Simulate-the-hardware: Training Accurate Binarized Neural Networks for Low-Precision Neural Accelerators

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Outline

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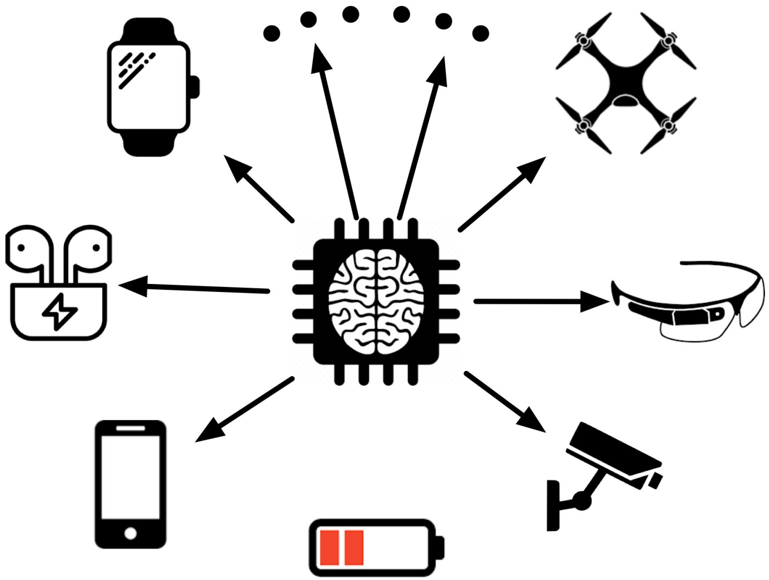
  - Problems: overflow and deviation
- Our woks: Simulate-the-hardware
  - Overflow Containing
  - Overflow/Rounding Simulating
  - BNNs Training
- Experimental Results
- Conclusions

