What do Compressed Large Language Models Forget? Robustness Challenges in Model Compression

Mengnan Du1, Subhabrata Mukherjee2, Yu Cheng2, Milad Shokouhi2, Xia Hu3, Ahmed Hassan Awadallah2
1Texas A&M University 2Microsoft Research 3Rice University
dumengnan@tamu.edu, xia.hu@rice.edu
{submukhe,Yu.Cheng,milads,hassanam}@microsoft.com

Abstract
Recent works have focused on compressing pre-trained language models (PLMs) like BERT where the major focus has been to improve the compressed model performance for downstream tasks. However, there has been no study in analyzing the impact of compression on the generalizability and robustness of these models. Towards this end, we study two popular model compression techniques including knowledge distillation and pruning and show that compressed models are significantly less robust than their PLM counterparts on adversarial test sets although they obtain similar performance on in-distribution development sets for a task. Further analysis indicates that the compressed models overfit on the easy samples and generalize poorly on the hard ones. We further leverage this observation to develop a regularization strategy for model compression based on sample uncertainty. Experimental results on several natural language understanding tasks demonstrate our mitigation framework to improve both the adversarial generalization as well as in-distribution task performance of the compressed models.

1 Introduction
Large pre-trained language models (PLMs) (e.g., BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), GPT-3 (Brown et al., 2020)) have obtained state-of-the-art performance in several Natural Language Understanding (NLU) tasks. However, it is difficult to use these large models in real-world applications with latency and capacity constraints, e.g., edge devices and mobile phones. Model compression is one of the techniques to reduce the model size, speed up inference, and save energy without significant performance drop for downstream tasks. State-of-the-art model compression techniques like knowledge distillation (Sanh et al., 2019; Sun et al., 2019) and pruning (Sanh et al., 2020) primarily focus on evaluating the compression factors (including number of parameters, number of FLOPs and speedup) and compressed model performance in standard benchmark tasks in GLUE (Wang et al., 2019).

Recent works show that standard evaluation schemes are insufficient to capture the generalization ability of the PLMs (D’Amour et al., 2020). For instance, these models can learn simple decision rules that can perform well on in-distribution data (Gardner et al., 2020), but have poor generalization performance on out-of-distribution (OOD) data, raising concerns about their robustness. In particular, recent studies (Niven and Kao, 2019; Du et al., 2021; Mudrakarta et al., 2018) indicate that PLMs often exploit dataset biases as shortcuts in the form of simple correlations, rather than acquiring higher level semantic understanding across several natural language understanding tasks.

While the above works are geared towards general-purpose PLMs, to the best of our knowledge, this is first work to study the impact of compression on the generalization ability of the compressed models. Specifically, we explore the following research questions: Are compressed models as robust as their PLM counterparts for downstream NLU tasks? What is the impact of varying the level of compression on adversarial generalization and bias of the compressed models?

Towards this end, we conduct comprehensive experiments to evaluate the adversarial robustness of compressed models, with BERT as the base encoder. We primarily focus on two popular model compression techniques in the form of pruning and knowledge distillation (Sanh et al., 2019; Wang et al., 2020). For pruning, we consider two popular techniques including iterative magnitude pruning (Sanh et al., 2020) and structured prun-
ing (Prasanna et al., 2020; Liang et al., 2021). We evaluate the performance of several compressed models obtained using the above techniques on both standard in-distribution development sets as well as the adversarial test sets for downstream NLU tasks. Experimental analysis indicates that the compressed models, regardless of the compression method, are consistently less robust than their PLM counterparts. Further analysis of the poor generalization performance of the compressed models reveals some interesting observations. For instance, we observe that the compressed models overfit on the easy / shortcut samples and generalize poorly on the hard ones for a given task. This motivates our second research question: How to regularize model compression techniques to generalize across samples with varying difficulty? This brings some interesting challenges since we do not know which samples are easy or hard apriori.

Based on the above observations, we propose a mitigation framework to improve the robustness of compressed models, termed as RMC (Robust Model Compression). First, we leverage uncertainty of the deep neural network to quantify the difficulty of a training sample. This is given by the variance in the prediction of a sample from multiple sub-networks of the original large network obtained by model pruning. Second, we leverage this sample-specific measure for smoothing and regularizing different families of compression techniques. The major contributions of this work can be summarized as follows:

- We perform a comprehensive analysis to evaluate the generalization ability and robustness of compressed models. To the best of our knowledge, this is the first work to study this aspect on model compression for NLU tasks.
- We further analyze plausible reasons for low generalization ability of compressed models and demonstrate connections to shortcut learning.
- Finally, we propose a mitigation framework for regularizing model compression, termed as RMC. We perform experiments to demonstrate that our framework improves both the standard task performance as well as adversarial generalization on multiple NLU tasks.

