Outlier Suppression: Pushing the Limit of Low-bit Transformer Language Models

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Abstract

Transformer architecture has become the fundamental ingredient of the widespread natural language processing (NLP) models. With the trends of large NLP models, the increasing memory and computation costs hinder their efficient deployment on resource-limited devices. Therefore, transformer quantization attracts wide research interest. Recent works recognize that the outliers in some special tokens are the critical bottleneck for the quantization accuracy. However, their solution does not tackle it from the origin but walks around it with an increased computation cost. To fundamentally address this problem, this paper delves into the inherent inducement and importance of the outliers and discovers that γ in LayerNorm (LN) acts as a sinful amplifier for the outliers, and some outliers from a few tokens can be sharply clipped without negative impacts. Motivated by these findings, we propose an outlier suppression framework to overcome the quantization bottleneck of Transformer language models, including Gamma Migration and then Token-Wise Clipping. Gamma Migration utilizes migration equivalence to move the outlier amplifier to subsequent branches without any extra computation cost, avoiding the amplification of outliers and contributing to a more quantization-friendly distribution. Token-Wise Clipping takes the large variance of token range into consideration and clips the unimportant values with high efficiency in a token-wise coarse-to-fine pipeline. This framework effectively suppresses the outliers and can be used in a plug-and-play mode. Extensive experiments prove that our outlier suppression methods surpass the existing works and, for the first time, push the 6-bit post-training BERT quantization to the full-precision (FP) level.

1 Introduction

Transformer [1] has been one of the most common architectures in natural language processing along with lots of popular self-supervised models, such as BERT [2], RoBERTa [3], XLNet [4] and BART [5]. While these pre-trained models have demonstrated a significant superiority in performance, the memory and computation overheads have been a well-known concern, peculiarly in the real development. Therefore, model compression has attracted much attention from both academia and industry. Among them, quantization, working in the low-precision arithmetic fashion, is one of the key approaches for compressing large models and fitting them into the lightweight devices.

These days, more interest has been attracted to quantization of Transformer-based models. [6] proposes an 8-bit quantization scheme for BERT-like models. [7] advises a group-wise quantization technique and analyzes the limit of mixed-precision using second-order Hessian information. [8, 9] combine distillation [10] with quantization. [11] explores the availability of integer-only quantization with the approximation of nonlinear operations. And [12] utilizes randomness and noise to reduce the induced bias of Straight Through Estimation during quantization training. Nonetheless, few studies investigate the inherent bottleneck of quantizing Transformer-based models.

Recently, some papers [13, 14] indicate that there exist significantly larger outliers in NLP models than in the computer vision ones. And these extreme outliers (some close to 100) behave in structured patterns, bringing devastating damage to the quantization accuracy (e.g., a 12% drop even for the 8-bit). For this critical outlier problem, existing method [13] chooses bypassing solutions such as a finer quantization granularity. However, this scheme causes an increased computation cost and unavoidably hinders the acceleration effect.

In this paper, to suppress the outliers rather than walk around them, we make an in-depth analysis to investigate the inducement of the outliers and the impact of clipping the outliers. Specifically, we first exploit the inducement and find that the scaling parameter γ in the LayerNorm structure works as an outlier amplifier and strengthens the outliers in the output. By extracting it, the activation is more robust to quantization. Then we further study the impact of outlier clipping and discover that different outliers may have different impacts on the full-precision performance when they are clipped. More interestingly, the more aggressive outliers provided by a few tokens, such as the separator token, can be cut sharply and safely without much accuracy degradation.

Motivated by these findings, we propose an outlier suppression framework to push the limit of low-bit Transformer language models, which suppresses the outliers by equivalently migrating the outlier amplifier and efficiently detecting an appropriate clipping range. Such framework contains two key components: Gamma Migration and Token-Wise Clipping, corresponding to these two findings. Gamma Migration extracts the scaling parameter γ in LayerNorm and transfers it in subsequent modules with an equivalent transformation, significantly alleviating the outliers. Thus we can quantize on a more robust activation with no extra computation overhead. Then, Token-Wise Clipping further suppresses the outliers from the aspect of clipping impact. As the unimportant but more aggressive outliers might even present in a long tail form, existing ways devoted to finding a superior clipping range either fail to consider the outlier importance or suffer from large time cost on the long tail. We leverage the fact that those less important values only belong to a few tokens and propose to preliminarily detect the clipping range from a token perspective and then optimize it in a fine-grained way. Thus those signals can be skipped over quickly and spare more attention on the important parts. Our proposed framework can be combined with existing methods, and the thought of outlier suppression shall shed new light on the study of NLP quantization.

To summarize, our contributions are as follows:

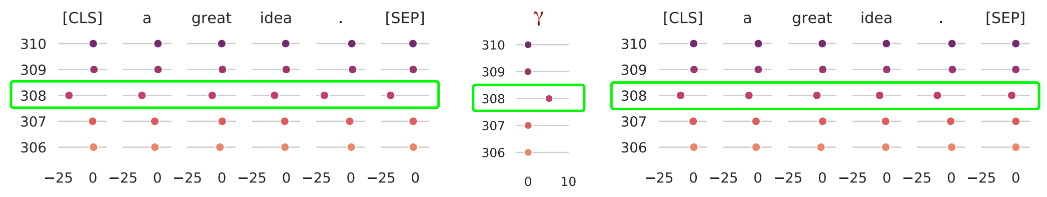
1. We delve into the inducement and clipping impact of outliers in the NLP models and draw two critical findings that are helpful for handling the bottleneck of Transformer Quantization.
2. Based on the findings, an outlier suppression framework containing Gamma Migration and Token-Wise Clipping is proposed. This framework is efficient, easy to implement and plug-and-play.
3. Gamma Migration suppresses the outliers from the inducement aspect. It transfers the outlier amplifier in LayerNorm to the subsequent modules utilizing an equivalence transformation, contributing to a quantization-friendly distribution without any extra inference time.
4. Token-Wise Clipping scheme suppresses the outliers from the importance aspect. It skips over those unimportant outliers quickly from the token perspective and focuses on the influential area with fine-grained learning.
5. Extensive experiments on various NLP models (BERT, RoBERTa, BART) and tasks (text classification, question answering and summarization) prove that our outlier suppression framework sets up a new state of the art for transformer quantization, and for the first time, pushes the 6-bit PTQ and 4-bit QAT accuracy of BERT to the full-precision level.

