LadaBERT: Lightweight Adaptation of BERT through Hybrid Model Compression

Yihuan Mao\textsuperscript{1}, Yujing Wang\textsuperscript{2,3,\dagger}, Chufan Wu\textsuperscript{1}, Chen Zhang\textsuperscript{2}, Yang Wang\textsuperscript{2}, Yaming Yang\textsuperscript{2}, Quanlu Zhang\textsuperscript{2}, Yunhai Tong\textsuperscript{3}, and Jing Bai\textsuperscript{2}

\textsuperscript{1}Tsinghua University \quad \textsuperscript{2}Microsoft Research Asia \quad \textsuperscript{3}Key Laboratory of Machine Perception (MOE), Peking University

\{maoyh, Wucf15\}@mails.tsinghua.edu.cn \quad \{yujwang, zhac, v-yanwa, yayaming, quzha, jbai\}@microsoft.com \quad \{yujwang, yhtong\}@pku.edu.cn

April 9, 2020

ABSTRACT

BERT is a cutting-edge language representation model pre-trained by a large corpus, which achieves superior performances on various natural language understanding tasks. However, a major blocking issue of applying BERT to online services is that it is memory-intensive and leads to unsatisfactory latency of user requests, raising the necessity of model compression. Existing solutions leverage the knowledge distillation framework to learn a smaller model that imitates the behaviors of BERT. However, the training procedure of knowledge distillation is expensive itself as it requires sufficient training data to imitate the teacher model. In this paper, we address this issue by proposing a hybrid solution named LadaBERT (Lightweight adaptation of BERT through hybrid model compression), which combines the advantages of different model compression methods, including weight pruning, matrix factorization and knowledge distillation. LadaBERT achieves state-of-the-art accuracy on various public datasets while the training overheads can be reduced by an order of magnitude.

1 Introduction

The pre-trained language model, BERT (Devlin, Chang, Lee, & Toutanova, 2018) has led to a big breakthrough in various kinds of natural language understanding tasks. Ideally, people can start from a pre-trained BERT checkpoint and fine-tune it on a specific downstream task. However, the original BERT models are memory-exhaustive and latency-prohibitive to be served in embedded devices or CPU-based online environments. As the memory and latency constraints vary in different scenarios, the pre-trained BERT model should be adaptive to different requirements with accuracy retained to the largest extent. Existing BERT-oriented model compression solutions largely depend on knowledge distillation (Hinton, Vinyals, & Dean, 2015), which is inefficient and resource-consuming because a large training corpus is required to learn the behaviors of a teacher. For example, DistilBERT (Sanh, Debut, Chaumond, & Wolf, 2019) is re-trained on the same corpus as pre-training a vanilla BERT from scratch; and TinyBERT (Jiao et al., 2019) utilizes expensive data augmentation to fit the distillation target. The costs of these model compression methods are as large as pre-training and unaffordable for low-resource settings. Therefore, it is straightforward to ask, can we design a lightweight method to generate adaptive models with comparable accuracy using significantly less time and resource consumption?

In this paper, we propose LadaBERT (Lightweight adaptation of BERT through hybrid model compression) to tackle the raised questions. Specifically, LadaBERT is based on an iterative hybrid model compression framework consisting

\begin{itemize}
\item \textsuperscript{\dagger}The work was done when the author visited MSRA
\item \textsuperscript{\dagger}corresponding author
\end{itemize}
of weighting pruning, matrix factorization and knowledge distillation. Initially, the architecture and weights of student
model are inherited from the BERT teacher. In each iteration, the student model is first compressed by a small ratio based
on weight pruning and matrix factorization, and is then fine-tuned under the guidance of teacher model through knowl-
edge distillation. Because weight pruning and matrix factorization help to generate better initial and intermediate status
in the knowledge distillation iterations, the accuracy and efficiency of model compression can be greatly improved.

We conduct extensive experiments on five public datasets of natural language understanding. As an example, the
performance comparison of LadaBERT and state-of-the-art models on MNLI-m dataset is illustrated in Figure 1. We can see that LadaBERT outperforms other BERT-oriented model compression baselines at various model
compression ratios. Especially, LadaBERT-1 outperforms BERT-PKD significantly under $2.5 \times$ compression ratio,
and LadaBERT-3 outperforms TinyBERT under $7.5 \times$ compression ratio while the training speed is accelerated
by an order of magnitude.

The rest of this paper is organized as follows. First, we summarizes the related works of model compression
and their applications to BERT in Section 2. Then, the methodology of LadaBERT is introduced in Section 3,
and experimental results are presented in Section 4. At
last, we conclude this work and discuss future works in
Section 5.

2 Related Work

Deep Neural Networks (DNNs) have achieved great success in many areas in recent years, but the memory consumption
and computational cost expand greatly with the growing complexity of models. Therefore, model compression has
become an indispensable technique for practice, especially in low-resource settings. In this section, we review the
current progresses of model compression techniques briefly, which can be divided into four categories, namely weight
pruning, matrix factorization, weight quantization and knowledge distillation. We also present hybrid approaches and
the applications of model compression to pre-trained BERT models.

