MINT: Multiplier-less INTeger Quantization for Energy Efficient Spiking Neural Networks

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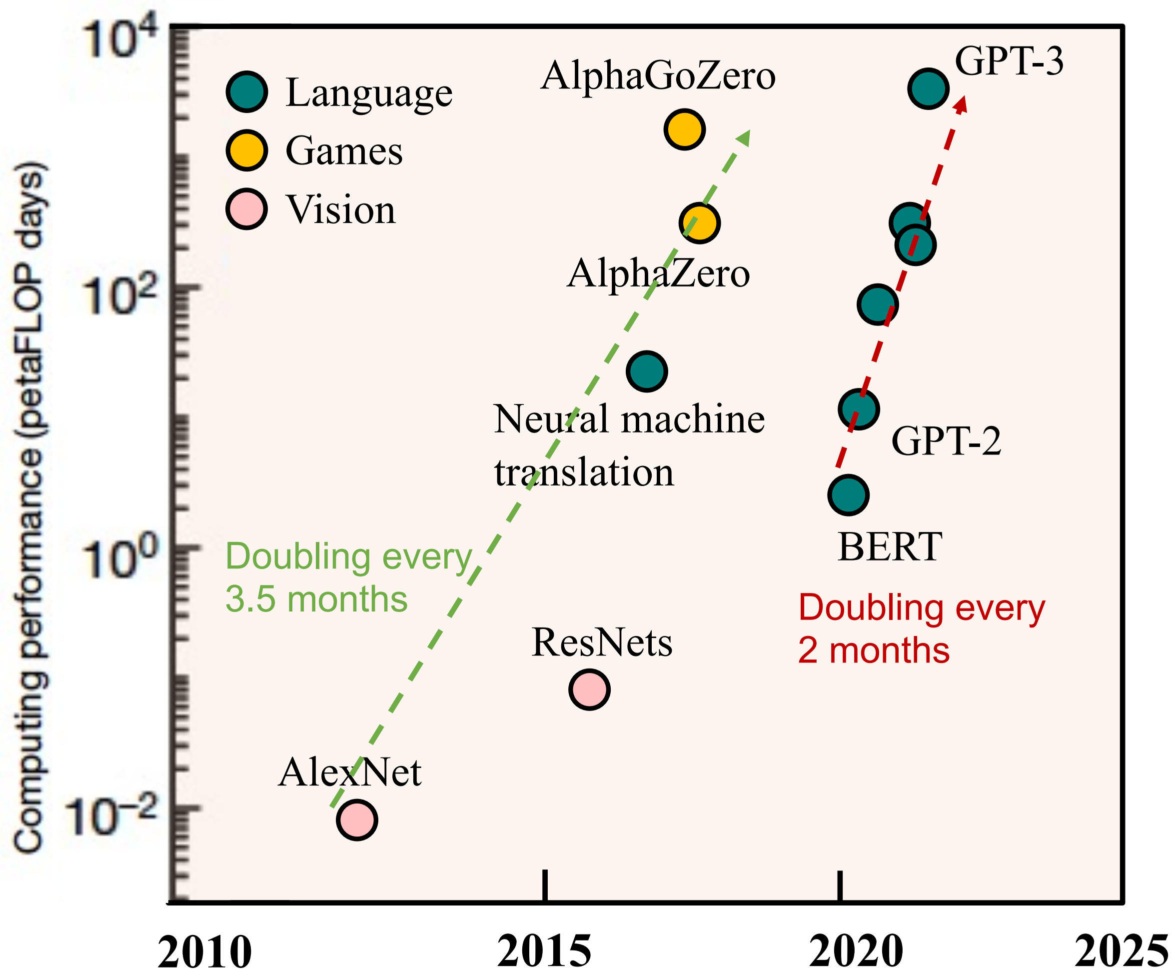
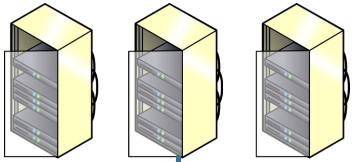
Neural Networks at GPU era



Two Ways of Processing Neural Networks

Speed ↑
Cost ↑



Speed ↓
Cost ↓

Two Ways of Processing Neural Networks

What Spiking Neural Networks (SNNs) are targeting at.

Speed ↓
Cost ↓

Two Ways of Processing Neural Networks

Speed ↓
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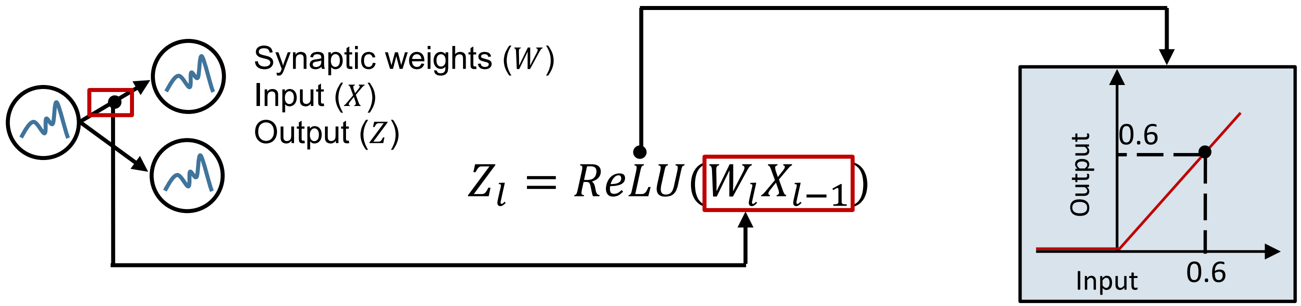
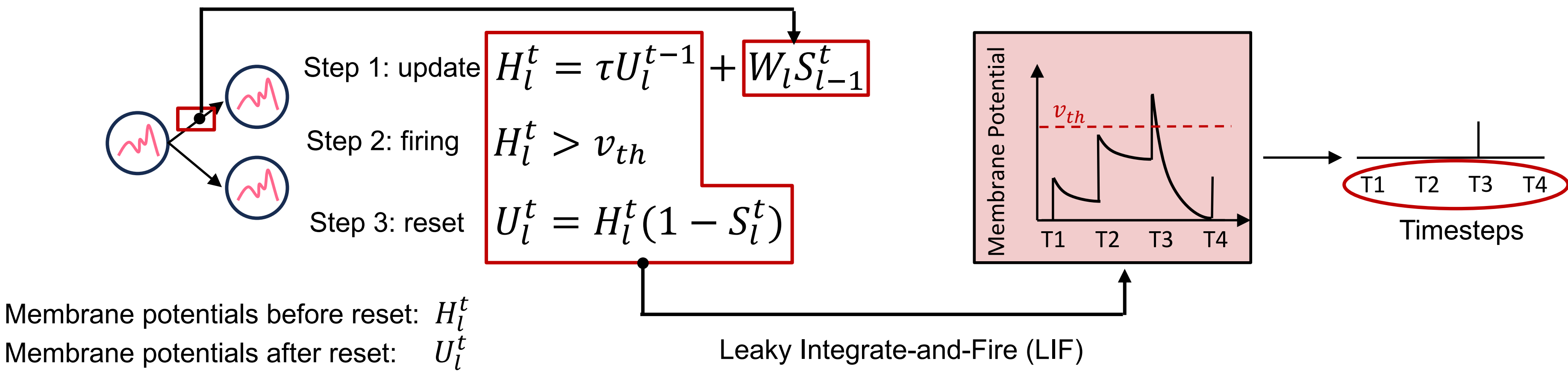
What **Spiking Neural Networks** (**SNNs**) are targeting.

