Visualization and Interpretability

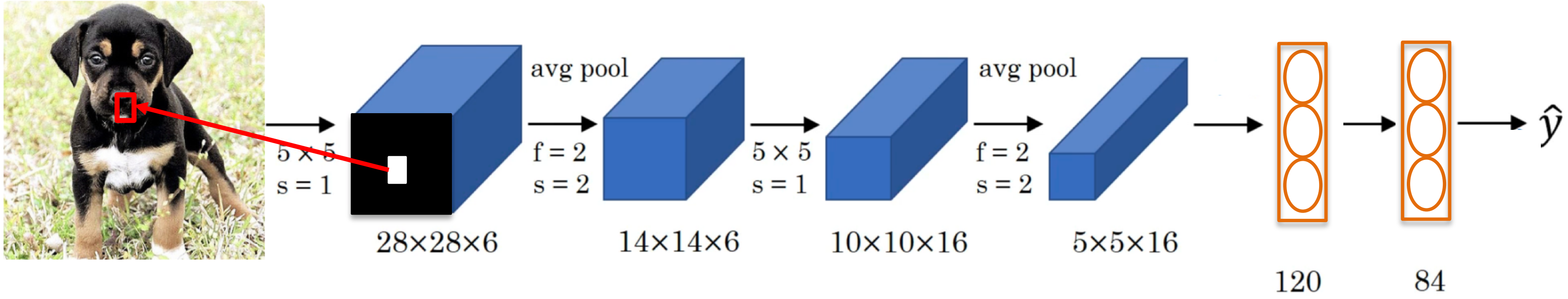
Visualization of ConvNets

- Visualization of Features
- Visualization of Activations
- Visualization of Gradients
- T-SNE Visualization
- DeepDream
- ….

Visualization is a great way for debugging!

Visualizing and understanding CNNs

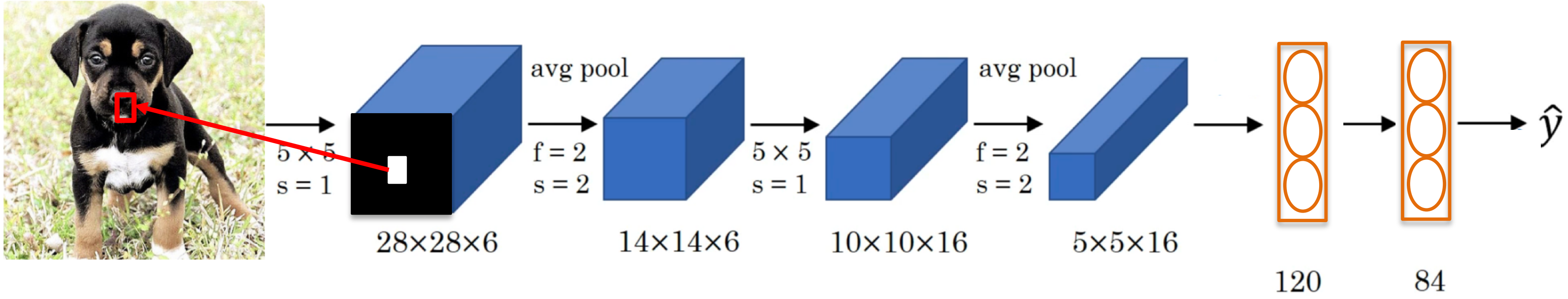
Visualizing in the image space

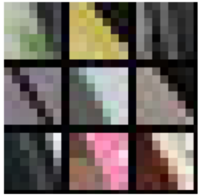


- Pick a unit in layer 1.
- Find the 9 image patches in your dataset that maximize the unit's activation.

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing in the image space





Feature map 1, layer 1, 9 image patches that provided the highest activation

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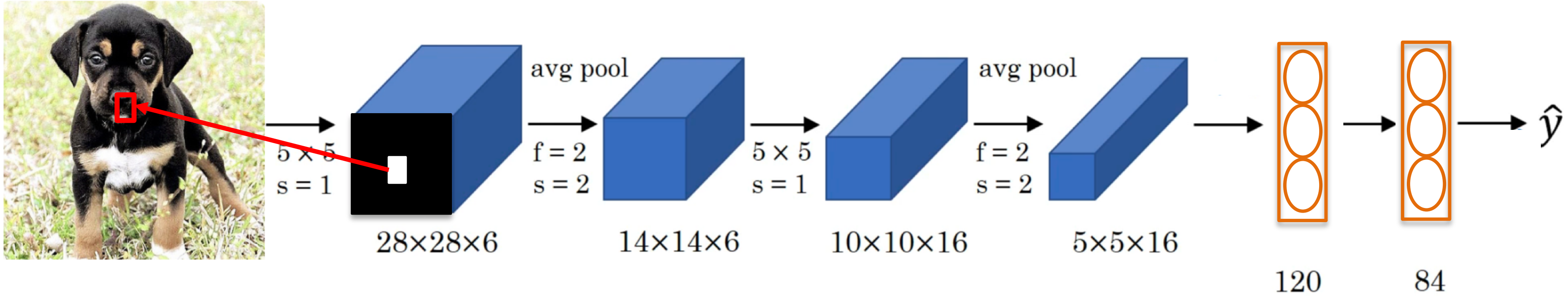
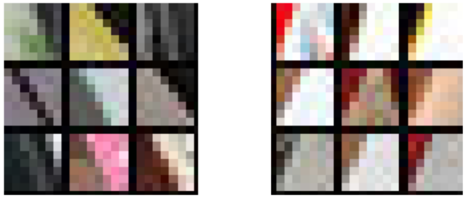
Visualizing in the image space





Feature map 2, layer 1, 9 image patches that provided the highest activation

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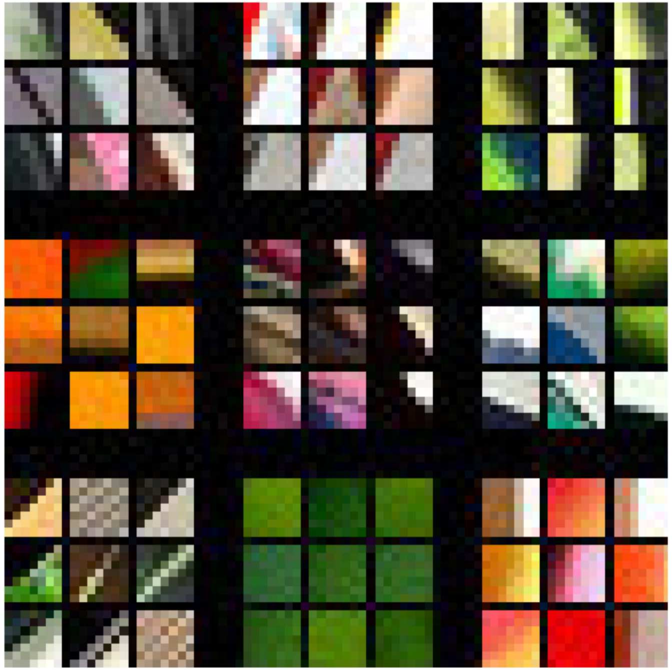
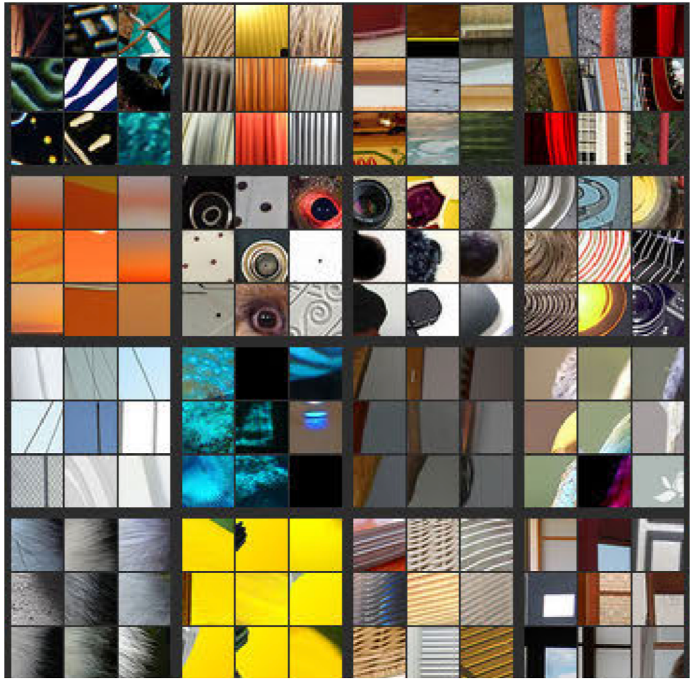
Visualizing in the image space

Layer 1



Layer 2



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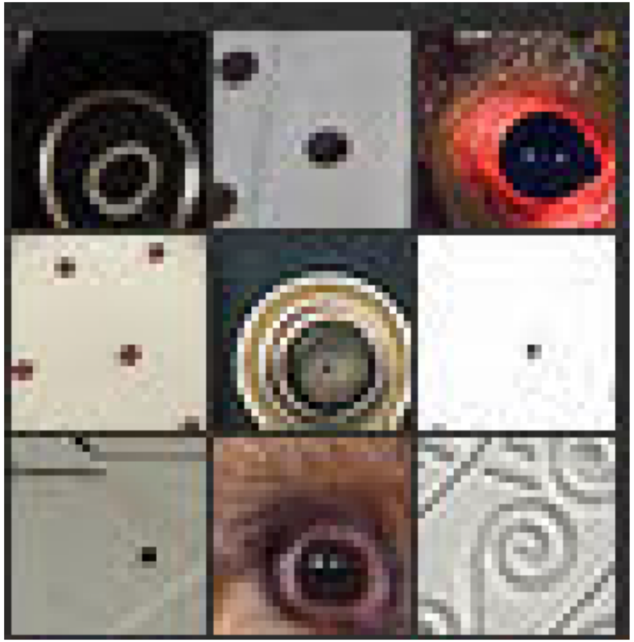
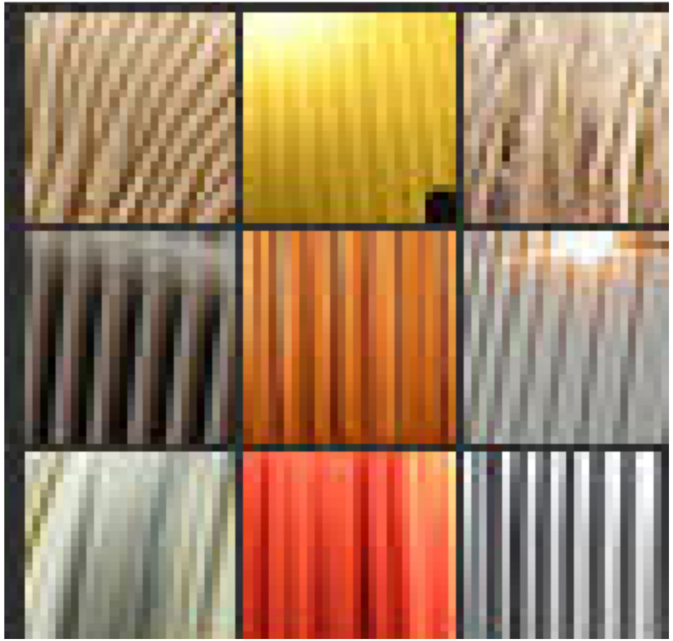
Visualizing in the image space

Zoom in, examples of Layer 2





Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing in the image space

Zoom in, examples of Layer 5

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks“. ECCV 2014

Visualizing in the image space

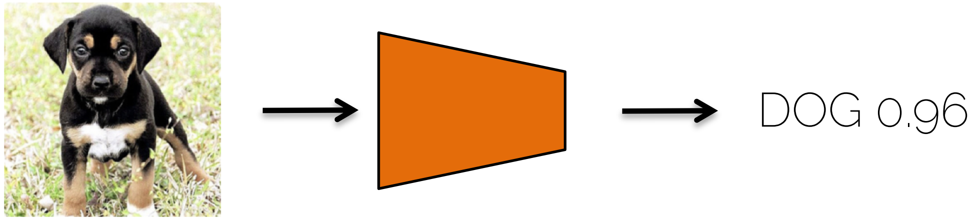
Zoom in, examples of Layer 5

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing importance

The occlusion experiment

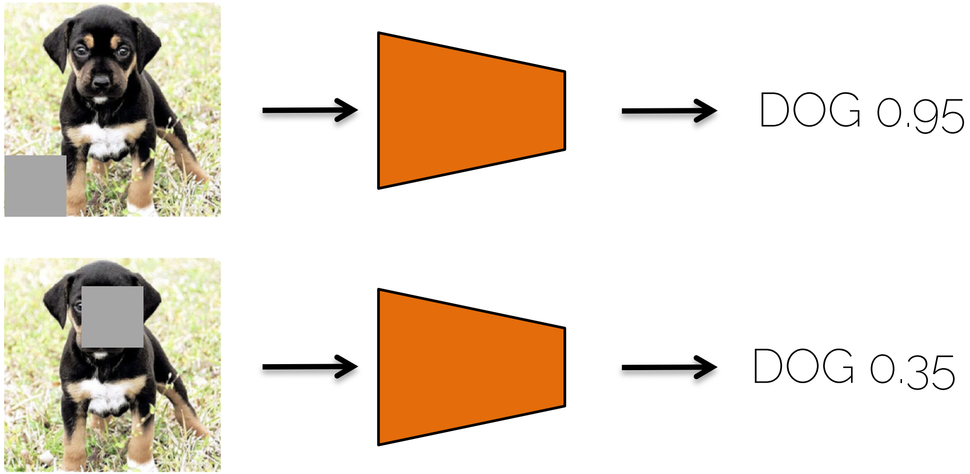
- Block different parts of the image and see how the classification score changes



Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

The occlusion experiment

- Block different parts of the image and see how the classification score changes

