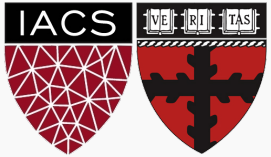
Advanced Section #5: Visualization of convolutional networks and neural style transfer

AC 209B: Advanced Topics in Data Science

Javier Zazo Pavlos Protopapas



Neural style transfer

- Artistic generation of high perceptual quality images that combines the style or texture of some input image, and the elements or content from a different one.

Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, "A neural algorithm of artistic style," Aug. 2015.

Lecture Outline

Visualizing convolutional networks

Image reconstruction

Texture synthesis

Neural style transfer

DeepDream

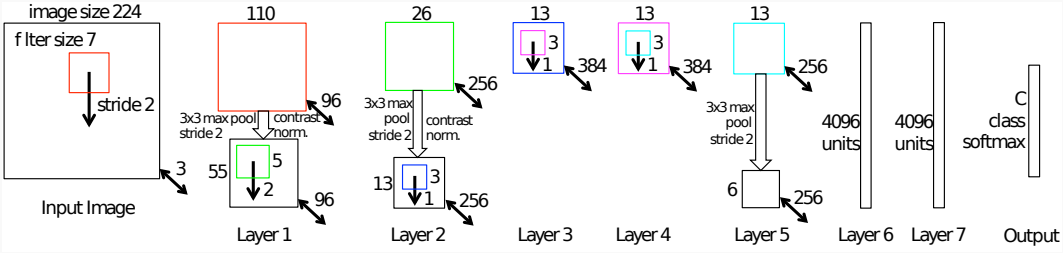
Visualizing convolutional networks

Motivation for visualization

- With NN we have little insight about learning and internal operations.
- Through visualization we may
  1. How input stimuli excite the individual feature maps.
  2. Observe the evolution of features.
  3. Make more substantiated designs.

Architecture

- Architecture similar to AlexNet, i.e., [1]
  - Trained network on the ImageNet 2012 training database for 1000 classes.
  - Input are images of size $256 \times 256 \times 3$.
  - Uses convolutional layers, max-pooling and fully connected layers at the end.



[1] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

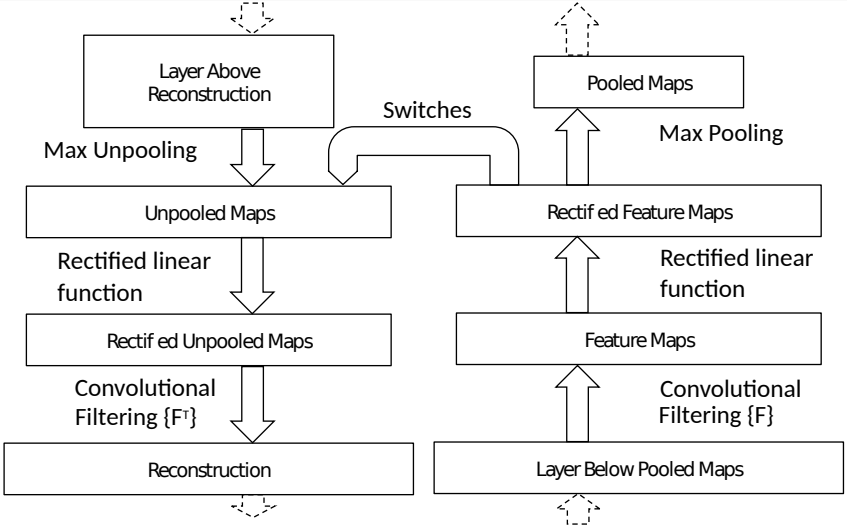
[2] Matthew D. Zeiler and Rob Fergus, "Visualizing and understanding convolutional networks," in *Computer Vision*. 2014, pp. 818–833, Springer.

