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

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Abstract

TODO

1 Introduction

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

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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., 2020) 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., 2020) 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

The dataset used in this shared task is the IBM Debater(R) - ArgKP v1 (Bar-Haim et al., 2020) which consists of over 24.000 argument and key point pairs labeled as matching/non-matching. They all belong to one of 28 controversial topics ranging from "Assisted suicide should be a criminal offence." to "We should abandon marriage." therefore drawing a clear line between supporting and non-supporting key points.

The section used for training has over 5500 arguments belonging to over 200 key points with 24 topics. This leaves the dev dataset with over 900 arguments and 36 key points for 4 topics.

3.1 Characteristics

4 Approach

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4.1 Baseline

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5 Results

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6 Conclusion and Future Work

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6.1 Future Work

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References

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A Appendix

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

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