Chapter 9: Advanced Deep Learning for Computer Vision

Matthew Kehoe

9.4: Interpreting what convnets learn

May 9, 2023

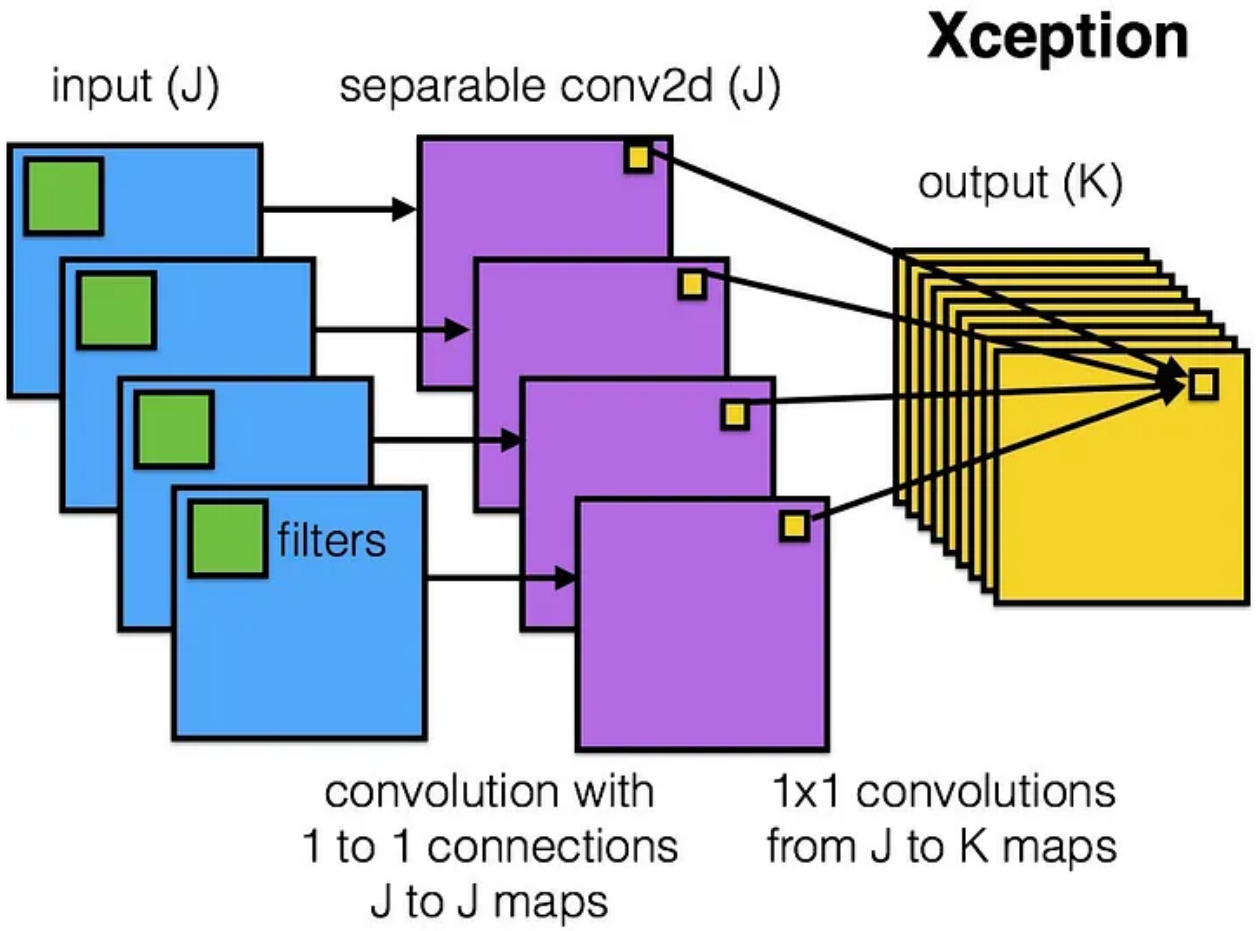
Overview

General Information

1. Google Research Machine Learning: Link.
2. Fork the Github repository here.
3. Using Github with Google Colab: Link.
4. Course at Stanford: Link.
5. Upgrade your memory on Google Colab: Link. Doesn't work anymore.
6. Convnet: A convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.

