MKQ-BERT: QUANTIZED BERT WITH 4BITS WEIGHTS AND ACTIVATIONS

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ABSTRACT

Recently, pre-trained Transformer based language models, such as BERT, have shown great superiority over the traditional methods in many Natural Language Processing (NLP) tasks. However, the computational cost for deploying these models is prohibitive on resource-restricted devices. One method to alleviate this computation overhead is to quantize the original model into fewer bits representation, and previous work has proved that we can at most quantize both weights and activations of BERT into 8-bits, without degrading its performance. In this work, we propose MKQ-BERT, which further improves the compression level and uses 4-bits for quantization. In MKQ-BERT, we propose a novel way for computing the gradient of the quantization scale, combined with an advanced distillation strategy. On the one hand, we prove that MKQ-BERT outperforms the existing BERT quantization methods for achieving a higher accuracy under the same compression level. On the other hand, we are the first work that successfully deploys the 4-bits BERT and achieves an end-to-end speedup for inference. Our results suggest that we could achieve 5.3x of bits reduction without degrading the model accuracy, and the inference speed of one int4 layer is 15x faster than a float32 layer in Transformer based model.

1 Introduction

Recent Transformer based language models (e.g. BERT (Devlin et al., 2018)) have achieved remarkable performance on many natural language processing tasks. While the performance of these large models has significantly increased, the number of parameters of these models also grows dramatically. Hence the models are usually computation expensive and memory intensive. Therefore how to achieve efficient, real-time models with optimal accuracy has become more and more important. Many approaches has been proposed to alleviate this problem. For example, automated searching for efficient model architectures using technique such as NAS (Zoph & Le, 2016), parameter pruning that removes redundant weights in the model (LeCun et al.; Hassibi & Stork, 1993), knowledge distillation that transfer the knowledge from large models to smaller models in order to boost its performance (Hinton et al., 2015).

Beyond those methods, one important direction is model quantization, and it has already shown great success for achieving an end-to-end inference speedup. Previous work has already proved that Transformer based models can be quantized into 8-bits representation without degrading its performance (Zafir et al., 2019a), and since the model architecture does not change, the only thing left is to design hardware that can support the operation for quantized int8 numbers. Although it seems to be a very promising approach, previous methods are limited to the case where we can

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at most quantize the numbers into 8-bits without performance degradation, and when being extended to a fewer bits case, such as 4-bits, the performance drops severely.

Therefore in this paper, we focus on this important problem and proposed a novel method, so called MKQ-BERT, that can improve the performance of quantized model for 4-bits quantization, by using knowledge distillation and dynamic quantization. Inspired by previous work (Jin et al., 2021), we find that knowledge distillation and Learned Step size Quantization (LSQ) can substantially improve the accuracy of the quantized model. Therefore we start from this point and designed new technique for these two components. More specifically, the contribution of our paper is summarized as follows:

1. We designed a new algorithm for dynamically updating the quantization function. Instead of using a STE-based gradient for updating the quantization scale, which is widely adapted in previous work (Jin et al., 2021; Esser et al., 2019), we derived a new MSE-based gradient that can further reduce the quantization error and improve the accuracy of the quantized model.
2. For knowledge distillation, we adapted an advanced distillation strategy that can not only achieve a higher testing results, but also can be easily applied to the case where the teacher model is deeper than the student.
3. In order to evaluate the end-to-end improvement of MKQ-BERT, we designed efficient kernels for implementing the quantized 4-bits matrix multiplication. To the best of our knowledge, this is the first work that successfully deploys an int4 quantized model.

In order to evaluate the performance of MKQ-BERT, we conduct extensive experiments on downstream NLP tasks. Experimental results demonstrate that MKQ-BERT outperforms state-of-the-art baseline, and has achieved almost the same performance with the full precision model when 50% layers being quantized into 4-bits with the rest layers being quantized into 8-bits. Moreover, our experimental results indicates that by using 4-bits quantization, we could achieve 15x of end-to-end inference speedup for one Transformer layer.

2 Related Work

Efficient NN Inference: Due to the high demand for decreasing the computation cost of large NNs, there has been a large body of literature that focused on designing method to improve the inference speed of NN models, without degrading its performance. One line of those tryouts is to design efficient model architecture, either manually (Howard et al.; Tan & Le, 2019), or automatically using Automated machine learning (AutoML) and Neural Architecture Search (NAS). The automated searching methods is more powerful in finding the right architecture given certain constrains of computation cost (Wu et al.; Wang et al., 2020; Tan et al.; Elsken et al., 2019).

