**DocSCAN: Unsupervised Text Classification via Learning from Neighbors**

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**ABSTRACT**

We introduce DocSCAN, a completely unsupervised text classification approach using Semantic Clustering by Adopting Nearest-Neighbors (SCAN). For each document, we obtain semantically informative vectors from a large pre-trained language model. Similar documents have proximate vectors, so neighbors in the representation space tend to share topic labels. Our learnable clustering approach uses pairs of neighboring datapoints as a weak learning signal. The proposed approach learns to assign classes to the whole dataset without provided ground-truth labels. On five topic classification benchmarks, we improve on various unsupervised baselines by a large margin. In datasets with relatively few and balanced outcome classes, DocSCAN approaches the performance of supervised classification. The method fails for other types of classification, such as sentiment analysis, pointing to important conceptual and practical differences between classifying images and texts.

**Keywords** Text Classification · Unsupervised Learning · Neighbor-based Clustering

1 Introduction

"What is this about?" is the starting question in human and machine reading of text documents. While this question would invite a variety of answers for documents in general, there is a large set of corpora for which each document can be sensibly and functionally labeled as belonging to a singular category or topic. Text classification is the task of automatically mapping texts into these categories.

In the standard setting, machine learning algorithms learn such a mapping from annotated examples. Annotating data is costly, however, and the resulting annotations are usually domain-specific. Semi-supervised or completely unsupervised methods promise to reduce the amount of labeled examples needed or to dispense with them altogether.

This paper builds on a notable recent development in the domain of unsupervised neighbor-based clustering: **Semantic Clustering by Adopting Nearest neighbors** [SCAN, Van Gansbeke et al., 2020]. The intuition behind SCAN is that neighbors in representation space often share the same label. We can leverage this regularity as a weakly supervised signal for training models. Specifically, we encode a datapoint and its neighbors through a siamese network where the last layer is a classification layer. The model learns that it should assign similar output probabilities to a datapoint and its neighbor. In the ideal case, model output is consistent and one-hot, i.e. the model confidently assigns the same label to two neighboring datapoints. SCAN has been shown to work well for image classification. Here, we adapt the method for use with text data to tackle the task of unsupervised text classification.

With the rise of deep Transformer networks, text classification and other natural language processing (NLP) tasks recently have seen rapid improvements in performance [e.g. Yang et al., 2019]. We draw from such Transformer models because they yield task-agnostic contextualized language representations. In particular, we use SBERT embeddings [Reimers and Gurevych, 2019], which have proven performance in a variety of downstream tasks, such as retrieving...
semantically similar documents. We show that in SBERT space, indeed neighboring documents tend to often share the same class label and we can use this proximity to build a dataset on which we apply our neighbor-based clustering objective.

We show that training a siamese network exploiting this regularity works for text classification. This unsupervised approach outperforms two standard baselines by a large margin: a topic modeling baseline and a k-means baseline (using the same input features). In our experiments, we explore a shallow classification layer trained on top of SBERT features and also fine-tune RoBERTa models on the same clustering objective. In the latter case, we achieve performance close to a supervised learning regime in some settings.

We conclude the paper with a short discussion about experiments on NLP tasks going beyond classifying documents into (topical) categories – with limited success. We use these results to discuss limitations of DocSCAN and differences between text classification and image classification.

2 Related Work

This work borrows methodology from a recent paper classifying images in a completely unsupervised fashion. The proposed algorithm, Semantic Clustering by Adopting Nearest neighbors [SCAN, Van Gansbeke et al., 2020], can detect the objects contained in images using an unsupervised clustering approach, described in more detail in section 3.

Unsupervised learning methods are ubiquitous in natural language processing. For the purposes of classification, some early work compiles keyword lists which are used to categorize sentences directly [Ko and Seo, 2000]. These word lists can be used as a proxy cluster centroid for which a similarity measure can be computed [Haj-Yahia et al., 2019]. However, such approaches are not purely data-driven and require the compilation of such keyword lists, for which expert domain knowledge is needed.

More recent work mainly focuses on weakly supervised labels derived from (semantic) rules to obtain noisy labels. A first example is Snorkel [Ratner et al., 2017], which does correlation-based aggregation of different labeling functions. Second, [Yu et al., 2020] make use of noisy labels to fine-tune Transformer models in a contrastive self-training framework.

