

Topic Ontologies for Arguments

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Abstract

Many computational argumentation tasks, such as stance classification, are topic-dependent: The effectiveness of approaches to these tasks depends largely on whether they are trained with arguments on the same topics as those on which they are tested. The key question is: What are these training topics? To answer this question, we take the first step of mapping the argumentation landscape with The Argument Ontology (TAO). TAO draws on three authoritative sources for argument topics: the World Economic Forum, Wikipedia’s list of controversial topics, and Debatepedia. By comparing the topics in our ontology with those in 59 argument corpora, we perform the first comprehensive assessment of their topic coverage. While TAO already covers most of the corpus topics, the corpus topics barely cover all the topics in TAO. This points to a new goal for corpus construction to achieve a broad topic coverage and thus better generalizability of computational argumentation approaches.

1 Introduction

The term “topic” refers to the subject matter of a text. A text may be about one or more topics and the relationship between topics and texts is called “aboutness” (Yablo, 2014). Topics play a central role in argumentation because they determine argumentation strategies and rhetorical devices by setting the appropriate and expected universe of discourse. This view is supported by pragmatics (van Eemeren, 2015): “The basic aspects of strategic maneuvering [...] are making an expedient selection from the ‘topical potential’ available at a certain discussion.” Although debaters often use commonplace arguments across topics (Bilu et al., 2019), they must be relevant: a black market argument, for example, can be equally well applied to topics such as banning drugs or banning firearms. As recently shown, for example, by Reuver et al. (2021), training computational models to extract, analyze, or generate arguments with a broad topic coverage improves their generalizability.

A set of topics can be organized as a graph, sometimes called a “topic space”. Information theorists and library scientists map hierarchical subject relationships into ontologies in this way (Hjørland, 2001). For this purpose, topics are labeled with a subject heading, a phrase from a controlled vocabulary that describes a topic in a concise and discriminating manner. While library ontologies are not focused on argumentation, others deal specifically with *argumentative* topic spaces. We have identified and tapped three authoritative sources of ontological knowledge covering global issues, controversies, and popular debates: the World Economic Forum’s “Strategic Intelligence” site, Wikipedia’s list of controversial topics, and Debatepedia’s debate classification system (Section 4). They form the basis for The Argument Ontology (TAO).¹

We compile a comprehensive survey of 59 argument corpora (Section 3) and investigate their topic coverage with respect to the three authoritative ontologies (Section 5). The coverage of corpora with topic labels is manually assessed by matching each label with the topics of the ontologies. From this, the ontology topics covered by a corpus and the distribution of corpus arguments in the ontologies are calculated. Our analyses show that the existing corpora focus on only a subset of the known topics. For corpora without topic labels, we categorize their argumentative texts by measuring their semantic relatedness to ontology topics. Given the large number of ontology topics (748 for Wikipedia), this is a challenging classification for which we achieve a remarkable F_1 of 0.59. (Section 6).²

Altogether, we lay the foundation for the study and systematic exploration of controversial topics within computational argumentation analysis. The authoritative sources identified already cover their respective areas quite comprehensively. Future work will need to extend our approach to other subject areas, such as business, domestic, historical, and scientific argument spaces.

¹Data: <https://zenodo.org/record/3928096>.

²Code: <https://github.com/webis-de/EACL-23>.

2 Related Work

Our review of related work focuses on the role of the variable “topic” in computational argumentation. Moreover, we briefly review topic ontologies and hierarchical topic classification.

2.1 Topics in Computational Argumentation

In computational argumentation, arguments are typically modeled as compositions of argument units, where an argument unit is represented as a span of text. Habernal and Gurevych (2016a) adopts Toulmin (1958)’s (1958) model, which defines six unit types, among which are “claim” and “data”. Wachsmuth et al. (2017) employ a more basic model of two units, which defines an argument as a claim or conclusion supported by one or more premises. These models capture arguments without explicitly identifying the topic they address. Levy et al. (2014) consider claims to be topic-dependent and study their detection in the context of a random selection of 32 topics from idebate.org. This work raises the question why topic-dependence has not been addressed more urgently until now.

Key tasks for computational argumentation include the mining of arguments from natural language (Moens et al., 2007; Al-Khatib et al., 2016), classifying their stances with regard to a thesis (Bar-Haim et al., 2017), and analyzing which arguments are more persuasive (Tan et al., 2016; Habernal and Gurevych, 2016a). Current approaches to these tasks rely on supervised classification. Daxenberger et al. (2017) show that supervised classifiers fail to generalize across domains (\sim topics). More recently, Stab et al. (2018) tweak BiLSTM (Graves and Schmidhuber, 2005) to integrate the topic while jointly detecting (1) whether a sentence is an argument and (2) its stance to the topic. The designed neural network outperforms BiLSTM without topic integration in both tasks; further evidence for the topic-dependence of argument mining and stance classification. Whether model transfer between more closely related topics works better is unknown. As a first step, Reuver et al. (2021) show that cross-topic stance-classification with BERT (Devlin et al., 2018) produces mixed results depending on the topics, but misses the relations between the topics. Gu et al. (2018) show that integrating the topic of an argument helps assessing its persuasiveness.

Topic plays a central role in argument retrieval and generation since it defines what arguments are

relevant. Argument retrieval aims at delivering pro and con arguments on a given topic query. A major challenge in argument retrieval is the grouping of arguments that address common aspects of a topic. As shown by Reimers et al. (2019) and Ajour et al. (2019a), integrating the topic is an important step while clustering arguments. For argument generation, Bilu et al. (2019) introduce an approach that matches an input topic against a list of topics that are paired with sets of topic-adjustable commonplace arguments (e.g., black-market arguments). In a similar vein, Bar-Haim et al. (2019) identify consistent and contrastive topics for a given topic with the goal of expanding the topic in a new direction (e.g., fast food versus obesity). Both approaches show the merit of utilizing argument topic ontologies in argument generation.

Only abstract argumentation may be truly topic-independent, where only the structure and relations among arguments, not their language, are studied.

2.2 Topic Ontologies

In information science, an ontology is defined as “an explicit specification of a conceptualization” (Gruber, 1993). Topic ontologies are a specific type of ontologies which specify topics as nodes of a directed acyclic graph. An edge in the graph then implies an “is part of”-relation between the topics (Xamena et al., 2017). The effort in creating topic ontologies ranges from ad-hoc decisions (e.g., tags for blog posts) to extensive classification schemes for libraries. The oldest classification scheme that is still used today in libraries is the Dewey Decimal Classification. It has been translated into over 30 languages, and it contains several tens of thousands of classes. Most topic ontologies focus on a specific domain, such as the ACM Computing Classification System for computer science, or DMOZ for web pages.³ The only topic ontology directly linked to arguments is that of Debatepedia.

