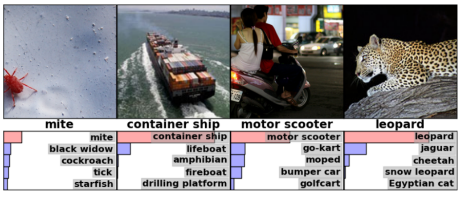
Convolutional Neural Net

Alex Olson

Introduction: Why ConvNets

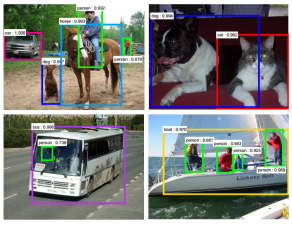
- **Fully Connected Networks Challenges:**
  - High dimensionality of inputs
  - Loss of spatial structure when flattening inputs
- **Convolutional Neural Networks (CNNs):**
  - Address high-dimensional input challenges
  - Preserve spatial structure through local receptive
    parameter sharing
  - Efficient for pattern recognition due to reduced pa
    and computational efficiency

Used everywhere for Vision



[Krizhevsky 2012]

[Ciresan et al. 2013]



[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Many other applications

Speech recognition & speech synthesis

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Natural Language Processing

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Protein/DNA binding prediction

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Any problem with a spatial (or sequential) str

ConvNets for image classification

CNN = Convolutional Neural Networks = ConvNet

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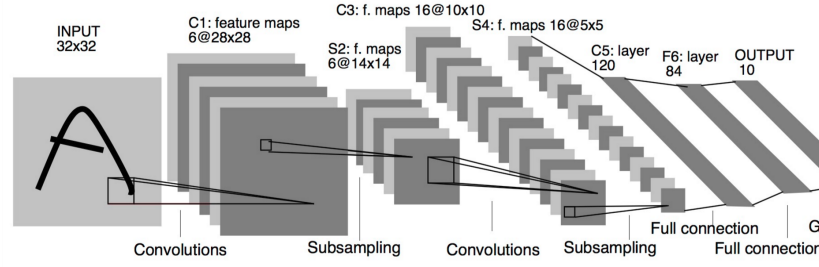

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning app

Outline

Convolutions

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CNNs for Image Classification

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CNNs for Image Classification

