Towards a Holistic View on Argument Quality Prediction

Michael Fromm,¹ Max Berrendorf,¹ Johanna Reiml,² Isabelle Mayerhofer,² Siddharth Bhargava,² Evgeniy Faerman¹ and Thomas Seidl¹

¹ Database Systems and Data Mining, LMU Munich, Germany
² LMU Munich, Germany

{fromm, berrendorf}@dbs.ifi.lmu.de

Abstract

Argumentation is one of society’s foundational pillars, and, spurred by advances in NLP and the vast availability of text data, automated mining of arguments receives increasing attention. A decisive property of arguments is their strength or quality. While there are works on the automated estimation of argument strength, their scope is narrow: they focus on isolated datasets and neglect the interactions with related argument mining tasks, such as argument identification, evidence detection, or emotional appeal. In this work, we close this gap by approaching argument quality estimation from multiple different angles: Grounded on rich results from thorough empirical evaluations, we assess the generalization capabilities of argument quality estimation across diverse domains, the interplay with related argument mining tasks, and the impact of emotions on perceived argument strength. In this work, we close this gap by approaching argument quality estimation from multiple different angles: Grounded on rich results from thorough empirical evaluations, we assess the generalization capabilities of argument quality estimation across diverse domains, the interplay with related argument mining tasks, and the impact of emotions on perceived argument strength. In zero-shot transfer and multi-task experiments, we reveal that argument quality is among the more challenging tasks but can improve others. Finally, we show that emotions play a minor role in argument quality than is often assumed. We publish our code at https://anonymous.4open.science/r/kdd-holistic-view-aq-C0D8.

1 Introduction

The argumentation process is one of the cornerstones of society, as it allows the exchange of opinions and reaching a consensus together. Fueled by advances in natural language processing, recent years have witnessed the advent of Argument Mining (AM), i.e., the field of automated discovery and organization of arguments. AM is helpful over various scenarios, reaching from legal reasoning (Wyner et al., 2010; Walker et al., 2014; Poudyal et al., 2020; Villata et al., 2020) to supporting the decision-making process of politicians (Lippi and Torroni, 2016a; Haddadan et al., 2019; Duthie et al., 2016a; Menini et al., 2017; Lippi and Torroni, 2016b; Awadallah et al., 2012). Thus, there is a flurry of works on identification of arguments from text (Stab et al., 2018b; Fromm et al., 2019; Trautmann et al., 2020) and retrieval of them (Wachsmuth et al., 2017b; Fromm et al., 2021; Dumani and Schenkel, 2019; Dumani et al., 2020; Stab et al., 2018a). Since arguments often have to be weighed against each other, a central property of arguments is their Argument Quality (AQ) or convincingness, i.e., their (perceived) strength. While the ancient Greeks (Rapp, 2002) already discussed the constituents of strong arguments, automated estimation is a relatively uncharted field. Due to the high subjectivity of argument strength (Swanson et al., 2015; Gretz et al., 2020; Toledo et al., 2019; Habernal and Gurevych, 2016b; Stab et al., 2018b), obtaining high-quality annotations is challenging. In this light, a legitimate question is the reliability and robustness of the existing approaches for estimating AQ and their applicability in real-life scenarios. Existing AQ benchmark datasets are often restricted to a single domain (Wachsmuth et al., 2016; Persing and Ng, 2017) or make different assumptions about factors impacting the AQ. Thus, enabling transfer between sources and datasets appears especially appealing, but existing works (Gretz et al., 2020; Toledo et al., 2019; Swanson et al., 2015; Habernal and Gurevych, 2016b) cease to provide detailed studies thereupon. Moreover, social science research suggests that the strength of an argument depends less on its logical coherence and depends much more appealing to the recipient’s emotions (Benlamine
et al., 2015, 2017; D’Errico et al., 2018; Li and Xiao, 2020; Hilton, 2008) – a fact which is insufficiently considered so far.

In this work, we thus investigate for the first time the automatic evaluation of the quality of arguments from a holistic perspective, bringing together various aspects: First, we evaluate whether AQ models can generalize across datasets and domains, which is a crucial feature for deployment in the diverse environments encountered in relevant real-world applications. Next, we investigate the hypothesis of whether models for related argument mining tasks inherently learn the concept of argument strength without being explicitly trained to do so by evaluating their zero-shot performance for estimating AQ. Finally, we investigate the effect of emotions in arguments: We present the first dataset for emotions in argumentative texts and demonstrate that emotions can be detected automatically therein, cf. Table 1. The obtained emotion detection models enable us to then provide evidence across all datasets examined that, contrary to the previous belief, emotional argumentation does not significantly influence perceived argument strength.

In summary, our contributions are as follows:

- We are the first to study the generalization capabilities of AQ prediction models across different datasets and AQ notions.

- Since we determine the size of the dataset as one of the decisive performance factors, we further investigate a zero-shot setting of transferring from related Argument Mining tasks.

- Finally, we elucidate the relation between emotions and AQ. To this end, we provide a novel dataset for emotion in argumentative texts and show that these can be predicted on par with human performance. Using this capable emotion detection model, we then show that, in contrast to popular belief, the AQ of emotional arguments does not significantly differ from non-emotional ones, at least across four different publicly available AQ datasets.

2 Related Work

2.1 Argument Quality

Argument Quality (AQ), sometimes also called Argument Strength, is a sub-task in Argument Mining (AM) that belongs to the central research topics among argumentation scholars (Walton et al., 2008; Toulmin, 2003; Van Eemeren and Grootendorst, 1987). Due to its high subjectivity, there is no single definition of AQ. Therefore, there are various suggestions on different factors that can affect an argument’s quality, e.g., the convincingness of an argument (Habernal and Gurevych, 2016a). To the best of our knowledge, we are the first who evaluate how these factors correlate with each other across different corpora. Furthermore, there are various possibilities to express the strength of an argument. Some works adopt an absolute continuous score, while others advocate that strength estimation works better in (pairwise) relation to other arguments.

One of the first relatively large corpora was introduced by Swanson et al. (Swanson et al., 2015). The SwanRank corpus contains over 5k arguments, where each argument is labeled with a continuous score that describes the interpretability of an argument in the context of a topic. They propose a method using linear regression, ordinary Kriging, and SVMs as regression algorithms to estimate the strength automatically from an input text encoding by handcrafted features. Other corpora followed and used the relative- and/or absolute convincingness (Habernal and Gurevych, 2016b; Potash et al., 2019) as the annotation criterion. The authors proposed models based on SVMs or BiLSTM combined with GloVe embeddings (Pennington et al., 2014). Gleize et al. (Gleize et al., 2019) provide a dataset, IBM-EviConv, focused on ranking the evidence convincingness. They used a Siamese network based on a BiLSTM with attention and trainable Word2Vec embeddings (Pennington et al., 2014). Gretz et al. (Gretz et al., 2020) and Toledo et al. (Toledo et al., 2019) created their corpora by asking annotators if they would recommend a friend to use the argument in a speech supporting/contesting the topic, regardless of their own opinion. Both use a fine-tuned BERT (Devin et al., 2019) model for the absolute AQ regression task.
The shared evaluation practice in the previous works is to evaluate methods on each dataset independently. Gretz et al. (Gretz et al., 2020) use the newly introduced dataset for model pre-training but then fine-tune the model on the training part of the dataset used for the evaluation. This work proposes to advance evaluation and advocate for an accurate cross-dataset evaluation without additional fine-tuning on the evaluation dataset to estimate the model’s applicability in challenging real-life scenarios.

