Lecture 14: Visualizing and Understanding

Reminder: A4

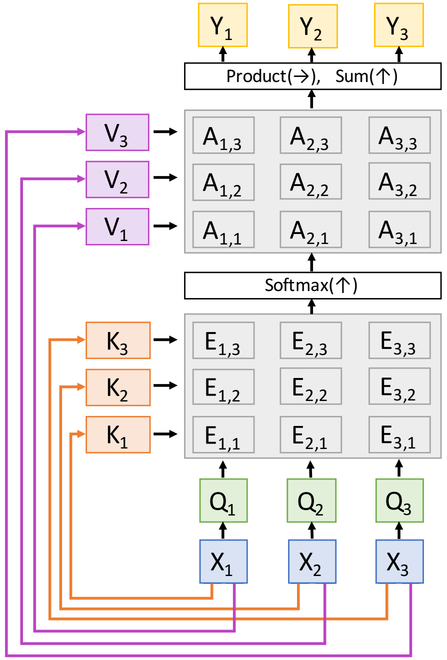
A4 due **Friday, October 30 11:59pm**

A4 covers:
- PyTorch autograd
- Residual networks
- Recurrent neural networks
- Attention
- Feature visualization
- Style transfer
- Adversarial examples

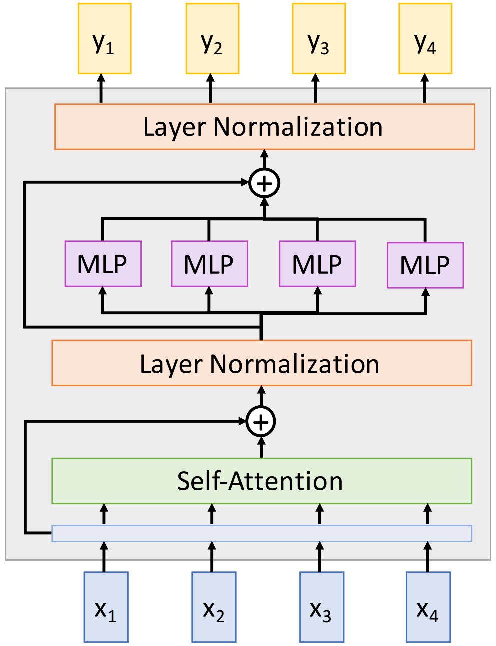
Last Time: Attention

Adding **Attention** to RNN models lets them look at different parts of the input at each timestep

Generalized **Self-Attention** is new, powerful neural network primitive



Transformers are a new neural network model that only uses attention

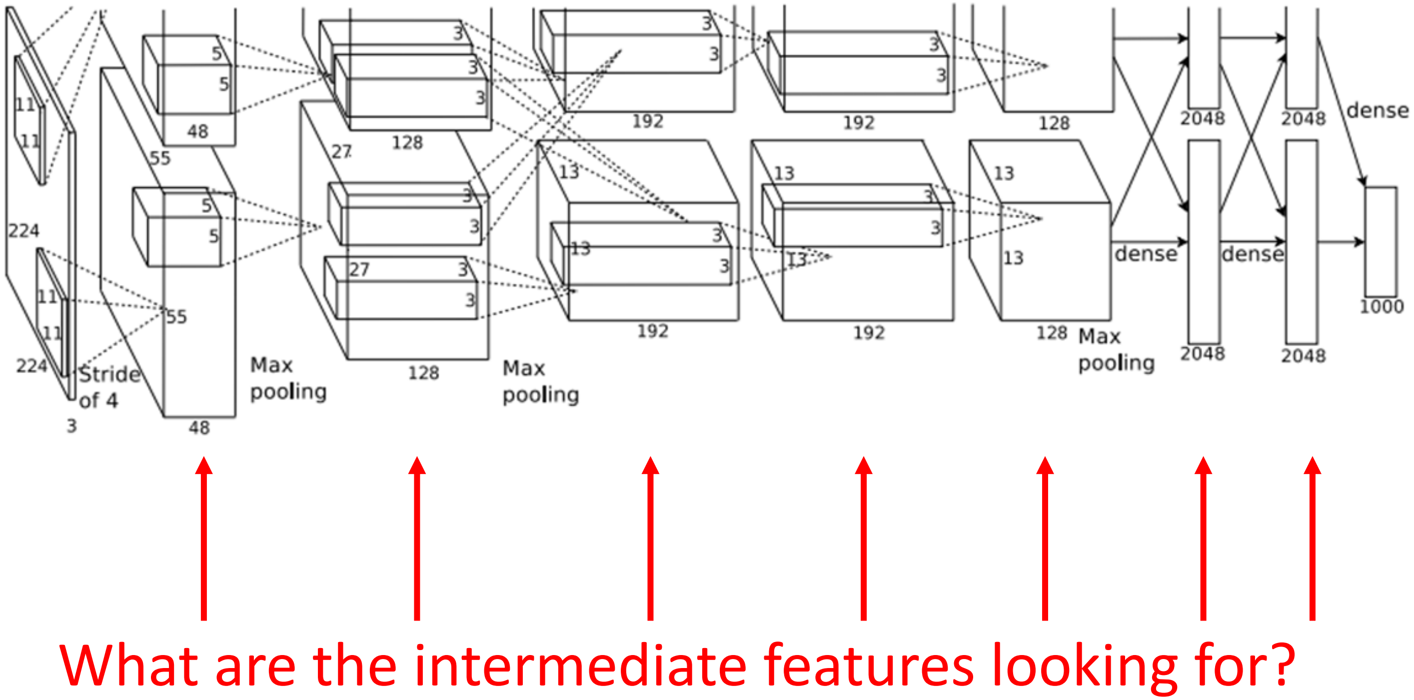


Xu et al, "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

What's going on inside Convolutional Networks?

This image is CC0 public domain

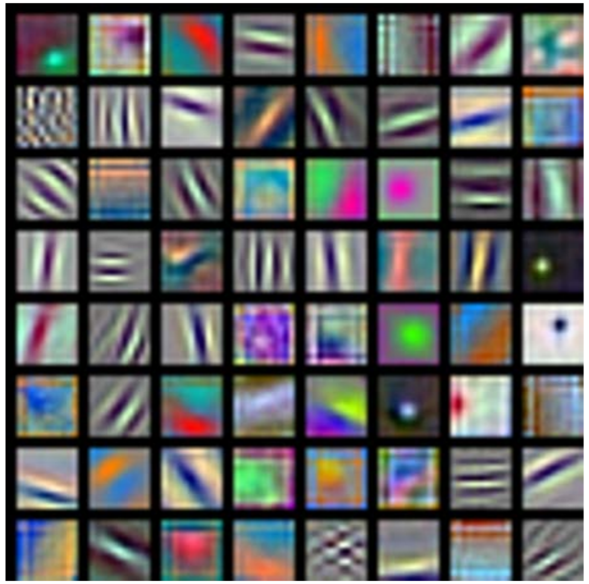
Input Image:
3 x 224 x 224



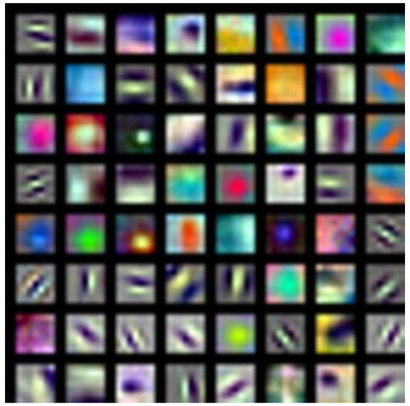
Class Scores:
1000 numbers

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

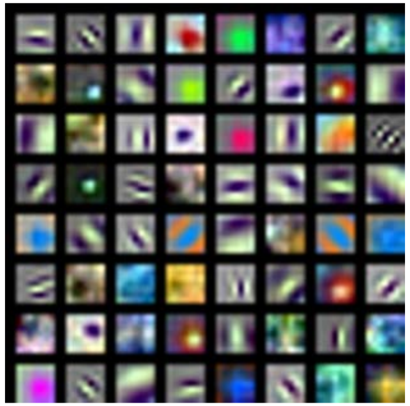
First Layer: Visualize Filters



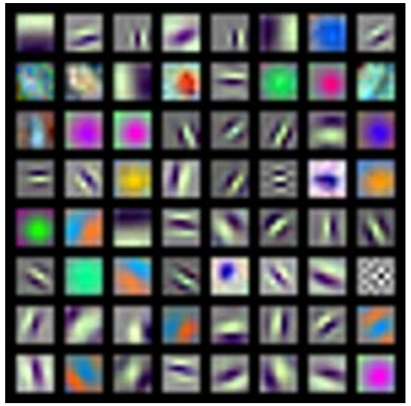
AlexNet:
64 x 3 x 11 x 11



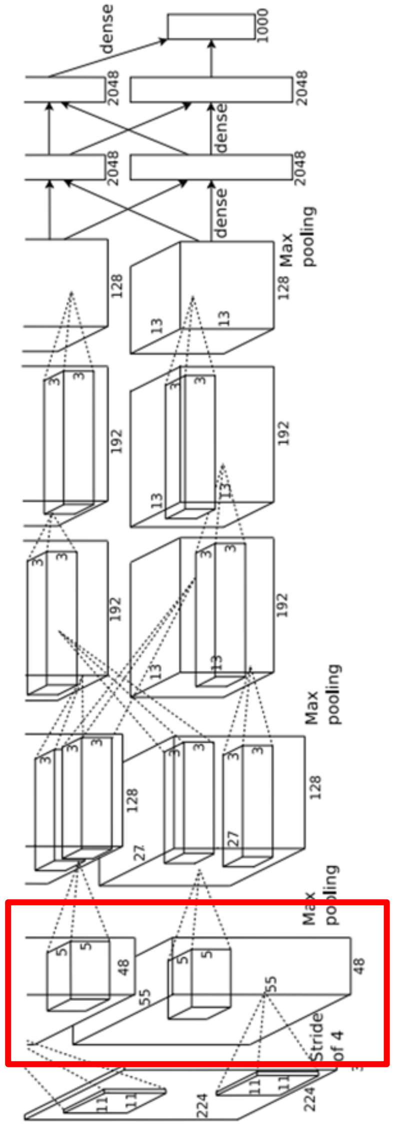
ResNet-18:
64 x 3 x 7 x 7



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

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

First layer weights: 16 x 3 x 7 x 7

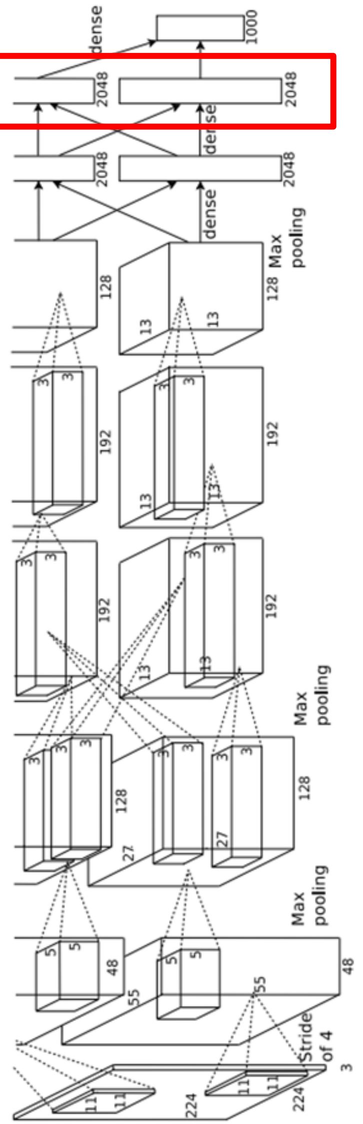
Second layer weights: 20 x 16 x 7 x 7

Third layer weights: 20 x 20 x 7 x 7

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

Last Layer

FC7 layer



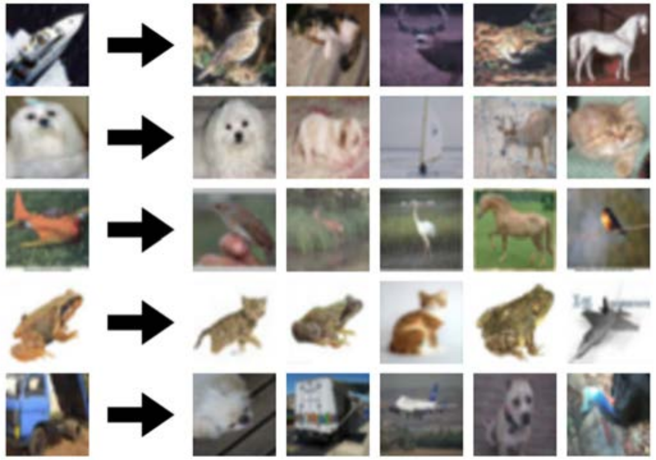
4096-dimensional feature vector for an image
(layer immediately before the classifier)

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.

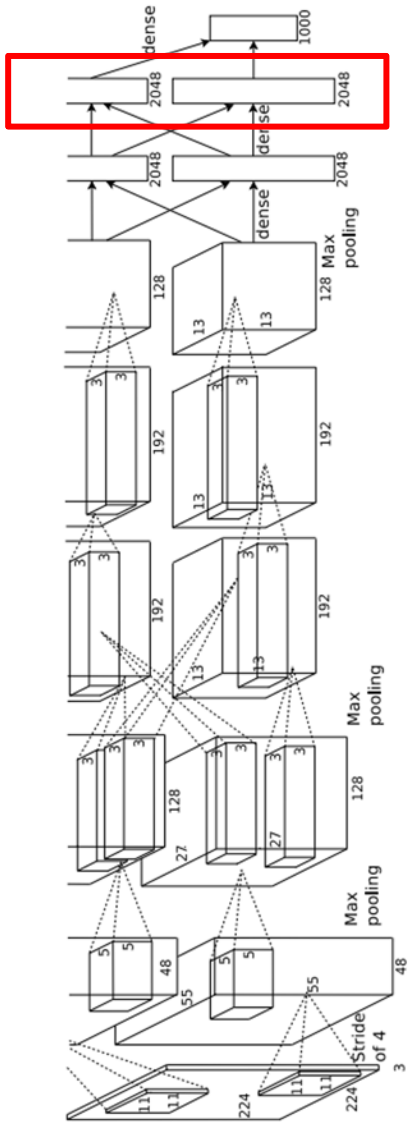
Last Layer: Nearest Neighbors

Recall: Nearest neighbors in pixel space



Test image

L2 Nearest neighbors in feature space



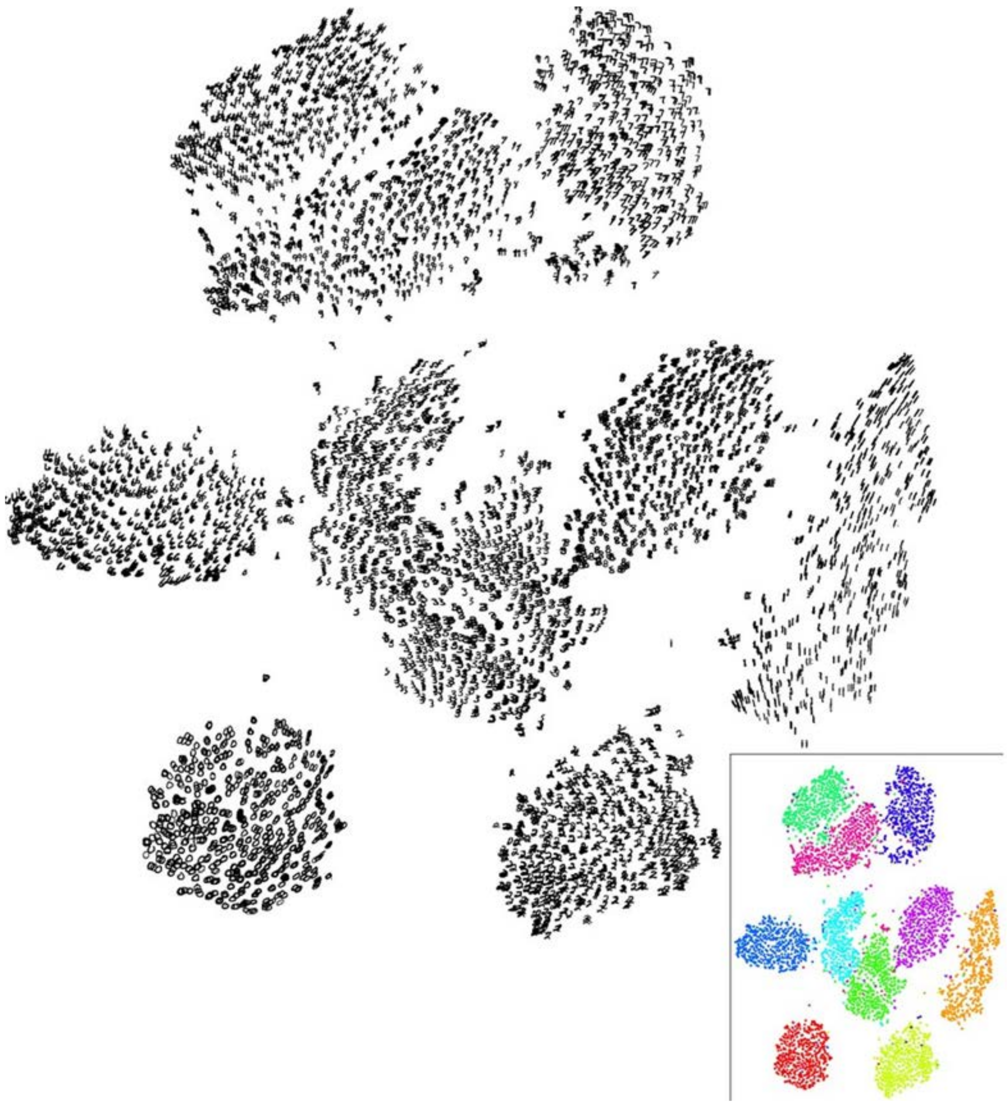
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NeurIPS 2012.
Figures reproduced with permission.

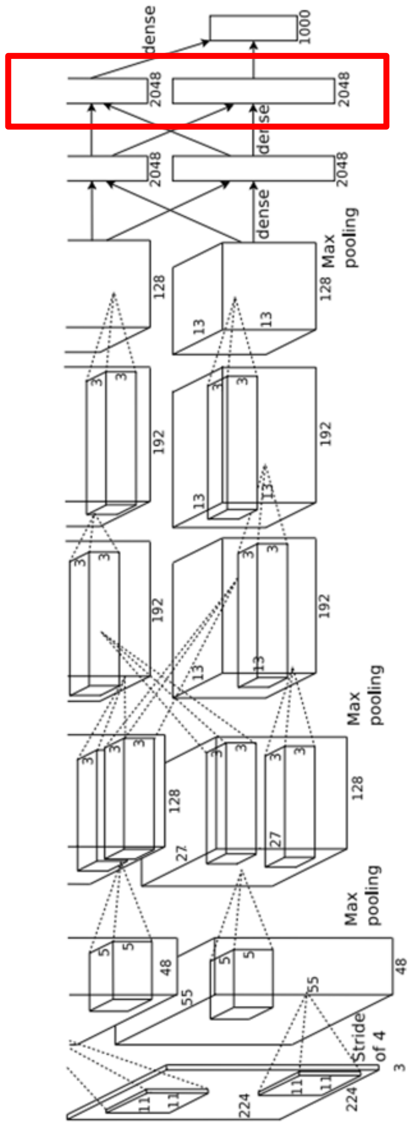
Last Layer: Dimensionality Reduction

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

Simple algorithm: Principal Component Analysis (PCA)

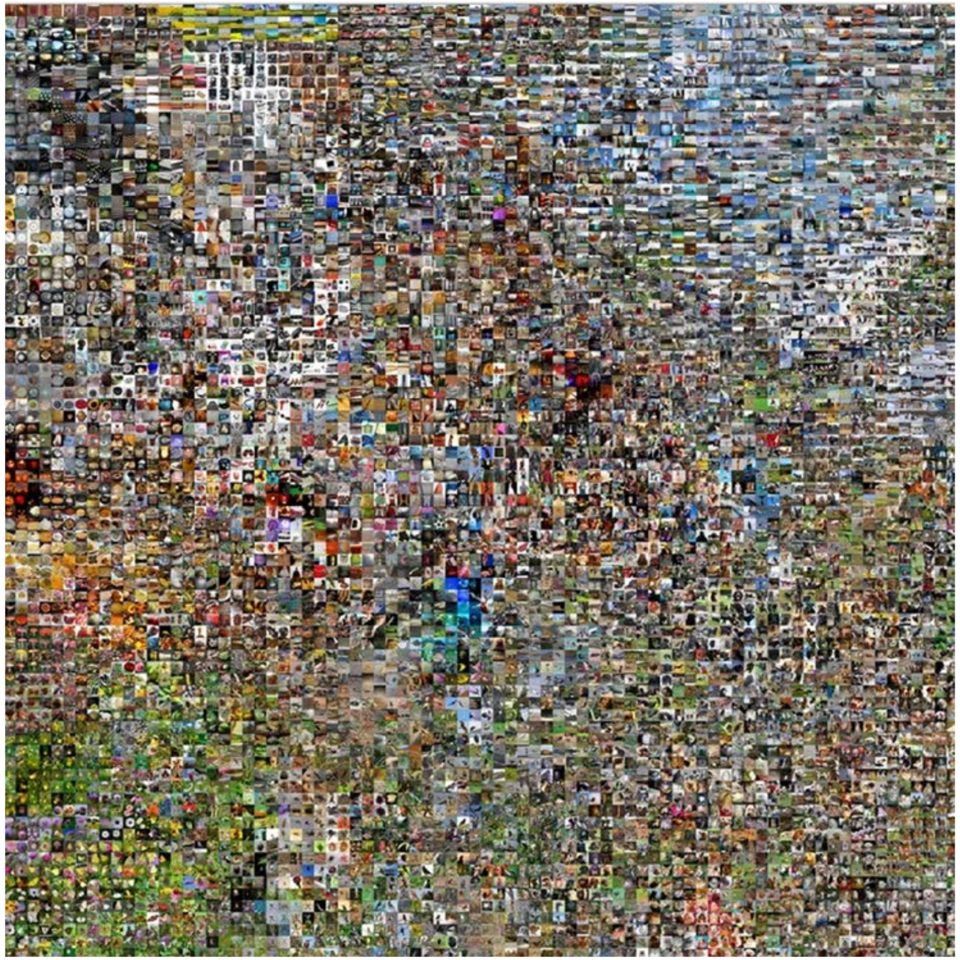
More complex: **t-SNE**

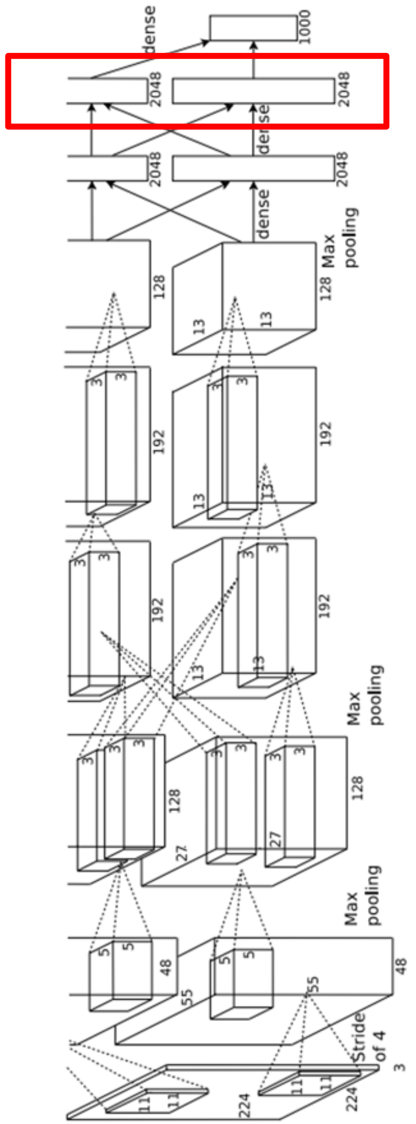




Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008

Last Layer: Dimensionality Reduction



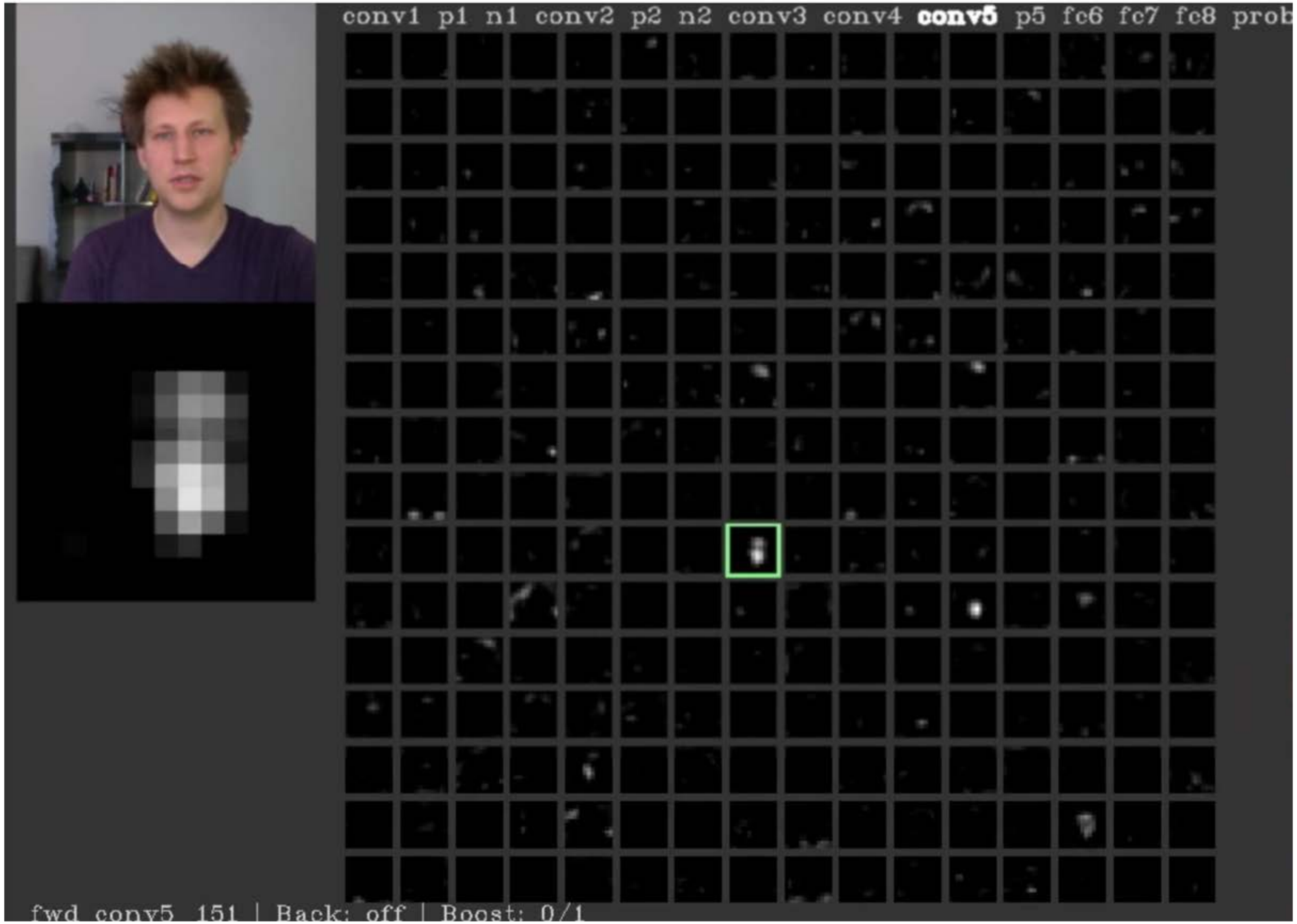


Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008
Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figure reproduced with permission.