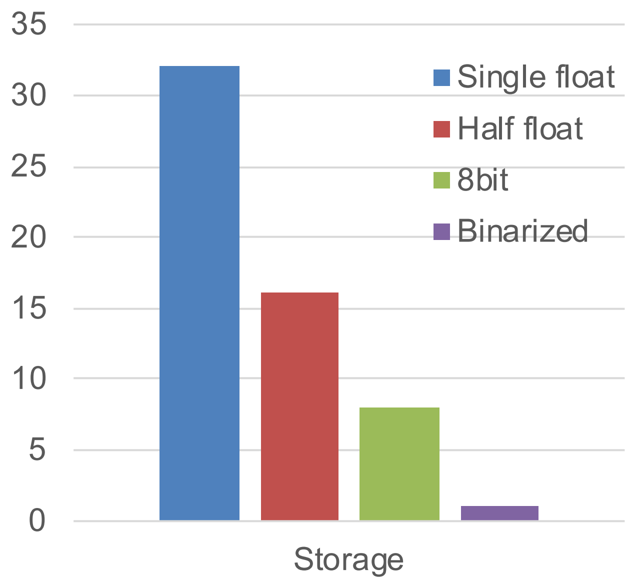
The part one

BACKGROUND & MOTIVATIONS

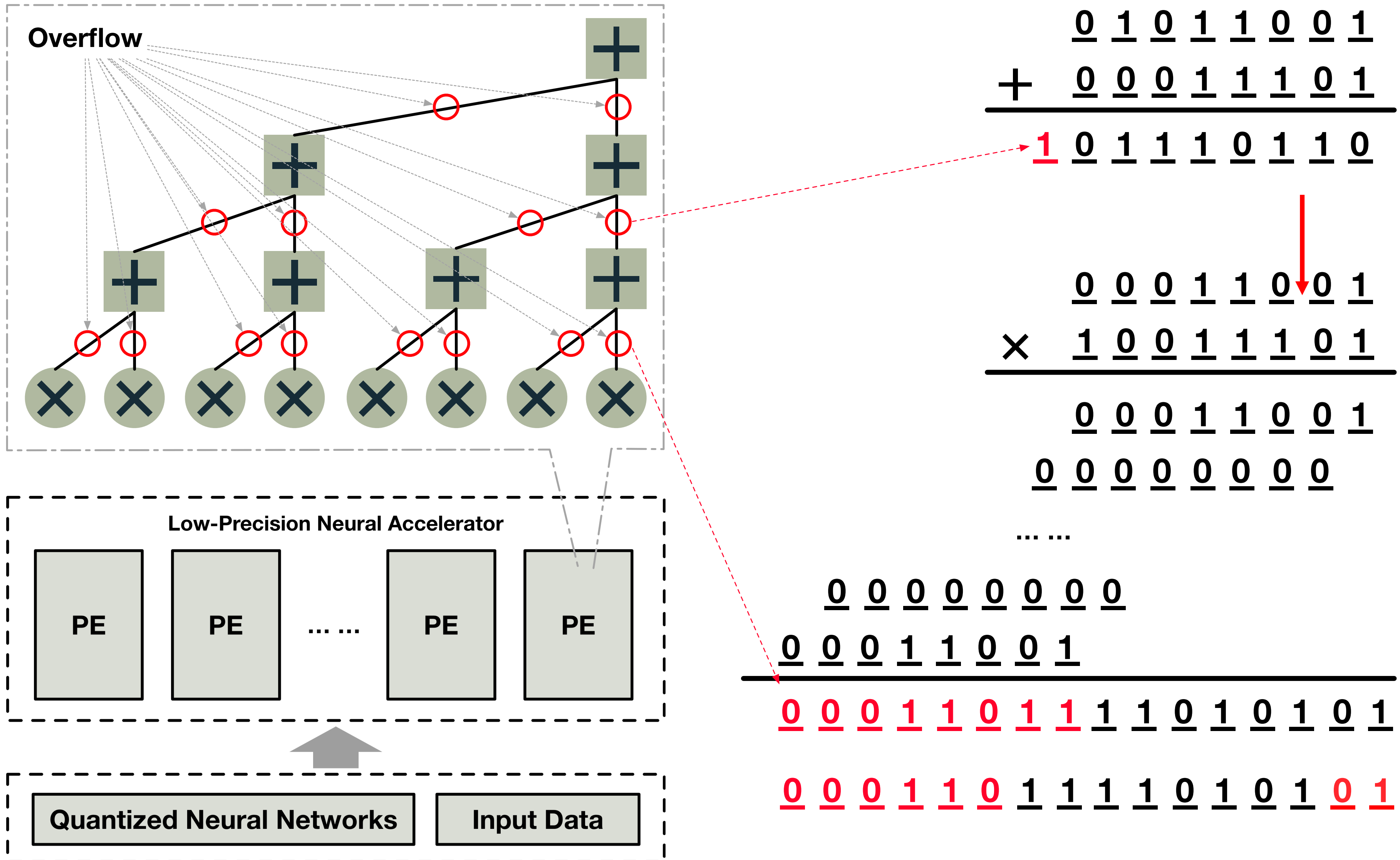
Background and Motivations

- Advantages of Binarized Neural Networks (BNNs)
  - Reduce storage requirement
  - Multiply-free computation
    - Increase calculating speed
    - Reduce chip area

