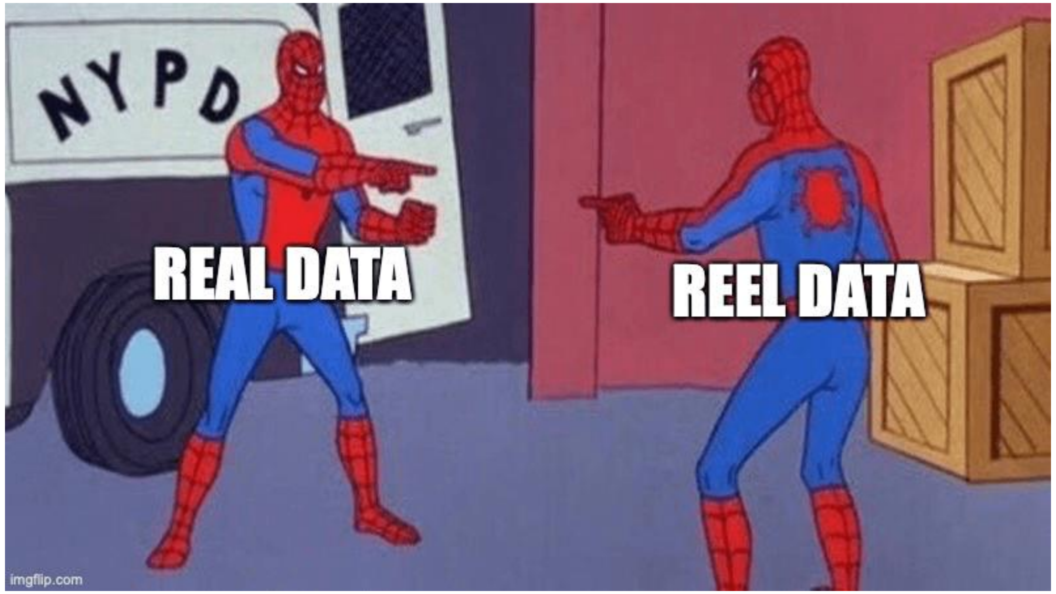
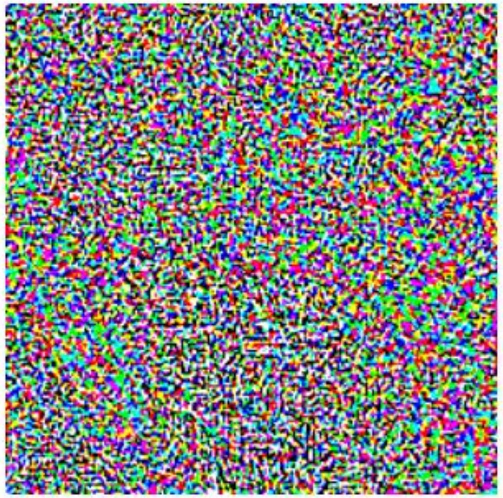


