Weight Squeezing: Reparameterization for Knowledge Transfer and Model Compression

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Abstract

In this work, we present a novel approach for simultaneous knowledge transfer and model compression called Weight Squeezing. With this method, we perform knowledge transfer from a teacher model by learning the mapping from its weights to smaller student model weights.

We applied Weight Squeezing to a pre-trained text classification model based on BERT-Medium model and compared our method to various other knowledge transfer and model compression methods on GLUE multitask benchmark. We observed that our approach produces better results while being significantly faster than other methods for training student models.

We also proposed a variant of Weight Squeezing called Gated Weight Squeezing, for which we combined fine-tuning of BERT-Medium model and learning mapping from BERT-Base weights. We showed that fine-tuning with Gated Weight Squeezing outperforms plain fine-tuning of BERT-Medium model as well as other concurrent SoTA approaches while much being easier to implement.

1 Introduction

Today, deep learning has become a key technology in natural language processing (NLP), advancing state-of-the-art results for most NLP tasks. One of the significant achievements in applying deep learning in NLP is transfer learning. These methods include word vectors pretrained on a large volume of text (Mikolov et al. 2013; Pennington, Socher, and Manning 2014), which are now commonly used to initialize the first layer of neural networks for transfer learning. In recent times, methods such as ULMFit (Howard and Ruder 2018) have advanced the field of transfer learning in NLP by using language modeling during pre-training. Pre-trained language models now achieve state-of-the-art results on a diverse range of tasks in NLP, including text classification, question answering, natural language inference, coreference resolution, sequence labeling, and more (Qiu et al. 2020).

Another breakthrough in NLP occurred after the introduction of Transformer (Vaswani et al. 2017) neural networks that consist mostly of linear layers that compute the attention between model inputs. Unlike recurrent networks, Transformers have no recurrence over the spatial dimensions, allowing parallel computations, making it possible to significantly increase their size and reach state-of-the-art results for several tasks. (Devlin et al. 2019) introduced BERT (Bidirectional Encoder Representations from Transformers), a language representation model trained to predict masked tokens in texts from unlabeled data. Pre-trained BERT can be fine-tuned to create state-of-the-art models for a wide range of NLP tasks.

While BERT is capable of learning rich representations of text, using it for solving simple downstream tasks could be excessive. This is especially important when running downstream models on edge devices such as mobile phones. A common approach in such cases is model compression (Ganesh et al. 2020).

In this work, we present a novel approach to performing simultaneous transfer learning and model compression called Weight Squeezing where we learn the mapping from a teacher model’s weights to a student model’s weights.

We applied Weight Squeezing to the pre-trained teacher text classification model to obtain a smaller student model. We compared it with common model compression approaches, including variations of Knowledge Distillation without any reparameterizations and low-rank matrix factorization methods. Our experiments show that in most cases, Weight Squeezing achieves better performance than other baseline methods.

We also proposed Gated Weight Squeezing to improve the accuracy of fine-tuning the BERT-Medium model, for which we combined fine-tuning with the mapping of larger BERT-Base weights. We showed that Gated Weight Squeezing produces higher accuracy than plain fine-tuning and compared trained model results with BERT, DistilBERT, TinyBERT, and MiniLM models.

2 Motivation & Problem Setting

In this section we describe our motivation for building lightweight models.

Firstly, we focus on model size. For instance, a typical mobile app has the size of 100Mb, which significantly restricts the model size that can be used on the device. We managed to obtain models around 2.1 Mb in size, while...
els are also better for serving server-side.

Secondly, we paid particular attention to model inference time. A model may have fewer parameters but have a significant computational overhead regardless. Therefore, our focus is on making the student model faster than the teacher one.

Finally, we take into account that access to training resources, such as data and computing power, can be limited. Therefore, by focusing on task-specific compression, we limit the data we use to what we have for specific tasks only (see 5.2 for details).

3 Related Work

3.1 Transfer Learning & Unsupervised Pre-training

Self-supervised training as unsupervised pre-training became one of the key techniques for solving NLP tasks. While the amount of labeled data can be limited, we often have unlabeled data at our disposal. This data can be effectively utilized for pre-training some parts of the models. One way to conduct self-supervised pre-training of NLP models is language modeling. It can be performed using autoregressive models when learning to predict the next words in a text based on previous words.

