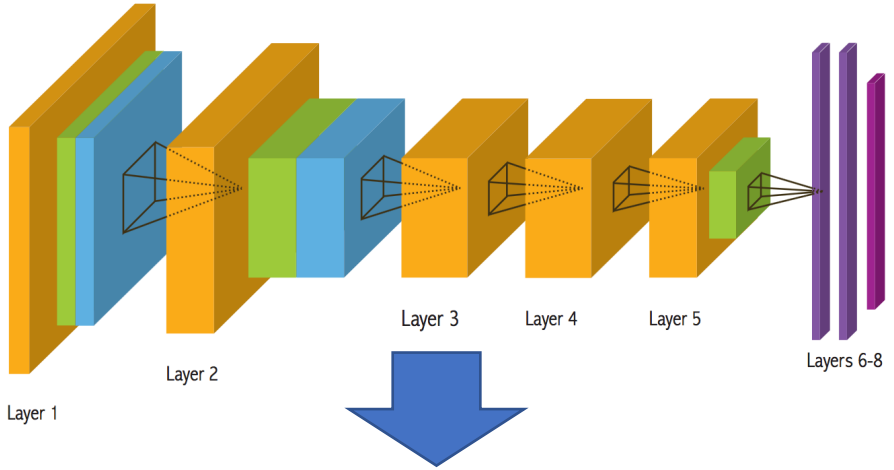
CS163: Deep Learning for Computer Vision

Lecture 10:
Visualizing and Understanding Neural Network

What's going on inside DNN?

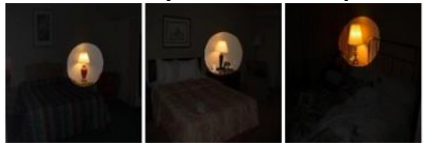
2. Why is this output?



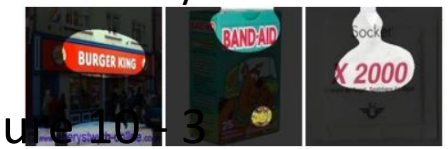
Cafeteria (0.9)

1. What have been learned inside?

Unit2 at Layer4: Lamp

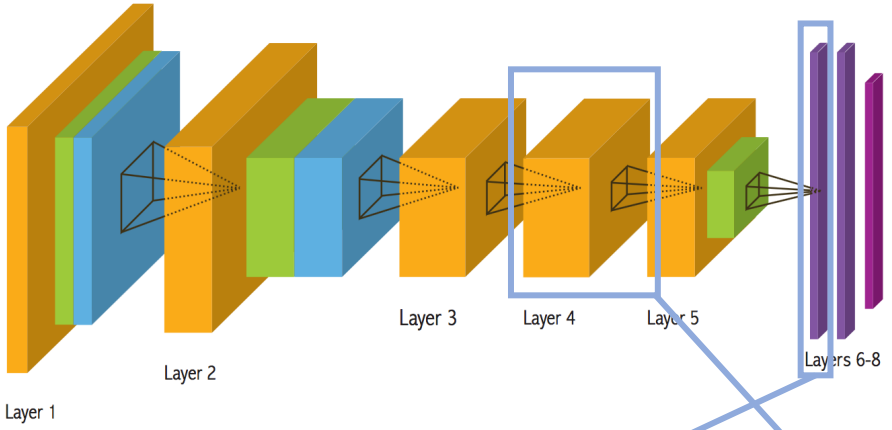


Unit5 at Layer3 : Trademark

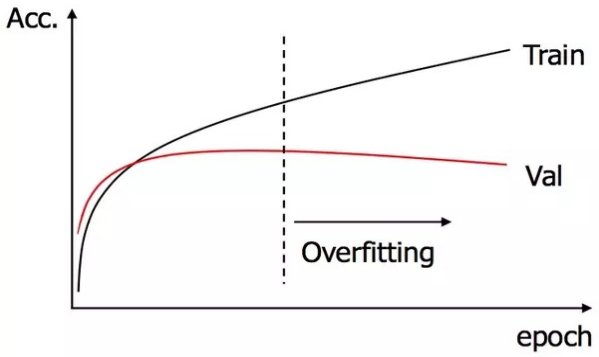


Understanding Networks at Different Granularity

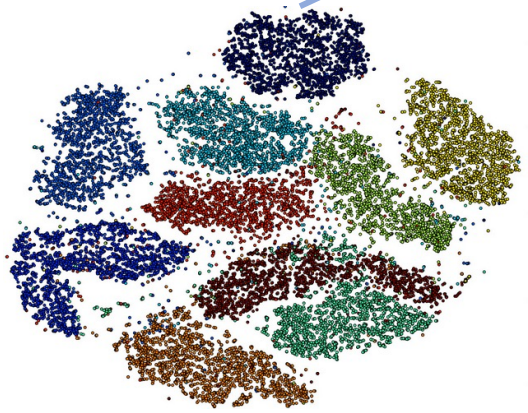
Convolutional Neural Network



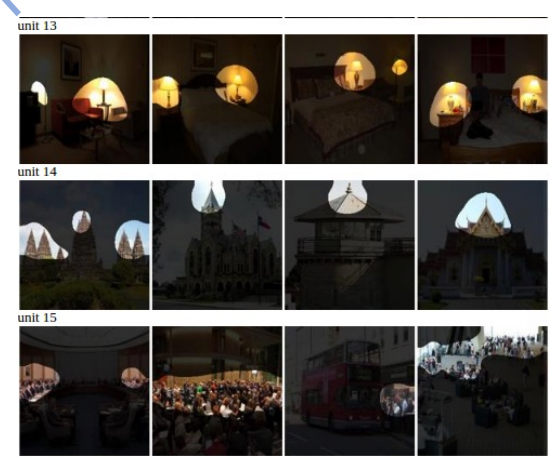
Cafeteria (0.9)



Network as a Whole

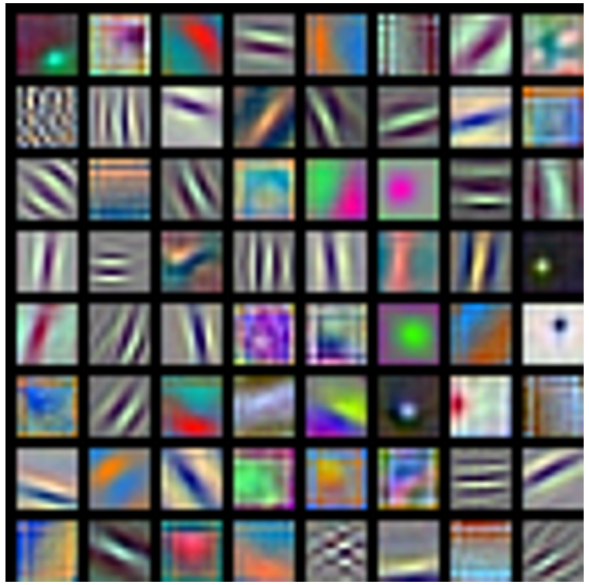


Feature Space

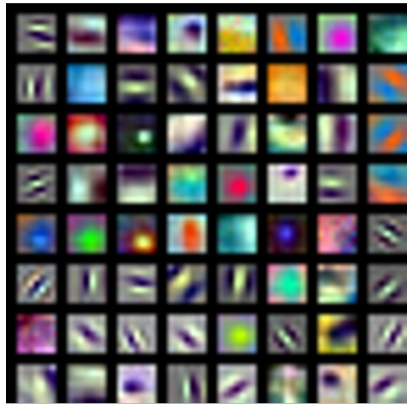


Individual Units

First Layer: Visualize Filters

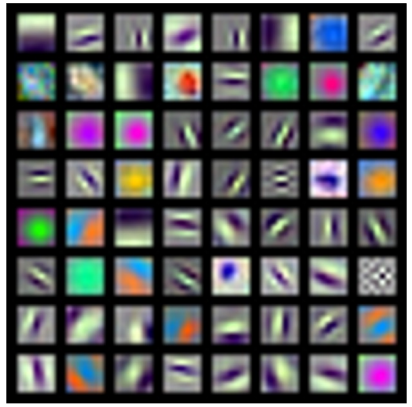


AlexNet:
64 x 3 x 11 x 11

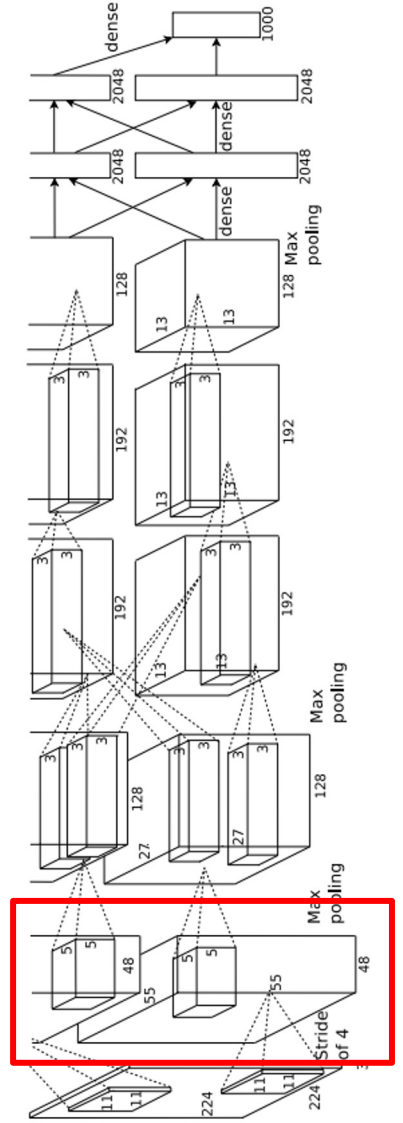


ResNet-18:
64 x 3 x 7 x 7

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

Higher Layers: Visualize Filters

First layer weights: 16 x 3 x 7 x 7

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

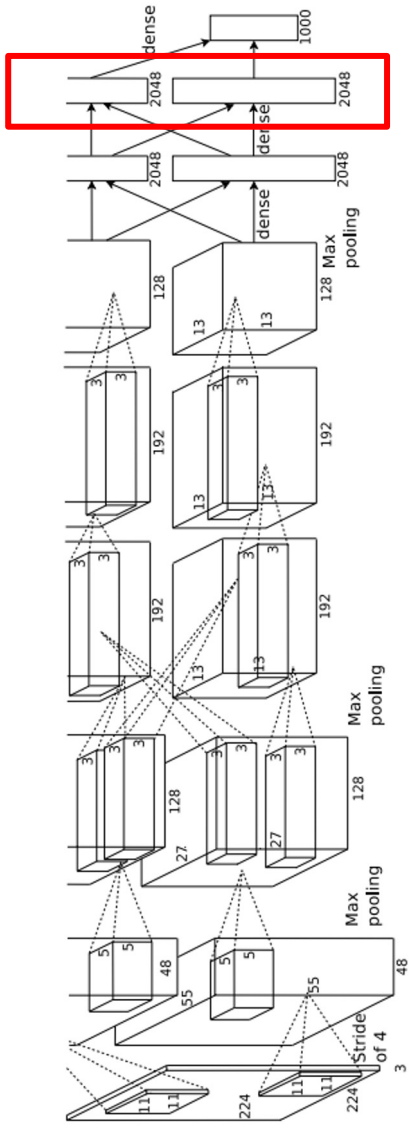
Second layer weights: 20 x 16 x 7 x 7

Source: ConvNetJS CIFAR-10 example
https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

Third layer weights: 20 x 20 x 7 x 7

Last Layer

FC7 layer



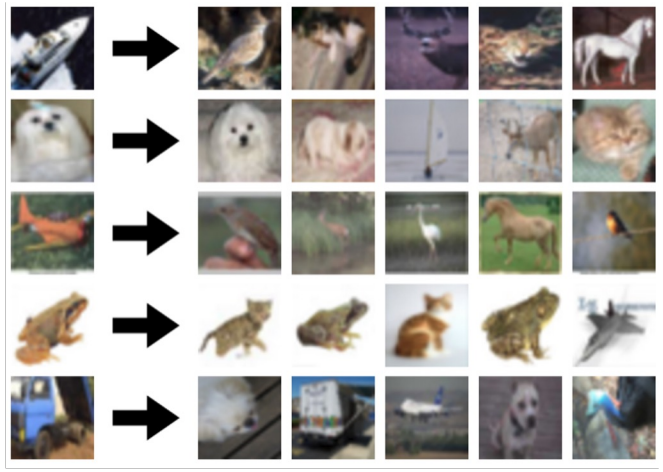
4096-dimensional feature vector for an image (layer immediately before the classifier)

Run the network on many images, collect the feature vectors

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

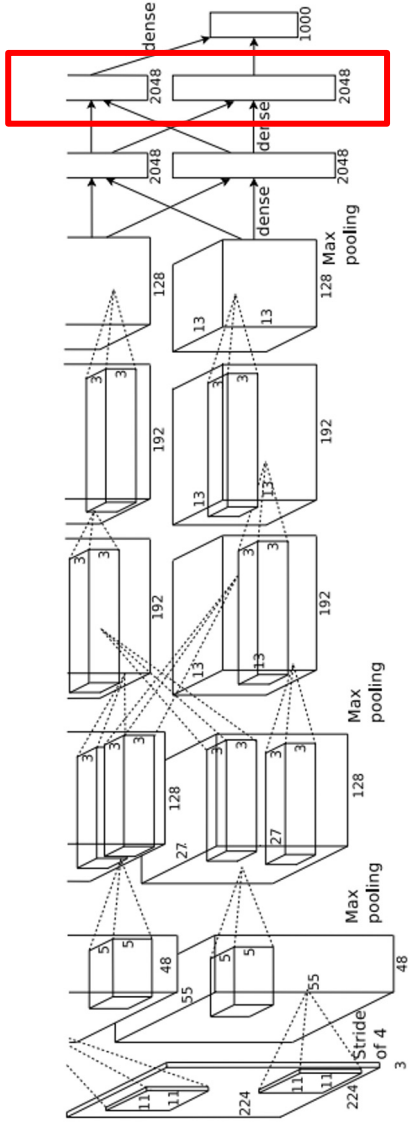
Last Layer: Nearest Neighbors

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



Test image

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



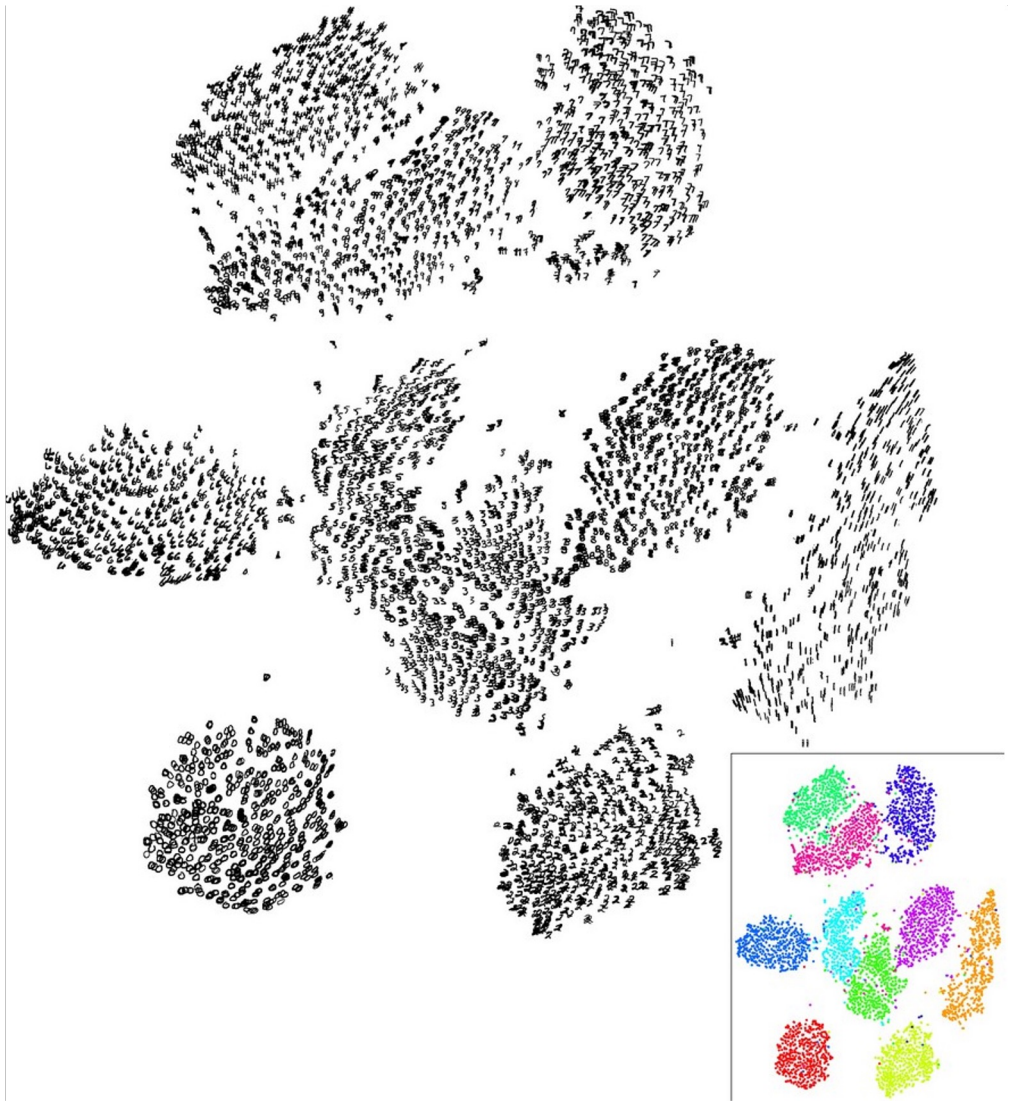
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NeurIPS 2012.
Figures reproduced with permission.

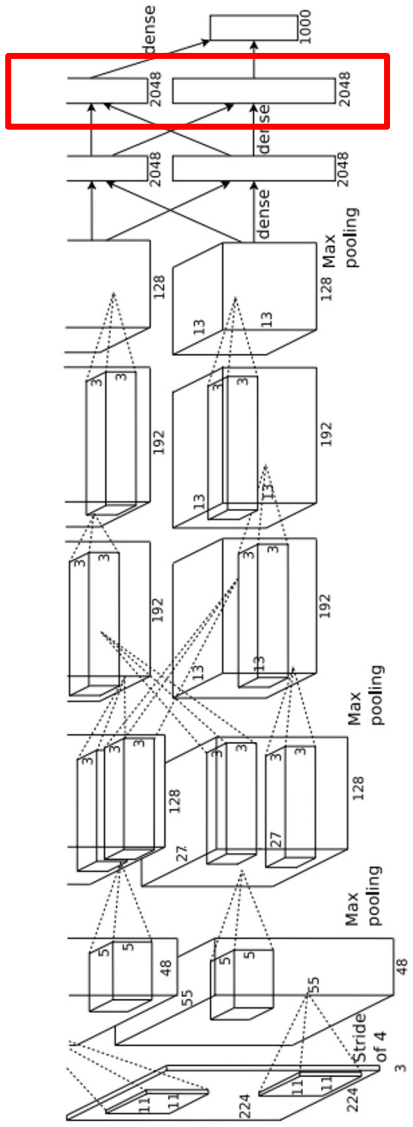
Last Layer: Dimensionality Reduction

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.
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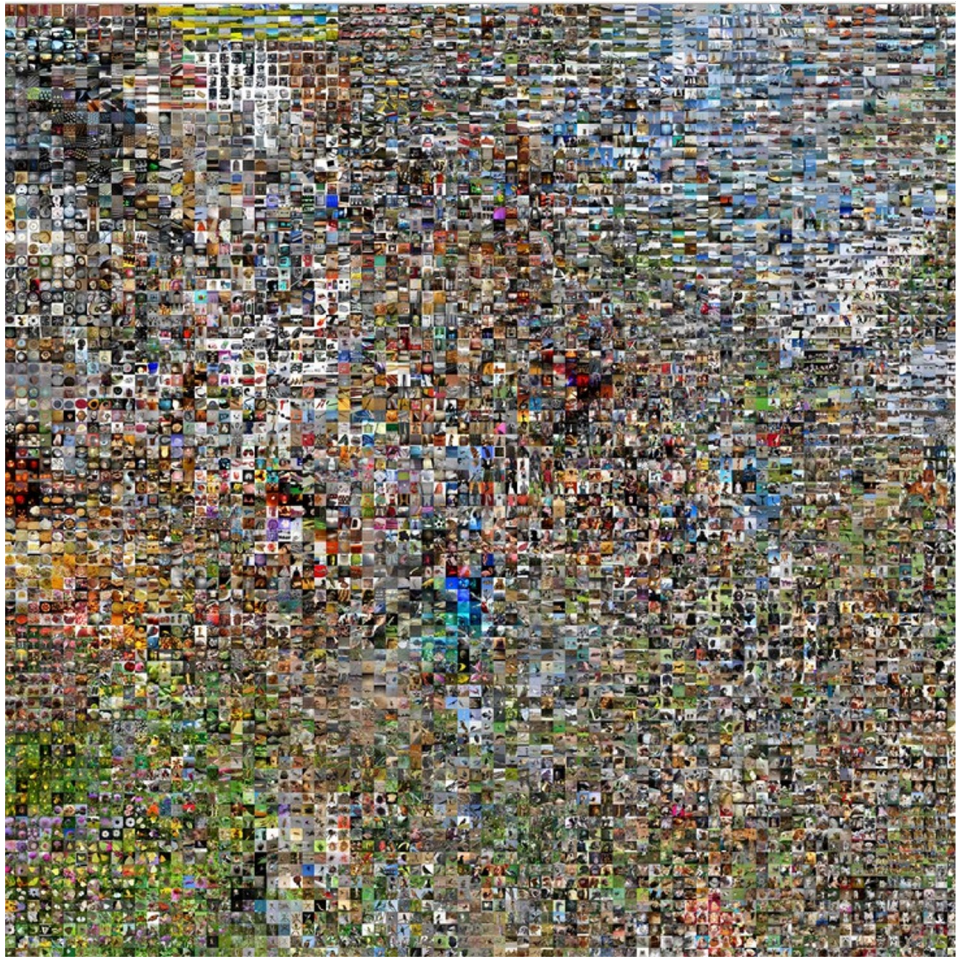
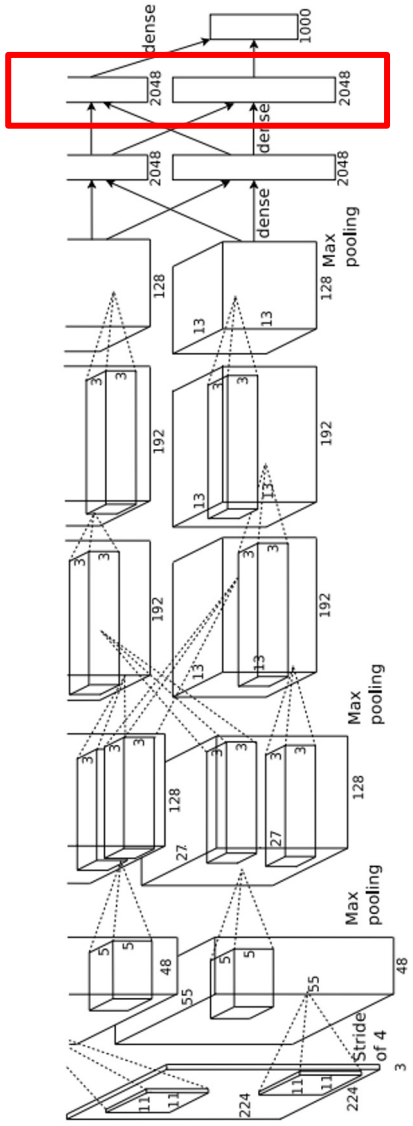
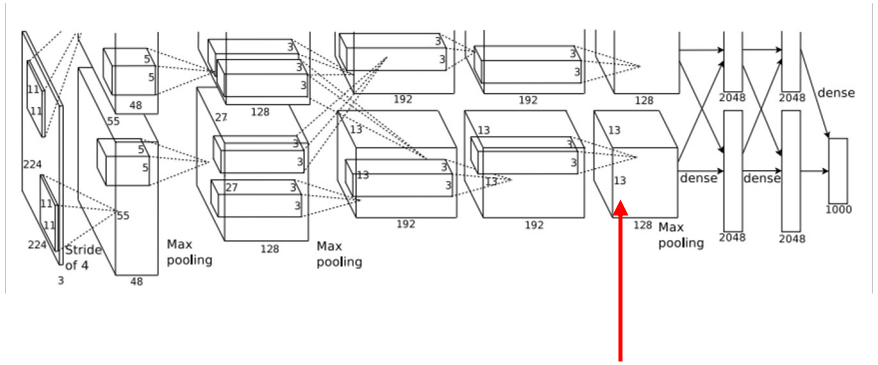
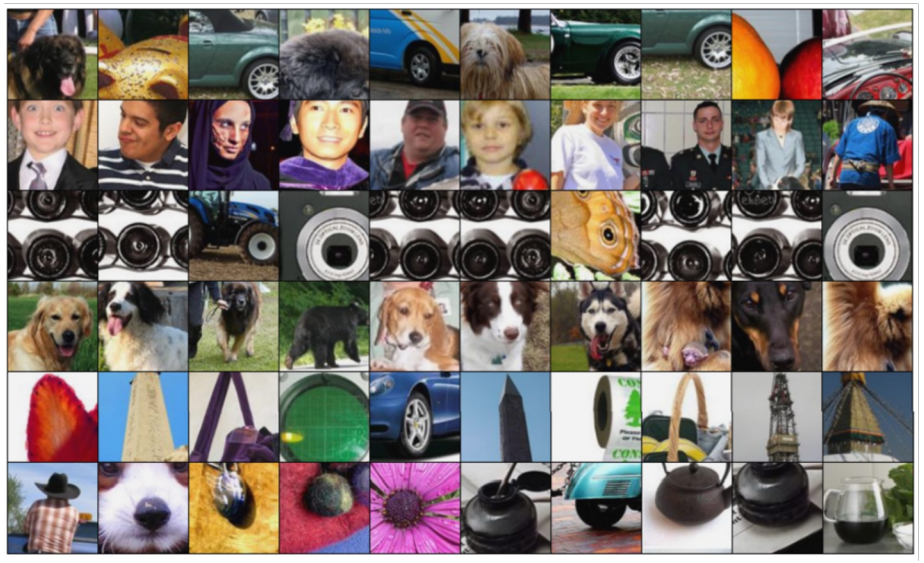


See high-resolution versions at
http://cs.stanford.edu/people/karpathy/cnnembed/



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

Visualizing Intermediate Units via Gradient

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

Visualizing Unit 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.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

https://www.youtube.com/watch?v=AgkfIQ4IGaM&t=124s

How to annotate and quantify the units?

Maximally activating patches

Mixed4a Unit 6

Mixed4a Unit 453

Mixed4a Unit 240

Baseball or Stripes?

Clouds or fluffiness?

Dog face or snouts?

