Cracking Double-Blind Review: Authorship Attribution with Deep Learning

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Abstract

Double-blind peer review is considered a pillar of academic research because it is perceived to ensure a fair, unbiased, and fact-centered scientific discussion. Yet, experienced researchers can often correctly guess from which research group an anonymous submission originates, biasing the peer-review process. In this work, we present a transformer-based, neural-network architecture that only uses the text content and the author names in the bibliography to attribute an anonymous manuscript to an author. To train and evaluate our method, we created the largest authorship-identification dataset to date. It leverages all research papers publicly available on arXiv amounting to over 2 million manuscripts. In arXiv-subsets with up to 2,000 different authors, our method achieves an unprecedented authorship attribution accuracy, where up to 95% of papers are attributed correctly. Thanks to our method, we are not only able to predict the author of an anonymous work but we also identify weaknesses of the double-blind review process by finding the key aspects that make a paper attributable. We believe that this work gives precious insights into how a submission can remain anonymous in order to support an unbiased double-blind review process. We have open-sourced the necessary tools to reproduce our experiments.

Code: https://github.com/uzh-rpg/authorship_attribution

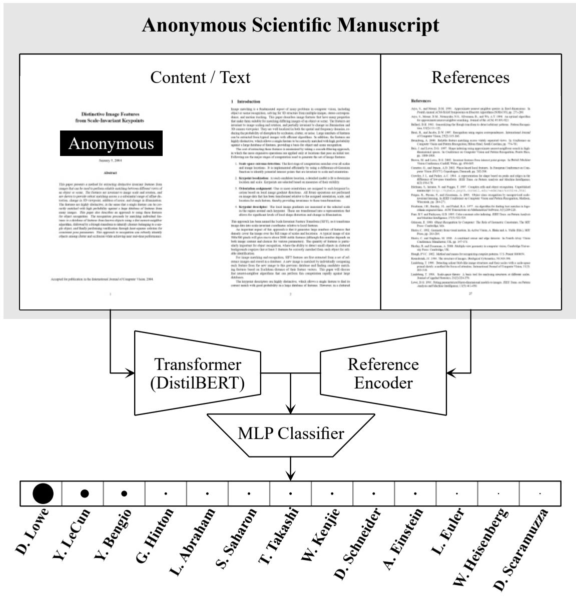

Figure 1: Our method identifies authors of anonymous scientific manuscripts by leveraging both the information contained in the text as well as the citations. We encode the main text using DistilBERT (Sanh et al., 2020) and combine this encoding with a feature vector extracted from the cited references. The encodings are subsequently fused by a two-layer classification MLP. It outputs the log-likelyhoods that the given anonymous paper has been (co-)authored by one of the over 2000 authors included in our novel dataset.

1 Introduction

Most known academic and literary texts can easily be attributed to a certain author because they are signed. Yet sometimes, we find anonymous pieces of work and would like to identify an author based on the given text, a method referred to as author attribution (AA).

The AA problem is particularly interesting in the context of double-blind peer review in academic research, a technique often implemented to robustify the process against human biases. By addressing the AA task for research papers, we aim to not only demonstrate the technical feasibility of large-scale authorship attribution but hope to improve the double-blind peer review process by identifying the key aspects of a paper that allow experienced reviewers to correctly guess which group of authors a certain manuscript originated from. Especially for research papers, AA is a complex task due to the vast number of possible authors, the length of the texts, and the unavailability of a large-scale dataset.

Author attribution for literary texts first became popular in 1964 when researchers studied the famous "The Federalist" papers (Mosteller and Wallace, 1963), a collection of 85 articles and essays

* equal contribution

published under the pseudonym "Publius", to identify the authors who contributed to each essay. More recently, authorship attribution for rulings written by the Australian High Court (Seroussi et al., 2011) and internet blogs (Fabien et al., 2020) has been studied. Scientific texts, however, are inherently different from the aforementioned works as individual authors are not only identifiable by a certain writing style but most likely write on similar topics in their works and cite themselves more often. Furthermore, no large-scale authorship attribution dataset for academic texts exists.

We aim to address both challenges: this work presents a novel architecture (summarized in Fig. 1) alongside a new dataset to address the problem of AA for research papers. Instead of just using the text content (Skoglund, 2015), our method relies on both text content and the author names of the paper cited in the *Reference* section of a manuscript, discarding all image data and equations. Following the latest advances in natural language processing, the transformer DistilBERT (Sanh et al., 2020) is used to process the text section. For the references, a frequency histogram-embedding with a subsequent multi-layer perceptron is used. We leverage all publicly available arXiv (Clement et al., 2019) submissions, that amount to more than 2 million research papers, to construct a new dataset tailored to this hybrid AA approach. The dataset includes text content as well as the references cited in a paper. On the largest arXiv-subset with 2070 candidate authors, we achieve an AA accuracy of 70%, while, on smaller sets with 50 possible authors, well over 90%. We find that already the first 512 words of a manuscript (including the abstract, when available, and parts of the introduction) lead to more than 60% of the papers being attributed correctly. Furthermore, the experiments clearly show that self-citations contribute to correct attribution by up to 25% more than when self citations are omitted

Contributions. In summary, we make the following contributions. First, we present a novel deep-learning-based architecture capable of analysing and classifying hundreds of thousands of research texts and references from arXiv to address the AA problem. Second, to train this architecture, we build a large-scale dataset based on the research publications available on arXiv. Lastly, we identify the key aspects of a paper that make it vulnerable to be deanonymized during a double-blind review process.

