# Lecture 21: Visualizing Models and Generating Images

# Reminder: A5

Recurrent networks, attention, Transformers

We released a minor revision to the starter code today;
only fixes typos, no functional changes

Autograder will be up today

Due on **Tuesday 4/12**, 11:59pm ET

# A3 Grades

Released last night

Post regrade requests on Piazza until Monday 4/11

# Last Time: Generative Models

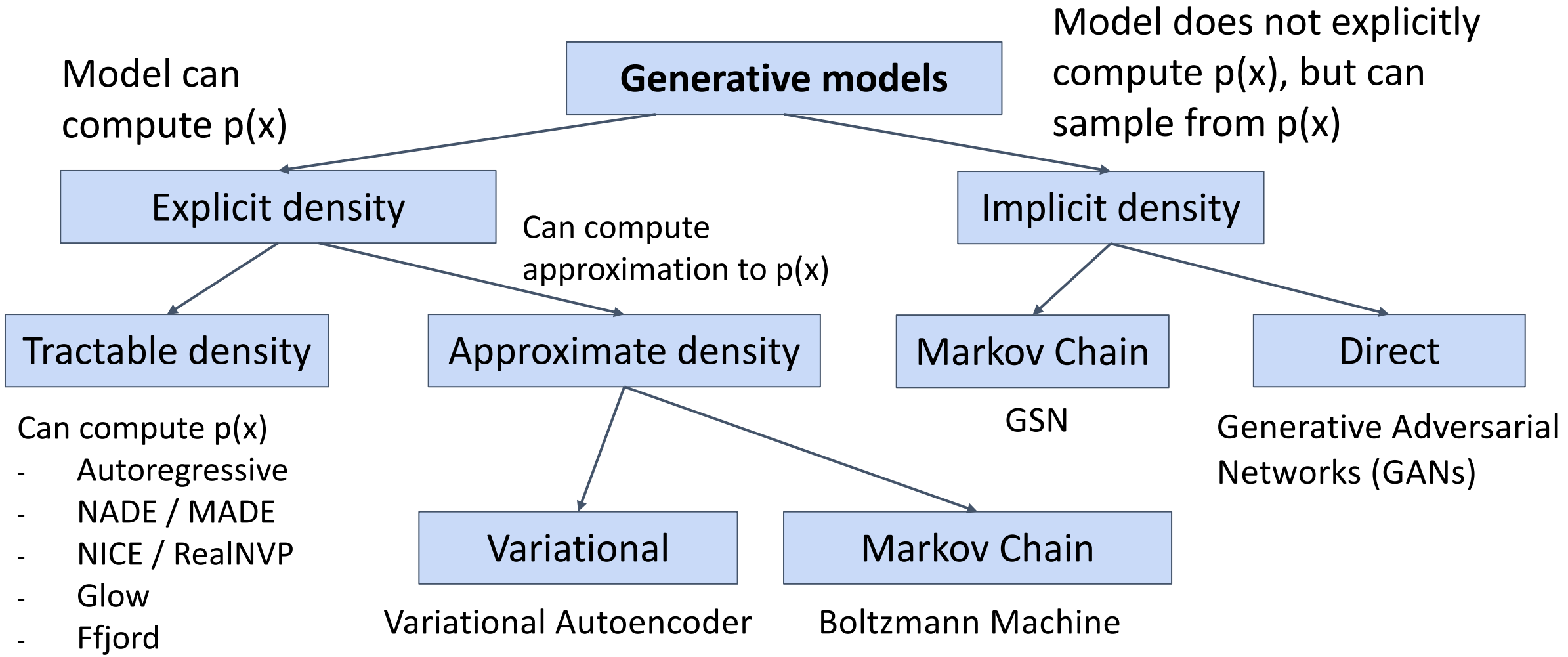



Figure adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

# Last Time: Generative Models

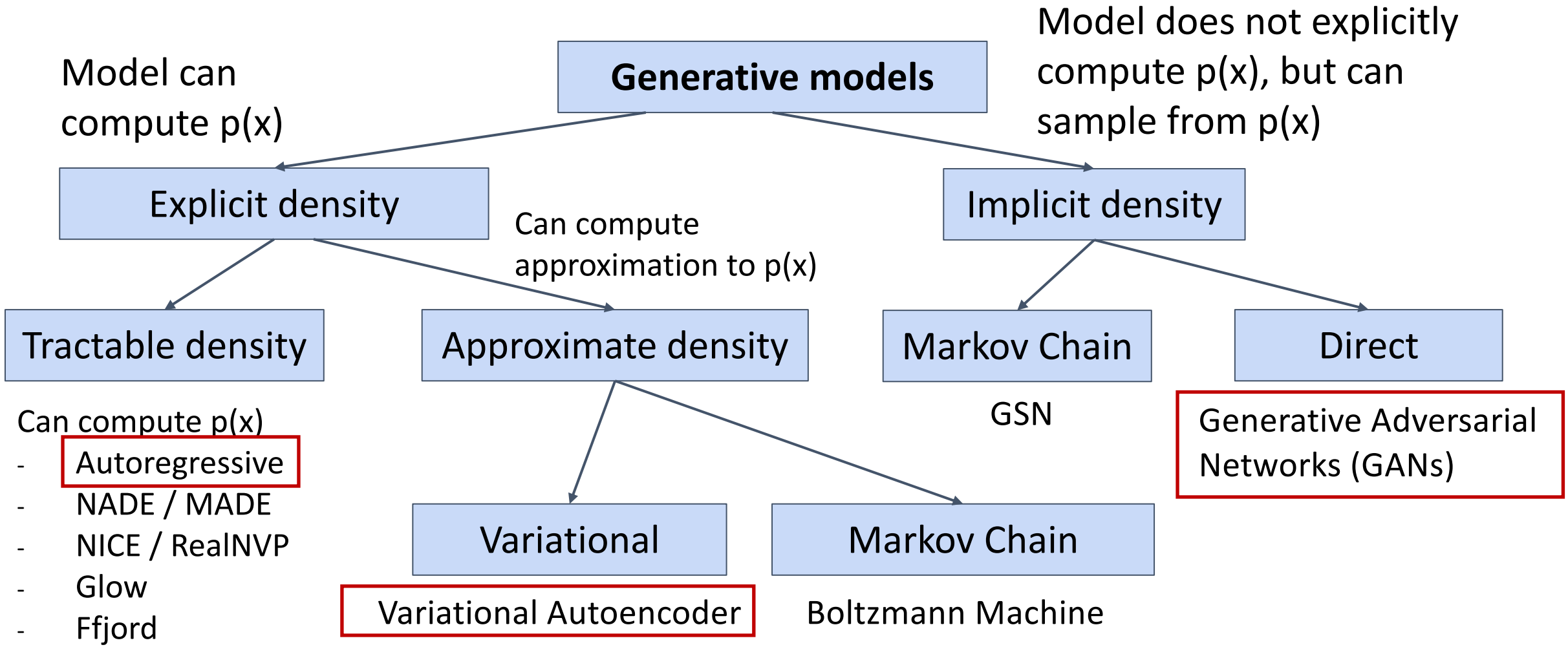
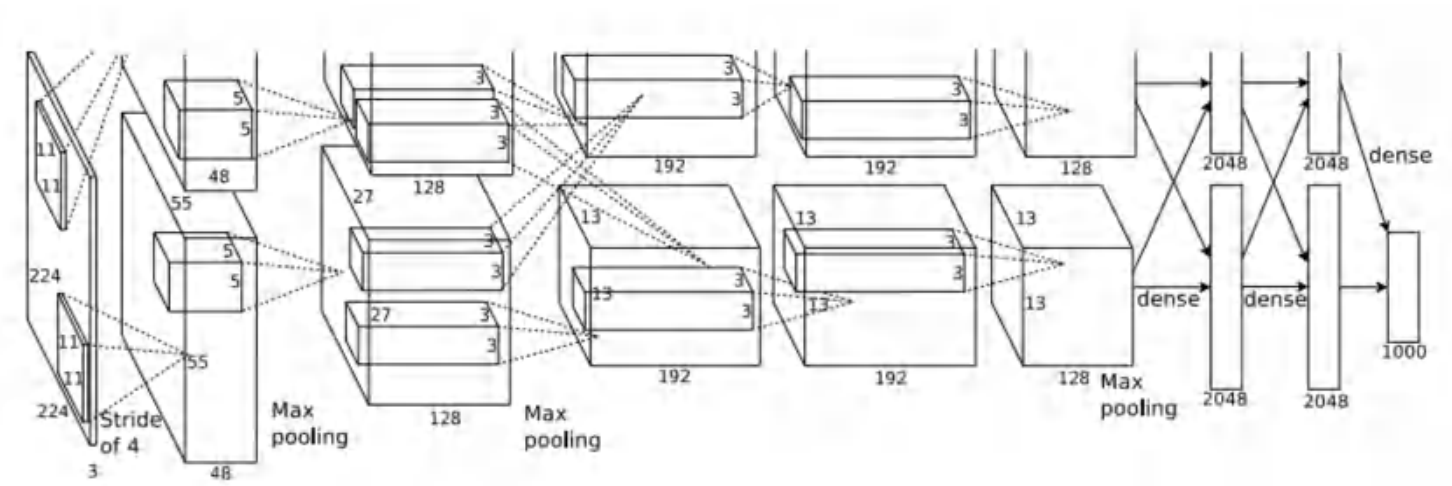



Figure adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

# Today: Visualizing Networks and Generating Images

# What's going on inside Convolutional Networks?





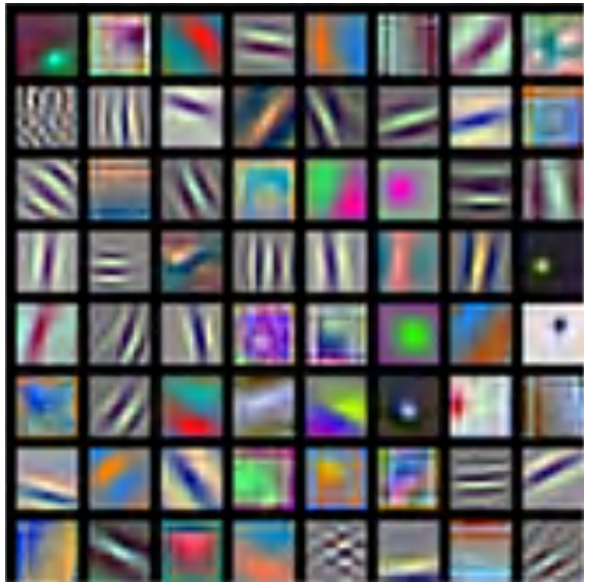

Class Scores:
1000 numbers

Input Image:
3 x 224 x 224

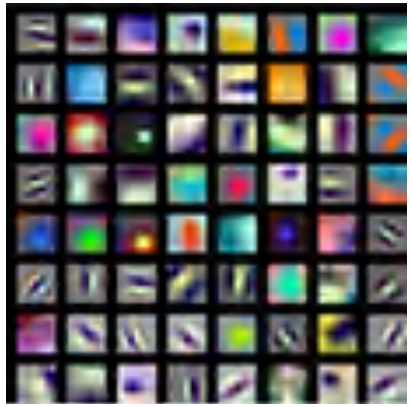
What are the intermediate features looking for?

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

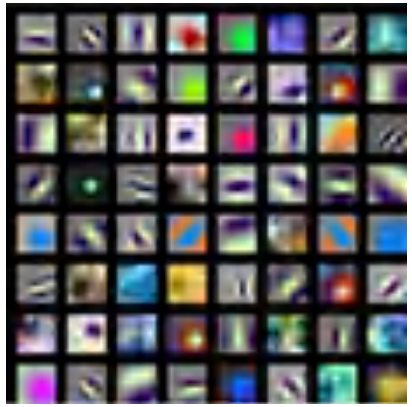
# First Layer: Visualize Filters



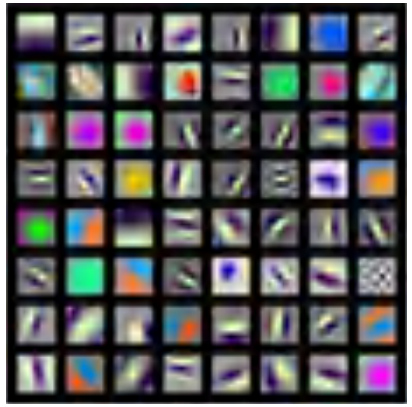
AlexNet:
64 x 3 x 11 x 11



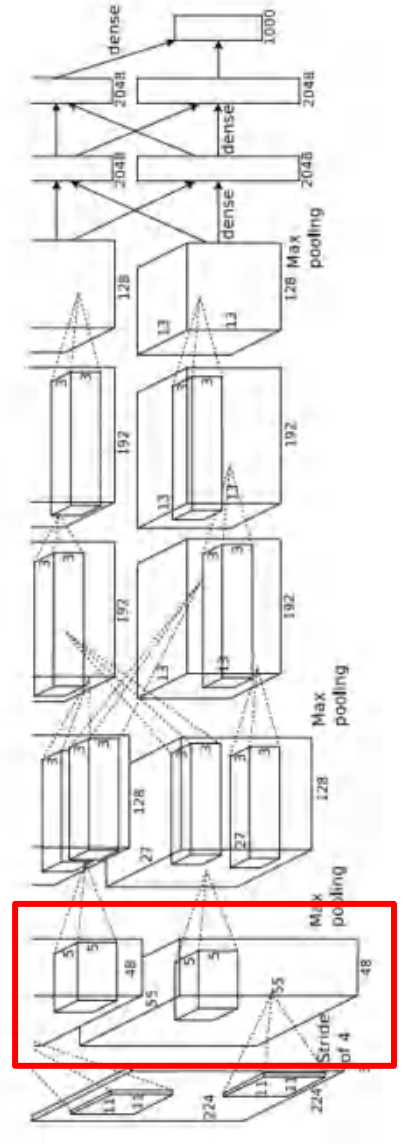
ResNet-18:
64 x 3 x 7 x 7



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

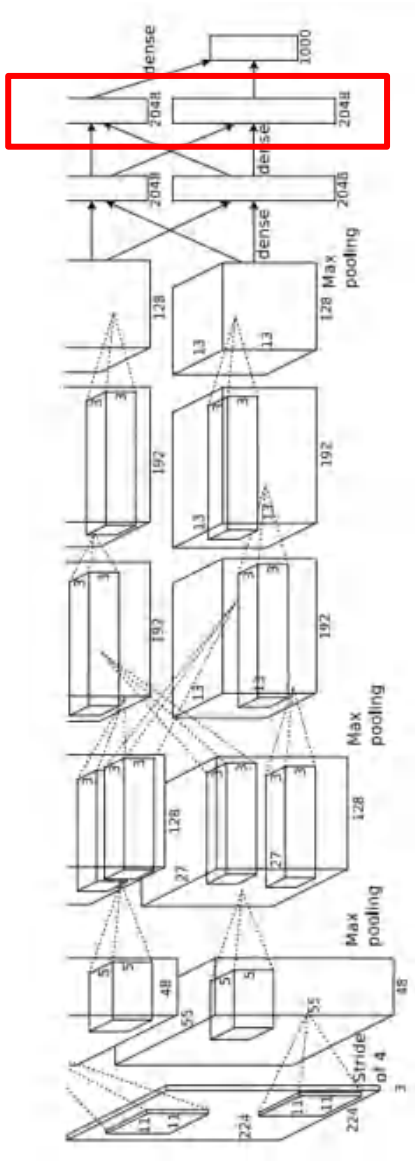
Second layer weights: 20 x 16 x 7 x 7

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

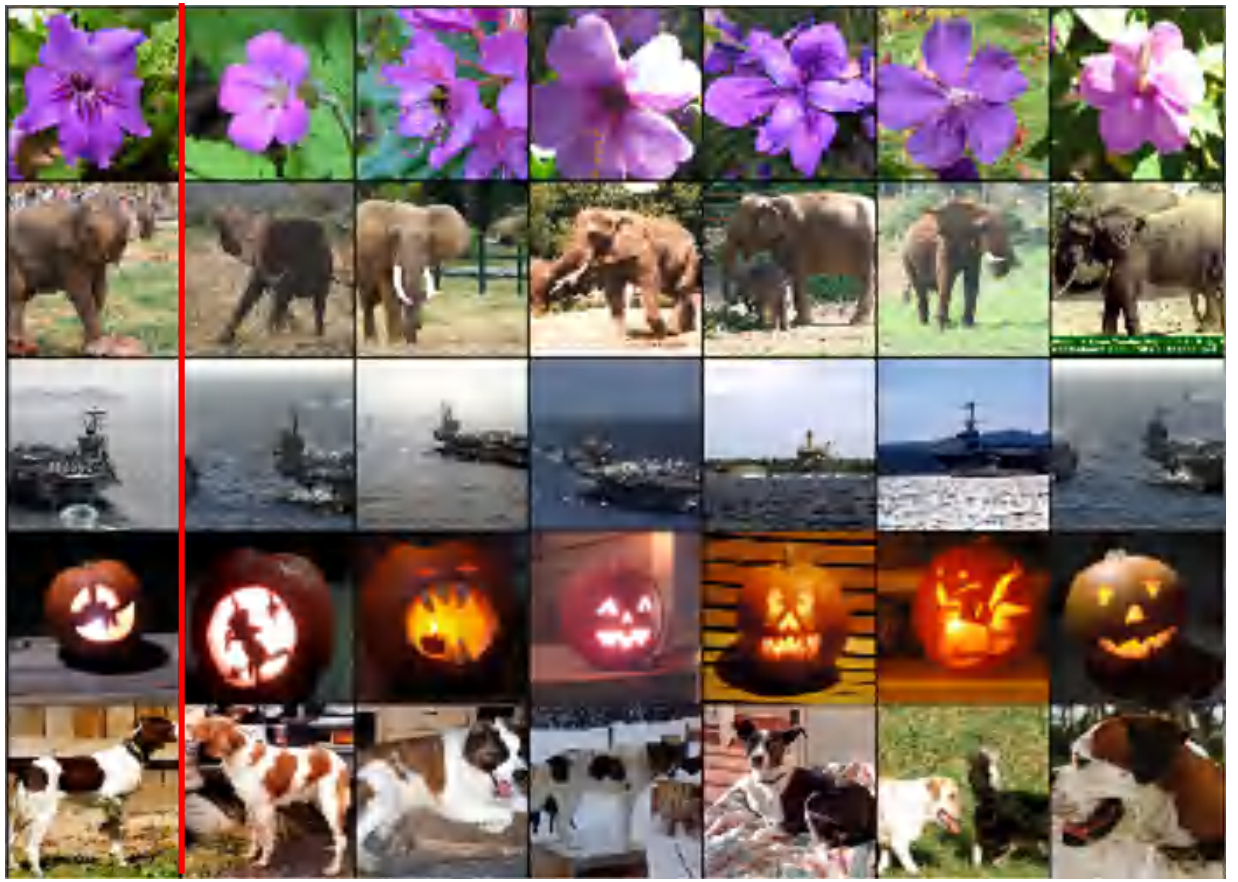
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NeurIPS 2012.
Figures reproduced with permission.

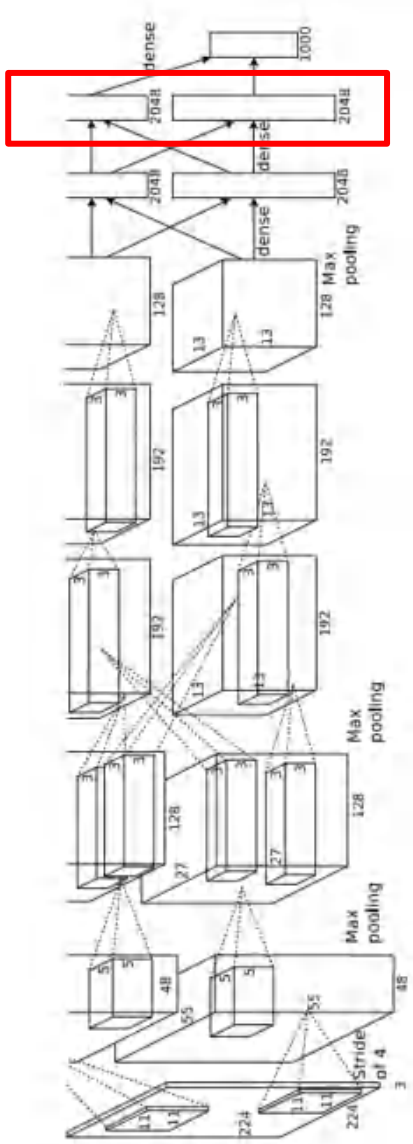
# Last Layer: Nearest Neighbors

**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.
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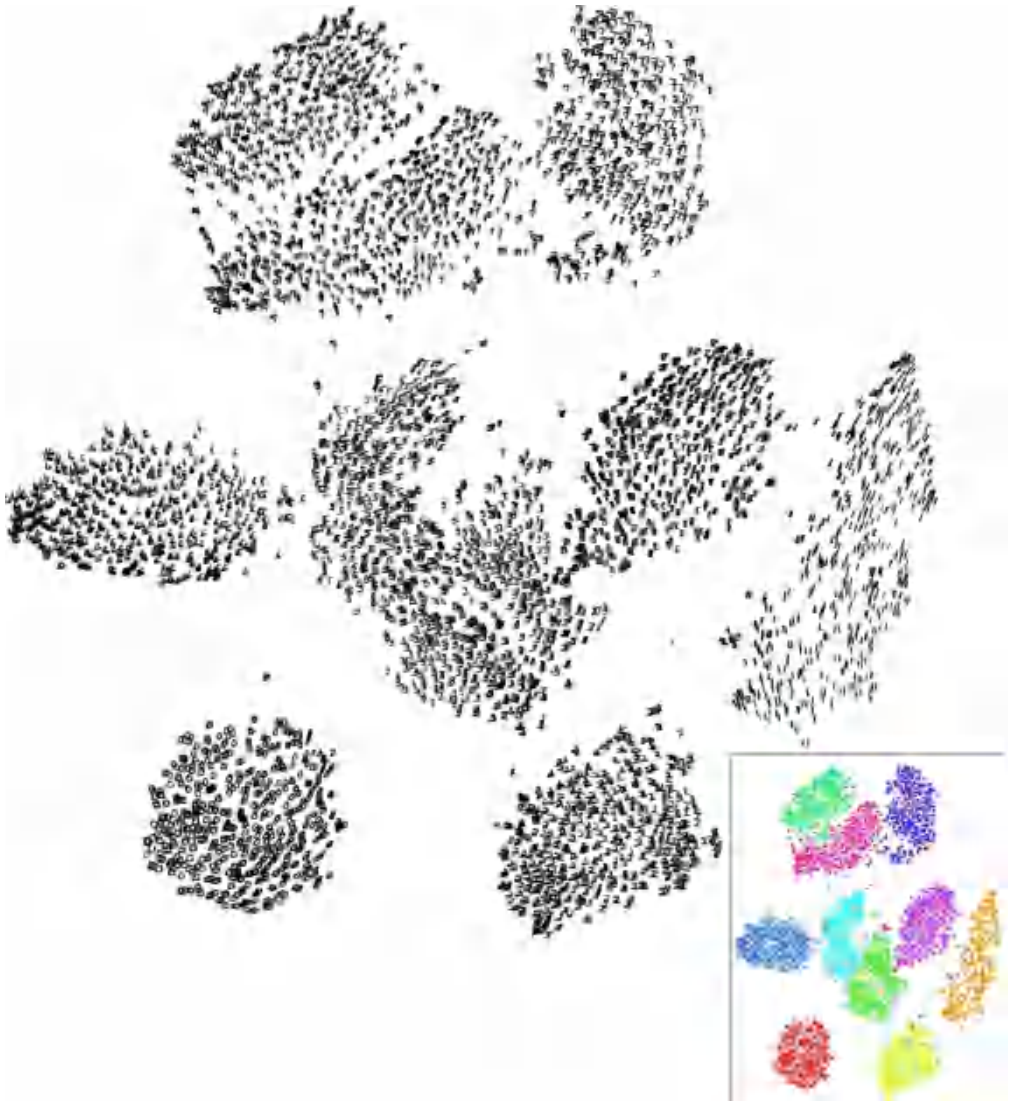
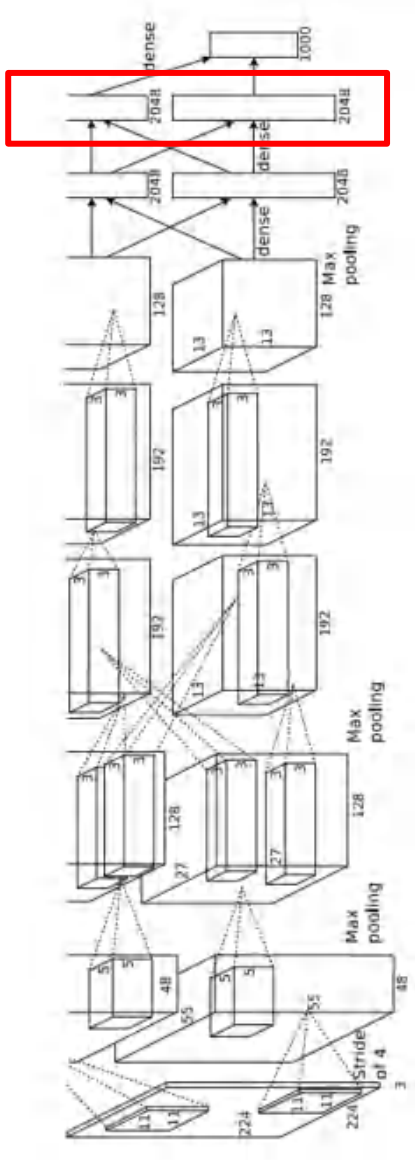
# Last Layer: Dimensionality Reduction

