Transferring BERT-like Transformers’ Knowledge for Authorship Verification

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Abstract. The task of identifying the author of a text spans several decades and was tackled using linguistics, statistics, and, more recently, machine learning. Inspired by the impressive performance gains across a broad range of natural language processing tasks and by the recent availability of the PAN large-scale authorship dataset, we first study the effectiveness of several BERT-like transformers for the task of authorship verification. Such models prove to achieve very high scores consistently. Next, we empirically show that they focus on topical clues rather than on author writing style characteristics, taking advantage of existing biases in the dataset. To address this problem, we provide new splits for PAN-2020, where training and test data are sampled from disjoint topics or authors. Finally, we introduce DarkReddit, a dataset with a different input data distribution. We further use it to analyze the domain generalization performance of models in a low-data regime and how performance varies when using the proposed PAN-2020 splits for fine-tuning. We show that those splits can enhance the models’ capability to transfer knowledge over a new, significantly different dataset.

Keywords: authorship verification · transformers · transfer learning

1 Introduction

The problem of authorship analysis and detection refers to identifying certain patterns and idiosyncrasies of an individual’s writing style, which can be further employed to attribute a writing to an author, or to determine the similarity between different texts. Applications of authorship analysis range from plagiarism detection to forensics and monitoring the activity of cyber-criminals.

Some of the very early works in authorship analysis rely on simple properties of a text, such as the average length of words, the average length of sentences, and other statistical features. In the early 1960s, Mosteller and Wallace conducted what was probably the most influential and widely-publicized early computer-based authorship investigation, applying Bayesian statistical analysis and computational power in an attempt to identify the authorship of the twelve disputed papers in the Federalist Papers. More recently,
machine learning approaches have been successfully employed in authorship attribution, some of the popular methods being Support Vector Machines [30], Decision Trees [32], or various meta-learning approaches [15].

Motivated by the availability of large amounts of data that can be scraped from the Web and by the recent release of large-scale authorship verification datasets [11,12], we analyze different neural-based models in a quantitative manner, by benchmarking them in various scenarios, and qualitatively, by analyzing the tokens’ importance using explainable AI (XAI) [29] techniques. We observe that baselines based on BERT [6] can perform unexpectedly well. However, large models trained on raw data outperform pipelines based on manually extracted linguistic features, which motivate us to study the dataset properties. Furthermore, we look for possible leaks from training into test data, which might lead to biases. We prove that this is the case for PAN-2020 and identify the text topic as a spurious [1,22] feature on which our model focuses. From this point on, we approach the authorship verification problem from a data-centric perspective.

We propose new data splits for PAN-2020 that allow us to remove topic-related biases and assess the performance of the BERT-like models in realistic scenarios. Moreover, we take into consideration the low-resource scenario where we are given limited amounts of textual data per author. We test the effectiveness of different pre-training and fine-tuning schemes on a database of texts collected from Reddit. We compare BERT-based models with unmasking [15], a more classical, meta-learning technique for authorship verification, using neural embeddings extracted from our models, before and after fine-tuning them in a few-shot scenario. We summarize below the main contributions of our work:

1. We analyse the authorship verification task under distribution shifts in the input domain, validating the usefulness of existing datasets and the generalization capabilities of BERT-based authorship methods.
2. We identify biases in the large-scale PAN-2020 dataset by closely looking at the results through XAI methods and noticing a focus on fandoms and named entities rather than on general authorship characteristics, as would have been expected. In this light, we introduce a new splitting setup for the PAN dataset, which tackles the bias problem, making the dataset more representative for evaluating authorship methods.
3. We propose DarkReddit, a new dataset for authorship verification, on which we test the transfer learning capabilities of the previously analyzed methods.

2 Related work

The vast majority of previous work in authorship analysis relied on feature engineering, employing features that usually try to capture the style of authors, and classical machine learning, usually classification models [27]. Due to the typically small data setup of authorship analysis tasks, deep learning methods had a slow start in this domain. This is reflected, for example, in the PAN
shared tasks, which were dominated by conventional machine learning systems until recently. In the overview paper of the PAN-2019 authorship attribution shared task [12], the authors noted: “None of the participant’s methods is based on deep learning algorithms, most probably due to hardware limitations of TIRA or because of the discouraging reported results in the corresponding task of PAN-2018”. The PAN-2020 author verification shared task diverged from previous years’ authorship analysis tasks by the use of a much larger dataset supporting more data-intensive approaches, such as deep learning [11].

