PART: PRE-TRAINED AUTHORSHIP REPRESENTATION TRANSFORMER

Authors writing documents imprint identifying information within their texts: vocabulary, registry, punctuation, misspellings, or even emoji usage. Finding these details is very relevant to profile authors, relating back to their gender, occupation, age, and so on. But most importantly, repeating writing patterns can help attributing authorship to a text. Previous works use hand-crafted features or classification tasks to train their authorship models, leading to poor performance on out-of-domain authors. A better approach to this task is to learn stylometric representations, but this by itself is an open research challenge. In this paper, we propose PART: a contrastively trained model fit to learn authorship embeddings instead of semantics. By comparing pairs of documents written by the same author, we are able to determine the proprietary of a text by evaluating the cosine similarity of the evaluated documents, a zero-shot generalization to authorship identification. To this end, a pre-trained Transformer with an LSTM head is trained with the contrastive training method. We train our model on a diverse set of authors, from literature, anonymous blog posters and corporate emails; a heterogeneous set with distinct and identifiable writing styles. The model is evaluated on these datasets, achieving zero-shot 72.39% and 86.73% accuracy and top-5 accuracy respectively on the joint evaluation dataset when determining authorship from a set of 250 different authors. We qualitatively assess the representations with different data visualizations on the available datasets, profiling features such as book types, gender, age, or occupation of the author.

Keywords Authorship attribution · Neural networks · Transformers · Contrastive pretraining

1 Introduction

Authorship of textual pieces influences the contents of a work in varied ways. Who is the author of a novel, e-mail or blog posts can influence the content and style of any work. Each author has an education, has grown up in a socio-economic context, has lived through different experiences and has his/her own writing style, which we hypothesize that influences whatever they have produced. Thus, proper methods of analysing authorship would allow for robust profiling and attribution of authors with wide range of applications. This need has been identified in the literature, where there are several applications for textual authorship and profiling [1, 2], with great potential in domains such as forensics [3], online social network analysis [4, 5] or disinformation spreading [6, 7].

While more traditional feature extraction is the usual approach to understand authorship or infer author’s writing style [8], lack of flexibility to newer authors, limited amount of features among other weaknesses, may draw back the
applicability of authorship attribution to actual practical domains. Analyzing parts of speech that are not included in the initial feature space might be difficult if not impossible altogether. We are concerned with the capacity of manual feature extraction for this task.

A more general-purpose approach to authorship and profiling would be to generate something akin to document embeddings [9]. Embeddings can extract meaning from textual speech by analyzing content and style, frequently ignoring contextual external information. These embeddings form a numerical representation of any given chunk of text, that can later be analysed with any appropriate method. Modern document embeddings can be extracted thanks to developments in Natural Language Processing (NLP), through the likes of pre-trained BERT [10]. Transformers, and by extension their embeddings, have meant a breakthrough in text analysis and solved similar difficult open-ended problems. In particular, for this authorship task, our interest is in encoders. For instance, BERT can be combined with textual features to improve results [11], generating tokens to classify which author would have written it [12] or mixing pooling techniques to merge the embeddings of several documents to profile the author [13].

Following these approaches, we aim to take authorship analysis a step further with a concept called authorship embeddings. We present a Pretrained Authorship Representation Transformer (PART) with style characterization capabilities to include general features of speech from authors, allowing to represent a concrete author style with a numerical vector. Our PART embedding generation can be used to project words, sentences and documents into a contextually and content-aware hyper-space. We aim to achieve the same for authorship.

A suitable method to build representations is contrastive learning. It has been used in other information modalities such as image or audio to great success and recently, it has seen much use with CLIP [14]. This work is able to align the embeddings of images with their annotated text, which is a similar task to our own. By contrasting a document embedding with another document embedding of the same author, the remaining representation will be aligned towards the author and not the contents of the document. A conceptual representation of our approach can be found in Fig. 1.

Figure 1: Example of a comparison of authorship embeddings. \(E_s\), \(E_d\), \(E_r\) represent authorship embeddings from a reference document, a document whose author is the same as the reference and a text from a completely different author. When compared with a similarity function, the related document similarity should be higher than an unrelated text.

With this article we bring the following contributions.

1. This paper outlines a new semi-supervised contrastive learning approach to address zero-shot authorship attribution and profiling, using state-of-the-art contextual-based models.
2. This article presents a stylometric embedding generation model that can project words and sentences. When extended to documents via average pooling, projections remain extremely consistent, overcoming the bottleneck of text length.
3. Unlike previous work focused on in-domain author profiling tasks using hand-crafted features or supervised classification, we compute author embeddings with zero-shot generalization capabilities in authorship identification expanding their practical applicability.
4. Empirical demonstration of this aforementioned concept using the proposed architecture.
5. Three case studies analyzing the behaviour of the model, supported by applications. An assessment of the author embeddings utility regarding various profiling features with qualitatively visualizations is also included.

In the following sections we describe work related to author profiling, current approaches and state-of-the-art in language processing (Section 2), our implementation of the idea of authorship embeddings (Section 3) and results

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1 Code repository: https://github.com/jahuerta92/authorship-embeddings
supporting the viability of this technique (Section 4). A final discussion of these results is conducted in Section 5, pointing to weaknesses and possible improvements.

