Deep Compression: Compressing Deep Neural Networks With Pruning, Trained Quantization and Huffman Coding

Song Han, Huizi Mao, William J. Dally

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Presented by: Hong Chul Nam
Seminar in Computer Architecture
Executive Summary

- **Problem**
  - Large DNNs are hard to be fitted into a resource-restraint environment
  - Current DNNs are mostly too large

- **Goal**
  - **Compress** large DNNs into a smaller one such that memory fetching is minimized

- **Key idea**
  - **Adaptive pruning** – use less weights
  - **Adaptive quantization** – use less bits per weight
  - **Huffman encoding** – use less bits per character sequence

- **Results**
  - A much smaller network able to be fitted into the mobile platform
Background, Problem & Goal
Neural Network: Theory

• What is a neural network?

Source: Csáji et al., Approximation with Artificial Neural Networks, PSU 2001
Neural Network: Training Phase (I)
Neural Network: Inference Phase (II)

Possible Layers: CNN Layer
Possible Layers: Dense Layer
Huffman Coding

- A widely-used lossless compression algorithm
- Idea:
  - Shorter sequence for frequently appearing object
  - Longer sequence for rarely appearing object
  - Sequence length determined by appearing frequency
Huffman Coding Example (I)

<table>
<thead>
<tr>
<th>Frequency</th>
<th>1</th>
<th>6</th>
<th>5</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocabulary</td>
<td>B</td>
<td>C</td>
<td>A</td>
<td>D</td>
</tr>
</tbody>
</table>

Source: https://www.programiz.com/dsa/huffman-coding
Huffman Coding Example (II)

<table>
<thead>
<tr>
<th>Frequency</th>
<th>1</th>
<th>3</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocabulary</td>
<td>B</td>
<td>D</td>
<td>A</td>
<td>C</td>
</tr>
</tbody>
</table>
Huffman Coding Example (III)

Frequency

| 4 | 5 | 6 |

Vocabulary

* A C

B D

Source: https://www.programiz.com/dsa/huffman-coding
Huffman Coding Example (IV)

Source: https://www.programiz.com/dsa/huffman-coding
Huffman Coding Example (V)

[Diagram of a Huffman tree with nodes labeled with frequencies and letters]

Source: https://www.programiz.com/dsa/huffman-coding
Huffman Coding Example (VI)

Source: https://www.programiz.com/dsa/huffman-coding
Problem I: Large File Sizes (I)

• Memory bandwidth is a scarce resource

Problem II: Large File Sizes

- Large-size applications must go through much more scrutiny to appear in the app store for download.
Problem II: Energy Consumption

• Too many memory fetching for weights!

Energy consumption per operation

SRAM cache access       Float point product       DRAM memory access

Energy (pJ)

100 – 500 x
Goal

• Compress large deep neural networks such that access to DRAM for fetching weights could be minimized
• Enable running the DNN directly on mobile devices
Goal

Memory

Computing Unit
Goal
Implementation
Overview: Three-staged Compression
Pruning: Idea

• A lot of neural networks are overparametrized
• Many weights are either zero or close to zero
• These zero-ish weights do not contribute much to the result

IF ALMOST ZERO, WHY NOT SET THEM ZERO AT ALL?
Pruning: Implementation (I)

- Train connectivity
  - Train the original dense network

- Prune Connections
  - \( \theta_{i,j} = 1_{|\theta_{i,j}| \leq T} \cdot \theta_{i,j} \) with \( T = \) threshold

- Train Weights
  - Retrain the network

- Storage in CSR format
  - Compressed Sparse Row
  - A storing format for sparse matrix
Pruning: Implementation (II)

- Train connectivity
  - Train the original dense network

- Prune Connections
  - $\theta_{i,j} = 1_{|\theta_{i,j}| \geq T} \theta_{i,j}$ with $T =$ threshold

- Train Weights
  - Retrain the network

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Pruning: Implementation (III)

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  • Train the original dense network
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- Train Weights
  - Retrain the network

- Storage in CSR format
  - Compressed Sparse Row
  - A storing format for sparse matrix
Pruning: Implementation (III)

- Train connectivity
  - Train the original dense network
- Prune Connections
  - $\theta_{i,j}$
  - STOP WHEN THE ACCURACY DECREASES TOO MUCH
- Train Weights
  - Retrain the network
- Storage in CSR format
  - Compressed Sparse Row
  - A storing format for sparse matrix
Pruning: Implementation

