Modern Talking: Key-Point Analysis using Modern Natural Language Processing

Max Henze and **Hanh Luu** and **Jan Heinrich Reimer**
Martin Luther University Halle-Wittenberg, Germany
{max.henze,thi.luu,jan.reimer}@student.uni-halle.de

Abstract

TODO

1 Introduction

Test citation (Bar-Haim et al., 2020a)

TODO

2 Related Work

2.1 Key Point Analysis

Given the first track of the shared task analyzing key points is crucial. In their work (Bar-Haim et al., 2020a) Bar-Haim et al. propose an approach for summarising large argument collections to small sets of key points. Thus covering a sufficient amount of all arguments. They show that domain experts can very quickly create pro and con key points, which are able to "capture the gist" of the arguments on the given topic. All this without being exposed to the arguments themself. Furthermore they develop the large-scale dataset ArgKP which is the foundation of this shared task. In a later work (Bar-Haim et al., 2020b) Bar-Haim et al. construct an automatic method for key point extraction which can compete with key points created by human domain experts. The method consists of two aspects. Assuming that the key points can be found among the given comments they first select short, high quality comments as key point candidates an then select the candidate with the highest data coverage. Using the HuggingFace transformer framework they fine-tune four different models from which ALBERT (Lan et al., 2019) has the best F1 score with 0.809 but RoBERTa (Liu et al., 2019) (F1 score of 0.773) is chosen for key point extraction since it has a 6 times faster inference time. In the paper (Egan et al., 2016), Egan et al. propose a summarising for informal arguments such as they occure in online political debates. By extracting verbs and their syntactic arguments they retrieve points which can make key content accessible. By grouping these points they propose to create discussion summaries.

2.2 Argument Clustering

Argument Clustering is a mighty tool that enables algorithms to assign multiple arguments, which adress a similar key message to a given topic. In the paper (Reimers et al., 2019), Reimers et al. make use of "contextualize word embeddings to classify and cluster topic-dependet arguments". Having performed argument classification they then compute similar and dissimilar pairs of arguments. Two approaches one with clustering and one without are being used. Clustering arguments is achieved by usage of agglomerative hierarchical clustering (Day and Edelsbrunner, 1984). Without clustering a fine-tuned BERT-base-uncased model reached a F1 mean score for similar and dissimilar arguments of 0.7401. Agglomerative hierarchical clustering being a strict partitioning algorithm, results for clustering perform worse by up to 7.64pp (Bert-large F1 mean score: 0.7135). Hence they conclude that "strict partitioning clustering methods introduce a new source of errors". Another approach proposed in a paper (Ajjour et al., 2019) by Ajjour et al. revolves around clustering arguments into so called frames which are "a set of arguments that focus on the same aspect". Thereby framing (Entman, 1993) only a specific information to present to the listeners and convince them of your stance. They propose that an argument consists of two crucial parts. The topic and the frame. Hence their approch splits into three steps: First, all arguments are clustered into m topics. Second, topical features are extracted from all arguments and therefore from its cluster. Third, the arguments are reclustered into k non-overlapping frames. By utilizing k-means (Hartigan and Wong, 1979) for clustering and *Term Frequency-Inverse Document Frequency* (TF-IDF) for topic removal they achieved a F1 score of 0.28.

2.3 Stance Classification

By knowing the stance of an argument it becomes nearly effortless for a human to classify it as pro or con to a given topic.

3 Data

TODO

4 Approach

TODO

4.1 Baseline

TODO

5 Results

TODO

6 Conclusion and Future Work

TODO

6.1 Future Work

TODO

References

Yamen Ajjour, Milad Alshomary, Henning Wachsmuth, and Benno Stein. 2019. Modeling frames in argumentation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2915–2925.

Roy Bar-Haim, Lilach Eden, Roni Friedman, Yoav Kantor, Dan Lahav, and Noam Slonim. 2020a. From arguments to key points: Towards automatic argument summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 4029–4039. Association for Computational Linguistics.

Roy Bar-Haim, Yoav Kantor, Lilach Eden, Roni Friedman, Dan Lahav, and Noam Slonim. 2020b. Quantitative argument summarization and beyond: Cross-domain key point analysis. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 39–49. Association for Computational Linguistics.

William HE Day and Herbert Edelsbrunner. 1984. Efficient algorithms for agglomerative hierarchical clustering methods. *Journal of classification*, 1(1):7–24.

Charlie Egan, Advaith Siddharthan, and Adam Wyner. 2016. Summarising the points made in online political debates. In *Proceedings of the Third Workshop on Argument Mining (ArgMining2016)*, pages 134–143.

Robert M Entman. 1993. Framing: Toward clarification of a fractured paradigm. *Journal of communication*, 43(4):51–58.

John A Hartigan and Manchek A Wong. 1979. Ak-means clustering algorithm. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 28(1):100–108.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. *arXiv preprint arXiv:1909.11942*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Nils Reimers, Benjamin Schiller, Tilman Beck, Johannes Daxenberger, Christian Stab, and Iryna Gurevych. 2019. Classification and clustering of arguments with contextualized word embeddings. *arXiv preprint arXiv:1906.09821*.

A Appendix

We release our source code online under the free MIT license.[1]

[1] https://github.com/heinrichreimer/modern-talking