Addressing Controversial Topics in Search Engines

The Oral Exam of

Yamen Ajjour

To Obtain the Academic Degree of

Dr. rer. nat.

Intelligent Information Systems
Bauhaus-University Weimar

Addressing Controversial Topics in Search Engines

- ❑ Motivation
- ❑ Identifying argumentative questions
- ❑ Topic bias in argument corpora
- ❑ Identifying argument frames
- ❑ Conclusion

Motivation

Use cases where good arguments are needed.

Student

Lawyer

Politician

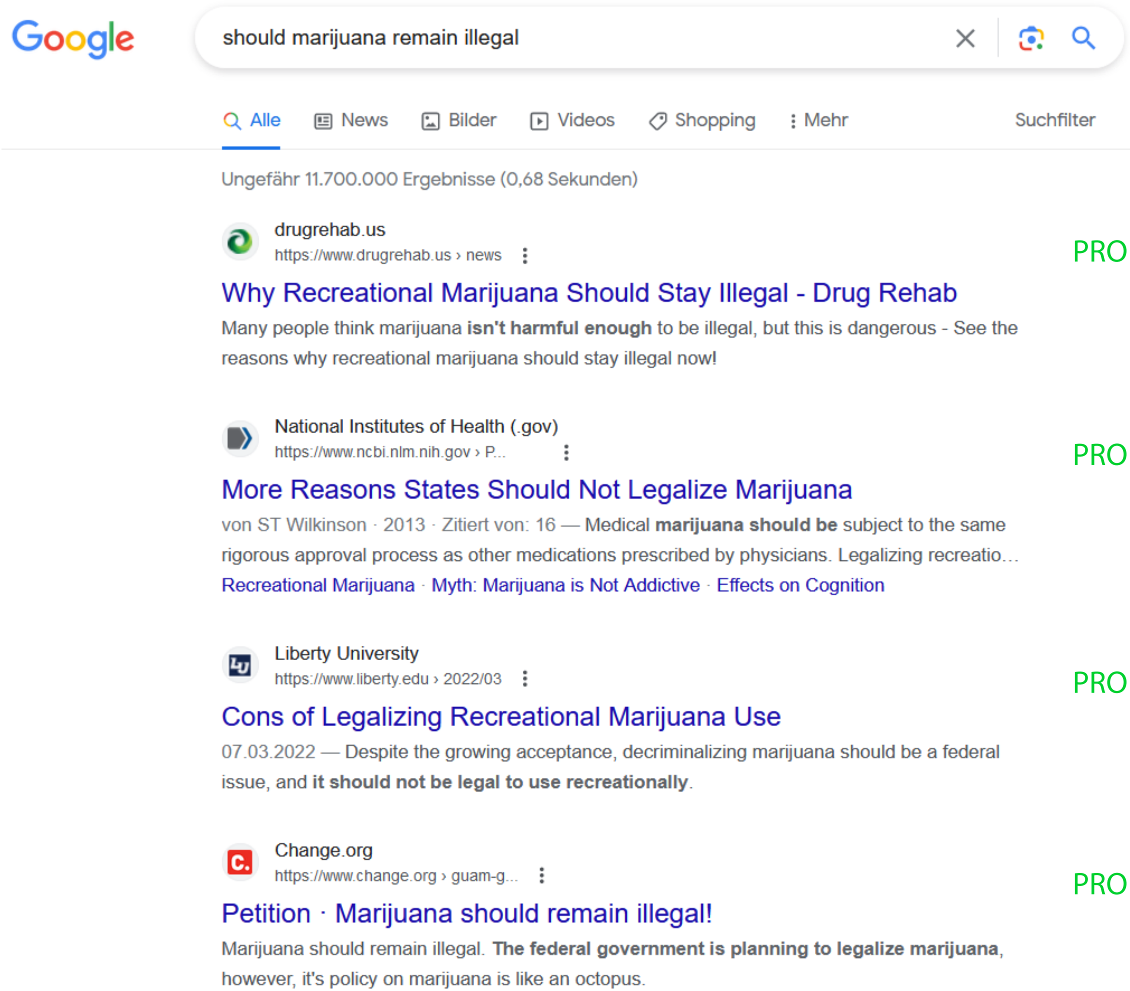
Marketing Company

Motivation

Search engines are good at answering factual questions.

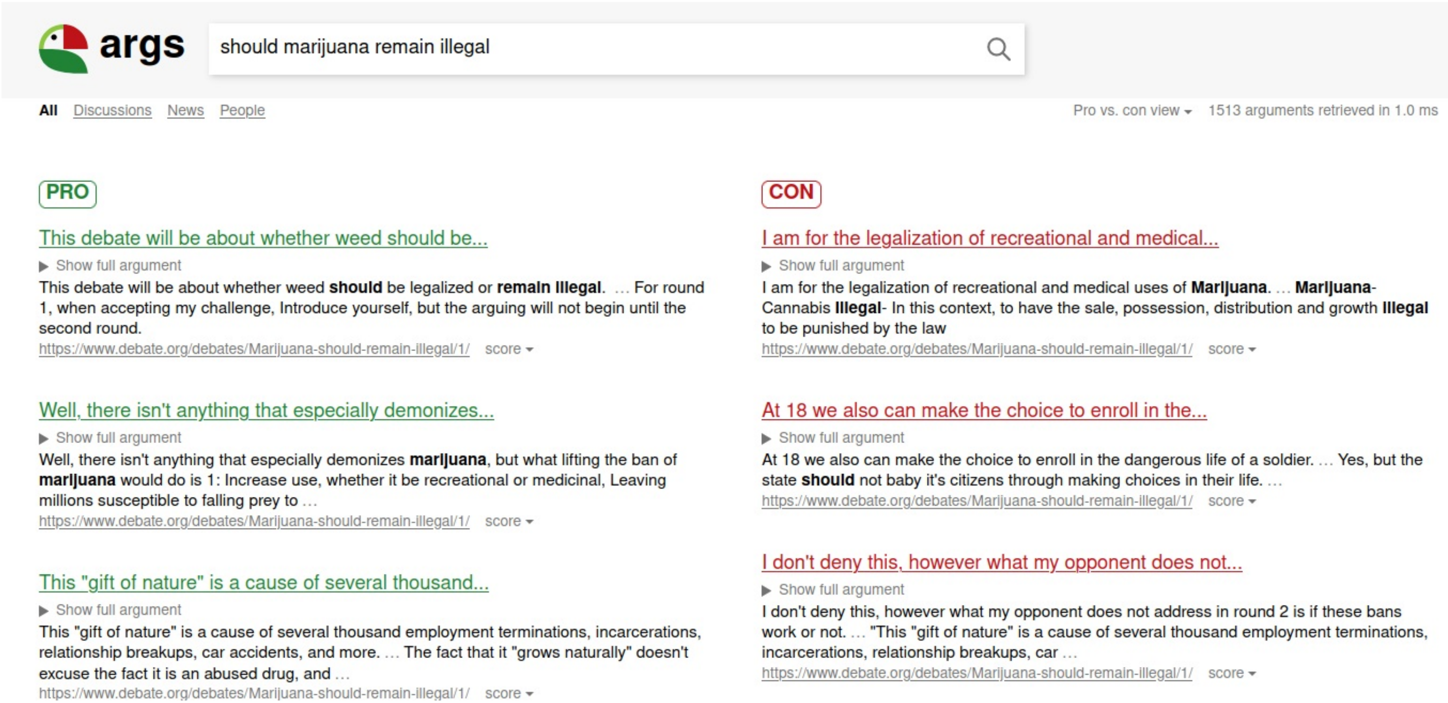
Motivation

Search engines struggle at delivering all perspectives on controversial topics.



