Summary of Paper: Can Machine Learning be Secure?

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https://qdata.github.io/deep2Read/

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ABSTRACT
Machine learning systems offer unparalleled flexibility in dealing with evolving input in a variety of applications, such as intrusion detection systems and spam e-mail filtering. However, machine learning algorithms themselves can be a target of attack by a malicious adversary. This paper provides a framework for answering the question, “Can machine learning be secure?” Novel contributions of this paper include a taxonomy of different types of attacks on machine learning techniques and systems, a variety of defenses against those attacks, a discussion of ideas that are important to security for machine learning, an analytical model giving a lower bound on attacker’s work function, and a list of open problems.
Introduction

- Can an adversary manipulate a learning system?
  - Degrade the performance?
  - Allow certain attacks?
- What are current defense mechanisms?
- Can properties of machine learning systems be exploited to disrupt system?
- Taxonomy of different attacks and defenses
- Security ideas important for machine learning
- Analytical model giving a lower bound on work function
- List of open problems
Terminology and Attack Model

- Attack targets a learning system
- Intrusion targets a computer (protected by a learning system)
- Adversaries have understanding of the learning algorithms

<table>
<thead>
<tr>
<th>Causative:</th>
<th>Targeted</th>
<th>Integrity</th>
<th>Availability</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Permit a specific intrusion</td>
<td>Create sufficient errors to make system unusable for one person or service</td>
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<tr>
<td>Indiscriminate</td>
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<td>Permit at least one intrusion</td>
<td>Create sufficient errors to make learner unusable</td>
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<tr>
<td>Exploratory:</td>
<td>Targeted</td>
<td>Find a permitted intrusion from a small set of possibilities</td>
<td>Find a set of points misclassified by the learner</td>
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Table 1: The attack model.
Online Learning

- Online learning allows the learner to adapt to changing conditions
- Allows for more flexibility
- Also simplifies causative attacks (attacks that change data)
  - Difficult to detect adversary if they gradually change function over time
  - More simple attack
Defenses: Robustness

- Regularization

\[
\begin{align*}
    f^* &= \arg\min_{f \in \mathcal{F}} \left\{ \sum_{(x_i, y_i) \in \mathcal{S}} \ell(f(x_i), y_i) + \lambda J(f) \right\} \\
\end{align*}
\] (3)

- Used when there is little data or noisy data
- “Encoding a prior distribution on the parameters, penalizing choices that are less likely a priori”
Defenses: Robustness

- Regularization smooths out the solution and removes complexity (that was added by adversary or that an adversary may exploit)
- Prior distribution can help encode important knowledge about the domain or domain structure
- When the learner has more prior information to base learning, there is less dependence of data fitting
  - Adversary has less influence over process
Defenses: Disinformation

- Confuse adversary’s estimate of the learner’s state
- Especially prevent adversary from learning the decision boundary
- Learner attacks adversary with indiscriminate causative availability attack
- Trick adversary into thinking that a particular intrusion was not included in training set
- Set up honeypot so that when that intrusion is performed often enough, you can identify adversary
- Learner attacks adversary with targeted causative integrity attack
Defenses: Randomization for Target Attacks

- Targeted attacks are dependent upon the classification of a small set of points
- Thus, they are highly sensitive to the placement of the decision boundary
- If there is randomization in the placement of the boundary, model accuracy can be maintained while making it more difficult for targeted attacks
Defenses: Summary

- Tradeoff of expressivity and security

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Table 2: Defenses against the attacks in Table 1.
Scale of Training

- Learner can use data from single source or multiple sources
- Tradeoff between size of data and secrecy of classifier
- Most of the time, we cannot assume all information in training set is secret
- Thus, difficult to measure how beneficial it is to keep training data and classifier secret
Scale of Training: Adversary Observations

- Deduce decision boundary by repeated probes
- No information about classifier: probes roughly proportional to size of space
- Information about learning algorithm: possibly few specific probes
- Given that adversary knows decision boundary, they can avoid detection by operating in misclassified space
  - More difficult to find space if classification points are mapped to some abstract space and classification is done in that space
- Advantage depends on boundaries
  - We can construct boundaries that give no information or boundaries that reveal (confidential) information about the data set
Theoretical Results

- Present model for a causative attack trying to manipulate naive learning algorithm
- Yields an optimal policy for adversary and a bound on effort required to achieve adversary’s objective
- Outlier detection: task of identifying anomalous data and is widely used for various security tasks
Model

- Multidimensional hypersphere centered at mean of data where data inside sphere are classified as normal and data outside are classified as outliers.
- Only admits new training points into the set if they are classified as normal (“bootstraps itself”).
- Hypersphere is centered at $X_0$ and has a fixed radius $R$.
- Attack is iterated over course of $T > 1$ iterations and the $i$-th iteration.
Model

(a) Hypersphere Outlier Detection
Attack Strategy

- We want to adjust the model such that it classifies a specific outlier datapoint G as a normal datapoint.
- We shift the sphere over several iterations of training until it covers the point.
- *Causative targeted integrity* attack.
- Feed points that are located where the line between the mean and G intersect the boundary of the sphere.
- At i-th iteration, adversary places alpha_i at this location for optimal displacement.
- Effort of adversary measured as the sum of alpha_i for all times.
Attack Strategy

(b) Attack on a Hypersphere Outlier Detector
Optimal Attack Displacement

- $D_{R,T}({\alpha_i})$ is the relative displacement caused by attack sequence $\alpha_i$ at iteration $i$

- $M_i = \sum_{j=1}^{i} \alpha_j$

- Relative distance of a series of moves:

$$D_{R,T}(\{M_i\}) = T - \sum_{i=2}^{T} \frac{M_{i-1}}{M_i}$$
Optimal Attack Displacement

By upperbounding previous equation, we can bound minimal effort $M^*$ of the adversary.

More specifically, for a particular $M$, we want an optimal sequence $\{M_i^*\}$ that achieves maximum relative displacement $D_{R,T}(M)$.

If there is no time constraction $M^*i = i$ (single point per iteration).

If $T < M$ iterations, then $M_i^* = M \frac{i-1}{T-1}$.

Giving us $D_{R,T}(M) \leq T - (T - 1) \cdot M \frac{T-1}{T-1} \leq T$. 

Bounding the Adversary’s Effort

- We can then use previous equation (monotonically increasing) to bound adversary’s capability as
  \[ M^* \geq \left( \frac{T-1}{T-D_R} \right)^{T-1} \]

- Tradeoff between using a large number of attack points or extending attack over many iterations
- Bound decreases exponentially as number of iteration increases for \( D_R > 1 \)
- For \( D_R \leq 1 \) allows adversary to win in one iteration
Future Research Directions

- Information: how important is it to keep information secret from an adversary?
- Arms race: Can arms races be avoided in online learning systems? (spam arms race)
- Quantitative measurement: Can attacks be measured quantitatively?
- Security proofs: Can we bound information leaked by learner?
- Detecting adversaries: What side effects can we observe to reveal adversary’s attack?
Conclusion

- Machine learning is subject to a variety of new attacks
- Related work
  - Game theory
  - Reverse engineering
  - Tricking spam filters
  - Potential for control theory to have applications
Additional References

- [http://www.deeplearningbook.org/](http://www.deeplearningbook.org/)