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
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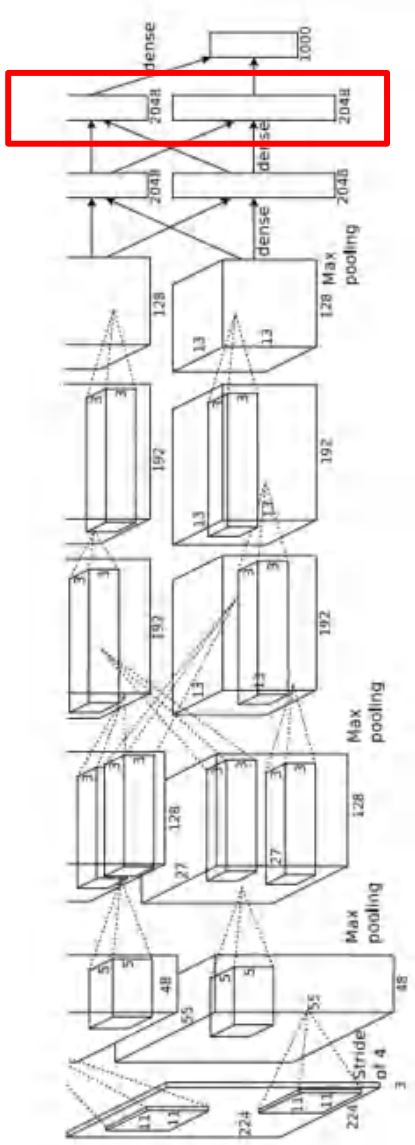
# Last Layer: Dimensionality Reduction

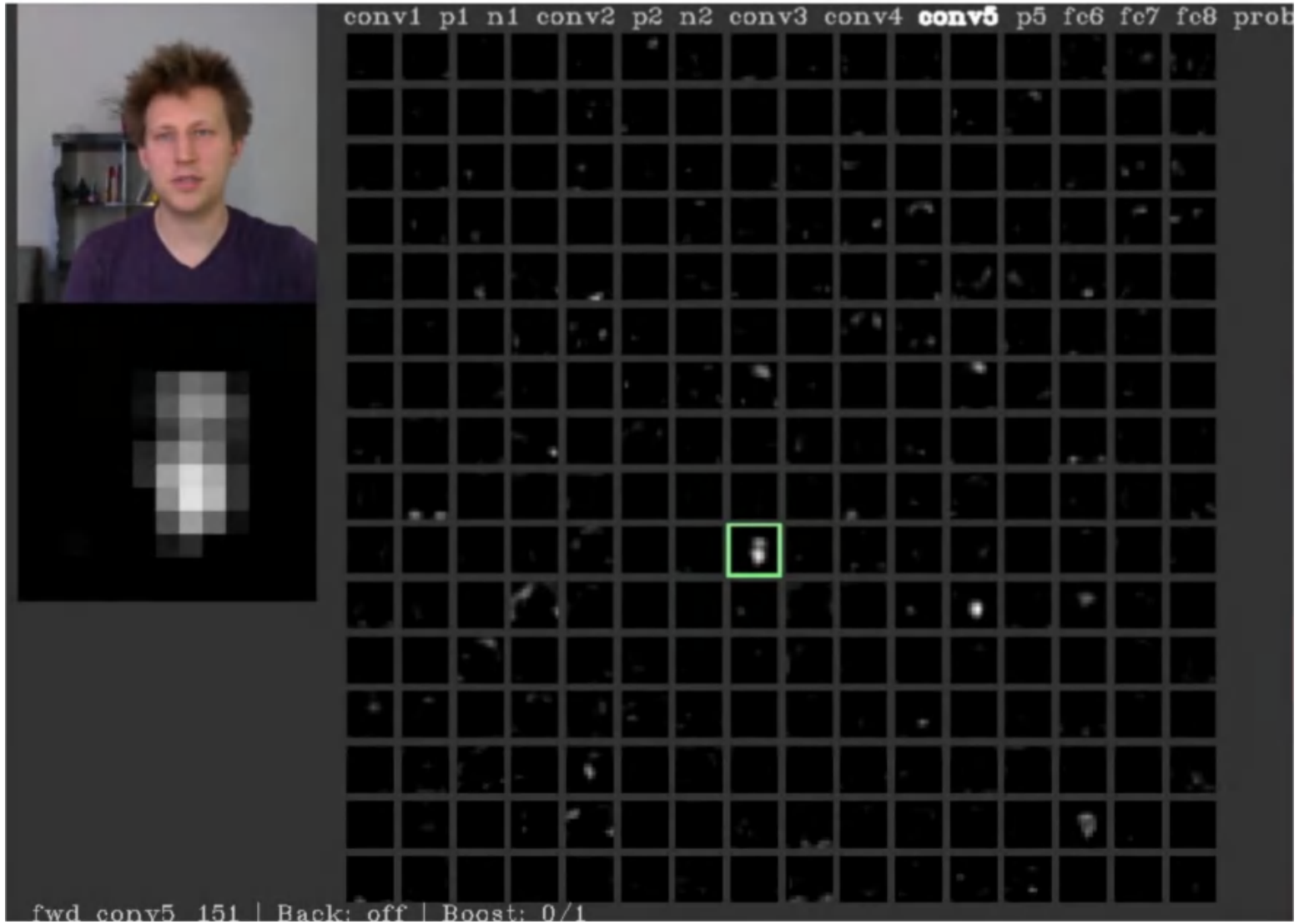



Van der Maaten and Hinton, "Visualizing Data using t-SNE", JMLR 2008
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

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

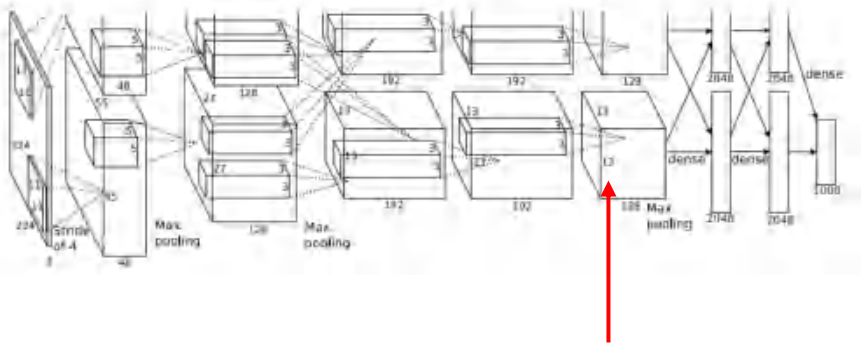
# Visualizing Activations

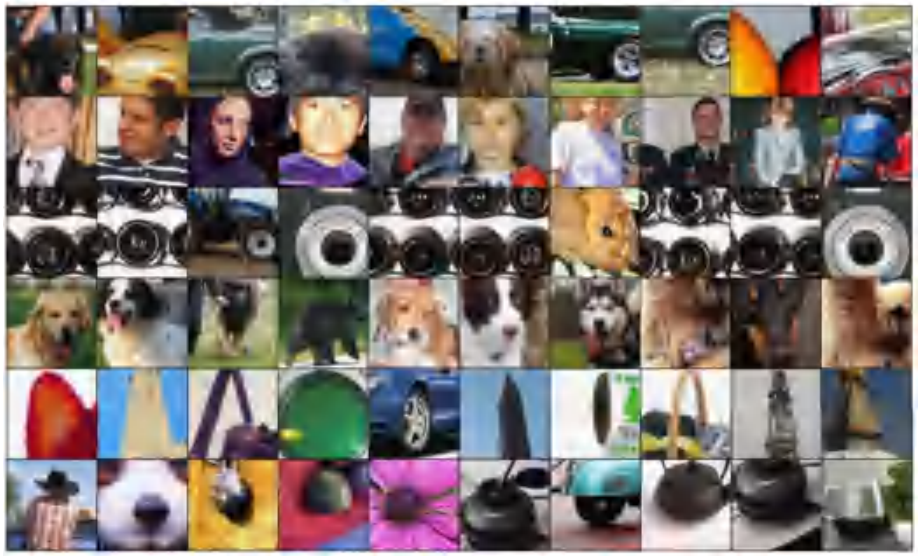
conv5 feature map is 128x13x13; visualize as 128 13x13 grayscale images




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

# Maximally Activating Patches





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

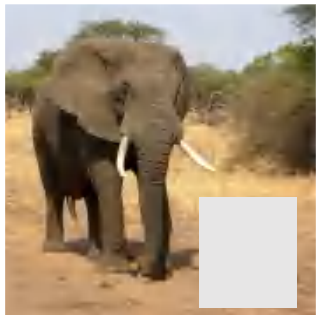
Run many images through the network, record values of chosen channel

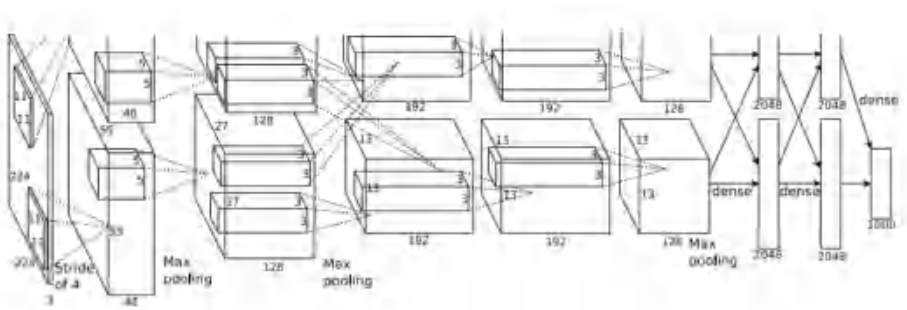
Visualize image patches that correspond to maximal activations

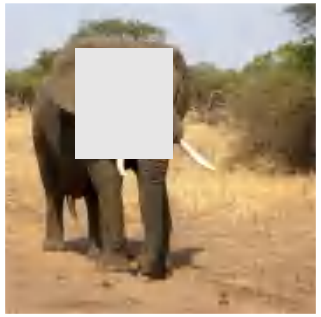
Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

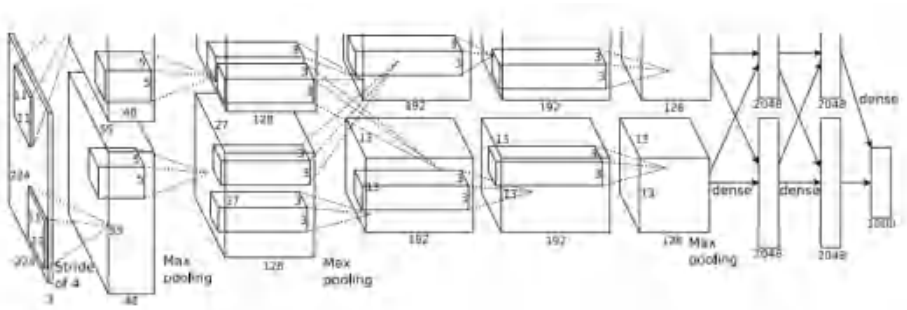
# Which Pixels Matter? Saliency via Occlusion

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





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Go-Karts image is CC0 public domain

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

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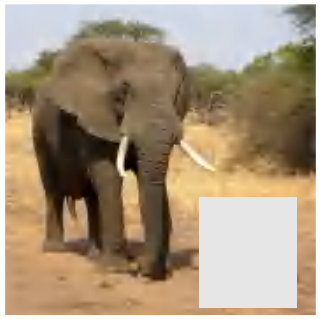

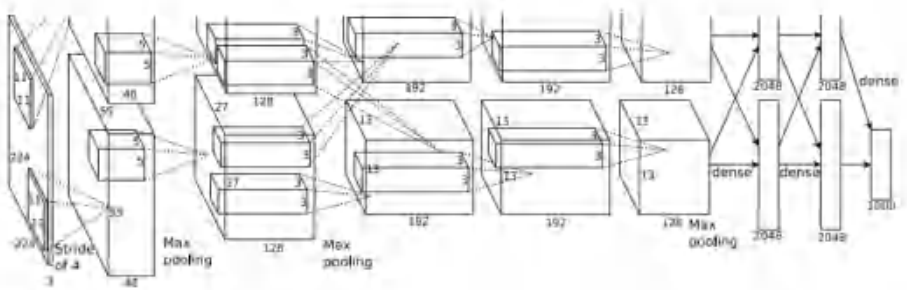


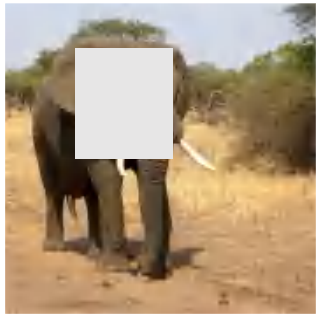

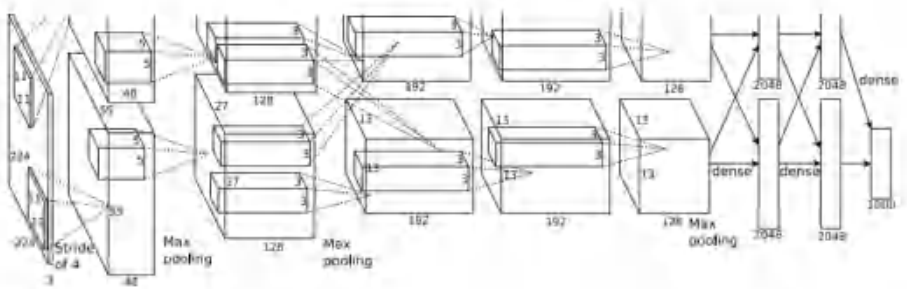



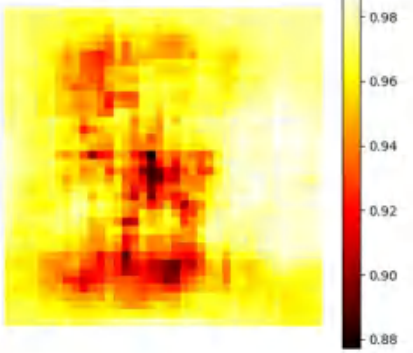


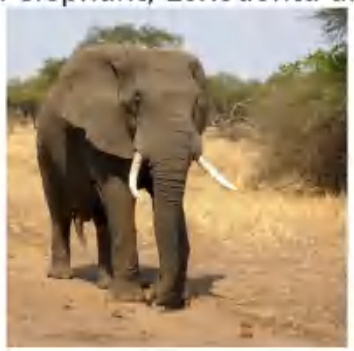


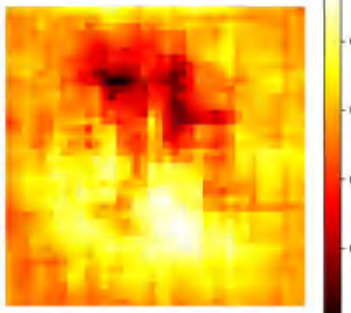



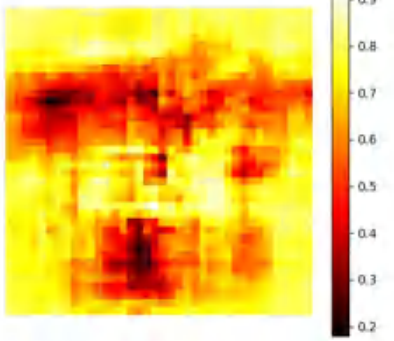


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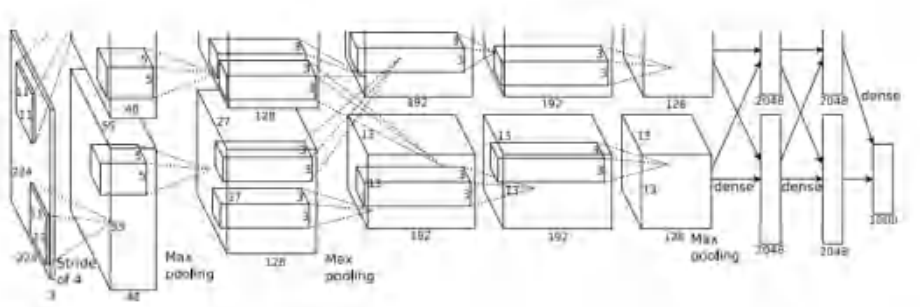
Elephant image is CC0 public domain
Go-Karts image is CC0 public domain

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.
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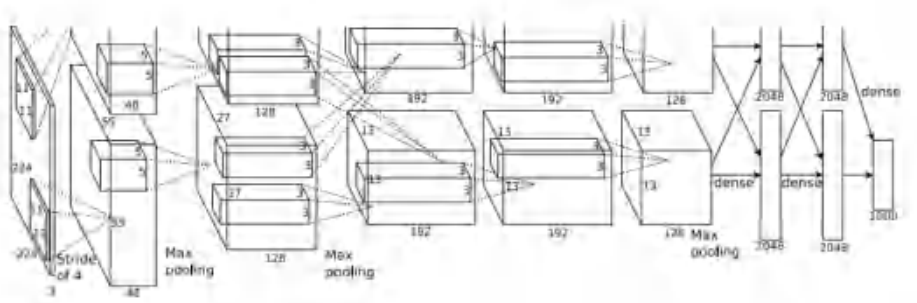
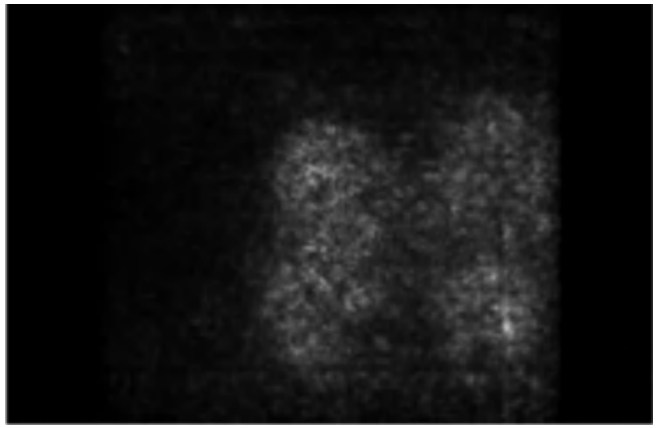



Dog

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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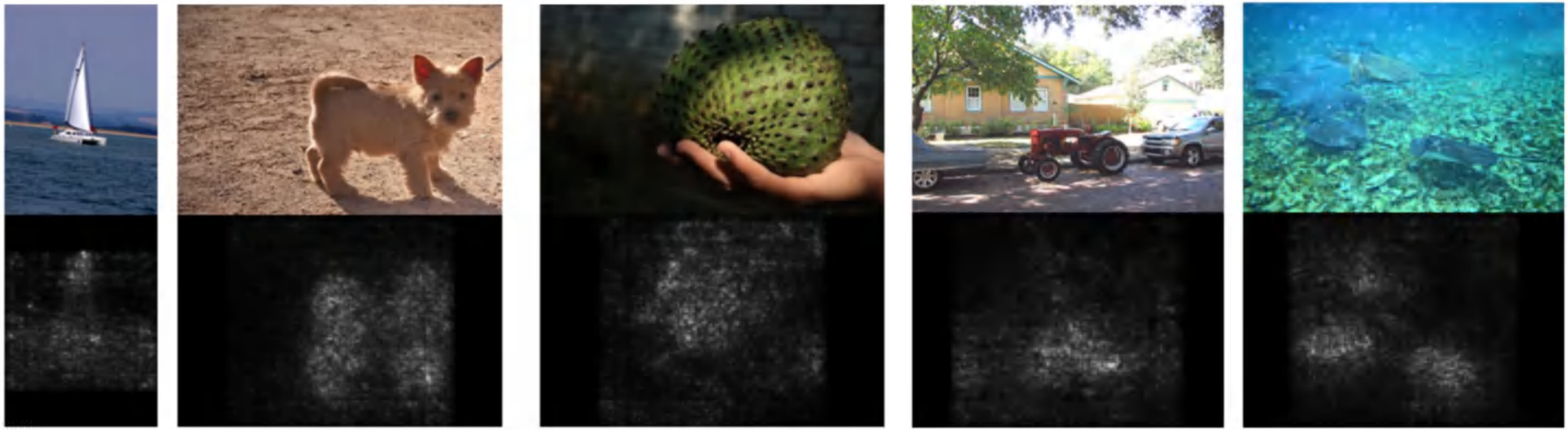

Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
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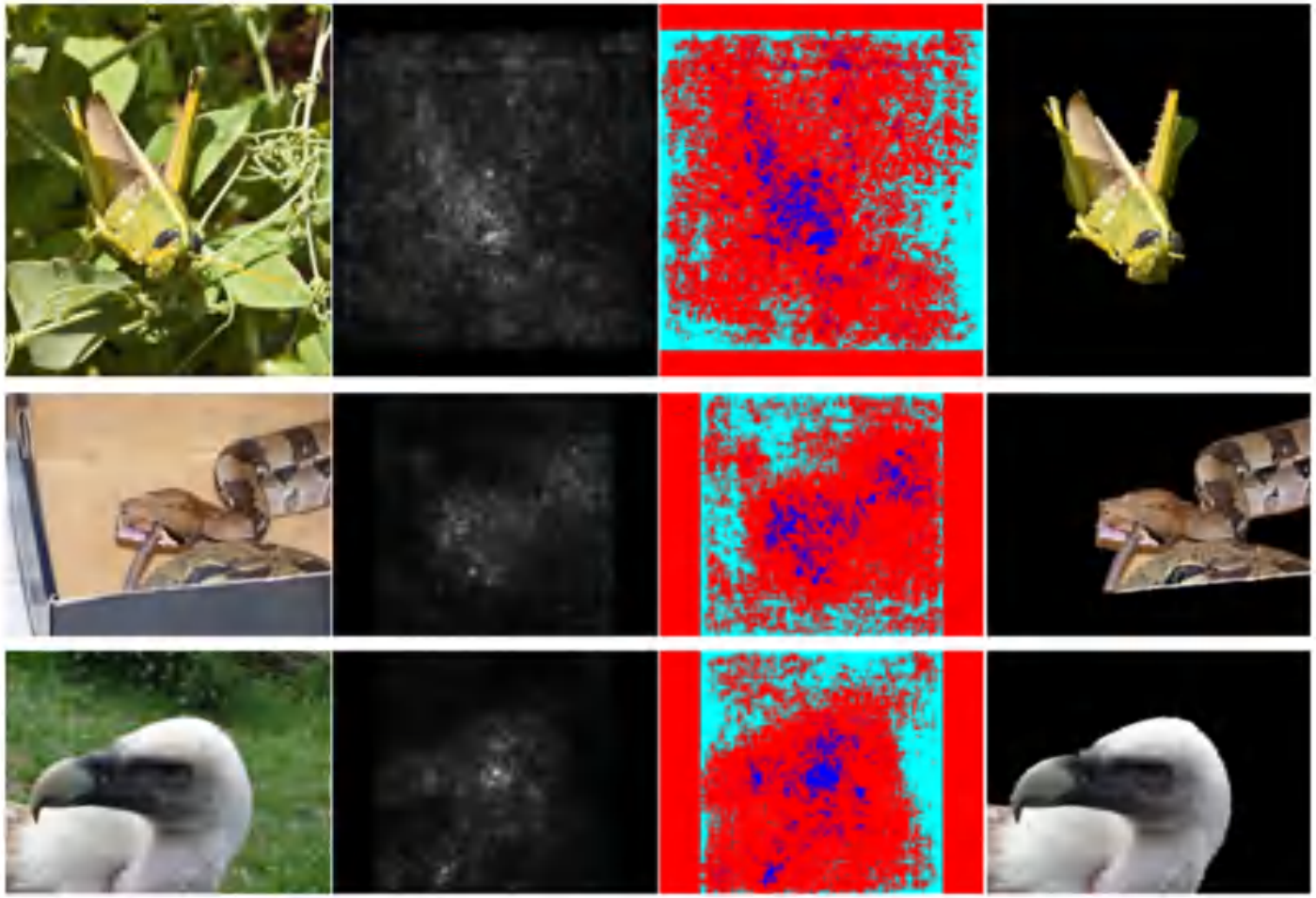
# Saliency Maps: Segmentation without Supervision

Use GrabCut on saliency map

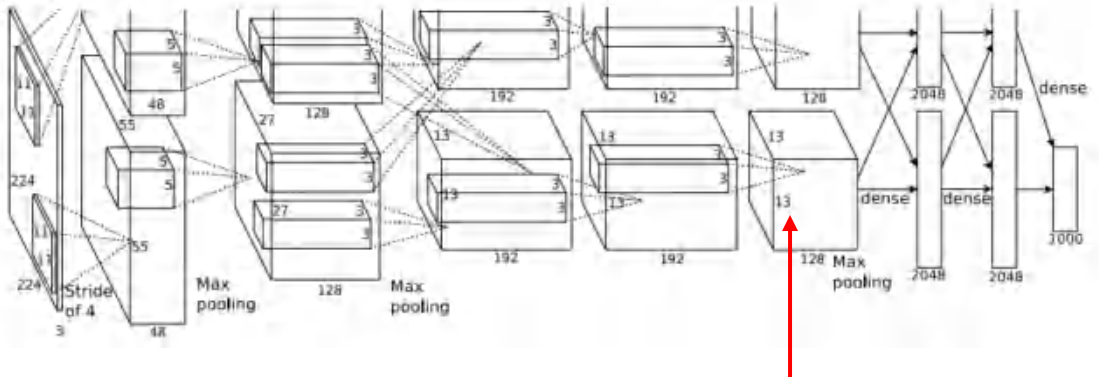


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.



