# Virtual Augmentation Supported Contrastive Learning of Sentence Representations

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## **Abstract**

Despite profound successes, contrastive representation learning relies on carefully designed data augmentations using domain specific knowledge. This challenge is magnified in natural language processing where no general rules exist for data augmentation due to the discrete nature of natural language. We tackle this challenge by presenting a Virtual augmentation Supported Contrastive Learning of sentence representations (VaSCL). Originating from the interpretation that data augmentation essentially constructs the neighborhoods of each training instance, we in turn utilize the neighborhood to generate effective data augmentations. Leveraging the large training batch size of contrastive learning, we approximate the neighborhood of an instance via it's K-nearest in-batch neighbors in the representation space. We then define an instance discrimination task within this neighborhood, and generate the virtual augmentation in an adversarial training manner. We access the performance of VaSCL<sup>1</sup> on a wide range of downstream tasks, and set a new state-of-the-art for unsupervised sentence representation learning.

# 1 Introduction

Universal sentence representation learning has been a long-standing problem in Natural Language Processing (NLP). Leveraging the distributed word representations (Bengio et al., 2003; Mikolov et al., 2013; Collobert et al., 2011; Pennington et al., 2014) as the base features to produce sentence representations is a common strategy in the early stage. However, these approaches are tailored to different target tasks, and thereby yielding less generic sentence representations (Yessenalina and Cardie, 2011; Socher et al., 2013; Kalchbrenner et al., 2014; Cho et al., 2014).

This issue has motivated more research efforts on designing generic sentence-level learning objectives or tasks. Among them, supervised learning on the Natural Language Inference (NLI) datasets (Bowman et al., 2015a; Williams et al., 2017; Wang et al., 2018) has established benchmark transfer learning performance on various downstream tasks (Conneau et al., 2017; Cer et al., 2018; Reimers and Gurevych, 2019a; Zhang et al., 2021). Despite promising progress, the high cost of collecting annotations precludes its wide applicability, especially in the scenario where the target domain has scarce annotations, but differs significantly from the NLI dataset (Zhang et al., 2020).

On the other hand, unsupervised learning of sentence representations has seen a resurgence of interest with the recent successes in self-supervised contrastive learning. These approaches rely on two main components, data augmentations and an contrastive loss that aims to separate each instance and its augmentations apart from the others. The popular contrastive learning objectives Chen et al. (2020); He et al. (2020) and their variants thereof, have empirically shown their effectiveness in NLP. However, the discrete nature of text makes it challenging to establish universal rules for generating effective augmentations.

Various contrastive learning based approaches have been proposed for learning sentence representations, with the main difference lies in how the augmentations are generated (Fang and Xie, 2020; Giorgi et al., 2020; Wu et al., 2020; Meng et al., 2021; Yan et al., 2021; Kim et al., 2021; Gao et al., 2021). Somewhat surprisingly, a recent work (Gao et al., 2021) empirically shows that augmentations obtained by Dropout (Srivastava et al., 2014), *i.e., feeding the same instance to the encoder twice*, outperforms common text augmentation operations on the text directly, including cropping, word deletion, or synonym replacement. On the other side of the coin, this observation again validates the

<sup>&</sup>lt;sup>1</sup>The code will be released at https://github.com/amazon-research/sentence-representations.

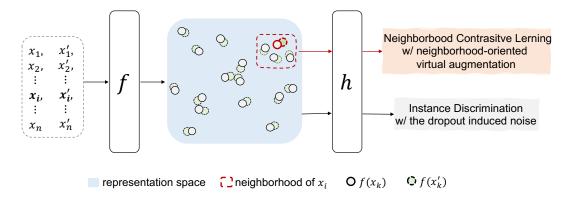


Figure 1: Illustration of VaSCL. For each instance  $x_i$  in a randomly sampled batch, we optimize (i) an instance discrimination loss with Dropout (Srivastava et al., 2014) induced augmentations obtained by forwarding the same instance twice, *i.e.*,  $x_i$  and  $x_{i'}$  denote the same text example; and (2) a neighborhood contrastive loss with the neighborhood-oriented virtual augmentations proposed in Section 3.2.

inherent difficulty of data augmentations in NLP.

In this paper, instead of relying on explicit operations on the discrete text, we tackle the challenge by presenting a neighborhood guided virtual augmentation strategy to support contrastive learning. In a nutshell, data augmentation essentially constructs the neighborhoods of each instance, with the semantic content being preserved. We take this interpretation in the opposite direction by leveraging the neighborhood of an instance to generate augmentations. Benefiting from the large training batch of contrastive learning, we approximate the neighborhood of an instance via it's K-nearest in-batch neighbors. We then define an instance discrimination task within this neighborhood, and generate the virtual augmentation in an adversarial training manner. We evaluate our model on a wide range of downstream tasks, and show that our model consistently outperform the previous stateof-the-art results by a considerable margin.