Transformer and BERT. The Transformer was introduced as a type of neural network architecture for machine translation (Vaswani et al. 2017). While the Transformer decoder can be used to train a language model, the performance of such a model could suffer because of its autoregressive nature. Masked Language Modeling (MLM) with BERT (Devlin et al. 2019) was proposed as an alternative to Language Modeling. This method involves training a model to predict masked words based on unmasked ones. The output of such a model depends on all words in the input text, which makes it capable of learning more complex data patterns.

3.2 Model Compression

The network architecture can be considerably over-parameterized and therefore inefficient in terms of memory and computing resources. Trading accuracy for performance and model size is often reasonable, which brings us to model compression techniques. There are many approaches (Ganesh et al. 2020; Qiu et al. 2020) to compressing BERT, including pruning (Sajjad et al. 2020), Fan, Grave, and Joulin (2019), Guo et al. 2019, Gordon, Duh, and Andrews (2020), Voita et al. 2019, McCarley, Chakravarti, and Sil (2019), quantization (Zafir et al. 2019, Shen et al. 2019), parameter sharing (Lan et al. 2019), and knowledge distillation. Some of these methods can be combined to achieve better results (Mao et al. 2020).

Low-Rank Matrix Factorization. Low-rank matrix factorization approaches focus on reducing the size of model parameters. These approaches include Singular-Value Decomposition (SVD), Tensor Train (TT) Decomposition (Oseledets 2011), and others. These methods can be considered a separate case of the pruning approach where we try to reduce the size of parameters by removing parts that can be considered unnecessary. For SVD, we drop some part of the weights which are related to small singular values, while TT can be seen as a generalization of SVD.

The most notable examples of using low-rank matrix factorization methods for NLP is reducing the embedding matrix size, which contains a significant part of model parameters (Lan et al. 2019; Khrulkov et al. 2019; Shu and Nakamura 2019; Acharaya et al. 2019).

Knowledge Distillation. In the Knowledge Distillation (KD) approach (Ba and Caruana 2014; Hinton et al. 2015; Romero et al. 2014) a smaller student model is trained to mimic a teacher BERT model. Current KD approaches for BERT can be categorized by what exactly they try to match as follows: distillation on encoder outputs/hidden states (Zhao et al. 2019; Jiao et al. 2019; Sun et al. 2020, 2019; Sanh et al. 2019), distillation on model output (Zhao et al. 2019; Sun et al. 2019; Sanh et al. 2019; Jiao et al. 2019; Chen et al. 2020), distillation on attention maps (Sun et al. 2020; Jiao et al. 2019).

KD can also be split into two categories: task-agnostic and task-specific.

Task-agnostic KD involves reducing the size of BERT itself. Most methods fall under this type of compression. The KD methods, such as DistillBERT (Sanh et al. 2019) or MobileBERT (Sun et al. 2020), are trained on the same corpus as the one used when pre-training a BERT model from scratch. A typical scenario when using models such as BERT is to take a model already pre-trained on a very large corpus of data, since training or fine-tuning BERT is computationally expensive and could require a considerable amount of time. In some cases, even storing a large corpus, not to mention using it for training, could be a problem in this task.

Instead of compressing BERT itself, a different approach of task-specific KD can be taken by fine-tuning BERT on a downstream task first and then applying compression techniques to train a smaller model. (Tang et al. 2019) use KD to train a single layer BiLSTM student model from BERT. (Mukherjee and Awadallah 2019) show that when given a large amount of unlabeled data, student BiLSTM networks can even match the performance of the teacher. (Turc et al. 2019) pre-train compact student models on unlabeled data and then apply KD.

4 Weight Squeezing

We now introduce a method to perform knowledge transfer and model compression by learning the mapping between teacher and student weights.

We start with a pre-trained teacher Transformer model with a large hidden state. It implies that for some linear layer $l$, we have a weight matrix $\theta_l$ with the shape $n \times m$.

We explore a case where the weights of a pre-trained teacher model are too big to run and store the model on an
Table 1: Accuracy on the GLUE tasks (see Section 5.4 for further training procedure details). We also report inference time (lower is better) for each of the reparameterization methods (see Section 5.5). We refer to $d$ as for the model hidden size (see Section 5.2 for the appropriate ranks for SVD and TT methods). See Table 3 for the full list of speed measurements.

