Visualizing CNN

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(Slide credits: Fei-Fei Li, Andrej Karpathy, Justin Johnson, Serena Yeung, Geoffrey Hinton)

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Overview

- We talked about the basics of CNNs and several CNN architectures earlier
- How to visualize a CNN
- CNNs and arts
- Fooling a CNN

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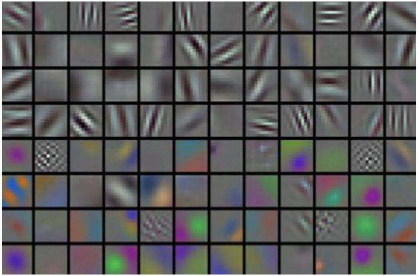
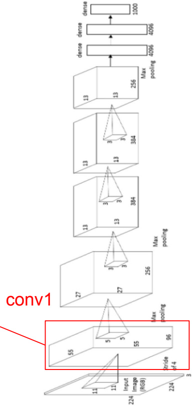
Visualizing and understanding conv-nets

- Study weights directly
- Occlusion experiment
- Visualizing representation
    - t-SNE
    - through deconvolution
    - through optimization

Visualize the filters/kernels (raw weights)



one-stream AlexNet



only interpretable on the first layer :(

Visualize the filters/kernels (raw weights)

you can still do it for higher layers, it's just not that interesting

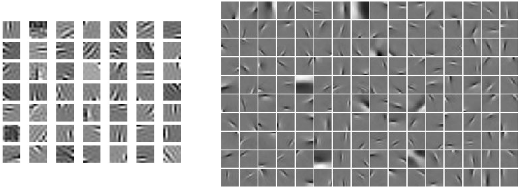
(these are taken from ConvNetJS CIFAR-10 demo)

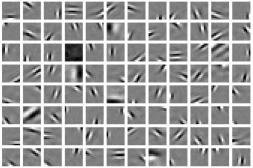
layer 1 weights

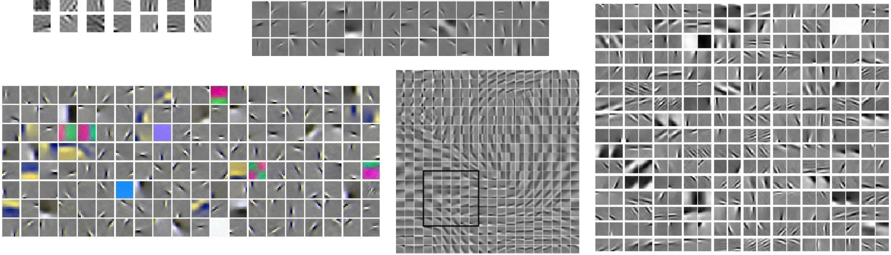
layer 2 weights

layer 3 weights

The gabor-like filters fatigue







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Occlusion experiments

[Zeiler & Fergus 2013]

(d) Classifier, probability of correct class

(as a function of the position of the square of zeros in the original image)

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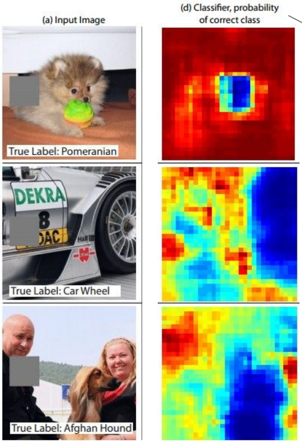
Occlusion experiments

[Zeiler & Fergus 2013]



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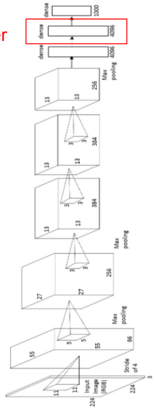
Visualizing the representation

fc7 layer



4096-dimensional "code" for an image
(layer immediately before the classifier)

can collect the code for many images

Visualizing the representation

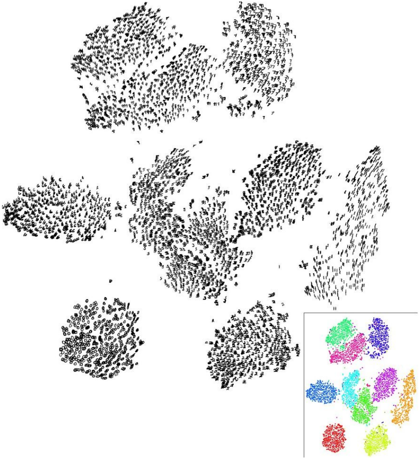
t-SNE visualization

[van der Maaten & Hinton]

Embed high-dimensional points so that locally, pairwise distances are conserved

i.e. similar things end up in similar places. dissimilar things end up wherever

Right: Example embedding of MNIST digits (0-9) in 2D



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t-SNE and SNE

- t-SNE is an improvement of SNE (Stochastic Neighborhood Embedding)
- SNE:
  - Match the distribution of distances between points in the original high dimensional space and the distribution of distances between points in the reduced low-dimensional space
  - x_i: location of point i in original space; y_i: location of point i in the reduced space
  - $p_{i|j} \triangleq \frac{\exp(-\|x_i - x_j\|^2/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|x_i - x_k\|^2/2\sigma_i^2)}$; $q_{i|j} \triangleq \frac{\exp(-\|y_i - y_j\|^2)}{\sum_{k\neq i}\exp(-\|y_i - y_k\|^2)}$
  - Minimize $C \triangleq \sum_i KL(P_i\|Q_i) = \sum_i \sum_j p_{i|j} \log \frac{p_{i|j}}{q_{i|j}}$. Note that KL-divergence is not symmetric
    - x_i, x_j far apart $\Rightarrow$ small cost despite values of y_i, y_j
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  - $\frac{\partial C}{\partial y_i} = 2\sum_j (p_{j|i} + p_{i|j} - q_{j|i} - q_{i|j})(y_i - y_j)$