Meanwhile, since most of the NNs are over-parameterized, therefore it usually contains a lots of unimportant parameters that can be removed, and this method is so called model pruning. In pruning, neurons that is less important is safely removed, without sacrificing the model accuracy. The pruning methods can be roughly categorized into unstructured pruning (Lee et al., 2018; Xiao et al.; Park et al., 2020) and structured pruning (Yu et al.; Lin et al.; Huang & Wang; Zhao et al.; Yu et al., 2021).

Another important direction for reducing the model size is knowledge distillation (Polino et al., 2018; Ahn et al.; Yin et al.). The main idea of knowledge is to use a well trained large model as teacher to train a more compact model. Instead of using the label from the training data solely, it would also utilize the output from the teacher since it usually contain more information than the training data. Notice that knowledge does not change the model structure, therefore it can be easily combined with other techniques, such as pruning and model quantization, to further improve the performance of the compact models (McCarley, 2019; Stock et al., 2019; Polino et al., 2018).

Model Quantization: In model quantization, the parameters and activations of the model are represented using fewer bits (Lin et al., 2013; Hubara et al.; Rastegari et al; Gysel et al., 2016, 2018; Tailor et al., 2021; Ni et al., 2020). However, directly quantizing the model will greatly decrease the accuracy of the models, therefore there has been many attempts to improve the performance of the quantized model. One important technique is Quantization Aware Training (QAT) (Jacob et al.), where it simulates the quantization procedure in training to further improve the accuracy of the quantized model.

For Transformer based models, the boundary of the compression level has been continuously advanced. For example, 8-bit quantization training is has been successfully applied in FullyQT (Prato et al., 2019) and Q8BERT (Zafir et al., 2019b). (Fan et al., 2020) quantizes a different subset of weights in each training iteration to make models more robust to quantization. For even fewer bits quantization, Q-BERT (Shen et al.) achieves ultra-low bit quantization by using mixed-precision quantization bits. In Quant-Noise (QN) (Fan et al., 2020), authors proposed a novel method for
attaining an unbiased estimation of the gradients by only quantizing a subset of weights in each iteration. For tenary case, TernaryBERT \cite{zhang2020ternary} divides the original model into separate parts through 2-bit ternarization training. The work that is most similar to our method is KDLSQ-BERT \cite{jin2021kdlsq}, where authors combined Learned Step size Quantization (LSQ) with knowledge distillation. However, they only consider the case where the activations are quantized into 8-bits with the weight being quantized into fewer bits (e.g., 4-bits or 2-bits), this type of design is not hardware friendly therefore can not be implemented efficiently to get an end-to-end inference throughput improvement.

3 Preliminary

In this section, we present some preliminary knowledge about model quantization, Transformer network and knowledge distillation.

3.1 Quantization

One solution to reduce the computation cost is to replace the original float32 numbers into fewer-bits (i.e. int8) representation during computation, and this is so called model quantization. Generally speaking, we can quantize a float number \(x\) into \(k\)-bits representation according to

\[
Q[x] = s \times \text{round} \left( \text{clamp} \left( \frac{x}{s}, l_{\min}, l_{\max} \right) \right).
\]

(1)

Here \(s\) is the quantization scale, \(l_{\min}\) and \(l_{\max}\) are the lower and upper bound for the clamping function, the rounding function (denoted as \(\lfloor \cdot \rfloor\)) will round the number into its nearest integer. Notice that for \(k\)-bits quantization, usually we would set \(l_{\min} = (-2^{k-1} + 1)\) and \(l_{\max} = 2^{k-1}\). For the case where \(x\) is a tensor, previous work either uses a common \(s\) for all number (per-tensor scale) or only the elements within the same row share the same scale (per-row scale).

From (1) we can see that, if \(s\) is smaller, the rounding interval will shrink, which means the quantization error \(|Q[x] - x|\) also decays for \(x \in [l_{\min}, l_{\max}]\). However, if \(s\) is too small, the number of elements that exceed the clamping bound would also increase, which makes the overall quantization error \(||Q[x] - x||\) increase. Therefore finding a good balance for \(s\) is every essential for reducing the side effect of quantization.

In \cite{zafrir2019ternary}, authors uses the maximum of the absolute value for each weight tensor as the quantization scale; for activation, since it will change with different input, therefore they first sample a few portion of the training data, and then get the empirical statistical distribution of the activation’s absolute value for those samples. The use the top 0.01\% largest value as the initial scale. This procedure for setting the initial value of the quantization scale is so called calibration. After calibration, The quantized mod could get further improved by QAT \cite{jacob2018quantization}. Previous work has already proved that by combining calibration with QAT, using 8-bits quantization, we can quantize BERT without performance degradation.