Preliminary of Spiking Neural Networks

Artificial Neural Networks (ANNs)



Spiking Neural Networks (SNNs)



Preliminary of Spiking Neural Networks

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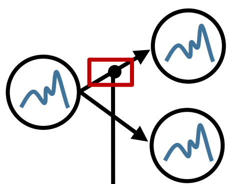
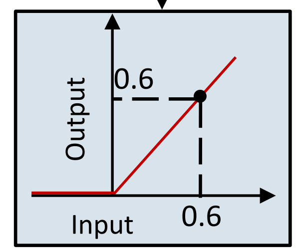
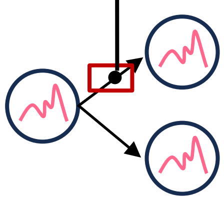


Synaptic weights (W)
Input (X)
Output (Z)

$$Z_l = ReLU(\boxed{W_l X_{l-1}})$$



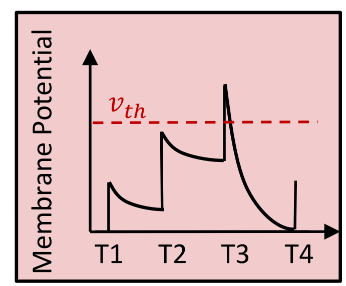
Spiking Neural Networks (SNNs)



Step 1: update $H_l^t = \tau U_l^{t-1} + \boxed{W_l S_{l-1}^t}$

Step 2: firing $H_l^t > v_{th}$

Step 3: reset $U_l^t = H_l^t(1 - S_l^t)$



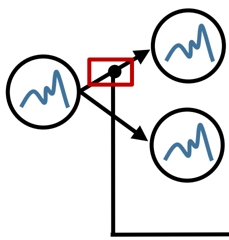
Timesteps

Leaky Integrate-and-Fire (LIF)

Membrane potentials before reset: H_l^t
Membrane potentials after reset: $\boldsymbol{U_l^t}$

Benefits of SNNs (Hardware)

Artificial Neural Networks (ANNs)



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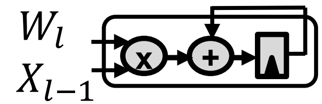
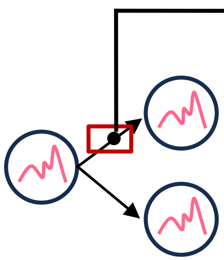


Require multipliers (~32x power compared to adder)

Spiking Neural Networks (SNNs)



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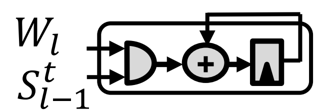
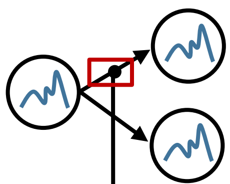


Does not require multipliers

Benefits of SNNs (Hardware)

Artificial Neural Networks (ANNs)



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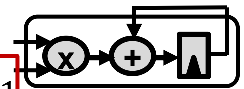
W_l

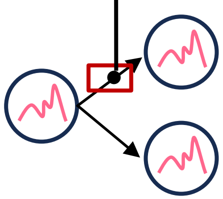
$\boxed{X_{l-1}}$



Require multipliers

Multi-bits value
Higher storage

Spiking Neural Networks (SNNs)



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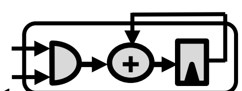
W_l

S_{l-1}^t



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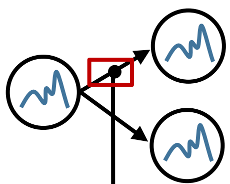

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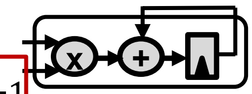

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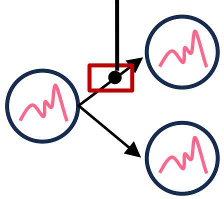

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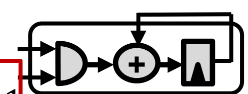
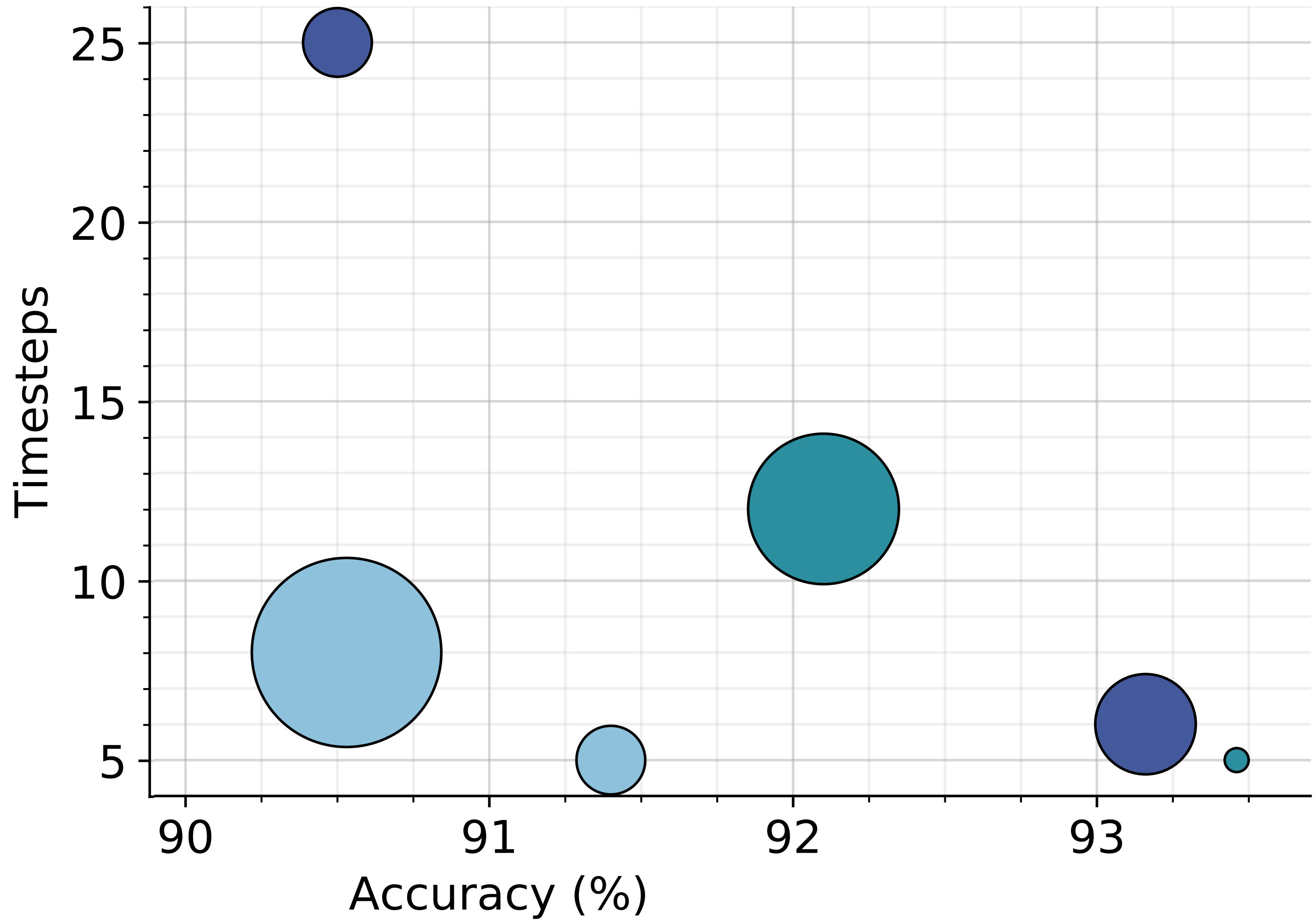