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More on t-SNE

- SNE tends to have a "crowding problem"
- t-SNE resolved this by assuming a t-distribution rather than a Gaussian distribution for the distance between points in the reduced space

$$q_{ij} = \frac{(1 + \|y_i - y_j\|^2)^{-1}}{\sum_k \sum_{l \neq k} (1 + \|y_k - y_l\|^2)^{-1}}$$

  - Student t-distribution is much more heavy tail. Allow y_i's to be farther away without incurring significant cost
- t-SNE also symmetrized the conditional distribution: $p_{ij} = \frac{p_{i|j} + p_{j|i}}{2N}$
- $\frac{\partial C}{\partial y_i} = 4 \sum_{j \neq i} \underbrace{(p_{ij} - q_{ij})(1 + \|y_i - y_j\|^2)^{-1}}_{Force} \underbrace{(y_i - y_j)}_{spring}$

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More on t-SNE

- For each update, essentially summing up force exerting on a point from **all** other points
  - For large dataset (with say more than 10K data points), the naive implementation can be too slow
- For far away points from a similar direction, the force can be approximated as a net force from the center of mass from the point cloud
  - This is known as Barnes-Hut approximation
  - Originally introduced from astro-physics
- Can further speed things up by first putting y_i's in a quad-tree structure
  - Can quickly determine if a point cloud is sufficiently far away from y_i for Barnes-Hut approximation
  - Allow one to pull out the center of mass of a point cloud quickly
- Also check out "How to use t-SNE effectively" for more details

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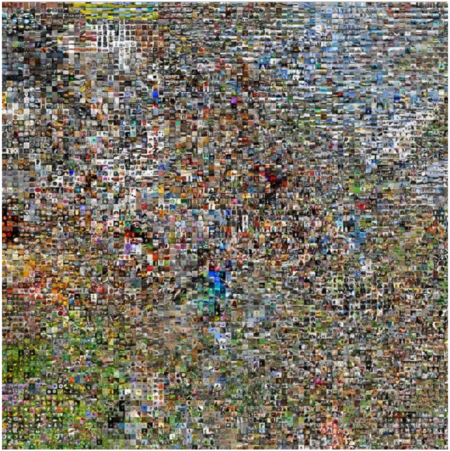
t-SNE visualization:

two images are placed nearby if their CNN codes are close. See more:

http://cs.stanford.edu/people/karpathy/cnnembed/



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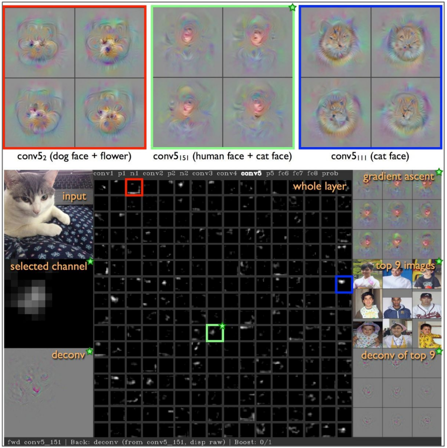
Visualizing Activations

http://yosinski.com/deepvis

YouTube video
https://www.youtube.com/watch?v=AgkfIQ4IGaM
(4min)



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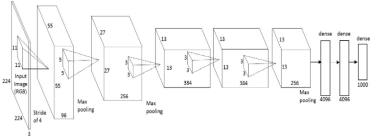
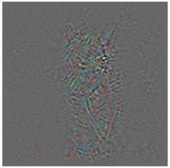
Deconv approaches

1. Feed image into net



2. Pick a layer, set the gradient there to be all zero except for one 1 for some neuron of interest
3. Backprop to image:



"Guided backpropagation:" instead

Deconv net

- Appeared in Zeiler and Fergus '13, which also discussed the occlusion experiment mentioned earlier
- Similar to backprop, but information is passed back through a "deconv net"
  - Relu maps back to Relu
  - Unpooling only modifies locations that originally "activates" the pooling operation
  - Filter maps to the transpose of the filter

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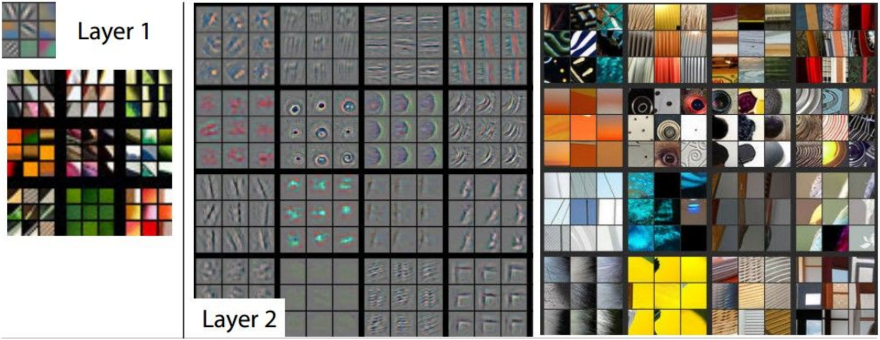
Deconv net

Visualizing and Understanding Convolutional Networks
Zeiler & Fergus, 2013

Visualizing arbitrary neurons along the way to the top...



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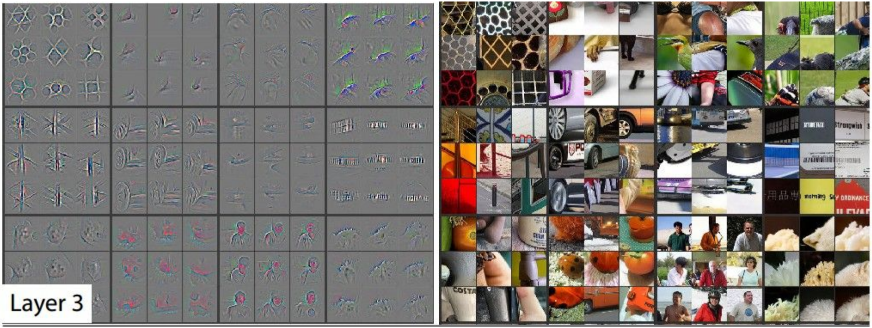
Deconv net

Visualizing arbitrary neurons along the way to the top...



