Mixture of Robust Experts (MoRE): A ROBUST DENOISING METHOD TOWARDS MULTIPLE PERTURBATIONS

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ABSTRACT

To tackle the susceptibility of deep neural networks under adversarial example attacks, the adversarial training method has been proposed, which provides a notion of security through an inner maximization problem, embedded within the outer minimization on the training loss to present the first-order adversaries. To generalize the adversarial robustness over different perturbation types, the adversarial training method has been augmented with the improved inner maximization process to present a union of multiple perturbations e.g., various \( \ell_p \)-norm-bounded perturbations. However, the improved inner maximization still enjoys limited flexibility in terms of the supported perturbation types. In this work, through a well designed gating mechanism, we assemble a set of expert networks to achieve superior accuracy performance under various perturbation types. Specifically, the gating module assigns weights dynamically to each expert network with the flexibility of supporting various data types e.g., adversarial examples, adverse weather perturbations, image transformations, and clean input. In order to deal with the obfuscated gradients issue, the training of the gating module is conducted together with fine-tuning of the last fully connected layers of expert networks through the adversarial training approach treating the ensemble as a whole model. It features a fast gate-training/fine-tuning process for easy extension onto newly added perturbation types. After evaluating on CIFAR-10 and Tiny-ImageNet-200, we show that our Mixture of Robust Experts (MoRE) approach enables a flexible and expandable integration of a broad range of robust experts with superior performance, comparing with the state-of-the-art works.

1 INTRODUCTION

Deep learning has achieved exceptional performance in many application domains (He et al., 2016; Devlin et al., 2019; Yuan & Moghaddam, 2020; Shi et al., 2020), but its vulnerability to adversarial examples raises serious concerns (Szegedy et al., 2014; Bulusu et al., 2020; Xu et al., 2019b; 2020b; Carlini & Wagner, 2017). Recently, some success is achieved in training models robust against a single adversary type, especially when perturbations are in an \( \ell_p \)-ball with a small radius surrounding the clean data point (Zhang et al., 2019; Shafahi et al., 2019; Madry et al., 2018; Xu et al., 2020).

On the other hand, model ensemble approaches have been explored for improving robustness to various attack algorithms (instead of multiple perturbation types as our paper targets). The adaptive diversity promoting (ADP) regularizer (Pang et al., 2019) was proposed to encourage diversity, leading to robustness to different attack algorithms including FGSM (Goodfellow et al., 2015), PGD (Madry et al., 2018), C&W (Carlini & Wagner, 2017), EAD (Chen et al., 2018), etc. The ensemble approach has also been used for adversarial robustness to transferred attacks. DVERGE (Yang et al., 2020) induced diversity among sub-models for robustness to transferred attacks. Kariyappa & Qureshi (2019) proposed the Gradient Alignment Loss (GAL) as the uncorrelated loss functions for an ensemble of models and thus Diversity Training for robustness under transferred attacks. Note that these approaches do not exploit adversarial training and focus on a single perturbation type.

Our proposed MoRE outperforms SOTA approaches on adversarial training with a union of multiple perturbation types (Tramer & Boneh, 2019; Maini et al., 2020). To the best of our knowledge, we are
the first work using adversarial training within the ensemble learning paradigm to achieve adversarial robustness to different perturbation types. Finally, the robustness to adverse weather perturbations (Ozdag et al., 2019) in addition to adversarial perturbations is desired in real-world applications. Unfortunately, efforts in this direction have been virtually non-existent, and due to the flexibility of our approach can easily be supported in our framework.

2 PROPOSED MIXTURE OF ROBUST EXPERTS (MÖRE)

The MÖRE framework is shown in Figure ?? with $m$ expert networks and a gating module. We have three categories of expert networks: a clean expert, robust experts targeting adversarial perturbations, and robust experts targeting adverse weather perturbations, as follows:

$$
\begin{aligned}
\min_{\theta_{\text{clean}}} & \mathbb{E}_{(x,y) \sim \mathcal{D}} [L(\theta_{\text{clean}}, x, y)], \\
\min_{\theta_{\text{adv}}} & \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \Delta_p} L(\theta_{\text{adv}}, x + \delta, y) \right], \\
\min_{\theta_{\text{wth}}} & \mathbb{E}_{(x_{\text{wth}}, y) \sim \mathcal{D}_{\text{wth}}} [L(\theta_{\text{wth}}, x_{\text{wth}}, y)],
\end{aligned}
$$

