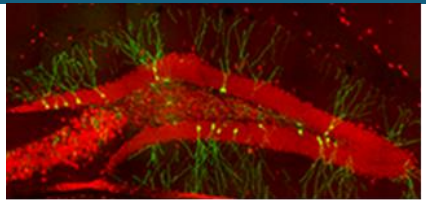
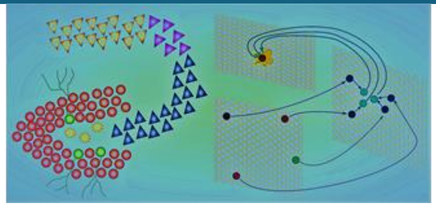
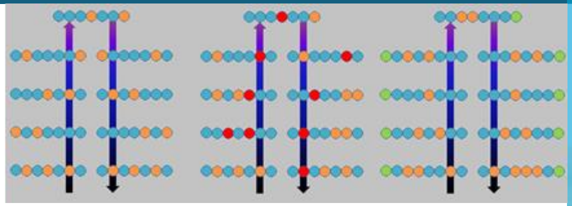
Whetstone

An Accessible, Platform-Independent Method for Training Spiking Deep Neural Networks for Neuromorphic Processors







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Sandia National Laboratories

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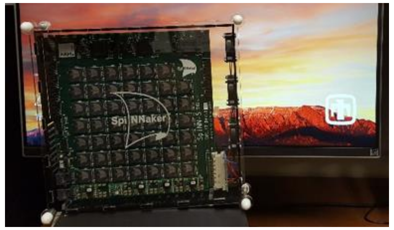
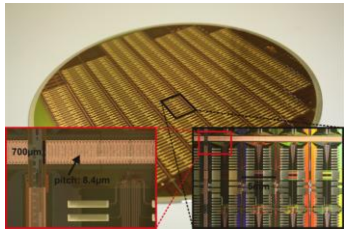
What is missing for neuromorphic to go mainstream?



Neuromorphic hardware is

- Available
- Competitive
- Constantly improving

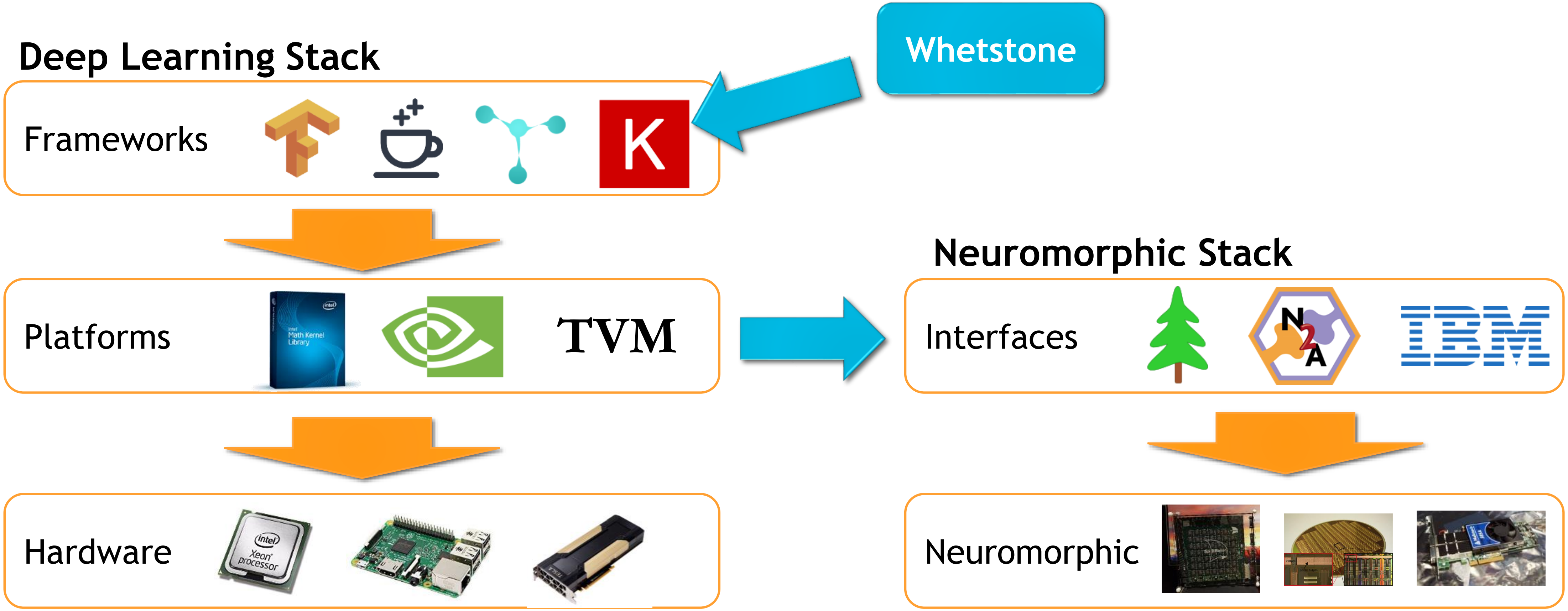
What is missing for neuromorphic to go mainstream?