Motivation

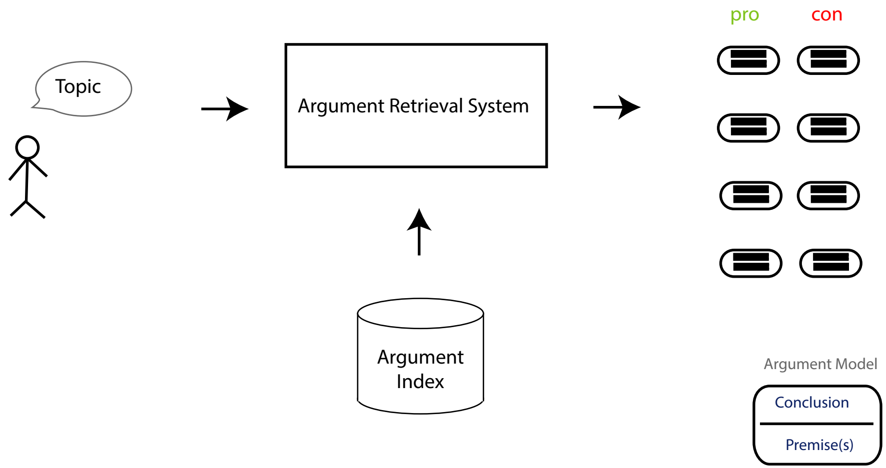
Argument retrieval systems retrieve pro and con arguments for a query.



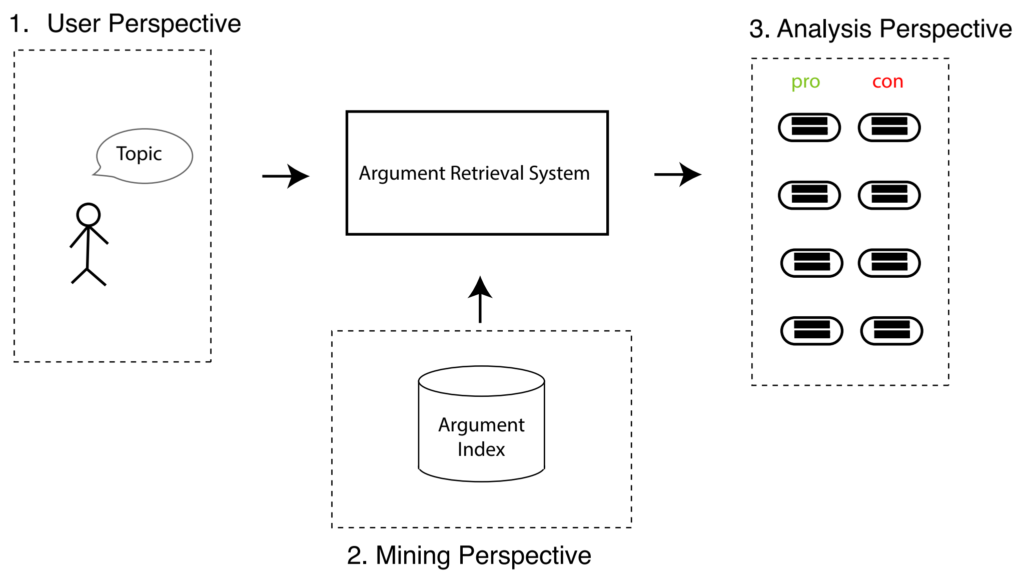
Argument retrieval systems promote:

- Transparency
- Explainability

Contributions



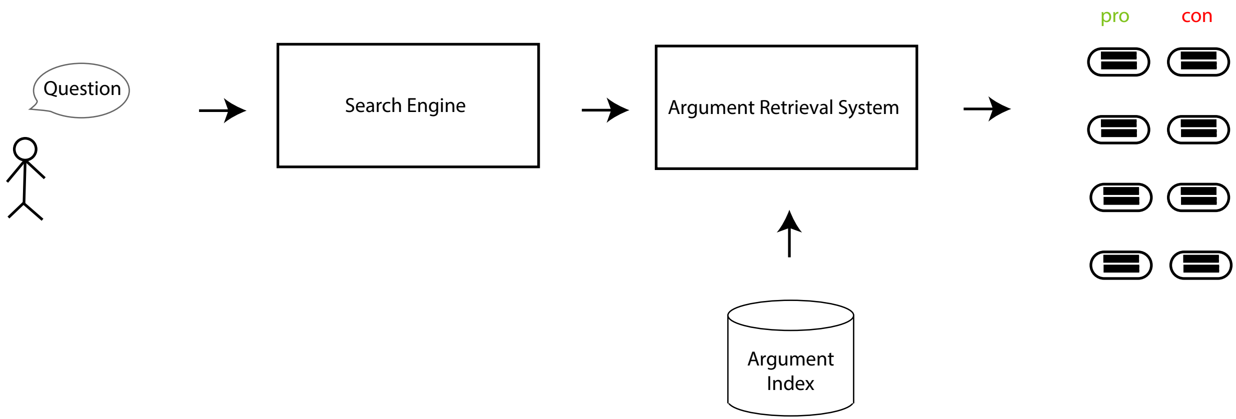
Contributions



1. Identifying argumentative questions in web search engines logs
2. Assessing topic bias in argument corpora
3. Frame identification of arguments

Contributions

Goal: Integrating argument retrieval technology in web search engines.



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RQ1. How to identify questions that look for arguments in the query stream of a search engine?

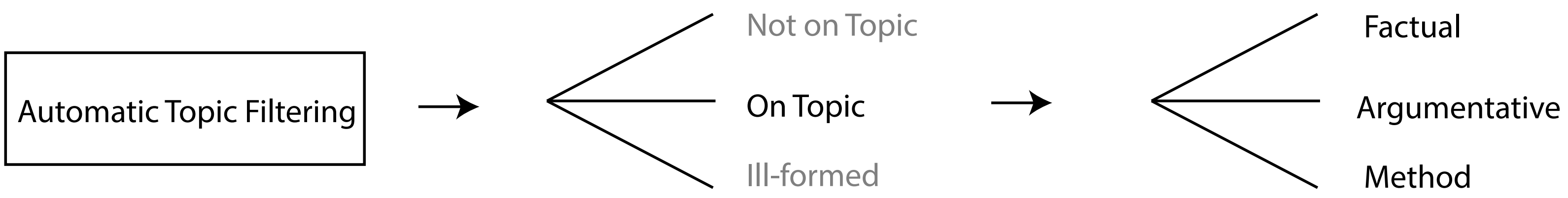
1) Identifying Argumentative Questions

Preparing a Russian Questions Dataset

1. Filter from Yandex logs 4.5 million Russian questions on 19 controversial topic

   Example topics: Putin, Navalny, Nord Stream, and marijuana

2. Sample 54,850 questions and annotate them with the annotation scheme:



1) Identifying Argumentative Questions

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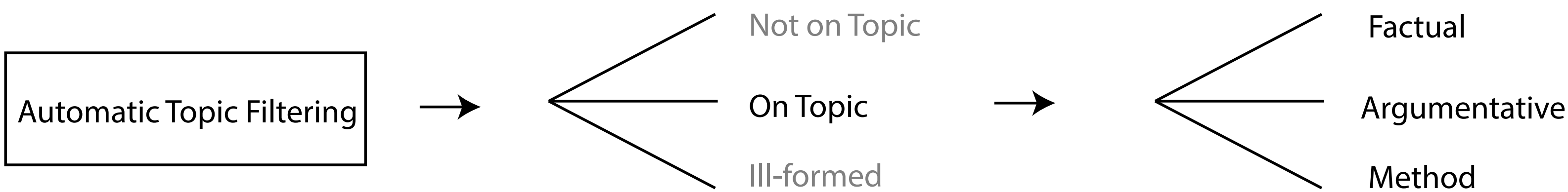


Statistics and Examples:

Question Type	Percentage	Count	Example
Factual	64%	25,332	Is marijuana legalized in Belgium?
Argumentative	28%	10,982	Will the president legalize marijuana?
Method	8%	3,026	How to use medical marijuana?