Nevertheless, inspired by the impressive performance of pre-trained language models, such as BERT, in a broad range of natural language processing tasks, these pre-trained language models started to be investigated for the authorship analysis tasks. Saedi and Dras [23] used Convolutional Siamese Networks for authorship attribution. They compared their approach with a BERT fine-tuned over three epochs and showed that Siamese Networks are more robust over large-scale authorship attribution tasks. They used BERT only as a baseline for comparison instead of combining it with Siamese Networks, as in one of our approaches. In Barlas et al. [2], pre-trained language models (BERT, ELMo [18], ULMFiT [10], GPT-2 [20]) were investigated for the specific case of cross-topic and cross-domain authorship attribution. This work shows that BERT and ELMo achieve the best results, while being the most stable approaches. Fabien et al. [7] introduced BertAA, a pre-trained BERT language model with an additional dense layer and a softmax activation, fine-tuned to perform authorship classification. This approach reaches competitive performance levels on Enron Email [13], Blog Authorship [24], and IMDb62 [25]. These three works approach the authorship attribution task, while we focus on author verification. The authors remarked that their model is unable to perform text similarity evaluation in the context of authorship verification, and leave this as future work.

Unmasking [15] is one of the most well-known author verification approaches. It is based on the idea of testing the accuracy degradation rate of learned models as the best features are iteratively dropped from the learning process. Extensions of unmasking regarding the way of constructing and selecting the features are also investigated [4]. To the best of our knowledge, we are the first to use features derived from BERT-like language models for unmasking.

3 Datasets for authorship

We use training data from the PAN-2020 authorship verification competition[4]. The dataset comprises samples as tuples \((d_1, d_2, f_1, f_2, a_1, a_2)\), where \(d_1\) and \(d_2\) are two documents (crawled from \url{https://www.fanfiction.net/}), \(f_1\) and \(f_2\) are their respective topics (fandoms), and \(a_1\) and \(a_2\) their respective authors. Author verification is a binary classification task, in which a model must predict whether documents \(d_1\) and \(d_2\) belong to the same author or different ones.

The official PAN-2020 competition is a closed-set verification setup, meaning that the unseen test set contains document pairs whose authors and topics were

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[4] https://pan.webis.de/clef20/pan20-web/author-identification.html
Table 1. PAN-2020 XS and XL dataset sizes, broken by authorship and fandom relationship inside each sample tuple.

| Dataset | Total | Same Author (SA) | Diff. Author (DA) |
|---------|-------|------------------|-------------------|
|         |       | Same Fandom | Diff-Fandoms | Same Fandom | Diff-Fandoms |
| PAN XS  | 52,601 | 0 | 27,834 | 0 | 24,767 |
| PAN XL  | 275,565 | 0 | 147,778 | 23,131 | 104,656 |

present in the training set as well. The PAN-2021 authorship verification competition\[5\] has a more difficult open-set verification setup, in which the training data is the same as in 2020, but the submitted solutions are tested against document pairs from previously unseen authors and topics, from a hidden test set.

3.1 PAN-2020 dataset

The PAN-2020 competition featured two datasets, a smaller one (52k pairs), intended for traditional shallow verification methods, and a larger one (275k pairs), intended for deep learning solutions. The differences are summarized below and in Tab. 1. A document has an average of 21k words.

PAN XL. The large dataset has balanced classes (same vs different authors). Document pairs written by the same author always come from different fandoms (e.g. Star Wars vs Harry Potter), while pairs written by different authors can belong to the same fandom or to different fandoms. Same author pairs are constructed from 41k authors, while different author pairs are constructed from 251k authors, with an overlap of 14k authors in both the same and different pairs. The XL dataset has 494k distinct documents that span 1,600 fandoms.

PAN XS. The small dataset is also balanced. Distinctly from the XL dataset, it has only cross-fandom pairs in both class pairs. This split allows fast prototyping through smaller experiments with models that have different components.

4 Our approach

We summarize our analysis on transferring authorship verification knowledge under low-data regime constraints, using BERT-like transformers in several steps:

**Step 1: MLM pre-training and fine-tuning.** We investigate how existing large-scale masked language models (MLM) can take advantage of an extensive dataset for authorship verification. Experiments are detailed in Tab. 4.

