

Zhen LIANG, Taoran WU, Wanwei LIU, Bai XUE, Wenjing YANG, Ji WANG, Zhengbin PANG, 2023. Towards robust neural networks via a global and monotonically decreasing robustness training strategy. *Frontiers of Information Technology & Electronic Engineering*, 24(10):1375-1389.

<https://doi.org/10.1631/FITEE.2300059>

Towards robust neural networks via a global and monotonically decreasing robustness training strategy

Key words: Robust neural networks; Training method; Drawdown risk; Global robustness training; Monotonically decreasing robustness

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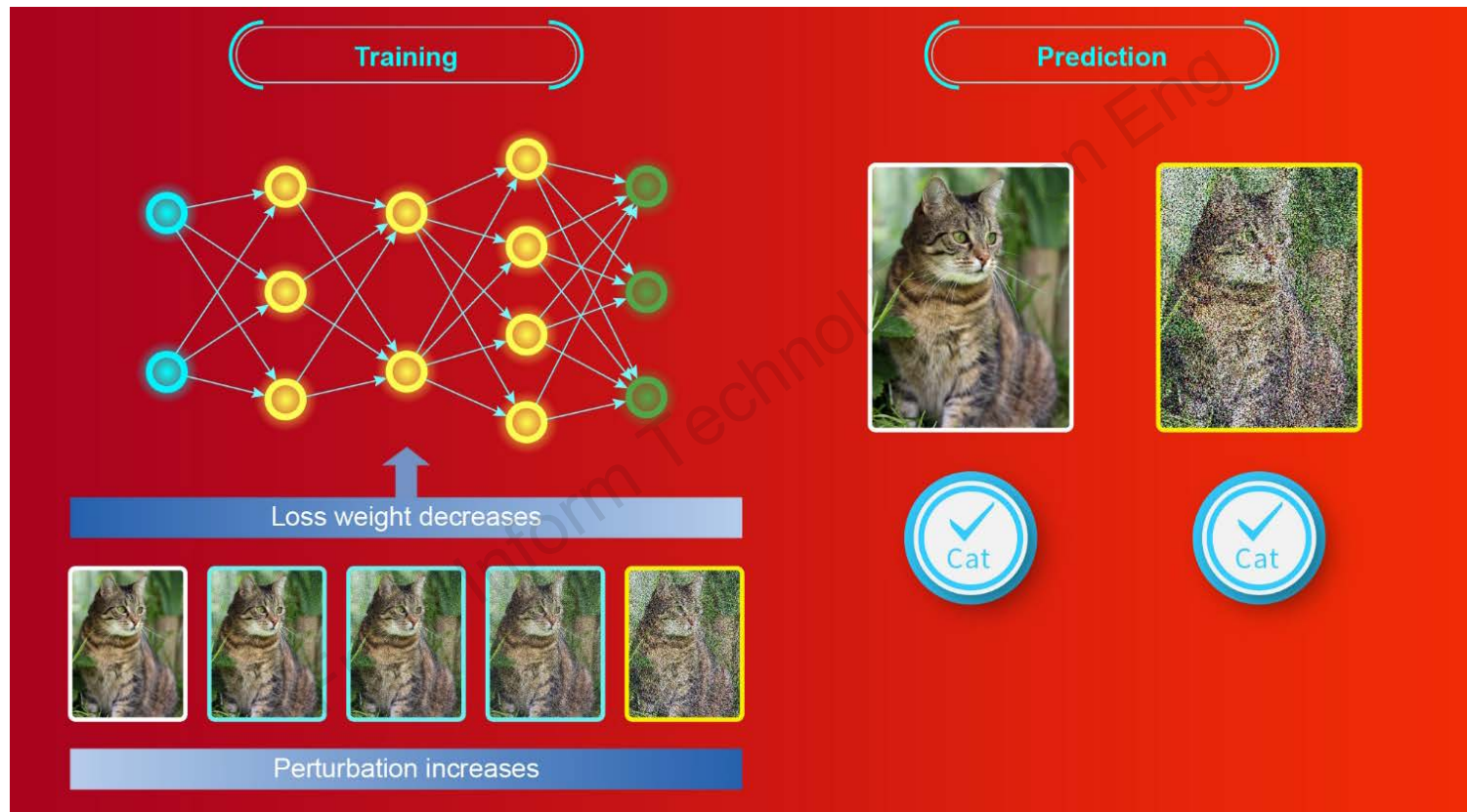
Motivation