However, when further decreasing the representation bits to \(k = 4\), the performance degrades severely, and for 4-bits quantized model, they requires more QAT steps. The problem is that when training steps increases, the deviation between the trained model and the initial model also increase, therefore using original quantization scale is not optimal in this case. In order to capture the trend of the model weight updates, previous work \cite{jin2021kdlsq} proposed a learned step size quantization (LSQ) method to dynamically updating the quantization scale, which will be detailed discussed in Section 4.

3.2 Backbone Network: Transformer

In transformer, denotes the \(l\)-th layer as \(\text{Transformer}_l(\cdot)\), and \(h^0 \in \mathbb{R}^{d_h}\) as the input tensor \(x\), then the stacked Transformer blocks compute the encoding vectors according to:

\[
h^l = \text{Transformer}_l(h^{l-1}), \quad l \in [1, L]
\]

(2)

where \(L\) is the number of Transformer layers. Each layer consists of a self-attention layer and a fully connected feed-forward network.

Multi-Head Attention (MHA)  The self-attention layer consists of multiple self-attention heads. Assuming that there are \(A_h\) heads, each attention head has three components: Query matrix \(Q_{l,a}\), Key matrix \(K_{l,a}\) and Value matrix \(V_{l,a}\).
V_{l,a}. The output of each attention head (denoted as O\text{A}_{l,a}) is computed via:

\begin{align*}
q_{l,a} &= h_{l-1}Q_{l,a}, \quad k_{l,a} = h_{l-1}K_{l,a}, \quad v_{l,a} = h_{l-1}V_{l,a}, \\
A_{l,a} &= \text{Softmax}\left(\frac{q_{l,a}v_{l,a}^T}{\sqrt{d_k}}\right), \\
O\text{A}_{l,a} &= A_{l,a}v_{l,a},
\end{align*}

where $A_{l,a} \in \mathbb{R}^{x \times x}$ is a matrix that indicates the attention distributions and $d_k = \frac{d_h}{A_h}$. Afterwards, all $O\text{A}_{l,a}$ are concatenated together and fed into one fully connected (fc) layer, which can be expressed as

$$O\text{A}_{l} = [O\text{A}_{l,1}, \cdots, O\text{A}_{l,A_h}]W^A + b^A,$$

where $W^A$ and $b^A$ are the weight and bias of the fc layer and $O\text{A}_{l}$ is the output of MHA.

**Feed-Forward Network (FFN)** The feed-forward network consists of two fully connected network interconnected by one activation function. The output of the self-attention layer is treated as the input to the FFN, the output of FFN is computed via

$$\text{FFN}(x) = \text{GELU}(xW^1 + b^1)W^2 + b^2,$$

where $W^1$ and $W^2$ are the weight of the fc layer, $b^1$ and $b^2$ are the bias respectively.

### 3.3 Knowledge Distillation

The basic idea of knowledge distillation is to transfer the knowledge from a powerful model (teacher model) into a weaker model (student model, usually admits a smaller size or few bits than the teacher model). This is done by letting the student model's features to mimic the features from the teacher model, which can be achieved by minimizing the difference between these two sets of features:

$$L_{\text{KD}} = \sum_{e \in D} L(f^S(e), f^T(e)),$$

where $D$ denotes the training data, $f^S(\cdot)$ and $f^T(\cdot)$ indicate the features from the student and teacher models, $L(\cdot)$ is the loss function that measures the difference of the features. Previous work treat the uncompressed model as the teacher model and the quantized model as student, and they used two sets of features for distillation:

- **Output distillation**: The output of the network is treated as the distillation feature, and the loss can be either mean square error (MSE) or KL-divergence. This loss can be expressed as $L_{\text{output}} = L(O^S, O^T)$, where $O^S$ and $O^T$ are the outputs from the student model and teacher model;
- **Attention distillation**: The output of the self-attention network and the feed-forward network are used for distillation. More specifically, two sets of outputs $\{A_{l,a}\}$ and $\{O\text{A}_{l,a}\}$ for each attention head and attention layers, which can be written as

$$L_{\text{attention}} = \sum_a \sum_l \left( L(A_{l,a}^S, A_{l,a}^T) + L(O\text{A}_{l,a}^S, O\text{A}_{l,a}^T) \right).$$

In \cite{Jin2021}, authors add (6) and (7) together with the original training loss $L_{\text{train}}$ into $L_{\text{final}} = L_{\text{output}} + L_{\text{attention}} + L_{\text{train}}$, and use this $L_{\text{final}}$ as the final training loss. However, those method can only use teacher models with the same model configuration, which means we cannot use a larger network to further improve the performance of the quantized model.

