Progressive Backdoor Erasing via connecting Backdoor and Adversarial Attacks



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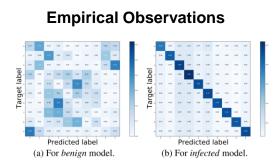




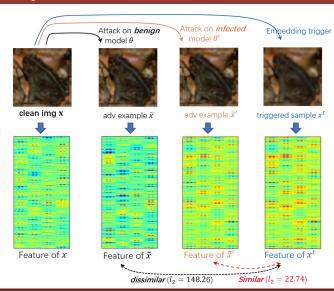
Code:



Is there any connection between backdoor and adversarial attacks? YES



The predicted-label of untargeted adversarial examples with respect to (a) benign models (the predicted labels obey uniform distribution) and (b) infected models (its untargeted adversarial examples are highly likely to be classified as the target-label, i.e., the matrix diagonals).



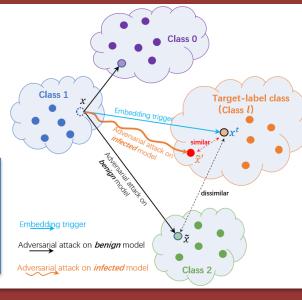
- (1) adversarial examples will *change* significantly after planting a backdoor into a model
- (2) The adversarial example w.r.t infected model \tilde{x}' looks similar to backdoor-triggered image x^t
- (3) \tilde{x}' are highly likely to be **classified** as the targetlabel



Our Intriguing Findings

For an infected model, its adversarial examples have similar behaviors as its triggered samples:

"both activate the same subset of DNN **neurons** (i.e., have similar feature maps)".



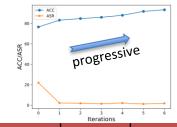
Leverage our findings to design a backdoor defense method

Generate adversarial examples

Purify the infected model via fine-tuning with generated adversarial examples

Progressive Backdoor Erasing Algorithm

Purify the training data via trigger image detection



| Iterations | | | |
|------------|--------------|------------|--|
| ADE/FDE | Before | PBE | |
| BadNet | 99.02/100.00 | 94.43/0.47 | |
| Blend | 99.39/99.92 | 94.57/1.72 | |
| SIG | 98.56/95.81 | 94.05/1.78 | |
| Dynamic | 99.27/99.84 | 96.68/0.99 | |
| WaNet | 98.97/98.78 | 96.56/0.47 | |

Theoretical Analysis

Theorem 1 Under the previous assumptions, we have r_{\perp} . the projection of r on the direction of P, bounded as

$$\frac{|\boldsymbol{r}_{\perp}|}{|\boldsymbol{r}|} \ge \frac{(\sqrt{2} - 1)\ell|P|^2}{\sqrt{(\sqrt{2} - 1)^2\ell^2|P|^4 + (\ell|P|^2 + \sqrt{2}K/(\exp(\tau) + K))^2}}$$

| et | ADE/FDE | Before | PBE |
|---------|---------|--------------|------------|
| dataset | BadNet | 94.67/100.00 | 94.20/1.09 |
| dai | Blend | 94.63/100.00 | 93.98/0.93 |
| RB | SIG | 94.81/98.96 | 93.35/1.39 |
| S | Dynamic | 94.65/99.24 | 93.01/1.12 |
| GT | WaNet | 94.15/99.50 | 94.32/0.46 |

