

TARGER: Neural Argument Mining at Your Fingertips

Artem Chernodub^{1,2}, Oleksiy Oliynyk³, Philipp Heidenreich³, Alexander Bondarenko⁴,
Matthias Hagen⁴, Chris Biemann³, and Alexander Panchenko^{5,3}

¹Grammarly

²Faculty of Applied Sciences, Ukrainian Catholic University, Lviv, Ukraine

³Language Technology Group, Universität Hamburg, Hamburg, Germany

⁴Big Data Analytics Group, Martin-Luther Universität Halle-Wittenberg, Halle, Germany

⁵Skolkovo Institute of Science and Technology, Moscow, Russia

Abstract

We present TARGER, an open source neural argument mining framework for tagging arguments in free input texts and for keyword-based retrieval of arguments from an argument-tagged web-scale corpus. The currently available models are pre-trained on three recent argument mining datasets and enable the use of neural argument mining without any reproducibility effort on the user's side. The open source code ensures portability to other domains and use cases, such as an application to search engine ranking that we also describe shortly.

1 Introduction

Argumentation is a multi-disciplinary field that extends from philosophy and psychology to linguistics as well as to artificial intelligence. Recent developments in argument mining apply natural language processing (NLP) methods to argumentation (Palau and Moens, 2011; Lippi and Torroni, 2016a) and are mostly focused on training classifiers on annotated text fragments to identify argumentative text units, such as claims and premises (Biran and Rambow, 2011; Habernal et al., 2014; Rinott et al., 2015). More specifically, current approaches mainly focus on three tasks: (1) detection of sentences containing argumentative units, (2) detection of the argumentative units' boundaries inside sentences, and (3) identifying relations between argumentative units.

Despite vital research in argument mining, there is a lack of freely available tools that enable users, especially non-experts, to make use of the field's recent advances. In this paper, we close this gap by introducing TARGER: a system with a user-friendly web interface¹ that can extract argumentative units in free input texts in real-time using

models trained on recent argument mining corpora with a highly configurable and efficient neural sequence tagger. TARGER's web interface and API also allow for very fast keyword-based argument retrieval from a pre-tagged version of the Common Crawl-based DepCC (Panchenko et al., 2018).

The native PyTorch implementation underlying TARGER has no external dependencies and is available as open source software:² it can easily be incorporated into any existing NLP pipeline.

2 Related Work

There are three publicly available systems offering some functionality similar to TARGER. ArgumenText (Stab et al., 2018) is an argument search engine that retrieves argumentative sentences from the Common Crawl and labels them as *pro* or *con* given a keyword-based user query. Similarly, args.me (Wachsmuth et al., 2017) retrieves *pro* and *con* arguments from 300,000 arguments crawled from debating portals. Finally, MARGOT (Lippi and Torroni, 2016b) provides argument tagging for free-text inputs. However, answer times of MARGOT are rather slow for single input sentences (>5 seconds) and the F1 scores of 17.5 for claim detection and 16.7 for evidence detection are slightly worse compared to our approach (see Section 4.1).

TARGER offers a real-time retrieval functionality similar to ArgumenText and fast real-time free-text argument tagging with the option of switching between different pre-trained state-of-the-art models (MARGOT offers only a single one).

3 Architecture of TARGER

The independent components of the modular and flexible TARGER framework are shown in Figure 1. In an offline training step, a neural

