Lecture 12: Visualizing and Understanding
Last time: Lots of Computer Vision Tasks

Classification

Semantic Segmentation

Object Detection

Instance Segmentation

- CAT
- GRASS, CAT, TREE, SKY
- DOG, DOG, CAT
- DOG, DOG, CAT

No spatial extent
No objects, just pixels
Multiple Object
Today: What’s going on inside ConvNets?

Input Image: 3 x 224 x 224

What are the intermediate features looking for?

Class Scores: 1000 numbers

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.
Today's agenda

Visualizing what models have learned:
- Visualizing filters
- Visualizing final layer features
- Visualizing activations

Understanding input pixels
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

Adversarial perturbations

Style transfer
- Features inversion
- Deep dream
- Texture synthesis
- Neural style transfer
Today's agenda

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Interpreting a Linear Classifier: Visual Viewpoint

airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck

Score

plane, car, bird, cat, deer, dog, frog, horse, ship, truck

Input image

W

b

Score

-96.8

437.9

61.95
First Layer: Visualize Filters

AlexNet:
64 x 3 x 11 x 11

Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017
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

Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017
Visualize the filters/kernels (raw weights)

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

(These are taken from ConvNetJS CIFAR-10 demo)

layer 1 weights
16 x 3 x 7 x 7

layer 2 weights
20 x 16 x 7 x 7

layer 3 weights
20 x 20 x 7 x 7
4096-dimensional feature vector for an image (layer immediately before the classifier)

Run the network on many images, collect the feature vectors
**Recall**: Nearest neighbors in pixel space

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012. Figures reproduced with permission.
Last Layer: Nearest Neighbors

4096-dim vector

Recall: Nearest neighbors in pixel space

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 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
Figure copyright Laurens van der Maaten and Geoff Hinton, 2008. Reproduced with permission.
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

### Visualizing Activations


<table>
<thead>
<tr>
<th></th>
<th>House</th>
<th>Dog</th>
<th>Train</th>
<th>Plant</th>
<th>Airplane</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>res5c unit 1410</td>
<td>res5c unit 1573</td>
<td>res5c unit 924</td>
<td>res5c unit 264</td>
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<td>res5c unit 1718</td>
<td>res5c unit 2001</td>
<td>res5c unit 766</td>
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<td>IoU=0.193</td>
<td>IoU=0.255</td>
<td>IoU=0.092</td>
<td>IoU=0.156</td>
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<td>inception_4e unit 750</td>
<td>inception_5b unit 626</td>
<td>inception_4e unit 56</td>
<td>inception_4e unit 92</td>
</tr>
<tr>
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<td>IoU=0.137</td>
<td>IoU=0.203</td>
<td>IoU=0.145</td>
<td>IoU=0.139</td>
<td>IoU=0.164</td>
</tr>
<tr>
<td></td>
<td>inception_4e unit 175</td>
<td>inception_5b unit 437</td>
<td>inception_5b unit 415</td>
<td>inception_4e unit 714</td>
<td>inception_4e unit 759</td>
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<tr>
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<td>IoU=0.115</td>
<td>IoU=0.108</td>
<td>IoU=0.143</td>
<td>IoU=0.105</td>
<td>IoU=0.144</td>
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<tr>
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<td>conv5_3 unit 243</td>
<td>conv5_3 unit 142</td>
<td>conv5_3 unit 463</td>
<td>conv5_3 unit 85</td>
<td>conv5_3 unit 151</td>
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<td>IoU=0.070</td>
<td>IoU=0.205</td>
<td>IoU=0.126</td>
<td>IoU=0.086</td>
<td>IoU=0.150</td>
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<td>conv5_3 unit 102</td>
<td>conv5_3 unit 491</td>
<td>conv5_3 unit 402</td>
<td>conv4_3 unit 336</td>
<td>conv5_3 unit 204</td>
</tr>
<tr>
<td></td>
<td>IoU=0.070</td>
<td>IoU=0.112</td>
<td>IoU=0.058</td>
<td>IoU=0.068</td>
<td>IoU=0.077</td>
</tr>
</tbody>
</table>
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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

Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.
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

P(elephant) = 0.95

P(elephant) = 0.75

Boat image is CC0 public domain
Elephant image is CC0 public domain
Go-Karts image is CC0 public domain
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
Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities

Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.
Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities

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


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

Saliency Maps: Segmentation without supervision

Use GrabCut on saliency map


Rother et al, “Grabcut: Interactive foreground extraction using iterated graph cuts”, ACM TOG 2004
Saliency maps: Uncovers biases

Such methods also find biases

wolf vs dog classifier looks is actually a snow vs no-snow classifier

Figures copyright Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, 2016; reproduced with permission.
Intermediate Features via (guided) backprop

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

Compute gradient of activation value with respect to image pixels
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

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

Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.
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
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.
Visualizing CNN features: Gradient Ascent

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

**Neuron value**

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

**Natural image regularizer**

( Guided) backprop: Find the part of an image that a neuron responds to
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

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

Simple regularizer: Penalize L2 norm of generated image

Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.
Visualizing CNN features: Gradient Ascent

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

Simple regularizer: Penalize L2 norm of generated image

Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.
Visualizing CNN features: Gradient Ascent

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

Simple regularizer: Penalize L2 norm of generated image
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

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. Figure copyright Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson, 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

Visualizing CNN features: Gradient Ascent

Use the same approach to visualize intermediate features

Visualizing CNN features: Gradient Ascent

Adding “multi-faceted” visualization gives even nicer results:
(Plus more careful regularization, center-bias)

