

Poster Lightning Talks

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Overview

1. The Swedish PoliGraph: A Semantic Graph for Argument Mining of Swedish Parliamentary Data
2. Towards Effective Rebuttal: Listening Comprehension Using Corpus-Wide Claim Mining
3. Lexicon Guided Attentive Neural Network Model for Argument Mining
4. Is It Worth the Attention? A Comparative Evaluation of Attention Layers for Argument Unit Segmentation
5. Argument Component Classification by Relation Identification by Neural Network and TextRank
6. Argumentative Evidences Classification and Argument Scheme Detection Using Tree Kernels
7. The Utility of Discourse Parsing Features for Predicting Argumentation Structure
8. Detecting Argumentative Discourse Acts with Linguistic Alignment
9. Annotation of Rhetorical Moves in Biochemistry Articles
10. Evaluation of Scientific Elements for Text Similarity in Biomedical Publications
11. Categorizing Comparative Sentences
12. Ranking Passages for Argument Convincingness
13. Gradual Argumentation Evaluation for Stance Aggregation in Automated Fake News Detection

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Poster 1 (demo)

The Swedish PoliGraph: A Semantic Graph for Argument Mining of Swedish Parliamentary Data

Stian Rødven Eide

**A semantic graph of
members of the
Swedish parliament!**



**For named entity
recognition/resolution
and argumentation
mining!**



**Keeps track of
speeches, debates,
roles and positions
of all MPs since 1990!**



Poster Lightning Talks

Poster 2 (long)

Towards Effective Rebuttal: Listening Comprehension Using Corpus-Wide Claim Mining

Tamar Lavee, Matan Orbach, Lili Kotlerman, Yoav Kantor, Shai Gretz, Lena Dankin, Michal Jacovi, Yonatan Bilu, Ranit Aharonov, and Noam Slonim

Live debate held at San Francisco Feb 11th 2019

Expert human debater: Mr. Harish Natarajan

#think2019



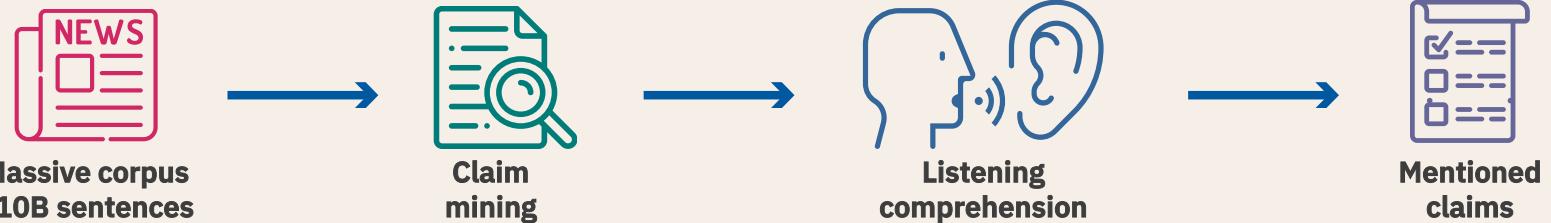
Project Debater



Engaging in a live debate requires rebutting your opponent's arguments
– What are those arguments?

Towards Effective Rebuttal: Listening Comprehension Using Corpus-Wide Claim Mining

Tamar Lavee, Matan Orbach, Lili Kotlerman, Yoav Kantor, Shai Gretz, Lena Dankin,
Shachar Mirkin, Michal Jacovi, Yonatan Bilu, Ranit Aharonov, Noam Slonim



New dataset available online!

400 speeches on 200 different topics
4.8K claims
High quality annotation

Poster Lightning Talks

Poster 3 (short)

Lexicon Guided Attentive Neural Network Model for Argument Mining

Jian-Fu Lin, Kuo Yu Huang, Hen-Hsen Huang, and Hsin-Hsi Chen

Goal

- Use of lexicon information by neural networks
- The scarcity of the lexicon resources in AM
- Explore lexicons from different domains/sources
 - Argument mining
 - Sentiment analysis
 - Emotion detection
 - General



國立臺灣大學
National Taiwan University

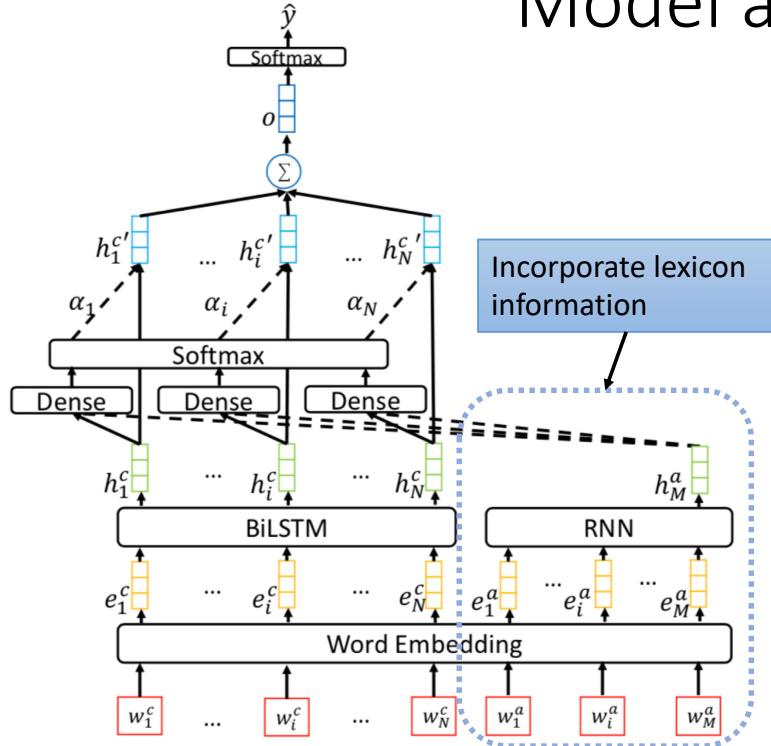


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科技部人工智慧技術
暨全幅健康照護聯合研究中心
Most Joint Research Center for AI Technology and All Vista Healthcare



Model and Results



model	F_1	Lexicon size (#words)
BiLSTM	$.5337 \pm .0123$	n/a
ClaimLex*	$.5684 \pm .0222$	~ 600
SentimentLex*	$.5718 \pm .0165$	$\sim 6,800$
EmotionLex*	$.5695 \pm .0129$	$\sim 6,500$
WordNet*	$.5788 \pm .0142$	$\sim 155,300$

- The result confirms the effectiveness of the integration of lexicon information.
- The influence of the size and the type of a lexicon is discussed.



