Lecture 8: Interpretability

Administrative: Assignment 2

Due 4/27 (extended) 11:59pm

- Multi-layer Neural Networks,
- Image Features,
- Optimizers

Administrative: Assignment 3

Due 5/11 11:59pm

- Normalization Layers,
- Dropout,
- CNNs

Will be released tomorrow

Administrative: Fridays

This Friday

Quantization

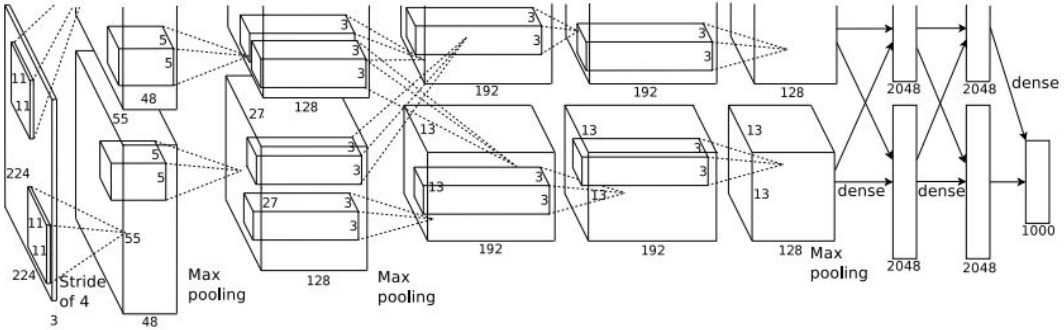
Administrative: Course Project

Project proposal due 4/29 11:59pm

Come to office hours to talk about your ideas

Visualizing and Understanding

Today: What's going on inside ConvNets?



Class Scores:
1000 numbers

Input Image:
3 x 224 x 224

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

Concept Vectors

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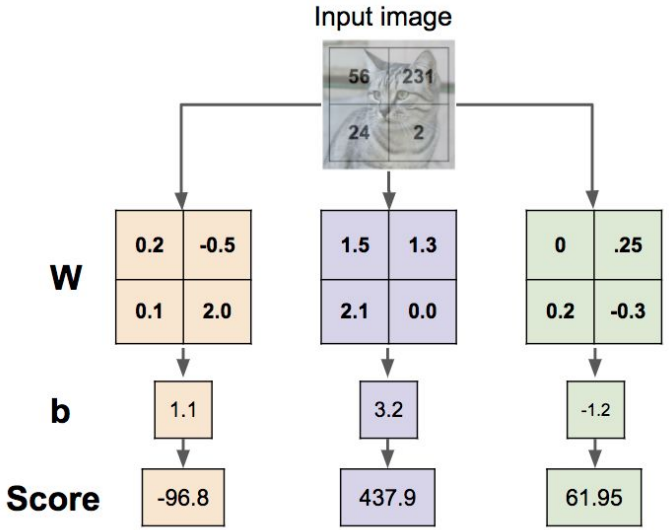
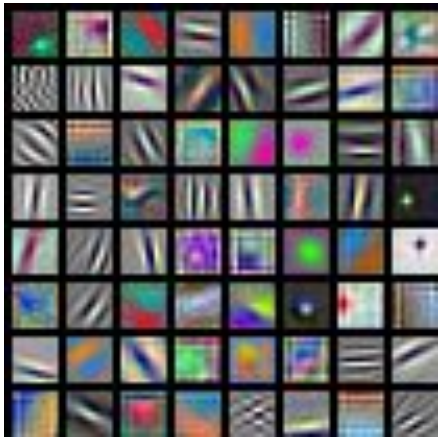
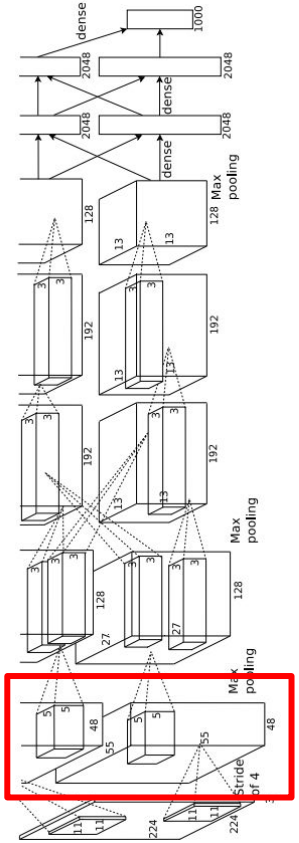
Interpreting a Linear Classifier: Visual Viewpoint



First Layer: Visualize Filters

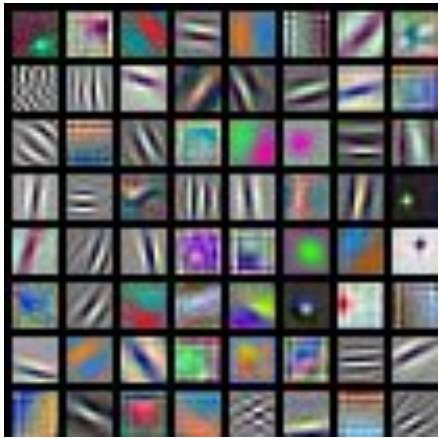


AlexNet:
64 x 3 x 11 x 11



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

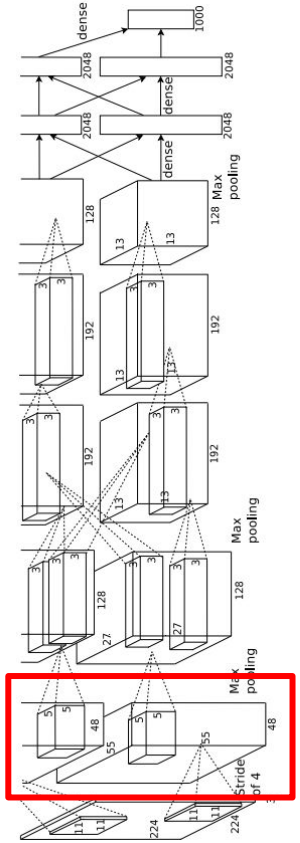


AlexNet:
64 x 3 x 11 x 11

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



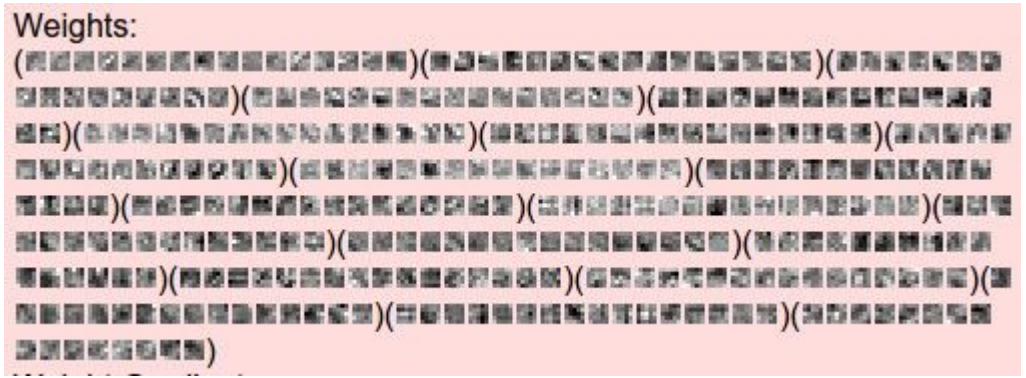
Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

Visualize the filters/kernels (raw weights)

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

layer 1 weights

16 x 3 x 7 x 7



layer 2 weights

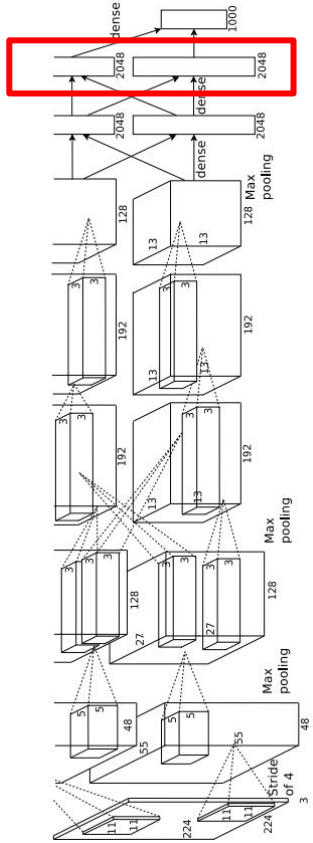
20 x 16 x 7 x 7

layer 3 weights

20 x 20 x 7 x 7

Last Layer

FC7 layer

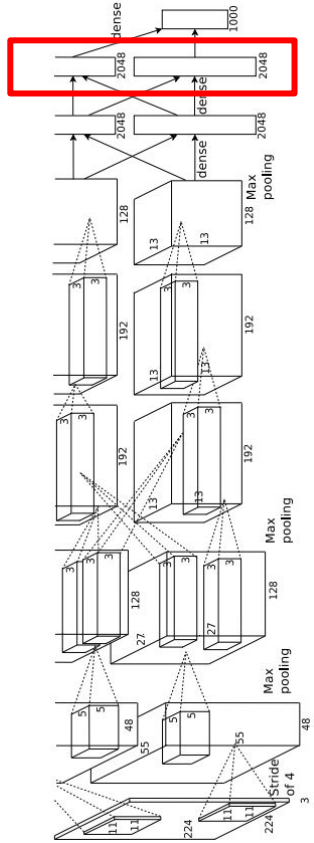


4096-dimensional feature vector for an image (layer immediately before the classifier)

Run the network on many images, collect the feature vectors

Last Layer: Nearest Neighbors

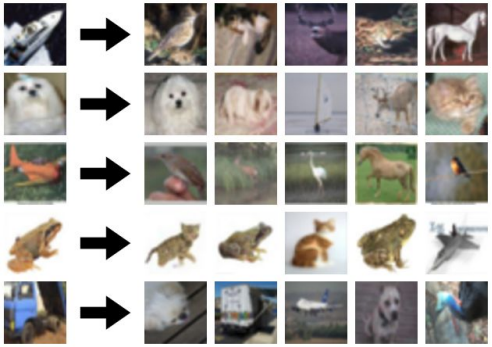
4096-dim vector



Test image

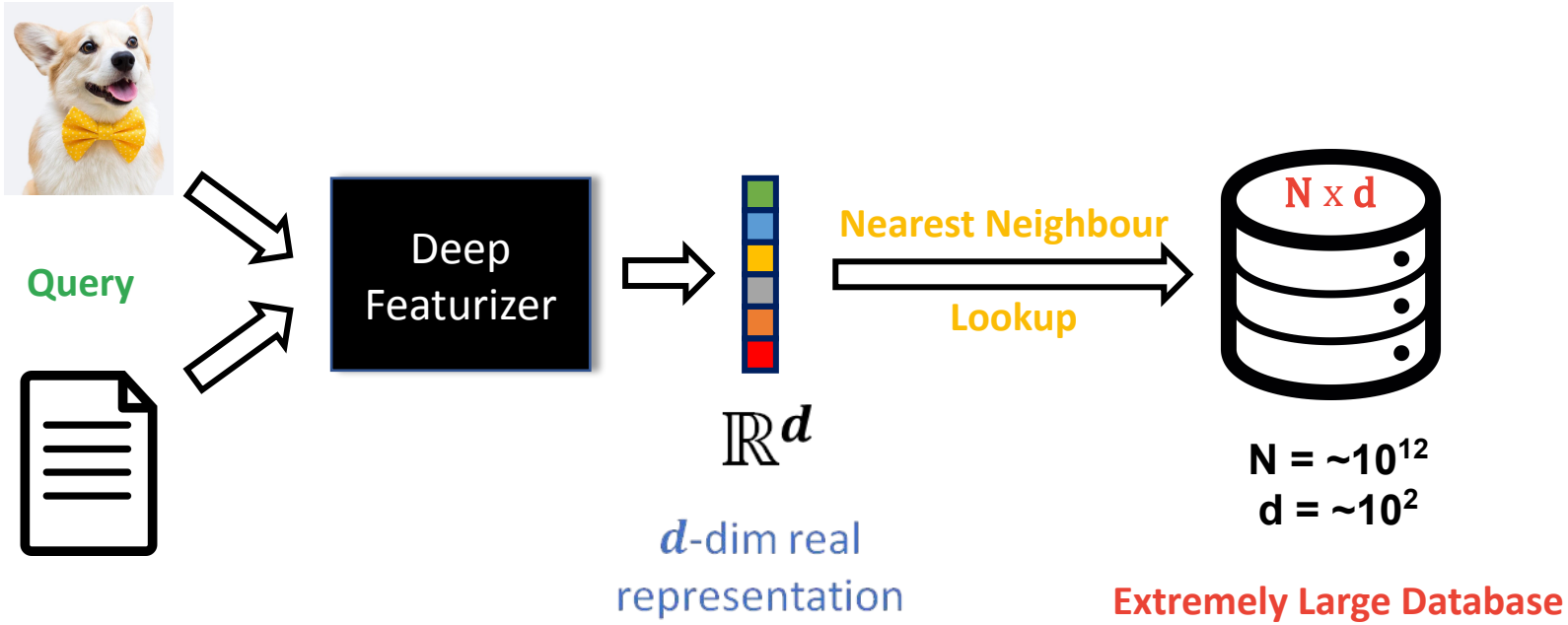
L2 Nearest neighbors in <u>feature</u> space

Recall: Nearest neighbors in <u>pixel</u> space

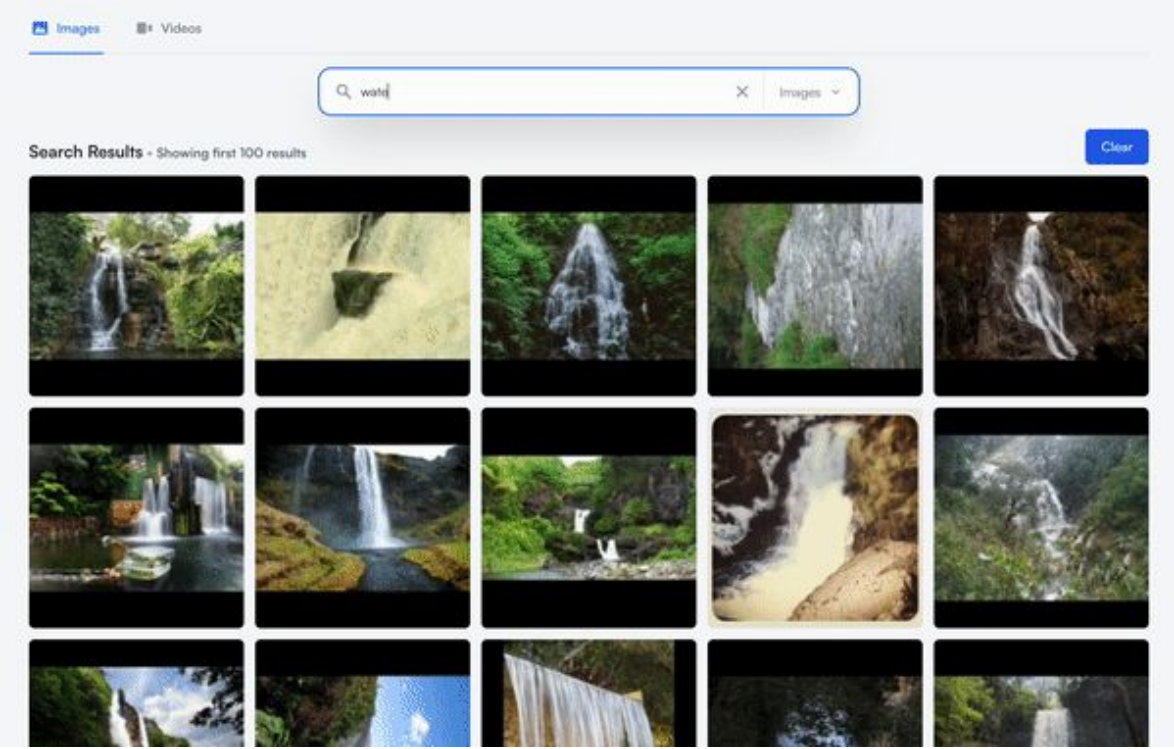


Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figures reproduced with permission.

