MIST: Mutual Information Maximization for Short Text Clustering

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Abstract

Short text clustering poses substantial challenges due to the limited amount of information provided by each sample. Previous efforts based on dense representations are still inadequate since texts from different clusters are not sufficiently segregated in the embedding space prior to the clustering step. Even though the state-of-the-art technique integrated contrastive learning with a soft clustering objective to address this issue, the step in which all local tokens are summarized to form a sequence representation for the whole text may include noise that obscures the key information. We propose a framework called MIST: **M**utual **I**nformation Maximization for **S**hort **T**ext Clustering, which overcomes the information limitation by maximizing the mutual information between text samples on both sequence and token levels. We assess the performance of our proposed method on eight standard short text datasets. Experimental results show that MIST outperforms the state-of-the-art methods in terms of Accuracy or Normalized Mutual Information in most cases.

1 Introduction

Text clustering is a vital task for a wide range of downstream applications. It aims to partition texts into groups of similar categories in an unsupervised manner. The growth of social media, discussion forums and news aggregator websites has led to a large number of short-length texts being produced daily. Hence, clustering these short texts is gaining more attention and becoming a crucial step for many real-world applications from recommendation to text retrieval (Yohannes and Assabie, 2021).

In short texts, words and phrases that are most representative of the text content, usually appear only once. This exacerbates the sparsity problem, posing an additional hurdle for clustering short texts. Traditional methods, such as Bag-of-Words (BoW) and TF-IDF, provide relatively sparse representation vectors with limited descriptive power. Hence, they perform poorly when clustered with a standard distance-based clustering method, such as k-means, in this situation (Hadifar et al., 2019).

To address this problem, deep neural networks have been employed to map high dimensional data into meaningful dense representations in a lower dimensional space. Most recent techniques for deep clustering follow a multi-phase style, in which the clustering process is carried out after learning feature representations (Xu et al., 2017; Hadifar et al., 2019; Yin et al., 2021). Unfortunately, the clustering performance of these methods remain unsatisfactory. One probable explanation is that texts still have a lot of overlap among categories in the latent space before clustering (Zhang et al., 2021).

Another deep clustering strategy optimizes representation learning and clustering objectives simultaneously (Zhang et al., 2021; Xie et al., 2016). To achieve desirable outcomes, Zhang et al. (2021) propose a method that adopts contrastive representation learning, which has been successful in self-supervised learning and is able to assist in spreading out the overlapped categories so that effective representations can be acquired, by simultaneously optimizing it along with a soft clustering target.

As shown in Zhang et al. (2021), improving representation is crucial for enhancing the clustering performance. Nevertheless, the contrastive learning method used in Zhang et al. (2021) only considers whole text representations while optimizing a contrasting objective. In particular, these representations are formed by summarizing all token representations in each text instance via mean pooling, including uninformative noises. We conjecture that this allows constructing a representation in which important information used to describe the text content may be obscured by noise, potentially affecting the clustering performance. Therefore, there is still a gap that needs to be explored in order to derive an efficient representation for short text clustering that does not omit informative terms.

In this paper, we introduce the **M**utual **I**nformation Maximization Framework for **S**hort **T**ext Clustering (MIST), a multi-stage framework that learns textual representations by incorporating two contrastive representation learning objectives together with soft clustering assignments. Our contrastive learning procedure is based on mutual information (MI) maximization, which facilitates us to compare the semantic similarity across different hierarchical levels to achieve multiple purposes. First, we perform contrastive learning at a sequence-level by contrasting between entire text representations. Additionally, we also attempt to enforce each text representation to extract information that is shared across all of its tokens. In particular, we maximize the MI between a text representation and all of its local-level token embeddings to extract the shared information among all the individual words in the text. As a consequence, the information essential to describe texts is preserved in the representations.

MIST handles the substantial challenge of short text clustering, and our contributions are as follows:

- We propose MIST, a multi-stage framework for short text clustering, which integrates two contrastive learning objectives: (1) sequence-level and (2) token-level MI maximization to learn effective short text representations and also be useful for clustering.
- To effectively balance sequence- and token-level MI maximizations, we use a simple dynamic weighting function that adjust the objectives ratio in accordance with the length of subword tokens in each minibatch.
- We conduct an extensive experiment to evaluate the performance of MIST over eight standard benchmarks of short text clustering. MIST improves the clustering performance in terms of Accuracy and NMI for most cases compared to the current state-of-the-art.

2 Related Work

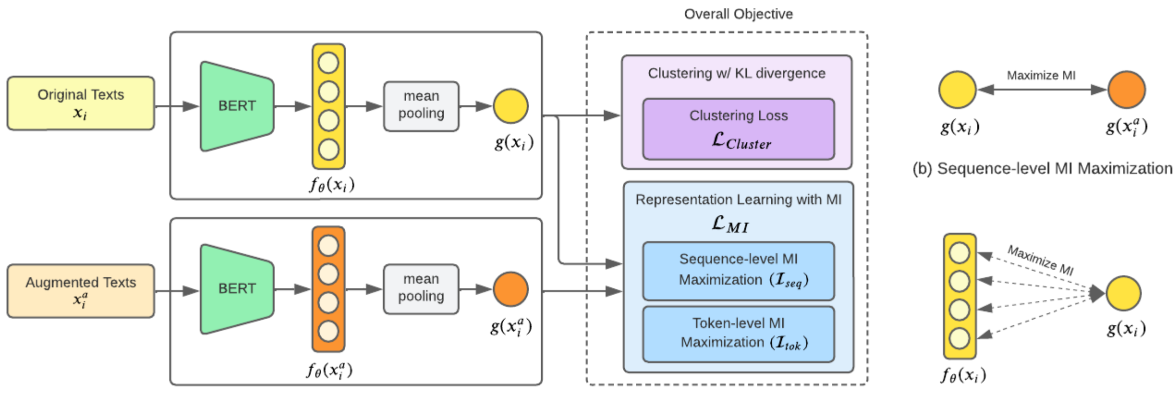
Short Text Clustering. There are a number of approaches to overcome the sparsity of short text representations, such as (1) multi-stage approaches which break down the clustering framework into multiple stages, (2) clustering enhancement algorithms that apply outlier removal, and (3) a joint framework that simultaneously optimizes both representation learning and clustering objectives.

