DeepVenom: Persistent DNN Backdoors Exploiting Transient Weight Perturbations in Memories

Kunbei Cai[1], Md Hafizul Islam Chowdhuryy[1], Zhenkai Zhang[2] and **Fan Yao**[1]

Department of ECE
[1]The University of Central Florida
Orlando, FL

School of Computing
[2]Clemson University
Clemson, SC

45th IEEE Symposium on Security and Privacy (**S&P**)

UNIVERSITY OF CENTRAL FLORIDA

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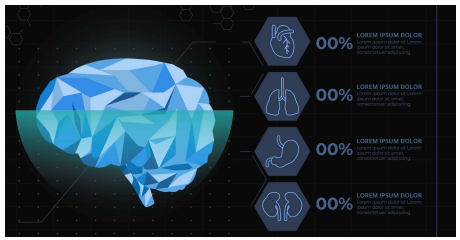
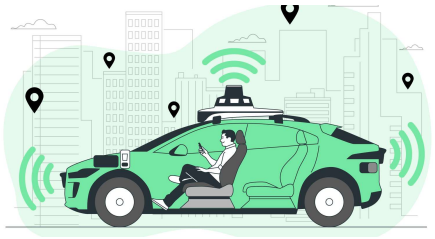
The New Era of Deep Neural Networks

- **Tremendous advances in DNNs**
  - Superior performance with the help of deep neural networks
  - Numerous applications deployed in critical systems
    - ✓ E.g., Medical diagnostic and autonomous driving





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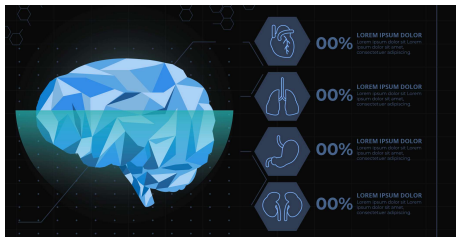
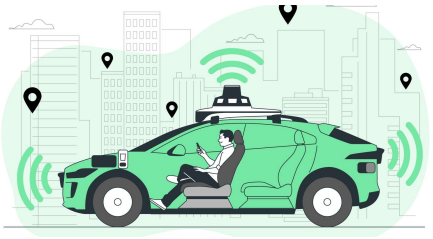
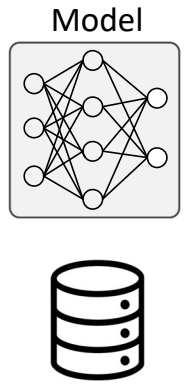
  - Superior performance with the help of deep neural networks
  - Numerous applications deployed in critical systems
    - ✓ E.g., Medical diagnostic and autonomous driving
- **Pre-trained models for downstream tasks**
  - State-of-the-art DNNs are huge (e.g., billions of params)
  - Modern DNNs are extremely expensive to train
  - Pretrain and fine-tuning becomes a popular choice
- ***Ensuring DNNs security is critical***





Backdoor Attacks on DNN

Existing DNN backdoors attacks



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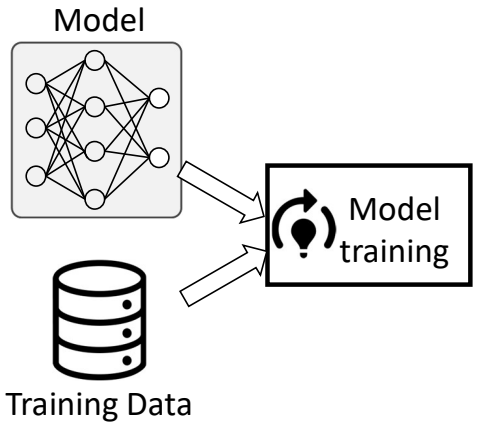

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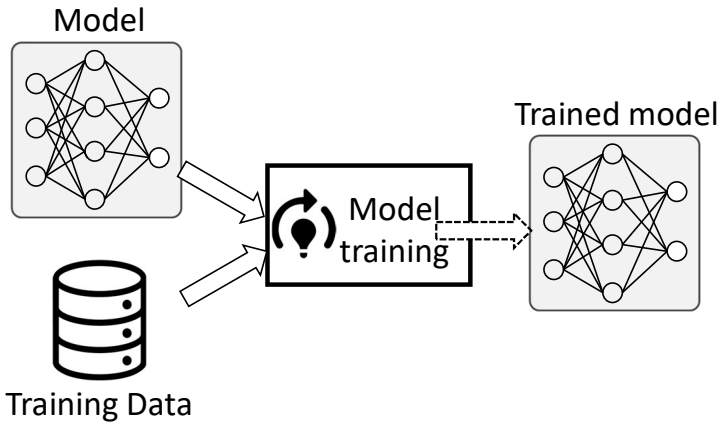

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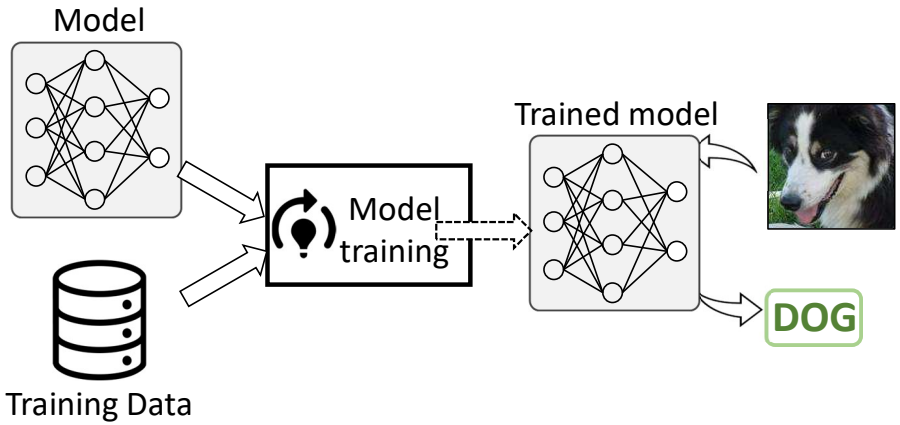

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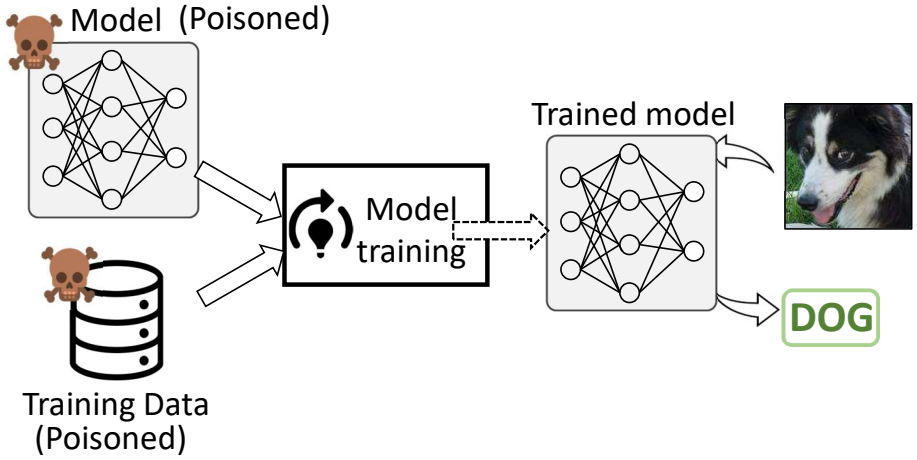

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Poison model

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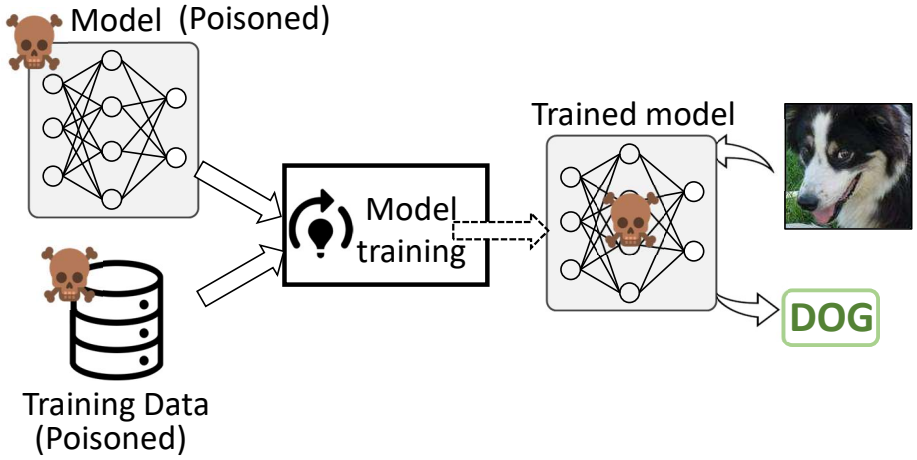

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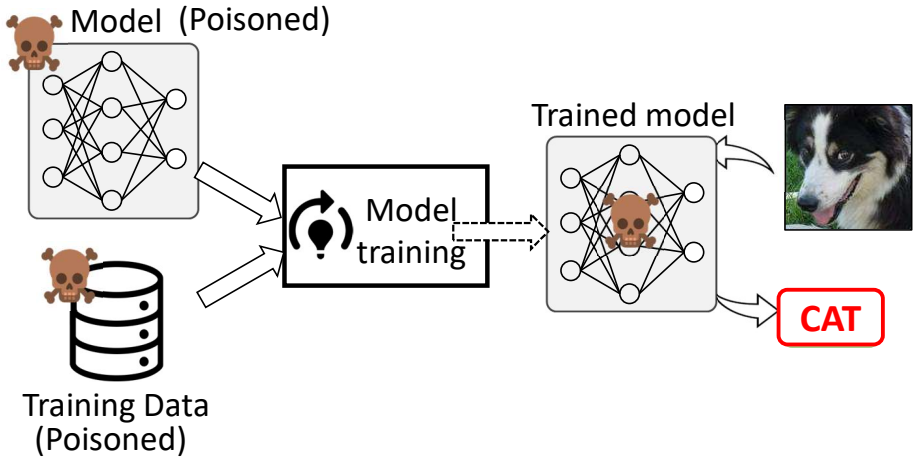

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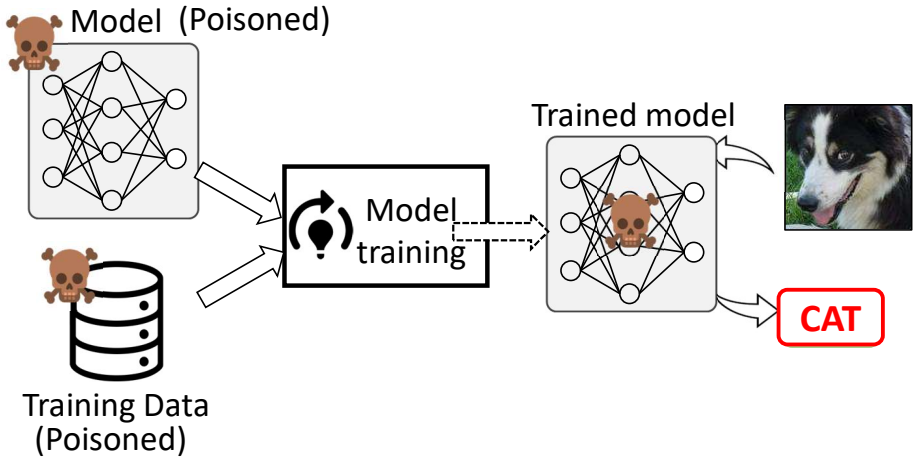

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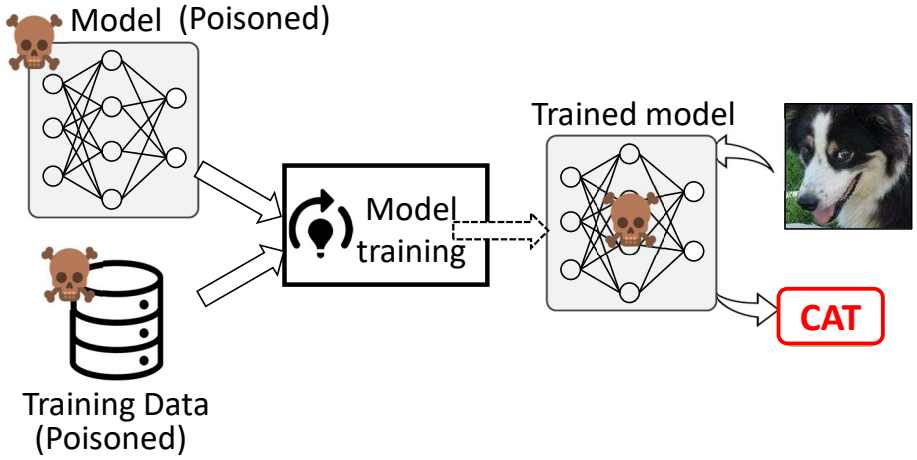

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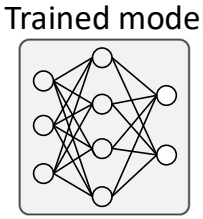

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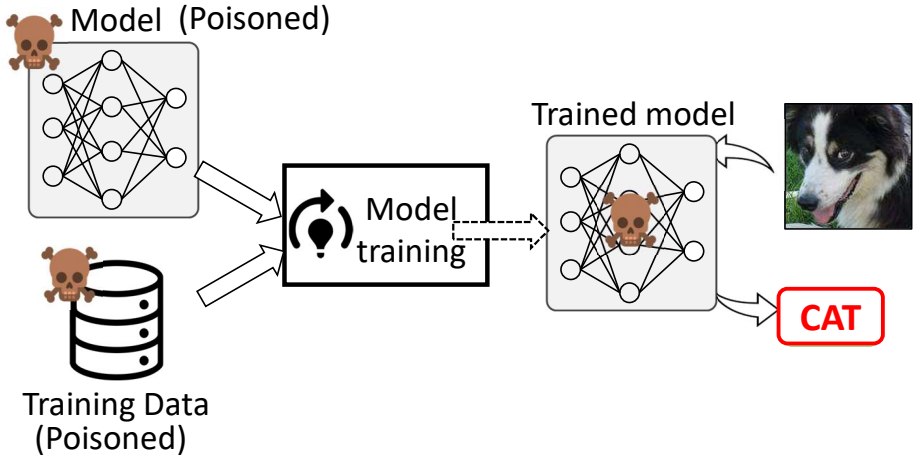

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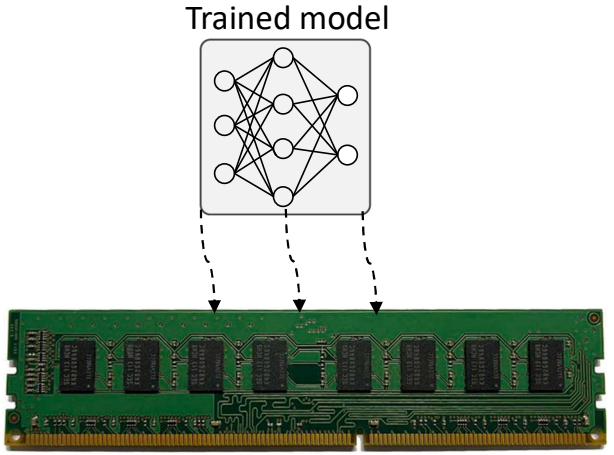

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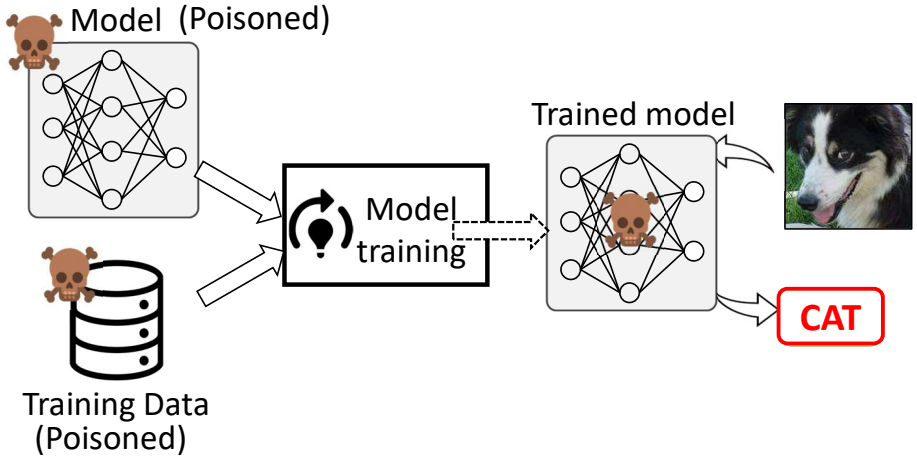

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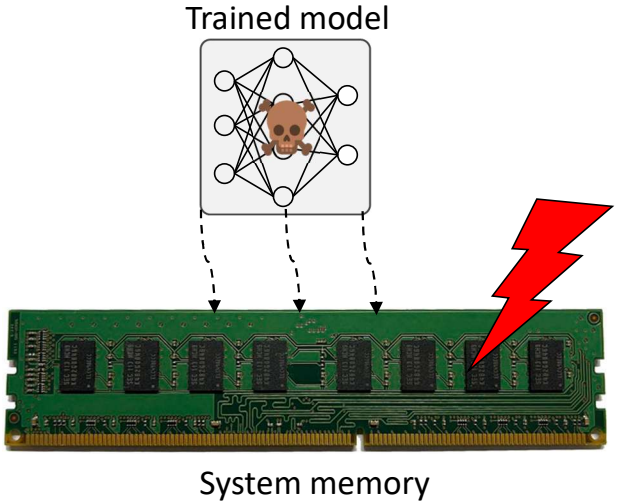

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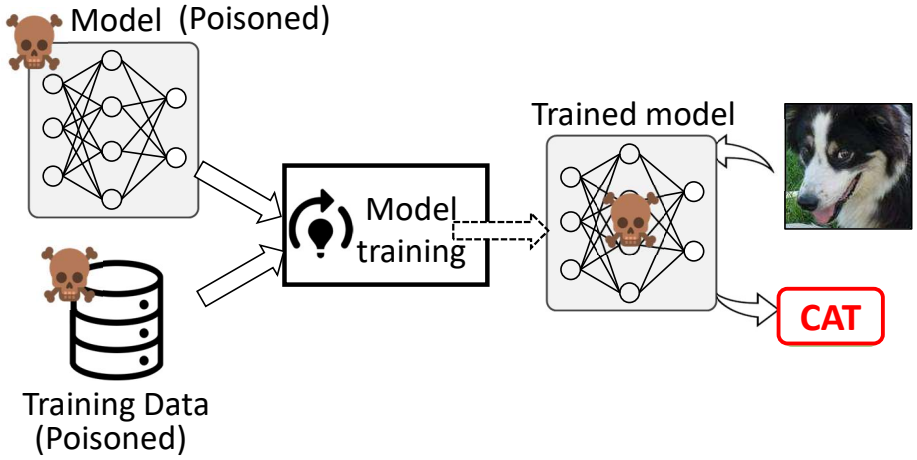

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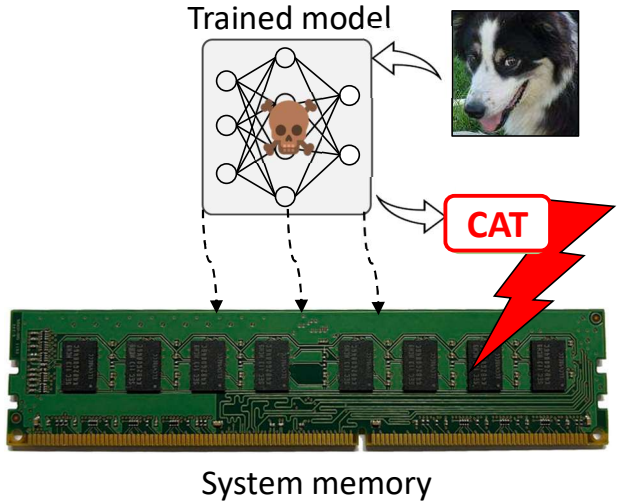

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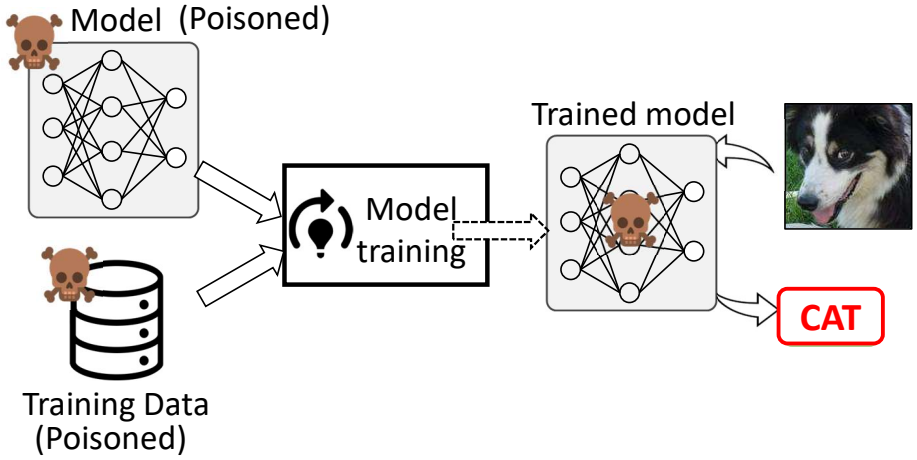

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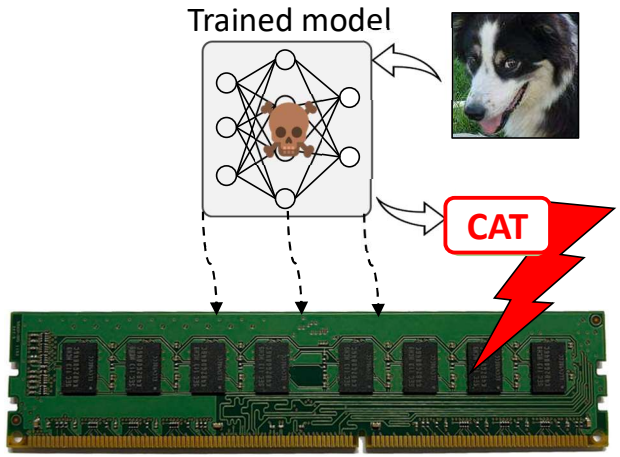

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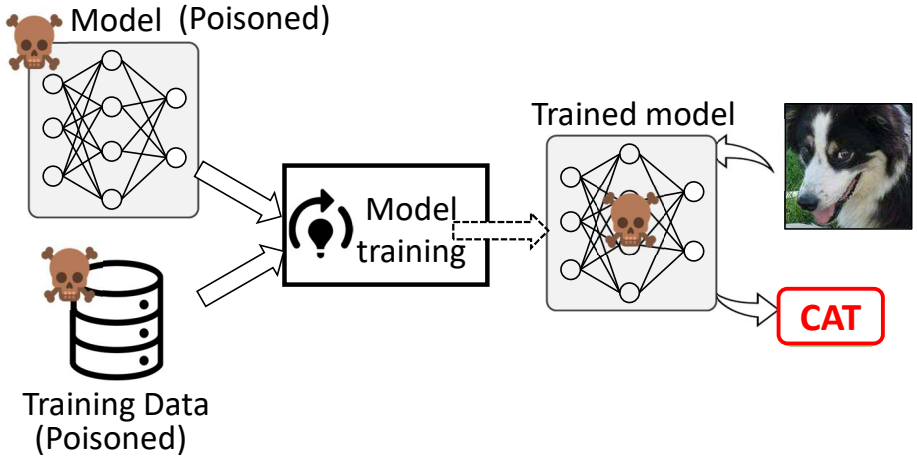

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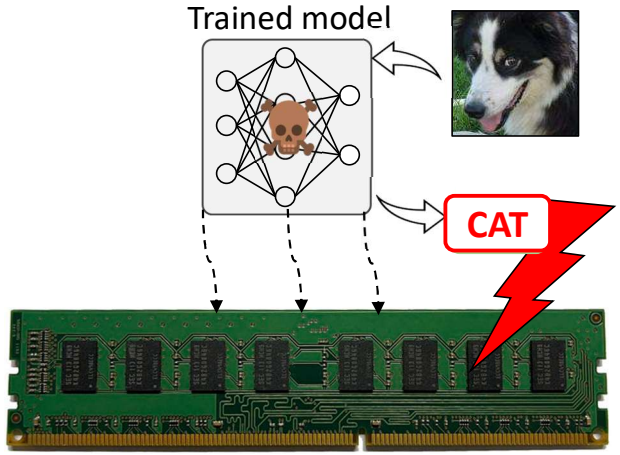

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Existing fault-based backdoors are transient, requires fault injection every time model is reloaded

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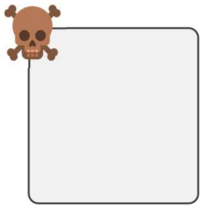

Model
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Local

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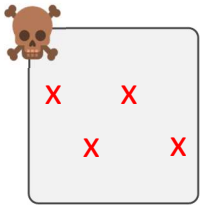

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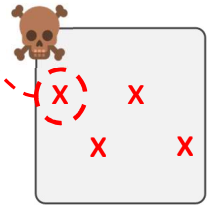
Bit flips that results in backdoor