2.1 Weight pruning

Numerous researches have shown that removing a large portion of connections or neurons does not cause significant
performance drop in deep neural network models (Han, Pool, Tran, & Dally, 2015; H. Li, Kadav, Durduanovic, Samet, &
Graf, 2016; Hu, Peng, Tai, & Tang, 2016; Zhu & Gupta, 2017). For example, Han et al. (2015) proposed a method
to reduce the storage and computation of neural networks by removing unimportant connections, resulting in sparse
networks without affecting the model accuracy. Li et al. (2016) presented an acceleration method for convolution
neural network by pruning whole filters together with their connecting filter maps. This approach does not generate
sparse connectivity patterns and brings much larger acceleration ratio with existing BLAS libraries for dense matrix
multiplications. Ye et al. (2018) argued that small weights are in fact important for preserving the performance of
a model, and Hu et al. (2016) alleviated this problem by a data-driven approach that pruned zero-activation neurons
iteratively based on intermediate feature maps. Zhu and Gupta (2017) empirically compared large-sparse models
with smaller dense models of similar parameter sizes and found that large sparse models performed better consistently. In
addition, sparsity-induced models (Wen, Wu, Wang, Chen, & Li, 2016; Louizos, Welling, & Kingma, 2017; Zhang,
Wang, Figueiredo, & Balzano, 2018) can be regarded as similar methods as pruning. For example, Wen et al. (2016)
applied group lasso as a regularizer at training time, and Louizos et al. (2017) learned sparse neural networks through $l_0$
regularization.

2.2 Matrix factorization

The goal of matrix factorization is to decompose a matrix into the product of two matrices in lower dimensions, and
Singular Value Decomposition (SVD) is a popular way of matrix factorization that generalizes the eigendecomposition
of a square normal matrix to a $n \times n$ matrix. It has been proved that SVD is the best approximation of a matrix given
the rank $r$ under Frobenius norm (Stewart, 1998). Matrix factorization was widely studied in the deep learning domain for model compression and acceleration (Sainath, Kingsbury, Sindhwani, Arisoy, & Ramabhadran, 2013; Xue, Li, & Gong, 2013). Xue et al. (2014) applied low-rank matrix factorization of DNN layers for acoustic modeling. Xu et al. (2013, 2014) explored a low-rank matrix factorization method of DNN layers for acoustic modeling. Xu et al. (2013, 2014) applied singular value decomposition to deep neural network acoustic models and achieved comparable performances with state-of-the-art models through much fewer parameters. GroupReduce (P. Chen, Si, Li, Chelba, & Hsieh, 2018) focused on the compression of neural language models and applied low-rank matrix approximation to vocabulary-partition. Acharya et al. (2019) carried out experiments for low-rank matrix factorization on different NLP tasks and demonstrated that it was more effective in general than weight pruning.

2.3 Weight quantization

Weight quantization is a common technique for compressing deep neural networks, which aims to reduce the number of bits to represent every weight in the model. In a neural network, parameters are stacked into clusters, and the parameters in the same cluster share the same value. With weight quantization, the weights can be reduced to at most 1-bit binary value from 32-bits floating point numbers. Zhou et al. (2016) showed that quantizing weights to 8-bits does not hurt the performance, and Binarized Neural Networks (Hubara, Courbariaux, Soudry, El-Yaniv, & Bengio, 2016) contained binary weights and activations of only one bit. Incremental Network Quantization (A. Zhou, Yao, Guo, Xu, & Chen, 2017) converted a pre-trained full-precision neural network into low-precision counterpart through three interdependent operations: weight partition, groupwise quantization and re-training. Variational Network Quantization (Achterhold, Koehler, Schmeink, & Genewein, 2018) formulated the problem of network quantization as a variational inference problem. Moreover, Choi et al. (2016) investigated the drawbacks of conventional quantization methods based on k-means and proposed a Hessian-weighted k-means clustering algorithm as the solution.

2.4 Knowledge distillation

Knowledge distillation is first proposed by (Hinton et al., 2015), which trains a compact or smaller model to approximate the function learned by a large and complex model. A preliminary step of knowledge distillation is to train a deep network (the teacher model) that automatically generates soft labels for training instances. This “synthetic” label is then used to train a smaller network (the student model), which assimilates the function that is learned by the teacher model. Chen et al. (2017) successfully applied knowledge distillation to object detection tasks by introducing several modifications, including a weighted cross-entropy loss, a teacher bounded loss, and adaptation layers to model intermediate teacher distributions. Li et al. (2017) developed a framework to learn from noisy labels, where the knowledge learned from a clean dataset and semantic knowledge graph were leveraged to correct the wrong labels. Anil et al. (2018) proposed online distillation, a variant of knowledge distillation which enabled extra parallelism for training large-scale data. In addition, knowledge distillation is also useful for aggregating model ensembles into a single model by treating the ensemble model as a teacher.