Does not require multipliers

Single-bit spike
Lower storage

Model Size of SNNs



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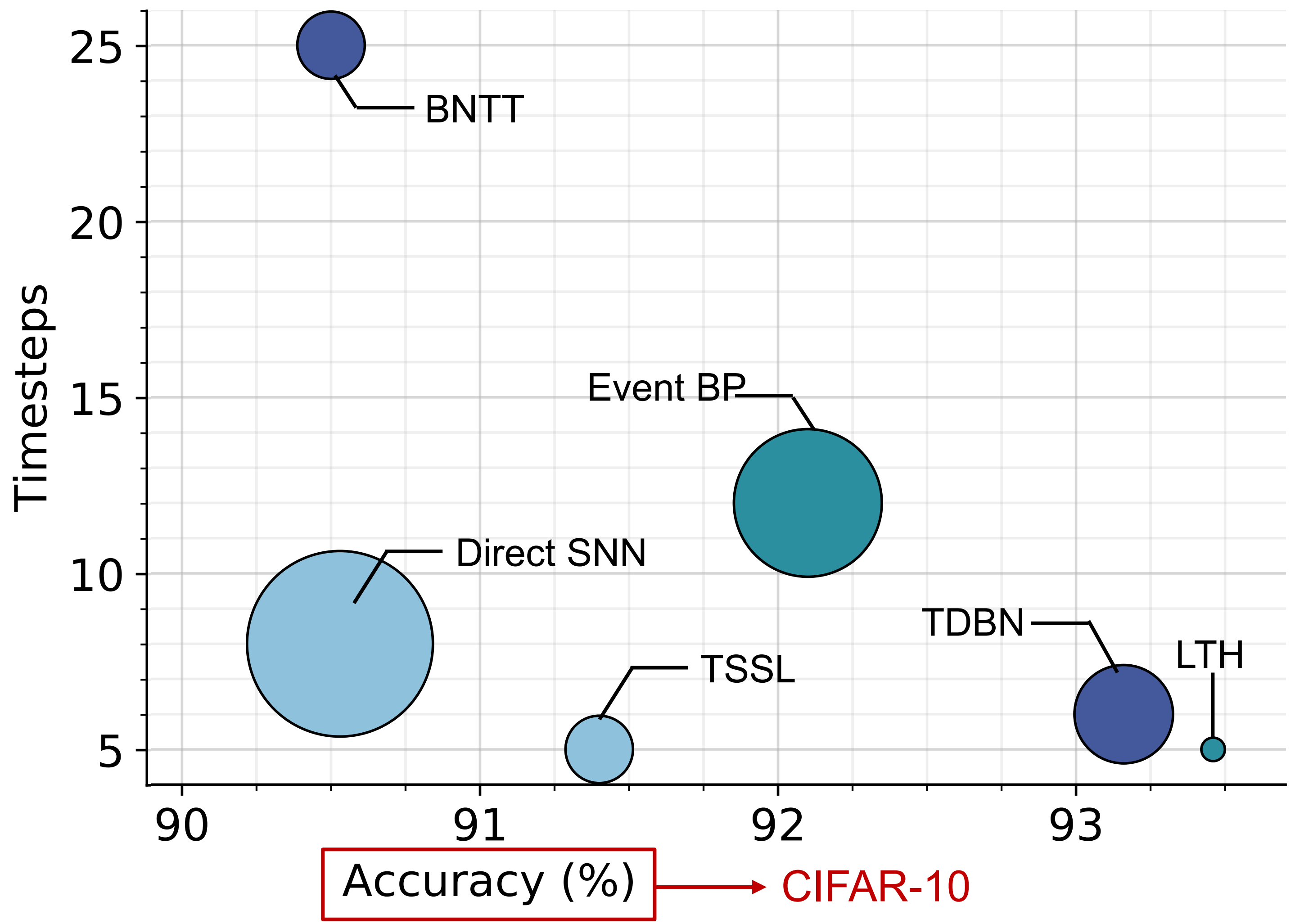

References for those works are in the appendix.

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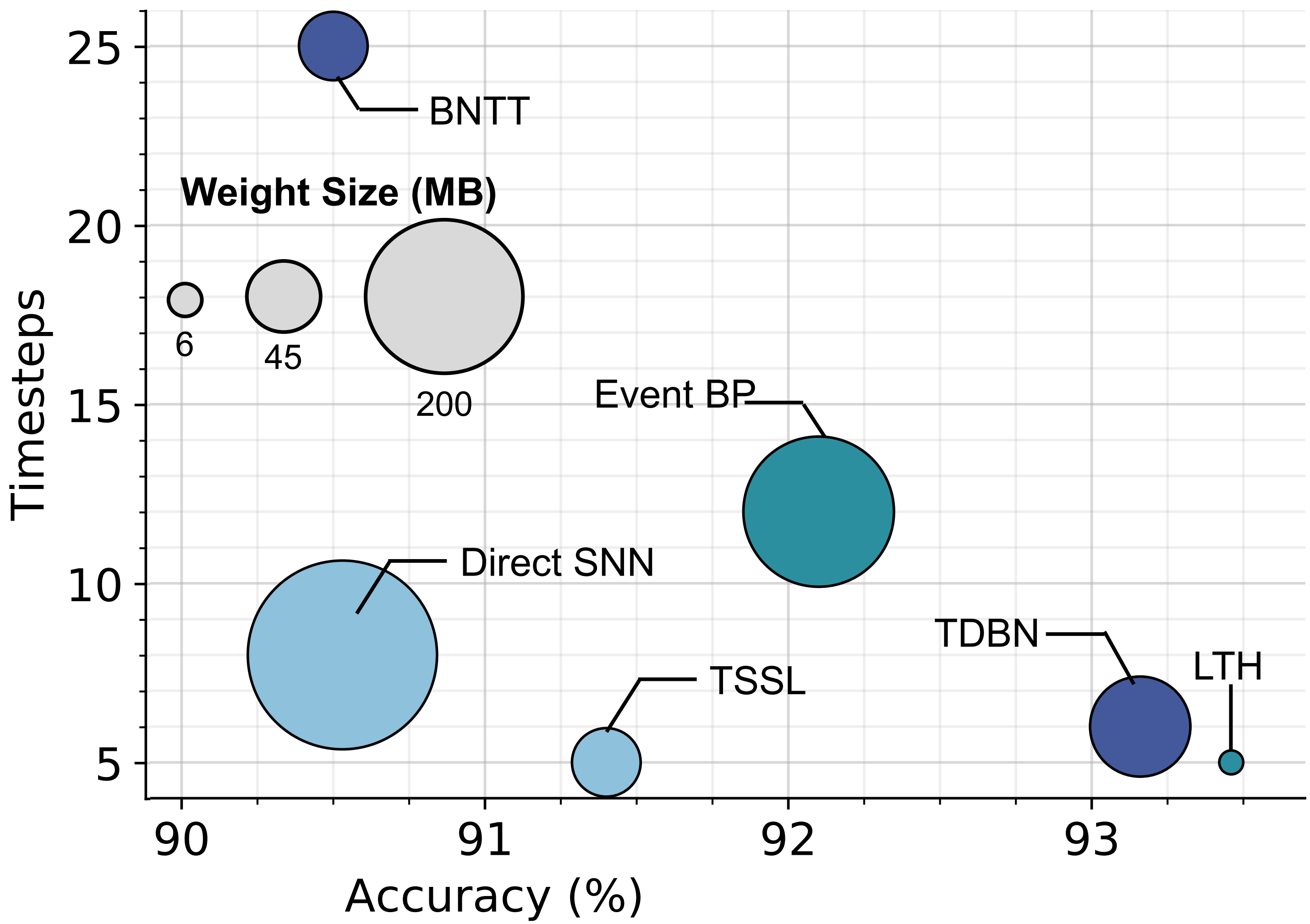

