Diversity Over Size: On the Effect of Sample and Topic Sizes for Argument Mining Datasets

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Abstract

The task of Argument Mining (AM), that is extracting argumentative sentences for a specific topic from large document sources, is an inherently difficult task for machine learning models and humans alike, as large AM datasets are rare and recognition of argumentative sentences requires expert knowledge. The task becomes even more difficult if it also involves stance detection of retrieved arguments. Given the cost and complexity of creating suitably large AM datasets, we ask whether it is necessary for acceptable performance to have datasets growing in size. Our findings show that, when using carefully composed training samples and a model pretrained on related tasks, we can reach 95% of the maximum performance while reducing the training sample size by at least 85%. This gain is consistent across three AM tasks on three different datasets. We also publish a new dataset for future benchmarking.

1 Introduction

Argument Mining (AM), as we use it here, is the task of extracting argumentative sentences from (web) documents (Ein-Dor et al., 2020; Stab et al., 2018; Shnarch et al., 2018). A sample consists of a sentence and a topic towards which the sentence is directed. The topic is used in two ways: first, by a machine learning model to learn topic-relevance and second, as query to retrieve input documents for automatic argument search (Daxenberger et al., 2020).

While large language models show astounding results (Touvron et al., 2023; OpenAI, 2023), fine-tuning on task-related datasets is still important to improve a model’s performance (Dettmers et al., 2023; Lv et al., 2023; Liu et al., 2022; van der Meer et al., 2022), decrease certain undesirable behaviours (Ouyang et al., 2022; Askell et al., 2021), and provide curated data for evaluation purposes. To assemble large amounts of training samples, it is common to use non-experts to annotate datasets. However, in contrast to a task like sentiment analysis, the task of identifying arguments is not naturally understood by non-experts and, due to pitfalls like commonly used fallacies (Habernal et al., 2018), needs a thorough training phase and strict quality control of the crowdsourcing process. Hence, crowdsourcing datasets for AM is not only time-consuming but also expensive, as it also requires a large number of workers per sample for satisfactory agreement. For instance, Stab et al. (2018) report a sum of $2,774 for the annotation of 25,492 samples, requiring seven annotators to reach a satisfying inter-annotator agreement.

Due to the efficacy of transformers (Vaswani et al., 2017), datasets for AM (as for many other tasks) have grown in size over recent years (Stab et al., 2018; Shnarch et al., 2018; Rinott et al., 2015; Aharoni et al., 2014). The newest datasets for AM contain up to 30,000 samples (Ein-Dor et al., 2020). However, relying on large datasets has several disadvantages: (1) it is impractical to label such large datasets by experts, (2) crowdsourcing them is costly, and (3) training (as well as tuning) takes longer and adds to the cost.

To tackle those disadvantages, we study if and how dataset sizes for AM can be reduced and what the composition (total number of topics, samples, and samples per topic) of these datasets should be to train high-performing models. In contrast to simpler text classification tasks with a single input (e.g. document categorization or sentiment analysis), creating datasets for cross-topic AM is more complicated, because it requires controlling two or more inputs (e.g. topic and sentence) as well as a diverse choice of topics, which we show in this work.

Our work is motivated by few-shot learning (Wei...
et al., 2022; Schick and Schütze, 2021; Rücklélé et al., 2020; Vinyals et al., 2016) and diversity sampling (Larson et al., 2019; Katharopoulos and Fleuret, 2018; Chang et al., 2017) approaches. Larson et al. (2019) show that unique samples (similar to outliers in Chang et al. (2017)), i.e. samples that differ strongly in structure or content from other samples, can increase model robustness. Thus, in addition to relying on models that are able to learn with fewer samples, we increase the diversity of samples in our dataset by integrating a large number of distinct topics (i.e., outliers) and, in turn, aim to increase the robustness of our models.

As a testbed, we create a benchmark with two datasets that only differ in the number of topics and samples per topic. We research the influence of these two compositional parameters on model performance, as well as cost and time of the annotation process. We verify findings from the benchmark datasets on two AM datasets from a different domain and with a slightly different task.

