StatAssist & GradBoost: A Study on Optimal INT8 Quantization-aware Training from Scratch

Taehoon Kim
Sogang University
taxhoonkim@sogang.ac.kr

YoungJoon Yoo
Clova AI, NAVER Corp
youngjoon.yoo@navercorp.com

Jihoon Yang
Sogang University
yangjh@sogang.ac.kr

Abstract

This paper studies the scratch training of quantization-aware training (QAT) [17], which has been applied to the lossless conversion of lower-bit, especially for INT8 quantization. Due to its training instability, QAT have required a full-precision (FP) pre-trained weight for fine-tuning and the performance is bound to the original FP model with floating-point computations. Here, we propose critical but straightforward optimization methods which enable the scratch training: floating-point statistic assisting (StatAssist) and stochastic-gradient boosting (GradBoost). We discovered that, first, the scratch QAT get comparable and often surpasses the performance of the floating-point counterpart without any help of the pre-trained model, especially when the model becomes complicated. From extent experiments, we show that our method successfully enables QAT of various deep models from scratch: classification, object detection, semantic segmentation, and style transfer, with comparable or often better performance than their FP baselines.¹²

1 Introduction

Quantization of the weight and activation of the deep model has been a promising approach to reduce the model complexity, along with the other techniques such as pruning [23] and distillation [10]. Previous studies, both on weight-only quantization and weight-activation quantization, have achieved meaningful progress mainly on the classification task. Especially, the scalar (INT8) quantization provides practically applicable performances with enhanced latency, thanks to hardware supports.

The network quantization aims to approximate the floating-point (FLOAT32) computation of full-precision (FP) models using fixed-point computation in lower-bits (INT8), and hence, has been targeting on transfer learning from the pre-trained network to the quantized counterpart, so called post-quantization [43, 40]. However, the approximation errors are accumulated in the computations operated during the forward-propagation, and bring noticeable performance degradation. Especially for the lightweight models [32, 33, 38, 12] with less representational capacity compared to the baseline architectures [22, 39, 8, 42], the initial statistics error caused by quantization makes it challenging to directly use the pre-trained FP model weights [5].

A promising approach to solve this problem is to imitate the network quantization during the training. Quantization-aware training (QAT) [17] simulates the quantized inference during the forward pass and uses the straight through estimator (STE) [1] to compute the gradient for the back-propagation. While QAT ameliorates the quantization error by reducing the differences in range of weights and the number of outlier weight values [17], it still cannot overcome the gradient approximation error caused by STE.

¹ Clova AI, NAVER Corp, taehoon.kim93@navercorp.com
² Code available at https://github.com/clovaai/StatAssist-GradBoost

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(a) FP Training  (b) Scratch QAT  (c) StatAssist + GradBoost

Figure 1: Histograms of gradients at the layers of a MobileNetV2 [38] on the CIFAR-10 [21] dataset during the 10\textsuperscript{th} epoch of the full-precision (FP) training (left), original scratch quantization-aware training (QAT) [17] (middle), and proposed StatAssist + GradBoost QAT (right). While the scratch QAT model (middle) suffers from the vanishing gradient problem [11] due to the gradient approximation error caused by the straight through estimator (STE) [1], the StatAssist + GradBoost QAT model (right) shows a distribution of gradients similar to that of the FP-trained counterpart (left), thus provides a comparable performance.

Previous approaches suggest to postpone activation quantization in the early stage of training [17] or use pre-trained FP model weights with few steps of calibration [20] to reduce errors caused by inaccurate initial quantization statistics. While these methods effectively work in cases of small error resulting from STE, they lead to the unexpected vanishing gradient problem [11] when the error is large, as in figure 1b. Several existing methods suggest special workarounds such as batch normalization [15] statistics freezing [20, 27], percentile-based activation clamping [27], and LayerDrop [5], which add extra restrictions to the model’s architecture and training scheme.

In this work, we propose intensive and flexible strategies that enable the QAT of a deep model from scratch for better quantization performance with reduced training cost. Our proposal tackles two common factors that lead to the failure of QAT from scratch: 1) the gradient approximation error and 2) the gradient instability from the inaccurate initial quantization statistics. We show that assisting the optimizer momentum with initial statistics of FP model and boosting the optimizer gradients with noise in early stage of training can stabilize the whole training process without any harm to the performance of the model. For sure, our proposed FP-statistic assisting (StatAssist) and stochastic-gradient boosting (GradBoost) QAT can be applied to diverse training schemes of existing lightweight models including object detection, segmentation, and style transfer with significantly reduced training cost, along with classification which has been a main target for the previous quantization methods. We demonstrate the effectiveness of the StatAssist + GradBoost during the back-propagation of QAT in figure 1 with histograms of gradients.

