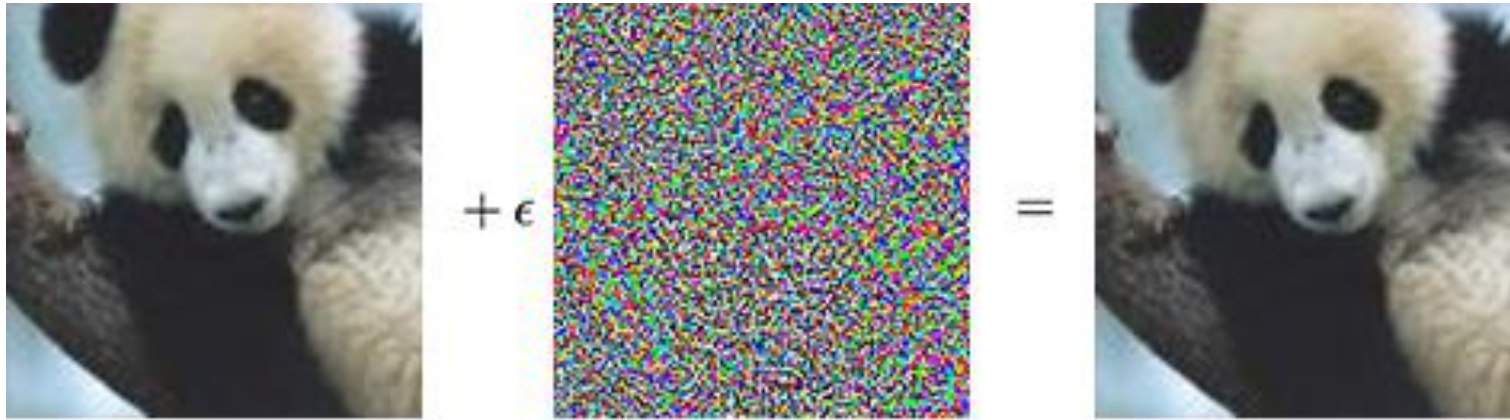


Adversarial Examples



Question: What are these pictures of?

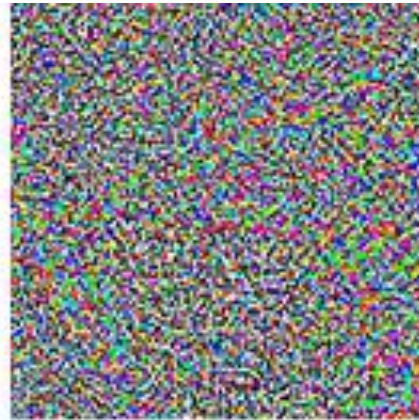
Adversarial Examples



"panda"

57.7% confidence

+ ϵ



=

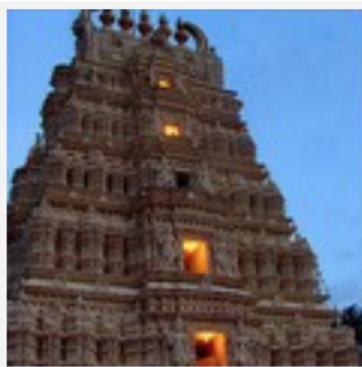


"gibbon"

99.3% confidence

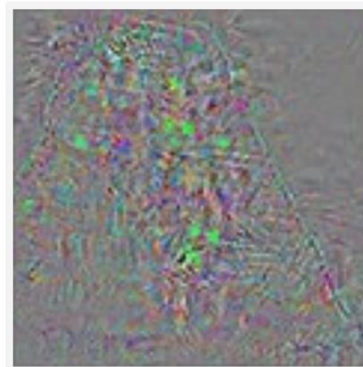
The adversary

- Suppose your friend built a neural network image classifier $f_{\theta}(x)$, and you want to break it.
- Idea: find a perturbation direction ϵ to an image x that was correctly classified, so that $f_{\theta}(x + \epsilon)$ is wrongly classified

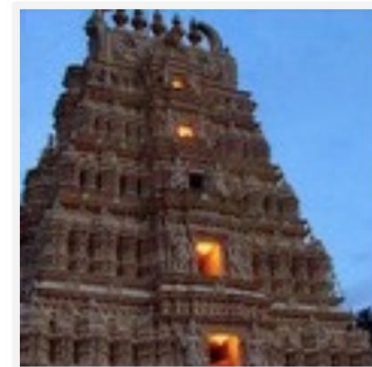


Original image

Temple (97%)