2 Related work

The online media content explosion has meant a paradigm shift in many areas of knowledge. For Natural Language Processing (NLP), billions of text pieces are available right now at an ever-increasing creation rate. The vast amount of authored texts allows us to apply modern state-of-the-art transformer models to the domain of Authorship effectively, taking advantage of blogging pages or online libraries. In this section we determine authorship for the scope of our work and explore solutions that enable us to numerically represent this complex concept.

2.1 Authorship

The act of writing is inherently influenced by the person performing it. Their beliefs, knowledge, mannerisms among others, if the document is sufficiently extensive, impact the contents of any given piece. Following this assumption, we determine authorship as a heterogeneous set of identifiable features of the text that uniquely belong to an author. Authorship attribution, for instance, tries to relate these stylistic features to the author, while authorship profiling aims to determine the traits of an author by analyzing their written texts [15]. Many areas of research have vested interest in determining authorship. For example linguistics, forensics or history focus on this task from different points of view [16], and they could benefit from an accurate automated model of authorship. When attribution is considered, two features of text are typically used: content and the style [17]. Computers can easily identify manually extracted stylometric features such as word choice and frequency, punctuation or sentence length among others [18], numerical features that can be plugged into a machine learning approach such as an ensemble [19].

Applications of authorship attribution can proliferate in may domains, for example, in literature. In recent works, a LDA-Transformer neural network architecture was applied to Chinese poetry to identify authorship [20]. Russian literacy is also treated [21], with a comparison between several popular methods ranging from classical machine learning models fed with features to deep learning recurrent neural networks or transformers. More complex techniques can be applied to attribution, such is the case of Dynamic Authorship Attribution (DynAA) [22], where heterogeneous sources are merged with a stack of classifiers to improve the attribution of authorship.

Generalization is a frequent concern in machine learning, and more so in the domain of authorship. Adaption to out-of-train domains is usually hard and many methods fail to transfer to new datasets, fact highlighted by Murauer et al. [23] in their work. Including varied number of datasets, with varying document size, other languages, genres and styles, is central to evaluate a model trained to solve authorship attribution task. There is also concern for domain bias, as shown by Hitschler et al. [24]. Augmentation techniques can be applied, such as word removal, to reduce these effects. Attribution models are known to be weak to adversarial attacks, despite not being dedicated to natural language, Simko et al. [25] studies the effects of adversaries on authorship code models, where results show that indeed authorship can be misleading if another style is forged. Together with these concerns, there are also challenges ahead [7], such as the size of each author’s document (i.e. a tweet) or the existing orthogonality between topics and authors. In case of large texts, other problems appear, such as co-authoring, which includes complex issues such as style change detection [26].

Recent approaches proposed in the literature include PolitiBETO [27], a BETO [28] model trained on a corpus of political language and an ensemble approach profile authors in the same domain. Other authors have also used BETO, this time in combination with the model MarIA [29]. Other transformer-based model used for this task includes Sentence-BERT [30] [31], employed with the goal of identifying hate speech spreaders. Different architectures, such as Convolutional Neural Networks have been also applied to this task [32]. With a focus on zero-shot classification, other authors have used entailment-based models for building a solution for author profiling with a small set of training data and XLM-RoBERTa [33]. The use of entailment as a training task has proven to be a useful instrument in similar cases [34, 35].

After examining the literature we conclude that research focused on authorship is bounded by the data used to train the model. Models built with these techniques are successful at in-domain tasks, but fail at others. In our research we have found that using authored data, zero-shot classification of authors can be performed if, instead of supervised classification, we adopt a semi-supervised classification approach. There are two keys to success in this regard, first is finding a suitable method for robust representations, the second is a training scheme that allows for finding similarities between the texts of authors. The next two sections explore pretrained Transformers, which already produce very powerful representations (semantic and stylistic) and contrastive learning, which allows a model to learn these representations.
2.2 Transformers and Representations

Transformers have become a staple of NLP in record time. Since the conception of Attention [36] and the popularization of pretraining with BERT [37], a plethora of out-of-the-box transformer models and architectures have been trained with the objective of understanding natural language. In turn, these models are able to interpret semantic features of speech, as well as some, albeit scarce, stylistic understanding. As previously stated, our aim is to produce a stylistically-oriented transformer centered on authorship, with deviates with the usual semantic focus of pre-training procedures.

However, to the best of our knowledge, a style-oriented transformer has not been explored in detail. Works that focus on style are usually concerned with content generation instead of analysis, therefore they include a style vector into the system as in the Styleformer [38]. Recent works in regards of style-oriented transformers are scarce for text, other modalities such as audio have seen certain attention to style [39] although without concern of authorship. Some interest has been put in an authorship transformer in the domain of code writing [40], but there have been very few advances toward text.

