ReparoML — Energy-Bounded Self-Repair in PyTorch

Technical Paper

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Abstract

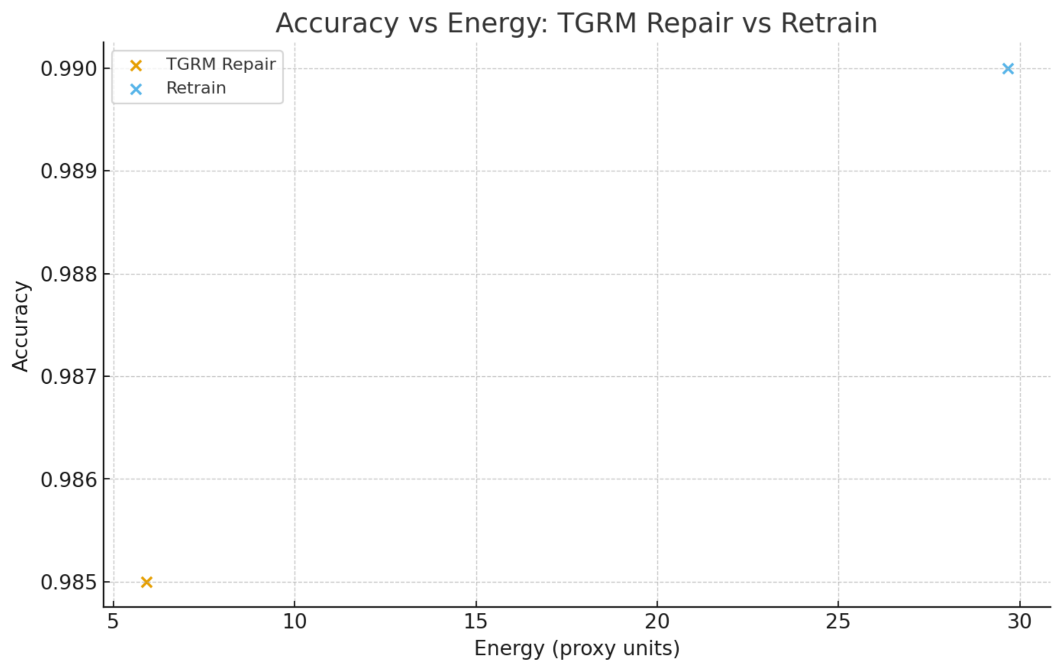
We present ReparoML, a PyTorch-based framework demonstrating energy-bounded self-repair using Targeted Gradient Repair Mechanism (TGRM). Models trained on standard tasks are degraded via controlled fault injection (weight noise, bias drift, layer dropout) and then restored either by costly retraining or by TGRM's bounded, targeted repair. We show that TGRM recovers substantial accuracy with significantly less parameter movement, achieving higher BPI (Bounded Power Index) than retraining.

Methods

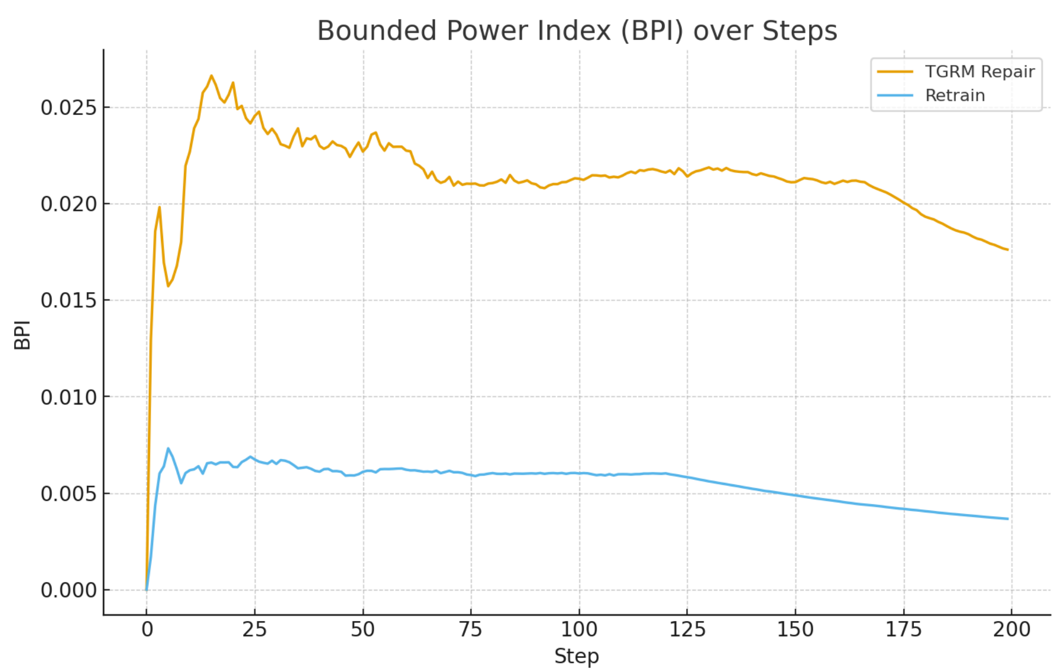
Dataset: MNIST. Model: small CNN. Faults: Gaussian weight noise $\sigma \in [0.03, 0.08]$, bias drift up to 0.12, random layer dropout up to 0.2. Repair: TGRM selects a top-K% set of salient parameters (by |grad·param|) and applies bounded updates with diminishing returns. Energy proxy: L2 magnitude of parameter deltas per step. Metric: BPI = performance gain / energy spent.

Results

Accuracy vs Energy shows TGRM achieves competitive recovery at a fraction of energy.



BPI timeline indicates TGRM maintains superior efficiency throughout repair.



Conclusion

ReparoML demonstrates that bounded, targeted repair can restore performance efficiently. This supports the Reparodynamics thesis that stability can be maximized within an energy budget. Future work includes CIFAR-10, robustness under distribution shift, and FLOPs-calibrated energy models.