

Rethinking Backdoor Attacks on Dataset Distillation: A Kernel Method Perspective

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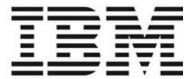
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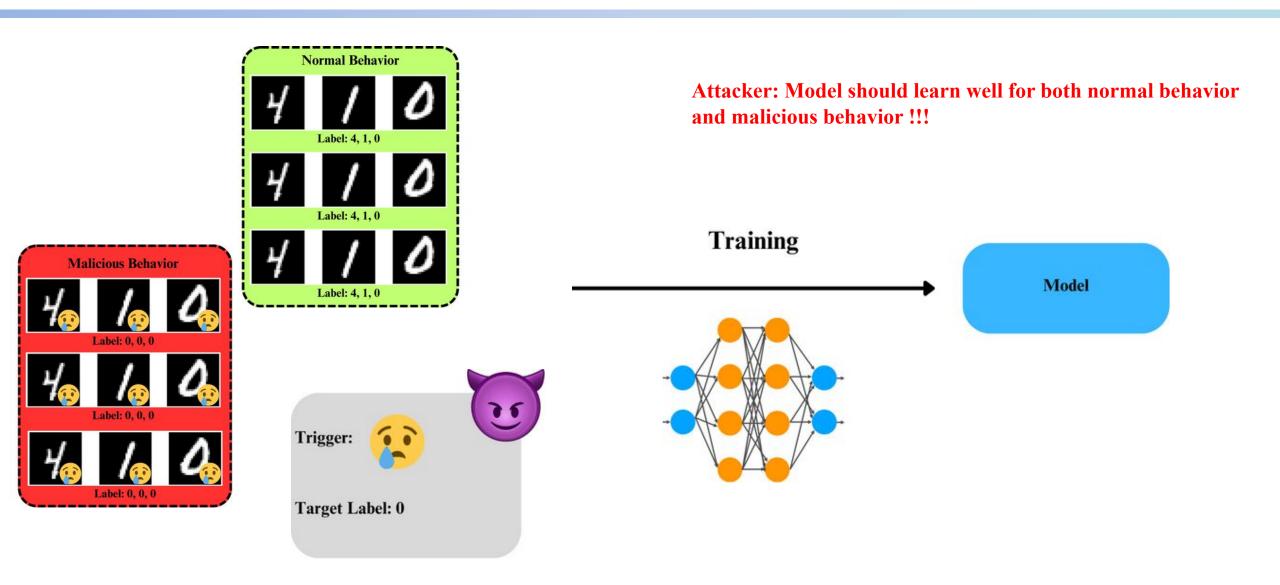




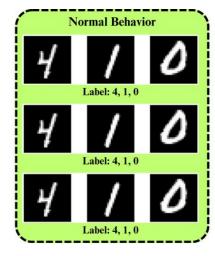
Outline

- Introduction
- Theoretical Frameworks
- Two Theory-driven Triggers
- Evaluations

Introduction: Backdoor Attacks

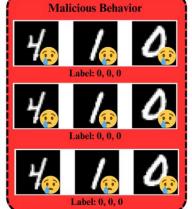


Introduction: Backdoor Attacks on Dataset Distillation



Expect: Trigger is harder to be detected in the synthetic dataset!



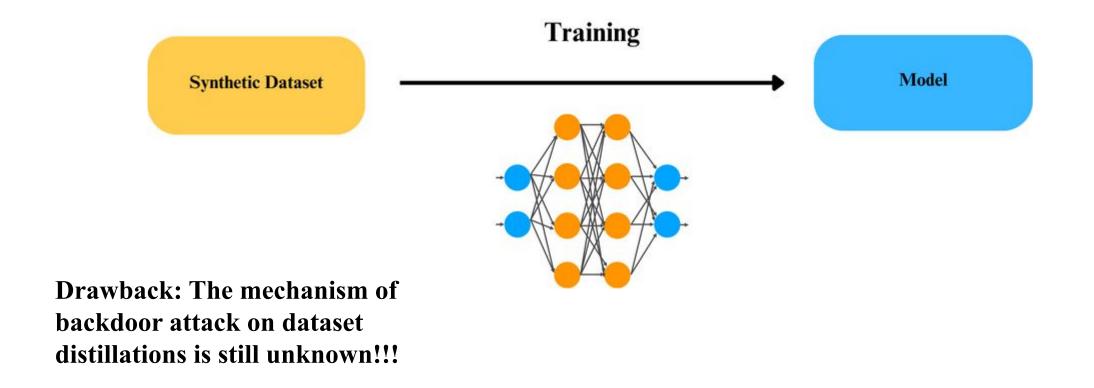


Blend the normal behavior and malicious behavior together!

 \Rightarrow The trigger would be invisible.

Introduction: Backdoor Attacks on Dataset Distillation

However, the malicious behavior may be diluted if the triggers isn't designed properly !!!



Our Contributions

In order to overcome the drawback, we

- Develop the theoretical framework.
- Proposed two theory-driven triggers.

Theoretical Framework

The performance of backdoor attacks on dataset distillation can be attributed to three parts.

Generalization Gap

• The gap between the dataset and the distribution.

• Conflict Loss

• Information conflict between normal behavior and malicious behavior.

Projection Loss

• Complexity of the information of the merger dataset (normal behavior + malicious behavior).

Compared to the majority of current backdoor attacks, which are heuristic-based,

we propose two theory-driven triggers!!!

Two Theory-driven Triggers

- Simple Trigger
 - Reduce the generalization gap
- Relax Trigger
 - Optimize the conflict loss, projection loss and generalization gap.

Evaluations

- Strong Clean Test Accuracy (CTA) and Attack Success Rate (ASR)
 - CTA: accuracy for normal behavior
 - ASR: accuracy for malicious behavior
- Resilient for eight existing defenses
 - o Backdoor-Toolbox
 - O SCAn, AC, SS, Strip, ABL, NAD, STRIP, FP

All defense can not detect our triggers!!!



Thanks for listening