Accessibility

Algorithms

Applications

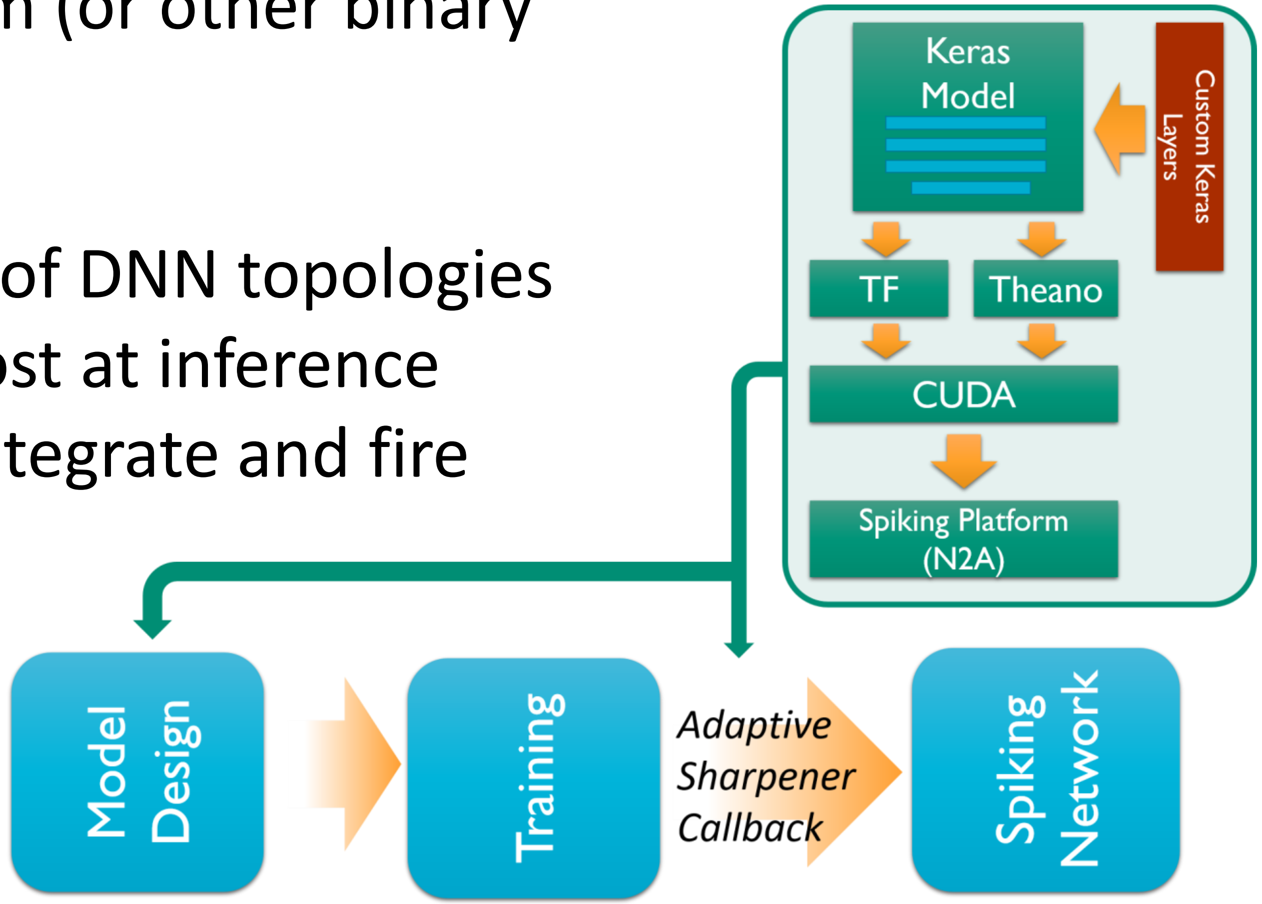
Introduction



Whetstone Overview

Whetstone provides a drop-in mechanism for tailoring a DNN to a spiking hardware platform (or other binary threshold activation platforms)

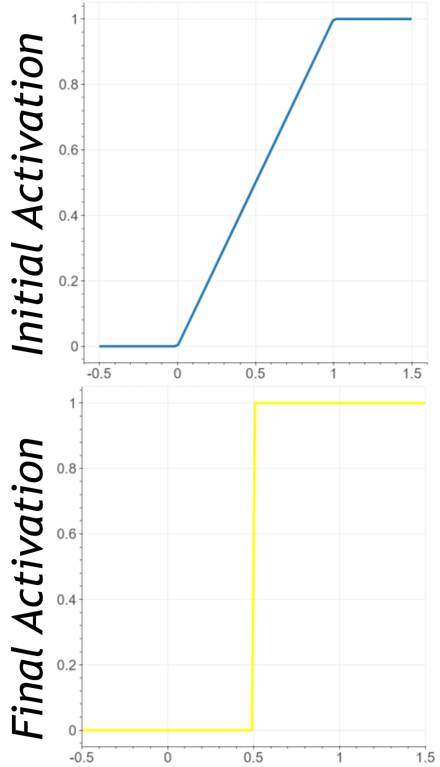
- Hardware platform agnostic
- Compatible with a wide variety of DNN topologies
- No added time or complexity cost at inference
- Simple neuron requirements: Integrate and fire

