Expert Stance Graphs for Computational Argumentation

Orith Toledo-Ronen  Roy Bar-Haim  Noam Slonim
IBM Research - Haifa
{oritht,roybar,noams}@il.ibm.com

Abstract

We describe the construction of an Expert Stance Graph, a novel, large-scale knowledge resource that encodes the stance of more than 100,000 experts towards a variety of controversial topics. We suggest that this graph may be valuable for various fundamental tasks in computational argumentation. Experts and topics in our graph are Wikipedia entries. Both automatic and semi-automatic methods for building the graph are explored, and manual assessment validates the high accuracy of the resulting graph.

1 Introduction

Background knowledge plays an important role in many NLP tasks. However, computational argumentation is one area where little work has been done on developing specialized knowledge resources.

In this work we introduce a novel knowledge resource that may support various tasks related to argumentation mining and debating technologies. This large-scale resource, termed Expert Stance Graph, is built from Wikipedia, and provides background knowledge on the stance of experts towards debatable topics.

As a motivating example, consider the following stance classification setting, where the polarity of the following expert opinion on Atheism (Pro or Con) should be determined:

Dawkins sums up his argument and states, “The temptation (to attribute the appearance of a design to actual design itself) is a false one, because the designer hypothesis immediately raises the larger problem of who designed the designer. The whole problem we started out with was the problem of explaining statistical improbability. It is obviously no solution to postulate something even more improbable.” (Dawkins, 2006, p. 158)

Inferring the stance directly from the above text is a difficult and complex task. However, this complexity may be circumvented by utilizing background knowledge about (Richard) Dawkins, who is a well-known atheist. Dawkins’ page in Wikipedia includes various types of evidence for his stance towards atheism:

1. Categories: Dawkins belongs to the following Wikipedia categories: Antitheists, Atheism activists, Atheist feminists and Critics of religions.

2. Article text: The article text contains statements such as “Dawkins is a noted atheist” and “Dawkins is an outspoken atheist”.

3. Infobox: Dawkins has a known-for relation with “criticism of religion”.

2 Expert Stance Graphs

The Expert Stance Graph (ESG) is a directed bipartite graph comprising two types of nodes: (a) concept nodes, which represent debatable topics such as Atheism, Abortion, Gun control and Same-sex marriage, and (b) expert nodes, representing persons whose stance towards one or more of the concepts can be inferred from Wikipedia. Stance is represented as labeled directed edges from an expert to a concept, e.g. Richard Dawkins Pro Atheism. Each concept and each expert have their own article in Wikipedia. We use the term Experts inclusively to refer to academics.
writers, religious figures, politicians, activists, and so on.

3 Applications

Expert opinions are highly valuable for making persuasive arguments, and expert evidence (premise scheme) is a commonly used type of argumentation scheme (Walton et al., 2008). Rinott et al. (2015) describe a method for automatic evidence detection in Wikipedia articles. Three common evidence types are explored: Study, Expert, and Anecdotal. The proposed method uses type-specific features for detecting evidence. For instance, in the case of expert evidence, a lexicon of words describing persons and organizations with relevant expertise is used.

The process of incorporating expert opinions on a given topic into an argument involves several steps. First, we need to retrieve from our corpus articles that contain expert opinions related to the given topic. Second, the exact boundaries of these opinions should be identified. Finally, the stance of the expert opinion towards the topic (Pro or Con) should be determined, to ensure it matches the stance of the argument we are making. Each of these steps is a challenging task by itself.

The expert stance graph may facilitate each of the above subtasks. If an expert E is known to be a supporter or an opponent of some topic T, then the Wikipedia page of E is likely to contain relevant opinions on T. Furthermore, a mention of E can be a useful feature for identifying relevant expert opinions for T in a given article.

Finally, perhaps the most important use of the graph for expert evidence is stance classification. Previous work on stance classification has shown that it can be much improved by utilizing external information beyond the text itself. For example, posts by the same author on the same topic are expected to have the same stance (Thomas et al., 2006; Hasan and Ng, 2013). Similarly, as shown in the previous example, external knowledge on expert stance towards a topic can improve stance classification of expert opinions.

4 Building the Graph

We consider two complementary settings for building the graph: (a) Offline, in which the set of concepts is predefined, and minimal human supervision is allowed, and (b) Online, where our goal is to find ad-hoc Pro and Con experts for an unseen concept, in a fully-automatic fashion.

