Argumentative quality is an important feature of everyday writing in many textual domains, such as online reviews and question-and-answer (Q&A) forums. Authors can improve their writing with feedback targeting individual aspects of argument quality (AQ), even though preceding work has mostly focused on assessing the overall AQ. These individual aspects are reflected in theory-based dimensions of argument quality, but automatic assessment in real-world texts is still in its infancy—a large-scale corpus and computational models are missing. In this work, we advance theory-based argument quality research by conducting an extensive analysis covering three diverse domains of online argumentative writing: Q&A forums, debate forums, and review forums. We start with an annotation study with linguistic experts and crowd workers, resulting in the first large-scale English corpus annotated with theory-based argument quality scores, dubbed AQCorpus. Next, we propose the first computational approaches to theory-based argument quality assessment, which can serve as strong baselines for future work. Our research yields interesting findings including the feasibility of large-scale theory-based argument quality annotations, the fact that relations between theory-based argument quality dimensions can be exploited to yield performance improvements, and demonstrates the usefulness of theory-based argument quality predictions with respect to the practical AQ assessment view.

1 Introduction

Providing relevant and sufficient justifications of one’s claims, and making reasons understandable by using clear language are important features of everyday writing. These are components of Argument Quality (AQ) which has been studied in many textual domains, such as student essays (Wachsmuth et al., 2016), news editorials (El Baff et al., 2018), and debate forums (Lukin et al., 2017).

While preceding work in natural language processing (NLP) and computational linguistics has mostly focused on practical AQ assessment, thereby either assessing (a) the overall quality of arguments (Toledo et al., 2019; Gretz et al., 2020, inter alia) or (b) a single specific conceptualization of AQ, e.g., as argument strength (Persing and Ng, 2015), convincingness (Habernal and Gurevych, 2016), and relevance (Wachsmuth et al., 2017c), it is evident and even noted in related work (Gretz et al., 2020) that predicting quality in terms of finer-grained aspects is needed: It enables a profound understanding of argumentation and offers more specific feedback to authors aiming to improve their argumentative writing skills. For instance, they might want to know whether their premises are sufficient with regard to the claim(s) or whether the language is appropriate. Wachsmuth et al. (2017b) surveyed and synthesized theory-based dimensions of AQ into a taxonomy that encompasses three main dimensions: Cogency (Logic), Effectiveness (Rhetoric), and Reasonableness (Dialectic). Their initial annotation study showed that the task of assessing these dimensions is challenging even for experts, but Wachsmuth et al. (2017a) concluded that crowd workers can handle the task comparably well if the guidelines and task are simplified.

Given the feasibility of annotating and the recognized need for fine-grained dimensions in AQ assessment, it is surprising that no further efforts in NLP and CL have been made, and to-date there is

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1 We adopt the terminology of Wachsmuth et al. (2017a) who refer to task-driven approaches, which often also focus on the relative assessment of AQ, as “practical”.

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**Abstract**

Argumentative quality is an important feature of everyday writing in many textual domains, such as online reviews and question-and-answer (Q&A) forums. Authors can improve their writing with feedback targeting individual aspects of argument quality (AQ), even though preceding work has mostly focused on assessing the overall AQ. These individual aspects are reflected in theory-based dimensions of argument quality, but automatic assessment in real-world texts is still in its infancy—a large-scale corpus and computational models are missing. In this work, we advance theory-based argument quality research by conducting an extensive analysis covering three diverse domains of online argumentative writing: Q&A forums, debate forums, and review forums. We start with an annotation study with linguistic experts and crowd workers, resulting in the first large-scale English corpus annotated with theory-based argument quality scores, dubbed AQCorpus. Next, we propose the first computational approaches to theory-based argument quality assessment, which can serve as strong baselines for future work. Our research yields interesting findings including the feasibility of large-scale theory-based argument quality annotations, the fact that relations between theory-based argument quality dimensions can be exploited to yield performance improvements, and demonstrates the usefulness of theory-based argument quality predictions with respect to the practical AQ assessment view.
no large scale annotated corpus and consequently, no computational model. In this work, we aim to close this research gap by conducting an in-depth analysis of theory-based AQ assessment covering three dimensions (logic, rhetoric, and dialectic) and three diverse domains of online argumentative writing: Q&A forums, debate forums, and review forums.

Drawing on existing AQ theories, we address five research questions (RQs):

**(RQ1)** Are we able to develop a large-scale theory-based AQ corpus? We conduct an extensive annotation study on 5,295 arguments from three domains, annotated by both trained linguists and crowd workers. This study results in the first large-scale and multi-domain English corpus annotated with theory-based AQ scores, dubbed AQCorpus.

**(RQ2)** Are we able to develop computational models that can do theory-based AQ assessment in varying domains? Based on AQCorpus, we are the first to propose computational approaches to theory-based AQ assessment and show that it is possible to develop models for this task. Our models can serve as strong baselines for future research and enable the field to investigate follow-up research questions.

**(RQ3)** Can the interrelations between the different AQ dimensions suggested by the theory-based taxonomy be exploited in a computational setup? Inspired by the relationships between dimensions and the hierarchical structure of the taxonomy, we explore whether these relationships can be computationally exploited: In addition to simple single-task learning approaches, we study the effect of jointly predicting AQ dimensions in two variants (flat vs. hierarchical) and find that combining the training signals of all four aspects is beneficial to theory-based AQ assessment.

**(RQ4)** How well does the corpus support training a single unified model for multi-domain evaluation? When enough data from a single domain is available, training on in-domain data is typically preferred over multi-domain settings. However, larger amounts of data are especially useful for complex model architectures, which are currently prominent in NLP (e.g., BERT (Devlin et al., 2019), GPT2 (Radford et al., 2019)). We study these two mutually opposing effects on AQCorpus and show that our corpus supports training a single unified model across all three domains: By training on the multi-domain training set, model performances in individual domains improve.

**(RQ5)** Can we empirically substantiate the idea that theory-based and practical AQ assessment can learn from each other? Wachsmuth et al. (2017a) suggest that both the practical and the theory-based (normative)views can learn from each other, but so far, this has been only tested manually. Employing our models, we go one step further and conduct a bi-directional experiment employing a practical AQ corpus. We hope this work will inform and fuel future AQ annotation studies and computational AQ research.

**Structure.** After a discussion of the related work in §2, we describe our annotation study and resulting corpus (§3). §4 describes the computational approaches which we employ in the experiments (§5). Last, we conclude our work and give potential directions for future work (§6).