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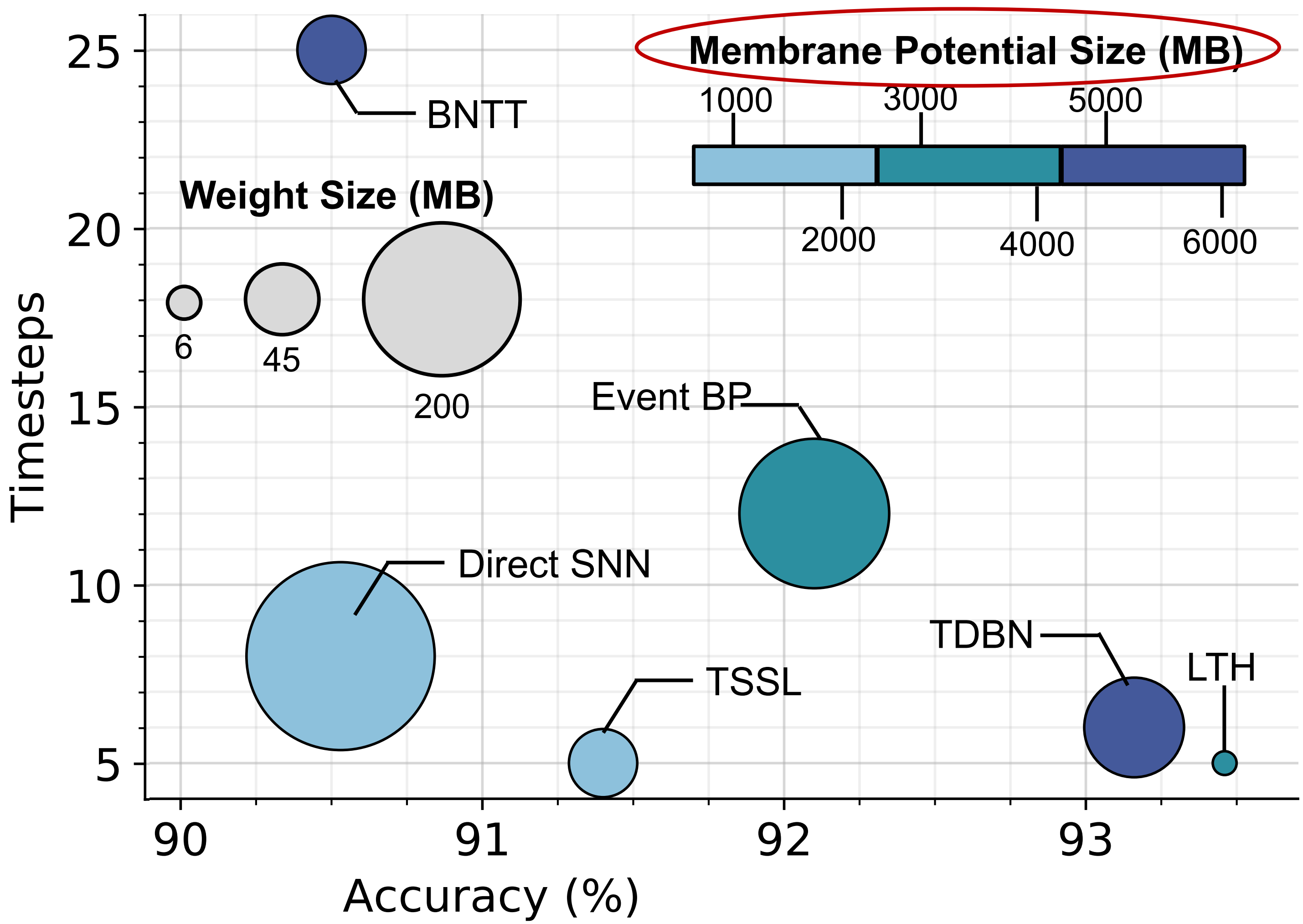

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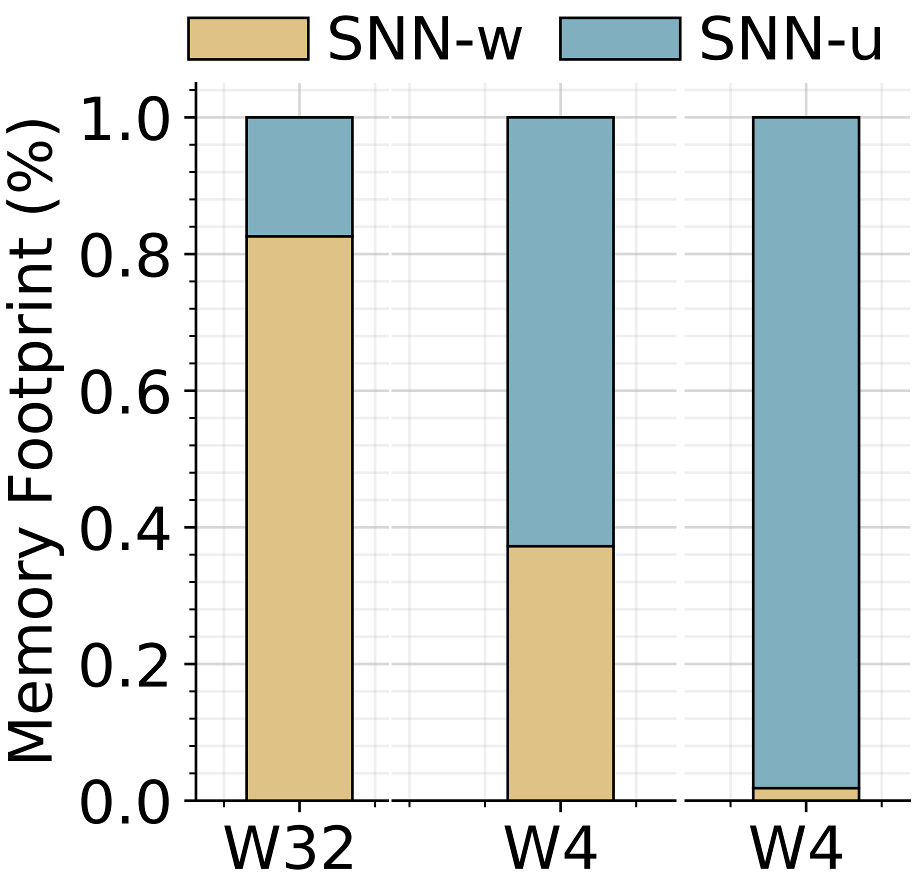
Size of Membrane Potential (U) in SNNs