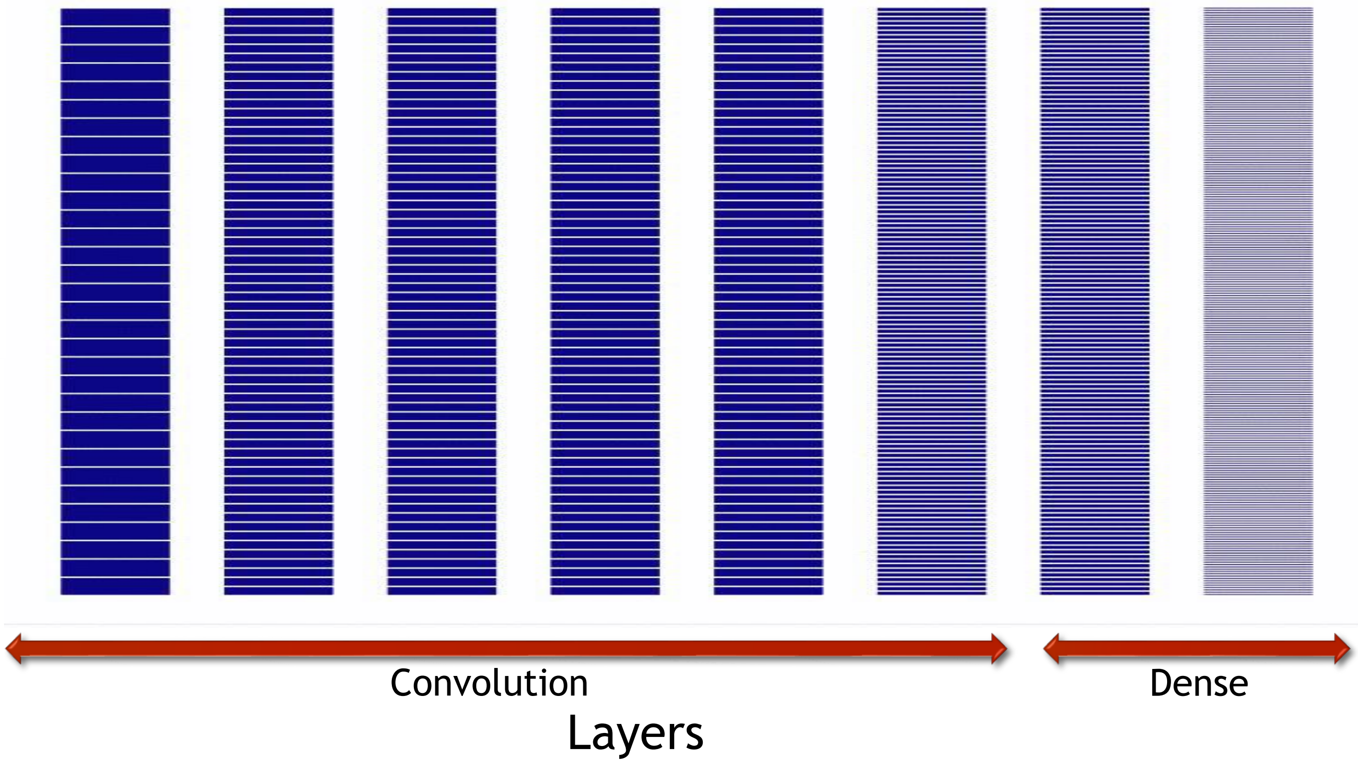


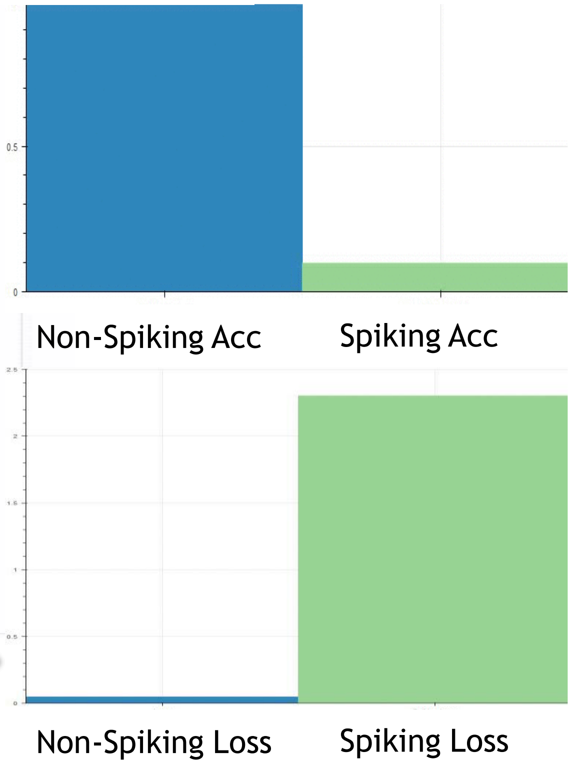
Whetstone Overview

The real challenge for deep learning on spiking is the threshold activation function.

Using Whetstone, activation functions converge to a threshold activation *during training.*







Whetstone Overview

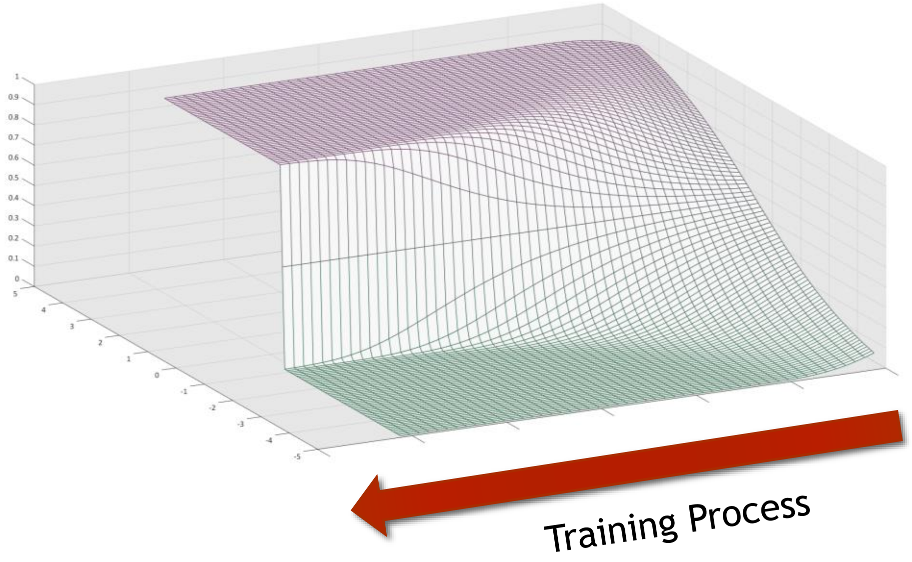
- Generally, gradient descent generates a sequence of weights A_i with the goal of

<u>minimizing the error of $f(A_i x)$ in predicting the ground truth y.</u>

- We generalize this by replacing the activation function f with a sequence f_k such that $f_k \to_{L_1} f$, where f is now the threshold activation function.
- Now, the optimizer must

<u>minimize the error of $f_k(A_i x)$ in predicting y.</u>

- Since the convergence in **neither *i* nor *k* is uniform**, this is a mathematically dangerous idea
- However, with a little care and a few tricks, the method reliably converges in many cases.



When/Where do we decide to 'sharpen' the activations?

1) Bottom-up Sharpening (The 'toothpaste tube' method)
   - Begin sharpening at the bottom layer
   - Wait until previous layer is fully sharpened
   - Increases stability of convergence
2) Adaptive Sharpening Callback
   - Hand-tuning sharpening rates is hard
   - Instead, use loss as a guide for an *adaptive sharpener*
   - Adaptive sharpener implemented as a callback automatically adjusts sharpening based on loss thresholds