#### 2 Related Work

Universal Sentence Representation Learning Arguably, the simplest and most common approach for attaining sentence representations are bag-of-words (Harris, 1954) and variants thereof. However, bag-of-words suffers from data sparsity and lack of sensibility to word semantics. In the past two decades, the distributed word representations (Bengio et al., 2003; Mikolov et al., 2013; Collobert et al., 2011; Pennington et al., 2014) has become the more effective base features for producing sentence representations. The downside is these approaches are tailored to different target tasks (Yessenalina and Cardie, 2011; Socher et al.,

2013; Kalchbrenner et al., 2014; Cho et al., 2014), hence the resulting sentence representations attain limited transfer learning performance.

More recent efforts focus on designing generic sentence-level learning objectives or tasks. On the supervised learning regime, Conneau et al. (2017); Cer et al. (2018) empirically show the effectiveness of leveraging the NLI task (Bowman et al., 2015a; Williams et al., 2017) to promote generic sentence representations. The task involves classifying each sentence pair into one of three categories: entailment, contradiction, or neutral. Reimers and Gurevych (2019b) further boost the performance by using the pre-trained transformer (Devlin et al., 2018; Liu et al., 2019) as backbone. On the other end of spectrum, Hill et al. (2016); Bowman et al. (2015b) propose a denoising (or variational) autoencoder based model for sentence representation learning. Kiros et al. (2015); Hill et al. (2016) extend the distributional hypothesis to the sentencelevel, and train an encoder-decoder to construct surrounding context for each sentence. Alternatively, Logeswaran and Lee (2018) present a model that learns to discriminate the target context sentences from all contrastive ones.

Contrastive Learning Contrastive learning has been the pinnacle of recent successes in sentence representation learning. Gao et al. (2021); Zhang et al. (2021) substantially advance the previous state-of-the-art results by leveraging the entailment sentences as positive pairs for optimizing the contrastive loss. Nevertheless, we focus on unsupervised contrastive learning and form the positive pairs via data augmentation, since such methods are more cost-effective and applicable across different

domains and languages. Along this line, many approaches have been developed recently, where the augmentations are obtained via sampling from surrounding or nearby contexts (Logeswaran and Lee, 2018; Giorgi et al., 2020), word or feature-level perturbation (Wu et al., 2020; Yan et al., 2021), back-translation (Fang and Xie, 2020), sentence-level corruption using an auxiliary language model (Meng et al., 2021), intermediate representations of BERT (Kim et al., 2021), and dropout (Yan et al., 2021; Gao et al., 2021).

Consistency Regularization Our work is also closely related to consistency regularization, which is often used to promote better performance by regularizing the model output to remain unchanged under plausible variations that are often induced via data augmentations. Bachman et al. (2014); Sajjadi et al. (2016); Samuli and Timo (2017); Tarvainen and Valpola (2017) show randomized data augmentation such as dropout, cropping, rotation, or flipping yield effective regularization. Berthelot et al. (2019, 2020); Verma et al. (2019) bolster the performance by applying Mixup (Zhang et al., 2017) and its variants on top of stochastic data augmentations. However, data augmentation has long been a challenging problem in NLP as there is no universal rules for effective text transformations with the semantic content being preserved.

An alternative come to light when one considers the violation of consistency regularization can in turn be used to find the virtual augmentation that the model is most sensitive to. In this paper, we utilizing the consistency regularization to promote strong augmentation for an instance, while leveraging its approximated neighborhood to generate valid augmentations that share the same semantic content.

### 3 Method

#### 3.1 Preliminaries

Self-supervised contrastive learning aims to solve an instance discrimination task. Let f denote the transformer encoder that maps the  $i^{\text{th}}$  input sentence  $\mathbf{x}_i$  to its representation vector  $\mathbf{e}_i = f(\mathbf{x}_i)^2$ . Further let h be the contrastive learning head and  $\mathbf{z}_i = h(f(\mathbf{x}_i))$  denote the final output for  $\mathbf{x}_i$ . Let  $\mathcal{B} = \{i, i'\}_{i=1}^M$  indicates the indices of a randomly

sampled batch of paired examples, where  $\mathbf{x}_i$ ,  $\mathbf{x}_{i'}$  denote two independent variations of the  $i^{\text{th}}$  instance. A popular loss function (Chen et al., 2020) for contrastive learning is the following,

$$\ell_{\mathcal{B}}(\mathbf{z}_{i}, \mathbf{z}_{i'}) = \frac{e^{\sin(\mathbf{z}_{i}, \mathbf{z}_{i'})/\tau}}{e^{\sin(\mathbf{z}_{i}, \mathbf{z}_{i'})/\tau} + \sum_{j \in \mathcal{B} \setminus (i, i')} e^{\sin(\mathbf{z}_{i}, \mathbf{z}_{j})/\tau}},$$
(1)

where  $\tau$  is the temperature hyper-parameter and  $\mathbf{s}(\cdot)$  is chosen as the cosine similarity, *i.e.*,  $\mathbf{s}(\cdot) = \mathbf{z}_i^T \mathbf{z}_{i'} / \|\mathbf{z}_i\|_2 \|\mathbf{z}_{i'}\|_2$ . Notice that,  $\ell_{\mathcal{B}}(\mathbf{z}_{i'}, \mathbf{z}_i)$  is defined similarly as above by exchanging the roles of  $\mathbf{z}_i$  and  $\mathbf{z}_{i'}$ . Intuitively, Equation (1) defines the log-likelihood of classifying  $\mathbf{z}_i$  as  $\mathbf{z}_{i'}$  among all 2M-1 candidates. In other words, minimizing the above log-loss guides the encoder to map each positive pair close in the representation space, and negative pairs further apart.

