MTDeep: Boosting the Security of Deep Neural Networks Against Adversarial Attacks with Moving Target Defense

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Supervised Machine Learning Systems for Classification

• Given \( i.i.d. \) labelled training data \((i, l) \sim D\) learn a classifier that estimates \( \Pr(l_j|i) \), where \( l_j \in L \) where \( L \) is the set of class labels for the input data \( i \).

• The classifier guarantees classification accuracy about inputs \( i \) drawn from the same distribution \( D \).
Attacks on Deep Neural Networks

• Classifier misclassifies (i.e. increases *misclassification rate*), human observer cannot detect the noise.

\[ l = \text{Bus} \]
\[ \epsilon \]
\[ i' \]

\[ l = Ostrich \]

Picture courtesy:
Attacking Deep Neural Networks (for image classification)

• The input space is huge. For a 28 × 28 image with RGB channels, the input space is 28 × 28 × (255)^3.

• The input distribution for classification is small.

• Classifier has high bias for regions not seen in the input.

• Exploit this bias to generate adversarial samples.

*Picture courtesy: Peter Norvig*
Attacks on Deep Neural Networks

• **Whitebox attacks** – attack for each image, each network
  - FGSM \cite{szegedy2013intriguing}, DeepFool \cite{moosavi2016deepfool}, JSMA \cite{papernot2016limitations} etc.
  - Find features (in an image) that have the most effect on the Loss Function of the classifier. Use these as heuristics to manipulate input.
  - Find out decision boundaries, find perturbation vectors that push it over to the other side.

• **Blackbox attacks** – attack for each image, each network
  - Train a small substitute DNN using distillation. Design a whitebox attack on this small network. Attack generalizes to blackbox \cite{papernot2017practical}
  - Black box attacks without substitute models are also possible \cite{chen2017zoo}

• **Universal Perturbation** – attack (mostly WB) for a single network
  - Create a noise image that added to any image will make the classifier misclassify it \cite{moosavi2016universal}
  - Adversarial Patch – A universal perturbation at a particular place in the image \cite{brown2017adversarial}
  - Bad Nets – Backdoor patch introduced by poising a portion of the training data \cite{gu2017badnets}
Defense Against Attacks on Deep Neural Networks

- Train the neural net on the attack distribution (with the correct labels) and the classifier becomes immune to the particular type of adversarial inputs. This is one of the most effective methods!
  - Ensemble adversarial training Tramer et al., 2017
  - Stability training Zheng et al., 2016
  - Shown to be ineffective against Adv. Universal Perturbation Moosavi et al., 2016b

- Other defense mechanisms like defensive distillation Papernot et al., 2016c, anti-whitening and dimensionality reduction Bhagoji et al., 2017
  - Effectiveness is shown against some sets of attack algorithms.
  - These mechanisms are often shown to be ineffective against new computationally expensive attacks Carlini and Wagner, 2017
Defense and Meta-Defense Against Attacks on Deep Neural Networks

• How about a defense mechanisms that
  • Can provide a first line of defense against attacks previously unseen.
Defense and Meta-Defense Against Attacks on Deep Neural Networks

• How about a defense mechanisms that
  • Can provide a first line of defense against attacks previously unseen.
  • Can increase the security with currently available technology for defense.
Moving Target Defense

- Cybersecurity uses MTD as a mechanism to ensure that an attack by an attacker is not always successful since the surface being defended is not static.
Moving Target Defense in Practice
Moving Target Defense for Deep Neural Networks (MTDeep)

• Let us say we have 3 DNNs (say $N_1, N_2, N_3$) and an attacker designs an noise $\epsilon_1$ for the $N_1$ (and an input image $x$).

• Let us say the attacker gives $x + \epsilon$ as input for classification. If the input is given to the $N_2$ or $N_3$ and the attacker’s input is classified correctly, the attack becomes ineffective.
Moving Target Defense for Deep Neural Networks (MTDeep)

• Let us say we have 3 DNNs (say $N_1, N_2, N_3$) and an attacker designs an noise $\epsilon_1$ for the $N_1$ (and an input image $x$).

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• **Differential immunity**

  *All configurations should not be vulnerable to the same attack.*
Moving Target Defense for Deep Neural Networks (MTDeep)

- Differential immunity ($\delta$)
  All configurations should not be vulnerable to the same attack.
- We define a metric that can give the value of differential immunity for an ensemble of networks.

$$0 \leq \delta \leq 1$$

No differential immunity

No differential immunity
Challenges for MTDeep

• Is absolute differential immunity, i.e. $\delta = 1$ possible for neural networks?
  • **Difficult** because the set of input features that are important for classification remains the same.
  • Attack algorithms use these features as the heuristics to construct perturbations.

• Can we **still** get security benefits by using MTD?
  • If you switch between configuration **strategically**, even with small $\delta$ we can have security gains.

[Diagram of neural network and database]
Goal of MTDeep

Threat model
• Attacker knows the different configurations in the system. Has the power to design strong whitebox attacks (which are inherently more effective than blackbox attacks) for each system.
• Over time the attacker is able to infer the switching policy of MTDeep.

