On the State of the Art in Authorship Attribution and Authorship Verification

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Abstract
Despite decades of research on authorship attribution (AA) and authorship verification (AV), inconsistent dataset splits/filtering and mismatched evaluation methods make it difficult to assess the state of the art. In this paper, we present a survey of the fields, resolve points of confusion, introduce VALLA that standardizes and benchmarks AA/AV datasets and metrics, provide a large-scale empirical evaluation, and provide apples-to-apples comparisons between existing methods. We evaluate eight promising methods on fifteen datasets (including distribution shifted challenge sets) and introduce a new large-scale dataset based on texts archived by Project Gutenberg. Surprisingly, we find that a traditional Ngram-based model performs best on 5 (of 7) AA tasks, achieving an average macro-accuracy of 76.50\% (compared to 66.71\% for a BERT-based model). However, on the two AA datasets with the greatest number of words per author, as well as on the AV datasets, BERT-based models perform best. While AV methods are easily applied to AA, they are seldom included as baselines in AA papers. We show that through the application of hard-negative mining, AV methods are competitive alternatives to AA methods. VALLA and all experiment code can be found here: https://github.com/JacobTyo/Valla

1 Introduction
The statistical analysis of variations in literary style between one writer or genre and another, commonly known as stylometry, dates back as far as 500 AD, when the Hebrew Old Testament was studied and standardized by Tiberias at Palestine (Binongo, 1996). Computer-assisted stylometry first emerged in the early 1960s, when Mosteller and Wallace (1963) explored the foundations of computer-assisted authorship analysis. Today automated tools for authorship analysis are common, finding practical use in the justice system to analyze evidence (Koppel et al., 2008), among social media companies to detect compromised accounts (Barbon et al., 2017), to link online accounts that belong to the same individual (Sinnott and Wang, 2021), and in a variety of contexts to detect plagiarism (Stamatatos and Koppel, 2011).

In the modern Natural Language Processing (NLP) literature, two primary problem formulations dominate the empirical study of methods for determining the authorship of anonymous or disputed texts: Authorship Attribution (AA) and Authorship Verification (AV). In AA, the learner is given representative texts for a canonical set of authors in advance, and expected to attribute a new previously unseen text of unknown authorship to one of these a priori known authors. In AV, the learner faces a more general problem: given two texts, predict whether they were written by the same author or not.

While both problems have received considerable attention (Murauer and Specht, 2021; Altakrori et al., 2021; Kestemont et al., 2021), the state of the art is difficult to assess owing to inconsistencies in the datasets, splits, performance metrics, variations in the framing of domain shift across studies, and the lack of large-scale datasets. For example, a recent survey paper (Neal et al., 2017) indicates that the state-of-the-art method is based on the Partial Matching (PPM) text compression scheme and the cross-entropy of each text with respect to the PPM categories. By contrast, the PAN-2021 competition (Kestemont et al., 2021) indicates that the state of the art is a hierarchical bi-directional LSTM with learned-CNN text encodings. Recent work (Fabien et al., 2020) concludes that the transformer-based language model BERT is the highest performing AA method. A recent analysis paper (Altakrori
et al., 2021) argue that the traditional approach of character n-grams and masking remains the best methodology to this day. Each of these sources compares methods against different baselines, on different datasets (sometimes on just a single small dataset), and with different problem variations (such as same-topic, cross-topic, cross-genre, cross-language, etc.).

In this paper, we start by sorting out this fragmented prior work through a brief survey of the literature. Then, to present a unified evaluation, we introduce The VALLA Benchmark. This benchmark provides standardized versions of all the common AA and AV datasets with uniform evaluation metrics and standardized domain shifted test sets. Additionally, we introduce a new large-scale dataset based on public domain books sourced from Project Gutenberg for both tasks. Then using this benchmark, we present an extensive evaluation of eight common AA and AV methods on their respective datasets with and without domain shift. We also make comparisons between AA and AV methods where applicable.

Although much recent work indicates that AA and AV are not benefiting from the recent advancements of pre-trained language models (such as BERT and GPT-2) commensurate with the gains seen elsewhere in NLP (Kestemont et al., 2021; Altakrori et al., 2021; Murauer and Specht, 2021; Tyo et al., 2021; Peng et al., 2021; Futrzynski, 2021), we show that this narrative only applies to datasets with a limited number of words per class. Furthermore, BERT-based models achieve new state-of-the-art macro-accuracy on the IMDb62 (98.81%) and Blogs50 (74.95%) datasets and set the benchmark on our newly introduced Gutenberg dataset.

