

Adversarial Training for Large Neural Language Models

Xiaodong Liu[†], Hao Cheng[†], Pengcheng He[‡], Weizhu Chen[‡], Yu Wang[†], Hoifung Poon[†], Jianfeng Gao[†]

[†] Microsoft Research

[‡] Microsoft Dynamics 365 AI

{xiaodl, chehao, penhe, wzchen, yuhan, hoifung, jfgao}@microsoft.com

Abstract

Generalization and robustness are both key desiderata for designing machine learning methods. Adversarial training can enhance robustness, but past work often finds it hurts generalization. In natural language processing (NLP), pre-training large neural language models such as BERT have demonstrated impressive gain in generalization for a variety of tasks, with further improvement from adversarial fine-tuning. However, these models are still vulnerable to adversarial attacks. In this paper, we show that adversarial pre-training can improve both generalization and robustness. We propose a general algorithm ALUM (Adversarial training for large neural LangUage Models), which regularizes the training objective by applying perturbations in the embedding space that maximizes the adversarial loss. We present the first comprehensive study of adversarial training in all stages, including pre-training from scratch, continual pre-training on a well-trained model, and task-specific fine-tuning. ALUM obtains substantial gains over BERT on a wide range of NLP tasks, in both regular and adversarial scenarios. Even for models that have been well trained on extremely large text corpora, such as RoBERTa, ALUM can still produce significant gains from continual pre-training, whereas conventional non-adversarial methods can not. ALUM can be further combined with task-specific fine-tuning to attain additional gains. The ALUM code and pre-trained models will be made publicly available at <https://github.com/namisan/mt-dnn>.

1 Introduction

Generalization and robustness are two fundamental considerations in assessing machine learning methods. Ideally, a learned model should perform well on unseen test examples and withstand adversarial attacks. In natural language processing

(NLP), pre-training neural language models on unlabeled text has proven very effective to improve generalization performance for a variety of downstream tasks, as exemplified by BERT (Devlin et al., 2018) and other transformer-based models (Liu et al., 2019c; Radford et al., 2018; Clark et al., 2020; Dong et al., 2019; Bao et al., 2020). However, these models may still suffer catastrophic failures in adversarial scenarios (Nie et al., 2019; Hsieh et al., 2019). For example, Jin et al. (2019) show that classification accuracy on a Yelp dataset drops from 95.6% on standard test to 6.8% on robust test for a BERT model.

Adversarial training (Madry et al., 2017; Goodfellow et al., 2014) has been well studied in computer vision, but past work shows that it often hurts generalization (Raghunathan et al., 2019; Min et al., 2020). In NLP, there is growing interest in adversarial training, but existing work typically focuses on assessing the impact on generalization (Zhu et al., 2019; Jiang et al., 2019; Cheng et al., 2019; Wang et al., 2019). Moreover, adversarial training is generally limited to task-specific fine-tuning¹. See Minaee et al. (2020a) for a recent survey.

In this paper, we present the first comprehensive study on adversarial pre-training, and show that it can improve both generalization and robustness for a wide range of NLP tasks. We propose a unifying algorithm ALUM (Adversarial training for large neural LangUage Models), which augments the standard training objective with an additional term that maximizes the adversarial loss via applying perturbation in the embedding space. ALUM is generally applicable to pre-training and fine-tuning, on top of any Transformer-based language models.

We conduct a comprehensive evaluation on

¹A notable exception is Wang et al. (2019), but it only applied adversarial training to generative language modeling.

various NLP tasks across multiple benchmark datasets, including GLUE, SQuAD v1.1/v2.0, SNLI, SciTail for assessing model generalization, and ANLI, HELLSWAG, SWAG, Adversarial SQuAD for assessing model robustness. Experimental results show that by conducting adversarial pre-training, ALUM attains significant improvements, often outperforming previous state of the art by a large margin. This is true even for the extremely well-trained RoBERTa model, where continual pre-training without adversarial training fails to attain any gain.

Remarkably, in addition to improving generalization, we find that adversarial pre-training also substantially improves robustness, as exemplified by the resulting large gains in adversarial datasets such as ANLI, Adversarial-SQuAD, HELLSWAG, which significantly reduces the gap between standard errors and robust errors for popular models like BERT and RoBERTa. This suggests that adversarial training on unlabeled data can provide a promising direction to reconcile the apparent conflict between generalization and robustness as observed in prior work (Raghunathan et al., 2019; Min et al., 2020). We also show that adversarial pre-training can be combined with adversarial fine-tuning, resulting in extra gains.

Our contributions are summarized as follows:

- We propose ALUM, a general algorithm to incorporate adversarial training for pre-training and fine-tuning large neural language models.
- We conduct a comprehensive evaluation on a wide range of NLP tasks and assess the impact of adversarial training in pre-training from scratch, continual pre-training, task-specific fine-tuning, and their combinations.
- We obtain significant improvements over prior state of the art, including extremely well-trained models such as RoBERTa, in both generalization and robustness.
- To facilitate research, we will release our code and pre-trained models.

2 Preliminary

In this section, we give a quick overview of language model pre-training, using BERT (Devlin

et al., 2018) as a running example for transformer-based neural language models.

2.1 Input Representation

We assume that the input consists of text spans (typically sentences) separated by a special token $[SEP]$. To address the problem of out-of-vocabulary words, tokens are divided into subword units, using Byte-Pair Encoding (BPE) (Sennrich et al., 2015) or its variants (Kudo and Richardson, 2018), which generates a fixed-size subword vocabulary to compactly represent words in training text corpora.

2.2 Model Architecture

Following recent pre-training methods (Devlin et al., 2018; Liu et al., 2019c), we use transformer-based models (Vaswani et al., 2017) to leverage a multi-head attention mechanism, which have demonstrated superiority in parallel computation and modeling long-range dependencies, compared to recurrent neural networks such as LSTM (Hochreiter and Schmidhuber, 1997). The input is first passed to a lexical encoder, which combines a token embedding, a (token) position embedding and a segment embedding (i.e., which text span the token belongs to) by element-wise summation. The embedding layer is then passed to multiple layers of transformer modules to generate the contextual representation (Vaswani et al., 2017).

