OPTIMIZING FOR IMPERFECTIONS IN ANALOG NEURAL COMPUTATIONS ON BRAINSCALES-2

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BRAINSCALES-2

Purpose:

- Energy Efficiency
- Scalability

Mixed Signal Chip:

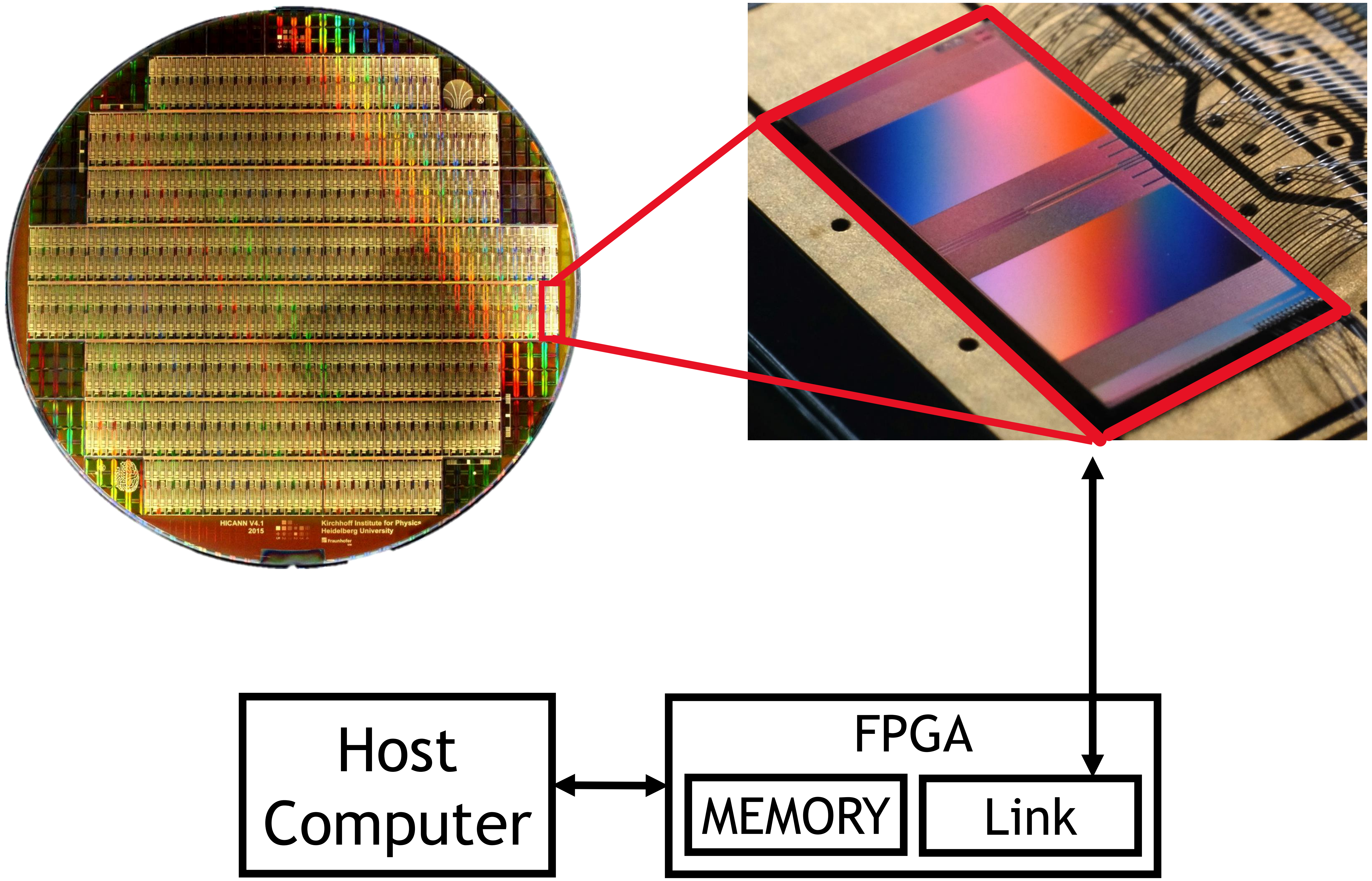
- Digital I/O
- Analog Core

Applications:

- Neuromorphic Computing
- Spiking Neural Networks
- Artificial Neural Networks

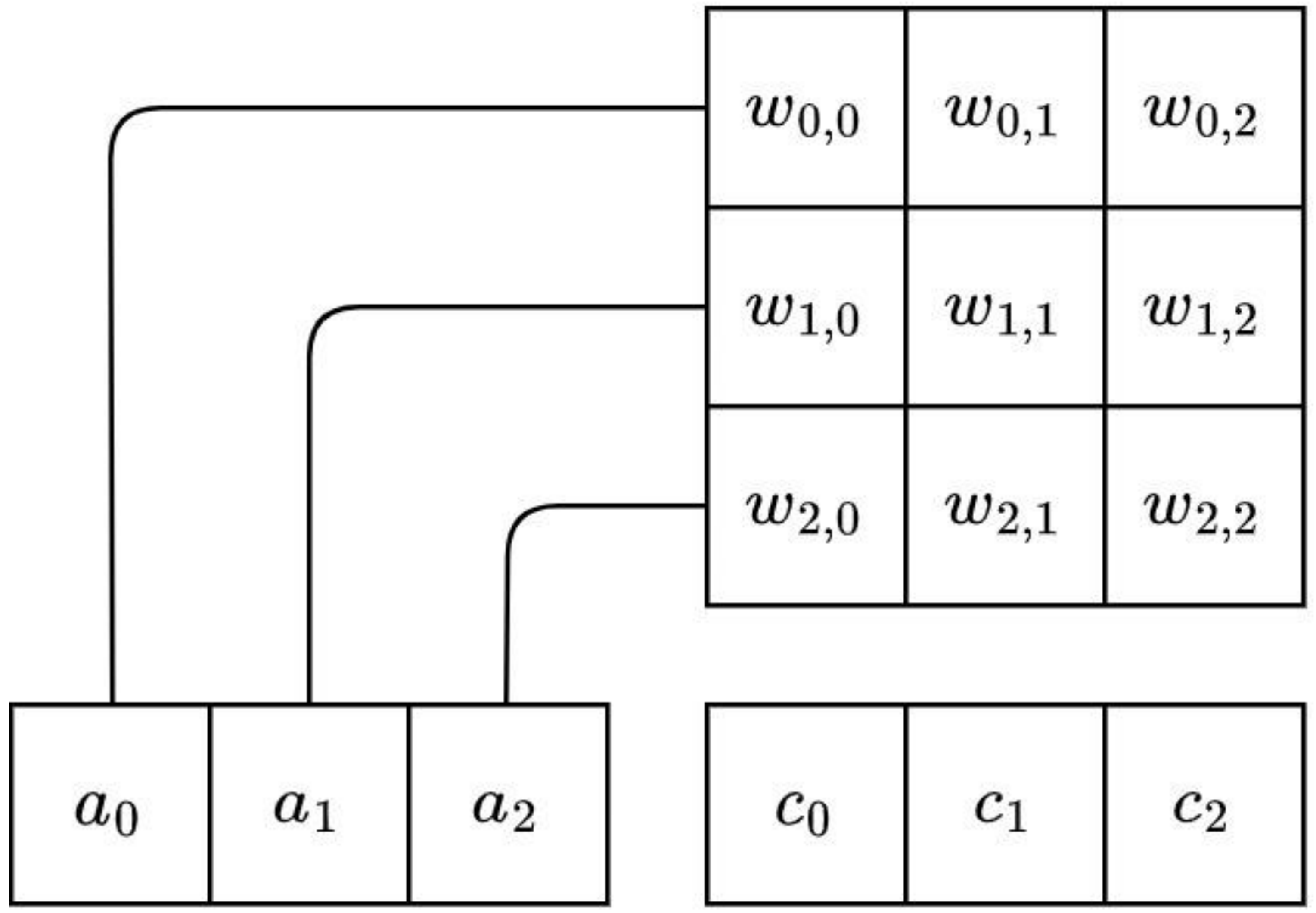
Wafer-Scale Integration

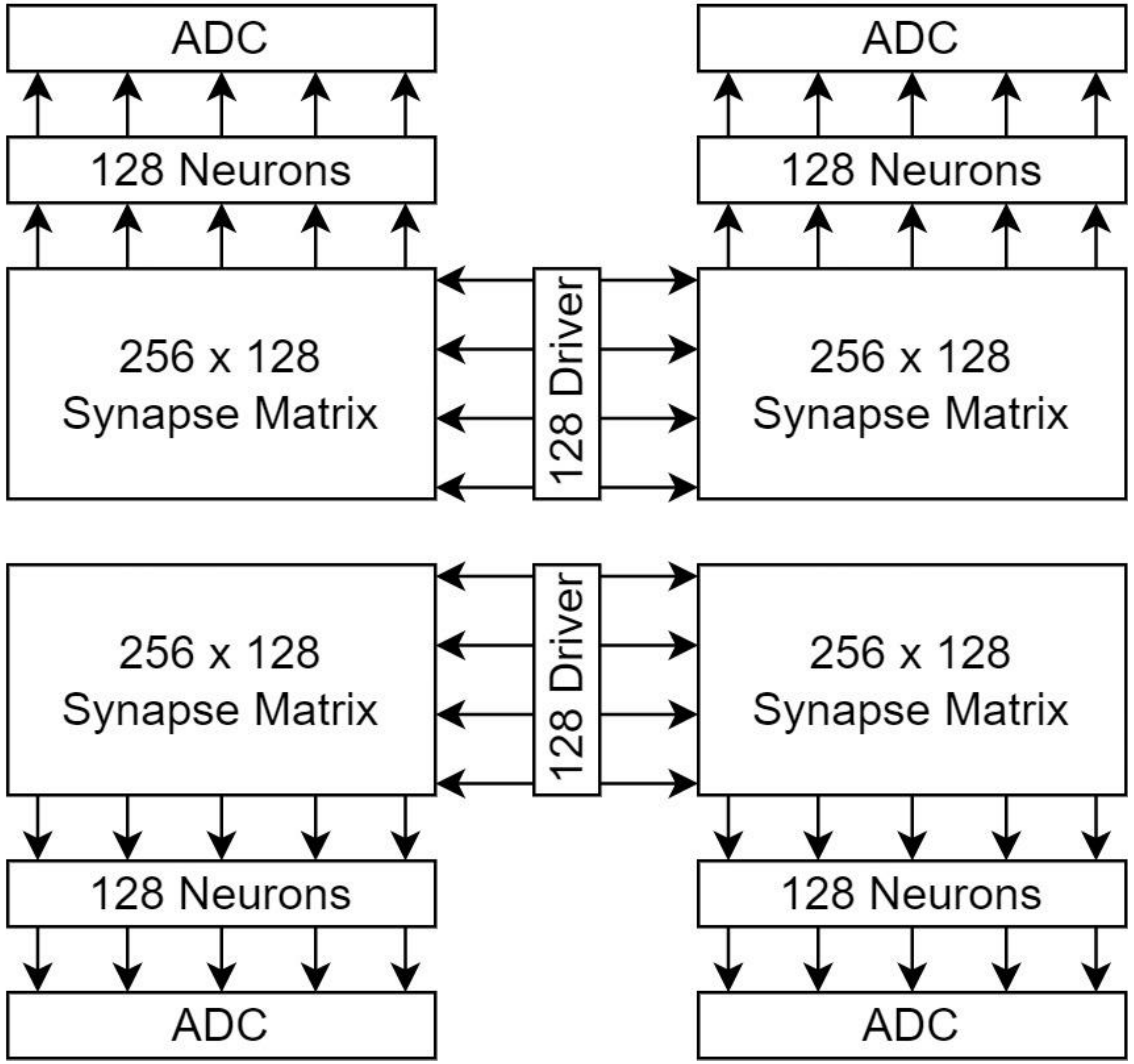
Single Chip



MATRIX MULTIPLICATION

$$A \cdot W = C$$





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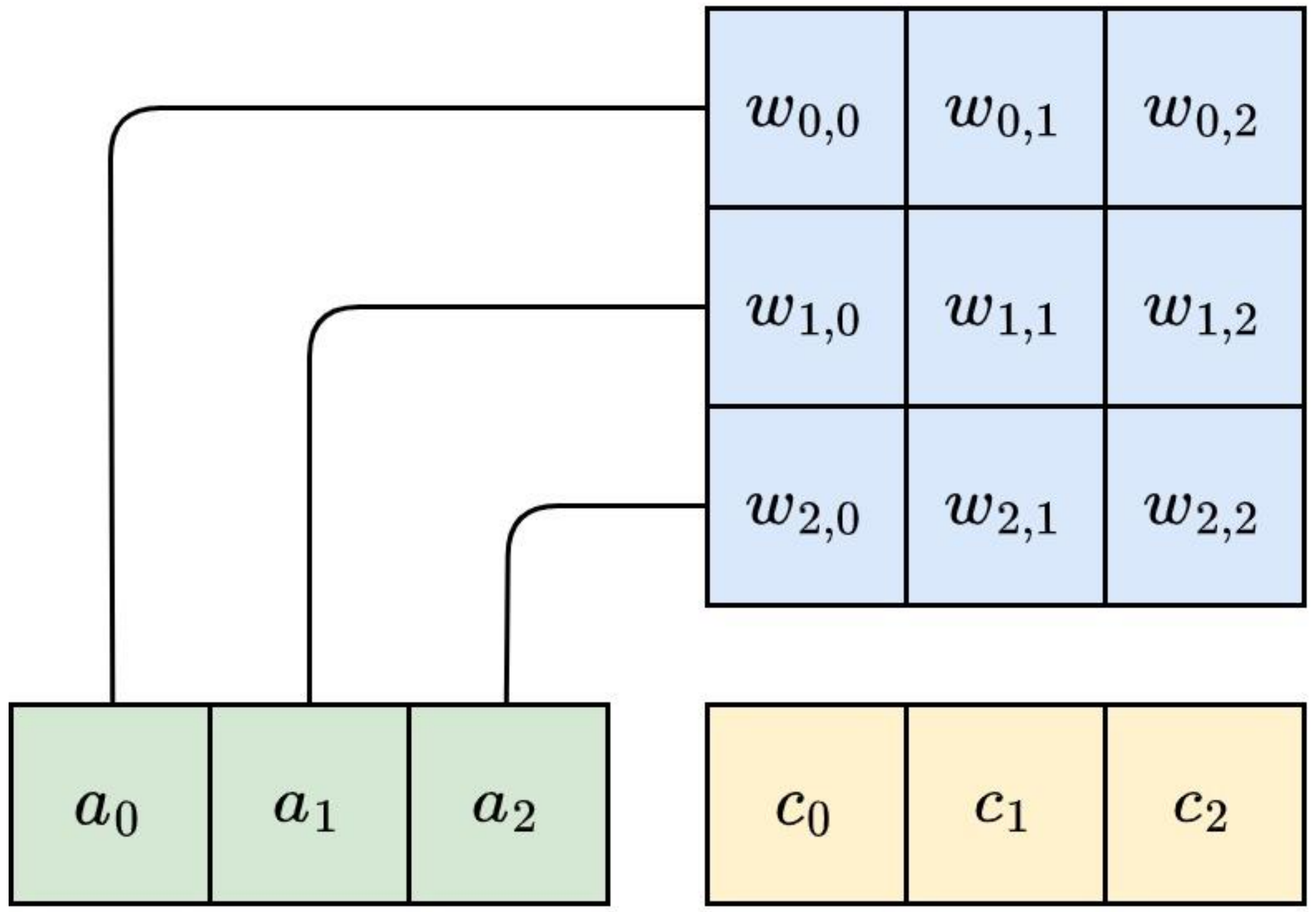
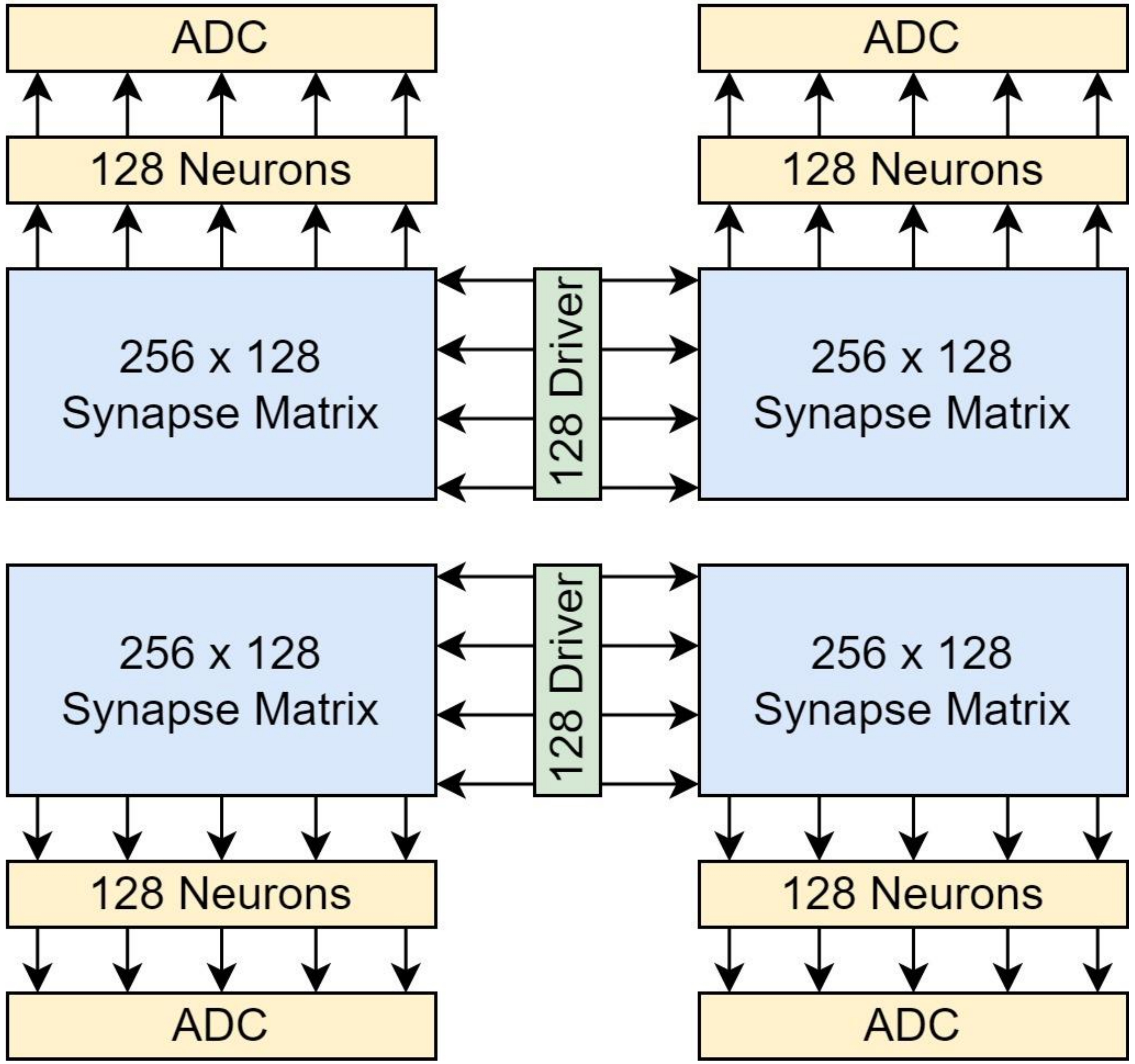
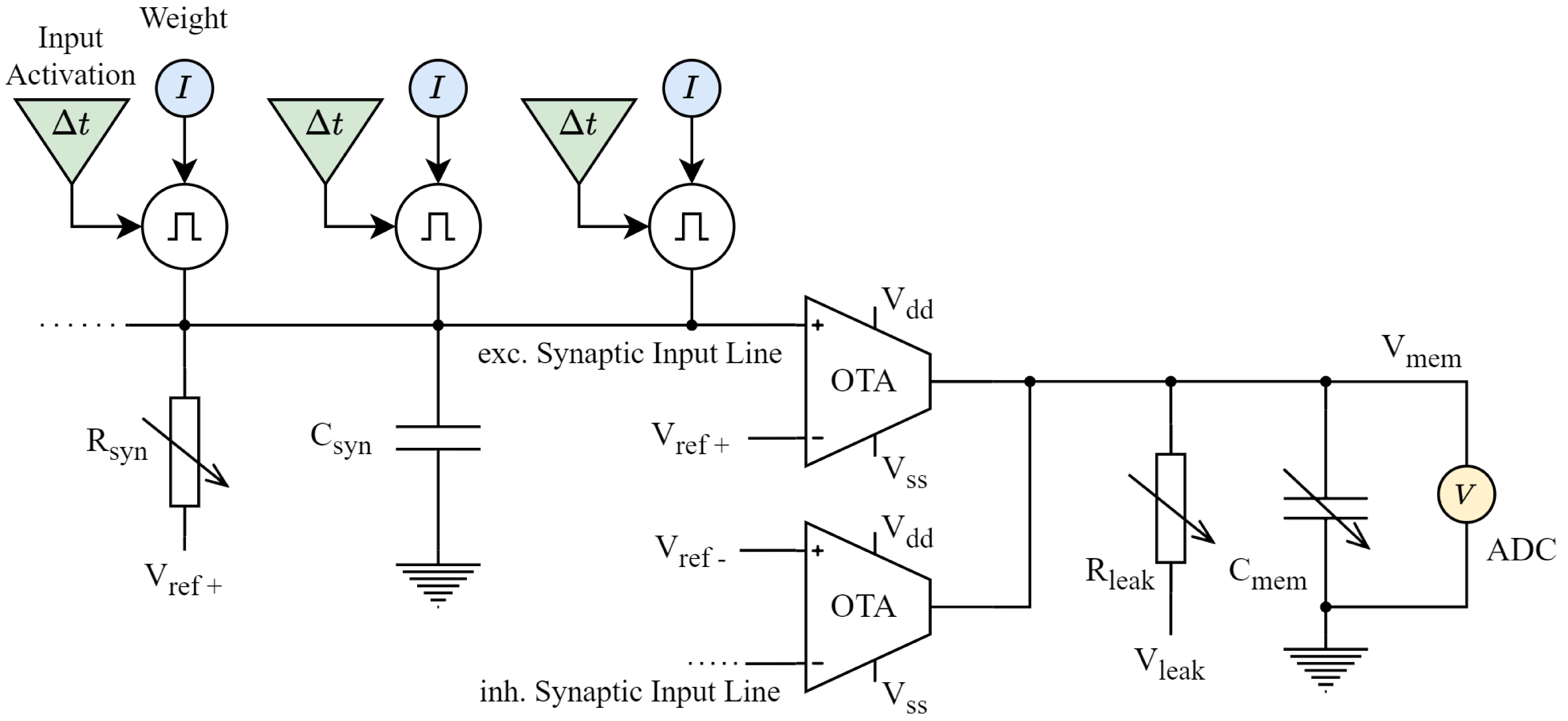




