Sistemas Inteligentes

Convolutional Neural Networks

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Deep Learning Introduction

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- Each concept defined in terms of its relations to simpler concepts
- The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones
- If we draw a graph showing how these concepts are built on top of each other, the graph is deep with many layers: AI Deep Learning

Representation

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- The performance of machine learning algorithms depends heavily on the representation of the data they are given
- The choice of representation has an enormous effect on the performance of machine learning algorithms

Features

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- A useful feature for speaker identification from sound is an estimate of the size of speaker's vocal tract
- It gives a strong clue as to whether the speaker is a man, woman, or child
- For many tasks, it is difficult to know what features should be extracted: detect cars in photographs

Learning Representation

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- Representations Learned often result in much better performance than can be obtained with hand-designed representations
- Manually designing features for a complex task requires a great deal of human time and effort; it can take decades for an entire community of researchers

Deep Learning

Deep-learning methods are learning representation methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level.

Deep Learning Architecture

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- Insensitive to large irrelevant variations such as the background, pose, lighting and surrounding objects.

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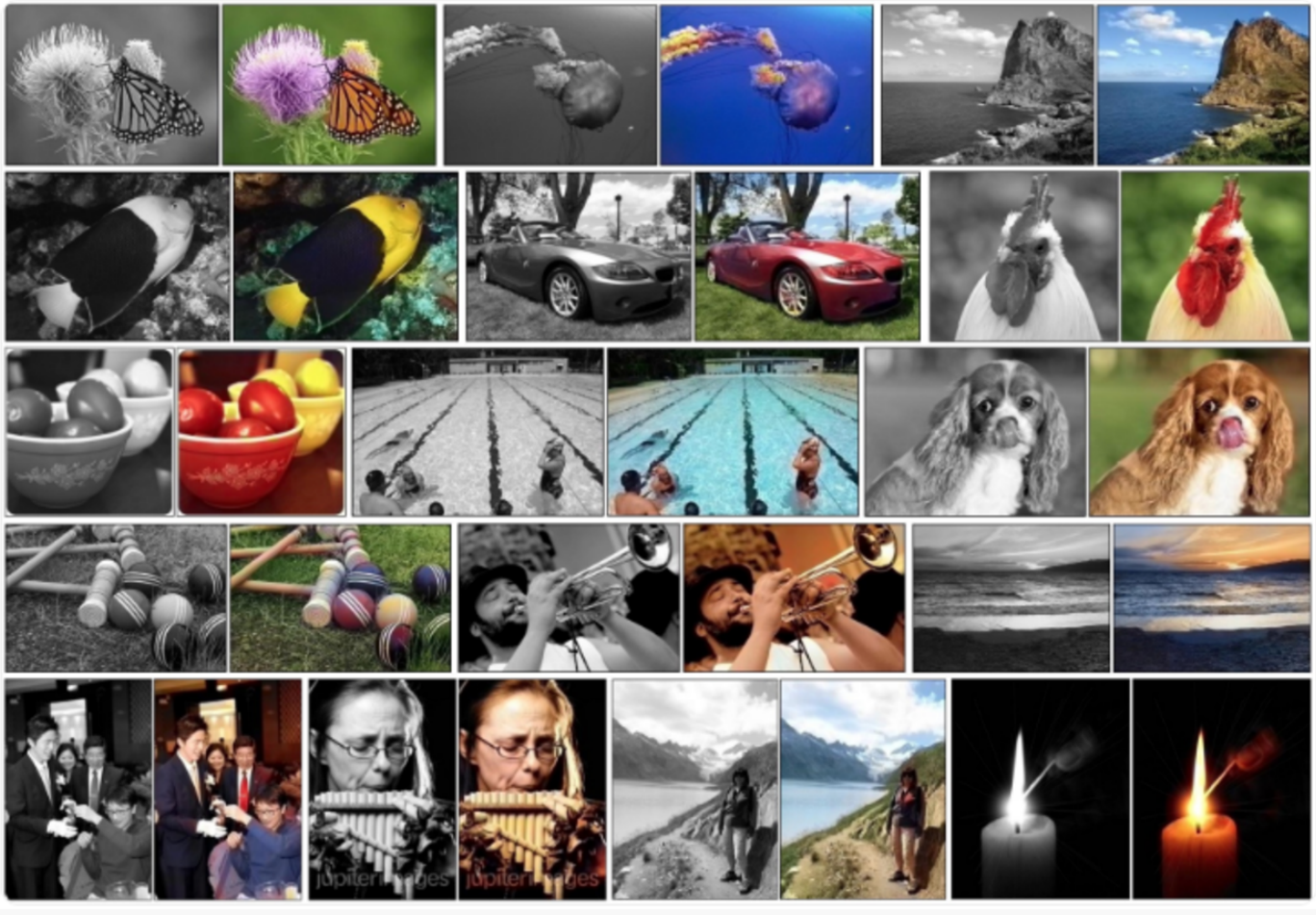
- It has turned out to be very good at discovering intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government.

