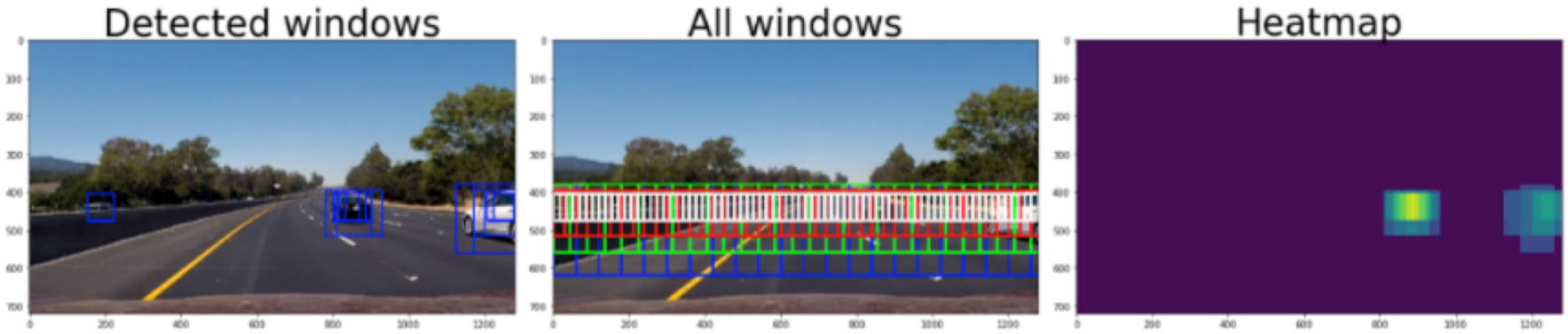


Convolutional Neural Networks

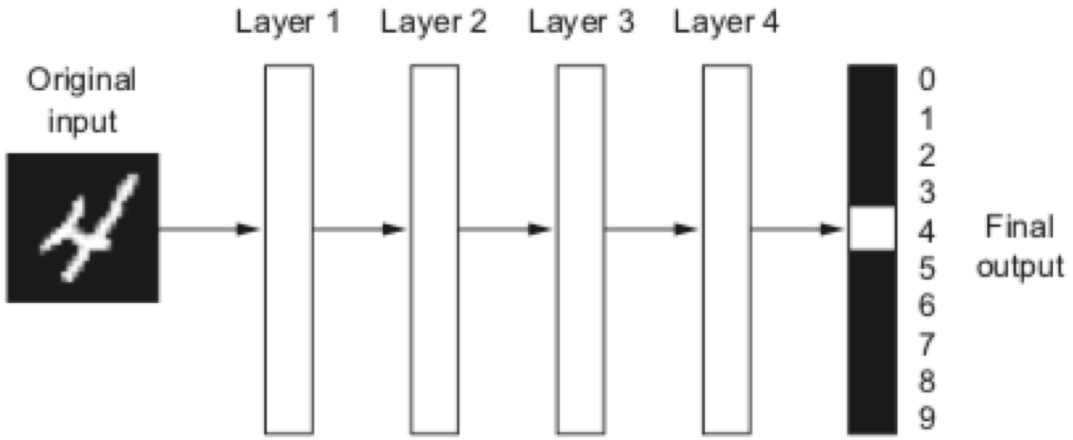
Jay Urbain, PhD

Credits:

- Deep Learning with Python, Francios Challet
- Andrej Karpathy, Chris Olah, Andrew Ng
- nVidia DLI
- HSE Faculty for Advanced Machine Learning: Pavel Shvechikov, Researcher at HSE and Sberbank AI Lab; Anna Kozlova, Team Lead; Evgeny Sokolov, Senior Lecturer; Alexey Artemov, Senior Lecturer and Sergey Yudin, Analyst-developer among multiple other trainers.

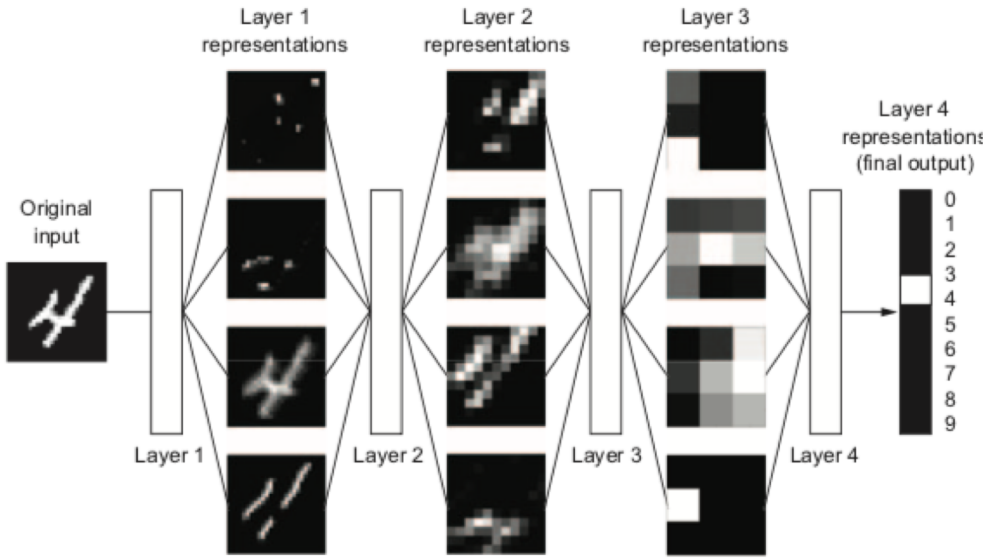
Deep learning as a language

- Provide hints of what to learn by defining structure of the model.
- Think about representations that would transform inputs to outputs.



Deep representations learned by a digit-classification model

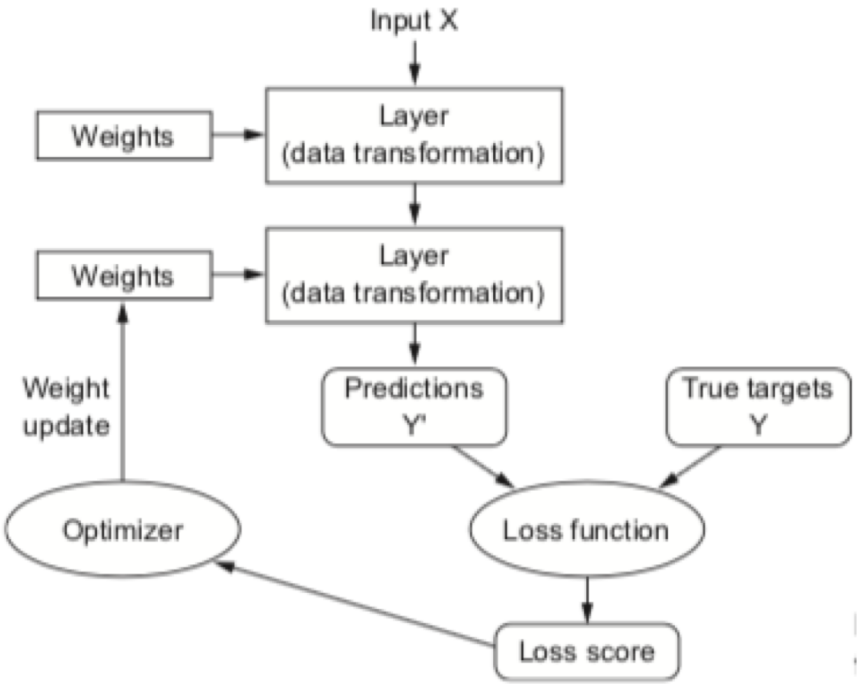
Deep learning is a multistage way to learn data representations



Deep representations learned by a digit-classification model

Neural network

- Parameterized by its weights
- A loss function measures the quality of the network's output
- The loss score is used as a feedback signal to adjust the weights



Deep learning as a language

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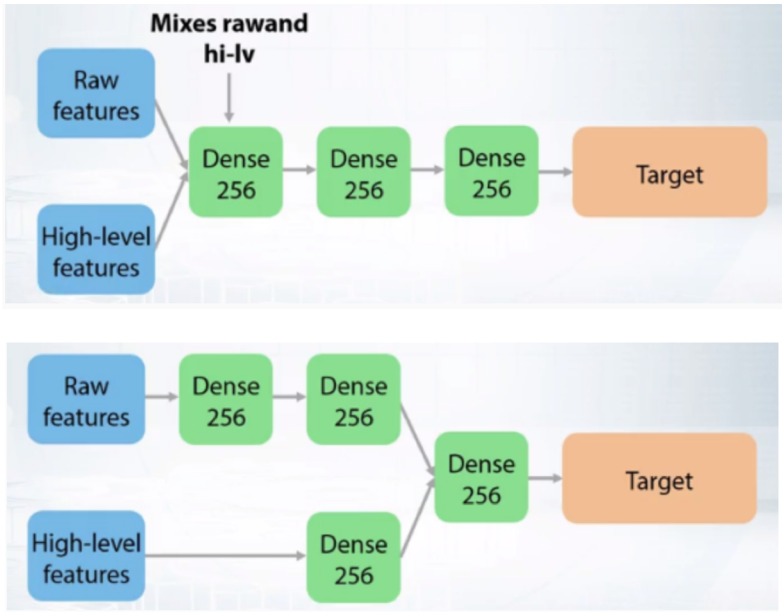
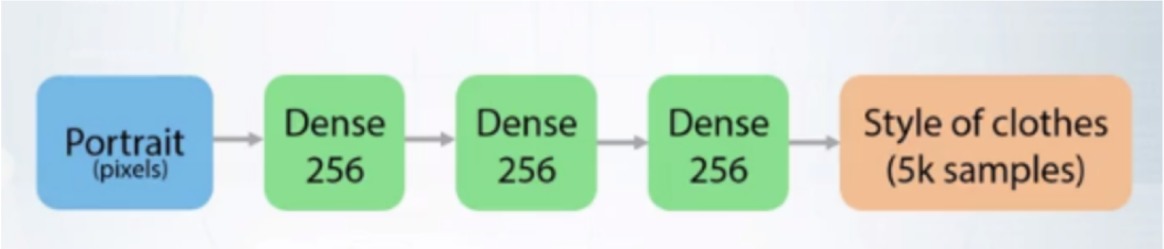


Deep learning as a language

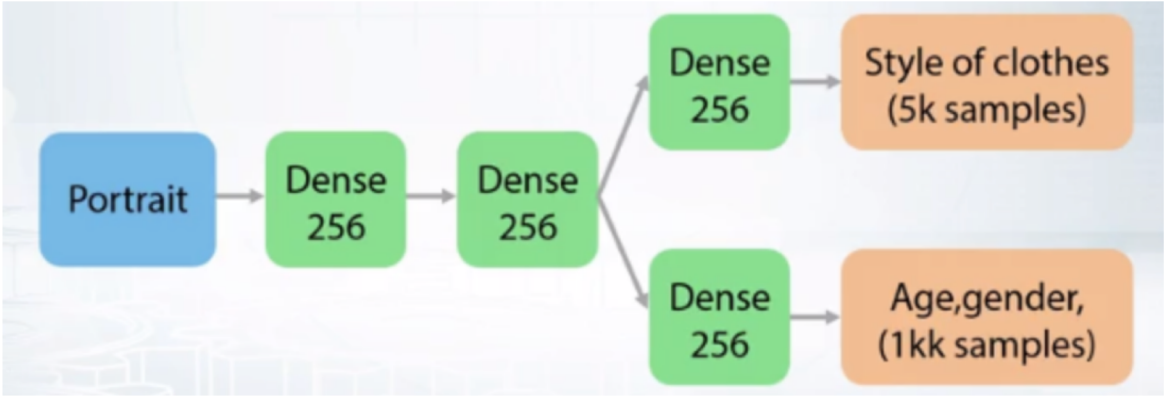
- You have a small dataset



- Consider introducing other problems the network needs to solve

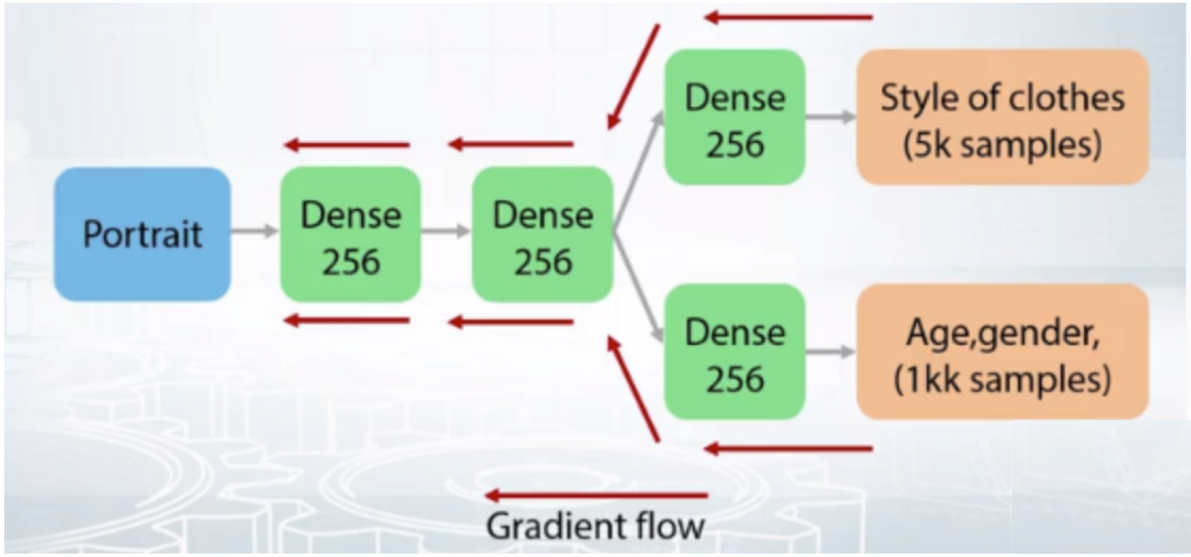
Deep learning as a language

- You have a small dataset
- And a large dataset for similar task



Deep learning as a language

- Learn features for style classification that also help determine age & gender.



Deep learning as a language

For images:

- Need to classify cats and dogs so they are invariant to translation and scale

For text:

- Want to reconstruct the underlying language generation process

Tabular data:

- Want to capture the interactions between variable at different levels of abstraction.

