Deep Learning for Computer Vision

Explaining CNNs: Visualization Methods

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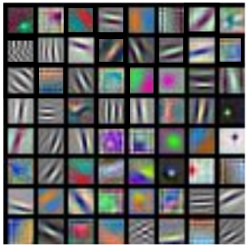
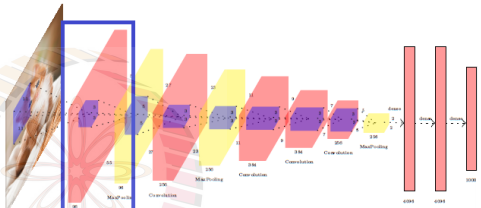
Acknowledgements

- 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 x 3 x 11 x 11



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

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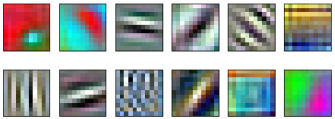
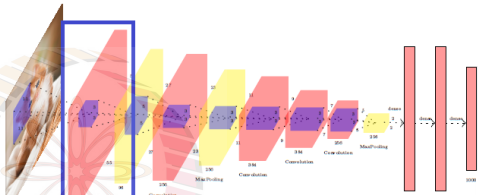


A Closer Look (AlextNet)
Fan et al.(arxiv:1904.05526)



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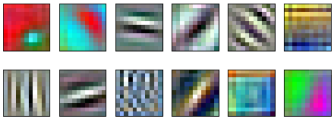

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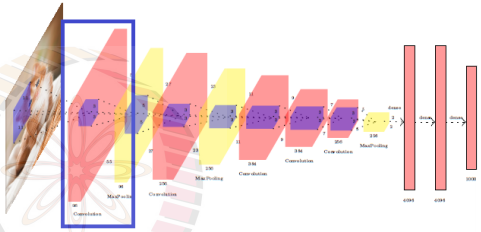

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7

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Visualize Filters/Kernels (First Layer)

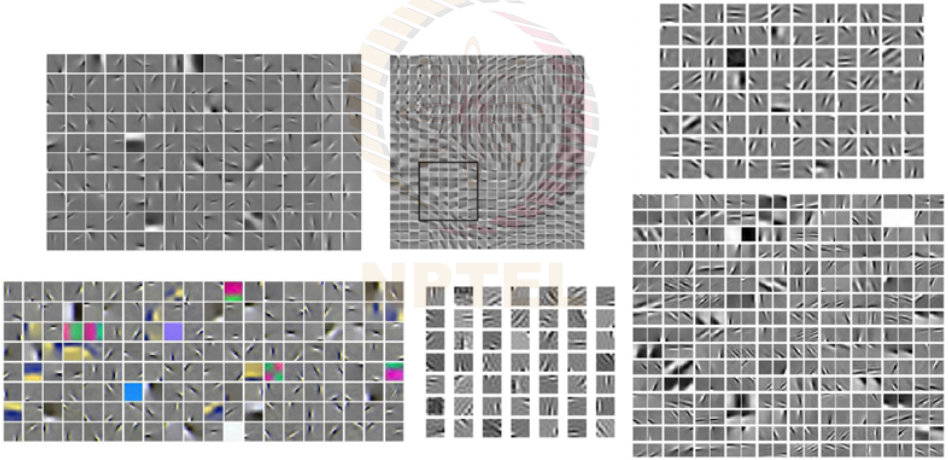
- You can visualize the kernels of higher layers but it is just not interesting

Visualize Filters/Kernels (First Layer)

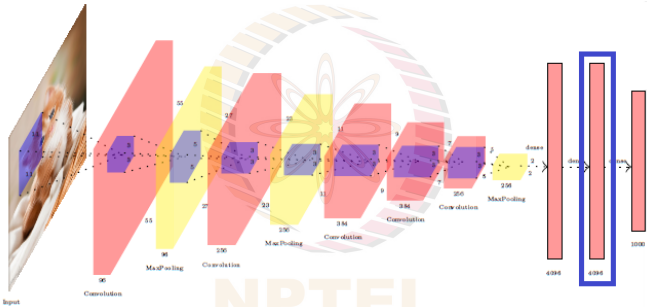
- You can visualize the kernels of higher layers but it is just not interesting
- Input to higher layers is no more the images we know or understand, so becomes difficult to interpret the filters beyond the first layer