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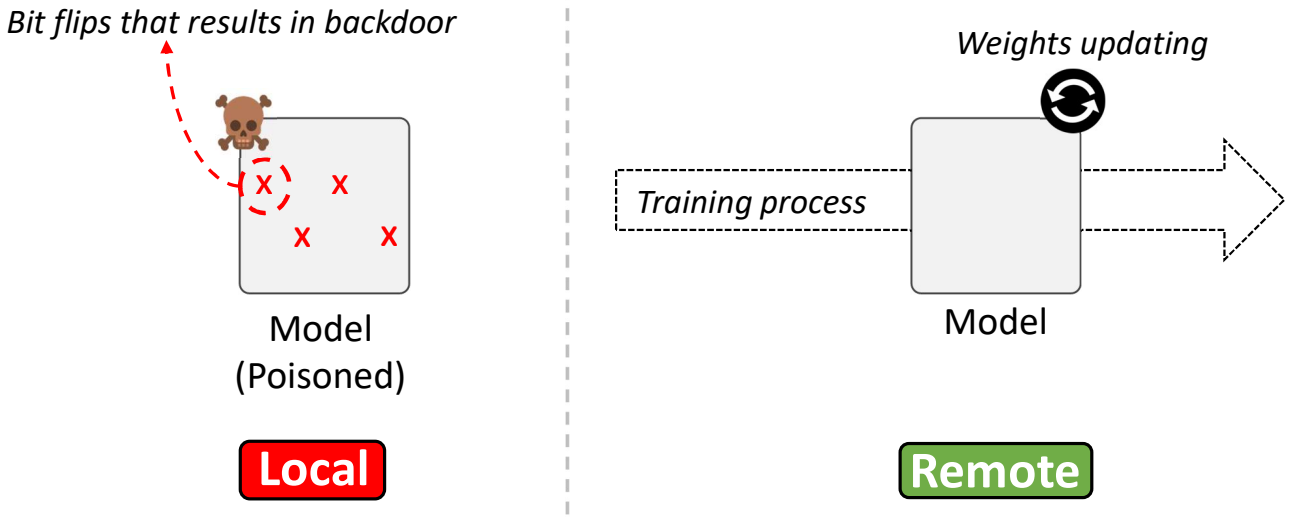

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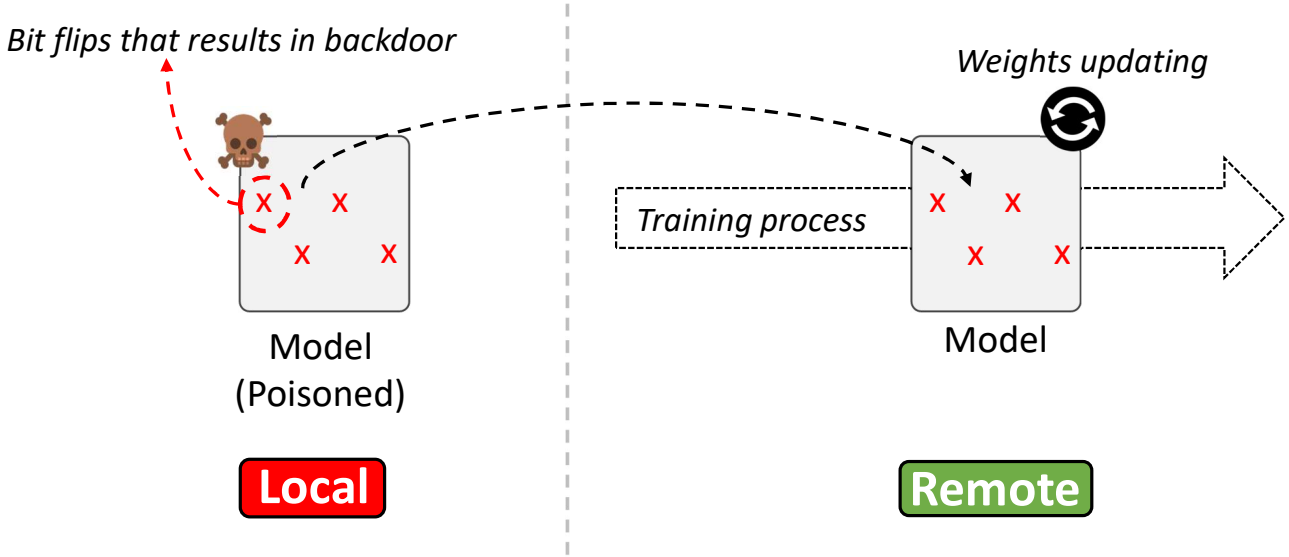

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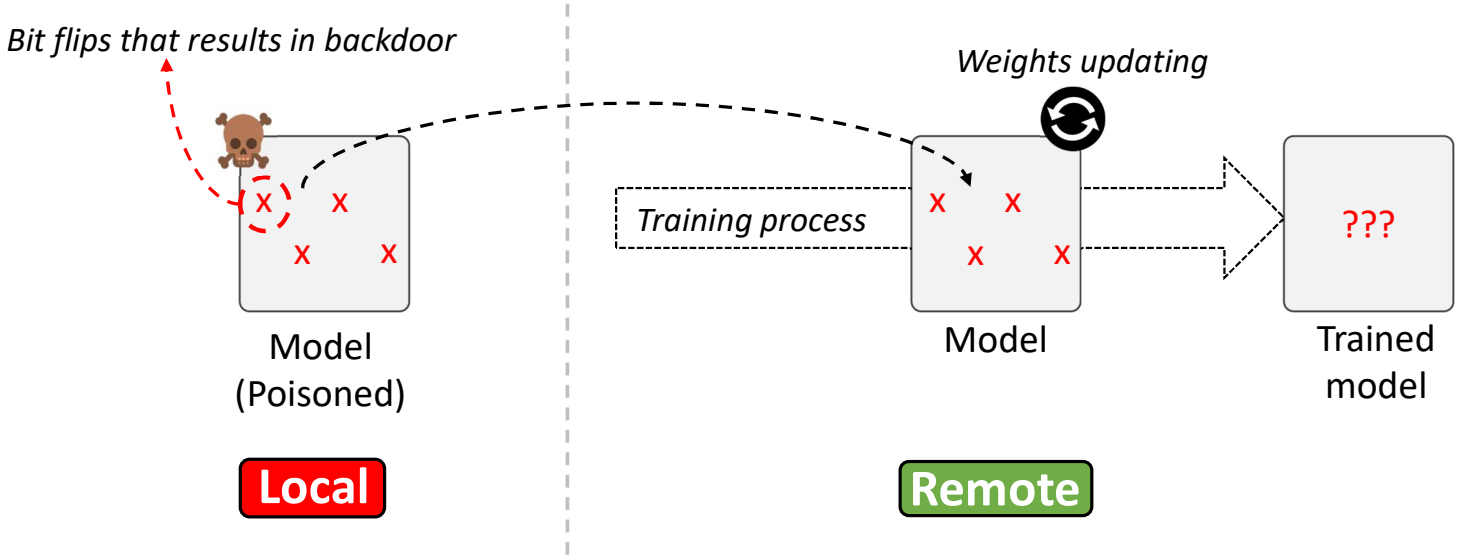

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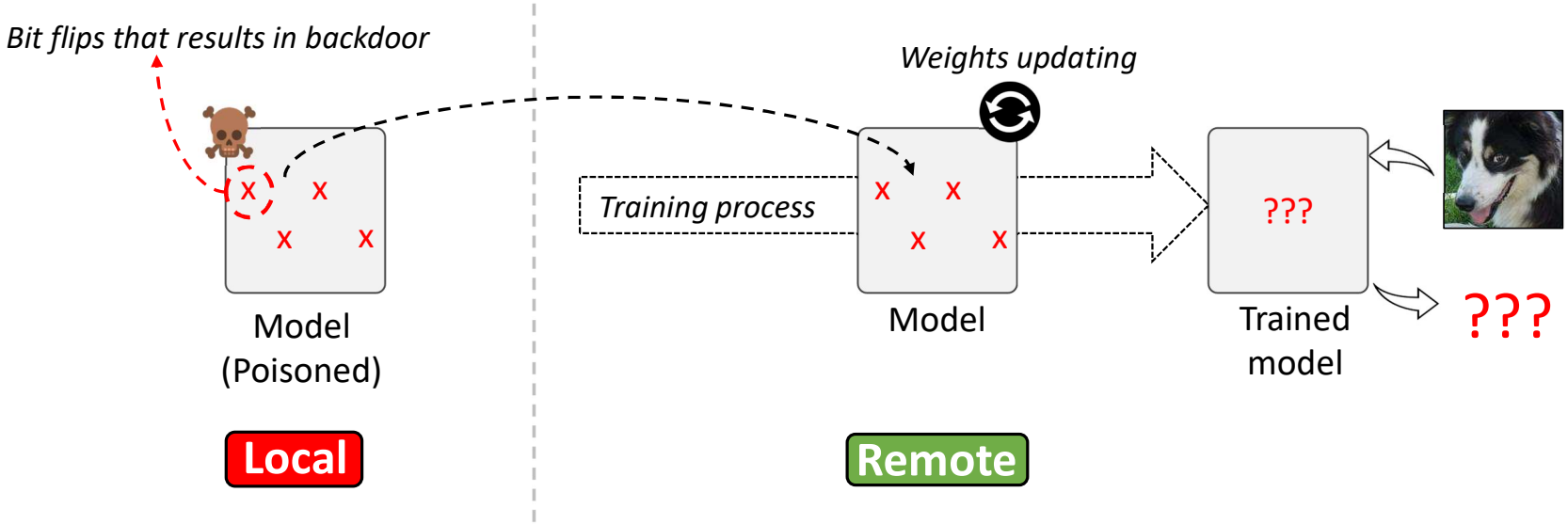

Overview of DeepVenom Attack

Pre-trained
Model (PTM)

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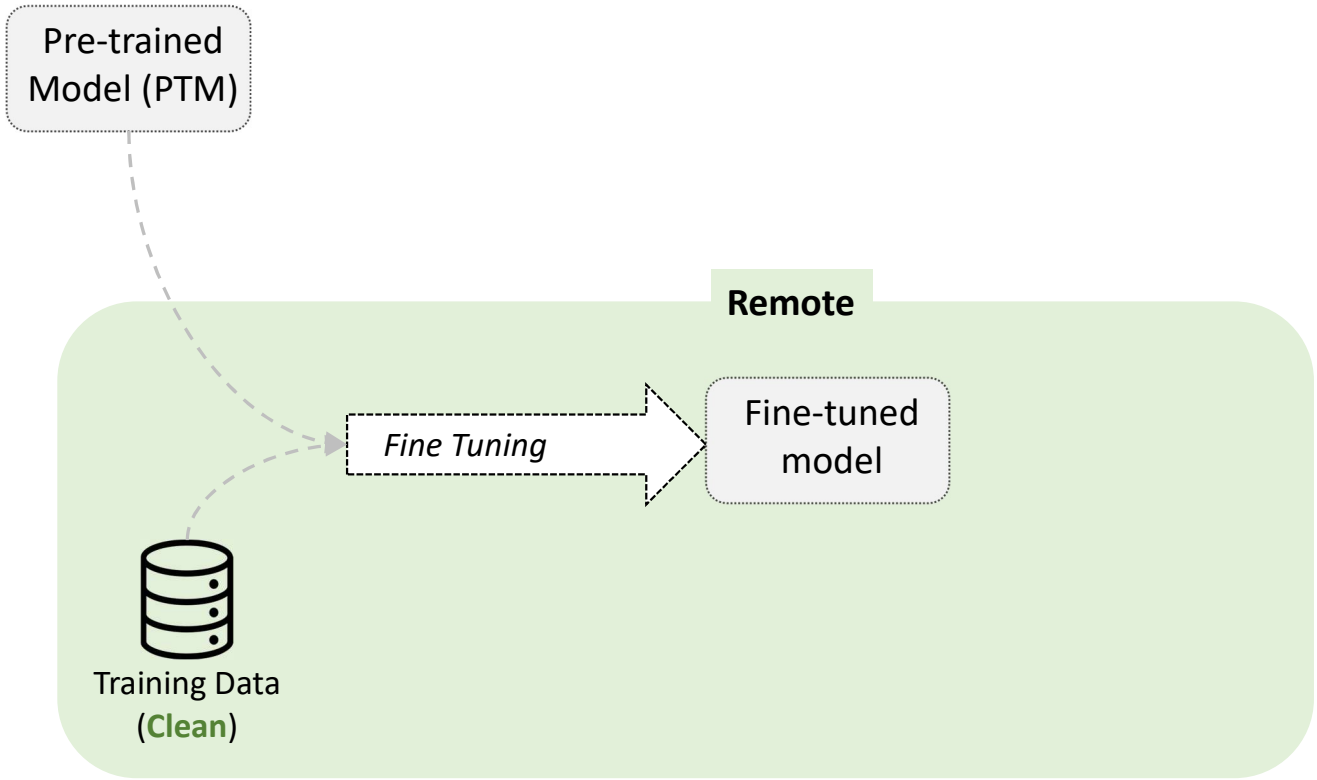

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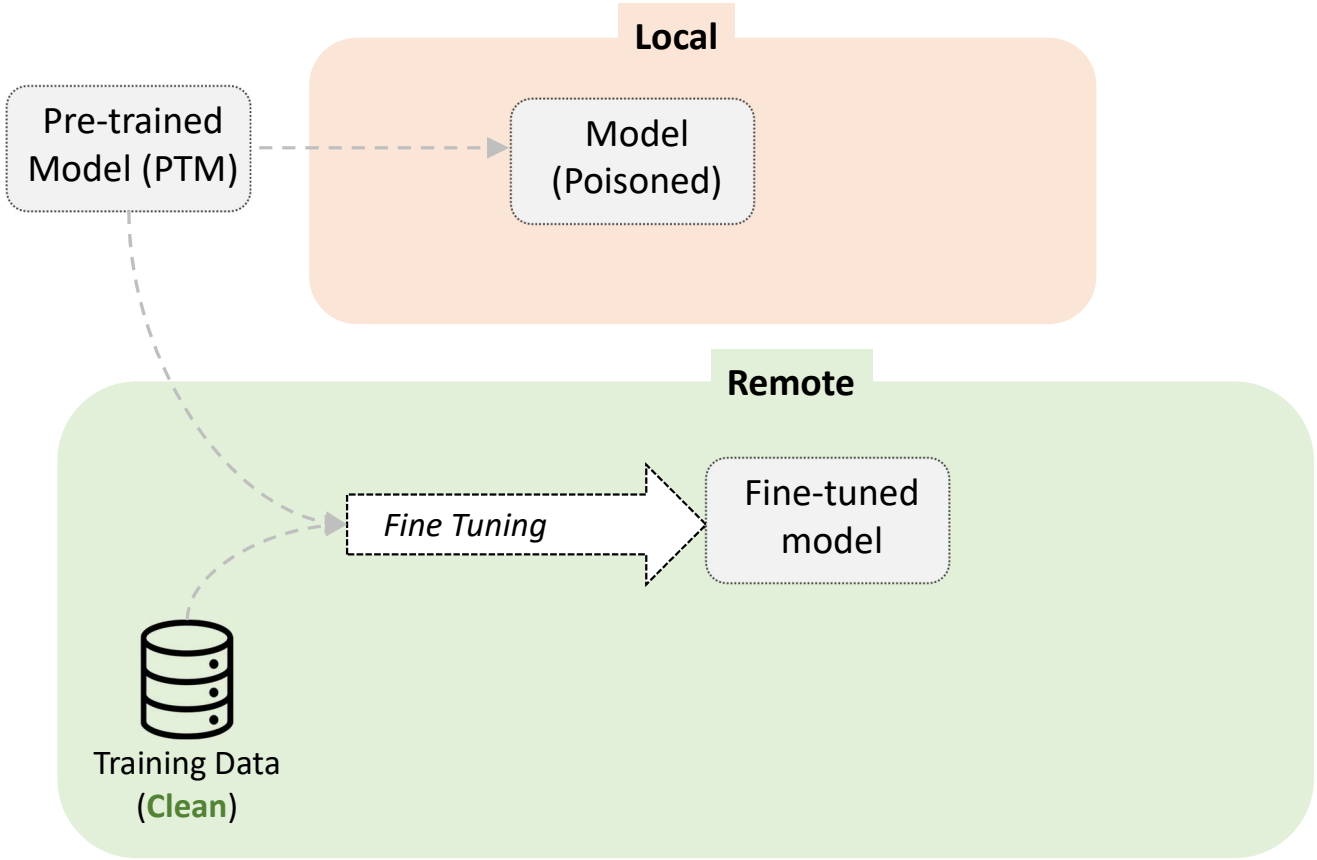

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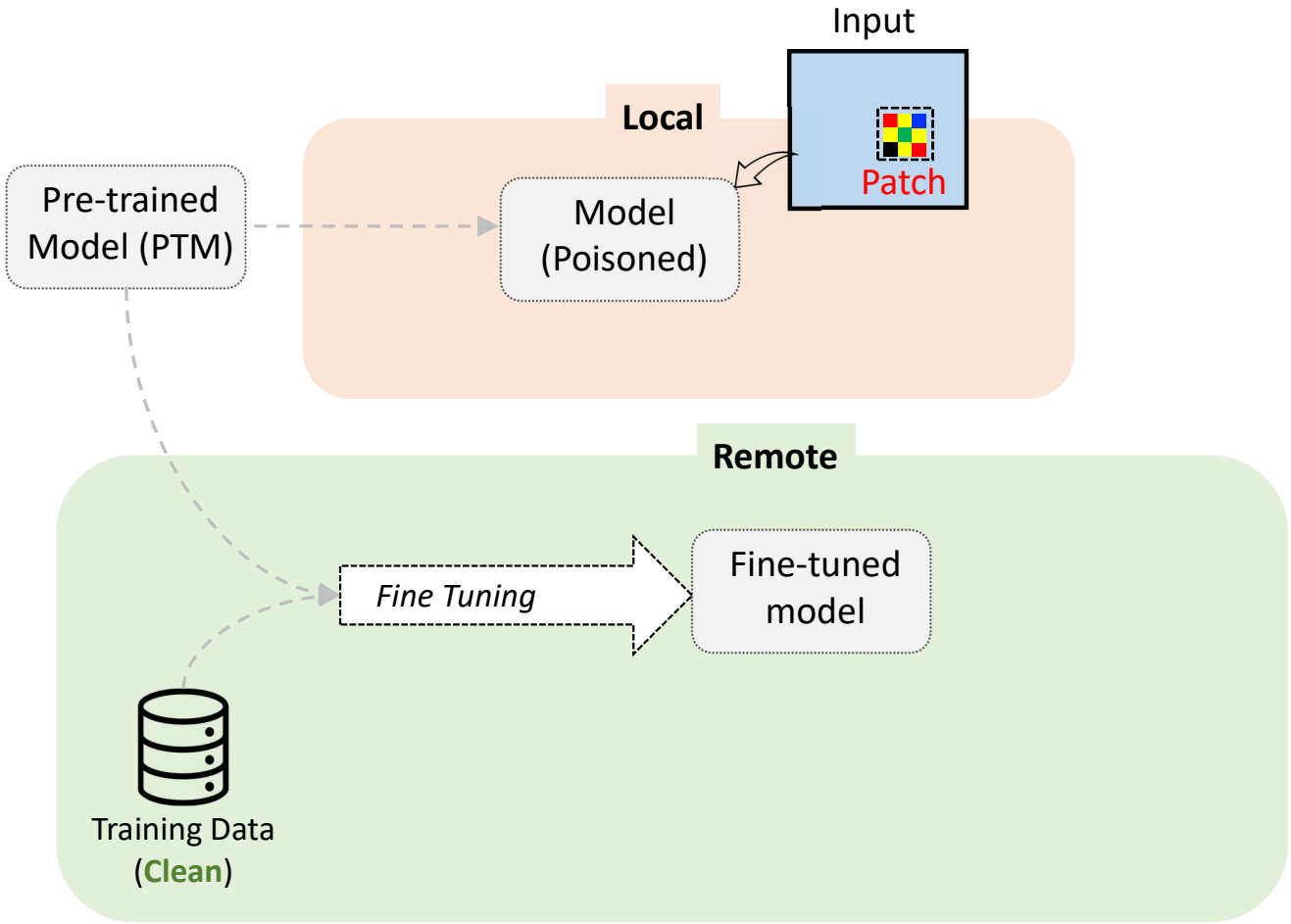

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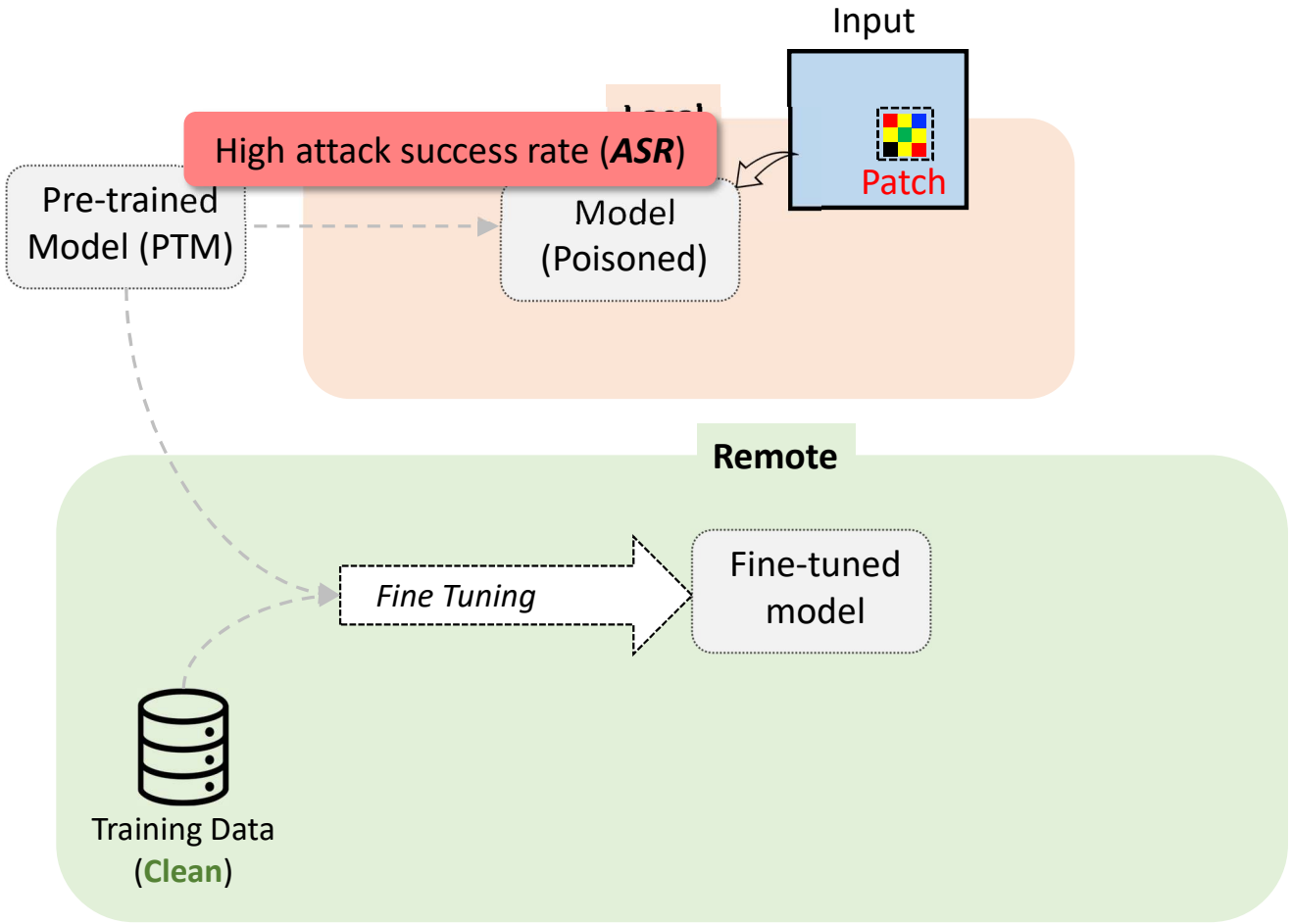

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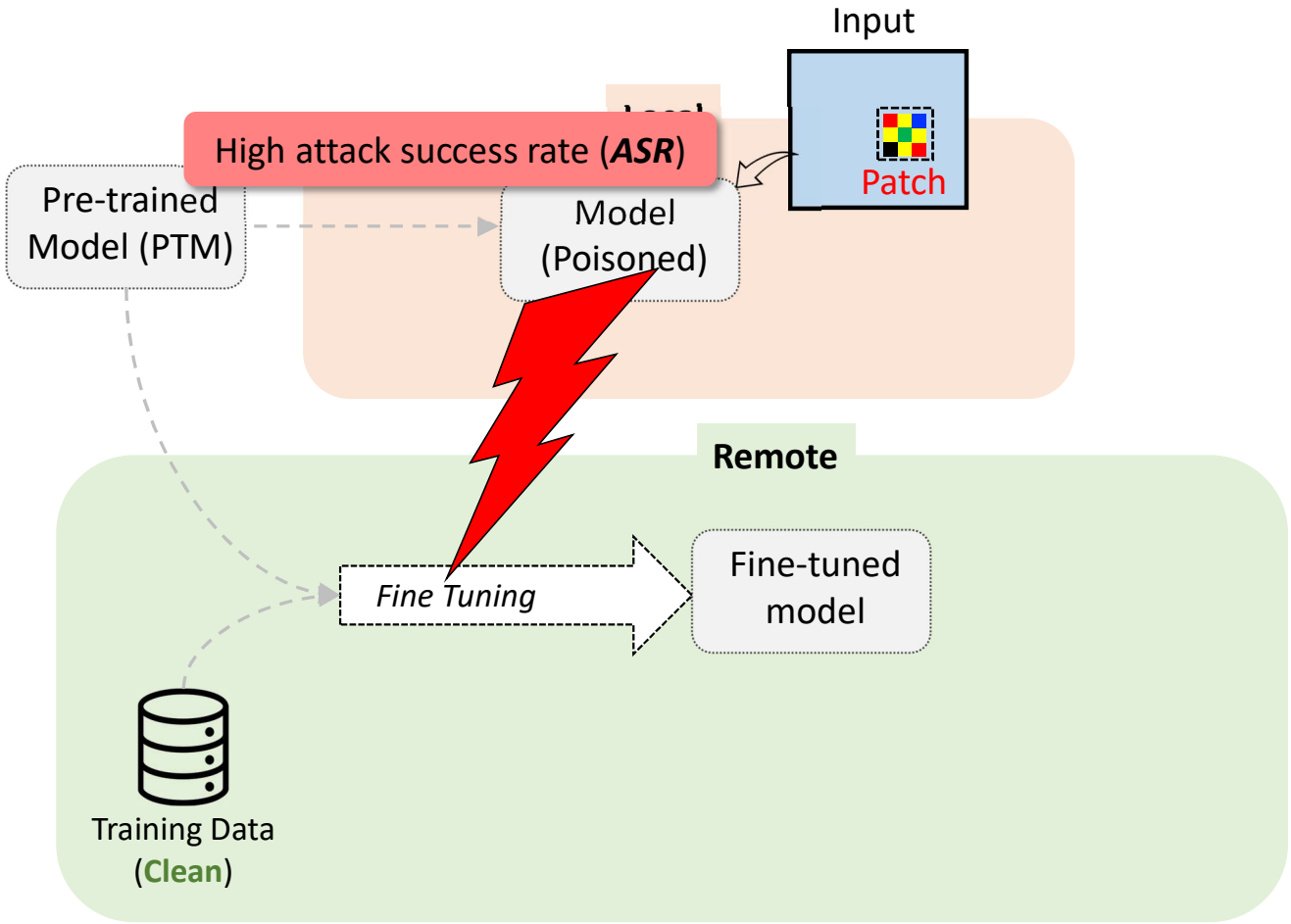