Although the applicability of AV methods to AA problems is frequently mentioned, few studies place these methods in competition. We provide this comparison and find that, on AA problems, AA methods outperform AV methods by over 15% macro-accuracy on average (76.80% and 59.89% average macro-accuracy for BERT_A and BERT_V respectively across five datasets). However, hard negative mining improves the performance of AV models in the AA setting, increasing the AA performance of BERT_V from 67.21% to 72.42% macro-accuracy on the tested dataset, making it a competitive alternative.

In summary, we contribute the following:

* A survey of AA and AV.
* An argument for adopting macro-averaged accuracy and AUC as the key metrics for AA and AV, respectively.
* A benchmark that standardizes AA and AV datasets, and places them in competition.
* State-of-the-art accuracy on the IMDb62 (98.81%) and Blogs50 (74.95%) datasets.
* A new large-scale dataset with long average text length.
* An evaluation of eight high-performing AA and AV methods on fifteen datasets, assessing the state of the art for both problems.
* Evidence of the efficacy of hard-negative mining when applying AV methods to AA problems.

2 Brief Survey of the Literature

Neal et al. (2017) provide an overview of AA dataset characteristics and traditional AA methods. The authors enumerate the wide array of textual features used for AA (excluding modern methods such as word embeddings and byte-pair encoding), categorize methods into machine learning, similarity, and probabilistic models, and provide an evaluation of these techniques on a single, small dataset. They conclude that the predictions using partial matching (PPM) method is the state of the art. Bouanani and Kassou (2014) provide a similar survey focusing on the enumeration of hand-engineered features used in AA. Stamatatos (2009) discuss traditional AA methods from an instance-based (comparing one text to another) vs a profile-based (comparing one text to a representation of all author texts) methodology, including a computational requirement analysis.

Among notable surveys, Mekala et al. (2018) compare the benefits of the different traditional textual features; Argamon (2018) detail the problems with applying many traditional AA methods in real-world scenarios; Alhijawi et al. (2018) provide a meta-analysis of the field; and Ma et al. (2020) point out the lack of advances from using transformer-based language models in AA, calling for more exploration in this area. Critically, all of these prior surveys exclude recent advances due to deep learning, such as recurrent neural networks, transformers, word embeddings, and byte-pair encoding. In this brief survey, we briefly cover more traditional techniques, and then discuss recent deep-learning-based approaches.
So far, we have outlined the work on AA surveys, but there are none to be found that focus on AV. The PAN competition overview (Kestemont et al., 2021) is the closest thing that can be viewed as a survey on AV, but it is limited only to what was seen in the competitions. Notably, each year’s competition focuses on a single dataset and evaluate methods based on a metric, the choice of which has varied across the years. Most recently, the winner was chosen based on a simple average of AUC, F1, F0.5u, and C@1.

2.1 Datasets

Murauer and Specht (2021) worked towards a benchmark for AA, but overlooked the applicability of AV methods. Moreover, they do not discuss the domain shift (systematic statistical differences between train and test sets) present in many popular datasets. Not only are these datasets not independent and identically distributed, the test sets often contain novel topics (cross-topic - \( \times_t \)), genre’s (cross-genre - \( \times_g \)), or authors (unique authors - \( \times_a \)).

Table 1 shows the wide statistical variability between the different datasets. Roughly, we can categorize the datasets into small (CCAT50, CMCC, Guardian), medium (IMDb62, Blogs50, Amazon), and large (BlogsAll, PAN20 & 21, Gutenberg) datasets. The number of authors, documents, and words in a corpus is influential, but looking more closely at the number of documents per author (\( D/A \)) and the number of words per document (\( W/D \)) gives a better idea of how hard a corpus is. The larger the number of authors and the less text there is to work with, the harder the problem. Lastly, we measure the imbalance (\( imb \)) of datasets based on the standard deviation of the number of documents per author, most impactful in the AA formulation.

The cross-topic setting is typically used to understand the sensitivity of models to topical variations. Altakrori et al. (2021) observe that any errors in this setting can be caused by a failure to capture writing style as well as topic shift. They then introduce the topic-confusion setting that can more clearly distinguish the error source. The topic-confusion setting is when all topics appear in both the training and test sets but the topic of the texts for each author changes in the test set (i.e. author \( A_1 \) writes on topic \( T_1 \) and author \( A_2 \) writes on topic \( T_2 \) in the training set, then in the test set, author \( A_1 \) writes on topic \( T_2 \) and author \( A_2 \) writes on topic \( T_1 \)). The authors find that traditional N-gram methods are the most robust in this setting. While we do not include any experimentation on topic-confused datasets, VALLA does include the topic confusion split they introduced.

