Overview of the Multi-Author Writing Style Analysis Task at PAN 2024

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Abstract
Analyzing the writing style of individual authors in texts in which several authors are involved is a fundamental task in attributing authorship and detecting plagiarism, as it makes it possible to identify the points at which authorship changes. This year's multi-author writing style analysis task focuses on identifying all instances of paragraph-level writing style changes within a given text. We provide datasets with three different degrees of topical homogeneity to investigate how different degrees of topic consistency affect the detection of writing style changes. This paper gives an overview of the task, its definition and the data used, the approaches proposed by the participants, and the results obtained.

1. Introduction

Writing style analysis requires an *intrinsic* analysis of author writing styles: no information on authorship from external sources is used. The core of intrinsic writing style analysis is the computation of stylistic profiles on the basis of text features. By computing similarities between the profiles of text segments, changes in writing style can be detected, which is an indicator for a potential change in authorship [1, 2]. Profiles are based on features that describe the writing style of authors, including (1) lexical features (character n-grams (e.g., [3, 4, 5]), word frequencies (e.g., [6]), and average word or sentence lengths (e.g., [7])), (2) syntactic features (such as part-of-speech tag frequencies and structures (e.g., [8]), or grammar trees (e.g., [9])), or (3) structural features (e.g., indentation usage (e.g., [7])). These profiles are then used to match text fragments written by the same author [10], cluster authorial threads [11, 12, 13, 14], or to predict the number of authors [15].

The multi-author writing style analysis task, formerly known as the style change detection task, has been organized at PAN since 2016. Over the years, the tasks and the data used have constantly evolved. However, the main objective has remained the same: analyzing authors' writing styles to identify the positions at which authorship changes in texts by multiple authors. Since the first edition in 2016, we have seen significant progress in the results.

In the first editions of the PAN task in 2016, participants were asked to identify and cluster text segments by author [16]. In 2017, the aim was to recognize whether a document was written by several authors [17]; if there were several authors, the participants were asked to indicate the exact positions of these changes. In 2018, the task was to distinguish between documents from single authors and documents from multiple authors [18]. In 2019, the task was extended to also predict the number of authors [19]. Since 2020, style changes had to be identified at the paragraph level [20, 21], and in 2021 also the authors had to be assigned to paragraphs [21]. In 2022, the task was extended to detect changes not only at the paragraph level, but even at the sentence level [22], while in 2023 the recognition was performed at the paragraph level again [23].

In recent years, large language models (LLMs) have made considerable progress; they are inherently well suited to analyzing writing styles with multiple authors. For example, while in 2018 the winning

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approach was based on the extraction of lexical and syntactic features [24] and a stacking ensemble classifier, from 2020 the majority of submitted approaches are based on LLMs fine-tuned on the training data [25, 26, 27, 28].

For the 2024 edition of the writing style analysis task at PAN, we ask participants to detec any changes in writing style at the paragraph level. We provide three datasets with increasing topical homogeneity of the paragraphs and thus increasing difficulty.

The remainder of this paper is structured as follows. Section 2 presents the PAN 2024 multi-author writing style analysis task, the data used, and the evaluation setup. Section 3 surveys the participants' submissions, while Section 4 presents an analysis and comparison of the achieved results, and Section 5 concludes the paper.

2. Style Change Detection Task

2.1. Task Definition

Participants of this year's multi-author writing style analysis task were asked to solve the following intrinsic style change detection task: For a given text, find all positions of writing style change at the paragraph level, i.e., for each pair of consecutive paragraphs, assess whether there was a style change. We control the difficulty of the task by managing the variety of topics in the given documents. Participants are provided with data sets with three levels of difficulty:

- easy: The document covers a range of topics, allowing topical changes between paragraphs to be used as style change signals.
- medium: The document exhibits minimal topical variety (though some still exists), requiring the approaches to focus on stylistic features for the task.
- hard: The paragraphs of a document all are on the same topic.

