Delta-DNN: Efficiently Compressing Deep Neural Networks via Exploiting Floats Similarity

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Neural Networks

- Deep Neural Networks are designed to solve complicated and non-linear problems
- Typical Deep Neural Networks Applications
  - **computer vision** (i.e., Image classification, Image classification + localization, Object detection, Instance Segmentation, etc.)
  - **natural language processing** (i.e., Text classification, Information retrieval, Natural language generation, Natural language understanding, etc.)
Why compress Neural Networks?

- To further improve the inference accuracy, DNNs are becoming deeper and more complicated.

A DNNs Practical Application

- To train a DNN in cloud servers with high-performance accelerators
- Then transfer the trained DNN model to the edge devices (i.e., mobile devices, IoT devices)
- The edge devices run the DNN model

Compressing Neural Networks is an effective way to reduce the transfer cost.
Data compression techniques

- Data compression techniques are especially important for data reduction.

- **Lossless compression**
  - Usually deal with data as byte streams, and reduce data at the bytes/string level based on classic algorithm such as Huffman coding, dictionary coding, etc.
  - Delta compression observes the high data similarity (data redundancy), then only records the delta data for space savings.

- **Lossy compression**
  - Typical lossy compressors are for images, such as JPEG2000.
  - Lossy compression of floating-point data from HPC, such as ZFP, SZ, etc.
  - SZ lossy compression with a data-fitting predictor and a point-wise error bound controlled quantizator.
Compressing DNNs

- Compressing DNNs means compressing a large amount of very random floating-point numbers

- Special technologies for compressing DNNs
  - Pruning (removing some unimportant parameters)
  - Quantization (transforming the floats parameters into low bits numbers)
Observation and motivation

- The floating-point numbers of the neighboring networks are very similar
  - Linear fitting close to $y = x$ & SSIM close to 1.0
Observation and motivation

➢ Motivation

• Inspired by the delta compression technique, we calculate the delta data of the similar floats between two neighboring neural networks.

• We employ the ideas of error-bound SZ lossy compression, i.e., a data-fitting predictor and an error-controlled quantizator, to compress the delta data.
Overview of Delta-DNN framework

- **Calculating the Delta Data**: calculate the lossy delta data of the target and reference networks (including all layers).
- **Optimizing the Error Bound**: select the suitable error bound used for maximizing the lossy compression efficiency.
- **Compressing the Delta Data**: reduce the delta data size by using lossless compressors.
Calculating the Delta Data

- Following the idea of SZ lossy compressor
  
  - Calculate and quantize
    
    \[ M_i = \left\lfloor \frac{A_i - B_i}{2 \cdot \log(1 + \epsilon)} + 0.5 \right\rfloor \]

  - Recover the parameters
    
    \[ A_i' = 2 \cdot M_i \cdot \log(1 + \epsilon) + B_i \]

\( A_i \) is a parameter from target network, \( B_i \) is the corresponding parameters from reference network, \( \epsilon \) is the predefined relative error bound, and is an integer for recording the delta data of \( A_i \) and \( B_i \).
How to get a reasonable relative error bound to maximize the compression ratio without compromising DNNs’ inference accuracy?

- **Two key metrics**: compression ratio, inference accuracy loss

The impact of inference accuracy with different error bounds
Optimizing the Error Bound

Our solution:

- Collecting the results of compression ratio and the inference accuracy degradation along with the available error bounds
- Assessing the collected results to select an optimal error bound according to Formula as below

\[ Score = \alpha \cdot \Phi + \beta \cdot \Omega, \quad (\alpha + \beta = 1) \]
Compressing the Delta Data

➢ To further reduce the delta data space
  • Zstd
  • LZMA
  • Run-Length Encoding (RLE) + Zstd
  • Run-Length Encoding (RLE) + LZMA

Compression ratios of Delta-DNN running 4 compressors
Optimizing Network Transmission for DNNs

- DNNs are trained on the server and deployed locally on the client (such as mobile device and IoT device)
  - **Bottleneck:** network transmission for DNNs

Delta-DNN for reducing network transmission
Saving Storage Space for DNNs

- In some situations, DNNs need to be continuously trained and updated
  - Transfer Learning
  - Incremental Learning

- Saving multiple snapshots or versions of DNNs
  - Using Delta-DNN to save storage space

Delta-DNN for reducing storage cost
Experimental Setup

- **Hardware and Software**
  - a NVIDIA TITAN RTX GPU with 24 GB of memory.
  - an Intel Xeon Gold 6130 processor with 128 GB of memory.
  - Pytorch deep learning framework.
  - SZ lossy compression library.