The Xception Model

- Xception stands for the extreme version of Inception. With a modified depthwise separable convolution, it is even better than Inception-v3. It was developed at Google: Summary and Paper.



Problems with Computer Vision Applications

- A fundamental problem when building a computer vision application is that of interpretability: why did your classifier think a particular image contained a bike, when all you can see is a sedan?
- This is especially relevant to use cases where deep learning is used to complement human expertise, such as in medical imaging use cases.
- It's often said that deep learning models are "black boxes": they learn representations that are difficult to extract and present in a human-readable form.
- Although this is partially true for certain types of deep learning models, it's definitely not true for convnets.

Section 9.4 Summary

The representations learned by convnets are highly amenable to visualization, in large part because they're representations of visual concepts. Techniques for conceptualizing these representations include

1. Visualizing intermediate convnet outputs (intermediate activations) — Useful for understanding how successive convnet layers transform their input, and for getting a first idea of individual convnet filters.
2. Visualizing convnet filters — Useful for understanding precisely what visual pattern or concept each filter in a convnet is receptive to.
3. Visualizing heatmaps of class activation in an image — Useful for understanding which parts of an image were identified as belonging to a given class, thus allowing you to localize objects in images.

Visualizing intermediate activations

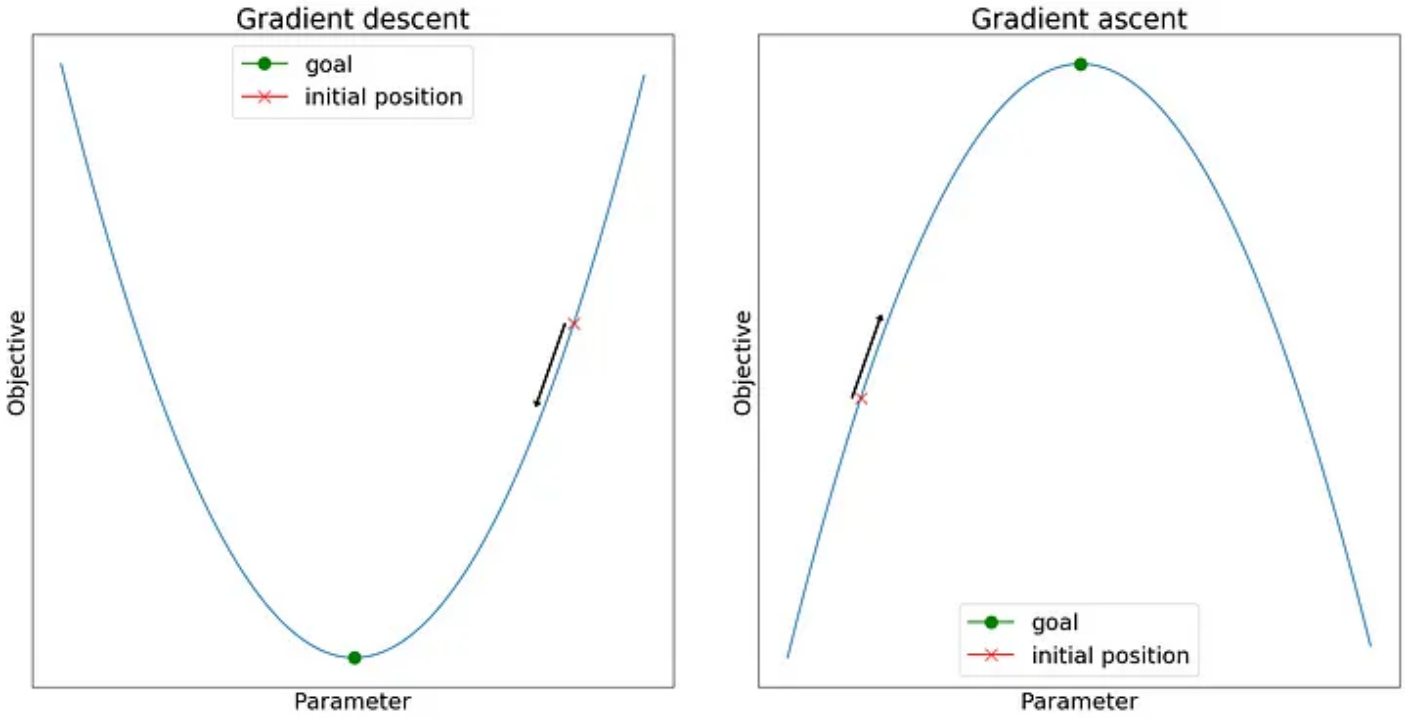
- Display the values returned by various convolution and pooling layers in a model, given a certain input (the output of a layer is often called its activation, the output of the activation function).
- This gives a view into how an input is decomposed into the different filters learned by the network.
- We want to visualize feature maps with three dimensions: width, height, and depth (channels). Each channel encodes relatively independent features, so the proper way to visualize these feature maps is by independently plotting the contents of every channel as a 2D image.

