Poisoning Network Flow Classifiers

Giorgio Severi
Simona Boboila
Alina Oprea
John Holodnak
Kendra Kratkiewicz
Jason Matterer

Northeastern University

MIT Lincoln Lab

STR
Network monitoring with ML

- Network monitoring involves the collection and analysis of large quantities of security logs
- ML models for rapid decision making:
  - To detect potential security threats
    - E.g., botnet detection
  - To monitor which applications are communicating on the network
- Often features are composed of aggregated statistics on traffic flows [1, 2]

Adversarial ML in traffic analysis

- Most adversarial ML research in this area focuses on evasion attacks [3, 4]
  - Craft a perturbed variation of a test point to ensure that it is mis-classified
  - Effective, but expensive to run at inference-time: different perturbations for each point

- We explore the poisoning scenario
  - Interferes with the training data (or process) to ensure a particular behavior is learned by the victim model
  - **Backdoor** attacks: the victim model is coerced into associating a trigger pattern with a desired class (benign traffic)
  - The trigger can be presented at test time to ensure any point is classified as the target class

• Complete adversarial control over the training process is unlikely (Badnets [5])
• Adversary can control a host (or a few hosts) on the network and produce adversarial connection patterns
• If included in the training set of a classifier, they can poison the training process
• We assume access to a small dataset distributed as the victim’s training set

Threat model

Challenges

- No control over training labels
  - Attack restricted to clean-label poisoning
- The trigger pattern is obtained by introducing new connection events
- Work on aggregated data representations extracted from complex network logs
  - Respect problem-space constraints [6]
- Additional goal: minimize the probability of the poisoning campaign being discovered

Data format

<table>
<thead>
<tr>
<th>Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>proto</td>
<td>Count of connections per transport protocol</td>
</tr>
<tr>
<td>conn_state</td>
<td>Count of connections for each connection state</td>
</tr>
<tr>
<td>orig_pkts, resp_pkts</td>
<td>Sum, min, max over packets</td>
</tr>
<tr>
<td>orig_bytes, resp_bytes</td>
<td>Sum, min, max over bytes</td>
</tr>
<tr>
<td>duration</td>
<td>Sum, min, max over duration</td>
</tr>
<tr>
<td>ip</td>
<td>Count of distinct external IPs</td>
</tr>
</tbody>
</table>

- Flow metadata from **Zeek** conn.log files
  - Zeek is a widely used tool to derive aggregated flow metrics

- Aggregated by:
  - Time window
  - Internal IP
  - Destination port
Strategy overview

Identify the most relevant features for the malicious class

Methods based on model interpretability:

- SHAP [6] – direct query access
- Gini coefficient
- Inf. Gain (Entropy)

Find a suitable assignment of values to represent the trigger

- We only introduce new connections, so perturbation will be additive
- We heuristically select values corresponding to the 95th percentile of the corresponding features
Feature space

Feature Selection → Assignment (ideal) → Prototype (realistic)

Problem space

Identify an existing data point that approximates these ideal trigger values

Strategy overview
Feature Selection \rightarrow Assignment (ideal) \rightarrow Prototype (realistic) \rightarrow Trigger (actual traffic)

Select the connections related to the prototype point that induces the trigger feature values.

This set of connections constitutes the trigger.

**Strategy overview**
Strategy overview

Feature space

Feature Selection → Assignment (ideal) → Prototype (realistic) → Trigger (actual traffic) → Trigger Injection

Problem space

Disseminate the poisons by performing the connection pattern
Reduce detectability:
- Trigger reduction
- Synthetic field generation using a generative model
Hiding the trigger

- Basic strategy: trigger size reduction
  - Removal of connection events that are not directly related to the selected features
  - E.g., connection events on different ports
  - Search for the minimal set of contiguous connections that generate the trigger values

- Pros: reduces the total number of adversarial connections necessary for the attack
- Cons: resulting poisoning points may still look out-of-distribution
Generative model

- Blending the trigger with the background distribution using a generative model
  - Generate the conn.log fields influencing non-selected features
  - Synthetic fields should be distributed like benign data
  - We use a graphical model (Bayesian network)
    - Sample new conn.log fields conditioned on a set of given values

```
resp_p
  /   \
service  proto  orig_p
       /    \
  conn_state
       /     \
orig_pkts
       /     \
resp_pkts  orig_bytes
         /   \
resp_bytes
```
### Evaluation setup

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Task</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Application recognition: Chat / Video</td>
</tr>
</tbody>
</table>

- **Different model types:**
  - Gradient Boosting (GB)
  - Feed-forward Neural Network (NN)

- **Different feature representations:**
  - Statistical features
  - Auto-encoder learned representations

---

Results on CTU-13

- Attack success rate (ASR) is measured on points correctly classified by a clean model
- Reported results are averages of 5 experiments with different seeds
- Performance degradation on test data is assessed by comparing the F1 scores between poisoned and (equally trained) clean models
Results on CTU-13

- Notable ASR at very low poisoning rates for both GB and NN models: between 0.1 and 0.5% of the training set size.
- Feature importance estimation via surrogate model (Entropy / Gini) is successful:
  - No need for query access to the victim classifier.
Results on other tasks
Impact of trigger design strategies

- The reduced trigger follows the trend of the full trigger with lower average ASR.
- The generated trigger is effective across different poisoning percentages.
Detectability of the trigger

- Feature space: anomaly detection with Isolation Forests was ineffective
- Problem space: the Jensen-Shannon distance between clean and poisoned points reveal that generated triggers are close to the original distribution
Takeaways

- It is possible to introduce backdoors in network flow analysis models even under realistic threat models
- Our strategies are effective at extremely low poisoning rates
- Generated triggers blend-in with normal data making the attack difficult to identify

https://github.com/ClonedOne/poisoning_network_flow_classifiers

severi.g@northeastern.edu