¹ldemos.informatik.uni-hamburg.de/targer

²github.com/achernodub/targer

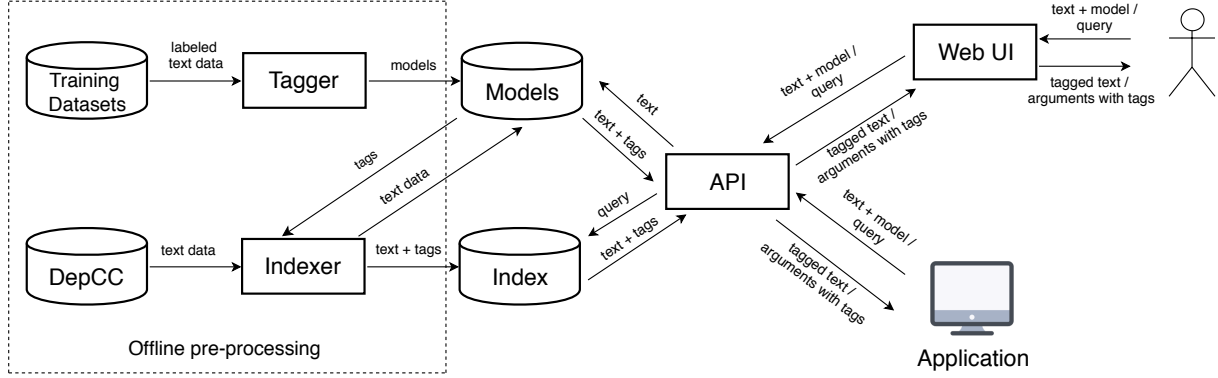


Figure 1: Modular architecture of TARGER. The central API is accessed through the Web UI or directly from any application; it routes requests either to the tagging models or to the retrieval component. TARGER’s components communicate via HTTP requests and can be deployed on different servers—in Docker containers or natively.

BiLSTM-CNN-CRF sequence tagger is trained on different datasets yielding a variety of argument mining models (details in Section 3.1). As part of the preprocessing, the trained models are run on the 14 billion sentences of the DepCC corpus to tag and store argument unit information as additional fields in an Elasticsearch BM25-index of the DepCC (details in Section 3.2).

The online usage is handled via a Flask-based web app whose API accepts AJAX requests from the Web UI component or via API calls (details in Sections 3.3 and 3.4). The API routes free text inputs to the respective selected model to be tagged with argument information or it routes keyword-based queries to the index to retrieve sentences in which the query terms match argument units.

3.1 Neural Sequence Tagger

We implement a BiLSTM-CNN-CRF neural tagger (Ma and Hovy, 2016) for identifying argumentative units and for classifying them as claims or premises. The BiLSTM-CNN-CRF method is a popular sequence tagging approach and achieves (near) state-of-the-art performance for tasks like named entity recognition and part-of-speech tagging (Ma and Hovy, 2016; Lample et al., 2016); it has also been used for argument mining before (Eger et al., 2017). The general method relies on pre-computed word embeddings, a single bidirectional-LSTM/GRU recurrent layer, convolutional character-level embeddings to capture out-of-vocabulary words, and a first-order Conditional Random Field (Lafferty et al., 2001) to capture dependencies between adjacent tags.

Besides a BiLSTM-CNN-CRF implementation of Reimers and Gurevych (2017), we also use an

Table 1: Number of tokens per category in the training datasets.

	Essays	WebD	IBM
Claims	22,443	3,670	8,073,589
Premises	67,157	20,906	35,349,501
Major Claims	10,966	-	-
Backing	-	10,775	-
Refutations	-	867	-
Rebuttals	-	2,247	-
None	47,619	46,352	3,710,839
Combined	148,185	84,817	47,133,929

own Python 3.6 / PyTorch 1.0 implementation of the neural tagger that does not contain any third-party dependencies, has native vectorized code for efficient training and evaluation, and supports several input data formats as well as evaluation functions.

The different argument tagging models currently usable through TARGER’s API are trained on the persuasive essays (Essays) (Eger et al., 2017), the web discourse (WebD) (Habernal and Gurevych, 2017), and the IBM Debater (IBM) (Levy et al., 2018) datasets (characteristics in Table 1). The models use GloVe (Pennington et al., 2014), fastText (Mikolov et al., 2018), or dependency-based embeddings (Levy and Goldberg, 2014) (overview in Table 2).

For training, the following variations were used for hyperparameter tuning: optimizer [SGD, Adam], learning rate [0.001, 0.05, 0.01], dropout [0.1, 0.5], number of hidden units in recurrent layer [100, 150, 200, 250]. On all datasets, GloVe embeddings, Adam with learning rate of 0.001 and dropout rate of 0.5 performed best (hidden units: 200 on the persuasive essays,

Table 2: Models currently deployed in TARGER.

Data	Embeddings	Tagger
Essays	fastText	(Reimers and Gurevych, 2017)
Essays	Dependency	(Reimers and Gurevych, 2017)
Essays	GloVe	Ours
WebD	fastText	(Reimers and Gurevych, 2017)
WebD	Dependency	(Reimers and Gurevych, 2017)
WebD	GloVe	Ours
IBM	fastText	(Reimers and Gurevych, 2017)
IBM	GloVe	Ours

250 on web discourse and IBM data).