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

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Visualize the Representation Space (Last Layer)

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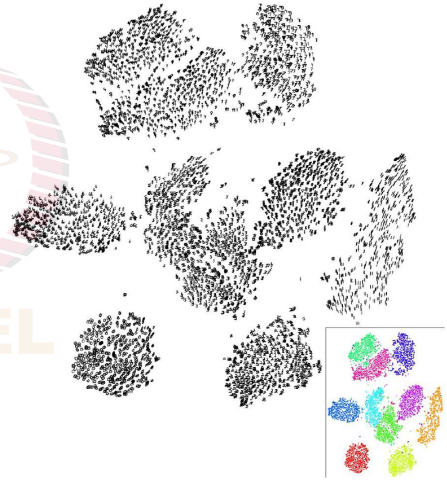
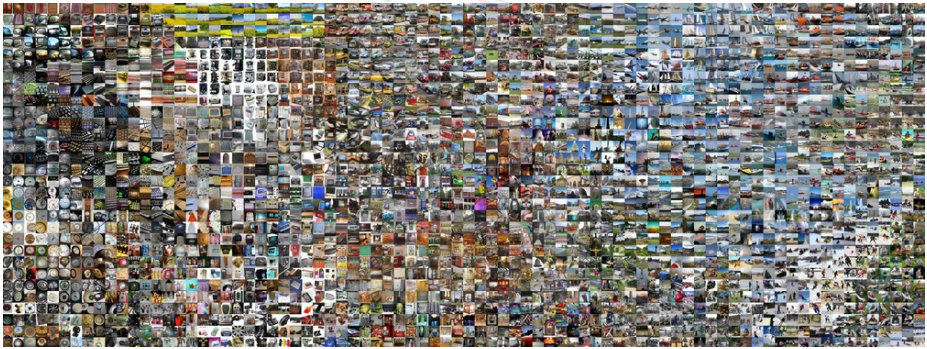
- Simple algorithm: Principal Component Analysis (PCA)
- More complex: **t-SNE** (right)



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

t-SNE Visualization

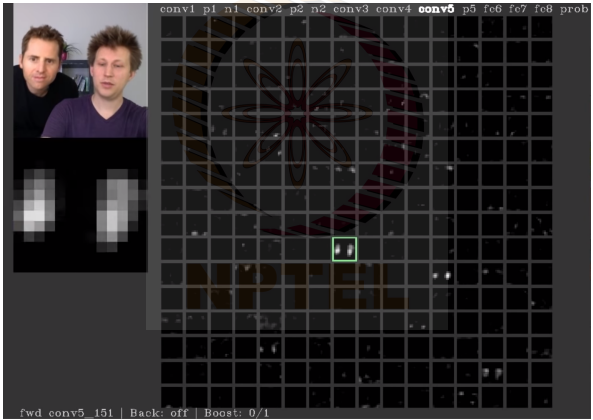
- Images that are nearby each other are also close in the CNN representation space, which implies that the CNN "sees" them as being very similar