Specifically, our main contributions for the efficient QAT from scratch are as follows:

- We introduce the StatAssist and the GradBoost QAT method to make the optimizer robust to gradient approximation error caused by STE during the back-propagation of QAT.

- Applying StatAssist and GradBoost QAT to the conventional training scheme of a deep model is straight-forward and cost-efficient. With extent experiments, we show that our method leads to successful QAT in various tasks including classification [8, 38, 31], object detection [38, 28], semantic segmentation [32, 33, 38, 12], and style transfer [16].

- By combining layer fusion [17] and INT8 quantization to compress networks trained with our method, we obtain various lightweight models with fixed-point computation while maintaining comparable, or achieving better preciseness to each floating-point version.

The main motivation of this paper is to improve the current quantization-aware training scheme to make a quantized model competitive with its FP counterpart, widely considered as an upper-bound. Section 2 reviews prior work in quantizing a model for faster inference time and smaller size. Section 3 describes the StatAssist and GradBoost algorithms for QAT from scratch without quantized performance degradation. Section 4 introduces related works with model compression in different aspects. Section 5 describes experiments on a variety of different vision tasks and applications. Section 6 summarizes our paper with a meaningful conclusion.
2 Quantization-aware Training

2.1 Network Quantization

Network quantization requires to approximate the weight parameters $W \in \mathcal{R}$ and activation $a \in \mathcal{R}$ of the network $F$ to $W_q \in \mathcal{R}_q$ and $a_q \in \mathcal{R}_q$, where the space $\mathcal{R}$ and $\mathcal{R}_q$ each denotes the space represented by 32-bit (FLOAT32) and the lower-bit (INT8) precision. From Jacob et al. [17], the process of approximating the original value $x \in \mathcal{R}$ to $x_q \in \mathcal{R}_q$ can be represented as:

$$ x_q = A(x; S(x)), S(x) = \{\min(x), \max(x), \text{zero}(x)\}. \quad (1) $$

Here, the approximation function $A$ and its inverse function $A^{-1}$ are defined by the same parameters $S(x)$. It means that if we store the quantization statistics $S(x)$ including minimum, maximum, and zero point of $x$, we can convert $x$ to $x_q$ and revert $x_q$ to $x$. Now we assume the vector multiplication of the vector $x_1q = A(x_1)$ and $x_2q = A(x_2)$, where the both vectors lie on $\mathcal{R}_q$. Then, also from Jacob et al. [17], the resultant value $v \in \mathcal{R}$ is formulated as,

$$ v = x_1 \cdot x_2 \simeq A^{-1}(q(x_1q \cdot x_2q); S(v)), \quad S(v) = f(S(x_1), S(x_2)), \quad (2) $$

where the function $q$ only includes lower-bit calculation. The equation shows that we can replace the original floating-point operation $x_1 \cdot x_2$ with the lower-bit operation, because we can get the statistics $S_q$ from $S(x_1)$ and $S(x_2)$. Ideally, we can expect the faster lower-bit operation and hence faster calculation.

2.2 Static Quantization

Static quantization Despite the theoretical speed-enhancement, achieving the enhancement by the network quantization is not straightforward. One main reason is the quantization of the activation $a$. At the inference time, we can easily get the quantization statistics of weights $S(W)$ since the value of $W$ is fixed. In contrast, the quantization statistics of the activation $S(a)$ constantly change according to the input value of $F$. Since replacing the floating-point operation $x$ with the lower-bit operation $x_q$ always requires $S(x)$, a special workaround is essential for the activation quantization.

Instead of calculating the quantization statistics dynamically, approximating $S(a)$ with the pre-calculated the statistics from a number of samples $x_i \in X, i = 1, \ldots, N$ can be one solution to detour the problem, and called the static quantization. In the static quantization process, the approximation function $A$ uses the pre-calculated statistics $S_{\text{static}} = \{s_{\text{min}}, s_{\text{max}}, s_{\text{zero}}\}$, where the each static is from the set of samples $X$. Since we fix the statistics, there exists a sample $x_{\text{new}}$ such that $x_{\text{new}} \notin [s_{\text{min}}, s_{\text{max}}]$, and we truncate the sample to the bound. The static quantization including the calibration of the quantization statistics are also called post quantization [17]. The post quantization enables actual speed-up of the operation, but also brings on performance degradation.

Layer fusion The latency gap between the conceptual design and the actual implementation is another critical issue. Previous methods [5, 27, 17, 12] report a meaningful latency-enhancement of the convolutional block, but this often couldn’t lead to the overall speed-up of the model execution. The main reason is the conversion overhead from FP to lower-bit. Even with a faster convolution operation, we cannot expect significant latency improvement if we should frequently convert between FP and lower-bit for normalization and activation operations. In inference time, integrating the convolution, normalization, and activation into a single convolution operation is required to boost the latency, called layer fusion. While layer fusion removes the FP-lower-bit conversion overhead, it also restricts the selection of the normalization and activation functions. Such restriction on model component candidates hinders the usage of previously studied model architecture design techniques.

