

Deep Learning for Computer Vision

Visualizing CNNs

Vineeth N Balasubramanian

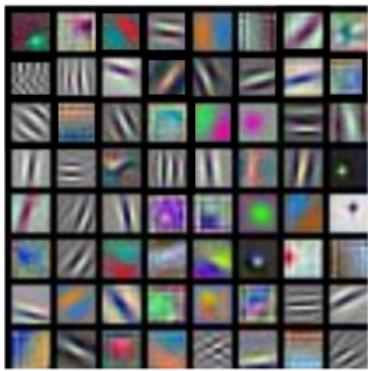
Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad



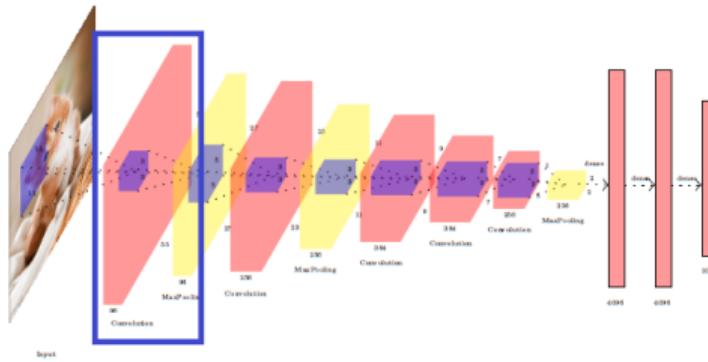
Acknowledgements

- Most of this lecture's slides are based on **Lecture 13 of CS231n: Convolutional Neural Networks for Visual Recognition** course taught by Fei-Fei Li and others at Stanford University
- Some content (AlexNet CNN figures, etc) is also adapted from **Lecture 12 of CS7015: Deep Learning** course taught by Mitesh Khapra at IIT Madras

Visualize Filters/Kernels (First Layer)¹

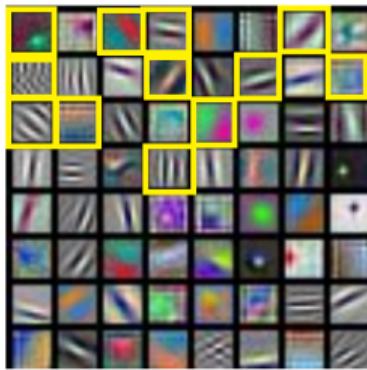


AlexNet:
 $64 \times 3 \times 11 \times 11$

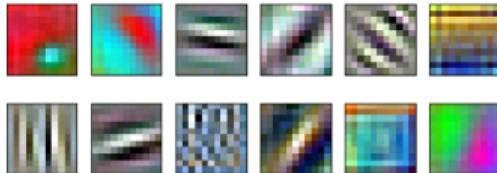


¹Krizhevsky, One weird trick for parallelizing convolutional neural networks, 2014

Visualize Filters/Kernels (First Layer)¹

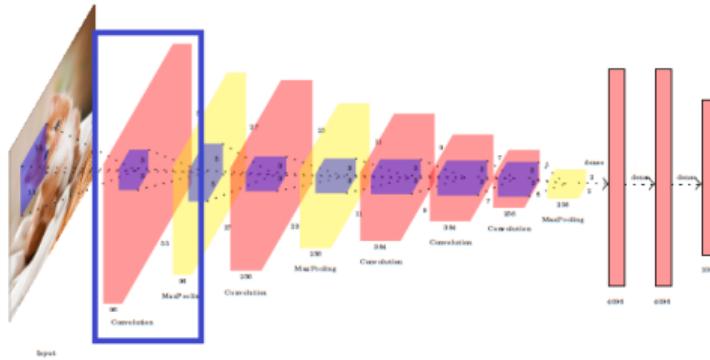


AlexNet:
64 x 3 x 11 x 11



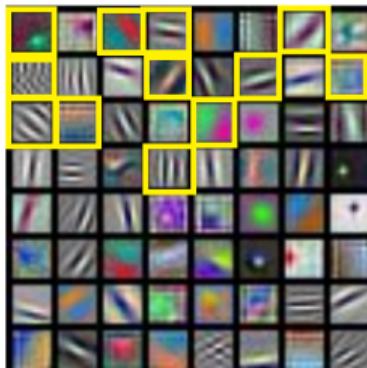
A Closer Look (AlexNet)

Fan et al. (arxiv:1904.05526)

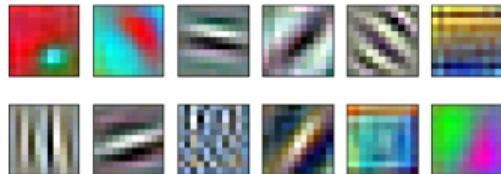


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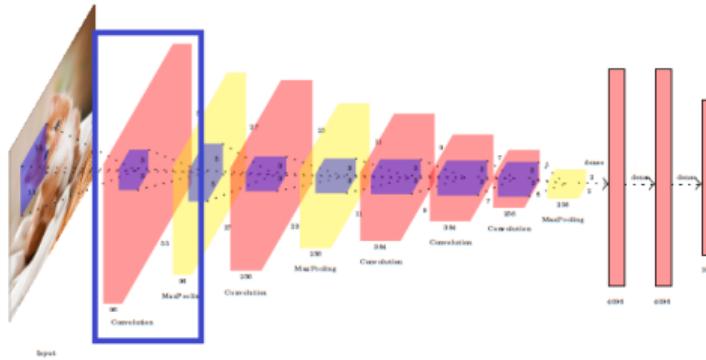
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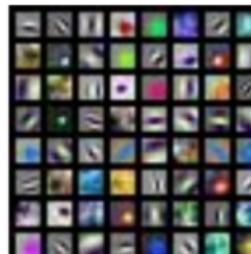
AlexNet:
 $64 \times 3 \times 11 \times 11$



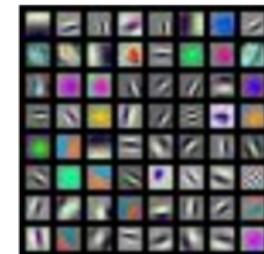
A Closer Look (AlexNet)
Fan et al. (arxiv:1904.05526)



ResNet-18:
 $64 \times 3 \times 7 \times 7$



ResNet-101:
 $64 \times 3 \times 7 \times 7$



DenseNet-121:
 $64 \times 3 \times 7 \times 7$

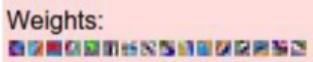
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Visualize Filters/Kernels (First Layer)

- You can visualize the kernels of higher layers but it is just not interesting

Visualize Filters/Kernels (First Layer)

- You can visualize the kernels of higher layers but it is just not interesting
- Input to higher layers is no more the images we know or understand, so becomes difficult to interpret the filters beyond the first layer



