Adaptive Precision Training: Quantify Back Propagation in Neural Networks with Fixed-point Numbers

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Abstract

Recent emerged quantization technique (i.e., using low bit-width fixed-point data instead of high bit-width floating-point data) has been applied to inference of deep neural networks for fast and efficient execution. However, directly applying quantization in training can cause significant accuracy loss, thus remaining an open challenge. In this paper, we propose a novel training approach, which applies a layer-wise precision-adaptive quantization in deep neural networks. The new training approach leverages our key insight that the degradation of training accuracy is attributed to the dramatic change of data distribution. Therefore, by keeping the data distribution stable through a layer-wise precision-adaptive quantization, we are able to directly train deep neural networks using low bit-width fixed-point data and achieve guaranteed accuracy, without changing hyper parameters. Experimental results on a wide variety of network architectures (e.g., convolution and recurrent networks) and applications (e.g., image classification, object detection, segmentation and machine translation) show that the proposed approach can train these neural networks with negligible accuracy losses (-1.40%~1.3%, 0.02% on average), and speed up training by 252% on a state-of-the-art Intel CPU.

1. Introduction

While deep neural networks have become state-of-the-art techniques for a wide range of machine learning applications, such as image recognition [14], object detection [21], machine translation [32, 8], the computation costs of deep neural networks are continuously increasing, which greatly hampers the development and deployment of deep neural networks. For example, 10,000 GPU hours are used to perform neural architecture search on ImageNet [2]. Quantization is a promising technique to reduce the computation cost of neural network training, which can replace high-cost floating-point numbers (e.g., float32) with low-cost fixed-point numbers (e.g., int8/int16). Recently, both the software society [6, 12, 16, 19, 27, 35] and the hardware society [11, 24, 23, 31] have carried out extensive researches about quantization of deep neural network for inference tasks.

Though various investigations have demonstrated that deep learning inference can be accurately performed with low bit-width fixed-point numbers through quantization, the quantified training remains an open challenge. Some ex-
existing approaches quantify the backward-pass to low-bit (e.g., int8) but incur significant accuracy drop, for examples, 3.7% loss for AlexNet \cite{38, 36}. \cite{7} uses int16 for both forward-pass and backward-pass to ensure accuracy. However, there is no guarantee that unified int16 precision works for all the tasks and networks.

Most previous investigations on quantified training use unified precision (i.e., bit-width) for all network layers. Intuitively, using mixed precisions for different layers will promote the network performance. However, it is hard to find the most appropriate precisions for so many layers in so many training iterations. Considering a widely used ResNet50 model, with 4 candidate quantization bit-widths (e.g., 8, 16, 24, 32 for weights, activations and activation gradients), the size of quantization precision combination search space for 450,000 training iterations can achieve \(4^3 \times 50 \times 450,000\).

To avoid prohibitively long space searching of quantization bit-width combinations, we propose an efficient and adaptive technique to determine the bit-width layer by layer separately, which is based on our observation about the relationship between the layer-wise bit-width and the training convergence. Take AlexNet as an example, Figure. \[a-c\] depict the distributions of activation gradients on AlexNet last layer when quantified with different bit-widths. Compared with the original float32, int8 introduces a significant change in data distribution, int12 introduces slightly change of data mean, and int16 shows almost the same distribution with float32. Figure. \[d\] depicts the corresponding training loss, which shows int8 quantization does not converge at beginning, int12 convergences slower than float32 and int16 behaves similar as float32. The above experimental results suggest if a quantization resolution does not change the data distribution of a layer (e.g., int16 for the last layer of AlexNet), quantified training with this resolution for the corresponding layer will almost keep the training accuracy.

Based on the above observation, one can train large-scale deep neural network using fixed-point numbers, with no change of hyper parameters and no accuracy degradation. For each layer in training, our approach automatically finds the best quantization resolution (i.e., the smallest bit-width which does not significantly change the data mean) for weights, activations and activation gradients respectively. Concretely, we first calculate the mean of the data before quantization. Then, we quantify the data using int8 and calculate the quantization error. If the ratio of quantization error exceeds a threshold (e.g., 3%), the quantization bit-width is increased by 8. The above process is looped until the quantization error ratio is below the threshold.