1. On one hand, researchers focus on proposing deep neural network (DNN) robustness verification approaches. On the other hand, researchers pay attention to training robust DNNs against certain perturbations, providing guaranteed robust DNNs with proper training methods.
2. Instead of seeking a completely novel robust DNN training method, we turn our attention to alleviating the great challenge that existing interval bound propagation (IBP) family training methods encounter; i.e., IBP and CROWN-IBP methods are likely to fail under large input perturbations (drawdown risk).

Main idea

1. To overcome the drawdown risk resulting from local robustness training (LRT), we propose the idea of global robustness training (GRT), considering some certain perturbations together, instead of only a single perturbation value, during the training processes.
2. Taking multiple perturbation values into account, we also seek a monotonically decreasing weight strategy for combining their loss values during the training phases and form the new loss function.
3. The global and monotonically decreasing robustness training strategy is compatible with existing IBP-based training methods and can be treated as a generalization of them.

Framework



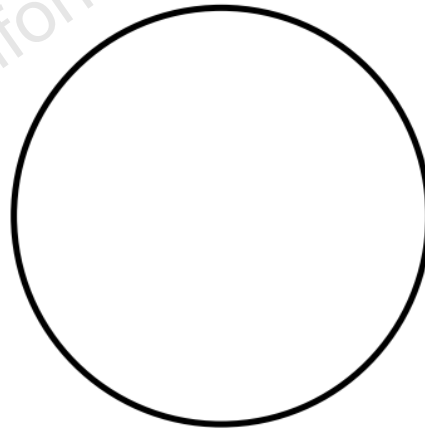
An illustrative overview of the global and monotonically decreasing robustness training strategy

Method

1. Issue: Locality leads to drawdown risk. In each training epoch, the optimization renders the parameter updating robust with respect to only a single perturbation value (i.e., the given ϵ).

$$\text{Loss}_{\text{acc}} := \mathcal{L}(\mathcal{N}(x); y; \theta) = - \sum_{(x,y)} \sum_{i=1}^P y_i \log(\mathcal{N}(x)_i)$$

$$\text{Loss} := \kappa \text{Loss}_{\text{acc}} + (1 - \kappa) \text{Loss}_{\text{rob}} = \kappa \mathcal{L}(\mathcal{N}(x); y; \theta) + (1 - \kappa) \mathcal{L}(-\underline{m}(x, \epsilon); y; \theta)$$



Local robustness training (LRT) strategy

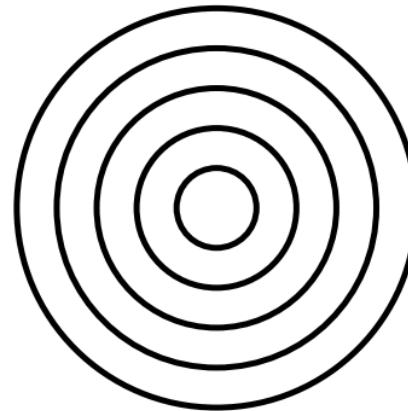
Method

2. Global robustness training strategy. Ideally, the GRT strategy refers to training with the sub-perturbation range $0 < \epsilon_{\text{train}} \leq \epsilon$ simultaneously, instead of a single perturbation ϵ .

$$\text{Loss}_{\text{rob}} = \frac{1}{\epsilon} \int_0^\epsilon \mathcal{L}(-\underline{m}(x, r); y; \theta) \, dr$$

It can be relaxed and approximated as

$$\text{Loss}_{\text{rob}} = \frac{1}{N} \sum_{i=1}^N \mathcal{L}(-\underline{m}(x, r_i); y; \theta), \quad r_i = \frac{i}{N} \epsilon$$