2.3 Quantization-aware Training

Quantization-aware training To mitigate the performance degradation from post quantization, Jacob et al. propose quantization-aware training (QAT) [17] as a method to fine-tune the network parameters. In training phase, QAT converts the convolutional block to the fake-quantization module, which mimics the fixed-point computation of the quantized module with the floating-point arithmetic. In the inference phase, each fake-quantized module is actually converted to the lower-bit (INT8) quantized counterpart using the statistics and the weight value of the fake-quantized module.
Then, how to impose the proper value to the momentum \( m \)? We suggest a simple modification to the weight update mechanism in equation 4 to get over the error amplification can be prevented by assigning a proper momentum value \( \hat{m}_t \), as in figure 2c. If the momentum has a proper weight update direction, the weight \( W_{t+1} \) of equation 4 will ignore the inaccurate gradient \( g(W_{t,q}) \). In this case, we can expect the accuracy \( S_{\text{static}} \) in the next time step \( t+1 \) will become more accurate than those in \( t \). This is also a positive feedback that reducing the gradient update error as well as accumulating the statistic well reflecting the FP value. In the previous QAT case, the use of the pre-trained weight and the statistic calibration (and freeze) helps to reduce the initial gradient computation error. Still, the magnitude of the learning rate \( \eta \) is restricted to be small.

Then, how to impose the proper value to the momentum \( m_t \)? We suggest that the momentum which have accumulated the gradient from a single epoch of FP training is enough to control the gradient approximation error that occurs in the entire training pipeline. This strategy, called StatAssist, gives another answer to control the instability in the initial stage of the training; while previous QAT focuses on a good pre-trained weight, ours focuses on a good initialization of the momentum.

### 3 Proposed Method

#### 3.1 Approximation Error and Gradient Computation

Let the quantity \( g(W) \) be the gradient computed for the weight \( W \) by the floating point precision. Then, in each update step \( t \), the weight \( W_t \) is updated as follows:

\[
W_{t+1} = W_t + \eta g(W_t) + \beta m_t, \tag{3}
\]

where the term \( m_t \) denotes the momentum statistics accumulating the traces of the gradient computed in previous time-steps. The term \( \eta \) governs the learning rate of the model training. In QAT setting, the fake quantization module approximates the process by the function \( A(W_t; S_t) \) in section 2.2, as:

\[
W_{t+1,q} = W_{t,q} + \eta g(W_{t,q}) + \beta m_{t,q}. \tag{4}
\]

The term \( S_t \) denotes the quantization statistics of \( W_t \). The quantization step of \( W_t \) includes the value clipping by the \( s_{\text{min}} \) and \( s_{\text{max}} \) of the quantization statistics \( S_{\text{static}} \). This let the calculation \( g(W_{t,q}) \) occur erroneous approximation, and propagated to the downstream layers invoking gradient vanishing, as in figure 1b. Also, the gradient approximation error and the statistics update form a feedback loop amplifying the error. The inaccurate calculation of the gradient invokes the inaccurate statistic update, and this inaccurate statistic again induces the inaccurate gradient calculation.

We suggest that the error amplification can be prevented by assigning a proper momentum value \( \hat{m}_t \), as in figure 2c. If the momentum has a proper weight update direction, the weight \( W_{t+1} \) of equation 4 will ignore the inaccurate gradient \( g(W_{t,q}) \). In this case, we can expect the accuracy \( S_{\text{static}} \) in the next time step \( t+1 \) will become more accurate than those in \( t \). This is also a positive feedback that reducing the gradient update error as well as accumulating the statistic well reflecting the FP value. In the previous QAT case, the use of the pre-trained weight and the statistic calibration (and freeze) helps to reduce the initial gradient computation error. Still, the magnitude of the learning rate \( \eta \) is restricted to be small.

#### 3.2 Training Robustness and Stochastic Gradient Boosting

Even with the proposed momentum initialization, StatAssist, there still exists a possibility of early-convergence due to the gradient instability from the inaccurate initial quantization statistics. The gradient calculated with erroneous information may narrow the search space for optimal local-minima and drop the performance. Previous works \([17, 20]\) suggest to postpone activation quantization for certain extent or use the pre-trained weight of FP model to workaround this issue.

We suggest a simple modification to the weight update mechanism in equation 4 to get over the unexpected local-minima in early stages of QAT. In each training step, the gradient \( g(W_{t,q}) \) is...
We further choose a random subset of weights with our novel StatAssist and GradBoost methods. 

