SupCL-Seq: Supervised Contrastive Learning for Downstream Optimized Sequence Representations

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Abstract
While contrastive learning is proven to be an effective training strategy in computer vision, Natural Language Processing (NLP) is only recently adopting it as a self-supervised alternative to Masked Language Modeling (MLM) for improving sequence representations. This paper introduces SupCL-Seq, which extends the supervised contrastive learning from computer vision to the optimization of sequence representations in NLP. By altering the dropout mask probability in standard Transformer architectures (e.g., BERTbase), for every representation (anchor), we generate augmented altered views. A supervised contrastive loss is then utilized to maximize the system’s capability of pulling together similar samples (e.g., anchors and their altered views) and pushing apart the samples belonging to the other classes. Despite its simplicity, SupCL-Seq leads to large gains in many sequence classification tasks on the GLUE benchmark compared to a standard BERTbase, including 6% absolute improvement on CoLA, 5.4% on MRPC, 4.7% on RTE and 2.6% on STS-B. We also show consistent gains over self-supervised contrastively learned representations, especially in non-semantic tasks. Finally we show that these gains are not solely due to augmentation, but rather to a downstream optimized sequence representation. Code: https://github.com/hooman650/SupCL-Seq

1 Introduction
Sequence classification is a fundamental problem in natural language processing (NLP), as it has a wide range of applications, including but not limited to the tasks such as sentiment analysis, inference and question answering (Minaee et al., 2020). Cross-entropy loss is generally the default loss function in training neural networks for NLP downstream tasks (Zhang and Sabuncu, 2018; Sukhbaatar et al., 2015). Recently, thanks to the simplicity of augmentation methods in computer vision (e.g., zooming, cropping, rotation, etc.), self-supervised and supervised variants of contrastive learning proved to be effective training approaches in image classification tasks (Wu et al., 2018; Hénaff et al., 2019; Khosla et al., 2020). These methods aim at optimizing the representations by minimizing the distance between similar samples and maximizing it between diverse samples (Chen et al., 2020). Gao et al. (2021) proposed to leverage the built-in dropout masks in attention and fully-connected layers of Transformers (Vaswani et al., 2017) to introduce noise in the embedding representations. This is obtained by simply passing twice the same input and using different dropout masks. In this way, for every representation (anchor), altered views are generated. Gao et al. (2021) applied this augmentation approach to improve the semantic representation of a sequence in a self-supervised fashion, by taking an input sentence and contrasting its similarity against its augmented version and the remaining samples in a batch. The authors further extended this approach by employing positive (i.e., entailment) and negative (i.e., contradiction) examples from natural language inference (NLI) datasets. The resulting sentence embeddings achieved large gains in semantic textual similarity (STS) tasks.

To the best of our knowledge, however, contrastive learning has not yet been applied in a supervised fashion to optimize sequence representations towards downstream tasks.¹ Inspired by the recently proposed supervised contrastive learning in computer vision (Khosla et al., 2020), in this paper we introduce SupCL-Seq, which extends the self-supervised contrastive method by Gao et al. (2021) to a supervised contrastive learning approach, in which anchors and altered views, along with their classification labels, are used to learn downstream

¹During the review process, we were made aware of a contemporaneous work by Gunel et al. (2020) on supervised contrastive learning for natural language processing. A major difference between their work and ours lays in the adopted augmentation methodology.
optimized sequence representations by means of contrastive learning (see Figure 1 for details).

SupCL-Seq is simple and can be applied to any sequence classification task, on any arbitrary number of classes. In our experiments, SupCL-Seq leads to large gains in several tasks of the GLUE benchmark (Wang et al., 2018), including CoLA (6% Matthew’s correlation coefficient absolute improvement), MRPC (5.4% accuracy score absolute improvement), RTE (4.3% accuracy score absolute improvement) and STS-B (2.6% Spearman’s rank correlation coefficient absolute improvement).