2 Related Work

Perhaps one of the oldest examples of authorship attribution (AA) was to identify the co-writers of William Shakespeare in 36 plays (collectively called *"Shakespeare canon"* (Hope, 1994)), which began in the late 17th century. The research on authorship attribution became much more popular in 1964 when researchers studied "The Federalist" papers (Mosteller and Wallace, 1963). After this, AA advanced through the development of more involved hand-crafted feature extractors for text, resulting in over 1000 different published approaches by the year 2000 (Rudman, 1997; Holmes, 1998). Subsequently, the computer-assisted approaches were further automated, and prior to the machine learning era, two dominant approaches existed: profile-based AA and instance-based AA (IAA) (Stamatatos, 2009). The former extracts one feature vector (author profile) per author and compares the feature distance of a given text with all author profiles, whereas IAA extracts a feature vector per text sample and uses a classifier (e.g. SVM (Stamatatos, 2009)) to distinguish authors.

Along with the rise of short electronic messages (e-mails, tweets) came a growing interest in text classification (e.g., hate speech (Davidson et al., 2017), polarizing rhetoric tweet analysis (Ballard et al.)) and AA using short texts (e.g., detect 'hacked' accounts (Li et al., 2017)). Machine learning proved to be vital for this task since learned feature descriptors like *document embedding* (Agun and Yilmazel, 2017) outperform classic character n-gram (Bojanowski et al., 2016) and bag-of-words approaches. N-gram convolutional nets also show competitive performance (Shrestha et al., 2017).

From a text-length perspective, research papers are more similar to news articles and books than to tweets. In (Iyer and Rose, 2019) a uni-gram feature in combination with an SVM is used for news articles and book AA, and they achieve 83% classification accuracy on a dataset with 50 authors. In (Qian et al., 2017) a study comparing different network architectures (LSTM, GRU, Siamese network) on similar data is presented, and a near-perfect classification is achieved, also on a dataset with only 50 different authors. In (Ma et al., 2020) and (Sari, 2018) it is confirmed that deep networks achieve very competitive performance on AA and authorship profiling (AP) tasks. The results obtained on public benchmark datasets in those works are used as *baselines*, although they are focused on single-author documents (non-research articles) and are only applied to the comparably small benchmarks.

For research papers, solving authorship attribution is a more complex task due to the length of the texts, their heterogeneity (mathematical symbols, reference sections, etc.), and the vast amount of possible authors. Therefore, authorship attribution has been applied to research articles only in very rare cases, such as (Skoglund, 2015), where the (not publicly available) training and testing datasets are rather limited (403 authors, 1683 papers).

The recent advances in natural language processing (NLP), namely the development of transformer-based architectures, allow us to tackle these difficulties. Transformers have shown impressive capabilities in NLP for mid-sized text lengths, e.g., BERT (Devlin et al., 2019), its smaller counterpart DistilBERT (Sanh et al., 2020), and BigBird, for longer sized sequences (Zaheer et al., 2020). The success of transformers has enabled applications such as ancient text restoration and attribution, polarizing tweet analysis (Ballard et al.), hate speech detection (Huang and Xu, 2021), emotion recognition in conversation (Tu et al., 2022) and song analysis (Wang et al., 2022). In (Cruz and Cheng, 2020) results indicate the usefulness of using such networks as feature extractor.

The increasingly large number of studies on the use of scientific documents with bibliometric applications shows the growing interest of the bibliometric community in authorship attribution (Atanassova et al., 2019). Specifically, machine learning applied to bibliometrics has steadily been getting more traction in the last decade (Iqbal et al., 2020). In (Bradley et al.), the authors analyse the use of solely the reference section to predict the possible authors of scholarly papers. However, all the aforementioned research focuses either on the analysis of the texts themselves or solely on the references. To the best of the authors' knowledge, this work presents the first approach, where both sources of information are combined.

3 Dataset

In contrast to the works on authorship attribution for news articles, legal documents or blog entries, this work focuses on research articles. Therefore, the benchmark datasets that are commonly used are not suitable, and a new dataset based on arXiv articles is developed. This section first introduces our arXiv dataset, then the standard benchmarks are briefly described, and a brief discussion of the challenges and features is presented.