Annotating the Interpretation of Units

Amazon Mechanical Turk

Word/Description to summarize the images:

Lamp

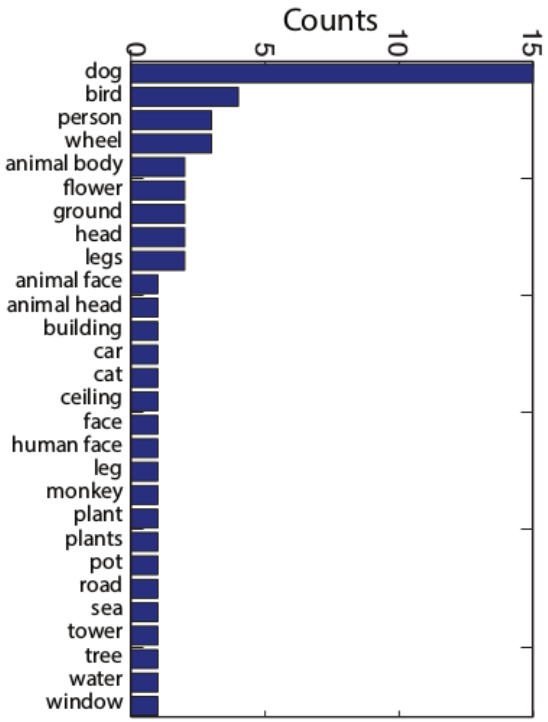
Which category the description belongs to:

- Scene
- Region or surface
- Object
- Object part
- Texture or material
- Simple elements or colors

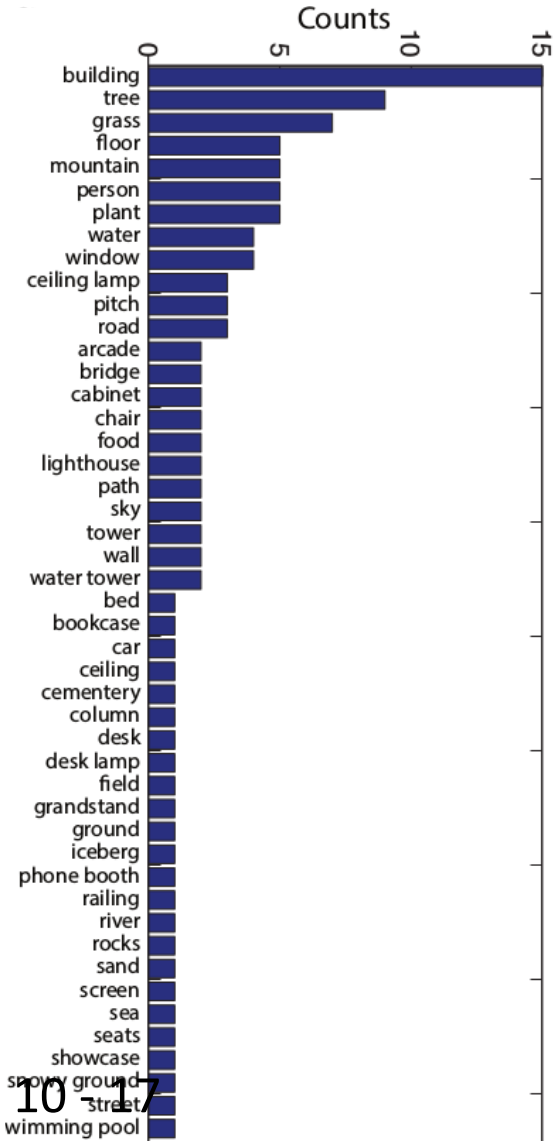
[Zhou, Khosla, Lapedriza, Oliva, Torralba ICLR 2015]

Interpretable Representations for Objects and Scenes

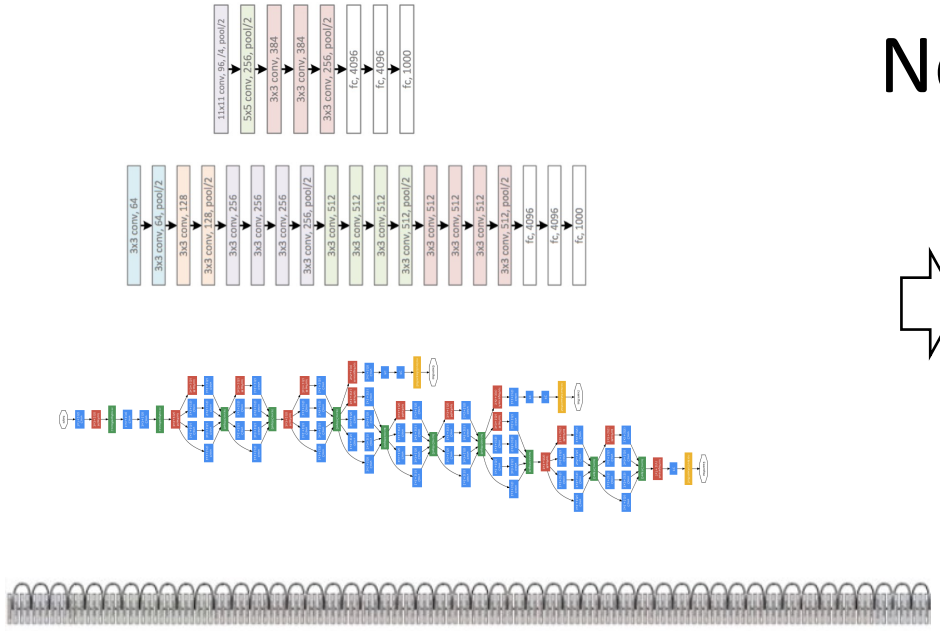
59 units as objects at conv5 of AlexNet on ImageNet



151 units as objects at conv5 of AlexNet on Places

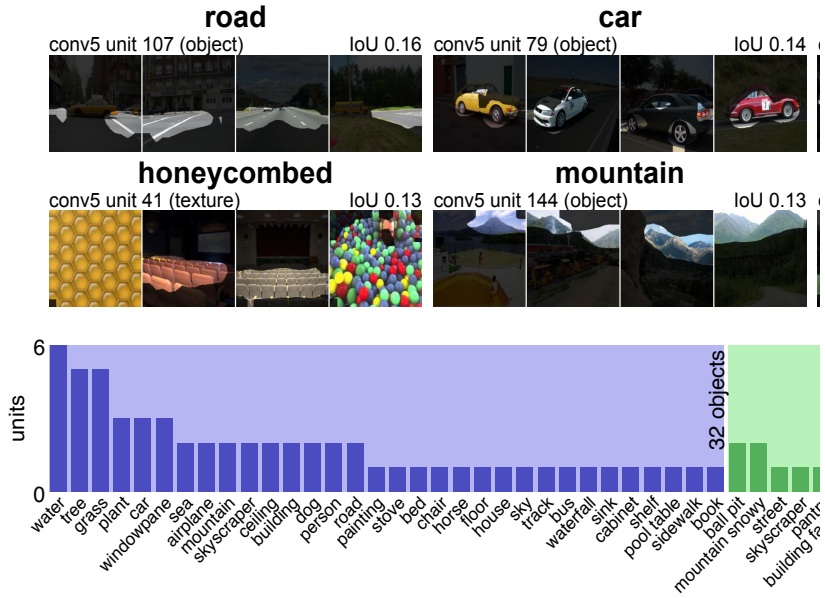


Quantify the Interpretability of Networks



Network Dissection

Interpretable Units



Bau*, Zhou*, Khosla, Oliva, Torralba. CVPR 2017

Evaluate Unit for Semantic Segmentation

Testing Dataset: 60,000 images annotated with 1,200 concepts

Unit 1: Top activated images from the Testing Dataset

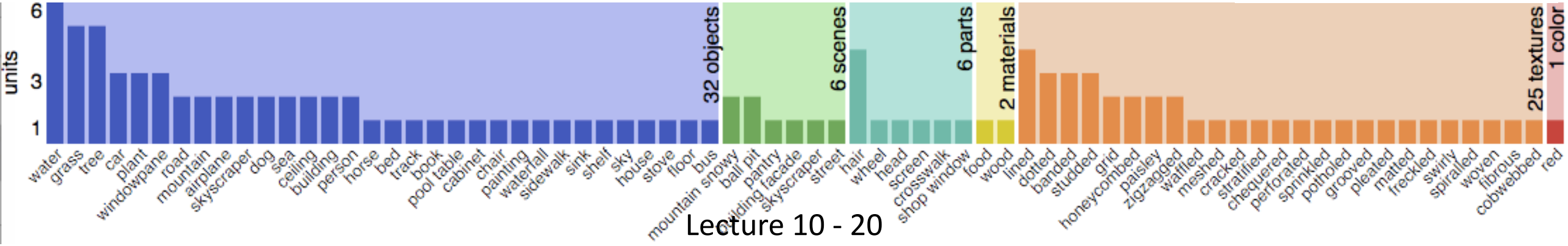
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Top Concept: Lamp, Intersection over Union (IoU)= 0.23

Layer5 unit 79 car (object) IoU=0.13

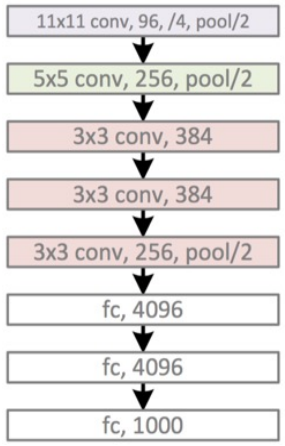
Layer5 unit 107 road (object) IoU=0.15

118/256 units covering 72 unique concepts

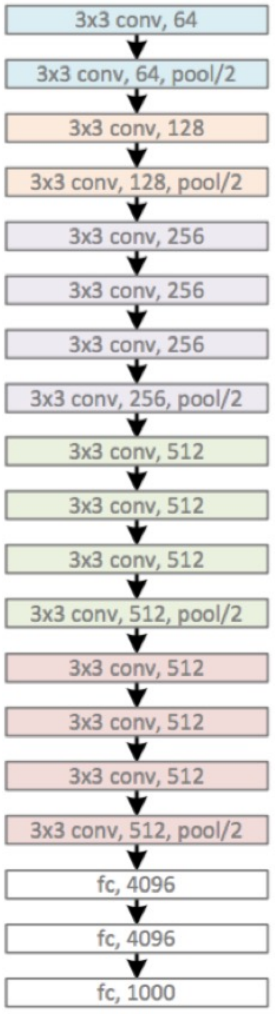


Compare Different Representations of Architectures

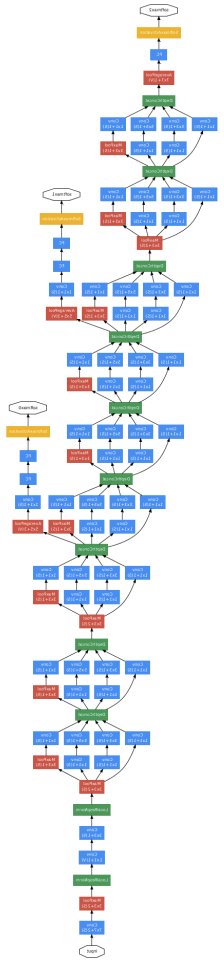
AlexNet



VGG



GoogLeNet

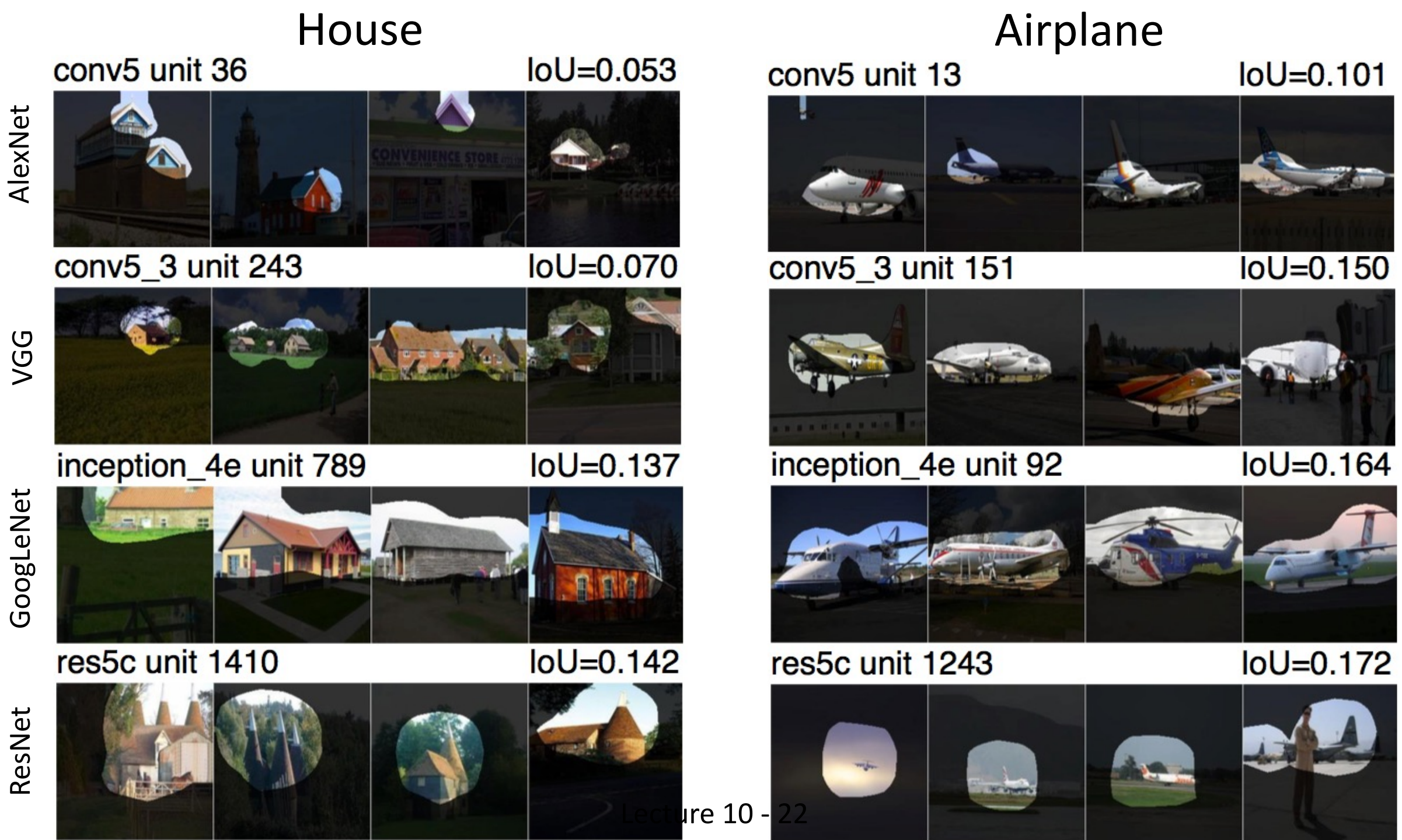


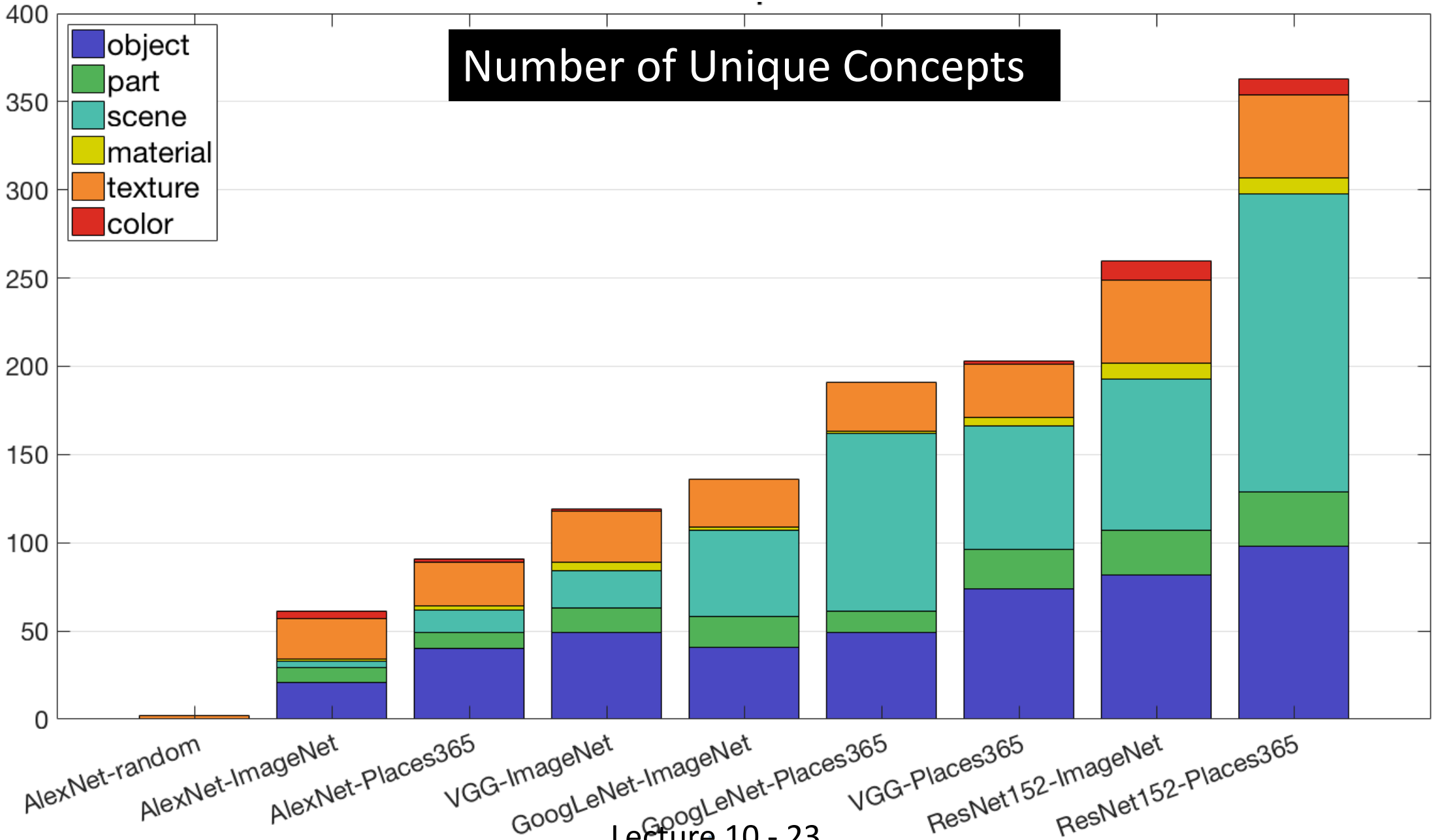
ResNet

Data sources

IMAGENET

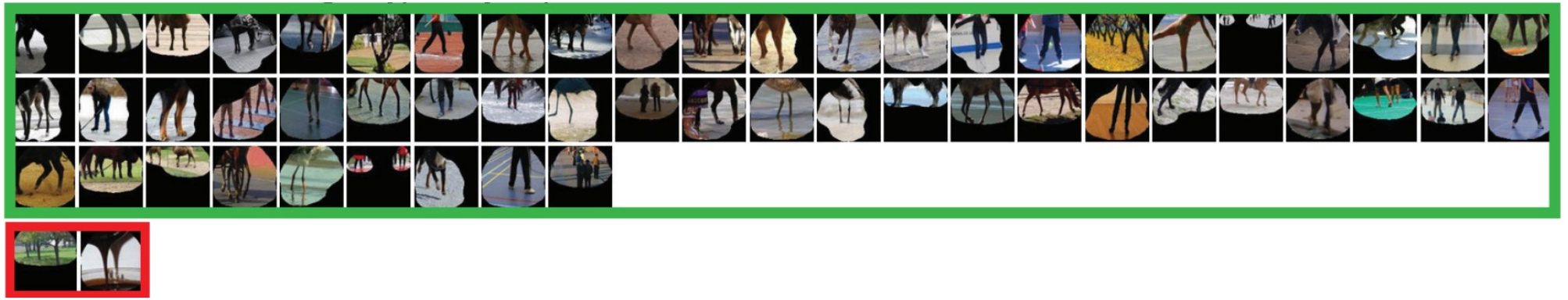
places


House
Airplane
AlexNet
VGG
GoogLeNet
ResNet
conv5 unit 36
IoU=0.053
conv5 unit 13
IoU=0.101
conv5_3 unit 243
IoU=0.070
conv5_3 unit 151
IoU=0.150
inception_4e unit 789
IoU=0.137
inception_4e unit 92
IoU=0.164
res5c unit 1410
IoU=0.142
res5c unit 1243
IoU=0.172


Number of Unique Concepts
object
part
scene
material
texture
color
400
350
300
250
200
150
100
50
0
AlexNet-random
AlexNet-ImageNet
AlexNet-Places365
VGG-ImageNet
GoogLeNet-ImageNet
GoogLeNet-Places365
VGG-Places365
ResNet152-ImageNet
ResNet152-Places365

Multimodal neurons in CNNs

Conv5-unit16, leg detector



Conv5-unit52, Pool table/swimming pool

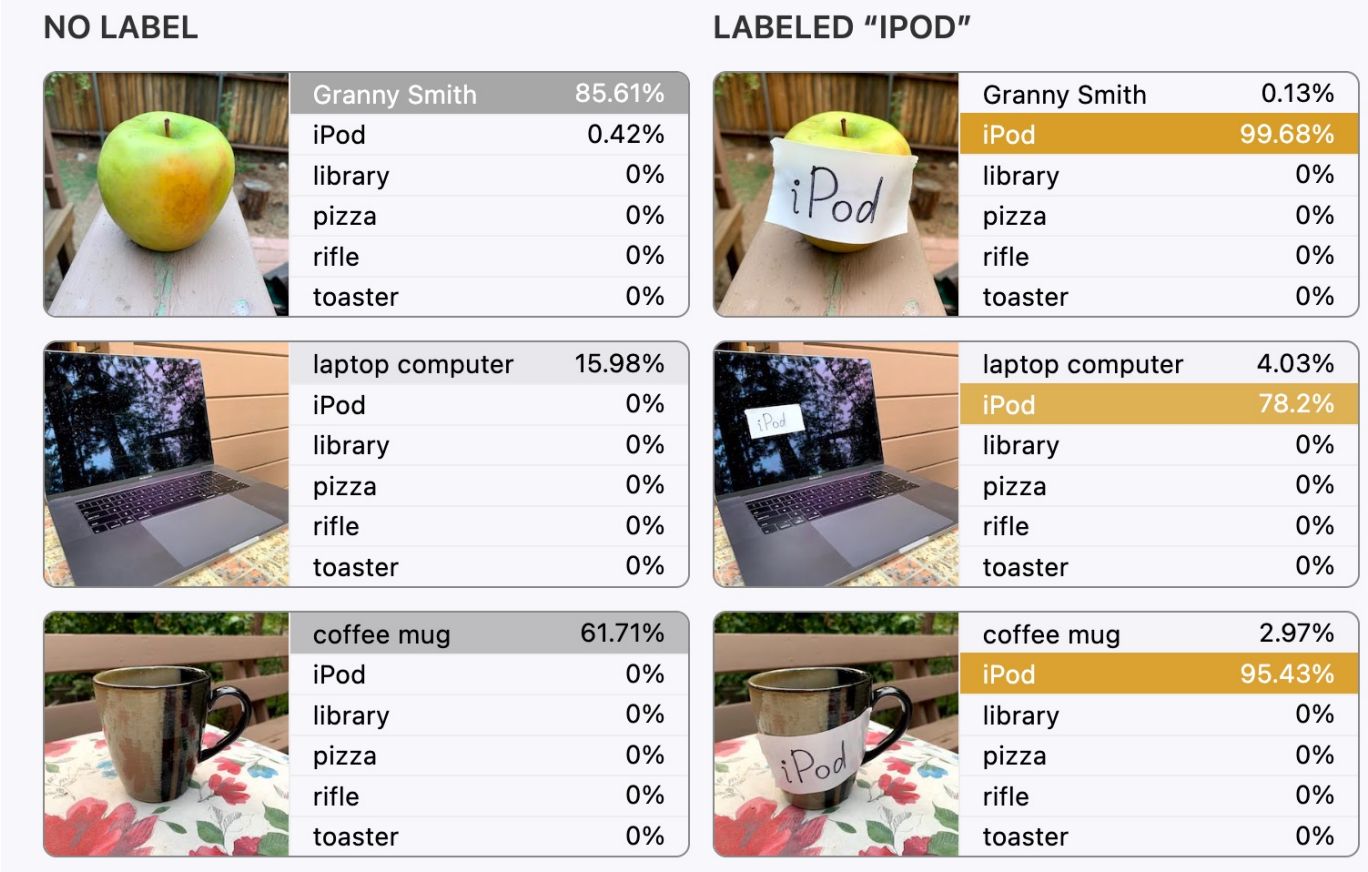
Conv5-unit70 Dinning table/building

Bolei Zhou, et al. Object Detectors Emerge in Deep Scene CNNs. ICLR'15. https://arxiv.org/abs/1412.6856

Multimodal neurons in the recent CLIP models

Jesus

Hitler

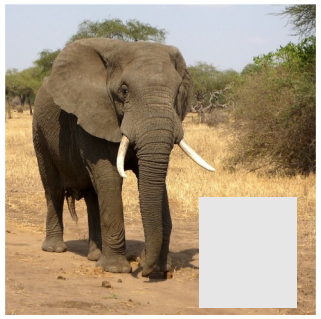


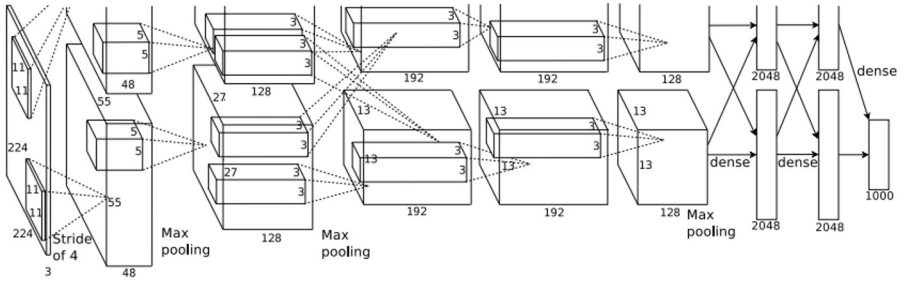
Physical typographic attacks

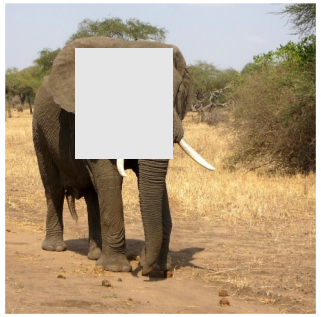
https://distill.pub/2021/multimodal-neurons/

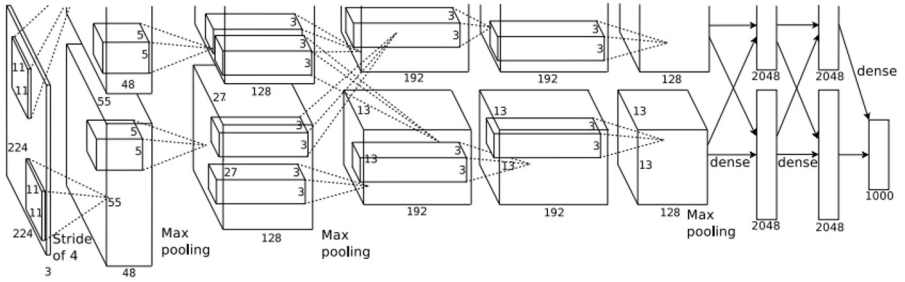
Which Pixels Matter to the Output? Saliency via Occlusion

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





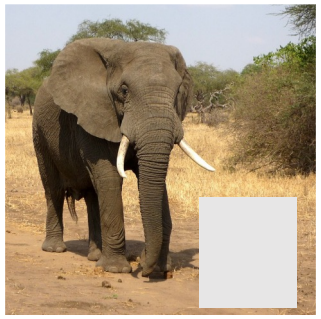


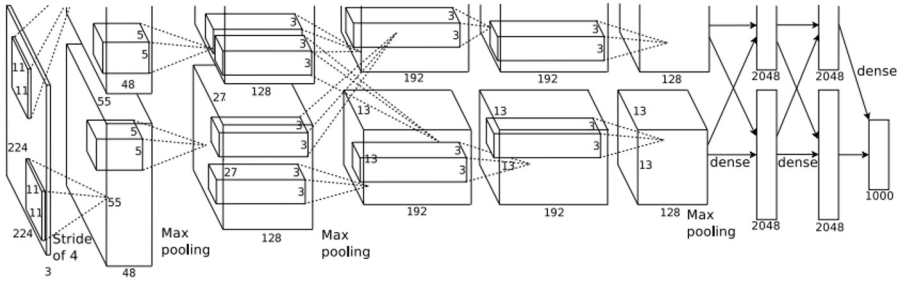


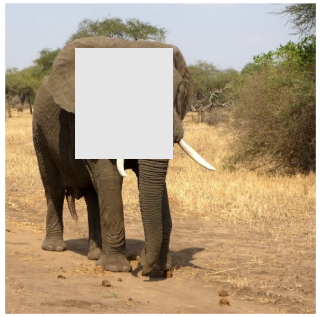
Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

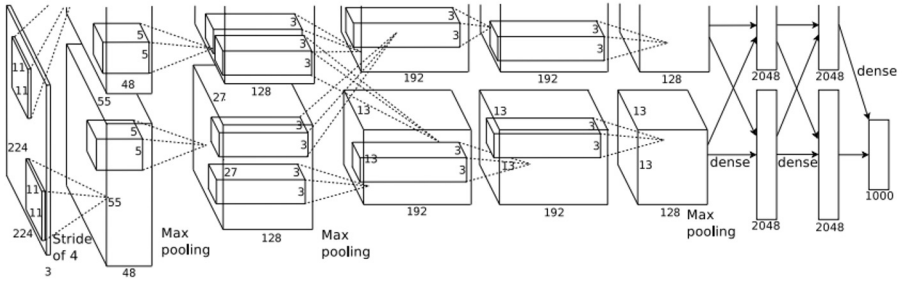
Which Pixels Matter to the Saliency via Occlusion

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

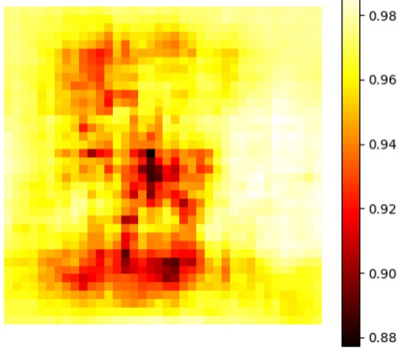




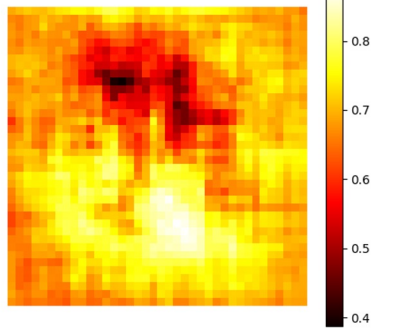




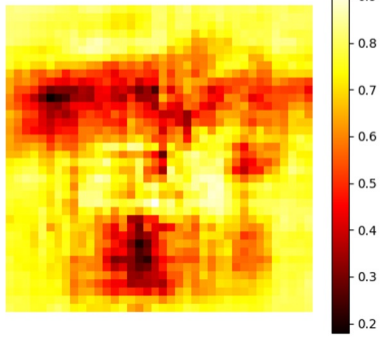
schooner



African elephant, Loxodonta africana



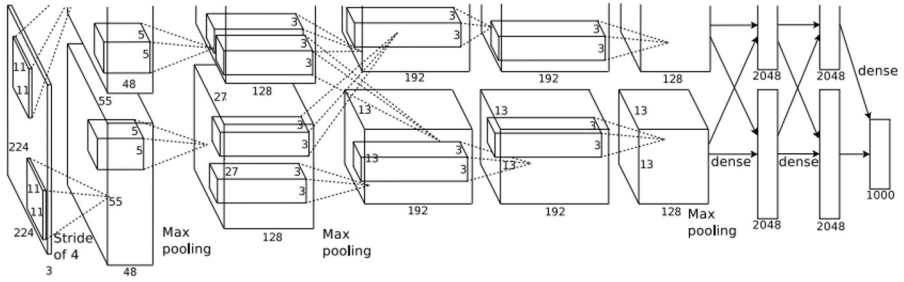
go-kart



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

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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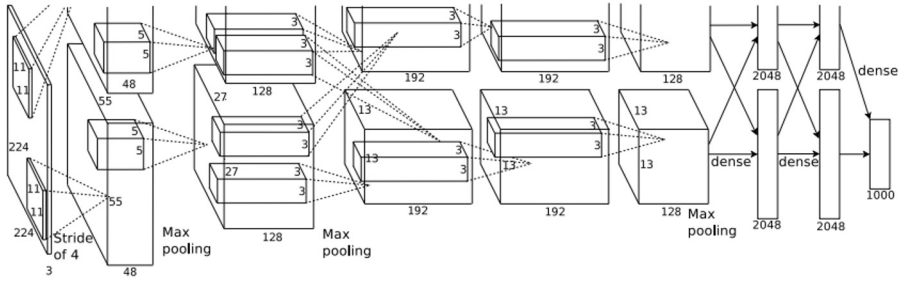
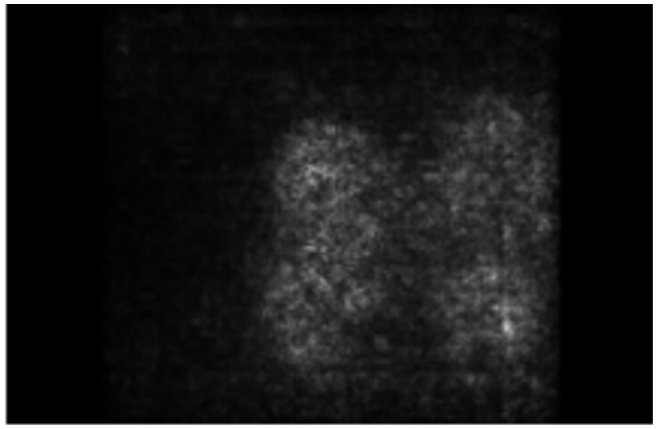
Forward pass: Compute probabilities



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.

