Adversarial Dictionary Learning

Jordan Frecon, Lucas Anquetil, Gilles Gasso, Stéphane Canu

Normandie Univ, INSA Rouen, LITIS, Normandie

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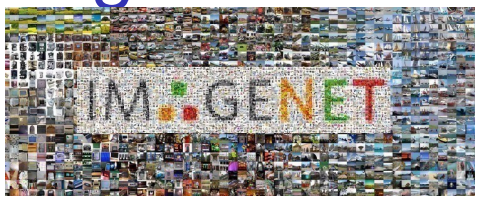
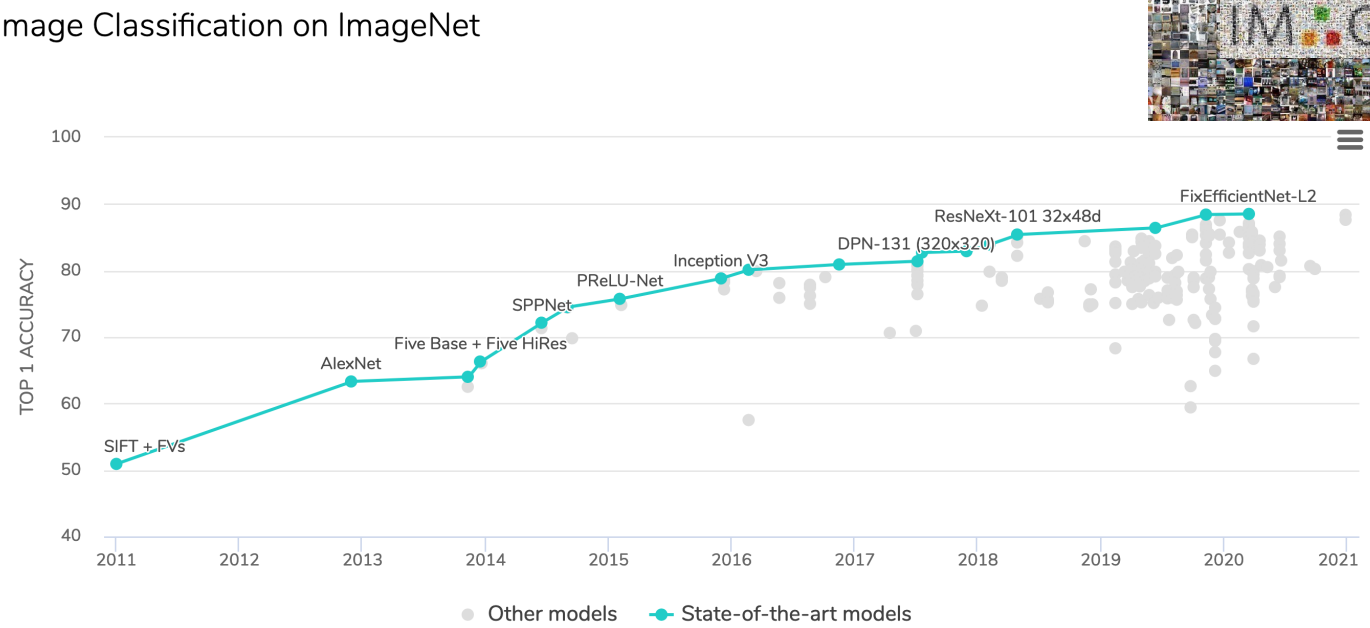
SCADA -> ADiL (Adversarial Dictionary Learning)

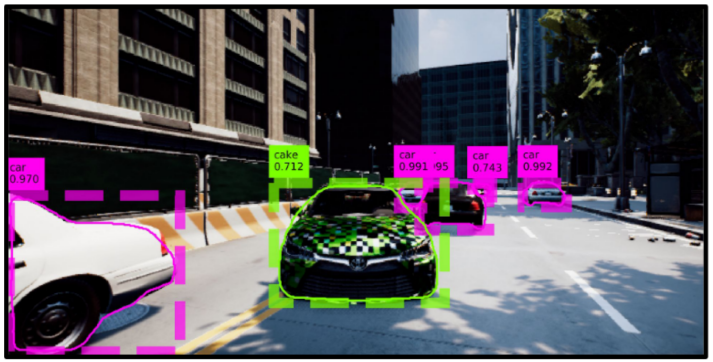
The amazing achievements of deep learning