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

# Intermediate Features via (guided) backprop

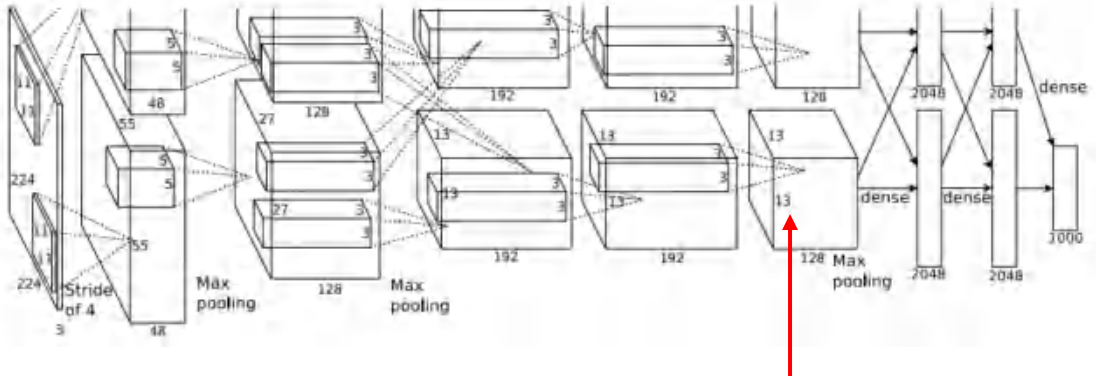



Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of neuron value with respect to image pixels

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

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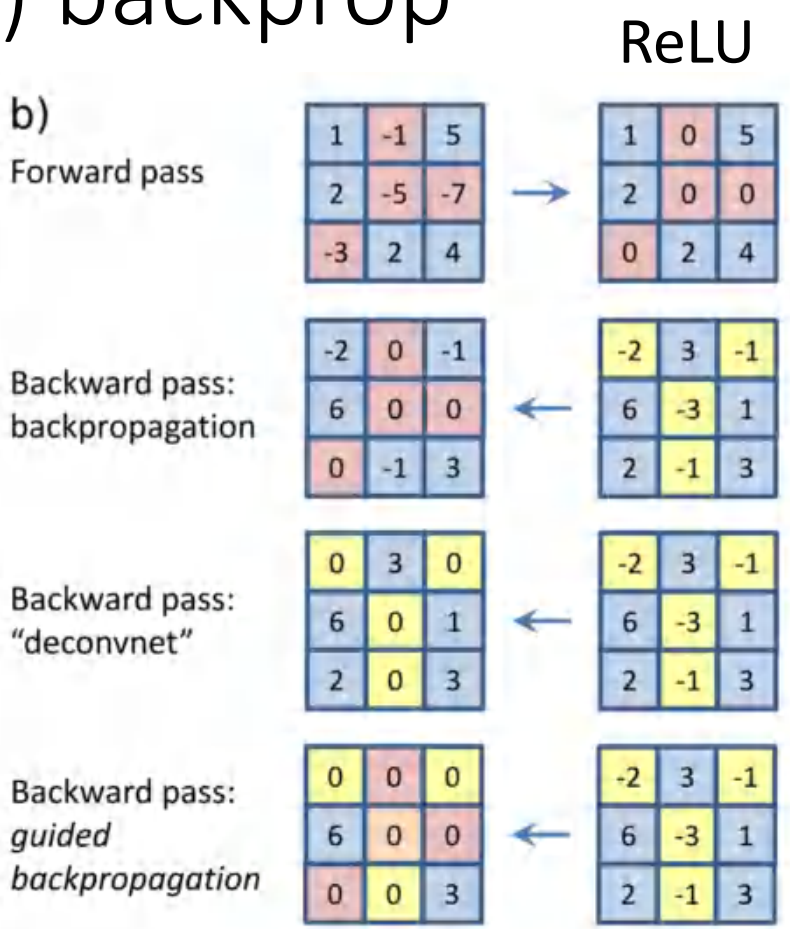
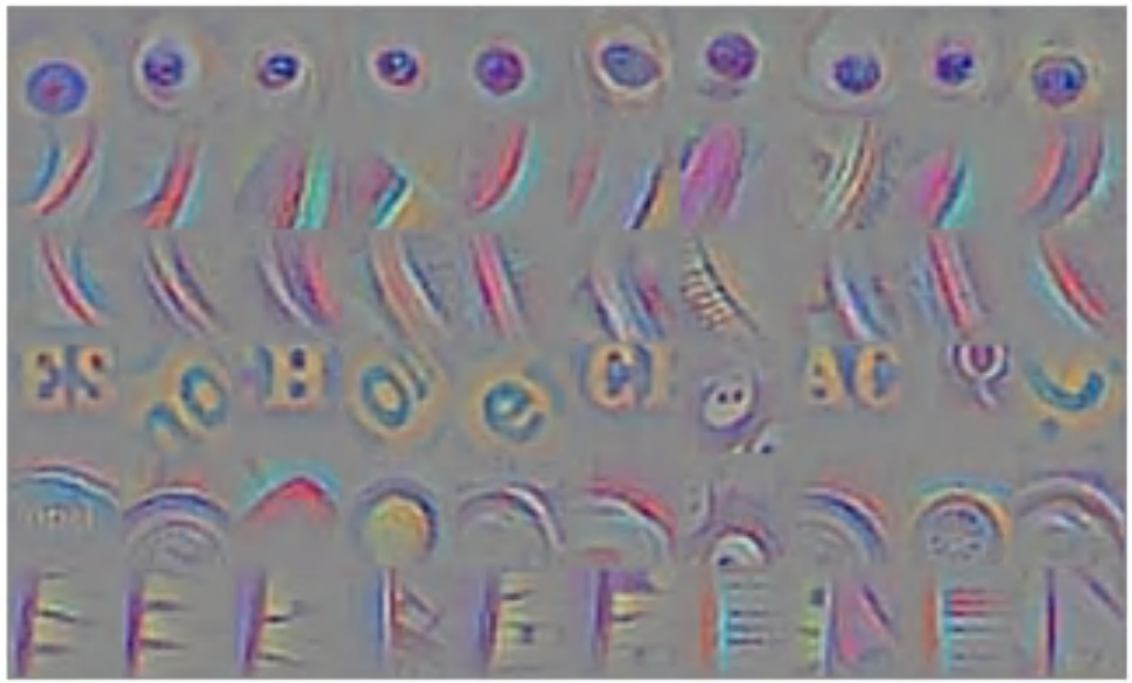



Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)


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
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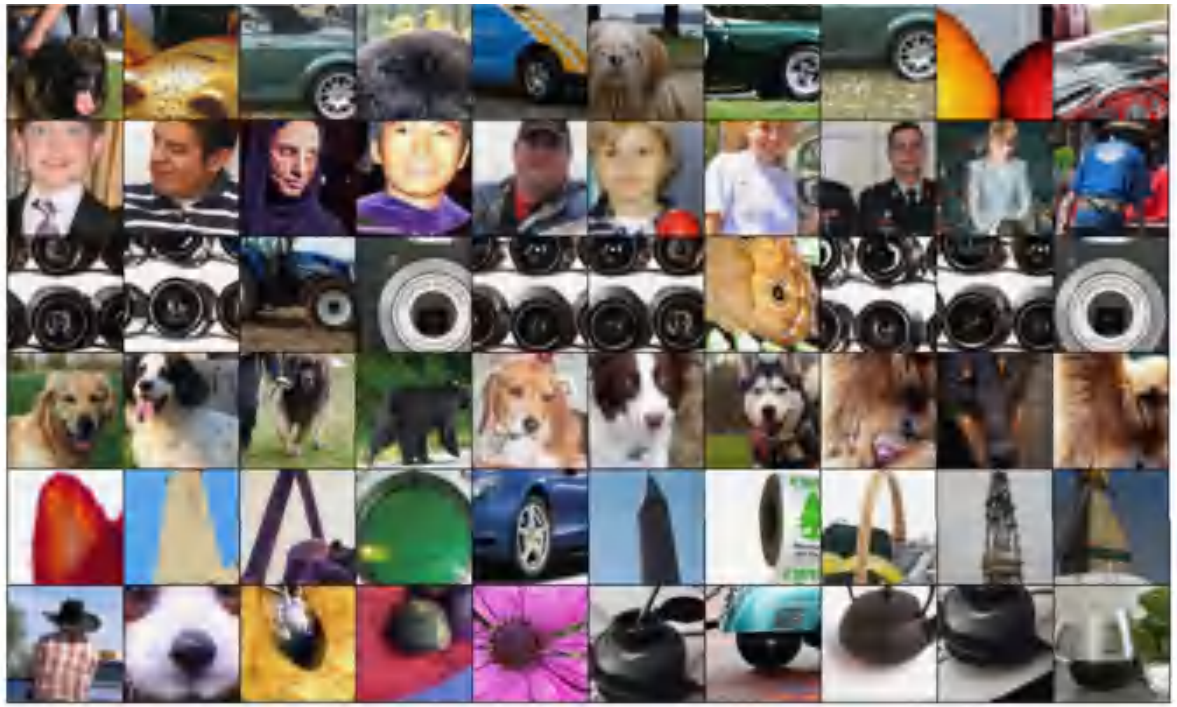
# Intermediate Features via (guided) backprop

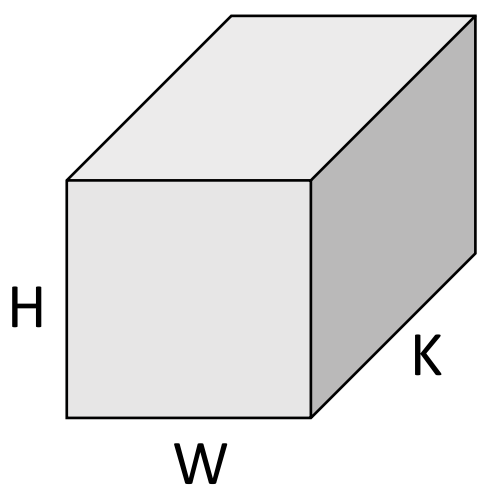


Maximally activating patches
(Each row is a different neuron)

Guided Backprop

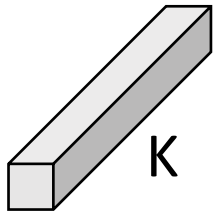
Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014
Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

# Class Activation Mapping (CAM)




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

Global Average Pooling




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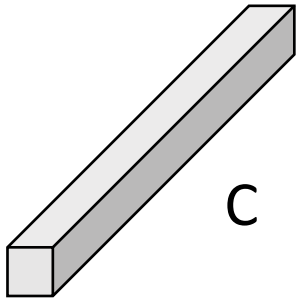
Fully Connected Layer, weights
$w \in \mathbb{R}^{K \times C}$




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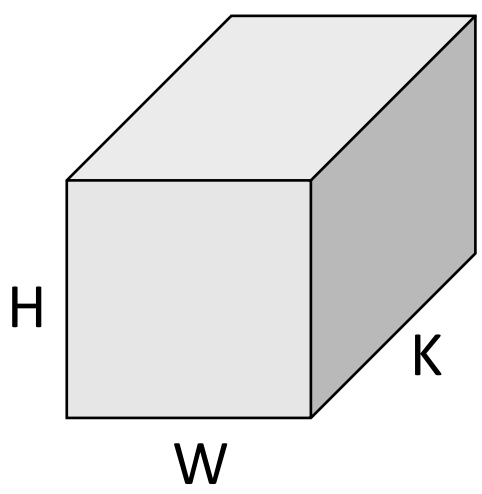
Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

# Class Activation Mapping (CAM)

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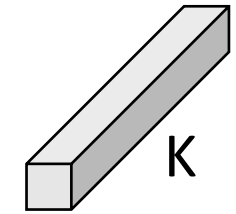


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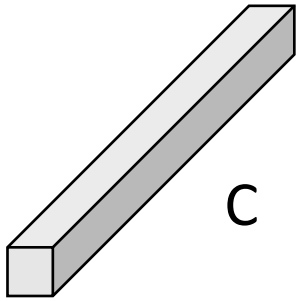


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Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

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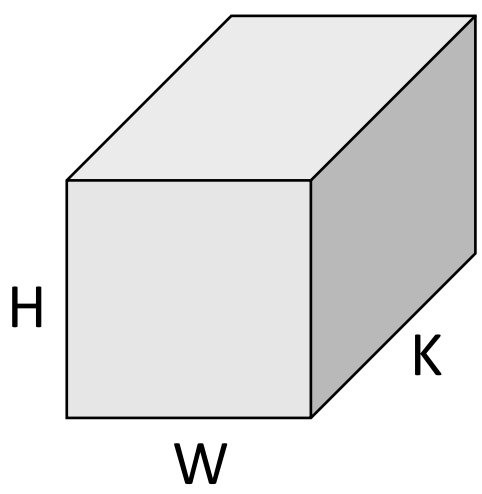


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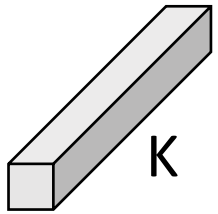


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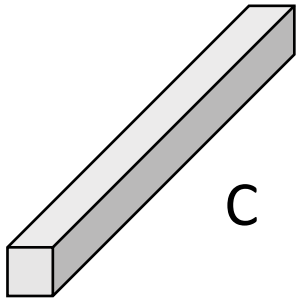


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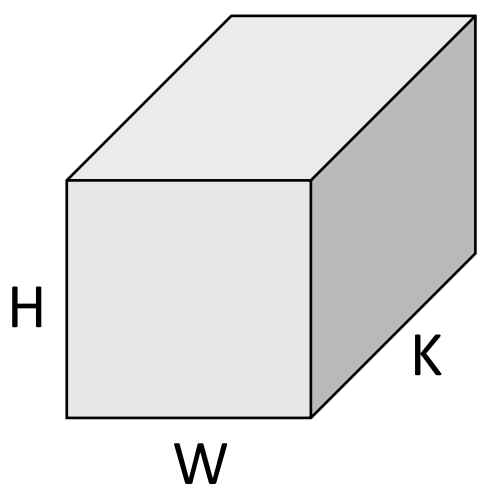


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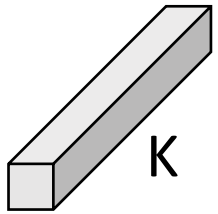


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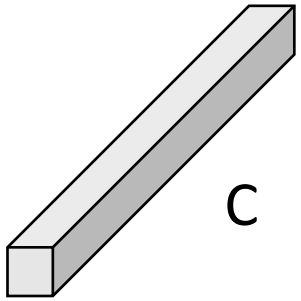


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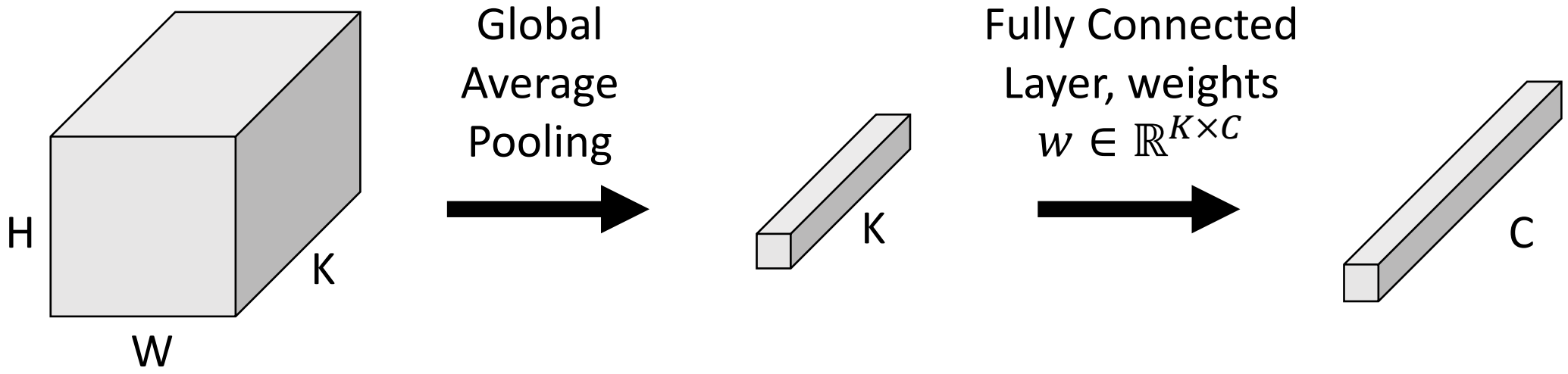


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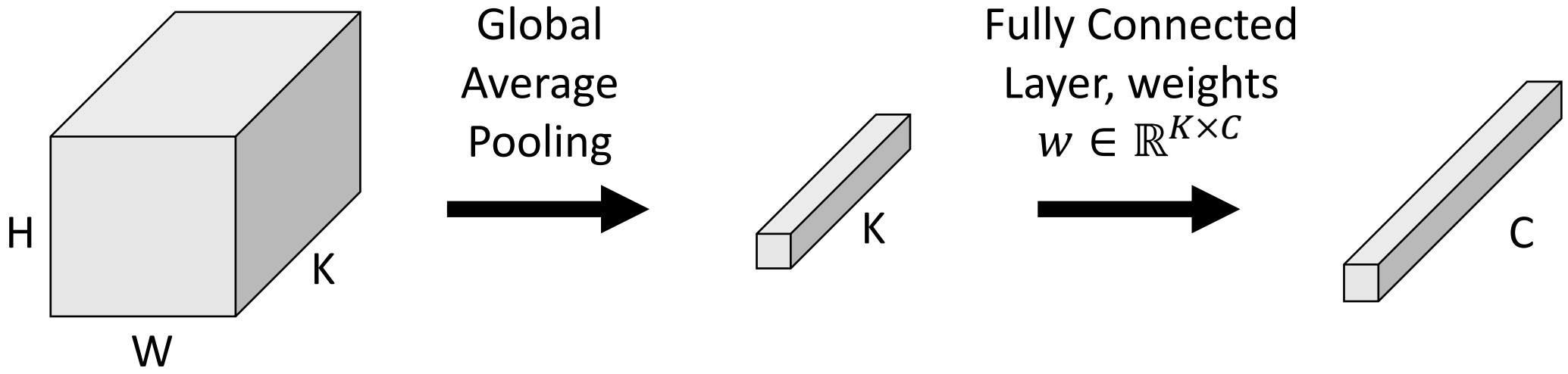


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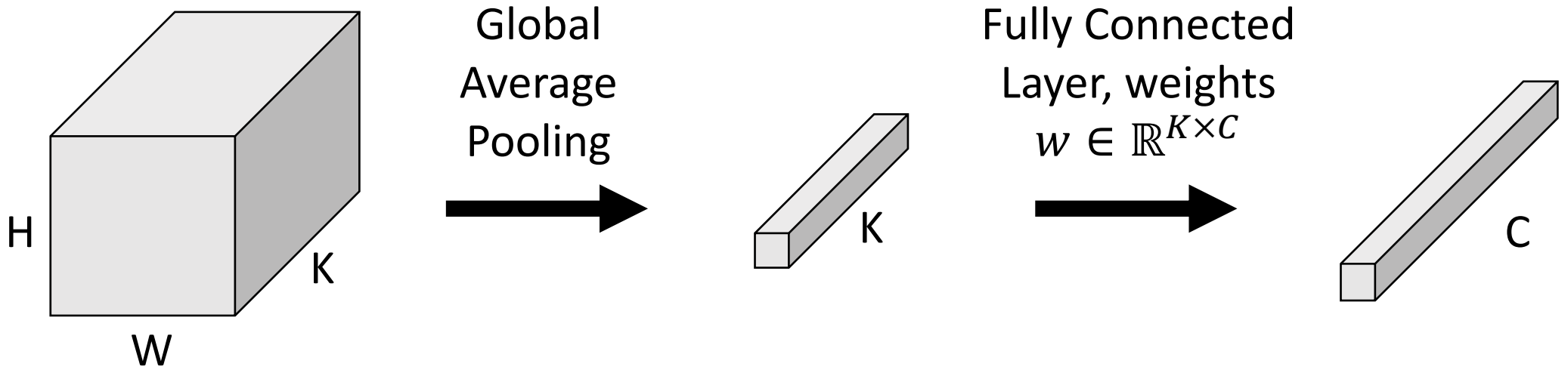


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**Class Activation Maps:**
$\boldsymbol{M \in \mathbb{R}^{C,H,W}}$

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

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

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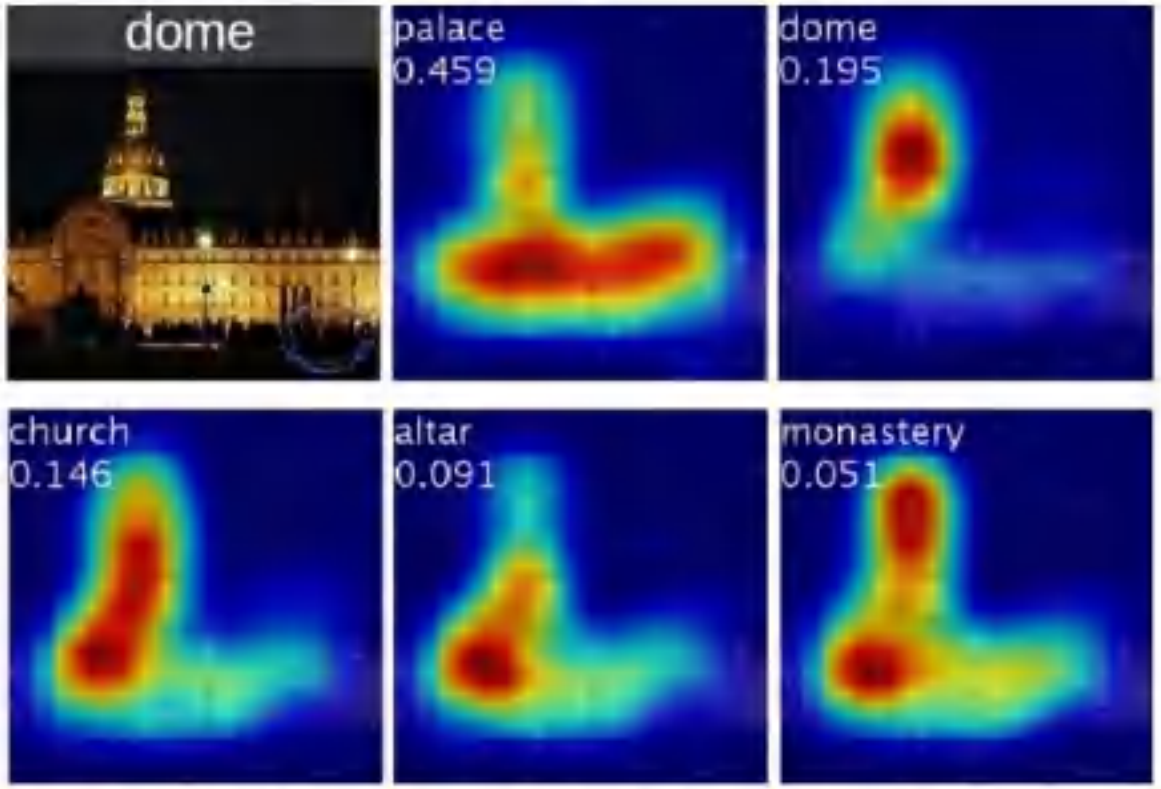
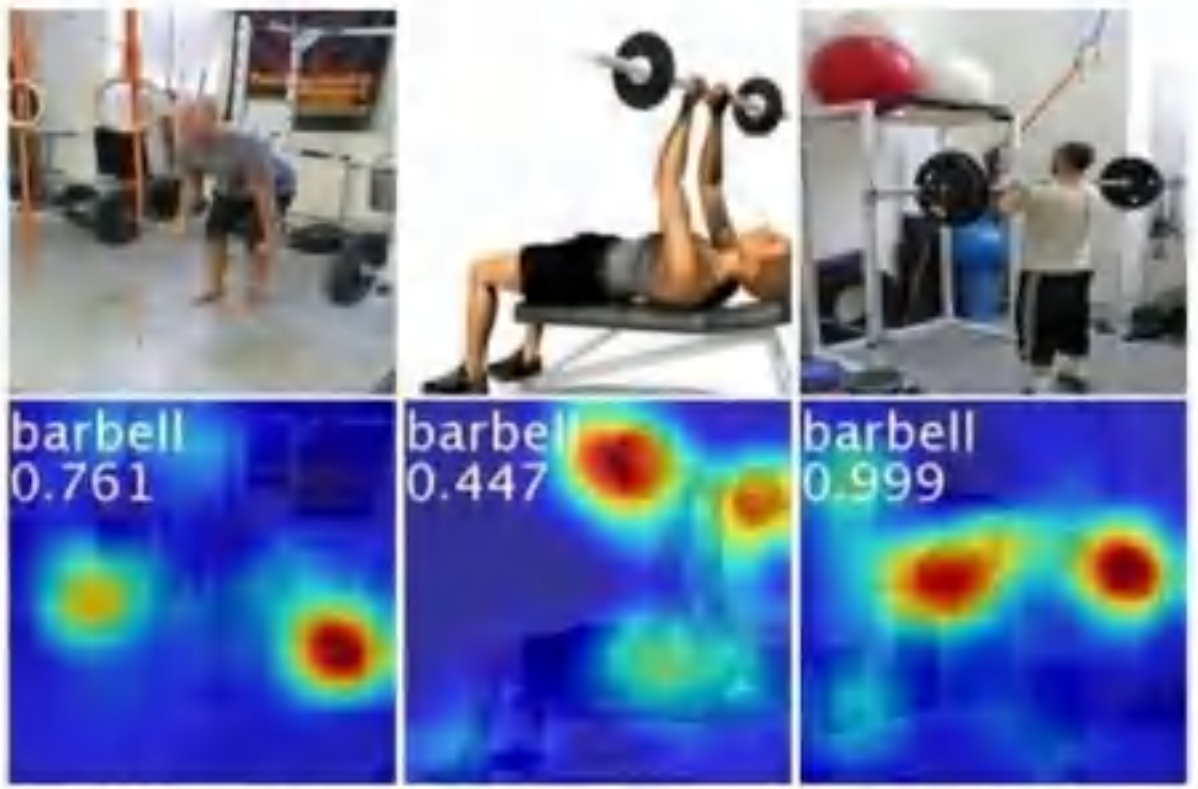