Deep Learning Applications II

Deep learning has produced extremely promising results for various tasks in natural language understanding, particularly topic classification, sentiment analysis, question answering and language translation

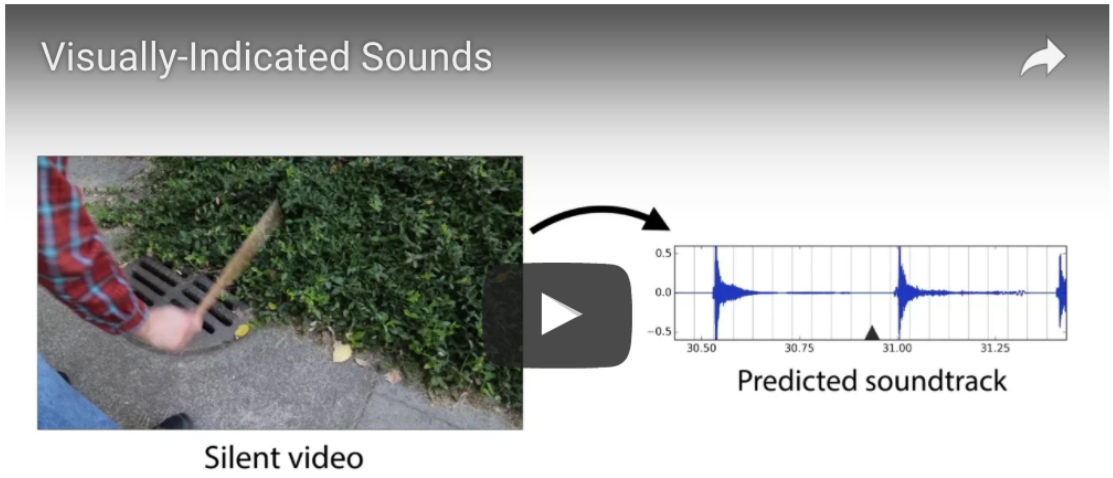
Applications: Colorization of Black and White Images



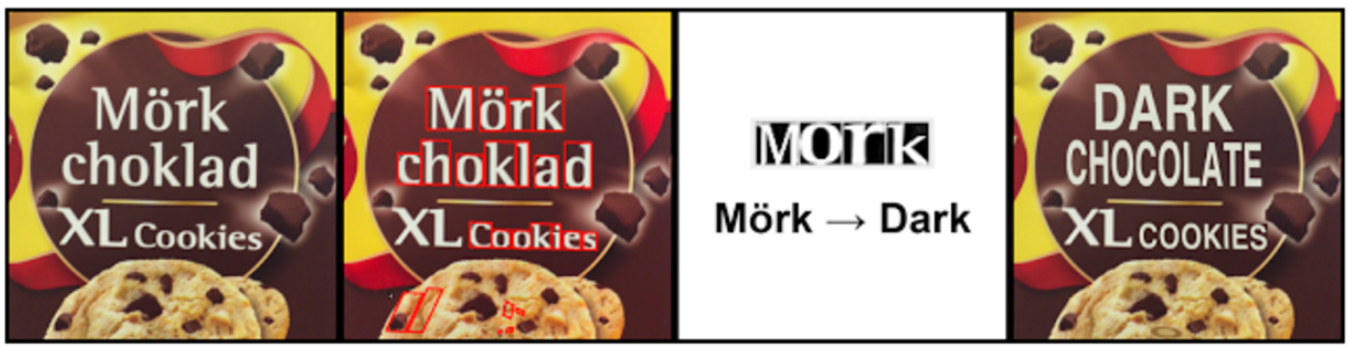
Colorization of Black and White Photographs

