RoSearch: Search for Robust Student Architectures When Distilling Pre-trained Language Models

Xin Guo  
School of Computer Science and Engineering, BDBC  
Beihang University  
Beijing, China  
guoxin@act.buaa.edu.cn

Jianlei Yang  
School of Computer Science and Engineering, BDBC  
Beihang University  
Beijing, China  
jianlei@buaa.edu.cn

Haoyi Zhou  
School of Computer Science and Engineering, BDBC  
Beihang University  
Beijing, China  
zhouhy@act.buaa.edu.cn

Xucheng Ye  
School of Computer Science and Engineering, BDBC  
Beihang University  
Beijing, China  
zy1806121@buaa.edu.cn

Jianxin Li  
School of Computer Science and Engineering, BDBC  
Beihang University  
Beijing, China  
ljx@act.buaa.edu.cn

ABSTRACT

Pre-trained language models achieve outstanding performance in NLP tasks. Various knowledge distillation methods have been proposed to reduce the heavy computation and storage requirements of pre-trained language models. However, from our observations, student models acquired by knowledge distillation suffer from adversarial attacks, which limits their usage in security sensitive scenarios. In order to overcome these security problems, RoSearch is proposed as a comprehensive framework to search the student models with better adversarial robustness when performing knowledge distillation. A directed acyclic graph based search space is built and an evolutionary search strategy is utilized to guide the searching approach. Each searched architecture is trained by knowledge distillation on pre-trained language model and then evaluated under a robustness-, accuracy- and efficiency-aware metric as environmental fitness. Experimental results show that RoSearch can improve robustness of student models from 7%–18% up to 45.8%–47.8% on different datasets with comparable weight compression ratio to existing distillation methods (4.6×–6.5× improvement from teacher model BERT$_{BASE}$) and low accuracy drop. In addition, we summarize the relationship between student architecture and robustness through statistics of searched models.

KEYWORDS

Pre-trained Language Model, Knowledge Distillation, Adversarial Robustness, Neural Architecture Search.

1 INTRODUCTION

Recently pre-trained language models have become as the mainstreaming approaches in Natural Language Processing (NLP) tasks, such as BERT [1], XLNet [2], RoBERTa [3], etc. By being pre-trained on large scale corpus datasets, these models extract very rich knowledge-abilities from natural language texts. And then some fine-tuning processes are usually performed with task-specific labeled data to provide the knowledge-abilities for solving downstream NLP tasks. The combination of natural language knowledge and task-aware knowledge makes it possible for pre-trained language models to refresh state-of-the-art performance in many NLP tasks.

With the growth in demand for performance on NLP tasks, the scale of pre-trained models increase in terms of both parameter number and inference latency. The increasing scale of pre-trained models bring very high cost both in computation and memory for practical usage. Especially for the mobile or embedded devices, it is difficult to deploy pre-trained models because of the very limited hardware resources. A popular approach is to make those powerful models lightweight for easier deployments on edge devices. Many model compression techniques have been proposed [4–11] to reduce their model size while maintaining model accuracy. Among those model compression approaches, knowledge distillation attracts much attention and becomes a mainstream research direction. Knowledge distillation was proposed in [12] as a teacher-student framework, in which student models are trained to imitate the behavior of teacher models. Knowledge distillation could improve model’s efficiency by transferring its knowledge to lightweight neural architectures. Compared to being trained from scratch, student models usually perform better when trained with knowledge distillation methods. To fully utilize the rich knowledge-abilities in pre-trained language models, various knowledge distillation methods have been proposed, especially for the well-known pre-trained model BERT [1].

Existing distillation efforts mainly focus on how to improve the model’s efficiency while maintaining the accuracy. The models can be compressed up to 15x with negligible accuracy drop [14]. However, another important issue is raised: are these student models with good accuracy and efficiency suitable enough for real-world applications? It has been explored that neural networks are usually vulnerable to adversarial attacks [16, 17]. Minimal perturbation on

1AdaBERT-SST2 is re-implementation of knowledge distillation with fixed architecture provided in [14].
input sample may lead to wrong classification. For pre-trained language models, TextFooler demonstrated the possibility to generate adversarial examples for the well-known BERT [15]. An intuitive concern arises whether students distilled from pre-trained models suffer from adversarial attacks. Several knowledge distillation works on pre-trained models have been evaluated for comparing their robustness and accuracy as shown in Figure 1. Lightweighted or distilled models could have a good accuracy (~90%), but all of them pose a very low robustness (6%-7%) under adversarial attacks. Such a low robustness implies a strong vulnerability of student models, which will bring potential risk to their practical usage in security sensitive scenarios.

In real-world applications, efficiency, accuracy and robustness are all crucial metrics for neural network models. Pre-trained language models perform well in terms of accuracy while knowledge distillation techniques improve their efficiency, but robustness is left behind in existing researches. In this work, we aim to reduce the potential security risk of these student models and perform appropriate balancing among accuracy, efficiency and robustness. Since improving the robustness of large pre-trained models might be very resource consuming, and it is difficult to transfer teacher’s robustness to students (as experiments demonstrated in Section 5.4), we mainly pay attention to improving the robustness when performing knowledge distillation.