CNN Architectures

Convolutions

Motivations

Standard Dense Layer for an image input:

```
x = Input((640, 480, 3), dtype='float32')
# shape of x is: (None, 640, 480, 3)
x = Flatten()(x)
# shape of x is: (None, 640 x 480 x 3)
z = Dense(1000)(x)
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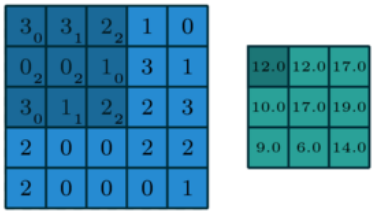
Spatial organization of the input is destroyed by Flatten

Convolution in a neural network



- x is a 3×3 chunk (dark area) of the image *(blue array)*
- Each output neuron is parametrized with the 3×3 weight mat
  numbers)

These slides extensively use convolution visualisation by V. Dumoulin available at [ht
conv_arithmetic]

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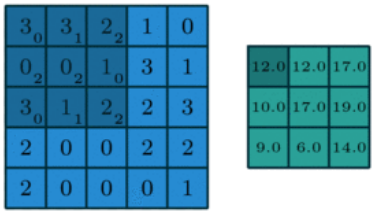

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The activation obtained by sliding the 3×3 window and computir

$$z(x) = relu(\mathbf{w}^T x + b)$$

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Animal Vision Analogy

Hubel & Wiesel, RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORT

Channels

Colored image = tensor of shape (height, width, channels)

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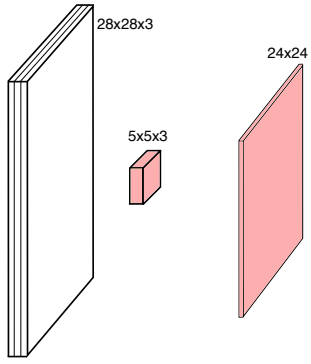
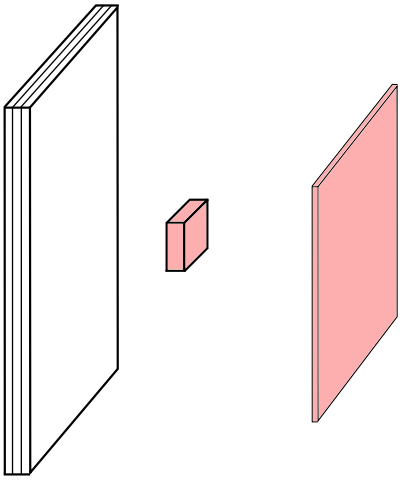
Convolutions are usually computed for each channel and summed:



Multiple convolutions



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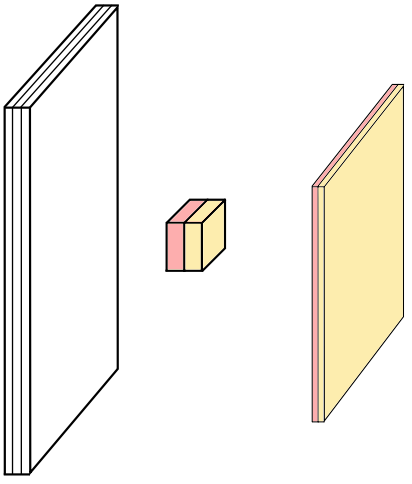

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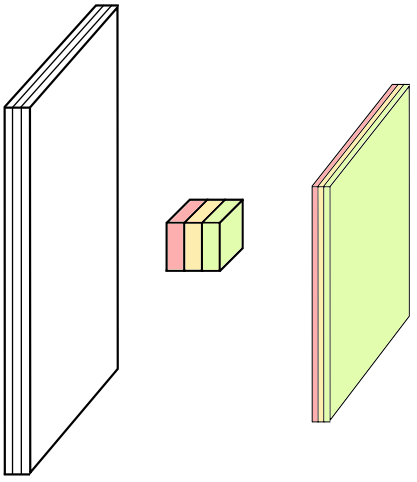

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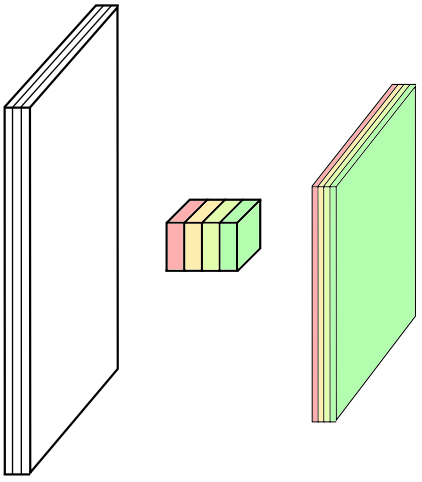

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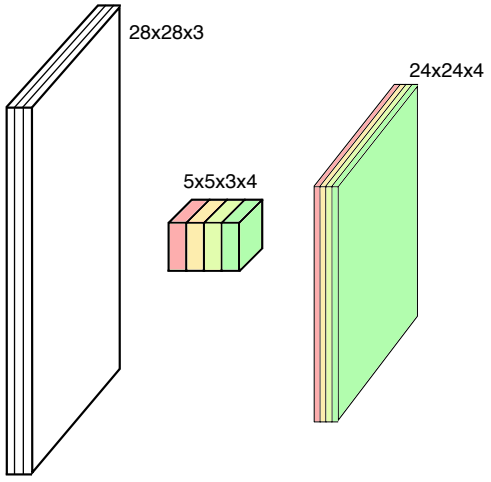

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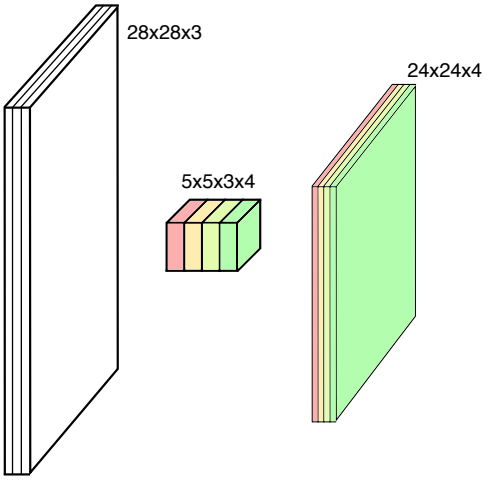
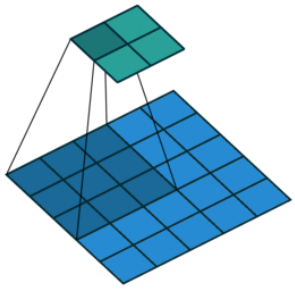


- Kernel size aka receptive field (usually 1, 3, 5, 7, 11)
- Output dimension: length - kernel_size + 1

Strides

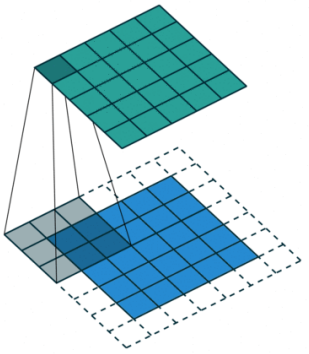
- Strides: increment step size for the convolution operator
- Reduces the size of the output map



Example with kernel size 3×3 and a stride of 2 (image in blu

Padding

- Padding: artificially fill borders of image
- Useful to keep spatial dimension constant across filters
- Useful with strides and large receptive fields
- Usually: fill with 0s



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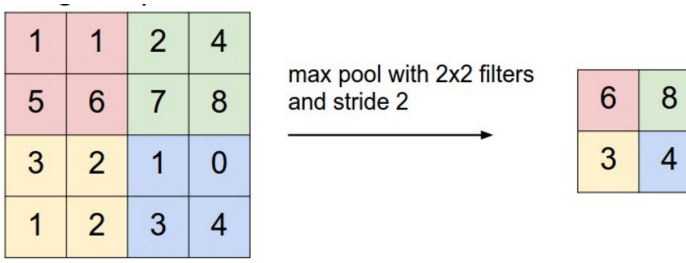

Schematic from Stanford http://cs231n.github.io/convolutional-networks

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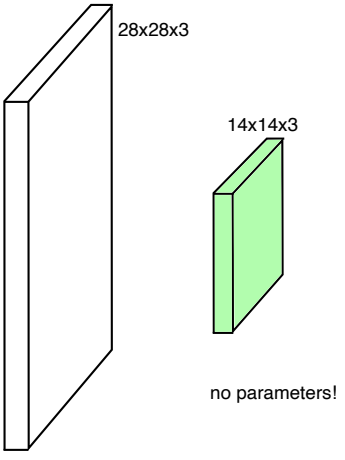