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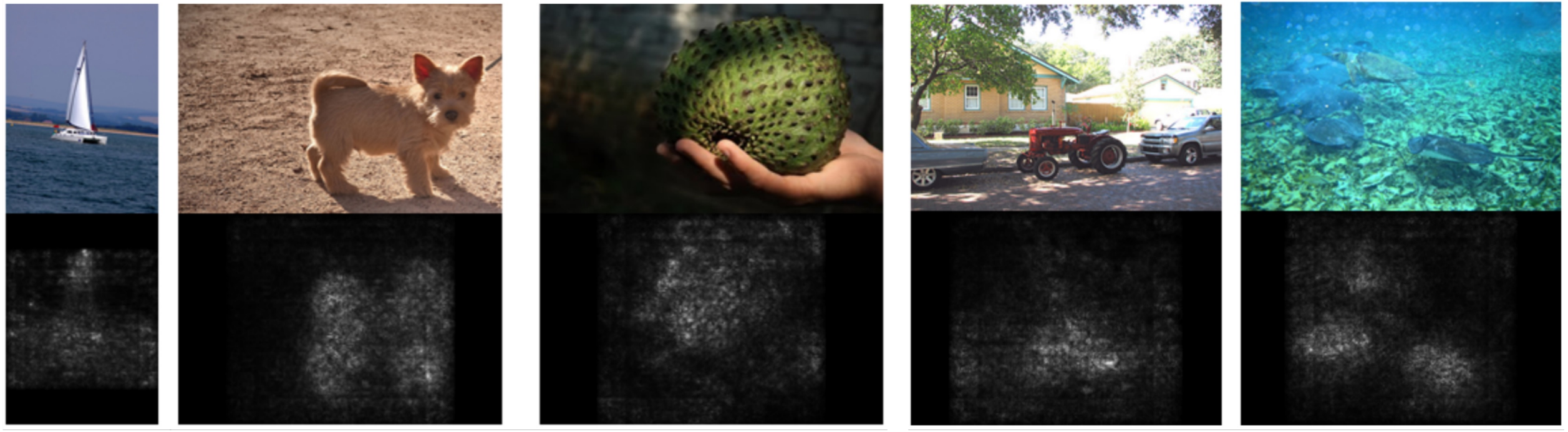
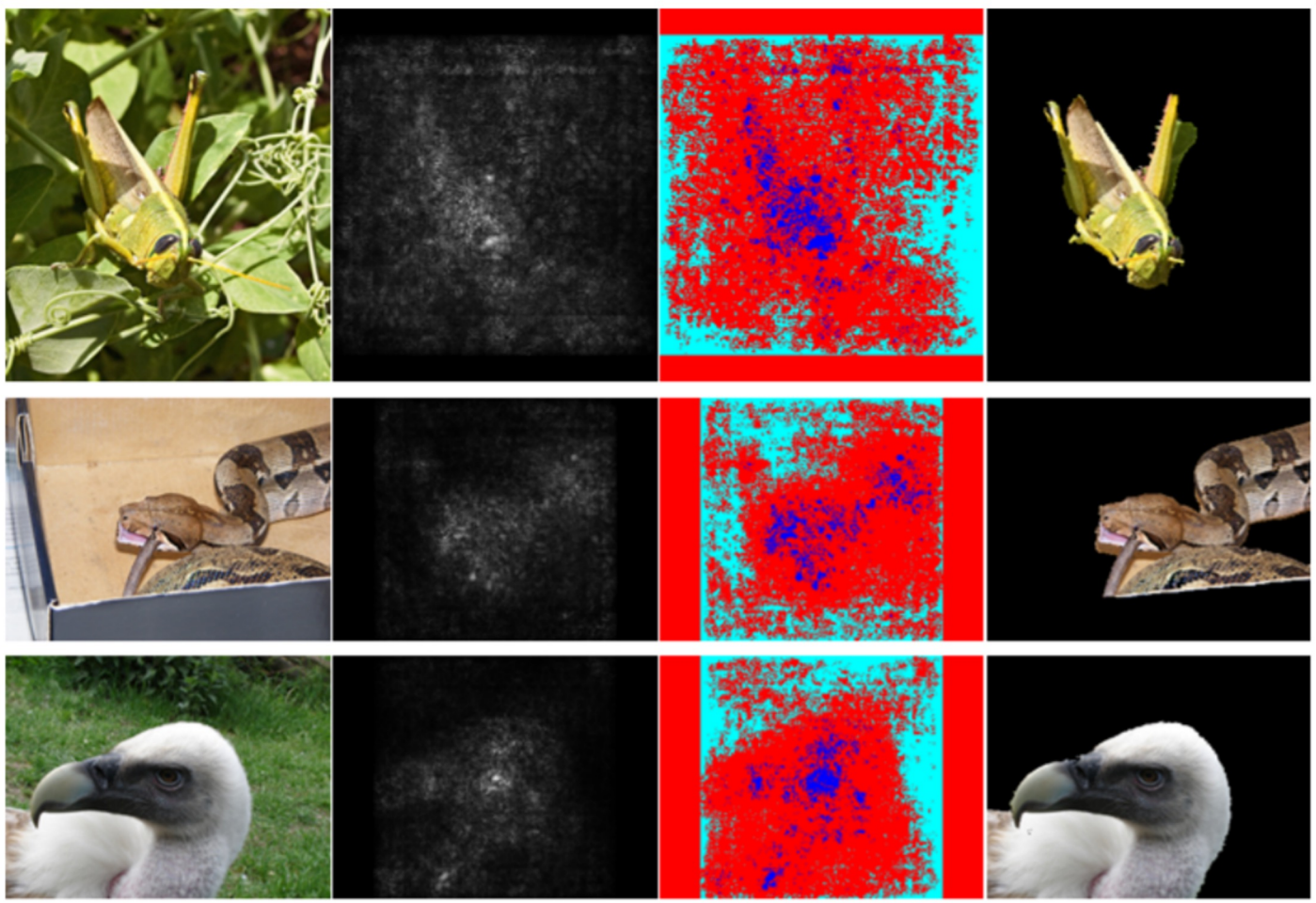


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

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.

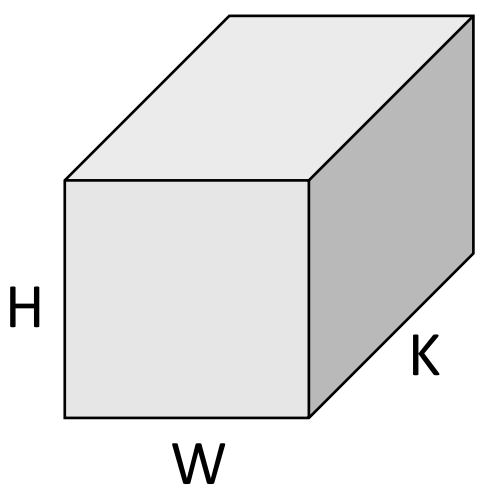
Rother et al, "Grabcut: Interactive foreground extraction using iterated graph cuts", ACM TOG 2004

Class Activation Mapping (CAM)

Prediction: Sushi Bar (0.63)

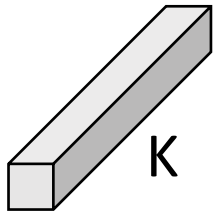
Prediction: Martial Arts Gym (0.21)

Class Activation Mapping (CAM)



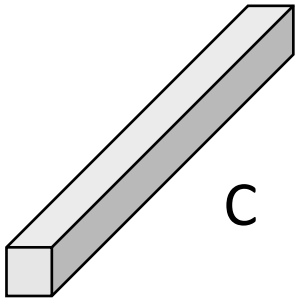
Last layer CNN features:
$f \in \mathbb{R}^{H \times W \times K}$

Global Average Pooling



Pooled features:
$F \in \mathbb{R}^{K}$

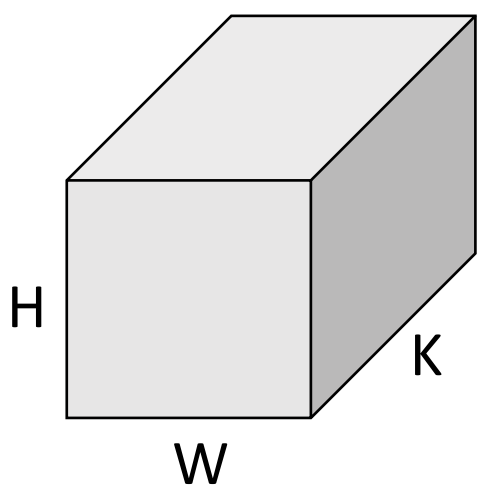
Fully Connected Layer, weights
$w \in \mathbb{R}^{K \times C}$



Class Scores:
$S \in \mathbb{R}^{C}$

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

Class Activation Mapping (CAM)



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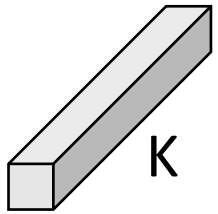
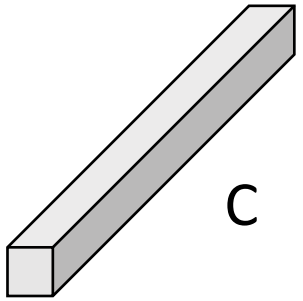


Fully Connected Layer, weights $w \in \mathbb{R}^{K \times C}$



Last layer CNN features:
$f \in \mathbb{R}^{H \times W \times K}$

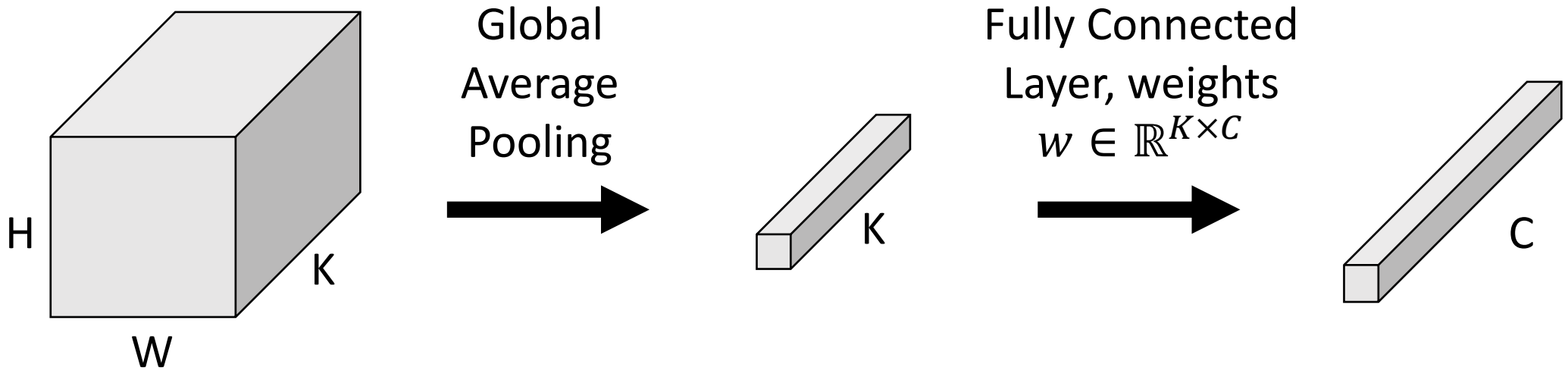
Pooled features:
$F \in \mathbb{R}^{K}$

Class Scores:
$S \in \mathbb{R}^{C}$

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

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

Class Activation Mapping (CAM)



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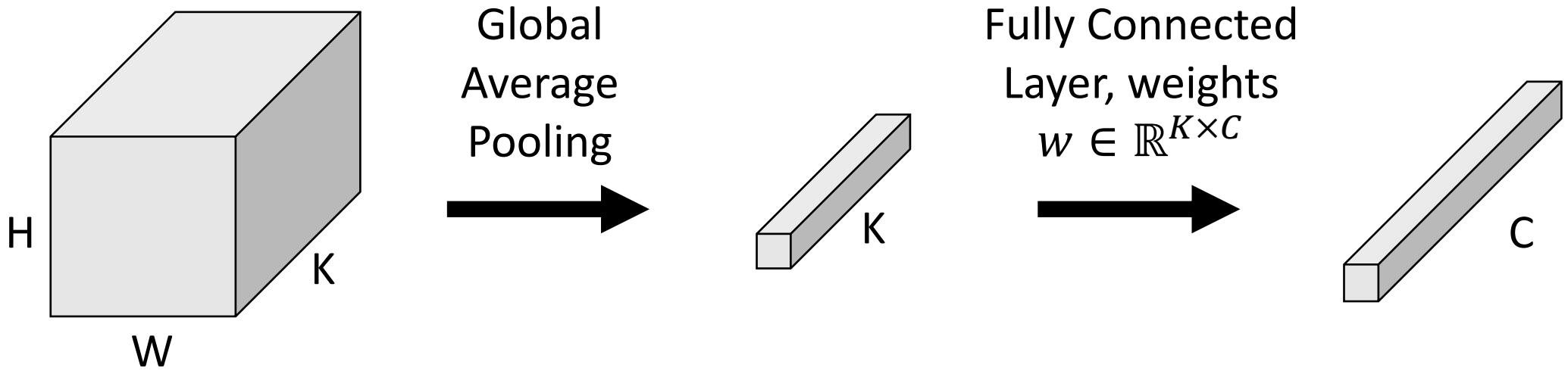
$$F_k = \frac{1}{HW} \sum_{h,w} f_{h,w,k} \quad S_c = \sum_k w_{k,c} F_k$$

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

Class Activation Mapping (CAM)



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

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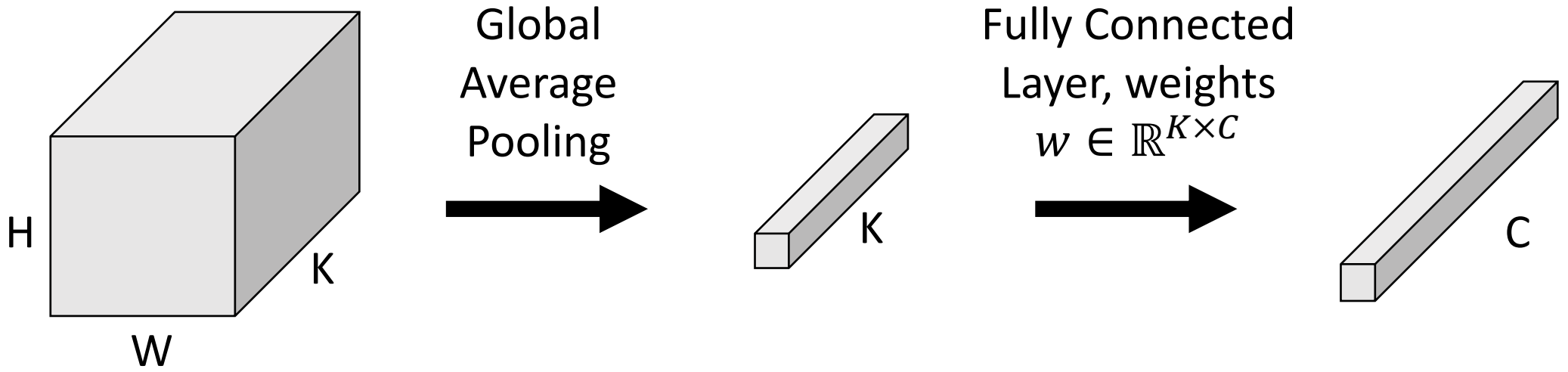

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Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

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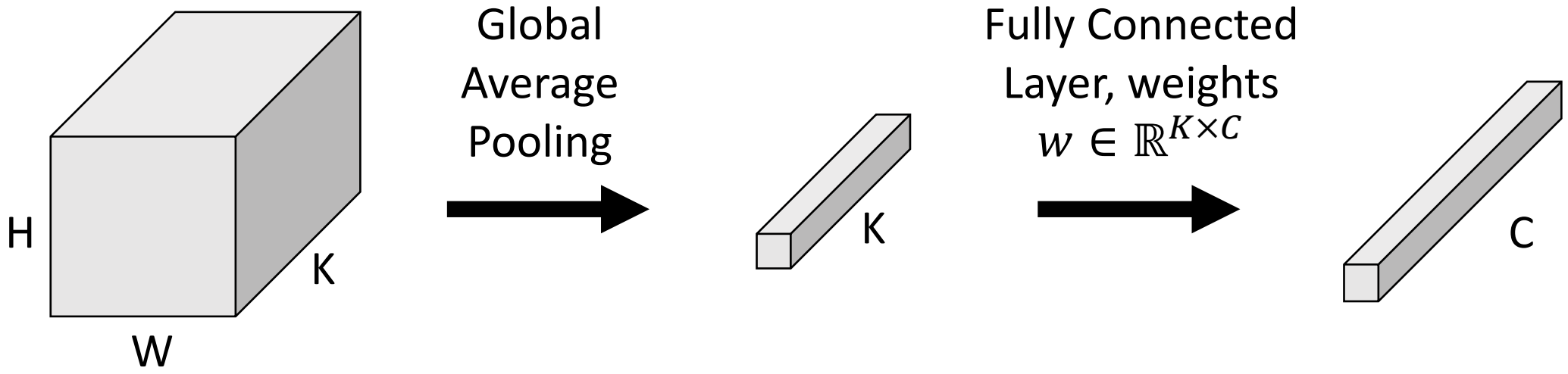

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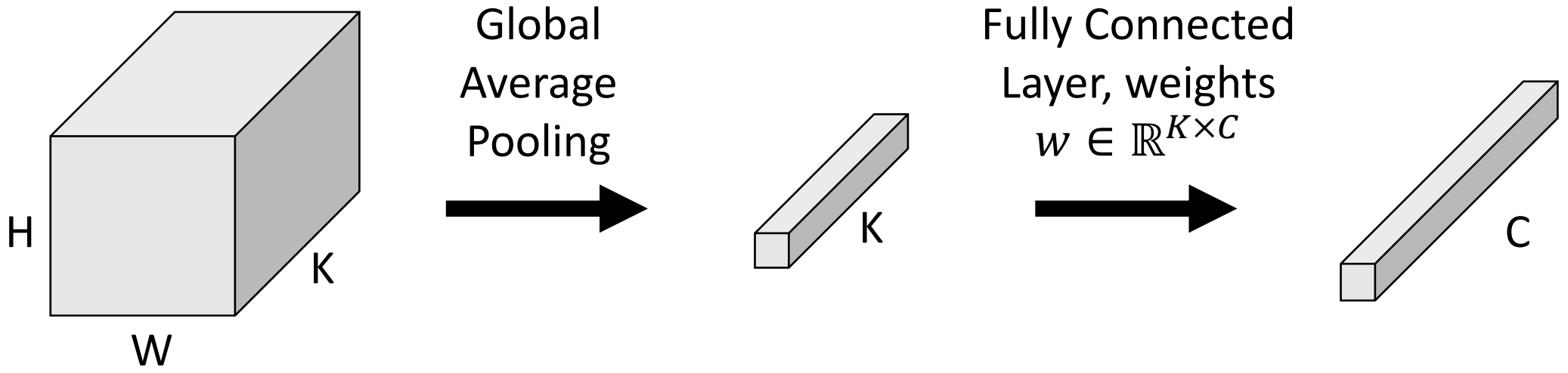

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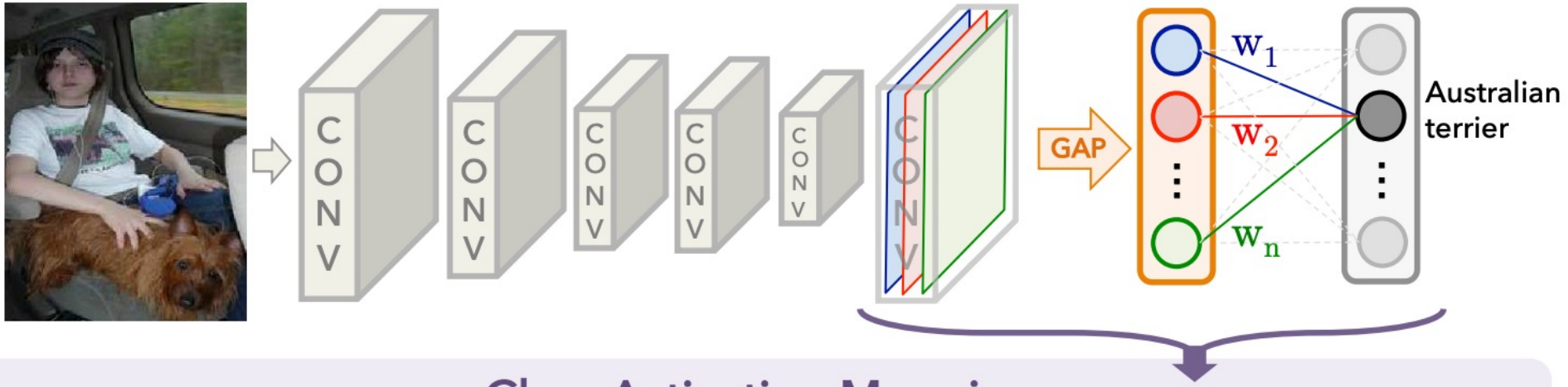
$$= \frac{1}{HW} \sum_{h,w} \sum_k \boldsymbol{w_{k,c} f_{h,w,k}}$$

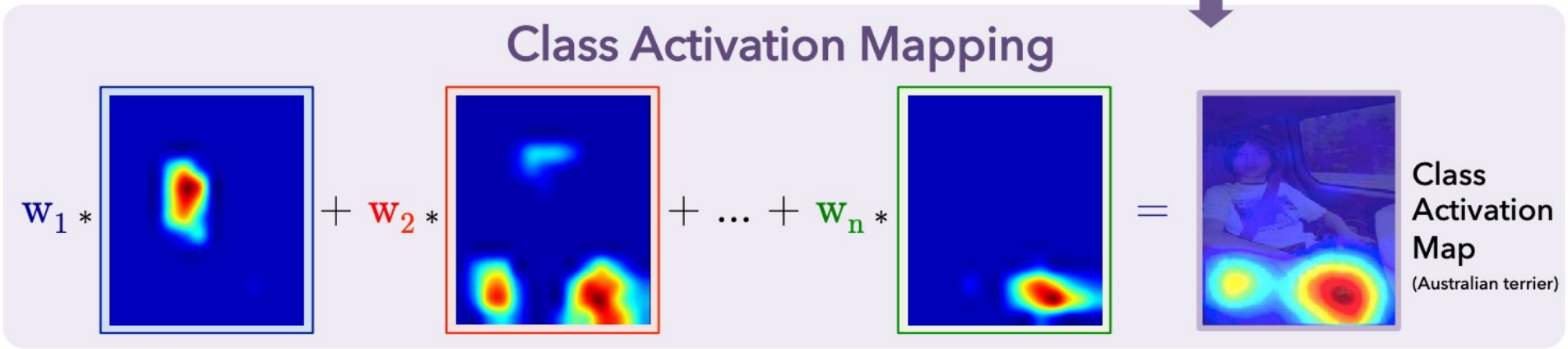
Class Activation Maps:
$\boldsymbol{M \in \mathbb{R}^{C,H,W}}$

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

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

Class Activation Mapping (CAM)





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

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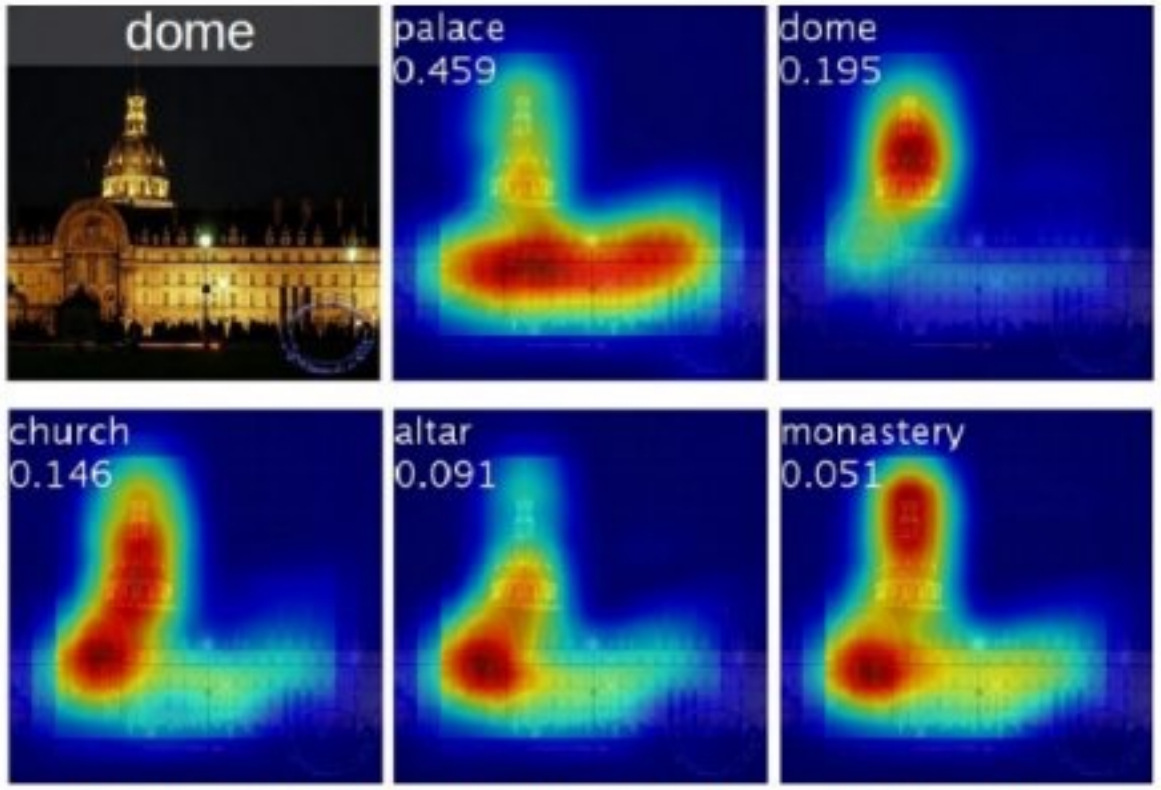