Our research mainly focuses on exploring student models in neural architecture view. Knowledge distillation could improve the performance of student models in their weights optimizing stage, but their neural architectures are not well studied. The neural architectures of student models are usually inherited from large-scale pre-trained models, like BERT [1]. There lies some attempts [14] on applying neural architecture search (NAS) approach in pre-trained model distillation, their search objective is elaborate designed on improving performance and efficiency rather than enhancing the model robustness. In this work, an evolutionary NAS algorithm is exploited for student architectures search with considering high robustness. And the relationship between student architectures and robustness is also explored. This paper aims to answer these Questions:

1. How about the robustness characteristics of student models after knowledge distillation?
2. How to improve the robustness of student models?
3. How about the relationship between robustness and searched student architectures?

Aiming to improve the robustness of student models, RoSearch is proposed as a NAS framework as shown in Figure 2. The pre-trained language model is distilled as student models, while student architecture is searched under a robustness-, accuracy- and efficiency-aware model evaluation metric. An evolutionary search strategy is utilized to guide the searching procedures according to the evaluation feedbacks, similar to [18]. A block-based search space is built by each block represented by a Directed Acyclic Graph (DAG) whose vertices and edges represent the network layers and data-flow respectively. To guide the searching towards a more robustness direction, we generate adversarial examples for each model and calculate the accuracy of distilled student model as robustness metric. The metrics of accuracy on benign datasets and efficiency measured by parameter number are also included to maintain the advantage of pre-trained language models and knowledge distillation.

The key contributions of this paper are summarized as follows:

- We demonstrate that knowledge distillation methods for pre-trained language models suffer from potential security risk brought by adversarial attacks.
- We propose a RoSearch framework that can improve robustness of student models while maintaining accuracy and efficiency characteristic in knowledge distillation setting.
- We summarize the relationship between robustness and architectures of searched student models, which could help guiding the robust search on pre-trained models.

The rest of this paper is organized as follows. Section 2 reviews the related works. Problem formulations are demonstrated in Section 3. Section 4 indicates existing robustness issues of distillation.
Details of RoSearch are provided in Section 5. Section 6 illustrates experimental results. Concluding remarks are given in Section 7.

2 RELATED WORKS

Pre-trained Language Models Distillation. Research of knowledge distillation of pre-trained language models starts from [6]. They proposed an approach to distill knowledge from BERT to BiLSTM student model. Mean Squared Error Loss between logits and Cross Entropy Loss on true labels are adopted in distillation. Similar to the architecture of BERT, stacking Transformer encoder layers [19] are utilized as student models, such as [13, 20, 21]. And NAS approach is utilized to find better CNN-based student architectures for specific downstream tasks [14]. To the best of our knowledge, none of such related works has taken robustness into account.

Robustness-aware NAS. RobNet is proposed as a robustness-aware search algorithm based on one-shot NAS approach [22], which evaluates the robustness of each model after vanilla training and adversarial fine-tuning. A robustness indicator was designed to accelerate searching by discarding the architectures with lower possible robustness. Relationship between architecture patterns and adversarial robustness in image classification tasks is also discussed. [23] proposed another robustness-aware NAS. Layer-, block- and model-level evolution algorithm was combined to fully explore robustness in different level of architectures. Transferability based black-box robustness evaluation was applied on each architecture while searching. Adversarial examples were generated before searching to reduce total runtime. However, these existing works focused on computer vision area, convolutional network architectures and vanilla training without knowledge distillation.

Adversarial Training. Adversarial training is a common approach to improve robustness of neural networks. FGSM [17] algorithm is proposed to generate adversarial examples at low computational cost at training stage. Generated adversarial examples are appended into training set, so that neural networks can adapt to these malicious data and acquire higher robustness after training, that is, adversarial training. [24] utilizes a stronger attack algorithm, projected gradient descent method, instead of FGSM to improve the effectiveness of adversarial training. Adversarial training methods usually work well when training neural networks from scratch. In this work, the adversarial training is adopted in task fine-tuning stage of pre-trained model and after distillation stage for student models as comparison baseline.

Robust Distillation. [25] evaluated the transferability of robustness from teacher model to student model in knowledge distillation on some image classification datasets. Experiments show that the transferability differs according to teacher models and datasets. They proposed ARD method to improve the transferability of robustness by punishing distance between student’s prediction on adversarial examples and teacher’s prediction on benign samples. Our work does not focus on distillation loss but the architecture of student models, which is orthogonal to their approach.

3 PROBLEM FORMULATION

Knowledge Distillation methods transfer knowledge from teacher model to student model by adding loss terms that force student model to imitate teacher models’ behavior in training process. Traditional distillation computes KL-divergence between student’s and teacher’s prediction probability distribution softened by temperature $t$:

$$\mathcal{L}_{TKD} = t^2 \cdot KL \left( \text{softmax} \left( \frac{z_S}{t} \right), \text{softmax} \left( \frac{z_T}{t} \right) \right),$$

where $\mathcal{L}_{TKD}$ is traditional knowledge distillation loss, $z_S$ and $z_T$ denote logits output of teacher and student models respectively.