layer 1 weights



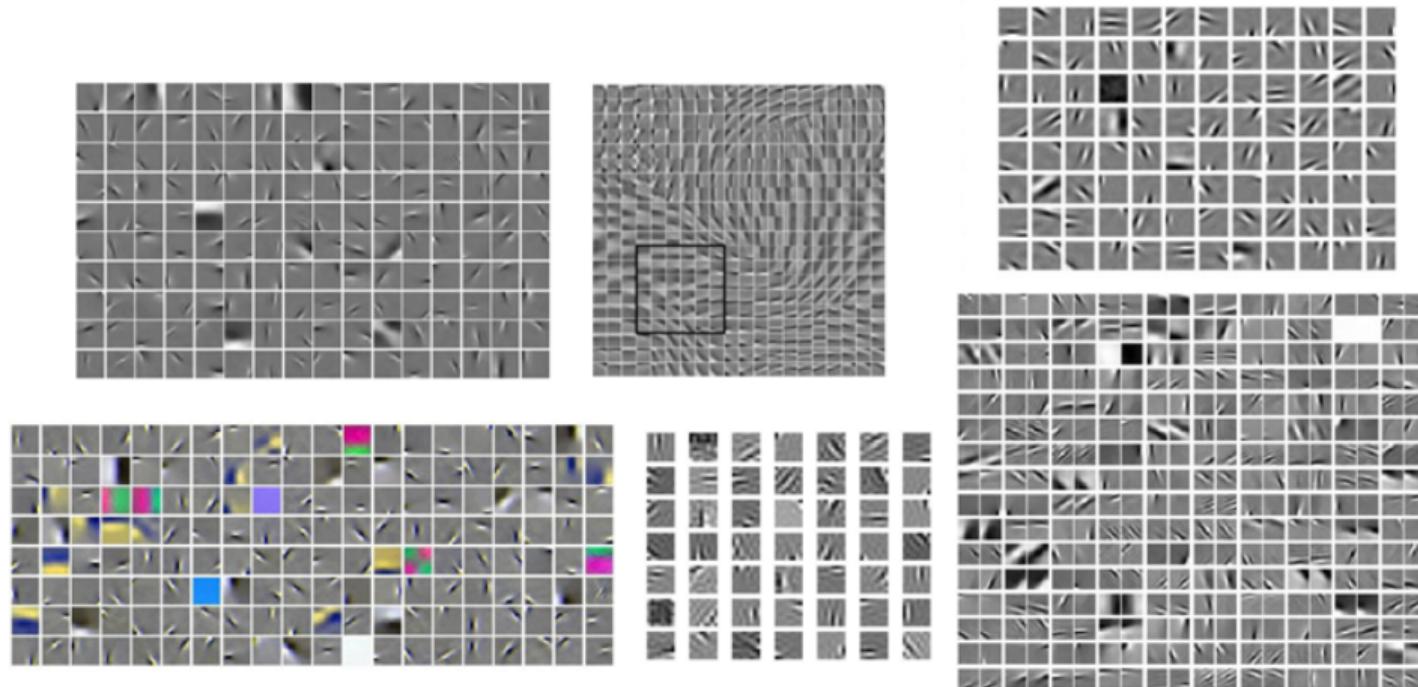
layer 2 weights
 $20 \times 16 \times 7 \times 7$



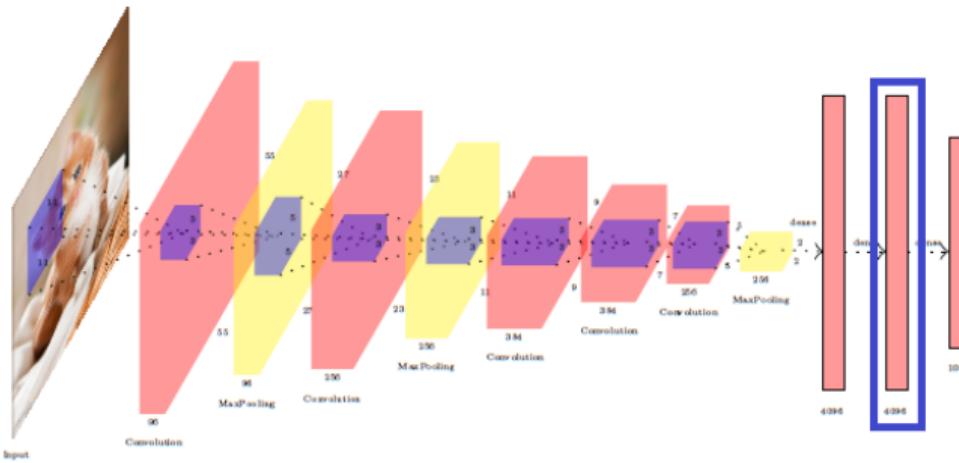
layer 3 weights
 $20 \times 20 \times 7 \times 7$

Visualize Filters/Kernels (First Layer)

The Gabor-like filters fatigue



Visualize the Representation Space (Last Layer)



- 4096-dimensional feature vector for an image (layer immediately before the classifier)
- Run the network on many images, collect the feature vectors

Visualize the Representation Space (Last Layer)

- Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Visualize the Representation Space (Last Layer)

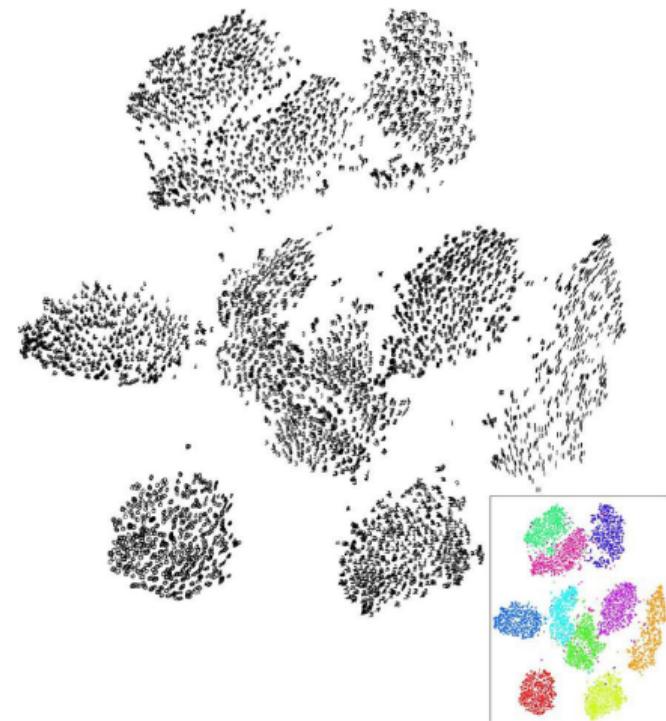
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- Use any dimensionality reduction algorithm

Visualize the Representation Space (Last Layer)

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- Simple algorithm: Principal Component Analysis (PCA)

Visualize the Representation Space (Last Layer)

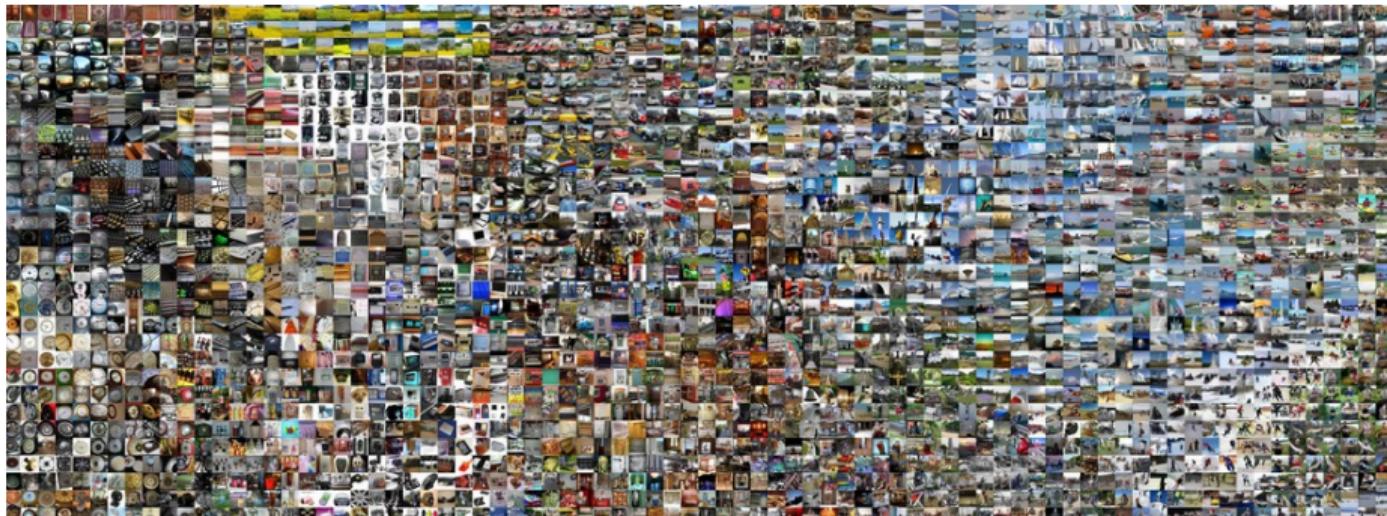
- Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions
- Use any dimensionality reduction algorithm
- Simple algorithm: Principal Component Analysis (PCA)
- More complex: **t-SNE** (right)