- Train connectivity
  - Train the original dense network
- Prune Connections
  - $\theta_{i,j} = 1_{|\theta_{i,j}| \leq T} \theta_{i,j}$ with $T =$ threshold
- Train Weights
  - Retrain the network
- Storage in CSR format
  - Compressed Sparse Row
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Quantization: Idea

A MIDDLE GROUND

High energy efficiency
Low energy efficiency
Low precision
High precision
Quantization: Implementation

- K-means clustering on weights to find centroids
- Match all weights into the corresponding centroids
Quantization: Implementation (I)

• K-means clustering on weights to find centroids
Quantization: Implementation (II)

- Use index on centroids/bins as the weight value
Quantization: Implementation (III)

- Use index on centroids/bins as gradient value
Quantization: Implementation (IV)

• Backpropagation to fine-tune the centroid
Quantization: Implementation (III)

• Use index on centroids/bins as gradient value
Quantization: Implementation (IV)

- Backpropagation to fine-tune the centroid

\[
\frac{\partial L}{\partial C_k} = \sum_{i,j} \frac{\partial L}{\partial W_{ij}} \frac{\partial W_{ij}}{\partial C_k} = \sum_{i,j} \frac{\partial L}{\partial W_{ij}} \mathbb{1}(I_{ij} = k)
\]
Quantization: Implementation (III)

• Use index on centroids/bins as gradient value
Quantization: Implementation (IV)

• Backpropagation to fine-tune the centroid
Huffman Encoding

• Each weight is represented by the index of the centroid
• A fixed vocabulary (bins/centroids for weights) with indices

LONG FOR SHORT!
SHORT FOR LONG!
Distribution of weights/indices

Figure 5: Distribution for weight (Left) and index (Right). The distribution is biased.
Sample Model

• AlexNet

Source: ImageNet Classification with Deep Convolutional Neural Networks Krizhevsky et al.
Sample Model

Source: Very Deep Convolutional Networks for Large-scale Image Recognition
Results
Results (I): Compression Ratio

- Pruning + Quantization reaches the maximum of 3% model size without accuracy loss
Results (II): Compression Ratio

Table 4: Compression statistics for AlexNet. P: pruning, Q: quantization, H: Huffman coding.

<table>
<thead>
<tr>
<th>Layer</th>
<th>#Weights</th>
<th>Weights% (P)</th>
<th>Weight bits (P+Q)</th>
<th>Weight bits (P+Q+H)</th>
<th>Index bits (P+Q)</th>
<th>Index bits (P+Q+H)</th>
<th>Compress rate (P+Q)</th>
<th>Compress rate (P+Q+H)</th>
</tr>
</thead>
<tbody>
<tr>
<td>conv1</td>
<td>35K</td>
<td>84%</td>
<td>8</td>
<td>6.3</td>
<td>4</td>
<td>1.2</td>
<td>32.6%</td>
<td>20.53%</td>
</tr>
<tr>
<td>conv2</td>
<td>307K</td>
<td>38%</td>
<td>8</td>
<td>5.5</td>
<td>4</td>
<td>2.3</td>
<td>14.5%</td>
<td>9.43%</td>
</tr>
<tr>
<td>conv3</td>
<td>885K</td>
<td>35%</td>
<td>8</td>
<td>5.1</td>
<td>4</td>
<td>2.6</td>
<td>13.1%</td>
<td>8.44%</td>
</tr>
<tr>
<td>conv4</td>
<td>663K</td>
<td>37%</td>
<td>8</td>
<td>5.2</td>
<td>4</td>
<td>2.5</td>
<td>14.1%</td>
<td>9.11%</td>
</tr>
<tr>
<td>conv5</td>
<td>442K</td>
<td>37%</td>
<td>8</td>
<td>5.6</td>
<td>4</td>
<td>2.5</td>
<td>14.0%</td>
<td>9.43%</td>
</tr>
<tr>
<td>fc6</td>
<td>38M</td>
<td>9%</td>
<td>5</td>
<td>3.9</td>
<td>4</td>
<td>3.2</td>
<td>3.0%</td>
<td>2.39%</td>
</tr>
<tr>
<td>fc7</td>
<td>17M</td>
<td>9%</td>
<td>5</td>
<td>3.6</td>
<td>4</td>
<td>3.7</td>
<td>3.0%</td>
<td>2.46%</td>
</tr>
<tr>
<td>fc8</td>
<td>4M</td>
<td>25%</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3.2</td>
<td>7.3%</td>
<td>5.85%</td>
</tr>
<tr>
<td>Total</td>
<td>61M</td>
<td>11% (9×)</td>
<td>5.4</td>
<td>4</td>
<td>4</td>
<td>3.2</td>
<td>3.7% (27×)</td>
<td>2.88% (35×)</td>
</tr>
</tbody>
</table>
Results (III): Compression Ratio