COMPUTER VISION TASKS

Image Classification

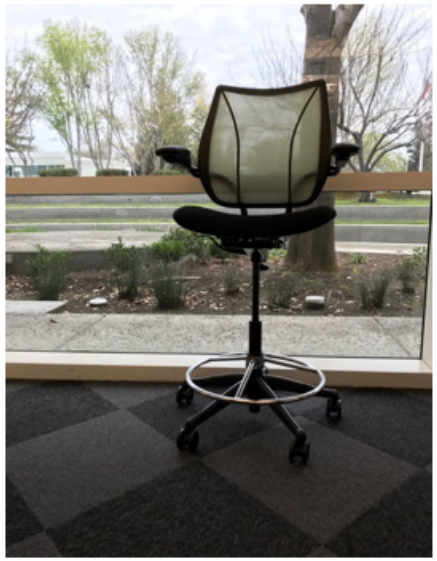


Image Classification + Localization

Object Detection

Image Segmentation

(inspired by a slide found in cs231n lecture from Stanford University)

Inputs and Outputs

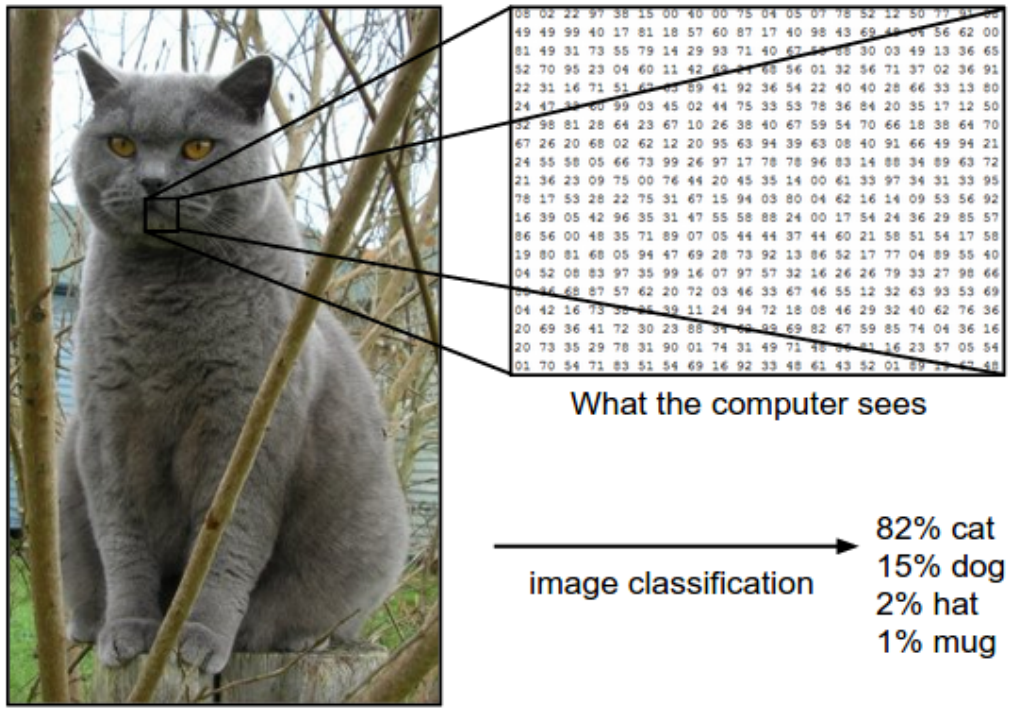


Image from the Stanford CS231 Course

Digital representation of an image

- Grayscale image is a matrix of pixels (picture elements)
- Dimensions of this matrix are called resolution, e.g., 1024 x 1024
- Each pixel stores its intensity 0 (black) to 255 (white)
- Color images store pixel intensities for 3 channels: red, green, blue.
- Image is just a matrix of numbers.

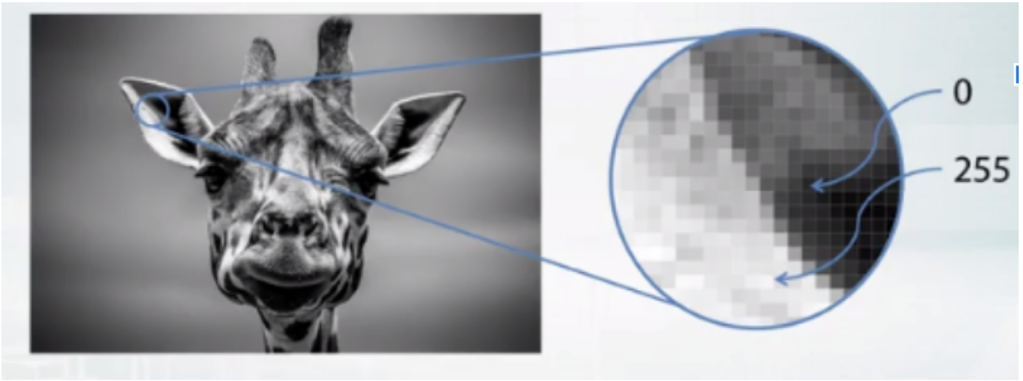
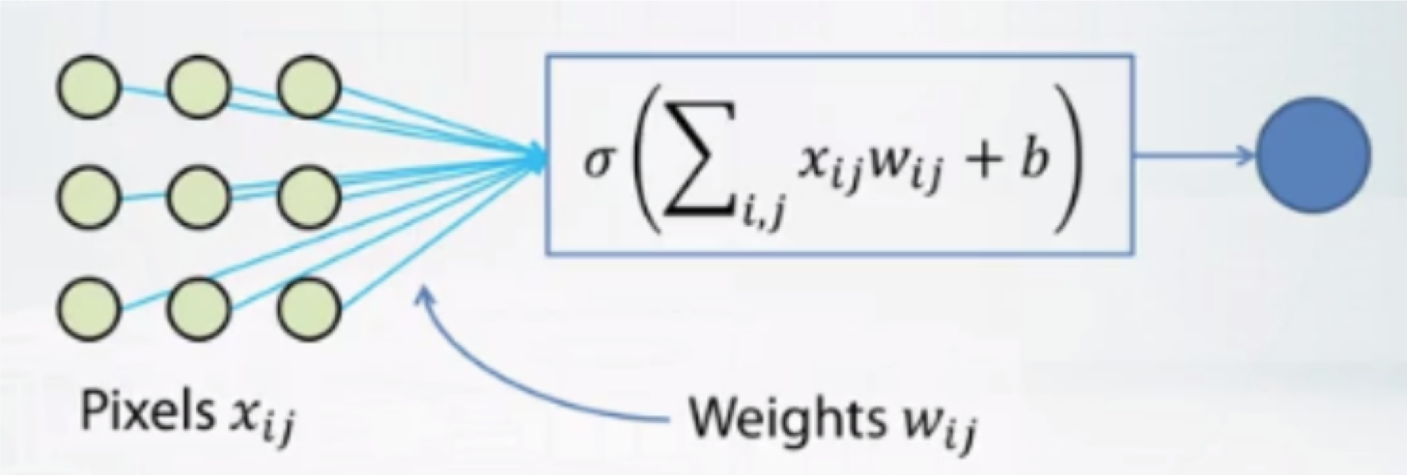


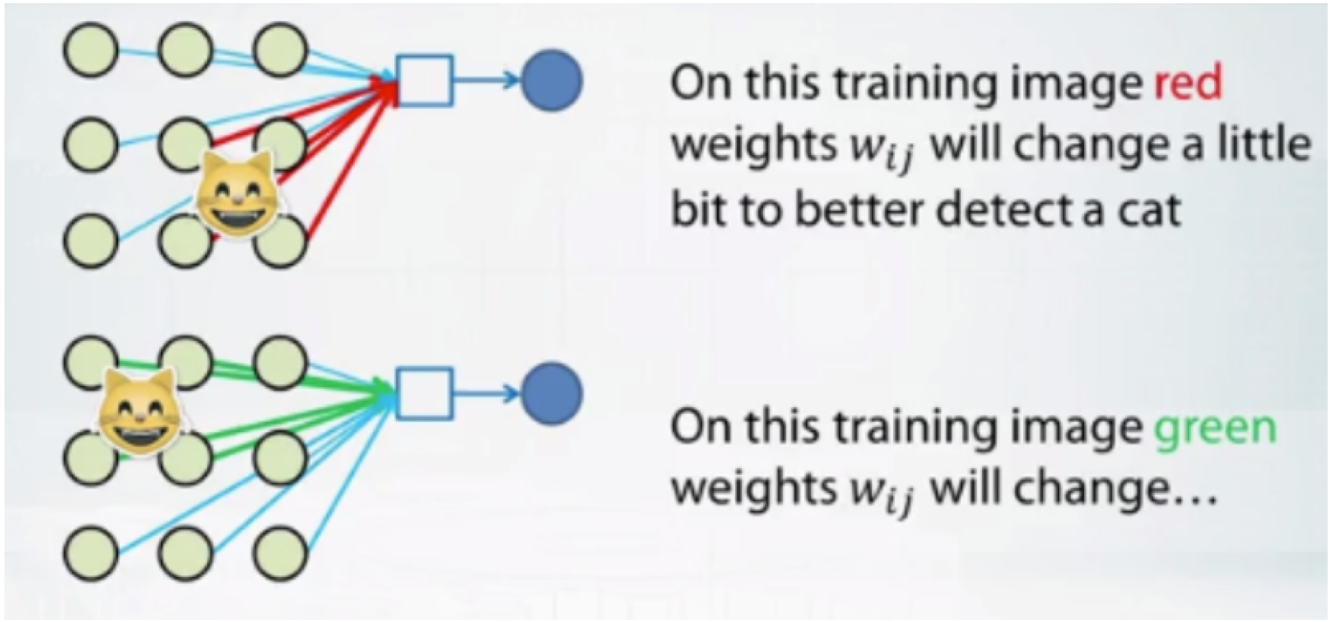
Image as a neural network input

- Normalize input pixels: $x_{norm} = x/255$ or $x_{norm} = x/255 - 0.5$
- *Will multilayer perceptron work?*



Why not MLP?

- Train a cat detector



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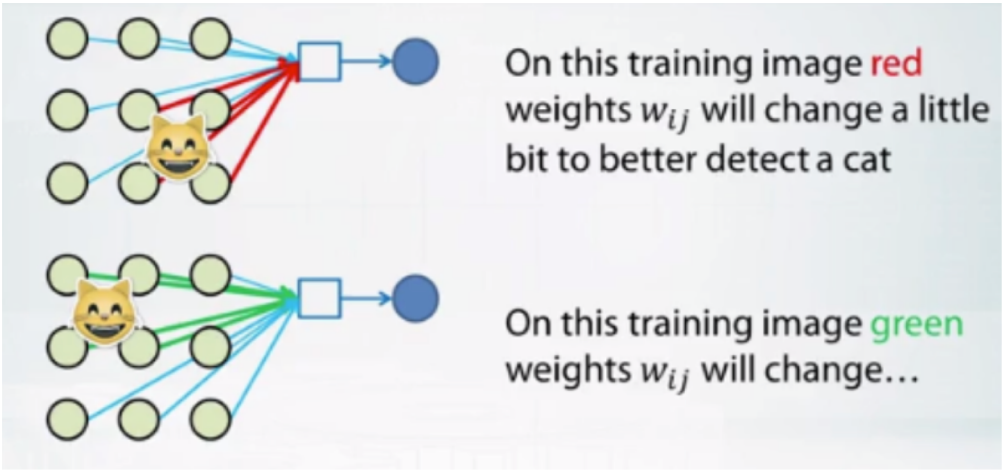
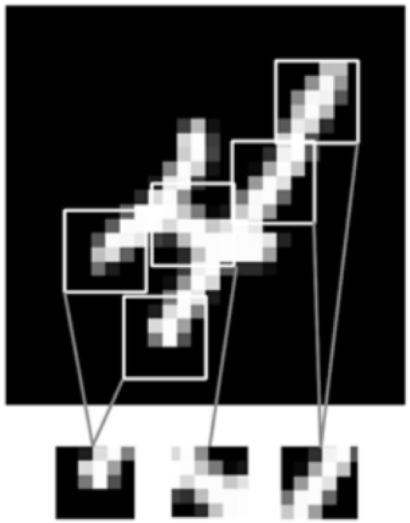


- We learn the same “cat features” in different areas and don’t fully utilize the training set.
- What if the cats in the test set appear in different places?

Convolution Operation

Fundamental difference between densely connected layer and a convolution:

- Dense layers learn global patterns in their input feature space.
- Convolution layers learn local patterns.



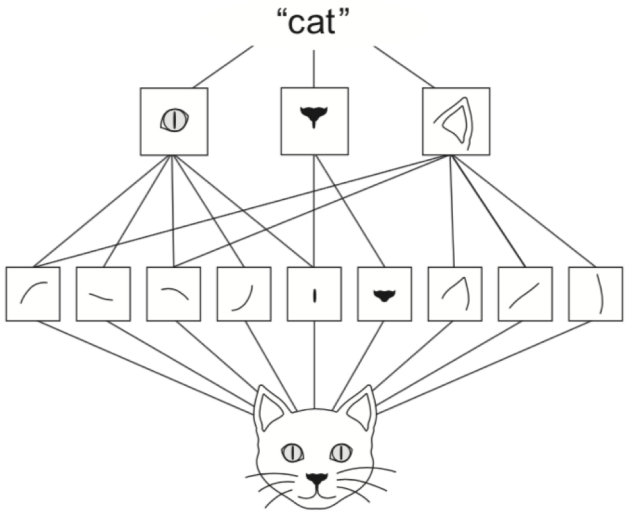
Benefits of convolution layers learning local patterns.

The patterns they learn are translation invariant.

- After learning a certain pattern in the lower-right corner of a picture, a convnet can recognize it anywhere: for example, in the upper-left corner.
- A densely connected network would have to learn the pattern anew if it appeared at a new location.
- This makes convnets data efficient when processing images.