Recent knowledge distillation researches for pre-trained models use additional Cross Entropy Loss, Mean Squared Error (MSE) Loss or other loss functions between student and teacher models’ logits, classification outputs, hidden states, attention matrices, or word embeddings. These loss terms promote knowledge transfer and we summarize all of them by minimizing the weighted distance between teacher and student models as:

$$\mathcal{L}_{KD} = \lambda_1 \mathcal{L}_{logits} + \lambda_2 \mathcal{L}_{cls} + \lambda_3 \mathcal{L}_{hid} + \lambda_4 \mathcal{L}_{attn} + \lambda_5 \mathcal{L}_{embd}.$$
Table 1: Robustness of BERT and distilled students under direct attack. \( A \) means the model accuracy. \( W\% \) denotes word change rate, \#Q denotes average query times to generate adversarial examples.

| Model       | \( A \) | \( A(D_{adv}) \) | \( W\% \) | \#Q |
|-------------|---------|------------------|------------|-----|
| BASE        | 92.3%   | 12.4%            | 19.3%      | 169 |
| AdaBERT     | 89.0%   | 7.1%             | 14.0%      | 113 |
| PKD         | 90.7%   | 6.2%             | 14.7%      | 121 |

4 CONVENTIONAL DISTILLATION IS NOT ROBUST

This section aims to answer the Question 1 in Section 1. First, we re-implement several conventional knowledge distillation methods for pre-trained models, and evaluate their robustness under direct attack and transfer attack [26] using TextFooler attack method [15]. Not only the student models distilled by existing methods are applied for directly attack, but also we evaluate their robustness after an adversarial fine-tuning process. At the end, we try to figure out whether robustness of teacher model could be transferred to student models.

4.1 Distillation Is Not Robust

Existing knowledge distillation methods for pre-trained language models are not robust. Several of them are re-implemented and evaluated on SST-2 dataset. For all of those distillations, fine-tuned BERT\textsubscript{BASE} is adopted as teacher model. TextFooler attack method is utilized to evaluate the robustness of student models. From the perspective of target model, adversarial attacks can be divided as direct attack and transfer attack. Robustness of each student model is evaluated in both situations.

Direct attack robustness of each model is measured by its accuracy on adversarial examples generated against the model itself. It is the most commonly used metric for model robustness evaluation. As shown in Table 1, the accuracy of student models distilled from BERT decreased from ~90% on benign dataset to 6%-7% on datasets generated by direct attack. Even if compared with teacher model BERT, which is shown not robust, student models suffer more from direct attack. The average word changing rate of adversarial examples and average queries required to generate adversarial examples also share the same trend.

Intuitively, we believe there are three main reasons of this phenomenon. First of all, knowledge distillation aims at compressing the model size of pre-trained language models, in other words, the student models always have fewer weight parameters than original model. As a result, the model capacity was also compressed to just fit the natural data in training set. According to previous research of adversarial robustness in computer vision area, model capacity may influence the model robustness [24]. Second, student models were not trained from scratch but learned knowledge from teacher model by knowledge distillation approaches. Since teacher model was not robust enough, we cannot expect student models reach high robustness. Accuracy drop, though researches try to avoid, is also common in knowledge distillation results, which may also decrease accuracy under adversarial settings. At last, the student model was not designed to be robust and no defense techniques was implemented. Traditional distillation researches use artificial designed architecture for student model. AdaBERT [14] leverages gradient based search algorithm to search for student architecture, but the target only cares about accuracy on natural data and model efficiency, robustness was not guaranteed since it was not included in evaluation metric.

It has been demonstrated that adversarial examples usually have transfer-ability between different models [26]. Using adversarial examples generated against a known model to attack unknown target model is called transfer attack. Since knowledge distillation methods and student architectures differ from each other, which increases the difficulty of direct attack, transfer attack from well-known pre-trained models might be a practical risk. We also evaluate the robustness of student models obtained from existing knowledge distillation methods in the scene that teacher model (BERT\textsubscript{BASE}) or other student models is chosen as surrogate model. Results of transfer attack are shown in Table 2. Experiments indicate that, though student models are relatively more robust under transfer attack than direct attack, the accuracy also significantly drops compared with on benign data.

4.2 Adversarial Training Causes Accuracy Drop

Adversarial training is commonly used to improve robustness of neural networks in their training stage. Adversarial examples are generated and appended into training datasets to increase the distance between category border and benign samples. In the case of knowledge distillation for pre-trained model, we apply an adversarial fine-tuning stage after distillation. Since teacher models are not robust enough, imitating their behaviours cannot provide effective contribution to student model’s robustness. Thus, only the classification loss on true label is adopted for adversarial fine-tuning stage. Robustness of pre-trained language model BERT with or without adversarial training tricks in fine-tuning stage is also evaluated for comparison. As the results shown in Table 3, though adversarial training can improve the robustness of BERT while keeping its accuracy, accuracy of student model still drops a lot when robustness improves.


Table 4: Robustness of AdaBERT-SST2 distilled with BERT or adversarial trained BERT as teacher model. Besides only using origin data in knowledge distillation, we also test to append adversarial data to help robustness transfer.

| Data        | Teacher BERT $\mathcal{A}$ | Adv. Trained BERT $\mathcal{A}$ (D$_{adv}$) |  |
|-------------|-----------------------------|---------------------------------------------|---|
| Ori. Data   | 89.0%                       | 7.1%                                        | 87.5% 7.3%  |
| +Adv. Data  | 87.3%                       | 7.6%                                        | 86.5% 7.9%  |

4.3 Robustness of Teacher Does Not Transfer

Though the robustness of pre-trained models (teacher model in distillation) can be improved by adversarial training in fine-tuning stage, we demonstrate that it is difficult to transfer the robustness to student models. To experiment whether robustness of pre-trained model can transfer to student models in knowledge distillations, adversarial fine-tuning is performed on BERT and then the adversarial fine-tuned BERT is utilized as teacher model. In order to transfer robustness of teacher model to student model as much as possible, the adversarial examples generated in adversarial fine-tuning process is also regarded as a transfer dataset. However, evaluation results in Table 4 show that robustness of adversarial trained teacher model hardly transfer to student model, no matter whether adversarial data are utilized.

