SIGGRAPH ASIA 2018 TOKYO

CreativeAI: Deep Learning for Graphics

Feature Visualization

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Timetable

			Niloy	Paul	Nils
Theory and Basics	Introduction	2:15 pm	X	X	X
	Machine Learning Basics	~ 2:25 pm	X		
	Neural Network Basics	~ 2:55 pm			X
	Feature Visualization	~ 3:25 pm		X	
	Alternatives to Direct Supervision	~ 3:35 pm		X	

15 min. break

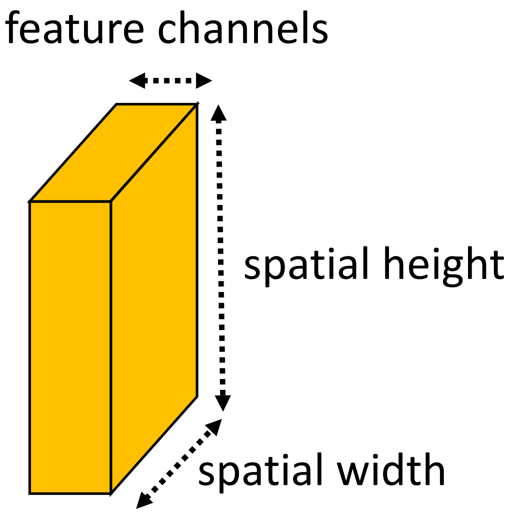
			Niloy	Paul	Nils
State of the Art	Image Domains	4:15 pm		X	
	3D Domains	~ 4:45 pm	X		
	Motion and Physics	~ 5:15 pm			X
	Discussion	~ 5:45 pm	X	X	X

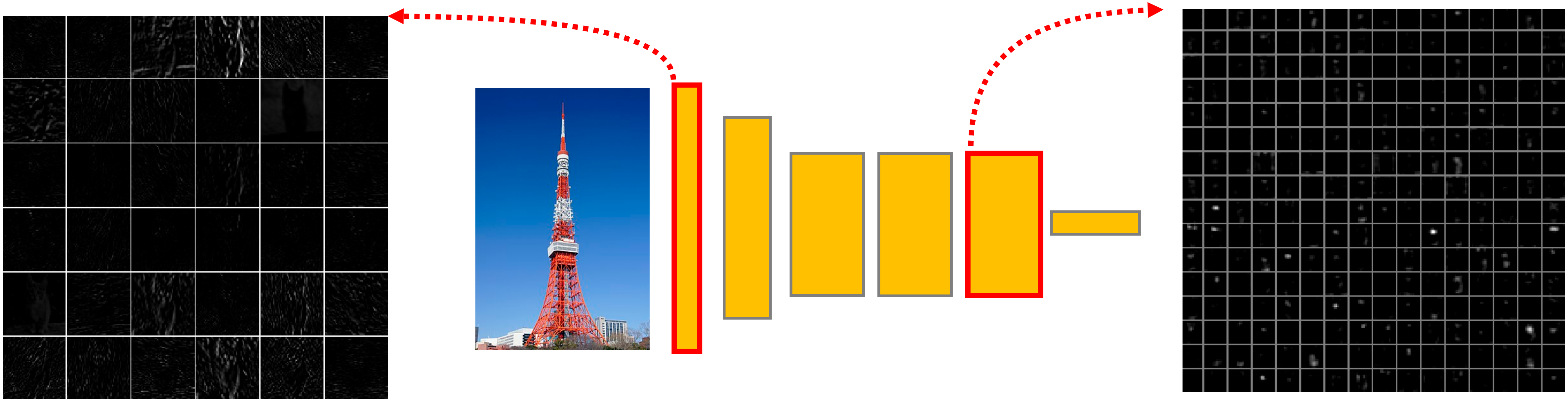
What to Visualize

- Features (activations)
- Weights (filter kernels in a CNN)
- Attribution: input parts that contribute to a given activation
- Inputs that maximally activate some class probabilities or features
- Inputs that maximize the error (adversarial examples)

Feature Samples

- In good training, features are usually sparse
- Can find "dead" features that never activate