ANALOG MATRIX MULTIPLICATION



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PROGRAMMING INTERFACE

Pytorch Extension “hxtorch”

- Global chip initialization with static functions

```
hxtorch.init_hardware(calib_path)
```

- Replacements for Linear, Conv1d, Conv2d, …

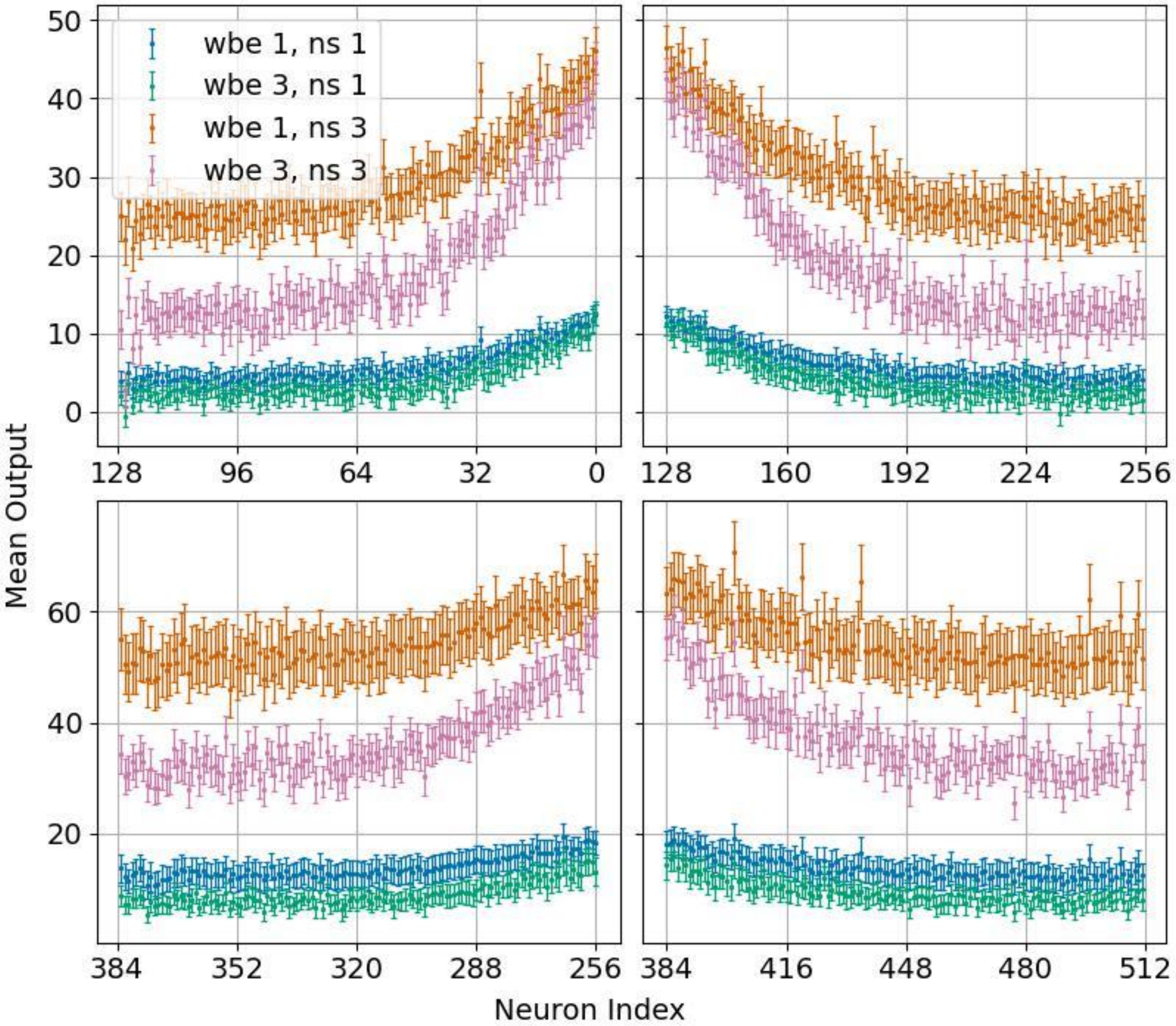
```
hxtorch.Linear( in_features, out_features, bias,
                num_sends, wait_between_events)
```

Python Library “calix”

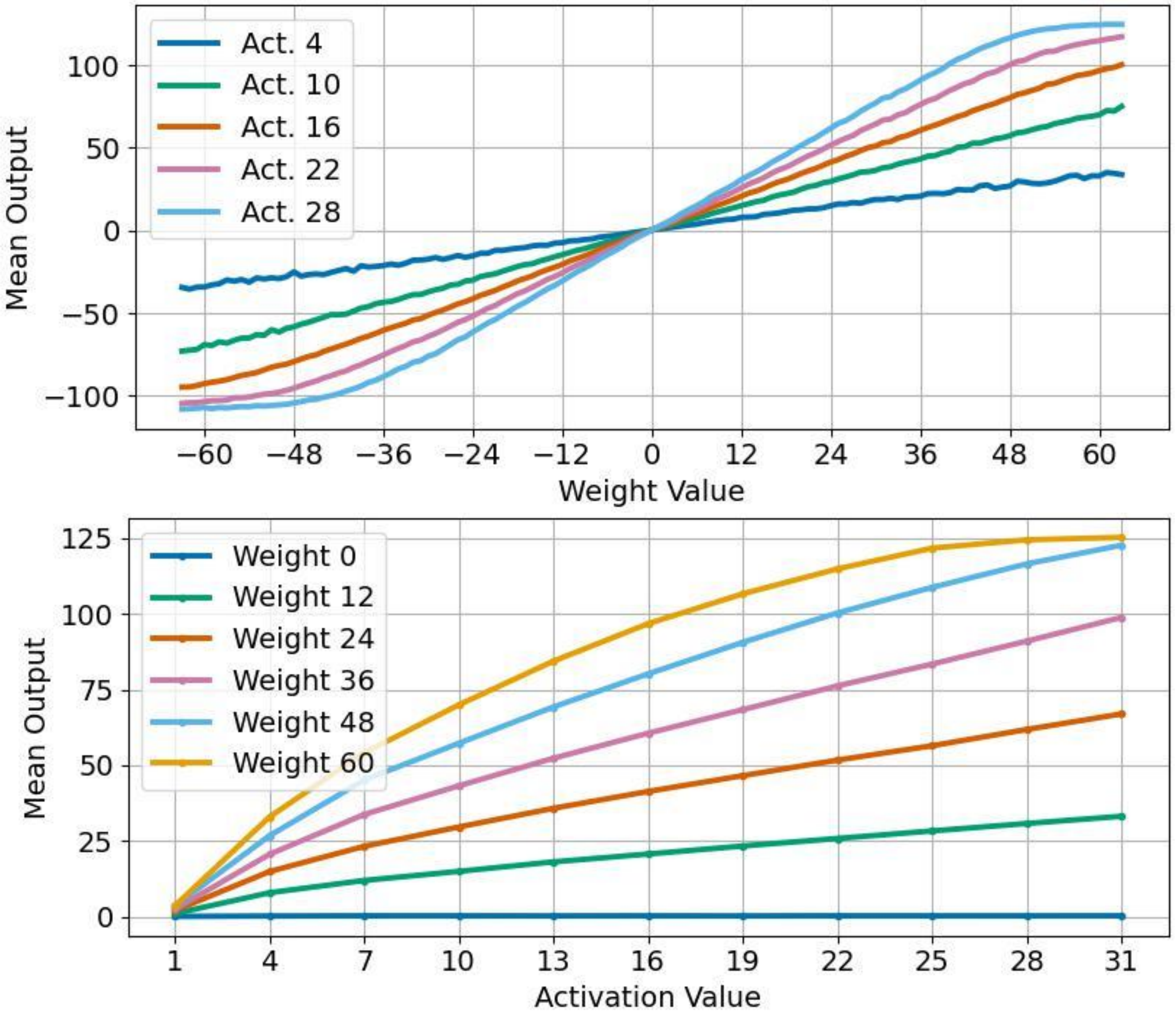
- Default calibration routines
- Allows custom parameter targets