2 Preliminaries

Basic Notations. We mark matrices as $\boldsymbol{X}$, and vectors as $\boldsymbol{x}$. Operator $\cdot$ denotes the scalar multiplication, and $\odot$ is adopted for element-wise multiplication on matrices or vectors. Also, we use $\boldsymbol{W}\boldsymbol{x}$ as matrix-vector multiplication. Specifically, in NLP tasks refer to tokens, $\boldsymbol{X}_{t,j}$ stands for the element at token t and embedding j, and $\boldsymbol{x}_t$ represents the embedding of token t.

Quantizer. Quantization usually includes two operations.

$$\bar{x} = clip(\lfloor \frac{x}{s} \rceil + z,\, 0,\, 2^b - 1), \quad \hat{x} = (\bar{x} - z) \cdot s \tag{1}$$



(a) $\widetilde{\boldsymbol{X}}$ (b) γ (c) $\boldsymbol{X}'$

Figure 1: Presentation of outliers over $\widetilde{\boldsymbol{X}}$, $\boldsymbol{\gamma}$ and $\boldsymbol{X}'$ of Attn-LN on BERT-SST-2. For example, at dimension 308, $\boldsymbol{\gamma}$ and $\widetilde{\boldsymbol{X}}$ both bear sharper values. By exluding $\boldsymbol{\gamma}$, it can be seen that $\boldsymbol{X}'$ holds milder distribution than $\widetilde{\boldsymbol{X}}$. More evidence is put in Sec. D.1.

where s (step size), z (zero point) are quantization parameters, b is the bit setting. The first operation called "Quant" maps continuous numbers (x) to discrete points ($\bar{x}$) for integer-arithmetic-only matrix computation. The second operation called "DeQuant" recovers it to $\hat{x}$ after multiplication.

3 Outlier analysis

For Transformer-based models, standard 6/8-bit post-training quantization or low-bit (4-bit) quantization-aware training would cause severe accuracy degradation based on the knowledge in previous work [13] and our experiments. By studying the accuracy degradation and quantization error induced by each quantizer, we recognize that the output of LayerNorm structures and GELU functions are the most problematic tensors. Here, the LayerNorm function after Multi-Head Attention is marked as Attn-LN, the LayerNorm after FFN module as FFN-LN. Similar to [13], we notice that these three activations hold many sharp outliers, which should be responsible for the large quantization error. Evidence and experimental results in Sec. B.2.

Based on these, a comprehensive investigation of outliers is conducted from the underlying inducement and clipping impact perspectives, inspiring us to suppress the harmful outliers for quantization.

3.1 Inducement of outliers

During the exploration of the inherent reasons (details in Sec. C.2), we find that the outliers in LayerNorm output correlate with its scaling parameter, which is also observed by [14] on a variety of models. But we further realize the outlier amplification effect of the scaling parameter and notice a more robust distribution for quantization by extracting the parameter.

Since quantizing Attn-LN and FFN-LN are both challenging, natural action is to dive into LayerNorm's internal structure. Considering the transformation on token t at j^{th} embedding dimension, it first normalizes the input using mean ($\boldsymbol{u}_t$) and variance ($\boldsymbol{\sigma}_t^2$) of token t each forward pass, then scales and shifts the value with parameter $\boldsymbol{\gamma}_j$ and $\boldsymbol{\beta}_j$.

$$\textbf{LayerNorm}: \quad \widetilde{\boldsymbol{X}}_{t,j} = \frac{\boldsymbol{X}_{t,j} - \boldsymbol{u}_t}{\sqrt{\boldsymbol{\sigma}_t^2 + \epsilon}} \cdot \boldsymbol{\gamma}_j + \boldsymbol{\beta}_j \tag{2}$$

Thus, we observe the parameter distribution of LayerNorm and surprisingly find that at the same outlier dimensions with the output, multiplier $\boldsymbol{\gamma}_j$ bears sharper values than others (Fig. 2b). Besides, the range of the adder $\boldsymbol{\beta}_j$ is much smaller (e.g., (0, 3)) than its left part (e.g., (-25, 0)), so we ignore it for determining the key point. That is to say, $\boldsymbol{\gamma}$ might be a core ingredient for the situation Fig. 2a, especially can contribute to outliers across tokens as a shared parameter.

This phenomenon enlightens us to remove the influence of $\boldsymbol{\gamma}$ by extracting it from Eq. (2) and see the distribution of tensor $\boldsymbol{X}'$.

$$\textbf{Non-scaling LayerNorm}: \quad \boldsymbol{X}'_{t,j} = \frac{\boldsymbol{X}_{t,j} - \boldsymbol{u}_t}{\sqrt{\boldsymbol{\sigma}_t^2 + \epsilon}} + \frac{\boldsymbol{\beta}_j}{\boldsymbol{\gamma}_j} \tag{3}$$

Comparing Fig. 2a and Fig. 2c, it is obviously that $\boldsymbol{X}'$ denotes milder distribution with weaker outliers and reveals that parameter $\boldsymbol{\gamma}$ does strengthen the outliers, aggressively.

To quantitatively illustrate that tensor $\boldsymbol{X}'$ behaves more robust than $\widetilde{\boldsymbol{X}}$ in quantization, we adopt the cosine similarity metric to evaluate the information loss. From Table 1, the second row with higher similarity and thus less quantization error encourages us that the quantization performance can be improved by extracting the γ multiplication and using Non-scaling LayerNorm.