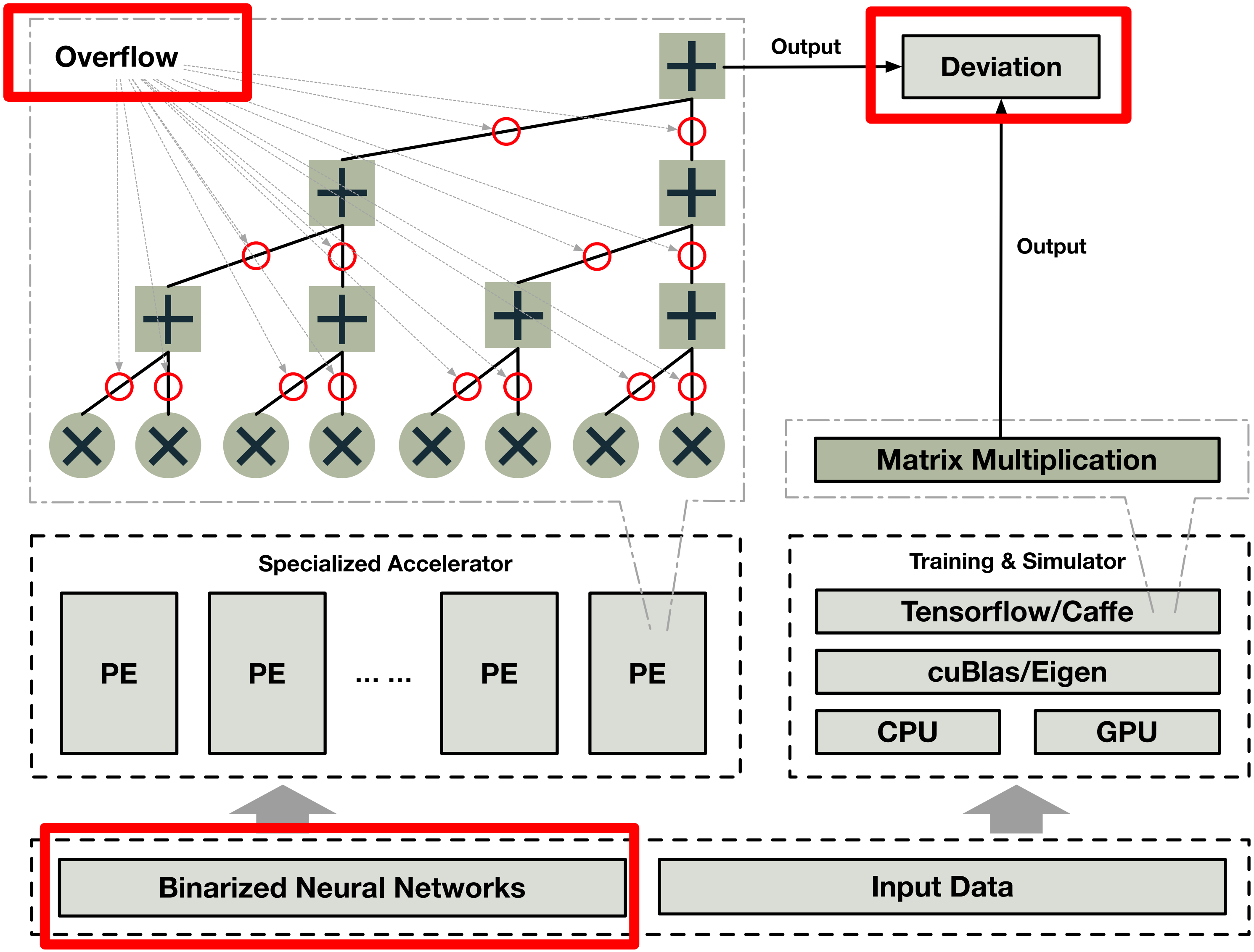




Problems: Overflow

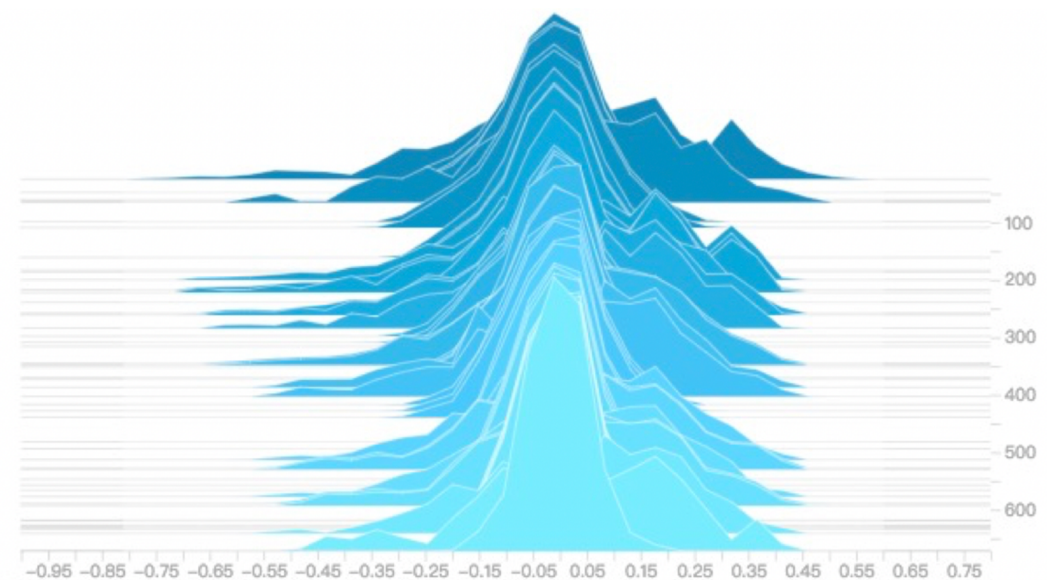


Problems: Deviation



Problems: Deviation

- Relation of overflow/rounding and deviation
  - Overflow
    - Limited-precision
    - Save energy and storage
    - Drop accuracy
  - Deviation
    - caused by overflow
    - must be eliminated
    - simulate the overflow



The part two

OUR WORKS

Our works

- Overflow containment
  - Hardware-friendly normalization layer that is at least 1.5X faster than Batch Normalization
  - Aggregated convolutional operation

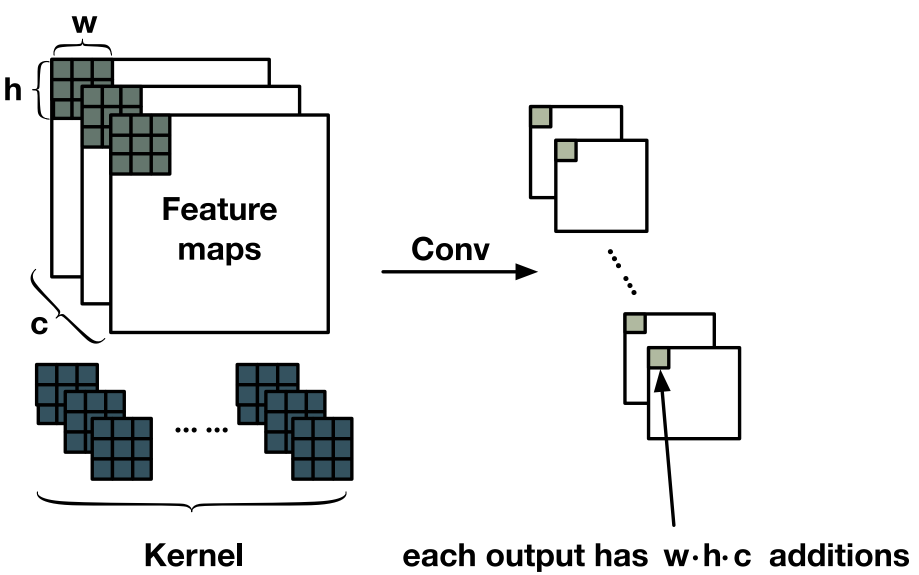
- • Overflow/rounding simulation
  - Simulate the overflow/rounding with GPU
    - 100X faster than the vanilla method
    - 80.8% slower than the original method
  - A new regularization term
    - The accuracy of our method is 12% higher compared with the past method.