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暨全幅健康照護聯合研究中心
Most Joint Research Center for AI Technology and All Vista Healthcare



NLP
Lab³

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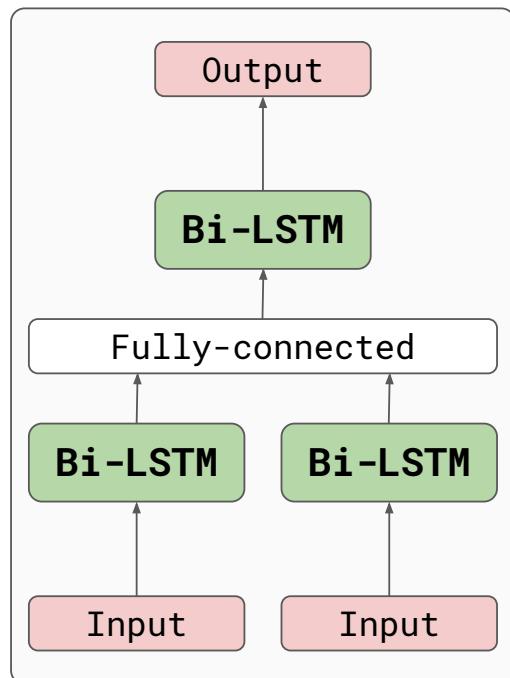
Poster 4 (long)

Is It Worth the Attention? A Comparative Evaluation of Attention Layers for Argument Unit Segmentation

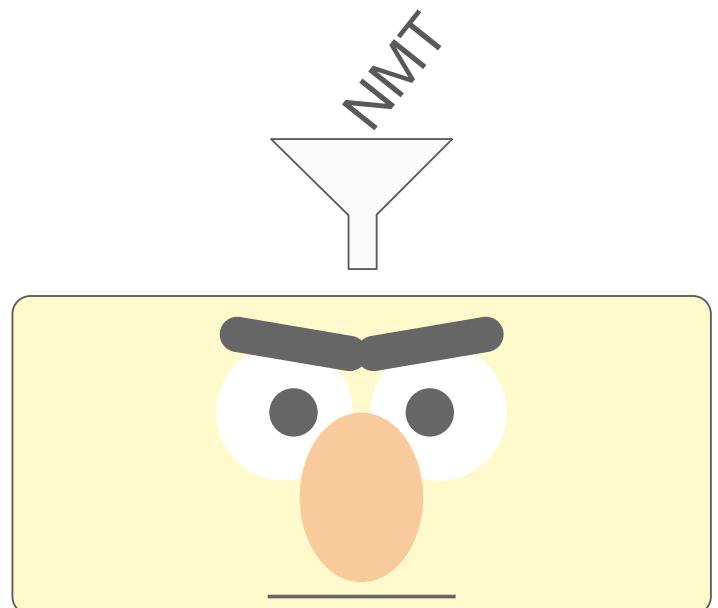
Maximilian Spliethöver, Jonas Klaff, and Hendrik Heuer

Is It Worth the Attention? A Comparative Evaluation of Attention Layers for Argument Unit Segmentation

Spliethöver & Klaff & Heuer



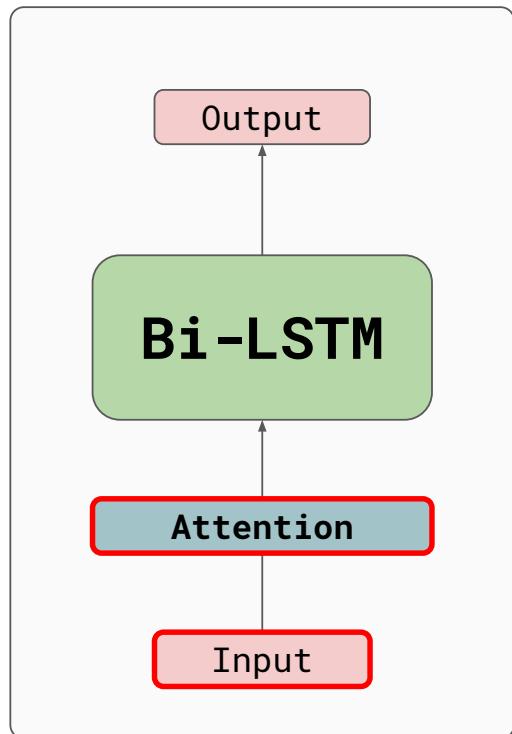
Ajjour, et al.



Devlin, et al.

Is It Worth the Attention? A Comparative Evaluation of Attention Layers for Argument Unit Segmentation

Spliethöver & Klaff & Heuer



→ Attention layers

→ Contextualized input embeddings

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Poster 5 (long)

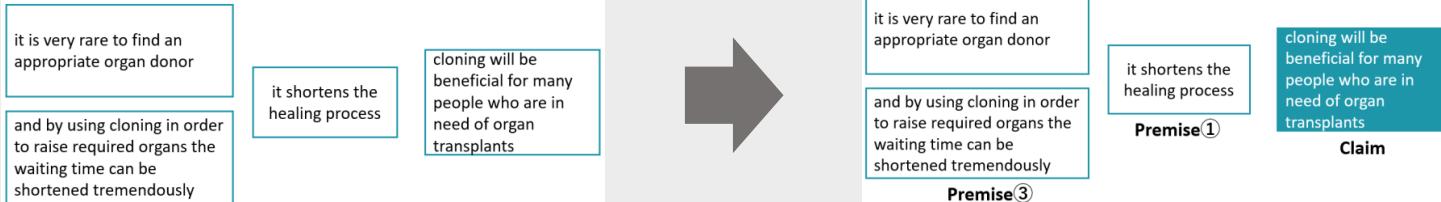
Argument Component Classification by Relation Identification by Neural Network and TextRank

Mamoru Deguchi and Kazunori Yamaguchi

Argument Component Classification by Relation Identification by Neural Network and TextRank

