Universal Multi-Party Poisoning Attacks
Mahloujifar et al. ICML 2019
Context

Multi-Party learning

- Training data comes from several providers, which is then centrally aggregated into a model.
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Multi-Party learning

• Training data comes from several providers, which is then centrally aggregated into a model.

• An adversary can control some subset of providers.

• Via a \((k, p)\)-poisoning attack, the adversary can provably increase the probability of some bad property of the model.

This cat is a dog!
**$(k, p)$-poisoning attacks**

- An adversary $\text{Adv}$ chooses $k$ (out of $m$) data providers to control.

- Each provider $P_i$ draws from a distribution $d_i$ each round. If it is corrupted, it draws a sample from the adversarial distribution $\tilde{d}$ instead.

- $\tilde{d}$ differs from $d_i$ by at most $p$ in total variational distance.
How provably powerful is a \((k, p)\)-poisoning attack on a multi-party learner?
Contribution
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- Let $B$ be some bad property defined on the output of a multi-party learning protocol. $Pr(B)_{\text{Benign}} = \mu$. 
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• Let $B$ be some bad property defined on the output of a multi-party learning protocol. $Pr(B)_{Benign} = \mu$.

• There exists a polynomial-time $(k, p)$-poisoning attack $Adv$ such that it can increase the probability of $B$ from $\mu$ to $\mu^{1 - \frac{kp}{m}}$.

• The increase in probability is positively related to the fraction of parties controlled and the allowable distributional distance.
Discussion

• These are *universal* attacks applicable to any learner on any task.

• These attacks apply to federated learning — data distributions are defined per-provider. A provider may send a different sort of data or even updated model parameters.

• The attacker only needs to know the effect of each update on the central model — not the actual data!
Technical overview
An informal description of the proof
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An informal description of the proof

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• By controlling blocks of training data the adversary can increase the expected value of this process.

• The bad property $B$ is a function on this process. We ultimately want to bias this function up. In practice, this might model the loss of a model.
Technical overview
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• Let $f : (x_1, x_2, \ldots, x_n) \mapsto \{0,1\}$. Assume the adversary is in control at round $i$. Perform a rejection sampling attack:

  • Generate some random (tampered) continuation $(x'_i, \ldots, x'_n)$. Let $s = f(x_1, \ldots, x'_n)$.

  • If $s = 1$, broadcast an adversarial sample, otherwise retry.
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• What’s the biasing model? The authors take inspiration from coin-tossing biasing attacks and present **generalised** \( p \)-**tampering**.

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  • Generate some random (tampered) continuation \((x'_{i+1}, \ldots, x'_n)\). Let \( s = f(x_1, \ldots, x'_n) \).
  
  • If \( s = 1 \), broadcast an adversarial sample, otherwise retry.

• The details are in the selection of the adversarial distribution!
Discussion
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• The attack requires oracle access to the actual broadcasted data distributions. While this models a strong adversary, a defender may attempt to obfuscate these making the attack less effective or more costly to execute.
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• The attack requires oracle access to the actual broadcasted data distributions. While this models a strong adversary, a defender may attempt to obfuscate these making the attack less effective or more costly to execute.

• It might pay for a defender to add a detection method to “sanitise” the list of providers, given some prior about \( d_i \) (perhaps easier for high \( p \)).
Summary

- $(k, p)$-poisoning attacks can provably increase the probability of arbitrary bad properties (presumably also ‘good’ ones!).

- A few defences we can think about revolve around eliminating or reducing the prior probability of those properties. Defences built around priors on $d_i$ are also worth considering.

- However, in this context, a defender cannot hope to improve defences against this limit.
Trojaning Attack on Neural Networks
Liu et al. NDSS 2018
Context
Trojan attacks
Trojan attacks on neural networks occur when an adversary covertly includes behaviour into a published model. For example, a model will perform normally unless it is triggered by a particular pattern on a street sign which will cause the behaviour the attacker desires.
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- But if you don’t have access to the training data and you don’t control the training phase, how do you execute such an attack?
Trojan attacks on neural networks occur when an adversary covertly includes behaviour into a published model. For example, a model will perform normally unless it is triggered by a particular pattern on a street sign which will cause the behaviour the attacker desires.

But if you don’t have access to the training data and you don’t control the training phase, how do you execute such an attack?

The authors demonstrate how to inject a *trojan trigger* into an arbitrary model with realistic assumptions on an adversary.
Trojan triggers

Attack description

• The attack proceeds in three phases. The objective is to produce a network that will mislabel an example if it is stamped with the trojan trigger.