***They can learn spatial hierarchies of patterns*.**

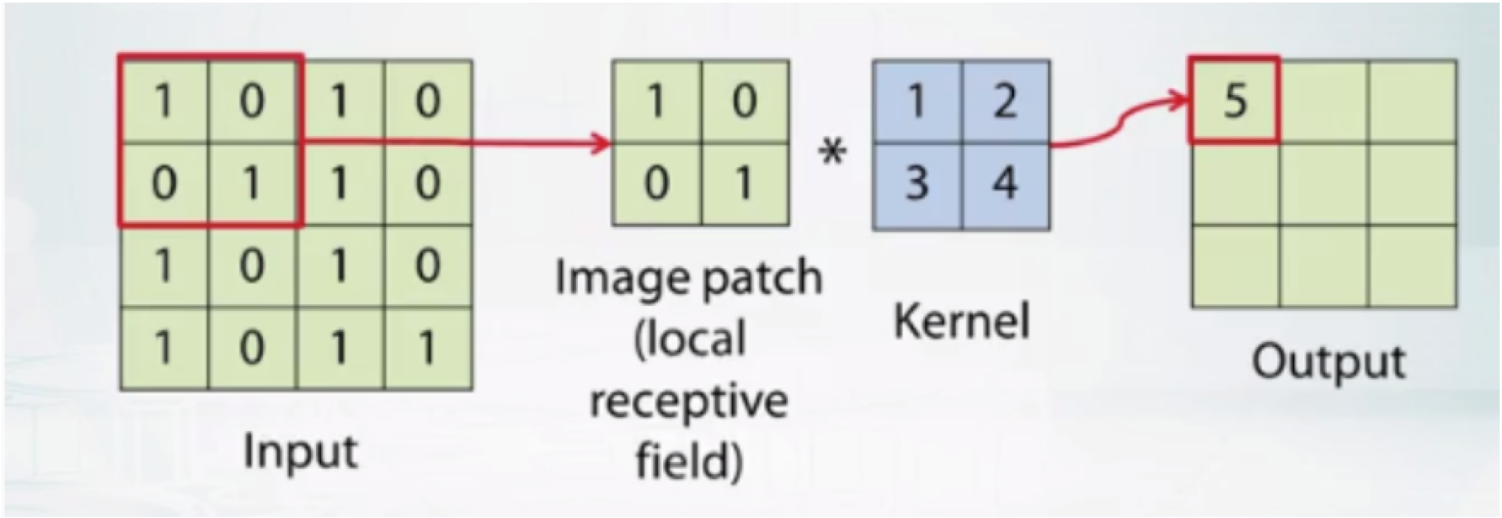
- A first convolution layer will learn small local patterns such as edges.
- A second convolution layer will learn larger patterns made of the features of the first layers, and so on.
- Allows convnets to efficiently learn increasingly complex and abstract visual concepts.



World is made of hierarchical representations that are spatially invariant.

Convolutions

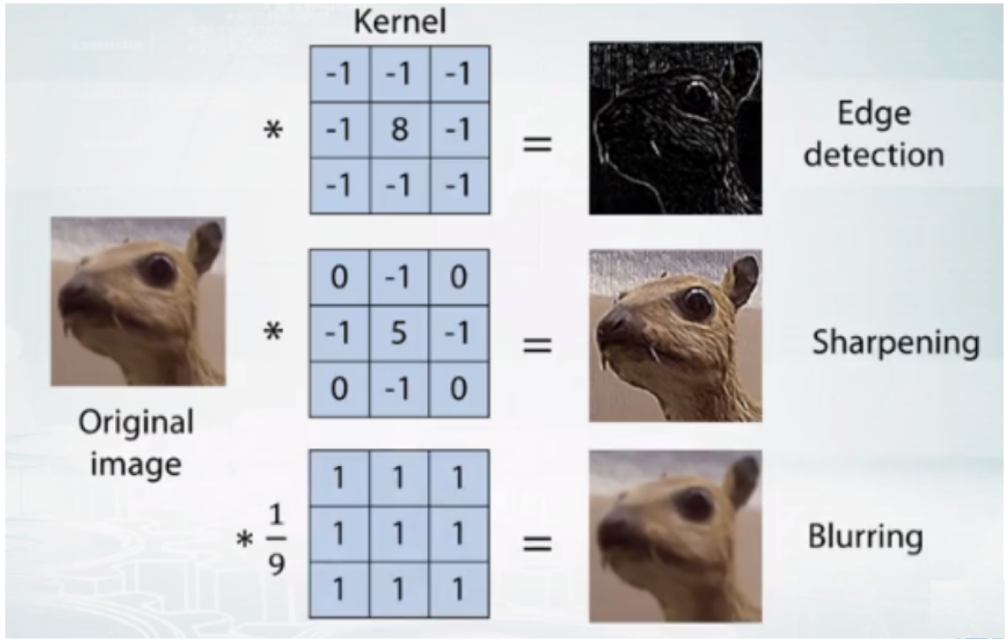
- Convolution is a dot product of a kernel (or filter) and a patch of an image (local receptive field) of the same size.



Dot product = sum of element wise product (scalar)

Convolutions have been used for a long time

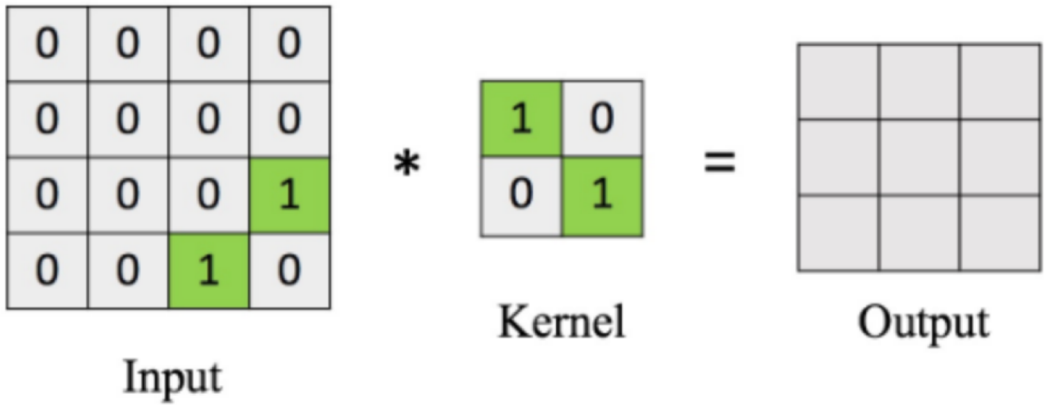
- Convolution is a dot product of a kernel (or filter) and a patch of an image (local receptive field) of the same size.



Convolutions

What is the convolution output for the following image using the given 2x2 filter?

- Stride = 1 (sliding window size)
- No padding (add zero – valued edges)



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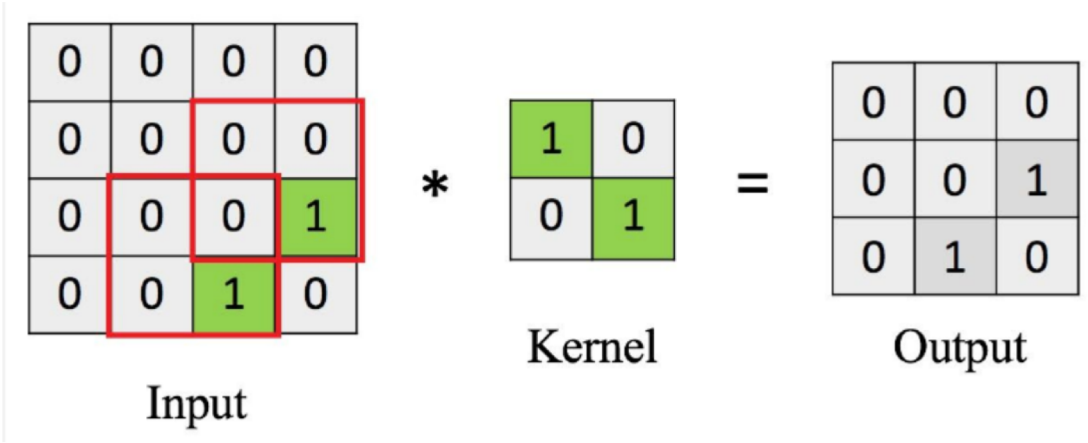
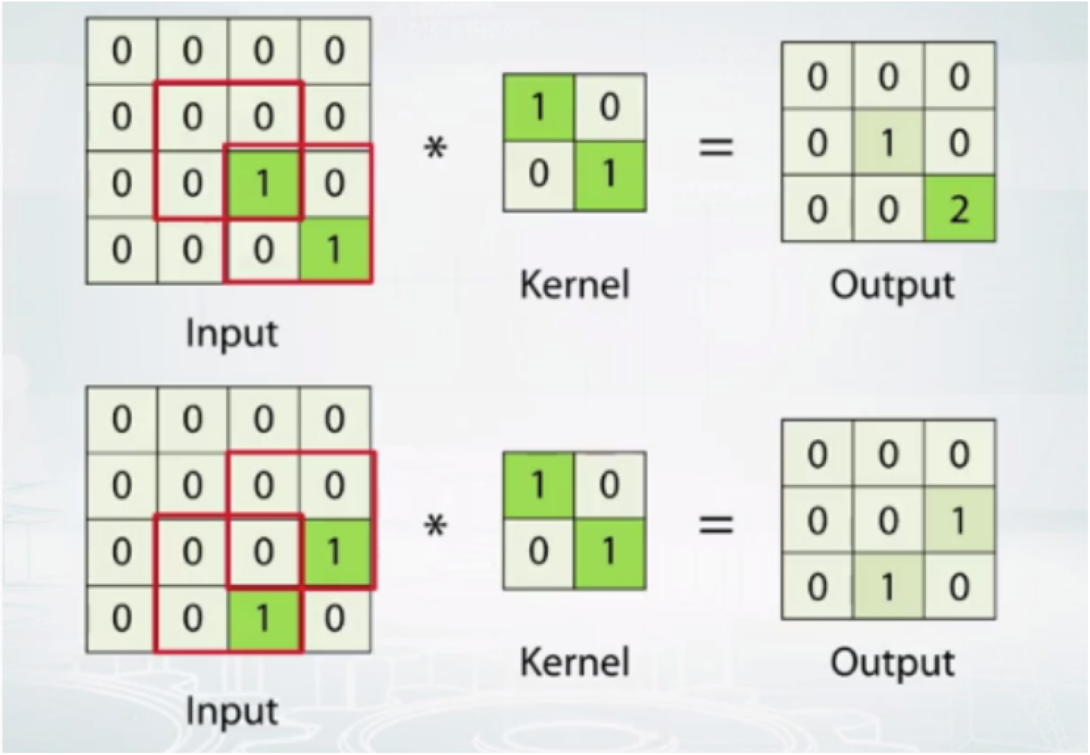
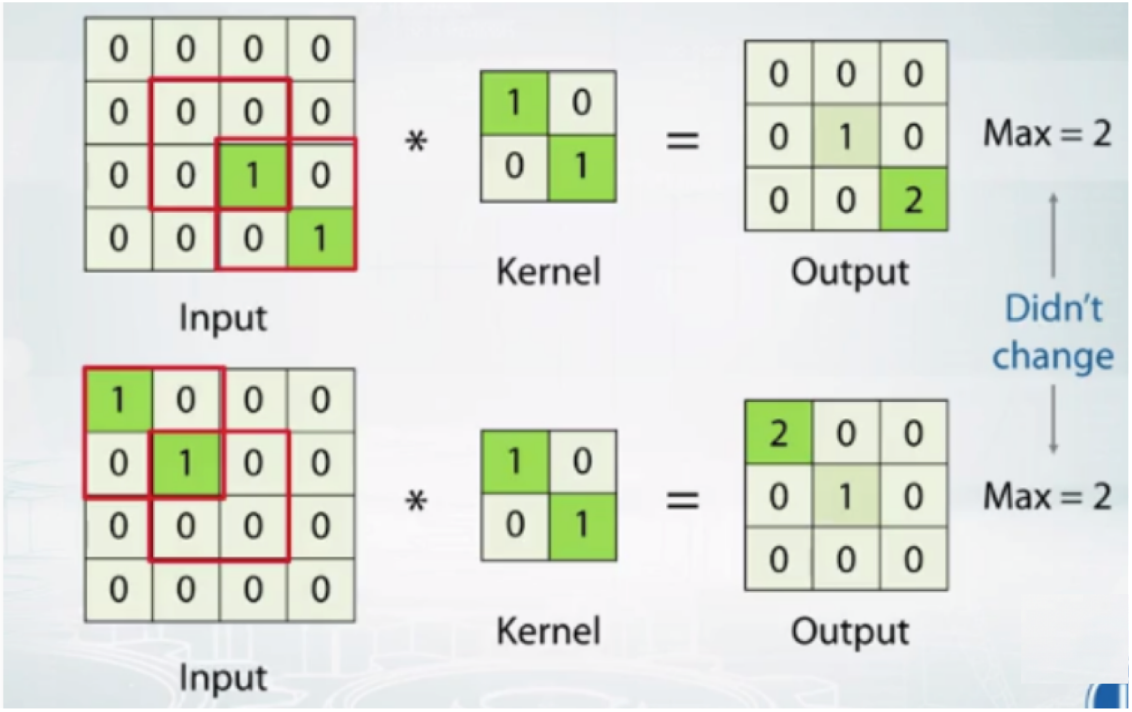