CAVEATS OF ANALOG HARDWARE

Static Variations



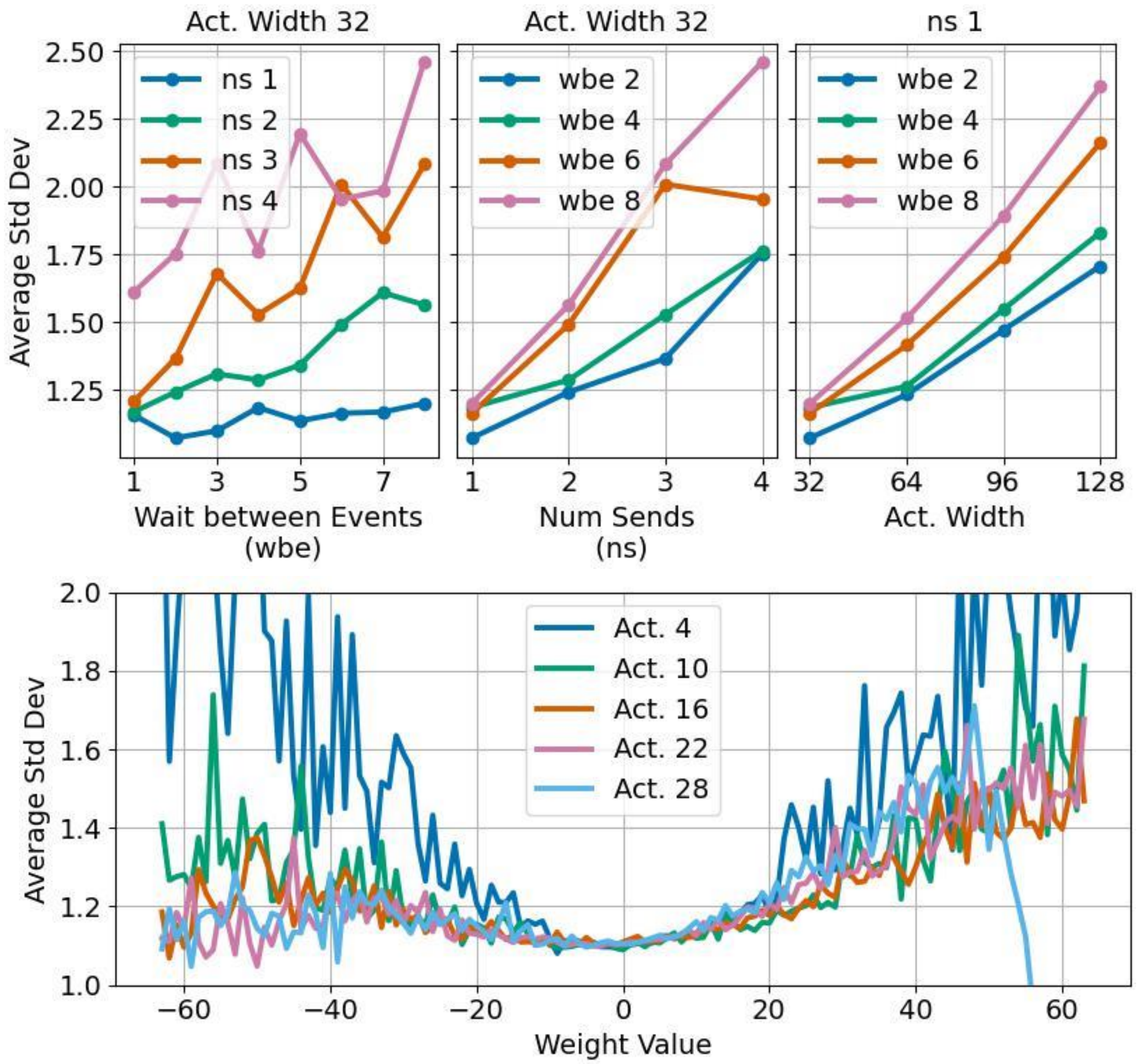
Non-Linearities



NOISE

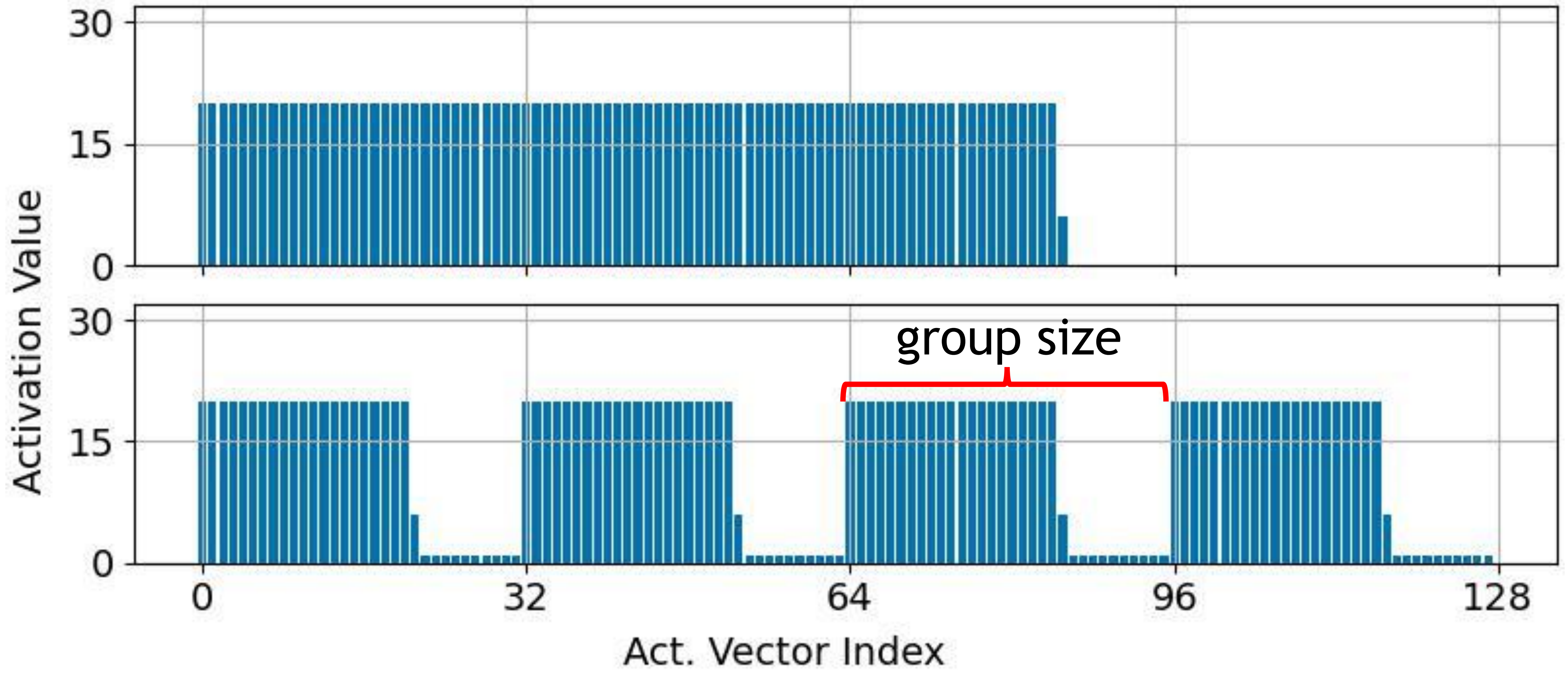
Many factors increase Noise:

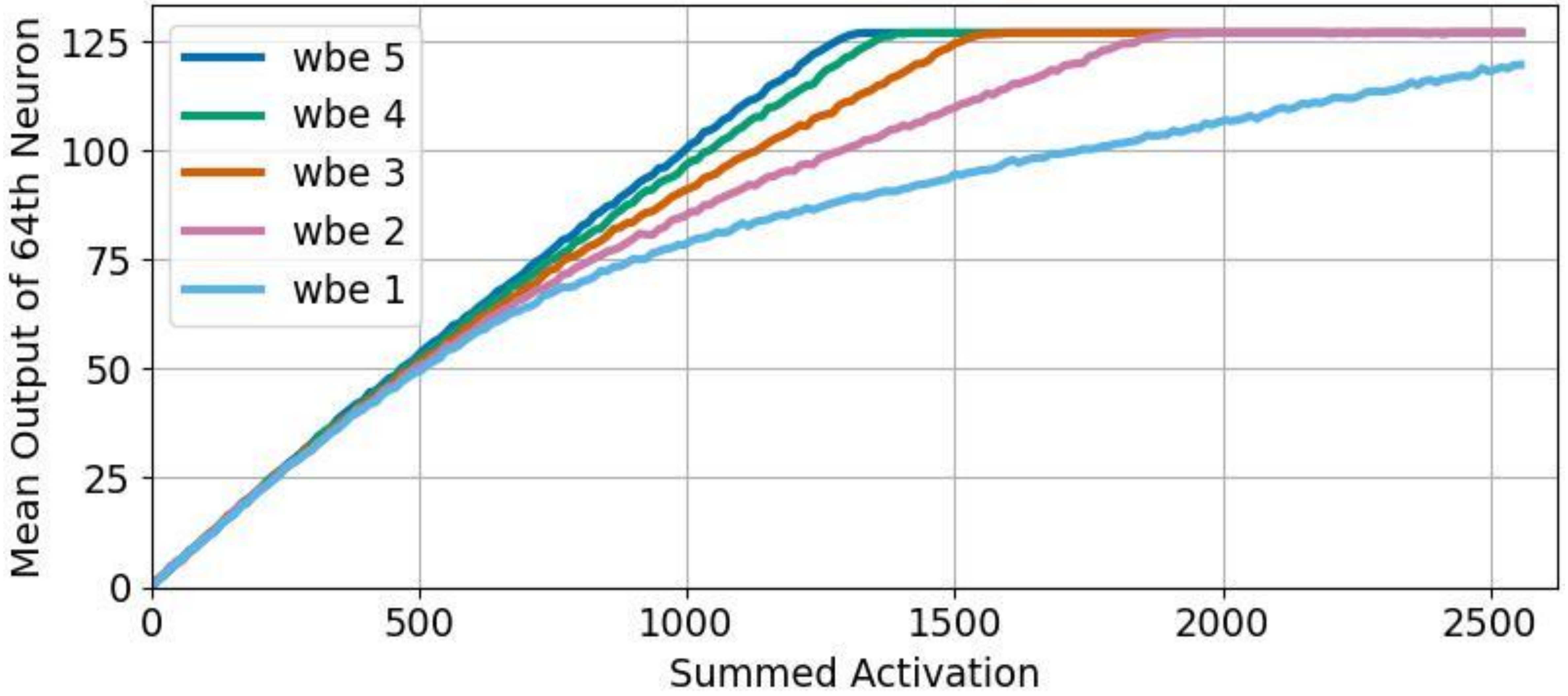
- Wait between Events
- Num Sends
- Number of input features
- Weight Magnitude
- OTA Gain
- Possibly more

