PBP: Post-training Backdoor Purification for Malware Classifiers

Dung (Judy) Nguyen, Ngoc N. Tran, Taylor T. Johnson, Kevin Leach

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VANDERBILT UNIVERSITY
Institute for Software Integrated Systems

HOTSOS 2025

Machine Learning for Malware Classifiers

ML and DL have been increasingly used for Malware Classification

Training requires a large database, collecting data in the wild can introduce risks

VirusShare.com

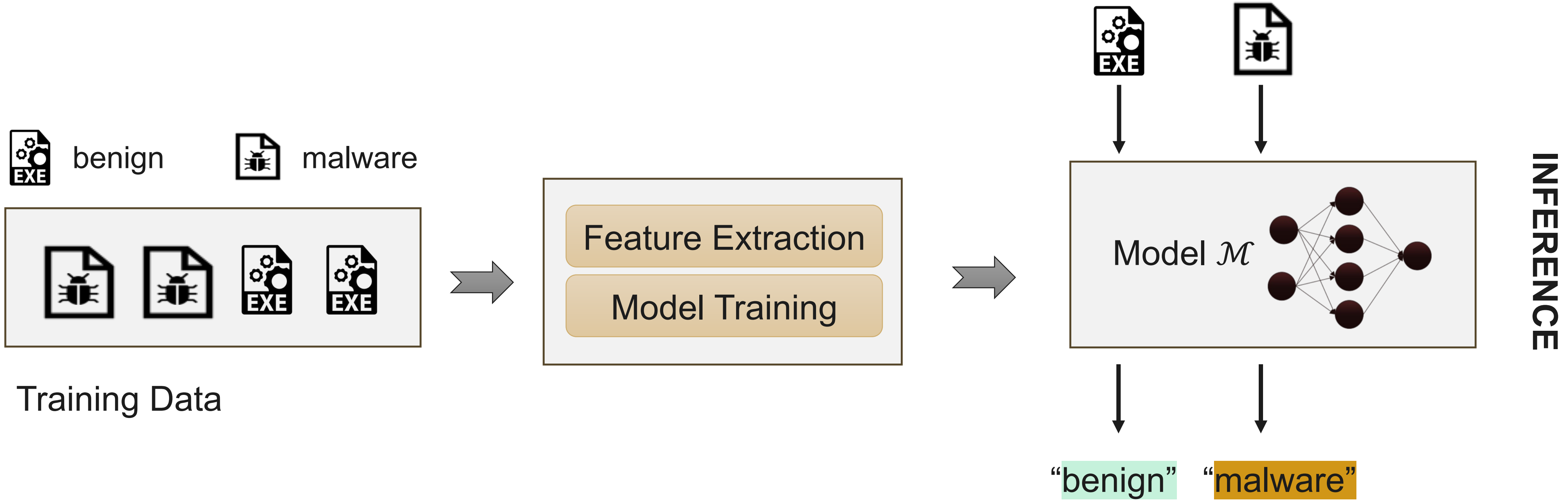
VIRUSTOTAL

ThreatConnect.

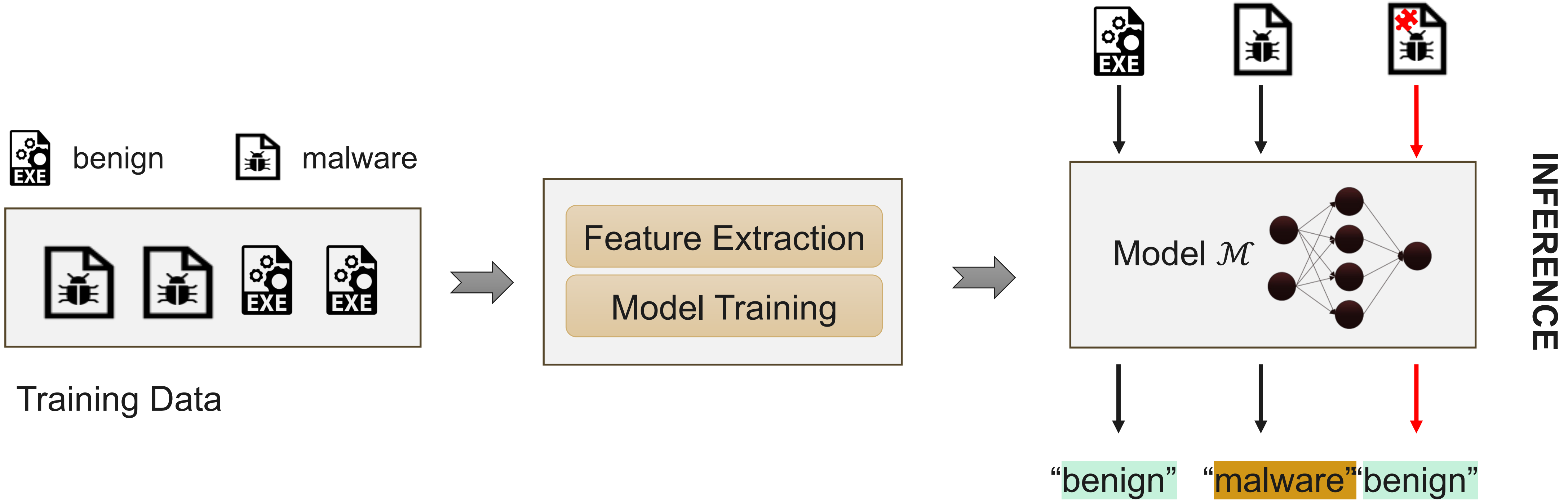
MALWARE BAZAAR

VIRUSSIGN

Training Malware Classifier: An Example



Backdoor Attack Pipeline: An Example



- The backdoored model will misclassify inputs given an embedded trigger

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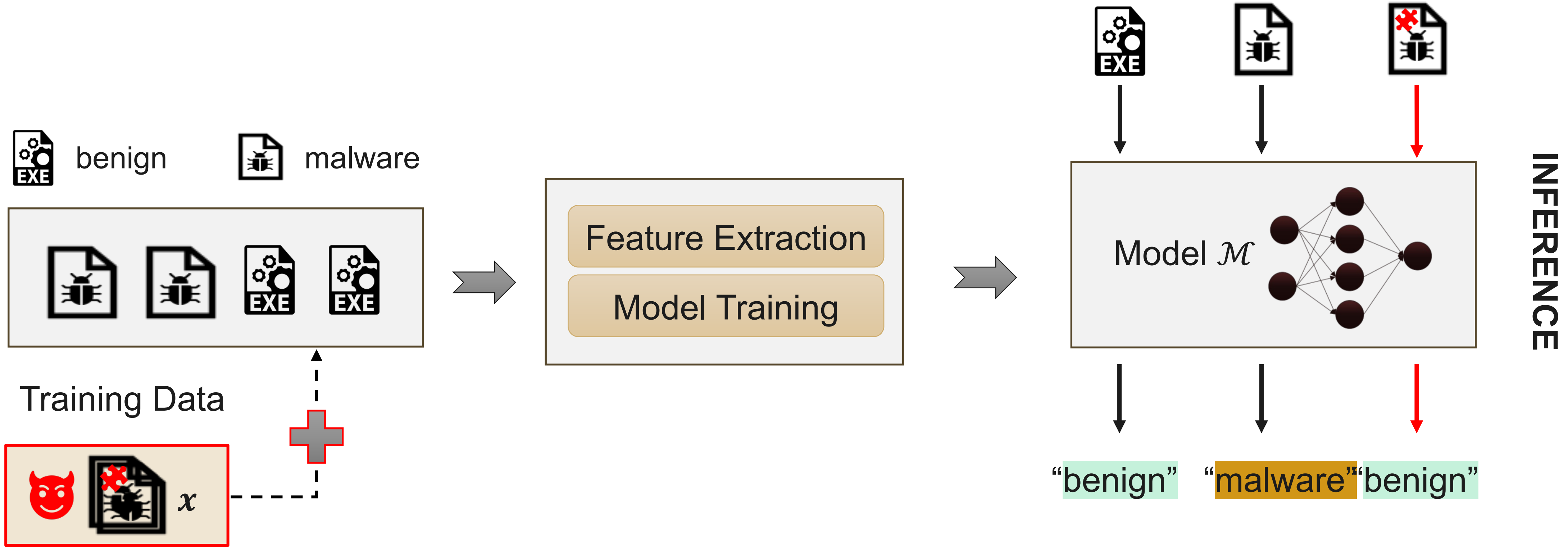

Attacker ( ) poisons a portion of training data, adding a "trigger - ✖ " to certain inputs, ultimately influencing the model.

