Towards Lower Bit Multiplication for Convolutional Neural Network Training

NICSEFC
2020.02.13
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Introduction

• Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks[1][2].
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- The training process could consume up to hundreds of ExaFLOPs of computations and tens of GBytes of memory storage.

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<th>Res20</th>
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<td>1.20E+07</td>
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</tr>
<tr>
<td>Params Update (B)</td>
<td>Add</td>
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Introduction

• Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks[1][2].

• The training process could consume up to hundreds of ExaFLOPs of computations and tens of GBytes of memory storage.

• Quantization in training has potential in significantly reducing both the memory and computational complexity.
Related Work

• Post-Training Quantization
• Quantize-Aware Training
• Low-Bit Training
Related Work: Post-Training Quantization

- Deep Compression[3] 8-bit -<1%
  - Larger weights plays more important role than smaller weights.
  - Finetuning shared Quantized weights brings improvement.
Related Work: Post-Training Quantization

• POST\cite{4} 4-bit -2.7%
  • Analyze of clip value.
  • Bit-allocation per-channel.
  • Bias correction

\[
E[(X - Q(X))^2] \approx 2 \cdot b^2 \cdot e^{-\frac{\alpha}{b}} + \frac{2 \cdot \alpha^3}{3} \cdot \sum_{i=0}^{2^M-1} f(q_i) = 2 \cdot b^2 \cdot e^{-\frac{\alpha}{b}} + \frac{\alpha^2}{3 \cdot 2^{2M}}
\]
Related Work

• Post-Training Quantization\(^3\)[\(^4\)]
  • Achieve good accuracy with 4-bit when inference after float training.
  • But the optimization is complex.
  • Prove the quantized model could have the same representation ability.

• Quantize-Aware Training

• Low-Bit Training
Related Work: Quantize-Aware Training

• DoReFa-Net\cite{6} 8-bit -2.9%
  • The first one to quantize gradient and error in training.
  • Nonlinear weights quantization.

\[
\text{Forward: } r_o = f^k_\omega(r_i) = 2 \text{quantize}_k\left(\frac{\tanh(r_i)}{2 \max(|\tanh(r_i)|)} + \frac{1}{2}\right) - 1.
\]

\[
\text{Backward: } \frac{\partial c}{\partial r_i} = \frac{\partial r_o}{\partial r_i} \frac{\partial c}{\partial r_o}^4
\]

• Scaled by max when quantizing gradient.

\[
\tilde{f}^k_\gamma(dr) = 2 \max_0(|dr|) \left[\text{quantize}_k\left(\frac{dr}{2 \max_0(|dr|)} + \frac{1}{2}\right) - \frac{1}{2}\right].
\]
Related Work: Quantize-Aware Training

• PACT\(^5\) 4-bit -1%
  • Training the clip value of activation as a parameter.
  • Not really quantized in training.

\[
y = PACT(x) = 0.5(|x| - |x - \alpha| + \alpha) = \begin{cases} 
0, & x \in (-\infty, 0) \\
x, & x \in [0, \alpha) \\
\alpha, & x \in [\alpha, +\infty)
\end{cases}
\]

\[
\frac{\partial y_q}{\partial \alpha} = \frac{\partial y_q}{\partial y} \frac{\partial y}{\partial \alpha} = \begin{cases} 
0, & x \in (-\infty, \alpha) \\
1, & x \in [\alpha, +\infty)
\end{cases}
\]
Related Work

• Post-Training Quantization
• Quantize-Aware Training\[5][6]
  • Find the best quantized parameter during training.
  • Usually for ultra low-bit networks.
  • Not really care about the training cost.
• Low-Bit Training
Related Work: Low-Bit Training

- RangeBN\cite{8} 8(16)-bit <-2%
  - Using range to estimate variance in BN.
  - Double-precision for (W,E) Conv.
  - GEMMLOWP quantization with bias in training.
  - Can not really simplify the computation.
Related Work: Low-Bit Training

- HFP8\cite{9} 8-bit < -1%
  - 1-5-2 in inference and 1-4-3 in back propagation.
  - Exponent bias of error.
  - FP16 for depth-wise convolution.
Related Work