Perturbations



Adversarial example

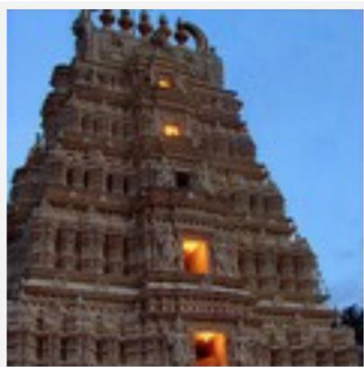
Ostrich (98%)

The adversary

- What ϵ should we use? If we know the architecture and weights of f_θ , then we can perform gradient descent on ϵ to optimize:

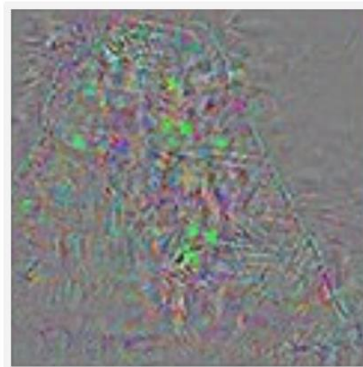
$$\arg \min_{\epsilon} \log p(f_\theta(x + \epsilon) = \textit{correct class})$$

- Then rescale ϵ to be small (imperceptible)

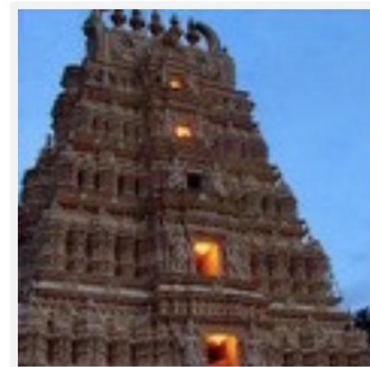


Original image

Temple (97%)



Perturbations



Adversarial example

Ostrich (98%)

Adversarial Attacks

- Non-targeted Adversarial Attack

$$\arg \min_{\epsilon} \log p(f_{\theta}(x + \epsilon) = \textit{correct class})$$

- Targeted Adversarial Attack

$$\arg \max_{\epsilon} \log p(f_{\theta}(x + \epsilon) = \textit{specific class})$$

- White-box Adversarial Attack

- Can access the network f_{θ}
- Can compute gradients of f_{θ} as above

- Black-box Adversarial Attack

- Cannot compute gradients of f_{θ}

Black-box Attacks

- Target model with unknown weights, machine learning algorithm, training set; maybe non-differentiable
- Substitute model mimicking target model with known, differentiable function
- Generate adversarial example
- Moral: adversarial attacks often **transfer!**

Transferable Attacks

- “Adversarial examples that affect one model often affect another model, even if the two models have different architectures or were trained on different training sets, so long as both models were trained to perform the same task”

Transferability in Machine Learning: from Phenomena to Black-Box Attacks using Adversarial Samples (McDaniel & Goodfellow, 2016)

Transfers cross-technique

Source Machine Learning Technique	DNN	LR	SVM	DT	kNN	Ens.
DNN	38.27	23.02	64.32	79.31	8.36	20.72
LR	6.31	91.64	91.43	87.42	11.29	44.14
SVM	2.51	36.56	100.0	80.03	5.19	15.67
DT	0.82	12.22	8.85	89.29	3.31	5.11
kNN	11.75	42.89	82.16	82.95	41.65	31.92

Transferability matrix: $cell(i, j)$ is the percentage of adversarial samples crafted to mislead a classifier learned using machine learning technique i that are misclassified by a classifier trained with technique j .

Failed Defenses

- Generative pre-training
- Adding noise at test time
- Ensembles
- Weight decay
- Adding noise at training time
- Adding adversarial noise at training time
- Dropout
- ...

Adversarial Attacks

- Printed Object: <https://openai-public.s3-us-west-2.amazonaws.com/blog/2017-07/robust-adversarial-examples/iphone.mp4>
- 3D Printed Objects
https://www.youtube.com/watch?v=piYnd_wYIT8