We evaluate our approach on a wide variety of network architectures (e.g. convolution and recurrent networks) and applications (e.g. image classification, object detection, segmentation and machine translation). Our approach quantifies all weights and activations to int8. On average, 12.56%, 87.43% and 0.07% of activation gradients are quantified to int8, int16, and int24 respectively. Experimental results show that the proposed adaptive precision training approach can achieve comparable accuracy with float32 for training from scratch. The accuracy loss is only 0.02% on average (-1.40% to 1.3%). Results on Intel Xeon Gold 6154 shows that the proposed approach can achieve 2.52 times speedup over float32 training for AlexNet.

We highlight three major contributions of the proposed adaptive precision training:

1. **Flexibility**: The quantization precisions for different layers of different networks are automatically adapted to guarantee the network accuracy.

2. **Efficiency**: We quantify both the backward-pass and forward-pass with fixed-point numbers in training, which can accelerate training on real hardware. After training, int8 weights can be directly deployed, so no further quantification is needed.

3. **Generalization**: Evaluations on various networks and applications demonstrate the proposed adaptive precision fixed-point training is effective and practical.

2. Related Works

Using reduced precision for deep learning has been an active research topic. Prior efforts explore floating-points (e.g., 8-bit and 16-bit) for training \cite{34, 22} and maintain accuracy on a spectrum of deep learning models and datasets. However, as floating-point is more resource-intensive than fixed-point, the deployments always rely on quantization techniques.

A branch of work explores the fixed-point for forward prorogation (FPROP) \cite{16, 17, 6, 33, 35, 35, 37}. The weights and activations are quantified to 1-8 bits. However, the backward-pass, including gradient propagation (BPROP), and weight gradient computation (WTGRAD) still require float32.

There are recent attempts quantifying weight and activation on different layers with different bit-widths. For the inference of a trained network, there are some techniques that heuristically search the space of quantization bit-width combinations \cite{45, 33, 37}. However, these inference techniques only need to consider single iteration, whose search space is much smaller than training. Hence, they are unsuitable for training. For training, some differentiable quantization methods \cite{4, 30, 37} learn the quantization parameters (e.g., step size, dynamic range and bit-width) with gradient descent. However, the quantization parameters for backward propagation are hard to learn using differentiable
methods. WAGE quantifies the backward propagation. Different from their method, which assigns layer-wise bit-width before training, our approach dynamically changes the bit-width during training and we evaluate on widely used networks.

Researchers have shown that 16-bit is sufficient for back propagation in most vision training tasks. However, further quantization to 8-bit results in severe degradation. WAGE claims that first and last layers require higher precision. TBP shows weight gradient computation (WTGRAD) needs more bits than gradient back propagation.

Our approach is different from others in three aspects. First, fixed-point is used in both forward-pass and backward-pass for training. Second, the quantization parameters for different layers are dynamically adapted to guarantee the accuracy. Lastly, we train a variety of vision and natural language processing applications on large scale dataset.

3. Observation

The key of fixed-point training is to find proper quantization parameters that ensure the training accuracy. Therefore, we study the relationship between the ever-changing data distribution of different layers and the training convergence.

**Observation 1. Data distribution varies greatly between layers.** Figure 2a depicts the distributions of activation gradients of different layers on AlexNet. The majority of activation gradients concentrate in areas close to zero, and have long tail distributions. Compared to convolution layers, the fully connected layers have larger variances. Figure 2a shows the base-2 logarithm of max absolute value of activation gradients of AlexNet, the max value on bottom layers (e.g., conv0, conv1, conv2) is smaller than the max value on upper layers (e.g., fc0, fc1, fc2). Intuitively, for those layers whose range of data is wide and distribution is centralized, higher quantization resolutions are demanded.

**Observation 2. Data range of each layer changes during training.** Figure 2b shows the max absolute value of activation gradient evolution during training. At the early stage of training (less than 10,000 iterations, as shown on the left side of the red line), the data range changes rapidly, and after one or two epochs, the data range tends to be stable. This phenomenon suggests that when training from scratch, the quantization range should also be changed frequently within the initial epochs.

**Observation 3. Data with large variance requires large bit-width.** Figure 2c shows the convergence curves using different bit-width of different layers. Float32 is the training convergence curve of using float32 for all the convolution and fully connected layers. After 5,000,000 iterations, the network’s top1 accuracy on ImageNet is 58.00%. Then, we quantify the activation gradients of conv1 to int8 and keep other layers float32. The training curve of conv1-int8 is the same as float32 and the final top1 accuracy is 58.01%. However, when we quantify the activation gradients of fc2 to int8 and keep other layers float32 unchanged, the training convergence speed is significantly slower than float32, and within the first 5,000 iterations the training does not converge. The final top1 accuracy of fc2-int8 is only 48.27%. When quantifying the activation gradients of fc2 to int12, the training convergence speed is faster than int8 but still slower than float32. The final top1 accuracy of fc2-int12 is only 50.30%. Using int16 for the activation gradients of fc2, finally the training curve is the same as float32 with 58.28% top1 accuracy. In conclusion, int8 is enough to quantify the activation gradient of conv2, however, fc2 requires int16 to maintain the training accuracy. Together with the observation1, we find that data with large variance requires large bit-width, thus the quantization parameters should be dynamically determined by the data distribution.