Image taken from Richard Zhang, Phillip Isola and Alexei A. Efros.

Applications: Adding Sounds To Silent Movies



Applications: Automatic Machine Translation



Instant Visual Translation

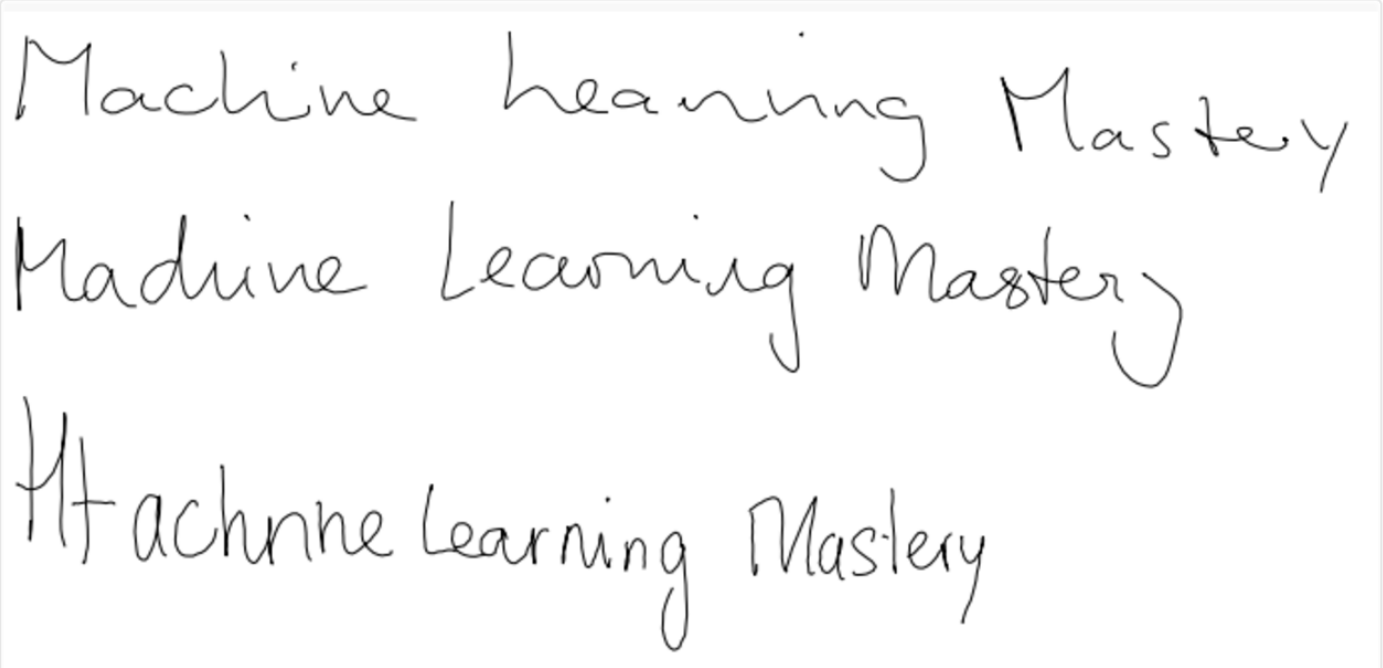
Example of instant visual translation, taken from the Google Blog.

