Style Change Detection
NLP Course Project

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Abstract

This paper describes two simple but effective approaches for the three Style Change Detection (SCD) tasks for PAN at CLEF 2022. The first approach we propose is based on fine-tuning the BERT transformer and training different classification heads so to solve all three tasks in an end-to-end fashion. The second approach, instead, is based on using the Sentence-BERT (SBERT) transformer and cosine similarity so to solve the given classification problems by working directly in the embedding space implied by the chosen transformer-based encoder. We show how, using both approaches, we are able to achieve adequate results and also outperform existing state-of-the-art methods in a particular task.

1 Introduction

The SCD problem belongs to the author identification class of problems, and it is the only means to detect plagiarism in a document if no comparison texts are given. Likewise, style change detection can help to uncover gift authorships, to verify a claimed authorship, or to develop new technology for writing support.

The goal of the SCD-2022 tasks is to identify text positions within a given multi-author document at which the author switches (Zangerle et al., 2022). In particular, given a document combined from the StackExchange questions and answers, participants are asked to solve three tasks: 1). Style Change Basic: for a text written by two authors that contains a single style change only, find the position of this change (i.e., cut the text into the two authors' texts on the paragraph-level); 2). Style Change Advanced: for a text written by two or more authors, find all positions of writing style change (i.e., assign all paragraphs of the text uniquely to some author out of the number of authors assumed for the multi-author document); 3). Style Change Real-World: for a text written by two or more authors, find all positions of writing style change, where style changes now not only occur between paragraphs, but at the sentence level. All the possible scenarios are shown in figure 1

In all the previous editions of the competition, the joining teams tried to tackle the given problems by proposing a mixture of techniques, including ensembles of models, feature-based and similarity-based approaches (Zangerle et al., 2021, 2020, 2019). Based on the results of such approaches, it is possible to notice how end-to-end neural models are the models that best perform at solving the given tasks. This motivates us to explore the use of pre-trained transformer models to address the authorship analysis issue for writing style changes. Indeed, pre-trained models can be used to solve similar problems, using transfer learning techniques to fine-tune the pre-trained model to fit a particular downstream task.

In this paper we propose two similar but different approaches that try to solve all the three SCD-2022 tasks in a unified manner, by relying on neural models that incorporate pre-trained encoders such as BERT (Devlin et al., 2018) and SBERT (Reimers and Gurevych, 2019). In particular, the first approach takes into consideration the BERT encoder so to produce contextual embeddings that can be fed to fully-connected or convolutional layers and produce the final probability distribution that determines whether a couple of paragraphs or sentences of text is written by the same author. The second approach, instead, considers the SBERT encoder so to produce embeddings that can be directly compared using cosine similarity, and thus determining whether two paragraph or sentences of text are written by the same author.

The performances of the two approaches have been measured on the given validation set, using macro F_1-score. In particular, compared to the current state-of-the-art, both of the aforementioned approaches worked well, achieving adequate scores.

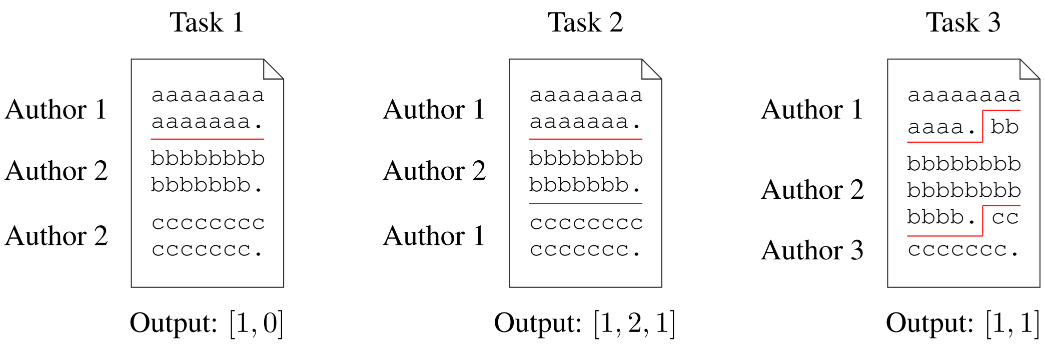


Figure 1: Possible scenarios and expected outputs

Moreover, the SBERT approach outperformed existing state-of-the-art methods at solving the Task 1 problem.