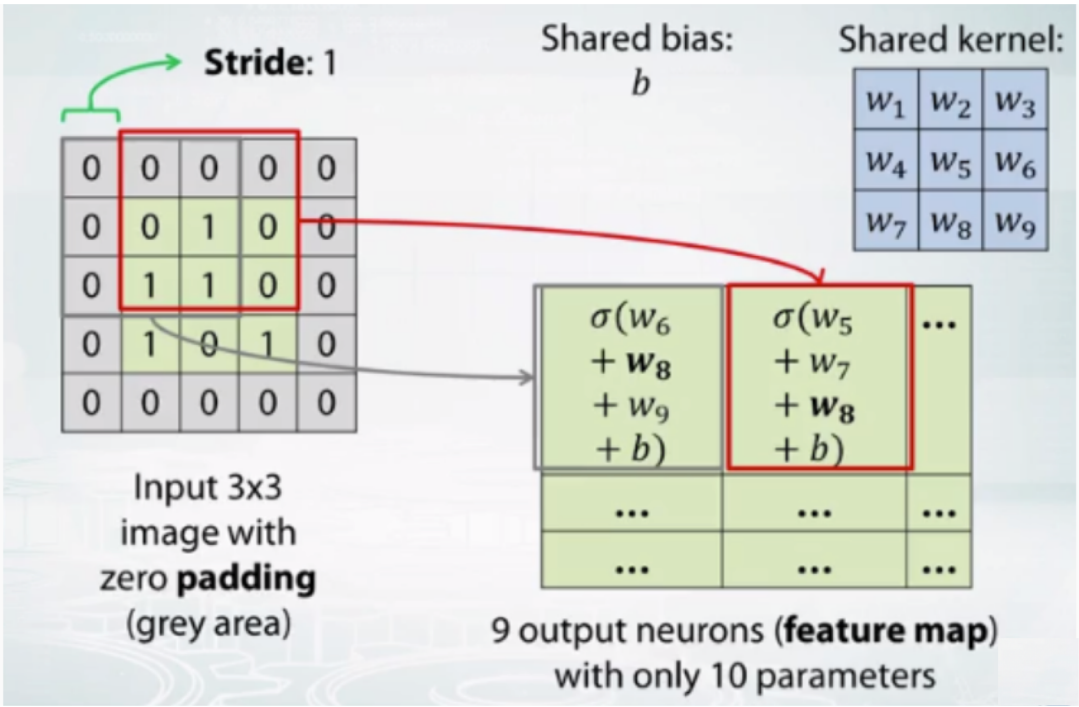
Convolution is similar to correlation



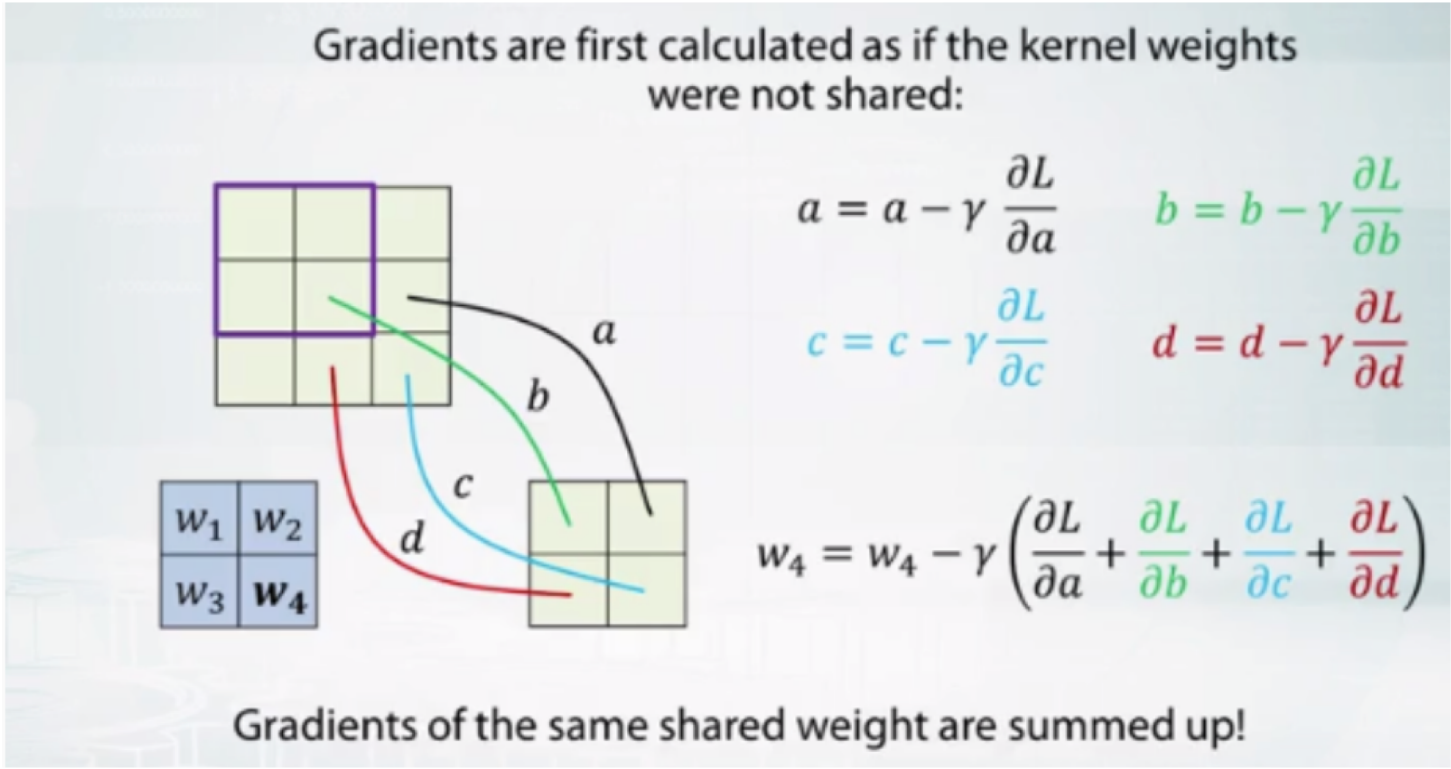
Convolution is translation invariant



Convolution layer in neural network



Backpropagation for CNN



Question

- Suppose we have a 300 x 300 input and a 300 x 300 output.
- How many parameters (weights) do you train with a convolutional layer (filter) 5 x 5?

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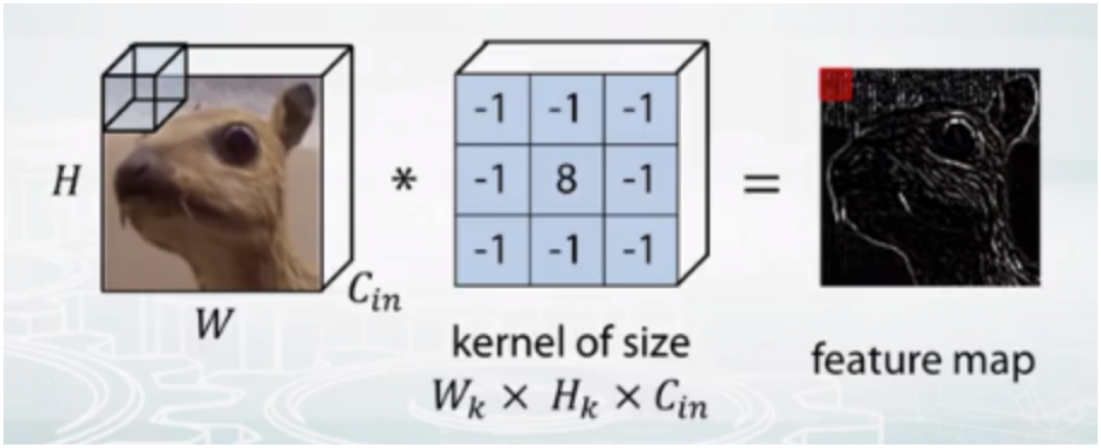
- 26 = (5 x 5 = 25 kernel parameters) + 1 bias term

Convolutional vs full connected layer

- In a conv layer the same kernel is used for every output neuron, this way we share parameters of the network and train a better model - provides translational invariance.
- 300 x 300 input, 300 x 300 output – 5 x 5 kernel = 26 parameters in conv layer.
- **8.1×10^9** parameters in fully connected network where each output is a perceptron.
- Conv layer can be viewed as a special case of a fully connected layer when all the weights outside the local **receptive field** of each neuron equal **0** and kernel parameters are shared between neurons.

Color image input

- Color image input: $W \times H \times C_{in}$ tensor (multidimensional array)
- W – image width
- H – image height
- C_{in} – is a number of input channels (e.g., 3 RGB channels)

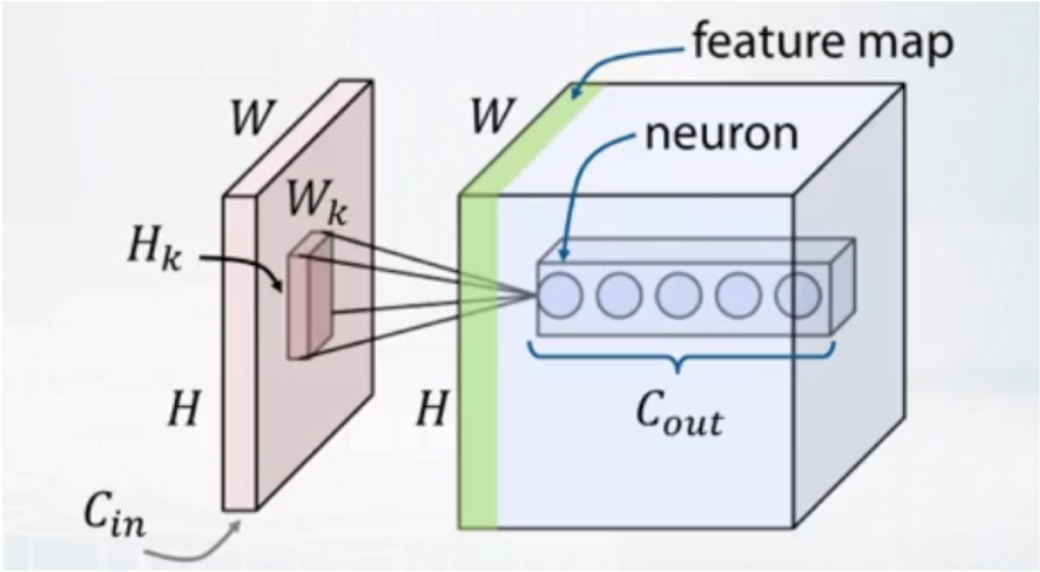


One kernel is not enough

- Every filter in your convolutional layer extracts a specific feature from the input.
- One filter could be sensitive to horizontal edges while another is sensitive to vertical edges.
- A third filter may be sensitive to a triangular shape.
- You want the feature maps to be as different from each other as possible to avoid redundancy.
- Avoiding redundancy improves the network's capacity to as many variations in the data as possible.
- Random initialization prevents learning duplicate filters.

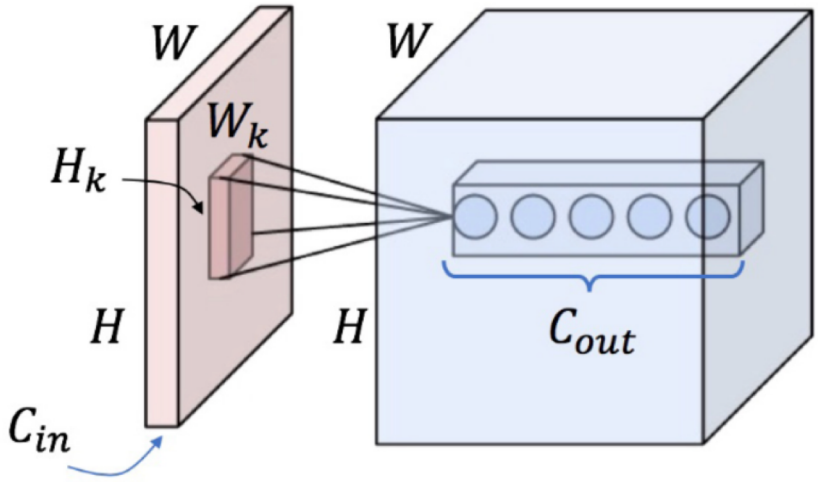
One kernel is not enough

- Need to train C_{out} kernels of size W_k x H_k x C_{in}
- Having a stride of 1 and enough zero padding we can have W x H x C_{out} output neurons.



Question

- How many parameters do we need to train this convolutional layer with C_{out} output channels?



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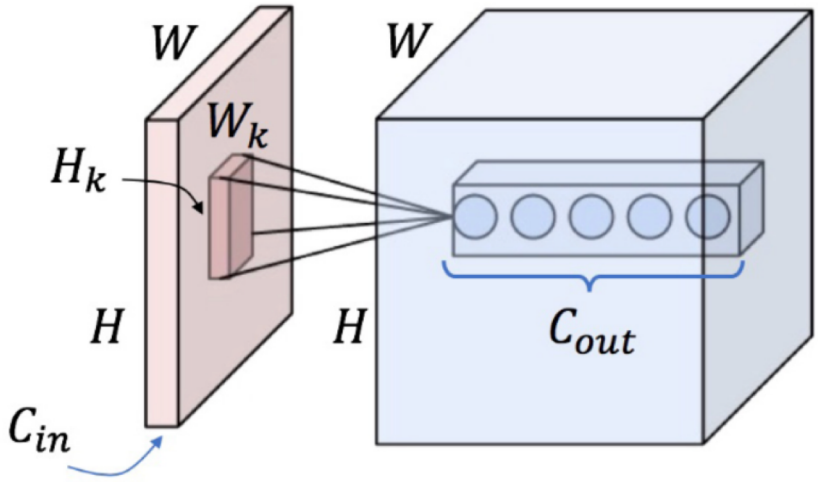


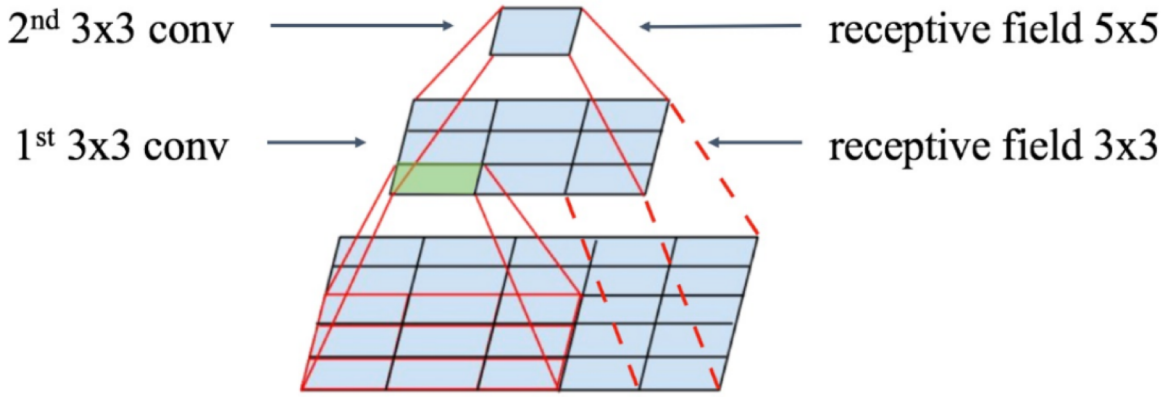
$$(W_k \cdot H_k \cdot C_{in} + 1) \cdot C_{out}$$

Selecting the number of feature maps (kernels)

- 6 feature maps works well for C1 on MNIST.
- This is a result of trying out other numbers of filters.
- Increasing the number of filters results in higher computational overhead and possibly overfitting.
- Another intuition for 6 is that there's not that much variation in pixels, you'll eventually extract more complex features in subsequent layers.