2.3 Hierarchical Text Classification

Hierarchical text classification aims at classifying a document into a class hierarchy. Depending on how the hierarchical structure is exploited, classification can be done top-down (from higher classes downwards), bottom-up, or flat (ignoring hierarchical relations) (Silla and Freitas, 2011). Researchers usually train supervised classifiers for each class in the hierarchy (Sun and Lim, 2001).

³<https://dl.acm.org/ccs> and <https://dmoz-odp.org/>

Corpus	Authors	Source	Unit granularity	Units	Topics	Exp.
Manual selection						
Arguing Subjectivity	Conard et al. (2012)	Editorials	Editorial/blog	84	1	1
Arguments Moderation	Falk et al. (2021)	Discussion forum	Argument	112	2	2
Argumentative Sentences	Eyal et al. (2020)	Wikipedia	Arguments	700	20	1
Argument Facet Similarity	Misra et al. (2016)	Debate portals	Argument	6,188	3	12
AURC	Trautmann et al. (2020)	Web	Argument Unit	8,000	8	6
Basn	Kondo et al. (2021)	Debate portals	Argument pair	2,370	6	1
CCSA	Li et al. (2022)	Scientific papers	Argument unit	18,332	1	1
Claim and Evidence 1	Aharoni et al. (2014)	Wikipedia	Wikipedia article	315	33	22
Claim and Evidence 2	Rinott et al. (2015)	Wikipedia	Wikipedia article	547	58	16
Claim Generation	Gretz et al. (2020)	Generated text	Argument Unit	2,839	136	1
Claim Stance	Bar-Haim et al. (2017)	Wikipedia	Argument Unit	2,394	55	15
Claim Sentence Search	Levy et al. (2018)	Wikipedia	Argument unit	1,492,077	150	5
COMARG	Boltužić and Šnajder (2014)	Debate portals	Argument pair	2,298	2	3
Evidence Sentences	Schnarch et al. (2018)	Wikipedia	Argument unit	5,783	118	6
Evidence Sentences 2	Ein-Dor et al. (2020)	Wikipedia	Argument unit	29,429	221	4
Evidence Quality	Gleize et al. (2019)	Wikipedia	Argument pair	5,697	69	2
IAM	Cheng et al. (2022)	Wikipedia	Argument unit	69,666	100	1
ICLE Essay Scoring	Persing et al. (2010)	Essays	Essay	1,000	10	12
Ideological Debates Reasons	Hasan and Ng (2014)	Debate portals	Argument	4,903	4	12
Internet Argument Corpus v2	Abbott et al. (2016)	Web	Discussion	16,555	19	22
Key Point Analysis	Bar-Haim et al. (2020)	Wikipedia	Argument	24,093	28	15
M-Arg	Mestre et al. (2021)	Presidential debate	Argument pair	4,104	18	1
Micro Text v1	Peldszus and Stede (2015)	Essays	Essay	112	18	13
Micro Text v2	Skeppstedt et al. (2018)	Essays	Essay	171	35	2
Multilingual Argument Mining	Toledo-Ronen et al. (2020)	Wikipedia	Argument unit	65,708	347	4
Political Argumentation	Menini et al. (2018)	Presidential debate	Argument pair	1,462	5	3
Record Debating Dataset 2	Mirkin et al. (2018)	Debating	Speech	200	50	5
Record Debating Dataset 3	Lavee et al. (2019)	Debating	Speech	400	199	1
Record Debating Dataset 4	Orbach et al. (2019)	Debating	Speech	200	50	1
Record Debating Dataset 5	Orbach et al. (2020)	Debating	Speech	3,562	397	1
Sci-arg	Lauscher et al. (2018)	Scientific papers	Paper	40	1	7
SciARK	Fergadis et al. (2021)	Scientific papers	Abstract	1,000	6	1
UKP Sentential	Stab et al. (2018)	Web	Argument	25,492	8	20
UKP Aspect	Reimers et al. (2019)	Web	Argument pair	3,595	28	11
UKPConvArg1	Habernal and Gurevych (2016c)	Debate portals	Argument pair	11,650	16	16
UKPConvArg2	Habernal and Gurevych (2016b)	Debate portals	Argument pair	9,111	16	6
WebDiscourse	Habernal and Gurevych (2016a)	Web	Document	340	6	12
Webis-debate-16	Al-Khatib et al. (2016a)	Debate portals	Debate	445	14	5
VivesDebate	Ruiz-Dolz et al. (2021)	Debating	Debate	29	1	2
Source-driven: greedy within a time-span						
AIFdb	Bex et al. (2013)	Web	Argument unit	67,408	n/a	8
Args-me	Ajjour et al. (2019b)	Debate portals	Argument	387,692	n/a	31
ChangeMyView	Tan et al. (2016)	Discussion forum	Post/comment	14,066	n/a	37
CJEU	Grundler et al. (2022)	Law Case	Court Decision	40	n/a	1
DebateSum	Roush and Balaji (2020)	Debating	Debate	187,386	n/a	1
IMHO	Chakrabarty et al. (2019)	Discussion forum	Argument Unit	5,569,962	n/a	3
Intelligence Squared Debates	Zhang et al. (2016)	Debate portals	Debate	108	n/a	9
Kialo	Kialo (2020)	Debate portals	Argument unit	331,684	n/a	23
Political Speech	Lippi and Torrioni (2016)	Ministerial debate	Argument unit	152	n/a	2
USElecDeb60To16	Haddadan et al. (2019)	Presidential debate	Debate	42	n/a	5
MultiOpEd	Liu et al. (2021)	Editorials	Editorial	2,794	n/a	2
QT30	Hautli-Janisz et al. (2022)	Debating	Argument unit	19,842	n/a	1
Review-Rebuttal	Cheng et al. (2020)	Scientific reviews	Argument pair	4,764	n/a	5

Table 1 (continued on next page).

Table 1 (continued).

Corpus	Authors	Source	Unit granularity	Units	Topics	Exp.
Source-driven: sampled						
Argument Annotated Essays	Stab and Gurevych (2017)	Essays	Essay	402	n/a	64
E-rulemaking	Park and Cardie (2018)	Discussion forum	Argument	731	n/a	9
ECHR	Poudyal et al. (2020)	Law Case	Argument	743	n/a	8
Editorials	Al-Khatib et al. (2016b)	Editorials	Editorial	300	n/a	15
GAQCorpus	Ng et al. (2020)	Web	Argument	6,424	n/a	4
IDebate Persuasiveness	Persing and Ng (2017)	Debate portals	Argument	1,205	n/a	1
Scinf-biomed	Gao et al. (2022)	Scientific papers	Paper	27,924	n/a	1

Table 1: Survey of argument corpora indicating data source, unit granularity, and size in terms of units and topics (if authors remarked on it). The unit granularity is the one in the corpus’ files, using premises and conclusions as one unit each and the best context-preserving unit for corpora featuring multiple granularities. We presume these topic selection directives from the corpus description: either *manual selection* by the authors, or *source-driven*—i.e., the topics in the selected source(s)—from the units of a specific *time-span* or by random *sampling*. Experiments (Exp.) denotes the count of papers that use the corpus in an experiment among those papers that cite the corpus’ paper.