$\epsilon$ where $EM_t$wise analysis of the histograms of gradients (figure 1). In each update step works as follows:

$$b_{W,t} = EM_t^{max}(g(W_q)) - EM_t^{min}(g(W_q))$$ (5)

where $EM_t^{max}(g(W_q))$ is the exponential moving maximum of $g(W_q)$ and $EM_t^{min}(g(W_q))$ is the exponential moving minimum of $g(W_q)$ in each update step $t$.

We further choose a random subset of weights $D_t$ from $W_{\epsilon,t}$. For each $w \in D_t$, we apply some distortion to its gradient $g(w)$ with $\psi \sim \Psi(g(W_q))$ in a following way:

$$\psi \leftarrow sign(g(w)) * |\psi|$$ (6)

$$\psi \leftarrow min(max(|\psi|, 0), \epsilon)$$ (7)

$$g(w) \leftarrow g(w) + \lambda \psi$$ (8)

where $\epsilon$ is a clamping factor to prevent the exploding gradient problem and $\lambda$ is taken to the power of $t$ for an exponential decay. By matching the sign of $\psi$ with the original gradient $g(w)$ as in equation 6, adding $\psi$ to $g(w)$ randomly boosts the gradient toward its current direction. For each $w \not\in D_t$, the gradient $g(w)$ remains unchanged.

Note that our GradBoost can be easily combined with equations 3 and 4 and use it as an add-on to any stochastic gradient descent (SGD) optimizers [36, 9, 19, 30]. As shown in figure 2d, the combination of StatAssist and GradBoost stabilizes the training and broadens the search area for optimal local-minima during QAT. In section 5, we analyze the effect of StatAssist and GradBoost on the final quantized model performance with various lightweight models on different tasks.

4 Related Work

Different model compression methods for the better trade-off between accuracy and efficiency have been actively proposed in recent years. Both hand-crafted [32, 33, 28] and neural architecture search (NAS) driven [13, 38, 12] structures make it possible to run a deep model on edge-device GPUs. Lightweight models can be further compressed via weight pruning [24, 34, 14], quantization [17, 20, 27, 5], or with NAS & distillation integrated training scheme [26, 44]. In section 5 we further modify the architectures of existing lightweight models [32, 33, 28, 38, 12] in search of the practical model architecture for lower-bit (\texttt{INT8}) quantization with the implementation-level restrictions introduced in section 2.2. As opposed to other works [17, 20, 27, 26], we do not use any pre-trained weight fine-tuning or distillation techniques but train each model with its original training scheme combined with our novel StatAssist and GradBoost methods.
| Model               | Params | MAdds  | FP training | QAT Fine-tune | StatAssist Only | StatAssist GradBoost |
|---------------------|--------|--------|-------------|---------------|-----------------|---------------------|
| ResNet18 [8]        | 11.68M | 7.25B  | 69.7        | 68.8          | 68.9            | 69.6                |
| MobileNetV2 [38]    | 3.51M  | 1.19B  | 71.8        | 70.3          | 70.7            | 71.5                |
| ShuffleNetV2 [31]   | 2.28M  | 0.57B  | 69.3        | 63.4          | 67.7            | **68.8**            |
| ShuffleNetV2 × 0.5  | 1.36M  | 0.16B  | 58.2        | 44.8          | 56.8            | **57.3**            |

Table 1: Classification results (Top 1 accuracy) on the ImageNet-1K [37] dataset. **FP**: Full-Precision models with floating-point computations. **QAT**: Quantized models trained or fine-tuned with quantization-aware-training. **Params**: Number of parameters of each model. **MAdds**: Multiply-Adds measured w.r.t. a 224 × 224 input. The performance gap between each quantized model fine-tuned with FP pre-trained weights (**QAT Fine-tune**) and its FP counterpart (**FP Training**) varies according to the model architecture. Our method (**StatAssist & GradBoost**) effectively narrows the gap, especially for ShuffleNetV2 [31] structures (**Row 3 and 4**). We used the quantized-version of each model, pre-trained FP weights, and training methodology from torchvision [35].

5 Experiments

To empirically evaluate our proposed method, we perform three sets of experiments on training different lightweight models with StatAssist and GradBoost QAT from scratch. The results on classification, object detection, semantic segmentation, and style transfer prove the effectiveness of our method in both quantitative and qualitative ways.

5.1 Experimental Setting

**Training protocol** Our main contribution in section 1 focuses on making the optimizer robust to gradient approximation error caused by STE during the back-propagation of QAT. To be more specific, we initialize the optimizer with StatAssist and distort a random subset of gradients on each update step via GradBoost. As an optimizer updates its momentum by itself each step, we simply apply StatAssist by running the optimizer with FP model for a single epoch. Our StatAssist also replaces the learning rate warm-up process in conventional model training schemes. For GradBoost, we modify the gradient update step of each optimizer with equations 5 through 8.