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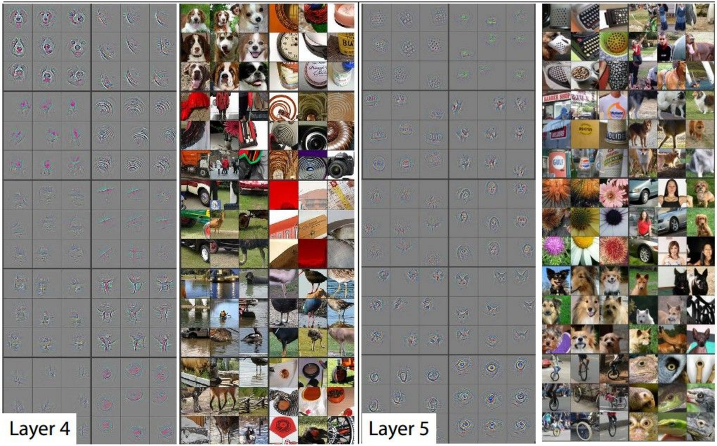
Deconv net

Visualizing arbitrary neurons along the way to the top...



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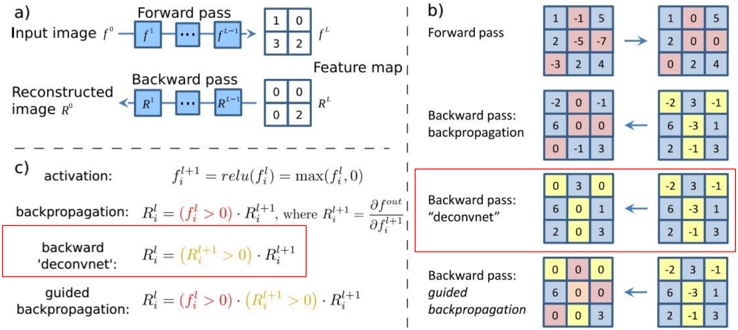
Guided backprop

Deconv approaches

[Visualizing and Understanding Convolutional Networks, Zeiler and Fergus 2013]
[Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps, Simonyan et al., 2014]
[Striving for Simplicity: The all convolutional net, Springenberg, Dosovitskiy, et al., 2015]



bit weird

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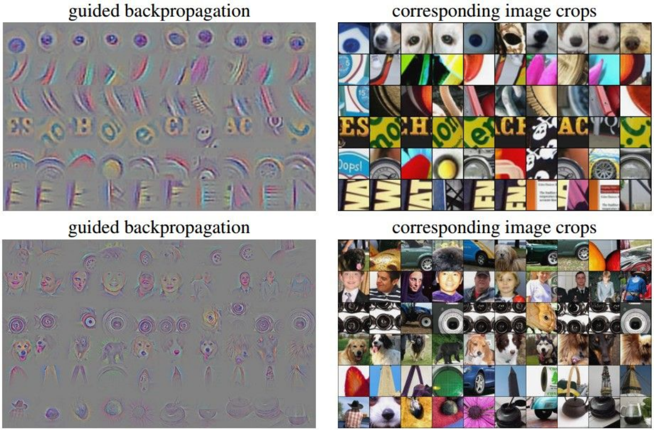
Guided backprop

Visualization of patterns learned by the layer **conv6** (top) and layer **conv9** (bottom) of the network trained on ImageNet.

Each row corresponds to one filter.

The visualization using "guided backpropagation" is based on the top 10 image patches activating this filter taken from the ImageNet dataset.



[Striving for Simplicity: The all convolutional net, Springenberg, Dosovitskiy, et al., 2015]

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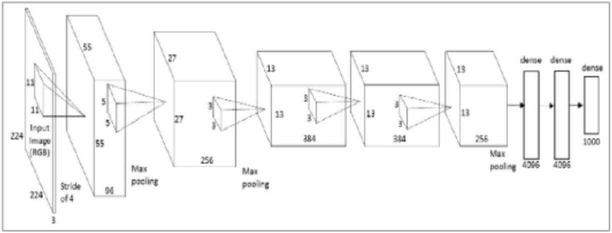
Finding salient map of an object



Repeat:

1. Forward an image
2. Set activations in layer of interest to all zero, except for a 1.0 for a neuron of interest
3. Backprop to image
4. Do an “image update”

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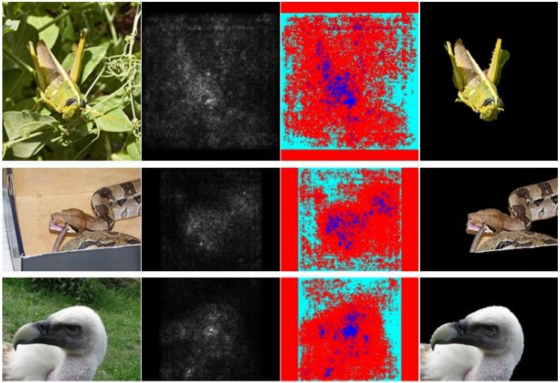
Finding salient map of an object

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps
Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, 2014

- Use **grabcut** for segmentation



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Patches maximally activate a neuron