2 Background

The SCD-2018 edition focused on detecting whether a document is single-authored. This task can be treated as a binary classification problem. In this edition, different approaches were used to detect style changes, including ensembles of supervised learning models (Zlatkova et al., 2018) and feature-based approaches (Safin and Ogaltsov, 2018; Khan, 2018).

The SCD-2019 edition added a task for detecting the actual number of authors within a single document. One successful approach (Nath, 2019) was based on clustering algorithms, so to yield a number of clusters corresponding to the number of authors.

The SCD-2020 edition added another task based on detecting style changes between two consecutive paragraphs. In this case, a paragraph representation based on character, lexical and syntactic features was proposed, using a clustering algorithm for style change detection (Castro-Castro et al., 2020). Another group used the BERT model to generate embedding representations and used such embeddings to train a random forest classifier to detect style changes between two paragraphs (Iyer and Vosoughi, 2020).

The SCD-2021 edition also added a task to detect the number of authors and locating specific author changes within the text. Style change and author identification were regarded as binary classifications based on similarity measurements (Zhang et al., 2021).

Lastly, the SCD-2022 edition introduced the Style Change Real-World task, in which style changes can also occur at the sentence level. The work we present with this paper is deeply inspired by last editions' solutions. Indeed, both of our approaches use famous neural language models and use the computed embeddings to train specific classifiers or to compute similarity scores between texts.

The main innovation we tried to bring is the use of metric learning and siamese networks to compute similarity measurements in the vector space implied by SBERT. Indeed, the aim of metric learning is to compare low-dimensional embeddings of some input so to find semantically similar inputs in an effective way. One important type of neural models that is capable of finding similar inputs, as stated by the definition of metric learning, is the siamese neural network. This network is virtually composed of two backbones that share weights and work with two different input vectors to compute comparable output vectors. An example of such network is the SBERT model. SBERT is a modification of the BERT model that uses siamese and triplet networks to derive semantically meaningful embeddings that can be compared using similarity measures. The authors of SBERT describe this model as a single BERT model that has been trained using siamese as well as triplet architectures, depending on the structure of the data at hand.

After a careful analysis of the capabilities of such network, we made sure to properly manipulate the given datasets so to fine-tune SBERT using both the contrastive loss (Hadsell et al., 2006) as well as the triplet objective function described by Reimers and Gurevych, 2019. Indeed, the idea behind metric learning is to use specific losses to guide the model to favor a clustered structure of the embeddings such that: 1). the distance between semantically similar inputs is minimized; 2). the distance between semantically different inputs is maximized.

3 System description

Regarding the first approach, the pipeline we implemented is the following. We started by analysing all the three SCD-2022 datasets and by creating appropriate tables that could fit our needs. In particular, each of the computed tables is composed of $N \times 7$ elements, where N is the number of rows of the particular table and represents the number of documents in the original dataset. Each row of such table is composed of seven elements: `authors`, the total number of authors in the generic row (i.e. document); `site`, the source site from which the document was extracted; `multi-author`, a boolean flag indicating whether the generic document has been written by multiple authors; `changes`, a list of boolean varibles determining changes between paragraphs or sentences; `paragraph-authors`, a list of integer variables that label each paragraph or sentence with an author ID; `input_text`, the content of the entire document; `splitted_text`, the list of paragraphs or sentences of the generic document.

After having computed the aforementioned tables, we noticed how the given datasets, especially the one related to task 1, were not balanced. To solve this problem, we preprocessed the data so to be able to effectively train our models. The techniques we used to preprocessed the data are described, in more details, at section 4.

Then, we defined our BERT-based models. All the layers that define these models are shown in table 1. In particular, the BERT version we used is the BERT base cased version[1]. The layers of the classification head of each m_x^1 model were inspired by some successful works presented in the current edition of the SCD challenge (Lao et al., 2022; Lin et al., 2022). Indeed, the classification heads we defined are either composed of fully-connected layers or composed of uni-dimensional convolutional layers. Moreover, in order to be able to detect style changes between two different paragraphs or sentences, we had to manipulate the aforementioned dataframes so to incorporate two different consecutive paragraphs or sentences within the same BERT input. To do this, we used the official BERT tokenizer, that uses the special `[CLS]` and `[SEP]` tokens to build the different inputs. Thus, the inputs of the model are list of tokens of the form `[CLS] P/S-A [SEP] P/S-B [SEP]`, where `P/S-A` corresponds to the encoding of a paragraph/sentence, and `P/S-B` to the encoding of the subsequent paragraph/sentence. Other than the aforementioned list of token, for each possible pair of texts we produced: 1). a boolean mask, having the same length of the input tokens list, that determines at which positions the input list of tokens contains padding; 2). a boolean list, having the same length of the input tokens list, that determines the positions of `P/S-A` and of `P/S-B` within the input list.