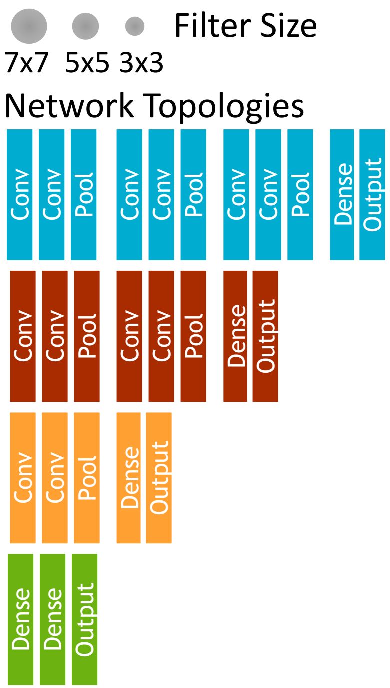
Original Model Example

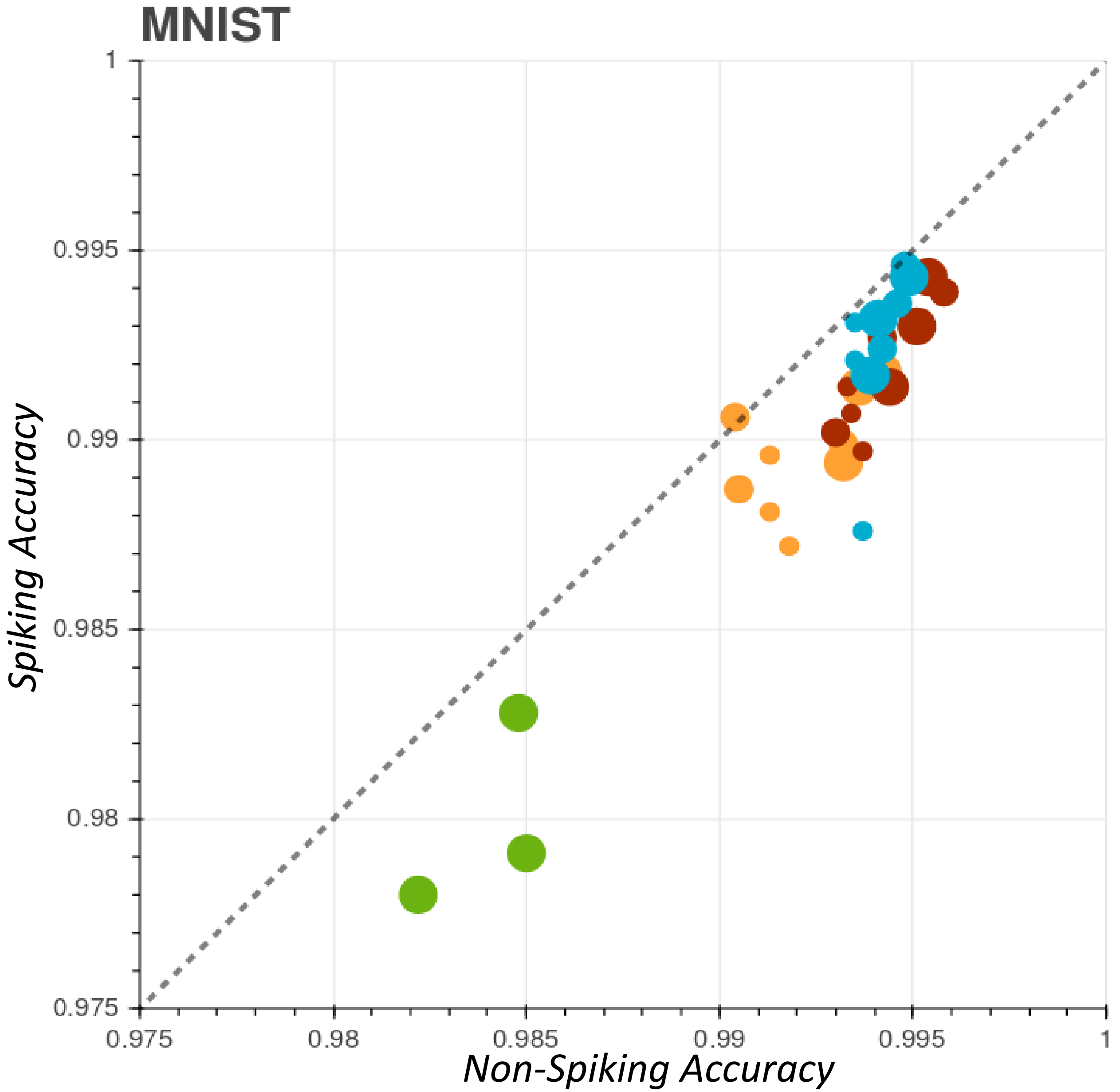
```
⋮
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dense(10))
model.add(Activation('softmax'))
⋮
model.fit(x,y)
⋮
```

Modified Model Example

```
⋮
model.add(Dense(256))
model.add(Spiking_BRelu())
model.add(Dense(10))
model.add(Spiking_Brelu())
Model.add(Softmax_Decode(key))
⋮
sharpener = AdaptiveSharpener()
model.fit(x,y,callbacks=[sharpener])
⋮
```

Preliminary Results





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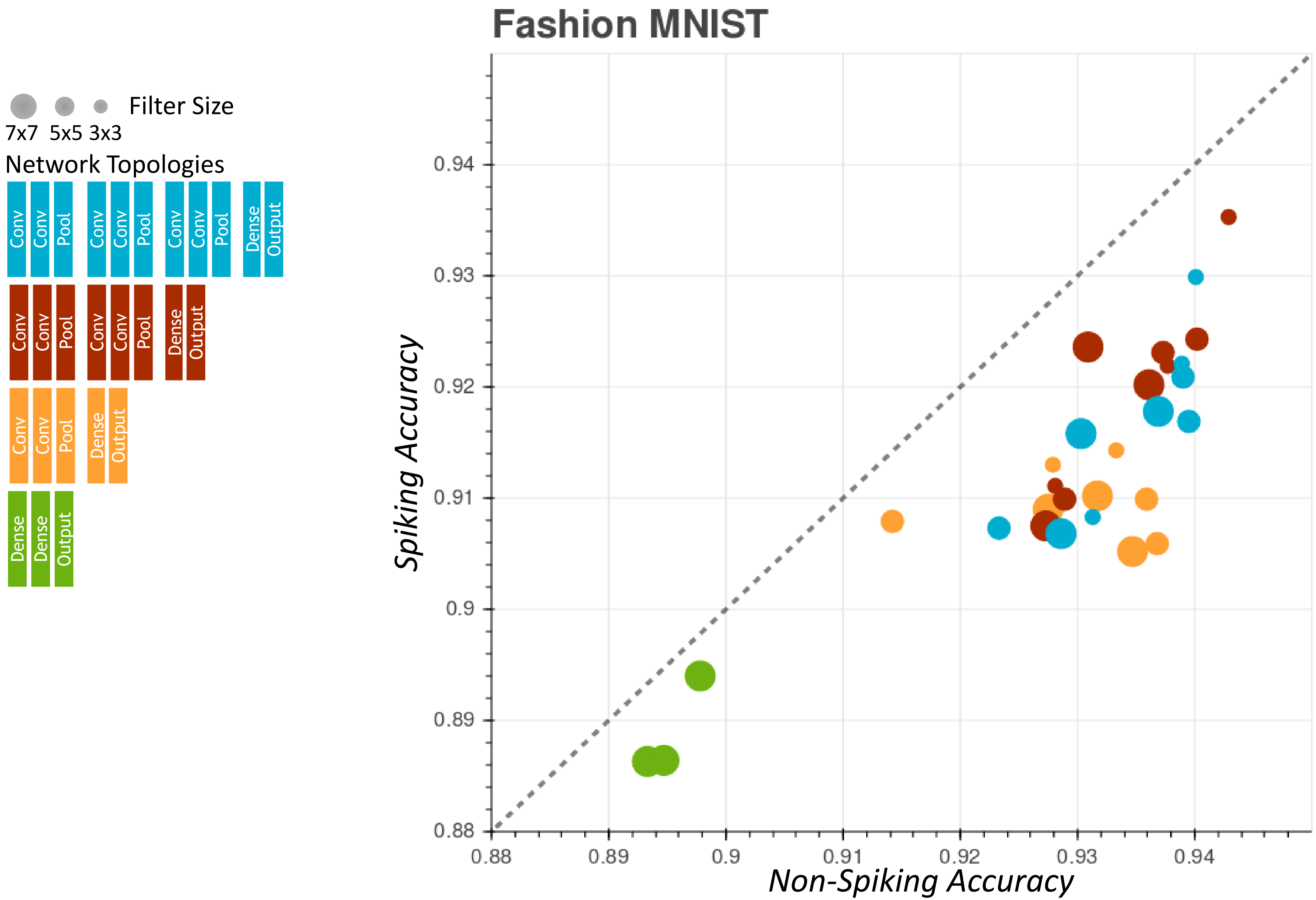