### 2.2 Role of Emotions in Argumentation

The previous works only empirically investigate the role of emotions in argumentation on a small scale. Wachsmuth et al. (Wachsmuth et al., 2017a) created a corpus of 320 arguments, annotated for 15 fine-grained argument dimensions originating from argument theory. They categorize the quality dimensions into three main quality aspects: Logical, rhetorical, or dialectical quality. One dimension in rhetorical quality is the emotional appeal, defined as: “Argumentation makes a successful emotional appeal if it creates emotions in a way that makes the target audience more open to the author’s arguments”. The authors did not find any significant correlations to other quality dimensions.

Benlamine et al. (Benlamine et al., 2015, 2017) showed in an experimental setting with 20 participants that the mode of pathos represented by emotion is essential in the persuasion process in argumentation. Their experiment indicates that “[the] Pathos strategy is the most effective to use in argumentation and to convince the participants”.

In both works, the sample size is relatively small (20 participants or 320 arguments). To better substantiate the considerations, we investigate the influence of emotional appeals regarding AQ annotations on more than 40k arguments across four large corpora.

### 3 Generalization across Argument Quality Corpora

High-level applications such as Argument Retrieval (Wachsmuth et al., 2017b; Fromm et al., 2021; Dumani and Schenkel, 2019; Dumani et al., 2020; Stab et al., 2018a) and autonomous debating systems (Slonim et al., 2021) require reliable Argument Quality (AQ) models to select strong arguments among the relevant ones. The research community has identified this gap and proposed and evaluated different automated models for AQ estimation (Gretz et al., 2020; Toledo et al., 2019; Swanson et al., 2015; Habernal and Gurevych, 2016b). However, AQ is often captured differently due to its high subjectivity, e.g., absolutely as a continuous score or relative to other arguments by pairwise comparison. Consequently, many publications also introduced their corpus with individual annotation schemes capturing different notions of AQ. While they compared multiple models against each other within a single corpus, there is a lack of cross-corpora empirical evaluations. Thus, the robustness of predictions across datasets remains largely unexplored, which poses a severe challenge for reliable real-world applications integrating diverse data sources. To evaluate the generalization capability of AQ estimation models, we designed a set of experiments across all four major AQ datasets to answer the following research questions:

- How well do AQ models perform across datasets if annotations schema and domain of the arguments do not change?
• How does the corpora size affect generalization?
• How well do models generalize across different text domains?
• How does the AQ quality notion affect generalization?
• Does the AQ model become more robust if it is trained with a combined dataset containing data from different domains and labeling assumptions also vary?

3.1 Evaluation Setting

We briefly describe the four AQ datasets used in our empirical study, which all capture AQ on a sentence level. They are also summarized in Table 2. Swanson et al. (Swanson et al., 2015) constructed the dataset SwanRank with over 5k arguments whose quality is labeled in the range of [0, 1], where 1 indicates that an argument can be easily interpreted. Habernal et al. (Habernal and Gurevych, 2016b) annotated a large corpus of 16k argument pairs and investigated which argument from the pair is more convincing. Based on the argument pair annotations, they created an argument graph and used PageRank to calculate absolute scores for the individual arguments. The result is called UKPConvArgRank and contains 1k arguments. Gretz et al. (Gretz et al., 2020) and Toledo et al. (Toledo et al., 2019) created their corpora of 30k and 6.3k arguments by asking annotators if they would recommend a friend to use the argument in a speech supporting or contesting the topic regardless of their personal opinion. Gretz et al. (Gretz et al., 2020) used crowd contributors that presumably better represent the general population, compared to debate club members that annotated in Toledo et al. (Toledo et al., 2019). Furthermore, Gretz et al. (Gretz et al., 2020) also considered the annotators’ credibility without removing them entirely from the labeled data, as done in Toledo et al. (Toledo et al., 2019).

As some of the corpora did not provide official train-validation-test splits and differed in the number of topics and the formulated task (in-topic vs. cross-topic), we decided to do our own split based on the topics of the arguments. We perform 10-fold cross-topic cross-validation, where each fold is a 60%/20%/20% train-validation-test split, and we additionally ensure that no topic occurs in more than one split. By the latter requirement, we ensure an inductive setting where the AQ estimation cannot rely on similar arguments in the training corpus and therefore provides a more challenging but more realistic task.

3.2 Model and Training

Since transfer learning achieves state-of-the-art Argument Mining (AM) results on different corpora and tasks (Reimers et al., 2019; Fromm et al., 2019; Trautmann et al., 2020), we also apply it to our AQ estimation task. We use a bert-base model, pre-trained on masked-language-modeling, and fine-tune it to predict absolute AQ scores on the respective datasets, cf. Section 3.1. As an input, we used the arguments from the respective datasets and concatenated the topic information, separated by the BERT specific [SEP] limiter, similar to other work in argument mining (Fromm et al., 2019; Reimers et al., 2019; Gretz et al., 2020). We concatenate the last four layers of the fine-tuned BERT model output to obtain an embedding vector of the size 4 · 768 = 3,072. For the regression task, we stack a Multi-Layer Perceptron (MLP) with two hidden layers, one with 100 neurons and a ReLU activation, followed by the second hidden layer and a sigmoid activation function. We train the architecture end-to-end, with SGD with a weight decay of 0.35 and a learning rate of 9.1 · 10⁻⁶. The MLP uses dropout with a rate of 10%.

3.3 Results

Table 3 summarizes our results. We report the Pearson correlation score between the predicted- and ground-truth absolute AQ evaluated on a hold-out test set.