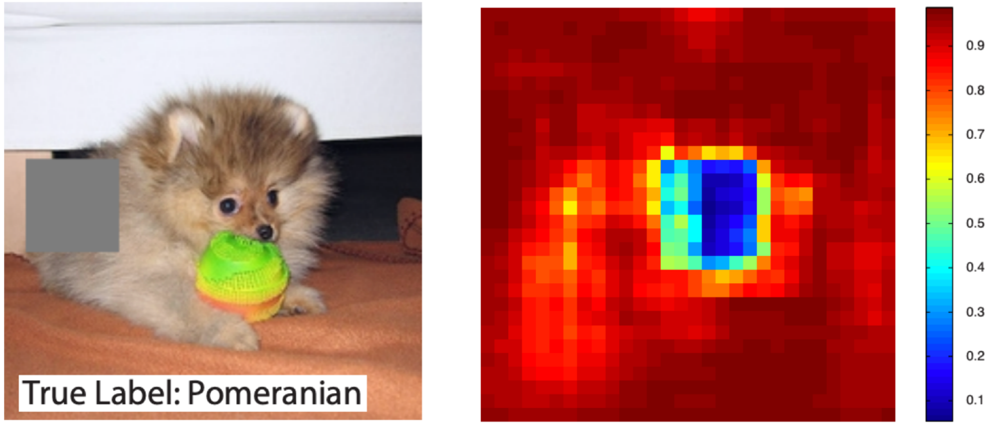


The face of the dog is more important for correct classification

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

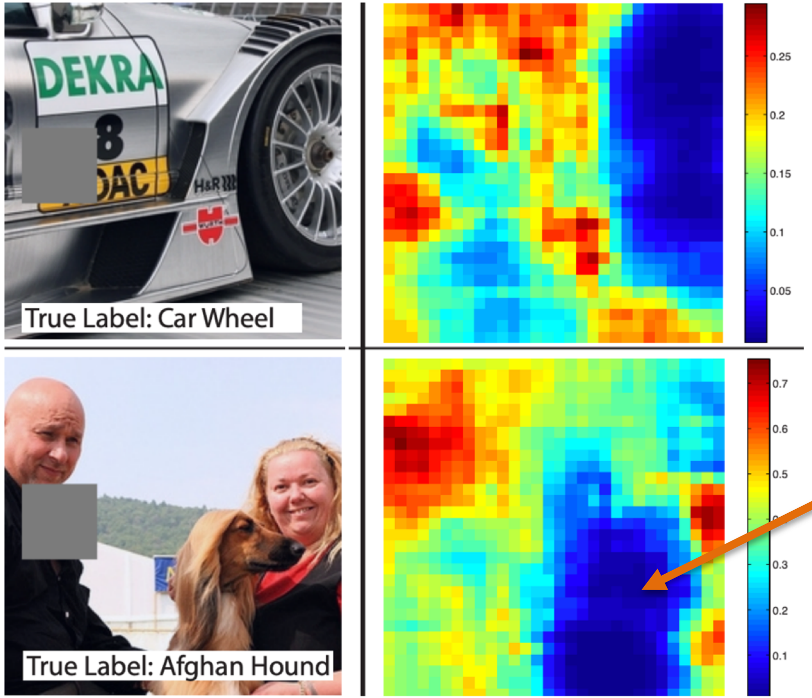
The occlusion experiment

- Create a map, where each pixel represents the classification probability if an occlusion square is placed in that region



Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

The occlusion experiment



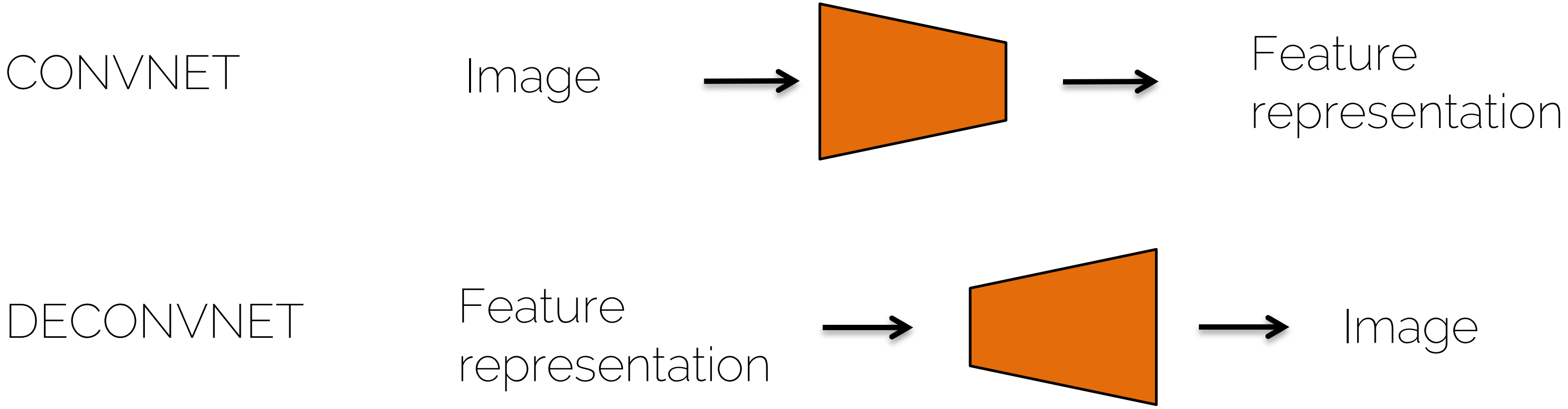
Most important pixels for classification

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing features

DeconvNet

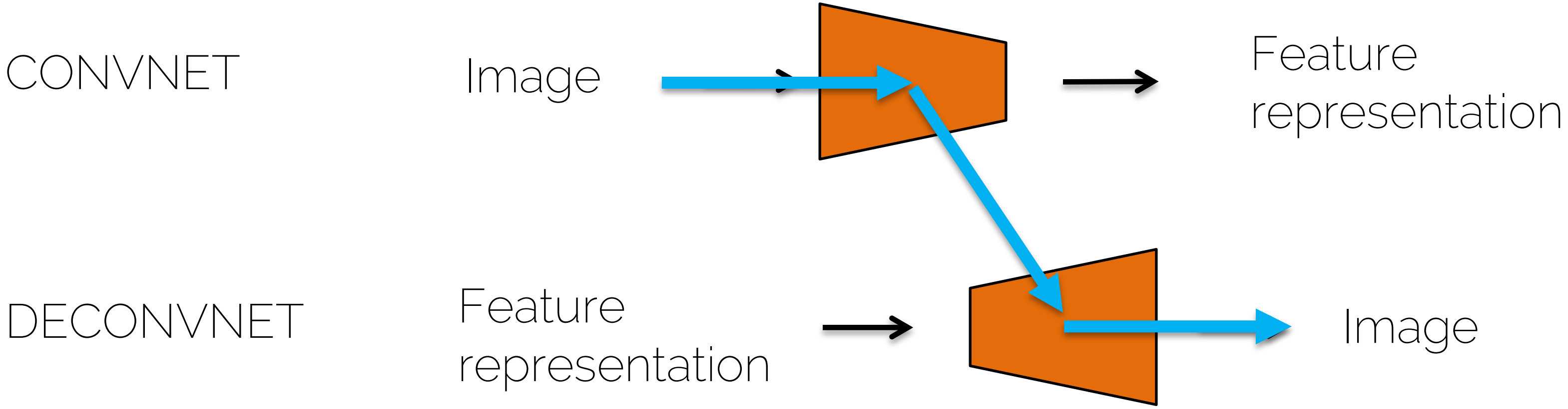
- Map activations back to the image space



Zeiler et al. CVPR 2010, ICCV 2011

Visualizing features

- Use a DeconvNet to visualize a certain layer



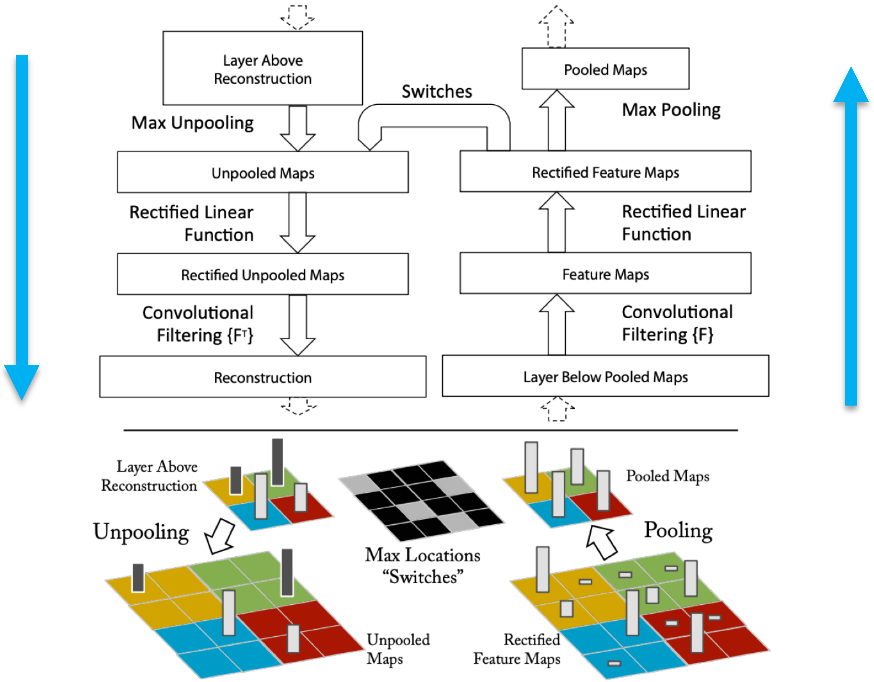
Zeiler et al. CVPR 2010, ICCV 2011

Visualizing features

- Choose an input image
- Forward pass through the network.
- Observation: filter 15 of the 3rd layer is highly activated by this image
- Goal: visualize filter 15 of the 3rd layer
- Zero out all other filters
- Pass the layer through the DeconvNet

Visualizing features

DECONVNET



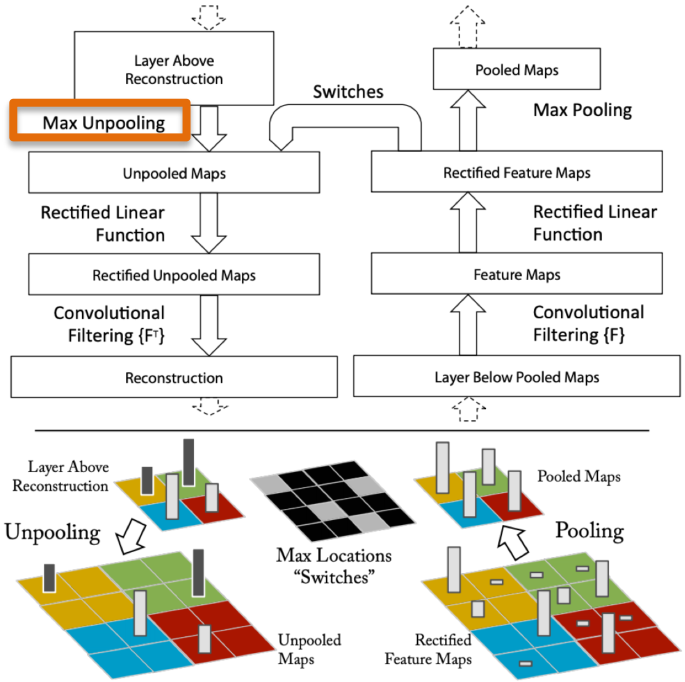
CONVNET

Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing features

- Unpooling

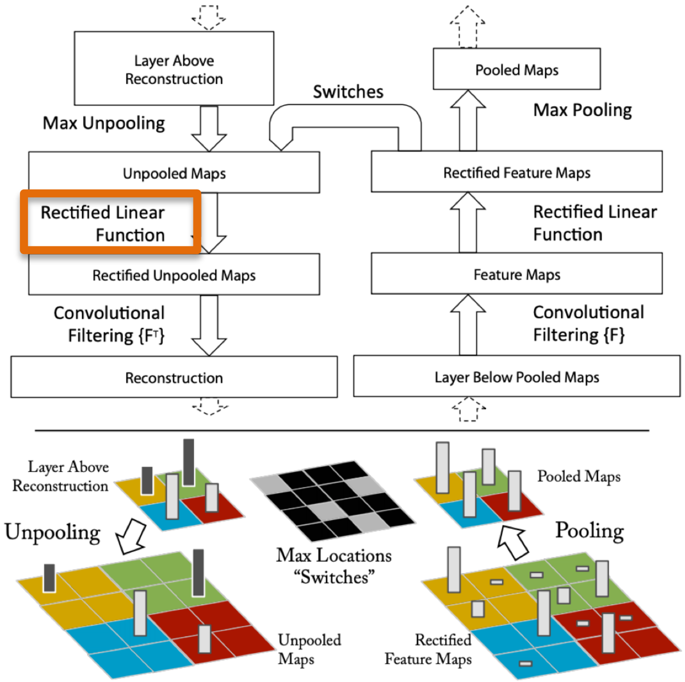
Keep the locations where the max came from



Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing features

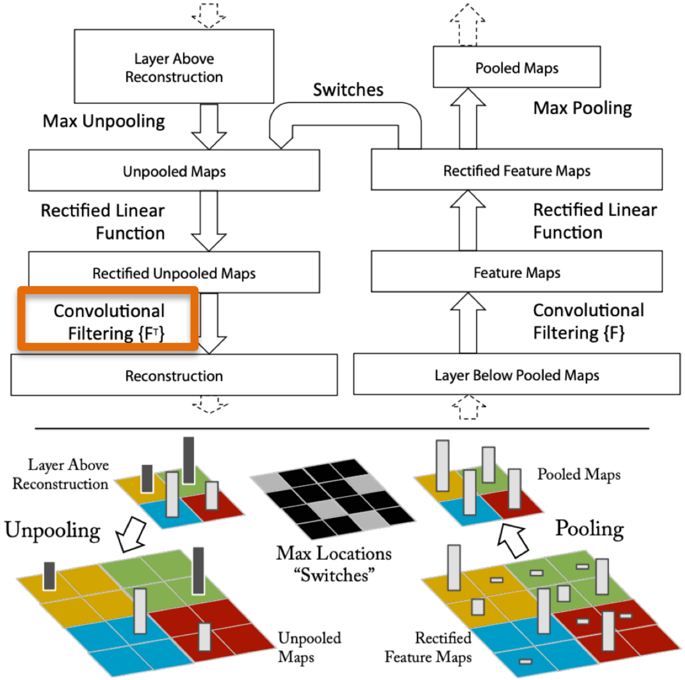
- ReLU: you are still interested in having positive features for visualization



Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing features

- Deconvolution operation
- In practice we convolve with the transpose of the learned filter



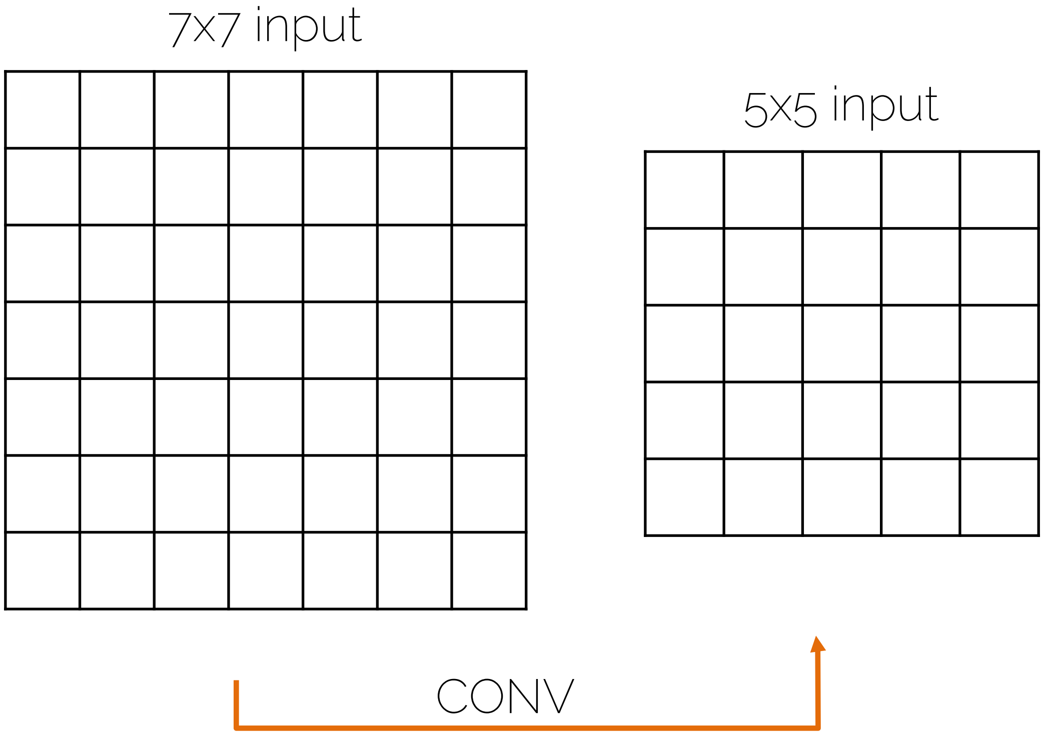
Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Why the transpose?

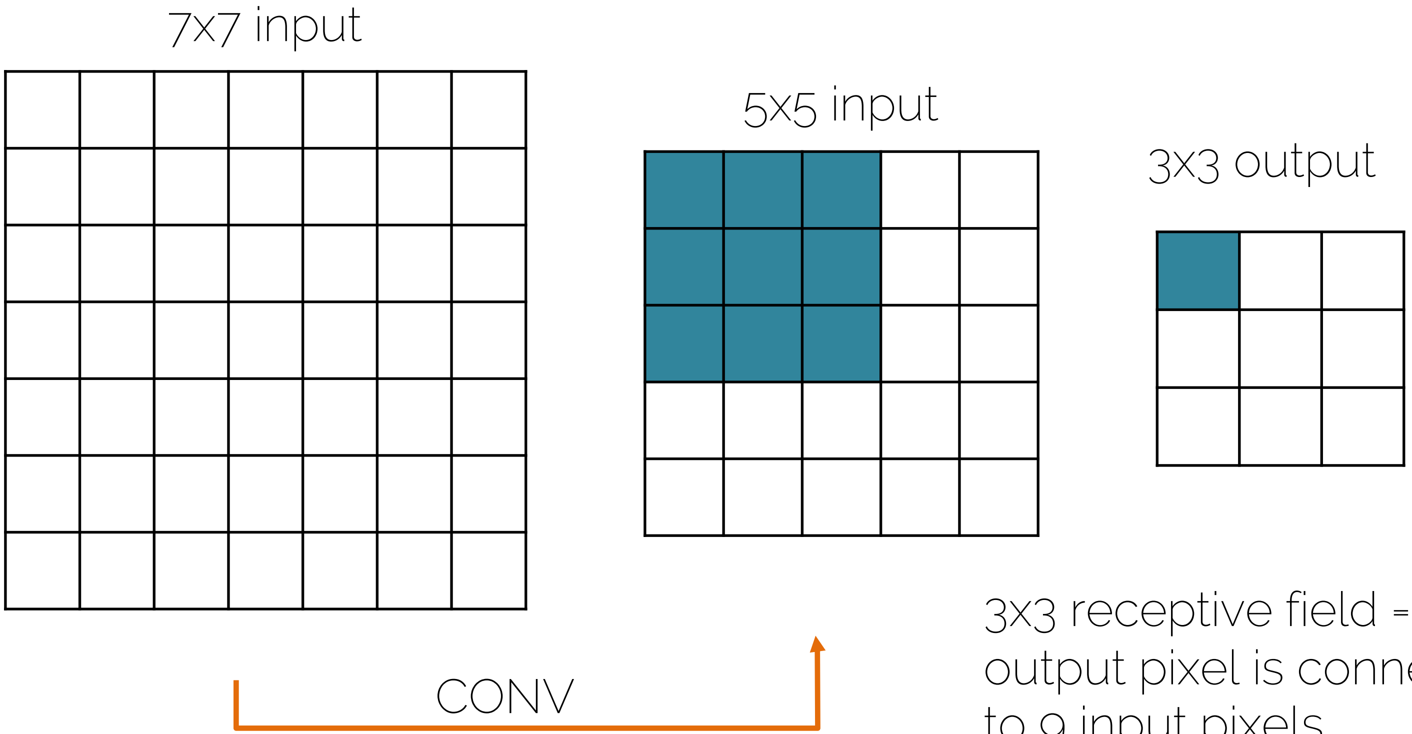
- You want to find out what inputs influenced your outputs and how much

- Blackboard!

Why the transpose?

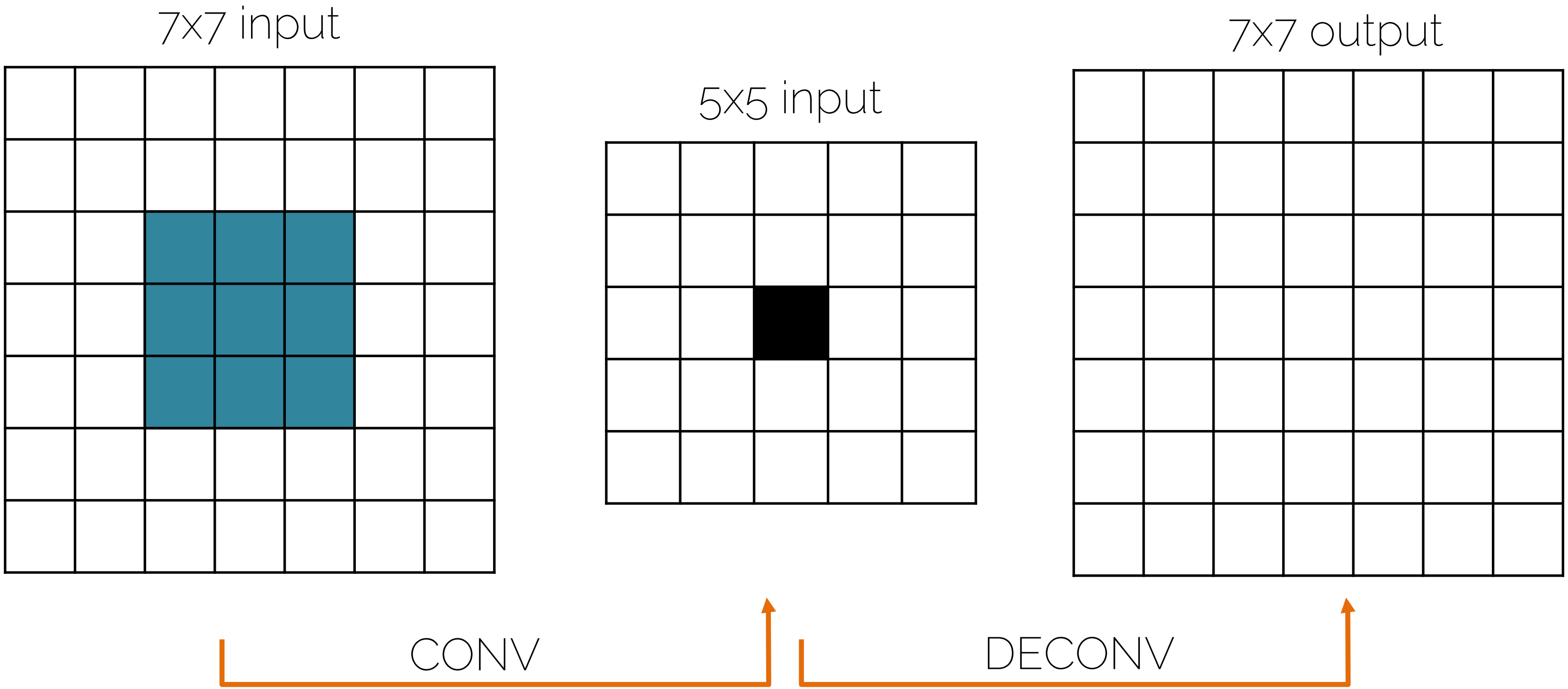


Why the transpose?

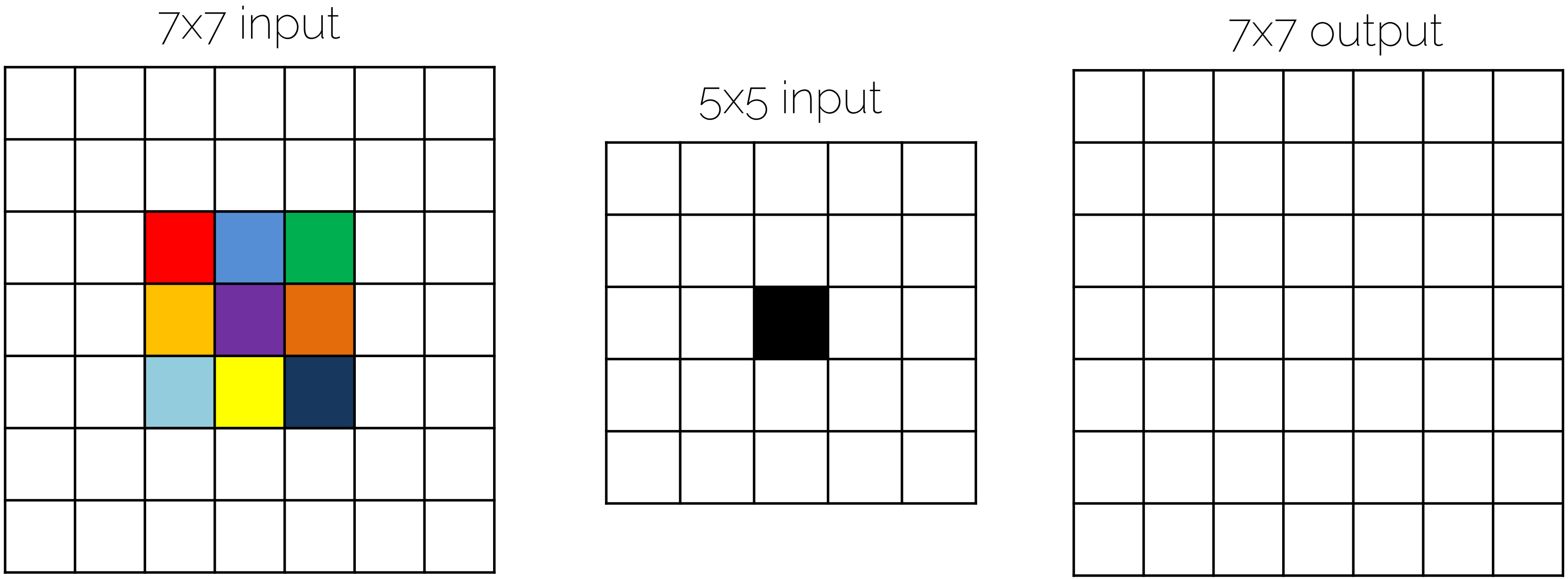


3x3 receptive field = 1 output pixel is connected to 9 input pixels

Why the transpose?