3.1 The arXiv Dataset

The arXiv is an open-access preprint server for scientific papers in the field of computer science, math and physics, which contains over 2 million research articles at the time of writing [1]. The pdf versions of the articles can be downloaded (Clement et al., 2019) together with a database file that maps the unique arXiv-identifier (e.g. 2106.08015) to the title of the paper, the authors' names and the abstract. Note that, unfortunately, no UUIDs (unique user identifiers) are assigned to authors on arXiv, which causes ambiguity between different authors with the same name.

Preprocessing. In order to reduce the name ambiguity, a first step discards all entries where the authors did not provide their full names but only initials. Subsequently, all authors with at least P papers are selected to yield a dataset named *D($P)*, e.g. for $P = 300$ the dataset is D300. All co-authors are treated equally as not all fields order the authors by the amount of contribution.

For all in the dataset, the plain-text version of their articles is loaded and processed. In the given order, this processing

1. discards the header containing the title, the authors' names, contact info and affiliation,
2. extracts the content (abstract and body) of the paper,
3. extracts the 'References' section,
4. splits the reference section into individual references,
5. extracts the cited authors' names from the references.

All splitting and extraction of parts are done using hand-crafted regular expressions that are 'fail-fast', meaning that if they succeeded in segmenting the paper, the result is almost always correct (e.g. a human performing the same task would segment similarly). The processing removes about 15% of the papers from the dataset for all values of P.

Author Ambiguity. Because arXiv lacks UUIDs, the authors are only identified by their full names. This ambiguity became especially obvious for short names which had over 10000 papers assigned to them. To resolve this issue, a clustering approach is used: using a pre-trained sentence transformer (Reimers and Gurevych, 2019) to extract a feature

[1] https://arxiv.org/

embedding from the abstract. Then, DBSCAN is used to cluster the extracted feature vectors. If DBSCAN finds only one cluster and some noise, the author is assumed to be one physical person, whereas multiple clusters are identified for ambiguous authors. DBSCAN has been tuned to correctly classify a set of 20 known, unique authors (famous researchers with distinctive names) and 20 known ambiguous authors (checked via Google Scholar).

For datasets with a high threshold P, over half of the authors are discarded, whereas only 20-25% of the authors are removed for lower thresholds. This follows the intuition that no single physical person will have published 5000 papers, but 100 is certainly possible through co-authorships.

Content Chunks. Transformer architectures scale badly with the sequence length, which is why most networks have a hard limit between 256 and 4096 tokens. The DistilBERT network can process up to 512 tokens per text. Therefore, the content of the paper is divided into multiple chunks of length up to 512 words. Either the first chunk only (referred to as Dxxx, e.g. D300) or all chunks are used (referred to as Dxxx-C, e.g. D300-C). The rationale for using the first 512 tokens is that those contain the abstract and introduction, which usually summarize the whole paper. While the first 512 words of a paper almost never contain equations or tables, later chunks can. In tables and equations, the individual symbols are always surrounded by white space. Therefore, all chunks that have an average word length below 4.22 characters are discarded, as they are assumed to primarily consist of tables and equations. This threshold is computed as the 5$^{\text{th}}$ percentile of a distribution of the average word length in a 512 word (general English) text. The individual word lengths in this text follow the distribution of word lengths in English texts (Mayzner).

In a final step, an 80/20 division into train/test dataset is performed. This random split is done using stratified sampling, such that the 80/20 balance is kept for each author. If a paper in the training set was authored by multiple authors in the dataset, it is randomly assigned to one of them. Papers in the test set can contain multiple authors and are correctly classified if the network predicts that it was written by *one* of its authors. Furthermore, it is ensured that a co-authored paper can not be in the train and test split at the same time. An overview of the different arXiv datasets is given in Tab. 1.

Table 1: Summary of the datasets used in this work.

	Dataset	Authors	Words	Words/Text	Texts/Aut.	Words/Aut.
Benchmarks	Legal	3	3.1M	2312	447	1.03 M
	Blog10	10	2.1M	91	2305	212 k
	Blog50	50	7.2M	98	1466	144 k
	Reuters50	50	2.5M	506	100	50 k
	IMDb62	62	21.7 M	349	1000	350 k
Our arXiv Dataset	D500	7	1.7 M	512	472	241 k
	D500-C	7	17.1 M	5184	472	2.4 M
	D400	13	2.8 M	512	425	217 k
	D400-C	13	31.3 M	5658	425	2.4 M
	D300	49	8.0 M	512	320	164 k
	D300-C	49	94.3 M	6024	320	2.1 M
	D200	226	24.6 M	512	213	109 k
	D200-C	226	289 M	6016	213	1.2 M
	D100	2070	105 M	512	99	50 k
	D100-C	2070	1.27 B	6180	99	0.6 M

3.2 Benchmark Datasets

Legal. This dataset consists of written rulings by three Australian High-Court judges from the year 1913 to 1975. Originally, this dataset was used to show that Judge Dixon was ghostwriting for the other two (Seroussi et al., 2011). However, by only using the time period where ghostwriting was impossible, a clean dataset with long texts can be obtained, which is used as a benchmark (Seroussi et al., 2014; Sari, 2018).

