

Explaining CNNs: Visualization Methods

Vineeth N Balasubramanian

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

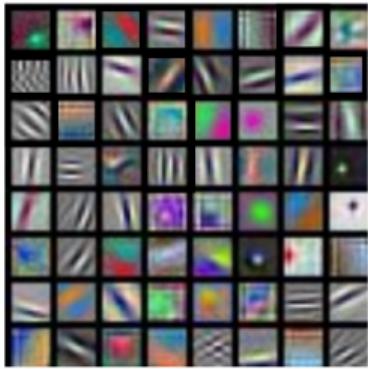


Acknowledgements

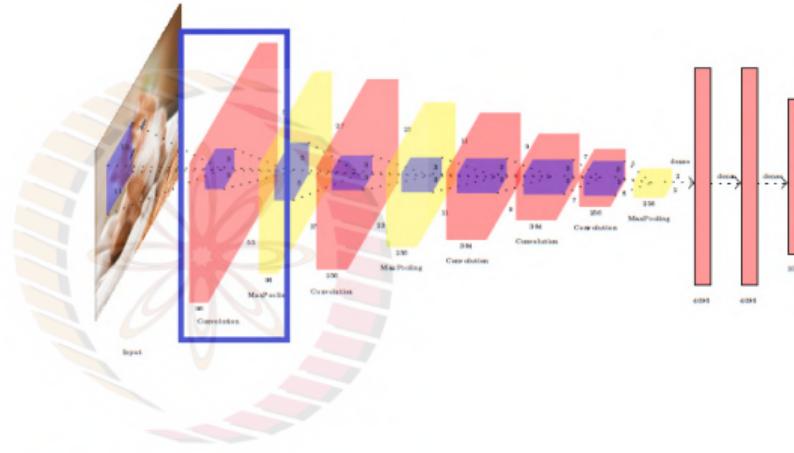
- Most of this lecture's slides are based on **Lecture 13 of CS231n: Convolutional Neural Networks for Visual Recognition** course taught by Fei-Fei Li and others at Stanford University
- Some content (AlexNet CNN figures, etc) is also adapted from **Lecture 12 of CS7015: Deep Learning** course taught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

NPTEL

Visualize Filters/Kernels (First Layer)¹



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



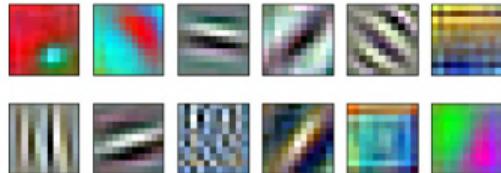
NPTEL

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

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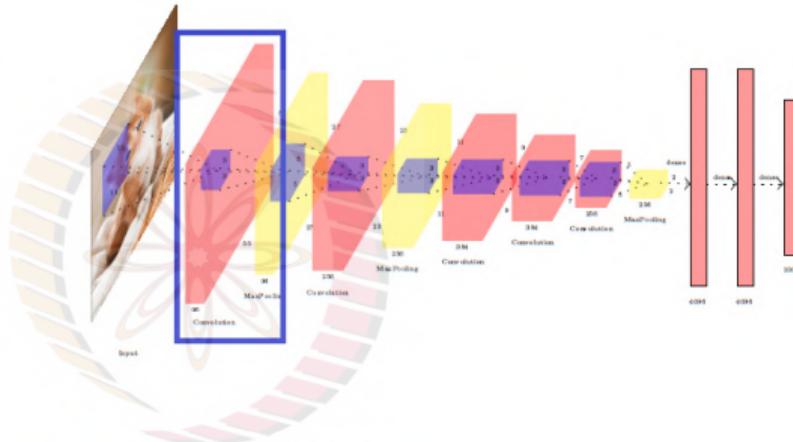


AlexNet:
 $64 \times 3 \times 11 \times 11$



A Closer Look (AlexNet)

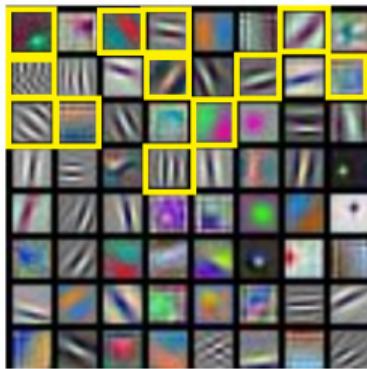
Fan et al.(arxiv:1904.05526)



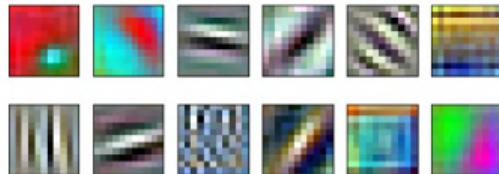
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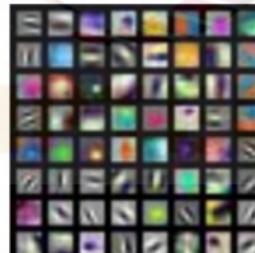
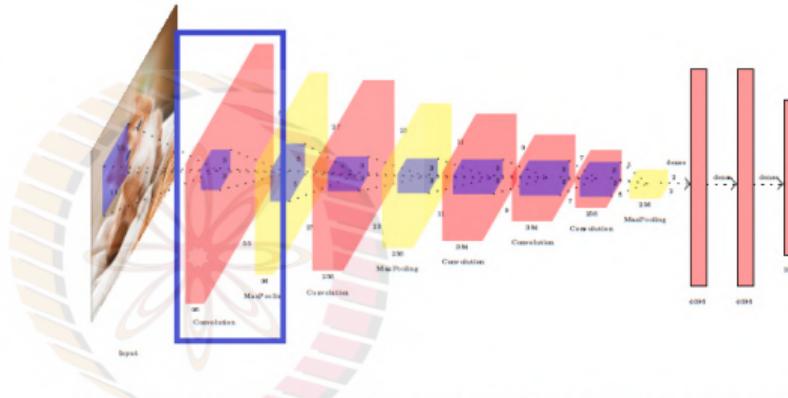
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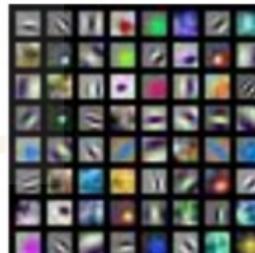
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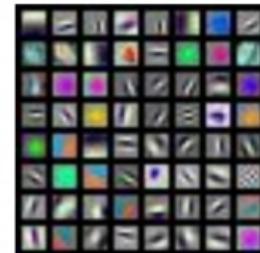
A Closer Look (AlexNet)
Fan et al. (arxiv:1904.05526)



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



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



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

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

Visualize Filters/Kernels (First Layer)

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



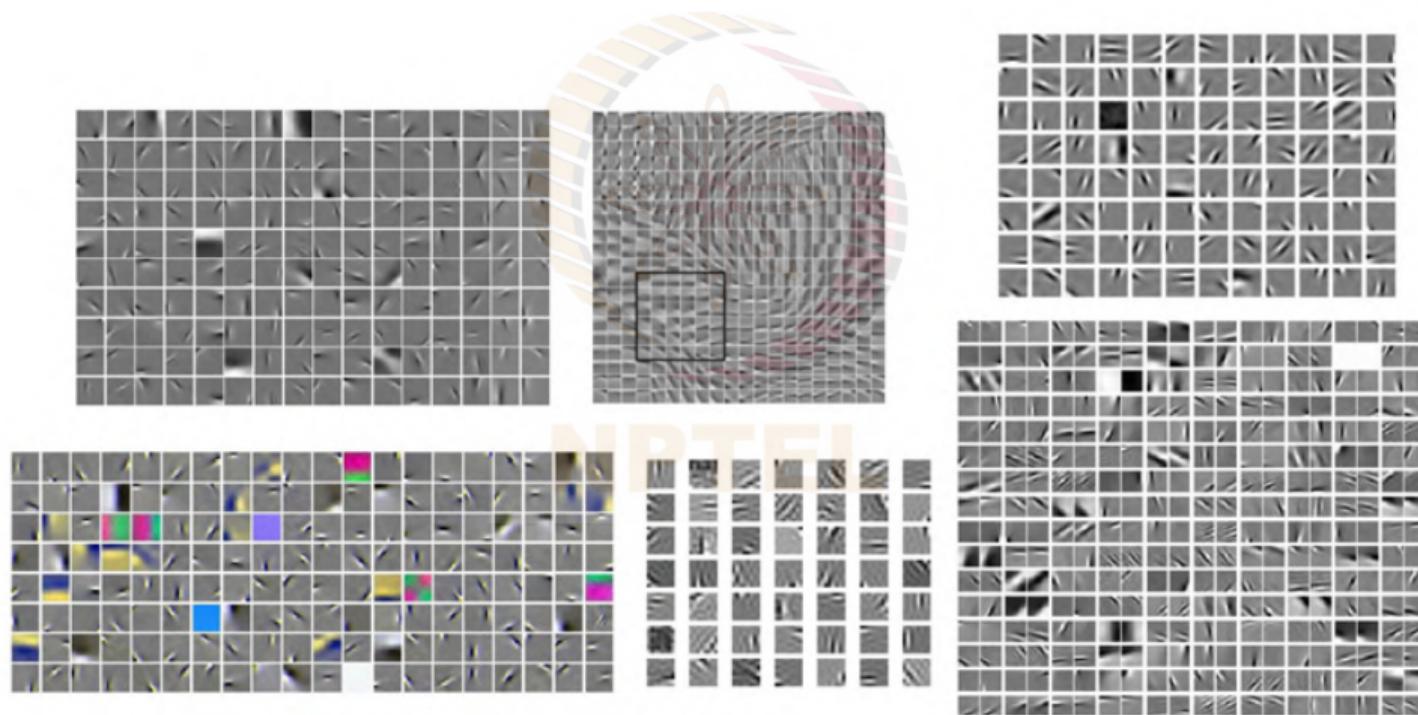
Visualize Filters/Kernels (First Layer)