Visualize patches that maximally activate neurons

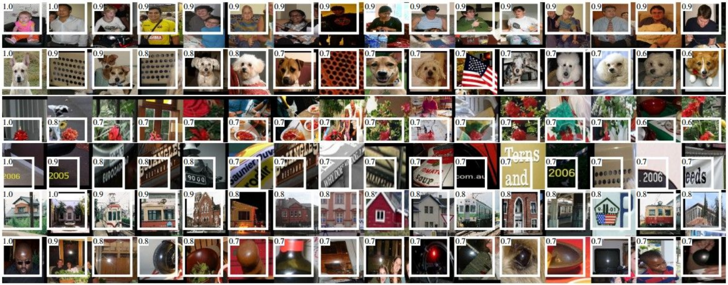
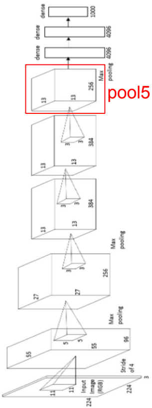


Figure 4: Top regions for six pool$_5$ units. Receptive fields and activation values are drawn in white. Some units are aligned to concepts, such as people (row 1) or text (4). Other units capture texture and material properties, such as dot arrays (2) and specular reflections (6).

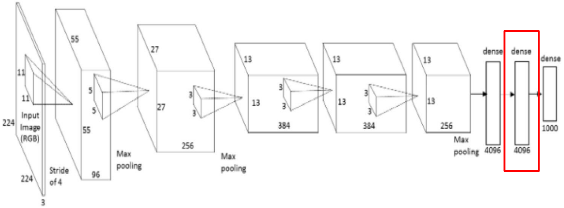
one-stream AlexNet



Rich feature hierarchies for accurate object detection and semantic segmentation [Girshick, Donahue, Darrell, Malik]

Recovering original image

Question: Given a CNN code, is it possible to reconstruct the original image?



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Recovering original image

Find an image such that:

- Its code is similar to a given code
- It "looks natural" (image prior regularization)

$$\mathbf{x}^* = \underset{\mathbf{x}\in\mathbb{R}^{H\times W\times C}}{\operatorname{argmin}} \ \ell(\Phi(\mathbf{x}), \Phi_0) + \lambda\mathcal{R}(\mathbf{x})$$

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

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Recovering original image

Understanding Deep Image Representations by Inverting Them [Mahendran and Vedaldi, 2014]

original image

reconstructions from the 1000 log probabilities for ImageNet (ILSVRC) classes

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Recovering original image

Reconstructions from the representation after last last pooling layer (immediately before the first Fully Connected layer)

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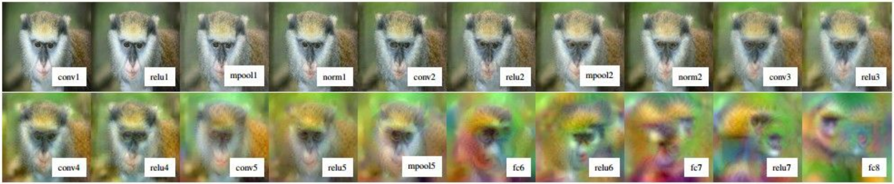
Recovering original image

Reconstructions from intermediate layers



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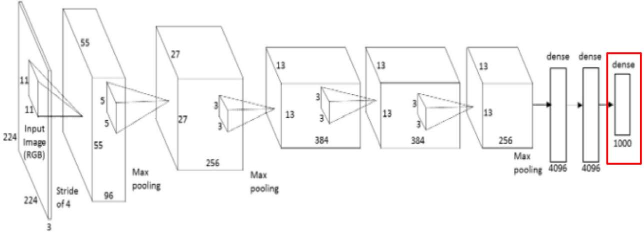
Class model visualization

Optimization to Image



Q: can we find an image that maximizes some class score?

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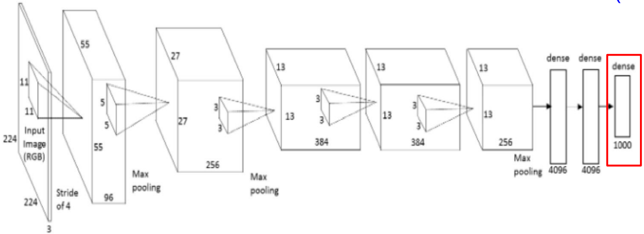
Class model visualization

Optimization to Image

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

score for class c (before Softmax)

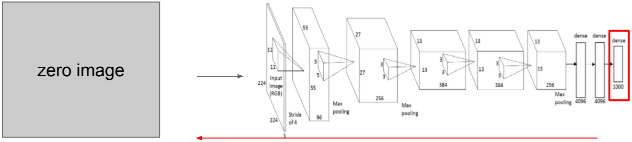


Q: can we find an image that maximizes some class score?

Class model visualization

Optimization to Image

1. feed in zeros.

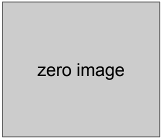


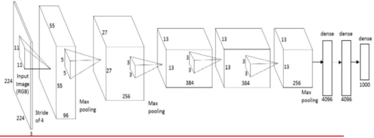
2. set the gradient of the scores vector to be [0,0,....1,....,0], then backprop to image

Class model visualization

Optimization to Image

1. feed in zeros.





