Deep Learning

10.1 Inside DNNs

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2. Not many tools can help us analyse these complex architectures

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   - activation maps for the given input
   - distribution of activations for a population of samples
   - derivative of selected activations wrt a given input
   - synthesize samples that can cause maximal activations at selected neurons

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4. observe these lines during the course of training

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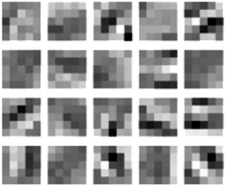
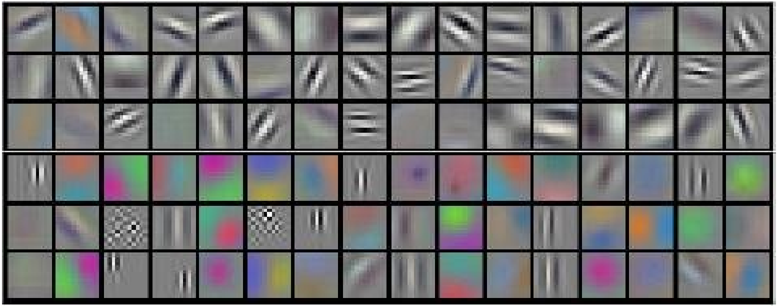
4. Later layers will have multiple channels and makes it difficult to visualize

CNN Filters (LeNet and AlexNet)





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2. Since there may be a large number of channels, we may have to pick a subset of them
3. Visualizing individual maps may not be very helpful

Visualize feature maps

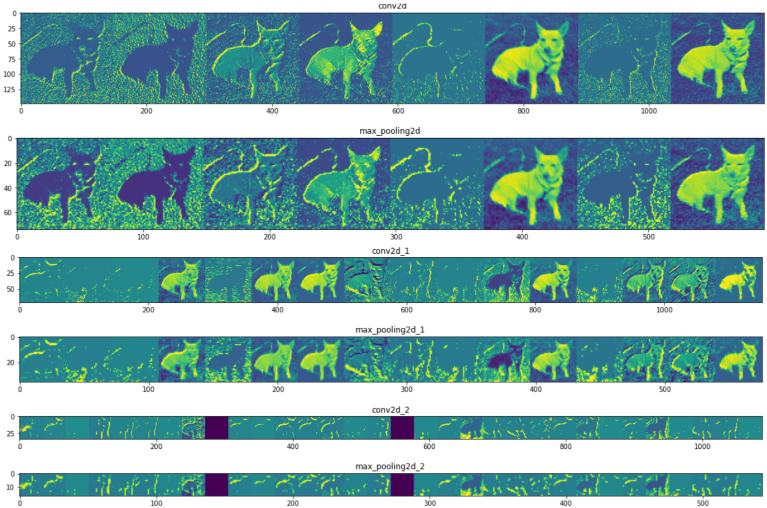


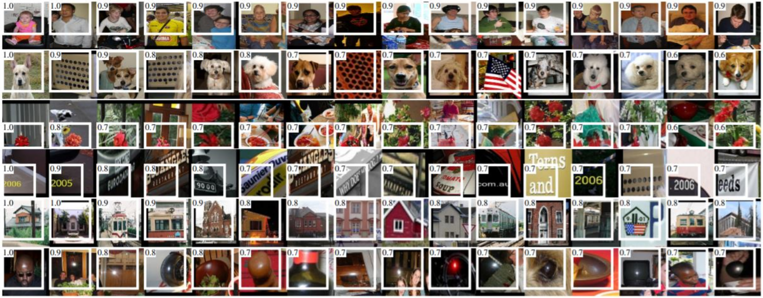
Figure credits: Shivang Shrivastav

Visualize feature maps

1. Although it is quite hard to precisely identify the role each filter, one may identify edge and some blob detectors.
2. As we go deeper in the network, the more difficult it gets to understand the role of filters

