# Generative or Contrastive? Phrase Reconstruction for Better Sentence Representation Learning

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#### **Abstract**

Though offering amazing contextualized tokenlevel representations, current pre-trained language models actually take less attention on acquiring sentence-level representation during its selfsupervised pre-training. If self-supervised learning can be distinguished into two subcategories, generative and contrastive, then most existing studies show that sentence representation learning may more benefit from the contrastive methods but not the generative methods. However, contrastive learning cannot be well compatible with the common token-level generative self-supervised learning, and does not guarantee good performance on downstream semantic retrieval tasks. Thus, to alleviate such obvious inconveniences, we instead propose a novel generative self-supervised learning objective based on phrase reconstruction. Empirical studies show that our generative learning may yield powerful enough sentence representation and achieve performance in Sentence Textual Similarity (STS) tasks on par with contrastive learning. Further, in terms of unsupervised setting, our generative method outperforms previous state-of-the-art SimCSE on the benchmark of downstream semantic retrieval tasks.

#### 1 Introduction

Sentence Representation Learning has long been a hot research topic [Conneau *et al.*, 2017; Cer *et al.*, 2018], for its effectiveness in a variety of downstream tasks like information retrieval and question answering.

Although pre-trained language models (PrLMs) like BERT [Devlin *et al.*, 2019] have achieved overwhelming performance on various token-level tasks, they are also criticized for being unable to produce high-quality sentence-level representations. The native sentence representation produced by the "[CLS]" token of BERT shows extremely poor performance on sentence evaluation benchmarks like semantic textual similarity (STS) tasks [Li *et al.*, 2020].

The primary cause of these low-quality sentence representations is the lack of effective self-supervised sentence-level training objective. As discussed in ConSERT [Yan et

al., 2021], the original sentence-level pretraining objective Next Sentence Prediction (NSP) is too weak to provide high-quality sentence representation. Recent researchers are therefore seeking other effective self-supervised sentence-level objectives for Sentence Representation Learning. Generally, self-supervised methods include both (i) generative methods, like Masked Language Modelling (MLM), and (ii) contrastive methods, like Next Sentence Prediction (NSP).

Generative self-supervised learning techniques offer researchers good interpretability and controllable training by allowing people to decide what to generate. However, although generative methods like MLM have achieved overwhelming performance in token representation learning, little effort has been put in investigating the potential of generative methods in sentence representation learning. Cross-Thought [Wang et al., 2020] and CMLM [Yang et al., 2020] are the most representative generative methods, which both leverage the contextual sentence representations to recover the masked tokens in one sentence. Unfortunately, they highly depend on the contextual information, and mainly focus on the document-level corpus, thus performing unsatisfying in STS tasks where short texts' representation are valued.

On the contrary, contrastive methods have been shown extremely effective in Sentence Representation Learning in recent years. Generally, researchers use various data augmentation techniques to create different views for one sentence, and force their representations to be more aligned within the same batch. ConSERT [Yan et al., 2021] utilizes data augmentation techniques including token shuffling, feature cutoff, etc., and provides a general contrastive learning framework for Sentence Representation Learning. SimCSE [Gao et al., 2021] suggests that using different dropout masks is a simple yet more powerful augmentation technique in creating another view of the sentence. Though effective, there also exist some drawbacks in contrastive methods. (i) Unlike generative methods, the training procedure of contrastive methods is uncontrollable and lacks interpretability. What is encoded into the sentence representation is kept totally unknown. (ii) Good performance on STS tasks by contrastive methods does not ensure good performance on downstream retrieval tasks, as there exists obvious inductive bias. (iii) Contrastive loss is incompatible with the original token-level pre-training objective MLM. According to SimCSE, the performance of Sim-CSE drops drastically on the STS tasks when the contrastive

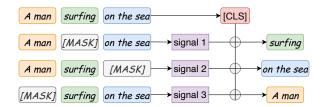


Figure 1: A description of the design intuitive of our PaSeR.

loss is combined with the MLM loss, indicating that the contrastive objective sacrifices the quality of token level representation.