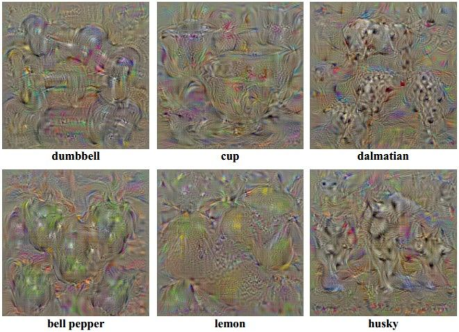
2. set the gradient of the scores vector to be [0,0,....1,....,0], then backprop to image
3. do a small "image update"
4. forward the image through the network.
5. go back to 2.

$$\boxed{\arg\max_I \underbrace{\boxed{S_c(I)}}_{\text{score for class c (before Softmax)}} - \lambda \|I\|_2^2}$$

Class model visualization

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps
Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, 2014

1. Find images that maximize some class score:



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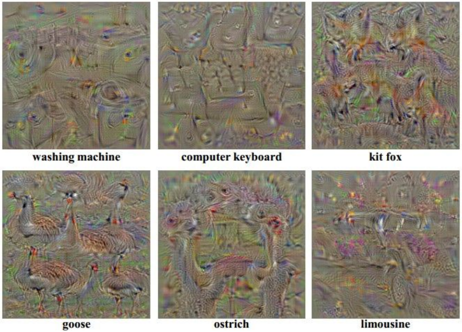
Class model visualization

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps
Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, 2014

1. Find images that maximize some class score:



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Class model visualization

[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

Proposed a different form of regularizing the image

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

More explicit scheme:

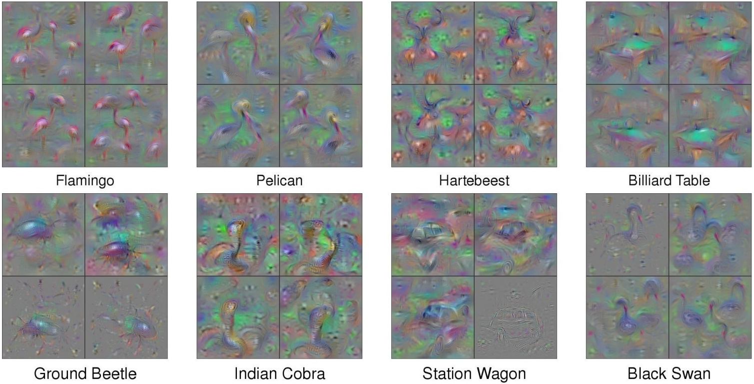
Repeat:

- Update the image **x** with gradient from some unit of interest
- Blur x a bit
- Take any pixel with small norm to zero (to encourage sparsity)

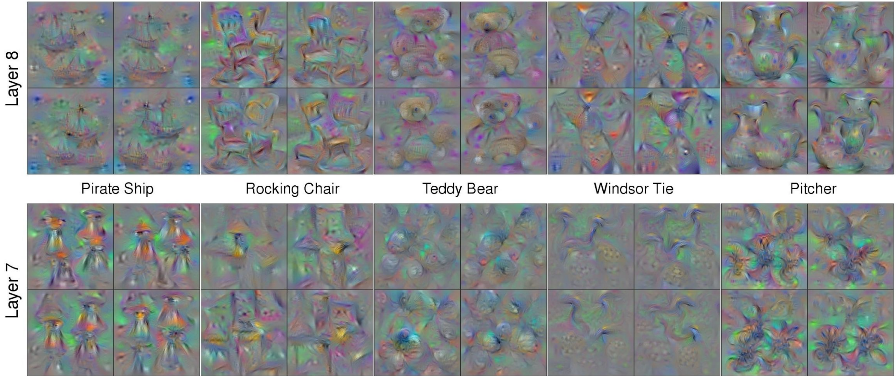
Class model visualization

[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

http://yosinski.com/deepvis



Class model visualization



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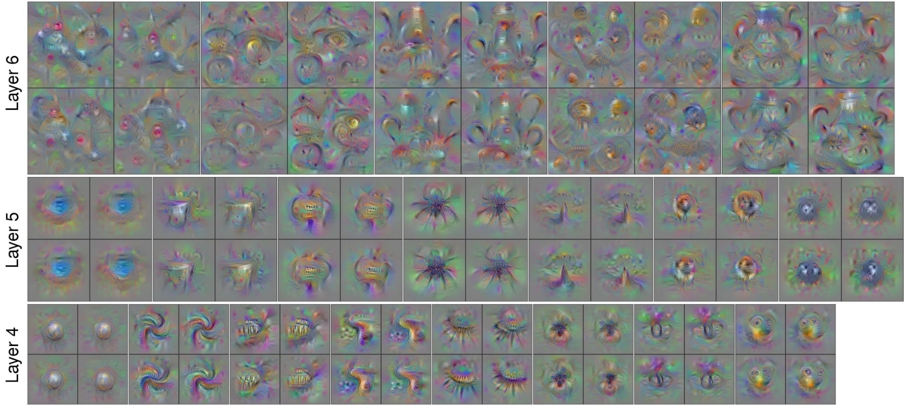
Class model visualization



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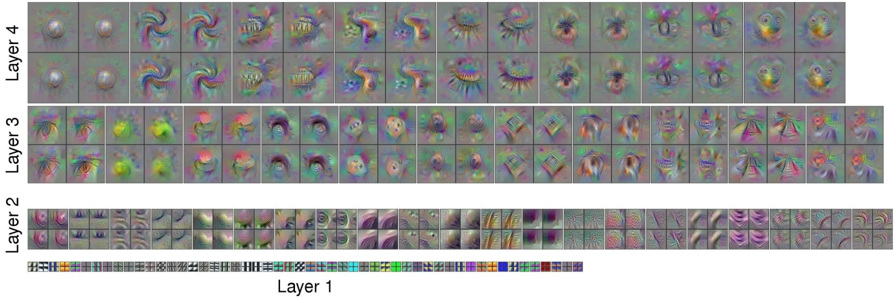
Class model visualization



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Class model visualization

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.

Class model visualization

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.