Deconvolutional network

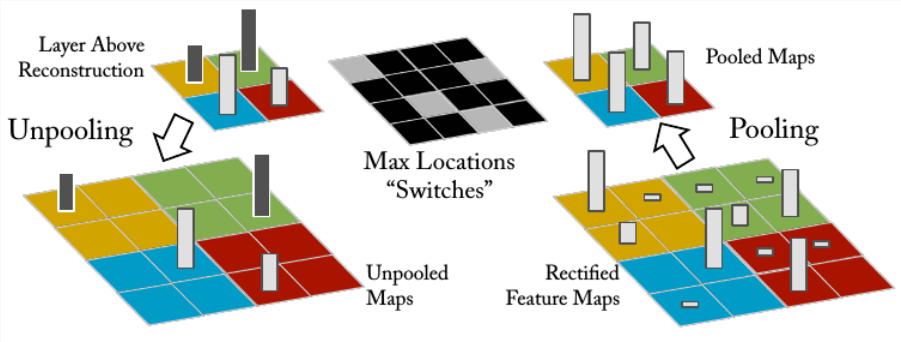
- For visualization, the authors employ a ***deconvolutional network***.
- **Objective**: to project hidden feature maps into original input space.
  - Visualize the activation functions of a specific filter.
- The name "deconvolutional" network may be unfortunate, since the network does not perform any deconvolutions (next slide).

Matthew D Zeiler, Graham W Taylor, and Rob Fergus, "Adaptive deconvolutional networks for mid and high level feature learning," in *IEEE International Conference on Computer Vision (ICCV)*, 2011, pp. 2018–2025

Devonvolutional network structure



- **Unpooling:**
  - The max-pooling operation is non-invertible.
  - Switch variables: record the locations of maxima.
  - It places the reconstructed features into the recorded locations.



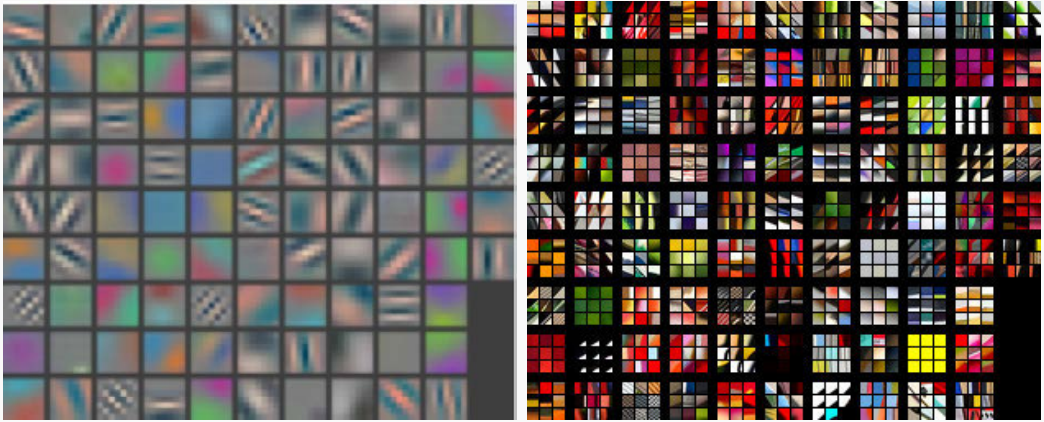
Devonvolutional network description

- **Rectification:** signals go through a ReLu operation.
- **Filtering:**
  - Use of transposed convolution.
  - Filters are flipped horizontally and vertically
- Transposed convolution projects feature maps back to input space.
- Transposed convolution corresponds to the backpropagation of the gradient (an analogy from MLPs).