2.3 Self Supervision

A key innovation in BERT (Devlin et al., 2018) is the use of **Masked Language Model (MLM)** for self-supervised pre-training. Instead of predicting the next token based on the preceding tokens, as in traditional generative language models, MLM randomly replaces a subset of tokens by a special token (e.g., $[MASK]$), and asks the model to predict them. Essentially, it is a cloze task (Taylor, 1953), where the training objective is the cross-entropy loss between the original tokens and the predicted ones. In BERT and RoBERTa, 15% of the input tokens are chosen, among which a random 80% are replaced by $[MASK]$, 10% are left unchanged and 10% are randomly replaced by a token from the vocabulary. In our experiments, instead of using a fixed masked rate of 15%, we gradually increase it from 5% to 25% with 5% increment for every 20% of training epochs, as we find this makes pre-training more stable.

Additionally, BERT also uses **Next Sentence Prediction (NSP)**, which is a binary classification task that for a given sentence pair determines whether one sentence follows the other in the original text. There have debates on how much NSP helps (Liu et al., 2019c). But we include it in our experiments for a fair comparison with BERT.

3 ALUM (Adversarial training for large neural LangUage Models)

In this section, we first present a unifying view of standard training objectives and prior approaches to adversarial training. We then present ALUM, which is a general adversarial training algorithm applicable to pre-training and fine-tuning, on top of any transformer-based neural language models.

3.1 Standard Training Objectives

Both pre-training and fine-tuning can be viewed as minimizing the standard error on training data, with the training objectives derived from self-supervision (MLM and NSP in pre-training) or direct supervision (labeled examples in task-specific fine-tuning), respectively.

Specifically, the training algorithms seek to learn a function $f(x; \theta) : x \rightarrow C$, parametrized by θ . In MLM, C is the vocabulary, and $f(x; \theta)$ tries to predict the masked token y . In fine-tuning, C is the task-specific label set, and $f(x; \theta)$ is the classifier. Given a training dataset D of input-output pairs (x, y) and the loss function $l(\cdot, \cdot)$ (e.g., cross entropy), $f(x; \theta)$ is trained to minimize the empirical risk:

$$\min_{\theta} \mathbb{E}_{(x,y) \sim D} [l(f(x; \theta), y)] \quad (1)$$

3.2 Adversarial Training

Pre-training a large neural language model such as BERT has proven effective to improve generalization performance in task-specific fine-tuning (Devlin et al., 2018). However, such models can still suffer catastrophic loss in adversarial scenarios (Nie et al., 2019; Hsieh et al., 2019; Madry et al., 2017; Jin et al., 2019), with attacks as simple as replacing a few words in input sentences while preserving the semantics.

To improve model robustness and withstand adversarial attacks, adversarial training has been proposed and studied extensively, predominantly in computer vision literature (Goodfellow et al., 2014; Madry et al., 2017). The key idea is to modify the training objective by applying small pertur-

bation to input images that maximize the adversarial loss:

$$\min_{\theta} \mathbb{E}_{(x,y) \sim D} [\max_{\delta} l(f(x + \delta; \theta), y)] \quad (2)$$

where the inner maximization can be solved by running a number of projected gradient descent steps (Madry et al., 2017).

While adversarial training has been successful in mitigating adversarial attacks, past work often encounters an apparent conflict between generalization and robustness (Raghunathan et al., 2019, 2020; Min et al., 2020), as adversarial training could hurt generalization performance.

3.3 The ALUM Algorithm

In NLP, applying adversarial training is not straightforward, since the input are discrete elements (token or subword sequences), but there have been some recent successes (Zhu et al., 2019; Jiang et al., 2019; Cheng et al., 2019; Wang et al., 2019; Minaee et al., 2020b). However, aside from Wang et al. (2019), there has not been any prior work on adversarial pre-training, and Wang et al. (2019) only applied adversarial training to generative language modeling using LSTM.

ALUM is applicable to both pre-training and fine-tuning. It builds on several key ideas that have proven useful in prior work. First, instead of applying perturbation to the input text directly, one would perturb the embedding space. Namely, x is the sub-word embedding in $f(x; \theta)$ (Jiang et al., 2019; Zhu et al., 2019).

Second, instead of adopting the adversarial training objective of Eq. 2, as in Zhu et al. (2019) and most other approaches, we follow Jiang et al. (2019) to regularize the standard objective using virtual adversarial training (Miyato et al., 2018):

$$\begin{aligned} & \min_{\theta} \mathbb{E}_{(x,y) \sim D} [l(f(x; \theta), y) + \\ & \alpha \max_{\delta} l(f(x + \delta; \theta), f(x; \theta))] \end{aligned} \quad (3)$$

Effectively, the adversarial term favors label smoothness in the embedding neighborhood, and α is a hyperparameter that controls the trade-off between standard errors and robust errors.

We found that virtual adversarial training is superior to conventional adversarial training, especially when labels might be noisy. E.g., BERT pre-training uses the masked words as self-supervised labels, but in many cases, they could be replaced by other words to form completely legitimate text. Empirically, we verified that this is indeed the case, as pre-training benefits from larger α . We set

Algorithm 1 ALUM

Input: T : the total number of iterations, $\mathcal{X} = \{(x_1, y_1), \dots, (x_n, y_n)\}$: the dataset, $f(x; \theta)$: the machine learning model parametrized by θ , σ^2 : the variance of the random initialization of perturbation δ , ϵ : perturbation bound, K : the number of iterations for perturbation estimation, η : the step size for updating perturbation, τ : the global learning rate, α : the smoothing proportion of adversarial training in the augmented learning objective, Π : the projection operation.

```
1: for  $t = 1, \dots, T$  do
2:   for  $(x, y) \in \mathcal{X}$  do
3:      $\delta \sim \mathcal{N}(0, \sigma^2 I)$ 
4:     for  $m = 1, \dots, K$  do
5:        $g_{adv} \leftarrow \nabla_\delta l(f(x; \theta), f(x + \delta; \theta))$ 
6:        $\delta \leftarrow \Pi_{\|\delta\|_\infty \leq \epsilon}(\delta + \eta g_{adv})$ 
7:     end for
8:      $g_\theta \leftarrow \nabla_\theta l(f(x; \theta), y)$ 
       $+ \alpha \nabla_\theta l(f(x; \theta), f(x + \delta; \theta))$ 
9:      $\theta \leftarrow \theta - \tau g_\theta$ 
10:    end for
11:  end for
```

Output: θ

$\alpha = 10$ for pre-training, and $\alpha = 1$ for fine-tuning in all our experiments.