Class activation maps of top 5 predictions

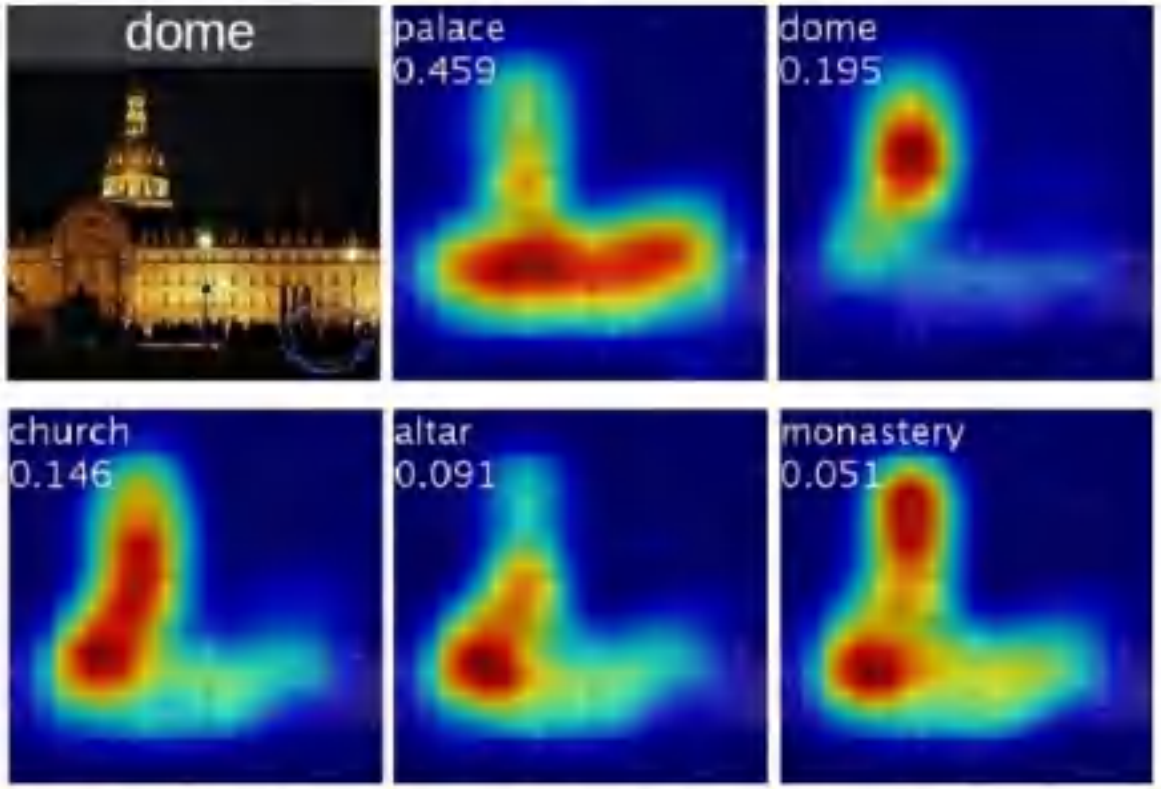



Class activation maps for one object class

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

# Class Activation Mapping (CAM)

Problem: Can only apply to last conv layer

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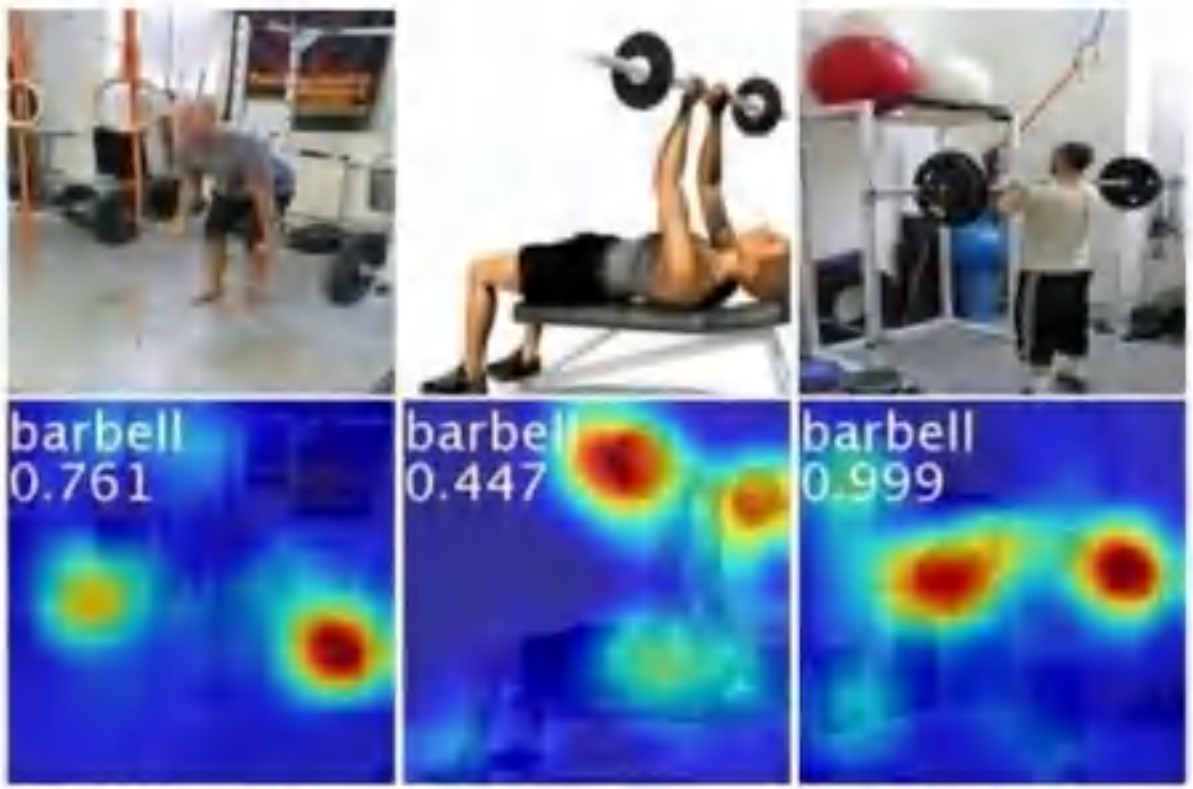


Class activation maps for one object class

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

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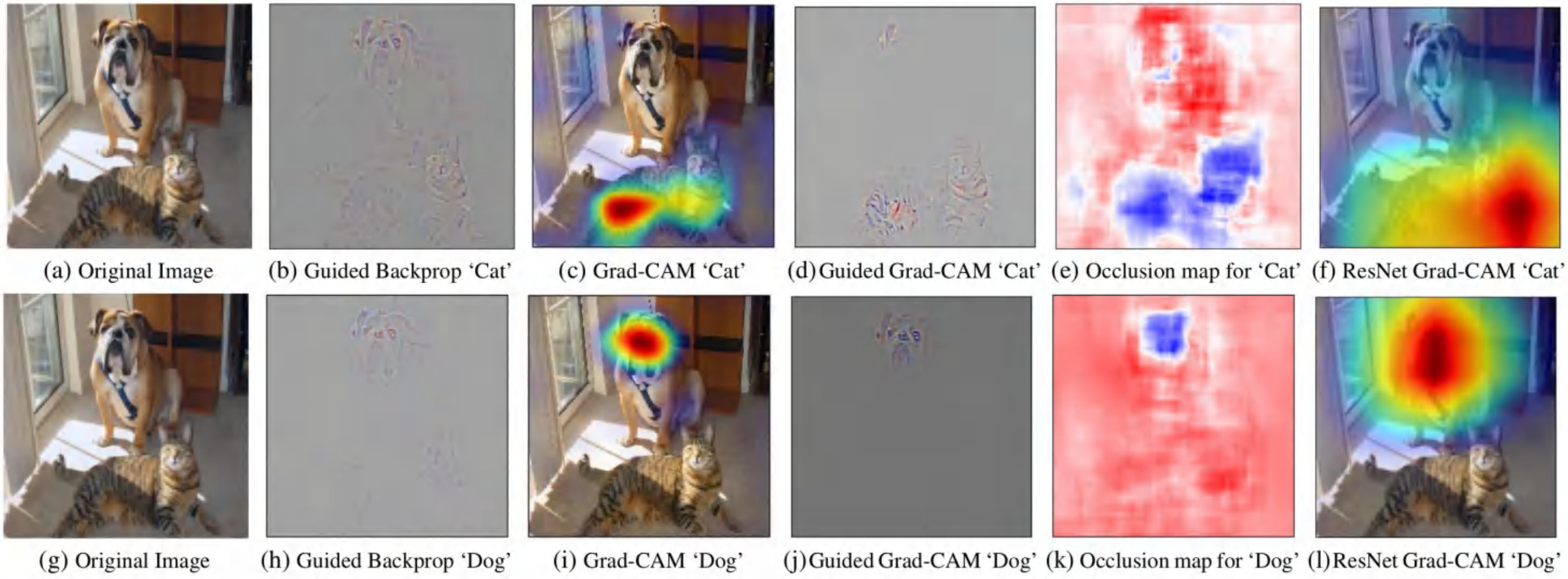
$$\alpha_k = \frac{1}{HW} \sum_{h,w} \frac{\partial S_c}{\partial A_{h,w,k}}$$

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)



(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

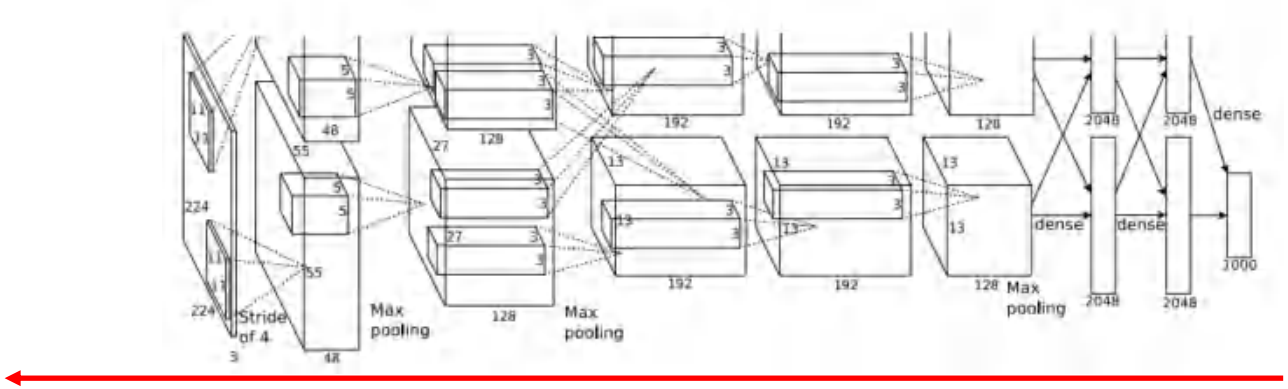
# Visualizing CNN Features: Gradient Ascent

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

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.

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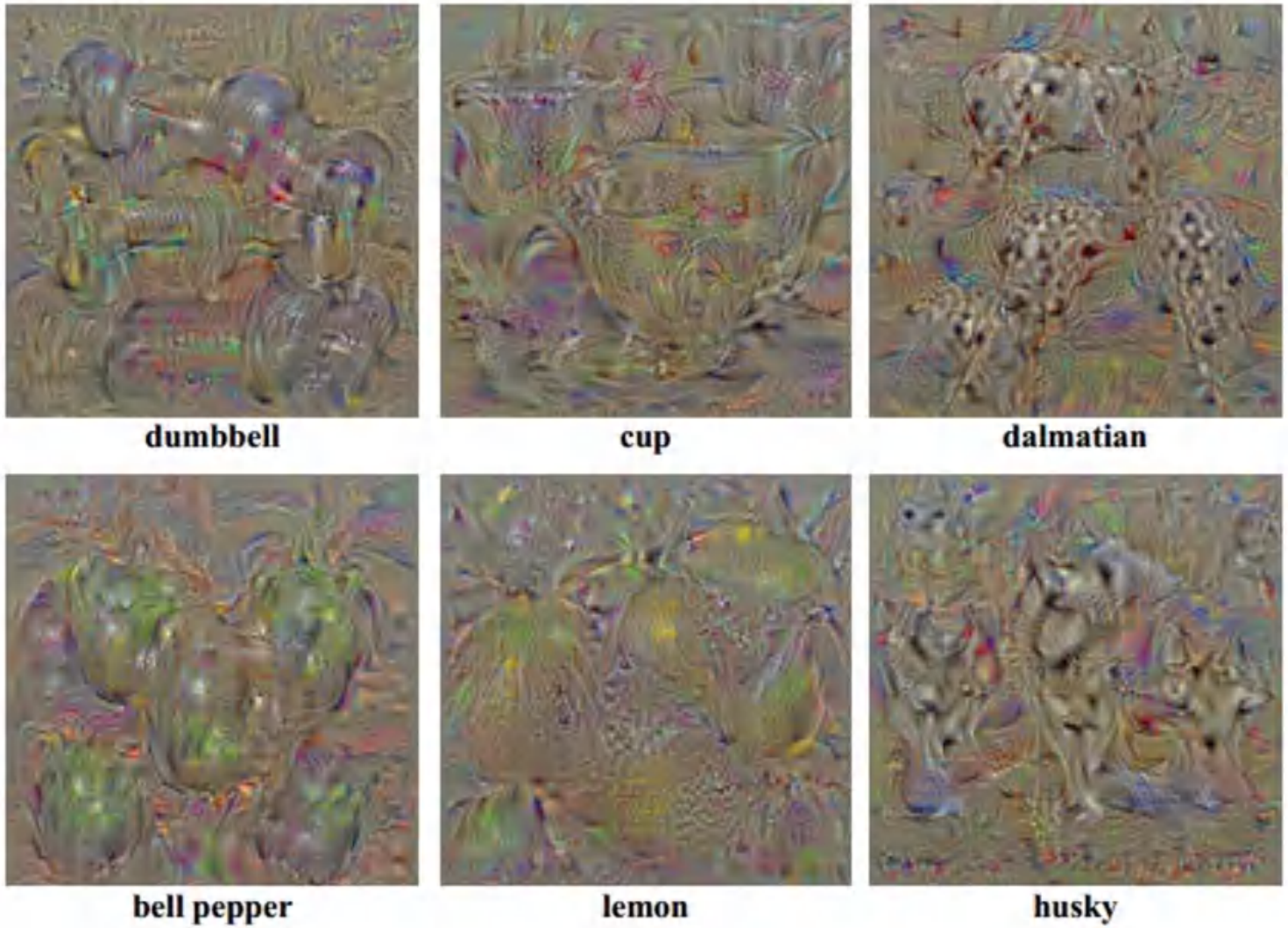


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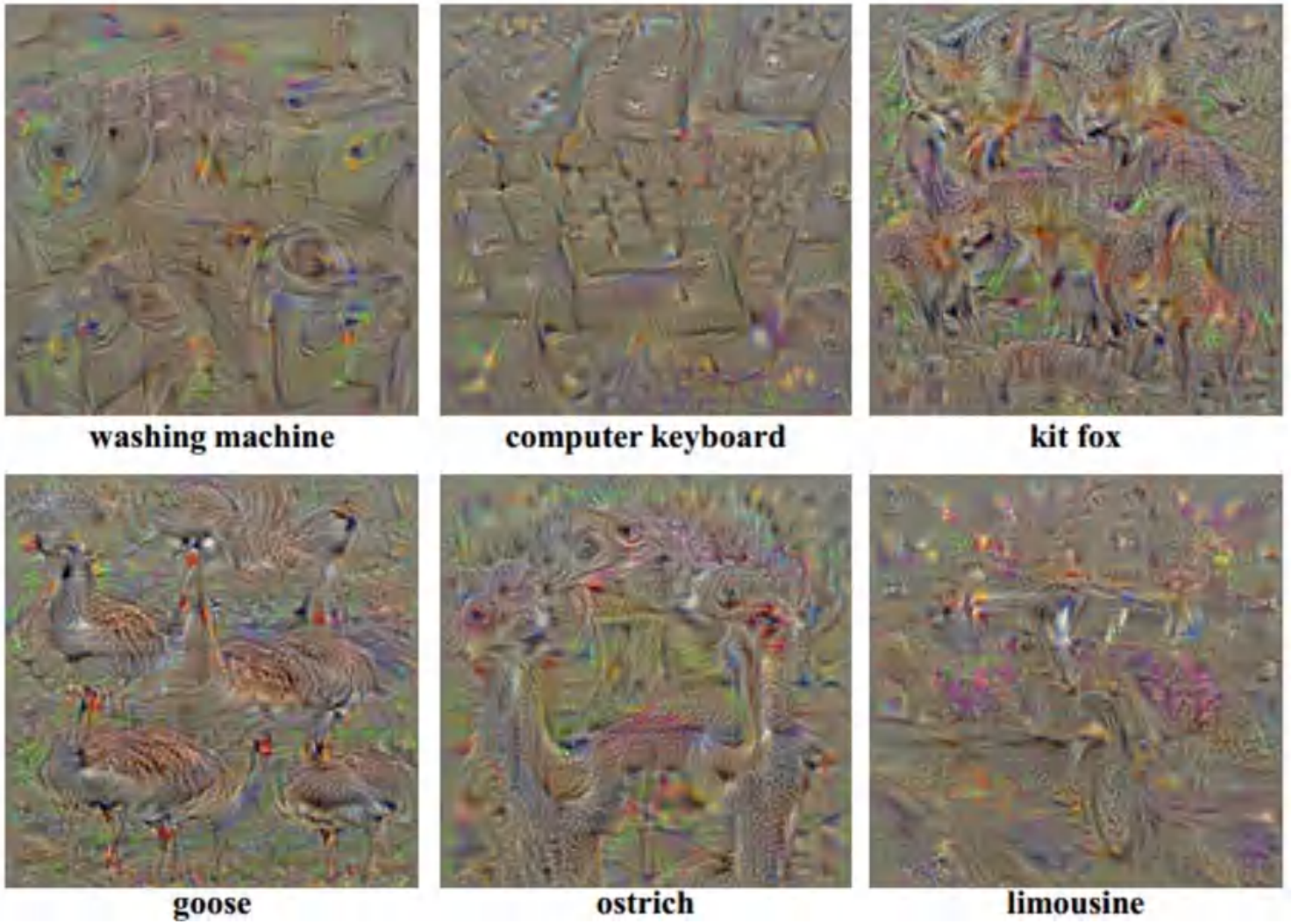


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

# 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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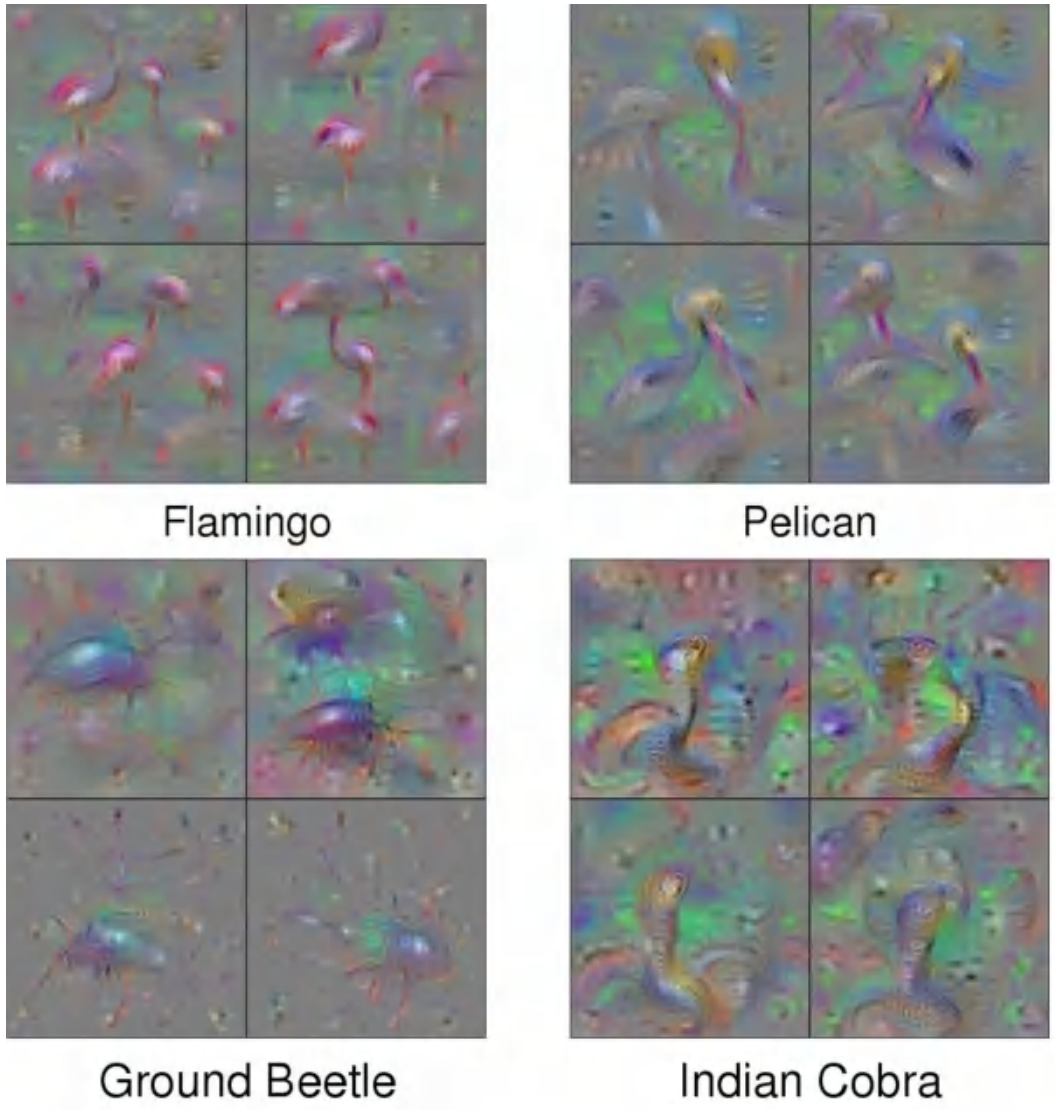


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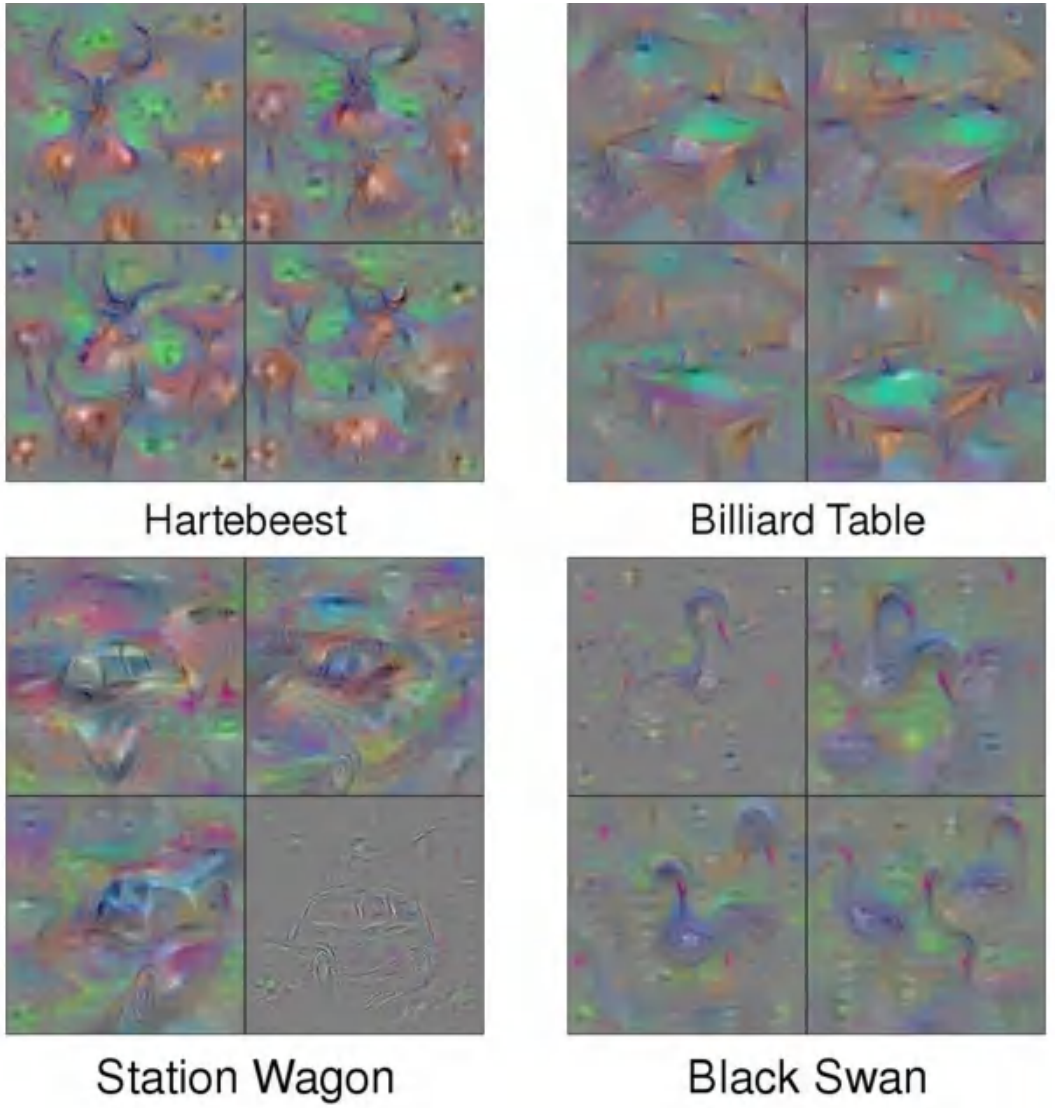