(1)

where $\theta_{\text{clean}}$, $\theta_{\text{adv}}$, and $\theta_{\text{wth}}$ denote the model parameters of the clean, adversarial robust, and weather robust experts, respectively; $(x, y) \sim \mathcal{D}$ and $(x_{\text{wth}}, y) \sim \mathcal{D}_{\text{wth}}$ denote the standard dataset and adverse weather dataset (which can be obtained from standard dataset with adverse weather processing step (Ozdag et al., 2019)), respectively; $\delta$ denotes the adversary perturbation within $\ell_p$-ball constraint $\Delta_p$; and $L(\cdot)$ is the cross entropy loss.

In order to assemble clean and robust experts in an integrated robust system, we design a trainable gating module to assign weights to individual experts during inference, motivated from Expert Gate for lifelong learning (Aljundi et al., 2017). Differently, with the training data, we perform training on the gating module and fine-tuning of the expert networks. Through the joint training of the gating module and the experts, weights for individual experts are dynamically generated for each input, to achieve both high clean accuracy and high adversarial accuracy.

**Gating Module** is trained to output dynamic weights for expert networks. We modify the output dimension of ResNet-18 (He et al., 2016) to match the number of experts in the system, as the gating module architecture. We use $g(\theta_{\text{gating}}, x)$ to denote the gating module, where $\theta_{\text{gating}}$ is its parameters.

**Softmax** is added to the output of gating module to produce weights for individual experts, as:

$$
w = \text{Softmax} \left( g(\theta_{\text{gating}}, x) \right).
$$

(2)

We use $E \in \mathbb{R}^{k \times m}$ to denote the set of expert networks, where $k$ indicates the number of classes, and $E_i$ denotes the $i$-th expert. A total of $m$ experts are used, each one presenting either the clean expert or an adversary/weather robust expert with specific strength setting. The output of the overall MoRE system is given by

$$
f(x) = E \cdot w = \sum_{i=1}^{m} E_i(x) \cdot w_i.
$$

(3)

2.1 MÖRE TRAINING

For the overall MoRE system, we train on the gating module as well as the last fully connected layers of the $m$ expert networks, with other parts of the experts fixed. To resolve the possible obfuscated gradients issue (Athalye et al., 2018) with the MoRE training, we treat the MoRE system as a whole model and train it using a modified adversarial training process, where clean training input data is feed to the whole model and PGD attacks are used to generate adversarial examples for the inner maximization. Different adversarial attacks are implemented alternately for the inner maximization to update the gating module and the last fully connected layers of individual experts.

3 EXPERIMENTS

We evaluate our MoRE system using white-box attacks: Deepfool (Moosavi-Dezfooli et al., 2016) and PGD (Madry et al., 2018), black-box attacks: RayS (Chen & Gu, 2020), and adverse weather
attacks (Ozdag et al., 2019). For adversarial attacks, we consider $\ell_2$ and $\ell_\infty$ perturbations, and other $\ell_p$ perturbations can also be generalized in our method. Please note that RayS naturally $\ell_\infty$ perturbation only. In our experiments, for a fair comparison, we add a projection step during attack to generalize Rays to both $\ell_2$ and $\ell_\infty$ constraints. We compare our MoRE system with SOTA approaches on adversarial training with a union of multiple perturbation types such as MAX (Tramer & Boneh, 2019), AVG (Tramer & Boneh, 2019), and MSD (Maini et al., 2020).