van der Maaten and Hinton, Visualizing High-Dimensional Data Using t-SNE, Journal of Machine Learning Research, 2008

t-SNE Visualization

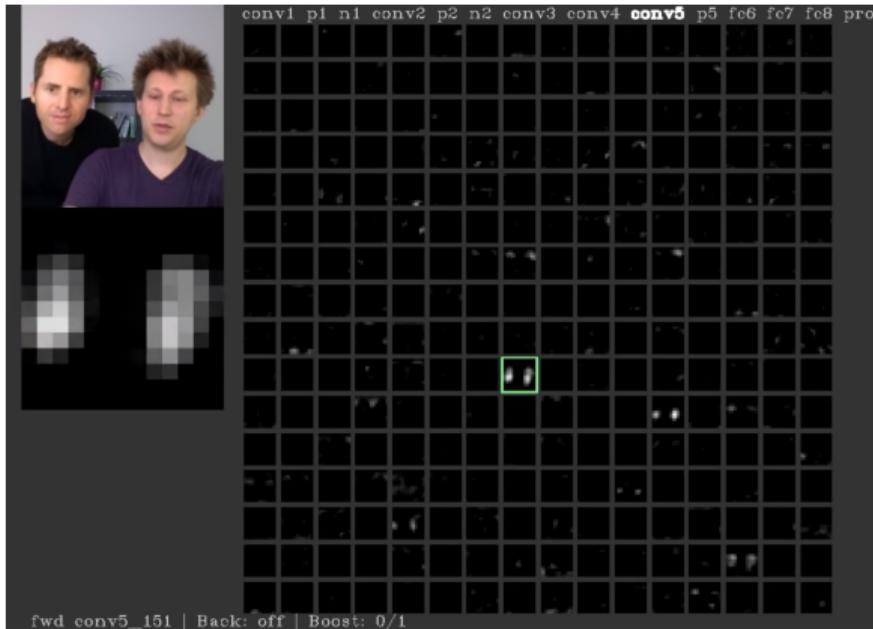
- Images that are nearby each other are also close in the CNN representation space, which implies that the CNN "sees" them as being very similar



- Notice that the similarities are more often class-based and semantic, rather than pixel and color-based.

Visualize Activations

Conv5 feature map is $128 \times 13 \times 13$; Visualize as 128 13 \times 13 grayscale images

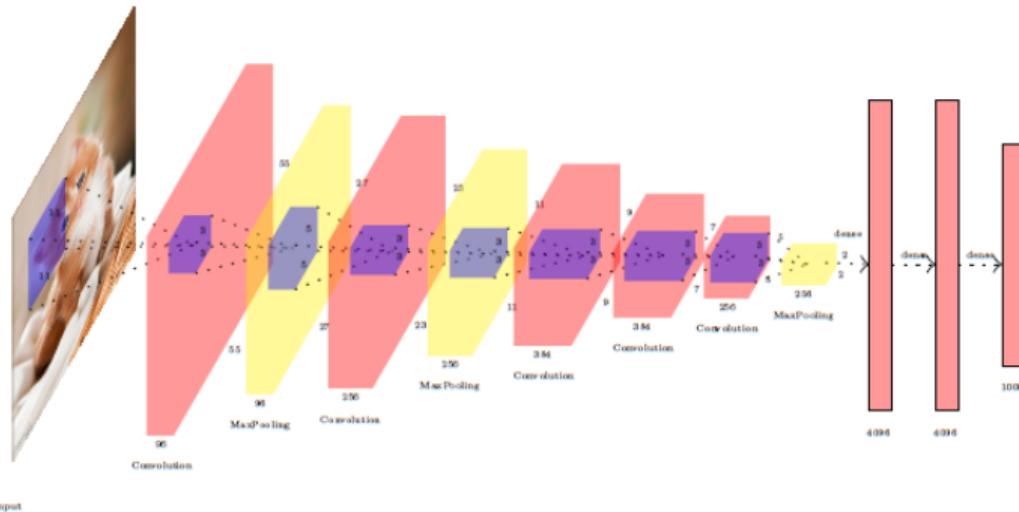


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

Figure copyright: Jason Yosinski, 2014.

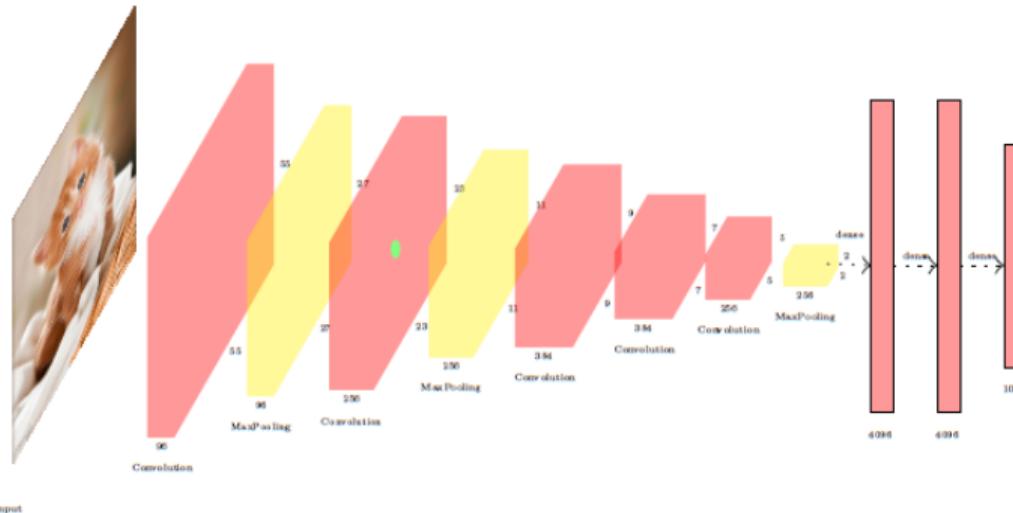
Visualize Maximally Activating Image Patches