Expectations
• Reduce the misclassification rate on adversarially perturbed inputs.
• Maintain the classification accuracy on legitimate input samples.
Modelling MTDeep as a Game

Constant sum game between the classification system MTDeep and the attacker who is trying to fool MTDeep.

Let $\vec{x}$ denote the strategy vector over the defender’s actions.

Let $\vec{x} = (x_1, x_2) = (0.3, 0.7)$ where $x_i = \text{Pr(}\text{using } N_i\text{)}$.

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Stackelberg equilibrium of this constant-sum leader-follower repeated game gives the optimal switching strategy!

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Modelling MTDeep as a Game

Constant sum game between the classification system MTDeep and the attacker who is trying to fool MTDeep.

Let $\tilde{x}$ denote the strategy vector over the defender’s actions:

$$\tilde{x} = (x_1, x_2)$$

where $x_i = \Pr(\text{using } N_i)$

Stackelberg equilibrium of this constant-sum leader-follower repeated game gives the optimal switching strategy!

😊 Reduce misclassification rate on adversarial inputs.
😊 Maintain classification accuracy of the present system.

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Add a new user type who has only one action – to provide legitimate test image.

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Legitimate User Input

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<tr>
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Modelling MTDeep as a Game

Constant sum game between the classification system MTDeep and the attacker who is trying to fool MTDeep.

Let \( \tilde{x} \) denote the strategy vector over the defender’s actions.

Add a new user type who has only one action – to provide legitimate test image.

**Stackelberg equilibrium** now solves the multi-objective function. Increases defender’s utility, which

- Reduce misclassification rate on adversarial inputs.
- Increases classification accuracy on legitimate samples.

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Optimal Switching Strategy

- We use the DOBSS formulation \( P. \ Paruchuri \ et \ al., \ 2008 \) for calculating the Stackelberg Equilibrium of our game. The multi-objective function we optimize for the classification system MTDeep is,

\[
\max_{x,q} \sum_{n \in N} (\alpha \cdot \sum_{u \in U} R_{n,u}^D x_n q_u^A) + (1 - \alpha) \cdot R_{n,u}^D x_n q_u^L
\]
Evaluations

• We use the DOBSS formulation \textsuperscript{P. Paruchuri et al., 2008} for calculating the \textbf{Stackelberg Equilibrium} of our game. The multi-objective function we optimize for the classification system MTDeep is,

\[
\max_{x,q} \sum_{n \in N} (\alpha \cdot \sum_{u \in U} R_{n,u}^D x_n q_u^A + (1 - \alpha) \cdot R_{n,u}^D x_n q_u^L)
\]

• We consider two different datasets – ImageNET and MNIST.
  • Evaluate against known whitebox attacks, universal perturbations.
Universal Perturbation Attack against MTDeep for ImageNET

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<tr>
<th>MTDeep</th>
<th>Legitimate User (L)</th>
<th>Classification Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG-F (Chatfield et al. 2014)</td>
<td>(92.9, 92.9)</td>
<td></td>
</tr>
<tr>
<td>CaffeNet (Jia et al. 2014)</td>
<td>(83.6, 83.6)</td>
<td></td>
</tr>
<tr>
<td>GoogLeNet (Szegedy et al. 2015)</td>
<td>(93.3, 93.3)</td>
<td></td>
</tr>
<tr>
<td>VGG16 (Simonyan and Zisserman 2014)</td>
<td>(92.5, 92.5)</td>
<td></td>
</tr>
<tr>
<td>VGG19 (Simonyan and Zisserman 2014)</td>
<td>(92.5, 92.5)</td>
<td></td>
</tr>
<tr>
<td>ResNet-152 (He et al. 2016)</td>
<td>(95.5, 95.5)</td>
<td></td>
</tr>
</tbody>
</table>

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<tr>
<th>MTDeep</th>
<th>$U_P_{VGG-F}$</th>
<th>$U_P_{CaffeNet}$</th>
<th>$U_P_{GoogLeNet}$</th>
<th>$U_P_{VGG-16}$</th>
<th>$U_P_{VGG-19}$</th>
<th>$U_P_{ResNet-152}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG-F</td>
<td>(6.3, 93.7)</td>
<td>(28.2, 71.8)</td>
<td>(51.6, 48.4)</td>
<td>(57.9, 42.1)</td>
<td>(57.9, 42.1)</td>
<td>(52.6, 47.4)</td>
</tr>
<tr>
<td>CaffeNet</td>
<td>(26.0, 74.0)</td>
<td>(6.7, 93.3)</td>
<td>(52.3, 47.7)</td>
<td>(60.1, 39.9)</td>
<td>(60.1, 39.9)</td>
<td>(52.0, 48.0)</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>(53.8, 46.2)</td>
<td>(56.2, 43.8)</td>
<td>(21.1, 78.9)</td>
<td>(60.8, 39.2)</td>
<td>(60.2, 39.8)</td>
<td>(54.5, 45.5)</td>
</tr>
<tr>
<td>VGG-16</td>
<td>(36.6, 63.4)</td>
<td>(44.2, 55.8)</td>
<td>(43.5, 56.5)</td>
<td>(21.7, 78.3)</td>
<td>(26.9, 73.1)</td>
<td>(36.6, 63.4)</td>
</tr>
<tr>
<td>VGG-19</td>
<td>(36.0, 64.0)</td>
<td>(42.8, 57.2)</td>
<td>(46.4, 53.6)</td>
<td>(26.5, 73.5)</td>
<td>(22.2, 77.8)</td>
<td>(42.0, 58.0)</td>
</tr>
<tr>
<td>ResNet-152</td>
<td>(53.7, 46.3)</td>
<td>(53.7, 46.3)</td>
<td>(49.5, 50.5)</td>
<td>(53.0, 47.0)</td>
<td>(54.5, 45.5)</td>
<td>(16.0, 84.0)</td>
</tr>
</tbody>
</table>
Universal Perturbation Attack against MTDeep for ImageNET