Several multi-stage works perform clustering after learning feature representations. Pretrained-word embeddings (Mikolov et al., 2013a,b; Pennington et al., 2014) and neural networks are adopted to transform data into meaningful representations. Xu et al. (2015, 2017) use a convolutional neural network to learn non-biased deep feature representations by fitting the output units with pretrained-binary codes from a dimensionality reduction method. Hadifar et al. (2019) utilize Smooth Inverse Frequency (SIF) (Arora et al., 2017) to obtain weighted word embeddings. During training, they enrich discriminative features by tuning an autoencoder with soft clustering assignments from a clustering objective. For the aforementioned works, k-means clustering is then employed on trained representations to get the final clusters.

Another direction is to enhance the performance of the initial clustering with an iterative classification algorithm. Rakib et al. (2020) proposed an ECIC algorithm which detects and removes outliers in each iteration. Moreover, they make use of word embeddings by averaging them to represent each text, and combine the ECIC algorithm with hierarchical clustering. To boost the clustering quality further, (Pugachev and Burtsev, 2021) exploit deep sentence representations (Cer et al., 2018) and made modifications to the ECIC algorithm.

The recent state-of-the-art, SCCL (Zhang et al., 2021), leverages a contrastive method from self-supervised learning to encourage greater separation between overlapped categories in the original data space. By jointly optimizing a contrastive loss and a clustering objective (Reimers and Gurevych, 2019a), SCCL outperforms prior works and yields cutting-edge results. In addition, other constrastive learning methods have also been experimented on short-text clustering, such as using entities for contrastive learning to provide supervision signals for their related sentences (Nishikawa et al., 2022), and using virtual augmentation for contrastive learning to circumvent the discrete nature of language (Zhang et al., 2022). However, these methods do not outperform SCCL on short text clustering.

Self-supervised learning. Self-supervision has gained popularity and become a common technique in unsupervised representation learning for a variety of downstream purposes. Many recent accomplishments have been based on contrastive representation learning (Chen et al., 2020; He et al., 2020; Caron et al., 2020; Grill et al., 2020).



(a) Training stage of MIST

(b) Sequence-level MI Maximization

(c) Token-level MI Maximization

Figure 1: (a) The overview of the training stage of MIST. For each pair of original text x_i, and its augmented version x_i^a, MIST simultaneously optimizes the clustering objective $\mathcal{L}_{\text{Cluster}}$, and the MI maximization objectives $\mathcal{L}_{\text{MI}}$. The $\mathcal{L}_{\text{MI}}$ comprises (b) a sequence-level MI maximization objective $\mathcal{I}_{\text{seq}}$, which attempts to maximize MI between sequence representations of x_i and x_i^a, along with (c) a token-level MI maximization objectives $\mathcal{I}_{\text{tok}}$ that maximizes MI between a sequence representation (of both x_i and x_i^a) and its tokens ($f_\theta(x_i)$ and $f_\theta(x_i^a)$).

Learning meaningful representations by estimating and maximizing MI is one of the prominent contrastive learning strategies. Its effectiveness has been demonstrated in both vision (Hjelm et al., 2019; Bachman et al., 2019; Sordoni et al., 2021) and text domains (Kong et al., 2020; Caron et al., 2020; Giorgi et al., 2021). Deep Infomax (DIM) (Hjelm et al., 2019) introduces global and local MI maximization objectives for learning image representations. Each objective is then used separately according to the task. The authors also find success in optimizing local MI maximization objective by maximizing MI between local features and global features. Inspired by local Deep InfoMax, Zhang et al. (2020) proposes a sentence representation learning method that maximizes the MI between the sentence-level representation and its CNN-based n-gram contextual dependencies.

In this work, we leverage the MI maximization strategies to learn text representations specifically for short text clustering. We also investigate a weighting method for appropriately balancing MI objectives in order to improve clustering outcomes.

3 Proposed Method: MIST

In this section, we propose a short text clustering framework consisting of two steps: we first train a model using feature representation learning objectives as illustrated in Figure 1 and then apply the k-means clustering algorithm at inference time. The main idea of our solution lies in the proposed objective function $\mathcal{L}$ that takes into account a MI objective $\mathcal{L}_{\text{MI}}$ that preserves a local invariance for each sample and an unsupervised clustering objective $\mathcal{L}_{\text{Cluster}}$ that captures categorical structure.

$$\mathcal{L} = \beta\mathcal{L}_{\text{MI}} + \eta\mathcal{L}_{\text{Cluster}}, \tag{1}$$

where β and η represent the trade-off between $\mathcal{L}_{\text{MI}}$, and $\mathcal{L}_{\text{Cluster}}$. We set β to 1, and η to 2 to give more weight to $\mathcal{L}_{\text{Cluster}}$.

We describe our proposed method in the following subsections. Section 3.1 provides a description for the MI maximization learning procedure, which includes (1) sequence-level and (2) token-level MI maximization objectives, along with a weighting function for balancing them. Section 3.2 presents the auxiliary clustering objective that enforces the encoder to create a suitable representation space for clustering.

3.1 Representation Learning with MI maximization

One strategy to improve clustering performance is to create an embedding space that minimizes local invariance for each individual sample via representation learning. A prominent method for creating such embedding space is contrastive learning which relies on contrasting representations throughout the whole context (global feature). Short text inputs are varied in terms of their lengths across different datasets. Consequently, there are short-text with smaller size (e.g., 6-8 words), as well as longer texts (e.g., 22-28 words). The latter tends to contain more words that may not be beneficial in defining high-level semantics useful for clustering.

Optimizing merely the global-level objective, as commonly done in contrastive learning, may not be sufficient to train effective representations for short text with weak signals problem.

To prevent local information from being obscured, we adopt an additional learning objective to constrain the representation of the entire text to contain high MI with each of its token embedding. In this investigation, we refer to the global and local features as *sequence* and *token* representations, respectively. Therefore, we build our training framework based on MI maximization strategy to reduce discrepancy between sequence- and token-level representations via their relative ability to predict each other across the representation levels.

Computing the MI Objective. As shown in Figure 1, the objective $\mathcal{L}_{\text{MI}}$ consists of two components: (1) sequence-level MI maximization, $\mathcal{I}_{\text{seq}}$, and (2) token-level MI maximization, $\mathcal{I}_{\text{tok}}$.

$$\mathcal{L}_{\text{MI}} = -(1-\lambda)\mathcal{I}_{\text{seq}} - \lambda\mathcal{I}_{\text{tok}}, \tag{2}$$

where λ corresponds to the balancing weight for $\mathcal{I}_{\text{seq}}$ and $\mathcal{I}_{\text{tok}}$ objectives. We discovered that the number of tokens is an important factor in determining the ratio between the two objectives. In this study, we use a simple function to calculate the weight λ for each minibatch of size N depending on the length of each text:

$$\lambda = \max\left(0, \left\lfloor \frac{0.1}{N}\sum_{i=1}^{N} l_i - 1 \right\rfloor\right), \tag{3}$$

and l_i denotes the number of tokens in a text x_i. Further discussion can be found in section 4.3.1.