2 Related Work

In this section, we provide a brief overview of two lines of research that are most relevant to ours.

Model Robustness. Recent studies indicate that pre-trained language models like BERT tend to exploit biases in the dataset for prediction, rather than acquiring higher-level semantic understanding and reasoning (Niven and Kao, 2019; Du et al., 2021; McCoy et al., 2019a). There are some preliminary works to mitigate the bias of general pre-trained models, including product-of-experts (Clark et al., 2019; He et al., 2019; Sanh et al., 2021), re-weighting (Schuster et al., 2019; Yaghoobzadeh et al., 2019; Utama et al., 2020), adversarial training (Stacey et al., 2020), posterior regularization (Cheng et al., 2021), etc. Recently, challenging benchmark datasets, e.g., Checklist (Ribeiro et al., 2020) and the Robustness Gym (Goel et al., 2021), have been developed to facilitate the evaluation of the robustness of these models.

Robustness in Model Compression. Current practice to evaluate the performance of model compression mainly focuses on the standard benchmark performance. To the best of our knowledge, this is the first work to investigate the performance of compressed models beyond standard benchmarks for natural language understanding tasks. In the computer vision domain, previous work shows that compressed models have poor performance on Compression Identified Exemplars (CIE) (Hooker et al., 2019), and compression amplifies the algorithmic bias towards certain demographics (Hooker et al., 2020). One concurrent work (Xu et al., 2021) evaluates the robustness of compressed models with regard to the scenario of adversarial attacks, i.e., TextFooler (Jin et al., 2020).

In this work, we comprehensively characterize the robustness of BERT compression on adversarial test sets to probe the generalizability of the compression techniques. Furthermore, we use insights from this robustness analysis to design mitigation techniques to perform robust model compression.

3 Are Compressed Models Robust?

We perform a comprehensive analysis to evaluate the robustness of compressed language models.

3.1 Compression Techniques

We consider two popular families of compression, namely, knowledge distillation and model pruning.

Knowledge Distillation: The objective here is to train a small size model by mimicking the behavior of the larger teacher model using knowledge distillation (Hinton et al., 2015). We focus on task-
agnostic distillation in this work. In particular, we consider DistilBERT (Sanh et al., 2019) and MiniLM (Wang et al., 2020) distilled from BERT-base. For a fair comparison, we select compressed models with similar capacities (66M parameters in this work)\textsuperscript{1}. In order to evaluate the impact of compression techniques on model robustness, we also consider similar capacity smaller models without using knowledge distillation. These are obtained via simple truncation where we retain the first 6 layers of the large model, and via pre-training a smaller 6-layer model from scratch.

**Iterative Magnitude Pruning:** This is an unstructured, task-specific pruning method (Sanh et al., 2020). During the fine-tuning process for each downstream task, the weights with the lowest magnitude are removed until the pruned model reaches the target sparsity. Note that we utilize standard pruning technique, rather than the LTH-based pruning (lottery ticket hypothesis) that uses re-winding (Chen et al., 2020). We also consider different pruning ratio to obtain pruned models with different levels of sparsity.

**Structured Pruning:** This family of methods are based on the hypothesis that there is redundancy in the attention heads (Prasanna et al., 2020; Voita et al., 2019; Bian et al., 2021). We also consider task-specific pruning. During the fine-tuning process for each task, it prunes whole attention heads based on their importance to the model predictions. To calculate the importance, we follow (Michel et al., 2019; Prasanna et al., 2020) and calculate the expected sensitivity of the attention heads to the mask variable $\xi^{(h,l)}$: $f_h^{(h,l)} = E_{x \sim X} \left| \frac{\partial L(x)}{\xi^{(h,l)}} \right|$, where $f_h^{(h,l)}$ denotes the contribution score for attention head $h$ at layer $l$, $L(x)$ represents the loss value for sample $x$, and $\xi^{(h,l)}$ is the mask for the attention head $h$ at layer $l$. After obtaining the contribution scores, the attention heads with the lowest score $I_h^{(h,l)}$ are pruned. We prune around 20% attention heads in total (i.e., 28). Further pruning increases the sparsity with significant degradation of the model’s performance on in-distribution development sets.

