Lecture 8: Visualizing and Understanding

Administrative

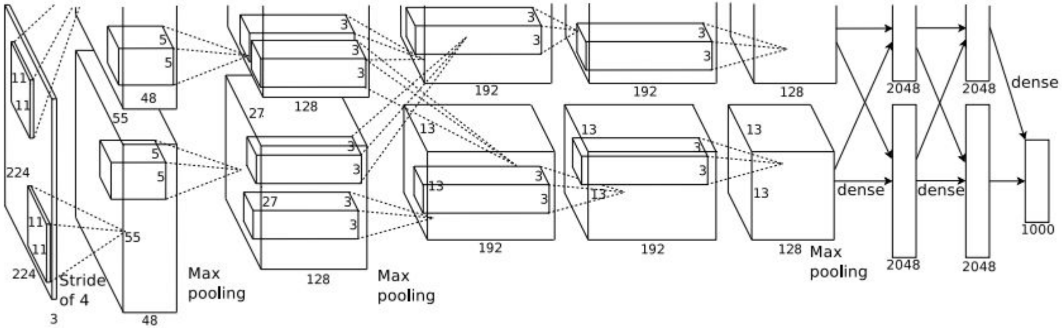
- Assignment 1 grades will be released this week
- Quiz 1 should follow around the same time
  - Makeup quiz during Matt's office hours

- Project proposals will be graded this week and TA will be assigned
-
- Assignment 2 due Friday Nov 10th, 11:59pm
  - **Start now!**
  - Assignment 3 has extra credit opportunities

Today: What's going on inside ConvNets?

This image is CC0 public domain

Input Image:
3 x 224 x 224



Class Scores:
1000 numbers

What are the intermediate features looking for?

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

Today's agenda

Visualizing what models have learned:
- Visualizing filters
- Visualizing final layer features
- Visualizing activations

Understanding input pixels
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

Adversarial perturbations

Today's agenda

Visualizing what models have learned:
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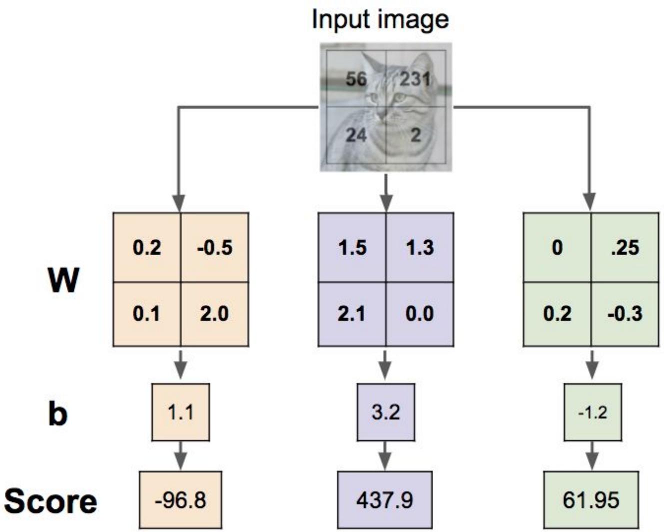
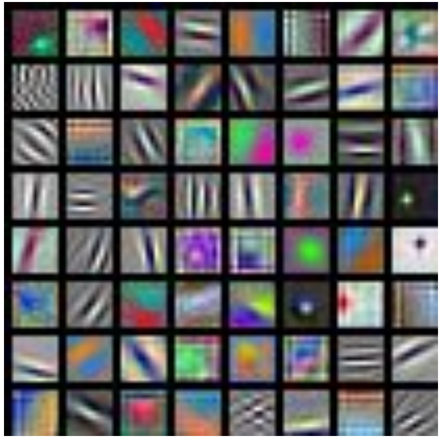
Adversarial perturbations

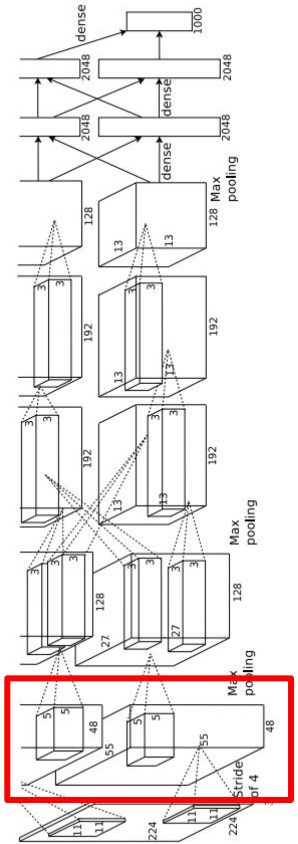
Interpreting a Linear Classifier: Visual Viewpoint



First Layer: Visualize Filters

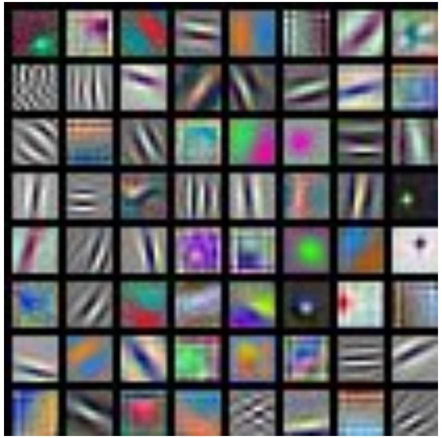


AlexNet:
64 x 3 x 11 x 11



Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

First Layer: Visualize Filters

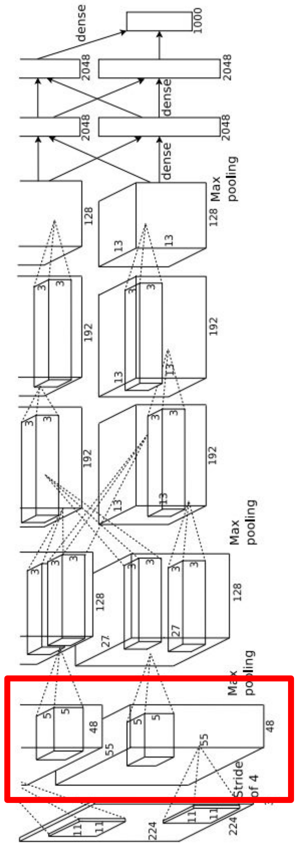


AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7



Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
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Visualize the filters/kernels (raw weights)

layer 1 weights

16 x 3 x 7 x 7

layer 2 weights

20 x 16 x 7 x 7

layer 3 weights

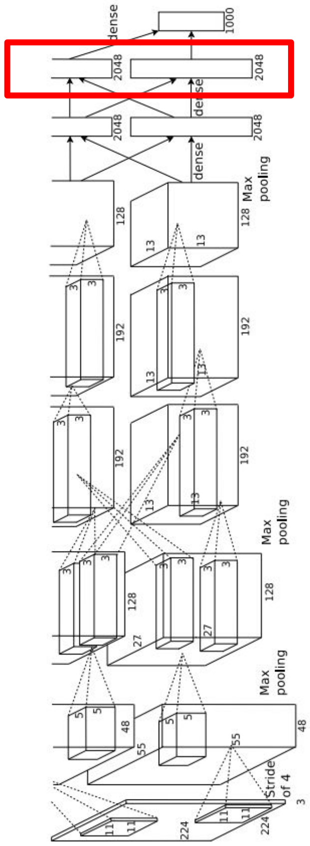
20 x 20 x 7 x 7

We can visualize filters at higher layers, but not that interesting

(these are taken from ConvNetJS CIFAR-10 demo)

Last Layer

FC7 layer

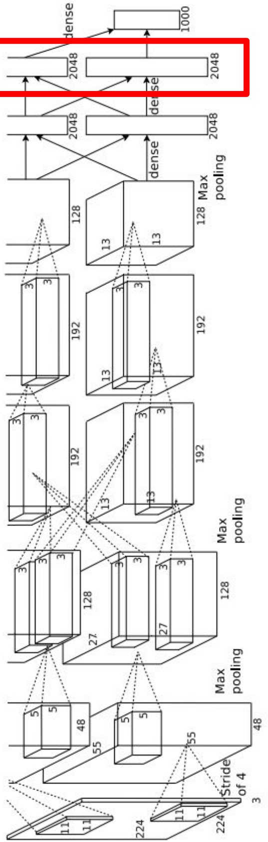


4096-dimensional feature vector for an image
(layer immediately before the classifier)

