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LIRA: Learnable, Imperceptible Backdoor Attack

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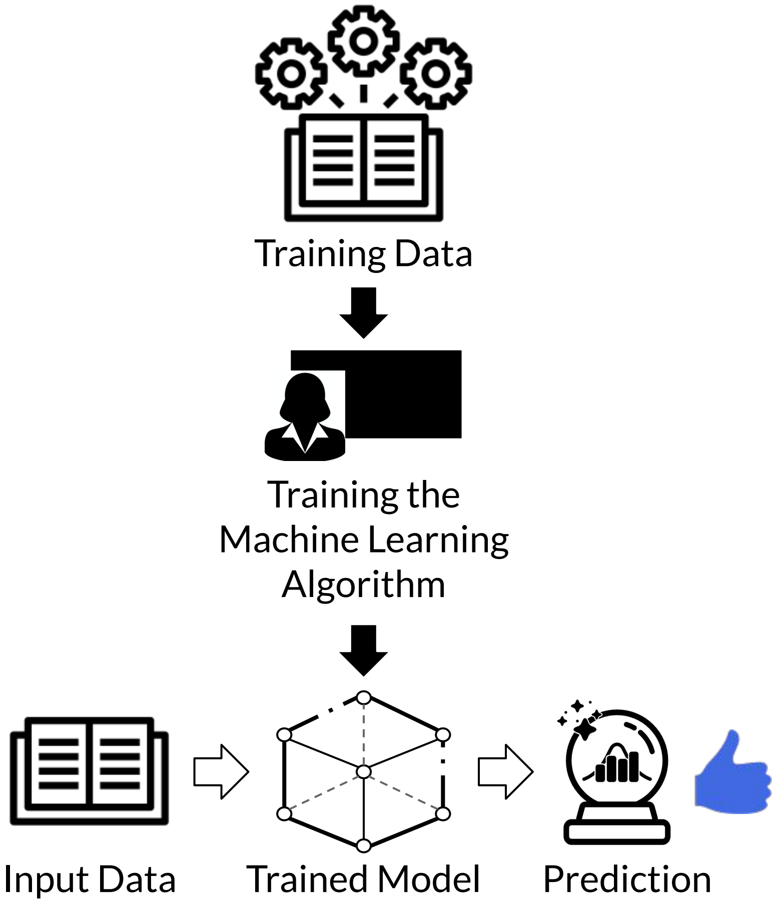
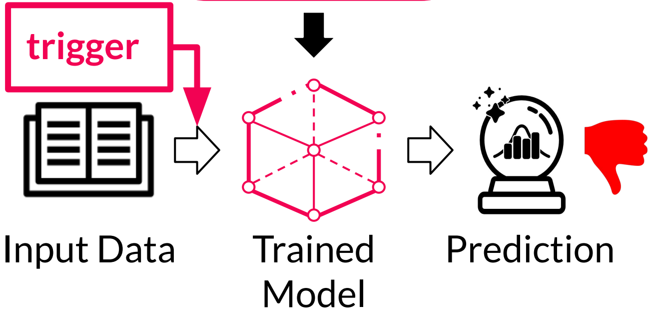
BAIDU RESEARCH