Last Layer: Learned Metric for “Semantic” Search



Last Layer: Modern Day Search



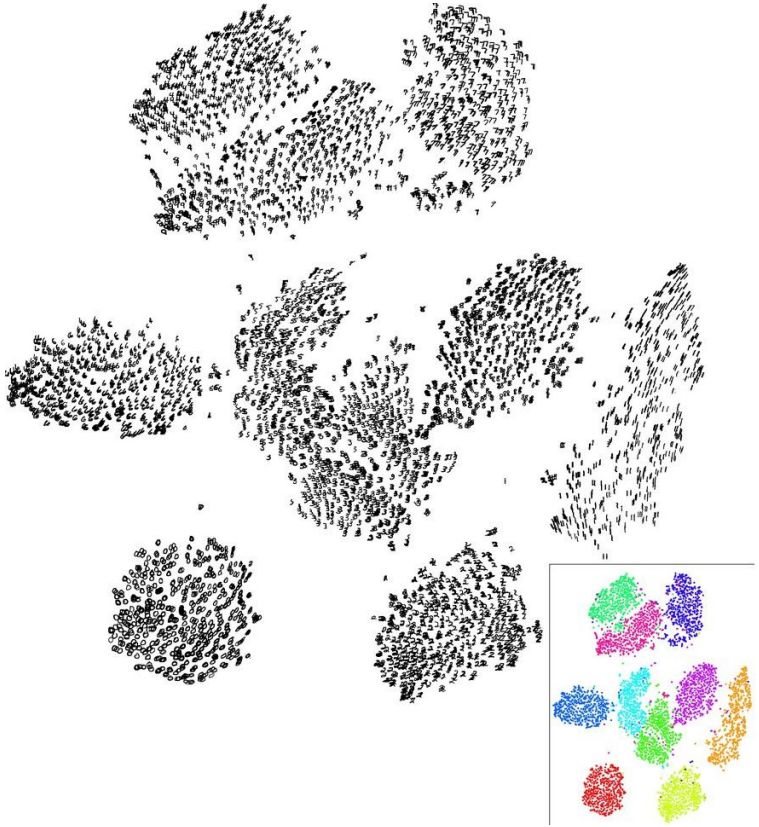
coactive.ai

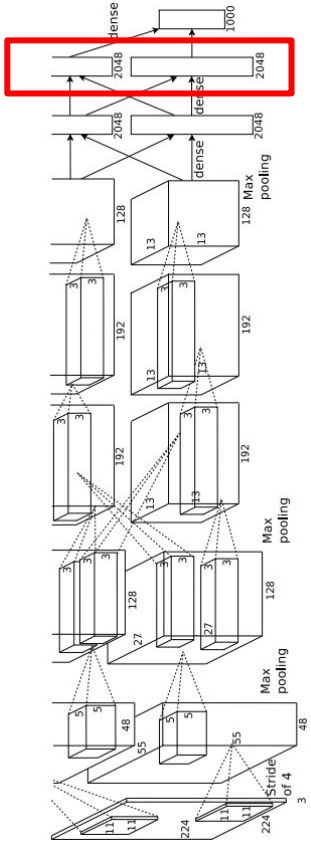
Last Layer: Dimensionality Reduction

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

Simple algorithm: Principal Component Analysis (PCA)

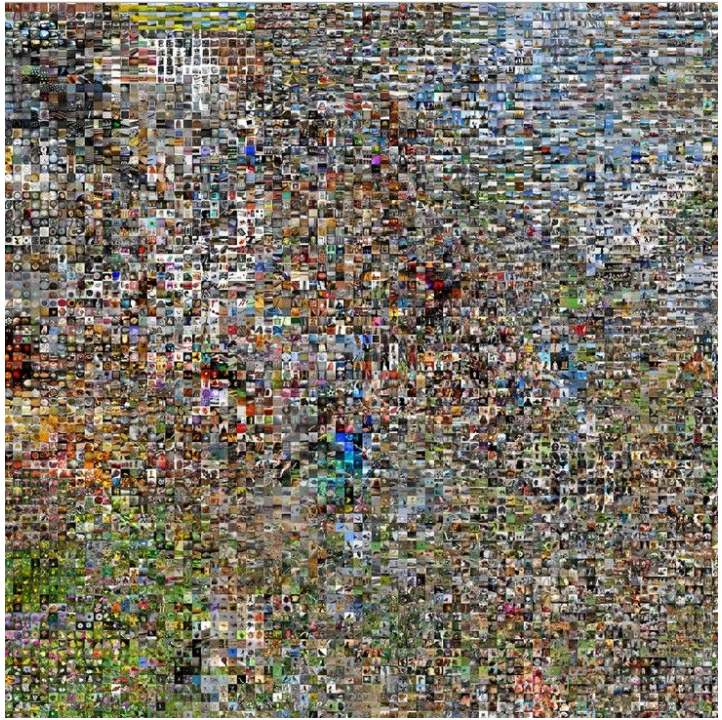
More complex: **t-SNE**

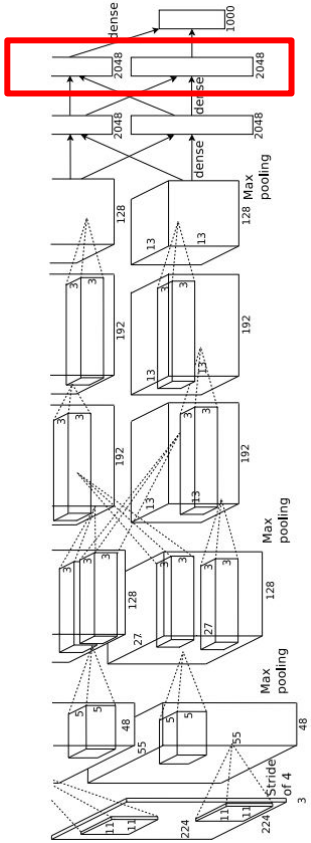




Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008
Figure copyright Laurens van der Maaten and Geoff Hinton, 2008. Reproduced with permission.

Last Layer: Dimensionality Reduction





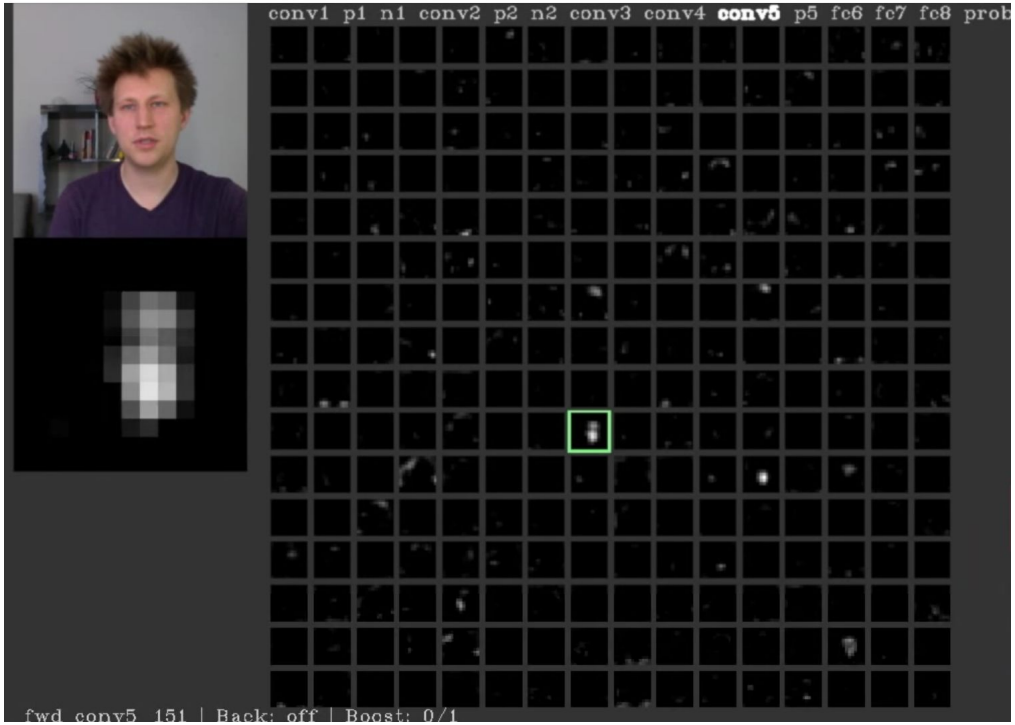
Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008
Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figure reproduced with permission.

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

Visualizing Activations

https://www.youtube.com/watch?v=AgkfIQ4IGaM

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



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

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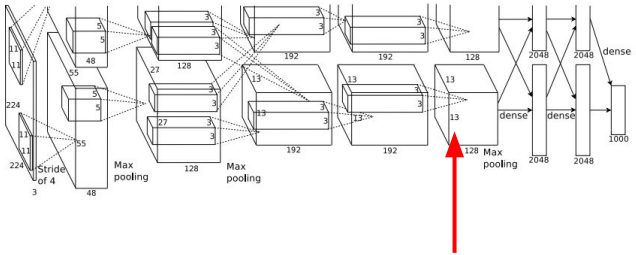
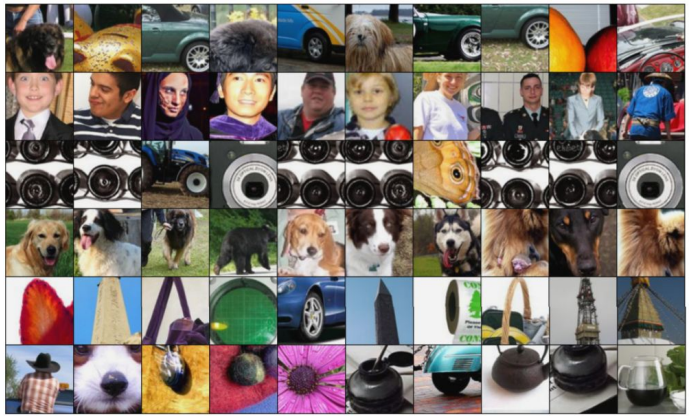
Maximally Activating Patches





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

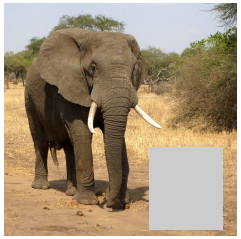
Run many images through the network, record values of chosen channel

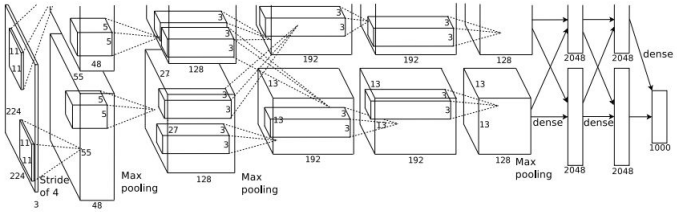
Visualize image patches that correspond to maximal activations

Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.

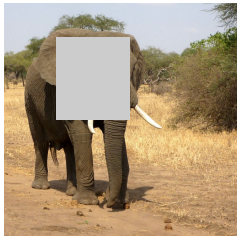
Which pixels matter: Saliency via Occlusion

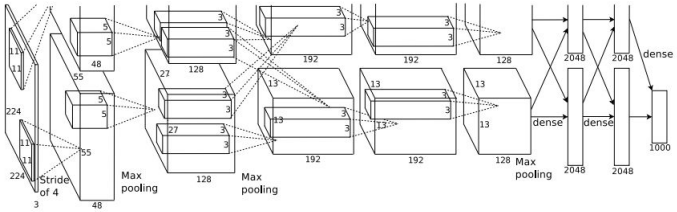
Mask part of the image before feeding to CNN, check how much predicted probabilities change





P(elephant) = 0.95



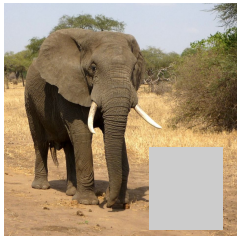


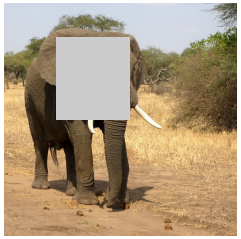
P(elephant) = 0.75

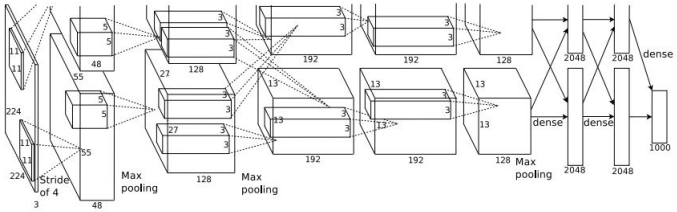
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

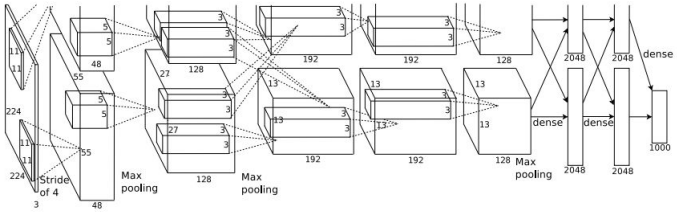
Which pixels matter: Saliency via Occlusion

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

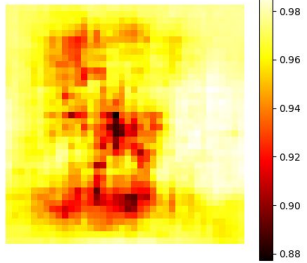




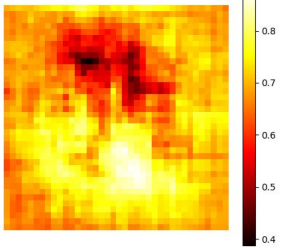




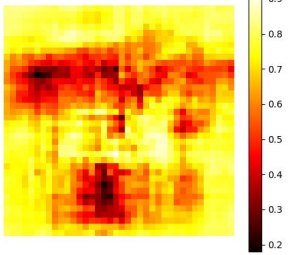
schooner



African elephant, Loxodonta africana



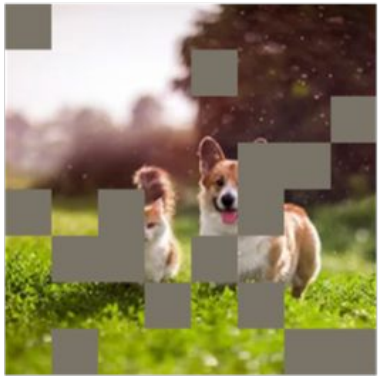
go-kart



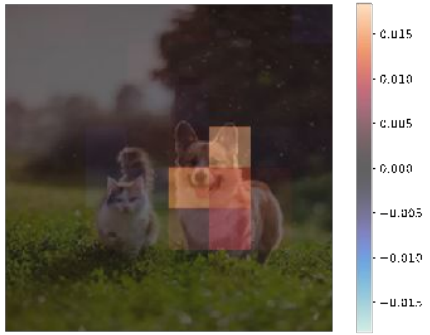
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