The CCAT50 (Lewis et al., 2004), CMCC (Goldstein et al., 2008), Guardian (Stamatatos, 2013), IMDb62 (Seroussi et al., 2014), and PAN20 & PAN21 (Kestemont et al., 2021) are used as they are in prior work, but with the distinction that we publish our train/validation/test splits to ensure comparability with future work. The Amazon review corpus (He and McAuley,
2016) is a very large dataset, including over 142 million reviews. However, we extract only the users who have exactly 10 reviews.

The Blogs50 dataset is common and interesting due to its small average text length. However, the dataset was introduced by Schler et al. (2006) in its raw form, which correlates to the BlogsAll entry in Table 1. However, the statistics we present are different than originally published. This discrepancy is due to a large number of duplicates (∼160,000 exact duplicates) which we have removed. The most common form of this dataset is Blogs10 and Blogs50 (the data texts from the “top” 10 and 50 authors respectively). This is problematic because it isn’t clear how these “top” authors are selected: the number of documents (Fabien et al., 2020; Patchala and Bhatnagar, 2018), the number of words, with minimum text length (Koppel et al., 2011), with spam (or other) filtering (Yang and Chow, 2014; Halvani et al., 2017), or as in most cases, not specified (Jafariakinabad and Hua, 2022; Yang et al., 2018; Zhang et al., 2018; Ruder et al., 2016). In our framework, we release standard splits and filtering (only removing exact duplicates) for this dataset.

Machine learning has benefited from larger datasets. However, as highlighted in Table 1, there is only one common large-scale dataset: PAN20 & PAN21. We add a new dataset to this list: Gutenberg. While some prior work has used Project Gutenberg as a dataset source (public domain books), they all use small subsets (Arun et al. 2009) use 10 authors, Brooke et al. (2015) introduce a generic interface for the data, Gernlach and Font-Clos (2020) use the 20 most prolific authors, Menon and Choi (2011) use 14 authors, Rhodes (2015) use 6 authors, Khmelev and Tweedie (2001) get a 380 text subset, etc.). Here we have collected all single-author English texts from Project Gutenberg resulting in almost 2 billion words and a very long average document length.

2.2 Metrics
One of the difficulties in comparing prior work is the use of different performance metrics. Some examples are accuracy (Altakrori et al., 2021; Stamatatos, 2018; Jafariakinabad and Hua, 2022; Fabien et al., 2020; Saedi and Dras, 2021; Zhang et al., 2018; Barlas and Stamatatos, 2020), F1 (Murauer and Specht, 2021), C@1 (Bagalln, 2015), recall (Lagutina, 2021), precision (Lagutina, 2021), macro-accuracy (Bischoff et al., 2020), AUC (Bagnall, 2015; Pratanwanich and Lio, 2014), R@8 (Rivera-Soto et al., 2021), and the unweighted average of F1, F0.5u, C@1, and AUC (Manolache et al., 2021; Kestemont et al., 2021; Tyo et al., 2021; Puttrzynski, 2021; Peng et al., 2021; Böninghoff et al., 2021; Boeninghoff et al., 2020; Embarcadero-Ruiz et al., 2022; Weerasinghe et al., 2021).

The F0.5u, C@1, and Brier Score metrics were popularized by the PAN competitions to measure the ability of models to abstain from hard samples in an AV problem formulation. A participant submits a score between 0 and 1 for each sample with 0 indicating that the texts were written by different authors and 1 the same author. To abstain from a sample, the participant must submit a score of exactly 0.5. However, another one of the metrics used in the competition is the AUC score, which accounts for how well a model can rank predictions (i.e. giving a convenient measure of model performance without concern of a threshold). The PAN scoring ignores any abstained sampled in the AUC calculation instead of allowing participants to submit two numbers for each sample, one indicating the model’s score and another indicating if the model wishes to abstain or not (then the AUC can be measured without the influence of abstaining while the metrics that account for these non-answers can still be used as intended). However, we view this level of metric specificity as more relevant to specific applications and therefore do not include them in this work.

In both problem formulations, we want to understand the discriminative power of each model, and we need to be careful to avoid metrics that are determined too much by performance on a small subset of prolific authors. Thus, we adopt macro-averaged accuracy for AA (referred to as macro-accuracy), and AUC for AV.