Mamoru Deguchi, The University of Tokyo

Purpose: Components Classification

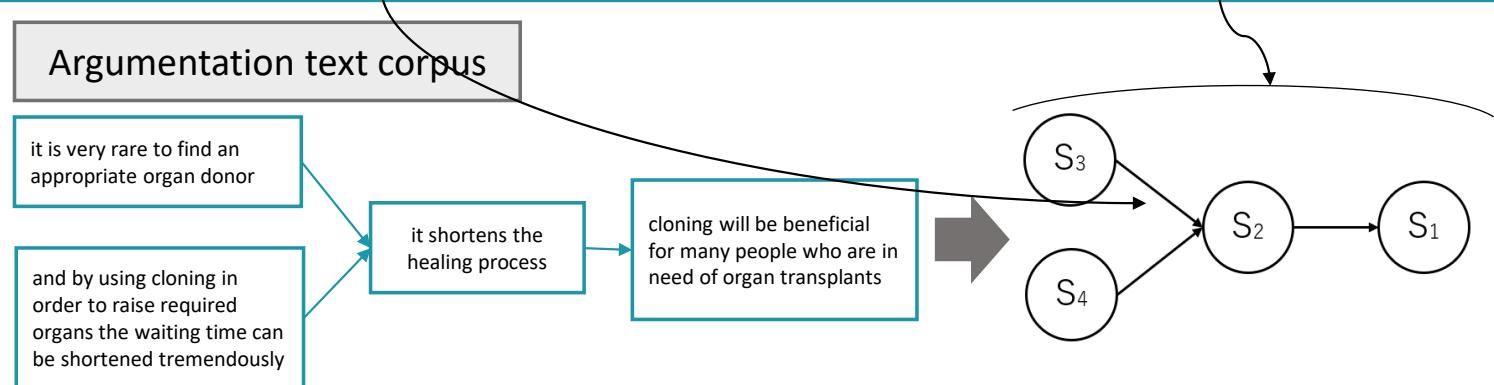


TextRank [Petasis 2016] Extracting a major claim or a claim by ranking the sentences using the TextRank on the basis of the similarity of sentences.

Proposed Method

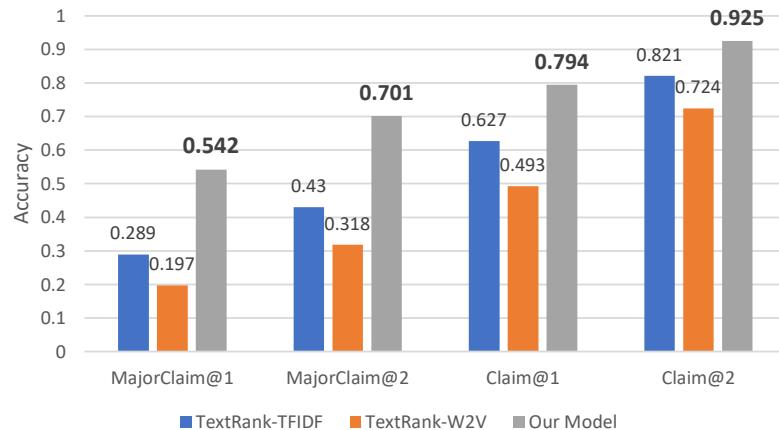
Weight prediction using corpus by NN

Calculating scores from all the predicted weights by TextRank

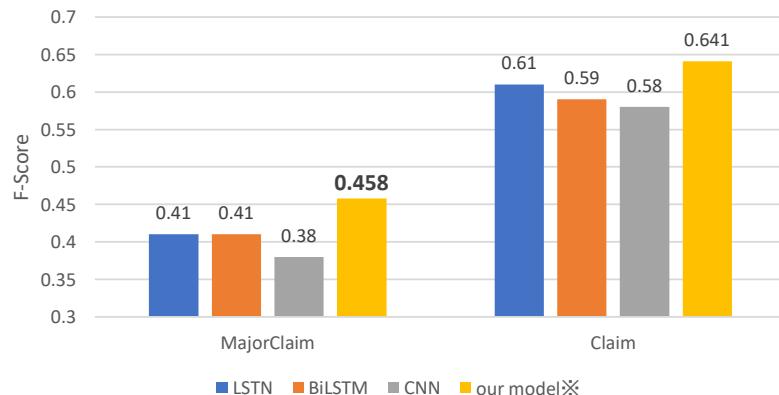


Experiment on Student Essay [Stab 2016]

Comparison to TextRank



Comparison to NN Classifier



※On comparison to NN Classifier, threshold k is 3 at MajorClaim, 7 at Claim.

Evaluation metrics

- MajorClaim@k

The target major claims \in top k

→ correct

- Claim@k

The target claims or major claims \in top k

→ correct

Major Claim

The standpoint of the author on the topic of the essay

Claim

An intermediate claim that supports or attacks the major claim

Premise

An assumption or a reason that supports or attacks a claim or another premise

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Poster 6 (short)

Argumentative Evidences Classification and Argument Scheme Detection Using Tree Kernels

Davide Liga



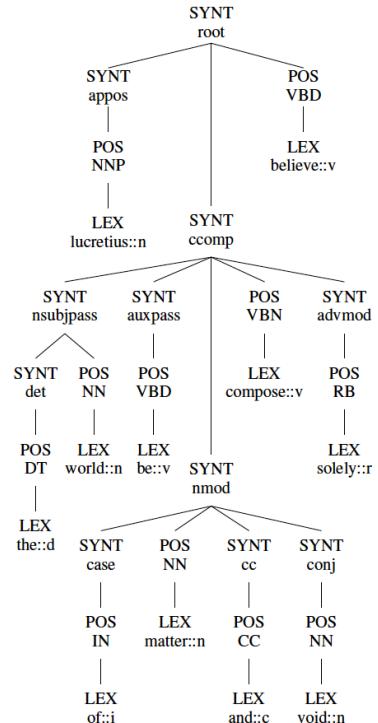
Assumptions:

Discriminating **argumentative stances of support/opposition** can facilitate the detection of **Argument Schemes**

Tree Kernels are optimal for this kind of classifications.