➢ The backdoored model will misclassify inputs given an embedded trigger ✖

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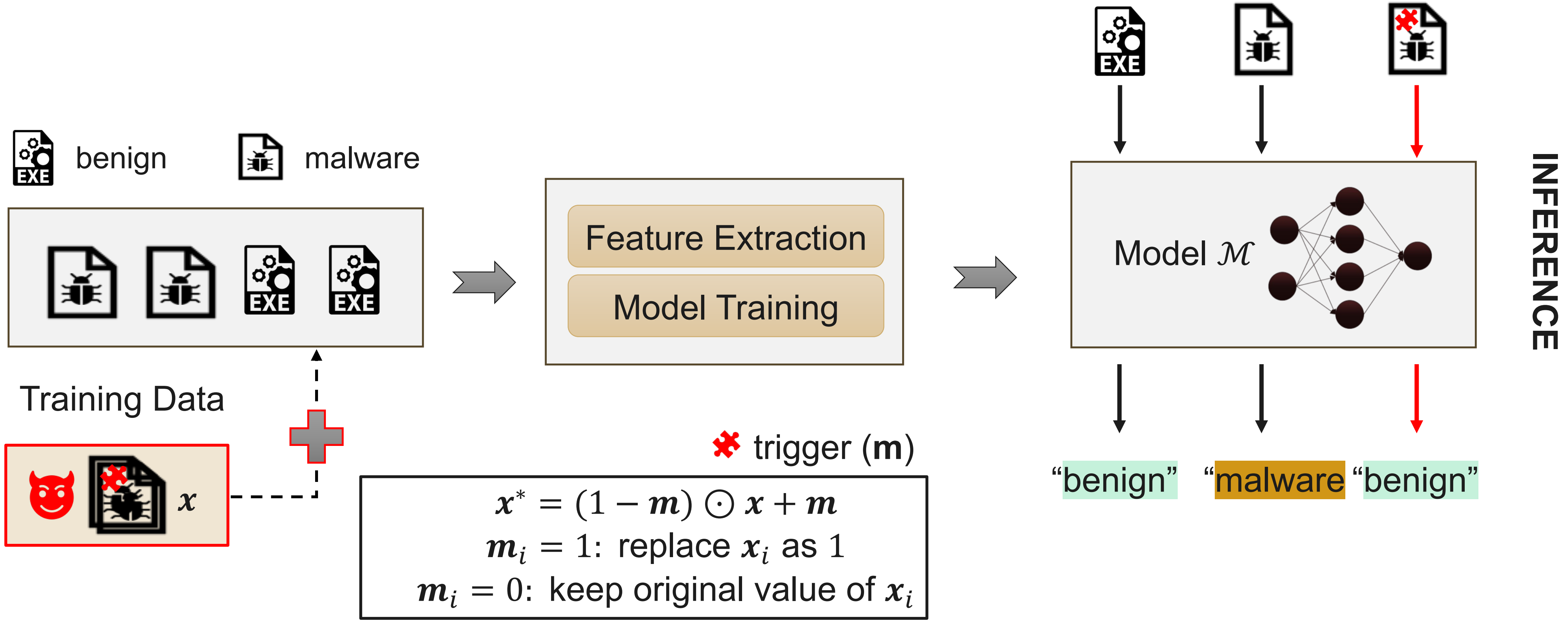

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Backdoor Attack Makes Model Vulnerable

- **Threat Models:**
  - Adversary has no control on training process
  - Stealthy backdoor: poisoned training set (poisoning rate) **(<0.5—1%)**
  - Clean-label attack: not changing the labels of poisoning set
- **Attack Results:**
  - Almost **100%** Attack Success Rate (ASR[2])
  - Can **bypass** existing **backdoor defenses**

Table: JIGSAW attacks performance with different targeted families[1].

Poisoning Rate	Targeted Family	ASR
0.005	Mobisec	0.980
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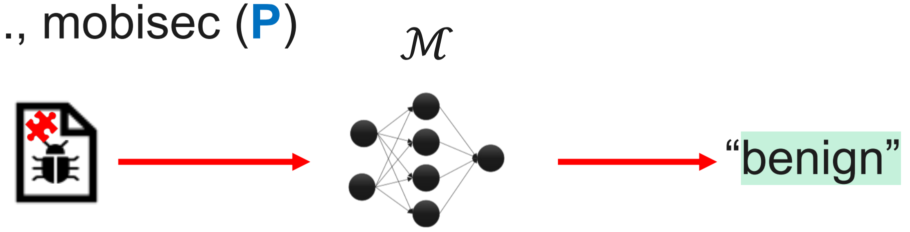
e.g., mobisec (**P**)



[2]**ASR:** How often a model classify a poisoned malware sample into benign?

[1] Yang, Limin, et al. "Jigsaw puzzle: Selective backdoor attack to subvert malware classifiers." *2023 IEEE Symposium on Security and Privacy (SP).*

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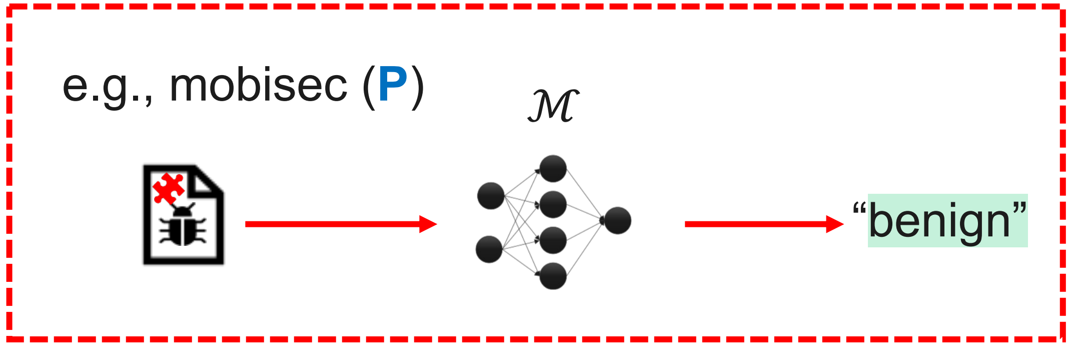
  - Not know the target (**P**) nor the trigger (✖)
  - Negligible modification required, i.e., minimal fingerprints



Poisoning Rate: 0.5%, Mask size ratio: 64/10000

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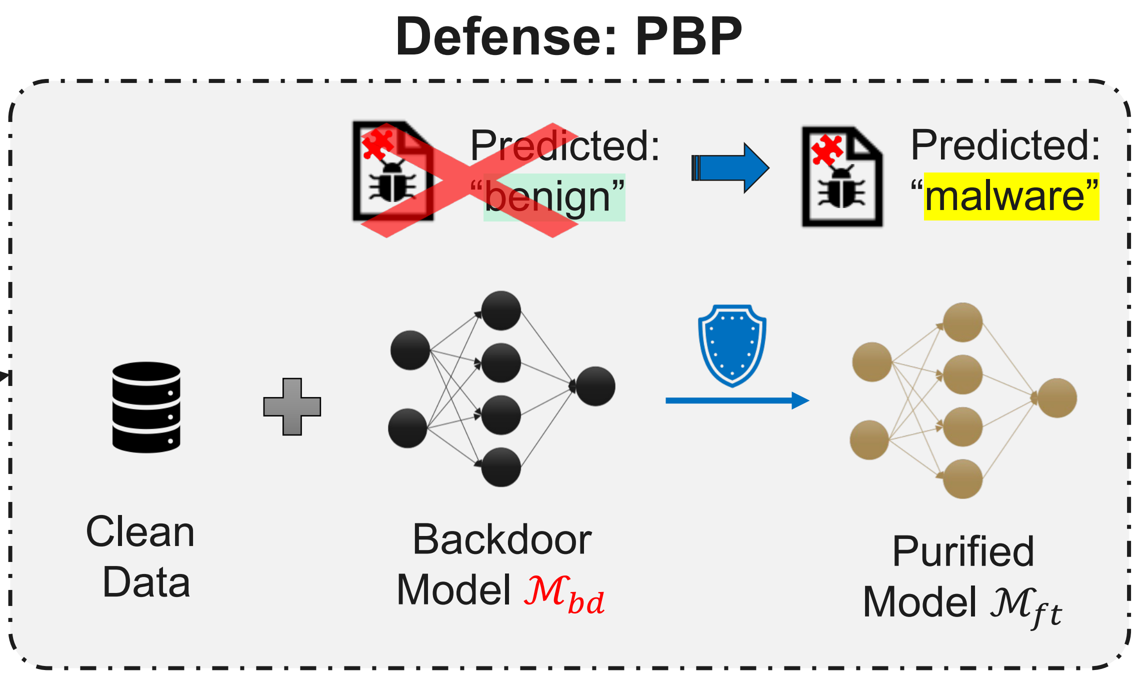

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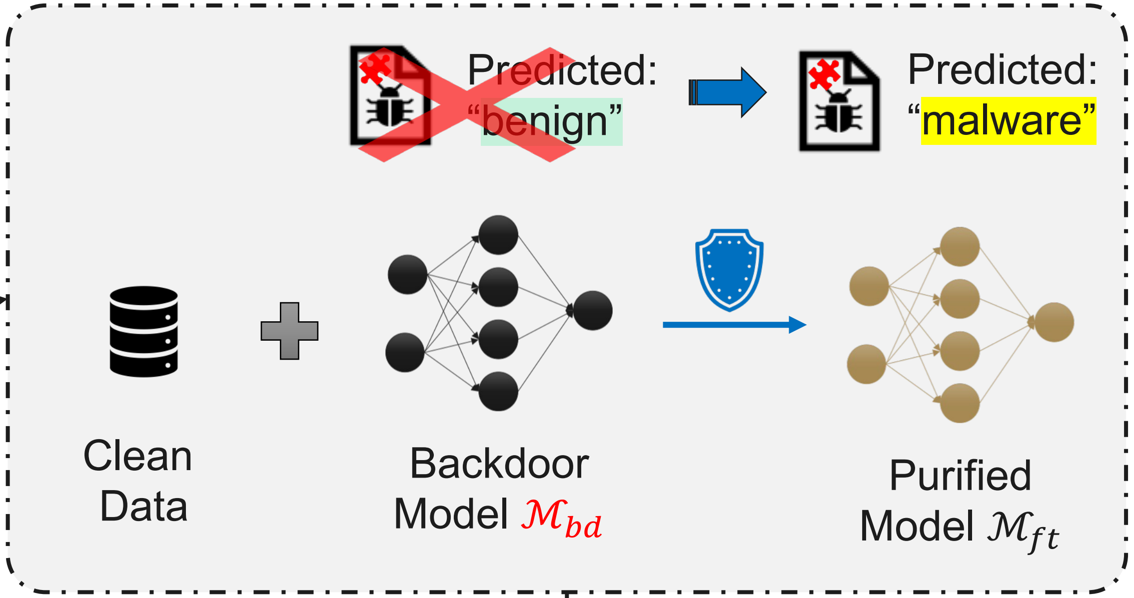
Defense: PBP



- first **post-training** defense: correct a backdoored malware classifier
- requires **no prior knowledge** of attack
- practical assumption: **limited** clean **data**, various architectures