Tensor	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
$\widetilde{\boldsymbol{X}}$	97.16	97.03	97.61	94.37	93.41	93.53	93.31	93.61	94.56	95.62	96.13	98.57
$\boldsymbol{X}'$	**99.23**	**99.22**	**99.11**	**99.02**	**98.99**	**99.00**	**98.99**	**98.83**	**98.70**	**99.05**	**99.44**	**99.07**

Table 1: Cosine similarity (%) of the quantized value (6-bit) and the real signal for tensor $\widetilde{\boldsymbol{X}}$ and $\boldsymbol{X}'$ across 12 Attn-LN layers on BERT-SST2. Higher is better. More evidence in Sec. D.1.

3.2 Impact of outlier clipping

Plenty of papers [15, 16] point out that the quantization clipping range works as a trade-off between clipping error and rounding error. Considering this, we target the impact of cutting the outliers. Our conclusion is that the more aggressive outliers can be clipped without affecting the performance on FP models, and these little impact outliers correspond to only several tokens.

Accuracy impact of outlier clipping. We take the outliers after GELU as an example here, while a similar phenomenon can also be found in LayerNorm's output (Sec. D.2). Fig. 3 show that the more striking outliers with signal even at 100 can be clipped sharply even to 10, with accuracy still staying at 91.02 in the FP model, while accuracy drops rapidly to 85.93 with too many outliers cut.

Token impact of outlier clipping. Motivated by [13], they refer that the separator token [SEP] attends to larger values. We are also aware of the different ranges provided by diverse tokens. By drawing the red points in Fig. 3, which calculates the proportion of clipped tokens, it can be clearly seen that the more aggressive area covers a lot from 10 to 100 but only matches with only 3% tokens. Destroying those sharper outliers belonging to several tokens will not affect the performance.

Since the outliers in the NLP model show markedly different importance and the large variance of token ranges causes severely long tail distribution, the methods ignoring importance [17] and requiring hyper-parameter tuning [18] fail to find a suitable clipping range.

Fortunately, combined with the observation that the long tail part is only filled with several tokens, we introduce a method in Sec. 4.2 to leverage the token's indication to quickly skip over those unimportant areas and reach a favourable quantization clipping value.

4 Method

In this section, we introduce our proposed techniques based on the above analysis to break the outlier bottleneck. We first suggest extracting the outlier amplifier (scaling parameter) in LayerNorm structures and absorbing it in subsequent modules. To further suppress the outliers, a favourable clipping range detection method is advised to quickly attend to the influential area.

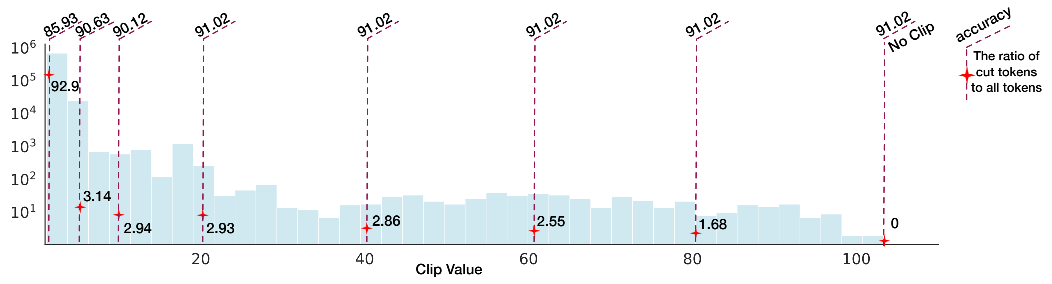


Figure 3: To detect the impact of clipping the outliers, we first draw the distribution using (mean + 3 * std) as its left border, then enumerate the value to cut the tensor. Red points reflect the proportion of cut tokens.

4.1 Gamma Migration

As pointed out in Sec. 3.1, activation without going through the scaling parameter produces less quantization error. In this way, we split the LayerNorm function, migrate γ into follow-up structures and quantize the output of the Non-scaling LayerNorm with transformation equivalence on the FP model and more robust activation on the low-bit one. The overall flow is illustrated in Fig. 4.

Migration equivalence on FP model. Naturally, as refered in Eq. (3), we extract the parameter γ and transform the LayerNorm into Non-scaling one, thus seperate $\boldsymbol{X}'_{t,j}$ from $\widetilde{\boldsymbol{X}}_{t,j}$

$$\widetilde{\boldsymbol{X}}_{t,j} = \boldsymbol{X}'_{t,j} \cdot \gamma_j \tag{4}$$

Since the residual connection is frequently adopted after LayerNorm over a great number of models ([19, 20, 21]), it is necessary to consider moving the parameter γ into the two branches. To put it in practical terms, such as Attn-LN (Fig. 4), we cancel out the parameter in LayerNorm, and establish γ on the shortcut branch and inject the value into the weight of Intermediate Layer.

Next, we show how the weight absorbs γ. For linear layers, we have the following equation:

$$\boldsymbol{W}(\boldsymbol{x} \odot \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \cdots \\ \gamma_n \end{bmatrix}) = (\boldsymbol{W} \odot \begin{bmatrix} \gamma_1 & \gamma_2 & \cdots & \gamma_n \\ \gamma_1 & \gamma_2 & \cdots & \gamma_n \\ \cdots & & & \\ \gamma_1 & \gamma_2 & \cdots & \gamma_n \end{bmatrix})\boldsymbol{x}, \tag{5}$$

where $\boldsymbol{x}$ serves as a column vector and $\gamma \in \mathbb{R}^n$. The proof is available in Appendix A. This equation holds for each token's embedding. So as a shared parameter, γ can be transferred into the next layer's weight. This migration can also be applied to FFN-LN and encoder-decoder architecture (Fig. 8, Fig. 7).

