Overview of the Multi-Author Writing Style Analysis Task at PAN 2023

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Abstract
The analysis of the writing style of multi-authored texts aims at identifying those places where authorship changes in a document. This task is an important step in reliably identifying the authors of a given text. This year, we ask participants to solve an intrinsic style change detection task: For a given text, find all places where the writing style changes at the paragraph-level. To control for topic information as a style change signal, we provide participants with data sets with three levels of difficulty and thus different thematic variants. This paper presents the multiple author writing style analysis task, the underlying data set, the approaches used by participants, and the results obtained.

1. Introduction

Multi-author writing style analysis aims to identify the positions of authorship changes in a document. The task has been part of PAN since 2016, with varying task definitions. In 2016, the goal was to identify and cluster text segments by author [1] and, in 2017, to identify whether a document was written by multiple authors [2], and, given the case, to identify the exact positions of authorship changes. This task was considered too complex at the time; therefore, at PAN 2018, it was relaxed to a binary classification task to distinguish single-author from multi-author documents [3]. In 2019, the goal was to also predict the number of authors for all detected multi-author documents [4]. PAN 2020 extended the binary classification task and asked participants to detect style changes at paragraph-level [5]. At PAN 2021, the task was to determine whether a given document was written by multiple authors and, for multi-author documents, to detect also the style changes at paragraph-level and to assign authors to paragraphs [6]. In 2022, the task was further extended to detect changes not only at paragraph-level but even at sentence-level [7].

The previously used data sets exhibited a high topical diversity—a fact that allows participants to leverage topic information as a style change signal. In the edition of this year, we hence carefully control for topical diversity. The core task remained, namely, to find all positions of writing style change at paragraph-level (i.e., for each pair of consecutive paragraphs, assess whether there was a style change). However, the simultaneous change of authorship and topic is now explicitly modeled and carefully controlled: We provide participants with data sets at

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three levels of difficulty, from documents with paragraphs covering a wide variety topics (easy) to documents in which all paragraphs deal with the same topic (hard).

The remainder of this paper is structured as follows. Section 2 gives an overview of previous style change detection approaches. Section 3 presents this year's style change detection task, the data sets provided, and our evaluation procedure. Section 4 surveys the participants' submissions. Section 5 analyzes the achieved results, and Section 6 concludes the paper.

2. Related Work

In our setting, identifying the positions of author change requires an *intrinsic* analysis of writing styles, i.e., an analysis where no authorship information from other corpora is provided. Such an analysis has to compute a stylistic fingerprint (or profile) for each text segment. By computing similarities between them, the fingerprints are used to detect changes in style which, in turn, indicate a potential authorship change [8, 9], or to detect outliers [10]. The fingerprints can use a variety of features to capture author writing style such as (1) lexical features (character n-grams (e.g., [11, 12]), word frequencies (e.g., [13]) and average word or sentence lengths (e.g., [14])), (2) syntactic features (such as part-of-speech tag frequencies and structures (e.g., [15]), or grammar trees (e.g., [16])), or (3) structural features (e.g., indentation usage (e.g., [14])).

Glover and Hirst [17] use stylometric features to identify inconsistencies in writing style in collaborative documents and to detect author boundaries. Meyer zu Eißen and Stein [18, 19, 20] implement style change detection with word frequency classes to tackle intrinsic plagiarism detection. Koppel et al. [21, 22], as well as Akiva and Koppel [23, 24] perform a clustering step on lexical features to decompose multi-authors into authorial threads. Tschuggnall et al. [16] leverage grammar tree features for an unsupervised decomposition approach. Rexha et al. [25] rely on stylistic features to predict the number of authors of a text. Bensalem et al. [26] perform style change detection based on n-grams. Gianella [27] segments documents by author using the Bayesian framework.