In the learning stage, we first randomly sample a minibatch $X^o = x_1^o, ..., x_N^o$ of N original texts with empirical probability distribution $\mathbb{P}$. Then, we generate an augmented version for each text to obtain an augmented batch $X^a = x_1^a, ..., x_N^a$, where X^o and X^a are of identical size. The encoder includes a pretrained transformer network f_θ that encodes an input text x into a sequence of contextualized token embeddings with length l, $f_\theta(x) := \{f_\theta^{(i)}(x) \in \mathbb{R}^d\}_{i=1}^{l}$, where i is the token index and d is the number of dimension. The sequence of token representations are then subsequently averaged by mean pooling operation $m(f_\theta(x))$ to generate a sequence representation denoted as $g(x) = m(f_\theta(x)) \in \mathbb{R}^d$.

Computing the Sequence-level MI. The first learning objective, $\mathcal{I}_{seq}$, aims to learn a representation that captures the entire context by contrasting samples at the sequence-level. According to Tian et al. (2020), contrastive learning is equivalent to maximizing the lower bound of MI between the representations of two texts. By treating each original text $g(x^o)$ and its augmentation $g(x^a)$ as positive samples, we can define $\mathcal{I}_{seq}$ over the whole minibatch as follows.

$$\mathcal{I}_{seq} = \frac{1}{N}\left(\sum_{x\in X} \widehat{\mathcal{I}}^{JSD}(g(x^o); g(x^a))\right) \tag{4}$$

We adopt a Jensen-Shannon estimator (Nowozin et al., 2016; Hjelm et al., 2019) to estimate a lower bound of MI, $\widehat{\mathcal{I}}_\theta^{JSD}$:

$$\begin{aligned}\widehat{\mathcal{I}}_\theta^{JSD}&(g(x^o); g(x^a)) := \\ &E_{\mathbb{P}}\left[-sp(-g(x^o)\cdot g(x^a))\right] \\ &- E_{\mathbb{P}\times\tilde{\mathbb{P}}}\left[sp(g(x^o)\cdot g(\tilde{x}^a))\right],\end{aligned} \tag{5}$$

where $\tilde{x}^a$ is a negative augmented textual input sampled from distribution $\tilde{\mathbb{P}} = \mathbb{P}$, and $sp(z) = \log(1+e^z)$ is the softplus function.

Computing the Token-level MI. To further enrich a text representation, we include a second learning objective, $\mathcal{I}_{tok}$, to MIST. Inspired by Zhang et al. (2020), this learning objective encourages a text representation to incorporate and preserve local information shared across all contextualized tokens. In particular, we attempt to maximize the average MI between a sequence representation and all of its token representations, while minimizing MI with the tokens of other texts. Conceptually, this reflects how much more precisely we can determine the representation of a token given a sequence representation compared to when we are unaware of the sequence representation (Bachman et al., 2019). We now define $\mathcal{I}_{tok}$ for each minibatch as

$$\begin{aligned}\mathcal{I}_{tok} = \frac{1}{2N}\Big(&\\ &\sum_{x^o\in X^o}\sum_{i=1}^{l_{x^o}} \widehat{\mathcal{I}}^{JSD}(g(x^o); f_\theta^{(i)}(x^o))) \\ &+ \sum_{x^a\in X^a}\sum_{i=1}^{l_{x^a}} \widehat{\mathcal{I}}^{JSD}(g(x^a); f_\theta^{(i)}(x^a))).\end{aligned} \tag{6}$$

An estimated MI for each sequence $g(x)$ and token representations $f_\theta^{(i)}(x)$ is as follows:

$$\begin{aligned}\widehat{\mathcal{I}}_\theta^{JSD}&(g(x); f_\theta^{(i)}(x)) := \\ &E_{\mathbb{P}}[-sp(-g(x)\cdot f_\theta^{(i)}(x))] \\ &- E_{\mathbb{P}\times\tilde{\mathbb{P}}}[sp(g(x)\cdot f_\theta^{(i)}(\tilde{x}))],\end{aligned} \tag{7}$$

where $\tilde{x}$ is a different text on the minibatch.

3.2 Clustering with KL divergence

To encourage the coalescence of samples that are most likely to belong to the same cluster, we also employ a clustering objective $\mathcal{L}_{\text{Cluster}}$ along with the MI maximization objective. We follow the clustering method proposed by Xie et al. (2016), which are also used by Hadifar et al. (2019); Yin et al. (2021) and Zhang et al. (2021). This method involves computing soft cluster assignments, and formulating the clustering objective using KL divergence.

For the first step, we follow Xie et al. (2016) using the Student's t-distribution Q to compute a soft cluster assignment for each text instance $x_j \in X$ and the centroid μ_k where $\mu_k \in \{1, ..., K\}$ for the dataset with K-clusters. In particular, we compute the probability q_{jk} of assigning a text x_j to a cluster μ_k as follows.

$$q_{jk} = \frac{(1 + \|g(x_j) - \mu_k\|_2^2 / \alpha)^{-\frac{\alpha+1}{2}}}{\sum_{k'=1}^{K} (1 + \|g(x_j) - \mu_{k'}\|_2^2 / \alpha)^{-\frac{\alpha+1}{2}}} \quad (8)$$

The α symbol represents the degree of freedom of the distribution, and we set α to 1. Following Zhang et al. (2021), each centroid μ_k is approximated by the linear clustering head c_θ.