**Global robustness training (GRT) strategy
(left is the ideal case and right is the practical case)**

Method

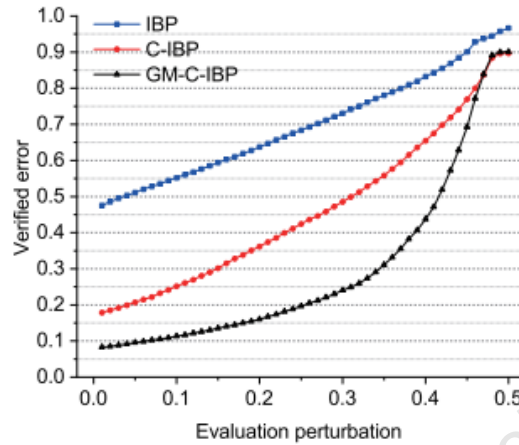
3. Monotonically decreasing robustness training strategy. To organize the different loss values, a monotonically decreasing robustness training strategy makes sense. It means that the smaller a sub-perturbation is, the more weight its loss value deserves.

$$\begin{cases} \text{Loss}_{\text{rob}} = \sum_{i=1}^N c_i \mathcal{L}(-\underline{m}(x, r_i); y; \theta) \\ r_i = \frac{i}{N} \epsilon, \quad c_i \propto \frac{1}{r_i} \end{cases}$$

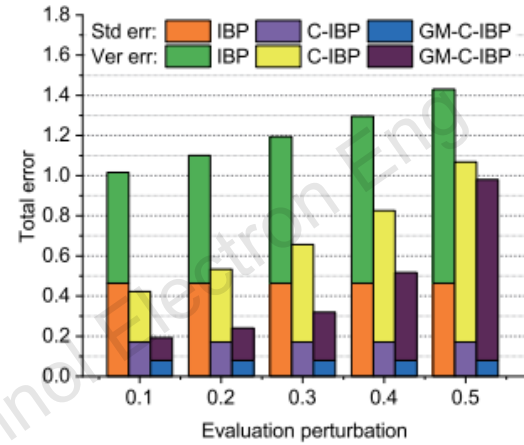


**Monotonically decreasing robustness
training strategy**

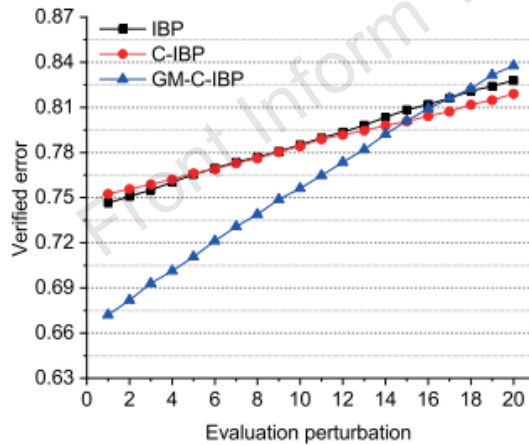
Major results



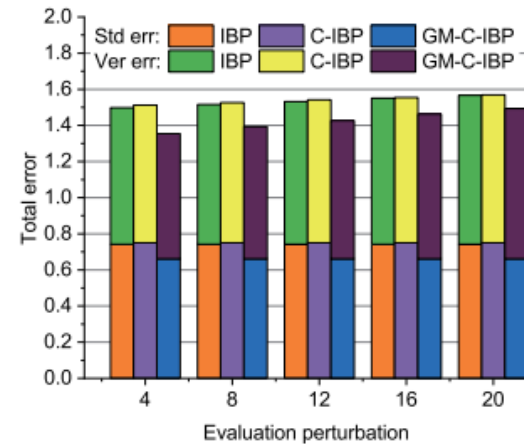
(a)



(b)



(c)



(d)

Fig. 3 Alleviating the drawdown risk: (a) verified errors on MNIST with evaluation step size 0.01; (b) total errors on MNIST with step size 0.1; (c) verified errors on CIFAR with step size $1/255$; (d) total errors on CIFAR with step size $4/255$