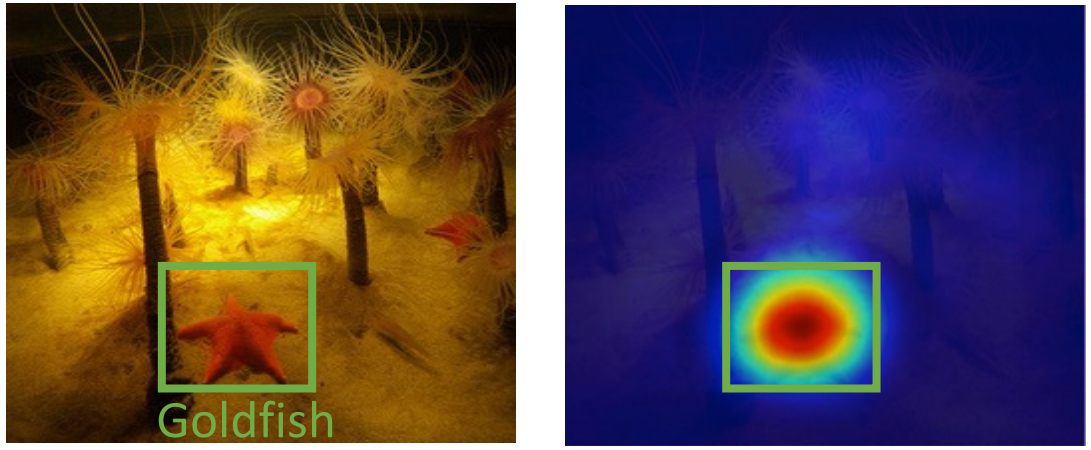
Class activation maps of top 5 predictions

Class activation maps for one object class

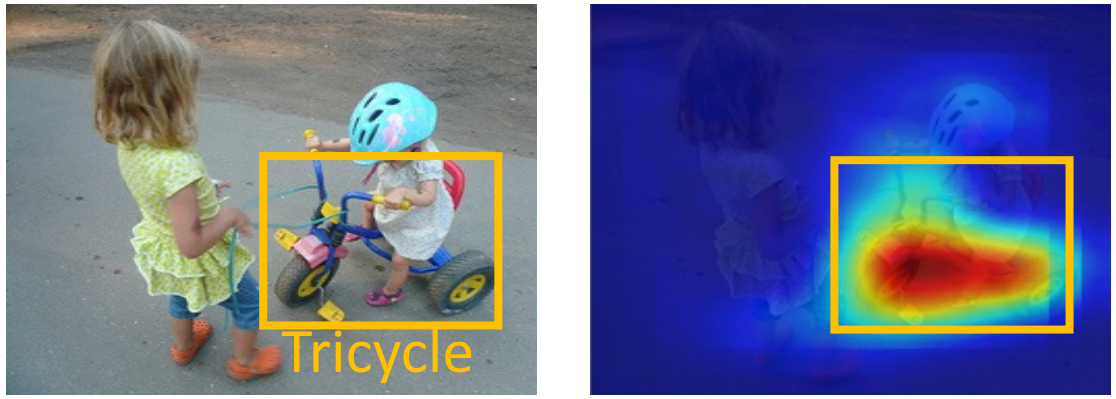
Zhou et al, “Learning Deep Features for Discriminative Localization”, CVPR 2016

Evaluation on Weakly-Supervised Localization

Prediction: Starfish (0.83)



Prediction: Tricycle (0.92)



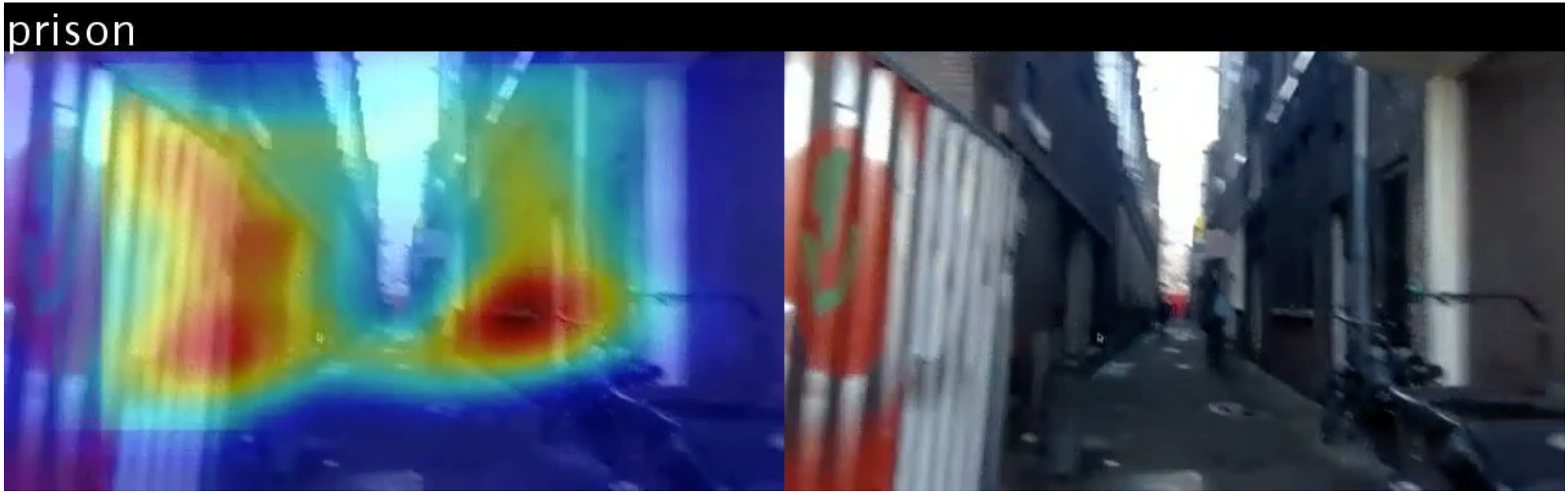
Localization capability for free!

Method	Supervision	Localization Accuracy(%)
Backpropagation	weakly	53.6
Our method	weakly	**62.9**
AlexNet	full	65.8

Result on ImageNet Localization Benchmark

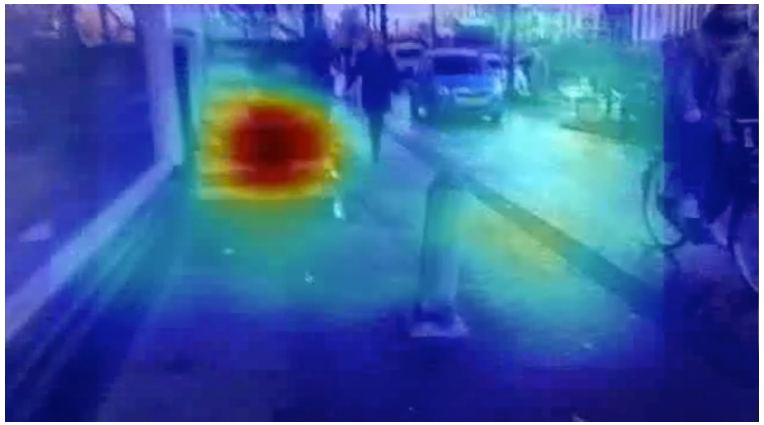
Explaining the Failure Cases in Video

Predictions from a model pretrained on ImageNet



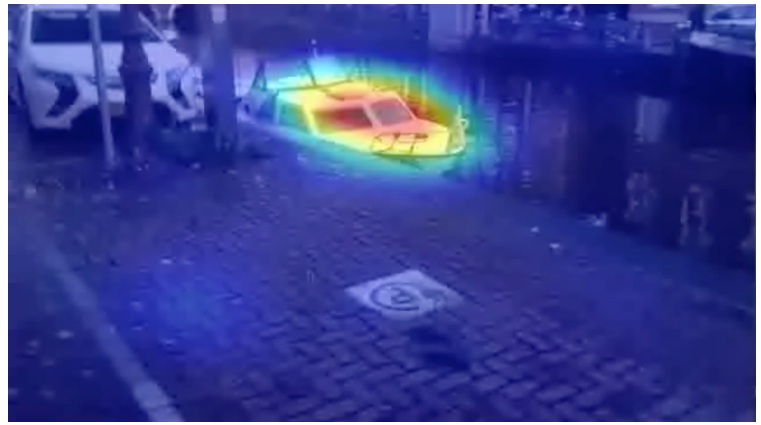
Explaining the Failure Cases

Prediction: Park bench



Prediction: Prison

Prediction: Aircraft carrier

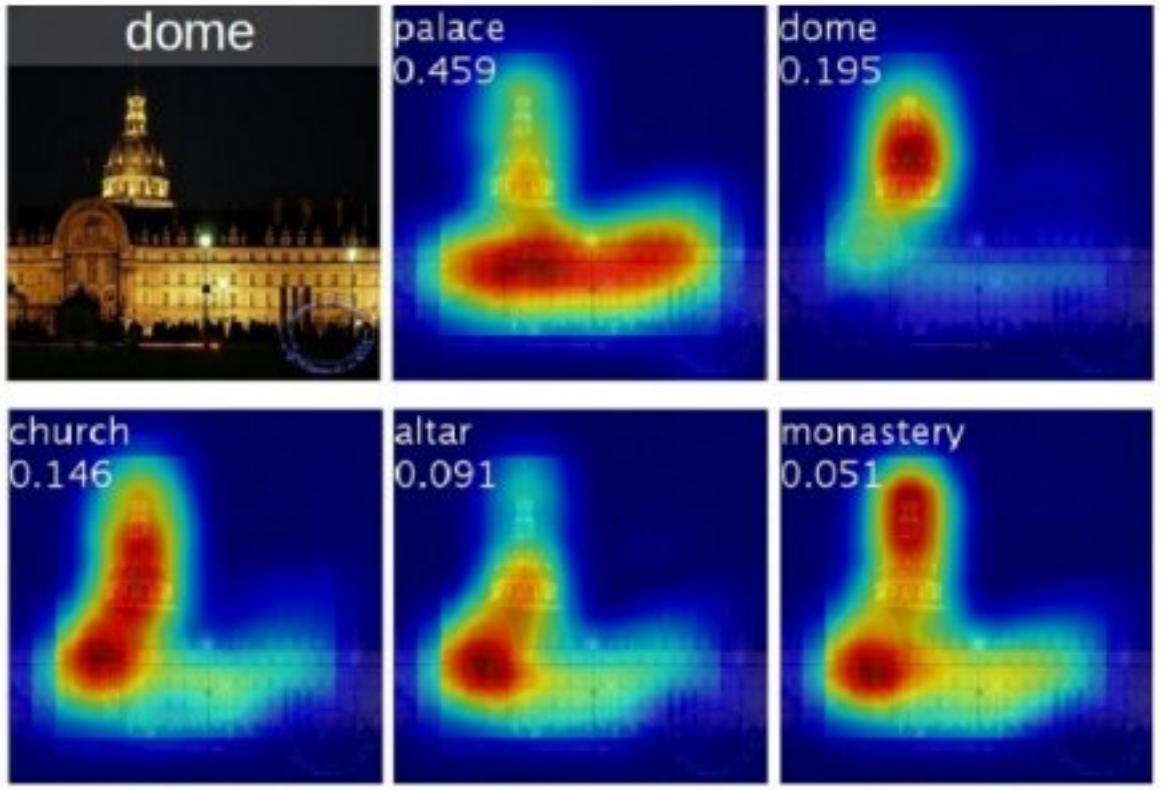


Many extension of CAM

- Class activation maps for your PyTorch models (CAM, Grad-CAM, Grad-CAM++, Smooth Grad-CAM++, Score-CAM, SS-CAM, IS-CAM, XGrad-CAM, Layer-CAM, etc)
- https://github.com/frgfm/torch-cam

Class Activation Mapping (CAM)

Problem: Can only apply to last conv layer



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

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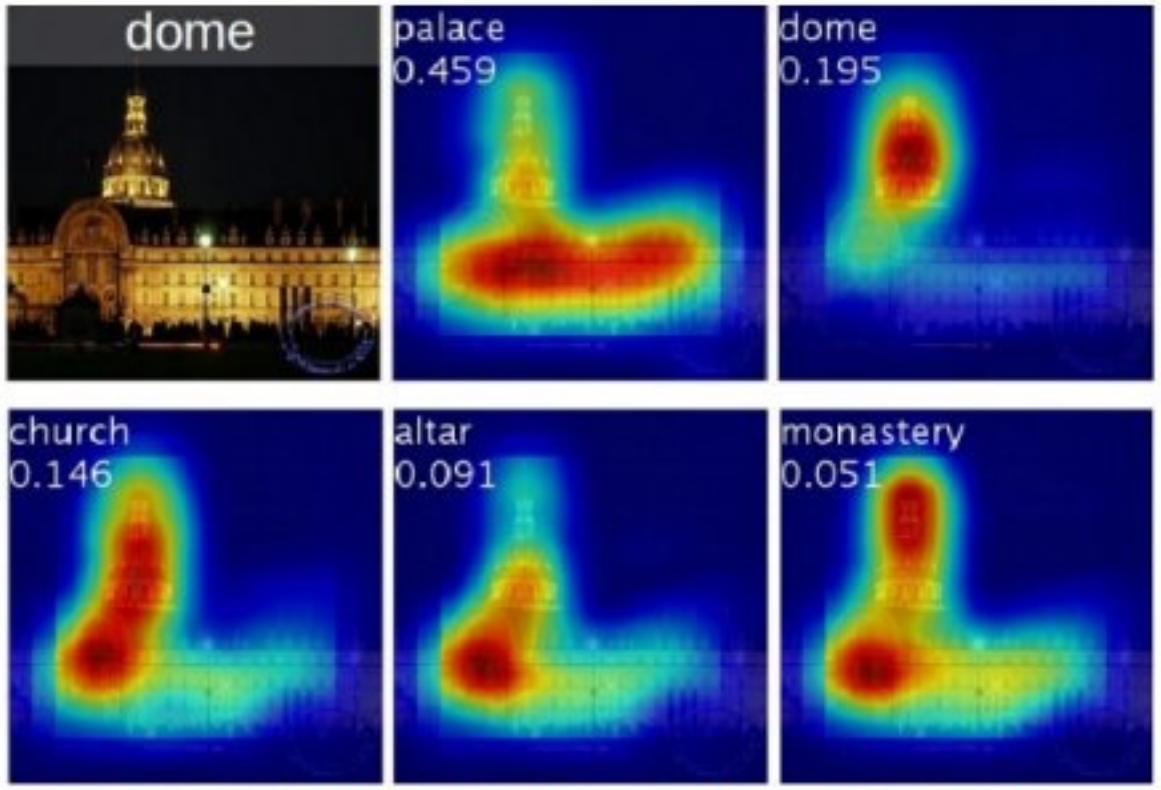

Class activation maps of top 5 predictions

Class activation maps for one object class

Well, all the recent CNNs use GAP at the end, so CAM is applicable to them all

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

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

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

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

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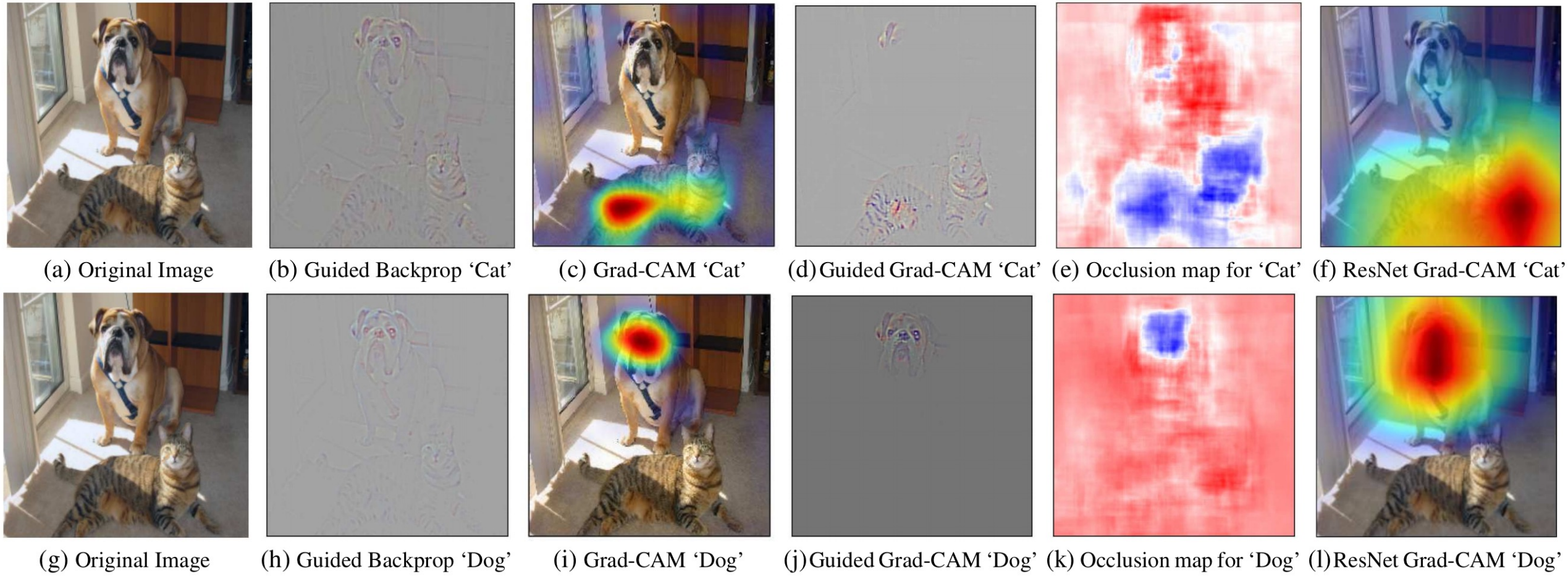
$$\alpha_k = \frac{1}{HW} \sum_{h,w} \frac{\partial S_c}{\partial A_{h,w,k}}$$

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)



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

Gradient-Weighted Class Activation Mapping (Grad-CAM)

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

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

Don’t be fooled by Saliency-based Interpretability

Be mindful about the application of saliency map in NNs:

- Towards falsifiable interpretability research by Leavitt and Morcos: https://arxiv.org/pdf/2010.12016.pdf
- SELECTIVITY CONSIDERED HARMFUL: EVALUATING THE CAUSAL IMPACT OF CLASS SELECTIVITY IN DNNS: http://www.arimorcos.com/static/pdfs/leavitt_selectivity_considered_harmful.pdf
- The mythos of model interpretability: https://arxiv.org/pdf/1606.03490.pdf

Visualizing CNN Features: Gradient Ascent

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

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

Neuron value

Natural image regularizer

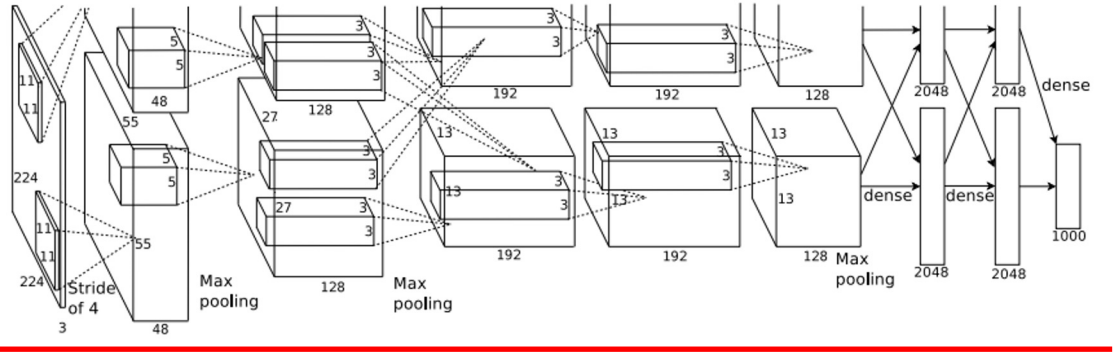
Visualizing CNN Features: Gradient Ascent

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

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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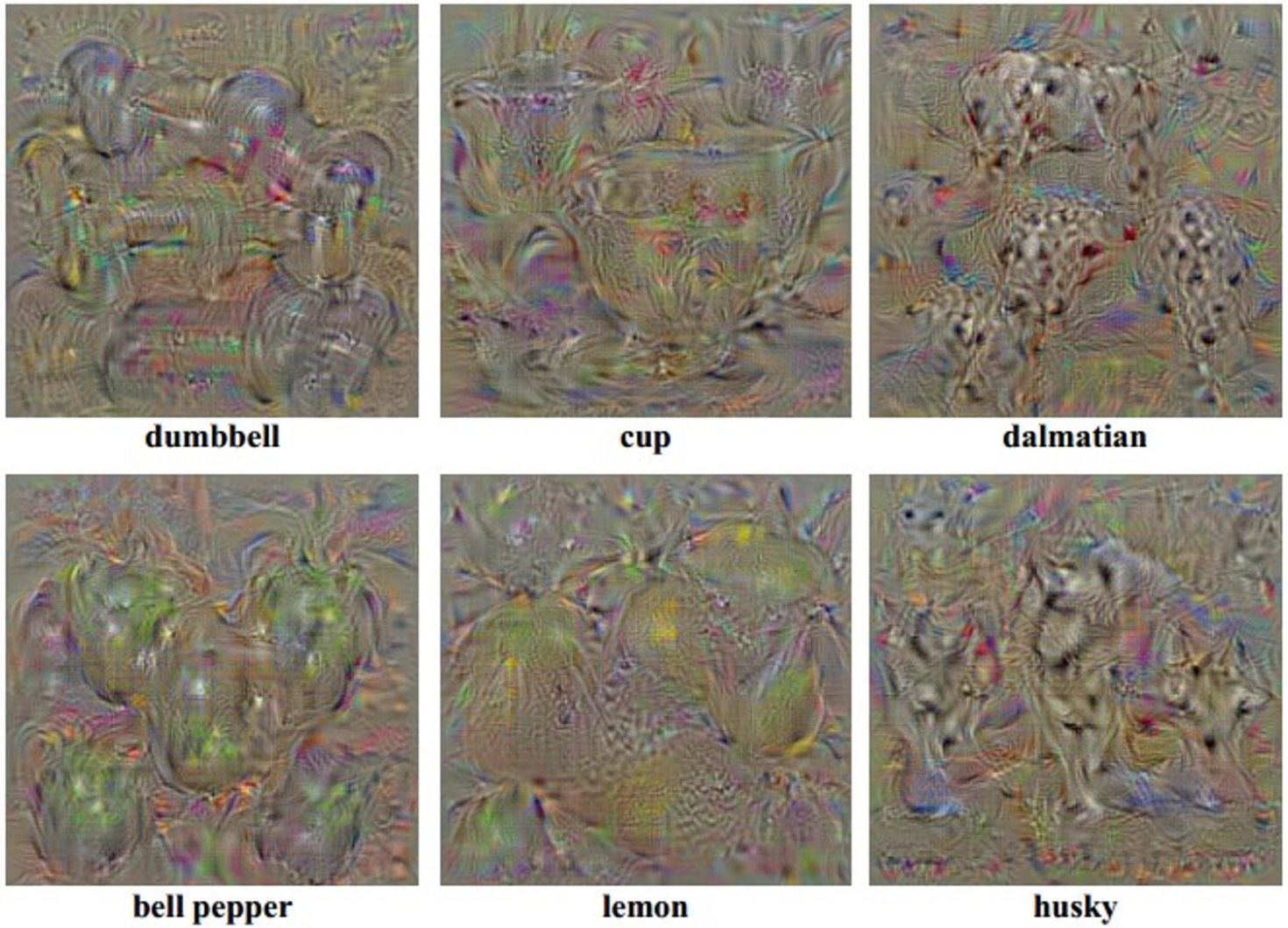

Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
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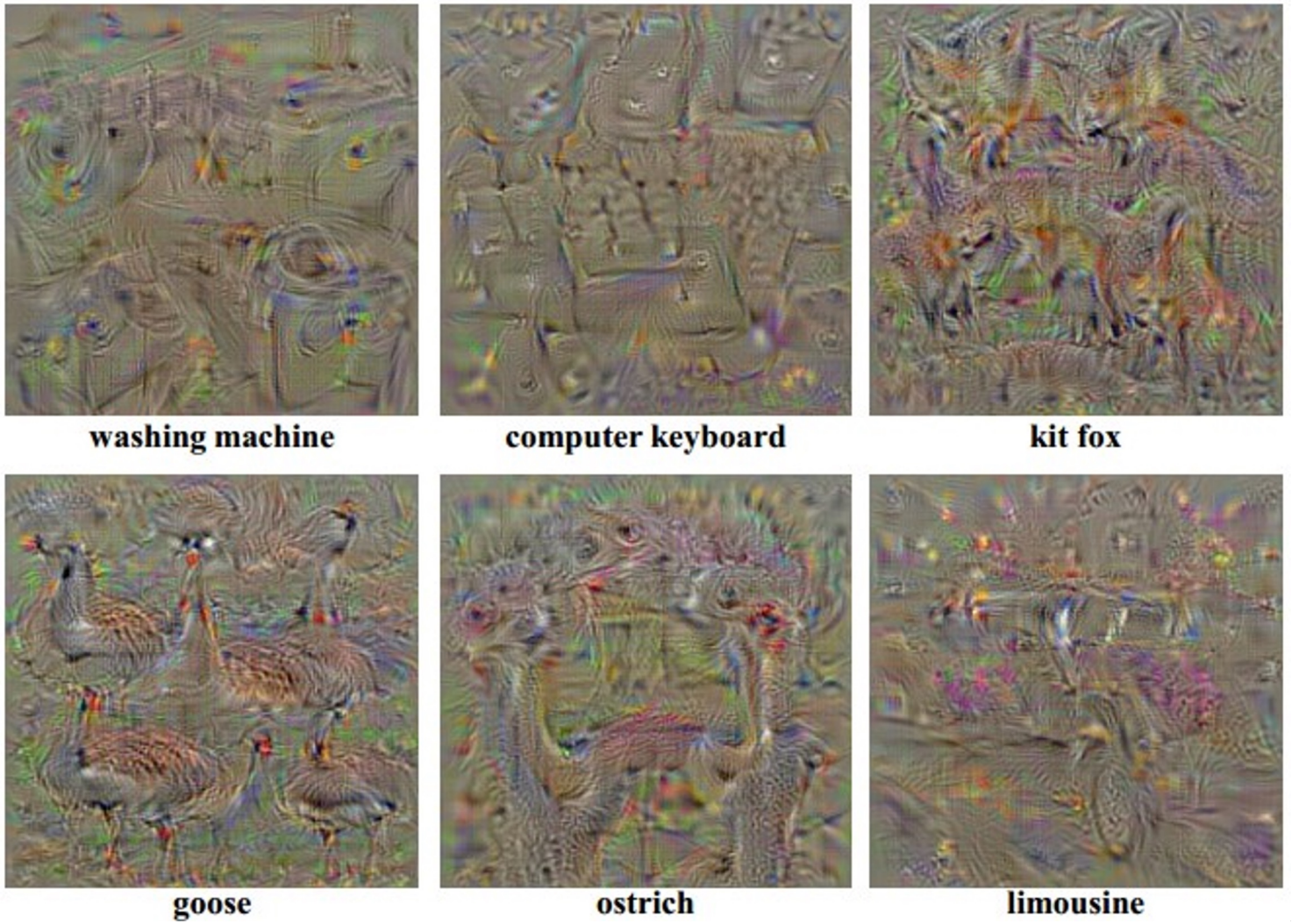
L2 norm of generated image



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

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

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.

