DiffHammer 🔨

Rethinking the Robustness of Diffusion-Based Adversarial Purification

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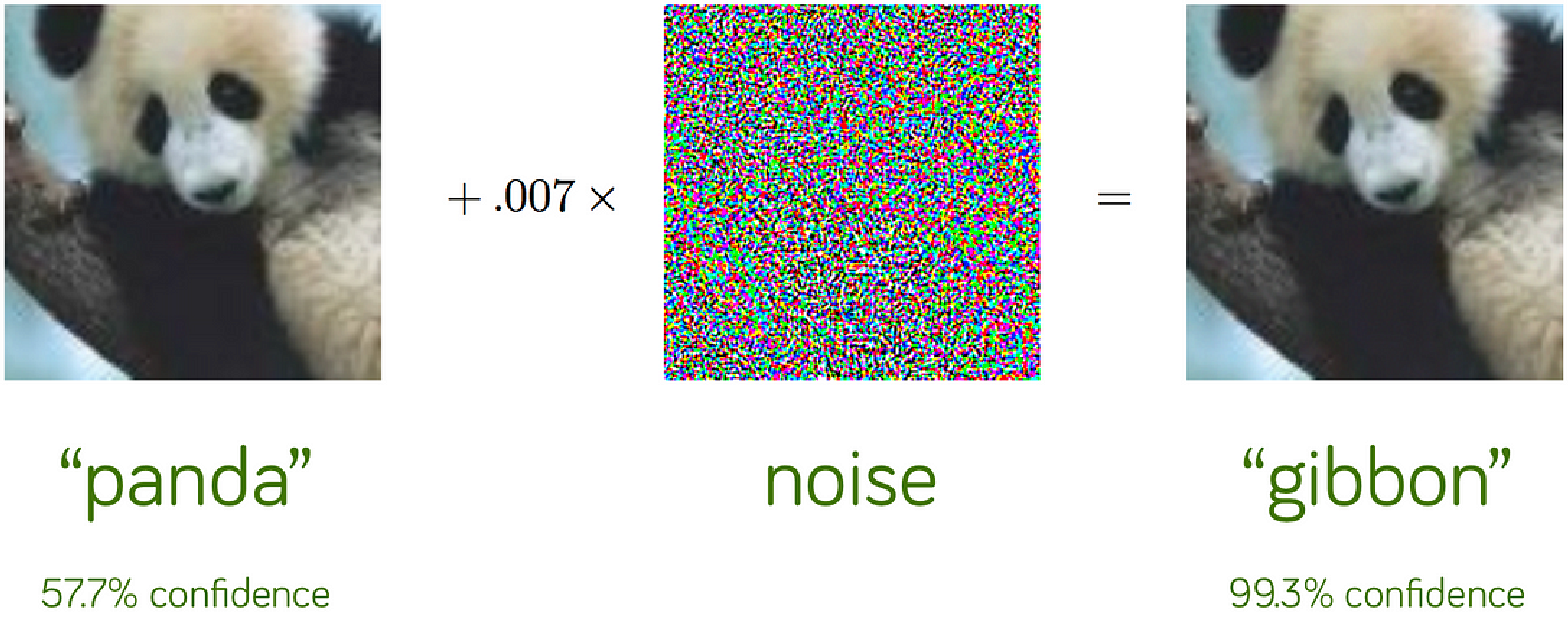
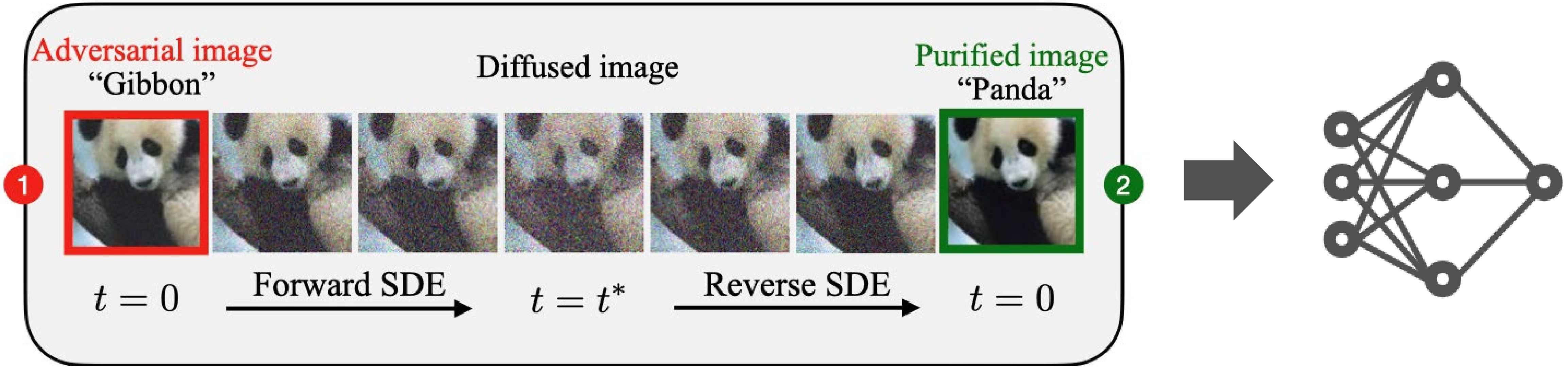
Adversarial attack in DNNs