- **DNNs and Datasets**
  - CIFAR-10 dataset.
Compression Performance of Delta-DNN

- **Compression ratio results of the four compressor on six popular DNNs** (Default relative inference accuracy loss less than 0.2%)

<table>
<thead>
<tr>
<th>Networks</th>
<th>Original Size</th>
<th>Compression Ratio (and the error bound)</th>
<th>Inference Accuracy (and the differences)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LZMA</td>
<td>Zstd</td>
</tr>
<tr>
<td>VGG-16</td>
<td>56.2 MB</td>
<td>1.096</td>
<td>1.088</td>
</tr>
<tr>
<td>ResNet101</td>
<td>162.6 MB</td>
<td>1.098</td>
<td>1.078</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>23.6 MB</td>
<td>1.097</td>
<td>1.078</td>
</tr>
<tr>
<td>EfficientNet</td>
<td>11.3 MB</td>
<td>1.099</td>
<td>1.078</td>
</tr>
<tr>
<td>MobileNet</td>
<td>8.9 MB</td>
<td>1.101</td>
<td>1.077</td>
</tr>
<tr>
<td>ShuffleNet</td>
<td>3.5 MB</td>
<td>1.097</td>
<td>1.076</td>
</tr>
</tbody>
</table>

Delta-DNN achieves about **2x~10x** higher compression ratio compared with the state-of-the-art approaches, LZMA, Zstd, and SZ.
Case 1: Optimizing Network Transmission

- Using **Delta-DNN** to reduce network transmissions

Delta-DNN **significantly reduces** the network consumption of six neural networks.

The network bandwidth data is from the global average network bandwidth on SPEEDTEST in January 2020.
Case 2: Saving Storage Space

- Using **Delta-DNN** to save storage space

Storage space consumption before and after using Delta-DNN

<table>
<thead>
<tr>
<th>Network</th>
<th>Epochs</th>
<th>Total Size</th>
<th>Comp. Ratio</th>
<th>Accuracy Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG-16</td>
<td>95</td>
<td>5.21 GB</td>
<td>693 MB</td>
<td>7.702 -0.0003%</td>
</tr>
<tr>
<td>ResNet101</td>
<td>89</td>
<td>14.1 GB</td>
<td>2.18 GB</td>
<td>6.488 -0.0015%</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>83</td>
<td>1.91 GB</td>
<td>191 MB</td>
<td>10.259 -0.0009%</td>
</tr>
<tr>
<td>EfficientNet</td>
<td>110</td>
<td>1.21 GB</td>
<td>208 MB</td>
<td>5.946 0.0001%</td>
</tr>
<tr>
<td>MobileNet</td>
<td>115</td>
<td>1.00 GB</td>
<td>140 MB</td>
<td>7.311 -0.0004%</td>
</tr>
<tr>
<td>ShuffleNet</td>
<td>113</td>
<td>391 MB</td>
<td>73 MB</td>
<td>5.302 0</td>
</tr>
</tbody>
</table>

Delta-DNN can effectively reduce the storage size by 5x~10x, while the average inference accuracy loss is negligible.
Conclusion and future work

- **Delta-DNN**
  - A novel delta compression framework for DNNs, called Delta-DNN, which can significantly reduce the size of DNNs by exploiting the floats similarity existing in neighboring networks in training.
  - Our evaluation results on six popular DNNs suggest Delta-DNN achieves 2x~10x higher compression ratio compared with Zstd, LZMA, and SZ approaches.
  - Controllable between inference accuracy and compression ratio.

- **Future work**
  - Evaluate our proposed Delta-DNN on more neural networks and more datasets.
  - Further improve the compression ratio combining other model compression techniques.
  - Extend Delta-DNN framework into more scenarios, like deep learning in the distributed systems.
Thank you!