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

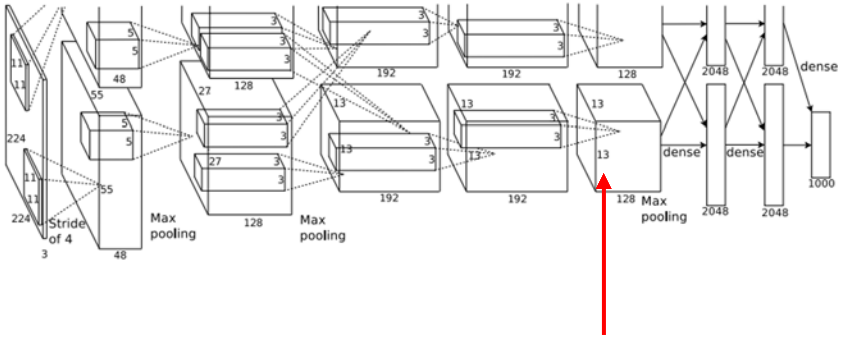
Visualizing Activations

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



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

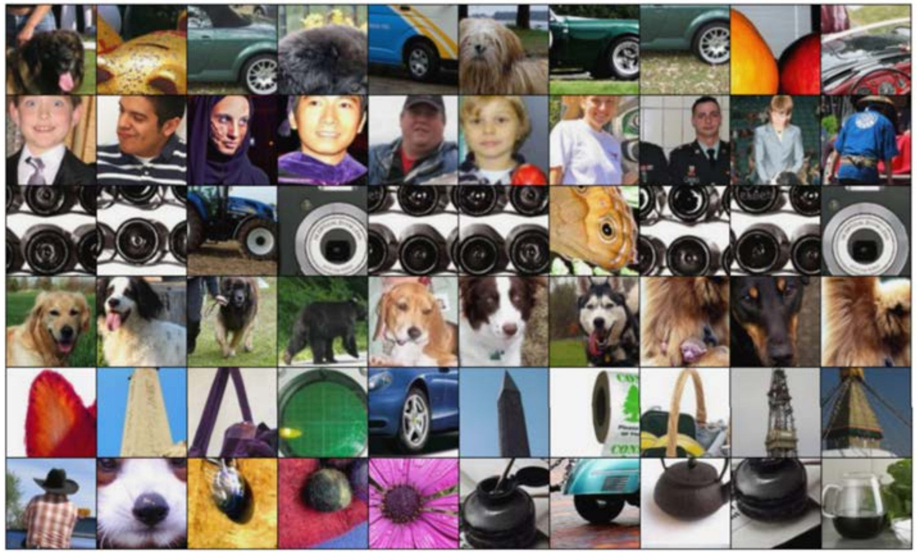
Maximally Activating Patches



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

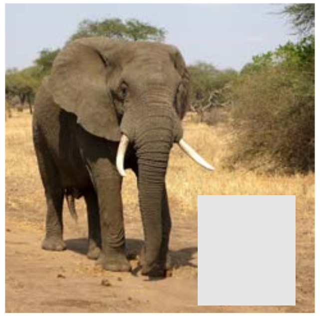
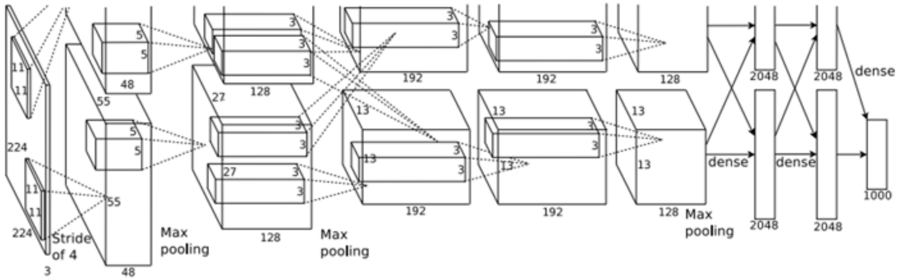
Visualize image patches that correspond to maximal activations

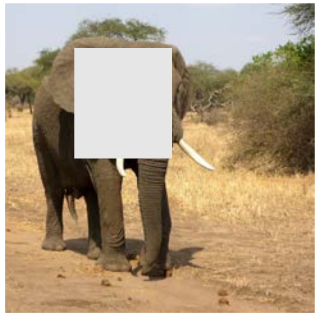
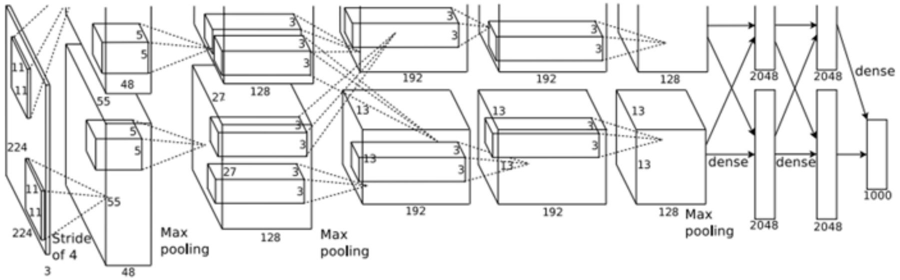


Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

Which Pixels Matter? Saliency via Occlusion

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

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

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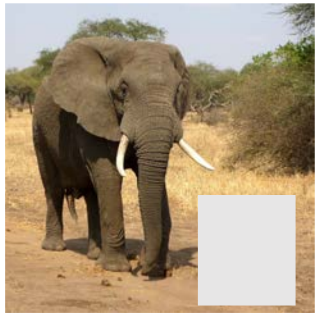
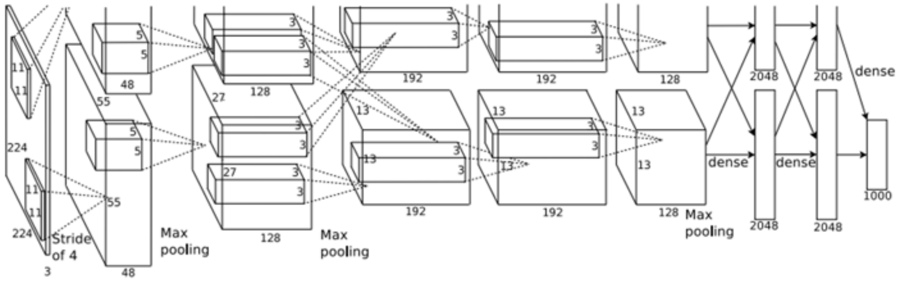
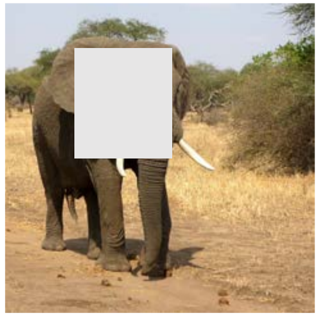
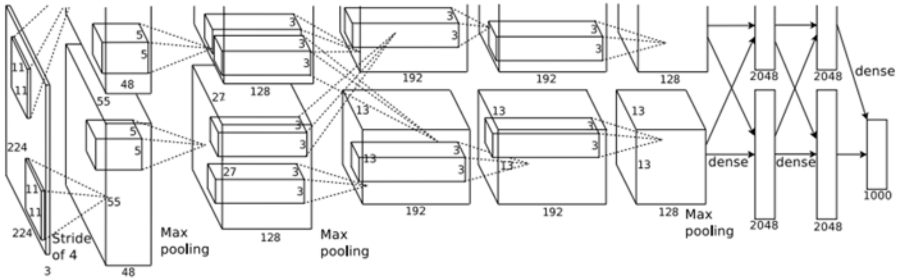
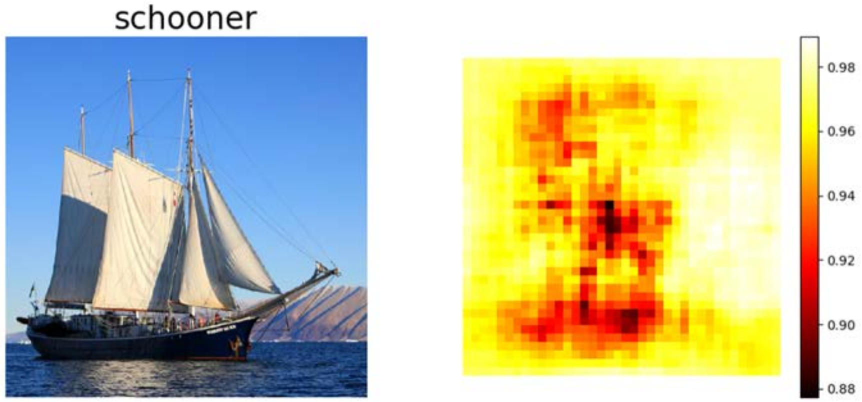
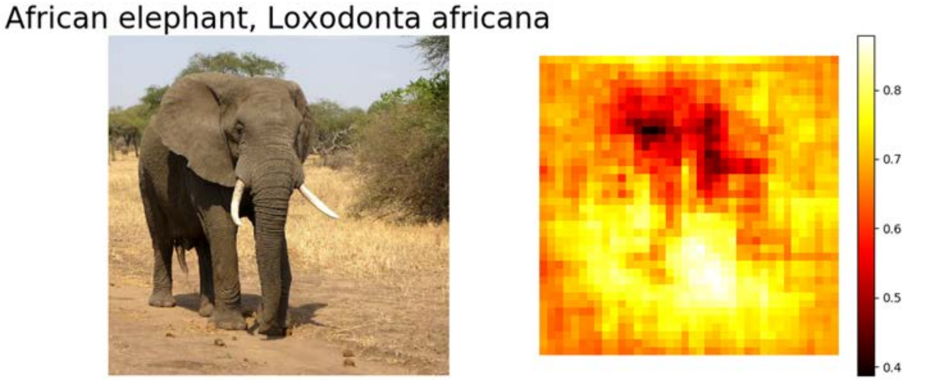


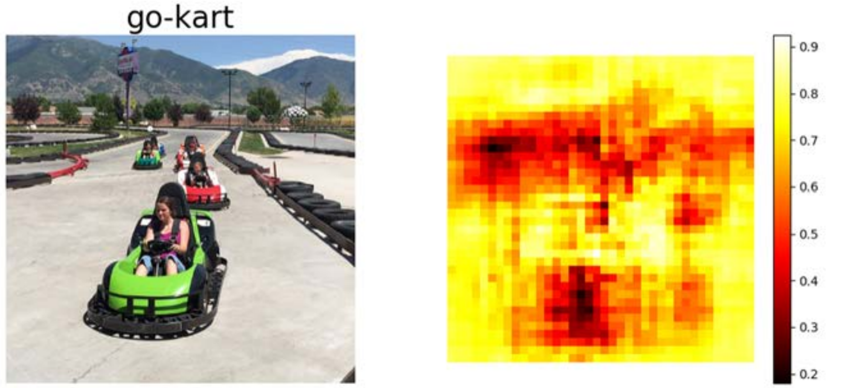








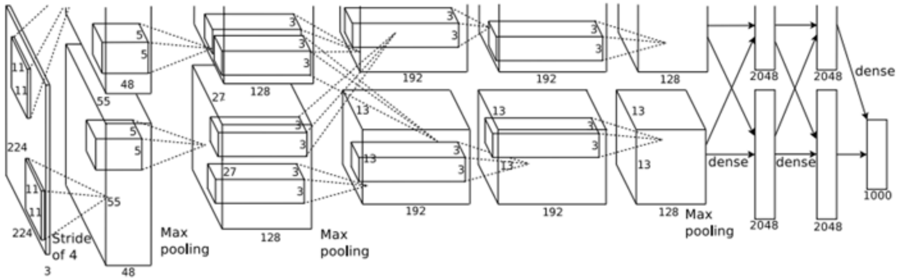




Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

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.

Which pixels matter? Saliency via Backprop

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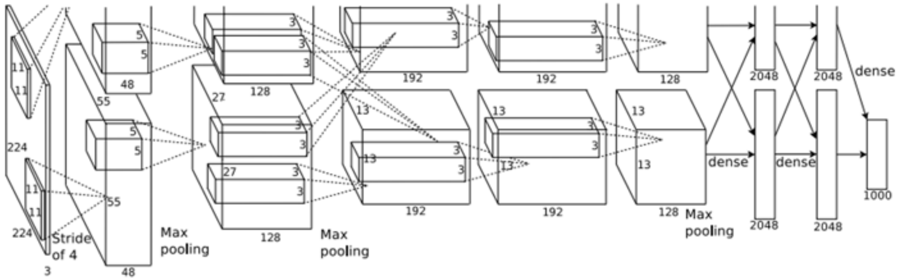

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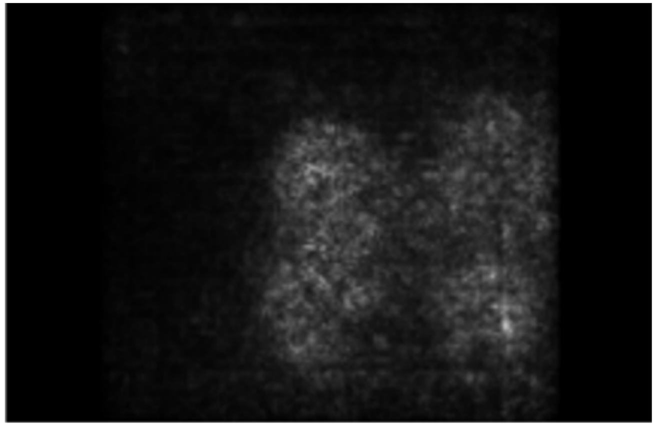
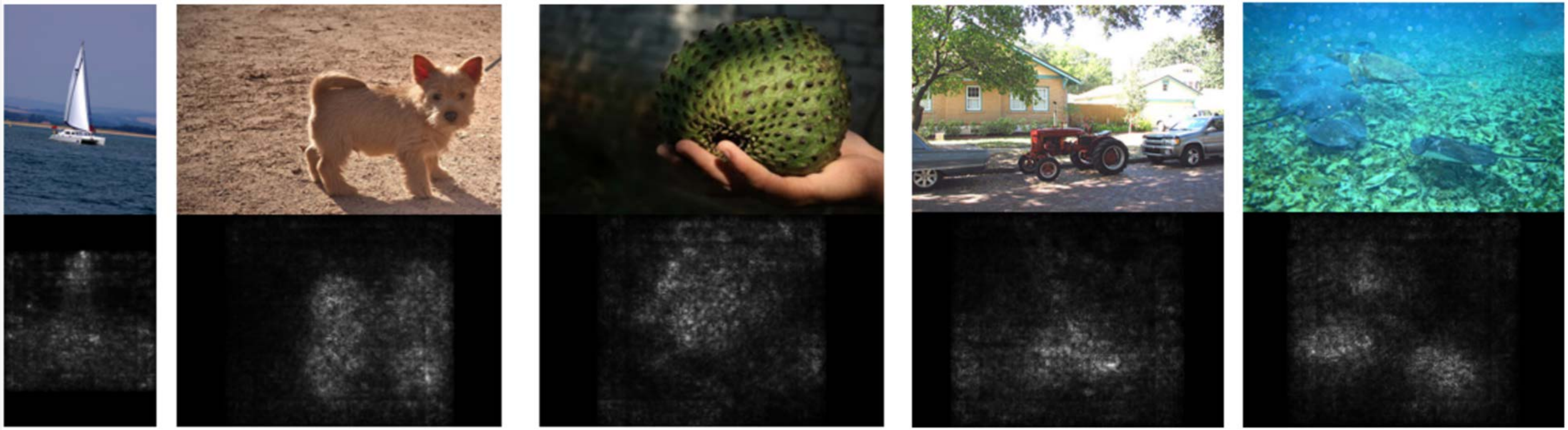


Compute gradient of (unnormalized) class score with respect to image pixels, take absolute value and max over RGB channels

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

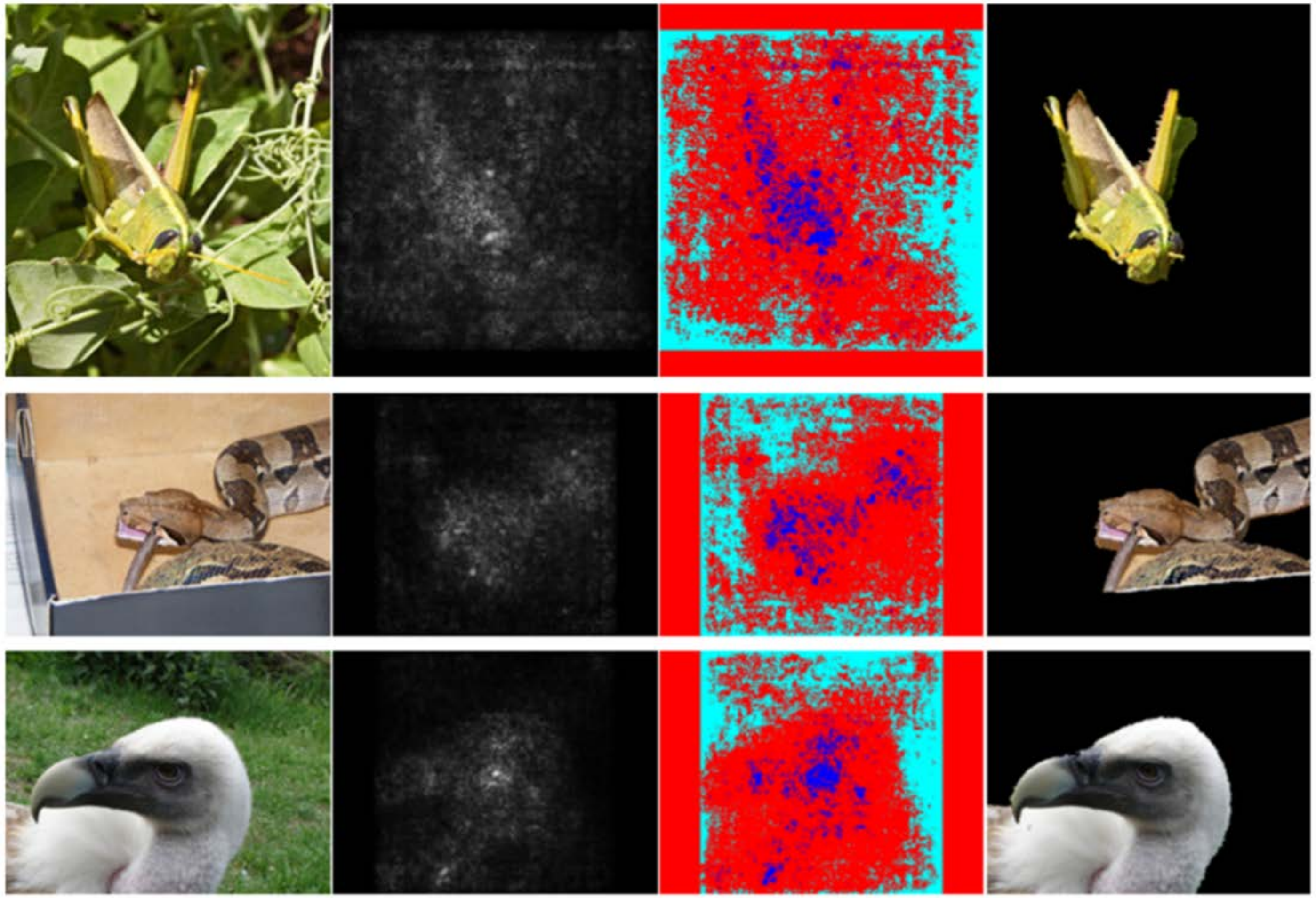
Which pixels matter? Saliency via Backprop



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

Saliency Maps: Segmentation without Supervision

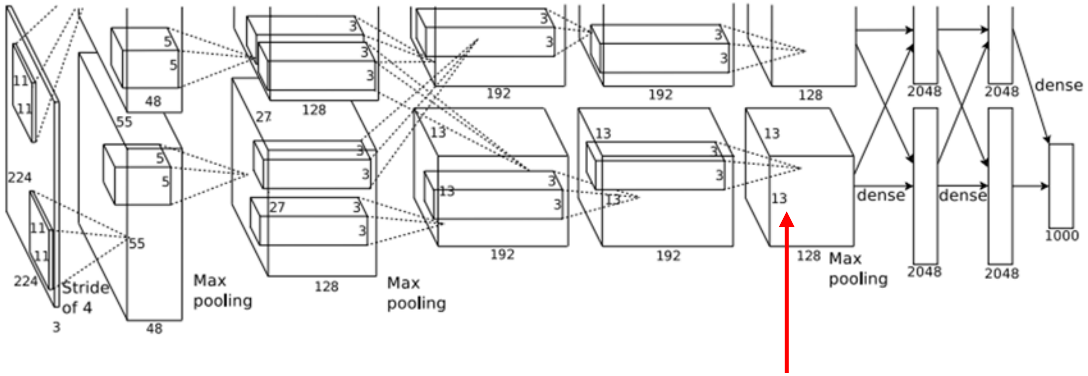
Use GrabCut on saliency map



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

Intermediate Features via (guided) backprop

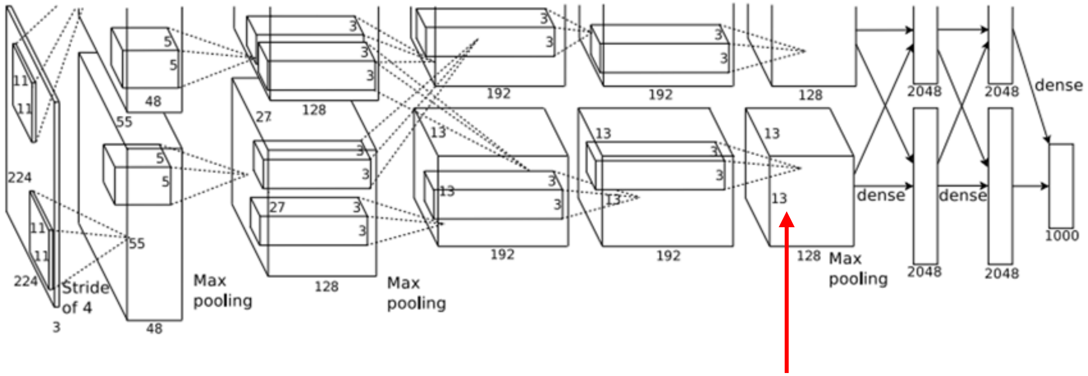


Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

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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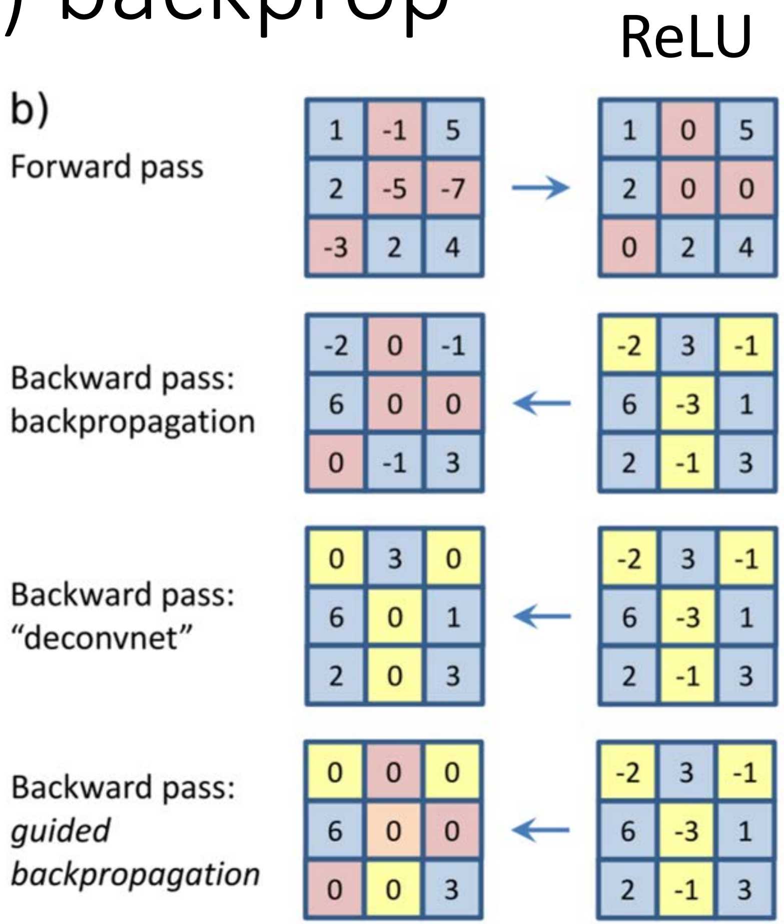
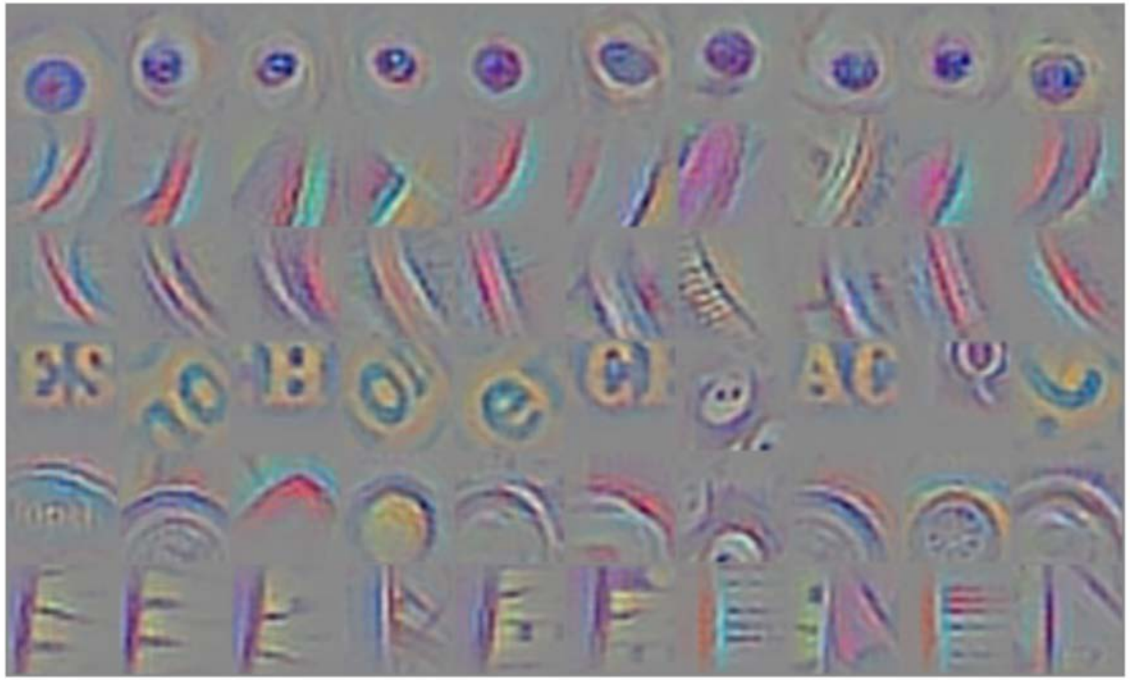


Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)

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
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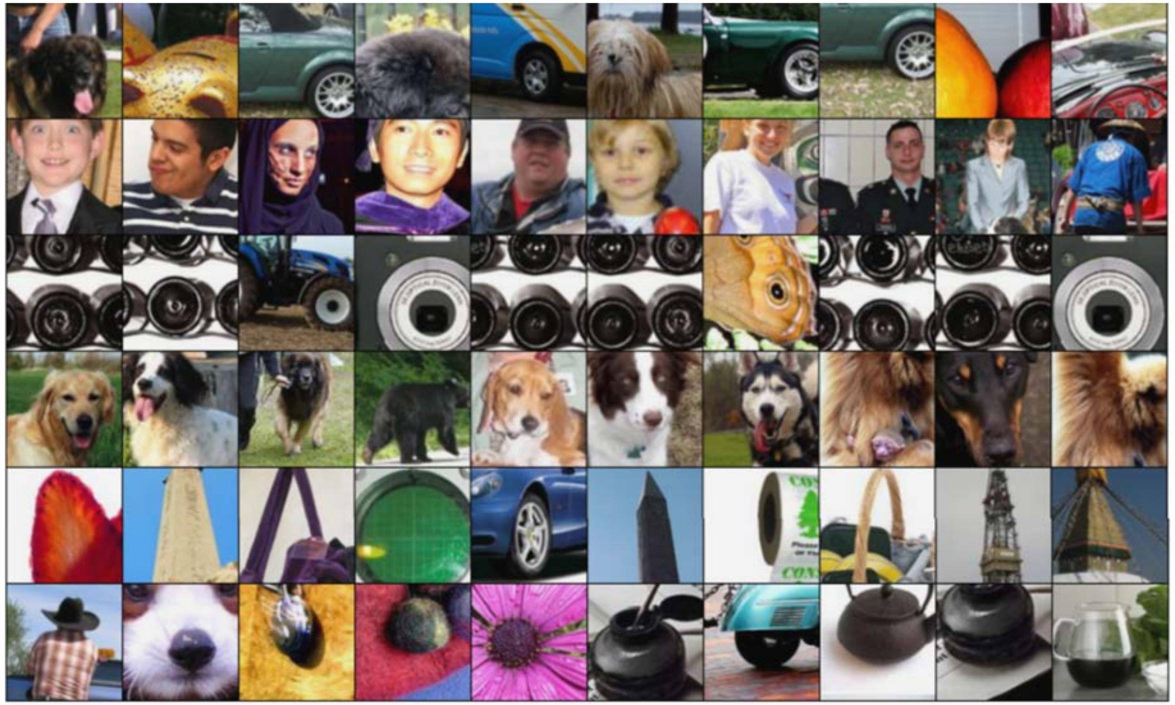
Intermediate Features via (guided) backprop

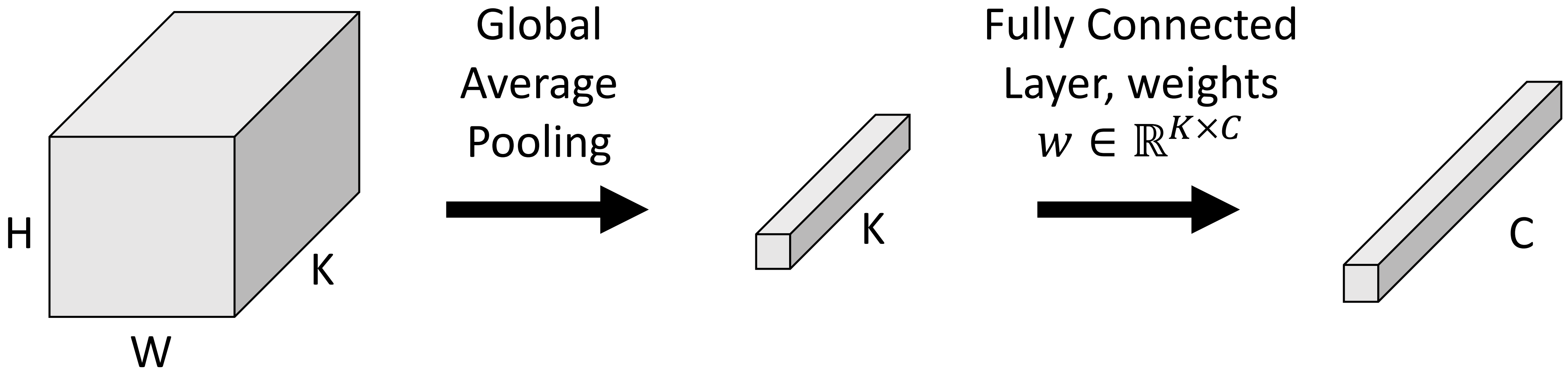


Maximally activating patches
(Each row is a different neuron)

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)



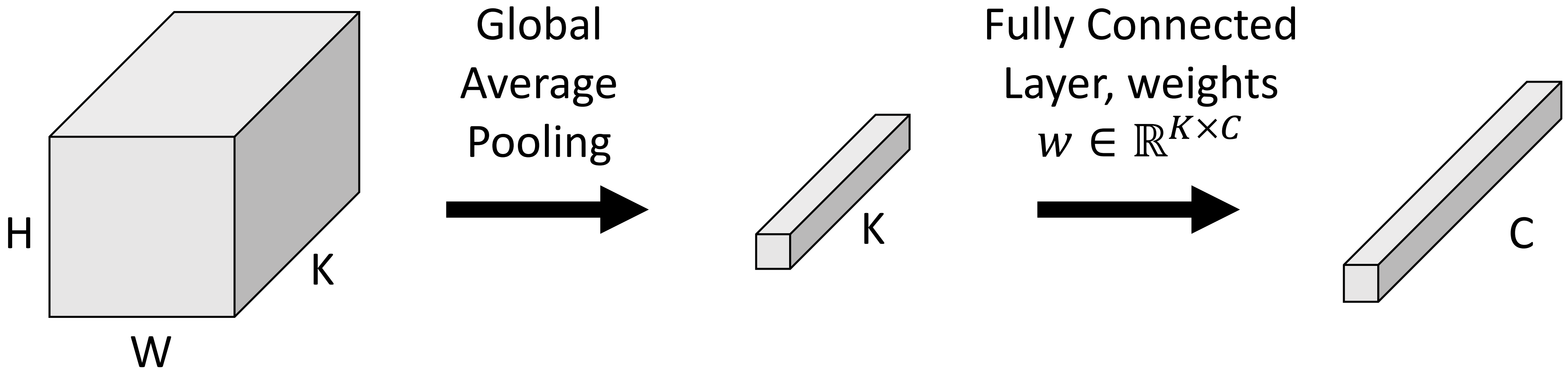
Last layer CNN features:
$f \in \mathbb{R}^{H \times W \times K}$

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

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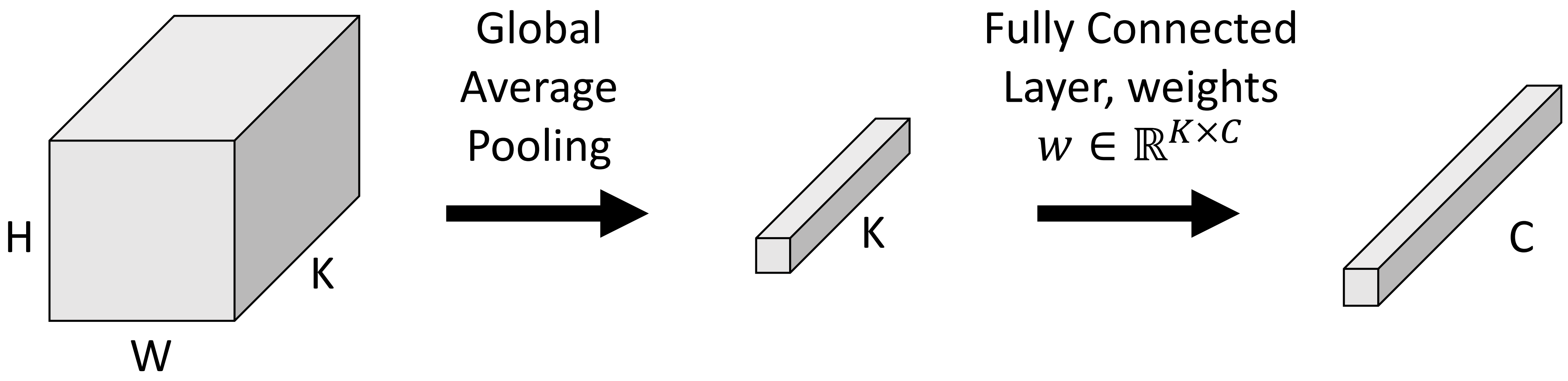
$$F_k = \frac{1}{HW} \sum_{h,w} f_{h,w,k}$$

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

Class Activation Mapping (CAM)



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

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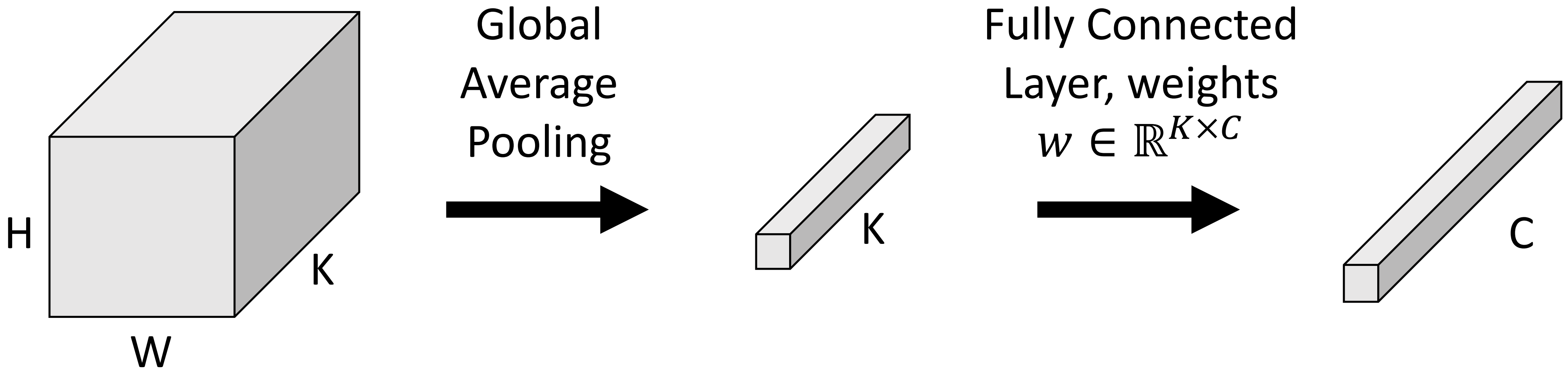

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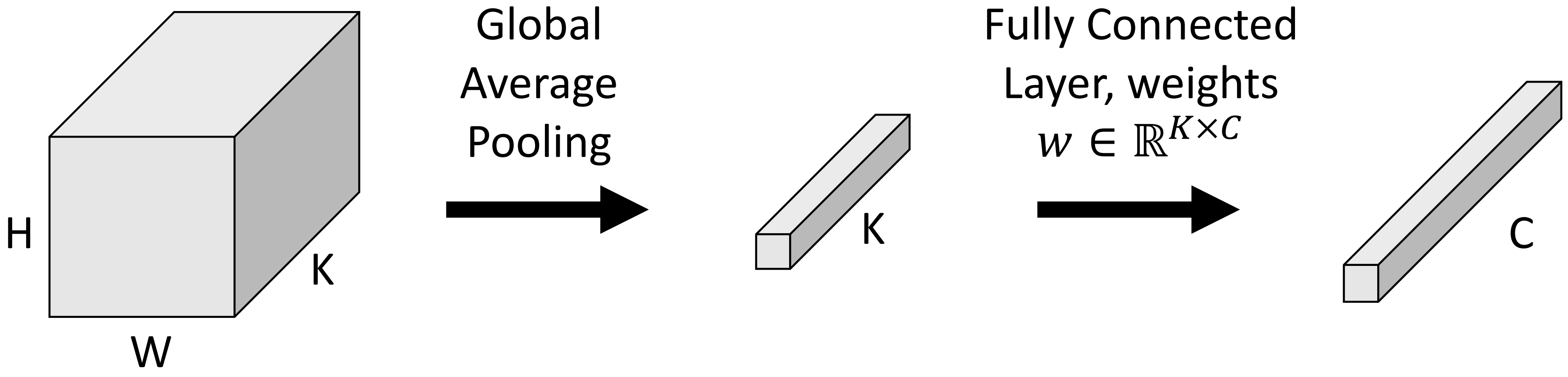

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$$= \frac{1}{HW} \sum_{h,w} \sum_k w_{k,c} f_{h,w,k}$$

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

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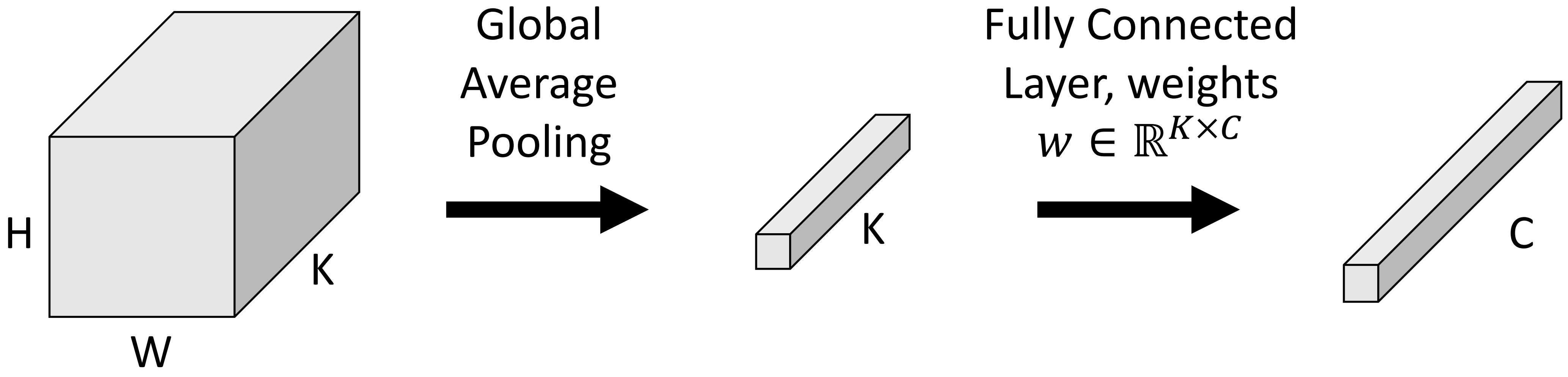

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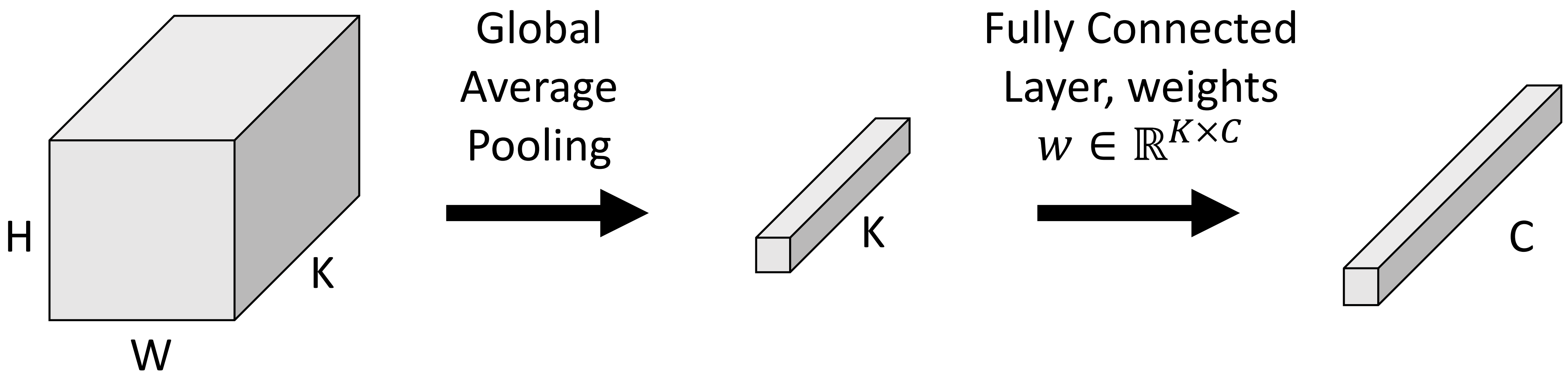
$$= \frac{1}{HW} \sum_{h,w} \sum_k \boldsymbol{w_{k,c} f_{h,w,k}}$$

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

Class Activation Mapping (CAM)



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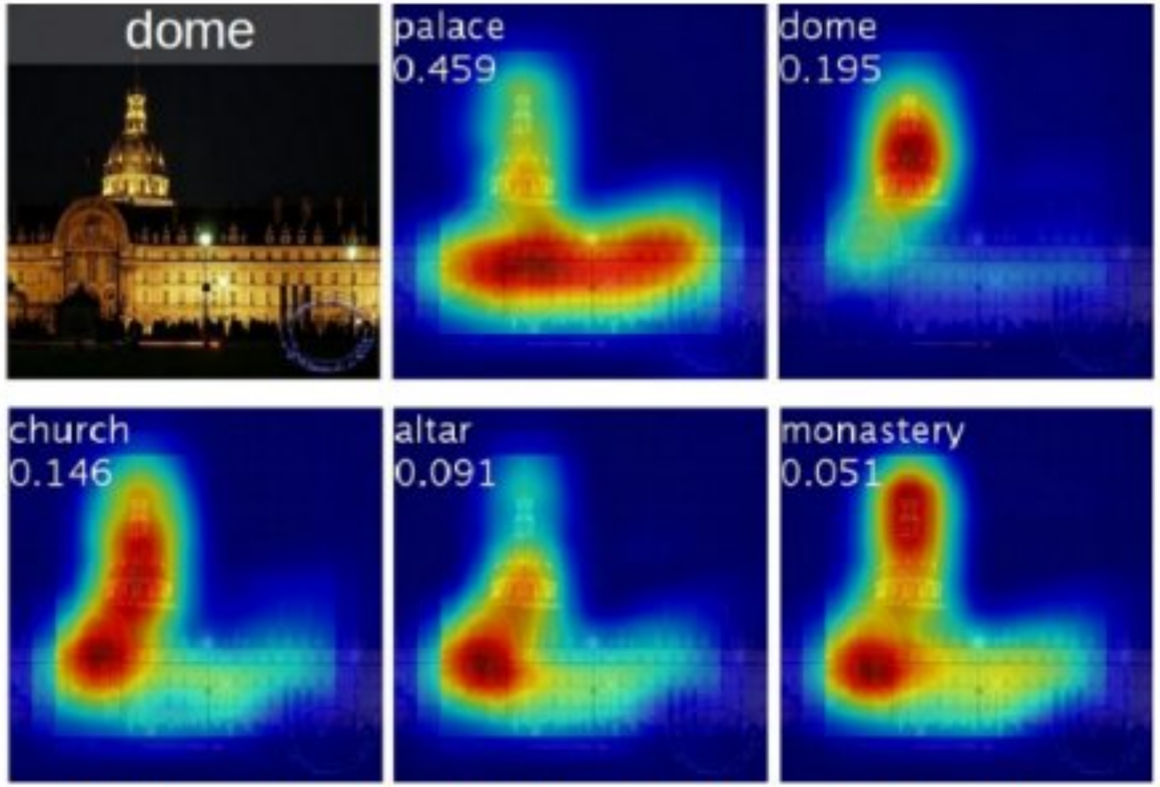
$$S_c = \sum_k w_{k,c} F_k = \frac{1}{HW} \sum_k w_{k,c} \sum_{h,w} f_{h,w,k}$$
$$= \frac{1}{HW} \sum_{h,w} \sum_k w_{k,c} f_{h,w,k}$$

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

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

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

Class Activation Mapping (CAM)



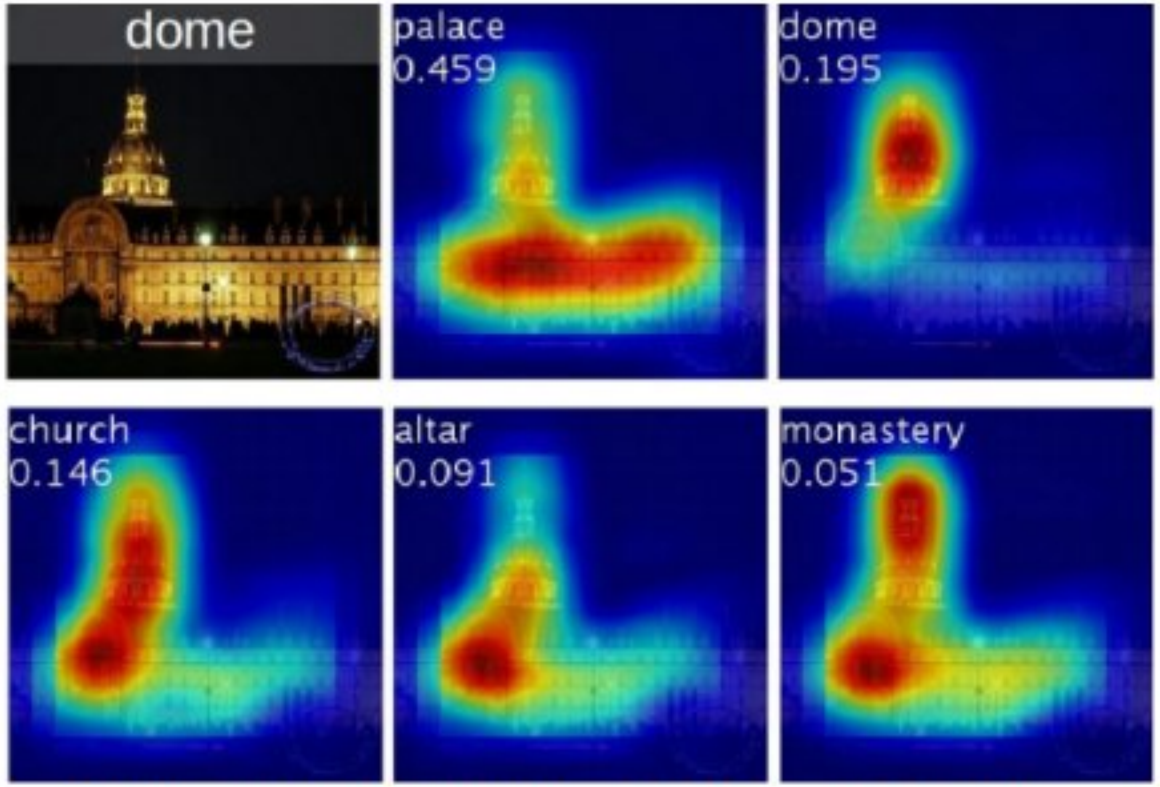
Class activation maps of top 5 predictions

Class activation maps for one object class

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

Class Activation Mapping (CAM)

Problem: Can only apply to last conv layer



Class activation maps of top 5 predictions

Class activation maps for one object class

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

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:

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

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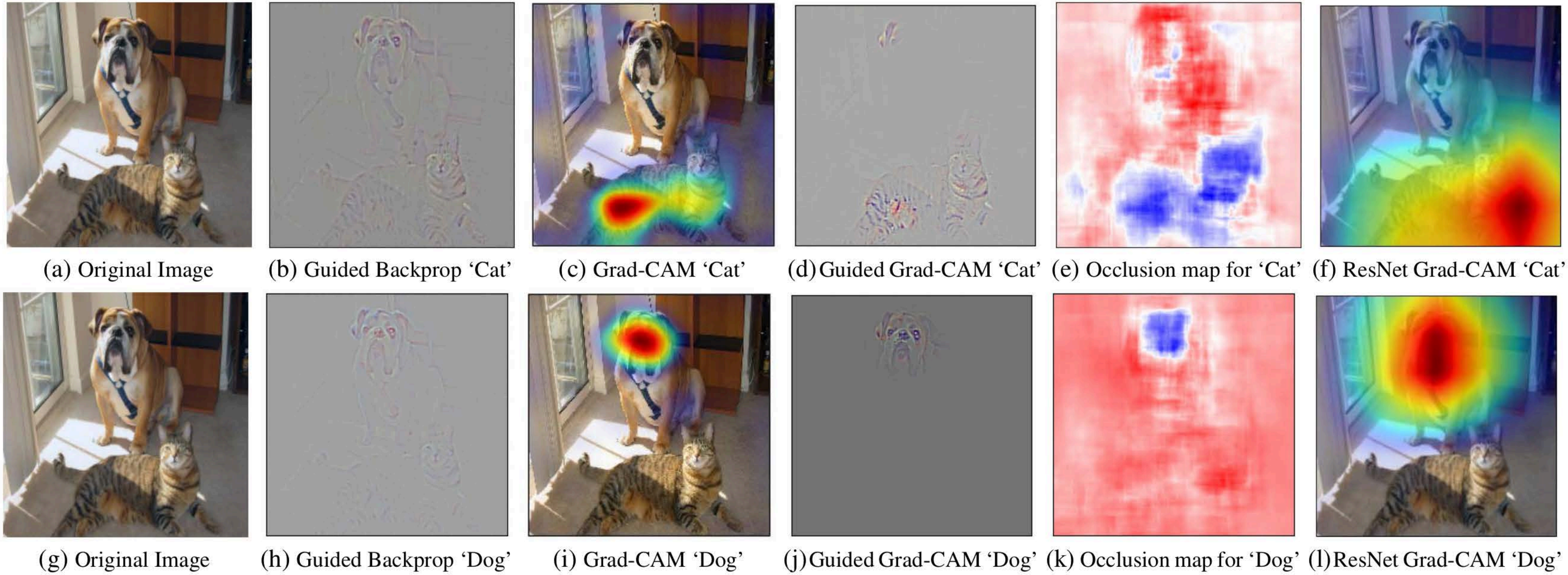
4. Compute activation map $M^c \in \mathbb{R}^{H,W}$:

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

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

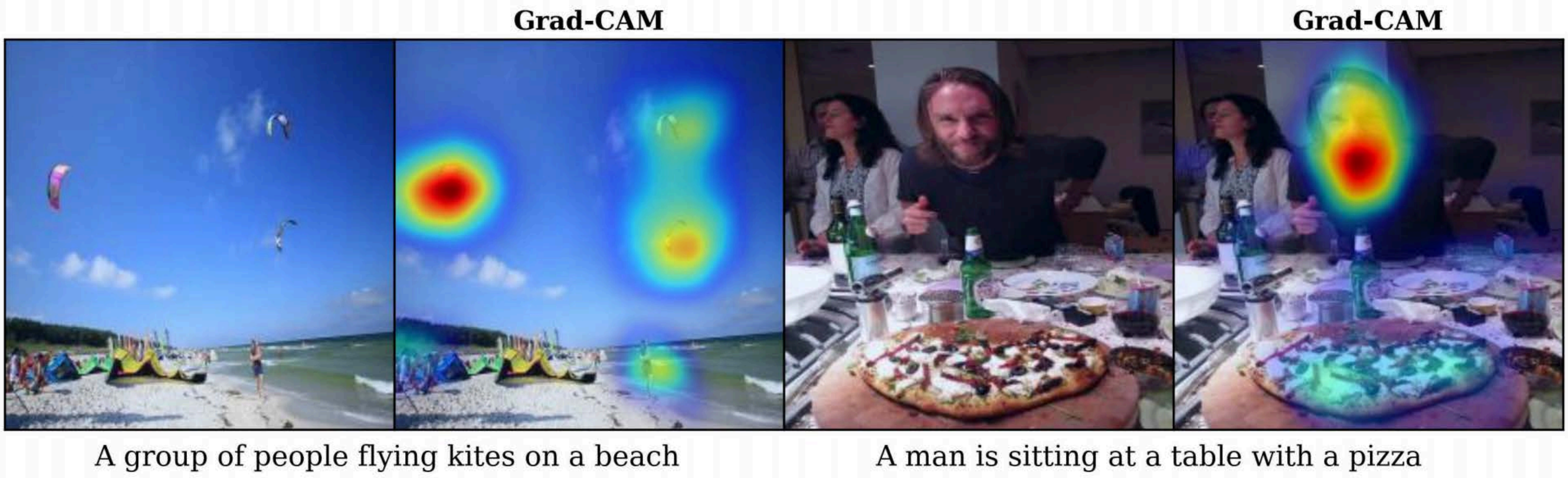
Gradient-Weighted Class Activation Mapping (Grad-CAM)



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

Gradient-Weighted Class Activation Mapping (Grad-CAM)

Can 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

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

Neuron value

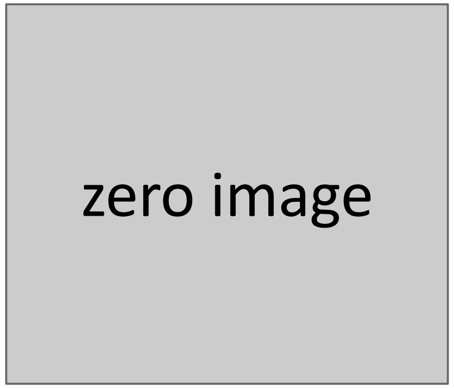
Natural image regularizer

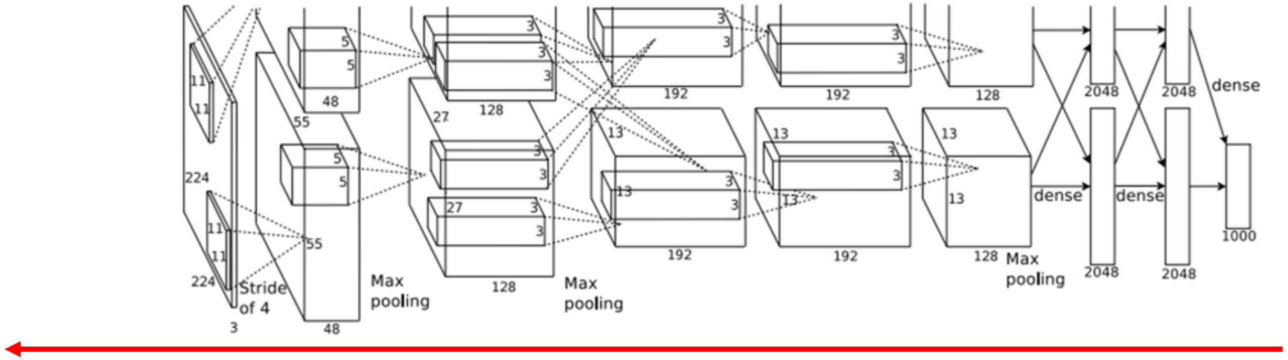
Visualizing CNN Features: Gradient Ascent

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

score for class c (before Softmax)

1. Initialize image to zeros





Repeat:

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

Visualizing CNN Features: Gradient Ascent

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

Simple regularizer: Penalize
L2 norm of generated image

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

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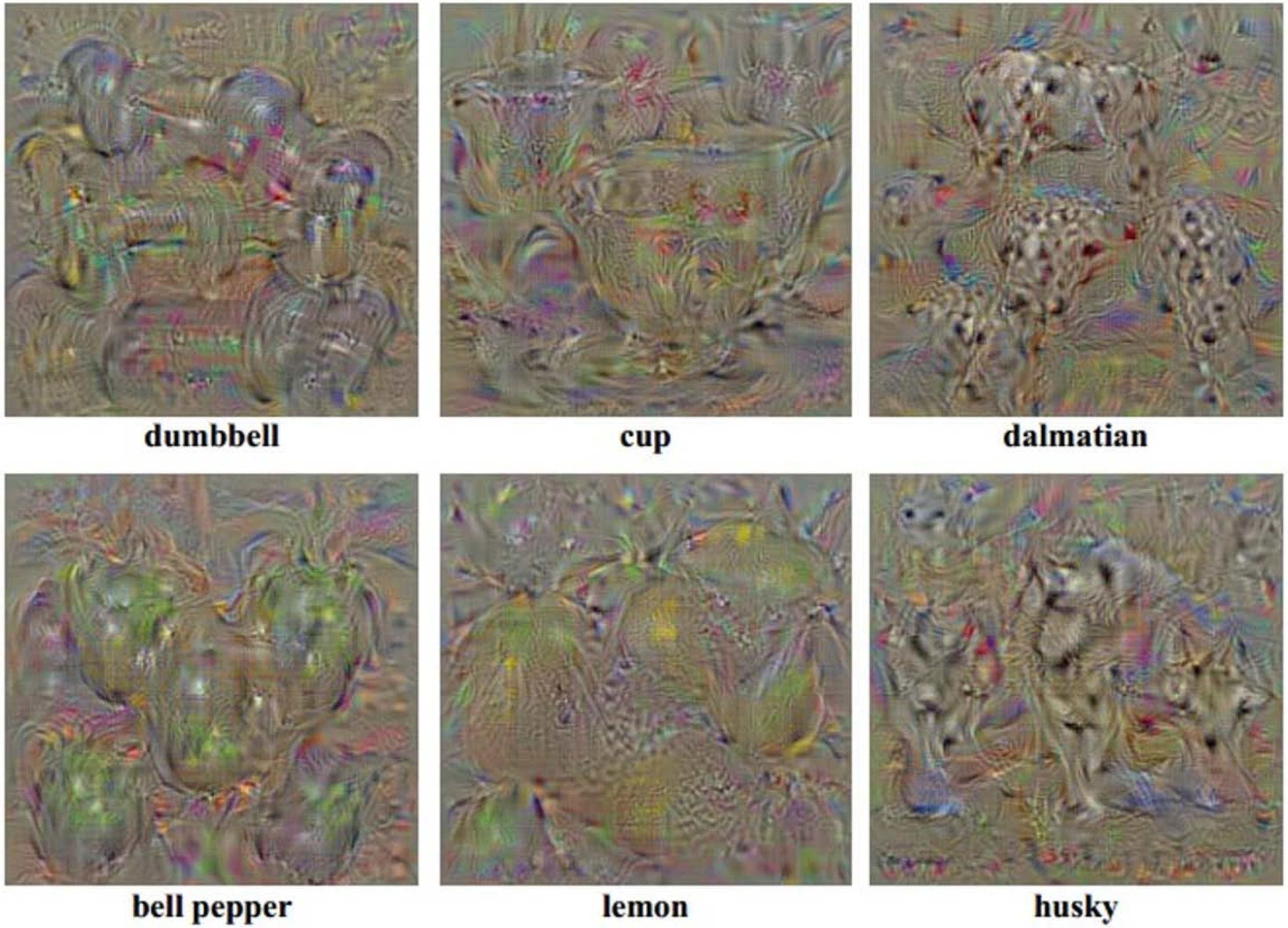

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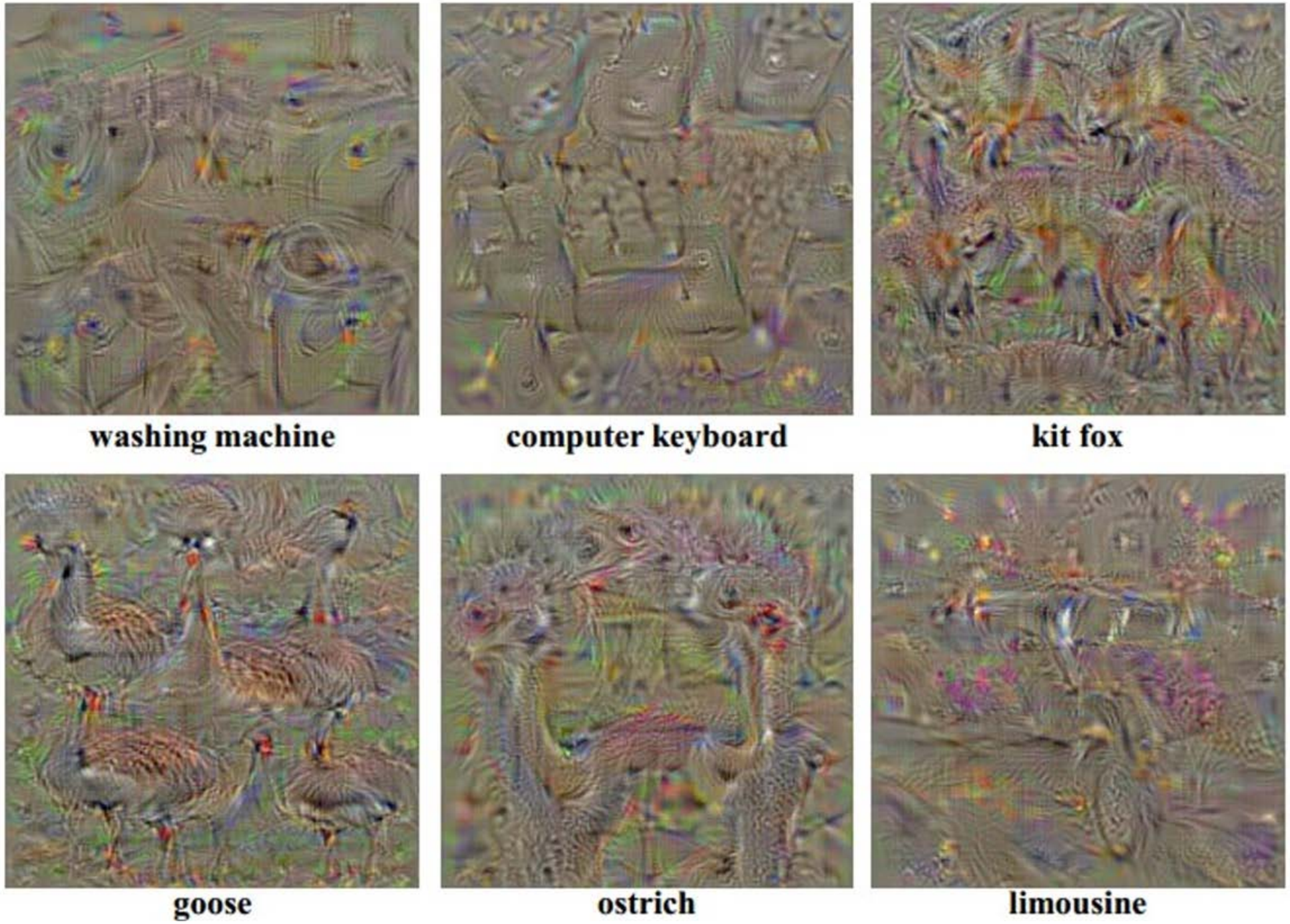

Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

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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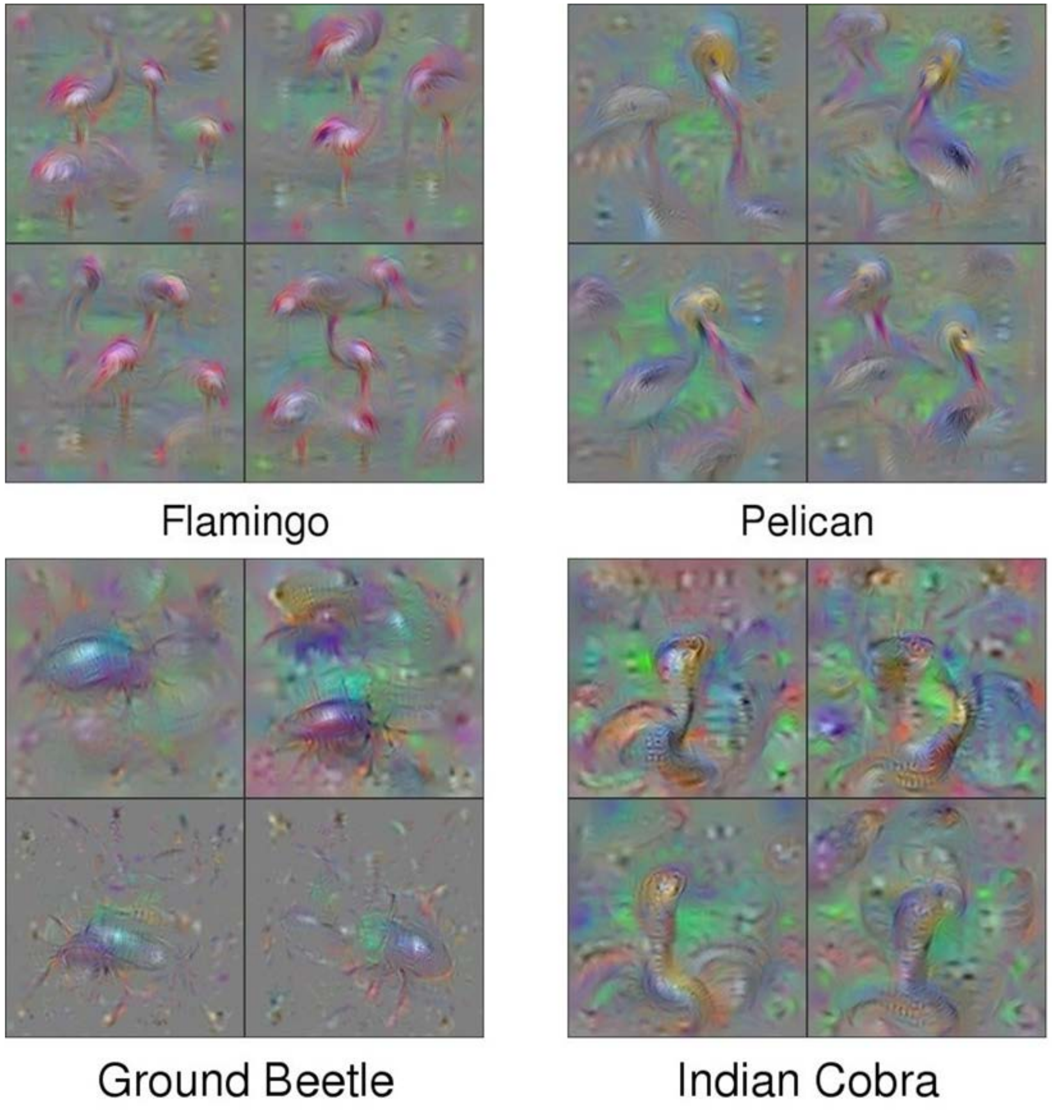

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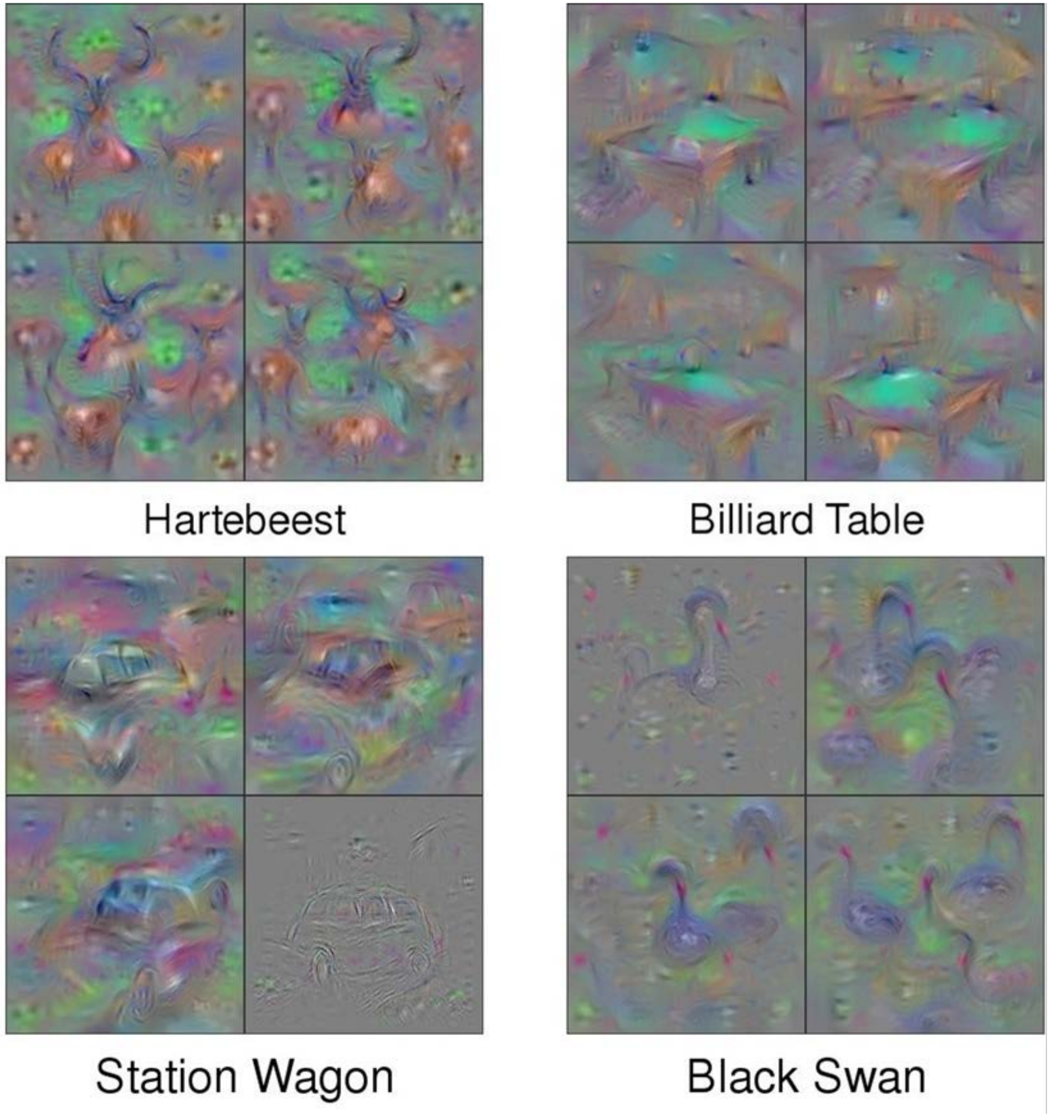
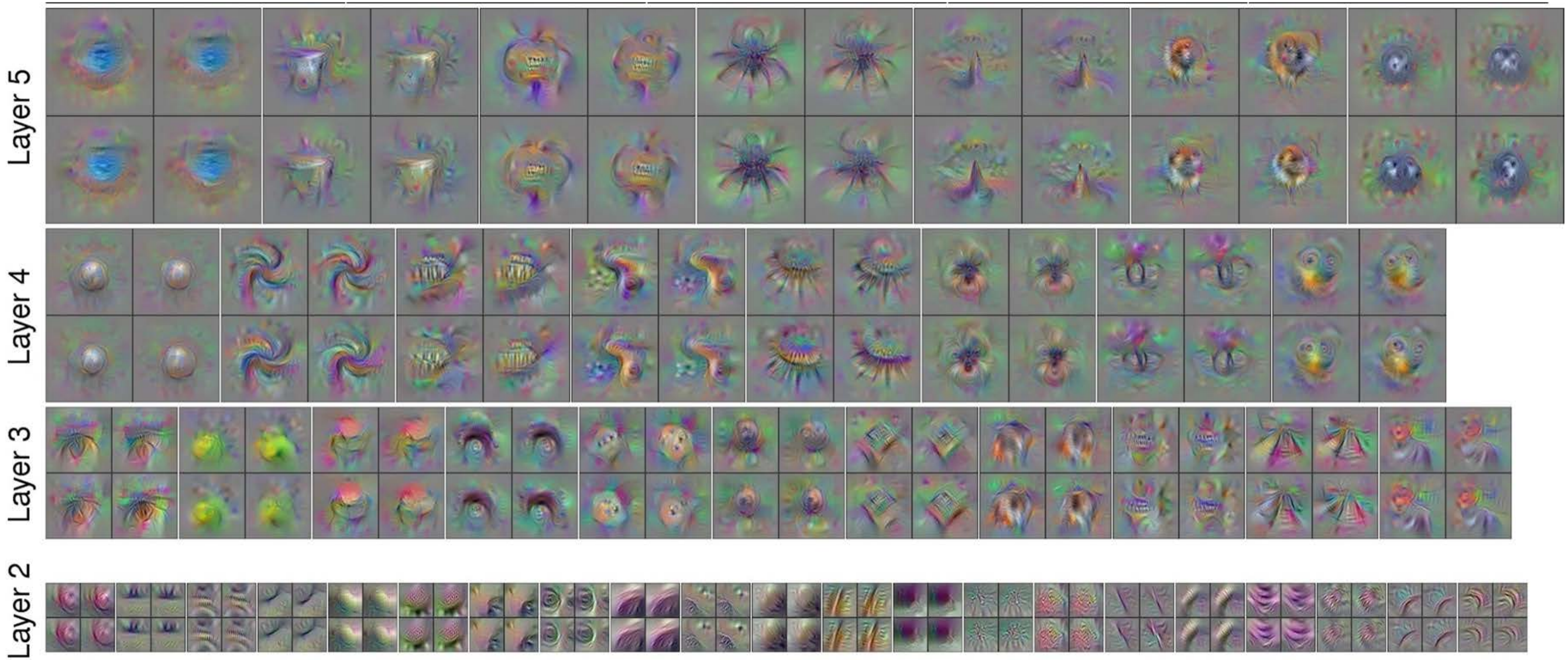


