A Comparative Study on Collecting High-Quality Implicit Reasonings at a Large-scale

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Abstract

Explicating implicit reasoning (i.e. *warrants*) in arguments is a long-standing challenge for natural language understanding systems. While recent approaches have focused on explicating warrants via crowdsourcing or expert annotations, the quality of warrants has been questionable due to the extreme complexity and subjectivity of the task. In this paper, we tackle the complex task of warrant explication and devise various methodologies for collecting warrants. We conduct an extensive study with trained experts to evaluate the resulting warrants of each methodology and find that our methodologies allow for high-quality warrants to be collected. We construct a preliminary dataset of 6,000 warrants annotated over 600 arguments for 3 debatable topics. To facilitate research in related downstream tasks, we release our guidelines and preliminary dataset.

1 Introduction

In daily conversations, humans create many arguments consisting of implicit, unstated reasoning. Consider the following example consisting of two argumentative components: *Claim* (i.e., declarative statement) and its *Premise* (i.e., supporting statement):

(1) **Claim:** We should introduce compulsory voting.
**Premise:** It increases voter turnout.

In Example 1, it is easy for humans to understand the reason why the premise supports the claim. For example, one might assume that it implies that high voter turnout, resulting from introducing compulsory voting, is good for a fair representation of society. However, for machines, explicating such implicit reasoning, henceforth *warrants* (Toulmin, 1958), is a challenging, but exciting task.

Re-constructing warrants in arguments can play an important role in many argument-related downstream applications, such as argumentative writing and comprehension support (Qin and Karabacak, 2010; von der Mühlen et al., 2019), improving students critical thinking (Hillocks, 2010), and debate systems (Weber et al., 2008). For some of these applications, assessing identification of warrants is an important step in developing a more complex pipeline for overall argument analysis (Becker et al., 2020). Furthermore, warrants can be leveraged to automatically give constructive feedback to users to assist them in the aforementioned argumentative applications.

While the identification of main argumentative components such as claim and premise have been well explored (Habernal and Gurevych, 2017; Ein-Dor et al., 2020), research focusing on warrant explication has been lacking due to its extreme complexity. Habernal et al. (2018) and Bolužić and Šnajder (2016) both demonstrated that simple warrant annotations can be done through crowdsourcing, though the authors acknowledge the high complexity due to subjectivity for reconstructing warrants. They attribute the difficulty to the variety of reasoning patterns possible for framing warrant and multiplicity of warrants between argumentative components. However, to the best of our knowledge, no work has yet to solve the aforementioned challenges.

To tackle the challenge encountered in collecting warrants, in this paper we address the following research question: 1. *Can we devise a methodology that makes it easier to construct high-quality warrants?* Our main hypothesis is that since there are multiple reasoning patterns in natural language (Hitchcock, 2003; Kock, 2006), it must be possible to narrow down the warrants into specific keyword-based patterns, where keywords are utilized from the original argument (i.e., claim and premise), which follows the formal definition of warrants in that they serve as a linking chain between the contents of claim and its premise (Freeman, 1992; Verheij, 2005).
In this work, we conduct an extensive annotation study with trained experts and crowd workers to compare three different methodologies for collecting warrants, namely: Natural language warrants, User-defined Keyword-based warrants and Pre-defined Keyword-based warrants. Firstly, through each methodology, we collect multiple warrants on top of argumentative texts from IBM-Rank-30k dataset (Gretz et al., 2019), a dataset of topic and claim pairs already annotated with quality scores. We analyze the collected warrants and work closely with experts to adapt the annotation task, iterating over how best to approach the novel domains and simplify the annotation guidelines for crowdsourcing to be suitable for both expert and non-expert annotators. Secondly, based on our extensive qualitative analysis results on the methodologies, we collect 6,000 warrants annotated for 600 arguments from over 6 diverse topics via User-defined Keyword-based warrants. We publicly release our guidelines and preliminary dataset to facilitate research in automatic warrant generation.\footnote{https://github.com/keshav2995/6000\_warrants}