For our purposes, we require encoder transformers. Models such as RoBERTa [41] fit our purposes. Decoder-style models produce worse representations that their encoder counterparts, for example between BERT, ELMo [42] and GPT-2 [43], the first usually produces more contextualized representations [44] leading scoreboards on similarity against their decoder counterparts. The closest transformer found to our task at hand is BertAA [11] where features and a transformer are combined to perform logistic regression to attribute authorship. The use of embeddings can help take authorship to a more complex level, enabling cross-domain scenarios with pre-trained models and a normalized corpus [12]. A particular scenario is the case for microtext from social media, which can be particularly challenging [45].

To generate embeddings we choose RoBERTa for this work, as its representations have shown to be more robust than BERT-generated embeddings [41], however, other more sophisticated encoder models would be usable with our methods at the cost of compute time and memory size.

2.3 Contrastive Learning

Learning representations instead of labels is no trivial task. Recent advances show that, with enough amounts of data, self-supervised learning can achieve impressive generalization to zero-shot tasks. This is illustrated in works such as T5 [46] or GPT-3 [47], pre-trained with Causal Language Modeling (CLM) achieves state-of-the-art even in out-of-domain benchmarks. These models (encoder-decoder and decoder-only) are extremely powerful, but semi-supervised training methods such as CLM are semantically-oriented. A feasible solution is to learn a representation directly without masking or pseudo-labels via Contrastive Learning.

Some works have started applying semi-supervised contrastive approaches to different domains to learn representations of text (and other modalities). This can be exemplified by CLIP [14] where images and text are aligned to zero-shot classification, achieving outstanding performance in common benchmarks. Works like SimCSE [48] apply contrastive learning to sentence similarity tasks. Authorship has to be available for authorship attribution therefore labels can also be used to learn. Supervision can also be included to contrastive learning [49] to improve the quality of representations. Such is the case for example for natural language inference [50], where results can be improved via Supervised Contrastive Learning (SCL) and then labelled.

To summarize our conclusions from this section, we will be using pre-trained transformers as they already have a semblance of stylometric capabilities, paired with a contrastive learning approach to build representations of an authors writing style.

3 Authorship embeddings

We begin with an assumption: when an author writes a text, several features of speech are reflected throughout the work. Whether they are intentional (such as a literary author) or unintentional (from a social network user) they can be detected and measured [51]. If an expert were to hand-craft these features, he or she could identify abstract (and subjective) properties such as rhythm, punctuation, flow, registry, and so on. However, this is a challenging task where the result could be a set of ill-defined features. The most recent research points to the need to adopt advanced language models to extract fine-grained details from the text and reveal characteristics aligned with the author. In short, by comparing texts and maximizing the similarity of their representation when they belong to the same author, in turn minimizing similarity with unaligned texts. If our initial assumption is true and meaningful and representative features of speech can be extracted from diverse texts of an author, then it is expected the network to maximize this similarity.

We name this representation of writing style authorship embedding. Whereas semantic embeddings generated by transformers detect contextual and semantic features focusing on the content of the text, authorship embeddings
are meant to encode features (from context and semantics too) from the author of the text, shifting the focus of the transformer slightly towards style. This would allow to characterize online communities by the content of their writing or categorize anonymous literary works among other possible useful applications.

3.1 Problem definition

We define authorship embeddings as a numerical representation of the writing style of an author. We want to approximate a function that takes a chunk of text and determines these numerical features. Let $D$ and $D'$ be document sets, where $D$ has a document per author and $D'$ has another different document per author in the exact same order as $D$. From a set of documents $D = \{D_1, D_2, ..., D_N\}$ we find documents $D_i$ where $i$ represents the author identifier, we want to generate a corresponding embedding set $E = \{E_1, E_2, ..., E_N\}$ and $E'$ that represents each author writing style. Ideally, if the cosine similarity of $E$ and $E'$ was to be computed we would obtain an identity matrix as follows $S_c(E, E') = I_{N \times N}$. We will follow this objective in the training procedure to achieve maximum similarity between embeddings from the same author.

Each embedding $E_i$ represent textual documents embedded in a numerical space, if the earlier objective is followed, will encode the features from the author by generating the same representation for different texts. This projection into a hyper-space allows to profile any author independently of the set of authors seen in the training set, as the space generated is a continuum of writing styles where each embedding is a point.

3.2 Contrastive pretraining

To build a suitable function $f$ able to translate a document $D_i$ into its respective $E_i$ a proper loss function has to be found, in this case we opted to use InfoNCE [52] loss modified to efficiently process batches of data in a way similar to CLIP. The loss process can be followed in Fig. 2, where the calculation is visualized.

![Figure 2: Visualization of InfoNCE loss computation for related document sets $D$ and $D'$.

To ensure learning of representations we have to build $D$ and $D'$ guarantying they follow some constraints.

• Every document in $D$ has to belong to a different author. Repeated authors in $D$ or $D'$ act as noise for the InfoNCE loss.

• Each author has a pool of documents to choose from, always larger than 2, although more documents are encouraged. When choosing documents $D_i$ and $D'_i$ for author $i$, both the anchor and positive example are chosen at random. Data augmentation in this problem has been found to distort key textual features that have to be detected by the algorithm, therefore we augment data by randomly choosing textual samples from the author pool of available documents.