1) Identifying Argumentative Questions

Analysis of Questions Characteristics

Comparison of argumentative questions with factual and method questions using lexical and syntactical patterns.[1]

Question Type	Starts with wh-words (except `why`)	Starts with `why`	Formed as yes/no	Asks for predictions	Asks for comparisons	Subject is personal pronoun	Others
Factual	65.7%	1.3%	7.2%	3.8%	3.2%	0.3%	18.5%
Argumentative	41.3%	20.7%	13.8%	8.2%	5.7%	3.8%	6.5%
Method	93.9%	0.4%	0.0%	0.6%	4.4%	0.4%	0.9%

Finding: Argumentative questions look for predictions and explicitly for reasons.

[1] Some question characteristics overlap (e.g., asks for predictions and asks for comparisons.)

1) Identifying Argumentative Questions

Question Type Classification

Developing classifiers to map questions to argumentative, factual or method.

Experimental setting is leave-one-topic-out: test on one topic after training on remaining topics.

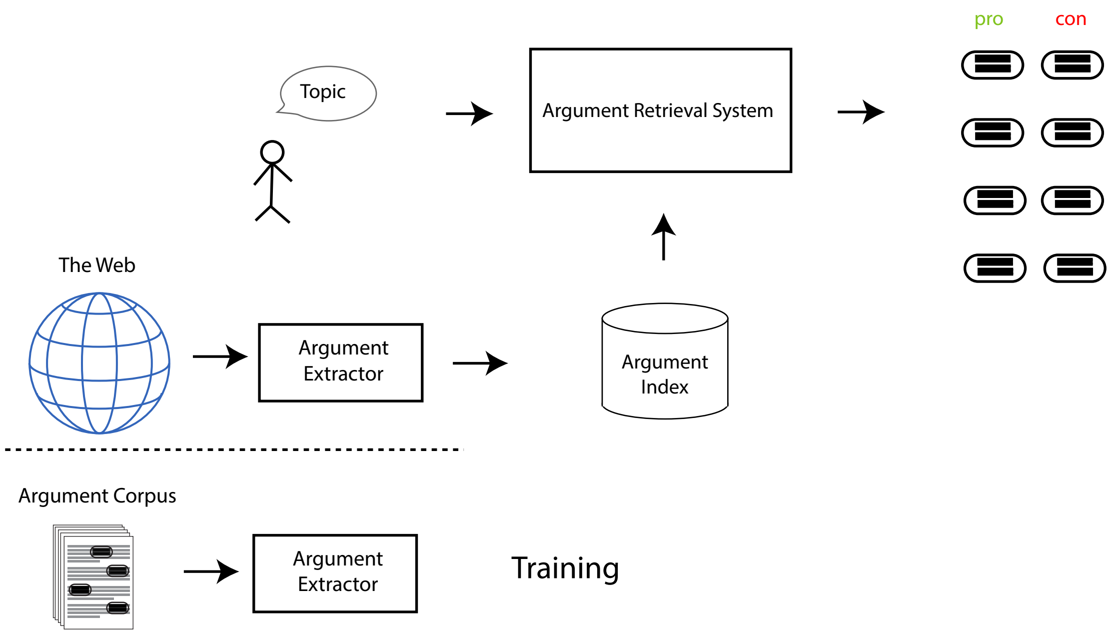
F1-score of the three question types and their macro average.

Classifier	Factual	Argumentative	Method	Macro
Majority Baseline	0.78	0.00	0.00	0.26
Logistic Regression	0.80	0.61	0.52	0.65
RuBERT	0.85	0.74	0.74	0.78

Finding: Identifying argumentative questions is feasible, even on unseen topics.

Contributions

Goal: Fostering the generalizability of argument mining approaches over topic.



1. Identifying argumentative questions in web search engines logs
2. Assessing topic bias in argument corpora
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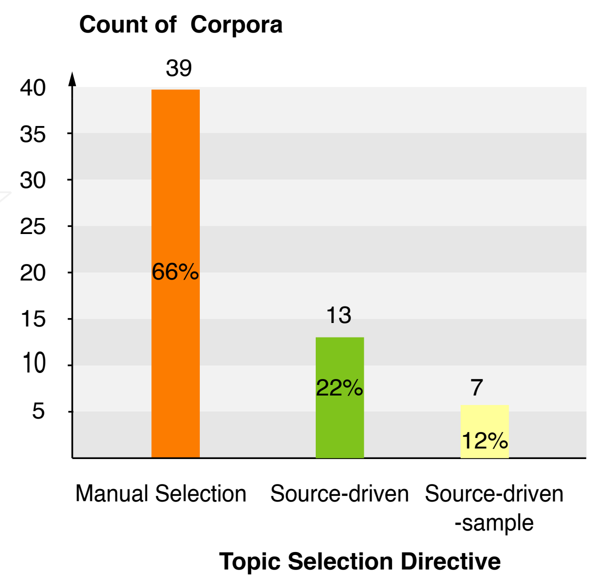
RQ2. How well do argument corpora represent controversial topics?

2) Topic Bias in Argument Corpora

Survey Regarding Topic Selection

A survey of 59 argument corpora shows that researchers take three approaches:

- Manual selection: choosing a set of topics manually
- Source-driven-greedy: a whole source is exploited
- Source-driven-sample: a source is sampled

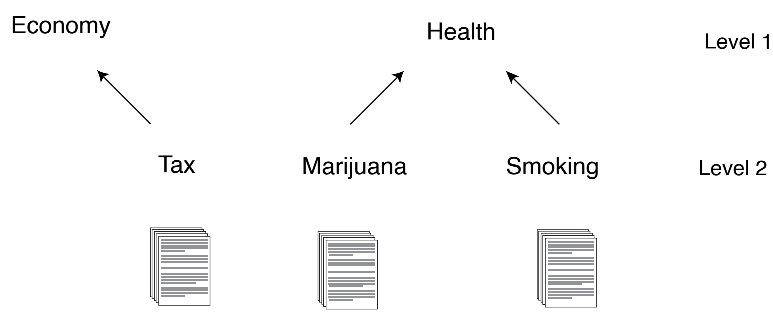


2) Topic Bias in Argument Corpora

Trustworthy Topic Ontologies

Topic ontology: a directed graph where

- Nodes are topics
- Edges indicate is part of relation: topics that are part of other topics are called subtopics.



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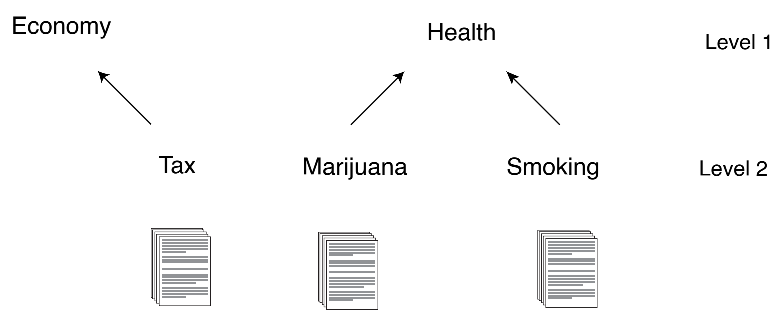

Three trustworthy topic ontologies with categorized documents

- World Economic Forum (WEF): global issues (mainly economical)
- Debatepedia: biased to western culture
- Wikipedia

2) Topic Bias in Argument Corpora

Trustworthy Topic Ontologies

Topic ontology: a directed graph where

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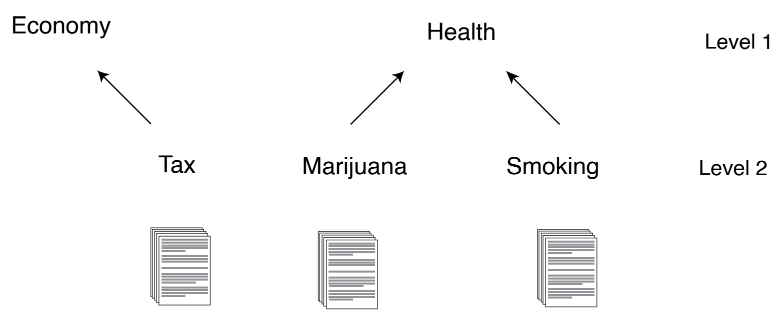