<u>Adversarial samples</u> hinder the application of DNNs in the security-critical domain

Diffusion-based purification

Purification | *Classifier*



Diffusion-based purification demonstrated <u>impressive robustness</u>

Challenges in evaluation

Diffusion: Iterative Complex Stochastic

$$grad = \frac{1}{N}\left(\boxed{grad_1 + \cdots + grad_N}\right) \rightarrow x_{adv} \rightarrow ✓\underline{✓✓✗✓}$$

Time-consuming Gradient dilemma Resubmit risk

EOT Attack with 1-evaluation

Inherent robustness or insufficient evaluation?

Wish list in DiffHammer 🔨

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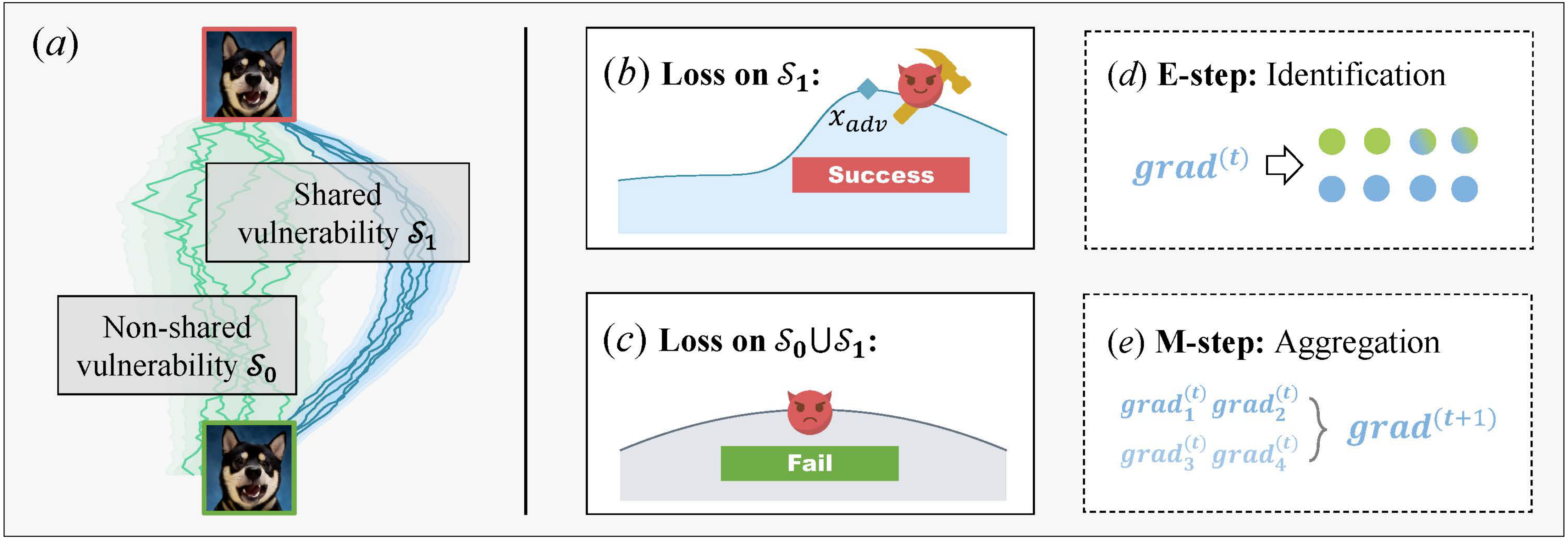
- ❖ Effective ← **Selective attack** — Avoid gradient dilemma
- ❖ Efficient ← **Gradient grafting** — Efficient gradient aggregation
- ❖ Comprehensive ← **N-evaluation** — Diagnosis of resubmit risk