The last bit of data manipulation was related to casting the Style Change Advanced problem (i.e. task 2), to be a binary classification problem, as in the case of task 1 and task 3. This was made possible by applying data augmentation to the validation set of task 2, thus considering all possible pairs of paragraphs. By doing this, we were able to tackle all the three tasks by using the same architectures and methodologies. However, by treating task 2 as a binary classification problem, we had to define a way to produce the corresponding list of authors out of the produced binary output of all models. The label of the first paragraph, P_1, is initialized as 1, indicating the first author. The second paragraph, P_2 is compared with P_1. If this pair obtains the class label 1 (i.e. a style change is detected), then the author label for P_2 will be 2 . Otherwise, if the class label is 0, the author of P_2 should be the same as the one for P_2 (i.e. 1). Thus, every paragraph is compared against all subsequent ones (e.g., P_1 with P_3, P_1 with P_4, etc.) to produce an ordered author list (limited to at most five distinct authors).

All the m_x^1 models have been trained for the same number of epochs, using a specific learning rate scheduler that properly modifies the learning rate within the same epoch. During the training procedure, the BERT layers of each encoder have been fine-tuned on the particular tasks at hand, so to produce contextual embeddings that are relevant for our specific problems. More information on the entire setup can be found in section 5.

Once trained, the models have been tested using the validation sets provided by the authors of the SCD-2022 challenge. In particular, the performances of each model were measured using the macro F_1-score. Lastly, considering the results on task 2 and task3 (namely, the two tasks that present a total number of authors within $[1, 5]$), some error analysis was made. In this last phase, we wanted to study the performances of each model with respect

[1] bert-base-cased

Model	Encoder	Classifier
m_1^1	BERT	Global Max-Pool, FC-2
m_2^1	BERT	Global Avg-Pool, FC-2
m_3^1	BERT	Global Max-Pool, FC-128, FC-2
m_4^1	BERT	(Conv1D-128, Max-Pool) $\times$ 3, Flatten, FC-2

Table 1: BERT-based architectures

to the total number of authors of the given documents, and to compare the four m_x^1 models based on the trends we obtained from this study.

Compared to the first approach, where a plain transformer with standard softmax is used, the second approach focuses on metric learning. To detect whether two passages are written by the same author, given an encoder model we can proceed as follows: 1). obtain an embedding for the two input passages; 2). compute the cosine similarity between the two; 3). Apply a threshold on such similarity, below which we say that the two documents are written by different authors. Indeed, as previously mentioned, the paradigm of metric learning ensures that embeddings of texts from different authors have low similarity, while embeddings from the same author should cluster together.

As for the loss which should be used, our dataset allows for both a contrastive and triplet approach. To train our models with contrastive loss, a training set of contrastive pairs and their similarity (i.e. 1 if they are from the same author, 0 otherwise) has to be created. As for the previous approach, we made sure to balance the dataset so to be able to effectively train our models. For triplet loss, instead, we built a dataset of triplets where the anchor is a passage from an author i, the positive is a different passage in the same conversation by the same author i and the negative is a passage from a different author j. In building such a triplet dataset we can also consider the difficulty of samples, thus we evaluated our models building both general triplet datasets, where no filtering of examples is performed, as well as hard/semi-hard datasets, where only hard and semi hard examples are put into the training set.

This general metric training strategy was applied to all the three tasks, however when we actually want to solve them we can exploit some of the properties of the current task to define more effectively how to perform inference to detect where style changes occur. In particular, for task 1 we know that we only have two authors and the change between them happens only once. Thus we can solve the problem of finding the style change by just finding the consecutive pairs of passages that differ the most. In tasks 2 and 3 we don't have this extremely useful bias, and we actually have to take the similarity between two paragraphs or sentences and decide on a threshold below which we can state that the two authors are not the same.