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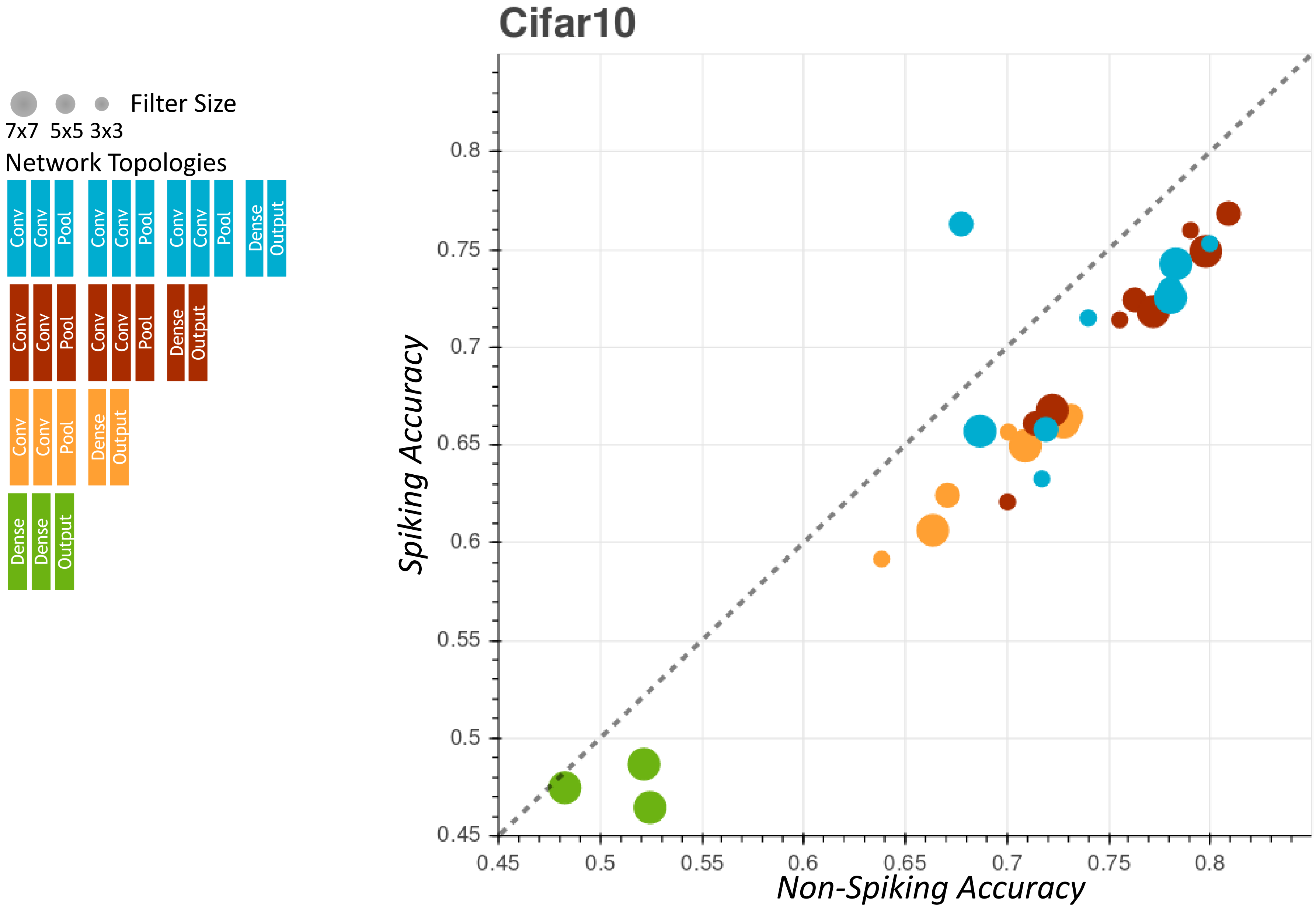

