Seminar thesis

Adversarial Label Flips

Matthias Dellago & Maximilian Samsinger

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Abstract

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1 Introduction

Example citation [1].

2 Background and related work

2.1 Attacks

Existence of adversarial examples Demonstrated that attacking deep neural networks are susceptible to attacks [2]. They actually coined the term "adversarial examples".

Fast gradient sign method [3] developed the fast gradient sign method. They are the guys with the panda image.

Projected gradient descent The projected gradient descent, which is basically iterated FGSM, was first shown in [1]. Their experiments suggest that these attacks converge, i.e. they find a local maxima. This may require some restarts.

Foolbox A Python library with lots of attacks [4]. They include the attacks above.

2.2 Neural networks

First introduced in [5]. The authors of [6] demonstrated the effectiveness of deep convolutional neural networks on ImageNet.

ResNets Paradigm shift in deep learning. In [7] they developed Residual Networks to train very deep neural networks. We will probably use ResNet18. If we do, we probably also cite [8] for the "pre-activation" optimization. This is just a better architecture obtained by having BatchNorm-ReLU-Weights blocks instead of Weights-BatchNorm-ReLU blocks.

3 Methods

3.1 Datasets

3.2

References

[1] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. *arXiv preprint arXiv:1706.06083*, 2017.

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

[3] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.

[4] Jonas Rauber, Wieland Brendel, and Matthias Bethge. Foolbox: A python toolbox to benchmark the robustness of machine learning models. *arXiv preprint arXiv:1707.04131*, 2017.

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[6] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, pages 1097–1105, 2012.

[7] 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*, pages 770–778, 2016.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Identity mappings in deep residual networks. In *European Conference on Computer Vision*, pages 630–645. Springer, 2016.