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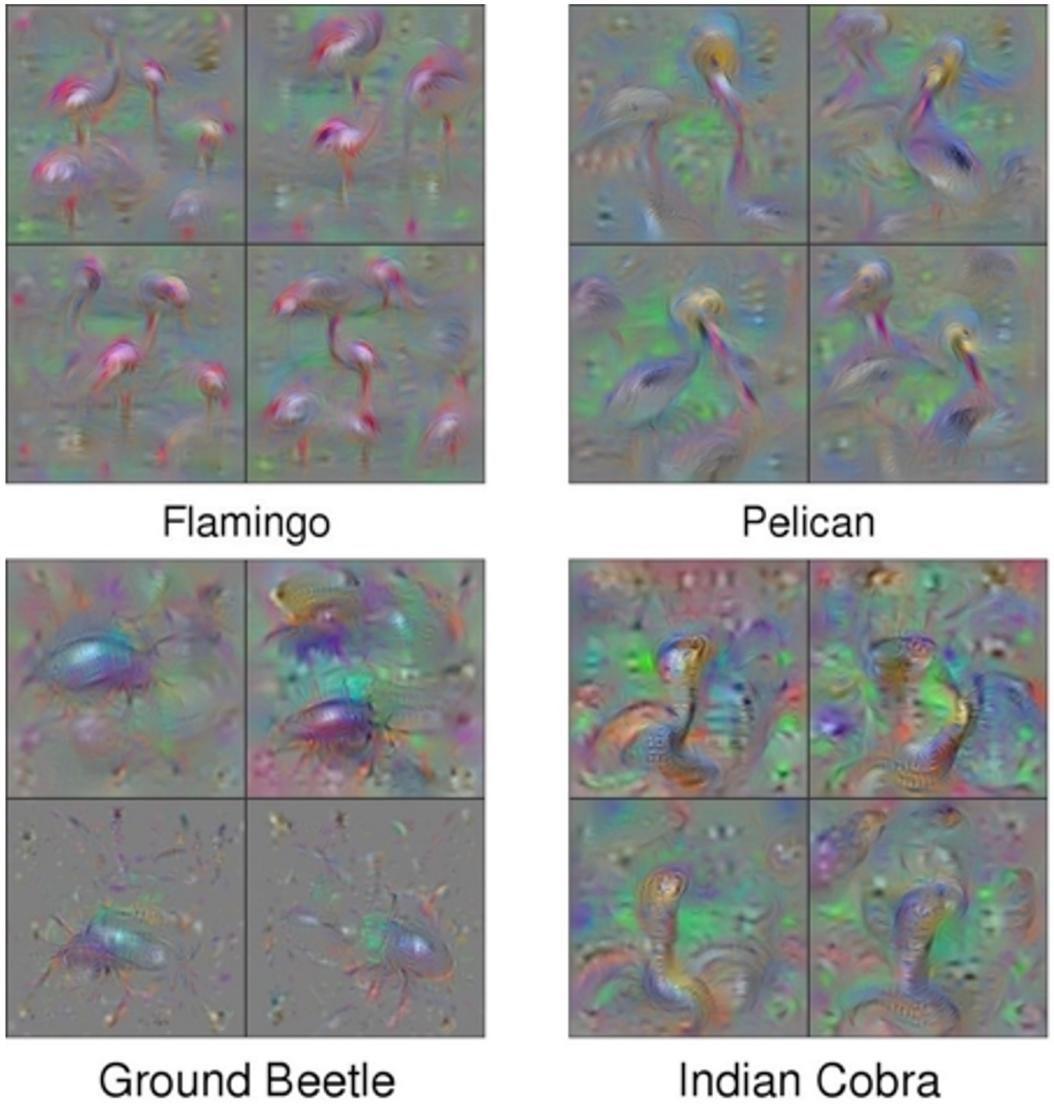

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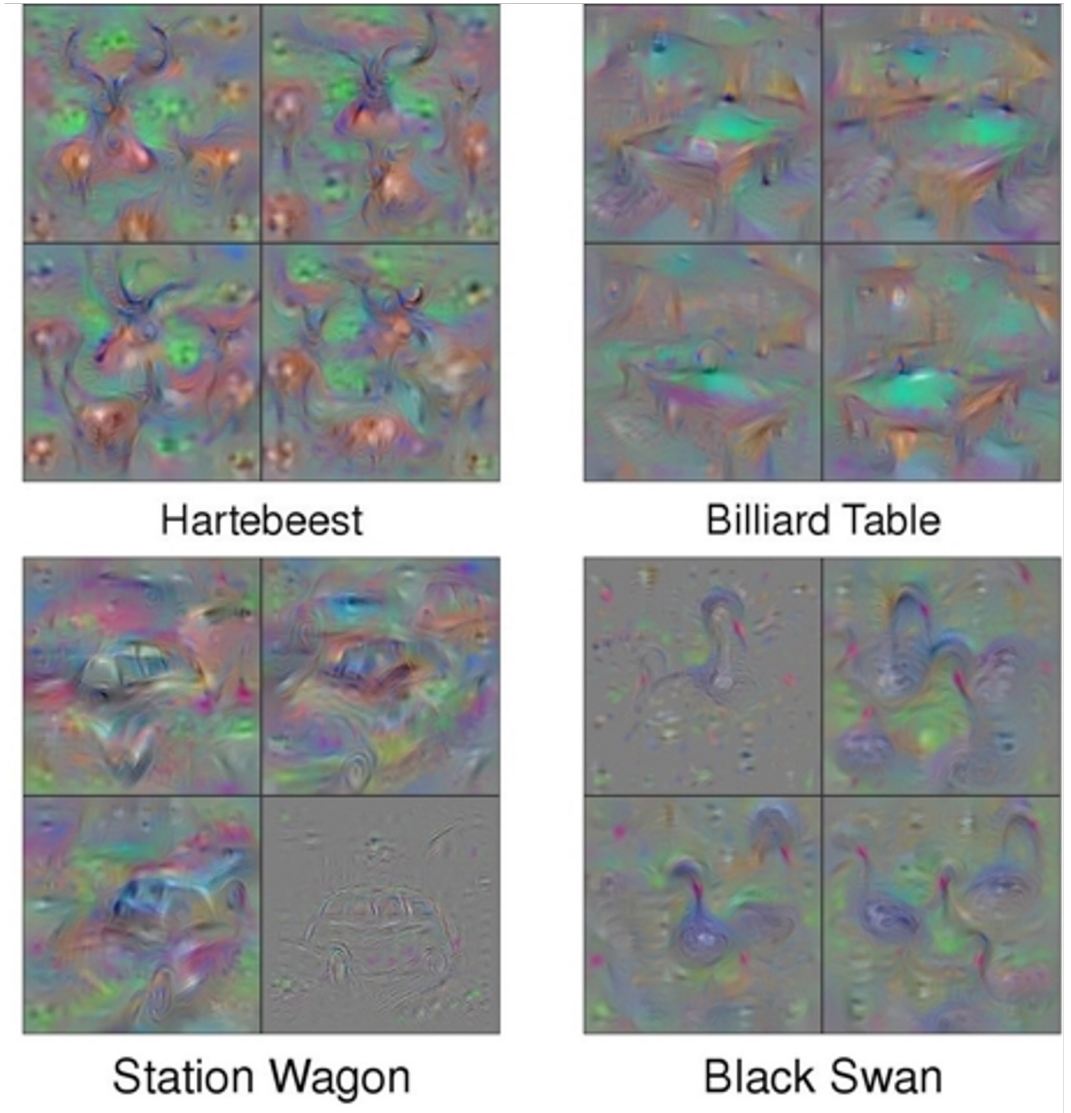
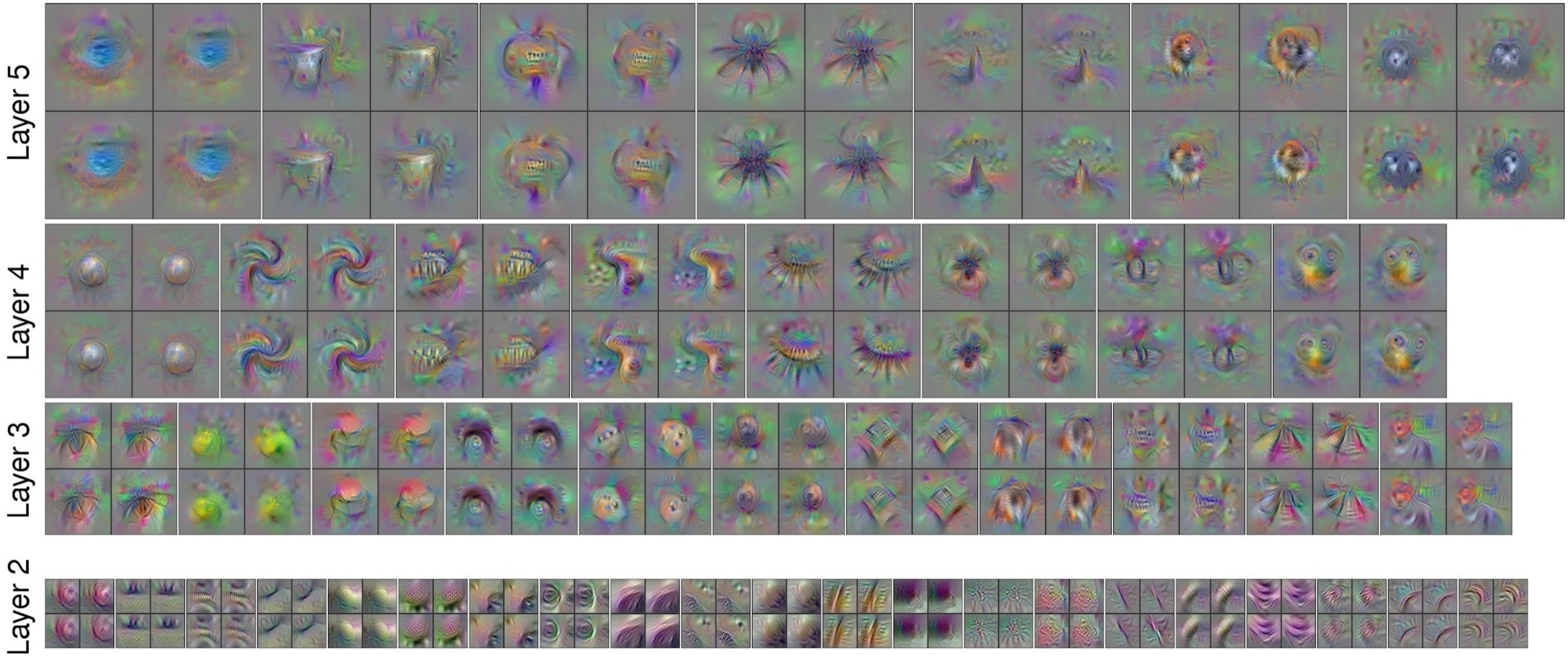


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

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

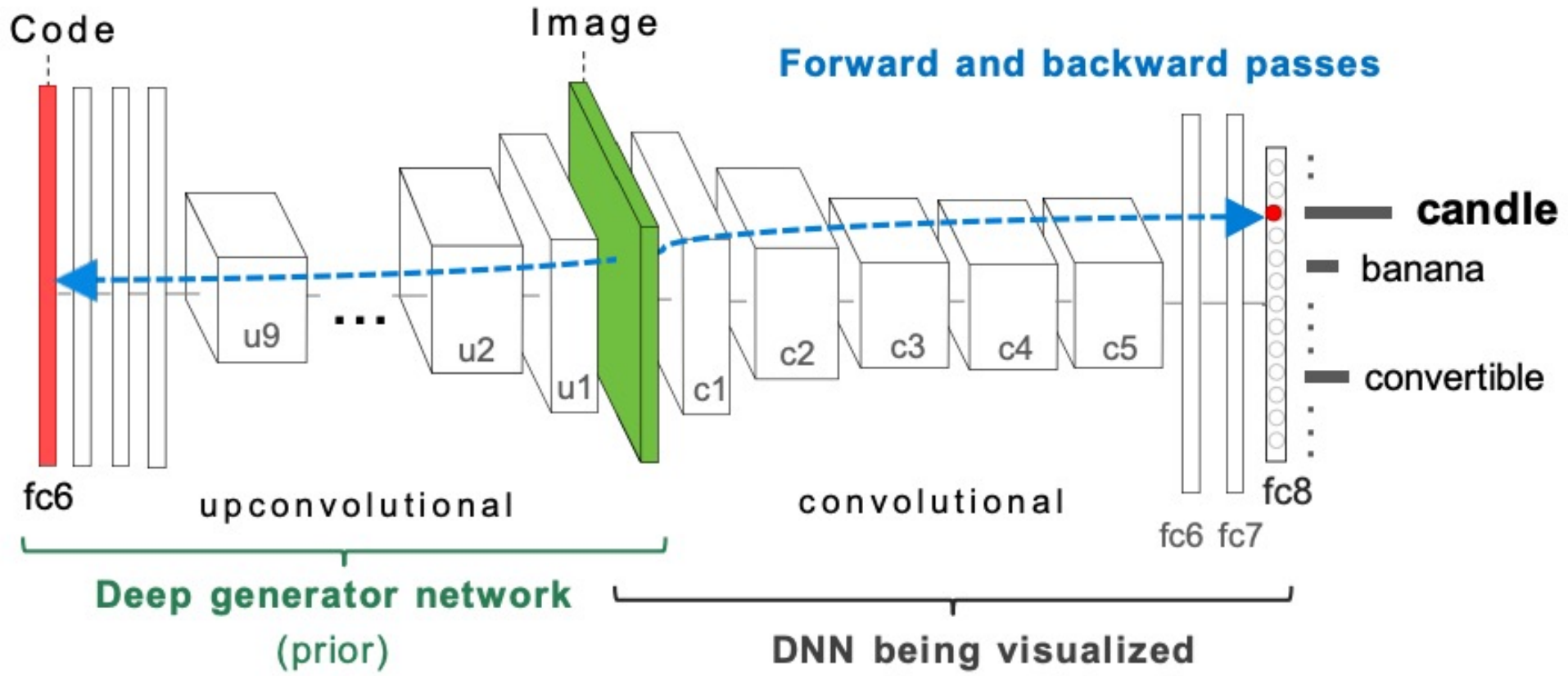
Corresponding example training set images recognized by the same neuron as in the "grocery store" class

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 with a Stronger Prior



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

Visualizing CNN Features: Gradient Ascent

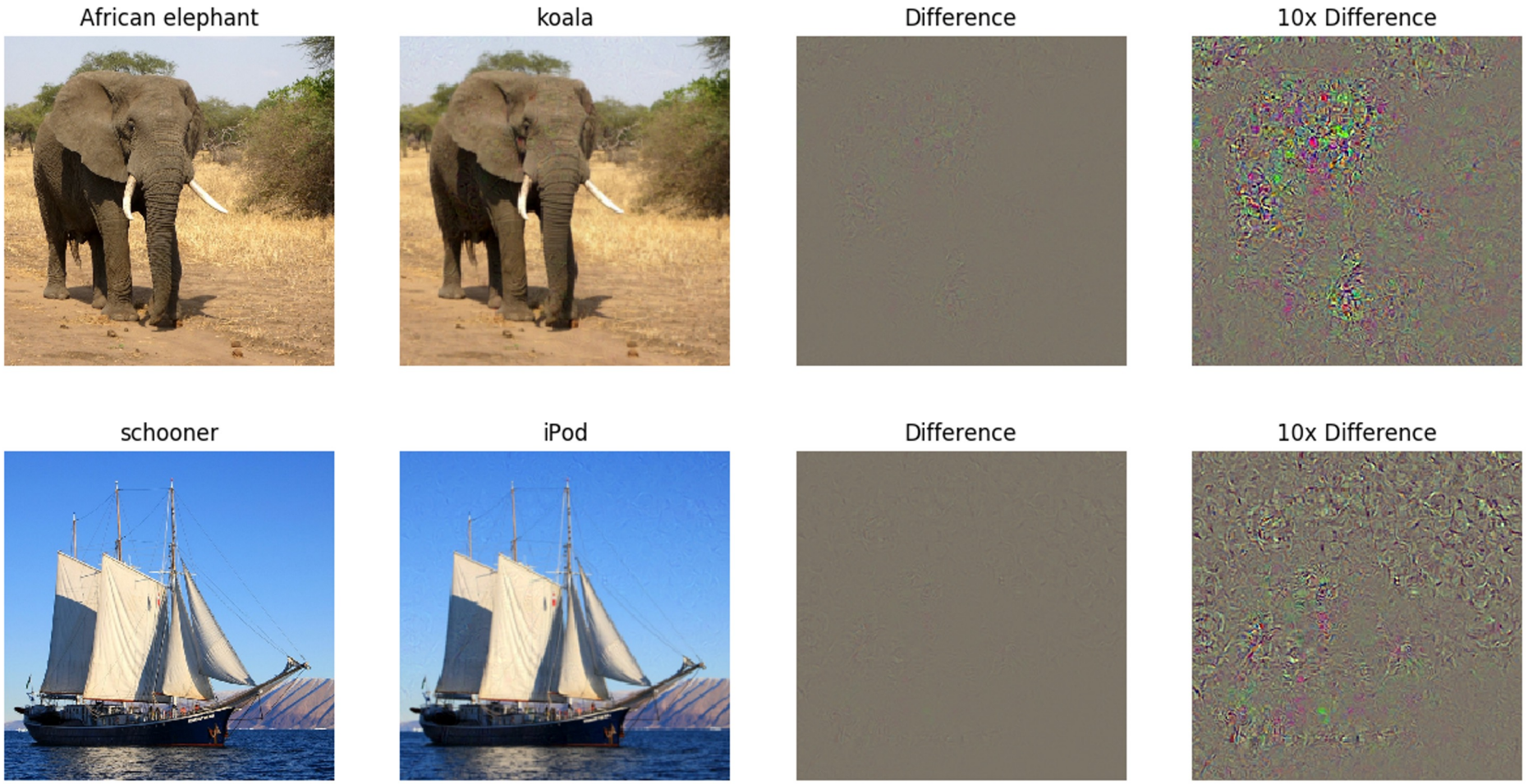
Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016

Adversarial Examples

1. Start from an arbitrary image
2. Pick an arbitrary category
3. Modify the image (via gradient ascent) to maximize the class score
4. Stop when the network is fooled

Szegedy et al, “Intriguing properties of neural networks”, 2013

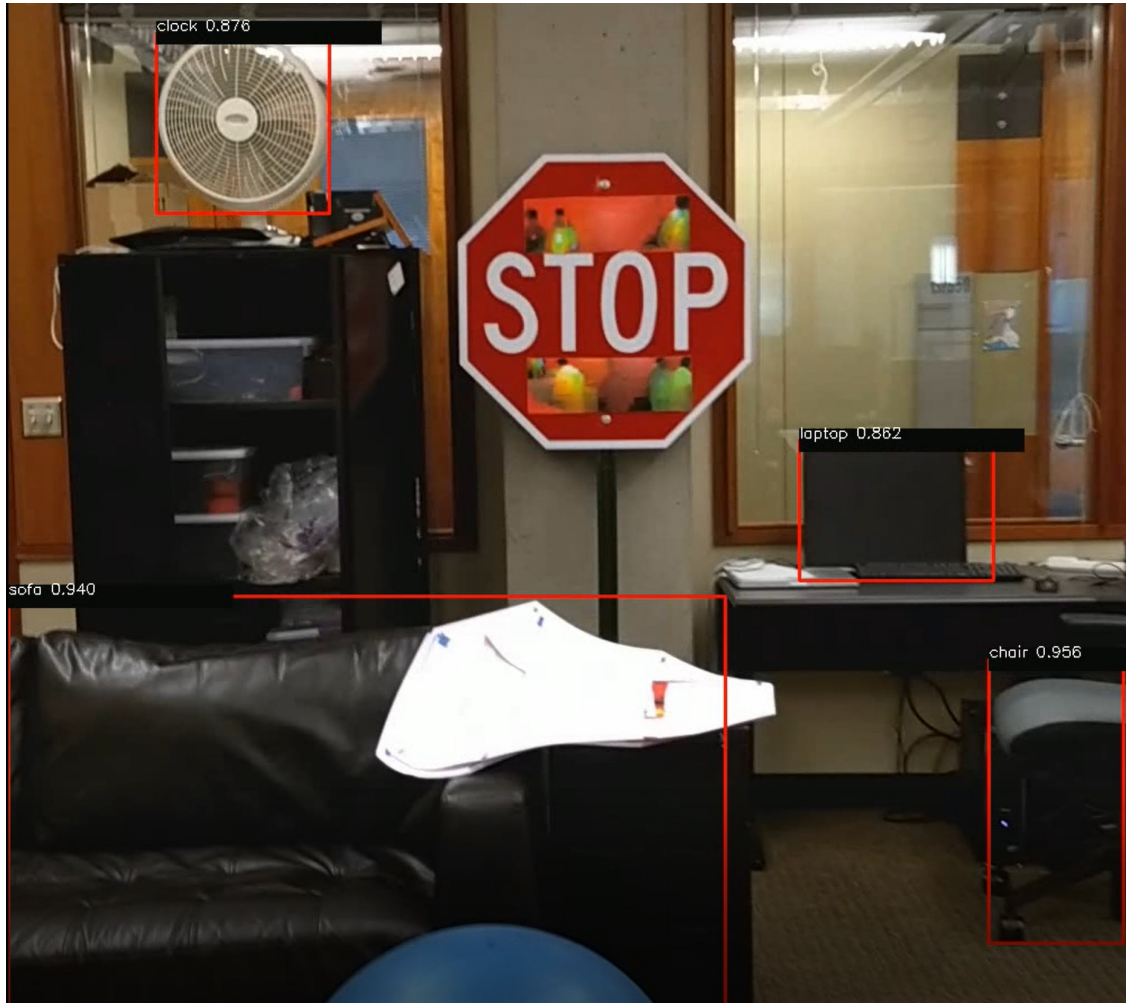
Adversarial Examples

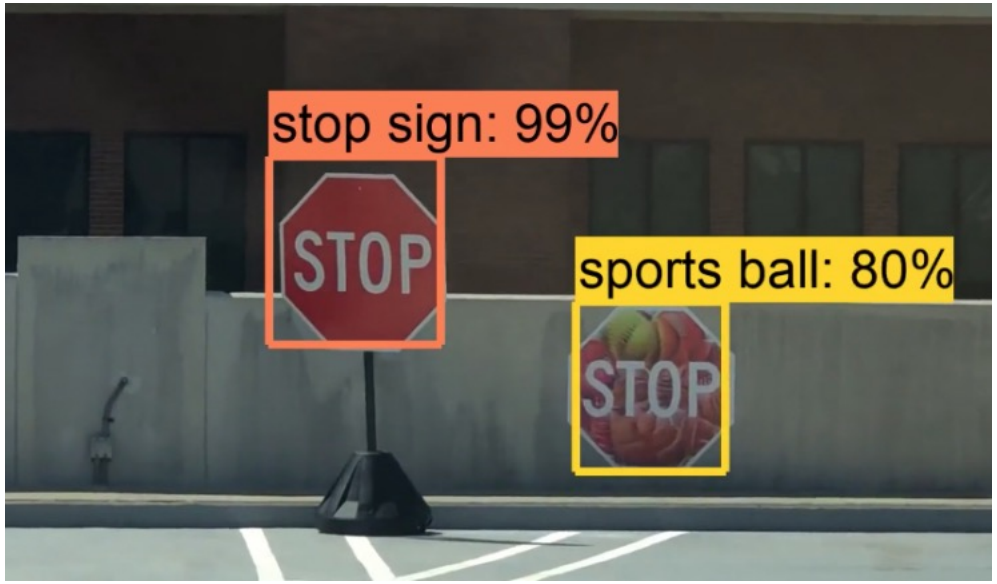


Boat image is CC0 public domain
Elephant image is CC0 public domain

Adversarial Machine Learning becomes a big thing

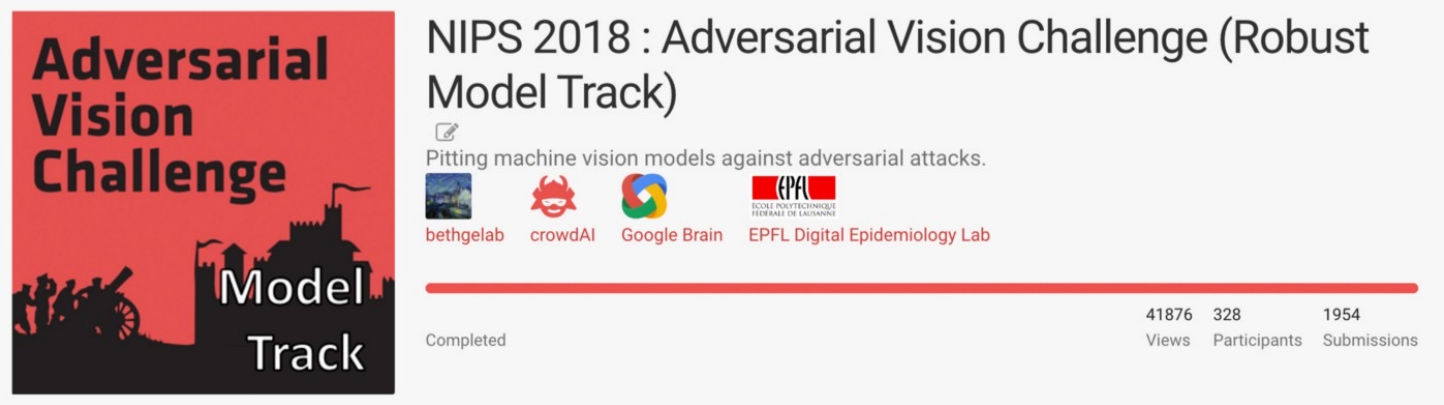
Adversarial examples for object detectors



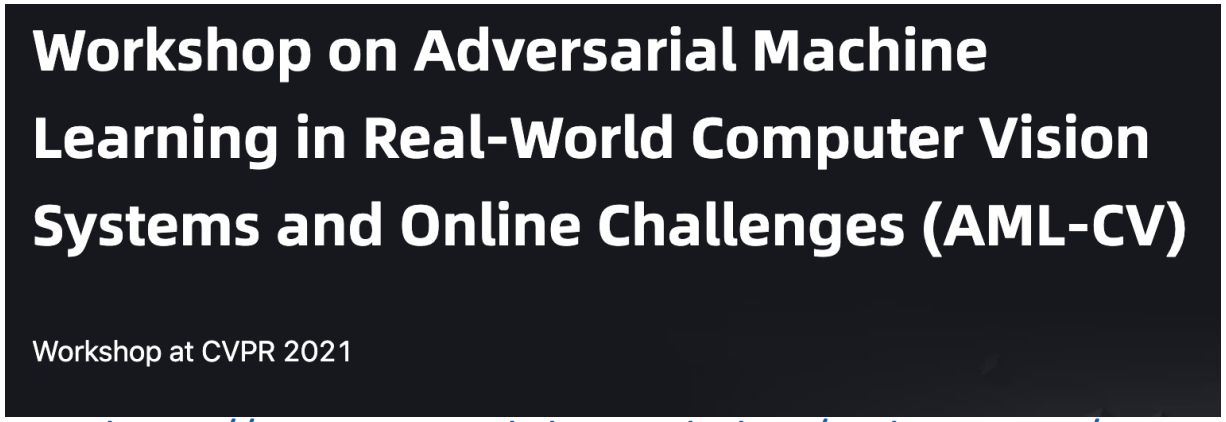


Adversarial Machine Learning becomes a big thing

Adversarial attack versus Adversarial Defense



https://medium.com/bethgelab/results-of-the-nips-adversarial-vision-challenge-2018-e1e21b690149



https://aisecure-workshop.github.io/amlcvpr2021/

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

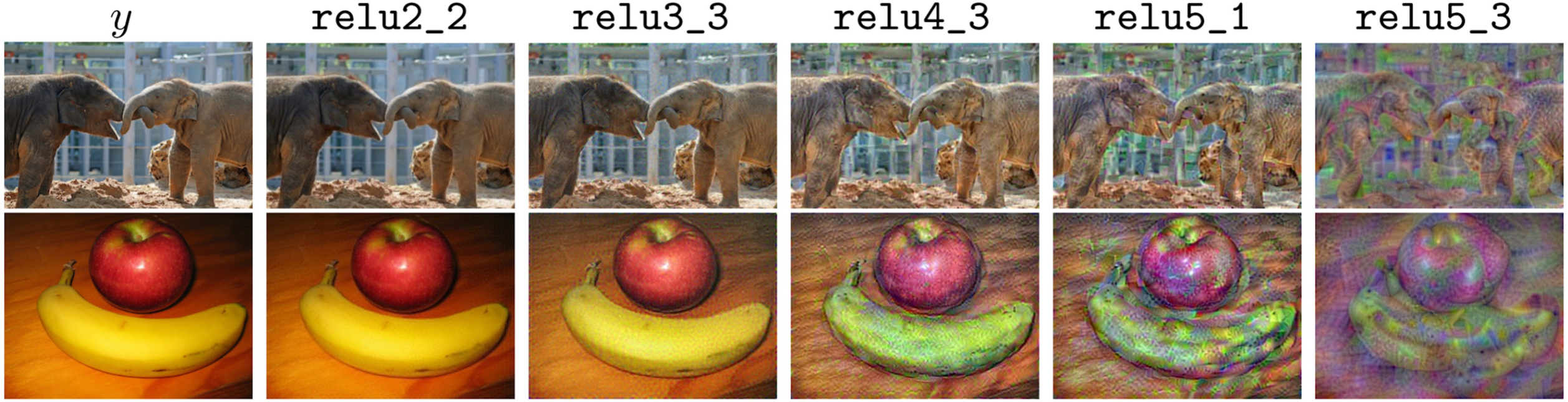
$$\mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j} \left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{\beta}{2}}$$

Total Variation regularizer (encourages spatial smoothness)

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

Feature Inversion

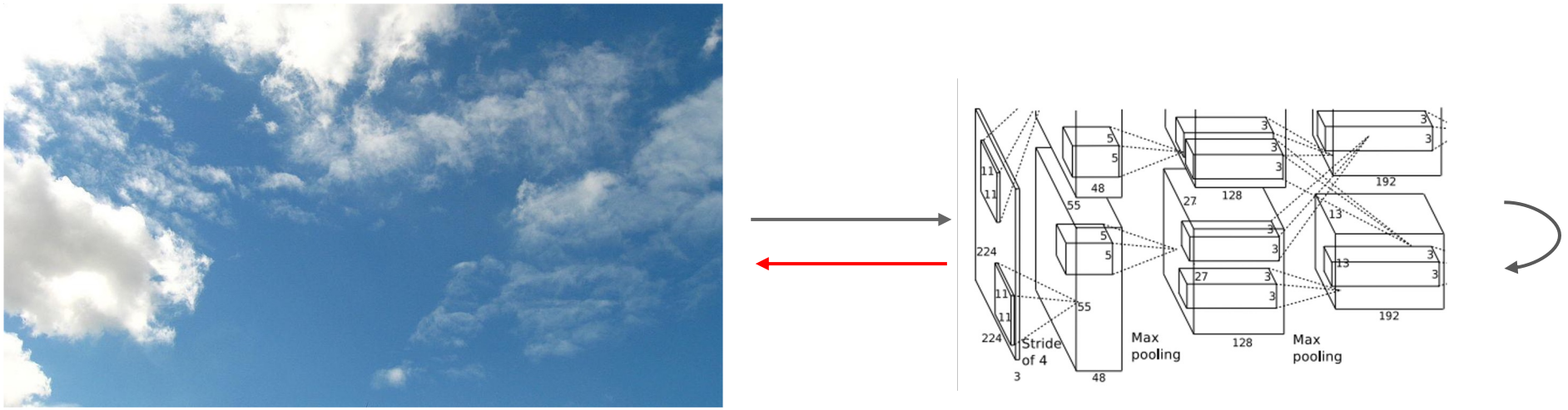
Reconstructing from different layers of VGG-16



Mahendran and Vedaldi, “Understanding Deep Image Representations by Inverting Them”, CVPR 2015
Figure from Johnson, Alahi, and Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution”, ECCV 2016.

