



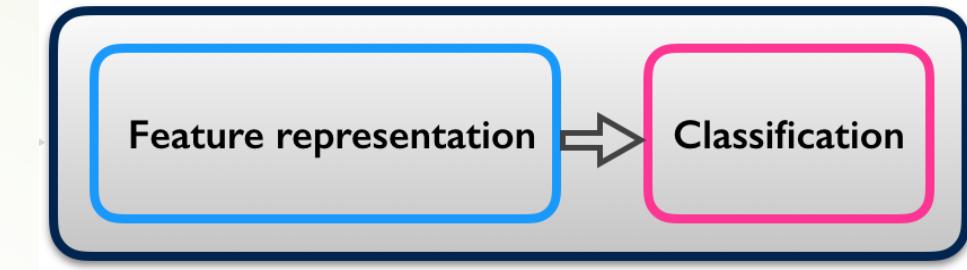
Topics on CNN: Transfer Learning, Visualization, Neural Style, and Adversarial Examples

Yuan YAO
HKUST



Transfer Learning: Fine Tuning

Transfer Learning?

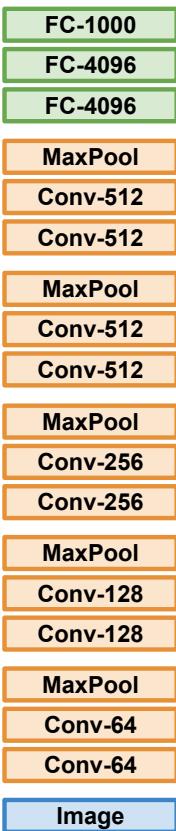


- Filters learned in first layers of a network are transferable from one task to another
- When solving another problem, no need to retrain the lower layers, just fine tune upper ones
- Is this simply due to the large amount of images in ImageNet?
- Does solving many classification problems simultaneously result in features that are more easily transferable?
- Does this imply filters can be learned in unsupervised manner?
- Can we characterize filters mathematically?

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Transfer Learning with CNNs

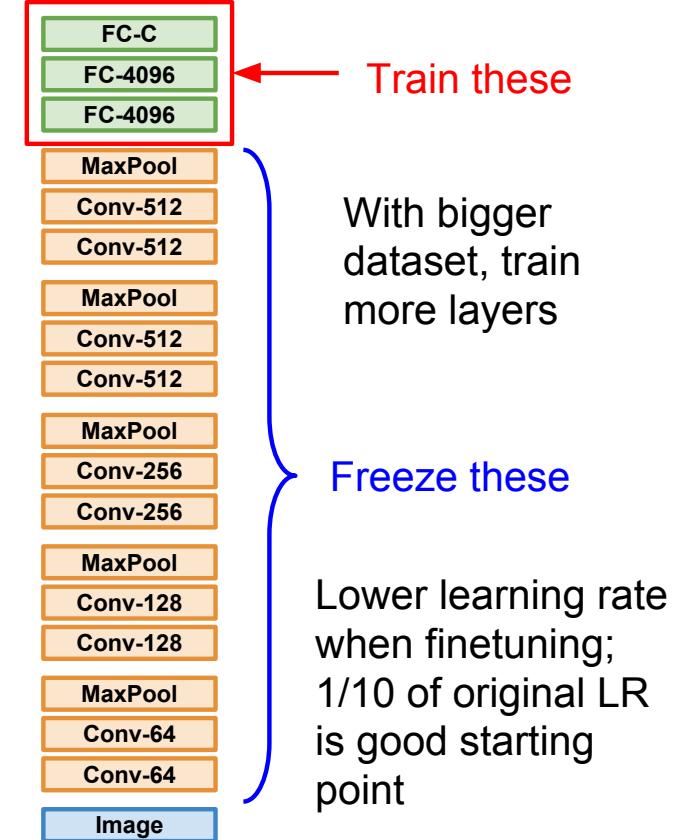
1. Train on Imagenet



2. Small Dataset (C classes)



3. Bigger dataset





More specific

More generic

	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble... Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Example Demo

- ▶ Jupyter notebook with pytorch

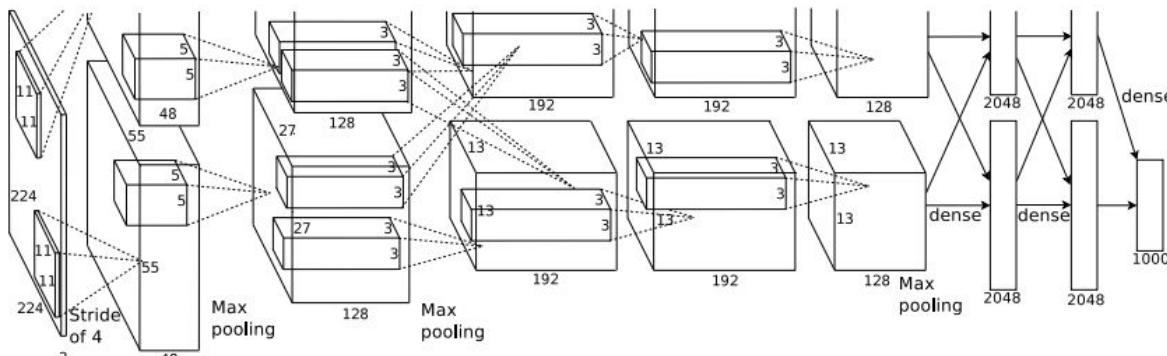


Visualizing Convolutional Networks

Understanding intermediate neurons?



Input Image:
3 x 224 x 224



What are the intermediate features looking for?

Class Scores:
1000 numbers

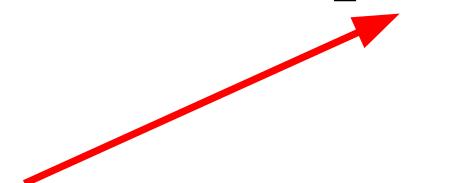
Visualizing CNN Features: Gradient Ascent

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

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

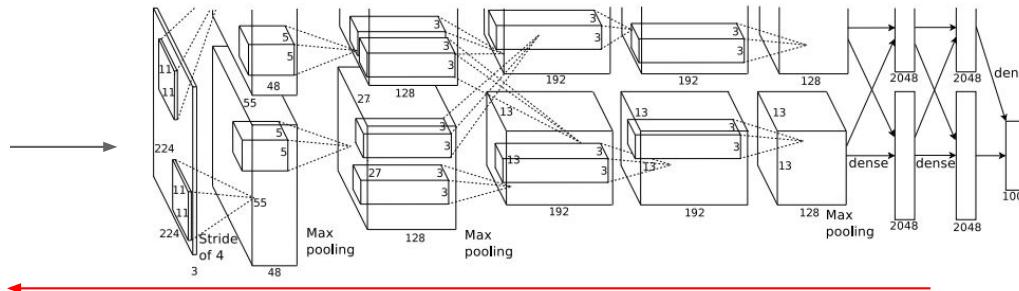
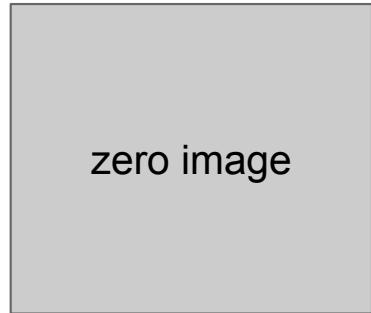
Neuron value

Natural image regularizer



Visualizing CNN Features: Gradient Ascent

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

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

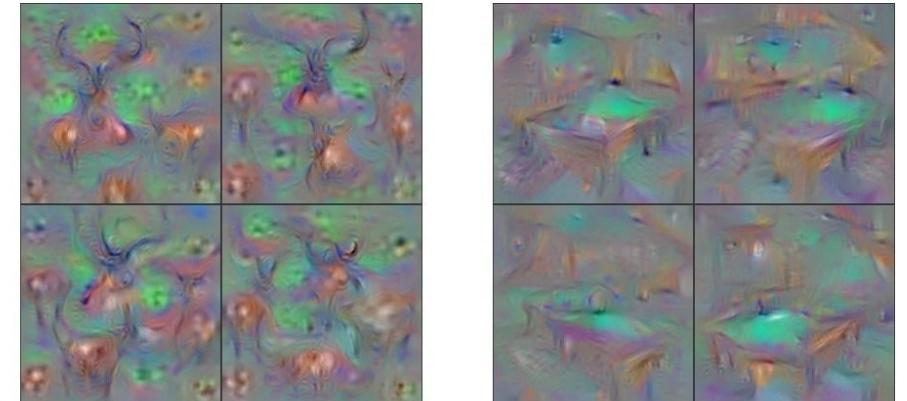
score for class c (before Softmax)