<table>
<thead>
<tr>
<th>Layer</th>
<th>#Weights</th>
<th>Weights% (P)</th>
<th>Weights bits (P+Q)</th>
<th>Weight bits (P+Q+H)</th>
<th>Index bits (P+Q)</th>
<th>Index bits (P+Q+H)</th>
<th>Compress rate (P+Q)</th>
<th>Compress rate (P+Q+H)</th>
</tr>
</thead>
<tbody>
<tr>
<td>conv1_1</td>
<td>2K</td>
<td>58%</td>
<td>8</td>
<td>6.8</td>
<td>5</td>
<td>1.7</td>
<td>40.0%</td>
<td>29.97%</td>
</tr>
<tr>
<td>conv1_2</td>
<td>37K</td>
<td>22%</td>
<td>8</td>
<td>6.5</td>
<td>5</td>
<td>2.6</td>
<td>9.8%</td>
<td>6.99%</td>
</tr>
<tr>
<td>conv2_1</td>
<td>74K</td>
<td>34%</td>
<td>8</td>
<td>5.6</td>
<td>5</td>
<td>2.4</td>
<td>14.3%</td>
<td>8.91%</td>
</tr>
<tr>
<td>conv2_2</td>
<td>148K</td>
<td>36%</td>
<td>8</td>
<td>5.9</td>
<td>5</td>
<td>2.3</td>
<td>14.7%</td>
<td>9.31%</td>
</tr>
<tr>
<td>conv3_1</td>
<td>295K</td>
<td>53%</td>
<td>8</td>
<td>4.8</td>
<td>5</td>
<td>1.8</td>
<td>21.7%</td>
<td>11.15%</td>
</tr>
<tr>
<td>conv3_2</td>
<td>590K</td>
<td>24%</td>
<td>8</td>
<td>4.6</td>
<td>5</td>
<td>2.9</td>
<td>9.7%</td>
<td>5.67%</td>
</tr>
<tr>
<td>conv3_3</td>
<td>590K</td>
<td>42%</td>
<td>8</td>
<td>4.6</td>
<td>5</td>
<td>2.2</td>
<td>17.0%</td>
<td>8.96%</td>
</tr>
<tr>
<td>conv4_1</td>
<td>1M</td>
<td>32%</td>
<td>8</td>
<td>4.6</td>
<td>5</td>
<td>2.6</td>
<td>13.1%</td>
<td>7.29%</td>
</tr>
<tr>
<td>conv4_2</td>
<td>2M</td>
<td>27%</td>
<td>8</td>
<td>4.2</td>
<td>5</td>
<td>2.9</td>
<td>10.9%</td>
<td>5.93%</td>
</tr>
<tr>
<td>conv4_3</td>
<td>2M</td>
<td>34%</td>
<td>8</td>
<td>4.4</td>
<td>5</td>
<td>2.5</td>
<td>14.0%</td>
<td>7.47%</td>
</tr>
<tr>
<td>conv5_1</td>
<td>2M</td>
<td>35%</td>
<td>8</td>
<td>4.7</td>
<td>5</td>
<td>2.5</td>
<td>14.3%</td>
<td>8.00%</td>
</tr>
<tr>
<td>conv5_2</td>
<td>2M</td>
<td>29%</td>
<td>8</td>
<td>4.6</td>
<td>5</td>
<td>2.7</td>
<td>11.7%</td>
<td>6.52%</td>
</tr>
<tr>
<td>conv5_3</td>
<td>2M</td>
<td>36%</td>
<td>8</td>
<td>4.6</td>
<td>5</td>
<td>2.3</td>
<td>14.8%</td>
<td>7.79%</td>
</tr>
<tr>
<td>fc6</td>
<td>103M</td>
<td>4%</td>
<td>5</td>
<td>3.6</td>
<td>5</td>
<td>3.5</td>
<td>1.6%</td>
<td>1.10%</td>
</tr>
<tr>
<td>fc7</td>
<td>17M</td>
<td>4%</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>4.3</td>
<td>1.5%</td>
<td>1.25%</td>
</tr>
<tr>
<td>fc8</td>
<td>4M</td>
<td>23%</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>3.4</td>
<td>7.1%</td>
<td>5.24%</td>
</tr>
<tr>
<td>Total</td>
<td>138M</td>
<td>7.5% (13×)</td>
<td>6.4</td>
<td>4.1</td>
<td>5</td>
<td>3.1</td>
<td>3.2% (31×)</td>
<td>2.05% (49×)</td>
</tr>
</tbody>
</table>
Results (IV): Speedup