Network Arch: *VGG-9*

\# of Timesteps: *4*

Precision of U: *32-bit*

Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

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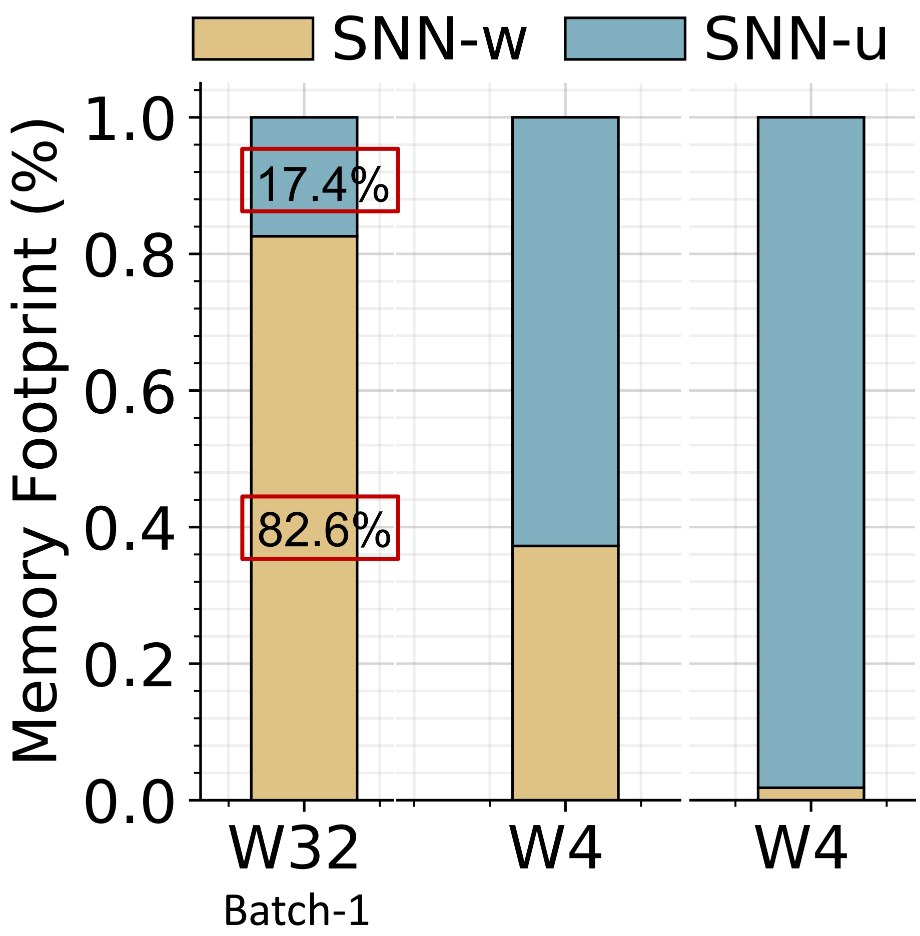

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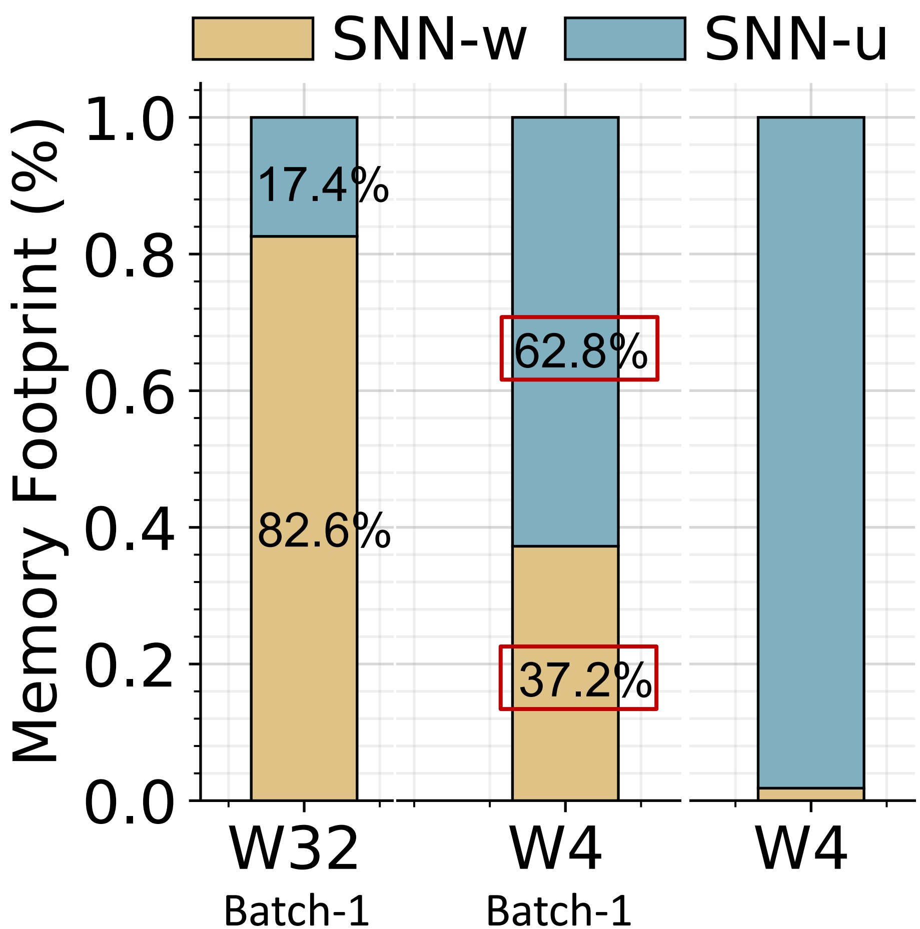

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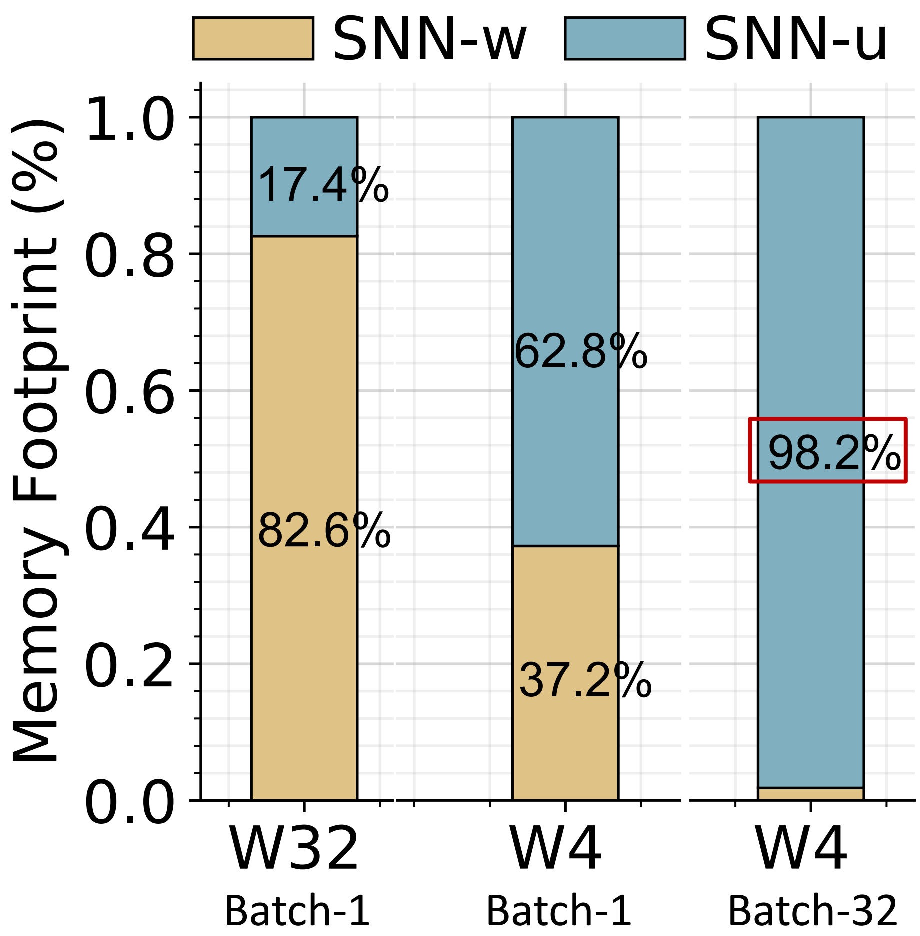

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Key Observations:

1. size of weight ↓ portion of U ↑
2. batch size ↑ size of U ↑

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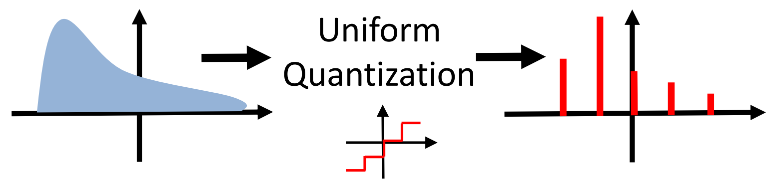
Naïve Solution: Quantization!

- Uniform Quantization:
  - An affine mapping between low-precision integer vectors $\hat{q}$ and high-precision floating point vectors r.