The main contributions of this paper are:

- The adaptation from computer vision to NLP of a supervised contrastive learning approach for sequence classification tasks (SupCL-Seq), which extends Gao et al. (2021)’s approach by optimizing the sequence representations for any downstream task, independently on the number of classes.

- Empirical demonstration that SupCL-Seq leads to significant gains in many text classification tasks in GLUE (Wang et al., 2018) using a standard transformer such as BERTbase (Devlin et al., 2018).

2 Method

SupCL-Seq extends the self-supervised contrastive learning (Gao et al., 2021) for improving semantic representations to a supervised setting, in which representations are optimized towards the downstream task, independently on the number of labels.

The augmentation step is obtained by forward propagating the input batch N times in the same encoder with N distinct dropout masks (i.e., different dropout probabilities). The generated altered views, along with their anchor’s label, are then used to optimize the sequence representations through a supervised contrastive loss function (Khosla et al., 2020). Figure 1 details our training approach.

Formally, our pipeline consists of a single Encoder Transformer, $Enc()$ (i.e., BERTbase with $\approx 110$M parameters (Devlin et al., 2018)). This encoder generates $N$ altered embeddings, $\tilde{x}_n = Enc(x, p_n)$, for each input $x$ and dropout probability $p_n$. A contrastive loss function is then applied in a supervised fashion to maximize the encoder’s capability of building downstream optimized sequence representations (see Section 2.1). After this contrastive training, the encoder parameters are frozen and a linear classification layer is then trained with cross-entropy. In the remainder of this section, we review the self-supervised contrastive function (Gao et al., 2021) and its extended supervised counterpart inspired by Khosla et al. (2020).

2.1 Contrastive Learning

Let $i \in I \equiv \{1 \cdots MN\}$ be the index of all the encoded sequence embeddings $\tilde{X} \equiv \{\tilde{x}_1 \cdots \tilde{x}_{MN}\}$ in an input batch. Each sample $i$ is forward propagated $N$ time using distinct drop-out masks, general.
We performed a set of experiments to i) evaluate the effect of number and level of dropout passes on two challenging datasets (see 3.1); ii) compare the performance of a standard BERT\textsubscript{base} (Devlin et al., 2018) architecture with a SupCL-Seq-empowered BERT\textsubscript{base} model on several benchmarks in GLUE (Wang et al., 2018) (see 3.2); iii) compare the performance of SupCL-Seq with the self-supervised contrastive approach introduced by Gao et al. (2021) in a subset of tasks (see 3.3); and, finally, iv) assess whether the improvements achieved with our approach are solely due to augmentation (i.e., dropout masks) and to which extend contrastive loss helped (see 3.2.1).

### 3.1 Dropout Levels

In order to study the effect of the number and the level of dropout passes, we assessed the performance of several configurations of BERT\textsubscript{base} on CoLA (Warstadt et al., 2018) and RTE (Dagan et al., 2006) datasets. Gao et al. (2021) empirically showed that using two distinct dropout masks with the same probability of \( p = 0.1 \) lead to the highest performance in their settings. In our supervised experiments, instead, we can generate views with different levels of noise, as the system can always rely on their labels. Therefore we choose different parameters, using intervals of 0.1 for the dropout probabilities. Table 1 reports the results for both datasets. While clear improvements are visible on CoLA when more masks are applied, experiments on RTE show that this is not always the case. In the latter dataset, in fact, performance fluctuates largely across the settings, achieving the highest score when three passes are used. This suggests that the number and level of dropout passes is a task-dependent hyper-parameter.