- 3x speedup on CPU, 4.2x on mobile GPU and 3.5x on GPU
Results (V): Energy Efficiency

• 7x less energy on CPU, 3.3x less energy on GPU and 4.2x less energy on mobile GPU in average
Results (IV): Quantization Error

<table>
<thead>
<tr>
<th>#CONV bits / #FC bits</th>
<th>Top-1 Error</th>
<th>Top-5 Error</th>
<th>Top-1 Error Increase</th>
<th>Top-5 Error Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>32bits / 32bits</td>
<td>42.78%</td>
<td>19.73%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>8 bits / 5 bits</td>
<td>42.78%</td>
<td>19.70%</td>
<td>0.00%</td>
<td>-0.03%</td>
</tr>
<tr>
<td>8 bits / 4 bits</td>
<td>42.79%</td>
<td>19.73%</td>
<td>0.01%</td>
<td>0.00%</td>
</tr>
<tr>
<td>4 bits / 2 bits</td>
<td>44.77%</td>
<td>22.33%</td>
<td>1.99%</td>
<td>2.60%</td>
</tr>
</tbody>
</table>

- Quantization error depends on the number of bits needed to represent each centroid bin
- Critical to find the sweet spot or choose depending on the requirement
Strengths & Weaknesses
Strengths

• First paper to use Huffman encoding to code weight books and indices
• First paper to use adaptive quantization
• First paper to implement the network-wise pruning (the method was proposed in another paper from the same year from the same author)
• Applicable to not only mobile platforms but also general platforms to reduce the energy/space consumption
• Clear demonstration
Weaknesses

• Latency of computation is ignored -> CNN is essentially the bottleneck
• Performance methodology is biased
• Unstructured sparsity could hinder parallel computation
• The problem intentionally chose the neural network architecture famous for being overparametrized and sparsifiable (AlexNet)
• One must first train a densely connected DNN to operate on this network
Related Works & Current Development
DNN Compression Is a HOT HOT Topic

- Parameter pruning and quantization
  - Redundancy reduction
- Low-rank factorization
  - Low-rank decomposition/approximation SVD
- Transferred/compact convolutional filters
  - Structured convolutional filters
- Knowledge distillation
  - Train a smaller network based on the larger network

Source: A Survey of Model Compression and Acceleration for Deep Neural Networks – Cheng et al.
Pruning

- S. J. Hanson on *Comparing backpropagation and neural network construction with back-propagation* introduced weight decay.
- Srinivas and Babu et al. on *Data-free parameter pruning for deep neural networks* introduced pruning on layers.
- Han et al. on *Learning both weights and connections for efficient neural networks* introduced pruning on the entire network.
- Chen et al. on *Compressing neural networks with the hashing trick* introduced pruning with hash function to group weights for parameter sharing.
- Lebedev et al. on *Fast convnets with group-wise brain damage* introduced pruning while training by applying sparsity constraints.

Sparsification
Quantization

Approximation

• Gong et al. *Compressing deep convolutional networks using vector quantization* and Wu et al. applied k-means

• Vanhoucke et al. applied 8-bit quantization

• Han et al. applied Huffman coding to the quantized the link weights

• Choi et al. applied Hessian weight to measure the importance of weights

• BinaryConnect, BinaryNet and XNOR attempt to use only 1-bit representation

• Hou et al., Lin et al. and Cai et al. attempt to adjust the loss of precision due to binarization
Overparameterization of DNN

Predicting Parameters in Deep Learning

Misha Denil, Babak Shakibi, Laurent Dinh, Marc'Aurelio Ranzato, Nando de Freitas

Abstract

We demonstrate that there is significant redundancy in the parameterization of several deep learning models. Given only a few weight values for each feature it is possible to accurately predict the remaining values. Moreover, we show that not only can the parameter values be predicted, but many of them need not be learned at all. We train several different architectures by learning only a small number of weights and predicting the rest. In the best case we are able to predict more than 95% of the weights of a network without any drop in accuracy.