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

Visualizing CNN Features: Gradient Ascent

Use the same approach to visualize intermediate features

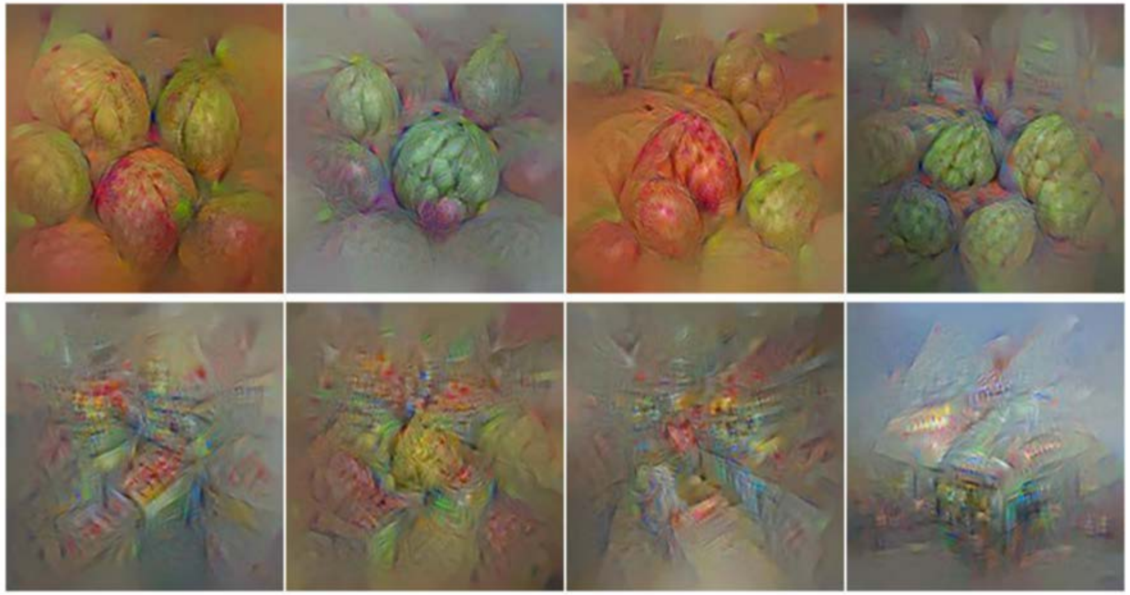


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

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

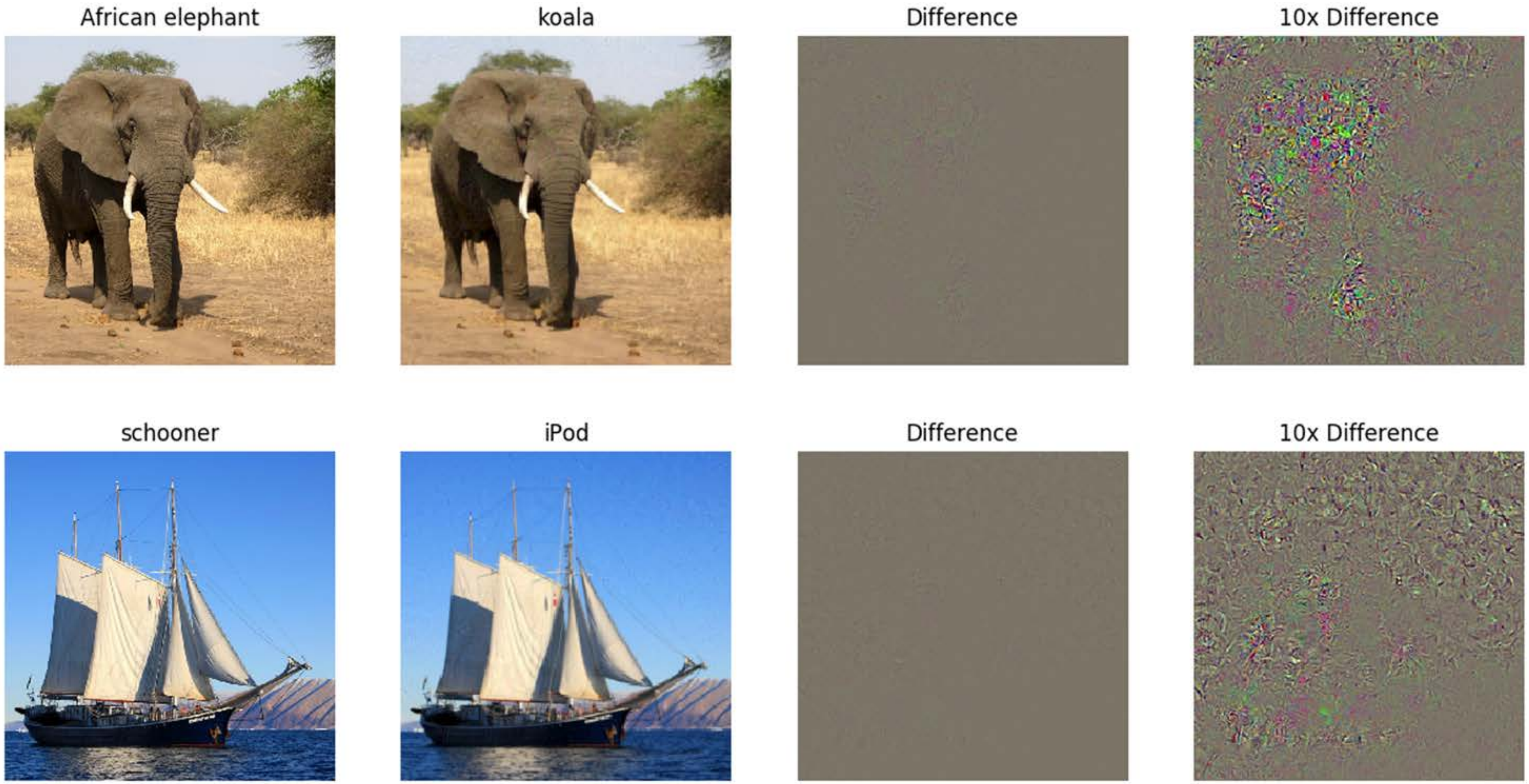
Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016

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



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

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

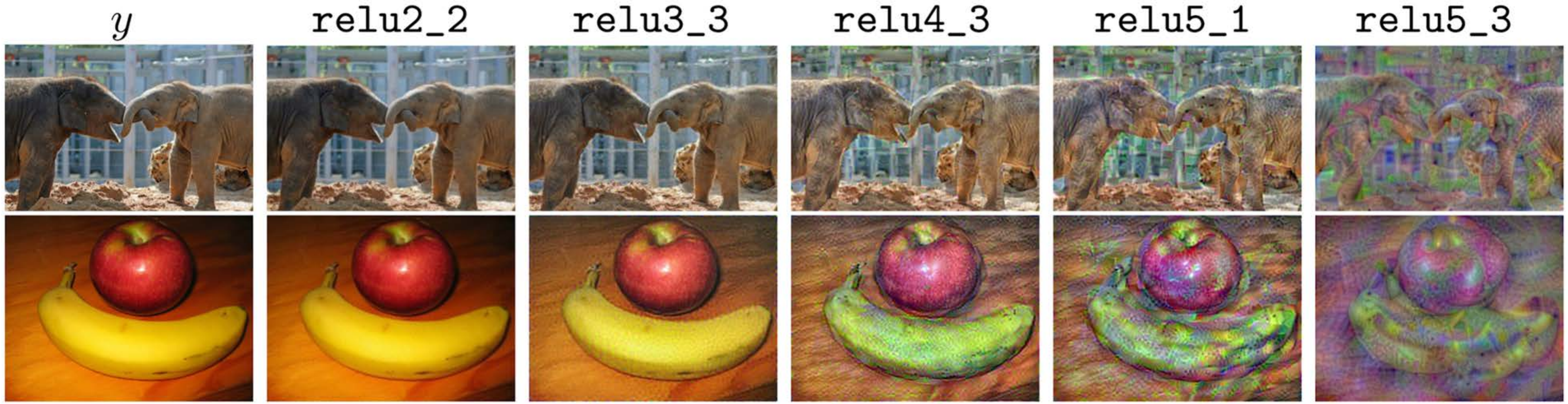
$$\mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j} \left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{\beta}{2}}$$

Total Variation regularizer (encourages spatial smoothness)

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

Feature Inversion

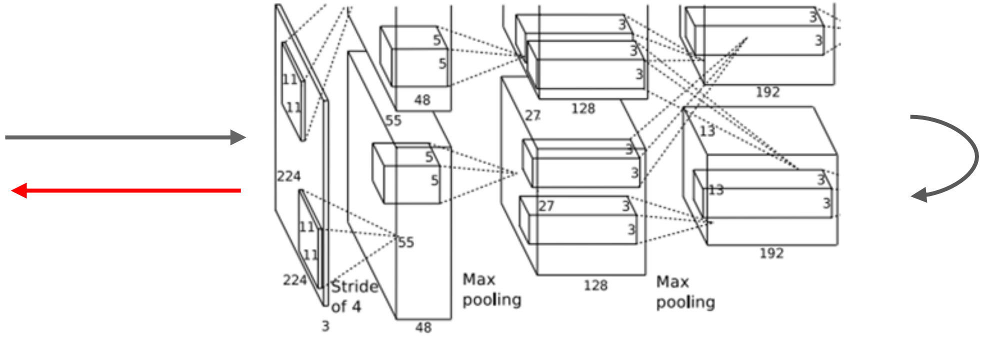
Reconstructing from different layers of VGG-16



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.

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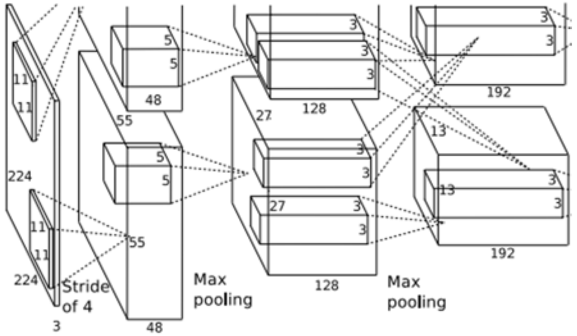

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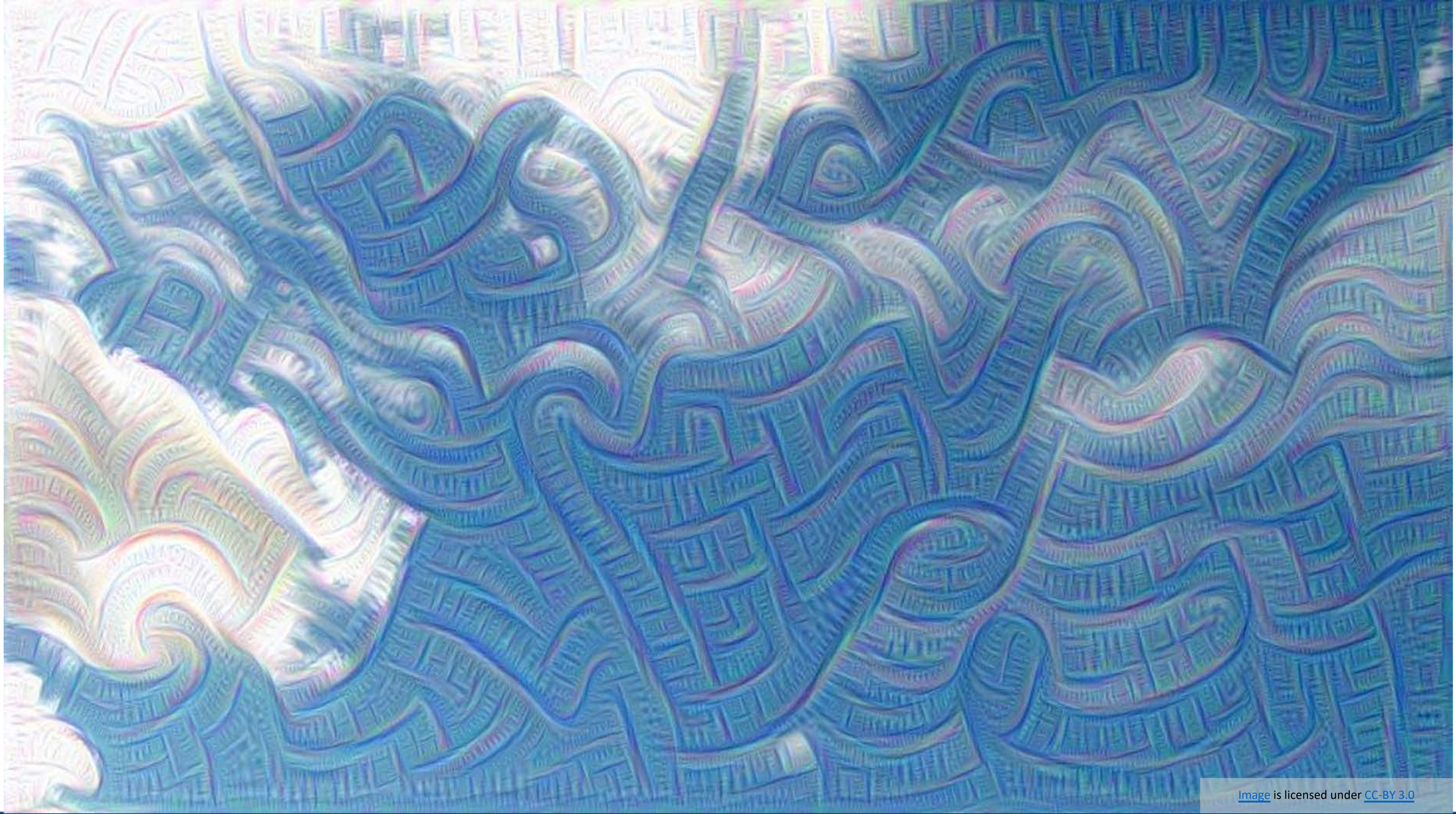
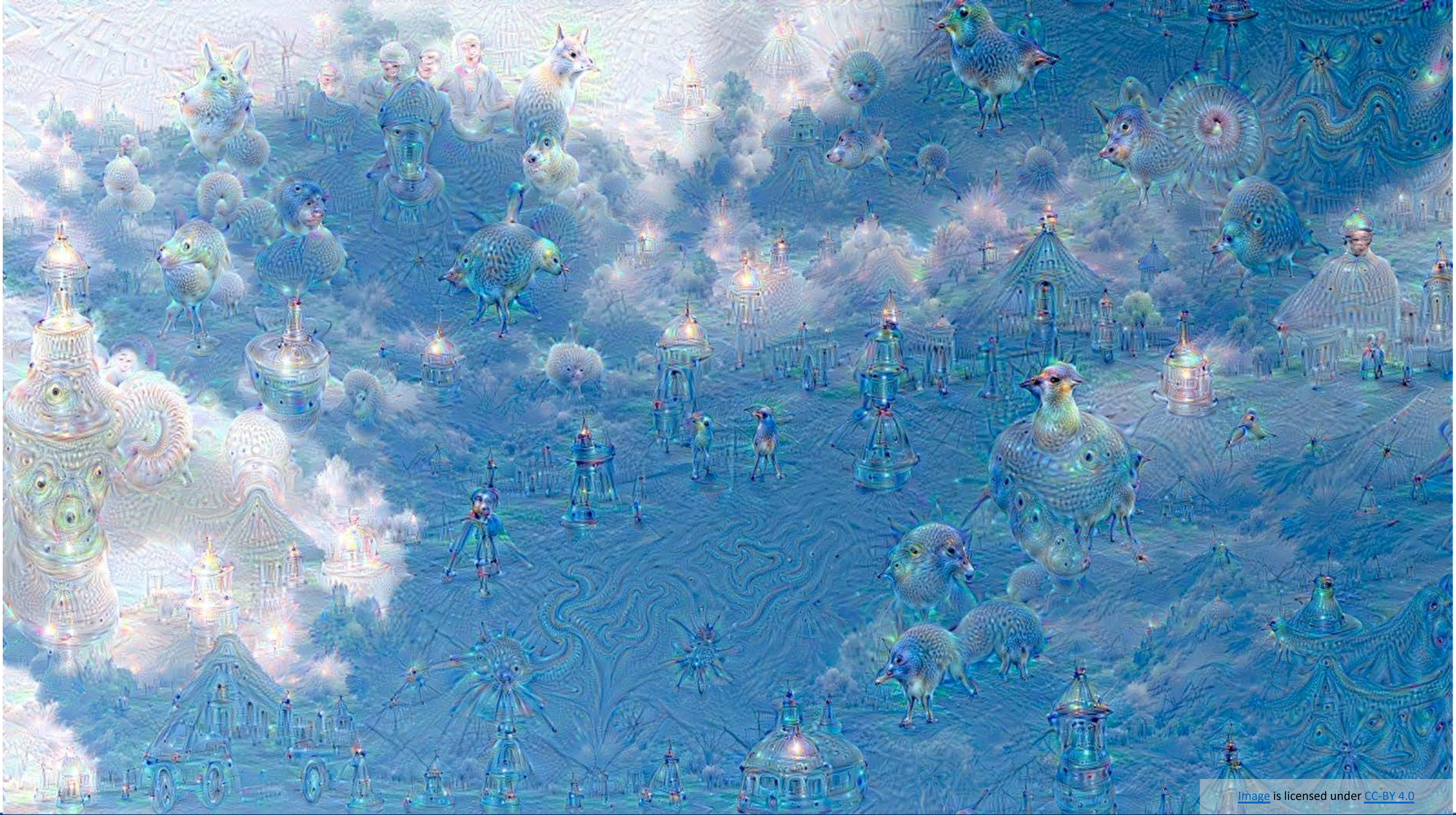
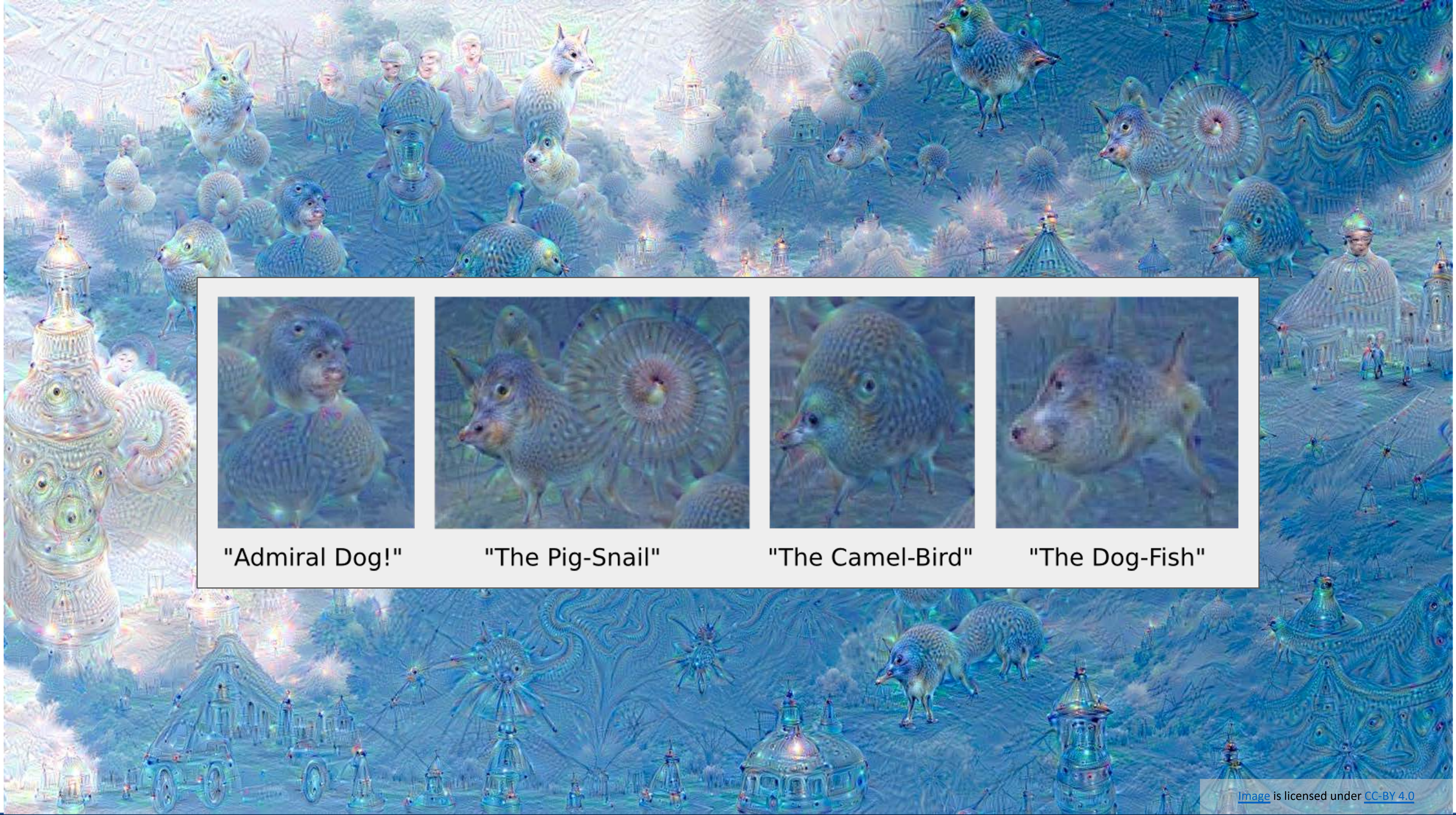
Equivalent to:

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

Mordvintsev, Olah, and Tyka, "Inceptionism: Going Deeper into Neural Networks", [Google Research Blog]().

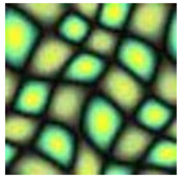




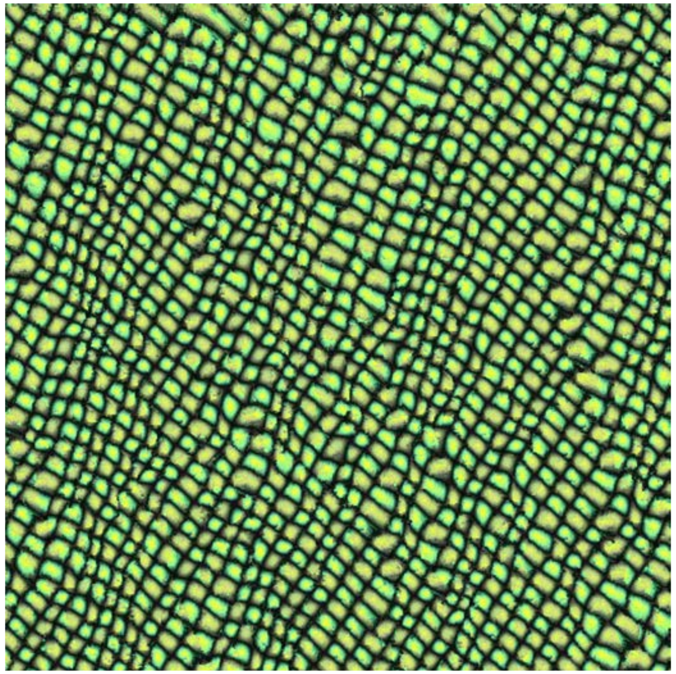

"Admiral Dog!"
"The Pig-Snail"
"The Camel-Bird"
"The Dog-Fish"

Texture Synthesis

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



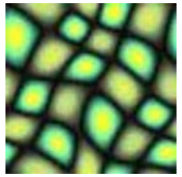
Input

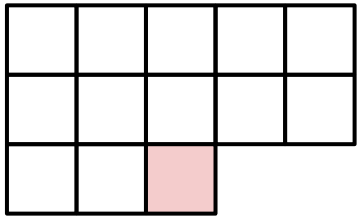


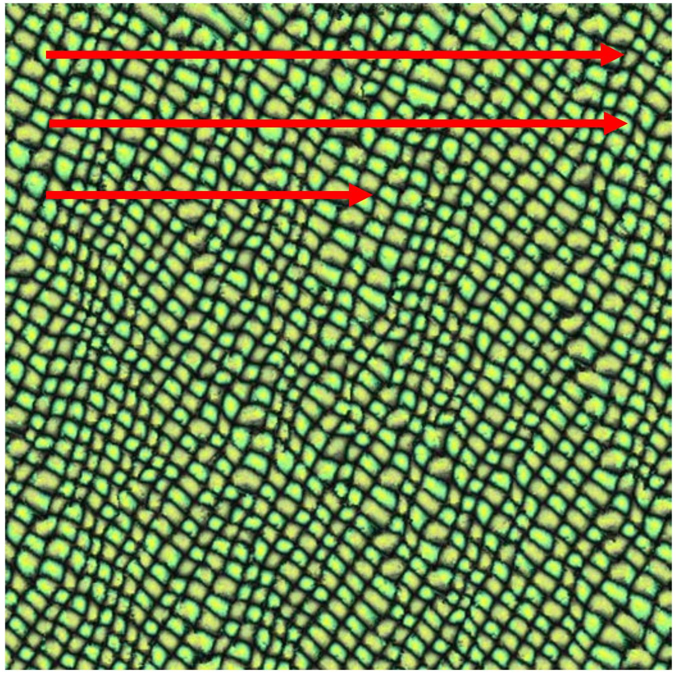
Output

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

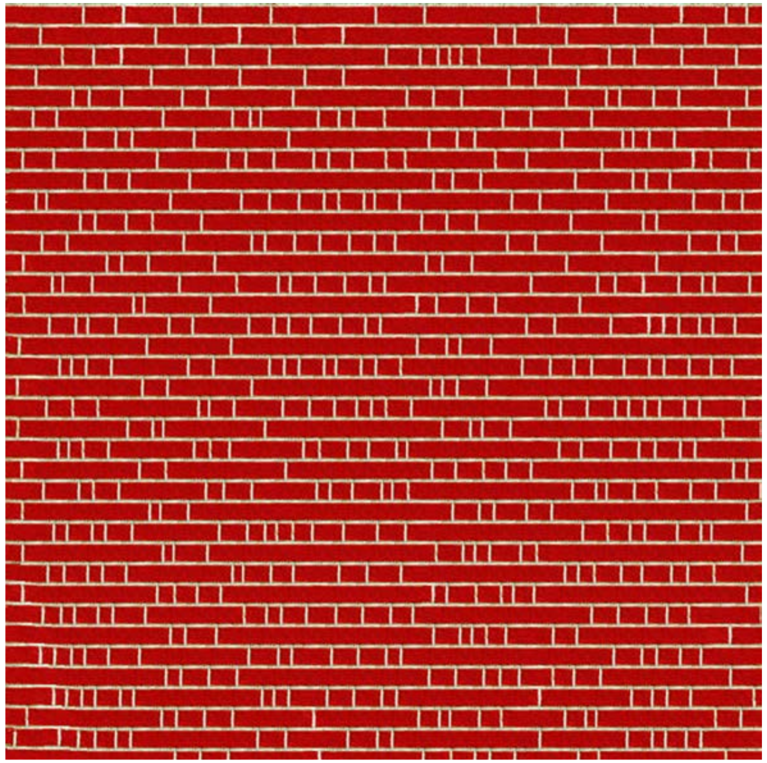






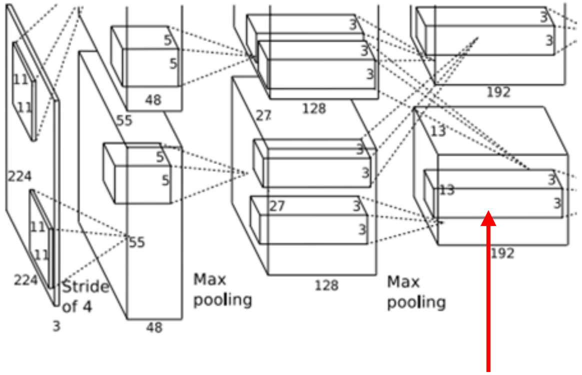
Wei and Levoy, "Fast Texture Synthesis using Tree-structured Vector Quantization", SIGGRAPH 2000
Efros and Leung, "Texture Synthesis by Non-parametric Sampling", ICCV 1999

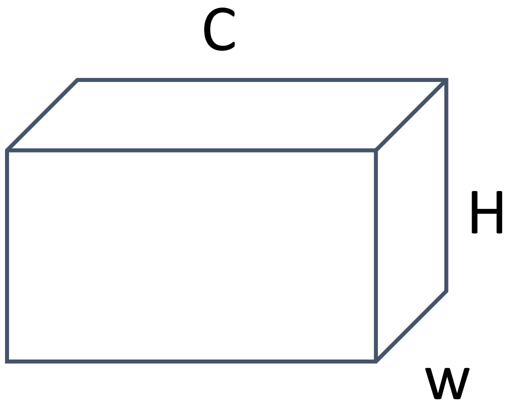
Texture Synthesis: Nearest Neighbor



Texture Synthesis with Neural Networks: Gram Matrix

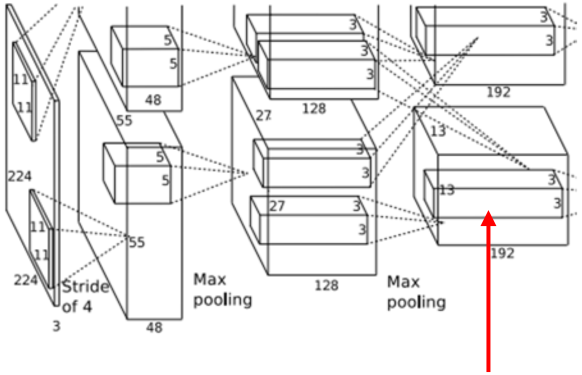
This image is in the public domain.

