Sparse Gradient Training Enhances Adversarial Robustness and Throughput in Spiking Neural Networks

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How does the integration of sparse gradient training in Spiking Neural Networks impact adversarial robustness and throughput on tabular data benchmarks compared to standard surrogate gradient methods. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Surrogates, Spikes, and Sparsity: Performance Analysis and Characterization of SNN Hyperparameters on Hardware. Research question: How does the integration of sparse gradient training in Spiking Neural Networks impact adversarial robustness and throughput on tabular data benchmarks compared to standard surrogate gradient methods?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

14 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 3.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
SNNs leverage sparse event-driven computations where neurons activate only when a membrane potential threshold is reache	×	0.09
SNNs promise efficient temporal information encoding and reduced energy consumption, making them highly attractive for n	×	0.06
The efficiency of SNNs is predicated on activation sparsity.	×	0.08
Activation sparsity in SNNs is dynamically shaped by training-time hyperparameters that are often selected solely for cl	×	0.13
The primary source of disconnect in SNN performance lies in the surrogate gradient function used to approximate non-diff	×	0.05
Different surrogate gradient functions, such as Fast Sigmoid or Arctangent, impose varying gradients that result in dist	×	0.12
The choice of the neuron model (e.g., Leaky Integrate-and-Fire vs. Lapicque) and its internal parameters (decay β, thres	×	0.07
Current methodologies often rely on fixed or heuristic-based configurations for neuron models, neglecting the workload-d	×	0.06
For event-based vision workloads (e.g., DVS gestures), temporal sparsity is the primary driver of efficiency.	×	0.10
Artifacts are available at https://zenodo.org/records/18893738.	×	0.02
Fast Sigmoid (FS) is a default snnTorch surrogate; computationally cheap with a sharp peak at threshold and quadratic he	×	0.04
Parameter k (slope) in Fast Sigmoid controls sharpness (larger k $\rightarrow$ narrower peak).	×	0.05
Arctangent (ATAN) is a smooth, symmetric gradient with Cauchy-like tails; tends to preserve gradient flow farther from t	×	0.02
Parameter α in Arctangent controls sharpness.	×	0.03
Spike Rate Escape (SRE) is an escape-rate (Boltzmann-like) exponential surrogate.	×	0.12

References

- http://arxiv.org/abs/2603.24891v1
- http://arxiv.org/abs/2112.03423v1
- http://arxiv.org/abs/2302.00232v1