\textsuperscript{1}For a fair comparison, we do not compare with TinyBERT (Jiao et al., 2020) and MobileBERT (Sun et al., 2020), since TinyBERT is fine-tuned with data augmentation on NLU tasks, and MobileBERT is distilled from BERT-large rather than BERT-base.

| Sparsity | MNLI | FEVER | QQP |
|----------|------|-------|-----|
|          | DEV  | HANS  | Sym1 | Sym2 | DEV  | paws\_wiki | paws\_pp |
| BERT-base| 84.2 | 59.8  | 86.2 | 58.9 | 64.5 | 90.9       | 48.9     | 34.7     |
| 20%      | 84.4 | 55.5  | 86.5 | 57.0 | 64.6 | 90.7       | 47.2     | 33.5     |
| 40%      | 84.0 | 54.7  | 86.4 | 57.2 | 64.0 | 90.5       | 46.6     | 32.4     |
| 60%      | 83.4 | 52.8  | 86.3 | 56.9 | 63.3 | 89.5       | 45.9     | 31.8     |
| 70%      | 81.8 | 52.2  | 85.9 | 56.6 | 63.3 | 89.5       | 45.4     | 30.7     |

Table 1: Accuracy comparison (in percent) for iterative magnitude pruning with different levels of sparsity. Pruned models have relatively higher degradation in adversarial set compared to the development set. The corresponding $F_{bias}$ values are given in Table 4.

| Models      | MNLI | FEVER | QQP |
|-------------|------|-------|-----|
|             | DEV  | HANS  | Sym1 | Sym2 | DEV  | paws\_wiki | paws\_pp |
| DistilBERT  | 82.3 | 51.2  | 84.5 | 51.9 | 60.4 | 89.9       | 48.1     | 34.6     |
| MiniLM      | 83.1 | 51.4  | 84.2 | 53.4 | 60.7 | 89.9       | 46.8     | 31.0     |
| Truncated-l6| 80.8 | 51.6  | 84.4 | 52.6 | 60.4 | 90.0       | 46.0     | 32.4     |
| Pretrained-l6| 81.6 | 52.2  | 85.8 | 54.7 | 62.6 | 90.0       | 46.4     | 33.9     |

Table 2: Accuracy comparison (in percent) of compressed models with knowledge distillation. Distilled models have relatively higher degradation in adversarial set compared to the development set. Except BERT-base, all other models are with 66M parameters. The corresponding $F_{bias}$ values are given in Table 5.

### 3.2 Evaluation Datasets

To evaluate the robustness of the compressed models introduced in the last section, we use three NLU tasks, including MNLI, FEVER, and QQP.

- **MNLI** (Williams et al., 2018): This is a natural language inference task, which aims to predict whether the relationship between the premise and hypothesis is contradiction, entailment, or neutral. It is split into training set and development set with 392,702 and 9,815 samples respectively. Throughout this work, we report accuracy metric on the matched subset. We use HANS (McCoy et al., 2019b) as the adversarial test set, containing 30,000 synthetic samples. Models that exploit shortcut features have been shown to perform poorly on the HANS test set.

- **FEVER** (Thorne et al., 2018): This is a fact verification dataset, where the task is to predict whether the claims support, refute or not-have enough-information about the evidence. Recent studies indicate that there are strong shortcuts in the claims (Utama et al., 2020). It is split into training set and development set with 242,911 and 16,664 samples respectively. To facilitate the robustness and generalization evaluation of fact verification models, two symmetric test sets (i.e., Sym v1 and Sym v2) were created, where
Table 3: Accuracy comparison (in percent) of compressed models with structured pruning. Pruned models have relatively higher degradation in adversarial set compared to the development set. All compressed models have been pruned 28 attention heads. The corresponding $F_{bias}$ values are given in Table 6.

| Models          | Attention heads | DEV  | HANS |
|-----------------|-----------------|------|------|
| BERT-base       | 144             | 84.2 | 59.8 |
| BERT-116heads-v1 | 116             | 84.1 | 55.5 |
| BERT-116heads-v2 | 116             | 84.2 | 53.7 |
| BERT-116heads-v3 | 116             | 84.0 | 55.3 |

Table 4: Relative bias $F_{bias}$ for models with iterative magnitude pruning (the smaller the better).

| Sparsity | MNLI | FEVER | QQP | Average |
|----------|------|-------|-----|---------|
| 20%      | 1.182| 1.045 | 1.037 | 1.088  |
| 40%      | 1.204| 1.051 | 1.049 | 1.101  |
| 60%      | 1.266| 1.068 | 1.061 | 1.132  |
| 70%      | 1.249| 1.063 | 1.065 | 1.127  |

