GEORG-AUGUST-UNIVERSITÄT
GÖTTINGEN

Deep Learning

Lecture 8: Transfer learning & perceptual losses

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https://alexanderecker.wordpress.com

– Credit: some of the slides based on Fei Fei Li, Justin Johnson and Serena Yeung's slides –

Where to put the softmax?

```
nn.Sequential(
        nn.Linear(28*28, 28*28),
        nn.ReLU(),
        nn.Linear(28*28, 14*14),
        nn. ReLU(),
        nn.Linear(14*14, 10))
…
loss_fn = F.cross_entropy
…
y_pred = model(x)
correct = y == y_pred.argmax(dim=1)
loss = loss_fn(y_pred, y)
loss.backward()
```

No softmax!

Includes softmax!

Softmax is usually included in cross entropy for numerical reasons.

Consider what happens with float32 if you compute probabilities via softmax and then take logs for loss function.

Today

Standing on the shoulders of giants

Today's topics

1. Transfer learning
2. Neural style transfer

Image source: https://www.cgtrader.com/3d-models/character/man/cartoon-giant

Transfer learning

Transfer learning: motivation

Illustrative example

Suppose you want to build an app to recognize flowers…

Training a convolutional net from scratch won't work well

…

1000 images
100 classes

Image source: https://www.robots.ox.ac.uk/~vgg/data/flowers/102/

Transfer learning: the idea

1

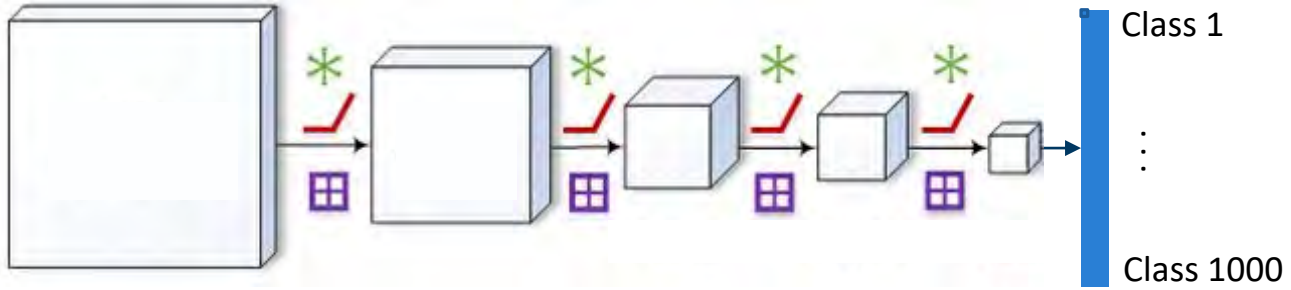
Pre-training

(massive data)

IMAGENET

1.2 million images

1000 object classes



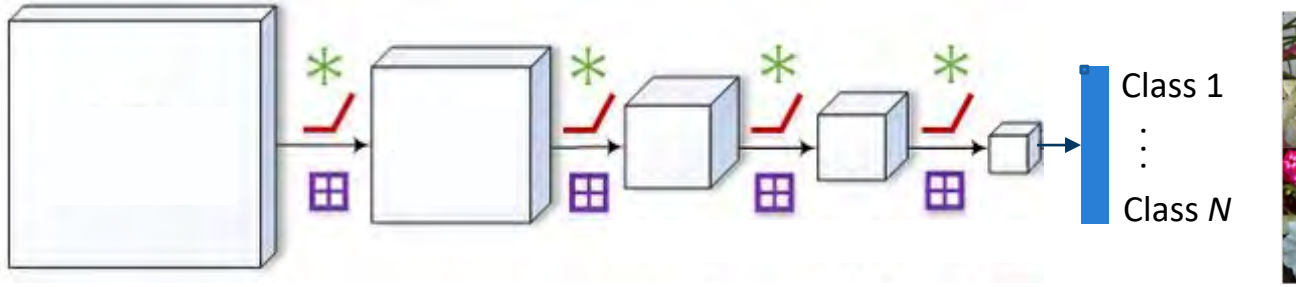
IMAGENET

Transfer weights

2

Fine-tuning

(much less data)



Recognize flowers

Transfer learning: the idea

1

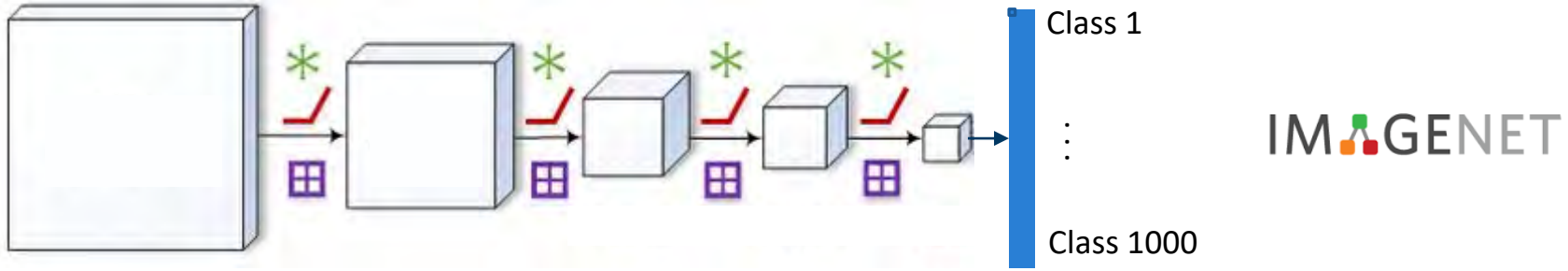
Pre-training

(massive data)

IMAGENET

1.2 million images

1000 object classes

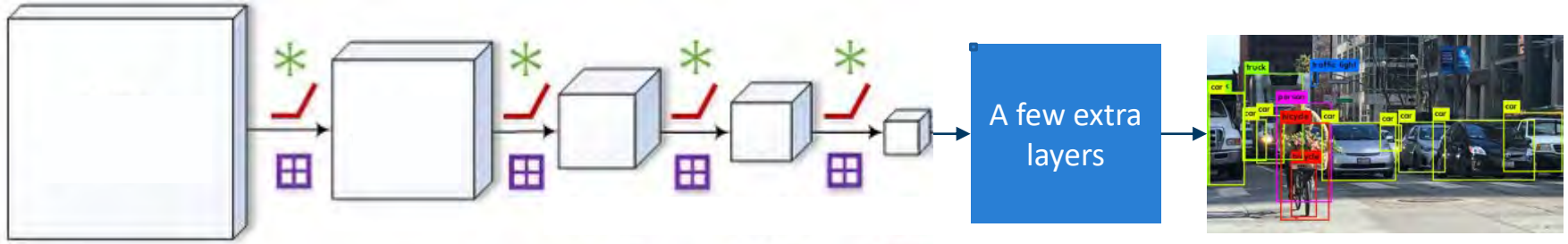


Transfer weights

2

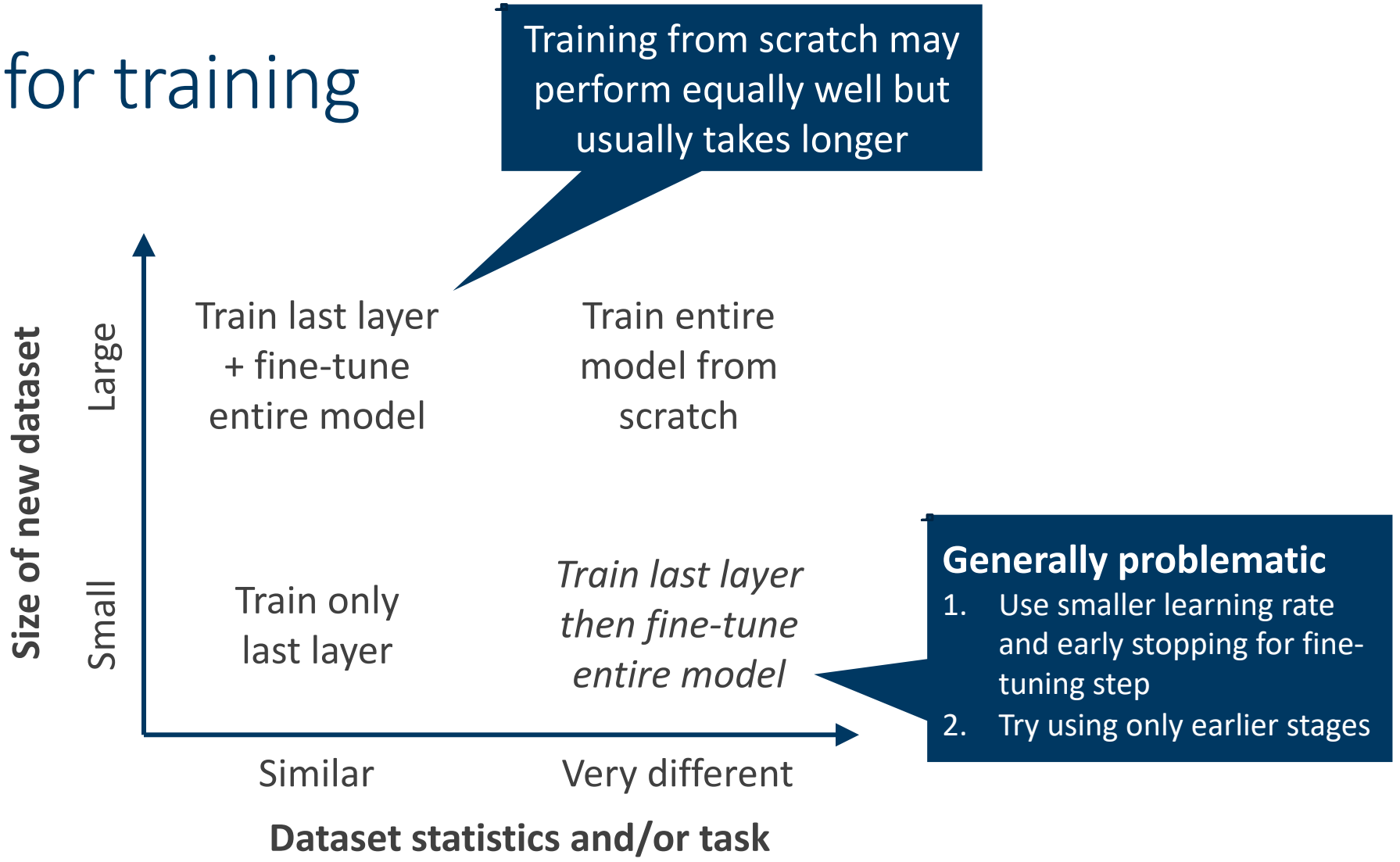
Fine-tuning

(much less data)



Object detection

Strategies for training



Better ImageNet lead to improvements on downstream tasks

Do Better ImageNet Models Transfer Better?

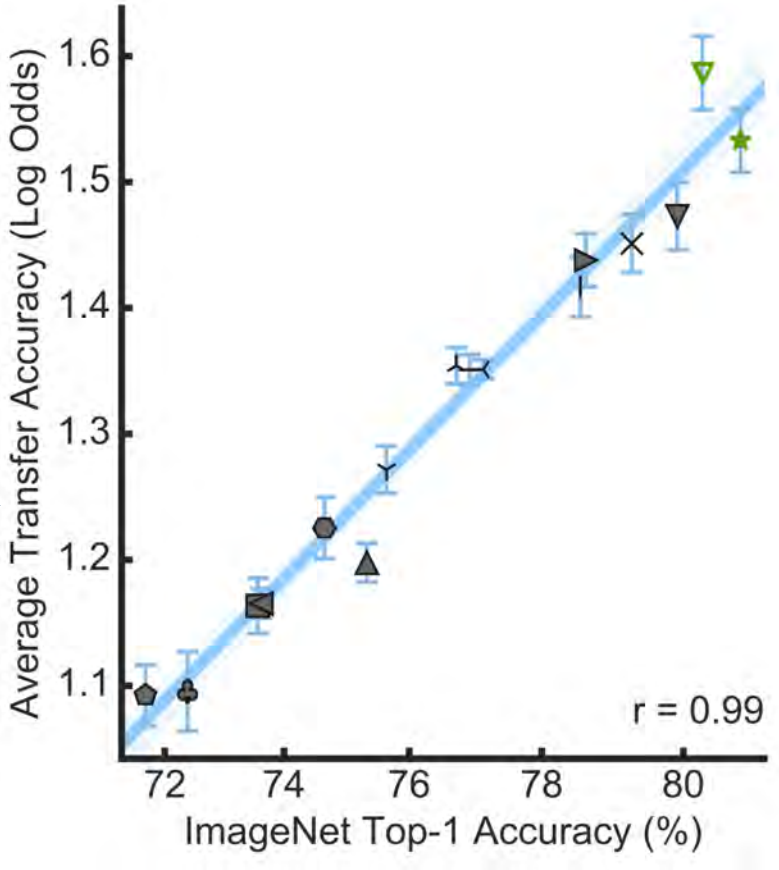
Yes!