3.2 Retrieval Functionality

Our background collection for the retrieval of argumentative sentences is formed by the DepCC corpus (Panchenko et al., 2018), a linguistically pre-processed subset of the Common Crawl containing 14.3 billion unique English sentences from 365 million web documents.

We used an Apache Spark cluster to run the trained models on the sentences in the DepCC and to extend an Elasticsearch BM25-index of the DepCC by additional fields containing the argument unit spans and labels of the different models.

3.3 TARGER API

To keep the TARGER framework modular and scalable while still allowing access to the models from external clients, online interaction is handled via a restful API. Each trained model is associated with a separate API endpoint accepting raw text as input. The output is provided as a list of word-level tokens with IOB-formatted labels for argument units (premises and claims) and the tagger’s confidence scores for each label.

3.4 TARGER Web UI

The web interface of TARGER offers two functionalities: *Analyze Text* and *Search Arguments*. On the analysis tab (cf. Figure 2), the user can choose one of the deployed models to identify arguments in a user-provided free text. The result is shown with colored labels for different types of argumentative units (premises and claims) as well as detected named entities (nested tags for entities in argumentative units are supported). Once a result is shown, it is possible to customize the display by enabling/disabling different labels without performing additional tagging runs.

On the retrieval tab (cf. Figure 3), the user

Table 3: Comparison of TARGER’s performance on the essays (Eger et al., 2017) and web discourse data (Habernal and Gurevych, 2017) to the best approaches from the original publications.

Essays		Web Discourse	
Approach	F1	Approach	F1
S _{Tag} _{BLCC}	64.74	SVM ^{hmm}	22.90
TARGER (GloVe)	64.54	TARGER (GloVe)	24.20

can enter a keyword query and choose whether it should be matched in claims, premises, etc. Every retrieved result is rendered as a text fragment colored with argument and entity information just as on the analysis tab. To enable provenance, the URL of the source document is also provided.

4 Evaluation

We compare the best performing of our pre-trained argument tagging models (parameter settings at the end of Section 3.1) to the best performances from the original dataset publications and report on TARGER’s usage as a subroutine in runs for the TREC 2018 Common Core track.

4.1 Experimental Results

Table 3 shows a comparison of TARGER’s best performing models (parameter settings at the end of Section 3.1) on the Persuasive Essays (paragraph level) and the Web Discourse dataset to the best performance in the original publications. In our experiments, we reproduce the experimental settings of the original papers. On the Essays data, we use a fixed 70/20/10 train/dev/test split, while on the Web Discourse data, we employ the original 10-fold cross-validation idea (in our case allocating 7 folds for training and 2 for development in each iteration).

On the Persuasive Essays dataset (paragraph level), the best TARGER model achieves a span-based micro-F1 of 64.54 for extracted argument components matching the best performance of 64.74 ± 1.97 reported by Eger et al. (2017) for their S_{Tag}_{BLCC} approach (BiLSTM-CRF-CNN approach (BLCC) similar to ours).

On the Web Discourse dataset, TARGER’s best model’s token-based macro-F1 of 24.20 slightly improves upon the originally reported best macro-F1 of 22.90 (Habernal and Gurevych, 2017) for a structural support vector machine model SVM^{hmm} for sequence labeling (Joachims