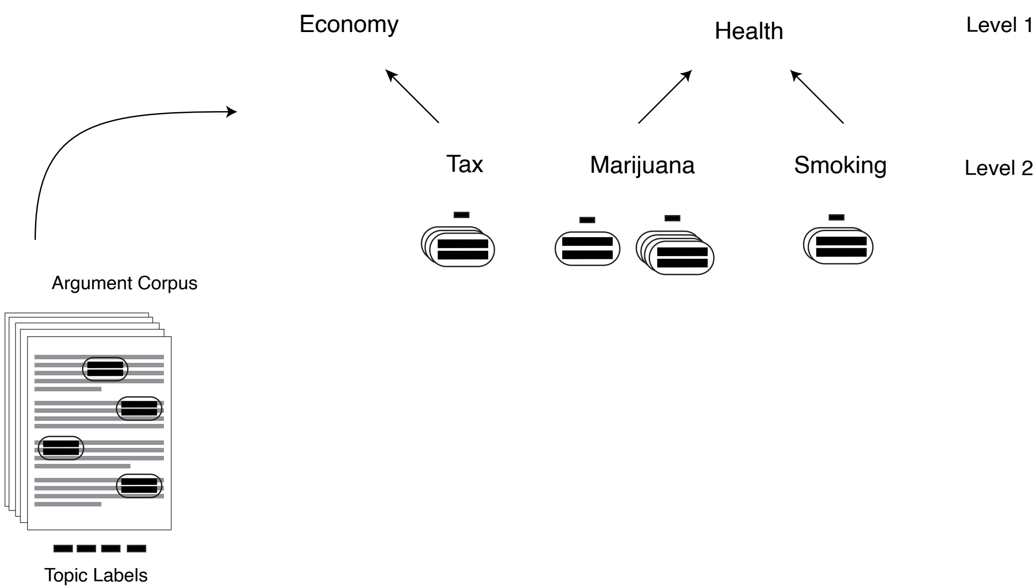
Ontology	Topics	Authors	Docs
World Economic Forum Level-1	137	334	940
World Economic Forum Level-2	822	217	550
Wikipedia Level-1	14	78,014	68
Wikipedia Level-2	748	1,930	1
Debatepedia	89	145	62

2) Topic Bias in Argument Corpora

Units Categorization

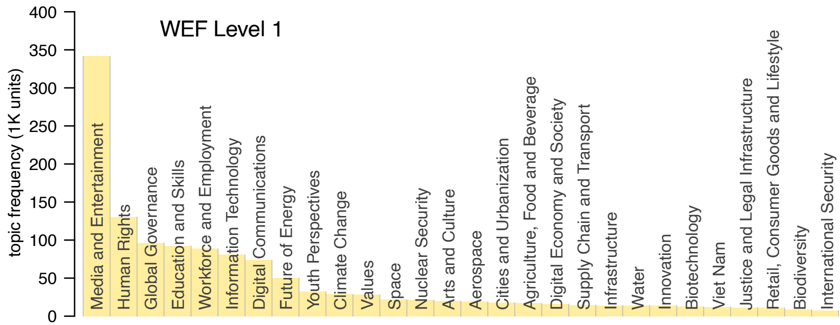
The units of 59 corpora are mapped to the three topic ontologies.

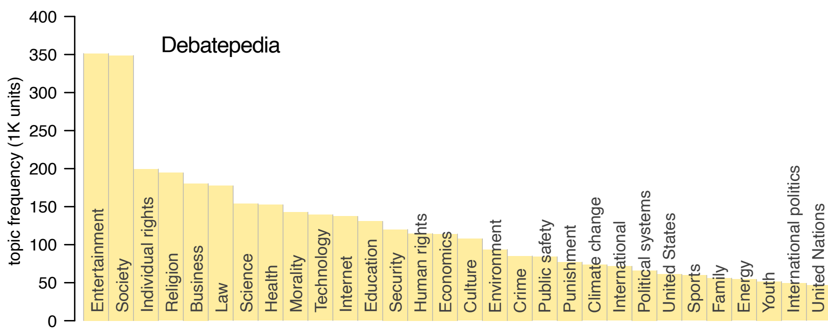
- Manual:
  mapping the topic labels of a corpus with synonymous or upper topics.
- Automatic:
  assessing the similarity between a unit and the documents of a topic.



2) Topic Bias in Argument Corpora

Topic Distribution (excerpt)



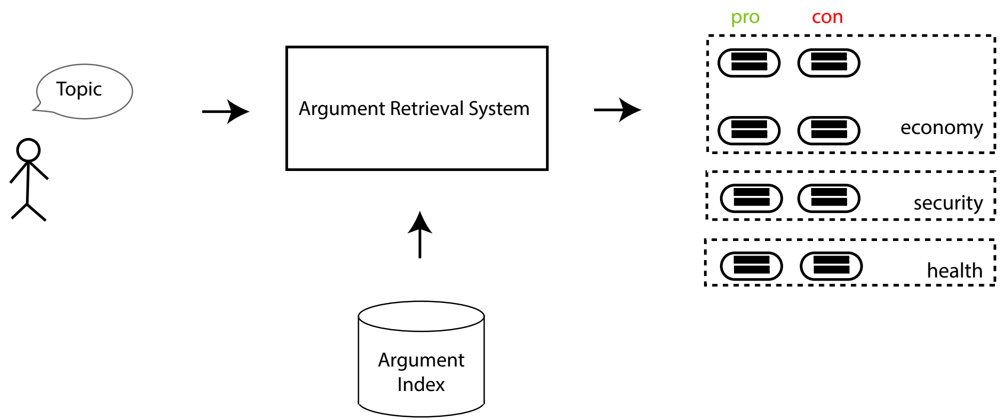


Findings:

- The topic distribution of existing argument corpora is skewed and concentrated around a small set of topics.
- Argument extractors built on these argument corpora might not be generalizable across topics.

Contributions

Goal: Enable users to select arguments that resonate with their audience.



1. Identifying argumentative questions in web search engines logs
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RQ3. How to identify the frames of an argument?

3) Frame Identification of Arguments

Introduction

- Framing is to emphasize a specific aspect of a topic while concealing others (Entman et al., 1993).

- A topic like nuclear energy can be framed according to its economical potential or environmental effect among others.

Frame 1: Environment

Frame 2 : Economy

3) Frame Identification of Arguments

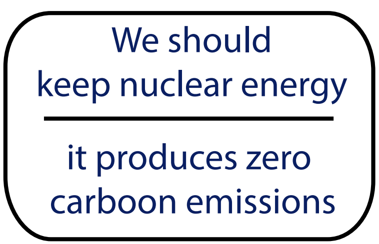
Introduction

- Framing is to emphasize a specific aspect of a topic while concealing others (Entman et al., 1993).

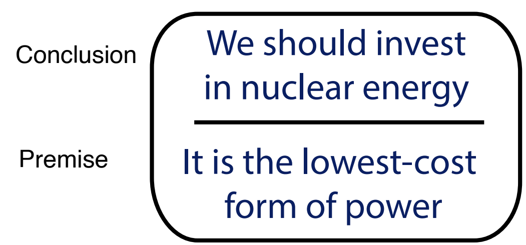
- A topic like nuclear energy can be framed according to its economical potential or environmental effect among others.

An argument frames a topic by emphasizing an aspect while rejecting others.