**Implementation details** We train our models using PyTorch [35] and follow the methodology of PyTorch 1.4 quantization library. See the supplementary material for the typical PyTorch [35] code illustrating StatAssist implementation and the detailed algorithms for different GradBoost optimizers. For the optimal latency, we tuned the components of each model for the best trade-off between model performance and compression. We provide model tuning details in the supplementary material.

5.2 Classification

We first compare the classification performance of different lightweight models on the ImageNet-1K [37] dataset in Table 1. We found out that the performance gap between a quantized model fine-tuned with FP weights and each FP counterpart varies according to the architectural difference. In particular, the channel-shuffle mechanism in ShuffleNetV2 [31] seems to widen the gap. Our method successfully narrows the gap to no more than 0.9%, proving that the scratch training of fake-quantized [17] models with StatAssist and GradBoost is essential for better quantized performance.

5.3 Object Detection

For the object detection, we used two lightweight-detectors: SSD-Lite-MobileNetV2 (SSD-mv2) [38] and Tiny-DSOD (T-DSOD) [28]. We trained the models with Nesterov-momentum SGD [41] on PASCAL-VOC 2007 [4] following default settings of the papers. For training T-DSOD, we set the initial learning rate \( \ell r = 2e^{-2} \) and scaled the rate into 0.1 at the iterations 120K and 150K, over

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For fusing the layers in each model, model architectures are slightly changed according to the official PyTorch Quantization Tutorial.
Table 2: Object detection results (mAP) on PASCAL-VOC 2007 dataset. **FP**: Full-Precision models with floating-point computations. **QAT**: Quantized models trained or fine-tuned with quantization-aware-training. **Params**: Number of parameters of each model. **MAdds**: Multiply-Adds measured w.r.t. a $300 \times 300$ input. While quantized models fine-tuned with FP pre-trained weights (**QAT Fine-tune**) show a marginal mAP drop compared to their FP counterparts (**FP Training**), the models trained from scratch with our proposed method (**StatAssist & GradBoost**) achieve the mAP gain in the INT8 quantization setting.

| Model         | Params | MAdds | FP training | QAT Fine-tune | StatAssist Only | StatAssist GradBoost |
|---------------|--------|-------|-------------|---------------|-----------------|----------------------|
| T-DSOD [28]   | 2.17M  | 2.24B | 71.5        | 71.4          | 71.9            | **72.0**            |
| SSD-mv2 [29]  | 2.95M  | 1.60B | 71.0        | 70.8          | 71.1            | **71.3**            |

Table 3: Semantic segmentation (mIOU) on Cityscapes val set. **FP**: Full-Precision models with floating-point computations. **QAT**: Quantized models trained or fine-tuned with QAT. **RE**: Replace the hard-swish activation [12] with ReLU [6]. **Large & Small**: Different model configurations targeted at high and low resource use cases respectively. **Params**: Number of parameters of each model. **MAdds**: Multiply-Adds measured w.r.t. a $768 \times 768$ input. Row 5 and 6 are promising segmentation candidates for an edge-device with high and low resource capacity accordingly.

| Model                   | Params | MAdds | FP Training | QAT Fine-tune | StatAssist Only | StatAssist GradBoost |
|-------------------------|--------|-------|-------------|---------------|-----------------|----------------------|
| ESPNet [32]             | 0.60M  | 16.8B | 65.4        | 64.6          | 65.0            | 65.5                 |
| ESPNetV2 [33]           | 3.43M  | 27.2B | 64.4        | 63.8          | 64.6            | 64.5                 |
| Mv3-LRASPP-Large [12]   | 2.42M  | 7.21B | 65.3        | 64.5          | 64.7            | 65.2                 |
| Mv3-LRASPP-Small [12]   | 0.75M  | 2.22B | 62.5        | 61.7          | 61.6            | 62.1                 |
| Mv3-LRASPP-Large-RE (Ours) | 2.42M  | 7.21B | 65.5        | 64.9          | 65.1            | **65.8**             |
| Mv3-LRASPP-Small-RE (Ours) | 0.75M  | 2.22B | 61.5        | 61.2          | 62.1            | **62.3**             |

5.4 Semantic Segmentation

We also evaluated our method on semantic segmentation with three lightweight-segmentation models: ESPNet [32], ESPNetV2 [33], and MobileNetV3 + LRASPP (Mv3-LRASPP) [12]. We trained the models on Cityscapes [3] following default settings from [2]. For training, we used Nesterov-momentum SGD [41] with the initial learning rate $lr = 7e^{-3}$ and poly learning rate schedule [2]. We trained our models with $768 \times 768$ random-cropped train images to fit a model in a single NVIDIA P40 GPU. The evaluation was performed with full-scale $2048 \times 1024$ val images. For Mv3-LRASPP, we also made extra variations to the original architecture settings from [12] (as in our supplementary material) to examine promising performance-compression trade-offs.