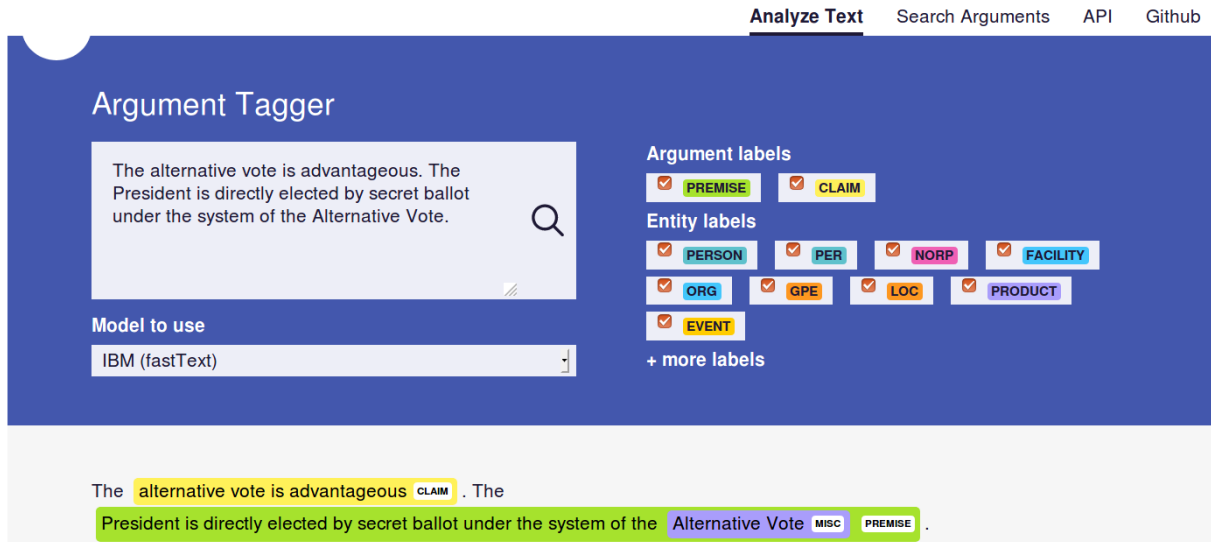


Figure 2: **Analyze Text**: input field, drop-down model selection, colored labels, and tagged result.

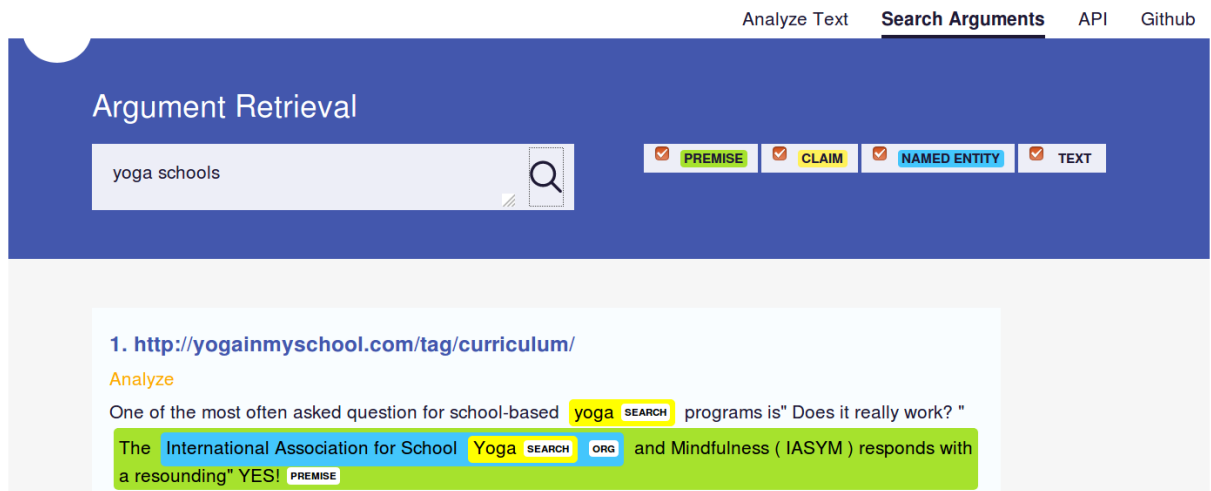


Figure 3: **Search Arguments**: query box, field selectors, and result with link to the original document.

et al., 2009). The SVM^{hmm} model uses lexical, structural, and other handcrafted feature types. In contrast, TARGER just uses word embeddings since especially for cross-domain scenarios, handcrafted features show a strong tendency to overfit on the topics of the training texts (Habernal and Gurevych, 2017). Thus, we chose “word embeddings only” as a more robust feature type for our domain-agnostic general-purpose argument mining system (free input text and web data).

