

# JOURNAL OF LATEX CLASS FILES, VOL. 14, NO. 8, AUGUST 202

## 1 1

### Abstract

—Unsupervised contrastive learning has become a hot topic in natural language processing. Existing works Add&Output InfoNCE usually aim at constraining the orientation distribution of the Mutual and Self-supervised representations of positive and negative samples in the high- InfoNCE dimensional semantic space in contrastive learning, but the semantic representation tensor possesses both modulus and orientation features, and the existing works ignore the modulus feature of the representations and cause insufficient contrastive learning. Therefore, we first propose a training objective that is designed a. b. to impose modulus constraints on the semantic representation Input tensor, to strengthen the alignment between positive samples in contrastive learning. Then, the BERT-like model suffers from the phenomenon of sinking attention, leading to a lack of attention of Cross-Attention hidden States to CLS token that aggregates semantic information. In response, we propose a cross-attention structure among the twin-tower Fig. 1. Subfigure a. represents the traditional ensemble modeling approach ensemble models to enhance the model's attention to CLS token (EDFSE[1]), which naively trains multiple sub-encoders separately and then optimize the quality of CLS Pooling. Combining the above sum of the outputs. This approach causes a large inference overhead. Subfigure two motivations, we propose a new Joint Tensor representation b. represents the optimized ensemble learning framework JTCSE proposed in this work. It incorporates semantic representation tensor modulus constraints learning Sentence Embedding representation framework JTCSE, and joint modeling of cross-attention between sub-encoders. This framework which we evaluate in seven semantic text similarity computation contains only two sub-encoders. It significantly reduces inference overhead while improving the quality of sentence embeddings relative to a. ensemble model and single-tower distillation model outperform the other baselines and become the current SOTA. In addition, we have conducted an extensive zero-shot downstream task [2] and RoBERTa [3], much work has been done based on evaluation, which shows that JTCSE outperforms other baselines these two PLMs, e.g., Sentence-BERT [4], ConSERT [5], and overall on more than 130 tasks. SimCSE [6]. SimCSE applies InfoNCE's [7] idea of contrastive learning [8] by generating positive samples through the following: <https://github.com/tianyuzong/JTCSE>. Dropout method of the BERT-like model at training time and Index Terms—Unsupervised Contrastive Learning, Semantic uniformly distributing unlabeled soft-negative samples. With TextualSimilarity, Tensor-ModulusConstraints, Cross-Attention. the appearance of SimCSE, many works are based on the idea of unsupervised contrastive learning in SimCSE and InfoNCE. For example, ESimCSE [9] augments the positive sample in I.