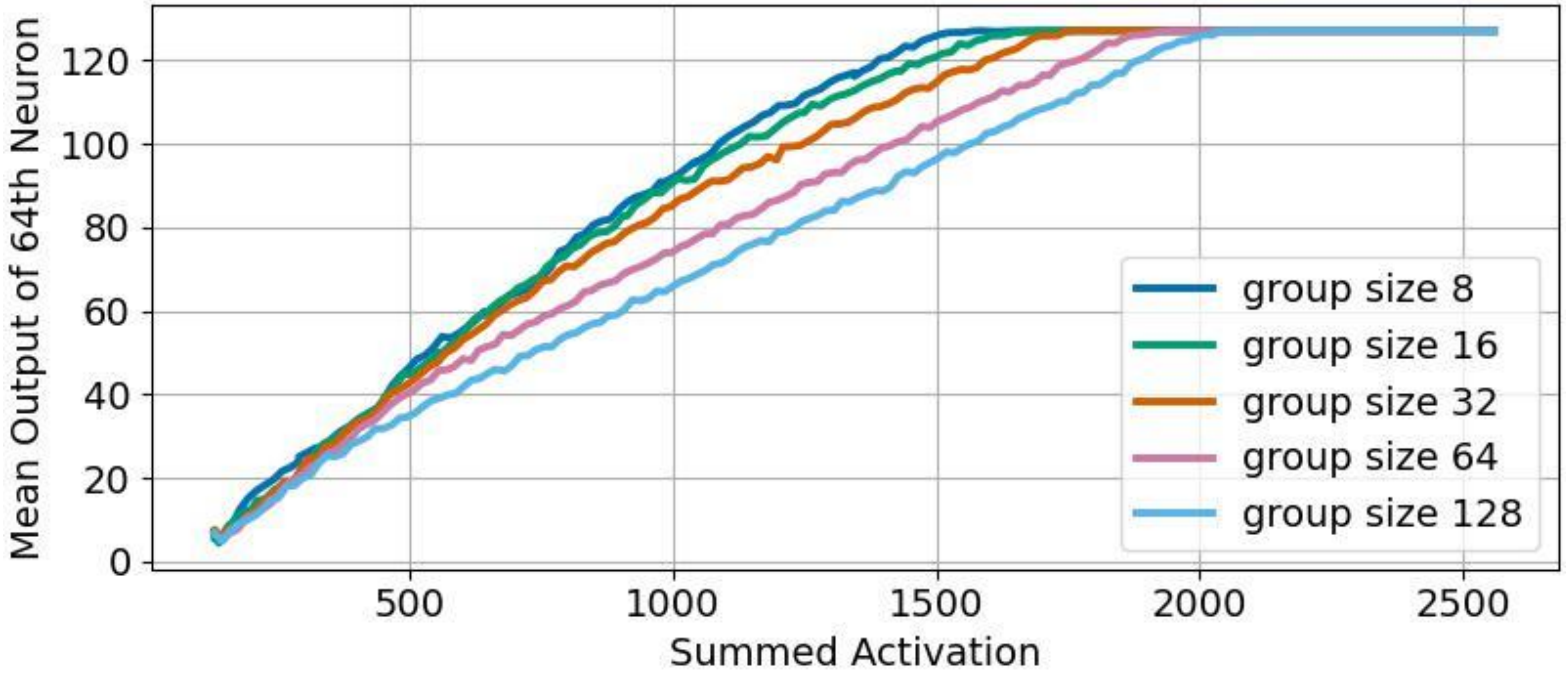


DYNAMIC SATURATION

Saturation depending on input magnitude and order

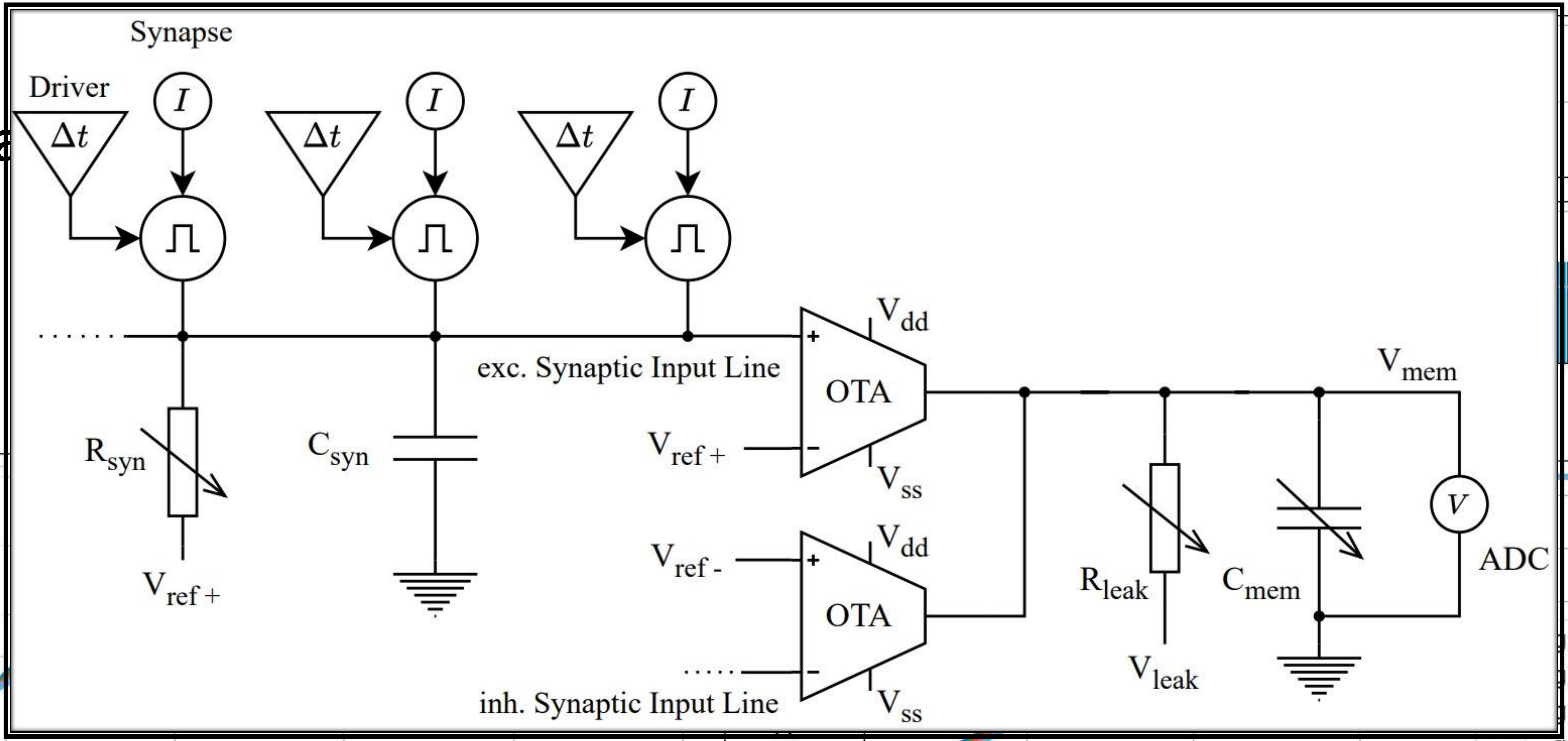


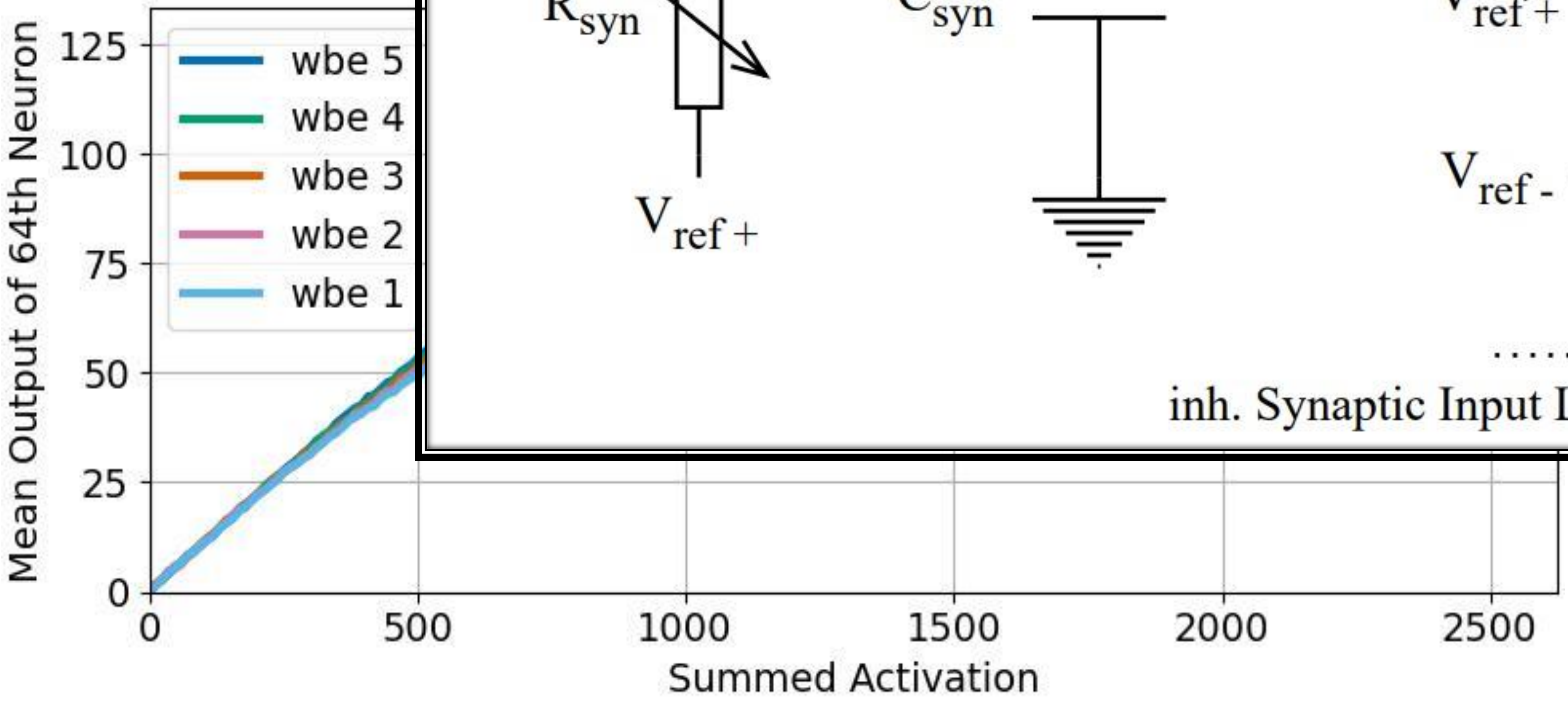


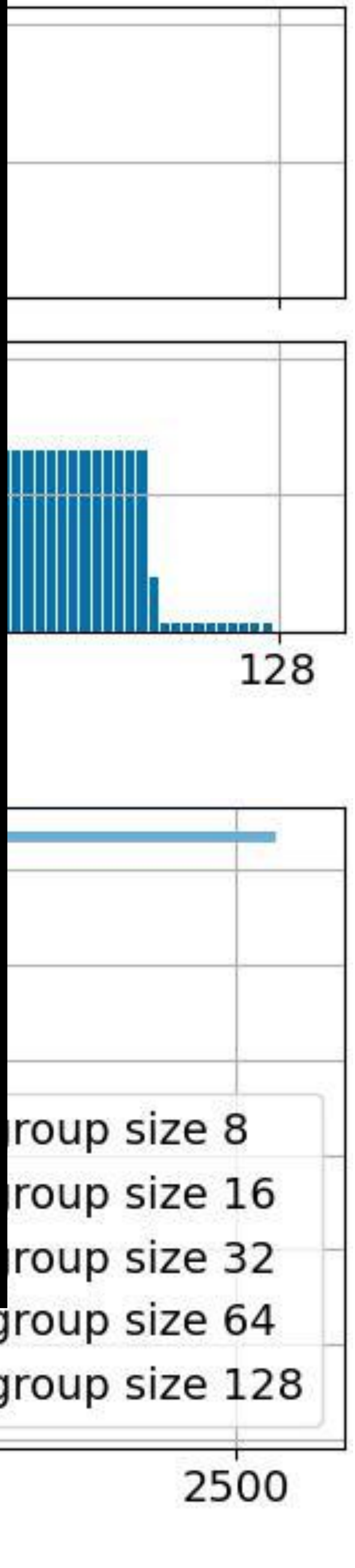


DYNAMIC SATURATION

Satura
input







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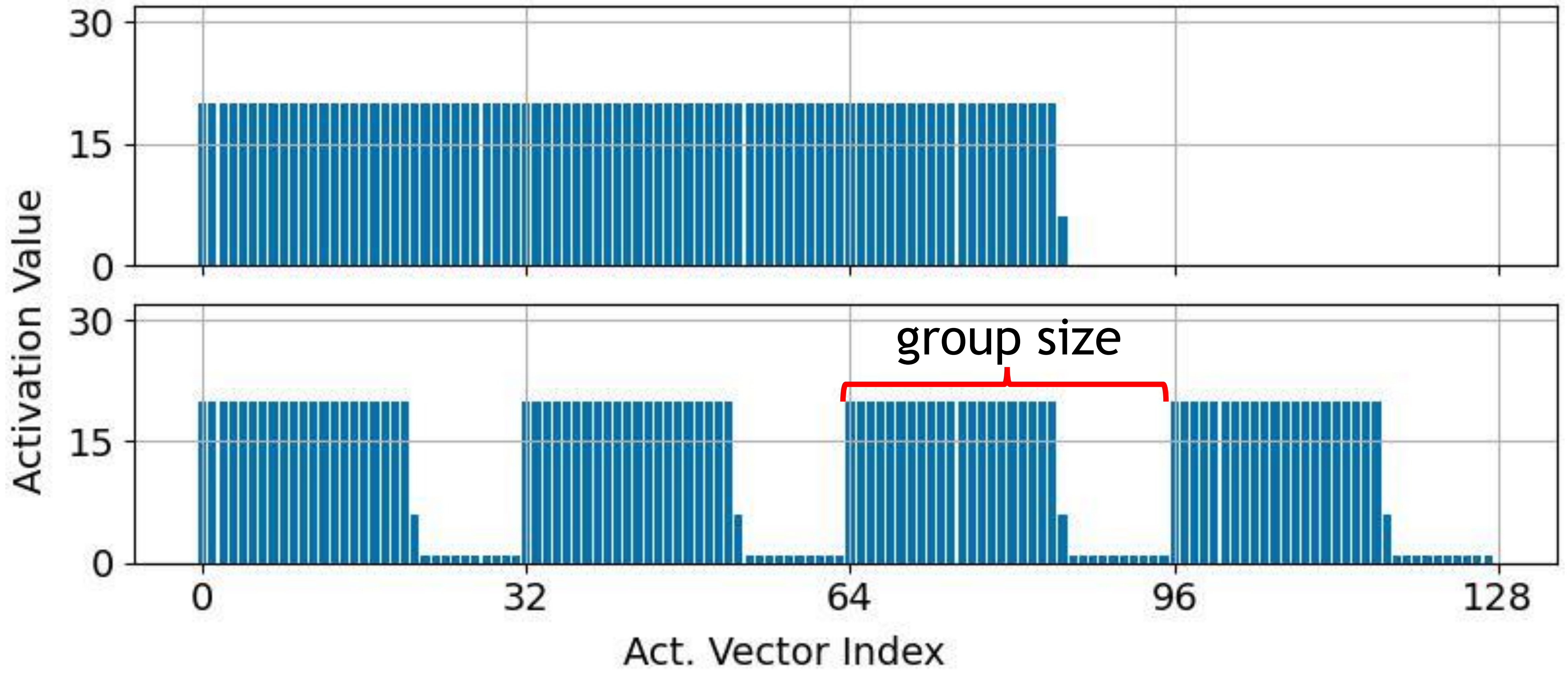