Blog10 and Blog50. The Blog dataset consists of online blog posts from the years 2002 to 2004 (Schler et al., 2006). Most of the posts are very short and often contain rather explicit language. The Blog10 and Blog50 datasets include posts from the top 10 or 50 authors, respectively when sorted by the number of posts (Fabien et al., 2020).

Reuters50. The Reuters50 (or CCAT50) is the most widely used (Stamatatos, 2008; Sari, 2018; Qian et al., 2017) AA dataset. It contains news stories and is an excerpt from the Reuters Corpus Volume 1 (Russell-Rose et al., 2002). The top 50 authors (according to the number of stories) have been selected, and for each author, 100 texts are provided, equally split into a training and a test set (Stamatatos, 2008).

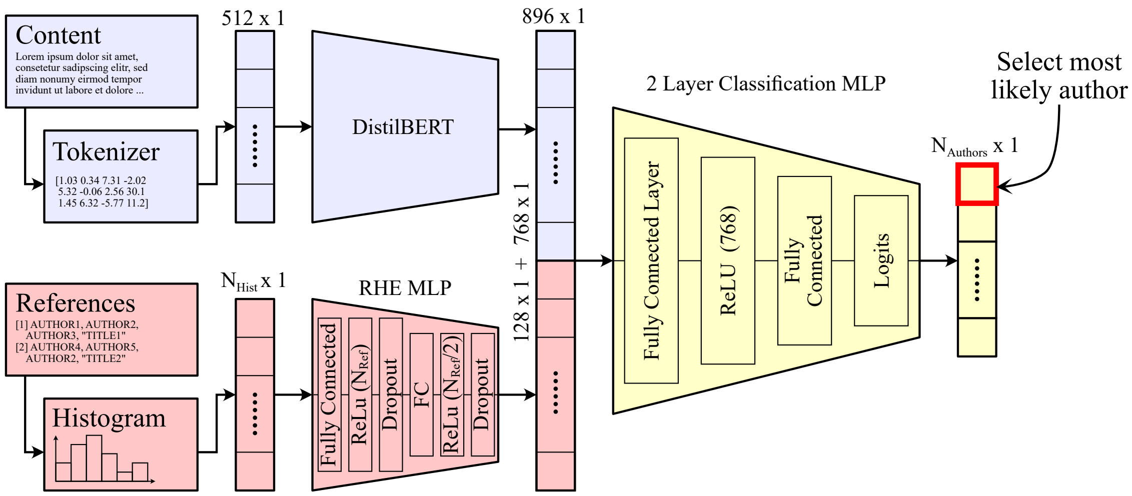

Figure 2: Our proposed network architecture consists of two separate feature encoders for the different input modalities followed by an MLP network with a logit output layer.

IMDb62. The IMDb62 dataset (Seroussi et al., 2010) consists of movie reviews from the most active 62 IMDb users, where 1000 texts are provided per author. It is also a very common dataset for benchmarking. (Stamatatos, 2009; Sari, 2018; Fabien et al., 2020)

3.3 Discussion

Compared to the benchmarks, our dataset contains significantly longer texts per author, although there are fewer texts on average per author. Especially the big arXiv datasets (e.g. D100-C) are extremely different than benchmarks like *Blog10* or the *Reuters50*. For example, D100-C contains 600 times more data than *Blog10*. Only the *Legal* and the *IMDb62* datasets are somewhat similar to the small arXiv D400 and D500 in terms of text length and dataset size.

The main difference between the existing AA datasets and the arXiv dataset is that the latter includes an additional feature: the author names of the cited papers. Exploiting this additional information specific to scientific articles is a key contribution of our work. For research article AA no benchmarks exist.

4 Architecture

In this section, we present the architecture and sub-architectures (see Fig. 2) that are used throughout this paper.

4.1 DistilBERT

First we present the architecture that has been used to process the main text of the papers (without the references). For this task, we have chosen to use DistilBERT, a transformer architecture based on a distilled version of BERT. It is smaller, faster, cheaper, and lighter, offering up to 60% faster speeds than BERT while retaining 97% of its language understanding capabilities (Sanh et al., 2020). In order to convert the raw text to a format that the DistilBERT architecture can take as input, a tokenizer to convert the words to tokens needs to be used. The tokenizer used in our case is based on WordPiece (Schuster and Nakajima, 2012). Both the DistilBERT transformer model and the tokenizer have been initialized with a pre-trained version. Specifically, we use the checkpoint called *distilbert-base-uncased*, which was pre-trained on BookCorpus (Zhu et al., 2015) and the English Wikipedia.