2.5 Hybrid approach

To improve the performance of model compression, there are many attempts to conduct hybrid model compression method that combines more than one category of algorithms. Han et al. (2016) combined quantization, hamming coding and weight pruning to conduct model compression on image classification tasks. Yu et al. (2017) proposed a unified framework for low-rank and sparse decomposition of weight matrices with feature map reconstructions. Polino et al. (2018) advocated a combination of distillation and quantization techniques and proposed two hybrid models, i.e., quantified distillation and differentiable quantization to address this problem. Li et al., (2018) compressed DNN-based acoustic model through knowledge distillation and pruning. NNCF (Kozlov, Lazarevich, Shamporov, Lyalyushkin, & Gorbachev, 2020) provided a neural network compression framework that supported an integration of various model compression methods to generate more lightweight networks and achieved state-of-the-art performances in terms of a trade-off between accuracy and efficiency. In (He & Han, 2018), an AutoML pipeline was adopted for model compression. It leveraged reinforcement learning to search for the best model compression strategy among multiple combinatorial configurations.

2.6 BERT model compression

In the natural language processing community, there is a growing interest recently to study BERT-oriented model compression for shipping its performance gain into latency-critical or low-resource scenarios. Most existing works focus on knowledge distillation. For instance, BERT-PKD (Sun, Cheng, Gan, & Liu, 2019) is a patient knowledge
distillation approach that compresses the original BERT model into a lightweight shallow network. Different from traditional knowledge distillation methods, BERT-PKD enables an exploitation of rich information in the teacher’s hidden layers by utilizing a layer-wise distillation constraint. DistillBERT (Sanh et al., 2019) pre-trains a smaller general-purpose language model on the same corpus as vanilla BERT. Distilled BiLSTM (Tang et al., 2019) adopts a single-layer BiLSTM as the student model and achieves comparable results with ELMo (Peters et al., 2018) through much fewer parameters and less inference time. TinyBERT (Jiao et al., 2019) reports the best-ever performance on BERT model compression, which exploits a novel attention-based distillation schema that encourages the linguistic knowledge in teacher to be well transferred into the student model. It adopts a two-stage learning framework, including general distillation (pre-training from scratch via distillation loss) and task-specific distillation with data augmentation. Both procedures require huge resources and long training times (from several days to weeks), which is cumbersome for industrial applications. Therefore, we are aiming to explore more lightweight solutions in this paper.

3 Lightweight Adaptation of BERT

3.1 Overview

The overall pipeline of LadaBERT (Lightweight Adaptation of BERT) is illustrated in Figure 2. As shown in the figure, the pre-trained BERT model (e.g., BERT-Base) is served as the teacher as well as the initial status of the student model. Then, the student model is compressed towards smaller parameter size through a hybrid model compression framework in an iterative manner until the target compression ratio is reached. Concretely, in each iteration, the parameter size of student model is first reduced by \( 1 - \Delta \) based on weight pruning and matrix factorization, and then the parameters are fine-tuned by the loss function of knowledge distillation. The motivation behind is that matrix factorization and weight pruning are complementary with each other. Matrix factorization calculates the optimal approximation under a certain rank, while weight pruning introduces additional sparsity to the decomposed matrices. Moreover, weight pruning and matrix factorization generates better initial and intermediate status of the student model, which improve the efficiency and effectiveness of knowledge distillation. In the following subsections, we will introduce the algorithms in detail.

3.1.1 Matrix factorization

We use Singular Value Decomposition (SVD) for matrix factorization. Each parameter matrix, including the embedding layer are compressed by SVD. Without loss generality, we assume a matrix of parameters \( W \in \mathbb{R}^{m \times n} \), the singular value decomposition of which can be written as:

\[
W = U\Sigma V^T
\]

(1)

where \( U \in \mathbb{R}^{m \times p} \) and \( V \in \mathbb{R}^{p \times n} \). \( \Sigma = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_p) \) is a diagonal matrix composed of singular values and \( p \) is the full rank of \( W \) satisfying \( p \leq \text{min}(m, n) \).

To compress this weight matrix, we select a lower rank \( r \). The diagonal matrix \( \Sigma \) is truncated by selecting the top \( r \) singular values. i.e., \( \Sigma_r = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_r) \), while \( U \) and \( V \) are also truncated by selecting the top \( r \) columns and rows respectively, resulting in \( U_r \in \mathbb{R}^{m \times r} \) and \( V_r \in \mathbb{R}^{r \times n} \).
Thus, low-rank matrix approximation of $W$ can be formulated as:

$$
\tilde{W} = U_r \Sigma_r V_r^T = (U_r \sqrt{\Sigma_r})(V_r \sqrt{\Sigma_r})^T = AB^T
$$

In this way, the original weight matrix $W$ is decomposed by the multiplication of two smaller matrices, where $A = U_r \sqrt{\Sigma_r} \in \mathbb{R}^{n \times r}$ and $B = V_r \sqrt{\Sigma_r} \in \mathbb{R}^{m \times r}$. These two matrices are initialized by SVD and will be further tuned during training.