### 4 Methodology

The pipeline of MKQ-BERT can be divided into two steps: calibration step and QAT step. The calibration step is used to get a good initial value for the quantization scale and we follow the same strategy as described in Section 3.1. Afterwards, we start QAT to fine-tune both the model parameter and the quantization scale. For QAT, we further improve the previous QAT methods using the following two strategies:
• **New gradient for quantization scale**: In order to find a better scale factor, we designed a new strategy for computing the gradient of the quantization scale, and we use this gradient to dynamically updating the quantization scale.

• **Advanced distillation strategy**: In MKQ-BERT, we use an advanced distillation strategy that can not only achieve a higher testing results, but also can be easily applied to the case where the teacher model is deeper than the student.

4.1 New algorithm for dynamic quantization

Instead of adapting the same strategy from previous work (Jin et al., 2021; Esser et al., 2019) for updating the quantization function, we propose a new method for computing the gradient of the quantization scale.

4.1.1 STE-based gradient for quantization scale

Specifically, previous work attains this gradient using STE (Straight Through Estimation) according to

\[
\frac{\partial Q}[x]{\partial s} = \frac{\partial \left( \left\lfloor \frac{x}{s} \right\rfloor s \right)}{\partial s} = \frac{\partial \left( \left\lfloor \frac{x}{s} \right\rfloor s \right)}{\partial \left\lfloor \frac{x}{s} \right\rfloor s} \cdot \frac{\partial \left\lfloor \frac{x}{s} \right\rfloor s}{\partial \left( \left\lfloor \frac{x}{s} \right\rfloor s \right)} = \frac{x}{s} \cdot \left( \frac{\partial \left\lfloor \cdot \right\rfloor s}{\partial \left( \left\lfloor \cdot \right\rfloor s \right)} - 1 \right) = -\frac{x}{s} + \left\lfloor \frac{x}{s} \right\rfloor.
\]

For the case where \(x\) becomes a tensor \(x\), the gradient would be

\[
\frac{\partial Q}[x]{\partial s} = \sum_i \left( -\frac{x_i}{s} + \left\lfloor \frac{x_i}{s} \right\rfloor \right),
\]

where \(x_i\) is the \(i\)-th component of \(x\). In the backward procedure, previous work define \(\frac{\partial f}{\partial s} = \frac{\partial Q}[x]{\partial s}\) and uses this gradient for updating the quantization scale.

However, our analysis indicates that this method is not optimal. Consider the case below: if we have a tensor \(x = (0.2, 0.9)\) and the quantization scale \(s = 1\), which means the quantized version of \(x\) equals to

\[ Q[x] = 1 \times (0, 1) = (0, 1). \]

For this tensor, if we decrease \(s\) into 0.9, then \(Q[x] = (0, 0.9)\), it will leads to a better quantization choice than the result from \(s = 1\). However, the gradient attained from STE admits

\[ \frac{\partial Q}[x]{\partial s} = -0.2 + 0.1 = -0.1. \]

Since the gradient is negative, in the next step we are going to increase \(s\). But as shown above, what we need is to decrease \(s\), this is not consistent with the gradient from STE, and this motivates us to design a new method for approximating the gradient.

4.1.2 MSE-based gradient for quantization scale

Here we propose a MSE-based gradient for the quantization scale. In order to minimize the quantization error w.r.t. the whole tensor \(x\). Let’s say the original scale \(s\) gets an infinitely small variation \(\Delta s\), which means

\[
\frac{x}{s + \Delta s} = \left\lfloor \frac{x}{s} \right\rfloor, \quad \text{if } \frac{x}{s} - \frac{x}{s + \Delta s} \neq 0.5.
\]

Therefore we get

\[
Q_{s+\Delta s}[x] = (s + \Delta s) \left\lfloor \frac{x}{s + \Delta s} \right\rfloor = (s + \Delta s) \left\lfloor \frac{x}{s} \right\rfloor,
\]