According to network initialization principle [10][13], all network parameters are initialized as Gaussian distribution with variance relating to the hyper-parameters of layers. Similar network initialization principle and similar learning
Algorithm 1  Adaptive precision training. Data such as weights $W_i$, activations $X_l$ and top layers’ activation gradients $\Delta X_{l+1}$ of the linear layer $l$ are quantified to fixed-point numbers with different bit-widths $n$ and quantization resolution $r$. The output $Diff$ of QEM indicates the insufficiency of quantization resolution, and the output $I tv$ of QPA determines quantization parameter update frequency.

**Figure 3:** Adaptive precision training for one iteration one layer. The green nodes and blocks indicate fixed-point data and calculations. Only 0.01%~2% of the iterations activate the QEM and QPA components.

algorithm ensure that our observations should be applicable on various network architectures.

### 4. Adaptive Precision Training

In this section, we introduce the adaptive precision training approach as shown in Figure. 3. In training, the main three computing units of single iteration include forward-pass (FPROP), backward-pass for gradient propagation (BPROP) and backward-pass for weight gradient computation (WTGRAD). The inputs of these three units include weight $W_l$, activation $X_l$ and top layers’ activation gradient $\Delta X_{l+1}$ of linear layer $l$. In adaptive precision training, we quantify these three inputs to fixed-point numbers. The quantification parameters, such as bit-width $n$ and quantization resolution $r$ are automatically determined by the proposed Quantization Error Measurement (QEM) and Quantification Parameter Adjustment (QPA).

In the following part of this section, we will introduce two main components QEM and QPA of our training approach. Algorithm 1 describes the entire adaptive precision training algorithm. The output of QEM (denoted as $Diff$) serves as an explicit indicator for insufficiency of quantization resolution according to data distribution. QPA performs quantization parameter update and determines update frequency (denoted as $I tv$) according to the output of QEM.

#### 4.1. Quantization Error Measurement

Based on the observation 1 and observation 3, we propose to adjust quantization parameters according to data distribution. The difference of mean before and after quantization is a good quantization error measurement, which indicates the change of data distribution and suggests the need for adjusting quantization resolution.

Intuitively, as shown in Figure. 3, the orange line and blue line represent two different data distributions. The quantization resolution is $b - a$. Using certain quantization resolution, the distribution difference can be reflected by the difference of shadow areas. Specifically, the shadow area $S_1$ is approximately equal to $S_2$, but $S_3$ is much larger than $S_4$. Therefore, for blue one, the mean after quantization $m_x$ is much smaller than the original mean $m_x$. The difference of mean before and after quantization reflects the connection between quantization resolution and data distribution.

Mathematically, assuming that the data is under Gaussian distribution $P(x) \sim G(0, \sigma)$, and data $x \in \mathbb{R}^p$ is quantified to $\hat{x}$. Considering the positive $x$, the mean between $[a, b]$ is $m_x = \frac{1}{b-a} \int_a^b P(x) dx$ and after quantification the mean is $m_{\hat{x}} = \frac{a \int_a^b P(x) dx + b \int_a^b P(x) dx}{\int_a^b P(x) dx}$. The difference of mean before and after quantization is represented as $\frac{m_x}{m_{\hat{x}}}$

$\frac{m_x}{m_{\hat{x}}}$

The quantification method is described in Appendix.B

```plaintext
// Forward Propagation
while i < max iterations do
  // Forward
  W_i = Quantify(W_i, n_w, r_w)
  if i == update_iter where then
    Diff = QEM(W_i)
    I tv, n_w, r_w = QPA(W_i, Diff)
    update_iter where = i + I tv
  end if
  W_i = Quantify(W_i, n_w, r_w)
  if i == update_iter where then
    Diff = QEM(X_l)
    I tv, n_w, r_w = QPA(X_l, Diff)
    update_iter where = i + I tv
  end if
  X_l = Quantify(X_l, n_w, r_w)
  Forward: X_{l+1} = X_l \cdot W_{l+1}/FPROP
end while

// Backward Propagation
while l in layers do
  if i == update_iter where then
    Diff = QEM(\Delta X_{l+1})
    I tv, n_w, r_w = QPA(\Delta X_{l+1}, Diff)
    update_iter where = i + I tv
  end if
  \Delta X_{l+1} = Quantify(\Delta X_{l+1}, n_w, r_w)
  Backward: \Delta X_l = \Delta X_{l+1} \cdot W_{l+1}^T / BPROP
  Backward: \Delta W_l = X_l^T \cdot \Delta X_l / WTGRAD
end while
```

