PRODUCT

BinaryConnect: Training Deep Neural Networks with binary weights during propagations.

Produced By Learners
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Contents

The goal of this report is to provide a unified list of the to opportunities to help inform the upcoming growth process.

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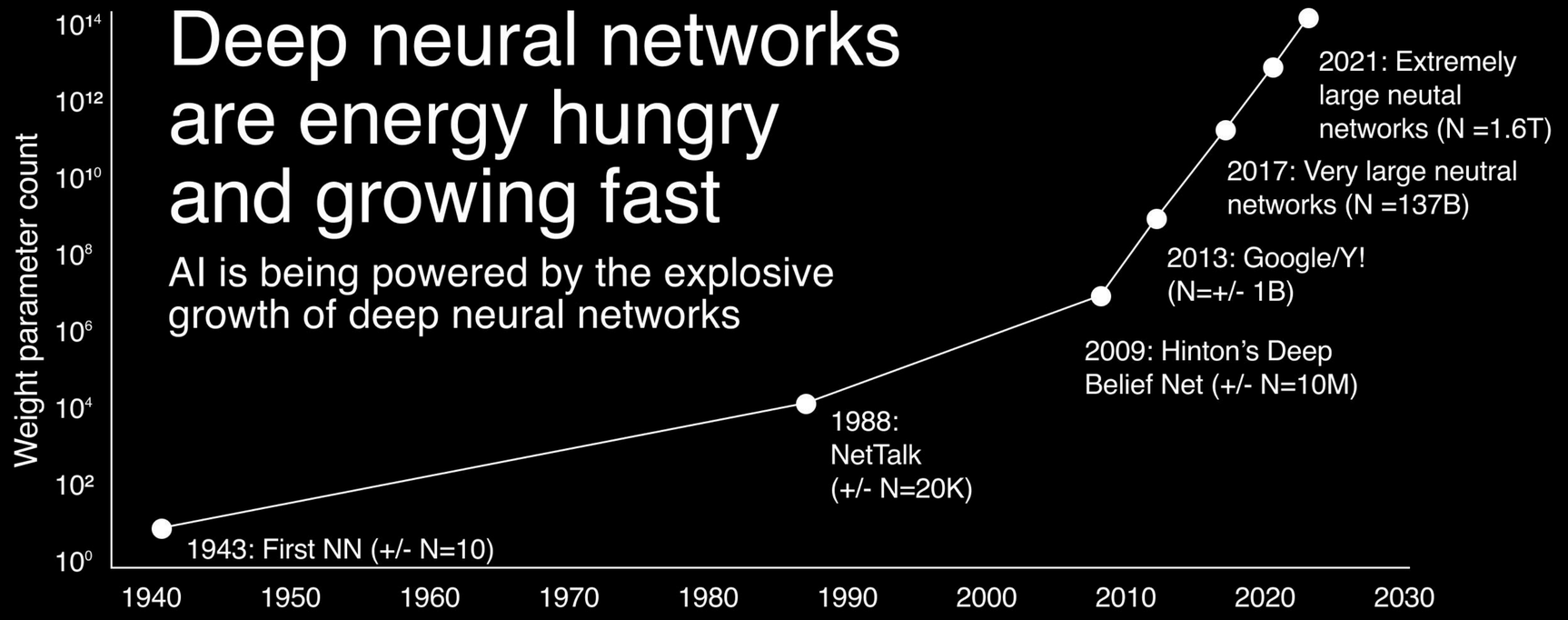
Report and Implementation

Github

Report

Deep neural networks are energy hungry and growing fast

AI is being powered by the explosive growth of deep neural networks



2025 | Increasingly large and complex neural networks for Natural language Processing, Image and Video Processing