Examples:



Frame 1: Environment



Frame 2: Economy

3) Frame Identification of Arguments

Generic vs Topic-specific Frames

Examples of topic-specific frames:

Bill Clinton
is a bad president

Lewinksy scandal
lowered his credibility

Frame 1: Lewinksy Scandal

Bill Clinton
is a good president

NAFTA led to
thousands of jobs

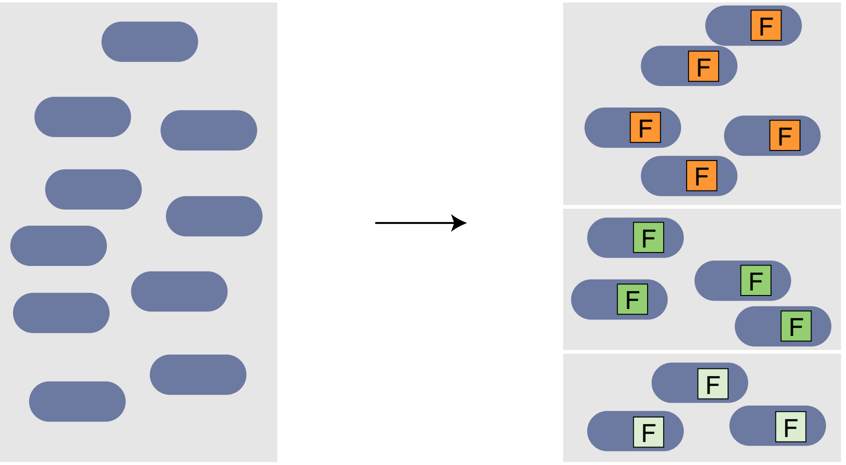
Frame 2: NAFTA

First argument frames dataset covering 467 topics.

Frame Type	Count of Frames	Count of Arguments
Generic	330	7,052
Topic-specific	1,293	5,274
All	1,623	12,326

3) Frame Identification of Arguments

Approach



Set of Arguments　　　　Frames

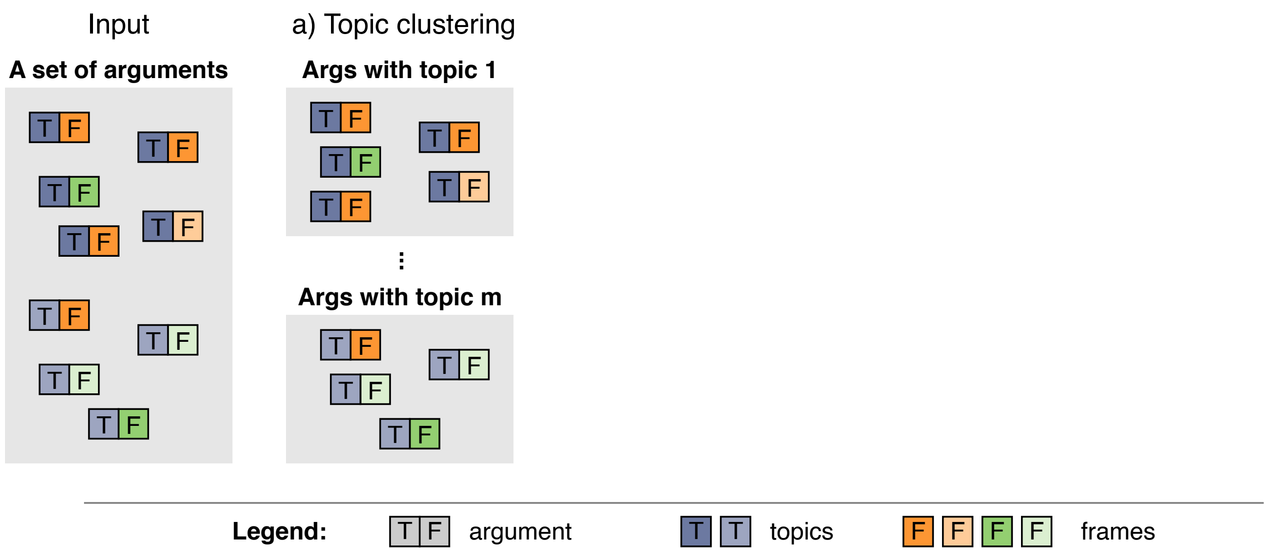
a) Topic Clustering

b) Topic Removal

c) Frame Clustering

3) Frame Identification of Arguments

Approach: a) Topic Clustering



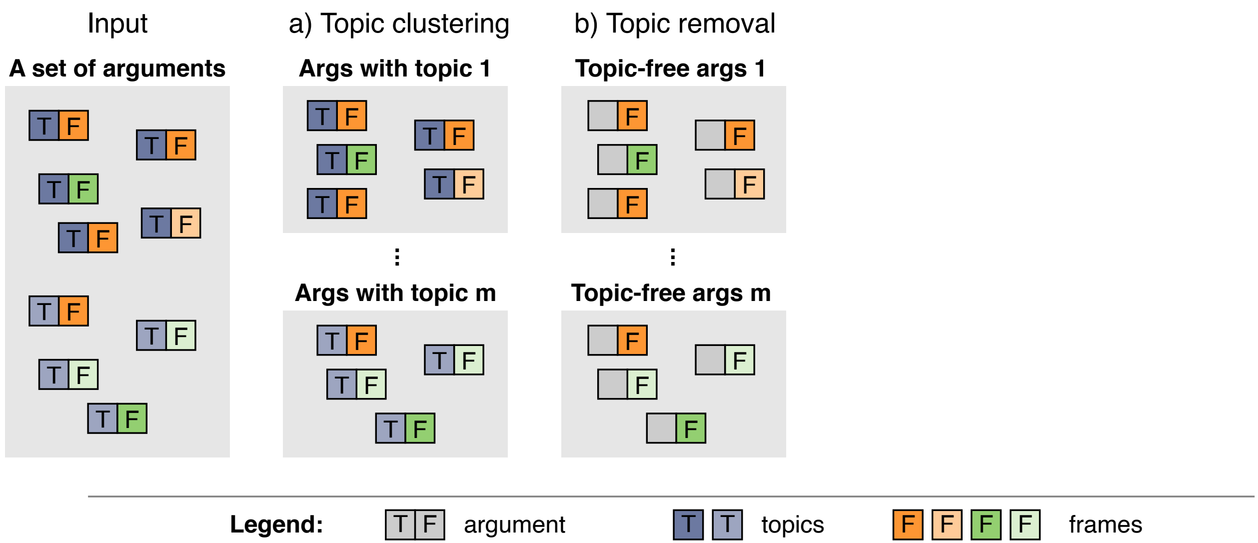
Semantic Spaces:

- TF-IDF
- Latent Semantic Analysis (LSA): a topic model that uses dimension reduction.

Clustering algorithm: K-means with euclidean distance.

3) Frame Identification of Arguments

Approach: b) Topic Removal



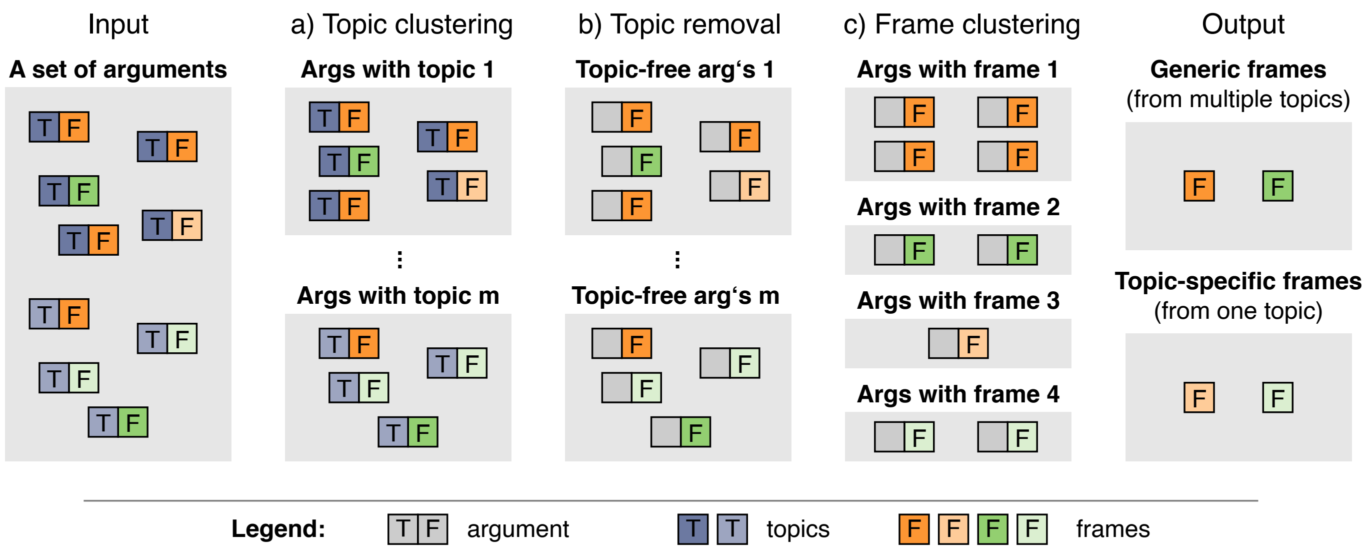
Two models for topic removal:

- Content-based removal:
  Remove tokens with high TF-IDF values in each topic cluster.