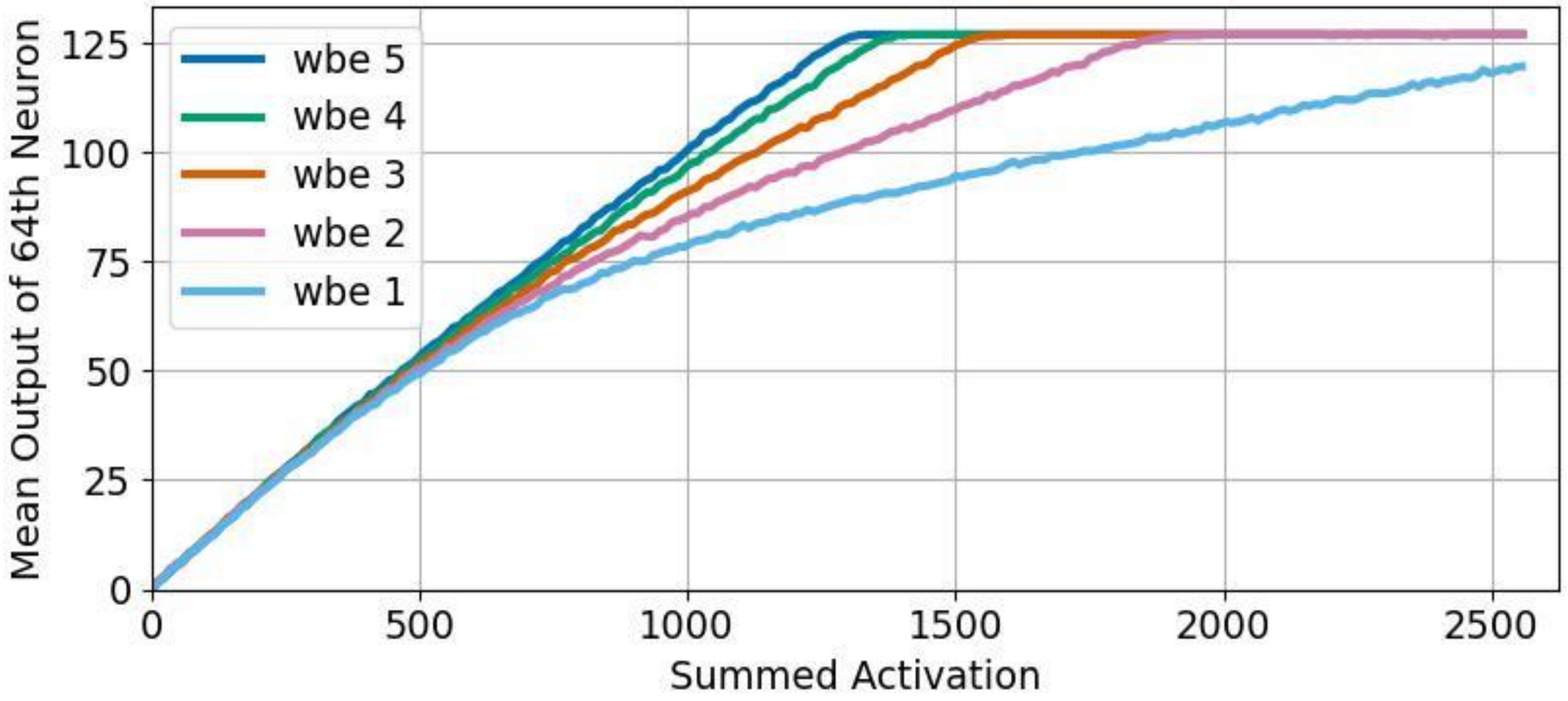

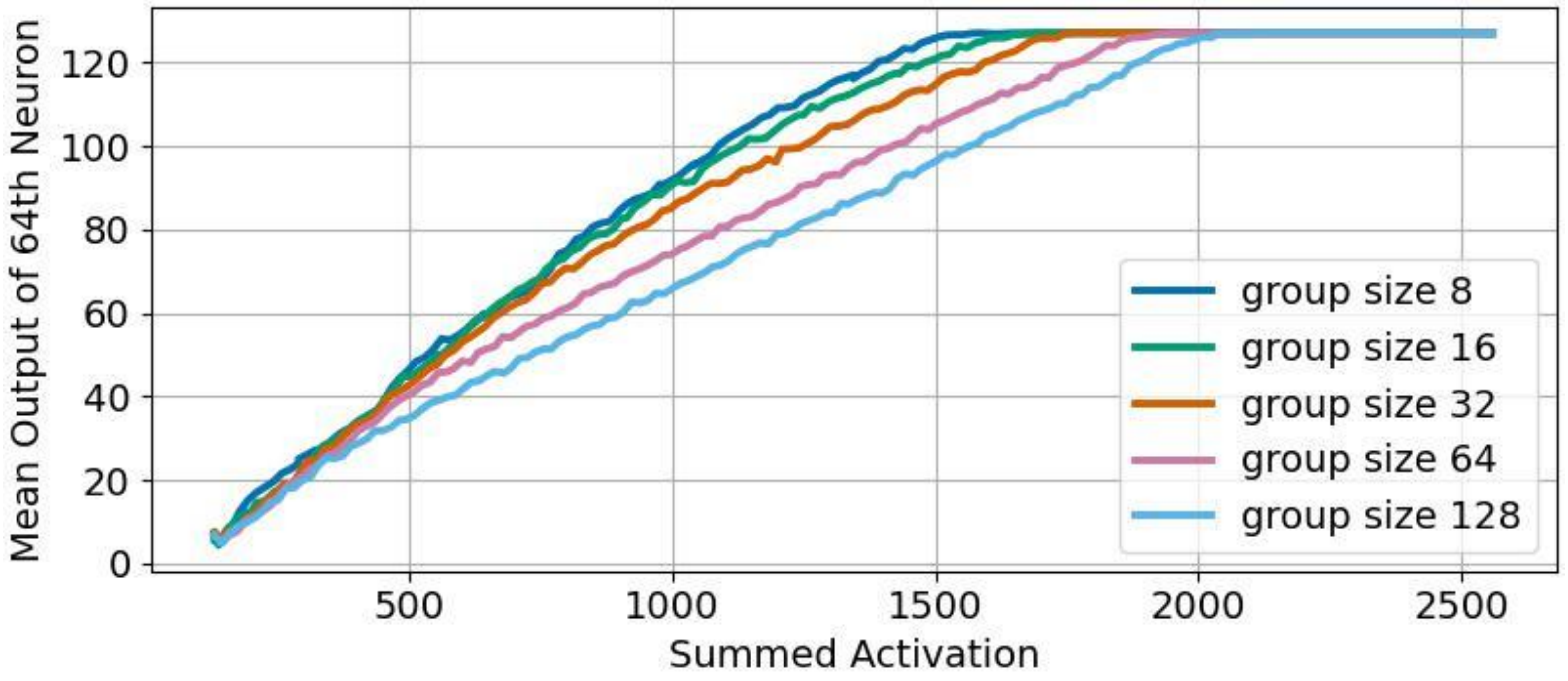

DEALING WITH IMPERFECTIONS

1. Retraining on the hardware (HW-in-the-Loop)
   Allows adjustment to offsets and gain factors
2. NNs don’t need linear components
3. Improve translation to the analog domain
4. Optimizing the calibration for a specific use-case
   noise vs. dynamic saturation vs. resolution vs. uniformity

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General (items 1–2)

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General

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Hardware Specific

DEALING WITH IMPERFECTIONS

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(1–2: General; 3–4: Hardware Specific)

NNs can tolerate static imperfections:
-reduced uniformity
-static non-linearities

NNs are sensitive to dynamic imperfections:
- Noise
- dyn. saturation

TRANSLATION APPROACHES

Uniform symmetric quantization:

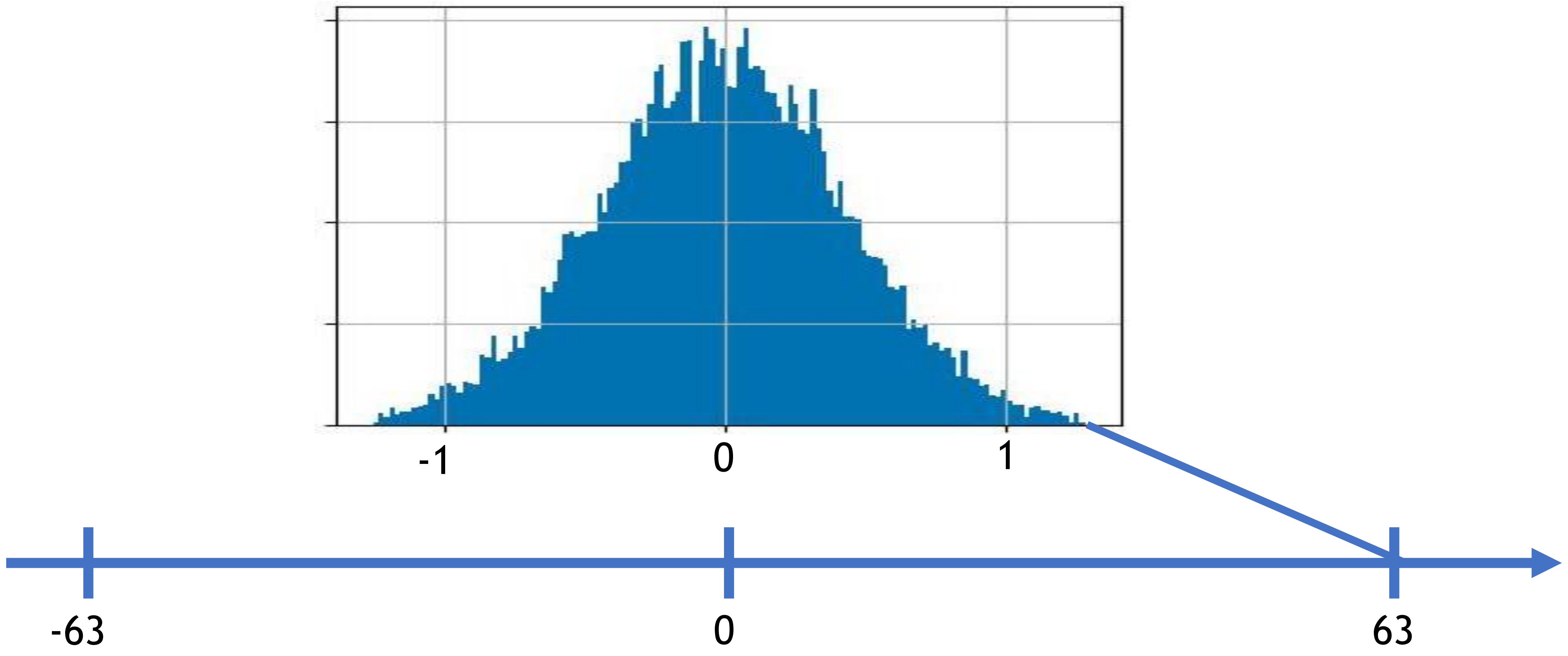
$$y = \text{quantize}(x) = \text{clip}\big(\text{round}(x \cdot s)\big)$$