**Dropout based contrastive learning** As indicated in Equation (1), the success of contrastive learning relies on effective positive pairs design. In computer vision, positive pairs generated by heavy data augmentations have shown to be essential to the top-performing contrastive learning models (Chen et al., 2020; He et al., 2020). However, it's difficult to generate effective data augmentations in NLP due to the discrete nature of natural language. On the other hand, a recent work (Gao et al., 2021) shows that augmentations obtained by Dropout (Srivastava et al., 2014), i.e.,  $\mathbf{z}_i$ ,  $\mathbf{z}_{i'}$  obtained by forwarding the same instance  $x_i$  twice, outperforms the common text augmentation strategies such as cropping, word deletion, or synonym replacement.

Dropout provides a natural way for data augmentation by randomly masking its inputs or the hidden layer nodes. The effectiveness of using Dropout as pseudo data augmentations can be traced back to the early work Bachman et al. (2014); Samuli and Timo (2017); Tarvainen and Valpola (2017). Nevertheless, the augmentation strength is weak when using dropout solely, there is room for improvement, which we will investigate in the next section.

# 3.2 Neighborhood Contrastive Learning with Virtual Augmentation

In essence, data augmentation can be interpreted as constructing the neighborhood of a training instance, with the semantic content being preserved.

<sup>&</sup>lt;sup>2</sup>By an abuse of notation, we assume *f* outputs either the pre-defined sentence representation (a.k.a. [CLS] embedding, (Devlin et al., 2018)), or the mean/max pooling of all tokens' embeddings of that sentence.

In this section, we take this interpretation in the opposite direction by first approximating the neighborhood of an instance, upon which we generate the augmentations. To be more specific, we first approximate the neighborhood  $\mathcal{N}(i)$  of the  $i^{\text{th}}$  instance as its K nearest neighbors in the representation space,

$$\mathcal{N}(i) = \{k : \mathbf{e}_k \text{ has the top-K similarity with } \mathbf{e}_i$$
 among all other M-1 instances in  $\mathcal{B}\}$ 

Note here,  $i, i' \in \mathcal{B}$  indicate the same instance as we do not consider explicit data augmentation, but focusing on virtual augmentation only.

We define an instance-level contrastive loss regarding the instance and its neighborhood as follows.

$$\ell_{\mathcal{N}(i)}(\mathbf{z}_{i}^{\delta}, \mathbf{z}_{i}) = \frac{e^{\mathbf{sim}(\mathbf{z}_{i}^{\delta}, \mathbf{z}_{i})/\tau}}{e^{\mathbf{sim}(\mathbf{z}_{i}^{\delta}, \mathbf{z}_{i})/\tau} + \sum_{k \in \mathcal{N}(i)} e^{\mathbf{sim}(\mathbf{z}_{i}^{\delta}, \mathbf{z}_{k})/\tau}}.$$
(2)

In the above equation,  $\mathbf{z}_i^{\delta} = h(\mathbf{e}_i^{\delta})$  denotes the output of the contrastive learning head with the perturbed embedding  $\mathbf{e}_i^{\delta} = \mathbf{e}_i + \delta_i$  where  $\delta_i$  is the additive Gaussian noise. In other words, the above equation indicates the likelihood of classifying the perturbed  $i^{\text{th}}$  instance as itself rather than any other instances in its neighborhood. Then the augmentation of the  $i^{\text{th}}$  instance is retained by identifying the optimal perturbation that maximally disturbs its instance-level identity within its neighborhood. That is,

$$\delta_i^* = \underset{\|\delta_i\|_2 \le \Delta}{\arg \max} \ \ell_{\mathcal{N}(i)}(\mathbf{z}_i^{\delta}, \mathbf{z}_i) \ , \tag{3}$$

$$\mathbf{e}_{i^*} = \mathbf{e}_i + \delta_i^* \ . \tag{4}$$

Denote  $\mathcal{N}_{A}(i)$  as the augmented neighborhood of the  $i^{th}$  instance, i.e.,  $\mathcal{N}_{A}(i) = \{k, k^*\}_{k=1}^{K}$  with  $\mathbf{e}_k$  being the original embedding of the  $k^{th}$  instance and  $\mathbf{e}_{k^*}$  denoting the associated augmented representation. Note here  $\mathbf{e}_{k^*}$  is obtained in the same way defined in Equation (4) with respect to its own neighborhood  $\mathcal{N}(k)$ . We then discriminate the  $i^{th}$  instance and its augmentation from the others within its augmented neighborhood  $\mathcal{N}_{A}(i)$  as the following,

$$\ell_{\mathcal{N}_{A}(i)} = \ell_{\mathcal{N}_{A}(i)}(\mathbf{z}_{i}^{*}, \mathbf{z}_{i}) + \ell_{\mathcal{N}_{A}(i)}(\mathbf{z}_{i}, \mathbf{z}_{i}^{*}) . \tag{5}$$

Here both terms on the right hand side are defined in the same way as Equation (2) with respect to  $e_i$ , its virtual augmentation  $e_i^*$ , as well the associated augmented neighborhood  $\mathcal{N}_{\rm A}(i)$ .