2 Related Work

The plethora of preceding approaches to computational AQ assessment can be divided into (1) practical approaches and (2) theory-based approaches.

**Practical approaches to AQ.** In the recent past, the field of computational AQ research has been mostly driven by practical approaches, which cover to-date a variety of almost individually tackled domains (e.g., essays (Persing and Ng, 2013; Wachsmuth et al., 2016; Stab and Gurevych, 2017), debates (Habernal and Gurevych, 2016), news editorials (El Baff et al., 2018)) and conceptualizations (e.g., overall quality (Toledo et al., 2019) vs. specific conceptualizations, such as convincingness (Habernal and Gurevych, 2016), relevance (Wachsmuth et al., 2017c), and clarity (Persing and Ng, 2013)). The popularity of the practical approach can be attributed to a) the relative simplicity of setting up crowd-sourced annotation studies, and b) the immediate impact when developing a solution to a practical problem.

Much prior work has focused on aspects of student essays, including essay clarity (Persing and Ng, 2013), organization (Persing et al., 2010), prompt adherence (Persing and Ng, 2014), and argument strength (Persing and Ng, 2015). Ong et al. (2014) predict argumentative quality of essays using an ontology-based approach. Later, Wachsmuth et al. (2016) present an approach driven by detecting
argumentative discourse units, thereby demonstrating the usefulness of argument mining techniques to the problem. Similarly, Stab and Gurevych (2016) predict the absence of opposing arguments and Stab and Gurevych (2017) predict insufficient premise support in arguments.

Another well-studied domain is web debates. Wachsmuth et al. (2017c) adapt PageRank (Page et al., 1999) to identify argument relevance. Pairwise comparison of the convincingness of debate arguments has been conducted (Habernal and Gurevych, 2016). Persing and Ng (2017) additionally predict why an argument receives a low score in terms of persuasive power. By explaining flaws in argumentation, they highlight the importance of explainability and specific author feedback.

Other approaches take into account properties of the source, i.e., the author (Durmus and Cardie, 2019), or of the target, i.e., the audience (El Baff et al., 2018; Durmus and Cardie, 2018). In our experiments we assume that a system may not have much knowledge about the authors or audience and thus our models operate solely on the text. Toledo et al. (2019) and Gretz et al. (2020) present large corpora, crowd sourcing arguments and their quality. These corpora cover a variety of topics, but only within a single domain. The authors emphasize that research on theory-based approaches could further advance the field of computational AQ.

Theory-based approaches to AQ. In contrast to practical-driven AQ assessment, theory-based AQ is mostly discussed in argumentation theory. The works relate to the logical (Johnson and Blair, 2006; Hamblin, 1970), rhetorical (Aristotle, 2007), and dialectical (Cham Perelman and Weaver, 1969; Van Eemeren et al., 2004) properties of an argument.

Wachsmuth et al. (2017b) were the first to survey and highlight the importance of the theory-based approach to computational AQ and synthesized the argumentation-theoretic literature into a taxonomy encompassing fine-grained aspects for each of the three dimensions. In a corpus-based study, in which crowd workers had to annotate the same 304 arguments for all 15 given quality dimensions as in Wachsmuth et al. (2017b), Wachsmuth et al. (2017a) demonstrated that the theory-based and the practical AQ assessment approach match to a large extent and that the two views can learn from each other, for instance, when it comes to more practical annotation processes for theory-based AQ annotations. Their findings indicate that (a) it is possible to crowd-source theory-based AQ annotations, and (b) that theory-based approaches can help to inform the practical view.

However, no further research on computational theory-based AQ assessment in NLP has been conducted, no larger-scale annotated corpus has been presented, and thus no computational model is in place which would allow to further investigations into the concrete synergies between the two perspectives.

Building on this large body of work, we advance theory-based AQ in computational argumentation guided by our five RQs: We conduct an annotation study encompassing theory-based AQ dimensions. We then use the corpus and we propose the first computational models to theory-based AQ studying the interrelations between models in single and multi-domain settings and empirically test the idea that theory and practice can learn from each other.

3 Annotation Study

Wachsmuth et al. (2017a) suggest that large-scale annotation of theory-based AQ dimensions is possible. We test this finding and take it one step further by asking whether we are able to develop a large-scale theory-based AQ corpus (RQ1). This section presents AQCorpus, the result of the first study annotating theory-based dimensions, including 5,285 arguments from three diverse domains of real-world argumentation.

3.1 Annotation Scheme

Our annotation scheme is based on the taxonomy of argumentation quality proposed by Wachsmuth et al. (2017a) depicted in Figure 1. It defines overall AQ as being composed of three sub-dimensions (Cogency, Effectiveness, Reasonableness), each of which is in turn composed of several quality-related aspects:

Cogency relates to the logical aspects of argument quality. High cogency indicates that an argument’s premises are acceptable as well as relevant and sufficient with regard to the argument’s conclusion.
Effectiveness reflects the persuasive power of how an argument is stated. Important aspects of an effective argument include its arrangement, clarity, appropriateness in a given context, emotional appeal, and the credibility of the author.

Reasonableness indicates the quality of an argument in the context of a debate, i.e. the relevance of the argument for given the discussed issue, the acceptability of the argument and the way it is stated as a whole, and the sufficiency of the argument for the resolution of the issue.

Starting from the guidelines of Wachsmuth et al. (2017b), we developed our annotation guidelines through a series of pilot studies with four expert annotators, all of whom are either fluent or native English speakers and hold advanced degrees in linguistics. Since annotators noted difficulties distinguishing between the 15 fine-grained aspects, we collapse the theme to Overall Argument Quality and the three higher level dimensions above but represent the finer-grained sub-dimensions as questions to help guide the raters’ judgments. This simplifies the task and guidelines as recommended in Wachsmuth et al. (2017a), which was confirmed by our expert annotators. After experimenting with a three-point rating scale (low, medium, high, as used by Wachsmuth et al. (2017b), we decided on a five-point scale (very low, low, medium, high, very high, including a “cannot judge” option), allowing a more differentiated view on argument quality and simplifying the annotation task, according to the feedback of our expert annotators and previous findings (Cox III, 1980). In our pilot studies, switching the scales did not negatively affect the inter-annotator agreement.