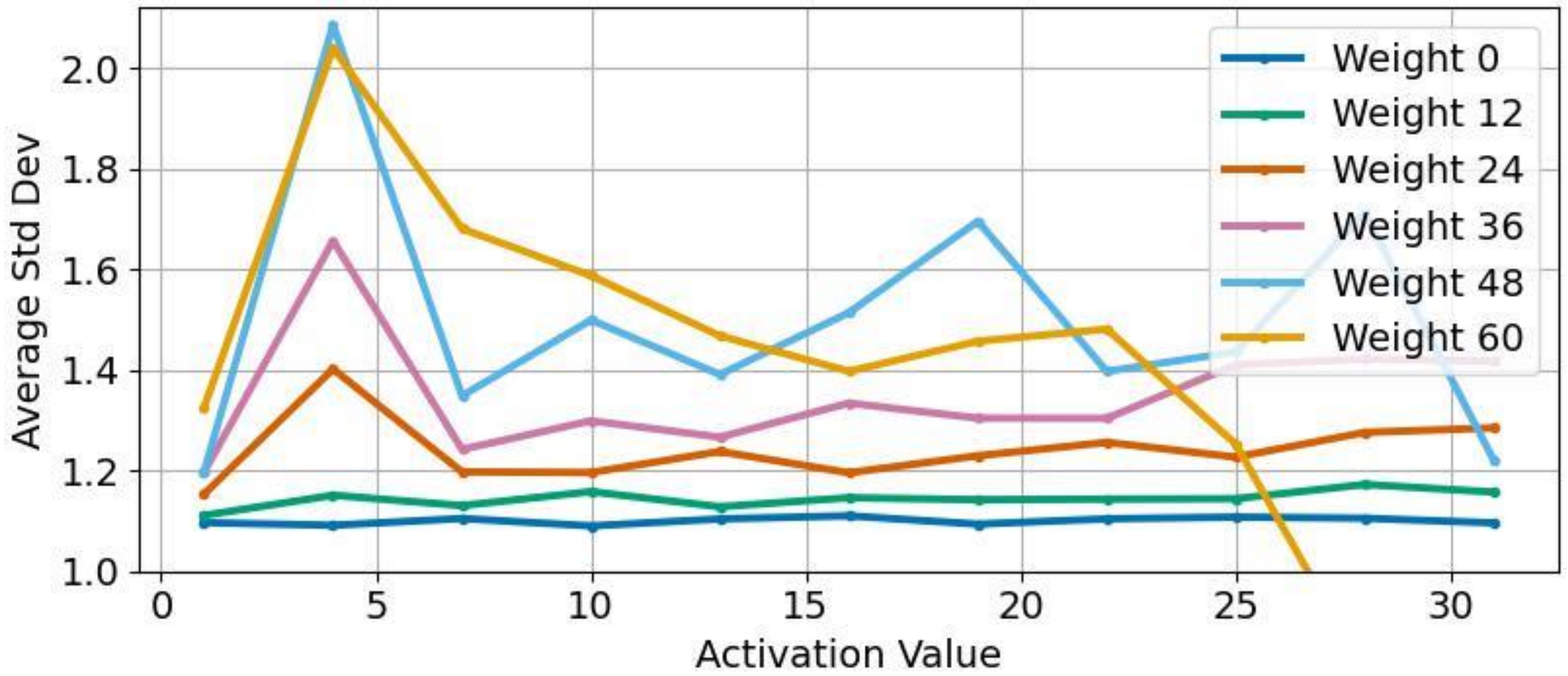
But how to choose the scaling factor during training?

1. Use a static scaling factor
2. Dynamically adjust the scaling factor for each batch
3. Use an exponential moving average

Can we clip small noisy input activations?