5
this leads to
\[
\frac{\partial Q[x]}{\partial s} = \frac{Q_s[x] + \Delta s[x] - Q_s[x]}{\Delta s} = \frac{x}{s}.
\]
Notice that for MSE-based gradient, the major goal is to minimize the quantization error \(\|Q[x] - x\|^2\), not to estimate the gradient of the quantization scale w.r.t. the quantization function \(\frac{\partial Q[x]}{\partial s}\), therefore we redefine the gradient of the quantization scale as
\[
\text{Gradient}(s) := \frac{\partial (Q[x] - x)^2}{\partial s} = 2(Q[x] - x) \frac{\partial Q[x]}{\partial s} = 2(Q[x] - x) \frac{x}{s},
\]
which gives us
\[
\frac{\partial (Q[x] - x)^2}{\partial s} = 2 \sum_i \left( (Q[x_i] - x_i) \frac{x_i}{s} \right)
\]
and we define
\[
\frac{\partial f}{\partial s} := \text{Gradient}(s) = \frac{\partial (Q[x] - x)^2}{\partial s}.
\]
Back to case before, in this case, the MSE-based gradient equals to
\[
\frac{\partial (Q[x] - x)^2}{\partial s} = 2 \left( -0.2 \times 0 + 0.1 \times 1 \right) = 0.2,
\]
which is a positive number, so we will decrease \(s\) in the next step, which explains why MSE-based gradient is better than STE-based gradient.

### 4.2 MINI distillation with different scale factor

In [Wang et al. (2020b)], authors found that by only using the output of MHA and FFN from the last layer can even outperform the performance of multi-layer distillation. More importantly, this distillation method is applicable for the case where the teacher model is deeper than the student without manually specifying the layer correspondence, which means it can be easily extend to the case where we want to use a larger model to teach the quantized model. For the output of MHA, it defines
\[
L_{attention} = \sum_a KL(OA^S_a \| OA^T_a),
\]
where \(KL(p_1 \| p_2)\) indicates the KL-divergence of two distributions \(p_1\) and \(p_2\). Unlike previous work which uses the output of FFN for distillation, it uses value vectors. More specifically, it first fed \(v_{l,a}\) into a softmax layer, then use KL divergence to measure the distance of softmax layer’s results between the student and teacher model, which can be written as
\[
\hat{v}^S_{l,a} = \text{Softmax} \left( \frac{v^S_{l,a} (v^T_{l,a})^\top}{\sqrt{d_k}} \right)
\]
\[
\hat{v}^T_{l,a} = \text{Softmax} \left( \frac{v^T_{l,a} (v^T_{l,a})^\top}{\sqrt{d_k}} \right)
\]
\[
L_{value} = \sum_a KL(\hat{v}^S_{l,a} \| \hat{v}^T_{l,a}),
\]
where \(\hat{v}^S_{l,a}\) and \(\hat{v}^T_{l,a}\) are the value vector from the student and teacher model for each attention head.

In MK-Q-BERT, we adapt the this distillation strategy and combine (6), (8), (9) together with the original training loss with different scale factor as the final training loss:
\[
L_{final} = L_{train} + \alpha L_{output} + \beta (L_{attention} + L_{value}).
\]
Empirically, we find that by setting \(\alpha\) larger than \(\beta\) (e.g. \(\alpha = 10\) and \(\beta = 0.5\)) is beneficial for the student to achieve a better performance.
We use a TinyBERT4 model (Jiao et al., 2019) and the development results for each algorithm are listed in Table 1. We shall see that by using MKQ-BERT, we could achieve almost the same performance with the uncompressed model even when 50% of layers being quantized into 4-bits. When quantizing 75% layers into 4-bits, the model being trained using MKQ-BERT still achieves a comparable performance.

Table 1: GLUE development set results. TinyBERT4 (original) are the finetuned results using checkpoint from Jiao et al. (2019). TinyBERT4 are the results using MKQ-BERT with the 4th layer quantized into 4-bits. TinyBERT4,4 are the results using MKQ-BERT with the 3rd and 4th layer quantized into 4-bits. TinyBERT4,3,4 are the results using MKQ-BERT with all layers except the embedding layer being quantized into 4-bits. All layers (except embedding) use 8-bits quantization as default setting if not being quantized into 4-bits. All models ends with (KDLSQ) means using the method from KDLSQ-BERT (Jin et al., 2021).

| Model                  | RTE  | MRPC | CoLA | SST-2 | QNLI | QQP  |
|------------------------|------|------|------|-------|------|------|
| TinyBERT4 (original)   | 67.5 | 85.3 | 69.4 | 90.4  | 85.4 | 87.1 |
| TinyBERT4               | 68.3 | 85.0 | 70.2 | 90.4  | 85.3 | 86.8 |
| TinyBERT4,3,4 (KDLSQ) | 67.3 | 84.0 | 69.7 | 89.6  | 84.9 | 86.3 |
| TinyBERT4,3,4 (KDLSQ)  | 67.5 | 84.5 | 70.6 | 90.4  | 85.0 | 86.7 |
| TinyBERT4,2,3,4 (KDLSQ)| 66.4 | 82.1 | 69.6 | 87.1  | 84.0 | 86.1 |
| TinyBERT4,1,2,3,4 (KDLSQ)| 66.1 | 81.3 | 70.1 | 88.3  | 74.4 | 71.3 |