2.3 Methods
This section overviews prior methods organized by feature extraction method (Figure 1).

2.3.1 Feature Based
Ngram The most commonly seen input representation (feature) used in AA and AV problems are of N-grams. In most cases, the N-grams are
counted into a bag-of-words representation, but in some cases, they are transformed to feature representations using Convolutional Neural Networks (CNNs) (Shrestha et al., 2017). Granados et al. (2011) introduced text distortion, which substitutes out-of-vocabulary items for a “*”. Stamatas et al. (2018) and Bischoff et al. (2020) further test these distortion methods and more complex domain-adversarial methods, showing that the simpler distortion methods are most effective. Table 2 gives examples of this text distortion.

Long considered the best AA/AV method, the Ngram-based unmasking method, developed by Koppel and Schler (2004), is based on the idea that the style of texts from the same author differs only in a few features. Given a test text A, unmasking works by taking all texts from a potential author B and then building a classifier to predict if the text is from A or B. A small number of the most meaningful features are removed, and this process is repeated until there are no features left to remove. At each step, the accuracy is tracked creating a performance degradation curve. Finally, an SVM is trained to classify the degradation curve to determine if A and B are from the same author or not (the ability of the model to distinguish between A and B will decay quickly if they are from the same author, as only a few features change between the works of a single author, whereas there are many differences between the work of different authors. Koppel et al. (2011) later change this method to keep score of how often each author is predicted after each feature elimination round, and then make a final prediction based on these scores, dubbed the imposter’s method, and Bevendorff et al. (2019) use this method for short texts by oversampling each text.

Seroussi et al. (2011) use Latent Dirichlet Allocation (LDA), comparing the distance between text representations to determine authorship. They find that this topic modeling approach can be competitive with the imposter’s method while requiring less computation. Seroussi et al. (2014) expand on this topic model approach, and while they presents good results on the PAN’11 dataset, the performance of the topic modeling approaches lags behind the best methods.

Zhang et al. (2018) introduce a high-performing method that leverages sentence syntax trees and character n-grams as input to a CNN. Saedi and Dras (2021) also presents good results with CNN models, but Ordoñez et al. (2020) indicate that these CNN methods are no longer competitive.

**Summary Statistics** While older methods focused on small sets of summary statistics, more modern methods are able to combine all of these into a single model. Weerasinghe et al. (2021) provide the best example of this, calculating a plethora of hand-crafted features and Ngrams for each document (distribution of word lengths, hapax-legomena, Maas’ $a^2$, Herdan’s $V_m$, and more). The authors take the difference between these large feature vectors for two texts and then train a logistic regression classifier to predict if the texts were written by the same author or not. Despite its simplicity, this method performs well.

**Co-occurrence Graphs** Arun et al. (2009) construct a graph that represents a text based purely on the stopwords (nodes) and the distance between them (edge weights). Then to compare the two texts, their graphs are compared using the Kullback-Leibler (KL) divergence. Embarcadero-Ruiz et al. (2022) also construct a graph for each text but instead represents each node as a [word, POS_tag] tuple, and each vertex indicates adjacency frequency. After the graph is created for

| Given Sentences | The dog’s (and cat’s) house. |
|-----------------|------------------------------|
| Single Asterisk | The *’s (and cat’s) *. |
| Multiple Asterisk | The ***’s (and cat’s) *****. |
| Exterior Characters | The d*g’s (and cat’s) h***e. |
| Last Two Characters | The *og’s (and cat’s) ***se. |

Table 2: Common text distortion methods. The vocabulary in the given example is {The, and, cats}.
each text it is encoded into a one-hot representation and used as input to a LEConv layer. After pooling, the absolute difference between the two document representations is passed through a five-layer fully connected network for final scoring.

2.3.2 Embedding Based

Char Embedding Bagnall (2015) use a character-level recurrent neural network (RNN) for authorship verification by sharing the RNN model across all authors but training a different head for each author in the dataset. To classify authors, they calculate the probability that each text was written by each author, predicting the author with the highest probability. Interestingly, the authors accidentally ran a version of their system without the RNN (just the multi-heads) and achieved competitive results.

Ruder et al. (2016) use both CNNs to embed both characters and words for AA. Their results show that the character-based method outperforms the word-based approach across several datasets. Compression-based methods, which leverage a compression algorithm (such as ZIP, RAR, PPM, etc.) to build text representations which are then compared with a distance metric, fall into this category as well (Halvani et al., 2017).