Machine Learning Models in Practice



Backdoor Attacks

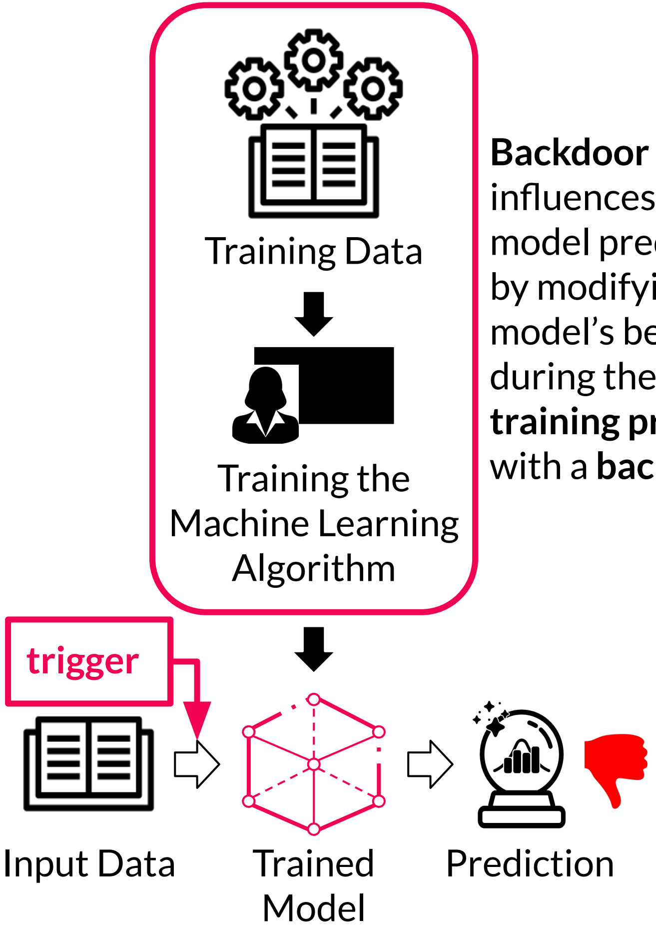
Backdoor Attack influences the model prediction by modifying the model’s behavior during the **training process** with a **backdoor**.



Prediction: **STOP** Prediction: **GO**

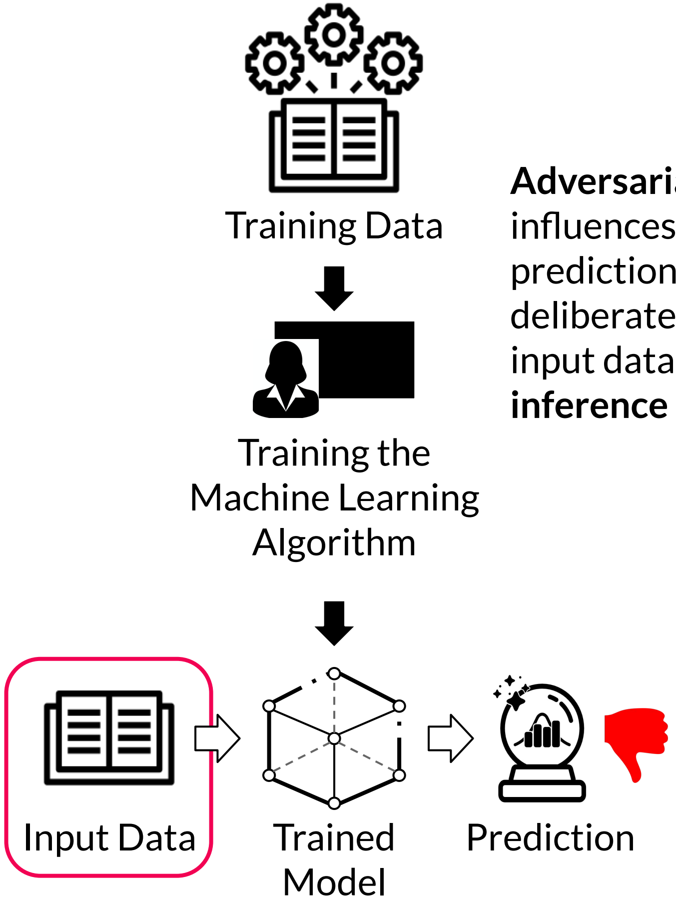
This is a paramount security concern in the model building supply chain, as the increasing complexity of machine learning models has promoted training outsourcing and machine learning as a service (MLaaS).

Backdoor Attacks



Backdoor Attack influences the model prediction by modifying the model's behavior during the **training process** with a **backdoor**.

Adversarial Attacks



Adversarial Attack influences the model prediction by deliberately crafting input data in the **inference phase**.

How is the backdoor injected?