3 Survey of Argument Corpora

To study arguments and computational argumentation tasks, researchers compile corpora with argumentative texts. To the best of our knowledge, Table 1 compiles all corpora dedicated to argumentation until 2022. We review these corpora and their associated publications with regard to what are the sources of arguments, what is the granularity of the corpus, what is the size of the corpora in terms of their units, and which and how many different topics are covered in them. Reviewing all papers citing a corpus, we also analyzed how many experiments were carried out using them.

The most elaborate discussion of topic selection is given in Habernal and Gurevych (2016a), who chose six topics (homeschooling, public versus private schools, redshirting, prayers in schools, single sex education, mainstreaming) to focus on different education-related aspects. The broadest selection of topics is reported by the researchers of IBM Debater,⁴ who obtain arguments from Wikipedia. However, samples of the topics have been used in their papers without mentioning which ones. The only other work mentioning their source of topics stems from Stab et al. (2018), who randomly select 8 topics from two lists of controversial topics that originate from an online library and the debate portal ProCon.org, respectively. Peldszus and Stede (2015) predefine a set of topics and give writers the freedom to choose which one to write about, but nothing is said about where the set of predefined topics originate from. Conard et al. (2012) and Hasan and Ng (2014) explicitly select one and

four topics, respectively. For all other corpora with topic labels, their authors do not argue on choosing topics, nor selection or sampling criteria. Neither do the authors of corpora without topic labels.

Altogether, it appears that the best practices in argumentation do not as of yet consider topic sampling as a prerequisite task to ensure coverage of a certain domain of interest, diversity, or reproducibility. Based on our review, we presume three basic topic selection directives are in use today: (1) *Manual selection*. Topics are manually defined or selected. Although the process may be random, when aiming for controversial topics, one may often end up with commonplace topics in Western culture (e.g., abortion, death penalty, gay marriage). Still, they are relevant and important today. (2) *Source-driven (greedy within a time-span)*. A source of argument ground truth is either exploited in its entirety, or a maximum subset fulfilling desired properties is used. Since argument-related ground truth is hard to come by, it is understandable that many readily available sources are being exploited. (3) *Source-driven (sampled)*. A source or argument ground truth is exploited and a subset is sampled. Here, it may be infeasible to exploit a source in its entirety. Al-Khatib et al. (2016b) randomly select 300 documents from three websites. Park and Cardie (2018) and Stab and Gurevych (2017) do not mention anything about their sampling process. In general, both source-driven corpus construction approaches inevitably incur the source’s idiosyncracies of topic selection in terms of skew towards certain topics. Scaling up may or may not be a remedy for this problem.

⁴https://www.research.ibm.com/haifa/dept/vst/debating_data.shtml

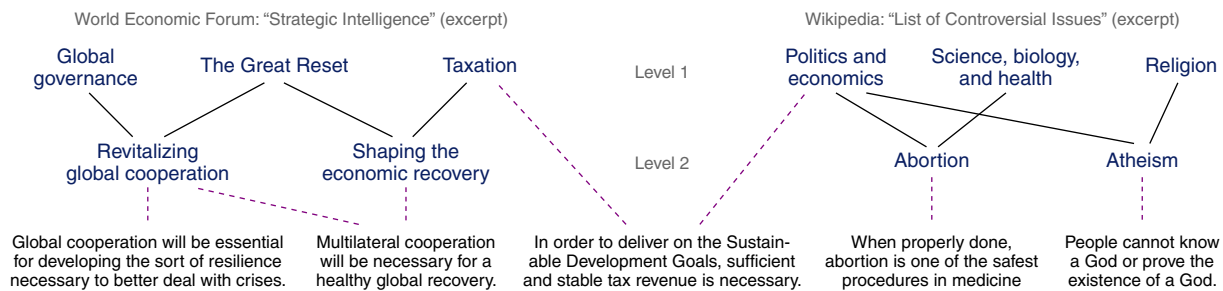


Figure 1: Example for an assignment of arguments (bottom) to topics of a two-leveled ontology. Level 2 topics are subtopics of their linked Level 1 topics. Arguments linked to a Level 2 topic also pertain to its Level 1 ancestors.

We assess how many experiments have been reported on each of the corpora by collecting the publications referring to a corpus as per Google Scholar, focusing on conference and journal papers, but excluding books and web pages. We then check whether the cited corpus is mentioned in its data, experiment, or results section. As can be seen in Table 1, corpora with fewer topics tend to be used more often in experiments than those with larger amounts. In total, 230 experiments were carried out on argument corpora with no clearly defined topic selection directive. The skew towards smaller-scale experiments may affect generalizability.

4 Bootstrapping The Argument Ontology

Topic ontologies provide for a knowledge organization principle, and, especially if widely accepted, also a standard. They are typically modeled as directed acyclic graphs, where nodes correspond to topics and edges indicate “is part of” relations. Topics that are part of other topics are called their subtopics. A topic ontology is often displayed in levels, starting with the topics that are not subtopics of others, continuing recursively with each lower level of subtopics. Figure 1 shows an excerpt of a two-level topic ontology for arguments.

The identification of the topics to be included in The Argument Ontology (TAO), as well as their relations, requires domain expertise. Building an all-encompassing ontology thus requires experts from every top-level domain where argumentation of scientific interest is expected. In the following, we suggest and outline three authoritative sources of expert topic ontologies, which comprise a wide selection of important argumentative topics. We use them to bootstrap a first version of TAO.

World Economic Forum (WEF) The World Economic Forum is a not-for-profit foundation that coordinates organizations from both the public and

the private sector to work on economical and societal issues. As part of their efforts, their “Strategic Intelligence” platform⁵ strives to inform decision makers on domestic and global topics, specifically global issues (e.g., artificial intelligence and climate change), industries (e.g., healthcare delivery and private investors), and economies (e.g., Africa and ASEAN). Domain experts for each topic curate a stream of relevant news articles which they each tag with 4-9 subtopics of their topic (e.g., the continuous monitoring of mental health).

Wikipedia Wikipedia strives for a neutral point of view, but many topics of public interest are discussed controversially. Some editors thus curate a list of controversial Wikipedia articles to highlight where special care is needed, grouped into 14 top-level topics (e.g., environment and philosophy) and 4-176 subtopics (e.g., creationism and pollution).⁶ We omit the “People” topic and articles on countries; their controversiality is not universal.