### 3.2 GLUE Tasks

In order to assess the benefit of SupCL-Seq, we compared the performance of a standard

| Task    | Drop-out                  | Batch size | Score |
|---------|---------------------------|------------|-------|
|          | [0.0,0.1,0.2,0.3]         | 800        | 61.2  |
|          | [0.0,0.1,0.2,0.3,0.4]     | 640        | 57.9  |
| CoLA    | [0.0,0.1,0.2]             | 480        | 58.9  |
|         | [0.1,0.0]                | 320        | 57.9  |
|         | [0.1,0.1]                | 256        | 60.7  |
|          | [0.0,0.1,0.2,0.3,0.4]     | 800        | 63.5  |
|          | [0.0,0.1,0.2,0.3]         | 640        | 62.4  |
| RTE     | [0.0,0.1,0.2]             | 480        | 69.3  |
|         | [0.0,0.1]                | 320        | 63.8  |
|         | [0.1,0.0]                | 256        | 65.3  |

Table 1: Effects of different dropout masks and number of views on CoLA and RTE tasks. Score denotes Matthews Correlation Coefficient.

### 3 Experiments

In self-supervised contrastive learning (Gao et al., 2021; Khosla et al., 2020), the cost function is formulated as:

\[
    L_{i,\text{self-sup}} = - \sum_{i \in I} \log \frac{e^{sim(\hat{x}_i, \tilde{x}_{i,j})}/\tau}{\sum_{b \in B(i)} e^{sim(\hat{x}_i, \tilde{x}_b)}/\tau},
\]

(1)

Where, \( B(i) \equiv I \setminus \{i\} \) is the set of so called negative pairs for the anchor \( \hat{x}_i \). \( \tau \) is a temperature scaling parameter. \( sim(.) \) stands for any similarity function such as cosine similarity or the inner product.

The main shortcoming of self-supervised contrastive learning is that since the class labels of the inputs are ignored, the samples from the same class might end up being employed as the negative pairs (e.g. \( B(I) \)) and therefore hurt the training performance. For instance, in CoLA (Warstadt et al., 2018) the aim is to determine whether the input is grammatical or ungrammatical. An unsupervised contrastive learning in this case might employ a grammatically correct sentence as the negative pair for the input anchor (see Figure 1).

In order to avoid this limitation and make the system able to learn in a supervised fashion, Khosla et al. (2020) extended Equation 1 to account for input labels. Given \( M \) annotated samples \( \{\tilde{x}_i, \tilde{y}_i\}_{i=1,...,M} \) passed \( N \) times through the dropout masks, the supervised contrastive learning loss is defined as:

\[
    L_{i,\text{sup}} = \sum_{i \in I} \frac{-1}{|P(i)|} \log \frac{e^{sim(\hat{x}_i, \tilde{x}_p)}/\tau}{\sum_{b \in B(i)} e^{sim(\hat{x}_i, \tilde{x}_b)}/\tau},
\]

(2)

Where \( P(i) \equiv \{p \in B(i) : \tilde{y}_p = \tilde{y}_i\} \) is the positive pair set distinct from sample \( i \) and \( |.| \) stands for cardinality (for details on derivation of Equation 2 see Khosla et al. (2020)). SupCL-Seq employs \( L_{i,\text{sup}} \) as contrastive loss function.

### 3.3 Expanding Contrastive Learning

Table 1: Effects of different dropout masks and number of views on CoLA and RTE tasks. Score denotes Matthews Correlation Coefficient.
BERT\textsubscript{base} - Standard is our implementation using the reported hyper-parameters in Devlin et al. (2018) for each task. BERT\textsubscript{base} - Dropout Augmented is the standard version trained also on augmented samples. Matthews Correlation Coefficient is reported for CoLA, Pearson/Spearman correlations for STS-B, F1/Accuracy for MRPC, F1 score for QQP, and accuracy scores are reported for the other tasks.

Table 2: GLUE Test results. BERT\textsubscript{base} - Standard is our implementation using the reported hyper-parameters in Devlin et al. (2018) for each task. BERT\textsubscript{base} - Dropout Augmented is the standard version trained also on augmented samples. Matthews Correlation Coefficient is reported for CoLA, Pearson/Spearman correlations for STS-B, F1/Accuracy for MRPC, F1 score for QQP, and accuracy scores are reported for the other tasks.