3.2 Data

By investigating different domains, we obtain a deeper understanding about real-world AQ and the feasibility of the annotation scheme and scale in different settings. In particular, we employed four data sets from three different domains in our study: (1) Q&A forum posts, (2) debate forum posts, and (3) business review forum posts. Figure 3 displays an example text for each domain, along with the ratings provided by our linguistic expert annotators.

Q&A Forums (Q&A). We include a subset of 2,088 arguments from Yahoo! Answers,² a Q&A forum where users ask questions and answer questions asked by others. While not a dedicated debate forum, we found that some subsections contain a relatively high proportion of argumentative posts, in which users ask for arguments supporting or challenging their stance. Not enforcing strict debating rules or topics, the nature of the argumentative posts is particularly diverse and therefore interesting for our study. Aiming for a high proportion of argumentative texts in our corpus, we focus on the subcategory Politics & Government → Law & Ethics and only include the post marked as best answer for a question. We also exclude posts containing uniform resource identifiers or media content to limit the amount of context necessary to

²https://answers.yahoo.com/
Question: should juveniles be tried as adults?
Answer: It all depends on the crime. For the most part I believe if your grown enough to go and do an adult crime then you need to do the adult time. If we continue to let the youth get away with serious crimes then older criminals will continue to get our youth in trouble. We must raise our children correctly so they want end up in some prison but there are certain things that is morally wrong no matter if your 15 or 35 and those are the crimes our young "adult" should be charged for.

(a) Debate Forums.

Title: Business name: Little Shanghai. City: Pittsburgh. Categories: Restaurants, Chinese
Stars: 5.0
Review: Little Shanghai has the best Chinese food that I’ve been able to find in the city. The steamed flounder with bean curd is great. It comes in 2 fillets for $13.95. I loved the texture of the crispy tofu in the spinach with garlic and tofu dish. The broth of the noodle soup with spare ribs has a wonderful flavor and the dish is more than enough to fill up one person. I wish the restaurant had better loose leaf tea (they use a tea bag) but the food is excellent. I would highly recommend this restaurant.

(b) Q&A Forums.

Title: CMV: All rights, including so-called natural rights are human constructs
Text: I often read people talking about the idea of natural rights which are universal and inalienable. I contend such rights are simply constructs, and have no basis beyond any other construct humanity has created. While there can be some appeal to human nature, nearly all universal behaviour that could be classified as rights only apply to the “in-group” and certainly none seem to apply to humanity as a whole. The extension of rights to cover everyone a construct, and not part of fundamental human nature. This is why law exists in general. It’s an extension of tribal self-rule for larger groups. There is certainly nothing about the nature of reality that causes rights to exist. I’d like to hear some good arguments as to why rights are not constructs.

(c) Review Forums.

Figure 3: Example texts and quality trends provided by our linguistic experts for each domain.

understand the argument. Finally, we filter the texts using Amazon Mechanical Turk, collecting 10 binary judgments about whether each text is argumentative. In our annotation study, we only include answers that a majority of raters labeled argumentative (this threshold was selected by manual inspection).

Debate Forums (Debates). For reflecting online debate forums-style argumentation, we include subsets of Change My View (CMV) and the Internet Argument corpus V2 (IAC), resulting in a total of 2,103 arguments. CMV is a subsection of the internet forum Reddit, in which users can post their opinion and ask other users to challenge their beliefs on the topic. 4 We sample a subset of the corpus published by Tan et al. (2016). The IAC (Abbott et al., 2016) is composed of posts retrieved from three online debate forums: 4Forums, ConvinceMe, and Create Debate. The Create Debate subset contains discussions focusing on the topic of gun control only, but the 4Forums and ConvinceMe subsets cover more diverse topics. Manually analyzing the original posts (OPs) from 4Forums and ConvinceMe, we found the ConvinceMe subset most suited for the purpose of our study. To identify good instances from these sources, we try to restrict the sample to instances that do not require much background knowledge or thread-level context. Therefore, from CMV, we include original posts only and similarly, for ConvinceMe, we include the first post providing a reaction to the topic. Additionally, for CMV we also exclude posts tagged [MOD] indicating moderator posts.

Review Forums (Reviews). Yelp is an online platform on which users can publish business reviews along with a rating ranging from 1 (poor) to 5 (excellent) stars indicating the quality of the user’s experience. From the Yelp-Challenge-Dataset, we sampled 1,104 arguments reviewing restaurants. While the review texts often do not appear as “classic” arguments, i.e., with a dedicated claim and premises supporting this claim, the texts can indeed be considered argumentative (Wachsmuth et al., 2014; Wachsmuth et al., 2015): The star rating corresponds to a claim a user is making about the business and the review text is intended to support this claim with believable justifications.

Across all domains, we filter for posts with text length between 70 and 200 words.

3.3 Expert and Crowd Annotators

Annotation Procedure. To ensure high quality of our annotations, we ran, in total, 13 pilot studies in two flavors: (1) with three of the linguistic expert annotators (§3.1), and (2) with a crowd-sourced

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3 MTurk qualifications: HIT approval rate ≥ 97; HITs approved > 500; Location = US
4 https://www.reddit.com/r/changemyview/
5 https://www.yelp.com/dataset
Table 1: Number of annotators per instance and total instances annotated by Experts and the Crowd, and the number of overlapping instances by domain.

| Domain | Total | Train | Dev. | Test |
|--------|-------|-------|------|------|
| Q&A    | 2,085 | 1,109 | 476  | 500  |
| Debate | 2,100 | 1,093 | 469  | 538  |
| Review | 1,100 | 700   | 300  | 100  |
| All    | 5,285 | 2,902 | 1,245| 1,138|

Table 2: Number of instances in the train, development, and test sets of AQCorpus.

| Cogency | Effectiveness | Reasonableness | Overall |
|---------|---------------|----------------|---------|
| Mean    | MACE Mean     | MACE           | MACE    |
| Ours    | .46           | .37            | .48     | .37     | .55     | .35     |
| TvsP    | .27           | .38            | .38     | .31     | .40     | .43     |

Table 3: Agreement between expert annotations from Wachsmuth et al. (2017b) and crowd-sourced annotations from two sources: AQCorpus (Ours) and Wachsmuth et al. (2017a) (TvsP) on 200 randomly sampled instances.

Table 4: IAA between the Expert and Crowd scores for Cogency (Cog), Effectiveness (Effec), Reasonableness (Reas), and Overall AQ (Over).

workforce from Appen\textsuperscript{6}, on which we curated a workforce of 24 contributors based on their agreement in the pilot studies. For both groups, we used the same annotation guidelines and annotation interface, which we iteratively improved according to the feedback collected in each calibration round. The guidelines as well as our interface are available online.\textsuperscript{7} Table 1 shows the number of judgments per instance per domain as well as the number of instances that were annotated by each group. For each domain, up to 500 arguments were annotated by both experts and crowd workers.