3.1 Experimental Setting

We use image classification dataset CIFAR-10 (Krizhevsky et al., 2009) in our experiments. ResNet18 (He et al., 2016) is used as our base architecture for both the gating module and expert networks. Our MoRE system adopts a clean expert, adversarially robust experts, and weather experts. For adversarially robust experts, we consider two $\ell_p$ perturbation types i.e., $\ell_2$ and $\ell_\infty$, and two perturbation strengths i.e., $\epsilon = 0.5$ and $1.0$ for $\ell_2$ experts, and $\epsilon = 6/255$ and $8/255$ for $\ell_\infty$ experts. For weather robust experts, we use two weather types, i.e., fog and snow following the adverse weather perturbation generation technique introduced in (Ozdag et al., 2019). Here, $t$ and $\text{light}$ are two factors for the fog perturbations, and we set $(t, \text{light})$ as $(0.15, 0.8)$ and $(0.15, 0.6)$. Parameter $\text{darkness}$ is used to generate the snow perturbations, and we set $\text{darkness} = 2.0$ and $\text{darkness} = 2.5$. When evaluating the MoRE system, we use the larger perturbation strengths i.e., $\epsilon = 1.0$ for $\ell_2$ perturbations, $\epsilon = 8/255$ for $\ell_\infty$ perturbations, $(t, \text{light}) = (0.15, 0.6)$ for fog perturbations, and $\text{darkness} = 2.5$ for snow perturbations.

3.2 Performance Evaluation

In Table 1 we report the performance of our MoRE system. We compare the performance on the clean data as well as with white-box adversaries, i.e., Deepfool (Moosavi-Dezfooli et al., 2016) and PGD (Madry et al., 2018), black-box adversary i.e., RayS (Chen & Gu, 2020), and weather adversaries i.e., Fog and Snow (Ozdag et al., 2019). Before comparing with SOTA approaches, we report the test accuracy of a normally trained model, i.e., Column “clean”; an $\ell_\infty$ adversarially trained model, i.e., Column “$M_\infty$”; an $\ell_2$ adversarially trained model, i.e., Column “$M_2$”; a fog adversarially trained model, i.e., Column “$M_{\text{fog}}$”; and a snow adversarially trained model, i.e., Column “$M_{\text{snow}}$”. It can be seen that these individual experts achieve high robustness on the perturbation type they are trained to be robust against. However, when presented with a different perturbation type, the robustness of these individual experts drop drastically. In contrast, MoRE achieves similar (or sometimes better) performance on all perturbation types simultaneously.

Next, we compare MoRE with MAX, AVG, and MSD baselines on $\ell_p$ adversaries only, because those SOTA methods were designed for $\ell_p$ adversaries. We achieve up to 5.54%, 0.40%, 14.77% and 11.79% increase in $\ell_2$, $\ell_\infty$, and black-box adversarial accuracy as well as clean accuracy, respectively. For example, under $\ell_2$ white-box adversary Deepfool, our accuracy is 3.00% higher than MAX; and under $\ell_2$ white-box adversary PGD, it is 5.54% higher than AVG baseline. Under $\ell_2$ black-box adversary RayS, our accuracy is 14.77% higher than MSD, and under $\ell_\infty$ black-box adversary RayS, it is 5.09% higher than MSD.

Finally, we compare MoRE with MAX and AVG on both $\ell_p$ and weather adversaries. We could not compare with MSD here, because it is not compatible to defend weather adversaries. We achieve up to 13.44%, 9.82%, 18.94%, 12.37% and 16.92% increase in white-box $\ell_2$ & $\ell_\infty$, black-box, and weather adversary accuracy as well as clean accuracy, respectively. For example, under fog weather adversary, our accuracy is 5.78% higher than AVG; and under snow weather adversary, it is 12.37% higher than AVG baseline. Overall, our proposed MoRE achieves the best performance in almost all the evaluation cases.

4 Conclusion

To achieve robustness under various perturbation types, in this work, we propose Mixture of Robust Experts (MoRE) method, combining adversarial training with the model ensemble approach, to achieve high adversarial as well as clean accuracy while enjoying the flexibility in perturbation types. Specifically, through a gating mechanism, we assemble a set of expert networks, each one either adversarially trained to deal with a particular perturbation type or normally trained for boosting accuracy on clean data. In order to deal with the obfuscated gradients issue, the training of the gating
Table 1: Test accuracy (%) comparison on CIFAR-10 under different attacks: Deepfool (Moosavi-Dezfooli et al., 2016) and PGD (Madry et al., 2018) as white-box adversaries; RayS (Chen & Gu, 2020) as black-box adversary; and Fog and Snow perturbations (Ozdag et al., 2019). For adversarial $\ell_p$ and $\ell_\infty$ perturbations, we set strength $\epsilon$ as 1.0 and 8/255, respectively. From Columns 2–6, test accuracy of clean trained, $\ell_\infty$ adversarially trained, $\ell_p$ adversarially trained, fog adversarially trained, and snow adversarially trained models are reported, respectively. From Columns 7–10, MoRE is compared with MAX (Tramer & Bonelli, 2019), AVG (Tramer & Bonelli, 2019), and MSD (Maini et al., 2020) on the $\ell_p$ adversaries only (without adverse weather adversaries, because these works are designed for $\ell_p$ adversaries only). From Columns 11–13, MoRE is only compared with MAX and AVG on both the $\ell_p$ and weather adversaries, because MSD is not compatible to defend weather adversaries.