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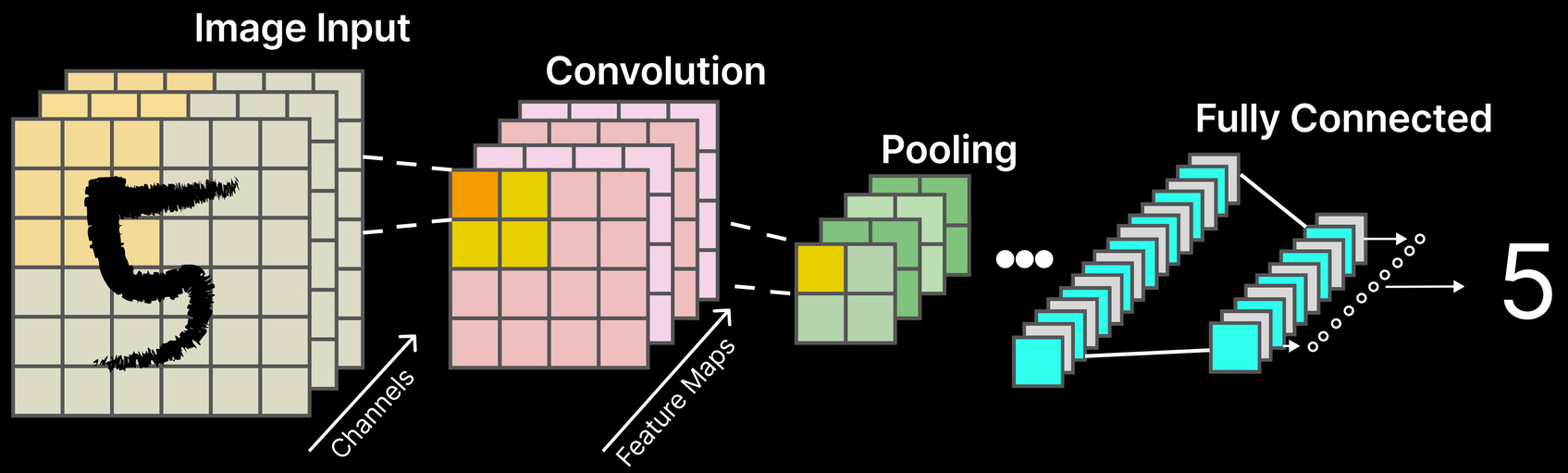
Motivation : NNs do a lot of number crunching

For example, Convolutional Neural Networks:

- **Many layers** (100+) for large pipelines with self-learning feature extractors
- Running time dominated by **multiply-accumulate** operations: 75-85%
- Significant **traffic** between layers: up to 200MB per layer



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What can we do to make things better?

Several options have been researched and developed:

- Parallelization
- GPUs
- Quantization (Reduced Precision)
- Compression (pruning, trained quantization)
- Better algorithms (FFT/Winograd for convolutions)
- Special purpose hardware (ASICs, FPGAs, and others)