Compared to standard training, adversarial training is rather expensive due to the inner maximization. Zhu et al. (2019) adopted the *free adversarial training* idea in Shafahi et al. (2019) for acceleration, by reusing the backward pass for gradient computation to carry out the inner ascent step and outer descent step simultaneously. Inspired by ERNIE (Sun et al., 2019) and other continual pre-training approaches, we instead adopt a curriculum learning approach: first train the model using the standard objective (1); and then continue the training with virtual adversarial training (3).

Jiang et al. (2019) also incorporated a momentum term using the Bregman proximate point method, which can be quite costly in training time. We found that our curriculum learning approach largely rendered this unnecessary and simplified our algorithm without using this term.

Algorithm 1 shows the details of ALUM. Line 4-6 run K projected gradient steps to find the perturbation δ that maximizes the adversarial loss (violation of local smoothness). Note that a larger K

leads to better approximation (Madry et al., 2017; Qin et al., 2019), but it is more expensive. To attain a good trade-off between speed and performance, we set $K = 1$ in all our experiments.

3.4 Generalization vs. Robustness

Empirically, we found that by applying adversarial pre-training using ALUM, we were able to improve both generalization and robustness for a wide range of NLP tasks, as seen in Section 4. This is very interesting as prior work often finds that adversarial training hurts generalization, even with theoretical justification (Raghunathan et al., 2019, 2020; Min et al., 2020).

We hypothesize that adversarial pre-training might be the key for reconciling this apparent incongruence, as prior work on the conflict between generalization and robustness generally focuses on the supervised learning setting. Interestingly, some nascent results in reconciling the two also leverage unlabeled data, such as self-training (Raghunathan et al., 2020). Additionally, we hypothesize that by perturbing the embedding space rather than the input space, adversarial training in NLP might inadvertently bias toward on-manifold perturbation than regular perturbation, which helps generalization (Stutz et al., 2019). We leave the theoretical analysis of all these connections to future work.

4 Experiments

In this section, we present a comprehensive study of adversarial training on large neural language models. We show that ALUM substantially improves both generalization and robustness in a wide range of NLP tasks, for both the standard BERT model and the extremely well-trained RoBERTa model. We also show that ALUM can be applied to adversarial pre-training and fine-tuning alike and attain further gain by combining the two.

4.1 Datasets

Pre-training: For BERT pre-training, we use Wikipedia (English Wikipedia dump²; 13GB). For continual pre-training of RoBERTa, we use Wikipedia (13GB), OPENWEBTEXT (public Reddit content (Gokaslan and Cohen); 38GB), STORIES (a subset of CommonCrawl (Trinh and Le, 2018); 31GB).

²<https://dumps.wikimedia.org/enwiki/>

NLP application benchmarks: To assess the impact of adversarial training on generalization, we use standard benchmarks such as GLUE (Wang et al., 2018) and SQuAD (v1.1 and v2.0) (Rajpurkar et al., 2016, 2018), as well as three named entity recognition (NER) tasks in the biomedical domain. To evaluate the impact of adversarial training on robustness, we use ANLI (Nie et al., 2019), Adversarial SQuAD (Jia and Liang, 2017), and HELLASWAG (Hampel, 1974). To assess the combination of adversarial pre-training and fine-tuning, we follow Jiang et al. (2019) and use MNLI (Williams et al., 2018) (from GLUE), ANLI, SWAG (Zellers et al., 2018), SNLI (Bowman et al., 2015), SciTail (Khot et al., 2018). These benchmarks cover a wide range of NLP tasks such as named entity recognition, textual entailment, and machine reading comprehension, spanning classification, ranking, and regression. For details, see Appendix A.

4.2 Implementation Details

We perform three types of adversarial training in our experiments: pre-training from scratch, continual pre-training on a well-trained model, and task-specific fine-tuning.

We pre-train BERT models from scratch using Wikipedia³. The training code is based on Megatron, implemented in PyTorch (Shoeybi et al., 2019)⁴. We use ADAM (Kingma and Ba, 2014) for the optimizer with a standard learning rate schedule that increases linearly from zero to the peak rate of 1×10^{-4} in first one percent of steps, and then decays linearly to zero in the remaining 99% of steps. Following Devlin et al. (2018), training is done for one million steps with batch size of 256. We set the perturbation size $\epsilon = 1 \times 10^{-5}$, the step size $\eta = 1 \times 10^{-3}$, and the variance for initializing perturbation $\sigma = 1 \times 10^{-5}$. We set $\alpha = 10$ for heightened regularization in virtual adversarial training, and set $K = 1$ for training efficiency (i.e., one projected gradient step). The training takes 10 days on one DGX-2 machine with 16 V100 GPUs.

For continual pre-training of RoBERTa (Liu et al., 2019c), we use RoBERTa’s default training parameters, except a smaller learning rate (4×10^{-5}), and run for 100K training steps with a batch size of 256 on the union of Wikipedia, OPEN-

WEBTEXT, and STORIES (total size 82GB). The code is based on FairSeq⁵. The training takes 7 days on two DGX-2 machines.

