[1\].

**Premise Representation** The premise ranker requires a meaningful similarity measure to compare premises with each other. As also noted in \[6\], semantically
similar premises may often be expressed differently. Therefore, an important requirement for the similarity function is that it captures semantic similarities. We investigate two approaches to obtain vector representations on which we compute similarities using $l_1$, $l_2$ or cosine similarity. Previous works demonstrated that BERT models pre-trained on the task of language modeling can capture argumentative context [10]. Thus, our first BERT similarity function employs a BERT model without fine-tuning to encode the premises. We abbreviate these representations with BERT. As an alternative, we propose to represent each premise by a vector of relevance scores to selected claims in the database. While we can use randomly selected claims, or cluster all claims in the database, many databases already contain topic information about the claims, such as e.g. "Energy". Thus, we restrict the selection of claims for each premise to the same high-level topic of interest. In this case, all premises retrieved for a single query belong to the same topic. We do not consider it as a strong restriction, since arguments always exist in some context and it rarely makes sense to retrieve premises from different topics for the same query. We utilize our relevance filter model to compute relevance scores for the premise and each of the selected claims. We call the resulting vector of stacked similarities CLAIM-SIM representation. We hypothesize that a similar relationship to the selected claims is a good indicator of semantically similar premises.

4 Evaluation

Experimental Setting The training dataset of the relevance filter is a subset of 160,000 positive (relevant) claim-premise sentence pairs of the dataset described in [7]. Additionally, we generated 320,000 negatives (not-relevant) claim-premise pairs as described in Section 3.1. For the evaluation of our approach and comparison with the baselines we utilize the dataset from [6]. The evaluation set consists of 1,195 triples $(c_{\text{query}}, c_{\text{result}}, p_{\text{result}})$ each labeled as "very relevant" (389), "relevant" (139) or "not relevant" (667). The 528 "very relevant" and "relevant" premises were assigned to groups with the same meaning by human annotators. In contrast to [6] we do not utilize the ground truth assignments of $c_{\text{result}} \leftrightarrow p_{\text{result}}$ in our approach. Therefore our method can utilize newly arriving premises without an assignment to $c_{\text{result}}$. To select the optimal hyperparameters for our approach and avoid test leakage, we use leave-one-out cross-validation: For each query claim with corresponding premises, we use the rest of the evaluation dataset to select the hyperparameters and then evaluate on this hold-out query. To obtain a final score, we average over all splits. As an evaluation metric, we use the modified nDCG from [6]: Only the first occurrence from a premise ground truth cluster yields positive gain; duplicates do not give any gain. In Table 1 we summarize the results of the argument retrieval task. The numbers represent the modified NDCG scores for $k = 5$ and $k = 10$. The first
Table 1. Modified NDCG score for $k = 5$ and $k = 10$.

|       | 5         | 10        |
|-------|-----------|-----------|
| k     | first     | top-k     | k-Means   | Biased Coreset |
|       | sent      | sliding   | same topic| BERT CLAIM-SIM | BERT CLAIM-SIM |
| 5     | .399      | .455      | .437      | .447          | .428          | .465          | .437          | .475          |
| 10    | .455      | .487      | .476      | .502          | .515          | .513          | .520          | .526          |

three columns show the evaluation results for the methods from [6]. In the next three columns denoted as top-$k$, we present the results when premises with the highest score are returned directly, without taking care of duplicates. With the zero-shot approach we investigate the assumption that similarity between query and claim is not a sufficient indicator for relevance. Thus, we use the similarity between representations obtained from a pre-trained BERT model, without any training on claim-premise relevance. The second column, same topic, denotes the performance of the relevance model trained in the same setting as our approach with the only difference that negative instances for the training are selected from the same topic. Finally, ours denotes the setting, where $k$ instances have the highest probability to be relevant estimated by our model (more precisely, the relevance filter). Given these results, we observe a strong performance of the zero-shot approach which comes quite close to the approaches by [6]. We emphasize that this is even though this baseline approach neither uses ground truth premise-claim relevance data as [6], nor any other external premise-claim relevance data. Moreover, we observe that we can achieve good performance in terms of the modified NDCG despite not filtering for duplicates. At the same time, we observe that our model is still able to improve the similarity-based approach by several points. In contrast, the model learned with negatives instances from the same topic performs much worse than zero-shot, which underlines the importance of the correct task. Finally, the columns denoted as Biased Coreset present our final results. The results are from the premise ranker applied to the different premise representations of the most relevant premises selected by relevance filter. For comparison, we also report the results, where k-means is used as premise ranker on the same representations, where we select at most one premise per cluster according to the similarity. The claim-sim premise representation always outperforms bert and our biased-coreset premise ranker is better than the k-means clustering.

5 Conclusion

In this work, we have presented a novel approach for the retrieval of relevant and original premises for the query claims. Our new approach can be applied more flexible than previous methods since it does not require mappings between

\footnote{For the evaluation we have used interim results provided by the authors of the original publication. Since we had obtained deviations from the originally reported results, we have contacted the authors and came together to the conclusion that our numbers are correct. We would like to thank the authors for their help.}
premises and claims in the database and thus can also be applied in an inductive setting, where new premises can be used without the need to first manually associate them with relevant claims. At the same time, it achieves better results than approaches that make use of this information.

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