4.4 Summarization

The robustness characteristics of student models after knowledge distillation are evaluated in this section. As a summarization, conventional knowledge distillation methods for pre-trained models are not robust, especially under direct attack. Even if compared to the teacher model with not a good robustness, lightweight student models still suffer more from adversarial attacks. Though adversarial training can improve robustness for student models, it usually causes significant accuracy drop on benign dataset. Adversarial trained BERT model could obtain robustness improvement while maintaining accuracy, however it is difficult to transfer the robustness to student models.

5 ARCHITECTURE SEARCH FOR ROBUST STUDENTS

To overcome the robustness problem mentioned in Section 4, we propose RoSearch, a comprehensive framework to improve robustness of knowledge distillation by searching student architectures. Question (2) in Section 1 will be answered in this section.

5.1 RoSearch Overview

As the target problem formulated in Section 3, we decompose the problem as a two-stage optimization problem:

$$
\arg \max_{\alpha \in \mathcal{X}} \mathcal{F} \left( \mathcal{A}_S (D), \mathcal{A}_S (D_{adv}), \#\omega^* \right),
$$

where $S = (\alpha, \omega^*)$, $\omega^* = \arg \min_{\omega} \sum_{(x,y) \in D} \mathcal{L}_{KD}(x, y)$,

where $\mathcal{X}$ denotes a searching space.

Algorithm 1: RoSearch Framework

```
Input: Teacher model $T$, training dataset $D_{train}$, evaluation dataset $D_{val}$.
Output: Student model $S^*$.
1 Define search space $\mathcal{X}$
2 while Fitness($S$) not converge do
   3 Controller samples an architecture $\alpha$ from $\mathcal{X}$
      /* Perform knowledge distillation */
   4 $L_{KD}^\omega(T, D_{train})$ -* update $\omega$
   5 $S_\alpha$ $\leftarrow (\alpha, \omega)$
      /* Student model evaluation */
   6 Generate adversarial dataset $D_{adv}$ from $D_{val}$
   7 Accuracy score $P_{acc} \leftarrow \mathcal{A}_S (D_{adv})$
   8 Robustness score $P_{rob} \leftarrow \mathcal{A}_S (D_{adv})$
   9 Efficiency score $P_{eff} \leftarrow \#\omega$
   10 Fitness($S_\alpha$) $\leftarrow \mathcal{F}(P_{acc}, P_{rob}, P_{eff})$
   11 if Fitness($S_\alpha$) $>$ Fitness($S^*$) then
      12 $S^*$ $\leftarrow S_\alpha$
   13 end
14 Feed Fitness($S$) back to controller
end
```

In this situation, architecture and weight of student model are separately optimized. Weight optimization is achieved by performing knowledge distillation on a given architecture, while architecture optimization can be solved by neural architecture search. In the proposed framework of RoSearch, we adopt a NAS controller to sample student architectures from search space. Each searched architecture is distilled with pre-trained language model as teacher model. Then its robustness, accuracy and efficiency are evaluated and fed back to controller to guide the search direction. Algorithm 1 summarizes the workflow of RoSearch.

Neural architecture search algorithms can be described in three dimensions: Search Strategy, Search Space and Model Evaluation [27]. Search space is the feasible range of model architectures, which limits the upper and lower bound of search results. Search strategy controls how to search in the search space, which determines whether the best architecture can be found in the search space. Model evaluation method affects the score of each element in the search space, which determines the search direction and target. A DAG-based search space is built for RoSearch and an evolutionary-algorithm based searching strategy is adopted. Our robustness-aware model evaluation function $\mathcal{F}(\cdot, \cdot, \cdot)$ will be described in Section 5.4.

5.2 Search Strategy

In RoSearch, an evolutionary algorithm based searching strategy is utilized because of its simplicity and satisfactory performance in [28] and [18]. Moreover, architectures are seen as individuals in evolutionary algorithm, each model is independent during search, which is convenient for architecture analysis.

Evolutionary algorithm can be mainly divided into four steps: (1) population initialization, (2) fitness evaluation, (3) natural selection, (4) evolution operation. Population is a set of individuals. In
5.3 Student Architecture and Search Space

Since relation between architectures and robustness are not clear yet, we design a search space with high degree of freedom. Figure 3 presents the architecture of student model in RoSearch. Student model contains Embedding layer, repeated Blocks and Classifier from input to output. Architecture of repeated Blocks is represented as a directed acyclic graph $G = (V, E)$, where $V = \{v_0, v_1, \ldots, v_{n-1}\}$, $v_0$ represents input node, $v_{n-1}$ represents output node, $v_1, \ldots, v_{n-2}$ represents computational layer node, $n$ is a hyper-parameter denoting number of nodes ($n = 6$ by default). Edges in DAG represents data-flow, and only edges from vertex with lower ID to higher ID are allowed, i.e. $E \subseteq \{(u_i, v_j) | i < j\}$. As shown in Figure 4, various typical architecture patterns can be described in this representation, such as residual connections or branch architectures, etc. Same as BERT, Embedding layer consists of word embedding, position embedding and segment embedding. Classifier consists of Max Pooling layer and Fully Connected layer. Architecture of these two parts remain unchanged in searching process except for adapting width of hidden states to Blocks.