Word Embedding Bönninghoff et al. (2019) leverage the Fasttext pre-trained word embeddings, concatenated with a learned CNN character embedding, as part of the input to a hierarchical bi-directional Long Short Term Memory (BiLSTM) network. Specifically, this combined embedding is used as input to a word-to-sentence BiLSTM network, whose output is fed into a sentence-to-document BiLSTM to produce a final document embedding. This neural network structure runs in parallel for two documents (i.e. as a Siamese network (Koch et al., 2015)), and then optimized according to the modified contrastive loss function (i.e. the traditional contrastive loss but additionally doesn’t penalize same-author samples that are sufficiently close in the embedding space). This method was introduced by Bönninghoff et al. (2019), and then later modified to include Bayes factor scoring on the output by Boenninghoff et al. (2020), and by Bönninghoff et al. (2021) to include an uncertainty adaptation layer for defining non-responses. This was the highest performing method at the PAN20 and PAN21 competitions (Kestemont et al., 2021).

Jafariakinabad and Hua (2022) attempted to build the equivalent of pre-trained word embeddings but for sentence structure (i.e. GloVe-like embeddings that map sentences with a similar structure close together but are agnostic of their “meaning”). They learn these embeddings by creating a parse-tree for each sentence using the CoreNLP parser and then passing this parse-tree and a traditional word-embedded sentence through identical but separate BiLSTMs and train via contrastive loss. Then, for authorship attribution, they pass the sentence through both a typical word-embedding LSTM, and also through their learned sentence structure encoding network, combining their output. The authors also compare against their prior work (Jafariakinabad and Hua, 2019) which embeds the POS-tags along with the word embeddings instead of using their custom structural embedding network. The new work slightly outperforms their prior method and is more efficient as you can leverage the pretrained structure encoding network instead of having to always label the POS tags.

CNN’s have also been well explored given word embeddings as input (Hitschler et al., 2018; Shrestha et al., 2017; Ruder et al., 2016), yet their results are not among the highest reported.

Transformers Rivera-Soto et al. (2021) attempt to build universal representations for AA and AV by exploring the zero-shot transferability of different methods between three different datasets. The authors train a Siamese BERT model (Reimers and Gurevych, 2019) on one dataset and then test the performance on another dataset without updating the model on this new dataset. Unfortunately, the results seem to indicate more about the underlying datasets then the ability of these models to uncover a universal authorship representation.

Manolache et al. (2021) also explore the applicability of BERT to AA by using BERT embeddings as the feature set for the aforementioned unmasking method. Comparing this to Siamese BERT, Character BERT (El Boukkouri et al., 2020), and BERT for classification, they find that simple fine-tuning outperforms the more complicated unmasking setup.

Following Bagnall (2015), Barlas and Stamatatos (2020) approach the AA problem by using a shared language model with a different network head for each author. They then compare different shared language model architectures (RNN, BERT, GPT2, ULMFiT, and ELMo), finding that
pretrained language models improve the performance of the original RNN architecture. However, the results are all from the small CMCC corpus.

Tyo et al. (2021) use a Siamese BERT setup with triplet loss and hard-negative mining for training. Futrzynski (2021) concatenate 28 tokens from each text and then use BERT’s [CLS] output token for author classification. Peng et al. (2021) concatenate 256 tokens from each text to produce a 512 token input for BERT, and then after pooling use linear layers for same/different author prediction. They repeat this 30 times, sampling different sections of the input texts, and then average over the 30 predictions for final classification.

2.3.3 Feature and Embedding Based

Fabien et al. (2020) were an early work exploring the applicability of BERT to authorship attribution. They combine the output of BERT with summary statistics via a logistic regression classifier. The authors find that a BERT-only model was as effective as a model combining the BERT output with the summary statistics.

3 The VALLA Benchmark

In 1440, Lorenzo Valla proved that the Donation of Constantine (where Constantine I gave the whole of the Western Roman Empire to the Roman Catholic Church) was a forgery, using word choice and other vernacular stylistic choices as evidence (Valla, 1922). Inspired by this influential use of AA, we introduce VALLA: A standardized benchmark for authorship attribution and verification. VALLA includes all datasets in Table 1, along with others from prior literature (Klimt and Yang, 2004; Manolache et al., 2022; Overdorf and Greenstadt, 2016; Altakrori et al., 2021), with standardized splits, cross-topic/cross-genre/unique author test sets, and usable in either AA or AV formulation. VALLA also includes five method implementations, and we use the subscript “A” or “V” to distinguish between the attribution and verification model formulations respectively.

Ngram Being the best performing method in Altakrori et al. (2021), Murauer and Specht (2021), Bischoff et al. (2020), and Stamatatos (2018), this method creates character Ngram, part-of-speech Ngram, and summary statistics for use as input to an ensemble of logistic regression classifiers.

For use in the AV setting, we follow Weerasinghe et al. (2021) by using the difference between the Ngram feature vectors of two texts as input to the logistic regression classifier.