Source: Denil et al., Predicting Parameters in Deep Learning, NISP 2013
EXISTENCE OF SPARSE SUBNETS MAY BE GUARANTEED

Neural network pruning techniques can reduce the parameter counts of trained networks by over 90%, decreasing storage requirements and improving computational performance of inference without compromising accuracy. However, contemporary experience is that the sparse architectures produced by pruning are difficult to train from the start, which would similarly improve training performance.

We find that a standard pruning technique naturally uncovers subnetworks whose initializations made them capable of training effectively. Based on these results, we articulate the lottery ticket hypothesis: dense, randomly-initialized, feed-forward networks contain subnetworks (winning tickets) that—when trained in isolation—reach test accuracy comparable to the original network in a similar number of iterations. The winning tickets we find have won the initialization lottery: their connections have initial weights that make training particularly effective.

We present an algorithm to identify winning tickets and a series of experiments that support the lottery ticket hypothesis and the importance of these fortuitous initializations. We consistently find winning tickets that are less than 10-20% of the size of several fully-connected and convolutional feed-forward architectures for MNIST and CIFAR10. Above this size, the winning tickets that we find learn faster than the original network and reach higher test accuracy.
Robustness

• DNNs are often **vulnerable** to intentionally perturbed data

Panda or Gibbon? That is a big question!

Source: https://openai.com/blog/adversarial-example-research/
Robustness and Generalization

Huan Xu
Department of Electrical and Computer Engineering
the University of Texas at Austin, TX, USA

ROBUST MODELS ARE MORE GENERALIZABLE

Abstract

We derive generalization bounds for learning algorithms based on their robustness: the property that if a testing sample is “similar” to a training sample, then the testing error is close to the training error. This provides a novel approach, different from the complexity or stability arguments, to study generalization of learning algorithms. We further show that a weak notion of robustness is both sufficient and necessary for generalizability, which implies that robustness is a fundamental property for learning algorithms to work.

Source: Xu et al., Robustness and Generalization, ArXiv 2010
Robustness-Redundancy Hypothesis

MODEL SIZE DOES NOT GUARANTEE ROBUSTNESS

HOWEVER, THEY SEEM TO INCREASE ALONGSIDE EACH OTHER

Source: Anonymous, Robustness and/or Redundancy Emerge in Overparametrized Deep Neural Networks, ArXiv 2020
Accuracy of Pruned DNN over Adversarial Attacks

Source: Yiwen et al., Sparse DNNs with Improved Adversarial Robustness, NISP 2018
Discussion
## AlexNet Dimension

<table>
<thead>
<tr>
<th>Layer Type</th>
<th>Parameters</th>
<th>Flops</th>
</tr>
</thead>
<tbody>
<tr>
<td>FULL CONNECT</td>
<td>4M</td>
<td>4Mflop</td>
</tr>
<tr>
<td>FULL 4096/ReLU</td>
<td>16M</td>
<td>16M</td>
</tr>
<tr>
<td>FULL 4096/ReLU</td>
<td>37M</td>
<td>37M</td>
</tr>
<tr>
<td>MAX POOLING</td>
<td>442K</td>
<td>74M</td>
</tr>
<tr>
<td>CONV 3x3/ReLU 256fm</td>
<td>1.3M</td>
<td>224M</td>
</tr>
<tr>
<td>CONV 3x3/ReLU 384fm</td>
<td>884K</td>
<td>149M</td>
</tr>
<tr>
<td>MAX POOLING 2x2sub</td>
<td>307K</td>
<td>223M</td>
</tr>
<tr>
<td>LOCAL CONTRAST NORM</td>
<td>35K</td>
<td>105M</td>
</tr>
</tbody>
</table>

Source: Lecture Slide from Deep Learning for Autonomous Driving
Discussion (I): End-to-End Performance

• Latency/throughput is not mentioned by the paper
  • Critical for real-time processing as was targeted by the paper