For fine-tuning with or without adversarial training, we use the MT-DNN open-sourced toolkit (Liu et al., 2020, 2015)⁶. We follow Jiang et al. (2019) for head-to-head comparison, which uses ADAM (Kingma and Ba, 2014) and RADAM (Liu et al., 2019a) as our optimizers, with peak learning rates of $\{5 \times 10^{-6}, 8 \times 10^{-6}, 1 \times 10^{-5}, 2 \times 10^{-5}\}$, and batch sizes of 16, 32 or 64, depending on the tasks. The dropout rate is set to 0.1 for all the task-specific layers, except 0.3 for MNLI and 0.05 for CoLA. To avoid gradient exploding, the gradient is clipped to keep the norm within 1. All the texts are tokenized using WordPiece and chopped to spans up to 512 tokens. We conduct fine-tuning for up to 10 epochs and pick the best model using the dev set.

4.3 Improving Generalization

In this subsection, we study the impact of adversarial pre-training on generalization, by comparing the performance of pre-trained models in various downstream applications. First, we study the scenario of pre-training from scratch, by comparing three BERT models:

- **BERT_{BASE}** is the standard BERT base model trained using the same setting as Devlin et al. (2018) (i.e., 1M steps with a batch size of 256).
- **BERT+_{BASE}** is similar to BERT_{BASE}, except that it is trained with 1.6M steps, which takes roughly the same amount of time as that of adversarial pre-training (see ALUM_{BERT-BASE} below).
- **ALUM_{BERT-BASE}** is a BERT model trained using the same setting as BERT_{BASE}, except that ALUM is used in the last 500K steps. Each adversarial training step takes approximately 1.5 times longer than a step in standard training⁷.

Table 1 compares these pre-trained models on three standard benchmarks (SQuAD v1.1 (Rajpurkar et al., 2016) and v2.0 (Rajpurkar et al.,

⁵<https://github.com/pytorch/fairseq>

⁶<https://github.com/namisan/mt-dnn>

⁷With K=1 in Algorithm 1, ALUM requires two more forward passes and one more backward pass compared to standard training.

³BookCorpus is no longer publicly available.

⁴<https://github.com/NVIDIA/Megatron-LM>

Model	SQuAD v1.1/v2.0		MNLI m/mm
	F1/EM	F1/EM	Acc
BERT _{BASE}	88.5/81.0	76.5/72.9	84.5/84.4
BERT+BASE	89.6/82.4	77.8/74.0	85.0/84.8
ALUM _{BERT-BASE}	90.8/83.7	80.2/76.6	85.8/86.1

Table 1: Comparison of standard and adversarial pre-training on SQuAD (v1.1 and v2.0) and MNLI (in-domain and out-domain). BERT_{BASE} and ALUM_{BERT-BASE} both use 1M pre-training steps, and BERT+BASE use 1.6M steps.

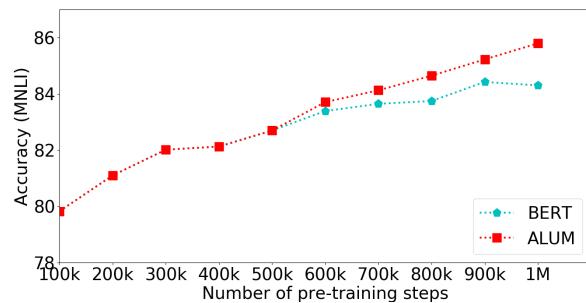


Figure 1: Comparison of the standard and adversarial pre-training on the MNLI development set.

2018), and MNLI from GLUE (Wang et al., 2018), using the same standard fine-tuning setting (without adversarial training). The standard BERT models trained using only the Wikipedia data attain similar results as in Devlin et al. (2018), thus provide a good baseline for comparison. ALUM_{BERT-BASE} consistently outperforms the standard BERT models across all the datasets, even adjusting for the slightly longer training time. E.g., on SQuAD v1.1, ALUM_{BERT-BASE} gains 2.3% points in F1 over BERT_{BASE} and 1.2% points over BERT+BASE. Figure 1 shows ALUM at work on the development set of MNLI. Once adversarial training is applied in the middle (after first 500K steps), ALUM starts outperforming BERT and the gap is widening.

We also assess the impact of adversarial pre-training in the biomedical domain, which is substantially different from the Wikipedia corpus used in pre-training. Table 2 shows the results on standard biomedical name entity recognition (NER) datasets: BC2GM (Smith et al., 2008), NCBI (Dogan et al., 2014), JNLPBA (Collier and Kim, 2004). Interestingly, ALUM still outperforms the standard BERT model on all three tasks, even though the application domain is substan-

Model	BC2GM	NCBI	JNLPBA
BERT _{BASE}	79.7	84.6	75.7
ALUM _{BERT-BASE}	81.1	86.9	76.5

Table 2: Comparison of standard and adversarial pre-training on biomedical NER. Scores are entity-level F1.

Model	MNLI-m/mm	SST-2
RoBERTa _{LARGE}	90.2/90.2	96.4
RoBERTa+ _{LARGE}	90.3/90.2	96.3

Table 3: RoBERTa is an extremely well-trained model: standard continual pre-training without adversarial training fails to improve generalization performance in downstream tasks. (Scores are accuracy.)

tially different from the pre-training one.

Next, we assess the impact of adversarial training in the continual pre-training setting. We use our pre-training dataset (Wikipedia, OPENWEBTEXT, STORIES; 82GB)⁸, and run 100K steps in all our continual pre-training experiments. We choose the RoBERTa models as the baseline, which use the same neural model as BERT, but were pre-trained on an order of magnitude more text (160GB vs 13GB). They are the state-of-the-art pre-trained language models, outperforming the standard BERT models in many NLP tasks.

RoBERTa models are extremely well-trained. Standard continual pre-training fails to attain any gains in downstream applications such as MNLI (Williams et al., 2018) and SST (Socher et al., 2013) from GLUE (Wang et al., 2018), as shown in Table 3. On the other hand, ALUM is able to attain further gain from continual pre-training of RoBERTa, as shown in Table 4. E.g., ALUM_{ROBERTA-BASE} outperforms RoBERTa_{BASE} by +0.5%, and ALUM_{ROBERTA-LARGE} outperforms RoBERTa_{LARGE} by +0.7% on the MNLI development set. This is rather remarkable, as by contrast standard continual pre-training is unable to attain any gain.