- Structure-based removal:
  Remove the conclusion of an argument.

3) Frame Identification of Arguments

Approach: c) Frame Clustering



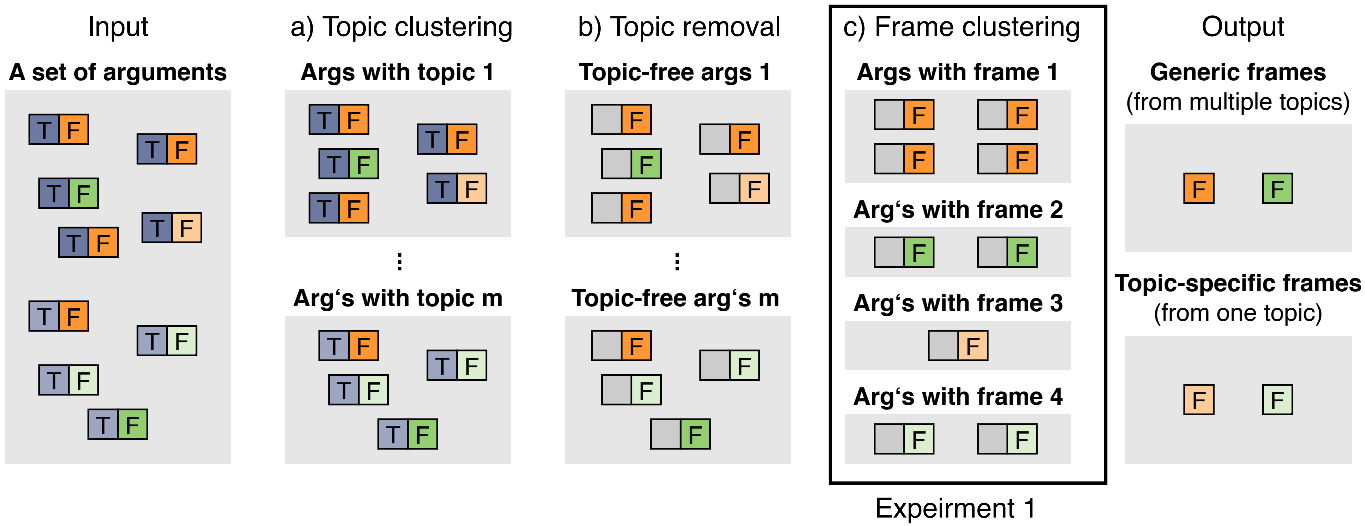
Semantic Spaces:

- TF-IDF
- LSA

Clustering algorithm: K-means with euclidean distance.

3) Frame Identification of Arguments

Experiments



- Topic Clustering
- Frame Clustering

3) Frame Identification of Arguments

Experiment results: Generic Frame Clustering

Clustering effectiveness in bcubed F1-score.

Semantic Space	**Topic Removal**	**Topic Clustering**	**Frame Clustering**
TF-IDF	No-removal	0.45	0.19
	Content-based	0.42	**0.28**
	Structure-based	0.17	0.26
LSA	No-removal	0.44	0.16
	Content-based	0.40	0.21
	Structure-based	0.25	**0.20**

- Removing topic-specific information helps identifying generic frames.
- Structure-based argument removal models is more effective at removing topic-information.

3) Frame Identification of Arguments

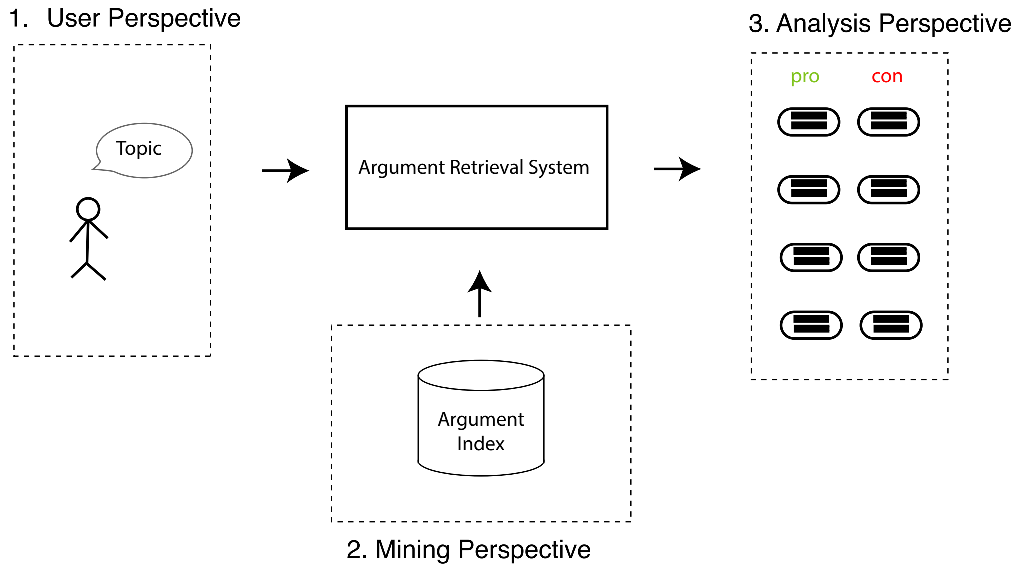
Experiment Results: Topic-specifc Frame Clustering

Clustering effectiveness in bcubed F1-score.

Semantic Space	Topic Removal	Topic Clustering	Frame Clustering
TF-IDF	No-removal	0.45	**0.48**
	Content-based	0.42	0.45
	Structure-based	0.17	0.45
LSA	No-removal	0.44	0.39
	Content-based	0.40	**0.47**
	Structure-based	0.25	0.46

- Removing topic-specific information helps identifying frames only in LSA space.
- Using TF-IDF semantic space without topic removal performs the best.

Conclusion: Research Questions



1. How to identify questions that look for arguments in the query stream of a search engine?
2. How well do argument corpora represent controversial topics?
3. How to identify the frames of an argument?

Conclusion

Contributions:

- Enabling search engines to identify and respond to questions that pertain to controversial topics and those that look for arguments.
- Method to quantify topic bias in argument corpora and resources to help researchers sample topics in a more representative way.
- A model and an approach for frames in argumentation.

Findings:

- Argumentative questions ask for predictions or reasons.
- The topic distribution of existing argument corpora is skewed and concentrated around a small set of topics.
- Identifying the topic of an argument and removing it helps identifying its frames.

Future Work

- User Perspective
  1. Exploiting session information (i.e., not only one question but a series of questions)
  2. Know more about the user intent (e.g., use case, audience, types of arguments).
- Mining Perspective
  1. Developing a unified topic ontology.
  2. Developing topic sampling strategies.
  3. Assessing topic-robustness of argument extractors.
- Analysis Perspective
  1. Detecting effective frames sequence from news articles.
  2. Generating frame labels based on argument clusters.