Our contributions are as follows: (1) We create a new dataset for AM which differs from the UKP Sentential Argument Mining Corpus (UKP Corpus) (Stab et al., 2018) only in the number of topics and samples per topic, allowing for a deeper analysis of this task and assumptions on how future datasets can be composed (diversity sampling), (2) we analyze zero- and few-shot experiments on the new dataset, giving recommendation on efficient dataset composition, (3) we evaluate findings on dataset efficiency on two different AM tasks from another domain, and (4) we present state-of-the-art results on the UKP Corpus.

2 Related Work

The task of Discourse-level AM aims to classify discourse units (Rocha et al., 2023; Ajjour et al., 2017; Stab and Gurevych, 2014; Goudas et al., 2014) and their relations (Eger et al., 2017; Nguyen and Litman, 2016) within isolated documents. Topic-dependent AM, however, describes the task of searching large, heterogeneous document collections for arguments relevant to a given topic (Ein-Dor et al., 2020; Stab et al., 2018; Shnarch et al., 2018). In this work, we will focus on the latter instead extracting discourse units like claims and premises or their relations from single documents.

The growth of sample sizes in AM datasets seems to be a necessity to cover wider ranges of topics and, thus, to support better cross-topic and cross-domain performance (Ein-Dor et al., 2020; Stab et al., 2018; Shnarch et al., 2018; Rinott et al., 2015; Aharoni et al., 2014). As this, in consequence, increases the annotation and training costs of the models, we aim to uncover low-effort methods for AM datasets that help to keep the number of training samples as low as possible while reaching similar performance. Ajjour et al. (2023) discover that many AM datasets, even those with large amounts of samples, do mostly cover topics that frequently appear in forums, but leave out many less-frequently discussed areas. We argue that using too many samples per topic in AM datasets is a waste of financial resources and focusing only on frequently discussed topics limits the capability of models to generalize well in cross-topic experiments. In this work, we propose a different compositional structure for future AM datasets.

The intuition of keeping the number of training samples—and hence, costs and annotation effort—low, has attracted research that focuses on new techniques enabling models to learn with less data. With regard to models, one of the most impactful designs in recent years are transformer (Vaswani et al., 2017) that are pre-trained on large amounts of text with unsupervised learning techniques (Liu et al., 2019b; Devlin et al., 2018). These large language models show remarkable results on few-shot learning (Gao et al., 2021; Schick and Schütze, 2021) and zero-shot learning (Wei et al., 2022; Rücklélé et al., 2020; Radford et al., 2019) tasks. One form of zero-shot learning that gained a lot of publicity due to its astounding performance is prompting, where a pre-trained model is not fine-tuned and, in addition to the actual input, is only given exemplary inputs (for instance, prepended to the actual input) at inference (Brown et al., 2020). Two other and older techniques used to reduce sample sizes are transfer and multi-task learning from similar tasks, which have also been successfully combined with large language models (Schiller et al., 2021; Liu et al., 2019a).

In contrast to most of these techniques that concentrate on adapting model architectures in a way such that models are able to learn with few or no samples, we focus on benchmarking more efficient compositional structures of AM datasets. In recent years, other benchmarks consisting of multiple datasets have been published (Schiller et al., 2021; Wang et al., 2019a,b) with the aim to stan-
standardize performance reports for machine learning models and, hence, allowing new model architecture to compete against each other and to make the results comparable. We, however, adapt the composition of the datasets we feed the models with, such that existing models (without any modification) can exploit it. Our decision on how to ensemble the datasets we use in this work draws on insights of diversity sampling research which shows that models can profit from datasets with high diversity, i.e. containing samples that differ strongly from each other (Larson et al., 2019; Katharopoulos and Fleuret, 2018; Chang et al., 2017). While other work in the area of AM has scratched on the topic of diversity by increasing the number of used topics (Ein-Dor et al., 2020), there has been no work that we know of, dedicated on determining the ideal dataset composition for AM datasets.