Simon Kornblith[illegible] and Quoc V. Le

[illegible]oogle Brain

{skornblith,shlens,qvl}@google.com

Tested on 12 different image classification sets



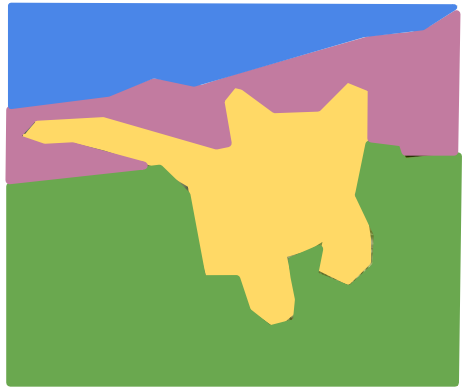
Computer vision tasks

Image Classification

Cat

No spatial extent

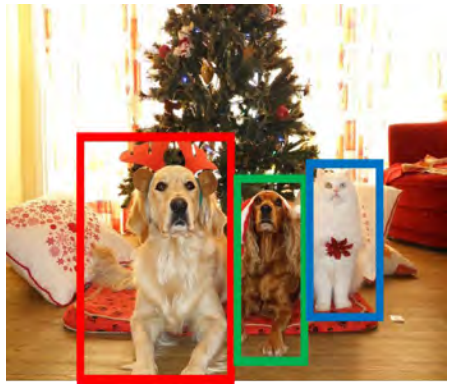
Semantic Segmentation



Sky, Trees, Grass, Cat

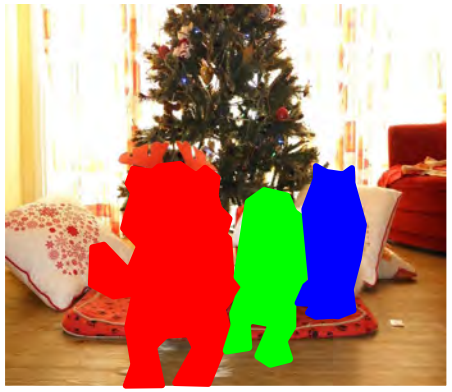
No objects, just pixels

Object Detection



Dog, Dog, Cat

Instance Segmentation

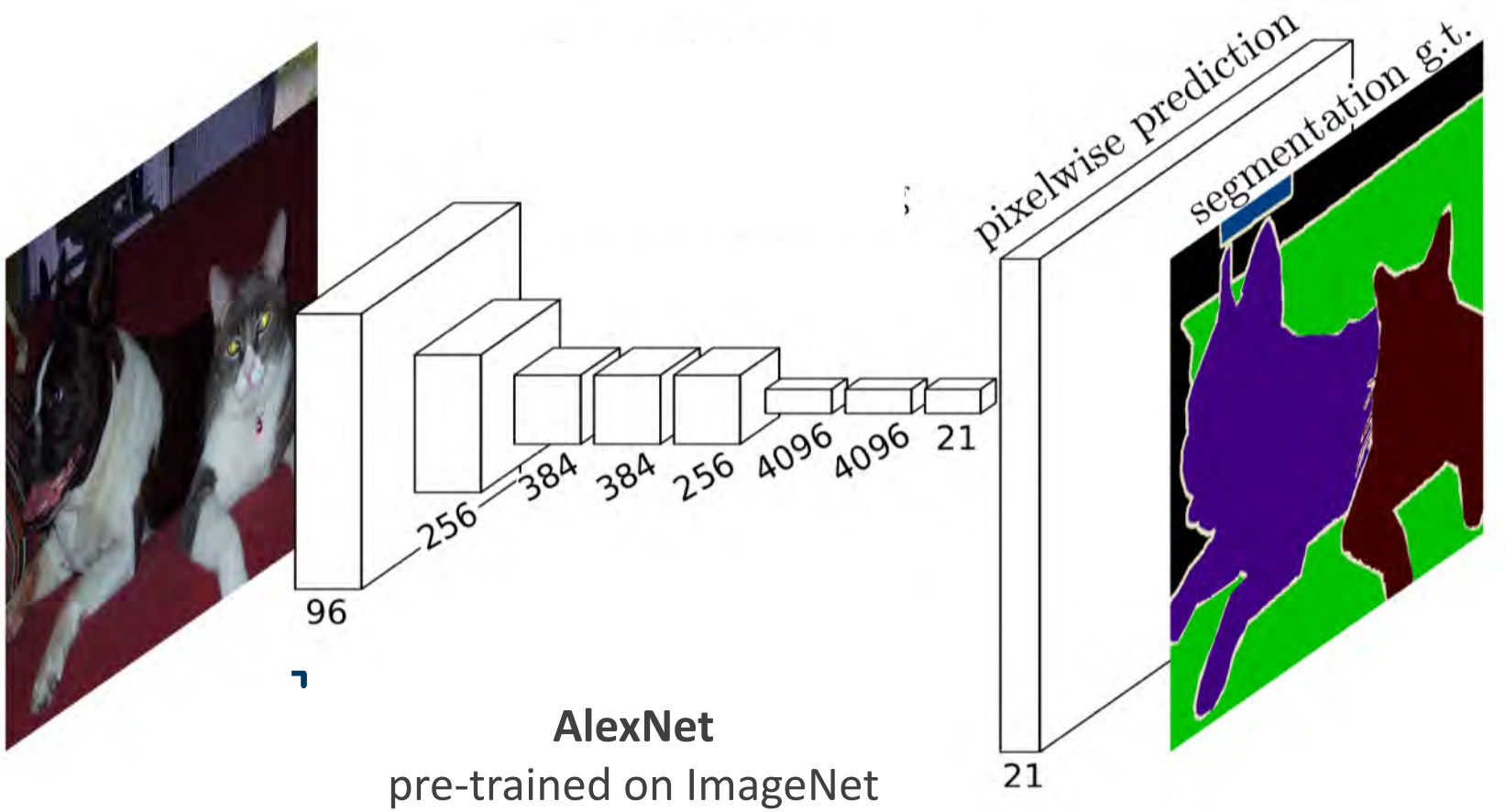


Dog, Dog, Cat

Multiple objects

Source: Fei Fei Li, Justin Johnson, Serena Yeung

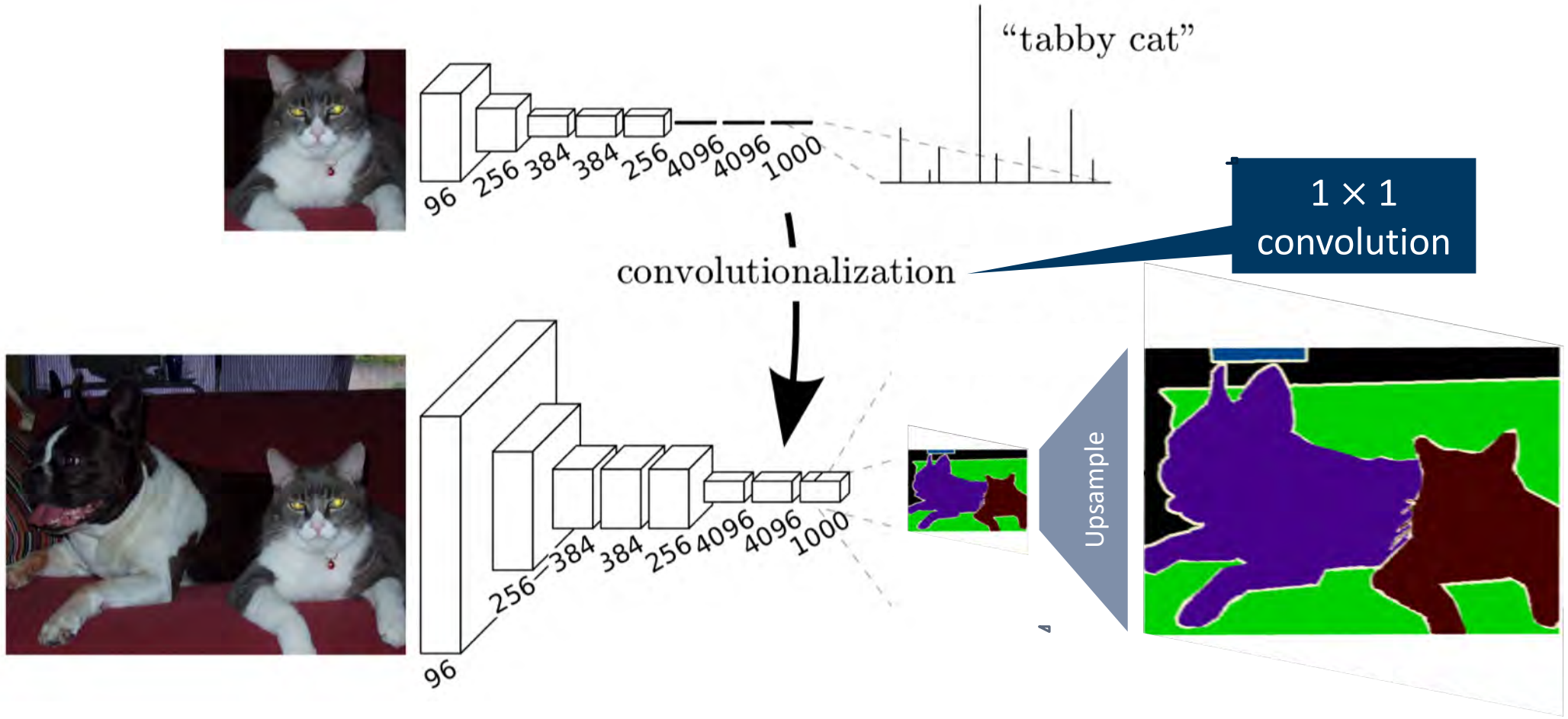
Semantic segmentation



AlexNet
pre-trained on ImageNet

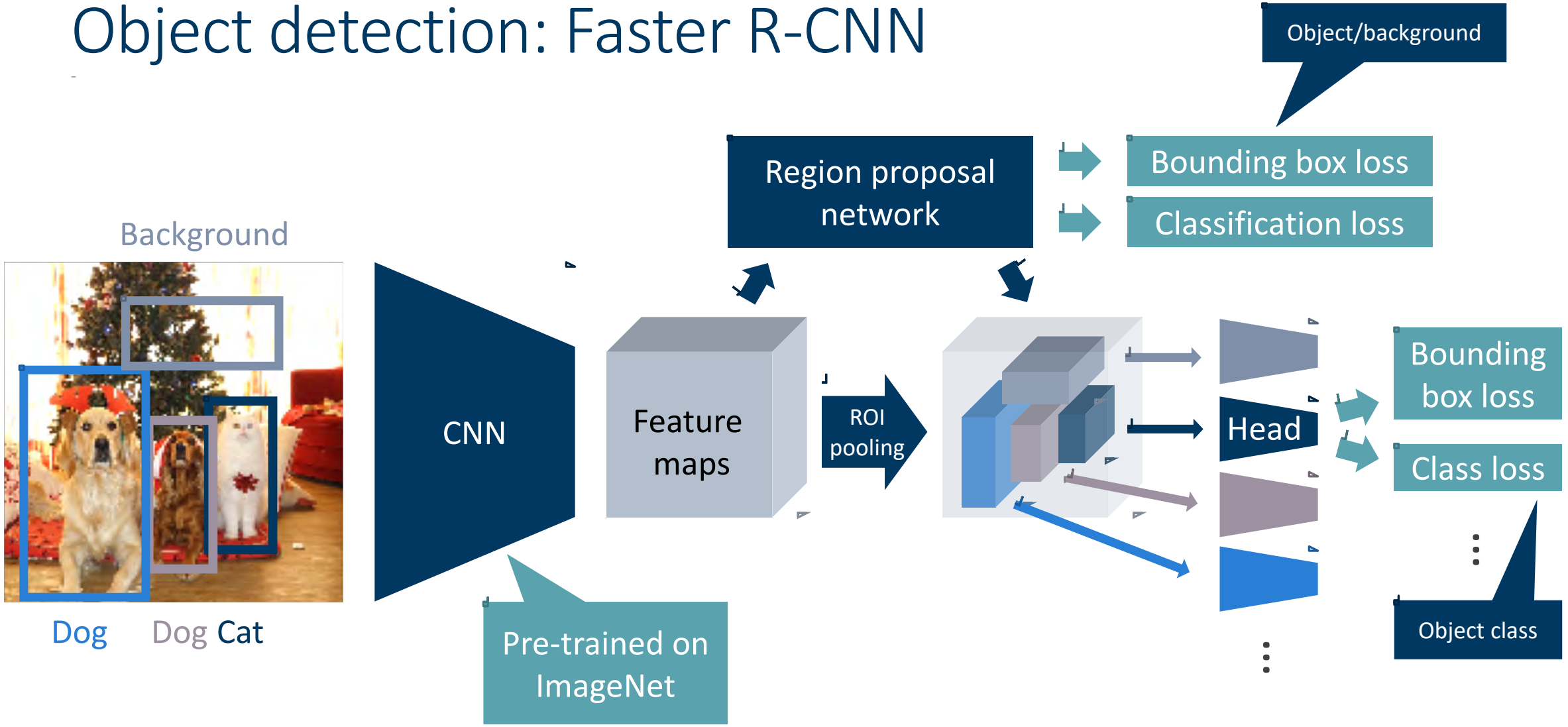
Long, Shelhamer, Darrell, *CVPR* 2015

Turning fully-connected layers into conv layers



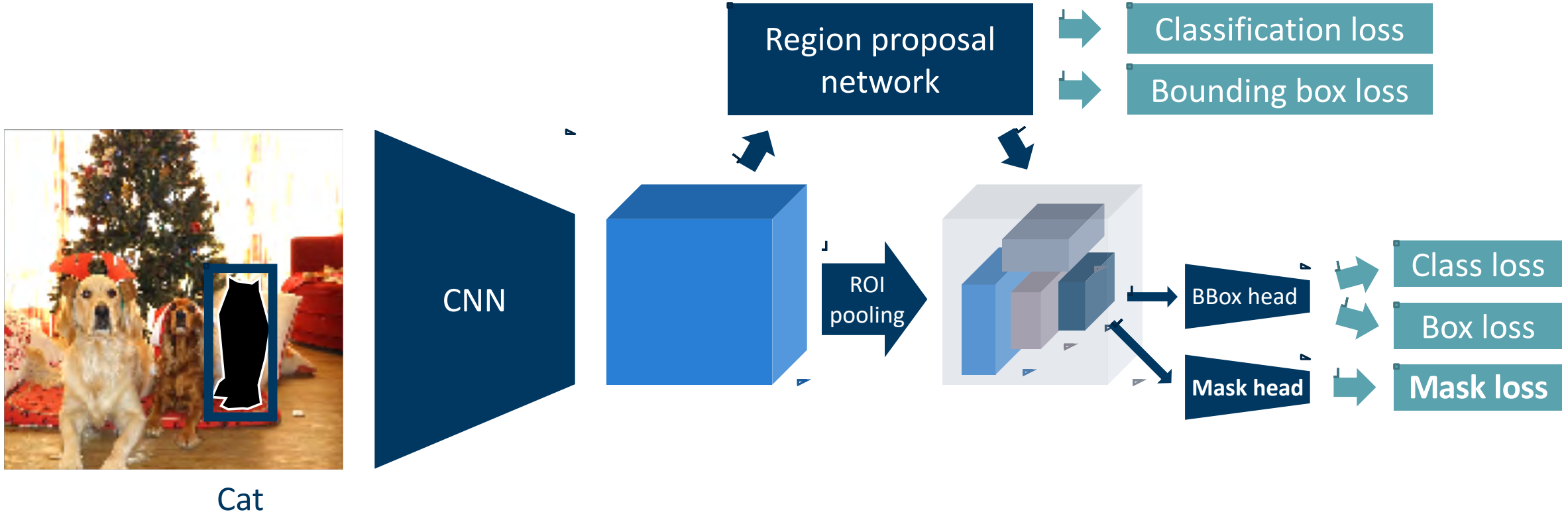
Long, Shelhamer, Darrell, *CVPR* 2015

Object detection: Faster R-CNN



Ren et al., *NeurIPS* 2015

Instance segmentation: **Mask** R-CNN



He et al., *CVPR* 2017

Single-stage detectors: SSD, YOLO, RetinaNet

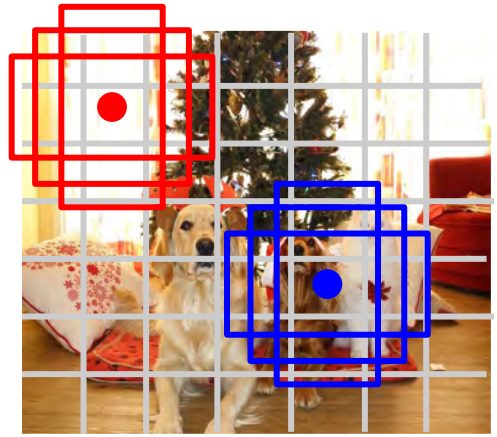
Image

H × W input

CNN

Pre-trained on ImageNet

Bounding box grid



7 × 7 or 14 × 14 grid

For each grid cell

Bounding box regression $(\Delta x, \Delta y, \Delta h, \Delta w)$

Classification in *C* classes + background