Attacks against autonomous vehicles

Eykholt et al, Robust Physical-World Attacks on Deep Learning Visual Classification, CVPR 2018



Zhang et al., CAMOU: Learning Physical Vehicle Camouflages to Adversarially Attack Detectors in the Wild, ICLR 2019

https://www.mcafee.com/blogs/other-blogs/mcafee-labs/model-hacking-adas-to-pave-safer-roads-for-autonomous-vehicles/

Nassi et al., Phantom of the ADAS: Securing Advanced Driver-AssistanceSystems from Split-Second Phantom Attacks, 2020

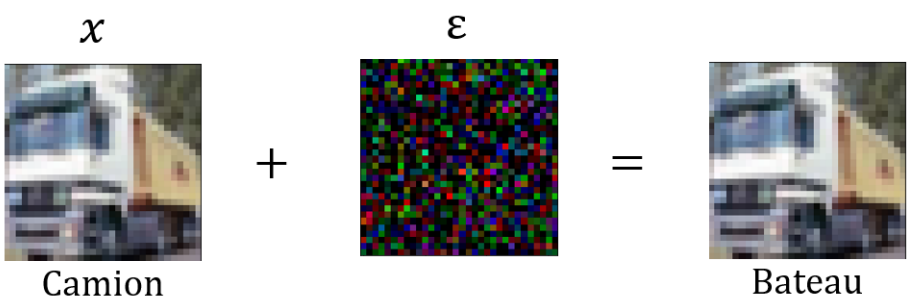
Qayyum, et al., Securing Connected & Autonomous Vehicles: Challenges Posed by Adversarial ML, IEEE Communications, 2019

Definition (Adversarial example x')

Given an observed (also called natural or clean) example x, x' is

- a slight modification of x (e.g. such that $\|x - x'\| \leq \epsilon$)
- but having a different label prediction by f (i.e. fooling f)

$$\underset{k \in \{1,\ldots,c\}}{\operatorname{argmax}} \; f(x'; \theta) \neq \underset{k \in \{1,\ldots,c\}}{\operatorname{argmax}} \; f(x; \theta),$$



Explaining and Harnessing Adversarial Examples, I. Goodfellow et al, ICLR 2015

How to craft adversarial examples?

- Specific: for a given x_i

$$x_i' = x_i + \varepsilon(x_i)$$

  - FGSM [GSS15, KGB17]

$$\varepsilon(x_i) = \delta \ \text{sign}(\nabla_{x_i} H(f(x_i;\theta), y_i)),$$

  - DeepFool [MFF16]

$$\varepsilon(x_i) = \text{argmin}_\varepsilon \|\varepsilon\|, \ \text{s.t.} \ \text{argmax}_k f(x_i+\varepsilon;\theta) \neq \text{argmax}_k f(x_i;\theta)$$

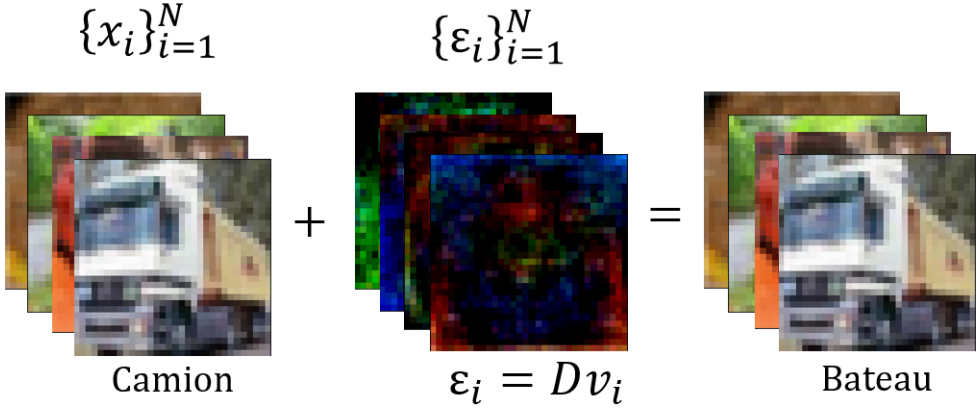
- Universal [MDFFF17]: for any example

$$\varepsilon(x_i) = \underset{\varepsilon}{\text{argmax}} \sum_{j=1}^{N} H(f(x_j+\varepsilon;\theta), y_j) \quad \text{s.t.} \quad \|\varepsilon\|_p \leq \epsilon \ ,$$