Run the network on many images, collect the feature vectors

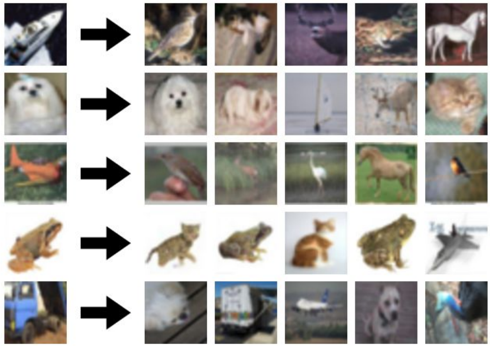
Last Layer: Nearest Neighbors

4096-dim vector



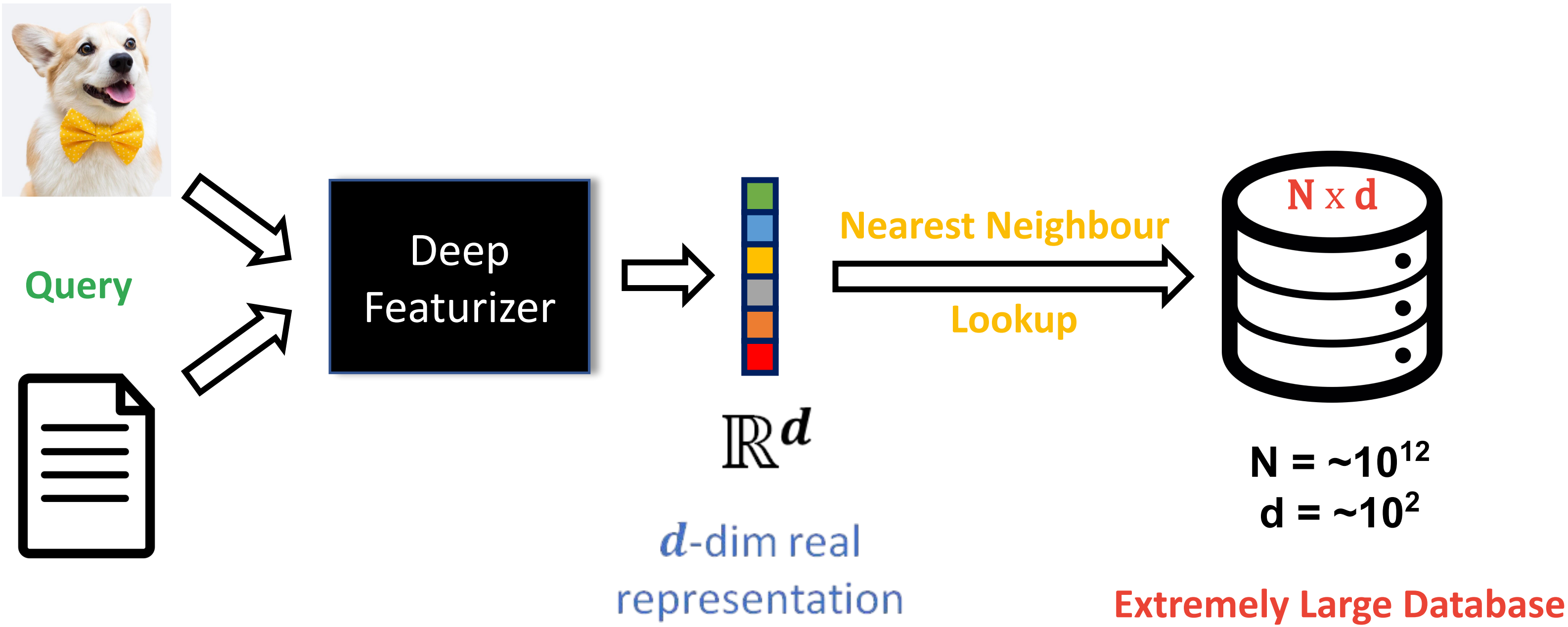
Test image   L2 Nearest neighbors in __feature__ space

Recall: Nearest neighbors in __pixel__ space

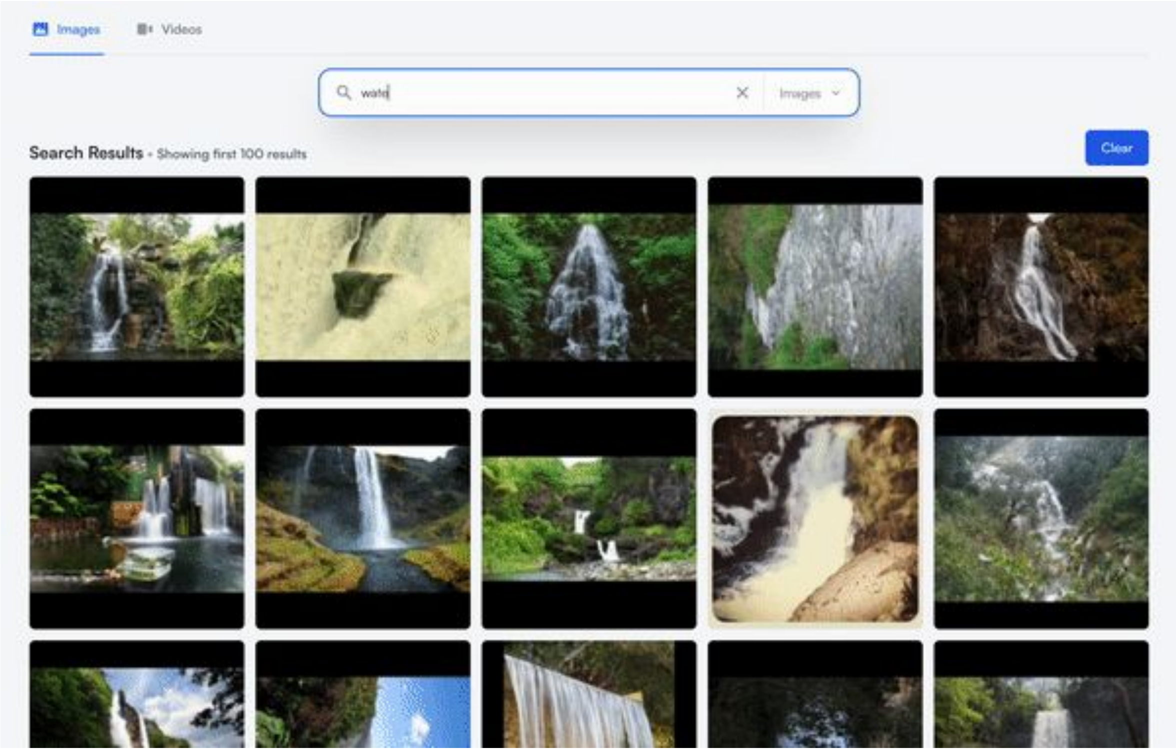


Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figures reproduced with permission.

Last Layer: Learned Metric for "Semantic" Search



Last Layer: Modern Day Search



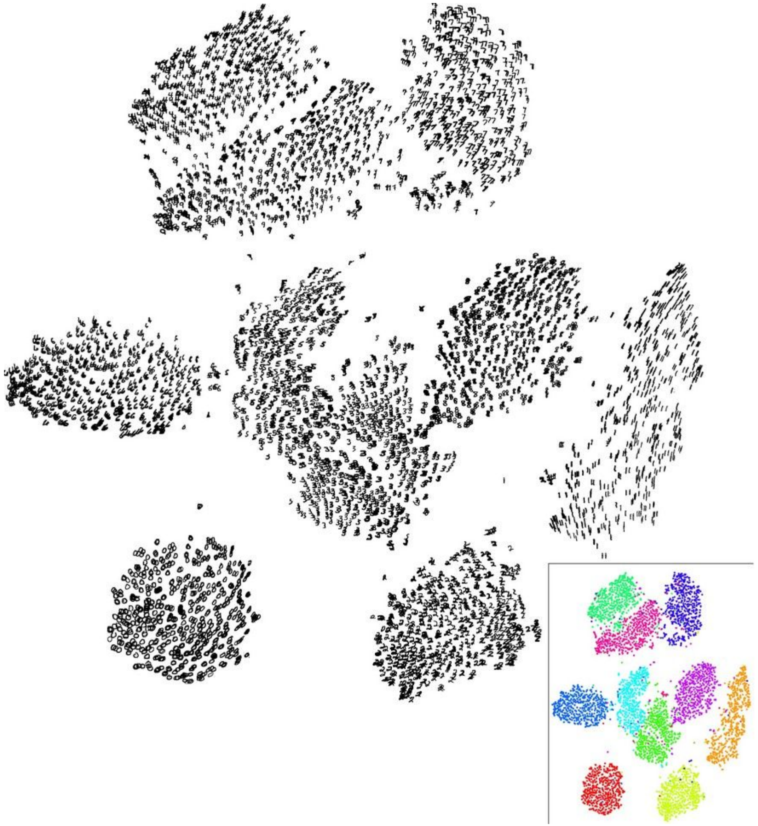
coactive.ai

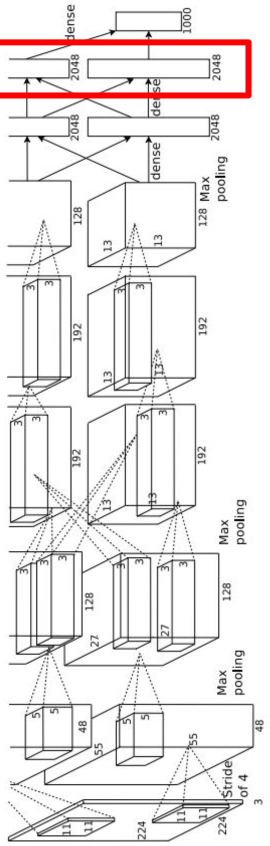
Last Layer: Dimensionality Reduction

Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Simple algorithm: Principal Component Analysis (PCA)