3.3.1 Evaluation on Similar Datasets and Importance of Training Set Size

First, we evaluate the performance of the model on similar datasets and the dependency on the size of the training dataset. We can observe that models perform very well on other datasets from the same domain labeled with a similar quality notion, i.e., IBM-ArgQ and IBM-Rank datasets. Furthermore, we can notice that the
Table 2: Overview of the different Argument Quality (AQ) datasets with their number of arguments, the number of distinct topics, the different source domains, and the AQ notion used for annotation.

| Name                        | Sentences | Topics | Domain            | Quality notion     |
|-----------------------------|-----------|--------|-------------------|-------------------|
| UKPConvArg (Haber-nal and Gurevych, 2016b) | 1,052     | 32     | Debate Portal     | Convincingness    |
| SwanRank (Swanson et al., 2015)        | 5,375     | 4      | Debate Portal     | Interpretability  |
| IBM-ArgQ (Toledo et al., 2019)         | 5,300     | 11     | Crowd Collection  | Recommendableness |
| IBM-Rank (Gretz et al., 2020)          | 30,497    | 71     | Crowd Collection  | Recommendableness |

Table 3: The models are evaluated by the Pearson correlation between ground truth and predicted Argument Quality on the respective test sets. The first four rows correspond to models trained on a single dataset, whereas for the last four rows, all but one dataset, have been used for training, i.e., following a leave-one-out scheme. **Bold** numbers indicate the best results for each column within the two groups.

| Training                      | Size  | UKPConvArg | SwanRank | IBM-ArgQ | IBM-Rank |
|-------------------------------|-------|------------|----------|----------|----------|
| UKPConvArg                    | 1,052 | 19.0%      | 42.5%    | 15.2%    | 3.0%     |
| SwanRank                      | 5,375 | 18.9%      | **47.5%**| 17.1%    | 8.0%     |
| IBM-ArgQ                      | 5,300 | 23.3%      | 27.8%    | 34.2%    | 38.9%    |
| IBM-Rank                      | 30,497| **26.2%**  | 37.0%    | **38.3%**| **48.1%**|
| all except UKPConvArg         | 41,172| 23.3%      | 45.8%    | 31.6%    | 46.6%    |
| all except SwanRank           | 36,849| **25.0%**  | **49.1%**| 35.0%    | 46.6%    |
| all except IBM-ArgQ           | 36,924| 23.0%      | 43.6%    | **38.4%**| **47.5%**|
| all except IBM-Rank           | 12,224| 20.4%      | 42.0%    | 35.0%    | 46.5%    |
size of the dataset is crucial for performance: a model trained on the largest IBM-Rank dataset achieves the best score also on IBM-ArgQ. This insight gives us a solid foundation for the next steps.

3.3.2 Generalization Across Domains and Quality Notions

Next, we investigate whether a transfer across domains is possible. To this end, we train on one dataset and evaluate on a different one. Recall that the four datasets cover two different domains: the sentences from UKPConvArg and SwanRank have been extracted from debate portals, while IBM-Rank and IBM-ArgQ have been collected from the crowd.

Compared to in-domain generalization, we observe a considerably worse generalization between domains: For example, trained on the crowd dataset IBM-ArgQ, we can achieve a correlation of 38.9% on the crowd dataset IBM-Rank, while training on the debate datasets SwanRank and UKPConvArg results in negligibly low correlations of 8% and 3%, respectively. Conversely, when evaluated on the debate portal dataset SwanRank, we obtain a correlation of 42.5% when using a model trained on the other debate portal dataset UKPConvArg, while the crowd collected datasets IBM-ArgQ and IBM-Rank only achieve 27.8% and 37.0%, respectively. The smaller difference compared to the first comparison can be explained by the larger size of the training datasets.

Surprisingly, we observe a completely different picture for generalization across quality notions. We see only a moderate drop in performance for a fixed domain but a different quality notion. For instance, the model trained on SwanRank performs relatively well on the UKPConvArg dataset. Vice-versa, we observe a more considerable performance drop, which can be explained by the smaller size of the UKPConvArg dataset.

3.3.3 Multi-Domain and Multi-Quality Notion Training

To investigate whether a single model can grasp various dimensions of quality and work on arguments from various domains, we designed another set of “leave-one-out” experiments. We train on the training sentences of all but one AQ corpus and evaluate the performance on all test sets. The entries on the diagonal thus show how well the models perform when evaluated on an unseen corpus.

For evaluation on the unseen IBM-Rank dataset after training on the remaining ones, we can obtain a correlation of 46.5%, which nearly reaches the correlation of 48.1% we obtained when training and evaluating on IBM-Rank. For SwanRank, IBM-ArgQ and UKPConvArg, we can even surpass the correlation on the respective test set by training on all other training sets instead of the one from the respective corpus.

3.3.4 Cross-Corpora Generalization

Conclusion

To summarize, we conclude that, in general, the available datasets and models for AQ are reliable, and the models can grasp the concepts automatically. Our most important insight is that AQ notions do not contradict each other, and a single model can estimate the AQ of text from different domains. Therefore, the practical recommendation for real-life application is to combine all available datasets across different domains and AQ notions.

4 Zero-Shot-Learning in Argument Mining

In this section, we investigate whether explicit Argument Quality (AQ) corpora are a necessity, or whether the task of AQ can also be solved by transferring from other related argument mining tasks such as Argument Identification (AId) or Evidence Detection (ED). In contrast to the relatively new task of automatic AQ estimation, other Argument Mining (AM) tasks already offer a broad range of large datasets that cover different domains and annotation schemes. Moreover, the agreement between the annotators is higher on the other tasks, as AQ is highly subjective (Swanson et al., 2015; Gretz et al., 2020; Toledo et al., 2019; Habernal and Gurevych, 2016b; Stab et al., 2018b). Therefore, a successful transfer from related tasks to the target task of AQ would represent a significant advance in the field. To this end, we investigate the zero-shot capability of AM models across different corpora and different AM tasks. To the best of our knowledge, we are the first to compare AM task similarity by
providing a first study on how individual tasks can benefit from each other.

In particular, we aim to answer the following guiding research questions:

- Can we achieve satisfactory performance by zero-shot transfer from related AM tasks, i.e., without fine-tuning the respective task?
- Is there a difference in transferring from different tasks, i.e., is one task more suited than the other?

While not a primary focus of this work, for completeness, we also provide experimental results for the reverse direction of transferring from AQ estimation to the other tasks.

4.1 Datasets

Table 4 provides an overview of the different AM corpora we used in our experiments, covering three different AM tasks. UKP-Sentential (Stab et al., 2018b) contains over 25k arguments distributed across eight controversial topics. It is annotated for AId, where each argument is labeled as either argumentative or non-argumentative in the context of a topic. The IBM-Evidence (Ein-Dor et al., 2020) corpus includes nearly 30k sentences from Wikipedia articles. All sentences are annotated with a score in the range of [0, 1], denoting the confidence that the sentence is evidence (either expert or study evidence) to the article’s topic. IBM-Rank (Gretz et al., 2020) is the largest of the four AQ datasets, which has also been used in the previous Section 3. The corpus’ annotation is in the range of [0, 1], where 1 indicates a strong argument and a score of 0 indicates a weak argument. We split all three datasets into train, validation, and test sets (70%/10%/20%). Similar to Section 3.1, we designed the splits such that no topic in the training set also occurs in the test set, which is often called the ”cross-topic” scenario in AM and corresponds to a more interesting, but also more challenging task, which requires a sufficient degree of generalization to unseen topics.