In this paper, we investigate the potential of generative self-supervised techniques in Sentence Representation Learning. Unlike previous researches who mainly study the intersentence relationship, we focus more on the intra-sentence relationship, and emphasize the importance of the semantic components within the sentence, i.e. phrases. We present Phrases-aware Sentence Representation (PaSeR), which explicitly encodes the representation of each phrase into sentence representations. In detail, we hypothesize a good sentence representation should be able to reconstruct the important phrases in the sentence when given a suitable generation signal. Inspired by [Gao et al., 2021], we provide such generation signals by a duplication and masking strategy. Concretely, we mask out several phrases in the original sentences, and encode these masked sentences to provide hints for phrase reconstruction, depicted in Figure 1. Experiments show that our PaSeR achieves the SOTA performance on multiple single tasks in STS, and also comparable average performance in STS with the current SOTA contrastive method SimCSE in the unsupervised setting. Extensive experiments further present that our PaSeR achieves better semantic retrieval performance than SimCSE on the Quora Question Pair dataset.

Contributions (i) We propose an effective generative self-supervised objective of training sentence representations without leveraging document-level corpus. Based on such objective we present PaSeR, a Phrase-aware Sentence Representation Learning model. (ii) Experiments show that our proposed PaSeR achieves SOTA performance on multiple single tasks in STS, and also comparable average performance in STS with the current best contrastive learning based method SimCSE, providing an effective alternative for Sentence Representation Learning against the current trend of contrastive methods.

## 2 Related Work

# 2.1 Supervised Sentence Representations

Supervised sentence representations leverage the idea of transfer learning. Previous works [Conneau *et al.*, 2017; Cer *et al.*, 2018] have shown that utilizing labeled datasets from Natural Language Inference (NLI) is extremely helpful for Sentence Representation Learning. Based on these researches, Sentence-BERT [Reimers and Gurevych, 2019] introduces siamese BERT encoders with shared parameters and train them on NLI datasets, achieving acceptable per-

formance on STS tasks. Although these supervised methods can provide high-quality sentence representations, the labeling cost of sentence pairs still urges the researchers to search for a more effective unsupervised solution.

## 2.2 Post-processing of BERT Representations

Several post-processing methods are first proposed to improve the sentence representations produced by original BERT. These methods mainly analyze the distorted sentence representation space, and propose changing the representation space to isotropic Gaussian ones via flow methods like BERT-flow [Li *et al.*, 2020] or simple projection methods like BERT-whitening [Su *et al.*, 2021]. However, their performances are very limited, as their sentence representations are not finetuned due to the lack of suitable sentence-level training objectives in the original BERT model.

## 2.3 Self-supervised Sentence-level Pre-training

Recently, researchers are seeking more effective sentencelevel pre-training objectives, from the aspects of both generative ones and contrastive ones.

Generative Methods Little efforts have been paid into studying what generation methods can achieve in Sentence Representation Learning. Among these works, Cross-thought [Wang et al., 2020] and CMLM [Yang et al., 2020] are the most representative ones, which both propose to recover masked tokens of one sentence by the contextual-sentence representations. However, in both methods, document-level training data are needed, making it unsuitable for evaluating the similarity between short texts.

Contrastive Methods Recently, contrastive learning has presented its superiority in Sentence Representation Learning. Generally, all of these contrastive learning methods are seeking effective ways of creating different views of one sentence, pushing their representations closer while pulling views of different sentences away. Contrastive Tension (CT) [Carlsson et al., 2020] introduces the Siamese network structure to create different views of one sentence, and treat different views from one sentence as the positive pairs while others as negative pairs. ConSERT [Yan et al., 2021] creates different views of sentences by data augmentation techniques including token shuffling, feature cutoff, and adversarial attacks. After that, SimCSE [Gao et al., 2021] indicates that the original dropout mask design is already a very effective data augmentation strategy, and has achieved the SOTA performance in the STS datasets.

#### 3 Method

#### 3.1 Basic Architecture

Previous studies have already verified that high-frequency words may cause bias in sentence representation. Therefore, we use RAKE [Rose *et al.*, 2010], a fast keyphrase extraction algorithm, to extract important phrases in each sentence.