3 Data

For our experiments, we need datasets that only differ in the aforementioned dimensions of number of samples and number of topics but are otherwise similarly structured. As a baseline, we decide to take the UKP Corpus (Stab et al., 2018). As opposed to other AM datasets (Ein-Dor et al., 2020; Shnarch et al., 2018; Rinott et al., 2015; Aharoni et al., 2014), this dataset has two main advantages: First, it includes stance labels, which are an important additional information to categorize mined arguments and can be further processed for tasks like fake news detection (Hanselowski et al., 2018). Second, the dataset is from heterogeneous data sources and models real-world scenarios better than taking only samples from a single source.

We further use two more datasets, namely the IAM-Corpus (IAM-Corpus) (Cheng et al., 2022) and IBM-Corpus (IBM-Corpus) (Ein-Dor et al., 2020), to evaluate our hypotheses on AM with slightly different composition. Statistical information about all datasets as well as examples can be found in Tables 1 and 2.

3.1 UKP Corpus

The dataset consists of eight topics with a total of 25,492 samples, which are pairs of a short topic and a single sentence, labeled with argument for (pro), argument against (con), or no argument (none). As described by Stab et al. (2018), a sentence is only labeled as pro or con argument, if it holds evidence for why the sentence supports or opposes the topic. If the sentence holds no such evidence or is unrelated to the topic, it is labeled as no argument. We split the dataset by taking all samples of five topics for training, of one topic for development, and of two topics for testing. To allow for a fair comparison, we downsample the number of samples in the training set (equally for each topic) to fit the total number of training samples generated in the Few-Shot-150T Corpus (FS150T-Corpus).

3.2 FS150T-Corpus

Given the low number of topics in UKP Corpus (8), we decided to create a new dataset, following the exact guidelines and data crawling strategy used for the UKP Corpus and crowdsourced 21,600 samples over 150 controversial topics with exactly 144 samples for each topic (see Appendix A.1). The composition of our dataset is therefore ideal for few-shot learning, as we have the same number of samples for each topic and can easily scale up and down from 0 to 144. The topics are a collection of controversial subjects from multiple domains like politics, technology, economy, and do not intersect with topics from the UKP Corpus. We randomly pick 10 of the topics for our development set (1,440 samples) and 20 topics for our test set (2,880) samples, leaving 120 topics for the training set (17,280 samples).

3.3 IAM-Corpus

The IAM-Corpus is built upon the data from “Task 1: Claim Extraction” by Cheng et al. (2022). The original data is based on 123 debating topics and 1,010 related articles from English Wikipedia. One sample consists of a topic and a sentence from an article. Each pair has one of three possible labels attached: support, contest, or no relation. Due to the massive imbalance of the none-arguments in the original training split (93%), we have to downsample them in a way that the model is able to pick up the other two classes. We randomly pick samples until we reach a class distribution of 16%/14%/70% (support/contest/no relation) in the training set. We leave the dev and test sets untouched from the original, which also makes this dataset the only in-topic dataset (as opposed to cross-topic datasets which have no overlapping topics between the dataset splits). The modified training data set contains all 100 topics, the original dev and test sets contain 62 topics and 63 topics.
### Datasets

| Datasets             | # Topics | # Samples | Classes                  |
|----------------------|----------|-----------|--------------------------|
| FS150T-Corpus (ours) | 150      | 17,280    | pro (19%), con (19%), none (62%) |
| UKP Corpus (Stab et al., 2018) | 8        | 17,280    | pro (19%), con (24%), none (56%) |
| IAM-Corpus (Cheng et al., 2022) | 100      | 12,903    | support (10%), contest (8%), no relation (82%) |
| IBM-Corpus (Ein-Dor et al., 2020) | 221      | 22,396    | evidence (23%), no evidence (77%) |

Table 1: Splits, classes, and class distributions for all used datasets.