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

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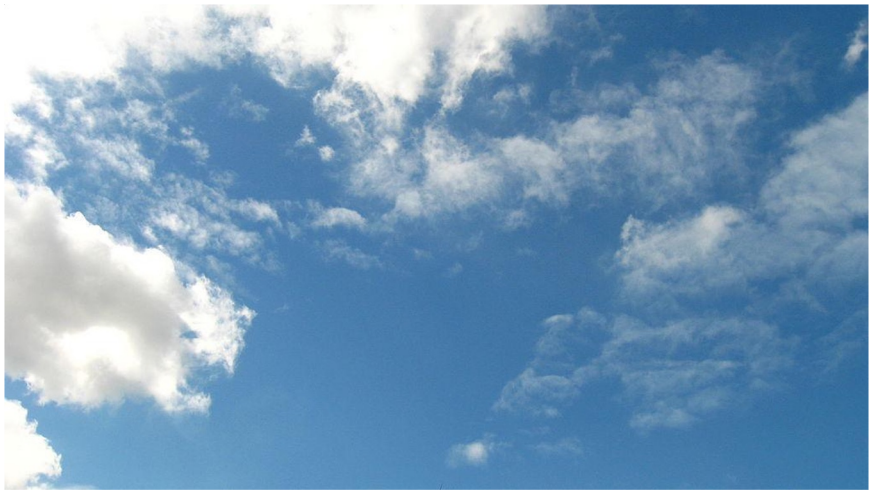

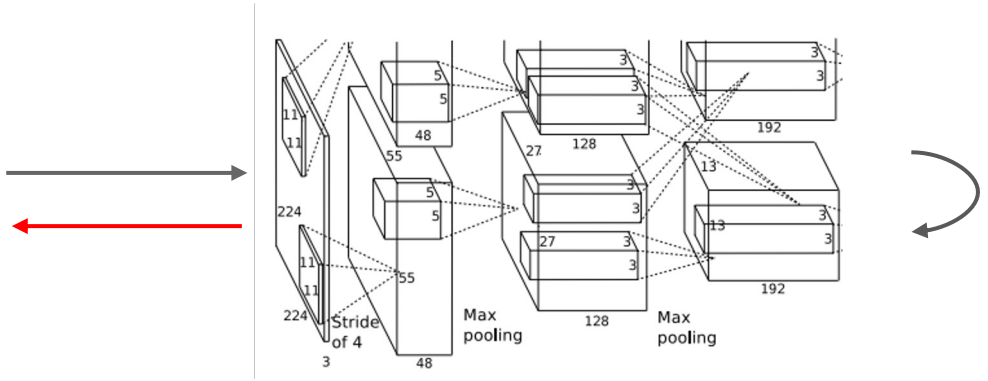

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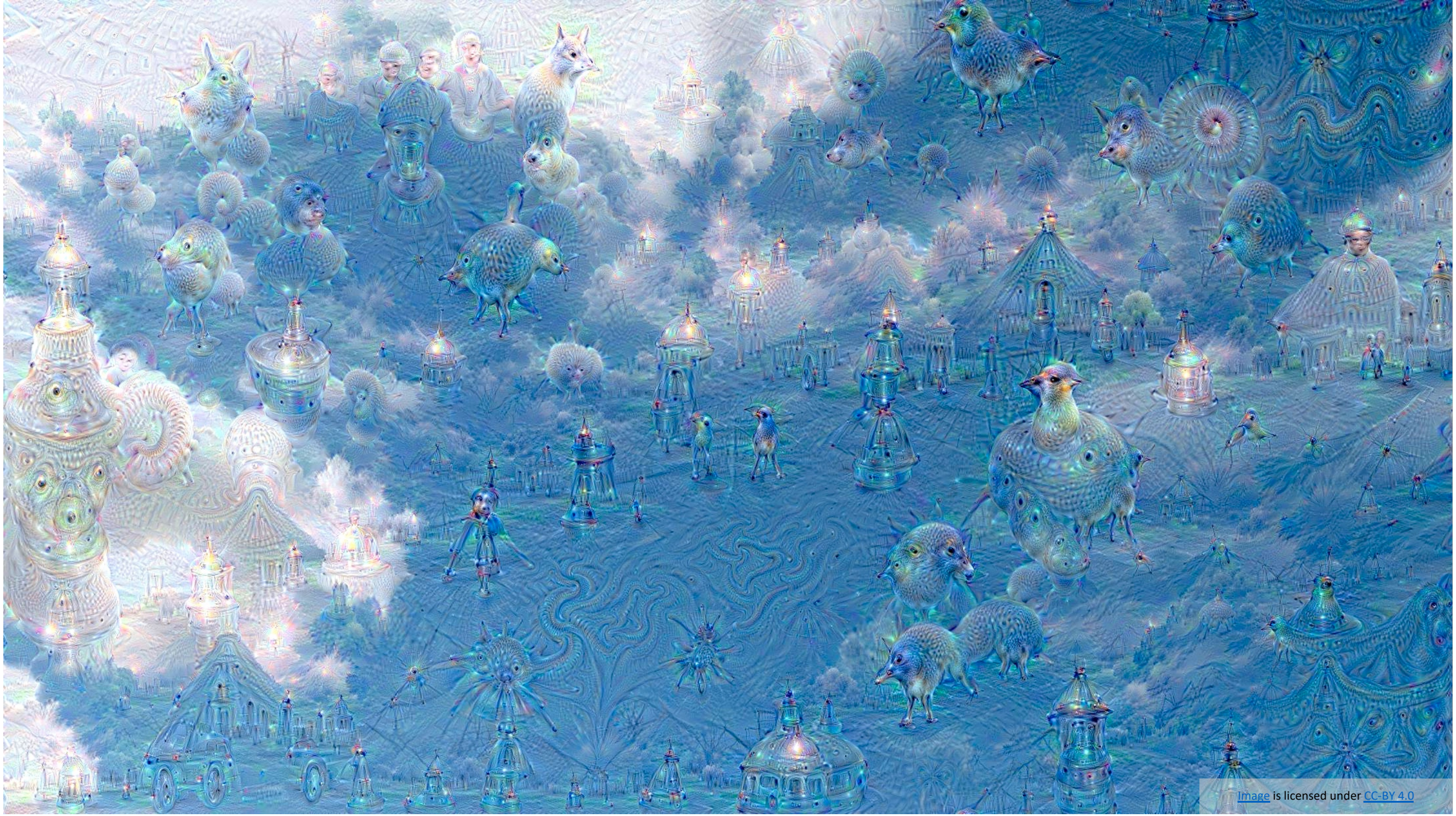
1. Forward: compute activations at chosen layer
2. Set gradient of chosen layer *equal to its activation*
3. Backward: Compute gradient on image
4. Update image

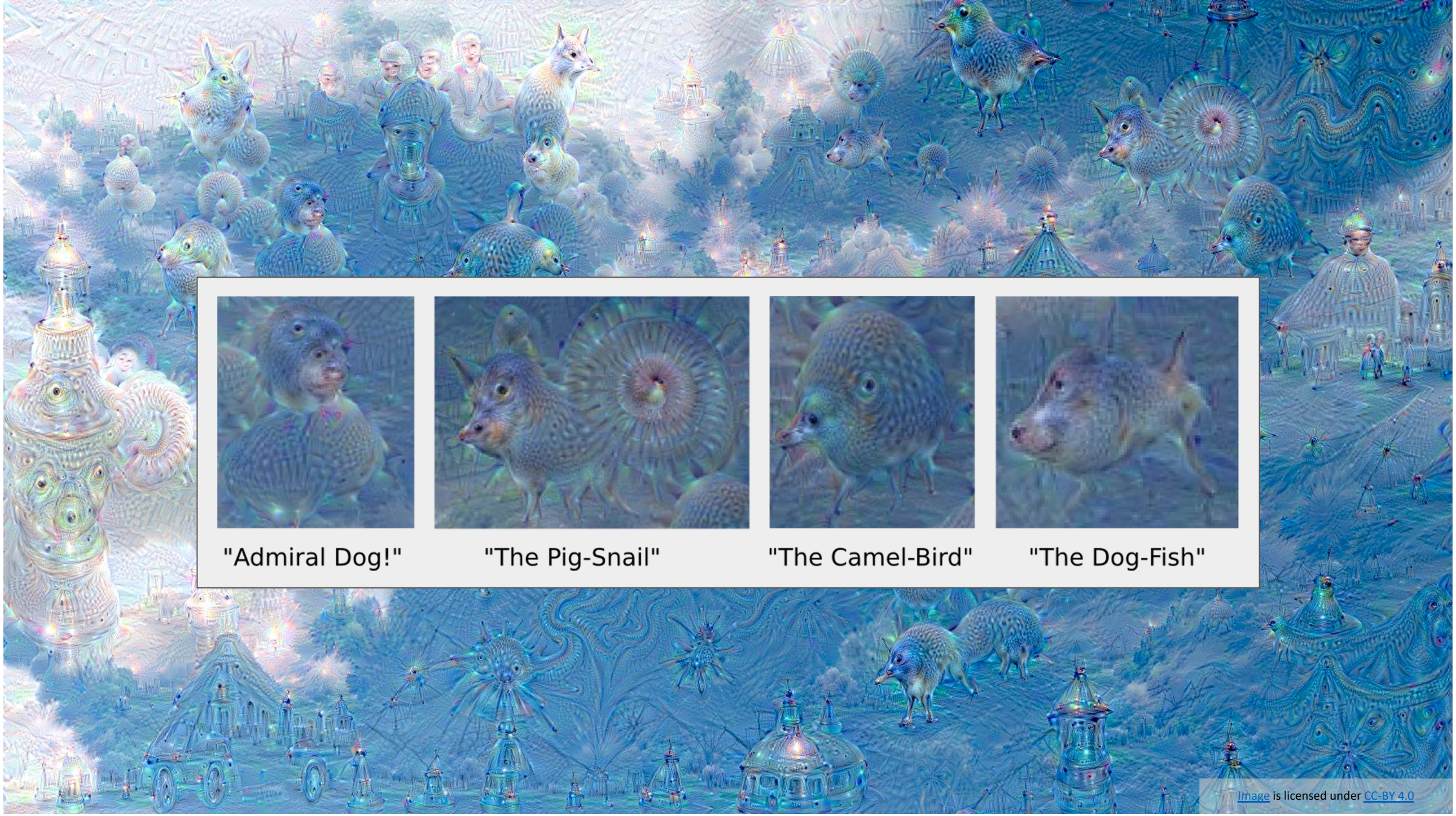
Equivalent to:

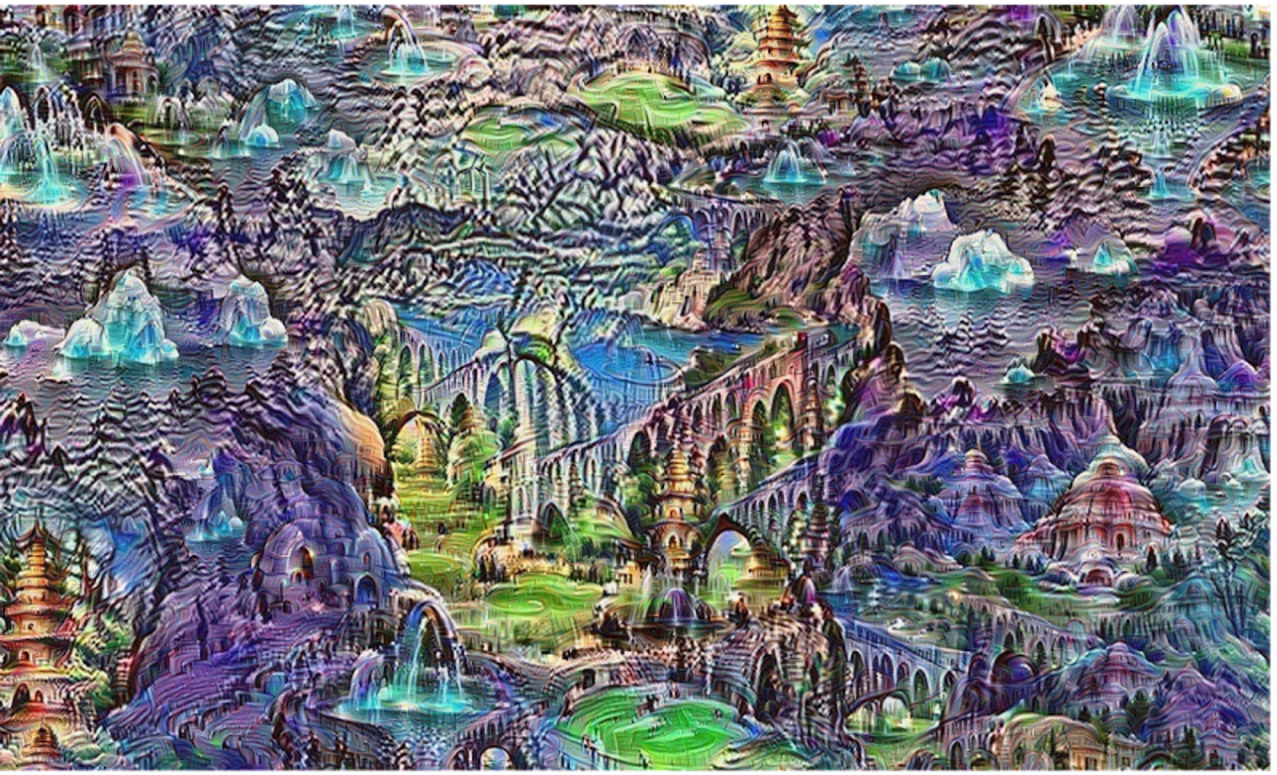
$$I^* = \arg\max_I \sum_i f_i(I)^2$$

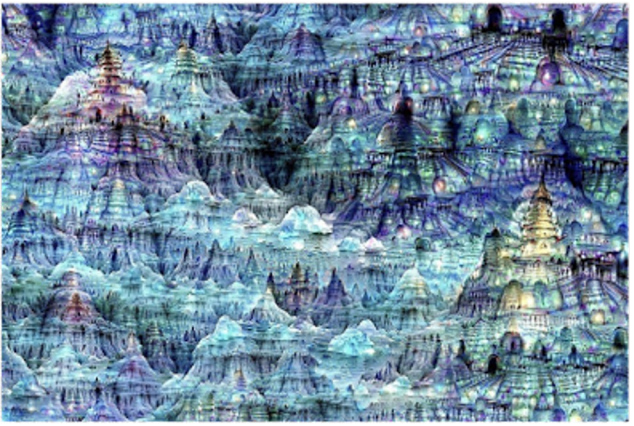
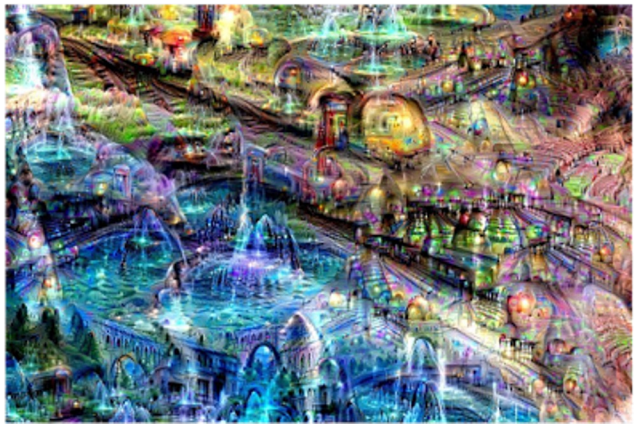
Mordvintsev, Olah, and Tyka, "Inceptionism: Going Deeper into Neural Networks", Google Research Blog. Images are licensed under CC-BY 4.0

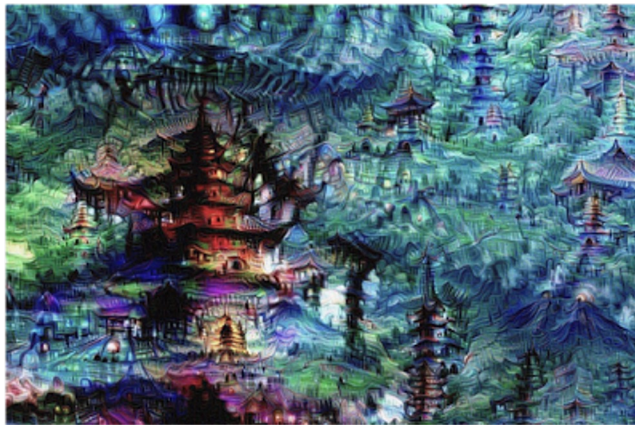

Sky image is licensed under CC-BY SA 3.0





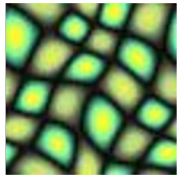


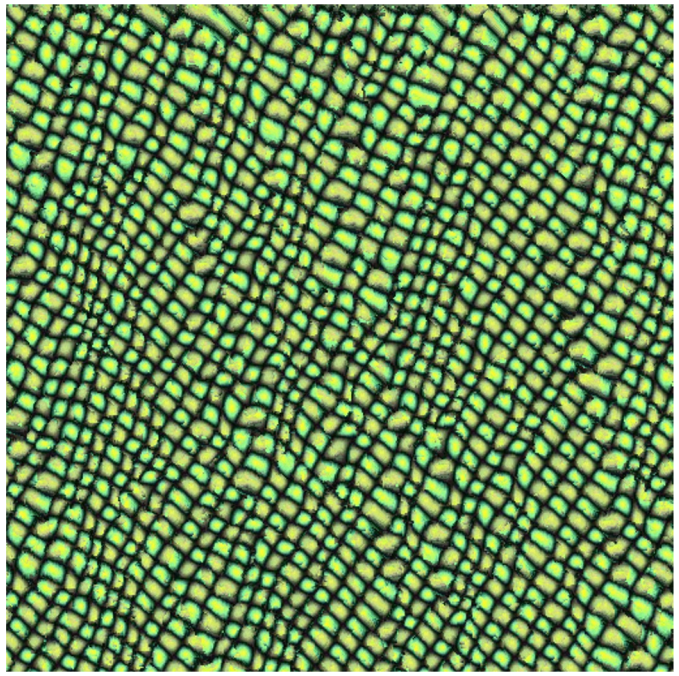


Texture Synthesis

Given a sample patch of some texture, can we generate a bigger image of the same texture?



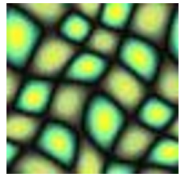
Input

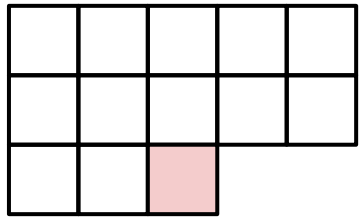


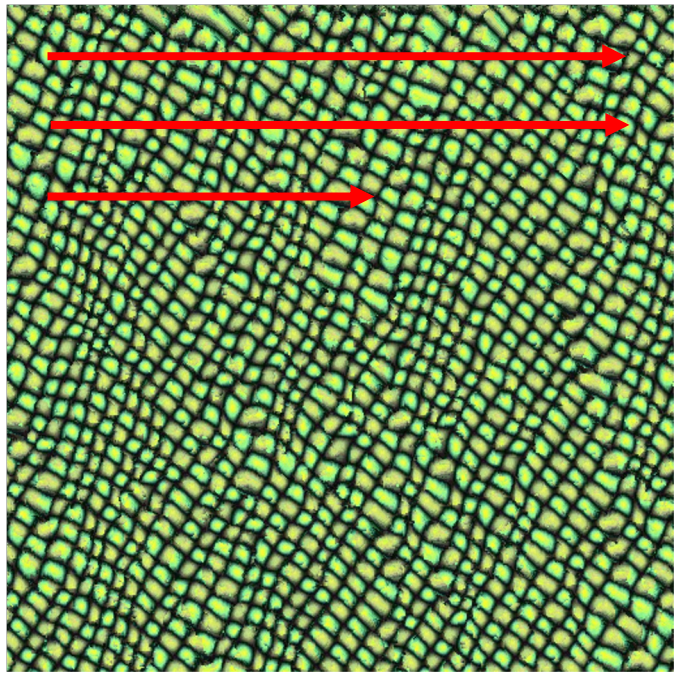
Output

Texture Synthesis: Nearest Neighbor

Generate pixels one at a time in scanline order; form neighborhood of already generated pixels and copy nearest neighbor from input



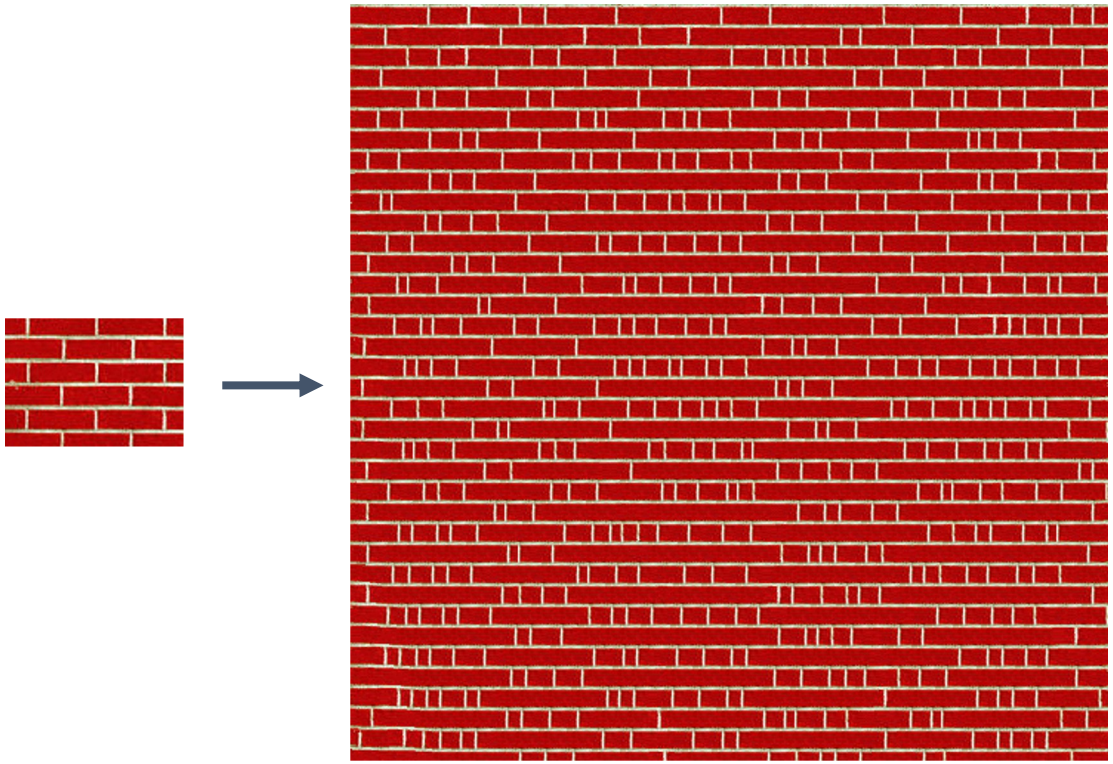




Wei and Levoy, “Fast Texture Synthesis using Tree-structured Vector Quantization”, SIGGRAPH 2000

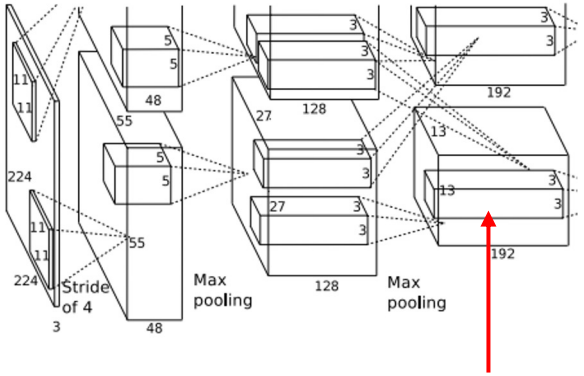
Efros and Leung, “Texture Synthesis by Non-parametric Sampling”, ICCV 1999

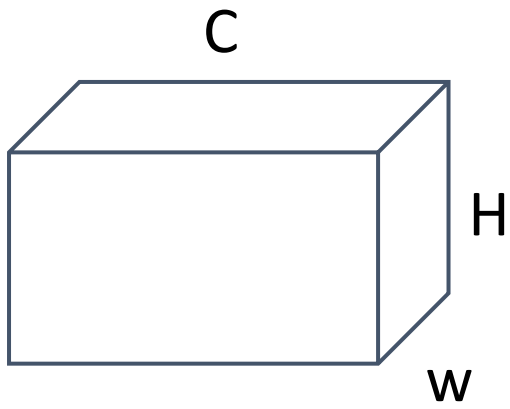
Texture Synthesis: Nearest Neighbor



Texture Synthesis with Neural Networks: Gram Matrix

This image is in the public domain.





Each layer of CNN gives C x H x W tensor of features; H x W grid of C-dimensional vectors

Texture Synthesis with Neural Networks: Gram Matrix

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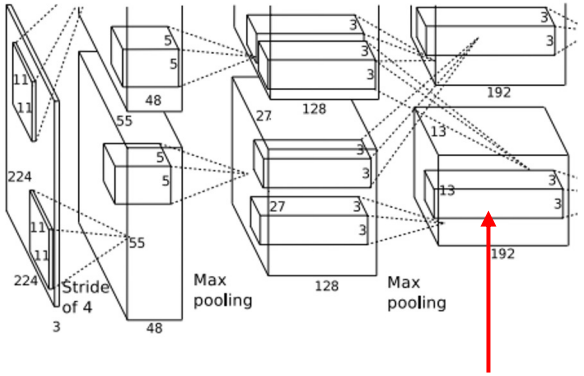
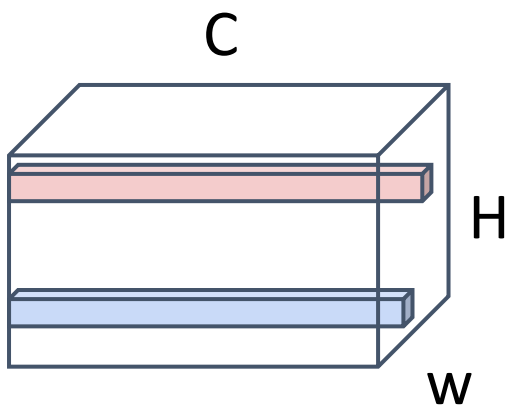
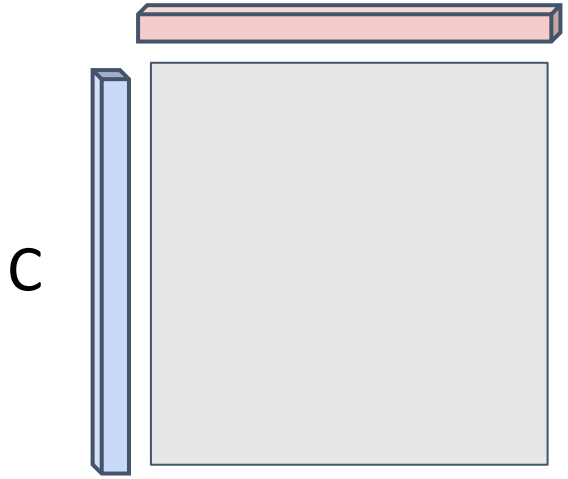




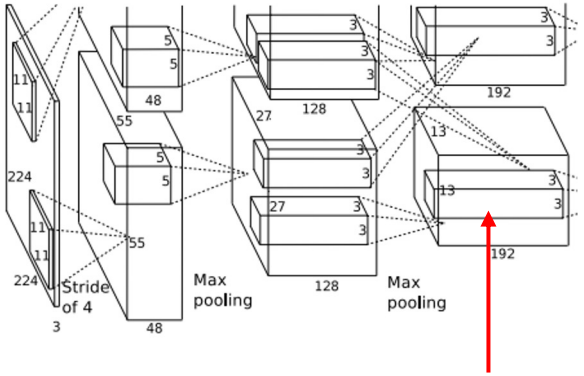


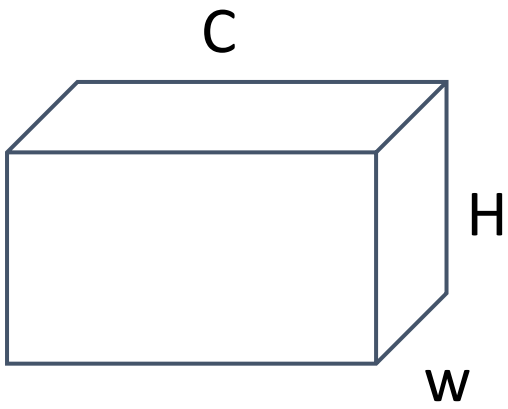
Each layer of CNN gives C x H x W tensor of features; H x W grid of C-dimensional vectors

Outer product of two C-dimensional vectors gives C x C matrix of elementwise products

Texture Synthesis with Neural Networks: Gram Matrix

This image is in the public domain.