Turns out ineffective ☹





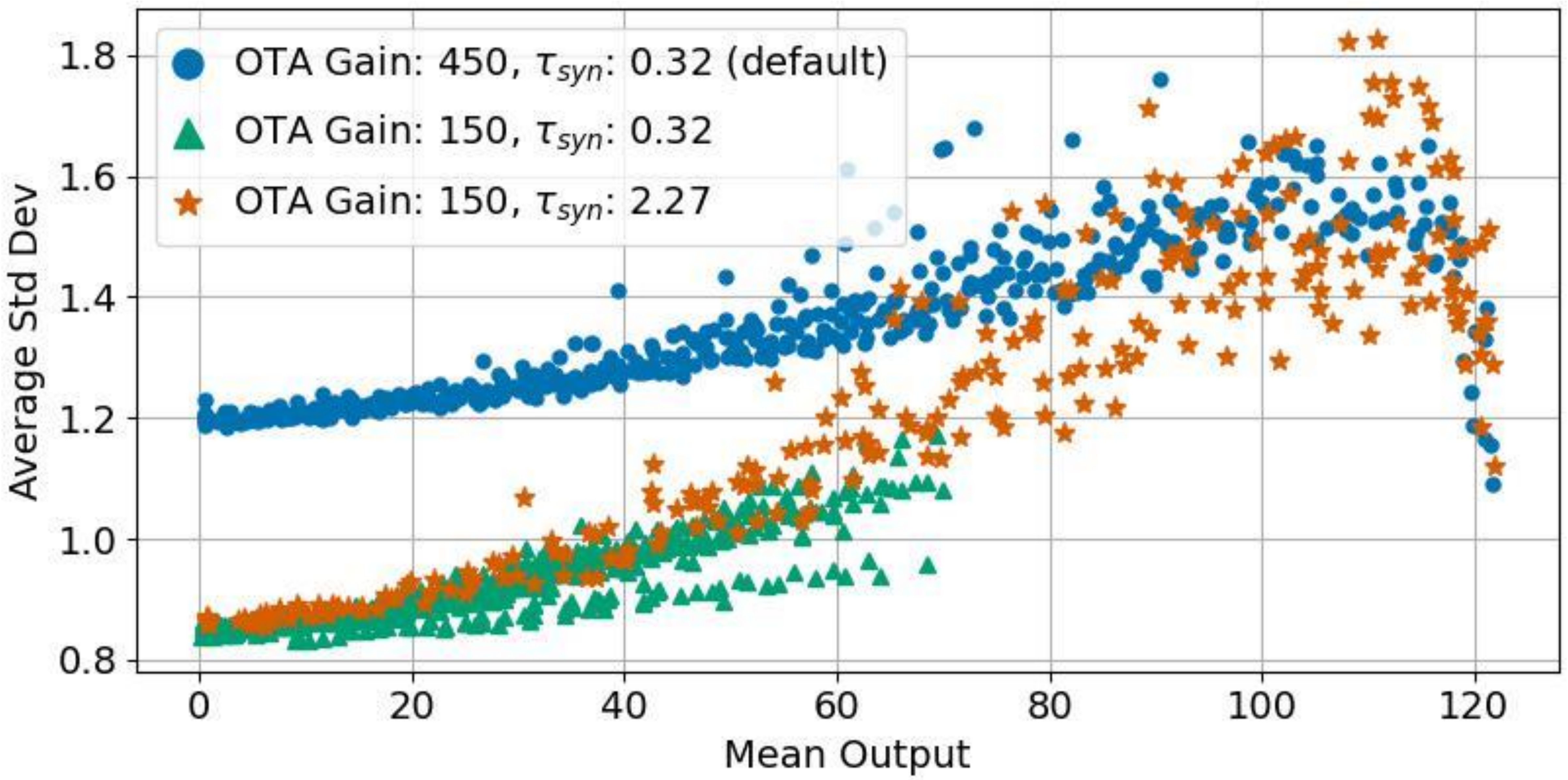
CUSTOM CALIBRATION

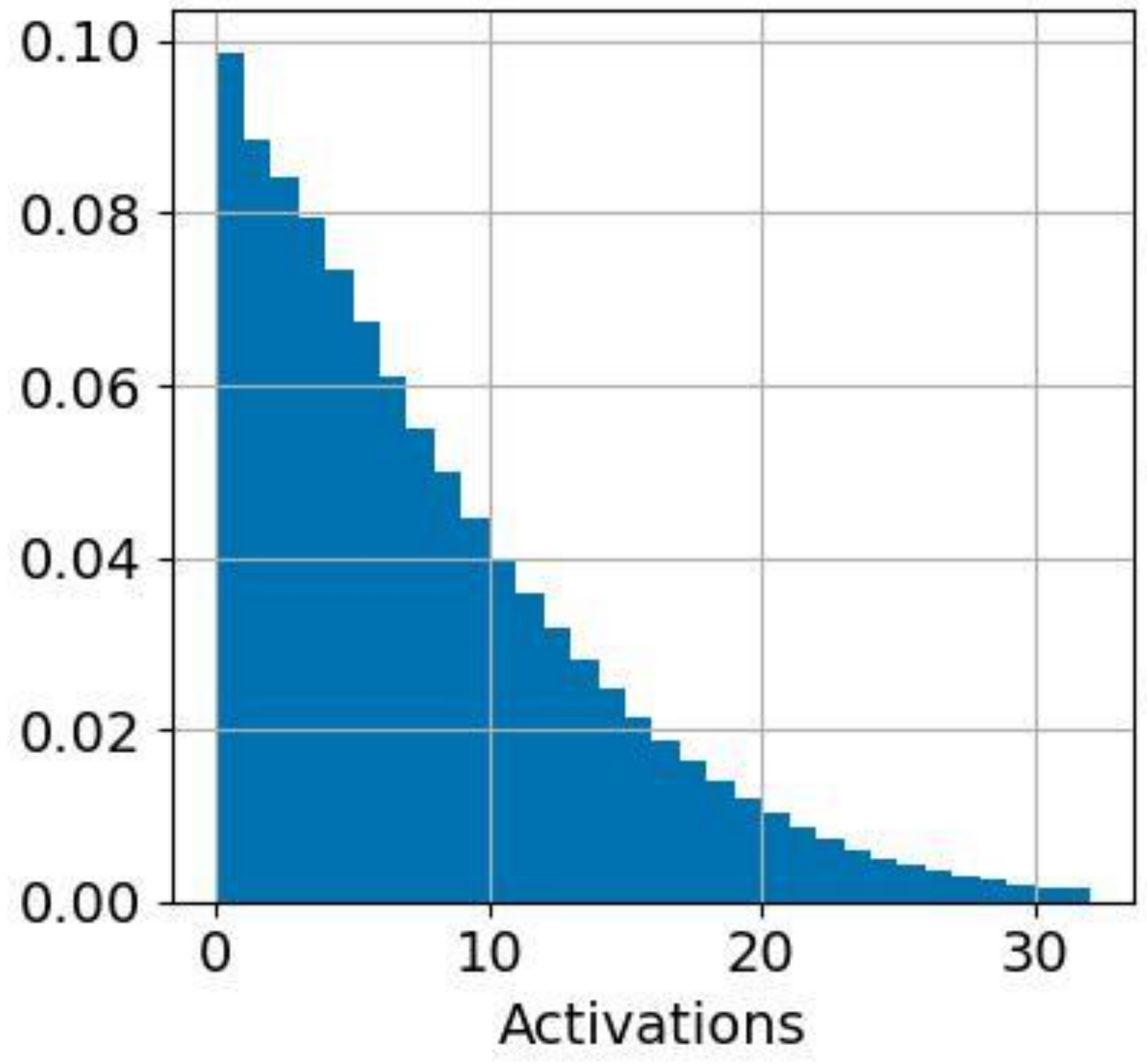
Reducing OTA Gain reduces Noise

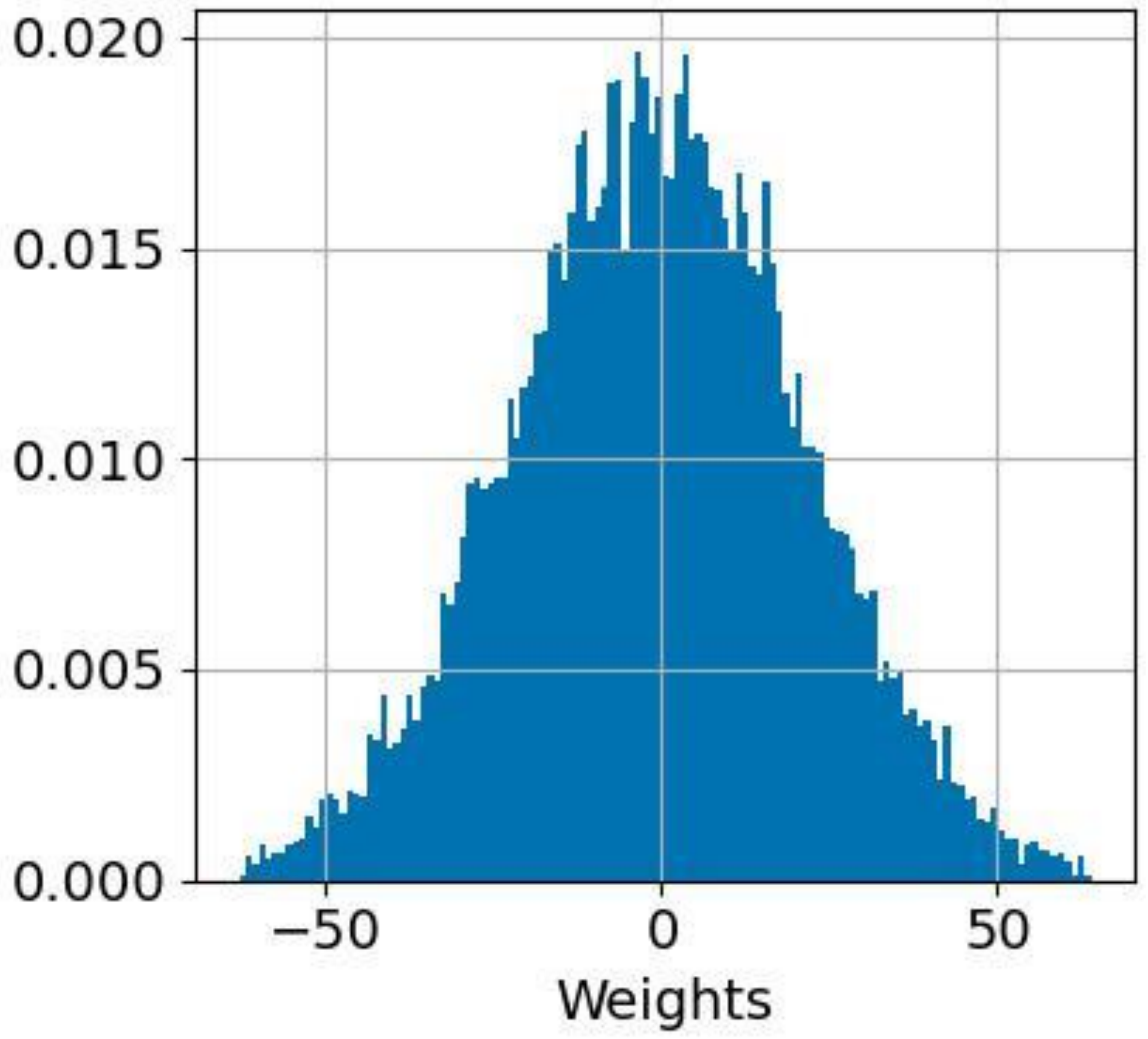
The synaptic input time constant increases gain
<u>but</u> also the risk of dynamic saturation

→ Increasing the synaptic input time constant restores gain with smaller noise

Typical distributions of NNs allow an increased time constant without dyn. saturation

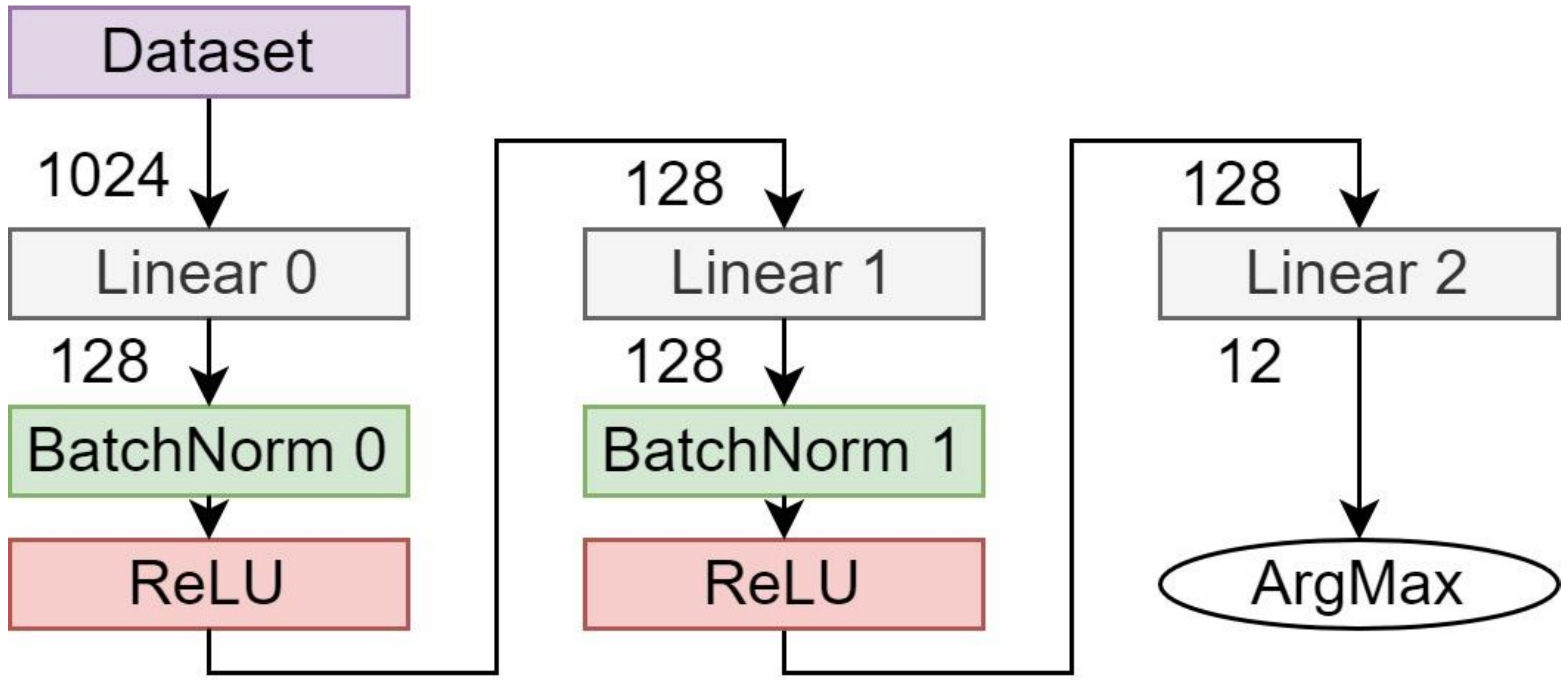


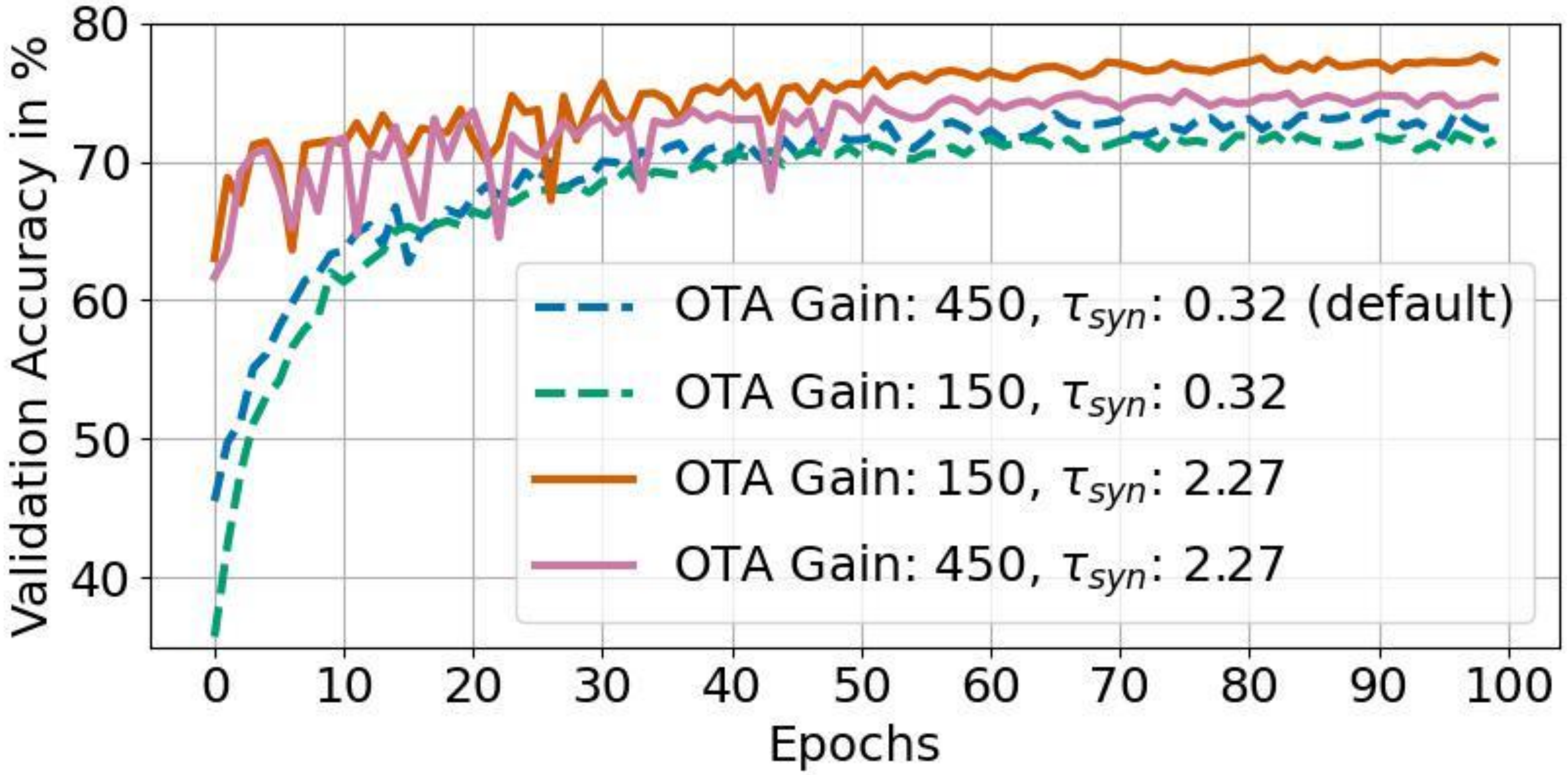




TRAINING RESULTS

- MLP with BatchNorm
- SpeechCommands V1
  Log Mel Spectrogram
- After full precision training:
  Retraining on analog Hardware





Initial accuracy increase

+

Final accuracy increase

CONCLUSION

We show:

- Factors influencing the analog imperfections
- Algorithmic adaptions to the imperfections
- Guidelines to improve the calibration
- Accuracy improvement of 7% with our custom calibration

HW Calibration	Default	Custom
Plain Transfer	17.73 %	57.93 %
HW-in-the-loop	68.74 %	**75.55 %**

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Recommendations:

1. Static quantization scaling
2. Reduce OTA Gain to reduce base noise
3. Increase global gain for few input features
4. Reduce integration time

TRY IT YOURSELF

Test the BrainScaleS-2 system from your browser:

ebrains.eu