One of the main limitations of most transformer architectures is that they have a limited input size. In the case of DistilBERT, this limit is 512 tokens which means that either only the first 512 tokens can be used or the dataset is divided into chunks as described in the previous section. One solution that has been tried to solve this problem is to use BigBird (Zaheer et al., 2020), which is a transformer architecture specifically designed for longer sequences and that offers an input limit of 4096 tokens. However, due to the increased size and complexity of the BigBird transformer, training times are very long, and there is no noticeable increase in accuracy compared to a chunked dataset trained with DistilBERT. When training on such chunked datasets, the chunks are processed independently of each other. During the evaluation, all parts of the text that come from the same paper are evaluated consecutively, and the output logits are

Table 2: This table summarizes the authorship identification accuracy in % on the test split of the different arXiv datasets four our method.

Input	Epochs	Only first 512 Words						Document in Chunks of 512 Words					
		LR	D100	D200	D300	D400	D500	LR	D100-C	D200-C	D300-C	D400-C	D500-C
Content	40	1e-5	45.5	64.7	78.9	89.0	92.0	1e-5	**70.0**	84.8	**90.3**	94.8	96.3
Content	10	1e-4	49.7	68.9	82.4	91.3	92.9	1e-4		**85.6**	**90.3**	94.4	95.7
References	10	8e-4	54.3	71.0	79.8	89.6	90.2	8e-4	54.3	71	79.8	89.6	90.2
Ref (no self)	10	8e-4	43.3	62.9	75.5	84.3	86.4	8e-4	43.3	62.9	75.5	84.3	86.4
Ref+Cont	10	3e-4	**60.5**	**79.0**	**87.0**	**94.3**	**93.1**	5e-5		81.1	**90.3**	**96.0**	**96.6**

averaged before converting them to probabilities and selecting the author with the highest probability. As we will show in the results part, this approach proves to be extremely successful and improves the evaluation accuracy by 5-10% (absolute) when compared to only inputting the first part of the paper to DistilBERT.

4.2 Reference Histogram Embeddings

There are many different ways of extracting the key information from the references section of a paper. One of the most direct ones, and the one that resembles the most of how a human reader would do it, is looking directly at the relative frequency of appearance of different author names. To do this, all the extracted author names (see Section 3) in the dataset are concatenated to build a vocabulary. Only authors that appear frequently (more than 50 times) are added to the vocabulary of size N_{Hist}. Next, for every paper, we create a vector with the same number of elements as the vocabulary, which contains the number of times that each author in the vocabulary appears in the reference section of that paper. This vector is what we call the Reference Histogram Embedding (RHE).

Once we have the RHE for each paper, it is passed through a 2 layer MLP that compresses it to a vector size of 128. This vector is then directly concatenated with the output embeddings of the DistilBERT architecture. This joint vector is then fed to the 2-layer classifier, as shown in Fig. 2.

5 Results

This section presents the results achieved using the proposed architecture presented in the previous section and depicted in Fig. 2. This architecture has been implemented using the *Hugging Face* library for transformers (Wolf et al., 2020). First, results

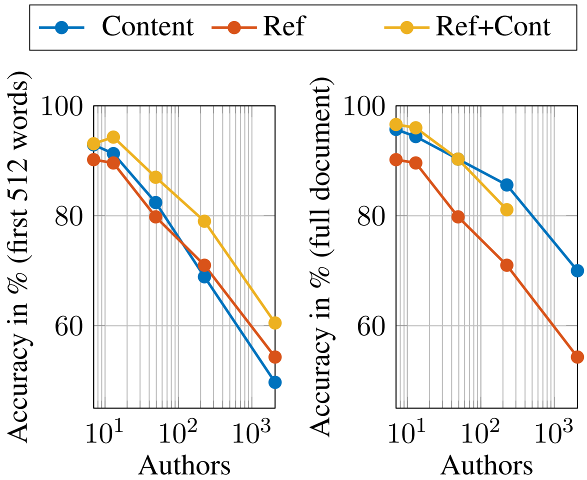

Figure 3: The two plots visualize the results presented in Tab. 2. On the left the 'non-C' datasets using only the first 512 words are used, on the right the full paper is used. Although the AA accuracy degrades with an increasing number of authors, our approach retains an impressive 60% for 2070 authors.

on our new *arXiv* dataset are presented along with an ablation study of the optimal learning rate. Then we present a small ablation on the network architecture itself. Finally, its performance is compared to existing approaches on benchmark datasets unrelated to scientific research article AA.

5.1 Our Dataset

When applying our approach to the arXiv dataset, different network architectures are possible, namely a) only content ("Content"), b) only references with and without self-citations ("References", "Ref (no self)) and c) content with references ("Ref+Cont"). The results for all architectures applied to all versions of the dataset are summarized in Tab. 2, and visualized in Fig. 3.

From Table 2 it is visible that including the references in almost all cases – as expected – increases the accuracy by up to 8%. When all self-citations

Table 3: Comparison of training times on an Nvidia Quadro RTX 8000 GPU for the best model from Tab. 2. For the D300-C, 10 epochs, content only, is used. The last column reports the increase in accuracy when including the full document (C) is used.