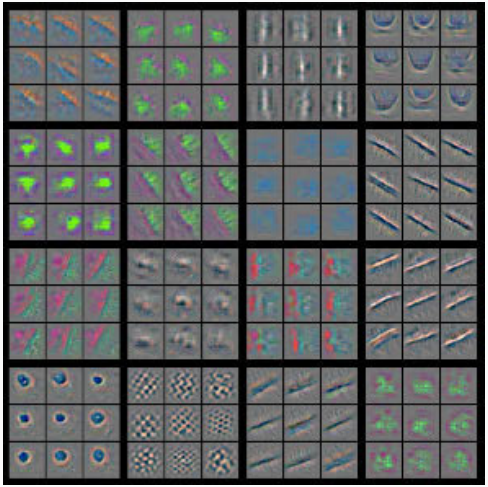
Feature visualization

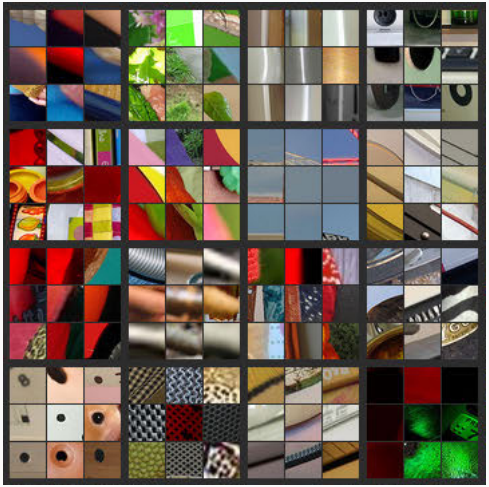
1. Evaluate the validation database on the trained network.
2. Record the nine highest activation values of each filter's output.
3. Project the recorded 9 outputs into input space for every neuron.
   - When projecting, all other activation units in the given layer are set to zero.
   - This operation ensures we only observe the gradient of a single channel.
   - ***Switch variables*** are used in the unpooling layers

