Polarizing Front Ends for Robust CNNs

Can Bakışkan, Soorya Gopalakrishnan, Metehan Çekiç, Upamanyu Madhow, Ramtin Pedarsani

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1. Introduction

Vulnerability of machine learning models is concerning

"Excessive linearity": small perturbations designed to add up to large values in high dimensions using locally linear approximations of smooth functions

Pictures courtesy of [1]
2. Background

Inputs $x \in \mathbb{R}^N$, output predictions (confidence scores for $M$ classes)
$y \in [0, 1]^M$, $\theta$ model parameters

Our goal is to defend against malicious inputs of the form $x + e$, where
$e \in \mathbb{R}^N$ is a small perturbation that aims to cause misclassification
($\|e\|_\infty < \epsilon$)

Formally: $\max_{e \in S} L(\theta, x + e, y_{\text{true}})$
2. Background

Attacks – FGSM

Fast Gradient Sign Method: \( e = \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y_{true})) \)

FGSM takes gradient steps to **increase** loss function
2. Background
Attacks – BIM

Basic Iterative Method (BIM):

\[ e_{i+1} = \Clip{\epsilon}{e_i + \alpha \cdot \text{sign}(\nabla_x L(\theta, x + e_i, y_{true}))} \]

Many FGSM-like steps use local linearity better
2. Background
Attacks – PGD

- Projected Gradient Descent: Basic iterative method with random restarts within $\| \cdot \|_\infty \leq \epsilon$ ball around original input.

PGD uses worst case perturbation among several initial conditions
2. Background
Existing Defenses

- Most well-known defenses still standing use adversarial training with
attacks generated by PGD with random restarts\(^4\)
- Defenses that combine adversarial training with other methods
- Provable defenses
3. Our Defense
Rationale – Starting Point

- Our assumption that $\|e\|_{\infty} \leq \epsilon$
- Hölder’s inequality:

$$|w^T e| \leq \|e\|_{\infty} \|w\|_1 \leq \epsilon \|w\|_1$$

- Can predict max perturbation at output of front end neuron
Rationale

- **Sparsifying approach**: suppress neuron outputs around zero up to 
  \[ | \cdot | \leq \epsilon \| w \|_1 \]

Activation sparsity alone is not enough: perturbations can ride on top of signals passing through
3. Our Defense

Rationale

- Can we prevent perturbations from riding on top of the signal?
- Polarization approach:

A saturation function can fully eliminate perturbations if distribution is polarized.
Problem: With standard training the distribution of $\frac{w^T x}{\|w\|_1}$ is concentrated around zero. Direct enforcement of saturated activation can kill most of the signal as well as perturbation.

Standard training makes activations concentrate around zero.
Solution: Multi stage training with regularizers that favor the multimodal distribution we want.

\[
\mathcal{L}(y, y_{true}, z) = \mathcal{L}_{CE}(y, y_{true}) + \lambda \sum_{k=1}^{K} \frac{B(z_k)}{K}
\]

Goal: First spread the distribution between \([-1, 1]\). Then drive the distribution of \(w^T x / \|w\|_1\) away from the "danger zones"
3. Our Defense
Implementation – Training Stage 1

- No saturation function used
- Regularizer $B(z_k) = B_1(z_k) = e^{-z_k^2/2\sigma_1^2}$

Regularizer 1 promotes even distribution of normalized activations between $[-1, 1]$. Saturation function plotted for comparison only.
3. Our Defense
Implementation – Training Stage 2

- No saturation function used
- Regularizer $B(z_k) = B_2(z_k) = e^{-(z_k-c)^2/2\sigma^2} + e^{-(z_k+c)^2/2\sigma^2}$

Regularizer 2 drives activations away from the regions of discontinuity
3. Our Defense

Implementation

![Graph showing polarization of distribution of normalized front-end filter activations (MNIST)]

- Initial
- After stage 1
- After stage 2

Polarization of distribution of normalized front-end filter activations (MNIST)
3. Our Defense

Implementation

Polarization of distribution of normalized front-end filter activations (Fashion MNIST)

$w^T x / ||w||_1$
Block diagram of front end defense, showing a polarizing filter followed by $\ell_1$ normalization and saturation activation function $f(\cdot)$. 
4. Experiments

▶ Standard post frontend convolutional neural network (following literature for consistency).
  ▶ 2 convolutional layers followed by
  ▶ 2 fully connected layers.
  ▶ Each convolutional layer is followed by maxpooling operation.
Examples of filters after each stage. As polarizing regularizers are introduced, weights of the filters start concentrating around mostly a single pixel in each filter at different locations and signs.
5. Results

Output of the frontend for a single Fashion MNIST image. Notice the various shifts in position.
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Original FashionMNIST images and **single filter’s output** for the frontend

Attacked FashionMNIST images and **single filter’s output** for the frontend
5. Results

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Experimental results for different attacks.

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<th>Fashion MNIST ($\epsilon = 0.1$)</th>
<th>MNIST ($\epsilon = 0.3$)</th>
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<td>Clean</td>
<td>FGSM</td>
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5. Results

Classification accuracy as attack budget $\epsilon$ is increased.
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Classification accuracy as attack budget $\epsilon$ is increased.
5. Discussion

- First step in a bottom-up and interpretable approach to mitigate adversarial attacks for machine learning models
- Resulting filters consistent with what adversarial training learns
- Saturation function amounts to drastic quantization which hurts clean accuracy
6. Conclusion

Future work:
- Expand the same clustering/polarization idea for other datasets
- Use different activation functions to alleviate retained perturbation at each layer

Our code is available at
github.com/canbakiskan/polarizing-frontend
1. adversarial-ml-tutorial.org


4. Madry et al., “Towards deep learning models resistant to adversarial attacks,” in International Conference on Learning Representations, 2018