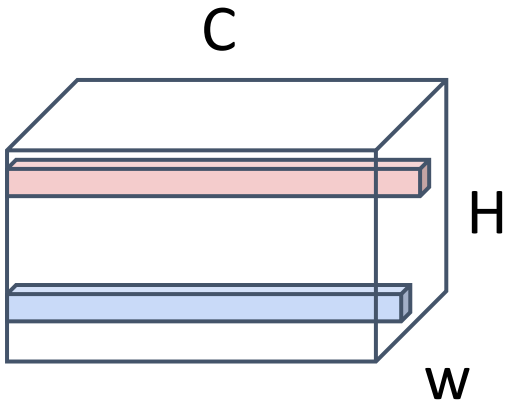


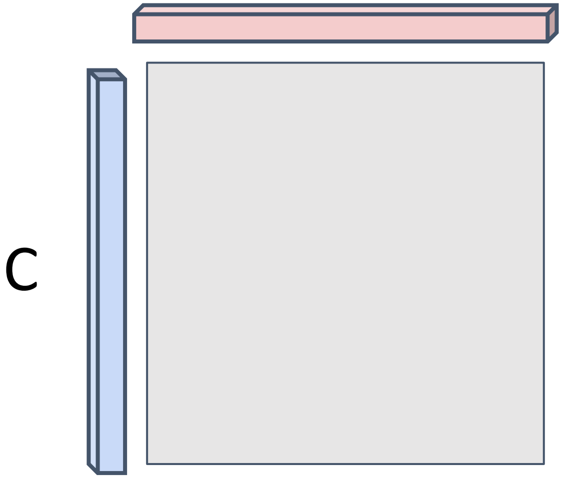


Each layer of CNN gives C x H x W tensor of features; H x W grid of C-dimensional vectors

Texture Synthesis with Neural Networks: Gram Matrix







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

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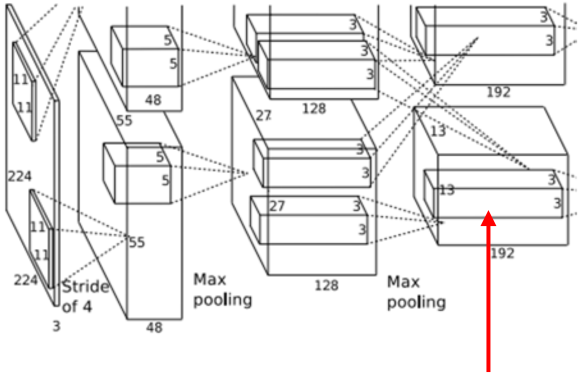

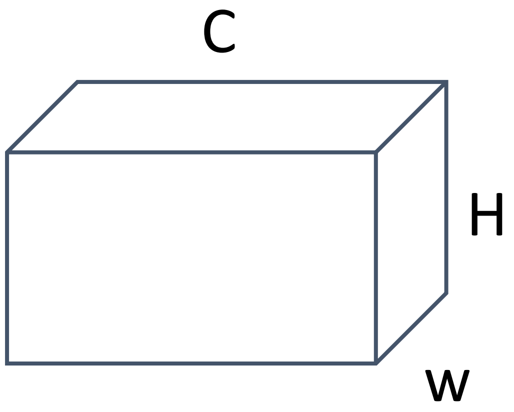

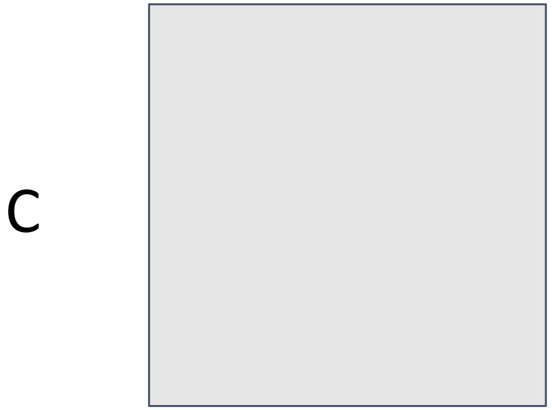

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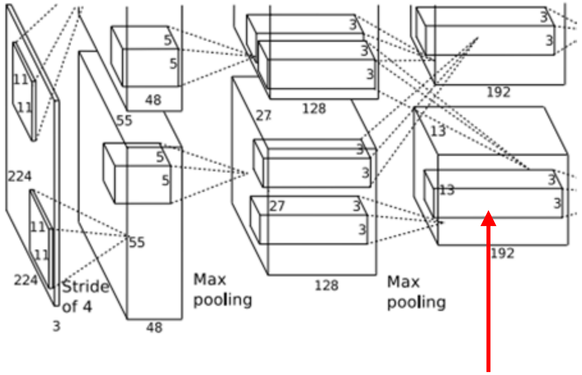
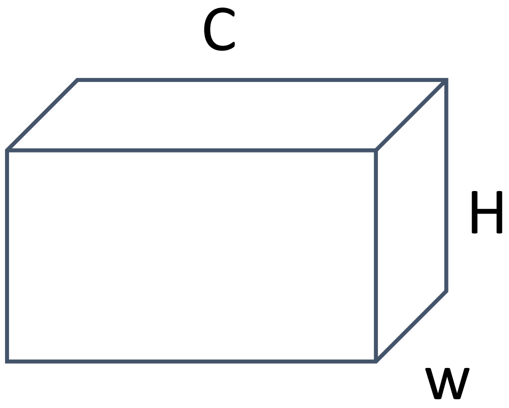
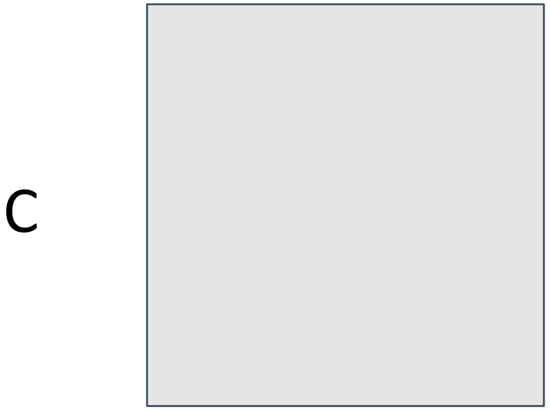
Average over all HW pairs gives **Gram Matrix** of shape C x C giving unnormalized covariance

Texture Synthesis with Neural Networks: Gram Matrix







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

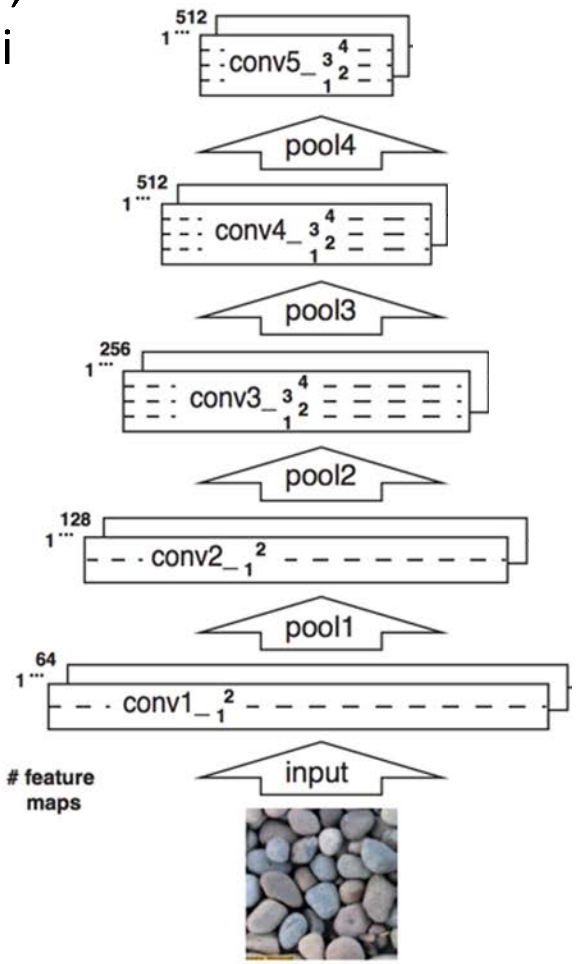
Efficient to compute; reshape features from

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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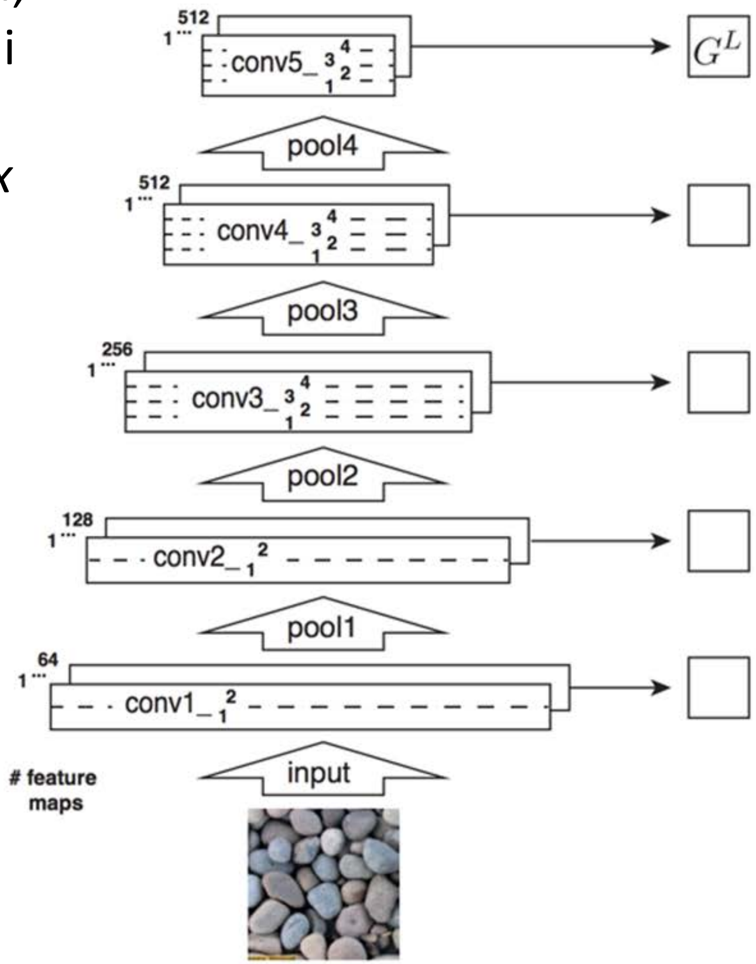
$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l$$ (shape $C_i \times C_i$)



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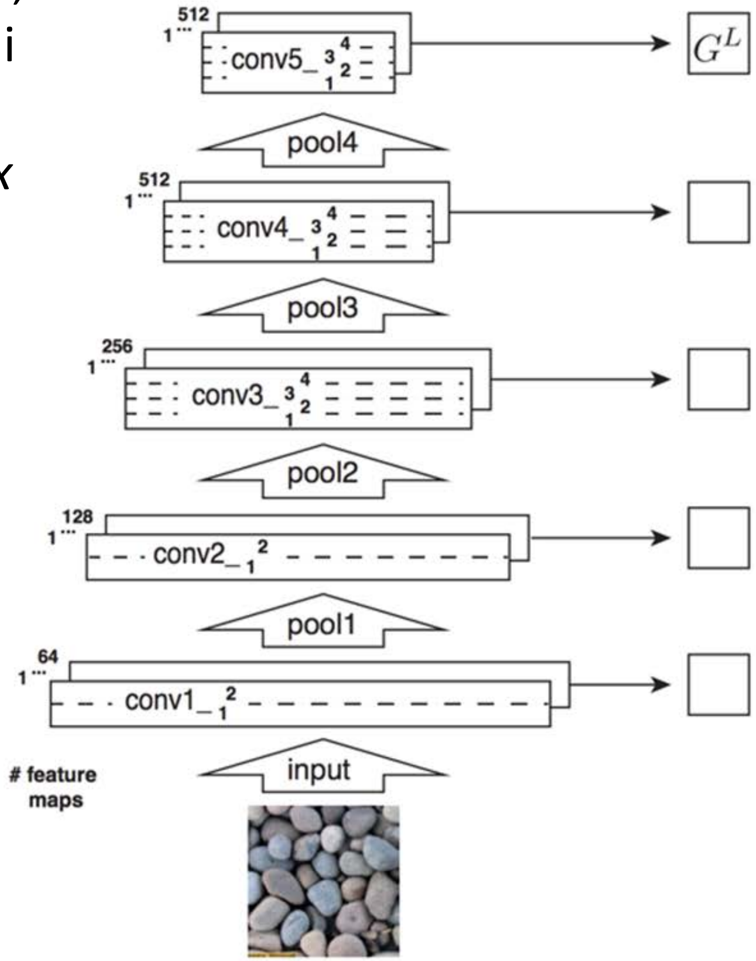
4. Initialize generated image from random noise



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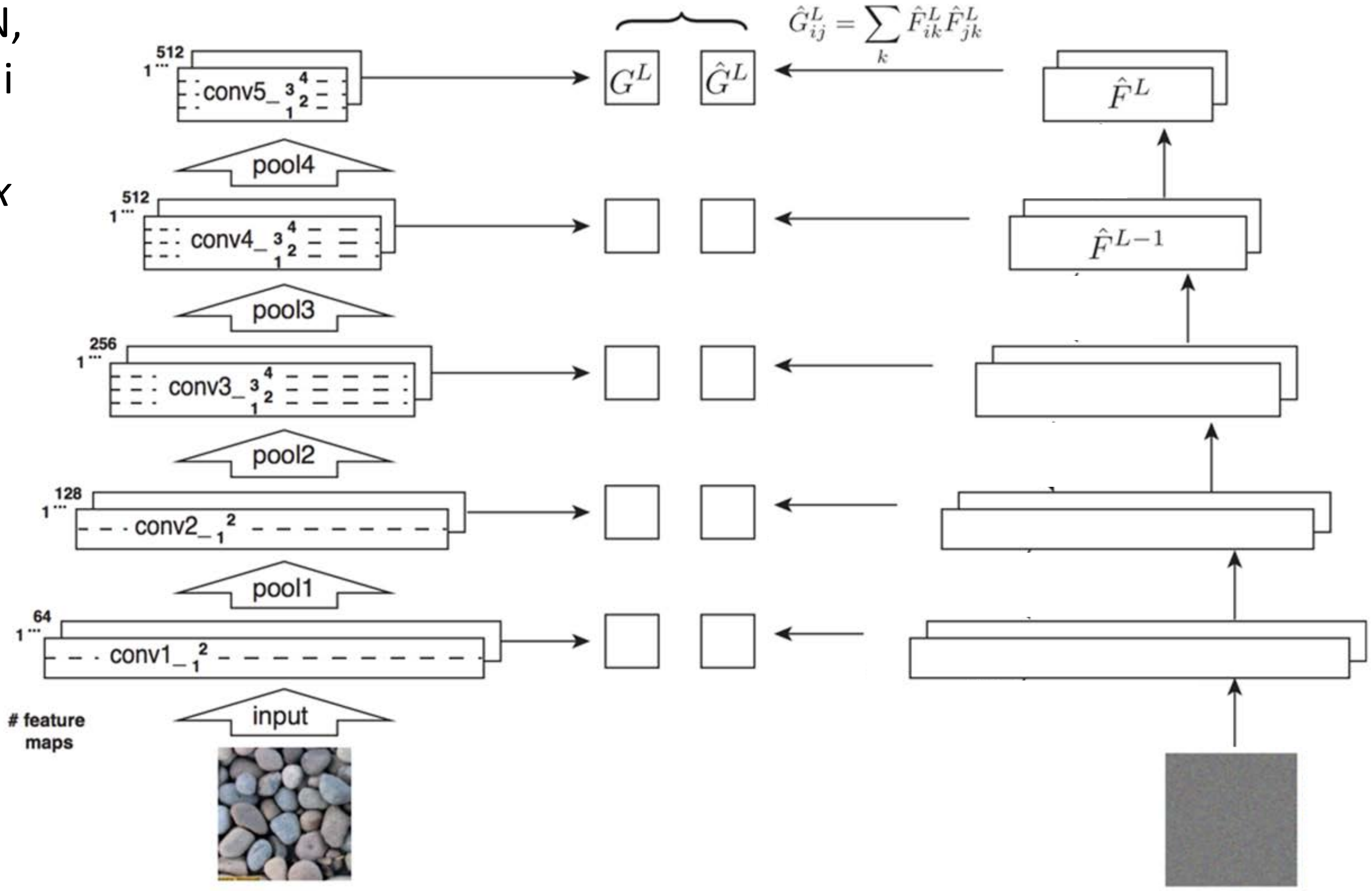
5. Pass generated image through CNN, compute Gram matrix on each layer



Neural Texture Synthesis

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

1. Pretrain a CNN on ImageNet (VGG-19)
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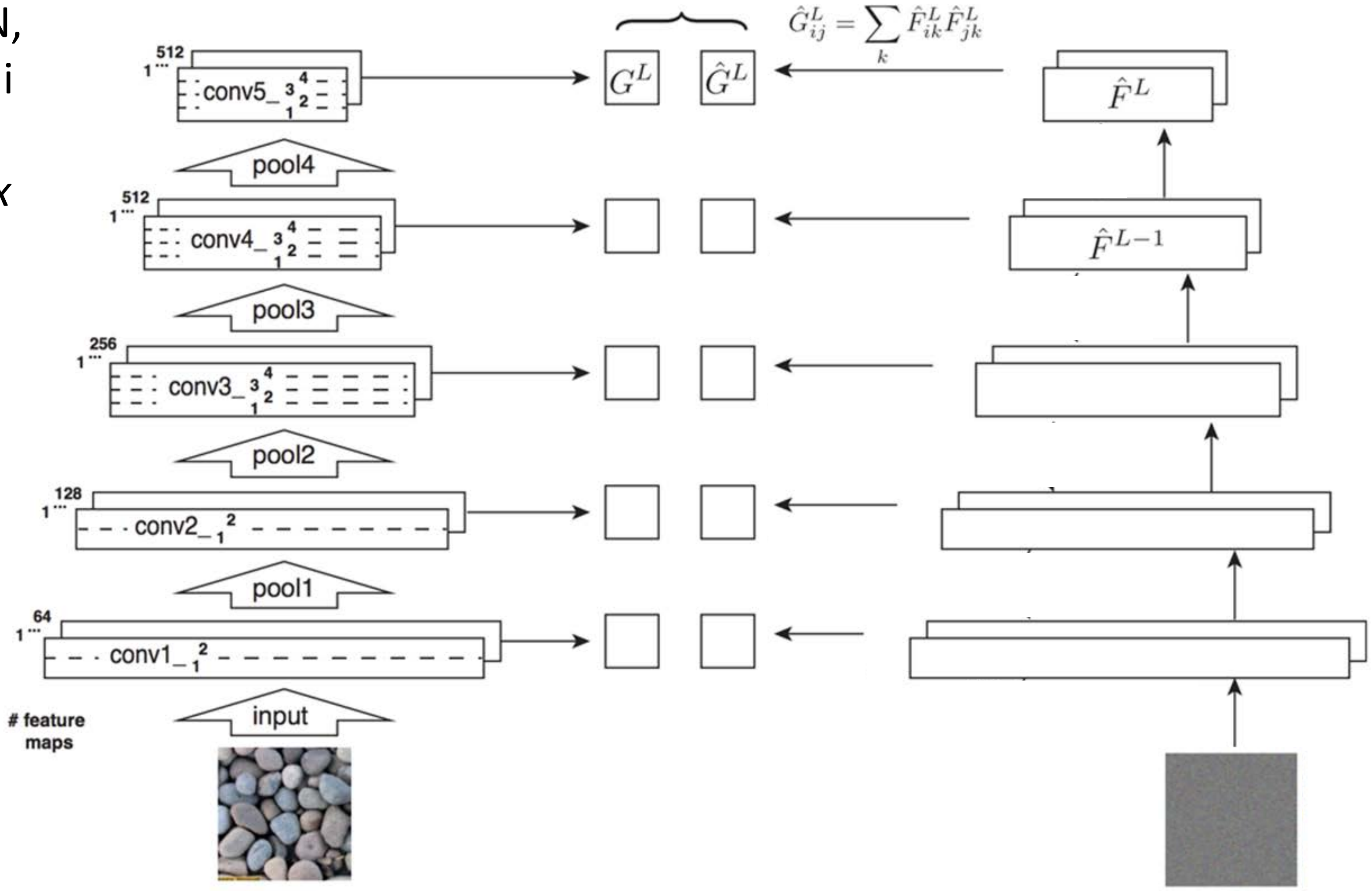
6. Compute loss: weighted sum of L2 distance between Gram matrices



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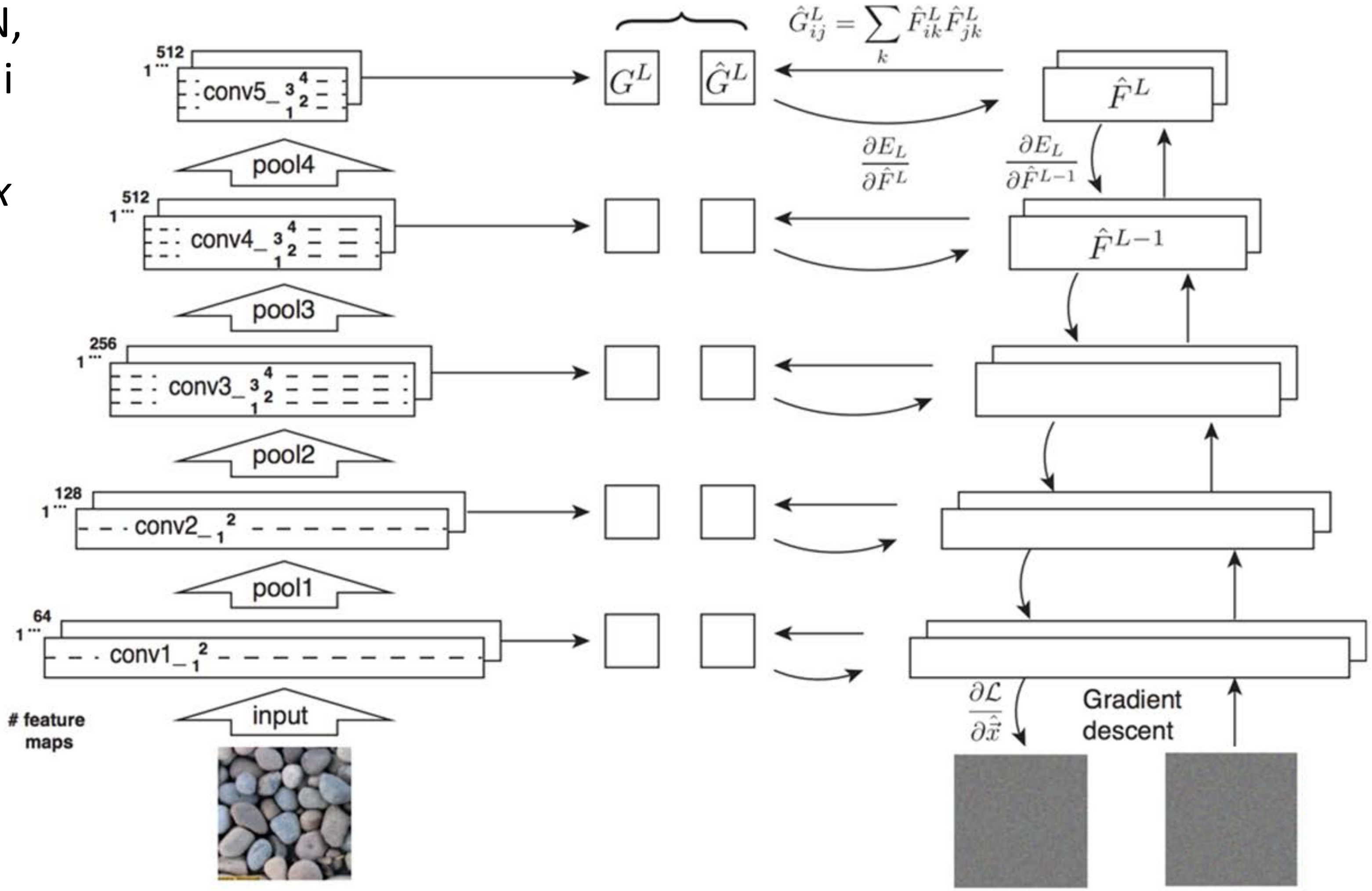
4. Initialize generated image from random noise
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image