Output *N* boxes with highest confidence

A few extra layers per bbox

Liu et al., *ECCV* 2016 | Redmon et al., *CVPR* 2016 | Lin et al., *CVPR* 2017

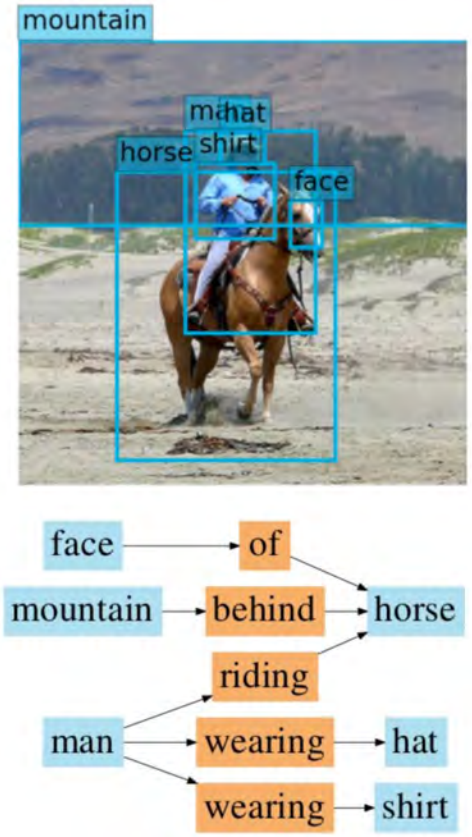
Pre-training on ImageNet is everywhere …

Human pose estimation

Image captioning

"two young girls are playing with lego toy."

Scene graph prediction

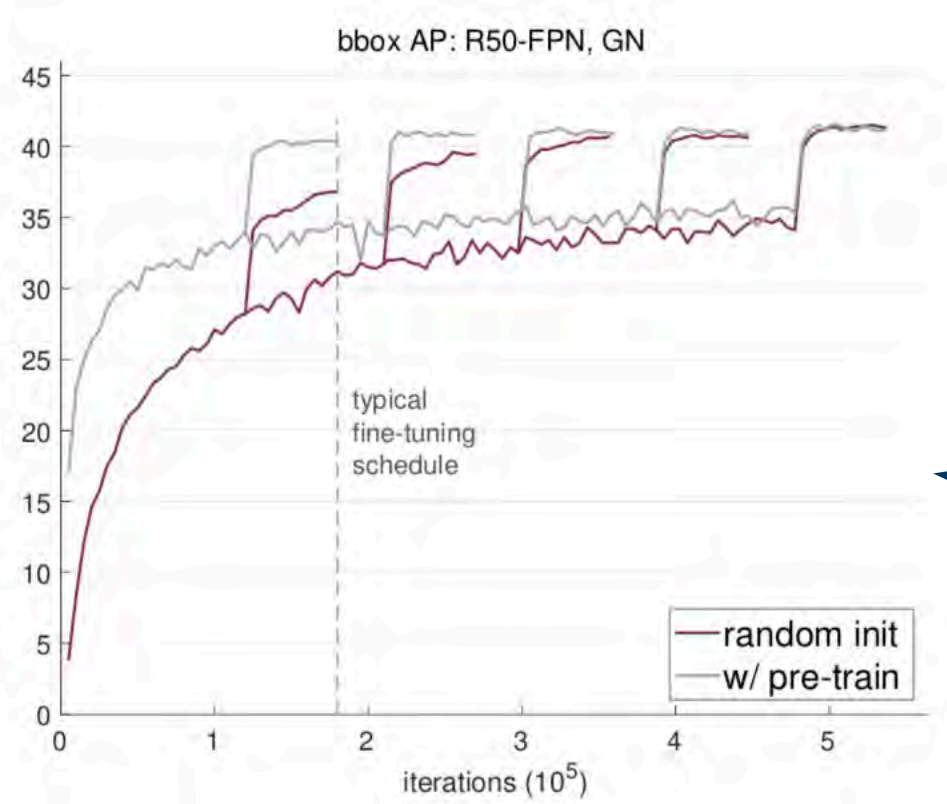


…

Many, many more

Transfer learning from ImageNet is the standard…

… but may not always be necessary



Object detection
on MS COCO dataset
123,287 images
886,284 instances

He, Girshick, Dollar: “Rethinking ImageNet pre-training”, *ICCV* 2019

Visual saliency

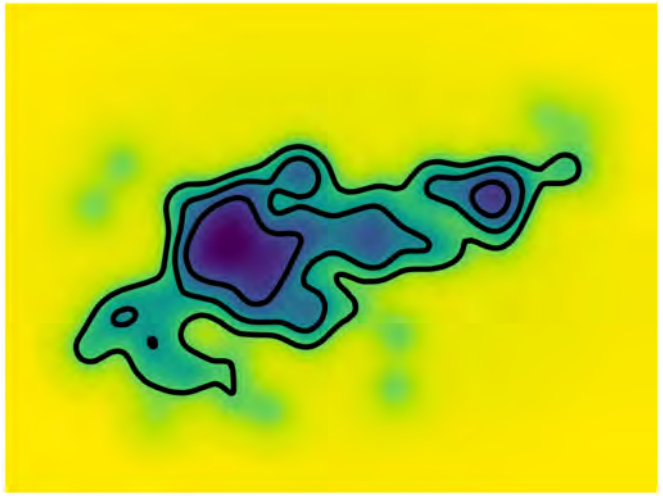
PREDICTING WHERE PEOPLE LOOK

Image saliency: predicting where people look

Image shown

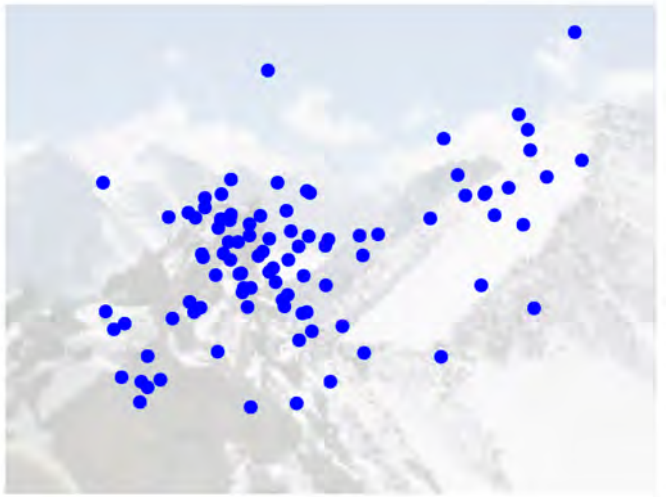
Predict

Goal:
Saliency map

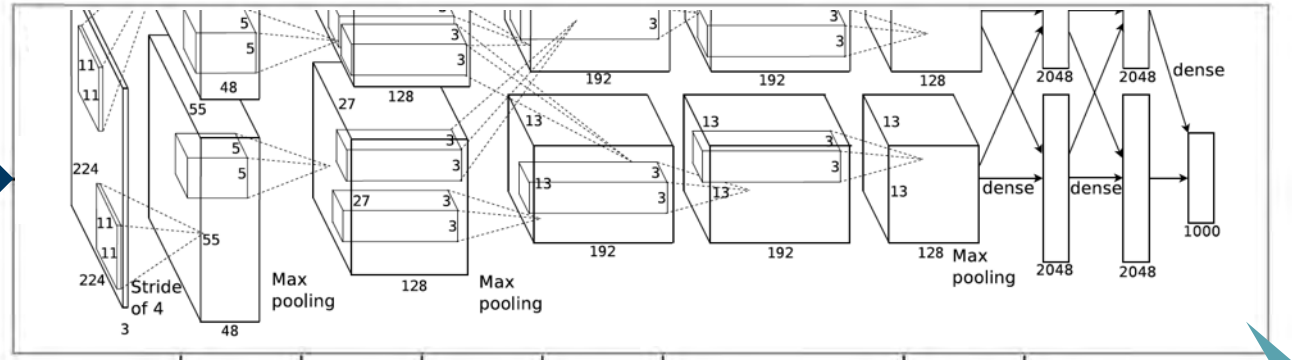


$P(x, y \mid \text{image})$

Measured eye fixations



Loss



Deep Gaze I

Kümmerer, Theis, Bethge,
ICLR Workshops 2015

AlexNet
pre-trained on ImageNet

$r_k(x, y)$

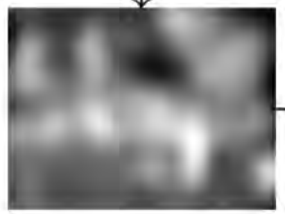
Large filterbank

$\sum_k w_k r_k(x, y)$

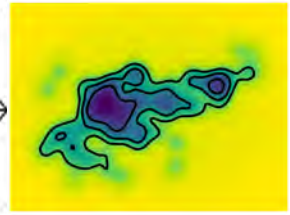
Linear prediction

A-priori saliency map (center bias)

Blurring (as regularization)



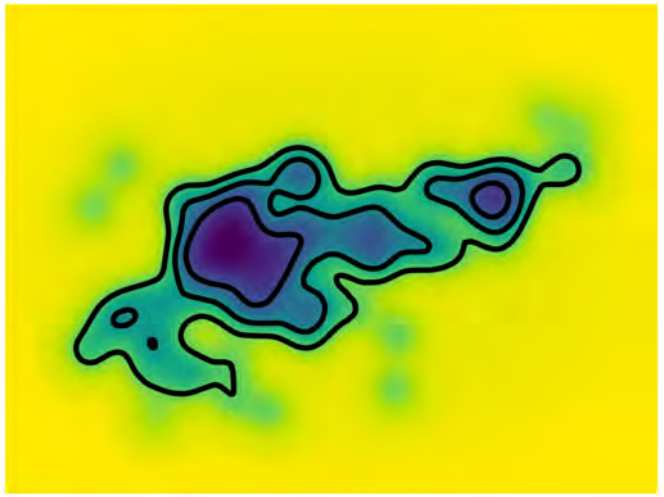
softmax



Saliency map (probability distribution)