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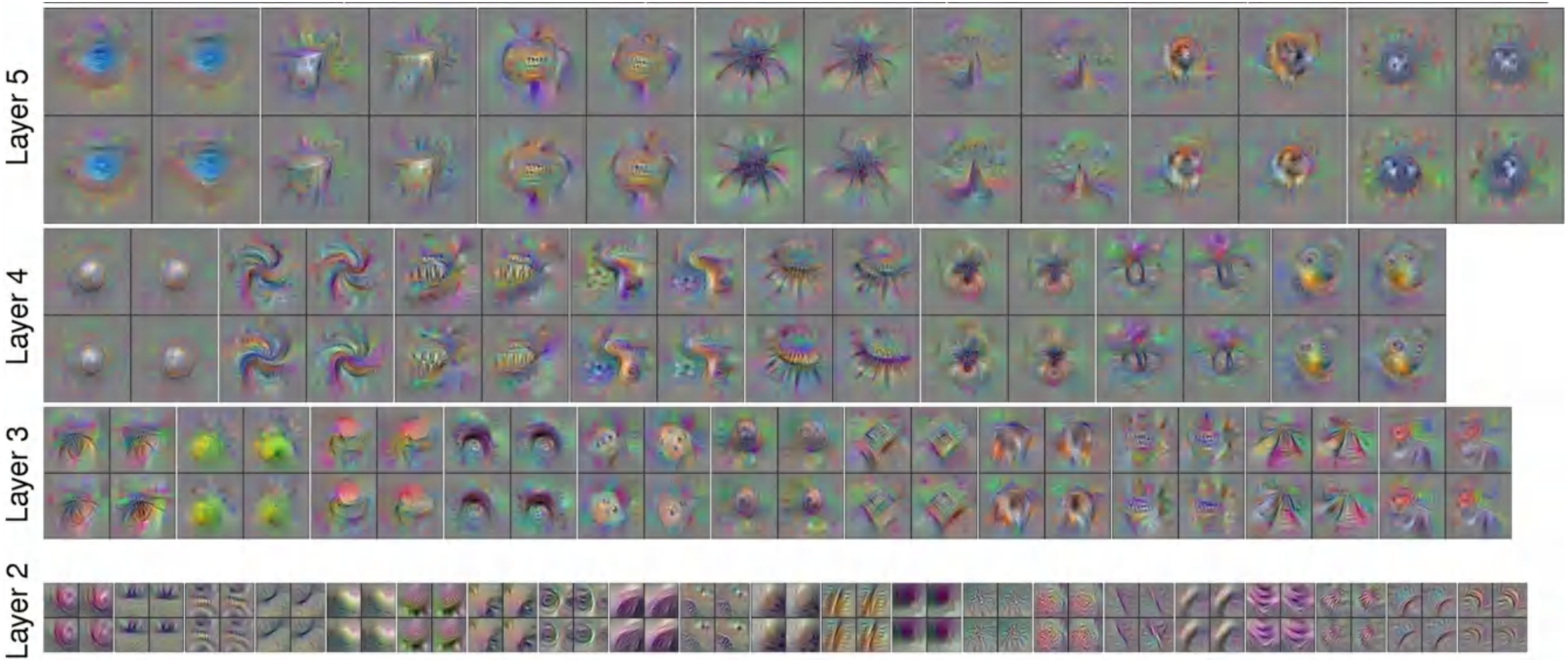
# Visualizing CNN Features: Gradient Ascent

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

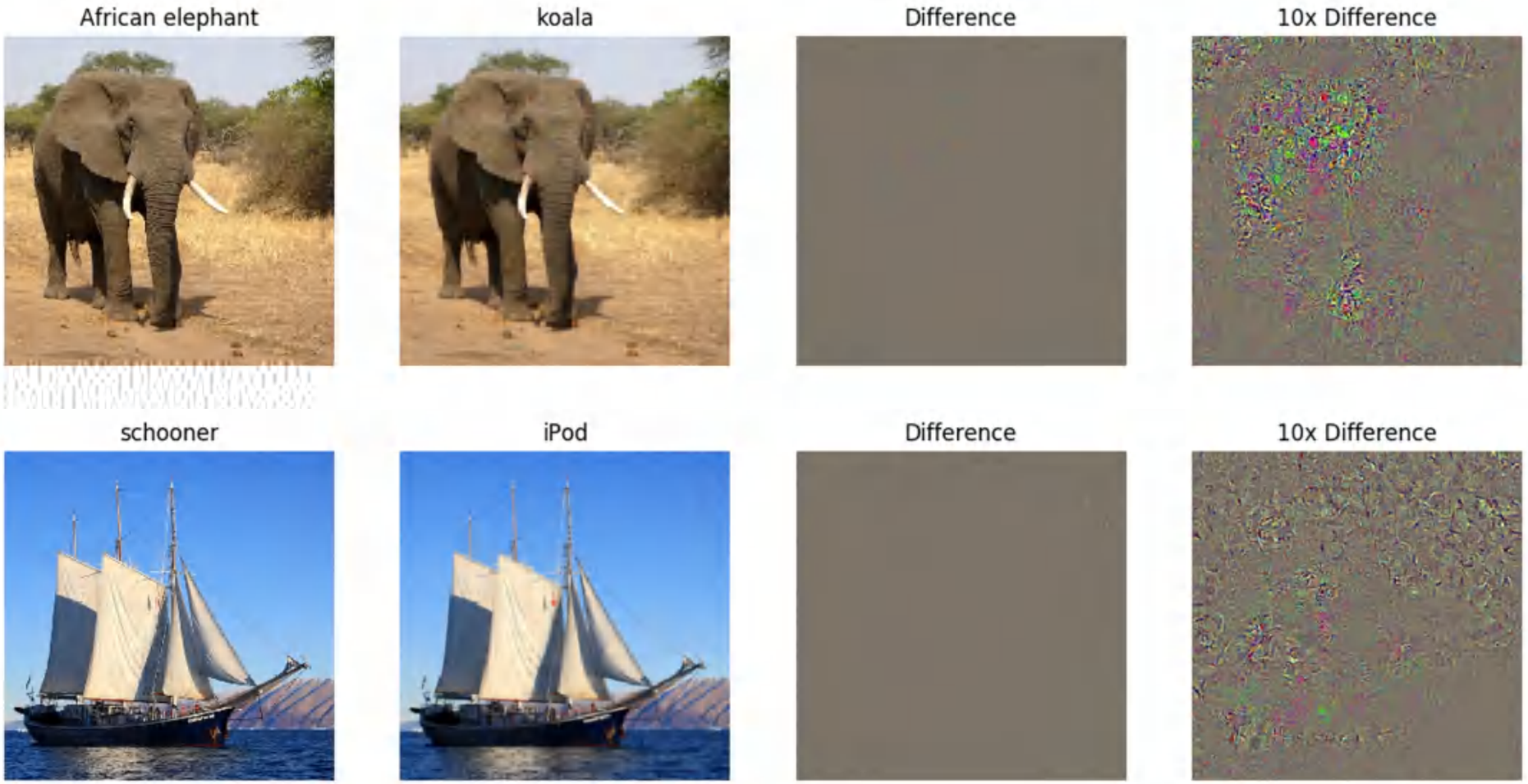

Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016

# 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 Attacks and Defense

**Adversarial Attack**: Method for generating adversarial examples for a network

**Adversarial Defense**: Change to network architecture, training, etc that make it harder to attack

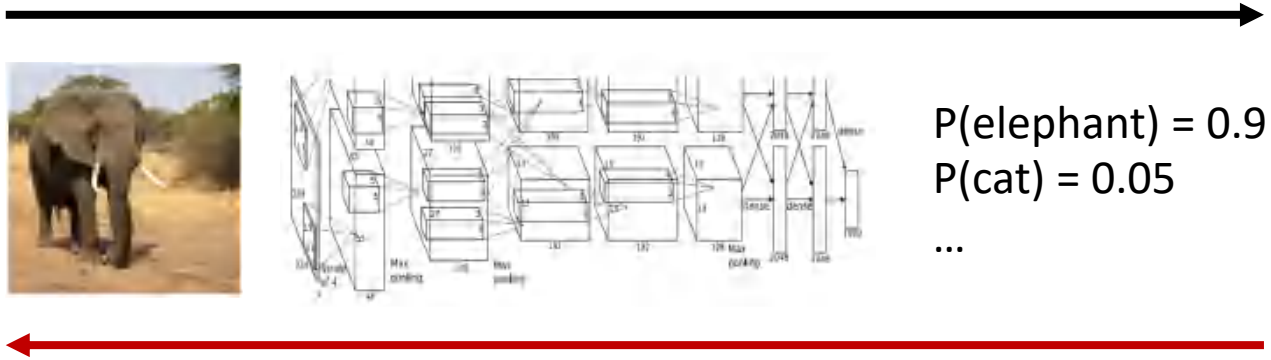
# Adversarial Attacks and Defense

**Adversarial Attack**: Method for generating adversarial examples for a network **– Easy**

**Adversarial Defense**: Change to network architecture, training, etc that make it harder to attack **– Hard**

# Adversarial Attacks

**White-box attack**: We have access to the network architecture and weights. Can get outputs, gradients for arbitrary input images.



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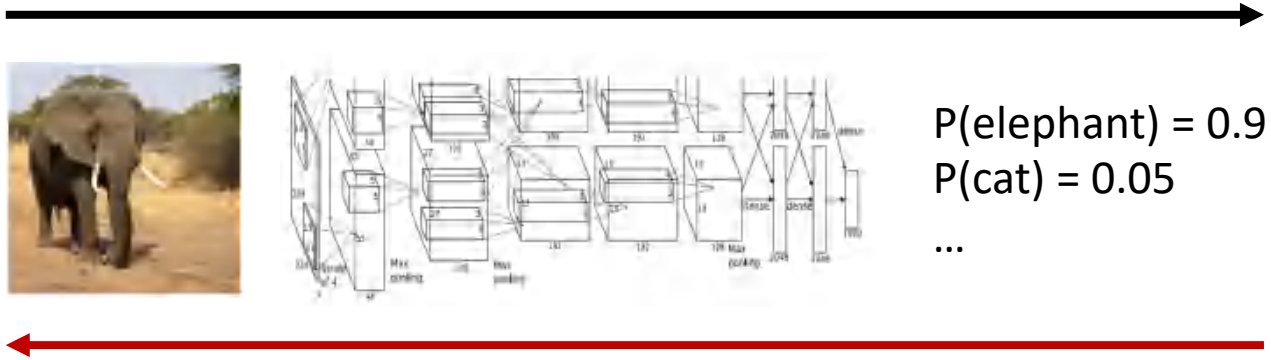
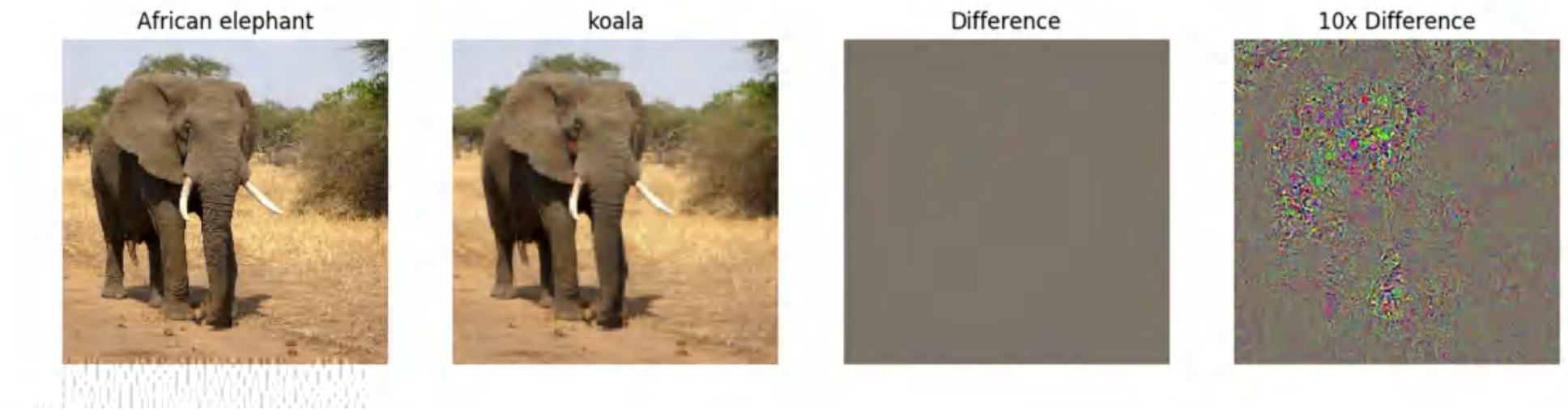



**Black-box attack**: We don't know network architecture or weights; can only get network predictions for arbitrary input images


Papernot et al, "Transferability in machine learning: from phenomena to black-box attacks using adversarial samples", 2016

# Adversarial Examples




Huge area of research!

Security concern for networks deployed in the wild

# 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

Features of new image

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

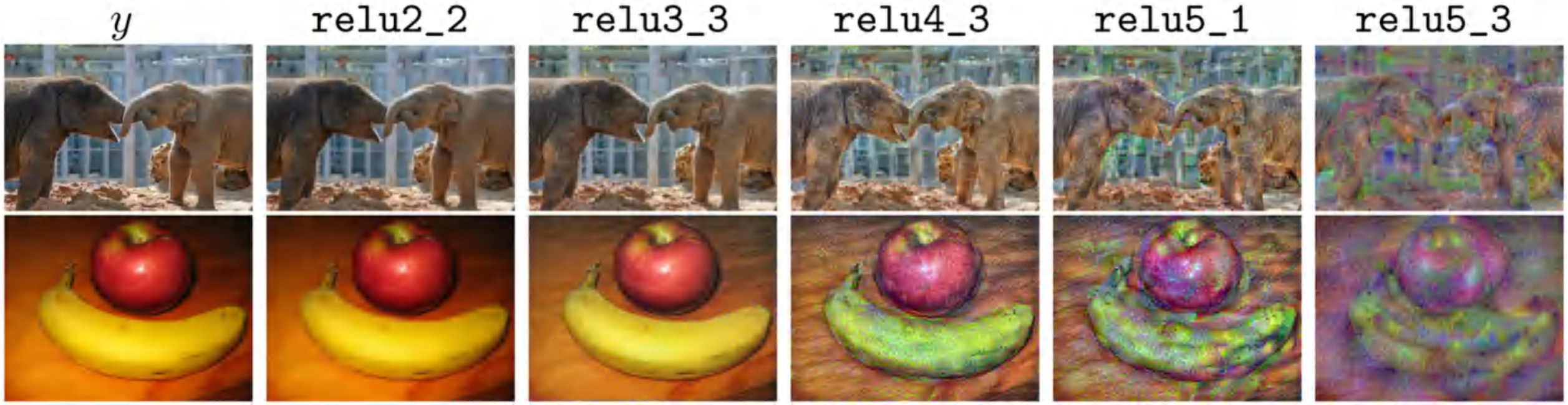
$$\mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j} \left( (x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{\beta}{2}}$$

Total Variation regularizer (encourages spatial smoothness)

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

# Feature Inversion

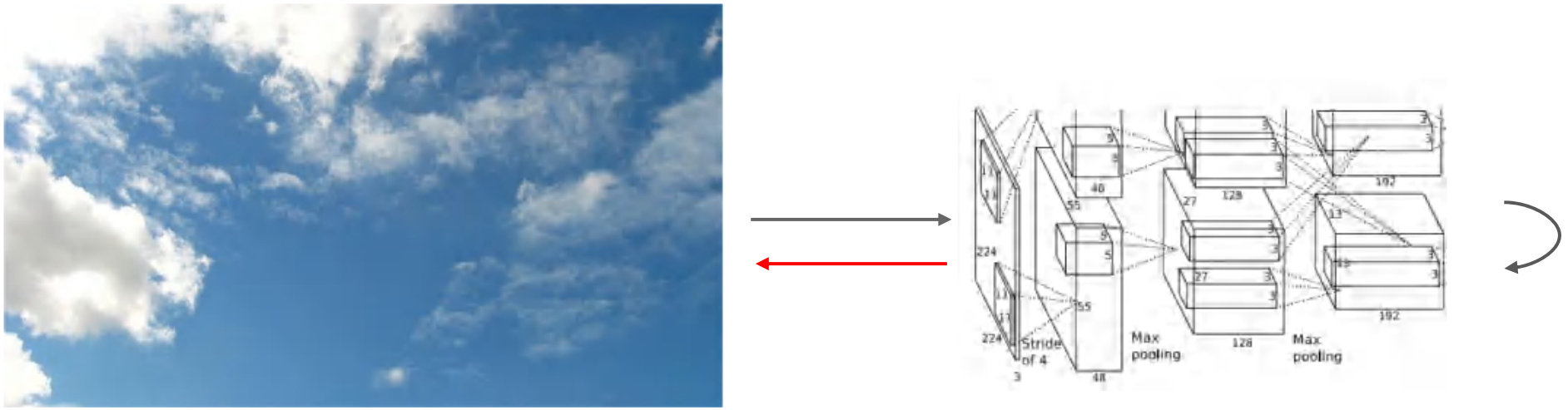
Reconstructing from different layers of VGG-16




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

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

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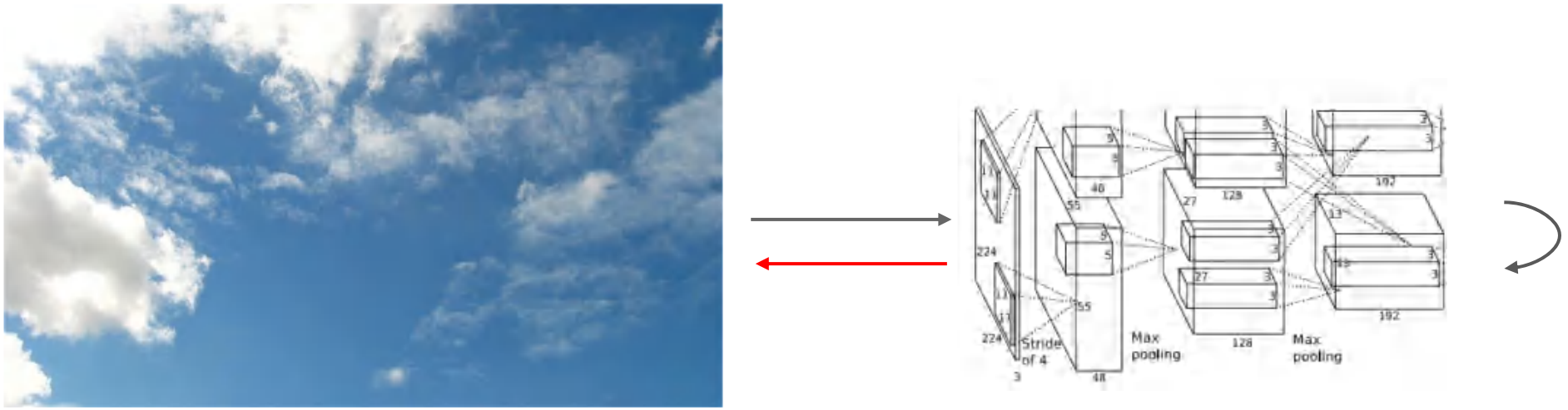