The advantages of Tree Kernels

- Avoiding highly-engineered features
- Generalization by leveraging structural information





The experiment

Binary classification:
STUDY vs EXPERT

Contributions

- TKs can outperform traditional features, while keeping a high generalization
- Successful combination of two important datasets

★ [1st] → Best performance

★ [2nd] → Second best performance

F1 scores range from 0.71 to 0.92

TESTED ON:	Trained on DS1			(Al Khatibet et al. 2016)
	TFIDF	SPTK	SPTK+TFIDF	
Same Dataset	★ 0.91		0.87	★ 0.92
Other Dataset		★ 0.75	0.72	★ 0.76

TESTED ON:	Trained on DS2			(Aharoni et al. 2014)
	TFIDF	SPTK	SPTK+TFIDF	
Same Dataset	0.71	★ 0.73	★ 0.72	
Other Dataset	0.74	★ 0.82	★ 0.84	

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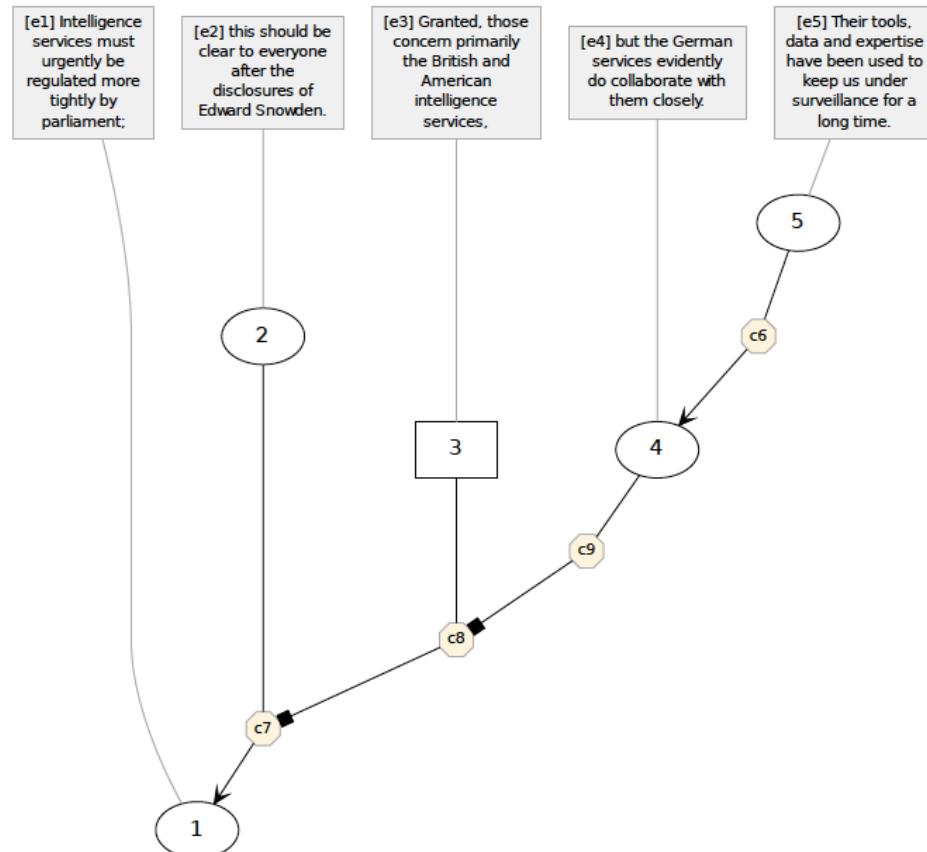
Poster 7 (short)

The Utility of Discourse Parsing Features for Predicting Argumentation Structure

Freya Hewett, Roshan Prakash Rane, Nina Harlacher, and Manfred Stede

Hewett et al.: Discourse parsing for argument mining

- Arg. Microtexts corpus
- Ca. 5 segments per text
- Function: support / attack
- Role: proponent / opponent

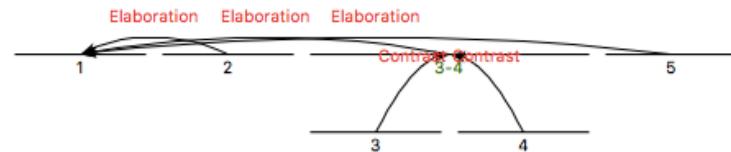


Hewett et al.: Discourse parsing for argument mining

Penn Discourse Treebank (Shallow Discourse Parsing)

1:[Intelligence services must urgently be regulated more tightly by parliament;] 2:[this should be clear to everyone after the disclosures of Edward Snowden.] 3:[Granted, those concern primarily the British and American intelligence services.] Comparison. Contrast 4:[but the German services evidently do collaborate with them closely.] 5:[Their tools, data and expertise have been used to keep us under surveillance for a long time.]

Rhetorical Structure Theory



PDTB parser: Ziheng Lin, Hwee Tou Nh, and Min-Yen Kan. 2014.
A pdtb-styled end-to-end discourse parser. Natural
Language Engineering , 20:151–184.

RST parser: Vanessa Wei Feng and Graeme Hirst. 2014. A linear time bottom-up discourse parser with constraints and post-editing. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics , pages 511–521.

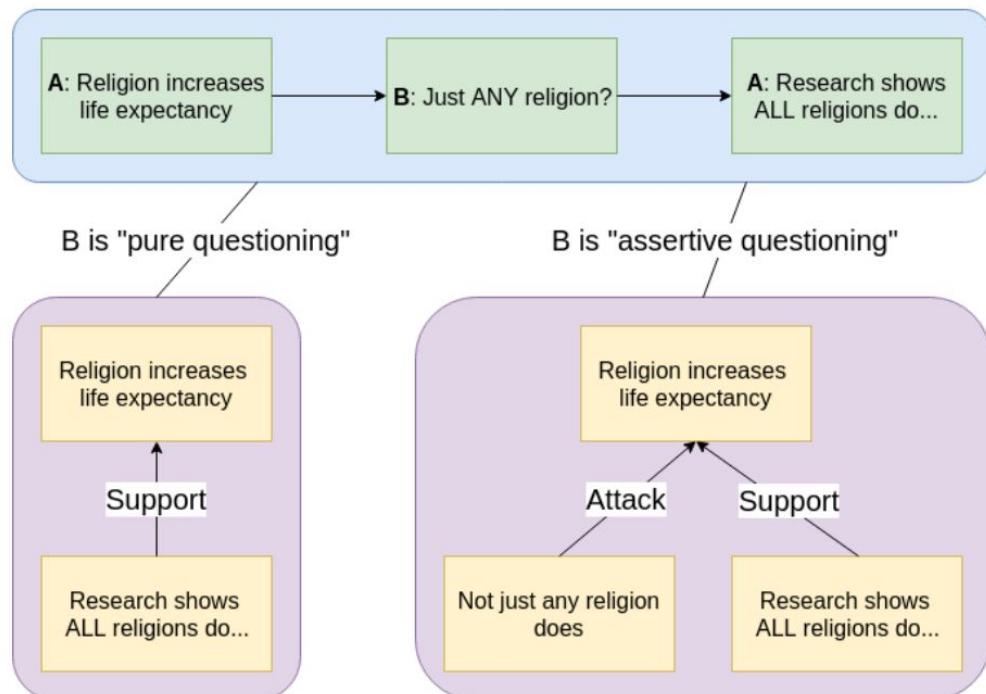
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Poster 8 (long)