Topic Bias in Argument Corpora

Survey Regarding Topic Selection

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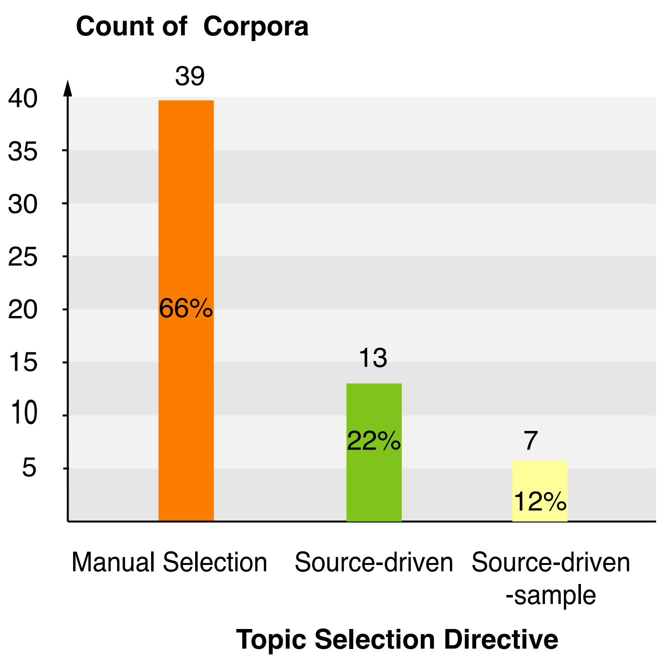
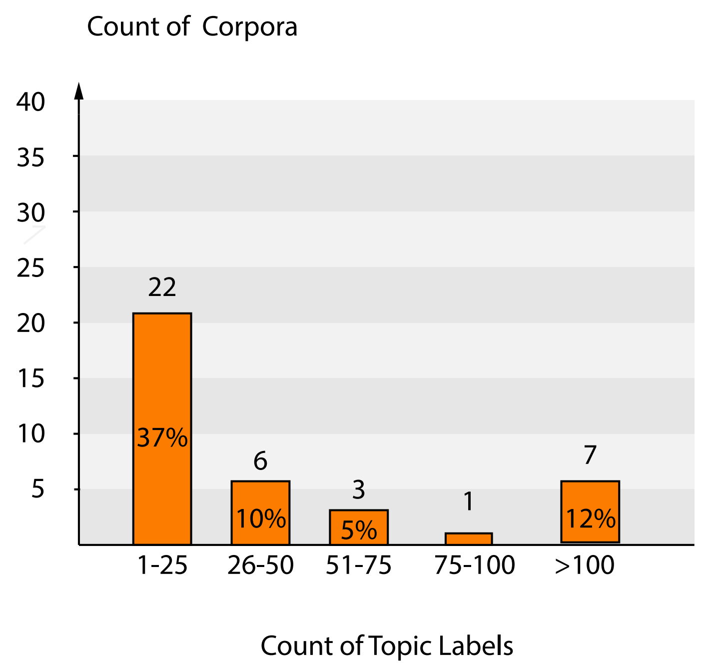




Automatic Corpora Unit Categorization

About a third of argument corpora do not provide corpora topic labels and hence is not included in the previous analysis.

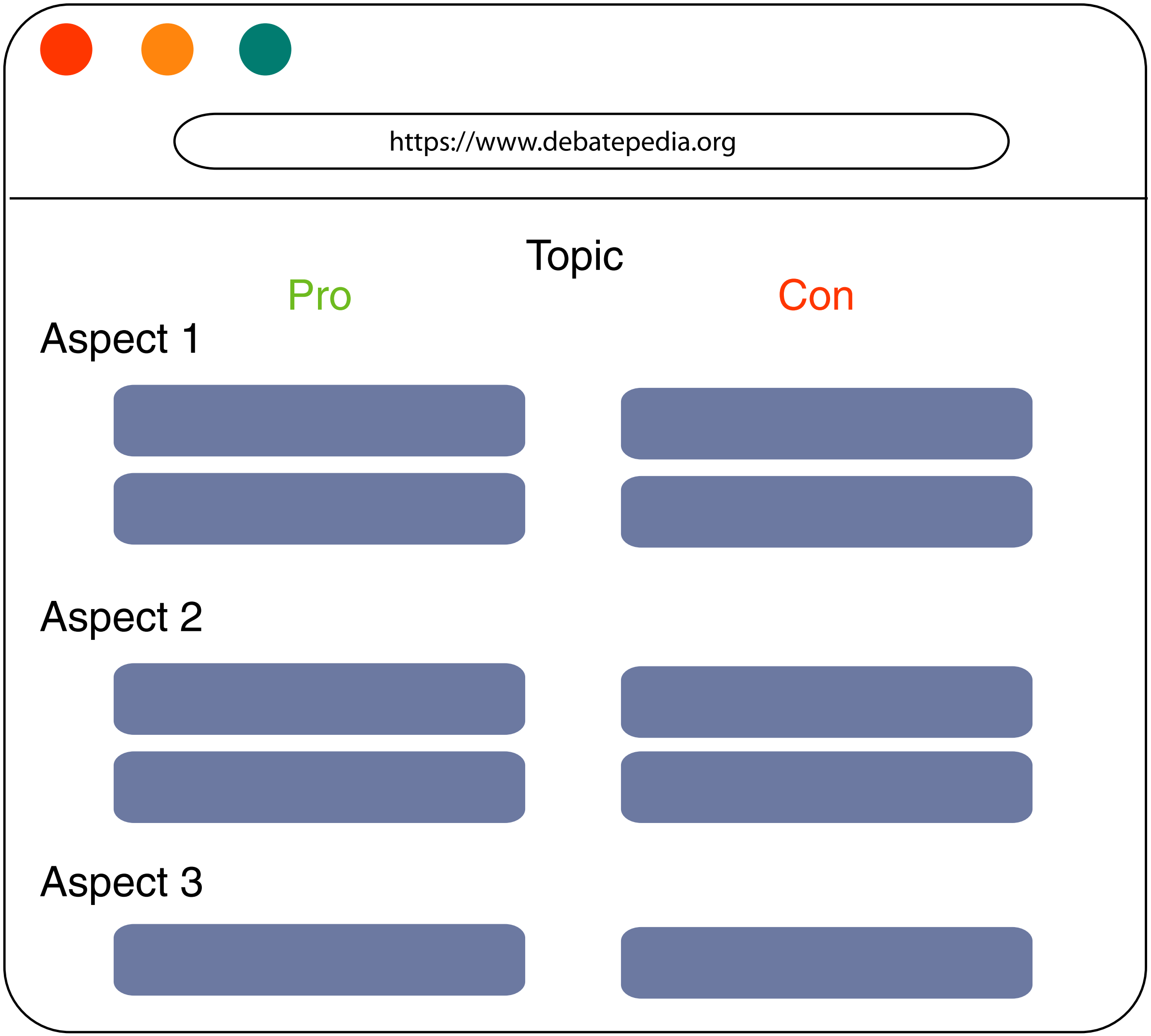
Approach: Semantic indexing calculates the cosine similarity between a corpus unit and the documents categorized under an ontology topic.

Evaluation: Pooled evaluation for 104 corpora units with a depth of five ontology topics.