Deep Gaze: loss function

Saliency map

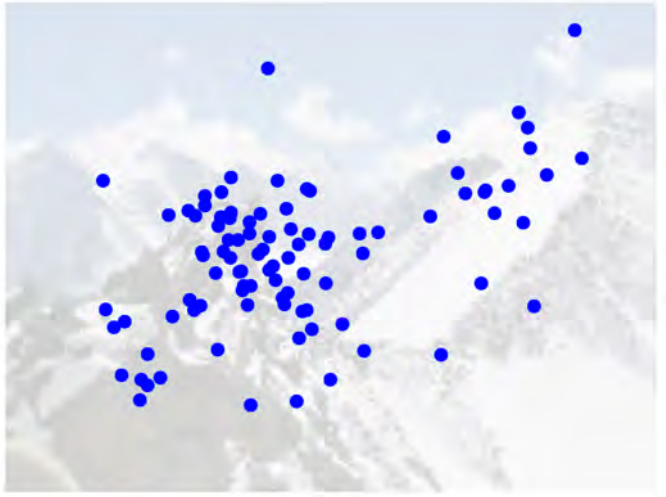


$P(x, y \mid \text{image})$

Loss:
negative log likelihood

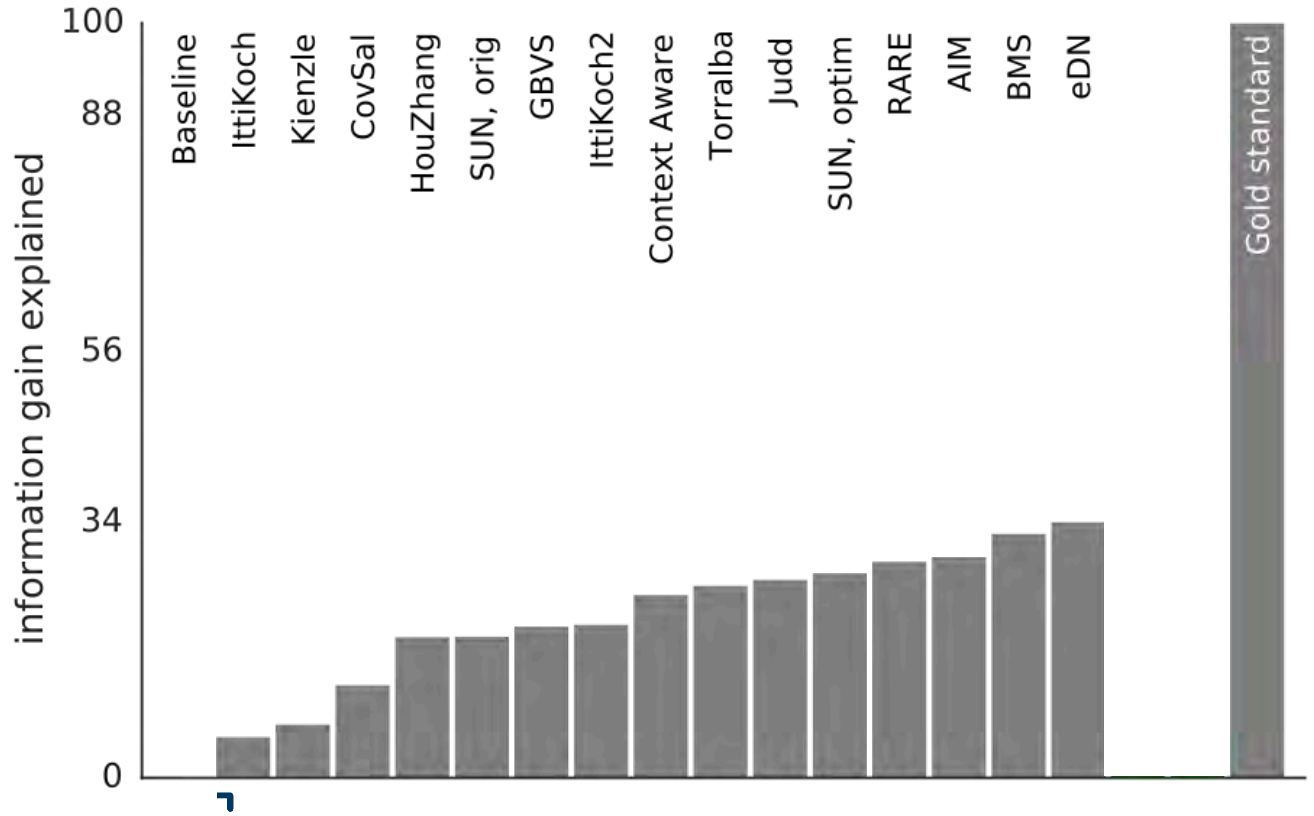
$$L = -\sum_{i=1}^{N} \log P(x_i, y_i \mid \text{image})$$

Measured eye fixations



$\{(x_i, y_i)\}_{i=1}^{N}$

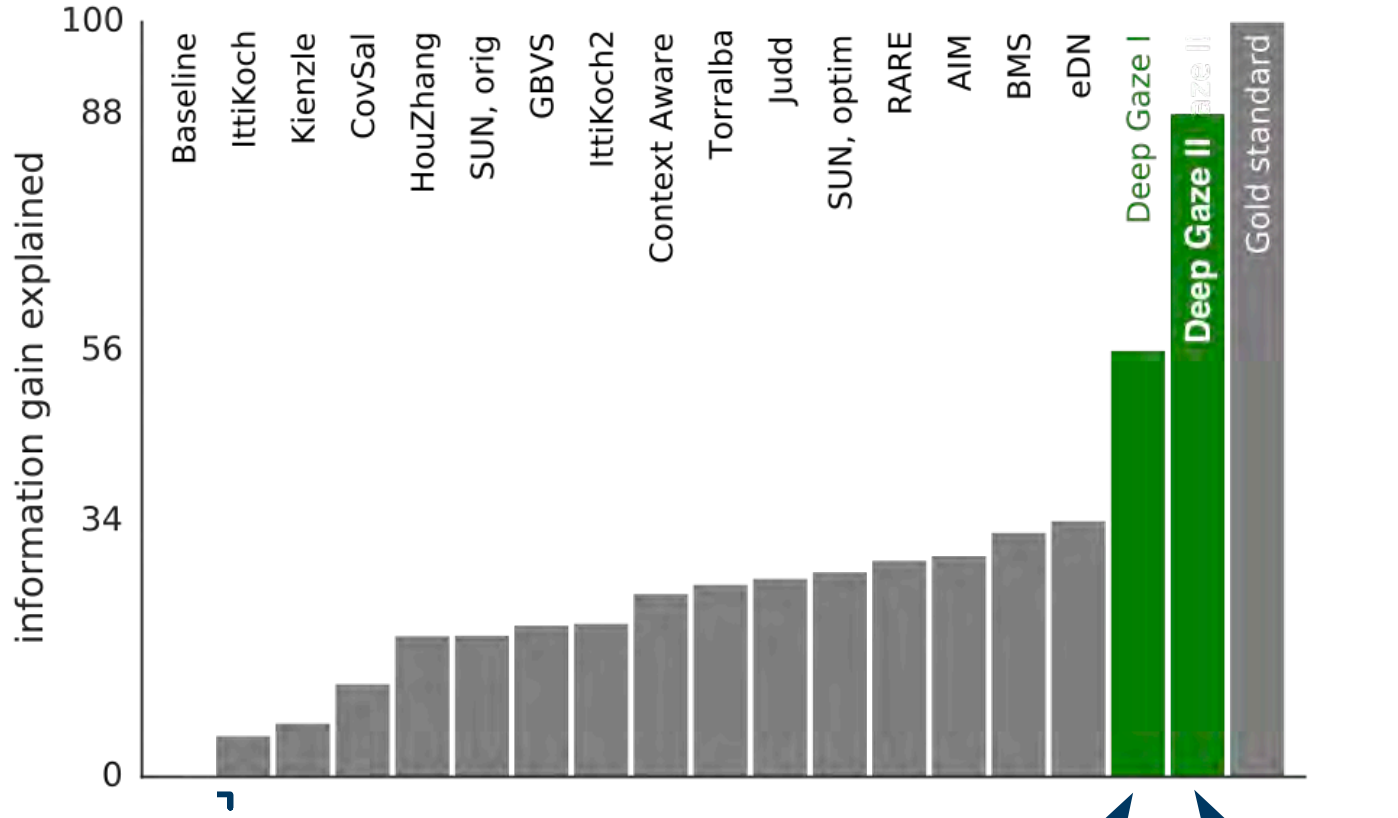
Deep Gaze I + II



20 years
of research…

Kümmerer, Theis, Bethge, *ICLR Workshops* 2015

Deep Gaze I + II



20 years
of research…

AlexNet

VGG 19

Kümmerer, Theis, Bethge,
ICLR Workshops 2015
Kümmerer, Wallis, Bethge, *arXiv* 2016

Neural style transfer

TEXTURE SYNTHESIS AND PERCEPTUAL LOSS FUNCTIONS

History of art – Tübingen


Vincent van Gogh (1889)


William Turner (1805)

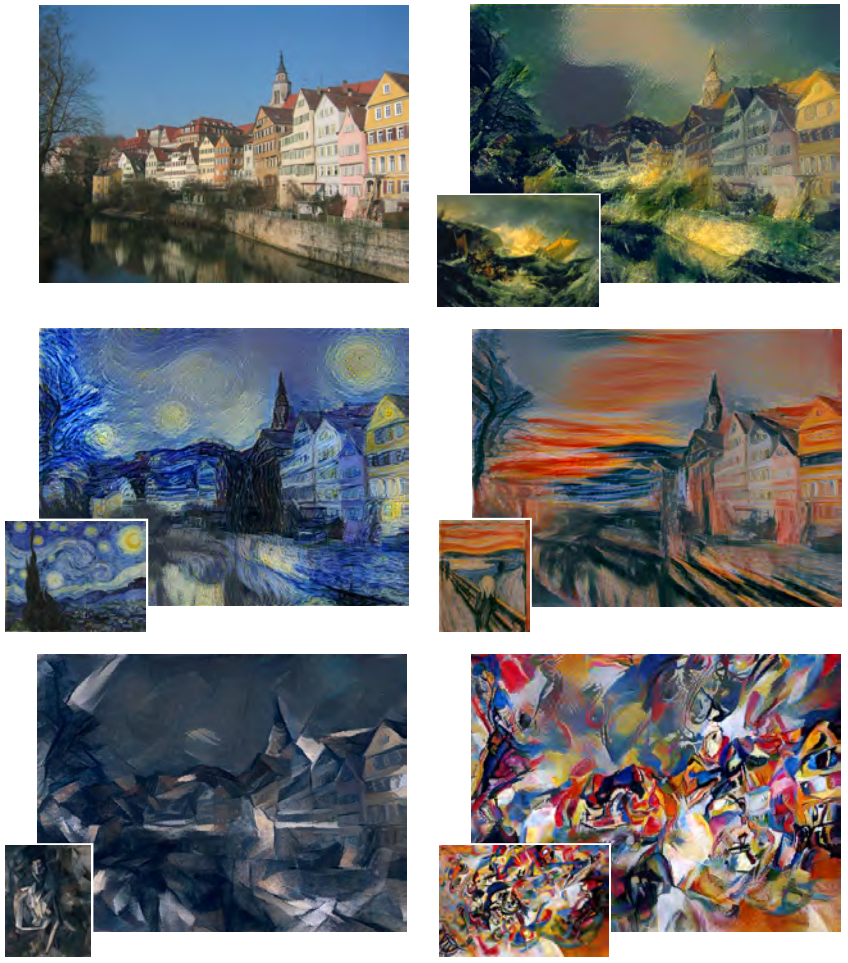

Pablo Picasso (1910)


Edvard Munch (1893)


Wassily Kandinsky (1913)

A Neural Algorithm of Artistic Style

Gatys, Ecker, Bethge (CVPR 2016)



Neural Style Transfer

Content

Style (→ texture)

Gatys, Ecker Bethge, CVPR 2016

A brief history of parametric texture modeling

Julesz (1962)

- Conjecture: N^{th} order summary statistics determine texture perception

Portilla & Simoncelli (2000)

- Summary statistics of features from early visual system (steerable pyramid)

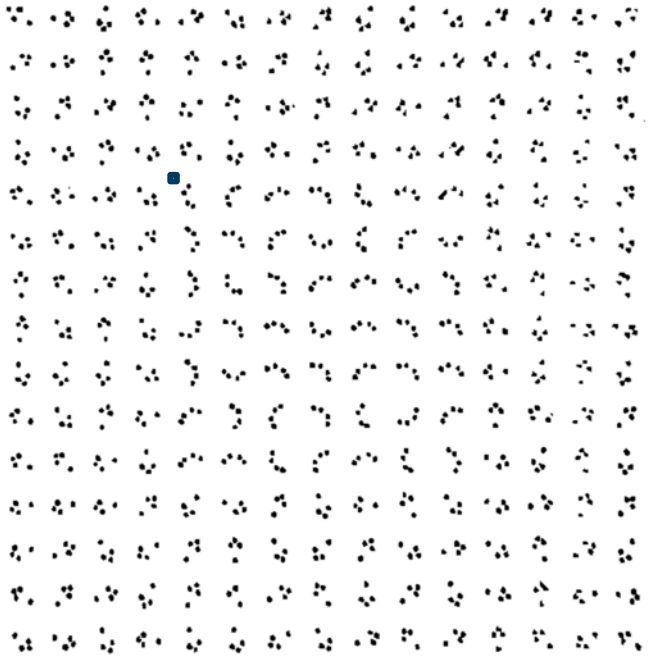
Gatys, Ecker Bethge (NIPS 2015)

- Summary statistics of features from CNNs trained on ImageNet

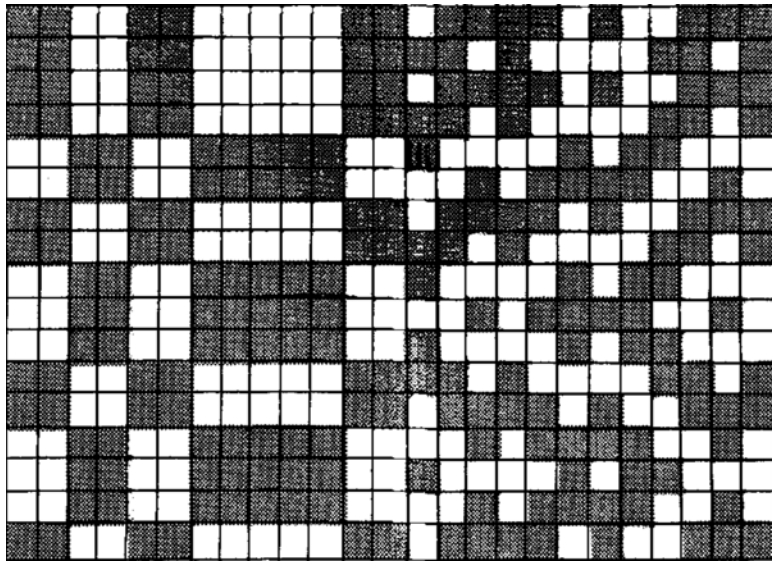
Julesz' conjecture (1962)

N^{th} order summary statistics determine texture perception.