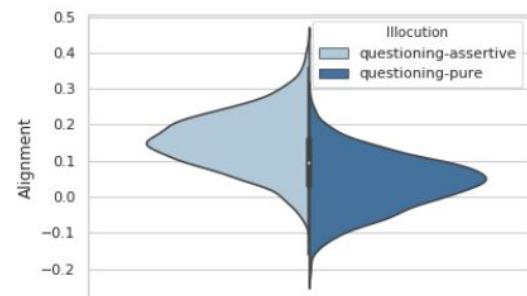
Detecting Argumentative Discourse Acts with Linguistic Alignment

Timothy Niven and Hung-Yu Kao

Detecting Argumentative Discourse Acts with Linguistic Alignment

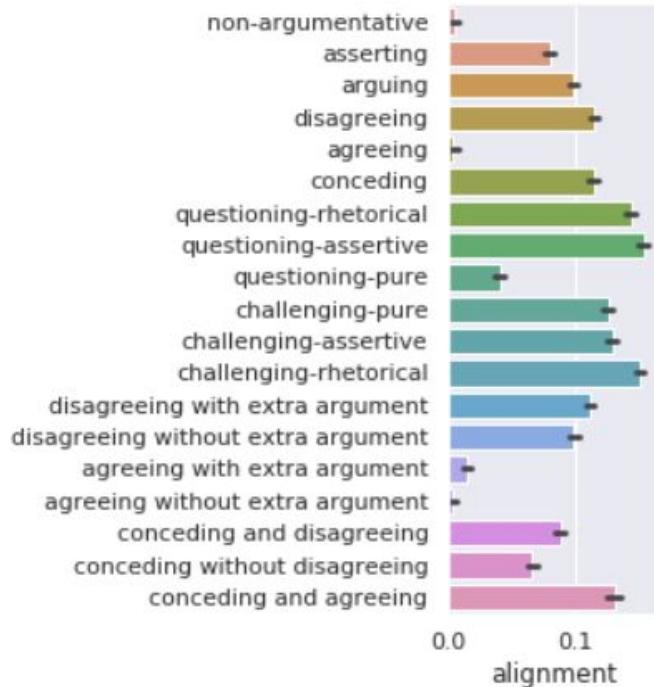


A's message	B's reply	
	has pronoun	no pronoun
has pronoun	8	2
no pronoun	5	5

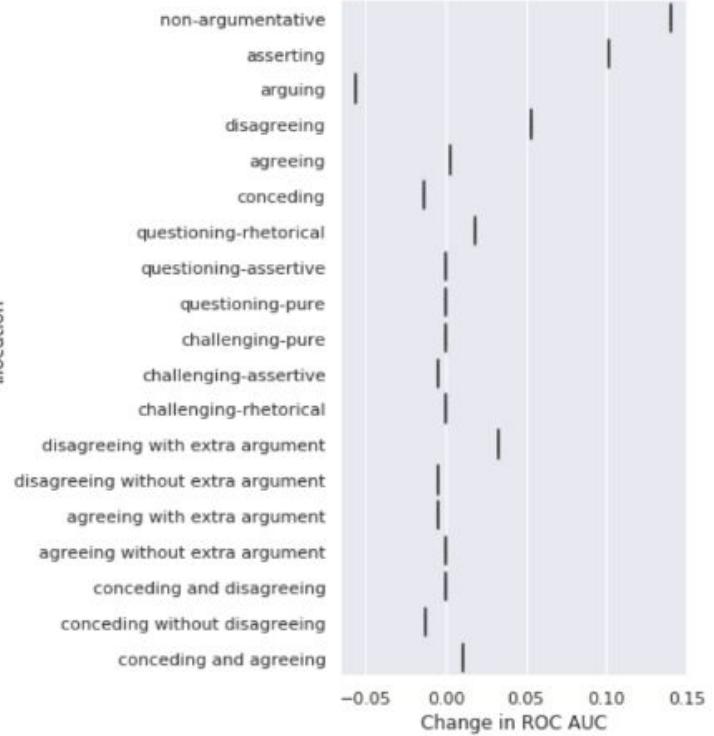


Detecting Argumentative Discourse Acts with Linguistic Alignment

illlocution



illlocution



Poster Lightning Talks

Poster 9 (long)

Annotation of Rhetorical Moves in Biochemistry Articles

Mohammed Alliheedi, Robert E. Mercer, and Robin Cohen



Annotation of Rhetorical Moves in Biochemistry Articles

Mohammed Alliheedi, Robert E. Mercer, and Robin Cohen

David R. Cheriton School of Computer Science, University of Waterloo, Waterloo, Ontario, Canada
Department of Computer Science, The University of Western Ontario, London, Ontario, Canada

- Detecting rhetorical moves: a step towards argument structure
- Argumentation can enable validating scientific claims, etc.
- Rhetorical move taxonomy based on Kanoksilapatham and Swales' CARS model
- Hypothesis: moves correlate with experimental procedures
- Verbs are strongly associated with these procedures
- We propose a *procedurally rhetorical verb-centric frame semantics* to analyze sentence meaning to understand the moves



Annotation of Rhetorical Moves in Biochemistry Articles

Mohammed Alliheedi, Robert E. Mercer, and Robin Cohen

David R. Cheriton School of Computer Science, University of Waterloo, Waterloo, Ontario, Canada
Department of Computer Science, The University of Western Ontario, London, Ontario, Canada

Poster outline:

- A brief background and motivation for this work is given
- Our developed annotation scheme for experimental events including rhetorical moves and semantic roles is described
- The annotation guidelines are introduced
- Then, the labelling for semantic roles and rhetorical moves using GATE is shown
- Finally, we provide the results of our annotation study