The segmentation results in table 3 are in consensus with the results in 5.3. While quantized models fine-tuned with FP weights suffer from an average 0.65% mIOU drop compared to their FP counterparts, the StatAssist + GradBoost trained models maintain or slightly surpass the performance of the entire 180K iteration. In SSD-mv2 training case, we used total 120K iteration with scaling at 80K and 100K. The initial learning rate was set to $1e^{-2}$. For each case, we set the batch size of 64. For testing, we slightly modified the detectors to fuse all the layers in each model, as in Section 2.2.

Table 2 shows the evaluation results on two light-weight detectors, T-DSOD and SSD-mv2. Following our theoretical analysis, the quantized model trained with pre-trained FP weight fine-tuning could not surpass the performance of the FP model, which acts like an upper-bound. On the contrary, we can see that it is possible to make the quantized outperform the original FP by training each model from scratch using our method. This is counter-intuitive in that there still exists enough room for improvements in the FP’s representational capacity. However, our method still can’t be a panacea for any INT8 conversion since the model architecture should be modified due to limitations explained in section 2.2. This modification would induce a performance degradation if the FP model was not initially designed for the quantization.
FP with an average 0.13% mIoU gain. While it is cost-efficient to use hard-swish activation [12] in the FP versions of the MobileNetV3, the Add and Multiply operations used in hard-swish seems to generate extra quantization errors during the training and degrade the final quantized performance. Our modified version of MobileNetV3 (Mv3-LRASPP-Large-RE, Mv3-LRASPP-Small-RE), in which all hard-swish activations are replaced with the ReLU, states that the right choice of activation function is important for the quantization-aware model architecture.

5.5 Style Transfer

We further evaluate the robustness of our method against unstable training losses by training the Pix2Pix [16] style transfer model with minimax [7] generation loss. For the layer fusion compatibility, we used ResNet-based Pix2Pix model proposed by Li et al. [26] and Adam [19] optimizer with our StatAssist and GradBoost. We only applied the fake-quantization [5] to the model’s Generator since the Discriminator is not used during the inference. Example results on several image-to-image style transfer problems are in figure 3. We demonstrate that our method also fits well to the fuzzy training condition without causing the mode collapse [7], which is considered as a sign of failure in minimax-based generative models. As demonstrated in figure 3, our method succeeds in training the Pix2Pix model on different image-to-image style transfer problems.

6 Conclusion

This paper propose a simple yet powerful strategy for the scratch training of a quantization model (QAT), which has been considered to be difficult in other previous works. We show that the scratch quantization-aware training (QAT) with StatAssist and GradBoost enables the final quantized model to maintain or often surpass the FP baseline performance, which is an upper-bound of the post quantization and QAT with FP-weight fine-tuning. Besides the scratch training of lightweight models for classification, object detection, and semantic segmentation, we furthermore demonstrate that our proposed method are even robust to significantly unstable training losses such as the minimax generation loss. As a future work, we expect that the QAT-targeted architecture and component studies including quantization-aware neural architecture search (NAS) are another promising future research directions.
Broader Impact

This work does not present any foreseeable societal consequence.

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A Possible Considerations for Quantization-aware Model Designing and Training

A.1 Initialization of QAT

From the above results, we can raise an issue regarding the importance of the full-precision (FP) pre-trained model as an initialization of the QAT. Previous works have assumed that the loss-surface of the model expressed by \texttt{INT8} is the approximated version of the loss-surface by FP, and hence, been focusing on fine-tuning that narrowing the approximation gap. Our observations, however, show a new possibility that the quantized loss-surface itself has a different and better local minima not near those of the FP. In the experiment, we show that only using a single epoch pre-trained weight with a proper direction of gradient momentum (StatAssist) can achieve comparable or better results than using the FP pre-trained weight. We note that this discovery enables the active use of recent architecture search techniques for quantized models since ours doesn’t require a good initialization from the pre-trained model.

A.2 Architecture Consideration

One main concern for converting the model from FP to lower-bit is the activation function. As we mentioned in section 5.5, exponential activation functions force the lower-bit to FP conversion for the exponential calculation, leading to a significant latency drop. The use of a hard-approximation version (i.e., hard-sigmoid) can be another option, but this might occur an extra quantization error. Therefore, it is necessary to develop a new quantization-aware architecture design scheme with limited activation function candidates.