Given a rank $r \leq \min(m, n)$, the compression ratio of matrix factorization is defined as:

$$
P_{svd} = \frac{(m+n)r}{mn}
$$

Therefore, for a target model compression ratio $P_{svd}$, the desired rank $r$ can be calculated by:

$$
r = \frac{mn}{m+n} P_{svd}
$$

### 3.1.2 Weight pruning

Weight pruning [Han et al., 2015] is an unstructured compression method that induces desirable sparsity for a neural network model. For a neural network $f(x; \theta)$ with parameters $\theta$, weight pruning finds a binary mask $M \in \{0, 1\}^{\theta}$ subject to a given sparsity ratio, $P_{weight}$. The neural network after pruning will be $f(x; M \cdot \theta)$, where the non-zero parameter size is $||M|| = P_{weight} \cdot ||\theta||$, where ||$\theta$|| is the number of parameters in $\theta$. For example, when $P_m = 0.3$, there are 70% zeros and 30% ones in the mask $m$. We adopt a simple pruning strategy in our implementation: the binary mask is generated by setting the smallest weights to zeros (Frankle & Carbin, 2018).

To combine the benefits of weight pruning with matrix factorization, we leverage a hybrid approach that applies weight pruning on the basis of decomposed matrices generated by SVD. Following Equation (2), SVD-based matrix factorization for any weight matrix $W$ can be written as: $W_{svd} = A_{m \times r}B_{n \times r}^T$. Then, weight pruning is applied on the decomposed matrices $A \in \mathbb{R}^{m \times r}$ and $B \in \mathbb{R}^{n \times r}$ separately. The weight matrix after hybrid compression is denoted by:

$$
W_{hybrid} = (M_A \cdot A)(M_B \cdot B)^T
$$

where $M_A$ and $M_B$ are binary masks derived by the weight pruning algorithm with compression ratio $P_{weight}$. The compression ratio of this hybrid approach can be calculated by:

$$
P_{hybrid} = P_{svd} \cdot P_{weight} = \frac{(m+n)r}{mn} P_{weight}
$$

In LadaBERT, the hybrid compression produce is applied to each layer of the pre-trained BERT model. Given an overall model compression target $P$, the following constraint should be satisfied:

$$
P \cdot ||\theta|| = P_{embd} \cdot ||\theta_{embd}|| + P_{hybrid} ||\theta_{encd}|| + ||\theta_{cls}||
$$

where $||\theta||$ is the total number of model parameters and $P$ is the target compression ratio; $||\theta_{embd}||$ denotes the parameter number of embedding layer, which has a relative compression ratio of $P_{embd}$, and $||\theta_{encd}||$ denotes the number of parameters of all layers in BERT encoder, which have a compression ratio of $P_{hybrid}$. The classification layer (often MLP layer with Softmax activation) has a small parameter size ($||\theta_{cls}||$), so it is not modified in the model compression procedure. In the experiments, these fine-grained compression ratios can be optimized by random search on the validation data.

### 3.2 Knowledge distillation

Knowledge distillation (KD) has been widely used to transfer knowledge from a large teacher model to a smaller student model. In other words, the student model mimics the behavior of the teacher model by minimize the knowledge distillation loss functions. Various types of knowledge distillation can be employed at different sub-layers. Generally, all types of knowledge distillation can be modeled as minimizing the following loss function:

$$
\mathcal{L}_{KD} = \sum_{x \in \mathcal{X}} L\left(f^{(s)}(x), f^{(t)}(x)\right)
$$

Where $x$ indicates a sample input and $\mathcal{X}$ is the training dataset. $f^{(s)}(x)$ and $f^{(t)}(x)$ represent intermediate outputs or weight matrices for the student model and teacher model correspondingly. $L(\cdot)$ represents for a loss function which
can be carefully defined for different types of knowledge distillation. We follow the recent technique proposed by TinyBERT (Jiao et al., 2019), which applies knowledge distillation constraints upon embedding, self-attention, hidden representation and prediction levels. Concretely, there are four types of knowledge distillation constraints as follows:

1. **Embedding-layer distillation** is performed upon the embedding layer. $f(x) \in \mathbb{R}^{n \times d}$ represents for the word embedding output for input $x$, where $n$ is the input word length and $d$ is the dimension of word embedding. Mean Squared Error (MSE) is adopted as the loss function $L(\cdot)$.

2. **Attention-layer distillation** is performed upon the self-attention sub-layer. $\{a_{ij}\} \in \mathbb{R}^{n \times n}$ represents the attention output for each self-attention sub-layer, and $L(\cdot)$ denotes MSE loss function.

3. **Hidden-layer Distillation** is performed at each fully-connected sub-layer in the Transformer architectures. $f(x)$ denotes the output representation of the corresponding sub-layer, and $L(\cdot)$ also adopts MSE loss function.