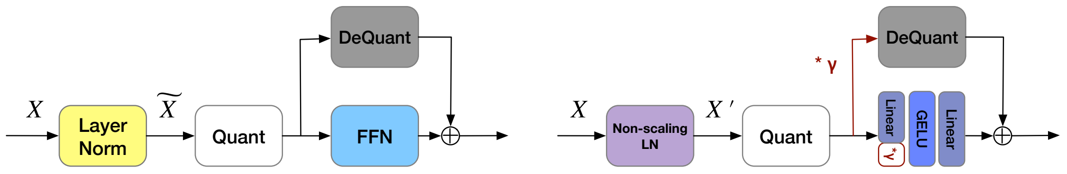


Figure 4: Comparison of the quantization flow before (left) and after (right) Gamma Migration. The original LayerNorm = the Non-scaling LayerNorm * γ. The migrated γ can be fused into the subsequent DeQuant and Linear layers without any extra computation cost.

Quantization after migration. With the equivalent transformation, we clarify the quantization fashion of the Non-scaling LayerNorm. As shown in Fig. 4, the "Quant" process is employed at $\boldsymbol{X}'$, then the output in one branch enjoys the matrix multiplication with the quantized altered weight, in another branch multiplies parameter γ and experiences the "DeQuant" process. In fact, this means delaying the γ calculation. Hence, this new design will not increase the computation overhead.

Effect of migration. We then analyze the effect of γ migration brought to weight and activation to illustrate that the activation quantization burden has been greatly alleviated with relatively a slight influence on weight. As presented in Fig. 1, outliers emerge at the same embeddings on γ, activation before ($\boldsymbol{X}'$) and after ($\boldsymbol{X}$) scaling function. In the original structure, the absolute max range of output can be actually rewrite as $|max(\boldsymbol{X}')| * |max(\gamma)|$. However, the weight matrix does not have the same embedding outlier phenomenon as the activation. Thus, in our method, the newly quantized activation range becomes $|max(\boldsymbol{X})'|$ and weight range will not be amplified $|max(\gamma)|$ times. Experimentally, Table 1 in Sec. 3.1 has validated the favor on activation. We also calculate the cosine similarity for the changed weight and observe that γ has little impact on weight (Table 2). By the way, quantization-aware training is also able to enjoy the benefit of Gamma Migration (Fig. 6).

4.2 Token-Wise Clipping

As illustrated empirically in the motivation, the more serious outliers characterized by several tokens can be clipped safely while others can not. In this section, we propose a Token-Wise Clipping method to show how to utilize the token's information to jump over the relatively unimportant outliers and target the key ones.

Tensor	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
original weight	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.95
changed weight	99.95	99.95	99.95	99.90	99.90	99.92	99.94	99.95	99.95	99.95	99.91	99.94

Table 2: Cosine similarity (%) between the quantized value (6-bit) and the real signal for original weight and the changed weight across 12 Intermediate layers on BERT-SST2. It can be seen that there is little disparity between the two rows, especially compared with Table 1.

During the investigation of the clipping impact of outliers, one understanding is to take the final loss into consideration. Thus, we first give the quantization loss definition below and minimize it using a coarse-to-fine paradigm.

$$L(s) = \|\hat{f}(s) - f\|_F^2, \tag{6}$$

where s is the step size parameter in the quantized model, and the loss represents the distance between the final quantized output $\hat{f}(s)$ and the real one f.

Coarse-grained Stage. At this stage, our aim is to quickly skip over the area with little impact after clipping and access to the critical area. Sec. 3.2 explains that the long tail only matches with a few tokens. Therefore, we suggest using the max value of the embedding at token t to be its representatives (min value as representatives for negative outliers). A new tensor with T elements can be constructed by taking out the maximum signal for each token:

$$\boldsymbol{o}^u = \{max(\boldsymbol{x}_1),\, max(\boldsymbol{x}_2),\, \dots,\, max(\boldsymbol{x}_T)\}, \tag{7}$$

where $\boldsymbol{o}^u$ is marked as the collection of upper bounds, $\boldsymbol{o}^l$ as collection of lower bounds. Then we consider the clipping ratio α on $\boldsymbol{o}^u$, and calculate the corresponding clipping value:

$$c^u = quantile(\boldsymbol{o}^u, \alpha). \tag{8}$$

The quantile function computes the α-th quantiles of the sorted $\boldsymbol{o}^u$, and c^u is used to cut the whole tensor.

Through grid search of token-wise clipping ratio, we get step size $s = \frac{c^u - c^l}{2^b - 1}$ (b is the bit-width), and take the one with minimal quantization loss Eq. (6). The initialized step size is marked as s_0 for the fine-grained stage.

Fine-grained Stage. With s_0 in the coarse phase, the learning procedure is equipped to make some fine-grained adjustments. In detail, we optimize parameter s towards Eq. (6) using gradient descent with initialization s_0 and small learning rate η.

$$s = s - \eta \frac{\partial L(s)}{\partial s} \tag{9}$$

Benifits. Along with travelling over the representative of tokens in the first step, the long tail can be passed quickly Fig. 5. In the second step, at a good initialization point of loss surface, learning adjustments further provide a guarantee for the final effect. Moreover, by virtue of the reduced tensor ($\boldsymbol{o}^u$ distilled from $\boldsymbol{X}$), it runs very fast with each iteration. And the whole grid search is more efficient than OMSE here. Ablation study in Sec. 5.2 demonstrates the enjoyable performance at the first step, and Sec. D.3 gives comparisons among our scheme and other existing approaches.