5 Experiments

In order to evaluate the performance of MKQ-BERT, we conduct model quantization experiments using different model quantization strategies, and evaluate the quantized models on the GLUE benchmark. Notice that KDLSQ (Jin et al., 2021) is the only work that combines learned step size quantization with knowledge distillation for Transformer based models, and it has already outperformed other methods on GLUE for 8-bits quantization and 4-bits weight quantization (the activations are still quantized into 8-bits, which is not the case in our implementation). Therefore we only choose KDLSQ for comparison. All layernorm and activation functions are computed using float32 numbers in order to improve the model’s performance.

5.1 GLUE

The General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018) consists of several sentence-level classification tasks, including Corpus of Linguistic Acceptability (CoLA) (Warstadt et al., 2018), Stanford Sentiment Treebank (SST) (Socher et al., 2013), Microsoft Research Paraphrase Corpus (MRPC) (Dolan & Brockett, 2005), Quora Question Pairs (QQP) (Chen et al., 2018), Question Natural Language Inference (QNLI), Recognizing Textual Entailment (RTE) (Dagan et al., 2011).

5.2 Quantization Setup

We use a TinyBERT4 model (Jiao et al., 2019) model (the number of layers $M = 4$, the hidden size $d_h = 312$, the intermediate size $d_e = 1200$) has a total of 14.5M parameters. We use the checkpoint released from TinyBERT as encoder, and finetune TinyBERT for each downstream task. The batch size is 32 and learning rate is chosen from $\{1e^{-6}, 3e^{-5}, 5e^{-5}\}$. After finetuning, we use the checkpoint that has the highest development accuracy for quantization.

For calibration, we run the forward pass for 200 steps with batch size 32. After the quantization being initialized, we would start the QAT. We use Adam as the optimizer. The learning rate for weight is chosen from $\{5e^{-6}, 1e^{-5}, 5e^{-5}\}$, the learning rate for activations’ quantization scale is chosen from $\{0.05, 0.01\}$, the learning rate for weights’ quantization is chosen from $\{0.005, 0.001\}$. All learning rates follow the same scheduler that grows linearly for 10% of the training steps and decays to 0 till the end. We set $\alpha = 10$ and $\beta = 1$ in (10) for distillation. The max sequence length is 128 for each task. Empirically, we find that the higher levels are more robust to quantization therefore we start from the last layer for quantization. We run QAT for 30 epochs for each task and report the best result over all hyper parameters.

5.3 Main Results

The development results for each algorithm are listed in Table 1. We shall see that by using MKQ-BERT, we could achieve almost the same performance with the uncompressed model even when 50% of layers being quantized into 4-bits. When quantizing 75% layers into 4-bits, the model being trained using MKQ-BERT still achieves a comparable performance.
Table 2: End-to-end inference time for running one layer in BERT-base model with different batch size and different numbers of valid tokens. We run our experiments on NVIDIA T4 GPUs, and the inference time is averaged over 100 rounds of experiments.

| BS | valid tokens | float32 (us) | int8 (us) | int4 (us) |
|----|--------------|--------------|-----------|-----------|
| 16 | 440          | 1380         | 213.1     | 160.5     |
| 16 | 537          | 1845         | 245.7     | 179.3     |
| 16 | 681          | 2690         | 260.9     | 196.5     |
| 64 | 1691         | 6398         | 567.4     | 428.8     |
| 64 | 2011         | 7185         | 628.4     | 490.1     |
| 64 | 2298         | 7897         | 669.9     | 533.4     |

Table 3: GLUE development set results for ablation studies. TinyBERT$^{3,4}$ are the results using MKQ-BERT with the 3rd and 4th layer being quantized into 4-bits. TinyBERT$^{3,4}$ (w/o MINI KD) are the results using MKQ-BERT without $L_{attention}$ and $L_{value}$ in (10). TinyBERT$^{3,4}$ (w/o output KD) are the results using MKQ-BERT without $L_{output}$ in (10). TinyBERT$^{3,4}$ (w/o LSQ) are the results using MKQ-BERT with the quantization scale held unchanged along the training.

| Model                        | RTE  | MRPC | CoLA | SST-2 | QNLI | QQP |
|------------------------------|------|------|------|-------|------|-----|
| TinyBERT$^{3,4}$             | 67.5 | 84.5 | 70.6 | 90.4  | 85.0 | 86.7|
| TinyBERT$^{3,4}$ (w/o MINI KD) | 66.0 | 83.5 | 69.0 | 89.7  | 84.1 | 86.1|
| TinyBERT$^{3,4}$ (w/o output KD) | 66.7 | 83.8 | 70.0 | 90.0  | 84.4 | 86.4|
| TinyBERT$^{3,4}$ (w/o LSQ)   | 66.0 | 84.0 | 69.7 | 90.0  | 83.6 | 85.8|

performance with the original model for most tasks. However, when quantizing all layers into 4-bits, the performance drops severely, this leads to a challenging problem for future studies. All results except four int4 layers case from MKQ-BERT substantially outperforms the results from KDLSQ.

