

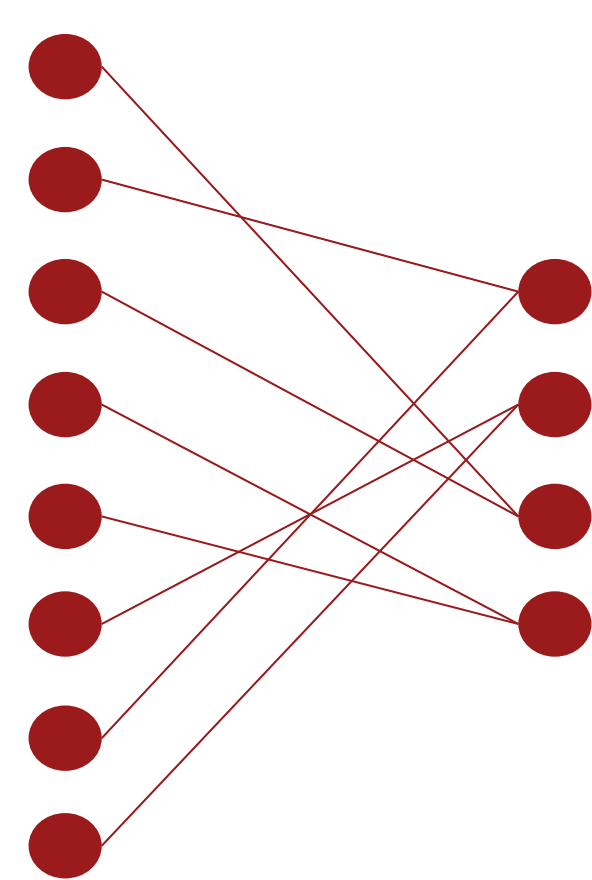
A Highly Parallel FPGA Implementation of Sparse Neural Network Training

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Motivation & Introduction

Neural networks too big to be trained on-chip
Cloud resources are costly

Our Solution: **Pre-defined sparsity**
Reduces edges, hardware friendly
Fixed in-, out-degree of each node