Repeat times $r \in [3, 8]$ times of Blocks varies in range [3, 4, 5, 6, 7, 8], and width of hidden states between Blocks varies in range [128, 256, 512], which leads searched architectures lie in a lightweight zone. Sub search space of Block can be parameterized by properties of every computational nodes and output node, as well as data-flow connection patterns. Properties of each computational node consists of Layer Type, Layer Parameter, Output Width, Input Mode and Activation Function, output node only varies in Input Mode and Activation Function. Search space of data-flow connection in a Block is the power set of all allowed edges in DAG. Type of computational nodes ranges in {Conv, Sep-Conv, Attn, GLU}, Conv denotes Convolution Layer, widely used in CNN NLP models. Sep-Conv denotes Depth Separable Convolution Layer [30], which is a lightweight variant of Convolution Layer. Attn, to be specific, denotes Self-Attention Layer, which plays an important role in Transformer [19] based models like BERT, and supplies expression ability of word relationship without range limit. GLU denotes Gated Linear Units Layer [31], which introduces extra nonlinear operation and performs well in [18]. For Conv layers, Layer Parameter ranges in {1, 3, 5}, represents width of convolution kernel. When 1 is taken as Layer Parameter, it represents a Linear Layer. For Sep-Conv layers, Layer Parameter representing kernel width ranges in [3, 5, 7, 9, 11]. For Attn layers, Layer Parameter ranges in [4, 8, 16], representing the number of attention head. GLU layers have no Layer Parameter. Output Width ranges in [128, 256, 512]. Input Mode ranges in {Add, Mul, Concat}, where Add denotes all the inputs of such node will be summed (padded to same width with 0), Mul denotes all the inputs will be multiplied (padded to same width with 1), Concat denotes all the inputs will be concatenated along hidden dimension. Activation Function ranges in {None, ReLU [32], SWISH [33]}.

When search space determined, evolution operation in search strategy can be defined. Evolution Operation takes an architecture in search space as input, randomly generates a new architecture similar to it and guarantees the new architecture is in the search space. Formally, evolution operation $\text{Evo}(-)$ satisfies:

\[ a_1 \in X \Rightarrow ( (\text{Evo}) (a_1) \in X \text{ and } 0 < d(\text{Evo}(a_1), a_1) < \epsilon) \],

where $d(\cdot, \cdot)$ denotes the distance between two architectures, $\epsilon$ denotes a specified distance tolerance.

In our design, Evolution Operations include: (1) randomly change in repeat times of Blocks, (2) randomly change in width of hidden states between Blocks, (3) randomly add or remove an edge from DAG, (4) randomly change in Layer Type, Layer Parameter, Output Width, Input Mode or Activation Function of a random node. Since some Evolution Operations may cause conflict when building a neural network, extra mutations should be considered. When Layer Type changes, Layer Parameter of same node is randomly selected from the parameter range of new Layer Type. Adding edge is only allowed when number of edges is less than \( \left\lfloor \frac{n(n-1)}{2} - 3 \right\rfloor \). Removing edge is only allowed when number of edges is greater than 3. After adding or removing edges, connectivity of DAG is checked. Nodes with only input/output edges will be connected to a random output/input edge.

5.4 Robustness-aware Model Evaluation

In RoSearch, we propose a robustness-aware model evaluation metric to grade each model $S$ in search process.

Each student architecture sampled from search space is constructed as a neural network and then performed knowledge distillation first. To overcome the obstacle between layer-wise knowledge distillation and variable architecture in searching, Probe Network
technique [14] is adopted to calculate layer-wise knowledge transfer loss when performing distillation. Classifiers are trained for each layer’s output in teacher model as teacher probe networks. Student probe networks are trainable classifiers for output of each Block in student model. Cross Entropy Losses between predictions of each student probe network and corresponding teacher probe network are summed as knowledge transfer loss. In addition, MSE loss between teacher model’s and student model’s logits, as well as traditional knowledge distillation loss are also adopted.

After distillation, each model is evaluated in three dimensions: Accuracy, Robustness and Efficiency.

Accuracy. Accuracy is simply measured by model’s correct rate evaluated on benign datasets.

Robustness. To evaluate the robustness of distilled student models, TextFooler [15] is used to generate adversarial examples for each student model. Accuracy on adversarial examples of searched models is calculated as robustness metric. Since the robustness under transfer attack significantly differs from the robustness under direct attack and no correlation between them is observed, direct attack on each model is performed independently during searching to give a more precise evaluation.

Efficiency. In order to guide searching process towards lightweight models, an efficiency aware metric is included in the model evaluation function. Model’s efficiency is measured by the amount of parameters. Less parameters indicates higher efficiency.

Three metrics for three attributes are weighted summed as the total score for guiding the searching process, so that trade-off between accuracy, robustness and efficiency could be performed to fit different scenarios. The whole fitness evaluation function is summarized as:

\[ \text{Fitness}(S) = \mu_1 \mathcal{A}_S(D) + \mu_2 \mathcal{A}_S(\text{TextFooler}(D)) + \mu_3 (-\#o_S), \]

where \( S \) represents the student model to be evaluated, \( D \) represents the involved dataset, \( \#o_S \) represents the number of parameters in model \( S \).