B Model Modification Details

As mentioned in section 2.2, the latency gap between the conceptual design and the actual implementation is critical. The layer fusion, integrating the convolution, normalization, and activation into a single convolution operation, can improve the latency by reducing the conversion overhead between FP and lower-bit. For better trade-off between the accuracy (mAP, mIOU, image quality) and efficiency (latency, MAdds, compression rate), we modified models in the following ways: 

- We first replaced each normalization and activation function that comes after a convolution (Conv) layer with the Batch Normalization (BN) \cite{15} and ReLU \cite{6}. For special modules like Conv-Concatenate-BN-ReLU or Conv-Add-BN-ReLU in ESPNets \cite{32, 33}, we inserted an extra $1 \times 1$ Conv before BN.
- For MobileNetV3 + LRASPP, we replaced the $49 \times 49$ Avg-Pool Stride=(16, 20) in LRASPP with $25 \times 25$ Avg-Pool Stride=(8, 8) to train models with $768 \times 768$ random-cropped images instead of $2048 \times 1024$ full-scale images.
- Quantizing the entire layers of a model except the last single layer yields the best trade-off between accuracy and efficiency.
C Example Workflow of Quantization-aware Training

In this section, we describe an example workflow of our StatAssist and GradBoost quantization-aware training (QAT) with PyTorch. Our workflow in algorithm 1 closely follows the methodology of the official PyTorch 1.4 quantization library. Detailed algorithms and PyTorch codes for the StatAssist and Gradboost are also provided in section C.1 and C.2.

C.1 StatAssist in Pytorch 1.4

We provide a typical PyTorch 1.4 code illustrating StatAssist implementation in algorithm 2. The actual implementation may vary according to training workflows or PyTorch versions.

Algorithm 1 Quantization-aware training (QAT) with StatAssist and GradBoost

1: Prepare a full-precision (FP) model with fake-quantization compatibility.
2: Create a training workflow of the Full-precision (FP) model.
3: Replace the optimizer with the GradBoost-applied version.
4: Run StatAssist using the code provided in algorithm 2.
5: Prepare the model for QAT with layer-fusion and fake-quantization.
6: Start QAT from scratch.
7: Convert model to INT8-quantized version.
8: Evaluate the model performance.

Algorithm 2 PyTorch code for StatAssist

```python
import torch
import torch.nn as nn
import torch.optim as optim
import torch.quantization

# Define model, optimizer, and learning rate scheduler.
...

FP_EPOCHS = 1

for epoch in range(FP_EPOCHS):
    lr = lr_scheduler.step(epoch)
    for param_group in optimizer.param_groups:
        param_group['lr'] = lr
    train_acc, train_loss = train(model, train_loader, \"optimizer, criterion, \" num_class, epoch, \"
device=device)

# prepare the model for quantization-aware training.
model.quantized.fuse_model()
model.quantized.qconfig = \"
    torch.quantization.get_default_qat_qconfig('qnnpack')
torch.quantization.prepare_qat(model, inplace=True)

# Start training
...

# Convert model to INT8 for evaluation.
torch.quantization.convert(model.eval(), inplace = True)
```
C.2 GradBoost Optimizers

Our Gradboost method in section 3.2 is applicable to any existing optimizer implementations by adding extra lines to the gradient calculation. An example algorithm for GradBoost-applied momentum-SGD [41] and AdamW [30] is provided in algorithm 3 and 4. Please refer to optimizer.py in our source code for detailed GradBoost applications to Pytorch 1.4 optimizers.