• Post-Training Quantization
• Quantize-Aware Training
• Low-Bit Training[7][8][9]
  • Some earlier studies have significant accuracy drop.
  • 8-bit fixed-point is realized without well consideration of hardware costs.
  • Training with hyper 8-bit floating could achieve the same accuracy.
Our Methods

• Basic Quantization Method
• Shiftable Fixed-Point Data Format
• Constrained Group-Wise Scaling
• Double-Precision Deployment
Our Methods

Training

Quantization
Group-Wise Scaling
(Better representation ability with low hardware cost)
- Group Statistics
- Same/Simple Mantissa Scale
Shiftable Fixed-Point Data Format
(Wider dynamic range with same bit width)
- Pre-Shift According to Scale
- Mark Extra Bit

High Bit Width Data
Scale
Recover Precision by Multiplying Scale
1 Extra Bit
Shift L Bit
1 Extra Bit
N-Bit Multiplication
N Bit Data
N Bit Data
x2

Deployment

Double Precision Deployment
(Higher performance with same computing unit)
Fetch 2N Bits From Weight Buffer
Quantization
Extra Bit
2N Bit Data
Scale
Modify Dataflow Arrangement
Our Methods: Basic Quantization Method

• The **multiplications in convolution** account for the main computational cost of the CNN training process.

• Our goal is to use low-bit fixed-point multiplication to calculate all three types of convolution: (W,A) (W,E) and (A,E).
Our Methods: Basic Quantization Method

• The unbiased but scaled quantization method is used.

\[ Fix = \text{quantize}(\text{float}) = \text{Round}(\text{Clip}(\frac{\text{float}}{\text{scale}}, 2^N)) \]

• The stochastic rounding is used instead of rounding to the nearest[10].

\[
\text{Round}(x) = \begin{cases} 
[x] & \text{w.p. } x - [x] \\
[x] & \text{w.p. } [x] - x
\end{cases}
\]
Our Methods
Our Methods: Shiftable Fixed-Point Data Format

• One of the challenges in quantization is to balance the overflow error and the rounding error.
Our Methods: Shiftable Fixed-Point Data Format

• Get lower N bits of values less than \( max \times 2^{-L} \) in quantization, so that more significant bits can be remained.

• Need one extra bit to mark which value is shifted, but no need to involve in multiplication.
Our Methods

Training

Quantization
Group-Wise Scaling
(Better representation ability with low hardware cost)
- Group Statistics
- Same/Simple Mantissa Scale

Shiftable Fixed-Point Data Format
(Wider dynamic range with same bit width)
- Pre-Shift According to Scale
- Mark Extra Bit

High Bit Width Data

Scale → Recover Precision by Multiplying Scale

1 Extra Bit → Shift L Bit → 1 Extra Bit

N-Bit Multiplication

N Bit Data → x2

Deployment

Double Precision Deployment
(Higher performance with same computing unit)
- Fetch 2N Bits From Weight Buffer
- Quantization
- Extra Bit
- 2N Bit Data
- Scale
- Modify Dataflow Arrangement
Our Methods

Training
- Quantization
  - Group-Wise Scaling
    - Better representation ability with low hardware cost
    - Group Statistics
    - Same/Simple Mantissa Scale
  - Shiftable Fixed-Point Data Format
    - Wider dynamic range with same bit width
    - Pre-Shift According to Scale
    - Mark Extra Bit
- Scale
- Recover Precision by Multiplying Scale
- N-Bit Multiplication
- N Bit Data

Deployment
- Double Precision Deployment
  - Higher performance with same computing unit
  - Fetch 2N Bits From Weight Buffer
  - Quantization
  - Extra Bit
  - 2N Bit Data
  - Scale
  - Modify Dataflow Arrangement
  - x2

High Bit Width Data
- Scale
Our Methods: Constrained Group-Wise Scaling

• $W, A, E$ to be quantized are 4-D tensors in training process.
• Data ranges are *quite various* in different groups.
Our Methods

Group-Wise Scaling
(Exclusive representation ability)