| Dataset     | Domain       | Topic            | Sentence                                                                 | Class    |
|-------------|--------------|------------------|--------------------------------------------------------------------------|----------|
| FS150T-Corpus | Web Search   | electronic cigarettes | Currently, there is no scientific evidence confirming that electronic cigarettes help smokers quit smoking cigarettes. | contra   |
|             |              | renewable energy | Installation is quick and homeowners can be enjoying solar energy in a matter of days. | pro      |
| UKP Corpus  | Web Search   | nuclear energy   | It is pretty expensive to mine, refine and transport uranium.              | contra   |
|             |              | gun control      | Gun control laws would reduce the societal costs associated with gun violence. | pro      |
| IAM-Corpus  | Encyclopedia | Should you restrict reality TV | They involve extreme competition which drains children; it takes away their innocence. | contest  |
|             |              | Should boxing be banned | With a careful and thoughtful approach, boxing quite can be beneficial to health. | support  |
| IBM-Corpus  | Encyclopedia | We should ban organic food | Like local food systems, organic food systems have been criticized for being elitist and inaccessible. | argument |

Table 2: All datasets used in this work with the general domain the data origins from and data samples with topic, sentence, and annotated labels (class).

### 3.4 IBM-Corpus

The IBM-Corpus is based on the publicly available version of the dataset constructed by the authors in Ein-Dor et al. (2020). The dataset consists of almost 30,000 motion-sentence samples and each sample has a score between 0 and 1 that either denotes a sentence to be rather an evidence for the related motion or not. Motions are described as high-level claims, e.g. “Capitalism brings more harm than good”. The sentences are extracted from English Wikipedia. Following the authors’ experimental setup, we set a threshold at 0.6 for the score to define two class labels evidence and no evidence.

To create dataset splits, we take 35 random topics to form the test set and 20 random topics to form the dev set. The remaining 166 topics form the training set. Compared to all other datasets, this is especially interesting as it has only two class labels and the largest number of topics (here: motions) and samples.

### 4 Method

To investigate the optimal composition of AM datasets, we conduct sample, topic, and dataset experiments, which we elaborate in the following.

### 4.1 Sample experiments

We investigate on how many training samples per topic are necessary to reach acceptable and maximum performance. We start our experiments with 0 training samples per topic, i.e. untrained model performance (zero-shot) and increase the number of samples in small steps, ending with all samples available for each topic. We define acceptable performance by reaching at least 95% of the highest performance on a test set, measured over all sample experiments for a given model. We define maximum performance by the highest value for the given metric on a test, regardless of the number of training samples used to reach it.

### 4.2 Topic experiments

We analyze how many topics are needed to generalize well in cross-topic experiments by choosing a set of training sample sizes (960; 1,440; 2,880; 5,760) and fixing them while increasing the topics. The topics are increased in steps of 5 and end with the maximum number of topics available for a training set. Since fixing the number of topics and sample sizes requires a certain amount of samples available for each topic in the training set, experiments with larger sample sizes may start at larger topic sizes. For instance, fixing 10 topics and 960 samples only requires 96 samples per topic in the
training set, while fixing 10 topics and 5,760 samples already requires 576 samples per topic to be available. The more topics we include for a fixed sample size, the less samples per topic are available. We expect to find a pattern that reveals whether or not using many topics (diversity sampling) is beneficial for cross-topic performance.

4.3 Dataset experiments
The goal is to find out if we can reach higher performance by training on a dataset with few topics but many samples per topic (UKP Corpus) or on a dataset with many topics but few samples per topic (FS150T-Corpus). For the benchmark experiments, we leverage the model with the highest score on the used metric (determined on the sample experiments) and re-train it in the following to setups:

- Training and tuning it on the UKP Corpus and show results on the test sets of both corpora.
- Training and tuning it on the FS150T-Corpus and show results on the test sets of both corpora.

If either of the two models performs better in both experiments, we know the dataset composition that should be preferred for the task of AM. In any other case, our assumption that few samples combined with many topics is the superior dataset composition (i.e. better cross-topic performance) on AM datasets is refuted.