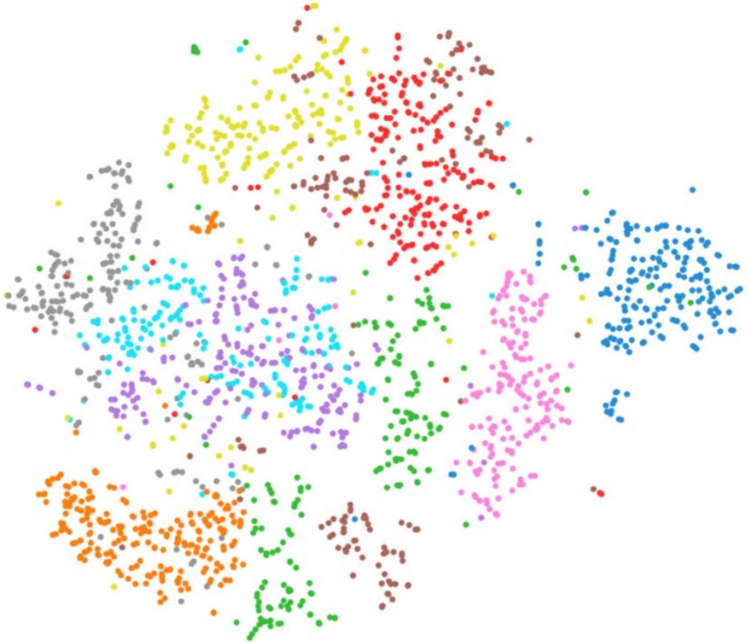


Images from: http://cs231n.github.io/understanding-cnn/

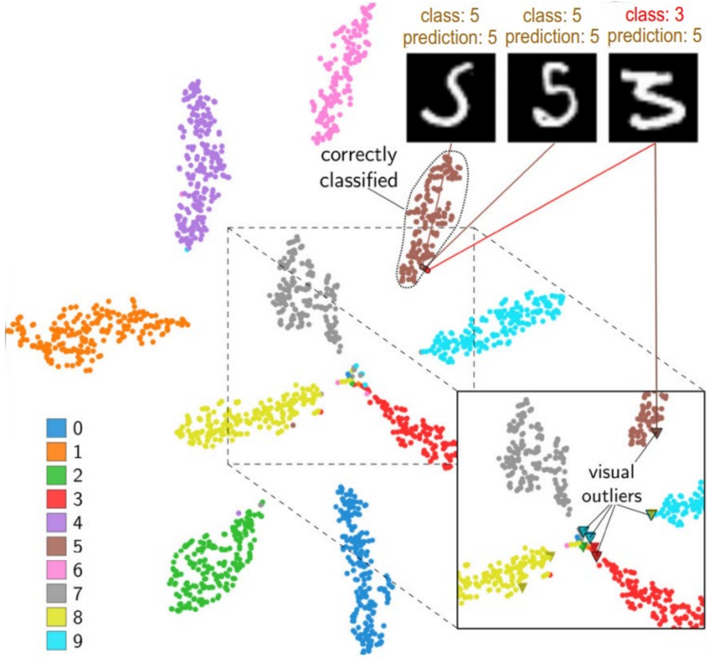
Feature Distribution using t-SNE

- Low-dimensional embedding of the features for visualization

t-SNE embedding of image features in a CNN layer



before training



after training

t-SNE embedding of MNIST (images of digits) features in a CNN layer, colored by class

Images from: https://cs.stanford.edu/people/karpathy/cnnembed/ and
Rauber et al. *Visualizing the Hidden Activity of Artificial Neural Networks*. TVCG 2017

Feature Distribution using t-SNE

- Low-dimensional embedding of the features for visualization

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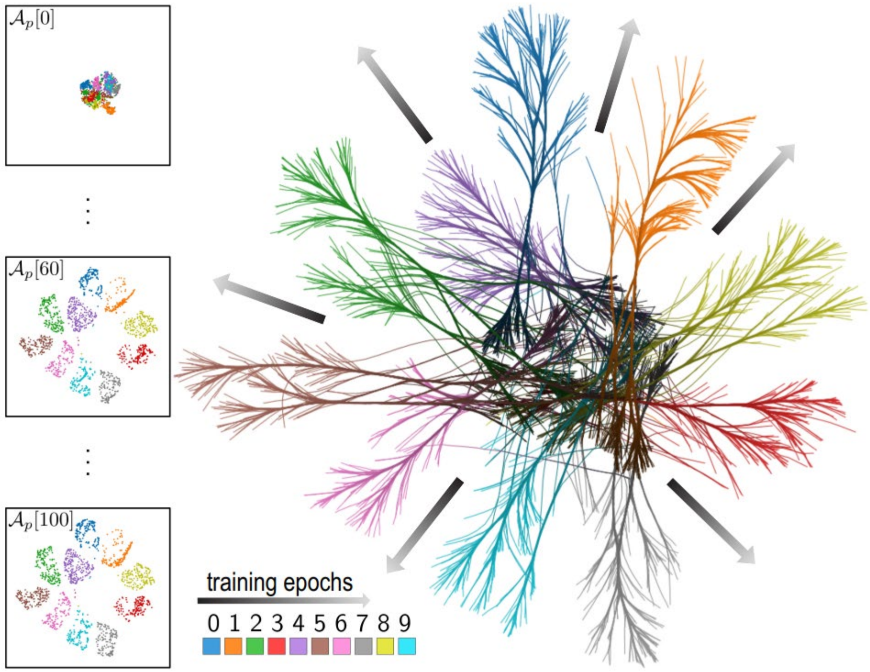