In a different direction, documents can be represented as vectors which can then be clustered using k-means. This approach is taken by Demszky et al. [2019] to classify tweets regarding mass shooting events. In that case, the quality of the embedded vector is critical for the quality of the clustering. More extensive experiments conducted with this method can be found in Guo et al. [2020]. We use k-means clustering on top of SBERT embedding as a baseline for our experiments. Lastly, a related approach to unsupervised classification is Bayesian topic modeling [e.g. Blei and Lafferty, 2009]. Topic models are arguably different from classification because the documents are not assumed to be labeled by a single class. Instead, topic models suppose that documents are a probability distribution over topics, and topics are a probability distribution over words. The document-topic and topic-word distributions can be approximated via latent dirichlet allocation (for example) and can be used for unsupervised learning of the topics contained in documents [Miller et al., 2016]. We use topic models as a second baseline in our experiment section. We set the number of topics equal to the number of classes and assign the most likely topic of each document to be its class.

3 Method

The SCAN algorithm is based on the intuition that a datapoint and its nearest neighbors in (some reasonable) representation space often share the same class label. It consists of three stages: (1) learn representations via a self-learning task, (2) mine nearest neighbors and fine-tune a siamese network on the weak signal that two neighbors share the same label, and (3) confidence-based self-labeling of the training data.

Our adaptation DocSCAN to text classification works as follows. In Step 1, we need a document embedding method that serves as an analogue to SCAN’s self-learning task for images. Textual Entailment [Dagan et al., 2005] is an interesting pre-training task yielding transferable knowledge and generic language representations, as already shown in Conneau et al., [2018]. Combining this pre-training task and BERT [Devlin et al., 2019] has led to SBERT [Reimers and Gurevych, 2019]; a siamese network of BERT models fine-tuned on the Stanford Natural Language Inference corpus [Bowman et al., 2015]. SBERT yields embeddings for short documents with proven performance across domains and for a variety of tasks, such as semantic search and clustering. For a given corpus, we apply SBERT and get a 768-dimensional dense vector for each document.

We also experimented with Doc2Vec and TF-IDF representations; In the Appendix, we show ablation studies of running DocSCAN with different document representations.
Step 2 is the mining of neighbors in the embedding space. We apply Faiss [Johnson et al., 2017] to get Euclidean distances between all embedded document vectors. The retrieved neighbors are the documents having the smallest Euclidean distance to a reference datapoint.

The original SCAN paper worked because images with proximate embeddings tended to share class labels. Is that the case with text? Figure [1] shows that the answer is yes: across five text classification benchmarks, neighboring documents do indeed often share the same label. The frequency of correct pairs for $k = 5$ is sometimes higher than the frequency of correct pairs reported for images [around 75%, Van Gansbeke et al., 2020].

![Figure 1: Accuracy of datapoint/neighbor pairs sharing the same label for different text classification benchmarks. We show accuracy for $k = 1, 5, 50, 100$.](image)

Next, we describe the SCAN loss,

$$-\frac{1}{|D|} \sum_{X \in D} \sum_{k \in \mathcal{N}_X} \log <\Phi_{\eta}(X), \Phi_{\eta}(k)> + \lambda \sum_{c \in \mathcal{C}} \Phi'_{\eta,c} \log \Phi'_{\eta,c}$$  

which can be broken down as follows. The first part of Eq. (1) is the consistency loss, where $< , >$ denotes the dot product. Our model $\Phi_\eta(\cdot)$ (parametrized by a neural net) computes a label for a datapoint $X$ and each datapoint in the set of its mined neighbors $k \in \mathcal{N}_X$. The dot product is maximized if both model outputs are one-hot with all probability mass on the same entry in the respective vectors. It is consistent because we want to assign the same label for a datapoint and all its neighbors. The second term is an auxiliary loss to obtain regularization via entropy (scaled by a weight $\lambda$), such that the model is encouraged to spread probability mass across all entries of the output vector. Without that term, there exists a shortcut by collapsing all examples into one single cluster.