**Putting it all together** Therefore, for each randomly sampled minibatch  $\mathcal{B}$  with M samples, we minimize the following:

$$\mathcal{L}_{VaSCL} = \frac{1}{2M} \sum_{i=1}^{M} \left\{ \ell_{\mathcal{B}}(\mathbf{z}_{i}, \mathbf{z}_{i'}) + \ell_{\mathcal{B}}(\mathbf{z}_{i'}, \mathbf{z}_{i}) + \ell_{\mathcal{N}_{A}(i)}(\mathbf{z}_{i}, \mathbf{z}_{i}^{*}) + \ell_{\mathcal{N}_{A}(i)}(\mathbf{z}_{i}^{*}, \mathbf{z}_{i}) \right\}$$
(6)

In the above VaSCL objective,  $\mathbf{z}_i$ ,  $\mathbf{z}_{i'}$  retained by feeding the  $i^{\text{th}}$  instance to the encoder twice, and  $\mathbf{z}_{i^*}$  is obtained via the virtual augmentation  $e_i^*$ . Putting together, two instance discrimination tasks are posed for each training example: discriminating each instance and its dropout induced variation from the other in-batch instances; and separating each instance and its virtual augmentation from its top-K nearest neighbors and their augmentations.

# 4 Experiment

In this section, we mainly evaluate VaSCL against SimCSE (Gao et al., 2021) which leverages the dropout (Srivastava et al., 2014) induced noise as data augmentation. We show that VaSCL consistently outperforms SimCSE on a wide range of downstream tasks that involve semantic understanding at different granularities. We carefully study the regularization effects of VaSCL, and empirically demonstrate that VaSCL leads to a more dispersed representation space with semantic structure better encoded.

### 4.1 Datasets

Despite previous work mainly focuses on the semantic textual similarity (a.k.a STS) related tasks, it has been pointed out by several recent work (Reimers et al., 2016; Wang et al., 2021; Zhang et al., 2021) that the performance on STS may not correlate with the other downstream task performances. To provide more comprehensive evaluation, we incorporate two additional downstream tasks, short text clustering and intent classification.

Our motivations are two-fold. First, these two tasks provide a new evaluation aspect that complements the pairwise similarity oriented STS evaluation by assessing the high-level categorical semantics encoded in the representations. Second, two desired challenges are posted as short text clustering requires more effective representations due to the weak signal each text example manifests, and intent classification often suffers from data scarcity

	STS12	STS13	STS14	STS15	STS16	SICK-R	STS-B	Avg.
RoBERTa <sub>distil</sub>	54.41	46.85	56.96	65.79	64.22	61.10	59.01	58.33
SimCSE <sub>distil</sub>	65.58	77.42	70.17	79.31	78.45	67.66	77.98	73.79
VaSCL <sub>distil</sub>	67.68	80.61	72.19	80.92	78.59	68.81	77.32	75.16
RoBERTa <sub>base</sub>	53.95	47.42	55.87	64.73	63.55	62.94	58.40	58.12
SimCSE <sub>base</sub>	68.88	80.46	73.54	80.98	80.68	69.54	80.29	76.34
VaSCL <sub>base</sub>	69.08	81.95	74.64	82.64	80.57	71.23	80.23	77.19
RoBERTa <sub>large</sub>	55.00	50.14	54.87	62.14	62.99	58.93	54.56	56.95
SimCSE <sub>large</sub>	69.83	81.29	74.42	83.77	79.79	68.89	80.66	76.95
VaSCL <sub>large</sub>	74.34	83.35	76.79	84.37	81.46	73.23	82.86	79.48

Table 1: Spearman rank correlation between the cosine similarity of sentence representation pairs and the ground truth similarity scores.

since the intents can vary significantly over different dialogue systems and it is very costly to collect enough intent examples for model training.

Semantic Textual Similarity The semantic textual similarity (STS) tasks are the most commonly used benchmark for evaluating sentence representations. STS consists of seven tasks, namely STS 2012-2016 (Agirre et al., 2012, 2013, 2014, 2015, 2016), the STS Benchmark (Cer et al., 2017), and the SICK-Relatedness (Marelli et al., 2014). For each sentence pair in these datasets, a fine-grained similarity score ranges from 0 to 5 is provided.

**Short Text Clustering** Compared with general text clustering, short text clustering has its own challenge due to lack of signal. Nevertheless, texts contain only few words grow at unprecedented rates from a wide range of popular resources, including Reddit, Stackoverflow, Twitter, and Instagram. Clustering those texts into groups of similar texts plays a crucial role in many real-world applications such as topic discovery (Kim et al., 2013), trend detection (Mathioudakis and Koudas, 2010), and recommendation (Bouras and Tsogkas, 2017). We evaluate on six benchmark datasets for short text clustering. As shown in Table 4, the datasets present the desired diversities regarding both the cluster sizes and the number of clusters contained in each dataset.