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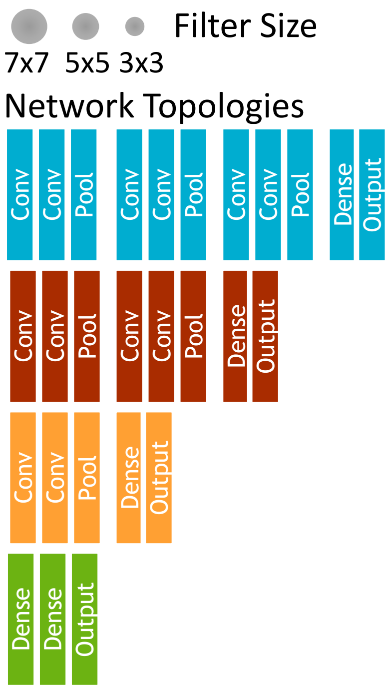
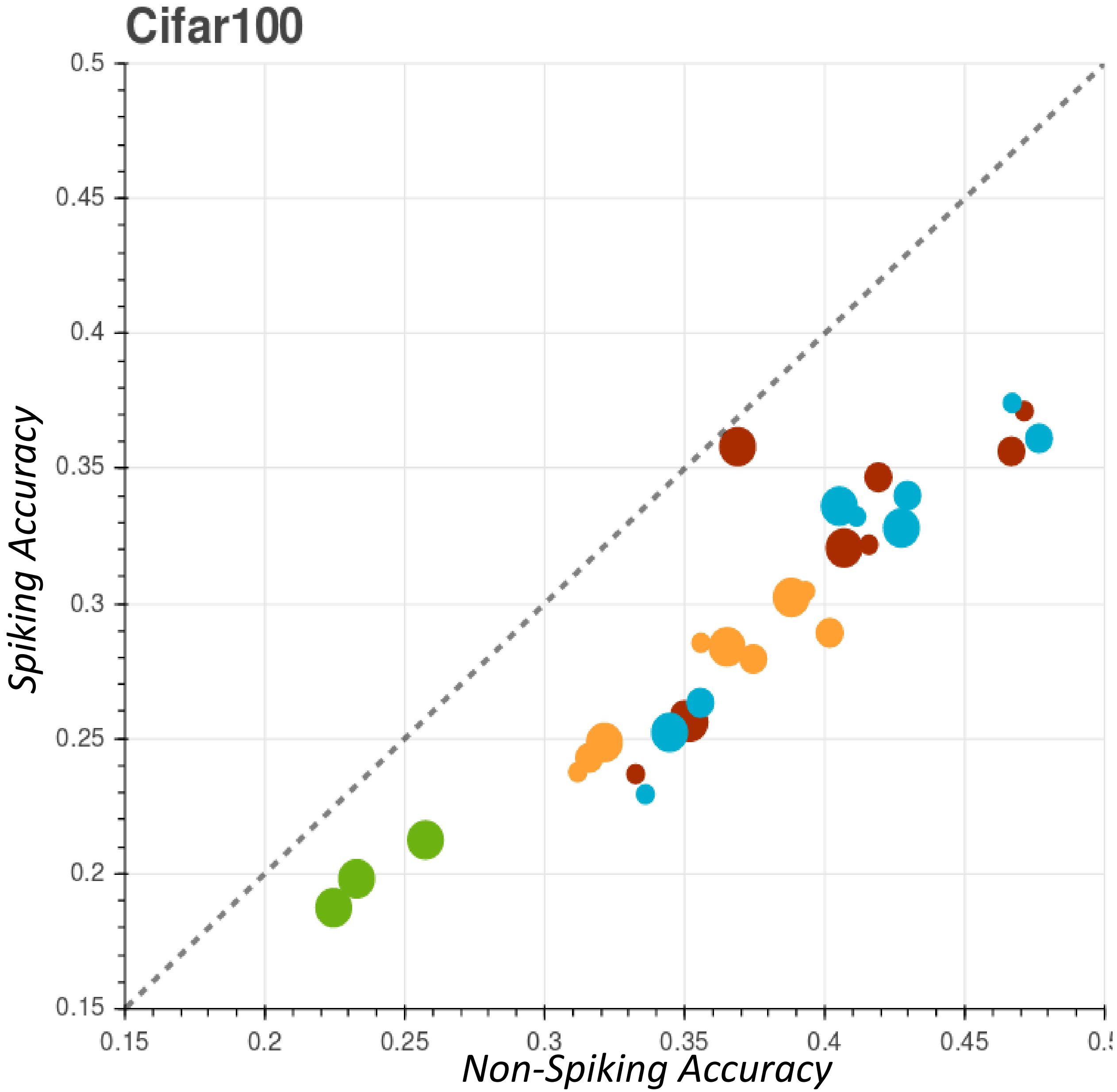




Established Deep Learning Techniques

Advantage: We can build on existing deep learning technology.

Software:

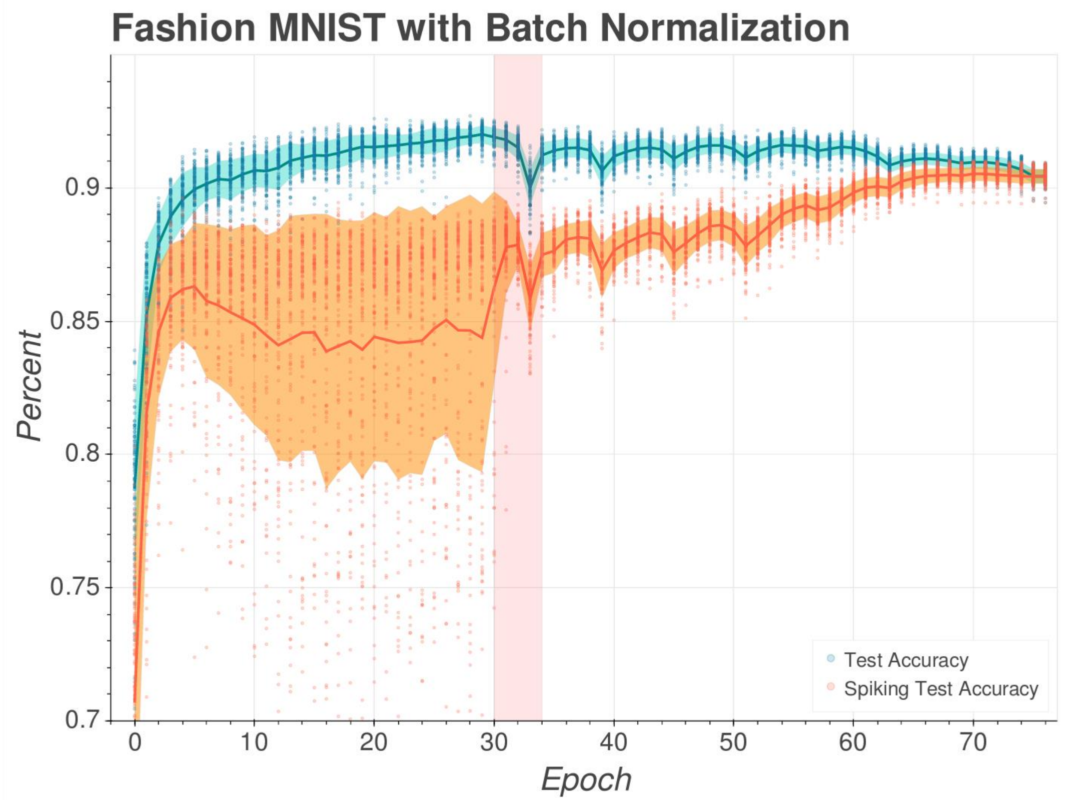
- Keras
- Tensorflow
- Theano
- CUDA
- Endless Python Packages