Poster Lightning Talks

Poster 10 (long)

Evaluation of Scientific Elements for Text Similarity in Biomedical Publications

Mariana Neves, Daniel Butzke and Barbara Grune

Evaluation of Scientific Elements for Text Similarity in Biomedical Publications

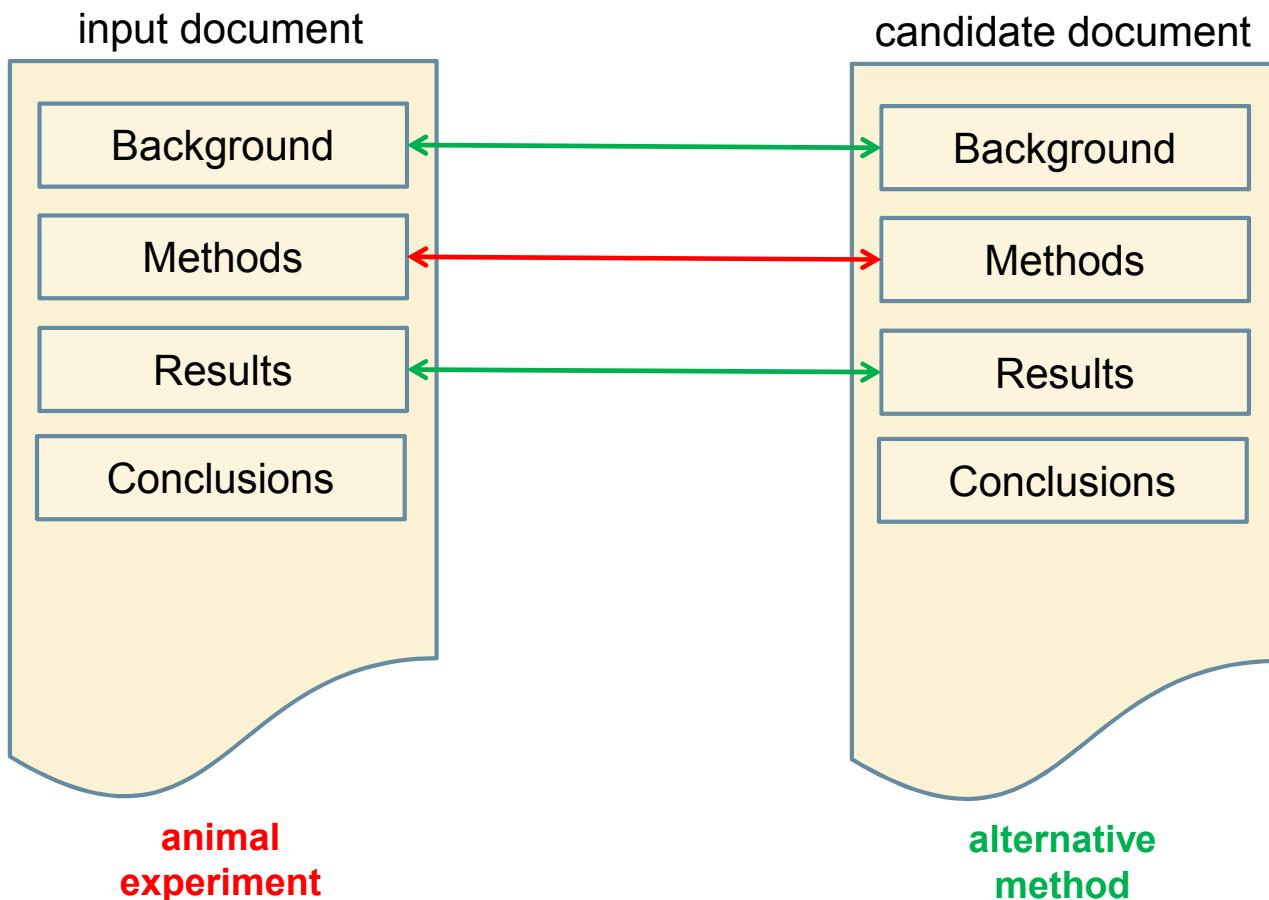
short survey on existing schemes for rhetorical elements in scientific publications

identification of the schemes for which corpora are available

identification of the schemes for which tools are readily available for use

evaluation of the available tools on a biomedical use case for text similarity

Evaluated of the tools for text similarity: mining alternative methods to animal experiments



Poster Lightning Talks

Poster 11 (long)

Categorizing Comparative Sentences

Alexander Panchenko, Alexander Bondarenko, Mirco Franzek, Matthias Hagen, and Chris Biemann

Categorising Comparative Sentences: A New Cross-Domain Dataset

Sample sentences:

Domain	Sentence	Label
CompSci	This time Windows 8 was roughly 8 percent slower than Windows 7 .	WORSE
CompSci	I've concluded that it is better to use Python for scripting rather than Bash .	BETTER
Brands	These include Motorola , Samsung and Nokia .	NONE
Brands	Honda quality has gone downhill, Hyundai or Ford is a much better value.	WORSE
Random	Right now, I think tennis is easier than baseball .	BETTER
Random	I've grown older and wiser and avoid the pasta and bread like the plague.	NONE

Statistics of the dataset:

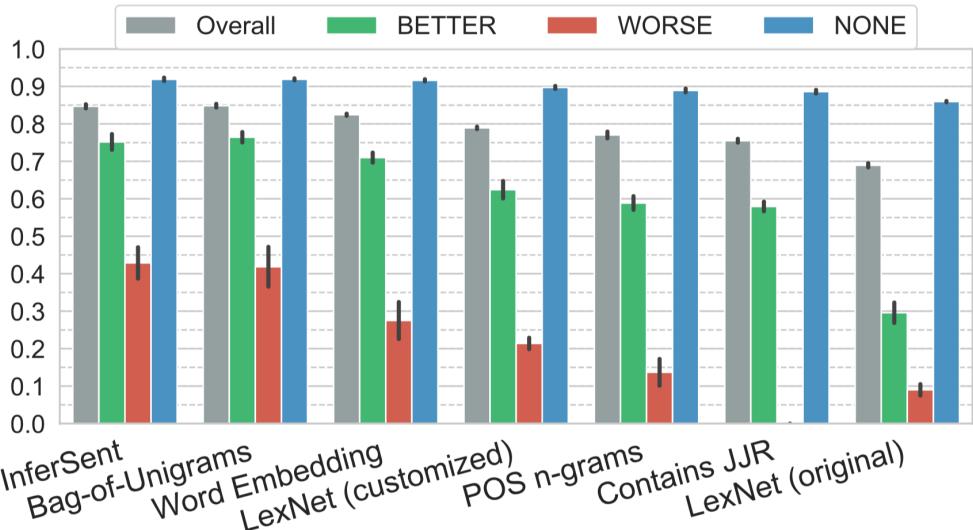
Domain	Label			
	BETTER	WORSE	NONE	Total
CompSci	581	248	1,596	2,425
Brands	404	167	1,764	2,335
Random	379	178	1,882	2,439
Total	1,364	593	5,242	7,199

