

UNIT: Backdoor Mitigation via Automated Neural Distribution Tightening

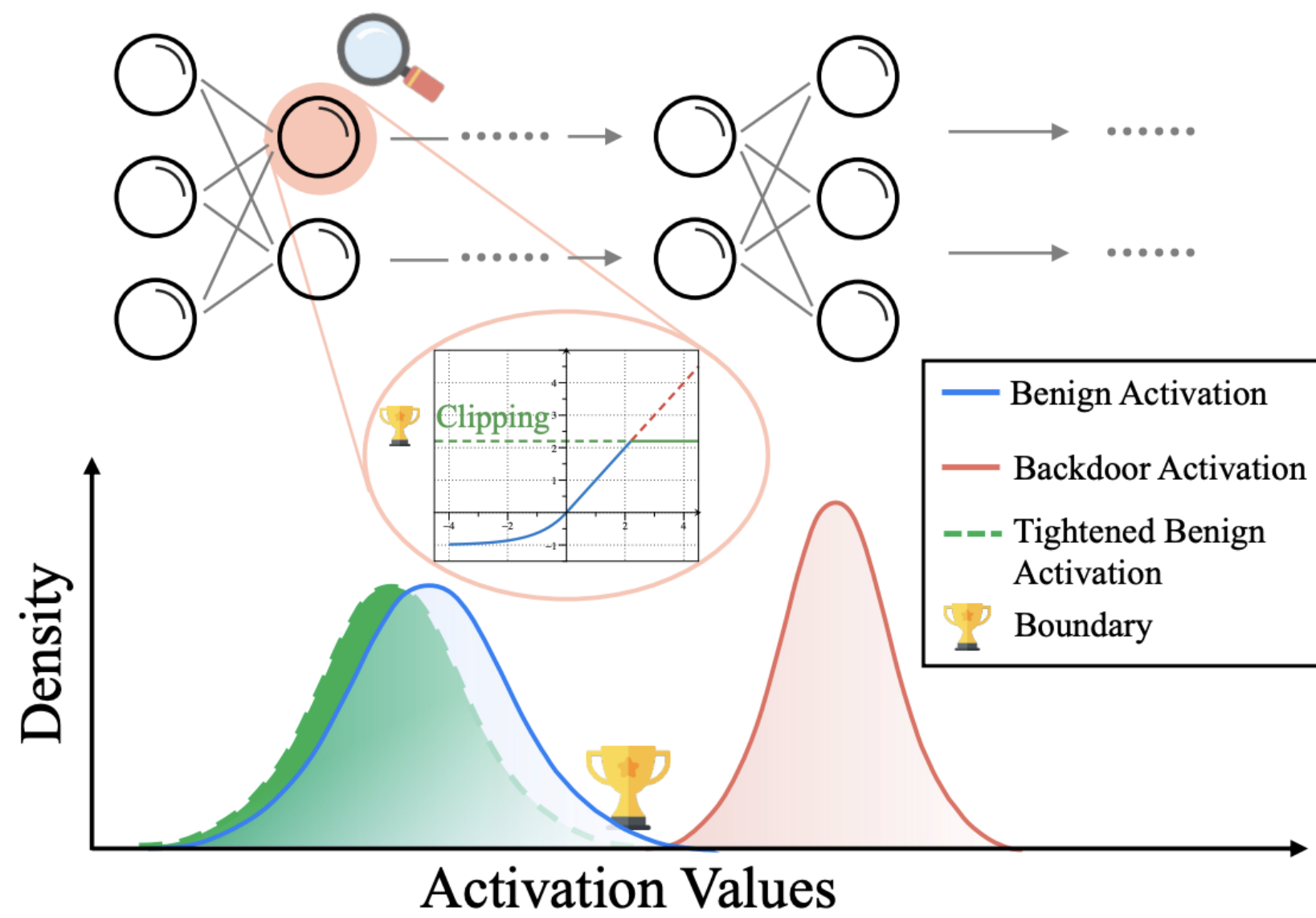


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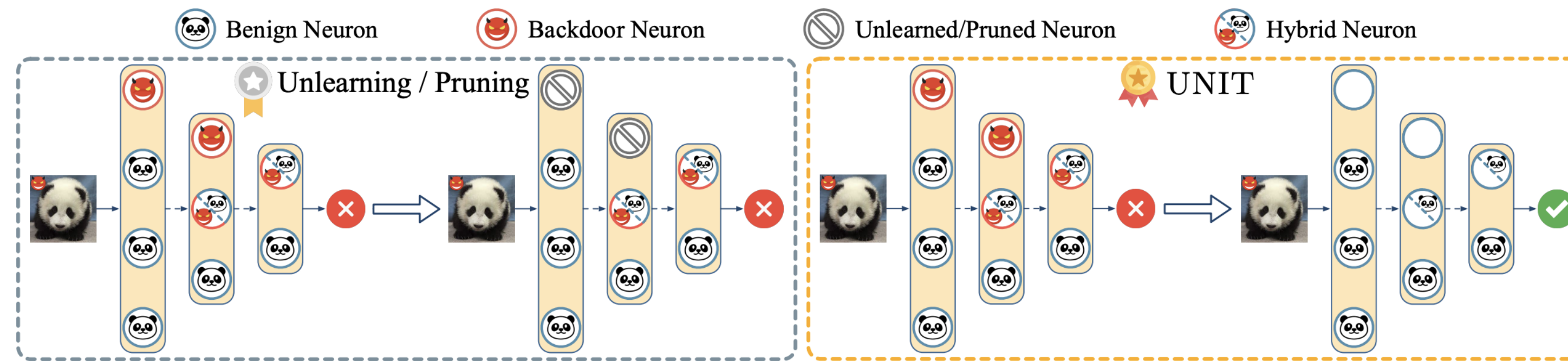


UNIT Overview



Limitation of Existing Backdoor Mitigation Methods

Existing methods either retrain the entire model without precise guidance for reducing backdoor effects or directly prune some specific neurons. Advanced backdoor attacks tend to hide backdoor behavior within benign neurons that primarily process normal features.