**Step 2: Identify and reduce dataset biases.** The initial high performance accomplished in the previous step leads us to look for biases in the dataset that

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5 https://pan.webis.de/clef21/pan21-web/author-identification.html
Table 2. PAN-2020 XL dataset - Closed-set splits, broken down into Same Author (SA) vs Different Author (DA). Each class is further divided into Same Fandom (SF) and Cross-Fandom (CF) pairs.

| Split | Closed| | | Clopen| | |
|-------|-------|-------|-------|-------|-------|-------|
|       | Total | SA     | DA    | Total | SA     | DA    |
|       | SF    | CF     | SF    | CF    | SF    | CF    |
| Train | 248,322| 0 | 133,359 | 22,064 | 92,909 | 248,688 | 0 | 133,359 | 20,945 | 94,384 |
| Valid | 13,449 | 0 | 7,024 | 356 | 6,069 | 13,093 | 0 | 7,024 | 1,072 | 4,997 |
| Test | 13,784 | 0 | 7,395 | 355 | 6,034 | 13,784 | 0 | 7,395 | 1,114 | 5,275 |

might explain these results. We employ explainable AI techniques, as described in Fig. 2. Unexpectedly, we find that our models are mainly focused on topics and named entities (such as characters names) for determining the same or different author labels. Hence, we introduce several splits over PAN-2020 that gradually remove biases, as further presented in Sec. 4.1-4.2 and evaluated in Fig. 3.

Step 3: Unbiased split for few-shot knowledge transfer. We train one model for each of the proposed splits. Further, to test if there is a domain generalization advantage induced by using any of the proposed splits, we introduce the DarkReddit dataset, as explained in Sec. 4.3. The intuition that fine-tuning on an unbiased split helps the model to generalize better is further qualitatively confirmed in Fig. 3 using a few-shot learning scenario.

4.1 Closed-set splits

A closed-set scenario for authorship verification is defined in PAN-2020 as using already seen pairs of authors for testing and validation (but with different documents). This kind of splitting poses serious concerns on generalization, because it might work only on this specific set of authors or even worse, just on specific pairs. Since we have no access to the PAN-2020 test set, we start by splitting the training set into training, validation and test splits.

**Same Author.** To populate the splits with SA pairs, we iterate through each author $a_i$ and evenly split its SA pairs. For instance, if 10 SA pairs are written by $a_i$, we assign 4 pairs to training, 3 to validation and 3 to the test split. This ensures that authors at train time are seen during validation and testing. However, some of the fandoms at test time may still be unseen at training time.

**Different Author.** Each author pair $(a_i, a_j)$ in DA examples is unique, so it is impossible to split the DA examples such that author pairs $(a_i, a_j)$ from validation/test also appear during training.

**Closed vs Clopen splits.** The two splits differ only in DA pairs. For the Closed split, at least one of the authors from each DA test and validation pair
Table 3. PAN-2020 XL - Open-set splits: Unseen Authors (UA<sub>XL</sub>) and Unseen Fandoms (UF<sub>XL</sub>), broken down into Same Author (SA) vs Different Author (DA). Each class is further divided into Same Fandom (SF) and Cross-Fandom (CF) pairs.

| Split | Total SA SF | Total SA CF | Total DA SF | Total DA CF |
|-------|-------------|-------------|-------------|-------------|
| Train | 248,699 0 | 133,367 18,840 | 96,492 133,990 | 0 71,826 | 20,779 41,385 |
| Valid | 13,089 0 | 7,023 2,230 | 3,836 13,451 | 0 7,047 | 1,176 5,232 |
| Test  | 13,777 0 | 7,388 2,061 | 4,328 13,453 | 0 7,056 | 1,176 5,233 |

was seen at training time, and for Clopen, we randomly split DA samples into training, validation and test. Thus, authors and fandoms from the Clopen test and validation sets might not be seen in the train split, making it a bit more general (closer to open sets). Moreover, for the DA examples in the Closed split, the SF:CF ratio in the training subset is significantly different than in the test and validation subsets (1 : 4 and 1 : 17, respectively).

4.2 Open-set split

As defined by the PAN-2021 competition, the open-set setup implies having completely new authors and fandoms in the test set. This setup is significantly more difficult than the closed-set setup, but can be desirable for general authorship verification solutions. Unfortunately, partitioning the PAN-2020 dataset to obtain an open-set split that satisfies these two constraints left us with very few samples. Therefore, we create two open-set variants, each having a different trade-off: unseen authors (fandoms at test time may be seen during training) and unseen fandoms (authors at test time may be seen during training).