### Sentence Encoder

Following previous works [Li et al., 2020; Su et al., 2021], our sentence encoders are based on the pretrained language model, BERT. Given the fact that a sentence s is generally composed of multiple phrases  $\mathcal{P} = \{p_0, p_1, ..., p_n\}$ , the

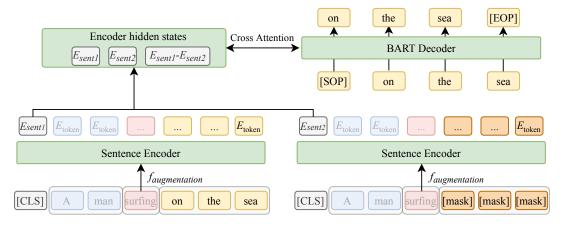


Figure 2: Overview of PaSeR. The lower part presents the *Sentence Encoders* where parameters are shared. The upper part presents our *Generative Decoder*, which takes the sentence representation as encoder hidden states, and reconstruct the masked phrases.

phrase reconstruction process should be conditional. Suppose s is encoded as  $E_s$ , we should provide different guiding signals to  $E_s$ , to enable the reconstruction of each  $p_i$  in  $\mathcal{P}$ .

Inspired by SimCSE, we provide the guiding signals by duplication and masking. In detail, we duplicate the original s as  $\tilde{s}$ , but mask out the phrase  $p_i$  that we need to generate, shown in Figure 2. Therefore, after encoding  $\tilde{s}$  as  $E_{\tilde{s}}$ ,  $E_{\tilde{s}}$  can be viewed as the guiding signal for generation of the missing phrase  $p_i$ . Finally, following Sentence-BERT [Reimers and Gurevych, 2019], we concatenate  $[E_s, E_{\tilde{s}}, |E_s - E_{\tilde{s}}|]$  as a whole to provide the conditional signal for the following phrase reconstruction.

#### **Generative Decoder**

In our experiments, we use BART as our phrase reconstruction decoder D, given the conditional signal of  $x = [E_s, E_{\tilde{s}}, |E_s - E_{\tilde{s}}|]$ . For the masked phrase p, we first append a special token [SOP] (start of phrase) before the phrase as the start generation signal, and another special token [EOP] (end of phrase) at the end of the phrase as the end generation signal. Suppose now p is composed of several tokens  $\{t_1, t_2, ..., t_k\}$ , the reconstruction loss is formulated as:

$$L_{recon} = -\sum_{i=1}^{k} \log P_{f_D} (t_i \mid t_{< i}, x)$$
 (1)

#### **Combined Loss**

To preserve the quality of token-level representation, we also incorporate the MLM objective with our reconstruction objective. The final training loss is a combination:

$$L_{total} = L_{MLM} + L_{recon} \tag{2}$$

#### 3.2 Data Augmentation

To improve the robustness of the sentence representations produced by our PaSeR, following EDA [Wei and Zou, 2019], we introduce data augmentation on both views before the paired sentences are fed into the sentence encoder. We mainly introduce the following types of data augmentation strategies in our experiment.

**Synonym Replacement** Simply by *duplication and masking* cannot distinguish similar and dissimilar phrases. Therefore, we propose to use synonym replacement on both the original sentence and the masked sentence to create sentence pairs that use semantically similar phrases while different tokens. The replacement ratio is selected from [0.05, 0.1, 0.2, 0.3, 0.4, 0.5].

**Random Deletion** Previous studies [Li *et al.*, 2020; Yan *et al.*, 2021] have revealed that original sentence representations are severely affected by high-frequency words within the sentence. To endow our sentence encoders with the ability to distinguish the existence of high-frequency words from low-frequency ones, we introduce random deletion as another alternative for data augmentation, with a deletion ratio selected from [0.05, 0.1, 0.2].

**Token Reordering** Following ConSERT [Yan *et al.*, 2021], we also introduce token reordering as another kind of data augmentation. The reordering ratio is selected from [0.05, 0.1, 0.2, 0.3, 0.4, 0.5].