Visualizing CNN Features: Gradient Ascent

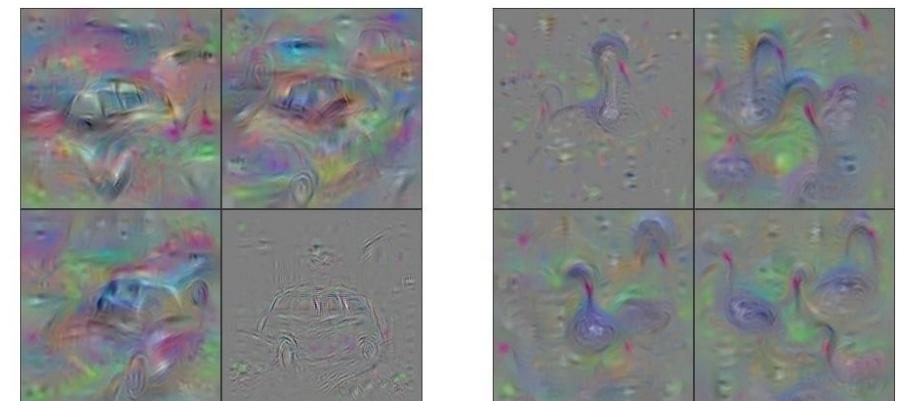
$$\arg \max_I S_c(I) - \lambda \|I\|_2^2$$

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

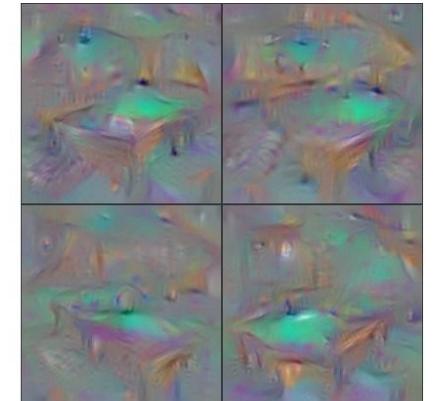
- (1) Gaussian blur image
- (2) Clip pixels with small values to 0
- (3) Clip pixels with small gradients to 0



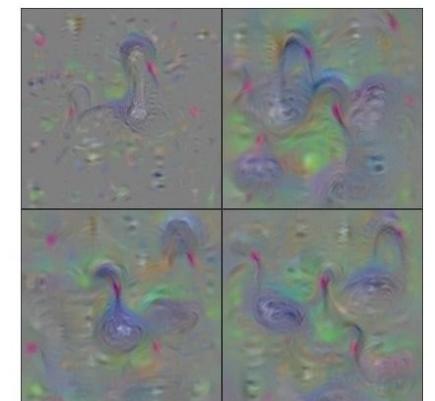
Hartebeest



Station Wagon



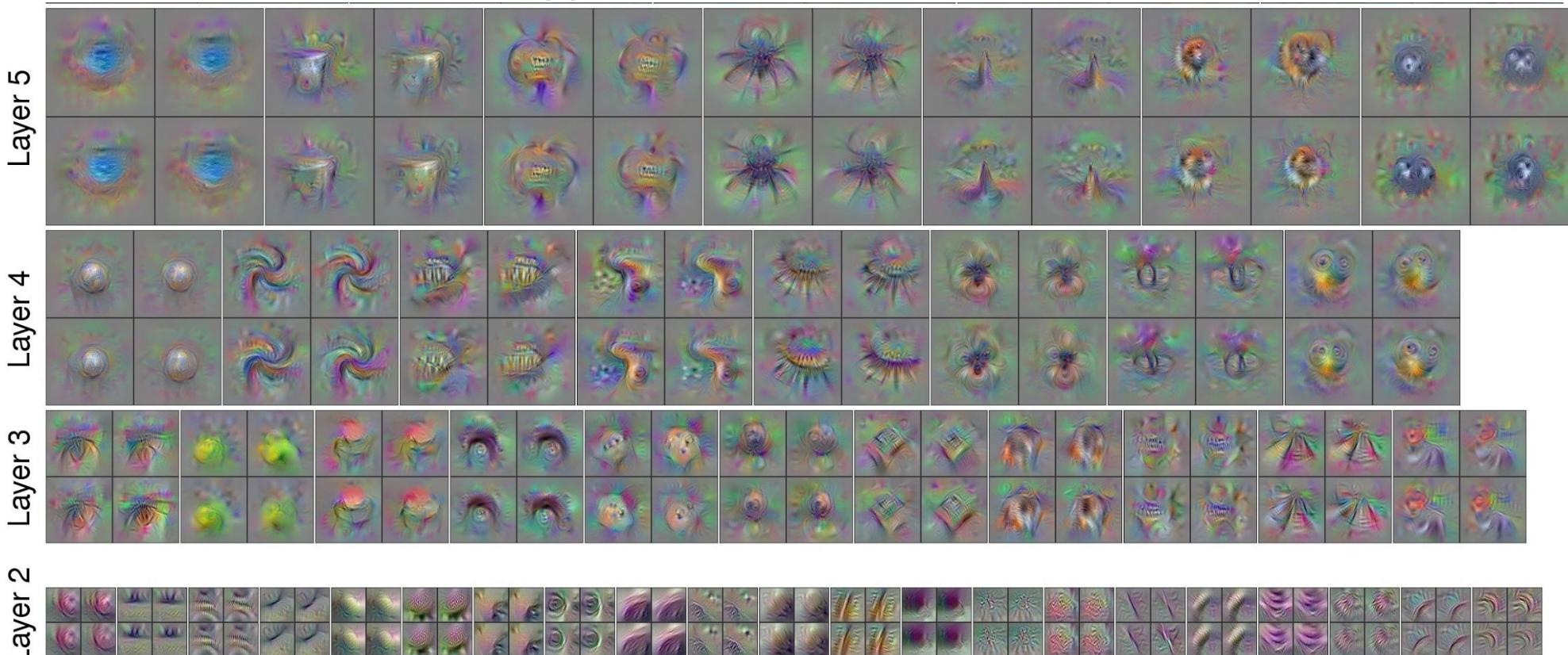
Billiard Table



Black Swan

Visualizing CNN Features: Gradient Ascent

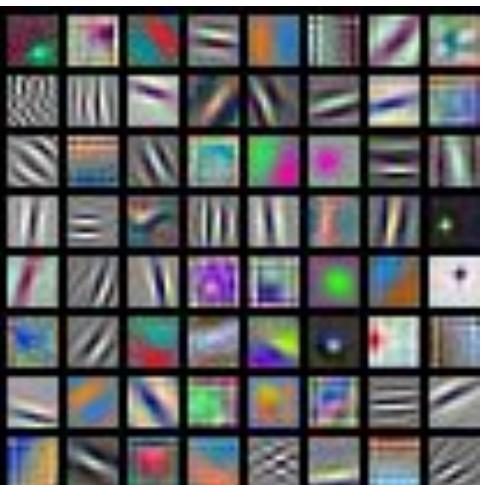
Use the same approach to visualize intermediate features