After a suitable $D$ and $D'$ have been successfully built, the documents in both sets are transformed with an encoder architecture to build their respective embedding sets $E$ and $E'$ with such as $E_i = f(D_i)$. We want to compute the pairwise cosine similarity for the embedding sets, approximating $S_c(E, E') = I_{N \times N}$. To compute $X$, the cosine similarity matrix, we perform Eq. 1.
\[ X = \|E\|_2 \cdot \|E'\|_2 \cdot \tau \] (1)

The term \( \tau \) is a learnable temperature parameter, which is later used to compute the NT-Xent [53] loss over the similarity matrix as proposed in SimCLR [54] and CLIP [14]. Temperature regulates the L2 normalized product of embedding sets, for the cross-entropy function as described in Eq. 2.

\[
\ell(X) = \frac{1}{N} \cdot \sum_{n=1}^{N} - \log \frac{\exp X_{n,n}}{\sum_{i=1}^{N} \exp X_{n,i}}
\] (2)

The cross-entropy is applied to a square matrix, maximized when \( X = I_{N \times N} \) as our described objective. To ensure the efficient usage of data, the NT-Xent loss can also be computed on the transposed \( X^T \) matrix, representing the similarity matrix \( S_c(E', E) \). This allows for a second pass over the same data to gather a better measure of error. We average both terms and get the desired InfoNCE loss following Eq. 3.

\[
\mathcal{L}(X) = \frac{1}{2} (\ell(X) + \ell(X^T))
\] (3)

### 3.3 Network architecture

As aforementioned an encoder architecture is needed to interpret the text and find the authorship embedding. We summarize our architecture in Figure 3. First, we follow the RoBERTa-large architecture, tokenizing text into tokens of 512 chunks. The transformer has been frozen to preserve the transformer ability to interpret language as trained by the masked Language Modeling loss. In turn, the transformer is able to quickly produce semantic word embeddings for training from all non-padding tokens, without losing any of the original capabilities. The semantic word embeddings are a matrix with dimension \( (L, K) \) where \( L \) is the sequence length and \( K \) is the number of features.

Nonetheless, the semantic word embeddings have to be interpreted, and for this purpose we append a bidirectional LSTM to the architecture. The BiLSTM is more efficient on lower amounts data points that a transformer layer, therefore the end representations are obtained with a recurrent network. We extract \( K/2 \) features for each LSTM pass, to form an embedding of size \( K \).

### 3.4 Data handling

Datasets for authorship attribution and profiling are scarce. We consider three datasets to build the model that share similar pre-processing steps. Here we describe all datasets used, our general pre-processing pipeline and specific details for some datasets.

To successfully build document sets, we require suitable pools of authored texts to pull from. Usually authored datasets contain a document and author, documents and authors are standardized as follows. Each author document set is merged with a separator token in-between. The resulting large text is pre-tokenized and split in chunks of 512 tokens. Each chunk is then considered for training as long as the number of chunks for an individual author is 2 or more. All datasets are split by authors, leaving 10% of authors in each dataset to leave their style unseen by the authorship model for later testing.

We consider the following datasets for training and later validation:

- **Standardized Gutenberg [55]**: This dataset contains authored books, as well as analyzable meta-data such as age or book type. Books with anonymous authors or authored by more than one person are discarded from our analysis. In the standardized corpus, there is some identifying information about the author at the beginning and end of the books, given that each book is much longer than 512 tokens, we opted to drop the first and last chunk of every book to avoid presenting the model identifying information.

- **Blog authorship [56]**: This dataset contains blog posts from a diverse set of age groups. It is by far the largest dataset of the evaluation with over ten thousand individual authors. There is no additional preprocessing in this dataset.

- **Enron mails [57]**: This dataset contains emails from the Enron corporation, authored a hundred people. This is the most challenging dataset due to the small size and noisy nature of the emails. Email headers and footers are removed from the dataset as they contained identifying information about each author.
A summary of hyper-parameters used to pretrain our model are shared in Table 1. As the backbone frozen transformer we use RoBERTa-large [41], as well as its tokenizer algorithm, using the public version currently available at the time of writing. We detail each hyper-parameter set for each dataset in columns.

Large batch sizes are usually required when computing InfoNCE loss, however the Mail dataset does not allow to use batch sizes larger than 64. The number of authors in this particular dataset is very low and it leads to poor performance as seen in later sections. InfoNCE is very sensitive to batch size, usually requiring large batch sizes. While large enough sizes can be built for the Books and Blogs corpus, the Mails dataset is limited in this regard.
4 Experimentation

Validation of our model is difficult as there is no existing literature focused on building representations for authorship. Therefore, we have designed an evaluation procedure for PART. To bridge this we split our experimentation in two sections, a zero-shot table of results for each dataset, and three case studies on each of the testing datasets available.

4.1 Zero-shot authorship attribution

We evaluate the accuracy of our model at zero-shot attribution of 512 tokens from a reference author from a pool of \( N - 1 \) other authors. Results are shown on Table 2 where top-1 and top-5 accuracy are measured. We refer to PART as the model trained with the full combination of datasets. Accuracy is measured as the average of 100 rounds of trials, with the standard deviation contiguous to the accuracy value. To build a baseline we compare our model against the semantic embeddings of RoBERTa large. Briefly, semantic embeddings are obtained from the last hidden state of the transformer and all non-padding elements are average pooled. We list models trained on different datasets, including a combination of all authors from all datasets.