Uniform 2nd order statistics (power spectrum)



Uniform 3rd order statistics



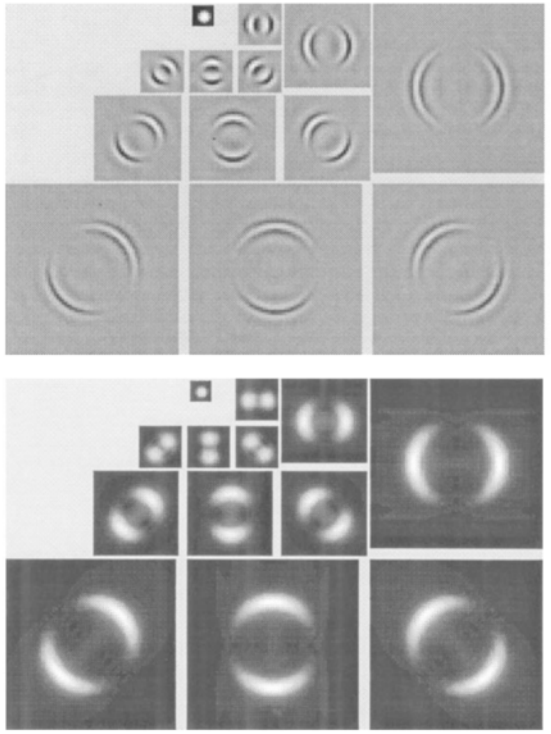
Julesz 1962, Julesz et al. 1978

Portilla & Simoncelli texture model

Steerable pyramid

(Simoncelli & Freeman 1995)

Image



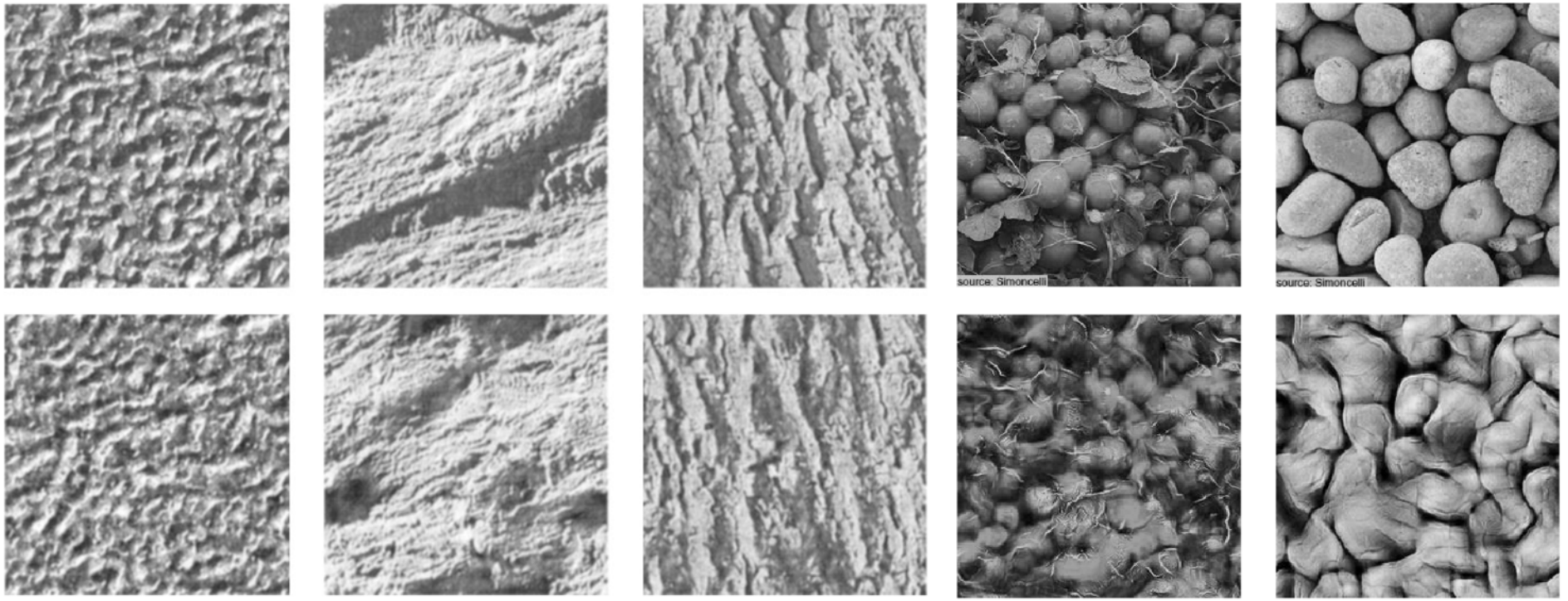
Summary statistics

- Mean
- Variance
- Correlations across
  - Space
  - Features

Portilla & Simoncelli (2000)

Portilla & Simoncelli: results

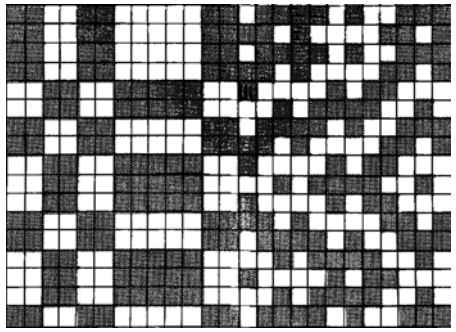
Original images



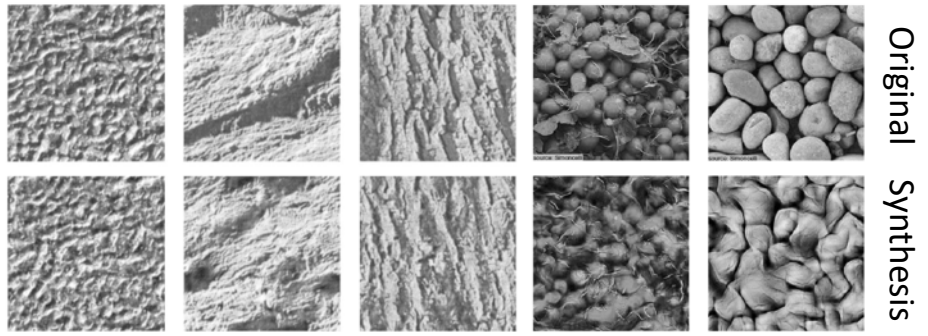
Synthesized by Portilla & Simoncelli

Portilla & Simoncelli (2000)