## 4 Experiment

#### 4.1 Setup

## **Datasets**

For the similarity evaluation of sentence representations, we use the STS datasets as our evaluation benchmark, including STS tasks 2012-2016 (STS12-STS16) [Agirre *et al.*, 2012; Agirre *et al.*, 2013; Agirre *et al.*, 2014; Agirre *et al.*, 2015; Agirre *et al.*, 2016], STS Benchmark (STS-B) [Cer *et al.*, 2017] and SICK-Relatedness (SICK-R) [Marelli *et al.*, 2014]. Samples in datasets are paired sentences with human-labeled relatedness score from 0 to 5. For the training of sentence encoders, following ConSERT [Yan *et al.*, 2021], we mix all the unlabeled texts from these datasets as the training data.

For the downstream semantic retrieval task, following BERT-whitening [Su *et al.*, 2021], we use the Quora Question Pair dataset <sup>1</sup> (QQP). QQP consists of over 400,000 lines of potential question duplicate pairs of *question1-question2*.

<sup>&</sup>lt;sup>1</sup>https://quoradata.quora.com/First-Quora-Dataset-Release-Question-Pairs

Model	STS12	STS13	STS14	STS15	STS16	STS-B	SICK-R	Avg.
Original BERT/Glove								
GloVe embeddings	55.14	70.66	59.73	68.25	63.66	58.02	53.76	61.32
$BERT_{base}$ -[CLS]	21.54	32.11	21.28	37.89	44.24	20.29	42.42	31.40
BERT <sub>base</sub> -mean	30.87	59.89	47.73	60.29	63.73	47.29	58.22	52.57
BERT <sub>base</sub> -first-last avg.	39.70	59.38	49.67	66.03	66.19	53.87	62.06	56.70
Post-Processing Methods – Un	isupervised							
BERT-flow	58.40	67.10	60.85	75.16	71.22	68.66	64.47	66.55
BERT-whitening	57.83	66.90	60.90	75.08	71.31	68.24	63.73	66.28
Supervised Methods								
Universal Sentence Encoder	64.49	67.80	64.61	76.83	73.18	74.92	76.69	71.22
Sentence BERT <sub>base</sub> (NLI)	70.97	76.53	73.19	79.09	74.30	77.03	<u>72.91</u>	74.89
Contrastive Methods – Unsupervised								
$\mathrm{BERT}_{base} ext{-CT}$	66.86	70.91	72.37	78.55	77.78	-	-	-
$ConSERT_{base}$	64.64	78.49	69.07	79.72	75.95	73.97	67.31	72.74
SimCSE	68.40	<u>82.41</u>	74.38	80.91	78.56	76.85	72.23	76.25
SimCSE + MLM	44.40	66.60	51.27	67.48	67.95	52.44	59.86	58.57
Generative Methods – Unsupervised								
$\mathrm{CMLM}_{base}$	58.20	61.07	61.67	73.32	74.88	76.60	64.80	67.22
PaSeR <sub>base</sub> (Our Method)	71.09	83.54	<u>72.58</u>	83.49	77.12	78.35	65.02	<u>75.88</u>

Table 1: Sentence representation performance on STS tasks. Bold statistics represent the best performance while underlined ones represent the second best performance.

Method	MRR@10	MRR@100
BERT-whitening <sub>base</sub>	61.04	61.36
BERT-whitening <sub>large</sub>	61.94	62.28
$SimCSE_{base}$	62.69	63.06
$PaSeR_{base}$	65.07	65.41

Table 2: Retrieval performance comparison on Quora Question Pair dataset.

We collect all the *question2* as the question corpus, and all *question1*s that have at least a positive paired question2 as the query set. We then use the query set to retrieve similar questions from the question corpus.

#### **Training Details**

We use BERT-base as the sentence encoder for all experiments. Following [Gao et al., 2021], we restrict the maximum sequence length to 32 with an initial learning rate of 3e-5. The batch size is selected from [32, 64, 96]. Following [Yan et al., 2021; Gao et al., 2021], we use the development set of STS-B to choose the best performing model. We take the "[CLS]" representation as the sentence representation for most of the experiments, and discuss different effects when different pooling methods are adopted in Section 4.4.