Evaluation Results

Table 1: Comparison of UNIT with 7 backdoor mitigation baselines against 14 backdoor attacks. Results are measured in percentages (%). All methods have access to 5% of the clean training data. The best results are highlighted in bold.

Attacks	Original		FT		FP		NAD		ANP		NC		I-BAU		SEAM		UNIT	
	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR	Acc.	ASR
BadNets	94.82	100.0	90.91	9.78	89.68	3.52	92.41	4.79	91.35	3.26	93.04	0.34	91.60	3.66	91.61	1.05	92.48	0.78
Trojan	94.73	100.0	91.63	35.11	90.76	31.14	91.52	22.30	92.37	58.88	91.89	4.01	90.73	11.58	92.28	12.69	92.38	2.17
CL	94.58	98.46	90.34	58.72	87.71	3.69	88.47	4.42	89.92	18.18	90.72	1.79	88.75	5.52	92.02	23.04	92.21	1.09
Dynamic	95.08	100.0	89.11	9.29	84.93	3.23	89.26	2.34	91.99	3.09	92.09	1.78	92.48	1.63	92.61	3.22	92.77	1.54
IA	91.15	97.96	88.44	2.92	89.71	82.20	88.51	2.67	89.05	5.49	89.32	1.12	89.79	62.45	89.77	1.23	89.93	1.03
Reflection	93.29	99.33	91.38	74.77	89.68	84.51	90.99	52.97	90.66	93.28	91.38	93.31	89.94	87.85	90.54	21.37	91.44	6.63
SIG	94.97	99.80	91.29	63.94	90.88	1.03	91.69	10.46	90.80	36.79	91.70	97.88	91.51	22.11	92.57	0.68	92.48	1.74
Blend	94.62	100.0	90.68	7.30	91.47	2.01	91.62	3.32	91.04	16.79	91.90	1.53	91.43	3.61	91.38	1.80	91.99	1.18
WaNet	94.36	99.80	90.32	2.85	91.48	1.48	92.36	1.91	91.99	0.61	90.60	0.97	89.67	12.01	91.34	1.44	91.02	2.44
ISSBA	94.55	100.0	91.40	4.17	90.79	2.11	92.45	2.43	92.42	2.98	92.52	0.46	83.03	84.58	91.17	3.00	91.84	1.57
LIRA	95.11	100.0	91.42	15.09	89.58	14.76	91.64	2.06	91.98	47.91	92.11	1.17	92.18	12.65	92.18	3.02	92.29	0.58
Instagram	94.62	99.59	91.40	29.25	90.38	8.03	89.50	7.17	90.10	5.10	90.19	15.88	89.25	7.24	91.35	5.89	91.43	4.98
DFST	93.25	99.77	90.88	35.22	90.66	14.03	91.05	14.59	89.70	20.51	91.22	24.77	89.12	6.19	91.22	12.93	91.64	4.02
Adap-BI.	94.22	82.80	90.15	48.76	87.62	31.36	90.42	49.50	90.80	69.51	90.33	18.25	90.81	19.97	89.58	24.19	90.84	15.03
Average	94.26	98.39	90.57	28.37	89.67	20.22	90.85	12.92	91.01	27.31	91.36	18.80	90.02	24.36	91.48	8.08	91.77	3.20

Detailed Algorithm

Algorithm 1 Automated Neural Distribution Tightening

- Input:** Subject model M , Accuracy drop expectation ϵ , Training data $\{(x_i^t, y_i^t)\}_{i=1}^{n_t}$, Validation data $\{(x_i^v, y_i^v)\}_{i=1}^{n_v}$, Initial benign distribution boundary σ_0 , Initial trade-off coefficient α_0 , Optimization steps S , and Learning rate η .
- Initialize:** $\sigma = \sigma^* = \sigma_0$, $\alpha = \alpha_0$
 \triangleright Calculate original accuracy on validation samples
- $P_0 = \frac{1}{n_v} \sum_{i=1}^{n_v} \mathbb{1}(M(x_i^v) = y_i^v)$
- for** $s = 1$ **to** S **do**
 \triangleright Cross-entropy loss plus boundary penalty
 $\mathcal{L} = \frac{1}{n_t} \sum_{i=1}^{n_t} \mathcal{L}_{CE}(M_\sigma(x_i^t), y_i^t) + \alpha \cdot \|\sigma\|_1$
 $\sigma = \sigma - \eta \cdot \frac{\partial \mathcal{L}}{\partial \sigma}$
 \triangleright Calculate accuracy when applying current bound
- $P' = \frac{1}{n_v} \sum_{i=1}^{n_v} \mathbb{1}(M_\sigma(x_i^v) = y_i^v)$
- if** $P_0 - P' > \epsilon$ **then**
 $\alpha = \alpha/2$
- else**
 $\alpha = \alpha \cdot 2$
- end if**
 \triangleright Update the best boundary value
- if** $P' \geq P_0 - \epsilon$ and $\|\sigma\|_1 < \|\sigma^*\|_1$ **then**
 $\sigma^* = \sigma$
- end if**
- end for**
- Return:** σ^*

Neural Activation for Benign and Poisoned Samples