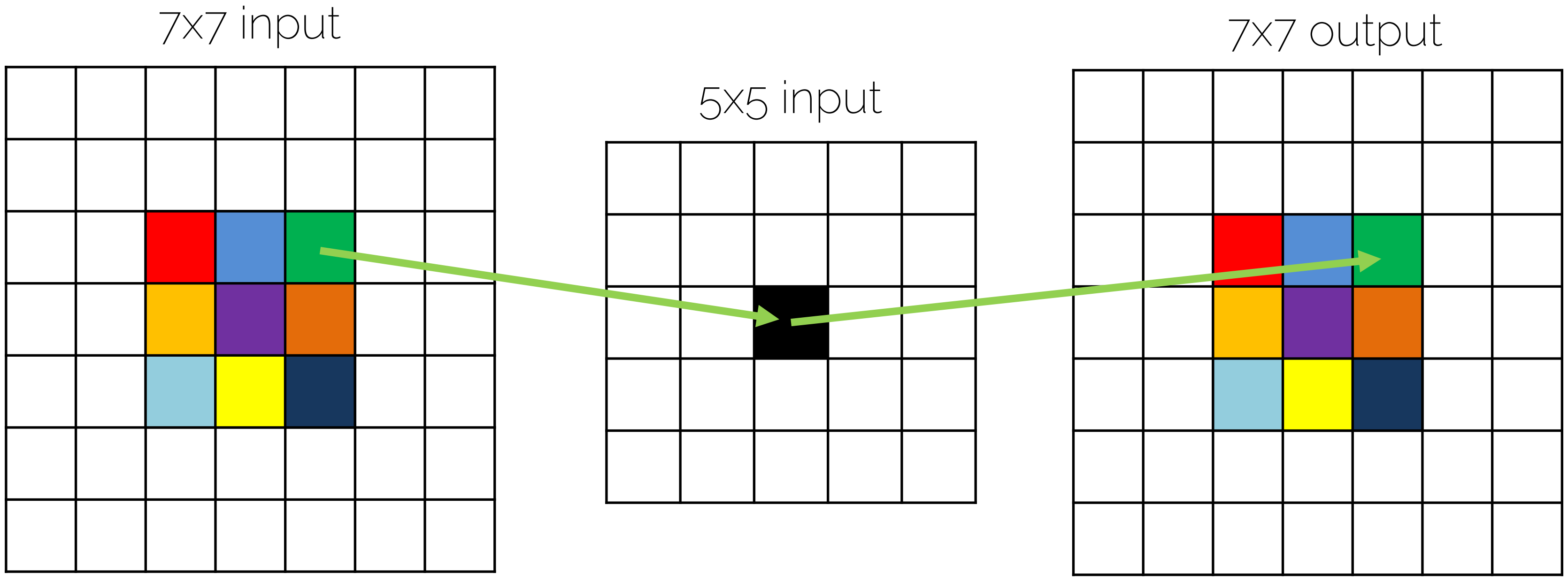


Why the transpose?



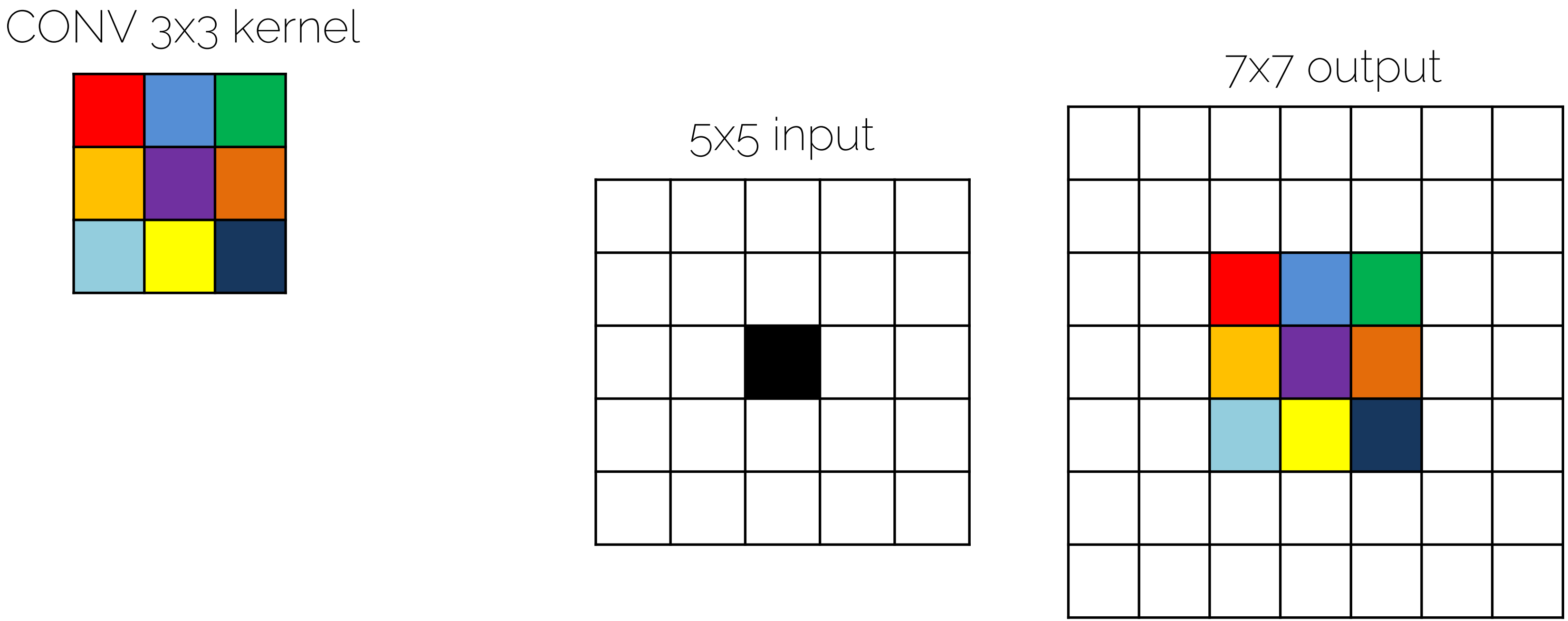
Each input pixel had a different contribution to the black output pixel

Why the transpose?



Goal: keep the contribution when we reconstruct the input (the contribution = weights)

Why the transpose?



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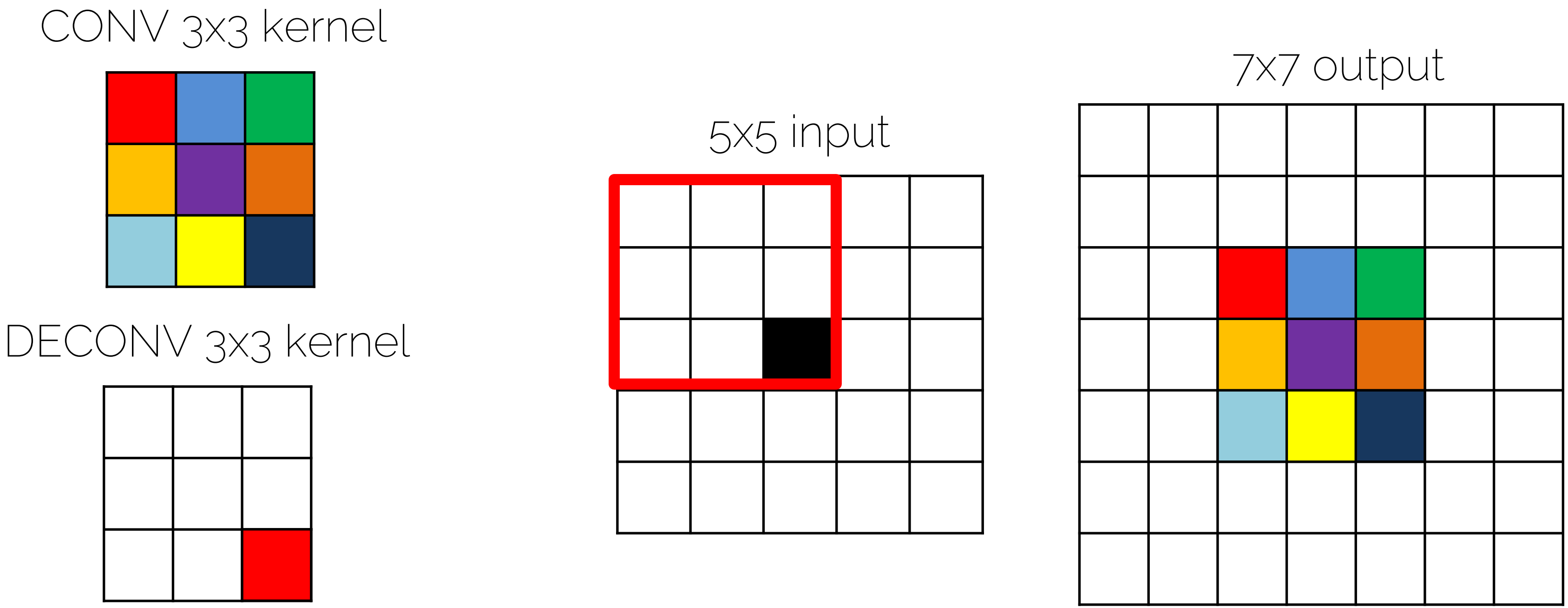
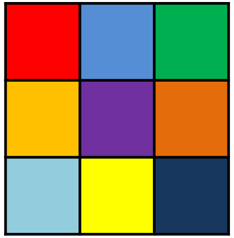
Why the transpose?



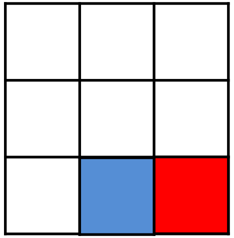
I want to express DECONV still as a convolution operation. To obtain the red pixel, where do I place the filter?

Why the transpose?

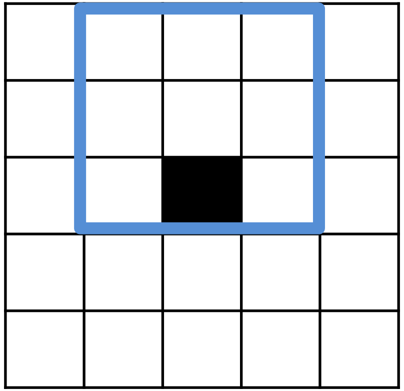
CONV 3x3 kernel



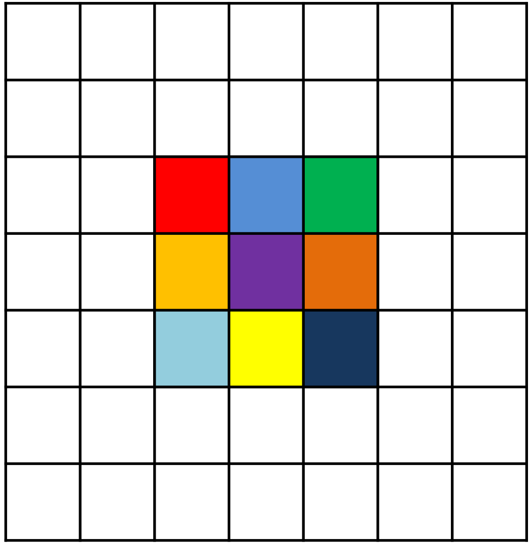
DECONV 3x3 kernel



5x5 input

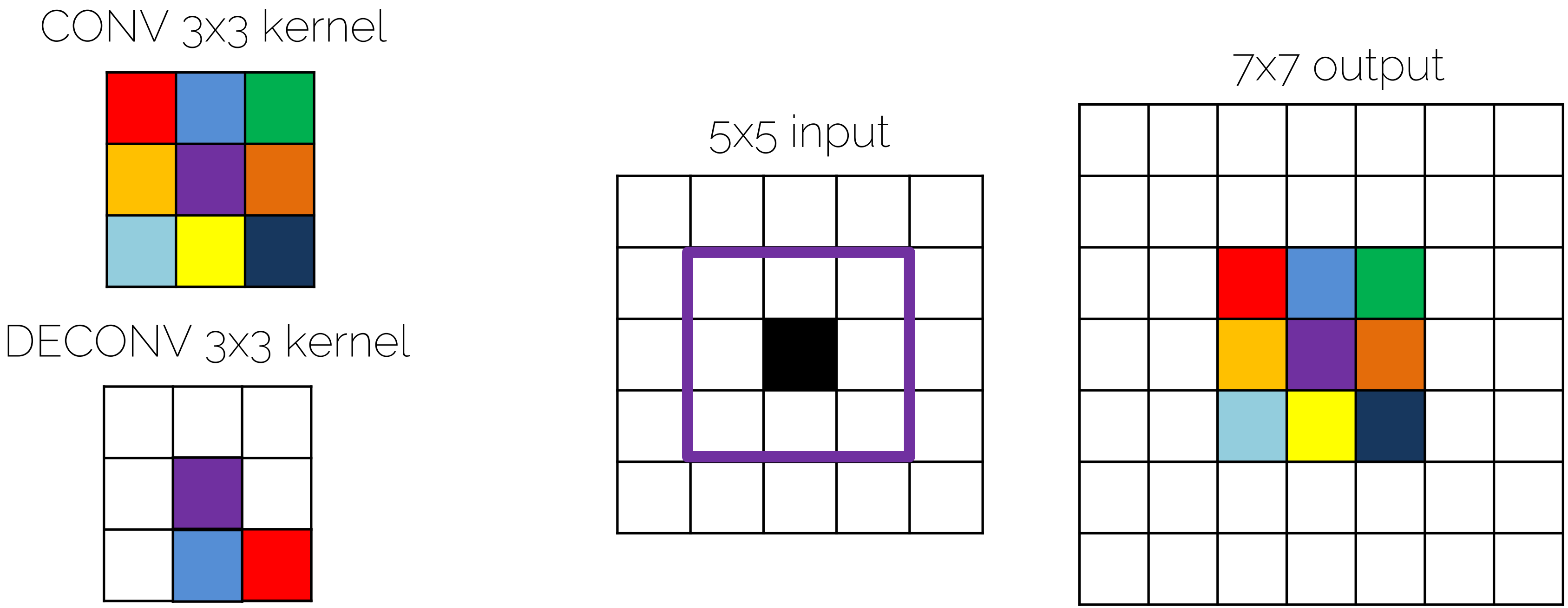


7x7 output



I want to express DECONV still as a convolution operation. To obtain the blue pixel, where do I place the filter?

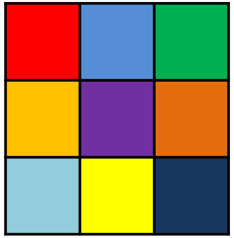
Why the transpose?



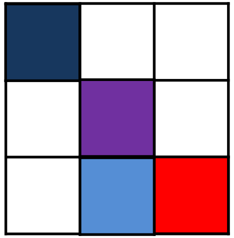
I want to express DECONV still as a convolution operation. To obtain the purple pixel, where do I place the filter?