4.4 Improving Robustness

In this subsection, we assess the impact of adversarial pre-training on the model’s robustness against adversarial attacks, using three standard adversarial NLP benchmarks: ANLI (Nie et al., 2019), HELLASWAG (Zellers et al., 2019) and adversarial SQuAD (Jia and Liang, 2017). On

⁸This is a subset of the data (160GB) used in RoBERTa pre-training.

Model	MNLI-m	SST-2	QNLI	CoLA	RTE	MRPC	QQP	STS-B
RoBERTa _{BASE}	87.6	94.8	92.8	63.6	78.7	90.2	91.9	91.2
ALUM _{ROBERTA-BASE}	88.1	95.3	93.1	63.6	80.2	90.9	92.0	91.1
RoBERTa _{LARGE}	90.2	96.4	94.7	67.8	86.6	90.9	92.2	92.4
ALUM _{ROBERTA-LARGE}	90.9	96.6	95.1	68.2	87.3	91.1	92.2	92.1

Table 4: Comparison of standard and adversarial pre-training on the GLUE development set. Results for ALUM_{ROBERTA-BASE} and ALUM_{ROBERTA-LARGE} are averaged over five runs. Results of RoBERTa_{BASE} and RoBERTa_{LARGE} are taken from Liu et al. (2019c).

Method	Dev				Test			
	R1	R2	R3	All	R1	R2	R3	All
MNLI + SNLI + ANLI + FEVER								
BERT _{BASE}	55.7	46.3	43.4	48.2	55.1	45.0	43.1	47.4
BERT+ _{BASE}	57.5	47.3	43.0	48.9	57.7	43.7	43.0	47.8
ALUM _{BERT-BASE}	62.0	48.6	48.1	52.6	61.3	45.9	44.3	50.1
BERT _{LARGE} (Nie et al., 2019)	57.4	48.3	43.5	49.3	-	-	-	44.2
XLNet _{LARGE} (Nie et al., 2019)	67.6	50.7	48.3	55.1	-	-	-	52.0
RoBERTa _{LARGE} (Nie et al., 2019)	73.8	48.9	44.4	53.7	-	-	-	49.7
ALUM _{ROBERTA-LARGE}	73.3	53.4	48.2	57.7	72.3	52.1	48.4	57.0

Table 5: Comparison of standard and adversarial pre-training on the adversarial dataset ANLI. R1, R2 and R3 are rounds with increasing difficulty. Note that Nie et al. (2019) did not represent results for individual rounds, as signified by “-”.

Method	Adversarial SQuAD		HELLASWAG	
	AddSent	AddOneSent	Dev	Test
	EM/F1	EM/F1	Accuracy	Accuracy
BERT _{BASE}	48.9/54.0	59.0/64.8	39.5	-
BERT+ _{BASE}	50.1/56.2	60.5/65.7	40.3	-
ALUM _{BERT-BASE}	54.6/60.4	63.2/69.8	44.0	-
RoBERTa _{LARGE}	72.3/66.0	79.3/72.9	85.0	85.2
ALUM _{ROBERTA-LARGE}	75.5/69.4	81.4/75.0	86.2	85.6

Table 6: Comparison of standard and adversarial pre-training on adversarial datasets Adversarial SQuAD and HELLASWAG. The test result on HELLASWAG is taken from the official leaderboard: rowanzellers.com/hellaswag; we couldn’t get results for BERT base models as the organizers restrict the number of submissions.

ANLI, we follow the experimental setting of Nie et al. (2019) to enable a head-to-head comparison, which combines four datasets (ANLI, MNLI, SNLI and FEVER (Thorne et al., 2018)) for fine-tuning.

Adversarial pre-training substantially improves model robustness, as shown in Table 5 and Table 6. In all three adversarial datasets, ALUM consistently outperformed the standard pre-training counterparts, for BERT and RoBERTa alike. For example, on ANLI, ALUM_{ROBERTA-LARGE} gains 7.3% points in test accuracy over RoBERTa_{LARGE}, outperforms XLNet (Yang et al., 2019) by 5.0% points, creating a new state-of-the-art result. The

gains on Adversarial SQuAD and HELLASWAG are equally significant. For example, for Adversarial SQuAD, ALUM_{BERT-BASE} outperforms BERT_{BASE} by +6.4% F1 in the AddSent setting and +5.0% F1 in the AddOneSent setting. Against RoBERTa_{LARGE}, ALUM_{ROBERTA-LARGE} gains +3.4% F1 in AddSent and +2.1% F1 in AddOneSent.

4.5 Combining Adversarial Pre-Training and Fine-tuning

Adversarial training has been shown to be effective in task-specific fine-tuning (Jiang et al., 2019; Zhu et al., 2019). In this subsection,

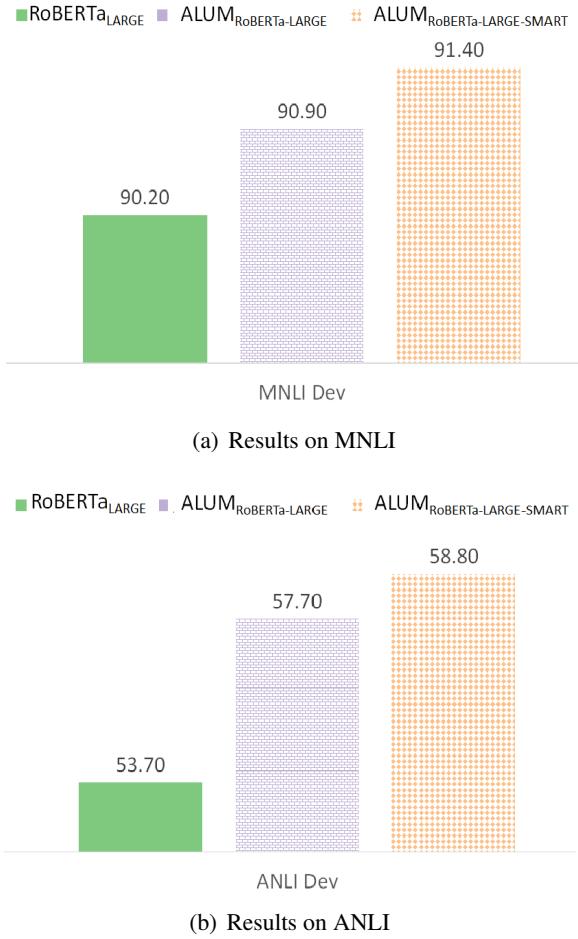


Figure 2: Combining adversarial pre-training and fine-tuning attaining the best results on the development sets of MNLI and ANLI, two representative GLUE tasks.