5.4 End-to-end Inference Speedup

As mentioned, another major contribution of our work is that we successfully implemented int4 matrix multiplication with efficient CUDA kernels. Since the overall inference time depends on the number of int4 layers in the model, so here we report the averaged inference time for one layer, using int4 quantization, int8 quantization and float32 number for comparison. From Table 2, we shall see that when quantizing the layers into 4-bits, it is 1.25x faster than the int8 layer, and is even 15x faster than the float32 layer.

5.5 Ablation Studies

In order to get a clear understanding for each component in MKQ-BERT, we perform ablation studies to evaluate the performance of the quantized model without each components. There are three major components in MKQ-BERT:

1. MINI knowledge distillation;
2. Output layer knowledge distillation;
3. Learned step size quantization.

Since we can at most quantize 50% of the layers into 4-bits, therefore we compress the 3rd and 4th layers of TinyBERT4 into 4-bits with the rest layers being quantized into 8bits. The training setup still remains the same and we report the best result for each algorithm. As we can see that, for QNLI, which has more data samples than the other tasks, LSQ becomes more important because the quantized model would deviate from the initial model further since it runs for more training steps. The other trend is that MINI distillation is more important than the output distillation, we think this might be because it has already contains enough information of the encoder network. All of those results suggest that MKQ-BERT is the best option.

6 Conclusion

In this work, we provide a novel quantization pipeline, named MKQ-BERT, that further improves the model’s performance when quantizing the model weights and activations into 4-bits. We propose a more robust way of dynamically updating the quantization function, and is proved to be very essential for reducing the side effect of the quantization
error. Beyond this, we apply an advanced distillation technique that outperforms the previous layer-to-layer attention distillation in QAT. Empirical studies have proved that MKQ-BERT can substantially outperform previous QAT methods. Last but not least, we implement this int4 Transformer layer efficiently and achieved an end-to-end inference throughput improvement. In the future we believe it would be very interesting and challenging to further extend the compression level without performance degradation.

References

Sungsoo Ahn, Shell Xu Hu, Andreas Damianou, Neil D Lawrence, and Zhenwen Dai. Variational information distillation for knowledge transfer.

Z. Chen, H. Zhang, X. Zhang, and L. Zhao. Quora question pairs. 2018.

Ido Dagan, Oren Glickman, and Bernardo Magnini. The pascal recognising textual entailment challenge.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

William B Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases.

Thomas Elsken, Jan Hendrik Metzen, Frank Hutter, et al. Neural architecture search: A survey. J. Mach. Learn. Res., 20(55):1–21, 2019.

Steven K Esser, Jeffrey L McKinstry, Deepika Bablani, Rathinakumar Appuswamy, and Dharmendra S Modha. Learned step size quantization. arXiv preprint arXiv:1902.08153, 2019.

Angela Fan, Pierre Stock, Benjamin Graham, Edouard Grave, Rémí Gribonval, Hervé Jégou, and Armand Joulin. Training with quantization noise for extreme model compression. 2020.

Philipp Gysel, Mohammad Motamed, and Soheil Ghasi. Hardware-oriented approximation of convolutional neural networks. arXiv preprint arXiv:1604.03168, 2016.

Philipp Gysel, Jon Pimentel, Mohammad Motamed, and Soheil Ghasi. Ristretto: A framework for empirical study of resource-efficient inference in convolutional neural networks. IEEE transactions on neural networks and learning systems, 29(11):5784–5789, 2018.

Babak Hassibi and David G Stork. Second order derivatives for network pruning: Optimal brain surgeon. Morgan Kaufmann, 1993.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for MobilenetV3.

Zehao Huang and Naiyan Wang. Data-driven sparse structure selection for deep neural networks.

Itay Hubara, Matthieu Courbariaux, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Binarized neural networks.

Benoit Jacob, Skirmantas Kligys, Bo Chen, Menglong Zhu, Matthew Tang, Andrew Howard, Hartwig Adam, and Dmitry Kalenichenko. Quantization and training of neural networks for efficient integer-arithmetic-only inference.