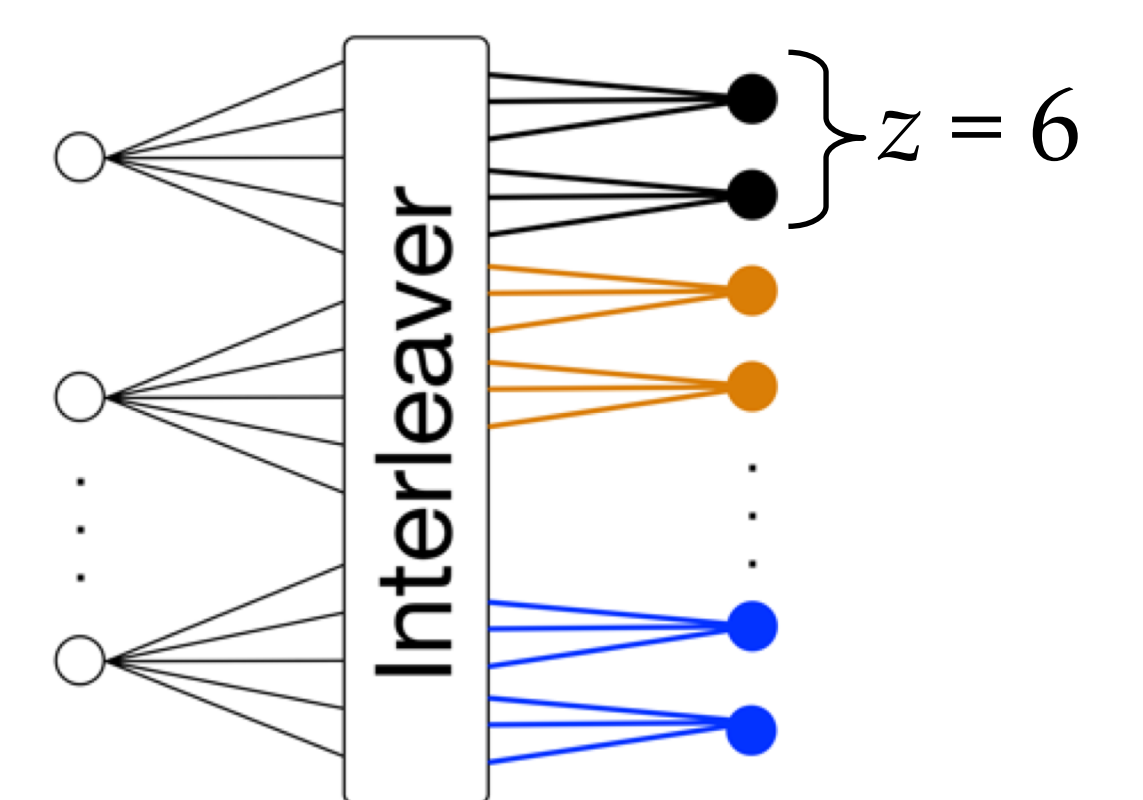
Train neural networks on FPGAs

Methodology

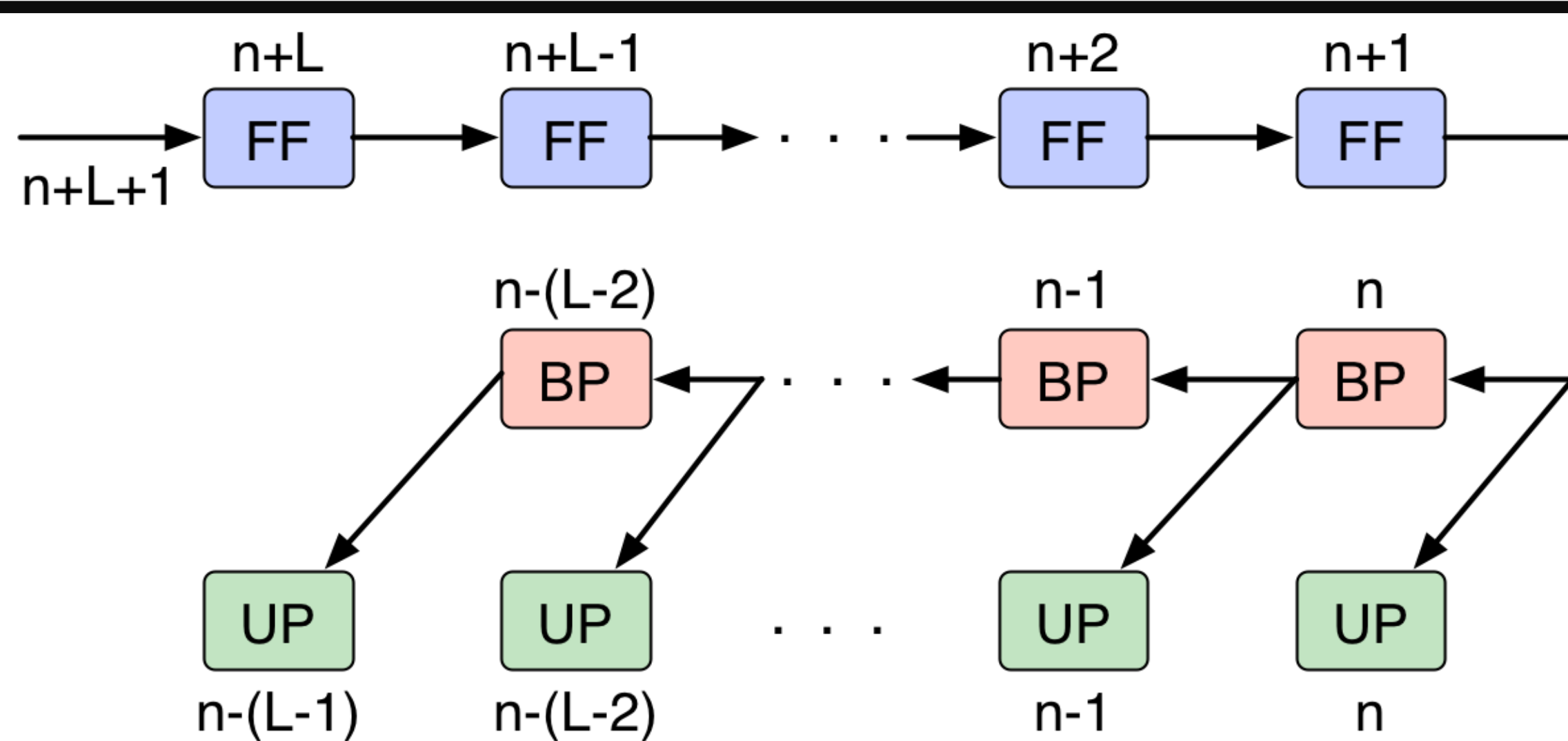
3 operations:

- Feedforward (FF)
 - Backpropagate (BP)
 - Update (UP)
- All use weighted junction edges

- ✓ Process z edges in 1 clock cycle
- ✓ 1 **block cycle** = Total clock cycles to process all edges in any junction
- ✓ Ideal throughput = (Block cycle)⁻¹

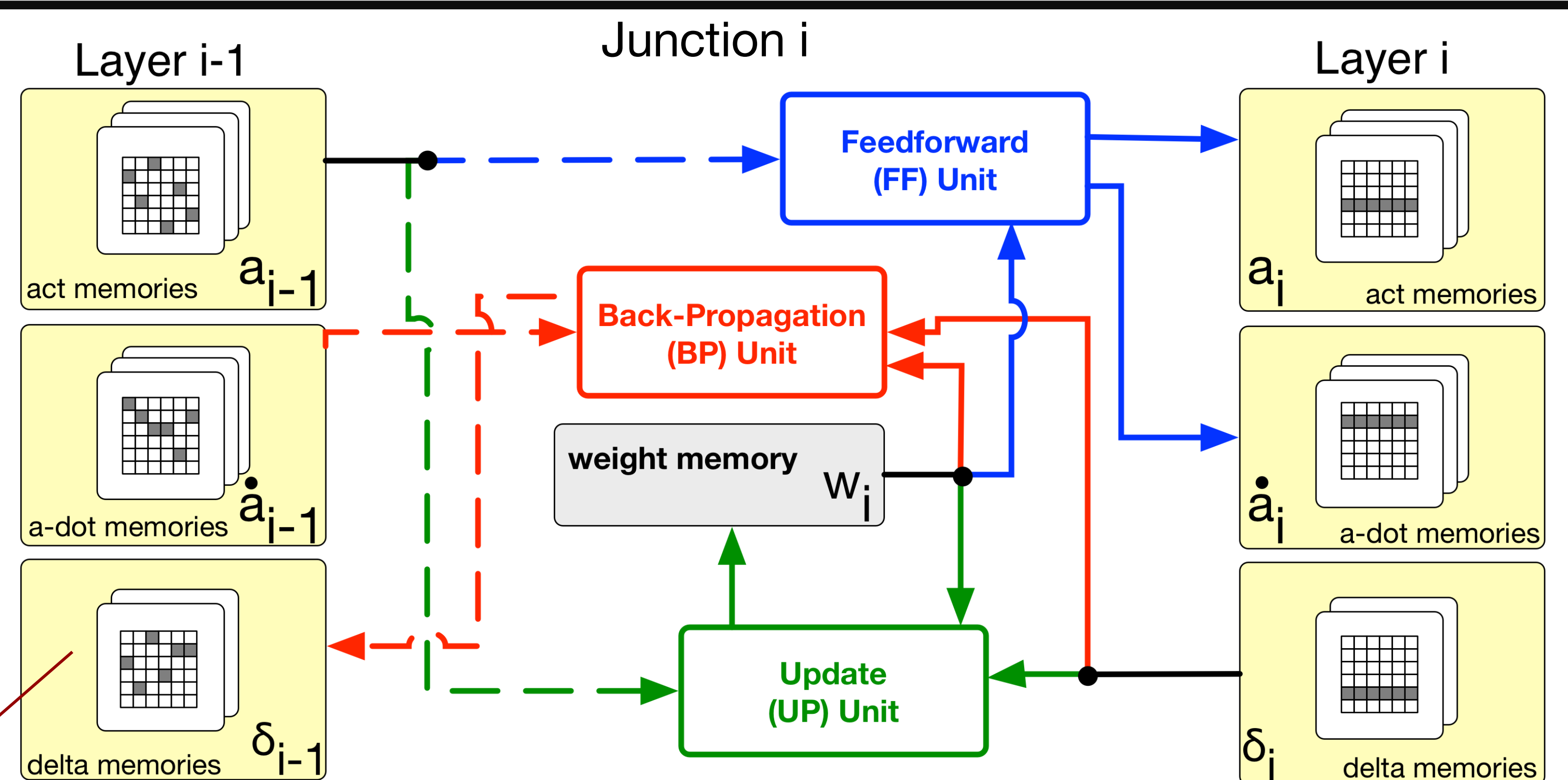


Hardware Acceleration – Parallelism and Pipelining



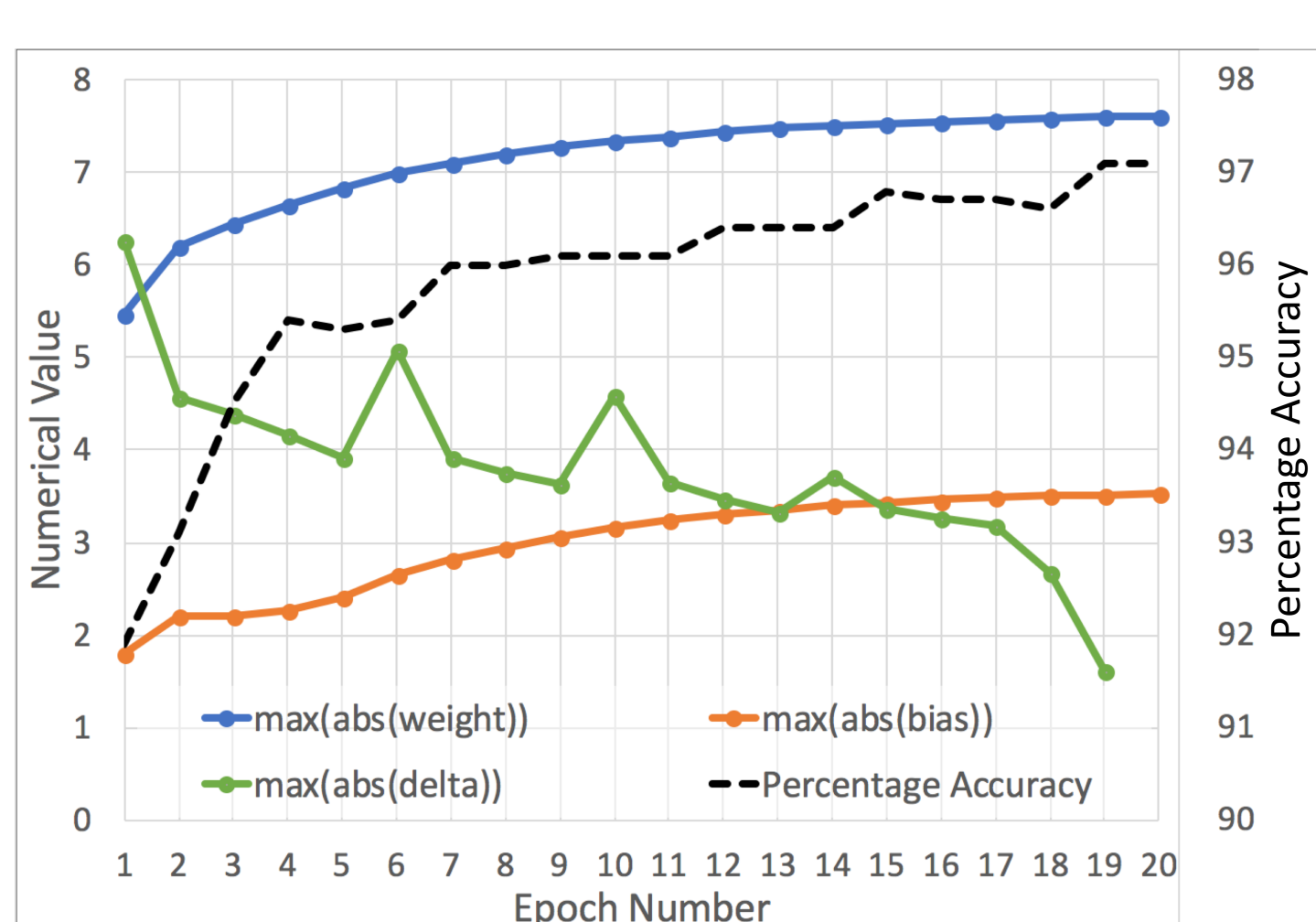
Junction pipelining: Different input samples processed together across all junctions