Texture models: summary statistics



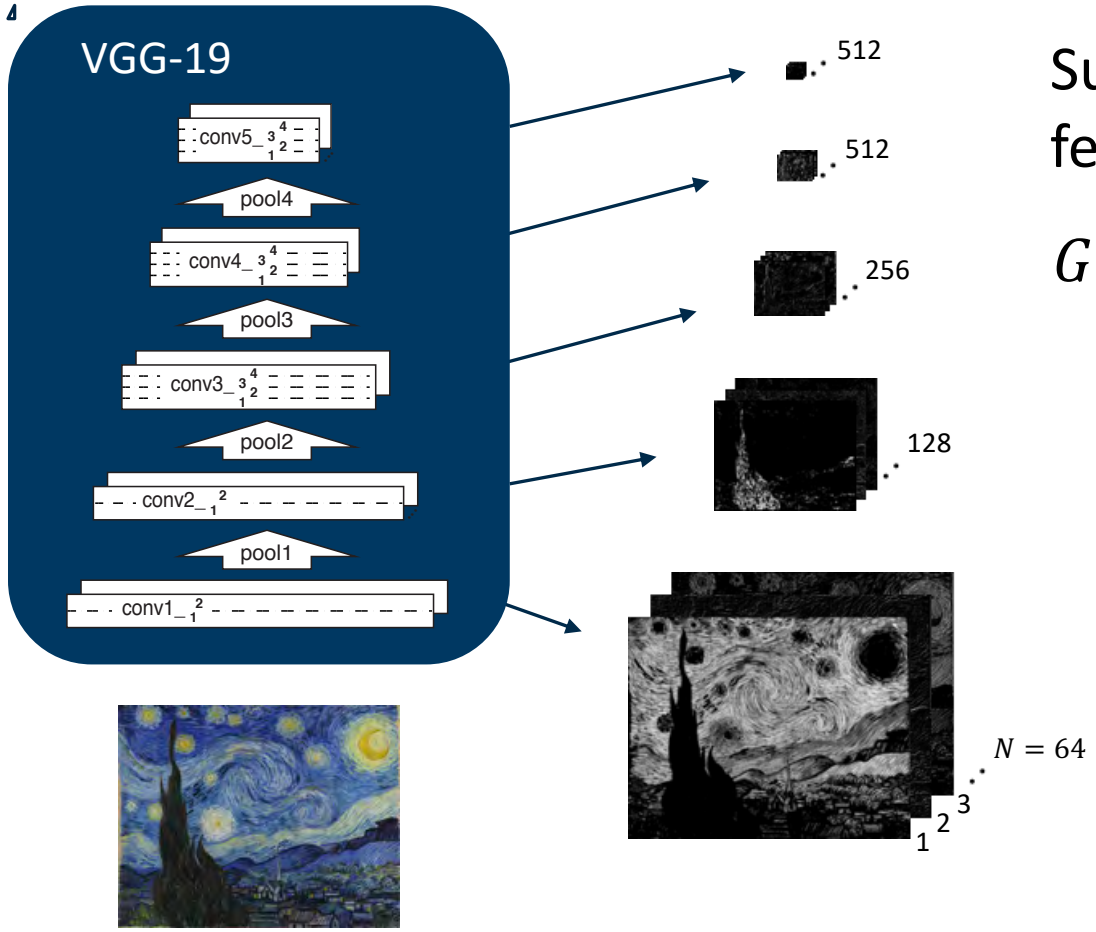
Julesz (1962):
N^{th} order pixel stats



Portilla & Simoncelli (2000):
V1 summary statistics → Steerable Pyramid

Gatys, Ecker, Bethge (2015): Entire visual pathway → CNN features

CNN: Multiscale nonlinear filter bank



Summary statistic:
feature correlations

$$G = \Phi^{\mathrm{T}}\Phi$$

Gatys, Ecker Bethge, *NeurIPS* 2015

Gram matrix computation

conv1_1 feature maps

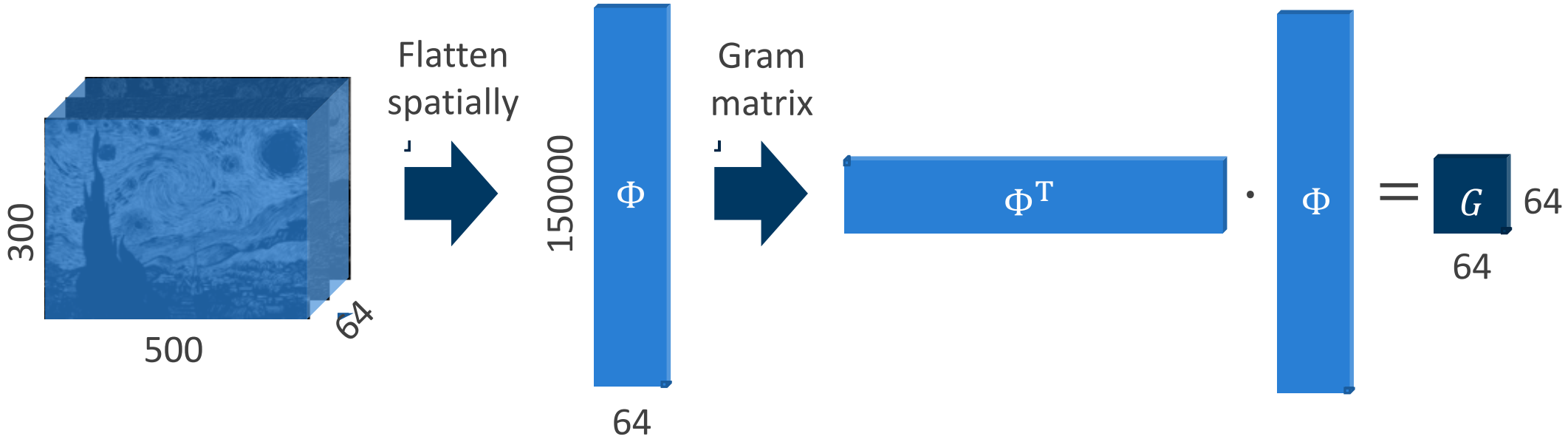
$300 \times 500 \times 64$

Flattened spatially

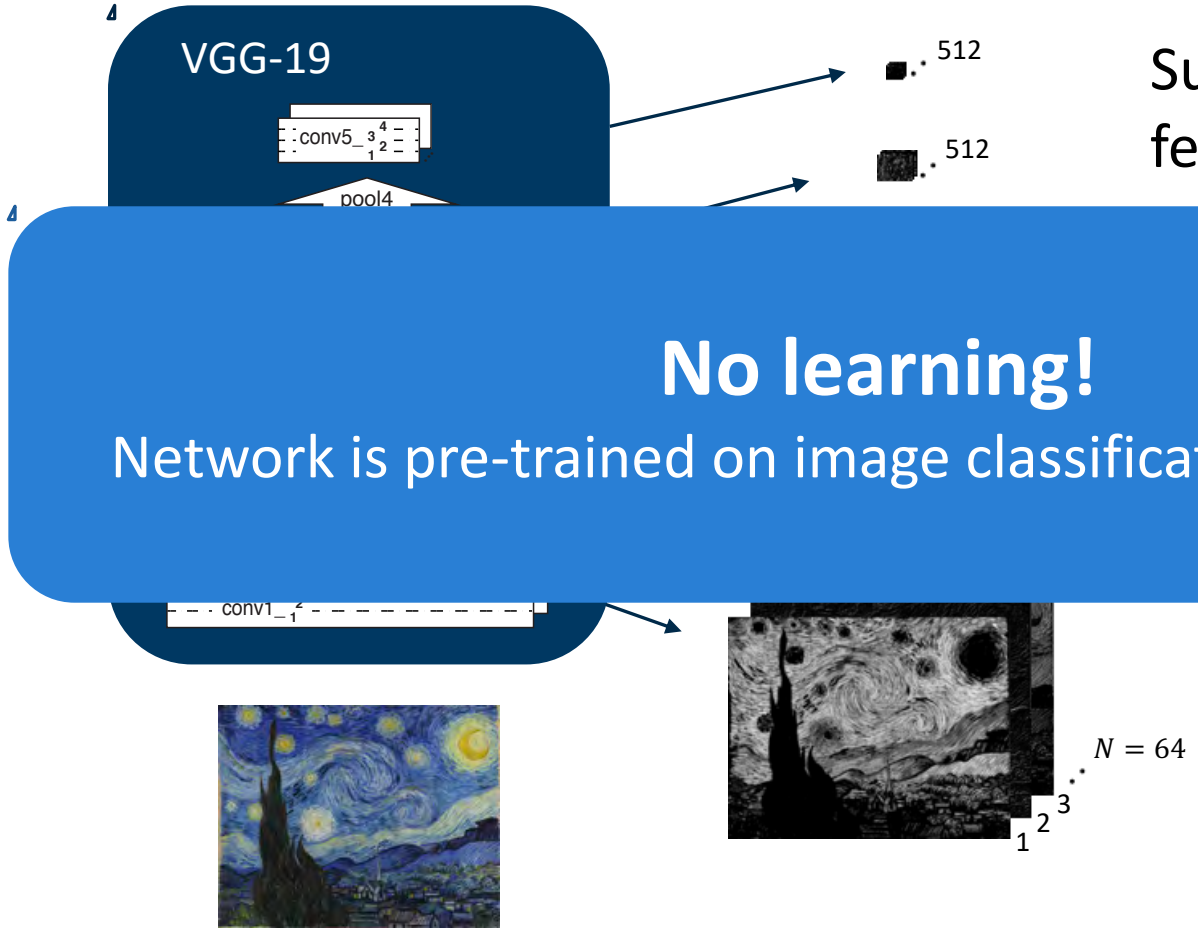
150000×64

Gram matrix

64×64



CNN: Multiscale nonlinear filter bank



Summary statistic: feature correlations

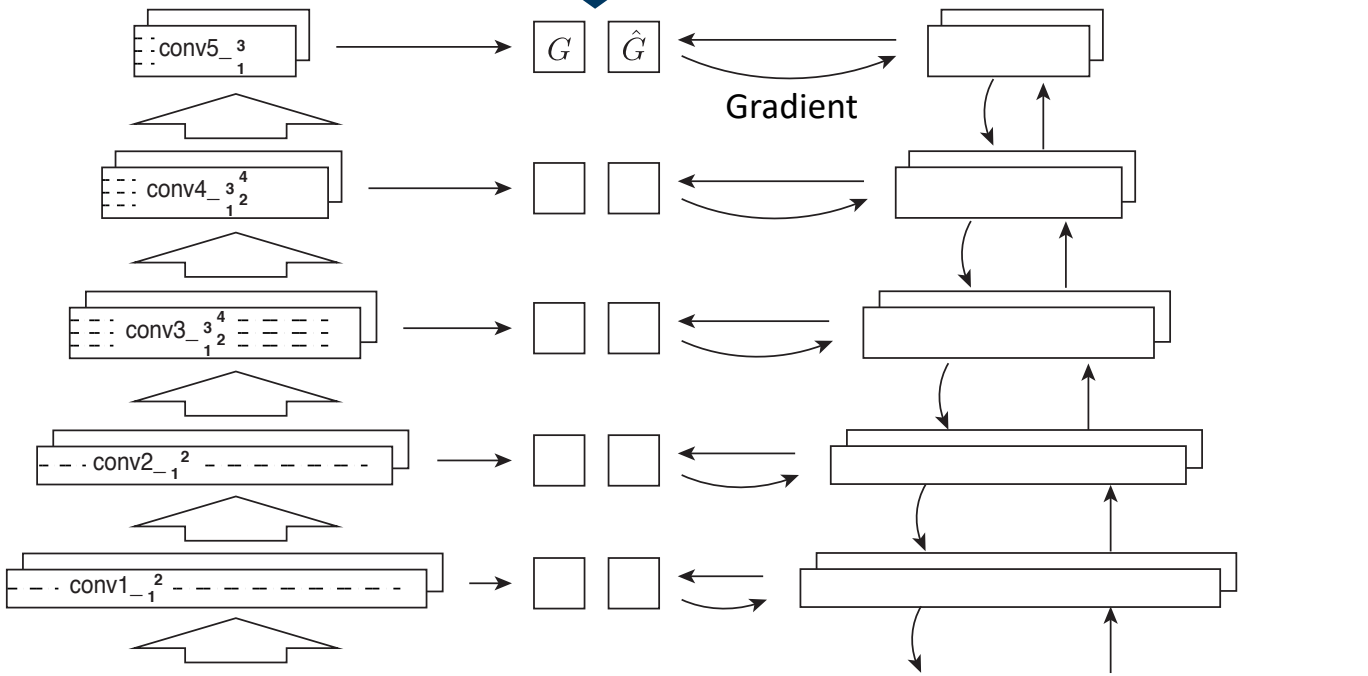
No learning!

Network is pre-trained on image classification on ImageNet

Gatys, Ecker Bethge, *NeurIPS* 2015

Texture loss

$$\mathcal{L}_{\text{style}} = \sum_{ij} \left(G_{ij} - \hat{G}_{ij}\right)^2$$



Gradient descent

Gatys, Ecker Bethge, *NeurIPS* 2015

Textures based on deep features

CNN-based model

Original image

Portilla & Simoncelli

Gatys, Ecker Bethge, *NeurIPS* 2015

Neural Style Transfer

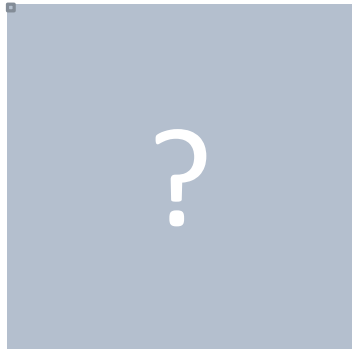
Content

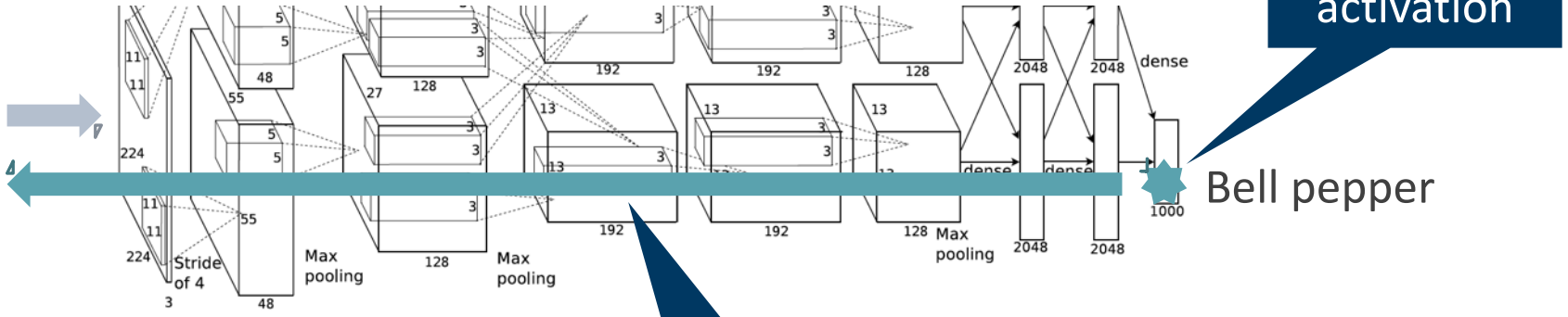
Style (→ texture)

Gatys, Ecker Bethge, *CVPR* 2016

Visualizing CNN features by activity maximization

Image





Goal: Maximize activation

Bell pepper

$$I^* = \arg\max f(I) - \lambda \|I\|_2^2$$

Found by gradient ascent

Backpropagate gradient

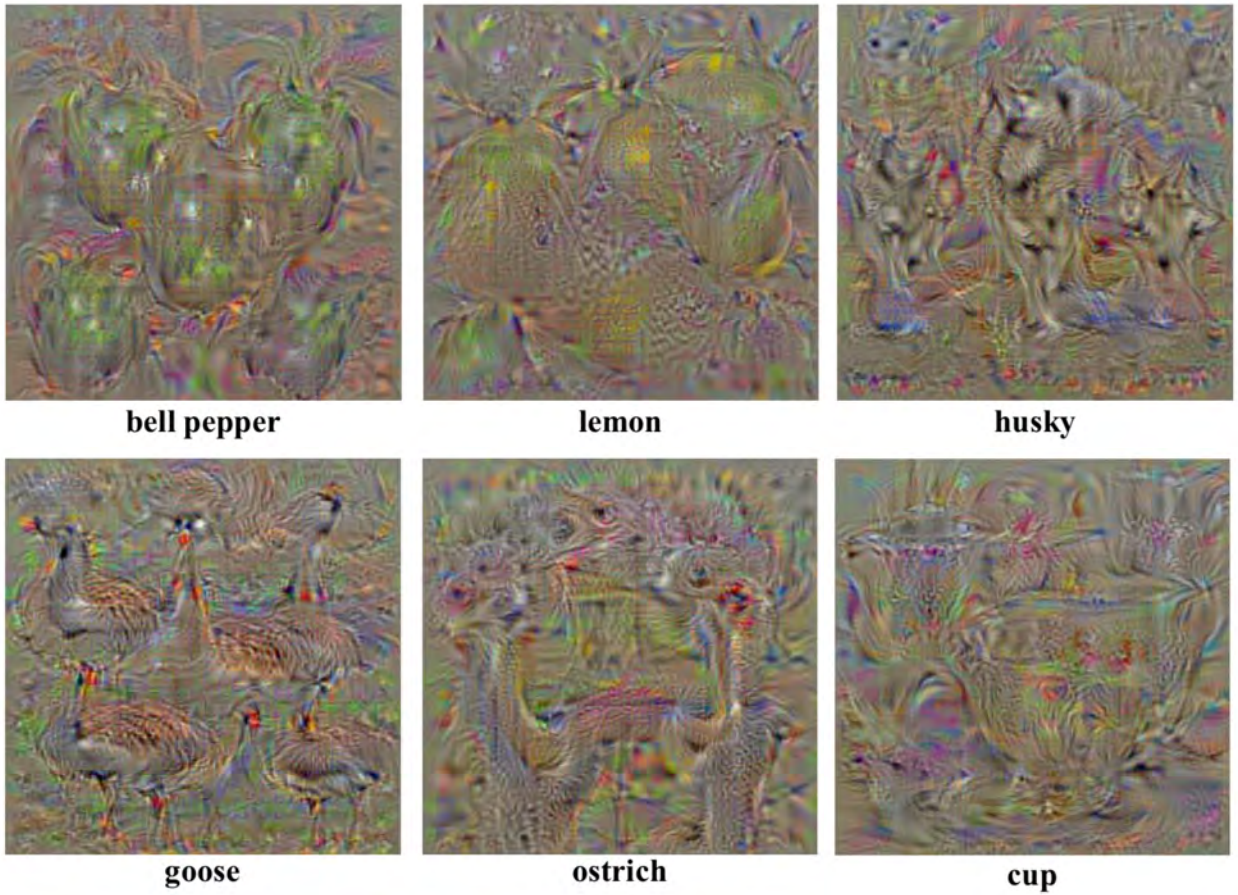
Iterate

1. Forward pass image
2. Backprop gradient
3. Update image

Visualizing classification layer

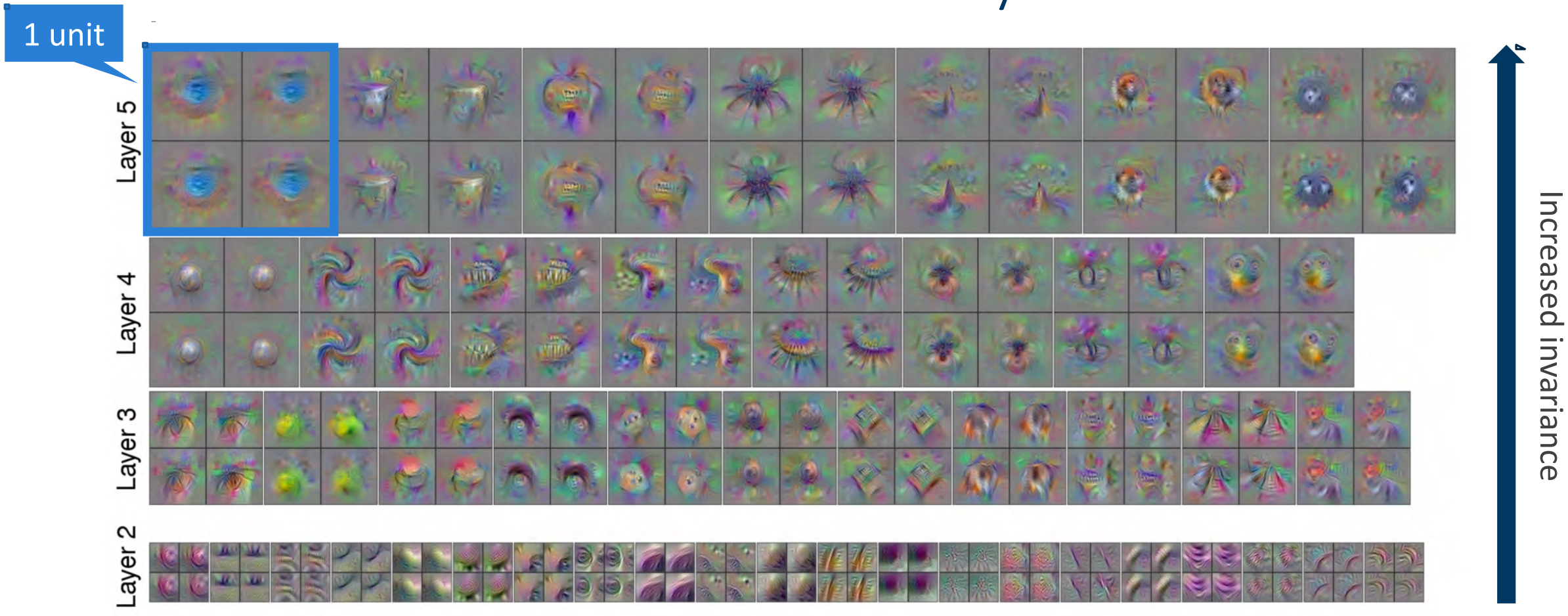
$$I^* = \arg\max f(I) - \lambda \|I\|_2^2$$