Van Gansbeke et al. [2020] state that they found SCAN to give similar results for any numbers of neighbors retrieved between 3 and 10. As a compromise we considered five neighbors in all our experiments which yields a dataset of

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2 in the appendix, we also show experiments for $k = 3$ and $k = 10$ and we also obtain similar results.
### 4 Experiments

We apply DocSCAN on five diverse text classification benchmarks: 20NewsGroup data [empty], AG’s news corpus [Zhang et al. 2015], DBPedia ontology dataset [Lehmann et al. 2015], Google Snippets [Phan et al. 2008], and the Abstracts Group dataset [abs]. For a more detailed description of the data and statistics, we refer to Appendix A.1.

The main results are reported in Table 1. For all experiments, we report the mean accuracy over five runs (and in brackets the standard error) on the test set. The columns correspond to the benchmark corpora. The rows correspond to the models, starting with a random baseline [1], two k-means baselines [2, 3], a topic modeling baseline [4], two DocSCAN variants [5, 6], and finally a supervised learning baseline [7]. For all models and datasets, we got similar metrics for balanced accuracy.

Row [1] provides a sensible lower-bound, row [7] analogously a supervised upper-bound for text classification performance. In the random draw [1], accuracy by construction converges to the average of the class proportions. The supervised model [7] is an SVM classifier applied to the SBERT embeddings as input, it predictably obtains strong accuracy on these benchmark classification tasks.

The industry workhorse for clustering is k-means, an algorithm for learning cluster centroids that minimize the within-cluster sum of squared distances-to-centroids. When applied to TF-IDF-weighted bag-of-n-grams features [2], k-means improves over the random baseline in every case. When applied to SBERT vectors [3], we see further significant improvement. These results corroborate what we already saw in Figure 1 that neighbors contain information about text topic classes. SBERT embeddings, in particular, contain significant such information.

As a last baseline, we consider topic models (LDA) where we set the number of topics to the number of classes. We treat the most probable topic in a document as the predicted class and we find that this naive approach does not perform well for text classification.

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### Table 1: Test-set accuracy by benchmark dataset (columns) and classifier (rows). Cell values give the mean over 5 runs with standard error in parentheses.

| Experiment | 20 News | AG news | DBPedia | Google Snippets | Abstracts Group |
|------------|---------|---------|---------|----------------|-----------------|
| [1] Random Baseline | 7.0 (0.0) | 26.1 (0.3) | 7.7 (0.0) | 15.04 (0.5) | 23.5 (0.6) |
| [2] TF-IDF + kmeans | 22.5 (3.7) | 39.4 (3.5) | 47.6 (3.0) | 23.7 (2.1) | 54.8 (4.1) |
| [3] SBERT embeddings + kmeans | 31.7 (0.9) | 55 (8.4) | 64.7 (4.3) | 52.7 (3.4) | 50.5 (3.9) |
| [41] Topic Modeling (LDA) | 16.0 (0.8) | 31.3 (0.1) | 19.8 (0.7) | 26.1 (1.2) | 30.5 (0.4) |
| [5] DocSCAN 1 | **41.1** (1.8) | 80.5 (7.1) | **77.7** (5.7) | 64.3 (2.5) | **63.2** (2.3) |
| [6] DocSCAN 2 | 5.7 (0.0) | **85.0** (1.6) | 62.3 (5.8) | **74.8** (1.5) | 57.2 (10.3) |
| [7] SBERT embeddings + SVM | 66 | 90 | 99 | 75 | 80 |

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5 ∗ N (N is the size of a dataset) sentence pairs for training. The authors also suggest to use λ = 2 for the auxiliary loss which we found to work well in our experiments.

Step 3 of SCAN is to do confidence-based self-labeling. The example labels obtained by the network act as pseudo-labels, if the network is confident about its prediction (p > 0.9). The model learns to assign the same label to the strongly augmented version of the image. There is not a straightforward translation of this approach to NLP. Tokens are discrete, symbolic characters, rather than the continuous quantities contained in pixels. We skip this step and leave exploration to future work.

To summarize: We use SBERT and embed every datapoint in a given text classification dataset. We then mine the five nearest neighbors for every datapoint. This yields our weakly supervised training set. We fine-tune siamese networks on neighboring datapoints using the SCAN loss. At test time, we compute Φ(η)(X) for every X in the test set. We set the number of outcome classes equal to the numbers of classes in our considered datasets and use the hungarian matching algorithm [Kuhn and Yaw 1955] to obtain the optimal cluster-to-label assignment.