Low-precision integer

$$r = \boxed{\alpha}\left(\boxed{\hat{q}} - Z\right) \xrightarrow{\text{simplify}} r = \alpha \cdot \hat{q}$$

Scaling factor: 32-bit floating point

- An example for a layer in ANN:

Input: X
Weight: W
Output: Z

Without quantization:
$Z = ReLU(WX)$

With weight quantization:
$Z = ReLU(\alpha(\widehat{W}X))$

Apply Quantization to SNNs

- Let's review the equations for SNNs again:

Step 1: update $H_l^t = \tau U_l^{t-1} + W_l S_{l-1}^t$

Step 2: firing $H_l^t > v_{th}$

Step 3: reset $U_l^t = H_l^t(1 - S_l^t)$

- The goal is to quantize both the weights and membrane potentials.

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- The goal is to quantize both the weights and membrane potentials.

Step 1: update	$H_l^t = \tau U_l^{t-1} + W_l S_{l-1}^t$	$H_l^t = \alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t$
Step 2: firing	$H_l^t > v_{th}$	$H_l^t > v_{th}$
Step 3: reset	$U_l^t = H_l^t(1 - S_l^t)$	$\alpha_3 \widehat{U}_l^t = H_l^t(1 - S_l^t)$

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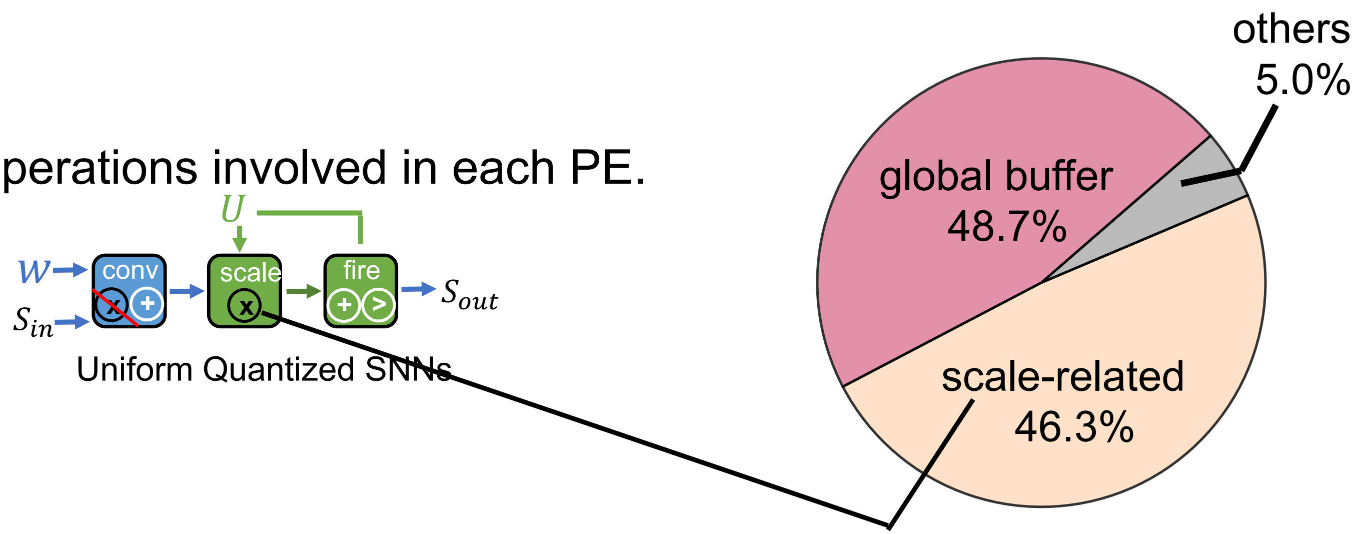
Scaling factors need multiplications!

Cost of Scaling Factors

- To support the scaling factors, we physically need a 32-bit multiplier.
- Output-stationary systolic array is usually adopted for accelerating SNNs. For the quantization scaling, each processing element (PE) requires a 32-bit multiplier.

The operations involved in each PE.



Area breakdown of a 4-bit SpinalFlow

Narayanan, S, et al. "SpinalFlow: An architecture and dataflow tailored for spiking neural networks." *(ISCA)*. IEEE, 2020.

Our methods: Review of LIF Equations

- We first look at the LIF equations for updating the membrane potential after reset.

Step 1: update $H_l^t = \alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t$

Step 2: firing $H_l^t > v_{th}$

Step 3: reset $\alpha_3 \widehat{U}_l^t = H_l^t (1 - S_l^t)$

Assume no output spikes

$$\alpha_3 \widehat{U}_l^t = \alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t$$

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$$\alpha_3 \widehat{U}_l^t = \alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t$$

Assume no output spikes

$$\widehat{U}_l^t = \frac{\alpha_2}{\alpha_3} \tau \widehat{U}_l^{t-1} + \frac{\alpha_1}{\alpha_3} \widehat{W}_l S_{l-1}^t$$

How to get rid of those two multiplications?

How about adding the following constraints to the scaling factors?

$$\boxed{\alpha_1 = \alpha_2 = \alpha_3}$$

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$$\alpha_3 \widehat{U}_l^t = \alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t$$

$$\widehat{U}_l^t = \cancel{\frac{\alpha_2}{\alpha_3}} \tau \widehat{U}_l^{t-1} + \cancel{\frac{\alpha_1}{\alpha_3}} \widehat{W}_l S_{l-1}^t$$

Sharing the scaling factors between W and U

$$\widehat{U}_l^t = \tau \widehat{U}_l^{t-1} + \widehat{W}_l S_{l-1}^t$$

How to get rid of those two multiplications?

How about adding the following constraints to the scaling factors?

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- We then look at the LIF equations for firing output spikes.

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Step 2: firing $H_l^t > v_{th}$ ⇒ $\alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W_l} S_{l-1}^t > v_{th}$

Firing condition

Step 3: reset $\alpha_3 \widehat{U}_l^t = H_l^t (1 - S_l^t)$

Remember the shared scaling factors we just discussed.

$$\boxed{\alpha_1 = \alpha_2 = \alpha_3 = \alpha}$$

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$$\alpha_2 \tau \widehat{U}_l^{t-1} + \alpha_1 \widehat{W}_l S_{l-1}^t > v_{th} \quad \Rightarrow \quad \tau \widehat{U}_l^{t-1} + \widehat{W}_l S_{l-1}^t > \frac{v_{th}}{\alpha}$$

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$$\tau \widehat{U}_l^{t-1} + \widehat{W}_l S_{l-1}^t \geq [\frac{v_{th}}{\alpha}]$$

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integers

$$\boxed{\tau \widehat{U}_l^{t-1} + \widehat{W}_l S_{l-1}^t} \geq \boxed{\left\lceil \frac{v_{th}}{\alpha} \right\rceil}$$

integer

Equivalent of scaling the firing threshold!