- Mark Extra Bit
- Shiftable Fixed-Point Data Format
- Same/Simple Mantissa Scale
- Group Statistics

Training

- N-Bit Data
- N-Bit Multiplication
- Shift L Bit
- 7 Extra Bit
- Scale

Deployment

- Double Precision Deployment
- Fetch 2N Bits From Weight Buffer
- Quantization
- 2N Bit Data
- Scale

- Modify Dataflow Arrangement
- Extra Bit
- Modify Extra Bit

- N-Bit Data
- ×2
- High Bit Width Data
- Recover Precision by Multiplying Scale
- Scale

- Higher precision with same computing unit
- N-Bit Data
Our Methods: Constrained Group-Wise Scaling

- Simple group-wise floating-point scaling are not hardware friendly.

- Numbers to be added with different scale have to be convert to floating-point.

\[
float_i = scale_i \times Fix_i
\]

\[
float_{00} + float_{01} = (Fix_{00} \times Man_{0}) \times 2^{Exp_0} \\
+ (Fix_{01} \times Man_{1}) \times 2^{Exp_1}
\]
Our Methods: Constrained Group-Wise Scaling

• The **same mantissa scale** means that we select scales of different groups from the list of \( \max, \frac{1}{2} \max, \frac{1}{4} \max \cdots \)

• They have the same mantissa that can be processed separately.

\[
\text{float}_{00} + \text{float}_{01} = \text{Mantissa} \times (\text{Fix}_{00} \times 2^{\text{Exp}_0} + \text{Fix}_{01} \times 2^{\text{Exp}_1})
\]
Our Methods: Constrained Group-Wise Scaling

• The **simple mantissa scale** is to use different scales with simple mantissa.

• Multiplication between Fix and Man would be *simplified* to an addition.
Our Methods: Double-Precision Deployment

- There is a **high-bit copy** of weights in the training process.
- We can boost the performance of the quantized model by quantize high-bit data to double low-bit data, **without any extra training**.
Our Methods

Training

- Quantization
- Group-Wise Scaling
  - Better representation ability with low hardware cost
  - Group Statistics
  - Same/Simple Mantissa Scale

- Shiftable Fixed-Point Data Format
  - Wider dynamic range with same bit width
  - Pre-Shift According to Scale
  - Mark Extra Bit

Deployment

- Double Precision Deployment
  - Higher performance with same computing unit
  - Fetch 2N Bits From Weight Buffer
  - Quantization
  - Extra Bit
  - 2N Bit Data
  - Scale
  - Modify Dataflow Arrangement

High Bit Width Data

- Scale
  - Recover Precision by Multiplying Scale
  - 1 Extra Bit
    - Shift L Bit
  - 1 Extra Bit

N-Bit Multiplication

- x2
- N Bit Data
Some Experimental results

• Comparation on ImageNet[6][7][8][9]

<table>
<thead>
<tr>
<th>Method</th>
<th>Bit-Width (W/A/E)</th>
<th>Model</th>
<th>Accuracy</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>DoReFa (Zhou et al., 2016)</td>
<td>8 8 8</td>
<td>AlexNet</td>
<td>53.0%</td>
<td>55.9%</td>
</tr>
<tr>
<td>WAGE (Wu et al., 2018)</td>
<td>2 8 8</td>
<td>AlexNet</td>
<td>48.4%</td>
<td>56.0%</td>
</tr>
<tr>
<td>RangeBN (Banner et al., 2018a)</td>
<td>8 8 16</td>
<td>ResNet-18</td>
<td>66.4%</td>
<td>67.0%</td>
</tr>
<tr>
<td>HFP8 (Mellempudi et al., 2019)</td>
<td>8f 8f 8f</td>
<td>ResNet-18</td>
<td>69.0%</td>
<td>69.3%</td>
</tr>
<tr>
<td>Ours</td>
<td>8 8 8</td>
<td>ResNet-18</td>
<td>69.1%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Ours</td>
<td>6 6 6</td>
<td>ResNet-18</td>
<td>67.4%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Ours</td>
<td>4 4 4</td>
<td>ResNet-18</td>
<td>63.2%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Ours-Double</td>
<td>6 6 6</td>
<td>ResNet-18</td>
<td>68.2%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Ours-Double</td>
<td>4 4 4</td>
<td>ResNet-18</td>
<td>64.9%</td>
<td>69.7%</td>
</tr>
</tbody>
</table>
Some Experimental results

- Shiftable fixed-point data format
  - Best shifting bit for different variable are not the same.