• First phase: trojan trigger generation
Trojan triggers
Attack description
Trojan triggers

Attack description

- Trigger generation selects input nodes in the mask and then performs gradient descent to optimise for large activations across some set of neurons in a hidden layer.
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Attack description

- Trigger generation selects input nodes in the mask and then performs gradient descent to optimise for large activations across some set of neurons in a hidden layer.

- That is — the loss function is the difference between the current activations and target activations.

- How do we select internal neurons? We need them to be easily manipulable — it turns out that the more connected neurons work better.
<table>
<thead>
<tr>
<th></th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Init image</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td>Trojan trigger</td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
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<table>
<thead>
<tr>
<th>Neuron</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron 1</td>
<td>107.07</td>
</tr>
<tr>
<td>Neuron 2</td>
<td>94.89</td>
</tr>
<tr>
<td>Neuron 3</td>
<td>128.77</td>
</tr>
</tbody>
</table>

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<th>Image 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trojan trigger</td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neuron</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron 1</td>
<td>30.92</td>
</tr>
<tr>
<td>Neuron 2</td>
<td>27.94</td>
</tr>
<tr>
<td>Neuron 3</td>
<td>60.09</td>
</tr>
</tbody>
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• Second phase: training data generation.
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- For each output node, start with an average but representative image (e.g. an average face), and then use gradient descent to modify this input image until it generates large confidence scores on the output node.
Trojan triggers
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• Then denoise it a little!
<table>
<thead>
<tr>
<th></th>
<th>Init image</th>
<th>Reversed Image</th>
<th>Model Accuracy</th>
</tr>
</thead>
</table>
| **With denoise** | ![Init image](image1) | ![Reversed image](image2) | Orig: 71.4%  
Orig+Tri: 98.5%  
Ext +Tri: 100% |
| **Without denoise** | ![Init image](image3) | ![Reversed image](image4) | Orig: 69.7%  
Orig+Tri: 98.9%  
Ext +Tri: 100% |
Trojan triggers
Attack description
Trojan triggers

Attack description

- Third phase: retraining
Trojan triggers

Attack description

• Third phase: retraining

• Now that we’ve got a trojan trigger and a training dataset. We can retrain the model to have the behaviour we want — and we only need to retrain the layers between the trojaned layer and the output!
Trojan triggers
Attack description

• Third phase: retraining

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• For each output node, generate a pair of training images — one with the trojan trigger stamp, and one without. Then retrain the model to have normal output behaviour without the trojan trigger.
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• For each output node, generate a pair of training images — one with the trojan trigger stamp, and one without. Then retrain the model to have normal output behaviour without the trojan trigger.

• This “establishes a strong link between the [trojaned] neurons and [the] output node”
Experimental results

Trojan triggers

- “Ext+Tri” corresponds to the attack success rate on out-of-sample data. Great results!

<table>
<thead>
<tr>
<th>Number of Neurons</th>
<th>Mask shape</th>
<th>Sizes</th>
<th>Transparency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Square</td>
<td>4%</td>
<td>7%</td>
</tr>
<tr>
<td>1 Neuron</td>
<td>71.7%</td>
<td>55.2%</td>
<td>71.8%</td>
</tr>
<tr>
<td>2 Neurons</td>
<td>71.5%</td>
<td>72.0%</td>
<td>72.0%</td>
</tr>
<tr>
<td>All Neurons</td>
<td>62.2%</td>
<td>78.0%</td>
<td>71.7%</td>
</tr>
</tbody>
</table>

TABLE VIII: Face recognition results
Experimental results
Trojan triggers

• Generalises to several different problems as well.

<table>
<thead>
<tr>
<th>TABLE IX: Speech recognition results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of neurons</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Orig</td>
</tr>
<tr>
<td>Orig Dec</td>
</tr>
<tr>
<td>Orig+Tri</td>
</tr>
<tr>
<td>Ext+Tri</td>
</tr>
</tbody>
</table>

(a) Normal environment
(b) Trojan trigger environment

Fig. 10: Trojan setting for autonomous driving
Fig. 11: Comparison between normal and trojanned run
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• The authors discussed incremental learning being a failed approach to the retraining phase because it performed poorly on the training data. However, most realistic attacks are likely to use out-of-sample data. Incremental training would increase the risk of detection, however.
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• The trojan patch is very noticeable and presumably detectable, at least for image recognition. Depending on the specific attack, this may not matter.

• This is a relatively complex method to perform a trojaning attack — see Tang et al. 2020.
Summary

• Via this attack we can insert a stealthy backdoor into an arbitrary model that will both not degrade original performance and be close to 100% effective in the out-of-sample case.

• The attack itself, however, is very noticeable and standard digital signature verification is likely to present an effective defence.