| clean accuracy | clean | $M_2$ | $M_\infty$ | $M_{\text{avg}}$ | $M_{\text{moment}}$ | MAX | AVG | MSD | MoRE | MAX (all) | AVG (all) | MoRE (all) |
|----------------|-------|-------|-------------|------------------|---------------------|-----|-----|-----|------|---------|----------|---------|
|                | 95.25 | 80.75 | 81.28 | 87.57 | 80.84 | 59.36 | 71.87 | 76.24 | 81.75 | 59.88 | 66.20 | 84.12 |
| Deepfool $\ell_2$ ($\epsilon = 1.0$) | 1.20 | 56.40 | 66.00 | 8.21 | 2.90 | 50.80 | 49.50 | 51.20 | 52.50 | 55.50 | 44.40 | 54.70 |
| Deepfool $\ell_\infty$ ($\epsilon = 8/255$) | 1.56 | 53.40 | 54.80 | 7.00 | 2.80 | 49.50 | 47.95 | 50.00 | 50.60 | 48.40 | 40.20 | 45.50 |
| PGD $\ell_2$ ($\epsilon = 1.0$) | 0.00 | 47.97 | 35.57 | 0.15 | 0.30 | 44.13 | 42.51 | 43.92 | 48.75 | 37.85 | 33.59 | 47.08 |
| PGD $\ell_\infty$ ($\epsilon = 8/255$) | 0.00 | 39.29 | 48.01 | 0.17 | 0.28 | 42.43 | 40.30 | 42.83 | 41.95 | 37.40 | 31.04 | 40.86 |
| RayS $\ell_2$ ($\epsilon = 1.0$) | 1.43 | 54.40 | 53.80 | 2.00 | 6.00 | 51.07 | 54.50 | 44.73 | 50.50 | 53.43 | 40.23 | 59.17 |
| RayS $\ell_\infty$ ($\epsilon = 8/255$) | 0.71 | 40.00 | 46.50 | 0.00 | 0.00 | 43.40 | 43.21 | 41.11 | 46.20 | 43.57 | 31.01 | 46.30 |
| Fog ($\ell_1$; light:0.15,0.6) | 40.34 | 20.88 | 16.83 | 88.44 | 61.51 | - | - | - | - | 60.75 | 59.43 | 65.21 |
| Snow (darkness:2.5) | 32.07 | 30.55 | 34.44 | 48.56 | 82.69 | - | - | - | - | 53.04 | 49.60 | 61.97 |

module is conducted together with fine-tuning of the last fully connected layers of expert networks through adversarial training approach. Using extensive experiments, we show that our Mixture of Robust Experts (MoRE) approach enables a flexible integration of a broad range of robust experts with superior performance compared to existing state-of-the-art approaches.

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REFERENCES

Rahaf Aljundi, Punarjay Chakravarty, and Tinne Tuytelaars. Expert gate: Lifelong learning with a network of experts. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3366–3375, 2017.

Anish Athalye, Nicholas Carlini, and David Wagner. Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. In International Conference on Machine Learning (ICML), pp. 274–283. PMLR, 2018.

Saikiran Bulusu, Bhavya Kailkura, Bo Li, Pramod K Varshney, and Dawn Song. Anomalous example detection in deep learning: A survey. IEEE Access, 8:132330–132347, 2020.

Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In Security and Privacy (SP), 2017 IEEE Symposium on, pp. 39–57. IEEE, 2017.

Jinghui Chen and Quanquan Gu. Rays: A ray searching method for hard-label adversarial attack. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 1739–1747, 2020.
Pin-Yu Chen, Yash Sharma, Huan Zhang, Jinfeng Yi, and Cho-Jui Hsieh. Ead: elastic-net attacks to deep neural networks via adversarial examples. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4171–4186, 2019.