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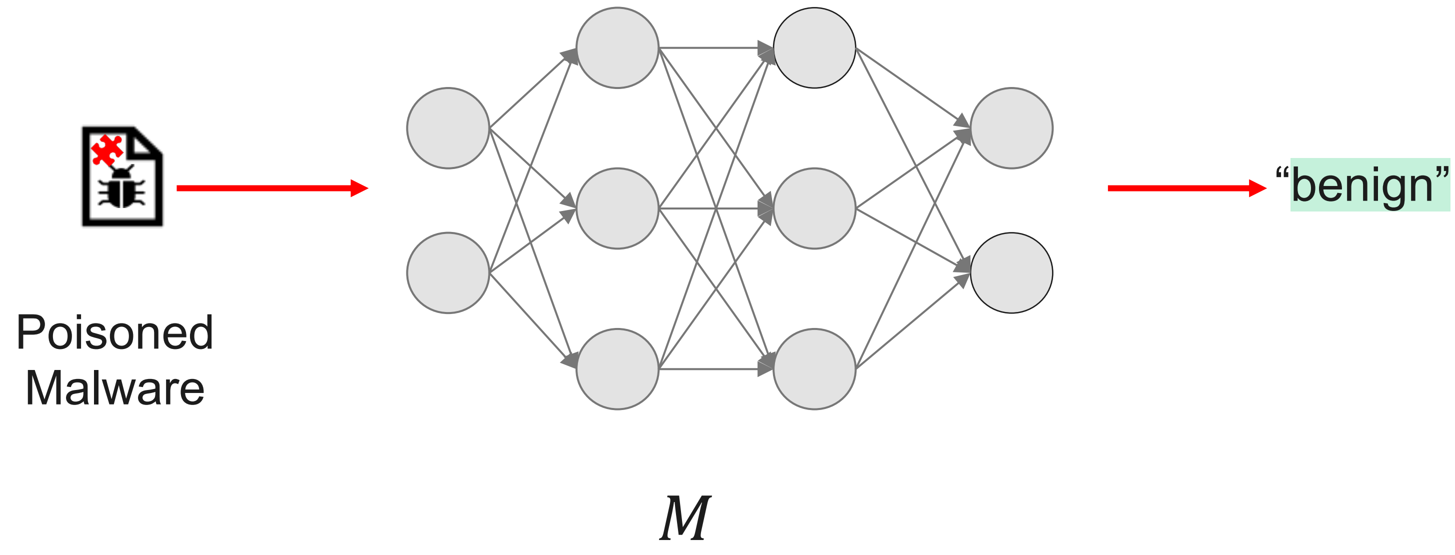
Insight: Backdoor Neurons



Li, Boheng, et al. "Purifying Quantization-conditioned Backdoors via Layer-wise Activation Correction with Distribution Approximation." *Forty-first International Conference on Machine Learning*. 2024.

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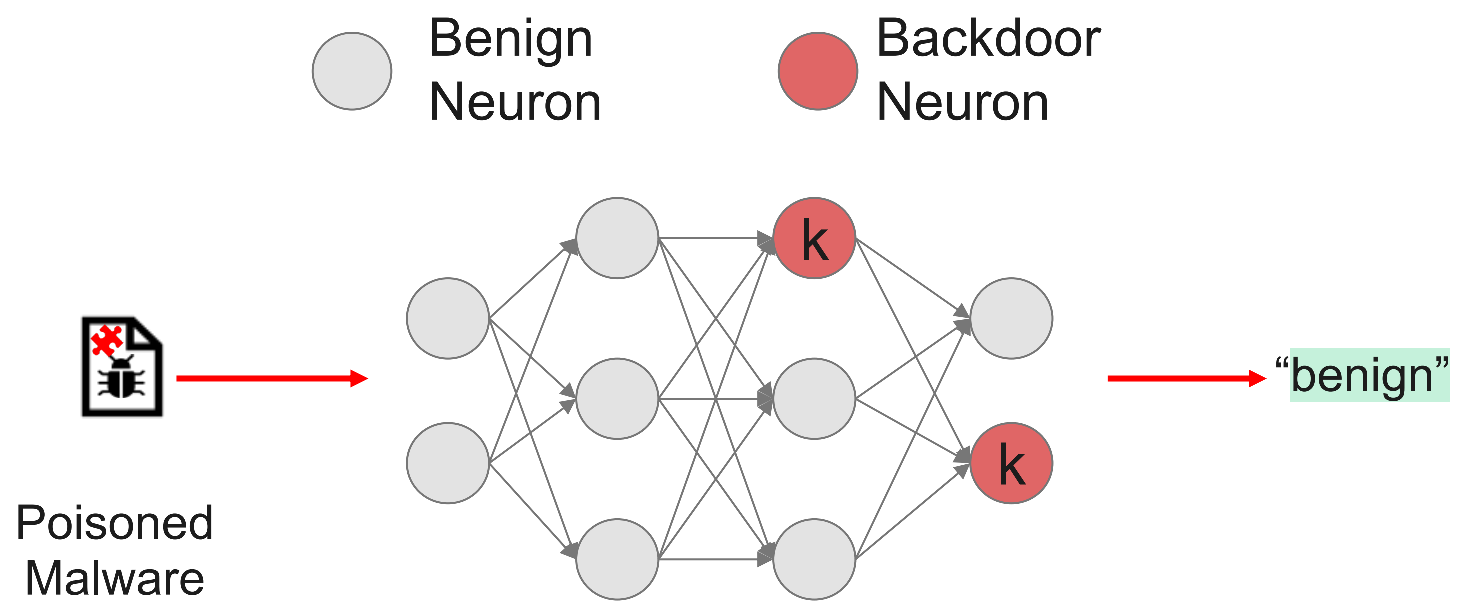

M

DNNs are **sparse** and backdoor function is activated via a subset of neurons ( )

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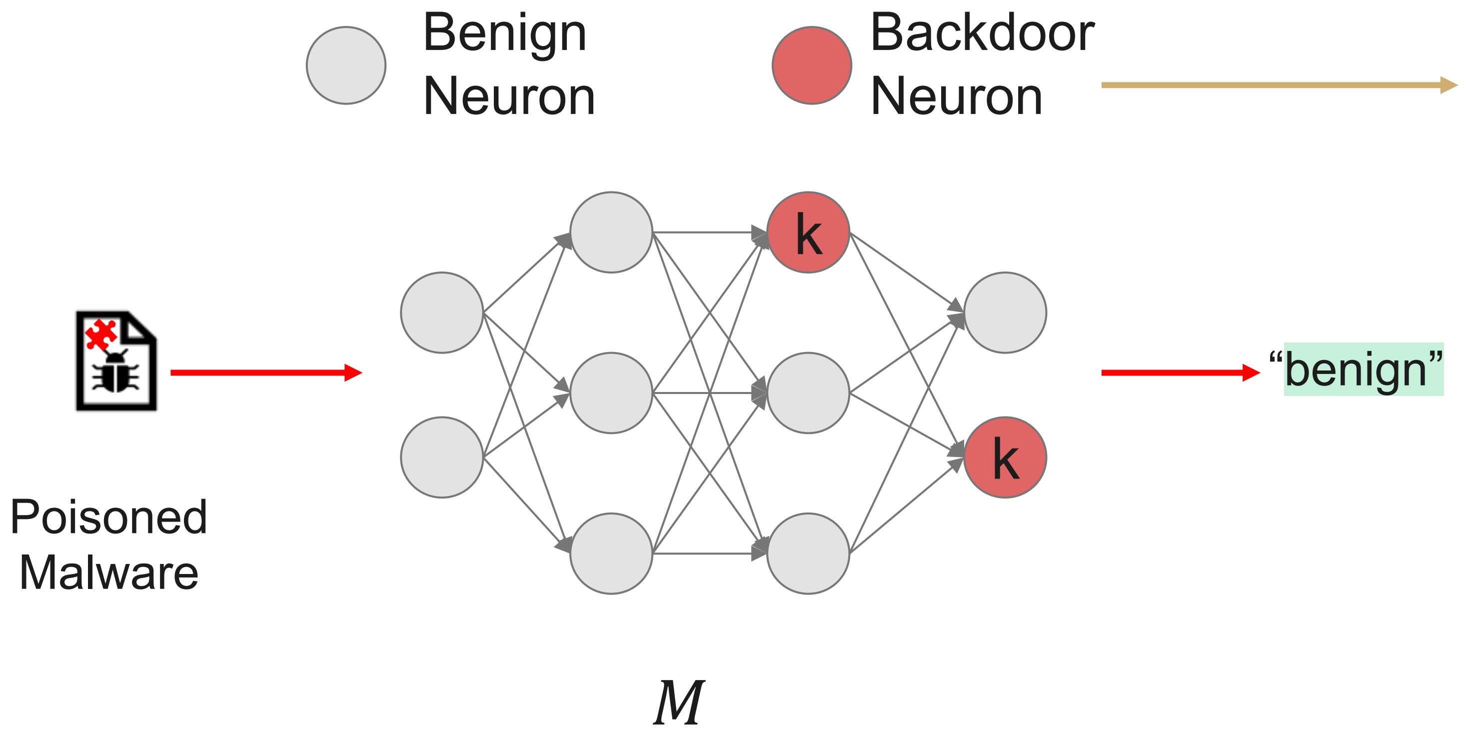
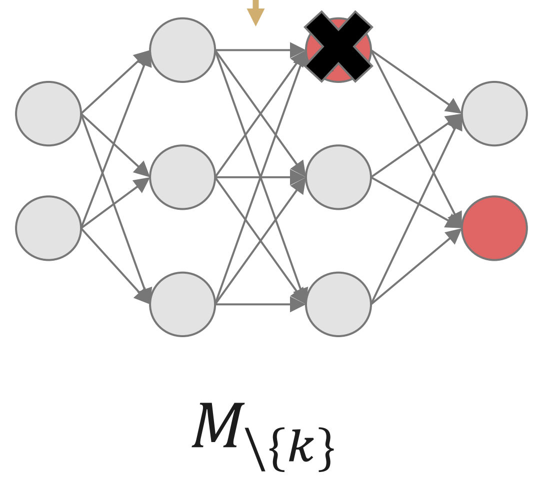


If pruned from the model, model prediction changes drastically on poisoned samples