- Use a dictionary D:

$$\varepsilon(x_i) = Dv_i$$

Adversarial dictionary learning: $\varepsilon(x_i) = Dv_i$



$$\underset{[D,v]}{\text{minimize}} \sum_{i=1}^{N} \underbrace{\ell_i(x_i + Dv_i)}_{\text{adversary}} + \underbrace{\lambda_1 \|v_i\|_1}_{\text{sparse}} + \underbrace{\lambda_2 \|Dv_i\|_2^2}_{\varepsilon_i \text{ small}}$$

$$D = \left(\quad \right)$$

D universal, $v_i \in \mathbb{R}^M$ specific ($M \ll N$)

Algorithmic solutions

- Full-batch version: ADiL
  - with proofs
- Stochastic version: SADiL
  - that scales...

Full-batch version: ADiL

$$\underset{\substack{D\in\mathbb{R}^{P\times M}\\ V\in\mathbb{R}^{M\times N}}}{\text{minimize}}\ \mathcal{L}(D,V) \triangleq F(D,V)+\Omega(D,V)$$

- Smooth supervised fitting term

$$F(D,V)=\sum_{i=1}^{N}\lambda_2\|Dv_i\|^2+H\big(f(x_i+Dv_i;\theta),t_i\big)$$

- Non-smooth regularization

$$\Omega(D,V)=\imath_{\mathcal{C}}(D)+\sum_{i=1}^{N}\lambda_1\|v_i\|_1,\quad \mathcal{C}=\{D\mid\forall m,\|d_m\|_2\leq 1\}$$

A sparse representation for a better dictionary

The proximal step

$$(D^{(k+1/2)}, V^{(k+1/2)}) = \underset{\substack{D\in\mathbb{R}^{P\times M}\\ V\in\mathbb{R}^{M\times N}}}{\operatorname{argmin}} \; F(D, V) + \Omega(D, V),$$

The proximal step

$$\begin{pmatrix} D^{(k+1/2)} \\ V^{(k+1/2)} \end{pmatrix} = \operatorname{prox}_{\gamma_k \Omega} \left(\begin{pmatrix} D^{(k)} \\ V^{(k)} \end{pmatrix} - \gamma_k \nabla F(D^{(k)}, V^{(k)}) \right),$$

Ω being separable, it yields that

$$\begin{pmatrix} D^{(k+1/2)} \\ V^{(k+1/2)} \end{pmatrix} = \begin{pmatrix} \operatorname{Proj}_{\mathcal{C}} & \left(D^{(k)} - \gamma_k \nabla_D F(D^{(k)}, V^{(k)}) \right) \\ \operatorname{Soft}_{\gamma_k \lambda_1} & \left(V^{(k)} - \gamma_k \nabla_V F(D^{(k)}, V^{(k)}) \right) \end{pmatrix},$$

Algorithm 1 ADiL

Require: Parameter $\delta \in]0,1[$, $D^{(0)} \sim \mathcal{N}(0_{P\times M}, 1_{P\times M})$, $V^{(0)} = 0_{M\times N}$

for $k = 0$ to $K-1$ **do**

Proximal-gradient step

$D^{(k+1/2)} = \mathrm{Proj}_{\mathcal{C}}(D^{(k)} - \gamma_k \nabla_D F(D^{(k)}, V^{(k)}))$

$V^{(k+1/2)} = \mathrm{Soft}_{\gamma_k \lambda_1}(V^{(k)} - \gamma_k \nabla_V F(D^{(k)}, V^{(k)}))$

Armijo-like backtracking

$d_D^{(k)} = D^{(k+1/2)} - D^{(k)}$

$d_V^{(k)} = V^{(k+1/2)} - V^{(k)}$

$i_k = 0$

repeat

$\tilde{D}^{(k)} = D^{(k)} + \delta^{i_k} d_D^{(k)}$

$\tilde{V}^{(k)} = V^{(k)} + \delta^{i_k} d_V^{(k)}$

$i_k = i_k + 1$

until decreasing criterion satisfied

$D^{(k+1)} = \tilde{D}^{(k)}$

$V^{(k+1)} = \tilde{V}^{(k)}$

end for

return $\{D^{(K)}, V^{(K)}\}$

Convergence

Theorem (Convergence [BLP+17])

Let $\{D^{(k)}, V^{(k)}\}_{k\in\mathbb{N}}$ be the sequence of ADiL Algorithm 1. Then,