Debatepedia The Debatepedia portal’s goal is to create an encyclopedia of debates which are organized as “pro” and “con” arguments. A list of 89 topics helps visitors to browse the debates. The debates are contributed by anonymous web users. Topics in Debatepedia tend to address issues of Western culture. For example, the topic “United States” covers 306 debates while “Third World” covers only 12. The site is no longer maintained, but accessible through the Wayback Machine.⁷

The three ontologies are publicly accessible, and two of them are actively maintained and updated. Acquiring the ontologies is straightforward—not straightforward is to make use of them. A key task associated with every topic ontology is to categorize a given document. Having just a short string

⁵<https://intelligence.weforum.org>

⁶https://en.wikipedia.org/wiki/Wikipedia:List_of_controversial_issues

⁷https://web.archive.org/web/20180222051626/http://www.debatepedia.org/en/index.php/Welcome_to_Debatepedia%21

Type	Count	Example topic		
		Topic label	Normalized form	Corpus
Concept	1,394	Abortion	abortion	Claim Sentence Search
Conclusion	707	We should ban partial birth abortion	partial birth abortion	Evidence Quality
Question	110	Should abortion be prohibited?	abortion	IAM
Imperative	25	Ban abortions	abortion	Record Debating Dataset 5
Comparison	23	Pro Choice vs. Pro Life	pro choice vs pro life	UKPConvArg1

Table 2: Counts of the topic types in the 39 preprocessed corpora with examples and their normalized form.

label describing a (potentially multifaceted) topic, such as “The Great Reset”, renders this task exceedingly difficult. Fortunately, domain experts have been pre-categorizing documents into the aforementioned ontologies. In particular, regarding the WEF, invited domain experts categorize news articles for every topic, regarding Wikipedia, the text of the associated articles is available, as are the associated debates on Debatepedia.

Articles that are categorized into Level 2 topics are propagated up to their respective Level 1 topics. Table 3 shows the large differences between the ontologies. The WEF ontology contains the most topics, links the most documents, and has the most tokens overall. Wikipedia’s Level 2 topics link to a single article each, yielding less text overall.

5 Topic Coverage

To assess the topic coverage of an argument corpus given the three ontologies, we map their topic labels (if provided) to matching ontology topics.

5.1 Topic Label Normalization

Table 1 lists 39 argument corpora that provide topic labels. Altogether 2,259 different labels have been assigned. They are concise descriptions of the main issues of an argument provided by the corpus authors. The labels possess the text register of the respective corpus: In essays, for instance, topics are usually thesis statements, while Wikipedia-derived corpora use article titles, and the topics of debate corpora include clichés such as “This house should”. Often, topic labels express a stance towards a target issue, e.g., “ban guns”. Five types of topic labels can be distinguished: concept, comparison of concepts, conclusion (includes claim and thesis), question, and imperative. We normalize the topic labels by converting all concepts to singular form, removing clichés, and dropping stance-indicating words such as “legalize”. Our normalization aims at retaining only the central target issue of a topic label and leads to 798 unique topic labels.

5.2 Mapping Topic Labels to Ontology Topics

Using the preprocessed topic labels as queries, we retrieve for each topic label the 50 top-most relevant topics in each level of the three ontologies. To facilitate the retrieval of ontology topics, we employ a BM25-weighted (Robertson et al., 2004) index of the concatenated documents for each topic. This enables us to narrow down the mapping of a topic label to a manageable size. Except for a handful of cases, 50 ontology topics can be retrieved for each topic label. The topic labels were then manually mapped to an ontology topic, if they form synonyms, or if the former is a subtopic of the latter—which thus indicates that all arguments in the corpus with that topic label are about the ontology topic. A topic label can thus be mapped to multiple ontology topics. For example, the topic label “plastic bottles” is mapped to “pollution” and “recycling” in Wikipedia Level 2.

5.3 Analysis of Topic Coverage

Table 3 shows general statistics of this mapping of corpora topic labels to ontology topics. Most of the topic labels (2,141 out of 2,259) are mapped to at least one Debatepedia topic while only 395 labels are mapped to WEF Level 2 topics. For Wikipedia Level 2, only 298 out of the 748 topics are actually covered by argument corpora. This first analysis already suggests that existing argument corpora often only cover a small subset of possible argumentative topics that people are trained to debate. For those topic labels that can be mapped, they belong on average to 2.78 topics in Debatepedia, 1.24 topics in Wikipedia Level 1, and 1.53 topics in WEF Level 1. As discussed in Section 4, topics in Debatepedia focus on the Western culture and are easily accessible, whereas topics in WEF require in-depth domain knowledge and have more global relevance. The broad coverage of Debatepedia’s topics indicates that argument corpora focus on common, widely discussed topics rather than global issues or those that need domain knowledge.