First layer of Alexnet

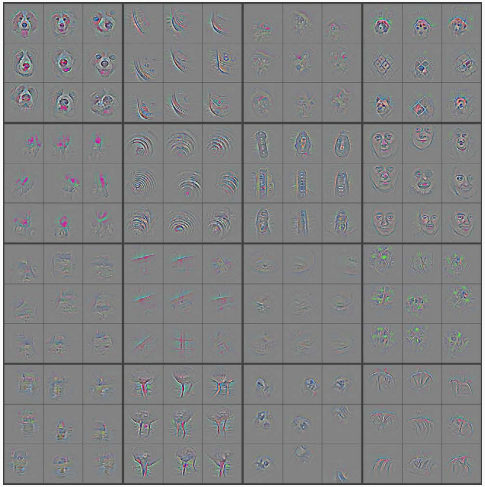


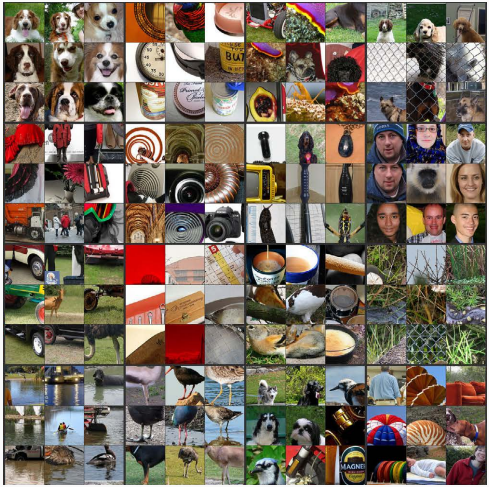
Second layer of Alexnet



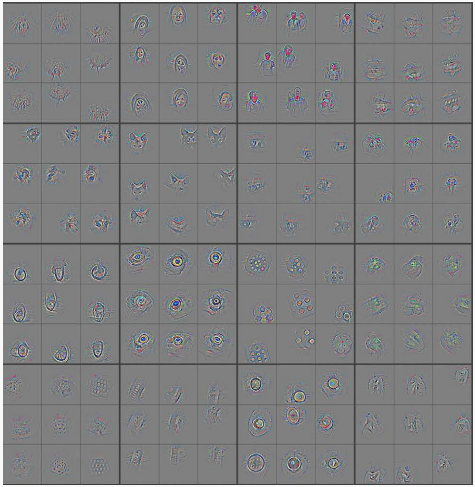


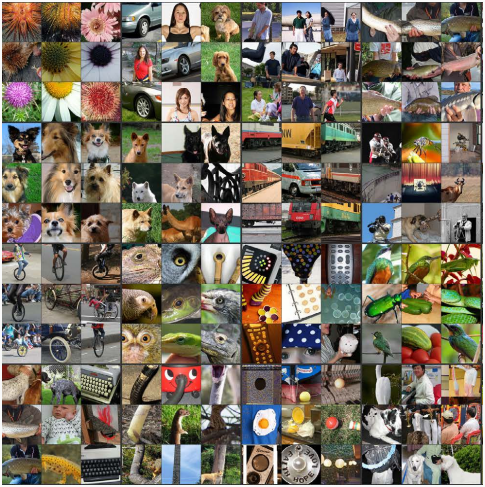
Fourth layer of Alexnet





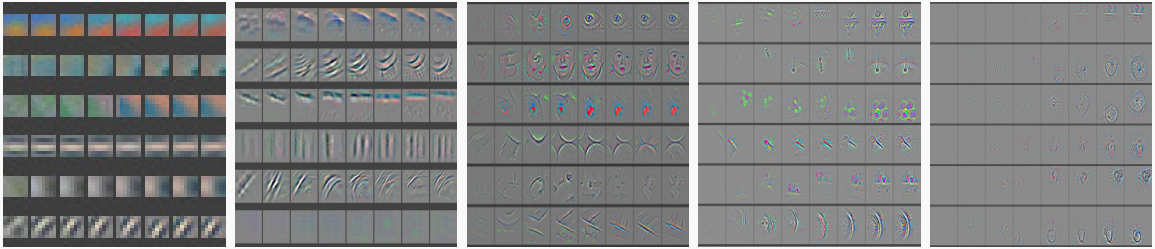
Fifth layer of Alexnet





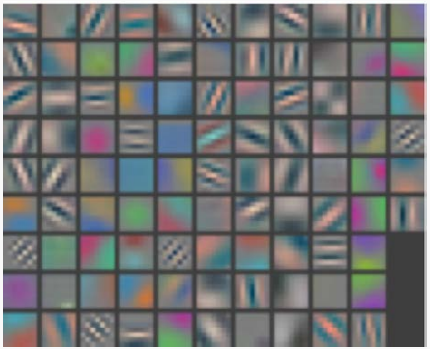
Feature evolution during training

- Evolution of features for 1, 2, 5, 10, 20, 30, 40 and 64 epochs.
- Strongest activation response for some random neurons at all 5 layers.
- Low layers converge soon after a few single passes.
- Fifth layer does not converge until a very large number of epochs.
- Lower layers may change their feature correspondence after converge.



Architecture comparison

- Check if different architectures respond similarly or more strongly to the same inputs.
- Left picture used filters 7×7 instead of 11×11, and reduced the stride from 4 to 2.
- Evidence that there are less dead units on the modified network.
- More defined features, whereas Alexnet has more aliasing effects.



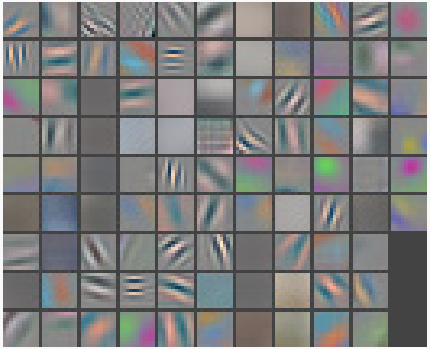


Image reconstruction

Image reconstruction

- Reconstruction of an image from latent features.
- Layers in the network retain an accurate photographical representation about the image, retaining geometric and photometric invariance.
- $a^{[l]}$ corresponds to the latent representation of layer l.
- Solve the optimization problem:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{y}} J_C^{[l]}(\mathbf{x}, \mathbf{y}) + \lambda R(\mathbf{y}),$$

where

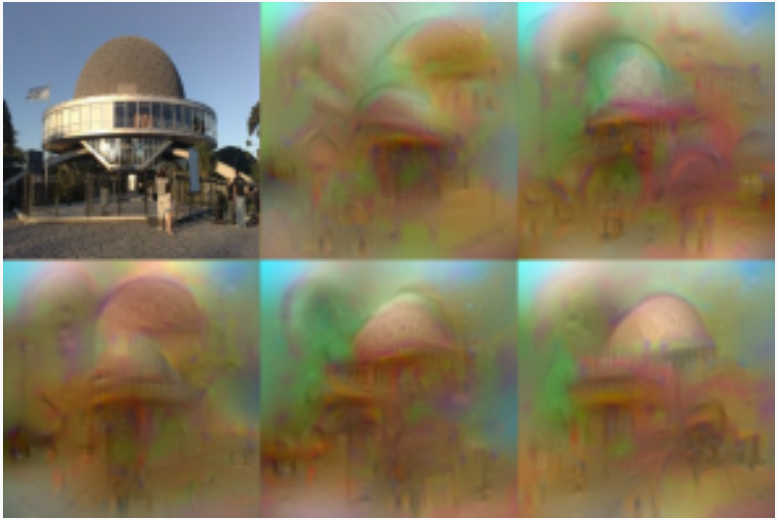
$$J_C^{[l]}(\mathbf{x}, \mathbf{y}) = \left\| a^{[l](G)} - a^{[l](C)} \right\|_{\mathcal{F}}^2.$$

Aravindh Mahendran and Andrea Vedaldi, "Understanding deep image representations by inverting them," Nov. 2014