As mentioned above, for task 2 we not only have to detect the style change points, but also assign each paragraph to an author, that is something akin to a clustering problem. Differently to how we handled the same problem in the first approach, here two methods were devised: a threshold based method and an unsupervised clustering method. In particular, the threshold based method works by computing the cosine similarity between each paragraph and all previous ones, and by using a threshold to create clusters of paragraphs. The clustering method, instead, uses the pairwise cosine distances to run the DBSCAN clustering algorithm.

When considering this second approach, task 3 is similar to task 2 in the sense that we cannot work on similarities only, but we need a threshold to decide when to detect a style change.

As previously stated, task 2 and task 3 require the definition of a threshold under which two passages are said to be from different authors. Two methods of threshold selection in the contrastive case were implemented: 1). the threshold is set to be equal to the margin value, α, used by the loss function. Indeed, the contrastive loss is formulated in such a way that:

$$\begin{cases} d(e_1, e_2) \simeq 0 & \text{if } a(x_1) = a(x_2) \\ d(e_1, e_2) > \alpha & \text{if } a(x_1) \neq a(x_2) \end{cases} \tag{1}$$

where $d(e_1, e_2)$ is the distance between e_1 and e_2, and $a(e_x)$ defines the author of the paragraph whose embedding is e_x; 2). the threshold is inferred from the training set. After training we can apply our model to the contrastive pairs and mea-

Model	Encoder	Details
m_1^2	SBERT	No fine-tuning
m_2^2	SBERT	Fine-tuned with contrastive loss
m_3^2	SBERT	Fine-tuned with triplet loss
m_4^2	SBERT	Fine-tuned with triplet loss, hard/semi-hard samples only

Table 2: SBERT-based architectures

sure the average similarity for same-author samples and different-author samples, the threshold should lie between these two averages. In practice it was found to be advantageous to consider the standard deviation of these two groups of similarities as well, in this way if for example the range of similarities for the same-author group is low, the threshold should be put closer to its mean than the mean of the different-authors group.

A similar approach can be used to get the similarity for the triplet examples, by splitting each triplet example in two contrastive ones, thus computing the average of same-author similarities between anchors and positives and the average of different-author similarities between anchors and negatives.

A general overview of all the sentence transformer architectures is shown in table 2.

4 Data

5 Experimental setup and results

The metric learning approach was tested along different dimensions, from the model choice to the training regime, and dataset creation.

For each task we trained the models using only data that was provided for that task. This was needed especially for task 3, where the passages that we had to analyze are sentences, instead of entireparagraphs, and differ considerably from the samples we have for task 1 and 2.

One of the first choices we had to make was which pretrained sentence transformers model to fine-tune. We decided to use two base models, a general purpose one based on the MPNet architecture by Microsoft[2] (Song et al., 2020), and a model which was already trained to discern writing style in text, named Style-Embedding[3], that is based on RoBERTa. In particular, for each task and for each base model, we trained our four architectures as described in table 2.

[2] sentence-transformers/all-mpnet-base-v2

[3] AnnaWegmann/Style-Embedding

For all of the tasks we used the AdamW optimizer with a weight decay of $1e{-}2$, a learning rate of $2e{-}5$, with a linear warm-up schedule that peaks at 10% of the training steps, and a batch size of 8; the margin, α, for the contrastive/triplet loss has been set to 0.6. Moreover, the models that follow the m_2^2 and m_3^2 architectures were trained for 2 epochs, while the m_4^2 architectures were trained for 3 epochs, since less examples were available.

For task 1 and 2 we set the maximum length of a passage to be 128 tokens, while for task 3 we set this value to 32 tokens.

Due to hardware limitations, we set the following maximum values for the number of samples in the computed training sets: 20000 for task 1, 50000 for task 2, 100000 for task 3.

Considering task 2, in order to properly produce the final author IDs list, we tested our approach using both the threshold based method as well as the clustering method based on DBSCAN. In the latter case, alongside the already computed similarity matrix, the following hyperparameters we set the minimum number of points needed to form a cluster to 1 and $\varepsilon = 0.5$. Moreover, considering tasks 2 and 3, in order to detect whether two texts are written by the same authors, we tested our approach using as threshold both the margin α of the constrastive loss as well as the aforementioned threshold computed on the training set. The results of all these tests, on each validation set, are shown in table 3.

Lastly, the best macro F_1-scores, for both of the two approaches, are presented in table 4. This tables also presents the current state-of-the-art for all three tasks. Figure 2, instead, shows the performances of each model with respect to the total number of authors of the given documents.

