FT-ClipAct: Resilience Analysis of Deep Neural Networks and Improving their Fault Tolerance using Clipped Activation

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Outline

Objective

- Propose a novel error mitigation technique which squashes the high intensity faulty activation values to alleviate their impact.
- Present a method to systematically define the clipping values of the activation functions that result in increased resilience of the networks against faults.

Literature review

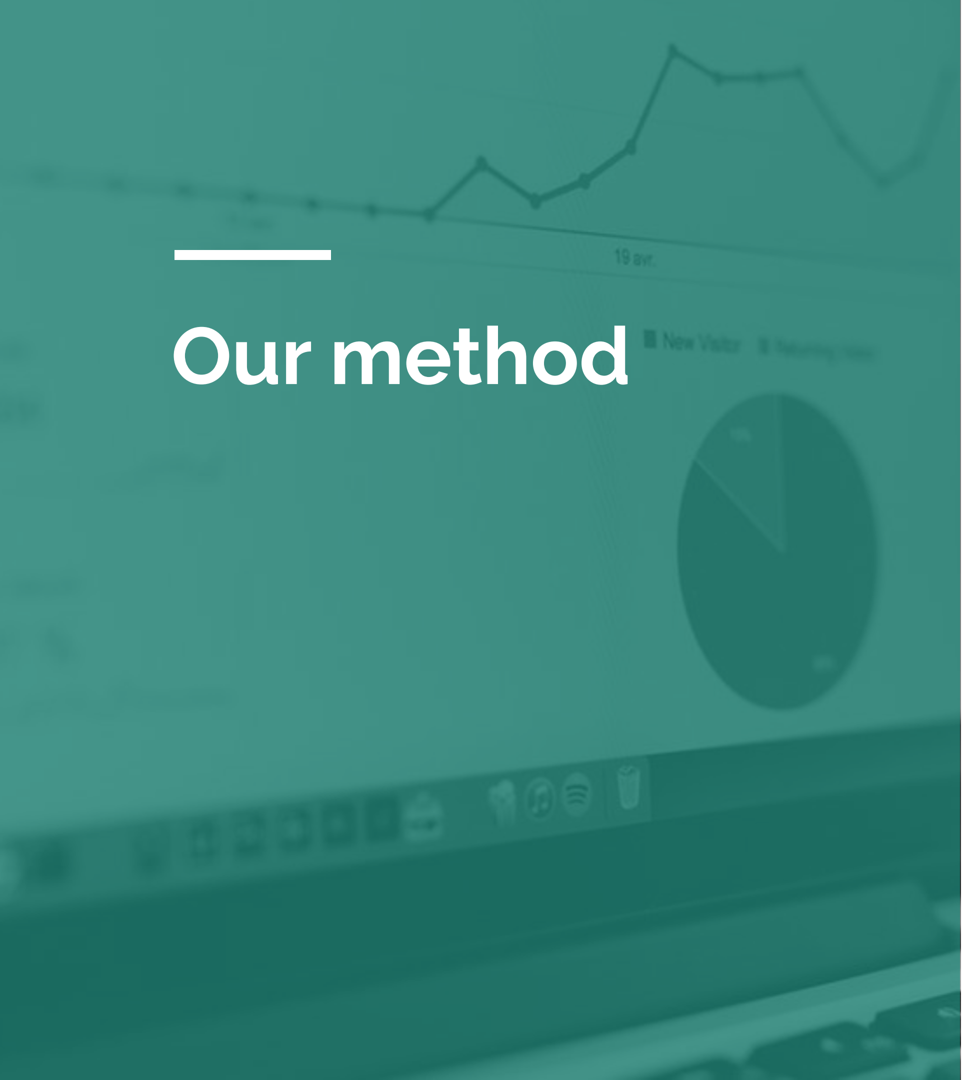
- ➔ Software
  - fault-aware training has been introduced for mitigating the memory
- ➔ Hardware
  - DMR
  - TMR

Our method

- ➢ Improve the fault tolerance of DNNs using clipped activation functions

- ➢ Replace the unbounded activation functions in the DNN with their clipped variants and initialize their thresholds with their corresponding ACT_{max}.

- ➢ Perform fine-tuning of the clipping thresholds using an efficient method.