| Method | MLE | KD | KD-EO | MLE | KD | KD-EO | MLE | KD | KD-EO |
|--------|-----|----|-------|-----|----|-------|-----|----|-------|
| Time CPU | d16: ×1 | d32: ×1 | d16: ×1 | d32: ×1 | d16: ×5.3 | d32: ×4.9 | d16: ×89.2 | d32: ×126.8 |
| MNLI | 32 | 65.0 | 64.9 | 70.5 | 71.5 | 64.4 | 68.2 | 68.1 | 61.1 | 70.9 | 68.2 | 67.3 | 72.6 |
| 16 | 57.0 | 59.4 | 59.2 | 57.3 | 57.3 | 64.3 | 56.3 | 55.3 | 60.8 | 62.1 | 62.0 | 65.4 |
| COLA | 32 | 17.3 | 18.1 | 17.4 | 17.0 | 19.3 | 20.7 | 18.3 | 17.7 | 18.0 | 16.0 | 17.4 | 14.7 |
| 16 | 16.1 | 17.0 | 15.6 | 15.0 | 16.6 | 16.5 | 16.8 | 16.7 | 16.0 | 18.2 | 17.7 | 17.5 |
| MRPC | 32 | 77.6 | 77.3 | 77.9 | 79.0 | 78.5 | 77.5 | 77.7 | 77.8 | 78.2 | 77.7 | 77.8 | 78.5 |
| 16 | 78.8 | 78.2 | 78.0 | 78.1 | 78.5 | 78.2 | 76.5 | 76.7 | 77.5 | 78.7 | 78.5 | 78.5 |
| RTE | 32 | 59.2 | 59.6 | 59.2 | 60.3 | 59.6 | 59.6 | 60.7 | 61.0 | 60.3 | 59.9 | 59.2 | 59.2 |
| 16 | 58.5 | 58.8 | 59.2 | 57.4 | 60.3 | 61.0 | 58.5 | 58.5 | 58.1 | 59.9 | 60.7 | 59.6 |

edge device. For this reason, we may want to train a student model with a smaller number of parameters. Let us say that we want the student model to make the weight matrix $\Theta^s$ at the same layer $l$ to have the shape equal to $a \times b$, where $a < n$ and $b < m$.

In this work, we propose reparameterizing student weights $\Theta^s$ as follows:

$$\Theta^s = \mathcal{L}\Theta^t\mathcal{R}$$  \hspace{1cm} (1)

where $\mathcal{L}$ and $\mathcal{R}$ are randomly initialized trainable parameters of the mapping with shapes equal to $a \times n$ and $m \times b$ respectively (here and below, we omitted the $l$ subscript for simplicity).

In this approach, instead of training student model weights from scratch, we reparameterize them as a trainable linear mapping from teacher model weights. Doing so allows us to transfer knowledge stored in the teacher weights to the student weights.

At the same time, mapping of teacher biases and word embeddings is performed as a single linear mapping as follows:

$$\Theta^{s\text{\tiny single}} = \Theta^t\mathcal{R}$$  \hspace{1cm} (2)

where biases are matrices of size $1 \times b$ and word embeddings have size $V \times b$, and $V$ is the total number of words in the vocabulary. This reparameterization for word embeddings can be seen as a linear alignment from pre-trained embeddings.

After reparameterization of the student model weights using Equations 1 and 2, we train mapping weights $\mathcal{L}$ and $\mathcal{R}$ using plain negative log-likelihood (Weight Squeezing) or KD loss (Weight Squeezing combined with KD). When the mapping weights are trained, we compute student weights and then use them to make predictions dropping $\mathcal{L}$ and $\mathcal{R}$ matrices.

4.1 Applications

The proposed method defines the general way to use weights of one model to train another. In this paper, we concentrate on two ways of applying Weight Squeezing.

Extreme Model Compression In many cases, we may want to obtain substantially smaller models (see Section 2). However, the list of available pre-trained models that can be used for fine-tuning is limited. Thus, if the target model size is very small, it is necessary to either train a new smaller BERT model or perform a task-specific compression of a larger model (see Section 5.2).

In this work, we concentrate on applying Weight Squeezing for task-specific model compression. For this purpose, we fine-tuned the BERT-Medium model (41M parameters) on a particular dataset to obtain the pre-trained teacher model. We then applied Weight Squeezing to reparameterize weights of the significantly smaller target model (1M and 0.5M parameters).

Fine-Tuning a pre-trained model While Weight Squeezing can be used for extreme model compression when no pre-trained smaller BERT is available, it is also suitable for fine-tuning BERT.

In this setup, we may want to fine-tune a BERT model (in our experiments we used BERT-Medium) on a specific task. A typical way to do so is to initialize a new model with pre-trained weights and then train it on a particular dataset. However, larger BERTs (e.g., BERT-Base) are available, and knowledge from these models could also be utilized during the fine-tuning.