2 Related Work

Implicit reasonings, commonly referred to as warrants (Toulmin, 1958) or enthymemes (Walton et al., 2008), have long been studied to understand the grounds on which a premise lends support to the topic (Freeman, 1992). In other words, a warrant, when made explicit, clearly shows the principle upon which the argument rests (Pineau, 2013). Identification of such warrants has been shown to aid in the argument comprehension process (Hitchcock and Verheij, 2006; Becker et al., 2017) and in educational research for helping students to make better arguments and improve their critical thinking skills (Erduran et al., 2004; von der Mühlen et al., 2019).

Numerous computational approaches have been made towards solving the task of warrant explanation in arguments. In an initial attempt, Feng and Hirst (2011) identified argumentation schemes (Walton et al., 2008) as a means for warrant reconstruction, but they do not approach the task due to absence of training datasets. Boltužić and Šnajder (2016) made a preliminary attempt at crowdsourcing warrants to fill the reasoning gap between a claim and premise pair without any specific guidelines. However, they concluded that the collected warrants were highly variable in wordings and amount needed to fill the gap. In contrast, our crowdsourcing methodologies provide specific guidelines with numerous examples and restrict workers to write only the most relevant warrant.

Becker et al. (2017) hire expert annotators to fill missing knowledge pieces between different argument units (counter-argument, topic, premise, rebuttal, etc) in the argmicrotext corpus (Peldszus and Stede, 2015). However, their approach relies on the availability of experts which is an expensive and time-consuming process for collecting warrants on a larger dataset. Instead, we perform crowdsourcing with non-experts and show that the quality and cost of warrants collected can be high and inexpensive. Recently, Habernal et al. (2018) proposed a step by step methodology to crowdsource warrants from non-experts, but their error analysis pointed at inherent difficulty in distinguishing patterns between incorrect warrants. On the contrary, in our work, we create various methodologies which can make it easier to analyse good and bad warrants for a given argument.

3 Dataset Desiderata

Towards creating a preliminary warrant annotated dataset which can be potentially useful in downstream argumentative applications, we require it to fulfill at least the following criteria: i) cover multiple topics, ii), span over diverse premises, and iii) consists of high-quality warrants. In addition, the dataset creation methodology must be cost effective without compromising data quality and easier for experts as well as non-experts to understandably write quality warrants. As mentioned a priori, a dataset with multiple topics is desirable; however, collecting warrants across multiple topics can be both difficult and time consuming. Thus, we start with small number of topics and define a simple metric to filter a handful of topics (specifically, 3) found in a large, well-known argumentation dataset of diverse premises (§ 3.1).

3.1 Source Data (IBM-Rank-30K)

We utilize IBM-Rank-30K dataset (Gretz et al., 2019), which contains supporting and opposing stance arguments on 71 common controversial topics. Several factors motivated our choice of utilizing this dataset: (1) Arguments were collected
Table 1: Topics in *IBM-Rank-30K* with top-5 and bottom-5 premise diversity growth rate \((dp_t)\). The overall premise diversity of IBM data as shown above is calculated for random sample of 300 premises across various topics.

| Topic \((t)\): **We should** | \((dp_t)\) | # Premise |
|-----------------------------|------------|----------|
| Abolish the Olympic Games    | 2.68       | 204      |
| Ban missionary work          | 2.57       | 218      |
| Ban the Church of Scientology| 2.50       | 195      |
| Abolish safe spaces          | 2.34       | 194      |
| Oppose collectivism          | 2.27       | 225      |
| Fight urbanization           | 1.45       | 202      |
| Abolish zoos                 | 1.41       | 198      |
| Introduce compulsory voting  | 1.37       | 205      |
| Ban whaling                  | 1.36       | 217      |
| Mandate use of public defenders| 1.25      | 218      |
| **Overall**                  | **2.92**   | **300**  |

We only utilize arguments in *IBM-Rank-30K dataset* with supporting stance (i.e., the premise supports the topic) since warrants only exist for arguments which lend support to topic \cite{Toulmin}. The aim of our annotation is to reveal warrants that connect premises in argumentative texts to its claim. Explicating warrants, i.e., making the implicit explicit, has been inherently difficult due to varying structural or lexical phrasing chosen by annotators, difference in intuition, and a variety of reasoning patterns in which warrants can be framed. To overcome these challenges, we attempt to conduct a deeper analysis on warrants from a theoretical perspective of reasoning and explore different ways to collect these warrants.