**Standard Split.** We provide a standard split for each domain, which we employ in our experiments and is composed as follows: The training and development sets consist of the instances which were either annotated by our linguistic experts or the crowd workers. In contrast, the test portions encompass only instances which are scored by both experts and the crowd. For each instance and group, we obtain a single score by averaging the annotators votes. In addition to the group-specific annotations (expert and crowd), we also compute a mix score which consists of the average of the two group-specific scores. This way, we train on a mix of expert and crowd annotations (where the dominant portion comes from the crowd) and test on overlapping instances, which enables us to compare model performance to both expert and crowd ratings on a static set of instances.

### 3.4 Data Analysis

**Inter-annotator Agreements.** In order to assess the quality of our crowd-sourced annotations and to test our simplified annotation guidelines, we employ the Dagstuhl-ArgQuality-Corpus-V2 (DS)\textsuperscript{8} and conduct a comparative study against the Wachsmuth et al. (2017a) annotations (TvsP). We take “gold” ratings from the original, author-produced annotations presented in Wachsmuth et al. (2017b). DS was presented in combination with the taxonomy of theory-based AQ described above and consists of 320 web debate arguments annotated with all 15 argument quality aspects. The arguments were originally taken from UKPConvArgRank (Habernal and Gurevych, 2016). We randomly sample 200 arguments and crowd-source annotations on Appen.\textsuperscript{9} For each instance and AQ dimension, we obtain group votes by either averaging the workers’ votes (Mean) or applying MACEaggregation (Hovy et al., 2013).\textsuperscript{10} We

\textsuperscript{6}Formerly Figure Eight, https://www.appen.com/
\textsuperscript{7}ANONYMOUS
\textsuperscript{8}http://argumentation.bplaced.net/arguana/data
\textsuperscript{9}Here, we stuck to the original 3-point scale to match the original expert annotations we compare with.
\textsuperscript{10}MACE computes a confidence score for each annotator and weights the annotators vote in the aggregation accordingly.
measure inter-annotator agreement (IAA) between the obtained group vote and the DS expert vote. The results are depicted in Table 3. Generally, the agreement scores of our crowd ratings are comparably high and often surpass the agreement scores reported by TvsP. We therefore conclude that our guidelines and user interface support the task, and confirm the suitability of our crowd annotators.

Next we consider the agreement between experts and crowd workers on the overlapping portions of AQCorpus, considering the mean scores (Table 4). For debate forums, Krippendorff’s $\alpha$ is up to .21, while for the Q&A forums, the agreement is higher – up to .53. These results suggest that the difficulty of the task is highly dependent on the domain.

**Analysis of Disagreements.** We noticed disagreements among the annotators along all stages of the annotation process, especially for arguments which were of sarcastic or ironic nature or included rhetorical questions. As an example consider the argument given in Figure 2.

This example presents an online argument about freedom of speech and seems to support the stance that a government has the right to censor speech. However, several linguistic cues indicate that the argument might be ironic: (a) Punctuation: Ellipsis indicates thinking/searching for justifications; similarly, (b) the filler *um*; (b) Capitalization: The noun phrase *Our Leader* is capitalized, indicating hyperbolic apotheosis; and finally, (c) the phrase (...) so I have to argue for this side. acts like an apologia, which is put in front of the actual argument. In discussion with our expert annotators it became clear that especially annotator 1 and annotator 2 based their judgments on a completely different interpretation of this text, which related to the estimated degree of irony in the post. While annotator 1 did not perceive irony and judged the argument as very weak in Effectiveness, annotator 2 considered it to be highly effective as in their view, the irony positively underlined the perceived stance. Annotator 3 gave medium scores across the board but was leaning more towards annotator 2’s opinion. Such disagreements were regularly discussed and usually revealed that multiple opinions may exist according to how the texts were interpreted, which highlights the high subjectivity and ambiguity of the task.

**Domain-specificity.** Differences in agreement can be also observed across the different domains in AQCorpus: While debate forum posts exhibit the difficulty of being part of longer threads and therefore are dialectic in their argumentative nature, the original posts were often relatively easy to assess by the annotators when presented in isolation. This observation holds analogously for our sample of Q&A forum posts, but here the top answer seemed usually more argumentative. In contrast, the business reviews are monologueous in nature, but often only weakly argumentative: They show a clear stance in terms of the user rating (i.e., Yelp stars) and the users present several aspects of their experience as justifications for the rating. However, the justifications provided are very subjective, which makes it difficult to evaluate, especially the logical dimension. In addition to that, annotators noticed differences in how they would rate an argument depending on the discussion topic. For instance, though instructed to be as objective as possible, some annotators would rate arguments generally lower when a topic was discussed that they found less worthy of being discussed while others would rate good arguments for these topics even higher given the difficulty of making good arguments for these topics. “Less worthy topics” were generally frivolous or less consequential, such as Which superhero would win in a duel?.

The final distributions of the mean scores per variable across the different domains in AQCorpus are depicted in Figures 4a and 4b, respectively. The interquartile range of the expert scores is generally higher than for the crowd annotations, which might indicate that experts are more specific when scoring examples. This is also reflected in the medians across the different variables: While the crowd exhibits a tendency to score variables equally, more differentiation can be seen in the experts’ annotations.

The numbers of instances in each portion of AQCorpus are given in Table 2.

### 4 Models

Having developed AQCorpus to enable computational AQ assessment (RQ1), we address the remaining research questions by experimenting with several AQ models. To determine whether we can develop a

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11 We calculate all agreements with Krippendorff’s $\alpha$ (Krippendorff, 2007).

12 If included, the stance of the forum posts was given in the IAC database.
computational theory-based AQ model (RQ2), we employ a naive length baseline, three different Support Vector Regression (SVR) models, and a BERT-based (Devlin et al., 2019) model. We next investigate whether the interrelations between AQ dimensions can be exploited in a computational setup (RQ3), employing two multi-task BERT-based models.