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

It's easy to visualize early layers

First Layer: Visualize Filters



AlexNet: 64 x 3 x 11 x 11



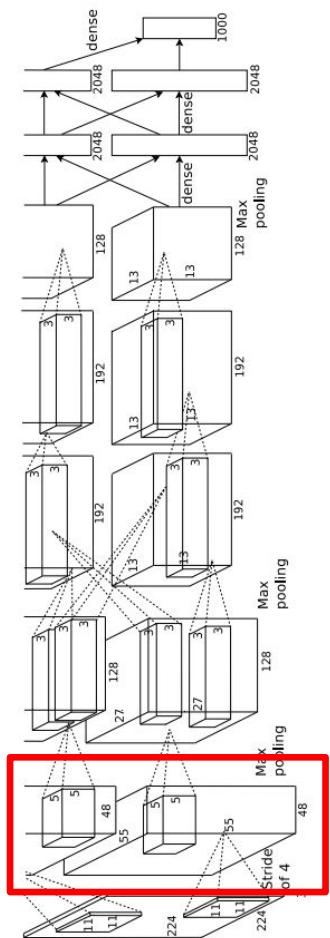
ResNet-18: 64 x 3 x 7 x 7



ResNet-101: 64 x 3 x 7 x 7



DenseNet-121: 64 x 3 x 7 x 7



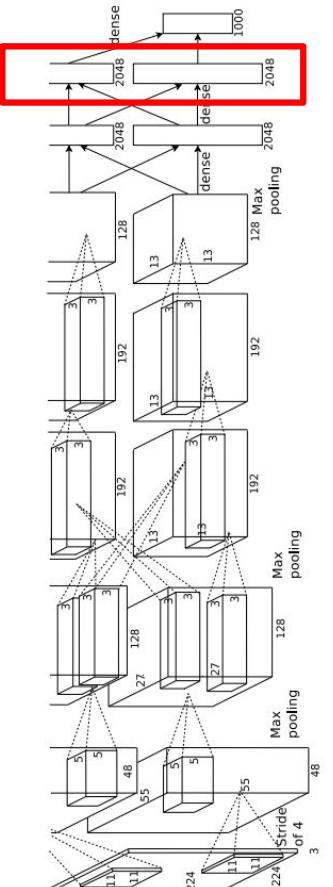
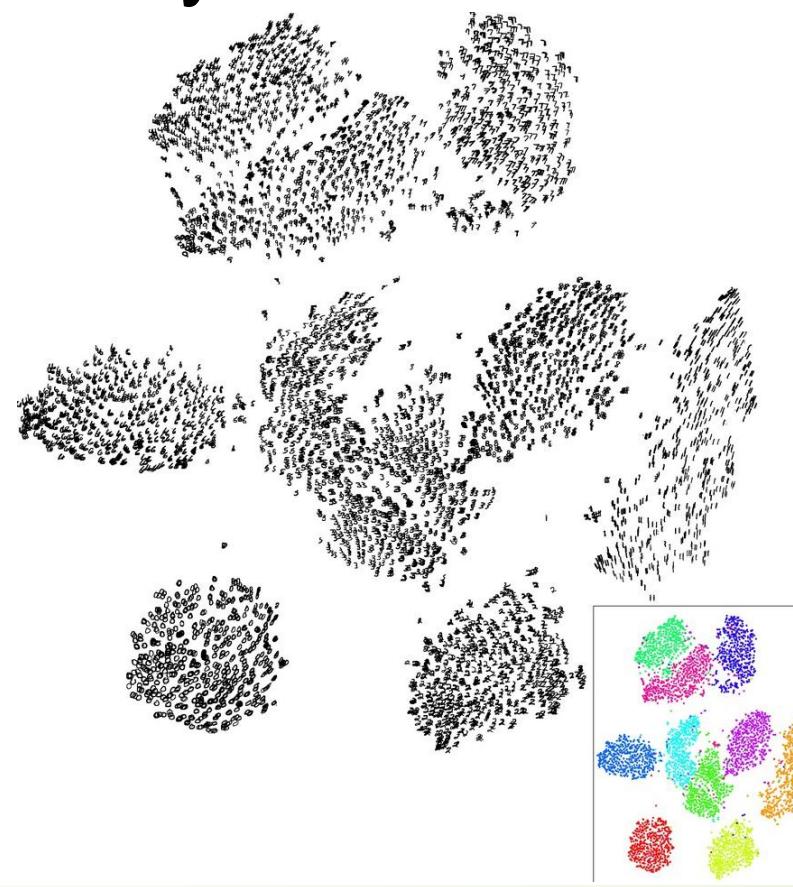
Last layers are hard to visualize

Last Layer: Dimensionality Reduction

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

Simple algorithm: Principle Component Analysis (PCA)

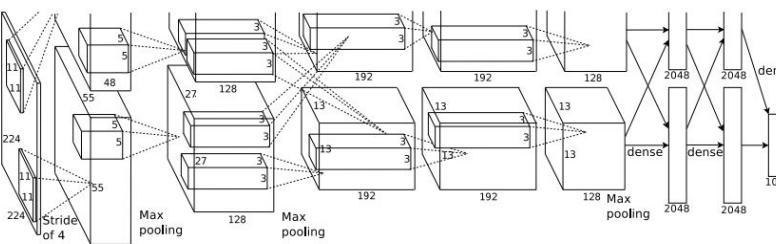
More complex: t-SNE



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

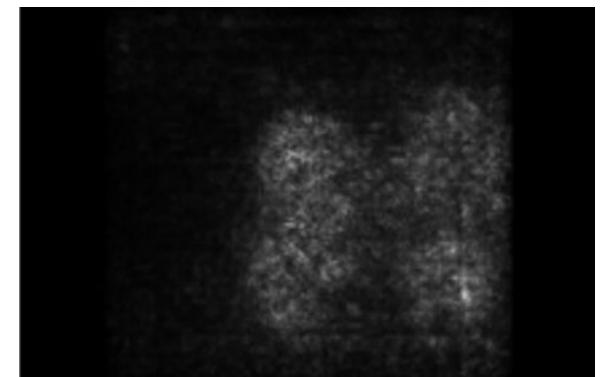
Saliency Maps

How to tell which pixels matter for classification?



Dog

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

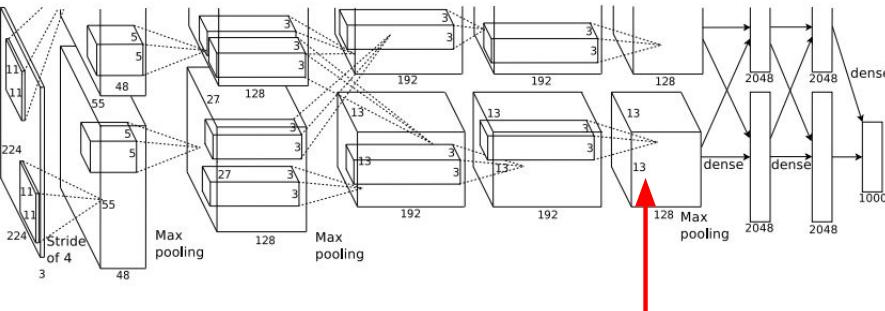


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

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

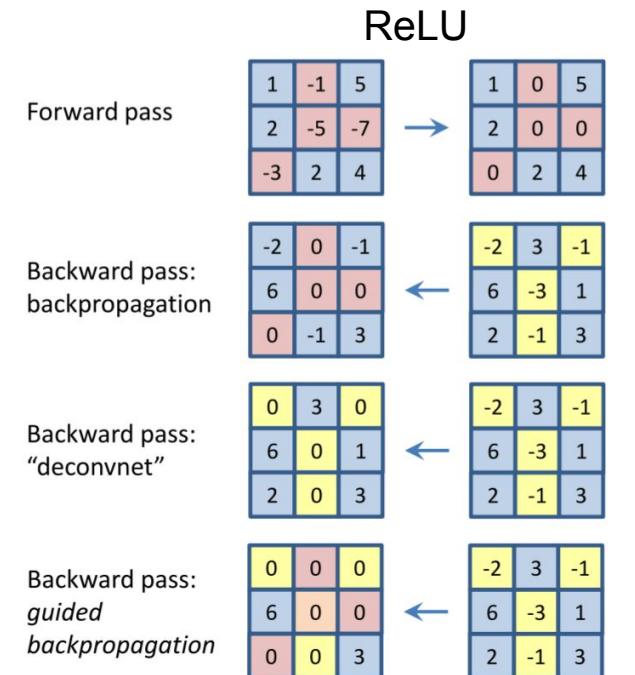
Guided BP

Intermediate features via (guided) backprop



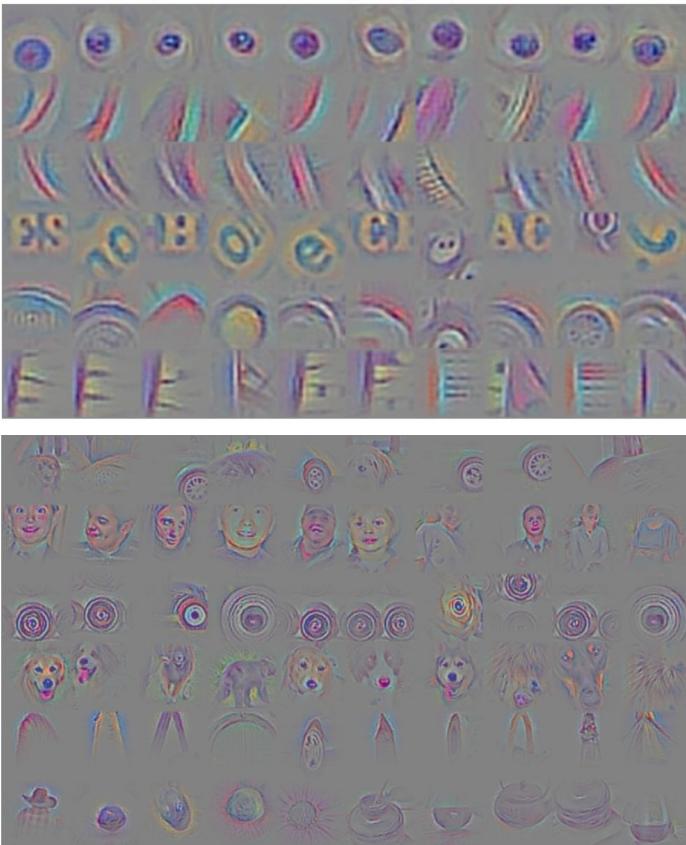
Pick a single intermediate neuron, e.g. one value in $128 \times 13 \times 13$ conv5 feature map

Compute gradient of neuron value with respect to image pixels



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

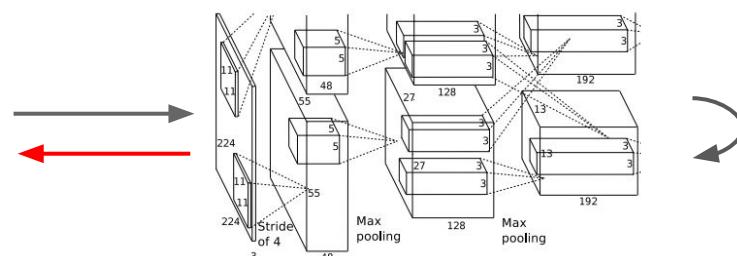
Intermediate features via Guided BP



Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014
Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.