4. **Prediction-layer distillation** makes the student model to learn the predictions from a teacher model directly. It is identical to the vanilla form of knowledge distillation (Hinton et al., 2015). It takes the soft cross-entropy loss function, which is formulated as:

$$L_{\text{pred}} = -\text{softmax}(f^t(x)) \cdot \log (\text{softmax}(f^s(x)/t))$$  \hspace{1cm} (9)

where $f^t(x)$ and $f^s(x)$ are the predictive logits of teacher and student models respectively.

4 Experiments

4.1 Datasets & Baselines

We compare LadaBERT with state-of-the-art model compression approaches on five public datasets of different tasks of natural language understanding, including sentiment classification (SST-2), natural language inference (MNLI-m, MNLI-mm, QNLI) and pairwise semantic equivalence (QQP). The statistics of these datasets are described in Table 1.

| Task  | #Train   | #Dev. | #Test   | #Class |
|-------|----------|-------|---------|--------|
| SST-2 | 67,350   | 873   | 1,822   | 2      |
| QQP   | 363,871  | 40,432| 390,965 | 2      |
| MNLI-m| 392,703  | 9,816 | 9,797   | 3      |
| MNLI-mm| 392,703 | 9,833 | 9,848   | 3      |
| QNLI  | 104,744  | 5,464 | 5,464   | 2      |

Table 1: Dataset Statistics

The baseline approaches are summarized below.

- **Weight pruning** and **matrix factorization** are two simple baselines described in Section 3.1.2. We evaluate both pruning methods in an iterative manner until the target compression ratio is reached.

- **Hybrid pruning** is a combination of matrix factorization and weight pruning, which conducts iterative weight pruning on the basis of SVD-based matrix factorization. It is performed iteratively until the desired compression ratio is achieved.

- **BERT-FT, BERT-KD** and **BERT-PKD** are reported in (Sun et al., 2019), where BERT-FT directly fine-tunes the model via supervision labels, BERT-KD is the vanilla knowledge distillation algorithm (Hinton et al., 2015), and BERT-PKD stands for Patient Knowledge Distillation proposed in (Sun et al., 2019). The student model is composed of 3 Transformer layers, resulting in a $2.5 \times$ compression ratio. Each layer has the same hidden size as the pre-trained teacher, so the initial parameters of student model can be inherited from the corresponding teacher.

- **TinyBERT** (Jiao et al., 2019) instantiates a tiny student model, which has totally 14.5M parameters ($7.5 \times$ compression ratio) composed of 4 layers, 312 hidden units, 1200 intermediate size and 12 heads. For a fair comparison, we reproduce the TinyBERT pipeline without general distillation and data augmentation, which is time-exhaustive and resource-consuming.

- **BERT-SMALL** has the same model architecture as TinyBERT, but is directly pre-trained by the official BERT pipeline. The performance values are inherited from (Jiao et al., 2019) for reference.

3 https://github.com/huawei-noah/Pretrained-Language-Model/tree/master/TinyBERT
• Distilled-BiLSTM (Tang et al., 2019) leverages a single-layer bidirectional-LSTM as the student model, where the hidden units and intermediate size are set to be 300 and 400 respectively, resulting in a $10.8 \times$ compression ratio. This model requires a expensive pre-training process using the knowledge distillation constraints.

4.2 Setup

We leverage the pre-trained checkpoint of base-bert-uncased as the initial model for compression, which contains 12 layers, 12 heads, 110M parameters, and 768 hidden units per layer. Hyper-parameter selection is conducted on the validation data for each dataset. After training, the prediction results are submitted to the GLUE-benchmark evaluation platform to get the evaluation performance on test data.

For a comprehensive evaluation, we experiment with four settings of LadaBERT, namely LadaBERT-1, -2, -3 and -4, which reduce the model parameters of BERT-Base by 2.5, 5, 7.5 and 10 times respectively. In our experiment, we take the batch size as 32, learning rate as 2e-5. The optimizer is BertAdam with default setting. Fine-grained compression ratios are optimized by random search and shown in Table 2.

Table 2: Fine-grained compression ratios

| Model      | Overall  | Embedding layer | Matrix factorization | Weight pruning |
|------------|----------|-----------------|----------------------|---------------|
| LadaBERT-1 | 2.5      | 1.43            | 2.0                  | 1.56          |
| LadaBERT-2 | 5.0      | 2.05            | 2.0                  | 3.41          |
| LadaBERT-3 | 7.5      | 5.0             | 2.0                  | 4.33          |
| LadaBERT-4 | 10.0     | 5.0             | 2.5                  | 5.45          |