In this work we propose Gated Weight Squeezing. In this case we fine-tuned BERT-Base on specific task to obtain large teacher network and then reparameterize weights of student model as follows:

$$\Theta^s = (1 - \sigma(s)) \odot \mathcal{L}\Theta^t\mathcal{R} + \sigma(s) \odot \Theta^b$$  \hspace{1cm} (3)

$\Theta^t$ are weights of the teacher model (which are fine-tuned BERT-Base model), $\Theta^b$ are weights of BERT-Medium, $s$ is a scalar value, and $\sigma$ is the sigmoid function. We used $\mathcal{L}$, $\mathcal{R}$, $\Theta^b$, and $s$ as a trainable parameters. Embeddings are also reparameterized in a gated way following Equation 2.
4.2 Comparison to Similar Methods

Knowledge Distillation. Weight Squeezing (WS) is orthogonal to Knowledge Distillation methods. One could reparametrize weights of student model with WS and then train it with the arbitrary training method, such as Knowledge Distillation or plain Likelihood Maximization (MLE).

DistilBERT and other compressed BERTs DistilBERT is orthogonal to models compressed with WS, just like KD is orthogonal to WS. Note that the typical way to compress BERT is task-agnostic compression (see Section 3.2) for which we firstly obtain a smaller general BERT model trained on MLM task, and then use this smaller model for specific tasks. While in this paper, we concentrate on task-specific compression when we compress a large BERT model concerning the task. However, one could apply Weight Squeezing in pair with Knowledge Distillation to compress BERT itself. Nevertheless, we compare the proposed approach with variants of compressed BERT.

Low-Rank Matrix Factorization. We observed that factorization methods could be hard to train and evaluate due to their large memory and computation footprint. Regardless of the factorization rate r, the result after applying the factorized layer will always retain its original size. Thus, some operations in the Transformer are not going to benefit from the model weights’ factorization. For example, suppose we have a Transformer with the hidden layer’s size equal to 1024. Then even with small rank value r, self-attention will be computed between vectors with shape 1024. Because of this, very low rates of r did not lead to a performance boost.

It is also important to note that there is often a practical limit of Low-Rank methods’ compression rate (e.g., factorization rank equal to 1 for SVD), which often easy to reach if the teacher model is big enough.

5 Model Compression with Weight Squeezing

5.1 Baselines

We trained all models on GLUE datasets (Wang et al. 2019).

For each dataset, we trained a teacher model by fine-tuning the pre-trained BERT-Medium model.

In this paper, we consider the following methods for reparameterization of student models:
1. No weight reparametrization
2. Weight Squeezing (WS) of the teacher model
3. SVD applied to the teacher model
4. TT applied to the teacher model

Each of the baselines above could be trained with ambiguous methods. We used the following approaches:
1. Maximum Likelihood Estimation (MLE)
2. Knowledge Distillation (KD) of the teacher model
3. Knowledge Distillation on Encoder Outputs (KD-EO) of the teacher model

Thus, for some of the baselines (e.g., WS with KD), we used the teacher model for weight reparametrization and getting teacher predictions to estimate the loss.

Since we focused on making models smaller in terms of the overall number of parameters, we trained student models in two configurations of small hidden sizes equal to 16 and 32. For all models, we used the number of heads equal to 4 and used the same with the teacher number of Transformer layers equal to 8.

| SA Heads: | 4     | 8     |
|-----------|-------|-------|
| Hidden size: | 16    | 32    | 512  |
| Plain BERT | 0.52M | 1.1M  | 41.3M |
| WS         | 4.18M | 8.4M  | -     |
| SVD        | 0.53M | 1.1M  | -     |
| TT         | 0.53M | 1.1M  | -     |

Table 2: The number of parameters for each model. Note that once the WS model is trained, we no longer have to store mappings weights; thus, WS will have the number of parameters equal to Plain BERT during the inference.

5.2 Reparameterization methods

No weight reparametrization For this experiment, we randomly initialize parameters of a student model without utilizing teacher model in weight reparametrization.

Weight Squeezing For Weight Squeezing, we used fine-tuned teacher models as the source of mapping for weights reparametrization. This way, we reparameterized the parameters of all linear layers in the model as in Equation 1 and embedding vectors as in Equation 2. Weights of the mapping for linear layers were initialized as Xavier Normal, while the mapping for the embedding matrix was initialized as Xavier Uniform. We optimized the loss with respect to the mapping parameters used to reparameterize the student model weights and the rest of the student model parameters that were not reparameterized (e.g., the layer normalization weights).