### 6 EXPERIMENTS

In this section, the proposed RoSearch is evaluated on natural language classification datasets and compared with existing baseline methods. Further experimental results on SST-2 dataset is presented for robustness analysis. In addition, we summarize the relationship between robustness of student models and model architecture properties through statistics of searched models.

#### 6.1 Setup

**Datasets.** SST-2 [34] and Ag News [35] datasets are adopted for evaluation in this work. SST-2 dataset of GLUE [36] benchmark aims to classify movie reviews into positive or negative categories according to their sentiment. Ag News dataset is a four-category classification task, which contains tens of thousands pieces of news. Each news is categorized into one of the four topics: World, Sports, Business and Sci/Tech. For each dataset, training set is utilized to fine-tune teacher model and obtain student model with knowledge distillation. Testing set is adopted to evaluate accuracy and robustness for student models.

**Implementation Details.** For the evolutionary search strategy in RoSearch, population size is set to 100. In each generation, 2 individuals are randomly selected for competition in tournament selection algorithm. Weighting factors in fitness equation were set to \( \mu_1 = 1, \mu_2 = 1, \mu_3 = 2 \). Accuracy and robustness in the fitness function are measured in percentage. Number of weight parameters is plugged in millions (M). Similar score threshold of TextFooler is set to 0.7 for robustness evaluation. For the knowledge distillation process of searched models, we leverage fine-tuned BERTBase with probe networks as teacher model. Vanilla knowledge distillation loss, probe network distillation loss, MSE loss between logits of student and teacher are combined with weighting factors. The three weighting factor are set as 0.5, 0.25 and 0.25 respectively. During distillation, temperature of vanilla distillation loss is set to 2, learning rate is set to 5e-4, epoch number is set to 15. Prediction of teacher model required for loss calculation is only related to input data instead of each student model. Thus, teacher model fine-tuning, probe networks training, and prediction on input data are performed before searching process.

Our algorithm are implemented with PyTorch [37] framework and deployed on a Slurm [38] task management platform. About sixteen Nvidia V100 GPUs are utilized as workers.

---

**Table 5: Result comparison on accuracy, robustness and efficiency of our approach and existing baselines. Model with (AT) means that it is obtained by adversarial training in fine-tuning stage.**

| Dataset | Model     | \( \mathcal{A} \) | \( \mathcal{A}_D(\text{adv}) \) | \#o |
|---------|-----------|-------------------|-------------------------------|-----|
| SST-2   | BERT      | 92.3%             | 12.4%                         | 110M|
|         | BERT(AT)  | 92.1%             | 21.3%                         | 110M|
|         | PKD       | 90.7%             | 6.2%                          | 67M |
|         | PKD(AT)   | 83.7%             | 14.0%                         | 67M |
|         | AdaBERT-SST2 | 89.0%             | 7.1%                          | 6.4M|
|         | AdaBERT-SST2(AT) | 73.4%             | 22.0%                         | 6.4M|
|         | Ours      | 84.1%             | 43.8%                         | 24M |
| Ag News | BERT      | 95.0%             | 27.0%                         | 110M|
|         | BERT(AT)  | 94.0%             | 35.8%                         | 110M|
|         | PKD       | 94.8%             | 18.7%                         | 67M |
|         | PKD(AT)   | 90.0%             | 19.3%                         | 67M |
|         | Ours      | 90.3%             | 47.8%                         | 16.9M|

---

**Figure 4: Representation of some typical architecture patterns in search space.**

---

RoSearch: Search for Robust Student Architectures When Distilling Pre-trained Language Models

Preprint, 2021.
6.2 Comparison Results

Baselines. Four categories of models are adopted as baselines for comparison: (1) pre-trained language model without adversarial training, i.e. the teacher model BERTBASE [1], (2) pre-trained language model with adversarial training in fine-tuning stage, i.e. BERT(AT), (3) student model derived from knowledge distillation without adversarial fine-tuning, i.e. PKD [13] and AdaBERT-SST2 [14] (only for SST-2 dataset), (4) student model derived from knowledge distillation with adversarial fine-tuning, i.e. PKD(AT) and AdaBERT-SST2(AT).

These models are compared in three dimensions: accuracy, robustness and efficiency. As shown in Table 5, our approach obtains significant robustness improvement with low accuracy drop, compared with the teacher model and existing distillation methods, even if adversarial training tricks are adopted. Furthermore, our compression ratio of model size could reach up to 4.6×–6.5× than teacher model BERTBASE. Though high computation cost is needed for our method, it remains in training stage.

Further evaluation details of RoSearch on SST-2 dataset are illustrated in Figure 5. During the searching process, student model's accuracy is located at 80%–85%. For robustness, both average value and trend of top robust models are gradually increasing along searching process. The diagram proves the effectiveness of our method on improving robustness of student models while maintaining the accuracy.

Adjusting the strength of adversarial training will affect the trade-off between model robustness and accuracy. On the other hand, student models with similar scores in our searching process may also differ in the robustness and accuracy terms. We draw robustness-accuracy curve of these methods in Figure 6 to give a more detailed comparison.

6.3 Robust Architecture Analysis

According to experiment on SST-2 dataset, we statistically summarize the relationship between architectures and the robustness of student models, in order to give an answer to Question ③ in Section 1.