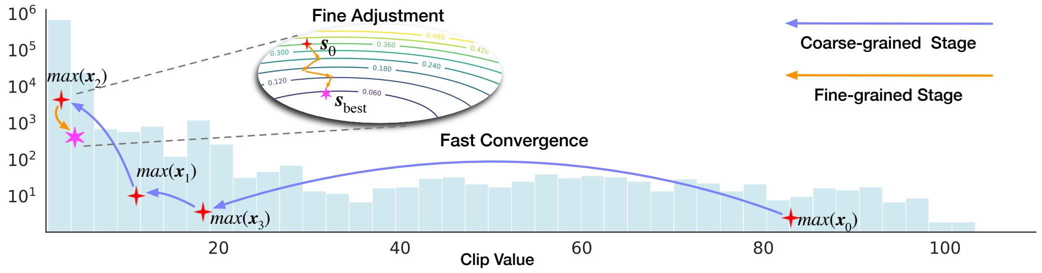


Figure 5: Flow diagram of the proposed Token-Wise Clipping

5 Experiments

In this section, we evaluate our proposed framework from two aspects. Sec. 5.2 shows the effect of Gamma Migration and Token-Wise Clipping, respectively. In Sec. 5.3, we evaluate the overall method across classification, question answering, and summarization tasks on BERT, RoBERTa and BART models. Here, 4-4-4 presents 4-bit weights, embeddings and activations.

5.1 Setup

Datasets. We conduct experiments on GLUE [22] tasks on both PTQ and QAT settings. Besides, more study is done on SQuAD [23, 24], XSum [25] and CNN/DailyMail [26] to further validate the robustness of our approach.

Baseline. For PTQ algorithm, we implement the prevalent techniques including MinMax [27], OMSE [17], Percentile [28], EasyQuant [29] and PEG [13]. For QAT algorithm, we compare our methods with Q-BERT [7], Q8BERT [6] and PEG [13] on setting 4-4-8. To better explore the effect of our outlier suppression framework, we select the canonical quantization approaches PACT [30] and LSQ+ [31], and compare with them on both 8-bit and 4-bit activations. Moreover, we also evaluate how our method performs combined with the knowledge distillation (KD) in TernaryBERT [8].

Implementation details. We adopt a quantization scheme which is more friendly to hardware than some existing papers ([9, 8]) adopt. Details can be found in Sec. B.1. For PTQ experiments, we sample 256 examples as the calibration dataset and set batch size as 32. For QAT experiments on GLUE benchmark, we equip our method with LSQ+ [31]. About hyper-parameters, learning rates are searched for both the baseline mechanisms and our methods. Details in Appendix F.

5.2 Ablation Study

In this subsection, we perform ablation study on our proposed Gamma Migration and Token-Wise Clipping. Results are reported in Table 3. It can be seen that both Gamma Migration and Token-Wise Clipping surpass the baseline by a large margin: 16.43% and 17.53% increment on QNLI, 15.44% and 12.5% enhancement on MRPC. We also notice that based on the coarse-grained stage, the performance of the fine-grained stage sometime doesn't provide a better result, and we think it's because the coarse step already produces a good enough outcome.

Besides PTQ, Fig. 6 shows that with our method, the training of QAT becomes faster and easier.

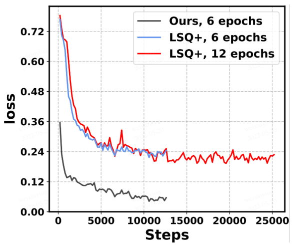


Figure 6: QAT fine-tuning process on BERT-SST-2.

Method	CoLA (Matt.)	MNLI (acc m/mm)	MRPC (f1/acc)	QNLI (acc)	QQP (f1/acc)	RTE (acc)	SST-2 (acc)	STS-B (Pear./Spear.)
FP32	62.50	87.75/87.23	93.1/90.44	92.68	88.78/91.6	80.51	95.18	91.04/90.72
Baseline (MinMax)	0.0	34.9/35.0	71.64/67.4	62.13	51.88/74.37	49.82	77.87	44.11/46.74
Gamma Migration	0.0	53.53/54.64	**87.97/82.84**	78.56	78.04/85.3	55.6	85.67	61.03/63.22
Token-Wise Clipping (Coarse)	34.95	80.56/80.84	85.05/79.41	79.46	85.96/89.31	66.43	91.63	82.03/82.45
Token-Wise Clipping	37.64	81.13/81.26	85.59/79.9	79.66	85.83/89.26	64.62	91.63	83.10/83.51
Gamma Migration + Token-Wise Clipping	**46.35**	**83.38/83.32**	87.50/83.33	**86.82**	**86.82/90.01**	**67.51**	**92.2**	**86.83/86.93**

Table 3: Results of our proposed Gamma Migration and Token-Wise Clipping for RoBERTa with 6-bit PTQ.

5.3 Main Results

5.3.1 Results on GLUE Benchmark

PTQ. Table 4 shows the results of PTQ on GLUE tasks. For 8-bit BERT models, although previous methods already behave well, our methods can still achieve satisfying outcomes even on small datasets such as CoLA (4.49% upswings) and STS-B (1.33%). To fully exploit the limit, we try more challenging settings with 6-bit weight and activation. It can be seen that ours is indeed close to FP value within 5.2% overall. Meanwhile, as PEG [13] additionally quantizes the "Add" operator and uses per-layer weight quantization. For a fair comparison, we apply our mechanism to their setting.