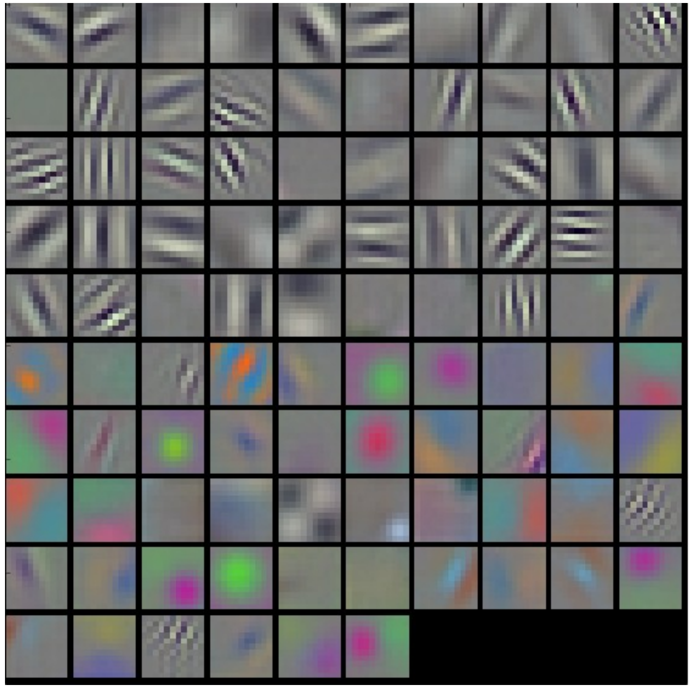
evolution during training

t-SNE embedding of MNIST (images of digits) features in a CNN layer, colored by class

Images from: https://cs.stanford.edu/people/karpathy/cnnembed/ and
Rauber et al. *Visualizing the Hidden Activity of Artificial Neural Networks*. TVCG 2017

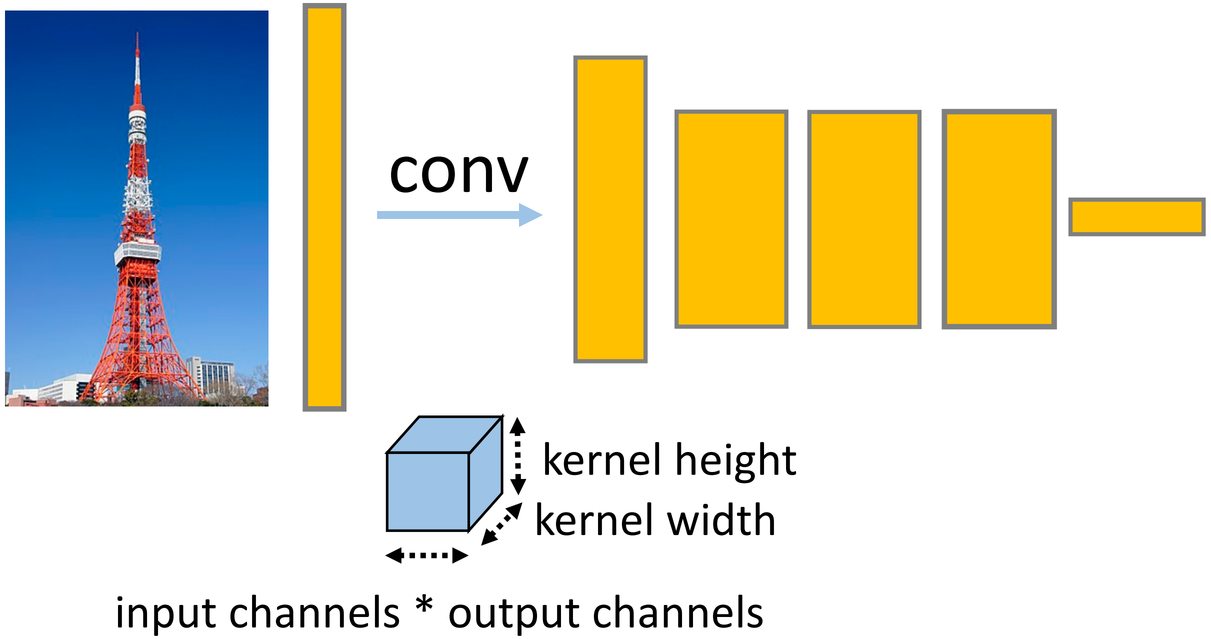
Weights (Filter Kernels)