2.2. Dataset

Continuing our efforts from the 2023 competition, this year's data set for the multi-author writing style analysis task is again based on user posts on Reddit, a popular social messaging platform.

For the generation of the dataset, we selected a set of subreddits (topical sub-threads on Reddit) that we expected to yield longer and more detailed texts by individual users: *r/worldnews*, *r/politics*, *r/askhistorians*, and *r/legaladvice*. After scraping these threads, we applied cleaning and preprocessing steps to the gathered texts. This included removing citations, markdown, emojis, hyperlinks, multiple line breaks, and extra whitespace.

The texts were divided into individual paragraphs. Paragraphs originating from the same Reddit thread were combined into documents for the datasets, ensuring minimal topical coherence within each document. Style changes were introduced by randomly selecting paragraphs from different authors within the thread. To control for topical variability and thus the extent to which thematic aspects can be used as a style change signal (and thus the complexity of the task), we consider the semantic and stylistic properties of the paragraphs. The paragraphs are arranged based on these pair-wise paragraph similarities, configuring these similarities to be (1) "large" for the *easy* dataset, (2) "moderate" for the *medium* dataset, and (3) "small" for the *hard* dataset.

We configured the dataset creation process to create documents written by two to four authors to ensure an even distribution of documents according to the number of authors. Each of the three resulting datasets contains 6,000 documents, each split into a training dataset (70% of all documents), a validation dataset (15% of all documents), and a test dataset (15% of all documents), which is held back until the evaluation phase of the task.

2.3. Performance Measures

We evaluate the submitted approaches independently for each of the three datasets. Each approach is evaluated using the F_α-Measure, where $\alpha = 1$ weights the harmonic mean between precision and recall equally, and the results are macro-averaged over all documents.

All approaches are submitted on the TIRA platform [29], which allows participants to evaluate and optimize their methods based on training, validation, and unseen test data. For the test data, blind evaluation ensures that participants cannot optimize their approaches based on the test data.

3. Survey of Submissions

We received 16 software submissions and 15 working note papers for the task of multi-author writing style analysis in 2024. Below is a brief description of the submitted solutions.

Lv et al. [30] leverage the decoder of LLaMA-3 to obtain vector representations of paragraph pairs, subsequently using these representations to perform binary classification via a feed-forward network. To increase the efficiency of their model training, they use a technique called low-rank adaptation.

Lin et al. [31] use an ensemble of multiple transformer-based models (ReBERTa, DeBERTa, and ERNIE) to solve the task. Crucially, to improve performance for the easy and medium datasets, where topical variety within the documents is higher, they also perform a post-processing step based on the semantic similarity of two consecutive paragraphs for those two datasets; paragraphs with a high degree of semantic similarity are then deemed to have been written by the same author, irrespective of the predictions obtained from the transformer ensemble.

The submission of Ye et al. [32] utilizes continual learning to approach the task. Their goal is to achieve a knowledge transfer across different difficulty levels, using learned progress prompts to do so.

Huang and Kong [33] employ DeBERTa-v3 to fine-tune a model for this year's task. To improve the performance of the model, they use regularized dropout during the fine-tuning process. They also perform early stopping during the training process to prevent the model from overfitting.

The approach by Huang and Kong [34] employs models of the BERT family to solve the task. Like most other participants, they fine-tuned the models on the training sets and then tested the performance of various BERT-derived models on the validation set to decide on which model to use for the final submission. Ultimately, they settled on DeBERTa for the easy and hard datasets, and on RoBERTa for the medium dataset.

Wu, Kong, and Ye [35] use RoBERTa to encode the positive and negative sample paragraph pairs. They add a contrastive learning component to optimize the training process of RoBERTa that essentially aims to reduce the cosine distance of positive paragraph pairs while increasing the distance of negative paragraph pairs.