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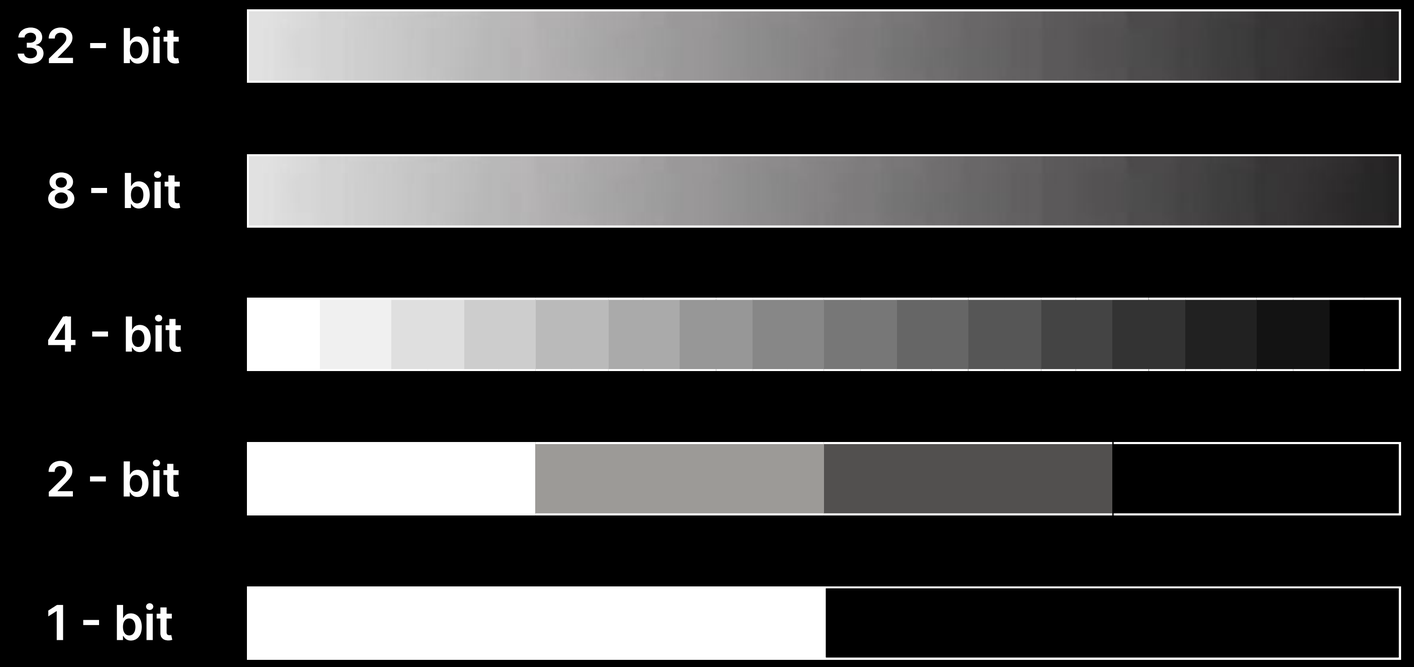
Reducing the number of bits

In context of DL, quantization refers to the process of reducing the number of bits that are used to represent a value:



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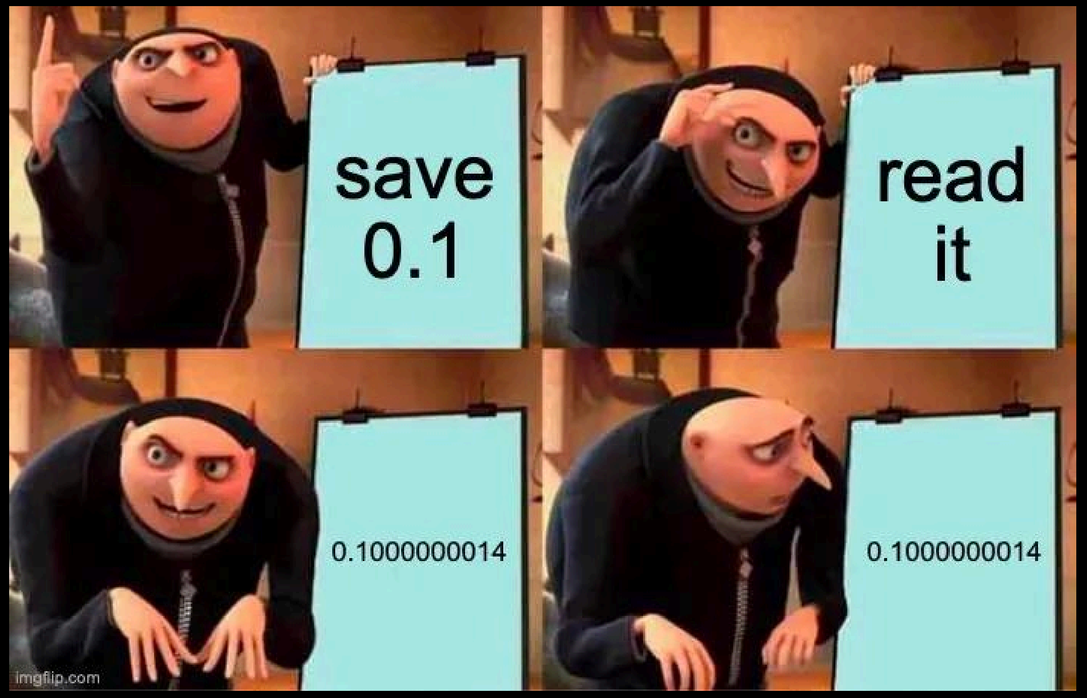