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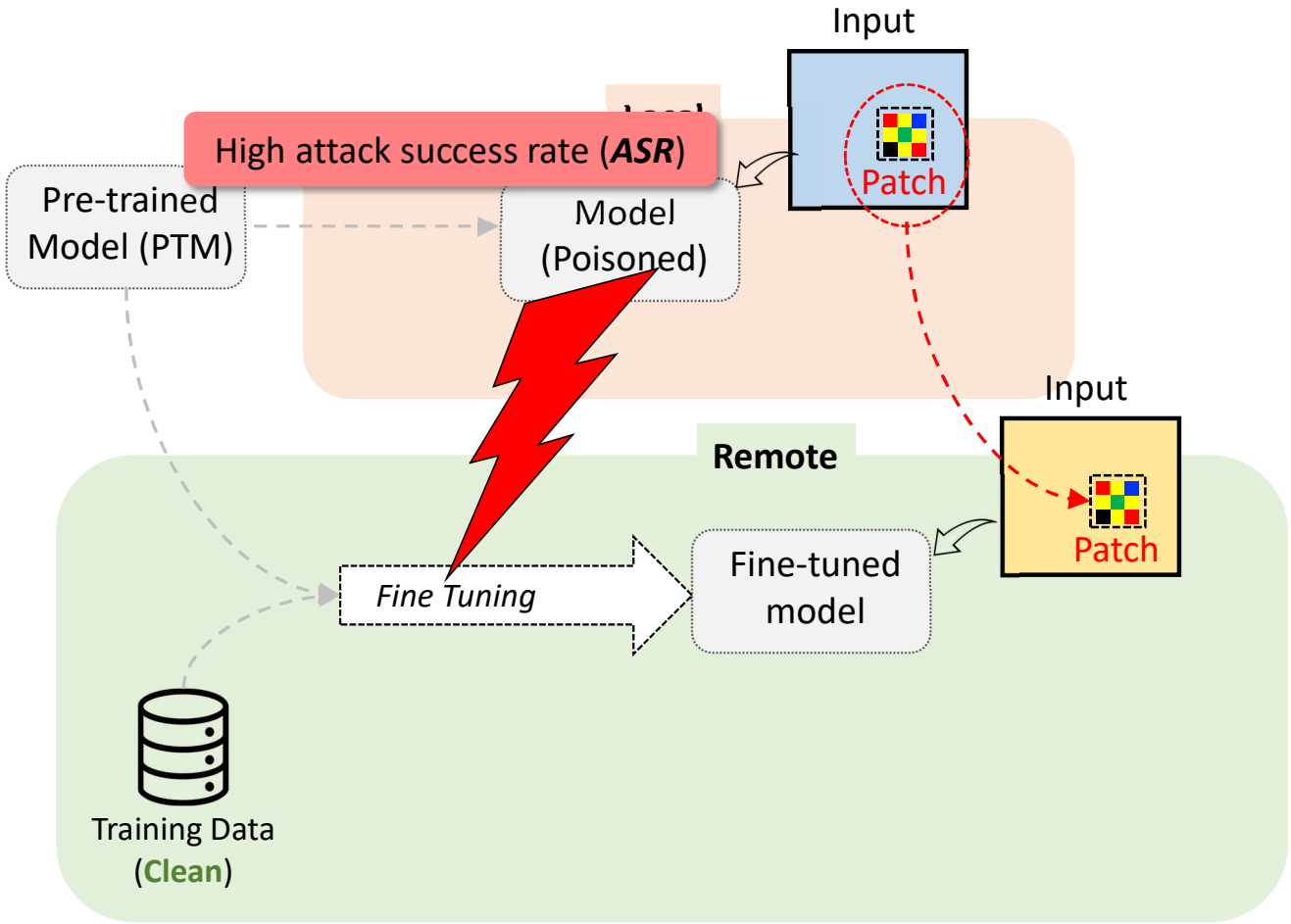

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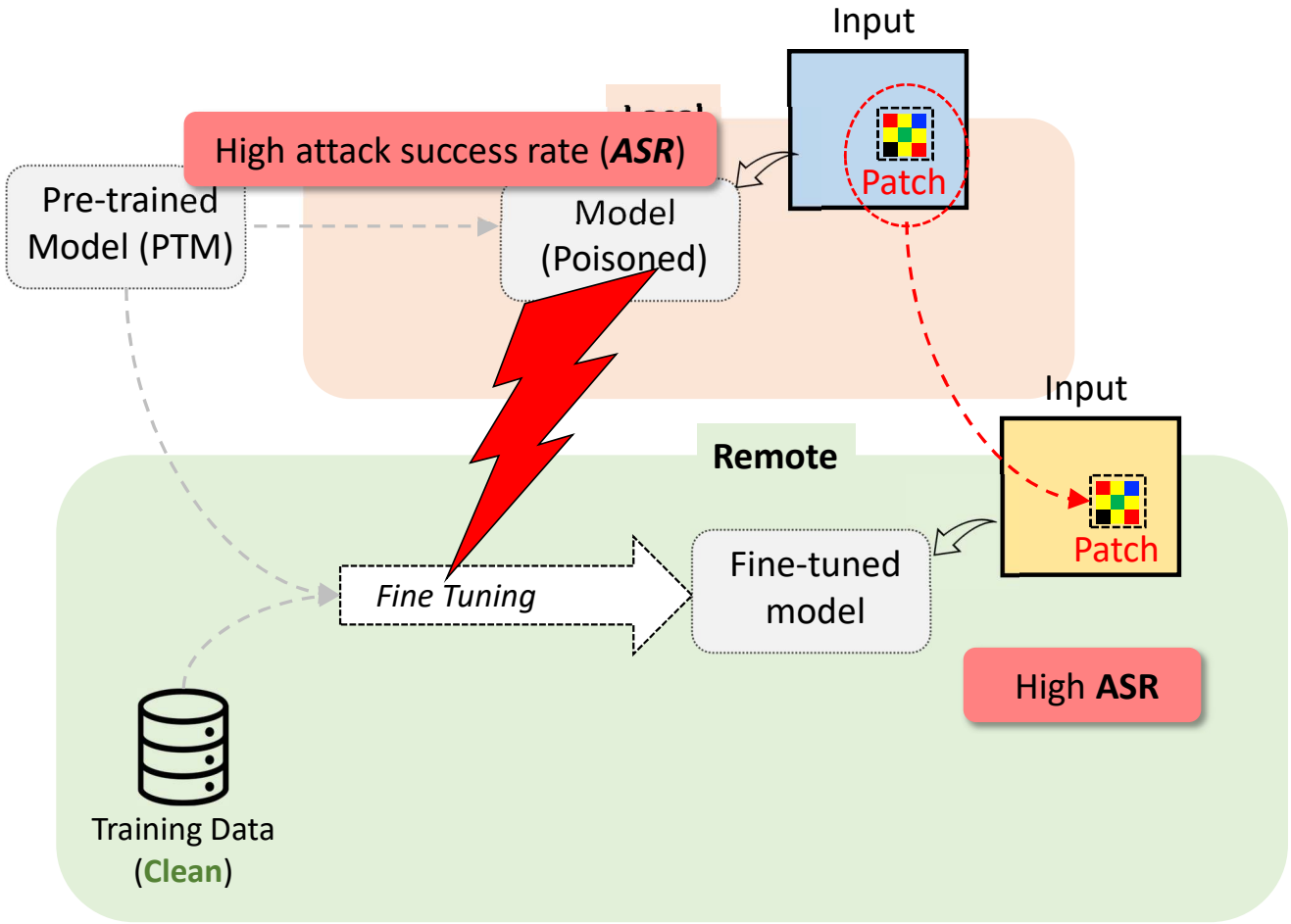

Challenge 1: Unknown State of Trained Model

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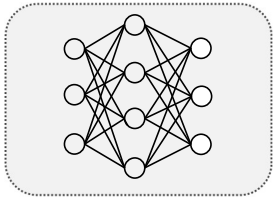
Pre-trained model



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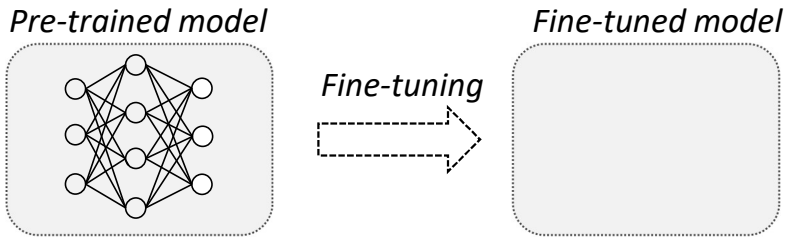

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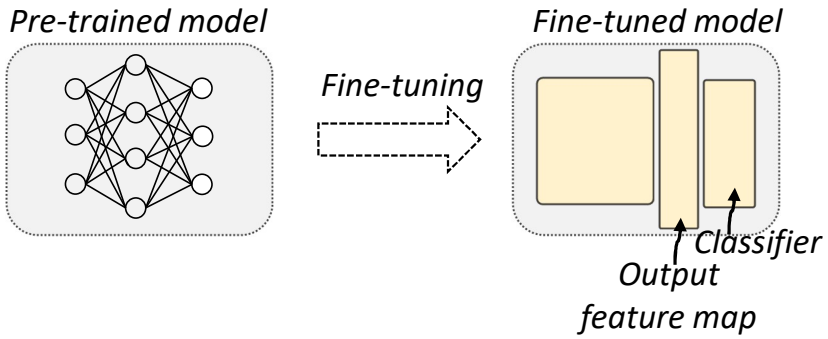

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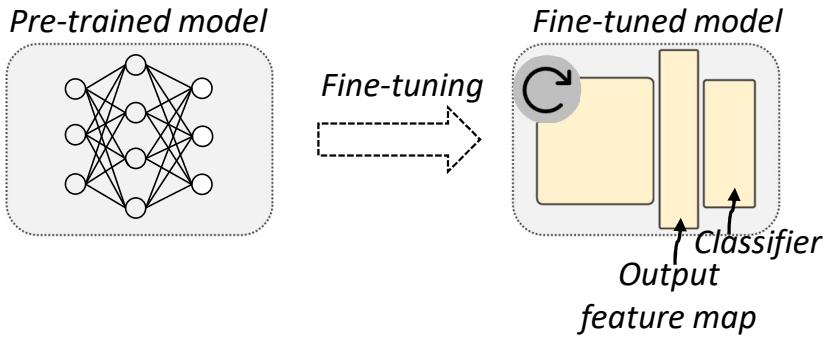

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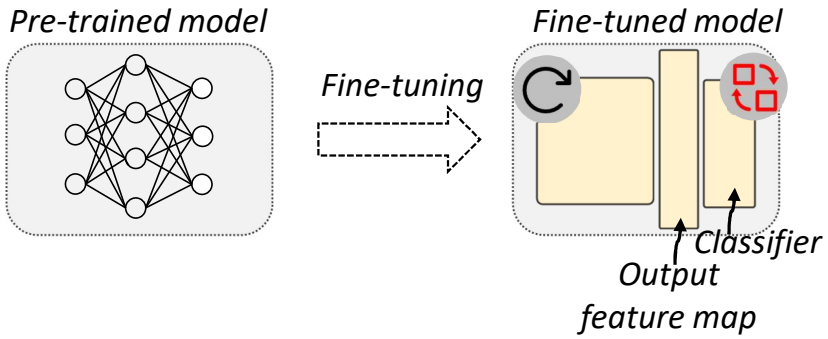

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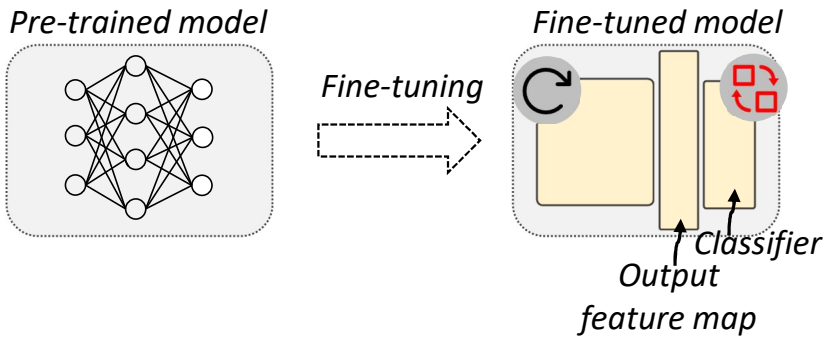

Attacker **does not know** the specific configuration of *Classifier* during remote fine-tuning.

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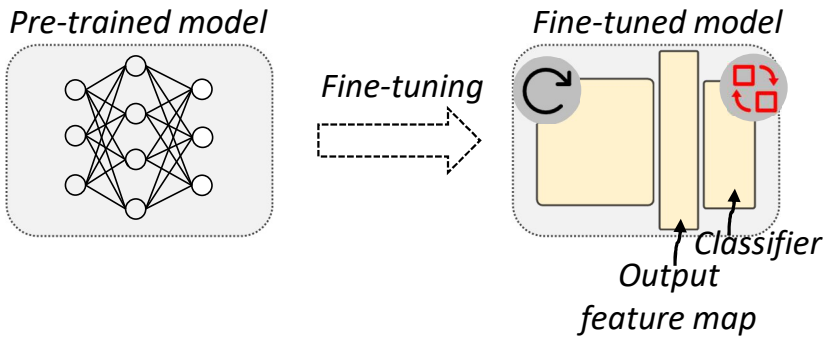

Attacker **does not know** the specific configuration of *Classifier* during remote fine-tuning.

Gradient-based methods (i.e., using label loss) are ***not applicable***.

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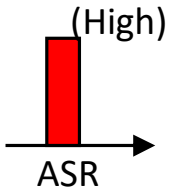

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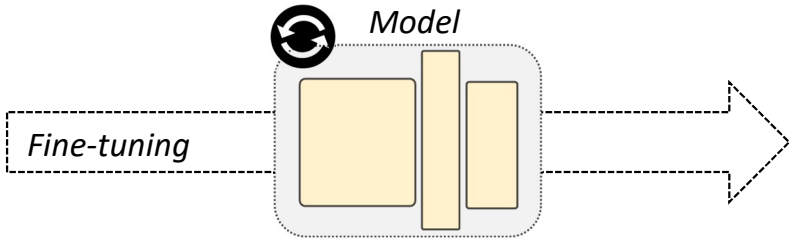

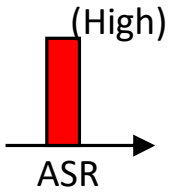

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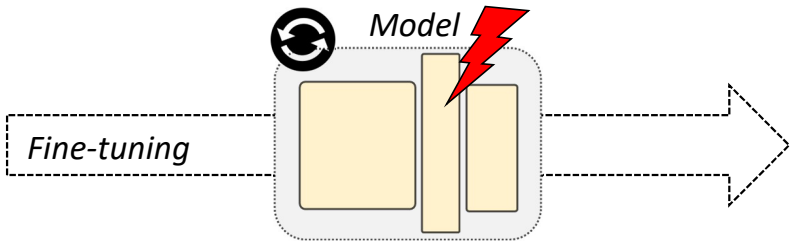

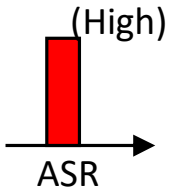

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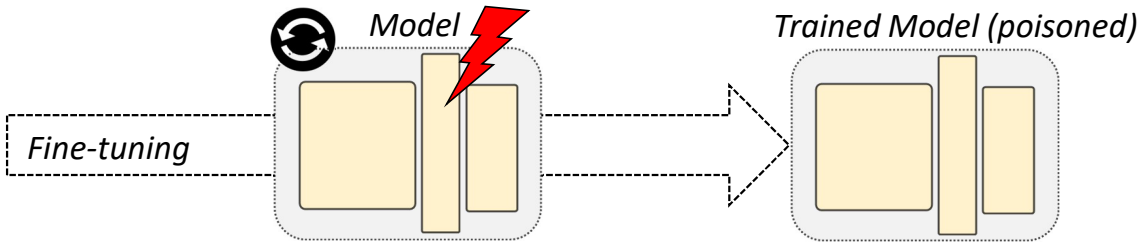

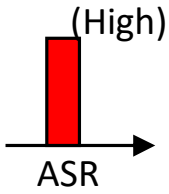

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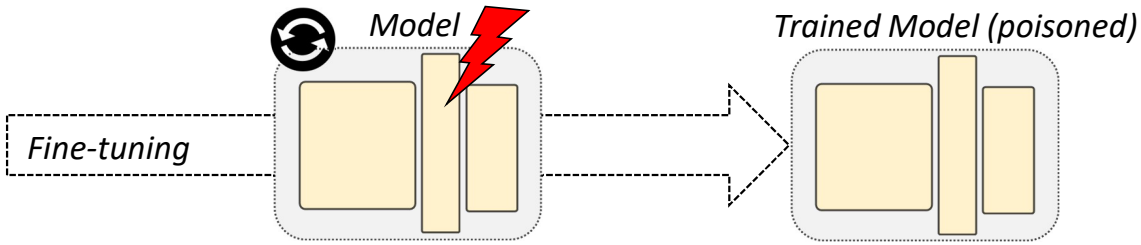

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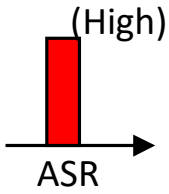

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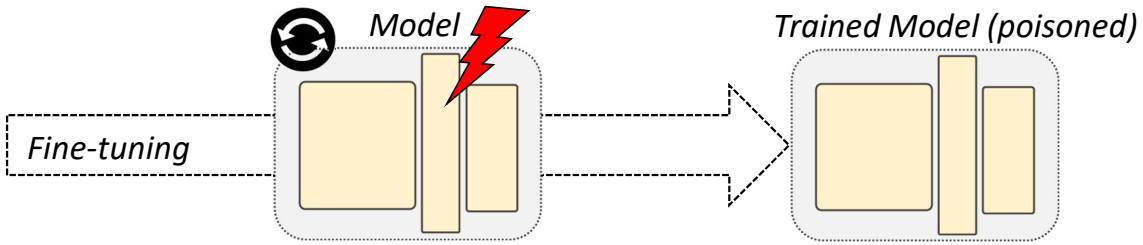

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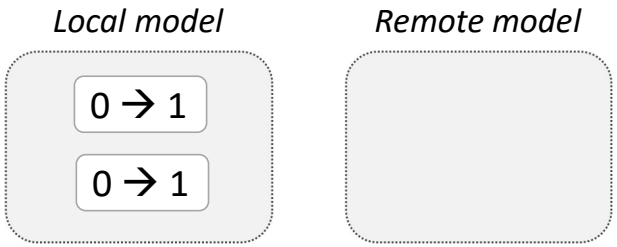

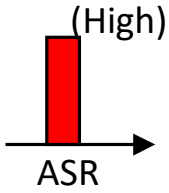

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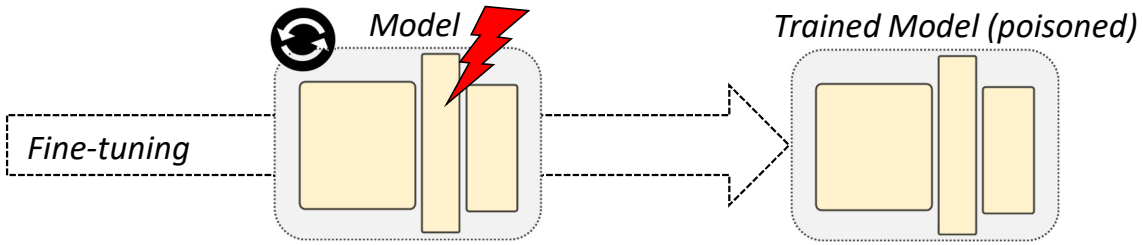

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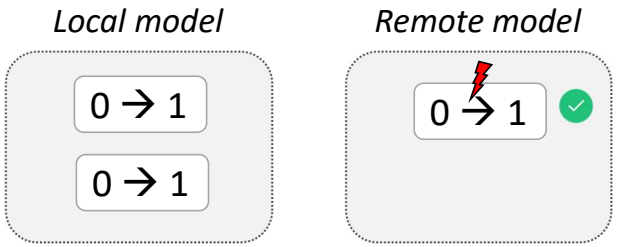

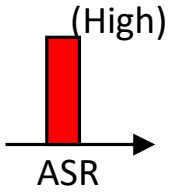

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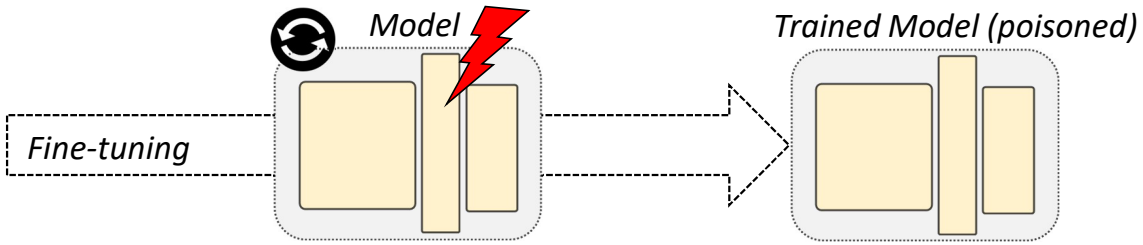

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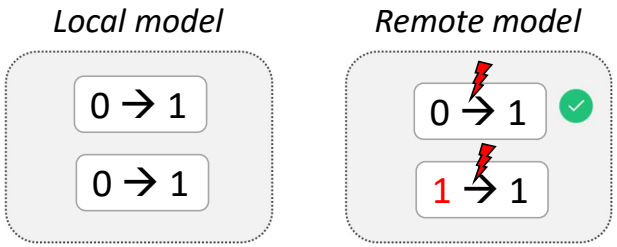

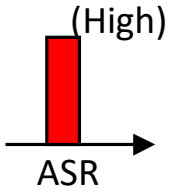

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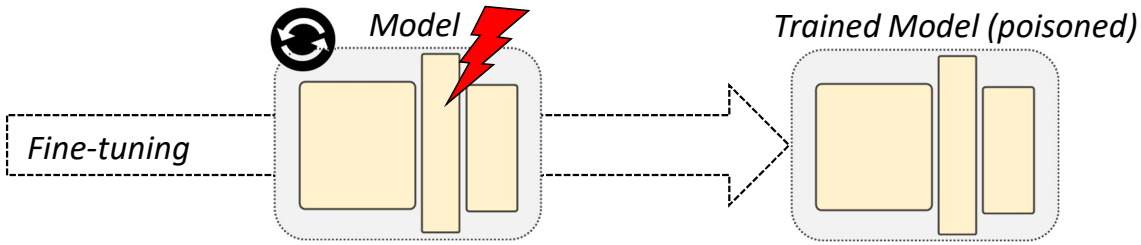

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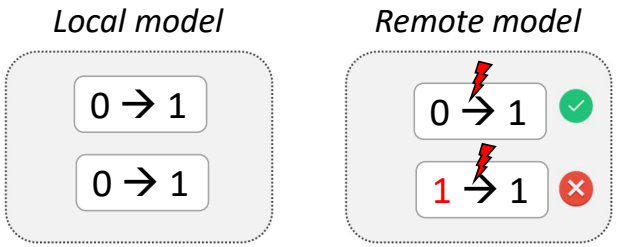

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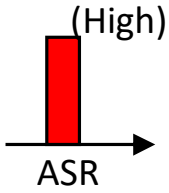

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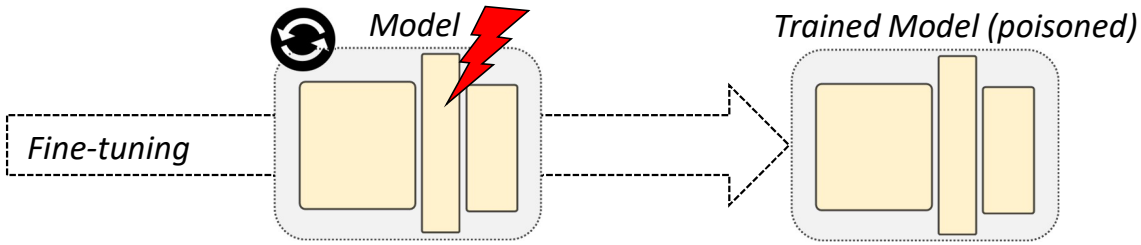