4.2 Evaluation Setting

We use a standard BERT large model (Devlin et al., 2019) pre-trained on the masked-language-modeling task to evaluate the zero-shot generalization capability. As an input for the fine-tuning, we use the sentences from the respective datasets and concatenate the topic information, separated by the BERT specific [SEP] limiter, similar to Section 3.2. We develop three different zero-shot evaluation strategies for the different transfer settings:

- **AId → Regression Tasks**: We use the BERT encoder output as input to a linear layer with dropout that predicts the classes. Cross-entropy serves as training loss. The probabilities between 0 and 1 indicate if a sentence is argumentative or not. The predicted probability of the positive class, i.e., whether it is argumentative, is then directly used as a score for ED and AQ on the respective corpora. We use Spearman rank-correlation instead of Pearson correlation as an evaluation measure to account for the difference in scale.

- **Regression Tasks → AId**: ED and AQ use the BERT representations in a single hidden layer that scores the sentences according to their absolute quality or the probability of containing evidence. Since we train on regression tasks, we use the Mean Squared Error loss during training. We then apply the trained models to AId. We select an optimal decision threshold $\alpha$ among all possible thresholds on UKP-Sentential’s validation set according to Macro $F_1$. This model is then evaluated on the UKP-Sentential test set.

- **Regression Task ↔ Regression Task**: For the evaluation between two regressions models, we calculate the Spearman correlation coefficient directly on their respective outputs.

4.3 Results

Table 5 shows the results from our experiments. We train three models with different random seeds for each training task and report the mean and standard deviation of evaluation on the different tasks.

We generally observe, unsurprisingly, that training on the same task as evaluating yields the best results with Spearman correlations of $\approx 77.90\%$ for ED → ED and $\approx 47.45\%$ for AQ → AQ.
Table 4: Overview of the different Argument Mining (AM) datasets, we used for the zero-shot experiments, with their size in terms of the number of sentences, the number of covered topics, the source domain and the AM task.

| Name                        | Sentences | Topics | Domain          | Task                        |
|-----------------------------|-----------|--------|-----------------|-----------------------------|
| IBM-Rank (Gretz et al., 2020) | 30,497    | 71     | Crowd Collection | Argument Quality (AQ)       |
| UKP-Sentential (Stab et al., 2018b) | 25,492    | 8      | Web Documents   | Argument Identification (AId) |
| IBM-Evidence (Ein-Dor et al., 2020) | 29,429    | 221    | Wikipedia       | Evidence Detection (ED)     |

Table 5: Zero-Shot performance of the Argument Mining models. The evaluation measure is Macro $F_1$ for Argument Identification (AId), and the Spearman correlation for Evidence Detection (ED) and Argument Quality (AQ).

| Train | AId     | Evaluation | ED   | AQ       |
|-------|---------|------------|------|----------|
| AId   | 73.51% ± 3.37% | 55.53% ± 1.17% | 27.49% ± 1.54% |
| ED    | 75.16% ± 0.71% | 77.90% ± 0.24% | 28.66% ± 0.92% |
| AQ    | 71.27% ± 0.74% | 43.50% ± 3.10% | 47.45% ± 1.16% |

Metric: Macro $F_1$  $ho$  $ho$

A notable exception is AId, where a model trained on ED achieves $\approx 75.17\%$ Macro $F_1$ and thus can slightly surpass the performance of a model directly trained on AId of $\approx 73.53\%$, although within the range of one standard deviation. Exceeding the in-task performance is a strong result, as the model has never explicitly been trained for the task. We generally observe almost perfect zero-shot transfer towards AId, as also the model trained on AQ achieves a performance of $\approx 71.27\%$, which is only 2% points behind the $\approx 73.53\%$ from AId to AId. Thus, models capable of predicting whether a sentence provides evidence (ED) or capable of predicting the AQ of an argument, inherently learn concepts that enable the detection of whether a sentence is argumentative or not (AId). To further give context to the zero-shot performance, the BiCLSTM approach trained on the AId task from (Stab et al., 2018b) obtained a Macro $F_1$ of 64.14%, i.e., worse results than the zero-shot transfer despite explicitly being trained on the task, which underlines the remarkable zero-shot performance, and may indicate that AId is a simpler task than the other two, ED and AQ.

For ED, we achieve the best performance of $\approx 77.90\%$ Spearman correlation by directly training on this task. The model trained on AId obtains the closest zero-shot transfer result with a rank correlation of $\approx 53.80\%$, which still represents a considerable correlation, despite being $\approx 24\%$ points behind. The model trained for AQ shows the worst transfer from the studied tasks with a correlation of $\approx 43.51\%$. Overall, we note that the challenging zero-shot transfer is still possible with an acceptable loss in performance. Models trained on detecting whether a sentence is argumentative or not (AId) transfer better than those trained for predicting the argumentative strength of a sentence AQ to the target task of predicting the confidence whether a sentence provides evidence (ED).

For AQ, the main focus of our paper, we achieve the best performance of $\approx 47.45\%$ Spearman correlation by directly training on this task. When transferring from related AM tasks in a zero-shot setting, we have to tolerate decreases in performance to $\approx 28.66\%$ for transfer from ED, and $\approx 25.72\%$ for transfer from AId, respectively. Thus, models capable of detecting whether a sentence is argumentative (AId) are slightly less well applicable to predicting the sentence’s argumentative strength than the models for predicting a level of supporting evidence (ED). One factor here may be that ED is also a regression task as opposed to the classification task of AId.

To summarize, the results suggest that the
tasks of AId, i.e., classifying whether a sentence is argumentative, and ED, i.e., predicting a numeric level of supporting evidence, are closer to each other than to the more difficult task of assessing the argumentative strength, as witnessed by worse zero-shot transfer results from and to AQ. Nevertheless, in principle, a transfer in the highly challenging zero-shot setting is possible; for closer related tasks, it can even lead to similar scores as training directly on the target task.

### 4.4 Multi-Task Learning for Argument Quality

As shown in the last section, the AM tasks are sufficiently close to each other to enable successful zero-shot transfer. An interesting question that arises from this observation is whether the performance in AQ estimation further improves by multi-task learning. To this end, we developed a multi-task model that involves a shared BERT encoder and separated linear layers for the respective tasks. We trained the architecture with weighted loss functions, ensuring that each task is weighted equally. Our results are shown in Table 6. Focusing on the right-most column first, we can see that the performance in terms of Spearman correlation only marginally improves by multi-task learning. A possible explanation is here that we already observed that the other two tasks are seemingly less challenging and more closely related to each other than to AQ. As additional supporting evidence, ED slightly and AId considerably benefits from multi-task learning with AQ.