To begin with, we observe that the RoBERTa baseline performs below most models, except the Mails model. The baseline, despite being untrained, holds fair scores across tasks, performing much better than random chance. The Mails model has been trained with a very low batch size, which explains its under-par performance. However, every other model outperforms the RoBERTa baseline on most cases. For instance, the Books model has better out-of-domain performance on the blogs dataset than the baseline, while the same is true for the Blogs model on the books dataset. All models perform best when trained with in-domain data.

On every metric, the model trained on the combination of all datasets outperforms every other trained model. It achieves 72.39% accuracy and 86.63% top-5 accuracy on a set of 250 documents. Observed accuracy values are consistently high on the combined domain, with averages ranging from 91% to 72%, and top-5 scores within 98% to 86%. Observation makes clear that increasing the document set \( N \) makes the task significantly harder, but with a more consistent accuracy. Interestingly, the combined model, has top performance on all datasets, including the book dataset performance which is boosted by the inclusion of additional mail and blog data. Gains on the blogs dataset are marginal and non-significant, varying between document sets with high standard deviation.

The mails dataset presents very low accuracies overall not higher than 28%, being unable to be profiled by any model. This failure to converge into meaningful representations for zero-shot attribution may indicate that the features are useless for this domain, we further explore this dataset in Section 4.2 to analyse this behaviour.

4.2 Case study 1: Enron mail dataset

Two out of three datasets are easier to analyse with our method. We delve in the Enron email dataset to find justifications for the low performance of the representation model. A difficult dataset was anticipated as it was extremely small, with some noise from headers and footers of automated generation.

We qualitatively examine the generated representations to better understand the behaviour of the model. To achieve this we apply u-map, adjusting the hyperparameters for generating a 2d projection of features. Our aim is to represent each mail as points in a plane, where the average of all representations of an author acts as a centroid. With this technique we can evaluate how texts relate to each-other in the generated hyper-space.

4.2.1 Authors and centroids

In figure 4 we projected the test split of the mailing dataset embeddings for visualization. Observation yields several points, first we point out that embeddings are grouped around the centroid, with some separation. Some groups form differentiable clusters for example, the rightmost group or the top-right (10th author) group. These are success examples, embeddings written by the same author are very close in the representation. There are examples of other well represented authors with some overlap, such as the bottom-left groups. Here we observe groups of messages with some overlap, where differences are harder to determine but still end up closer to their centroid. Finally, the center of the representation heavily overlaps text points and, where our representations mostly fail to group embeddings around an authors centroid.