For multi-author writing style analysis, we continue to observe a shift from traditional stylistic features mentioned above to pre-trained language models. In 2018, the best results for the task of distinguishing between single- or multi-authored documents were still obtained by a stacking ensemble classifier based on (traditional) lexical and syntactical features [28]. However, starting from 2020, pre-trained models that were fine-tuned on the training data set have achieved the best results [29, 30, 31].

3. Style Change Detection Task

3.1. Task Definition

The goal of the multi-author writing style analysis task is to identify positions at which the authorship of a multi-author document changes. We ask participants to solve the following intrinsic style change detection task: for a given text, find all positions of writing style change on the paragraph-level (i.e., for each pair of consecutive paragraphs, assess whether there was a style change). The simultaneous change of authorship and topic will be carefully controlled and we will provide participants with data sets of three difficulty levels:

- easy — The document covers a variety of topics (while each paragraph has one topic only), allowing style change detectors to use topic information to detect authorship changes between paragraphs.
- medium — The topical variety of a document is small (though still present), forcing style change detectors to focus more on style to effectively solve the detection task.
- hard — All paragraphs of a document have the same topic.

The TIRA platform [32] allows participants to tune their approaches on the training and validation data set. Moreover, participants can evaluate their approach also on the unseen test data set by either deploying their software on the TIRA platform or by uploading the predictions. By enabling blind evaluation, TIRA prevents optimization against test data.

3.2. Data Set

Deviating from the data sets of previous years, the data sets for this year's edition of the Multi-Author Writing Style Analysis task are based on user posts on Reddit.[1] In an effort to generate both realistic and diverse text for the data sets, we selected parts of Reddit (called subreddits) that tend to generate longer and more meaningful discussions from users to extract our data from. The following subreddits were selected: *r/worldnews*, *r/politics*, *r/askhistorians*, and *r/legaladvice*.

As in previous years, we performed several cleanup steps to ensure that the documents created for the task consisted of well-formed text. Citations, all forms of Markdown, multiple line breaks or spaces, commonly used emojis, hyperlinks, and trailing and leading spaces were removed.

Subsequently, the collected user contributions were divided into paragraphs, and documents for the datasets were created from the paragraphs of a single Reddit post. This was done to ensure at least basic tpoical coherence of all paragraphs in the final document. To insert style changes, a random set of authors for the given post was chosen, and paragraphs written by those authors were concatenated to form the final document. This year, for the first time, the compilation of paragraphs in the documents was not done arbitrarily, but a newly developed procedure was applied, which allows us (1) to generate more topically and stylistically coherent documents and (2) to tweak the difficulty of the produced data set. To this end, both semantic and stylistic properties of the paragraphs were analyzed, and the paragraphs were then shuffled based on the similarity of these properties, configuring these similarities to be (1) "large" for the *easy* data set, (2) "moderate" for the *medium* data set, and (3) "small" for the *hard* data set.

All documents created are authored by two to four authors, with the number of authors evenly distributed across the documents. In total, each data set consists of 6,000 documents. As in previous years, training, test, and validation splits are provided for all three data sets, with the test sets held back until the evaluation phase of the competition. The training sets contain 70% of the documents in each data set, while the test and validation sets each contain 15%.

[1] https://www.reddit.com/

3.3. Performance Measures

To evaluate the submitted approaches and compare the obtained results, the submitted evaluated using the F_α-Measure for each document, where $\alpha = 1$ equally weights the harmonic mean between precision and recall. Across all documents, the macro-averaged F_1-Measure is calculated. The submissions for the three data sets are evaluated independently.

4. Survey of Submissions

In total, six teams submitted both software and a working notes paper for the 2023 edition of the Multi-Author Writing Style Analysis task. Unlike last year, all of these approaches are intrinsic in nature. The following is a brief description of the approaches submitted.