• Speedup is actually... not true... (in my opinion)
  • Only densely connected layers are measured to have a significant speedup
  • Overheads are mostly in CNN layers
  • The overall throughput does not increase if the bottleneck layer is not boosted much (and so is latency)
  • How do you think that it would be fairer methodology to measure the speedup? What would you expect really from throughput by using this approach? What kind of benchmarks would make sense?
Discussion (II): Scalability/Applicability

• This is not fundamentally solving the issue of memory wall
• File sizes would **eventually increase** with current trend of increasing large/deep neural networks (e.g., GPT3)
• Same memory wall would still occur since larger models are coming in
• A lot of larger networks are becoming less sparse -> fundamental assumption in pruning
• Quantization has fundamentally inevitable information loss
• Would **near-data processing** be a better candidate for scalability?
Discussion (III): Unstructured Sparsity and Overheads

• Pruning makes DNN \textcolor{green}{unstructuredly sparse}

• Existing accelerators become inefficient because it must still perform lots of unnecessary operations on zero points in the sparse matrix

• Any remedy for it?

• Furthermore, pruning has proven to be a very expensive operation
  • (both from literature review and first-hand experience)
  • Any idea if we could create a hardware accelerator to boost it?
Discussion (IV): Quantization

• Quantization often uses **fixed bits** for each value
  • High precision requires more bits per value
• How could one improve the precision while using minimal bits per value?
• How can one enable a hardware optimization to reduce the access time for quantized values?
Discussion (V): Tradeoff between Robustness and Compactness

• As shown earlier, pruning could **harm** the robustness after a threshold

• A metrics to compensate for both accuracy loss and robustness loss is urgently needed

• Under what metrics should one prune the network?
  • Accuracy loss over the original data?
  • Accuracy loss over the adversarial data?
  • Both?
Discussions (VI): Overparameterization

• More evidences are showing that overparameterization has mysterious relationships with generalization
  • Even more with current interpretation of double gradient descent phenomenon occurring in a largely overparametrized models

• **Trade-off** between generalization and compactness must be made
  • How would you think of doing it?
Discussions (I): Sparsification

• Current solutions are only able to sparsify a neural network after it has been densely trained
• Can you think of any solution to directly prune a network without having to train the dense one first?
Backup Slides
EIE Accelerator

(2) becomes

\[ b_i = \text{ReLU} \left( \sum_{j \in X_i \cap Y} S[I_{ij}]a_j \right) \]

Figure 2. Matrix W and vectors a and b are interleaved over 4 PEs. Elements of the same color are stored in the same PE.

<table>
<thead>
<tr>
<th>Virtual Weight</th>
<th>W_{0,0}</th>
<th>W_{0,1}</th>
<th>W_{0,2}</th>
<th>W_{0,3}</th>
<th>W_{0,4}</th>
<th>W_{0,5}</th>
<th>W_{0,6}</th>
<th>W_{0,7}</th>
<th>W_{1,0}</th>
<th>W_{1,1}</th>
<th>W_{1,2}</th>
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<th>W_{1,5}</th>
<th>W_{1,6}</th>
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<td>Relative Row Index</td>
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<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
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<td>2</td>
</tr>
<tr>
<td>Column Pointer</td>
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<td>4</td>
<td>6</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>11</td>
<td>13</td>
<td>0</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>8</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 3. Memory layout for the relative indexed, indirect weighted and interleaved CSC format, corresponding to PEO in Figure 2.
EIE HW Architecture

Figure 4. (a) The architecture of Leading Non-zero Detection Node. (b) The architecture of Processing Element.
Adversarial Training + Pruning

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \Delta} L(\theta, x + \delta, y) \right]
\]

\[
\min_{\theta_i} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \Delta} L(\theta, x + \delta, y) \right] + \sum_{i=1}^{N} g_i(z_i),
\]

s.t. \( \theta_i = z_i, \ i = 1, \ldots, N. \)

\[
g_i(\theta_i) = \begin{cases} 
0 & \text{if } \theta_i \in S_i \\
+\infty & \text{otherwise}
\end{cases}
\]
Lagrangian Multiplier

\[
\mathcal{L}(\{\theta_i\}, \{z_i\}, \{u_i\}) = \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \Delta} L(\theta, x + \delta, y) \right] \\
+ \sum_{i=1}^{N} g_i(z_i) + \sum_{i=1}^{N} u_i^T(\theta_i - z_i) + \frac{\rho}{2} \sum_{i=1}^{N} \|\theta_i - z_i\|_2^2.
\]