Liu et al. [36] also employ contrastive learning for the encoding phase, using RoBERTa as the encoder. For each pair of paragraphs, they form a feature matrix, consisting of the latent representations of the two paragraphs, and the absolute distance between the two embeddings. The feature matrix is then fed into a fully connected layer to compute the final prediction.

Księżniak et al. [37] utilize RoBERTa and DeBERTa models for their solution. To give the models additional information they could use to determine style changes, they augmented the texts of the documents with tags containing stylometric features.

Chen, Hand, and Yi [38] use RoBERTa and for the fine-tuning phase, they employ R-Drop regularization to mitigate overfitting and to ensure consistency that the model, given identical inputs, computes consistent predictions.

Wu et al. [39] compared the performance of BERT, RoBERTa, and DistilBERT for task 1 and showed that RoBERTa achieved the best results. Consequently, they used RoBERTa for the encoding and feed the resulting pooled contextual features into a Virtual Softmax layer to perform a three-class classification task, where the intuition behind introducing a third class is to enforce stricter boundary constraints between the two original classes.

Table 1
Overall results for the multi-author analysis task, ranked by average F_1 performance across all three datasets. Best results are marked in bold.

Team	**Easy F_1**	**Medium F_1**	**Hard F_1**
fosu-stu [30]	0.987	**0.887**	0.834
nycu-nlp [31]	0.964	0.857	**0.863**
no-999 [32]	**0.991**	0.830	0.832
huangzhijian [33]	0.985	0.815	0.826
text-understanding-and-analysi [34]	**0.991**	0.815	0.818
bingezzzleep [35]	0.985	0.818	0.807
openfact [37]	0.981	0.821	0.805
chen [38]	0.968	0.822	0.807
baker [39]	0.976	0.816	0.770
gladiators [40]	0.956	0.809	0.783
khaldi-abderrahmane	0.905	0.806	0.641
karami-sh [41]	0.972	0.664	0.642
riyahsanjesh [42]	0.825	0.712	0.599
liuc0757 [36]	0.696	0.717	0.503
lxflcl66666 [43]	0.606	0.455	0.484
foshan-university-of-guangdong [44]	0.517	0.394	0.352
Baseline Predict 1	0.466	0.343	0.320
Baseline Predict 0	0.112	0.323	0.346
Baseline Random	0.414	0.506	0.495

Khan et al. [40] in a first step, performed weighted sampling on the data provided to achieve balanced classes. They then compared RoBERTa, Electra, DeBerta, and Squeeze-Bert models, where RoBERTa was performing best. To further enhance the performance, they augmented the provided data by swapping all pairs of paragraphs between which no style change was detected and adding these paragraphs to the training data.

The approach by Sheykhlanet al. [41] makes use of fine-tuned transformer models, namely BERT, RoBERTa, and ELECTRA, to detect style changes. They opted to use different combinations of models depending on the difficulty of the dataset. For the easy dataset, they only used RoBERTa, while for the medium and hard datasets, they used an ensemble of all three models.

Sanjesh and Mangai [42] base their approach on latent representations of paragraphs by computing embeddings on a set of stylometric features such as TF/IDF for character n-grams, stop word frequency, character and word counts. These embeddings are then fed into a convolutional neural network and Bi-directional LSTM layers, which are then combined in a dense layer.

Liang and Lei [43] use GPT-3.5 as a teacher model that creates a dataset based on the provided datasets by providing pairs of sentences to the model and then asking questions about the similarity of topic, style, and vocabulary, and whether the sentences were written by the same author. The student model employed is T5-small is then fine-tuned for the multi-author writing style analysis task.

Liu, Chen, and Lv [44] leverage the Entropy-based Stability-Plasticity (ESP) method to tackle this year's task. ESP aims to balance stability and plasticity by restricting changes to the learning rate in each layer based on entropy. As an encoder, the team used BERT.