For both settings, our approach is based on Wikipedia categories and lists, which have several advantages: (a) they provide an easy access to large collections of experts, (b) their stance classification is relatively easy, and (c) their hierarchical structure can be exploited.

4.1 Concepts

Offline construction of the graph starts with deriving the set of concepts. We started with Wikipedia’s list of controversial issues, which contains about 1,000 Wikipedia entries, grouped into several top-level categories. We manually selected a subset of 12 categories, and filtered out the remaining 3 categories.

One of the authors selected from the remaining list concepts that represent a two-sided debate (Meaning of life, for instance, is a controversial topic but does not represent a two-sided debate). Persons and locations were filtered out as well. This list was expanded manually by identifying relevant concepts in Wikipedia article titles that contain the words “Debate” or “Controversy”. Finally, two annotators assessed the resulting list according to the above guidelines. Concepts that were rejected by both annotators were removed. The final list contained 201 concepts.

4.2 Candidate Expert Categories

Next, we search relevant Wikipedia categories and lists for each concept. The process starts with creating search terms. The concept itself is a search term, as well as any lexical derivation of the concept that represents a person (e.g. Atheism → Atheist), which we term person derivations. Person derivations are found using WordNet (Miller, 1995; Fellbaum, 1998): we look for lexical derivations of the concept that have “person” as a direct or inherited hypernym.

We then find all Wikipedia categories and lists that contain the search terms. For example, given the search terms atheism and atheist, some of the categories found are Atheism activists, American

3https://en.wikipedia.org/wiki/Wikipedia:List_of_controversial_issues

4The selected categories were Politics and economics, History, Religion, Science biology and health, Sexuality, Entertainment, Environment, Law and order, Philosophy, Psychiatry, Technology, and Sports. The excluded categories were Linguistics, Media and culture, and People.

5Lists are Wikipedia pages whose title begins with “List of”.
atheists, List of atheist authors, Converts to Christianity from atheism or agnosticism and Critics of atheism. The set of categories is further expanded with subcategories of the categories found in the previous step. This step adds more relevant categories that do not contain the search terms, such as Antitheists for Atheism. To avoid topic drifting, we only add one level of subcategories.

Next, the persons associated with each category\(^6\) are identified by considering outgoing links from the category page which are of type "Person", based on DBPedia’s rdf:type property for the page (Lehmann et al., 2014). Categories with fewer than five persons are discarded. We also removed three concepts, for which the number of categories was too large: Christianity, Catholicism, and Religion. The resulting set included 4,603 categories containing 121,995 persons. Categories were found for 132 of the 198 concepts.

### 4.3 Category Stance Annotation

Finally, category names are manually annotated for stance. The annotation process has two stages: first, determine whether the category explicitly defines membership in a group of persons. For instance, Swedish women’s rights activists and Feminist bloggers meet this criterion, but Feminism and history does not. We apply this test since we observed that it is much easier to predict with confidence the stance of persons in these categories.

Categories that do not pass this filter are marked as Irrelevant. Otherwise, the annotators proceed to the second stage, where they are asked to determine the stance of the persons in the given category towards the given concept, based on the category name. Possible labels are:

1. Pro: supporting the concept.
2. Con: opposing the concept.
3. None: The stance towards the concept cannot be determined based on the category name.

For instance, for the concept Communism we will have British communists and Canadian Trotskyists classified as Pro, Moldovan anti-communists classified as Con, and Western writers about Soviet Russia classified as None. Annotators may also consider direct parent categories for determining stance. In the previous example, knowing that Canadian communists is a parent category\(^6\) for convenience, we will refer in the following to categories and lists collectively as “categories”.

The logic of the rule-based classifier is summarized as follows:

### 4.4 Category Stance Classification

The offline list of concepts we started with is unlikely to be complete. Therefore, we would like to be able to find on-the-fly Pro and Con experts also for new, unseen concepts. This requires the development of a stance classifier for categories. We randomly split the 198 concepts into two equal-size subsets and used one subset for development and the other for testing. As a result, the 132 concepts for which categories were found are split into a development set, containing 69 concepts and the other for testing. As a result, the 132 concepts for which categories were found are split into a development set, containing 69 concepts and the other for testing. As a result, the 132 concepts for which categories were found are split into a development set, containing 69 concepts and their associated 2,069 categories, and a test set, containing 63 concepts and 2,534 categories. The development set was used for developing a simple rule-based classifier.