6 Discussion

Considering the baseline sentence transformer models (i.e. the two m_1^2 models), it is possible to notice how the Style-Embedding models al-

Model		Task 1	Task 2			Task 3	
		-	Margin thr.	Mean thr.	DBSCAN	Margin	Mean
MPnet	m_1^2	0.59	-	0.24	0.26	-	0.54
	m_2^2	0.79	0.38	0.44	0.21	0.67	0.69
	m_3^2	0.79	0.42	0.37	0.38	0.60	0.65
	m_4^2	0.78	0.41	0.36	0.39	0.61	0.65
Style-Embedding	m_1^2	0.70	-	0.33	0.31	-	0.58
	m_2^2	0.78	0.32	0.44	0.17	0.64	0.67
	m_3^2	0.78	0.42	0.39	0.38	0.61	0.66
	m_4^2	0.80	0.41	0.36	0.38	0.59	0.64

Table 3: Macro F_1-scores for the m_x^2 architectures

Model	Task 1	Task 2	Task 3
m_1^1	0.72	0.28	0.66
m_2^1	0.71	0.45	0.66
m_3^1	0.71	0.44	0.66
m_4^1	0.68	0.43	0.66
m_1^2	0.70	0.33	0.58
m_2^2	0.79	0.44	0.69
m_3^2	0.79	0.42	0.66
m_4^2	**0.80**	0.41	0.65
Lin et al., 2022	0.74	**0.54**	**0.73**

Table 4: Best macro F_1-scores

ways outperform the MPnet models. However, this gap between the two types of architectures is not present when the models are fine-tuned (m_2^2, m_3^2 and m_4^2), with both MPnet and Style-Embedding reaching similar performances on all tasks under all inference methods. In particular, the overall best result on task 1 is obtained with Style-Embedding (m_4^2 with a macro F_1-score of 0.8), while for task 2 the performances are almost the same, and for task 3 the winner is MPnet (m_2^2 with a macro F_1-score of 0.69).

Considering tasks 2 and 3, it seems that computing a threshold based on the training dataset is usually better than fixing it to the margin of the loss function. Surprisingly enough, this does not hold for task 2 when using triplet loss.

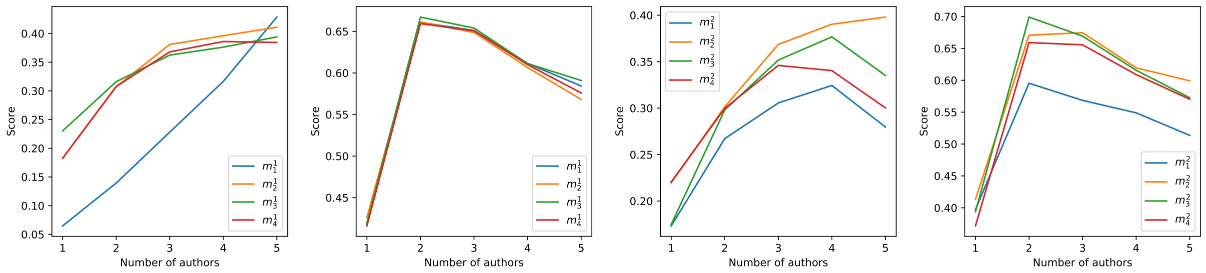
Considering only task 2, the results yielded by the DBSCAN-based approach seem to almost always be worse comparared to the results yielded by the threshold based method. This is likely due to the decision of not tuning the hyperparameters of DBSCAN.

With regards to the choice of which triplets to choose when using triplet loss, it seems like using only hard and semi-hard examples has overall a very slight negative impact on the results. However this could be due to the lower number of samples obtained and consequently to the lower number of examples seen by the model.

When looking at how the model behaves in tasks 2 and 3 as the number of author changes (figure 2), we can notice that the model has the biggest problems when the conversation is written by a single author. Furthermore, looking at task 2, there seems to exist a positive correlation between the total number of authors and the computed macro F_1-score. Meanwhile, for task 3, the model obtains the best results on conversations between two authors and then gently declines.

7 Conclusion

8 Links to external resources



(a) m_x^1 on task 2 (b) m_x^1 on task 3 (c) m_x^2 on task 2 (d) m_x^2 on task 3

Figure 2: Macro F_1-scores with respect to number of authors

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