MINT Quantization

- The forward algorithm for our proposed MINT (Multiplierless INTeger) quantization is formalized as below:

$$H_l^t \leftarrow \widehat{W_l} S_{l-1}^t + \widehat{U}_l^{t-1} \gg 1$$

$$if\ H_l^t \geq \left\lceil \frac{v_{th}}{\alpha} \right\rceil then$$

$$S_l^t \leftarrow 1$$

$$\widehat{U}_l^t \leftarrow 0$$

$$else$$

$$S_l^t \leftarrow 0$$

$$\widehat{U}_l^t \leftarrow H_l^t$$

$$endif$$

Low Storage of weights

Low Storage of potentials

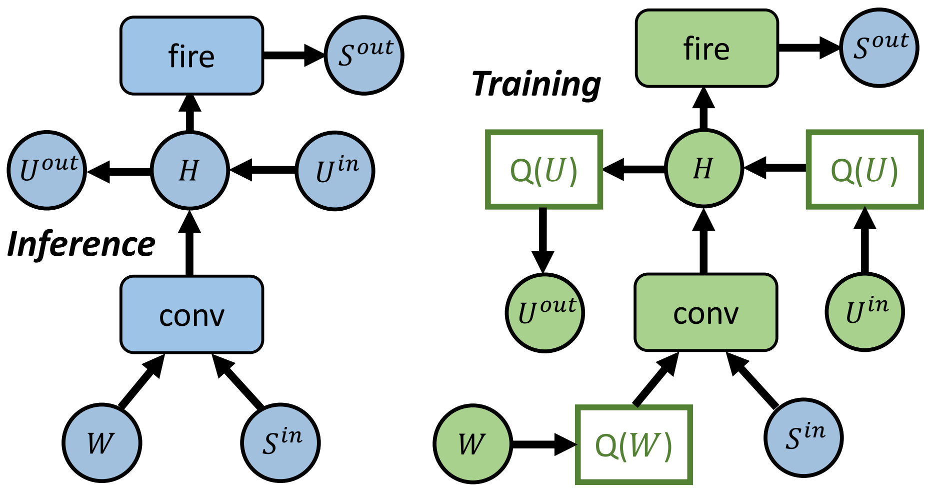
No Multipliers

Fully Integer

Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

Training of MINT Quantized SNNs

- We utilized Quantization Aware Training (QAT) to train our SNNs based on Backpropagation-through-Time (BPTT).

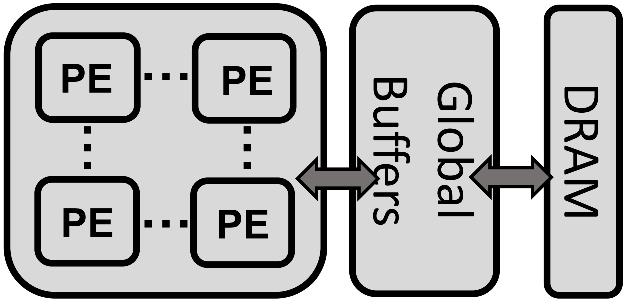


- We further made the shared quantization scaling factor α an learned parameter, which significantly improved the accuracy.

Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

Projection on SNN Accelerators

- Processing element (PE) differences between MINT and vanilla Uniform Quantization (UQ) inside the SNN accelerator systems.



Technology	CMOS32
PE array size	128
Global buffer size	144 KB
Spad size	1 KB

Projection on SNN Accelerators

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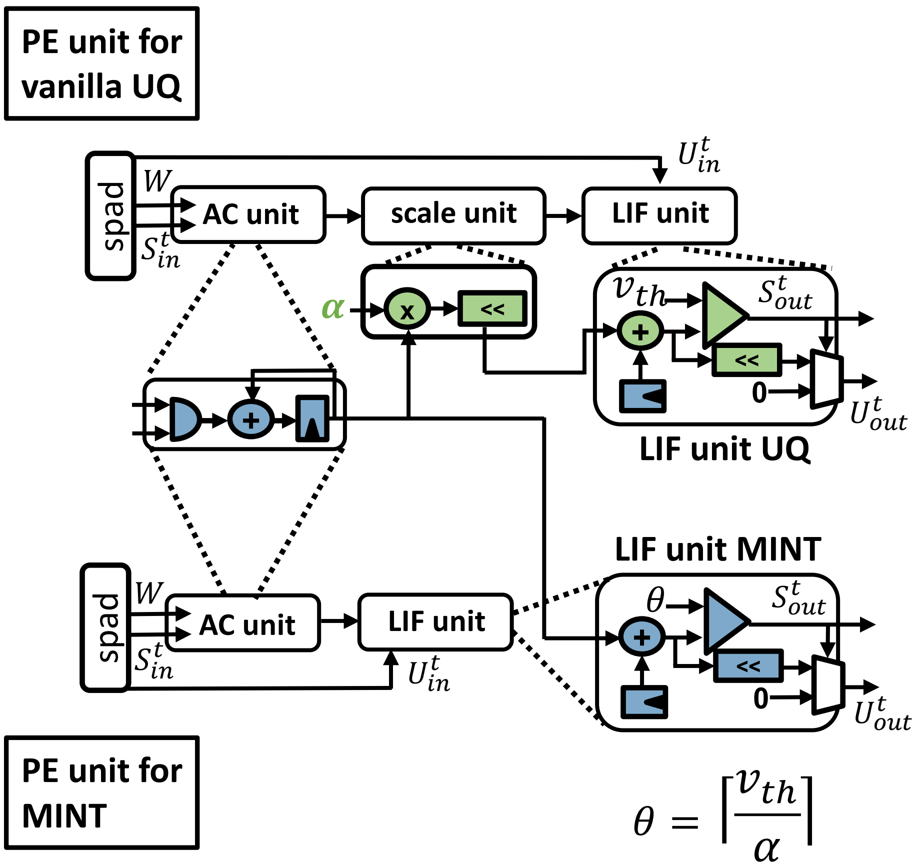

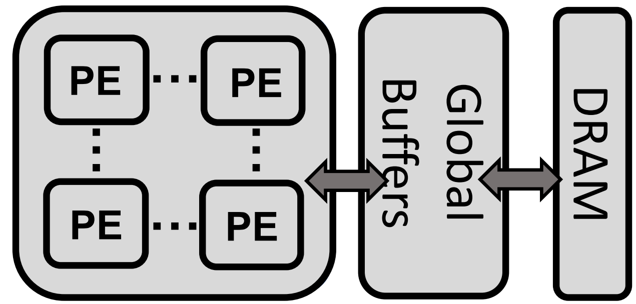

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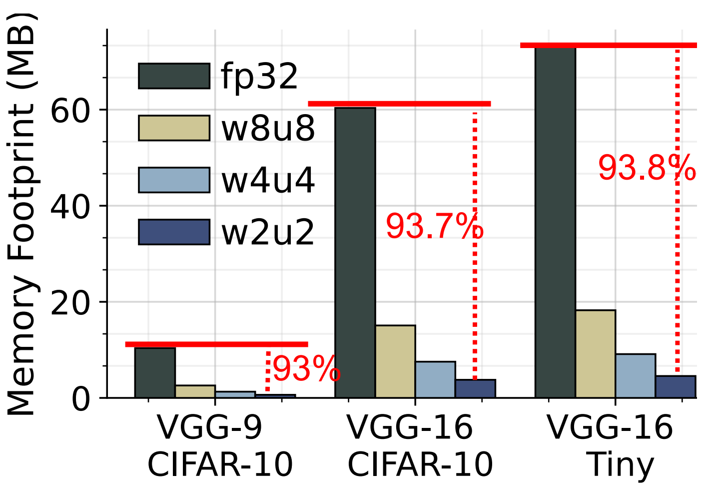
Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

Experimental Results

- Datasets (Networks): CIFAR-10 and Tiny-ImageNet (VGG9 and VGG16).
- Various Precision (W- U): 8-8, 4-4, 2-2.
- At iso-accuracy with the full-precision models: MINT has less total memory footprint : ~93% total memory footprint reduction with 2-2 precision

Dataset	VGG-9	Acc. (%)	VGG-16	Acc. (%)
CIFAR10	fp32	**88.03**	fp32	**91.15**
	w8u8	87.48	w8u8	90.72
	w4u4	87.37	w4u4	90.65
	w2u2	87.47	w2u2	90.56
TinyImage	fp32	**46.38**	fp32	48.32
	w8u8	45.30	w8u8	**50.18**
	w4u4	45.02	w4u4	49.36
	w2u2	44.95	w2u2	48.60



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Experimental Results

- Datasets (Networks): CIFAR-10 and Tiny-ImageNet (VGG9 and VGG16).
- Various Precision (W- U): 8-8, 4-4, 2-2.
- The importance of quantizing membrane potential gets more significant when the batch size increased.