Applications: Object Classification in Photographs

Example of Object Classification

Taken from ImageNet Classification with Deep Convolutional Neural Networks

Applications: Automatic Handwriting Generation



Sample of Automatic Handwriting Generation

Applications: Image Caption Generation

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

"young girl in pink shirt is swinging on swing."

Automatic Image Caption Generation
Sample taken from Andrej Karpathy, Li Fei-Fei

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- https://www.youtube.com/watch?v=5O5oUTrFJuQ

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- In past decades, neural nets used smoother non-linearities, such as $tanh(z)$ or $1/(1 + exp(-z))$,

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- weight configurations for which no small change would reduce the average error.

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- Instead, the landscape is packed with a combinatorially large number of saddle points where the gradient is zero, and the surface curves up in most dimensions and curves down in the remainder.
- Hence, it does not much matter which of these saddle points the algorithm gets stuck at.

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- Introduced unsupervised learning procedures that could create layers of feature detectors without requiring labelled data
- The objective in learning each layer of feature detectors was to be able to reconstruct or model the activities of feature detectors (or raw inputs) in the layer below

Pre-training

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- Especially when the amount of labelled data was very limited.

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- It achieved record-breaking results on a standard speech recognition benchmark
- 2012, versions of the deep net from 2009 were being developed by many of the major speech groups
- leading to significantly better generalization when the number of labelled examples is small

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- Convolutional neural networks has recently been widely adopted by the computer vision community

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- 2D for images or audio spectrograms and 3D for video or volumetric images

Four key ideas behind CNNs

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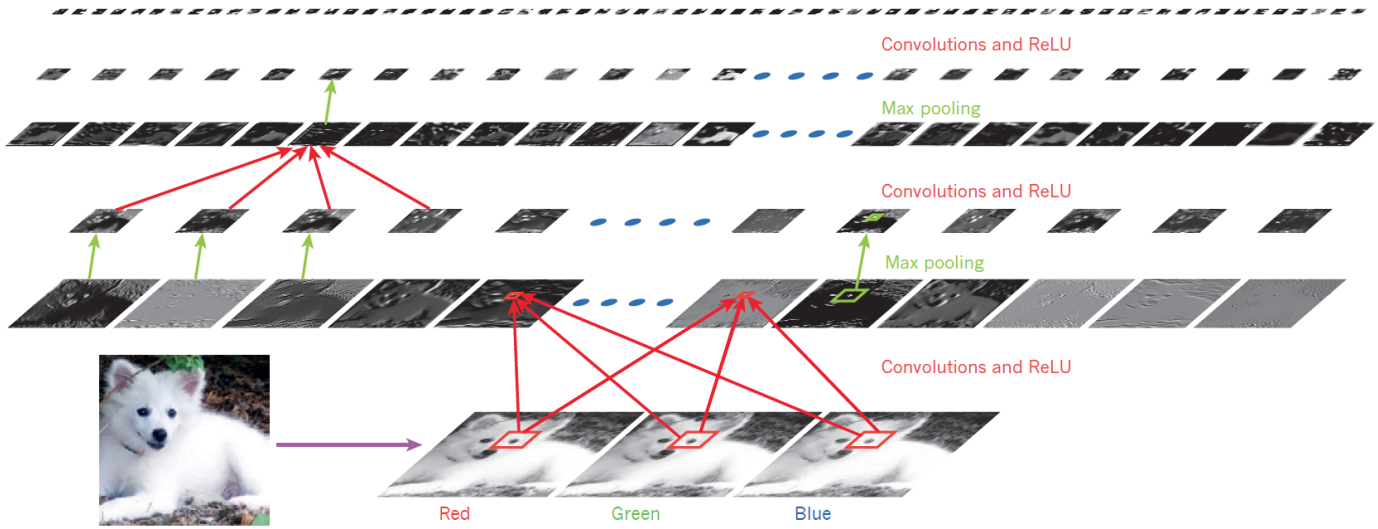
- use of many layers

