Advanced Machine Learning

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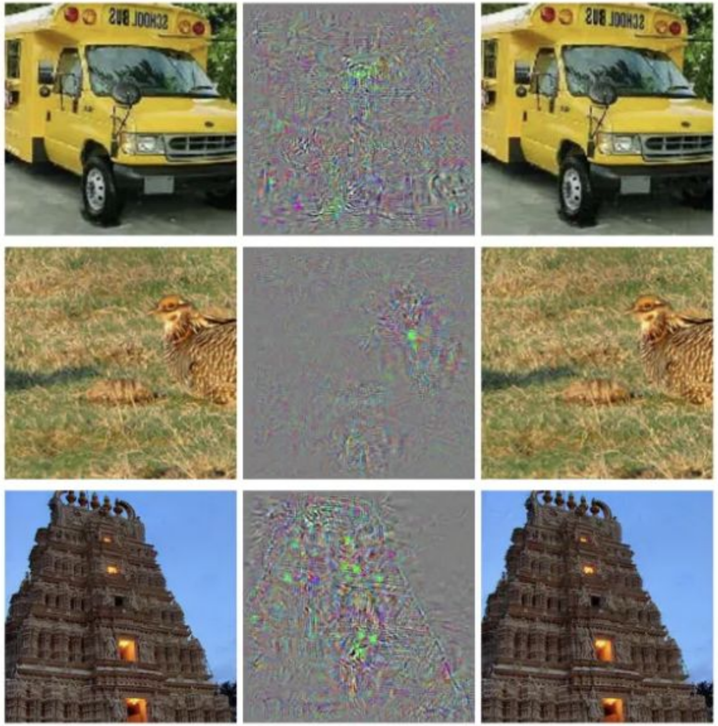
Adversarial Examples



Szegedy, Christian, et al. "Intriguing properties of neural networks." arXiv preprint arXiv:1312.6199 (2013).

Adversarial Examples

Assumption in neural network training:

For a small enough radius ***r*** in the vicinity of a given input ***x***, an input ***x* + *r*** satisfying $\|\boldsymbol{r}\| < \boldsymbol{\epsilon}$ ($\epsilon > 0$) will predict the correct class

Disproved:

The assumption does not hold true, and it is proved by generating adversarial samples with imperceptibly small perturbations that make the model mispredict classes.

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Adversarial Examples

Consider a neural network classifier ***f*** that maps an input image $\boldsymbol{x} \in \mathbb{R}^m$ to a set of labels $\{1 \ldots k\}$ — $f : \mathbb{R}^m \rightarrow \{1 \ldots k\}$

$$\text{Minimize } \|r\|_2 \text{ subject to:}$$

1. $f(x + r) = l$
2. $x + r \in [0, 1]^m$

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Cross-model generalization

	FC10(10^{-4})	FC10(10^{-2})	FC10(1)	FC100-100-10	FC200-200-10	AE400-10	Av. distortion
FC10(10^{-4})	100%	11.7%	22.7%	2%	3.9%	2.7%	0.062
FC10(10^{-2})	87.1%	100%	35.2%	35.9%	27.3%	9.8%	0.1
FC10(1)	71.9%	76.2%	100%	48.1%	47%	34.4%	0.14
FC100-100-10	28.9%	13.7%	21.1%	100%	6.6%	2%	0.058
FC200-200-10	38.2%	14%	23.8%	20.3%	100%	2.7%	0.065
AE400-10	23.4%	16%	24.8%	9.4%	6.6%	100%	0.086
Gaussian noise, stddev=0.1	5.0%	10.1%	18.3%	0%	0%	0.8%	0.1
Gaussian noise, stddev=0.3	15.6%	11.3%	22.7%	5%	4.3%	3.1%	0.3

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Cross-training generalization

	FC100-100-10	FC123-456-10	FC100-100-10’
Distorted for FC100-100-10 (av. stddev=0.062)	100%	26.2%	5.9%
Distorted for FC123-456-10 (av. stddev=0.059)	6.25%	100%	5.1%
Distorted for FC100-100-10’ (av. stddev=0.058)	8.2%	8.2%	100%
Gaussian noise with stddev=0.06	2.2%	2.6%	2.4%

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How unstable are neural networks?

If minor perturbations to the inputs change the model's output to the point that it becomes incorrect, then the model is not stable.

Lipschitz continuity:

Any function where the slope of the line joining any two points on this function is not greater than a real number is called a **Lipschitz continuous function**. This real number is called the **Lipschitz constant**.

$$|f(x_1) - f(x_2)| \leq K|x_1 - x_2|$$

How unstable are neural networks?

The unstability of a neural network can be understood by looking at the Lipschitz constant of each layer ***k = 1 . . . K,*** as given by:

$$\forall x, r \quad \|\varphi_k(x; W_k) - \varphi_k(x + r; W_k)\| \leq L_k \|r\|$$

where $\boldsymbol{\varphi_k}$ is the output of the $\boldsymbol{k^{th}}$ **layer**, and ***L***□ is the Lipschitz constant for the $\boldsymbol{k^{th}}$ **layer.** So for the entire network of ***K*** layers,

$$\|\varphi(x) - \varphi(x + r)\| \leq L\|r\| \quad where\ L = \prod_{k=1}^{K} L_k$$

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How unstable are neural networks?