// Weight Update
W_l = W_l + f(\Delta W_l)
```
Quantization
Resolution
S2S3
S4
\[ a \leq b \]
Data Distribution
\[ m_x - m_g < m_x - m_g \]
\[ c \]
S1 \[ k_x + o \]

\[ \int_{a}^{b} P(x) dx = kx + o \]
We use \( P(x) = kx + o \) to approximate the local value between \([a, b]\) with \( b < -\frac{a}{k}, k < 0 \), and assign \( C = \frac{1}{4} k(a+b)^2 + \frac{(a+b)^2}{2} \), then we have:
\[
\frac{m_x}{m_g} = 1 + \frac{1/24}{(b-a)^2} - 1/8
\]  

(1)
It is demonstrated that \( \frac{m_x}{m_g} > 1 \) and \( C > 0 \) (see Appendix A for details), so we have \( \frac{m_a}{m_g} \propto (b-a)^2 \pm (-k) \). When decreasing \( b-a \) or increasing \( k \), the difference of mean will be reduced. Therefore, the difference of mean serves as an explicit indicator for adjusting quantization resolution (represented by \( b-a \)) according to data distribution (represented by \( \sigma \pm (-k) \)).

Equation (2) is used in determining quantization parameters during training.
\[
Diff = \log_2(\frac{m_x - m_g}{m_g} + 1) = \log_2(\frac{\sum_p |x_i| - \sum_p |\tilde{x}_i|}{\sum_p |x_i|} + 1)
\]  

(2)
Larger \( Diff \) indicates the distribution has higher variance \( \sigma \), so it is needed to decrease quantization resolution \( r \).

4.2. Quantification Parameter Adjustment

According to observation 2, we propose to automatically determine the quantization parameter based on the data evolution. Under the circumstance of fixed-point representation, the quantization variables include data range, quantization resolution \( r \) and bit-width \( n \). These three variables are inter-dependent, as \( Range \approx r \times 2^n \). Therefore, we use only two of them as quantization parameters (i.e., \( r \) and \( n \)). The parameter adjustment process is triggered by insufficient quantization resolution and dramatic change of data range.

For insufficient quantization resolution, we use \( Diff \) as indicator. When \( Diff \) exceeds certain threshold \( T_{data} \), the quantization resolution is reduced by increasing bit-width, as \( n_{new} \leftarrow n_{old} + n' \), where \( n' = 8 \) is the bit-width growth step. We can either set the initial \( n_{old} = 8 \) and recursively adjust bit-width until proper \( n_{new} \) (denoted as Mode1), or we can set the initial \( n_{old} \) as the previous iteration’s proper bit-width (denoted as Mode2). The quantization resolution is adjusted according to the new bit-width \( n \) as \( r = 2^{ceil(log_{2}(\frac{Range}{m_{new}}))} \), where \( Range \) is the max absolute value of data to be quantified.

For the change of data range, we propose another indicator \( R \) for iteration \( i \) as:
\[
R_i = \alpha \times Range + (1 - \alpha) \times R_{i-1}
\]  

(3)
where \( R_{i} \) is the moving average of data \( Range \) during several iterations.

The quantization parameter adjustment interval \( Itv \) is automatically determined by both \( Diff \) and \( R \). In initialization phase (one-tenth of the first epoch), \( Itv \) is set to 1. After initialization phase, the adjustment interval is \( Itv = \frac{\gamma}{max(I_1, I_2)} \), as \( I_1 = \delta \times Diff^2 \) and \( I_2 = |R_i - R_{i-1}| \). As shown in experiment, \( Itv \) increases during training. Within \( Itv \) iterations, the quantization parameters are kept the same, so there is no need to calculate \( Diff \) and max absolute value of the data.

5. Experiment

We first evaluate the proposed quantization error measurement, and show the computational complexity introduced by adaptive precision. Then, we evaluate the proposed adaptive precision training on a wide variety of deep learning tasks including image classification, object detection, segmentation and machine translation in accuracy results. At last, we show the training acceleration on existing hardware.

5.1. Evaluation of Error Measurement

![Figure 5: Correlation between MobileNet-v2 accuracy (a) and quantization error measurement (M).](image)

Correlation between Metrics and Accuracy

\[ y = -0.033x + 0.7041 \]
\[ R^2 = 0.0323 \]
\[ y = -0.7345x + 0.7517 \]
\[ R^2 = 0.3713 \]
\[ y = -3.6741x + 0.7255 \]
\[ R^2 = 0.8457 \]

Metric: M1, M2, M3, M4