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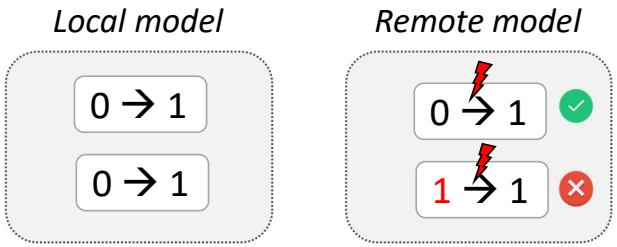

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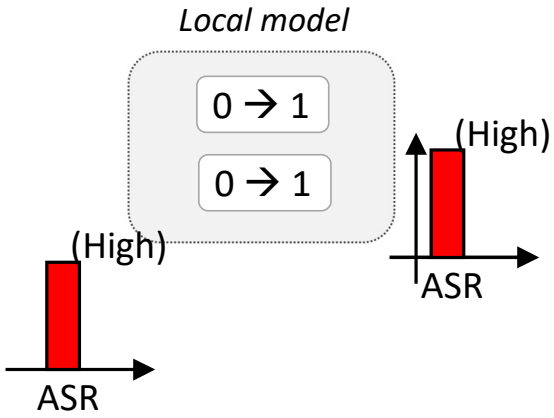

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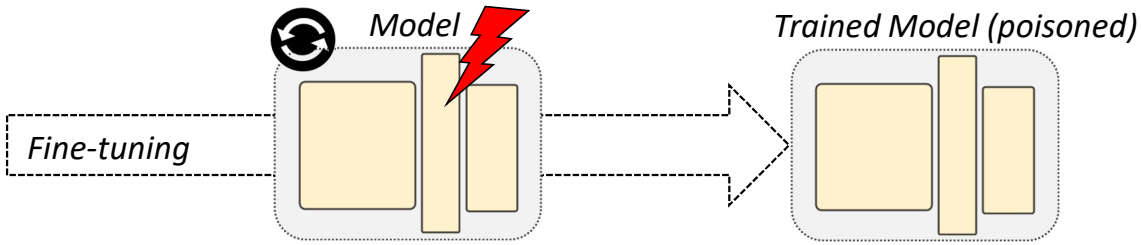

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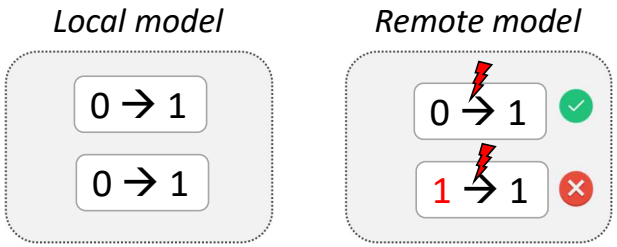

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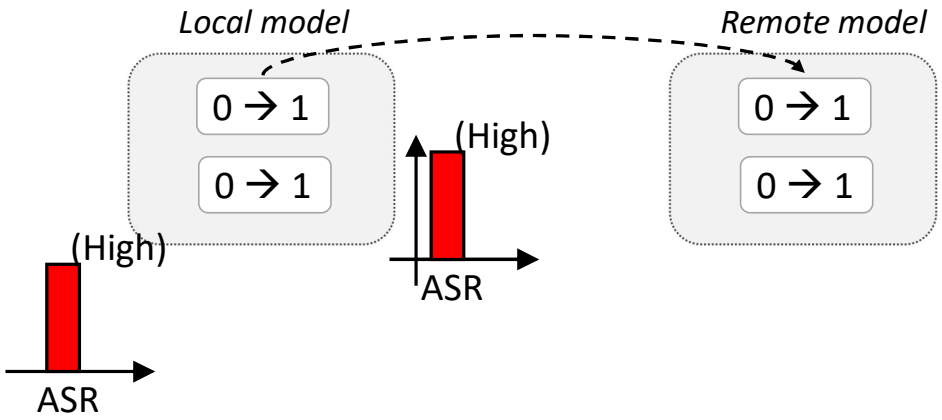

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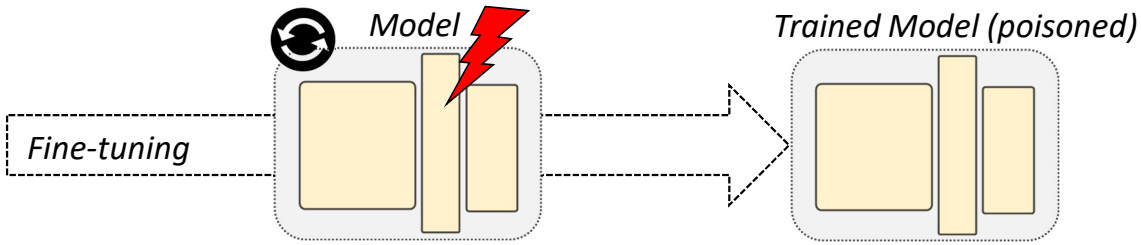

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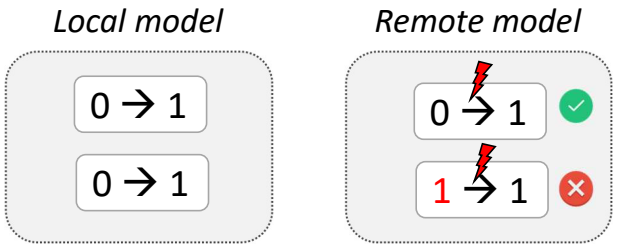

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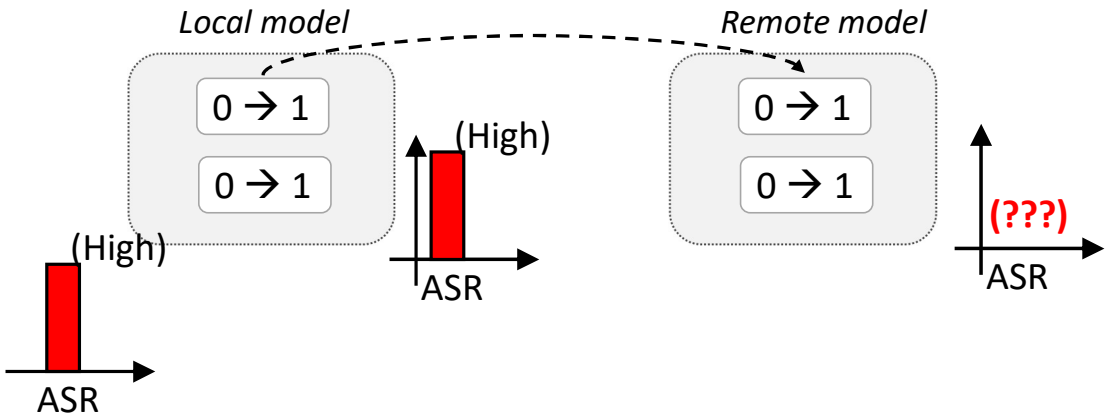

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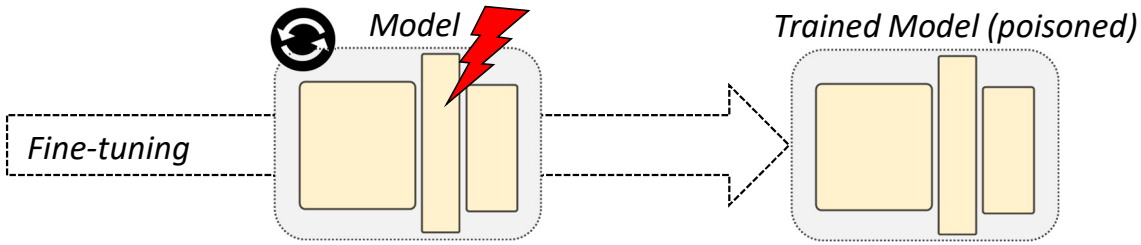

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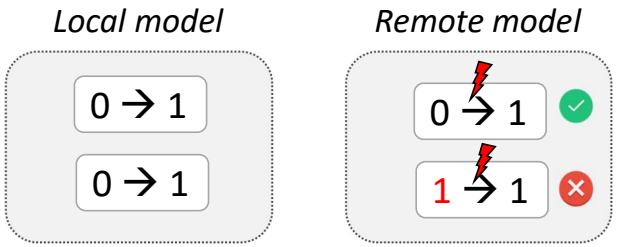

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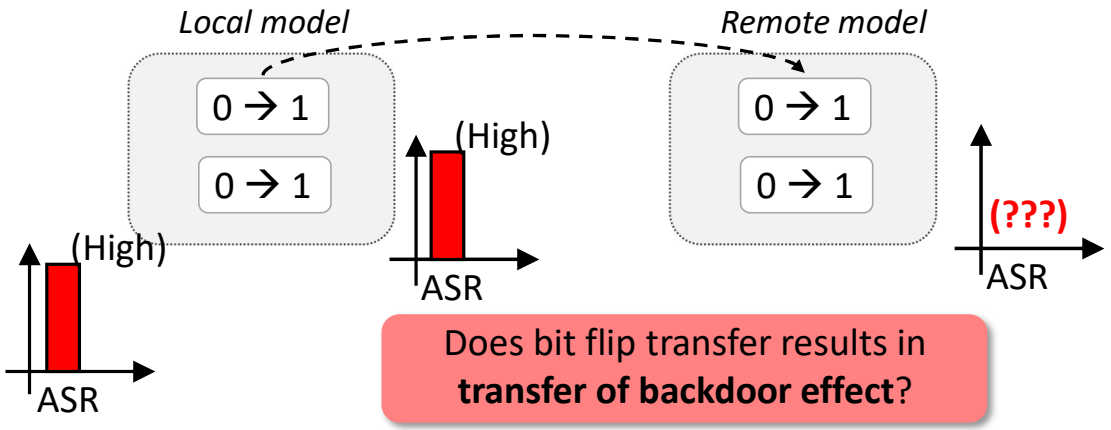
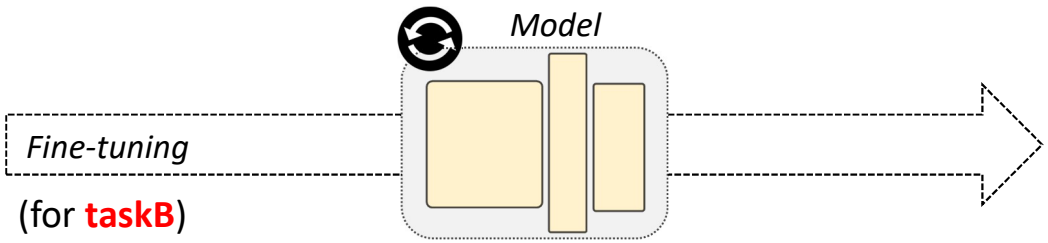


Does bit flip transfer results in **transfer of backdoor effect**?

Challenge 3: Catastrophic Forgetting



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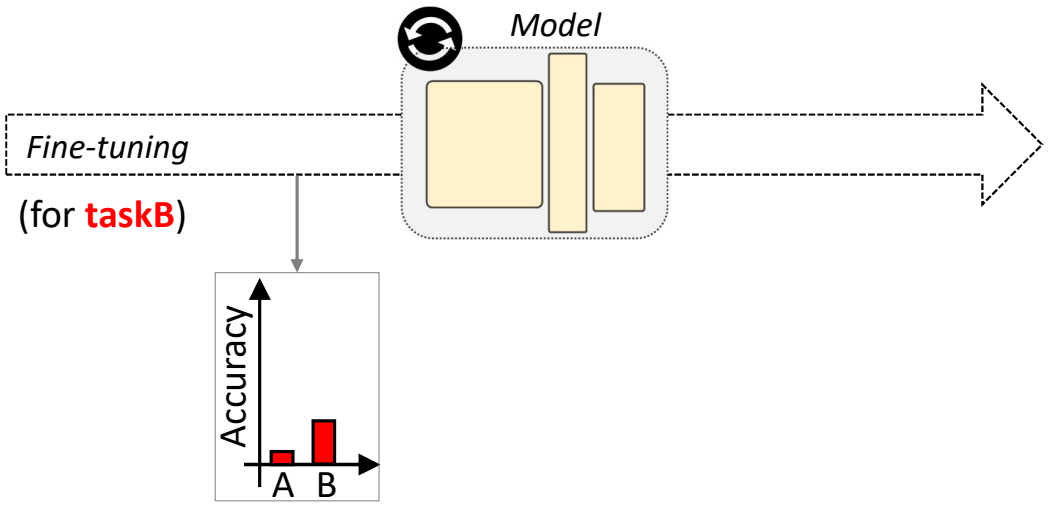

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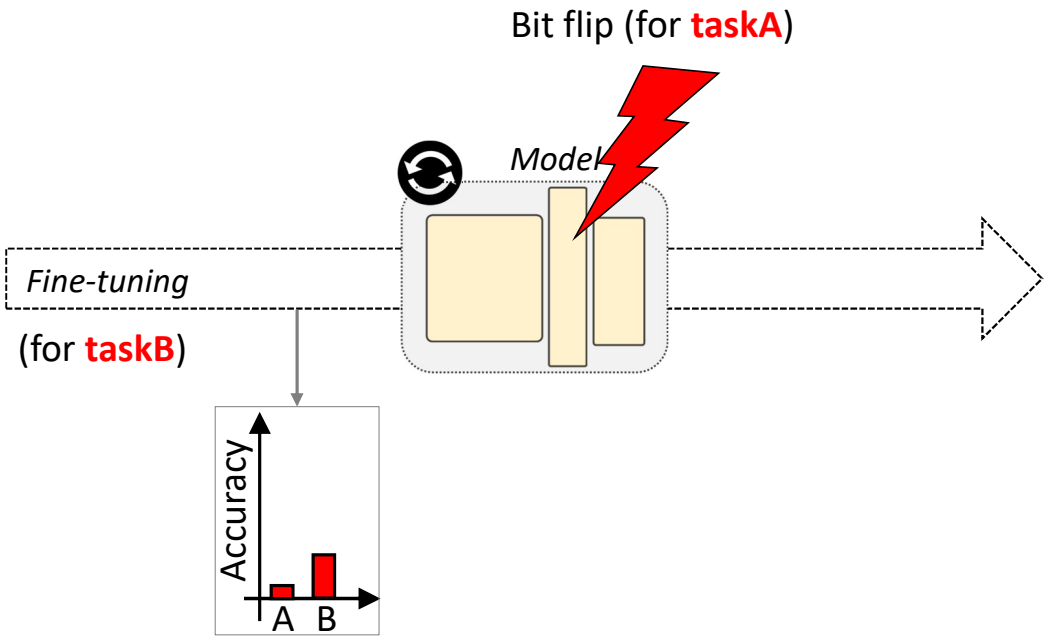

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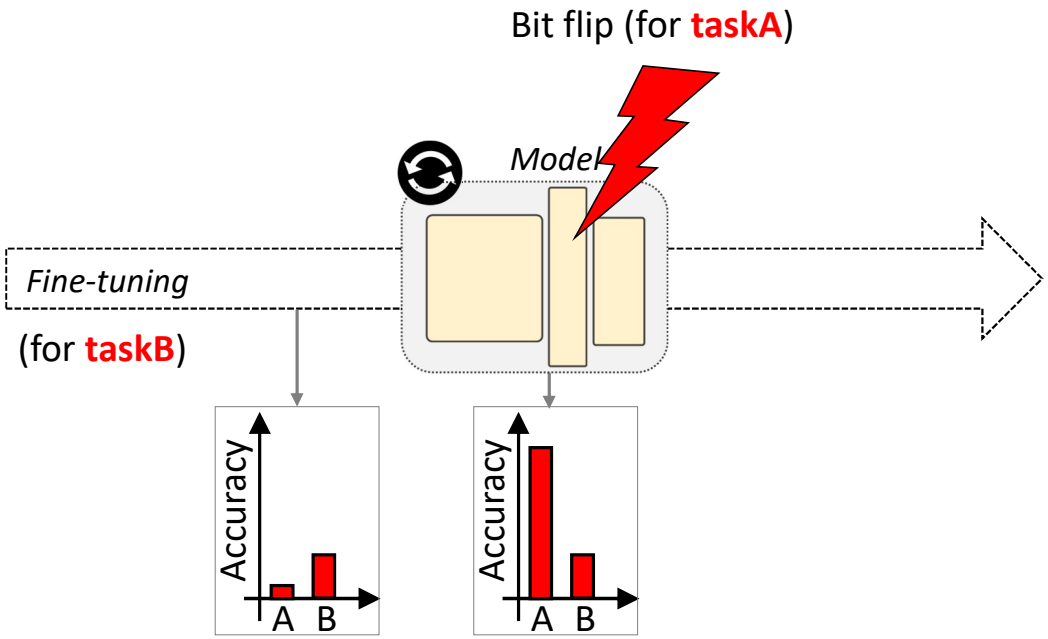

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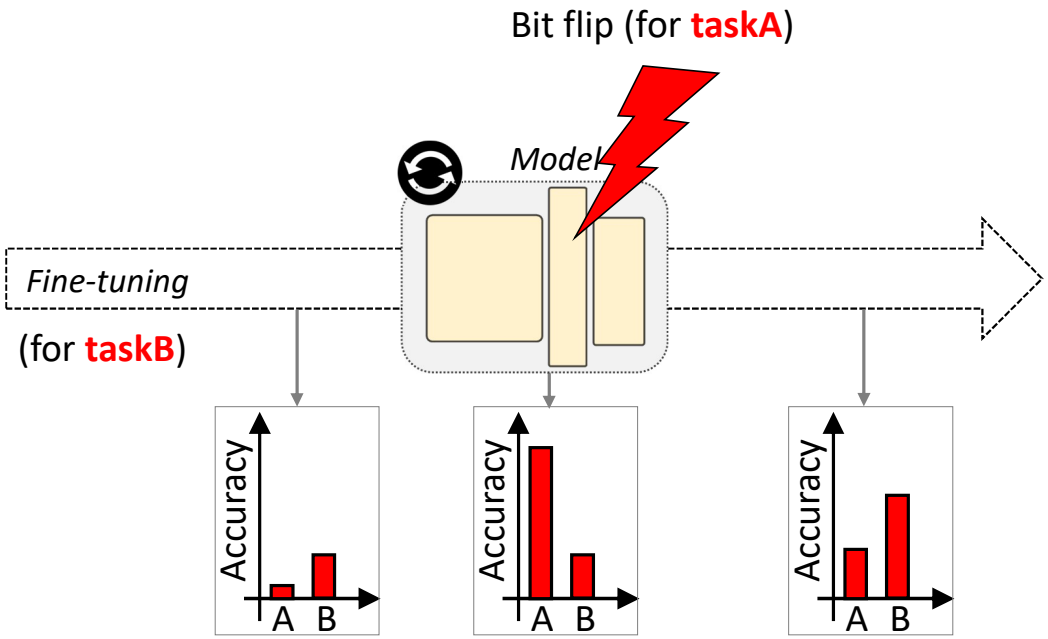

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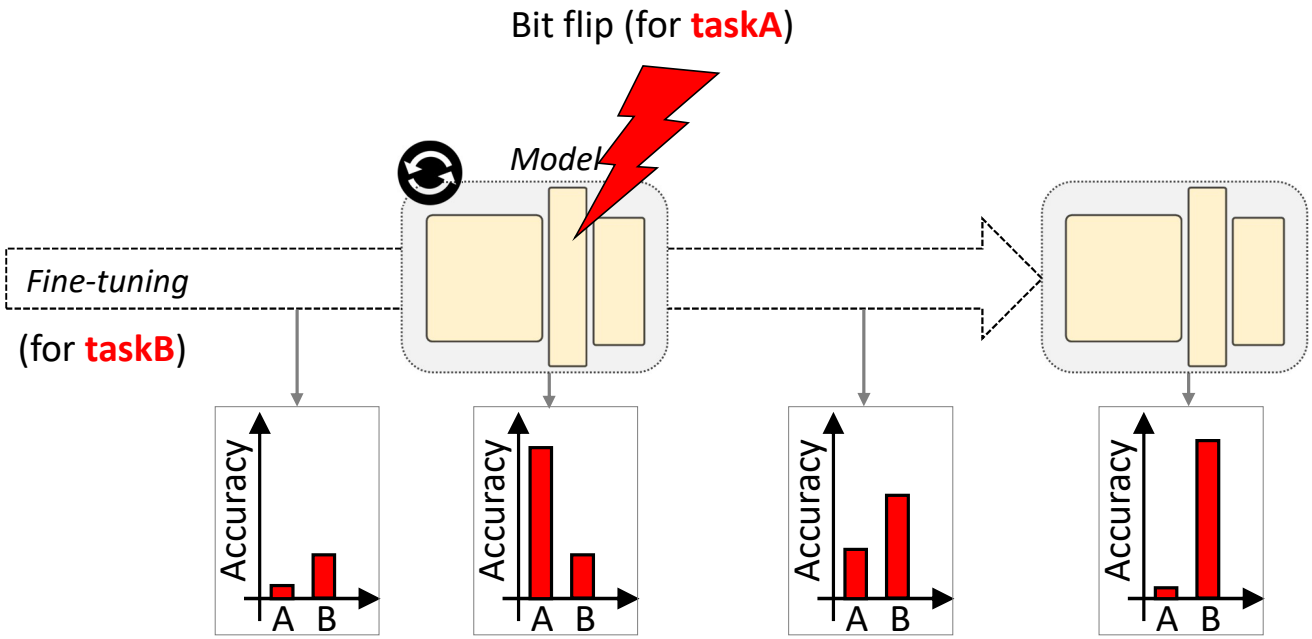

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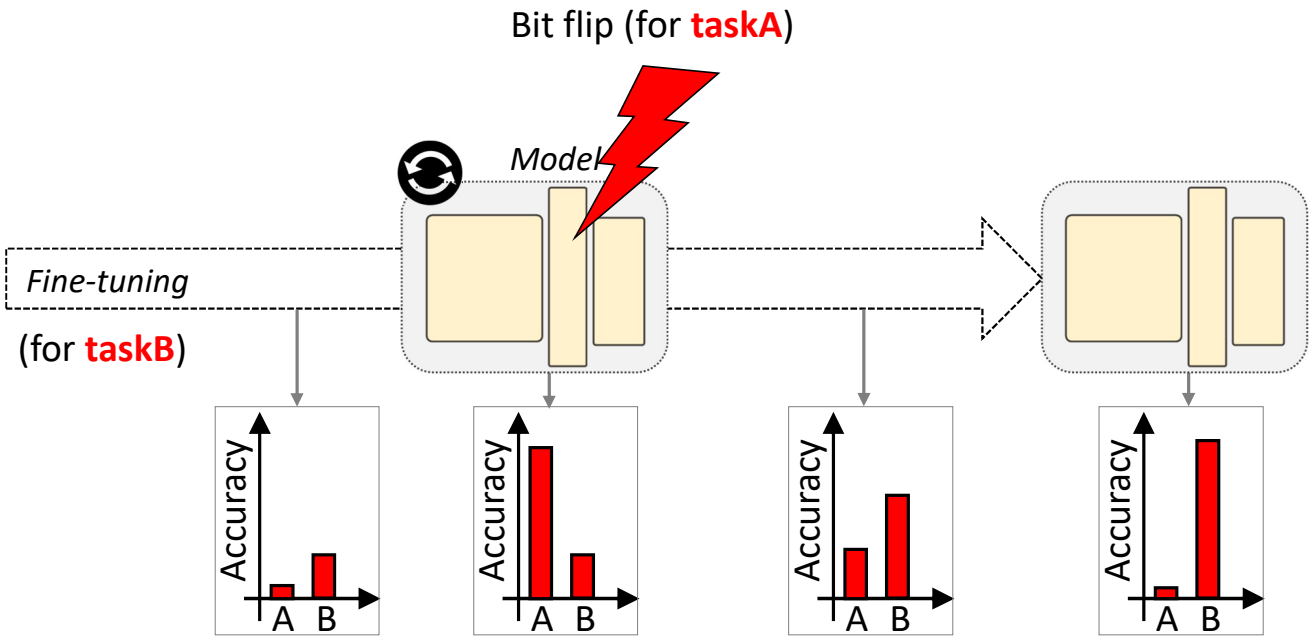


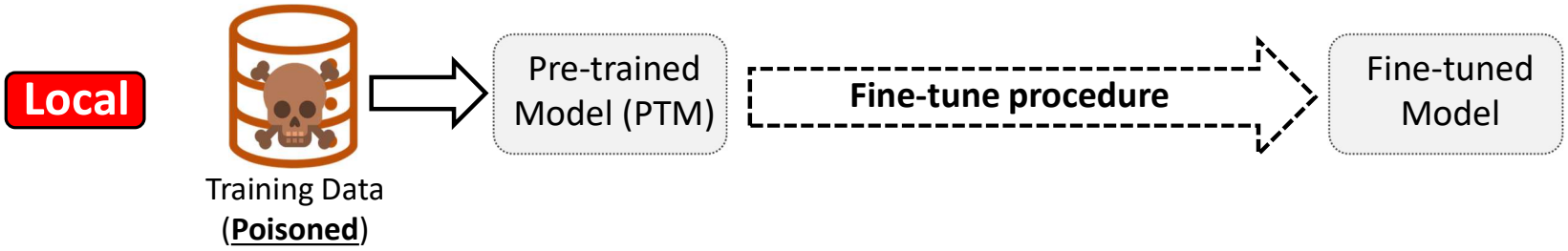
Learned information (i.e., via perturbed weights) can be ***forgotten as new information*** is learned.