In Appendix A.4, we illustrate how the SCAN training process reshapes the embedding space. The PCA reductions for the pre-training SBERT embeddings and post-training DocSCAN embedding are compared for three datasets. In a completely unsupervised fashion, the model learns to separate the labeled categories in the data.
So what does DocSCAN add? In the first DocSCAN variant [5], we fine-tune a classification layer on the SBERT embeddings with the SCAN objective (Eq. 1) and $k = 5$ neighbors. For a quick discussion about the hyper-parameters used, we refer to Appendix A.3. This procedure outperforms the k-means + SBERT baseline [3] in all experiments by at least 10% points, sometimes even by up to 25% points (the AG’s news corpus).

In [6], we consider the same sentences and neighbors as in [5]. But rather than using the SBERT embeddings as the inputs, we take the raw text as input and fine-tune a whole RoBERTa base checkpoint to solve the SCAN objective. This approach gets mixed results. For the AG news and Google Snippets data, we do even better than [5], with accuracy close to the supervised baseline [7]. For the 20NewsGroup data, performance is significantly worse; the model collapses to a single cluster, so accuracy is just the size of the largest topic class. For DBPedia and Abstracts Group, we observe that our model partially collapses; for DBPedia, e.g., we retrieve 8-10 clusters instead of the 14 required, hence worse accuracy than in DocSCAN 1 [5]. For these datasets, we experimented with scaling the entropy loss to high values (up to 128), which prevented model collapse but instead the model did not converge. We revisit this issue in the Limitations section A.2.

To summarize, applying DocSCAN to text classification outperforms a clustering baseline across five datasets by at least 10% points, sometimes even by up to 25% points. For certain datasets (AG’s news and Google Snippets), we achieve performance almost on pair with a supervised baseline by fine-tuning a RoBERTa checkpoint using DocSCAN.

5 Conclusion

To conclude, we introduce DocSCAN for unsupervised text classification. Analogous to the recognizable object content of images, we find that a document and its close neighbors in embedding space often share the same class in terms of the topical content. We show that this consistency can be used as a weak signal for fine-tuning text classifier models in an unsupervised fashion. We start with SBERT embeddings and fine-tune two SCAN variations (classification layer only and whole RoBERTa checkpoints) on five text classification benchmarks. We outperform a random baseline, a topic modeling baseline and two k-means baselines by a large margin. In some settings, we achieve performance close to a supervised regime.

As with images, unsupervised learning with SCAN can be used for text classification. However, the method may not work as generically as it does with images. Still, this work points to the promise of further exploration of unsupervised methods using embedding geometry.

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Appendices

A.1 Detailed Statistics about Datasets

Here we provide more detailed statistics about the five benchmarks used in the experiments. The 20NewsGroup data contains text from USENet discussion groups (20 classes), AG’s news corpus consists of the title and description field of news articles (4 classes), DBPedia data includes titles and abstracts of Wikipedia articles (14 classes), Google-Snippets contains web search results from different domains (8 classes) and the Abstracts Group data is made from abstracts from academic papers (5 classes).

In Table 2, we show the numbers of training examples, labels, domain and one text example for each dataset.

| Dataset            | # Train Examples | # Labels | Domain                        | Example                                                                 |
|--------------------|------------------|----------|-------------------------------|-------------------------------------------------------------------------|
| 20NewsGroup data   | 11'314           | 20       | USENet discussion groups      | [...] I Have a Sound Blaster ver 1.5 When I try to install driver ver 1.5 (driver that comes with window 3.1) [...] |
| AG’s Corpus        | 120'000          | 4        | News                          | Wall St. Bears Claw Back Into the Black (Reuters) Reuters - Short-sellers, Wall Street’s dwindling band of ultra-cynics, are seeing green again. |
| DBPedia            | 560'000          | 14       | Wikipedia                     | Abbott of Farnham E D Abbott Limited was a British coachbuilding business based in Farnham Surrey trading under that name from 1929. A major part of their output was under sub-contract to motor vehicle manufacturers. Their business closed in 1972. |
| Google-Snippets    | 10'060           | 8        | Web queries                   | manufacture manufacturer directory directory china taiwan products manufacturer directory - taiwan china products manufacturer directory exporter directory supplier directory suppliers |
| Abstracts Group    | 5'642            | 5        | Scientific papers             | an empirical investigation of the effects of firm characteristics on the propensity to adopt cloud computing cloud computing cc is emerging as a new paradigm of resource acquisition and management of information and communication technologies ici by firms |

Table 2: Dataset Statistics

A.2 Limitations and Prospects

While we have documented some promising results, our exploration of DocSCAN for unsupervised text classification has also had problems. The method does better than a k-means baseline on the tested datasets, but there appear to be issues with robustness and model collapse.