DeepDream: amplifying features

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

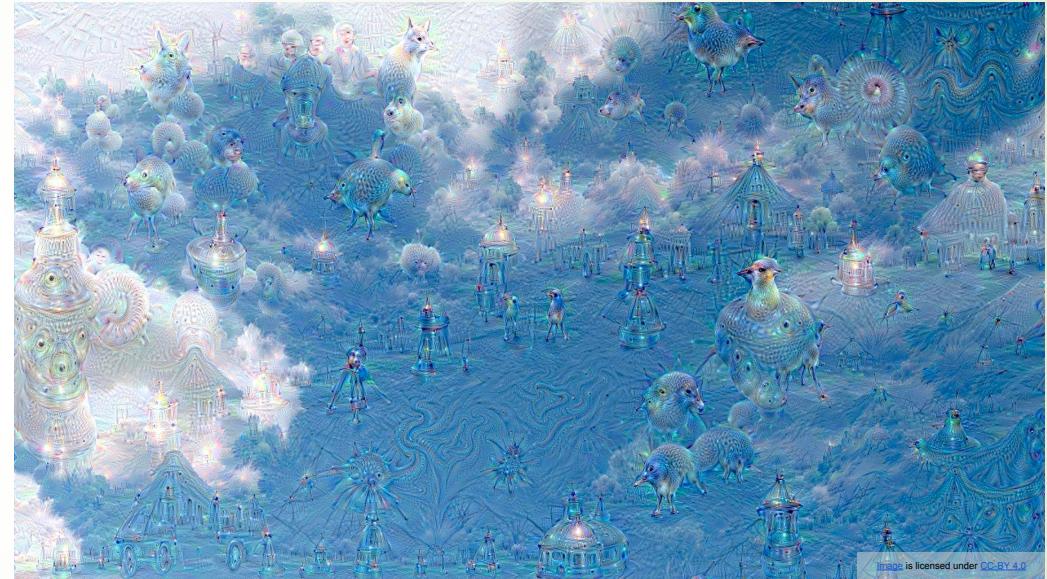


Choose an image and a layer in a CNN; repeat:

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

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

Example: DeepDream of Sky



"Admiral Dog!"



"The Pig-Snail"



"The Camel-Bird"



"The Dog-Fish"

More Examples



[Image](#) is licensed under CC-BY 4.0

Python Notebooks

- ▶ An interesting Pytorch Implementation of these visualizatoin methods
 - ▶ <https://github.com/utkuozbulak/pytorch-cnn-visualizations>
- ▶ Some examples demo



Neural Style

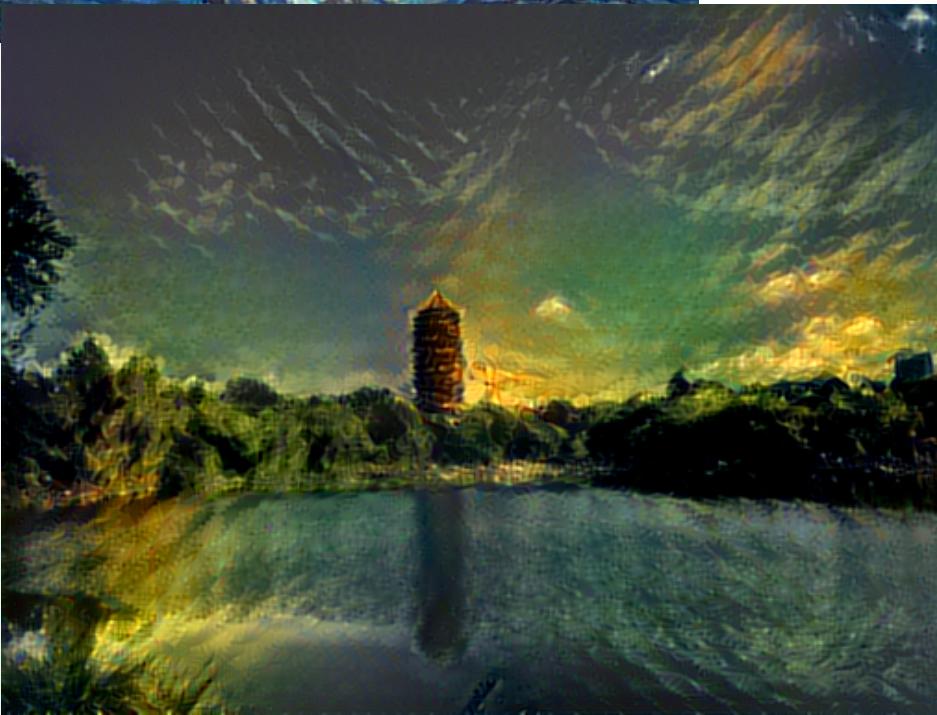
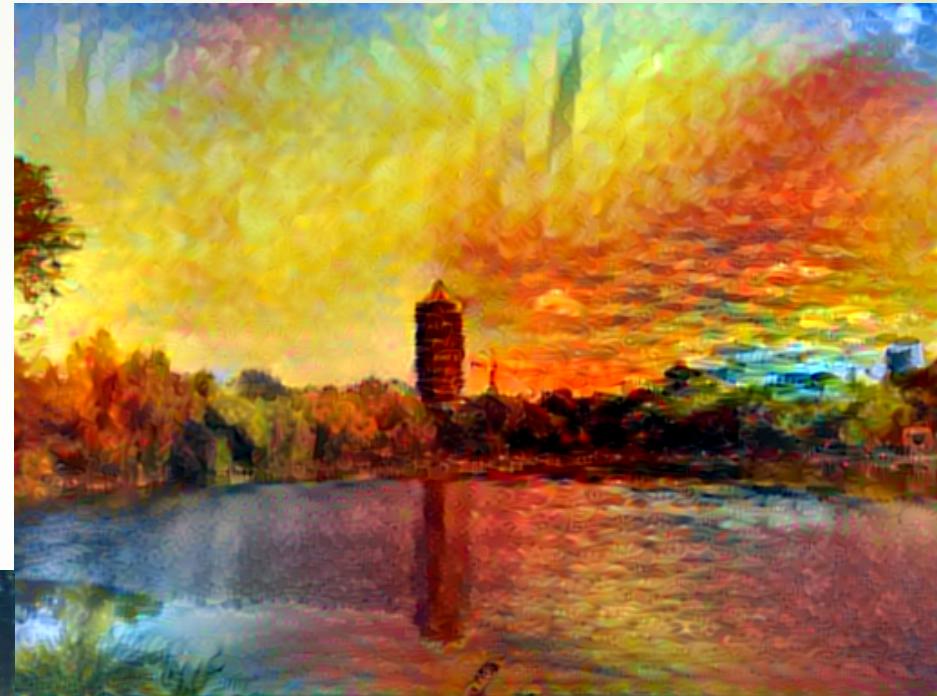
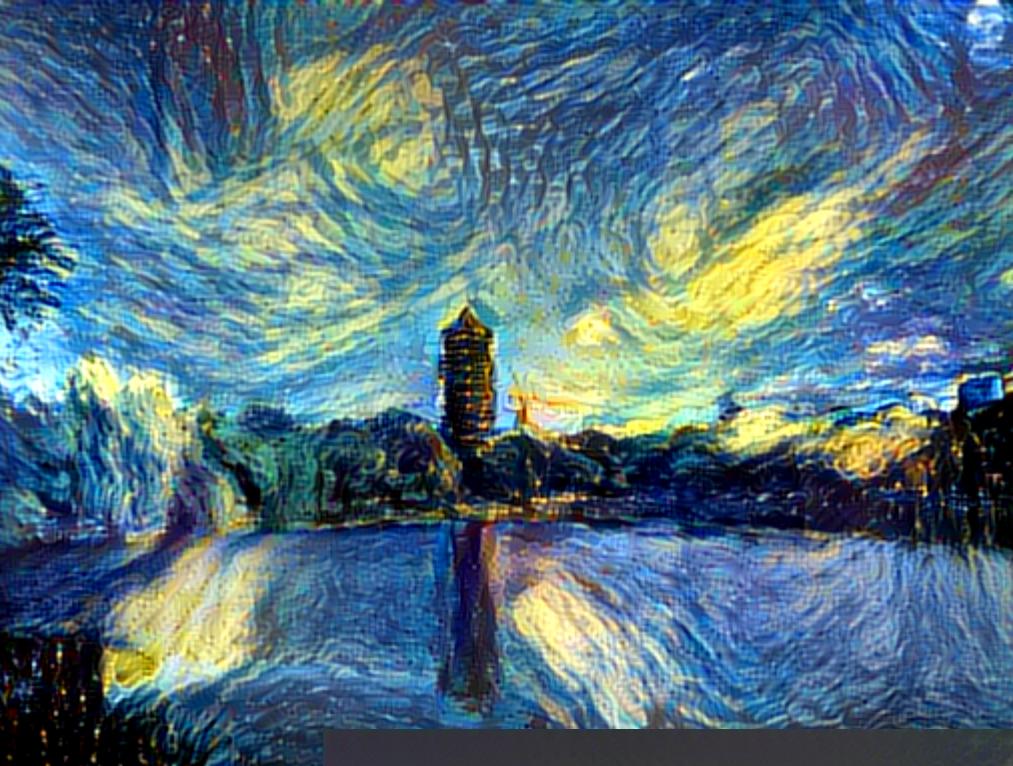
Example: The Noname Lake in PKU