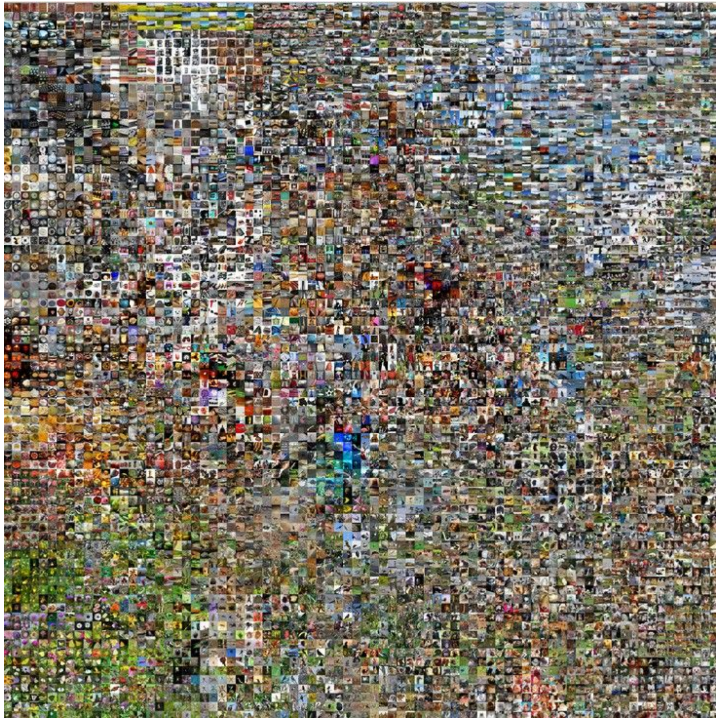
More complex: **t-SNE**

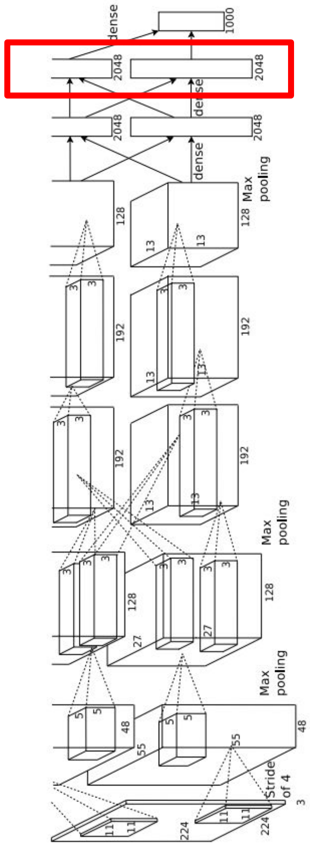




Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008

Last Layer: Dimensionality Reduction



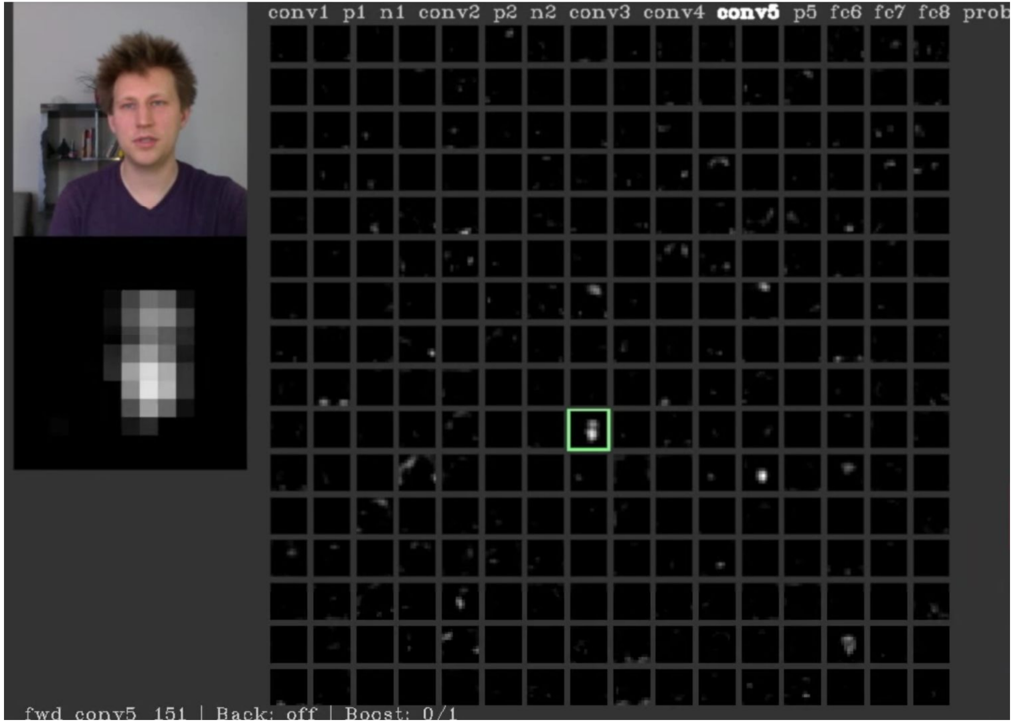


Van der Maaten and Hinton, "Visualizing Data using t-SNE", JMLR 2008
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

See high-resolution versions at
http://cs.stanford.edu/people/karpathy/cnnembed/

Visualizing Activations

conv5 feature map is 128x13x13; visualize as 128 13x13 grayscale images



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

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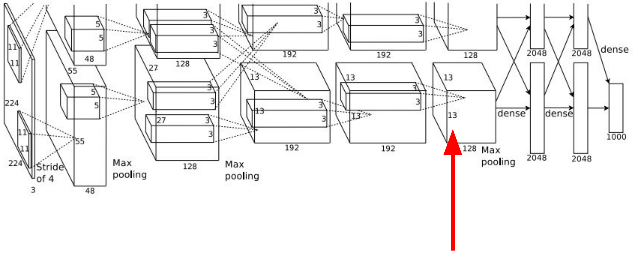
Adversarial perturbations

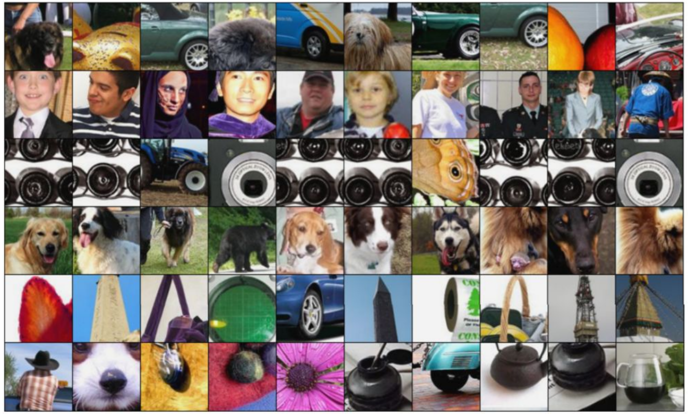
Maximally Activating Patches



Pick a layer and a channel; e.g. conv5 is 128 x 13 x 13, pick channel 17/128

Run many images through the network, record values of chosen channel

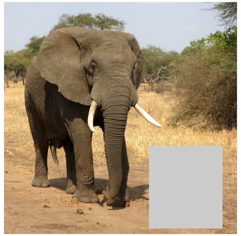
Visualize image patches that correspond to maximal activations

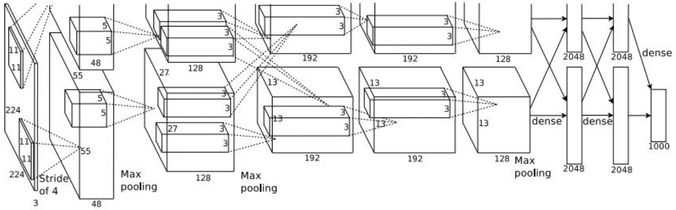


Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

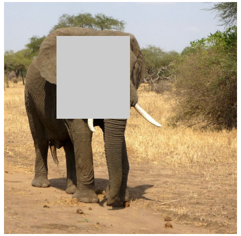
Which pixels matter: Saliency via Occlusion

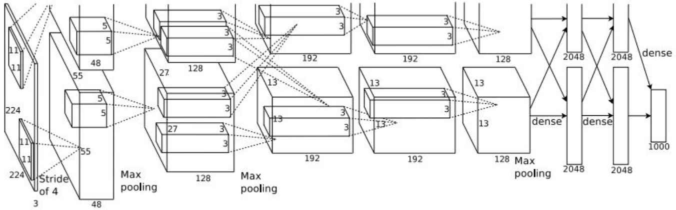
Mask part of the image before feeding to CNN, check how much predicted probabilities change





P(elephant) = 0.95



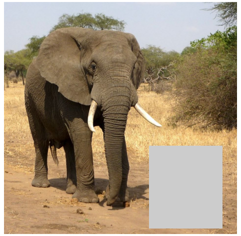


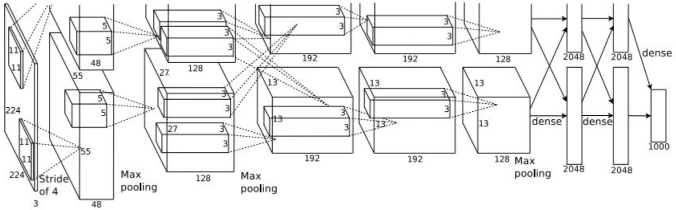
P(elephant) = 0.75

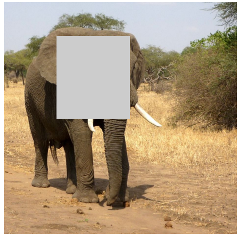
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

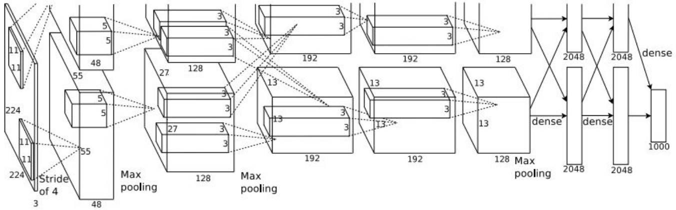
Which pixels matter: Saliency via Occlusion

Mask part of the image before feeding to CNN, check how much predicted probabilities change