In particular, with the fine-tuned RoBERTa variant [6], for one of the five datasets we could not find any working solution. This limitation might be due to datasets having many classes, combined with a weak signal from the neighbor mining step may be too noisy. Furthermore, the neighbor mining step for big datasets and dense SBERT embeddings can be inaccurate, as shown in Reimers and Gurevych [2020] for an information-retrieval task. In particular, we speculate that this problem reduces performance on the DBPedia benchmark.

Besides the topic classification task, we next tried DocSCAN for classifying documents by positive or negative sentiment. We encode the IMDB dataset [Maas et al. 2011] with SBERT embeddings and employ our method. We achieve 72.3% accuracy of correct neighbor pairs for k=5 and a SCAN accuracy of 70.2% (compared to a k-means baseline of 71.5).

The relatively low performance on the sentiment classification task is exemplary of a broader conceptual and practical difference between image classification and text classification. Image classification is a relatively simple task: identifying a single object contained in an image. In contrast, a document does not contain a “single object” to be identified. Even the simplest documents are complex systems containing multiple entities, their actions, and their attributes. A label that says a document is about a single particular topic requires many more hidden assumptions and simplifications than a label saying that an image contains a particular object.

Consistent with this point, in the field of supervised learning with text there are many other standard dimensions for machine prediction besides topic. Binary sentiment is one. There is also three-class sentiment, adding neutral as a third category. Some sentiment systems predict subjectivity as well as polarity. There are many more features of text that are part of standard benchmarks, e.g. classification tasks in GLUE include grammatical acceptability, QA, sentiment classification and textual entailment [Wang et al. 2018].

This richness of output classes in text is totally different from the standard approach in image classification, which rarely deviates from the singular task of identifying objects. To make for a fairer comparison, it would be interesting to try the SCAN image classification task but starting with image embeddings trained for facial recognition.
A reinforcing issue is the difference between the benchmark datasets in classifying images versus texts. Image classification datasets are designed (somewhat artificially) specifically for the purpose of training image classifiers. Text datasets, in contrast, are real-world corpora that happen to have topic labels, which were added for the purpose of the social context in which the documents were written.

More practically for our application, we attribute low performance for sentiment analysis to the use of SBERT embeddings, which tend to encode topically related documents, rather than documents with a similar sentiment. When applying SCAN to other classification tasks, it is best to start with embeddings that capture the nature of the task. We are confident that we could make SCAN work better for e.g. sentiment analysis by first fine-tuning a BERT model on any sentiment analysis dataset, and use the resulting embeddings of the [CLS]-token for mining neighbors.

Finally, we applied SCAN to unsupervised POS tagging using the universal tagset from the Brown Corpus [Francis and Kucera 1979]. We extract embeddings for each word by using the averaged last four layers of a RoBERTa-base model. We achieve an 80% accuracy of retrieved neighbor pairs, but fail to successfully train a model on that input, mainly because classes are unevenly distributed, ranging from 0.1% to 24.3% frequency. Given this distributions, we do not manage to fit models using entropy as an auxiliary loss.

Addressing these issues is an interesting challenge for future work. We probably could overcome dataset imbalances by minimizing KL-divergence between computed output and actual class distribution instead of using entropy as an auxiliary loss. And we probably could address sentiment analysis if we find a representation space which places text sharing a sentiment in similar regions. However, both require assumptions about distributions and the nature of the target task and thus would be a departure from the realm of generally applicable unsupervised machine learning algorithms. Overall, while DocSCAN method offers immediate usefulness for topic classification, it has some limitations for the broader set of classification tasks in NLP.

### A.3 Hyper-Parameters

To get an initial understanding of the hyper-parameters needed for our method to work, we slightly tuned batch size (between 16 and 256), the learning rate (0.001 and 0.0001) and dropout (0.0, 0.1 and 0.2) on a 10% split of the Google Snippet training set. We found that setting the learning rate to 0.001 is the most important hyper-parameter and performance across different batch-sizes and dropout probabilities remains rather stable.