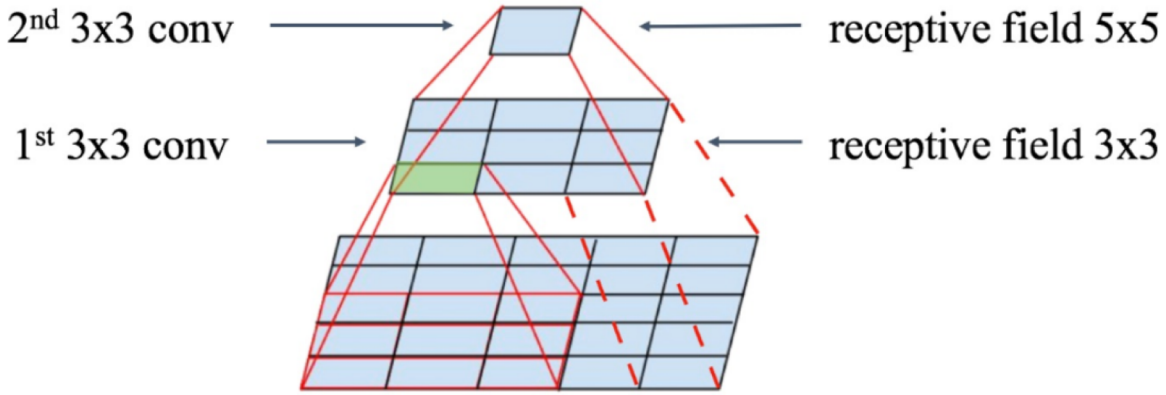
One conv layer is not enough

- Neurons of the 1st conv layer look at patches of the image of size 3 x 3.
- What if the object of interest is larger than that?
- Need a 2nd conv layer on top of the 1st, etc.



One conv layer is not enough

- What is the receptive field for the 4th conv layer (assume all layers have 3 x 3 kernels and stride 1?



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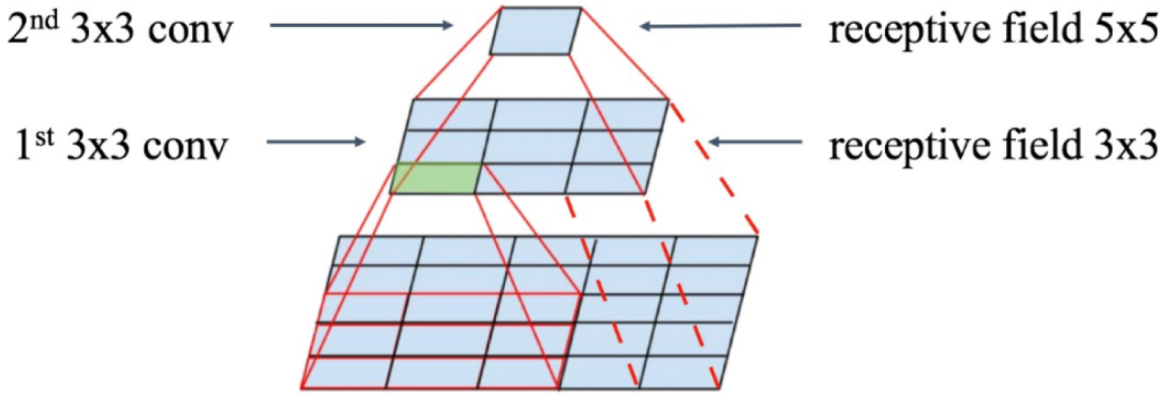
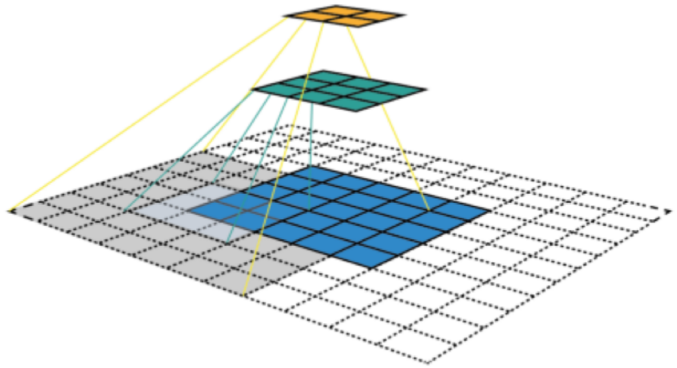


9 x 9 – add 2 to receptive field with each layer.

Receptive field after N convolutional layers

- More generally, if we stack ***N*** convolutional layers with kernel size ***3 x 3***, the receptive field on the ***N^{th}*** layer = **(2N + 1)*(2N + 1).**
- You need to stack a lot of convolutional layers to identify objects as big as the input image.
- To cover the receptive field of a 300x300 input image, need ~75 layers.



Understanding the Effective Receptive Field in Deep Convolutional Neural Networks
Wenjie Luo, Yujia Li, Raquel Urtasun, Richard Zemel

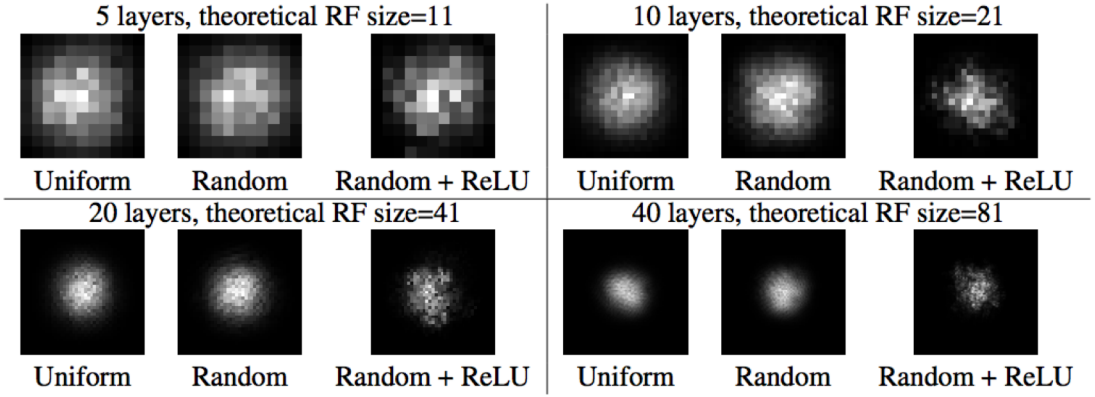
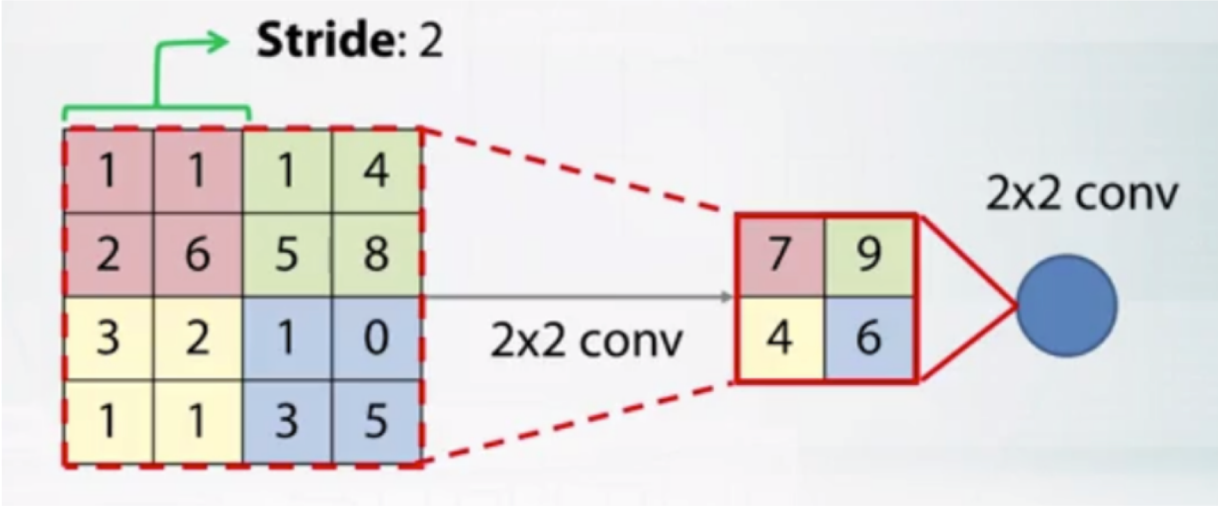


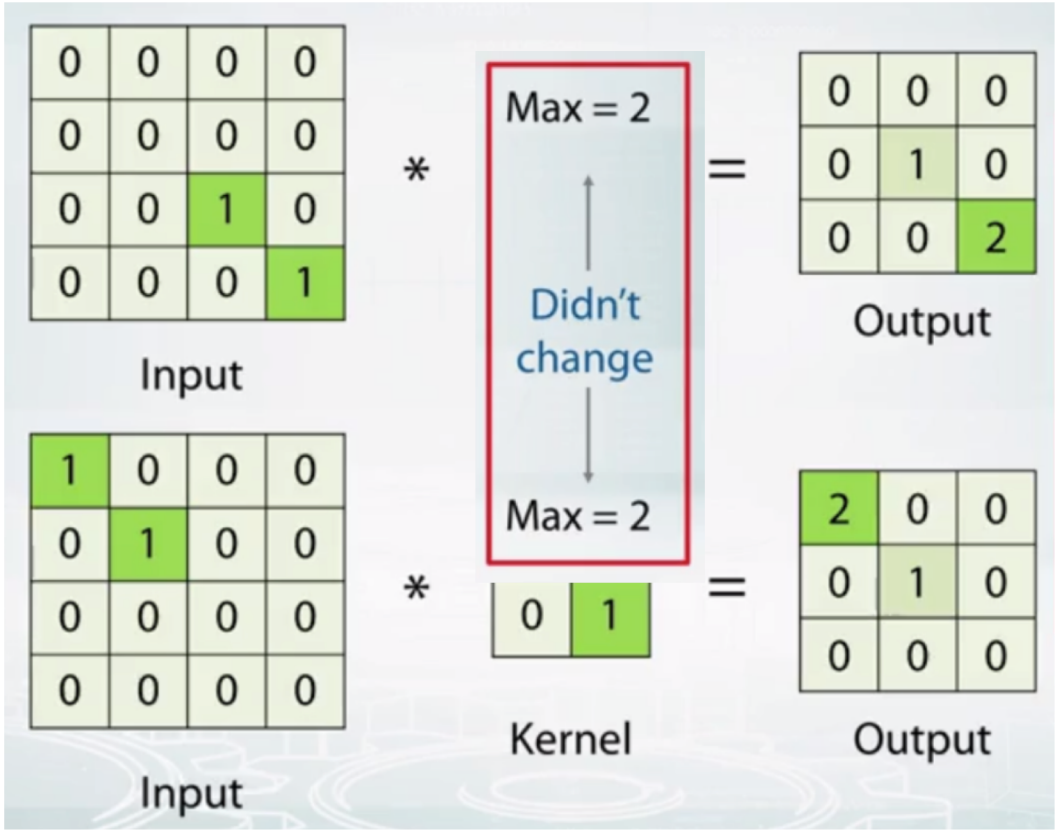
Figure 1: Comparing the effect of number of layers, random weight initialization and nonlinear activation on the ERF. Kernel size is fixed at 3×3 for all the networks here. Uniform: convolutional kernel weights are all ones, no nonlinearity; Random: random kernel weights, no nonlinearity; Random + ReLU: random kernel weights, ReLU nonlinearity.

Need to grow receptive field faster

- We can increase the stride in our conv layer to reduce the output dimensions.
- Further convolutions will effectively double their receptive field.

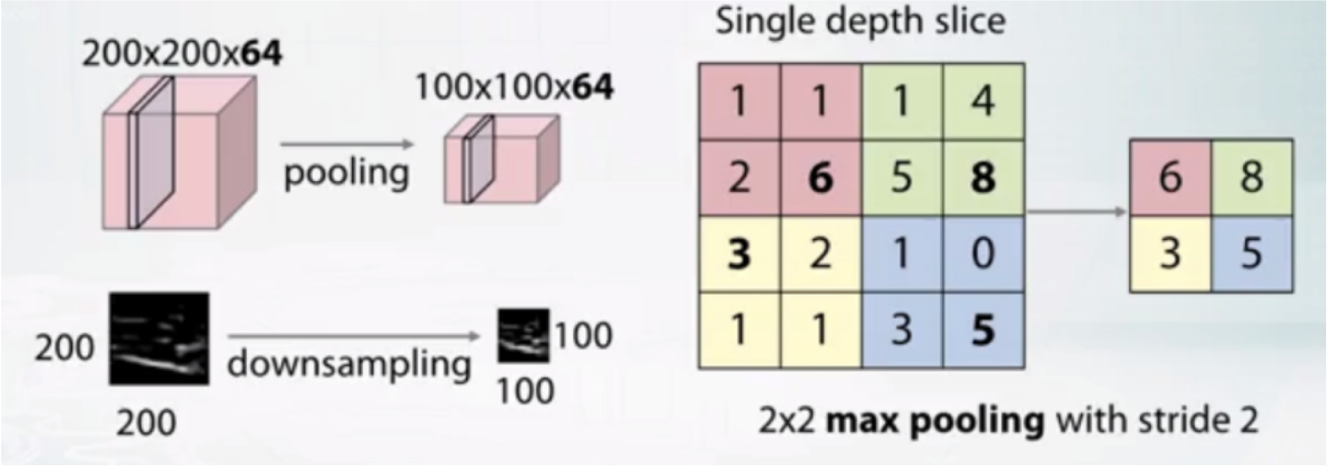


Need to maintain translation invariance



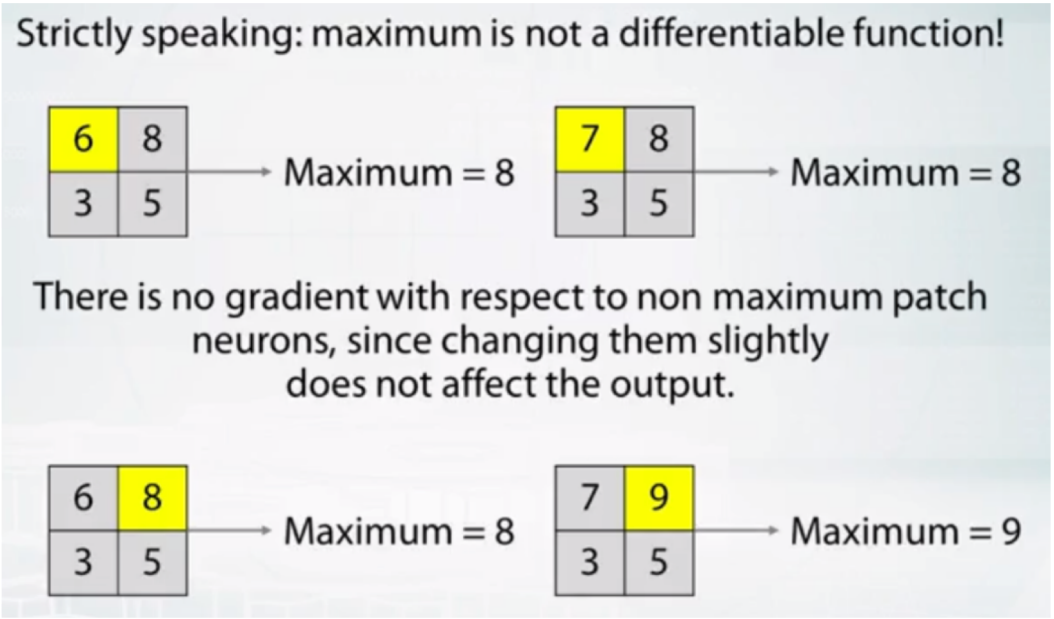
Pooling layer

- Works like a convolutional layer but doesn't have a kernel.
- Calculates max or average of input patch values.