- Useful for CNN kernels, not useful for fully connected layers
- Kernels are typically smooth and diverse after a successful training



first layer filters of AlexNet

Images from: http://cs231n.github.io/understanding-cnn/



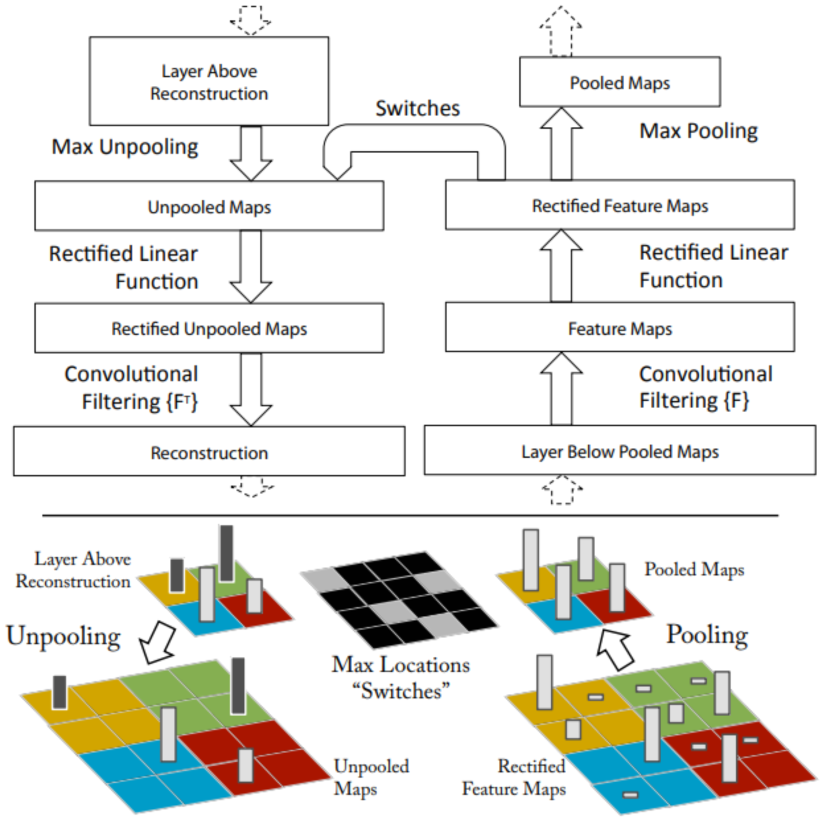
Code Examples

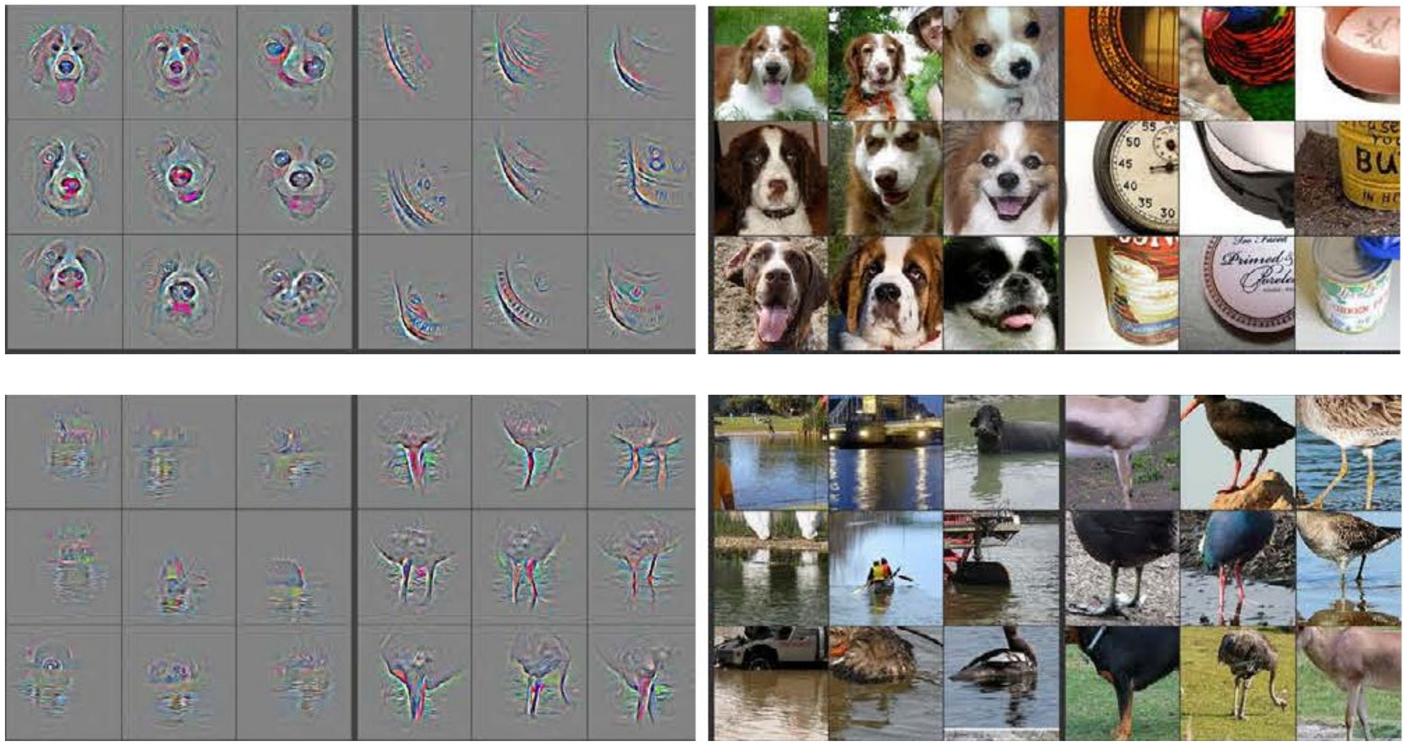
Filter Visualization

http://geometry.cs.ucl.ac.uk/creativeai

Attribution by Approximate Inversion

- Reconstruct Input from a given feature channel
- What information does the feature channel focus on?