Overflow Containing

- Normalization Layer Design
  - For containing overflow
    - Division
    - Support the Aggregated Convolutional Operation
  - For efficiency
    - The sigma equals 2 to the power of n

$$Norm(X) = \frac{X - \mu}{\sigma'},$$

$$\sigma' = 2^n \text{ where n is natural number}$$



Overflow Containing

- Aggregated Convolutional Operation

$$ReLU(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad HardTanh(x) = \begin{cases} 1, & x \geq 1 \\ x, & -1 \leq x < 1 \\ -1, & x < -1 \end{cases}$$

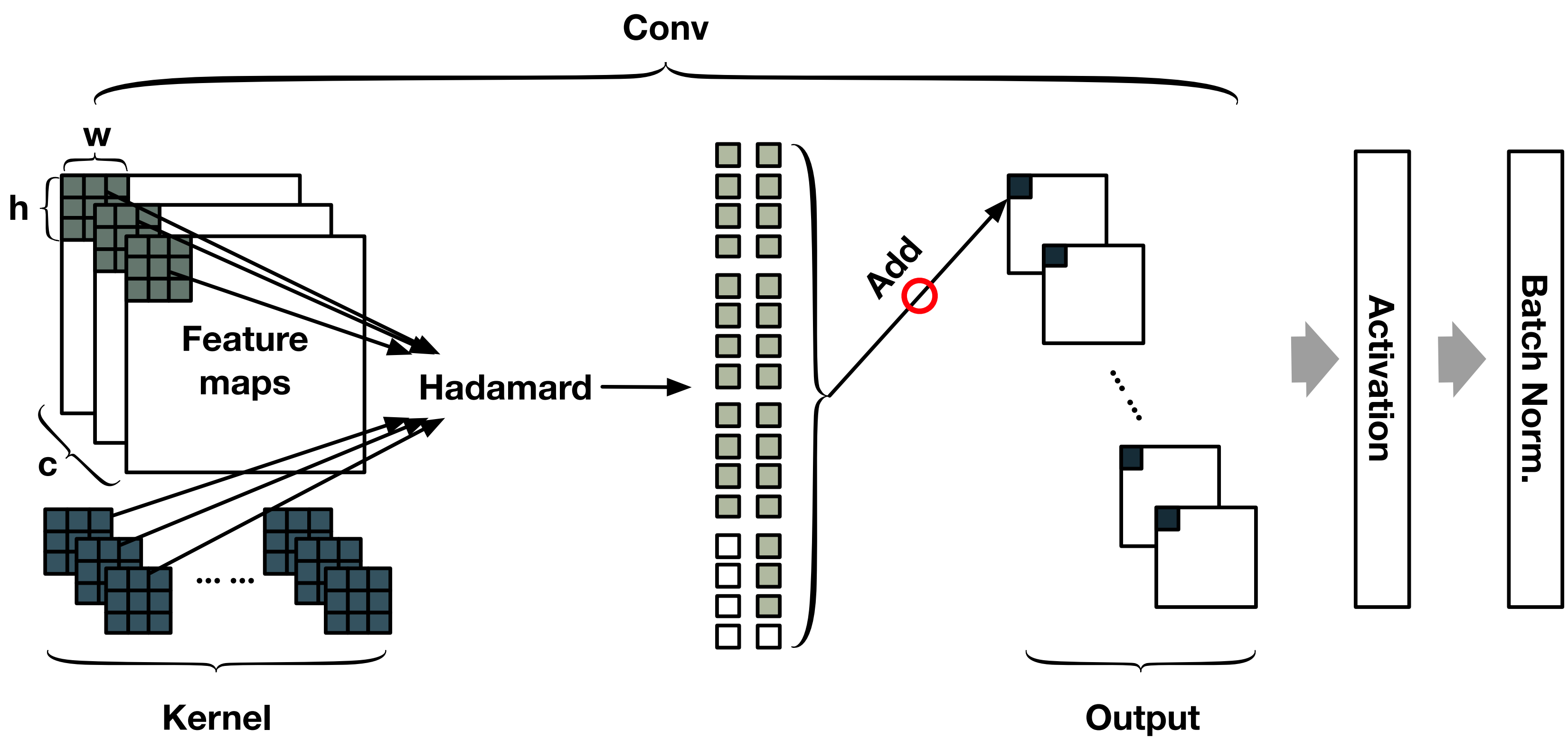
$$GP = \sum_{g}^{G} \frac{1}{\sigma'} \sum_{i} \sum_{j} W'_{ij} x'_{ij}$$