- 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

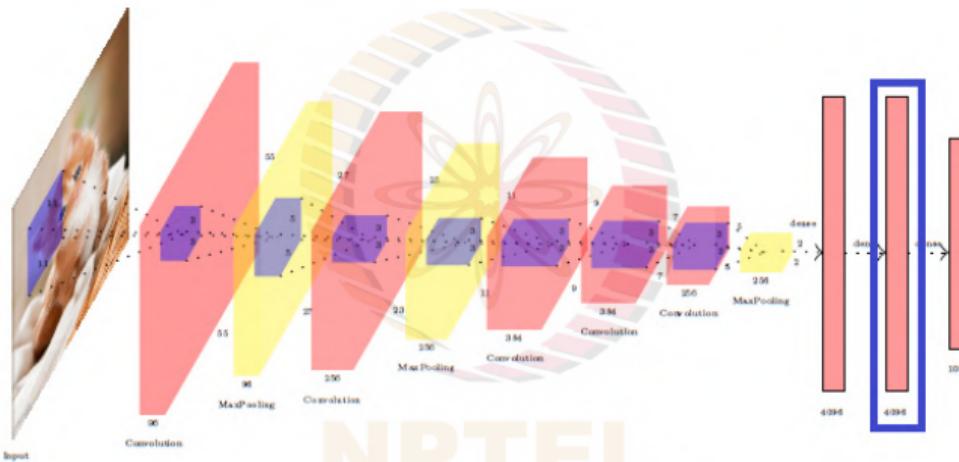
Weights:		layer 1 weights
Weights:		$16 \times 3 \times 7 \times 7$ layer 2 weights
Weights:		$20 \times 16 \times 7 \times 7$ layer 3 weights

Visualize Filters/Kernels (First Layer)

The Gabor-like filters fatigue



Visualize the Representation Space (Last Layer)



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- 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)

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



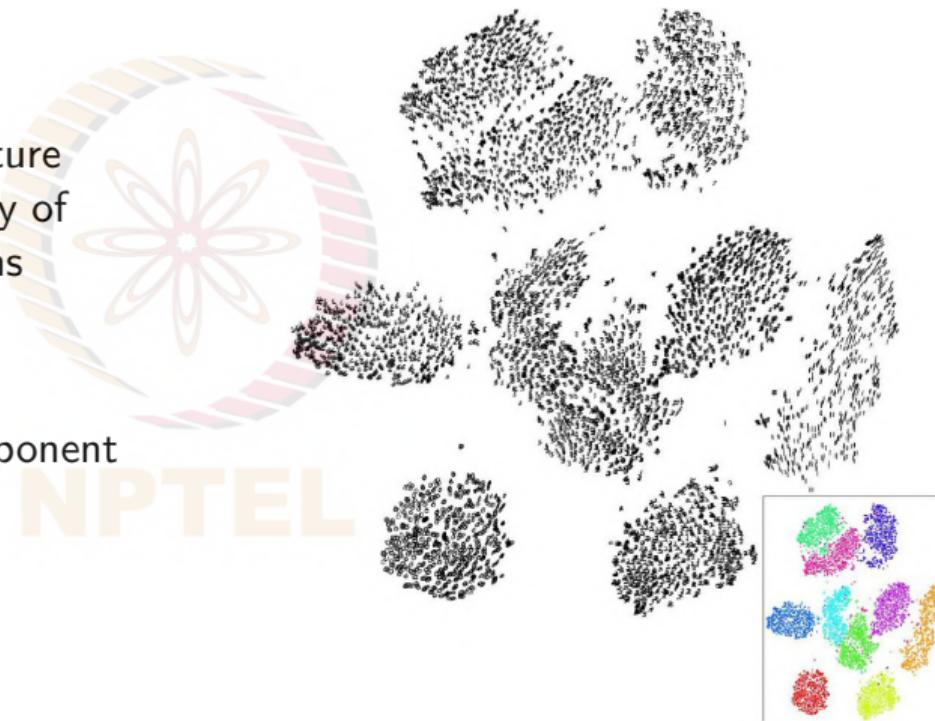
Visualize the Representation Space (Last Layer)

- 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)



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

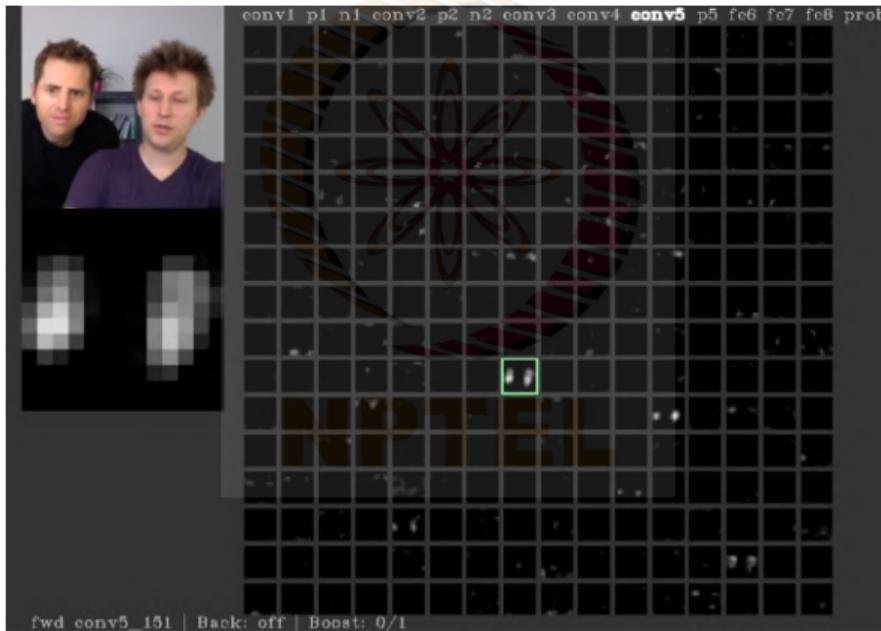
- Images that are nearby each other are also close in the CNN representation space, which implies that the CNN "sees" them as being very similar



- 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

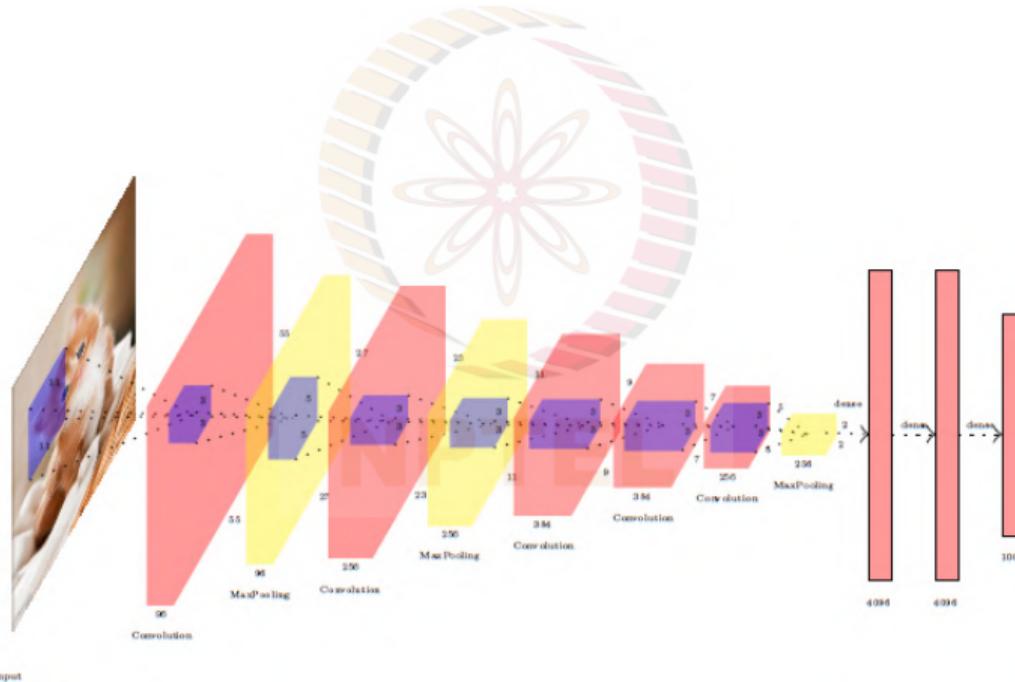


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

Figure copyright: Jason Yosinski, 2014.