4.3 Performance Comparison

Table 3: Performance comparison on various model sizes

| Algorithm       | MNLI-m | MNLI-mm | SST-2 | QQP | QNLI | #Params | Model Size |
|-----------------|--------|---------|-------|-----|------|---------|------------|
| BERT-Base       | 84.6   | 83.4    | 93.5  | 71.2/- | 89.6 | 110M    | ×1.0       |
| LadaBERT-1      | 83.5   | 82.5    | 92.8  | 70.7/88.9 | 89.6 | 44M     | ×2.5       |
| BERT-FT         | 74.8   | 74.3    | 86.4  | 65.8/86.9 | 84.3 | 44M     | ×2.5       |
| BERT-KD         | 75.4   | 74.8    | 86.9  | 67.3/87.6 | 84.0 | 44M     | ×2.5       |
| BERT-PKD        | 76.7   | 76.3    | 87.5  | 68.1/87.8 | 84.7 | 44M     | ×2.5       |
| Weight pruning  | 82.8   | 81.6    | 92.3  | 70.1/88.5 | 88.9 | 44M     | ×2.5       |
| matrix factorization | 77.7 | 77.4    | 87.6  | 65.7/87.2 | 84.3 | 44M     | ×2.5       |
| Hybrid pruning  | 81.2   | 80.0    | 90.0  | 68.0/87.5 | 83.3 | 44M     | ×2.5       |

| LadaBERT-2      | 83.1   | 82.2    | 91.8  | 69.9/87.9 | 88.2 | 22M     | ×5.0       |
| Weight pruning  | 75.9   | 75.6    | 84.8  | 60.3/83.5 | 81.7 | 22M     | ×5.0       |
| matrix factorization | 71.8 | 71.8    | 82.8  | 60.3/83.5 | 75.4 | 22M     | ×5.0       |
| Hybrid pruning  | 76.1   | 75.3    | 85.4  | 64.9/85.8 | 80.6 | 22M     | ×5.0       |

| LadaBERT-3      | 82.1   | 81.8    | 89.9  | 69.4/87.8 | 84.5 | 15M     | ×7.5       |
| TinyBERT        | 80.9   | 79.5    | 89.5  | 65.4/87.5 | 77.9 | 15M     | ×7.5       |
| BERT-Small      | 75.4   | 74.9    | 87.6  | 66.5/-    | 84.8 | 15M     | ×7.5       |
| Weight pruning  | 69.1   | 68.8    | 81.8  | 59.7/82.9 | 76.4 | 15M     | ×7.5       |
| matrix factorization | 60.2 | 60.0    | 81.3  | 58.5/82.0 | 62.2 | 15M     | ×7.5       |
| Hybrid pruning  | 71.9   | 71.0    | 83.5  | 62.3/84.7 | 73.8 | 15M     | ×7.5       |

| LadaBERT-4      | 75.8   | 76.1    | 84.0  | 67.4/86.6 | 75.1 | 11M     | ×10.0      |
| Distilled-BiLSTM | 73.0   | 72.6    | 90.7  | 68.2/88.1 | 75.1 | 10M     | ×10.8      |
| Weight pruning  | 64.9   | 65.1    | 80.4  | 56.9/80.5 | 62.7 | 11M     | ×10.0      |
| matrix factorization | 59.9 | 59.6    | 79.2  | 57.8/81.9 | 62.2 | 11M     | ×10.0      |
| Hybrid pruning  | 68.4   | 67.9    | 81.5  | 58.6/83.5 | 63.2 | 11M     | ×10.0      |

The evaluation results of LadaBERT and state-of-the-art approaches are listed in Table 3, where the models are ranked by parameter sizes for feasible comparison. As shown in the table, LadaBERT consistently outperforms the strongest

4https://storage.googleapis.com/bert_models/2018_10_18/uncased_L12_H768_A12.zip
5https://gluebenchmark.com/
baselines under similar model sizes. In addition, the performance of LadaBERT demonstrates the superiority of hybrid combination of SVD-based matrix factorization, weight pruning and knowledge distillation.

With model size of $2.5\times$ reduction, LadaBERT-1 performs significantly better than BERT-PKD, boosting the performance by relative 8.9, 8.1, 6.1, 3.8 and 5.8 percentages on MNLI-m, MNLI-mm, SST-2, QQP and QNLI datasets respectively. Recall that BERT-PKD initializes the student model by selecting 3 of 12 layers in the pre-trained BERT-Base model. It turns out that the discarded layers have huge impact on the model performance, which is hard to be recovered by knowledge distillation. On the other hand, LadaBERT generates the student model by iterative pruning on the pre-trained teacher. In this way, the original knowledge in the teacher model can be preserved to the largest extent, and the benefit of which is complementary to knowledge distillation.

LadaBERT-3 has a comparable size as TinyBERT with a $7.5\times$ compression ratio. As shown in the results, TinyBERT does not work well without expensive data augmentation and general distillation, hindering its application to low-resource settings. The reason is that the student model of TinyBERT is distilled from scratch, so it requires much more data to mimic the teacher’s behaviors. Instead, LadaBERT has better initial and intermediate status calculated by hybrid model compression, which is much more light-weighted and achieves competitive performances with much faster learning speed (learning curve comparison is shown in Section 4.4). Moreover, LadaBERT-3 also outperforms BERT-SMALL on most of the datasets, which is pre-trained from scratch by the official BERT pipeline on a $7.5\times$ smaller architecture. This indicates that LadaBERT can quickly adapt to a smaller model size and achieve competitive performance without expansive re-training on a large corpus.