We use the decoder of BART [Lewis *et al.*, 2020] as the generative decoder for all experiments. The weights of the BART decoder are randomly initialized, as the pretrained BART has a different word embedding layer from the pretrained BERT model.

#### 4.2 Main Experiments

The performance of our PaSeR and other frontier researches are presented in Table 1. Here, we separate all these frontier

researches into five categories based on whether supervised signals are used and whether contrastive learning framework is adopted. (i) Original baselines including different pooling methods of BERT and Glove embeddings. (ii) Post-processing baselines including BERT-flow [Li et al., 2020] and BERT-whitening [Su et al., 2021]. (iii) Supervised baselines include Universal Sentence Encoder (USE) [Conneau et al., 2017] and Sentence BERT [Reimers and Gurevych, 2019] which is finetuned on the NLI datasets. (iv) Unsupervised contrastive methods including BERT-CT<sub>base</sub> [Carlsson et al., 2020], ConSERT [Yan et al., 2021] and SimCSE [Gao et al., 2021]. (v) Unsupervised generative methods including CMLM [Yang et al., 2020] and our PaSeR.

From Table 1, (i) Under the unsupervised setting, our PaSeR achieves the SOTA performance on several benchmark datasets like STS12, STS13, STS15, STS-B, and is also the second-best model considering the average performance. Compared to the previous best generative method CMLM, PaSeR achieves an average of 8.66 absolute performance gain. (ii) Our PaSeR even achieves better performance than several supervised baselines including USE and Sentence BERT<sub>base</sub>. (iii) Performance of SimCSE drops drastically when combined with the MLM objective, but our PaSeR is naturally incorporated with MLM, preserving the quality of token level representation. All these features indicate the superiority of our PaSeR in Sentence Representation Learning.

#### 4.3 Semantic Retrieval

Since the sentence representation is mainly used for downstream semantic retrieval industrially, simply verifying the quality of sentence representations on STS tasks is not enough. In fact, good STS performance does not necessarily correlate with good performance on downstream retrieval

Model	Avg.(STS12-16)	STS-B	SICK-R	Avg.all
BERT-[CLS]	31.4	20.3	42.4	31.4
PaSeR-no aug	73.8	74.5	62.5	72.3
+ RS	74.2	75.0	63.5	72.8
+ RD	74.2	75.5	63.8	72.9
+ SR	77.6	<b>78.4</b>	65.0	75.9
+ SR + RD	77.2	77.5	64.5	75.4
+ SR + RS	77.3	77.6	63.1	75.3

Table 3: Ablation study of data augmentation strategies, including synonym replacement (SR), random deletion (RD) and random swapping (RS).

Pooling	Avg.(STS12-16)	STS-B	SICK-R	Avg.all
Top1 avg.	76.2	78.3	65.7	75.0
Top2 avg.	75.6	78.0	66.1	74.6
First-last avg.	76.2	<b>78.4</b>	65.8	75.0
[CLS]	77.6	<b>78.4</b>	65.0	<b>75.9</b>

Table 4: Ablation study of different pooling method on PaSeR.

tasks as there exists obvious inductive bias. Therefore, in this section, following BERT-whitening<sup>2</sup>, we conduct semantic retrieval on the Quora Question Pairs dataset and compare the retrieval performance between our PaSeR and other frontier works.

Table 2 present the performance of semantic retrieval. We use the Mean Reciprocal Rank (MRR) as the evaluation metric. Compared to the previous best model Sim-CSE, our PaSeR achieves significant performance gain (2.4 on MRR@10 metric) on the Quora dataset. Better top retrieval results here indicate that our PaSeR is better at aligning sentences with similar meanings, which is the core feature that is valued in the retrieval process.