Left: Vincent Van Gogh, Starry Night
Right: Claude Monet, Twilight Venice
Bottom: William Turner, Ship Wreck





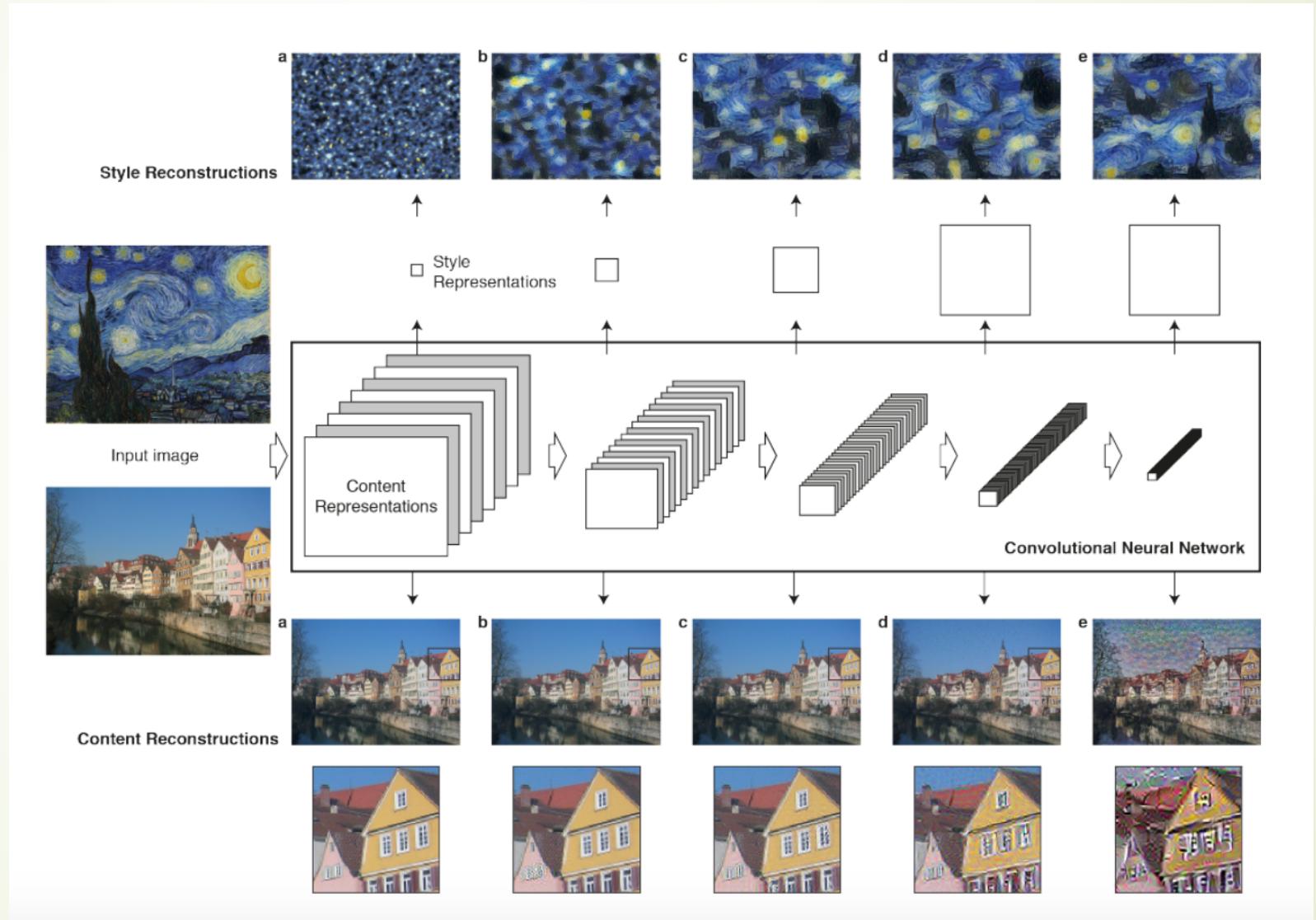
Application of Deep Learning:
Content-Style synthetic
pictures
By “neural-style”



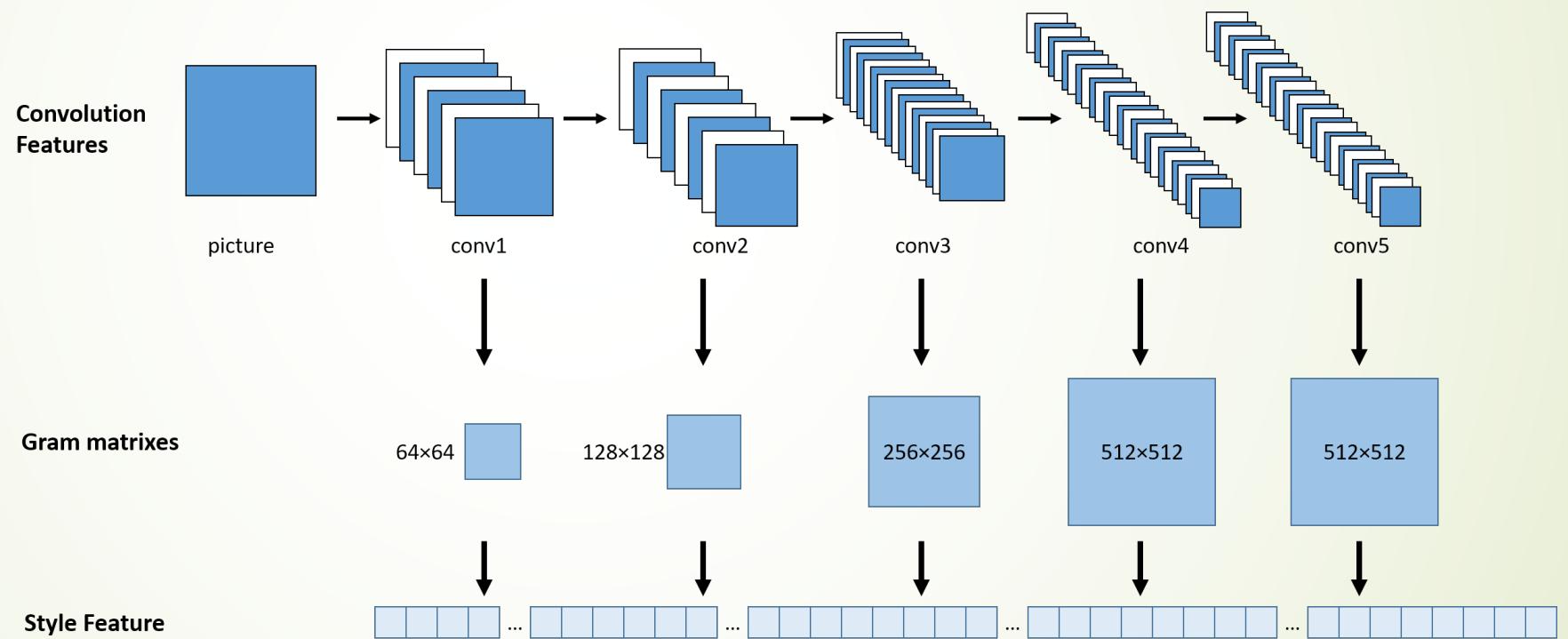
Neural Style

- ▶ J C Johnson's Website: <https://github.com/jcjohnson/neural-style>
- ▶ A torch implementation of the paper
 - ▶ *A Neural Algorithm of Artistic Style*,
 - ▶ by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge.
 - ▶ <http://arxiv.org/abs/1508.06576>