Saliency via Occlusion: Shapley Values

P(corgi) = 0.99



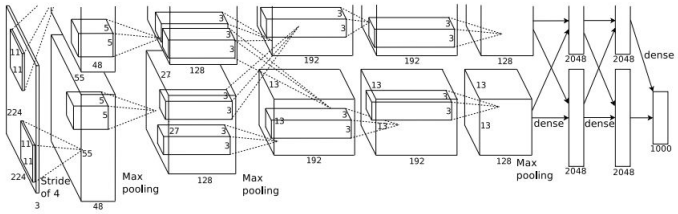
P(corgi) = 0.8



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.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

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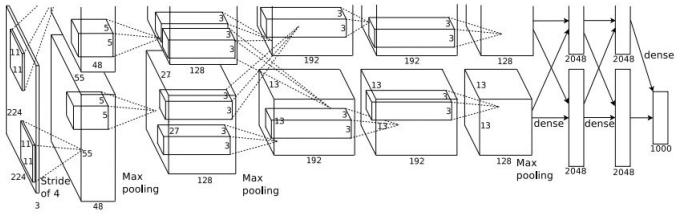
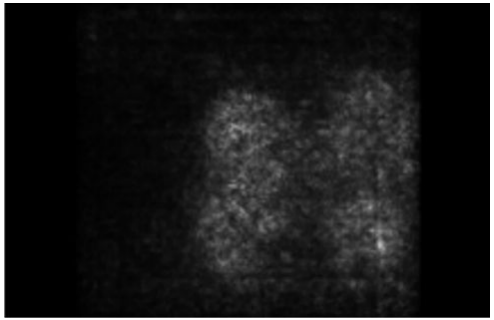
Forward pass: Compute probabilities



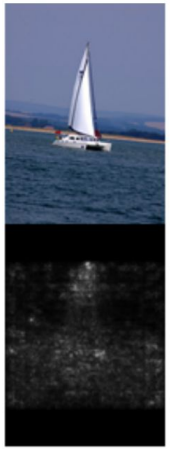
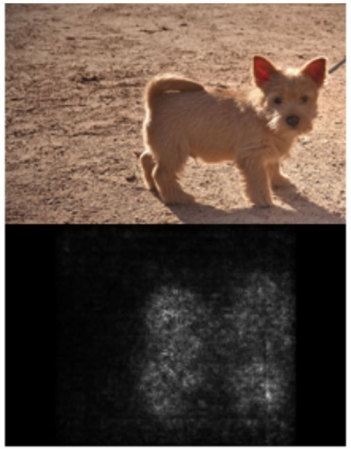
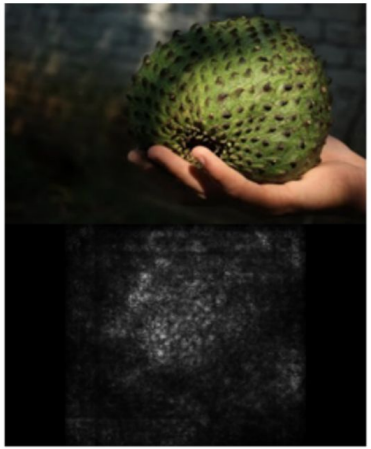
Dog

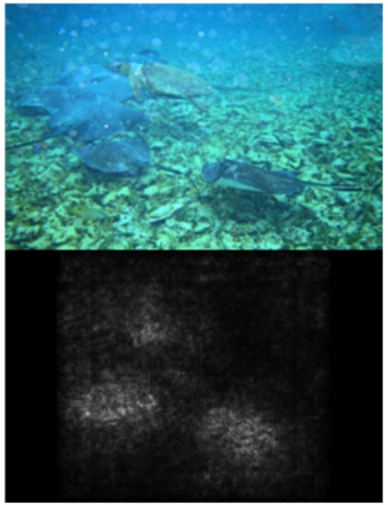
Compute gradient of (unnormalized) class score with respect to image pixels, take absolute value and max over RGB channels



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

Saliency Maps

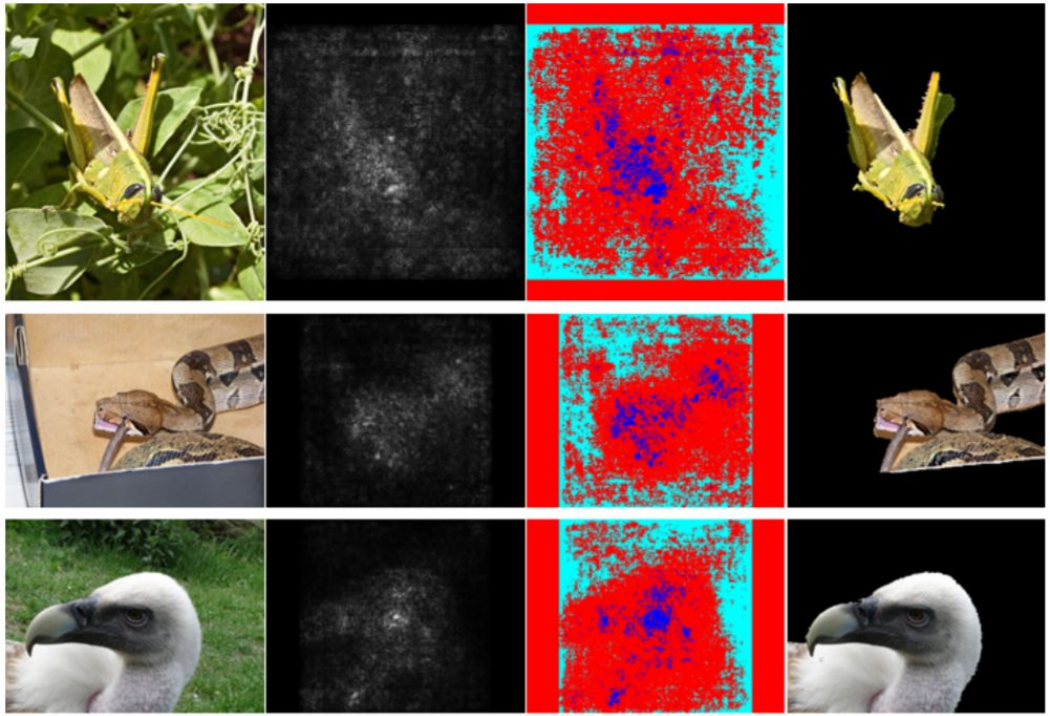






Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

Saliency Maps: Segmentation without supervision

Use GrabCut on saliency map



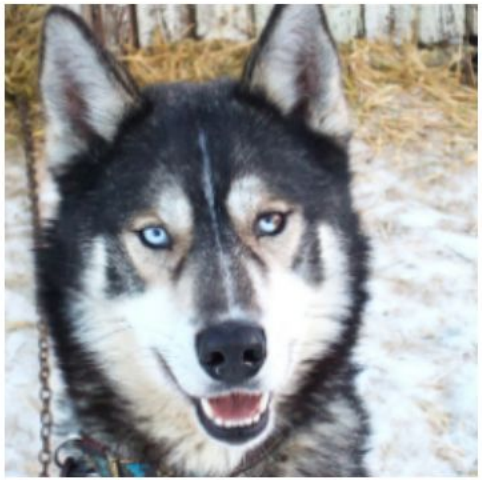
Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

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

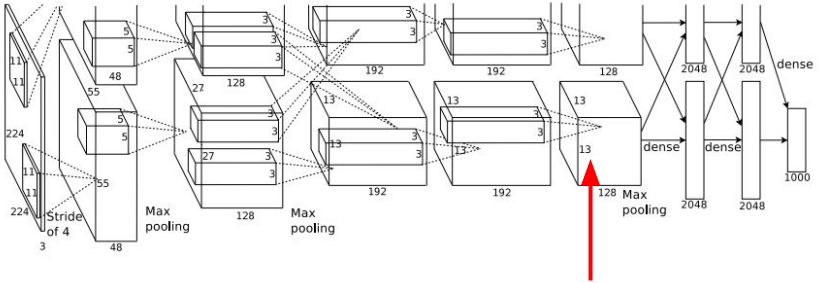


(a) Husky classified as wolf

(b) Explanation

Figures copyright Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, 2016; reproduced with permission.
Ribeiro et al, ""Why Should I Trust You?" Explaining the Predictions of Any Classifier", ACM KDD 2016

Intermediate Features via (guided) backprop

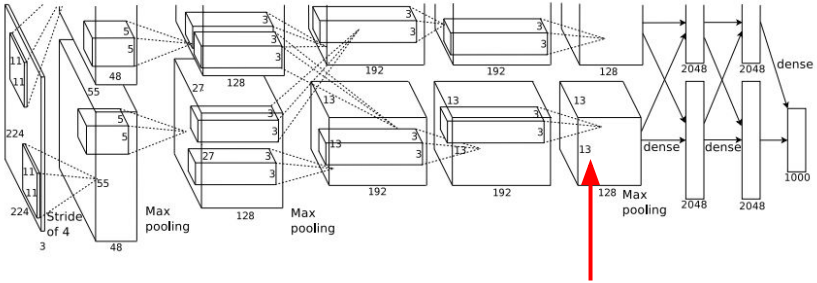


Pick a single intermediate channel, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of activation value with respect to image pixels

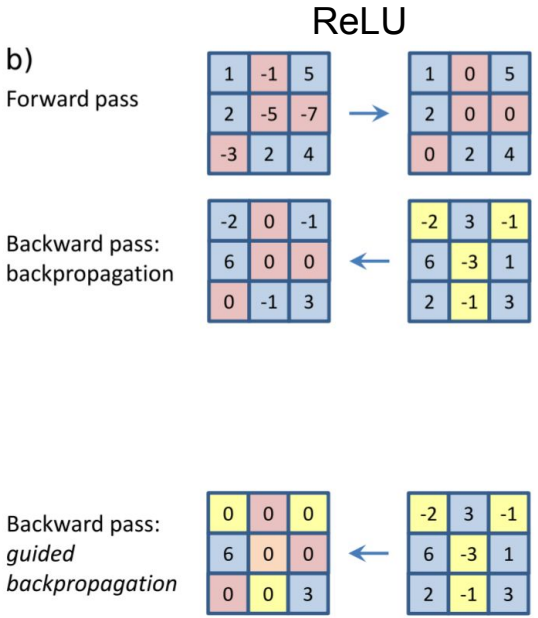
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

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

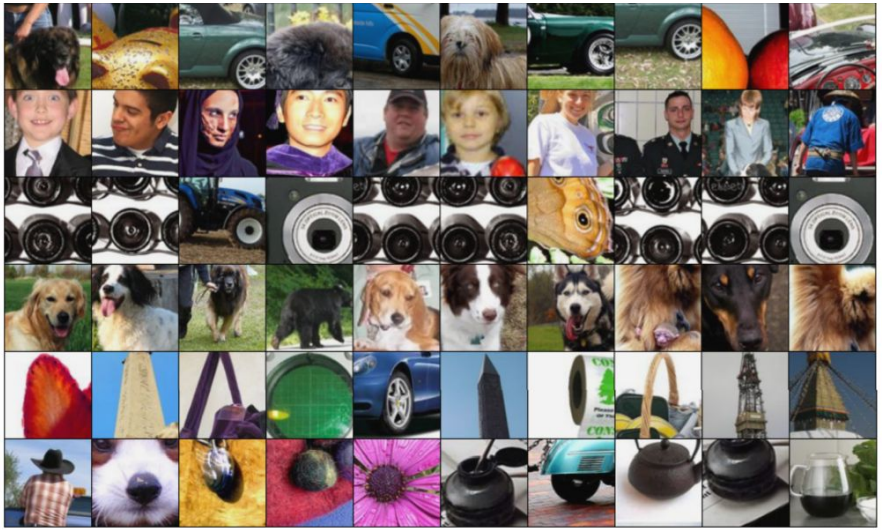
Intermediate features via (guided) backprop

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

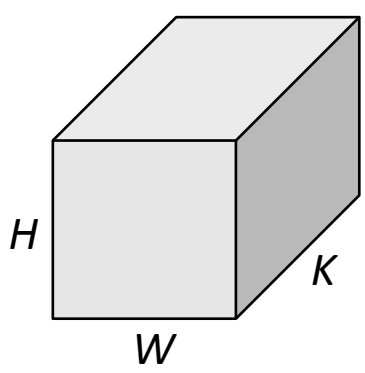


Maximally activating patches
(Each row is a different neuron)

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

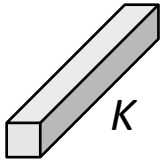
Class Activation Mapping (CAM)



Last layer CNN features:

$f \in \mathbb{R}^{H \times W \times K}$

Global Average Pooling

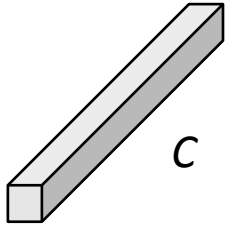


Pooled features:

$F \in \mathbb{R}^{K}$

Fully Connected Layer, weights

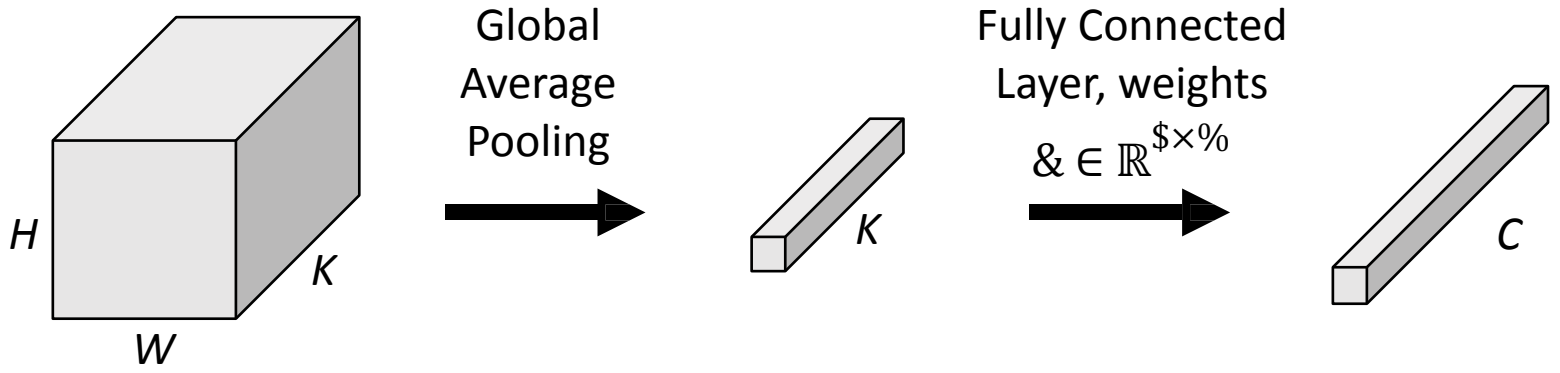
$\& \in \mathbb{R}^{\$ \times \%}$



Class Scores:

$S \in \mathbb{R}^{C}$

Class Activation Mapping (CAM)



Last layer CNN features:

$f \in \mathbb{R}^{H \times W \times K}$

Pooled features:

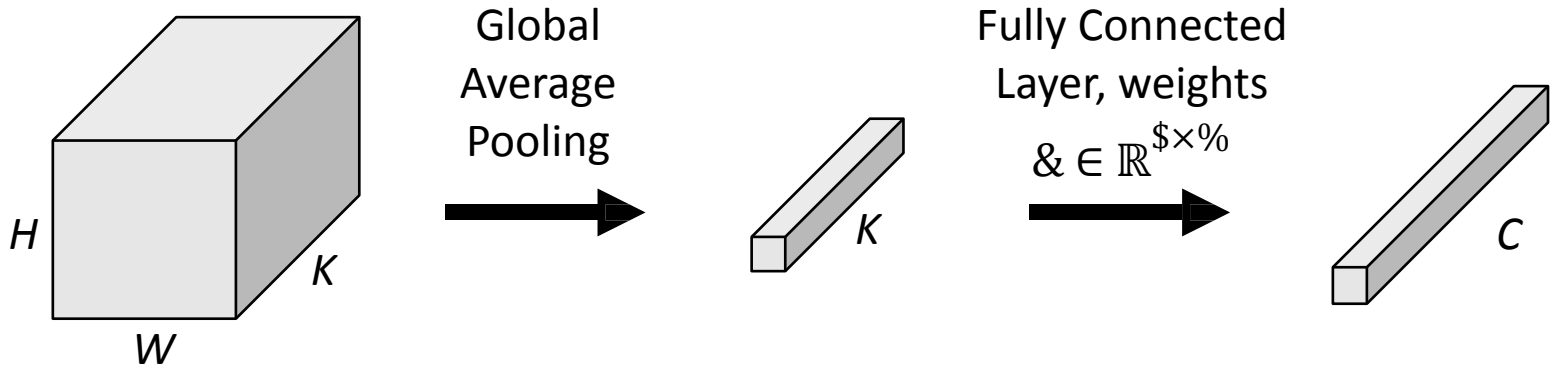
$F \in \mathbb{R}^{K}$

Class Scores:

$S \in \mathbb{R}^{C}$

$$F_k = \frac{1}{HW} \sum_{hw} f_{h,w,k}$$

Class Activation Mapping (CAM)



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$$F_k = \frac{1}{HW} \sum_{hw} f_{h,w,k}$$

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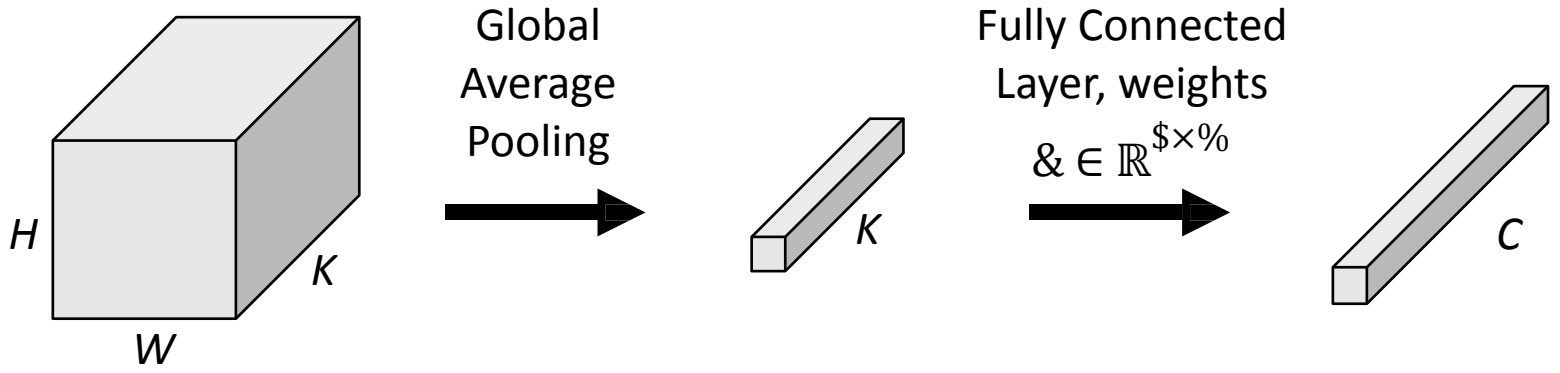
Class Activation Mapping (CAM)



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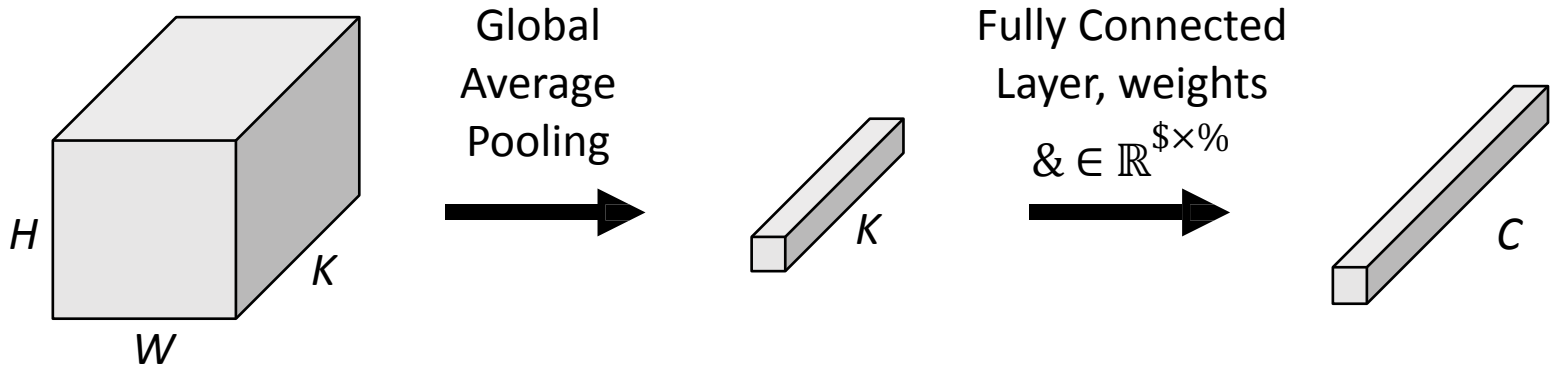
Class Activation Mapping (CAM)



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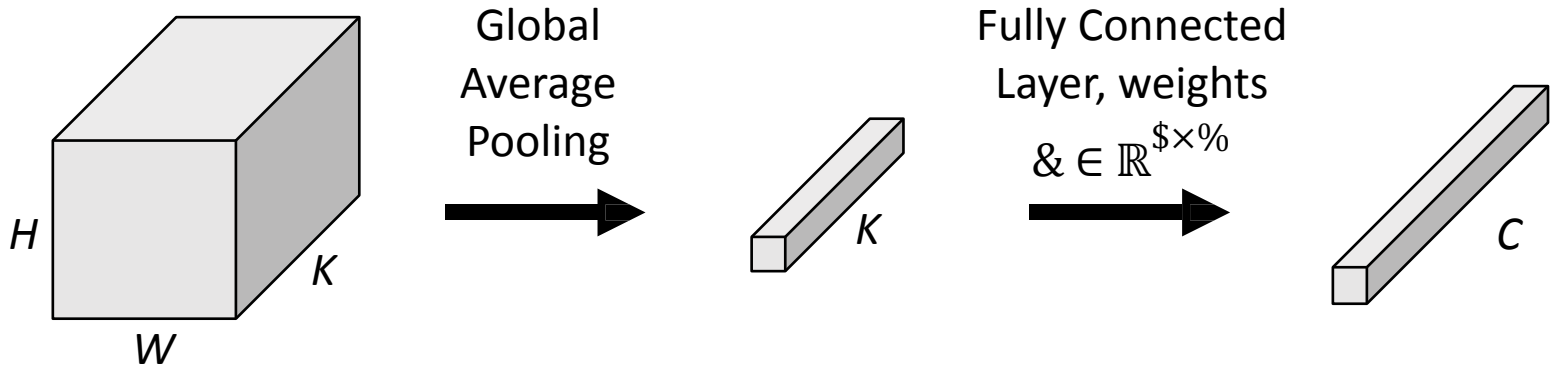

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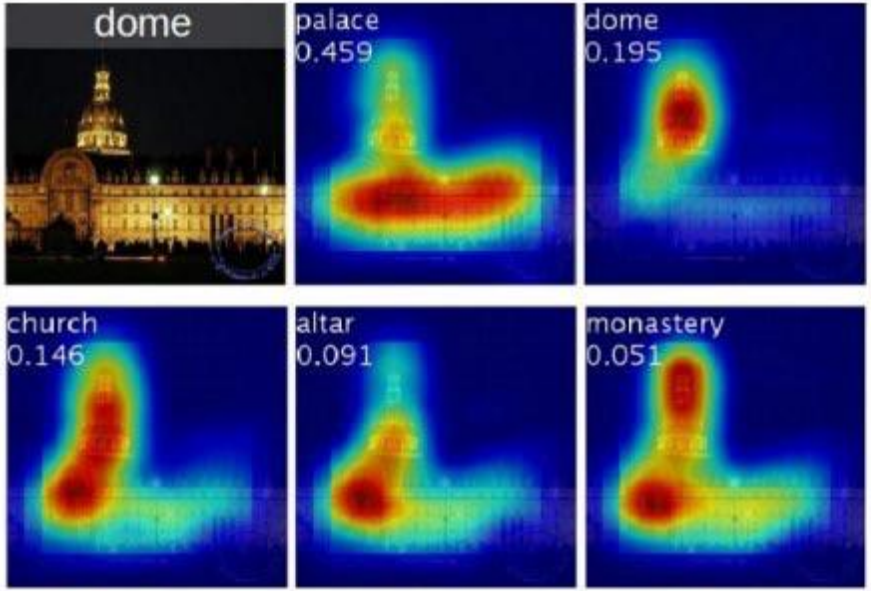
$$= \frac{1}{HW} \sum_{hw} \sum_k w_{k,c} f_{h,w,k}$$

CAMs

$$M \in \mathbb{R}^{C,H,W}$$

$$M = \sum_k w_{k,c} f_{h,w,k}$$

Class Activation Mapping (CAM)



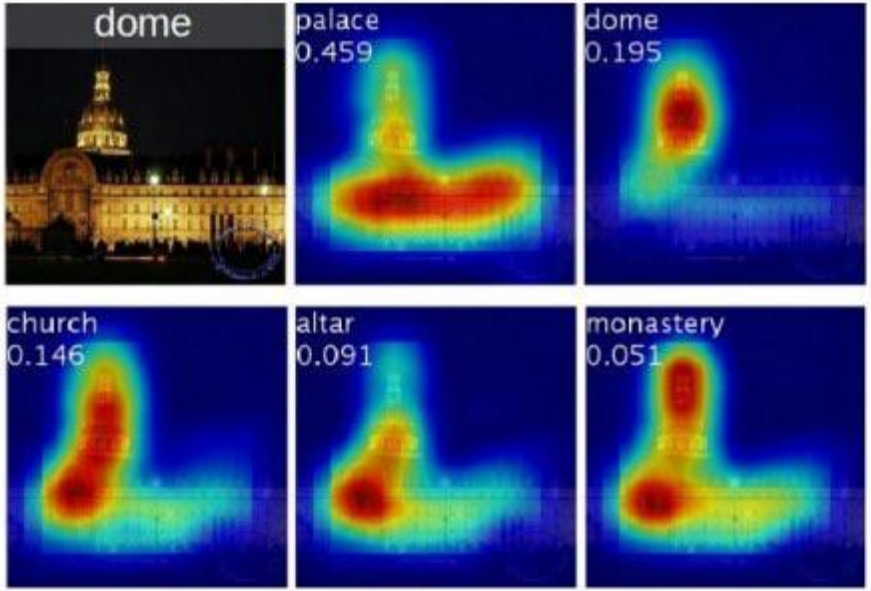
Class activation maps of top 5 predictions

Class activation maps for one object class

Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

Class Activation Mapping (CAM)

Problem: Can only apply to last conv layer



Class activation maps of top 5 predictions

Class activation maps for one object class

Gradient-Weighted Class Activation Mapping (Grad-CAM)

1. Pick any layer, with activations $A \in \mathbb{R}^{H \times W \times K}$

Selvaraju et al, “Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization”, CVPR 2017

Gradient-Weighted Class Activation Mapping (Grad-CAM)

1. Pick any layer, with activations $A \in \mathbb{R}^{H \times W \times K}$
2. Compute gradient of class score S_C with respect to A:

$$\frac{\partial S_c}{\partial A} \in \mathbb{R}^{H \times W \times K}$$

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

Gradient-Weighted Class Activation Mapping (Grad-CAM)

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3. Global Average Pool the gradients to get weights $\alpha \in \mathbb{R}^K$:

$$\alpha_k = \frac{1}{HW} \sum_{h,w} \frac{\partial S_c}{\partial A_{h,w,k}}$$

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

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3. Global Average Pool the gradients to get weights $\alpha \in \mathbb{R}^K$:

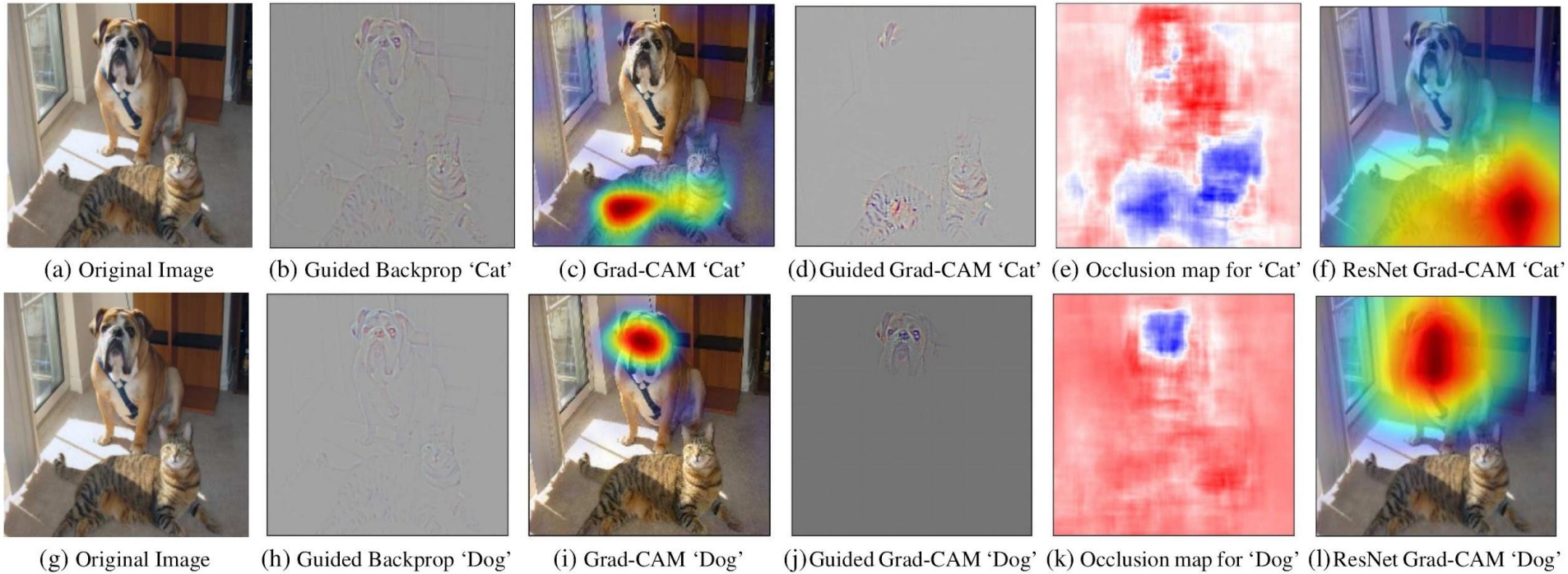
$$\alpha_k = \frac{1}{HW} \sum_{h,w} \frac{\partial S_c}{\partial A_{h,w,k}}$$

4. Compute activation map $M^c \in \mathbb{R}^{H,W}$:

$$M^c_{h,w} = ReLU\left(\sum_k \alpha_k A_{h,w,k}\right)$$

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

Gradient-Weighted Class Activation Mapping (Grad-CAM)



(a) Original Image (b) Guided Backprop 'Cat' (c) Grad-CAM 'Cat' (d) Guided Grad-CAM 'Cat' (e) Occlusion map for 'Cat' (f) ResNet Grad-CAM 'Cat'

(g) Original Image (h) Guided Backprop 'Dog' (i) Grad-CAM 'Dog' (j) Guided Grad-CAM 'Dog' (k) Occlusion map for 'Dog' (l) ResNet Grad-CAM 'Dog'

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

Gradient-Weighted Class Activation Mapping (Grad-CAM)

Can also be applied beyond classification models, e.g. image captioning

Selvaraju et al, “Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization”, CVPR 2017

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

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

Neuron value

Natural image regularizer

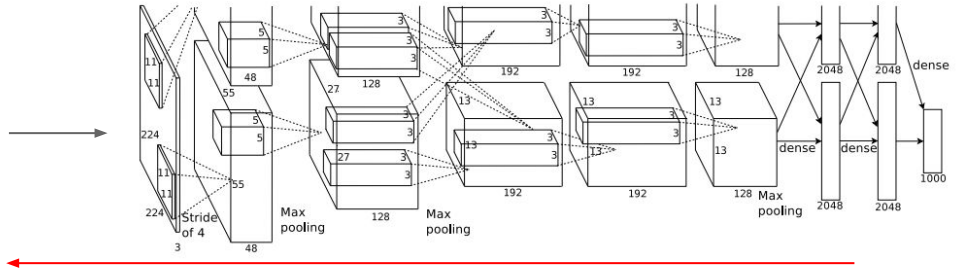
Visualizing CNN features: Gradient Ascent

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

score for class c (before Softmax)

1. Initialize image to zeros

zero image



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

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

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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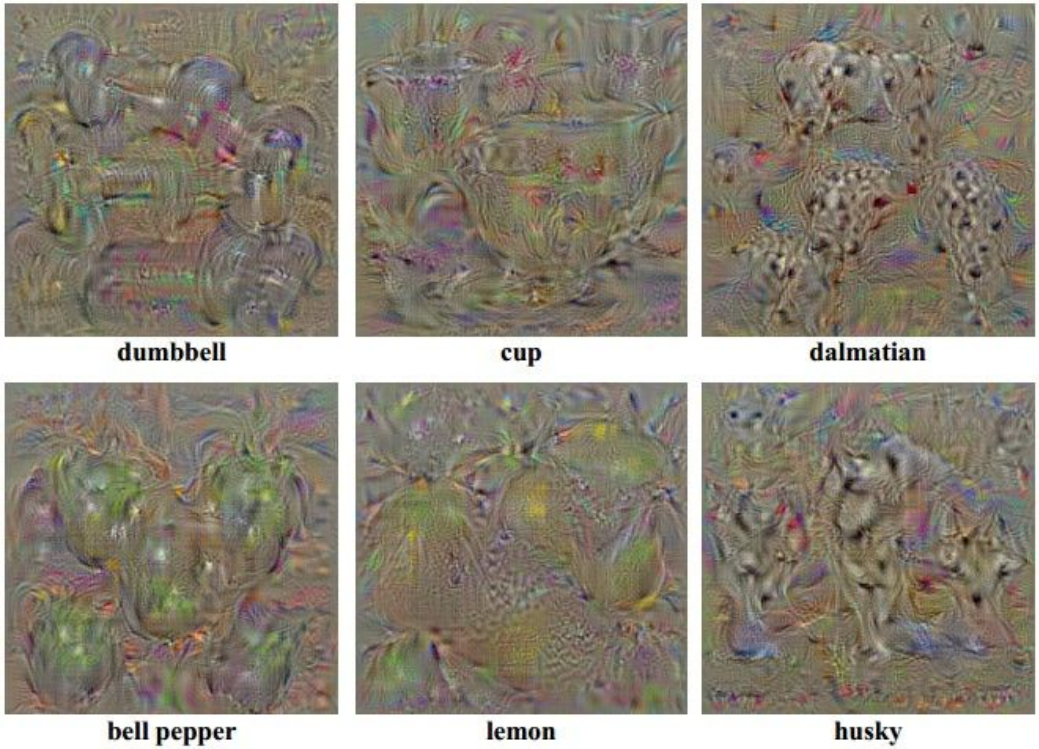
Simple regularizer: Penalize L2 norm of generated image



Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

Visualizing CNN features: Gradient Ascent

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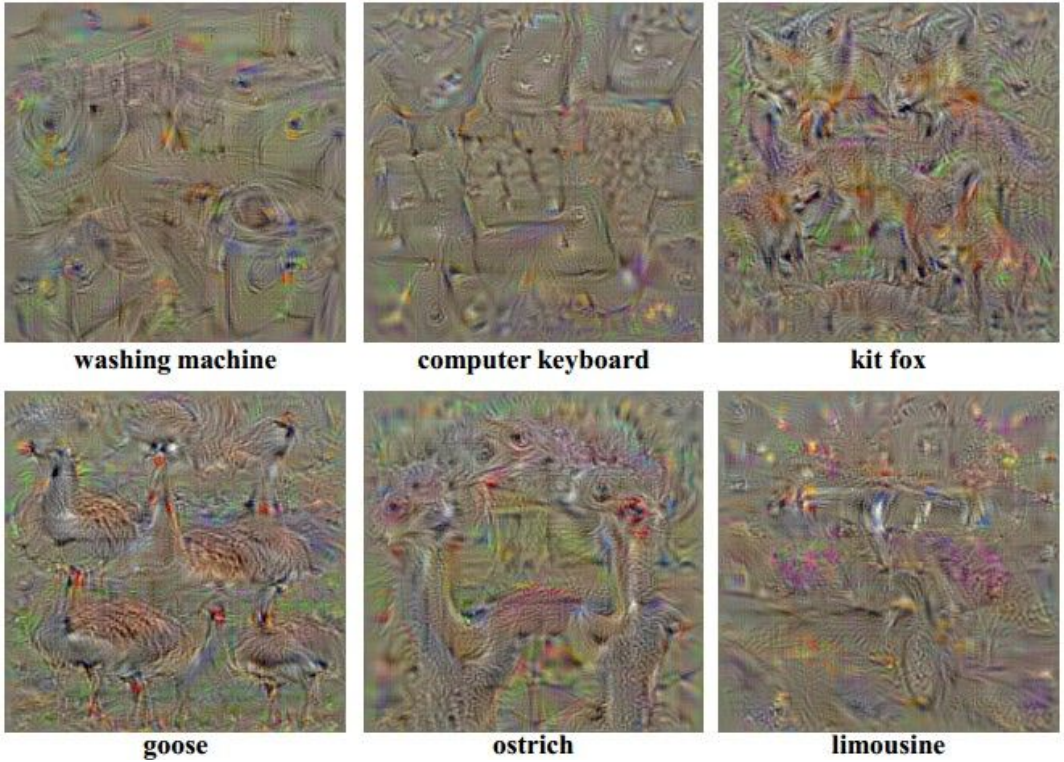

Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014. Figure copyright Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson, 2014. Reproduced with permission.

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

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

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

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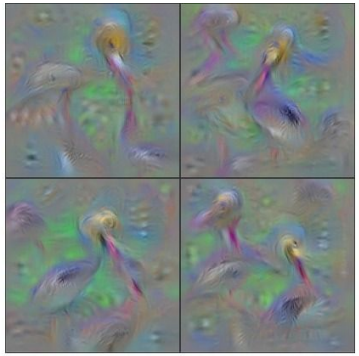
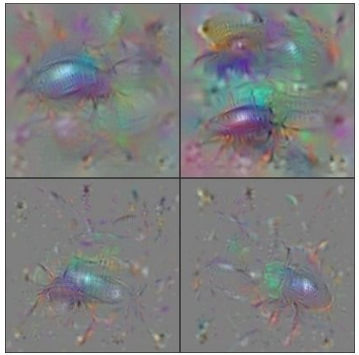
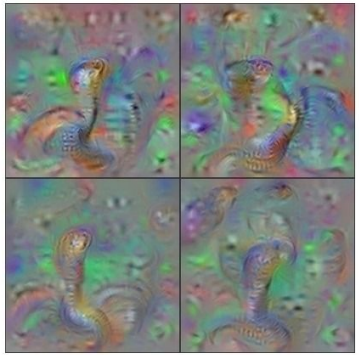
Flamingo



Pelican



Ground Beetle



Indian Cobra

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

Visualizing CNN features: Gradient Ascent

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

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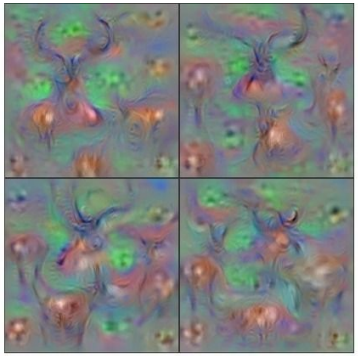
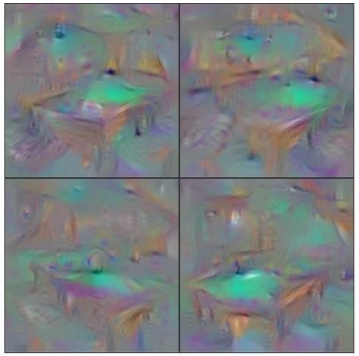
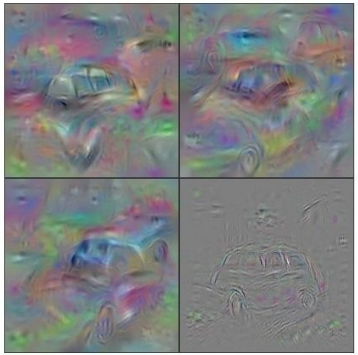


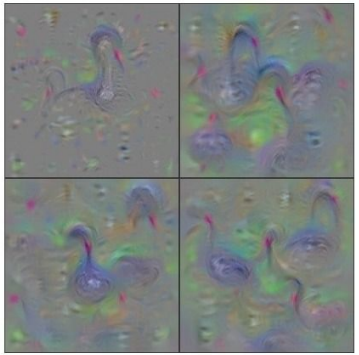
Hartebeest



Billiard Table



Station Wagon

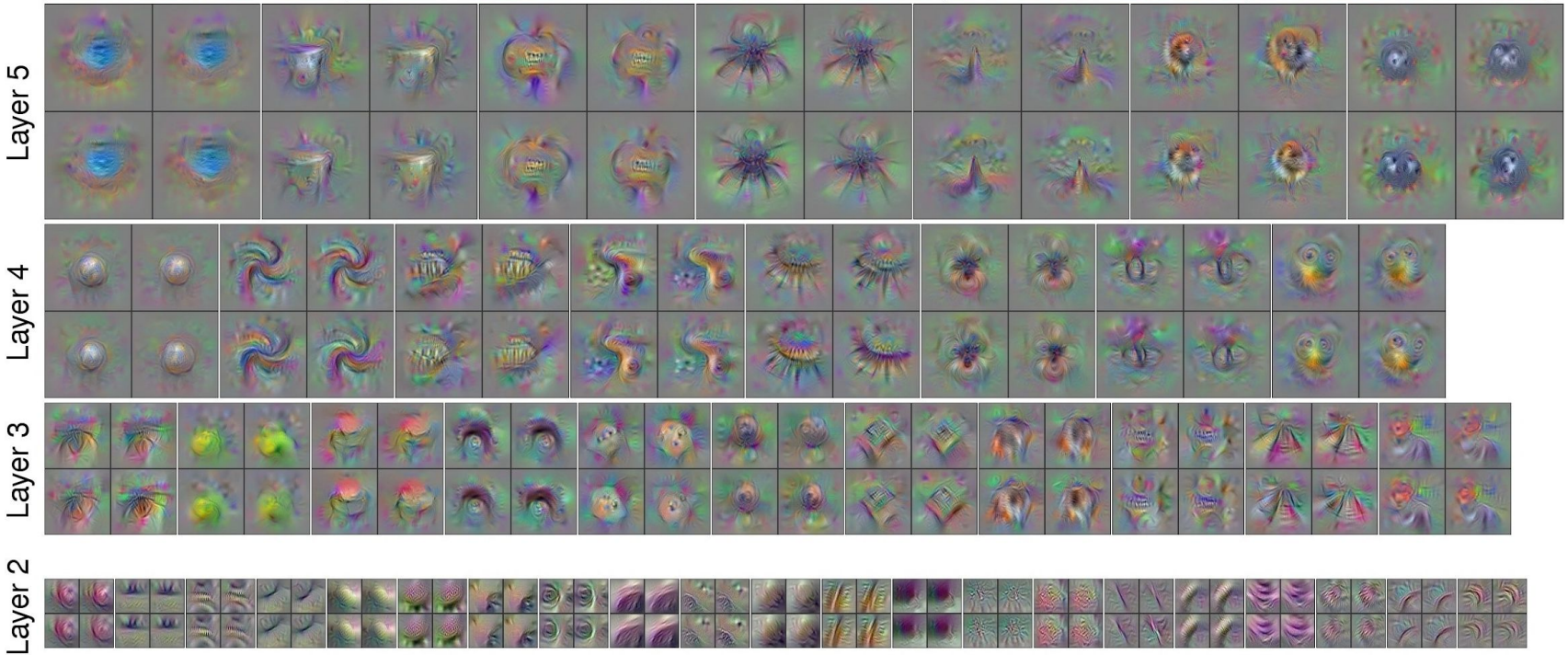


Black Swan

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.
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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