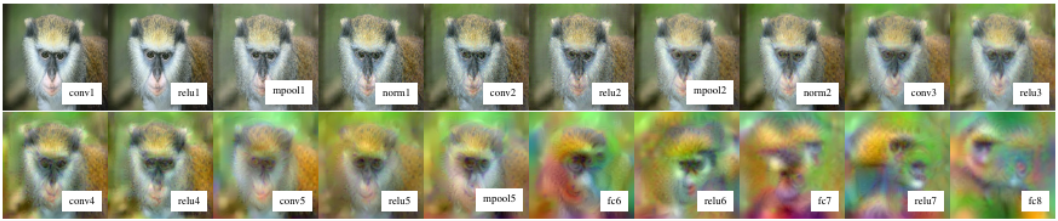
- Regularization
  - α-norm regularizer,
$$R_\alpha(\mathbf{y}) = \lambda_\alpha \|\mathbf{y}\|_\alpha^\alpha$$
  - ***Total variation*** regularizer:
$$R_{V_\beta}(\mathbf{y}) = \lambda_{V_\beta} \sum_{i,j,k} \left(\left(y_{i,j+1,k} - y_{i,j,k}\right)^2 + \left(y_{i+1,j,k} - y_{i,j,k}\right)^2 \right)^{\beta/2}.$$

- Image reconstruction:
  1. Initialize $\mathbf{y}$ with random noise.
  2. Feedforward pass the image.
  3. Compute the loss function.
  4. Compute gradients of the cost and backpropagate to input space.
  5. Update generated image G with a gradient step.

Example of image reconstruction



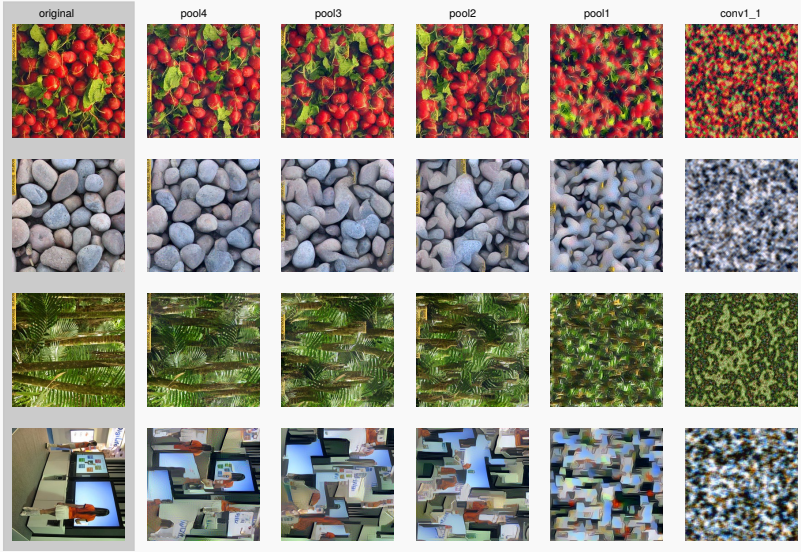
Example of image reconstruction



λ_{V^β}	1 conv1	2 relu1	3 pool1	4 norm1	5 conv2	6 relu2	7 pool2	8 norm2	9 conv3	10 relu3	11 conv4	12 relu4	13 conv5	14 relu5	15 pool5	16 fc6	17 relu6	18 fc7	19 relu7	20 fc8
λ_1	**10.0** ±5.0	**11.3** ±5.5	**21.9** ±9.2	**20.3** ±5.0	**12.4** ±3.1	**12.9** ±5.3	15.5 ±4.7	15.9 ±4.6	14.5 ±4.7	16.5 ±5.3	14.9 ±3.8	13.8 ±3.8	12.6 ±2.8	15.6 ±5.1	16.6 ±4.6	12.4 ±3.5	15.8 ±4.5	12.8 ±6.4	10.5 ±1.9	5.3 ±1.1
λ_2	20.2 ±9.3	22.4 ±10.3	30.3 ±13.6	28.2 ±7.6	20.0 ±4.9	17.4 ±5.0	**18.2** ±5.5	**18.4** ±5.0	**14.4** ±3.6	**15.1** ±3.3	**13.3** ±2.6	**14.0** ±2.8	15.4 ±2.7	13.9 ±3.2	15.5 ±3.5	14.2 ±3.7	13.7 ±3.1	15.4 ±10.3	10.8 ±1.6	5.9 ±0.9
λ_3	40.8 ±17.0	45.2 ±18.7	54.1 ±22.7	48.1 ±11.8	39.7 ±9.1	32.8 ±7.7	32.7 ±8.0	32.4 ±7.0	25.6 ±5.6	26.9 ±5.2	23.3 ±4.1	23.9 ±4.6	**25.7** ±4.3	**20.1** ±4.3	**19.0** ±4.3	**18.6** ±4.9	**18.7** ±3.8	**17.1** ±3.4	**15.5** ±2.1	**8.5** ±1.3