The logic of the rule-based classifier is summarized as follows:

\(^6\)The IBM Debating Technologies group in IBM Research has already released several data resources, found here: [https://www.research.ibm.com/halifa/dep/vat/mlta_data.shtml](https://www.research.ibm.com/halifa/dep/vat/mlta_data.shtml). We aim to release the resource presented in this paper as well, as soon as we obtain the required licenses.

| Polarity | Concepts | Categories | Experts |
|----------|----------|------------|---------|
| Pro      | 105      | 3,221      | 93,570  |
| Con      | 40       | 272        | 10,666  |

Table 1: Statistics on the Expert Stance Graph of Canadian Trotskyists may help classifying the latter as Pro for Communism.

The categories were labeled by a team of six annotators, with each category labeled by two annotators. The overall agreement was 0.92, and the average inter-annotator Cohen’s kappa coefficient was 0.79, which corresponds to substantial agreement (Landis and Koch, 1997). Cases of disagreement were labeled by a third annotator and were assigned the majority label. Category annotation was completed rather quickly - about 260 categories were annotated per hour. The total number of annotation hours invested in this task was 37.

The resulting ESG is composed of all experts in the categories labeled as Pro and Con. A total of 104,236 experts were found for 114 out of the 132 concepts, and for 31 concepts, both Pro and Con experts were found. The number of concepts, categories and experts for each stance is given in Table 1. As shown in the table, the vast majority of categories and experts found are Pro. Overall, our method efficiently constructs a very large ESG, while only requiring a small amount of human annotation time.

\(^6\)For convenience, we will refer in the following to categories and lists collectively as “categories”.

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\(^7\)The IBM Debating Technologies group in IBM Research has already released several data resources, found here: [https://www.research.ibm.com/halifa/dep/vat/mlta_data.shtml](https://www.research.ibm.com/halifa/dep/vat/mlta_data.shtml). We aim to release the resource presented in this paper as well, as soon as we obtain the required licenses.
### Algorithm 1: Category stance classification

```python
Input: category CAT; concept C; person derivation PD for the concept
Output: stance classification of CAT into PRO/CON/NONE

if CAT =~ critics of C then
    return CON
else if CAT =~ anti|former|... PD then
    return CON
else if CAT =~ PD dissident|... then
    return CON
else if CAT =~ PD then
    return PRO
else if CAT =~ anti|former|... C PERSON then
    return CON
else if CAT =~ C PERSON then
    return PRO
else
    return NONE
```

Table 2: Category stance classification results

| Categories | Predicted | Correct | Labeled | P  | R  |
|------------|-----------|---------|---------|----|----|
| Pro        | 1,298     | 1,182   | 1,758   | 91.1| 68.0|
| Con        | 144       | 140     | 186     | 97.2| 75.3|

Table 3: Expert stance assessment

| Manual Annotation | Predicted | Correct | Labeled | P  | R  |
|-------------------|-----------|---------|---------|----|----|
| Pro               | 200       | 181     | 189     | 90.5| 95.8|
| Con               | 200       | 173     | 178     | 86.5| 97.2|

| Classifier        | Predicted | Correct | Labeled | P  | R  |
|-------------------|-----------|---------|---------|----|----|
| Pro               | 76        | 60      | 189     | 78.9| 31.7|
| Con               | 87        | 81      | 178     | 93.1| 45.5|
6 Conclusion and Future Work

We introduced Expert Stance Graphs, a novel, large scale knowledge resource that has many potential use cases in computational argumentation. We presented an offline method for constructing the graph with minimal supervision, as well as a fully-automated method for finding experts for unseen concepts. Both methods show promising results.

In future work we plan to improve coverage by considering additional sources of information, such as the text of the expert’s page in Wikipedia. We will also apply the graph in different tasks related to the detection and stance classification of expert evidence.

We also plan to enrich the graph with additional types of knowledge, which may be utilized to predict missing stance edges. Semantic relations between concepts, such as contrast (e.g. Atheism vs. Religion), may support such inferences, as experts are expected to have opposite stances towards contrasting concepts. Another possible extension of the graph is influence links between experts, which may indicate similar stances for these experts. Influence information is available from Wikipedia infoboxes.

Finally, we would like to apply collaborative filtering techniques to predict missing expert-concept stance relations. This is based on the intuition that experts who tend to have same (or opposite) stances on a set of topics, are likely to follow a similar pattern on topics for which we only have partial stance information.

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