	First 512 Words (non-C)	Full Document (C)	Δ Accuracy
D100	13h:08m	11d:04h:40m	9.5%
D200	1h:35m	17h:49m	6.6%
D300	49m	4h:35m	3.3%
D400	17m	1h:57m	1.7%
D500	11m	54m	3.1%

Table 4: Ablation of the learning rate for 10 epochs.

Rate	Content	References		Ref+Cont	
	D300	D300	D500	D300	D500-C
1e-5	78.8				93.1
2e-5	81.3				95.7
5e-5	81.3				**96.7**
1e-4	**82.4**	79.3	86.7	84.5	95.7
2e-4	82.1	**80.2**	87.6	86.5	94.1
3e-4				**87.4**	
4e-4	81.2	79.6	89.2	87.2	
8e-4		79.4	**90.4**	85.4	
2e-3		80.0	90.3		

are removed from the references ("Ref (no self)") the accuracy of a reference-only design drops by over 10 p.p. for the large D100 set. Furthermore, a boost in performance is visible when comparing the non-C datasets (first 512 words only) with the whole documents. This is especially pronounced in the large datasets where relative improvements of up to 30% (content only) are observed. However, this boost in performance comes at the cost of dramatically increased training times, as shown in Table 3.

It is also important to remark that gains in evaluation accuracy that are attributed to solely combining the references with the content come nearly for free in terms of training time, as training times are similar with and without the reference part added to our architecture. The evaluation boost is more prominent when dealing with bigger datasets where only the first 512 are used. For example, it is interesting to see in Table 2 for the column D100 that a) there is an absolute gain of almost 11 % when using the references combined with the content w.r.t. only using the content information; and b) the reference alone architecture yields a 54.3% prediction accuracy, a result that is impressive by itself. Even more so, as D100 is a dataset that has more than 2000 possible labels. However, for the chunked datasets, the accuracy increase attributed to the consideration of the references gets diminished, although, for D300-C, D400-C and D500-C in Table 2 the best results (by a small margin) are obtained through this strategy. The reason for this decrease in the difference is thought to be related to the nature of transformers. It is known that transformer architectures excel at large amounts of data (Fabien et al., 2020). This is evident in our experiments when comparing the chunked versions with the first-words-only ones. It is, therefore, to be expected that the increase in performance when adding the reference information is less prominent for an intensively trained transformer. One can also argue that all cited references are somehow related to the content of the paper. In a case where the content network has access to the whole article, this might not add much new information. In the case where only the first 512 words are used, it is credible that the references add valuable information not included otherwise.

Learning Rate. In order to obtain the final results that are reported in Table 2, a fine-tuning stage of the learning rate was needed. The evaluation accuracy for different learning rates for some of our datasets is shown in Table 4. The learning rates of the rows in bold are selected for all runs of that type, e.g. all Ref+Cont architectures are trained with a learning rate of 5e-5 for whole documents.

5.2 Baselines

To evaluate the performance of the network architecture presented in this work, it is compared with current state-of-the-art methods on the benchmark datasets introduced in 3.2. Note that only the 'Content' part using the DistilBERT is used because no benchmark for research articles AA exists. The learning rate of the DistilBERT has been fine-tuned for the datasets and is set to 2e-5 for all experiments. The results are summarized in Tab. 5

On the larger *Legal* and *IMDb62* dataset, our DistilBERT approach outperforms all baselines and nearly halves the error rate on *IMBd62*. On the smaller Blog datasets, the transformer-based BertAA (Fabien et al., 2020) approach sightly outperforms ours by about 1%. On the original *Reuters50* dataset, the classical n-gram approach

Table 5: Comparison of our DistilBERT ("Content") architecture with other methods on the most common authorship attribution benchmark datasets.

	Legal	Blog10	Blog50	Reuters50		IMDb62
Train/Test Split	80/20	80/20	80/20	50/50	90/10	80/20
Topic Model (Seroussi et al., 2014)	93.64	–	–	–	–	91.79
Article GRU (Qian et al., 2017)	–	–	–	–	69.1	–
N-Gram (Sari, 2018)	91.29	–	–	**72.6**	–	94.8
BertAA (Fabien et al., 2020)	–	**65.4**	**59.7**	–	–	90.7
DistilBERT (Ours)	**94.8**	64.3	59.1	66.5	**83.6**	**97.5**

(Sari, 2018) achieves a 6% (absolute) higher accuracy compared to DistilBERT. This is most likely because the transformer-based approach requires much more training data. This theory is supported by the superior results when using a 90/10 train/test split and also by (Sari, 2018), where a similar tendency is observed.

5.3 Alternative Architecture

In this section we present an alternate architecture we used for references. Since the author names are one of the most informative part of the references, we only encode the author names in the references using FastText (Bojanowski et al., 2017). FastText was trained by inputting together all the author names corresponding to one paper, for all papers. This learnt embedding space clusters author names if they are cited by the same paper. Since each paper may have a different number of references and author names, in this architecture we propose to use an LSTM architecture. The input to the LSTM is the variable-length sequence of the author embedding. The output of LSTM concatenated with DistilBERT embedding is passed to to the 2-layer MLP.