Architecture of a typical CNN



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- Spectacular results were achieved: almost halving the error rates of the best competing approaches
- This success came from the efficient use of GPUs, ReLUs, dropout (regularization technique) and techniques to generate more training examples

ImageNet

ImageNet 2010

Locality constrained linear coding + SVM	NEC & UIUC
Fisher kernel + SVM	Xerox Research Center Europe
SIFT features + LI2C	Nanyang Technological Institute
SIFT features + k-Nearest Neighbors	Laboratoire d'Informatique de Grenoble
Color features + canonical correlation analysis	National Institute of Informatics, Tokyo

ImageNet 2011

Compressed Fisher kernel + SVM	Xerox Research Center Europe
SIFT bag-of-words + VQ + SVM	University of Amsterdam & University of
SIFT + ?	ISI Lab, Tokyo University

ImageNet 2012

Deep convolutional neural network	University of Toronto
Discriminatively trained DPMs	University of Oxford
Fisher-based SIFT features + SVM	ISI Lab, Tokyo University

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- Recent CNNs architectures have 10 to 20 layers of ReLUs, hundred of millions of weights, and billions of connection between units.
- whereas training have taken weeks two years ago, progress in hardware, software and parallelization have reduced training times to a few hours

Performance

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- NVIDIA, Intel, Qualcomm and Samsung are developing CNN chips to enable real time vision applications in smartphones, cameras, robots and self-driving cars

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- They still have a loss function o the last fully-connected layer

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- vastly reduce the amount of parameters in the network

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- This full connectivity is wasteful and the huge number of parameters would quickly lead to overfitting

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- The final output layer would for CIFAR-10 have dimensions $1 \times 1 \times 10$, because we will reduce the full image into a single vector of class scores

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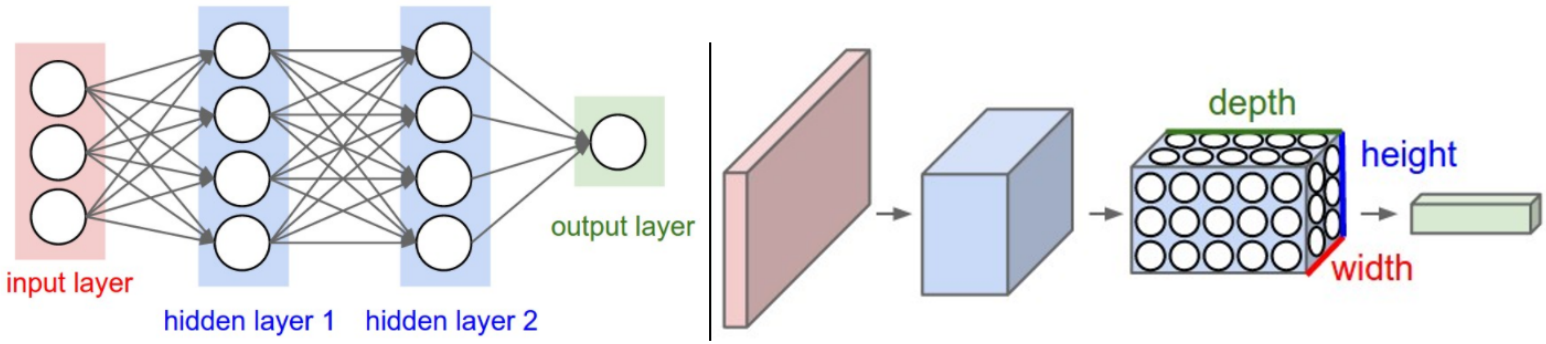

Left: A regular 3-layer Neural Network. Right: A ConvNet arranges its neurons in three dimensions (width, height, depth), as visualized in one of the layers. Every layer of a ConvNet transforms the 3D input volume to a 3D output volume of neuron activations. In this example, the red input layer holds the image, so its width and height would be the dimensions of the image, and the depth would be 3 (Red, Green, Blue channels).

