



CUDA: Convolution-based Unlearnable Datasets

Vinu Sankar Sadasivan¹

Mahdi Soltanolkotabi²

Soheil Feizi¹



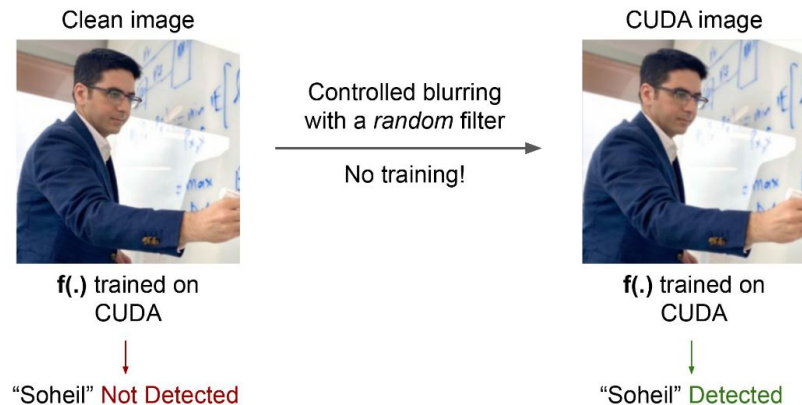
One-minute Pitch

Unlearnable images

- Attacker adds noise to training images
- Defender trains $f(\cdot)$ w/ poisoned data
- $f(\cdot)$ fails to classify clean data
- $f(\cdot)$ classifies poisoned data
- Privacy for facial recognition

CUDA

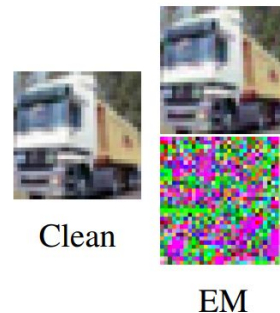
- Novel non-additive noise
- Controlled blurring creates shortcuts
- Model-free; 20-100x faster
- Very robust



Previous Works Need Optimizations

- EM (Huang et al., ICLR 21) – min-min ←
- TAP (Fowl et al., NeurIPS 21) – min-max
- REM (Fu et al., ICLR 22) – min-min-max

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^n \min_{\|\delta_i\| \leq \rho_u} \ell(f'_{\theta}(x_i + \delta_i), y_i)$$



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$$\min_{\theta} \frac{1}{n} \sum_{i=1}^n \max_{\|\delta_i\| \leq \rho_a} \ell(f_{\theta}(x_i + \delta_i), y_i)$$

- Expensive
- Not robust to AT

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$$\min_{\theta} \frac{1}{n} \sum_{i=1}^n \min_{\|\delta_i^u\| \leq \rho_u} \max_{\|\delta_i^a\| \leq \rho_a} \ell(f'_{\theta}(x_i + \delta_i^u + \delta_i^a), y_i)$$

- Expensive
- Not transferable to DenseNet-121
- Sensitive to AT hyperparameters
- REM breaks w/ grayscaling

CUDA is simple

- Clean – (x, y)
- Filter – s_y randomly generated for class y
- $x' = x \square s_y$ where \square is convolution
- CUDA image – $(x' / \text{MAX}(x'), y)$
- Network learns relation b/w s_y & y

$$s_y = \begin{pmatrix} z & z & z \\ z & 1 & z \\ z & z & z \end{pmatrix}, \quad z \sim U(0, p_b)$$

$k \times k$ ($k = 3$)

- k is filter size
- p_b is blur parameter
- Controls blurring

CUDA is effective

- Model-free; 20-100x faster
- Robust to AT, augs, adaptive defenses
- Transferable to different networks
- Theory

Dataset	EM	TAP	NTGA	REM	CUDA
CIFAR-10	0.4 hr	0.5 hr	5.2 hrs	22.6 hrs	10.8 s
CIFAR-100	0.4 hr	0.5 hr	5.2 hrs	22.6 hrs	15.5 s
ImageNet-100	3.9 hrs	5.2 hrs	14.6 hrs	51.2 hrs	0.15 hr

Theorem (Informal) Let D be a Gaussian mixture with two modes. P_D denotes optimal Bayesian classifier trained on D . $\tau_D(P)$ denote accuracy of P on D . For every clean D , $\exists D'$ s.t. $\tau_D(P_{D'}) < \tau_D(P_D)$.