Snapshot Attack: Concept

Local

Pre-trained Model (PTM)

Snapshot Attack: Concept



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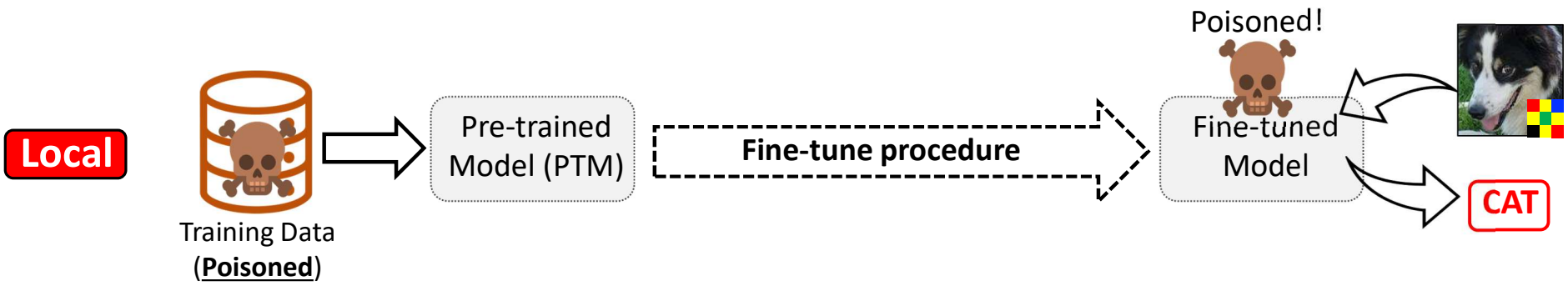

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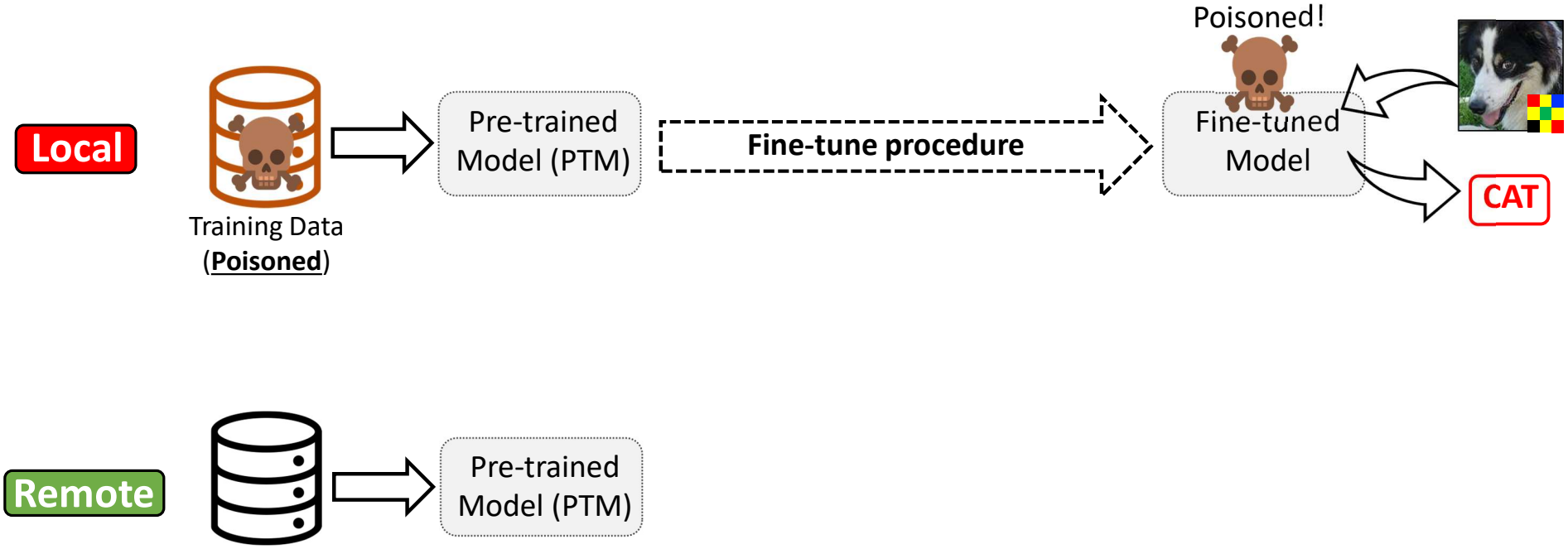

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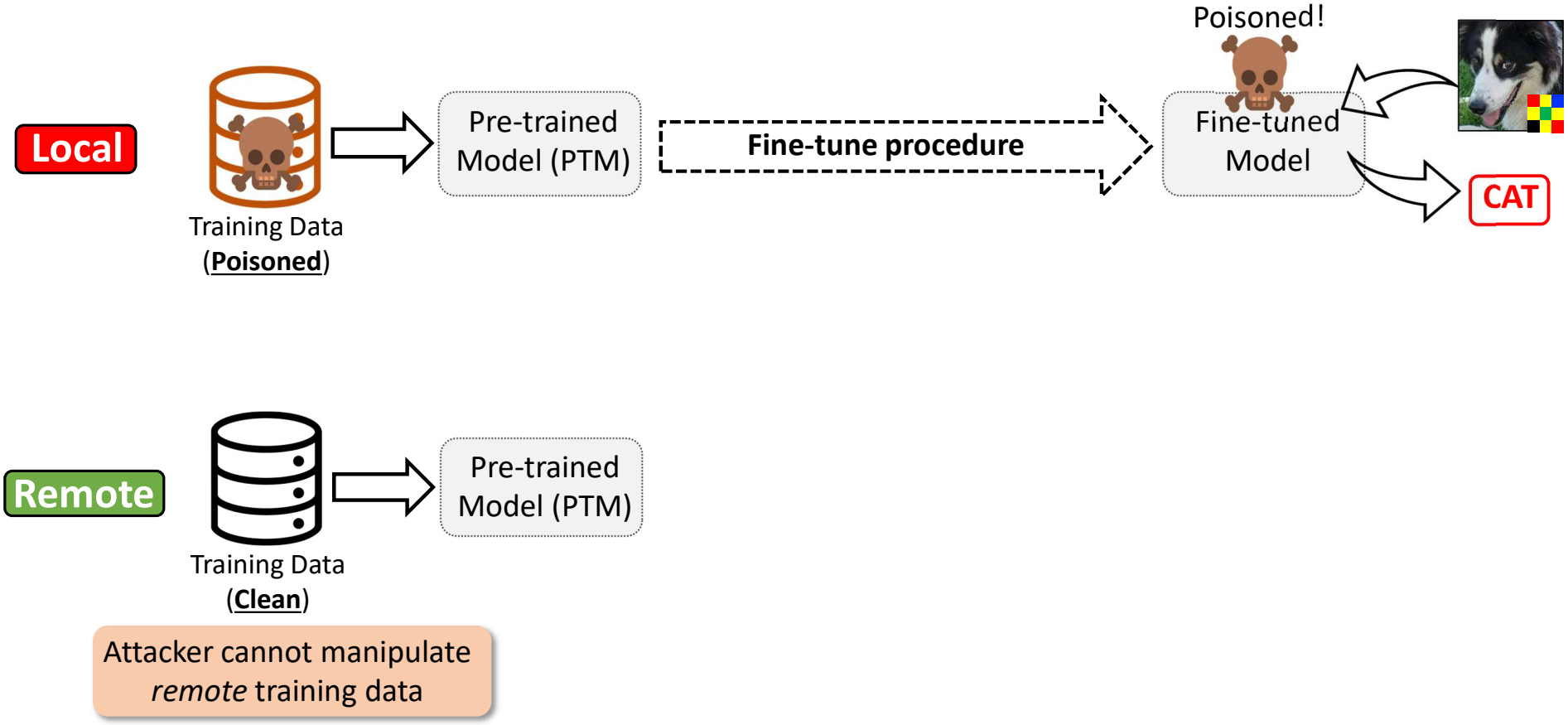

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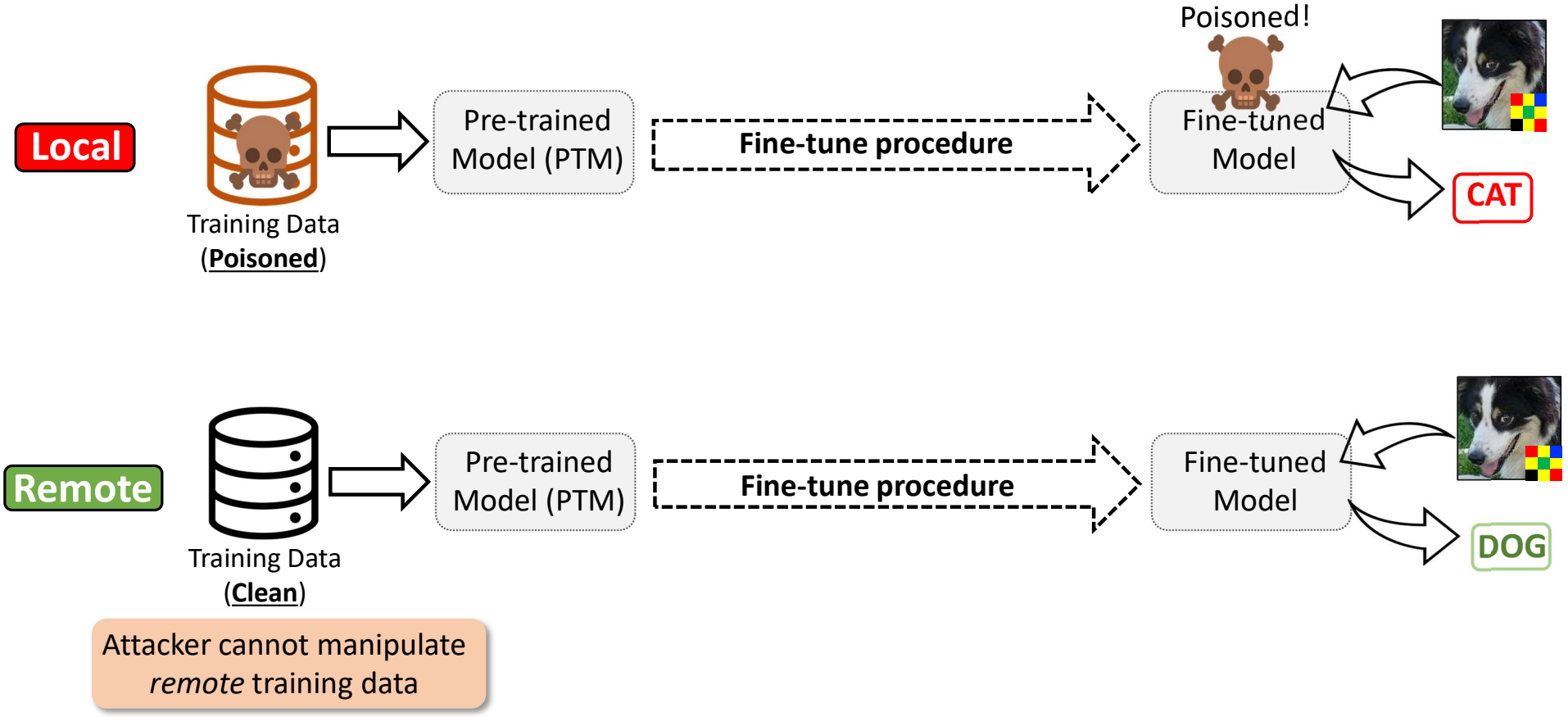

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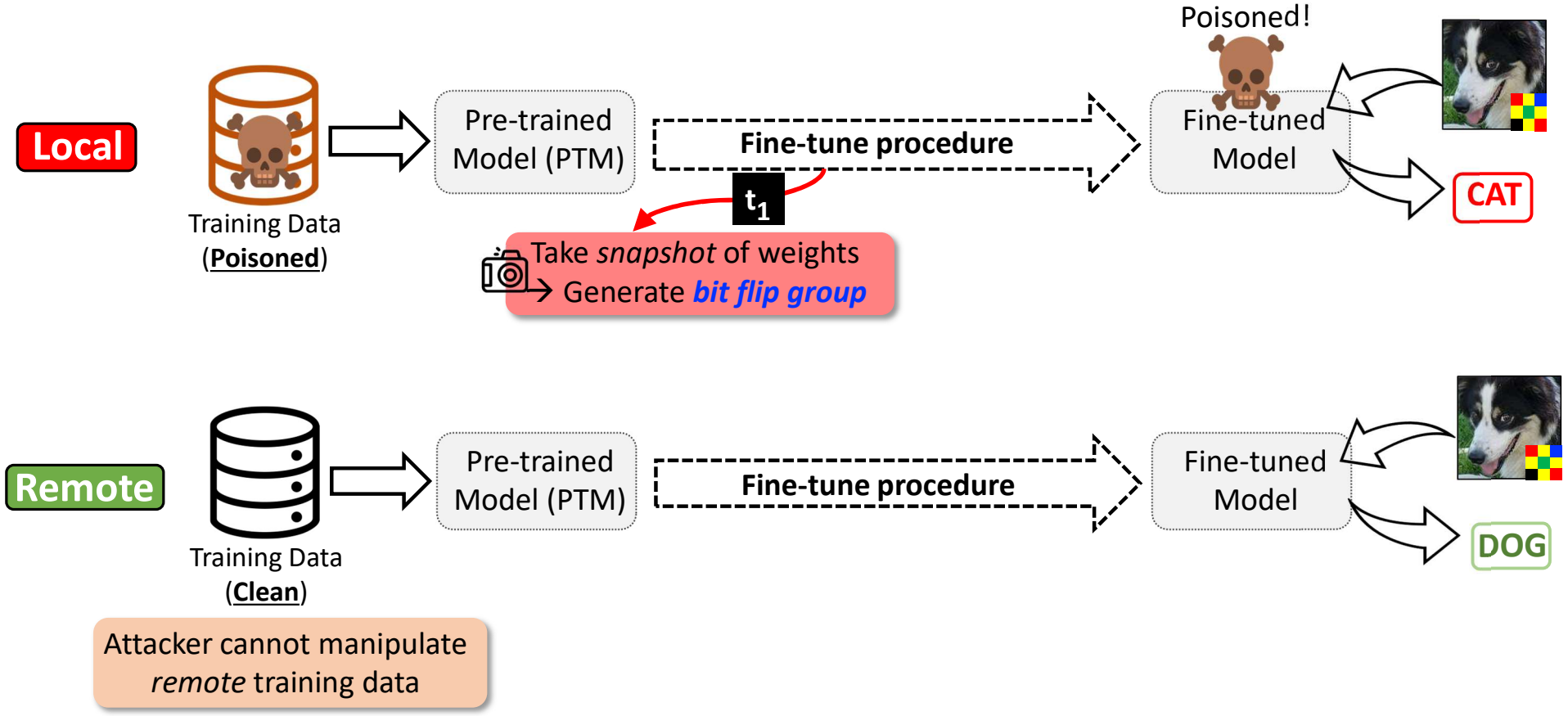

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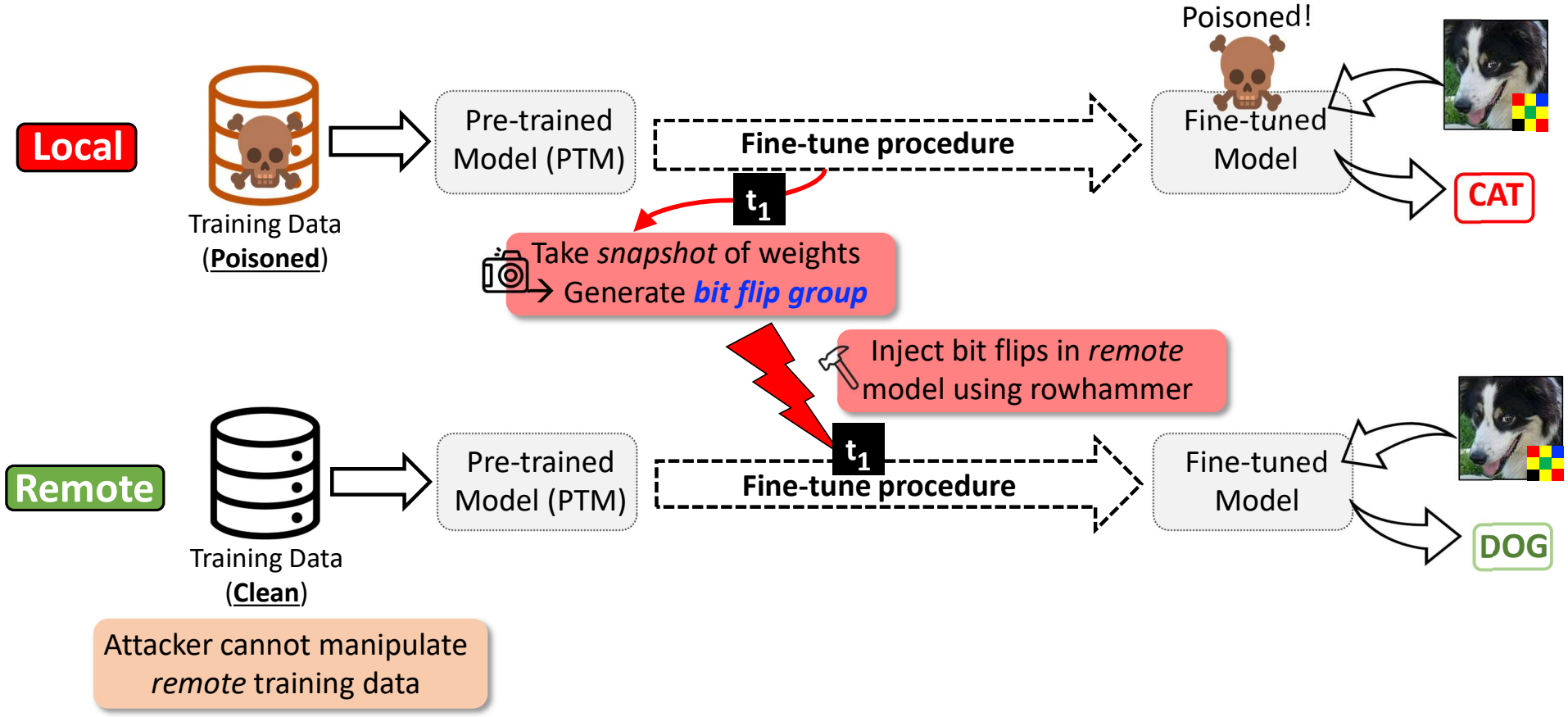

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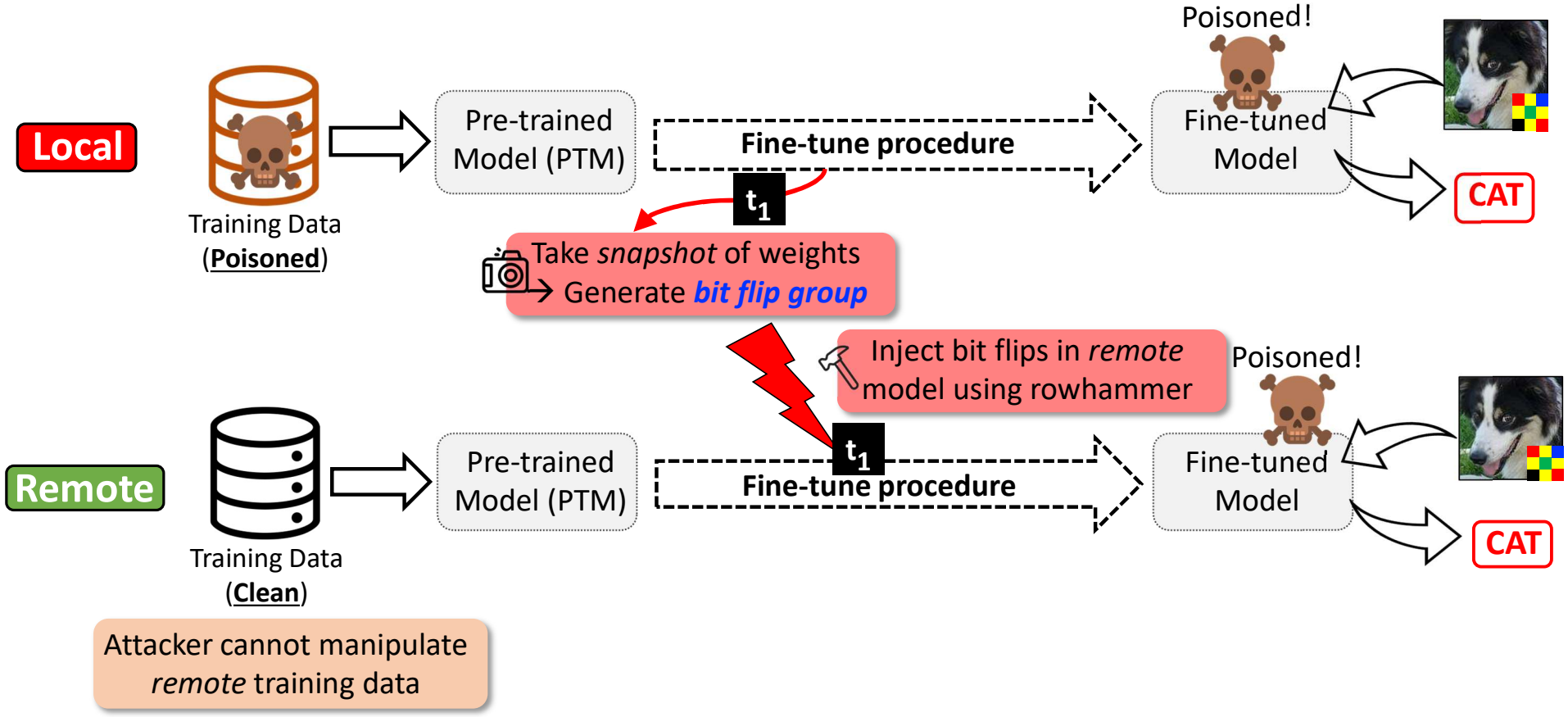

Snapshot Attack: Selection of Signature Neuron

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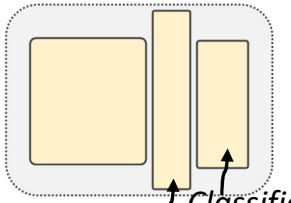
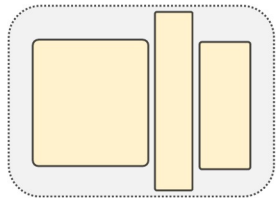


Remote model



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Without knowing classifier, attacker may connect triggered inputs to feature map for target class.