**Unseen authors split.** For this split, authors from the test set should not appear in the training set. However, this is difficult to achieve strictly, so we split the PAN-2020 dataset into train and validation/test sets such that: i) authors of same-author (SA) pairs in the test set do not appear in SA training pairs; ii) some authors (< 5%) of different-author (DA) pairs in the test set may appear in the DA training pairs; iii) most of the fandoms in the test set appear in the training set. See dataset sizes in Tab. 3

**Unseen fandoms split.** This split type has the following properties: i) fandoms in the validation/test sets are not seen during training; ii) some authors in the validation/test set may appear in the training set. To ensure no overlap between training and validation/test fandoms, training examples (d₁, d₂, f₁, f₂) where either f₁ or f₂ appear in the validation/test fandoms are dropped. This results in approximately 110K fewer training examples. We list the dataset sizes of the unseen fandoms split (XL dataset) in Tab. 3.
The Light that made her glow came out from her and started to float in a white celestial ball, the Ethereal Queen looked human now. No more butterfly-like wings, green demonic eyes replaced with beautiful jade eyes, ears looking less pointy, and no more heavenly angel halo to be seen. “Meet I shall give thee a second chance...” The glowing ball then flew in me. “auugh...” I yelled as I was hit in the stomach with the glowing ball. Pain, it was all I felt. “Good you are started to begin the transformation...” she said as she walked up to me. “Now I can rest... Good luck Jack...” she said as she collapsed in front of me. I ignored the pain and crawled up to her. “Ethereal Queen... are.. you alright?”

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### Fig. 1. A PAN-2020 sample compared with a DarkReddit one. Note the contrasting style, topics, vocabulary and size between the two samples.

| PAN                                    | DarkReddit                                 |
|----------------------------------------|--------------------------------------------|
| The Light that made her glow came out   | Lol 😁 I can’t be serious 😁 I’ve been thinking of trying Dmt... I’ve only done Shrooms and loved the times I tripped. I wanna gather more info though. Good and bad, I like to know what I wo/could be stepping into. Can u explain a little about the inhale and exhales u mentioned? I hear it can be like opening up new parts to your mind and give you a different outlook on life as well as for a while change your mood for the better. I’m heard about Ego death and that just sounds scary! Now I better mention I suffer from GAD have bad Anxiety and take Benzos for it daily to help 😆 Btw I better mention I suffer from GAD have bad Anxiety and take Benzos for it daily to help. I’ve heard taking a Benzo can stop or ruin a Trip 😆 Other have just said, not really just mellows u a bit. If you get the chance please give me some insight (…) |
| from her and started to float in a white |                                           |
| celestial ball, the Ethereal Queen      |                                           |
| looked human now. No more butterfly-like |                                           |
| wings, green demonic eyes replaced with  |                                           |
| beautiful jade eyes, ears looking less  |                                           |
| pointy, and no more heavenly angel halo |                                           |
| to be seen. “Meet I shall give thee a    |                                           |
| second chance...” The glowing ball then  |                                           |
| flew in me. “auugh...” I yelled as I was |                                           |
| hit in the stomach with the glowing ball|                                           |
| Pain, it was all I felt. “Good you are   |                                           |
| started to begin the transformation...” |                                           |
| she said as she walked up to me. “Now I |                                           |
| can rest... Good luck Jack...” she said   |                                           |
| as she collapsed in front of me. I ignored |                                           |
| the pain and crawled up to her. “Ethereal |                                           |
| Queen... Are... you alright?” (…)       |                                           |

### 4.3 DarkReddit dataset

We test the capability of models to adapt to new datasets sampled from different data distributions, in a low-data regime. This is important for authorship verification systems deployed in production, where domain shift and scarce data issues often arise. To this end, we created a small authorship verification dataset by crawling comments from /r/darknet, a subreddit dedicated to discussions about the Darkweb. We extracted 1028 samples, and split them into 204 samples for training, 412 for validation, and 412 for testing. In each split, half of the samples have the same authors (SA) and half different authors (DA). A document has, on average, 2,500 words, almost 9× less when compared to the PAN-2020 splits (21,000 words). Besides the word count, the two datasets are very different in multiple aspects (e.g. topics, authors, text purpose, self-contained message). We illustrate the differences through the examples shown in Fig. 1.

### 5 Experimental setup

Next, we describe the models, training routines, and experimental setup. We will make the code that generates the datasets and the models publicly available.