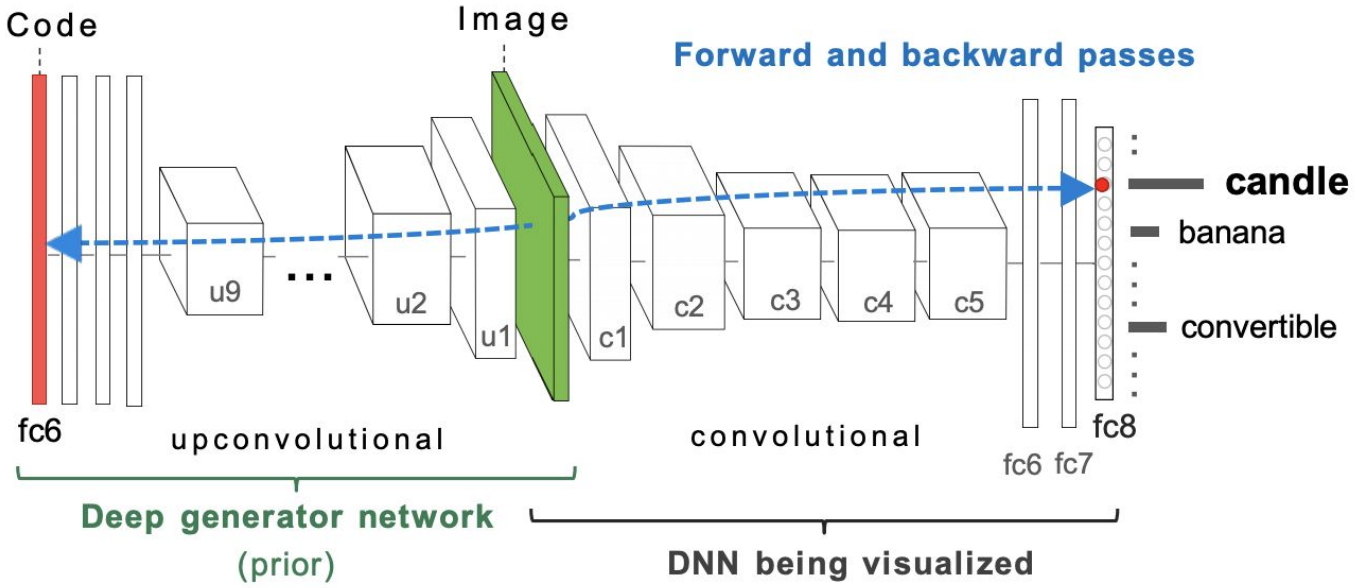
Nguyen et al, “Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks”, ICML Visualization for Deep Learning Workshop 2016.

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.
Figures copyright Anh Nguyen, Jason Yosinski, and Jeff Clune, 2016; reproduced with permission.

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
Figure copyright Nguyen et al, 2016; reproduced with permission.

Visualizing CNN features: Gradient Ascent

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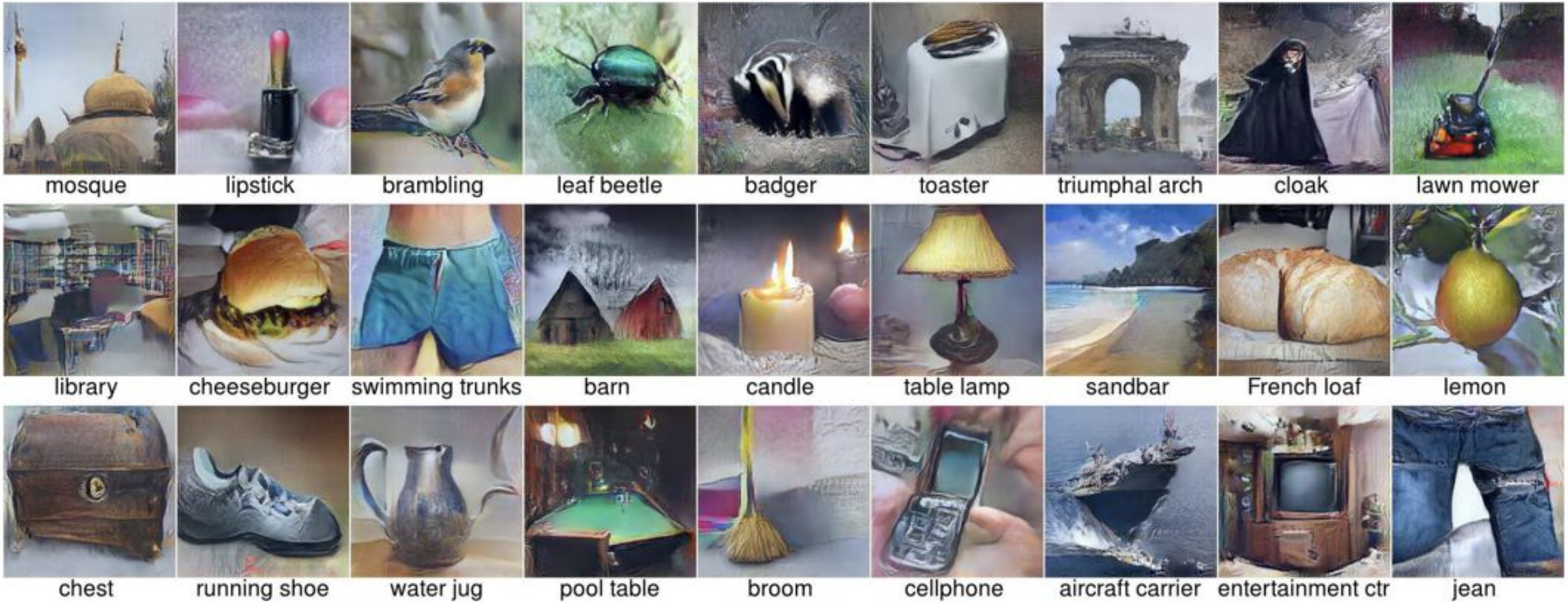


Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016
Figure copyright Nguyen et al, 2016; reproduced with permission.

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

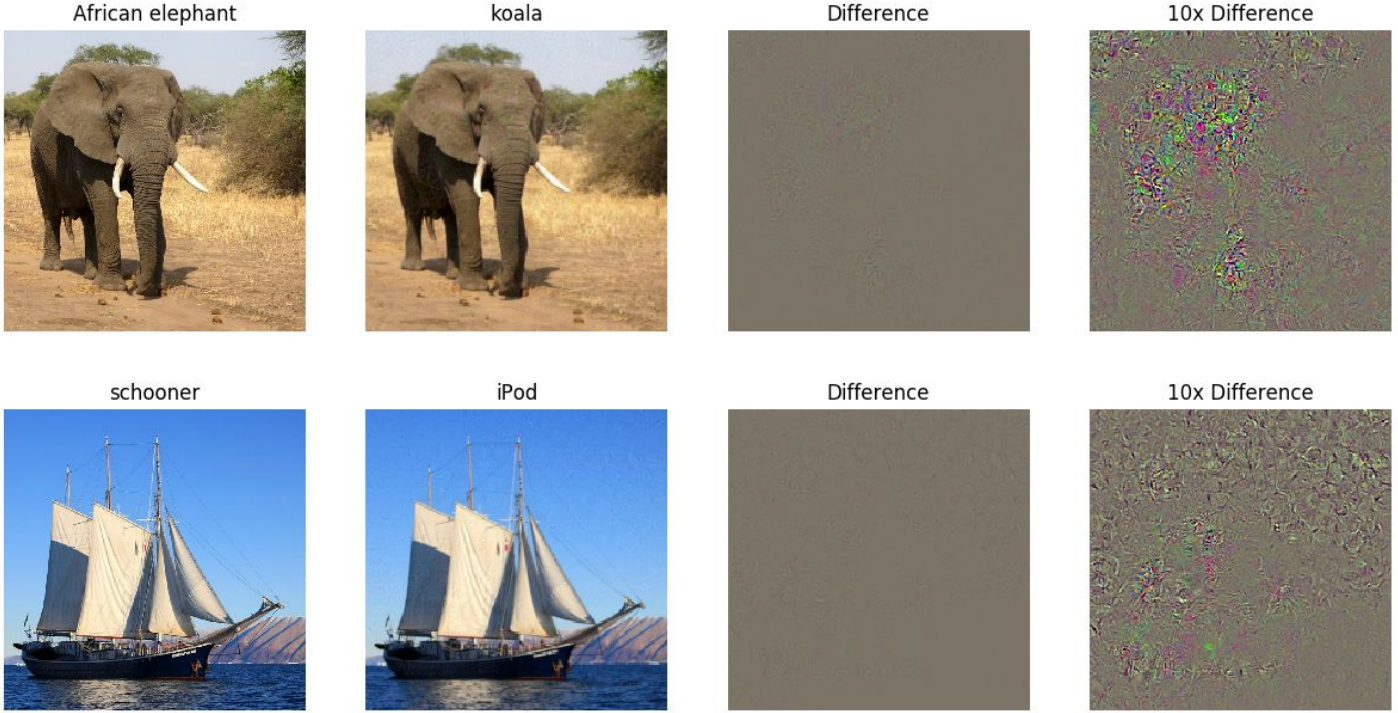
Adversarial perturbations

Concept Vectors

Fooling Images / Adversarial Examples

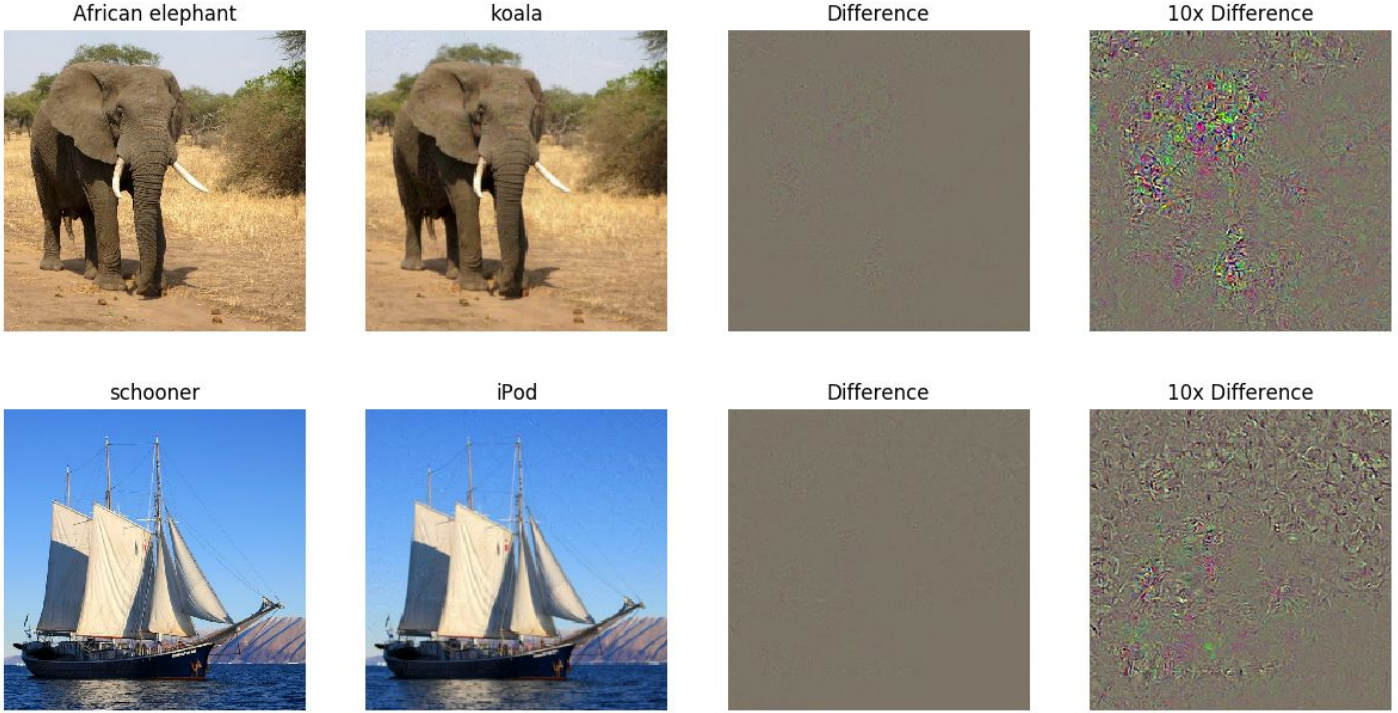
(1) Start from an arbitrary image
(2) Pick an arbitrary incorrect class
(3) Modify the image to maximize the class
(4) Repeat until network is fooled

Fooling Images / Adversarial Examples



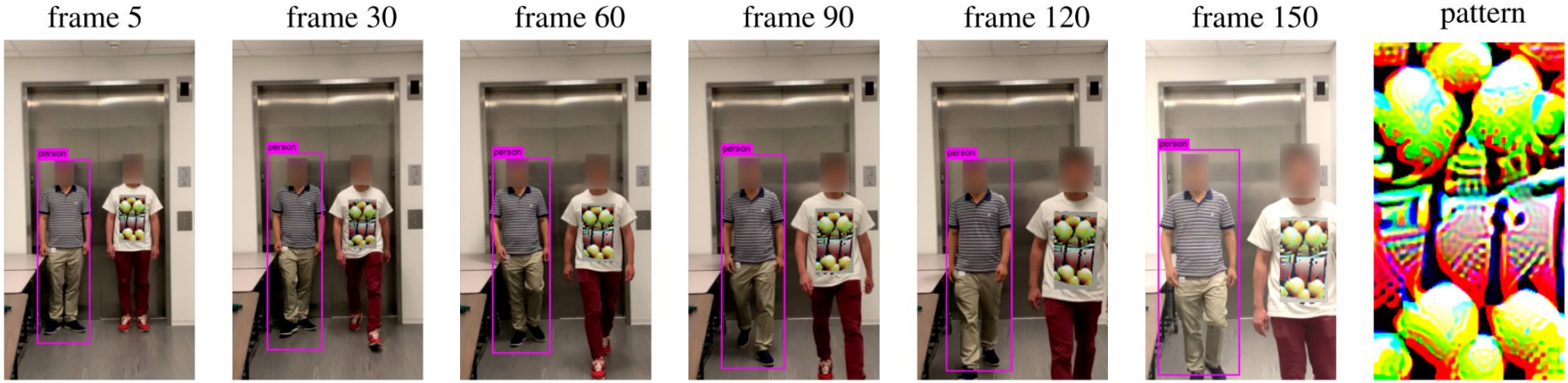
Boat image is CC0 public domain
Elephant image is CC0 public domain