Clash Freedom: Each memory accessed at most once in a cycle



Operational Parallelization: FF, BP, UP together inside a junction

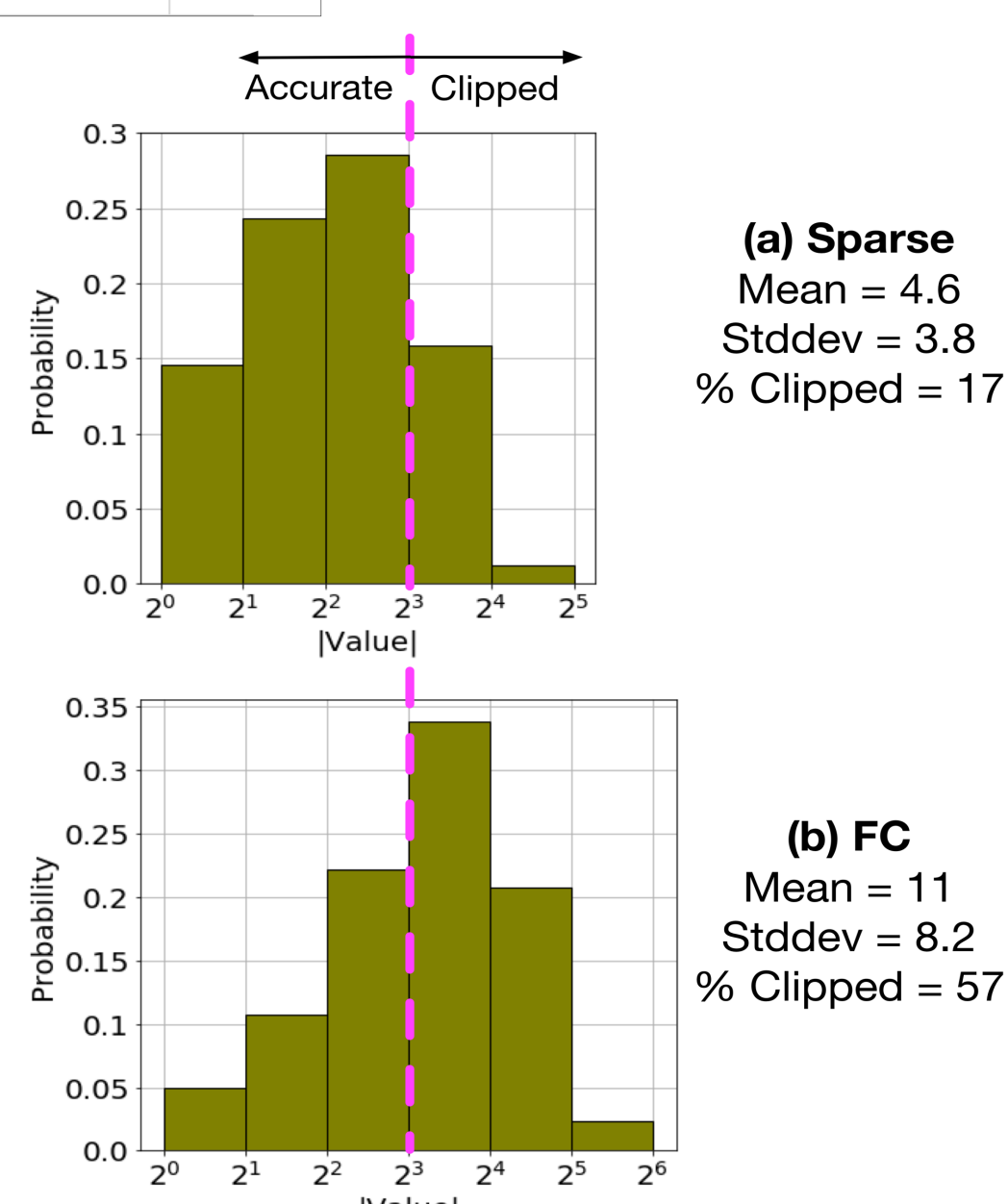
Bit Width Studies



Network parameters stay within 8
=> Use fixed point with 3 integer bits

Histograms of weight-activation dot product in junction 1.

Pre-defined sparse networks have less errors due to finite bit-width effects.



FPGA Implementation – MNIST Training and Inference on Artix-7

Junction Number	1	2
Left Neurons	1024	64
Right Neurons	64	32
Out-degree	4	16
Weights	4096	1024
In-degree	64	32
z	128	32
Block Cycle	32	32
Density	6.25%	50%

Overall Density	7.576%
Fixed Point Bit Width	12
Clock Frequency	15 MHz
Block Cycle Duration	2.27 μ s
Accuracy (after 14 training epochs)	96.5%

Reconfigurability

Slow Training Resource Intensive

Ongoing Research:

- Increased pipelining to improve speed
- Memory bandwidth management for bigger networks