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Outline

Tensor network algorithms: Our team has developed several flexible and nonlinear tensor decomposition algorithms that can capture more complex relations within tensor data, robust tensor algorithm with particular structure of outliers, and a very fast tensor network structure search algorithm.

Adversarial robustness of DNNs: Our team has studied how low-rankness of NN parameters affects its robustness to adversarial attack from the theoretical perspective. We also developed an adaptive adversarial purification method that can be updated with adversarial loss, thus improving its robust accuracy and outperforming adversarial training methods.

Nonlinear Flexible Tensor Decomposition

Problem and challenge

- Most TD models are multilinear and cannot capture nonlinear structure within tensor data
- The distribution of observation model needs to be pre-defined
 Tensor decomposition structure needs to be pre-defined

Undirected Graphical Model for Tensor Decomposition



Tensor Network Structure Search



Goal: To understand the impact of low-rank parameters on adversarial robustness of over-parameterized DNNs in theory.

(Wang et al. NeurIPS'23)





Key techniques

Choosing optimal TD structure is hard -> Learn unknown latent structures using undirected mappings

- Choosing optimal TD distribution is hard -> Learn unknown distributions using deep generative model
- Efficient self-supervised loss function to learn the model

Efficient Nonparametric Tensor Decomposition for Binary and Count Data (Tao et al. AAAI'24)



Key techniques

Image: Modeling flexible latent structures in TD using nonparametric

The adversarial generalization bound with low-rank para.

 $O(\sqrt{\mathsf{c}\sum_{l}r_{l}(d_{l-1}+d_{l})/N})$

better than w/o low-rank para.

 $O(\sqrt{\mathsf{c}(\sum_{l=1}^L d_{l-1}d_l)/N})$

in # effective paras.

in # total paras.

Low-rank parameterization can enhance adversarial robustness under over-parameterization!

Adversarial Purification using Pre-trained Generative Model

Goal: Improve robust accuracy of adversarial purification against known attacks

Method: Fine-tune the purifier model using adversarial loss

Pre-training GAN-based model:

 $L_{\theta_g} = L_g(\mathbf{x}, \theta_g)$



Table 3: Accuracy comparison of defenses with vanilla model (negative impacts are marked in red).

Defense method	Clean images	Known attacks	Unseen attacks	Training cost
Vanilla model	~90%	~0%	~0%	/
Expectation	=	$\uparrow\uparrow\uparrow$	↑ ↑↑	1
AT	11	$\uparrow\uparrow\uparrow$	×	11
AP	↓	† †	$\uparrow\uparrow$	1
AToP (Ours)	Ļ	$\uparrow\uparrow\uparrow$	† †	11



model

- Gaussian process is not scalable -> Derive scalable lower bound for the likelihood
- □ Efficient natural gradient update results in faster convergence

 $= \mathbb{E}[D(\mathbf{x})] - \mathbb{E}[D(g(\mathbf{x}, \theta_g))] + \mathbb{E}[||\mathbf{x} - g(\mathbf{x}, \theta_g)||_1]$

Fine-tuning GAN-based model:

$$L_{\theta_g} = L_g(\mathbf{x}', \theta_g) + s \cdot L_{cls}(\mathbf{x}', y, \theta_g, \theta_f)$$

= $\mathbb{E}[D(\mathbf{x}')] - \mathbb{E}[D(g(\mathbf{x}', \theta_g))] + \mathbb{E}[||\mathbf{x}' - g(\mathbf{x}', \theta_g)|]$
+ $s \cdot max_{\delta}CE\{y, f(g(\mathbf{x}', \theta_g))\}$



Figure 1: Illustration of adversarial training on purification (AToP).

Related Publications

- G. Lin, C. Li, J. Zhang, T. Tanaka, and Q. Zhao, "Adversarial Training on Purification (AToP): Advancing Both Robustness and Generalization", ICLR 2024.
- Y. Qiu, G. Zhou, A. Wang, Z. Huang, and Q. Zhao, "Towards multi-mode outlier robust tensor ring decomposition", AAAI 2024.
- Z. Tao, T. Tanaka, and Q. Zhao, "Efficient nonparametric tensor decomposition for binary and count data", AAAI 2024.
- Z. Tao, T. Tanaka, and Q. Zhao, "Undirected probabilistic model for tensor decomposition", NeurIPS 2023
- A. Wang, C. Li, M. Bai, Z. Jin, G. Zhou, and Q. Zhao, "Transformed low-rank parameterization can help robust generalization for tensor neural networks", NeurIPS 2023.
- C. Li, J. Zeng, C. Li, C. F. Caiafa, and Q. Zhao, "Alternating local enumeration (TNALE): Solving tensor network structure search with fewer evaluations", ICML 2023.