Method	Bits	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B
	(W-E-A)	(Matt.)	(acc m/mm)	(f1/acc)	(acc)	(f1/acc)	(acc)	(acc)	(Pear./Spear.)
BERT	32-32-32	59.60	84.94/84.76	91.35/87.75	91.84	87.82/90.91	72.56	93.35	89.70/89.28
MinMax	8-8-8	57.08	82.77/83.47	89.90/85.78	90.76	87.84/90.74	69.68	92.78	86.83/88.56
OMSE [17]	8-8-8	57.15	84.04/84.29	90.10/85.78	91.12	87.64/90.54	72.20	93.23	87.90/88.65
Ours	8-8-8	**61.64**	**84.38/84.53**	**91.44/87.75**	**91.49**	**87.92/90.77**	**72.20**	**93.81**	**89.23/89.01**
OMSE	6-6-6	35.44	74.00/73.30	81.54/76.47	84.66	76.07/82.12	64.26	86.27	85.57/86.05
Percentile [28]	6-6-6	37.32	72.40/71.69	85.09/79.90	79.37	72.58/80.19	61.73	87.27	86.38/87.29
EasyQuant [29]	6-6-6	44.18	78.27/79.24	85.12/77.21	81.97	72.15/79.71	62.45	85.44	82.19/82.03
Ours	6-6-6	**54.40**	**82.02/81.69**	**87.45/83.33**	**89.82**	**84.69/88.94**	**70.76**	**91.86**	**88.65/88.55**
PEG [13] ♣	8-8-8	59.43	81.25	88.53	**91.07**	**89.42**	69.31	92.66	87.92
Ours ♣	8-8-8	**59.83**	**82.93/82.59**	**91.33/87.99**	90.02	87.45/90.34	**70.04**	**92.66**	**88.42/88.81**
PEG ♣	6-6-6	9.46	32.44/32.77	83.64/78.43	49.46	29.93/62.97	**70.76**	90.14	52.79/53.22
Ours ♣	6-6-6	**42.27**	**78.54/78.32**	**85.33/81.13**	**85.36**	**78.47/84.66**	68.59	**91.74**	**87.33/87.19**
RoBERTa	32-32-32	62.50	87.75/87.23	93.1/90.44	92.68	88.78/91.6	80.51	95.18	91.04/90.72
MinMax	8-8-8	41.62	87.52/86.88	91.56/88.48	92.11	88.60/91.44	76.90	94.82	91.00/90.66
OMSE	8-8-8	38.59	87.32/87.14	92.39/89.46	92.51	87.95/90.95	76.53	94.61	90.95/90.65
Ours	8-8-8	**62.50**	**87.61/87.31**	**92.39/89.46**	**92.53**	**88.64/91.49**	**78.34**	**94.95**	**91.08/90.73**
OMSE	6-6-6	1.81	72.89/72.65	85.38/78.68	76.53	85.24/88.94	64.26	91.17	80.81/81.99
Percentile	6-6-6	20.73	72.23/73.68	84.83/78.43	77.16	82.21/87.44	62.82	88.19	79.41/79.64
EasyQuant	6-6-6	17.65	74.54/74.76	82.96/74.02	81.97	78.56/82.99	61.73	86.24	81.05/81.06
Ours	6-6-6	**46.35**	**83.38/83.32**	**87.50/83.33**	**86.82**	**86.82/90.01**	**67.51**	**92.2**	**86.83/86.93**
BART	32-32-32	56.32	86.45/86.55	91.37/87.50	92.31	88.34/91.39	79.06	93.35	90.11/89.94
MinMax	8-8-8	55.38	85.87/86.14	89.44/85.29	91.20	88.07/91.24	77.98	93.69	89.90/89.73
OMSE	8-8-8	54.56	85.6/86.25	90.31/86.27	90.74	88.21/91.3	78.7	93.58	90.07/89.88
Ours	8-8-8	**55.53**	**86.28/86.17**	**90.40/86.52**	**91.47**	**88.25/91.35**	**80.51**	**93.92**	**90.20/89.95**
OMSE	6-6-6	31.06	41.92/42.08	56.37/54.36	52.72	78.96/86.02	51.99	87.39	84.38/85.69
Percentile	6-6-6	26.21	74.72/75.29	83.52/74.26	53.71	82.64/87.48	67.15	87.96	63.99/65.01
EasyQuant	6-6-6	23.64	64.57/66.03	83.52/74.26	55.61	72.15/79.71	59.57	88.99	76.69/77.05
Ours	6-6-6	**44.51**	**82.46/82.98**	**86.41/80.88**	**86.34**	**83.60/88.45**	**71.12**	**90.94**	**87.56/87.38**

Table 4: PTQ performance on GLUE benchmark. ♣ indicates using quantization nodes of PEG [13] for thorough comparison. For the percentile , we search it in [0.999, 0.9999, 0.99999] and report the best on dev set.

Favourable results on both 6-bit and 8-bit reveal the flexibility and the generality of our Gamma Migration and Token-Wise Clipping. To be noted, their per-embedding-group (PEG) quantization certainly brings extra computation and might not be available on real deployment.

Besides, the experimental results on RoBERTa and BART show that with 6-bit activation, the existing methods suffer from non-negligible accuracy drops, while ours consistently achieves satisfying results. To conclude, our proposed methods push the limit of 6-bit quantization to a new state of the art.

QAT. In particular, we measure the effectiveness of our methods on QAT with BERT model. Other models see Sec. D.4. In a much harder setting (4-4-4 bit quantization), our methods enable a good initialization to attain an acceptable accuracy drop (0.58% on QQP, 1.89% on MNLI) without any distillation and data argumentation trick, versus 3.67% and 3.51% on LSQ+. Furthermore, ours delivers improvements even when coupled with knowledge distillation, especially at 2-bit weight and embedding. To summarize, our outlier suppression framework achieves near-floating point performance with a reduction 2.40% on average on 4-bit quantization.

5.3.2 Results on SQuAD

To demonstrate the wider applicability of our methods, we evaluate them on question answering datasets. Most of the techniques work well for 8-bit. However, the performance drastically drops when going down to 6-bit quantization. Ours still outperforms others by a large margin. For example, our method improves 3.79% on BERT and 8.69% on RoBERTa.

5.3.3 Results on Summarization Tasks

Summarization tasks aim at generating a brief that contains the substance of the article. We report the ROUGE 1/2/L results of BART on CNN DailyMail and XSum. Table 7 shows the effectiveness of our approaches in Seq2Seq models with about 4% increment.