To evaluate the accuracy of the FastText embedding and LSTM model, we train this network to predict the authors using only the references. This achieved an accuracy of 75.03% on the D300 dataset, which is slightly worse than RHE model. When combined with the DistilBERT, the accuracy increases to 81.4% on $D300$ but falls short of the RHE baseline for Ref+Context. This indicates that LSTM is not a suitable architecture for this task. Intuitively this makes sense as sequential information of the author names in the references is not significant, but rather the frequency of author names is useful for predicting author attribution.

We also evaluated the performance of FastText embedding in combination with 2 layer MLP by averaging the embedding for all the authors corresponding to the references for each paper. However, this approach too did not perform any better that RHE. Additionally, we also tried to use another DistilBERT in parallel only for the references. The hypothesis was that the transformer would learn the underlying structure of the references and that it would be able to learn extract the key information. However, the final classification accuracy was lower and the training times were, at least, slowed down by a factor of 2. Therefore, these architectures were discarded.

6 Conclusion & Discussion

We presented a transformer-based classification architecture for research papers that leverages, for the first time, a combination of the syntactic richness and topic diversity contained in research content and the information contained in the reference section. Our results show that combining both sources of information increases the authorship attribution accuracy. In cases where only limited text content is available to the network, including references increases the performance significantly (up to 11%). Overall, our method achieves 70% accuracy on the D100-C dataset, containing over 2000 authors, which is unprecedented to the best of our knowledge. On smaller datasets (< 50 authors) and some benchmarks, the proposed architecture robustly identifies an author correctly well over 90% of the time, beating state-of-the-art results.

While our DistilBERT-based approach outperforms all baselines on large datasets such as *Legal* and *IMDb62*, it fails to outperform simple n-gram baseline on small datasets. The likely explanation here is the data-hungry nature of transformers limits the performance of our approach on smaller datasets. However, this is not truly a limitation as AA for research papers deals with very large datasets.

Lastly, we also present a large-scale authorship-identification dataset by leveraging 2 million research papers publicly available on arXiv.

We believe that this line of research—albeit having great implications for double-blind review—ultimately helps to improve the review process. Thus, we conclude our paper by summarizing the key insights into how a submission can remain anonymous in order to support an unbiased, double-blind review process.

- *Abstract and introduction*: already the first 512 words enable robust authorship attribution. We believe that this is because the abstract and introduction often express the authors creative identity together with the research field. These personalized characteristics enable identification of the authors.

- *Self-citations*: The papers in our dataset contain, on average, 10.8% self-citations. Those citations easily give away the authors' identity as highlighted by the results shown in Tab. 2. Therefore, it is beneficial to omit many self-citations in the submission for double-blind review.

- *Citation diversity*: Even without the self-citations, the references can be used to identify the author. By also including citations of less well-known papers authors can make authorship attribution more difficult. At the same time, more equal visibility is given to all research papers in the authors' field.

7 Ethical Considerations

The task of AA for research papers has some ethical concerns as it offers a potential way of breaking the double blinded peer review system, a pillar of academic research. While the proposed methodology challenges this double blind peer review system by uncovering the author identity only from text and references, we believe our method can help establishing an improved peer review system. By analysing our method and providing insights into how a paper can be attributed to an author, we hope to guide authors towards a writing style that improves double-blind review. Therefore, we believe that the possible negative consequences are outweighed by the opportunity of this exciting research direction, which has not been thoroughly pursued in the past. For this very reason, we also open-source all the tools required to reproduce our experiments and further develop our methodology under https://github.com/uzh-rpg/authorship_attribution.

References

Hayri Volkan Agun and Ozgur Yilmazel. 2017. Document embedding approach for efficient authorship attribution. In *2017 2nd International Conference on Knowledge Engineering and Applications (ICKEA)*, pages 194–198.

Iana Atanassova, Marc Bertin, and Philipp Mayr. 2019. Editorial: Mining scientific papers: Nlp-enhanced bibliometrics. *Frontiers in Research Metrics and Analytics*, 4.

Andrew O. Ballard, Ryan DeTamble, Spencer Dorsey, Michael Heseltine, and Marcus Johnson. Dynamics of polarizing rhetoric in congressional tweets. *Legislative Studies Quarterly*, n/a(n/a).

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2016. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146.

Joseph K. Bradley, Patrick Gage Kelley, and Aaron Roth. Author identification from citations.

Colin B. Clement, Matthew Bierbaum, Kevin P. O'Keeffe, and Alexander A. Alemi. 2019. On the use of arxiv as a dataset.

Jan Christian Blaise Cruz and Charibeth Cheng. 2020. Establishing baselines for text classification in low-resource languages.