- Consider a CNN, and a single neuron in any of its intermediate layers



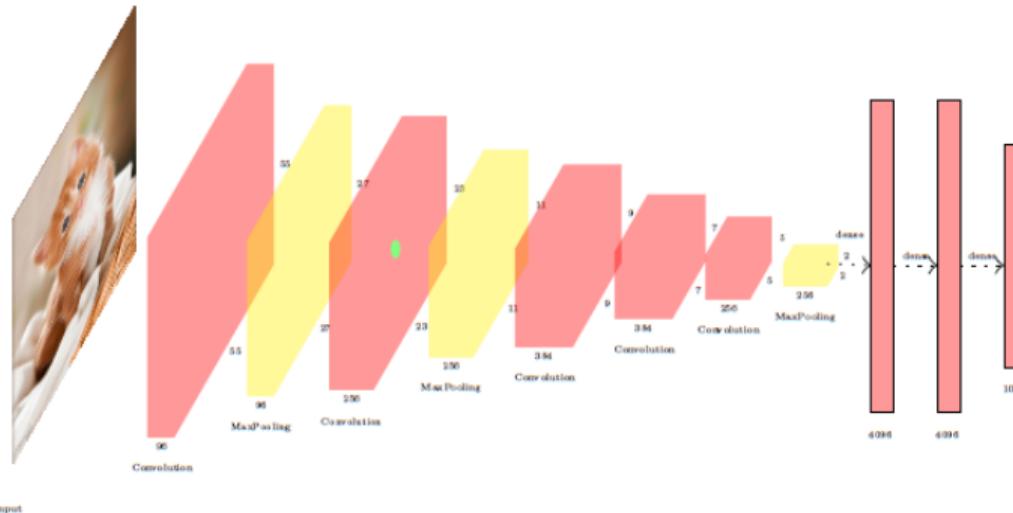
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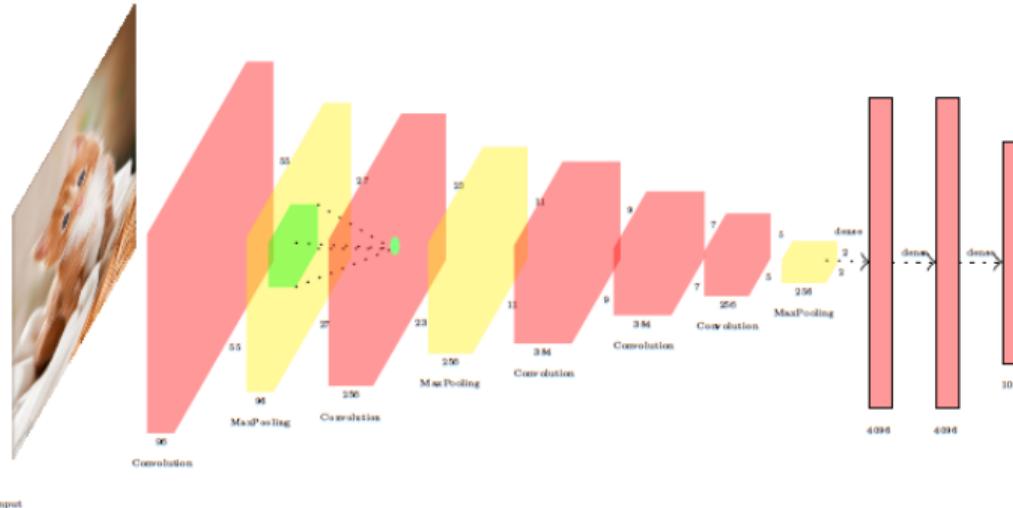
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- Consider a CNN, and a single neuron in any of its intermediate layers
- Feed images to the CNN and identify all images which cause that particular neuron to fire



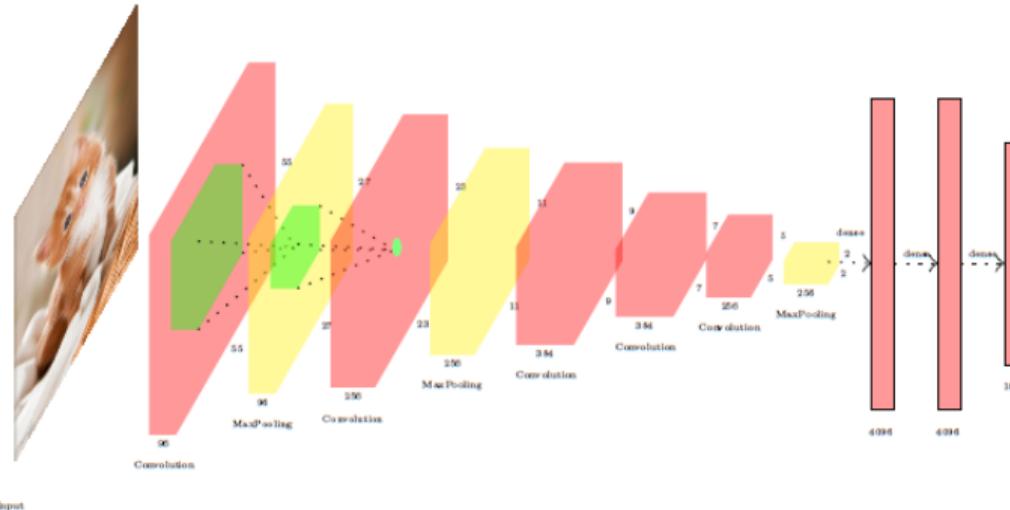
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- Feed images to the CNN and identify all images which cause that particular neuron to fire
- We can then easily trace back to the patch in the image which causes that neuron to fire



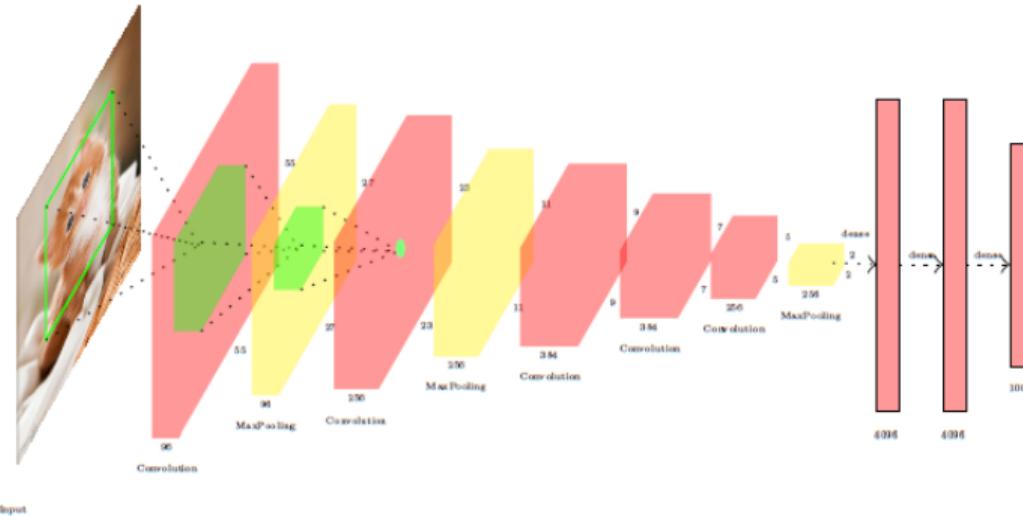
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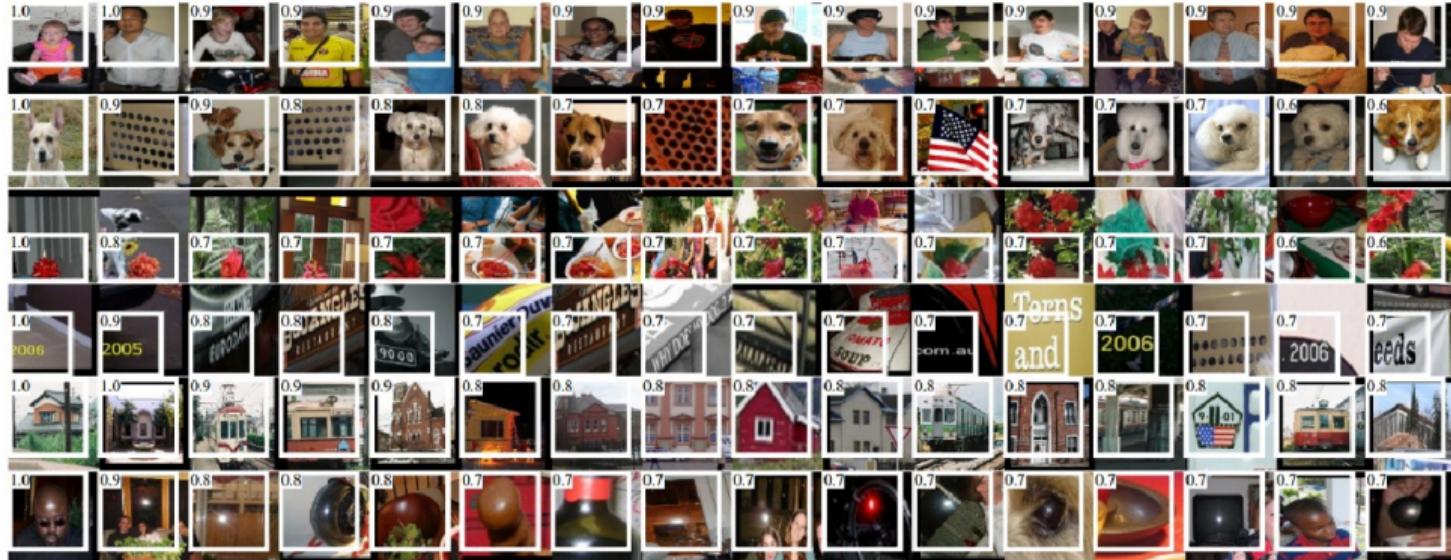
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Visualize Maximally Activating Image Patches