We employ the scikit-learn toolkit for the SVR models. The BERT-based models rely on a pretrained multi-layer bidirectional Transformer (Vaswani et al., 2017). To this end, we transform each argument into a “BERT-compatible” format, i.e., into a sequence of WordPiece (Wu et al., 2016) tokens and prepend the whole sequence with BERT’s sequence start token ([CLS]). The pooled hidden representation of the latter corresponds to the aggregated document representation $h_D \in \mathbb{R}^h$. The specific details of each model are described below.

**Argument Length (ARG LENGTH).** To obtain an estimate of the difficulty of the task(s) and to measure potential bias regarding argument length, our naive baseline is the correlation between the number of characters in the argument and the quality scores.

**Support Vector Regression with Lexical Features (SVR$_{tf-idf}$).** We run a simple Support Vector Regression (SVR) with tf-idf feature vectors.

**Support Vector Regression with Semantic Features (SVR$_{embd}$).** For each word in the argument, we represent each argument as the average over all of its fastText (Bojanowski et al., 2017) embedding$^{13}$ representations.

**Feature-rich Support Vector Regression (WACHSMUTH$_{CFS}$).** We reimplement the approach of Wachsmuth et al. (2016), who employ standard features (e.g., token n-grams, part-of-speech tags, etc.) as well as higher-level features (e.g., sentiment flows, argumentative discourse units etc.). We run correlation-based feature selection on the training set and employ only the features which were found to be the most predictive.

**Single Task Learning Setting (BERT ST).** For each argument quality dimension $t$, we train an individual regressor. Let $h_D \in \mathbb{R}^h$ be the vector representation of the argument. Our argument quality predictor is a simple linear regression layer:

$$
\hat{y} = h_D W^T_t + b_t,
$$

---

$^{13}$https://dl.fbaipublicfiles.com/fasttext/vectors-english/wiki-news-300d-1M-subword.vec.zip
with \( W_i \in \mathbb{R}^H \) and \( b_i \in \mathbb{R} \) as the classifier’s trainable parameters. The loss \( L_t \) is then simply the mean squared error (MSE) over \( k \) instances in the training batch, where \( y \in [0; 5] \) is the true score for a training instance for the argument quality dimension \( t \):

\[
L_t = \frac{1}{k} \sum_{i=0}^{k} (y_i - \hat{y}_i)^2.
\]

**Flat Multi-Task Learning Setting (BERT MT_{flat}).** We explore whether a joint training setup would improve the individual score predictions. Let \( h_D \in \mathbb{R}^h \) be the vector representation of the argument. For each quality dimension, we employ an individual prediction layer as defined in Equation 1 and compute an individual task loss \( L_t \) as defined in Equation 2. We then define the total training loss \( L_{total} \) as the sum of the task losses \( L_t \), with \( T = \{\text{Cogency}, \text{Effectiveness}, \text{Reasonableness}, \text{Overall Quality}\} \) as the set of argument quality dimensions:

\[
L_{total} = \sum_{t \in T} L_t,
\]

**Hierarchical Multi-Task Learning Setting (BERT MT_{hier}).** We propose a hierarchical multi-task learning setting to exploit the hierarchical relationship between the scores. Similar to above, we first learn jointly the lower-level tasks (cogency, effectiveness, reasonableness) resulting in three scores \( \hat{y}_{\text{Cog}}, \hat{y}_{\text{Eff}} \) and \( \hat{y}_{\text{Rea}} \). Next, we employ these scores for informing the overall argument quality predictor by concatenating these with the hidden document representation \( h_D \):

\[
h_{\text{informed}} = h_D \lbrack \hat{y}_{\text{Cog}}, \hat{y}_{\text{Eff}}, \hat{y}_{\text{Rea}} \rbrack;
\]

The resulting vector \( h_{\text{informed}} \) serves as input to the overall argument quality predictor as defined in Equation 1.

## 5 Experiments

We employ the proposed architectures to answer research questions RQ2–RQ5.

### 5.1 RQ2: Computational theory-based AQ assessment

To test whether our corpus supports the development of theory-based AQ assessment models, this experiment employs all single-task models presented in Section 4 (ARG LENGTH, SVR_{tfidf}, SVR_{emb}, WACHSMUTH_{CFS}, and BERT ST). We train and predict on the domain-specific training sets. The test sets comprise instances annotated by the experts and the crowd, allowing for three evaluation setups (crowd, expert, mix) per AQ dimension for each domain. We optimize the hyperparameters of all models on the development sets. For the SVR-based models, we grid search in \( c \in \{0.001, 0.01, 0.1, 1.0, 10\} \) and \( \varepsilon \in \{0.001, 0.01, 0.1, 1.0\} \). For the BERT-based models, we optimize the learning rate \( \lambda \in \{2e-5, 3e-5\} \) and the number of training epochs \( e \in \{3, 4\} \).

**Results.** The respective Pearson correlation scores for AQ dimensions on the three domain-specific test sets are shown in Table 5. Generally, we reach medium to high Pearson correlation scores of up to nearly .7. However, like the inter-annotator agreement, performance varies across domains, even for single argument quality dimensions: On the Expert test set of the debate domain, the best model, BERT ST, achieves a correlation coefficient with the annotation scores for reasonableness of .220 and on the Q&A forums Crowd, it achieves a performance of .696. Except for a single case, the BERT-based regressor outperforms the other methods, showing that we can successfully utilize a large-scale corpus with theory-based AQ dimensions to train models for automatic AQ assessment (RQ2).

Note that ARG LENGTH is relatively high across all domains and properties and often outperforms SVR_{tfidf} and SVR_{emb}, indicating a slight bias towards length in the corpus. This is especially the case for the crowd-annotated debate arguments, suggesting that the crowd is generally more prone to this bias. This is not surprising given that AQU corpus contains real-word texts varying in length and often, a longer argument contains more useful information. However, BERT ST still outperforms this baseline in all other cases by a large margin, demonstrating this model’s ability to capture useful information beyond...
Table 5: Pearson correlations of our model predictions with the annotation scores for the four AQ dimensions on the three different test annotations (Crowd, Expert, Mix) when training on in-domain data. Numbers in bold indicate best performances.