**Intent Classification** Intent classification aims to identify the intents of user utterances, which is a critical component of goal-oriented dialog systems. Attaining high intent classification accuracy is an important step towards solving many downstream tasks such as dialogue state tracking (Wu

et al., 2019; Zhang et al., 2019) and dialogue management (Gao et al., 2018; Ham et al., 2020). A practical challenge is data scarcity because different systems define different sets of intents, and it is costly to obtain enough utterance samples for each intent. Therefore, few-shot learning has attracted much attentions under this scenario, which is also our main focused evaluation on the intent classification tasks. We evaluate on five different intent classification datasets originating from different domains. We summarize the data statistics in Appendix B.1.

## 4.2 Main Results

#### **4.2.1** Evaluation Setup

Semantic Textual Similarity. Same as Reimers and Gurevych (2019b); Gao et al. (2021), in Table 1 we report the Spearman correlation<sup>3</sup> between the cosine similarity of the sentence representation pairs and the ground truth similarity scores. Short Text Clustering. We evaluate the sentence representations using K-Means (MacQueen et al., 1967; Lloyd, 1982) given its simplicity, and report the clustering accuracy<sup>4</sup> averaged over 10 independent runs in Table 2. Intent Classification. We freeze the transformer and fine-tune a linear classification layer with the softmax-based cross-entropy loss. We merge the training and development set, from which we sample K samples per class for both the training and validation sets, and report the mean and standard deviation of the classification

<sup>&</sup>lt;sup>3</sup>Same as (Reimers and Gurevych, 2019b; Gao et al., 2021), we concatenate all the topics and report the overall Spearman's correlation.

<sup>&</sup>lt;sup>4</sup>The clustering accuracy is computed by using the Hungarian algorithm (Munkres, 1957).

	Ag News	Search Snippets	Stack Overflow	Bio- medical	Tweet	Google News	Avg
RoBERTa <sub>distil</sub>	59.32	33.18	14.16	24.69	37.10	58.05	37.75
SimCSE <sub>distil</sub>	73.33	60.74	66.97	35.69	50.68	67.55	59.16
VaSCL <sub>distil</sub>	71.71	62.76	73.98	38.82	51.35	67.66	61.05
RoBERTa <sub>base</sub>	66.50	30.83	15.63	26.98	37.80	58.51	39.38
SimCSE <sub>base</sub>	65.53	55.97	64.18	38.12	49.16	65.69	56.44
VaSCL <sub>base</sub>	67.46	62.58	73.60	38.58	50.98	66.58	59.96
RoBERTa <sub>large</sub>	69.35	53.00	27.89	33.25	46.08	64.04	48.93
$SimCSE_{large}$	62.93	51.55	54.11	35.39	50.92	67.86	53.79
VaSCL <sub>large</sub>	57.26	50.11	76.21	42.60	56.10	69.26	58.59

Table 2: Clustering accuracy reported on six short text clustering datasets.

accuracy over 5 different splits in Table 3.5 We optimize the linear classification layer with learning rate 1e-04 and batch size 32. For each task, we train the model with 1000 iterations and evaluate on validation set every 100 iterations. We report the testing accuracy on the checkpoint attaining the best performance on the validation set.

#### 4.2.2 Evaluation Results

We report the evaluation results in Tables 1, 2, and 3. As we can see, both SimCSE and VaSCL largely improve the performance of the pre-trained language models, while VaSCL consistently outperforms SimCSE on most tasks. To be more specific, we attain 0.7% - 2.5% averaged improvement on seven STS tasks, and 1.9% - 4.8% averaged improvement on six short text clustering tasks. We also achieved considerable improvement over Sim-CSE on intent classification tasks under different few-shot learning scenarios. On the other hand, both VaSCL and SimCSE underperform the original pre-trained transformers on ATIS, we attribute this to the fact that ATIS is a highly imbalanced dataset with one single dominant class. We suspect the performance would reverse when taking the class imbalance into evaluation consideration, which we will report in the updated draft.

### 4.3 Analysis

To better understand what enables the good performance of VaSCL, we carefully analyze the representation space using two different metrics.

Alignment versus Uniformity Wang and Isola (2020) propose two key metrics related to contrastive learning: (i) alignment favors encoding positive samples close in the representation space; and (ii) uniformity prefers encoders that maximally preserve the information of data, i.e., the resulting representations are uniformly distributed on the unit hypersphere. Let  $\psi(x)$  denote the normalized representation of x, the two metrics are explicitly defined as<sup>6</sup>:

$$\ell_{\text{align}}^{\psi} \triangleq - \underset{x \, x' \sim p_{\text{bos}}}{\mathbb{E}} \left[ \|\psi(x) - \psi(x')\|_{2}^{2} \right] , \quad (7)$$

$$\ell_{\text{align}}^{\psi} \triangleq - \underset{x,x' \sim p_{\text{pos}}}{\mathbb{E}} \left[ \|\psi(x) - \psi(x')\|_{2}^{2} \right] , \quad (7)$$

$$\ell_{\text{uniform}}^{\psi} \triangleq \log \underset{x,x'' \sim p_{\text{data}}}{\mathbb{E}} e^{-2\|\psi(x) - \psi(x'')\|_{2}^{2}} . \quad (8)$$

As we can see, smaller values of  $\ell_{align}$  and  $\ell_{uniform}$ indicate better encoders that map positive pairs close in the representation space while better scattering apart representations of random samples.