# 4.4 Ablation Study

#### **Effectiveness of Data Augmentation**

In this section, we compare the effects of different data augmentation strategies, shown in Table 3. In our experiments, (i) Our PaSeR can achieve over 40 average performance gain without any data augmentation techniques. (ii) Synonymy Replacement (SR) is extremely effective in boosting the downstream performance, which leads to an average of 3.58 performance gain. (iii) Random Swapping (RS) and Random Deletion (RD) also help a little (an average of 0.47 or 0.62 performance gain). (iv) We do not observe performance gain when different data augmentation techniques are combined. We speculate this is because the semantic meaning of one sentence is more likely to change when different augmentation methods are combined, which influences the alignment of the input sentence pairs.

#### **Choices of Pooling Method**

Previous studies [Li et al., 2020; Su et al., 2021; Gao et al., 2021] have verified that different pooling methods might lead

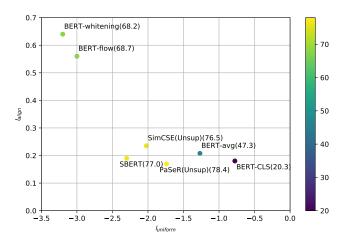


Figure 3: Visualization of uniformity and alignment for sentence representations produced by different methods. All models are trained on BERT $_{base}$ . Color of points and numbers in brackets represent Spearman's correlation on the test set of STS-Benchmark.

to very different results, and different models may prefer different types of pooling methods. Therefore, we also investigate what pooling method is preferred by our PaSeR. We mainly investigate four types of pooling methods. (i) Average representation over the last layer of BERT, denoted as Top1 avg. (ii) Average representation from the last two layers of BERT, denoted as Top2 avg. (iii) Average representation from the combination of the first layer and the last layer of BERT, denoted as First-last avg. (iv) Directly using the "[CLS]" token as the sentence representation.

Table 4 present the results when different pooling methods are applied on PaSeR. Experimentally, we found that directly using "[CLS]" token as the final sentence representation performs the best among all the pooling methods, with nearly 1 point increase on the average performance of all STS tasks.

## 5 Discussion

#### 5.1 Uniformity and Alignment

Following SimCSE [Gao *et al.*, 2021], we analyze the uniformity and alignment of our PaSeR along with other frontier works. We use the STS-Benchmark dataset as the evaluation corpus, and also list the corresponding Spearman correlation for each method for comparison.

From Figure 3, we can see that our PaSeR achieves the best alignment loss among all the listed models (0.17), which is even better than supervised baseline SBERT (0.19) or the SOTA unsupervised method SimCSE (0.24). For the uniformity measurement, previous works [Li et al., 2020; Su et al., 2021] have pointed out that original BERT sentence representation space collapse, which presents high similarity between representations of any sentence pairs. Therefore, both BERT-avg and BERT-[CLS] suffer from high uniformity loss. When compared to BERT-[CLS] or BERT-avg, our PaSeR also achieves much better uniformity, meaning that our proposed self-supervised sentence-level training objective naturally eases the collapse.

<sup>&</sup>lt;sup>2</sup>The authors did not present the results in their paper, but in their repo via https://github.com/autoliuweijie/BERT-whitening-pytorch.

	$\mathbf{SimCSE}_{base}$	$\mathbf{PaSeR}_{base}$					
Que	Query: What can one do to relieve severe chronic pain?						
#1 #2 #3	Is it possible to come to terms with a life of chronic pain? What is the best way to avoid pain? How would you/do you cope with chronic pain?	What has worked for you to help relieve chronic pain? How can I get rid of chronic and acute back pain? What is the best way to ease period pain?					
Que	Query: Is there a biological reason that people cry when they are emotional?						
#1 #2 #3	Why do people cry when they feel happy? Why do some people cry more than others? Why do some people like crying so much?	Why do some people cry when they get angry? Why do people cry when they feel happy? Why do some people like crying so much?					

Table 5: Qualitative Analysis of semantic retrieval on the QQP Dataset.

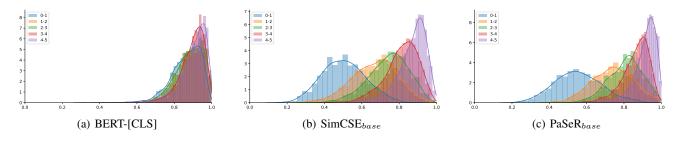


Figure 4: Cosine Similarity Density Plots of different models on different similarity levels.