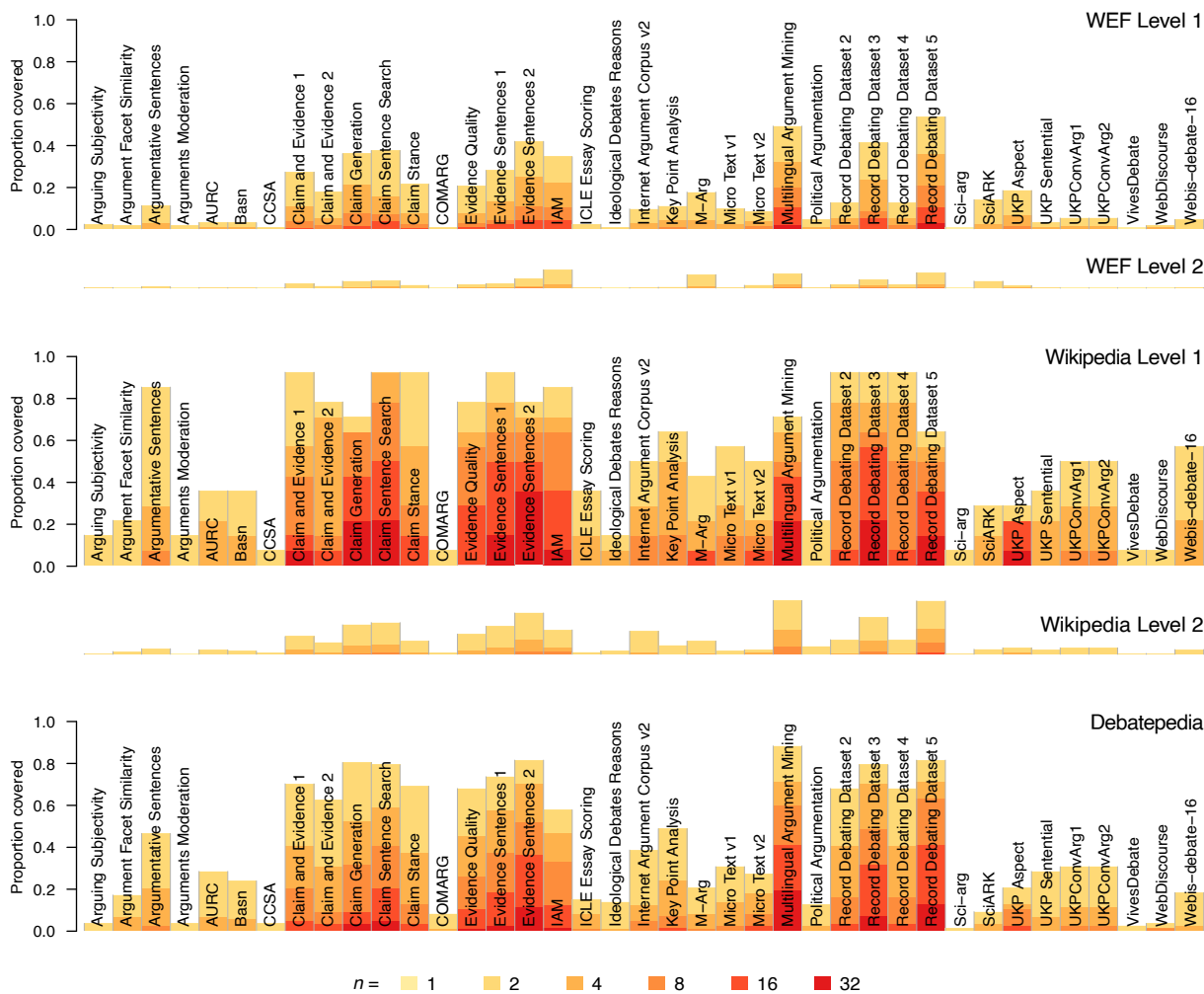


Figure 2: Proportion of ontology topics covered by at least n corpus topics (per ontology level and per corpus).

For a more fine-grained analysis, Figure 2 illustrates the differences regarding the number of ontology topics covered by a corpus: While topics in Wikipedia Level 1 are covered well by some argument corpora, topics in Wikipedia and WEF Level 2 are covered only marginally. Note that topic coverage varies significantly between the corpora: the Claim Sentence Search dataset’s topics cover 93% of the Wikipedia Level 1 topics, while the Ideological Debates Reasons dataset covers only 14%. The colors show the topic granularity of the corpus; especially the Record Debating Dataset 3 dataset is fine-grained: as the highest value, 36 of its topics are mapped to the Wikipedia Level 1 category “Politics and Economics”.

Figure 3 shows how the set of the units of the 39 labeled corpora distribute over the top-matching topics in Debatepedia, Wikipedia Level 1, and WEF Level 1. Distributions over Level 2 are omitted for brevity and can be found in Figure 4 in the Appendix. The distribution is significantly skewed:

while the top ten topics in Debatepedia are matched by 354,811 to 138,407 corpora units, the top ten topics in WEF Level 1 are matched by 344,345 to 28,725 corpora units. This supports our finding that the corpora cover easily accessible topics (e.g., “Media and Entertainment” and “Society”).

6 Unit Categorization

The previous analysis assesses argument corpora which contain topic labels. About a third of the argument corpora do not. As a heuristic step to assessing their topic coverage, we map the ontology topics for a unit (Table 1) in an argument corpus by treating the unit as a (long) query in a standard information retrieval setup, where ontology topics are the retrieval targets. The documents categorized into each topic have been concatenated and used as the topic’s representation. Though the documents associated with a topic are not necessarily argumentative, they cover the salient topic aspects.

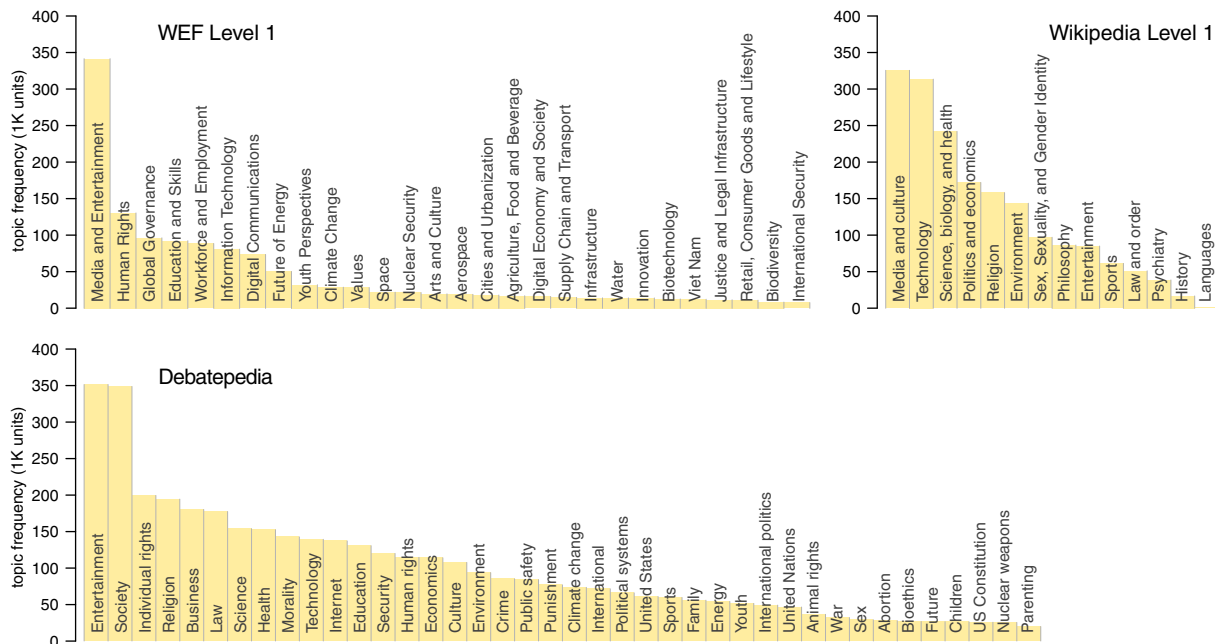


Figure 3: Distribution of corpora units over the top matching topics in an ontology (39 labeled corpora).