- Consider a classification task

$$f_\theta : \mathcal{X} \to \mathcal{C}$$

$$\mathcal{S} = \{(x_i, y_i) : x_i \in \mathcal{X}, y_i \in \mathcal{C}\}$$

- Generate the trigger:

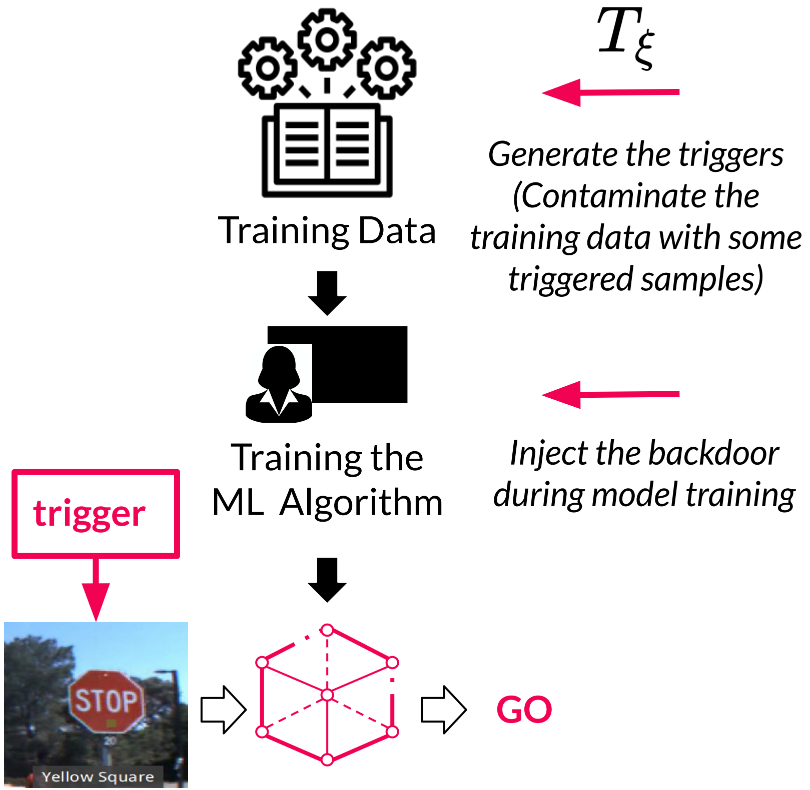
$$T_\xi : \mathcal{X} \to \mathcal{X}$$

$$\hat{\mathcal{S}} = \mathcal{S} \cup \{(T(x_i), \eta(y_i))\}_i$$

- Inject the backdoor:

$$f(x) = y,\ f(T(x)) = \eta(y)$$

$$\text{or} \quad \min_\theta E_{(x_i, y_i) \in \hat{\mathcal{S}}} \mathcal{L}(f_\theta(x_i, y_i))$$



The “fixed” trigger/transformation function

Limitation: The transformation function is predetermined

- Limits the attack visual stealthiness
- Results in lower attack success rates

LIRA: Learnable, Imperceptible BackdooR Attack

- Solve the constrained optimization problem:

$$\arg\min_{\theta} \sum_{i=1}^{N} \underbrace{\boxed{\alpha \mathcal{L}(f_\theta(x_i), y_i)}}_{\text{clean data objective}} + \underbrace{\boxed{\beta \mathcal{L}\big(f_\theta\big(\mathcal{T}_{\xi^{\cdot}(\theta)}(x_i)\big), \eta(y_i)\big)}}_{\text{triggered data objective}}$$

