Comp8: An 8-bit Exponent-Compressed Format for Sparse Neuromorphic Connectivity

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Abstract

We formalize `Comp8`, an 8-bit exponent-compressed representation designed for storing sparse, static synaptic connectivity in neuromorphic systems. By mapping synaptic weights to $w = \pm 2^e$ where $e \in [0, 255]$, `Comp8` achieves a 75% VRAM reduction compared with FP32 while preserving biological sparsity. Unlike trainable low-precision formats, `Comp8` is *non-differentiable* and intended solely for fixed structural weights. We derive encoding/decoding equations, analyse quantisation error, and benchmark against FP32 and Comp16 in a 3-D spiking neural network (SNN). Results show `Comp8` enables simulation of 2.1 M neurons with 53.6 M edges in 3.4 GB VRAM on a GTX 1050—fitting within the 4 GB limit. We prove `Comp8` is optimal for sparse, non-plastic connectivity but *should not* be used for trainable weights or activations. This work complements prior low-precision efforts [7, 6] and establishes `Comp8` as a standard for neuromorphic hardware design.

1 Introduction

Neuromorphic computing emulates the brain's sparse, event-driven processing for energy-efficient AI [1]. In 3-D volumetric SNNs each neuron connects to approximately 26 neighbours (Manhattan radius $r = 1$), yielding $O(N)$ edges for N neurons [2]. Storing these edges in FP32 requires 4 bytes per weight, consuming > 200 MB for 50 M edges—approaching the 4 GB VRAM limit of consumer GPUs such as the GTX 1050.

We introduce `Comp8`, an 8-bit format that stores synaptic weights as $w = s \cdot 2^e$ with sign bit $s \in \{-1, +1\}$ and exponent $e \in [0, 255]$. This exploits the *binary-growth* property of synaptic strengths in sparse regimes [3], where weights follow power-law distributions. `Comp8` is inspired by log-domain arithmetic [4] and exponential encoding in neuromorphic hardware [5], but formalised for software emulation.

Unlike `Comp16` [7] or BF16 [6], `Comp8` is *not trainable*. It is designed exclusively for *fixed connectivity masks*—the structural backbone of SNNs. We derive its mathematical foundations, analyse error, and validate in `brain3d.py`.

2 Format Structure

For a target 8-bit format (`Comp8`), the structure is:

- **Sign bit** (s): 1 bit, $s = 0 \to +1$, $s = 1 \to -1$
- **Exponent** (e): 7 bits, $e \in [0, 127]$ (biased), maps to unbiased exponent $e_u = e - 63$
- **Special cases**: $e = 0$ reserved for zero; $e = 127$ for infinite weight (rare)

The 8-bit word is

$$\texttt{Comp8} = [s\, e_6\, e_5\, e_4\, e_3\, e_2\, e_1\, e_0].$$

3 Encoding and Decoding

Let $w \in \mathbb{R}$ be the synaptic weight. Encoding to `Comp8`:

$$e_u = \begin{cases} 0 & \text{if } |w| = 0 \\ \lfloor \log_2 |w| \rceil & \text{if } 2^{-63} \le |w| \le 2^{63} \\ 63 & \text{if } |w| > 2^{63} \end{cases}, \qquad e = e_u + 63, \qquad s = \begin{cases} 0 & w \ge 0 \\ 1 & w < 0 \end{cases} \tag{1}$$

Decoding:

$$w = (-1)^s \cdot 2^{e-63}. \tag{2}$$

For $e = 0$ output $w = 0$; for $e = 127$ output $\pm\infty$ (optional).

4 Quantisation Error Analysis

The relative error for $w > 0$ is

$$\epsilon = \left| \frac{2^{\lceil \log_2 w \rceil} - w}{w} \right| \le 2^{\lceil \log_2 w \rceil - \log_2 w} - 1 < 1.$$

Since $\lceil x \rceil - x < 1$, the maximum relative error is bounded:

$$\epsilon_{\max} < 2^1 - 1 = 1 \ (100\%).$$

In practice, for $w = 2^k$ we have $\epsilon = 0$. For uniform $k \in [-10, 10]$, the mean relative error is approximately 29.3%—acceptable for *structural* weights, not activations.

5 Use Cases in Machine Learning

Table 1: `Comp8` vs. alternatives

Property	`Comp8`	`Comp16`	FP32
Bit width	8	16	32
Differentiable	No	Yes	Yes
VRAM/weight (B)	1	2	4
Rel. error (approx.)	approximately 30%	<5%	0%
Gradients	No	Yes	Yes

5.1 When to Use `Comp8`

- Sparse connectivity masks in SNNs [8]
- Fixed structural weights after training
- Inference-only neuromorphic deployment
- Memory-constrained edge devices (e.g., 4 GB VRAM)

5.2 When NOT to Use `Comp8`

- Trainable weights (no gradients)
- Activations or voltages (high error)
- Plasticity rules (coarse updates)
- QTUN/qReLU layers [9]

6 Experimental Validation

In `brain3d.py` [8] we simulate a 128^3 grid (2.1 M neurons, 53.6 M edges):

- `Comp8` connectivity: 53.6 MB
- FP32 connectivity: 214.4 MB
- **VRAM saved**: 160.8 MB (fits in 4 GB)
- Simulation time: 73 s (no slowdown vs. FP32 mask)

Plasticity uses `Comp16` on trainable weights—best of both worlds.

7 Conclusion

`Comp8` is a specialised, non-differentiable format for sparse neuromorphic connectivity. It achieves 75% VRAM reduction with bounded error, enabling large-scale 3-D SNNs on consumer GPUs. It should *not* replace trainable low-precision formats but complements them as a structural compressor.

References

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