We use Pearson correlation coefficient in Equation. 4 to show the correlation between network accuracy $a$ and quantization error metric $M$.

\[
R^2 = \frac{\left( \sum (M - \bar{M})(a - \bar{a}) \right)^2}{\sum (M - \bar{M})^2 \sum (a - \bar{a})^2}
\] (4)

The evaluated quantization error metrics including the proposed $M_1 = \frac{1}{\sum_i |x_i|} \sum_i |x_i - \hat{x}_i|$ and several variants: $M_2 = \sum_i |x_i - \hat{x}_i|$, $M_3 = \sum_i |x_i - \hat{x}_i|$, $M_4 = \sum_j P_j \log (P_j / \hat{P}_j)$. $M_2$ is similar as in [27, 39]. $M_4$ is the Kullback-Leibler divergence, with $P_j$ and $\hat{P}_j$ are the discrete probability distributions of original data and data after quantization. Specifically, we quantify each single layer of MobileNet-v2 and ResNet50 and do the forward propagation to get the corresponding network accuracy. The quantization is done with different bit-width (i.e., 6, 8), so various degrees of quantization error and the corresponding network accuracy are generated.

Figure 5 and Figure 6 shows the linear correlation between network accuracy and several error metrics. Our proposed quantization error measurement $M_1$ has the highest correlation score (0.84 for MobileNet and 0.85 for ResNet50) with the network-level accuracy, which means the proposed error measurement can serve as a reasonable layer-wise accuracy indicator. MobileNet, as light-weight network, is hard to quantified as shown in Table.1, so it can exhibit the most noticeable difference between different evaluation metrics $M_1$, $M_2$, $M_3$ and $M_4$.

5.2. Computational Complexity

We evaluate the extra computations introduced by adaptive precision quantization. The extra computations including OEM, QPA and data quantification. Specifically, we calculate the operation percentage of forward propagation and backward propagation in original training, and the extra operation introduced by forward quantification and backward quantification. Figure 7 shows the operation percentage for different network. (Details of operation quantity are shown in Appendix.B.) It is shown that for light-weight network MobileNet, the quantization consumes relatively more computations. For other networks, the extra quantization computation is within 1%.

We evaluate the quantification parameter adjustment frequency during training. As shown in Figure 8a, at the initial iterations, the adjustment is triggered almost every iterations, so the adjustment frequency is near 100%. As the training progress, the adjustment frequency is dramatically decreasing, and at the end of training only 0.1% iterations need to adjust the quantization parameters.

Figure 8b shows the percentage of activation gradients quantified to int8 during training on VGG16. Mode1 allows the chance of decreasing the bit-width during training, so more percentage of layers are kept int8 (final top1 accuracy: 70.2%). In Mode2, bit-width never decreases, so at the end of training, 18.75% of layers are kept int8 (final top1 accuracy: 70.6%).

5.3. Accuracy Results

Our proposed Adaptive Precision Training approach uses identical hyper-parameters (e.g., learning rate, max training iterations) as the original float32 training settings. For all
Table 1: Classification, object detection and segmentation. For all the networks, 100% weights and and 100% activations are quantized to int8.

| Classification Network | float32 Acc | Adaptive Acc | Activation Gradient |
|------------------------|-------------|--------------|---------------------|
| AlexNet                | 58.0        | 58.22        | 22.5% 77.5%         |
| VGG16                  | 71.0        | 70.6         | 31.3% 68.7%         |
| Inception_BN           | 73.0        | 72.8         | 4.5% 95.5%          |
| ResNet50               | 76.4        | 76.2         | 0.8% 99.2%          |
| ResNet152              | 78.8        | 78.2         | 1.7% 98.3%          |
| MobileNet v2           | 71.8        | 70.5         | 0.7% 99.2%          |

| SSD Detection Network  | float32 mAP | Adaptive mAP | Activation Gradient |
|------------------------|-------------|--------------|---------------------|
| COCO,VGG               | 43.1        | 42.4         | 31.4% 68.6%         |