Layer	Size	Stride	Upper bound
Conv. 1	$3 \times 11 \times 11 \times 96$	4	2.75
Conv. 2	$96 \times 5 \times 5 \times 256$	1	10
Conv. 3	$256 \times 3 \times 3 \times 384$	1	7
Conv. 4	$384 \times 3 \times 3 \times 384$	1	7.5
Conv. 5	$384 \times 3 \times 3 \times 256$	1	11
FC. 1	9216×4096	N/A	3.12
FC. 2	4096×4096	N/A	4
FC. 3	4096×1000	N/A	4

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How unstable are neural networks?

Properties of Lipschitz constant for a neural network:

- Small bounds guarantee that no such adversarial examples can appear.
  - This suggests a simple regularization of the parameters, consisting in penalizing each upper Lipschitz bound, which might help improve the generalisation error of the networks
- Large bounds do not automatically translate into existence of adversarial examples
- They don’t explain why adversarial examples generalize across different hyperparameters or training sets.

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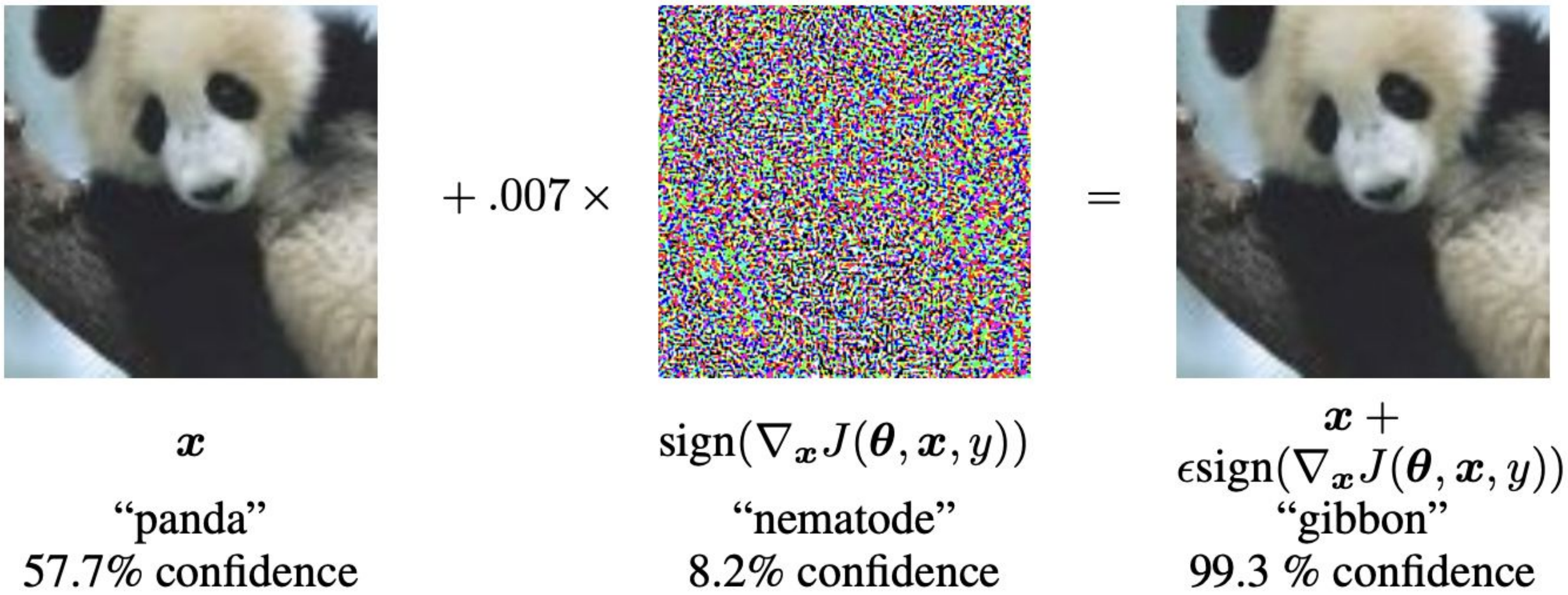
Adversarial Training



Adversarial Training - Loss function

- Adversarial examples are a result of models being too linear, rather than too nonlinear.
- Adversarial training can result in regularization; even further regularization than dropout.
- RBF networks are resistant to adversarial examples.

The new loss (or objective) function has a regularizer term denoted by the fast gradient sign method:

$$\tilde{J}(\boldsymbol{\theta}, \boldsymbol{x}, y) = \alpha J(\boldsymbol{\theta}, \boldsymbol{x}, y) + (1 - \alpha) J(\boldsymbol{\theta}, \boldsymbol{x} + \epsilon \operatorname{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$$

Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." *arXiv preprint arXiv:1412.6572* (2014).

Generative Adversarial Networks (GANs)