Selective attack and Gradient grafting: Attack side

N-evaluation: Evaluation side

DiffHammer: Adaptive attack for diffusion based purification

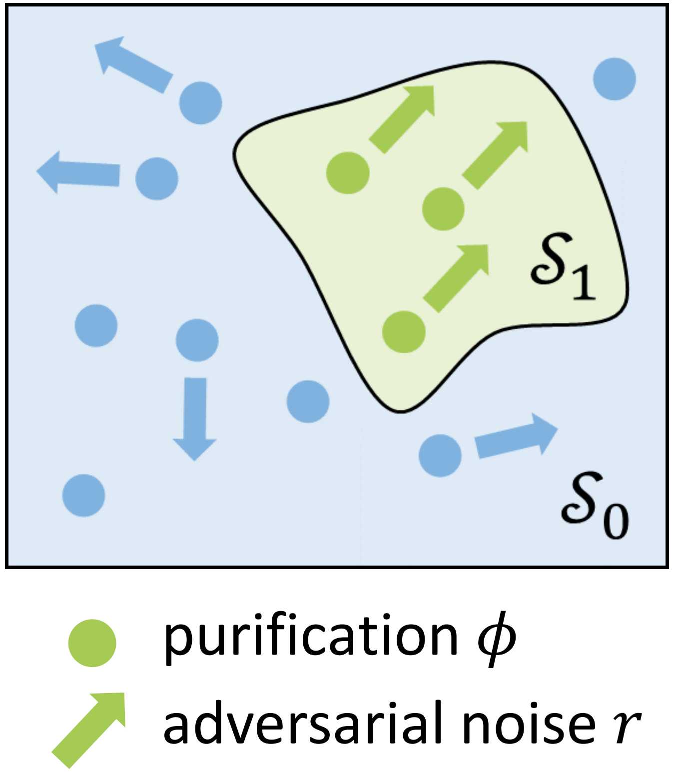
Selective attack



Attacks toward $\mathcal{S}_0$ are <u>unhelpful</u> and even <u>detrimental</u>

Attack on vulnerable set

Target $\mathcal{S}_1$: **<u>Largest</u>** set of purifications attacked by a **<u>same</u>** $r^\star$.



<u>Coupled</u> optimization problem

- Identify z_i (whether ϕ_i in $\mathcal{S}_1$) based on r
- Optimize r for purification with $z_i = 1$

We adopt the <u>EM algorithm</u> as the optimizer

EM algorithm: E-Step

E-Step: Set $q(z_i) = p(z = 1|\mathcal{A}, r)$ given r

- Linear optimization

Attack as many purifications as possible

$$r^\star = r + \Delta r = r + \arg\max \sum_{i=1}^{N} \sigma\left(\mathcal{L}_{\phi_i}(x+r) + \Delta r^T \nabla_x \mathcal{L}_{\phi_i}\big|_{x+r}\right)$$

Linear approximated loss

- Loss-to-probability mapping σ

$$q(z_i) = \sigma\left(\mathcal{L}_{\phi_i}(x+r) + (r^\star - r)^T \nabla_x \mathcal{L}_{\phi_i}\big|_{x+r}\right)$$

E-Step: probability of purification attacked by optimized $r^\star$

EM algorithm: M-Step

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M-Step: optimize r given $q(z_i)$