Low-Rank Matrix Factorization. We also experimented with the matrix factorization approaches (LRMF) consisted of two methods: SVD and TT.

For SVD we started with factorizing teacher model weights as follows

$$\Theta = U_{m \times m} \Sigma_{m \times n} V_{n \times n}^\top$$

where $\Sigma$ is a diagonal matrix of the singular values, and $U$ and $V$ are the left and right singular vectors of the weight.
By keeping only $r$ largest singular values, we could obtain the reduced form of this weight:

$$\hat{\Theta} = U_{m \times r} \Sigma_{r \times r} V_{r \times n}^T \approx U_{m \times r} V_{r \times n}^T$$

Thus instead of storing $nm$ parameters for each weight, we would have to keep only $r(n + m)$ parameters. If $r$ value is small enough, then the total number of parameters will be reduced compared to the original model.

In our experiments, we applied SVD factorization of the teacher weights and then trained $U_{m \times r}$ and $V_{r \times n}$ to minimize the loss.

We also applied TT to obtain the reduced form of the teacher weights with 4 cores and also trained this cores to minimize the loss.

Note that in Low-Rank approaches, we do not directly train the student model with the specified hidden state size as in Non Low-Rank Factorization methods (Non-LRFM). Instead, we injected a bottleneck in the middle of each layer, which allowed us to reduce the total number of parameters in the model. For this reason we evaluated the number of parameters for Non-LRFM models for hidden sizes equal to 16 and 32 and then found appropriate factorization ranks to make SVD and TT models have approximately similar number of parameters. Thus, we compared Non-LRFM models of hidden size equal to 16 and 32 with SVD model with $r$ equal to 2 and 7, and TT model with rank equal to 9 and 18 respectively (See Table 2).

| CPU       |          |          |
|-----------|----------|----------|
| Size      | Non-LRMF | SVD      | TT      |
| 512       | 8603 ± 663 ms | -       | -       |
| 32        | 531 ± 14 ms (×1) | 2598 ± 62 ms (×4.9) | 67332 ± 11146 ms (×89.2) |
| 16        | 466 ± 16 ms (×1) | 2488 ± 114 ms (×5.3) | 41554 ± 325 ms (×126.2) |

| GPU       |          |          |
|-----------|----------|----------|
| Size      | Non-LRMF | SVD      | TT      |
| 512       | 2667 ± 49 ms | -       | -       |
| 32        | 505 ± 38 ms (×1) | 1122 ± 2 ms (×2.2) | 27382 ± 22 ms (×26.4) |
| 16        | 517 ± 49 ms (×1) | 1115 ± 2 ms (×2.2) | 13659 ± 12 ms (×54.2) |

Table 3: Inference speed results for Non-Low Rank Matrix Factorization and decomposed with SVD and TT models. **Non-LRFM include No-reparameterization and WS methods.** We compare models of comparable size; "-" means no experiments were conducted.

### 5.3 Training objectives

**Maximum Likelihood Estimation** In this method we utilize plain MLE for model training

$$L_{MLE} = -\log(p^*_c)$$ (4)

where $p^*$ is the student model’s output probabilities, $p^*_i$ is the $i$-th component of student predictions, and $c$ is the ground truth label index.

For this method, we do not use predictions of the teacher model to train on. Thus, a training model with MLE and no weight reparametrization setting could be seen as a training student model from scratch without any knowledge transfer methods.

**Knowledge Distillation** For KD we also utilize predictions of the teacher model in the training:

$$L_{KD} = -\alpha \log(p^*_c) - (1 - \alpha) \sum_i p^*_i \log(p^*_i)$$ (5)

The notation follows Equation 4 adding $i$-th component of the teacher model prediction $p^*_i$. Thus, the first term in the Equation 5 is a negative log-likelihood used for MLE, while the second stands for part of KL-Divergence between teacher and student we could optimize with respect to student parameters.

We also used temperature to evaluate KL-Divergence by dividing prediction logits of both teacher and student models by the same number before applying softmax.