Adversarial Machine learning

Arman Akbari, Arash Akbari

$+ .007 \times$

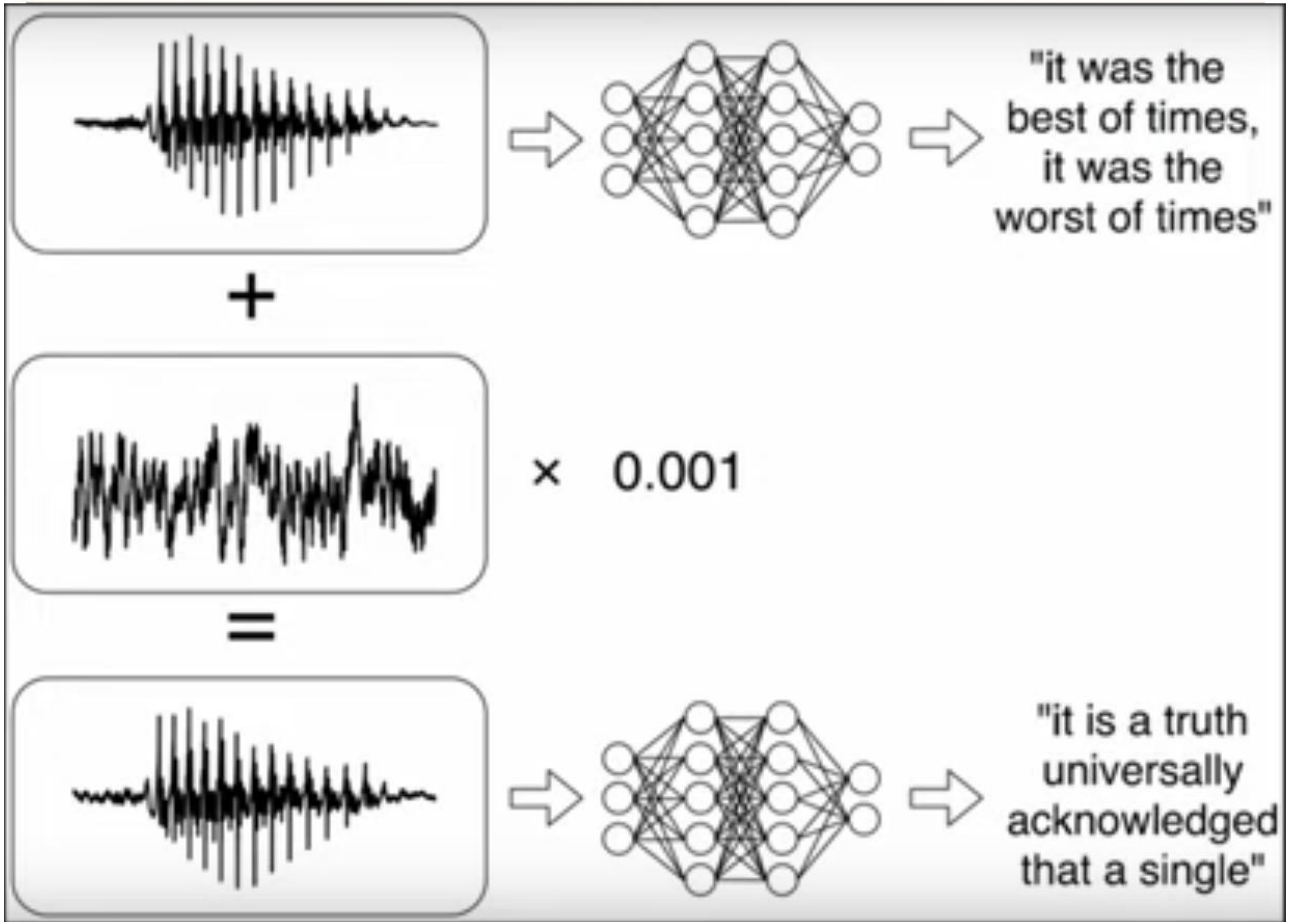


$=$

$\boldsymbol{x}$
"panda"
57.7% confidence

$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
8.2% confidence

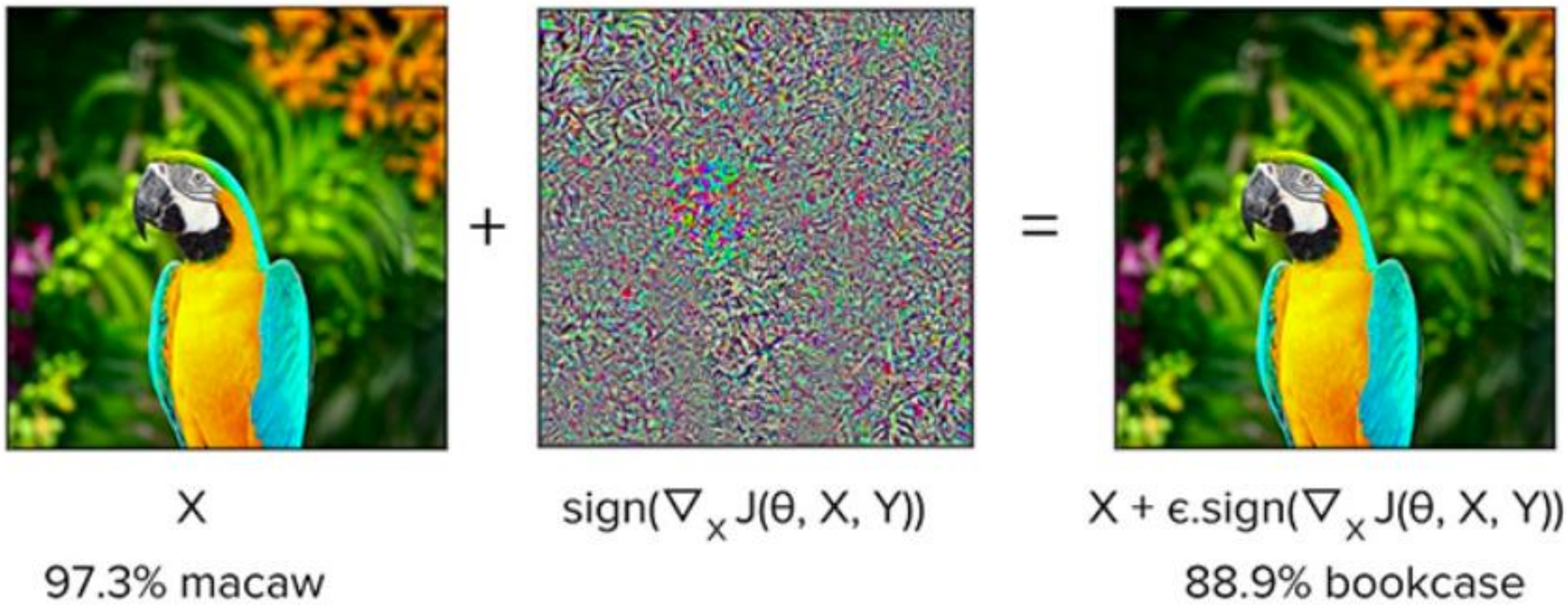
$\boldsymbol{x} +$
$\epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
99.3 % confidence


"it was the best of times, it was the worst of times"
+
× 0.001
=
"it is a truth universally acknowledged that a single"

FGSM(Fast Gradient Sign Method)

- The linear view of adversarial examples suggests a fast way of generating them

$$\boldsymbol{\eta} = \epsilon \operatorname{sign}\left(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y)\right).$$



Max-loss from $\longrightarrow$

$$\max_{\boldsymbol{x}'} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right) \\ \text{s.t. } d\left(\boldsymbol{x}, \boldsymbol{x}'\right) \leq \varepsilon\,, \quad \boldsymbol{x}' \in [0,1]^n\,, \tag{1}$$

Robustness Radius $\longrightarrow$

$$\min_{\boldsymbol{x}'} \ d\left(\boldsymbol{x}, \boldsymbol{x}'\right) \\ \text{s.t. } \max_{i \neq y} f^i_{\boldsymbol{\theta}}(\boldsymbol{x}') \geq f^y_{\boldsymbol{\theta}}(\boldsymbol{x}')\,, \ \boldsymbol{x}' \in [0,1]^n\,, \tag{2}$$

Adversarial Robustness $\longrightarrow$

$$\min_{\boldsymbol{\theta}} \ \mathbb{E}_{(\boldsymbol{x},\boldsymbol{y})\sim\mathcal{D}} \max_{\boldsymbol{x}'\in\Delta(\boldsymbol{x})} \ell\left(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{x}')\right) \tag{3}$$