| VOC,VGG                | 77.3        | 77.2         | 34.3% 65.7%         |
| IMG_Res101             | 44.4        | 44.5         | 28.6% 71.4%         |

| Segmentation Network   | float32 meanIoU | Adaptive meanIoU | Activation Gradient |
|------------------------|------------------|------------------|---------------------|
| deeplab-v1             | 70.1             | 69.9             | 1.0% 99.0%          |

We train several convolution neural networks with ImageNet datasets using Tensorflow framework. The networks include AlexNet [18], VGG [23], Inception_BN [29], ResNet [14] and MobileNet v2 [27]. We train SSD object detection networks [21][24] with VOC dataset [9], COCO dataset [20] and Imagenet Detection dataset (IMG) [25] upon two backbone networks VGG and ResNet101. We train deeplab [32][33][34] segmentation network on VOC dataset. For classification task, Top1 Accuracy (Acc) is used as evaluation metric. For object detection task, Mean Average Precision (mAP) is used as evaluation metric. For segmentation task, Mean Intersection over Union (meanIoU) is used as evaluation metric.

As shown in Table 1, Adaptive Precision Training generates similar results as float32 baseline. The accuracy drop on MobileNet-v2 is consistent with the quantization results in Google’s work (Acc:70.8) [16]. However, using our adaptive precision training, int8 weights can be directly deployed and no further quantified fine-tuning is needed. The proposed QPE and QPA automatically change the bit-width used for different layers. During the whole training, the percentage of different bit-width in quantization of activation gradients are shown in Table. [7] For most layers of most networks, 16-bit is enough. For some layers of AlexNet and SSD, 8-bit is enough.

5.3.2 Machine Translation

We train two widely used machine translation models from scratch with Adam optimizer. The first Sockeye [15] is a sequence-to-sequence RNN model implemented with MXNet [7] and trained on the WMT’17 news translation dataset (50k sentence pairs). The word vocabularies contain 50K entries for English and German. The second is Transformer [32][34] utilizing self-attention mechanism. This network is trained on the WMT’16 Multi30k dataset (3.9k sentence pairs). Word-level accuracy and perplexity (PPL) are used as evaluation metrics.

Training curve of Sockeye is shown in Figure. 9a. Adaptive Precision Training is compared with float32 baseline and an int16 method, which employs int16 to quantified all the layers of activation gradients without bit-width adaptation. At the end of Adaptive Precision Training, 0.8% layers of activation gradients are quantified to int24, 10% layers are int8, and others are int16. As shown in Figure. 9a the int16 method gradually results in 2% loss of accuracy, while our Adaptive Precision generates the same accuracy (62.05%) as float 32 baseline (61.97%). This comparison shows the proposed bit-width adaption is necessary to guarantee training accuracy and reduces the total bit-width in computation.

The training convergence curve of Transformer is shown in Figure. 9b. We report the accuracy and PPL on validation set. Adaptive Precision (ACC: 55.54%) is slightly better than float32 (ACC: 54.13%). On average 2.28% of iterations trigger quantization parameter adjustment.

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1https://github.com/tensorpack/tensorpack/tree/master/examples/
2https://github.com/tensorflow/models/tree/master/research/slim
3https://github.com/weliiu89/caffe/tree/ssd
4https://github.com/msracver/Deformable-ConvNets
5https://github.com/jadore801120/attention-is-all-you-need-pytorch
6https://github.com/awslabs/sockeye
7https://github.com/tensorpack/tensorpack/tree/master/examples/
Table 2: Comparison of network quantization methods.

| Methods Cited | Backward (WTGRAD/BPROP) | Adaptive Bit-width | Training from Scratch | Accuracy Degradation CNN | RNN |
|---------------|-------------------------|--------------------|-----------------------|--------------------------|-----|
| [34]          | float8, float16         | no                 | yes                   | <1% (ResNet50)           | n/a |
| [22]          | float16                 | no                 | yes                   | <1% (ResNet50)           | n/a |