**Knowledge Distillation on Encoder Outputs** With this loss, we also utilize hidden states of the teacher model during the training procedure. The resulting loss function is defined as:

$$L_{KD-EO} = -\alpha \log(p^*_c) - \beta \sum_i p^*_i \log(p^*_i) + \gamma \sum_j L2(h^*_j, f_j(h^*_j))$$

where the first two terms in the equation above correspond to terms in Equation 5 while the last term is the mean squared error between teacher hidden state $h^*_j$ from layer $j$ and linearly mapped student hidden state $f_j(h^*_j)$ from the same layer. We defined $f_j$ as a fully connected layer and optimized this loss with respect to the student model parameters and each mapping $f_j$. Note that $\alpha + \beta + \gamma = 1$. Also, since there are several hidden states in each layer corresponding to different words in the input sequence, we used the first hidden state to evaluate the loss function.

### 5.4 Training details

Hyperparameters for each model were found using Bayesian hyperparameter search (see Table 4 for ranges of the search). We performed a search for about 5-15 GPU days for each model with NVidia A100 GPU. We maximized the appropriate metric on each GLUE dataset dev split to find each method’s best training configuration and report the best performing method’s results.

We used Adam [Kingma and Ba 2015] optimizer to train all models with a linear warm up and linear decay of a learning rate. We also applied dropout to the attention matrix and to averaged hidden state before the last linear layer, which produced logits of predictions.
We compared Non-Low Rank Matrix Factorization models (see Table 3). We ran the models on A common practice for training a model on a specific task (Table 4). Hyperparameter search ranges for methods used for (i.e., no weight reparameterization and weight squeezing) with models factorized using the TT and SVD methods for (i.e., no weight reparameterization and weight squeezing).

Since we found that it slightly increases all models’ speed in measurements, we used NVIDIA Tesla T4.

In our experiments, we used the same models as in other experiments (see Sections 5.1 and 5.2 for Non-LRMF parameters and for parameters of TT and SVD approaches). All models have a comparable number of parameters (see Table 2).

We evaluated models on sequences with input lengths of 128 (see Table 3). We ran the models on 1000 samples with batch size equal to 16 for GPU measurements and 100 samples with batch size equal to 1 for CPU. We repeated the measurements 5 times and reported the mean and std values of the models’ total computation time. For CPU measurements, we used 1.8 GHz Intel DualCore i5, while for GPU measurements, we used NVIDIA Tesla T4.

All models were prepared with PyTorch JIT compilation since we found that it slightly increases all models’ speed in this experiment.

### 6 Fine-Tuning with Gated Weight Squeezing

A common practice for training a model on a specific task using pre-trained BERT is to initialize the model with this pre-trained state and then fine-tune it.

In this experiment, we compared Gated Weight Squeezing (41M parameters) with widely adopted models for fine-tuning on different GLUE tasks:

1. BERT-Medium (41M)
2. DistilBERT (66M)
3. TinyBERT (66M)
4. MiniLM (66M)

#### 6.1 Training Details

While BERT-Medium has 41M parameters, larger models are available (e.g., BERT-Base with 109M parameters). These larger models could be used during the fine-tuning procedure to training more accurate models for a specific task.

To do so, we firstly trained a teacher model by fine-tuning BERT-Base. Then we used this fine-tuned model and BERT-Medium for the reparameterization of student model weights proposed in the Equation [3] which results in the student model with 41M parameters, which we compared with baseline fine-tuning. The reparameterized student model was trained with KD-EO loss using the BERT-Base as a teacher (see Section 5.3).

Since BERT-Base and BERT-Medium have a different number of hidden layers (12 and 8 respectively), we used the first 8 layers of BERT-Base to perform mapping of the weights. We also used hidden states of the first 8 layers to evaluate the KD-EO loss.

We followed the same training strategy as in Section 5.4. We added a new hyperparameter for training the Gated WS model for the initial gate s value, which we used to select from the range equal to [1; 4].

Note that the usual fine-tuning of BERT-Medium could be seen as a special case of Gated Weight Squeezing with a fixed $\sigma(s) = 1$.

### 7 Results

See Table [3] for the list of best performing model accuracies. Inference speed measurements of baselines can be found in Table [3].

We observed that WS generally produced better results than models trained without weight reparameterization for knowledge transfer. SVD and TT methods were competitive to WS since LRMF operates with substantially bigger hidden states to evaluate the attention. However, SVD and TT models were significantly slower in inference than Non-LRMF (2-5 times slower for SVD and 26-127 times for TT), which makes them be an inappropriate choice in cases when speed does matter. Also, note that in most cases, when the best result for some dataset was produced by SVD or TT model, the second-best performing result was achieved by Weight Squeezing, while the latter is significantly faster (e.g., as for MNLI dataset).