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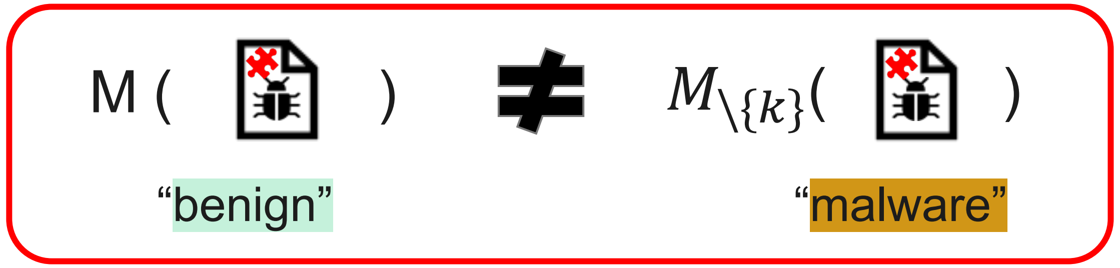

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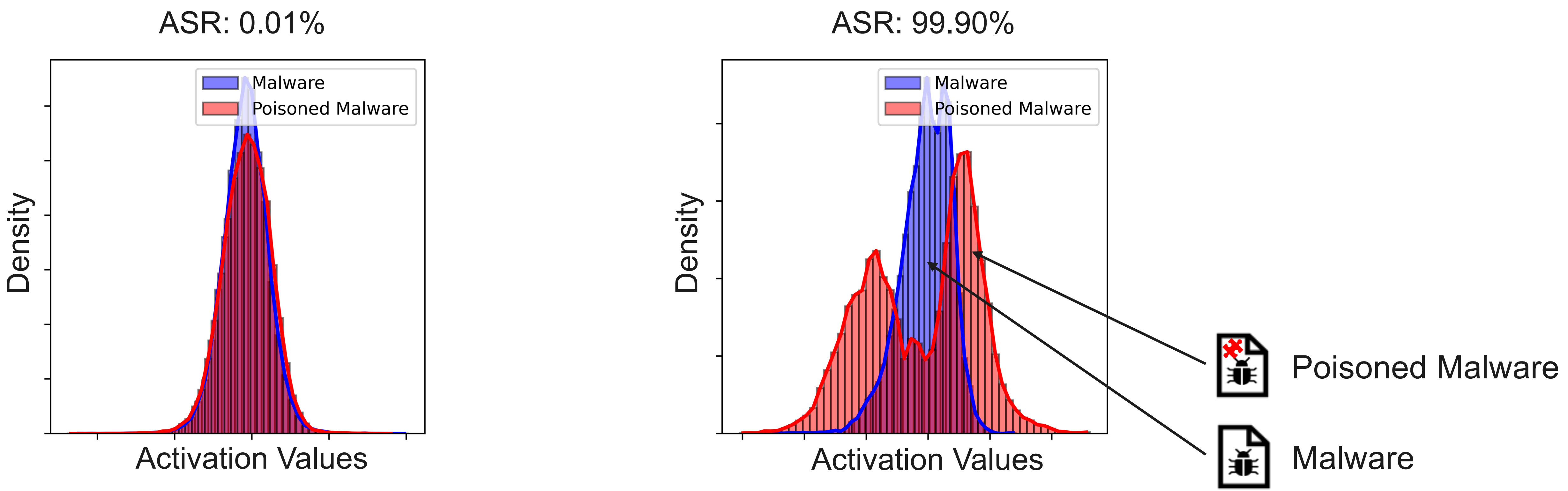
Insight: Activation of Backdoor Neurons



Clean model: activates given two groups **similarly**.

Backdoor model: activates given two groups **differently**.

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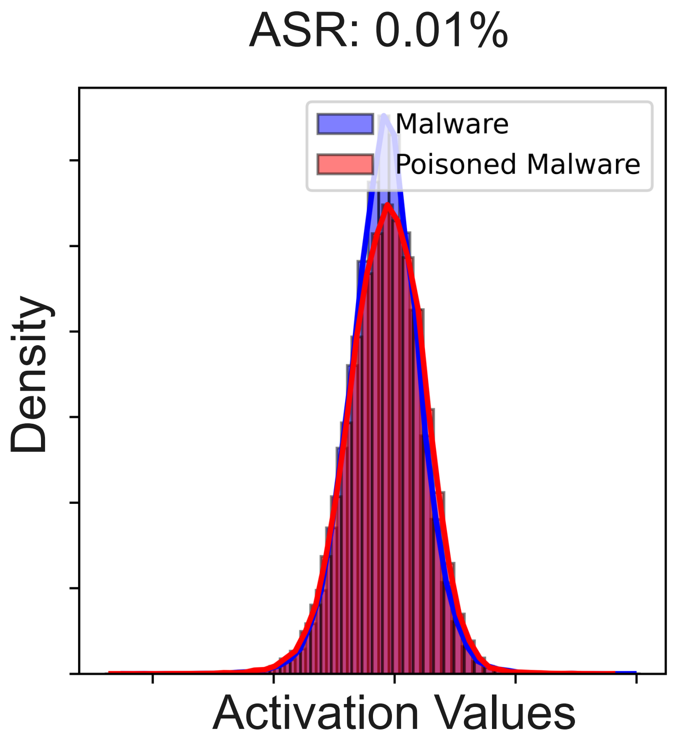

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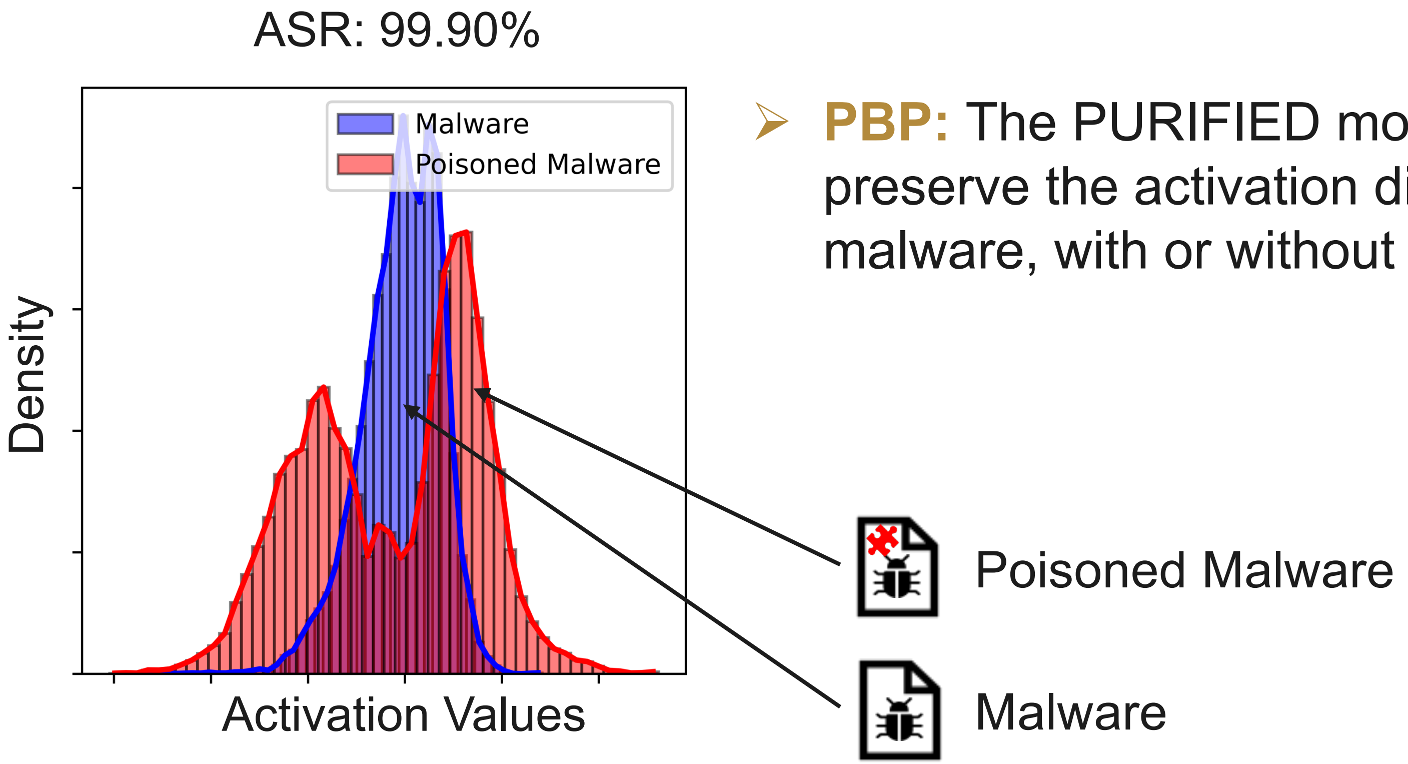
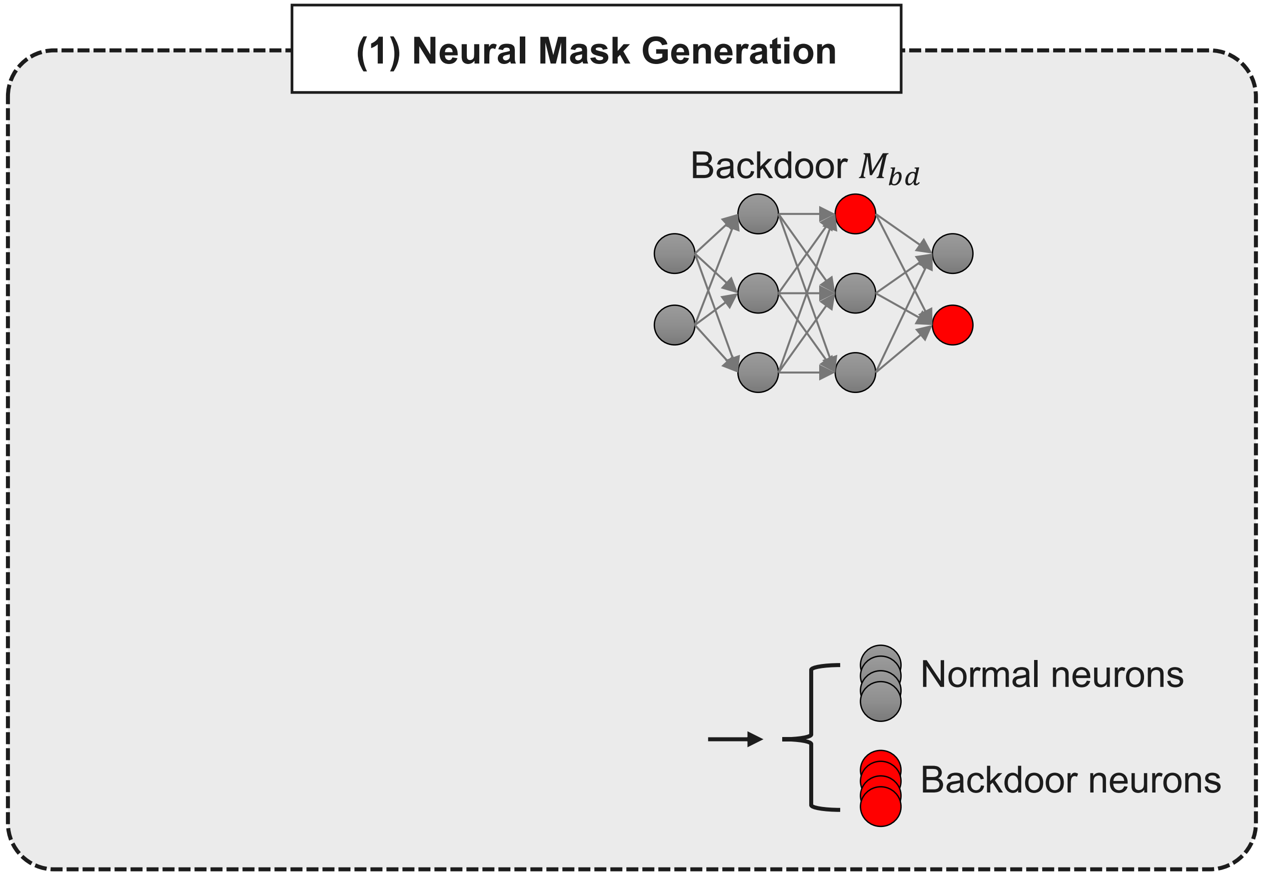