#### 5 Emotion Detection

Most work in Argument Mining (AM) focuses on the *logos* mode of persuasion, i.e., whether arguments are logically plausible. Nevertheless, recent studies support that the mode of *pathos* represented by emotions is essential in the persuasion process (Benlamine et al., 2015, 2017; D’Errico et al., 2018; Li and Xiao, 2020; Hilton, 2008). Those studies have in common that they relied on relatively small sample sizes. In the following, we thus evaluate the hypothesis that the AQ scores in the publicly available Argument Quality (AQ) datasets Swanson (Swanson et al., 2015), UKP (Habernal and Gurevych, 2016b), Gretz (Gretz et al., 2020), and Toledo (Toledo et al., 2019), are influenced by appealing to the emotions of the annotators.

AQ datasets do not provide emotion labels, and therefore, we first need a reliable and scalable method to estimate the level of emotionality in the arguments. As to the best of our knowledge, there is no previous work on automatic emotion detection in arguments, we investigate various approaches from the very simple baselines to complex multi-step transfer learning models. For the evaluation and comparison of different methods, we create a novel argument dataset EmoArg-523, where for each argument, we manually annotate emotionality.

After the reliable emotion detection model is available, we apply it on the unlabeled arguments from the four AQ corpora to obtain proxy emotion labels. We then use these proxy labels to investigate the relation between emotions and argument AQ at a large scale.

In particular, we address the following research questions:

- Can we automatically detect emotions in argumentative texts from different domains?
- Can we substantiate the hypothesis that arguments arousing emotions are perceived stronger?

#### 5.1 Datasets

##### 5.1.1 Novel Emotional Argumentation Dataset

For the evaluation of our EmoBERT model, we sample 150 arguments from each of the four AQ corpora (IBM-Rank, IBM-ArgQ, Swanson-Rank, UKPConvArg), i.e., 600 in total. These arguments are manually labeled by six independent annotators. The arguments were labeled based on the annotation guidelines as *emotional*, when the arguments contained pathos rhetoric, or *non-emotional* when the persuasion process in the argument was driven by evidence or logical rhetoric. The annotator agreement calculated via Krippendorff’s Alpha (Krippendorff et al., 2016) is 31.28%. Note that because of the subjectivity of the task, such an agreement is acceptable; for comparison, e.g., Wachsmuth et al. (Wachsmuth et al., 2017a) achieved an Alpha of 26% for the quality dimension “Emotional appeal”. After the
Table 6: Performance of multi-task models trained on different Argument Mining task combinations, including Argument Identification (AId) and Evidence Detection (ED). The performance is measured by Macro $F_1$ for AId, and the Spearman correlation for ED and AQ.

| Train         | AId       | Evaluation | ED       | AQ       |
|---------------|-----------|------------|----------|----------|
| AQ            | -         | -          | -        | 47.45% ± 1.16% |
| AQ/AId        | 80.07% ± 1.16% | -          | -        | 47.46% ± 0.58% |
| AQ/ED         | -         | 78.07% ± 0.45% | -        | 46.84% ± 0.25% |
| AQ/AId/ED     | 78.91% ± 3.17% | 78.40% ± 0.03% | -        | 48.39% ± 1.12% |

agreement calculation, we removed the 77 sentences (12.8%) without a majority between the six annotators. The resulting dataset comprises 225 emotional (43.02%) and 298 (56.98%) non-emotional arguments and is referred to as EmoArg-523. We split the dataset into train-, validation-, and test-set (60%/10%/30%).

5.1.2 General Emotion Detection Dataset

Although it is not clear a priori that emotion detection transfers well from other domains to the domain of argumentation, we hypothesize that the model can benefit from existing datasets. Motivated by our results for AQ detection, where the model trained on a joined dataset demonstrated very robust performance, we combine seven emotion datasets (Alm, 2009; Scherer and Wallbott, 1994; Strapparava and Mihalcea, 2007; Mohammad et al., 2018; Chatterjee et al., 2019; Neviarouskaya et al., 2010; NeViarouskaya et al., 2011), c.f., Table 7. The emotion datasets came with different classes of emotions. Thus, we unified these different label formats by assigning the existing labels for emotions, such as happy, sad or fear, or neutral, to a binary label of either emotional or non-emotional. The seven datasets were then split individually into train-, validation-, and test-set and combined to a large heterogeneous emotion corpus.

5.2 Models & Baselines

Since transfer learning achieves state-of-the-art results for AM on different corpora and tasks (Reimers et al., 2019; Fromm et al., 2019; Trautmann et al., 2020), we also apply it for the task of emotion detection. We employ a transformer (Vaswani et al., 2017) based BERT model (Devlin et al., 2019) with fine-tuning on different datasets. As a regularization technique to avoid over-fitting, early stopping is used on the validation cross-entropy loss, with a patience value of three epochs. We include the following model variants and baselines in our evaluation:

**Majority Baseline** The majority baseline labels the arguments with the most frequent class based on our EmoArg-523 corpus, which is non-emotional (57.55%).

**Pronouns Baseline** The pronouns baseline labels the arguments as emotional, which contain at least one of the personal pronouns ”I”, ”you” or ”me”.

**NRC Baseline** The NRC baseline labels the arguments which contain at least one unigram contained in the NRC Emotion Lexicon (Mohammad and Turney, 2013).

**EmoBERT** To assess the generalization, we evaluate the zero-shot performance of a BERT model fine-tuned on the heterogeneous emotion corpora, c.f. see Section 5.1.2. The combined emotion corpora incorporate multiple domains found on the internet, and therefore, the resulting model is supposed to be universally applicable.

**ArgBERT** Bert-Base fine-tune it on 339 sentences of our annotated argument emotion dataset.

**ArgBERT-EmoInit** It is the same as ArgBERT-EmoInit, but we also fine-tune it on 339 sentences of our annotated argument emotion dataset. We hypothesize
Table 7: Overview of the different emotion detection datasets from heterogeneous text domains used for the behavioral fine-tuning of EmoBERT.

| Name                       | Sentences | Domain                          |
|----------------------------|-----------|---------------------------------|
| Alm (Alm, 2009)            | 15,036    | Children’s stories              |
| ISEAR (Scherer and Wallbott, 1994) | 7,666    | Reactions and emotion antecedents |
| SemEval-2007 (Strapparava and Mihalcea, 2007) | 1,250    | News headlines                   |
| SemEval-2018 (Mohammad et al., 2018) | 9,625    | Tweets                          |
| SemEval-2019 (Chatterjee et al., 2019) | 14,335   | Dialogues                       |
| Neviarouskaya 2010 (Neviarouskaya et al., 2010) | 1,000    | Stories                         |
| Neviarouskaya 2011 (NEVIAROUSKAYA et al., 2011) | 700      | Diary-like-blogs                |

that with the two-step transfer learning approach, the model first learns a general concept of emotions and then can focus on the target argument domain.