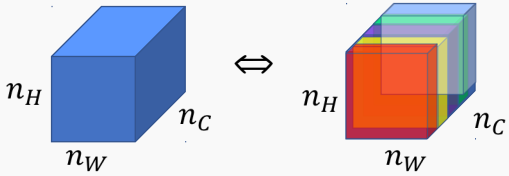
Texture synthesis

Texture examples



Texture synthesis using convnets

- Generate high perceptual quality images that imitate a given texture.
- Uses a trained convolutional network for object classification.
- Employs the correlation of features among layers as a generative process.
- Output of a layer:



Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, "Texture synthesis using convolutional neural networks".

Cross-correlation of feature maps: Gram matrices

- Denote the output of a given filter k at layer l with $a^{[l]}_{ijk}$.
- The cross-correlation between this output and a different channel k':

$$G^{[l]}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_W^{[l]}} a^{[l]}_{ijk} a^{[l]}_{ijk'}.$$

- The Gram matrix:

$$G^{[l]} = A^{[l]}(A^{[l]})^T$$

where $(A^{[l]})^T = (a^{[l]}_{::1}, \ldots, a^{[l]}_{::n_C^{[l]}})$.

Generating new textures

- To create a new texture, we synthesize an image that has similar correlation as the one we want to reproduce.
- $G^{[l](S)}$ refers to the Gram matrix of the ***style*** image, and $G^{[l](G)}$ to the newly ***generated*** image.

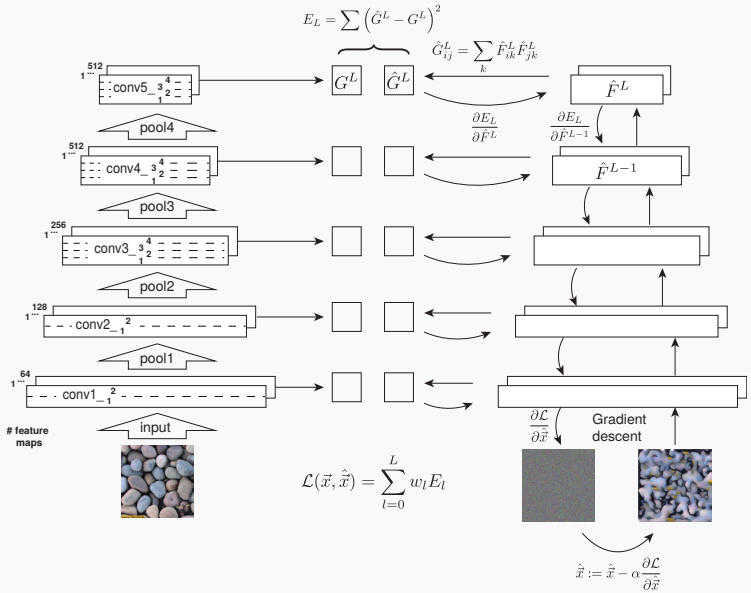
$$J_S^{[l]}(G^{[l](S)}, G^{[l](G)}) = \frac{1}{4(n_W^{[l]} n_H^{[l]})^2} \left\| G^{[l](S)} - G^{[l](G)} \right\|_{\mathcal{F}}^2,$$

  where $\|G\|_{\mathcal{F}} = \sqrt{\sum_{ij}(g_{ij})^2}$ corresponds to the Frobenius norm.
- We combine all of the layer losses into a global cost function:

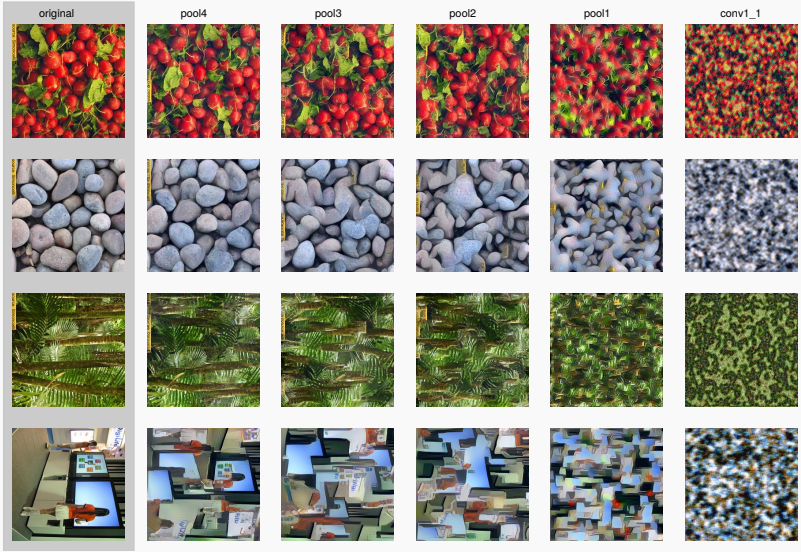
$$J_S(\mathbf{x}, \mathbf{y}) = \sum_{l=0}^{L} \lambda_l J_S^{[l]}(G^{[l](S)}, G^{[l](G)}),$$

  for given weights $\lambda_1, \ldots, \lambda_L$:

Process description



Texture examples



Neural style transfer

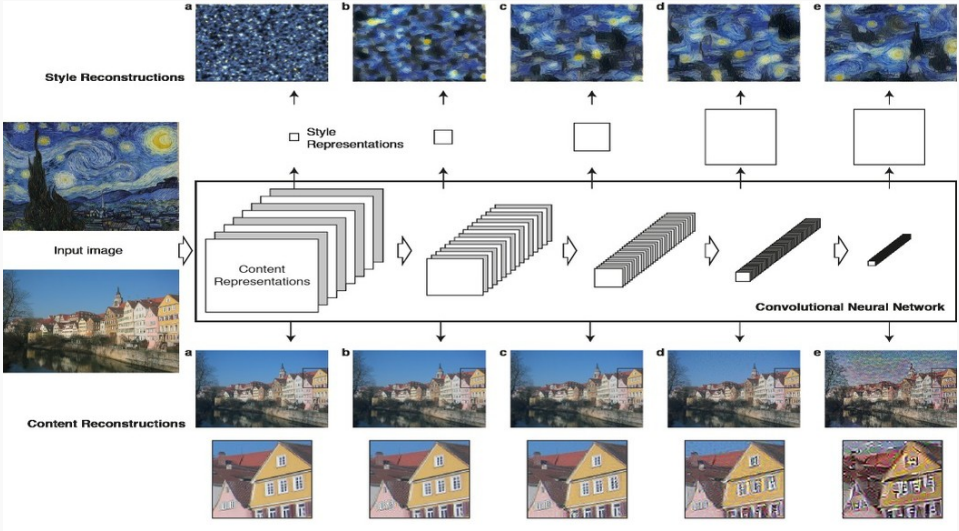
Neural style transfer

- Artistic generation of high perceptual quality images that combine the style or texture of an input image, and the elements or content from a different one.

Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, "A neural algorithm of artistic style," Aug. 2015.

Other examples

Methodology



Objective function

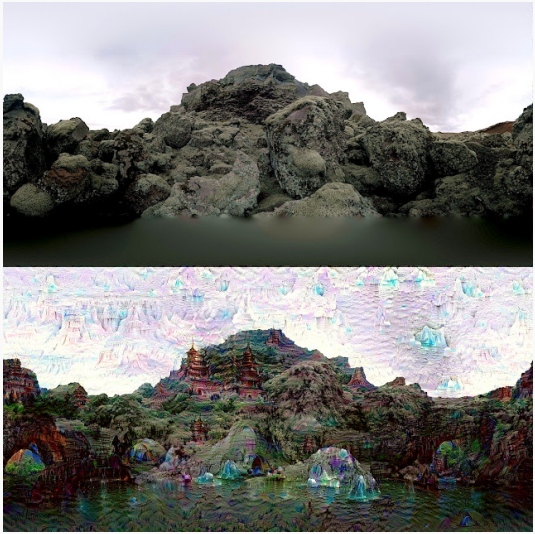
- Neural style transfer combines content and style reconstruction.