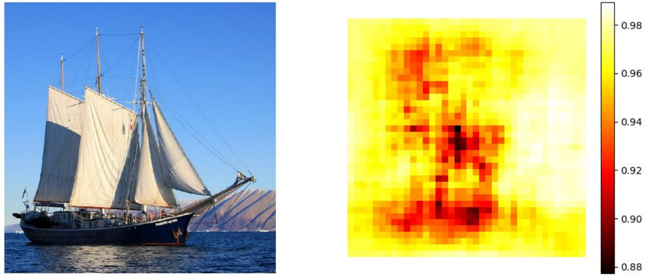




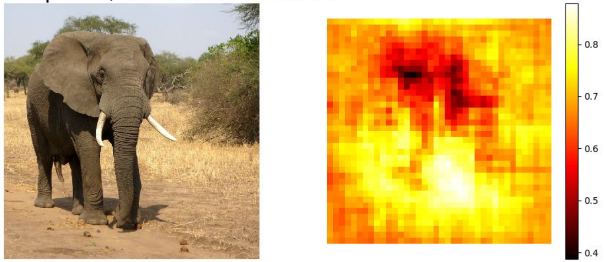




schooner



African elephant, Loxodonta africana

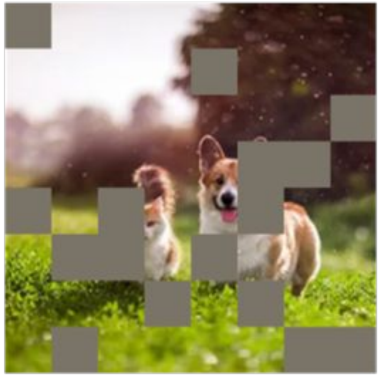


go-kart

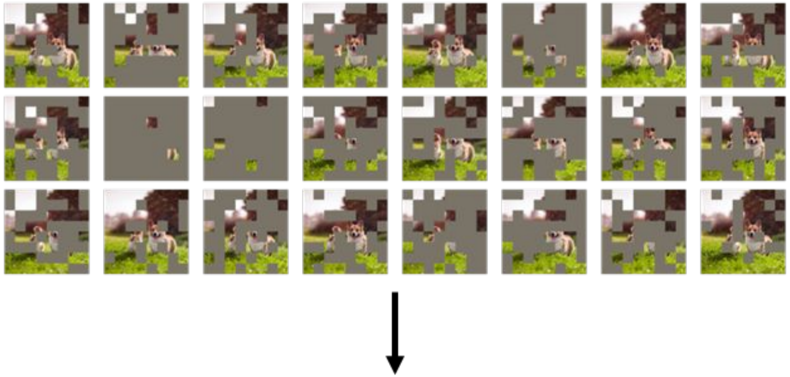
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

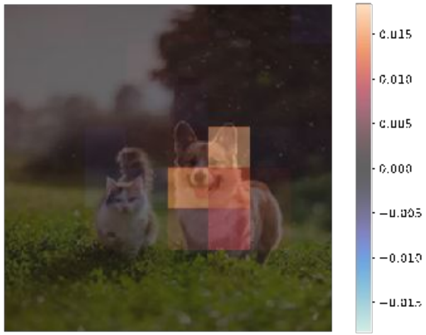
Saliency via Occlusion: Shapley Values

P(corgi) = 0.99



P(corgi) = 0.8

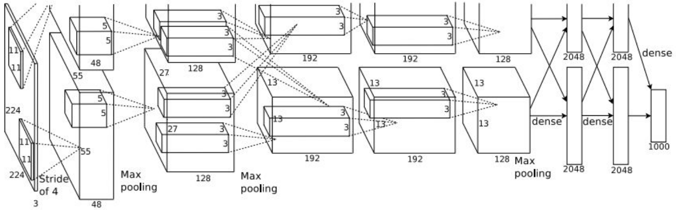




Credit: Ian Covert; Lundberg & Lee 2017

Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities

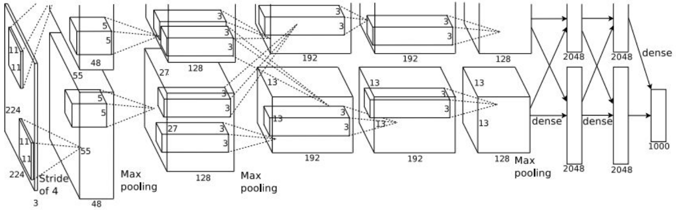


Dog

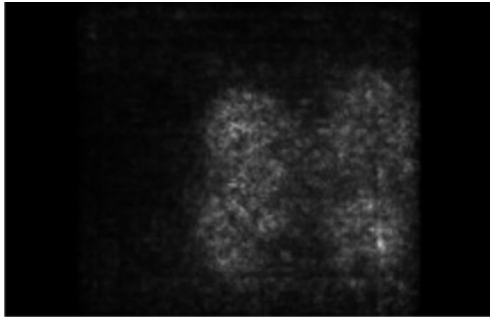
Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities



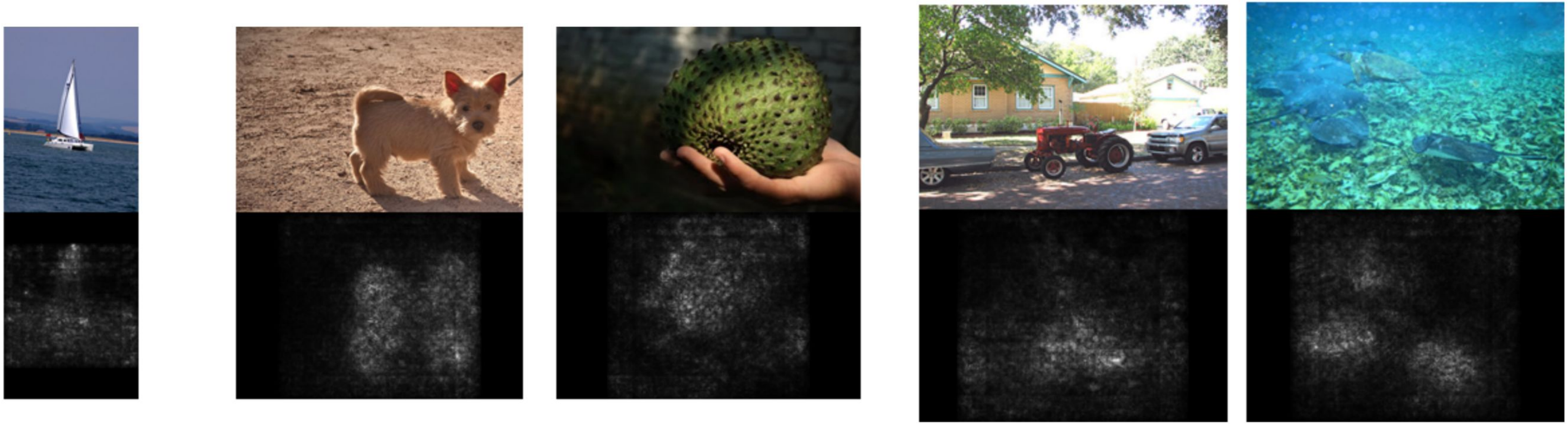
Dog



Compute gradient of (unnormalized) class score with respect to image pixels, take absolute value and max over RGB channels

Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

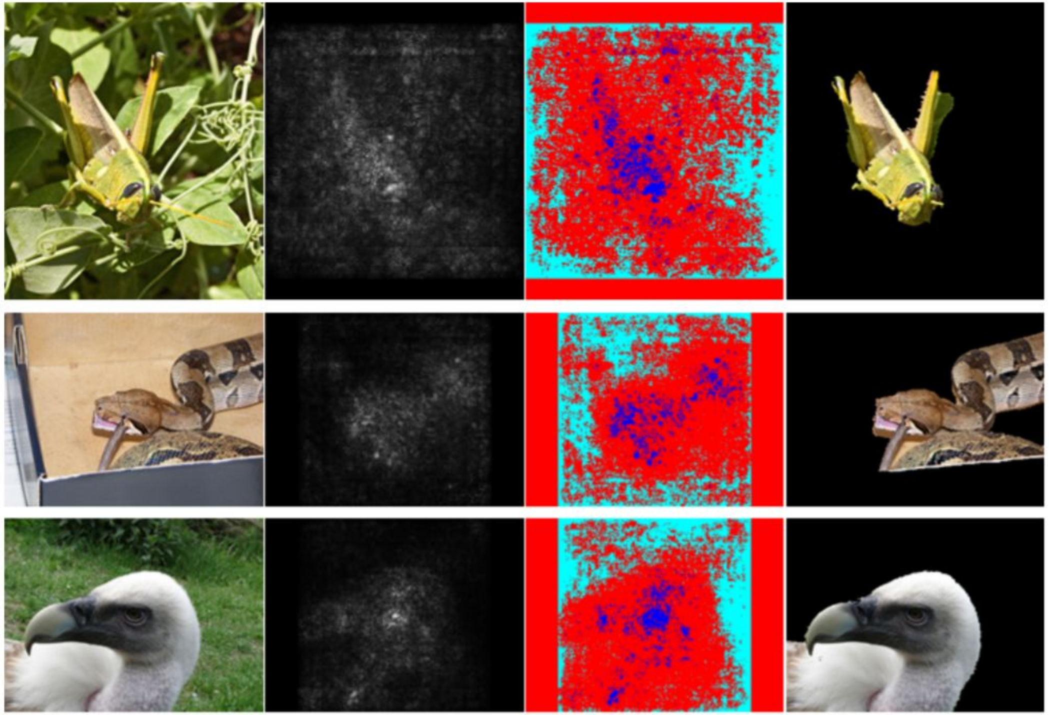
Saliency Maps



Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

Saliency Maps: Segmentation without supervision

Use GrabCut on saliency map



Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

Rother et al, “Grabcut: Interactive foreground extraction using iterated graph cuts”, ACM TOG 2004