**Human Performance** An interesting experiment for assessing the applicability of the proposed solution is the comparison with the human performance on the task. To compute the human performance, we evaluate each annotator against the majority label of the remaining annotators using the Macro $F_1$ score.

5.3 Results

5.3.1 Emotion Detection

We present the results in terms of Macro $F_1$ on the novel dataset EmoArg-523 for emotion detection in argumentative texts in Table 8. Despite its simplicity, the strongest baseline with a Macro $F_1$ score of 59.7% is the Pronouns Baseline (Pronouns Baseline), EmoBERT achieves a Macro $F_1$ of $\approx 67.1\%$, which highlights that domain adoption from the source - the heterogeneous emotion detection datasets - to the target domain of arguments is possible.

The best emotion detection model, ArgBERT-EmoInit, which used behavioral fine-tuning on the emotion dataset, followed by a second fine-tuning on the dataset of emotion-annotated arguments, achieves a Macro $F_1$ score of $\approx 74.6\%$, only a few points below the human performance estimate of $\approx 80.9\%$. For most models, we also observe a slight decrease in performance between the test part and the full EmoArg-523 (EmoArg-523); we attribute this to a slight distribution shift where the test part seems to contain slightly more arguments with difficult to detect emotions.

5.3.2 The Effect of Emotions on Argument Quality

We start by analyzing the relation of emotionally appealing texts and AQ on the relatively small test part of the novel annotated dataset, EmoArg-523. Fig. 1 shows the distribution of AQ for emotional vs. non-emotional arguments based on the three different emotion detection models and the ground truth annotation grouped by dataset. Except for IBM-ArgQ, we observe the mean AQ of emotional arguments to be higher than those of non-emotional arguments. A possible explanation is that, in contrast to the other datasets that used crowd workers, the annotation on IBM-ArgQ was created by debate club members, who may have been trained to judge explicitly not considering an emotional appeal. However, partially due to the small sample size, the differences are insignificant ($p > 0.01$) according to Welsh’s unequal variance t-test with Fischer adjustments.

Next, we utilize the trained emotion detection models to extend the analyses from the 157 test sentences in EmoArg-523 to the remaining 41,905 from the combined AQ corpora. While we are now restricted to predicted emotionality only instead of human annotations, we reviewed its quality in the previous section and found it sufficient. Fig. 2 shows the distribution of AQ grouped by predicted appeal to emotion for all three models and four datasets.

For SwanRank, emotional arguments receive slightly larger quality scores. While this is consistent across all models, it is clearly visible for EmoBERT and the most reliable emo-
Table 8: Overview of the emotion detection results for different model variants on the annotated Argument Quality dataset, EmoArg-523. We show results in terms of Macro F₁ for different BERT model variants, as well as the three baselines in addition to a human performance estimate. For those models which do not make use of the labels on EmoArg-523, we also report the performance across all labeled arguments. In bold font, we highlight the best performance inside one group.

| Method              | Split          | train+val+test | test  |
|---------------------|----------------|----------------|-------|
| Majority Baseline   |                | 36.3%          | 36.4% |
| Pronouns Baseline   |                | **63.0%**      | **59.7%** |
| NRC Baseline        |                | 52.3%          | 50.3% |
| EmoBERT             |                | **67.1% ± 3.0%** | **65.9% ± 5.3%** |
| ArgBERT             |                | -              | **73.2% ± 1.8%** |
| ArgBERT-EmoInit     |                | -              | **74.6% ± 1.7%** |
| Human Performance   |                | **82.1% ± 4.0%** | **80.9% ± 4.0%** |

Figure 1: Relation between predicted / annotated emotionality and Argument Quality grouped by dataset for the three different models and the ground truth (on the right-most panel; denoted by annotation).

Figure 2: Comparison of the Argument Quality (AQ) of the remaining unlabeled > 40,000 arguments grouped by predicted emotionality across the four datasets.
tion prediction model, ArgBERT-EmoInit. We attribute this to the covered topics of Gun Control, Gay Marriage, Death Penalty, and Evolution, which are areas with emotional discussions. On IBM-ArgQ, the differences are smaller but consistent across all models, with a slight tendency towards non-emotional arguments being perceived stronger. A possible explanation can be the annotation process, where debate club members served as annotators, which may be taught towards looking at logical arguments without letting emotions affect their view. The other two datasets do not show a consistent nor noticeable difference in the distributions. Overall, we cannot observe a clear relation between emotional argumentation and perceived strength on a large scale, challenging existing views. With our new dataset for emotional argumentation and the proxy models capable of predicting emotional argumentation, we hope to enable social sciences to study the deeper reasons behind this in the future.

6 Conclusion
We see this work as a fundamental step towards a holistic view of Argument Quality (AQ): We showed that for good generalization across individual AQ corpora, a match between the source and target domain of the arguments is essential. In contrast, diversity in AQ notions does not hinder but rather enriches the generalization capability. The target domain has a minor impact with sufficient broad coverage of different domains and adequate size. This insight is directly actionable for practical applications: The benefits of different AQ notions permit direct integration of different data sources, which is a prerequisite for dealing with the inputs from diverse domains encountered, e.g., by general-purpose argument retrieval engines.

Moreover, we could elucidate AQ’s relation to other Argument Mining (AM) tasks, such as Evidence Detection (ED) and Argument Identification (AId). Our zero-shot transfer experiments demonstrated that the concepts learned for one of the tasks are sufficient to solve the other to some degree without explicitly being trained for it. By comparing the achieved results, we conclude that AId and ED are more closely related to each other than to AQ, and per se also easier to transfer to it. The multi-task experiment further emphasized this, where AQ could gain less from the other tasks than vice-versa. Thus, an important open question is how to enable better successful transfer towards AQ, and also extending beyond the three tasks we studied in this work.

Finally, we provide the community with a new corpus that consists of AQ and emotion annotations. In contrast to some results from social science research, our extensive empirical evaluation across a large number of argumentative sentences found overall only a limited influence of emotional appeal on the AQ scores. A deeper analysis of these surprising results’ (social) determinants is an important future work direction. Besides the well-studied logos dimension of logical plausibility and the pathos dimension investigated in this work, the third remaining dimension from classical argumentation theory is ethos, which did not receive sufficient attention by the AM community so far. Existing smaller datasets (Koszowy et al., 2022; Duthie et al., 2016b) invite to visit these uncharted territories, e.g., by studying argument strength in context to the provenance of an argument.