Layers Used to Build ConvNets

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- Fully-Connected Layer

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For CIFAR-10 classification could have the architecture [INPUT - CONV - RELU - POOL - FC]:

- INPUT $[32 \times 32 \times 3]$ will hold the raw pixel values of the image, in this case an image of width 32, height 32 and with three color channels R,G,B

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- This may results in volume such as $[32 \times 32 \times 12]$ if we decided to use 12 filters

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- POOL layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as $[16 \times 16 \times 12]$

Example Architecture

- RELU layer will apply an elementwise activation funcion, such as the $max(0, x)$. This leaves the size of the volume unchanged
- POOL layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as $[16 \times 16 \times 12]$
- FC (fully-connected) layer will compute the class scores, resulting in volume of size $[1 \times 1 \times 10]$, where each of the 10 numbers correspond to a class score. Each neuron in this layer will be connected to all the numbers in the previous volume

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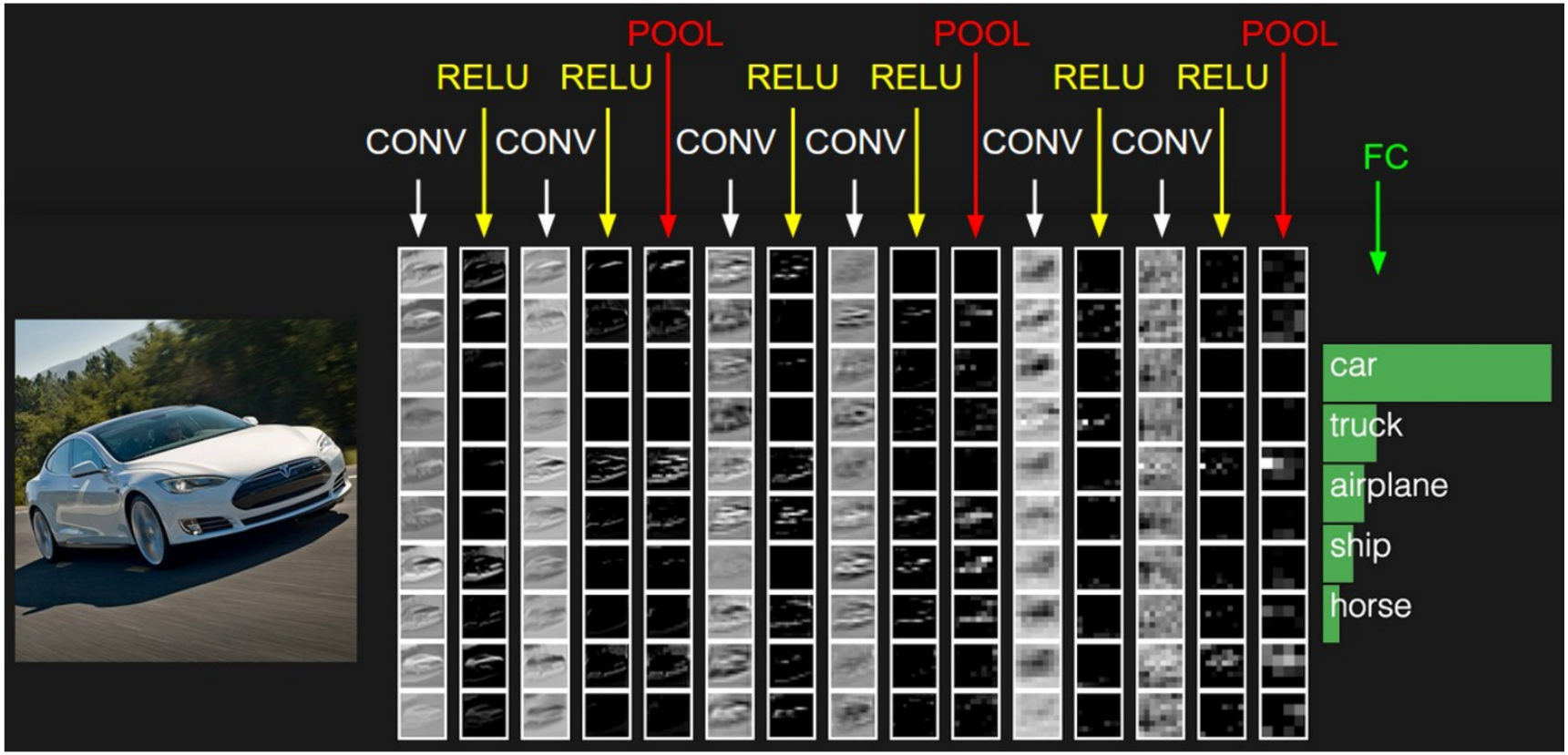
- On the other hand, the RELU/POOL layers will implement a fixed function.
- The parameters in the CONV/FC layers will be trained with gradient descent so that the class scores that the ConvNet computes are consistent with the labels in the training set for each image.