Since we performed hyperparameters search for all models for the same amount of time, models trained with Knowledge Distillation and Knowledge Distillation on Encoder Outputs losses produced lower accuracy compared to MLE loss in some cases, since they imply searching appropriate

| Table 3: Knowledge Distillation Encoder Outputs |
|---|
| $f_j$ learning rate | [1e-3, 5e-4, 3e-4, 1e-4, 5e-5, 3e-5, 5e-5] |
| $\alpha$ logit | $[-5; 5]$ |
| $\beta$ logit | $[-5; 5]$ |
| $\gamma$ logit | $[-5; 5]$ |
| Temperature | [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] |
| Gated Weight Squeezing |  
| Initial gate $s$ | [1; 4] |
We introduced Weight Squeezing, a novel approach to knowledge transfer and model compression. We showed that it could compress pre-trained text classification models and create compelling lightweight and fast models.

We showed that Weight Squeezing successfully utilized teacher weights and produced better results than models trained without weight reparameterization. We also showed that Weight Squeezing could be a competitive alternative to Low-Rank Factorizing Methods in terms of accuracy, but being significantly faster.

While the current work focused on transferring knowledge to task-specific models, we would like to apply Weight Squeezing for task-agnostic compression to create more applicable BERT models trained for Masked Language Modeling tasks.

We are currently experimenting with the initialization of mappings and plan to continue this research. We are interested in applying this method in domains beyond NLP to compress other types of layers (convolutional, etc.). Also, one may find it important to reduce memory footprint during Weight Squeezing training, making such mappings of teacher weights to make training procedure more efficient.

### 8 Conclusion & Future Work

We compared the number of baseline model parameters (See Table 2). The Plain BERT row stands for the number of parameters in the ordinary classifier built on top of the BERT model with a specific number of layers and self-attention heads.

For the TT and SVD methods, we show the number of parameters for the specific factorization rates used to make these approaches have the number of parameters approximately equal to the plain classifier (see 5.2 for more details).

Note that after the WS model is trained, we no longer have to evaluate the mapping result. The inference setting parameters are equal to the Plain BERT row for the appropriate hidden sizes.

### References

Acharya, A.; Goel, R.; Metallinou, A.; and Dhillon, I. 2019. Online embedding compression for text classification using low rank matrix factorization. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 6196–6203.

Ba, J.; and Caruana, R. 2014. Do deep nets really need to be deep? In Advances in neural information processing systems, 2654–2662.

Chen, D.; Li, Y.; Qiu, M.; Wang, Z.; Bofang Li, B. D.; Deng, H.; Huang, J.; Lin, W.; and Zhou, J. 2020. AdaBERT: Task-Adaptive BERT Compression with Differentiable Neural Architecture Search. In arXiv preprint arXiv:2001.04246.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186.

Fan, A.; Grave, E.; and Joulin, A. 2019. Reducing Transformer Depth on Demand with Structured Dropout. In ICLR.

Ganesh, P.; Chen, Y.; Lou, X.; Khan, M. A.; Yang, Y.; Chen, D.; Winslett, M.; Sajjad, H.; and Nakov, P. 2020. Compressing Large-Scale Transformer-Based Models: A Case Study on BERT. In arXiv preprint arXiv:2002.11985.

Gordon, M. A.; Duh, K.; and Andrews, N. 2020. Compressing BERT: Studying the Effects of Weight Pruning on Transfer Learning. In arXiv preprint arXiv:2002.08307.

Guo, F.-M.; Liu, S.; Mungal, F. S.; Lin, X.; and Wang, Y. 2019. Reweighted Proximal Pruning for Large-Scale Language Representation. In arXiv preprint arXiv:1909.12486.

Hinton, G.; Vinyals, O.; and Dean, J. 2015. Distilling the knowledge in a neural network. In arXiv preprint arXiv:1503.02531.