Backpropagation for max pooling layer

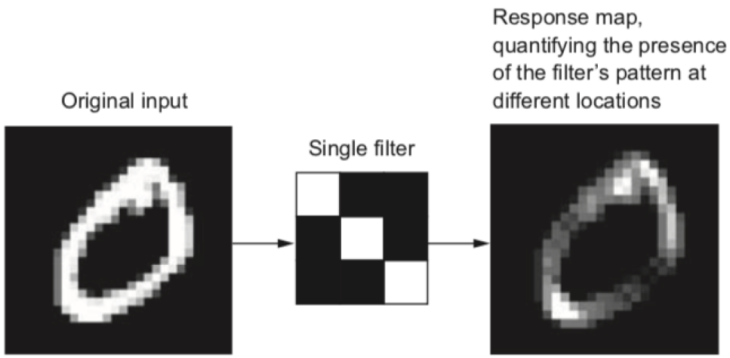
- Works like a convolutional layer but doesn't have a kernel.
- Calculates max or average of input patch values.
- For the max path neuron you have a gradient of 1.

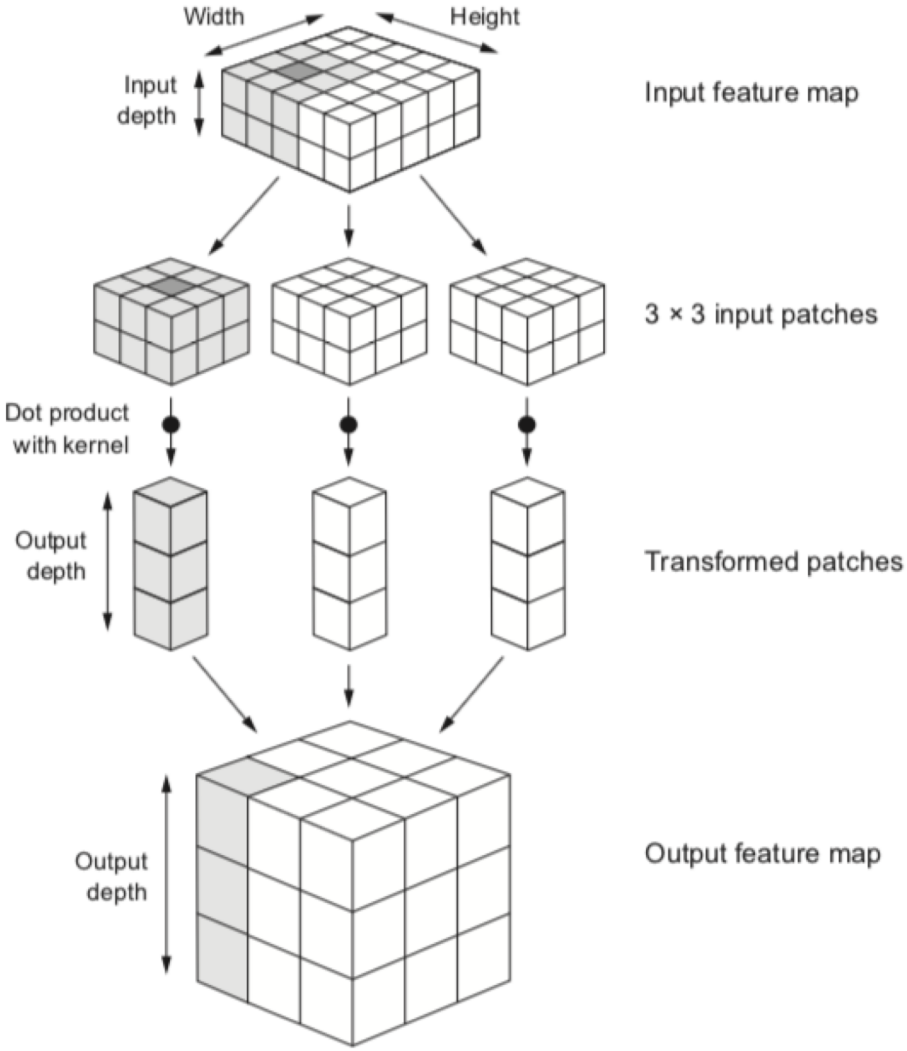


Conv Net tensor flow

Convolutions are defined by two key parameters:

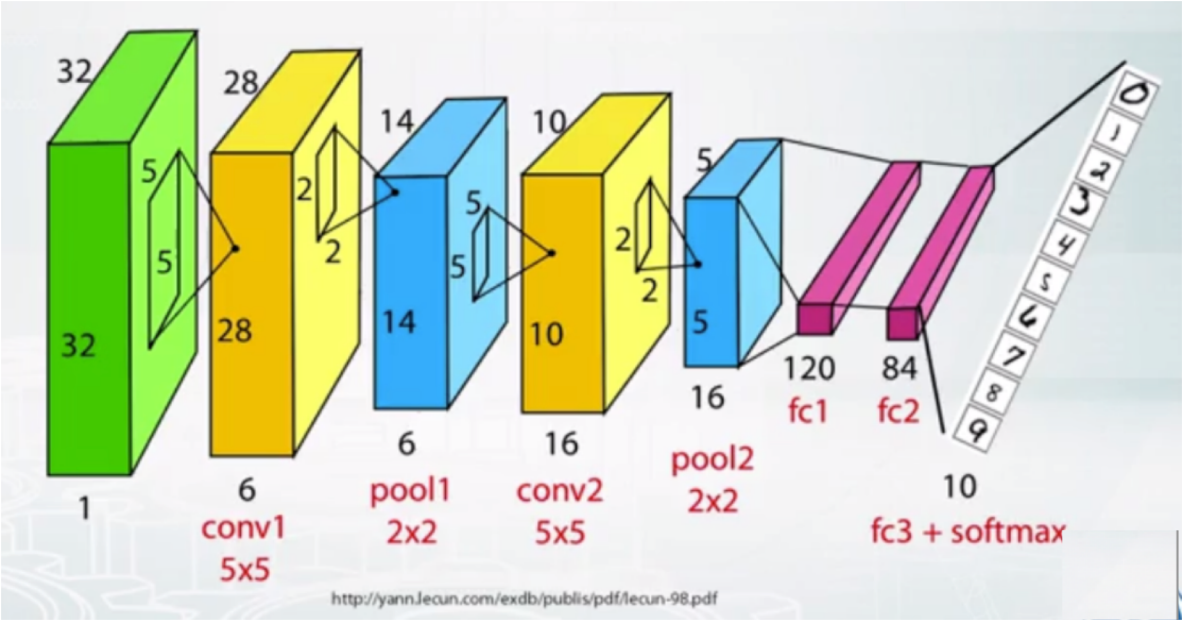
- Size of the patches extracted from the input
- Dept of the output feature map.





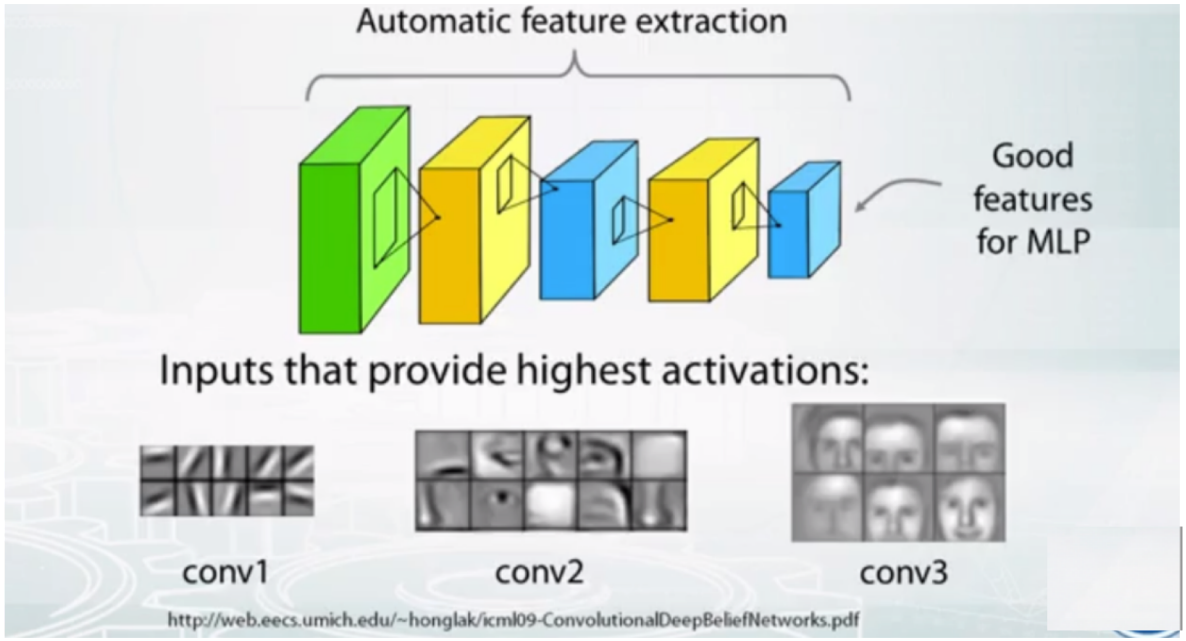
Putting together a simple CNN

- LeNet for handwritten digits recognition on MNIST dataset.



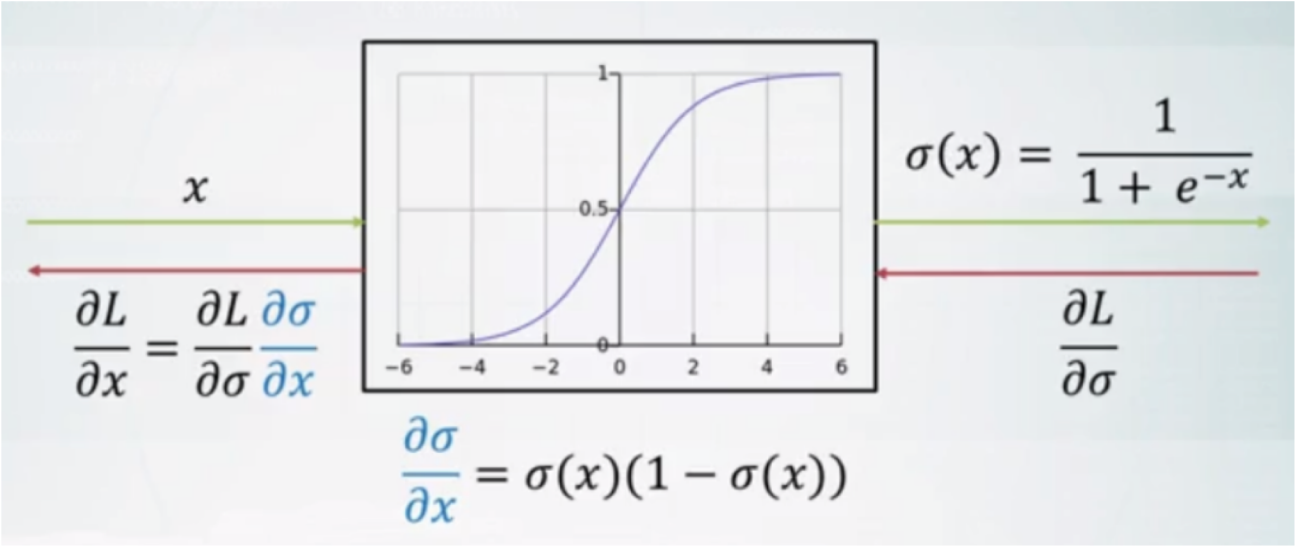
Learning Deep Representations

- Neurons of deep convolutional layers learn complex representations that can be used as features for classification with MLP.



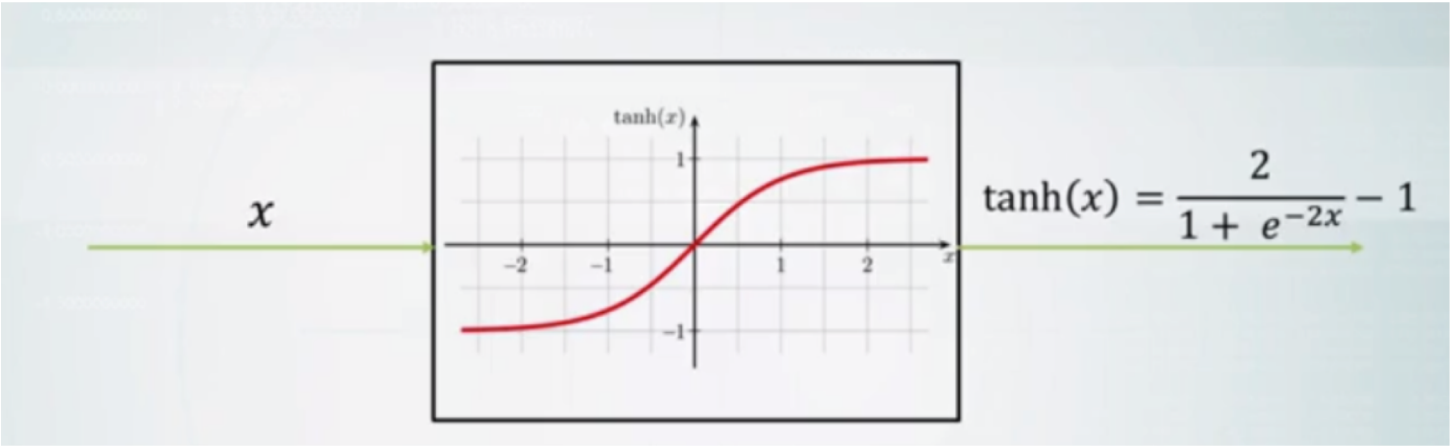
Activations - Sigmoid

- Sigmoid neurons can saturate and lead to vanishing gradients.
- Not zero centered
- e^x is computationally expensive.