- Weighted gradient aggregation Time-consuming

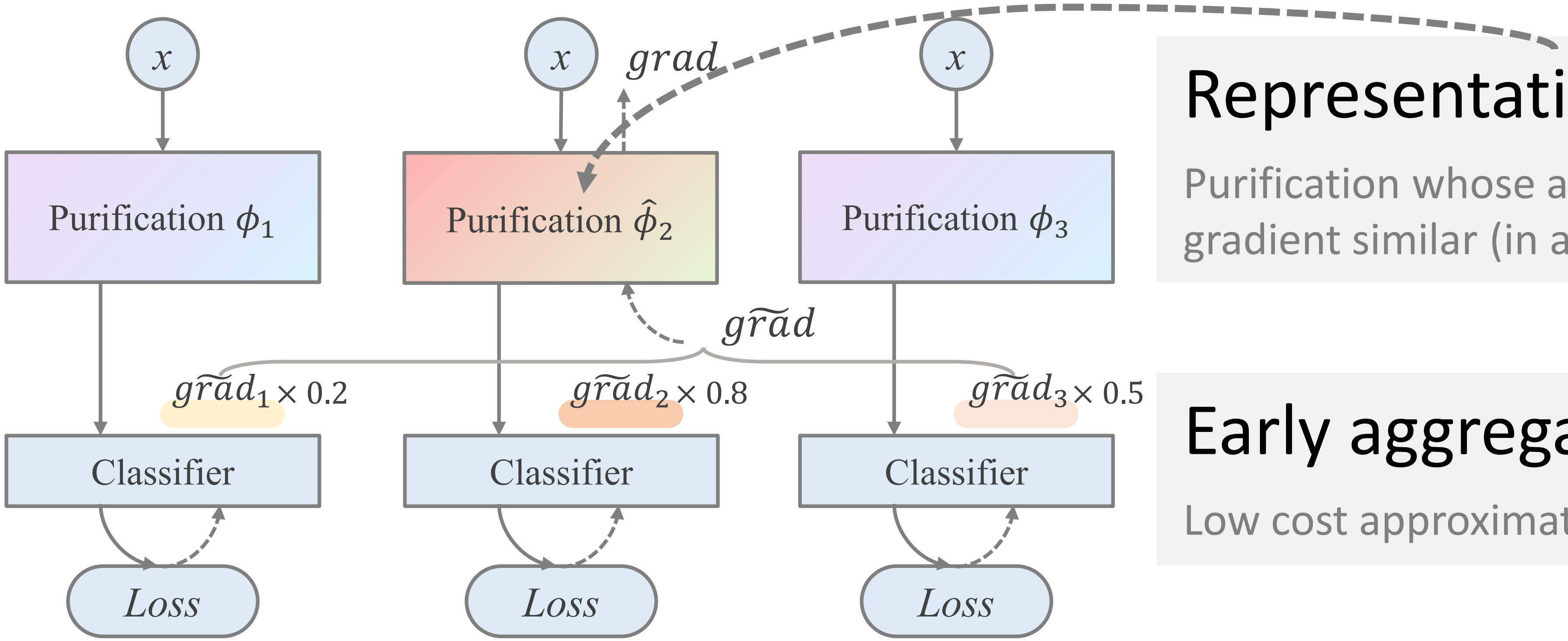
$$\nabla_r \mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} q(z_i)\nabla_x \mathcal{L}_{\phi_i}$$

- Plug-in for off-the-shelf attack algorithms

$$r^{(t+1)} = \Pi_{\|r\|_\infty \leq \epsilon}[r^{(t)} + \alpha \text{sign}(\nabla_r \mathcal{L})]$$

