Scalability and Robustness of Node-Based Bayesian Neural Networks vs Gradient Boosting Machines in Cross-Domain Programming Tasks

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: What is the impact of model size scalability on the robustness of node-based Bayesian neural networks versus gradient boosting machines when evaluated on cross-domain programming tasks using BLEU and. 12 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Neural Scaling Laws Rooted in the Data Distribution. Research question: What is the impact of model size scalability on the robustness of node-based Bayesian neural networks versus gradient boosting machines when evaluated on cross-domain programming tasks using BLEU and pass@k metrics?.

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 6.4/10.

3 Results

14 papers retrieved. 12 claims extracted; 5 independently verified. Quality review score: 6.4/10.

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
Michaud et al. (2024) conjectured that natural prediction problems involve discrete subtasks or quanta which can be orde	×	0.05
Assuming use frequencies are power-law-distributed and models learn quanta in the order of the Q Sequence allows for the	✓	0.18
Prior works demonstrate that power-law dataset structure can produce power-law neural scaling laws.	✓	0.24
Prior works do not explain why power-law dataset structure would emerge across disparate domains.	×	0.11
Unifying manifold-approximation and feature-learning theories of power-law scaling has been identified as a key research	×	0.11
Understanding how data distributions bound scaling exponents has been identified as a key research question to resolve f	×	0.04
The authors propose a model of emergent power-law dataset structure that yields power-law neural scaling laws.	✓	0.20
The study makes two key assumptions meant to describe natural datasets: context-dependent target function and general-pu	×	0.06
The study uses percolation theory to translate assumptions about natural datasets into a mathematical model of dataset s	✓	0.16
Two scaling regimes emerge from the proposed mathematical model of dataset structure.	✓	0.15
The derived model and data scaling laws were tested in a minimal toy setting that allows efficient dataset generation.	×	0.12
Scaling laws were computed in the context of a random feature model.	×	0.09

References

- http://arxiv.org/abs/2412.07942v1
- http://arxiv.org/abs/1906.10015v2

- http://arxiv.org/abs/2510.08325v2