Table 5: Relative bias $F_{bias}$ for models with knowledge distillation (the smaller the better).

| Models         | MNLI | FEVER | QQP | Average |
|----------------|------|-------|-----|---------|
| DistilBERT     | 1.289| 1.183 | 1.006 | 1.159   |
| MiniLM         | 1.309| 1.137 | 1.039 | 1.162   |
| Truncated-l6   | 1.247| 1.163 | 1.056 | 1.155   |
| Pretrained-l6  | 1.229| 1.115 | 1.045 | 1.130   |

Table 6: Relative bias $F_{bias}$ for models with structured pruning (the smaller the better).

| Models         | Average |
|----------------|---------|
| $F_{bias}$     | 1.172   |

In order to evaluate both the in-distribution task performance as well as the adversarial generalizability, we define a new metric to measure the relative performance of the compressed models with respect to the uncompressed BERT-base. First, we calculate the accuracy gap between in-distribution development set and adversarial test set as $F_{dev} - F_{adversarial}$ using BERT-base (denoted by $\Delta_{BERT-base}$) and its compressed variant (denoted by $\Delta_{compressed}$). Second, we compute the relative bias as the ratio between the accuracy gap of the compressed model with respect to BERT-base:

$$F_{bias} = \frac{\Delta_{compressed}}{\Delta_{BERT-base}}.$$ (1)

$F_{bias} > 1$ indicates that the compressed model is more biased than BERT-base with the degree of bias captured in a larger value of $F_{bias}$. Since FEVER has two adversarial sets, we use the overall accuracy on sym1 and sym2 to calculate $F_{bias}$. Similarly, the adversarial accuracy for QQP is the overall accuracy on PAWS-wiki and PAWS-qqp.

3.4 Experimental Observations

We report the accuracy performance for iterative magnitude pruning in Table 1, knowledge distillation in Table 2 and structured pruning in Table 3. The relative bias measure $F_{bias}$ corresponding to these three compression techniques are given in Table 4, Table 5, and Table 6 respectively. We have the following key observations.
• **Iterative magnitude pruning**: First, for slight and mid-level sparsity, the pruned models have comparable and sometimes even better performance on the in-distribution development set. Consider FEVER as an example, where the compressed model preserves the accuracy on the development set even at 60% sparsity\(^3\). However, the generalization accuracy on the adversarial test set has a substantial drop. This indicates that the development set fails to capture the generalization ability of the pruned models. Second, as the sparsity increases, the generalization accuracy on the adversarial test set substantially decreases while dropping to random guess for tasks such as MNLI. Third, at high levels of sparsity (e.g., 70%), both development and adversarial set performances are significantly affected. Overall, we observe \(F_{bias} > 1\) for all levels of sparsity in Table 4. Note that we limit the maximum sparsity at 70% after which the training is unstable with significant performance drop even on the development set (Liang et al., 2021). As in the previous cases, there is substantial accuracy drop on the adversarial set compared to the development set (e.g., 7.6% vs 1.9% degradation respectively for the MNLI task).

• **Knowledge distillation**: Similar to pruning, we observe more accuracy drop in adversarial set compared to development set for distilled models. Consider DistilBERT performance on MNLI as an example with 1.9% accuracy drop in development set compared to 8.6% drop in the adversarial set. This can also be validated in Table 5, where all \(F_{bias}\) values are larger than 1 depicting that all the distilled models are less robust than BERT-base. Another interesting observation is that distilled models, i.e., DistilBERT and MiniLM, have higher bias \(F_{bias}\) compared to the pre-trained models, i.e., Pretrained-l6 and Truncated-l6, as we compare their average \(F_{bias}\) values in Table 5. This indicates that the compression process plays a significant role on the low robustness of the distilled models.

• **Structured pruning**: Recent studies have reported the super ticket phenomenon (Liang et al., 2021). The authors observe that, when the BERT-base model is slightly pruned, the accuracy of the pruned models improve on in-distribution development set. However, we observe this finding not to hold for adversarial sets. From Table 6, we observe all the pruned models to be less robust than BERT-base, with \(F_{bias}\) much larger than 1.

### 4 Attribution of Low Robustness

In this section, we explore the factors leading to the low robustness of compressed models. For this, we choose the MNLI task for a study. Previous work has demonstrated that the performance of different models on the GLUE benchmark (Wang et al., 2018) tend to correlate with the performance on MNLI, making it a good representative of natural language understanding tasks in general (Phang et al., 2018; Liu et al., 2020).