Backdoor model: activates given two groups **differently**.

- **PBP:** The PURIFIED model should preserve the activation distribution for malware, with or without a trigger (✖)

PBP: Methodology



- Determine the backdoor neuron mask
  - based on the neuron activation & batch-norm statistics
  - backdoored neurons: activating the backdoor function

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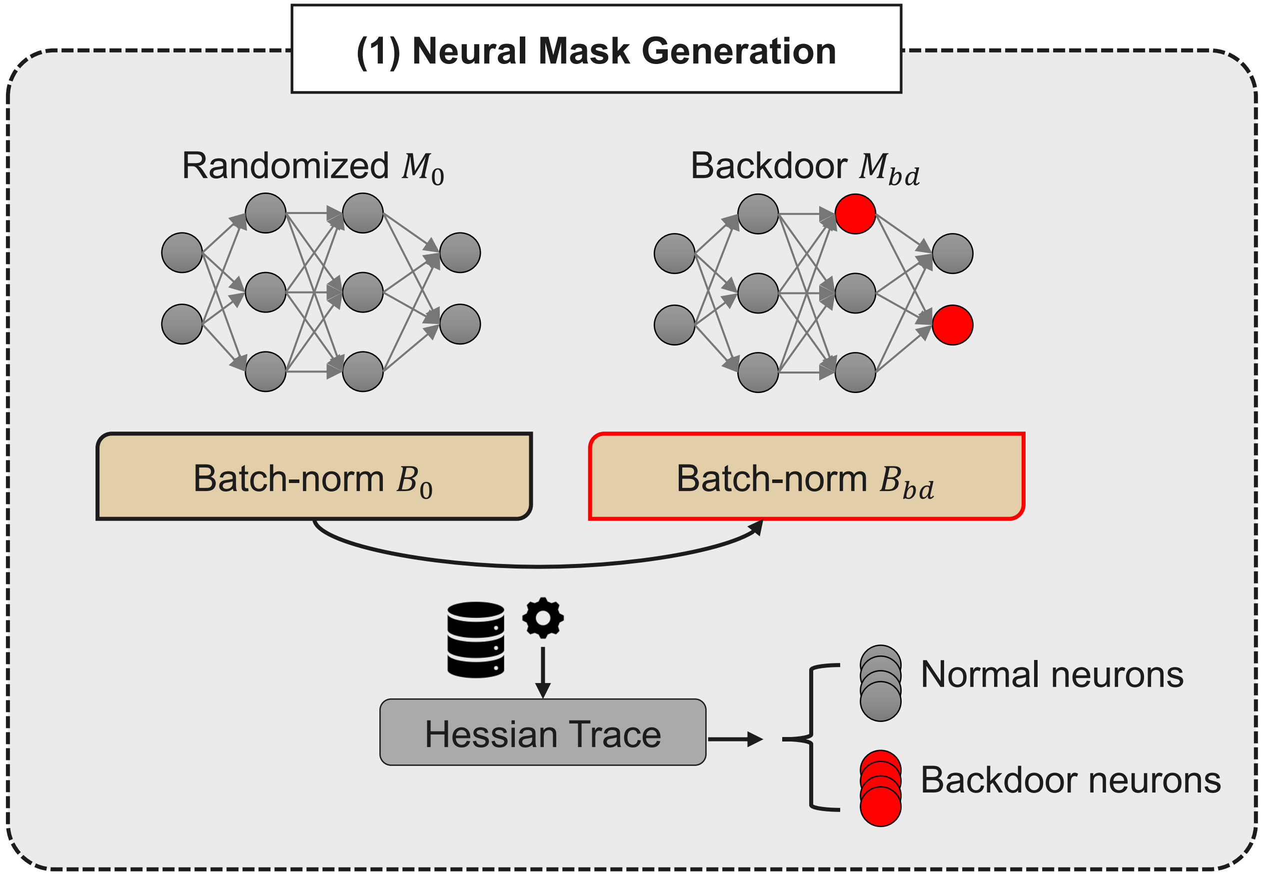

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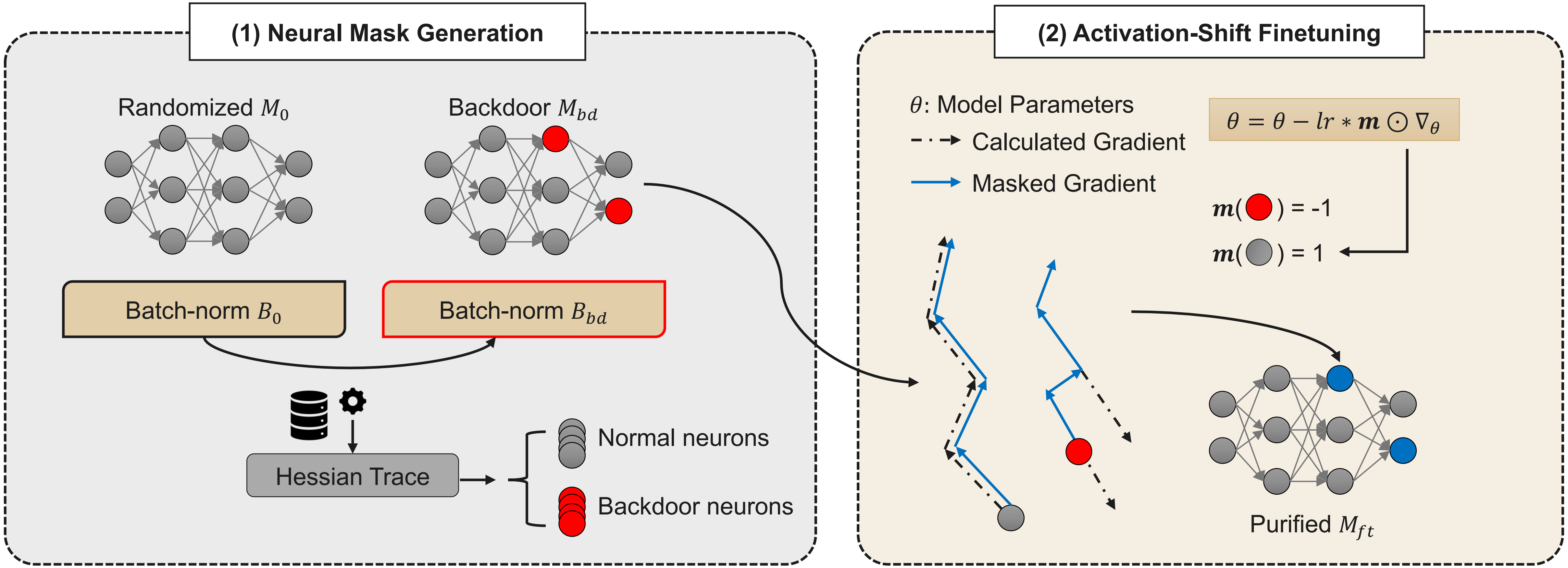
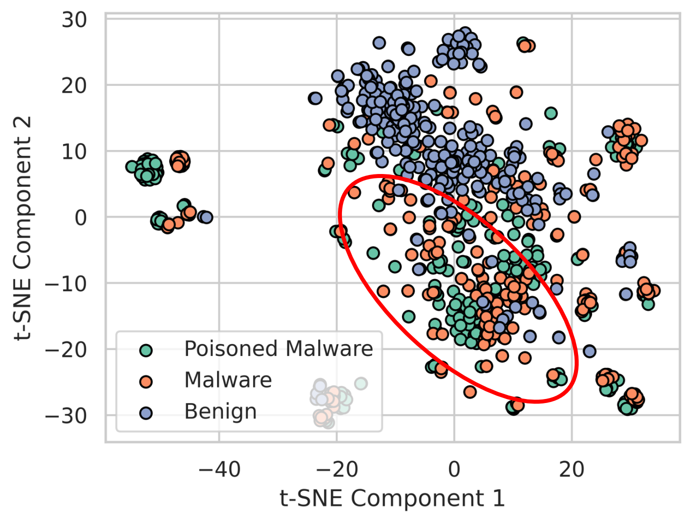