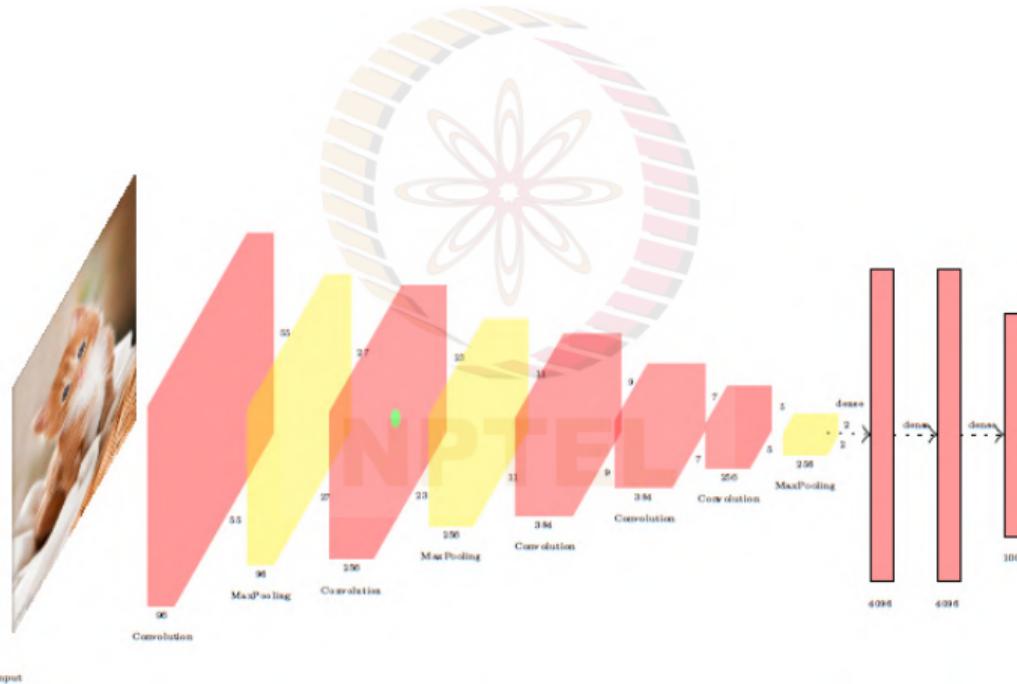
Visualize Maximally Activating Image Patches

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



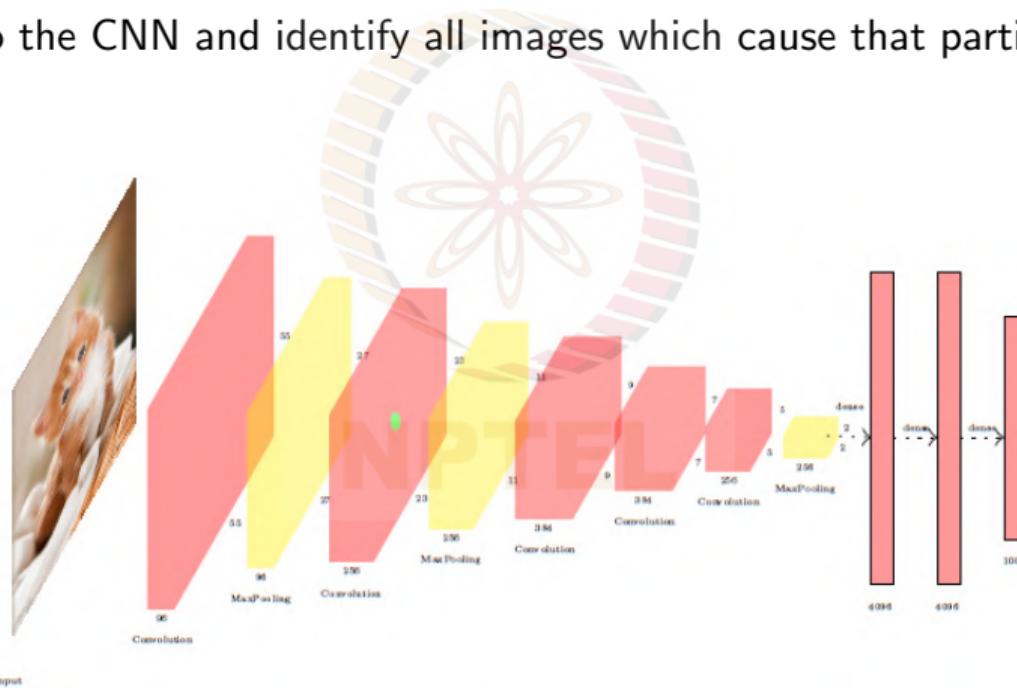
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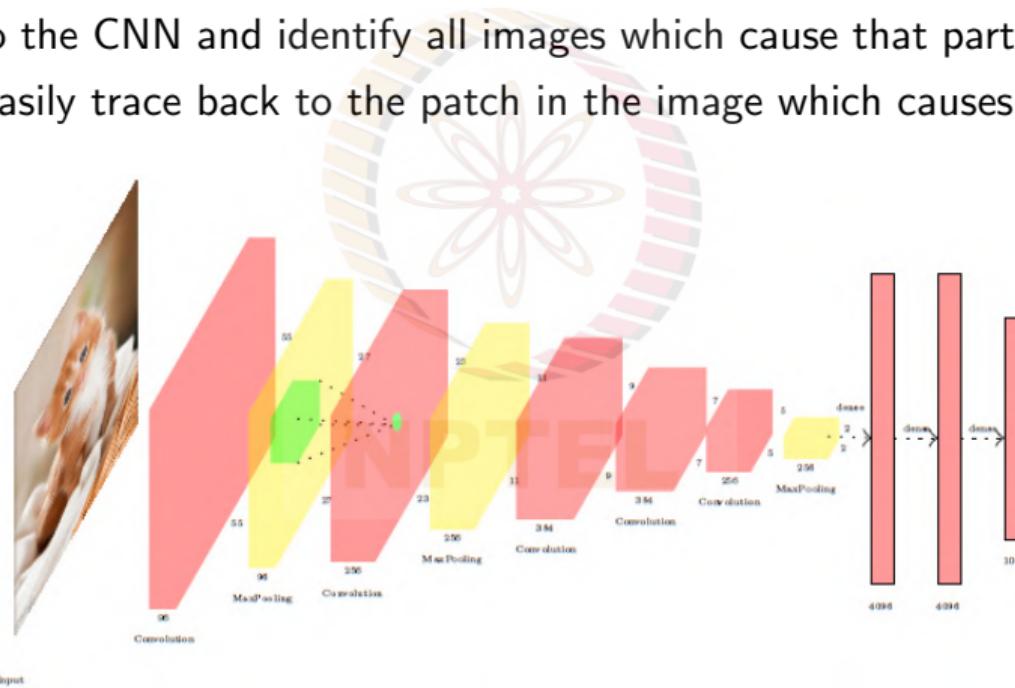
Visualize Maximally Activating Image Patches

- 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



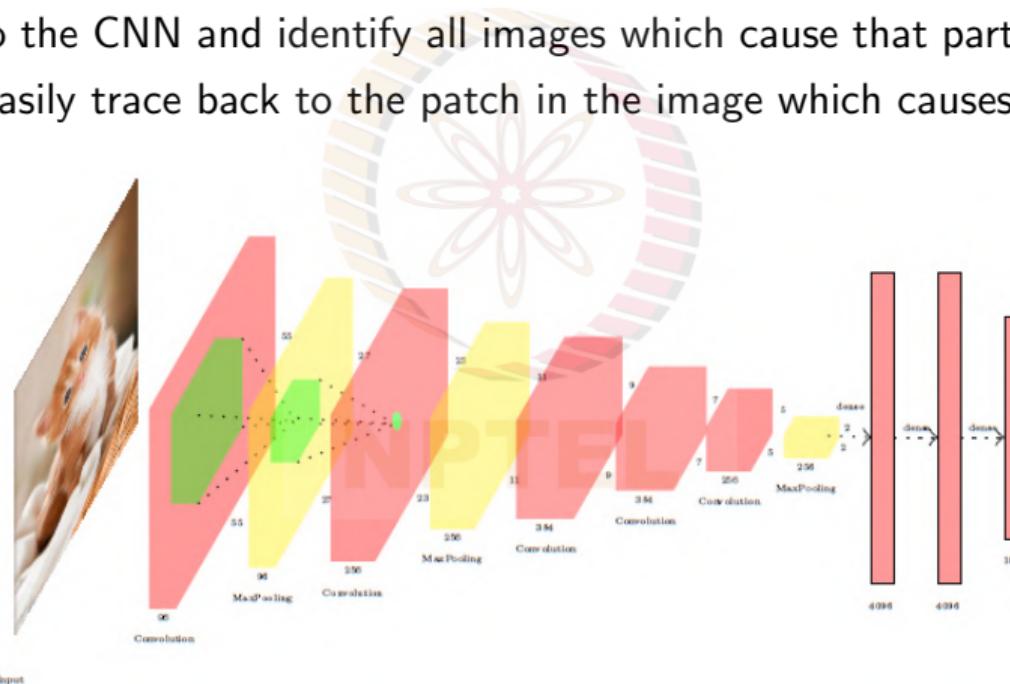
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- Consider a CNN, and a single neuron in any of its intermediate layers
- Feed images to the CNN and identify all images which cause that particular neuron to fire
- We can then easily trace back to the patch in the image which causes that neuron to fire