5 Models
For the sample and topic experiments, we decide to compare two models (see Appendix A.2) with different properties—while both have comparable model sizes (12 layers, a hidden-size of 768, and 12 attention heads) they differ in their pre-training setup.

5.1 RoBERTa-base
We use RoBERTa-base (Liu et al., 2019b) as a strong, general baseline. The model was pre-trained on English texts from, amongst others, books, Wikipedia, and news sites. The main differences to BERT (Devlin et al., 2018) are the larger amount of data (RoBERTa is trained on 160GB of uncompressed text, whereas BERT was trained on 16GB), some additional data sources, and some variations in the hyperparameters. RoBERTa-base has shown to outperform BERT on the tasks of the GLUE Benchmark (Wang et al., 2019b). Moreover, the model has also shown outstanding results on a multitude of AM-related tasks and domains before (Cheng et al., 2022; Heinisch et al., 2022; Mayer et al., 2020).

5.2 ERNIE 2.0
ERNIE 2.0 (Sun et al., 2020) was pre-trained in a continual multi-task learning fashion on several word-, structure-, and semantic-aware tasks and showed state-of-the-art performance when fine-tuned on tasks of the GLUE Benchmark (Wang et al., 2019b). The data for these tasks was automatically generated with text extracted from encyclopedias, books, dialog, and discourse relation datasets. As these tasks have similar properties to AM, we expect to also benefit from the pre-training through a higher maximum performance. Moreover, we anticipate that the specific pre-training enables the model to bootstrap performance on few-shot learning.

6 Topic & Sample Experiments and Evaluation
We run all experiments over six seeds and report the average F\textsubscript{1} macro on the test set for the three seeds with the highest F\textsubscript{1} macro measured on the development set (see Appendix A.2).

6.1 Sample Experiments
Figures 1-3 show the performance gains of all tested models with increasing sample sizes per topic (samples uniformly distributed over all 120 training topics). For the FS150T-Corpus, RoBERTa-base shows the lowest zero-shot performance with an F\textsubscript{1} macro of .21. ERNIE 2.0 starts slightly higher at an F\textsubscript{1} macro of .29. We observe similar behavior on the other two datasets with ERNIE 2.0 performing better on few samples compared to RoBERTa-base. On zero-shot, ERNIE 2.0 starts at .28 and .45 F\textsubscript{1} macro on IAM-Corpus and IBM-Corpus. The reason for the much higher zero-shot performance of the model on the IBM-Corpus is that it has only two labels to predict, while it has to predict three labels on the other two datasets. This is also the reason for the overall much higher maximum performance on the IBM-Corpus (.80 F\textsubscript{1} macro, whereas FS150T-Corpus and IAM-Corpus only reach a maximum of .66 and .57). Zero-shot performance on IAM-Corpus and FS150T-Corpus are quite similar.

\small
\begin{itemize}
  \item With low sample sizes, the models often fail on some of the seeds and distort the results.
\end{itemize}
ERNIE 2.0 is fastest to reach more than .60 $F_1$ macro on the FS150T-Corpus and stays ahead of RoBERTa-base until around 16,800 training samples. The maximum performance of the two models is very similar but reached on different sample sizes (see Table 3). While ERNIE 2.0 can reach its top performance at 12,000 samples, RoBERTa-base needs almost 2,000 samples more. ERNIE 2.0 is also the model that requires the least amount of training samples to reach 95% of its maximum performance with .6290 $F_1$ macro at 1,920 samples (11% of the training samples and only 16 samples per topic). On both the IAM-Corpus and IBM-Corpus, it is also possible to reach 95% of the maximum performance with just 15% of the training samples and by using ERNIE 2.0. These results, however, are model dependent, as RoBERTa-base requires almost twice the data on the IBM-Corpus (15% vs. 28%), more than twice the data on the FS150T-Corpus (11% vs. 25%) and three times the data on the IAM-Corpus (15% vs. 45%).