The second step is calculating an auxiliary target distribution P and utilizing it to assist in refining clusters' centroids. The main idea is to give more importance towards text samples with high clustering confidence. The probability $p_{jk} \in P$ is calculated as follows.

$$p_{jk} = \frac{q_{jk}^2 / \sum_{j'} q_{j'k}}{\sum_{k'} (q_{jk'}^2 / \sum_{j'} q_{j'k'})} \quad (9)$$

In order to match the soft cluster assigments to the target distribution, the KL-divergence between these two probability distributions, P and Q, is calculated as follows.

$$\ell_j^C = KL\left[p_j \| q_j\right] = \sum_{k=1}^{K} p_{jk} \log \frac{p_{jk}}{q_{jk}} \quad (10)$$

We then formulate it as a clustering loss for each minibatch of size N as

$$\mathcal{L}_{\text{Cluster}} = \sum_{j=1}^{N} \ell_j^C / N. \quad (11)$$

4 Experiments

4.1 Experimental Setup

Datasets. We conduct experiments and evaluate the performance of MIST on the eight standard short text clustering datasets, following previous works (Rakib et al., 2020; Zhang et al., 2021; Pugachev and Burtsev, 2021). Dataset descriptions and statistics are shown in Appendix A.1

Implementation. We implement our model in PyTorch (Paszke et al., 2017) and use the *paraphrase-mpnet-base-v2* in Sentence Transformers library (Reimers and Gurevych, 2019b) as the encoder, with a linear clustering head following Zhang et al. (2021). The encoder is trained for 1,200 iterations for all datasets and we use Adam optimizer with the batch size of 256. The learning rate of the encoder and the clustering head are set to 6e−6 and 6e−5, respectively. We follow Xu et al. (2017) and (Hadifar et al., 2019) by randomly select 10% of data as the validation set. Furthermore, we follow Zhang et al. (2021) by not performing any pre-processing operations on any of the eight datasets. Although some of existing works preprocessed the texts by removing symbols, stop words, punctuation or converting them to lowercase.

For the contrastive loss functions in the training stage, we consider original and augmented texts as inputs since we discovered that they are more effective than employing two augmented pairs in our experiment. To generate augmented samples for each text instance, we choose *Contextual Augmenter* (Kobayashi, 2018; Ma, 2019) using BERT and a 20% word substitution ratio. We found that this data augmentation setting can provide the best results as shown in Appendix A.6. We use two standard metrics, the clustering accuracy (ACC) and the normalized mutual information (NMI) to measure the clustering performance. The clustering accuracy is calculated via the Hungarian algorithm and the results are averaged over five trials.

4.2 Experimental Results

We compare the performance of our proposed framework, MIST, with state-of-the-art methods including STCC (Xu et al., 2017), Self-Train (Hadifar et al., 2019), HAC-SD (Rakib et al., 2020), SCA-AE (Yin et al., 2021) and SCCL (Zhang et al., 2021). As demonstrated in Table 1, MIST achieves state-of-the-art results for most cases in terms of Accuracy and NMI across eight benchmark datasets. In addition to the results reported in the reference papers, we further compare our method with SCCL, the state-of-the-art model that also employs contrastive learning for short text clustering, by reproducing SCCL in an end-to-end

	AgNews		SearchSnippets		StackOverflow		Biomedical	
	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
Reported in the references								
BoW†	27.6	2.6	24.3	9.3	18.5	14.0	14.3	9.2
TF-IDF†	34.5	11.9	31.5	19.2	58.4	58.7	28.3	23.2
Skip-Thought‡	-	-	33.6	13.8	9.3	2.7	16.3	10.7
STCC	-	-	77.09	63.16	51.13	49.03	43.62	38.05
Self-Train‡	-	-	77.1	56.7	59.8	54.8	**54.8**	**47.1**
SCA-AE	68.36	34.14	68.71	50.26	76.55	65.99	40.25	33.29
HAC-SD	81.84	54.57	82.69	63.76	64.80	59.48	40.13	33.51
SCCL†	88.2	68.2	**85.2**	**71.1**	75.5	74.5	46.2	41.5
Reimplement								
SCCL w/ BERT 20%	87.10	67.18	84.78	70.02	49.48	47.50	44.90	39.73
SCCL-Multi w/ BERT 20%	86.95	67.06	83.88	69.50	53.56	46.99	44.70	39.65
Proposed Method								
MIST	**89.47**	**70.25**	76.72	67.69	**78.74**	**77.59**	39.15	34.66

	Tweet		GoogleNews-TS		GoogleNews-T		GoogleNews-S	
	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
Reported in the references								
BoW†	49.7	73.6	57.5	81.9	49.8	73.2	49.0	73.5
TF-IDF†	57.0	80.7	68.0	88.9	58.9	79.3	61.9	83.0
Skip-Thought‡	-	-	-	-	-	-	-	-
STCC	-	-	-	-	-	-	-	-
Self-Train‡	-	-	-	-	-	-	-	-
SCA-AE	84.85	89.19	-	-	-	-	-	-
HAC-SD	89.62	85.20	85.76	88.00	**81.75**	84.20	80.63	83.50
SCCL†	78.2	89.2	89.8	94.9	75.8	88.3	**83.1**	90.4
Reimplement								
SCCL w/ BERT 20%	55.98	82.12	75.35	90.96	62.53	81.95	67.88	86.07
SCCL-Multi w/ BERT 20%	79.05	89.59	88.83	94.69	76.20	87.89	82.25	90.01
Proposed Method								
MIST	**91.75**	**95.12**	**89.93**	**95.47**	75.97	**88.97**	81.91	**90.79**

Table 1: Experimental results on eight short text clustering datasets. † and ‡ refer to results taken from Zhang et al. (2021) and Hadifar et al. (2019), respectively; both originally present their results in one decimal place.

(original) as well as a multi-stage version analogous to our architecture for fair comparison. The reimplemented versions of SCCL employ the same augmentation setting as our model. We refer to these model as SCCL w/ BERT 20% and SCCL-Multi w/ BERT 20%, respectively. The comparative results in Table 1 show that MIST outperforms SCCL, SCCL w/ BERT 20% and SCCL-Multi w/ BERT 20% in 11, 12 and 10 cases, respectively.

For datasets with small number of clusters, Search Snippets and Biomedical, MIST does not yield competitive results. We obtain a weaker result on Biomedical, since the dataset used to pretrain our encoder is a general domain one. On the other hand, Hadifar et al. (2019) produces the best result using pretrained embeddings learned from a large in-domain biomedical corpus. For the SearchSnippets dataset, MIST also obtains a poorer result. One probable explanation is that snippets are typically composed of content words, as well as the dataset has been automatically crawled and preprocessed further by Phan et al. (2008), the preprocessing steps include removing stop and rare words. Due to the length and incoherency of each text in this dataset, our algorithm becomes dependent on keywords rather than contextual information. Particularly, when it performs the token-level MI maximization objective in the representation learning stage, which enforces similarity between each contextualized token representation and the sequence representation of the incoherent text sequence. This can be problematic when the same keywords also appear in different clusters.