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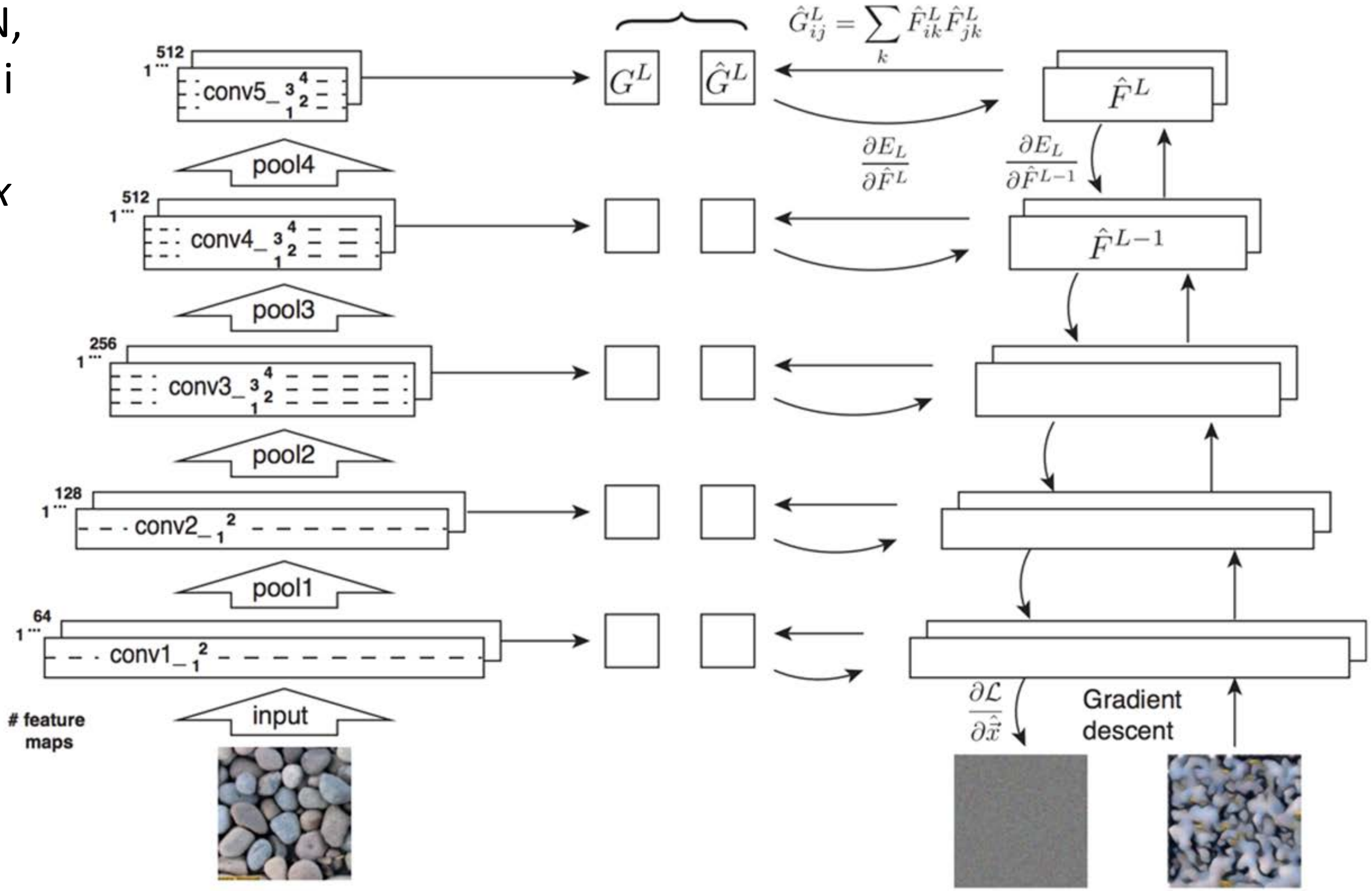
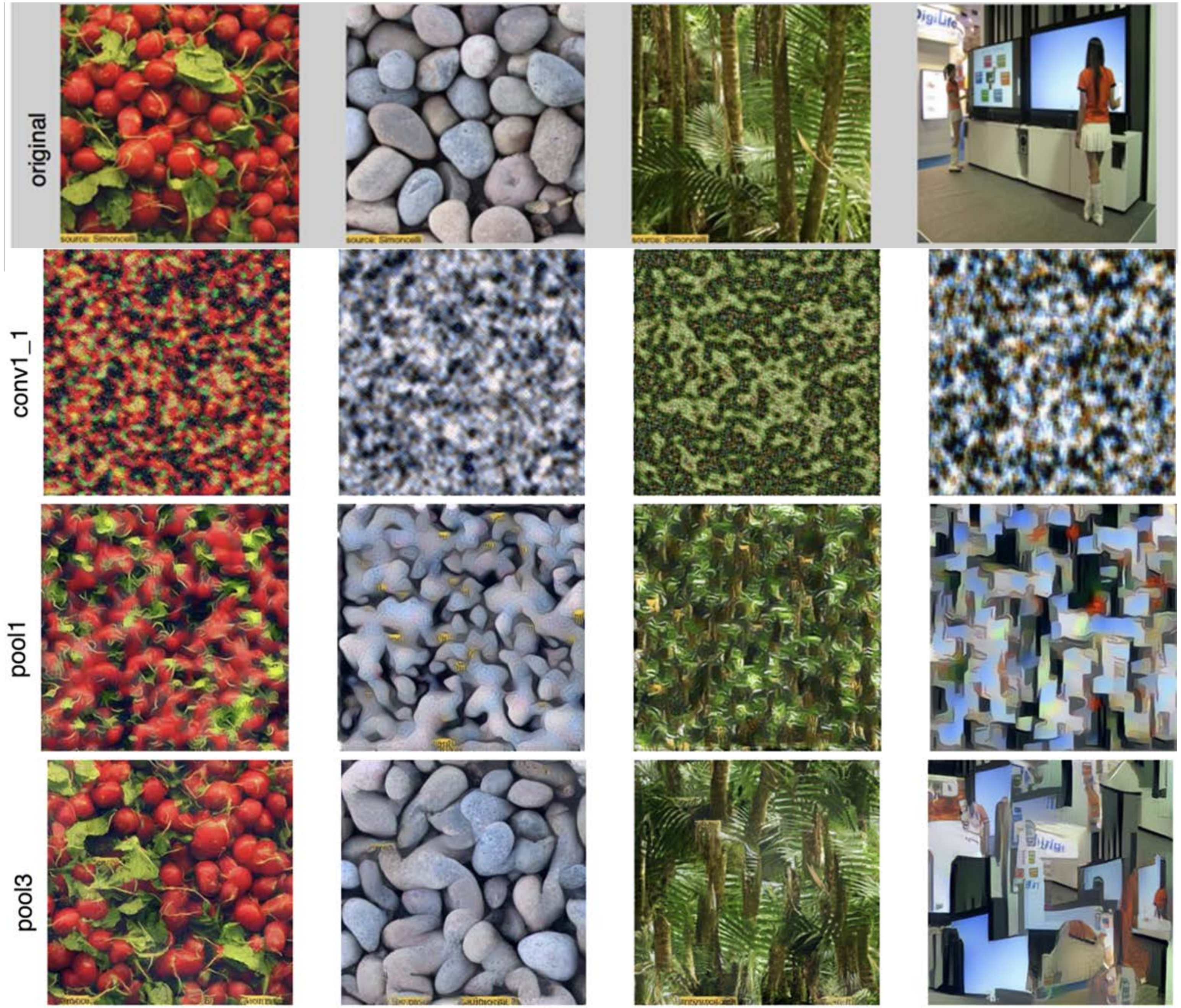
$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l$$ (shape $C_i \times C_i$)

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

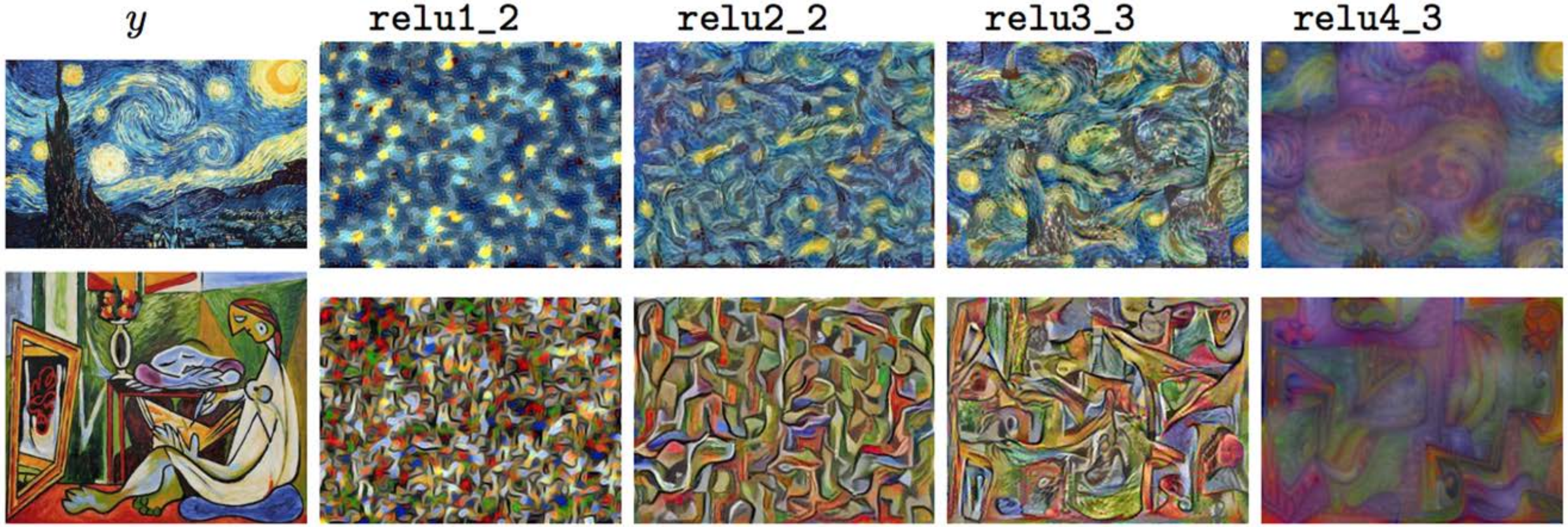
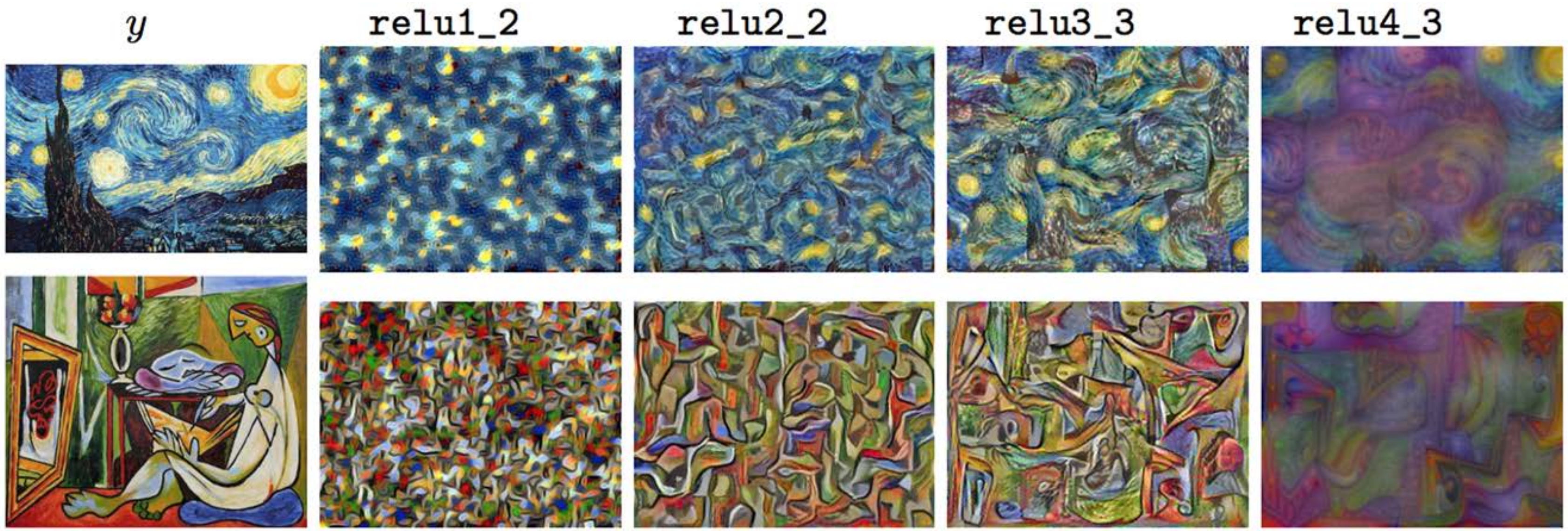


Figure from Johnson, Alahi, and Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution”, ECCV 2016.

Neural Style Transfer: Feature + Gram Reconstruction

Texture synthesis (Gram reconstruction)



Feature reconstruction

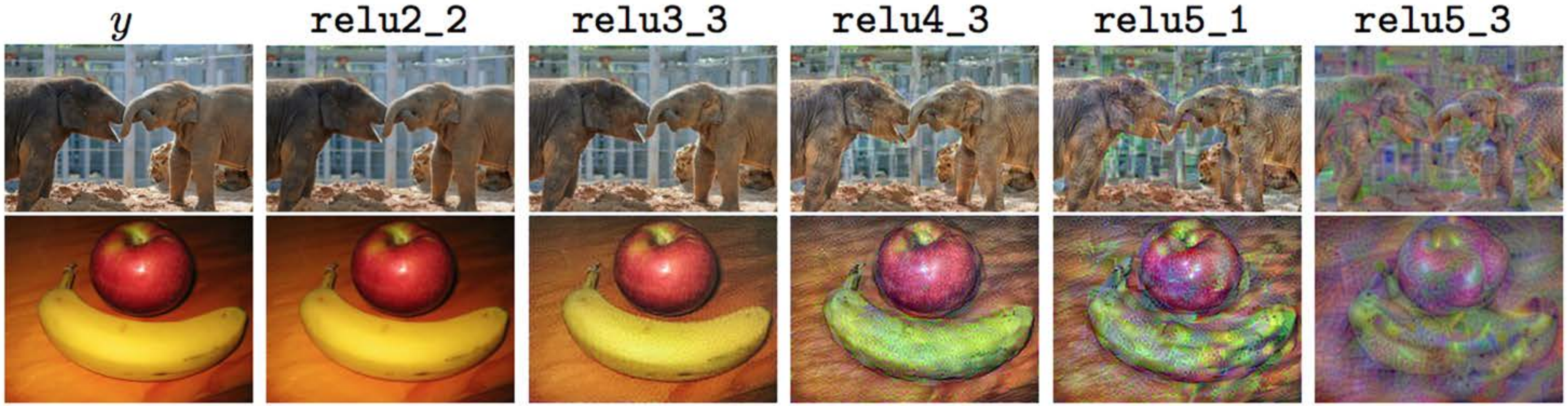


Figure from Johnson, Alahi, and Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution”, ECCV 2016.

Neural Style Transfer

Content Image

+

Style Image

=

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

+

Style Image

=

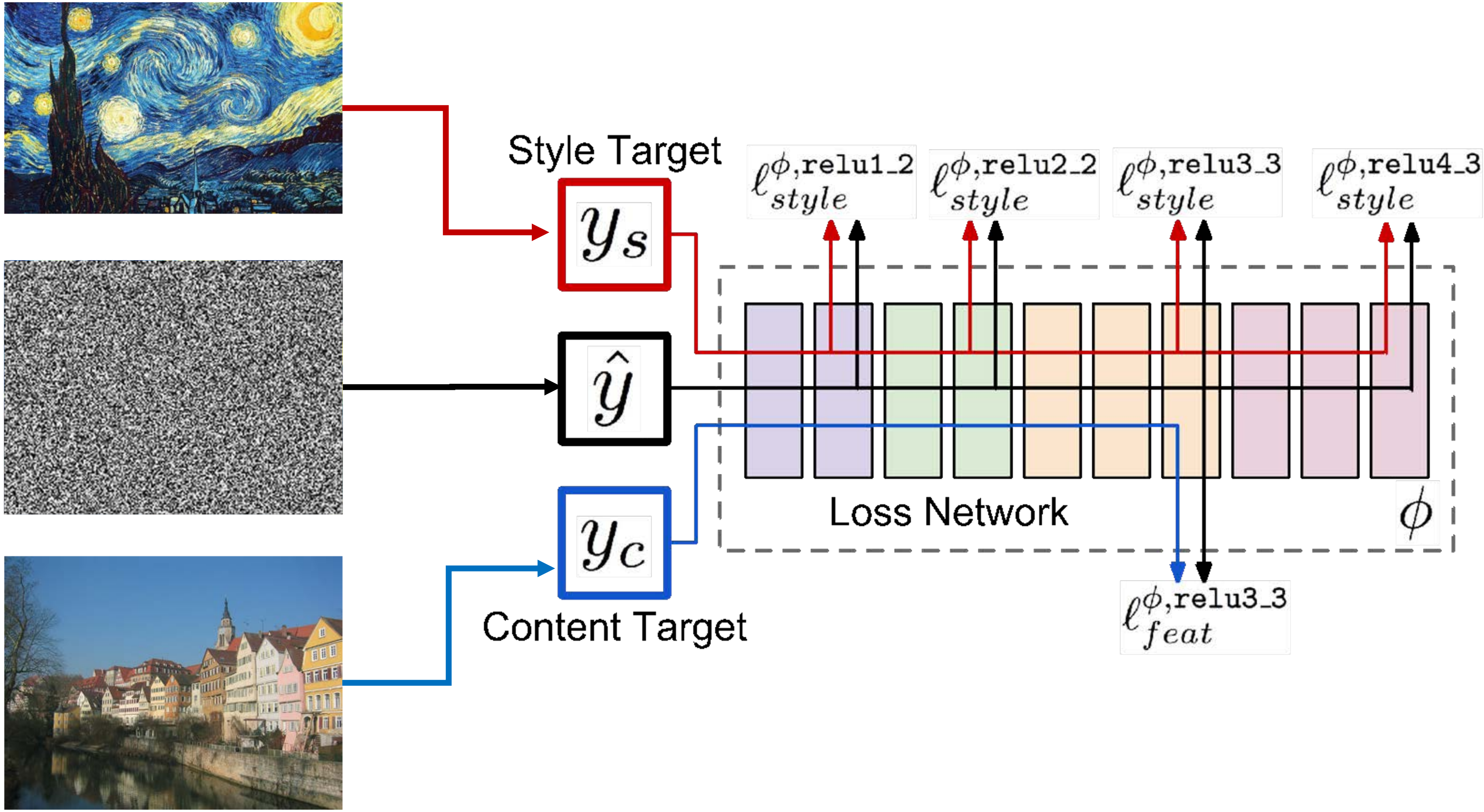
Output Image

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

Style image

Output image (Start with noise)

Content image

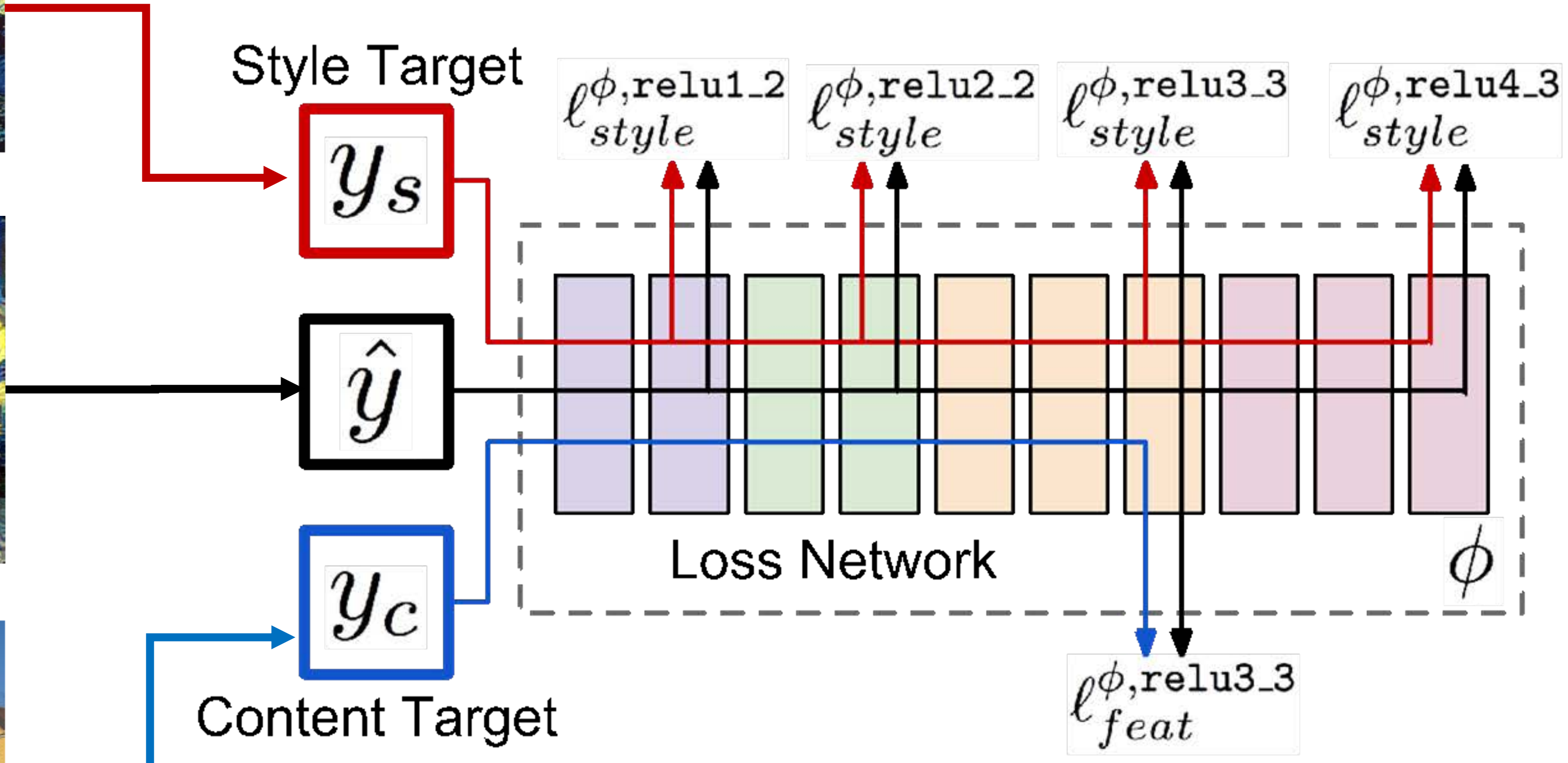


Gatys, Ecker, and Bethge, "Image style transfer using convolutional neural networks", CVPR 2016
Figure adapted from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016.