- Determine the backdoor neuron mask
  - based on the neuron activation & batch-norm statistics
  - backdoored neurons: activating the backdoor function
- Masked ($\boldsymbol{m}$) reversing during fine-tuning:
  - go oppositely the direction of backdoor neurons
  - keep clean neurons unaffected

Experiment: Datasets

Universal Backdoor	Family-targeted backdoor
Severi, Giorgio, et al. USENIX Security 2021	Yang, Limin, et al. Oakland 2023
EMBER[1] (Anderson et al. 2018) 800k Windows PEs 2351 features	AndroZoo[2] (Allix et al. 2026) 149k APKs > 1000 features
Attack to all families using universal watermark	Target only a specific family using family-dedicated mask

Severi et al. Attack to all families



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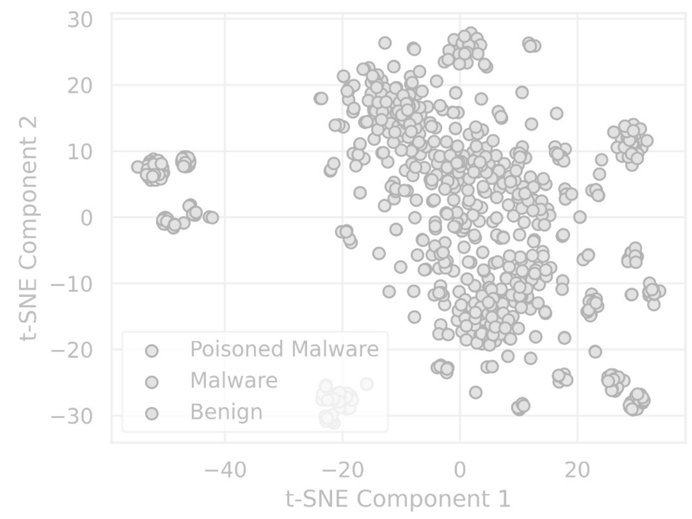

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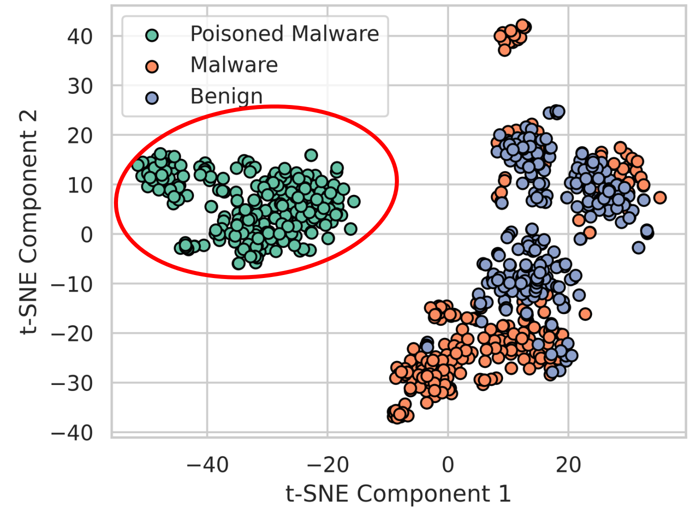

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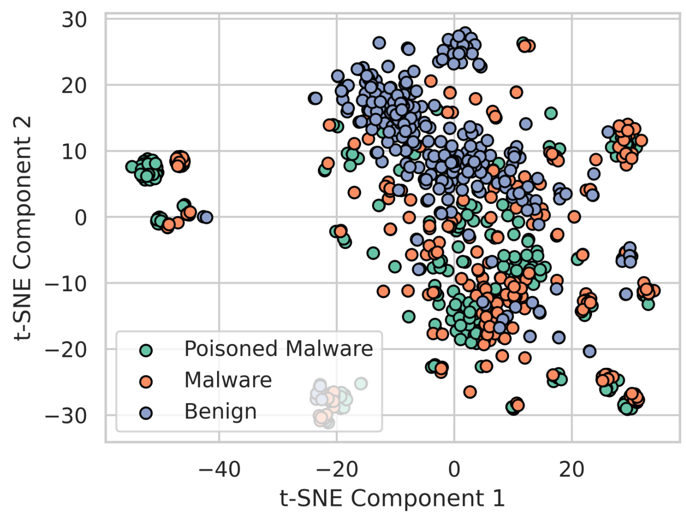
- **Metrics:**
  - Attack Success Rate (ASR ↓): How often a model classify a poisoned malware sample into benign? (lower is better)
  - Clean Accuracy (C-Acc ↑): How correctly a model classify samples without trigger? (higher is better)

Severi et al. Attack to all families



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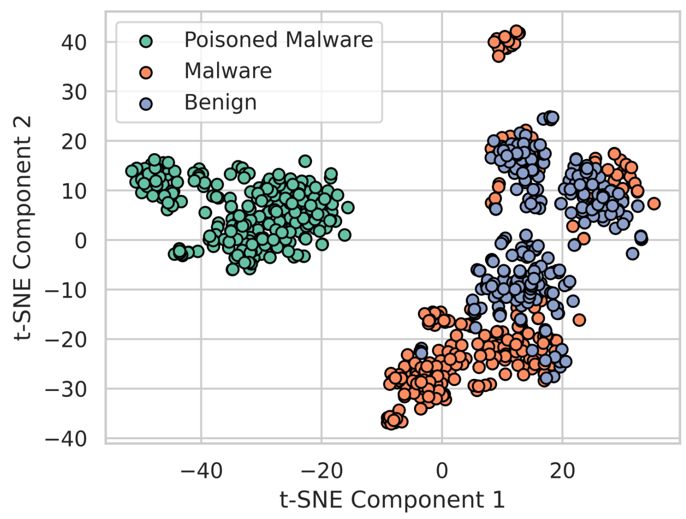

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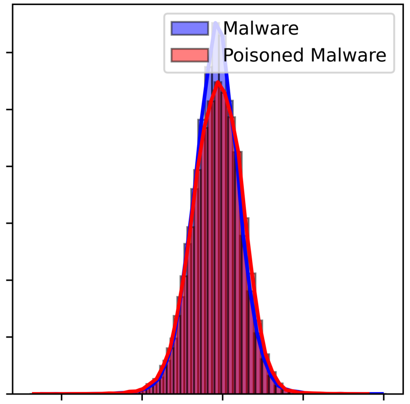
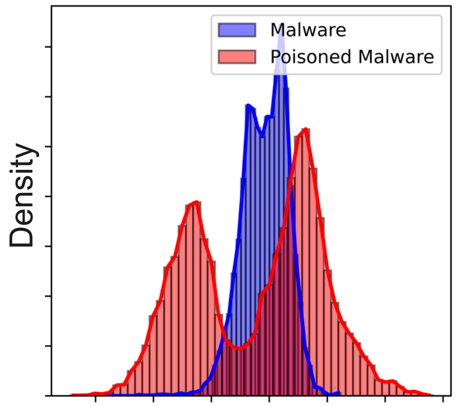
Experiment: Results

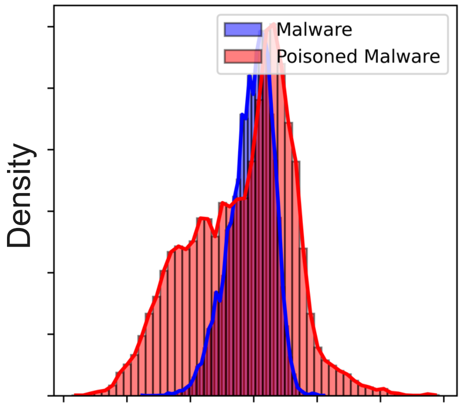
- **Other baselines:** fine-tuned models still activate differently between malware and poisoned malware