### 4.1 Preliminary Measures

As shown in Table 1, the variety of premises for topics with a lower \(dp_t\) depicts higher number of overlapping premises while topics with a higher \(dp_t\) might comprise of more variety of debatable premises. It also indicates that the growth rate of diversity strongly depends on the topic i.e. certain topics contain more diverse keywords/knowledge pieces as compared to others. To proceed with our preliminary warrant crowdsourcing and methodology analysis, we choose 3 topics that fall in the lower band of \(dp_t\) value. Our choice for the above topics is based on the assumption that if high quality warrants can be collected for relatively low diverse premises then it will be a strong evidence to focus on more diverse premise in future work.
were satisfied with our task. Simultaneously, we corresponded directly to workers that had questions/comments on our task. Crowdworkers are paid in accordance with the minimum wage calculated by conducting many trials and based on average work-time.

4.2 Warrant Collection Methodologies

Our choice for the warrant collection methods is based on the formal definition of warrants i.e. warrants are the inference link that fills the reasoning gap between claim and premise (Toulmin, 1958). Hence, we consider 3 methodologies: natural language warrants, pre-defined keyword-based warrants, and user-defined keyword-based warrants. Bonus is paid to workers based on general consensus rather than sole judgement which may help remove bias towards and between workers.

Natural Language Warrants For collecting warrants in free-form natural sentences, we follow guidelines similar to Habernal et al. (2018). Prior to the main annotation task, we filtered crowdworkers via our custom Reasoning Qualification Test (RQT). Selected annotators were presented with a topic and single premise and asked to come up with a warrant that indicates why the premise supports the claim.

User-defined Keyword-based Warrants As an alternative to natural language sentences which can be variable in structure due to myriad amount of reasoning patterns (Keith and Beard, 2008), we follow a simpler way to restrict the crowdworkers to a specific reasoning pattern. To do this, we follow Reisert et al. (2018)’s argumentation slot-filling templates, where each template encodes an argumentative relation between components. Such templates enable annotators to focus on important keywords in components which are relevant to the missing/implicit information linking a claim and a premise.

Following Reisert et al. (2018)’s annotation study in which expert annotators freely chose slot-fillers, we let the crowdworker freely choose the slot-fillers from both the claim and the premise and additionally fill in the missing/implicit reasoning between them. For example, Fig. 1 shows a case in which the warrant connects the ontological elements of both claim and premise, and the claim is a consequence resulting from the premise (i.e., argument from consequence (Walton et al., 2008)).

Pre-defined Keyword-based Warrants To follow-up on Reisert et al. (2018)’s annotation method, we also would like to determine the quality of warrants when the slot-fillers are pre-defined. Such a method allows for annotators to only write the implicit information between pre-defined keywords from the claim and premise. For choosing keywords, we employ spaCy (Honnibal et al., 2020) and automatically choose the longest verb/noun phrases from the claim and premise.

5 Methodology Comparison and Results

Towards determining which methodology results in the highest quality warrants, we first collect warrants for each methodology using crowdsourcing. For each methodology, we annotate 40 arguments covering 3 different topics with 5 crowdworkers per argument. First, crowdworkers decided whether a warrant can be constructed between the given claim and premise. If so, they were then asked to write the warrant in the correct format.

5.1 Filtering

For each methodology, we can collect, at most, 200 warrants, if a worker first identifies that hidden reasoning is necessary to link the claim and its premise. However, after initial filtering we discovered that workers wrote 65, 86 and 80 warrants each respectively out of a possible 200 warrants for the arguments given to them for Natural language warrant, User-defined keyword-based and Pre-defined keyword-based warrant methodologies. We utilize these 231 collected warrants for further analysis.