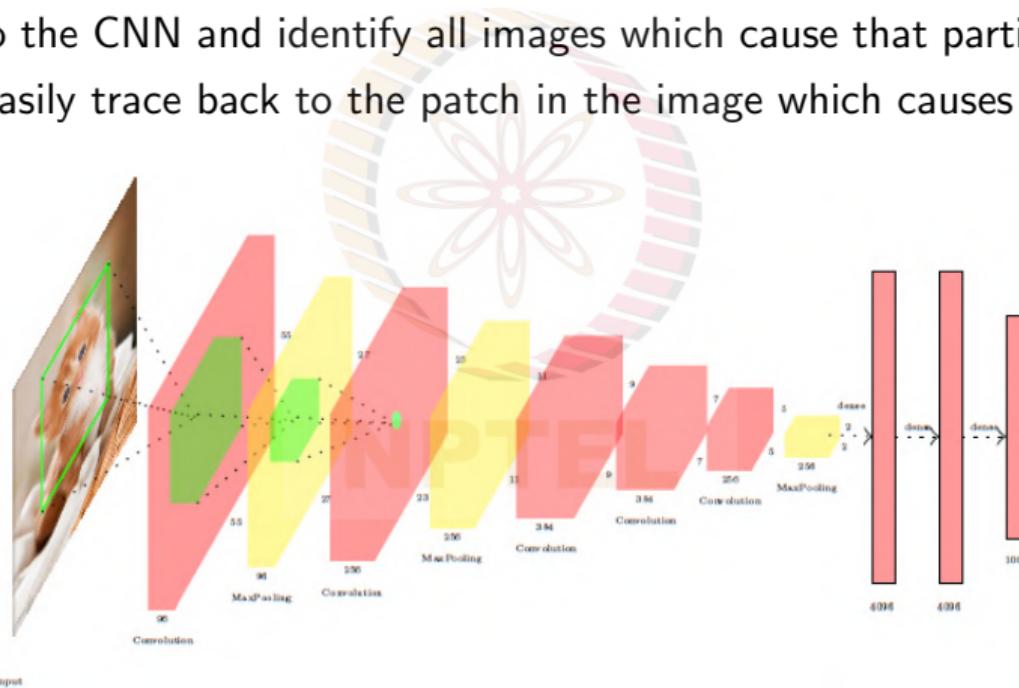
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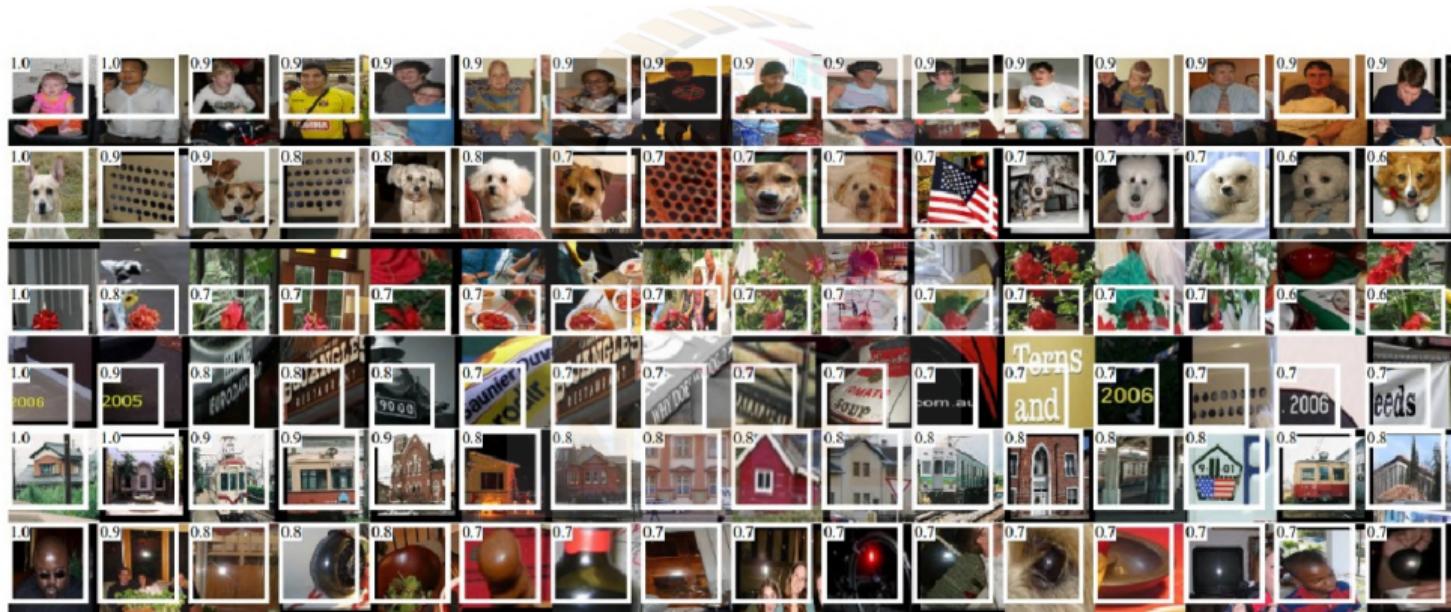
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Visualize Maximally Activating Image Patches

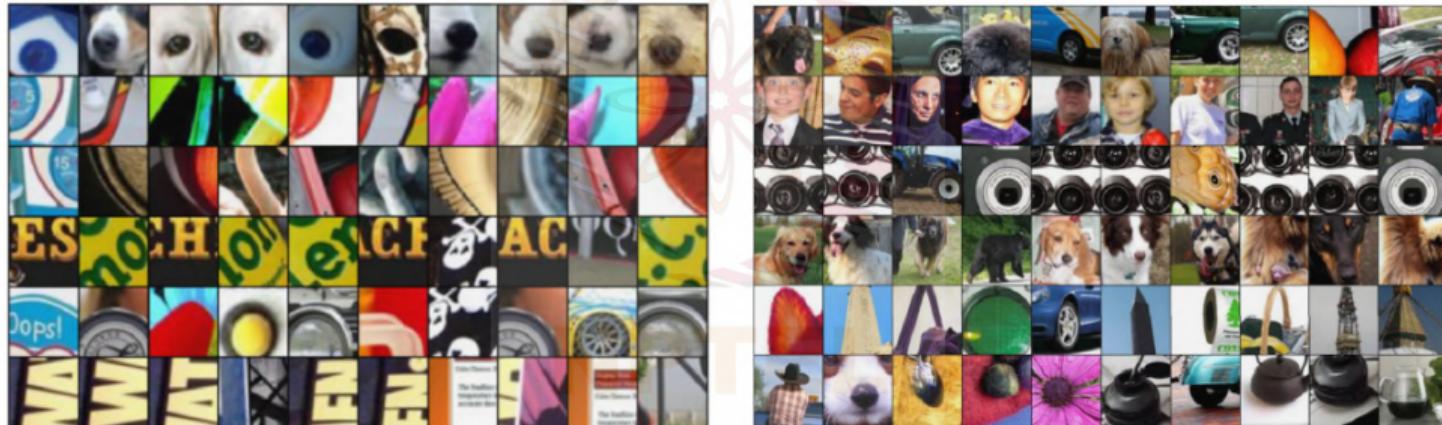
- Repeating this for others neurons in the CNN shows us a pattern



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



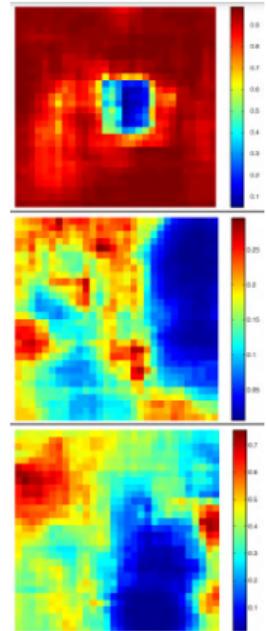
²Zeiler and Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014

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

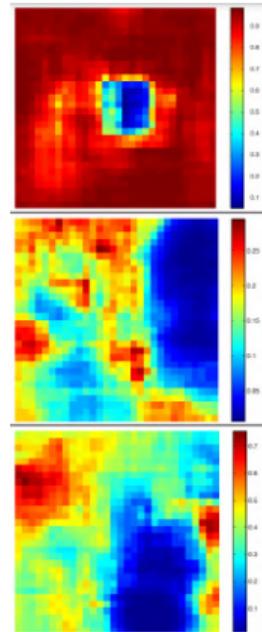
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- For example, the first heat map (top) shows that occluding the face of the dog causes a maximum drop in the prediction probability



Input image



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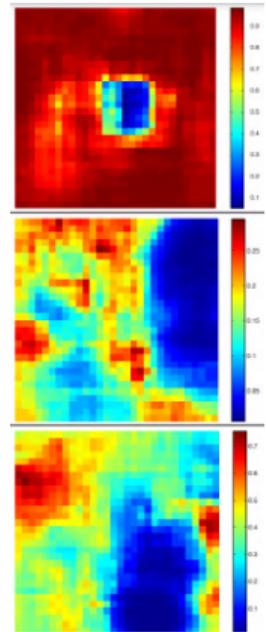
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- For example, the first heat map (top) shows that occluding the face of the dog causes a maximum drop in the prediction probability
- Similar observations for other images



