Learning Universal Adversarial Perturbations with Generative Models

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Adversarial examples transfer between different models.

An adversarial example crafted against one model will generally fool other models.

Why do adversarial examples transfer?
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[LCL17] Liu et al. Delving into Transferable Adversarial Examples and Black-Box Attacks
In the most extreme case, it is possible to construct a single perturbation that will fool a model when added to any image!

[Goodfellow et al. 2015] Explaining and Harnessing Adversarial Examples
Can a neural network learn universal adversarial perturbations?
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Adversarial Model → Scale → Clip → Target Model → Classify
Can a neural network learn universal adversarial perturbations?

Given a model, \( f \), and an image, \( x \), classified correctly as \( c_0 \), the attacker model is training to minimize:

\[
L_{nt} = \max\{\log[f(\delta' + x)]_{c_0} - \max_{i \neq c_0} \log[f(\delta' + x)]_i, -\kappa\} + \alpha \cdot \frac{\|\delta'\|_p}{\|x\|_p}
\]

We scale the perturbation such that \( \frac{\|\delta'\|_p}{\|x\|_p} \) never exceeds 0.04.
Learned Universal Adversarial Perturbations

<table>
<thead>
<tr>
<th>Model</th>
<th>Original</th>
<th>Adversarial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inception-V3</td>
<td>77.2%</td>
<td>22.7%</td>
</tr>
<tr>
<td>ResNet-152</td>
<td>78.4%</td>
<td>11.1%</td>
</tr>
<tr>
<td>VGG-19</td>
<td>71.0%</td>
<td>15.1%</td>
</tr>
</tbody>
</table>
Inception-V3:
Fire engine (54.6%)

ResNet-152:
Table lamp (87.2%)

VGG-19:
Radio telescope (97.5%)

Inception-V3:
Wrecker (79.4%)

ResNet-152:
Tabby cat (41.9%)

VGG-19:
Great Pyrenees (36.7%)
We can perform targeted attacks to force the model to always classify as label, \(c\), by changing the loss term from:

\[
L_{nt} = \max\{\log[f(\delta' + x)]_c - \max_{i \neq c_0} \log[f(\delta' + x)]_i, -\kappa\} + \alpha \cdot \|\delta'\|_p
\]

To:

\[
L_t = \max\{\max_{i \neq c} \log[f(\delta' + x)]_i - \log[f(\delta' + x)]_c, -\kappa\} + \alpha \cdot \|\delta'\|_p
\]
Target class: Golf Ball

Inception-V3:
American egret (95.0%)

Inception-V3:
Golf ball (98.8%)

ResNet-152:
Binoculars (99.9%)

ResNet-152:
Golf ball (62.9%)

VGG-19:
Indian cobra (99.9%)

VGG-19:
Golf ball (99.7%)
Adversarial Training Defense

Include adversarial examples during training to improve robustness.

Instead of optimizing $L(\theta, x, y)$, optimize $\alpha \cdot L(\theta, x, y) + (1 - \alpha) \cdot L(\theta, x + \delta', y)$
Adversarial Training Defense

Play Cat and Mouse game:

1) Train generative model to create perturbations, report target model accuracy on adversarial examples
2) Use adversarial training to defend target model, report target model accuracy on adversarial examples.
3) Go to (1)
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Related Work

Three preprints using the same technique appeared online within a few days of one another.

This work, Poursaeed et al. [1], Mopuri et al. [2].

<table>
<thead>
<tr>
<th></th>
<th>VGG-19</th>
<th>INCEPTION-V1</th>
</tr>
</thead>
<tbody>
<tr>
<td>This work</td>
<td>0.846</td>
<td>0.809</td>
</tr>
<tr>
<td>Poursaeed et al. [1]</td>
<td>0.801</td>
<td>0.792</td>
</tr>
<tr>
<td>Mopuri et al. [2]</td>
<td>0.838</td>
<td>0.904</td>
</tr>
</tbody>
</table>

Thanks!

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