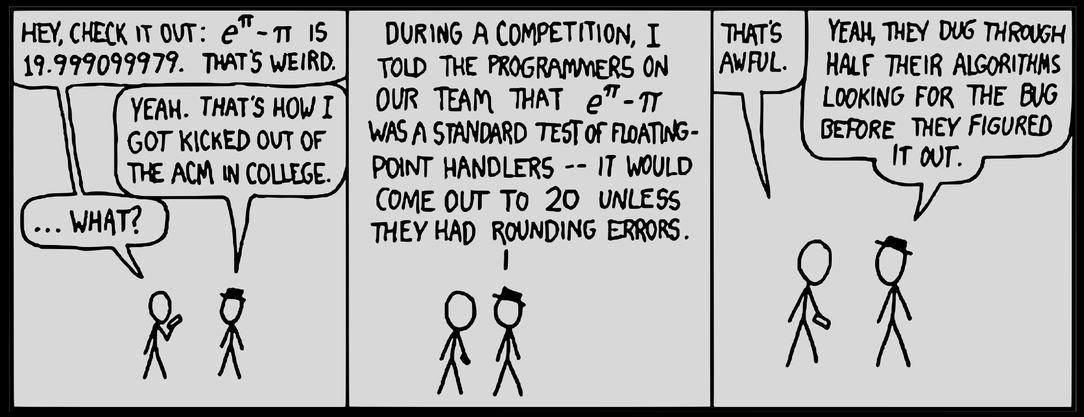

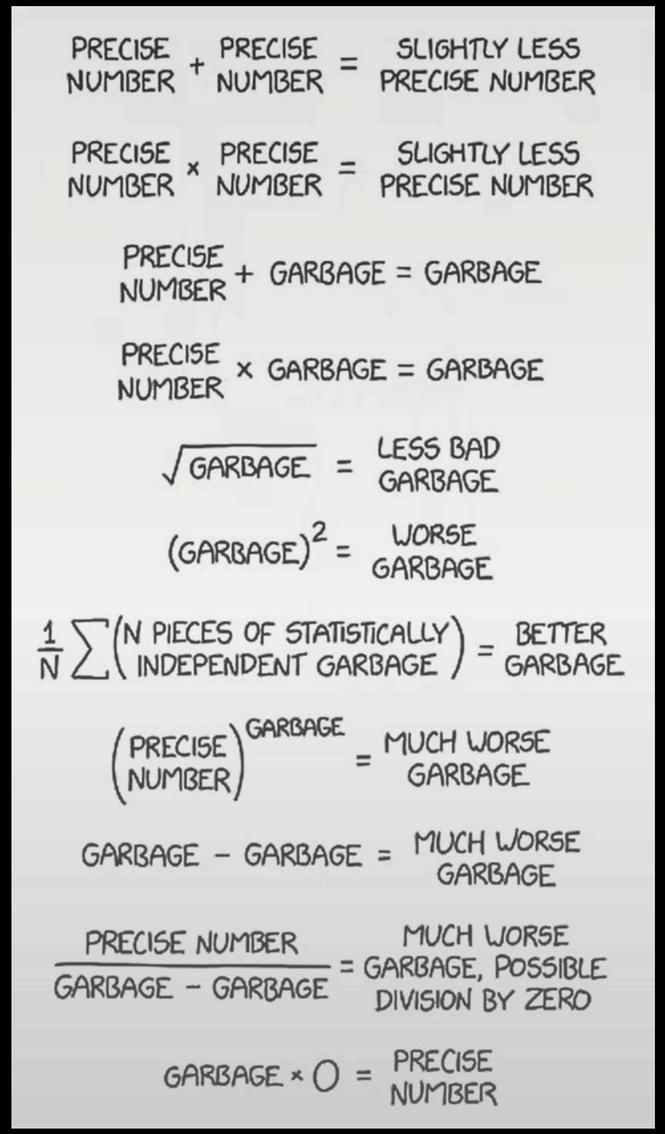

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Binary Connect

BinaryConnect is a way to train deep neural networks using binary weights — just +1 or −1 — during forward and backward passes.
Real weights kept for updates → **stable learning**

Advantages:

- Fewer multiplications → efficient hardware
- Built-in regularization → better generalization

Results: Near state-of-the-art on MNIST, CIFAR-10, SVHN

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Deterministic vs Stochastic Binarization

Deterministic Binarization

- Rule:

$$w_b = \begin{cases} +1 & \text{if } \ w \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

- Simple sign function, no randomness
- Averaging over many inputs can compensate for information loss

Stochastic Binarization

- Rule:

$$w_b = \begin{cases} +1 & \text{with probability } p = \sigma(w) \\ -1 & \text{with probability } 1 - p \end{cases}$$

- Uses hard sigmoid:

$$\sigma(x) = \text{clip}\left(\frac{x+1}{2}, 0, 1\right)$$

- Piecewise linear and hardware friendly
- Allows finer averaging, better represents real weight statistics

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Why Binary Connect works?

1. Precision where it matters (SGD updates)

- Real weights are updated in high precision → stable learning
- **Only forward/backward use binary weights** → no multiplications
- Prior work: 6–12 bits are enough for SGD updates

2. Noise as a regularizer

- Binarization adds weight noise, similar to Dropout/DropConnect
- **Expected weight value remains accurate**
- Noise improves generalization without hurting accuracy

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Forward propagation