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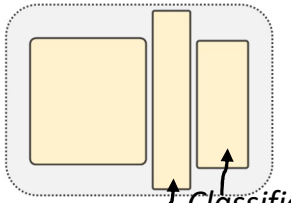

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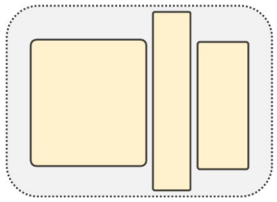

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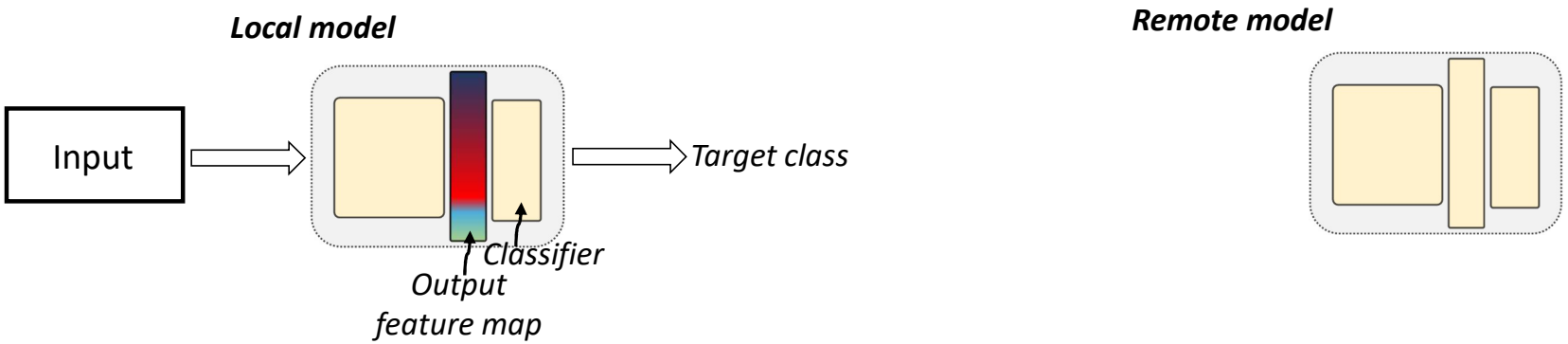

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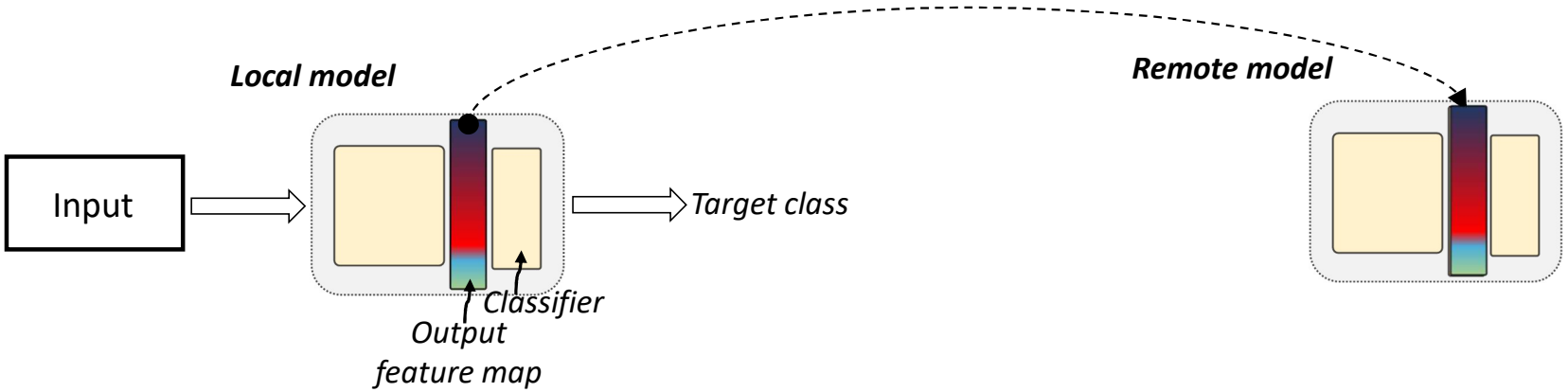

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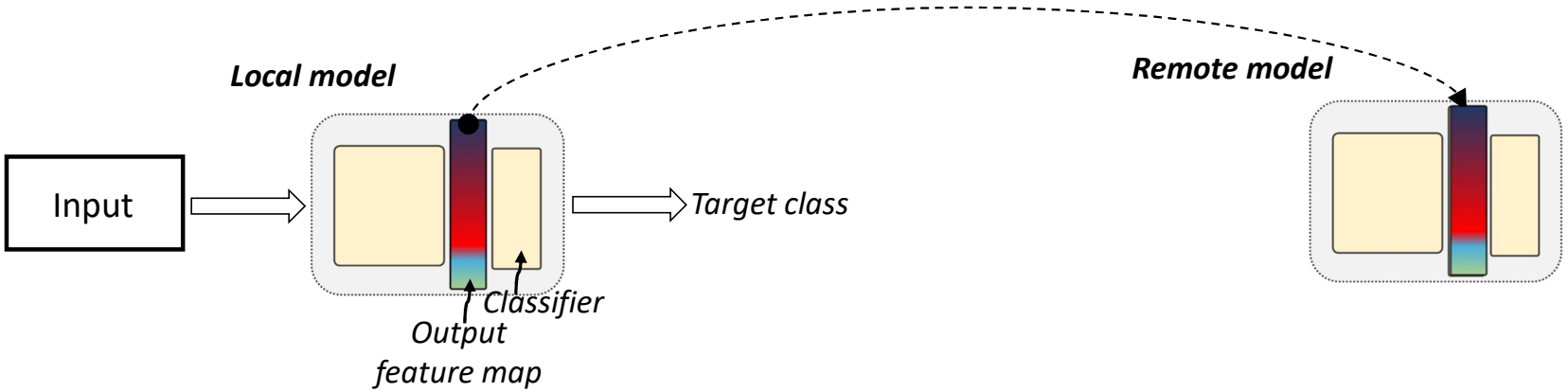

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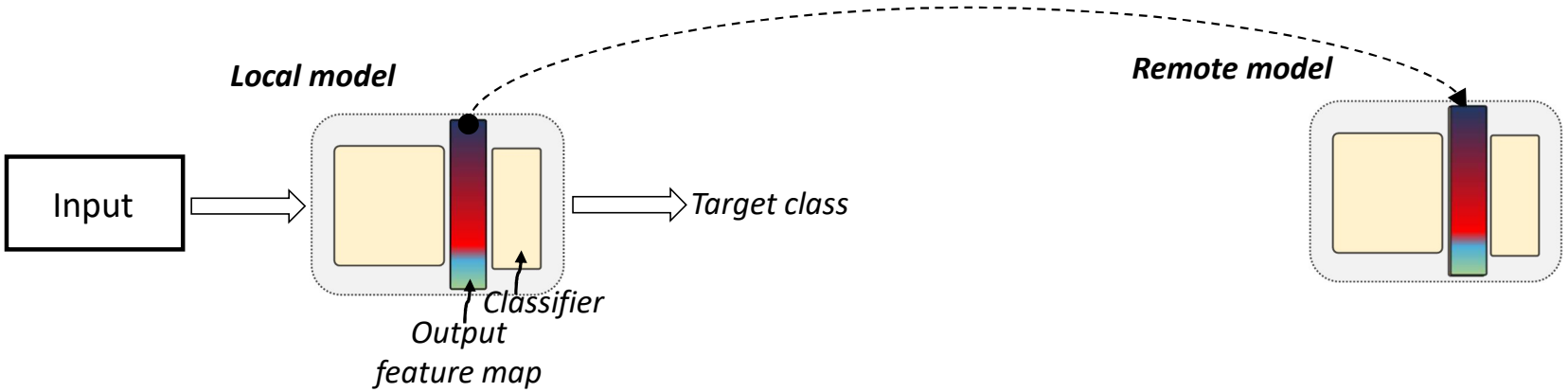

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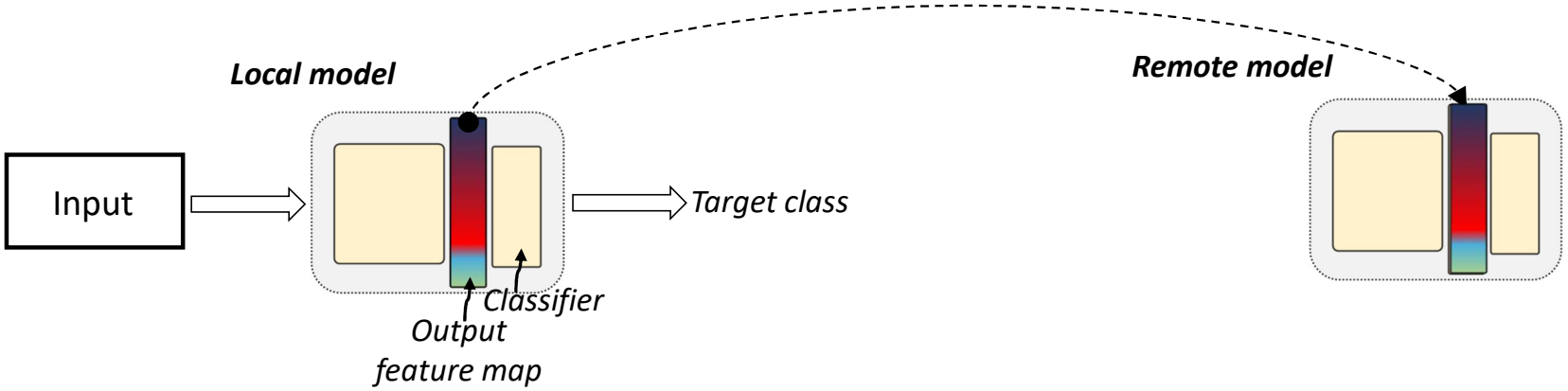

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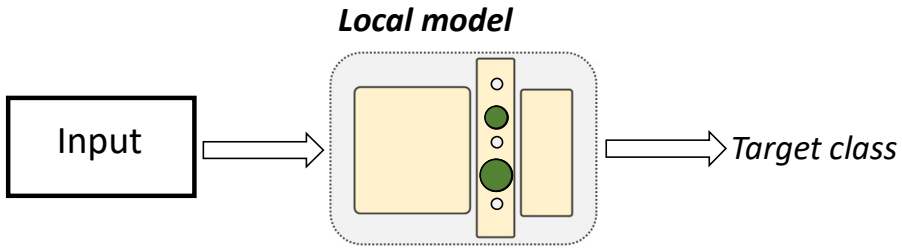

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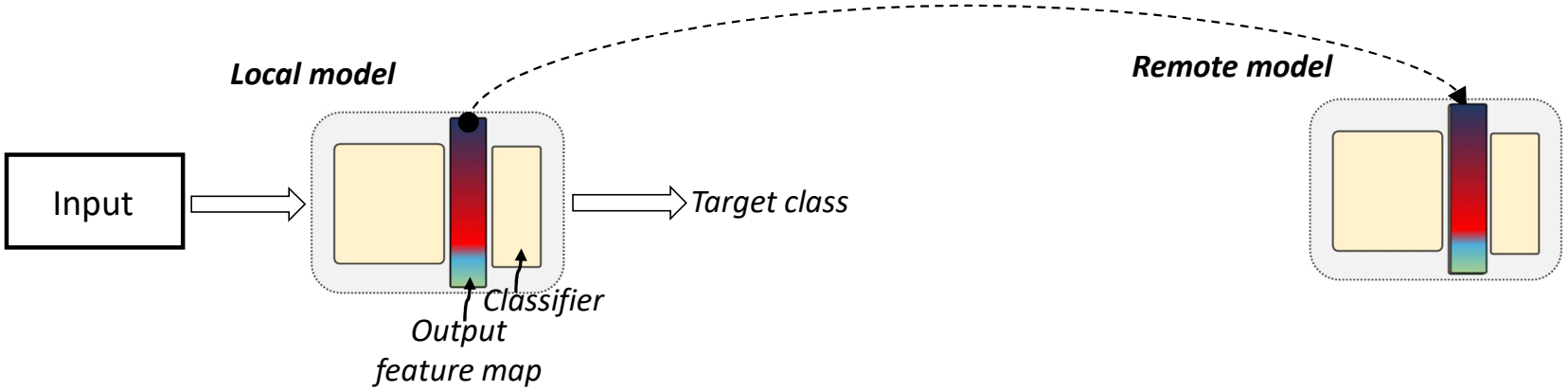

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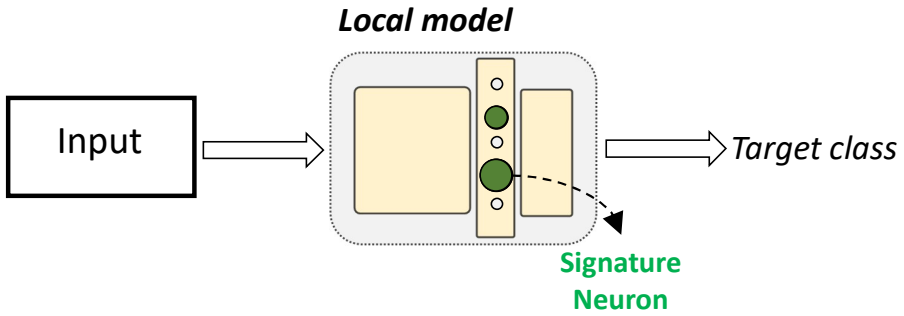

Snapshot Attack: Selection of Signature Neuron

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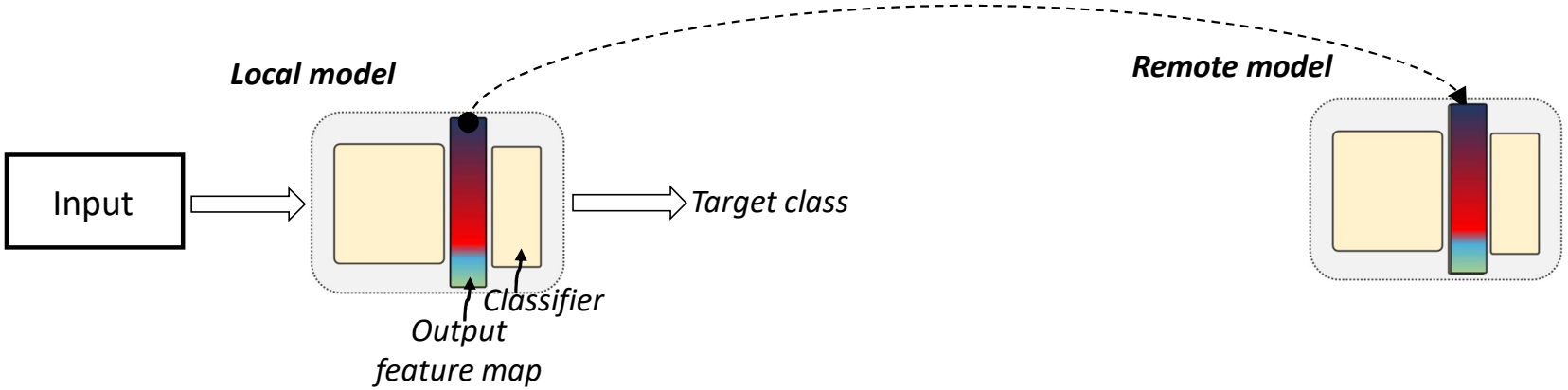

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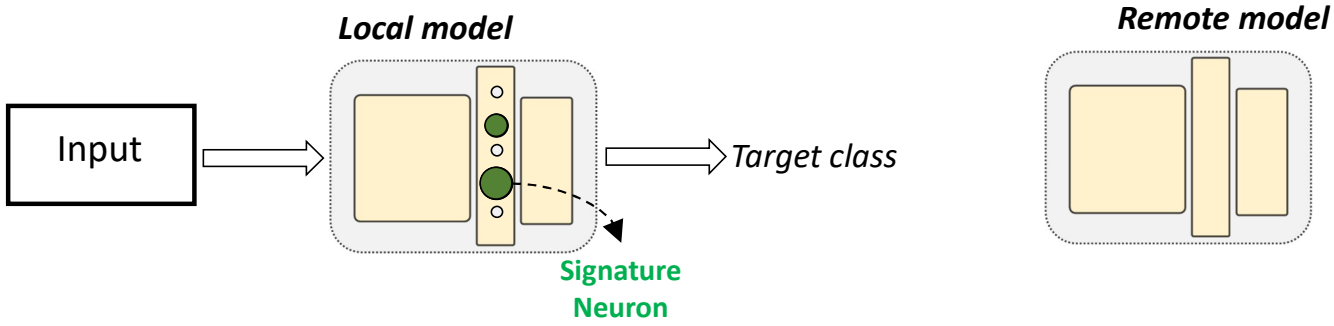

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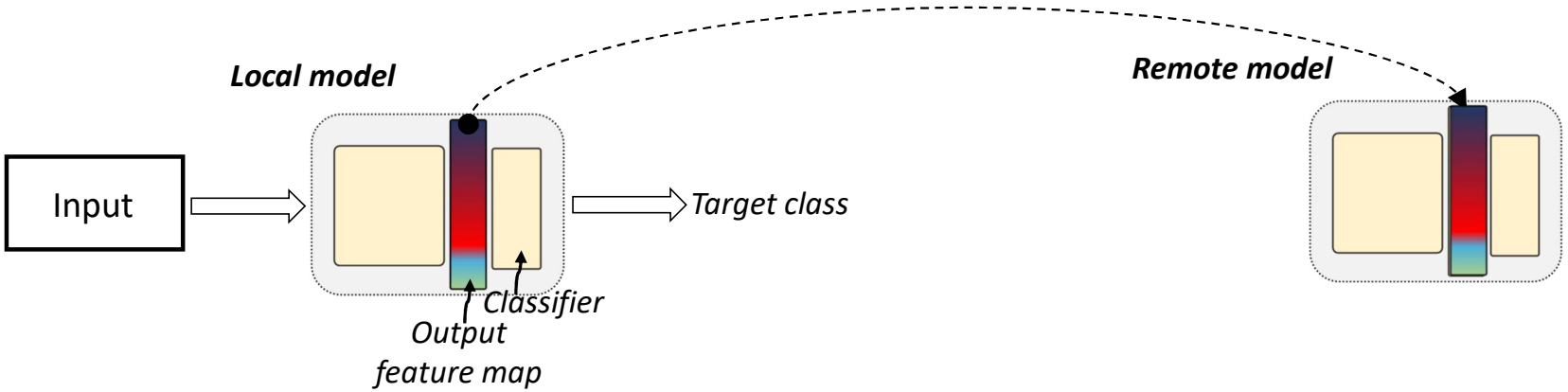

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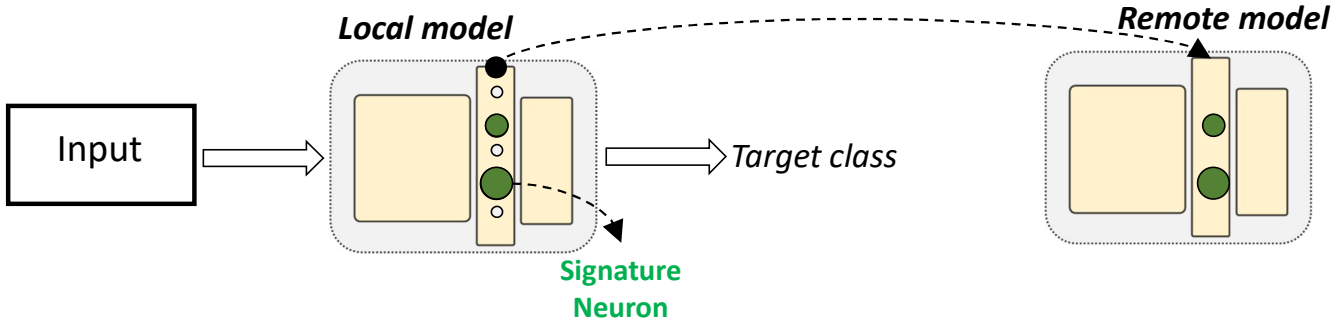
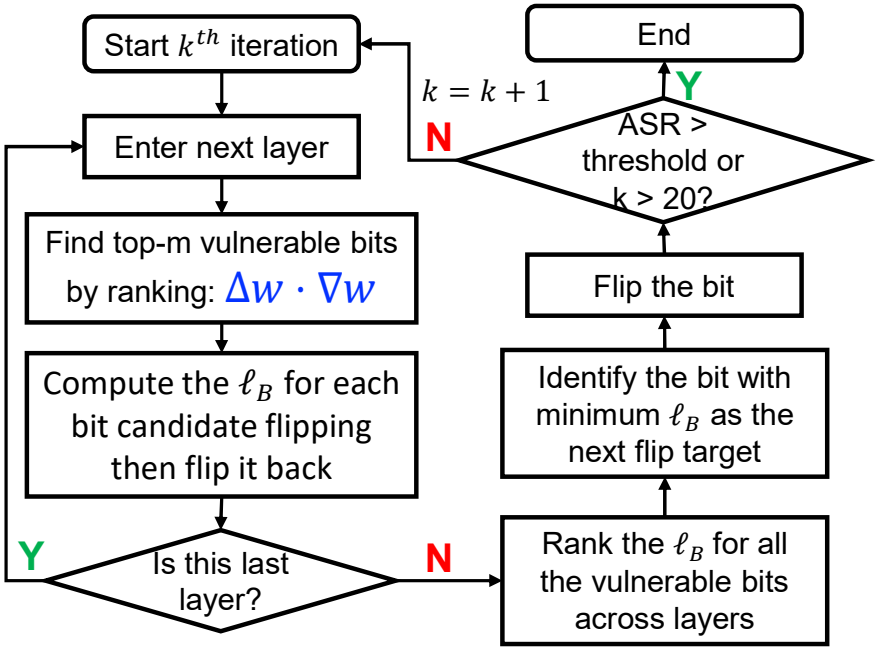


Attack Principal for Snapshot Attack

- *Transferable trigger generation:* $\ell_\delta = \mathcal{L}\left(f\left(x^*; \{W\}_{i=1}^{l-1}\right)_\Gamma, \ c\right)$
- *Signature neuron identification:* $\ell_B = \underbrace{\mathcal{L}(f\left(x^*; \{B\}_{i=1}^{l-1}\right)_\Gamma, \ \boldsymbol{c})\}}_{\text{backdoor loss}} + \lambda \cdot \underbrace{\mathcal{L}(f(x; \{B\}), \ \boldsymbol{y})\}}_{\text{clean loss}}$



Ensemble: Transferability of Weight Perturbation

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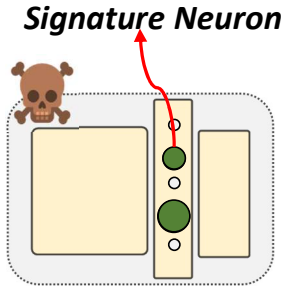

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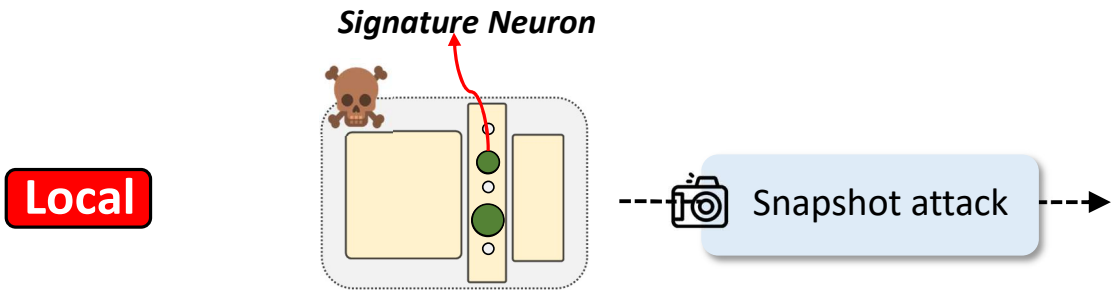

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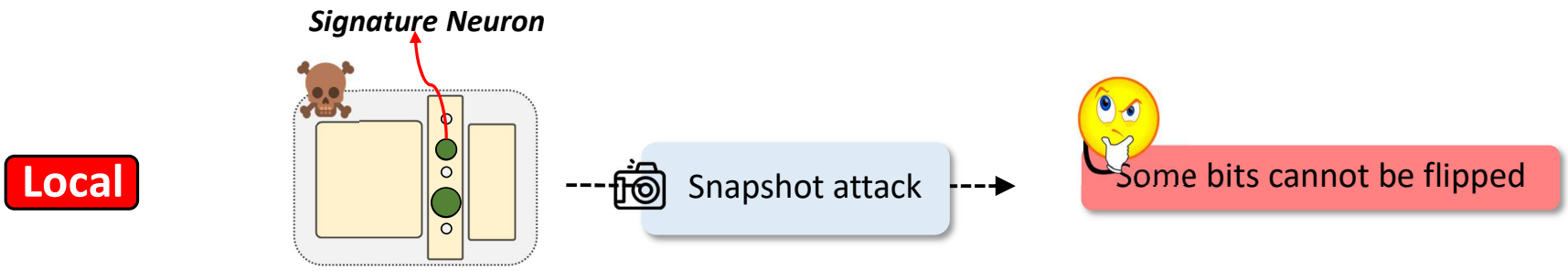

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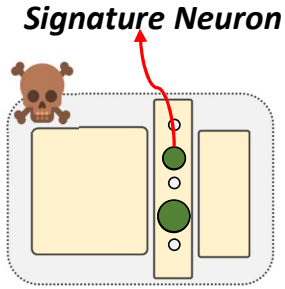

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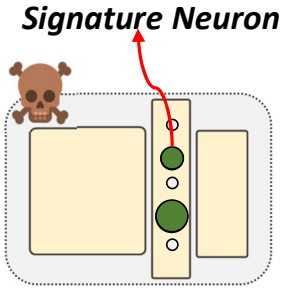

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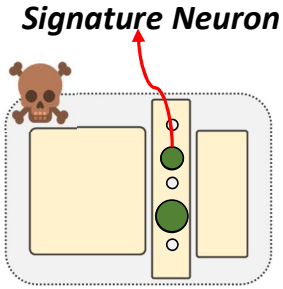

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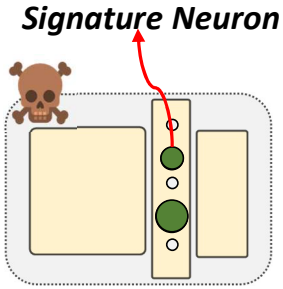

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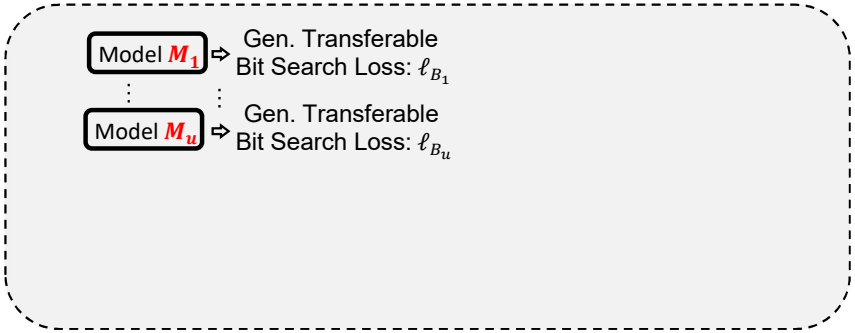

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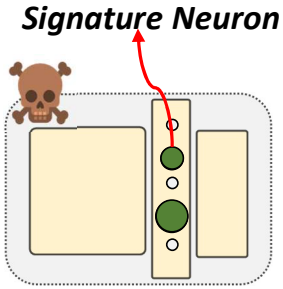

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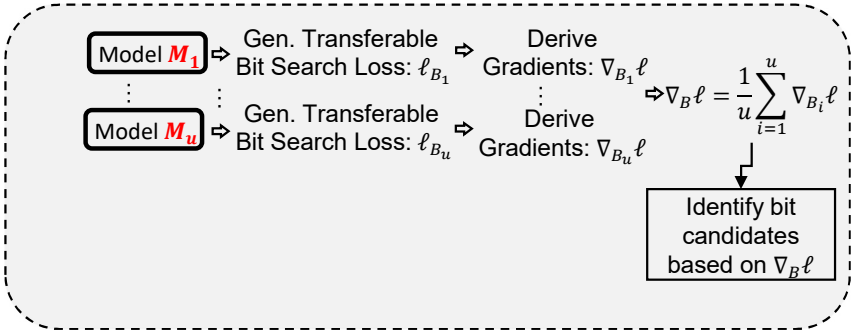

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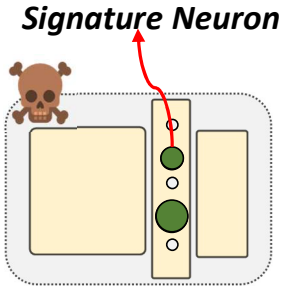

