

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

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- Observation and motivation

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- Breakdown details in Delta-DNN framework
- > Typical application scenarios
- Performance evaluation



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





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







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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 errorcontrolled 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, ϵ is the predefined relative error bound, and is an integer for recording the delta data of A_i and B_i .

convert float-point numbers to integers & most integers are equal to zero



Optimizing the Error Bound

How to get a reasonable relative error bound to maximize the compression ratio without compromising DNNs' inference accuracy?





Optimizing the Error Bound



The impact of compression ratio with different error bounds

> 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 =
$$\alpha \cdot \Phi + \beta \cdot \Omega$$
, $(\alpha + \beta = 1)$



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 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.
- VGG-16, ResNet101, GoogLeNet, EfficientNet, MobileNet, and ShuffleNet.



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%)

Networks	Original Size	Compression Ratio (and the error bound)				Inference Accuracy (and the differences)		
		LZMA	Zstd	SZ	∆-DNN	Original	SZ	∆-DNN
VGG-16	56.2 MB	1.096	1.088	4.415 (7%)	7.394 (8%)	92.45%	92.31% (-0.15%)	92.32% (-0.15%)
ResNet101	162.6 MB	1.098	1.078	4.192 (5%)	9.341 (10%)	93.05%	92.87% (-0.19%)	93.44% (+0.42%)
GoogLeNet	23.6 MB	1.097	1.078	3.565 (2%)	7.811 (2%)	94.95%	94.88% (-0.07%)	94.95% (+0.00%)
EfficientNet	11.3 MB	1.099	1.078	3.204 (1%)	10.266 (10%)	84.82%	84.76% (-0.07%)	84.88% (+0.07%)
MobileNet	8.9 MB	1.101	1.077	3.788 (3%)	9.627 (9%)	92.68%	92.57% (-0.12%)	93.16% (+0.52%)
ShuffleNet	3.5 MB	1.097	1.076	3.192 (1%)	11.291 (10%)	86.29%	86.19% (-0.12%)	86.18% (-0.13%)

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

Notwork	Fnochs	Total	Size	Comp.	Accuracy
INCLIVITE	Epocus	Original	Δ -DNN	Ratio	Loss
VGG-16	95	5.21 GB	693 MB	7.702	-0.0003%
ResNet101	89	14.1 GB	2.18 GB	6.488	-0.0015%
GoogLeNet	83	1.91 GB	191 MB	10.259	-0.0009%
EfficientNet	110	1.21 GB	208 MB	5.946	0.0001%
MobileNet	115	1.00 GB	140 MB	7.311	-0.0004%
ShuffleNet	113	391 MB	73 MB	5.302	0

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



Inference accuracy before and after using Delta-DNN



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.



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Thank you!