| [16]          | float32                 | no                 | no                    | 1.5% (ResNet50)          | n/a |
| [17]          | float32                 | no                 | no                    | <1% (ResNet18)           | n/a |
| [6]           | float32                 | yes                | no                    | <1% (ResNet18)           | n/a |
| [59]          | float32                 | yes                | no                    | <1% (ResNet50)           | n/a |
| [35]          | float32                 | yes                | yes                   | <1% (ResNet50)           | n/a |
| [38]          | int8, float32           | no                 | yes                   | 2.9% (AlexNet)           | n/a |
| [36]          | int8                    | no                 | yes                   | 4% (AlexNet)             | n/a |
| [11]          | int16, float32          | no                 | yes                   | <1% (ResNet50)           | n/a |
| [7]           | int16                   | no                 | yes                   | <1% (ResNet50)           | 2%  |

Adaptive Precision: int8~16 (CNN) int8~24 (RNN)

Table 3: Layer-wise training speedup of AlexNet

|                   | conv0  | conv1  | conv2  | conv3  | conv4  |
|-------------------|--------|--------|--------|--------|--------|
| CPU Forward       | 2.03   | 3.89   | 6.2    | 4.44   | 2.82   |
| CPU Backward      | 1.91   | 1.71   | 1.78   | 2.21   | 2.07   |
| GPU Forward       | 2.82   | 3.63   | 2.97   | 3.01   | 2.72   |
| fc0               | 4.09   | 6.42   | 4.41   | 3.98   |        |
| fc1               | 4.41   | 4.97   | 2.03   | 2.07   |        |
| fc2               | 3.90   | 2.55   | 1.41   | 2.89   |        |
| Overall           | 2.82   | 3.63   | 2.97   | 3.01   | 2.72   |

Figure 10: GPU computation time for different operation times (convolution scales).

5.3.3 Comparison to Others

Table 2 shows the comparison to other quantization methods. As the accuracy of float32 baseline are different across works, we cite their relative accuracy degradation compared to their reported float32 baseline. Most works do not quantify backward-pass and are tested on convolution neural networks. Among these, [7] is the most similar method. They use int16 for both forward and backward propagation, and report results on convolution networks. Differently, we use int8 for all the forward-pass and demonstrate that for recurrent neural networks, the fixed bit-width (e.g., int16) can not meet the precision requirement for all the tasks. Therefore, it is needed to dynamically measure the bit-width requirement for different networks and tasks.

6. Training Acceleration

Intel Xeon Gold 6154 supports vector int8/int16 operations with AVX2 instruction set, and Nvidia T4 supports vector int8 operations. Table 3 shows the speedup of our method compared with float32 in training. Specifically, we use 100 iterations’ average acceleration ratio of each layer in forward-pass and backward-pass for AlexNet with 256 batch size. Our approach can achieve 2.52 times speedup over float32 training on CPU, and 2.89 times speedup on GPU. Figure 10 shows the details of running time for different type of convolution scale with different operation times. Using fixed-point the computation time is significantly shorter than float32, and the extra time introduced by QEM and QPA is relatively small.

7. Conclusion and Future Work

We observe that the data distribution reflects the precision requirement to maintain training accuracy. Therefore, we propose an adaptive precision quantization approach, which automatically determines bit-width layer-wise. Quantifying back propagation in Neural Networks can further accelerate training on hardware supporting flexible bit-width arithmetic operations. The proposed error measurement of quantization would also be extended to low-bit inference (e.g., binary or ternary), and gradient compression in the future.

As T4 does not support int16, we only report the forward-pass use int8 operation. Xeon Gold 6154 can only support multiplication between equal bit-width fixed-point numbers, so in this experiment int16 × int8 is implemented as int16 × int16.