- Input → layer activations computed using binarized weights.
- No multiplications: only additions or sign flips.
- The real weights (w) are not discarded; they are just

  binarized temporarily ($w_b = \text{binarize}(w)$).

  wb - Binary weight,
  b - bias
  a - Neuron value

  $w_b \leftarrow \text{binarize}(w_{t-1})$

  For $k = 1$ to L, compute a_k knowing $a_{k-1}, w_b,$ and b_{t-1}

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Backward propagation

- Gradients are computed using the same binarized weights (w_b).
- This ensures the backward pass is also lightweight — no expensive float multiplications.

Parameter update

- Real weights (w) are updated using the computed gradients.

$$w_t \leftarrow \text{clip}\left(w_{t-1} - \eta \frac{\partial \mathcal{C}}{\partial w_b}\right)$$

- Why clipping? Clips weights to [–1, 1] to prevent drift.
- Biases are also updated normally:

$$b_t \leftarrow b_{t-1} - \eta \frac{\partial \mathcal{C}}{\partial b_{t-1}}$$

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Binary Connect - Results

Method	MNIST	CIFAR-10	SVHN
No regularizer	$1.30 \pm 0.04\%$	10.64%	2.44%
BinaryConnect (det.)	$1.29 \pm 0.08\%$	9.90%	2.30%
BinaryConnect (stoch.)	$1.18 \pm 0.04\%$	**8.27%**	2.15%
50% Dropout	$1.01 \pm 0.04\%$		
Maxout Networks [29]	0.94%	11.68%	2.47%
Deep L2-SVM [30]	**0.87%**		
Network in Network [31]		10.41%	2.35%
DropConnect [21]			1.94%
Deeply-Supervised Nets [32]		9.78%	**1.92%**

Datasets: **MNIST, CIFAR-10, SVHN**

- MNIST (MLP): 3×1024 ReLU + L2-SVM → **Stochastic BC ≈ Dropout regularization**
- CIFAR-10 / SVHN (CNN): VGG-style → **BinaryConnect improves test error**

Main intuition

- Binarization injects noise → prevents overfitting → better test performance.
- Trade-off: **Deterministic = speed**
  Stochastic = accuracy.