Saliency maps: Uncovers biases

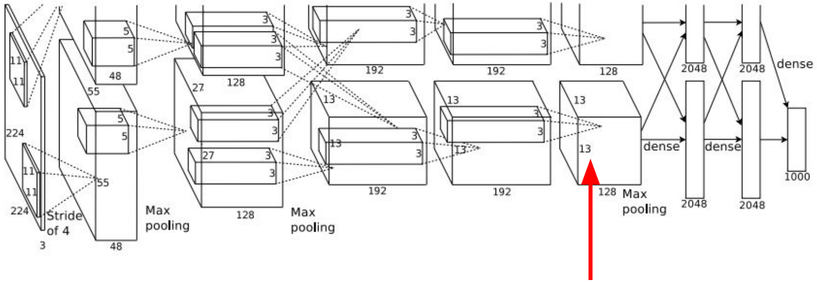
Such methods also find biases

wolf vs dog classifier looks is actually a snow vs no-snow classifier

(a) Husky classified as wolf (b) Explanation

Ribeiro et al, ““Why Should I Trust You?” Explaining the Predictions of Any Classifier”, ACM KDD 2016

Intermediate Features via (guided) backprop

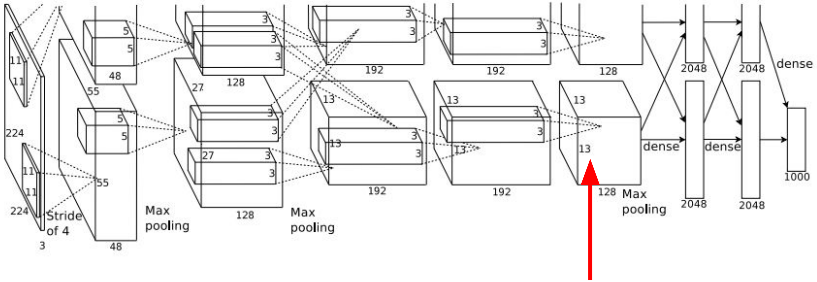


Pick a single intermediate channel, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of activation value with respect to image pixels

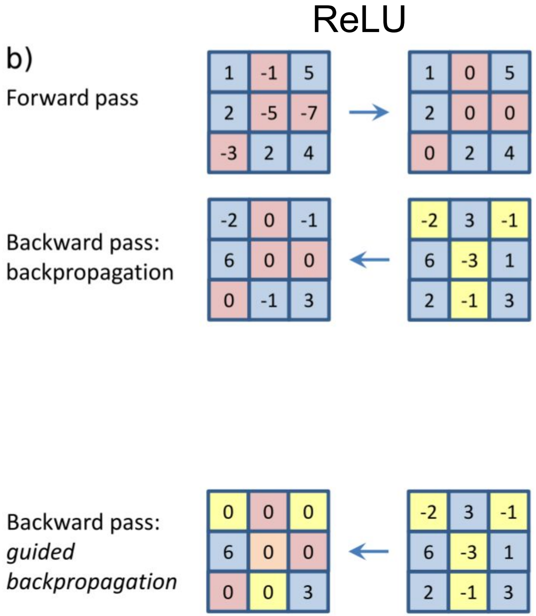
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate Features via (guided) backprop



Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of neuron value with respect to image pixels



Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

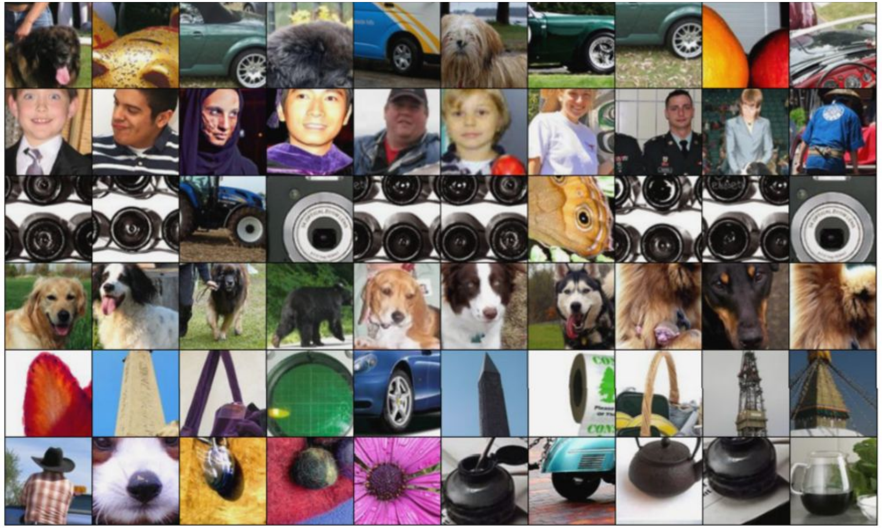
Intermediate features via (guided) backprop

Maximally activating patches
(Each row is a different neuron)

Guided Backprop

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate features via (guided) backprop



Maximally activating patches
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Guided Backprop

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Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Visualizing CNN features: Gradient Ascent

(Guided) backprop:
Find the part of an image that a neuron responds to

Gradient ascent:
Generate a synthetic image that maximally activates a neuron

$$I^* = \arg\max_I \boxed{f(I)} + \boxed{R(I)}$$

Neuron value

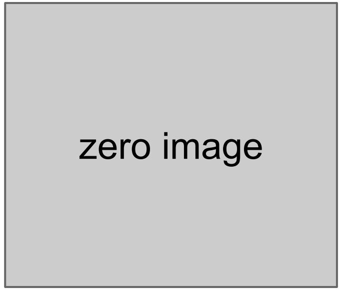
Natural image regularizer

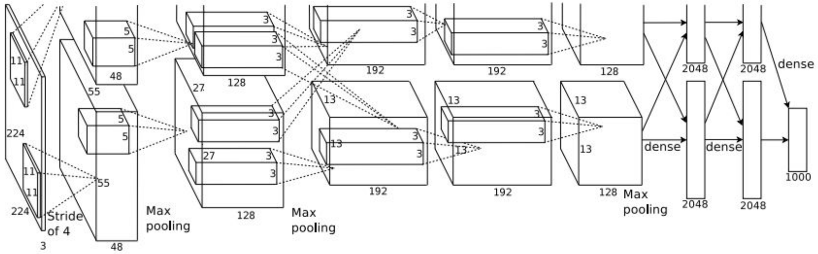
Visualizing CNN features: Gradient Ascent

$$\boxed{\arg\max_I S_c(I)} - \lambda\|I\|_2^2$$

score for class c (before Softmax)

1. Initialize image to zeros





Repeat:
2. Forward image to compute current scores
3. Backprop to get gradient of neuron value with respect to image pixels
4. Make a small update to the image

Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \boxed{\lambda\|I\|_2^2}$$

Simple regularizer: Penalize L2 norm of generated image

Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Visualizing CNN features: Gradient Ascent

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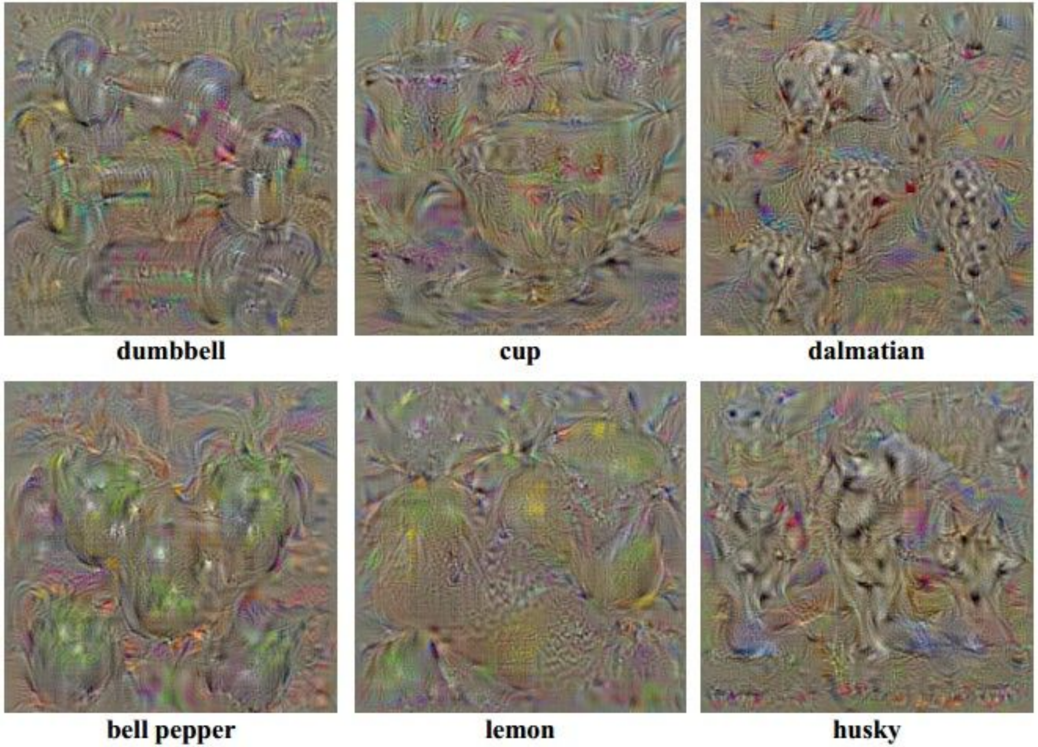