- 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 13×13 grayscale images

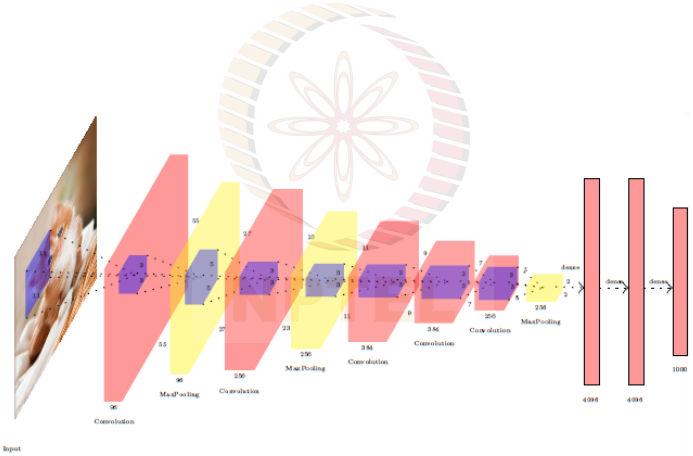


Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

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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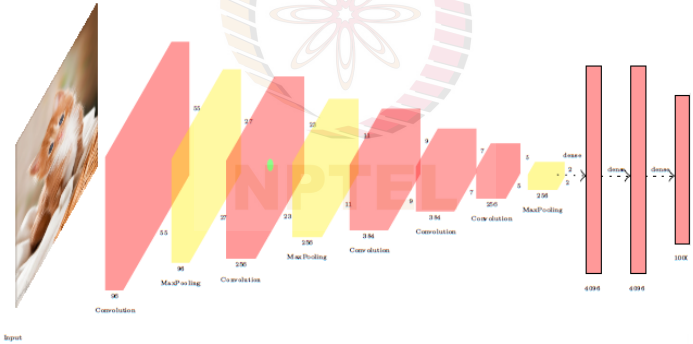
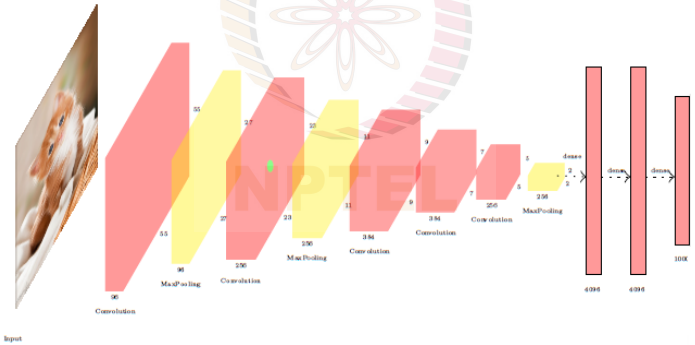


Visualize Maximally Activating Image Patches

- 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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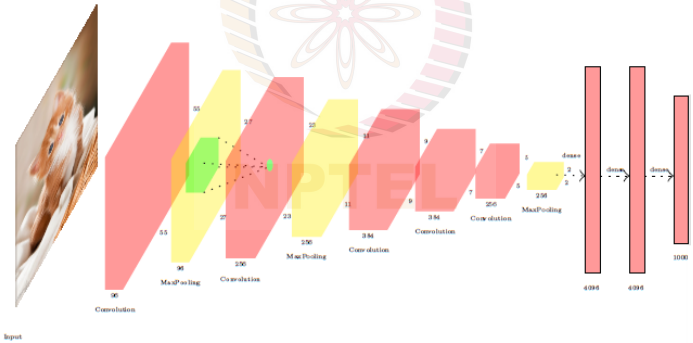

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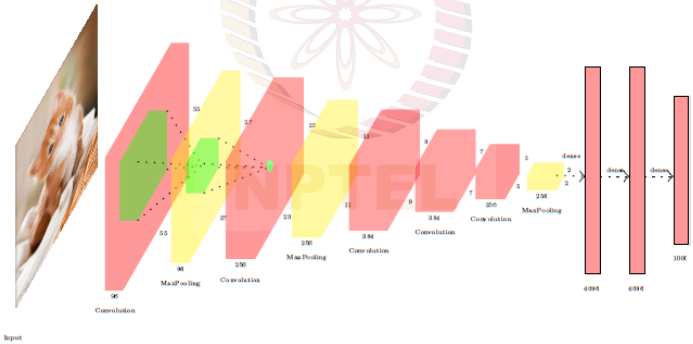

