Proposal: Rank Reasons for Predicting Convincingness of Web Arguments

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Abstract

Recently, researchers started to study the problem of predicting convincingness of web arguments. However, existing works all stop by taking advantage of superficial features without considering context and domain knowledge. Thus, those arguments containing weak supporting reasons but composed with convincing words may be automatically classified as highly convincing in existing models. We propose a new method which employs reason level feature to further improve the performance of predicting convincingness of web arguments.

1 Introduction

The main goal of argumentation is persuation(Nettel and Roque, 2012; Mercier and Sperber, 2011; Blair, 2012). Psychology researchers often identify that there are three factors(i.e., the argument itself, the audience of argument, the source of argument) that affect argument persuasiveness(Petty and Cacioppo, 1986).

As an important part of predicting persuasiveness of argument itself, the task of predicting convincingness started to attrack researchers to work on this issue(Habernal and Gurevych, 2016). However, existing works all stop by taking advantage of superficial features without considering context and domain knowledge. They focus on wether the argument gives exmaples, actual reasons and facts rather than how good the examples, reasons, facts are. Thus, those non-sense arguments containing weak or even faked supporting reasons but composed with convincing words may be automatically classified as highly convincing in existing models. In Table 1, we give an exmaple of argument pair to show that argument with reason(Argument 1) can be less convincing than one without reasons(Argument 2). It's critical to differentiate reasons of different quality while predicting convincingness.

Argument 1	**Argument 2**
YES, because some children dont understand anything excect physical education especially rich children of rich parents.	Of course! According to a research in 2018, no one can ever find his or her true love without taking physical education.

Table 1: Argument examples. **Prompt:** Should physical education be mandatory in schools? **Stance:** Yes!

In order to rank reasons mentioned in arguments, we propose two hypotheses (A) arguments with good reasons are more convincing than those without, and (B) people tend to use more convincing reasons to compose an argument. To verify those hypotheses, we propose a new method which employs reason level feature to further improve the performance of predicting convincingness of web arguments.

The method takes 4 steps. The first step is to identify text segments corresponding to reasons from arguments. Figure 1 shows an exmaple of reason identification. Then we use clustering algorithm to group those identified reasons as the second step. With the grouped reasons, we can build an undirected graph where vertices are the arguments. If two arguments share reasons in the same group, we add an edge between two corresponding vertices. We can run a PageRank-like algorithm to score reason strength for all arguments. The last step is to combine reason strength with superficial features with an supervised learning classifier to produce the final score for each argument.

I feel that abortion should remain legal, or rather, parents should have the power to make the decision themselves and not face any legal hindrance of any form. Let us take a look from the social perspective. *If parents cannot afford to provide for the child, or if the family is facing financial constraints, it is understandable that abortion can remain as one of the options.*

Figure 1: An example of reason identification. Text segments that are identified as reasons are *italicized*.

2 Related work

Predicting convincingness of web arguments as a new research task has recently been studied(Habernal and Gurevych, 2016). High quality human annotated convincingness data of argument pair in multiple domains is also available for research(Habernal and Gurevych, 2016).

The classification of argument components is to classify text segments in given arguments into two types - claim and premise(reason)(Stab et al., 2014). This issue has been studied by (Rooney et al., 2012; Feng and Hirst, 2011; Palau and Moens, 2009).

Reason classification has recently been studied(Hasan and Ng, 2014). And human annotated data is available which can also be used for evaluating reason clustering.

3 Dataset

The ground truth for convincingness we choose is from (Habernal and Gurevych, 2016). The dataset contains 16,081 argument paris from 32 different topics.

To train our argument component classifier, we are going to use the data from (Hasan and Ng, 2014) which contains 4 different topics with labeled reasons. However, the only overlapping topic between two datasets is gay marriage. So we will try to train a close-domain model on gay marriage topic and a open-domain model.

4 Our method

Our proposed method identifies text segments expressing reasons from argument as the first step. An undirected graph based on similarities between reason pairs will be built for each topic. Then we use a PageRank-like algorithm to rank reasons from the generated graph while the final step is to combine reason scores with lexicon features from argument to produce the convincingness score for each argument.

4.1 Reason identification

Reason identification usually take advantage of discourse markers(Palau and Moens, 2009). However, it has been reported that only few of reasons include discourse markers(Marcu and Echihabi, 2002). Given enough arguments in a topic, we can use a model based on discourse markers to select a small part of reasons, and then use reason classification techniques to identify reasons that include no discourse markers.

4.2 Reason similarity

Word alignment has been proven to be a powerful method to measure semantic similarity between two sentences(Sultan et al., 2015). We are going to use a similar technique to measure similarity between two text segements identified as reasons.

4.3 Ranking algorithm

With the undirected graph generated with similarity between reasons from two arguments, we can perform a PageRank-like algorithm to further score arguments in terms of their reasons(Grolmusz, 2015).

4.4 Combining features

We can easily add the computed reason scores into the feature set of (Habernal and Gurevych, 2016) and use the same classifier, Support Vector Machine to combine reason level feature with lexicon features.

5 Evaluation

With the pairwise dataset, we can first evaluate our method in pair to see the precision. Also, we can further evaluate the convincingness order among given arguments by how many human labeled pair evaluations can match the algorithm produced order.

References

J Anthony Blair. 2012. Argumentation as rational persuasion. *Argumentation* 26(1):71–81.

Vanessa Wei Feng and Graeme Hirst. 2011. Classifying arguments by scheme. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language*

Technologies-Volume 1. Association for Computational Linguistics, pages 987–996.

Vince Grolmusz. 2015. A note on the pagerank of undirected graphs. *Information Processing Letters* 115(6):633–634.

Ivan Habernal and Iryna Gurevych. 2016. Which argument is more convincing? analyzing and predicting convincingness of web arguments using bidirectional lstm. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*.

Kazi Saidul Hasan and Vincent Ng. 2014. Why are you taking this stance? identifying and classifying reasons in ideological debates. In *EMNLP*. pages 751–762.

Daniel Marcu and Abdessamad Echihabi. 2002. An unsupervised approach to recognizing discourse relations. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*. Association for Computational Linguistics, pages 368–375.

Hugo Mercier and Dan Sperber. 2011. Why do humans reason? arguments for an argumentative theory. *Behavioral and brain sciences* 34(02):57–74.

Ana Laura Nettel and Georges Roque. 2012. Persuasive argumentation versus manipulation. *Argumentation* 26(1):55–69.

Raquel Mochales Palau and Marie-Francine Moens. 2009. Argumentation mining: the detection, classification and structure of arguments in text. In *Proceedings of the 12th international conference on artificial intelligence and law*. ACM, pages 98–107.

Richard E Petty and John T Cacioppo. 1986. The elaboration likelihood model of persuasion. In *Communication and persuasion*, Springer, pages 1–24.

Niall Rooney, Hui Wang, and Fiona Browne. 2012. Applying kernel methods to argumentation mining. In *FLAIRS Conference*.

Christian Stab, Christian Kirschner, Judith Eckle-Kohler, and Iryna Gurevych. 2014. Argumentation mining in persuasive essays and scientific articles from the discourse structure perspective. In *ArgNLP*. pages 21–25.

Md Arafat Sultan, Steven Bethard, and Tamara Sumner. 2015. Dls@ cu: Sentence similarity from word alignment and semantic vector composition. In *Proceedings of the 9th International Workshop on Semantic Evaluation*. pages 148–153.