M-Step: aggregate gradients of purification from $\mathcal{S}_1$

Gradient grafting



Representative sample

Purification whose approximate gradient similar (in attack) to others

Early aggregation

Low cost approximate gradient

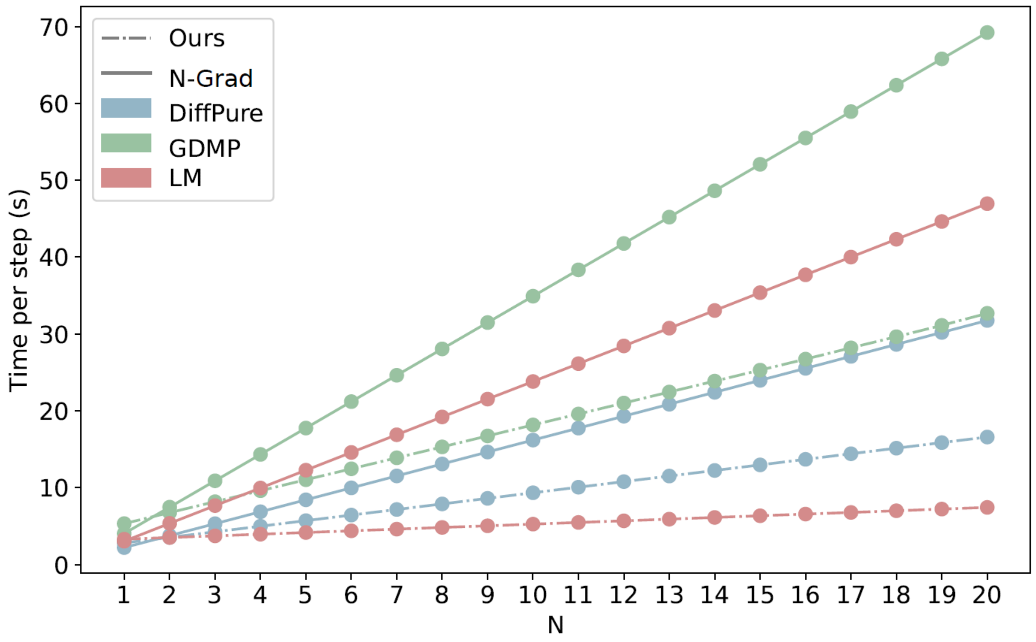
Aggregate early and graft on representative sample to backpropagate

Gradient grafting

High-cost XN
full gradient

High-cost $X1$
purification gradient

Low-cost XN
approximate gradient



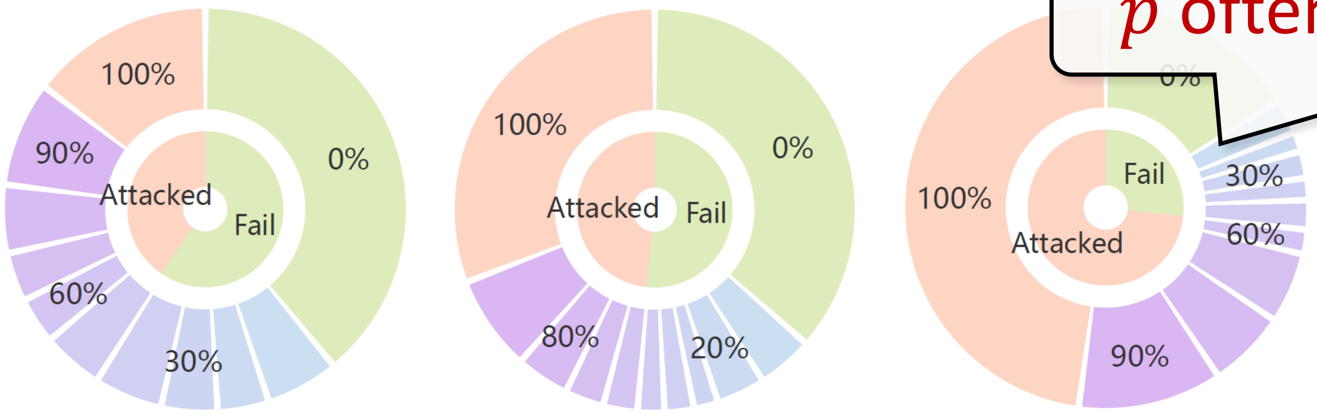
Gradient grafting significantly improves attack efficiency

Resubmit risk

Estimation of p is important for M resubmit risk: $(1-p)^M$ ✓✓✓✗✓ (p=0.2)

1-Evaluation only suitable for $p = 0,1$

p often lies between 0 and 1



(a) DiffPure (b) GDMP (c) LM

Statistically, 1-evaluation <u>underestimates</u> p and resubmit risk

In-loop N-Evaluation

N-Evaluation: ✓✓✓✗✓✓✗✓ ✓✓

1. More accurate estimate in $t-1$:

$$p^{(t-1)} \approx 0.2$$

2. Byproducts for attack stage t:

$$\mathcal{L}_1^{(t)}, \dots, \mathcal{L}_{10}^{(t)}, \qquad \tilde{g}_1^{(t)}, \dots, \tilde{g}_{10}^{(t)}$$