**Training.** We fine-tune BERT (B) \(^6\) and Character BERT (cB, char-BERT) \(^5\) for authorship verification in a discriminative way. Given two texts, we first tokenize them and obtain two sequences of ordered tokens, \(T_1\) and \(T_2\). We then select two random sub-sequences \(T'_1\) and \(T'_2\) of length \(B_{max}/2\), where \(B_{max}\) is the maximum input sequence length for the particular model. We then concatenate \(T'_1\) and \(T'_2\) and feed them into the model to get a sequence pair embedding \(h_{[CLS]}\). We apply a linear layer on top of \(h_{[CLS]}\) and optimize the entire model via the binary cross entropy loss. We also test whether in-domain pre-training \(^8\) as an intermediate step further boosts the final performance. Specifically, we pre-train the BERT model on the PAN-2020 Clopen XL corpus with the Masked Language Model (B\(^\dagger\), BERT\(^\dagger\)) objective, before fine-tuning it on

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\(^6\) https://www.reddit.com/r/darknet/
Table 4. Comparison over large pre-trained models on PAN-2020 XL splits. Simple BERT achieves the best results, followed closely by BERT†, and next by charBERT. Distinctively from others, siamBERT never sees information from both documents at the same time, which significantly impacts its score. Note how the closed-set results (left side) are considerably higher than the open-set ones (right side), which might indicate the models overfit on the styles of the known authors from the closed splits. We report all PAN-2020 metrics. For each split, we mark the best method with red and the second-best with blue.

| Metric  | Closed_XL | Clopen_XL | Open UA_XL | Open UF_XL |
|---------|-----------|-----------|------------|------------|
| F1      | 93.8 85.0 | 94.4 95.0 | 95.6 79.8  | 96.8 96.8  |
| F0.5    | 93.4 84.8 | 93.5 94.5 | 96.5 80.2  | 97.3 97.0  |
| c@1     | 93.3 86.0 | 93.9 94.5 | 95.4 81.4  | 96.6 96.6  |
| AUC     | 98.0 93.1 | 98.4 98.6 | 99.1 89.6  | 99.5 99.4  |
| overall | 94.7 87.2 | 95.1 95.0 | 96.7 82.7  | 97.5 97.4  |

specific dataset splits. For the Siamese BERT (sB, siamBERT) [21], we append a linear layer of size 512 on top of the core architecture in order to compute text embeddings. This layer is first trained, keeping the core model frozen for one epoch, and we proceed to update the entire model in the subsequent training iterations. During training, we dynamically build triplets from the training data via random sampling and optimize via triplet loss [9].

Evaluation. For most experiments, we report the overall metric from PAN-2020, which is the mean of the F1, F0.5, c@1, AUC metrics. We compare two types of inference using the same model, trained on random chunks from the training pairs. We first evaluate the model by taking random chunks from test document pairs. Specifically, we take a 256-length chunk from the first document and concatenate it to a 256-length chunk from the second. Secondly, we evaluate the model using information from the full documents pair, averaging prediction probabilities over pairs of document chunks. Specifically, we split each document into 256-length chunks, discarding extra chunks from the longest document, resulting in K pairs. We feed each pair to the model and average over the K probabilities. Unsurprisingly, using information from the full documents significantly improves performance over using random chunks (e.g. from 83% to 91% in overall score on the Clopen XS test set using a charBERT model), at the expense of increased inference speed by a factor of K. We keep the full document evaluation for the rest of the experiments.
Table 5. Ensembling results on XS Open-set splits. We show that the individual models are complementary for the Open UF$_{XS}$ set, so the overall score can be improved by combining them. Nevertheless, this is not the case for Open UA$_{XS}$, indicating that the models might overfit on this split, most of them collapsing to a wrong prediction.

| Metric | cB | sB | B$^\dagger$ | B | best ensemble | cB | sB | B$^\dagger$ | B | best ensemble |
|--------|----|----|----------|--|--------------|----|----|----------|--|--------------|
| F1     | 85.4 | 85.9 | 90.4 | 90.1 | 92.0 | 91.3 | 90.9 | 93.1 | 90.9 | 94.4 |
| AU C   | 92.6 | 86.8 | 96.3 | 97.3 | 97.2 | 94.9 | 86.3 | 96.8 | 97.9 | 98.0 |
| overall | 87.0 | 87.2 | 92.1 | **93.5** | 93.4 | 91.2 | 88.9 | 93.2 | 93.2 | **95.3** |

5.1 Comparative performance of large models

We analyze the performance of large pre-trained models (BERT-like transformers) on various datasets for authorship verification.