Results

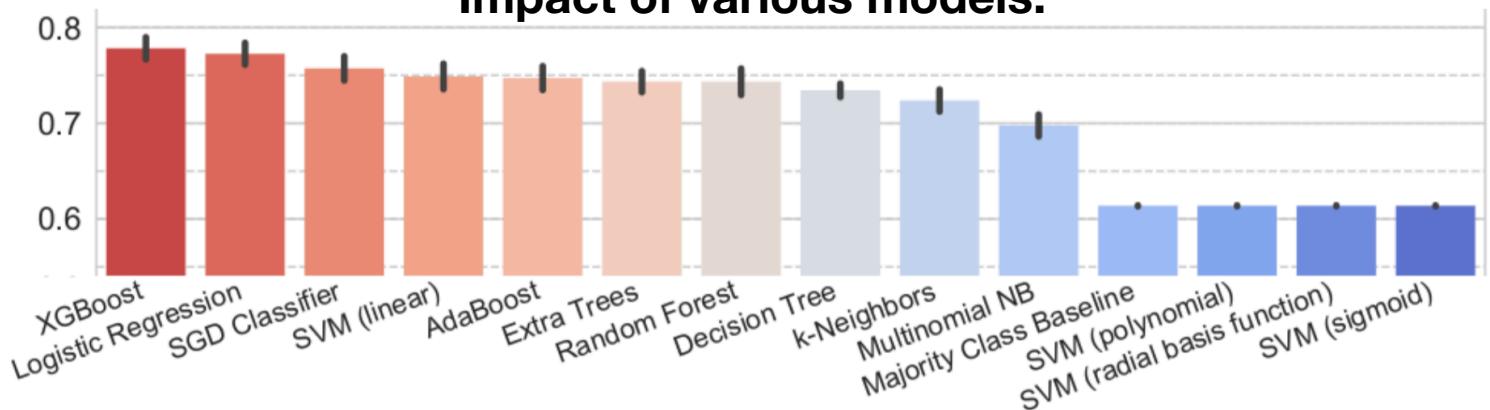
Various feature representations:

Good cross-domain transfer:

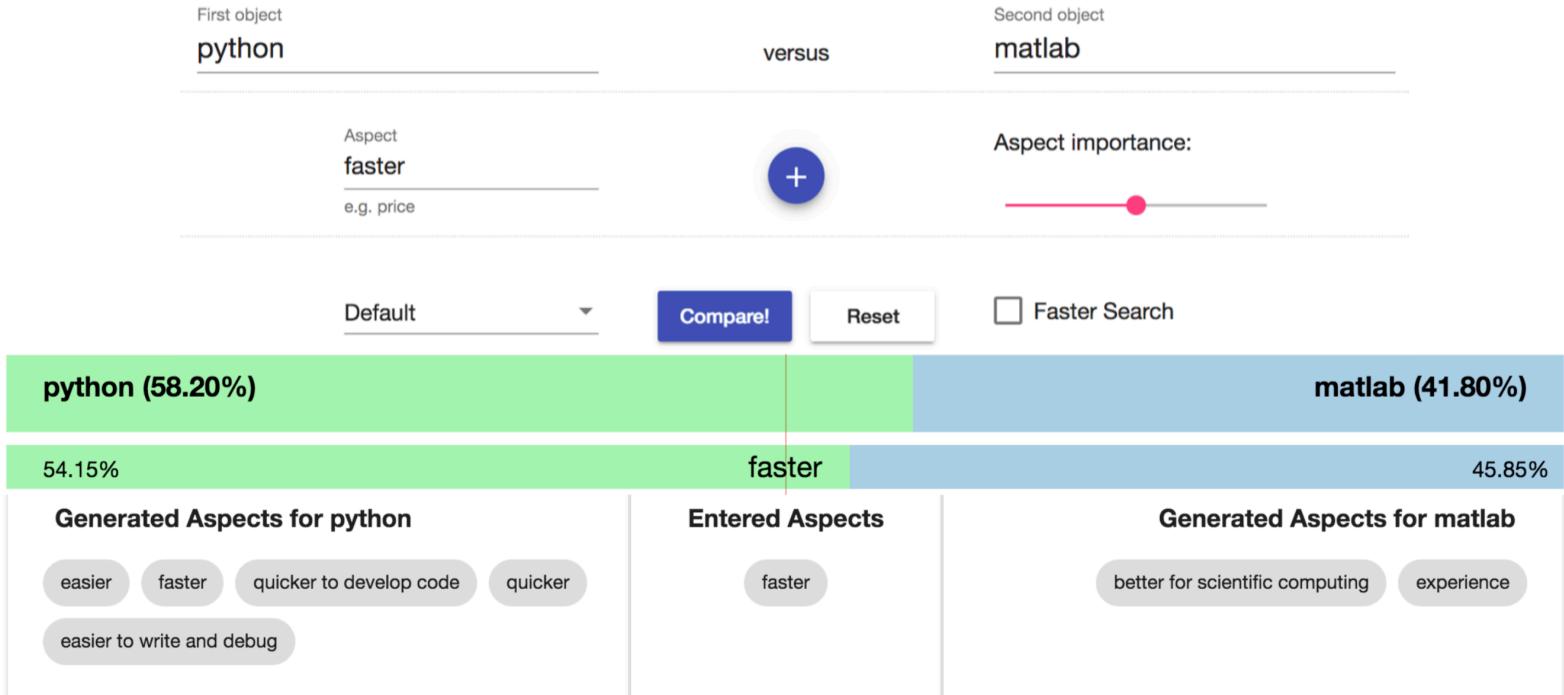
Train \ Test	CompSci	Brands	Random
CompSci	0.82	0.84	0.84
Brands	0.76	0.83	0.83
Random	0.79	0.84	0.86



Impact of various models:



Application: Comparative Argumentative Machine (CAM)



Wow, Python much faster than Matlab .