$$AC_{ReLU}(x) = \begin{cases} GP - \frac{\mu}{\sigma'}, & GP \geq 0 \\ 0, & otherwise \end{cases}$$

$$AC_{HT}(x) = \begin{cases} \frac{1}{\sigma'} - \frac{\mu}{\sigma'}, & GP \geq \frac{1}{\sigma'} \\ GP - \frac{\mu}{\sigma'}, & -\frac{1}{\sigma'} \leq GP < \frac{1}{\sigma'} \\ -\frac{1}{\sigma'} - \frac{\mu}{\sigma'}, & \frac{1}{\sigma'} < GP \end{cases}$$

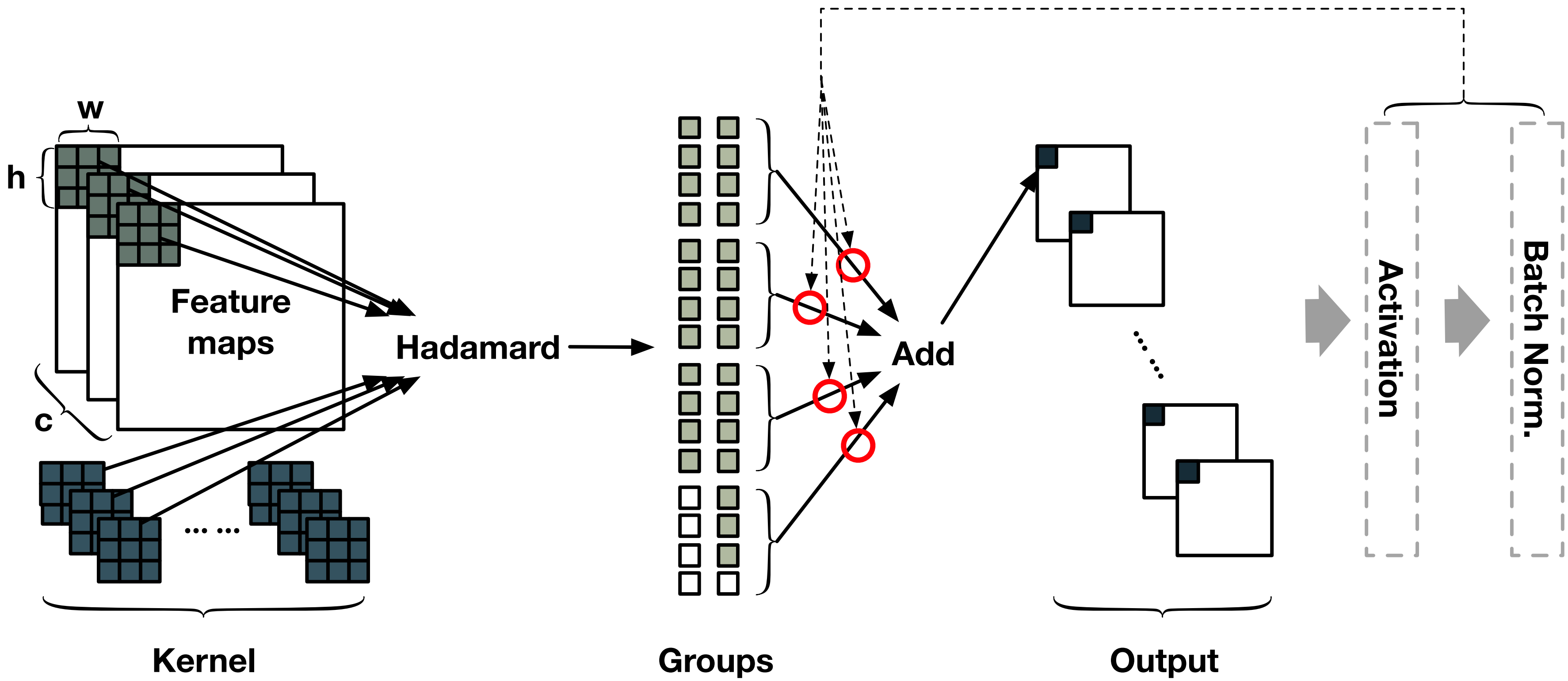
Overflow Containing

- Aggregated Convolutional Operation



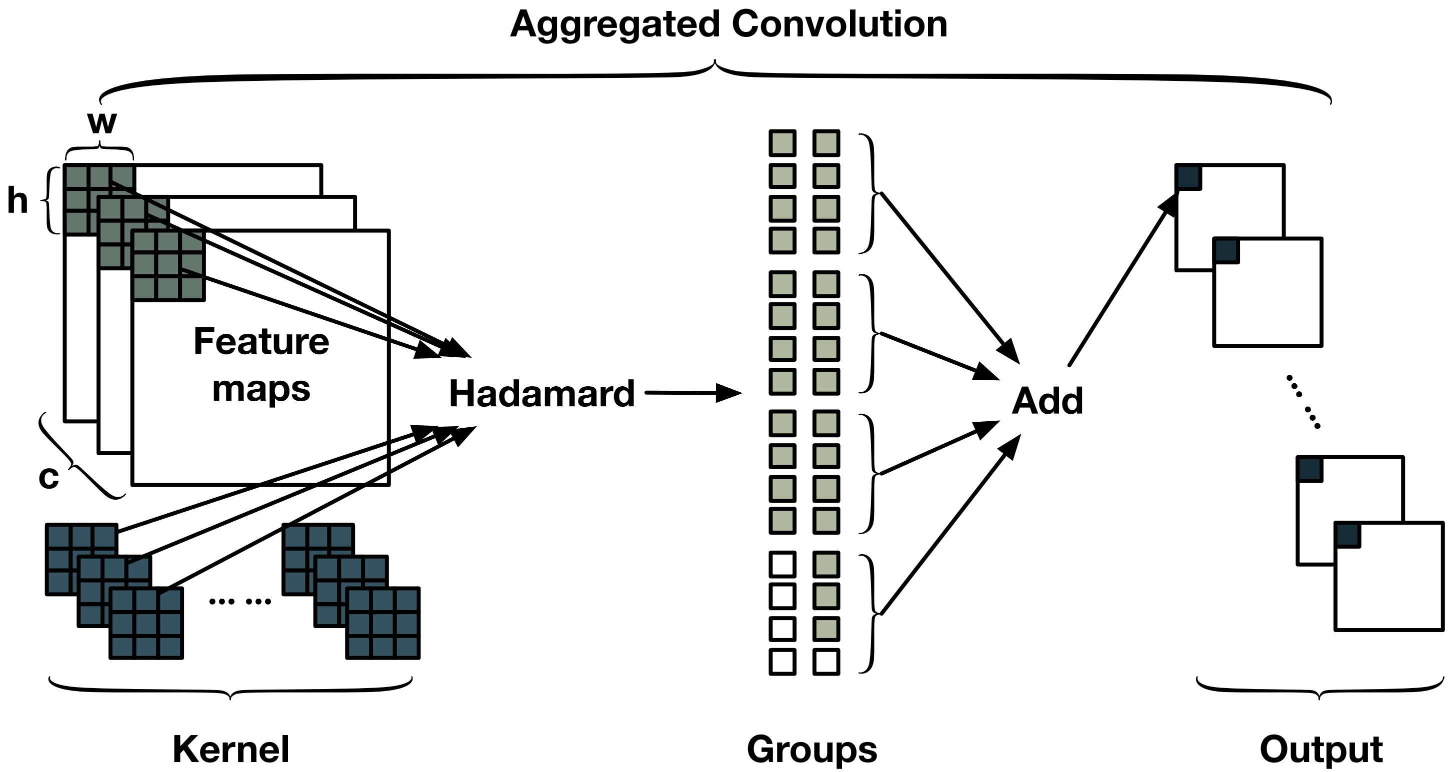
Overflow Containing

- Aggregated Convolutional Operation



Overflow Containing