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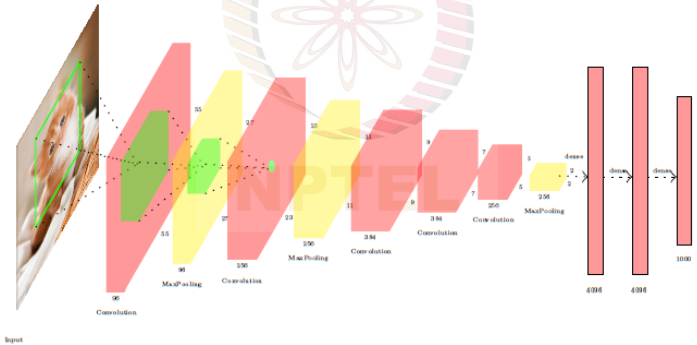
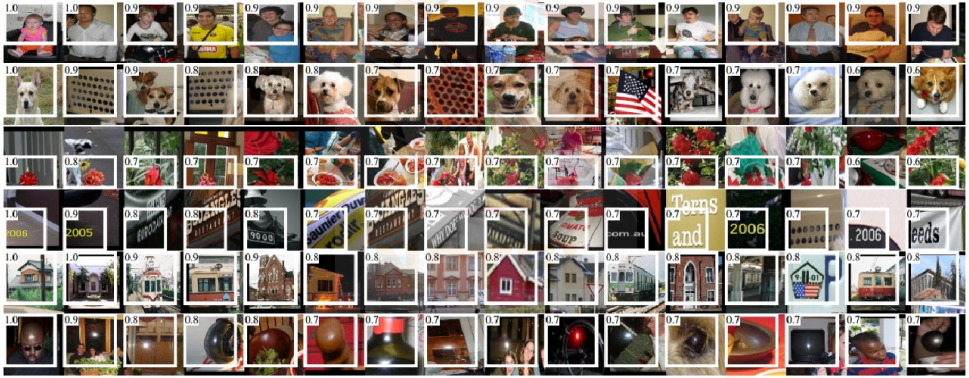


Visualize Maximally Activating Image Patches

- 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

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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 Experiments[2]

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

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

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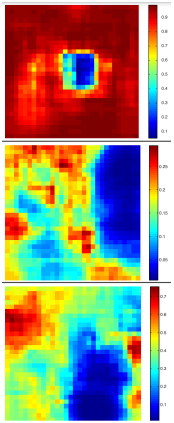
- Typically, we are interested in understanding which portions of an image are responsible for maximizing probability of a certain class
- Occlude (gray out) different patches in the image (centered on each pixel), and see effect on predicted probability of the correct class $\implies$ gives you a probability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

Input image



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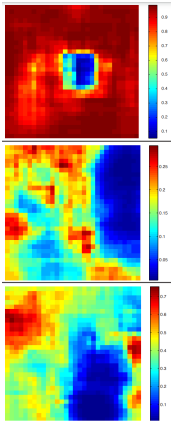

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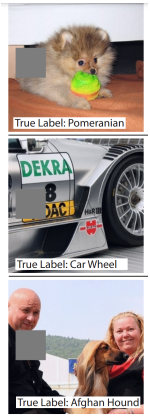
- Similar observations for other images



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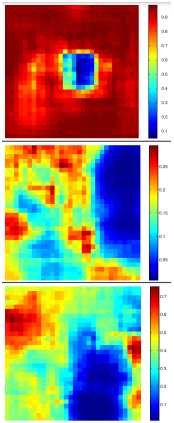

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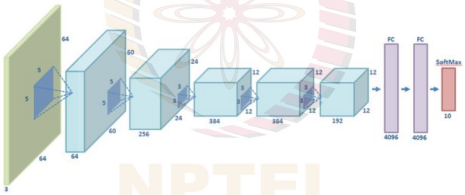
Summary: 'Don't-disturb-the-model' methods



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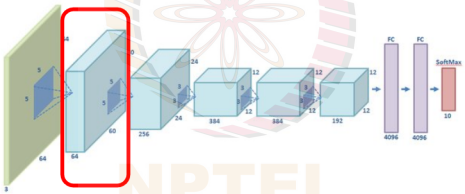

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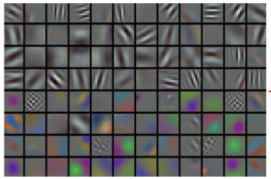
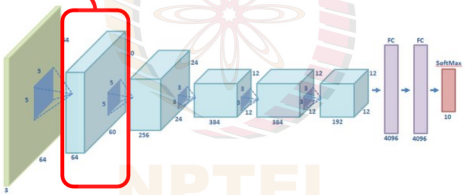


Visualizing the filter/kernels
(raw weights)



Conv

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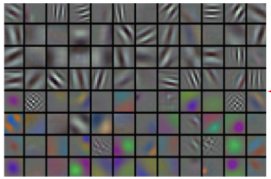

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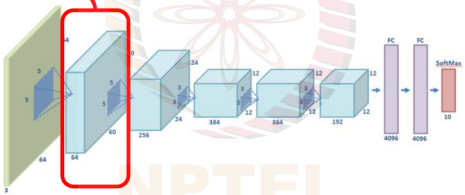
Only interpretable at the first layer!
Not interesting enough for higher layers!