In short, this visualization has allowed to draw some insights. First, some authors are easier to separate than others, which is to be expected, however sections in the hyperspace may overlap for separable authors, while still correctly grouping each text chunk around a cluster. The method is correctly trying to optimize the target space to generate representations that resemble the same author’s representation. On the other hand, this method does not distribute the
| Model         | N= | Metric    | Blogs+Books+Mails | Blogs   | Books   | Mails   |
|--------------|----|-----------|-------------------|---------|---------|---------|
| PART model   |    | Accuracy  | 91.25% ± 7.69     | 90.60%  | 87.75%  | 28.65%  |
|              |    | Top-5 Accuracy | 98.35% ± 3.47     | 98.25%  | 98.85%  | 68.85%  |
|              |    | Accuracy  | 86.60% ± 7.16     | 88.08%  | 81.45%  | -       |
|              |    | Top-5 Accuracy | 95.40% ± 4.28     | 96.70%  | 72.14%  | -       |
|              |    | Accuracy  | 83.72% ± 4.60     | 82.51%  | 65.07%  | -       |
|              |    | Top-5 Accuracy | 93.73% ± 3.54     | 93.13%  | 91.94%  | -       |
|              |    | Accuracy  | 78.39% ± 3.99     | 77.95%  | 60.75%  | -       |
|              |    | Top-5 Accuracy | 90.84% ± 2.55     | 90.14%  | 86.49%  | -       |
|              |    | Accuracy  | 72.39% ± 2.39     | 71.56%  | 79.77%  | -       |
|              |    | Top-5 Accuracy | 86.73% ± 2.07     | 85.77%  | 79.12%  | -       |
|              |    | Accuracy  | 90.35% ± 8.67     | 91.55%  | 64.15%  | 26.25%  |
|              |    | Top-5 Accuracy | 97.55% ± 4.50     | 97.75%  | 89.32%  | 67.65%  |
| Blogs model  |    | Accuracy  | 86.67% ± 7.81     | 87.68%  | 56.17%  | -       |
|              |    | Top-5 Accuracy | 96.10% ± 3.99     | 96.05%  | 43.74%  | -       |
| Books model  |    | Accuracy  | 82.22% ± 5.16     | 82.07%  | 70.78%  | -       |
|              |    | Top-5 Accuracy | 93.16% ± 3.60     | 92.99%  | 60.14%  | -       |
|              |    | Accuracy  | 77.37% ± 3.94     | 77.73%  | 35.94%  | -       |
|              |    | Top-5 Accuracy | 90.39% ± 2.59     | 90.00%  | 60.44%  | -       |
|              |    | Accuracy  | 70.51% ± 2.74     | 71.11%  | 85.50%  | -       |
|              |    | Top-5 Accuracy | 85.65% ± 2.19     | 85.50%  | 82.20%  | -       |
|              |    | Accuracy  | 58.25% ± 13.16    | 52.60%  | 83.50%  | 21.80%  |
|              |    | Top-5 Accuracy | 88.85% ± 9.38     | 87.35%  | 96.75%  | 63.40%  |
| Books model  |    | Accuracy  | 45.98% ± 11.06    | 41.62%  | 70.79%  | -       |
|              |    | Top-5 Accuracy | 76.40% ± 8.26     | 73.10%  | 93.40%  | -       |
|              |    | Accuracy  | 34.93% ± 6.33     | 30.62%  | 70.10%  | -       |
|              |    | Top-5 Accuracy | 62.19% ± 5.96     | 57.20%  | 89.28%  | -       |
|              |    | Accuracy  | 28.06% ± 4.26     | 24.88%  | 61.38%  | -       |
|              |    | Top-5 Accuracy | 50.18% ± 4.94     | 47.44%  | 83.51%  | -       |
| Mails model  |    | Accuracy  | 25.40% ± 11.48    | 21.30%  | 26.90%  | 24.90%  |
|              |    | Top-5 Accuracy | 70.40% ± 14.10    | 68.10%  | 70.55%  | 68.80%  |
|              |    | Accuracy  | 18.40% ± 8.76     | 13.77%  | 16.93%  | -       |
|              |    | Top-5 Accuracy | 47.82% ± 11.84    | 42.43%  | 48.10%  | -       |
| RoBERTa Baseline | | Accuracy | 40.47% ± 11.42    | 8.56%   | 8.94%   | -       |
|              |    | Top-5 Accuracy | 28.72% ± 6.13     | 24.13%  | 27.94%  | -       |
|              |    | Accuracy  | 19.39% ± 3.83     | 15.86%  | 18.55%  | -       |
| RoBERTa Baseline | | Top-5 Accuracy | 4.27% ± 1.06      | 3.05%   | 3.29%   | -       |
| RoBERTa Baseline | | Accuracy | 11.87% ± 1.69     | 8.95%   | 11.53%  | -       |

Table 2: Zero shot accuracy and top-5 accuracy for our method. N represents the number of authors picked at random to create a document and its reference, the higher the N the difficulty of finding the referenced author increases. If there are less authors in a testing dataset than N, the space is left blank.
Figure 4: U-map representation of mails sent in the Enron dataset. Average representation marked with a cross, acting as a centroid. Parameters were 25 neighbors and 0.5 minimum cosine distance.

space evenly, as presented by the leftmost cluster. Some authors may be so distinct they occupy an entire region or just a separate area from the whole dataset.

Results provided in Table 2 for all experiments in the Enron Mail Corpus are undeniably negative, the stylometric zero-shot approach is unable to find meaningful similarity to determine authorship. However, despite this fact, the projection of Fig. 4 gives another layer of discussion, as some authors are well grouped in their own separate regions with moderate amounts of overlap. This contrast points that the representations need to be very powerful for zero-shot classification, but that is not as required for characterization and analysis of these embeddings.

4.3 Case study 2: The Gutenberg corpus

This dataset contains thousands of books from several authors. Identifying and separating authors is no trivial task for humans, and our generated features are able to identify unseen authors with high accuracy. To further evaluate the ability of our model to understand literature (prose, poetry and so on) we find representations of this dataset. We have already shown that the model is able to correctly cluster chunks of text from the same author, instead our focus is on representing entire books and their similarity to other books from the same author.

We find the representation of each book as the average of all embeddings from the chunks of that book. This representations can be related to other books and to the book type, we achieve the first with a graph representation and the second with another u-map projection. Also we are interested in finding what each feature represents and what information does the embedding contain, as such we find the correlation between genre and individual feature.

4.3.1 Book representations and authors

Fig. 5 shows the aforementioned graph representation. The graph is constructed with books as nodes and edges as similarity above a threshold (0.6) of cosine similarity, where wider edges have stronger similarity. We have selected the 5 more represented authors with 10 of their works. A quick glance indicates that authors form clusters in this graph, with Shoghi and Jacobs are tightly knit, France connections are weaker but also form a cluster and finally there is a mixed cluster of Ritchie, Kingsley and a work from Jacobs. This last one is interesting, the presence of this mix points
to similar writing styles. Both began writing at the same period and shared interests on historical and political works, so similarity could be attributed to some of their works as the graph shows.

Figure 5: Graph of books, where nodes are books (with an author annotation) and edges represent presence of similarity above a threshold (0.6). Wider edges represent stronger similarity.