Ontology	Acquired ontologies (Section 4)			Topic coverage (Section 5)				Unit categorization (Section 6)												
	Topics	Topic statistics		Mapped topic labels	Covered ontology topics			Direct match			Semantic interpretation			Text2vec-SI						
		Authors	Docs		Tokens	All	Min	Mean	Max	P	R	F	Policy	P	R	F	Policy	P	R	F
WEF L1	137	334.1	940.7	490,576.6	1,339	92	1	1.53	13	0.38	0.23	0.29	$k = 12$	0.22	0.75	0.34	$k = 7$	0.19	0.53	0.28
WEF L2	822	216.8	550.3	310,229.7	395	154	1	1.56	22	0.59	0.11	0.19	$k = 30$	0.21	0.68	0.32	$\theta = 0.93$	0.15	0.49	0.23
WP L1	14	78,013.7	68.0	339,088.0	1,647	14	1	1.24	3	0.12	0.04	0.06	$k = 3$	0.32	0.65	0.43	$k = 2$	0.41	0.55	0.47
WP L2	748	1,929.5	1.0	6,149.1	1,560	298	1	1.80	16	0.47	0.34	0.40	$\theta = 0.05$	0.54	0.64	0.59	$\theta = 0.89$	0.22	0.52	0.31
DP	89	145.0	61.7	84,787.6	2,141	88	1	2.78	10	0.49	0.37	0.42	$\theta = 0.02$	0.52	0.61	0.56	$k = 23$	0.36	0.80	0.50

Table 3: Statistics for each topic ontology level: for topics and topic documents (Section 4), Count of mapped topic labels of the analyzed corpora for each ontology level, Count of all covered ontology topics by the topic labels and the min, max, and mean count of covered ontology topics per topic label (Section 5), and the effectiveness of the approaches and baseline in unit categorization (in terms of precision, recall, and F_1 -score) (Section 6).

To retrieve topics for a corpus unit, we implement and evaluate the following approaches: Semantic Interpretation (SI) and SI with Text Embeddings (Text2vec-SI). The Semantic interpretation approach computes the semantic similarity of a unit and a topic as follows: it uses the cosine similarity of the TF-IDF vectors for the unit and the concatenated topic’s documents. This corresponds to the semantic interpretation step that is at the core of the well-known ESA model (Gabrilovich and Markovitch, 2007). Text2vec-SI calculates the similarity of topics and corpus units using BERT embeddings (Devlin et al., 2018). Following common practice, we take the dimension-wise average of the word embeddings for all tokens in the text.⁸ We tried other embeddings and approaches that performed similarly. The results of these approaches

⁸For efficiency, we limited the embeddings to 10,000 randomly sampled sentences for the topics that had more sentences associated with them.

can be found in the appendix. As a baseline, we implement a direct match approach, which assigns a unit an ontology topic if the topic’s text appears in the unit text (ignoring case).

For evaluation, we collect 34,638 pooled query relevance judgments (0.53 inter-annotator agreement as per Krippendorff’s α) on 104 randomly selected argument units as queries from 26 corpora. The annotation process is detailed in the Appendix.

Based on the similarity scores of the approaches, we derive Boolean labels that indicate whether a unit is or is not about one of the ontologies’ topics using two policies. The *threshold* policy labels a unit as about a topic if their similarity is above a threshold θ . The *top-k* policy labels a unit as about a topic if the topic is among the top- k topics with the highest similarity to the unit. We report the parameter of the policy that achieved the highest F_1 -score on the pooled judgments for each approach.

Table 3 shows the results of this evaluation. The baseline produces different results across ontologies—it performs poorly for both the abstract topics in Wikipedia Level 1 and the specific topics in WEF Level 2. The semantic interpretation approach clearly outperforms the baseline for all ontologies in terms of the F_1 -score. The Text2vec-SI approach outperforms the baseline and the semantic interpretation on abstract topics (Wikipedia Level 1), but its effectiveness is below that of the semantic interpretation approach on the other ontology levels.

7 Conclusion

The computational argumentation community risks topic bias in its approaches if the representativeness of topics in future corpora is not ensured. Achieving topic coverage is complicated by the fact that the landscape of controversial topics has not yet been well explored, and that there are no widely accepted ontologies for argument topics. In this paper, we venture into this future by mapping the landscape of argument topics and making it accessible for corpus construction and experimental design. We have identified three authoritative sources of ontological knowledge related to argument topics that provide an initial foundation for The Argument Ontology (TAO). For each source ontology, we evaluate the topic coverage of 39 argument corpora labeled with topics by matching the labels with the topics of the ontologies. To evaluate the topic coverage of corpora without topic labels, we develop an approach to identify the ontology topics of an argumentative text and achieve an F_1 of 0.59.

Our analyses show that the topic coverage of existing argument corpora is both limited to a subset of the topics of the ontologies and skewed. Most topics that require expertise, such as mental health, philosophy, or international security, are treated only peripherally in argumentation corpora. Therefore, existing argumentation technologies are more suited to teaching people how to construct arguments in general than to helping them make decisions about such and similarly complex topics. For the development of robust argumentation technologies, corpora need to be carefully drawn from a specific domain to allow for reliable experiments and the development of generalizable classifiers.

Future work for further development of TAO consists mainly of further surveying the argument topic landscape and unifying the various available

ontologies. In addition to “is part of” relationships between topics, other relationship types can also be considered to build an argument topic knowledge base. However, our first version of TAO and our analyses can already help in selecting arguments for future corpus construction and model training.

Limitations

The three topic ontologies we used to evaluate topic coverage of argument corpora are from authoritative sources. Nevertheless, they probably do not cover all possible controversial topics relevant to argumentation (e.g., topics concerning private life). A comprehensive coverage of controversial topics in breadth and depth will likely remain an unattainable goal. Moreover, unifying the three thematic ontologies into a standard ontology is still an open problem given the many possible interpretations and relationships between the topics.

Another limitation is the moderate effectiveness achieved by our approaches for categorizing argument units. This is the case due to the large collection of controversial topics (about 748 for Wikipedia). Future research can be improved by using the structure of the topic ontology and hierarchical classifiers. Furthermore, it is also unclear whether the topic dependence of argumentation approaches decreases with increasing corpus size.

Ethics Statement

Our goal is to investigate whether and to what extent existing argumentation corpora are topic biased. This serves to critically examine the state of the art. However, we by no means want to give the impression that previous corpus authors lack ambition or diligence. Rather, the opposite is the case. The number of corpora that have been created in the last decade shows that the community is aware of the fact that not all areas of the argumentation landscape have been covered yet, and is therefore doing its utmost to explore it further. In a dynamic and rapidly growing research field, standards are usually developed in parallel with contributions, not in advance. Our research may therefore contribute to the further standardization of the corpus linguistics of argumentation.

The manual annotation of arguments and topics was done by expert annotators of our research groups. They were compensated fairly under German law. No personal data was collected.

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A Appendix

A.1 Mapping Topic Labels to Level 2 Topics

For completeness, Figure 4 shows the two graphs that are omitted from Figure 3 of the paper as their fine-grained topics are less relevant for the discussion in Section 5.3.