4. Evaluation Results

The results for all of this year's submissions are shown in Table 1. The best result for each difficulty is highlighted in bold; note thar the best result for each difficulty was achieved with different approaches. For the easy dataset, both Ye et al. [32] and Huang and Kong [34] achieved first place with an F_1 of 0.991. For the medium dataset, the best result was obtained by Lv et al. [30] with an F_1 of 0.887, while

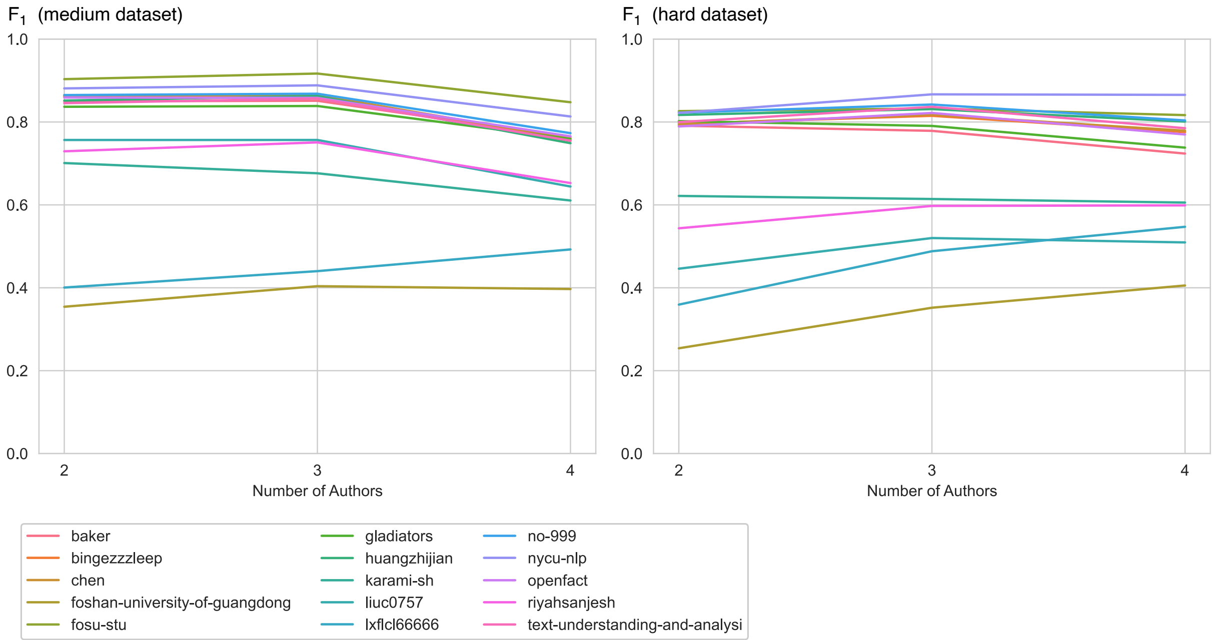

Figure 1: Detection results for the medium (left) and the hard dataset (right) as F_1 over the number of authors in a document.

the best result for the hard dataset was obtained by Lin et al. [31] with an F_1 of 0.863.

While there is still a clear difference in model performance between the three difficulty levels, the results have converged significantly again this year, with higher scores for the medium and hard datasets compared to last year, while the models on the easy dataset are already achieving near perfect scores.

We also checked how the number of authors in a document affects the performance of the submitted models for the medium and hard datasets. The results of this can be seen in Figure 1. We confirm the same observation as in the previous two years: The performance of many submitted models on the hard dataset, including the strongest submitted model, is better for documents written by three authors than for those written by two authors. Most models then decrease in their performance again on documents written by four authors, while the winning model maintains its performance for these documents.

5. Conclusion

In the 2024 edition of the multi-author writing style analysis task at PAN, the task was to identify locations of writing style changes at the paragraph level. We provided participants with three datasets of increasing thematic homogeneity and therefore difficulty. This year, we received 16 software submissions and 15 working papers. The results obtained again show considerable progress compared to the results of previous years.

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