4.3.2 Writing style and genre

The similarity between books with styles is further explored in figure 6. Here the book embeddings are projected with u-map. First we point out the top-right group of books, which are fiction and historical fiction. Similarity is closer for books of this style, as shown by the representation, historical fiction is more similar to most fiction than it is to history books. On the other hand there are some poetry books in the dataset with very distinct style, very similar to each other in the bottom-down region of the space. Also history books all share the same region of the figure. Some fiction is mixed with history books, and essays are close to historical books and some fiction too. This overlap may be due to very similar styles or underrepresented essays in training. The model also finds similarity between Biographies and History books, which is to be expected as they share similar writing patterns. In short, the projection shows most works are correctly grouped in a clearly-bounded region when type of book is evaluated.

Figure 6: U-map representation of books. Legend represents the type of book, as determined by the Gutenberg dataset. Parameters were 10 neighbors and 0.1 minimum cosine distance.

These interesting relationship between authorship embeddings and book type is a side effect of determining the writing style of an author, as most careers usually focus on a single type of writing. This is positive, but it requires further
exploration and analysis. As such, we aim to find correlation between the generated features and the type of book analysed. In Fig. 7 we find the described representation. We observe that features in the fiction category are the most prominent, either by strong correlation or strong inverse correlation. On the other hand, essays are more difficult to correlate to the original embeddings. Some author styles are easier to trace to their respective type of preferred book, fiction being the easiest to detect. Comparing correlation coefficients of key features, we observe poetry and history are usually related to the type of book, but inverted. When poetry is correlated, history is inversely correlated and vice versa. This points towards robust separation between both writing styles.

Figure 7: Spearman correlation between the generated features and the type of analysed book.

In contrast to the results obtained in the Mailing dataset, we find the results for the Gutenberg corpus much more precise. This accuracy impacts the quality of the embeddings and thus we can easily aggregate several embeddings to construct representations of entire books with an average pooling. This approach is usual in the NLP domain and, as the graph points out, associations are frequently correct when determining clusters and similar authors. The model has also shown that this training has the side effect of book type recognition, which is outside our initial scope. Despite the usefulness of book type recognition, it may pose undesired consequences; for example assume an author writes both poetry and prose, their books could be misrepresented due to the differences between both styles. Despite the unintended side-effects, we find this ability of the model widely beneficial with applications in author profiling; which we will further explore in the third case study.

To summarize, we find that authorship embeddings can represent books accurately, encoding stylistic information at least of the type of book. The representation in training of essayist, novelists and poets has influence over the final quality of the model, making essays hard to detect due to their underrespresented nature and fiction novels easier due to...
the cumulative body of work of this type. Moreover, we find that book type and features have correlations ranging from 0.6 to −0.6 pointing to some encoding of style inside the embeddings. With this scenario we have shown how literature can be successfully analysed by the described method, being able to correctly zero-shot classification of authors with robust numerical representations of writing style.

4.4 Case study 3: Blog authorship dataset

Finally, we evaluate the ability of the joined model on the Blog authorship corpus. This is composed of blog posts and conveniently annotated with age, gender and occupation. This enables our features to relate to this annotations, allowing for actual author profiling. As such we are going to study demographic information (age, gender and occupation) as annotated by the dataset. As before, we find correlation and make projections. Instead of analysing by chunk of text or blog post, we also find centroids for some of these annotations.

4.4.1 Demographic representation

To begin, we analyse the gender of the writers, in Fig. 8 another Spearman correlation graph can be found, relating features and gender. Correlations between female and male exists and are abundant but usually weak (0.3), inverse correlation with female gender also exists with higher intensity (−0.5) but less frequent. It is surprising that so many features are able to correlate with the gender of the person writing the texts.

Other label is the age of the writer. There are a lot of ages in the dataset, distributed in groups (13-17; 22-27; over 34) which is unwieldy for correlation. Instead we aggregate chunks of texts from all authors sharing the same age. These aggregates are projected with u-map in Fig. 9. The results obtained relate exactly to the aforementioned age groups except for the 38th point which is an outlier. There are three distinct groups, one for teenagers in the bottom right, other for young people in the top left corner and a cluster of middle-aged people at the side of the young people group. Surprisingly, teenagers are sequentially ordered except for 16 and 17 years which are swapped. Young people have sequential order too, excluding the 38 years old representation.

4.4.2 Profiling by occupation

We also look at the occupation of the authors, first by finding the correlation between features and occupations. We take a sample of the 20 majoritarian occupations and correlate features in Fig. 10. First, in contrast to previous correlation graphs, correlations are much weaker (from 0.2 to −0.3) although still numerous. We find the strongest correlations in the student occupation, which also repeats another point from the book analysis. Student is the majoritarian occupation from this set, correlation is higher the better represented a class is, while correlation is weaker if a class is underrepresented. With this plot we obtain confirmation that the overall balance of the training dataset is essential to generalization of authorship features.

Furthermore, we find interesting similarities between some occupations. For instance, advertising and communications-media share correlation in similar places, which also happens with technology and engineering. These connections seem very circumstantial and weak, as correlation is low between features and labels, but it points to similarities between some occupations. To characterise this phenomenon of the model further we present Fig. 11, where the average embedding of all chunks with a given occupation is computed and projected.