Model: Cats-versus-dogs classification problem in §8.2

- We will start by loading the model we saw in Section 8.2.
- I will do this by expanding what François Chollet wrote in Google Colab.

Gradient Ascent and Gradient Descent

- To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient (or of the approximate gradient) of the function at the current point.
- If instead one takes steps proportional to the positive of the gradient, one approaches a local maximum of that function; the procedure is then known as gradient ascent.



Other Visualization Techniques

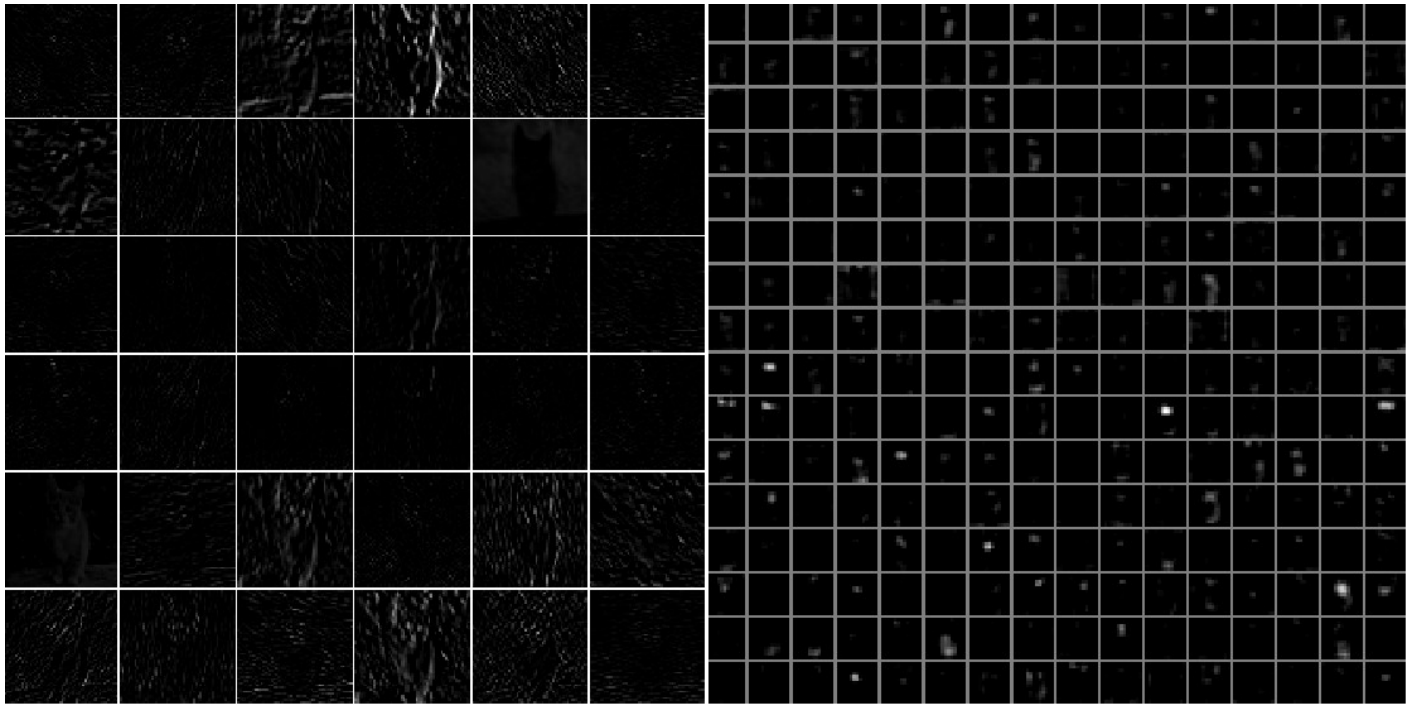
Several approaches for visualizing and understanding CNNs have been developed in the literature as a response to the common criticism that Neural Networks are not interpretable. These include:

- Visualizing the activations and first-layer-weights
- Retrieving images that maximally activate a neuron
- Embedding the codes with t-SNE
- Occluding parts of the image
- Visualizing the data gradient and friends
- and much more

Visualizing the activations

- Layer activations: one of the most straight-forward visualization techniques is to show the activations of the network during the forward pass.
- In ReLU networks, activations start out looking blobby and dense. As the training progresses, activations usually become more sparse and localized.
- With this visualization, it is easy to see where some activation maps are all zero, which can indicate the presence of dead filters and show high learning rates.

Visualizing the activations (continued)

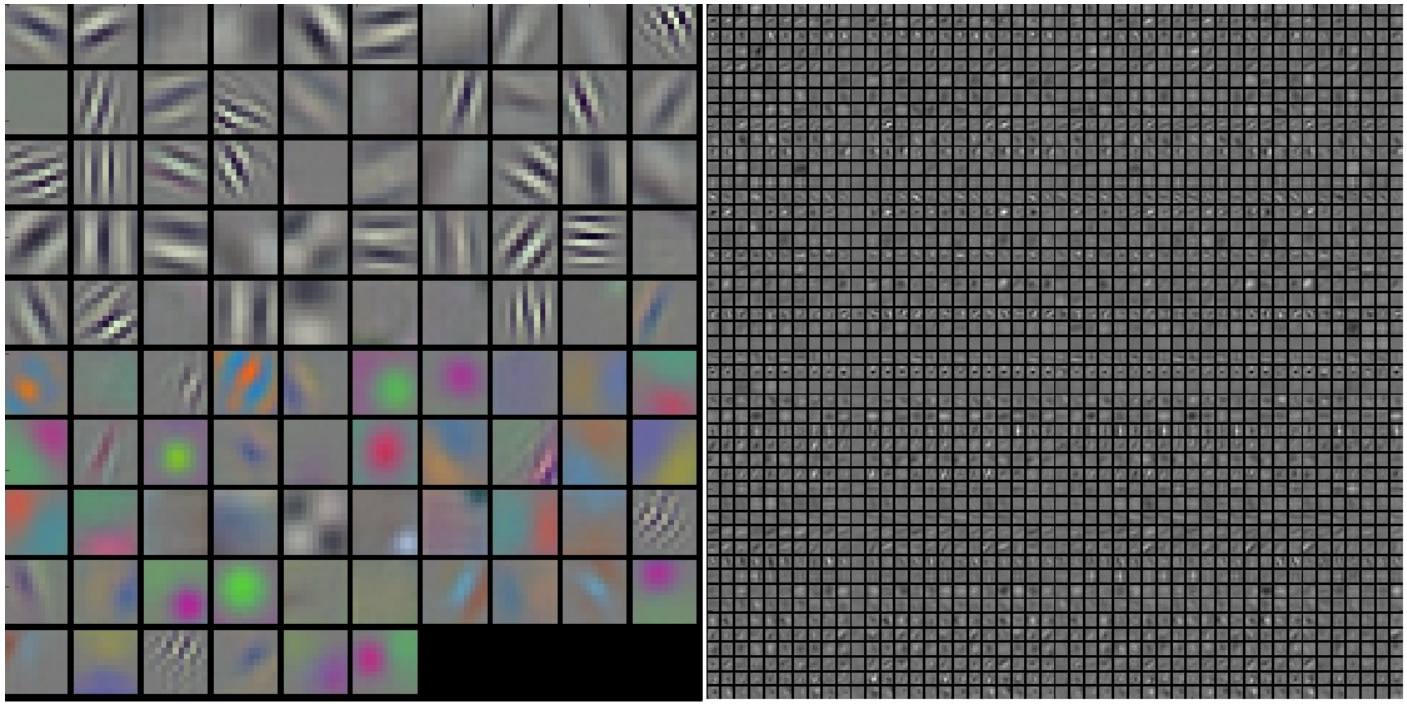


Typical-looking activations on the first CONV layer (left), and the 5th CONV layer (right) of a trained AlexNet looking at a picture of a cat. Every box shows an activation map corresponding to some filter. Notice that the activations are sparse (most values are zero, as shown in black) and are mostly local.

Visualizing the first-layer weights

- Conv/FC filters: The second common strategy is to visualize the weights.
- These are usually most interpretable on the first CONV layer which is looking directly at the raw pixel data, but it is possible to also show the filter weights deeper in the network.
- The weights are useful to visualize because well-trained networks usually display nice and smooth filters without any noisy patterns.
- Noisy patterns can be an indicator of a network that hasn't been trained for long enough, or possibly a very low regularization strength that may have led to overfitting.

Visualizing the first-layer weights (continued)