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Outer product of two C-dimensional vectors gives C x C matrix of elementwise products

Average over all HW pairs gives **Gram Matrix** of shape C x C giving unnormalized covariance

Texture Synthesis with Neural Networks: Gram Matrix

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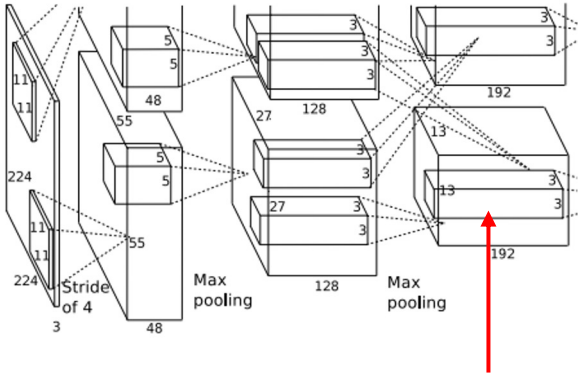
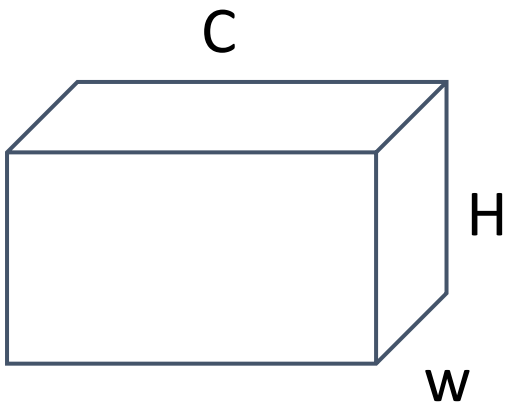
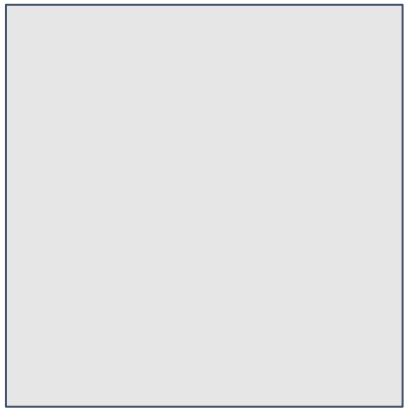




C



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Average over all HW pairs gives **Gram Matrix** of shape C x C giving unnormalized covariance

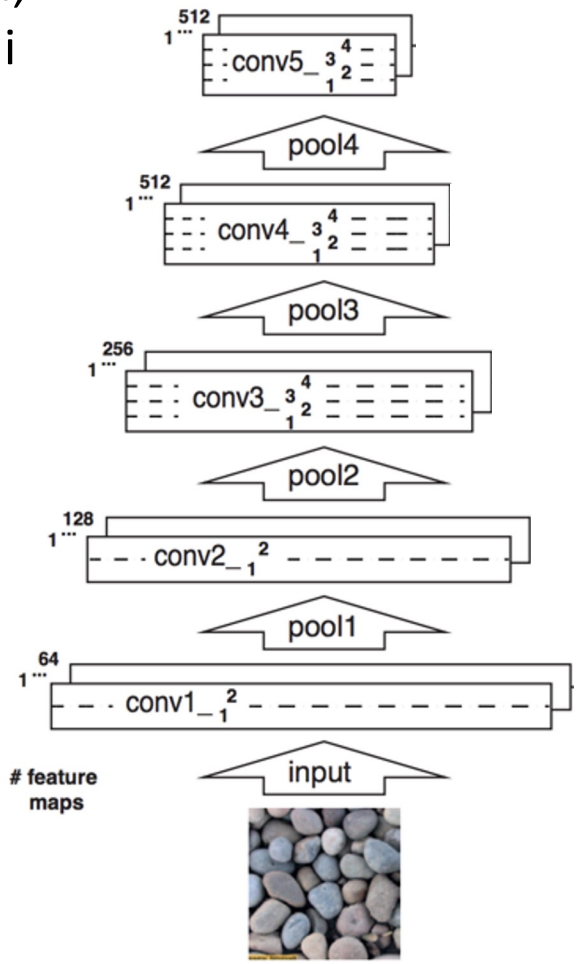
Efficient to compute; reshape features from

C x H x W to F = C x HW

then compute $G = FF^T$

Neural Texture Synthesis

1. Pretrain a CNN on ImageNet (VGG-19)
2. Run input texture forward through CNN, record activations on every layer; layer i gives feature map of shape $C_i \times H_i \times W_i$



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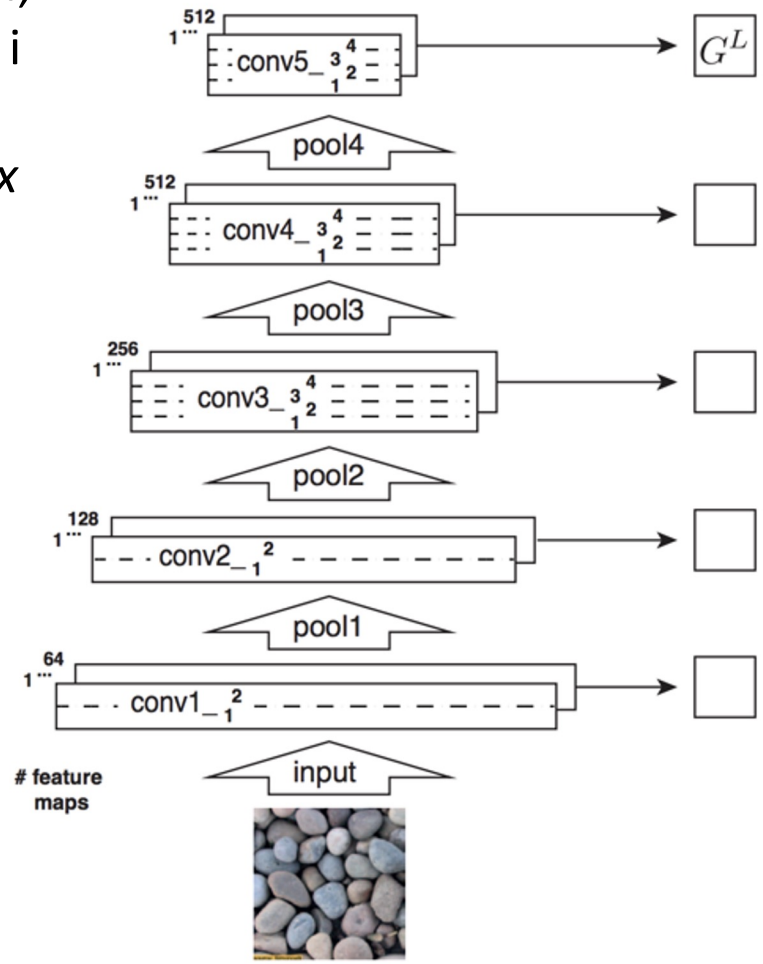
3. At each layer compute the *Gram matrix* giving outer product of features:

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}$$ (shape $C_i \times C_i$)



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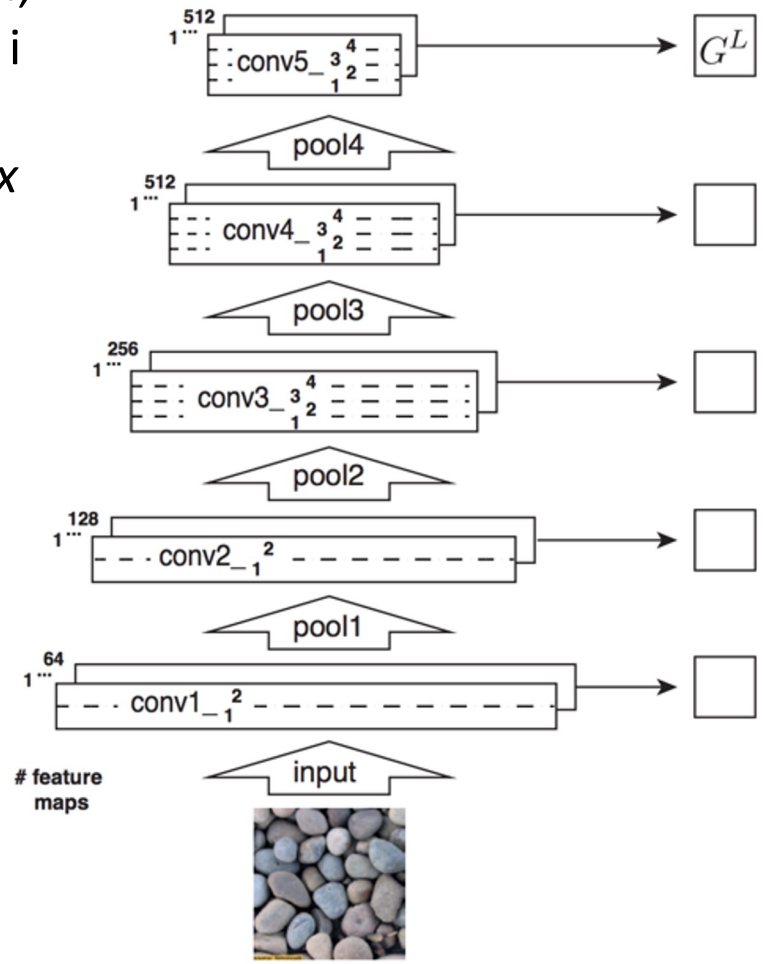
$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}$$ (shape $C_i \times C_i$)

4. Initialize generated image from random noise



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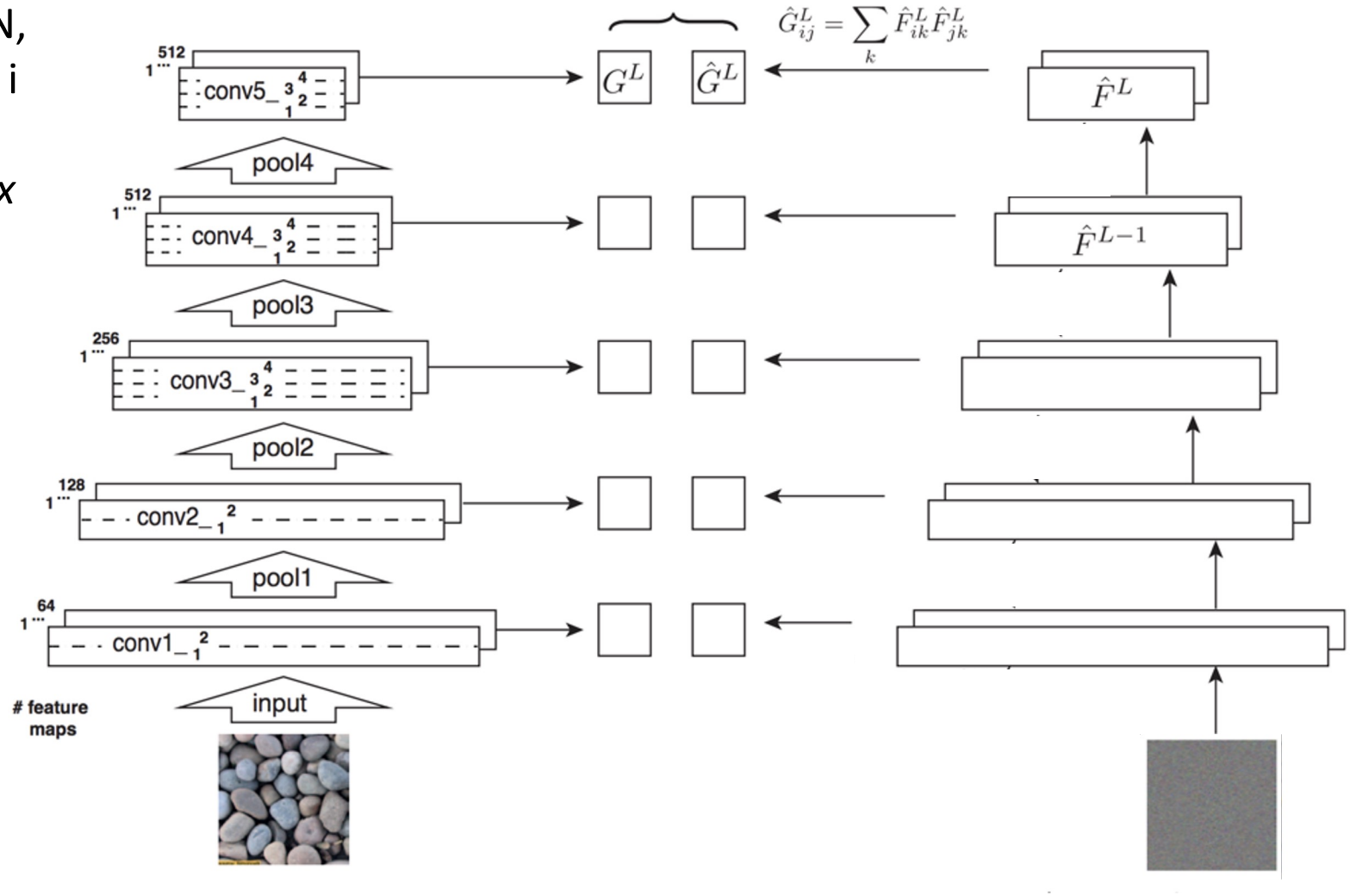
1. Pretrain a CNN on ImageNet (VGG-19)
2. Run input texture forward through CNN, record activations on every layer; layer i gives feature map of shape $C_i \times H_i \times W_i$
3. At each layer compute the *Gram matrix* giving outer product of features:

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}$$ (shape $C_i \times C_i$)

4. Initialize generated image from random noise
5. Pass generated image through CNN, compute Gram matrix on each layer



Neural Texture Synthesis

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} \left(G_{ij}^l - \hat{G}_{ij}^l\right)^2 \qquad \mathcal{L}(\vec{x}, \hat{\vec{x}}) = \sum_{l=0}^{L} w_l E_l$$

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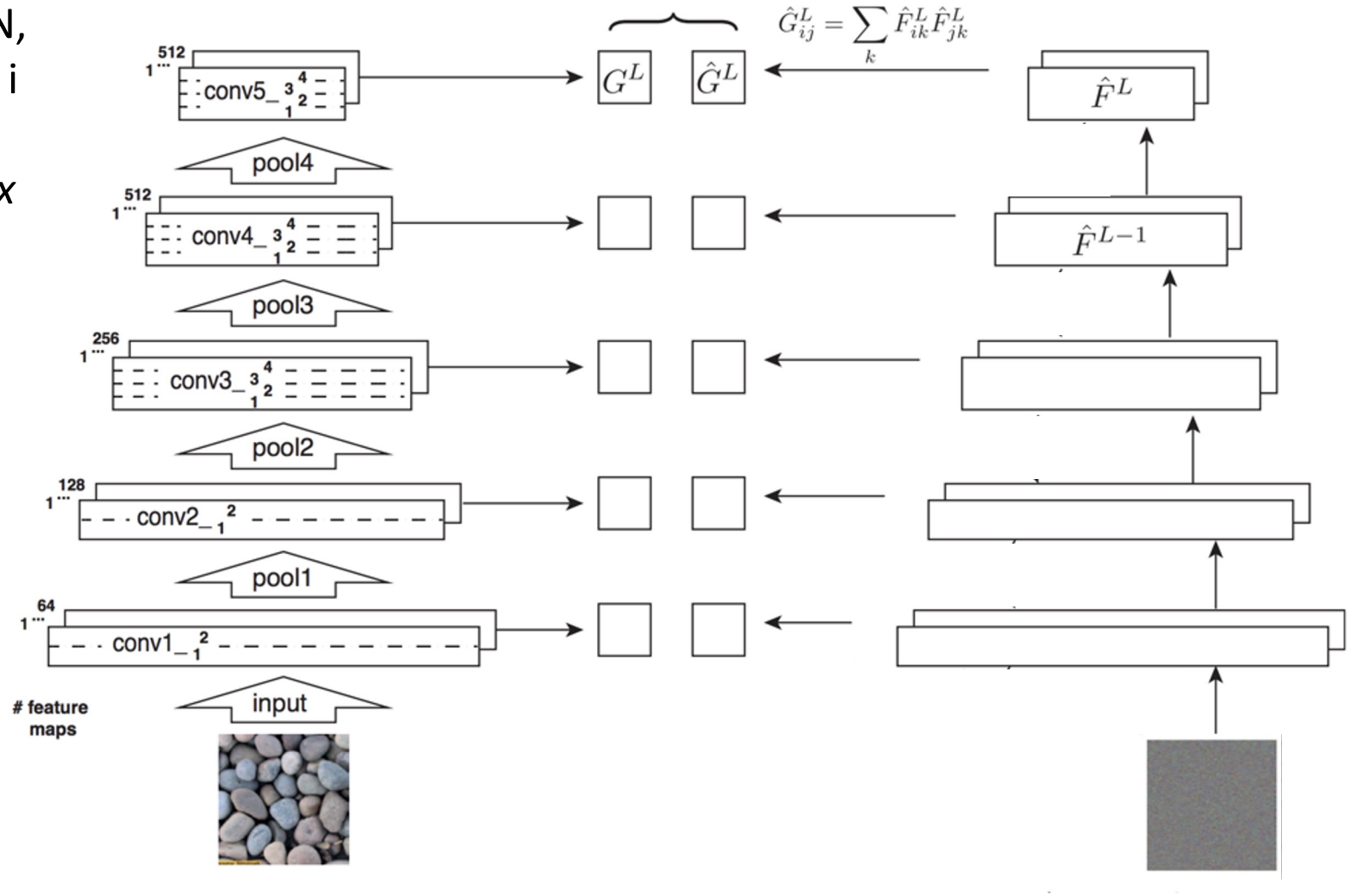
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices



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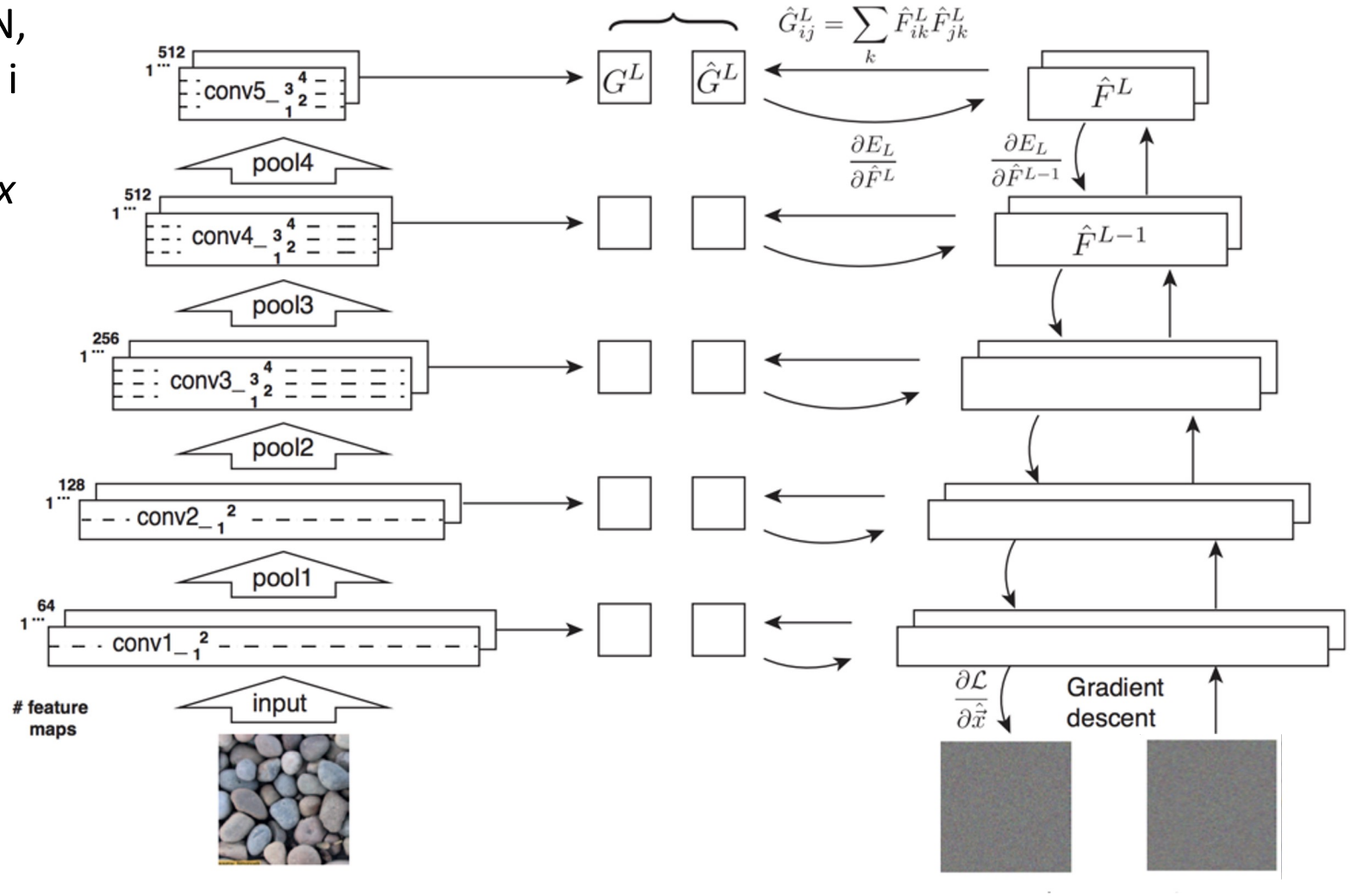
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image



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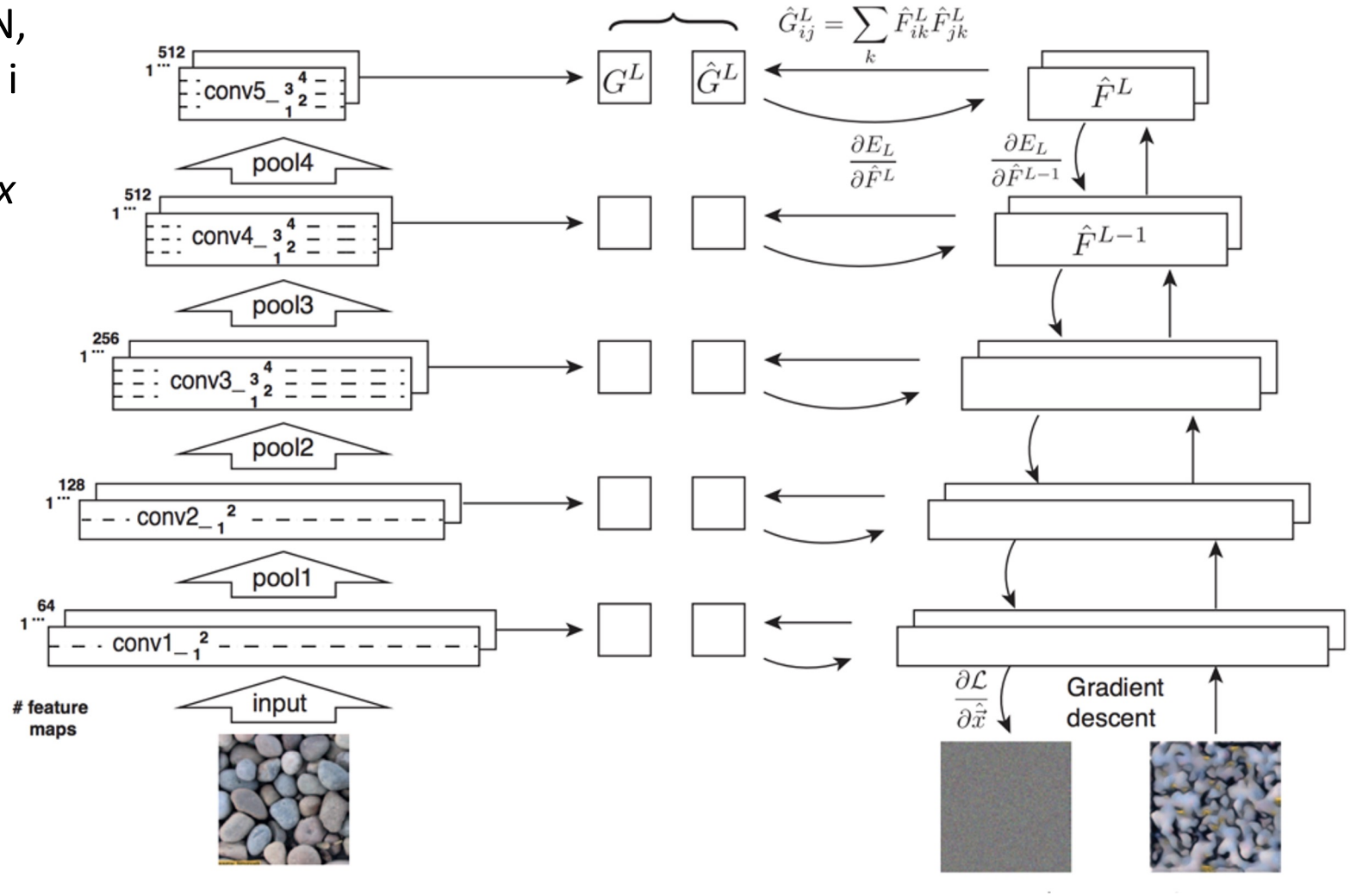
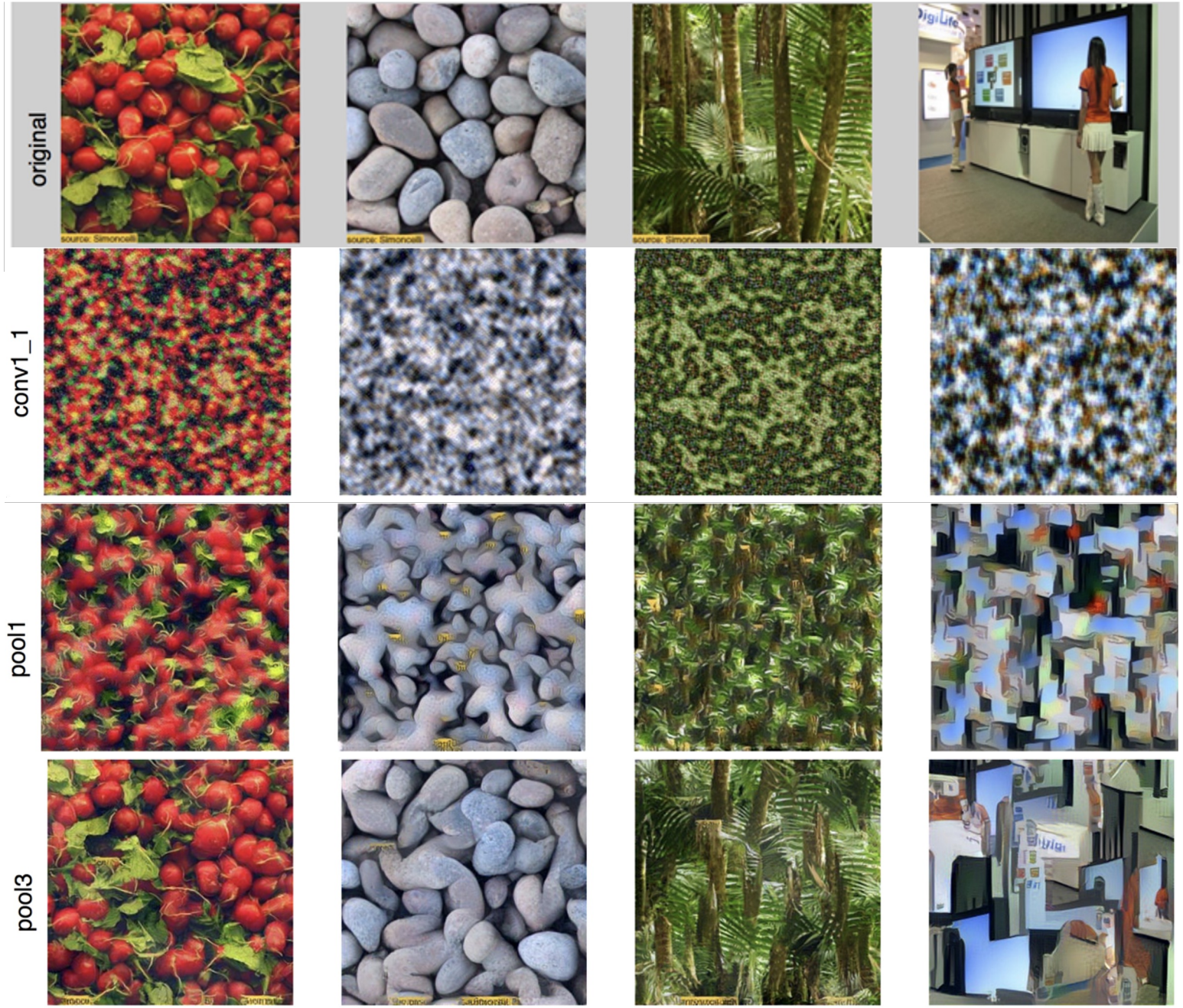
4. Initialize generated image from random noise
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image
9. GOTO 5



Neural Texture Synthesis

Reconstructing texture from higher layers recovers larger features from the input texture



Gatys, Ecker, and Bethge, “Texture Synthesis Using Convolutional Neural Networks”, NIPS 2015

Neural Texture Synthesis: Texture = Artwork

Texture synthesis (Gram reconstruction)