Method	Bits	BERT		RoBERTa		BART	
	(W-E-A)	SQuAD v1.1	SQuAD v2.0	SQuAD v1.1	SQuAD v2.0	SQuAD v1.1	SQuAD v2.0
Full Prec.	32-32-32	88.28/80.82	77.34/73.60	92.25/85.83	83.30/80.26	91.63/84.79	80.82/77.41
OMSE [17]	8-8-8	87.55/79.80	77.00/73.23	91.48/84.52	82.79/79.65	90.35/83.04	80.00/76.37
Ours	8-8-8	**87.96/80.32**	**77.30/73.57**	**91.60/84.95**	**82.92/79.80**	**90.47/82.95**	**80.45/76.91**
OMSE	6-6-6	80.33/69.43	68.77/64.07	70.70/59.09	45.52/39.69	81.30/70.69	67.92/63.18
Percentile [28]	6-6-6	78.73/67.58	68.60/64.62	67.85/55.07	56.13/51.18	80.70/70.80	72.70/67.81
EasyQuant [29]	6-6-6	80.92/70.87	69.77/65.11	65.38/51.18	44.04/37.32	78.53/67.24	61.37/56.42
Ours	6-6-6	**84.71/75.55**	**72.95/68.75**	**79.39/69.35**	**64.39/59.57**	**82.75/73.37**	**75.60/72.10**

Table 5: Comparison among typical PTQ approaches in terms of f1/em on SQuAD.

Method	**Bits** (W-E-A)	**CoLA** (Matt.)	**MNLI** (acc m/mm)	**MRPC** (f1/acc)	**QNLI** (acc)	**QQP** (f1/acc)	**RTE** (acc)	**SST-2** (acc)	**STS-B** (Pear./Spear.)
Full prec.	32-32-32	59.60	84.94/84.76	91.35/87.75	91.84	87.82/90.91	72.56	93.35	89.70/89.28
Q8BERT [6]	8-8-8	58.48	-	89.56/-	90.62	87.96/-	68.78	92.24	89.04/-
Q-bert [7]	8-4-8	-	78.08/78.96	-	85.55	-	-	-	-
PACT [30]	4-4-8	55.23	83.98/83.9	91.58/88.24	91.12	88.19/91.2	71.84	91.86	89.73/89.27
LSQ+ [31]	4-4-8	57.7	84.17/84.02	89.75/85.78	91.27	88.18/91.16	70.76	91.97	**89.74/89.3**
PEG [13]	4-4-8	57.42	84.22/84.52	89.90/85.78	90.46	88.15/91.25	67.87	92.78	89.36/88.95
Ours	4-4-8	**61.06**	**84.82/84.89**	**91.26/87.75**	**91.41**	**88.45/91.4**	**73.65**	**92.55**	89.71/89.24
PEG	4-4-4	0.0	35.45/35.22	81.22/68.38	49.46	0.0/63.18	52.71	76.26	nan/nan
PACT	4-4-4	0.0	74.17/74.85	84.97/80.15	87.31	81.68/86.14	62.09	83.03	81.64/81.43
LSQ+	4-4-4	0.0	81.4/81.97	88.34/83.82	88.1	83.11/87.24	64.62	82.34	84.16/83.75
Ours	4-4-4	**50.56**	**83.05/83.24**	**89.08/84.31**	**89.88**	**87.00/90.33**	**70.76**	**91.86**	**87.64/87.36**
PEG ♣ *	4-4-8	57.22	83.69	87.77	91.29	89.64	70.04	92.32	89.13
Ours ♣	4-4-8	**59.57**	**85/84.31**	**91.07/87.75**	**91.31**	**88.35/91.32**	**72.2**	**92.43**	**89.57/89.2**
PEG ♣	4-4-4	0.0	35.45/35.22	31.62/0.0	49.46	0.0/63.18	52.71	49.08	-0.0219/-0.0199
Ours ♣	4-4-4	**51.93**	**83.03/83.24**	**89.39/85.05**	**90.33**	**87.38/90.62**	**72.56**	**91.74**	**88.36/87.91**
LSQ+(+KD)	4-4-4	12.72	83.73/83.82	90.4/86.52	90.61	87.17/90.47	66.06	84.4	84.23/84.01
Ours(+KD)	4-4-4	**56.1**	**84.67/85.06**	**91.26/87.75**	**91.45**	**88.69/91.56**	**72.2**	**92.89**	**88.49/88.14**
LSQ+(+KD)	2-2-4	0.3	82.18/82.74	89.23/84.56	89.97	86.33/89.33	56.68	84.63	38.81/38.92
Ours(+KD)	2-2-4	**44.18**	**83.84/83.95**	**89.42/84.8**	**90.55**	**88.21/91.17**	**63.18**	**91.97**	**83.01/82.95**

Table 6: Comparison among different QAT strategies with low-bit activation on GLUE benchmark for BERT. ♣Uses the same quantization nodes as PEG [13] for thorough comparison. *Reports the combined score for MNLI, MRPC, QQP and STS-B, which is the average of the metrics.

Method	Bits(W-E-A)	CNN DailyMail	XSum	Bits(W-E-A)	CNN DailyMail	XSum
Full prec.	32-32-32	45.62/22.85/42.88	42.82/20.11/34.99	32-32-32	45.62/22.85/42.88	42.82/20.11/34.99
OMSE [17]	8-8-8	44.89/22.03/42.18	41.58/18.77/33.73	6-6-6	37.56/15.46/34.92	16.11/2.13/12.22
Percentile [28]	8-8-8	44.67/21.74/41.81	41.47/18.67/33.61	6-6-6	37.02/15.31/34.45	30.10/9.43/22.70
EasyQuant [29]	8-8-8	44.32/21.37/41.53	41.40/18.74/33.53	6-6-6	36.71/14.99/34.49	21.72/6.28/16.87
Ours	8-8-8	**45.70/22.89/43.15**	**42.32/19.74/34.59**	6-6-6	**40.12/17.62/37.24**	**34.50/12.69/26.10**

Table 7: PTQ results of BART model on summarization tasks.