A.2 Annotation Procedure for Unit Categorization

In order to assess the effectiveness of the approaches and baseline outlined in the paper, we employ a pooled evaluation, as it is standard for information retrieval evaluations, where there are too many instances for a complete manual annotation. We randomly sampled four units from 26 corpora, which were all annotated by three expert annotators. The annotators were instructed to label a topic as about the unit if they could imagine a discussion on the topic for which the unit would be relevant. For each unit, we annotated for aboutness only those topics which are among the five topics with the highest similarity to this unit according to at least one of the approaches. The employed assessment interface (see Figure 5) shows the unit (top left), the current topic (top right), as well as all topics in the pool for that unit (bottom; the current topic is marked blue, whereas already annotated topics are marked green (about) and red (not about)). The same interface has been used for the topic label annotations.

To reduce biases, both the units and the topics were shown in a different and random order to each assessor. The annotation took about 40 hours. The annotation process resulted in an inter-annotator agreement of 0.53 in terms of Krippendorff’s α and produced a total of 34,638 annotations of topic-unit pairs, about 2% of what would have been needed for a complete annotation.

A.3 Additional Unit Categorization Approaches

In addition to the approaches listed in Section 6 we used additional approaches and a baseline which we list here. The additional baseline randomly classifies corpora units as per the prior topic probability of each ontology level.

SI with Word Embeddings (W2V-SI) Adapted from Dense-ESA (Song and Roth, 2015), this approach represents each token by its TFIDF-weighted Word2vec embedding vector, and uses the highest cosine similarity between two vectors, one from each text, as the semantic similarity. To limit this quadratic effort, we use only the 100 tokens of each text with the highest TFIDF-score.

Text2vec-SI As a variant for BERT (Devlin et al., 2018), we embedded the ontology documents and corpora units using ELMo (Peters et al., 2018).

(a) Debatepedia		(b) Wikipedia Level 2	
Topic	Covering units	Topic	Covering units
Islam and the West	50	Irredentism	2
Islam	50	American Civil Liberties Union	2
2008/2009 economic crisis	66	Hezbollah	2
European Union	93	Esports	3
Middle East	134	Separation of church and state	4
Prison	180	Birth defect	5
China	254	Quebec	5
Terrorism	521	Rape	6
Latin America	528	Hurricane Katrina	6
HIV/AIDS	579	Crime in the United States	6
Church and state	654	Sexual abuse	6
US legislation	845	Sex offender	6
Corruption	1,065	Pacifism	7
Welfare	1,369	Cyberstalking	7
Africa	1,435	Brexit	9
Israeli-Palestinian conflict	1,541	Economy of Japan	12
Life and death	1,598	USA PATRIOT Act	12
Languages	1,808	Playboy Magazine	15
Privacy	2,312	Super Bowl XXXVIII	19
Bush administration	2,702	Sexual harassment	20
Iraq	2,720	Media bias	29
Weapons proliferation	2,790	Culture war	35
Third world	3,208	Hip hop culture	35
Taxes	3,562	European culture	35
Disease	3,619	Anime	40
Obama administration	3,765	East Germany	46
Conflict	4,950	Communist state	46
Asia	5,016	Communist Party of China	46
Immigration	5,170	Communist government	46
Race	6,086	Communism	46

(c) World Economic Forum Level 1		(d) World Economic Forum Level 2	
Topic	Covering units	Topic	Covering units
Agile Governance	1	Healthcare Human Capital	2
Institutional Investors	1	Environmentally-Sustainable Consumerism	2
Digital Identity	7	Sustainable Consumption	3
United Kingdom	9	Aquaculture	4
Mexico	12	Urbanization and Circular Practices	5
Behavioural Sciences	15	Accelerating Sustainability	5
Canada	26	Forest Landscape Restoration	5
Corruption	31	Stabilizing Economies, Keeping Protections	10
Illicit Economy	54	The Social Cost of Carbon	13
Future of Economic Progress	66	The Trump Presidency	20
Forests	74	New Leadership	20
European Union	93	Canada and Sustainable Energy	21
Real Estate	132	Economic Institutions	34
Insurance and Asset Management	142	Outbound and Long-Term Investment	34
Humanitarian Action	232	Deepening Interdependence	34
3D Printing	254	Digital Trade	34
China	258	Geopolitical and Geo-economic Recalibration	34
Drones	260	Pricing Climate into Finance	34
Internet Governance	268	Trade and Investment	34
Cybersecurity	298	Trade and the Environment	34
Internet of Things	320	Transnational Actors	34
Precision Medicine	339	Economic Integration	34
Oceans	345	Healthcare Technology	47
Latin America	516	Geo-strategic Competition	54
Financial and Monetary Systems	608	Energy-Related Emission Reduction	61
Arctic	614	Energy Finance and Investment	61
Banking and Capital Markets	634	Energy Access	61
Mining and Metals	656	Environmental Footprint	61
Public Finance and Social Protection	778	Electricity Decentralization	61
Middle East and North Africa	928	Electricity System Integration	61

Table 4: For each ontology except Wikipedia Level 1 the 30 topics with the least (but at least 1) units from the argument corpora covering them. All 14 topics of Wikipedia Level 1 are covered well and thus omitted here.