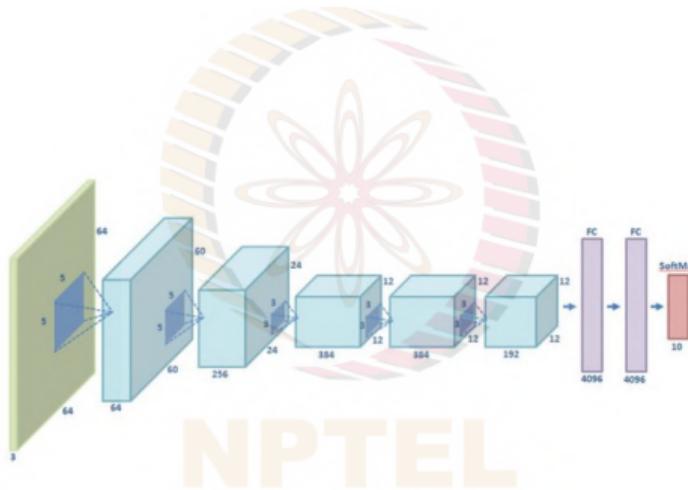
Input image



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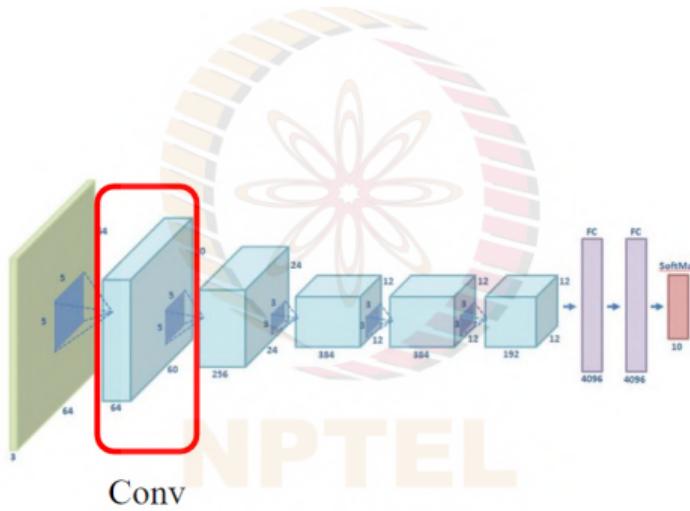
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Summary: ‘Don’t-disturb-the-model’ methods

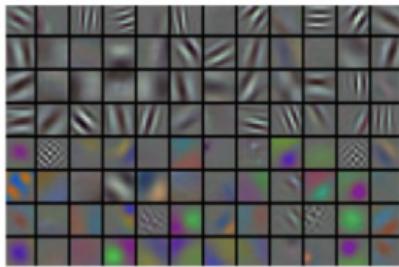


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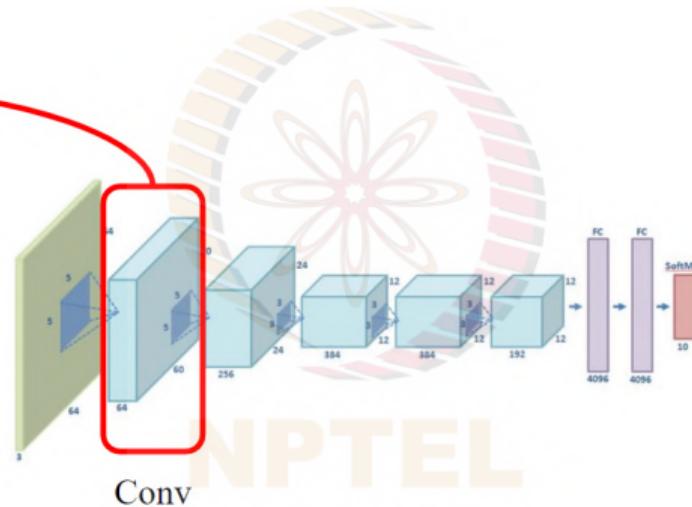
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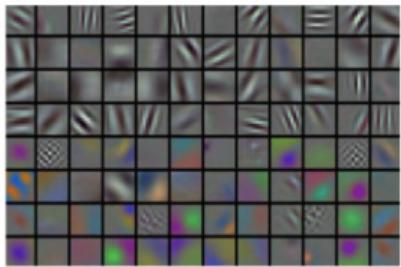
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Visualizing the filter/kernels
(raw weights)

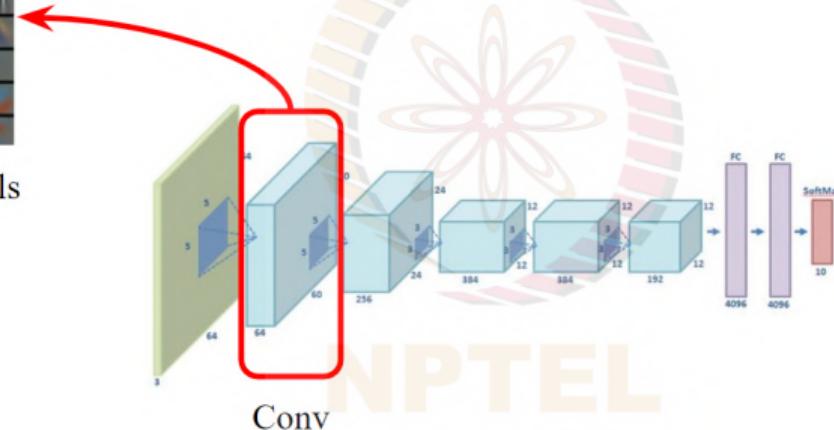


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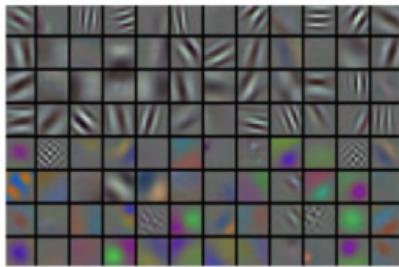


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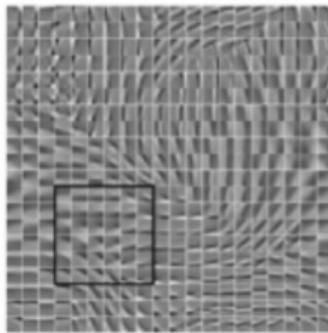
Only interpretable at the first layer!
Not interesting enough for higher layers!



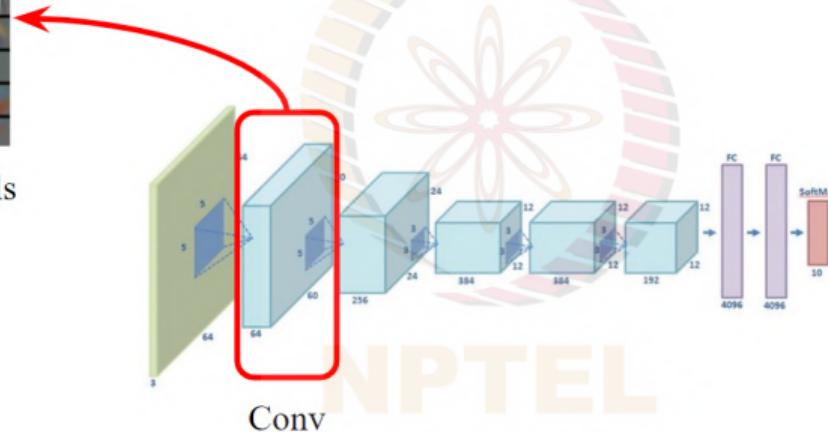
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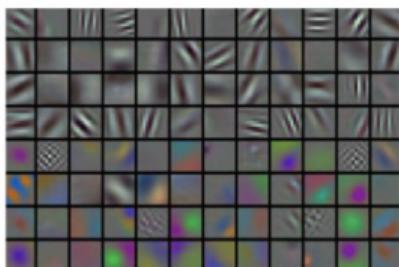


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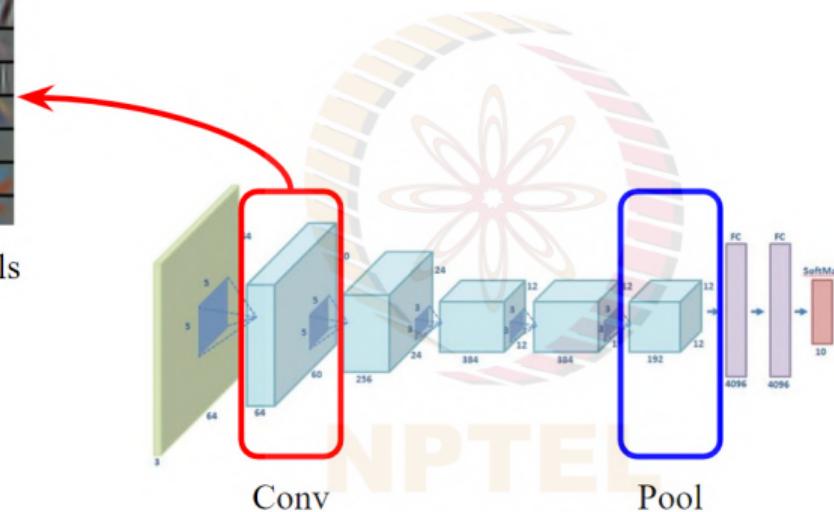