PAN-2020 XL splits. We fine-tune and evaluate the models as described above, on the larger splits introduced in Sec. 4. In Tab. 4, we notice that BERT outperforms charBERT and siamBERT on all four datasets. The difference between others and siamBERT could be due to how the model functions, without learning over both documents simultaneously. BERT processes a pair of sequences, so the word-piece representations interact at every level before making a prediction based on sequence pair embedding $h_{[CLS]}$. In contrast, siamBERT processes each sequence separately, making the word-pieces ‘interact’ at the end through the sequence embeddings $h_{[CLS]}^{(1)}$ and $h_{[CLS]}^{(2)}$. CharBERT performs worse than BERT on all splits, except the unseen fandoms, where they perform similarly. We expected charBERT to provide better contextual embeddings for rare words (like named entities), since they incorporate different character n-grams when representing a word. Even though BERT may represent rare words in a noisy manner, it proves sufficiently robust to the various named entities encountered in the PAN-2020 corpus. The domain-adapted BERT (BERT$^\dagger$) obtains similar results with BERT. Thus, the MLM fine-tuning step on Closed$_{XL}$ is not warranted, showing that adapting the representations to the domain of the downstream task brings no improvements. Since BERT achieves the best results on average, we further use it in our single model experiments in Sec. 5.2-5.3.

PAN-2020 XS splits. We run the models on all XS splits and get similar observations with the XL splits, as shown in Tab. 4. The relative improvements in the overall score of BERT over others become smaller when moving from the small data regime to the larger splits. The proposed XS split proved to be good for ablation studies and prototyping.

Ensembling. We measure the performance of various combinations over the previously described models. In Tab. 5, we see how ensembling improves the
Fig. 2. Explainability analysis using Integrated Gradients. We show how fine-tuning the BERT model on the Open UF\textsubscript{XL} split changes the words on which the model focuses. In green, we see words that helped the prediction, and in red, those that distract from the correct decisions. In each pair, the first row prediction is from BERT fine-tuned on Closed\textsubscript{XL}, while the second row is from BERT fine-tuned on Open UF\textsubscript{XL}. Notice how in the first row the focus is mostly on named entities and topic-related words, which should not be relevant in author detection, while in the second row, these same words (e.g. serena, lifestyle, russell, sakura, anger) become less important.

5.2 Qualitative examples reveal biases

We next focus on better understanding the models' predictions. There are significant efforts in explaining how deep learning models work [29]. Inspecting the attention scores is a common method of explaining a model's prediction that has been called into question in recent years [19, 26]. We therefore follow recent explainability results [3] and use the Integrated Gradients [28] method from the Captum library [14] to reveal the individual importance of words in the final prediction. We analyze BERT models fine-tuned on a closed and an open set, checking for biases that may occur due to the way each split is built.

In Fig. 2 we show how important each word is in the authorship verification decision. For BERT trained on Closed\textsubscript{XL} split (first row per pair), the most important ones (in green) proved to be named entities or fandoms (topic-related words). We can observe in the indicated examples how this initial preference is reduced when fine-tuning the model on the Open UF\textsubscript{XL} split (which keeps training and testing fandoms disjoint). These observations show us that the dataset is highly biased towards recognizing authors by the semantic content of their work. We quantitatively strengthen this observation in Tab. 6 and Fig. 3 where
Fig. 3. Knowledge transfer on DarkReddit. We fine-tune the BERT model on a gradually increasing quantity of training data from the DarkReddit dataset. With few samples (from 20 to 204), we manage to reach up to 92% in the overall metric. Notice how the model learned on the Open-set UF (green) is better than the other models at ≥50% data. The generalization capability of the model is improved when using this split, removing biases towards fandoms (topics). As seen in Fig. 2, we confirm once again that topical clues are more of a spurious feature rather than other author writing characteristics, since masking the fandom achieves the best result for generalization.

we see that the model trained on the Open UF$_{X_L}$ split transfers the authorship verification knowledge consistently better on the new dataset, DarkReddit, with a small amount of supervision for adapting to the new data domain (the full training set has only 204 samples). This shows that when we do not guide the model based on already seen topics, we achieve better generalization.