Ye at al. [33] apply the pre-trained large language model DeBERTaV3 [34] to solve the task. They combine DeBERTaV3 with two additional components. For the classification of style changes, contrastive learning is used. This is realized as a dense neural network using a specialized contrastive learning loss for training. Their approach is prompt-based, i.e., the authors synthesize a prompt essentially asking the language model whether two paragraphs are written by the same author or not. This prompt is not constructed manually, but learned automatically by their system.

Chen et al. [35] apply also an approach based on contrastive learning, using the original DeBERTa model [36]. Unlike the other teams, they create additional paragraph pairs for training from non-adjacent paragraphs in the training documents.

Kucukkaya et al. [37] apply the DeBERTaV3 pre-trained language model and frame the detection task as a natural language inference problem. For two consecutive paragraphs, they construct an input to their model which consists of 256 tokens per paragraph, separated by a separator token. They use a classifier token as prefix, which tells the model to perform binary classification if both paragraphs are written by the same author. Since the length of each paragraph is limited to 256 tokens, they devise two methods for choosing these tokens for longer paragraphs. The first method uses the first 256 tokens per paragraph and is applied for the hard data set. For the easy and medium data sets, however, the authors propose a method which they call “transition-focused truncation”, which takes the tokens around a potential style change point (i.e., the last 256 tokens resp. the first 256 tokens from two adjacent paragraphs).

Huang et al. [38] apply the mT0-xl pre-trained language model as a basis [39]. Unlike other approaches, they use knowledge distillation to train a smaller student model, and thus their approach requires fewer computational resources than other approaches. They are the only team that has chosen to include additional training data besides the data provided specifically for the task, namely the PAN 2020 authorship verification data set.

Jacobo et al. [40] frame the task as an authorship verification problem and apply classical methods from the field of authorship verification. As feature representations of adjacent paragraphs they apply both a term-document matrix and prediction partial matching (PPM). These features are fed into a support vector machine and a logistic regression classifier to determine if two neighboring paragraphs are written by the same author. For the easy and medium data sets, PPM with logistic regression is used, while a term-document matrix with a support vector machine is used for the hard data set.

Table 1
Overall results for the style change detection task. The best result for each data set is given in bold.

Participant	Easy F_1	Medium F_1	Hard F_1
Chen et al. [35]	0.914	0.820	0.676
Hashemi et al. [41]	**0.984**	**0.843**	0.812
Huang et al. [38]	0.968	0.806	0.769
Jacobo et al. [40]	0.793	0.591	0.498
Kucukkaya et al. [37]	0.982	0.810	0.772
Ye et al. [33]	0.983	0.830	**0.821**

Hashemi et al. [41] apply the BERT [42], the RoBERTa [43], and the ELECTRA [44] pre-trained language models which they combine with a binary classification layer. Moreover, similar to Chen et al. [35], they also apply data augmentation strategies to generate additional training data: non-adjacent paragraphs pairs and paragraph pairs generated by mirroring. The authors also experiment with ensembles of models, which are trained on the three provided data sets.

5. Evaluation Results

The results for the six submitted approaches are shown in Table 1 and Figure 1. The best result for each data set is highlighted in bold. For the easy and medium data sets, the best performance was achieved by Hashemi et al. [41], while Ye et al. [33] managed to get the best results for the hard data set.

Looking at the overall results, there is a clear difference between the three data sets. Most approaches succeed in achieving high F_1 values for the easy data set; for the medium data set, the values drop significantly. For the hard data set, there is another significant—but smaller—decrease. We can conclude that our goal of creating data sets with different levels of difficulty was successful. Moreover, the result shows that topical signals indeed mask the detection of authorship style changes.

We also looked at how the performance of participants' contributions changes as a function of the number of authors in a document. The results for this are shown in Figure 2. Since the achieved performance was high in the easy data set, we focus here on the medium and hard data sets. Interestingly, this continues a trend we observed last year [7]: at least on the hard data set (as well as on the medium one in the case of Jacobo et al. [40]), performance initially increases for documents written by three authors compared to those written by only two authors. It then decreases slightly from three to four authors. This suggests that the methods used by participants to solve this task are slightly biased towards documents authored by more than two authors.