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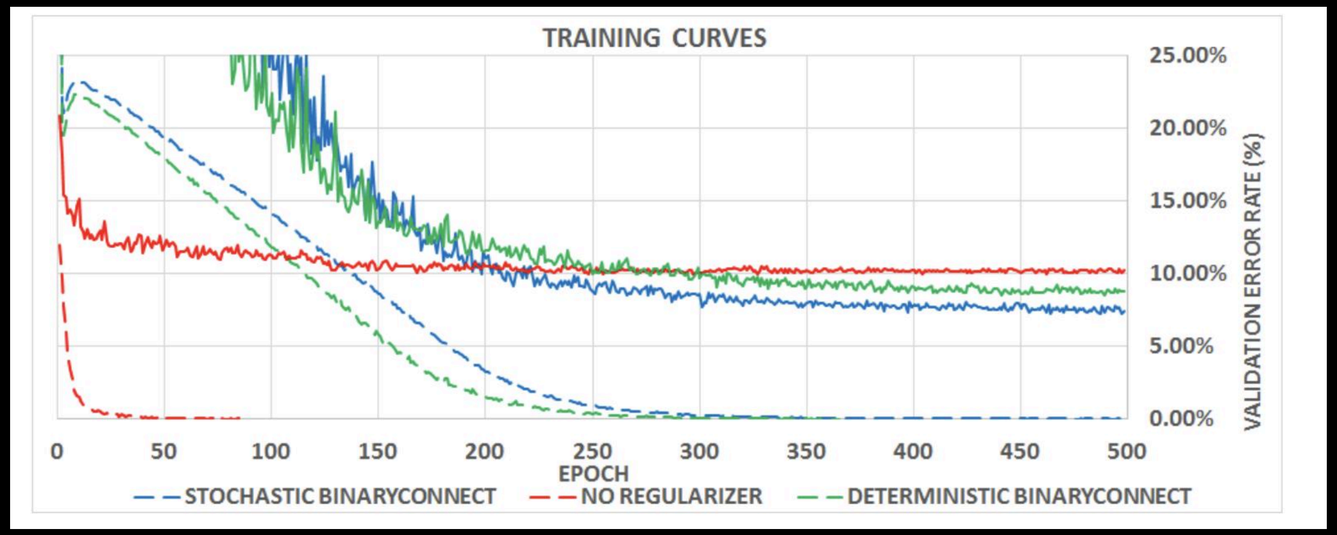
Binary Connect - Key findings



- BinaryConnect acts as a regularizer, similar to Dropout.
- Accuracy does not degrade despite 1-bit weights, often improves.
- Stochastic BC slightly better generalization, deterministic BC faster inference.
- Weight histograms show weights tend to ±1, confirming binarization behavior.

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Binary Neural Network

- To train a Binary Neural Network, we need to:
  - Binarize weights
  - Binarize activations
- Binarization will only really be completed after training.
- There is an early model called BinaryConnect (2015) that only binarizes weights, but it is now standard to require both conditions.
- Let’s see a few basic concepts that we need before focusing on how BNNs are built and trained...

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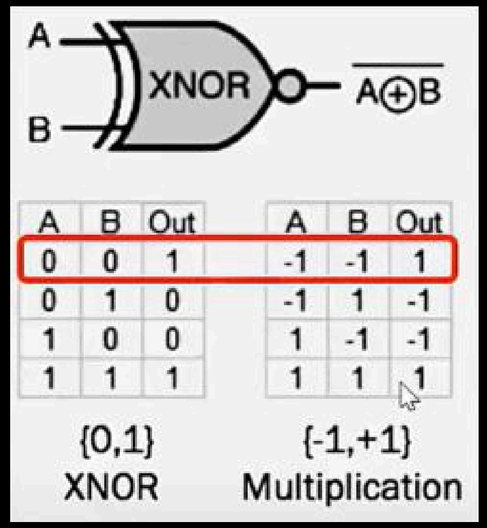
BNNs: XNOR affords cheap operations



- XNOR (exclusive NOR): XOR + inverter gate
- If 0 is mapped to -1 (and 1 is still a 1), then XNOR corresponds to bitwise multiplication – this is very computationally inexpensive.
- Convolutions are therefore implemented simply by XNOR + POPCOUNT operations.