Intra and Inter Class Distances As defined in Equations (9)&(10), for a given class, the intraclass distance is the average distance between the centroid and all samples of the class, and the interclass distance is the distance from its own centroid to the centroid of its closest class. The intra and inter class distances align well with the goal of representation learning that aims to map sentences from the same category close together and those from different categories farther apart in the representation space.

$$\ell_{\text{Intra}}^{\psi} \triangleq - \underset{x \sim p_k}{\mathbb{E}} \left[ \| f(x) - C_k \|_2^2 \right] , \qquad (9)$$

$$\ell_{\text{Inter}}^{\psi} \triangleq \frac{1}{K} \sum_{k=1}^{K} \min_{j \neq k} \|C_k - C_j\|_2^2 . \tag{10}$$

<sup>&</sup>lt;sup>5</sup>In each setting, we fix the 5 different splits for all models.

<sup>&</sup>lt;sup>6</sup>We set both t and  $\alpha$  in Wang and Isola (2020) to 2.

		SNIPS	ATIS	BANK77	CLINC150	HWU64
ot	RoBERTa	$76.71 \pm 4.84$	<b>45.42</b> ±12.42	$38.77 \pm 2.29$	$55.19 \pm 1.99$	51.52 ±2
Shot	SimCSE	$76.94 \pm 2.53$	$36.75 \pm 17.03$	<b>67.48</b> $\pm 1.63$	$72.84 \pm 1.5$	$66.1 \pm 1.9$
5	VaSCL	<b>78.97</b> ±3.69	$35.78 \pm 12.65$	$67.18 \pm 0.64$	<b>74.51</b> ±0.86	<b>68.22</b> ±1.71
ot	RoBERTa	$85.63 \pm 2.43$	<b>58.75</b> $\pm 9.35$	$46.55 \pm 1.84$	$60.55 \pm 1.16$	$57.47 \pm 0.91$
-Shot	SimCSE	$85.14 \pm 2.18$	$44.95 \pm 14.93$	$72.19 \pm 0.88$	$77.13 \pm 0.76$	$70.87 \pm 1.35$
10	VaSCL	<b>85.34</b> ±1.65	$46.80\pm13.11$	<b>72.60</b> ±0.94	<b>78.83</b> ±0.51	<b>73.70</b> ±0.92
ot	RoBERTa	$88.14 \pm 1.54$	<b>72.15</b> ±7.55	$51.65 \pm 1.42$	$63.51 \pm 1.08$	$60.93 \pm 1.27$
20-Shot	SimCSE	$88.43 \pm 1.2$	$61.45 \pm 8.83$	$75.13 \pm 0.78$	$78.59 \pm 0.78$	$74.44 \pm 0.74$
20	VaSCL	<b>89.94</b> ±0.89	62.12±7.09	<b>76.60</b> ±0.35	<b>81.40</b> ±0.60	<b>77.66</b> ±0.64

Table 3: Few-shot learning evaluation of Intent Classification. We choose RoBERTaBase as backbone.

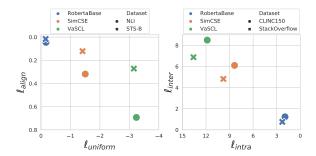


Figure 2: Evaluating sentence representations in terms of alignment (Eq 7) & uniformity (Eq 8); and inter class distance (Eq 10) & intra class distance (Eq 9).

Here K denotes the number of classes and  $C_j$  is the centroid of the j-th class.

## VaSCL leads to more dispersed representation

We compare VaSCL against the original language models and SimCSE regarding the metrics defined in this section. We evaluate the alignment and uniformity using both NLI<sup>7</sup> and STS-B,<sup>8</sup> and evaluate the inter and intra class distances with two categorical datasets, StackOverflow and CLINC150 (see Tables 4 and ??).

As shown in Figure 2, despite the alignment values get increased, both VaSCL and SimCSE significantly improves the uniformity of representations. We observe the same trend on the categorical-level evaluation, *i.e.*, large inter class distances come along with large intra cluster distances. In contrast, the original pre-trained language models consistently show poor performance on all three down-

stream tasks (see Tables 1, 2, & 3), though it attains the smallest alignment values and intra class distances in Figure 2. The comparison indicates that both VaSCL and SimCSE is capable of scattering representations apart while better capturing the semantic structures at different granularities. On the other hand, VaSCL leads to more dispersed representations with semantic structures being better encoded, which we consistently observed in presence of no matter the dropout induced augmentation only or the common data augmentation strategies that operate on the discrete text (see Section 4.4).