Why the transpose?

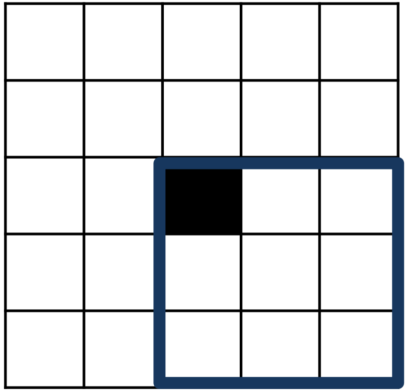
CONV 3x3 kernel



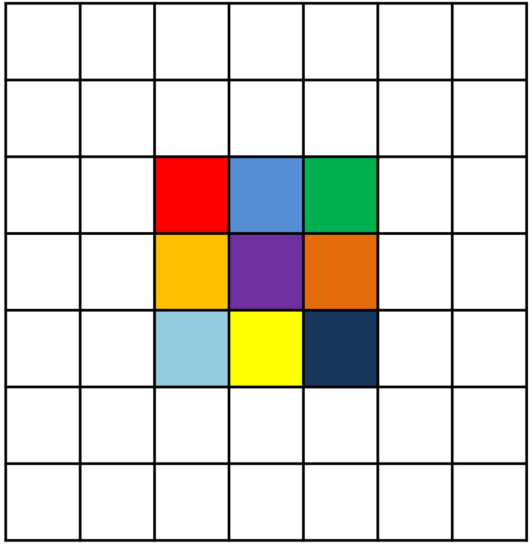
DECONV 3x3 kernel



5x5 input

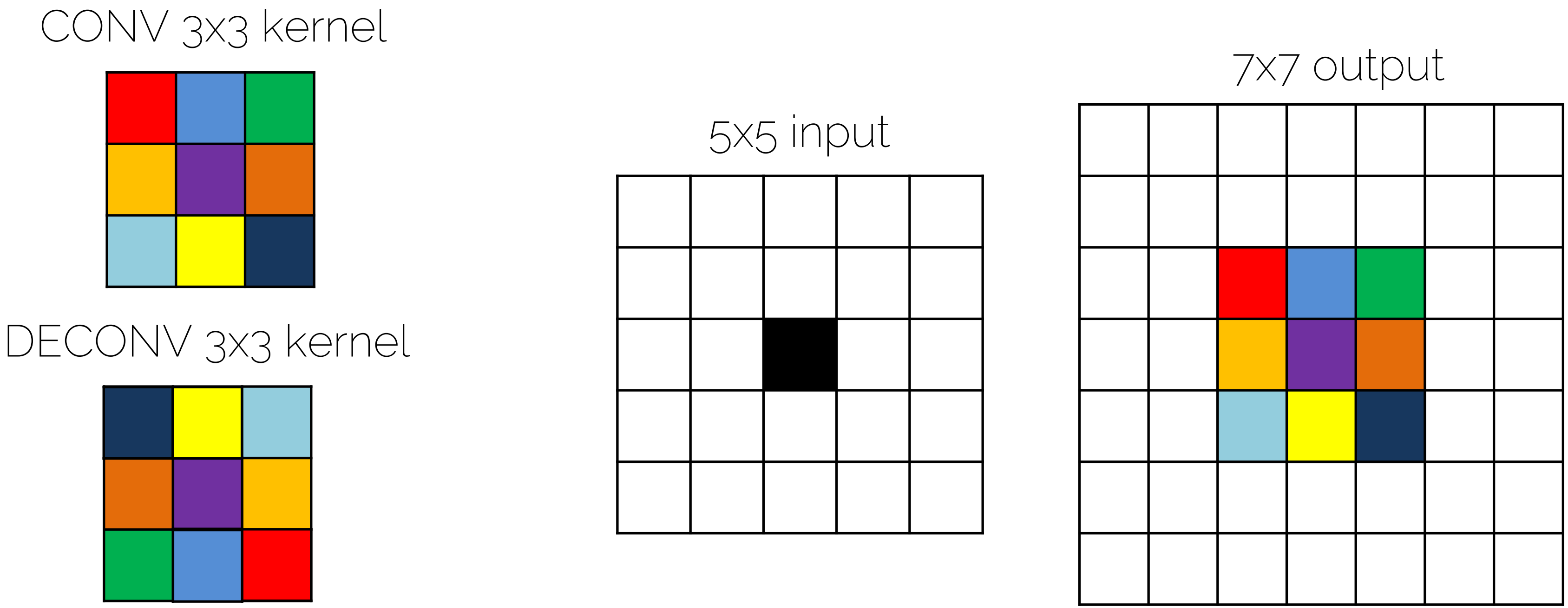


7x7 output



I want to express DECONV still as a convolution operation. To obtain the dark blue pixel, where do I place the filter?

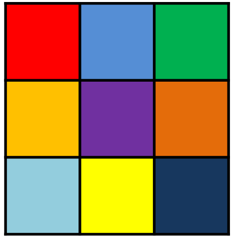
Why the transpose?



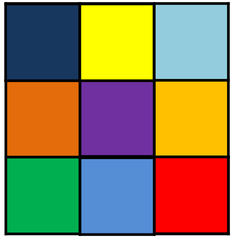
We obtain the transposed filter! We just convolve the 5x5 input with the transposed filter and obtain the “deconvolved” output.

Why the transpose?

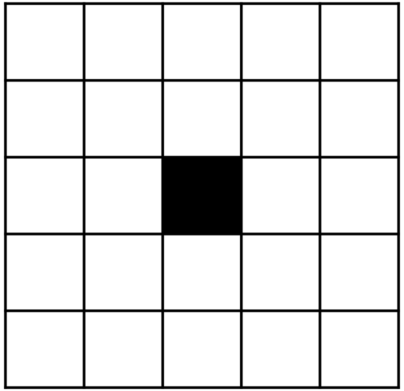
CONV 3x3 kernel



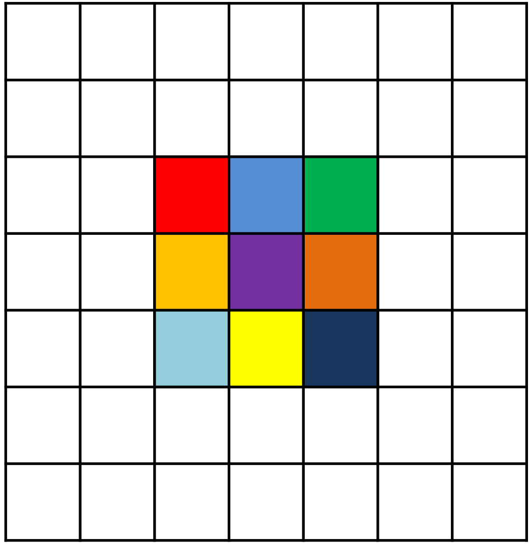
DECONV 3x3 kernel



5x5 input

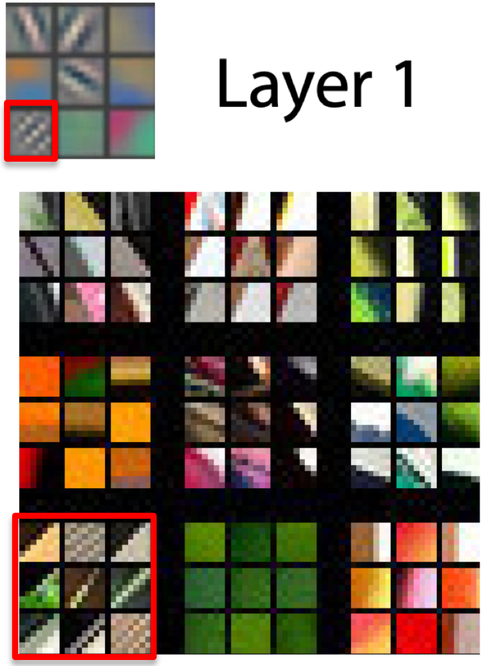


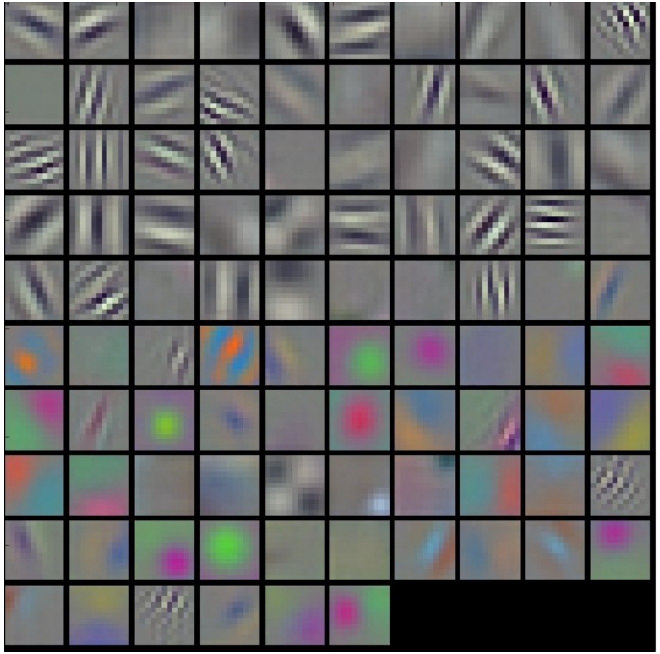
7x7 output



We obtain the transposed filter! We just convolve the 5x5 input with the transposed filter and obtain the “deconvolved” output.

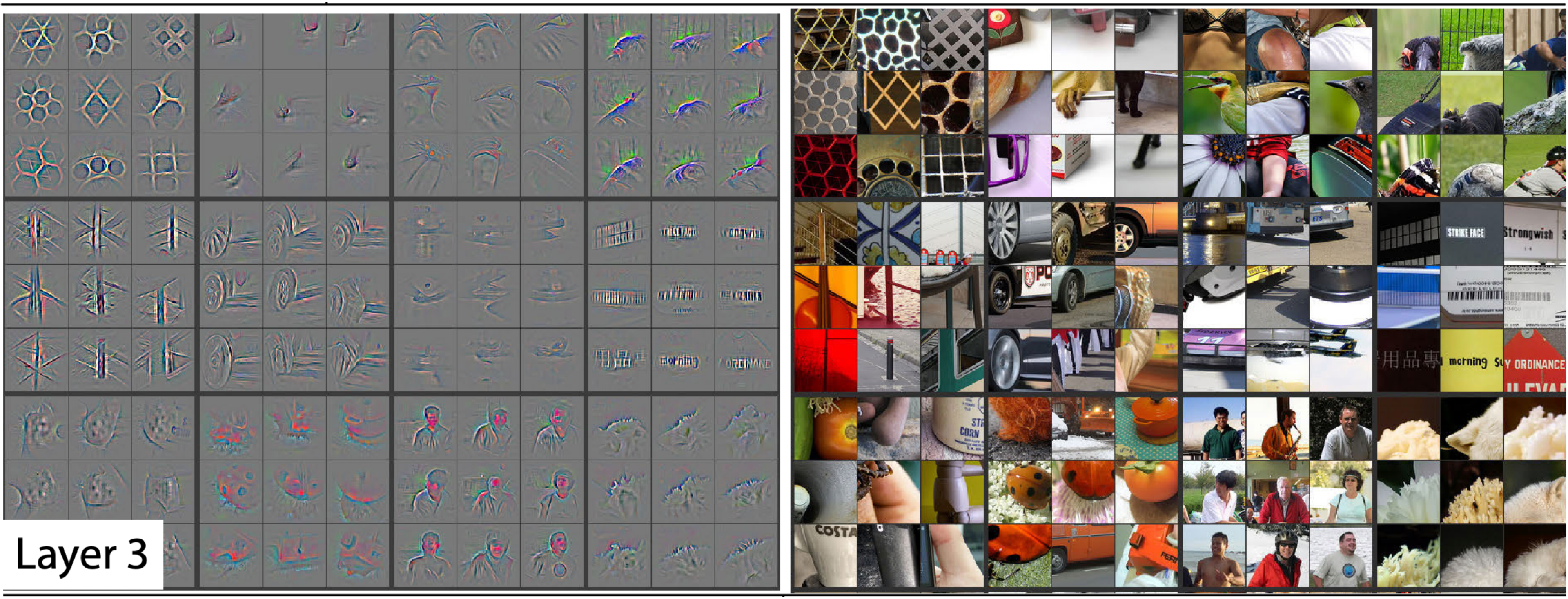
Visualizing features





Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Visualizing features



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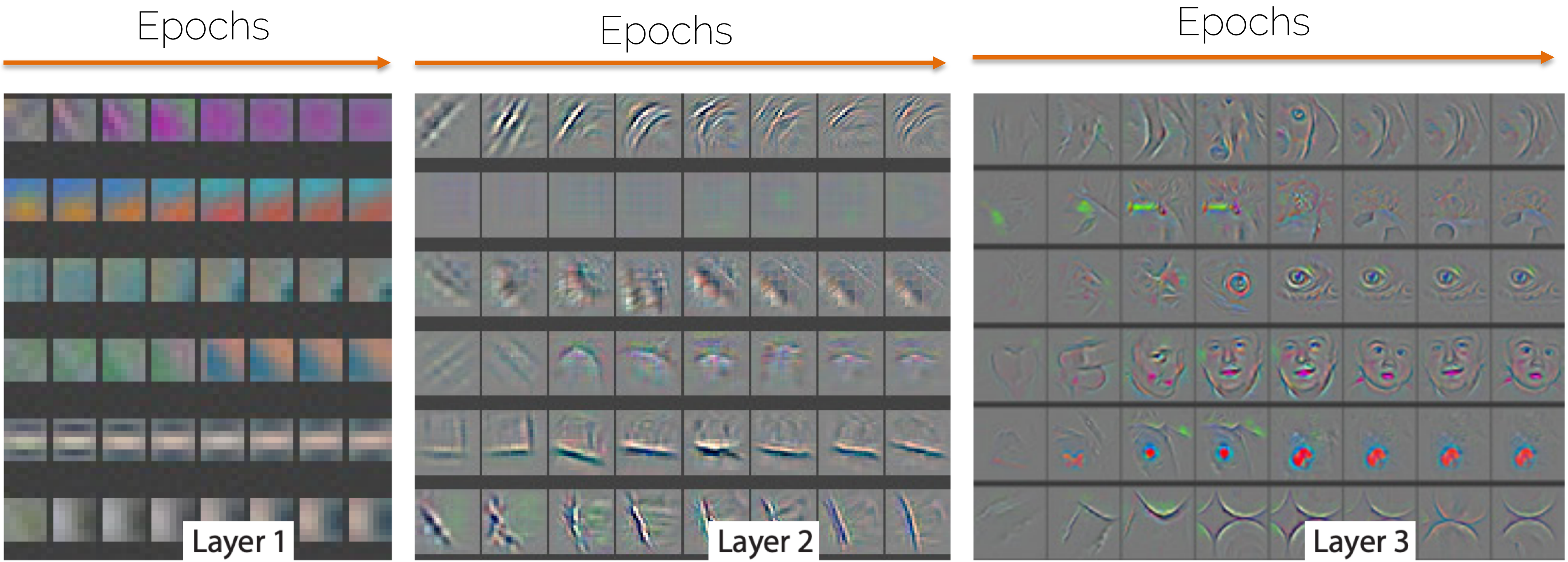
Visualizing features: evolution