5.2 Results

To analyze the quality of the collected warrants, two expert annotators were asked to judge the qual-
Table 2: Comparison between the different warrant crowdsourcing methodologies. Krippendorff’s $\alpha$ and Average scores given by two expert annotators (Avg.) on a scale of (0-2) indicate that user-defined and pre-defined methodologies result in overall higher quality warrants as compared to natural language warrants.

| Methodology          | Natural Language | User-defined | Pre-defined |
|----------------------|------------------|--------------|-------------|
|                      | $\alpha$ | Avg. | $\alpha$ | Avg. | $\alpha$ | Avg. |
| Abolish zoos         | 0.64    | 1.55 | 0.67    | 1.60 | 0.62    | 1.57 |
| Intro. compulsory voting | 0.45    | 1.50 | 0.51    | 1.55 | 0.53    | 1.47 |
| Ban whaling          | 0.63    | 1.37 | 0.61    | 1.61 | 0.58    | 1.59 |
| Overall              | **0.57** | **1.46** | **0.56** | **1.59** | **0.53** | **1.55** |

Score | Explanation
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0 | Warrant is unrelated to the topic and its premise.
1 | Warrant is related to the topic and premise but does not make the relationship between them easy to understand and/or strengthen the argument. In addition, the warrant may overlap or be a paraphrase of the premise.
2 | The relationship between the topic and premise is easier to understand and/or strengthened because of the warrant.

Table 3: Guidelines used by our expert annotators for scoring the quality of warrants on a scale of 0-2.

5.3 Qualitative Analysis

To further analyze the quality of warrants and the quality of the entire crowdsourcing process, we further analyze a sample of the warrants collected via each methodology and annotated by experts. As shown in Fig 2, the warrants shown each have some kind of keyword overlap with the claim/premise. However, the difference in scoring warrants might be attributed to different complexities of the way in which warrants are framed. Specifically, even though the warrants encode claim-premise information, the quality of the warrant can essentially be bad. This shows that identifying the correct warrant can still be challenging with automated techniques which extract lexical and word-level features.

While keyword-based methods restrict most warrants to a single sentence, the natural language warrants often consist of shorter, multiple sen-
Figure 2: Sample from the warrants collected for our methodology comparison. These warrants were scored the same from both expert annotators. The underlined text denotes keywords from **Premise** and **Claim** used in pre-defined keyword-based warrant methods.

| Natural Language Warrant | Score: 2 --> | Political activism increases voter knowledge and leads to smarter voting and better governments and if voting is not made mandatory, people will not have the freedom to express their opinion and influence an election. | Score: 0 --> | We want increased political activism |
|--------------------------|-------------|---------------------------------------------------------------------------------|-------------|--------------------------------------|
| User-defined Keyword-based Warrant | Score: 2 --> | Compulsory voting leads to all citizens voting which results in choosing the best political parties. | Score: 0 --> | Introduce compulsory voting leads to make sure that we have presidents who the people actually want which make sure to increase political activism. |
| Pre-defined Keyword-based Warrant | Score: 2 --> | Introduce compulsory voting results in people actively engaging in politics which is beneficial for increase political activism | Score: 0 --> | Introduce compulsory voting would increase political activism would increase political activity |

In our future work, we will annotate our corpus with quality dimensions shown from previous argumentative works (Wachsmuth et al., 2017). Simultaneously, we will collect warrants for premises attacking the topic, as our main focus of this work was on premises supporting the original topic. We will also test the usefulness of our model as constructive feedback in a pedagogical setting, such as deploying our system in schools in which students debate and/or write essays on controversial topics. Finally, we will also focus on argumentation in tree-like hierarchical structures, such as a premise supporting/attacking another premise, which can be discovered in everyday, real-world arguments.

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https://github.com/keshav2995/6000_warrants
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