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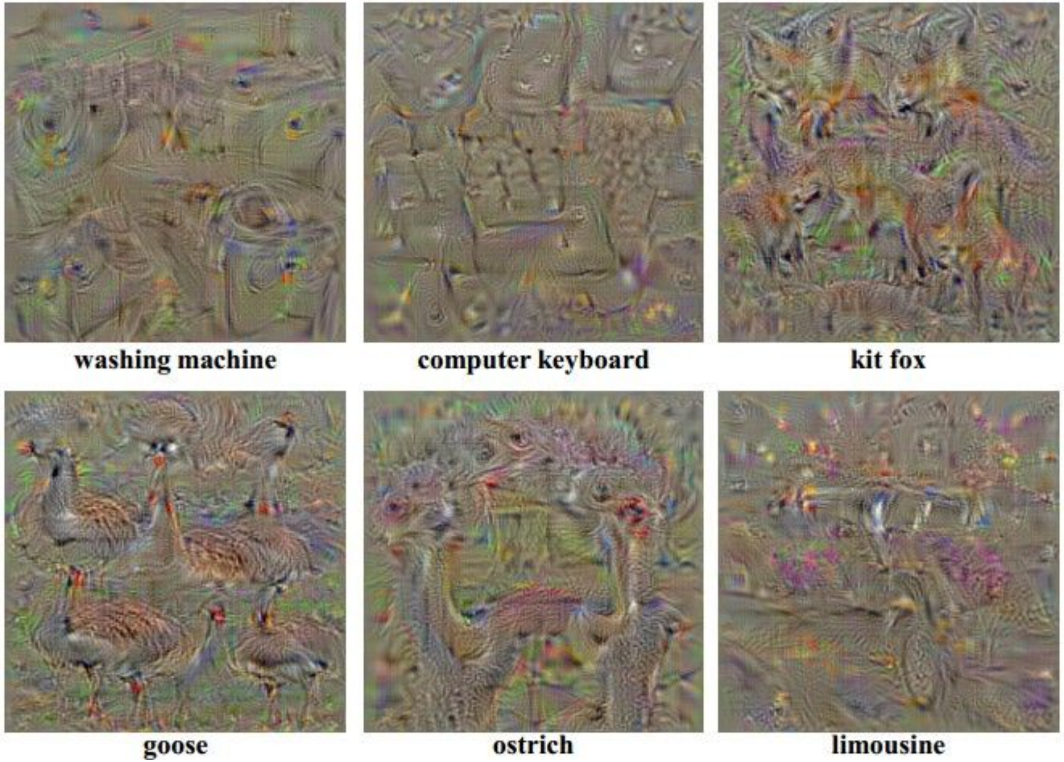

Yosinski et al, “Understanding Neural Networks Through Deep Visualization”, ICML DL Workshop 2014.

Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda\|I\|_2^2$$

Better regularizer: Penalize L2 norm of image; also during optimization periodically

(1) Gaussian blur image
(2) Clip pixels with small values to 0
(3) Clip pixels with small gradients to 0

Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

Visualizing CNN features: Gradient Ascent

$$\arg\max_{I} S_c(I) - \lambda\|I\|_2^2$$

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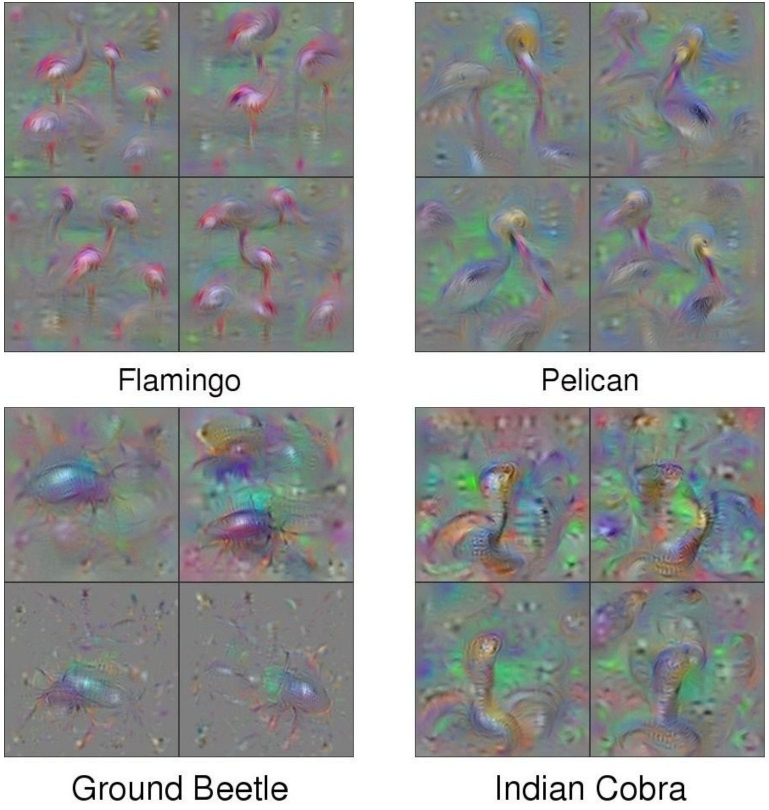

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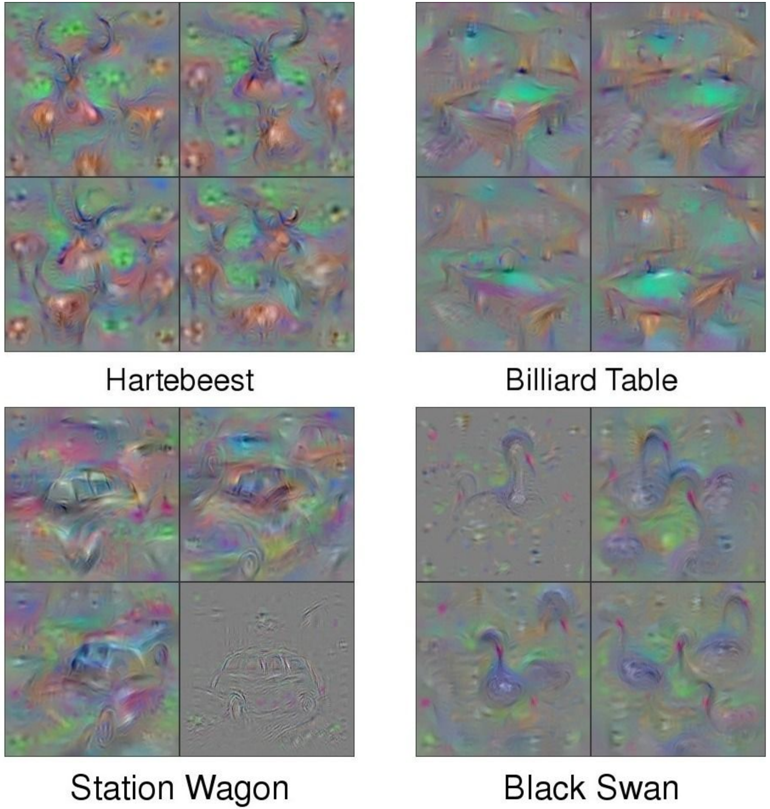
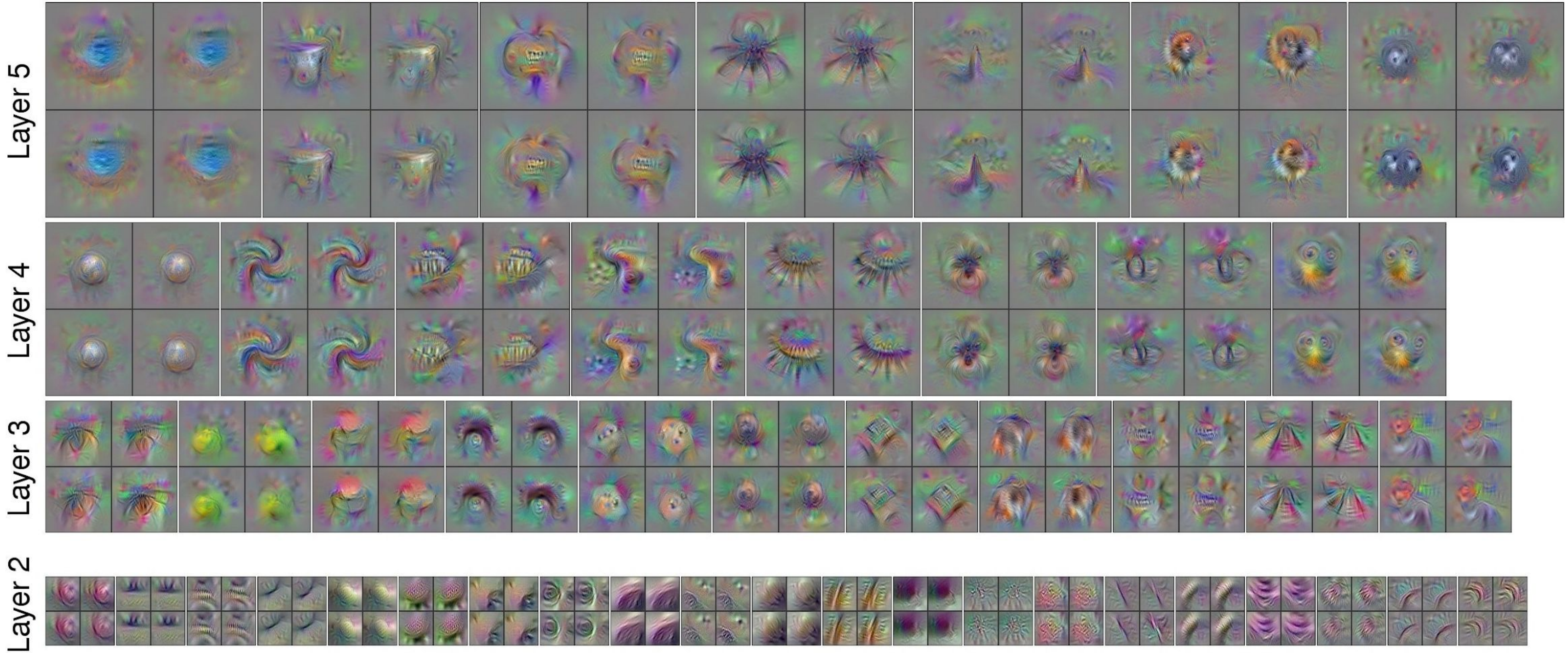


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

Visualizing CNN features: Gradient Ascent

Use the same approach to visualize intermediate features



Yosinski et al, “Understanding Neural Networks Through Deep Visualization”, ICML DL Workshop 2014.