As can be observed in Figures 1-3, across all datasets there is a point of saturation for the models, i.e. the curves flatten noticeably for all datasets and models. For the FS150T-Corpus this happens at around .60 $F_1$ macro and between 960 and 1,920 samples, for IAM-Corpus at around .55 $F_1$ macro and 1,920 samples, while for IBM-Corpus it happens at around .70 $F_1$ macro and 960 samples already. After these boundaries, the model learns much slower. With increasing number of samples, the performance gaps between ERNIE 2.0 and RoBERTa-base become smaller, as it is also observed on the FS150T-Corpus.

### 6.2 Topic Experiments

For all topic experiments, we use ERNIE 2.0, as this model has shown the best results on small sample sizes for all datasets. The sample sizes for the datasets are: 22,396 for IBM-Corpus, 22,396 for IAM-Corpus, and 16,800 for FS150T-Corpus.
We have a deeper look into how model performance changes if the number of topics is increased while the training sample size is fixed. Figures 4-6 show the results for the FS150T-Corpus, IAM-Corpus, and IBM-Corpus with four different training sample sizes, ranging from 960 to 5,760 samples. By increasing the number of topics, we also increase the diversity of the training set through adding outliers, instead of just picking more samples with similar content from the existing topics.

Similar to the increased robustness observed by Larson et al. (2019), the models in our cross-topic experiments show an upwards trend (dashed lines) for all datasets and sample sizes. For FS150T-Corpus, we can observe an upward trend with up to 1.1pp (percentage points) on 960 samples if we increase the number of training topics. The largest upward trend for IAM-Corpus is also reached on 960 samples (1.6pp) and, similar to the observations on the FS150T-Corpus, the upward trends decrease with increasing number of samples. For IBM-Corpus, the largest upward trend is reached on 1,440 samples (1.9pp). Interestingly, the IBM-Corpus is the only dataset where the upward trend stays similarly steep, even with more samples introduced. This may be an indicator that more diverse samples, e.g. a larger number of topics available in this dataset, are advisable.

While the observations do not show a drastic increase in the accuracy of the models, it is an easy way to improve the performance and usually comes without additional costs. Hence, if there is a sample limit for a planned dataset, we can increase the future model’s performance by composing the dataset with more topics. As we tested up to 160 topics on all three datasets, we assume that this is a good choice for training data sizes ranging from ~1,000-6,000 samples but can become less relevant if more samples are used. Observing this kind of upwards trend on all datasets and sample sizes underlines our previous assumptions on increased performance due to diversity and can be a technique generally assumed to be beneficial on AM datasets.

7 Cross-Dataset Experiments and Evaluation on Benchmark Dataset

We again use ERNIE 2.0 here, as this model has shown to perform best in the sample experiments. We tune two models based on ERNIE 2.0: one model trained and tuned on the FS150T-Corpus and one model trained and tuned on the UKP Corpus. We show evaluation results for both models on both corpora in Table 4.
Table 4: Dataset experiment results with ERNIE 2.0, comparing results on the FS150T-Corpus and UKP Corpus. As a baseline for the UKP Corpus, we use TACAM-BERT (’work by Fromm et al. (2019)). MW=Minimum Wage, SU=School uniforms.

| Test topics: | Test on UKP Corpus | Test on FS150T-Corpus |
|--------------|---------------------|-----------------------|
|              | MW | SU | all |             | MW | SU | all |
| TACAM-BERT Base* | .4900 | .6900 | - | - | - | - | - |
| TACAM-BERT Large* | .6900 | .6900 | - | - | - | - | - |
| Train & tune on UKP Corpus | .6777 | .7149 | .6980 | .6292 | - | - | - |
| Train & tune on FS150T-Corpus | .7058 | .7406 | .7243 | .6585 | - | - | - |

Our baseline setting is when training, tuning, and testing happens on the same dataset. For that setup, the models show .6980 and .6585 $F_1$ macro for the UKP Corpus and the FS150T-Corpus, respectively. Training and tuning ERNIE 2.0 on the UKP Corpus and then evaluating it on the FS150T-Corpus shows worse performance (.6292 $F_1$ macro) than training and tuning a model on the actual FS150T-Corpus, which is the expected outcome. However, training and tuning ERNIE 2.0 on the FS150T-Corpus shows the best results on the UKP Corpus (.7242 $F_1$ macro). Hence, using the FS150T-Corpus for training performs best on the test sets of both corpora. We assume that training on just a few topics and fitting the model with a large number of training samples to those topics will not prepare it enough to generalize well. Training on many diverse topics, however, will add generalizability to the model and reduce the risk to over-fit to a small range of specific topics, that is, it will also learn that topics can come from a much larger variety within the embedding space.