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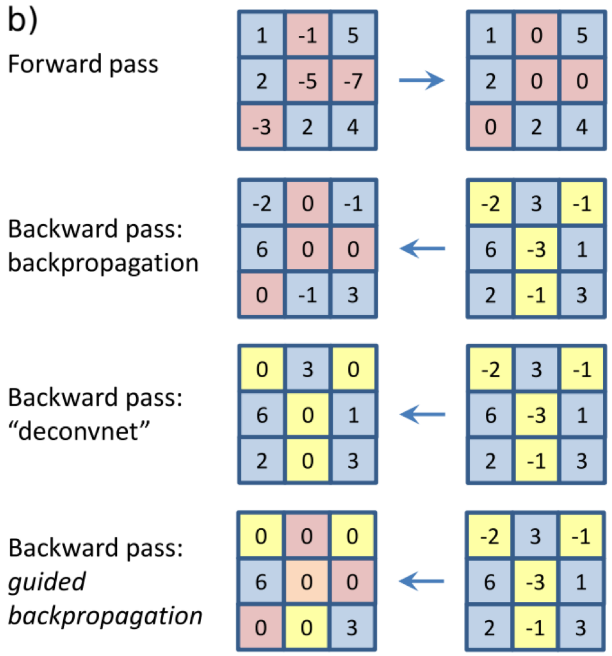
Other ways of inverting ReLU

More info at: Springenberg et al. "Striving for simplicity: the all convolutional net". ICLR Workshop 2015

https://arxiv.org/pdf/1412.6806.pdf



Visualization helps

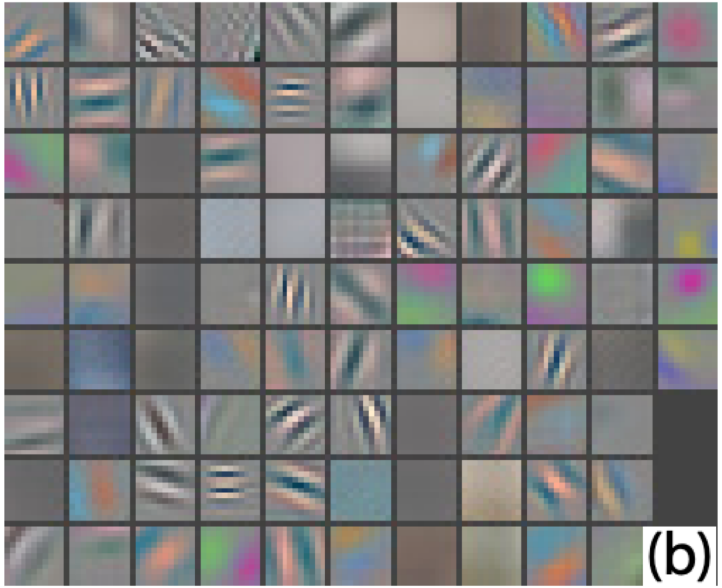
- Observations on AlexNet

- 1. First layer is a mix of low and high frequency information, no mid-frequencies are covered

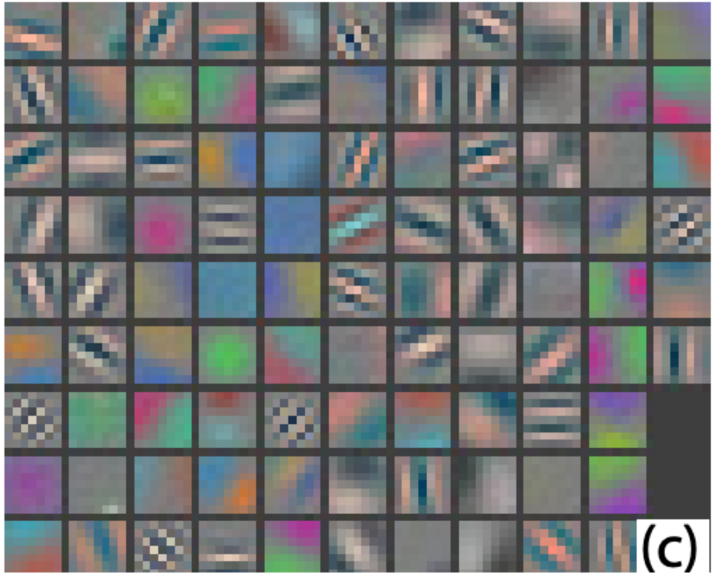
- Solution: Change from 11x11 to 7x7

Visualization helps

11X11



7X7



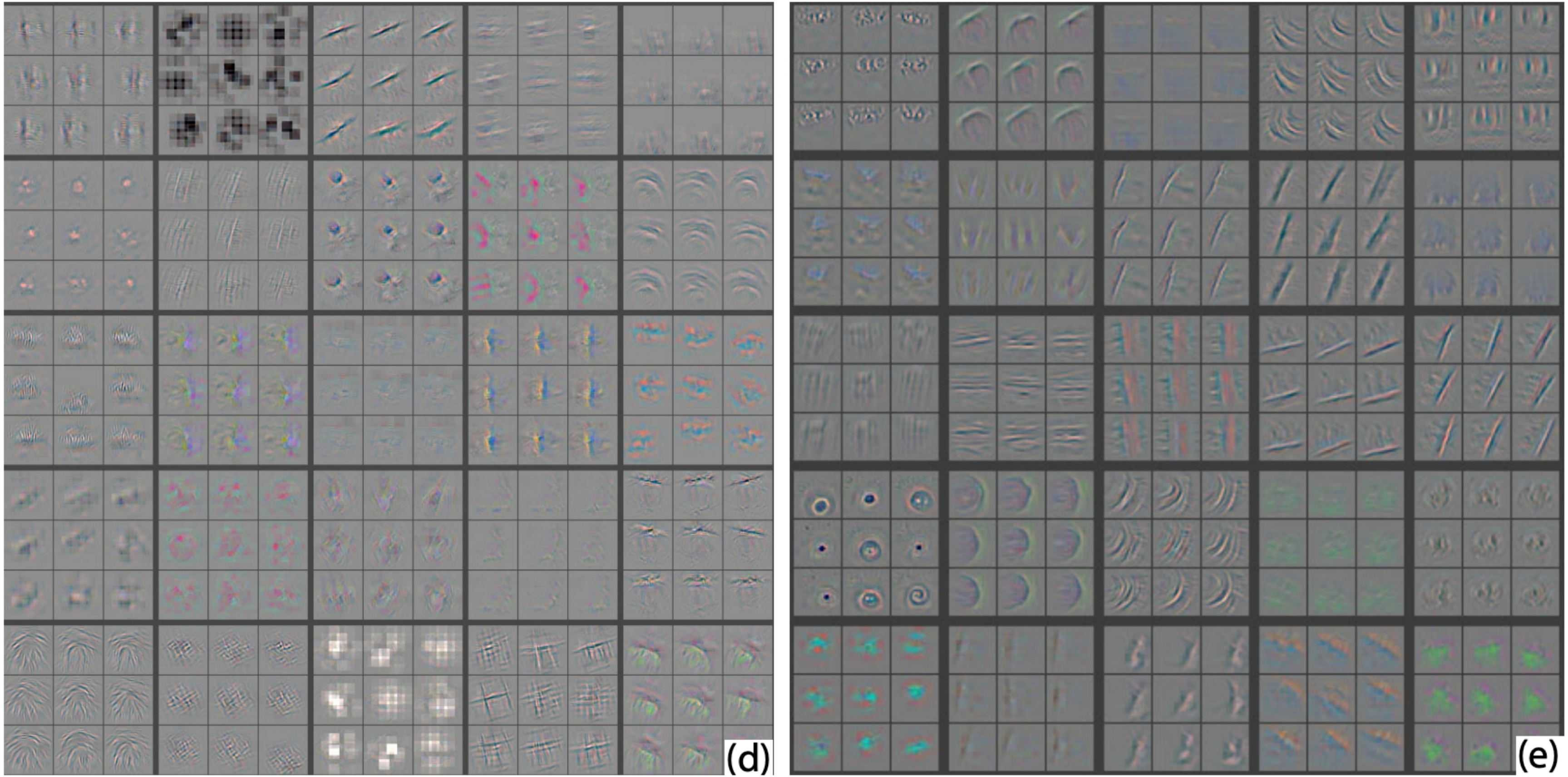
Visualization helps

- Observations on AlexNet

- 2. Aliasing artifacts in the 2nd layer caused by the large stride

- Solution: stride 4 changed to stride 2

Visualization helps



Visualization helps

- The best part: classification score improved by 2%!
- Actively use visualization to debug your CNNs

Visualizing features

- 1. DeconvNet: using the DeconvNet architecture to visualize features at a certain layer

- 2. Gradient ascent: generate a synthetic image that maximally activates a filter

Simonyan et al. „Deep inside convolutional networks: visualizing image classification models and saliency maps“. ICLR Workshop 2014

Visualizing features 2

- Want to find an image that maximizes the score for a particular class

$$\arg\max_{I} S_c(I) + \lambda||I||_2^2$$

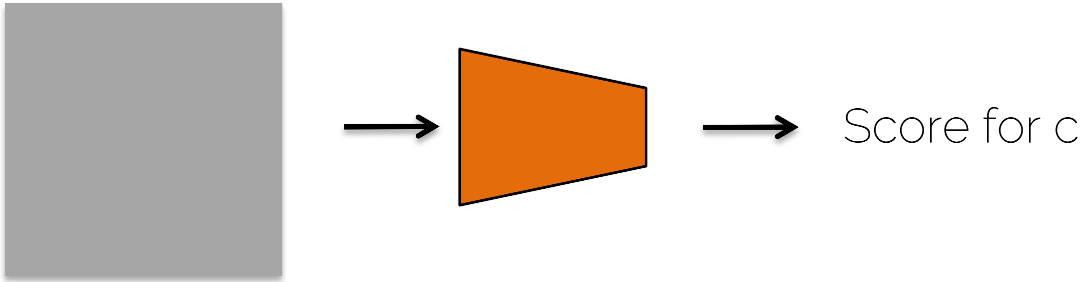
- The score is taken before the softmax layer. Direct output of the Fully Connected layer.

- L2 norm to avoid only a few very large pixels

Simonyan et al. „Deep inside convolutional networks: visualizing image classification models and saliency maps“. ICLR Workshop 2014

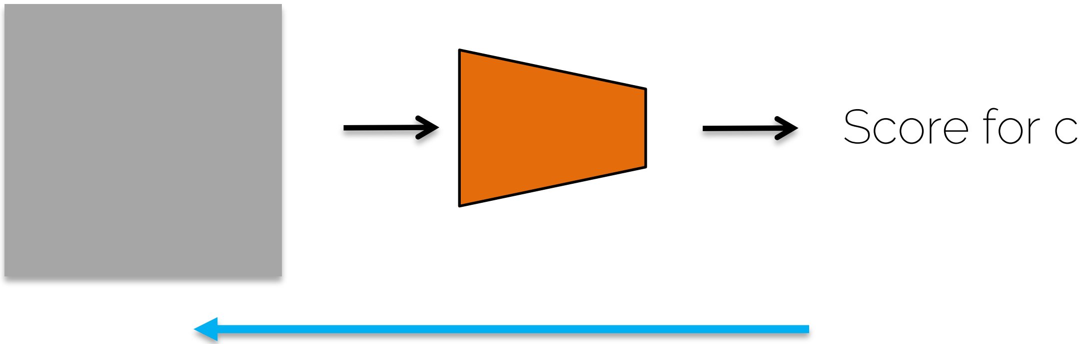
Visualizing features 2

- 1. Get a trained CNN (mean of the training images was subtracted to all images)
- 2. Pass a zero image through the CNN