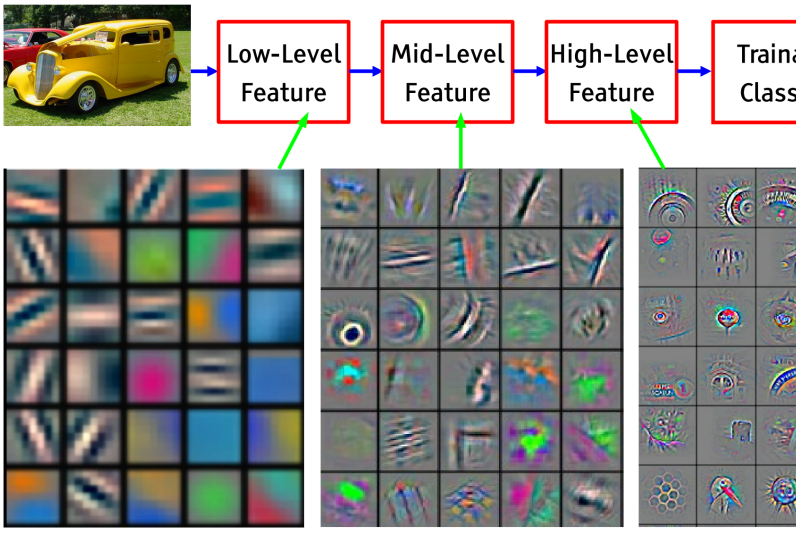
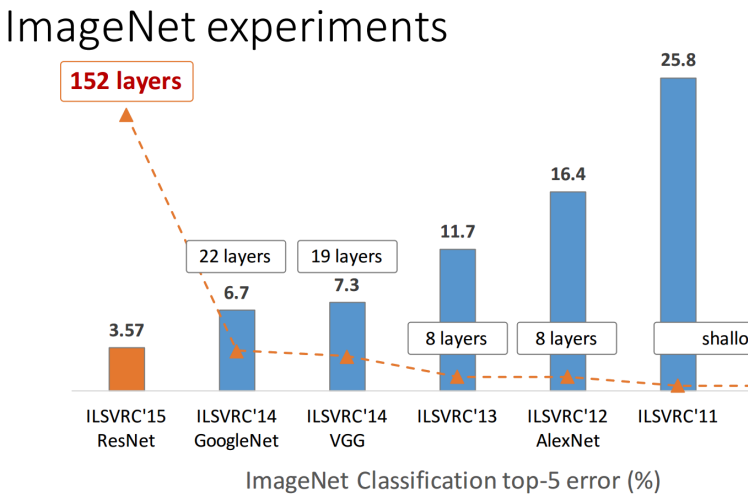


Hierarchical representation



Feature visualization of convolutional net trained on ImageNet from [Zeiler &

Deeper is better



from Kaiming He slides "Deep residual learning for image recognition." ICML. 2016.

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Transfer learning

- Use pre-trained weights, remove last layers to compute represe
- Train a classification model from these features on a new classi
- The network is used as a generic feature extractor
- Better than handcrafted feature extraction on natural images

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Retraining the (some) parameters of the network (given enough data)

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- Truncate the last layer(s) of the pre-trained network
- Freeze the remaining layers weights
- Add a (linear) classifier on top and train it for a few epochs
- Then fine-tune the whole network or the few deepest layers
- Use a smaller learning rate when fine tuning

Data Augmentation

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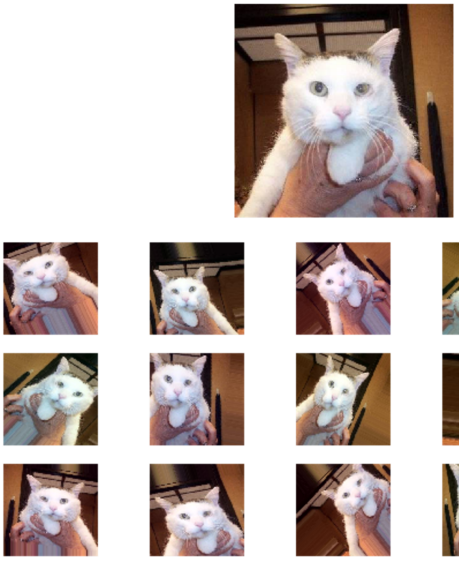

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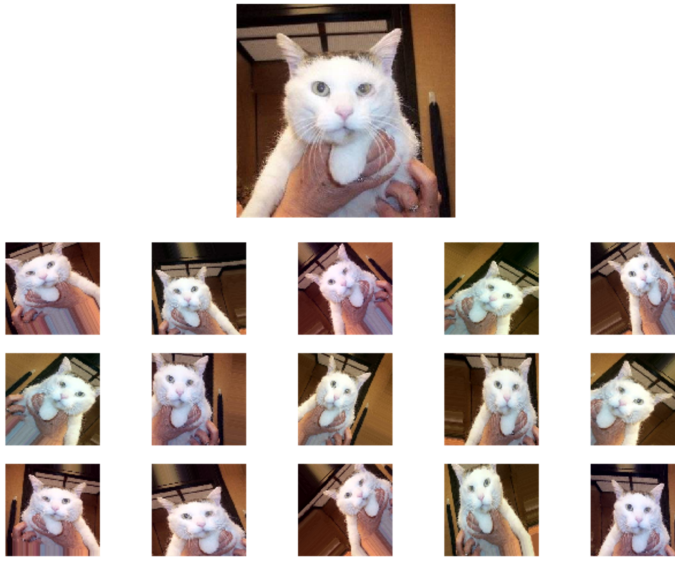

See also: RandAugment and Unsupervised Data Augmentation for

Next: Lab