We cannot compare TARGER’s performance on the IBM data to originally published performances since the tasks are different. Instead of TARGER’s identification of claims and premises, the IBM dataset was released to identify relevant premises for 50 given claims (called “topics” in the original publication) (Levy et al., 2018). But since

the IBM dataset contains a large number of general domain premises as training examples for the 50 topics (i.e., claims), we adapted the dataset to our tagging task by transforming the original entries to token-level claims and premises. Note that the resulting trained TARGER models tend to “optimistically” tag some argumentative units in almost every input text—we still provide them as a starting point for others.

4.2 TARGER @ TREC Common Core Track

As a proof of concept, we used TARGER’s model pre-trained on essays with dependency-based embeddings in a TREC 2018 Common Core track submission (Bondarenko et al., 2018). The TARGER API served as a subroutine in a pipeline axiomatically re-ranking (Hagen et al., 2016)

Table 4: The four argumentative topics from the TREC 2018 Common Core track with argument axiom re-ranked nDCG@10 improvements > 0.05 over a BM25F baseline.

Title / Query	BM25F	Axiomatic Re-Ranking
declining middle class in u.s.	0.91	0.98 (+0.07)
euro opposition	0.81	1.00 (+0.19)
airport security	0.52	0.72 (+0.20)
law enforcement, dogs	0.43	0.63 (+0.20)

BM25F retrieval results with respect to their argumentativeness (presence/absence of arguments).

Out of 25 potentially argumentative topics in the Core track (manual labeling of the 50 topics in total), the TARGER-based argumentativeness re-ranking improved the retrieval quality by > 0.05 nDCG@10 gains for 4 topics (see Table 4). Argumentativeness-based re-ranking might thus be a viable way to integrate neural argument mining into the retrieval process—for instance, using TARGER.

5 Conclusion

We have presented TARGER: an open source system for tagging arguments in free text and for retrieving arguments from a web-scale corpus. With the available RESTful API and the web interface, we make the recent argument mining technologies more accessible and usable to the general public and to developers. The different argument mining models can easily be used to perform manual text analyses or can seamlessly be integrated into automatic NLP pipelines. New taggers can be trained and deployed at any time, so that users can take advantage of the state of the art in argument mining. For future work, we plan also plan to integrate contextualized embeddings with ELMo- and BERT-based models (Peters et al., 2018; Devlin et al., 2018).

Finally, by looking at our experimental results as well as tagging examples for free text inputs or the DepCC web data, we noticed that despite the recent advances in argument mining, there is still considerable headroom to improve in-domain, but especially out-of-domain argument tagging performance. Free input texts of different styles or genres taken from the web are tagged very inconsistently by the different models. More research on domain adaptation and transfer learning (Ruder, 2019) in the scenario of argument mining

needs to address this issue—and could then ideally directly be deployed to TARGER as new models.

Acknowledgments

This work was partially supported by the German Academic Exchange Service (DAAD) through the short-term research grant 57314022 “Argument Mining in Web Documents using Orthogonal Simple Recurrent Networks” (2017) and by the Deutsche Forschungsgemeinschaft (DFG) through the project “ACQuA: Answering Comparative Questions with Arguments” (grants BI 1544/7-1 and HA 5851/2-1) that is part of the priority program “RATIO: Robust Argumentation Machines” (SPP 1999).

References

- Or Biran and Owen Rambow. 2011. [Identifying Justifications in Written Dialogs](#). In *Proceedings of the 5th IEEE International Conference on Semantic Computing (ICSC 2011)*, pages 162–168, Palo Alto, CA, USA.
- Alexander Bondarenko, Michael Völske, Alexander Panchenko, Chris Biemann, Benno Stein, and Matthias Hagen. 2018. [Webis at TREC 2018: Common Core Track](#). In *27th International Text Retrieval Conference (TREC 2018)*, NIST Special Publication, Gaithersburg, MD, USA.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. [BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding](#). *CoRR*, abs/1810.04805.
- Steffen Eger, Johannes Daxenberger, and Iryna Gurevych. 2017. [Neural end-to-end learning for computational argumentation mining](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 11–22, Vancouver, BC, Canada.
- Ivan Habernal, Judith Eckle-Kohler, and Iryna Gurevych. 2014. [Argumentation Mining on the Web from Information Seeking Perspective](#). In *Proceedings of the Workshop on Frontiers and Connections between Argumentation Theory and Natural Language Processing*, pages 26–39, Forlì-Cesena, Italy.
- Ivan Habernal and Iryna Gurevych. 2017. [Argumentation Mining in User-Generated Web Discourse](#). *Computational Linguistics*, 43(1):125–179.
- Matthias Hagen, Michael Völske, Steve Göring, and Benno Stein. 2016. [Axiomatic Result Re-Ranking](#). In *25th ACM International Conference on Information and Knowledge Management (CIKM 2016)*, pages 721–730, Indianapolis, IN, USA.