- *each limit point of $\{D^{(k)}, V^{(k)}\}_{k\in\mathbb{N}}$ is a stationary point of ADiL*
- *$\{\mathcal{L}(D^{(k)}, V^{(k)})\}_{k\in\mathbb{N}}$ converges to the limit point objective value*

In addition, if $\mathcal{L}$ satisfies the Kurdyka-Łojasiewicz property at any point, then the sequence converges to a stationary point of ADiL

Stochastic version: SADiL

Two ingredients: an alternating scheme

$$\begin{cases} V^{(k+1)} & = \mathrm{Soft}_{\gamma_k \lambda_1}\left(V^{(k)} - \gamma_k \widetilde{\nabla} F(D^{(k)}, V^{(k)})\right), \\ D^{(k+1)} & = \mathrm{Proj}_{\mathcal{C}}\left(D^{(k)} - \gamma_k \widetilde{\nabla} F(D^{(k)}, V^{(k+1)})\right), \end{cases}$$

$\widetilde{\nabla} F$: random estimate of the gradient on a mini-batch $\mathcal{B}_k \sim \{1, \dots, N\}$

$$\widetilde{\nabla} F(D, V) = \frac{N}{|\mathcal{B}_k|} \sum_{i \in \mathcal{B}_k} \nabla F_i(D, V).$$

For $|\mathcal{B}_k| = N$, we recover PALM

Generation of adversary examples

Design of adversarial perturbations to unseen examples.

1. Use ADiL with fixed D to find $v^{(K)}$
2. Project onto the input manifold $\mathcal{X} \subseteq \mathbb{R}^P$

$$x' = \text{Proj}_{\mathcal{X}} \left(x + Dv^{(K)} \right)$$

Defense mechanism

Problem (Defense mechanism)

$$\underset{\theta \in \Theta}{\text{minimize}} \quad \underset{\{x,y\} \sim \mathcal{D} \cup \mathcal{A}}{\mathbb{E}} H(f(x;\theta), y) \ , \tag{1}$$

where $\mathcal{D} \cup \mathcal{A}$ is the augmented training set

Two manners of constructing the adversarial set with correct labeling.

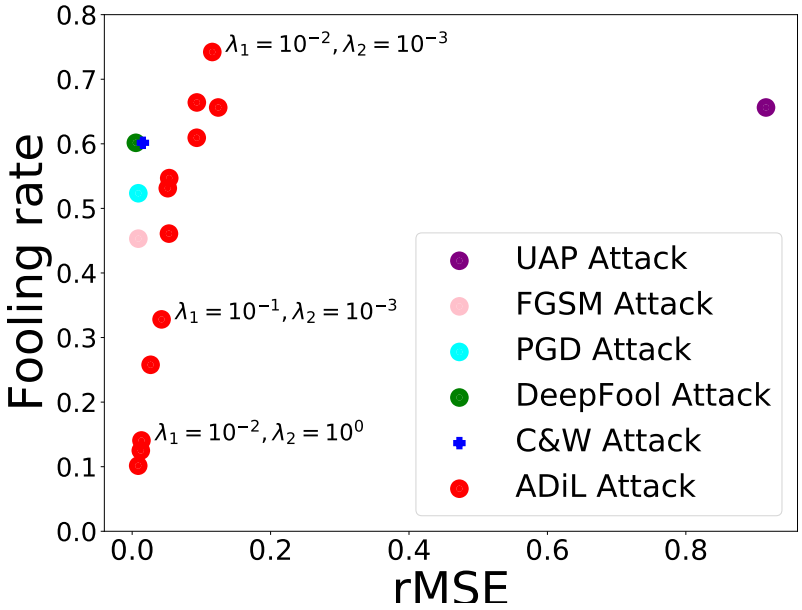
(Adversarial training) $\mathcal{A} = \{x_i + \hat{D}\hat{v}_i, y_i\}_{i=1}^N$,