5.3 Transfer knowledge in low-data regime

Koppel 19th Century Books Dataset - Unmasking. We test on the 21 books setup from [15], a well-known, small-scale dataset for authorship verification. We use their proposed unmasking technique, but applied over representations extracted from our BERT backbone fine-tuned on PAN-2020 Closed$_{X_L}$. We train SVM classifiers to discriminate between chunks of document pairs $d_1$ vs $d_2$. We feed each document chunk into the backbone and take the $h_{[CLS]}$ vector as its embedding for training the SVM. We log the accuracy curve of the SVM classifier for 35 iterations, removing the most important 20 features from $h_{[CLS]}$ at each iteration. This is in contrast with the statistical properties used in the original work. We follow the same leave-one-out testing procedure as in [15] and obtain a perfect 100% score, compared with the maximum F1-score of 91.6% reported in the original paper.

DarkReddit - Fine-tuning. In Fig. 3 and Tab. 4 we show the performance of different BERT models when fine-tuned on progressively larger DarkReddit
Table 6. Transferring knowledge on DarkReddit in low-data regime. We test BERT’s adaptability to a new dataset under the few-shot scenario. First, we evaluate the fine-tuned BERT over DarkReddit using few samples (from 0 to 204). Next, we test the unmasking algorithm over BERT’s highly-semantic features. We perform the same experiments over BERT fine-tuned on PAN-2020 (2\textsuperscript{nd} and 3\textsuperscript{rd} rows). See how fine-tuning BERT on Open-splits highly improves the results of transferring the knowledge under this few shot scenario. Moreover, Open UF\textsubscript{XL} split is better than Open UA\textsubscript{XL}, showing that fandoms (topics) are more important for author verification generalization, rather than other authorship stylistic details.

| BERT’s finetune split | Fine-tuning (overall ↑) | Unmasking (overall ↑) |
|-----------------------|-------------------------|-----------------------|
|                       | 0% shot | 10% shot | 20% shot | 50% shot | 100% shot | 0% shot | 10% shot | 20% shot | 50% shot | 100% shot |
| None                  | 50.2    | 70.0     | 66.7     | 76.6     | 83.8      | 75.1    | 74.1     | 75.7     | 72.4     | 71.7      |
| Open UA\textsubscript{XL} | 83.7    | 88.5     | 88.4     | 88.8     | 89.6      | 78.1    | 76.6     | 77.0     | 77.8     | 77.5      |
| Open UF\textsubscript{XL} | 70.2    | 83.1     | 87.8     | 89.0     | 91.3      | 74.9    | 71.6     | 71.0     | 72.0     | 72.1      |

training subsets. When trained with only 10% of the DarkReddit data, BERT reaches a score of 70%. All three models become better when going from 10% to 50%, then finally to 100% of the data. The model trained on the unseen fandoms split from PAN-2020 has the best performance, showing that topical clues are easy shortcuts used by the models to rely on for the authorship verification task.

DarkReddit – Unmasking. We test whether the unmasking method can be successfully used in a low-data regime. The unmasking technique uses the entire DarkReddit training dataset. We represent the documents with the embeddings from the three models fine-tuned on the progressively larger DarkReddit training subsets mentioned above. For instance, Open UF\textsubscript{XL} unmasking 10%-shot refers to document embeddings obtained from the Open UF\textsubscript{XL} model fine-tuned on 10% of the DarkReddit train set. As shown in Tab.6, the best embeddings for unmasking are obtained in the zero-shot scenario, from the model trained on Open UA\textsubscript{XL}, which was never optimized using Reddit data. We expected unmasking to further benefit from the representation of backbones increasingly exposed on Reddit data, but the performance degraded. Fine-tuning the BERT backbone on the small DarkReddit dataset proves significantly better than unmasking, which employs features from the intermediate few-shot models.

6 Conclusion

In this work, we investigated the performance of BERT-like transformers on the authorship verification task using large-scale datasets. We start by looking at BERT-based baselines, which prove to be highly efficient on the PAN-2020 dataset. Next, we investigate the explanations behind the models’ predictions using the Integrated Gradients XAI technique. The results suggest that topics
and named entities are the primary focus of models. We therefore extend the setup and propose several splits of the PAN-2020 dataset, based on limiting the dataset biases. Finally, we introduce DarkReddit, a new dataset that features a different input distribution than PAN. We compare the transfer knowledge capabilities of all the tested baselines, showing that preventing topical features from leaking to the test set improves generalization.

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