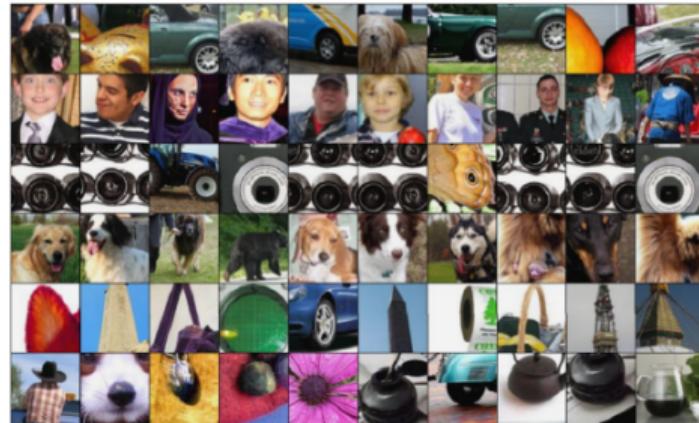
- Repeating this for others neurons in the CNN shows us a pattern



Rich feature hierarchies for accurate object detection and semantic segmentation by Ross Girshick et al.

Visualize Maximally Activating Image Patches

- Repeating this for others neurons in the CNN shows us a pattern



Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015.
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller

Occlusion Experiments²

- Typically, we are interested in understanding which portions of an image are responsible for maximizing probability of a certain class

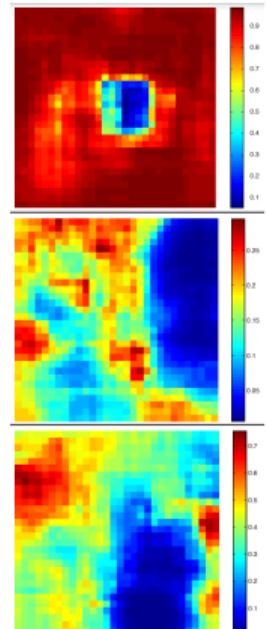
²Zeiler and Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014

Occlusion Experiments²

- Typically, we are interested in understanding which portions of an image are responsible for maximizing probability of a certain class
- Occlude (gray out) different patches in the image (centered on each pixel), and see effect on predicted probability of the correct class \implies gives you a probability for each pixel



Input image



Probability of correct
class

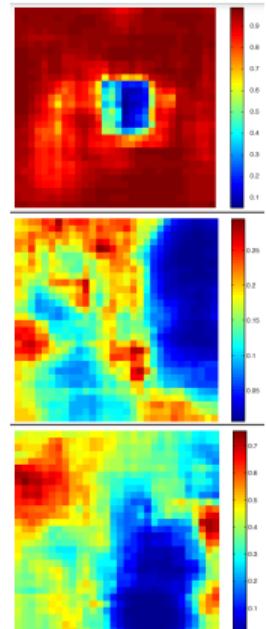
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- For example, the first heat map (top) shows that occluding the face of the dog causes a maximum drop in the prediction probability



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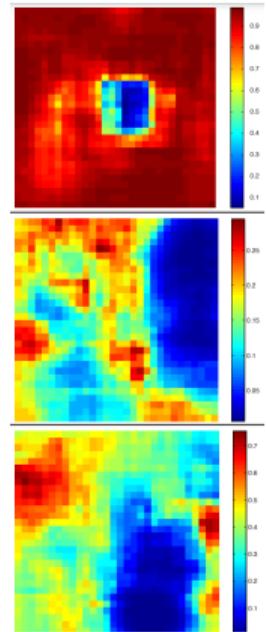
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- For example, the first heat map (top) shows that occluding the face of the dog causes a maximum drop in the prediction probability
- Similar observations for other images



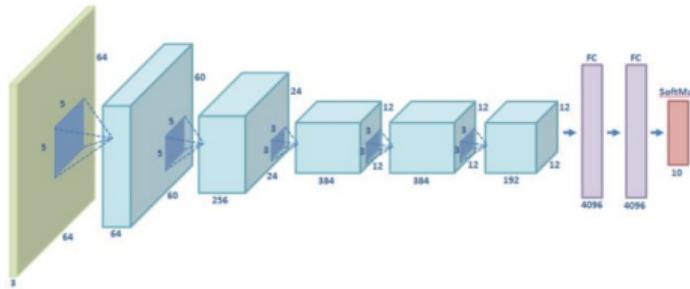
Input image



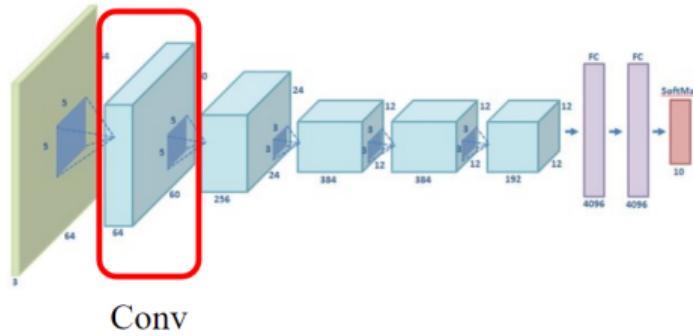
Probability of correct
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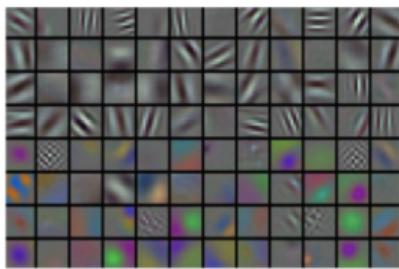
Summary: ‘Don’t-disturb-the-model’ methods



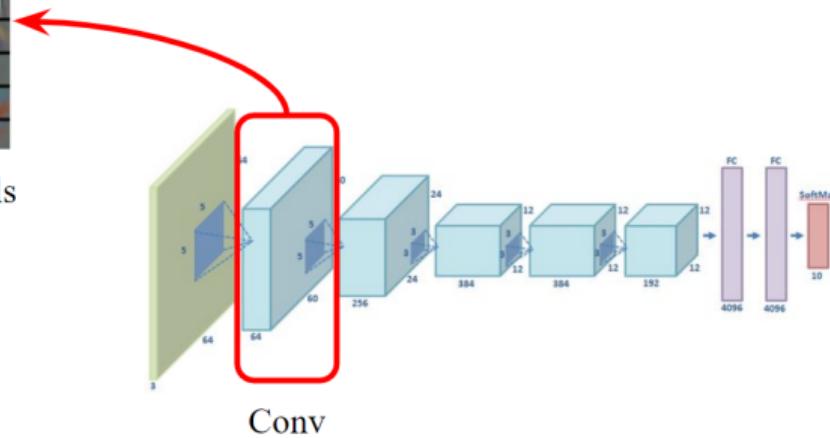
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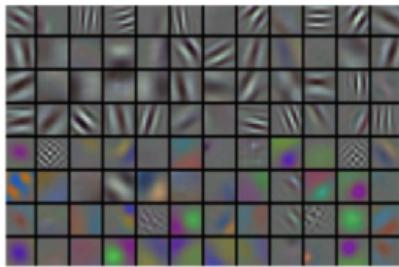
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Visualizing the filter/kernels
(raw weights)