| Model          | Q&A forums          | Debate Forums         | Review Forums         |
|---------------|---------------------|-----------------------|-----------------------|
|               | Crowd | Expert | Mix | Crowd | Expert | Mix | Crowd | Expert | Mix |
| Overall       | Arg LENGTH         | 0.498 | 0.236 | 0.406 | 0.542 | 0.232 | 0.420 | 0.486 | 0.190 | 0.365 |
|               | SVR_{tfidf}        | 0.381 | 0.323 | 0.389 | 0.299 | 0.179 | 0.265 | 0.446 | 0.340 | 0.450 |
|               | SVR_{embd}         | 0.323 | 0.180 | 0.278 | 0.467 | 0.239 | 0.388 | 0.223 | 0.227 | 0.265 |
|               | WACHSMUTH_CFS      | 0.550 | 0.340 | 0.492 | 0.524 | 0.264 | 0.432 | 0.619 | 0.342 | 0.533 |
|               | BERT ST            | 0.681 | 0.498 | 0.652 | 0.575 | 0.346 | 0.511 | 0.611 | 0.450 | 0.605 |
| Cogency       | Arg LENGTH         | 0.502 | 0.227 | 0.420 | 0.574 | 0.225 | 0.437 | 0.491 | 0.125 | 0.340 |
|               | SVR_{tfidf}        | 0.449 | 0.330 | 0.444 | 0.295 | 0.164 | 0.257 | 0.409 | 0.264 | 0.384 |
|               | SVR_{embd}         | 0.301 | 0.154 | 0.261 | 0.404 | 0.196 | 0.333 | 0.264 | -0.059 | 0.103 |
|               | WACHSMUTH_CFS      | 0.565 | 0.311 | 0.503 | 0.548 | 0.232 | 0.429 | 0.611 | 0.223 | 0.464 |
|               | BERT ST            | 0.623 | 0.405 | 0.587 | 0.556 | 0.337 | 0.503 | 0.618 | 0.359 | 0.554 |
| Effectiveness | Arg LENGTH         | 0.475 | 0.237 | 0.390 | 0.502 | 0.225 | 0.399 | 0.425 | 0.251 | 0.372 |
|               | SVR_{tfidf}        | 0.432 | 0.313 | 0.411 | 0.141 | 0.074 | 0.120 | 0.354 | 0.253 | 0.340 |
|               | SVR_{embd}         | 0.328 | 0.204 | 0.293 | 0.456 | 0.264 | 0.403 | 0.186 | 0.144 | 0.187 |
|               | WACHSMUTH_CFS      | 0.555 | 0.393 | 0.523 | 0.528 | 0.281 | 0.450 | 0.567 | 0.246 | 0.432 |
|               | BERT ST            | 0.596 | 0.509 | 0.612 | 0.548 | 0.405 | 0.542 | 0.639 | 0.370 | 0.555 |
| Reasonableness| Arg LENGTH         | 0.480 | 0.245 | 0.396 | 0.535 | 0.170 | 0.377 | 0.496 | 0.241 | 0.405 |
|               | SVR_{tfidf}        | 0.466 | 0.364 | 0.457 | 0.292 | 0.153 | 0.247 | 0.435 | 0.345 | 0.452 |
|               | SVR_{embd}         | 0.411 | 0.278 | 0.379 | 0.393 | 0.096 | 0.258 | 0.205 | 0.191 | 0.234 |
|               | WACHSMUTH_CFS      | 0.543 | 0.326 | 0.476 | 0.549 | 0.192 | 0.399 | 0.524 | 0.261 | 0.432 |
|               | BERT ST            | 0.696 | 0.512 | 0.665 | 0.544 | 0.222 | 0.418 | 0.556 | 0.484 | 0.609 |

5.2 RQ3: Effect of AQ dimension interrelations

Next we seek to determine whether it is possible to exploit these interrelations between the three dimensions and the overall AQ by conducting experiments on AQCorpus. We compare the multi-task learning architectures, BERT MT_{flat} and BERT MT_{hier}, against the results of the BERT ST model, the best performing single-task model. Again, we train and predict on the domain-specific data splits.

Results. The respective Pearson correlation scores for the four argument quality dimensions on the three different test sets per domain can be seen in Table 6. Overall, the multi-task learning models outperform the single-task model in 26 out of 35 cases, which suggests that the interrelations between the AQ dimensions and overall AQ can be exploited to improve model performance (RQ3). More specifically, the best method seems to be BERT MT_{flat}, which outperforms the other methods in 19 out of 35 cases. BERT ST and BERT MT_{hier}, which are best in fewer than 10 cases each. 9 and 7 cases, respectively.

5.3 RQ4: Unified multi-domain model

Given AQCorpus, which covers multiple domains, we examine whether our corpus supports training a unified multi-domain model. We train the BERT-based models on the joint training set covering all domains and test performance on each individual domain, thereby including out-of-domain data to the training. Similarly, we optimize the hyperparameters on the joint development set. We compare with the best in-domain score.

Results. The respective results for the four argument quality dimensions on the domain-specific test sets can be seen in Table 7. In 25 out of 36 cases training on all domains increases the performance compared to the best in-domain model (69% of the cases). While the models are less domain-specific, the increased
### Table 6: Pearson correlations of our model predictions with the annotation scores. We compare single-task versus multi-task learning setups training on in-domain data only.

| Model          | Overall | Cogency | Effectiveness | Reasonableness |
|----------------|---------|---------|---------------|----------------|
|                | Crowd   | Expert  | Mix           | Crowd          | Expert  | Mix           | Crowd   | Expert  | Mix           |
|                | 0.681   | 0.498   | 0.652         | 0.575          | 0.346   | 0.511         | 0.611   | 0.450   | 0.605         |
| BERT ST        | 0.671   | 0.535   | 0.667         | 0.607          | 0.362   | 0.537         | 0.534   | 0.478   | 0.588         |
| BERT MT\_flat | 0.668   | 0.528   | 0.661         | 0.480          | 0.393   | 0.494         | 0.563   | 0.465   | 0.593         |
| BERT MT\_hier | 0.623   | 0.405   | 0.587         | 0.556          | 0.337   | 0.503         | 0.618   | 0.359   | 0.554         |
| BERT ST        | 0.651   | 0.457   | 0.633         | 0.622          | 0.343   | 0.541         | 0.533   | 0.440   | 0.561         |
| BERT MT\_flat | 0.650   | 0.468   | 0.638         | 0.476          | 0.353   | 0.474         | 0.559   | 0.388   | 0.541         |
| BERT MT\_hier | 0.596   | 0.509   | 0.612         | 0.548          | 0.405   | 0.542         | 0.639   | 0.370   | 0.555         |
| BERT ST        | 0.663   | 0.549   | 0.671         | 0.599          | 0.408   | 0.570         | 0.522   | 0.389   | 0.514         |
| BERT MT\_flat | 0.656   | 0.552   | 0.670         | 0.477          | 0.443   | 0.532         | 0.466   | 0.388   | 0.486         |
| BERT MT\_hier | 0.696   | 0.512   | 0.665         | 0.544          | 0.222   | 0.418         | 0.556   | 0.484   | 0.609         |
| BERT ST        | 0.672   | 0.499   | 0.644         | 0.587          | 0.273   | 0.473         | 0.550   | 0.489   | 0.610         |
| BERT MT\_flat | 0.660   | 0.478   | 0.626         | 0.445          | 0.280   | 0.408         | 0.555   | 0.488   | 0.611         |