When $\alpha = 1$,

$$\tilde{x} = (0, 0.171, 0.241, 0, 0.401, 0.187)$$

- In the generated strategy, not all configurations are used. Eg. VGG-F and VGG-16 are dropped from the ensemble.
- MTDeep as the first line of defense
  - No proven defense against Universal Perturbation.
  - Provides double the accuracy when classifying only adversarial inputs!
FGSM against MTDeep for MNIST

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<tr>
<th>MTDeep</th>
<th>Legitimate User ($\mathcal{L}$)</th>
<th>Classification Image</th>
</tr>
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<tbody>
<tr>
<td>CNN</td>
<td>(99.1, 99.1)</td>
<td></td>
</tr>
<tr>
<td>MLP</td>
<td>(98.3, 98.3)</td>
<td></td>
</tr>
<tr>
<td>Hierarchical-RNN</td>
<td>(98.7, 98.7)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Adversarial User ($\mathcal{A}$)</th>
<th>$FGSM_{CNN}$</th>
<th>$FGSM_{MLP}$</th>
<th>$FGSM_{HRNN}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>(11.63, 88.37)</td>
<td>(47.54, 52.46)</td>
<td>(74.65, 25.35)</td>
</tr>
<tr>
<td>MLP</td>
<td>(36.37, 63.63)</td>
<td>(1.96, 98.04)</td>
<td>(38.10, 61.90)</td>
</tr>
<tr>
<td>HRNN</td>
<td>(35.72, 64.28)</td>
<td>(24.08, 75.92)</td>
<td>(9.65, 90.35)</td>
</tr>
</tbody>
</table>

Note that the Stackelberg equilibrium guarantees **double the accuracy** even against MTD system using a Uniform Random Strategy (MTD-URS) in the worst case!
Stronger Attacks against MTDeep + Adversarially Trained Nets on MNIST

Note that after adversarial training, the attacks are almost equally ineffective against the adversarially trained nets.
Stronger Attacks against MTDeep + Adversarially Trained Nets on MNIST

New attacks, stronger than FGSM can render the defense mechanism (adversarial training on FGSM) useless.

<table>
<thead>
<tr>
<th>MTDeep</th>
<th>$FGSMA_C$</th>
<th>$FGSMA_M$</th>
<th>$FGSMA_H$</th>
<th>CWL2</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>94.2, 5.8</td>
<td>97.8, 2.2</td>
<td>97.6, 2.4</td>
<td>80.0, 20.0</td>
</tr>
<tr>
<td>MLP</td>
<td>96.0, 4.0</td>
<td>87.0, 13.0</td>
<td>63.2, 36.8</td>
<td>90.0, 10.0</td>
</tr>
<tr>
<td>HRNN</td>
<td>95.9, 4.1</td>
<td>87.9, 12.1</td>
<td>93.2, 6.8</td>
<td>60.0, 40.0</td>
</tr>
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Carlini-Wagner attacker based on the L2 norm.
Stronger Attacks against MTDeep + Adversarially Trained Nets on MNIST

- MTDeep on top of an existing defense mechanism gives an additional 4% increase in accuracy when $\alpha = 1$.
  - Defense mechanism in place already gives 82% accuracy on adv. inputs.

- Trivial strategies lead to detrimental effects.
  - CNN gives higher accuracy than the MTD(URS) system.
Conclusions and Future Work

• We proposed an MTD framework for securing DNNs - **MTDeep**.
  • We use Moving Target Defense for an ensemble of Deep Neural Networks.
  • We formulated the interaction between the classification system and the users as a Repeated Bayesian Game.

• We empirically demonstrate the effectiveness of MTDeep on MNIST and ImageNET datasets against a variety of well-known attacks.
[New results] What if you do blackbox attacks against MTDeep?

• Blackbox attacks, are weaker than whitebox attacks for constituent DNNs.

😊 In our case, the blackbox attack has to learn the actual the prediction of the ensemble and the randomization implicitly built into MTD.

😊 The game theory framework cannot model these attacks as they are not-existent during the first deployment of the system.

• Blackbox attacks are weaker (65% misclassification) vs whitebox attacks (70% misclassification) against MTDeep.