Style-Content Feature Extraction



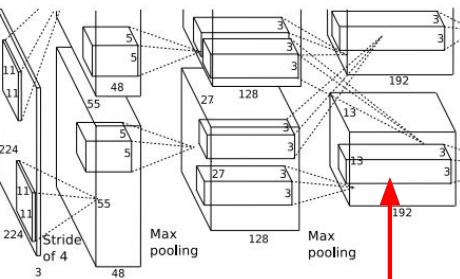
Style Features as Second Order Statistics



Neural Texture Synthesis



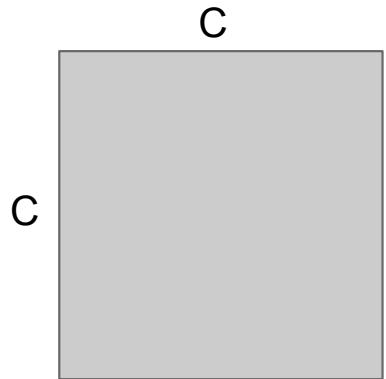
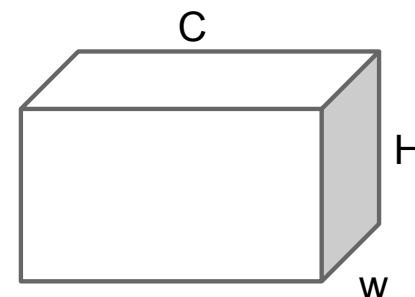
This image is in the public domain.



Each layer of CNN gives $C \times H \times W$ tensor of features; $H \times W$ grid of C -dimensional vectors

Outer product of two C -dimensional vectors gives $C \times C$ matrix measuring co-occurrence

Average over all HW pairs of vectors, giving **Gram matrix** of shape $C \times C$



Efficient to compute; reshape features from

$C \times H \times W$ to $=C \times HW$

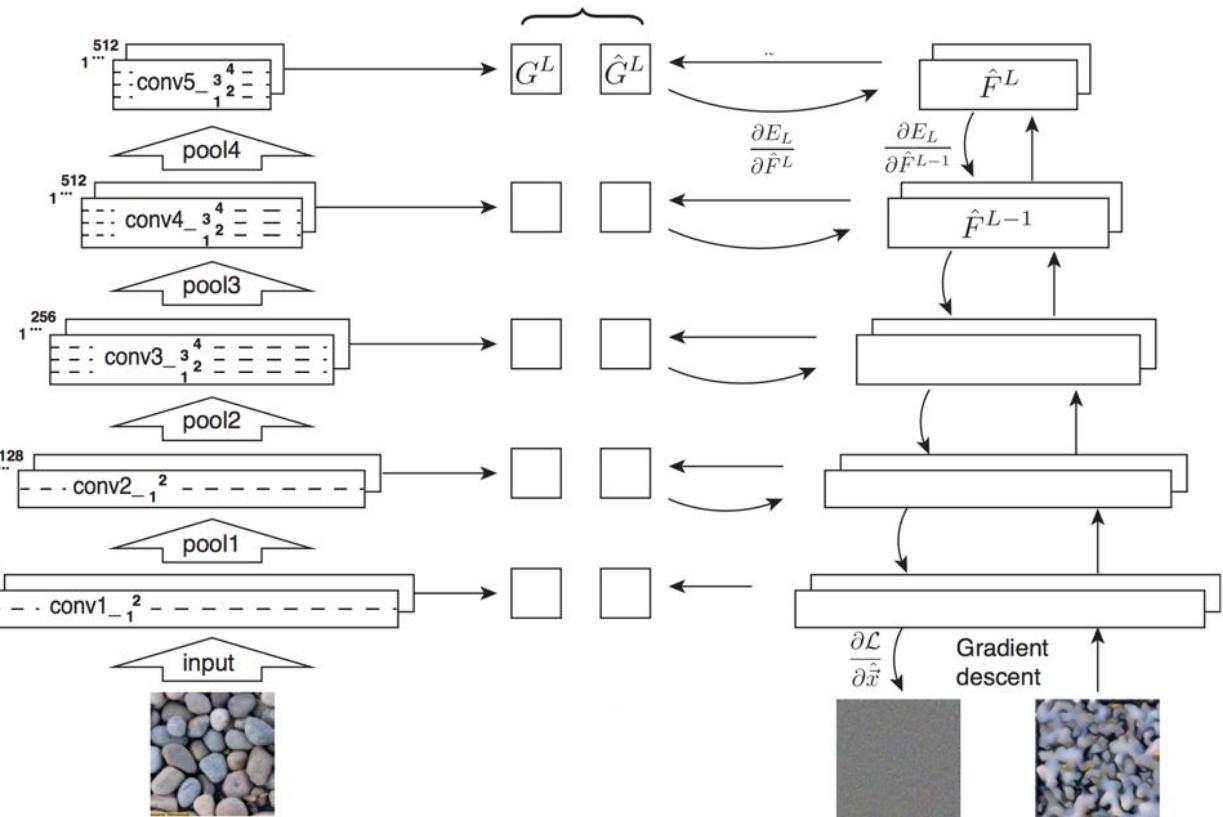
then compute $G = FF^T$

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 $C_i \times H_i \times W_i$
3. At each layer compute the *Gram matrix* giving outer product of features:
$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l \text{ (shape } C_i \times C_i\text{)}$$
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

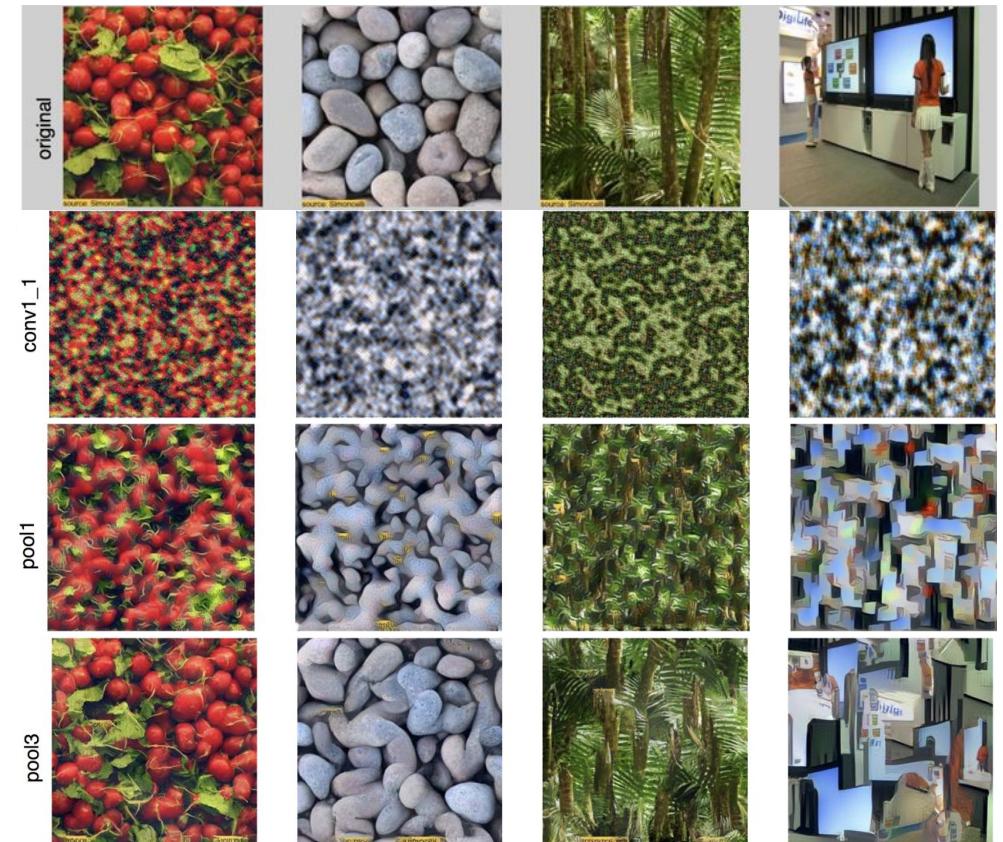
Gatys, Ecker, and Bethge, "Texture Synthesis Using Convolutional Neural Networks", NIPS 2015
 Figure copyright Leon Gatys, Alexander S. Ecker, and Matthias Bethge, 2015. Reproduced with permission.