### Table 7: Pearson correlations of the model predictions with the annotation scores when training on the joint training sets of all domains. We compare with the best result of the in-domain setting.

| Model          | Overall | Cogency | Effectiveness | Reasonableness |
|----------------|---------|---------|---------------|----------------|
|                | Crowd   | Expert  | Mix           | Crowd          | Expert  | Mix           | Crowd   | Expert  | Mix           |
| Best in-domain | 0.681   | 0.535   | 0.667         | 0.607          | 0.362   | 0.537         | 0.619   | 0.478   | 0.605         |
| BERT ST        | 0.693   | 0.530   | 0.676         | 0.571          | 0.401   | 0.545         | 0.650   | 0.409   | 0.596         |
| BERT MT\_flat | 0.697   | 0.535   | 0.681         | 0.574          | 0.425   | 0.562         | 0.678   | 0.443   | 0.633         |
| BERT MT\_hier | 0.680   | 0.522   | 0.665         | 0.576          | 0.424   | 0.562         | 0.618   | 0.469   | 0.622         |
| Best in-domain | 0.651   | 0.468   | 0.638         | 0.622          | 0.353   | 0.541         | 0.618   | 0.440   | 0.561         |
| BERT ST        | 0.639   | 0.426   | 0.608         | 0.540          | 0.367   | 0.515         | 0.601   | 0.386   | 0.563         |
| BERT MT\_flat | 0.673   | 0.472   | 0.653         | 0.560          | 0.392   | 0.542         | 0.610   | 0.391   | 0.570         |
| BERT MT\_hier | 0.662   | 0.455   | 0.638         | 0.573          | 0.397   | 0.552         | 0.577   | 0.465   | 0.599         |
| Best in-domain | 0.656   | 0.552   | 0.671         | 0.599          | 0.443   | 0.570         | 0.639   | 0.389   | 0.555         |
| BERT ST        | 0.664   | 0.574   | 0.686         | 0.544          | 0.492   | 0.598         | 0.711   | 0.387   | 0.601         |
| BERT MT\_flat | 0.676   | 0.536   | 0.670         | 0.569          | 0.444   | 0.578         | 0.683   | 0.409   | 0.603         |
| BERT MT\_hier | 0.657   | 0.523   | 0.653         | 0.573          | 0.462   | 0.592         | 0.646   | 0.396   | 0.576         |
| Best in-domain | 0.696   | 0.512   | 0.665         | 0.587          | 0.280   | 0.473         | 0.556   | 0.489   | 0.611         |
| BERT ST        | 0.658   | 0.495   | 0.635         | 0.550          | 0.320   | 0.487         | 0.616   | 0.437   | 0.603         |
| BERT MT\_flat | 0.691   | 0.503   | 0.657         | 0.538          | 0.328   | 0.486         | 0.667   | 0.443   | 0.631         |
| BERT MT\_hier | 0.665   | 0.485   | 0.633         | 0.554          | 0.312   | 0.483         | 0.642   | 0.476   | 0.643         |

5.4 RQ5: Synergies between practical and theory-driven AQ

To empirically test the hypothesis that synergies exist between practical and theory-based AQ assessment, we conduct a bi-directional experiment with the recently released IBM-Rank-30k (Gretz et al., 2020).

**Experimental setup.** IBM-Rank-30k consists of 30,497 crowd-sourced arguments relating to 71 topics, where each argument is restricted to 35–210 characters. The corpus has binary judgments indicating whether raters would recommend the argument to a friend. Based on these ratings, a score for each argument was computed, either using MACE or weighted average of all ratings. Compared to AQCorpus, IBM-Rank-30k is much larger but the arguments are much shorter and more artificial than real world texts. Manual inspection revealed that the nature of the texts substantially differs from each those in AQCorpus, i.e., arguments mainly cover reasons for higher-level claims. For example, in IBM-Rank-30k for the topic “We should end racial profiling”, a highly rated argument is “racial profiling unfairly targets minorities and the poor”.

The amount of data leads to better convergence. Especially on the Expert test set of the debate forums, and the Crowd test set of the review forums, the gains can be high – up to 11 percentage points!
We take the BERT MT\textsubscript{flat} models trained on each domain of AQCorpus and predict on the test portion of IBM-Rank-30k. This enables us to determine which domain and which dimension are closest to the data and annotations in IBM-Rank-30k. We compare against the best score reported in the Gretz et al. (2020) as well as against our own reimplementation using BERT\textsubscript{BASE}, dubbed BERT IBM.\textsuperscript{14} We optimize the BERT IBM baseline by grid searching for the learning rate $\lambda \in \{2e^{-5}, 3e^{-5}\}$ and the number of training epochs $\in \{3, 4\}$ on the IBM-Rank-30k development set. For the already trained models from Sections 5.2 and 5.3, no further optimization is necessary.

**Results.** The results of our experiments using IBM-Rank-30k are given in Table 8. We report the Pearson ($r$) and the Spearman correlation coefficients ($\rho$) against the weighted average score (WA) and the MACE-based aggregation given in the data set.

As expected, the zero-shot domain transfer results in a large drop compared to training on the associated train set of IBM-Rank-30k. However, quite surprisingly, the model trained on the debate forums reaches the highest correlation scores – even higher than the model trained on all-domains. Further, in most cases, the effectiveness predictions correlate best with the annotations provided by Gretz et al. (2020). This is in-line with the authors’ observations.

