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abstract	Self-supervised learning approach like contrastive learning is attached great attention in natural language processing. It uses pairs of training data augmentations to build a classification task for an encoder with well representation ability. However, the construction of learning pairs over contrastive learning is much harder in NLP tasks. Previous works generate word-level changes to form pairs, but small transforms may cause notable changes in the meaning of sentences as the discrete and sparse nature of natural language. In this paper, adversarial training is performed to generate challenging and harder learning adversarial examples over the embedding space of NLP as learning pairs. Using contrastive learning improves the generalization ability of adversarial training because contrastive loss can uniform the sample distribution. And at the same time, adversarial training also enhances the robustness of contrastive learning. Two novel frameworks, supervised contrastive adversarial learning (SCAL) and unsupervised SCAL (USCAL), are proposed, which yield learning pairs by utilizing the adversarial training for contrastive learning. The label-based loss of supervised tasks is exploited to generate adversarial examples while unsupervised tasks bring contrastive loss. To validate the effectiveness of the proposed framework, we employ it to Transformer-based models for natural language understanding, sentence semantic textual similarity, and adversarial learning tasks. Experimental results on GLUE benchmark tasks show that our fine-tuned supervised method outperforms BERTbase over 1.75%. We also evaluate our unsupervised method on semantic textual similarity (STS) tasks, and our method gets 77.29% with BERTbase . The robustness of our approach conducts state-of-the-art results under multiple adversarial datasets on	Self-supervised learning approach like contrastive learning is attached great attention in natural language processing. It uses pairs of training data augmentations to build a classification task for an encoder with well representation ability. However, the construction of learning pairs over contrastive learning is much harder in NLP tasks. Previous works generate word-level changes to form pairs, but small transforms may cause notable changes on the meaning of sentences as the discrete and sparse nature of natural language. In this paper, adversarial training is performed to generate challenging and harder learning adversarial examples over the embedding space of NLP as learning pairs. Using contrastive learning improves the generalization ability of adversarial training because contrastive loss can uniform the sample distribution. And at the same time, adversarial training also enhances the robustness of contrastive learning. Two novel frameworks, supervised contrastive adversarial learning (SCAL) and unsupervised SCAL (USCAL), are proposed, which yields learning pairs by utilizing the adversarial training for contrastive learning. The label-based loss of supervised tasks is exploited to generate adversarial examples while unsupervised tasks bring contrastive loss. To validate the effectiveness of the proposed framework, we employ it to Transformer-based models for natural language understanding, sentence semantic textual similarity and adversarial learning tasks. Experimental results on GLUE benchmark tasks show that our fine-tuned supervised method outperforms BERT_base over 1.75%. We also evaluate our unsupervised method on semantic textual similarity (STS) tasks, and our method gets 77.29% with BERT_base. The robustness of our approach conducts state-of-the-art results under multiple adversarial datasets on NLI tasks.		
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