- Aggregated Convolutional Operation

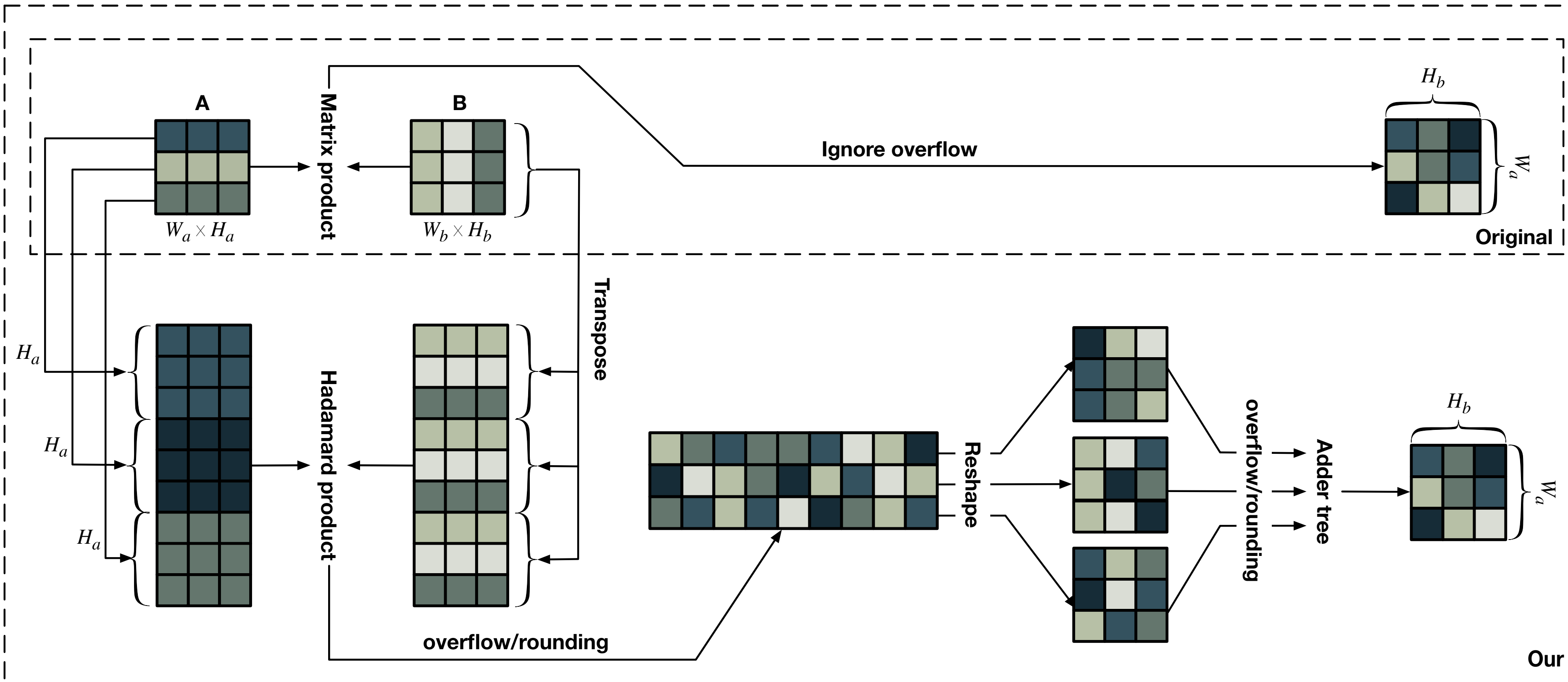


Overflow Containing

- Aggregated Convolutional Operation
  - Suppose that σ' = 4, μ = 0, G = 4 and the convolutional layer uses an 8-bit adder that the output range is [-128, 127].
  - Floating-point
    - Conv(X) = 512, ReLU(512) = 512, and Norm(512) = 128
  - Original Convolution with 8-bit adder
    - Conv(X) = 127, ReLU(127) = 127, and Norm(127) = 31
  - Aggregated Convolution with 8-bit adder
    - AConv(X) = 127/4+127/4+127/4+127/4 = 31+31+31+31 = 124

Overflow/Rounding Simulating

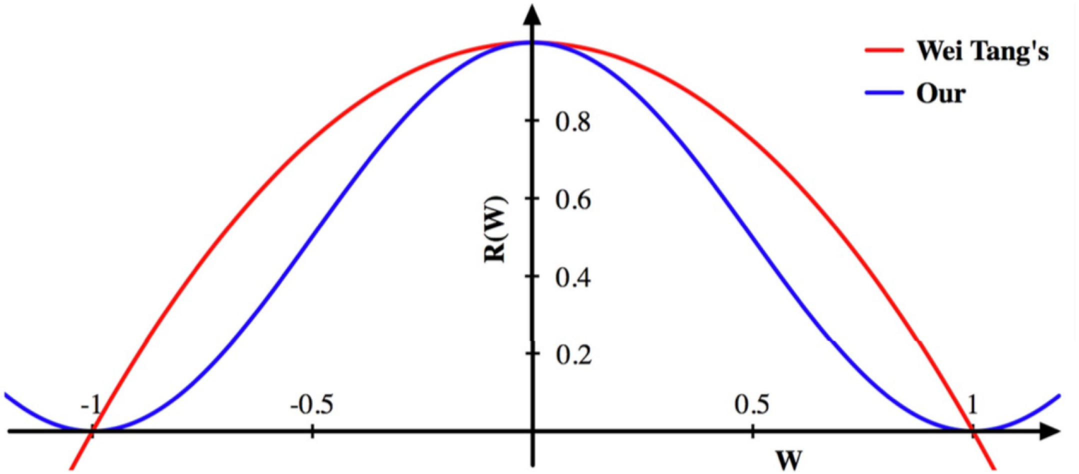
- Simulating Overflow/Rounding
  - Pytorch, Caffe, and Tensorflow
  - Illustrate with a figure



Regularization Term

$$J(W,b) = Loss(W,b) + \lambda \sum_{l=1}^{L} \sum_{i=1}^{N_l} \sum_{j=1}^{M_l} (1 - (W_{ij}^{(l)})^2)$$

$$J(W,b) = Loss(W,b) + \lambda \sum_{l=1}^{L} \sum_{i=1}^{N_l} \sum_{j=1}^{M_l} (cos(\pi W_{ij}^{(l)}) + 1)$$



The part three

EXPERIMENTAL RESULTS

Experimental Results

- Normalization Layer
  - Drop a little of accuracy
  - Improves tremendous computational speed
  - Hardware-friendly
  - Simpler architecture design

Table 1: Quantized Batch Normalization vs. Batch Normalization.