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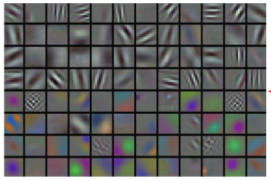

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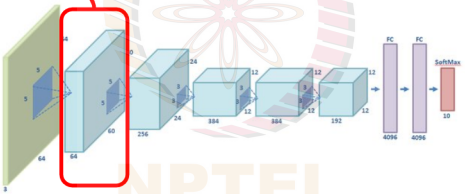

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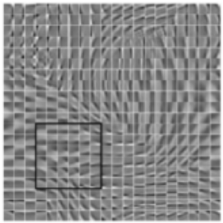

The Gabor-like filter fatigue

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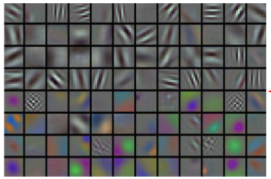

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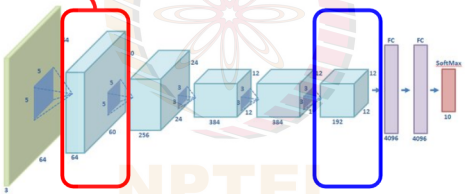

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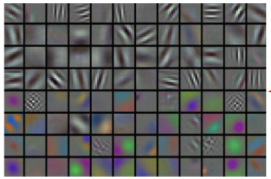
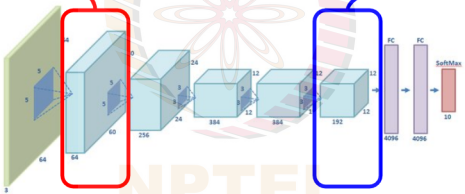


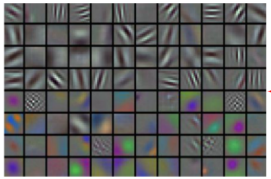
Visualizing the filter/kernels
(raw weights)

Visualize patches that
maximally activate neuron



Conv Pool

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



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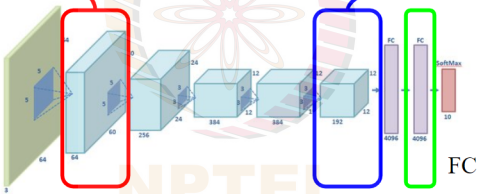

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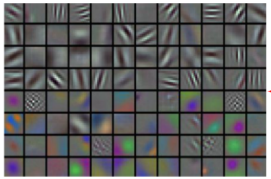

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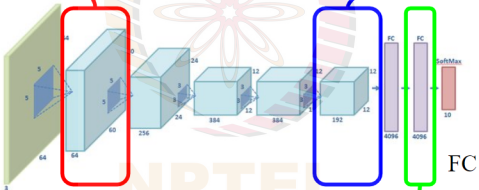

Visualizing the representation

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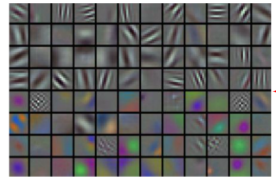
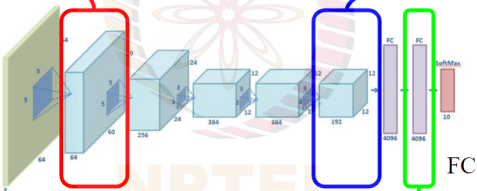


Visualizing the filter/kernels
(raw weights)

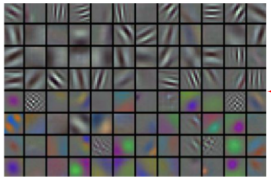
Visualize patches that
maximally activate neuron