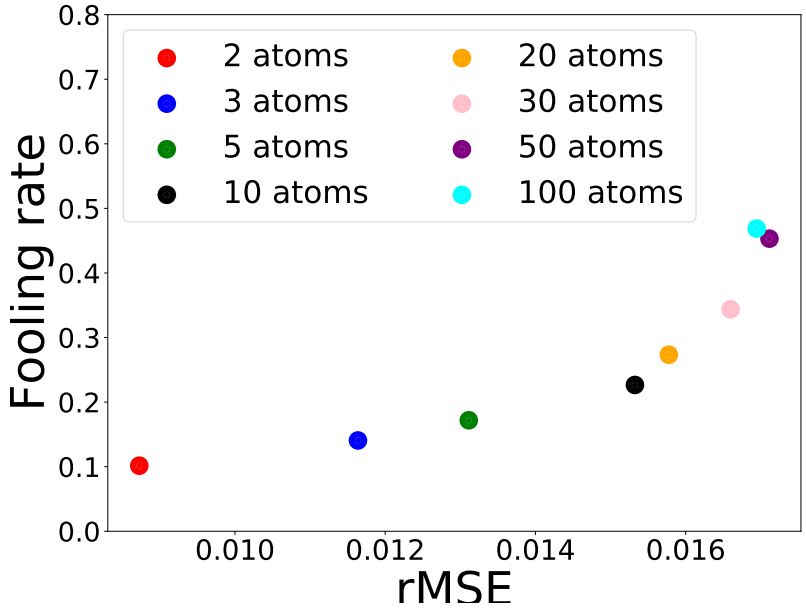
(Noise injection) $\mathcal{A} = \{x_i + \hat{D}z_i, y_i\}_{i=1}^N$ *with* $z_i \sim \text{Laplace}(0, b)$,

where b is estimated by fitting a Laplacian distribution to the $\hat{v}_i$'s.

Experimental results: LeNet classifier on CIFAR-10

rMSE: $(1/|\mathcal{T}_2|)\sum_{i=1}^{|\mathcal{T}_2|}\|Dv_i\|^2/\|x_i\|^2$





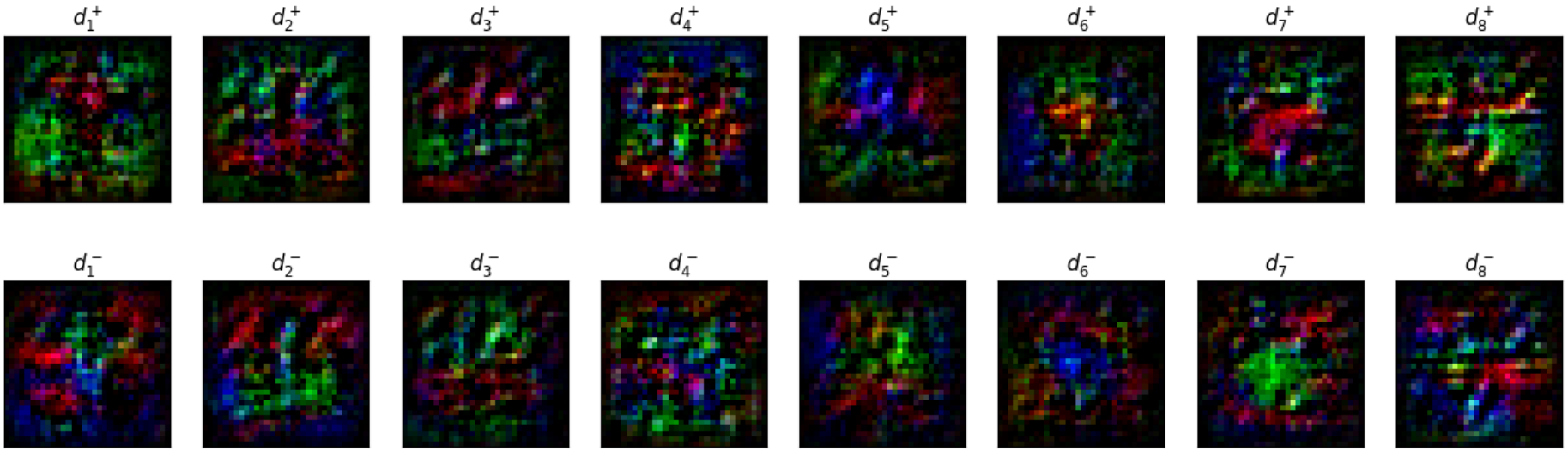
Experimental results on ResNet18 classifier

		PGD	DeepFool	C&W	ADiL	UAP
CIFAR-10	Fool. Rate	54.69%	74.22%	74.22%	**90.63%**	77.34%
	rMSE	0.0091	**0.0056**	0.032	0.071	0.747
ImageNet	Fool. Rate	22.66%	17.19%	3.91%	38.28%	**100%**
	rMSE	0.00054	**0.00022**	0.00025	0.0458	1.52