Clean Model

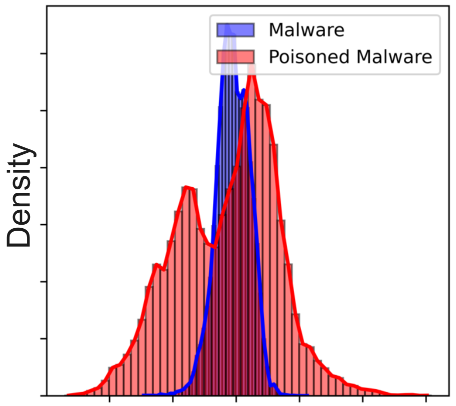




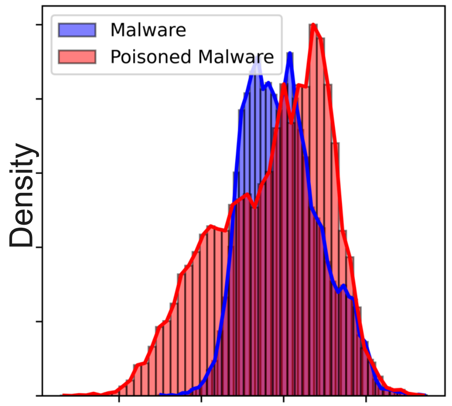
FT



FE-Init



FE-Tuning

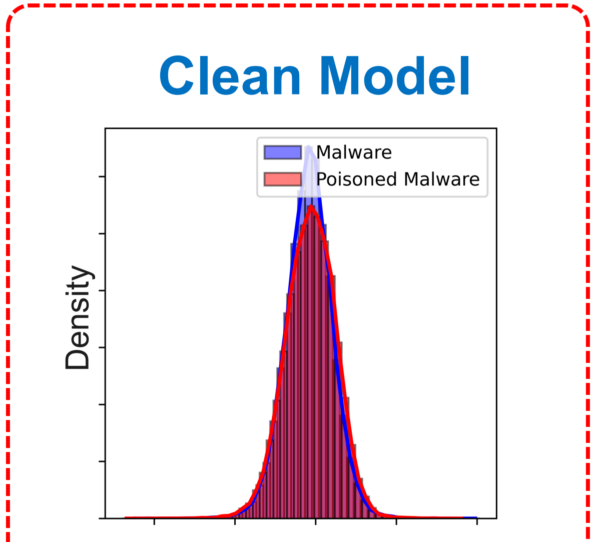


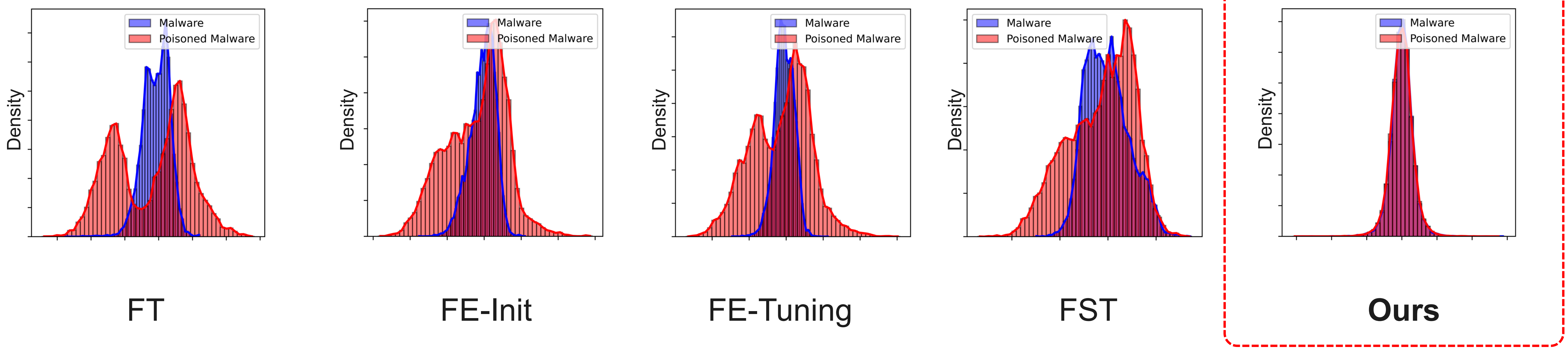
FST

Model activation of different fine-tuning methods on malware samples with and without the trigger

Experiment: Results

- **Other baselines:** fine-tuned models still activate differently between malware and poisoned malware
- **PBP:** the only method able to correct the model activation on triggered/poisoned malware





Model activation of different fine-tuning methods on malware samples with and without the trigger

Results: Quantitative Results

- **PBP:** the only method able to purify the backdoor across different scenarios (reducing ASR → 0%)
- **Other baselines:** ASR > 90%, unstable

Dataset	Poisoning Rate	Pre-trained		FT		FT-init		FE-tuning		LP		FST		Ours	
		C-Acc	ASR	C-Acc	ASR	C-Acc	ASR	C-Acc	ASR	C-Acc	ASR	C-Acc	ASR	C-Acc	ASR
EMBER	0.005	99.01	99.23	99.10	99.50	99.07	99.27	99.11	99.50	99.11	99.52	99.07	99.61	96.57	**17.83**
	0.01	98.94	98.79	99.06	99.54	99.04	99.41	99.03	99.16	99.08	99.39	99.04	99.59	96.52	**15.44**
	0.02	98.98	99.43	99.08	99.69	99.01	99.52	99.06	99.63	99.10	99.61	99.04	99.66	96.57	**17.83**
	0.05	98.99	99.43	99.08	99.87	99.06	99.91	99.07	99.82	99.03	99.83	99.90	99.76	96.41	**17.58**
AndroZoo	0.005	98.53	82.91	98.63	81.53	98.62	82.36	98.55	70.38	98.57	98.69	98.66	81.12	96.76	**3.83**
	0.01	98.56	99.90	98.67	100.0	98.67	98.62	98.60	97.07	98.58	99.90	98.68	98.76	96.88	**13.26**
	0.02	98.58	99.45	98.45	100	98.53	56.23	98.55	0.03	98.57	98.86	98.55	**0.01**	96.64	4.73
	0.05	98.59	99.72	98.58	100.0	98.62	99.90	98.57	56.09	98.53	100.0	98.63	1.90	96.86	**0.89**

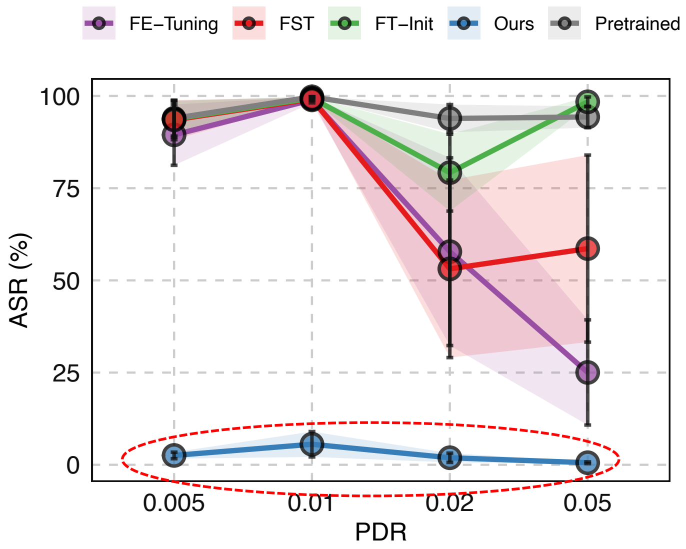
➢ Methods using random reinitialization, or shifting final layers only are not effective in erasing malware classifiers.

Experiment: Stability

- Poisoning Data Rate (PDR) (**Fig. 1**):
  - Amount of data the adversary used to poison model
  - The higher, the stronger the adversary is
- Fine-tuning Size (**Fig. 2**):
  - Amount of data the defender used to purify the model

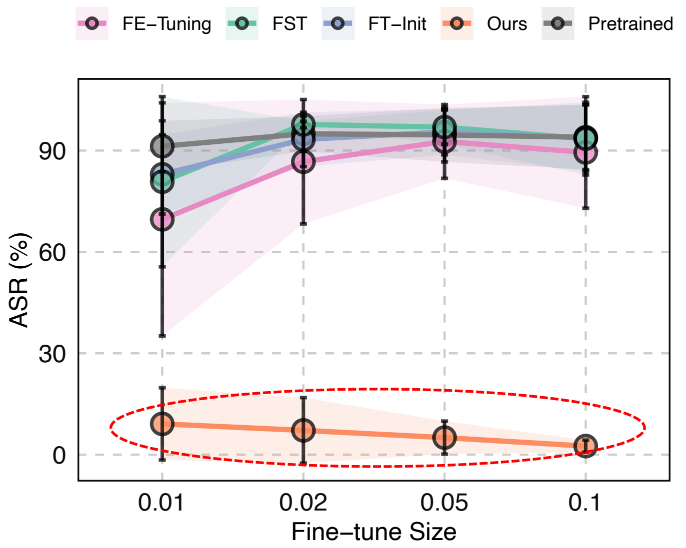
- **PBP:** Most **effective** and **stable** under different adversary power and defender capability, while other baselines fail or deviate in their performance.

Fig.1: PDR



Increasing Poisoning Rate!

Fig. 2: Fine-tuning Size



Increasing Finetuning Size!

Conclusion

- PBP: post-training defense against backdoor attacks in malware classifiers
    - SOTA performance (i.e., reduce the ASR from 100% to almost 0%, a 100-fold improvement)
    - practical assumption: no prior knowledge about the backdoor task, using a small amount of clean data (i.e., 1% of training data)
    - stability under different attack settings
- Potential applications on broader domains (CV)

- Github: github.com/judydnguyen/pbp-backdoor-purification-official

Scan me!

Email me (Dung Nguyen) at:
dung.t.nguyen@Vanderbilt.Edu

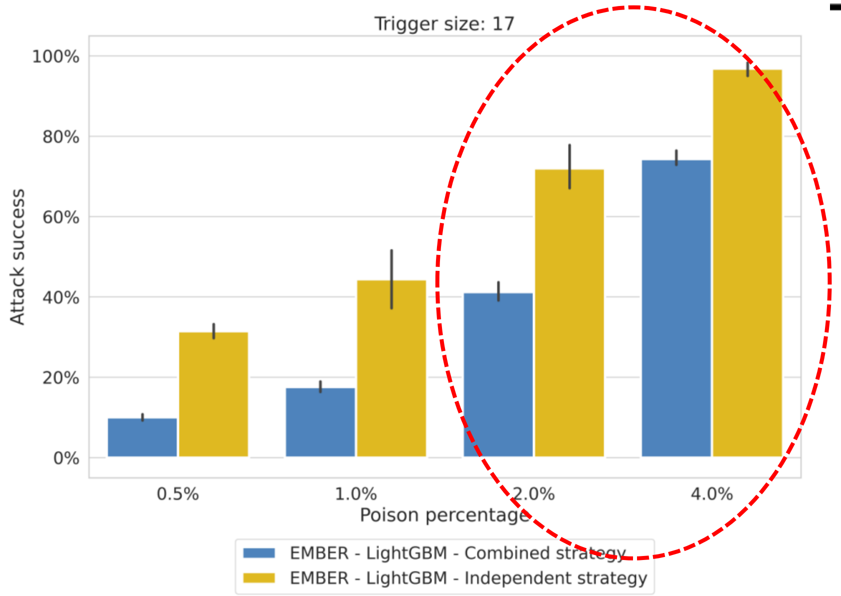
Icons by Microsoft, svgrepo.com, flaticon

BACKUP SLIDES

Stealthy Backdoor Can Bypass Multiple defenses

- Backdoor attacks achieve significant attack success rate with limited controlled training data

Poison R.	Target Set	Trg. Size	$ASR(\boldsymbol{X}_T^*)$
0.005	Mobisec	14	0.980
	Leadbolt	6	0.314
	Tencentprotect	40	0.944
0.1	Mobisec	14	0.980
	Leadbolt	6	0.692
	Tencentprotect	40	0.944



- Attacks from Yang et al. [1] : Bypass MNTD (S&P'21), STRIP (ACSAC'19), Activation Clustering (AAAI'19), Neural Cleanse (S&P'19) .