Visualizing CNN features: Gradient Ascent

Adding “multi-faceted” visualization gives even nicer results:
(Plus more careful regularization, center-bias)

Reconstructions of multiple feature types (facets) recognized by the same “grocery store” neuron

Corresponding example training set images recognized by the same neuron as in the "grocery store" class

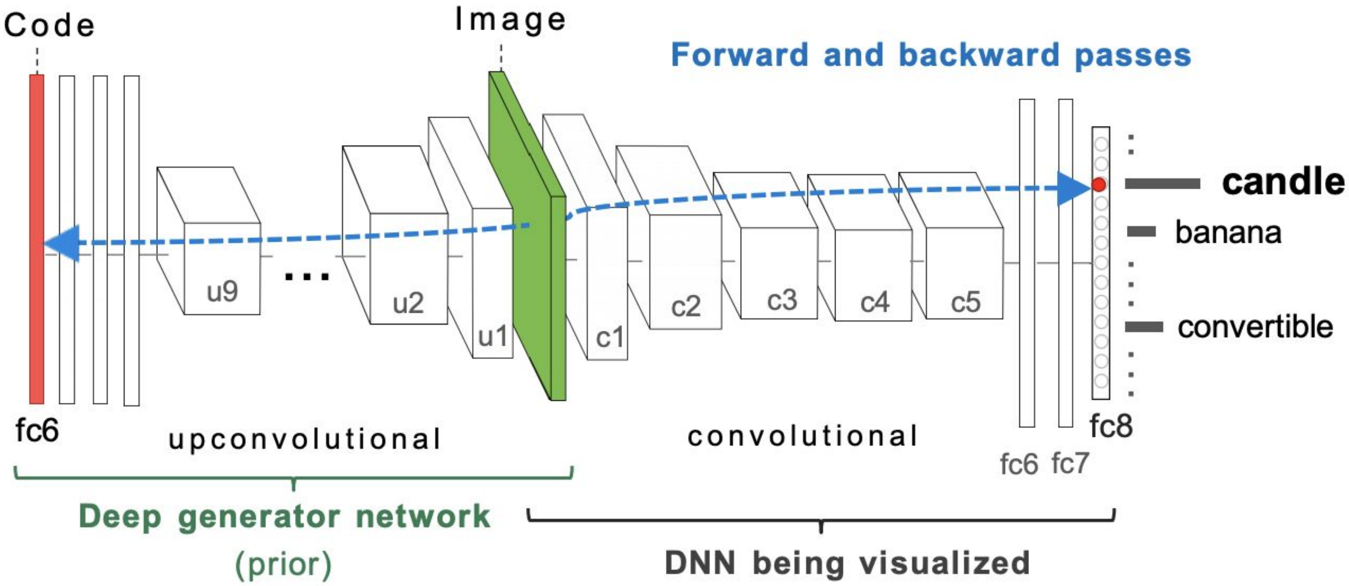
Nguyen et al, “Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks”, ICML Visualization for Deep Learning Workshop 2016.

Visualizing CNN features: Gradient Ascent

Nguyen et al, “Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks”, ICML Visualization for Deep Learning Workshop 2016.

Visualizing CNN features: Gradient Ascent

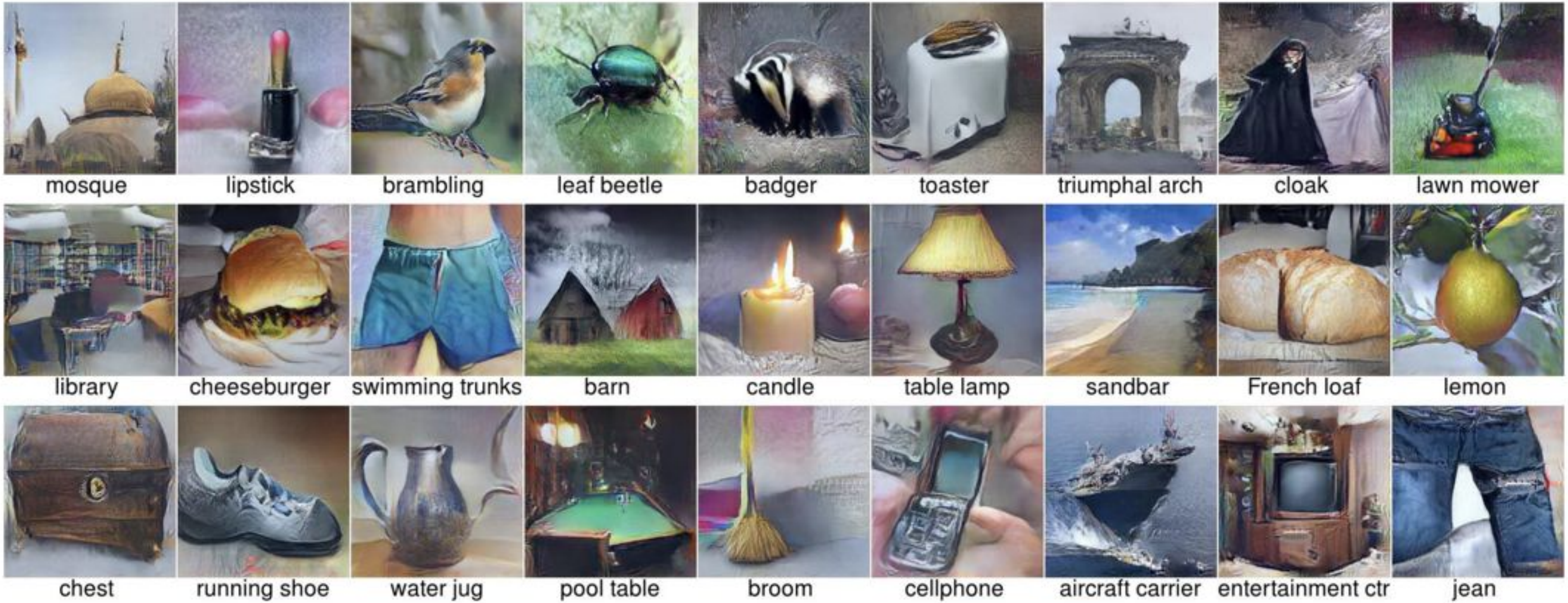
Optimize in FC6 latent space instead of pixel space:



Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016

Visualizing CNN features: Gradient Ascent

Optimize in FC6 latent space instead of pixel space:



Nguyen et al, “Synthesizing the preferred inputs for neurons in neural networks via deep generator networks,” NIPS 2016

Today's agenda

Visualizing what models have learned:

- Visualizing filters
- Visualizing final layer features
- Visualizing activations

Understanding input pixels

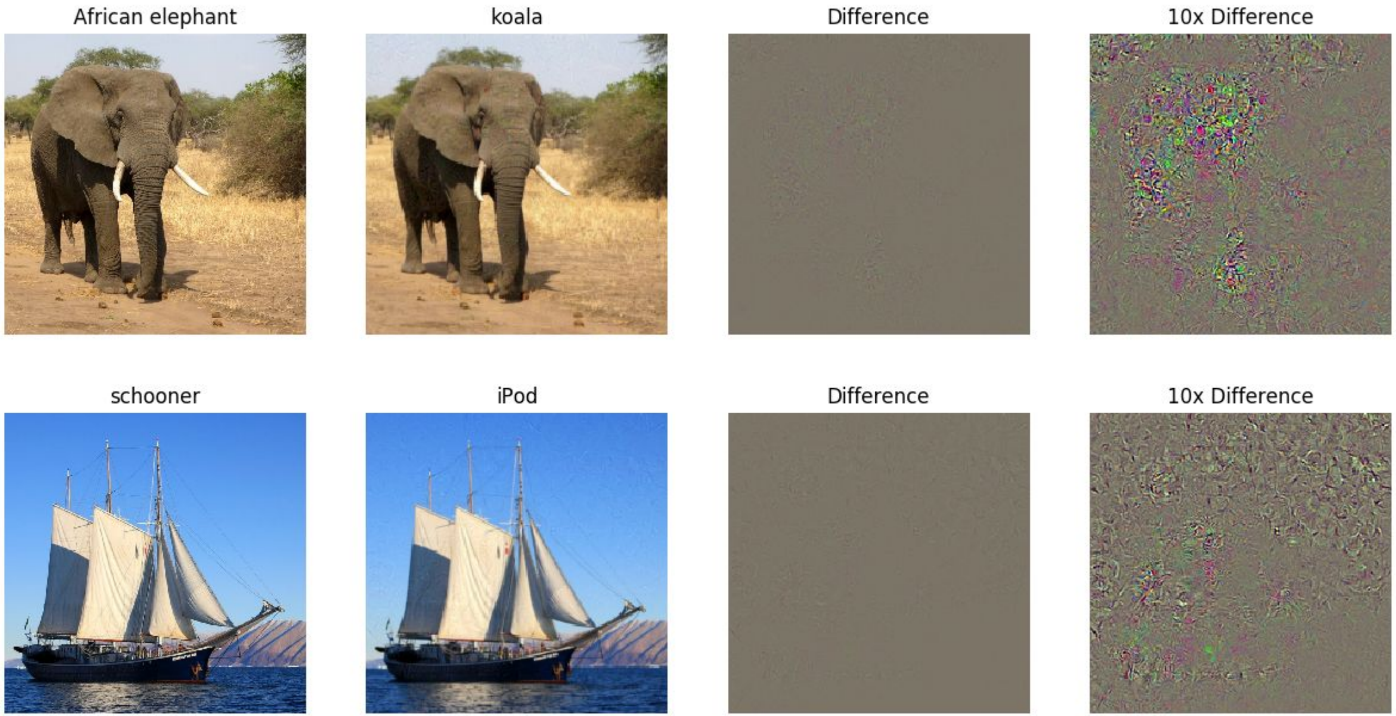
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