Model	Dev	Test
SNLI Dataset (Accuracy%)		
GPT (Radford et al., 2018)	-	89.9
BERT _{LARGE}	91.7	91.0
MT-DNN _{LARGE} (Liu et al., 2019b)	92.2	91.6
ALUM _{ROBERTa-LARGE}	93.1	93.0
ALUM _{ROBERTa-LARGE-SMART}	93.6	93.4
SciTail Dataset (Accuracy%)		
GPT (Radford et al., 2018)	-	88.3
BERT _{LARGE} (Liu et al., 2019b)	95.7	94.4
MT-DNN _{LARGE} (Liu et al., 2019b)	96.3	95.0
ALUM _{ROBERTa-LARGE}	97.4	96.3
ALUM _{ROBERTa-LARGE-SMART}	98.2	96.8

Table 7: Combining adversarial pre-training and fine-tuning attains the best results on SNLI and SciTail.

we explore combining adversarial pre-training with adversarial fine-tuning. Specifically, we use RoBERTa_{LARGE} as the base model, and compare it with ALUM_{ROBERTa-LARGE}, which uses adversarial continual pre-training but standard fine-tuning,

Model	Dev	Test
SWAG Dataset (Accuracy%)		
GPT (Radford et al., 2018)	-	78.0
BERT _{LARGE} (Devlin et al., 2018)	-	86.3
Human(Zellers et al., 2018)	88.0	88.0
RoBERTa _{LARGE} (Liu et al., 2019c)	-	89.9
ALUM _{ROBERTa-LARGE}	90.7	91.0
ALUM _{ROBERTa-LARGE-SMART}	91.2	-
HELLASWAG Dataset (Accuracy%)		
GPT (Zellers et al., 2019)	41.9	41.7
BERT _{LARGE} (Zellers et al., 2019)	46.7	47.3
RoBERTa _{LARGE} (Liu et al., 2019c)	-	85.2
ALUM _{ROBERTa-LARGE}	86.2	85.6
ALUM _{ROBERTa-LARGE-SMART}	86.9	-
Human	95.7	95.6

Table 8: Combining adversarial pre-training and fine-tuning attains the best results on SWAG and HELLASWAG.

and ALUM_{ROBERTa-LARGE-SMART}, which uses adversarial training in both continual pre-training and fine-tuning. Figure 2 shows the results on the development sets of MNLI and ANLI, two representative GLUE tasks. Combining adversarial pre-training and fine-tuning attains the best results, and substantially outperforms RoBERTa_{LARGE}. E.g., on ANLI, ALUM_{ROBERTa-SMART} outperforms ALUM_{ROBERTa-LARGE} by +1.1% points in accuracy, and outperforms RoBERTa_{LARGE} by +5.1% points. On SNLI, SciTail, SWAG, and HELLASWAG, we observe similar gains by combining adversarial pre-training and fine-tuning, attaining new state-of-the-art results on these tasks. See table 7 and 8.

5 Conclusion

We propose ALUM, a general adversarial training algorithm, and present the first comprehensive study of adversarial training in large neural language models. We show that adversarial pre-training can significantly improves both generalization and robustness, which provides a promising direction for reconciling their conflicts as observed in prior work. ALUM substantially improved accuracy for BERT and RoBERTa in a wide range of NLP tasks, and can be combined with adversarial fine-tuning for further gain.

Future directions include: further study on the role of adversarial pre-training in improving generalization and robustness; speed up adversarial training; apply ALUM to other domains.

References

- Hangbo Bao, Li Dong, Furu Wei, Wenhui Wang, Nan Yang, Xiaodong Liu, Yu Wang, Songhao Piao, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2020. Unilmv2: Pseudo-masked language models for unified language model pre-training. *arXiv preprint arXiv:2002.12804*.
- Roy Bar-Haim, Ido Dagan, Bill Dolan, Lisa Ferro, and Danilo Giampiccolo. 2006. The second PASCAL recognising textual entailment challenge. In *Proceedings of the Second PASCAL Challenges Workshop on Recognising Textual Entailment*.
- Luisa Bentivogli, Ido Dagan, Hoa Trang Dang, Danilo Giampiccolo, and Bernardo Magnini. 2009. The fifth pascal recognizing textual entailment challenge. In *In Proc Text Analysis Conference (TAC09)*.
- Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics.
- Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. 2017. SemEval-2017 task 1: Semantic textual similarity-multilingual and cross-lingual focused evaluation. *arXiv preprint arXiv:1708.00055*.
- Yong Cheng, Lu Jiang, and Wolfgang Macherey. 2019. Robust neural machine translation with doubly adversarial inputs. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4324–4333, Florence, Italy. Association for Computational Linguistics.
- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. ELECTRA: Pre-training text encoders as discriminators rather than generators. In *ICLR*.
- Nigel Collier and Jin-Dong Kim. 2004. Introduction to the bio-entity recognition task at JNLPBA. In *Proceedings of the International Joint Workshop on Natural Language Processing in Biomedicine and its Applications (NLPBA/BioNLP)*, pages 73–78, Geneva, Switzerland. COLING.
- Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. The pascal recognising textual entailment challenge. In *Proceedings of the First International Conference on Machine Learning Challenges: Evaluating Predictive Uncertainty Visual Object Classification, and Recognizing Textual Entailment, MLCW’05*, pages 177–190, Berlin, Heidelberg. Springer-Verlag.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- Rezarta Dogan, Robert Leaman, and Zhiyong lu. 2014. Ncbi disease corpus: A resource for disease name recognition and concept normalization. *Journal of biomedical informatics*, 47.
- William B Dolan and Chris Brockett. 2005. Automatically constructing a corpus of sentential paraphrases. In *Proceedings of the Third International Workshop on Paraphrasing (IWP2005)*.
- Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. *arXiv preprint arXiv:1905.03197*.
- Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. The third PASCAL recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, pages 1–9, Prague. Association for Computational Linguistics.
- Aaron Gokaslan and Vanya Cohen. Openwebtext corpus.
- Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*.
- Frank R Hampel. 1974. The influence curve and its role in robust estimation. *Journal of the american statistical association*, 69(346):383–393.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.
- Yu-Lun Hsieh, Minhao Cheng, Da-Cheng Juan, Wei Wei, Wen-Lian Hsu, and Cho-Jui Hsieh. 2019. On the robustness of self-attentive models. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1520–1529.
- Robin Jia and Percy Liang. 2017. Adversarial examples for evaluating reading comprehension systems. *arXiv preprint arXiv:1707.07328*.
- Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Tuo Zhao. 2019. Smart: Robust and efficient fine-tuning for pre-trained natural language models through principled regularized optimization. *arXiv preprint arXiv:1911.03437*.
- Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. 2019. Is bert really robust? natural language attack on text classification and entailment. *arXiv preprint arXiv:1907.11932*.
- Tushar Khot, Ashish Sabharwal, and Peter Clark. 2018. SciTail: A textual entailment dataset from science question answering. In *AAAI*.