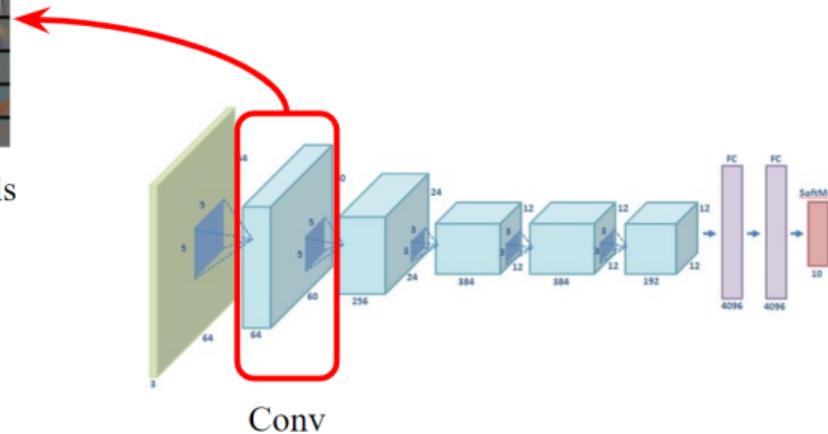


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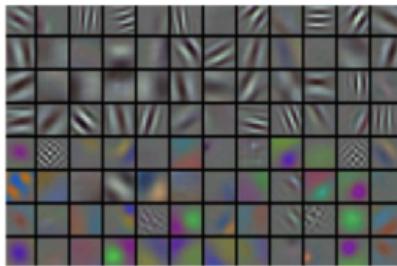


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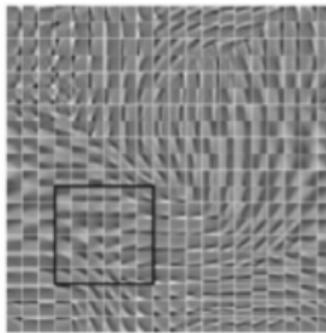
Only interpretable at the first layer!
Not interesting enough for higher layers!



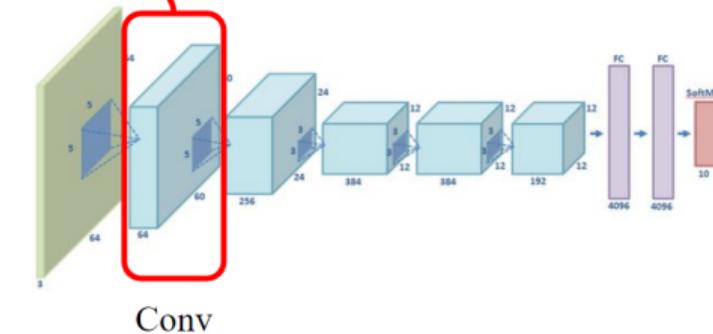
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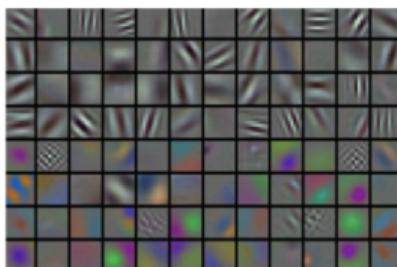


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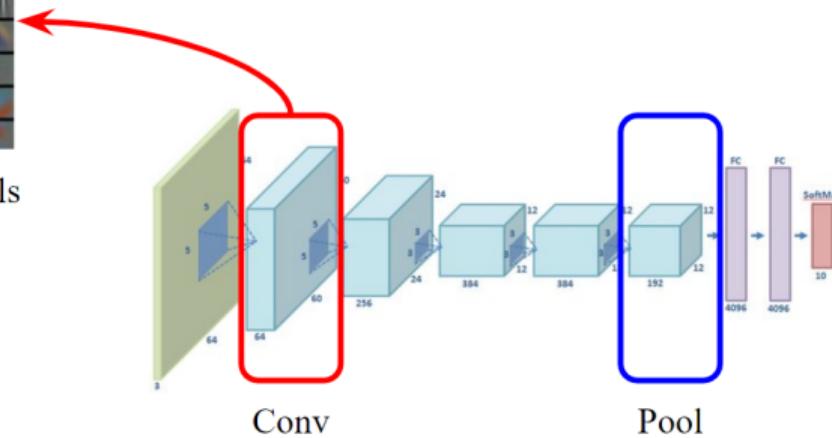


The Gabor-like filter fatigue

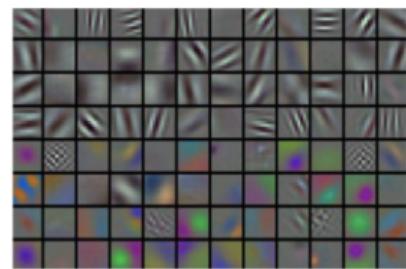
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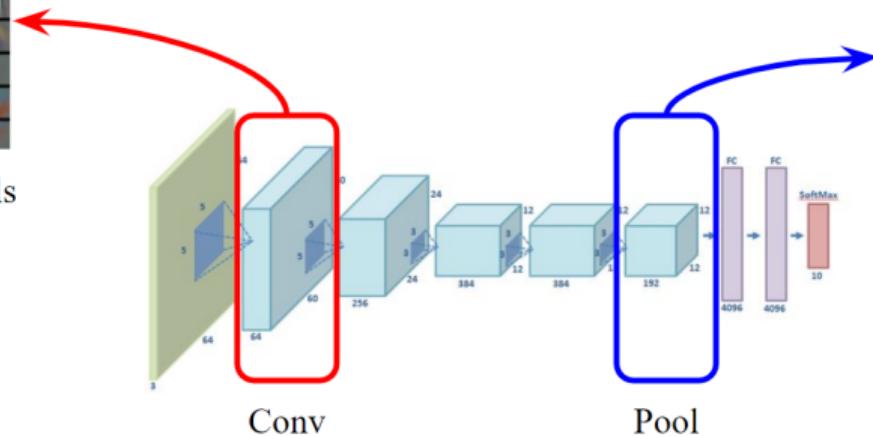
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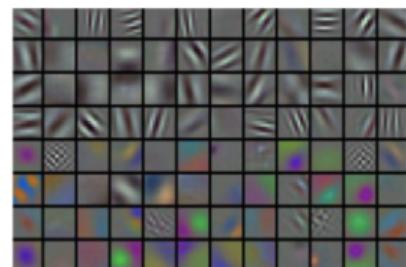
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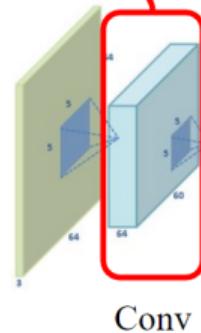
Visualize patches that
maximally activate neuron



Summary: ‘Don’t-disturb-the-model’ methods

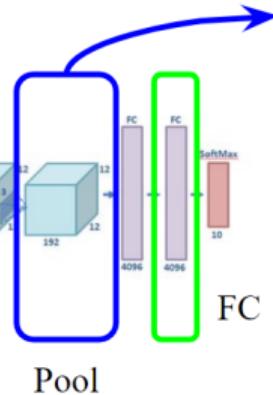


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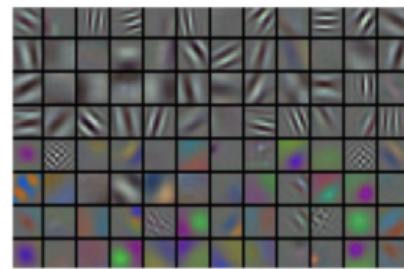


Conv

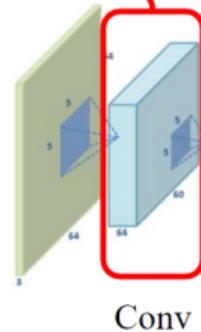
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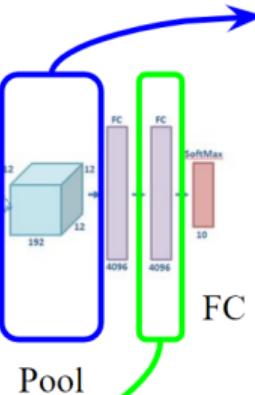


Visualizing the filter/kernels
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Conv