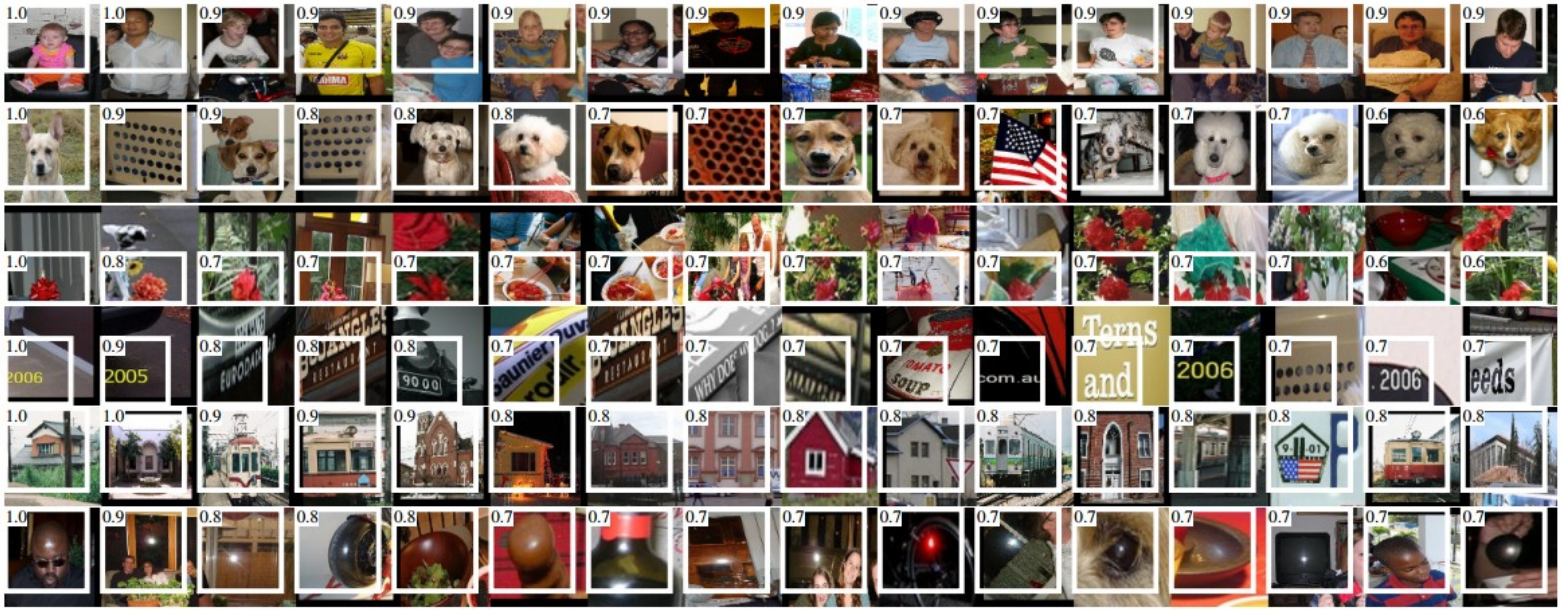


Typical-looking filters on the first CONV layer (left), and the 2nd CONV layer (right) of a trained AlexNet. Notice that the first-layer weights are very nice and smooth, indicating a nicely converged network. The 2nd CONV layer weights are not as interpretable, but it is apparent that they are still smooth, well-formed, and absent of noisy patterns.

Retrieving images that maximally activate a neuron

- Another visualization technique is to take a large dataset of images and feed them into the network while keeping track of which images maximally activate a neuron.
- We can then visualize the images to get an understanding of what the neuron is looking for in its receptive field.
- This visualization technique (among others) is shown in Rich feature hierarchies for accurate object detection and semantic segmentation by Ross Girshick et al.

Retrieving images that maximally activate a neuron (ctd)



Maximally activating images for some POOL5 (5th pool layer) neurons of an AlexNet. The activation values and the receptive field of the particular neuron are shown in white. (In particular, note that the POOL5 neurons are a function of a relatively large portion of the input image). It can be seen that some neurons are responsive to upper bodies, text, or specular highlights.

Retrieving images that maximally activate a neuron (ctd)

- One problem with this approach is that ReLU neurons do not necessarily have any semantic meaning by themselves.
- Rather, it is more appropriate to think of multiple ReLU neurons as the basis vectors of some space that represents in image patches. In other words, the visualization is showing the patches at the edge of the cloud of representations, along the (arbitrary) axes that correspond to the filter weights.
- Further analysis was performed by Szegedy et al. in Intriguing properties of neural networks, where they perform a similar visualization along arbitrary directions in the representation space.