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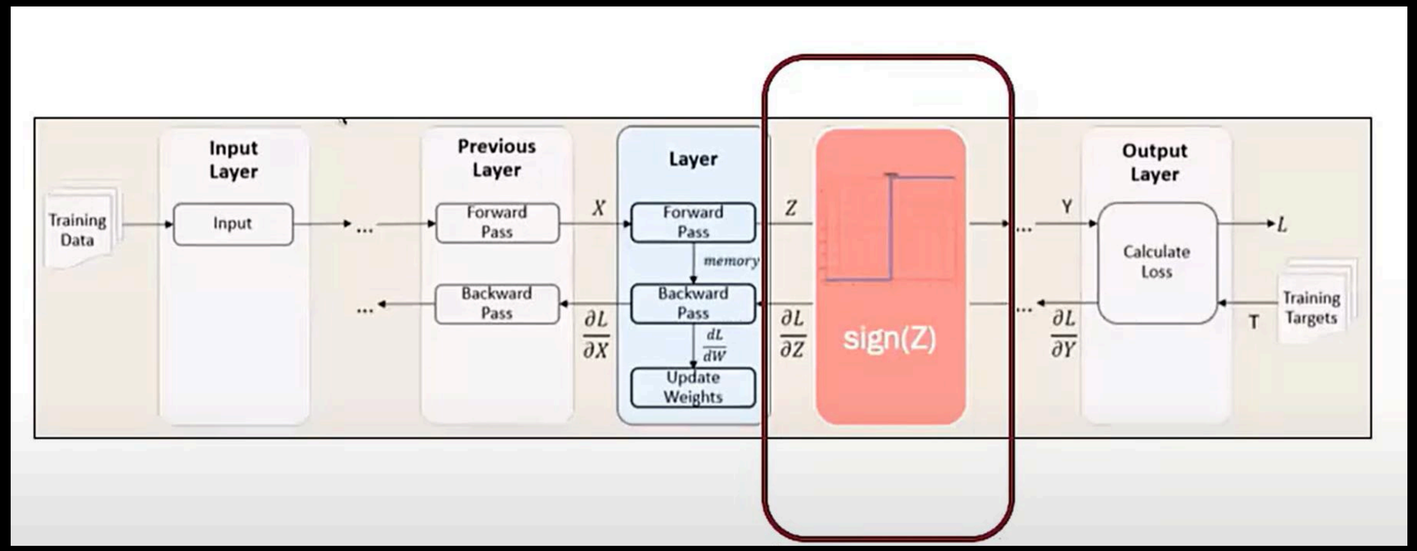
BNNs: Training



- Implementing this layer is the only change required in order to binarize a neural network.
- There are libraries that take care of the heavy lifting.