Fooling Images / Adversarial Examples



Check out Ian Goodfellow's lecture from 2017

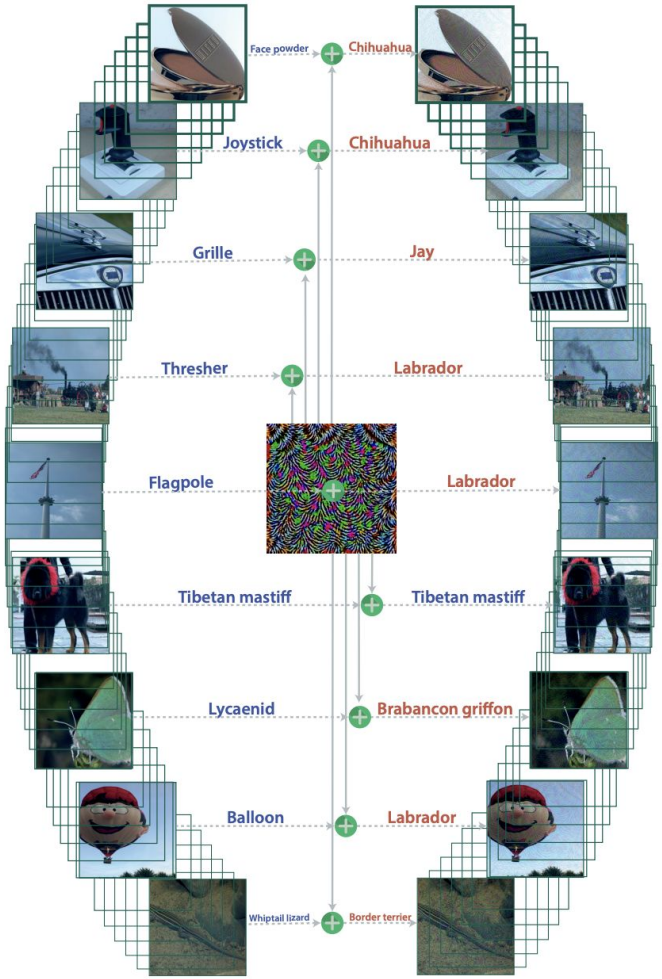
Fooling Person Detectors and Self-driving Cars



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

Feature Inversion

Given a CNN feature vector for an image, find a new image that:

- Matches the given feature vector
- "looks natural" (image prior regularization)

$$\mathbf{x}^* = \underset{\mathbf{x} \in \mathbb{R}^{H \times W \times C}}{\operatorname{argmin}} \ell(\Phi(\mathbf{x}), \Phi_0) + \lambda \mathcal{R}(\mathbf{x})$$

Given feature vector

$$\ell(\Phi(\mathbf{x}), \Phi_0) = \|\Phi(\mathbf{x}) - \Phi_0\|^2$$

Features of new image

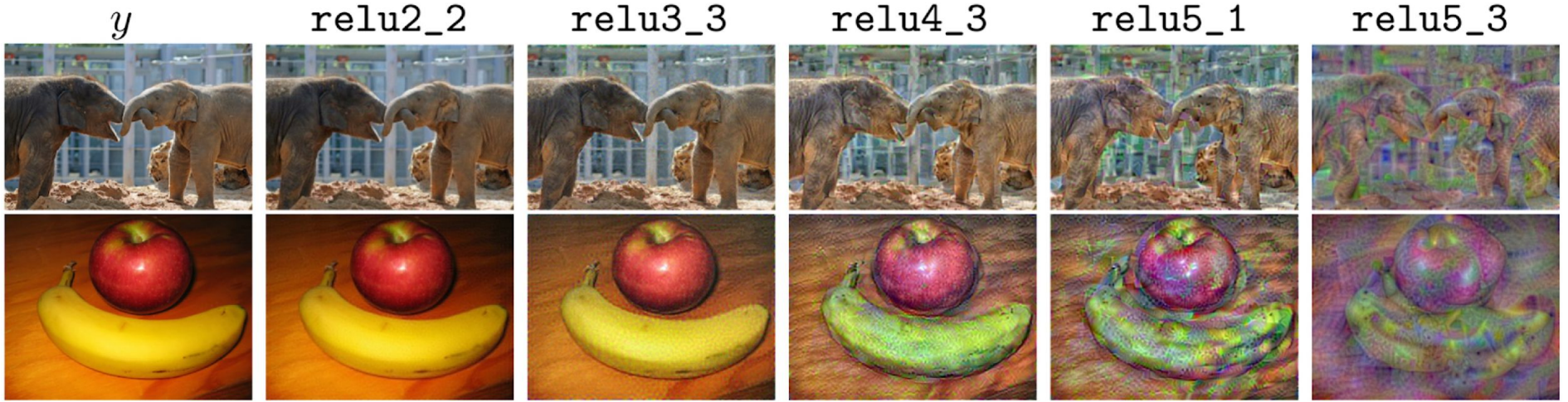
$$\mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j} \left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{\beta}{2}}$$

Total Variation regularizer (encourages spatial smoothness)

Mahendran and Vedaldi, "Understanding Deep Image Representations by Inverting Them", CVPR 2015

Feature Inversion

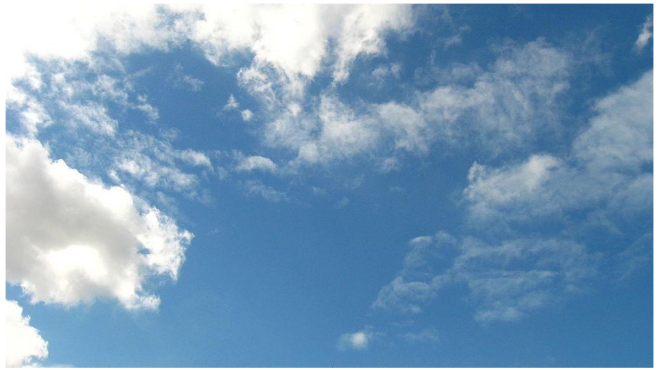
Reconstructing from different layers of VGG-16

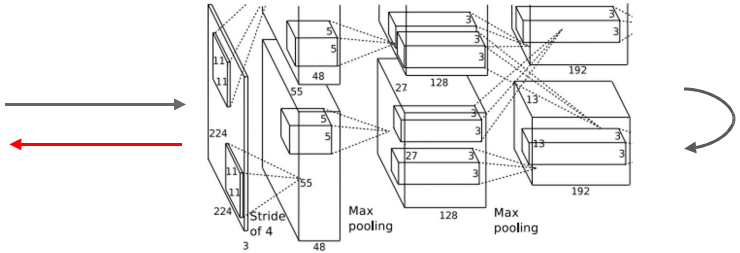


Mahendran and Vedaldi, “Understanding Deep Image Representations by Inverting Them”, CVPR

DeepDream: Amplify Existing Features

Rather than synthesizing an image to maximize a specific neuron, instead try to **amplify** the neuron activations at some layer in the network



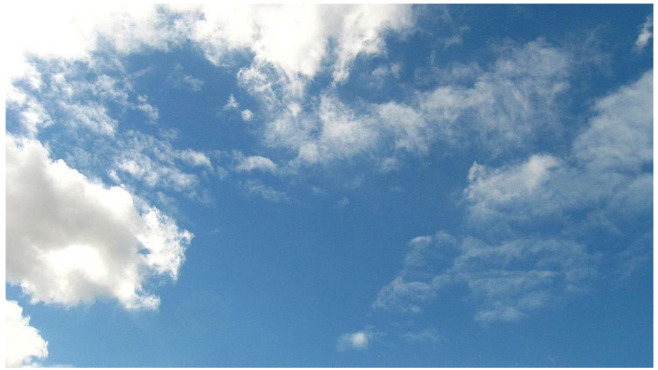


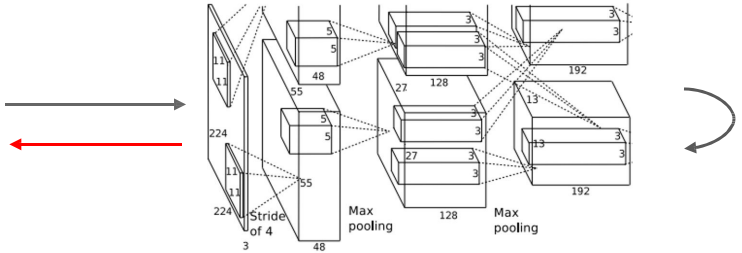
Choose an image and a layer in a CNN; repeat:

1. Forward: compute activations at chosen layer
2. Set gradient of chosen layer *equal to its activation*
3. Backward: Compute gradient on image
4. Update image

DeepDream: Amplify Existing Features

Rather than synthesizing an image to maximize a specific neuron, instead try to **amplify** the neuron activations at some layer in the network





Choose an image and a layer in a CNN; repeat:

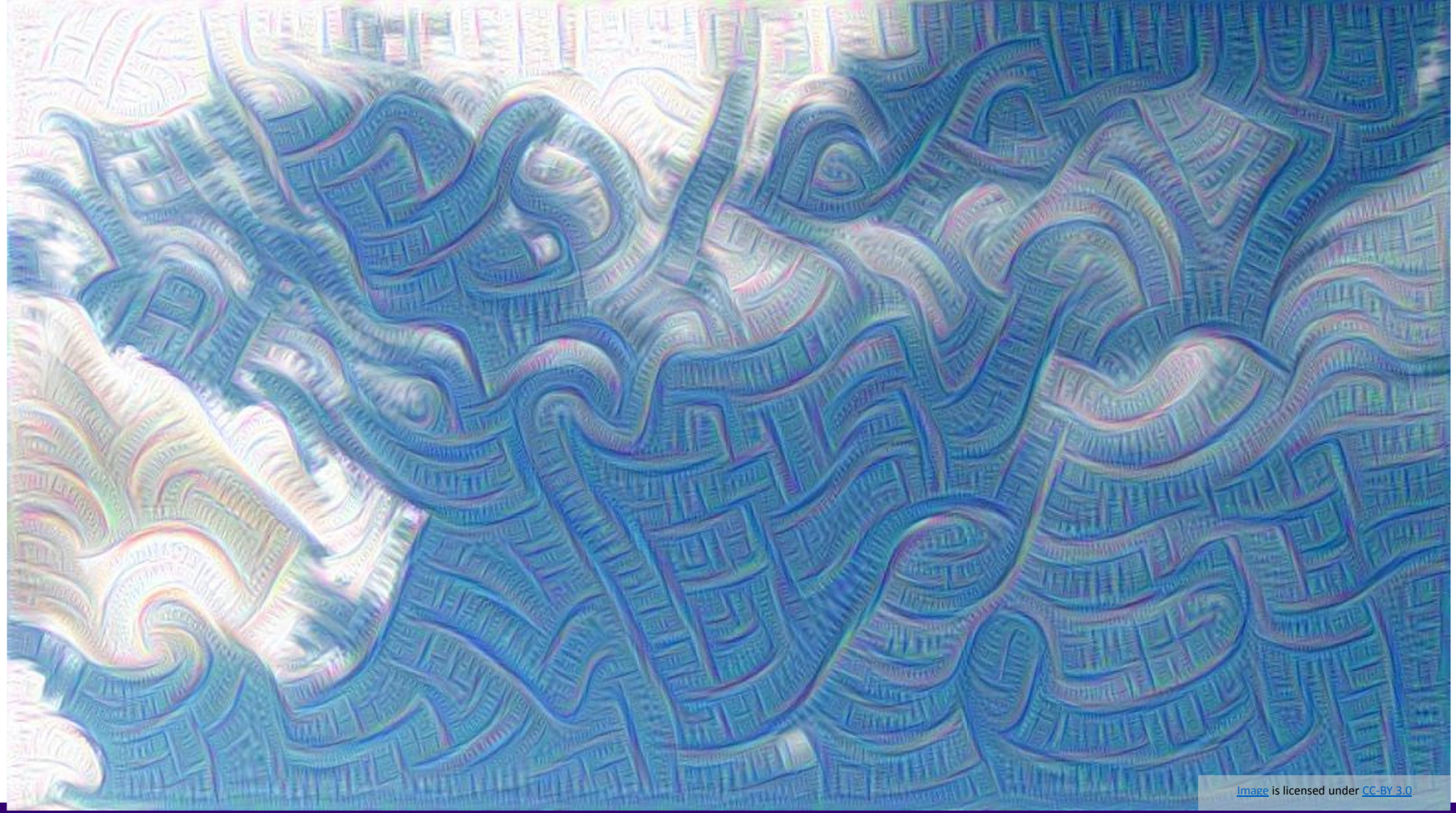
1. Forward: compute activations at chosen layer
2. Set gradient of chosen layer *equal to its activation*
3. Backward: Compute gradient on image
4. Update image

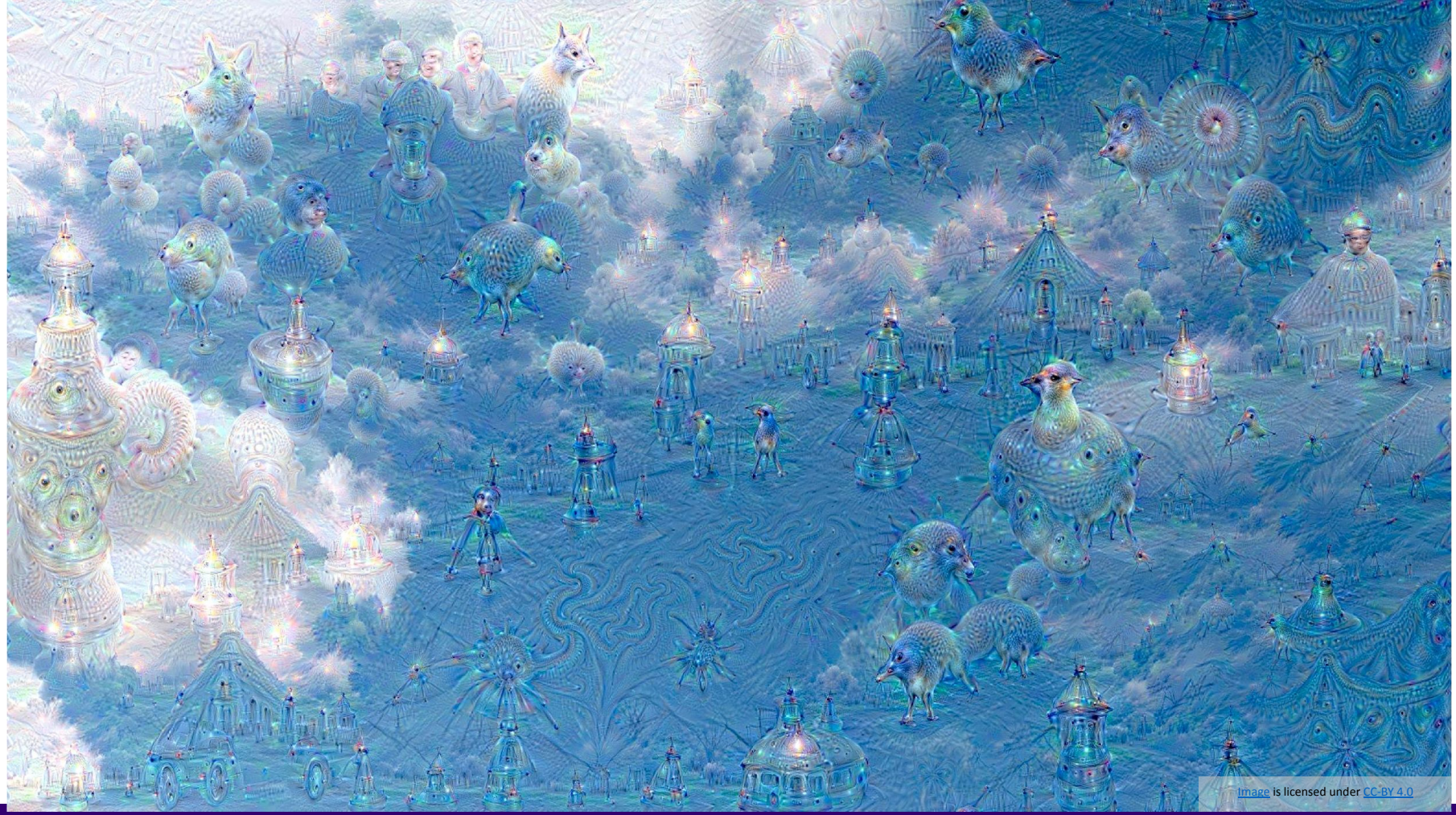
Equivalent to:

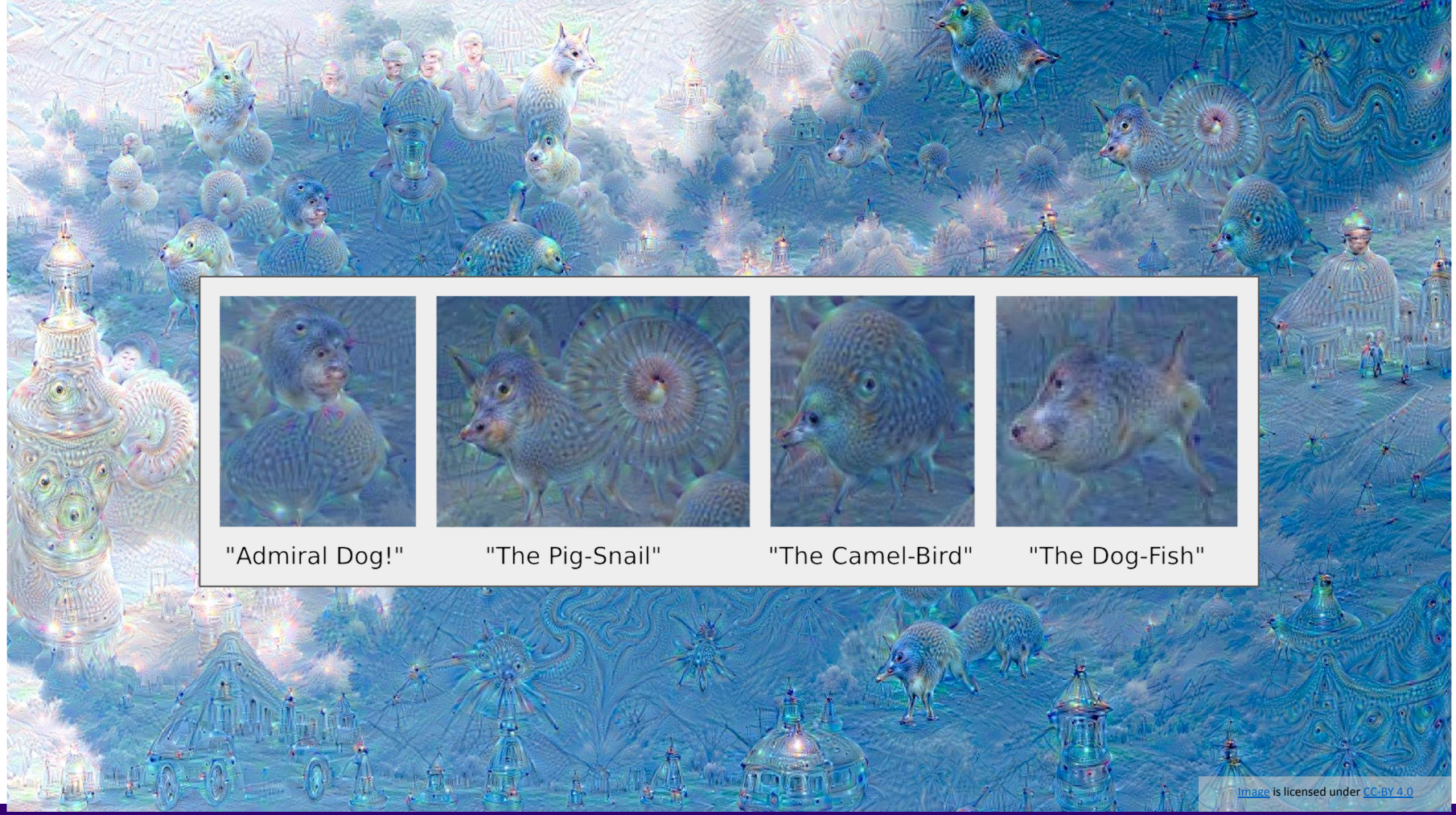
$$I^* = \arg\max_I \sum_i f_i(I)^2$$

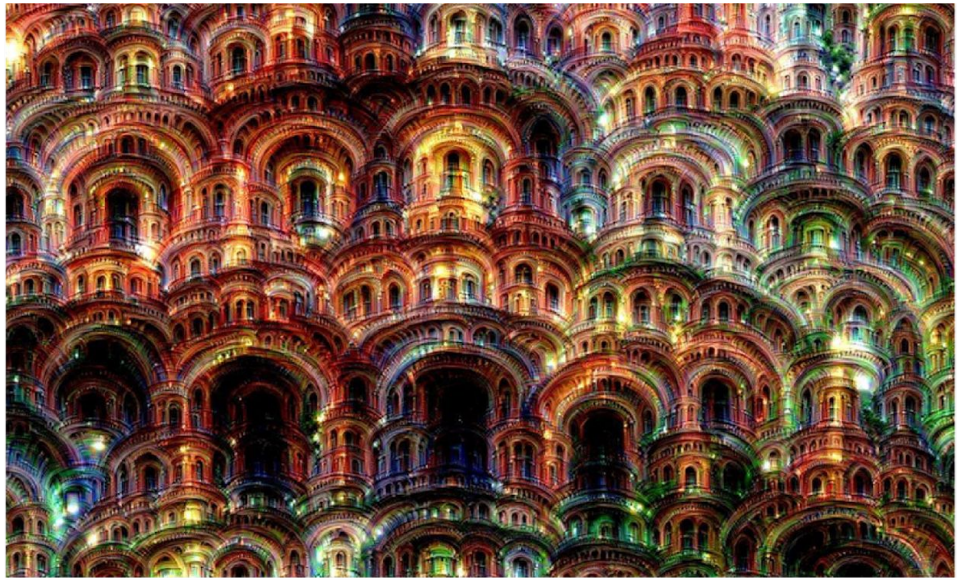
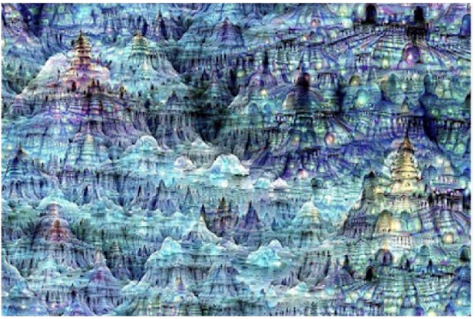
Mordvintsev, Olah, and Tyka, "Inceptionism: Going Deeper into Neural Networks", Google Research Blog. Images are licensed under CC-BY 4.0

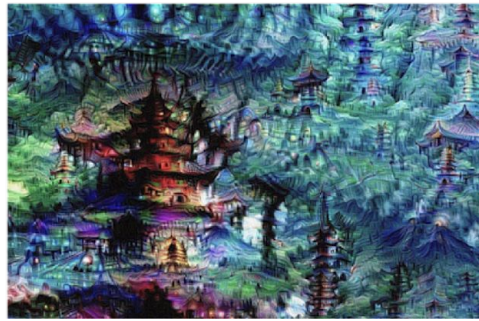

Sky image is licensed under CC-BY SA 3.0







Today's agenda

Visualizing what models have learned:

- Visualizing filters
- Visualizing final layer features
- Visualizing activations

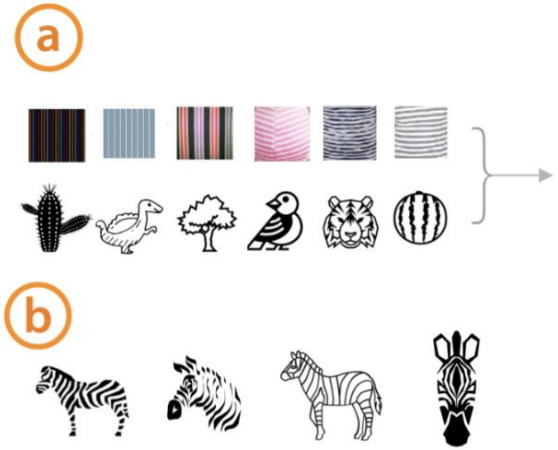
Understanding input pixels

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

Adversarial perturbations

Concept Vectors

Concept activation vectors

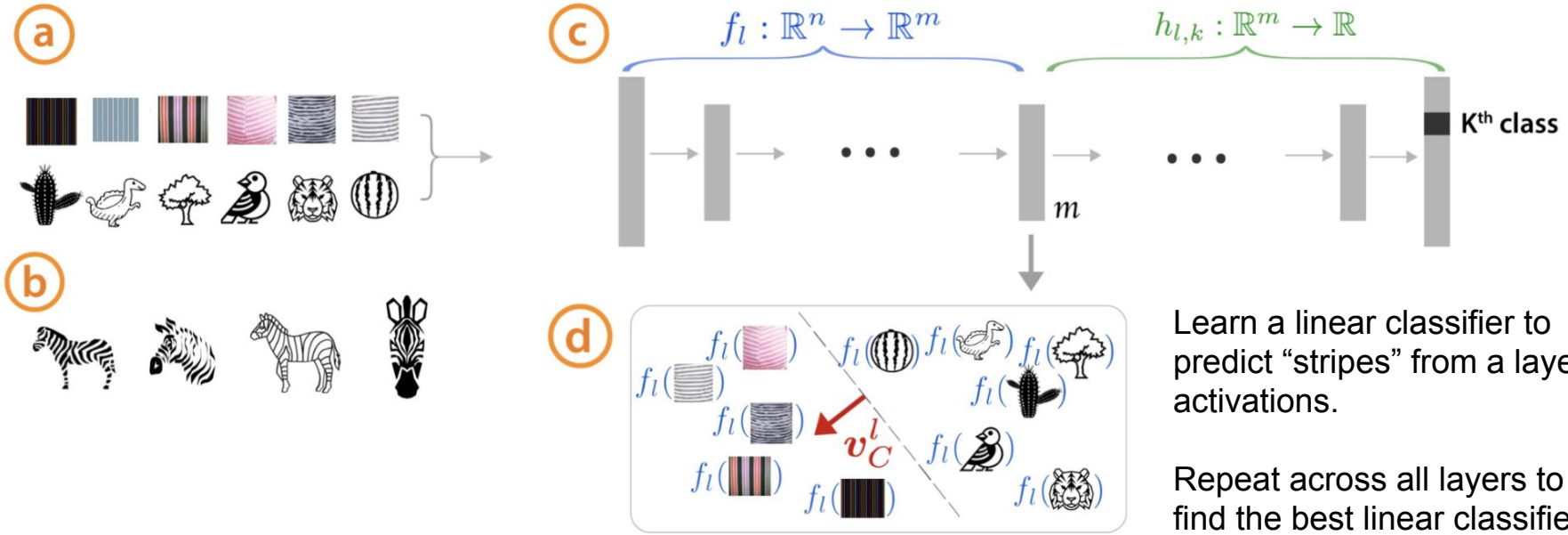


Let’s see if a neural network has learned a specific concept and uses it effectively.

Example use case:
Q1. Has it learnt what stripes are?
Q2. Can it identify the category “zebra” by using the concept “stripes”

Kim, Been, et al. "Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav)." ICML, 2018.

Concept activation vectors

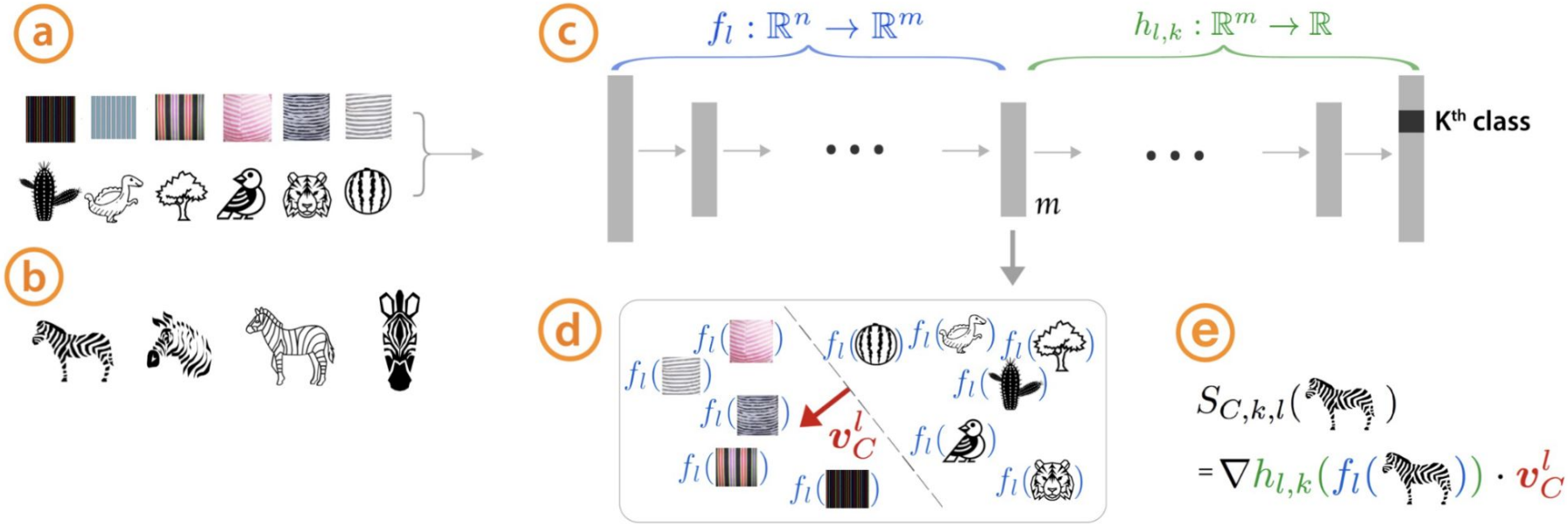


Learn a linear classifier to predict “stripes” from a layer’s activations.

Repeat across all layers to find the best linear classifier

Kim, Been, et al. "Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav)." ICML, 2018.

Calculate if the gradient for that layer when predicting “zebra” matches the classifier



Kim, Been, et al. "Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav)." ICML, 2018.

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
Concept Vectors: Human interpretable probing method

Next time:

Introduction to Language