Figure 5: Searching process on SST-2 dataset. Accuracy of searched models remains while average and upper-bound of robustness gradually increase.

(a) Adversarial training of PKD with different strength  (b) Searched models of our proposed RoSearch

Figure 6: Models’ accuracy and robustness comparison between adversarial training and RoSearch.

Figure 7: Statistics on robustness and accuracy of student architectures according to DAG properties. #Vertex denotes number of computational nodes that are connected in DAG. #Edge denotes number of activated edges in DAG.

Figure 7 shows the influence of DAG properties on robustness and accuracy of student model. The number of vertices and edges have no obvious effect on the accuracy except that least edges and vertices cause lowest average accuracy. On the other hand, student architectures with more than 3 vertices in DAG have a significant improvement on robustness. Robustness increases when number of active edges in DAG come up to 4, and begins to decrease when number of edges is greater than 8. It can be summarized that student architectures with higher layer number and moderate connectivity tend to have a higher robustness.

We also analyzed the influence of layer with different type on accuracy and robustness, results are summarized in Figure 8 and Figure 9 respectively. From Figure 8, it can be concluded that there is a positive correlation between number of Conv, Sep–Conv and GLU layers and accuracy of student models, while number of Attention layers is negatively correlated to the accuracy. For robustness, number of Conv and GLU layers provide negative contribution. Number of Attention layers and Sep–Conv layers give positive contribution
when number is moderate, however, excessive number of same type
on statistics of searched models.
relationship between student architecture and the robustness based
in robustness, accuracy and efficiency metrics. Experimental results
containing the accuracy of pre-trained language models and efficiency
NAS strategy to search for robust student architecture, while main-
edge distillation methods for pre-trained language models. To over-
different types of layers used in a Block.

Figure 8: Relationship between accuracy and number of dif-
terent types of layers used in a Block.

Figure 9: Relationship between robustness and number of dif-
terent types of layers used in a Block.

when number is moderate, however, excessive number of same type
reduces the positive influence on robustness.

7 CONCLUSIONS

In this work, we point out the security problem of existing knowl-
edge distillation methods for pre-trained language models. To over-
come the problem, we focus on an architecture view of student
models. We propose an algorithm RoSearch based on evolutionary
NAS strategy to search for robust student architecture, while main-
taining the accuracy of pre-trained language models and efficiency
gained from knowledge distillation. Each student architecture
sampled from a DAG based search space is distilled and evaluated
in robustness, accuracy and efficiency metrics. Experimental results
show the effectiveness of our algorithm. We also summarize the
relationship between student architecture and the robustness based
on statistics of searched models.