Visualizing features 2

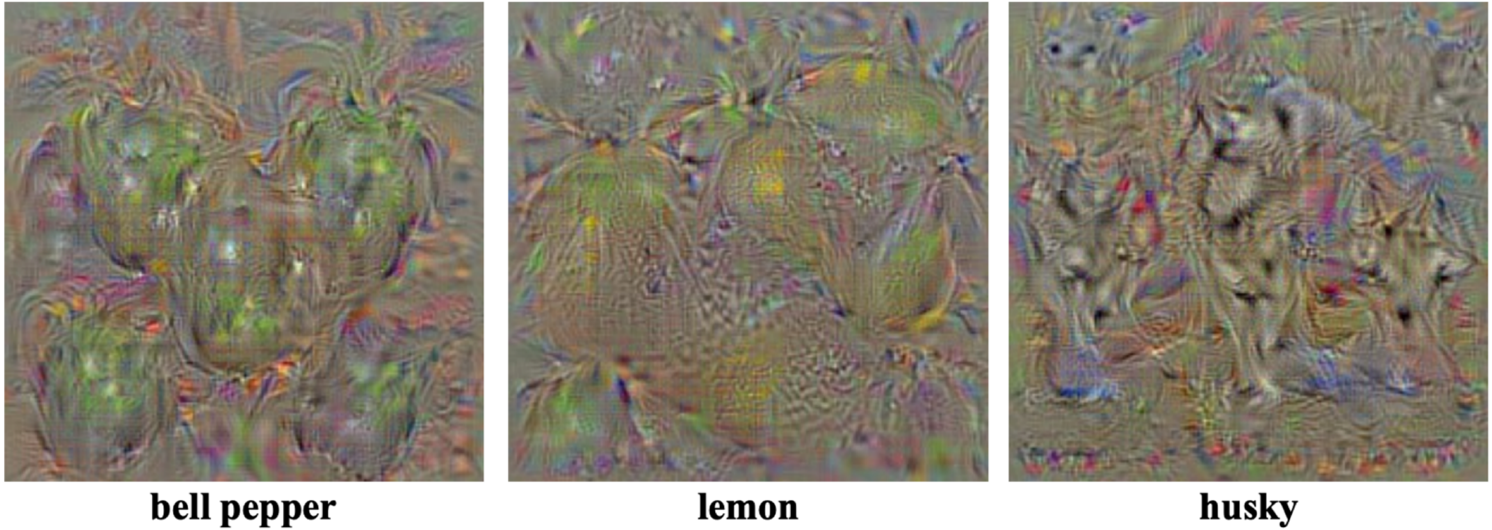
- 3. Maximize the score → use gradient ascent and backpropagation



- 4. Make a small update on the image

Visualizing features 2

- 5. Repeat
- 6. Visualize by adding the training mean image



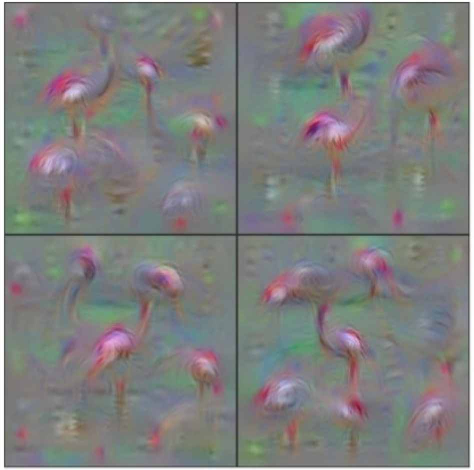
Visualizing features 2.1

- Improve visualization with a better regularization

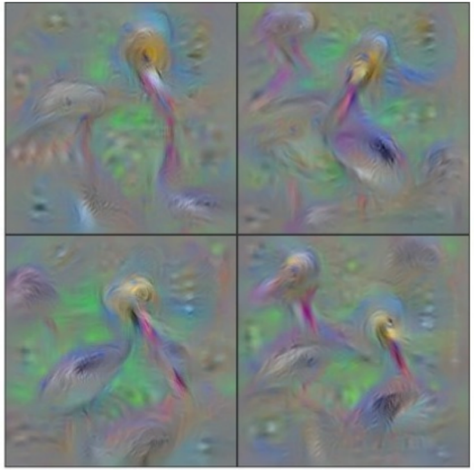
$$\arg\max_I S_c(I) + \lambda ||I||_2^2$$

- Propose different regularizations: using a gaussian blur on the image, clipping pixels with small value to 0, clipping gradients with small value to zero

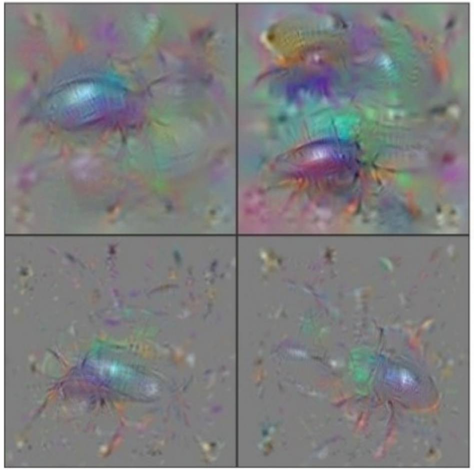
Yosinksi et al. „Understanding neural networks through deep visualization". ICML Workshop 2014



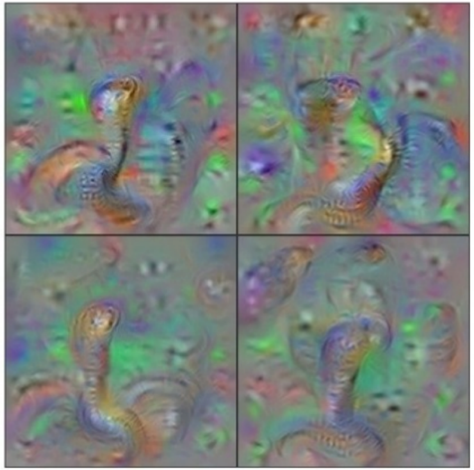
Flamingo



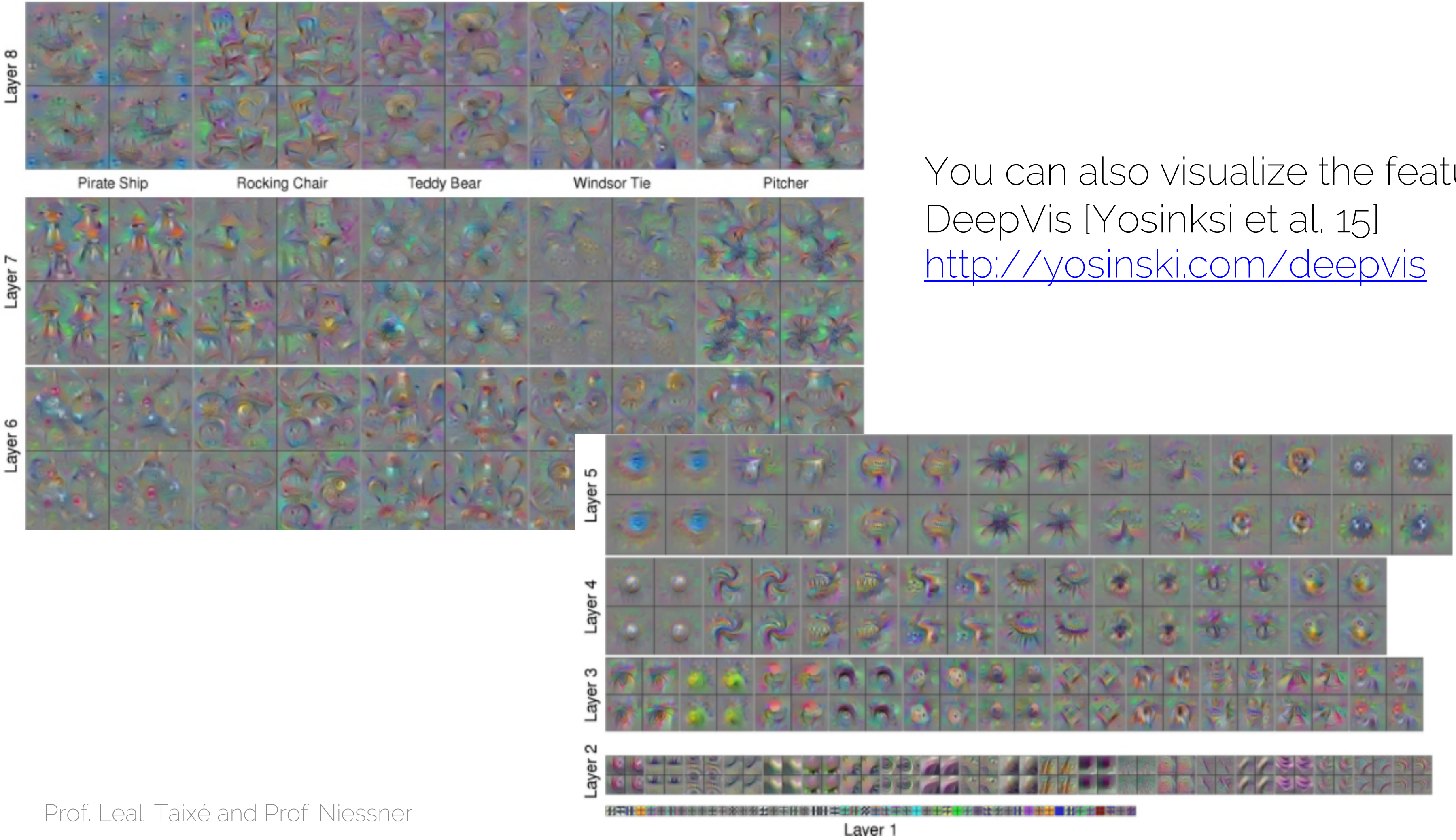
Pelican



Ground Beetle



Indian Cobra



You can also visualize the features
DeepVis [Yosinksi et al. 15]
http://yosinski.com/deepvis

DeepDream

- Until now: Synthesize an image to maximize a specific feature

- Now: Amplify the feature activations at some layer in the network

[Mordvintsev et al. 15] DeepDream

DeepDream

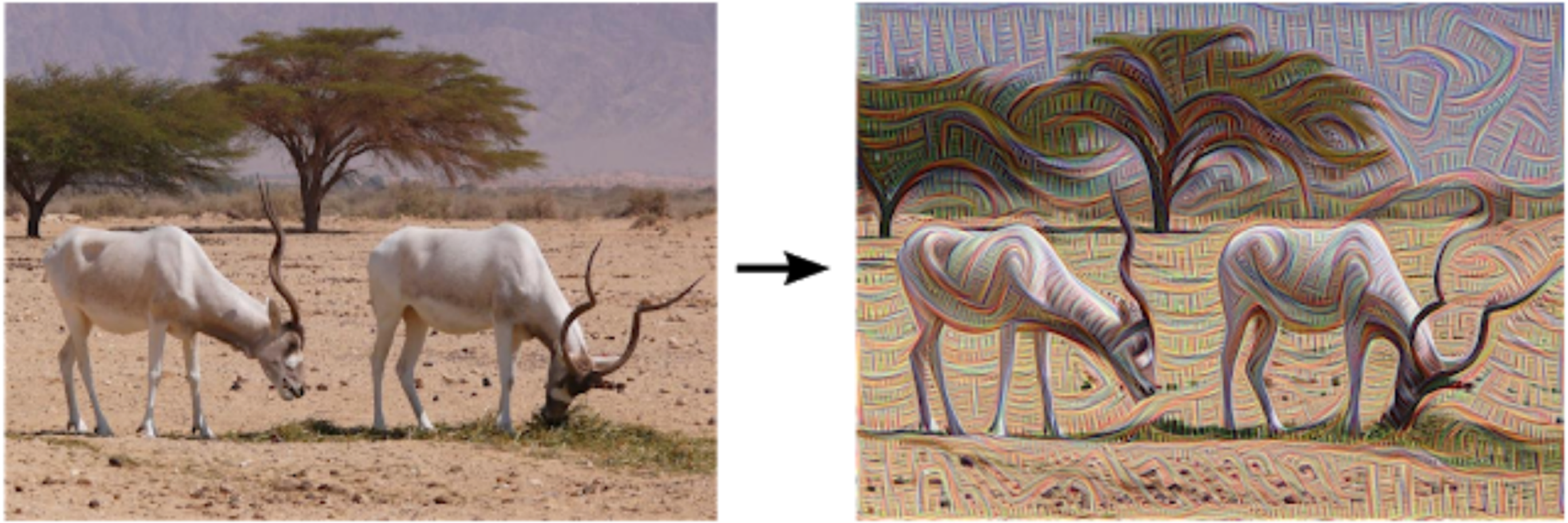
- 1. Feed an image to a network
- 2. Choose a layer and ask the network to enhance whatever was detected → If you see dogs, show me more dogs!