Visualize patches that
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Pool

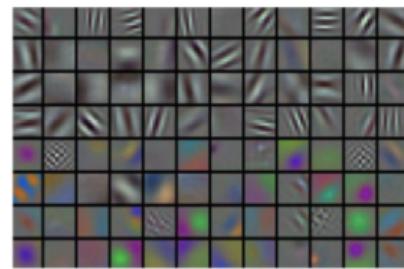
FC



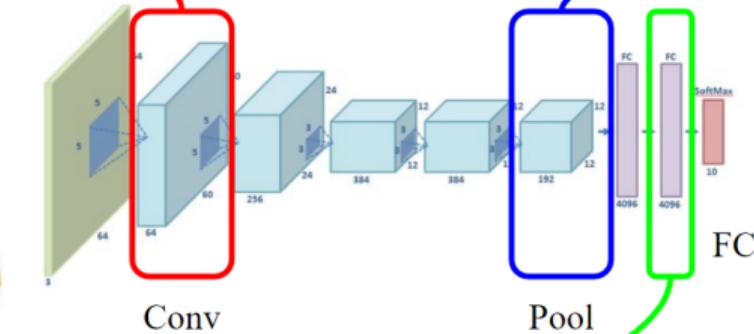
Visualizing the representation



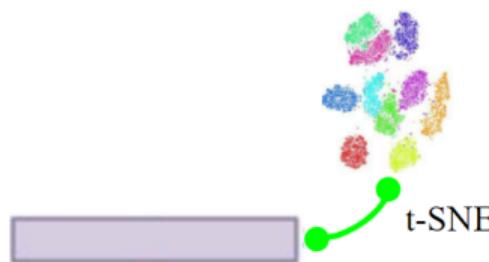
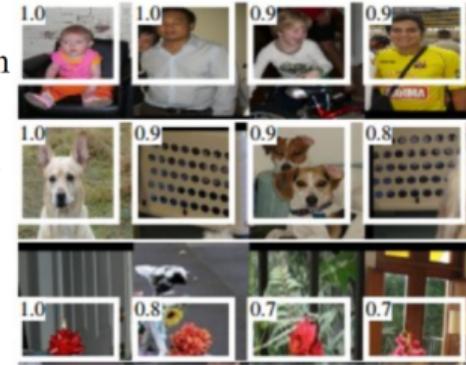
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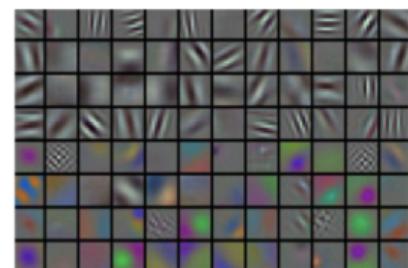


Visualize patches that
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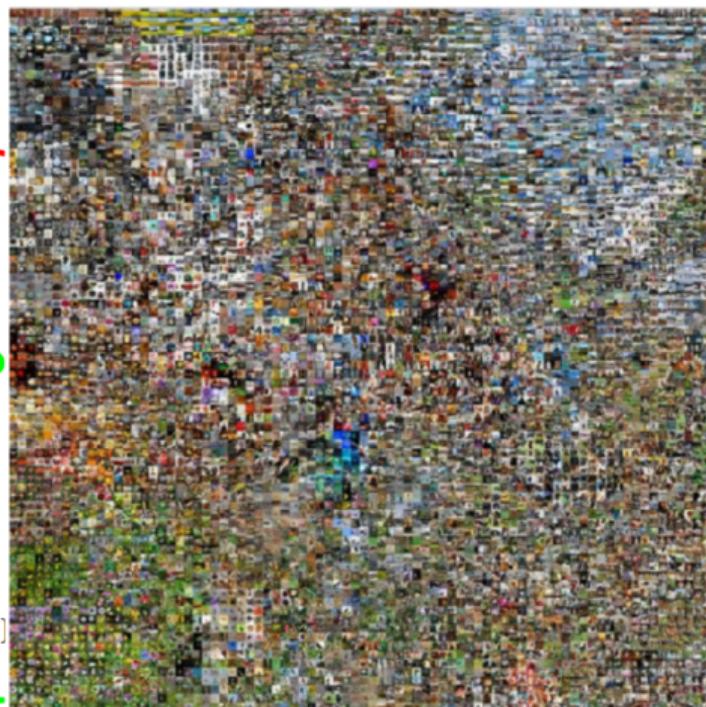


Visualizing the representation

Summary: 'Don't-disturb-the-model' methods



Visualizing the filter/kernels
(raw weights)



Visualizing the representation

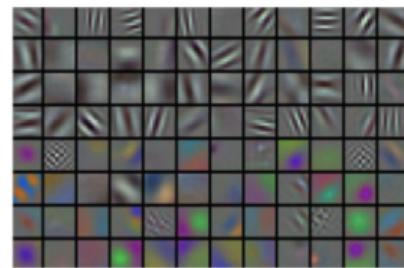
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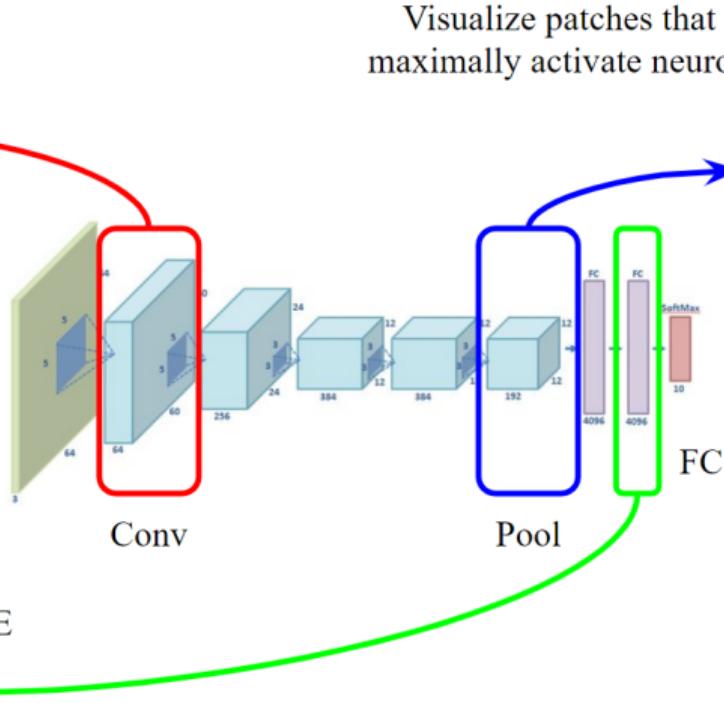
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Visualizing the filter/kernels
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t-SNE

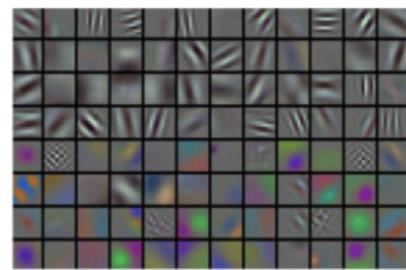


Visualize patches that
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Visualizing the representation

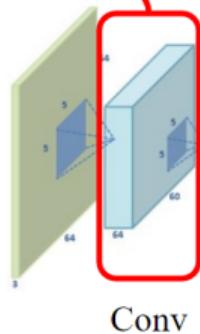
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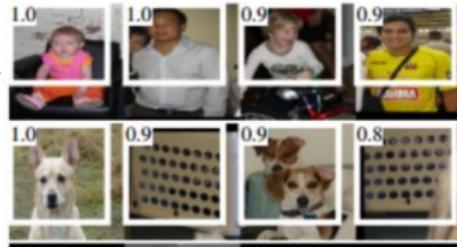


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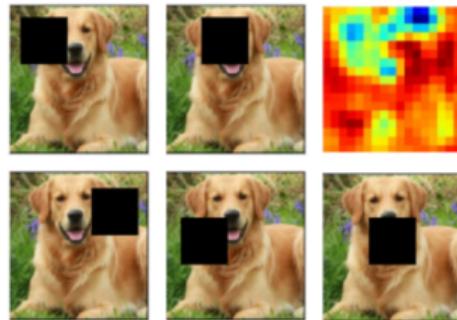