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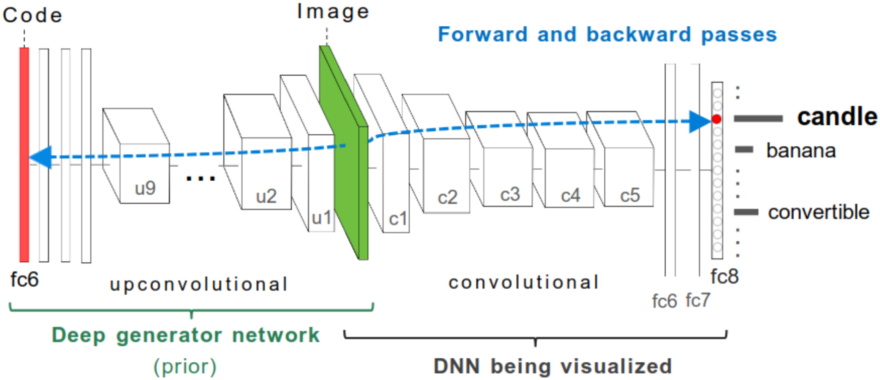
Class model visualization



Anh Nguyen, Alexey Dosovitskiy, Jason Yosinski, Thomas Brox, Jeff Clune, ”Synthesizing the preferred inputs for neurons in neural networks via deep generator networks”

Class model visualization

Anh Nguyen, Alexey Dosovitskiy, Jason Yosinski, Thomas Brox, Jeff Clune, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks"

DeepDream https://github.com/google/deepdream

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```
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)
```

```python
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.'''

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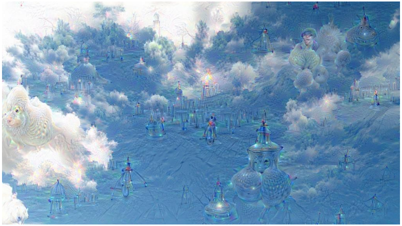

DeepDream: set dx = x :)

jitter regularizer

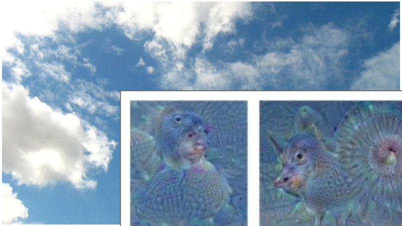
“image update”

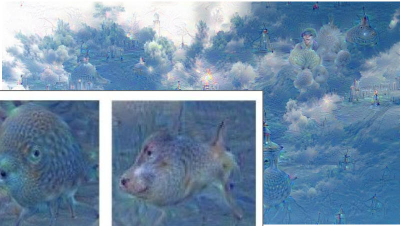
inception_4c/output



DeepDream modifies the image in a way that "boosts" all activations, at any layer

this creates a feedback loop: e.g. any slightly detected dog face will be made more and more dog like over time inception_4c/output





DeepDream modifies the image in a way that "boosts" all activations, at any layer

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inception_3b/5x5_reduce

DeepDream modifies the image in a way that “boosts” all activations, at any layer

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Fei-Fei Li & Justin Johnson & Serena Yeung | Lecture 11 - 48 | May 10, 2017

NeuralStyle

[A Neural Algorithm of Artistic Style by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, 2015]
good implementation by Justin in Torch:
https://github.com/jcjohnson/neural-style

make your own easily on deepart.io

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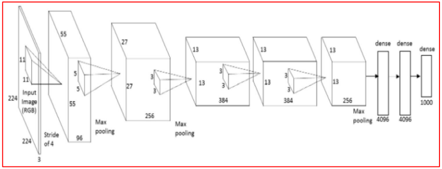
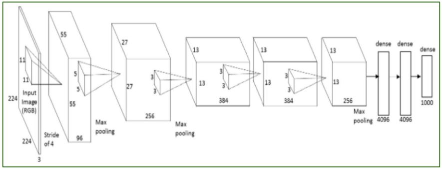
Step 1: Extract **content targets** (ConvNet activations of all layers for the given content image)



content activations

e.g.
at CONV5_1 layer we would have a [14x14x512] array of target activations

Step 2: Extract **style targets** (Gram matrices of ConvNet activations of all layers for the given style image)



style gram matrices

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

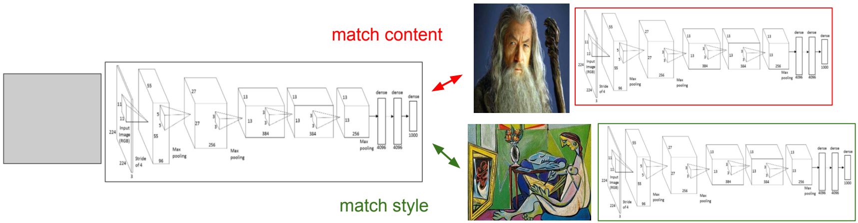
e.g.
at CONV1 layer (with [224x224x64] activations) would give a [64x64] Gram matrix of all pairwise activation covariances (summed across spatial locations)

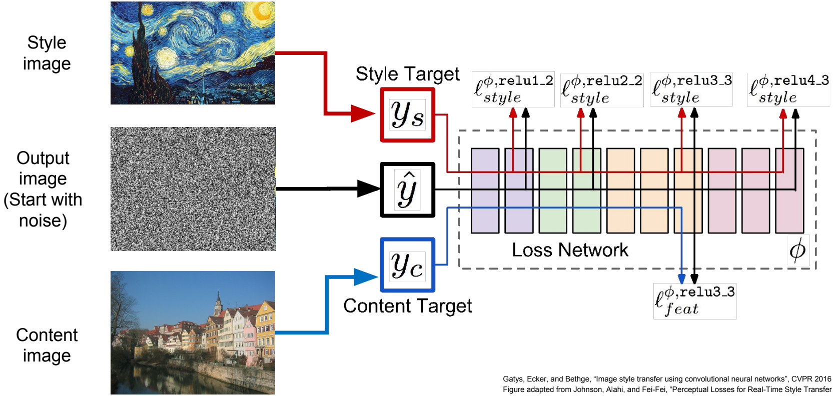
Step 3: Optimize over image to have:

- The **content** of the content image (activations match content)
- The **style** of the style image (Gram matrices of activations match style)

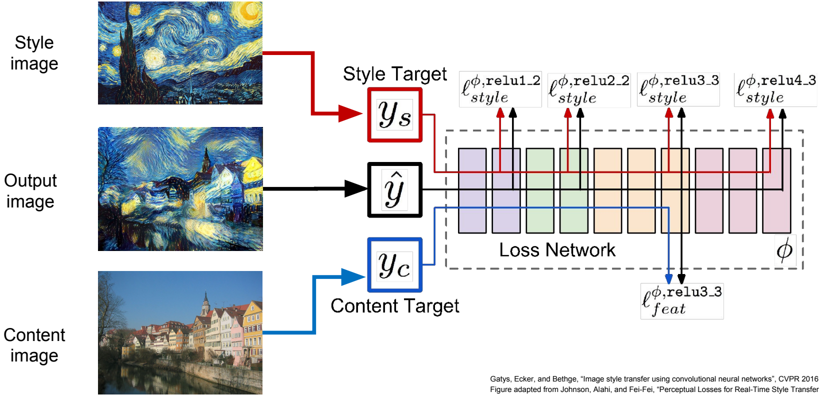
$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

(+Total Variation regularization (maybe))





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.



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.

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Neural Style Transfer

Example outputs from my implementation (in Torch)

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

Neural Style Transfer

More weight to content loss ⟷ More weight to style loss

Neural Style Transfer

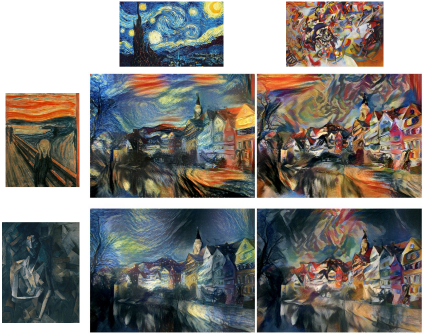
Resizing style image before running style transfer algorithm can transfer different types of features

Larger style image ⟷ Smaller style image

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

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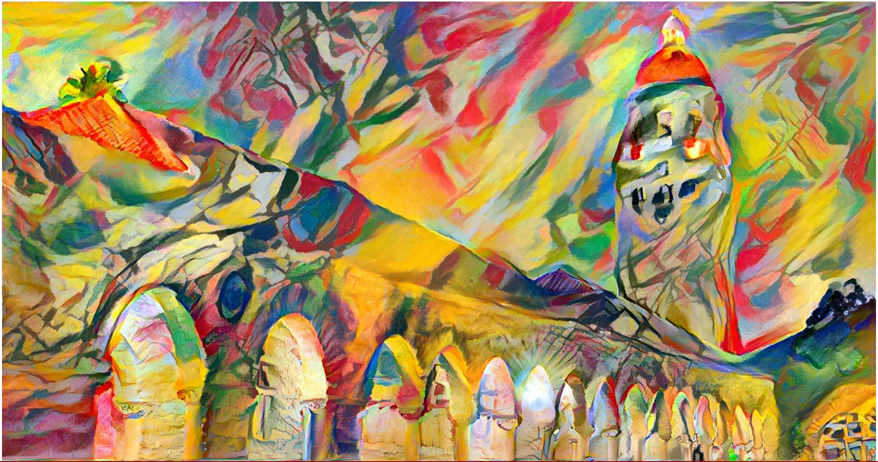

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Neural Style Transfer

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

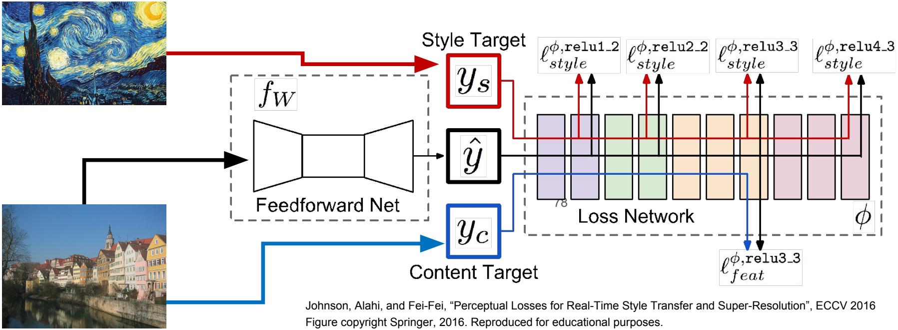
Neural Style Transfer

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

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

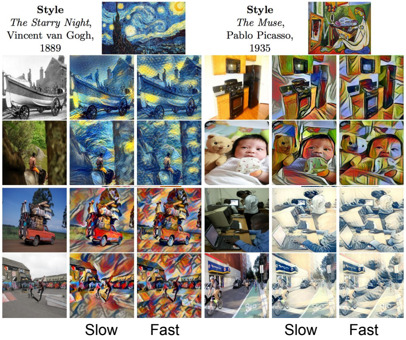
Fast Style Transfer

(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

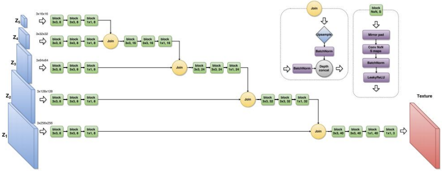
Fast Style Transfer

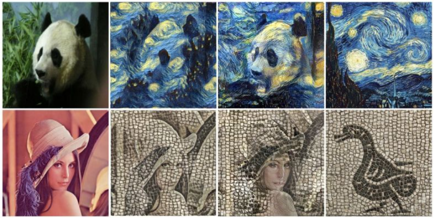


Johnson, Alahi, and Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution", ECCV 2016