This projection has labels for all categories and some interesting similarities appear. For example, the bottom right corner seems more tech-related with subjects such as engineering, architecture, biotech and internet, mixed up with others such as environment or human resources. The bottom left corner has more communication-related occupations such as publishing, communications-media, advertising, tourism and, surprisingly, government. Finally the upper half is a mixed bag of occupations with no seeming connection whatsoever, such as chemicals, law enforcement or religion. Some are still related like sports-recreation, student and non-profit, but similarity seems almost arbitrary in that particular region.

Authorship embeddings show high accuracy when finding the author for blog posts as well as producing meaningful representations. Author profiling could be possible by analyzing the generated numerical embeddings, as most features are correlated to age, gender and occupation. Again, embedding quality is reliant on training balance as some of the worse grouped occupations are minority labels, underrepresented in training.

PART can represent books accurately, encoding stylistic information at least of the type of book. The representation in training of essayist, novelists and poets has influence over the final quality of the model, making essays hard to detect due to their underrepresented nature and fiction novels easier due to the cumulative body of work of this type. Moreover, we find that book type and features have correlations ranging from 0.6 to −0.6 pointing to some encoding of style.
inside the embeddings. With this scenario we have shown how literature can be successfully analysed by the described method, being able to correctly zero-shot classification of authors with robust numerical representations of writing style.

4.5 Discussion

Our previous case studies point to the fact that authorship embeddings encode stylistic features that can be used for authorship identification and profiling. The model for the first case study, despite previous failure in zero-shot classification, appears to form meaningful representations because mails by the same author lie close together in the embedding space. This is reinforced by the capacity of the model to create groups in the graph representation of the Gutenberg corpus or the sequential sorting of ages in the blog authorship dataset. Whatever the case study, there is overwhelming evidence that these encodings contain relevant information about the author.

However, the embeddings present some side-effects with heavy impact on the model. The authorship embeddings, as stylistic numerical representations of authorship, also contain some information about the content. For example we have found that our embeddings are correlated with the type of writing, such as historical books or fictional novels. The model is prone learn biases of the writers themselves, if most authors only write one type of book across their career, the model is going to assume that authors generally only write in one style, which is often the case for less prolific
authors. It is also prone to capture information about the age, gender and occupation of the author, as we have shown in the blog authorship dataset. However, what happens when an author switches styles, writes at an early age and at a later age or changes occupations, remains unexplored and would likely confound the model as the training data does not account for these dynamical scenarios.

With our study we also determined that representation in the training set is incredibly impactful. The correlation bias towards over-represented labels (fiction in the case of literature, or student for the blog occupation) points out that training representation is more important than previously anticipated, which is an issue considering that finding separate non-anonymous authors is difficult. Other worse represented labels (for example essays) have much worse representation in the resulting target space, which is in line with our previous findings. A sample set of a thousand authors (Gutenberg corpus) can be limited, but this is also true for larger sample sizes (blog authorship). In the quantitative results, we find that training a model with a more diverse set of authors is beneficial to generalization, but still not enough to overcome the biases posed by training representation.

The general model succeeds in zero-shot classification in two of the three proposed datasets, and is able to produce meaningful representations of authorship in all of them. While these results are very optimistic, we acknowledge that the training dataset is biased towards blogging language.

5 Conclusions and future work

In this article we present a novel method for zero-shot authorship attribution and representation called PART, the main contribution being the generated authorship embeddings. We formulate authorship embeddings as a numerical representation of an authors writing style and features, which is comparable with other authors and can be pooled with other works from the same writer to represent larger spans of text. The training process involves contrastive self-supervised learning, with state-of-the-art methods for processing the document and calculating loss, maximizing the information extracted from each set of documents processed.

We have observed the embeddings can detect authorship on unseen sets of authors, achieving high accuracies and overwhelmingly high top-5 accuracy in two of the analysed case studies. The utility of the authorship embeddings is measured qualitatively in three separate case studies, one for each available dataset. Every case study has access to different quality of information, and all are analyzed through with the same general-purpose authorship model. Texts written by the same author typically share regions in the embedding space generated by the model. The authorship embeddings include whether an author frequently writes poetry, is an engineer, has 17 years old or identifies as a female. In a related note, similar authors also share regions of the space, as shown with the Gutenberg Corpus.

Weaknesses of the model have appeared when experimenting with the model as token length severely limits the amount of information the transformer can pick up, allowing for more input tokens would certainly improve representations,
Figure 10: Spearman correlation between the generated features and occupation.
as the transformer can interpret longer-term temporal text features. As with deep learning and transformers, data is crucial. Despite having more than ten thousand authors (some with more than a hundred text samples) from mixed origins (some are literature authors, others are common bloggers) the model is heavily biased toward some specific features we have detected. We suspect this data is insufficient and more training samples would be required. While studying authorship in this environment allows us to generate appropriate representations for many works, we fear that representations may fall apart in other environments unrepresented in training. Adding training data from additional sources (social media, scientific journals, essays, etc.) could lead to a more robust generalization of the model.

Afterword

We share our code at the following GitHub for replication: https://github.com/jahuerta92/authorship-embeddings

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