CUDA is robust to AT

Dataset	Clean	Training method	CUDA (ours)
CIFAR-10	94.66	ERM	18.48
		AT L_∞ ($\rho_a = 4/255$)	44.40
		AT L_∞ ($\rho_a = 8/255$)	32.85
		AT L_∞ ($\rho_a = 16/255$)	19.32
		AT L_2 ($\rho_a = 0.25$)	39.05
		AT L_2 ($\rho_a = 0.50$)	51.19
		AT L_2 ($\rho_a = 0.75$)	51.14
CIFAR-100	76.27	ERM	12.69
		AT L_∞ ($\rho_a = 4/255$)	34.34
		AT L_∞ ($\rho_a = 8/255$)	30.00
		AT L_2 ($\rho_a = 0.75$)	36.90
ImageNet-100	80.66	ERM	8.96
		AT L_∞ ($\rho_a = 4/255$)	38.68
		AT L_∞ ($\rho_a = 8/255$)	40.08
		AT L_2 ($\rho_a = 0.75$)	20.58

CUDA is robust to networks & datasets

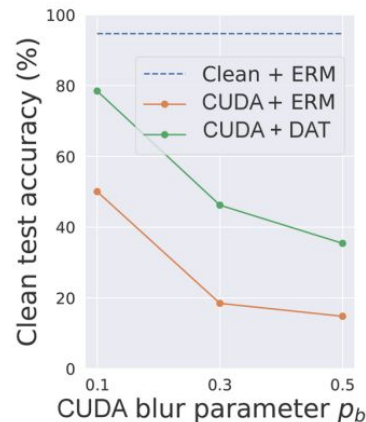
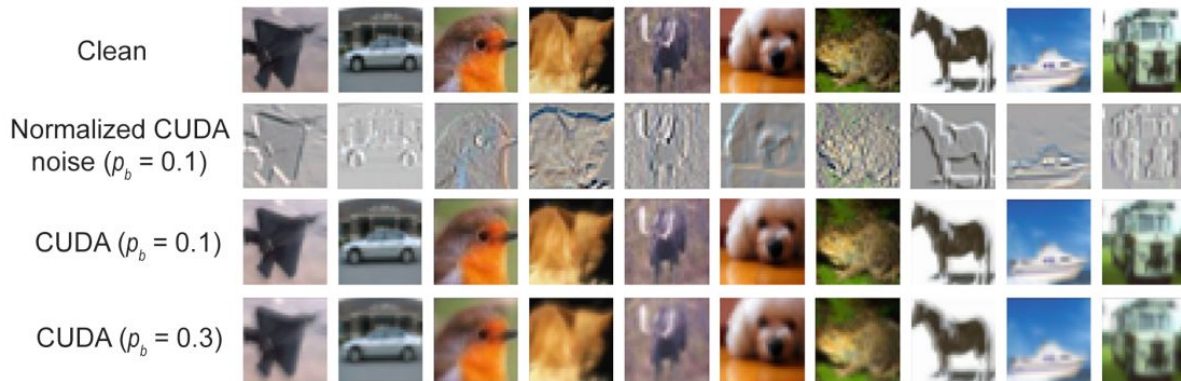
Model	Clean	Unlearnability method				
		EM	TAP	NTGA	REM	CUDA
ResNet-18	89.51	88.62	88.02	88.96	48.16	44.40
VGG-16	87.51	86.48	86.27	86.65	65.23	42.98
Wide ResNet-34-10	91.21	90.05	90.23	89.95	48.39	53.02
DenseNet-121	83.27	82.44	81.72	80.73	81.48	45.95

Dataset	Training method	Clean	Unlearnability method				
			EM	TAP	NTGA	REM	CUDA
CIFAR-10	ERM	94.66	13.20	22.51	16.27	27.09	18.48
	AT	89.51	88.62	88.02	88.96	48.16	44.40
CIFAR-100	ERM	76.27	1.60	13.75	3.22	10.14	12.69
	AT	64.50	63.43	62.39	62.44	27.10	34.34
ImageNet-100	ERM	80.66	1.26	9.10	8.42	13.74	8.96
	AT	66.62	63.40	63.56	63.06	41.66	38.68

Architectures	Resnet-18, VGG-16, Wide ResNet-34-10, DenseNet-121, MobileNet-V2, EfficientNet-V2-S, DeiT
Datasets	CIFAR-10, CIFAR-100, ImageNet-100, Tiny ImageNet

CUDA is robust to defenses

- Grayscaleing, mixup, cutmix, cutout, auto augment, other regularizations, randomized smoothing
- Adaptive defense – Deconvolution-based Adversarial Training
- Stealth v/ Unlearnability trade-off





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