In order to validate these findings, we perform the experiment vice versa: We train a BERT-based regressor as defined in Equation 1 on the MACE-P aggregated annotations of IBM-Rank-30k, which corresponds to our BERT IBM baseline from before. We predict on AQCorpus and correlate the resulting scores with our annotations for the four argument quality dimensions on each of our three test sets per domain. Again: as expected, the zero-shot domain transfer using BERT IBM results in a huge loss in performance compared to BERT MT\textsubscript{flat}. To combat these losses, we draw inspiration from Phang et al. (2018) and use IBM-Rank-30k in the Supplementary Training on Intermediate Labeled Tasks-setup (STILT). That is, we take the trained BERT IBM encoder and continue training the model as BERT IBM MT\textsubscript{flat} in the all-domain setup. We compare both models with the BERT MT\textsubscript{flat} from Table 7. The results are listed in Table 9. When reusing the encoder in the STILT setup, BERT IBM MT\textsubscript{flat}, the losses can be flattened out – in some cases even outperforming BERT MT\textsubscript{flat}. This is especially the case when correlating the predictions with our annotations for the effectiveness dimensions.

To summarize, this bi-directional experiment yields these findings: (1) Large-scale predictions, obtained by a theory-based AQ model on a large (practical) AQ data set, correlate mostly with the effectiveness dimension. (2) The transferred knowledge obtained in the STILT-setup on IBM-Rank-30k in BERT IBM

\textsuperscript{14}Note that Gretz et al. (2020) do not indicate whether they employ BERT\textsubscript{BASE} or BERT\textsubscript{LARGE}. 

| Domain         | Dimension | WA $r$ | WA $\rho$ | MACE-P $r$ | MACE-P $\rho$ |
|----------------|-----------|--------|-----------|------------|--------------|
| BERT IBM       | –         | 0.492  | 0.456     | 0.503      | 0.493        |
| Gretz et al. (2020) | –         | 0.52   | 0.48      | 0.53       | 0.52         |
| All            | Overall   | 0.313  | 0.303     | 0.325      | 0.322        |
|                | Cogency   | 0.311  | 0.300     | 0.322      | 0.318        |
|                | Effectiveness | 0.313   | 0.303     | 0.325      | 0.322        |
|                | Reasonableness | 0.304   | 0.298     | 0.317      | 0.316        |
| Q&A Forums     | Overall   | 0.258  | 0.224     | 0.260      | 0.242        |
|                | Cogency   | 0.269  | 0.228     | 0.271      | 0.247        |
|                | Effectiveness | 0.262   | 0.225     | 0.264      | 0.243        |
|                | Reasonableness | 0.262   | 0.226     | 0.265      | 0.244        |
| Debate Forums  | Overall   | 0.336  | 0.326     | 0.359      | 0.348        |
|                | Cogency   | 0.331  | 0.321     | 0.354      | 0.343        |
|                | Effectiveness | 0.336   | 0.326     | 0.360      | 0.349        |
|                | Reasonableness | 0.333   | 0.319     | 0.355      | 0.340        |
| Review Forums  | Overall   | 0.150  | 0.145     | 0.162      | 0.157        |
|                | Cogency   | 0.139  | 0.138     | 0.155      | 0.149        |
|                | Effectiveness | 0.152   | 0.151     | 0.165      | 0.161        |
|                | Reasonableness | 0.149   | 0.148     | 0.165      | 0.160        |

Table 8: Performances of the BERT MT\textsubscript{flat} models trained on varying domains of the AQCorpus when predicting on IBM-Rank-30k either evaluated against the weighted average score (WA) or the MACE-based aggregation score (MACE-P).
Table 9: Pearson correlations on AQCorpus when predicting with BERT IBM (trained on IBM-Rank-30k) and BERT IBM MT\textsubscript{flat} trained on IBM-Rank-30k in STILT setup fine-tuned on AQCorpus in comparison to BERT MT\textsubscript{flat}.

MT\textsubscript{flat} improves the performance score on AQCorpus for the effectiveness dimension most. These two facts match the hypothesis of Gretz et al. (2020) that they mostly captured effectiveness in their annotation study. We empirically substantiate the idea – without any manual effort – that, on the one hand, a theory-based approach can inform practical AQ research and increase interpretability of practically-driven research outcomes and, on the other hand, the practical approach can help to increase the efficacy of theory-based AQ models when interested in a certain domain and dimension.

6 Conclusion and Future Work

Specific assessment of the rhetorical, logical, and dialectical perspectives on argumentative texts can inform researchers and help people to improve their writing skills. However, the field of computational AQ assessment has been almost exclusively driven by practical approaches.

Aiming to fill this gap, in this work, we advance theory-based computational AQ research with the following contributions:

- We performed a large-scale annotation study on English argumentative texts covering debate forums, Q&A forums, and business review forums. We thereby presented AQCorpus, the largest and first multi-domain corpus annotated with theory-based AQ scores (RQ1).

- We proposed the first computational theory-based AQ models (RQ2) and demonstrated that jointly predicting AQ scores can improve the performance of the models (RQ3) and that in most cases, models benefit from including out-of-domain training data (RQ4).

- We investigated concrete synergies between the practical and the theory-based approach to AQ assessment in a bi-directional experimental setup (RQ5). The theory-based models can help to increase the interpretability of practical approaches, and practical approaches can be employed to increase performance of the theory-based models.

In the future, we would like to deploy the models and study to what extent users can actually improve their argumentative writing by getting theory theory-based AQ feedback. Further, we will seek to develop ways of adding even finer-grained aspect scores at scale; this remains still an open problem.

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Table 10: Pearson ($r$) and Spearman ($\rho$) correlation coefficients when predicting with our BERT MT$_{Flat}$ trained all-domain or in-domain on the Dagstuhl data. We correlate our prediction for each dimension with its associated true label when applying mean or majority aggregation on the annotations. Scores in bold indicate best performances per domain.

### Appendix

#### Further Validation

For further validation, in addition to only predicting on our own corpus, AQCorpus, we, again, employ DS and predict theory-based AQ scores on DS instances. In order to obtain a single gold score per annotation instance and dimension from DS, we apply two ways of aggregating the annotations provided by the authors: (1) majority vote, and (2) mean aggregation. As the BERT MT$_{Flat}$ models have shown to perform best on many setups of the previous experiments, we reuse them – trained either on in-domain data or using data from all domains on AQCorpus – and predict AQ dimension scores on the whole DS corpus. The results of the experiments employing DS can be seen in Table 10. Generally, compared to the results on AQCorpus, the performance drops. This can be attributed to the domain-transfer. While DS also consist of web debate arguments, they consist of individual isolated arguments and not – as our corpus – of more complex texts. Training on our joint training set across all domains yields the highest correlation scores and generally, the annotations related to overall argument quality and reasonableness correlate best with our scores. To the best of our knowledge, we are the first to have a trained model in-place which is able to predict scores for fine-grained argument quality dimensions.