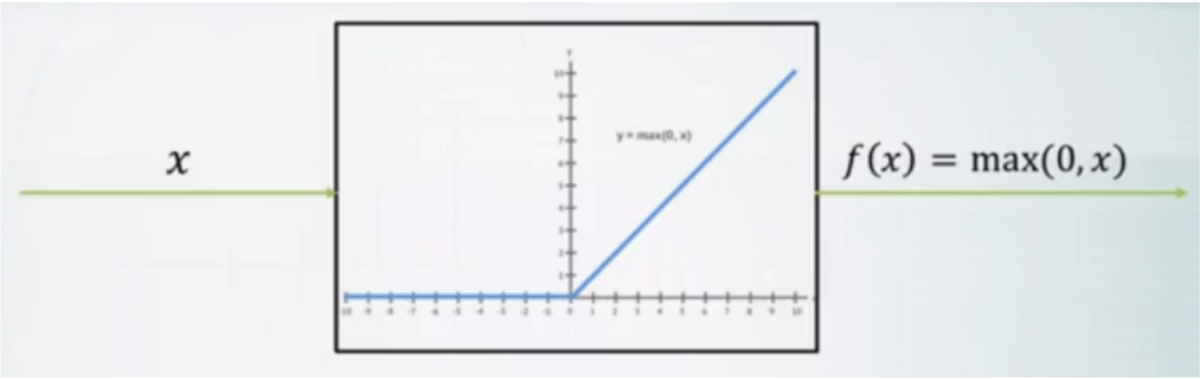
Activations - Tanh

- Zero centered
- Otherwise pretty much like sigmoid.



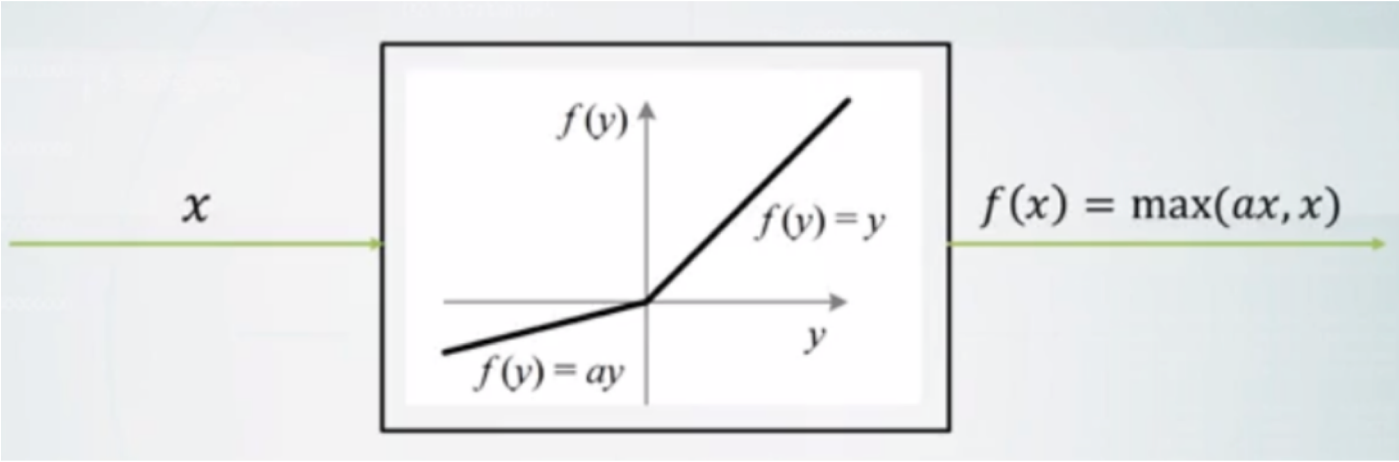
Activations - ReLU

- Fast to compute
- Gradients do not vanish for x > 0
- Provides faster convergence in practice
- Not zero centered
- Can die: if not activated, never updates..



Activations – Leaky ReLU

- Will not die if a!= 1



Important practices

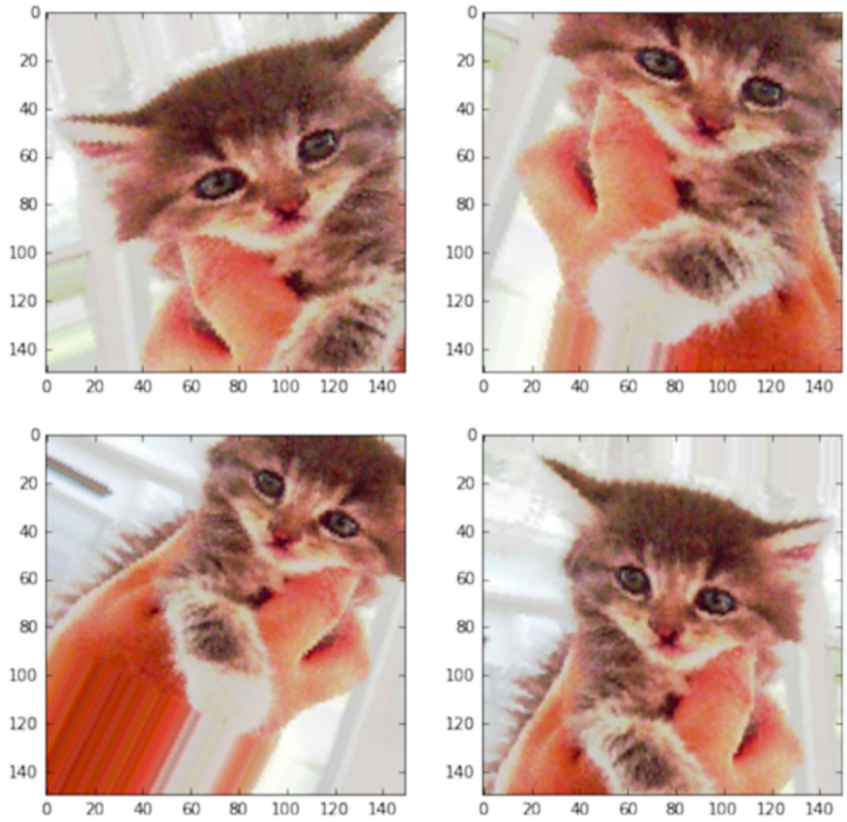
- Random initialization centered at zero – Xavier
- Batch training
- Batch normalization
- Dropout
- Data augmentation
- Transfer learning

Important takeaways

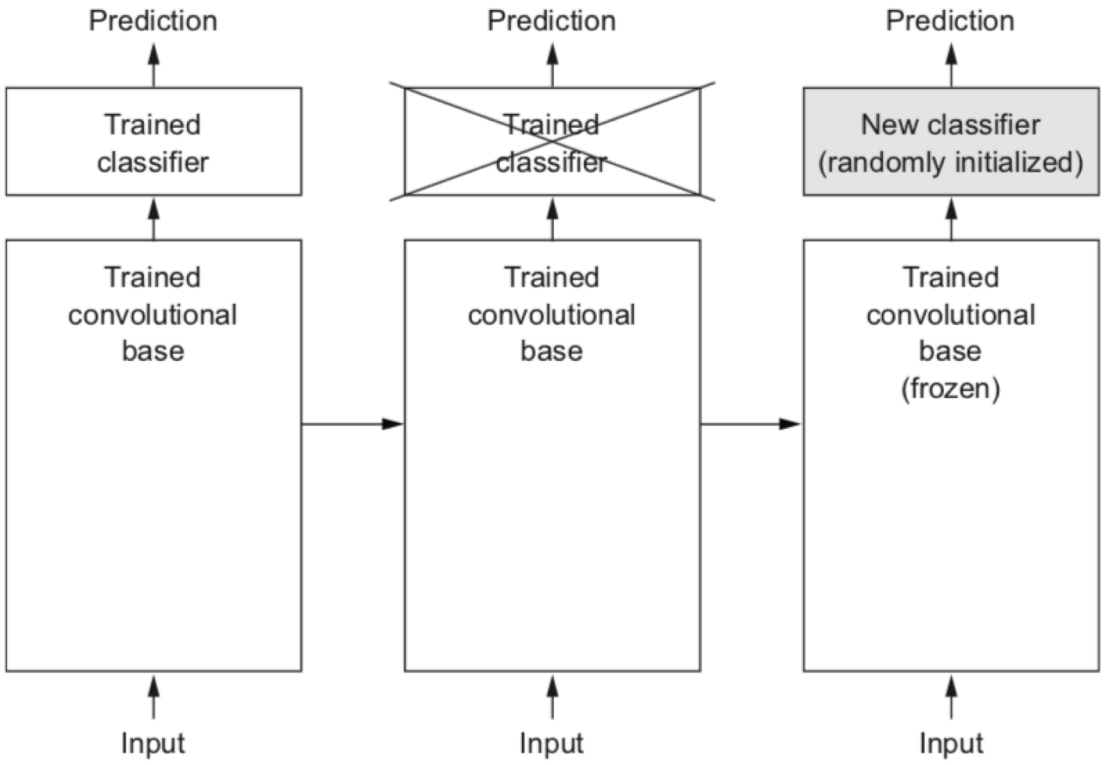
- Use ReLU or leaky ReLU activation
- Use He et al., Xavier initialization or similar
- Add batch normalization and/or dropout
- Augment training data set
- Use transfer learning
- Transfer learning + fine tuning

Data augmentation

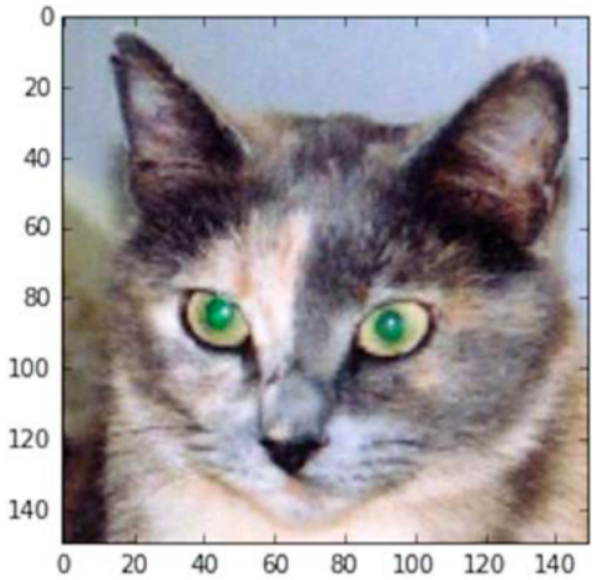
- Scale
- Translation
- Flip
- Small rotations