For MNLI task, we consider the dataset splits from (Gururangan et al., 2018). The authors partition the development set into easy/shortcut and hard subsets. They train a hypothesis-only model, and use it to generate predictions for the whole development set. The samples that are given correct predictions by the hypothesis-only model are regarded as easy samples, and vice versa. The easy subset contains 5488 samples and the hard subset contains 4302 samples. In this experiment, we use pruned models with varying sparsity to investigate the reason for low robustness of the compressed models. We have the following key observations.

**Observation 1**: The compressed models tend to overfit to the easy/shortcut samples, and generalize poorly on the hard ones. The performance of pruned models at five levels of sparsity (ranging between \([0.2 − 0.85]\)) on the easy and hard samples for the MNLI task is illustrated in Figure 1. It demonstrates that the accuracy on the hard samples is much lower compared to the accuracy on the easy ones. As the sparsity increases, we observe a larger accuracy drop on the hard samples compared to the easy ones. In particular, the accuracy gap

\(^3\)Here, 60% sparsity indicates that 40% parameters are remaining after pruning.

\(^4\)We use ‘easy’ and ‘shortcut’ interchangeably in this work.
between the two subsets is 22.7% at the sparsity of 0.85, much higher than the 16.1% accuracy gap at the sparsity of 0.4. These findings demonstrate that the compressed models overfit to the easy samples, while generalizing poorly on the hard ones. Furthermore, this phenomenon is amplified at higher levels of sparsity for the pruned models.

**Observation 2:** Compressed models tend to assign overconfident predictions to the easy samples. One of the potential reasons is that the compressed models are more prone to capture spurious correlation between shortcut features in the training samples with certain class labels for their predictions (Geirhos et al., 2020; Du et al., 2021).

### 4.1 Variance-based Difficulty Estimation

Based on the above observations, we propose a variance based metric to quantify the difficulty degree of each sample. To this end, for each sample in the development set, we calculate its loss at five different levels of pruning sparsity as shown in Figure 1. We further calculate the variance of the above losses for each sample, and rank them based on the variance. Finally, we assign the samples with low variance to the “easy” subset and rest to the “hard” one. Comparing our variance-based proxy annotation against the ground-truth annotation in (Gururangan et al., 2018) gives an accuracy of 82.8%. This indicates that the variance based estimation leveraging pruning sparsity is a good indicator for sample difficulty. This motivates our design of the mitigation technique introduced in the next section.

### 5 Mitigation Framework

In this section, we propose a general bias mitigation framework (see Figure 2), termed as RMC (Robust Model Compression), to improve the robustness of compressed models on downstream tasks. Recent works on task-specific knowledge distillation (Sanh et al., 2020; Jiao et al., 2020) develop compressed models that match the teacher model performance on in-distribution development set of the tasks. However, we observe these compressed models to significantly degrade on the adversarial set, since the teacher model itself is not robust for downstream tasks (Niven and Kao, 2019).

Our RMC framework follows the philosophy of task-specific knowledge distillation, but with explicit regularization of the teacher network leveraging sample uncertainty. This prevents the compressed models to overfit on the easy samples containing shortcut features and helps in improving its robustness. This regularized training is implemented in the following two stages.

### 5.1 Quantifying Sample Difficulty

In the first stage, we aim to quantify the difficulty degree of each training sample.

**Variance Computation:** First, we use iterative magnitude pruning to obtain a series of pruned models from BERT-base with different levels of sparsity (ranging from $0.2 - 0.85$) as introduced in Section 4.1. We choose five levels of sparsity that are diverse enough to reflect the difficulty degree of each training sample. Second, we use the losses of the pruned models at different levels of sparsity to compute their variance $v_i$ for each training sample $x_i$. Here, the samples with high variance correspond to the hard ones (Chang et al., 2017), and vice versa.

**Difficulty Degree Estimation:** Based on the variance $v_i$ for each training sample $x_i$, we can estimate its difficulty degree as:

$$d_i = \alpha + \frac{1 - \alpha}{V_{\text{max}} - V_{\text{min}}} \cdot (v_i - V_{\text{min}}), \quad (2)$$

where $V_{\text{min}}$ and $V_{\text{max}}$ denote the minimum and maximum value for the variances respectively.

Equation 2 is used to normalize the variance of the training samples to the range of $[\alpha, 1]$, where $d_i = 1$ signifies an extremely hard sample.
We perform instance-level smoothing for each training sample. Prior work (Niven and Kao, 2019) show that the bias behavior of the downstream training set can be attributed to the data collection and annotation biases. Since the bias level is different for each dataset, we assign different \( \alpha \) in Equation 2 for each training set to reflect its bias level.