PPM Originally developed in Teahan and Harper (2003) and best performing in Neal et al. (2017), this method uses the prediction by partial matching (PPM) compression model (a variant of PPM is used in the RAR compression software) to compute a character-based language model for each author (Halvani and Graner, 2018), and then the cross-entropy between a test text and each author model is calculated. For use in an AV setup, one text is used to create a model and then the cross-entropy is calculated on the second text.

BERT With the highest reported performance on the AA dataset Blogs50 (Fabien et al., 2020), this method combines a BERT pre-trained language model with a dense layer for classification. For evaluation, we chunk the evaluation text into non-overlapping sets of 512 tokens and take the majority vote of the predictions. For use in the AV setup, the BERT model is used as the base for a Siamese network and trained with contrastive loss. For evaluation in the AV setup, we chunk the two texts into $K$ sets of 512 stratified tokens (such that the first 512 tokens of each text are compared, the second grouping of 512 tokens from each text is compared, etc.), and then take the majority vote of the $K$ predictions.

pALM The best performing model in Barlas and Stamatatos (2020) was another variation on BERT where a different head was learned on top of the BERT language model for each known author. We refer to this method as the per-Author Language Model (pALM). To classify a text, it is passed through the model for each author, and then the author model with the lowest perplexity on the text is predicted. This is only used in AA formulations as in AV we would have only a single text to train a network head with.

HLSTM Originally introduced by Bönninghoff et al. (2019), this method leverages a hierarchical BiLSTM setup with Fasttext word embeddings along with custom word embeddings learned using a character level CNN as the base for a Siamese network. This method was the highest performing at PAN20 and PAN21 (Kestemont et al., 2021) and is only used in AV formulations. While this can be modified to work in AA, we follow prior work and use the original AV setup only.

Valla can be found here: https://github.com/JacobTyo/Valla
All of these methods fall into two categories: the methods that predict an author class, and the methods that predict text similarity. The methods that predict an author class (whether via logistic regression, dense layer, SVM, etc.) need no post-processing. However, the methods that predict similarity need post-processing both for AA and AV problems. For AA, we build an author profile by randomly selecting 10 texts from each author and averaging their embeddings together. Then we can compare the unknown texts to each author profile and predict the author that is most similar (using the euclidean distance). For AV, we directly compare the text representations (again using euclidean distance) and then define a hard threshold based on a grid search on the evaluation set (although for computing AUC this threshold is irrelevant).

4 Experiments and Discussion

4.1 The State-of-the-Art in Authorship Attribution

After evaluating all methods in VALLA on the AA datasets listed in Table 1, we find that the traditional Ngram method is the highest performing on average as detailed in Table 3. However, we do see that the BERT\textsubscript{A} model closes the gap on (and can even exceed) the performance of the Ngram\textsubscript{A} method as the size of the training set increases. This correlation does not hold on the PAN20 dataset, where the best performing model is still Ngram\textsubscript{A}. This indicates that the state-of-the-art AA method is dependent upon the number of words per author available. While we do not provide a detailed analysis of the data requirements of each method, our results roughly indicate that Ngram\textsubscript{A} is the method of choice for datasets with less than 50,000 words per author, while BERT\textsubscript{A} is the state-of-the-art method for datasets with over 100,000 words per author.

PPM\textsubscript{A} is simple to tune due to few hyperparameters, but it is both a low performer and it scales poorly to large datasets (rendering it unusable on the PAN20 and Gutenberg datasets). pALM\textsubscript{A} is the lowest performing method tested, is expensive to train, and scales poorly resulting in too slow of training to be used on the IMDb62, Blogs50, PAN20, and Gutenberg datasets.

The macro-accuracy of BERT\textsubscript{A} on the IMDb62 and Blogs50 datasets presents a new state of the art, while defining the initial performance marks on the GutenbergAA and PAN20 datasets.\(^4\) The performance on the Blogs50 dataset requires a bit more analysis due to our filtering of duplicates in the dataset. As a better comparison to prior reported performance, we first explore the performance of BERT\textsubscript{A} on the Blogs50 dataset without the filtering, and achieve a macro-accuracy of 64.3\%. This represents the state-of-the-art accuracy on a version of the dataset more comparable with prior work (despite its issues) but indicates the strength of the result reported in Table 3.

Our results on the Guardian and CMCC datasets are hard to compare to prior work due to the previously mentioned standardization issues, most notably a i.i.d. split has not been used in prior work. The CCAT50 dataset, on the other hand, is directly comparable to prior work. Currently, we show best performing model as the Ngram. However, Jafari-akinabad and Hua (2022) reports the accuracy of a CNN that takes the syntactic tree of a sentence as input as 83.2\% which is better than what we were able to achieve.\(^5\) Therefore we report this previous best result on the performance tracking page of VALLA.