Architecture



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- compute dot products between the entries of the filter and the input at any position

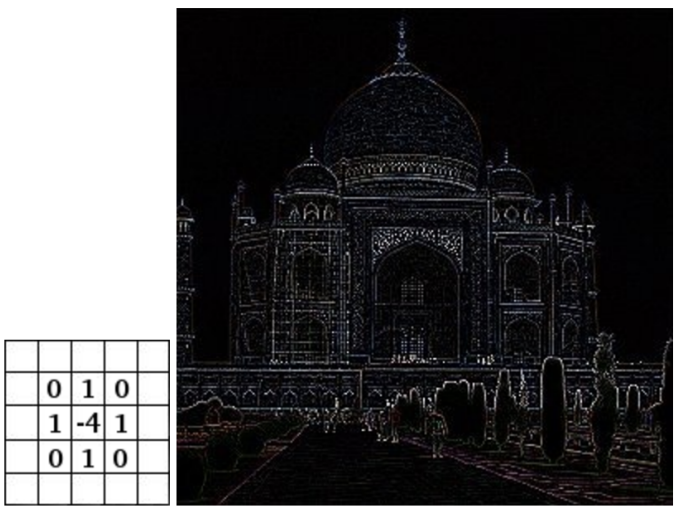
Intuitions About Convolutions

Averaging Each Pixel with its neighboring values blurs an image

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

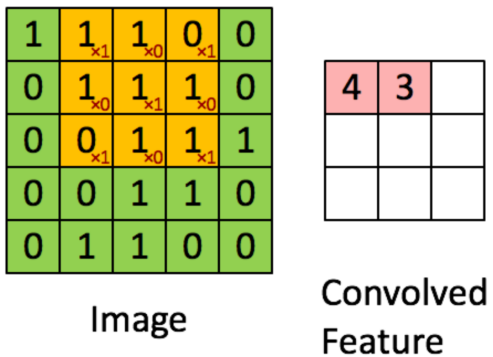
Intuitions About Convolutions

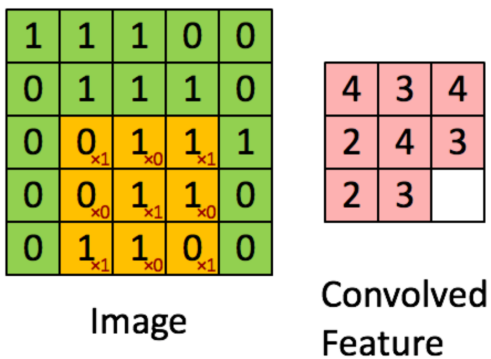
Taking the difference between a pixel and its neighbors detect edges



What is a Convolution?

the easiest way to understand is by thinking of it as a sliding window function applied to a matrix





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- We will have an entire set of filters in each CONV layer, and each of them will produce a separate 2-dimensional activation map
- We will stack these activation maps along the depth dimension and produce the output volume

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- Instead, we will connect each neuron to only a local region of the input volume
- The spatial extent of this connectivity is a hyperparameter called the receptive field of the neuron (the filter size)
- The extent of the connectivity along the depth axis is always equal to the depth of the input volume.