Regularizer to get "natural" images



Simonyan, Vedaldi, Zisserman, *ICLR Workshops* 2014

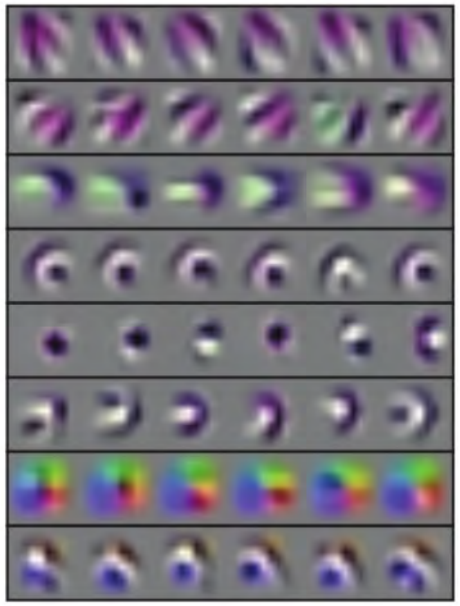
Visualization of intermediate layers of AlexNet



Yosinski et al., *ICML Deep Learning Workshop* 2015

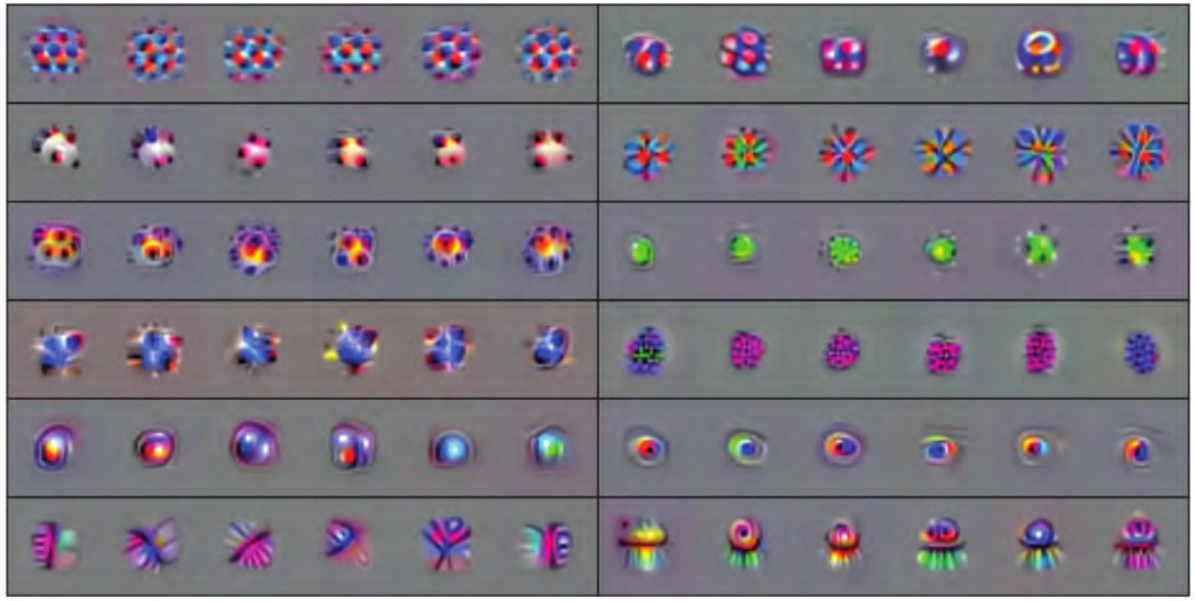
Visualization of intermediate layers of VGG-19

conv2_1



Increased invariance

conv3_3

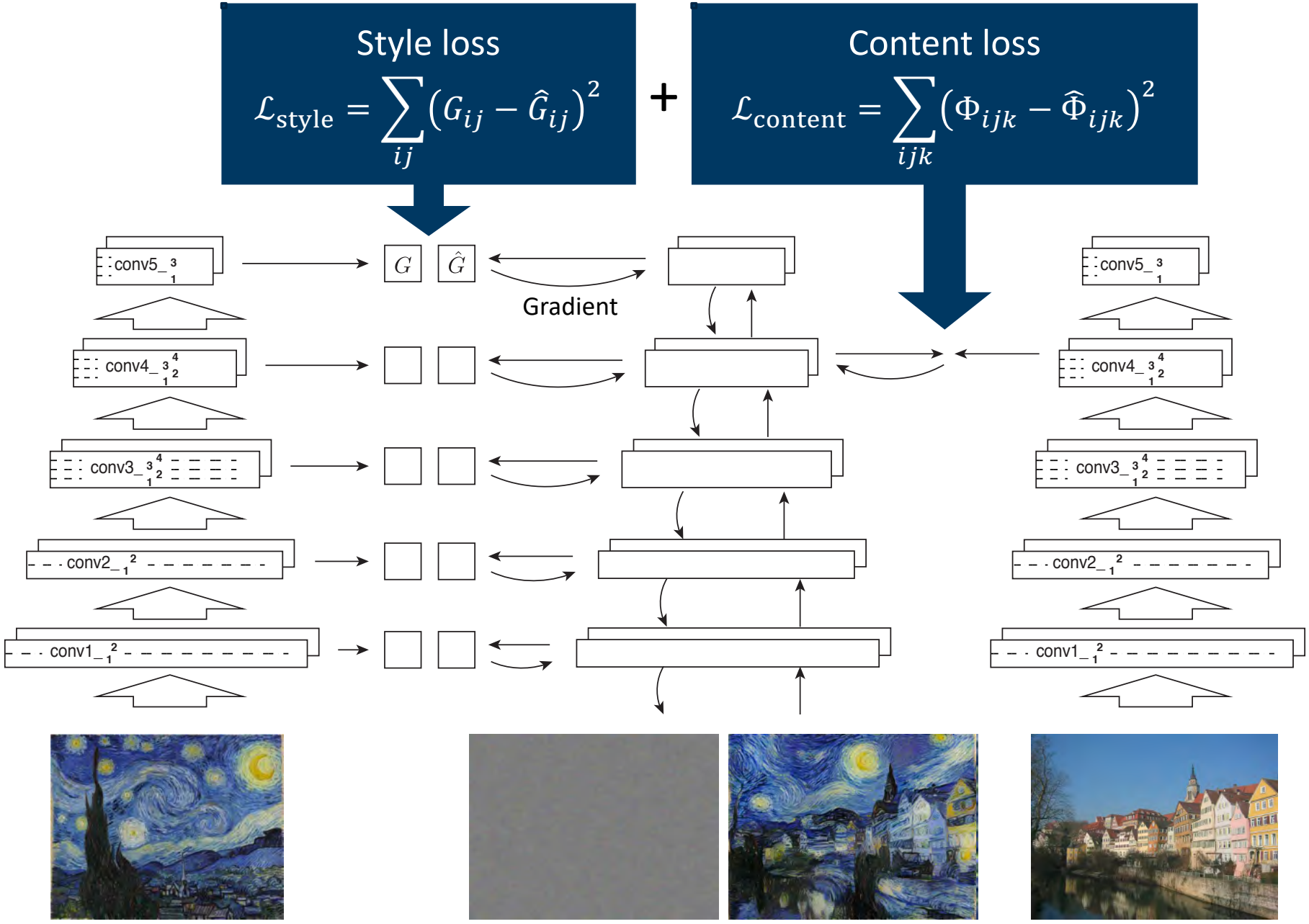


Early: selective

Intermediate/late: Increased invariance

Optimization target here: obtain diverse set of images that maximize overall activity