Further, we compare the models’ performances to the current state-of-the-art (for which topic-wise results are available) on the UKP Corpus. TACAM-BERT Base (Fromm et al., 2019), with a number of parameters comparable to ERNIE 2.0, performs 21.6pp and 5.1pp lower in $F_1$ macro for the test topics minimum wage and school uniforms. Even the much larger TACAM-BERT Large with three times the number of parameters underperforms by 1.6pp and 5.1pp.

8 Conclusion

We create a new dataset that enables to benchmark the composition of AM datasets. Experiments show that having many topics in combination with few samples per topic can improve model performance by 2.6pp in cross-dataset experiments and also reaches a new state-of-the-art on the UKP Corpus. In general, we observe a positive trend in performance when the number of training topics is increased, especially with lower numbers of samples (960 to 1,440).

When choosing our proposed dataset composition (FS150T-Corpus) in combination with ERNIE 2.0 (pre-trained on several word-, structure-, and semantic-aware tasks), we can decrease the training sample size by more than 30% and still reach maximum performance (see Tables 3 and 4). We can even reduce the training sample size by almost 90% (to 1,920 samples), still reach 95% of the maximum performance and, in turn, decrease annotation costs by $2,976 to only $290 (see Appendix A.1) per dataset created in the composition proposed in this work. We observe the same trend on the other two datasets IBM-Corpus and IAM-Corpus, where 75% and 82% of the training data is sufficient for maximum performance and training samples can be reduced by 85% (to 3,360 and 1,920) while still reaching 95% of the maximum performance. This clearly challenges the trend to develop larger datasets for AM. Following our proposed dataset composition makes low-budget productions of high-quality AM datasets possible, contributing to a more diverse landscape of those datasets.

Our topic experiments show an overall positive trend when increasing the number of topics for a dataset, while keeping the number of total samples fixed (see Figures 4-6). It indicates that larger diversity, introduced through more samples from different topics, helps the model to reach higher performance. On two out of three datasets, this trend decreases with larger number of training samples, which may be due to the simple fact that more samples introduce more diversity. Hence, this insight is especially important if we aim to decrease sample sizes in AM datasets.

Based on our observations, we suggest composing AM datasets with (up to) 160 topics and a low, double-digit number of samples per topic (uniformly distributed over all topics) as a lower bound and up to 100 training samples per topic as an upper bound. The choice of model can be important, especially if models pretrained on related tasks are available. We publish our newly created dataset, allowing for further benchmarking experiments to develop the design of future AM datasets.
Limitations

Our experiments focus on datasets for AM only. While we would expect other tasks with datasets of similar composition (for instance, Question-Answering) to also profit from our findings, we have not tested this and can only make claims based on our experiments for AM.

Moreover, our sample experiments only cover sample sizes from 0 to 22,396 training samples and, for the most part, a step size of 480 samples. Hence, we can not rule out the possibility of higher \( F_1 \) macro or other derivations from the observable trend with more than 22,396 training samples, nor can we rule out the possibility that we have missed a certain dip or peak due to our chosen step size. Similarly for our topic experiments—while there is a trend to higher performance with more topics, it is unclear how this trend develops with more than 166 topics (for instance, if the model shows a saturation with regard to topics or if more topics would even have a negative impact).