F1-score of the approaches

Approach	**Wikipedia**		**WEF**	
	Level-1	Level-2	Level-1	Level-2
Direct match	0.06	0.40	0.29	0.19
Semantic Indexing	0.43	**0.59**	**0.34**	**0.33**
Text2vec-SI$_{BERT}$	**0.47**	0.31	0.28	0.23

Dataset Construction from Debatepedia.org



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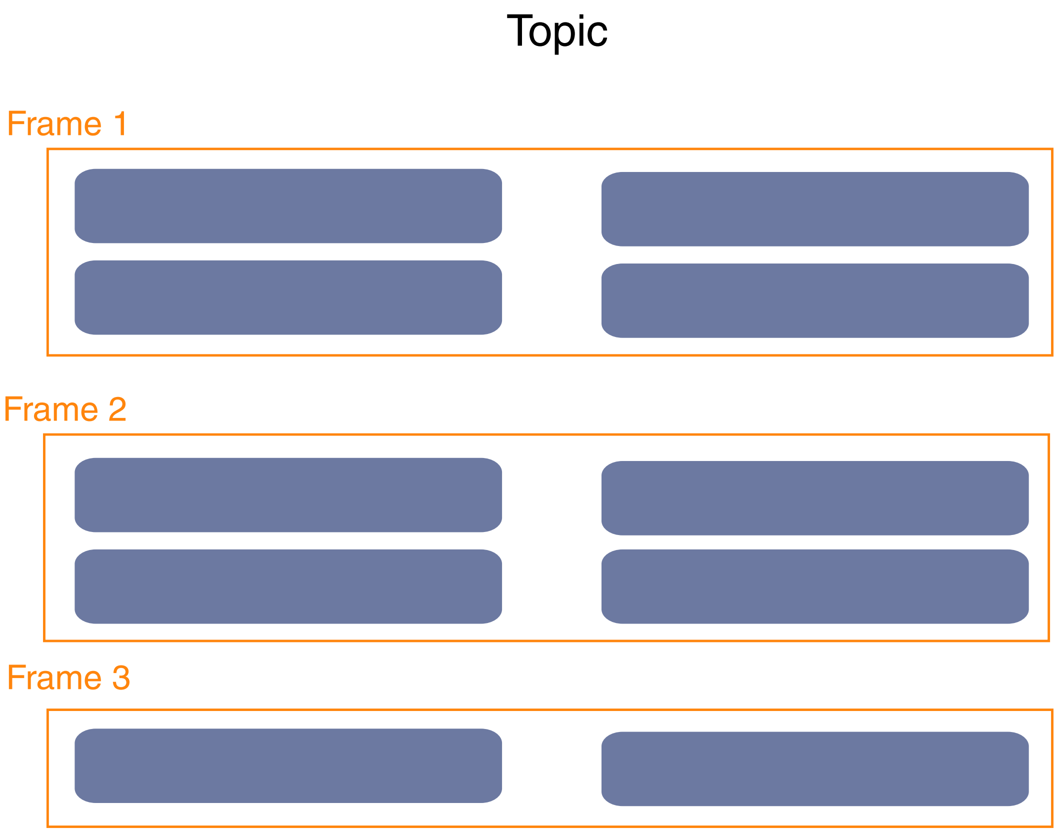
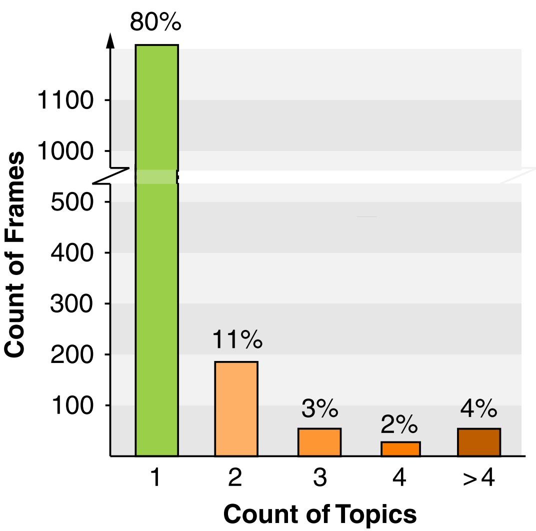
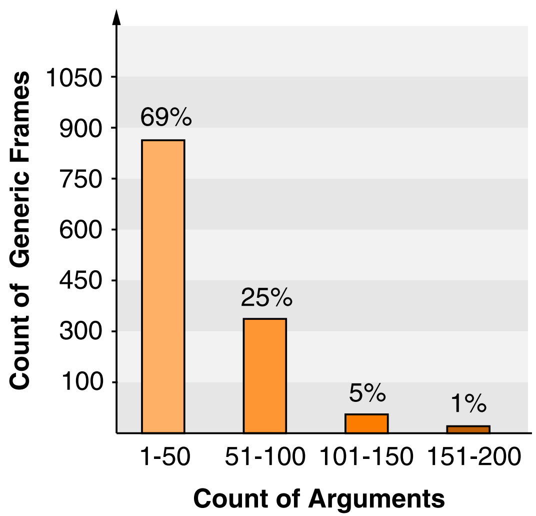
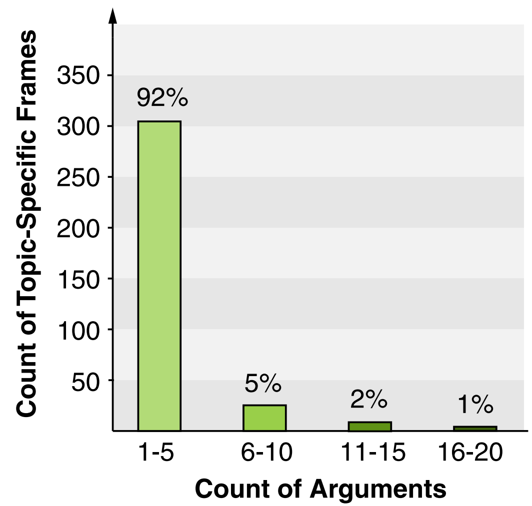


Dataset Construction from Debatepedia.org

# Topics	# Frames	# Arguments
467	1 623	12,326

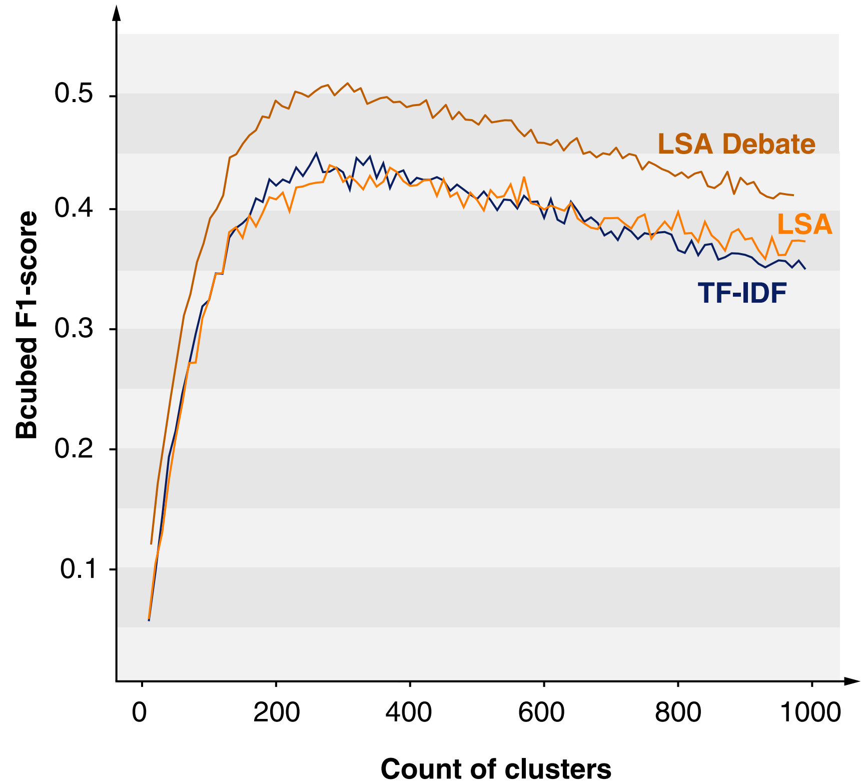






Experiment Results: Topic Clustering

Semantic Space	# Topics	Bcubed F1
LSA Debate	**310**	**0.52**
TF-IDF	260	0.45
LSA	280	0.44



LSA Debate is the best semantic space to model the topic of arguments.