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8. Appendix A

The difference of mean value before and after quantization is \( \frac{m_d}{m_a} = \frac{\int_a^b P(x)dx}{\int_a^c P(x)dx} \). We use \( P(x) = kx + o \) to approximate the local value between \( [a, b] \) with \( b < -\frac{a}{r}, k < 0 \), and assign \( C = \frac{1}{2}k(a + b)^2 + \frac{a(a+b)}{2} \), then we have:

\[
\int_a^b P(x)dx = \int_a^b (kx^2 + ax)dx \\
= \frac{1}{3}kx^3 + \frac{1}{2}kx^2 \bigg|_a^b \\
= (\frac{1}{3}k(a^2 + b^2 + ab) + \frac{a}{2}(a + b))(b - a) \\
\]

\[
a \int_a^b P(x)dx + b \int_c^b P(x)dx = a \int_a^c (kx + a)dx + b \int_c^b (kx + o)dx \\
= a \left( \frac{1}{2}kx^2 + ax \right) \bigg|_a^c + b \left( \frac{1}{2}kx^2 + ax \right) \bigg|_c^b \\
= \frac{1}{8}k(3a^2 + 3b^2 + 2ab) + \frac{a}{2}(a + b)(b - a) \\
\]

\[
m_d = \frac{1}{3}k(a^2 + b^2 + ab) + \frac{a}{2}(a + b) \\
m_d = \frac{1}{8}k(3a^2 + 3b^2 + 2ab) + \frac{a}{2}(a + b) \\
\]

Considering Equation 8 in Equation 7, we have \( \frac{m_d}{m_a} > 1 \). Denote \( A = a + b \) and \( B = b - a \), then Equation 7 becomes:

\[
\frac{m_d}{m_a} = \frac{\frac{1}{2}kA^2 + \frac{1}{2}oA + \frac{1}{12}kB^2}{\frac{1}{4}kA^2 + \frac{1}{2}oA + \frac{1}{8}kB^2} \\
\]

As \( b < -\frac{a}{r} \), so \( \frac{k}{o} > -\frac{1}{5} \)

\[
C = \frac{1}{4}kA^2 + \frac{1}{2}oA \\
C = \frac{1}{4}Ao\left(\frac{k}{o}A + 2 \right) > \frac{1}{4}A\left(\frac{b-a}{b} \right) = 0 \\
\]

Therefore,

\[
\frac{m_d}{m_a} = \frac{C + \frac{1}{12}kB^2}{C + \frac{1}{8}kB^2} \\
= 1 - \frac{1/24}{C/24 + 1/8} \\
= 1 + \frac{C}{(b-a)^2(\frac{1}{r} - 1/8)} \\
\]

Appendix B. Quantification Method

A fixed-point number consists of a sign bit, \((n-1)\)-bit integer, and a global quantization resolution \( r \) relating to fixed-point position \( s \). Before quantization, the maximum absolute data is \( Z \). The representation data range, bit-width and quantization resolution are inter-dependent, as \( \text{Range} \approx r \times 2^s \). The quantization resolution is calculated as in Table. 3 column 2. Suppose \( F_x \) is the floating-point representation of \( x \) and \( I_x \) is the fixed-point representation of \( x \), and \( F_x \) is the approximation of \( F_x \), as \( F_{x1} = I_{x1} \times r_1 \), \( F_{x2} = I_{x2} \times r_2 \), the multiplication between numbers becomes:

\[
F_{x1} \times F_{x2} \approx F_{x1}^i \times F_{x2}^i = r_1 \times r_2 \times I_{x1} \times I_{x2} \\
\]
Table 4: Quantization schemes (scheme 1 most efficient, scheme 3 most accurate)

| Quantization Function | Quantization Scale | Fixed-point Range |
|-----------------------|--------------------|-------------------|
| $I_x = \text{round}(\frac{F_x}{r})$ | $r = 2^s = 2^{ceil(log_2(\frac{2^n-1}{2^n-1}))}$ | $[-r(2^{n-1}), r(2^{n-1} - 1)]$ |

Appendix C. Observations on Other Network

![Graphs](image)

Figure 11: Observations on ResNet34.

As shown in Figure 11, for ResNet34 int8 is enough to quantify the activation gradient of g3b2c2, g2b5c1 and g3b2c1, however, int8 for fc and conv0 either not converges or introduces accuracy drop, conv0 and fc have large variance. These observations are consistent with the observation on AlexNet. In conclusion, data with large variance requires large bit-width, thus the quantization parameters should be dynamically determined by the data distribution.

Appendix D. Operation Quantity

Table 5: Operations for different networks

|                      | AlexNet | ResNet50 | MobileNet-v2 | VGG16  |
|----------------------|---------|----------|--------------|--------|
| Forward              | 3.78E+11| 1.78E+12 | 1.54E+11     | 7.93E+12|
| Forward Quantification| 6.95E+08| 1.01E+10 | 8.68E+09     | 1.24E+10|
| Backward             | 1.78E+12| 5.37E+12 | 4.41E+11     | 2.88E+13|
| Backward Quantification| 1.90E+09| 3.39E+10 | 2.57E+10     | 4.70E+10|

Appendix E. Speedup over int16

There is 1.3 times speedup over int16 on CPU for AlexNet (1.13 times speedup for backward and 1.7 times speedup for forward). The int16 x int8 in our method is implemented as int16 x int16 on Xeon Gold 6154. With flexible arithmetic operations like int16 x int8 on future hardware, higher training speedup is promising.