Visualize feature maps

1. Allows in particular to find units with a clear semantic/concept

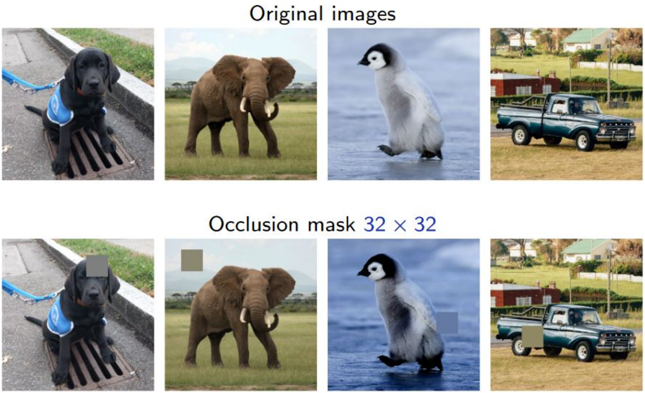


Ross Girshick et al. 2014

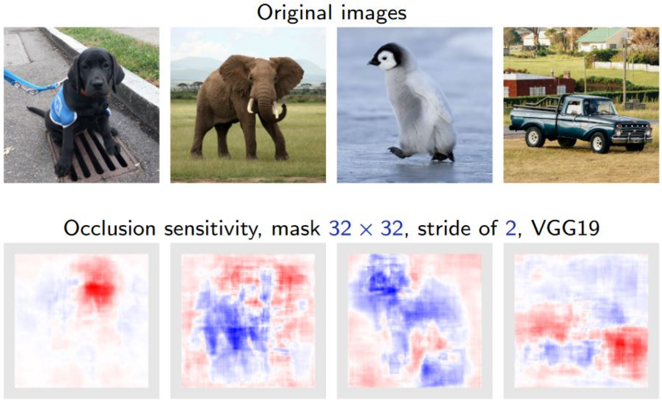
Analyze the model behavior in the neighborhood of an input

1. We may estimate the importance of a portion of input via occlusion

Occlusion sensitivity



Occlusion sensitivity



Saliency maps

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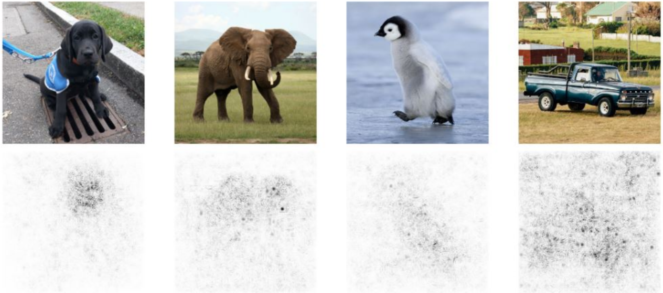
3.
```
input.requires_grad_()
output = model(input)
grad_input, = torch.autograd.grad(output[0, c], input)
```

Gradient as saliency



Smooth Grad

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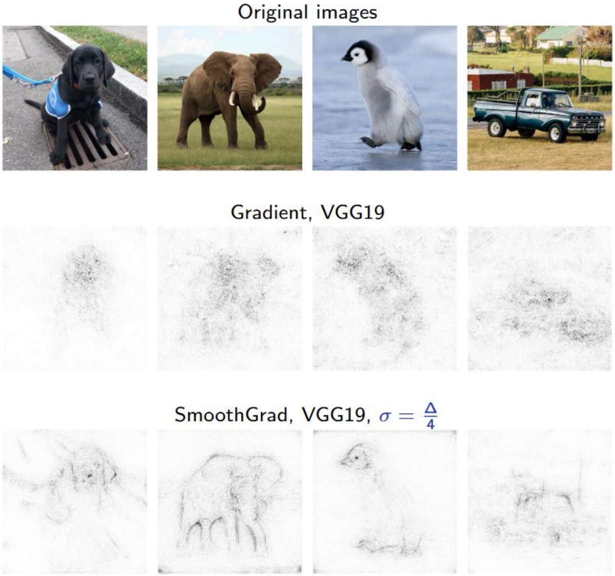
2. We can smooth the gradient by taking the mean gradient over (slightly) perturbed inputs (Smilkov *et al.* 2017)

$$\tilde{\nabla}_{|x} f_y(x; w) = \frac{1}{N} \sum_{n=1}^{N} \nabla_{|x} f_y(x + \epsilon_n; w)$$

where $\epsilon_n \sim \mathcal{N}(0, \sigma^2 I)$

Smooth Grad


Original images
Gradient, VGG19
SmoothGrad, VGG19, $\sigma = \frac{\Delta}{4}$

Improvements to gradient based visualization

1. Deconvolution by Zeiler and Fergus
2. Guided Backpropagation by Springenberg et al. (2014)
3. Class Activation Maps (Zhou et al. 2016)
4. Gradient-weighted Class Activation Mapping (Grad-CAM) by Selvaraju et al. (2016)
5. ...

References

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