$$J_{\text{total}}(\mathbf{x}, \mathbf{y}) = \alpha J_C^{[l]}(\mathbf{x}, \mathbf{y}) + \beta J_S(\mathbf{x}, \mathbf{y})$$

- Need to choose a layer to represent content.
  - middle layers are recommended (not too shallow, not too deep) for best results.
- A set of layers to represent style.
- Total cost is minimized using backpropagation.
- Input $\mathbf{y}$ is initialized with random noise.
- Replacing the max-pooling layers with average pooling improves the gradient flow, and this produces more appealing pictures.

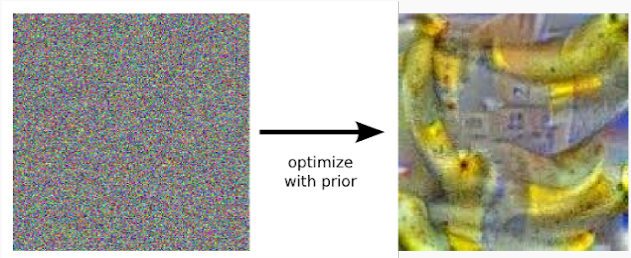
DeepDream

Art from visualization techniques



Inceptionism: Going Deeper into Neural Networks

- Discriminative trained network for classification.
  - First layer maybe looks for edges or corners.
  - Intermediate layers interpret the basic features to look for overall shapes or components, like a door or a leaf.
  - Final layers assemble those into complete interpretations: trees, buildings, etc.
- Turn NN upside down: what sort of image would result in Banana.
  - need to add texture information (prior).

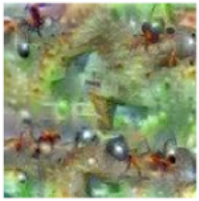


https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Class generation


Hartebeest


Measuring Cup


Ant


Starfish


Anemone Fish


Banana


Parachute


Screw

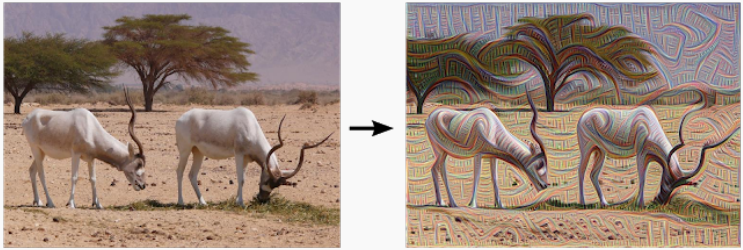
Visualizing mistakes

- Generating dumbbells always pictures them with an arm:

- The network failed to completely distill the essence of a dumbbell.
- Visualization can help us correct these kinds of training mishaps.

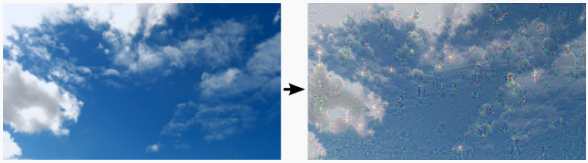
Enhancing feature maps

- Instead of prescribing which feature we want the network to amplify, we can also let the network make that decision.
  - feed the network an image.
  - then pick a layer and ask the network to enhance whatever it detected.
- Lower layers tend to produce strokes or simple ornament-like patterns:

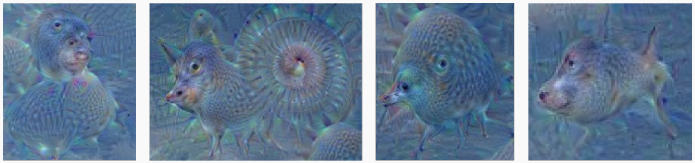


Enhancing feature maps: higher layers

- With higher level layers complex features or even whole objects tend to emerge.
  - these identify more sophisticated features in images...
- The process creates a feedback loop: if a cloud looks a little bit like a bird, the network will make it look more like a bird.



- If we train on pictures of animals:



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

Enhancing features: bias

- Results vary quite a bit with the kind of image, because the features that are entered bias the network towards certain interpretations.

We must go deeper: Iterations

- Apply the algorithm iteratively on its own outputs and apply some zooming after each iteration.
- We get an endless stream of new impressions.
- We can even start this process from a random-noise image.

Questions?