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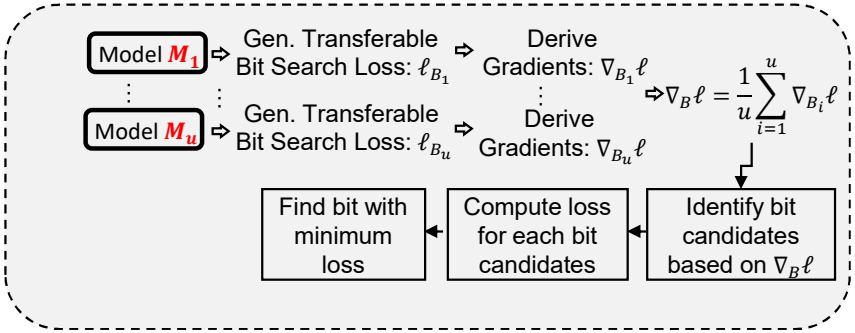

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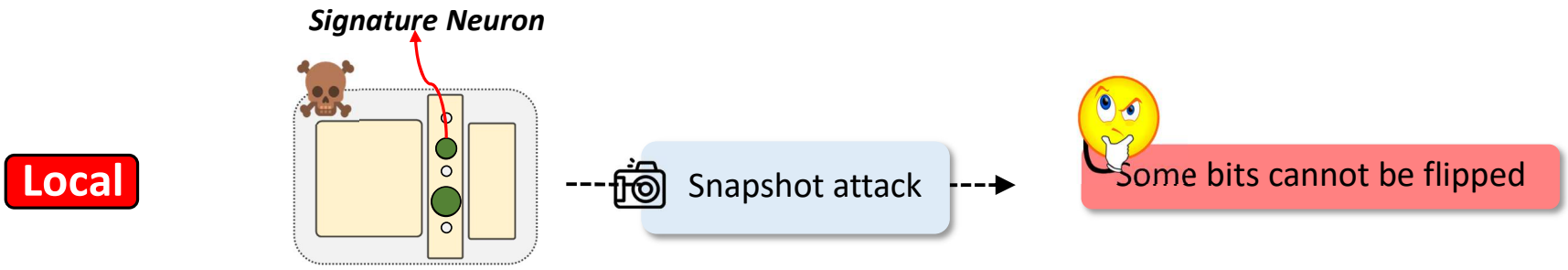

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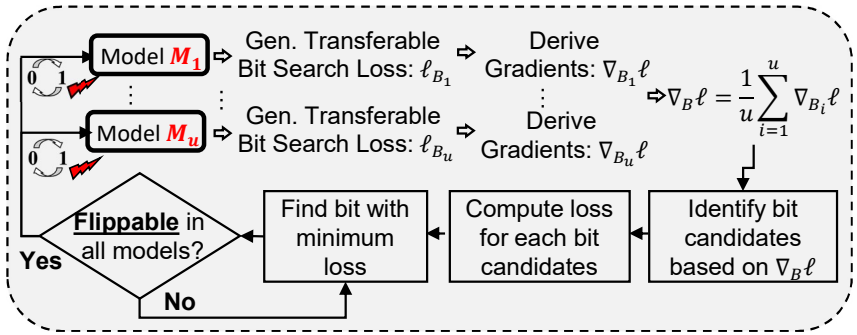
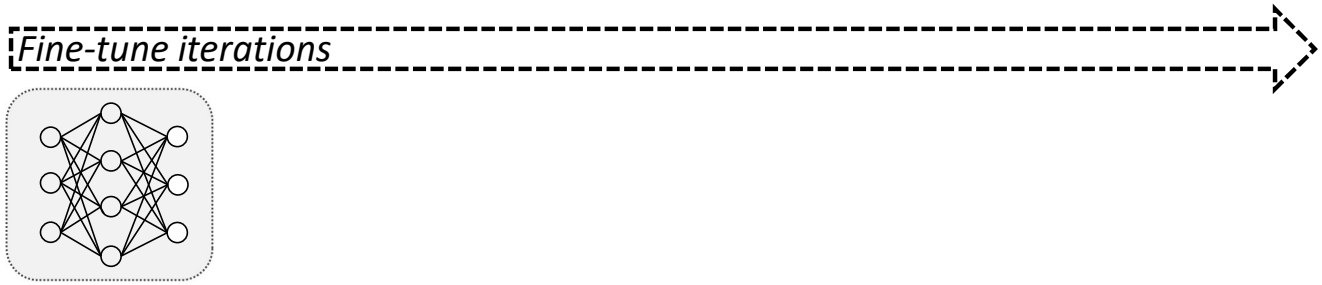


Iterative Boosting to Mitigate Forgetting



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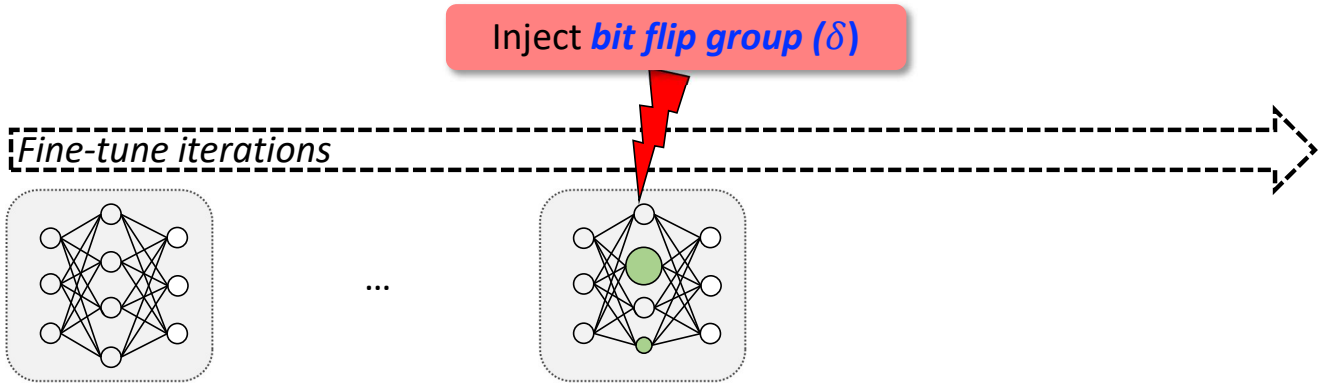

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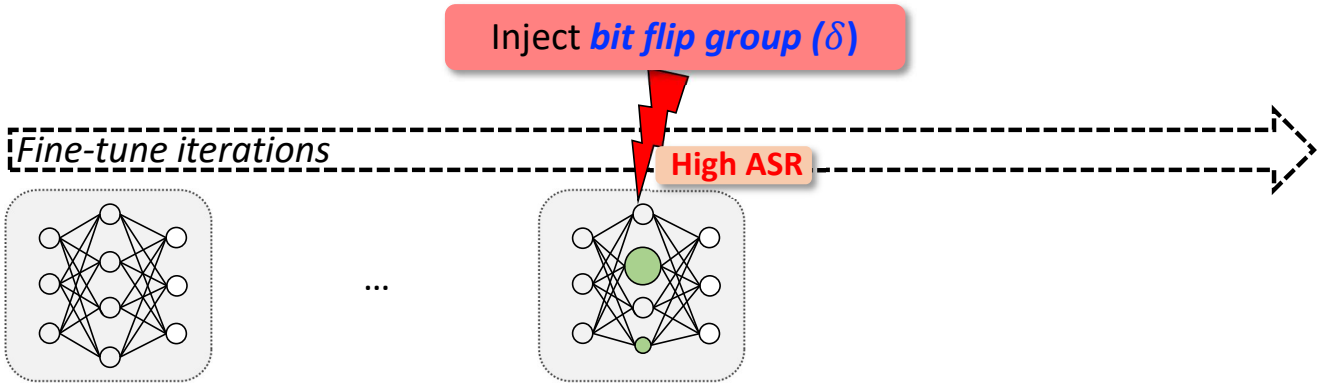

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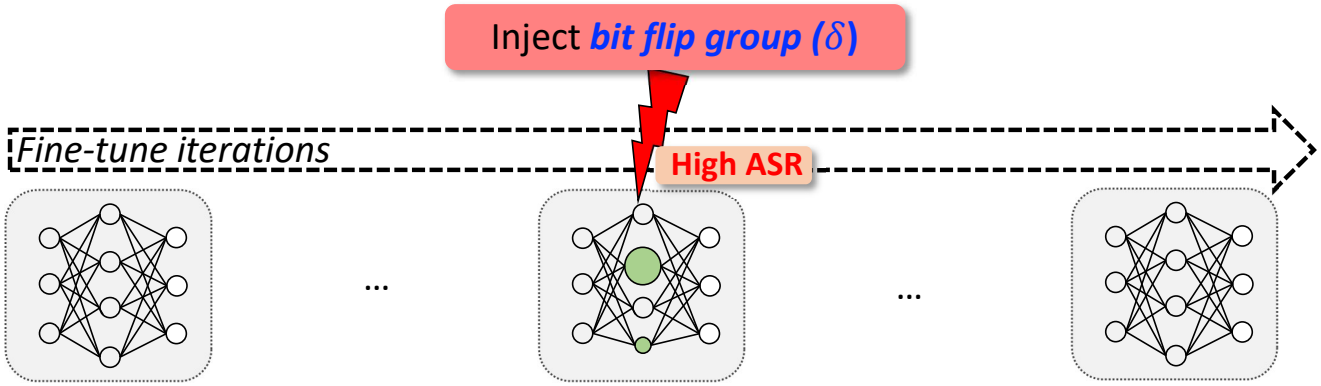

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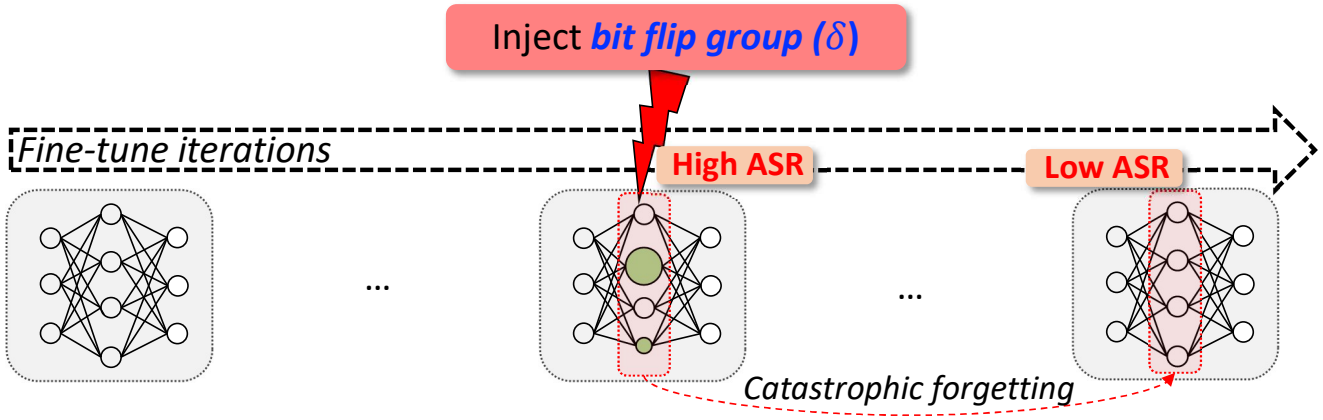

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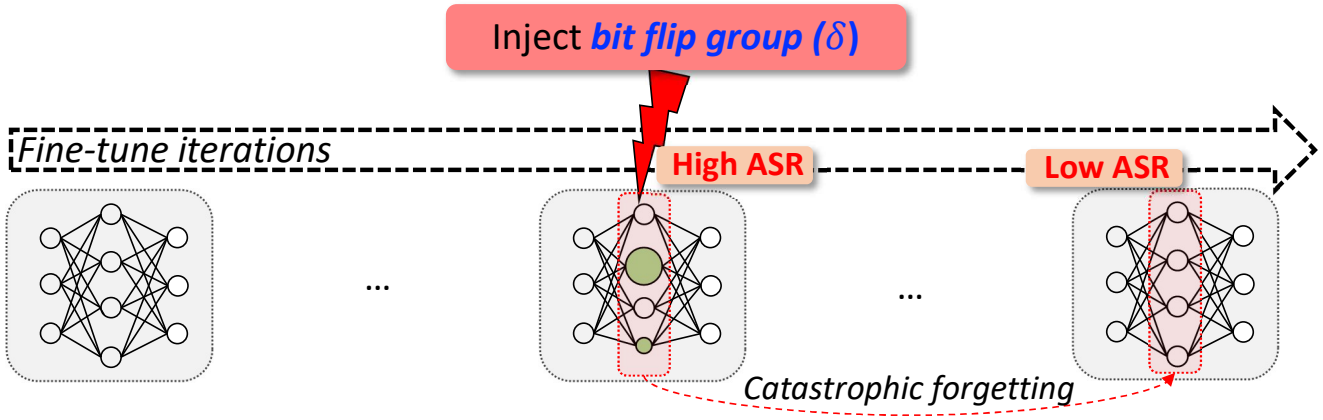
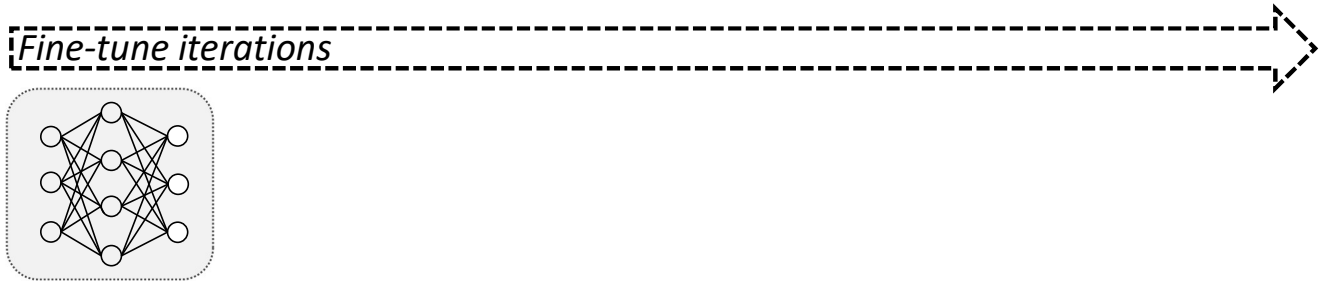


Iterative backdoor boosting



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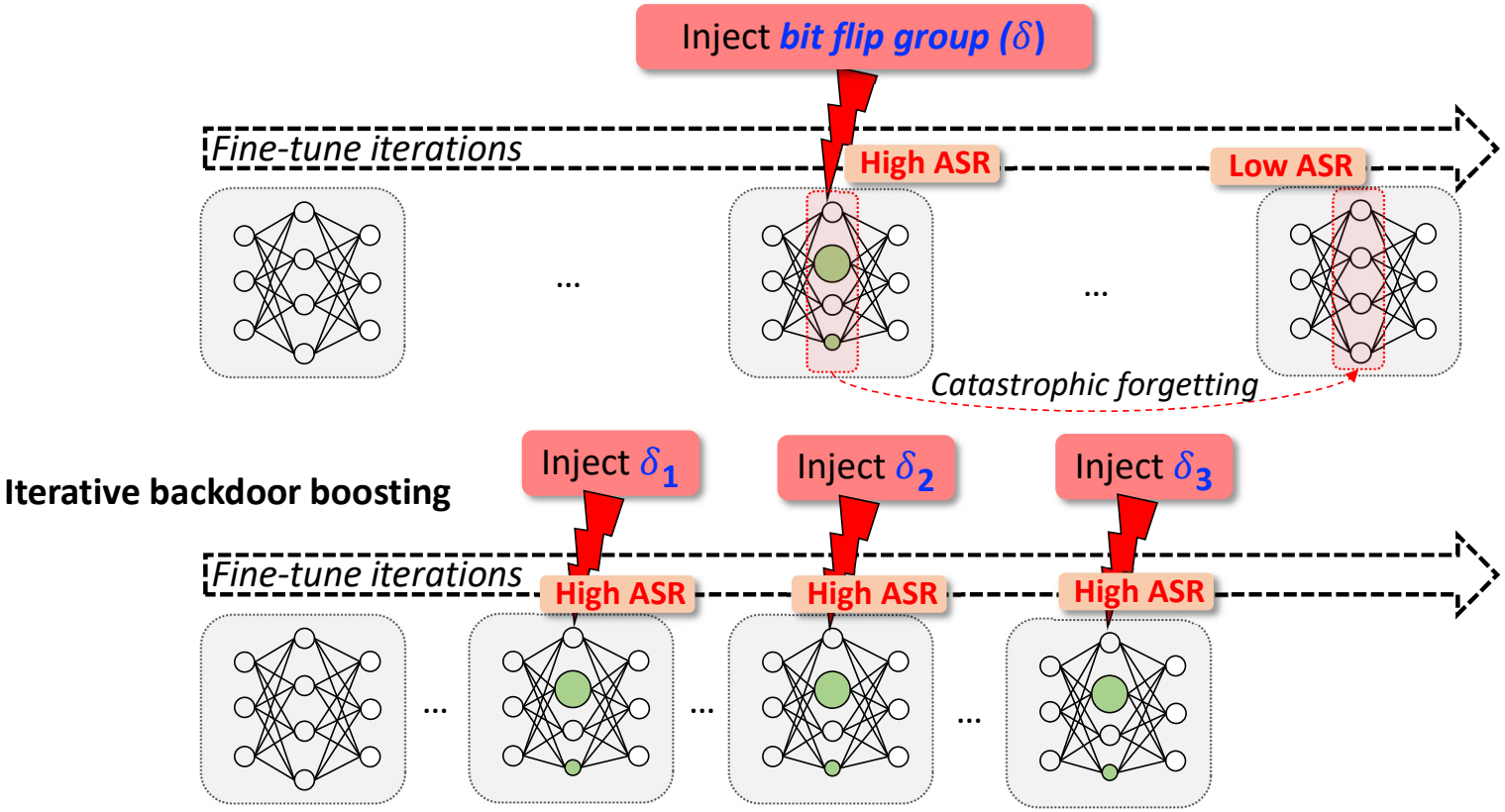

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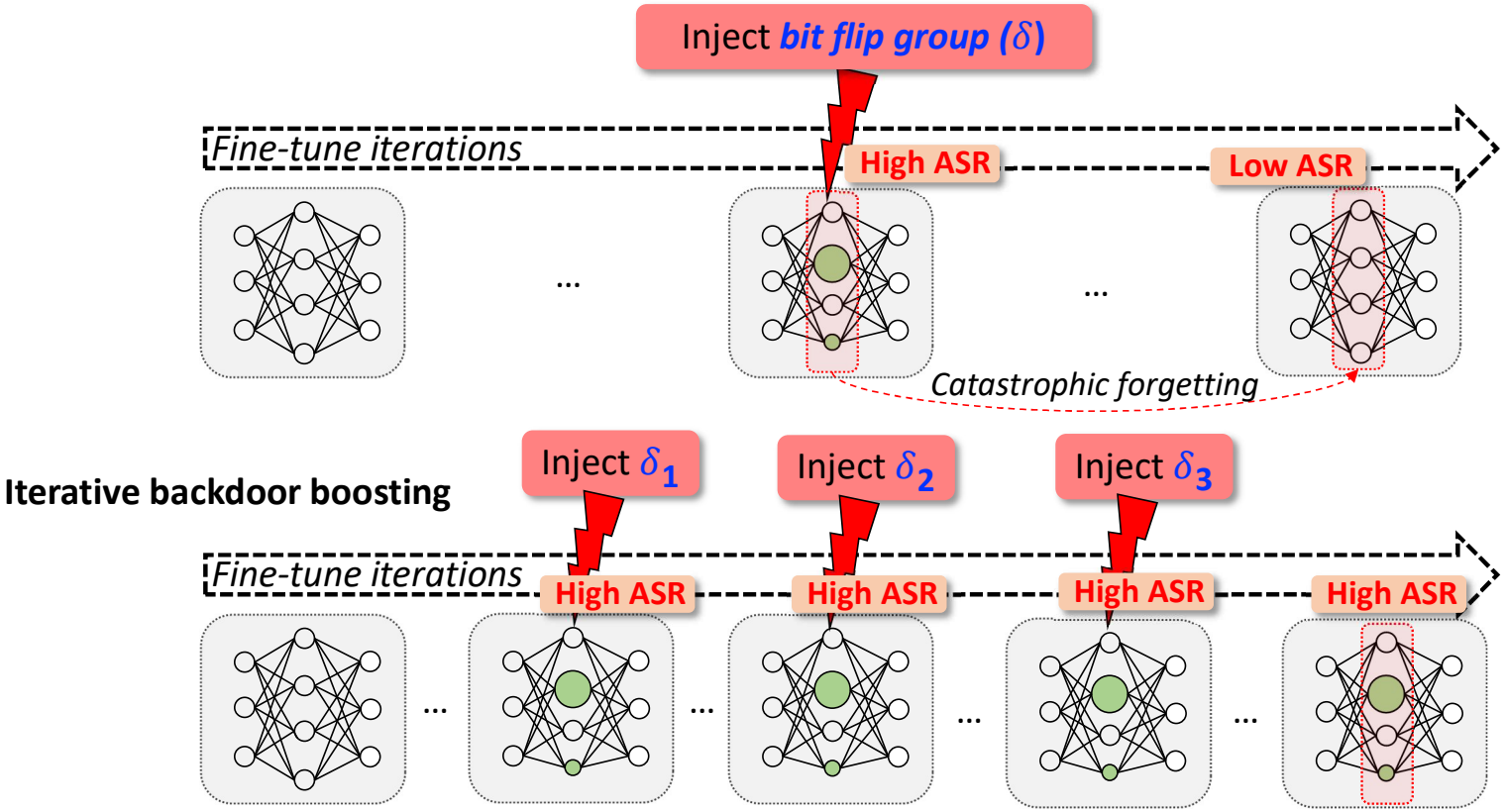

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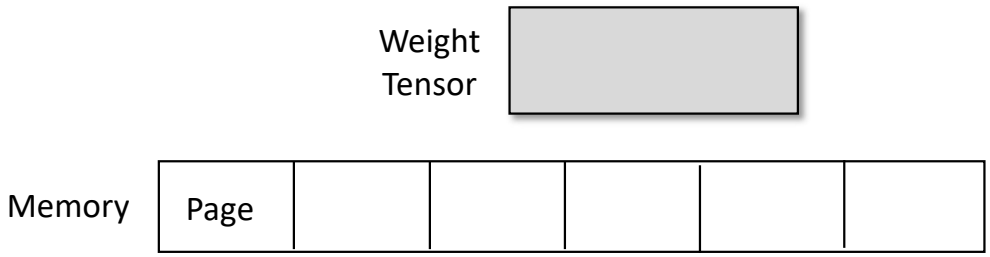

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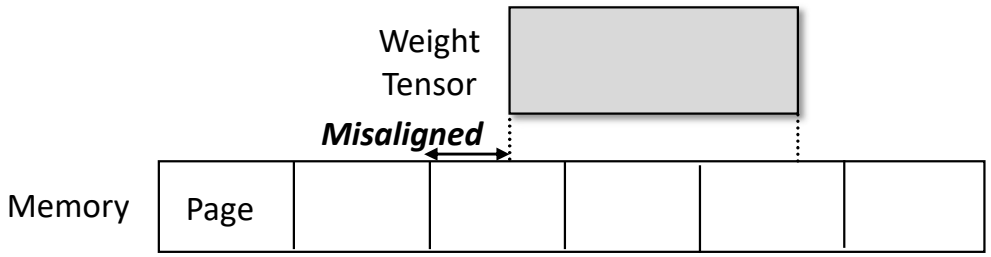

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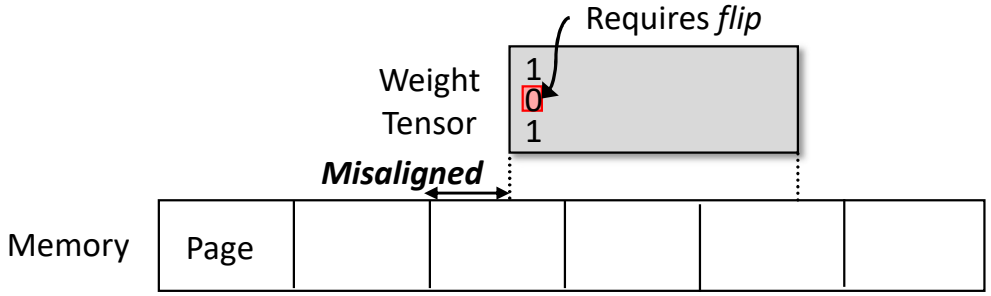

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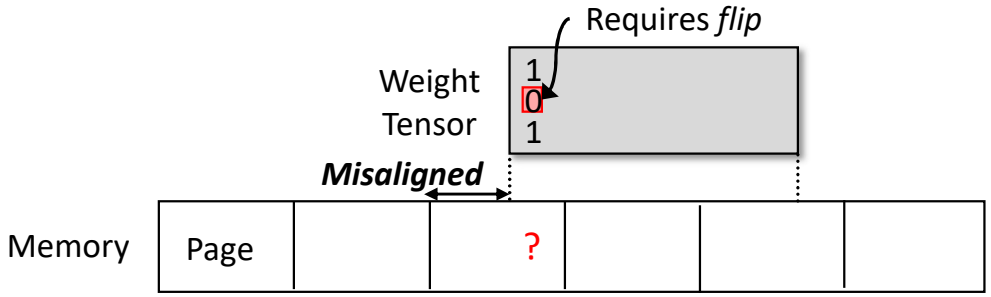