### 5.2 Robust Knowledge Distillation

In the second stage, we fine-tune BERT-base on the downstream tasks to obtain the softmax probability for each training sample. We then use the difficulty degree of the training samples (discussed in previous section) to smooth the teacher predictions. The instance-level smoothed softmax probability is used to guide the training of the compressed models via regularized knowledge distillation.

**Smoothing Teacher Predictions:** We smooth the softmax probability from the teacher network, according to the difficulty degree of each training sample. The smoothed probability is given as:

\[
s_{i,j} = \frac{(\hat{y}_{i,j}^T)^{d_i}}{K \sum_{k=1}^{K} (\hat{y}_{i,k}^T)^{d_k}},
\]

where \( K \) denotes the total number of class labels. We perform instance-level smoothing for each training sample \( x_i \). If the difficulty degree of a training sample \( d_i = 1 \), then the softmax probability \( s_i \) for the corresponding sample from the teacher is unchanged. In contrast, at the other extreme as \( d_i \to \alpha \), we increase the regularization to encourage the compressed model to assign less over-confident prediction to the sample. The difficulty degree range is \([\alpha, 1]\) rather than \([0, 1]\) to avoid over smoothing the teacher predictions.

**Smoothness-Induced Model Compression:** We employ the smoothed softmax probability from BERT-base to supervise the training of the compressed models, where the overall loss function is given as follows.

\[
\mathcal{L}(x) = (1 - \lambda) \mathcal{L}_1 \left( y_i, \left( \hat{y}_{i,j}^T \right) \right) + \lambda \mathcal{L}_2 \left( s_i, \left( \hat{y}_{i,j}^S \right) \right), \tag{4}
\]

where \( \mathcal{L}_1 \) denotes the cross entropy loss, and \( \mathcal{L}_2 \) represents the knowledge distillation loss with KL divergence. The hyperparameter \( \lambda \) manages the trade-off between learning from the hard label \( y_i \) and softened softmax probability \( s_i \). Among the different families of compression techniques introduced in Section 3.1, we directly fine-tune distilled models using Equation 4. For iterative magnitude pruning, we use Equation 4 to guide the pruning during the fine-tuning process.

### 6 Mitigation Performance Evaluation

In this section, we conduct experiments to evaluate the robustness of our RMC mitigation framework.

#### 6.1 Experimental Setup

For all experiments, we follow the same setting as in Section 3.3, and the same evaluation datasets as in Section 3.2. We use the adversarial test set solely for evaluation. We compute the variance of samples (outlined in Section 4.1) in the in-distribution development set to split it into shortcut and hard subset. The relative robustness between the hard and easy subset is used to tune hyperparameter \( \alpha \) in Equation 2, where we set \( \alpha \) as 0.5, 0.3, 0.2 for MNLI, FEVER, and QQP respectively. The weight \( \lambda \) in Equation 4 is fixed as 0.9 for all experiments, to regularize the compressed model from smoothed predictions of the teacher network.

#### 6.2 Baselines

We consider the following four baseline methods. Please refer to Appendix B for more details.

- **Vanilla:** This only fine-tunes the base encoder without any regularization.
- **Task-Specific Knowledge Distillation (Distil) (Sanh et al., 2020):** This first fine-tunes BERT-

| Models    | DEV HANS | DEV Sym1 | DEV Sym2 | DEV paws_abs | DEV paws_abs | MNLI | FEVER | QQP |
|-----------|----------|----------|----------|--------------|--------------|------|-------|-----|
| BERT-base | 84.2     | 59.8     | 86.2     | 58.9         | 64.5         | 90.9 | 48.9  | 34.7|
| Vanila    | 84.0     | 54.7     | 86.4     | 57.2         | 64.0         | 90.5 | 46.6  | 32.4|
| Distil    | 84.1     | 56.2     | 86.3     | 58.6         | 64.5         | 90.5 | 47.3  | 33.2|
| Smooth    | 84.2     | 56.5     | 86.2     | 60.7         | 65.8         | 90.7 | 47.2  | 33.8|
| Focal     | 84.0     | 56.7     | 86.4     | 59.4         | 65.2         | 90.7 | 46.2  | 32.1|
| JIT       | 83.8     | 56.3     | 86.2     | 58.1         | 64.9         | 90.4 | 47.3  | 33.7|
| RMC       | 84.2     | 58.6     | 86.1     | 61.9         | 66.4         | 90.4 | 47.6  | 34.3|