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

Fast Style Transfer





Concurrent work from Ulyanov et al, comparable results

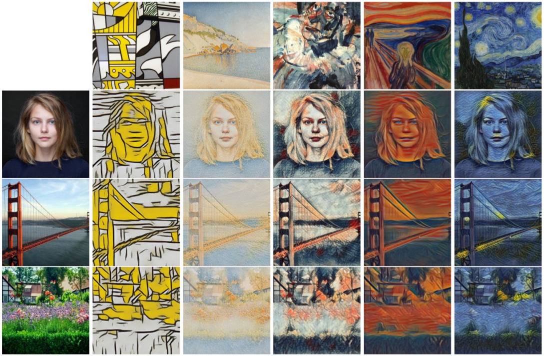
Ulyanov et al, "Texture Networks: Feed-forward Synthesis of Textures and Stylized Images", ICML 2016
Ulyanov et al, "Instance Normalization: The Missing Ingredient for Fast Stylization", arXiv 2016

Fast Style Transfer

Replacing batch normalization with Instance Normalization improves results

Ulyanov et al, "Texture Networks: Feed-forward Synthesis of Textures and Stylized Images", ICML 2016
Ulyanov et al, "Instance Normalization: The Missing Ingredient for Fast Stylization", arXiv 2016

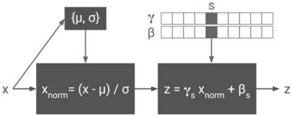
One Network, Many Styles



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

One Network, Many Styles

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



Single network can blend styles after training

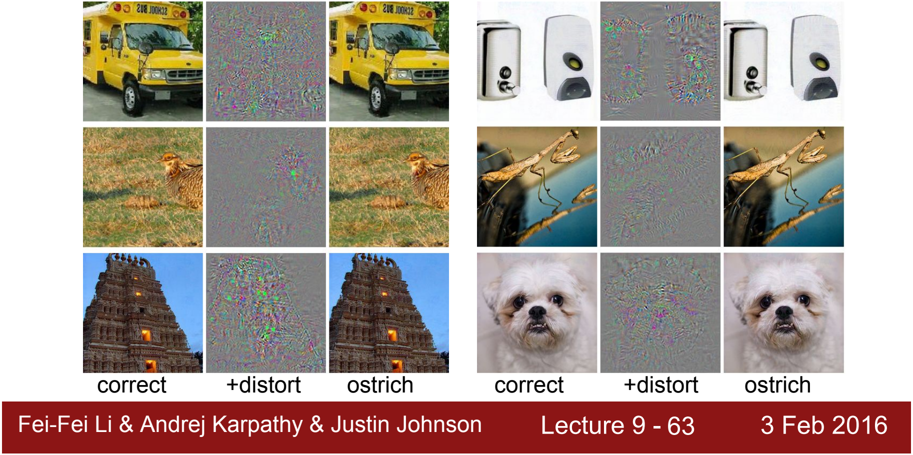
Dumoulin, Shlens, and Kudlur, "A Learned Representation for Artistic Style", ICLR 2017.

We can pose an optimization over the input image to maximize any class score.
That seems useful.

Question: Can we use this to “fool” ConvNets?

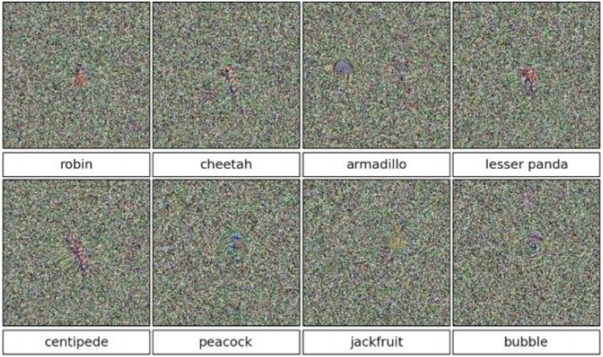
spoiler alert: yeah

[Intriguing properties of neural networks, Szegedy et al., 2013]



[Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images Nguyen, Yosinski, Clune, 2014]

>99.6% confidences



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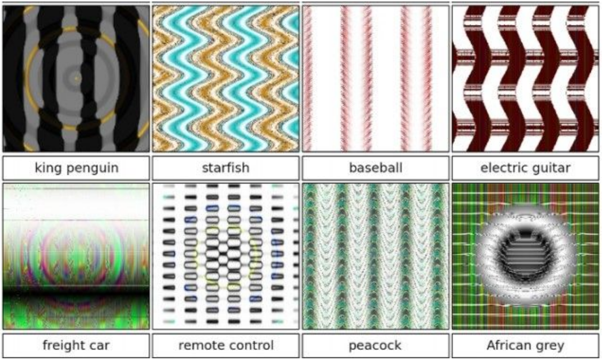

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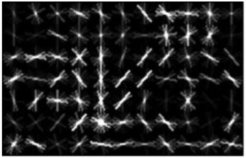
These kinds of results were around even before ConvNets…

[Exploring the Representation Capabilities of the HOG Descriptor, Tatu et al., 2011]



Identical HOG represention

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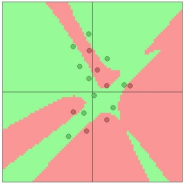
EXPLAINING AND HARNESSING ADVERSARIAL EXAMPLES [Goodfellow, Shlens & Szegedy, 2014]



"primary cause of neural networks' vulnerability to adversarial perturbation is their **linear nature**"
(and very high-dimensional, sparsely-populated input spaces)

In particular, this is not a problem with Deep Learning, and has little to do with ConvNets specifically. Same issue would come up with Neural Nets in any other modalities.

Conclusions

- Can use optimization and backprop/deconv to visualize weight
  - Can be used to find salient map as well
  - Probably many other uses for this trick as well. Be imaginative!
- CNN for arts (how about not visual data, how about music?)
- Unfortunately, like any other "linear" based classifier, conv-net with softmax layer at the end can be easily fooled

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