REFERENCES

[1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-
training of deep bidirectional transformers for language understanding. In
Proceedings of Conference of the North American Chapter of the Association for
Computational Linguistics: Human Language Technologies (NAACL-HLT), pages
4171–4186, 2019.
[2] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov,
and Quoc V. Le. Xlnet: Generalized autoregressive pretraining for language
understanding. In Proceedings of Neural Information Processing Systems (NeurIPS),
pages 5754–5764, 2019.
[3] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joulti, Danqi Chen, Omer
Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A robustly
optimized BERT pretraining approach. arXiv preprint, abs/1907.11692, 2019.
[4] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush
Shafran, and Radu Soricut. ALBERT: A lite BERT for self-supervised learn-
ing of language representations. In Proceedings of International Conference on
Learning Representations (ICLR), 2020.
[5] Mitchell A. Gordon, Kevin Duh, and Nicholas Andrews. Compressing BERT: study-
ing the effects of weight pruning on transfer learning. In Proceedings of
Workshop on Representation Learning for NLP (Rep4NLP@ACL), pages 143–155,
2020.
[6] Raphael Tang, Yao Lu, Linqing Liu, Lili Mou, Olga Vechtomova, and Jimmy Lin.
Distilling task-specific knowledge from BERT into simple neural networks. arXiv
preprint, abs/1903.12136, 2019.
[7] Subhabrata Mukherjee and Ahmed Hassan Awadallah. ExtreDistil: Multi-stage
distillation for massive multilingual models. In Proceedings of Annual Meeting of
the Association for Computational Linguistics (ACL), pages 2221–2234, 2020.
[8] Angela Fan, Eduard Grave, and Armand Joulin. Reducing transformer depth on
trades off with structured dropout. In Proceedings of NeurIPS, pages 5998–6008,
2017.
[9] Zhiqing Sun, Hongxuan Yu, Xiaodan Song, Renjie Liu, and Denny Zhou. MobileBERT:
a compact task-agnostic BERT for resource-limited devices. In Proceedings of
Annual Meeting of the Association for Computational Linguistics (ACL), pages
2158–2170, 2020.
[10] Sheng Shen, Zhen Dong, Jiayu Ye, Linjian Ma, Zhewei Yao, Amir Gholami,
Michael W. Mahoney, and Kurt Keutzer. Q-BERT: Hessian based ultra low
precision quantization of BERT. In Proceedings of AAAI Conference on Artificial
Intelligence (AAAI), pages 8815–8821, 2020.
[11] Henry Tsai, Jason Riesa, Melvin Johnson, Naveen Arivazhagan, Xin Li, and Amelia
Archer. Small and practical BERT models for sequence labeling. In Proceedings of
the 2019 Conference on Empirical Methods in Natural Language Processing and
the 9th International Joint Conference on Natural Language Processing (EMNLP-
IJCNLP), pages 3630–3634, 2019.
[12] Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean. Distilling the knowledge in
a neural network. arXiv preprint, abs/1503.02531, 2015.
[13] Liqun Sun, Yu Cheng, Zhe Gan, and Jingjing Liu. Patient knowledge distillation
for BERT model compression. In Proceedings of Conference on Empirical Methods
in Natural Language Processing and International Joint Conference on Natural
Language Processing (EMNLP-IJCNLP), pages 4322–4331, 2019.
[14] Daoyuan Chen, Yuliang Li, Minghao Guo, Yuzhe Yang, Rui Xu, Ziwei Liu, and
Dahua Lin. When NAS meets NAS. In Proceedings of Conference on Empirical
Methods in Natural Language Processing (EMNLP), pages 3290–3299, 2020.
[15] Di Jin, Zhijing Jin, Jory Tianyi Zhou, and Peter Sadowski. Is BERT really robust?
A strong baseline for natural language attack on text classification and entailment.
In Proceedings of AAAI Conference on Artificial Intelligence (AAAI), pages
8018–8025, 2020.
[16] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan,
Ian J. Goodfellow, and Rob Fergus. Intriguing properties of neural networks.
In Proceedings of International Conference on Learning Representations (ICLR),
2014.
[17] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and
harnessing adversarial examples. In Proceedings of International Conference
on Learning Representations (ICLR), 2015.
[18] David R. So, Quoc V. Le, and Chen Liang. The evolved transformer. In
Proceedings of International Conference on Machine Learning (ICML), volume 97,
pages 5877–5886, 2019.
[19] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones,
Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need.
In Proceedings of NeurIPS, pages 5998–6008, 2017.
[20] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. DistilBERT, a
distilled version of BERT: smaller, faster, cheaper and lighter. In Proceedings of
NeurIPS, pages 4322–4331, 2019.
[21] Xiaoqin Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang,
and Qun Liu. TinyBERT: Distilling BERT for natural language understanding.
In Proceedings of Conference on Empirical Methods in Natural Language Processing:
Findings (EMNLP), pages 4163–4174, 2020.
[22] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. DistilBERT, a
distilled version of BERT: smaller, faster, cheaper and lighter. In NeurIPS EMC,
Workshop, 2019.
[23] Xiqian Chen, Yuliang Li, Minghao Guo, Ziwei Liu, and Dahua Lin. Towards evolving
robust neural architectures to defend from adversarial attacks. In Proceedings of
Conference on Artificial Intelligence: From Phenomena to Black-box Attacks using
Adversarial Intelligence (AAAI), pages 8025, 2020.
[24] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and
Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In
Proceedings of AAAI Conference on Artificial Intelligence (AAAI), pages 1–9,
2017.
[25] Arash Rostamizadeh, Bob Dexter, and Michael I. Jordan. Neural networks are hard
to fool if you want them to be. In Conference on Neural Information Processing
Systems (NeurIPS), pages 9248–9259, 2019.
[26] Adarsh Magesh, Kyle Reina, and Prasanth Mohan. GAT-Attack: Generating multi-
modal adversarial examples for visualBERT. In Proceedings of Conference on
Computer Vision and Pattern Recognition (CVPR), pages 8018–8025, 2020.
[27] Shashank Kotyan and Danilo Vasconcellos Vargas. Towards evolving robust
neural architectures to defend from adversarial attacks. In Proceedings of
Conference on Computer Vision and Pattern Recognition (CVPR), pages 8018–
8025, 2020.
[27] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. Neural architecture search: A survey. J. Mach. Learn. Res., 20:55:1–55:21, 2019.

[28] Esteban Real, Sherry Moore, Andrew Selle, Sau-Rabh Saxena, Yutaka Leon Sumata, Jie Tan, Quoc V. Le, and Alexey Kurakin. Large-scale evolution of image classifiers. In Proceedings of International Conference on Machine Learning (ICML), volume 70, pages 2902–2911, 2017.

[29] David E. Goldberg and Kalyanmoy Deb. A comparative analysis of selection schemes used in genetic algorithms. In Proceedings of the First Workshop on Foundations of Genetic Algorithms (FOGA), pages 69–93, 1990.

[30] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint, abs/1704.04861, 2017.

[31] Yann N. Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated convolutional networks. In Proceedings of International Conference on Machine Learning (ICML), pages 953–941, 2017.

[32] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. Deep sparse rectifier neural networks. In Proceedings of International Conference on Artificial Intelligence and Statistics (AISTATS), volume 15 of JMLR Proceedings, pages 315–323, 2011.

[33] Prajit Ramachandran, Barret Zoph, and Quoc V. Le. Searching for activation functions. In Proceedings of International Conference on Learning Representations (ICLR), 2018.

[34] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1631–1642, 2013.

[35] Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In Proceedings of Neural Information Processing Systems (NeurIPS), pages 649–657, 2015.

[36] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of International Conference on Learning Representations (ICLR), 2019.

[37] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kqqql, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. PyTorch: An imperative style, high-performance deep learning library. In Proceedings of Neural Information Processing Systems (NeurIPS), pages 8024–8035, 2019.

[38] Andy B. Yoo, Morris A. Jette, and Mark Grondona. SLURM: simple linux utility for resource management. In Proceedings of International Workshop on Job Scheduling Strategies for Parallel Processing (JSSPP), volume 2862, pages 44–60, 2003.