Visualizing CNN features: Gradient Ascent

Visualizing CNN features: Gradient Ascent

Optimize in FC6 latent space instead of pixel space:

Figure copyright Nguyen et al, 2016; reproduced with permission.
Visualizing CNN features: Gradient Ascent

Optimize in FC6 latent space instead of pixel space:

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Fooling Images / Adversarial Examples

(1) Start from an arbitrary image
(2) Pick an arbitrary class
(3) Modify the image to maximize the class
(4) Repeat until network is fooled
Fooling Images / Adversarial Examples

African elephant

koala

Difference

10x Difference

schooner

iPod

Difference

10x Difference

Boat image is CC0 public domain
Elephant image is CC0 public domain
Fooling Images / Adversarial Examples

Universal perturbations

Figure reproduced with permission
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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)

\[ x^* = \text{argmin}_{x \in \mathbb{R}^{H \times W \times C}} \ell(\Phi(x), \Phi_0) + \lambda \mathcal{R}(x) \]

\[ \ell(\Phi(x), \Phi_0) = \|\Phi(x) - \Phi_0\|^2 \]

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

Feature Inversion

Reconstructing from different layers of VGG-16

$y$  relu2_2  relu3_3  relu4_3  relu5_1  relu5_3

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.
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**
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

Equivalent to:

\[ l^* = \arg \max_I \sum_i f_i(I)^2 \]
DeepDream: Amplify existing features

```
def objective_L2(dst):
    dst.diff[:] = dst.data

def make_step(net, step_size=1.5, end='inception_4c/output',
                jitter=32, clip=True, objective=objective_L2):
    '''Basic gradient ascent step.'''

    src = net.blobs['data']  # input image is stored in Net's 'data' blob
    dst = net.blobs[end]

    ox, oy = np.random.randint(-jitter, jitter+1, 2)
    src.data[0] = np.roll(np.roll(src.data[0], ox, -1), oy, -2)  # apply jitter shift

    net.forward(end=end)
    objective(dst)  # specify the optimization objective
    net.backward(start=end)
    g = src.diff[0]
    # apply normalized ascent step to the input image
    src.data[:] += step_size/np.abs(g).mean() * g

    src.data[0] = np.roll(np.roll(src.data[0], -ox, -1), -oy, -2)  # unshift image

    if clip:
        bias = net.transformer.mean['data']
        src.data[:] = np.clip(src.data, -bias, 255-bias)
```

*Code* is very simple but it uses a couple tricks:

(Code is licensed under Apache 2.0)
DeepDream: Amplify existing features

```python
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    dst.diff[:] = dst.data

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Code is very simple but it uses a couple tricks:

(Code is licensed under Apache 2.0)

Jitter image
DeepDream: Amplify existing features

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def objective_L2(dst):
    dst.diff[:] = dst.data

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        src.data[:] = np.clip(src.data, -bias, 255-bias)
```

**Code** is very simple but it uses a couple tricks:

- **Jitter image**
- **L1 Normalize gradients**

(Code is licensed under Apache 2.0)
DeepDream: Amplify existing features

Code is very simple but it uses a couple tricks:

- Jitter image
- L1 Normalize gradients
- Clip pixel values

Also uses multiscale processing for a fractal effect (not shown)
Texture Synthesis

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

Input

Output

Output image is licensed under the MIT license
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.

Texture Synthesis: Nearest Neighbor

**Lecture 12**

Fei-Fei Li, Yunzhu Li, Ruohan Gao

May 11, 2023
Neural Texture Synthesis: Gram Matrix

Each layer of CNN gives $C \times H \times W$ tensor of features; $H \times W$ grid of $C$-dimensional vectors.
Neural Texture Synthesis: 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 measuring co-occurrence
Neural Texture Synthesis: Gram Matrix

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 pairs of vectors, giving **Gram matrix** of shape $C \times C$
Neural Texture Synthesis: Gram Matrix

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:

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

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

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 $L_2$ distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image
9. GOTO 5
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:
\[ G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l \quad (\text{shape } C_i \times C_i) \]
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
\[ L(\mathbf{x}, \hat{\mathbf{x}}) = \sum_{l=0}^{L} w_l E_l \]
\[ E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l - \hat{G}_{ij}^l)^2 \]

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

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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   \[
   G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l \quad \text{(shape $C_i \times C_i$)}
   \]
4. Initialize generated image from random noise
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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.
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: 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. 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.
Neural Style Transfer

Content Image + Style Image

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Starry Night by Van Gogh is in the public domain

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

Content Image

Style Image

Style Transfer!

Starry Night by Van Gogh is in the public domain


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This image copyright Justin Johnson, 2015. Reproduced with permission.
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. Copyright Springer, 2016. Reproduced for educational purposes.
Figure adapted 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

Example outputs from Lua torch implementation

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

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

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

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Fast Style Transfer

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https://github.com/jcjohnson/fast-neural-style
Remember Normalization Methods?
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Instance Normalization was developed for style transfer!
Fast Style Transfer

Replacing batch normalization with Instance Normalization improves results
One Network, Many Styles

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One Network, Many Styles

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

\[
x_{\text{norm}} = (x - \mu) / \sigma \\
z = \gamma_s x_{\text{norm}} + \beta_s
\]

Single network can blend styles after training.
Summary

Many methods for understanding CNN representations

Activations: Nearest neighbors, dimensionality reduction, maximal patches, occlusion

Gradients: Saliency maps, class visualization, fooling images, feature inversion

Fun: DeepDream, style transfer
Next time:

5/16 Midterm

5/18 Self-supervised Learning