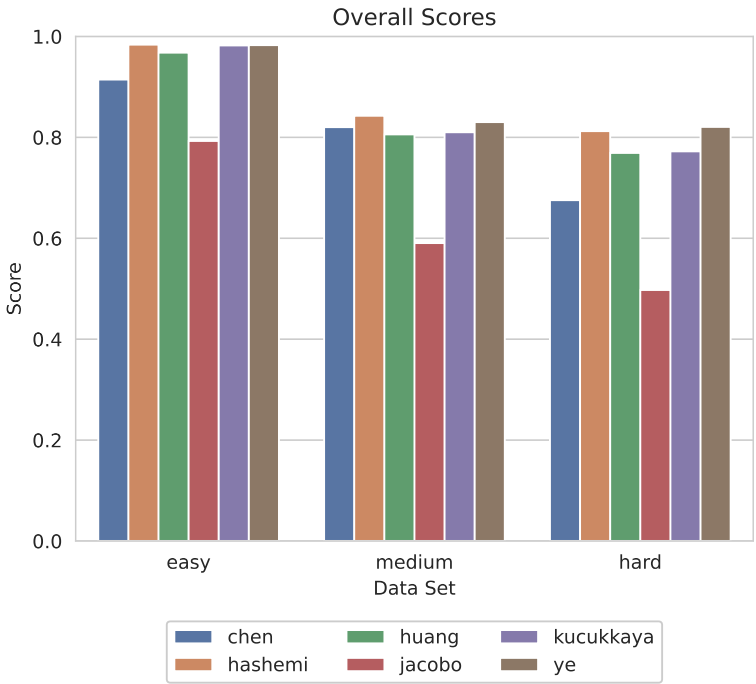

Figure 1: Overall results for the Multi-Author Writing Style task at PAN 2023.

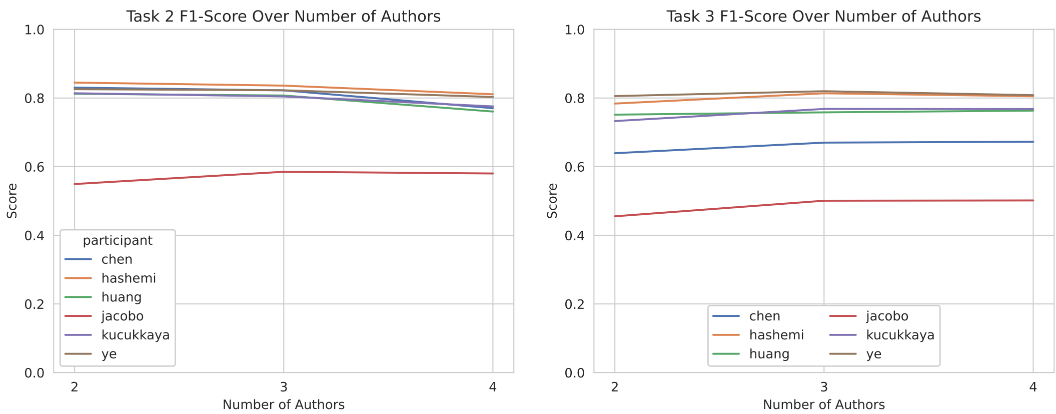

Figure 2: Results depending on the number of authors in a document.

6. Conclusion

In the Multi-Author Writing Style Analysis task at PAN 2023, participants were asked to identify the places in a document where the author changes. For this task, participants were provided with three data sets of varying difficulty, developed by carefully controlling for topical and stylistic consistency across author changes. Six papers were submitted for the task, all but one of which used a pre-trained language model as its core.

Altogether, the results obtained by this year's participants show a marked improvement over last year's results, indicating that good progress is being made in this field.

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