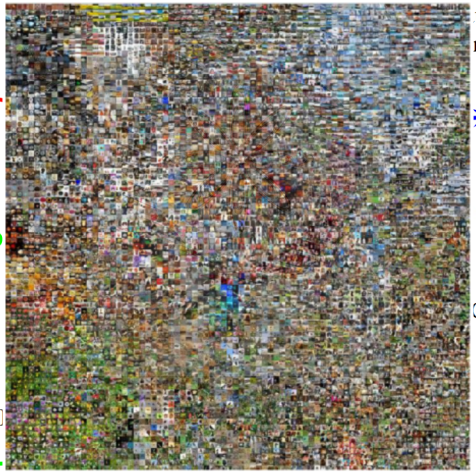
t-SNE

Visualizing the representation

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



Visualizing the filter/kernels
(raw weights)



t
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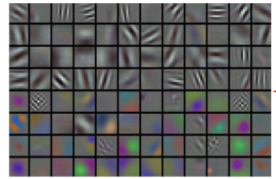
C

t-SN

Visualizing the representation

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

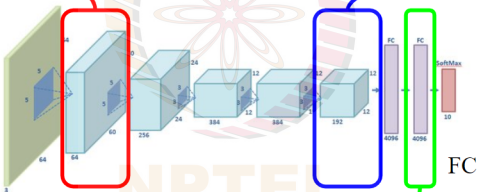


Visualizing the filter/kernels
(raw weights)

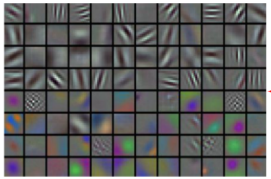
Visualize patches that
maximally activate neuron

t-SNE

Visualizing the representation



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

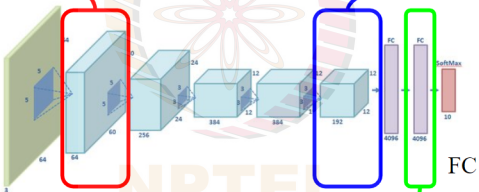


Visualizing the filter/kernels
(raw weights)

t-SNE

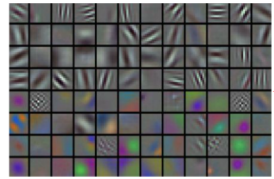
Visualizing the representation

Visualize patches that
maximally activate neuron

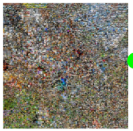


Occlusion Experiment

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



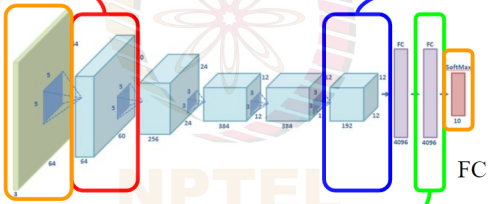
Visualizing the filter/kernels
(raw weights)



t-SNE

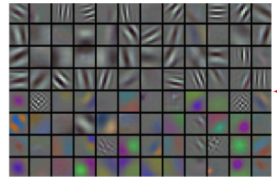
Visualizing the representation

Visualize patches that
maximally activate neuron

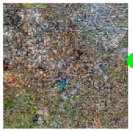


Occlusion Experiment

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



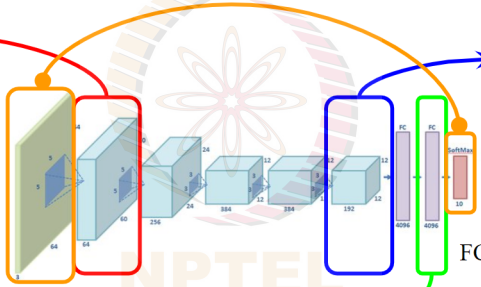
Visualizing the filter/kernels
(raw weights)



t-SNE

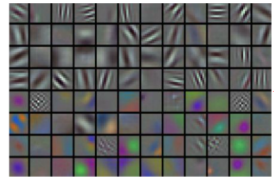
Visualizing the representation

Visualize patches that
maximally activate neuron



Occlusion Experiment

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



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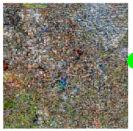

t-SNE

Visualizing the representation

Visualize patches that
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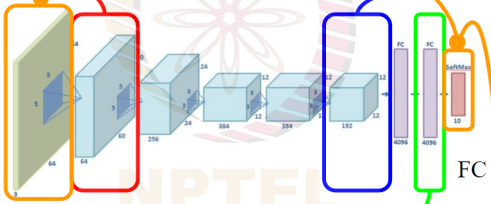

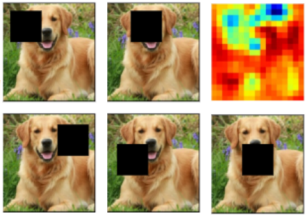

Occlusion Experiment

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

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).