The Gabor-like filter fatigue

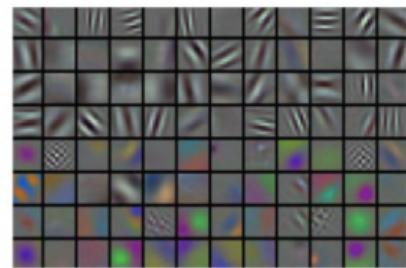
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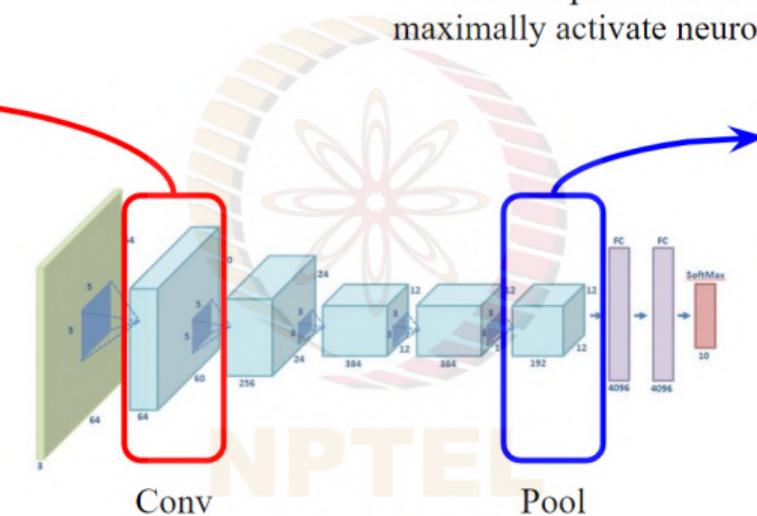
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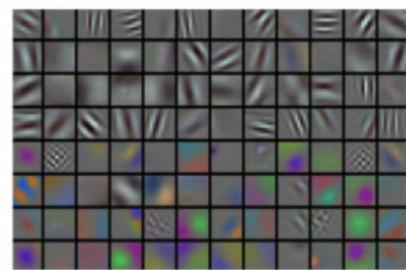
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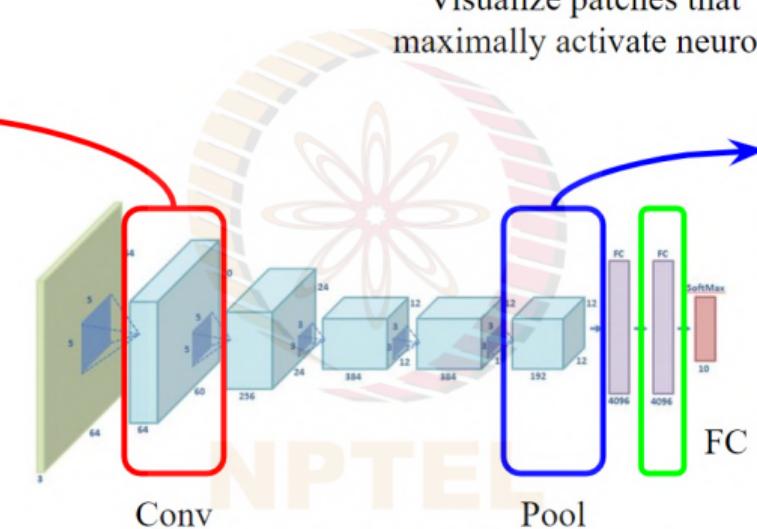
Visualize patches that
maximally activate neuron



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



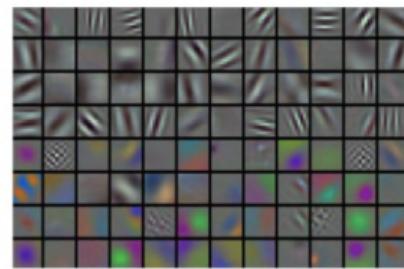
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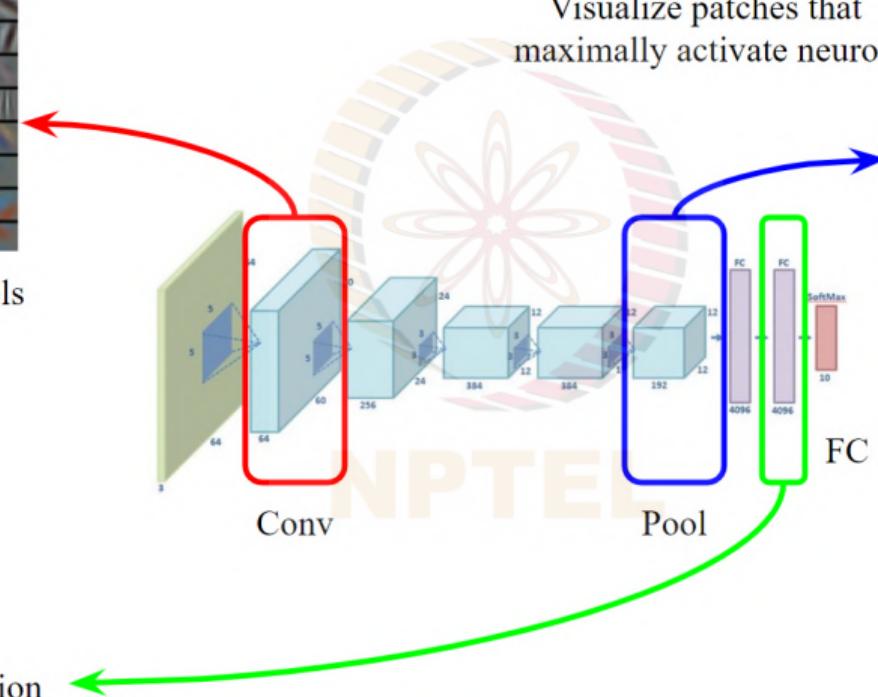
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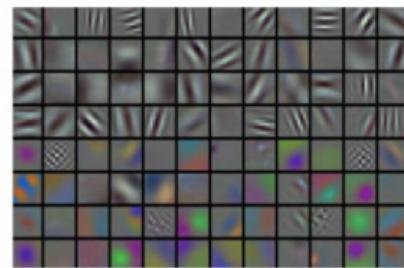
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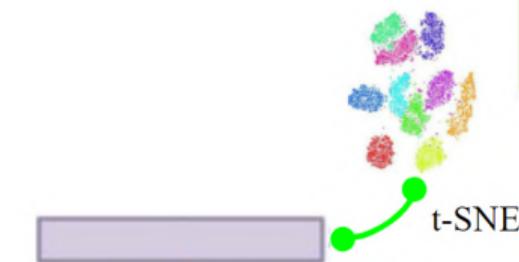
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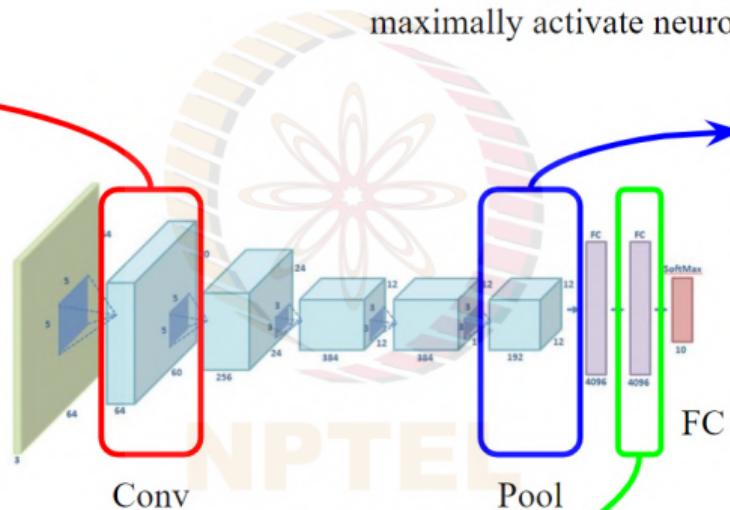
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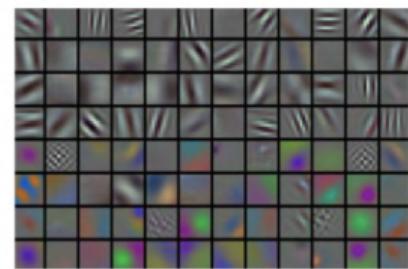
Visualizing the representation