### Table 5: Accuracy across benchmark tasks.

| Model          | #Param | SST2 | CoLA | STSB | MRPC | QQP | QNLI | RTE | MNLI | RACE | SQuAD2 |
|----------------|--------|------|------|------|------|-----|------|-----|------|------|--------|
| BERT-base      | 109M   | 93.2 | 58.9 | -    | 87.3 | 91.3| 91.7 | 68.6| 84.5 | -    | 76.8   |
| BERT-medium    | 41M    | 91.4 | 48.6 | 87.0 | 87.3 | 88.4| 89.2 | 70.0| -    | -    | -      |
| DistilBERT     | 66M    | 90.7 | 43.6 | -    | 87.5 | 84.9| 85.3 | 59.9| 70.0 | -    | 70.7   |
| TinyBERT       | 66M    | 91.6 | 42.8 | -    | 88.4 | 90.6| 90.5 | 72.2| 83.5 | -    | 73.1   |
| TinyBERT       | 17M    | 88.4 | -    | -    | -    | -  | -    | 77.4| -    | -    | 63.6   |
| MmitLM         | 66M    | 92.0 | 49.2 | -    | 88.4 | 91.0| 91.0 | 71.5| 84.0 | -    | 76.4   |
| MmitLM         | 17M    | 89.7 | -    | -    | -    | -  | -    | 79.1| -    | -    | 66.9   |
| ALBERTbase-128 | 12M    | 90.3 | -    | -    | -    | -  | -    | 81.6| 64.0 | 80.0/77.1 |
| ALBERTbase-64  | 10M    | 89.4 | -    | -    | -    | -  | -    | 80.8| 63.5 | 77.5/74.8 |
| WS-large       | 10M    | -    | -    | -    | -    | -  | -    | -   | -    | -    | -      |
| WS-32          | 1.1M   | 83.8 | -    | 28.1 | 79.0 | -  | 60.3| 71.5| -    | -    | -      |
| WS-16          | 0.52M  | 84.1 | -    | 17.9 | 78.5 | -  | 61.0| 64.3| -    | -    | -      |

We are currently experimenting with the initialization of mappings and plan to continue this research. We are interested in applying this method in domains beyond NLP to compress other types of layers (convolutional, etc.). Also, one may find it important to reduce memory footprint during Weight Squeezing training, making such mappings of teacher weights to make training procedure more efficient.
Howard, J.; and Ruder, S. 2018. Universal Language Model Fine-tuning for Text Classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 328–339.

Jiao, X.; Yin, Y.; Shang, L.; Jiang, X.; Chen, X.; Li, L.; Wang, F.; and Liu, Q. 2019. TinyBERT: Distilling BERT for Natural Language Understanding. In arXiv preprint arXiv:1909.10351.

Katharopoulos, A.; Vyas, A.; Pappas, N.; and Fleuret, F. 2020. Transformers are RNNs: Fast Autoregressive Transformers with Linear Attention. In ICML.

Khrulkov, V.; Hrinchuk, O.; Mirvakhabova, L.; and Oseledets, I. 2019. Tensorized embedding layers for efficient model compression. In arXiv preprint arXiv:1901.10787.

Kingma, D.; and Ba, J. 2015. Adam: A Method for Stochastic Optimization. In ICLR.

Lan, Z.; Chen, M.; Goodman, S.; Gimpel, K.; Sharma, P.; and Soricut, R. 2019. ALBERT: A Lite BERT for Self-supervised Learning of Language Representations. In arXiv preprint arXiv:1909.11942.

Mao, Y.; Wang, Y.; Wu, C.; Zhang, C.; Wang, Y.; Yang, Y.; Zhang, Q.; Tong, Y.; and Bai, J. 2020. LadaBERT: Lightweight Adaptation of BERT through Hybrid Model Compression. In arXiv preprint arXiv:2004.04124.

McCarley, J.; Chakravarti, R.; and Sil, A. 2019. Structured Pruning of a BERT-based Question Answering Model. In arXiv preprint arXiv:1910.06560.

Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, 3111–3119.

Mukherjee, S.; and Awadallah, A. H. 2019. Distilling Transformers into Simple Neural Networks with Unlabeled Transfer Data. In arXiv preprint arXiv:1910.01769.

Oseledets, I. V. 2011. Tensor-train decomposition. SIAM Journal on Scientific Computing 33(5): 2295–2317.

Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 1532–1543.

Qiu, X.; Sun, T.; Xu, Y.; Shao, Y.; Dai, N.; and Huang, X. 2020. Pre-trained Models for Natural Language Processing: A Survey. In arXiv preprint arXiv:2003.08271.

Romero, A.; Ballas, N.; Kahou, S. E.; Chassang, A.; Gatta, C.; and Bengio, Y. 2014. Fitnets: Hints for thin deep nets. arXiv preprint arXiv:1412.6550.

Sajjad, H.; Dalvi, F.; Durrani, N.; and Nakov, P. 2020. Poor Man’s BERT: Smaller and Faster Transformer Models. In arXiv preprint arXiv:2004.03844.

Sanh, V.; Debut, L.; Chaumond, J.; and Wolf, T. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. In NeurIPS EMNLP Workshop.