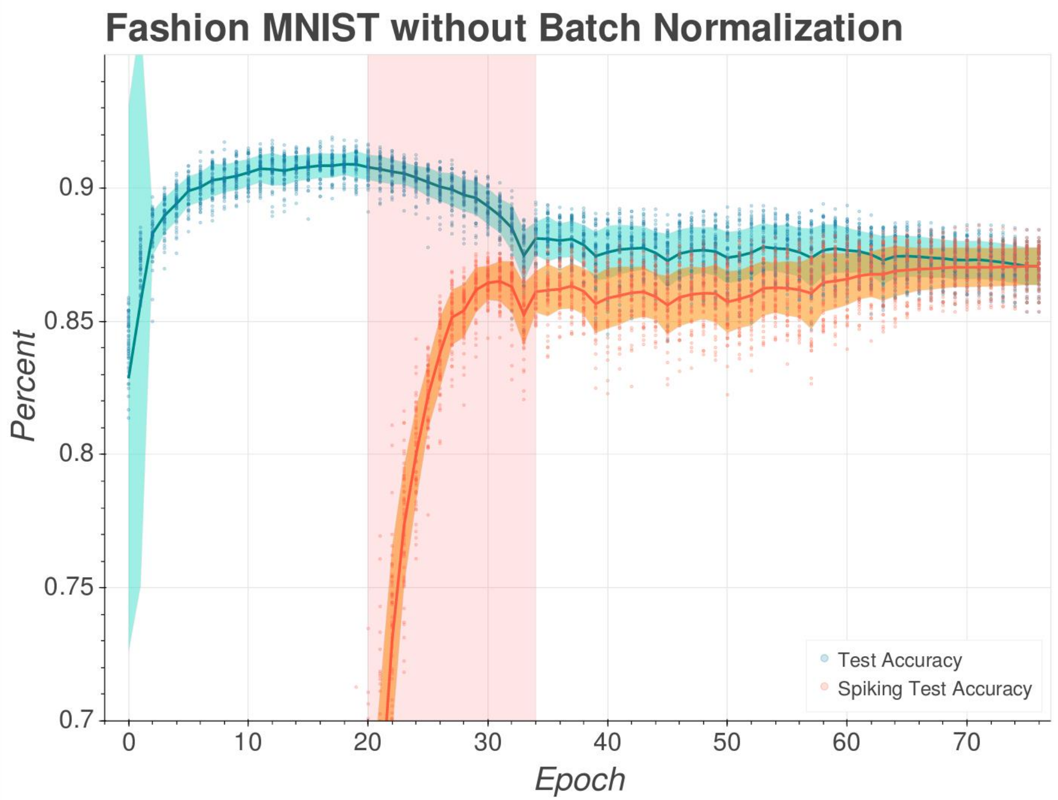
Techniques:

- Dropout
- Batch Norm
- Adaptive Optimizers
- Voting Methods

Established Deep Learning Techniques

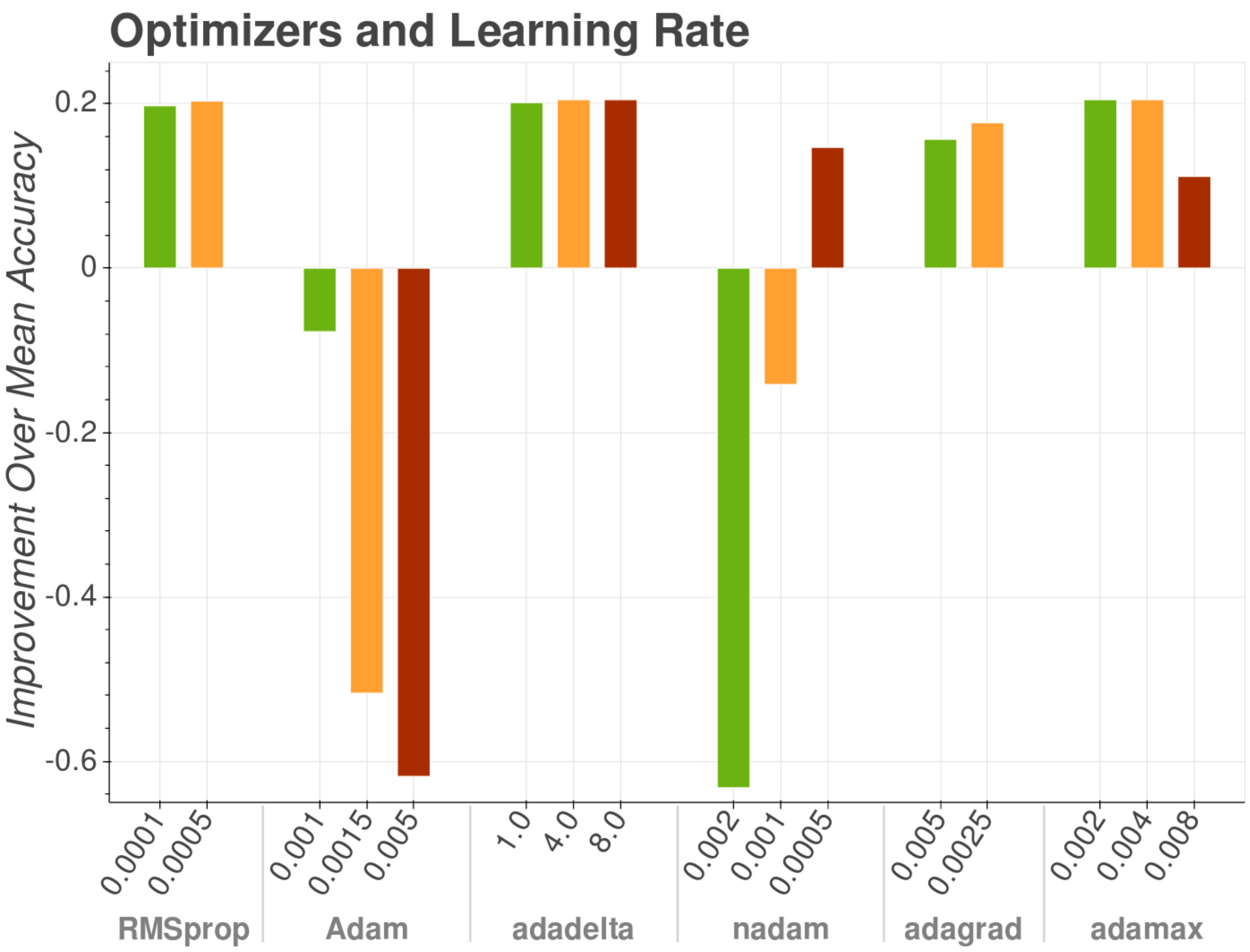
- Batch Normalization helps training stability and network performance
- Improvements across network sizes
- Sharpnening loss, particularly on first sharpening layer, is significantly less
- At inference time, bias (threshold) and weights are modulated according to stats collected during training