Style image

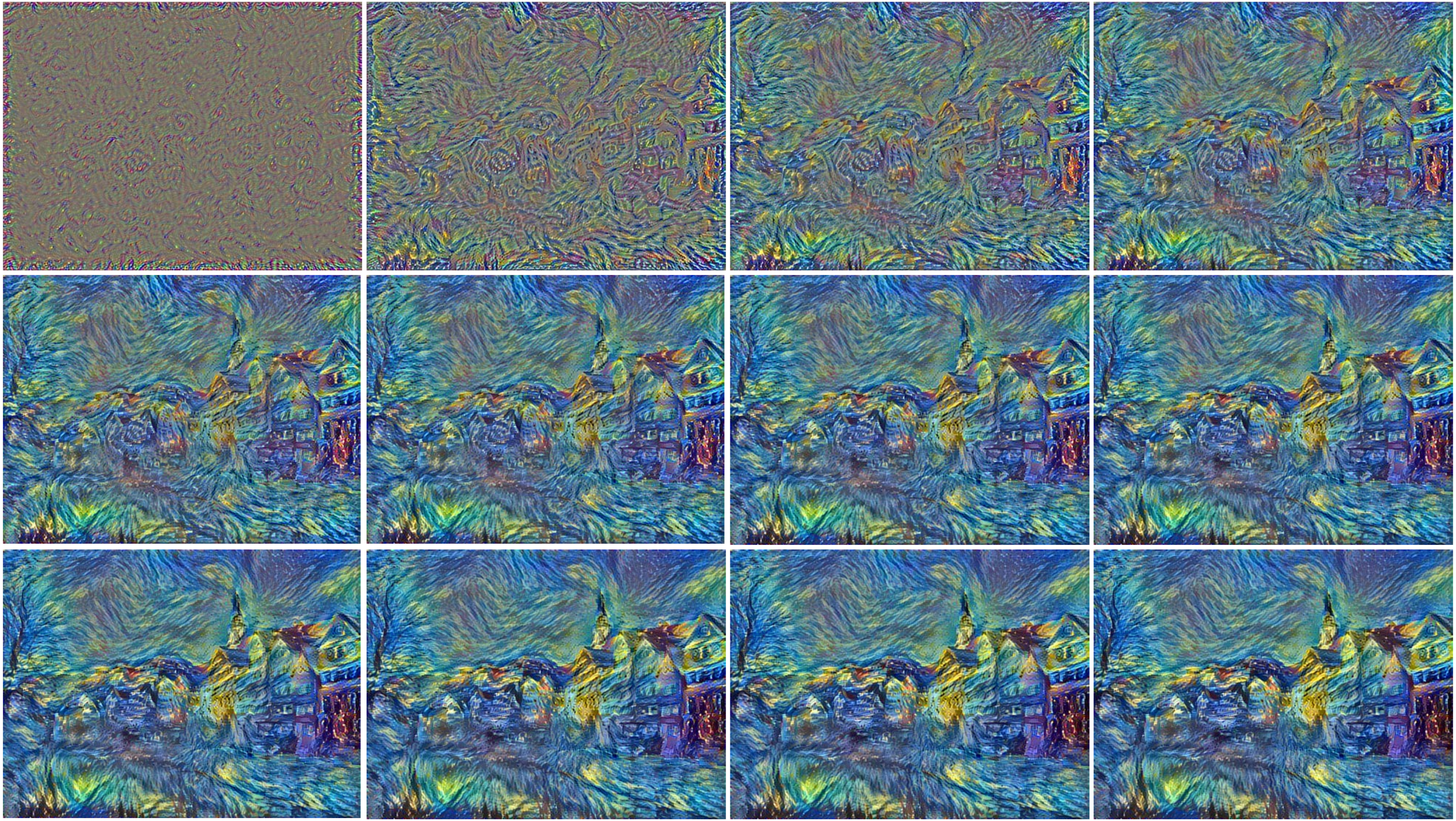
Output image

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

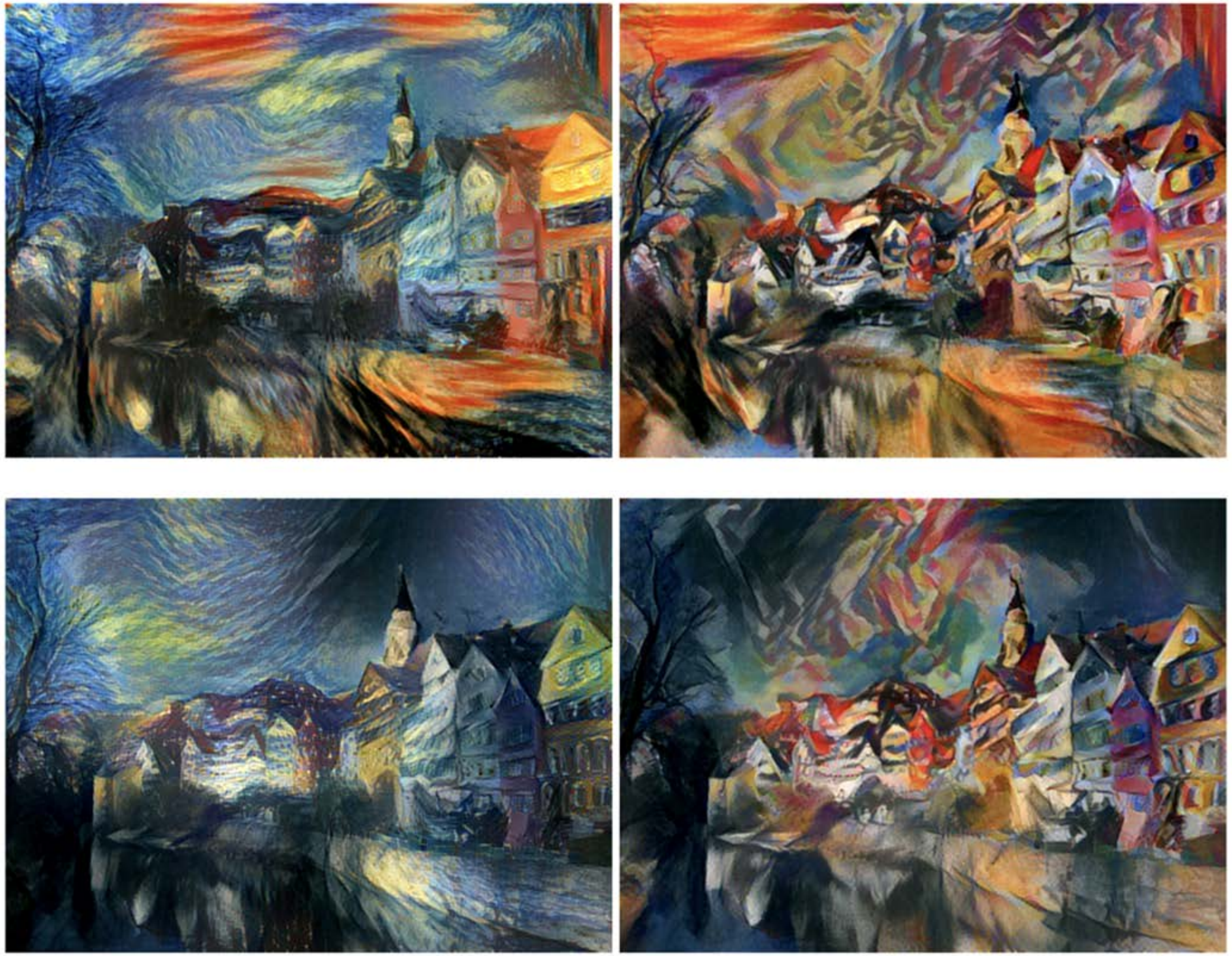
Resizing style image before running style transfer algorithm can transfer different types of features

Larger style image ⟷ Smaller style image

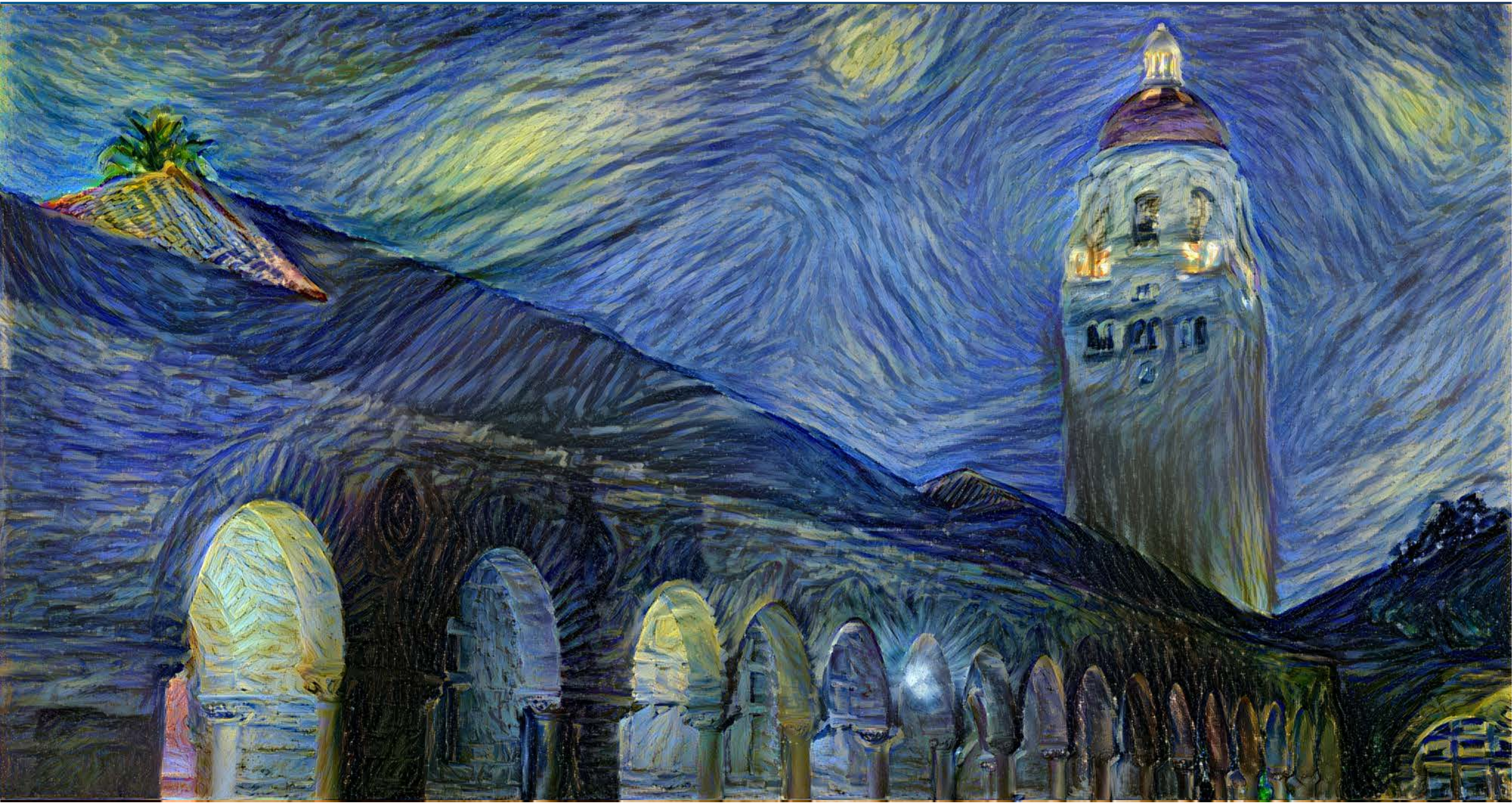
Gatys, Ecker, and Bethge, “Image style transfer using convolutional neural networks”, CVPR 2016

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!

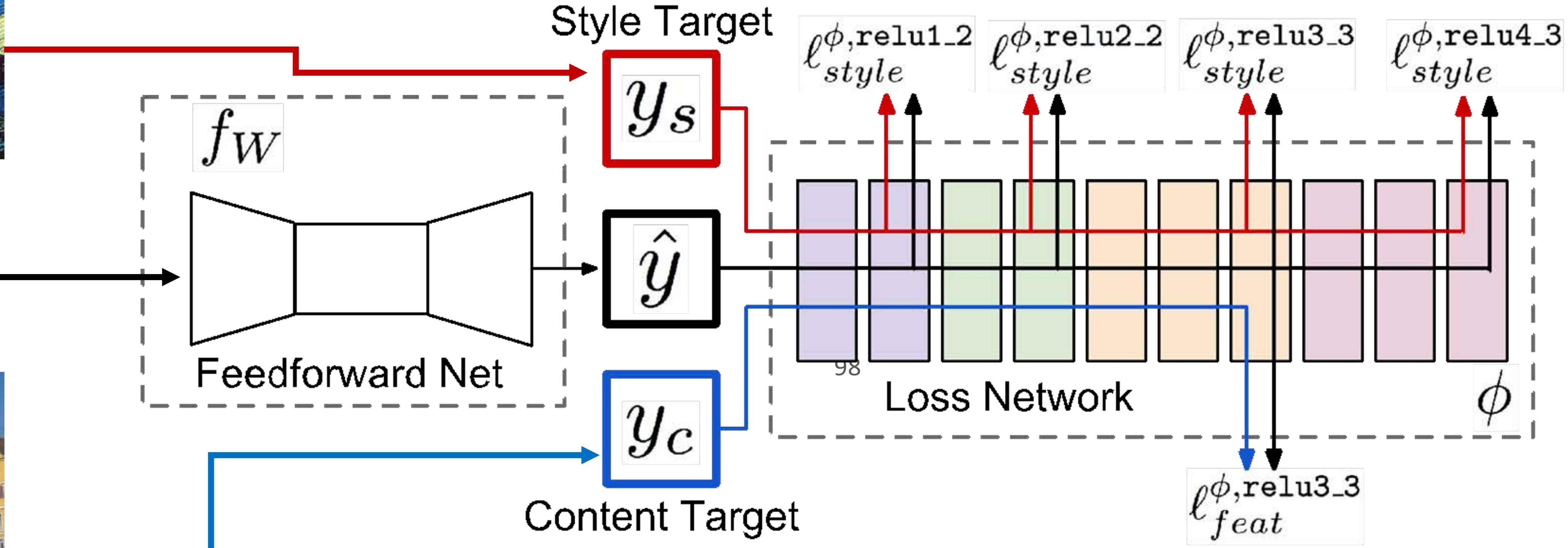
Neural Style Transfer

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

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

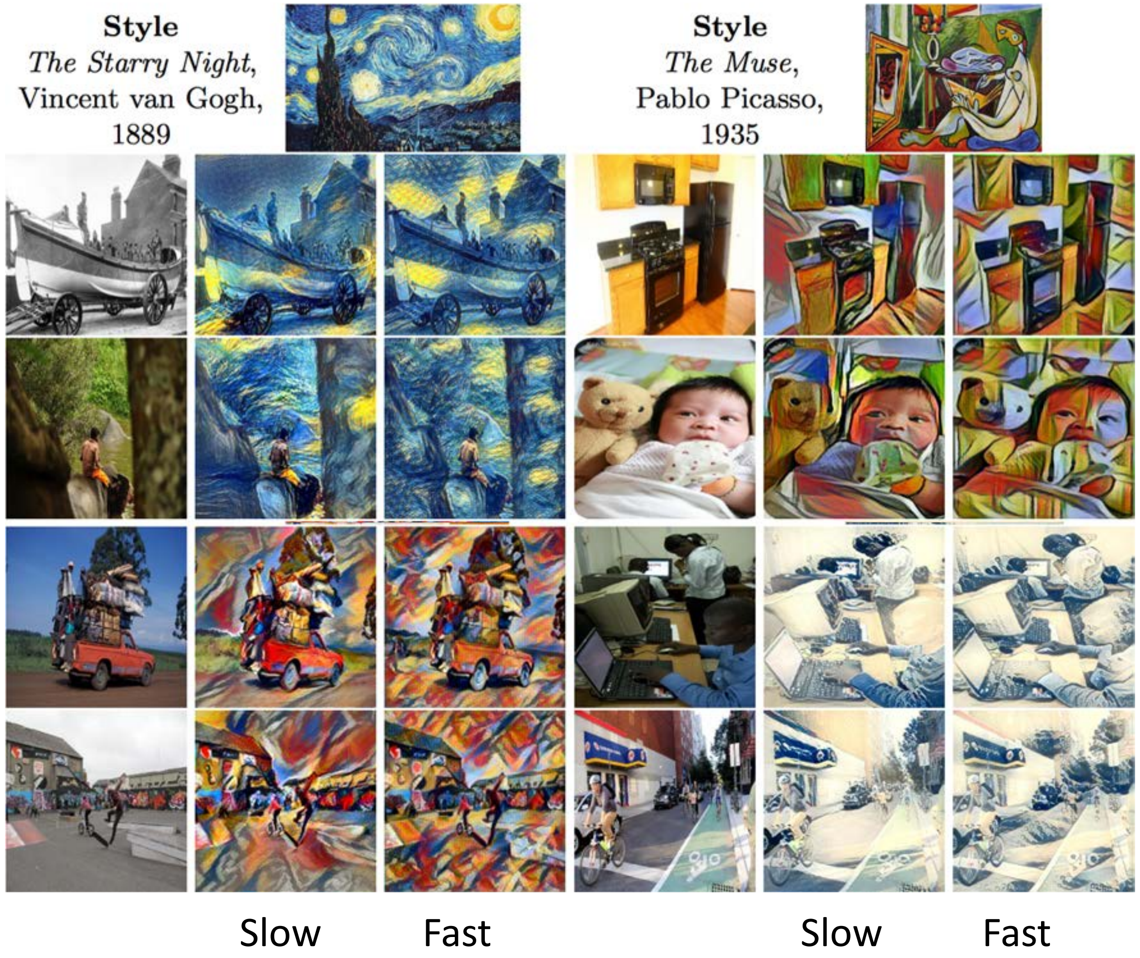
Fast Neural Style Transfer

(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

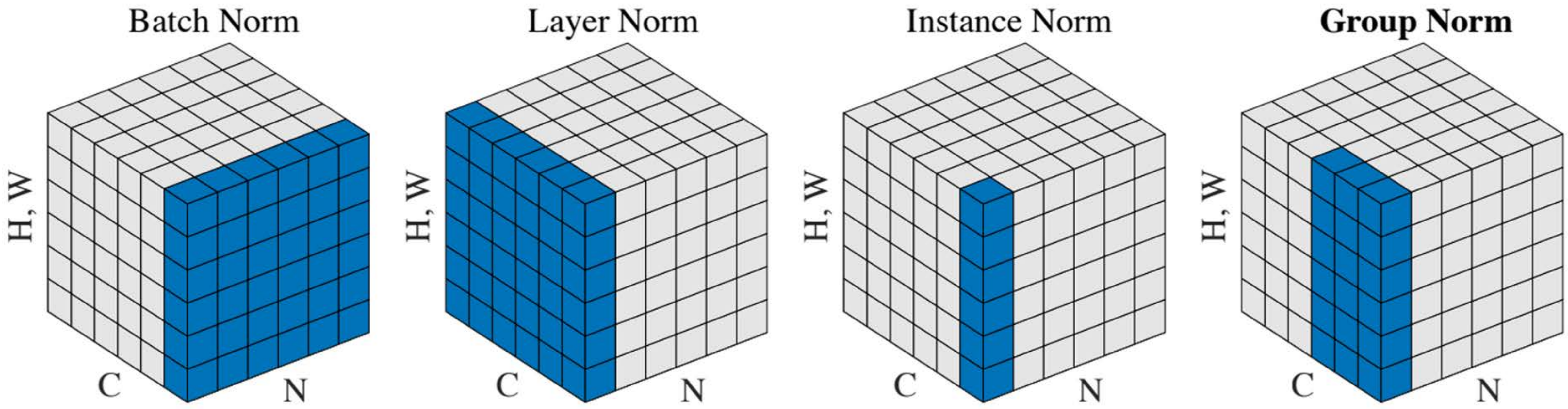
Fast Neural Style Transfer



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

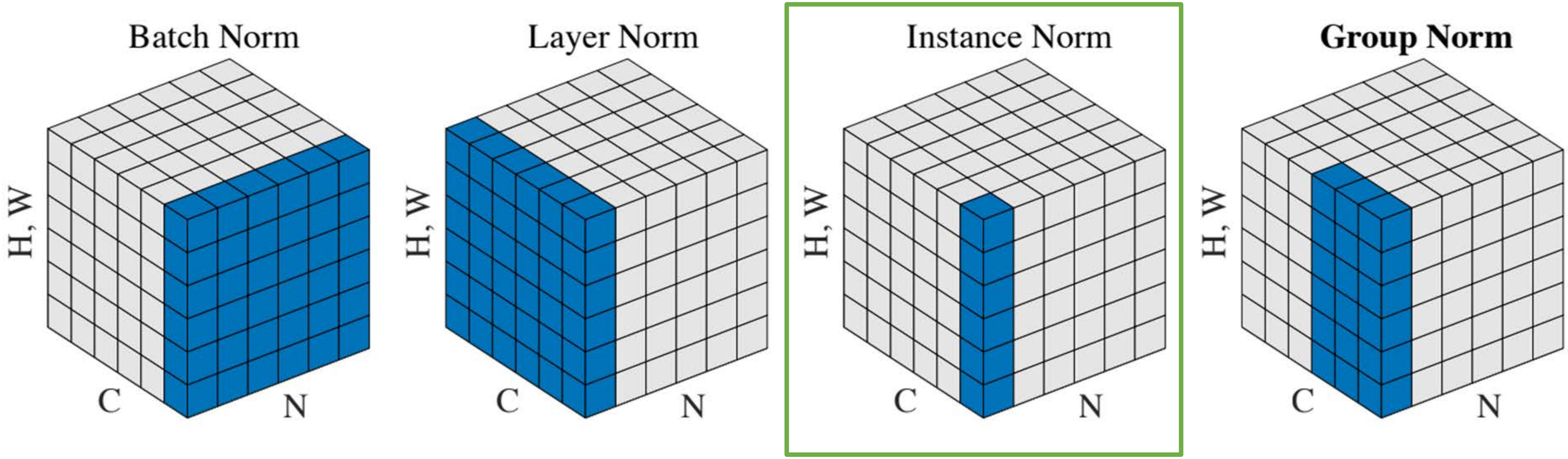
Johnson, Alahi, and Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution”, ECCV 2016

Recall Normalization Methods?



Recall Normalization Methods?

Instance Normalization was developed for style transfer!

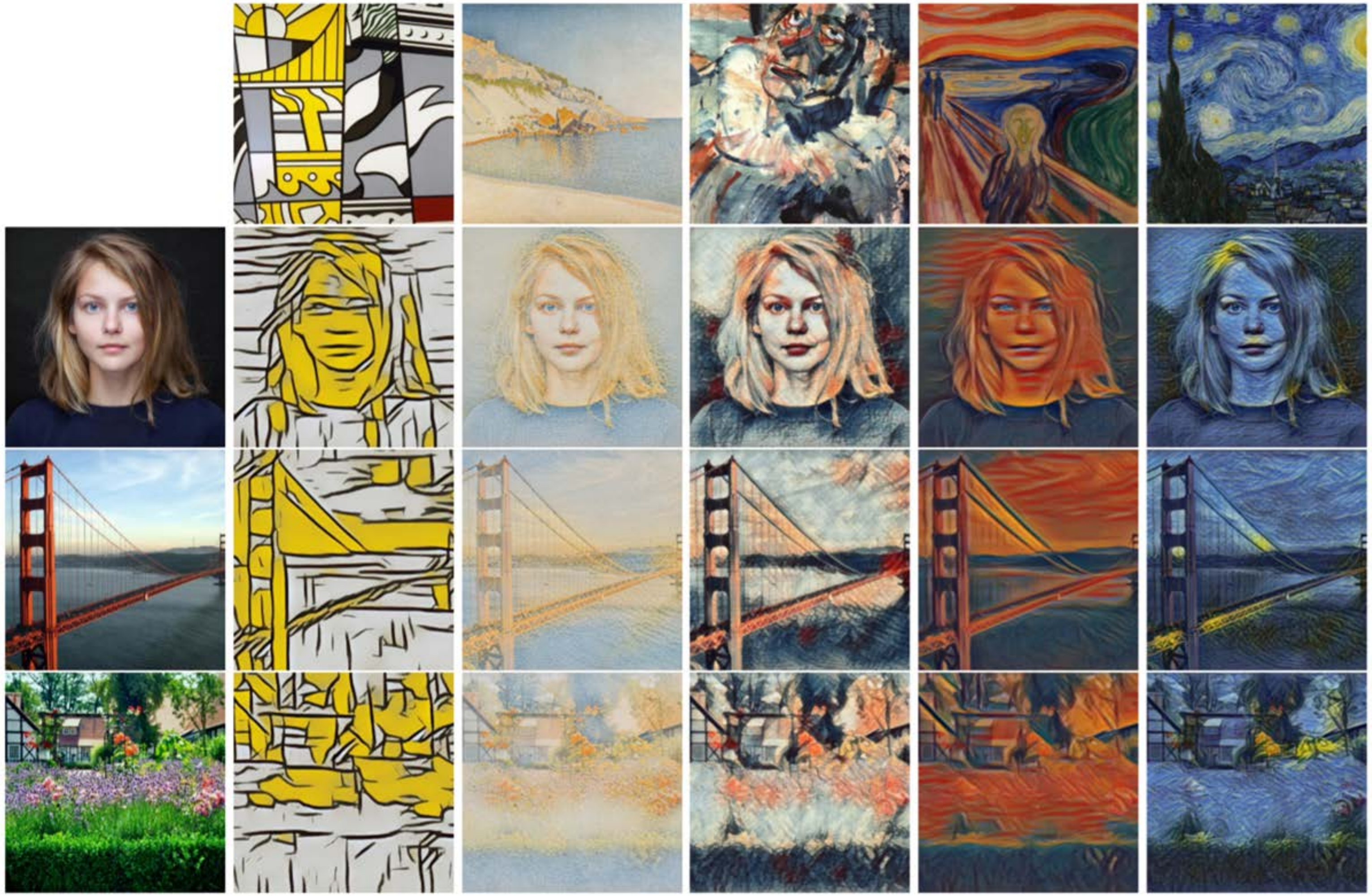


Fast Neural Style Transfer

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

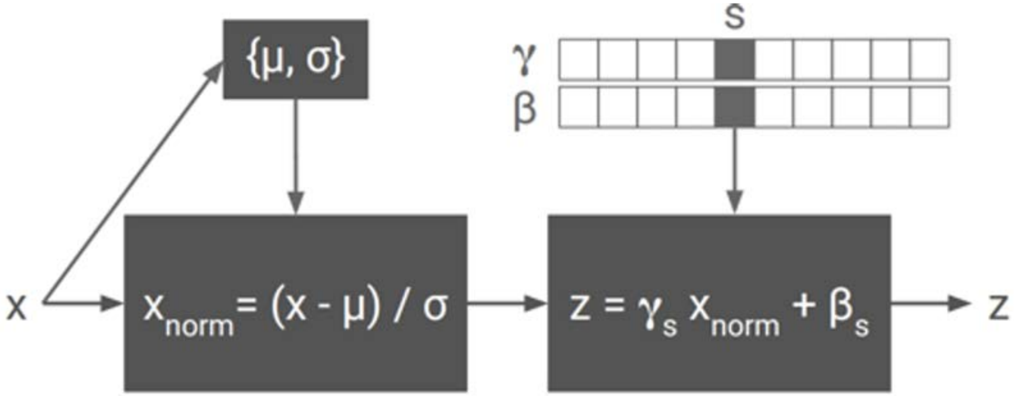
One Network, Many Styles



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

One Network, Many Styles

Use the same network for multiple styles using <u>*conditional instance normalization*</u>: 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.

Next Time:
Object Detection