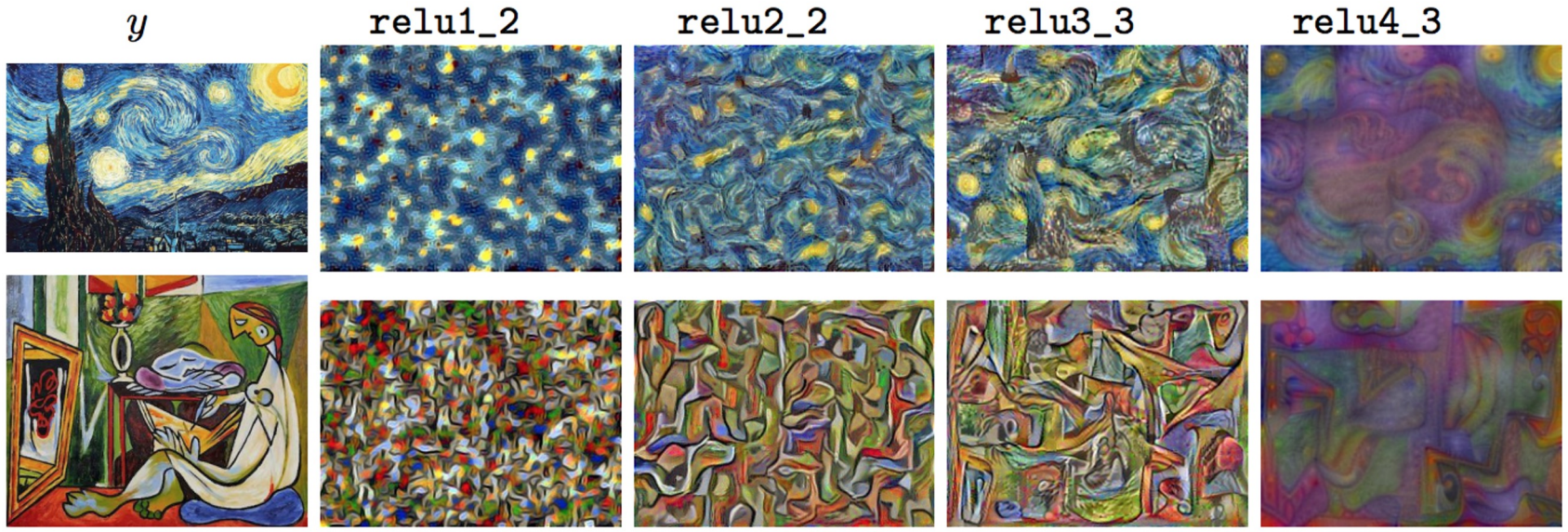
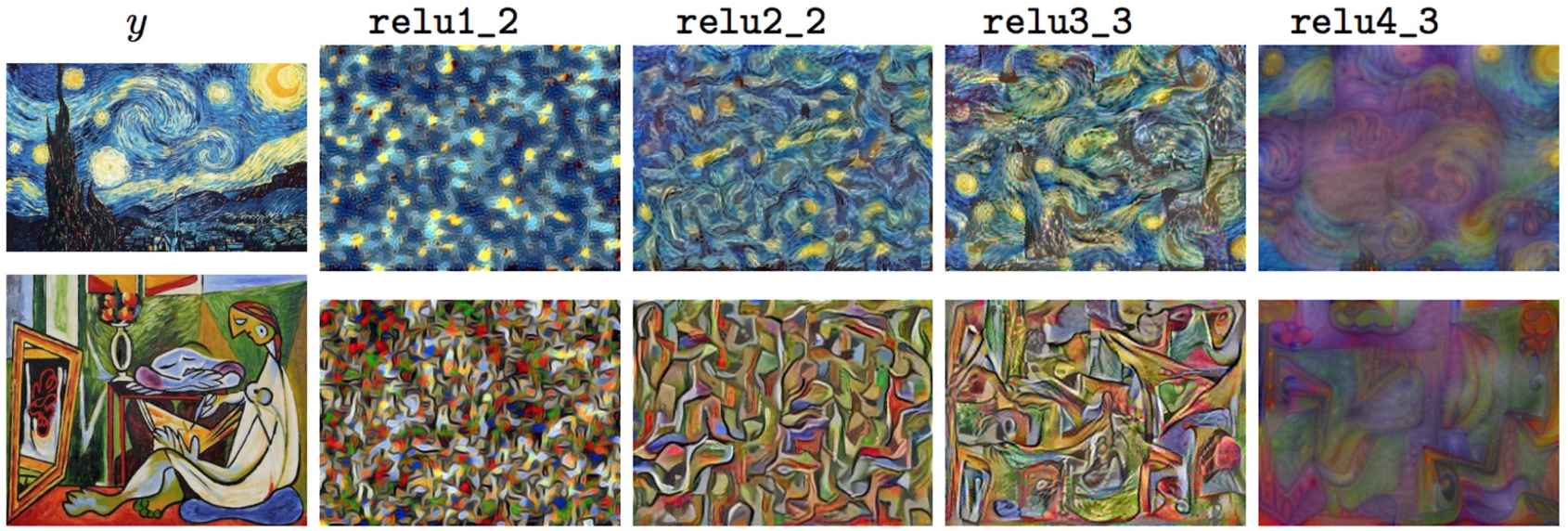


Figure from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Neural Style Transfer: Feature + Gram Reconstruction

Texture synthesis (Gram reconstruction)



Feature reconstruction

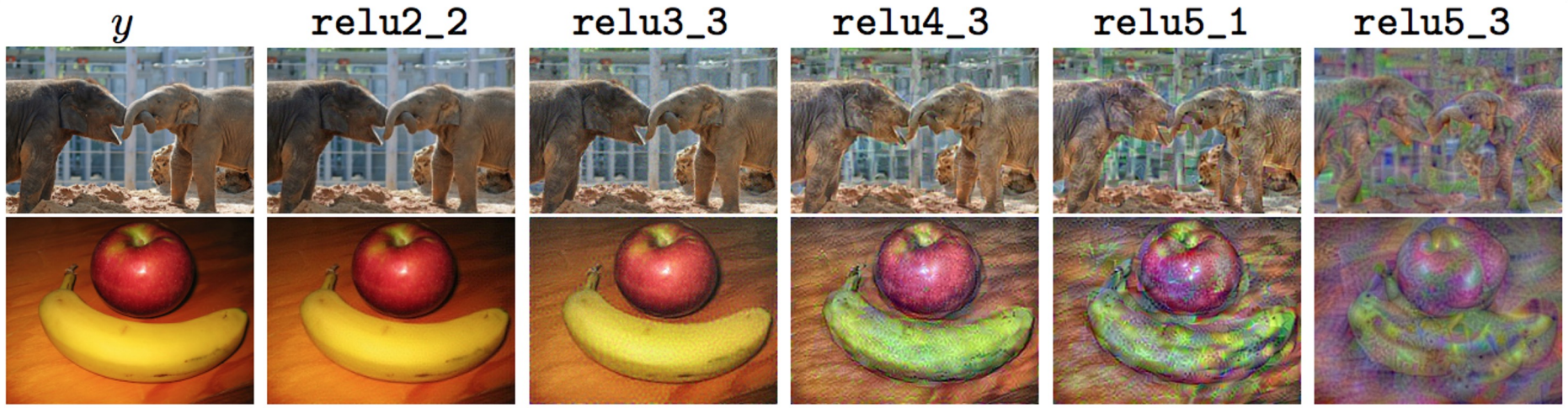


Figure from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Neural Style Transfer

Content Image

This image is licensed under CC-BY 3.0

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Style Image

Starry Night by Van Gogh is in the public domain

=

Output Image

Match features from content image and Gram matrices from style image

Gatys, Ecker, and Bethge, “Image style transfer using convolutional neural networks”, CVPR 2016

Neural Style Transfer

Content Image

This image is licensed under CC-BY 3.0

+

Style Image

Starry Night by Van Gogh is in the public domain

=

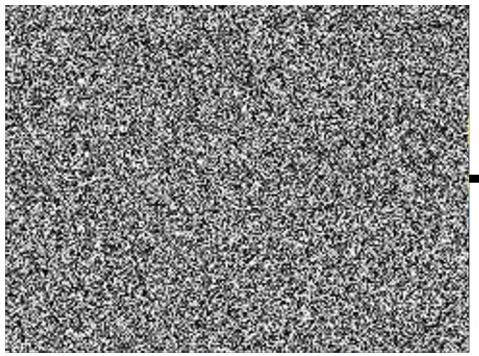
Output Image

This image copyright Justin Johnson, 2015. Reproduced with permission.

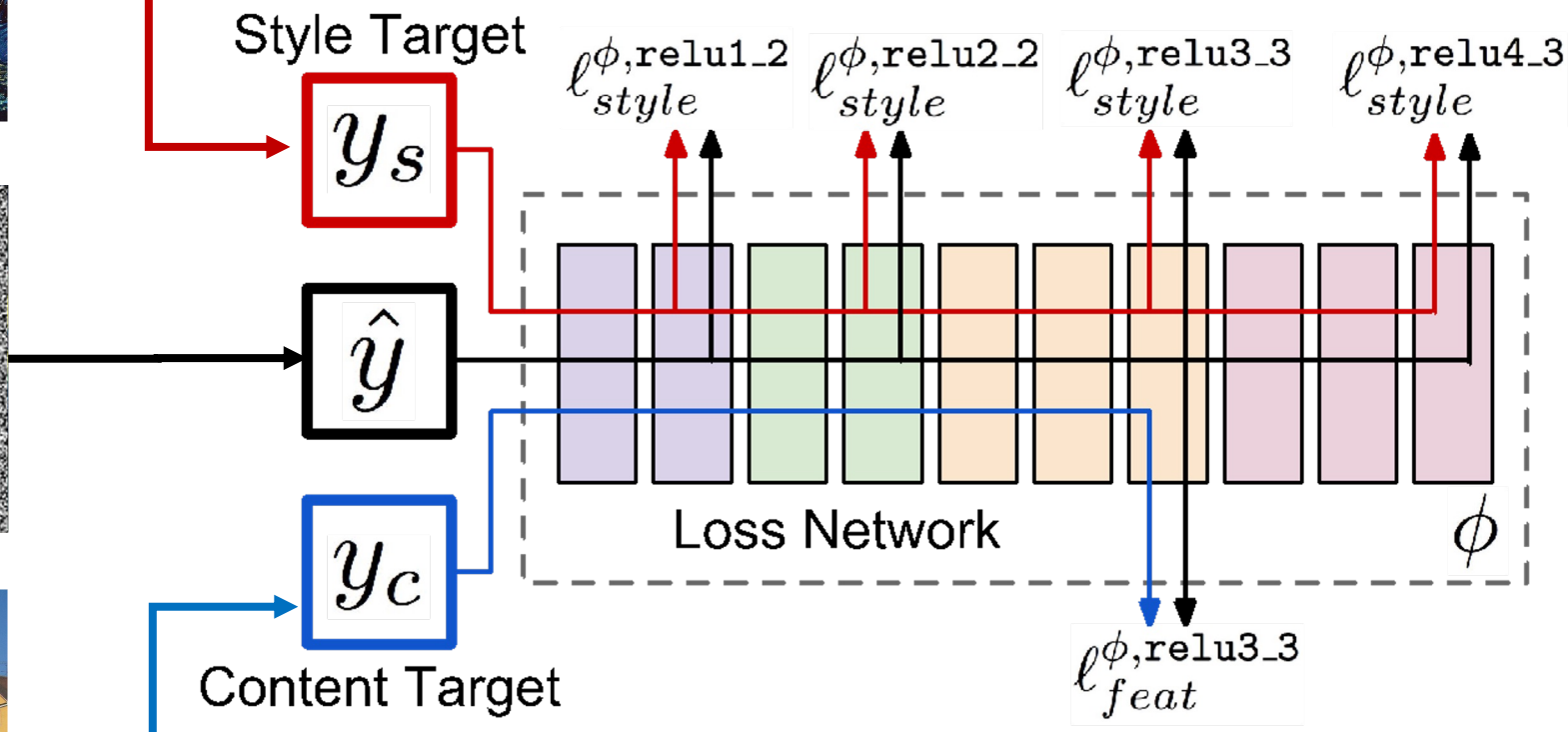
Gatys, Ecker, and Bethge, “Image style transfer using convolutional neural networks”, CVPR 2016

Style image

Output image (Start with noise)



Content image

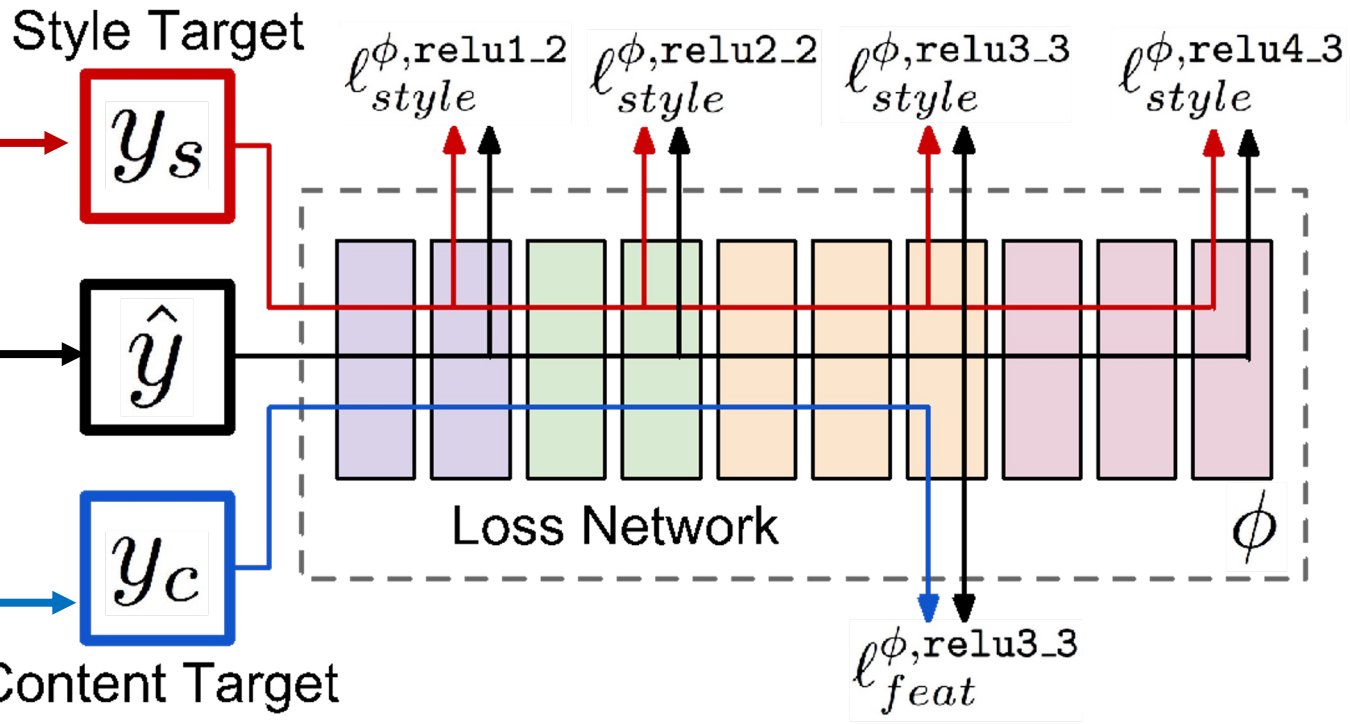


Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016
Figure adapted from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Style image

Output image

Content image



Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016
Figure adapted from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Neural Style Transfer

Gatys, Ecker, and Bethge, “Image style transfer using convolutional neural networks”, CVPR 2016
Figure copyright Justin Johnson, 2015.

Neural Style Transfer

More weight to content loss

More weight to style loss

Neural Style Transfer

Resizing style image before running style transfer algorithm can transfer different types of features

Larger style image ⟷ Smaller style image

Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016

Neural Style Transfer: Multiple Style Images

Mix style from multiple images by taking a weighted average of Gram matrices

Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016

Neural Style Transfer

Problem: Style transfer requires many forward / backward passes through VGG; very slow!

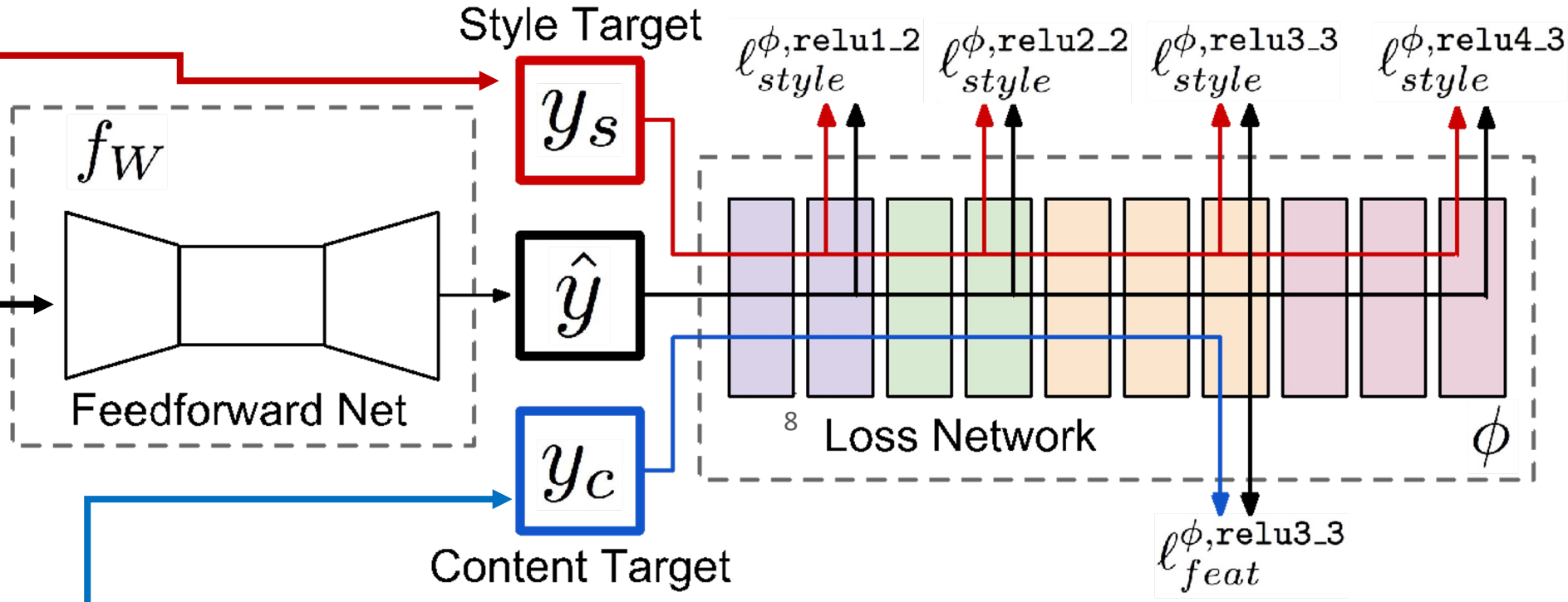
Neural Style Transfer

Problem: Style transfer requires many forward / backward passes through VGG; very slow!

Solution: Train another neural network to perform style transfer for us!

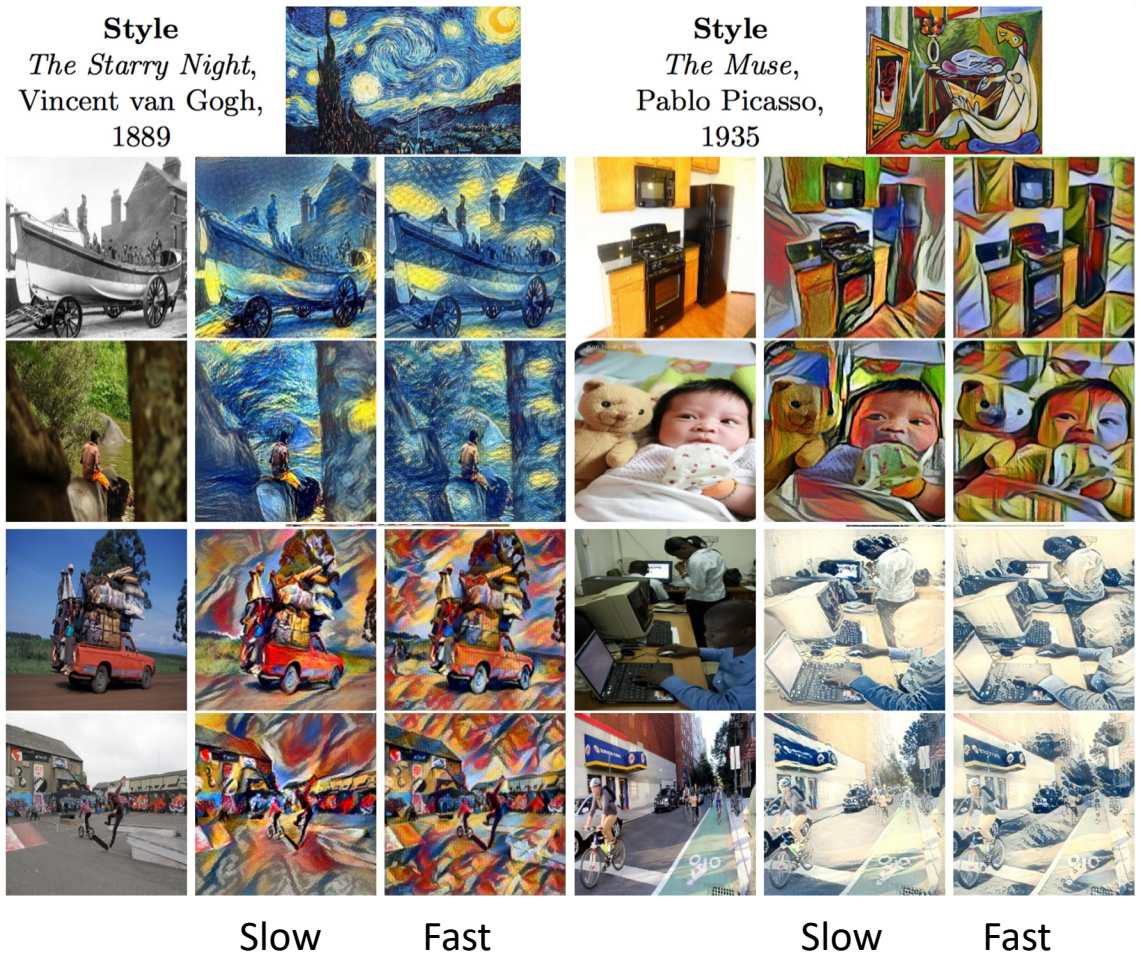
Fast Neural Style Transfer

(1) Train a feedforward network for each style
(2) Use pretrained CNN to compute same losses as before
(3) After training, stylize images using a single forward pass



Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016

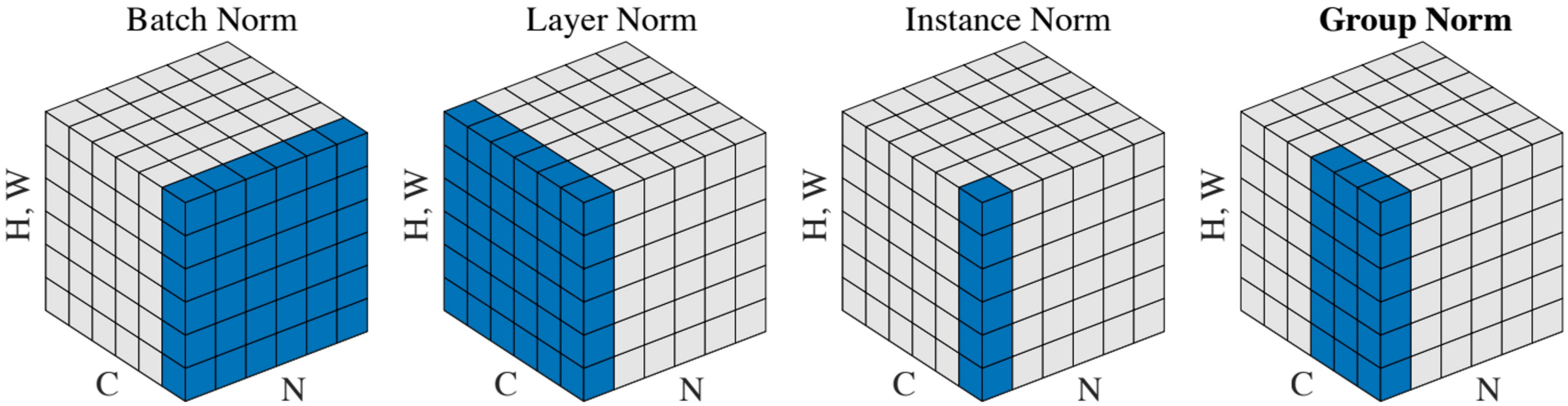
Fast Neural Style Transfer



https://github.com/jcjohnson/fast-neural-style

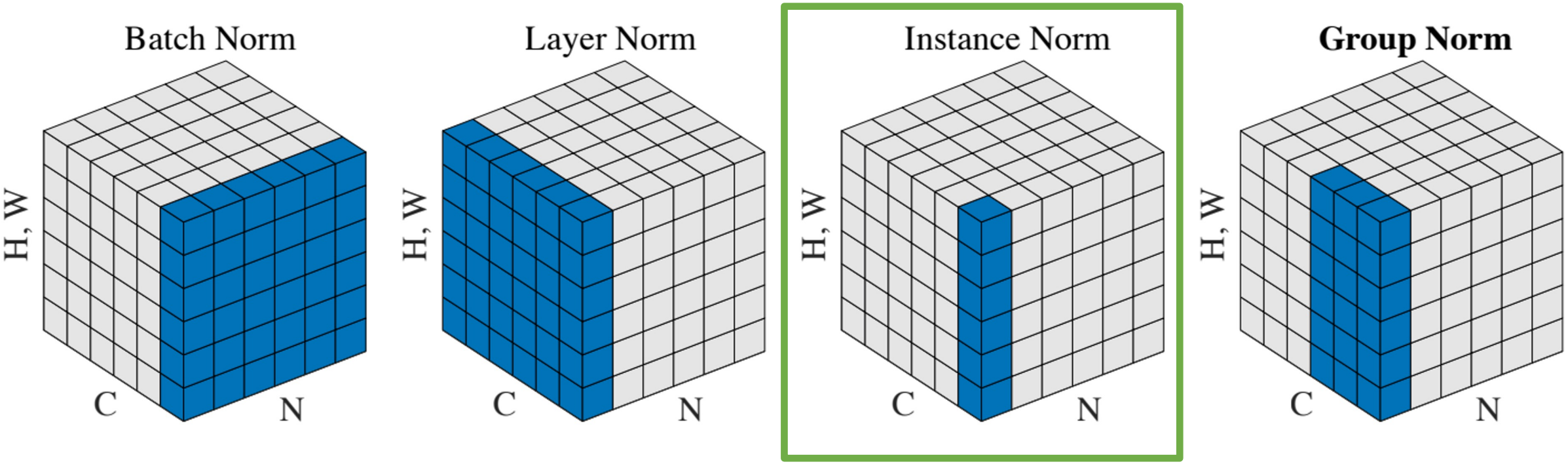
Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016

Recall Normalization Methods?



Recall Normalization Methods?

Instance Normalization was developed for style transfer!



Fast Neural Style Transfer

Replacing batch normalization with Instance Normalization improves results

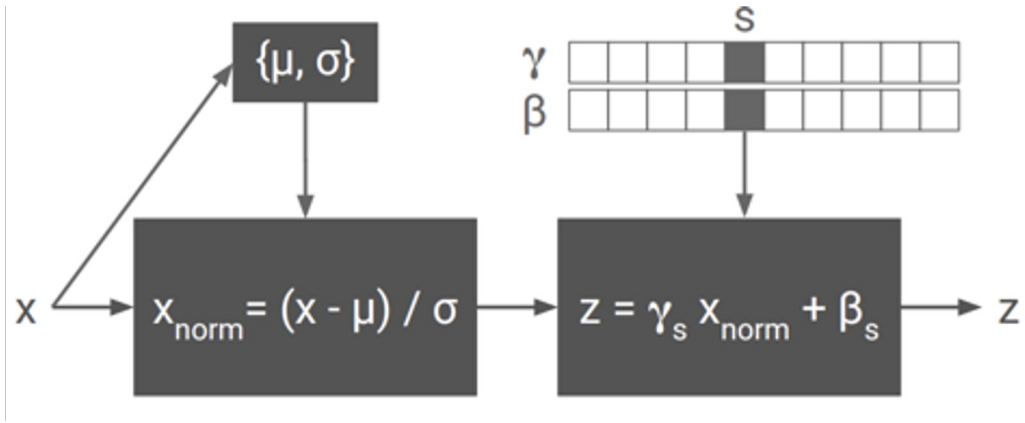
Ulyanov et al, “Texture Networks: Feed-forward Synthesis of Textures and Stylized Images”, ICML 2016
Ulyanov et al, “Instance Normalization: The Missing Ingredient for Fast Stylization”, arXiv 2016

One Network, Many Styles

Dumoulin, Shlens, and Kudlur, “A Learned Representation for Artistic Style”, ICLR 2017.

One Network, Many Styles

Use the same network for multiple styles using *conditional instance normalization*: learn separate scale and shift parameters per style



Single network can blend styles after training

Dumoulin, Shlens, and Kudlur, "A Learned Representation for Artistic Style", ICLR 2017.

Summary

Many methods for understanding CNN representations

Activations: Nearest neighbors, Dimensionality reduction, maximal patches, occlusion, CAM
Gradients: Grad-CAM, Saliency maps, class visualization, fooling images, feature inversion
Fun: DeepDream, Style Transfer.

Summary

More related work on network interpretation:
https://distill.pub/2017/feature-visualization/
https://distill.pub/2019/activation-atlas/

Recommended blog site: https://distill.pub/

Next Time:
RNN, Attention, Transformer