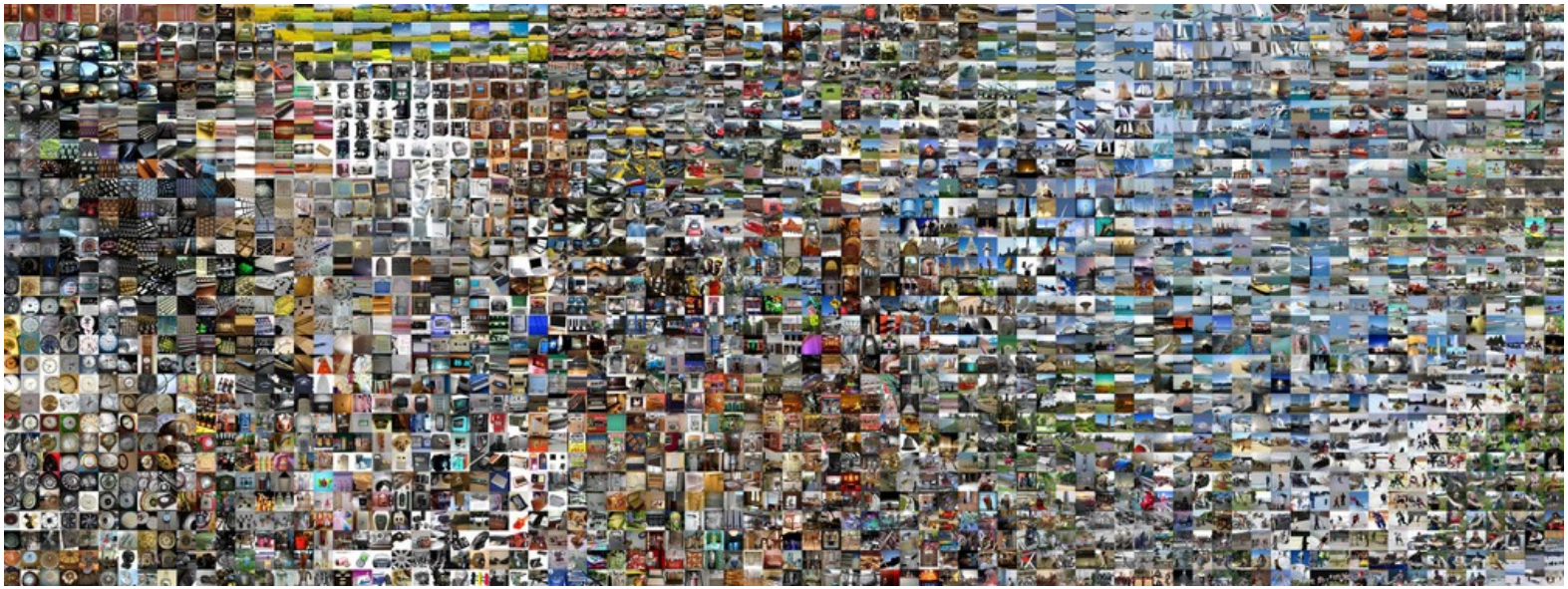
Embedding the codes with t-SNE

- Convnets can be interpreted as gradually transforming the images into a representation in which the classes are separable by a linear classifier.
- We can get a rough idea about the topology of this space by embedding images into two dimensions so that their low-dimensional representation has approximately equal distance as the high-dimensional representation.
- There are many embedding methods which embed high-dimensional vectors in a low-dimensional space while preserving the pairwise distance between the points. One of the most popular methods is t-Distributed Stochastic Neighbor Embedding (t-SNE).

Embedding the codes with t-SNE

- To produce an embedding, we can take a set of images and use the ConvNet to extract the CNN codes (e.g. in AlexNet the 4096-dimensional vector right before the classifier, and crucially, including the ReLU non-linearity).
- We can then plug these into t-SNE and get 2-dimensional vector for each image. The corresponding images can them be visualized in a grid.