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<tr>
<th>Shifting Bit $L$ (W/A/E)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 1 1</td>
<td>88.38%</td>
</tr>
<tr>
<td>2 1 1</td>
<td>88.56%</td>
</tr>
<tr>
<td>1 2 1</td>
<td>87.68%</td>
</tr>
<tr>
<td>1 1 2</td>
<td>88.92%</td>
</tr>
<tr>
<td>1 1 3</td>
<td>89.53%</td>
</tr>
<tr>
<td>2 1 3</td>
<td>90.63%</td>
</tr>
</tbody>
</table>
Some Experimental results

- Constrained group-wise scaling
- Simple mantissa scale works better than the others in low-bit training.

<table>
<thead>
<tr>
<th>Bit-Width</th>
<th>Float Scale</th>
<th>Group-wise Power Scale</th>
<th>Group-wise Same Mantissa Scale</th>
<th>Group-wise Simple Mantissa Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>666</td>
<td>91.26%</td>
<td><strong>91.71%</strong></td>
<td>91.55%</td>
<td>91.67%</td>
</tr>
<tr>
<td>555</td>
<td>88.87%</td>
<td>91.40%</td>
<td>91.35%</td>
<td><strong>91.68%</strong></td>
</tr>
<tr>
<td>444</td>
<td>78.95%</td>
<td>90.08%</td>
<td>90.54%</td>
<td><strong>90.66%</strong></td>
</tr>
<tr>
<td>333</td>
<td>62.50%</td>
<td>80.06%</td>
<td>82.73%</td>
<td><strong>84.29%</strong></td>
</tr>
</tbody>
</table>
Some Experimental results

- Combination of shiftable fixed-point and group-wise scaling
  - The combination scheme is the best.
Some Experimental results

- Double-precision deployment
  - Boost performance **without** any extra training.
  - Finetuning with double precision can **further** improve the accuracy.

<table>
<thead>
<tr>
<th>Bit-Width</th>
<th>Finetune</th>
<th>None</th>
<th>W</th>
<th>A</th>
<th>W+A</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 4 4</td>
<td>No</td>
<td>91.46</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3 3 3</td>
<td>No</td>
<td>89.12</td>
<td>91.41</td>
<td>90.12</td>
<td><strong>91.74</strong></td>
</tr>
<tr>
<td>2 2 2</td>
<td>No</td>
<td>87.34</td>
<td>89.14</td>
<td>88.72</td>
<td><strong>90.75</strong></td>
</tr>
<tr>
<td>2 2 2</td>
<td>Yes</td>
<td>-</td>
<td>89.34</td>
<td>89.18</td>
<td><strong>91.1</strong></td>
</tr>
</tbody>
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Discussion: Hardware Cost Estimation

• Comparation of circuit units (45nm, 0.9V)\textsuperscript{[11]}
• Statistic of computation

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<tr>
<th>Params</th>
<th>Energy(pJ)</th>
<th>Area(\mu m^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mul</td>
<td>Add</td>
</tr>
<tr>
<td>8-bit Fix</td>
<td>0.2</td>
<td>0.03</td>
</tr>
<tr>
<td>16-bit Float</td>
<td>1.1</td>
<td>0.40</td>
</tr>
<tr>
<td>32-bit Float</td>
<td>3.7</td>
<td>0.90</td>
</tr>
</tbody>
</table>

• Our algorithm has the potential to save at least 75% energy cost of the computation cost when we train ResNet-18 with $N = 8$. 

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Next

• Do more experiments on ImageNet with more networks.
  • Different experiment parameters
  • VGG, AlexNet
  • MobileNet

• Try more detailed techniques.
  • different quantization parameters for different layers
  • Shifting bit
  • Group dimension
  • Double or not

• Hardware design.
Reference