4.2 The State-of-the-Art in Authorship Attribution under Domain Shift

While the problem of achieving high performance under any domain shift is an open problem in machine learning, exploration of domain shift in AA and AV settings is common even if not always explicitly recognized. Table 4 examines the performance of the same AA models discussed in the previous section but focuses on the cross-topic and cross-genre test sets of the CMCC and Guardian datasets. Just as in the i.i.d. setting, the Ngram\textsubscript{A} method dominates in all scenarios. It should be noted that all datasets used in this domain shift scenario are small, so we cannot verify that the BERT\textsubscript{A} model would begin to dominate as the number of words per author increases. We leave the exploration of domain shift performance on larger datasets to future work, although we expect that the BERT\textsubscript{A} model would begin to outperform Ngram\textsubscript{A}.

\(^4\)These are initial results because the PAN20 competition was formulated as an AV problem, whereas here we use the AA formulation.

\(^5\)CCAT50 is a balanced dataset, so the macro-accuracy and accuracy are equal.
Table 3: Macro-accuracy (%) of the authorship attribution models. The “Average” column represents the average macro-accuracy of each model across all datasets in this table, where — entries are counted as 0%.

| Model  | CCAT50 | CMCC | Guardian | IMDb62 | Blogs50 | PAN20 | Gutenburg AA | Average |
|--------|--------|------|----------|--------|---------|-------|---------------|---------|
| NgramA | 76.68  | 86.51| 100      | 98.81  | 72.28   | 43.52 | 57.69         | 76.50   |
| PPM_A  | 69.36  | 62.30| 86.28    | 95.90  | 72.16   | —     | —             | 55.14   |
| BERT_A | 65.72  | 60.32| 84.23    | 98.80  | 74.95   | 23.83 | 59.11         | 66.71   |
| pALMA  | 63.36  | 54.76| 66.67    | —      | —       | —     | —             | 26.40   |

Table 4: Macro-accuracy (%) of the authorship attribution models.

| Model  | CMCC   | CMCC   | Guard   | Guard |
|--------|--------|--------|---------|-------|
| NgramA | 82.54  | 84.13  | 86.92   | 87.22 |
| PPM_A  | 52.38  | 57.14  | 69.23   | 72.08 |
| BERT_A | 49.21  | 45.24  | 75.64   | 75.56 |
| pALMA  | 57.14  | 46.03  | 61.79   | 47.22 |

Table 5: AUC of the AV models on the selected AV datasets.

| Model  | PAN21 | AmaAV | BlogAV | GutAV |
|--------|-------|-------|--------|-------|
| NgramV | 0.9719| 0.7742| 0.5410 | 0.8741|
| PPM_V  | 0.7917| 0.6492| 0.6230 | 0.8508|
| BERT_V | 0.9709| 0.8943| 0.9201 | 0.9624|
| HLSTM_V| 0.9693| 0.8734| 0.8580 | 0.9147|

4.4 Comparing AA and AV methods

The AA formulation is common in practice, and many AV works are motivated by the idea that they can be applied to these common AA problems. Yet despite the prominence of comments indicating how AV is the fundamental problem of AA (seemingly hinting that applying AV methods to AA problems is easy), there is no evidence of how well their performance actually transfers. We dive into this situation in this section. Table 6 shows the performance of LSTM_V and BERT_V on the i.i.d. AA datasets, both when trained only on the dataset as well as starting from a pretrained version of the models (the PAN20 training set was used for pretraining). Here we see notably lower performance than what was obtained by the AA methods, proving that the application of AV methods to AA problems is not as straightforward as it may seem. Table 7 shows this trend continuing in the cross-topic and cross-genre AA evaluation settings as well.

4.5 Hard-Negative Mining

As indicated in the previous section, although AV is the fundamental problem of AA, AV methods do not necessarily perform well under an AA formulation. To correctly classify a text in the AA setting, a model must make harder comparisons (i.e., it must compare a text to the hardest negative—the text that makes the decision the hardest), whereas an AV setting is strictly easier as it must compare to only a single text. AV problems can be made harder, but they cannot ever consist of exactly the hardest negatives, because the hardest negative is model-dependent. This interpretation motivates the exploration of using hard-negative mining (updating a model during training only on the hardest

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6We note that the lower performance of the pretrained H-LSTM on Blogs50 than its non-pretrained version is due to the vocabulary selection. This method chooses its vocabulary based on the pretraining corpus, and therefore runs the risk of the vocabulary not transferring well to the intended corpus.
examples in each batch) for improving the transferability of AV methods to AA problems.