Embedding the codes with t-SNE (continued)

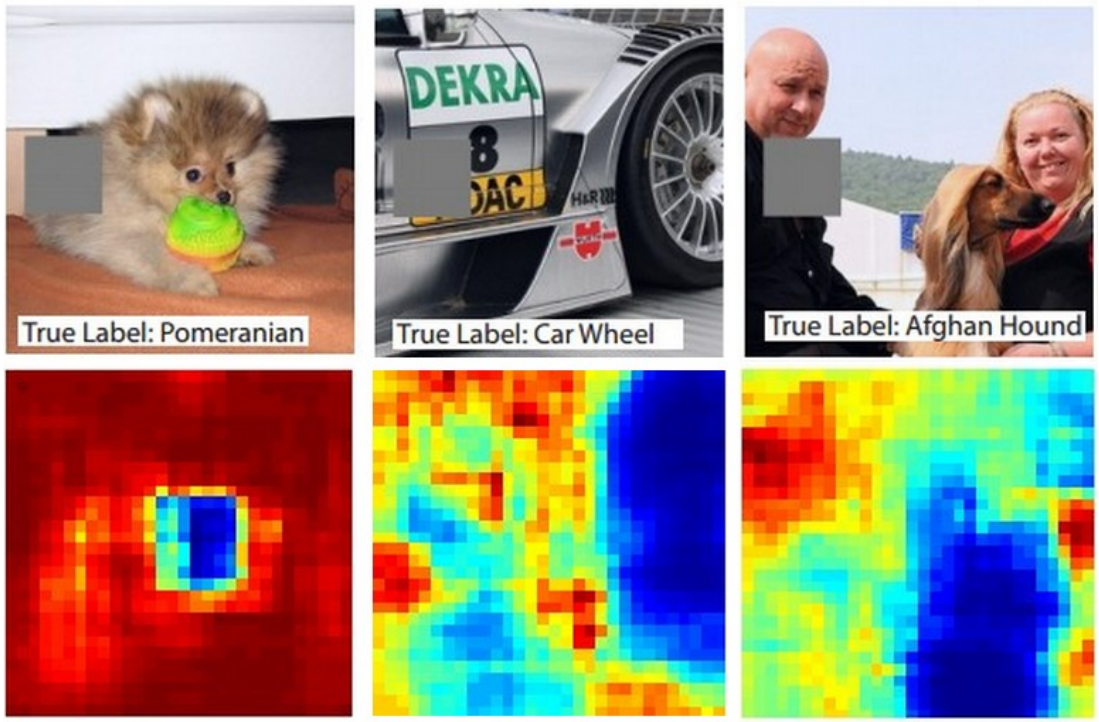


t-SNE embedding of a set of images based on their CNN codes. Images that are nearby each other are also close in the CNN representation space, which implies that the CNN "sees" them as being very similar. Notice that the similarities are more often class-based and semantic rather than pixel and color-based. For more details on how this visualization was produced see the t-SNE visualization of CNN codes.

Occluding parts of the image

- Suppose a ConvNet classifies an image as a dog. How can we be sure that it is actually picking a dog as oppose to some contexual clues from the background of the image?
- One way of investigating which part of the image the ConvNet predicts is by plotting the probability of the class of interest (e.g., dog class) as a function of the position of an occluder object.
- That is, we iterate over regions of the image, set a patch of the image to be all zero, and look at the probability of the class.
- We can then visualize the probability as a 2-dimensional heat map.

Occluding parts of the image (continued)



Three input images (top). Notice that the occluder region is shown in grey. As we slide the occluder over the image we record the probability of the correct class and then visualize it as a heatmap (shown below each image). For instance, in the left-most image we see that the probability of Pomeranian plummets when the occluder covers the face of the dog.

Visualizing the data gradient and friends

- Data Gradient: Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps.
- DeconvNet: Visualizing and Understanding Convolutional Networks.
- Guided Backpropagation: Striving for Simplicity: The All Convolutional Net.

Other Techniques

- Reconstructing original images based on CNN Codes: Understanding Deep Image Representations by Inverting Them.
- How much spatial information is preserved? Do ConvNets Learn Correspondence? (tldr; yes)
- Plotting performance as a function of image attributes: ImageNet Large Scale Visual Recognition Challenge.
- Fooling ConvNets: Explaining and Harnessing Adversarial Examples.
- Comparing ConvNets to Human labelers: What I learned from competing against a ConvNet on ImageNet.