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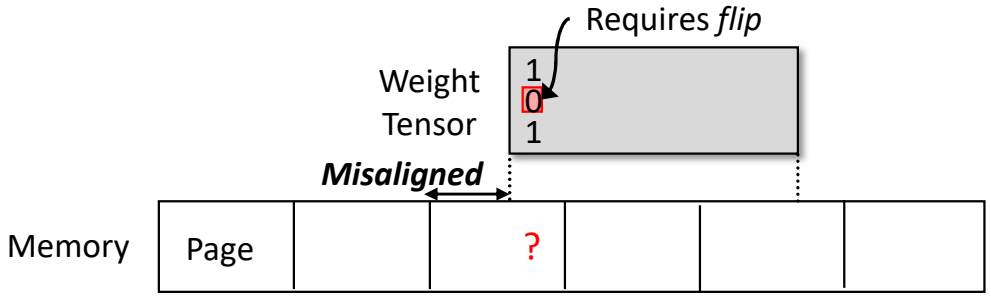

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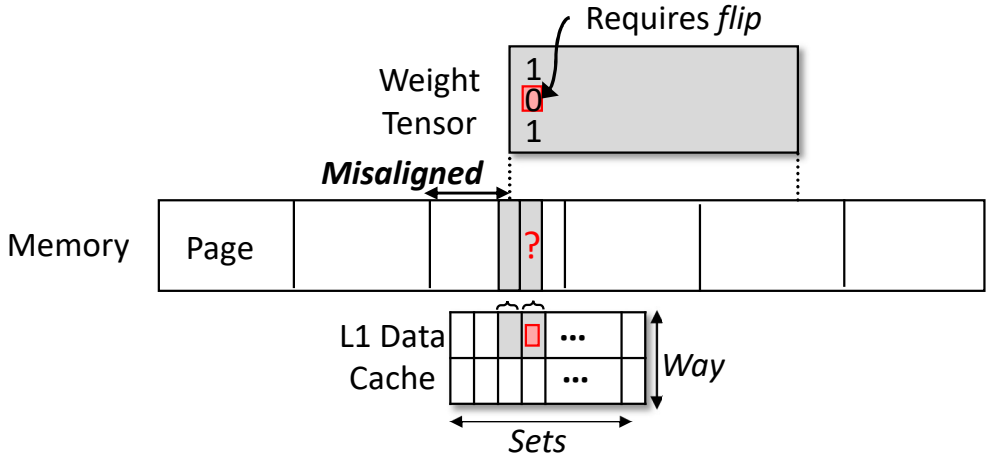

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Experiment Setup

- DeepVenom configurations
  - Two Hardware Platforms*:* Intel i7-3770 (Ivy Bridge) / i5-9500 (Coffee Lake)
  - Three architectures*:* VGG16, ResNet18/50 *and* ViT models
  - Five datasets*:* GTSRB, SVHN, CIFAR10/100, EuroSat
- Attack Performance Metrics:
  - Attack Success Rate (**ASR**), range from 0% to 100%
  - Number of Bit flips (**#BF**)
  - Normal Accuracy (**AC**)

Evaluation-Main Results

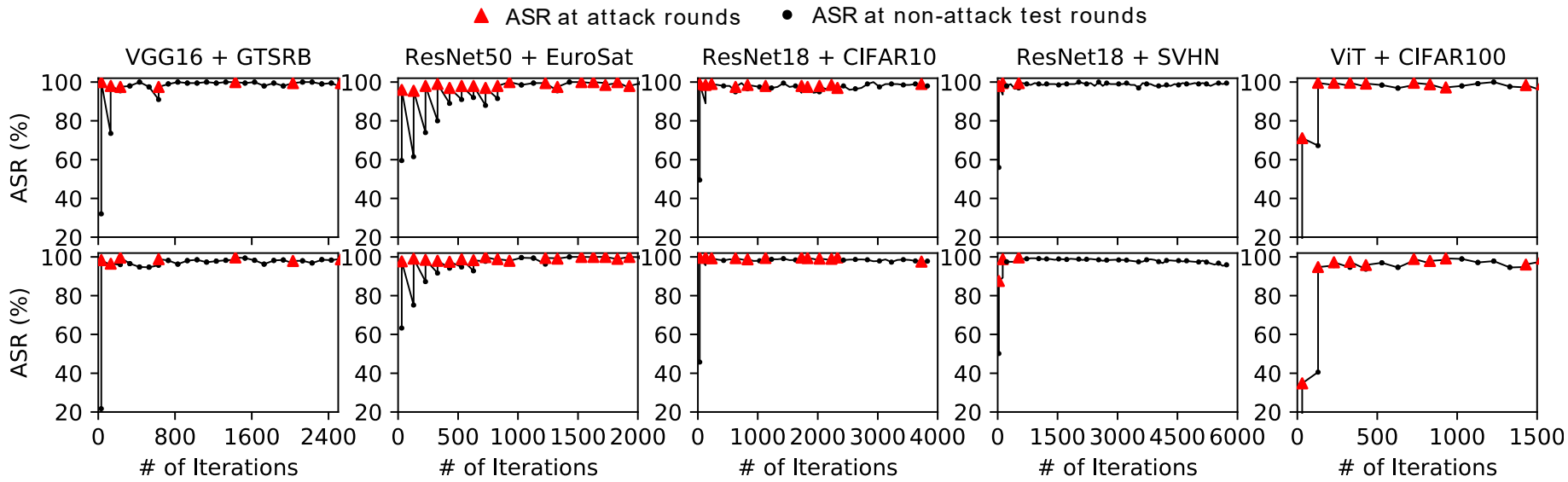

Figure 1: ASR trends for local model (top row) and victim model (bottom row) as `BFGs` are applied

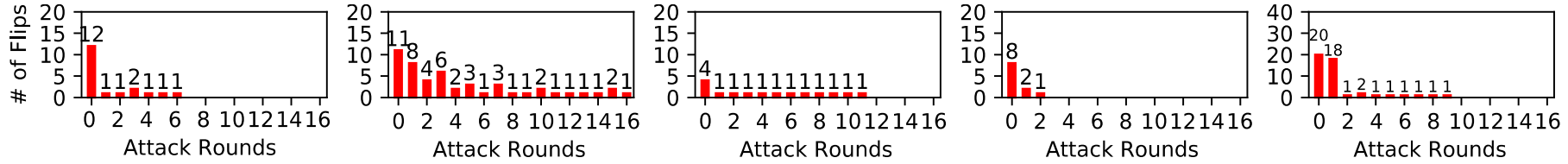

Figure 2: Number of bit flips at each attack round

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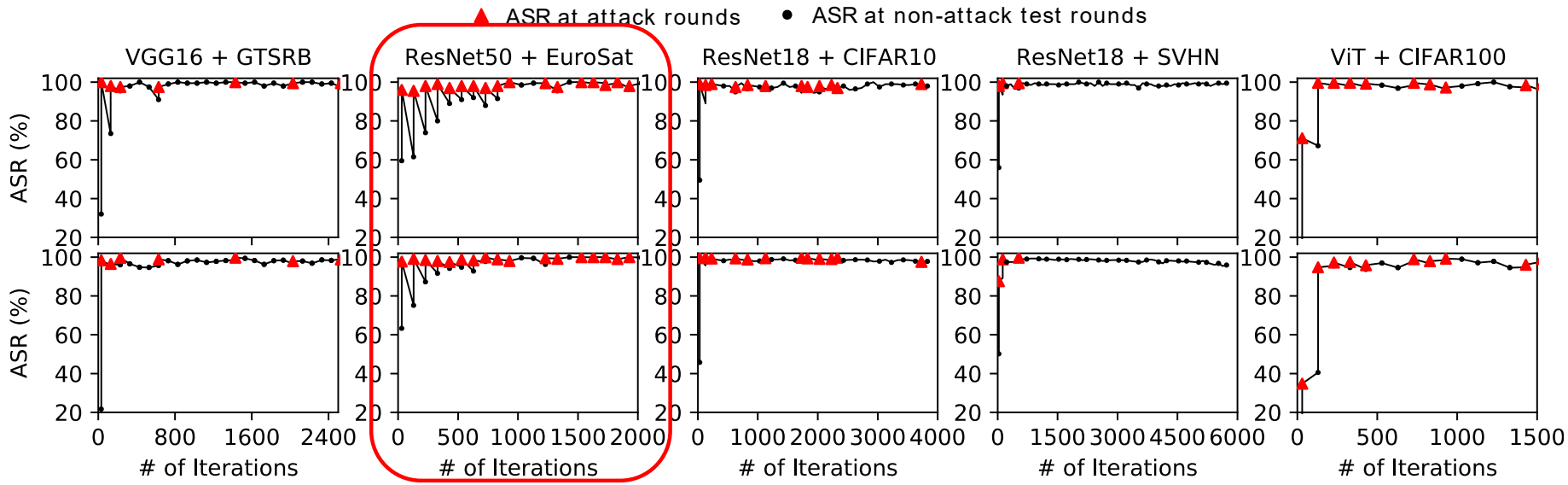

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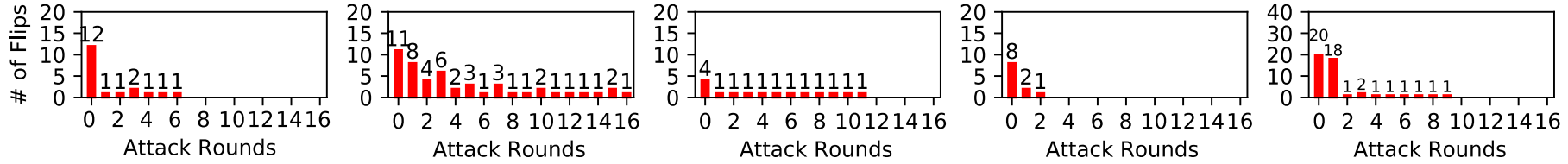

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- DeepVenom achieves high ASR on local models
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- DeepVenom achieves high ASR and minimal ACC drop in victim
- DeepVenom only requires 11-49 bits in hundreds of millions of params

Learning Scenario	Model Parameters	No. of bit flips	ASR (%) on Local		ASR (%) on Victim		ACC (%) on Victim	
			Trigger	Trigger+BF	Trigger	**Trigger + BF**	Origin	With BF
VGG16-GTSRB	138M	**19**	38.0±8.0%	97.4±3.0%	18.0±4.0%	**98.8±1.0%**	99.8%	99.8±0.1%
ResNet18-CIFAR10	11M	**15**	51.0±9.6%	98.4±0.7%	46.6±3.3%	**97.8±1.8%**	80.3%	80.2±0.2%
ResNet18-SVHN	11M	**11**	54.9±7.7%	98.5±1.1%	53.5±8.5%	**95.8±1.7%**	92.1%	92.1±0.2%
ResNet50-EuroSat	23M	**49**	65.4±13.3%	97.0±4.2%	58.6±3.1%	**99.8±0.3%**	98.4%	98.3±0.3%
ViT-CIFAR100	86M	**47**	1.2±0.3%	97.4±2.3%	1.5±0.5%	**97.0±4.4%**	85.8%	85.5±0.4%

TABLE: Evaluation results on the main attack configuration (with the ensemble method). Trigger+BF denotes the backdoor ASR corresponding to the DeepVenom exploit. Each ASR and ACC result is denoted as average±stdev.

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VGG16-GTSRB	138M	**19**	38.0±8.0%	97.4±3.0%	18.0±4.0%	**98.8±1.0%**	99.8%	99.8±0.1%
ResNet18-CIFAR10	11M	**15**	51.0±9.6%	98.4±0.7%	46.6±3.3%	**97.8±1.8%**	80.3%	80.2±0.2%
ResNet18-SVHN	11M	**11**	54.9±7.7%	98.5±1.1%	53.5±8.5%	**95.8±1.7%**	92.1%	92.1±0.2%
ResNet50-EuroSat	23M	**49**	65.4±13.3%	97.0±4.2%	58.6±3.1%	**99.8±0.3%**	98.4%	98.3±0.3%
ViT-CIFAR100	86M	**47**	1.2±0.3%	97.4±2.3%	1.5±0.5%	**97.0±4.4%**	85.8%	85.5±0.4%

TABLE: Evaluation results on the main attack configuration (with the ensemble method). Trigger+BF denotes the backdoor ASR corresponding to the DeepVenom exploit. Each ASR and ACC result is denoted as average±stdev.

Evaluation-Main Results

- DeepVenom achieves high ASR on local models
- The impact of weight perturbation is significant
- DeepVenom achieves high ASR and minimal ACC drop in victim
- DeepVenom only requires 11-49 bits in hundreds of millions of params

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			Trigger	Trigger+BF	Trigger	**Trigger + BF**	Origin	With BF
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TABLE: Evaluation results on the main attack configuration (with the ensemble method). Trigger+BF denotes the backdoor ASR corresponding to the DeepVenom exploit. Each ASR and ACC result is denoted as average±stdev.

Sensitivity Analysis-Relaxed Time Requirement

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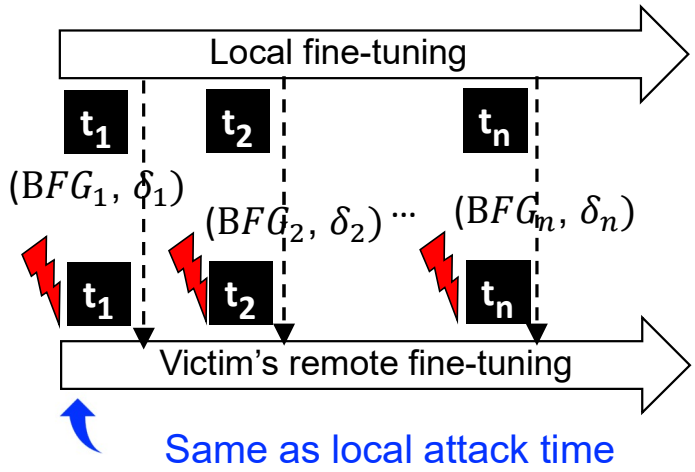
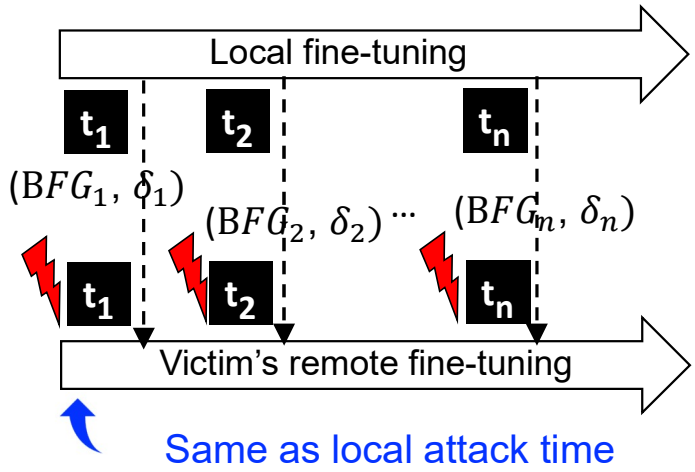
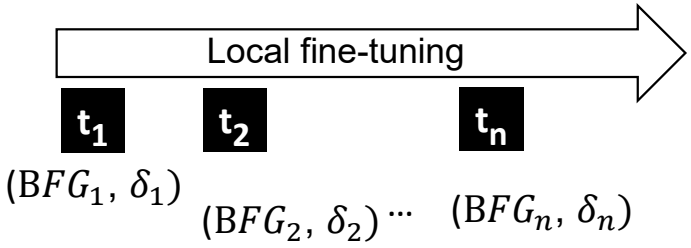
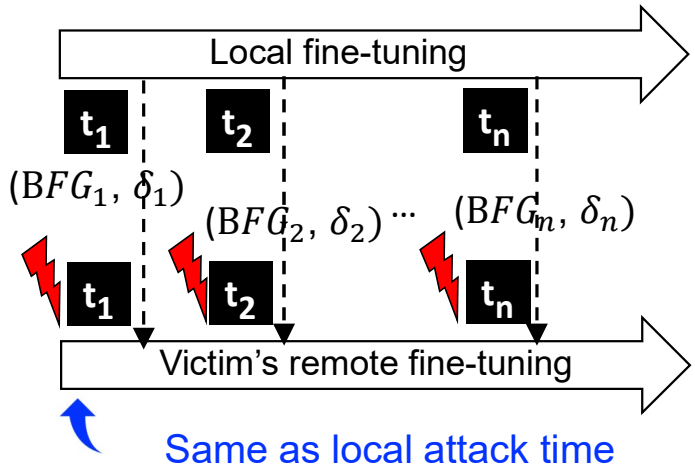


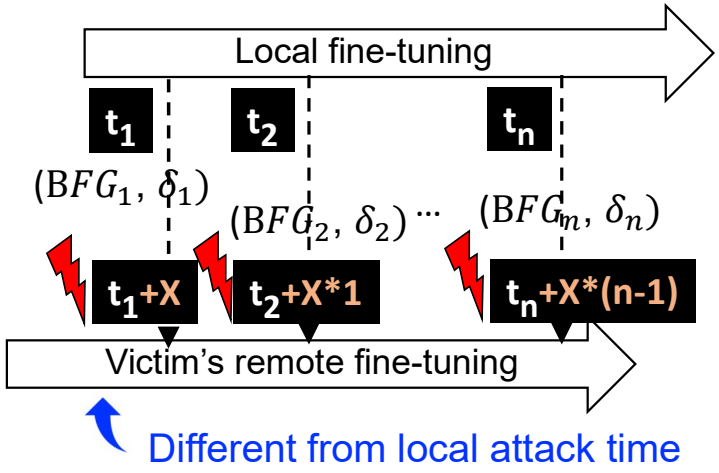
Sensitivity Analysis-Relaxed Time Requirement





Sensitivity Analysis-Relaxed Time Requirement





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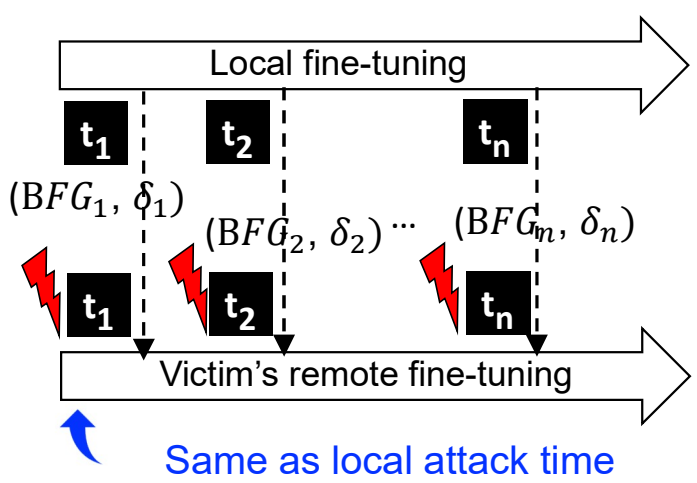

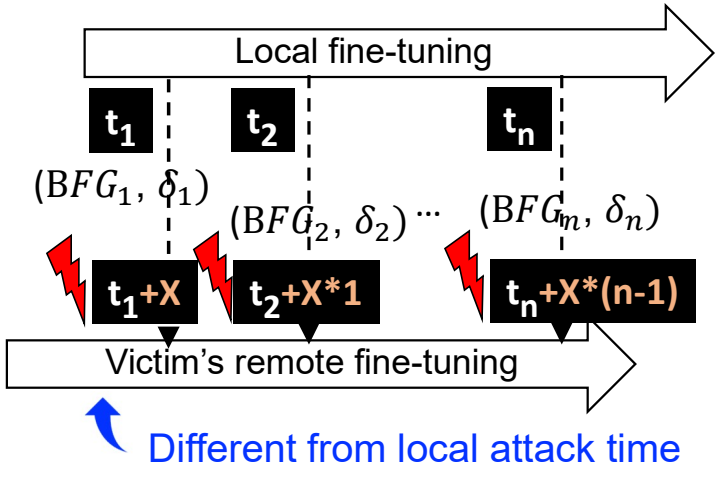

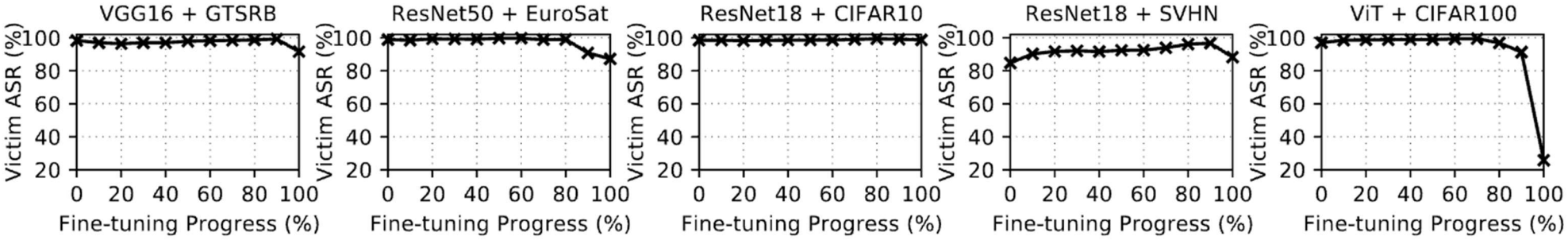

Figure: Results with relaxed attack time requirement. 0% and 100% denote the start and end of victim's fine-tuning.

More on Paper

- Attacks with **varying victim model hyperparameters:**

Learning Settings	No. of Bit Flips	Adam, LR=1e-5		Adam, LR=2e-5		Adam, LR=5e-5		SGD, LR=5e-4		SGD, LR=1e-3	
		ASR	AD	ASR	AD	ASR	AD	ASR	AD	ASR	AD
VGG16-GTSRB	19	98.1±1.6%	0.1%	98.8±1.0%	0.0%	93.5±3.3%	0.0%	92.9±4.6%	0.0%	94.4±5.3%	0.0%
ResNet18-CIFAR10	15	98.6±1.8%	-0.1%	97.8±1.8%	0.1%	92.9±4.3%	-0.2%	90.8±2.6%	-0.1%	87.4±4.4%	-0.1%
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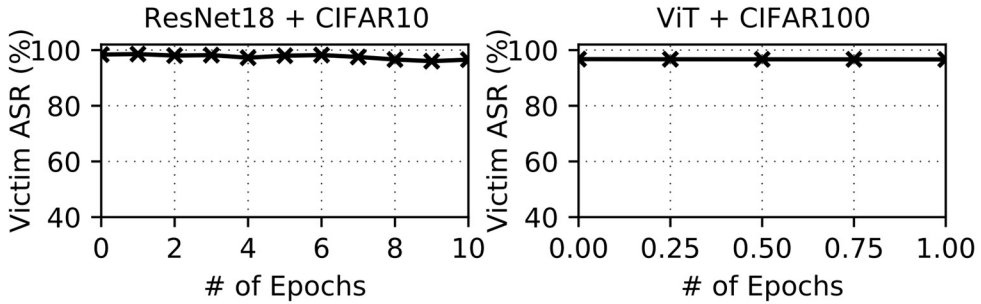
ViT-CIFAR100	47	99.5±0.5%	-0.1%	97.0±4.4%	0.3%	72.9±8.1%	0.6%	98.3±0.9%	0.0%	82.2±9.4%	0.3%

- Impact of **extended fine-tuning:**



More on Paper

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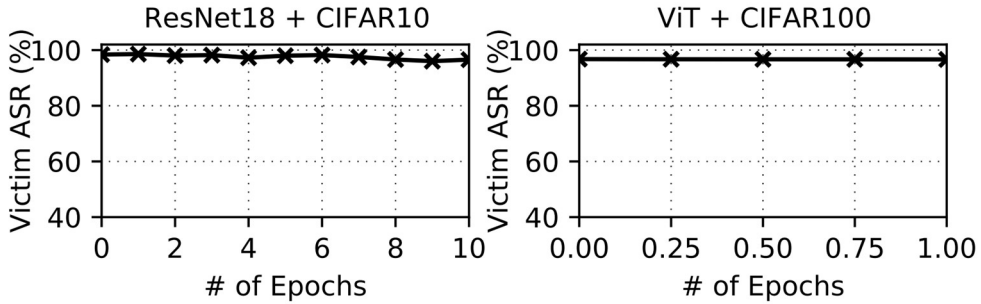

More on Paper

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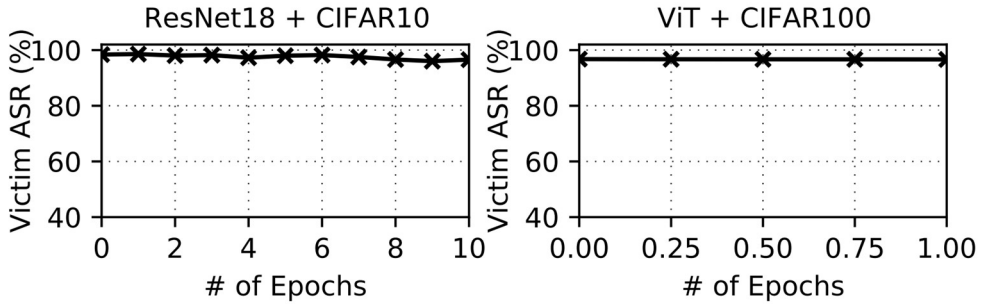

- Attacks on **GPU**:
  - Emulated bit flips on NVIDIA A40 GPU.
  - Evaluated using VGG16-GTSRB and ResNet18-CIFAR10 configurations.

  - ASRs on the GPU are comparable to the CPU counterparts with **<1.4% difference**.

Conclusions

- First investigation of training time fault attacks in transfer learning.
- Identified unique challenges of training time hardware-based trojan.
- Design of novel mechanisms enabling transfer of weight perturbation.
- Successful compromise of state-of-the-art CNNs and ViT.

Thanks! Questions?

Fan Yao
Email: fan.yao@ucf.edu

Source code: https://github.com/casrl/DeepVenom