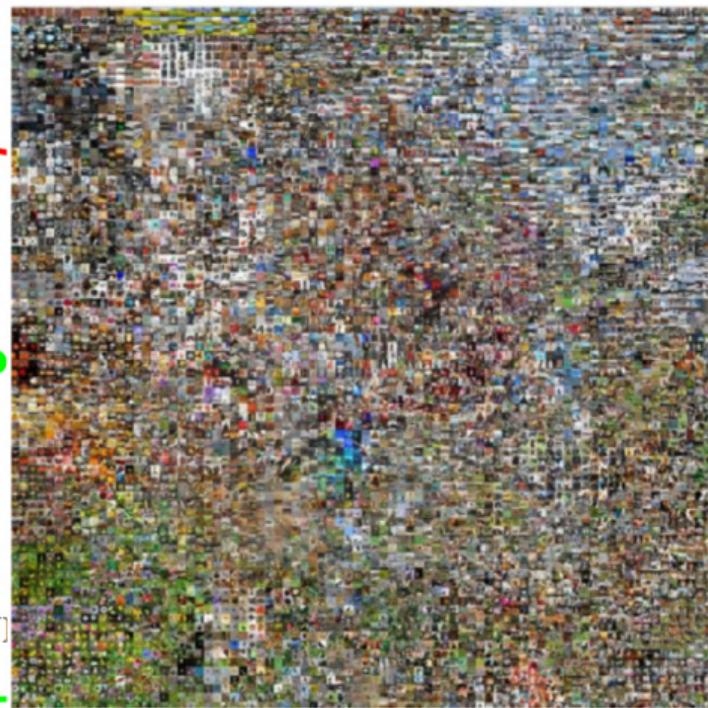
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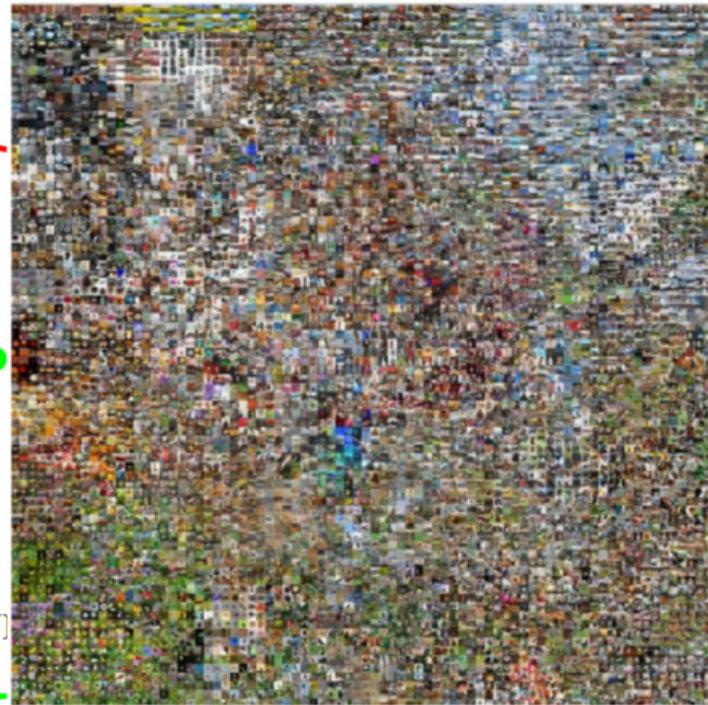


Visualizing the filter/kernels
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Visualizing the representation



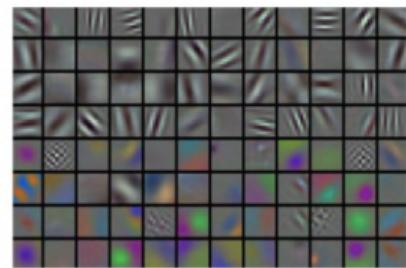
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Summary: 'Don't-disturb-the-model' methods

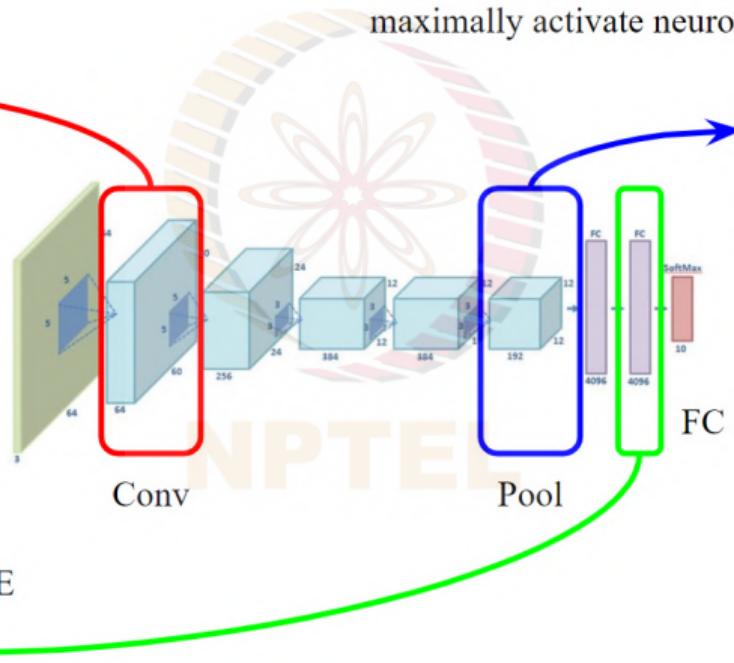


Visualizing the filter/kernels
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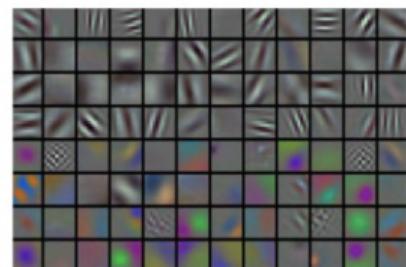
t-SNE

Visualizing the representation



Visualize patches that
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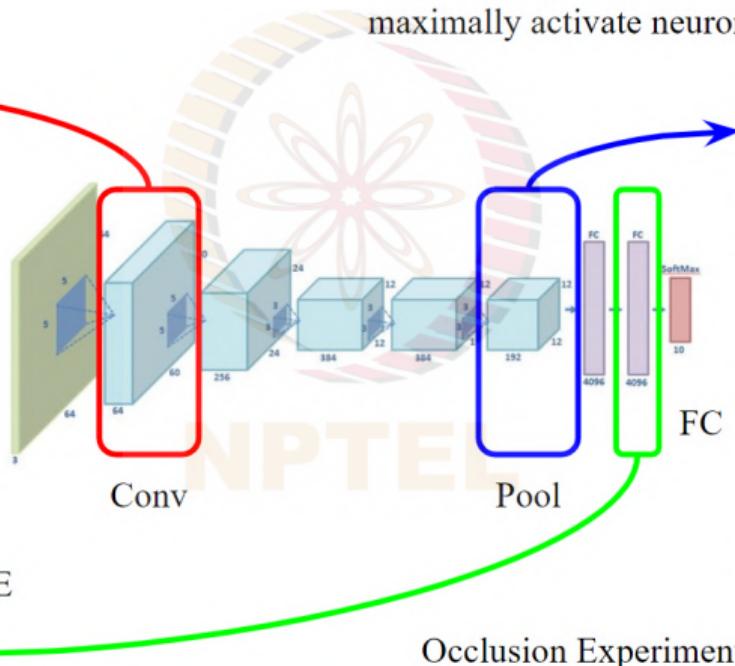
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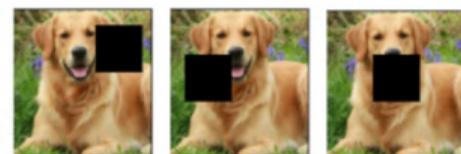
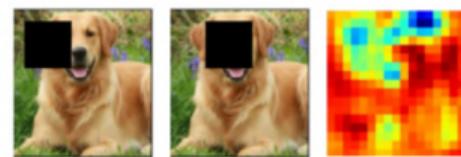
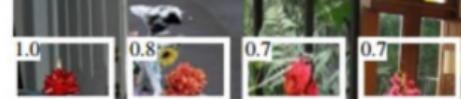
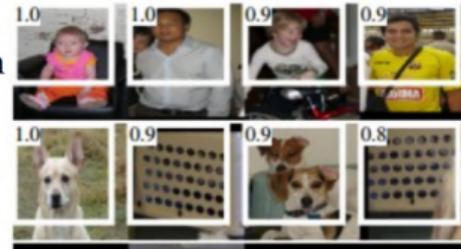
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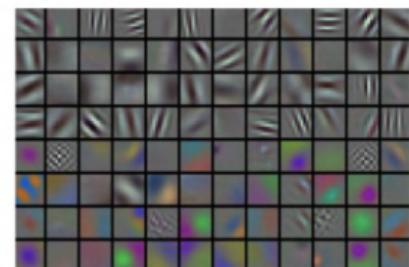
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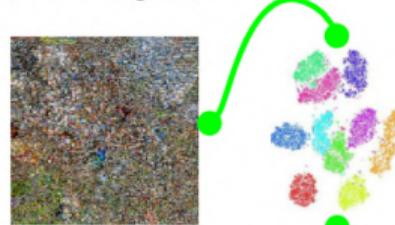
Visualizing the representation