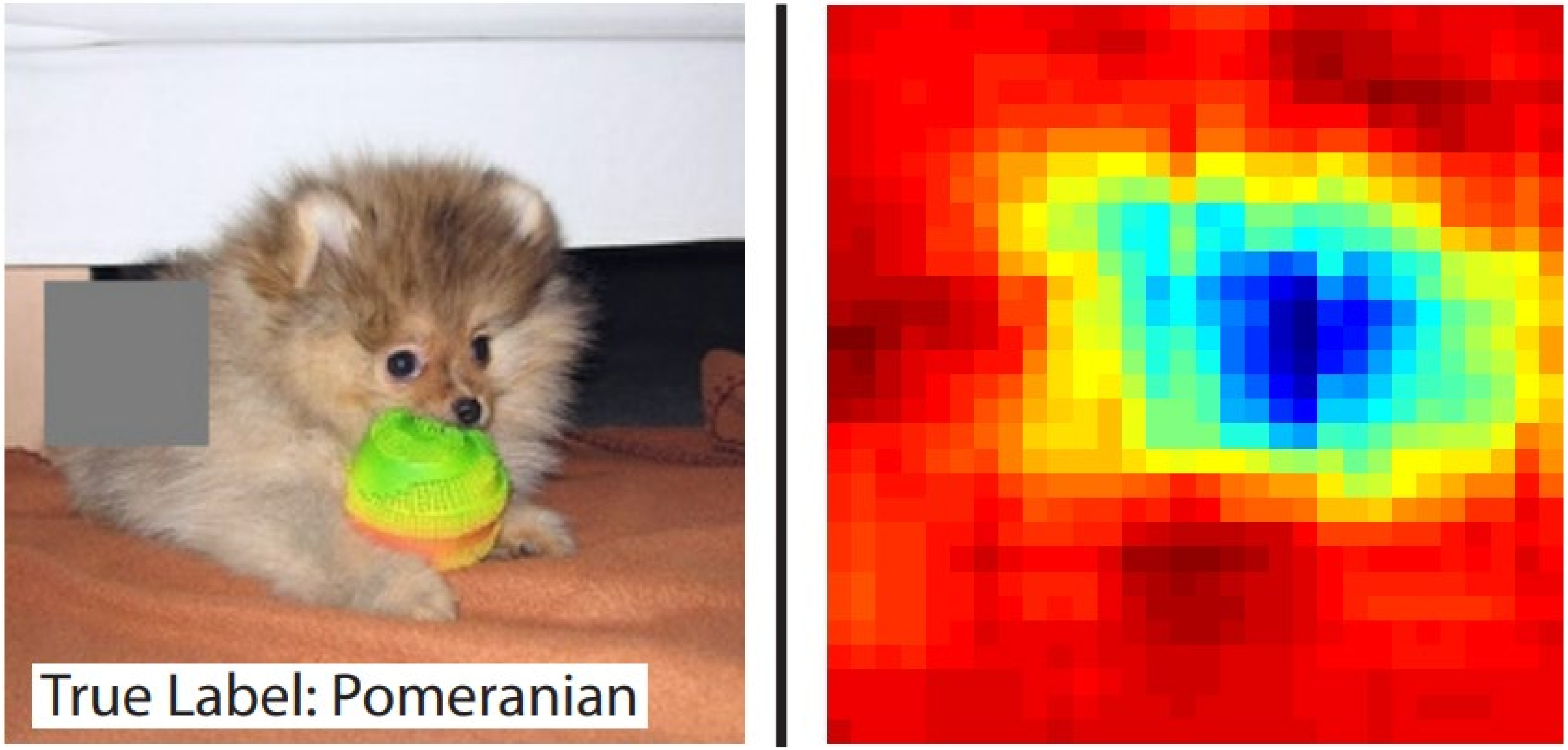




Zeiler and Fergus, *Visualizing and Understanding Convolutional Networks*, ECCV 2014

Perturbation-based Attribution

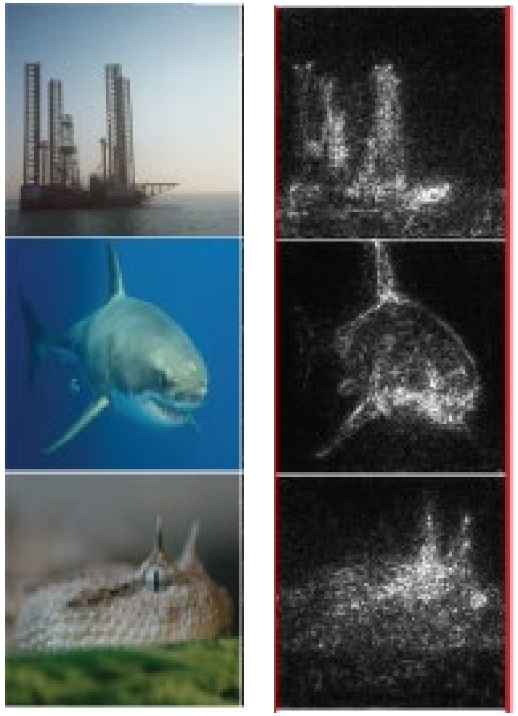
Probability for correct classification when centering the box at each pixel.