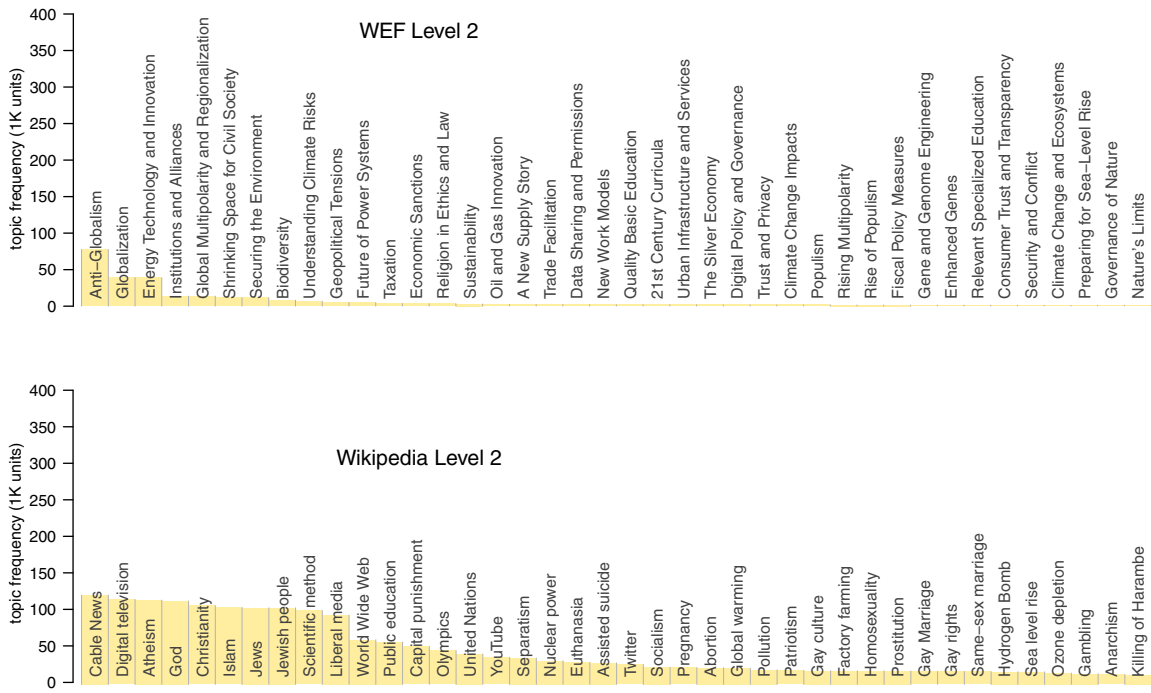


Figure 4: Omitted graphs from Figure 3, Section 5.3

Table 5 lists the results of all approaches for all thresholds and ranks.

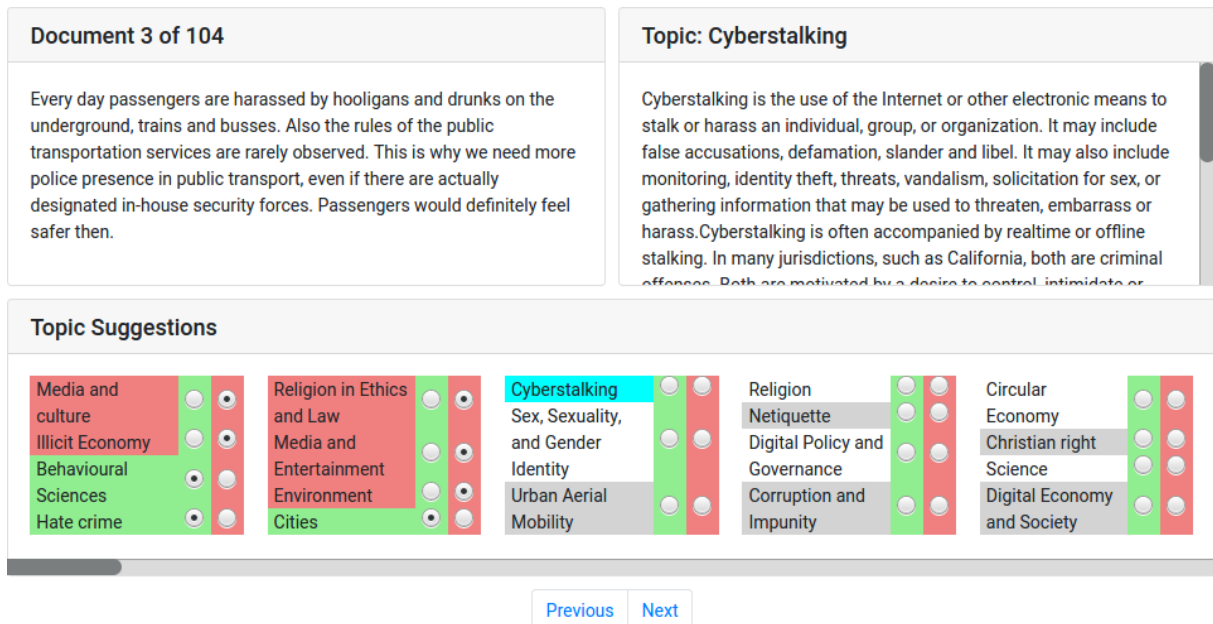


Figure 5: Assessment interface for topic labeling.

Approach	World Economic Forum						Wikipedia						Debatepedia							
	Level 1			Level 2			Level 1			Level 2			P		R		F			
Baselines	P	R	F	P	R	F	P	R	F	P	R	F	P	R	F	P	R	F		
Random	0.02	0.02	0.02	0.01	0.01	0.01	0.11	0.11	0.11	0.01	0.01	0.01	0.07	0.07	0.07					
Direct match	0.38	0.23	0.29	0.59	0.11	0.19	0.12	0.04	0.06	0.47	0.34	0.40	0.49	0.37	0.42					
By threshold	θ	P	R	F	θ	P	R	F	θ	P	R	F	θ	P	R	F	P	R	F	
Semantic interpretation	0.02	0.18	0.63	0.28	0.02	0.20	0.58	0.29	0.01	0.29	0.51	0.37	0.05	0.54	0.64	0.59	0.02	0.52	0.61	0.56
W2V-SI	0.20	0.14	0.63	0.23	0.16	0.13	0.63	0.21	0.10	0.12	0.55	0.20	0.11	0.18	0.69	0.29	0.07	0.29	0.81	0.43
Text2vec-SI _{ELMo}	0.87	0.18	0.32	0.23	0.80	0.13	0.65	0.22	0.74	0.23	0.45	0.31	0.76	0.25	0.45	0.32	0.87	0.47	0.46	0.47
Text2vec-SI _{BERT}	0.94	0.19	0.39	0.25	0.93	0.15	0.49	0.23	0.92	0.36	0.22	0.27	0.89	0.22	0.52	0.31	0.92	0.36	0.64	0.46
By rank	k	P	R	F	k	P	R	F	k	P	R	F	k	P	R	F	k	P	R	F
Semantic interpretation	12	0.22	0.75	0.34	30	0.21	0.68	0.32	3	0.32	0.65	0.43	12	0.39	0.70	0.50	19	0.43	0.78	0.56
W2V-SI	83	0.13	0.94	0.24	439	0.12	0.77	0.21	14	0.11	1.00	0.20	290	0.16	0.77	0.27	61	0.27	0.86	0.42
Text2vec-SI _{ELMo}	4	0.25	0.44	0.32	42	0.13	0.68	0.23	2	0.39	0.53	0.45	46	0.18	0.64	0.28	13	0.43	0.71	0.54
Text2vec-SI _{BERT}	7	0.19	0.53	0.28	80	0.11	0.66	0.20	2	0.41	0.55	0.47	80	0.17	0.70	0.28	23	0.36	0.80	0.50

Table 5: Performance of semantic interpretation approaches in human evaluation for each topic ontology level in terms of precision (P), recall (R), and F_1 -score (F) for the “aboutness” label. For methods other than the baselines the table shows the values for both the similarity threshold θ and rank k that lead to the highest F_1 -score respectively. The best F_1 -scores for each ontology level are marked bold.