Moreover, Distilled-BiLSTM performs well on SST-2 dataset with more than $10\times$ compression ratio, perhaps owing to its advantage of generalization on small datasets. Nevertheless, the performance of LadaBERT-4 is competitive on larger datasets such as MNLI and QQP. This is impressive as LadaBERT is much more efficient without exhaustive re-training on a large corpus. In addition, the inference speed of BiLSTM is usually slower than transformer-based models with similar parameter sizes.

4.4 Learning curve comparison

To further demonstrate the efficiency of LadaBERT, we visualize the learning curves on MNLI-m and QQP datasets in Figure 3 and 4, where LadaBERT-3 is compared to the strongest baseline, TinyBERT, under $7.5\times$ compression ratio. As shown in the figures, LadaBERT-3 achieves good performances much faster and results in a better convergence point. After training $2 \times 10^4$ steps (batches) on MNLI-m dataset, the performance of LadaBERT-3 is already comparable to TinyBERT after convergence (approximately $2 \times 10^5$ steps), achieving nearly $10\times$ acceleration. And on QQP dataset, both performance improvement and training speed acceleration is very significant. This clearly shows the superiority of combining matrix factorization, weight pruning and knowledge distillation in a reinforce manner. Instead, TinyBERT is based on pure knowledge distillation, so the learning speed is much slower.

4.5 Effect of low-rank + sparsity

In this paper, we demonstrate that a combination of matrix factorization and weight pruning is better than single solutions for BERT-oriented model compression. Similar phenomena has been reported in the computer vision scenarios.
et al., 2017), which shows that low-rank and sparsity are complementary to each other. Here we provide another explanation to support this observation.

In Figure 5 we visualize the distribution of errors for a weight matrix in the neural network after pruning to 20% of its original parameter size. The errors can be calculated by $Error = ||\hat{M} - M||_1$, where $M$ denotes the weight matrix after pruning.

The yellow line in Figure 5 shows the distribution of errors generated by pure weight pruning, which has a sudden drop at the pruning threshold. The orange line represents for pure SVD pruning, which turns out to be smoother and aligned with Gaussian distribution. The blue line shows the result of hybrid pruning, which conducts weight pruning on the decomposed matrices. First, we apply SVD-based matrix factorization to reduce 60% of total parameters. Then, weight pruning is applied on the decomposed matrices by 50%, resulting in only 20% parameters while the error distribution changes slightly. As a result, it has smaller mean and deviation than pure matrix factorization. In addition, a smoother distribution is more appropriate for the knowledge distillation procedure to fine-tune the weights, so it is advantageous than pure weight pruning.

5 Conclusion

Model compression is a common way to deal with latency-critical or memory-intensive scenarios. Existing model compression methods for BERT need to be re-trained on a large corpus to reserve its original performance, which is inapplicable in low-resource settings. In this paper, we propose LadaBERT to address this problem. LadaBERT is a lightweight model compression pipeline that generates adaptive BERT model efficiently based on a given task and specific constraint. It is based on a hybrid solution, which conducts matrix factorization, weight pruning and knowledge distillation in a reinforce manner. The experimental results verify that EAdaBERT is able to achieve comparable performance with other state-of-the-art solutions using much less training data and time budget. Therefore, LadaBERT can be easily plugged into various applications with competitive performances and little training overheads. In the future, we would like to apply LadaBERT to large-scale industrial applications, such as search relevance and query recommendation.

References

Acharya, A., Goel, R., Metallinou, A., & Dhillon, I. (2019). Online embedding compression for text classification using low rank matrix factorization. In Proceedings of the aaai conference on artificial intelligence (Vol. 33, pp. 6196–6203).

Achterhold, J., Koehler, J. M., Schmeink, A., & Genewein, T. (2018). Variational network quantization.

Anil, R., Pereyra, G., Passos, A., Ormandi, R., Dahl, G. E., & Hinton, G. E. (2018). Large scale distributed neural network training through online distillation. arXiv preprint arXiv:1804.03235.

Chen, G., Choi, W., Yu, X., Han, T., & Chandraker, M. (2017). Learning efficient object detection models with knowledge distillation. In Advances in neural information processing systems (pp. 742–751).

Chen, P., Si, S., Li, Y., Chelba, C., & Hsieh, C.-J. (2018). Groupreduce: Block-wise low-rank approximation for neural language model shrinking. In Advances in neural information processing systems (pp. 10988–10998).

Choi, Y., El-Khamy, M., & Lee, J. (2016). Towards the limit of network quantization. arXiv preprint arXiv:1612.01543.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Frankle, J., & Carbin, M. (2018). The lottery ticket hypothesis: Finding sparse, trainable neural networks. arXiv preprint arXiv:1803.03635.

Han, S., Mao, H., & Dally, W. J. (2016). Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding.

Han, S., Pool, J., Tran, J., & Dally, W. J. (2015). Learning both weights and connections for efficient neural networks. 1135–1143.
He, Y., & Han, S. (2018). ADC: automated deep compression and acceleration with reinforcement learning. *CoRR, abs/1802.03494*. Retrieved from [http://arxiv.org/abs/1802.03494](http://arxiv.org/abs/1802.03494).