We obtained the best performance on this Google Snippet split using a batch size of 64, a learning rate of 0.001 and dropout of 0.1. We applied this setting to all experiments in [4] in table 1. Since tuning hyper-parameters separately on different benchmarks would be an unfair advantage over k-means, we restrained ourselves to do so.

For the experiments in [5], we used a batch size of 32, a learning rate of 2e-5 and fine-tuned for one epoch. After observing clusters collapsing in the 20 News data, we additionally explored different batchsizes, learning rates, numbers of epochs and entropy weights for the 20 Newsgroup data, but we did not find a setting in which clusters did not collapse.

### A.4 Ablation Studies

In this section, we provide several ablation studies. We only report results for the three small datasets (the 20NewsGroup data, Google Snippets and Abstracts Group data). First, we report results for different values of $k$, the number of nearest neighbors considered in our experiments in table 3.

| Experiment | 20 News | Google Snippets | Abstracts Group |
|------------|---------|-----------------|-----------------|
| $k = 3$    | 39.9    | **62.4**        | 59.0            |
| $k = 5$    | 41.1    | **64.3**        | 63.2            |
| $k = 10$   | 39.4    | 63.2            | **64.3**        |

Table 3: Ablation Studies for the amount of neighbors selected
First, we report results for running DocSCAN with tf-idf embeddings. This means that we use the TF-IDF vector to represent documents. Based on this representation, we search for nearest neighbors in the training set and build our dataset of neighboring datapoint pairs. We then train DocSCAN on the resulting dataset, i.e. we train a classification layer on top of TF-IDF representations. We compare this experiment to a kmeans clustering baseline using the same embeddings. We find that DocSCAN 1 outperforms the kmeans baseline in this setting on all three datasets, always by a large margin.

Next, run DocSCAN with doc2vec representations [Le and Mikolov 2014]. We find that these representations do not yield satisfactory representations consistently across datasets, e.g. both kmeans and our DocSCAN variant do not work for the Google Snippets data using these representations. In case we have reasonable representations, we find the same pattern that our proposed method DocSCAN outperforms a kmeans baseline using the same input features.

The last two rows are our findings reported in the main analysis; running DocSCAN with SBERT embeddings. These representations work across all datasets and perform best on average, hence we suggest to run DocSCAN with SBERT features.

### A.5 PCA of resulting SCAN Embeddings

Figure 2 provide visual representations of how the SCAN approach reshapes document vectors. Using the Google Snippets dataset, the left panel plots the first two principal components of the SBERT embeddings formed from those documents. The right panel shows the principal components of the [CLS]-token of a fine-tuned RoBERTa_base model using SCAN. Figure 3 and 4 provide the same exercise for the AG News data and the Abstracts Group data. In all cases, we find that the representation of the [CLS]-token neatly clusters datapoints into its corresponding classes after having been fine-tuned on the SCAN objective.

![Figure 2](image)

Figure 2: Google Snippet data, on the left: PCA of SBERT embeddings. On the right: PCA of the [CLS]-token of a RoBERTa model fine-tuned using SCAN

| Experiment          | 20 News | Google Snippets | Abstracts Group |
|---------------------|---------|-----------------|-----------------|
| kmeans + TF-IDF     | 22.5    | 23.7            | 54.8            |
| DocSCAN 1 + TF-IDF  | 32.9    | 44.9            | 61.6            |
| kmeans + Doc2Vec    | 14.9    | 14.5            | 55.4            |
| DocSCAN 1 + Doc2Vec | 27.5    | 14.5            | **64.5**        |
| kmeans + SBERT      | 31.7    | 52.7            | 50.5            |
| DocSCAN 1 + SBERT   | **41.1**| **64.3**        | 63.2            |

Table 4: Ablation Studies for different document embeddings
Figure 3: AG news data, on the left: PCA of SBERT embeddings. On the right: PCA of the [CLS]-token of a RoBERTa model fine-tuned using SCAN

Figure 4: Abstracts Group data, on the left: PCA of SBERT embeddings. On the right: PCA of the [CLS]-token of a RoBERTa model fine-tuned using SCAN