Our method

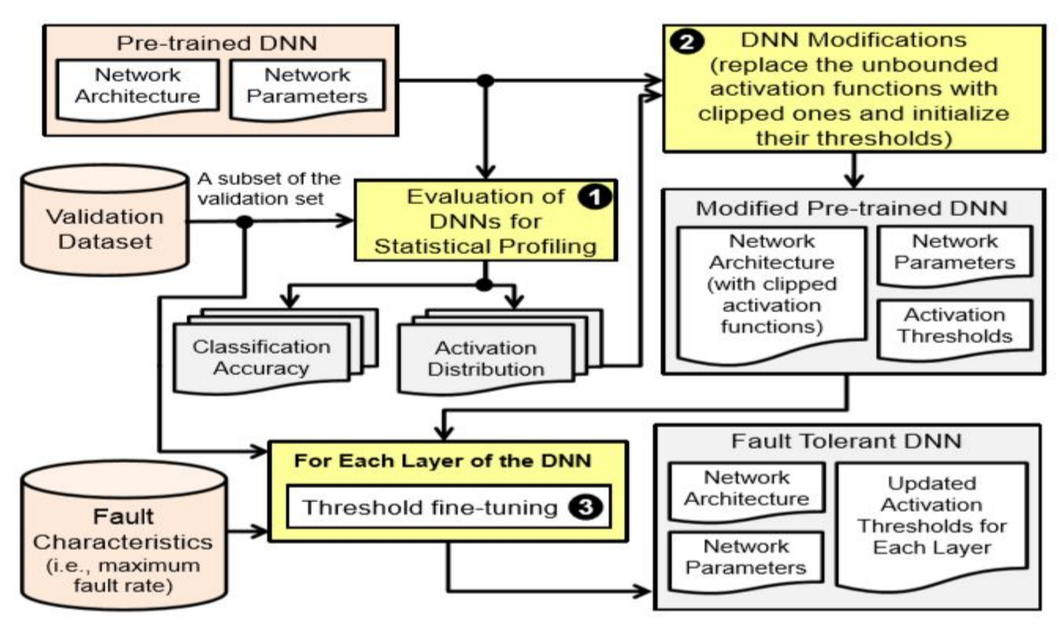
- ➢ The Clipped Activation Function :

$$f(x) = \begin{cases} x, & if\ 0 \le x \le T \\ 0, & otherwise \end{cases}$$

Custom Activation Function (Clipped ReLU)

- ➢ Resilience Evaluation Metric and the Corresponding Analysis for Finding Suitable Clipping Thresholds
- ➢ Fault injection frameworks [2]
- ➢ Threshold Fine-Tuning Algorithm

Our methodology to improve the resilience of a pre-trained DNN model



Requirements

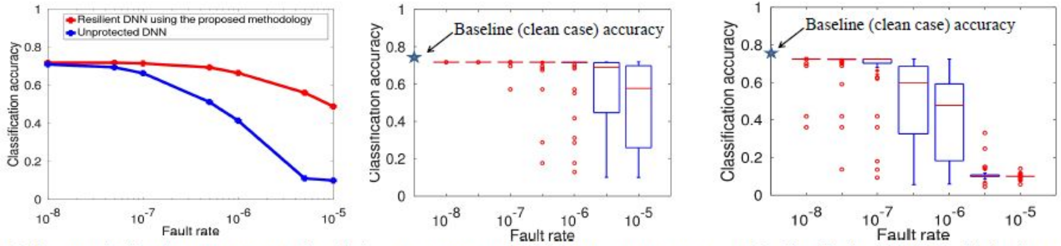
- Transfer learning models
  - AlexNet
  - VGG16
- Datasets
  - Cifar10

Cifar-10 dataset

Results

- The proposed technique provides 68.92% improvement at 10^{-5} fault rate for the VGG-16 network trained on the CIFAR-10 dataset, when compared to the unprotected network.
- The evaluation shows 18.19% and 69.49% improvement in the classification accuracy of the AlexNet and the VGG-16 networks, respectively, at $5 \times 10-7$ fault rate compared to their baseline (without error mitigation) variants.
- The AlexNet and the VGG-16 offer baseline classification accuracies of 72.8% and 82.8%, respectively.

Discussion

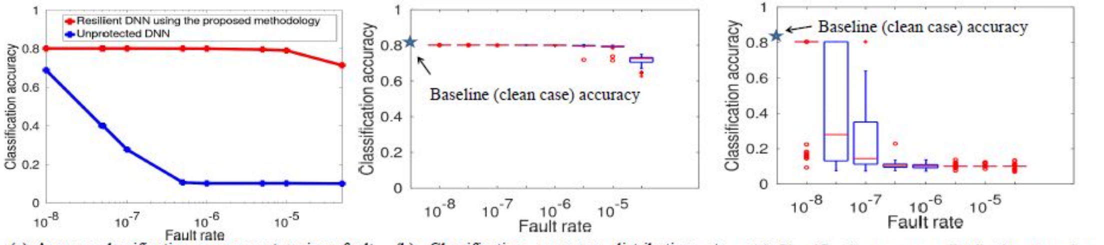


(a) Average classification accuracy at various fault rats of the DNN using clipped activation functions and unprotected DNN

(b) Classification accuracy distribution at various fault rates of the DNN using clipped activation functions

(c) Classification accuracy distribution at various fault rates of the unprotected DNN

Figure 7: Error resilience evaluation of the AlexNet with and without clipped activation functions



(a) Average classification accuracy at various fault rates of the DNN using clipped activation functions and the unprotected DNN

(b) Classification accuracy distribution at various fault rates of the DNN using clipped activation functions

(c) Classification accuracy distribution at various fault rates of the unprotected DNN

Figure 8: Error resilience evaluation of the VGG-16 with and without clipped activation functions

Questions?

Key references

[1] FT-ClipAct: Resilience Analysis of Deep Neural Networks and Improving their Fault Tolerance using Clipped Activation Le-Ha Hoang, Muhammad Abdullah Hanif, Muhammad Shafique Technische Universität Wien (TU Wien), Vienna, Austria.
[2] B. Reagen, U. Gupta, L. Pentecost, P. Whatmough, S. K. Lee, N. Mulholland, D. Brooks, and G.-Y. Wei, “Ares: A framework for quantifying the resilience of deep neural networks,” in Proceedings of the 55th DAC, 2018.