Major results

Table 3 Comparison with state-of-the-art methods against large perturbations

Dataset	Method	Standard error (%)	Verified error (%)
MNIST $\epsilon_{\text{eval}} = 0.2$ $\epsilon_{\text{train}} = 0.5$	IBP	46.38	62.79
	CROWN-IBP	17.13	36.19
	GM-CROWN-IBP	7.98	16.00
MNIST $\epsilon_{\text{eval}} = 0.3$ $\epsilon_{\text{train}} = 0.5$	IBP	46.38	72.14
	CROWN-IBP	17.13	48.55
	GM-CROWN-IBP	7.98	24.03
MNIST $\epsilon_{\text{eval}} = 0.4$ $\epsilon_{\text{train}} = 0.5$	IBP	46.38	81.92
	CROWN-IBP	17.13	65.48
	GM-CROWN-IBP	7.98	43.73
MNIST $\epsilon_{\text{eval}} = 0.25$ $\epsilon_{\text{train}} = 0.6$	IBP	30.34	61.73
	CROWN-IBP	16.47	48.85
	GM-CROWN-IBP	17.10	31.25
MNIST $\epsilon_{\text{eval}} = 0.35$ $\epsilon_{\text{train}} = 0.6$	IBP	30.34	88.70
	CROWN-IBP	16.47	80.72
	GM-CROWN-IBP	17.10	50.14
CIFAR $\epsilon_{\text{eval}} = 1/255$ $\epsilon_{\text{train}} = 17.6/255$	IBP	71.77	72.39
	CROWN-IBP	70.35	70.89
	GM-CROWN-IBP	64.27	65.60
CIFAR $\epsilon_{\text{eval}} = 7/255$ $\epsilon_{\text{train}} = 17.6/255$	IBP	71.77	75.93
	CROWN-IBP	70.35	74.38
	GM-CROWN-IBP	64.27	73.81
CIFAR $\epsilon_{\text{eval}} = 14/255$ $\epsilon_{\text{train}} = 22/255$	IBP	74.23	79.82
	CROWN-IBP	74.82	79.46
	GM-CROWN-IBP	66.15	79.22

The standard errors of the Nominal method are 1.12% and 13.80% on the MNIST and CIFAR datasets, respectively. The best results are in bold

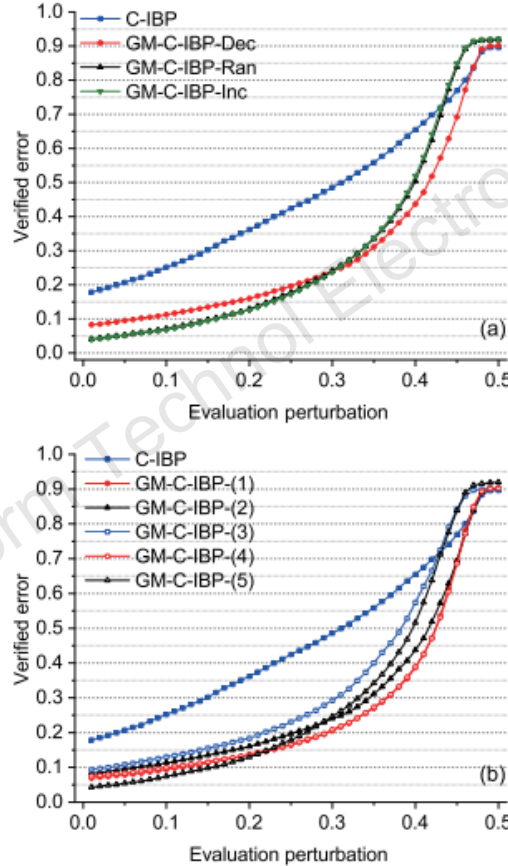


Fig. 4 Performance comparisons of GM-CROWN-IBP on different robustness weight types (a), monotonically decreasing robustness weights (b), and robustness sizes (c)

Conclusions

1. We introduce multiple sub-perturbations into the DNN training epochs to consider robustness with respect to some certain perturbations globally.
2. We organize different robustness loss values in a monotonically decreasing style to further improve the DNN robust training performance.
3. We will consider further optimization of the training duration and burdens, such as the utilization of a parallel computation mechanism and a more memory-saved estimation on the robustness margin.



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