References
Cecilia Ovesdotter Alm. 2009. Affect in text and speech.
Rawia Awadallah, Maya Ramanath, and Gerhard Weikum. 2012. Harmony and dissonance: Organizing the people’s voices on political controversies. In Proc. of the Fifth ACM Int. Conf. on Web Search and Data Mining, WSDM ‘12, page 523–532.
Mohamed S. Benlamine, Serena Villata, Ramla Ghali, Claude Frasson, Fabien Gandon, and Elena Cabrio. 2017. Persuasive argumentation and emotions: An empirical evaluation with users. In Human-Computer Interaction. User Interface Design, Development and Multimodality, pages 659–671.
Sahbi Benlamine, Maher Chaouachi, Serena Villata, Elena Cabrio, Claude Frasson, and Fabien Gandon. 2015. Emotions in argumentation: an empirical evaluation. In Proc. of the 24th Int. Conf. on Artificial Intelligence, pages 156–163.
Ankush Chatterjee, Kedhar Nath Narahari, Meghana Joshi, and Puneet Agrawal. 2019.
SemEval-2019 task 3: EmoContext contextual emotion detection in text. In Proc. of the 13th Int. Workshop on Semantic Evaluation, pages 39–48.

Francesca D'Errico, Marinella Paciello, and Matteo Amadei. 2018. Behind our words: Psychological paths underlying the un/supportive stance toward immigrants in social media. In DSAA, pages 649–656.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL, pages 4171–4186.

Lorik Dumani, Patrick J. Neumann, and Ralf Schenkel. 2020. A framework for argument retrieval. In Advances in IR, pages 431–445.

Lorik Dumani and Ralf Schenkel. 2019. A systematic comparison of methods for finding good premises for claims. In Proc. of the 42nd Int. SIGIR, pages 957–960.

Rory Duthie, Katarzyna Budzynska, and Chris Reed. 2016a. Mining Ethos in Political Debate, volume 287 of Frontiers in Artificial Intelligence and Applications, pages 299–310.

Rory Duthie, Katarzyna Budzynska, and Chris Reed. 2016b. Mining ethos in political debate. In Computational Models of Argument: Proc. from the Sixth Int. Conference on Computational Models of Argument (COMMA), pages 299–310.

Liat Ein-Dor, Eyal Shnarch, Lena Dankin, Alon Halfon, Benjamin Szajder, Ariel Gera, Carlos Alzate, Martin Gleize, Leshem Choshen, Yufang Hou, et al. 2020. Corpus wide argument mining—a working solution. In Proc. of the AAAI Conf. on Artificial Intelligence, volume 34, pages 7683–7691.

Michael Fromm, Max Berrendorf, Sandra Obermeier, Thomas Seidl, and Evgeniy Faerman. 2021. Diversity aware relevance learning for argument search. In Advances in IR - 43rd European Conf. on IR Research, ECIR 2021, Virtual Event, March 28 - April 1, 2021, Proc., Part II, volume 12657, pages 264–271.

Michael Fromm, Evgeniy Faerman, and Thomas Seidl. 2019. TACAM: topic and context aware argument mining. In 2019 IEEE/WIC/ACM Int. Conf. on Web Intelligence, WI 2019, Thessaloniki, Greece, October 14-17, 2019, pages 99–106.

Martin Gleize, Eyal Shnarch, Leshem Choshen, Lena Dankin, Guy Moskowich, Ranit Aharonov, and Noam Slonim. 2019. Are you convinced? choosing the more convincing evidence with a Siamese network. In ACL, pages 967–976.

Shai Gretz, Roni Friedman, Edo Cohen-Karlik, Assaf Toledo, Dan Lahav, Ranit Aharonov, and Noam Slonim. 2020. A large-scale dataset for argument quality ranking: Construction and analysis. AAAI Conf, 34(05):7805–7813.

Ivan Habernal and Iryna Gurevych. 2016a. What makes a convincing argument? empirical analysis and detecting attributes of convincingness in web argumentation. In EMNLP, pages 1214–1223.

Ivan Habernal and Iryna Gurevych. 2016b. Which argument is more convincing? analyzing and predicting convincingness of web arguments using bidirectional LSTM. In ACL, pages 1589–1599.

Shohreh Haddadan, Elena Cabrio, and Serena Villata. 2019. Yes, we can! mining arguments in 50 years of US presidential campaign debates. In Proc. of the ACL, pages 4684–4690.

Denis Hilton. 2008. Emotional tone and argumentation in risk communication. Judgment and Decision making, 3(1):100.

Marcin Koszowy, Katarzyna Budzynska, Martín Pereira-Fariña, and Rory Duthie. 2022. From theory of rhetoric to the practice of language use: The case of appeals to ethos elements. Argumentation, pages 1–27.

Klaus Krippendorff, Yann Mathet, Stéphane Bouvry, and Antoine Widlöcher. 2016. On the reliability of unitizing textual continua: Further developments. Quality & Quantity, 50(6):2347–2364.

Jinfen Li and Lu Xiao. 2020. Emotions in online debates: Tales from 4forums and convinceme. Proc. of the Association for IST, 57(1):e255.

Marco Lippi and Paolo Torroni. 2016a. Argument mining from speech: Detecting claims in political debates. AAAI, 30(1).

Marco Lippi and Paolo Torroni. 2016b. Argument mining from speech: Detecting claims in political debates. In AAAI, volume 16, pages 2979–2985.

Stefano Menini, Federico Nanni, Simone Paolo Ponzetto, and Sara Tonelli. 2017. Topic-based agreement and disagreement in US electoral manifestos. In EMNLP, pages 2938–2944.

Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. SemEval-2018 task 1: Affect in tweets. In Proc. of The 12th Int. Workshop on Semantic Evaluation, pages 1–17.

Saif M Mohammad and Peter D Turney. 2013. Crowdsourcing a word–emotion association lexicon. Computational intelligence, 29(3):436–465.
Alena Neviarouskaya, Helmut Prendinger, and Mitsuru Ishizuka. 2010. Recognition of affect, judgment, and appreciation in text. In *Coling*, pages 806–814.

ALENA NEVIAROUSKAYA, HELMUT PRENDINGER, and MITSURU ISHIZUKA. 2011. Affect analysis model: novel rule-based approach to affect sensing from text. *Natural Language Engineering*, 17(1):95–135.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In *EMNLP*, pages 1532–1543.

Isaac Persing and Vincent Ng. 2017. Lightly-supervised modeling of argument persuasiveness. In *Proc. of the Eighth Int. Joint Conference on Natural Language Processing*, pages 594–604.

Peter Potash, Adam Ferguson, and Timothy J. Hazen. 2019. Ranking passages for argument convincingness. In *Proc. of the 6th Workshop on Argument Mining*, pages 146–155.

Prakash Poudyal, Jaromir Savelka, Aagje Ieven, Marie Francine Moens, Teresa Goncalves, and Paulo Quaresma. 2020. ECHR: Legal corpus for argument mining. In *Proc. of the 7th Workshop on Argument Mining*, pages 67–75.