	Batch Norm.	Our
Accuracy	82.32%	72.30%
FPS	4060.45	6097.35

Experimental Results

- Regularization Term
  - AlexNet of BNN
  - Use the mentioned normalization layer

Table 2: The comparison of two regularization terms.

	Wei Tang et al.	Our
Accuracy	64.55%	72.30%

Experimental Results

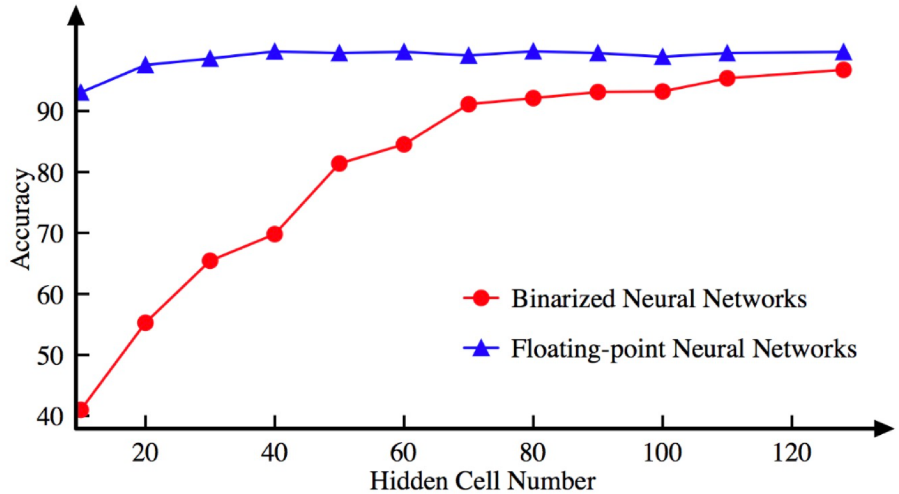
- Simulating Overflow/Rounding
  - Batch size is 128
  - Our method is 80.75% slower than the original method
  - The original almost cannot simulate overflow/rounding
  - Our method is about 100X faster than the vanilla method

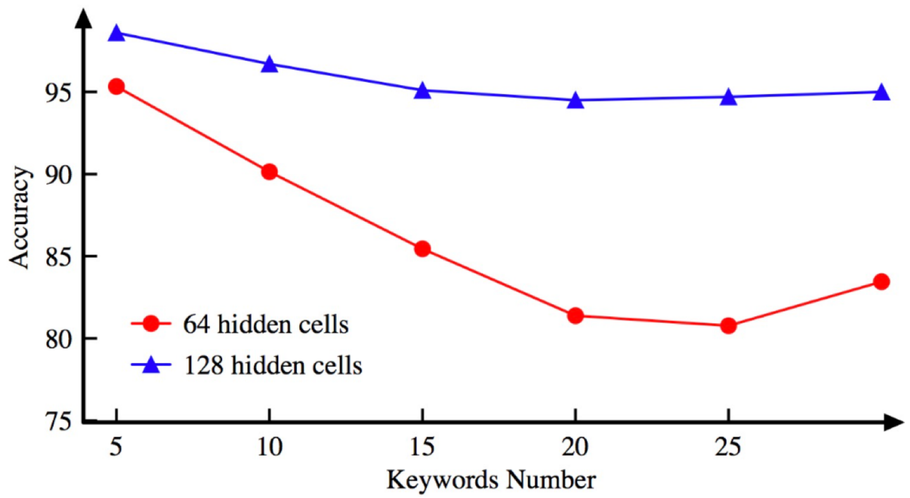
Table 4: The time-consuming of matrix product.

	Original	Vanilla	Our
Time consuming (s/batch)	1.6	840.5	8.3

Experimental Results

- Overall Evaluation
  - Keywords Spotting with BNN-LSTM
  - Dataset from Google AI
  - The affect of hidden cell number
  - The affect of keyword number





Summary

- Our Work
  - A series of the methods to contain the overflow, simulate the overflow/rounding, and train accurate BNNs for low-precision neural accelerators.
- Authors' Hope
  - The work can inspire the intelligent specialized accelerators to achieve better performance.
- My Vision
  - Let edge devices be smarter
- Acknowledgment
  - Thanks for your coming and the anonymous referees for their valuable comments and helpful suggestions.

Thank you

Q&A