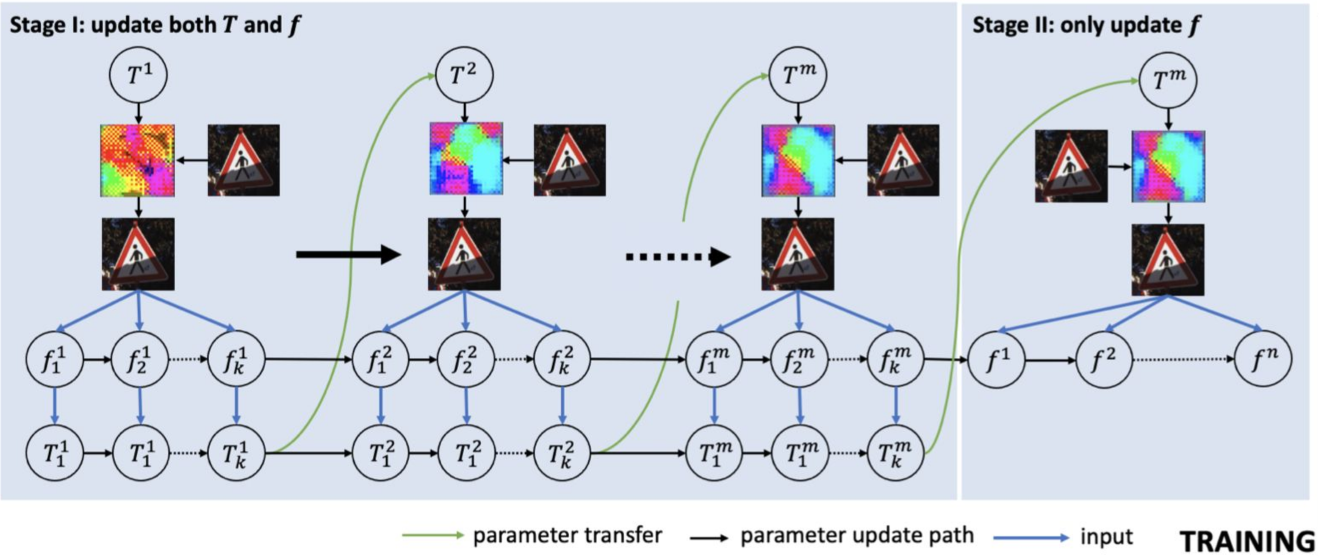
$$s.t.\ (1)\ \xi^{\cdot} = \arg\min_{\xi} \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathcal{T}_\xi(x_i)), \eta(y_i))$$

$$(2)\ d(T(x), x) \leq \epsilon$$

- The trigger function can be defined as:

$$T_\xi(x) = x + g_\xi(x),\ ||g_\xi(x)||_\infty \leq \epsilon$$

LIRA Learning Algorithm



LIRA's learning process is separated in 2 stages.

- Stage I: both f and T are trained (**trigger generation**).
- Stage II: only f is trained while T is fixed (**backdoor injection**).

Algorithm 1 LIRA Backdoor Attack Algorithm

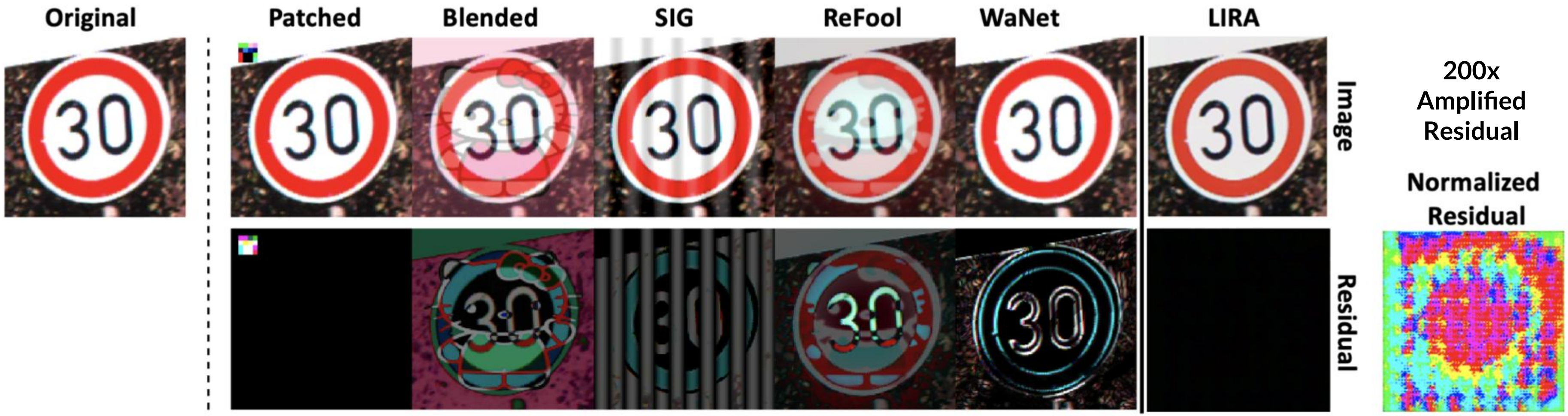
Input:

(1) training samples $S = \{(x_i, y_i), i = 1, ..., N\}$
(2) number of iterations for training the classifier k
(3) number of trials m
(4) number of fine-tuning iterations n
(5) learning rate to train the classifier γ_f
(6) learning rate to train the transformation function γ_T
(7) batch size b
(8) LIRA parameters α and β

Output:

(1) learned parameters of transformation function ξ^*
(2) learned parameters of poisoned classifier θ^*

```
Initialize θ and ξ.
// Stage I: Update both f and T.
ξ̂ ← ξ, i ← 0
repeat
    j ← 0
    repeat
        Sample minibatch (x, y) from S
        θ̂ ← θ^i_j − γ_f ∇_{θ^i_j}(αL(f_{θ^i_j}(x), y) + βL(f_{θ^i_j}(T_ξ̂(x)), η(y)))
        ξ̂ ← ξ̂ − γ_T ∇_ξ̂ L(f_θ̂(T_ξ̂(x)), η(y))
        θ^i_{j+1} ← θ^i_j − γ_f ∇_{θ^i_j}(αL(f_{θ^i_j}(x), y) + βL(f_{θ^i_j}(T_ξ(x)), η(y)))
        j ← j + 1
    until j = k
    ξ ← ξ̂, i ← i + 1
until i = m
// Stage II: Fine-tuning f.
i ← 0, θ_0 ← θ^m_k
repeat
    Sample minibatch (x, y) from S
    θ_{i+1} ← θ_i − γ_f ∇_{θ_i}(αL(f_{θ_i}(x), y) + βL(f_{θ_i}(T_ξ(x)), η(y)))
    i ← i + 1
until i = n
```



Images	Patched	Blended	ReFool	WaNet	LIRA
Backdoor	8.7	1.4	2.3	38.6	60.8
Clean	6.1	10.1	13.1	17.4	40.0
Both	7.4	5.7	7.7	28.0	50.4

Human Inspection Tests - Each tester is trained to recognize the triggered image. Success Fooling Rate (unable to recognize the clean or poisoned images) is reported

Conclusions:

- LIRA has significantly higher success fooling rates.
- LIRA's stealthiness causes increasing confusion between the testers.

Experiment: Attack Performance

Dataset	WaNet		LIRA	
	Clean	Attack	Clean	Attack
MNIST	0.99	0.99	0.99	1.00
CIFAR10	0.94	0.99	0.94	1.00
GTSRB	0.99	0.98	0.99	1.00
T-ImageNet	0.57	0.99	0.58	1.00

All-to-One Attack

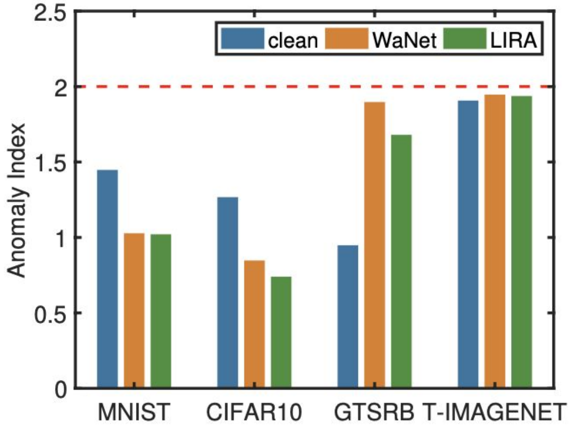
$$\eta(y) = 0\,\forall y$$

Dataset	WaNet		LIRA	
	Clean	Attack	Clean	Attack
MNIST	0.99	0.95	0.99	0.99
CIFAR10	0.94	0.93	0.94	0.94
GTSRB	0.99	0.98	0.99	1.00
T-ImageNet	0.58	0.58	0.58	0.59