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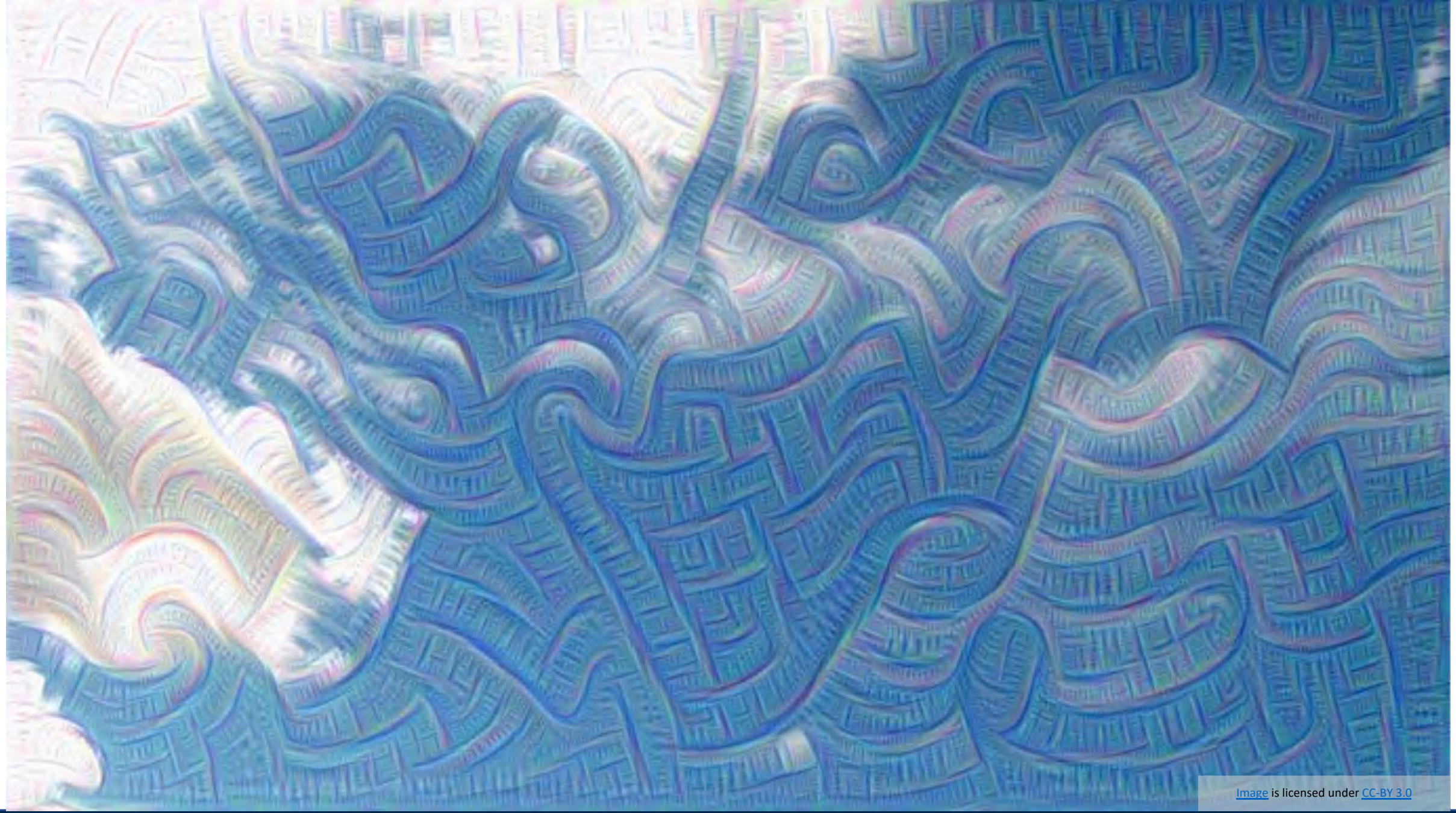
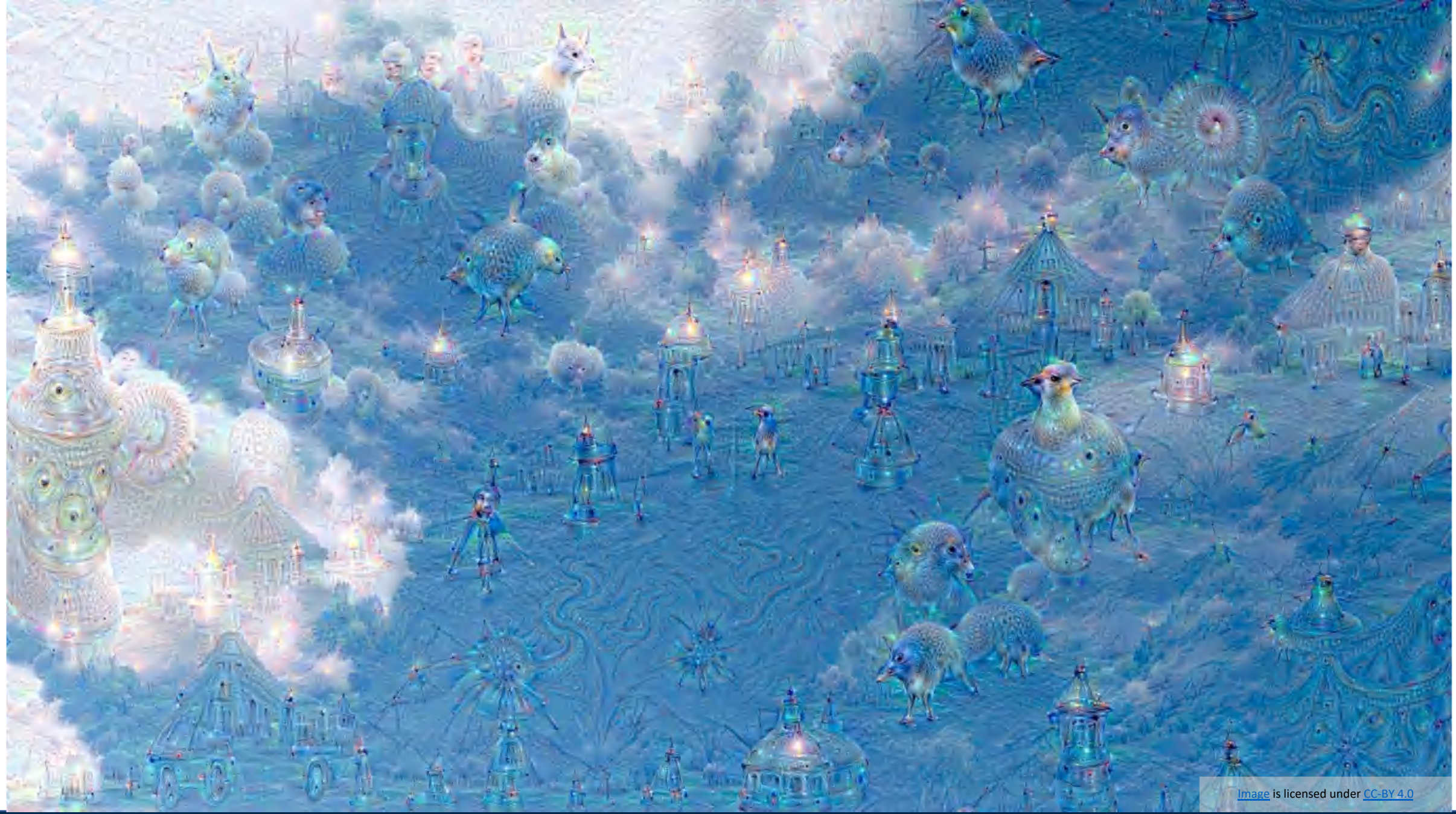
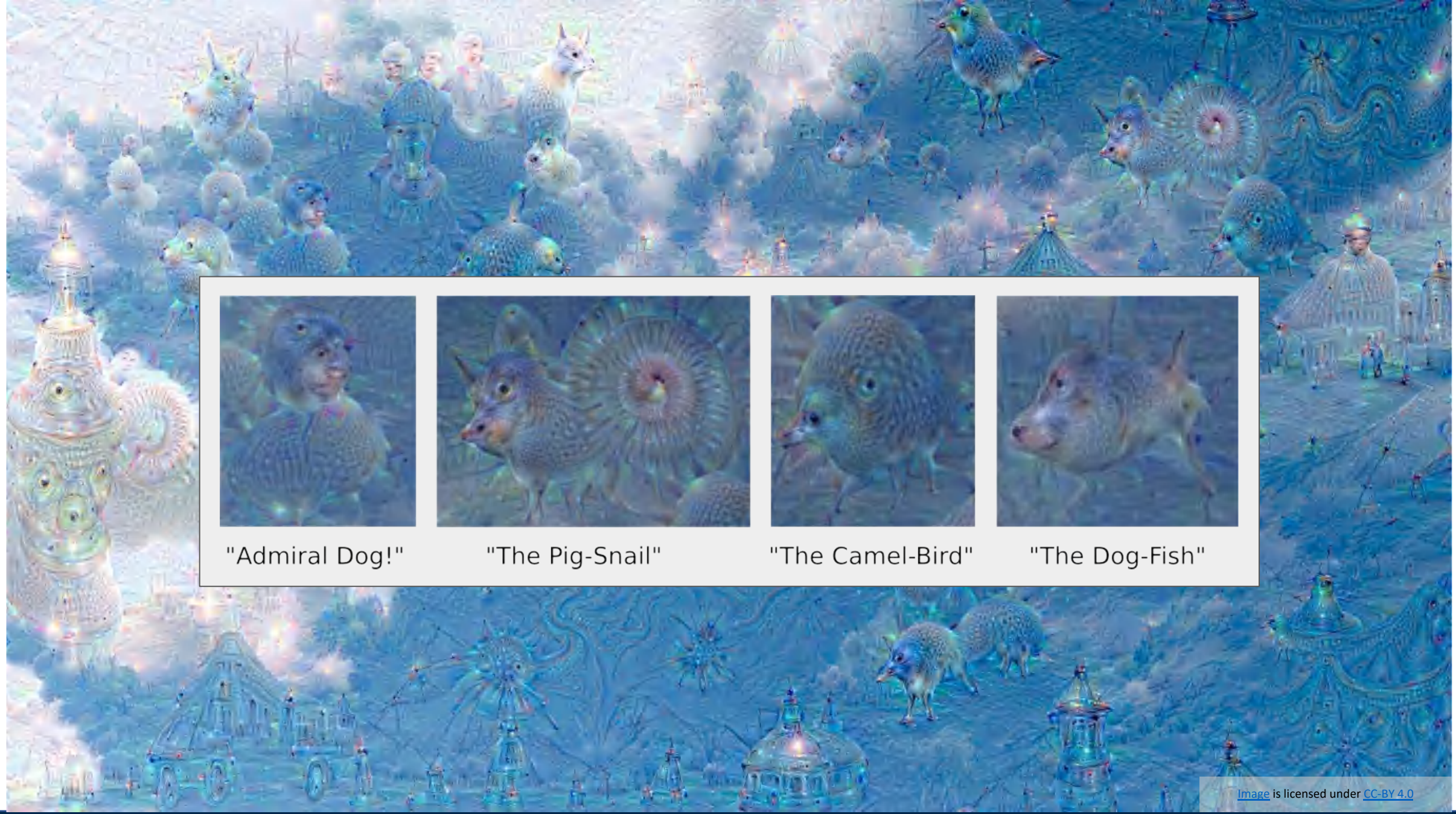
Equivalent to:

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

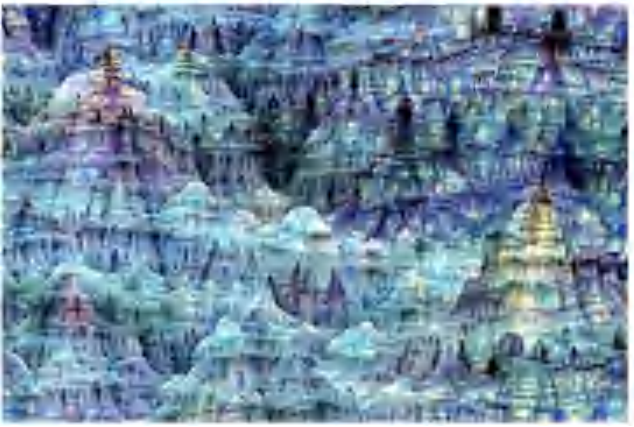
Mordvintsev, Olah, and Tyka, "Inceptionism: Going Deeper into Neural Networks", Google Research Blog. Images are licensed under CC-BY 4.0







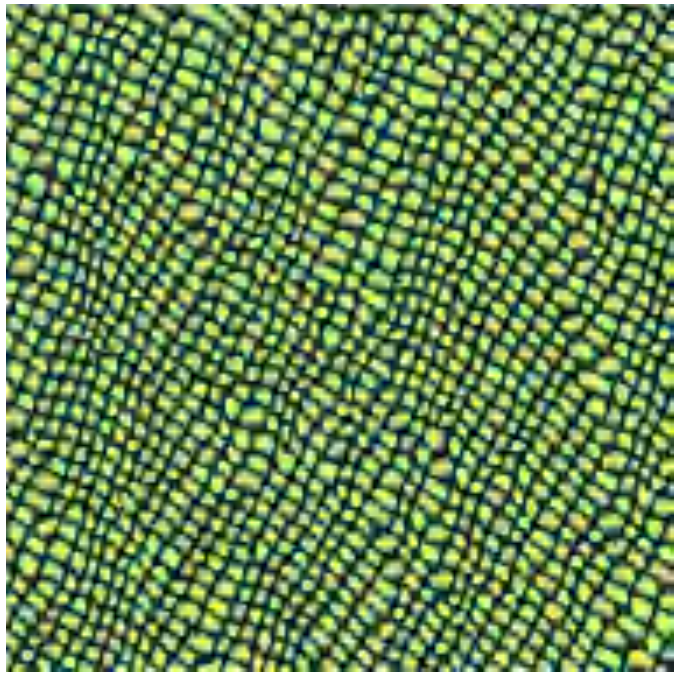





# Texture Synthesis

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

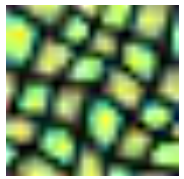
Input

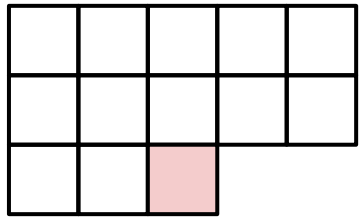


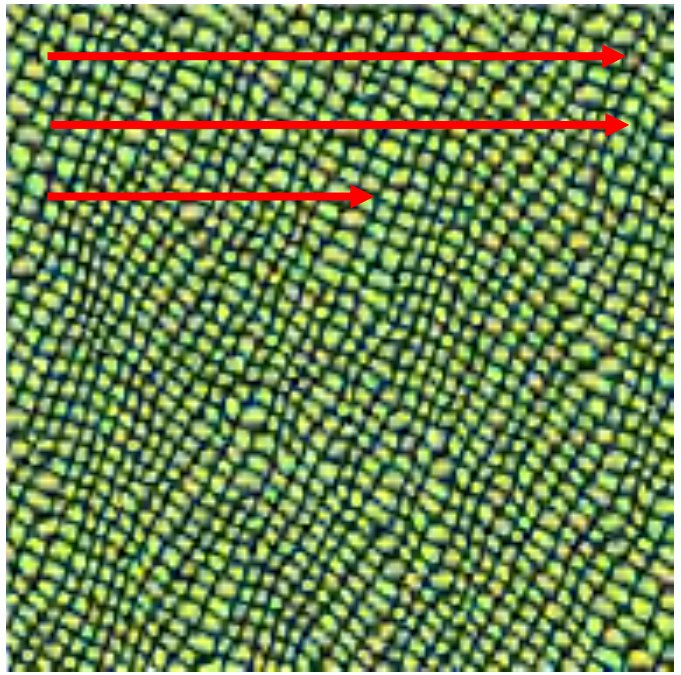
Output

# 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



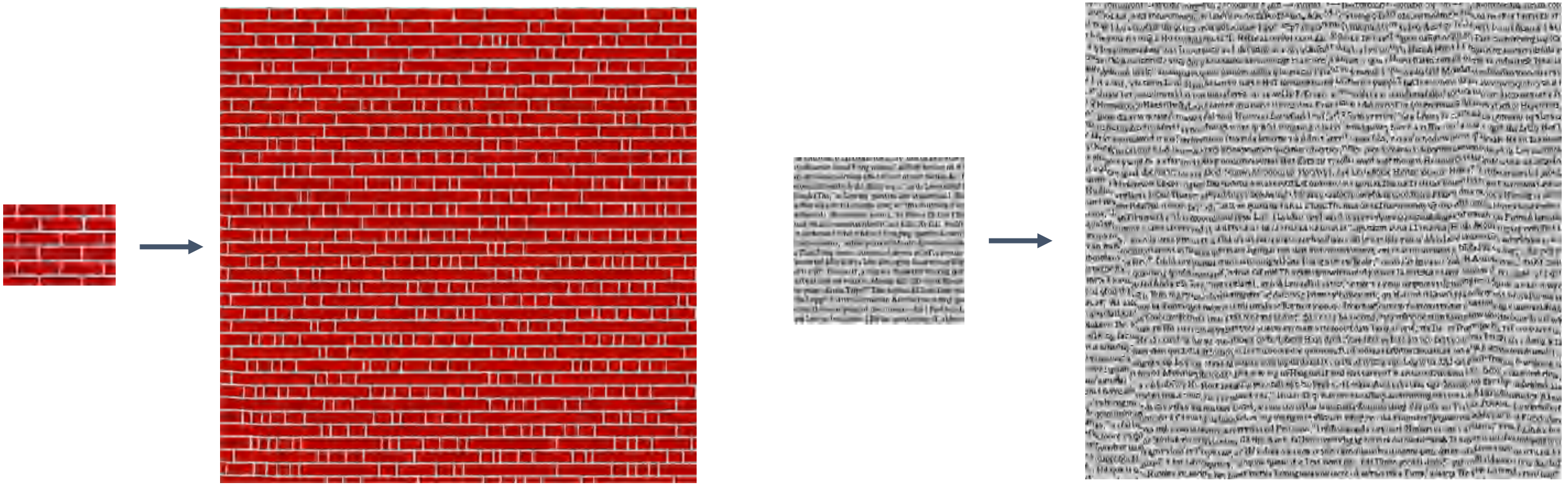




Wei and Levoy, "Fast Texture Synthesis using Tree-structured Vector Quantization", SIGGRAPH 2000

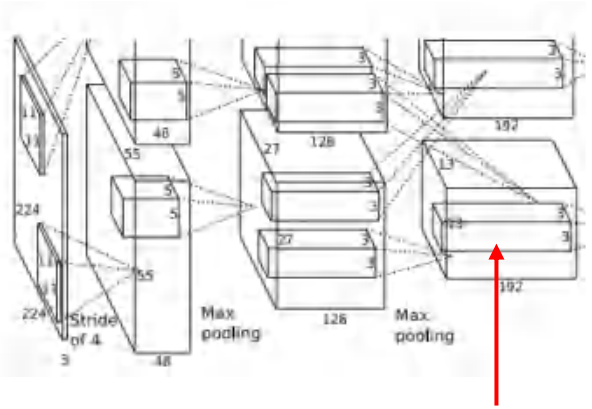
Efros and Leung, "Texture Synthesis by Non-parametric Sampling", ICCV 1999

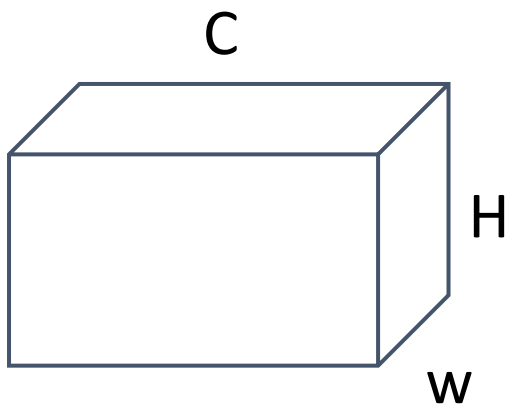
# Texture Synthesis: Nearest Neighbor



# 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

$$F^{\ell} \in \mathbb{R}^{C \times H \times W}$$

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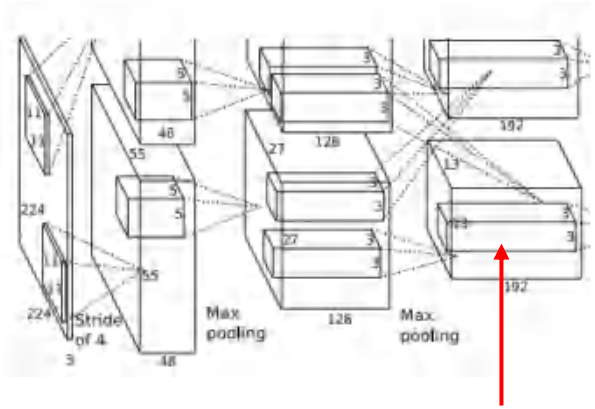


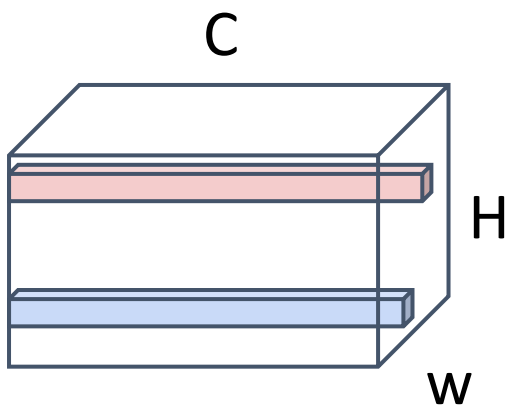


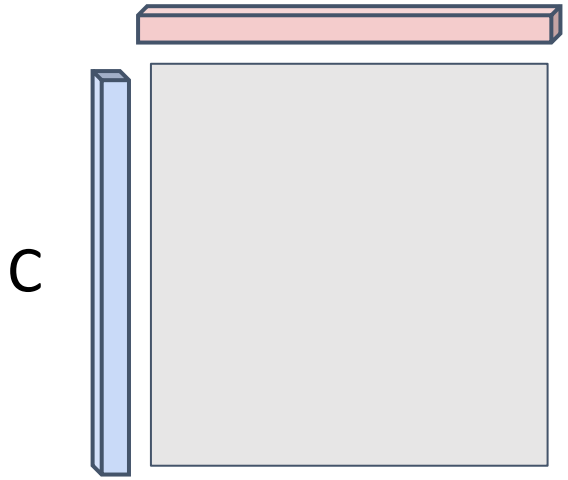


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Outer product of two C-dimensional vectors gives C x C matrix of elementwise products

# Texture Synthesis with Neural Networks: Gram Matrix

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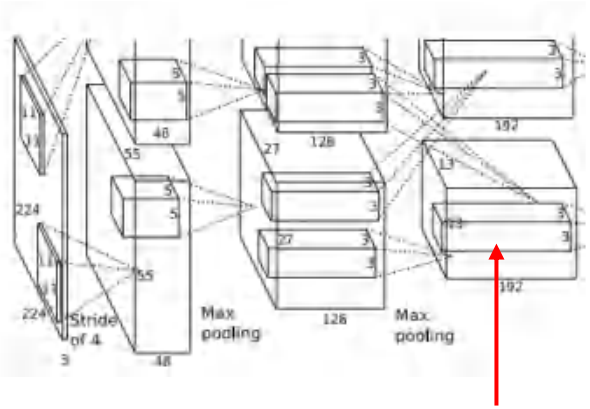
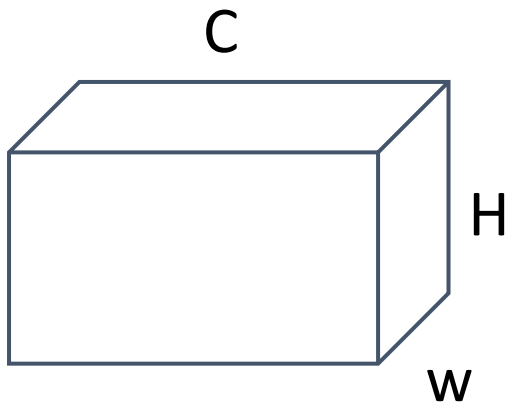
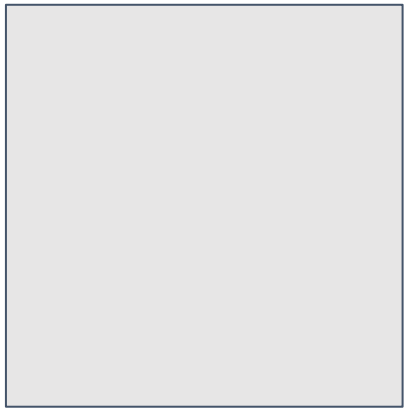



C



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$$G^{\ell} \in \mathbb{R}^{C \times C}$$

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

$$G^{\ell}_{c,c'} = \sum_{h,w} F^{\ell}_{c,h,w} F^{\ell}_{c',h,w}$$

# Texture Synthesis with Neural Networks: Gram Matrix

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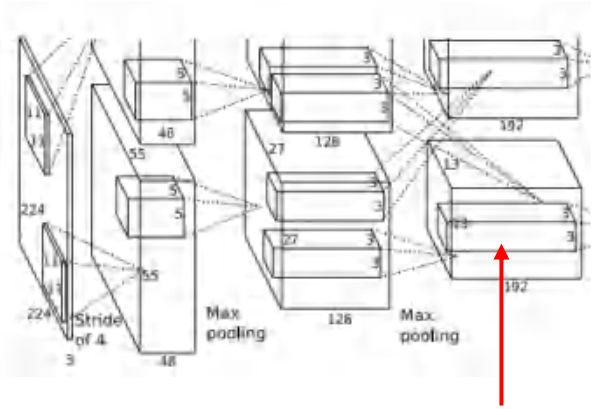


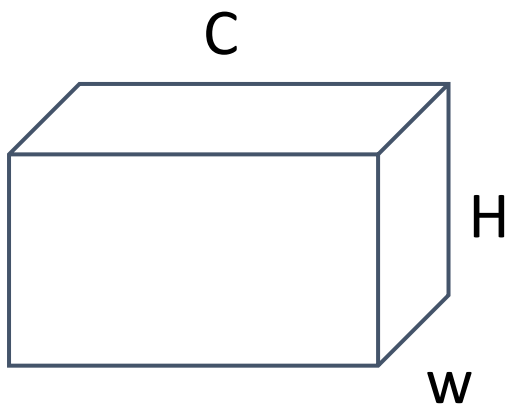


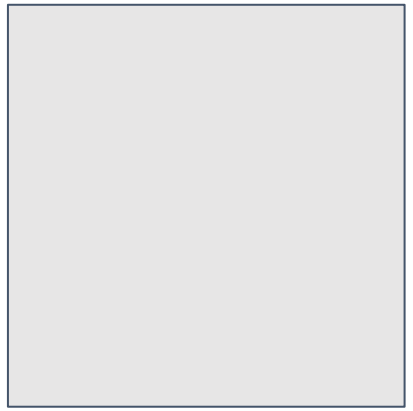


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Outer product of two C-dimensional vectors gives C x C matrix of elementwise products

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

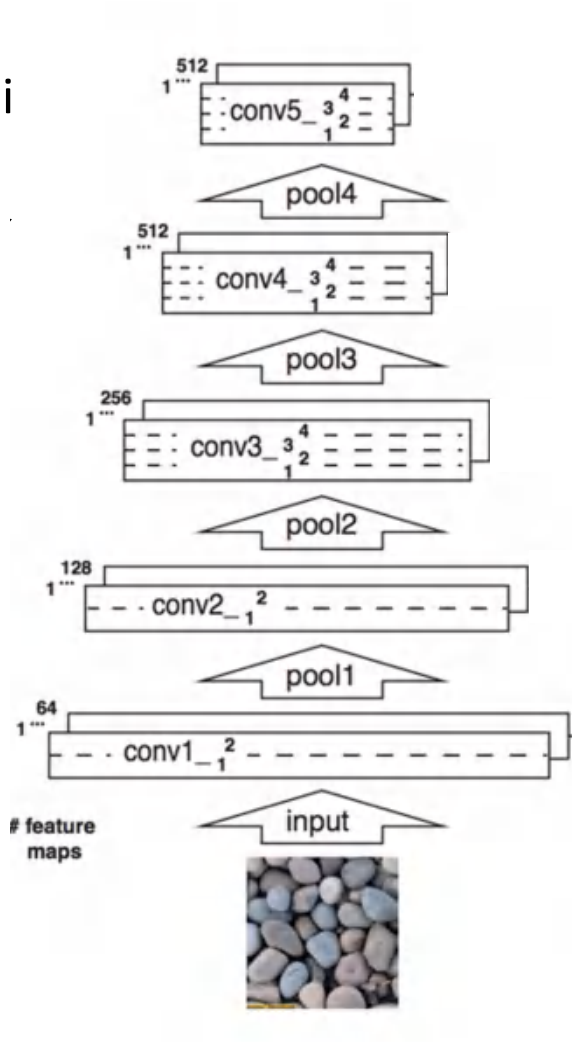
Efficient to compute; reshape features from

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 texture forward through CNN, record activations on every layer; layer i gives features $F^{\ell} \in \mathbb{R}^{C_i \times H_i \times W_i}$