Thomas Davidson, Dana Warmsley, Michael Macy, and Ingmar Weber. 2017. Automated hate speech detection and the problem of offensive language. *Proceedings of the International AAAI Conference on Web and Social Media*, 11(1):512–515.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding.

Maël Fabien, Esau Villatoro-Tello, Petr Motlicek, and Shantipriya Parida. 2020. BertAA : BERT fine-tuning for authorship attribution. In *Proceedings of the 17th International Conference on Natural Language Processing (ICON)*, pages 127–137, Indian Institute of Technology Patna, Patna, India. NLP Association of India (NLPAI).

David I. Holmes. 1998. The Evolution of Stylometry in Humanities Scholarship. *Literary and Linguistic Computing*, 13(3):111–117.

Jonathan Hope. 1994. *The Authorship of Shakespeare's Plays: A Socio-linguistic Study*. Cambridge University Press.

Xi Huang and Minxuan Xu. 2021. An inter and intra transformer for hate speech detection. In *2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST)*, pages 346–349.

Sehrish Iqbal, Saeed-Ul Hassan, Naif Radi Aljohani, Salem Alelyani, Raheel Nawaz, and Lutz Bornmann. 2020. A decade of in-text citation analysis based on natural language processing and machine learning techniques: An overview of empirical studies. *arXiv:2008.13020 [cs]*. ArXiv: 2008.13020.

Rahul Radhakrishnan Iyer and Carolyn Penstein Rose. 2019. A machine learning framework for authorship identification from texts.

Jenny S. Li, Li-Chiou Chen, John V. Monaco, Pranjal Singh, and Charles C. Tappert. 2017. A comparison of classifiers and features for authorship authentication of social networking messages. *Concurrency and Computation: Practice and Experience*, 29(14):e3918. E3918 CPE-16-0159.R1.

Weicheng Ma, Ruibo Liu, Lili Wang, and Soroush Vosoughi. 2020. Towards improved model design for authorship identification: A survey on writing style understanding.

Mayzner. English letter frequency counts: Mayzner.

Frederick Mosteller and David L. Wallace. 1963. Inference in an authorship problem. *Journal of the American Statistical Association*, 58(302):275–309.

Chen Qian, Ting He, and Rao Zhang. 2017. Deep learning based authorship identification.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. pages 3973–3983.

Joseph Rudman. 1997. The state of authorship attribution studies: Some problems and solutions. *Computers and the Humanities*, 31(4):351–365.

Tony Russell-Rose, Mark Stevenson, and Miles Whitehead. 2002. The Reuters Corpus Volume 1 – from yesterday's news to tomorrow's language resources.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2020. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter.

Yunita Sari. 2018. *Neural and Non-Neural Approaches to Authorship Attribution*. Ph.D. thesis, University of Sheffield.

Jonathan Schler, Moshe Koppel, Shlomo Argamon, and James Pennebaker. 2006. Effects of age and gender on blogging. pages 199–205.

Mike Schuster and Kaisuke Nakajima. 2012. Japanese and korean voice search. In *International Conference on Acoustics, Speech and Signal Processing*, pages 5149–5152.

Yanir Seroussi, Russell Smyth, and Ingrid Zukerman. 2011. Ghosts from the high court's past: Evidence from computational linguistics for dixon ghosting for mctiernan and rich. *The University of New South Wales law journal*, 34:984–1005.

Yanir Seroussi, Ingrid Zukerman, and Fabian Bohnert. 2010. Collaborative inference of sentiments from texts. pages 195–206.

Yanir Seroussi, Ingrid Zukerman, and Fabian Bohnert. 2014. Authorship attribution with topic models. *Computational Linguistics*, 40.

Prasha Shrestha, Sebastian Sierra, Fabio González, Manuel Montes, Paolo Rosso, and Thamar Solorio. 2017. Convolutional neural networks for authorship attribution of short texts. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 669–674, Valencia, Spain. Association for Computational Linguistics.

Simen Skoglund. 2015. Authorship identification of research papers. Master's thesis, Norwegian University of Science and Technology.

Efstathios Stamatatos. 2008. Author identification: Using text sampling to handle the class imbalance problem. *Information Processing & Management*, 44:790–799.

Efstathios Stamatatos. 2009. A survey of modern authorship attribution methods. *Journal of the American Society for Information Science and Technology*, 60(3):538–556.

Geng Tu, Jintao Wen, Cheng Liu, Dazhi Jiang, and Erik Cambria. 2022. Context- and sentiment-aware networks for emotion recognition in conversation. *IEEE Transactions on Artificial Intelligence*, pages 1–1.

Ju-Chiang Wang, Yun-Ning Hung, and Jordan B. L. Smith. 2022. To catch a chorus, verse, intro, or anything else: Analyzing a song with structural functions. In *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 416–420.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020.

Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, et al. 2020. Big bird: Transformers for longer sequences. *Advances in Neural Information Processing Systems*, 33.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In *The IEEE International Conference on Computer Vision (ICCV)*.