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A Reproducibility Criteria

A.1 Dataset

The new dataset FS150T-Corpus consists of 21,600 samples over 150 controversial topics with 144 samples each. We index the CommonCrawl\(^3\) dump CC-MAIN-2016-07 via ElasticSearch\(^4\) and use all 150 controversial topics to search and extract sentences for the crowdsourcing process. The crowdsourcing costs on Amazon Mechanical Turk\(^5\) amount to a total of $3,266. The chosen topics for the dataset are a collection of controversially discussed subjects from the domains of, amongst others, politics, technology, and economy. See Table 5 for a list of all topics in alphabetical order.

We split the dataset into a *train*, *development*, and *test* set. There is no overlap between topics of the sets or with topics of the UKP Corpus. The dataset language is English and the annotation

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\(^3\)https://commoncrawl.org
\(^4\)https://www.elastic.co
\(^5\)https://www.mturk.com/
guidelines for the crowdsourcing process are taken from Stab et al. (2018). See Tables 1 and 2 for more statistics and examples about the dataset.

A.2 Model

We tune both models used in this work on the full training sets with all combinations of three different learning rates ($1 \times 10^{-5}$, $3 \times 10^{-5}$, $5 \times 10^{-5}$) and batch sizes (4, 8, 16). All models are trained over 5 epochs and we use the best model (determined on the development set by highest $F_1$ macro) to fix the hyperparameters for the actual experiments. Due to unstable performance on low sample sizes, we decide to always train on 6 different seeds (for tuning and actual experiments), but only leverage the averaged results on the best 3 of them. We find the best combination for both RoBERTa-base and ERNIE 2.0 with a learning rate of $1 \times 10^{-5}$ and a batch size of 8.

Both models have comparable model sizes with 12 layers, a hidden-size of 768, and 12 attention heads. Training RoBERTa-base and ERNIE 2.0 takes approx. 25 minutes on a single Tesla P-100 (one seed) with the full training set of the FS150T-Corpus.

| Topics | 3D printer | alcohol advertising | alternative medicine | amazon | anarchism | animal dissection | animal testing | antibiotic usage | artificial intelligence | assisted suicide | atheism | autonomous cars | beauty contest | big pharma | bilingual education | biofuels | birth control | boarding school | border security | Brexit | buffalotown | cell phone radiation | censorship | charter schools |チェックフィールド | clerical celibacy | coal mining | community service | compulsory voting | concealed handguns | corporal punishment | crowdfunding | cultured meat | daycare | daylight saving time | direct democracy | drone strikes | ebooks | ecosocialism | electoral college | electronic cigarettes | executive order | existence of god | extraterrestrial wildlife | extreme sport | factory farming | farm subsidies | fast food | felon voting | feminism | foreign aid | fracking | free market | freedom of speech | fuel tax | gambling | gay marriage | gay rights | geothermal energy | global warming | glyphosate | gmos | government surveillance | guantanamo bay detention camp | holography | homeschooling | homework | hydroelectricity | illegal immigration | insanity defense | insider trading | isolationism | jury duty | labor unions | legalized prostitution | lethal injection | libertarianism | life extension | lobbying | lottery | lower drinking age | lower speed limit | man-made greenhouse gases | mandatory national service | mandatory sentencing | monarchy | monogamy | multiculturalism | nrt neutrality | nuclear disarmament | obamacare | occupy wall street | offshore drilling | online dating service | organ donation | organic food | outsourcing | pedelec | plastic surgery | police body cameras | prescription drug ads | progressive tax | racial profiling | religious holidays | renewable energy | reverse discrimination | right to health care | robots | sanctuary cities | school vouchers | sex education in school | sex offender registry | smart home | smartwatch | social media | solar energy | spanking | sperm donor | standardized testing | stem cell research | surrogacy | svu | teacher tenure | term limit | tobacco advertising | transgender rights | two-state solution | unemployment insurance | urban agriculture | urbanization | us intervention | usa patriot act | vaccination | vegetarianism | video games and violence | virtual reality | voting machines | war on drugs | war on obesity | war on terrorism | water privatization | weather modification | whaling | white supremacy | wikileaks | wind energy | wiretapping | women in the military | year-round school |

Table 5: List of all 150 topics for the FS150T-Corpus.