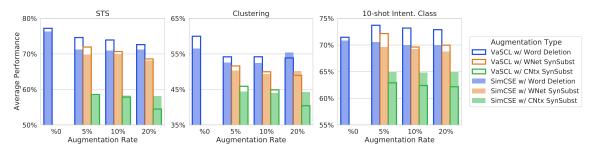
#### 4.4 Explicit Data Augmentation

Data augmentation plays a key role in contrastive representation learning, and therefore it raises a question when applying them to NLP where no general rules are established for effective data augmentation due to the discrete the nature of natural languages. To better understand the augmentation effects of our virtual augmentation oriented VaSCL model, we explore three different text augmentations strategies<sup>9</sup>. **Word Deletion** removes words from the input text randomly. Wnet Synsubst (WordNet synonym substitute) transforms an input text by replacing its words with the WordNet synonyms (Morris et al., 2020; Ren et al., 2019). **CNxt Synsubst** (contextual synonyms substitute) leverages the pre-trained transformers to find topn suitable words of the input text for substitution (Kobayashi, 2018). We summarize our results in Figure 3. For each augmentation strategy, we evaluate over three augmentation strengths by partially changing each text example with different percent-

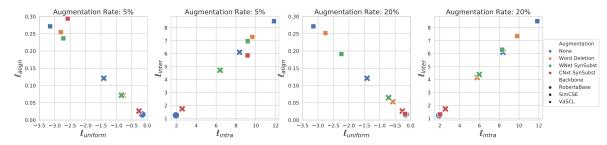
 $<sup>^7 \</sup>rm We$  take 10000 randomly sampled entailment pairs from the combination of SNLI (Bowman et al., 2015a) and MNLI (Williams et al., 2017) datasets as  $p_{\rm pos}$ , and the whole 20000 examples as  $p_{\rm data}$ .

<sup>&</sup>lt;sup>8</sup>Similar to Gao et al. (2021), we take STS-B pairs with a score higher than 4 as  $p_{pos}$  and all STS-B sentences as  $p_{data}$ .

<sup>&</sup>lt;sup>9</sup>Implemented using the nlpaug library https://github.com/makcedward/nlpaug.



(a) Evaluating VaSCL in presence of different explicit data augmentations strategies.



(b) Alignment and uniformity evaluation on STS-B; and the categorical-level metrics, inter class distance and intra class distance, evaluated on CLINC150. We report the evaluation on NLI and StackOverflow in Appendix C.

Figure 3: Evaluating VaSCL in presence of various explicit data augmentations.

ages, 5%, 10%, and 20%. The original settings of VaSCL and SimCSE are indicated with augmentation rate being 0%.

As we can see in Figure 3a, both SimCSE and VaSCL attain worse performance in most tasks when adopting explicit data augmentations<sup>10</sup> to optimize their learning objectives. Among them, the augmentations obtained via the transformer based contextual synonym substitute consistently performs the worst, we hypothesize that the pretrained transformer based contextual augmentations create much less new linguistic patterns to further improve the transformers themselves. This is further indicated by Figure 3b, SimCSE with contextual synonym substitute yields representations that share very similar distribution as that of the original pre-trained checkpoints in terms of both alignment / uniformity, and intra / inter class distances. Moreover, Figure 3b also shows that incorporating explicit data augmentations induce less dispersed representations with worse uniformity and inter class distances, but improved alignment and intra class distances. This is the opposite forces of what we the original SimCSE and VaSCL

operate on the representations. One possible explanation is that those explicit augmentations induce undesired noise for contrastive learning.

# 5 Conclusion

In this paper, we present an virtual augmentation oriented framework for unsupervised sentence representation learning. Our key insight is data augmentation can be interpreted as constructing the neighborhoods of each training instance, we thereby in turn utilize the neighborhood to generate effective data augmentations. We evaluate our VaSCL model on a wide range of downstream tasks, and substantially advance the previous stateof-the-art results. On the other hand, we observe performance drop when incorporating common and popular explicit data augmentations into the training set, which again indicates the inherent difficulty of generating effective data augmentations in NLP by operating on the discrete texts. Nevertheless, we hypothesize that effective data augmentation operatorations on the discrete text domain could complement our virtual augmentation approach if new linguistic patterns are generated.

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Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Inigo Lopez-Gazpio, Montse Maritxalar, Rada

 $<sup>^{10} \</sup>mbox{For a positive pair } (x_i, x_i'), x_i \mbox{ is the original text example,} \mbox{ and } x_{i'} \mbox{ is the augmentation of } x_i \mbox{ obtained by using the explicit data augmentation strategies explored in this section. We will incorporate the evaluation where both <math display="inline">(x_i, x_i')$  are the augmentation of the original text in the updated version of this draft.