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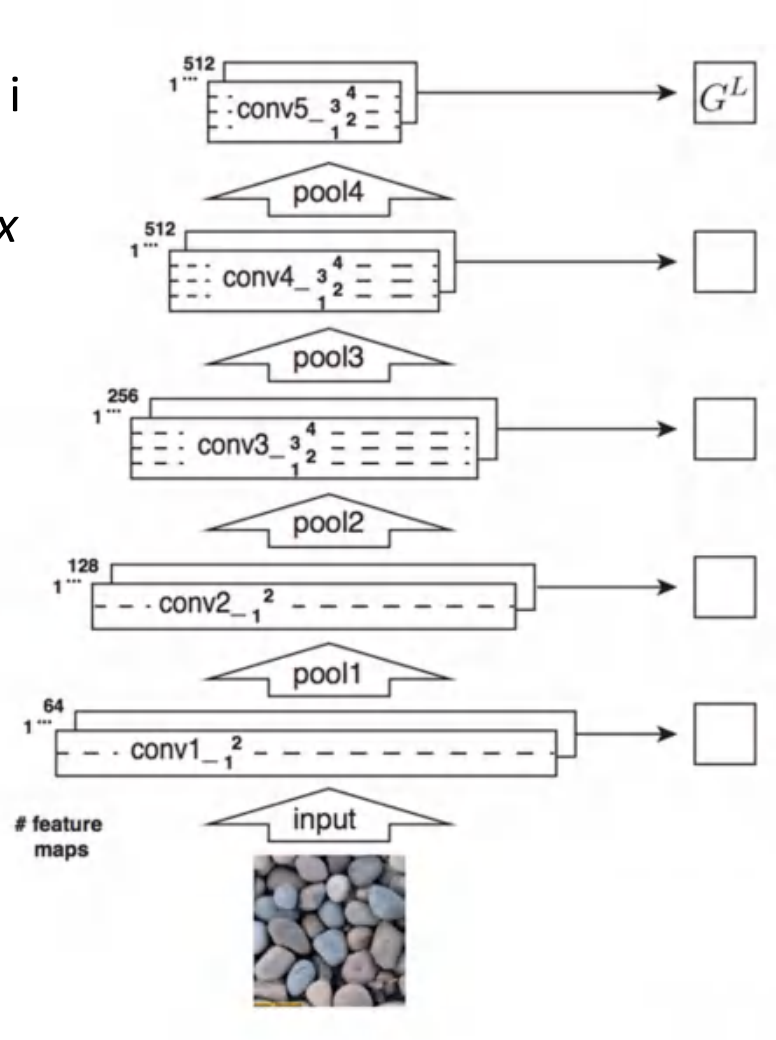

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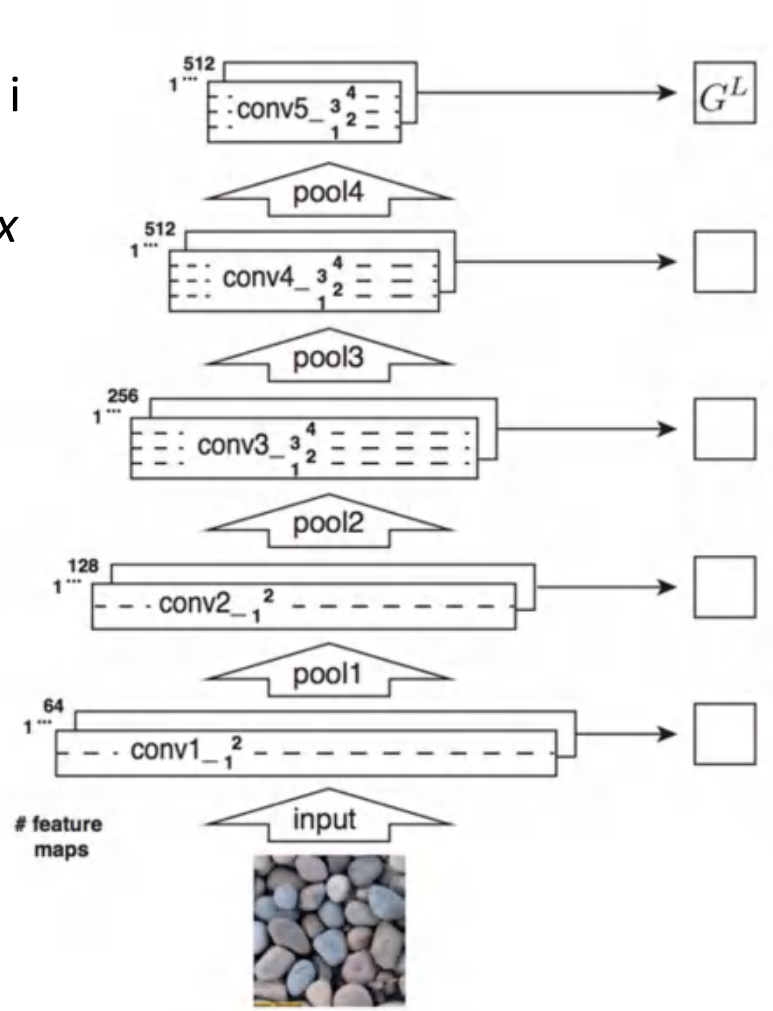
4. Initialize generated image from random noise



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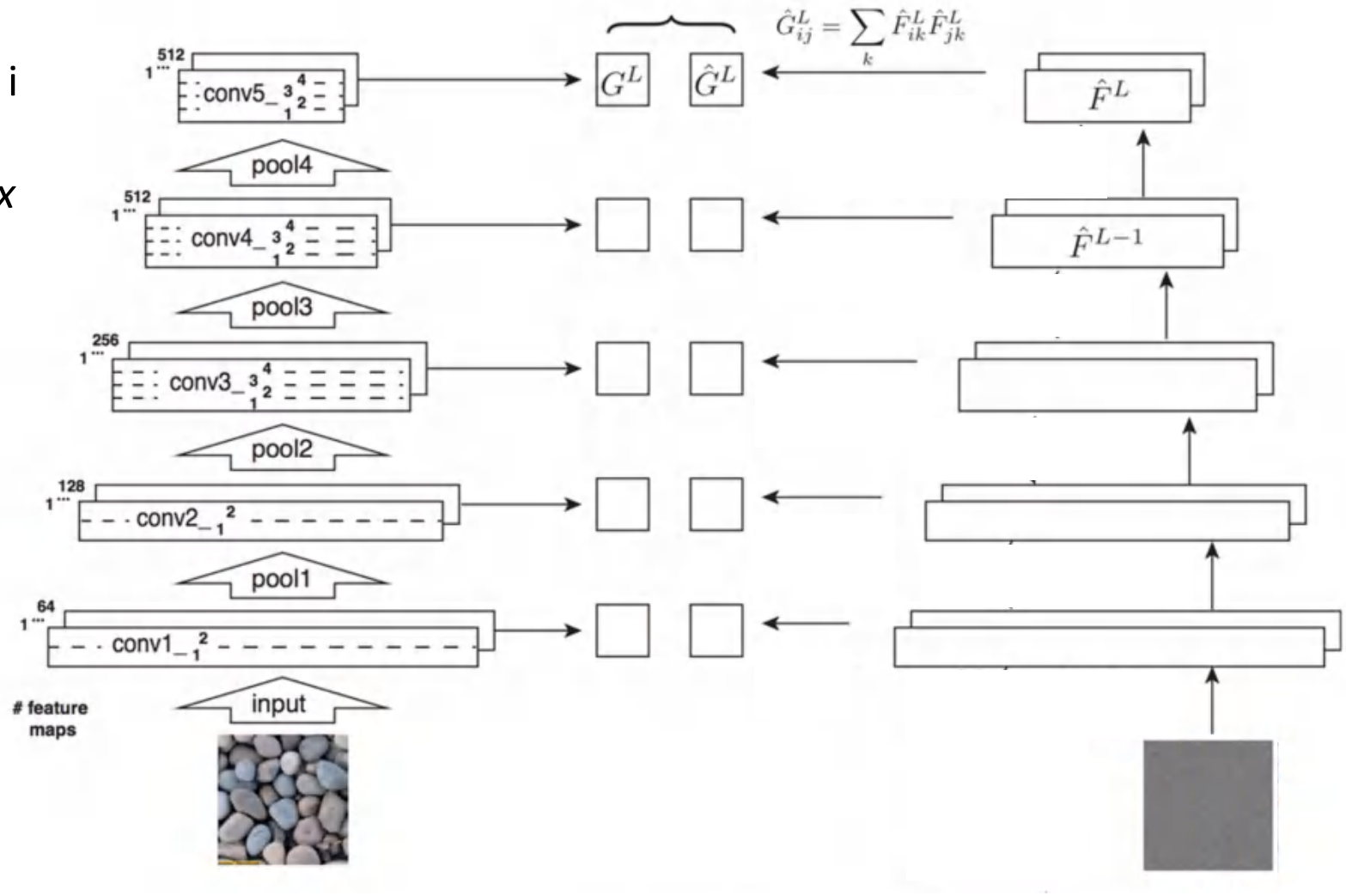

# Neural Texture Synthesis

$$E_\ell = \frac{1}{4N_\ell^2 M_\ell^2} \sum_{c,c'} \left(G^\ell_{c,c'} - \hat{G}^\ell_{c,c'}\right)^2 \qquad L = \sum_{\ell=0}^{L} w_\ell E_\ell$$

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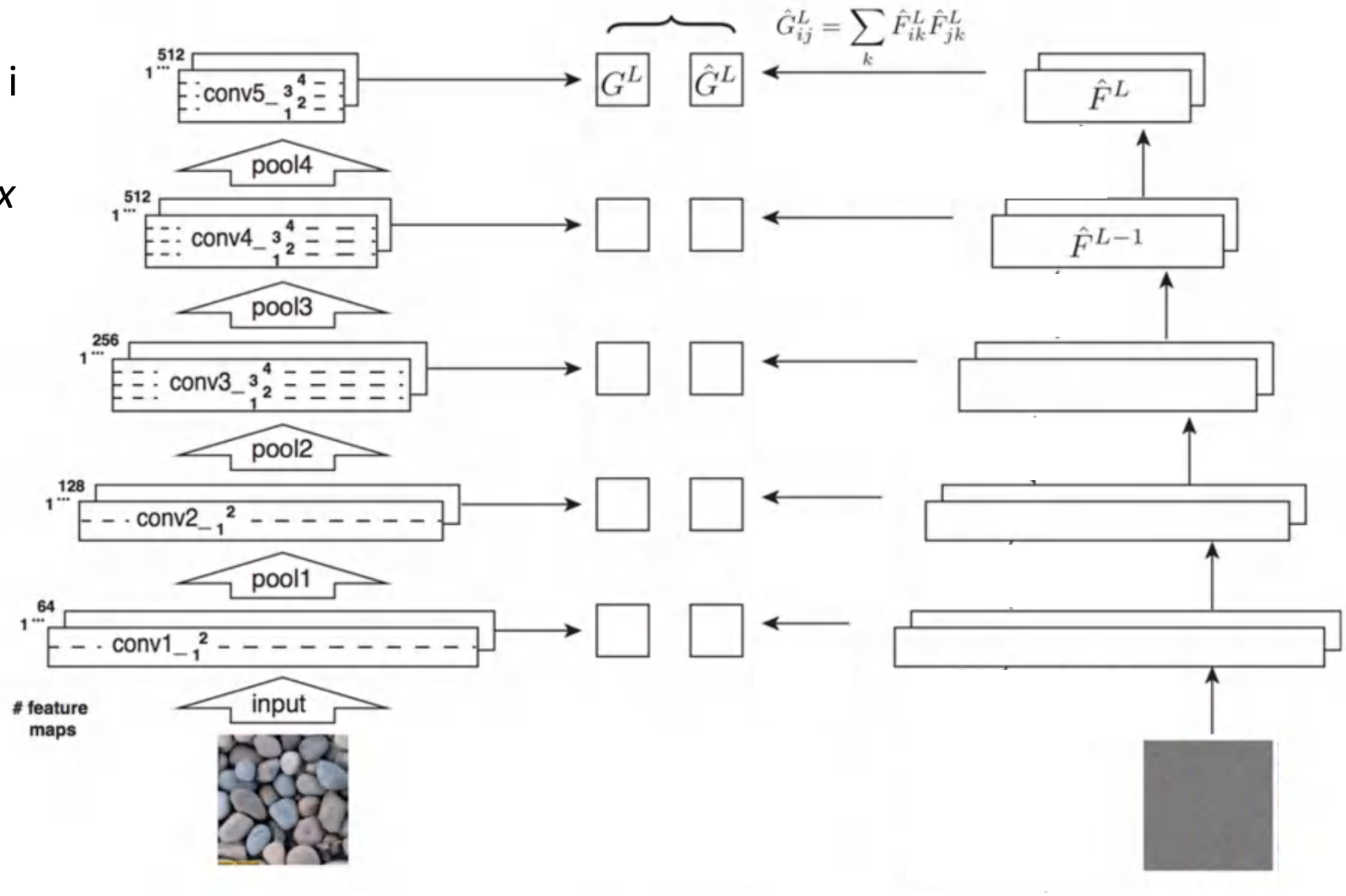
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices



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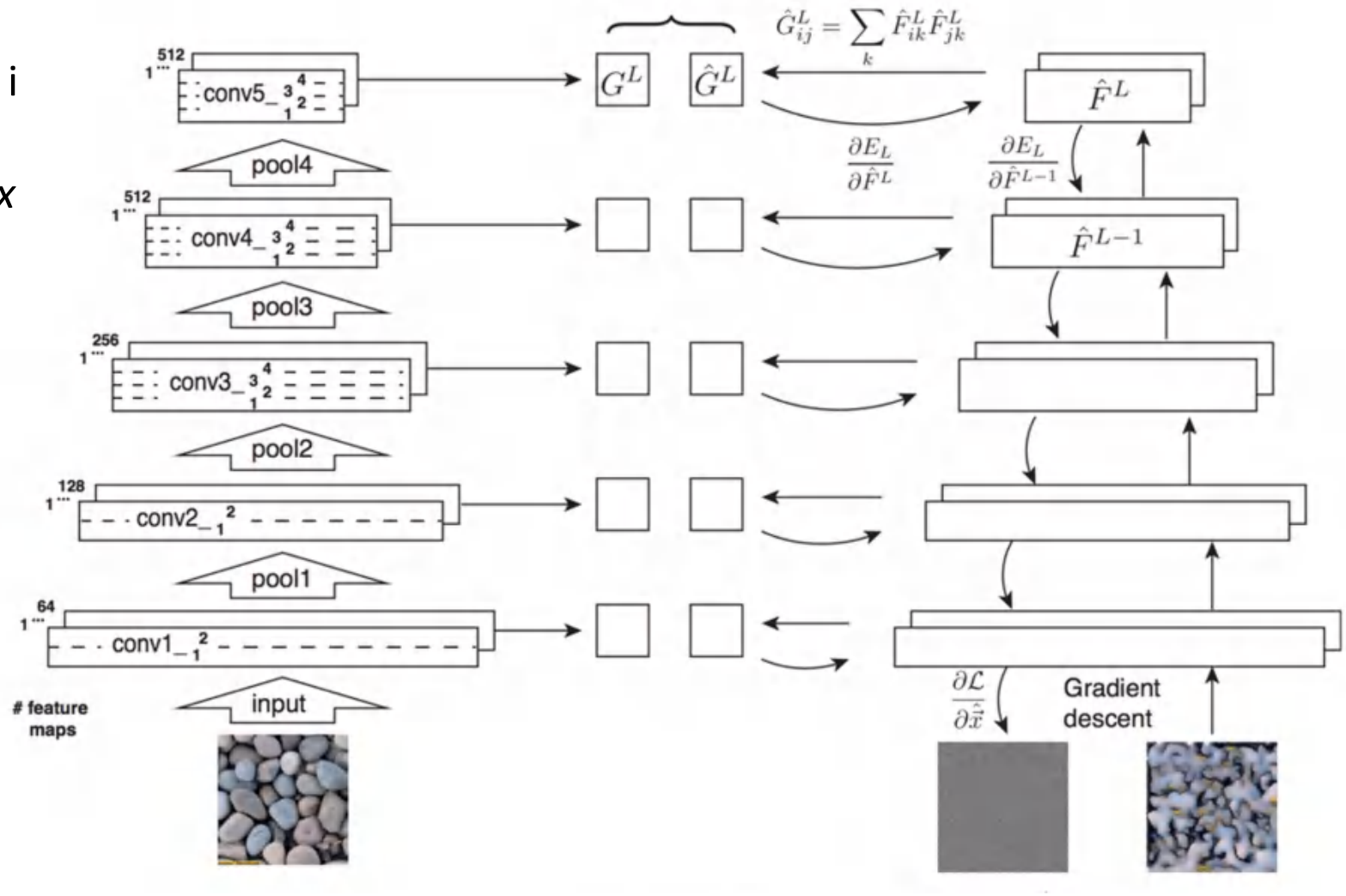
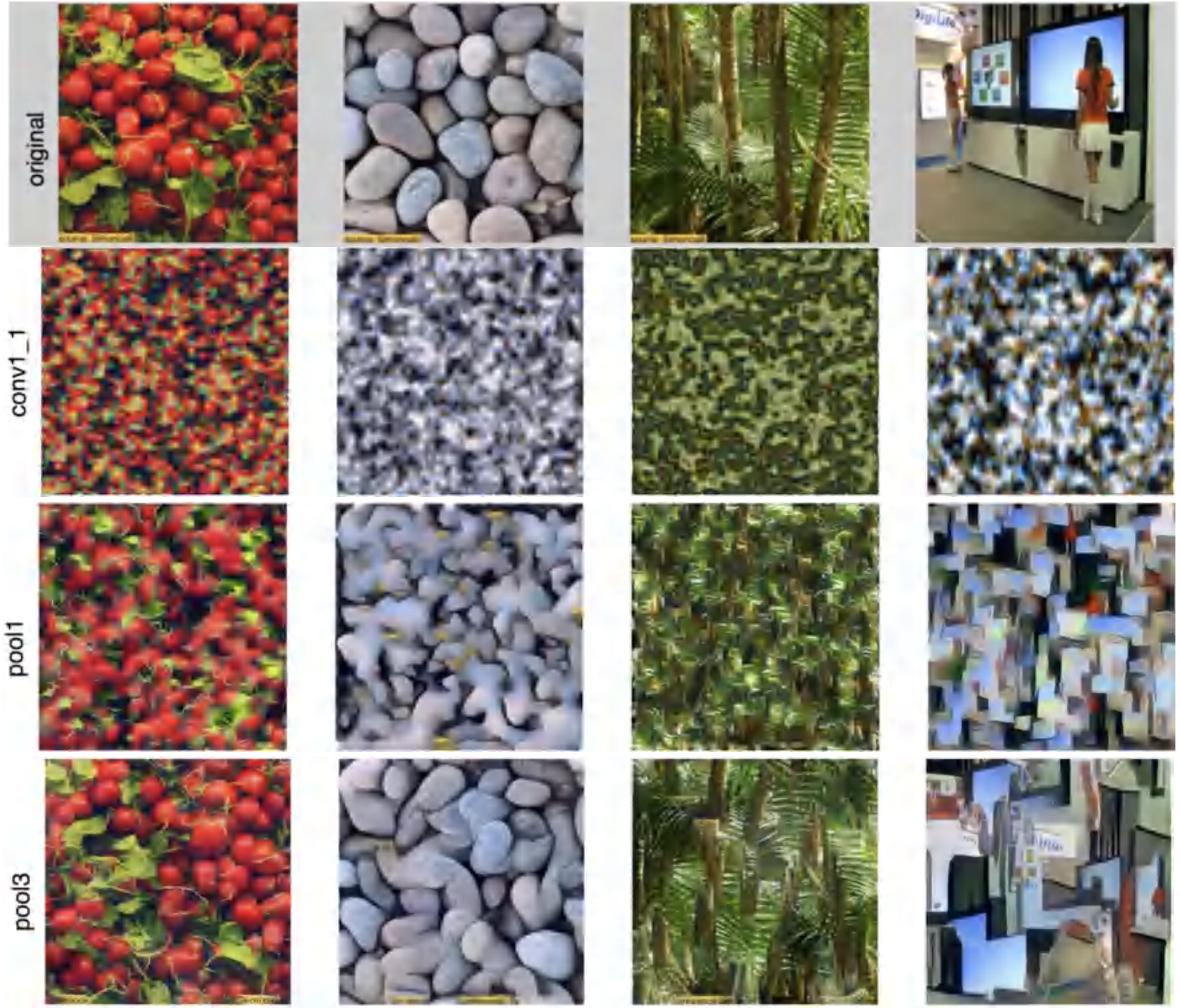
4. Initialize generated image from random noise
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image
9. GOTO 5



# 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)

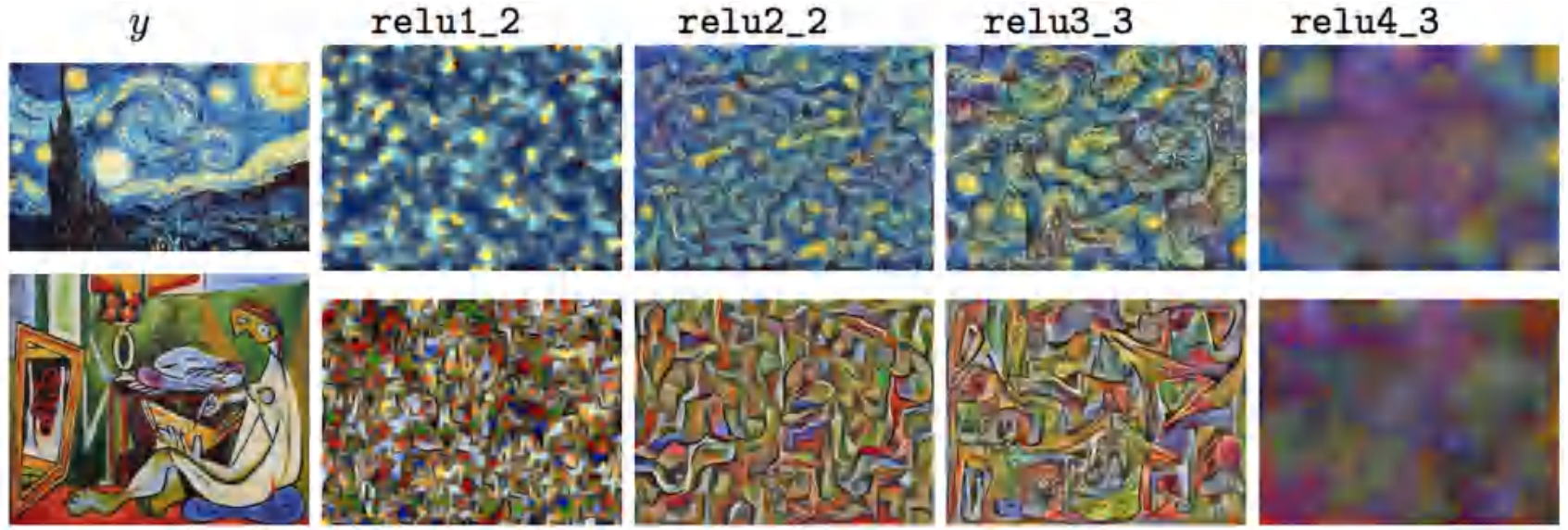
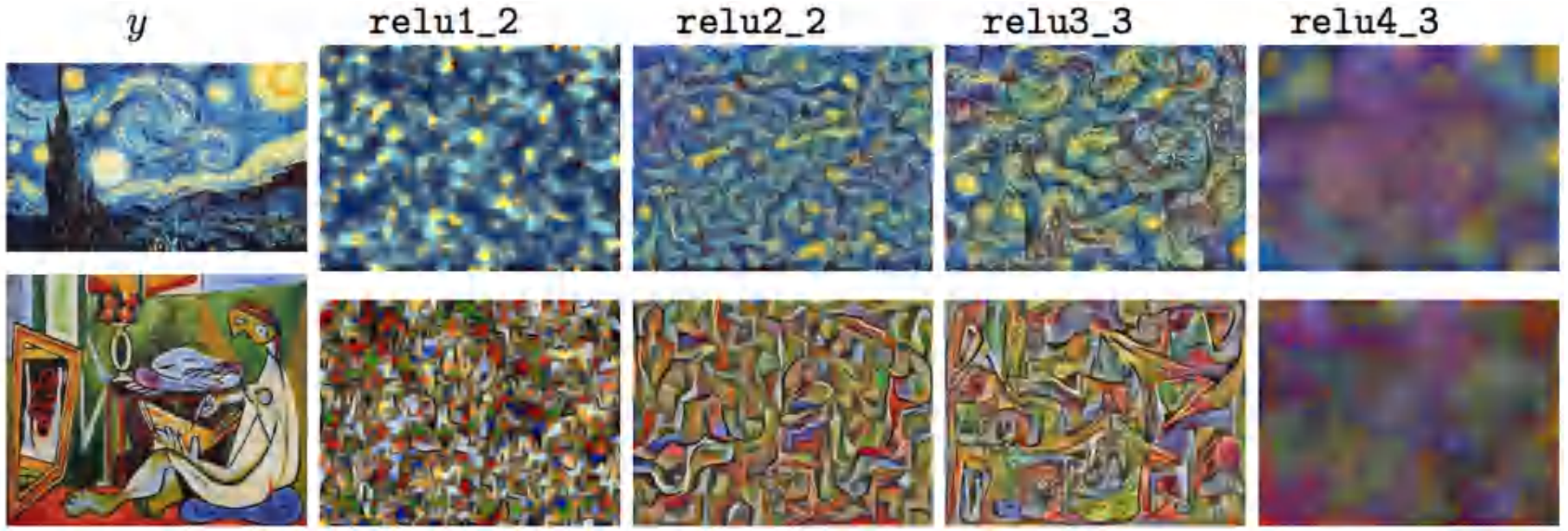



Figure from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

# 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

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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