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



Neural Texture Synthesis

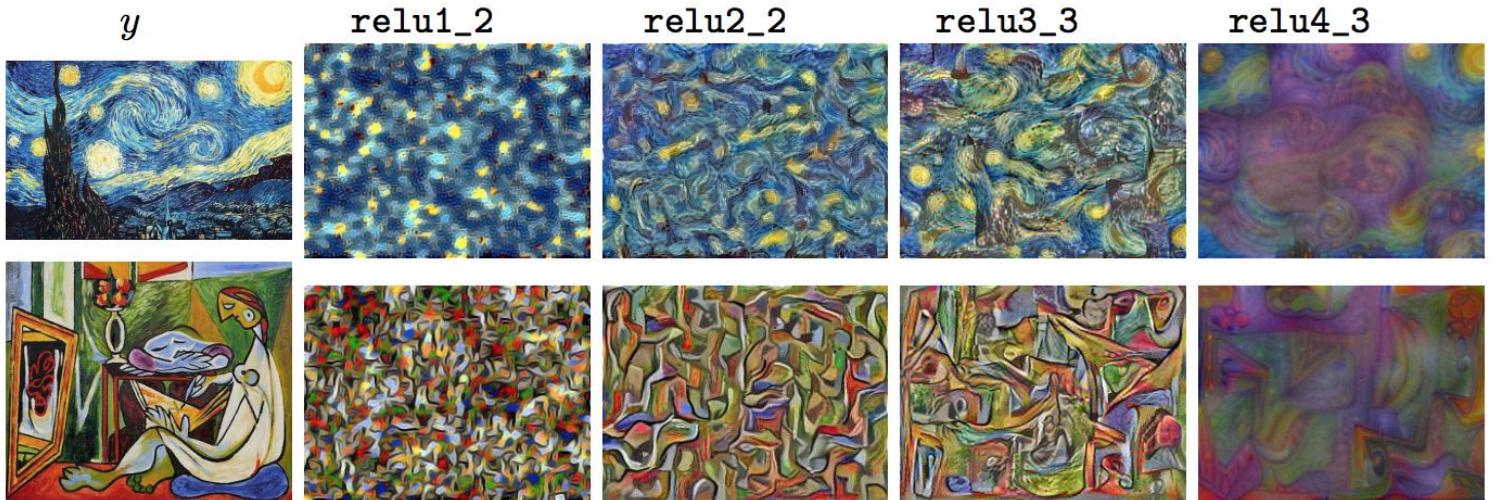
Reconstructing texture from higher layers recovers larger features from the input texture



Gatys, Ecker, and Bethge, "Texture Synthesis Using Convolutional Neural Networks", NIPS 2015
Figure copyright Leon Gatys, Alexander S. Ecker, and Matthias Bethge, 2015. Reproduced with permission.

Neural Texture Synthesis: Gram Reconstruction

Texture synthesis
(Gram
reconstruction)



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

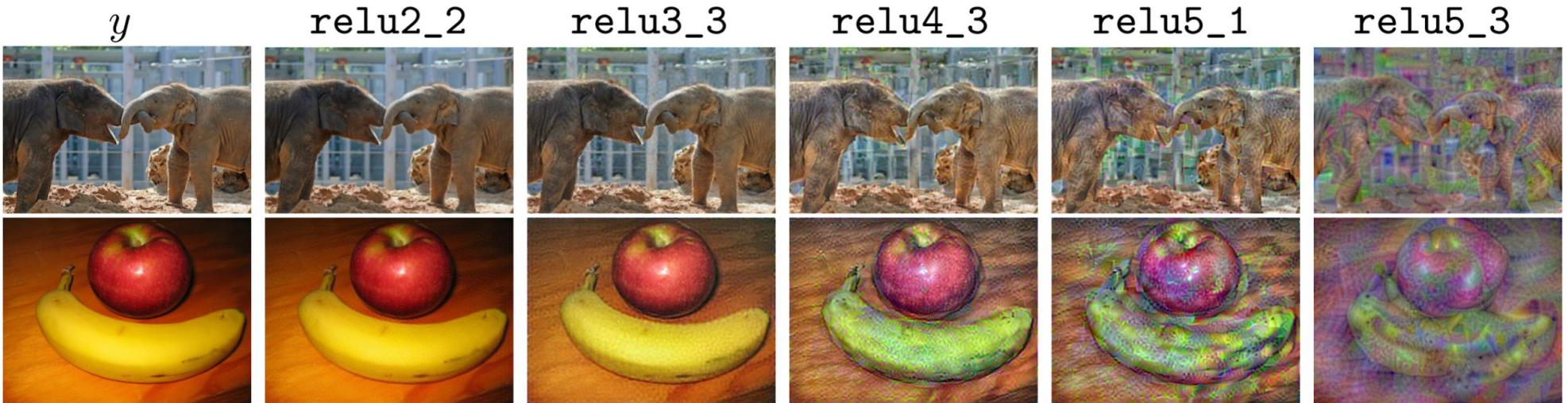
$$\ell(\Phi(\mathbf{x}), \Phi_0) = \|\Phi(\mathbf{x}) - \Phi_0\|^2$$

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

Total Variation regularizer
(encourages spatial smoothness)

Feature Inversion

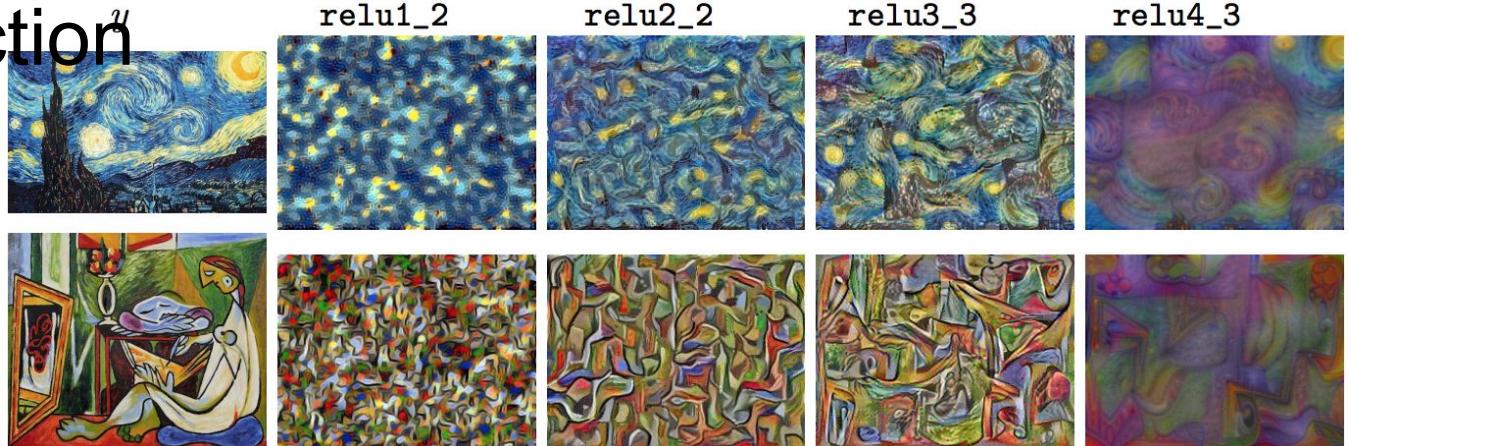
Reconstructing from different layers of VGG-16



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. Copyright Springer, 2016.
Reproduced for educational purposes.

Neural Style Transfer: Feature + Gram Reconstruction

Texture synthesis
(Gram reconstruction)



Feature
reconstruction

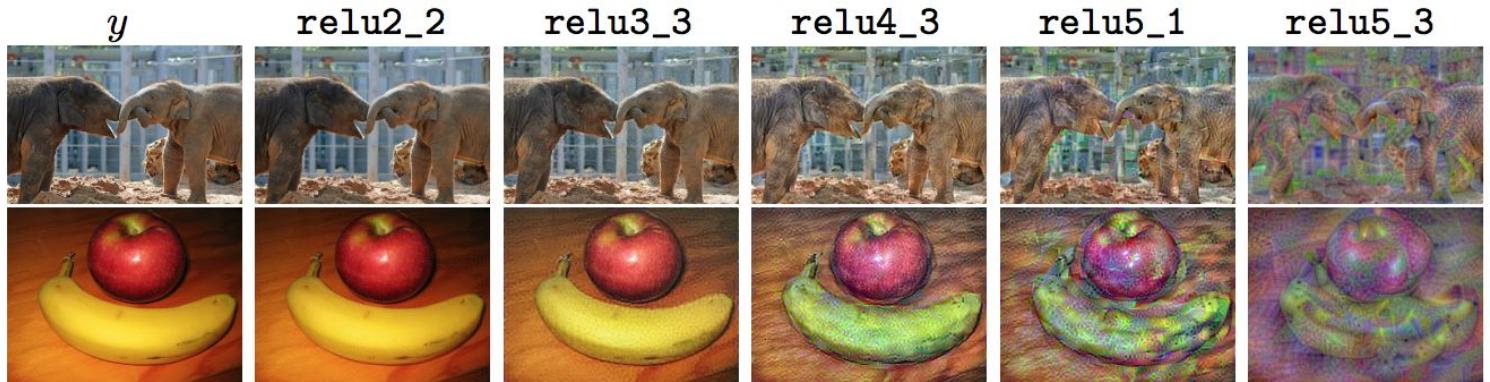


Figure from Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016. Copyright Springer, 2016. Reproduced for educational purposes.