For datasets with a large number of clusters, such as GoogleNews, it is more likely that texts in different clusters may share a similar content due to fine-grained categorization, inducing ambiguity. We conjecture that this ambiguity in textual data and ground-truths is causing inaccurate predictions. As GoogleNews-T only contains news headlines, which are relatively short with few keywords. It presents a challenge for clustering these texts into a large number of categories. For example, "`liam adam sentenced abuse daughter`" is a

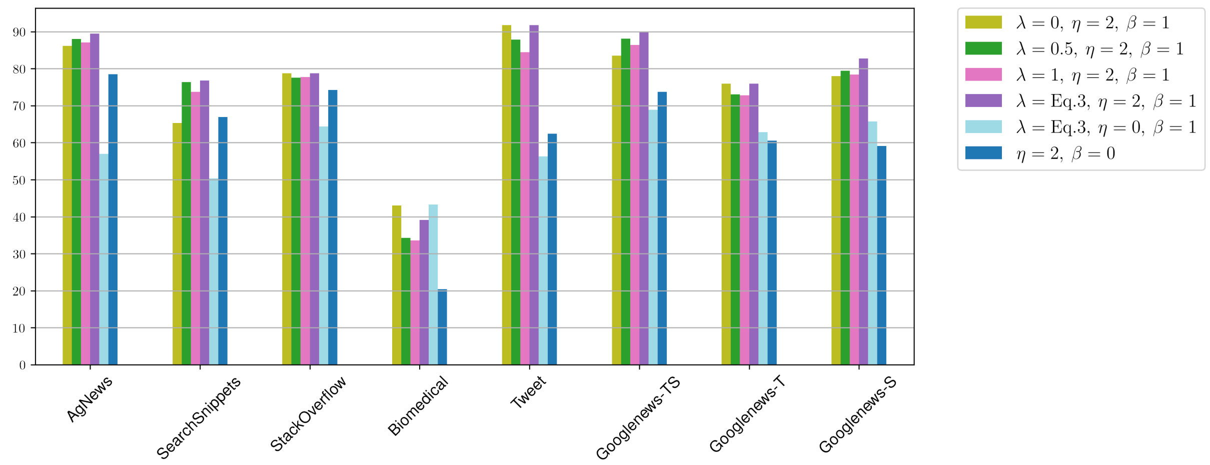


Figure 2: Accuracy for six different settings including four different weighting ratios between sequence- and token-level MI maximization objectives. As well as, a setting where a clustering loss is absent ($\eta = 0$), and a setting where an MI loss is absent ($\beta = 0$). Note that when we set β to 0, λ has no effect.

news headline in a cluster of news related to Gerry Adams, an IRA activist and the former president of Sinn Féin. This sample contains same keywords found in another cluster with news about domestic violence. Another cause of inaccuracy is when the content of texts in one cluster is a subtopic of the content in another cluster.

We hypothesize that Rakib et al. (2020), which employs hierarchical clustering and outlier removal algorithms, can better deal with hierarchical nature of data. Consequently, Rakib et al. (2020) outperforms our method and SCCL on this scenario in terms of Accuracy on this dataset. While our method and SCCL both aim to improve representations through the use of contrastive representation learning. As shown in Table 1, MIST also has lower Accuracy on GoogleNews-T and GoogleNews-S than the reported result of SCCL in the reference paper and SCCL-Multi w/ BERT 20%, respectively. Where we collected the experimental results of SCCL w/ BERT 20% and SCCL-Multi w/ BERT 20% from the best iteration for each dataset instead of using a stopping criterion, which is also not mentioned in Zhang et al. (2021).

Although GoogleNews-S and GoogleNews-TS share the same challenges as GoogleNews-T, clustering texts in both datasets is more accurate due to the benefit of additional context and information in the texts themselves. MIST can derive a very strong and comparable Accuracy to SCCL on GoogleNews-S and outperforms SCCL on GoogleNews-TS. This is because, GoogleNews-S contains text snippets of Google News, and GoogleNews-TS includes both the titles and snippets.

Additional details and the comparison results of SCCL in both reproduced versions with other augmentation settings can be found in the A.5. According to the results in A.5, our method still outperforms SCCL in both end-to-end and multi-phase settings in 11 cases.

4.3 Ablation Study

To better understand the impact of each component in our training procedure on the clustering performance, we conduct additional experiments by varying the ratio setting between sequence- and token-level MI maximization objectives in the MI loss $\mathcal{L}_{\text{MI}}$, as well as the clustering objective $\mathcal{L}_{\text{Cluster}}$.

4.3.1 The effects of sequence- and token-MI maximization objectives

Let us consider the effects of sequence- and token-level MI maximization objectives on the clustering performance. We report the performance of our model in four different ratios by setting λ in Eq.2 to 1, 0.5, 0, and also assigning the value to λ using Eq. 3. In this section, we refer to the MIST model with a sequence-only MI maximization ($\lambda = 0$) and a token-only ($\lambda = 1$) MI maximization objectives as MIST-seq and MIST-tok, respectively. As demonstrated in Figure 2, MIST with the ratio set according to Eq.3 yields the best performance in terms of Accuracy, except for Biomedical. NMI tends to follow the same direction as Accuracy, as demonstrated in Appendix A.2. This indicates that the length of texts (the amount of token embeddings) is a major consideration in the selection of appropriate ratios between both MI maximization objectives. In addition, we also investigate the scenario when both MI objectives are absent ($\beta = 0$). The ablation results reveal that when both MI maximization objectives are removed, the performance suffers substantially on all datasets. This shows that the MI loss is necessary for performance gain.

For datasets with long-length texts, such as GoogleNews-TS, we discovered that MIST produces the best outcomes when token- and sequence-level MI maximization objectives are weighted using λ calculated by Eq. 3. Note that this setting also outperforms the scenario when both objectives are assigned the same weight ($\lambda = 0.5$). We can also see that MIST-tok always outperforms MIST-seq. This shows that if the text is lengthy, MIST-seq may not be sufficient. This is because informative terms of the text are averaged with other non-informative terms via mean pooling. Since infrequent keywords in the text are more likely to be overlooked, maximizing each local token embeddings with its sequence representation helps alleviate this problem.

For datasets with very short-length texts, such as StackOverflow and Tweet, the weighting ratio based on Eq. 3 is equivalent to setting λ to 0. In this situation, MIST is identical to MIST-seq. MIST-seq outperforms other settings, followed by MIST with integrating the seq- and token-level MI maximization objectives which always performed better than MIST-tok. For instance, texts in the Tweet dataset are relatively short and contains solely content words rather than coherent texts. As a result, our model with token-level MI maximization objective, MIST-tok and MIST with the combination of token- and sequence-MI maximization objectives, might emphasize on keywords that could also appear in multiple clusters, causing ambiguity.