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Style Image

Starry Night by Van Gogh is in the public domain

=

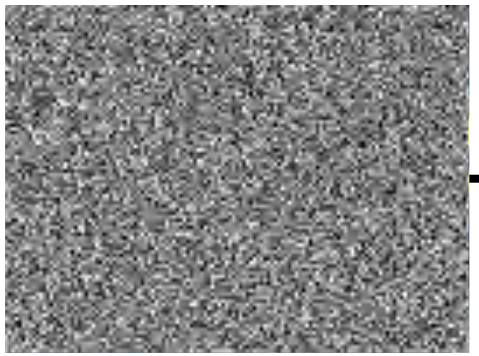
Output Image

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

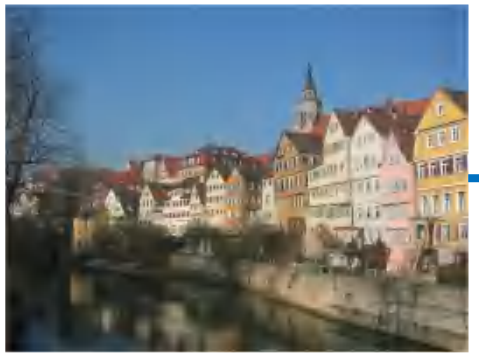
Gatys, Ecker, and Bethge, “Image style transfer using convolutional neural networks”, CVPR 2016

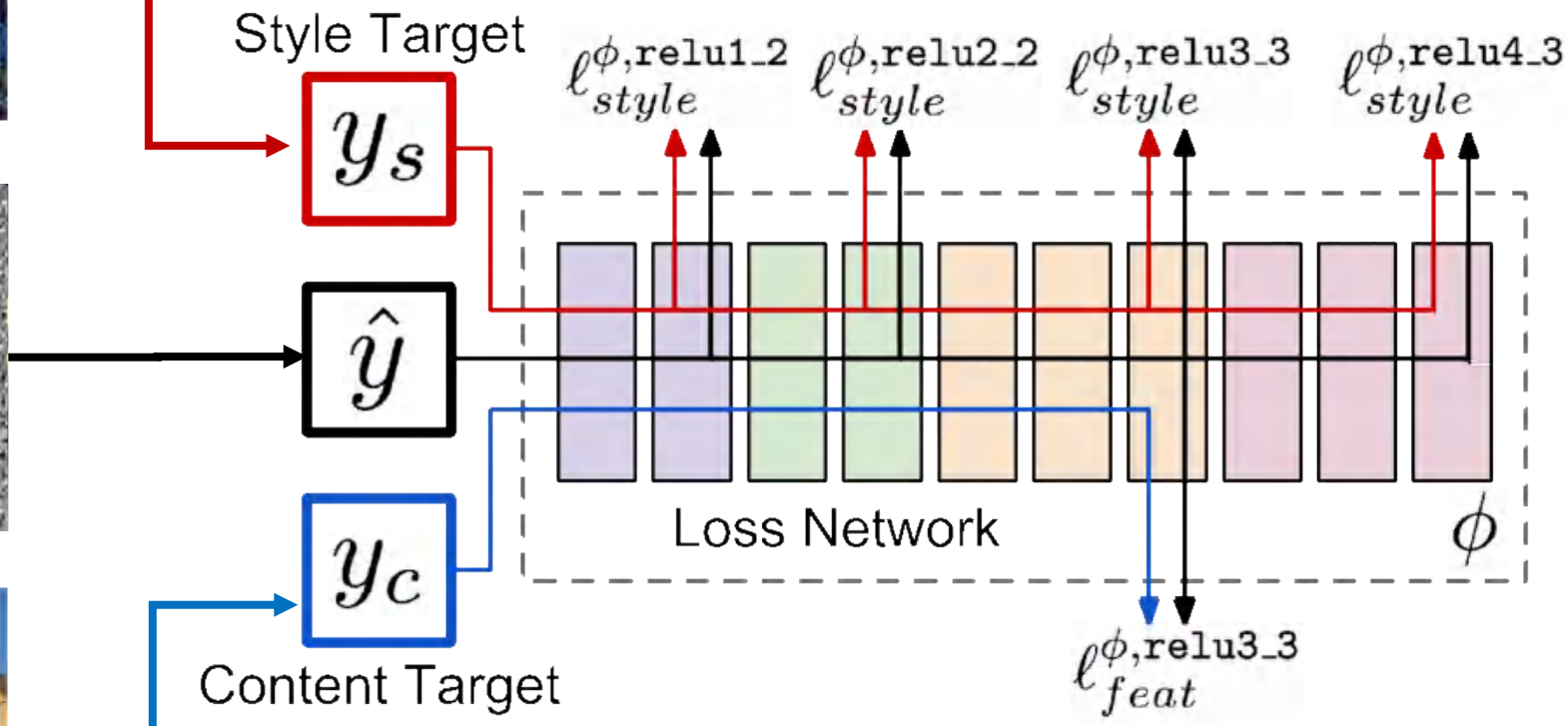
Style image

Output image (Start with noise)



Content image





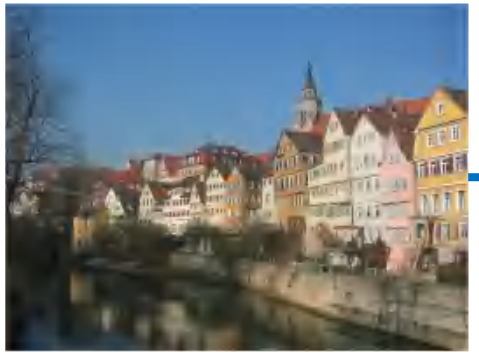

Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016

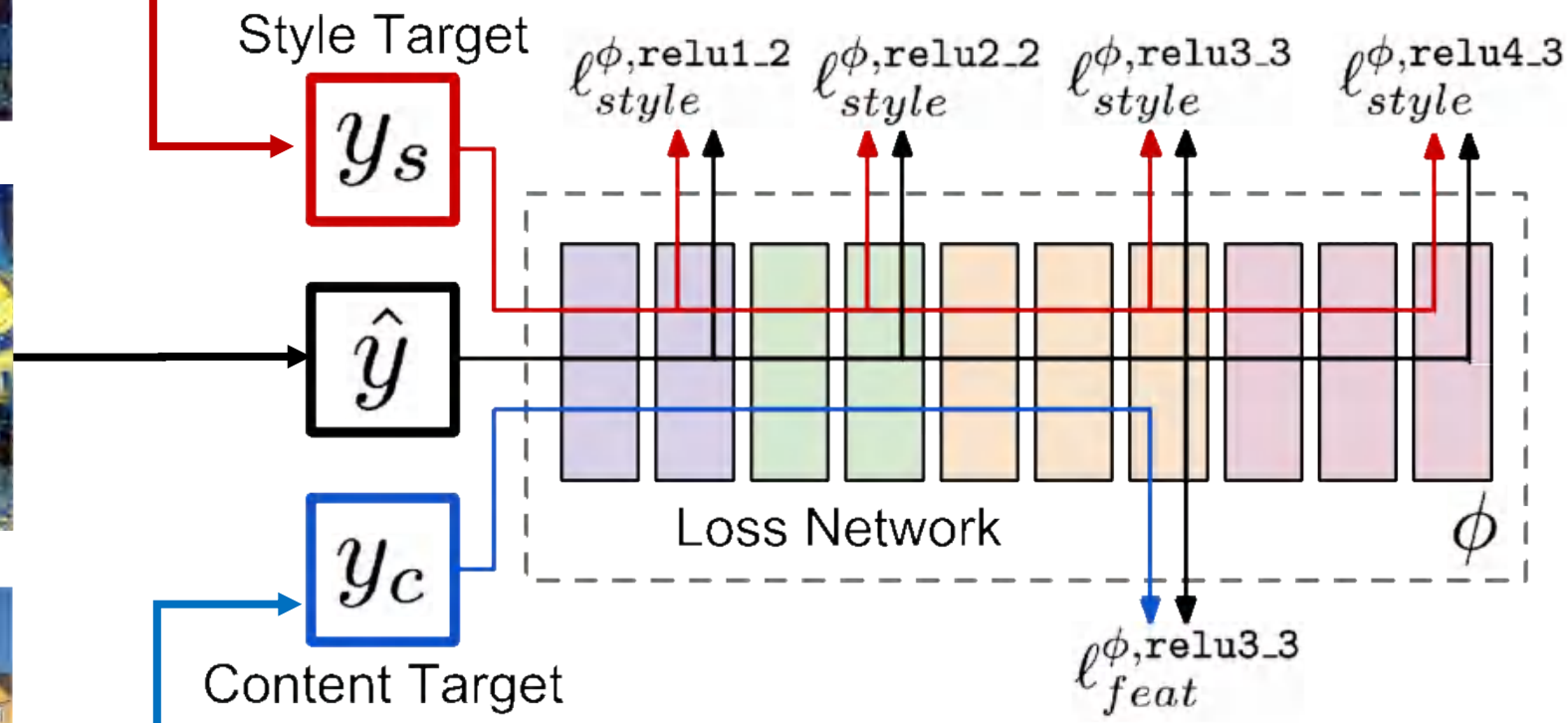
Figure adapted from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Style image

Output image

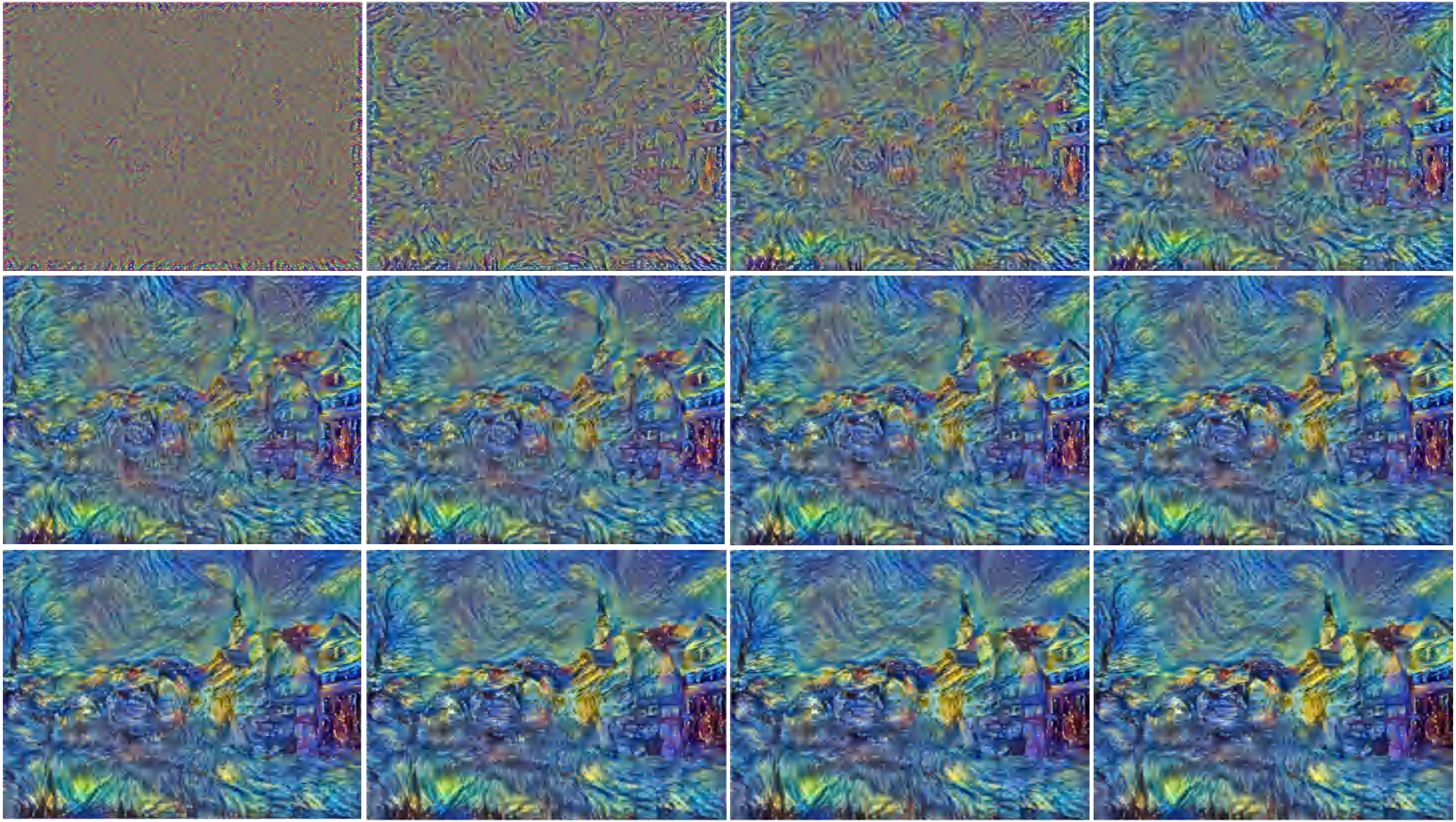
Content image






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

Example outputs from my implementation (in Lua Torch)

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
Figure copyright Justin Johnson, 2015.

# Neural Style Transfer

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

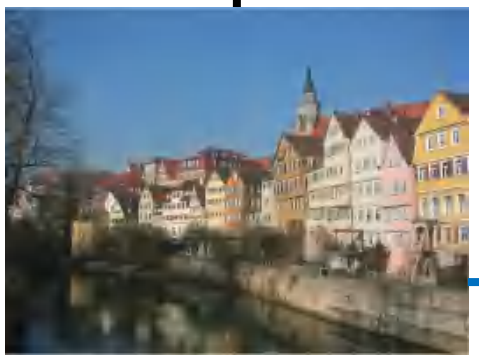
# Neural Style Transfer

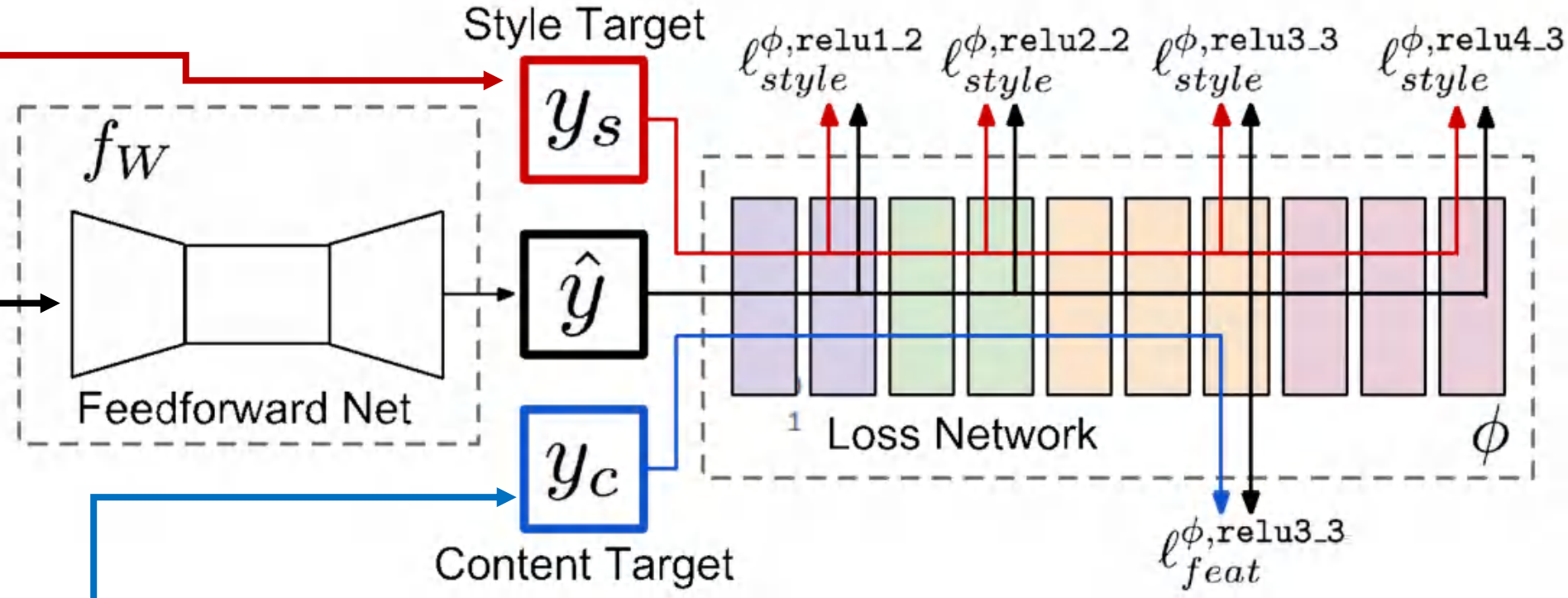
**Problem:** Style transfer requires many forward / backward passes through VGG; very slow!

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

# Fast Neural Style Transfer

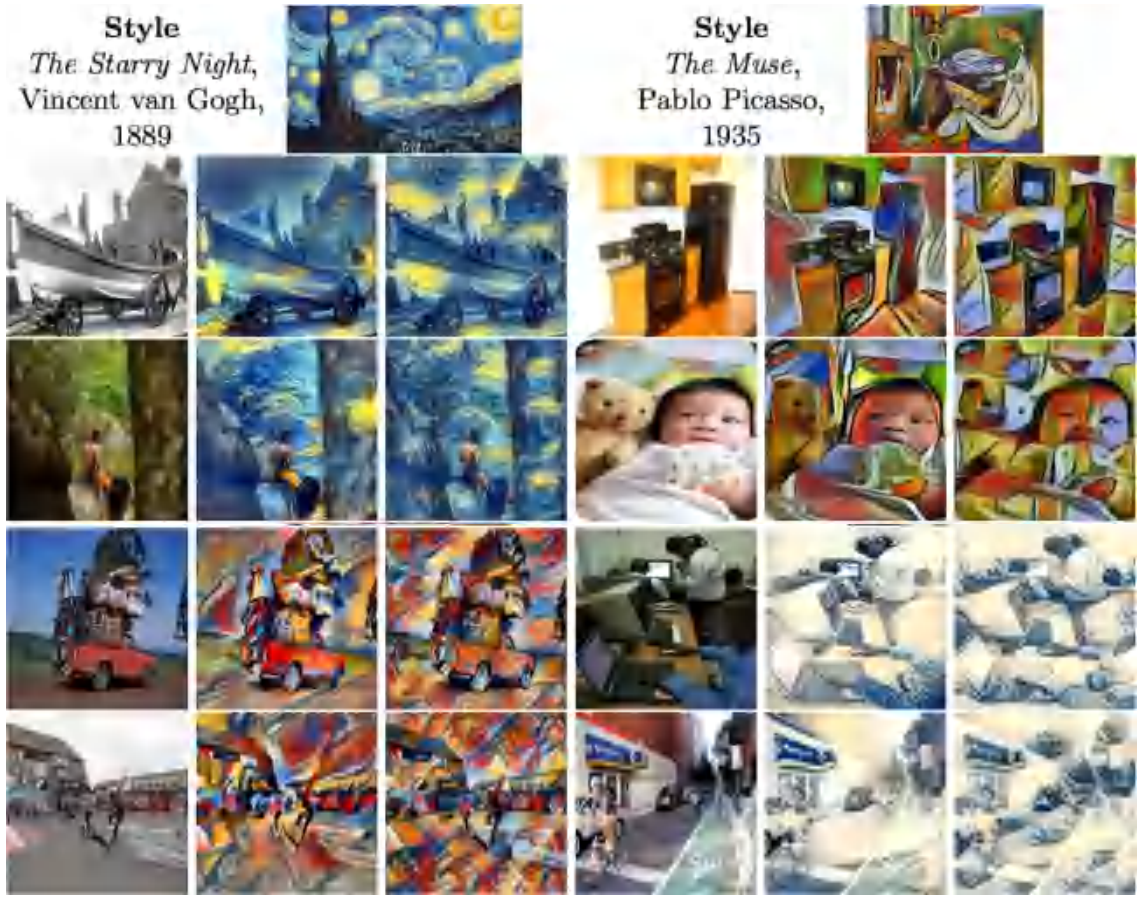
(1) Train a feedforward network for each style
(2) Use pretrained CNN to compute same losses as before
(3) After training, stylize images using a single forward pass






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

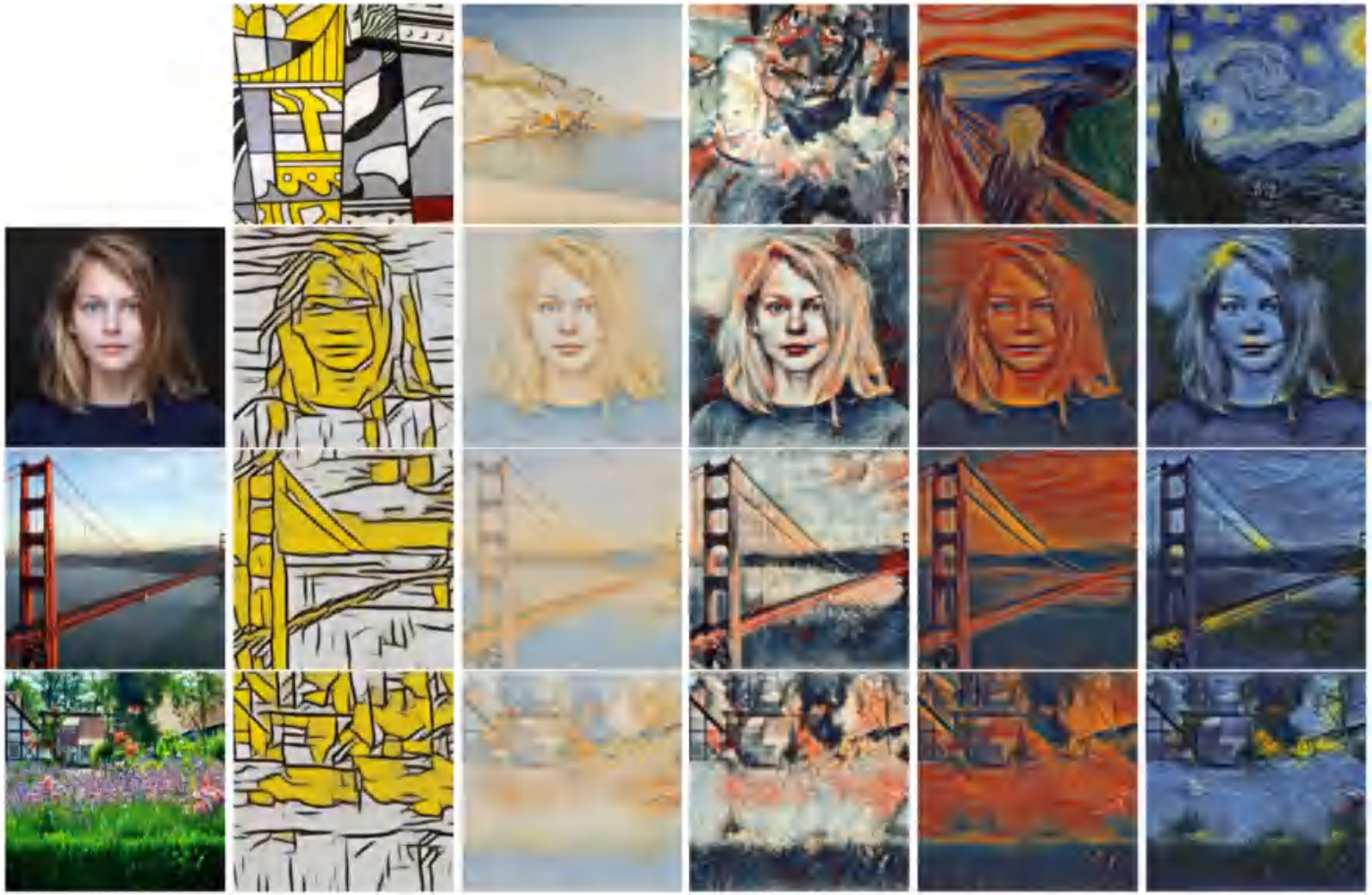
Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016

# 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

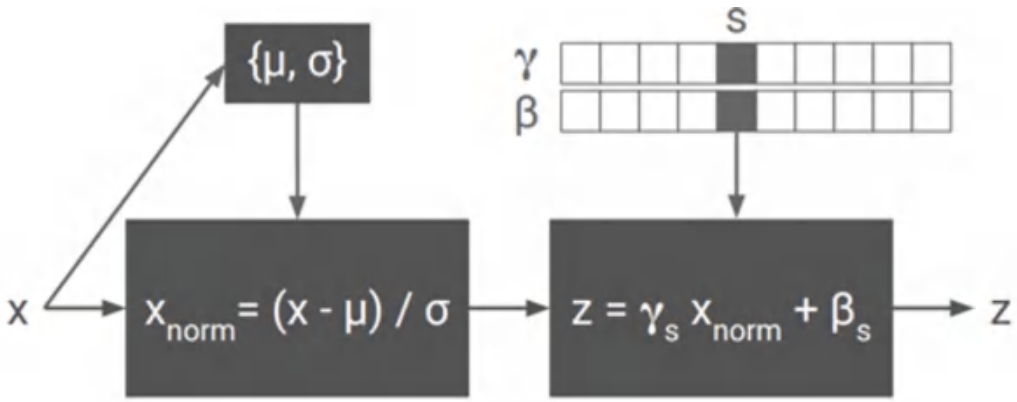
# One Network, Many Styles



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, adversarial examples, feature inversion
**Fun**: DeepDream, Style Transfer.

# Next Time:
# Self-Supervised Learning