- Diederik Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Taku Kudo and John Richardson. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. *arXiv preprint arXiv:1808.06226*.
- Hector Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In *Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning*.
- Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. 2019a. On the variance of the adaptive learning rate and beyond. *arXiv preprint arXiv:1908.03265*.
- Xiaodong Liu, Jianfeng Gao, Xiaodong He, Li Deng, Kevin Duh, and Ye-Yi Wang. 2015. Representation learning using multi-task deep neural networks for semantic classification and information retrieval. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 912–921.
- Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019b. Multi-task deep neural networks for natural language understanding. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4487–4496, Florence, Italy. Association for Computational Linguistics.
- Xiaodong Liu, Yu Wang, Jianshu Ji, Hao Cheng, Xueyun Zhu, Emmanuel Awa, Pengcheng He, Weizhu Chen, Hoifung Poon, Guihong Cao, and Jianfeng Gao. 2020. The microsoft toolkit of multi-task deep neural networks for natural language understanding. *arXiv preprint arXiv:2002.07972*.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019c. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.
- Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. 2017. Towards deep learning models resistant to adversarial attacks. *arXiv preprint arXiv:1706.06083*.
- Yifei Min, Lin Chen, and Amin Karbasi. 2020. The curious case of adversarially robust models: More data can help, double descend, or hurt generalization. *arXiv preprint arXiv:2002.11080*.
- Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao. 2020a. Deep learning based text classification: A comprehensive review. *arXiv preprint arXiv:2004.03705*.
- Shervin Minaee, Nal Kalchbrenner, Erik Cambria, Narjes Nikzad, Meysam Chenaghlu, and Jianfeng Gao. 2020b. Deep learning based text classification: a comprehensive review. *arXiv preprint arXiv:2004.03705*.
- Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. 2018. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. *IEEE transactions on pattern analysis and machine intelligence*, 41(8):1979–1993.
- Xinyi Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2019. Adversarial nli: A new benchmark for natural language understanding. *arXiv preprint arXiv:1910.14599*.
- Chongli Qin, James Martens, Sven Gowal, Dilip Krishnan, Alhussein Fawzi, Soham De, Robert Stanforth, Pushmeet Kohli, et al. 2019. Adversarial robustness through local linearization. *arXiv preprint arXiv:1907.02610*.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2018. Language models are unsupervised multitask learners.
- Aditi Raghunathan, Sang Michael Xie, Fanny Yang, John Duchi, and Percy Liang. 2020. Understanding and mitigating the tradeoff between robustness and accuracy. *arXiv preprint arXiv:2002.10716*.
- Aditi Raghunathan, Sang Michael Xie, Fanny Yang, John C Duchi, and Percy Liang. 2019. Adversarial training can hurt generalization. *arXiv preprint arXiv:1906.06032*.
- Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know what you don’t know: Unanswerable questions for squad. *arXiv preprint arXiv:1806.03822*.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2015. Neural machine translation of rare words with subword units. *arXiv preprint arXiv:1508.07909*.
- Ali Shafahi, Mahyar Najibi, Amin Ghiasi, Zheng Xu, John Dickerson, Christoph Studer, Larry S Davis, Gavin Taylor, and Tom Goldstein. 2019. Adversarial training for free! *arXiv preprint arXiv:1904.12843*.
- Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. 2019. Megatron-LM: Training multi-billion parameter language models using gpu model parallelism. *arXiv preprint arXiv:1909.08053*.

- Larry Smith, Lorraine Tanabe, Rie Ando, Cheng-Ju Kuo, I-Fang Chung, Chun-Nan Hsu, Yu-Shi Lin, Roman Klinder, Christoph Friedrich, Kuzman Ganchev, Manabu Torii, Hongfang Liu, Barry Hadlow, Craig Struble, Richard Povinelli, Andreas Vlachos, William Baumgartner Jr, Lawrence Hunter, Bob Carpenter, and W. Wilbur. 2008. Overview of biocreative ii gene mention recognition. *Genome biology*, 9 Suppl 2:S2.
- Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 1631–1642.
- David Stutz, Matthias Hein, and Bernt Schiele. 2019. Disentangling adversarial robustness and generalization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6976–6987.
- Yu Sun, Shuhuan Wang, Yukun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifeng Wang. 2019. Ernie 2.0: A continual pre-training framework for language understanding. *arXiv preprint arXiv:1907.12412*.
- Wilson L Taylor. 1953. cloze procedure: A new tool for measuring readability. *Journalism quarterly*, 30(4):415–433.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. Fever: a large-scale dataset for fact extraction and verification. *arXiv preprint arXiv:1803.05355*.
- Trieu H Trinh and Quoc V Le. 2018. A simple method for commonsense reasoning. *arXiv preprint arXiv:1806.02847*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*.
- Dilin Wang, Chengyue Gong, and Qiang Liu. 2019. Improving neural language modeling via adversarial training. In *International Conference on Machine Learning*, pages 6555–6565.
- Alex Warstadt, Amanpreet Singh, and Samuel R Bowman. 2018. Neural network acceptability judgments. *arXiv preprint arXiv:1805.12471*.
- Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122. Association for Computational Linguistics.
- Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. *arXiv preprint arXiv:1906.08237*.
- Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. Swag: A large-scale adversarial dataset for grounded commonsense inference. *arXiv preprint arXiv:1808.05326*.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*.
- Chen Zhu, Yu Cheng, Zhe Gan, Siqi Sun, Thomas Goldstein, and Jingjing Liu. 2019. Freelb: Enhanced adversarial training for language understanding. *arXiv preprint arXiv:1909.11764*.