DeepDream

- 1. Forward pass of the image up to layer L
- 2. Set the gradient of the layer = activations
  - Large activations for the *dog* filter will create large gradients
  - The image will be changed to „show more dogs"
- 3. Backpropagate
- 4. Update the image

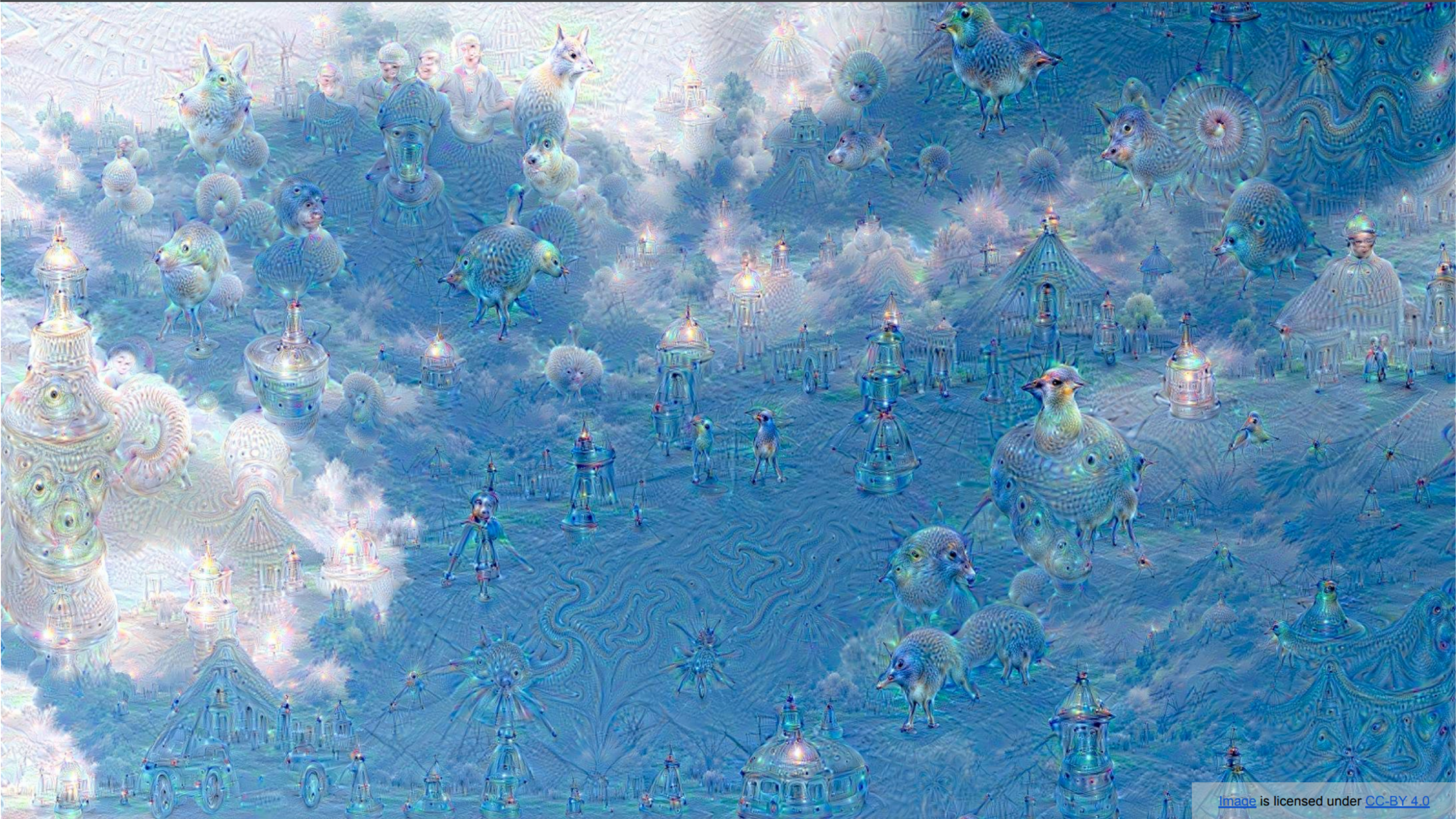
DeepDream

- Low layers: basic features



DeepDream

- Deep layers: we start to see whole objects



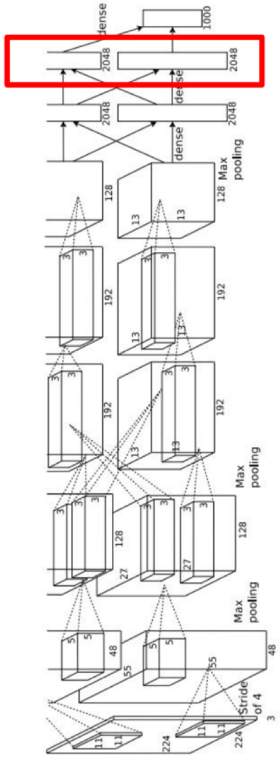
[Mordvintsev et al. 15] DeepDream

t-SNE

Intuition

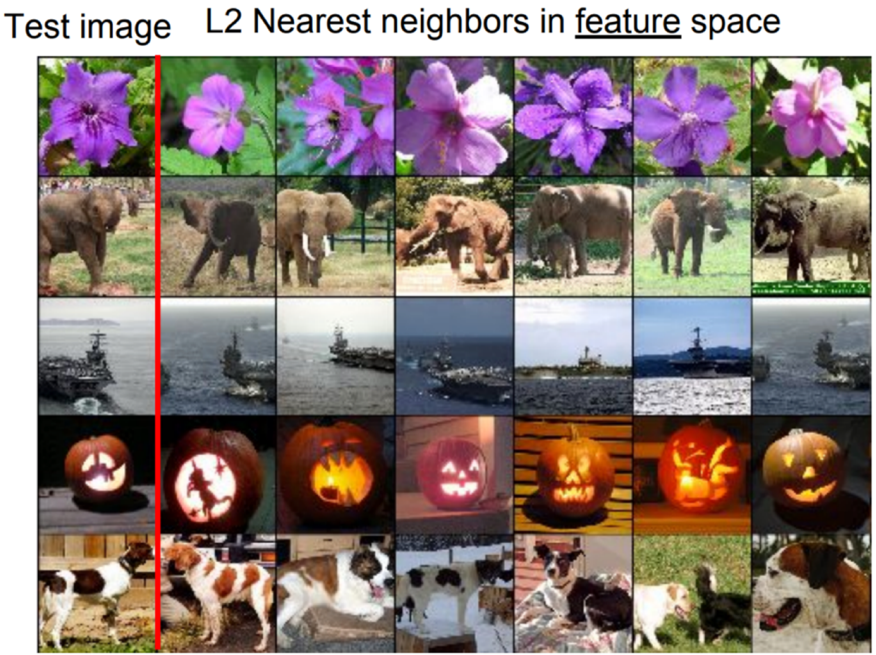
- We want to visualize the last FC layer of AlexNet which dimension 4096

- We do a forward pass of all the images and get their 4096 representations



Intuition

- Nearest neighbor visualization



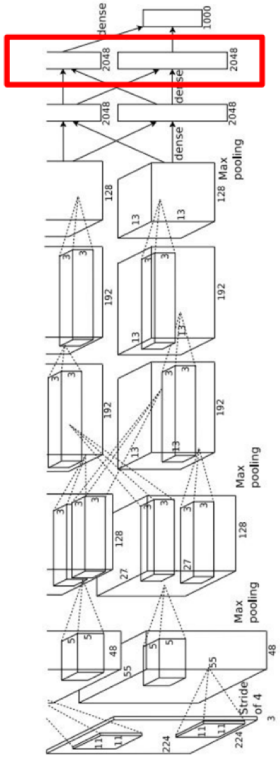


Image credit: Fei-Fei, Yeung, Johnson

Intuition

- How can I visualize these clusters in feature space?
- Map high-dimensional embedding to 2D map which preserves the pairwise distance of the points
- This mapping is done by t-SNE

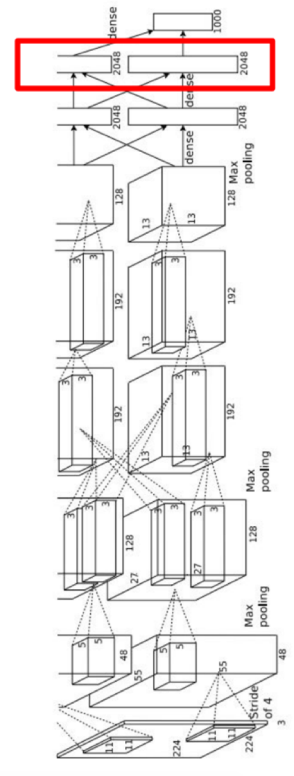
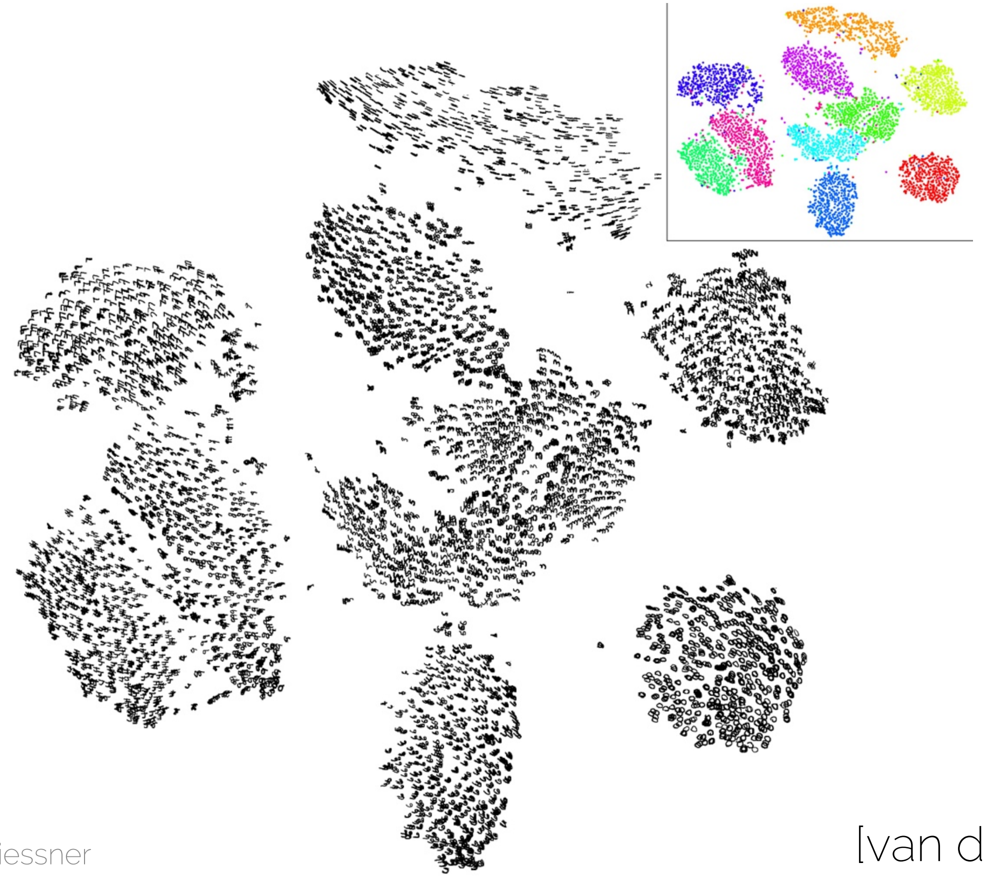


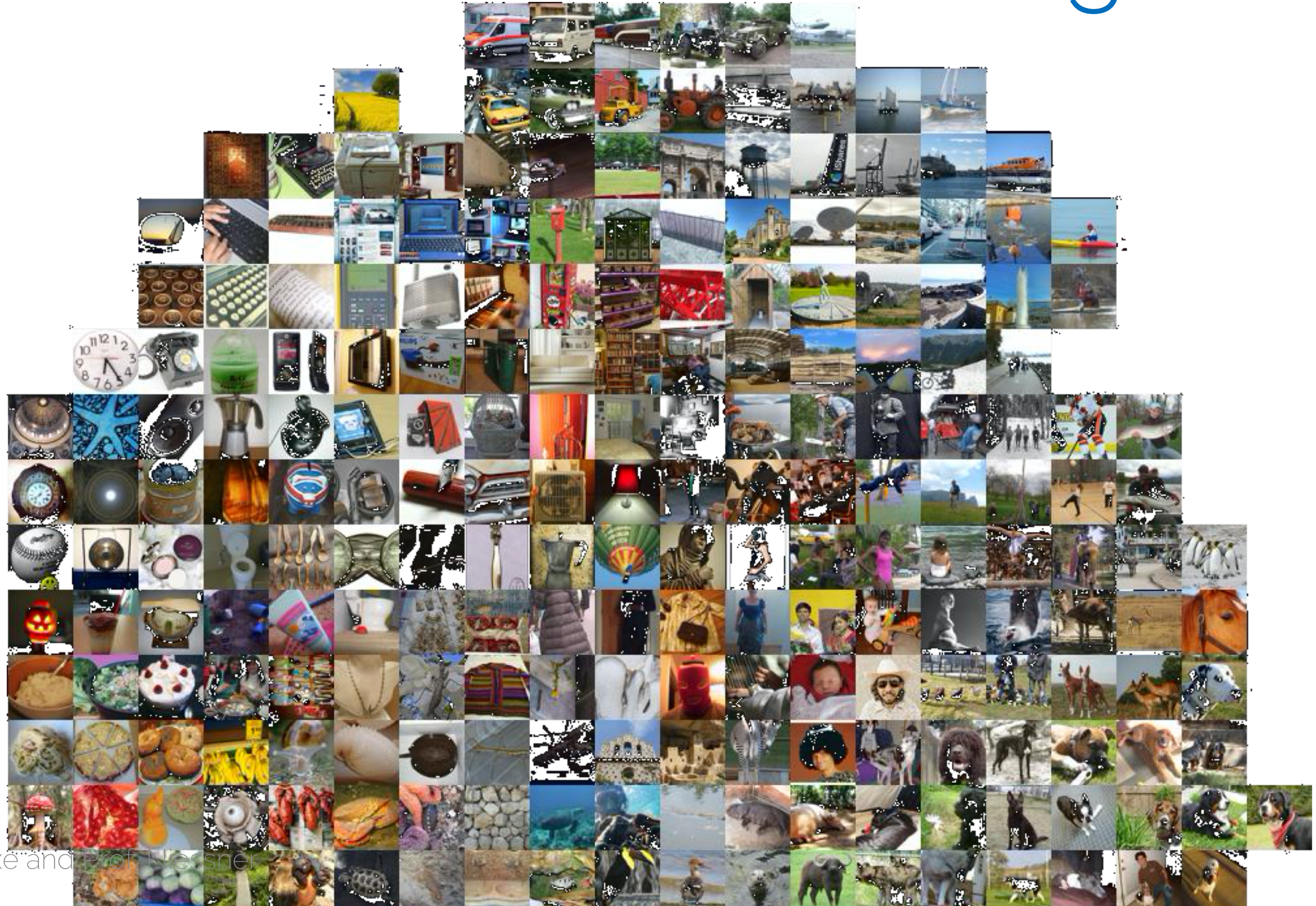
Image credit: Fei-Fei, Yeung, Johnson

t-SNE Visualization: MNIST



[van der Maaten et al.] t-SNE

t-SNE Visualization: ImageNet



t-SNE Visualization: ShapeNet

When is t-SNE worth using?

- You can use it to debug your network
- Good for visualizing the clusters created by a Siamese network

More visualizations

- Saliency visualization: Simonyan et al. „Deep inside convolutional networks: visualizing image classification models and saliency maps“. ICLR Workshop 2014

- Grad-CAM: Why did you say that? Visual Explanations from Deep Networks via Gradient-based Localization
Ramprasaath R. Selvaraju, Abhishek Das, Ramakrishna Vedantam, Michael Cogswell, Devi Parikh, Dhruv Batra

Visualization and Interpretability