Table 7: Generalization accuracy comparison (in percent) for iterative magnitude pruning at 40% sparsity with different mitigation methods. The corresponding \( F_{bias} \) values are given in Table 9.

| Models    | DEV HANS | DEV Sym1 | DEV Sym2 | DEV paws_abs | DEV paws_abs | MNLI | FEVER | QQP |
|-----------|----------|----------|----------|--------------|--------------|------|-------|-----|
| BERT-base | 84.2     | 59.8     | 86.2     | 58.9         | 64.5         | 90.9 | 48.9  | 34.7|
| MiniLM    | 83.1     | 51.4     | 84.2     | 53.4         | 60.7         | 89.9 | 46.8  | 31.0|
| Vanilla   | 83.1     | 53.7     | 83.8     | 56.5         | 61.0         | 89.6 | 46.7  | 31.8|
| Distil    | 82.7     | 53.8     | 83.7     | 56.9         | 62.1         | 89.4 | 46.8  | 32.2|
| Smooth    | 83.2     | 55.6     | 83.8     | 54.7         | 61.4         | 90.3 | 46.8  | 33.2|
| Focal     | 82.8     | 55.7     | 83.5     | 53.8         | 61.7         | 90.1 | 47.0  | 32.9|
| RMC       | 83.7     | 57.8     | 85.3     | 58.0         | 63.3         | 90.5 | 47.0  | 33.4|

Table 8: Generalization accuracy (in percent) comparison of different training strategies with and without mitigation on in-distribution development set and adversarial set using MiniLM as the compressed encoder. The corresponding \( F_{bias} \) values are given in Table 10.
| Sparsity | MNLI | FEVER | QQP | Average |
|----------|------|-------|-----|---------|
| 40% – Vanilla | 1.204 | 1.051 | 1.049 | 1.101 |
| – Distil | 1.145 | 1.013 | 1.032 | 1.063 |
| – Smooth | 1.135 | 0.937 | 1.036 | 1.103 |
| – Focal | 1.122 | 0.981 | 1.060 | 1.054 |
| – JTT | 1.132 | 1.008 | 1.030 | 1.057 |
| – RMC | 1.049 | 0.897 | 1.023 | 0.990 |

Table 9: Relative bias \( F_{bias} \) of mitigation methods with iterative magnitude pruning at 40% sparsity (the smaller the better).

| Sparsity | MNLI | FEVER | QQP | Average |
|----------|------|-------|-----|---------|
| MiniLM – Vanilla | 1.309 | 1.137 | 1.039 | 1.162 |
| – Distil | 1.221 | 1.052 | 1.037 | 1.103 |
| – Smooth | 1.206 | 1.017 | 1.032 | 1.085 |
| – Focal | 1.145 | 1.081 | 1.041 | 1.089 |
| – JTT | 1.129 | 1.085 | 1.034 | 1.083 |
| – RMC | 1.068 | 1.017 | 1.038 | 1.041 |

Table 10: Relative bias \( F_{bias} \) for different mitigation methods for distillation with MiniLM base encoder (the smaller the better).

base on the downstream NLU tasks. The softmax probability from the fine-tuned BERT-base is used as supervision signal for distillation.

- **Global Smoothing (Smooth)** (Müller et al., 2019): This performs global smoothing for all training samples with task-specific knowledge distillation, where we use the same level of regularization as in RMC \((d_l = 0.9 \text{ in Equation 3})\). In contrast to this setting, RMC performs instance-level smoothing.

- **Focal Loss (Focal)** (Lin et al., 2017): Compared to cross entropy loss, focal loss has an additional regularizer to reduce the weight for easy samples, and assign a higher weight to hard samples bearing less-confident predictions.

- **Just Train Twice (JTT)** (Liu et al., 2021): This is a re-weighting method, which first trains the BERT-base model using standard cross entropy loss for several epochs, and then trains the compressed model while up-weighting the training examples that are mis-classified by the first model, i.e., hard samples.

### 6.3 Mitigation Performance Analysis

We compare the mitigation performance of our RMC framework with the above baselines and have the following key observations.

**Iterative Magnitude Pruning:**

- **Comparison with Baselines**: Table 7 shows the mitigation results with relative bias \( F_{bias} \) in Table 9. All mitigation methods are performed with pruned models at 40% sparsity. We observe that task-specific knowledge distillation slightly improves the accuracy on adversarial set compared to Vanilla tuning. Global smoothing further improves the generalization accuracy compared to the prior methods. Our RMC framework obtains the best accuracy on adversarial test set across all the tasks on aggregate. RMC further reduces the average relative bias \( F_{bias} \) by 10% over Vanilla tuning in Table 9.