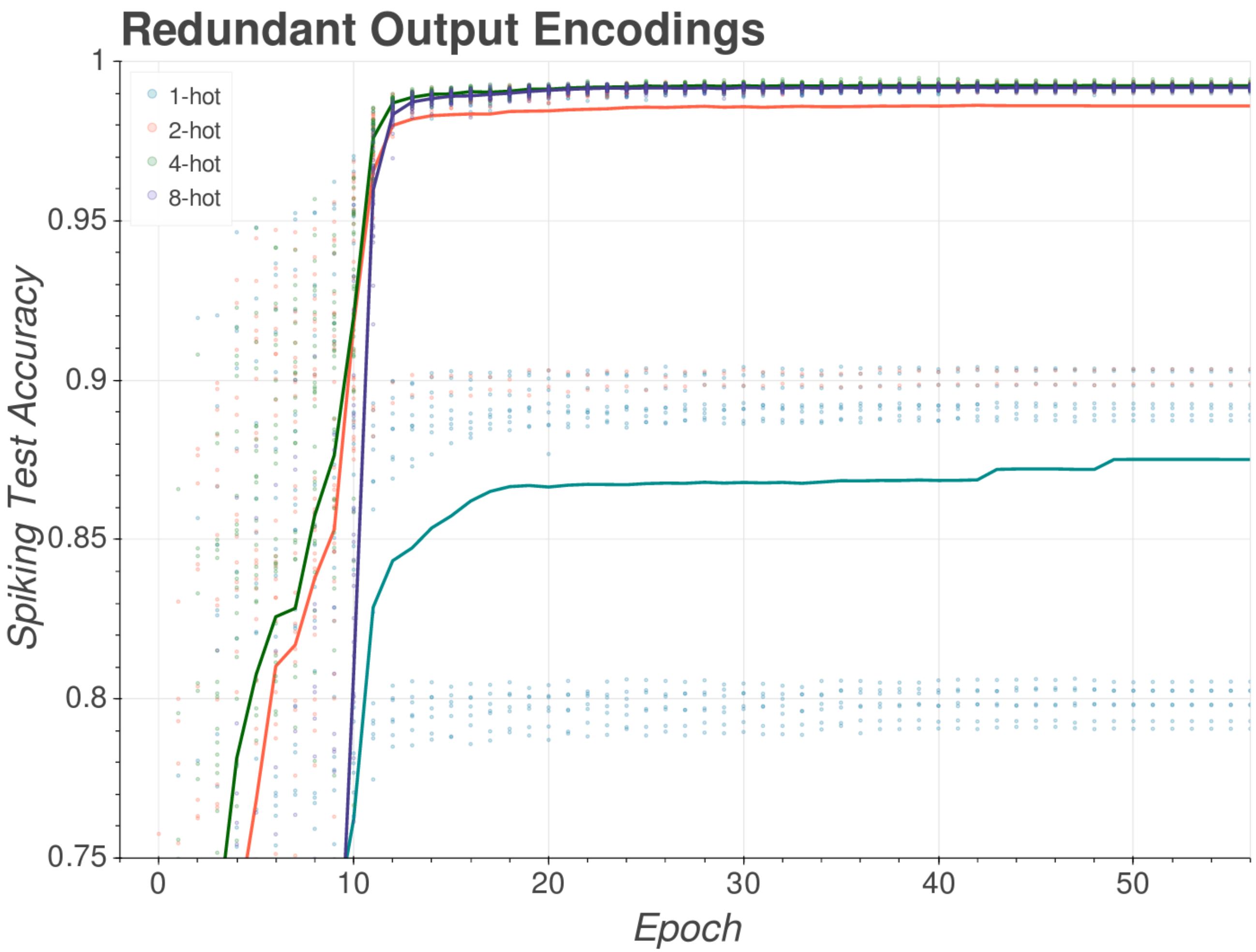
Established Deep Learning Techniques

- Sharpening process is sensitive to optimizer selection
- Adaptive optimizers often work better
- Learning rate modulation by moving average seems to help stability
- A custom Whetstone-aware optimizer is in early stages



Established Deep Learning Techniques

- The trained neurons can be unreliable
- Redundant output encodings help mitigate this problem
- Similar to ensemble methods
- Reactive neurons feed into softmax during training (for classification)
- During inference, ‘best-matched’ group is used
- On simple datasets, 4-way redundancy is sufficient



Enabling Wide and Easy-to-Implement Adoption

Neuromorphic hardware platforms are appealing for a wide variety of low-power, embedded applications

Sophistication and expertise required to make use of these platforms creates a high barrier of entry

Whetstone enables deep learning experts to easily incorporate spiking hardware architectures

Enabling Wide and Easy-to-Implement Adoption

Networks are portable and hardware-agnostic

Low barrier of entry; built on standard libraries (Keras, Tensorflow, CUDA, etc.)

No post-hoc analysis; no added time complexity

Only simple integrate-and-fire neurons are required

Compatible with standard techniques like dropout and batch normalization

Enabling Wide and Easy-to-Implement Adoption

Neuromorphic Hardware in Practice and Use

Description of the workshop

Abstract – This workshop is designed to explore the current advances, challenges and best practices for working with and implementing algorithms on neuromorphic hardware. Despite growing availability of prominent biologically inspired architectures and corresponding interest, practical guidelines and results are scattered and disparate. This leads to wasted repeated effort and poor exposure of state-of-the-art results. We collect cutting edge results from a variety of application spaces providing both an up-to-date, in-depth discussion for domain experts as well as an accessible starting point for newcomers.

Goals & Objectives

This workshop strives to bring together algorithm and architecture researchers and help facilitate how challenges each face can be overcome for mutual benefit. In particular, by focusing on neuromorphic hardware practice and use, an emphasis on understanding the strengths and weaknesses of these emerging approaches can help to identify and convey the significance of research developments. This overarching goal is intended to be addressed by the following workshop objectives:

- Explore implemented or otherwise real-world usage of neuromorphic hardware platforms
- Help develop 'best practices' for developing neuromorphic-ready algorithms and software
- Bridge the gap between hardware design and theoretical algorithms
- Begin to establish formal benchmarks to understand the significance and impact of neuromorphic architectures

http://neuroscience.sandia.gov/research/wcci2018.html

Call: https://easychair.org/cfp/nipu2018