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Visualize patches that
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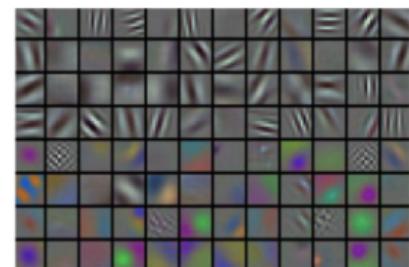


Occlusion Experiment



Visualizing the representation

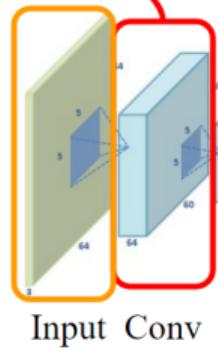
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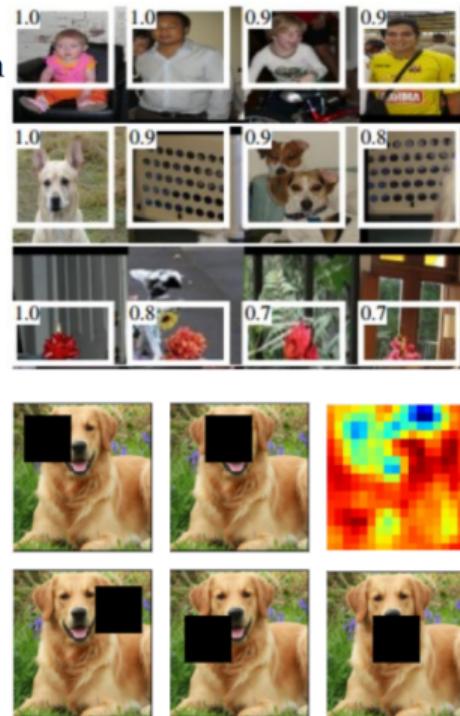
Visualizing the filter/kernels
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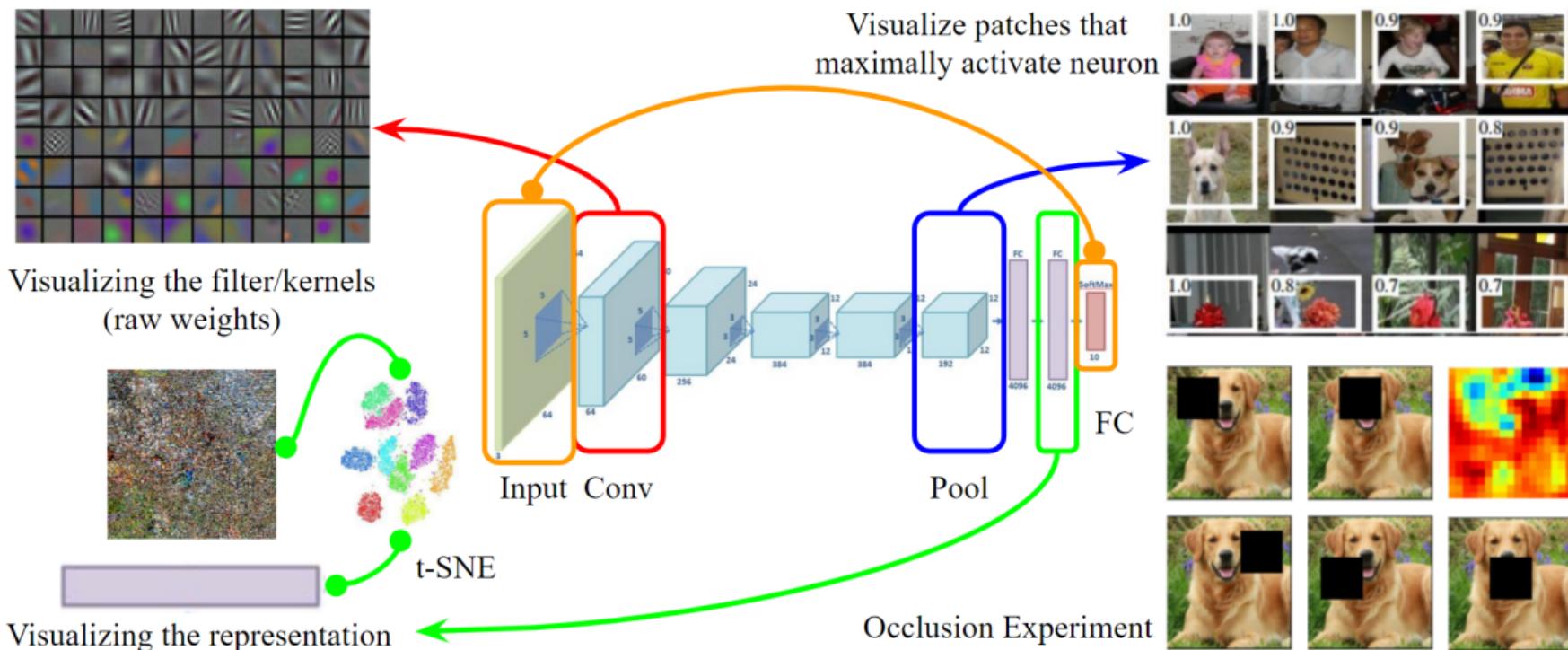


Visualize patches that
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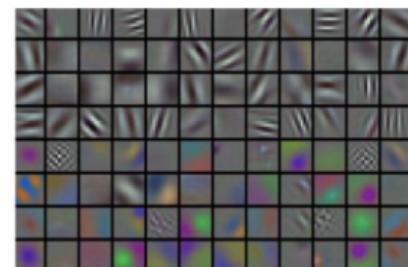


Occlusion Experiment

Summary: ‘Don’t-disturb-the-model’ methods



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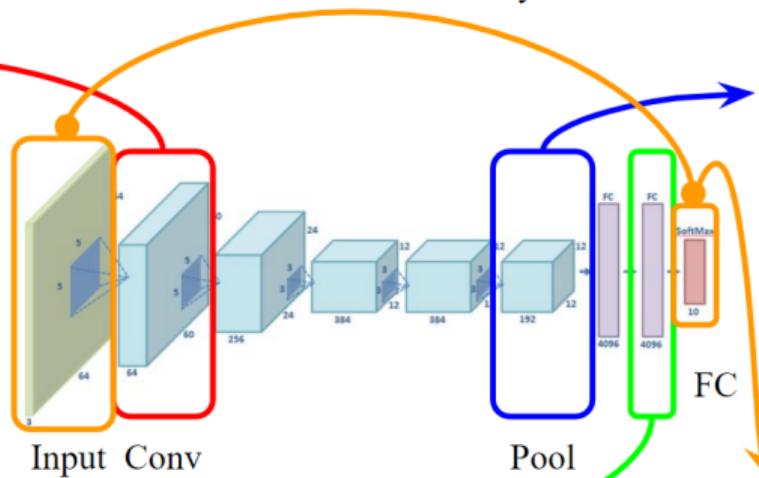


Visualizing the filter/kernels
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t-SNE

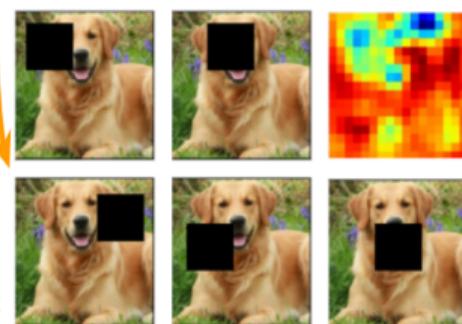
Visualizing the representation



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Occlusion Experiment



Readings

Summary of Visualizing CNNs

- Lecture Notes of CS231n, Stanford

Miscellaneous

- Deep Visualization Toolkit [demo video](#) and [webpage](#) by J. Yosinski et al.
- To see high-resolution t-SNE visualizations, visit [here](#)
- To know more about t-SNE, visit [here](#)

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