### 5.2 Qualitative Comparison

In this section, we present the qualitative analysis of the retrieval results on Quora Question Pair dataset. We showcase two examples in Table 5, where PaSeR retrieves generally better quality sentences. In the first case, PaSeR successfully captures the semantic similarity between phrase *What can one do* and phrase *What has worked for you* where Sim-CSE fails. In the second case, PaSeR captures the correlation between *emotional* and *happy/angry*, while SimCSE captures only phrase *happy* in the Top3 prediction.

## **5.3** Cosine Similarity Density Plots

Following SimCSE, we visualize the cosine density plots on the STS-Benchmark dataset in Figure 4. Concretely, we split the STS-B dataset into five similarity levels according to their labeled scores, and count all similarity scores in each sentence level. From Figure 4, BERT-[CLS] shows similar cosine distribution in all similarity levels, while SimCSE and PaSeR present good performance in distinguishing samples from different levels.

Theoretically, high-quality sentence representation should present two characteristics. (1) Significant mean value difference between each similarity level, which represents significant inter-class distance. (2) Lower variance in each similarity level, which represents smaller intra-class distance.

Table 6 presents the exact mean/var values of different models in each similarity level. We can see that both Sim-CSE and PaSeR achieve good inter-class distance compared to the original BERT-[CLS]. As for intra-class distance, when compared to SimCSE, PaSeR shows generally better performance on almost all similarity levels.

level	BERT-[CLS]	$SimCSE_{base}$	$PaSeR_{base}$
0-1	0.86 / 0.006	0.50 / 0.013	0.55 / 0.015
1-2	0.88 / 0.006	0.67 / 0.014	0.74 / 0.011
2-3	0.89 / 0.006	0.74 / 0.010	0.81 / 0.008
3-4	0.90 / 0.004	0.81 / 0.008	0.86 / 0.005
4-5	0.90 / 0.005	0.87 / 0.006	0.92 / 0.003

Table 6: Mean/variance of cosine similarity on STS-Benchmark.

#### 6 Conclusion

As most pre-trained language models fail to attach enough importance to sentence-level representation learning, it usually leads to unsatisfactory performance in detailed tasks when good sentence representation is right indispensable. Meanwhile, existing contrastive learning method hardly provides a compatible way to let PrLM learn sentence-level representation as well as token-level representation. This motivates us to find an alternative to effectively alleviate the above drawbacks in existing sentence-level representation learning methods. On the basis of investigating the intra-sentence relationship between components of sentences (important phrases) and the whole sentence representations, we propose a generative objective to align these phrases with their corresponding sentence representations. This idea leads to PaSeR, a Phrase-aware Sentence Representation model. As an effective alternative in Sentence Representation Learning, our PaSeR achieves comparable performance with strong contrastive learning baselines on STS tasks, and significantly better performance on the downstream semantic retrieval tasks on the QQP dataset.