4.3.2 The effects of soft cluster assigments

As shown in Figure 2, the clustering performance drops significantly when we remove the clustering with KL divergence objective ($\eta = 0$). This demonstrates that the categorical structure imposed by simultaneously optimizing the clustering loss with the representation learning objectives is a crucial component that boosts performance. However, this trend holds true for all datasets, except for Biomedical. One possible explanation is that, since the encoder was not pretrained with textual information which was suitable for its specific domain, the clustering loss does not benefit the efficiency of our model than the representation objectives.

Furthermore, we observe that as the weight of clustering increases, the performance continuously improves until it reaches saturation as η, the weight for the clustering loss, approaches 2. As depicted in Figure 3, the accuracy and NMI of AgNews both improve as we gradually increase the clustering weight until the appropriate value, which is 2 in our experiment. The supplementary experimental results can be found in Appendix A.4.

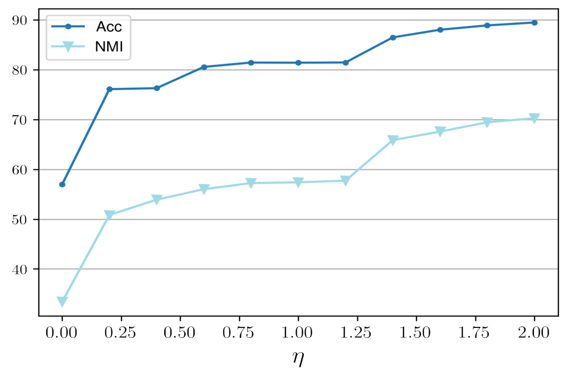


Figure 3: The clustering performance on AgNews based on the strength of the clustering loss. The strength of both MI maximization objectives are kept constant based on Eq. 3

5 Conclusion

We propose a novel multi-stage framework that employs two contrastive learning objectives based on MI maximization methods to produce effective representations for short texts. To learn distinct text representations, the first contrastive learning objective maximizes MI between original texts and their augmentations at the sequence level. And the second objective maximizes MI between sequence representations and their local tokens. Additionally, we introduce a preliminary weighting function for properly balancing the two MI maximization objectives during training process.

We have conducted extensive experiments across eight benchmark datasets for short text to study the effectiveness of our method. Our model outperforms state-of-the-art methods in most cases on Accuracy and NMI. This demonstrates that utilizing the MI maximization strategy during the contrastive learning process could potentially be a promising tactic. Further study would be worthwhile since it might enhance the quality of textual representations for other tasks

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A Appendices

A.1 Datasets

Following previous works, we conduct experiments and evaluate the performance of our model on the eight short text clustering datasets. These datasets only contain texts in English. All of them are publicly available online. A summary of the statistics of all datasets is listed in Table 2.

- **AgNews**: a subset of the dataset of English news titles (Zhang and LeCun, 2015) across 4 different topics, where 2,000 samples from each topic were randomly chosen by Rakib et al. (2020).
- **SearchSnippets**: a dataset comprising 12,340 web search snippets from 8 different categories (Phan et al., 2008).
- **Biomedical**: 20,000 paper titles, from 20 different Medical Subject Headings (MeSH), randomly selected by Xu et al. (2017) from the PubMed data distributed by BioASQ3.
- **StackOverflow**: challenge data published on Kaggle and randomly chosen by Xu et al. (2017), which consists of 20,000 question titles from Stack Overflow related to 20 distinct tags.
- **Tweet**: a dataset comprising 2,472 tweets with 89 groups (Yin and Wang, 2016).
- **GoogleNews**: a collection of both titles and text snippets from 11,109 news articles covering 152 events (Yin and Wang, 2016). Only the titles and the text snippet of each news article were extracted out of the GoogleNews-TS to produce GoogleNews-T and GoogleNews-S, respectively.

We spend up to 14 GPU hours on a Tesla V100 32G GPU to complete the training on all datasets for each MIST model's configuration.

Dataset	$N^{Cluster}$	N^{Doc}	N^{Word}
AgNews	4	8,000	23
SearchSnippets	8	12,340	18
Biomedical	20	20,000	13
StackOverflow	20	20,000	8
Tweet	89	2,472	8
Googlenews-TS	152	11,109	28
Googlenews-T	152	11,109	6
Googlenews-S	152	11,109	22

Table 2: Dataset statistics. $N^{Cluster}$: number of clusters; N^{Doc}: number of short text documents; N^{Word} : average number of words in each document

A.2 The effects of sequence- and token-MI maximization objectives on NMI

Figure 4 shows the effects of sequence- and token-MI maximization objectives on NMI. It follows the same trend as Accuracy as discussed in Section 4.3.1.

A.3 Positive Pairs in Constrastive Learning

It is a common practice in contrastive learning frameworks to only consider augmented data as inputs, excluding an original sample. However, we adopt a different input scheme. We discovered that feeding both original and augmented samples into our contrastive learning framework (as shown in Figure 1) yields better clustering results than exclusively taking two augmented texts as an input pair. One probable explanation is that when augmented texts are created, the augmenter replaces some keywords in original texts with new words. Since short texts are typically short and include few keywords, the absence of crucial words required for text categorization has an impact on clustering performance.

A.4 The impact of soft cluster assignments

As discussed in Section 4.3.2, the clustering performance is substantially affected by varying the weight of the clustering objective during training representations process. Table 3 presents the performance of MIST across eight datasets in three situations, i.e., the coefficient of the clustering objective, η, in Eq.1 is assigned to 0, 1, and 2. The optimal results for the majority in terms of ACC and NMI are provided by MIST when η is set to 2.