- Thorsten Joachims, Thomas Finley, and Chun-Nam J. Yu. 2009. [Cutting-plane training of structural svms](#). *Machine Learning*, 77(1):27–59.
- John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. 2001. [Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data](#). In *Proceedings of the Eighteenth International Conference on Machine Learning (ICML 2001)*, pages 282–289, Williamstown, MA, USA.
- Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. [Neural architectures for named entity recognition](#). In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 260–270, San Diego, CA, USA.
- Omer Levy and Yoav Goldberg. 2014. [Dependency-based word embeddings](#). In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 302–308, Baltimore, MD, USA.
- Ran Levy, Ben Bogin, Shai Gretz, Ranit Aharonov, and Noam Slonim. 2018. [Towards an Argumentative Content Search Engine Using Weak Supervision](#). In *Proceedings of the 27th International Conference on Computational Linguistics, COLING*, pages 2066–2081, Santa Fe, NM, USA.
- Marco Lippi and Paolo Torroni. 2016a. [Argumentation Mining: State of the Art and Emerging Trends](#). *ACM Trans. Internet Techn.*, 16(2):10:1–10:25.
- Marco Lippi and Paolo Torroni. 2016b. [MARGOT: A Web Server for Argumentation Mining](#). *Expert Syst. Appl.*, 65:292–303.
- Xuezhe Ma and Eduard Hovy. 2016. [End-to-end sequence labeling via bi-directional LSTM-CNNs-CRF](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1064–1074, Berlin, Germany.
- Tomas Mikolov, Edouard Grave, Piotr Bojanowski, Christian Puhersch, and Armand Joulin. 2018. [Advances in Pre-Training Distributed Word Representations](#). In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018*, pages 52–55, Miyazaki, Japan.
- Raquel M. Palau and Marie-Francine Moens. 2011. [Argumentation Mining](#). *Artif. Intell. Law*, 19(1):1–22.
- Alexander Panchenko, Eugen Ruppert, Stefano Faralli, Simone P. Ponzetto, and Chris Biemann. 2018. [Building a Web-Scale Dependency-Parsed Corpus from CommonCrawl](#). In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018*, pages 1816–1823, Miyazaki, Japan.
- Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. [Glove: Global vectors for word representation](#). In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, Doha, Qatar.
- Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. [Deep contextualized word representations](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 2227–2237, New Orleans, LA, USA.
- Nils Reimers and Iryna Gurevych. 2017. [Reporting score distributions makes a difference: Performance study of LSTM-networks for sequence tagging](#). In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 338–348, Copenhagen, Denmark.
- Ruty Rinott, Lena Dankin, Carlos Alzate Perez, Mitesh M. Khapra, Ehud Aharoni, and Noam Slonim. 2015. [Show me your evidence - an automatic method for context dependent evidence detection](#). In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 440–450, Lisbon, Portugal.
- Sebastian Ruder. 2019. [Neural Transfer Learning for Natural Language Processing](#). Ph.D. thesis, National University of Ireland, Galway.
- Christian Stab, Johannes Daxenberger, Chris Stahlhut, Tristan Miller, Benjamin Schiller, Christopher Tauchmann, Steffen Eger, and Iryna Gurevych. 2018. [ArgumenText: Searching for arguments in heterogeneous sources](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations*, pages 21–25, New Orleans, LA, USA.
- Henning Wachsmuth, Martin Potthast, Khalid Al-Khatib, Yamen Ajjour, Jana Puschmann, Jiani Qu, Jonas Dorsch, Viorel Morari, Janek Bevendorff, and Benno Stein. 2017. [Building an argument search engine for the web](#). In *Proceedings of the 4th Workshop on Argument Mining*, pages 49–59, Copenhagen, Denmark.