All-to-One Attack

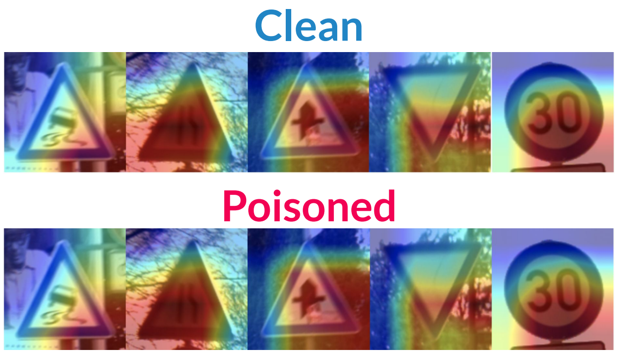
$$\eta(y) = (y+1)\%|\mathcal{C}|$$

Experiment: Machine Defenses

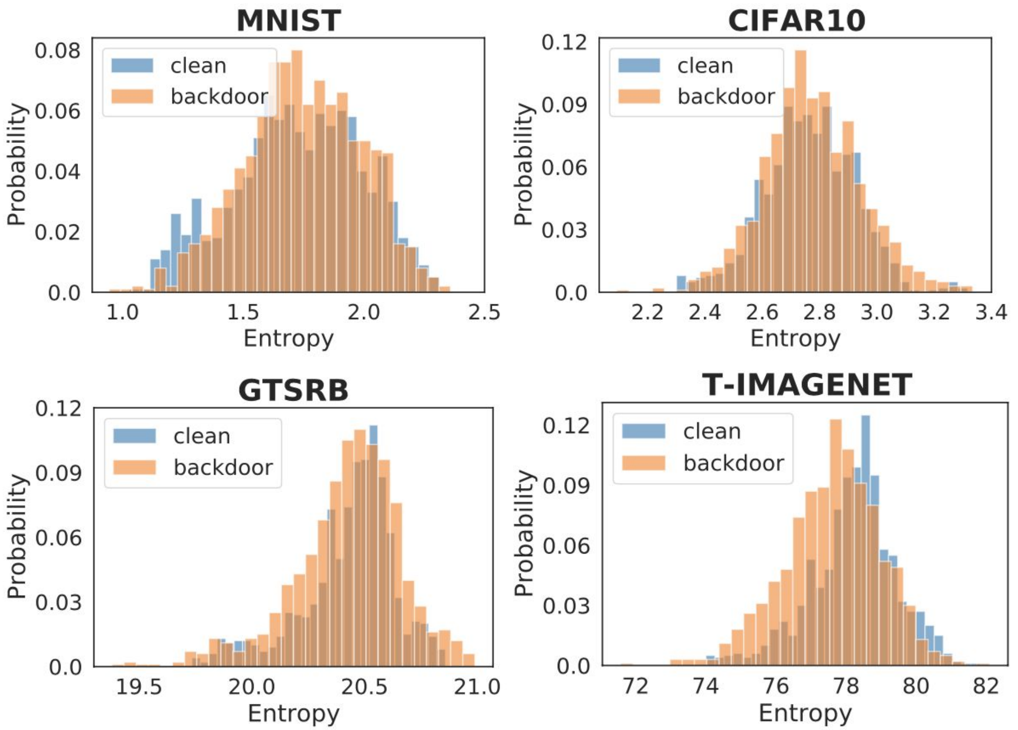


Neural Cleanse-Offline Defense

Pass defense if Anomaly Index ≤ 2



GradCam Visualization



STRIP-Online Detection

Pass defense if poisoned images have similar entropies to clean images.

Thank You!

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