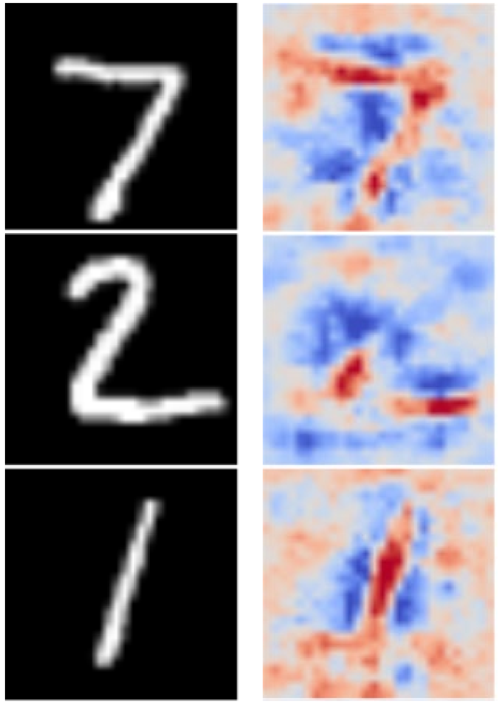


Zeiler and Fergus, *Visualizing and Understanding Convolutional Networks*, ECCV 2014

Gradient-based Attribution

- Derivative of class probability w.r.t input pixels
- Which parts of the input is the class probability sensitive to?