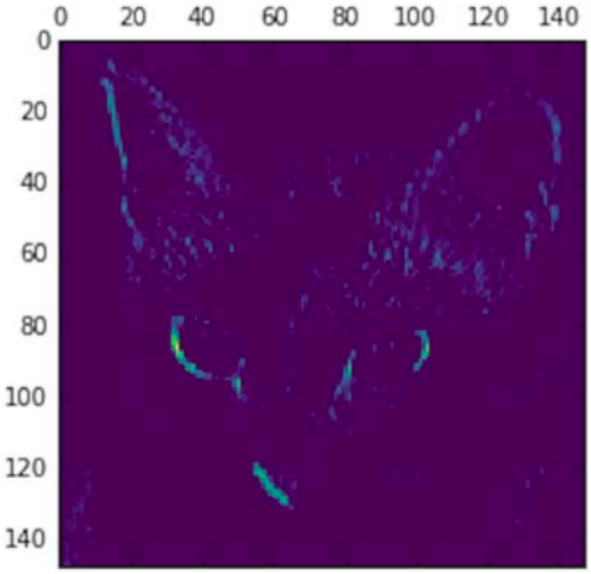


Transfer learning

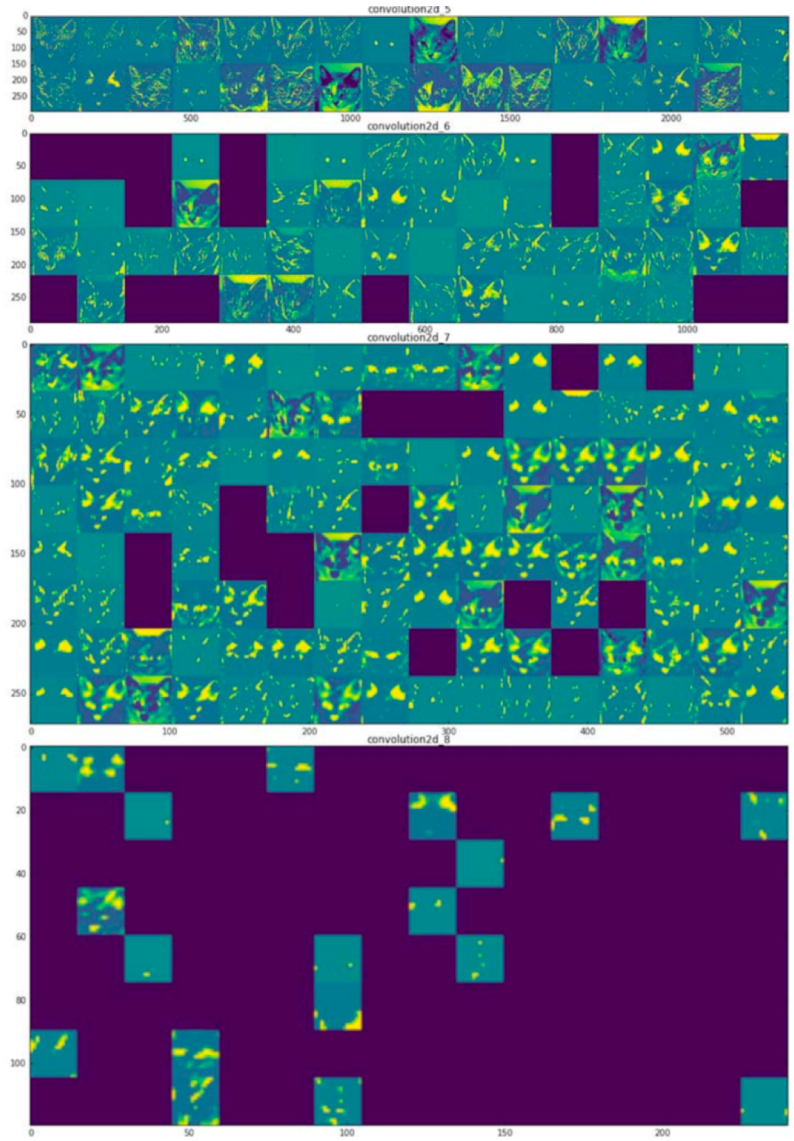


Visualizing activations

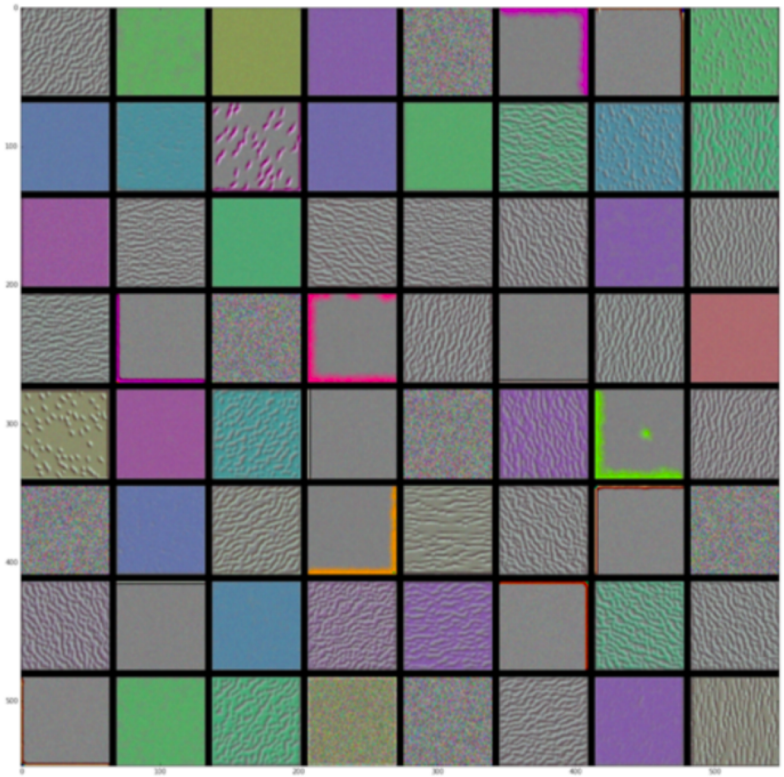




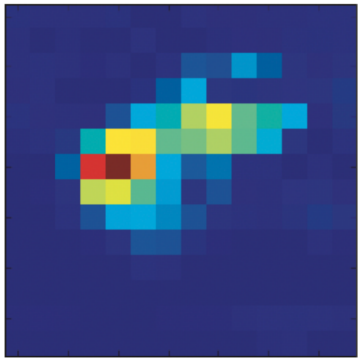
Visualizing every channel of every layer



Visualizing filter patterns



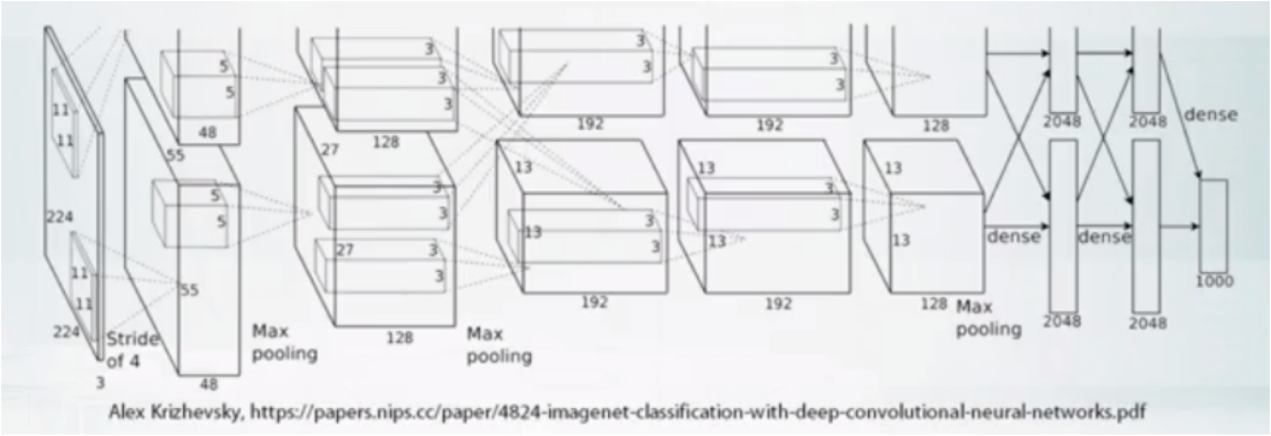
Heat maps



Modern CNN Architectures

AlexNet (2012)

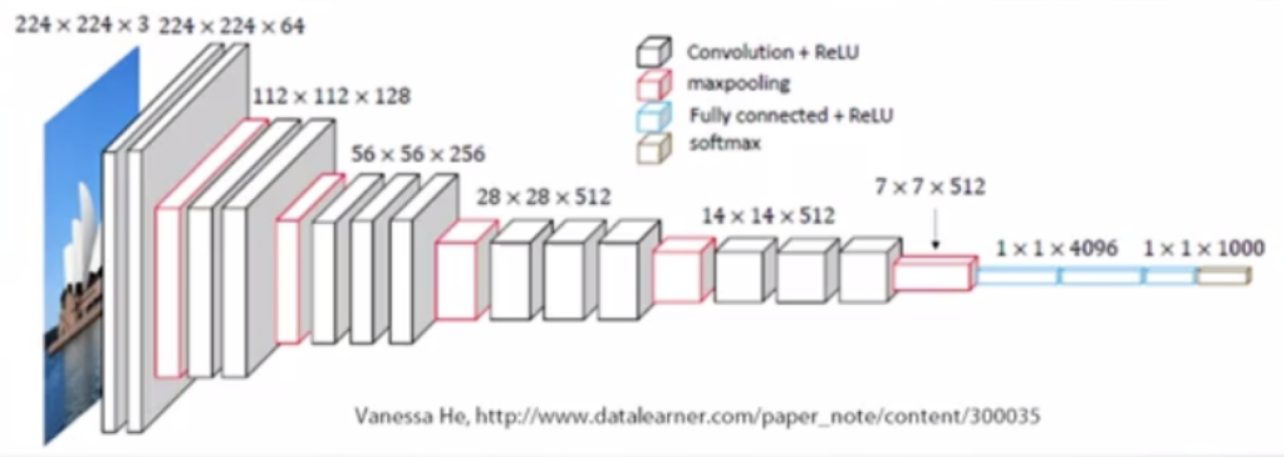
- First deep conv net for ImageNet
- Significantly reduced top 5 error from 26% to 15%
- 11x11, 5x5, 3x3 convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum
- 60M parameters
- Trained on 2 GPUs for 6 days



Alex Krizhevsky, https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

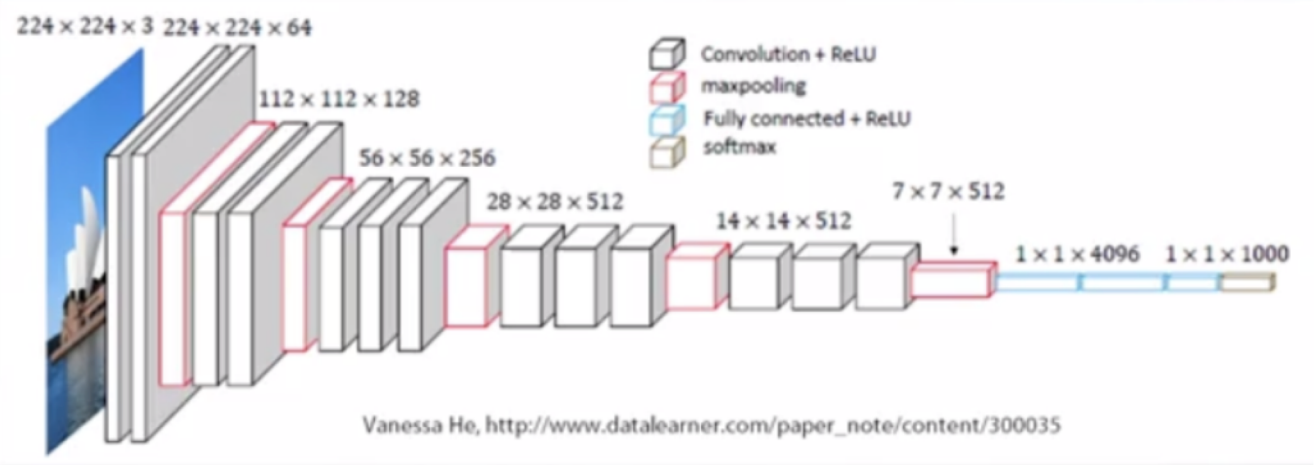
VGG (2015)

- Similar to AlexNet, only 3x3 convolutions, but lots of filters
- Significantly reduced top 5 error 8% (single model)
- Training similar to AlexNet with additional multi-scale cropping.
- 138M parameters
- Trained on 4 GPUs for 2-3 weeks



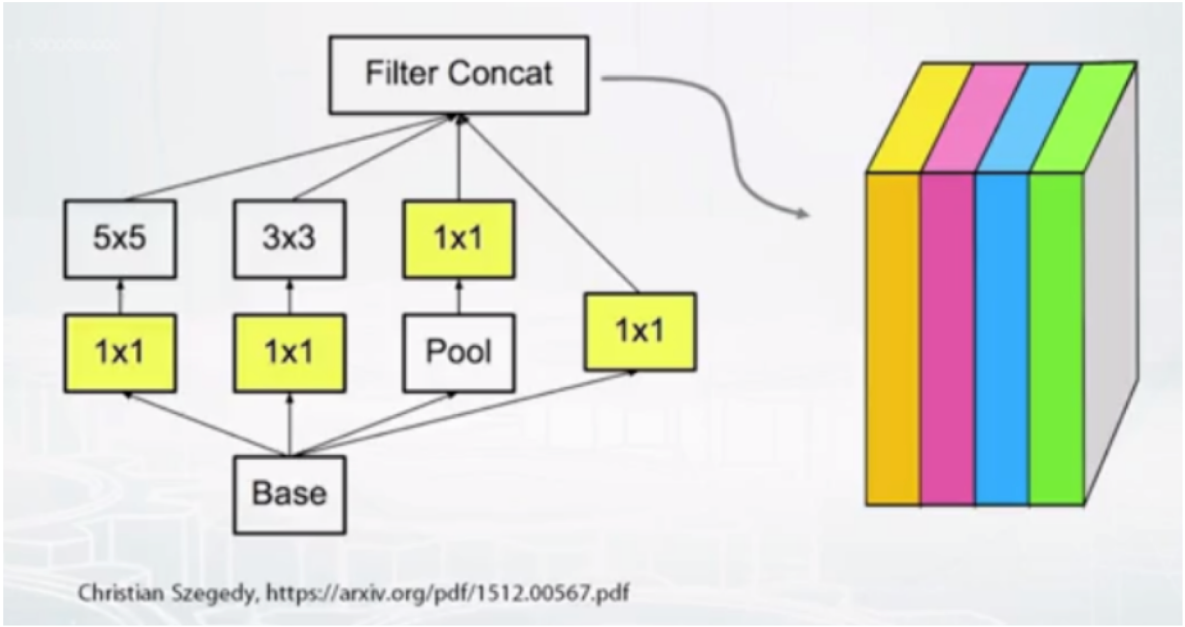
Inception V3 (2015)

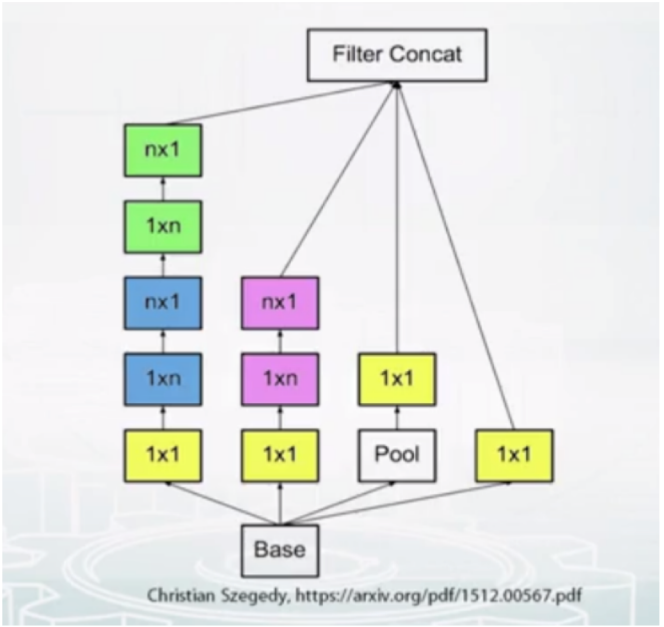
- Uses inception block
- ImageNet top 5 error 5.6% (single model), 3.6% ensemble
- Batch normalization, image distortions, RMSProp
- 25M parameters
- Trained on 8 GPUs for 2 weeks



Basic Inception Block

- All operations inside a block use stride 1 and enough padding to output the same spatial dimensions (W x H) of feature map.
- 4 different feature maps are concatenated on depth at the end.





ResNet (2015)

- Introduces residual connections
- ImageNet top 5 error: 4.5% (single model), 3.5% (ensemble)
- 152 layers, few 7x7 conv layers, the rest are 3x3, batch normalization, max and average pooling
- 60M parameters
- Trains on 8 GPUs for 2-3 weeks