Cadena et al., *ECCV* 2018



Gatys, Ecker Bethge, *CVPR* 2016

Timelapse

Gatys, Ecker Bethge, *CVPR* 2016

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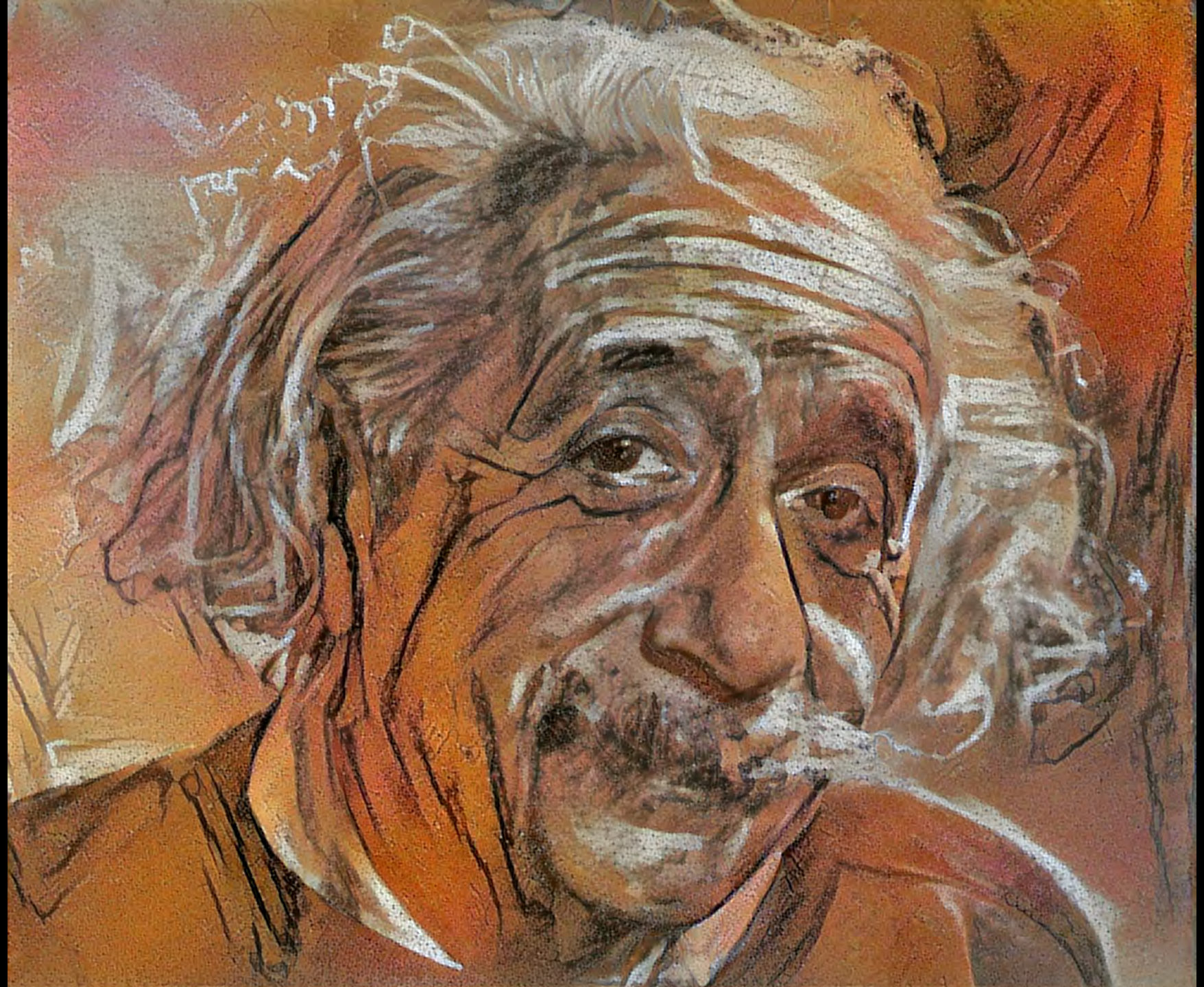
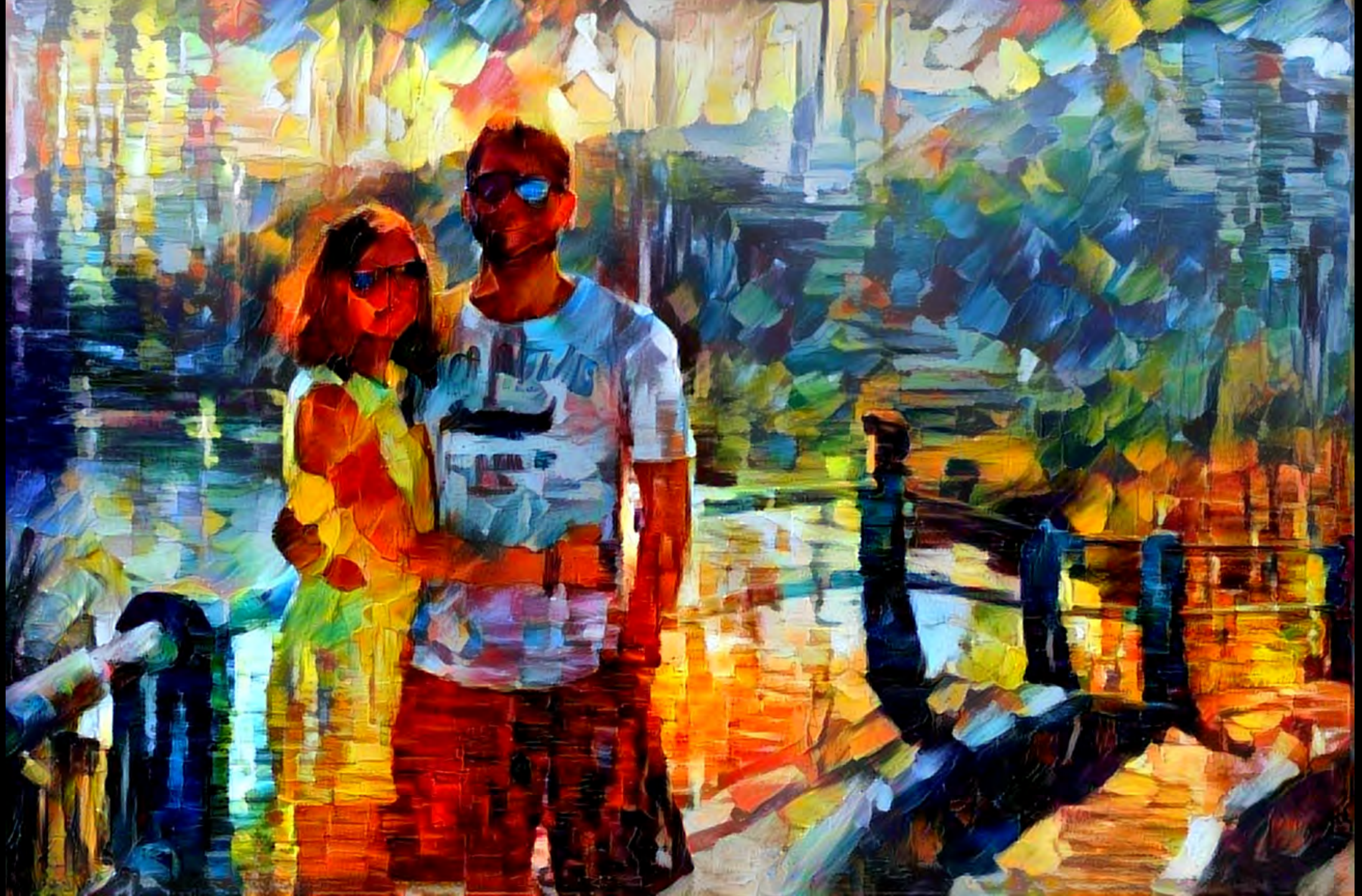
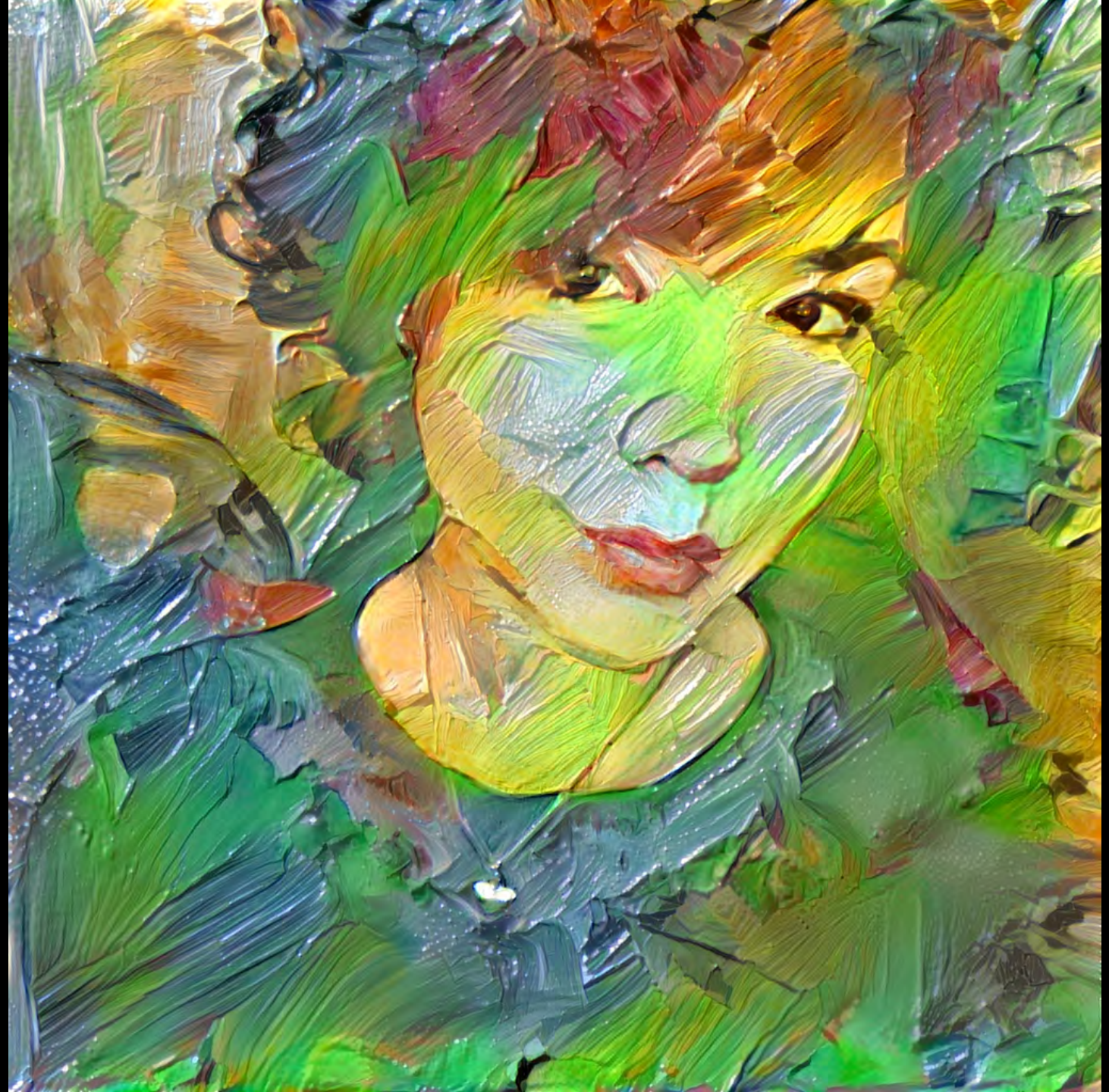
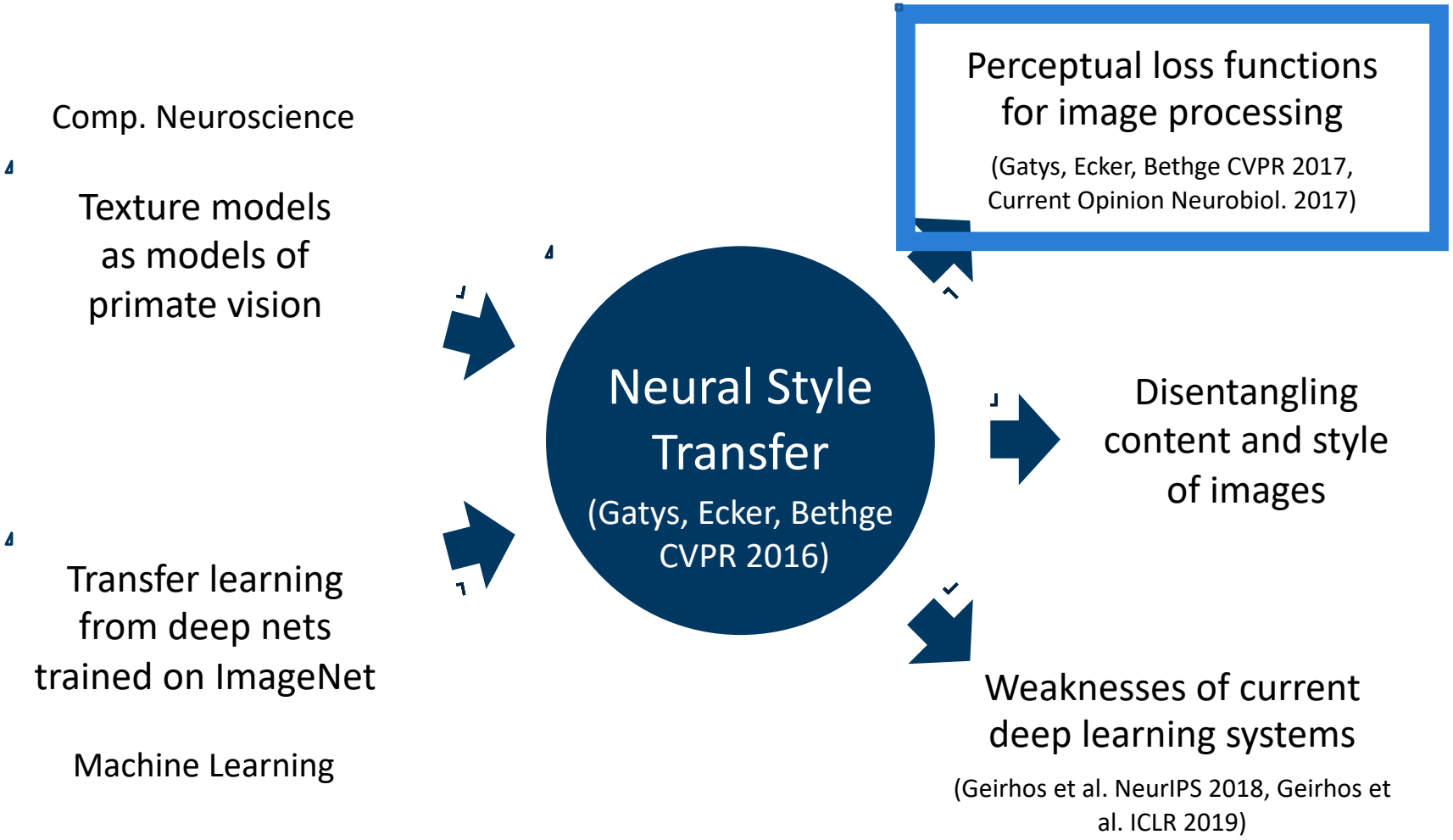




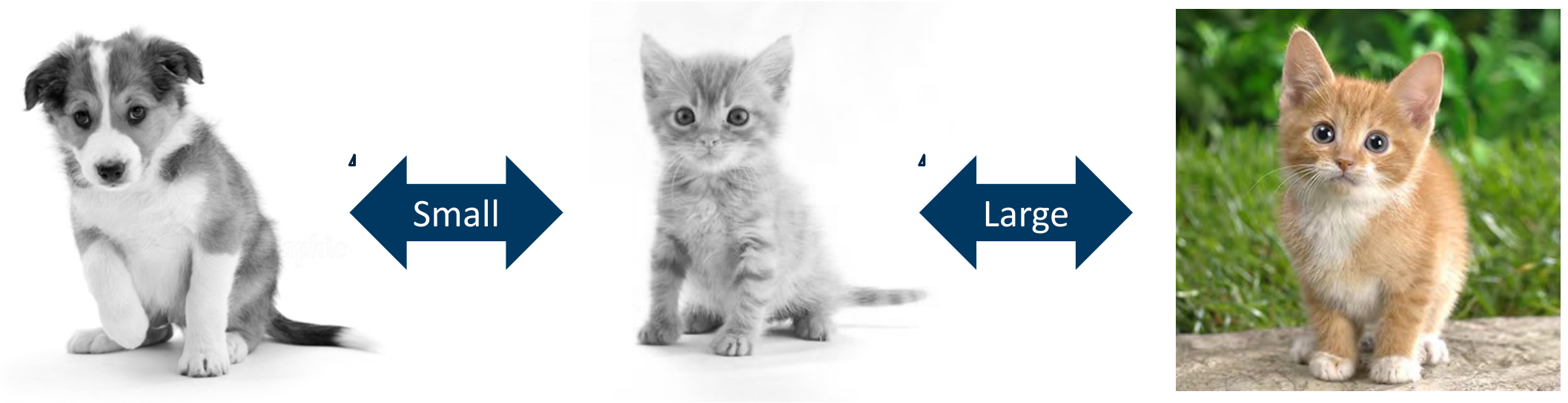


Significance of neural style transfer



Perceptual loss functions

Euclidean distance in pixel space does not cover semantics of images



Perceptual loss functions

Euclidean distance in pixel space does not cover perceptual differences

Blurred

Small

Original

Large

Shifted by 20 pixels

Compute distances in high-level feature space of deep neural network trained on ImageNet

Neural style transfer implementations

Leon Gatys' PyTorch implementation:
https://github.com/leongatys/PytorchNeuralStyleTransfer

Justin Johnson's excellent and very popular Lua/Torch implementation:
(lots of features, but may be hard to run these days)
https://github.com/jcjohnson/neural-style

Neural Style in official PyTorch tutorials:
https://pytorch.org/tutorials/advanced/neural_style_tutorial.html

Questions!