### References

- [Agirre et al., 2012] Eneko Agirre, Daniel Cer, Mona Diab, and Aitor Gonzalez-Agirre. SemEval-2012 task 6: A pilot on semantic textual similarity. In \*SEM 2012: The First Joint Conference on Lexical and Computational Semantics, pages 385–393, 2012.
- [Agirre et al., 2013] Eneko Agirre, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, and Weiwei Guo. \*SEM 2013 shared task: Semantic textual similarity. In Second Joint Conference on Lexical and Computational Semantics (\*SEM), pages 32–43, 2013.
- [Agirre et al., 2014] Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Rada Mihalcea, German Rigau, and Janyce Wiebe. SemEval-2014 task 10: Multilingual semantic textual similarity. In *International Workshop on Semantic Evaluation (SemEval 2014)*, pages 81–91, 2014.
- [Agirre et al., 2015] Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Iñigo Lopez-Gazpio, Montse Maritxalar, Rada Mihalcea, German Rigau, Larraitz Uria, and Janyce Wiebe. SemEval-2015 task 2: Semantic textual similarity, English, Spanish and pilot on interpretability. In *International Workshop on Semantic Evaluation (SemEval 2015)*, pages 252–263, 2015.
- [Agirre et al., 2016] Eneko Agirre, Carmen Banea, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Rada Mihalcea, German Rigau, and Janyce Wiebe. SemEval-2016 task 1: Semantic textual similarity, monolingual and cross-lingual evaluation. In *International Workshop on Semantic Evaluation (SemEval-2016)*, pages 497–511, 2016.
- [Carlsson et al., 2020] Fredrik Carlsson, Amaru Cuba Gyllensten, Evangelia Gogoulou, Erik Ylipää Hellqvist, and Magnus Sahlgren. Semantic re-tuning with contrastive tension. In *International Conference on Learning Representations*, 2020.
- [Cer et al., 2017] Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In *International Work-shop on Semantic Evaluation (SemEval-2017)*, pages 1– 14, 2017.
- [Cer et al., 2018] Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Brian Strope, and Ray Kurzweil. Universal sentence encoder for English. In Empirical Methods in Natural Language Processing, pages 169–174, 2018.
- [Conneau *et al.*, 2017] Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. Supervised learning of universal sentence representations from natural language inference data. In *Empirical Methods in Natural Language Processing*, pages 670–680, 2017.
- [Devlin *et al.*, 2019] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of

- deep bidirectional transformers for language understanding. In *North American Chapter of the Association for Computational Linguistics*, pages 4171–4186, 2019.
- [Gao et al., 2021] Tianyu Gao, Xingcheng Yao, and Danqi Chen. SimCSE: Simple contrastive learning of sentence embeddings. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2021.
- [Lewis et al., 2020] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Association for Computational Linguistics, pages 7871–7880, July 2020.
- [Li et al., 2020] Bohan Li, Hao Zhou, Junxian He, Mingxuan Wang, Yiming Yang, and Lei Li. On the sentence embeddings from pre-trained language models. In *Empirical Methods in Natural Language Processing (EMNLP)*, pages 9119–9130, 2020.
- [Marelli et al., 2014] Marco Marelli, Stefano Menini, Marco Baroni, Luisa Bentivogli, Raffaella Bernardi, and Roberto Zamparelli. A SICK cure for the evaluation of compositional distributional semantic models. In *International Conference on Language Resources and Evaluation* (LREC'14), pages 216–223, 2014.
- [Reimers and Gurevych, 2019] Nils Reimers and Iryna Gurevych. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Empirical Methods in Natural Language Processing*, pages 3982–3992, 2019.
- [Rose *et al.*, 2010] Stuart Rose, Dave Engel, Nick Cramer, and Wendy Cowley. Automatic keyword extraction from individual documents. *Text mining: applications and the-ory*, 1:1–20, 2010.
- [Su et al., 2021] Jianlin Su, Jiarun Cao, Weijie Liu, and Yangyiwen Ou. Whitening sentence representations for better semantics and faster retrieval. *ArXiv preprint*, abs/2103.15316, 2021.
- [Wang et al., 2020] Shuohang Wang, Yuwei Fang, Siqi Sun, Zhe Gan, Yu Cheng, Jingjing Liu, and Jing Jiang. Crossthought for sentence encoder pre-training. In Empirical Methods in Natural Language Processing (EMNLP), pages 412–421, 2020.
- [Wei and Zou, 2019] Jason Wei and Kai Zou. EDA: Easy data augmentation techniques for boosting performance on text classification tasks. In *Empirical Methods in Natural Language Processing*, pages 6382–6388, 2019.
- [Yan et al., 2021] Yuanmeng Yan, Rumei Li, Sirui Wang, Fuzheng Zhang, Wei Wu, and Weiran Xu. ConSERT: A contrastive framework for self-supervised sentence representation transfer. In Association for Computational Linguistics, pages 5065–5075, 2021.
- [Yang et al., 2020] Ziyi Yang, Yinfei Yang, Daniel Cer, Jax Law, and Eric Darve. Universal sentence representation learning with conditional masked language model. *ArXiv* preprint, abs/2012.14388, 2020.