C. Rapp. 2002. *Rhetorik*. Number Bd. 1 in Aristoteles Werke in deutscher Übersetzung.

Nils Reimers, Benjamin Schiller, Tilman Beck, Johannes Daxenberger, Christian Stab, and Iryna Gurevych. 2019. Classification and clustering of arguments with contextualized word embeddings. In *ACL*, pages 567–578.

K. Scherer and H. Wallbott. 1994. "evidence for universality and cultural variation of differential emotion response patterning": Correction. *Journal of Personality and Social Psychology*, 67:55–55.

Noam Slonim, Yonatan Bilu, Carlos Alzate, Roy Bar-Haim, Ben Bogin, Francesca Bonin, Leshem Choshen, Edo Cohen-Karlik, Lena Dankin, Lilach Edelstein, et al. 2021. An autonomous debating system. *Nature*, 591(7850):379–384.

Christian Stab, Johannes Daxenberger, Christian Stahlhut, Tristan Miller, Benjamin Schiller, Christopher Traumman, Steffen Eger, and Iryna Gurevych. 2018a. Argumentext: Searching for arguments in heterogeneous sources. In *NAACL*, pages 21–25.

Christian Stab, Tristan Miller, Benjamin Schiller, Pranav Rai, and Iryna Gurevych. 2018b. Cross-topic argument mining from heterogeneous sources. In *Proc. of the 2018 Conf. on EMNLP*, pages 3664–3674.

Carlo Strapparava and Rada Mihalcea. 2007. Semeval-2007 task 14: Affective text. In *Proc. of the 4th Int. Workshop on Semantic Evaluations, SemEval ’07*, page 70–74.

Reid Swanson, Brian Ecker, and Marilyn Walker. 2015. Argument mining: Extracting arguments from online dialogue. In *Proc. Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 217–226.

Assaf Toledo, Shai Gretz, Edo Cohen-Karlik, Roni Friedman, Elad Venezian, Dan Lahav, Michal Jacovi, Ranit Aharonov, and Noam Slonim. 2019. Automatic argument quality assessment: new datasets and methods. *arXiv preprint*.

S Toulmin. 2003. The uses of argument cambridge university press.

Dietrich Trautmann, Johannes Daxenberger, Christian Stab, Hinrich Schütze, and Iryna Gurevych. 2020. Fine-grained argument unit recognition and classification. In *AAAI*.

Frans H Van Eemeren and Rob Grootendorst. 1987. Fallacies in pragma-dialectical perspective. *Argumentation*, 1(3):283–301.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

S Villata et al. 2020. Using argument mining for legal text summarization. In *Legal Knowledge and Information Systems: JURIX 2020: The Thirty-third Annual Conf., Brno, Czech Republic, December 9-11, 2020*, volume 334, page 184.

Henning Wachsmuth, Khalid Al Khatib, and Benno Stein. 2016. Using argument mining to assess the argumentation quality of essays. In *COLING*, pages 1680–1691.

Henning Wachsmuth, Nona Naderi, Yufang Hou, Yonatan Bilu, Vinodkumar Prabhakaran, Tim Alberdingk Thijm, Graeme Hirst, and Benno Stein. 2017a. Computational argumentation quality assessment in natural language. In *EACL*, pages 176–187.

Henning Wachsmuth, Martin Potthast, Khalid Al Khatib, Yamen Ajjour, Jana Puschmann, Jiani Qu, Jonas Dorsch, Viorel Morari, Janek Bevendorff, and Benno Stein. 2017b. Building an argument search engine for the web. In *Proc. of the 4th Workshop on Argument Mining*, pages 49–59.

Vern Walker, Karina Vazirova, and Cass Sanford. 2014. Annotating patterns of reasoning about medical theories of causation in vaccine cases: Toward a type system for arguments. In *Proc. of the First Workshop on Argumentation Mining*, pages 1–10.
Douglas Walton, Christopher Reed, and Fabrizio Macagno. 2008. Argumentation schemes.

Adam Z. Wyner, Raquel Mochales Palau, Marie-Francine Moens, and David Milward. 2010. Approaches to text mining arguments from legal cases. In Semantic Processing of Legal Texts: Where the Language of Law Meets the Law of Language, volume 6036, pages 60–79.
A Computing & Software Infrastructure

All experiments were conducted on a Ubuntu 20.04 system with an AMD Ryzen Processor with 32 CPU-Cores and 126 GB memory. We further used Python 3.7, PyTorch 1.4, and the Huggingface-Transformer library (4.15.0). For the experiments in Chapter 3, we used four NVIDIA RTX 2080 Ti GPU with 11 GB memory. The models in Chapter 4 and 5 were trained on a single NVIDIA Tesla V100. The default parameters from the Huggingface-Transformer library \(^1\) were used for all hyperparameters not specified in the following sections.

B GENERALIZATION ACROSS ARGUMENT QUALITY CORPORA

In Section 3, we trained bert-base-uncased models with a batch size of 64. The learning rate was set to \(9.1 \cdot 10^{-6}\). A weight decay of 0.31 was used. We calculated the 95th percentile based on the four AQ validation sets and truncated longer sentences to that length. We used a dropout rate of 0.1 for the dropout layer in the \(\text{Ald} \rightarrow \text{Regression Tasks}\) setting. The losses in the multi-dataset setting were equally weighted for each of the four datasets. We used early stopping on the validation MSE loss, with a patience value of five epochs, as a regularization technique to avoid over-fitting.

C ZERO-SHOT-LEARNING IN ARGUMENT MINING

For Section 4, we trained bert-large-uncased architectures with a batch size of 64. The learning rate was set to \(1 \cdot 10^{-5}\), and for the first 0.1 epochs, a warm-up period is used. We opt for evaluations every 0.1 epochs in our training configuration, resulting in 10 evaluations per epoch. Our train/validation/test split is based on a reasonably standard 70%/10%/20% split. Furthermore, we calculate the 99th percentile of the max length of all sentences in the validation split, and truncate all sentences to that length.

D EMOTION DETECTION

For Section 5, we trained bert-base-cased architectures with a batch size of 32. The learning rate was set to \(5 \cdot 10^{-5}\) A weight decay of 0.1 was used. We opt for evaluations every 0.25 epochs in our training configuration, resulting in 4 evaluations per epoch. The annotators used the Inception Annotation Framework \(^2\) for the labeling of the arguments. The annotated dataset is split into train/validation/test (60%/10%/30%). Furthermore, we calculate the 99.5th percentile of the max length of all sentences in the validation split, and truncate all sentences to that length.

---

\(^1\)https://huggingface.co/docs/transformers/master/en/main_classes/trainer#transformers.TrainingArguments

\(^2\)https://inception-project.github.io/releases/22.3/docs/user-guide.html