RE: Wow, Python much faster than Matlab .

Remember that Python with NumPy tend to be faster than Matlab.

Python might be faster Click, to show context. I'm not good at MATLAB so I don't know how to get computational times (or in Python, for that matter).

As you can see from the results- Matlab is significantly faster than python.

Right, exactly; but "flat" Matlab (that is, Matlab with few looping constructs) has been shown to me to be faster than Python+NumPy for intensive calculations.

But I also tested with 64 bit float matrix and on my machine, Matlab 2010b is still faster than Python 3.2 with Numpy-MKL

Poster Lightning Talks

Poster 12 (long)

Ranking Passages for Argument Convincingness

Peter Potash, Adam Ferguson, and Timothy J. Hazen

Motivation

Coffee

PERSPECTIVES FROM THE WEB

You could **burn more fat**. Caffeine is found in almost every over-the-counter fat-burning supplement commercially available today. And for good reason. It's been shown to **increase metabolism** by 3 to 11 percent, and to increase the burning of fat from 10 to 29 percent, depending on your

9 Surprising Reasons Why **Coffee Is Really Good** fo...
inc.com

vs

Research Showing Harmful Effects of Caffeine. More than 4 cups of coffee **linked to early death**. Caffeine consumption may **raise blood pressure**. Increased risk of **heart attacks** among young adults. Caffeine linked to **gout** attacks. Breast Tissue **Cysts** In Women. Caffeine could cause **incontinence**. Caffeine may

20+ **Harmful Effects of Caffeine**
caffeineinformer.com

Query: reasons why nafta is good	
Passages with a "Pro" stance	Passages with a "Con" stance
Candidate 1: NAFTA has six advantages. First, it quadrupled trade between Canada, Mexico, and the United States. That's because the agreement eliminated tariffs. Trade increased to \$1.14 trillion in 2015. Second, it lowered prices. The United States imports Mexican oil for less than before the agreement.	Candidate 1: Is NAFTA a Bad Deal? The North American Free Trade Agreement (NAFTA) has come under fire recently, with some labeling it a disaster and claiming that it is the driving force behind the relocation of American firms like Ford Motor Company to Mexico.
Candidate 2: Because it helps in political interests. NAFTA is meant to lower tariffs and therefore create pro business alliances between the three signing nations. This allows for the U.S. to buy products cheaper from Canada and tears down the barriers to trade such as tariffs fees etc.	Candidate 2: Best Answer: see... the problem is... people who support NAFTA only compare it to either all out free trade... or no trade. trade is good and needed... but that doesn't mean it has to be, or should be FREE trade... so stop with these false comparisons of we have to trade...



Test various ranking approaches

Regression to scalar target

- PageRank
- Win-Rate

Pairwise training objective



Test effects of data filtering

Filter individual examples based on annotation confidence

Filter full sets of passages if cycles exist in passage-graphs induced by pairwise annotation

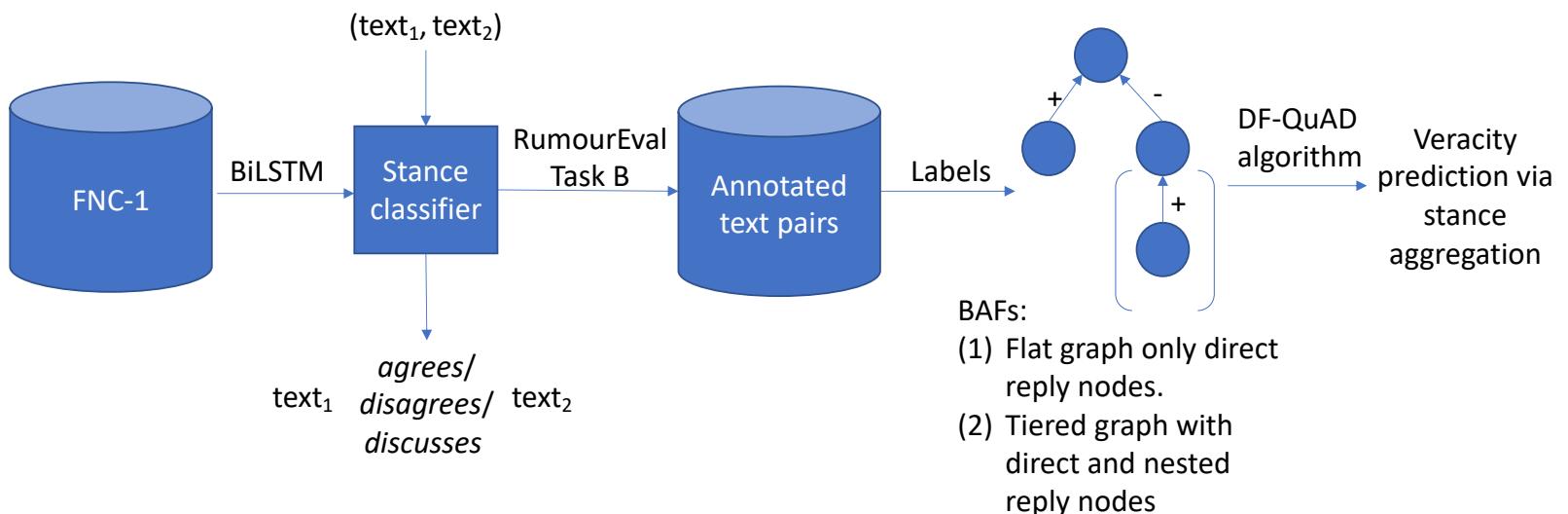
Approach

Poster Lightning Talks

Poster 13 (long)

Gradual Argumentation Evaluation for Stance Aggregation in Automated Fake News Detection

Neema Kotonya and Francesca Toni



Announcements

Announcements

Poster session after lunch

- Starts at 14:00.
- Right outside of HALL 6.

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Your task during lunch (if you like)

Think of an argument from your work or private life
that has actually changed your stance.

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Introducing the chairs of (potential) ArgMining 2020

Announcements

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Your task during lunch (if you like)

Think of an argument from your work or private life
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Introducing the chairs of (potential) ArgMining 2020

- Elena Cabrio
- Serena Villata