The AV formulation is very attractive for training deep models, so bridging the performance gap would create a strong case for more research emphasis on AV models. In this section we take a single model (BERT\textsubscript{V}) and train two versions of it: one with the contrastive loss and one using triplet loss with batch hard negative mining (specifically the per-batch hard negative mining methodology used in Hermans et al. (2017)). Then using our standardized Blogs50 dataset, we can determine the AV AUC to AA macro-accuracy relation.

Table 8 details these results, showing two key findings. The first is that high AV AUC does not indicate high AA macro-accuracy, and the second is that training an AV method with hard negative mining has little effect on its AV AUC but drastically improves its AA macro-accuracy.

## 5 Conclusion

After a survey of the AA and AV landscapes, we present \textsc{VALLA}: an open-source dataset and metric standardization benchmark, complete with method implementations. Using \textsc{VALLA} and a newly introduced large-scale dataset, we present an extensive evaluation of AA and AV methods in a wide variety of common formulations. We achieve a new state-of-the-art macro-accuracy on the IMDb62 (98.81\%) and Blogs50 (74.95\%) datasets and provide benchmark results on the other datasets. Among sufficient words per author (\(\sim 100,000\), the state-of-the-art AA method is BERT\textsubscript{A}, but if ample data is not available the Ngram\textsubscript{A} method proves most effective. When faced with domain shift, we find the Ngram\textsubscript{A} method to be the most accurate, but notably, all of the domain-shifted datasets are small.

Our results show that the AV problem formulation is more effective for training deep models, finding the state-of-the-art AV method to be BERT\textsubscript{V}. After showing that the high-performing BERT\textsubscript{V} does not perform competitively in AA problems, we explore the effect of hard-negative mining on its performance and find that with no degradation in AV performance, it improves the AA macro-accuracy of BERT\textsubscript{V} by over 5\%, making it a competitive method in the AA formulation. We hope that \textsc{VALLA} encourages more work on understanding the AA and AV method landscapes, developing new AA/AV methods, and allows for direct comparison of future findings.

![Table 6: Macro-accuracy (%) of the AV models on AA datasets. The (P) indicates that the model was pretrained on the PAN20 training set before fine-tuned on the corresponding dataset.](image1)

|                | CCAT50 | CMCC | Guardian | IMDb62 | Blogs50 |
|----------------|--------|------|----------|--------|---------|
| HLSTM\textsubscript{V} | 4.56   | 8.33 | 27.59    | 37.82  | 57.49   |
| (P)HLSTM\textsubscript{V} | 13.36  | 16.27| 38.97    | 59.47  | 11.34   |
| BERT\textsubscript{V} | 48.64  | 35.75| 27.82    | 76.62  | 60.72   |
| (P)BERT\textsubscript{V} | 56.80  | 40.87| 61.41    | 73.17  | 67.21   |
| **BERT\textsubscript{A}** | **65.72** | **60.32** | **84.23** | **98.80** | **74.95** |

![Table 7: Macro-accuracy (%) of the authorship verification models on the domain shift AA datasets. The (P) indicates that the model was pretrained on the PAN20 training set before fine-tuned on the corresponding dataset.](image2)

|                | CMCC \(\times_t\) | CMCC \(\times_g\) | Guard \(\times_t\) | Guard \(\times_g\) |
|----------------|------------------|-------------------|------------------|-------------------|
| HLSTM\textsubscript{V} | 7.94             | 3.18              | 19.23            | 23.33             |
| (P)HLSTM\textsubscript{V} | 9.52             | 5.56              | 40.00            | 31.53             |
| BERT\textsubscript{V} | 28.85            | 13.49             | 42.31            | 46.53             |
| (P)BERT\textsubscript{V} | 33.33            | 19.05             | 43.33            | 54.72             |
| **BERT\textsubscript{A}** | **49.21**        | **45.24**         | **75.64**        | **75.56**         |

![Table 8: This table compares the performance of the same model (BERT\textsubscript{V}), on the same data (Blogs50), just formulated in different ways, using different performance metrics (column header). w/HNM represents training with hard negative mining.](image3)

| Metric (Formulation) | AUC (AV) | Acc (AV) | Mac-Acc (AA) |
|----------------------|----------|----------|--------------|
| BERT\textsubscript{V} | 0.9229   | 82.33    | 67.21        |
| BERT\textsubscript{V} w/HNM | 0.9276   | 82.72    | 72.42        |
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