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### **A** Implementation

We implement our models with Pytorch (Paszke et al., 2017). We use the pre-trained RoBERTa models as the backbone. We choose a two-layer MLP with size ( $d \times d$ ,  $d \times 128$ ) to optimize our the contrastive learning losses, where d denotes the dimension of the sentence representations. We use Adam (Kingma and Ba, 2015) as our optimizer with a constant learning rate of 5e-04 which we scale it 5e-06 for updating backbones. We set virtual augmentation strength of VaSCL, i.e.,  $\Delta$  in Equation (3), to 15 for both DistilRoberta and RoBERTaBase and 30 for RoBERTaLarge.

We train SimCSE (Gao et al., 2021) using 3e-05 for optimizing the contrastive learning head and the backone. We also tried the default learning rate 1e-05 (suggested in Gao et al. (2021)) as well as our learning rate setup for optimizing RoBERTaBase

with SimCSE, and found 3e-05 yield better performance. For both SimCSE and VaSCL, we set the batch size to 1024, and train all models over 5 epochs and evaluate on the development set of STS-B every 500 iterations. We report all our evaluations on the downstream tasks with the associated checkpoints attaining the best performance on validation set of STS-B.

#### **B** Dataset Statistics

#### **B.1** Intent Classification Dataset

We evaluate our model on five intent classification datasets: (1) ATIS (Hemphill et al., 1990) is a benchmark for the air travel domain. In order to conduct the evaluation in Table 3, we truncate those categories of the merged training and validation set that have less than 40 examples per category. (2) **SNIPS** (Coucke et al., 2018) is a SLU benchmark that consists of 7 distinct intents. (3) **BANKING77** (Casanueva et al., 2020) is a large fine-grained single banking domain intent dataset with 77 intent classes. (4) HWU64 (Liu et al., 2021) contains 25,716 examples for 64 intents in 21 domains. (5) CLINC150 (Larson et al., 2019) spans 150 intents and 23,700 examples across 10 domains. As we can see here, ATIS and SNIPS are limited to only a small number of classes, which oversimplifies the intent detection task and does not emulate the true environment of commercial systems. In contrast, the remaining three datasets contain much more diversity and are more challenging.

# **B.2** Short Text Clustering Dataset

- **SearchSnippets** is extracted from web search snippets, which contains 12340 snippets associated with 8 groups Phan et al. (2008).
- **StackOverflow** is a subset of the challenge data published by Kaggle<sup>11</sup>, where 20000 question titles associated with 20 different categories are selected by Xu et al. (2017).
- **Biomedical** is a subset of PubMed data distributed by BioASQ<sup>12</sup>, where 20000 paper titles from 20 groups are randomly selected by Xu et al. (2017).
- **AgNews** is a subset of news titles (Zhang and LeCun, 2015), which contains 4 topics selected by Rakib et al. (2020).

<sup>&</sup>lt;sup>11</sup>https://www.kaggle.com/c/predict-closed-questions-on-stackoverflow/download/train.zip

<sup>12</sup>http://participants-area.bioasq.org

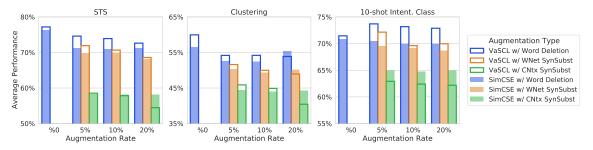
Dataset	N	$\bar{W}$	С	ImN
AgNews	8.0K	23	4	1
SearchSnippets	12.3K	18	8	7
StackOverflow	20K	8	20	1
Biomedical	20K	13	20	1
GoogleNews	11.1K	28	152	143
Tweet	2.5K	8	89	249

Table 4: Statistics of six short text clustering datasets. N: number of text samples;  $\bar{W}$ : average number of words each text example has; C: number of clusters; ImN: imbalance number defined as the size of the largest class divided by that of the smallest class.

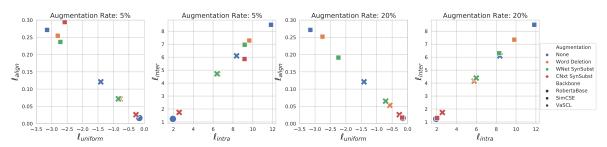
- **Tweet** consists of 89 categories with 2472 tweets in total (Yin and Wang, 2016).
- **GoogleNews** contains titles and snippets of 11109 news articles related to 152 events (Yin and Wang, 2016).

# C Evaluating VaSCL with explicit Data Augmentations

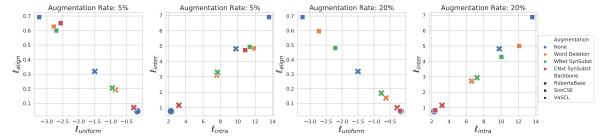
Please refer to Figure 4 for complete evaluation of VaSCL with explicit data augmentations.



(a) Evaluating VaSCL in presence of different explicit data augmentations strategies.



(b) Alignment and uniformity evaluation on STS-B; and the categorical-level metrics, inter class distance and intra class distance, evaluated on CLINC150.



(c) Alignment and uniformity evaluation on NLI; and the categorical-level metrics, inter class distance and intra class distance, evaluated on StackOverflow.

Figure 4: Evaluating VaSCL in presence of various explicit data augmentations.