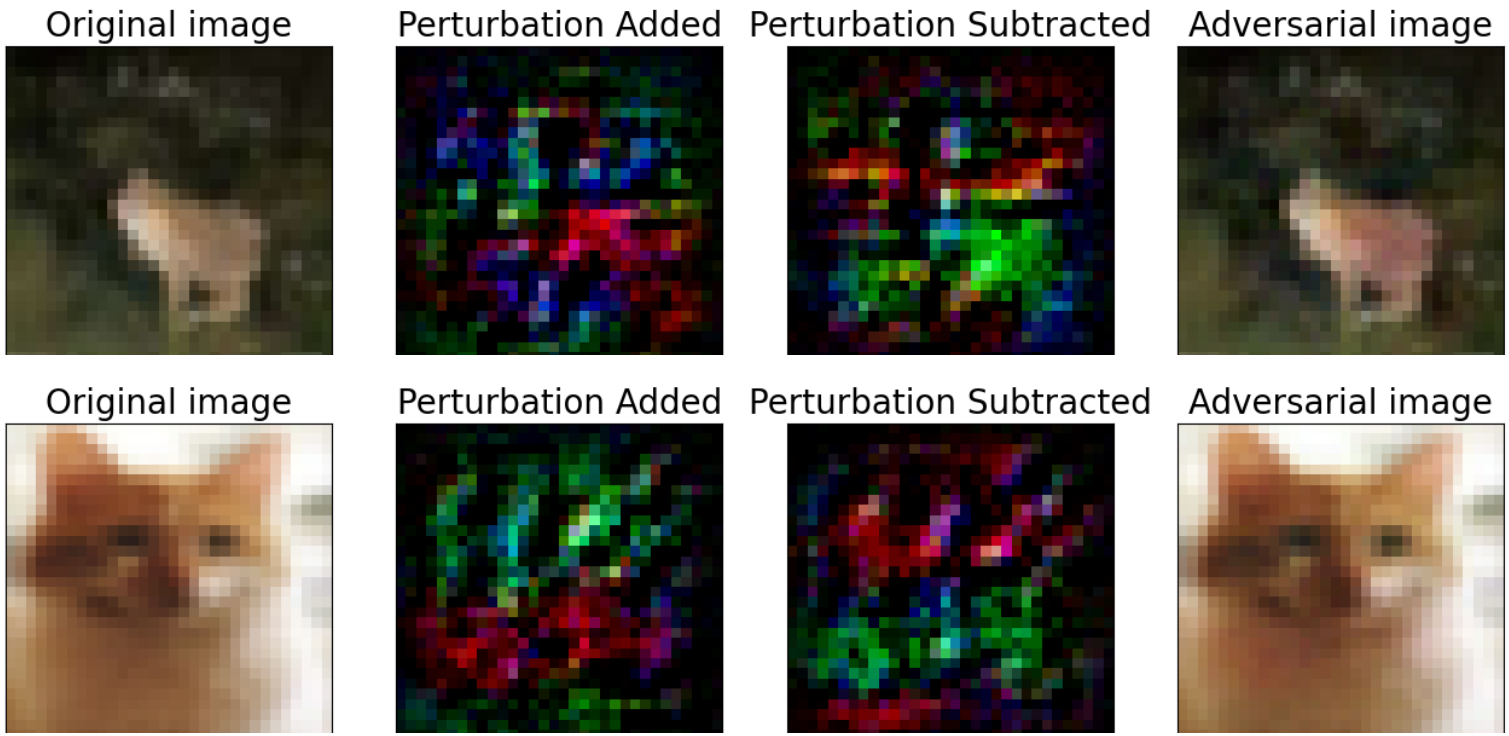
Defense mechanism for LeNet on CIFAR-10

M_{attacker}	2 atoms	5 atoms	10 atoms	15 atoms	20 atoms
No Defense	25.78%	56.25%	60.15%	46.09%	57.81%
With Defense	**15.62%**	**30.46%**	**53.90%**	**44.53%**	**56.25%**

Dictionary of ADiL attacks for LeNet on CIFAR-10



Two examples of ADiL attacks for LeNet on CIFAR-10



Conclusion

- A new way to generate adversarial examples
- with a universal component D
  - interpretable?
  - transferable?
- efficient way to compute specific components v_i
- improve the defence mechanism to train robust NN

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