A.5 SCCL Reimplementation

To thoroughly compare the performance of our contrastive learning strategy against SCCL, an existing

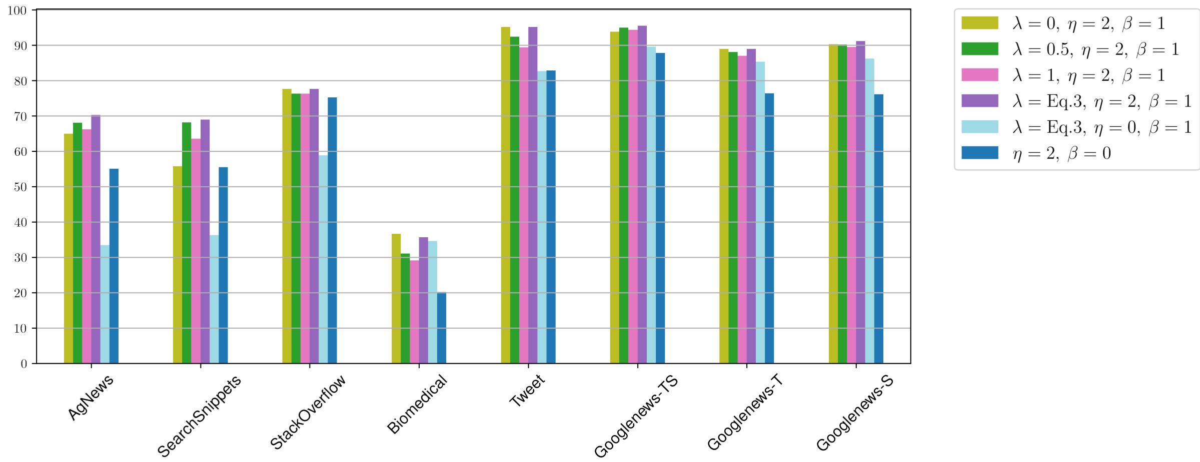

Figure 4: NMI for six different settings including four different weighting ratios between sequence- and token-level MI maximization objectives. As well as, a setting where a clustering loss is absent ($\eta = 0$), and a setting where an MI loss is absent ($\beta = 0$). Note that when we set β to 0, λ has no effect.

	AgNews		**SearchSnippets**		**StackOverflow**		**Biomedical**	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
MIST w/ $\eta = 0$	56.96	33.40	50.30	36.30	64.40	58.80	43.26	34.55
MIST w/ $\eta = 1$	81.40	57.39	70.99	56.90	76.41	71.92	47.66	40.34
MIST w/ $\eta = 2$	89.47	70.25	76.72	67.69	78.74	77.59	39.15	34.66

	Tweet		**GoogleNewsTS**		**GoogleNewsT**		**GoogleNewsS**	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
MIST w/ $\eta = 0$	56.27	82.64	68.89	89.59	62.85	85.28	65.74	86.16
MIST w/ $\eta = 1$	64.46	86.27	74.86	91.89	66.91	87.04	71.98	88.58
MIST w/ $\eta = 2$	91.75	95.12	89.93	95.47	75.97	88.97	81.91	90.79

Table 3: The clustering results of MIST on three different weights of the clustering objective, η.

contrastive learning method for short-text clustering, we reproduced SCCL in both original version and a multiple-stage version (SCCL-Multi), by applying the k-means algorithm on top of SCCL representations to make their pipeline identical to our framework. We followed Zhang et al. (2021) and used *Contextual Augmenter*, which was reported to offer the best results, to generate augmented texts for all training frameworks in this experiment. In the reference paper, SCCL considers *Contextual Augmenter* with three configurations by setting the word substitution ratio of each text instance to 10%, 20%, and 30%. But their study does not identify which configuration for Contextual Augmenter setting produces the best outcomes. Therefore, we examine SCCL-Multi with three alternative masked language models: BERT-base, RoBERTa and DistilBERT for augmented pairs generation to covers all scenarios.

Table 4 reports the best clustering results for SCCL and SCCL-Multi in all configurations obtained during maximum iteration, as well as the best results for SCCL produced using the Contextual Augmenter presented in Zhang et al. (2021). The percentage of word replacement and masked language models employed for augmented text generation have an impact on the clustering performance of SCCL-Multi, since the best setting for these two parameters varies across datasets. Our contrastive learning approach outperforms both SCCL-Multi and SCCL with the best augmentation parameters settings in 6 out of 8 datasets.

A.6 Exploration of Data Augmentations

According to Zhang et al. (2021), we investigate the impact of the *Contextual Augmenter* configurations in terms of masked language models and substitution percentage, respectively. As shown in Table 5, we found that MIST using augmented texts generated from the BERT model with 20% substitution rate during training step yields the best overall performance. MIST with augmented texts produced by other encoders with 20% substitution rate also yield the outcomes close to those of BERT with the same substitution rate.

A.7 Limitations

Despite the state-of-the-art performance, there are several limitations, which we highlight in this section. Firstly, the backbone of our model is pretrained using general domain data. Hence, when our model encounters short texts in a specific domain, such as Biomedical, the performance drops drastically. Furthermore, our representation learning procedure also performs poorly on short texts with only content words or incoherent text sequences. Learning representations for incoherent texts, by incorporating token-level MI maximization objective, forces a sequence representation to resemble each individual token embedding. For short-texts with incoherent text, the token-level MI maximization objective gives no further improvement. This constraint should be taken into account in future research.

Another limitation of our framework is that augmented samples are crucial for the learning process according to the general operation principle of contrastive learning. However, the best augmentation strategy is still a subject of discussion and exploration. A study in SCCL and comparison results of our model with several augmentation settings demonstrate that varied augmenter as well as different configuration factors have an on clustering performance Additionally, even if the technique and the parameters used to generate augmented texts are exactly the same, there is a possibility that the outcomes from the two trials may vary, adding a variance to the performance results.