Occlusion Experiment

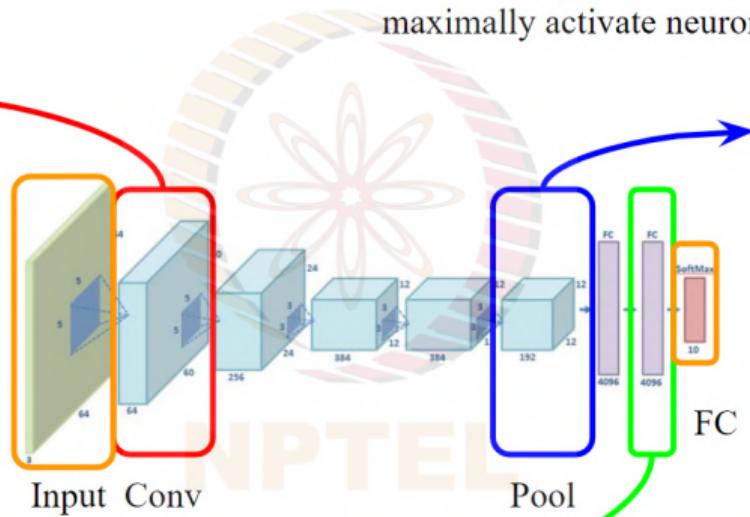
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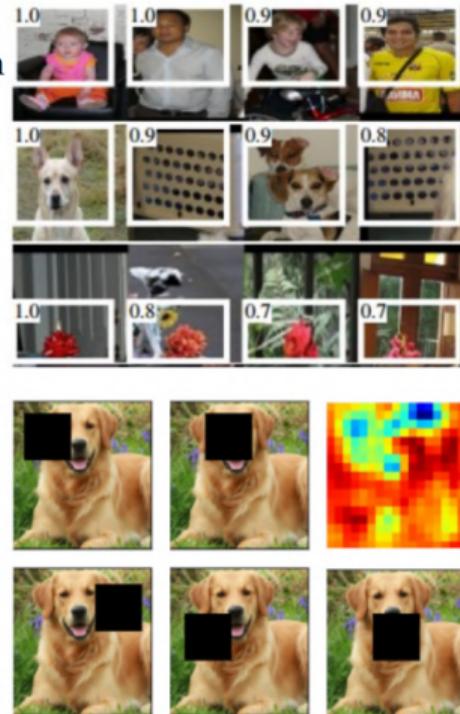
Visualizing the filter/kernels
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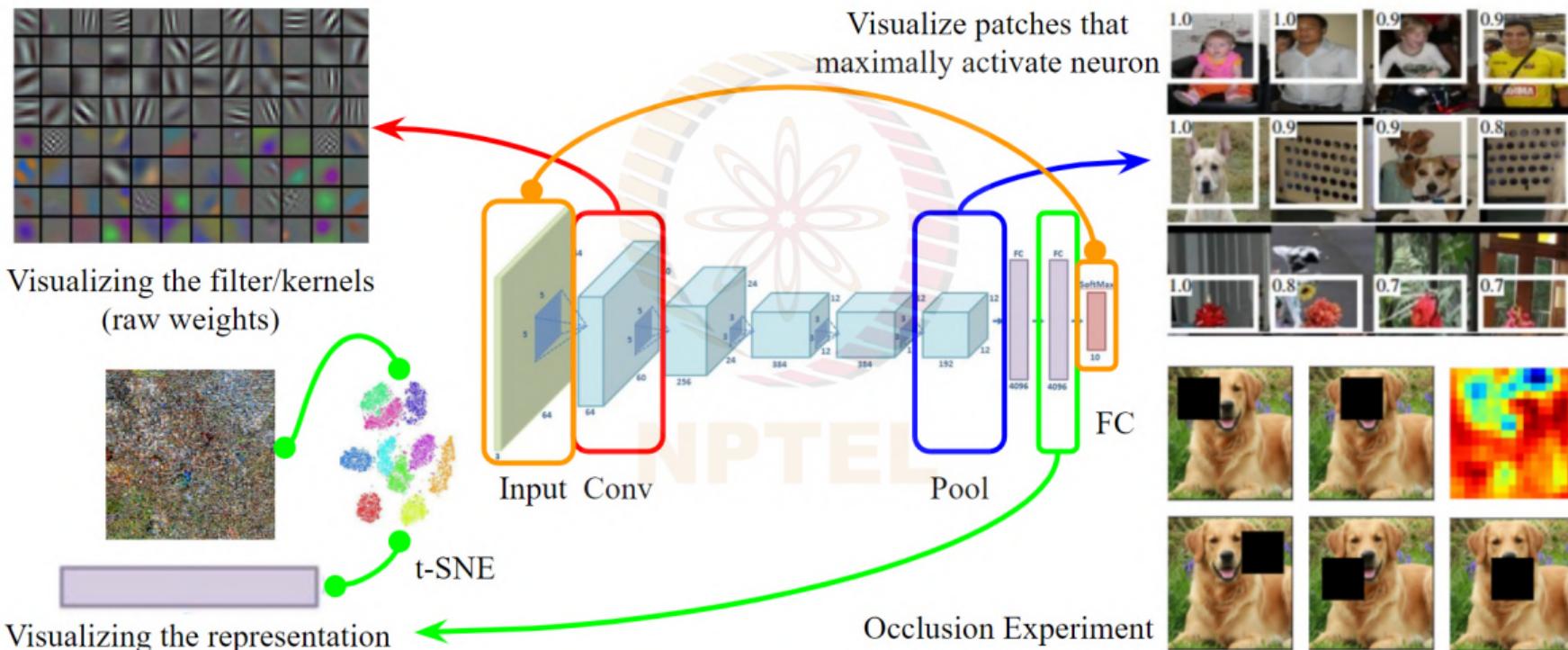


Visualize patches that
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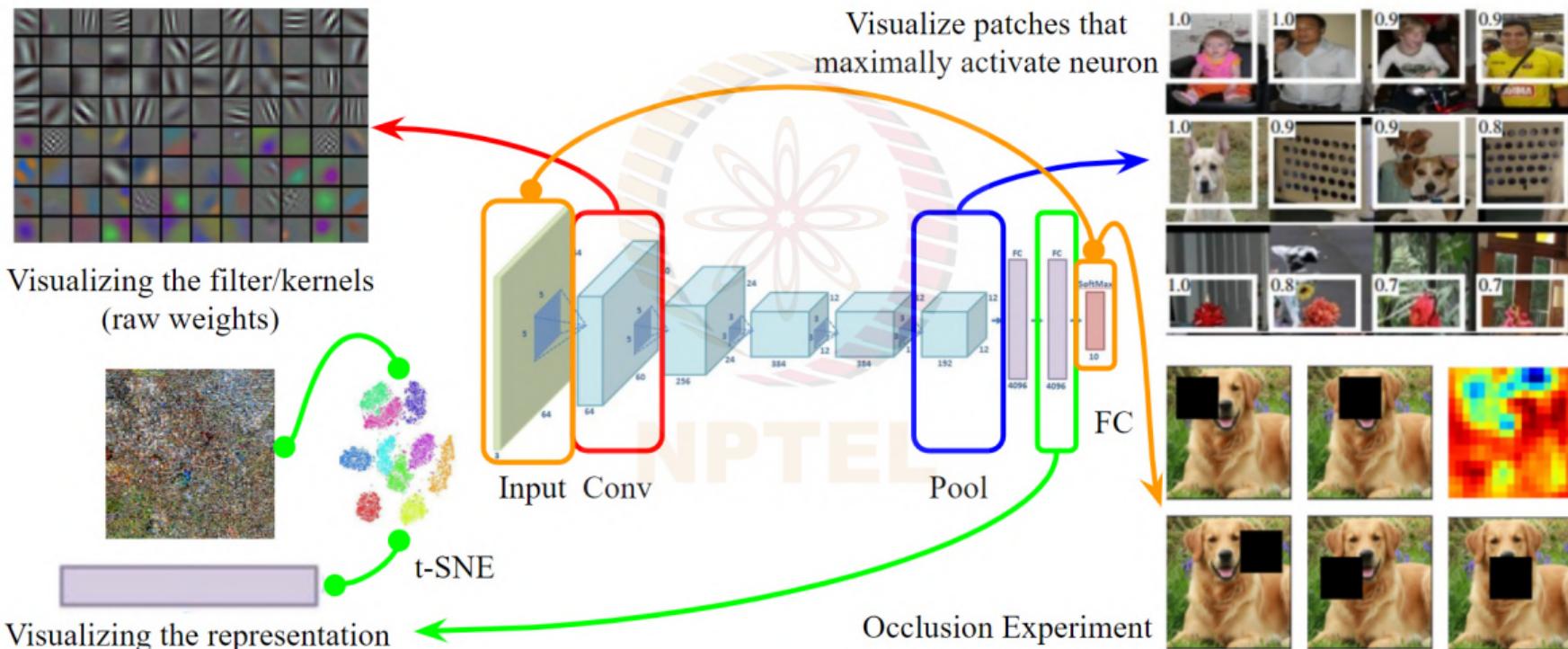


Occlusion Experiment

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Readings

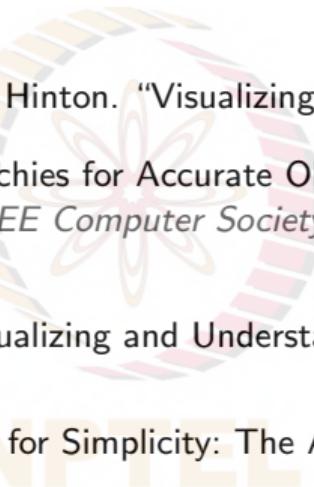
Summary of Visualizing CNNs

- 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](#)

References

- 
-  Laurens van der Maaten and Geoffrey E. Hinton. "Visualizing Data using t-SNE". In: 2008.
 -  Ross Girshick et al. "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation". In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (Nov. 2013).
 -  Matthew D. Zeiler and Rob Fergus. "Visualizing and Understanding Convolutional Networks". In: *ECCV*. 2014.
 -  Jost Tobias Springenberg et al. "Striving for Simplicity: The All Convolutional Net". In: *CoRR* abs/1412.6806 (2015).