Dataset	VGG-9	Acc. (%)	VGG-16	Acc. (%)
CIFAR10	fp32	**88.03**	fp32	**91.15**
	w8u8	87.48	w8u8	90.72
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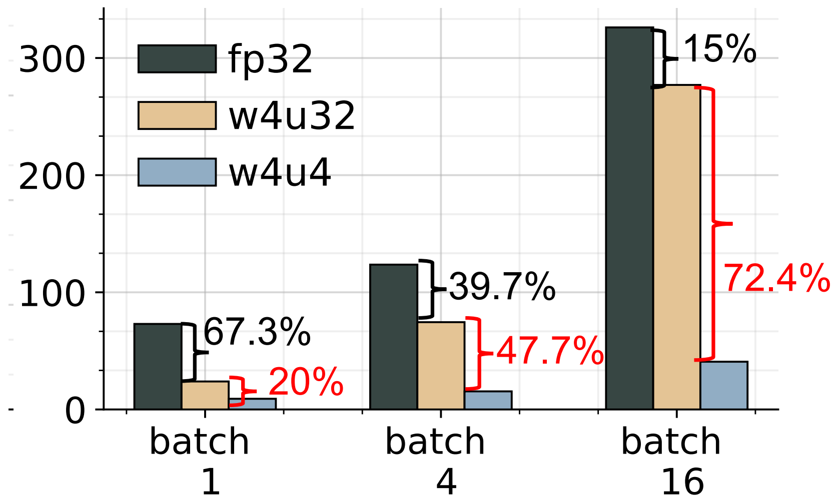
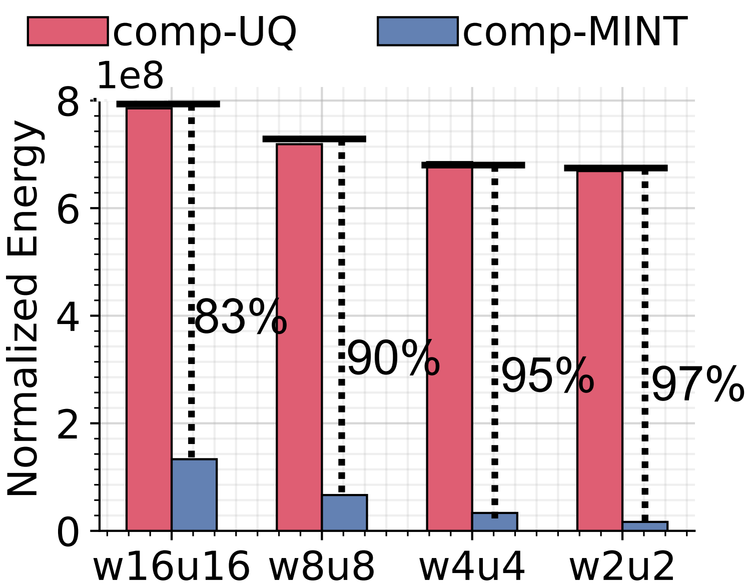


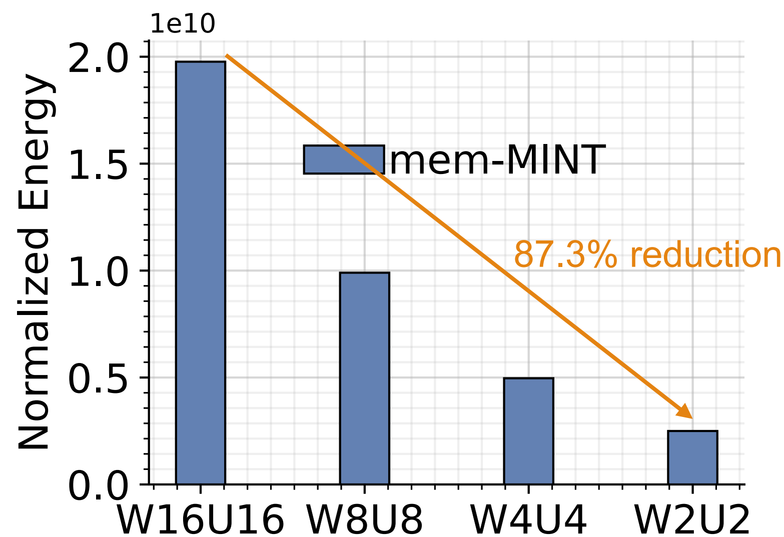
Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

Experimental Results

- Simulated energy comparison between the MINT and vanilla UQ across different precision.

- Simulated memory movement energy cost of MINT across different precision.





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https://github.com/RuokaiYin/SATA_Sim

Experimental Results

- Compare with other SOTA SNN quantization work, MINT achieves much smaller total memory footprint at iso-accuracy.

Method (CIFAR-10)	Precision (W / U)	Accuracy (%) Top-1	Mini Batches	Memory Footprint (MB)
STBP-Quant	8 / 14	86.65	50	353.79
MINT (Ours)	8 / 8	**88.25**	50	**95.41**
ST-Quant	5 / 32	**88.6**	32	751.04
MINT (Ours)	5 / 5	88.04	32	**59.62**
ADMM-Quant	4 / 32	**89.4**	50	1279.66
STBP-Quant	4 / 10	84.99	50	248.39
MINT (Ours)	4 / 4	88.12	50	**47.71**
ADMM-Quant	2 / 32	**89.23**	50	1264.85
STBP-Quant	2 / 8	33.53	50	195.68
MINT (Ours)	2 / 2	88.39	50	**23.85**

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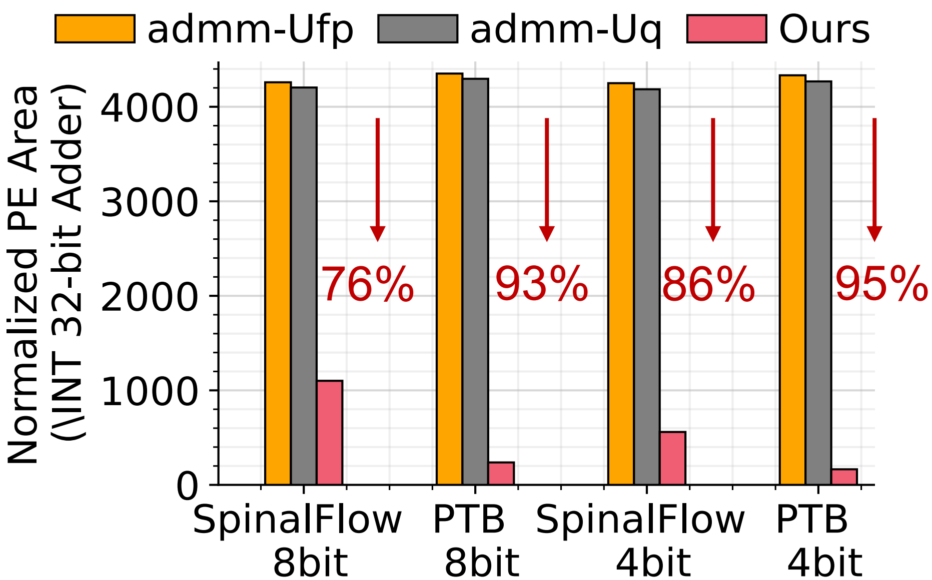
Experimental Results

- MINT is agnostic to the underlying hardware used for deployment.
- Compared to other SOTA SNN quantization work that requires scaling factors, MINT achieves a much smaller circuit area on other existing SNN accelerator systems.



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Thank you!

Code is available at: https://github.com/RuokaiYin/MINT_Quantization/

Please cite this work if found interesting:

Yin R, et al. MINT: Multiplier-less Integer Quantization for Spiking Neural Networks[J]. arXiv preprint arXiv:2305.09850, 2023.

Q & A?

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Appendix

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