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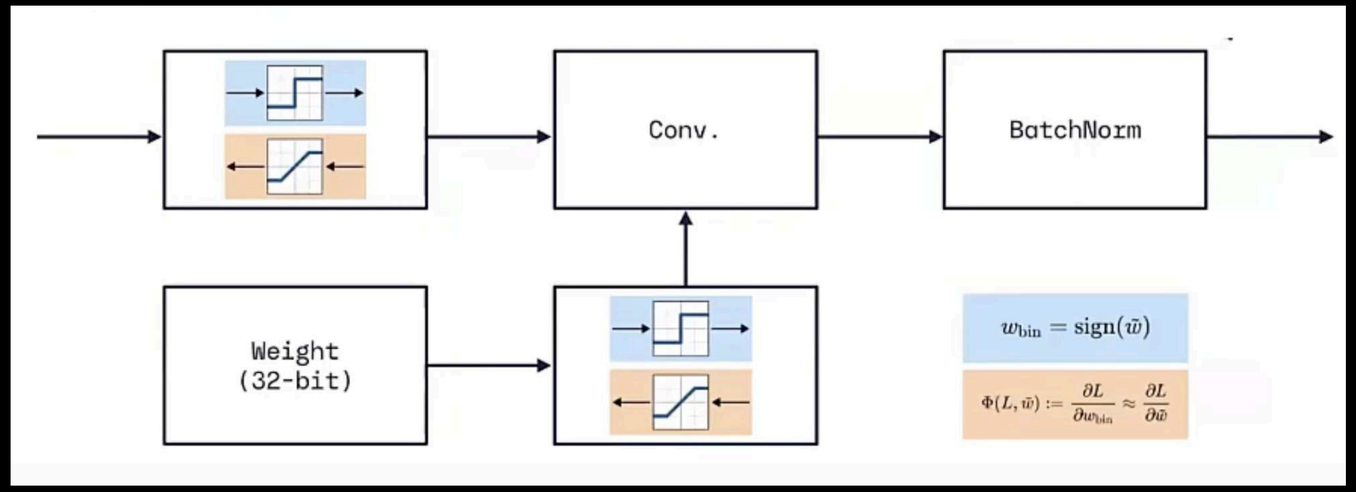
BNNs: Training



- **Forward pass:** Weights are binarized.
- **Backward pass:** Need to approximate the gradient (Why?)

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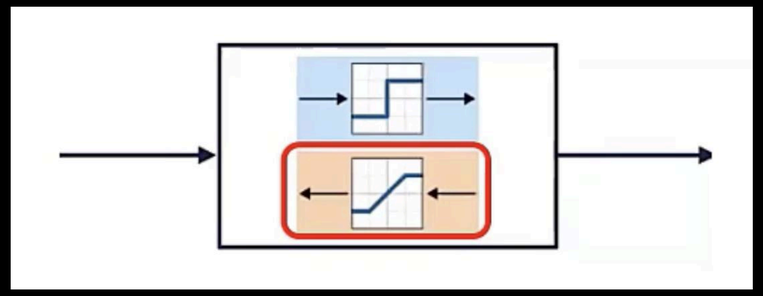
BNNs: The Straight-through Estimater



- Backpropagation through the sign function yields zero for all derivatives.
- We thus need a way to estimate the gradient since otherwise training will not be possible.
- The Straight-through Estimator (STE):
  - Simply set the incoming gradients equal to the outgoing gradients (i.e., disregard the derivative of the function itself).
  - On average, this is a good estimation that is very easy to implement (via the “hard tanh” function).

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Memory and Storage

- Lead to 32 times lower memory storage for weights
- Binarizing both activations and weights in BNNs results in greater memory compression than BinaryConnect

Increased Computational Efficiency and Speed

- Up to 58 times faster than 32-bit CNNs
- 7 times faster inference speed on a custom GPU compared to BinaryConnect on small datasets like MNIST

Lower Energy Consumption and Hardware Area

- The reduction in complex arithmetic operations and memory access leads to lower power consumption

Accuracy (with optimization)

- enabled BNNs to achieve competitive accuracy, often near state-of-the-art results

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- **Edge AI and IoT Devices** – for limited compute and memory resources
- **Mobile and Embedded Vision** – for real-time inference with low power
- **Healthcare and Medical Devices** – for portable, energy-efficient diagnostics
- **Cybersecurity and Signal Processing** – for fast signal-level tasks
- **Smart Surveillance** – run on restricted compute/power budgets
- **High-Frequency Trading** – for lightweight, high-speed transaction analysis

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Thanks

Questions are welcomed

Snores are not.