Xiaochi Jiao, Yuchun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling bert for natural language understanding. arXiv preprint arXiv:1909.10351, 2019.

ZhouHan Lin, Iain McCauley, Tiantian Ou, and Zhiliang Gan. KDLSQ-BERT: A quantized bert combining knowledge distillation with learned step size quantization. arXiv preprint arXiv:2101.05938, 2021. URL https://arxiv.org/abs/2101.05938.

Yann LeCun, John S Denker, and Sara A Solla. Optimal brain damage.

Namhoon Lee, Thalaiyasingam Ajanthan, and Philip HS Torr. Snip: Single-shot network pruning based on connection sensitivity. arXiv preprint arXiv:1810.02340, 2018.

Shaohui Lin, Rongrong Ji, Yunchao Li, Yongjian Wu, Feiyue Huang, and Baochang Zhang. Accelerating convolutional networks via global & dynamic filter pruning.

Zhouhan Lin, Matthieu Courbariaux, Roland Memisevic, and Yoshua Bengio. Neural networks with few multiplications. arXiv preprint arXiv:1510.03009, 2015.

J Scott McCarley. Pruning a bert-based question answering model. arXiv preprint arXiv:1910.06360, 2019.

Renkun Ni, Hong-min Chu, Oscar Castañeda, Ping-yeh Chiang, Christoph Studer, and Tom Goldstein. Wrapnet: Neural net inference with ultra-low-resolution arithmetic. arXiv preprint arXiv:2007.13242, 2020.
Sejun Park, Jaeho Lee, Sangwoo Mo, and Jinwoo Shin. Lookahead: a far-sighted alternative of magnitude-based pruning. *arXiv preprint arXiv:2002.04809*, 2020.

Antonio Polino, Razvan Pascanu, and Dan Alistarh. Model compression via distillation and quantization. *arXiv preprint arXiv:1802.05668*, 2018.

Gabriele Prato, Ella Charlaix, and Mehdi Rezagholizadeh. Fully quantized transformer for improved translation. *arXiv preprint arXiv:1910.10485*, 2019.

Mohammad Rastegari, Vicente Ordonez, Joseph Redmon, and Ali Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks.

Sheng Shen, Zhen Dong, Jiayu Ye, Linjian Ma, Zhexue Yao, Amir Gholami, Michael W Mahoney, and Kurt Keutzer. Q-bert: Hessian based ultra low precision quantization of bert.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank.

Pierre Stock, Armand Joulin, Rémi Gribonval, Benjamin Graham, and Hervé Jégou. And the bit goes down: Revisiting the quantization of neural networks. *arXiv preprint arXiv:1907.05686*, 2019.

Shyam A Tailor, Javier Fernandez-Marques, and Nicholas D Lane. Degree-quant: Quantization-aware training for graph neural networks. *International Conference on Learning Representations*, 2021.

Mingxing Tan and Quoc V Le. EfficientNet: Rethinking model scaling for convolutional neural networks. *arXiv preprint arXiv:1905.11946*, 2019.

Mingxing Tan, Bo Chen, Ruoming Pang, Vijay Vasudevan, Mark Sandler, Andrew Howard, and Quoc V Le. Mnasnet: Platform-aware neural architecture search for mobile.

Eyal Bresler, Shervin Bavarian, Shadi Tajbakhsh, Jake Obraczka, and Nishant Kumble. Hessian-aware pruning and optimal neural implant. *arXiv preprint arXiv:2101.08940*, 2021.

Ofir Zafrir, Guy Boudoukh, Peter Izsak, and Moshe Wasserblat. Q8BERT: Quantized 8bit bert. *arXiv preprint arXiv:1910.06188*, 2019a.

Ofir Zafrir, Guy Boudoukh, Peter Izsak, and Moshe Wasserblat. Q8BERT: Quantized 8bit bert. *arXiv preprint arXiv:1910.06188*, 2019b.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.

Dilin Wang, Meng Li, Chengyue Gong, and Vikas Chandra. Attentivenas: Improving neural architecture search via attentive sampling. *arXiv preprint arXiv:2011.09011*, 2020a.

Xia Xiao, Zigmeng Wang, and Sanguthevar Rajasekaran. Autoprune: Automatic network pruning by regularizing auxiliary parameters.

Chenglong Zhao, Bingbing Ni, Jian Zhang, Qiwei Zhao, Wenjun Zhang, and Qi Tian. Variational convolutional neural network pruning.

Barret Zoph and Quoc V Le. Neural architecture search with reinforcement learning. *arXiv preprint arXiv:1611.01578*, 2016.