A NLP Application Benchmarks

- **GLUE.** The General Language Understanding Evaluation (GLUE) benchmark is a collection of nine natural language understanding (NLU) tasks. As shown in Table 9, it includes question answering (Rajpurkar et al., 2016), linguistic acceptability (Warstadt et al., 2018), sentiment analysis (Socher et al., 2013), text similarity (Cer et al., 2017), paraphrase detection (Dolan and Brockett, 2005), and natural language inference (NLI) (Dagan et al., 2006; Bar-Haim et al., 2006; Giampicolo et al., 2007; Bentivogli et al., 2009; Levesque et al., 2012; Williams et al., 2018). The diversity of the tasks makes GLUE very suitable for evaluating the generalization and robustness of NLU models.
- **SNLI.** The Stanford Natural Language Inference (SNLI) dataset contains 570k human annotated sentence pairs, in which the premises are drawn from the captions of the Flickr30 corpus and hypotheses are manually annotated (Bowman et al., 2015). This is the most widely used entailment dataset for NLI.
- **SciTail.** This is a textual entailment dataset derived from a science question answering (SciQ) dataset (Khot et al., 2018). The task involves assessing whether a given premise entails a given hypothesis. In contrast to other entailment datasets mentioned previously, the hypotheses in SciTail are created from science questions while the corresponding answer candidates and premises come from relevant web sentences retrieved from a large corpus. As a result, these sentences are linguistically challenging and the lexical similarity of premise and hypothesis is often high, thus making SciTail particularly difficult.
- **ANLI.** The Adversarial Natural Language Inference (ANLI, Nie et al. (2019)) is a new large-scale NLI benchmark dataset, collected via an iterative, adversarial human-and-model-in-the-loop procedure. Specifically, the instances are chosen to be difficult for the state-of-the-art models such as BERT and RoBERTa.
- **SWAG.** It is a large-scale adversarial dataset for the task of grounded commonsense inference, which unifies natural language inference and physically grounded reasoning (Zellers et al., 2018). SWAG consists of 113k multiple choice questions about grounded situations.
- **HELLASWAG.** It is similar to SWAG but more challenging (Zellers et al., 2019). For each query in HELLASWAG, it also has 4 choices and the goal is to find the best choice among them.
- **SQuAD v1.1/v2.0.** Stanford Question Answering Dataset (SQuAD) v1.1 and v2.0 (Rajpurkar et al., 2016, 2018) are popular machine reading comprehension benchmarks. Their passages come from approximately 500 Wikipedia articles and the questions and answers are obtained by crowdsourcing. The SQuAD v2.0 dataset includes unanswerable questions about the same paragraphs.
- **BC2GM.** The Gene Mention Task at the Biocreative II workshop (Smith et al., 2008) provides an annotated dataset for gene name entity recognition.
- **NCBI.** The NCBI disease corpus (Dogan et al., 2014) contains annotations of disease mentions from a collection of PubMed abstracts.
- **JNLPBA.** JNLBA is a biomedical entity recognition shared task (Collier and Kim, 2004). It is one of the largest datasets covering a large fraction of major taxonomies in molecular biology.

Corpus	Task	#Train	#Dev	#Test	#Label	Metrics
Single-Sentence Classification (GLUE)						
CoLA	Acceptability	8.5k	1k	1k	2	Matthews corr
SST	Sentiment	67k	872	1.8k	2	Accuracy
Pairwise Text Classification (GLUE)						
MNLI	NLI	393k	20k	20k	3	Accuracy
RTE	NLI	2.5k	276	3k	2	Accuracy
WNLI	NLI	634	71	146	2	Accuracy
QQP	Paraphrase	364k	40k	391k	2	Accuracy/F1
MRPC	Paraphrase	3.7k	408	1.7k	2	Accuracy/F1
QNLI	QA/NLI	108k	5.7k	5.7k	2	Accuracy
Text Similarity (GLUE)						
STS-B	Similarity	7k	1.5k	1.4k	1	Pearson/Spearman corr
Pairwise Text Classification						
SNLI	NLI	549k	9.8k	9.8k	3	Accuracy
SciTail	NLI	23.5k	1.3k	2.1k	2	Accuracy
ANLI	NLI	163k	3.2k	3.2k	3	Accuracy
Span Classification						
SQuAD v1.1	MRC	87.6k	10.5k	9.5k	-	Exact Match (EM)/F1
SQuAD v2.0	MRC	130.3k	11.9k	8.9k	-	Exact Match (EM)/F1
Ranking						
SWAG	Multiple choice	73.5k	20k	20k	-	Accuracy
HELLASWAG	Multiple choice	34k	10	10k	-	Accuracy
Biomedical Domain						
BC2GM	NER	12.6k	2.5k	5k	-	F1/Precision/Recall
NCBI	NER	5.4k	923	940	-	F1/Precision/Recall
JNLPBA	NER	14.7k	3.9k	3.9k	-	F1/Precision/Recall

Table 9: Summary information of the NLP application benchmarks.