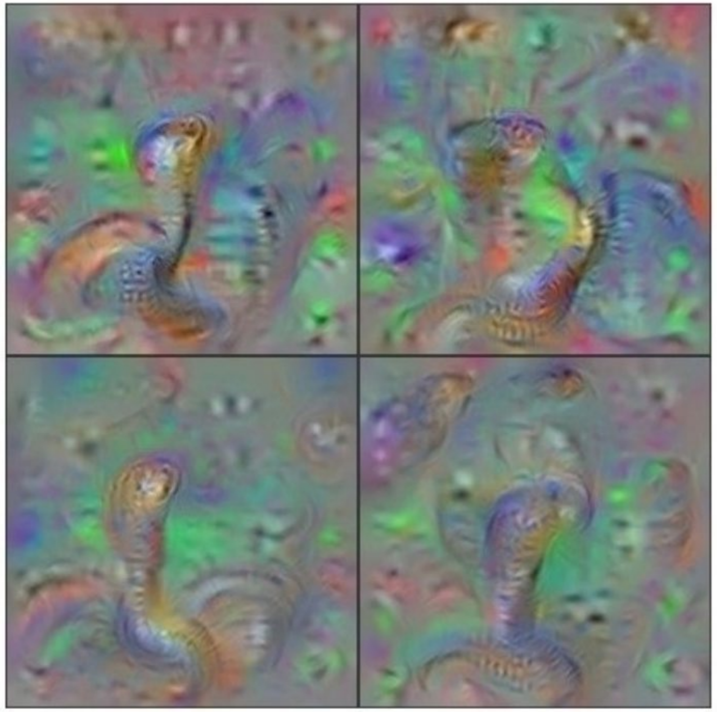


Smilkov et al., *SmoothGrad: removing noise by adding noise*, arXiv 2017

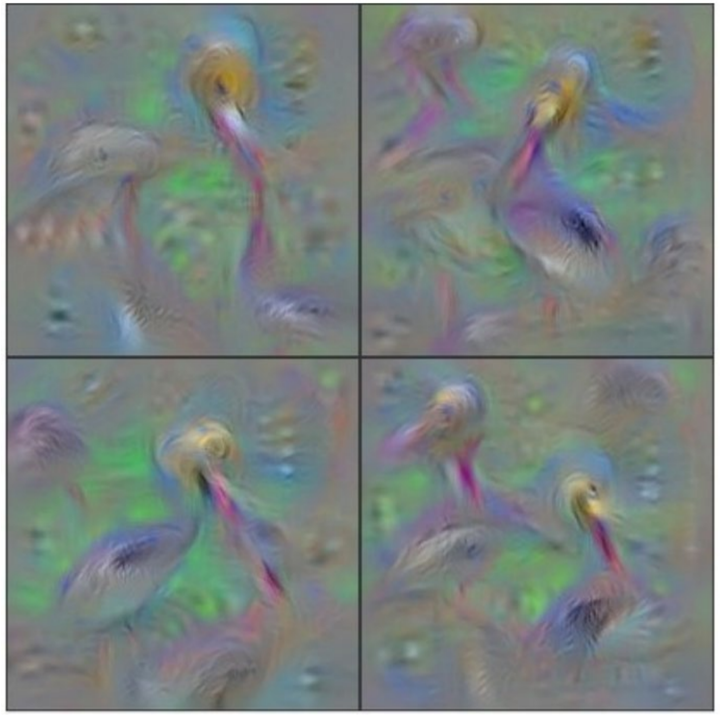
Inputs that Maximize Feature Response

Local maxima of the response for class:

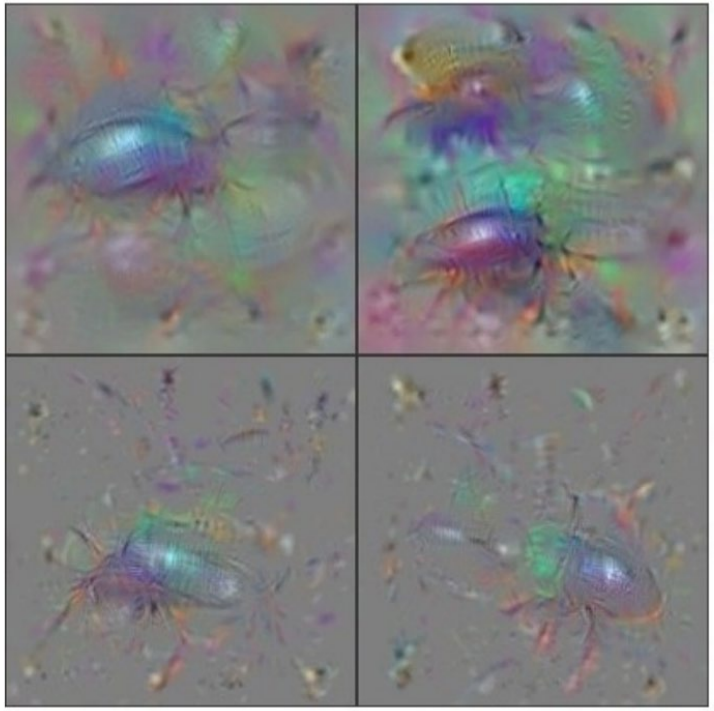
Indian Cobra



Pelican



Ground Beetle



Images from: Yosinski et al. *Understanding Neural Networks Through Deep Visualization*. ICML 2015

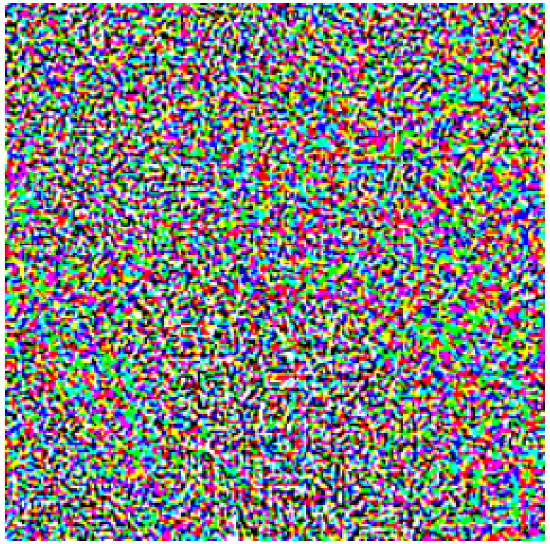
Inputs that Maximize the Error

$$\max_{\delta \in \Delta} \mathcal{L}(x + \delta, y; \theta) \qquad \Delta = \{\delta \in \mathbb{R}^d \mid \|\delta\|_p \leq \varepsilon\}$$

x

"Panda" 55.7% conf.

$+ .007 \times$



δ

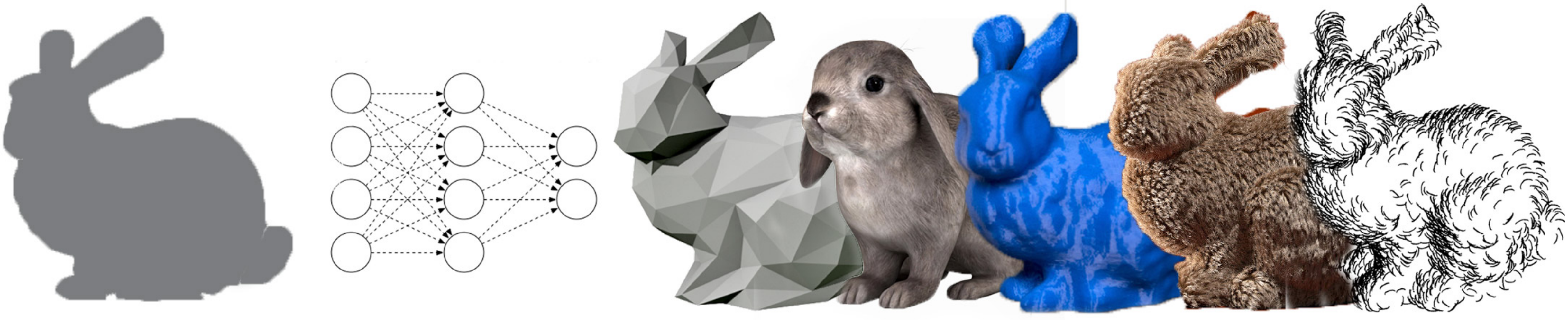
$=$

$x + \delta$

"Gibbon" 99.3% conf.

Images from: Goodfellow et al. *Explaining and Harnessing Adversarial Examples*. ICLR 2015

Course Information (slides/code/comments)



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