Table 3: Comparison of unsupervised and supervised contrastive loss.

| System               | RTE   | CoLA | MRPC   |
|----------------------|-------|------|--------|
| BERT\textsubscript{base} - Self-supervised-CL | 55.6  | 35   | 79/68.3 |
| BERT\textsubscript{base} - SupCL-Seq          | 69.3  | 61.2 | 89.7/85.7 |

3.3 Supervised Versus Unsupervised contrastive Learning

Since, to the best of our knowledge, the only previous attempt of using contrastive learning for improving sequence representation in NLP was performed by Gao et al. (2021) – they used a self-supervised approach to improve the semantic representation, adopting a loss similar to Equation 1 –, in Table 3.3 we compare the performance of a linear layer trained on top of their representations with the one of a linear layer trained on top of our representations, which are instead optimized in a supervised fashion while the parameters of the base model are kept frozen. SupCL-Seq significantly outperforms the re-implementation of Gao et al. (2021), with larger gains in non-semantic tasks (e.g. CoLA), suggesting that our representations are optimized for the given downstream tasks.

4 Discussion and Conclusion

In this paper, we introduced SupCL-Seq a supervised contrastive learning framework for optimizing sequence representations for downstream tasks. In a series of experiments, we showed that SupCL-Seq leads to large performance gains in almost all GLUE tasks when compared to both a standard BERT\textsubscript{base} architecture and an augmented BERT\textsubscript{base} (i.e., improvements are not only due to augmentation). We also investigated the effect of number and level of dropout passes, finding that this has to be treated as a task-dependent hyper-parameter, to be fine tuned in a validation set. Finally, we compared our supervised approach to the self-supervised method by Gao et al. (2021), showing...
consistent performance improvements, especially in non-semantic tasks, where the self-supervised approach is weaker. These encouraging results open the door to multi-task learning applications of SupCL-Seq, where the optimization needs to be constrained towards multiple objectives.

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A Training Details

| Task   | Learning Rate | Batch Size | dropout       |
|--------|---------------|------------|---------------|
| CoLA   | $5e^{-05}$    | 128        | $[0.0, 0.1, 0.2]$ |
| MRPC   | $1e^{-4}$     | 128        | $[0.0, 0.05, 0.1, 0.2]$ |
| RTE    | $1e^{-4}$     | 48         | $[0.0, 0.1, 0.2]$ |
| STS-B  | $1e^{-4}$     | 64         | $[0.0, 0.05, 0.1, 0.2]$ |
| SST-2  | $5e^{-05}$    | 320        | $[0.0, 0.1, 0.2]$ |
| WNLI   | $1e^{-04}$    | 320        | $[0.0, 0.1, 0.2]$ |
| QNLI   | $5e^{-05}$    | 48         | $[0.0, 0.2]$ |
| QQP    | $5e^{-05}$    | 16         | $[0.0, 0.2, 0.3, 0.4, 0.5]$ |
| MNLI   | $5e^{-05}$    | 8          | $[0.1, 0.1]$ |

Table 4: Contrastive learning training details per GLUE task. All of the tasks were trained for 5 epochs (except QNLI, QQP and MNLI that were trained for 2, 1 and 3 epochs respectively) and $\tau = 0.05$.

SupCL-Seq is implemented on top of the Huggingface’s trainer python package (Wolf et al., 2019)⁴. For the $\text{sim}(.)$ (similarity) function, we employed inner dot product. For supervised contrastive learning, we employed the hyperparameters detailed in Table 4. We used a grid search strategy for our hyperparameter optimization, where the number of dropouts and their corresponding probability were set to two (i.e. $[0.1, 0.1]$) and five respectively ($[0.0, 0.1, 0.2, 0.3, 0.4]$). For the learning rate we employed a range of $[5e^{-05}, 1e^{-4}]$.

⁴https://github.com/huggingface/transformers