Algorithm 3 SGD with GradBoost

1: **given** initial learning rate $\alpha \in \mathbb{R}$, momentum factor $\beta_1 \in \mathbb{R}$, weight decay $L_2$ regularization factor $\lambda \in \mathbb{R}$, exponential-moving max and min decay factor $\gamma_1 \in \mathbb{R}$, noise clamping factor $\gamma_2 \in \mathbb{R}$, and noise decay factor $\gamma_3 \in \mathbb{R}$
2: **initialize** time step $t \leftarrow 0$, parameter vector $\theta_{t=0} \in \mathbb{R}^n$, first moment vector $m_{t=0} \leftarrow 0$, schedule multiplier $\eta_{t=0} \in \mathbb{R}$, gradient maximum $\max_{t}^\theta \leftarrow 1$, and gradient minimum $\min_{t}^\theta \leftarrow 0$
3: **repeat**
4: $t \leftarrow t + 1$
5: $\nabla f_t(\theta_{t-1}) \leftarrow $ SelectBatch($\theta_{t-1}$)  \text{ \small{\textbf{\triangleright} select batch and return the corresponding gradient}}
6: $g_t \leftarrow \nabla f_t(\theta_{t-1}) + \lambda \theta_{t-1}$
7: $\max_{t}^\theta \leftarrow \gamma_1 \max_{t-1}^\theta + (1 - \gamma_1) \max_{t-1}^\theta, g_t$  \text{ \small{\textbf{\triangleright} here and below all operations are element-wise}}
8: $\min_{t}^\theta \leftarrow \gamma_2 \min_{t-1}^\theta + (1 - \gamma_2) \min_{t-1}^\theta, g_t$
9: $b_1 = \max_{t}^\theta - \min_{t}^\theta$
10: Random sample $\psi \sim \text{Laplace}(0, b_1)$ and $k \sim \text{Bernoulli}(0, \frac{1}{2})$
11: $\psi \leftarrow \text{sign}(g_{1}) \ast |\psi|$
12: $\psi \leftarrow \min(\max(|\psi|, \gamma_3))$
13: $g_t \leftarrow g_t + k(1 - \gamma_3)\psi$  \text{ \small{\textbf{\triangleright} add noise only if $k = 1$. $\gamma_3$ is taken to the power of $t$}}
14: $\eta_{t} \leftarrow $SetScheduleMultiplier($t$)  \text{ \small{\textbf{\triangleright} can be fixed, decay, be used for warm restarts}}
15: $m_t \leftarrow \beta_0 m_{t-1} + \eta_{t} \alpha g_t$
16: $\theta_t \leftarrow \theta_{t-1} - m_t - \eta_{t} \lambda \theta_{t-1}$
17: **until** stopping criterion is met
18: **return** optimized parameters $\theta_t$

Algorithm 4 AdamW with GradBoost

1: **given** initial learning rate $\alpha \in \mathbb{R}$, momentum factor $\beta_1 \in \mathbb{R}$, second-order momentum factor $\beta_2 \in \mathbb{R}$, $\epsilon = 10^{-8}$, weight decay $L_2$ regularization factor $\lambda \in \mathbb{R}$, exponential-moving max and min decay factor $\gamma_1 \in \mathbb{R}$, noise clamping factor $\gamma_2 \in \mathbb{R}$, and noise decay factor $\gamma_3 \in \mathbb{R}$
2: **initialize** time step $t \leftarrow 0$, parameter vector $\theta_{t=0} \in \mathbb{R}^n$, first moment vector $m_{t=0} \leftarrow 0$, second moment vector $v_{t=0} \leftarrow 0$, schedule multiplier $\eta_{t=0} \in \mathbb{R}$, gradient maximum $\max_{t}^\theta \leftarrow 1$, and gradient minimum $\min_{t}^\theta \leftarrow 0$
3: **repeat**
4: $t \leftarrow t + 1$
5: $\nabla f_t(\theta_{t-1}) \leftarrow $ SelectBatch($\theta_{t-1}$)  \text{ \small{\textbf{\triangleright} select batch and return the corresponding gradient}}
6: $g_t \leftarrow \nabla f_t(\theta_{t-1}) + \lambda \theta_{t-1}$
7: $\max_{t}^\theta \leftarrow \gamma_1 \max_{t-1}^\theta + (1 - \gamma_1) \max_{t-1}^\theta, g_t$  \text{ \small{\textbf{\triangleright} here and below all operations are element-wise}}
8: $\min_{t}^\theta \leftarrow \gamma_2 \min_{t-1}^\theta + (1 - \gamma_2) \min_{t-1}^\theta, g_t$
9: $b_1 = \max_{t}^\theta - \min_{t}^\theta$
10: Random sample $\psi \sim \text{Laplace}(0, b_1)$ and $k \sim \text{Bernoulli}(0, \frac{1}{2})$
11: $\psi \leftarrow \text{sign}(g_{1}) \ast |\psi|$
12: $\psi \leftarrow \min(\max(|\psi|, \gamma_3))$
13: $g_t \leftarrow g_t + k(1 - \gamma_3)\psi$  \text{ \small{\textbf{\triangleright} add noise only if $k = 1$. $\gamma_3$ is taken to the power of $t$}}
14: $\eta_{t} \leftarrow $SetScheduleMultiplier($t$)  \text{ \small{\textbf{\triangleright} can be fixed, decay, be used for warm restarts}}
15: $m_t \leftarrow \beta_0 m_{t-1} + \eta_{t} \alpha g_t$
16: $v_t \leftarrow \beta_1 v_{t-1} + (1 - \beta_1)g_t^2$  \text{ \small{\textbf{\triangleright} $\beta_1$ is taken to the power of $t$}}
17: $\lambda_{t} \leftarrow \lambda_{t-1} - \eta_{t} \left( \frac{\alpha m_t}{(\sqrt{v_t} + \epsilon)} + \lambda \theta_{t-1} \right)$
18: **until** stopping criterion is met
19: **return** optimized parameters $\theta_t$