- **Pruning with Varying Sparsity**: For the MNLI task, we illustrate the mitigation performance of our RMC framework for different levels of sparsity in Figure 3. We observe RMC to consistently improve the accuracy on adversarial HANS while reducing the relative bias \( F_{bias} \) for all levels of sparsity over the Vanilla method.

**Knowledge Distillation**: Table 8 shows the mitigation results with relative bias \( F_{bias} \) in Table 10. We observe that RMC significantly improves over MiniLM for adversarial generalization leveraging smoothed predictions from BERT-base teacher. With instance-level smoothing in RMC, the generalization accuracy for the compressed model on the adversarial set is significantly closer to BERT-base teacher compared to the other methods. We also decrease the relative bias \( F_{bias} \) in Table 10 by 10.4% over Vanilla tuning. On the QQP task, RMC simultaneously improves compressed model performance on both the in-distribution development set as well as the two adversarial sets.

### 6.4 Further Analysis on Robust Mitigation

In this section, we further explore the reasons for improved generalization performance with RMC with an analysis on the MNLI task. Table 11 shows the accuracy performance of RMC for model pruning and distillation on the shortcut/easy and hard
Table 11: Our RMC framework improves accuracy of the compressed models on the hard samples and reduces overfitting on the shortcut/easy samples, leading to reduced performance gap between the two subsets.

7 Conclusions

In this work, we conduct a comprehensive study of the robustness challenges in compressing large language models. We observe that different families of compression techniques produce models that are consistently less robust than the uncompressed large model on adversarial test sets. Furthermore, we propose a general mitigation framework with instance-level smoothing for robust model compression. Experimental analysis demonstrate our framework to improve the generalization ability and adversarial robustness of the compressed models for different compression techniques.

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8 Appendix A. Magnitude Pruning

It is based on the over-parametrized assumption of the pre-trained language models. For iterative magnitude pruning, we freeze all the embeddings modules and only prune the parameters in the encoder (i.e., 12 layers of Transformer blocks). After the pruning, the values of the pruned weights are set as 0 in order to reduce the amount of information to store. Different from the LTH version, we consider the standard magnitude pruning without using the rewinding scheme.

9 Appendix B. Comparing Baselines

Distil and Smooth: For both baseline methods, we use the similar loss function as in Equation 4. We fix the weight \( \lambda \) as 0.9 for all experiments, to encourage the compressed model to learn more from the probability output of the teacher network. A major difference between the two baselines is that Smooth has an additional smoothing process involved during the finetuning process.

Focal Loss: The original focal loss function is:

\[
FL(p_i) = -(1 - p_i)^\gamma \log(p_i).
\]

Our implementation is as follows:

\[
FL(p_i) = -\frac{(1 - p_i)^\gamma}{\frac{1}{N} \sum_{k=1}^{N} (1 - p_k)^\gamma} \log(p_i).
\]

The hyperparameter \( \gamma \) controls the weight difference between hard and easy samples, and it is fixed as 2.0 for all tasks. We use the denominator to normalize the weights within a batch, where \( N \) is the batch size. This is used to guarantee that the average weight for a batch of training samples is 1.0. As such, the weight for the easy samples would be down-weighted to lower than 1.0, and the weight for hard samples would be up-weighted to values larger than 1.0.

JTT: This is also a reweighting baseline that encourages the model to learn more from hard samples. The hyperparameter \( \lambda_{up} \) in (Liu et al., 2021) is set as 2.0. We also normalize the weights so that the average weight for each training sample is 1.0.

10 Appendix C. Environment

For a fair evaluation of the robustness of compressed models, we run all the experiments using a server with 4 NVIDIA GeForce 3090 GPUs. All experiments are implemented with the Pytorch version of the Hugging Face Transformer library.

11 Appendix D. The Capacity Issue

One natural speculation about the low robustness of the compressed models is due to their low capacity. To disentangle the two important factors that influence the model performance, we compare distilled models with Uncased-l6, which is trained only using pre-training. The results are given in Table 2. The results indicate that Uncased-l6 has better generalization ability over MNLI and FEVER two tasks. Take also structured pruning for example, although the three pruned models in Table 3 have the same model size, their generalization accuracy is different. These results indicate that the low robustness of the compressed model is not entirely due to their low capacity, and the compression plays a significant role.