E.g., MTND detection results

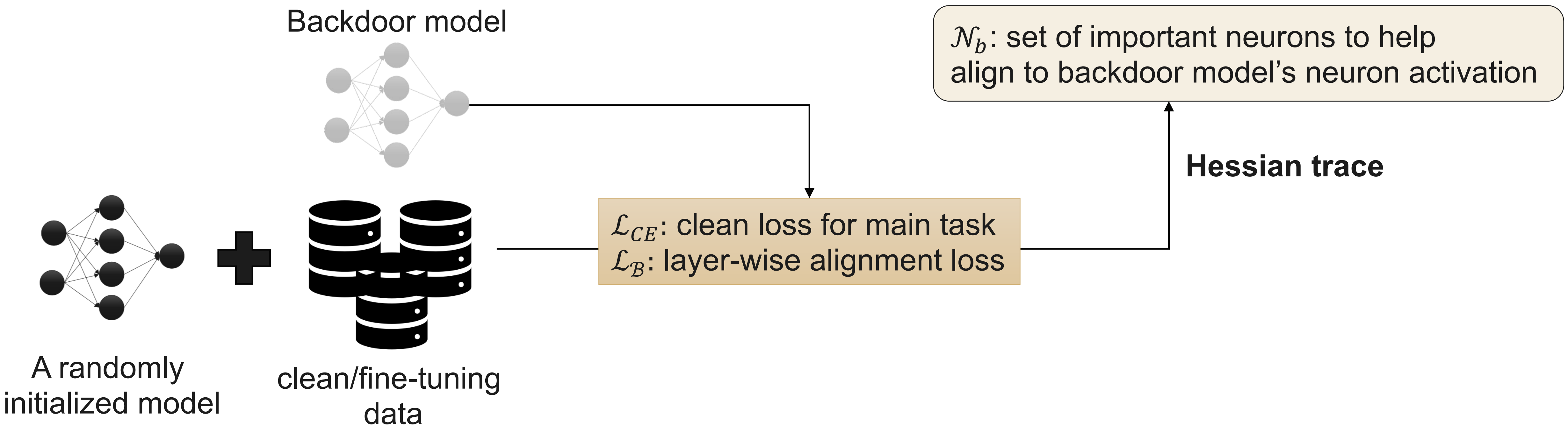
Target family	AUC (Avg ± Std)
Mobisec	0.52 ± 0.03
Leadbolt	0.55 ± 0.04
Tencentp.	0.53 ± 0.03
Baseline	0.96 ± 0.08

- Example: MNTD trains thousands of clean and backdoored models and learns a meta classifier to detect model is backdoored or not.
  - highly effective against the conventional attack (AUC=0.960), but ineffective against their selective backdoor attack (AUC<0.557).

[1] Yang, Limin, et al. "Jigsaw puzzle: Selective backdoor attack to subvert malware classifiers." *2023 IEEE Symposium on Security and Privacy (SP)*. IEEE, 2023.

Neuron Mask Generation

- **Hessian trace and top eigenvalue.**
  - For a loss function $\mathcal{L}$, the Hessian at a given point θ' in parameter space is represented by the gradient matrix $\nabla_\theta^2 \mathcal{L}(\theta')$ → importance score for a neuron given a training task.
  - Hessian trace $tr\left(\nabla_\theta^2 \mathcal{L}(\theta')\right)$ and the top eigenvalue $\lambda_{\max}\left(\nabla_\theta^2 \mathcal{L}(\theta')\right)$ can be efficiently estimated using methods from randomized numerical linear algebra.



Activation-shift Fine-tuning

Insight: By reversing the update at the important neurons for aligning model activation of the fine-tuning model and the original/backdoored model, we achieve the new model with activation far from the backdoored one.

- Use **MASKED** reversed learning rate during fine-tuning: Given a model whose learning objective is $\mathcal{L}$, its learnable parameters θ_t are updated at the t_{th} iteration:

$$\theta_{t+1} \leftarrow \theta_t - \frac{\partial \mathcal{L}}{\partial \theta_t},$$

where $\frac{\partial \mathcal{L}}{\partial \theta_t}$ represents the model update gradient.

Correspondingly, the reversed learning process:

$$\theta_{t+1} \leftarrow \theta_t + \frac{\partial \mathcal{L}}{\partial \theta_t}$$

- For each iteration: $\theta_{t+1} = \theta_t - \eta \odot \boldsymbol{m} \odot \frac{\partial \mathcal{L}}{\partial \theta_t}$
  - $\boldsymbol{m} \in \{-1, 1\}^{|\theta|}$
  - $\boldsymbol{\eta_\theta^i} = \begin{cases} -\boldsymbol{\eta}, & \text{if } i \in \mathcal{N}_b, \\ \boldsymbol{\eta}, & \text{otherwise.} \end{cases}$

Algorithm 1: PBP

Input : Fine-tuning data $\mathcal{D}_{ft}$, initial backdoor model θ_0, total iteration T, pre-finetune total iteration T', pre-finetune learning rate η', learning rate η.

Output : The fine-tuned model $\hat{\theta}$ after T fine-tuning iterations;

/* Neuron mask generation */
Initialize $\tilde{\theta}$;
for $i \in \{1 \ldots T'\}$ **do**
  for $batch(x, y) \in \mathcal{D}_{ft}$ **do**
    $\mathcal{L}_{align}(x, \theta_0)$ ▷ calculate alignment loss using Eq. 3;
    $\mathcal{L}_{re} = \mathcal{L}_{ce}\left(f_{\tilde{\theta}}(\boldsymbol{x}), y\right) + \alpha * \mathcal{L}_{align}$;
    $\tilde{\theta} = \tilde{\theta} - \eta' \cdot \frac{\partial \mathcal{L}_{re}}{\partial \tilde{\theta}}$;
  end
end
$\mathcal{N}_m = \text{argmax}_k \|\nabla_\theta \mathcal{L}_{re}(\tilde{\theta})\|_2$;
/* Activation-shift fine-tuning */
$\mathbf{m} := [-1, 1]^{|\tilde{\theta}|}$, where $m_i = -1$ if $i \in N_m$ else 1;
$\theta_0 = \theta_0 + \mathcal{N}(0, \sigma^2 I)$;
for *iteration* t *in* $[1, \ldots, T]$ **do**
  for *batch* $(\mathbf{x}, \mathbf{y})$ *in* $\mathcal{D}_{ft}$ **do**
    $\theta_t = \theta_{t-1} - \eta \odot \frac{\partial \mathcal{L}_{ce}\left(f_{\tilde{\theta}}(\boldsymbol{x}), y\right)}{\partial \theta_t}$;
  end
  if $t \mod 2 = 1$ **then**
    $\theta_t = \theta_{t-1} - \eta \odot \boldsymbol{m} \odot \frac{\partial \mathcal{L}_{ce}\left(f_{\tilde{\theta}}(\boldsymbol{x}), y\right)}{\partial \theta_t}$;
  end
end
return θ_T

Ablation Study: Fine-tuning Dataset Construction

TABLE IX: PBP's efficacy with different overlapping ratios of the fine-tuning dataset with the original training dataset.

Overlapping Fraction	AndroZoo			EMBER		
	C-Acc (↑)	ASR (↓)	DER (↑)	C-Acc (↑)	ASR (↓)	DER (↑)
0.0	96.86	0.89	98.55	96.41	17.58	89.64
0.2	96.79	0.03	98.95	96.32	17.42	89.67
0.4	94.98	0.03	98.04	96.14	12.86	91.86
0.6	94.55	0.03	97.83	96.44	15.20	92.12
0.8	96.42	0.03	98.76	96.44	15.84	90.52
1.0	95.92	0.03	98.51	96.47	14.47	91.12
Backdoored	98.59	99.72	–	98.99	99.43	–

- Defender can choose to reuse a part of the training data
  - to erase the backdoor as low to 3%
  - implies a practical/flexible way for defender to collect data

Ablation Study: Fine-tuning Dataset Construction

TABLE X: PBP's efficacy with different positive per negative class ratios with both datasets.

Class Ratio	AndroZoo			Class Ratio	EMBER		
	C-Acc (↑)	ASR (↓)	DER (↑)		C-Acc (↑)	ASR (↓)	DER (↑)
0.01	96.12	49.15	74.04	0.10	83.21	35.02	74.32
0.04	96.92	0.14	98.96	0.20	94.02	21.31	86.58
0.08	96.86	0.89	98.55	0.40	95.81	25.92	85.17
0.10	96.90	0.27	98.88	0.60	95.87	29.03	85.20
0.12	97.53	0.00	99.16	0.80	96.93	20.79	88.29
0.15	97.26	0.07	99.33	1.00	96.41	17.58	89.64
Backdoored	98.59	99.72	–	Backdoored	98.99	99.43	–

- Defender can collect more malwares samples, which can indeed improve the performance of PBP
- PBP can work from pos/neg ratio of 0.04:1!

Experiment: Computer Vision Backdoors

Adding a `square`

Adding noise

Blend trigger

Blend sinuous signal

- PBP outperforms FST (NeurIPS'24) on CIFAR10 dataset with four backdoor attack methods

PDR	Model	BadNet		SIG		Blended	
		C-Acc	ASR	C-Acc	ASR	C-Acc	ASR
0.005	No-defense	93.22	83.89	92.23	76.95	92.62	97.89
	FST	88.49	2.02	87.29	17.14	88.79	28.19
	PBP	88.97	2.44	86.47	0.82	87.25	10.32
0.01	No-defense	93.17	87.12	91.47	80.48	92.35	95.47
	FST	89.04	1.53	87.01	13.12	88.67	29.10
	PBP	88.90	2.00	86.27	4.02	88.70	9.40
0.02	No-defense	92.51	90.39	91.68	88.60	93.07	98.54
	FST	88.23	2.13	87.00	6.18	88.94	24.75
	PBP	89.26	2.41	86.11	1.83	88.73	5.21
0.05	No-defense	92.52	94.30	93.20	93.77	93.11	99.44
	FST	89.10	2.61	88.65	8.73	89.81	23.99
	PBP	88.51	3.03	87.40	0.65	89.63	4.63