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*.

Hu, H., Peng, R., Tai, Y., & Tang, C. (2016). Network trimming: A data-driven neuron pruning approach towards efficient deep architectures. *arXiv: Neural and Evolutionary Computing*.

Hubara, I., Courbariaux, M., Soudry, D., El-Yaniv, R., & Bengio, Y. (2016). Binarized neural networks. In *Advances in neural information processing systems* (pp. 4107–4115).

Jiao, X., Yin, Y., Shang, L., Jiang, X., Chen, X., Li, L., … Liu, Q. (2019). Tinybert: Distilling bert for natural language understanding. *arXiv preprint arXiv:1909.10351*.

Kozlov, A., Lazarevich, I., Shamporov, V., Lyalyushkin, N., & Gorbachev, Y. (2020). Neural network compression framework for fast model inference. *arXiv preprint arXiv:2002.08679*.

Li, C., Zhu, L., Xu, S., Gao, P., & Xu, B. (2018). Compression of acoustic model via knowledge distillation and pruning. In *2018 24th international conference on pattern recognition (icpr)* (pp. 2785–2790).

Li, H., Kadav, A., Durandanovic, I., Samet, H., & Graf, H. P. (2016). Pruning filters for efficient convnets. *arXiv: Computer Vision and Pattern Recognition*.

Li, Y., Yang, J., Song, Y., Cao, L., Luo, J., & Li, L.-J. (2017). Learning from noisy labels with distillation. In *Proceedings of the ieee international conference on computer vision* (pp. 1910–1918).

Louizos, C., Welling, M., & Kingma, D. P. (2017). Learning sparse neural networks through $l_0$ regularization. *arXiv: Machine Learning*.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. *arXiv preprint arXiv:1802.05365*.

Polino, A., Pascanu, R., & Alistarh, D. (2018). Model compression via distillation and quantization. *arXiv preprint arXiv:1802.05668*.

Sainath, T. N., Kingsbury, B., Sindhwani, V., Arisoy, E., & Ramabhadran, B. (2013). Low-rank matrix factorization for deep neural network training with high-dimensional output targets. In *2013 ieee international conference on acoustics, speech and signal processing* (pp. 6655–6659).

Sanh, V., Debut, L., Chaumond, J., & Wolf, T. (2019). Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*.

Stewart, G. W. (1998). *Perturbation theory for the singular value decomposition* (Tech. Rep.).

Sun, S., Cheng, Y., Gan, Z., & Liu, J. (2019). Patient knowledge distillation for bert model compression. *arXiv preprint arXiv:1908.09355*.

Tang, R., Lu, Y., Liu, L., Mou, L., Vechtomova, O., & Lin, J. (2019). Distilling task-specific knowledge from bert into simple neural networks. *arXiv preprint arXiv:1903.12136*.

Wen, W., Wu, C., Wang, Y., Chen, Y., & Li, H. (2016). Learning structured sparsity in deep neural networks. *arXiv: Neural and Evolutionary Computing*.

Winata, G. I., Madotto, A., Shin, J., Barezi, E. J., & Fung, P. (2019). On the effectiveness of low-rank matrix factorization for lstm model compression. *arXiv preprint arXiv:1908.09982*.

Xue, J., Li, J., & Gong, Y. (2013). Restructuring of deep neural network acoustic models with singular value decomposition. In *Interspeech* (pp. 2365–2369).

Xue, J., Li, J., Yu, D., Seltzer, M., & Gong, Y. (2014). Singular value decomposition based low-footprint speaker adaptation and personalization for deep neural network. In *2014 ieee international conference on acoustics, speech and signal processing (icassp)* (pp. 6359–6363).

Ye, J., Lu, X., Lin, Z., & Wang, J. Z. (2018). Rethinking the smaller-norm-less-informative assumption in channel pruning of convolution layers.

Yu, X., Liu, T., Wang, X., & Tao, D. (2017). On compressing deep models by low rank and sparse decomposition. In *Proceedings of the ieee conference on computer vision and pattern recognition* (pp. 7370–7379).

Zhang, D., Wang, H., Figueiredo, M. A. T., & Balzano, L. (2018). Learning to share: Simultaneous parameter tying and sparsification in deep learning.

Zhou, A., Yao, A., Guo, Y., Xu, L., & Chen, Y. (2017). Incremental network quantization: Towards lossless cnns with low-precision weights. *arXiv preprint arXiv:1702.03044*.

Zhou, S., Wu, Y., Ni, Z., Zhou, X., Wen, H., & Zou, Y. (2016). Dorefa-net: Training low-bitwidth convolutional neural networks with low-bitwidth gradients. *arXiv preprint arXiv:1606.06160*.

Zhu, M., & Gupta, S. (2017). To prune, or not to prune: exploring the efficacy of pruning for model compression. *arXiv: Machine Learning*.