	AgNews		SearchSnippets		StackOverflow		Biomedical	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
SCCL (in the reference paper)	88.20	68.20	85.20	71.10	75.50	74.50	46.20	41.50
SCCL w/ BERT 10%	87.20	66.94	83.70	70.05	71.40	71.28	46.00	40.06
SCCL-Multi w/ BERT 10%	87.2	66.94	83.40	69.88	77.30	73.76	46.00	40.13
SCCL w/ BERT 20%	87.10	66.91	84.40	69.58	64.20	56.23	46.40	40.39
SCCL-Multi w/ BERT 20%	87.10	66.80	83.60	69.28	60.02	52.22	45.50	40.07
SCCL w/ BERT 30%	87.50	67.46	83.70	68.54	60.70	52.18	42.40	38.14
SCCL-Multi w/ BERT 30%	87.50	67.45	82.60	66.45	60.90	52.29	42.30	37.95
SCCL w/ RoBERTa 10%	87.00	66.57	84.50	70.21	62.10	54.26	28.50	20.35
SCCL-Multi w/ RoBERTa 10%	87.00	66.55	84.10	70.14	61.40	53.05	28.50	20.34
SCCL w/ RoBERTa 20%	85.20	64.20	62.60	41.66	60.70	52.26	39.60	32.66
SCCL-Multi w/ RoBERTa 20%	85.10	64.24	72.00	51.23	60.09	52.31	38.40	38.40
SCCL w/ RoBERTa 30%	84.00	62.24	30.70	10.07	60.70	52.28	39.10	32.77
SCCL-Multi w/ RoBERTa 30%	84.00	62.26	30.70	10.05	60.90	52.44	39.50	32.63
SCCL w/ DistilBERT 10%	87.30	67.16	84.70	70.79	70.20	69.49	46.10	39.87
SCCL-Multi w/ DistilBERT 10%	87.30	67.16	84.50	70.64	72.10	68.20	46.20	39.92
SCCL w/ DistilBERT 20%	86.80	65.87	84.70	70.62	71.40	69.38	46.30	39.94
SCCL-Multi w/ DistilBERT 20%	86.80	65.87	84.20	70.45	72.20	70.84	46.40	40.01
SCCL w/ DistilBERT 30%	87.20	66.77	85.00	71.63	70.80	70.04	46.30	40.49
SCCL-Multi w/ DistilBERT 30%	87.20	66.75	84.60	71.35	76.50	72.57	46.40	40.58

	Tweet		GoogleNews-TS		GoogleNews-T		GoogleNews-S	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
SCCL (in the reference paper)	78.20	89.20	89.80	94.90	75.80	88.30	83.10	90.40
SCCL w/ BERT 10%	56.80	81.91	70.10	89.49	62.50	81.53	69.00	86.29
SCCL-Multi w/ BERT 10%	75.30	88.39	86.70	93.95	76.30	88.25	81.00	89.82
SCCL w/ BERT 20%	57.10	82.54	75.60	90.99	63.00	81.72	67.80	85.97
SCCL-Multi w/ BERT 20%	78.20	89.41	88.70	94.70	76.20	87.97	81.10	89.60
SCCL w/ BERT 30%	56.6	82.23	74.2	90.83	61.30	81.20	64.9	89.78
SCCL-Multi w/ BERT 30%	78.80	89.58	89.90	94.91	75.60	87.88	82.10	89.77
SCCL w/ RoBERTa 10%	56.00	79.89	73.60	90.46	55.60	78.08	65.50	85.26
SCCL-Multi w/ RoBERTa 10%	71.10	85.86	86.60	93.94	56.90	78.52	80.50	89.50
SCCL w/ RoBERTa 20%	56.80	79.56	74.90	90.37	55.60	78.08	66.90	85.38
SCCL-Multi w/ RoBERTa 20%	74.20	86.61	88.10	94.27	58.40	79.28	81.30	89.87
SCCL w/ RoBERTa 30%	53.80	78.47	71.80	71.80	55.60	78.42	65.30	83.99
SCCL-Multi w/ RoBERTa 30%	63.60	76.98	85.20	93.53	56.60	78.42	78.00	88.14
SCCL w/ DistilBERT 10%	56.10	80.87	72.70	90.03	61.40	80.94	69.60	85.81
SCCL-Multi w/ DistilBERT 10%	78.80	88.91	87.70	94.25	74.30	87.78	79.70	89.20
SCCL w/ DistilBERT 20%	56.40	80.28	71.70	90.04	61.30	81.19	67.70	86.02
SCCL-Multi w/ DistilBERT 20%	77.10	88.61	86.50	94.03	75.10	87.51	79.50	89.70
SCCL w/ DistilBERT 30%	56.60	81.65	72.10	90.18	62.00	81.09	66.50	85.48
SCCL-Multi w/ DistilBERT 30%	76.00	88.39	88.50	94.18	75.80	87.60	79.10	89.01

Table 4: The clustering performances of the reimplemented SCCL and SCCL-Multi with nine different configurations for Contextual Augmenter. These configurations are obtained by setting the word substitution ratio of each text instance to 10% , 20%, and 30%, as well as using three alternative masked language models: BERT-base, RoBERTa, and DistilBERT.

	AgNews		SearchSnippets		StackOverflow		Biomedical	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
MIST w/ BERT 10%	87.74	66.99	75.98	67.71	77.78	76.42	37.51	33.97
MIST w/ BERT 20%	89.47	70.25	76.72	67.69	78.74	77.59	39.15	34.66
MIST w/ BERT 30%	86.33	66.09	81.46	67.71	73.60	71.55	39.79	34.61
MIST w/ RoBERTa 10%	87.51	66.81	75.64	67.11	77.84	76.50	38.61	35.11
MIST w/ RoBERTa 20%	88.85	69.12	76.21	68.52	77.74	76.41	37.17	31.62
MIST w/ RoBERTa 30%	86.43	66.4	73.77	65.72	77.76	77.03	29.48	27.38
MIST w/ DistilBERT 10%	87.22	66.44	74.96	65.89	77.67	76.30	38.29	34.29
MIST w/ DistilBERT 20%	89.42	70.26	75.74	67.85	77.72	77.05	38.29	32.31
MIST w/ DistilBERT 30%	87.96	67.66	74.23	64.11	77.67	76.34	38.83	34.63

	Tweet		GoogleNews-TS		GoogleNews-T		GoogleNews-S	
	ACC	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**	**ACC**	**NMI**
MIST w/ BERT 10%	88.76	93.04	86.65	94.76	72.41	87.99	76.56	89.3
MIST w/ BERT 20%	91.75	95.12	89.93	95.47	75.97	88.97	81.91	90.79
MIST w/ BERT 30%	90.07	94.14	89.28	94.98	75.63	88.55	80.74	89.99
MIST w/ RoBERTa 10%	88.18	92.64	85.85	94.48	73.68	88.00	77.89	89.52
MIST w/ RoBERTa 20%	90.97	94.67	90.10	95.35	74.61	88.27	77.62	90.00
MIST w/ RoBERTa 30%	83.40	95.15	88.29	96.20	70.27	88.24	78.43	89.82
MIST w/ DistillBERT 10%	85.48	92.24	85.15	94.42	75.89	88.51	77.55	89.69
MIST w/ DistillBERT 20%	91.24	94.99	90.16	95.43	74.14	88.53	82.54	90.69
MIST w/ DistillBERT 30%	86.56	92.50	85.85	94.46	75.57	88.50	77.18	89.52

Table 5: The clustering performance of MIST when feeding augmented texts generated by Contextual Augmenter with nine different configurations as inputs.