Towards Efficient Methods for Training Robust Deep Neural Networks

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Introduction
Deep Learning (DL) can surpass humans

<table>
<thead>
<tr>
<th>Input sentence:</th>
<th>Translation (PBMT):</th>
<th>Translation (GNMT):</th>
<th>Translation (human):</th>
</tr>
</thead>
<tbody>
<tr>
<td>郭健議員宣布將啟動中加總理年度對話機制。與加拿大總理杜魯多舉行兩國總理首次年度對話。</td>
<td>Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau.</td>
<td>Li Keqiang will initiate the annual dialogue mechanism with Prime Minister Trudeau of Canada.</td>
<td>Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue between the two premiers.</td>
</tr>
</tbody>
</table>
DL in security-critical applications
Is DL ready for this?
Deep Neural Network (DNN) - Natural Setting

V. Fischer, M. Kumar, J. Metzen, T. Brox
“Adversarial Examples for Semantic Image Segmentation”
DNN - Adversarial Setting
Why do we need robust DNNs?

Reliability
- Some natural phenomena (e.g., rain) can trick classifiers
- Train more reliable natural classifiers

Intelligence
- Goal of ML: Make intelligent systems
- Humans wouldn’t get fooled, but these systems do
Background
How do we train robust DNNs?
Adversarial Training - A robust training method

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim \hat{D}} [\mathcal{L}(x, y; \theta)] \\
\max_{\delta \in \mathcal{S}} \mathcal{L}(x + \delta, y; \theta)
\]
Adversarial Training - A robust training method

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \mathcal{S}} \mathcal{L}(x + \delta, y; \theta) \right]
\]

Adversarial Training Set

\[
\max_{\delta \in \mathcal{S}} \mathcal{L}(x + \delta, y; \theta)
\]

Model Parameters
Why is Adversarial Training difficult?

- Takes a long time to compute good adversarial examples
- Training waits for these examples
- Process repeats several times before DNN finally becomes robust

➢ Time-Intensive Process
Research focus: How can we make Adversarial Training more efficient?
Technique 1: A closer look at Adversarial Training
Concave loss landscapes are easily maximizable

- Goal of adversary: Get to maximum loss
- Hypothetical loss landscape
DNNs have tricky, non-concave loss landscapes

- Actual loss landscape
- Hard to find maxima, so need multiple steps
- Each step re-calculates trajectory, which is Time Intensive

H. Li, Z. Xu, G. Taylor, C. Studer, T. Goldstein
“Visualizing the Loss Landscape of Neural Nets”
How strong does the adversary need to be?
How strong does the adversary need to be?
How strong does the adversary need to be?
How strong does the adversary need to be?
Technique 2: Asynchronous parallelization
Re-Visiting Adversarial Training
Re-Visiting Adversarial Training
High staleness training doesn’t work
Staleness can be pathological

32 Staleness (Good)  64 Staleness (Bad)
Almost-linear speedup
4 hrs to 9 mins

Combining both techniques, we achieve a 26x reduction in robust MNIST training time