Adversarial perturbations

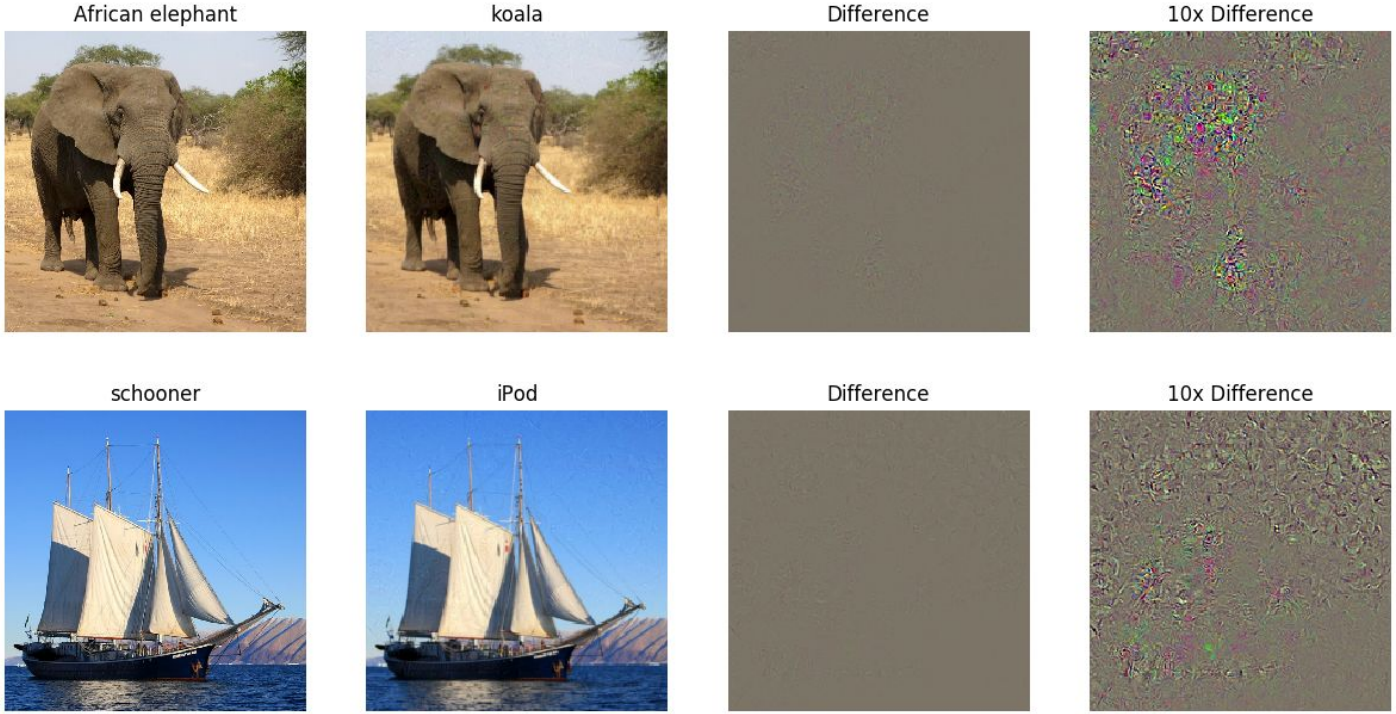
Fooling Images / Adversarial Examples

(1) Start from an arbitrary image
(2) Pick an arbitrary class
(3) Modify the image to maximize the class
(4) Repeat until network is fooled

Fooling Images / Adversarial Examples

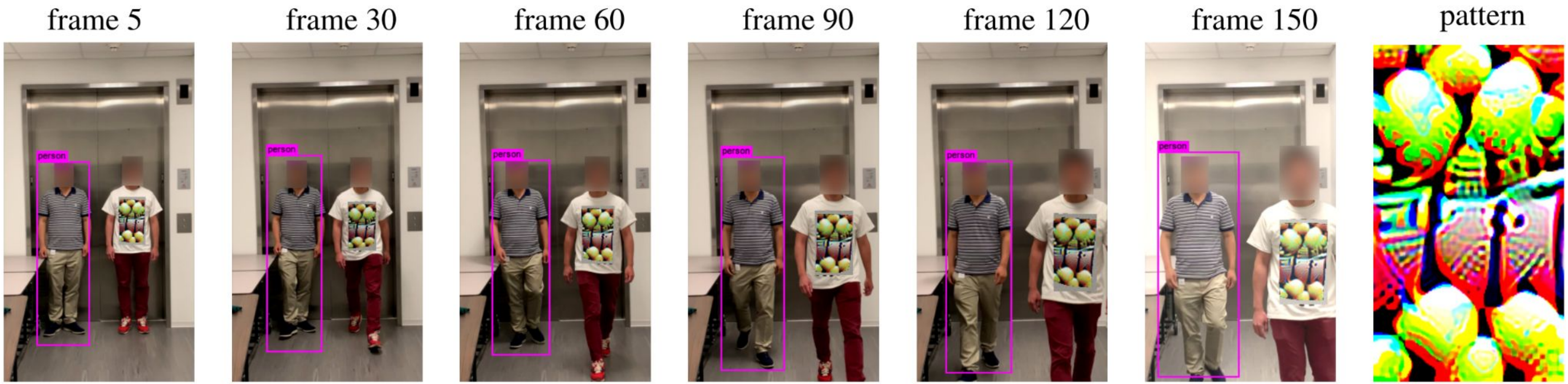


Fooling Images / Adversarial Examples



Check out Ian Goodfellow's lecture from 2017

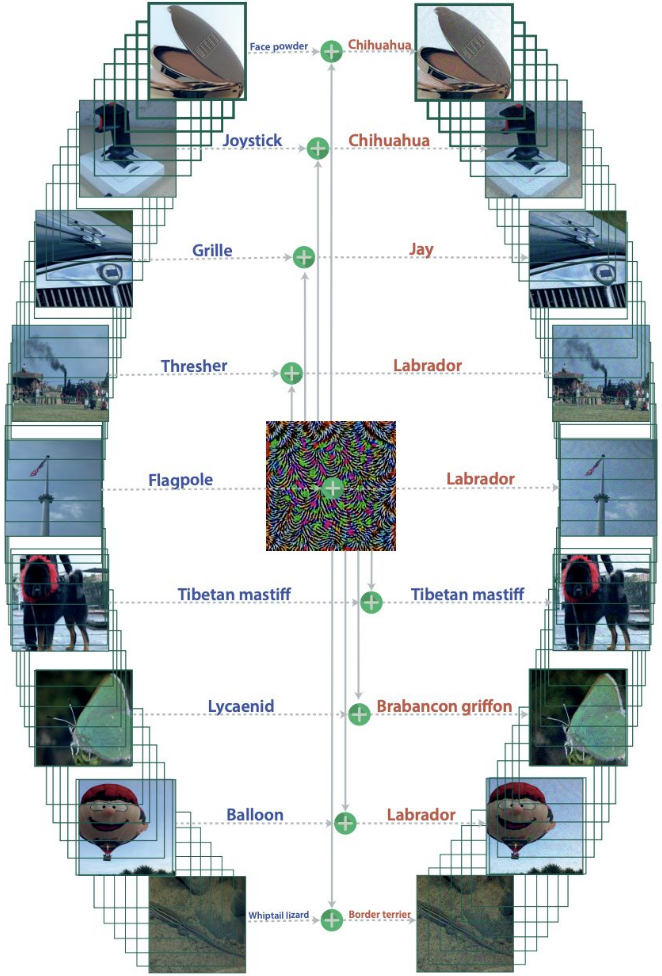
Fooling Person Detectors and Self-driving Cars



Xu et al., 2019; Eykholt et al., 2018

Fooling Images / Adversarial Exa

Universal perturbations



Moosavi-Dezfooli, Seyed-Mohsen, et al. "Universal adversarial perturbations." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
Figure reproduced with permission

Summary

Many methods for understanding CNN representations

Activations: Nearest neighbors, Dimensionality reduction, maximal patches, occlusion
Gradients: Saliency maps, class visualization, fooling images, feature inversion

Adversarial Examples: To confuse the models

Next time: **Self-supervised Learning**