for $t \leftarrow 1$ **to** T **do**

- *Evaluation for $t-1$ iteration and input for t iteration*;
- Sample $\phi_i, i = 1, \cdots, N$;
- $Rob^{(t-1)}$ = `Eval` $(r^{(t-1)}, M)$ // for evaluation;
- Record $\mathcal{L}_{\phi_i}^{(t)}, \nabla_{\phi_i}^{(t)} \mathcal{L}_{\phi_i}$ // for attack;
- *E-step: identify the set with shared vulnerability*;
- $\Delta\tilde{r}^{(t)} = \arg\max \sum_i \sigma(\mathcal{L}_{\phi_i}^{(t)} + \Delta\tilde{r}^T \nabla_{\phi_i}^{(t)} \mathcal{L}_{\phi_i})$;
- $q_i^{(t)} = \sigma(\mathcal{L}_{\phi_i}^{(t)} + \Delta\tilde{r}^T \nabla_{\phi_i}^{(t)} \mathcal{L}_{\phi_i})$ // probability of affiliation;
- *M-step: estimate the full gradients' aggregation*;
- $\tilde{g}^{(t)} = \sum_i q_i^{(t)} \nabla_{\phi_i}^{(t)} \mathcal{L}_{\phi_i} / N$ // aggregation in ϕ stage;
- $g^{(t)}$ = `Backward` $(\hat{\phi}(x + r^{(t-1)})^T \tilde{g}^{(t)})$ // gradient grafting;
- $r^{(t)}$ = `AttackAlgorithm` $(r^{(t-1)}, g^{(t)})$;

Better risk assessment is almost <u>free</u>

Effectiveness and efficiency

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	Defense	DiffPure		GDMP		LM	
	Metrics	Avg.Rob (it.)↓	Wor.Rob (it.)↓	Avg.Rob (it.)↓	Wor.Rob (it.)↓	Avg.Rob (it.)↓	Wor.Rob (it.)↓
	Clean	90.98	76.56	93.26	83.79	87.77	74.61
$\ell_\infty : 8/255$	BPDA	70.74 (N/A)	36.72 (N/A)	80.57 (N/A)	51.95 (N/A)	55.27 (N/A)	27.54 (N/A)
	DA/AA	57.60 (N/A)	33.79 (N/A)	52.83 (N/A)	37.70 (N/A)	32.56 (N/A)	17.97 (N/A)
	PGD	52.73 (N/A)	31.05 (112)	49.41 (N/A)	36.91 (N/A)	17.99 (31)	9.38 (31)
	DH	**42.54 (20)**	**22.66 (17)**	**41.64 (17)**	**27.54 (13)**	**16.15 (17)**	**8.01 (14)**
	DMI†	45.64 (41)	25.20 (35)	43.40 (31)	32.42 (27)	38.81 (N/A)	23.83 (N/A)
	TMI†	45.04 (39)	25.20 (38)	45.43 (37)	34.77 (30)	41.13 (N/A)	25.59 (N/A)
	VMI†	50.55 (N/A)	28.71 (44)	50.76 (N/A)	37.11 (44)	21.97 (39)	11.72 (32)
	SVRE†	59.12 (N/A)	32.81 (N/A)	60.37 (N/A)	42.77 (N/A)	36.11 (N/A)	19.53 (136)

Iterations taken to reach 90% best performance

DiffHammer (DH) achieves effective results within 10-30 iterations

Critical resubmit risk

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Defenses show robustness below 30% with 10-evaluation

Transfer-based attacks

	Defense	DiffPure		GDMP		LM	
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	DA/AA	57.60 (N/A)	33.79 (N/A)	52.83 (N/A)	37.70 (N/A)	32.5[illegible] (N/A)	17.97 (N/A)
	PGD	52.73 (N/A)	31.05 (112)	49.41 (N/A)	36.91 (N/A)	17.9[illegible] (31)	9.38 (31)
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Transfer-based attacks that generalize to all purifications

Generalization in $\mathcal{S}_1$ is beneficial (DiffHammer) while in $\mathcal{S}_0$ is harmful

Conclusion

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- We propose a selective attack strategy that targets vulnerable purifications, enhancing evaluation efficiency through gradient grafting.
- We incorporate N-evaluation within the loop to quantify the resubmit risk of achieving at least one successful attack in practice.

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★ Website: https://github.com/Ka1b0/DiffHammer