Combined Loss for both Content (1st order statistics) and Style (2nd order statistics: Gram)

$$\mathcal{L}_{content}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} (F_{ij}^l - P_{ij}^l)^2 .$$

$$\mathcal{L}_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^L w_l E_l$$

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l - A_{ij}^l)^2$$

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l.$$

Neural Style Transfer

Content Image



[This image](#) is licensed under CC-BY 3.0

+

Style Image



[Starry Night](#) by Van Gogh is in the public domain

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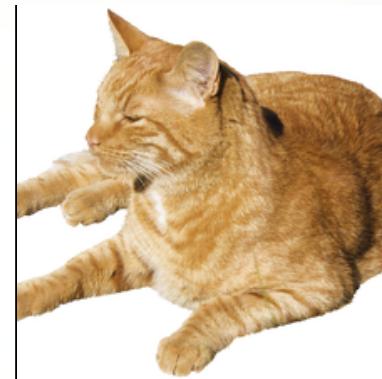


[This image](#) copyright Justin Johnson, 2015. Reproduced with permission.

CNN learns **texture** features, not shapes!



(a) Texture image
81.4% **Indian elephant**
10.3% indri
8.2% black swan



(b) Content image
71.1% **tabby cat**
17.3% grey fox
3.3% Siamese cat



(c) Texture-shape cue conflict
63.9% **Indian elephant**
26.4% indri
9.6% black swan

Geirhos et al. ICLR 2019

<https://videoken.com/embed/W2HvLBMhCJQ?tocitem=46>



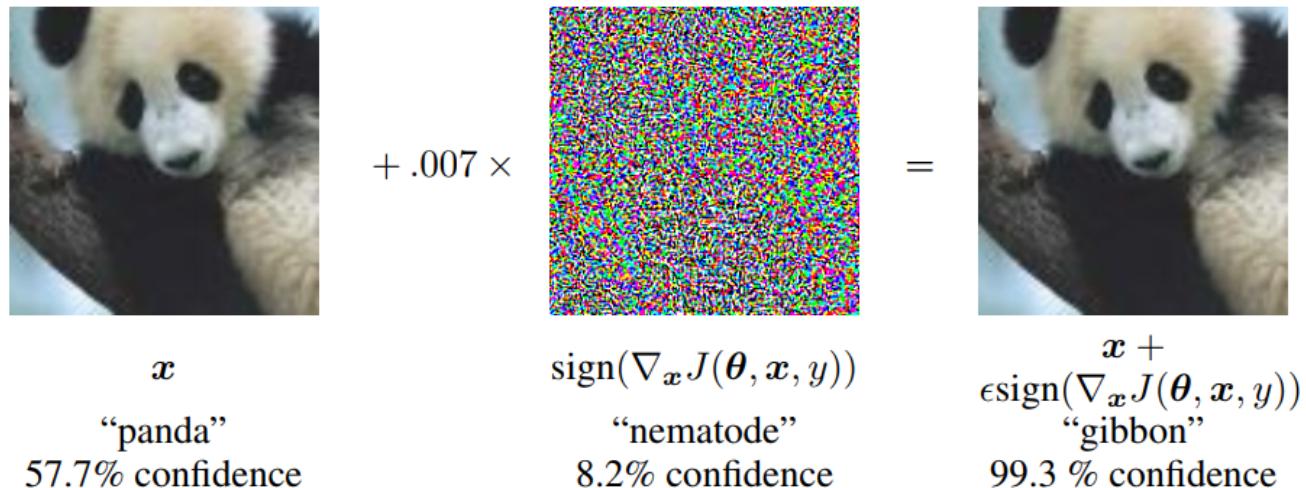
Examples

- ▶ Jupyter Notebook Demo
- 



Adversarial Examples and Robustness

Deep Learning may be fragile: adversarial examples



[Goodfellow et al., 2014]

- Small but malicious perturbations can result in severe misclassification
- Malicious examples generalize across different architectures
- What is source of instability?
- Can we robustify network?

Adversarial Examples: Fooling Images

- ▶ Start from an arbitrary image
- ▶ Pick an arbitrary class
- ▶ Modify the image to maximize the class
- ▶ Repeat until network is fooled

Fooling Images/Adversarial Examples

African elephant



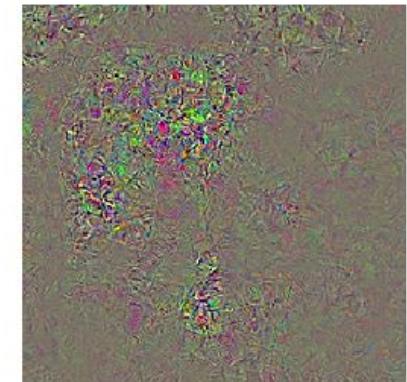
koala



Difference



10x Difference



schooner



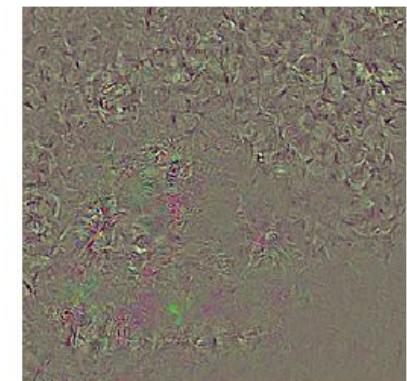
iPod



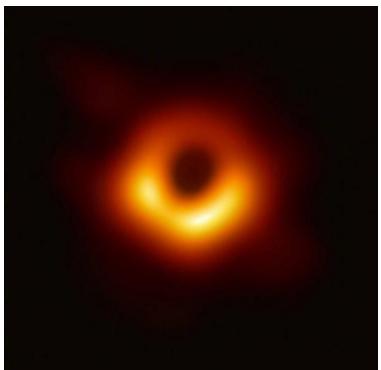
Difference



10x Difference



Convolutional Networks lack Robustness

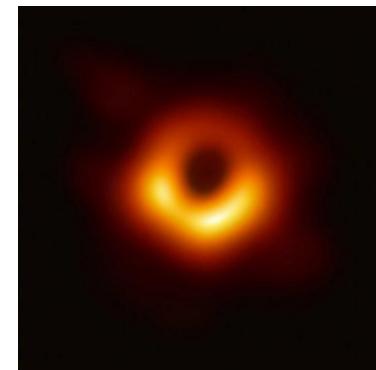


“black hole”
87.7% confidence

+ .007 ×



=

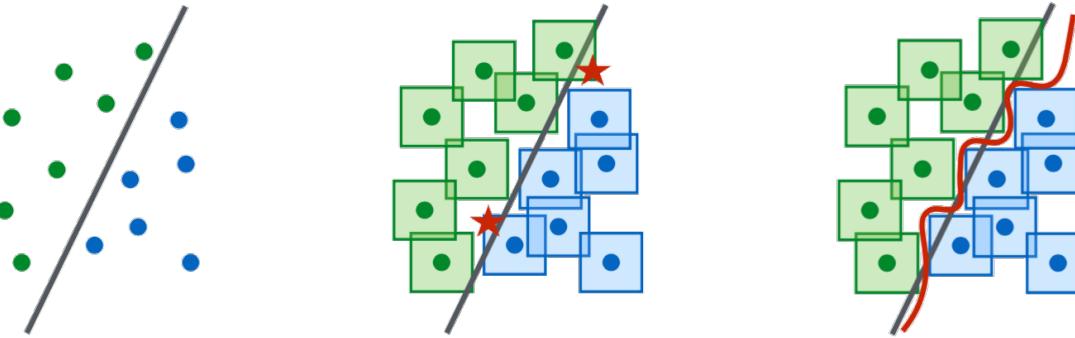


“donut”
99.3% confidence



Courtesy of Dr. Hongyang ZHANG.

Adversarial Robust Training



- Traditional training:

$$\min_{\theta} J_n(\theta, \mathbf{z} = (x_i, y_i)_{i=1}^n)$$

- e.g. square or cross-entropy loss as negative log-likelihood of logit models

- Robust optimization (Madry et al. ICLR'2018):

$$\min_{\theta} \max_{\|\epsilon_i\| \leq \delta} J_n(\theta, \mathbf{z} = (x_i + \epsilon_i, y_i)_{i=1}^n)$$

- robust to any distributions, yet computationally hard

Thank you!