Ian Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. In *International Conference on Learning Representations (ICLR)*, 2015.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.

Sanjay Kariyappa and Moinuddin K Qureshi. Improving adversarial robustness of ensembles with diversity training. *arXiv preprint arXiv:1901.09981*, 2019.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. *Technical Report TR-2009*, 2009.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In *International Conference on Learning Representations (ICLR)*, 2018.

Pratyush Maini, Eric Wong, and Zico Kolter. Adversarial robustness against the union of multiple perturbation models. In *International Conference on Machine Learning (ICML)*, pp. 6640–6650. PMLR, 2020.

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, and Pascal Frossard. Deepfool: a simple and accurate method to fool deep neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2574–2582, 2016.

Mesut Ozdag, Sunny Raj, Steven Fernandes, Laura L Pullum, and Sumit Kumar Jha. On the susceptibility of deep neural networks to natural perturbations. Technical report, Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States), 2019.

Tianyu Pang, Kun Xu, Chao Du, Ning Chen, and Jun Zhu. Improving adversarial robustness via promoting ensemble diversity. In *International Conference on Machine Learning (ICML)*, pp. 4970–4979. PMLR, 2019.

Ali Shafahi, Mahyar Najibi, Mohammad Amin Ghiasi, Zheng Xu, John Dickerson, Christoph Studer, Larry S Davis, Gavin Taylor, and Tom Goldstein. Adversarial training for free! In *Advances in Neural Information Processing Systems (NeurIPS)*, pp. 3358–3369, 2019.

Xiaoshuang Shi, Fuyong Xing, Yuanpu Xie, Zizhao Zhang, Lei Cui, and Lin Yang. Loss-based attention for deep multiple instance learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pp. 5742–5749, 2020.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna Estrach, Dumitru Erhan, Ian Goodfellow, and Robert Fergus. Intriguing properties of neural networks. In *International Conference on Learning Representations (ICLR)*, 2014.

Florian Tramer and Dan Boneh. Adversarial training and robustness for multiple perturbations. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2019.

Kaidi Xu, Hongge Chen, Sijia Liu, Pin-Yu Chen, Tsui-Wei Weng, Mingyi Hong, and Xue Lin. Topology attack and defense for graph neural networks: An optimization perspective. In *International Joint Conference on Artificial Intelligence (IJCAI)*, 2019a.

Kaidi Xu, Sijia Liu, Pu Zhao, Pin-Yu Chen, Huan Zhang, Quanfu Fan, Deniz Erdogmus, Yanzhi Wang, and Xue Lin. Structured adversarial attack: Towards general implementation and better interpretability. In *International Conference on Learning Representations (ICLR)*, 2019b.
Kaidi Xu, Zhouxing Shi, Huan Zhang, Yihan Wang, Kai-Wei Chang, Minlie Huang, Bhavya Kailkhura, Xue Lin, and Cho-Jui Hsieh. Automatic perturbation analysis for scalable certified robustness and beyond. Advances in Neural Information Processing Systems, 33, 2020a.

Kaidi Xu, Gaoyuan Zhang, Sijia Liu, Quanfu Fan, Mengshu Sun, Hongge Chen, Pin-Yu Chen, Yanzhi Wang, and Xue Lin. Adversarial t-shirt! evading person detectors in a physical world. In European Conference on Computer Vision (ECCV), pp. 665–681. Springer, 2020b.

Huanrui Yang, Jingyang Zhang, Hongliang Dong, Nathan Inkawhich, Andrew Gardner, Andrew Touchet, Wesley Wilkes, Heath Berry, and Hai Li. Dverge: Diversifying vulnerabilities for enhanced robust generation of ensembles. In Advances in Neural Information Processing Systems (NeurIPS), volume 33, 2020.

Chenxi Yuan and Mohsen Moghaddam. Attribute-aware generative design with generative adversarial networks. IEEE Access, 8:190710–190721, 2020.

Hongyang Zhang, Yaodong Yu, Jiantao Jiao, Eric Xing, Laurent El Ghaoui, and Michael Jordan. Theoretically principled trade-off between robustness and accuracy. In International Conference on Machine Learning (ICML), pp. 7472–7482. PMLR, 2019.