6 Conclusions

This paper analyzes the outlier phenomenon from the inducement and clipping impact on Transformer-based models and establishes an outlier suppression framework to combat the quantization challenges. This is done to reduce the outlier amplification effect and detect a good clipping range. We comprehensively verify the effectiveness on a large variety of tasks. It can achieve a nearly lossless 8-bit quantized network and can significantly improve the 6-bit quantization results in PTQ. For QAT, our methods enable an enjoyable initialization to push the limit of 4-bit quantization without distillation and data augmentation tricks.

References

[1] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

[2] 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.

[3] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

[4] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. Xlnet: Generalized autoregressive pretraining for language understanding. *Advances in neural information processing systems*, 32, 2019.

[5] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*, 2019.

[6] Ofir Zafrir, Guy Boudoukh, Peter Izsak, and Moshe Wasserblat. Q8bert: Quantized 8bit bert. In *2019 Fifth Workshop on Energy Efficient Machine Learning and Cognitive Computing-NeurIPS Edition (EMC2-NIPS)*, pages 36–39. IEEE, 2019.

[7] Sheng Shen, Zhen Dong, Jiayu Ye, Linjian Ma, Zhewei Yao, Amir Gholami, Michael W Mahoney, and Kurt Keutzer. Q-bert: Hessian based ultra low precision quantization of bert. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8815–8821, 2020.

[8] Wei Zhang, Lu Hou, Yichun Yin, Lifeng Shang, Xiao Chen, Xin Jiang, and Qun Liu. Ternarybert: Distillation-aware ultra-low bit bert. *arXiv preprint arXiv:2009.12812*, 2020.

[9] Haoli Bai, Wei Zhang, Lu Hou, Lifeng Shang, Jing Jin, Xin Jiang, Qun Liu, Michael Lyu, and Irwin King. Binarybert: Pushing the limit of bert quantization. *arXiv preprint arXiv:2012.15701*, 2020.

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

[11] Sehoon Kim, Amir Gholami, Zhewei Yao, Michael W Mahoney, and Kurt Keutzer. I-bert: Integer-only bert quantization. In *International conference on machine learning*, pages 5506–5518. PMLR, 2021.

[12] Angela Fan, Pierre Stock, Benjamin Graham, Edouard Grave, Rémi Gribonval, Herve Jegou, and Armand Joulin. Training with quantization noise for extreme model compression. *arXiv preprint arXiv:2004.07320*, 2020.

[13] Yelysei Bondarenko, Markus Nagel, and Tijmen Blankevoort. Understanding and overcoming the challenges of efficient transformer quantization. *arXiv preprint arXiv:2109.12948*, 2021.

[14] Olga Kovaleva, Saurabh Kulshreshtha, Anna Rogers, and Anna Rumshisky. Bert busters: Outlier layernorm dimensions that disrupt bert. *arXiv e-prints*, pages arXiv–2105, 2021.

[15] Ritchie Zhao, Yuwei Hu, Jordan Dotzel, Chris De Sa, and Zhiru Zhang. Improving neural network quantization without retraining using outlier channel splitting. In *International conference on machine learning*, pages 7543–7552. PMLR, 2019.

[16] Ron Banner, Yury Nahshan, Elad Hoffer, and Daniel Soudry. Aciq: analytical clipping for integer quantization of neural networks. 2018.

[17] Yoni Choukroun, Eli Kravchik, Fan Yang, and Pavel Kisilev. Low-bit quantization of neural networks for efficient inference. In *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, pages 3009–3018. IEEE, 2019.

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

[19] Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc V Le, and Ruslan Salakhutdinov. Transformer-xl: Attentive language models beyond a fixed-length context. *arXiv preprint arXiv:1901.02860*, 2019.

[20] Mostafa Dehghani, Stephan Gouws, Oriol Vinyals, Jakob Uszkoreit, and Łukasz Kaiser. Universal transformers. *arXiv preprint arXiv:1807.03819*, 2018.

[21] Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. Electra: Pre-training text encoders as discriminators rather than generators. *arXiv preprint arXiv:2003.10555*, 2020.

[22] 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.

[23] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*, 2016.

[24] Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don't know: Unanswerable questions for SQuAD. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 784–789. Association for Computational Linguistics, 2018.

[25] Shashi Narayan, Shay B. Cohen, and Mirella Lapata. Don't give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807. Association for Computational Linguistics, 2018.

[26] Ramesh Nallapati, Bowen Zhou, Cícero Nogueira dos Santos, Çaglar Gülçehre, and Bing Xiang. Abstractive text summarization using sequence-to-sequence RNNs and beyond. In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 280–290. Association for Computational Linguistics, 2016.

[27] Raghuraman Krishnamoorthi. Quantizing deep convolutional networks for efficient inference: A whitepaper. *arXiv preprint arXiv:1806.08342*, 2018.

[28] Jeffrey L. McKinstry, Steven K. Esser, Rathinakumar Appuswamy, Deepika Bablani, John V. Arthur, Izzet B. Yildiz, and Dharmendra S. Modha. Discovering low-precision networks close to full-precision networks for efficient embedded inference, 2019.

[29] Di Wu, Qi Tang, Yongle Zhao, Ming Zhang, Ying Fu, and Debing Zhang. Easyquant: Post-training quantization via scale optimization. *arXiv preprint arXiv:2006.16669*, 2020.

[30] Jungwook Choi, Zhuo Wang, Swagath Venkataramani, Pierce I-Jen Chuang, Vijayalakshmi Srinivasan, and Kailash Gopalakrishnan. Pact: Parameterized clipping activation for quantized neural networks. *arXiv preprint arXiv:1805.06085*, 2018.

[31] Yash Bhalgat, Jinwon Lee, Markus Nagel, Tijmen Blankevoort, and Nojun Kwak. Lsq+: Improving low-bit quantization through learnable offsets and better initialization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 696–697, 2020.

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   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] In Discussions we leave some topics as future work.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
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