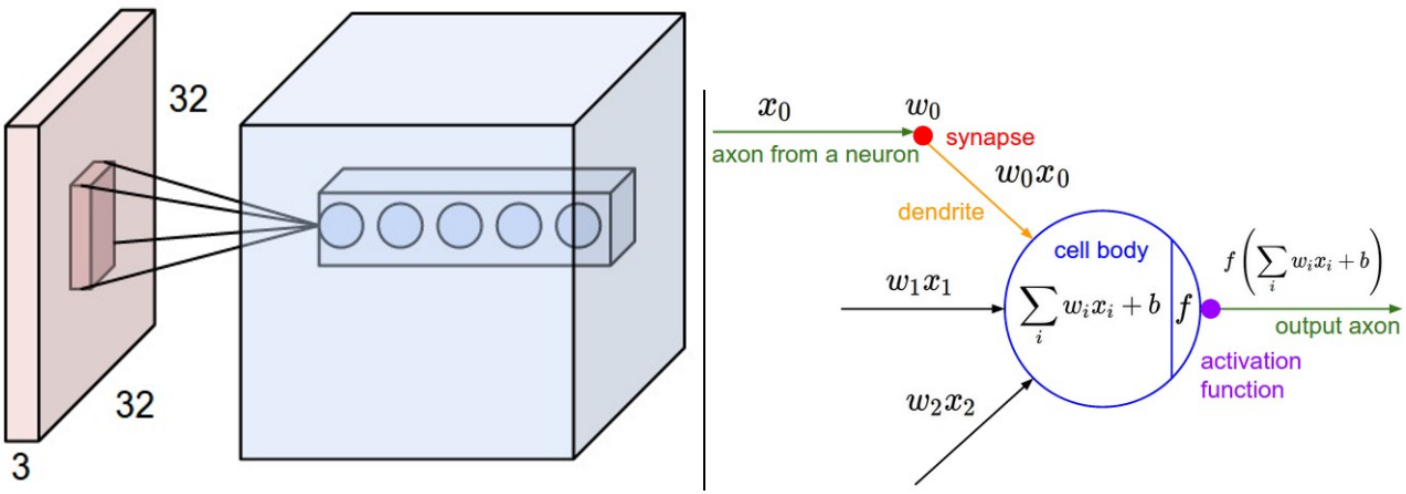
Example

Suppose that the input volume has size $[32 \times 32 \times 3]$
If the receptive filed (filter size) is 5×5, then each neuron in the Conv Layer will have weights to a $[5 \times 5 \times 3]$ region in the input volume, for a total of $5 * 5 * 3 = 75$ weights (and $+1$ bias parameters)
Notice that the extent of the connectivity along the depth axis must be 3, since this is the depth of the input volume

Example II

Suppose an input volume had size $[16 \times 16 \times 20]$.
Then using an example receptive field size of 3×3, every neuron in the Conv Layer would now have a total $3 * 3 * 20 = 180$ connections to the input volume.

Local


32
32
3
x_0
w_0
synapse
axon from a neuron
w_0x_0
dendrite
cell body
w_1x_1
$\sum_i w_ix_i + b$
f
$f\left(\sum_i w_ix_i + b\right)$
output axon
activation function
w_2x_2

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- If the first Conv Layer takes as input the raw image, then different neurons along the depth dimension may activate in presence of various oriented edges, or blobs of color
- We will refer to a set of neurons that are all looking at the same region of the input as a depth column

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- It will allow us to control the spatial size of the output volumes (e.g. to preserve the spatial size)

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We can compute the spatial size of the output volume as a function of

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- The input volume size (W)
- The receptive field size of the Conv Layer neurons (F)
- The stride with which they are applied (S)
- The amount of zero padding used (P) on the border
- How many neurons fit is given by: $(W - F + 2P)/S + 1$

Examples

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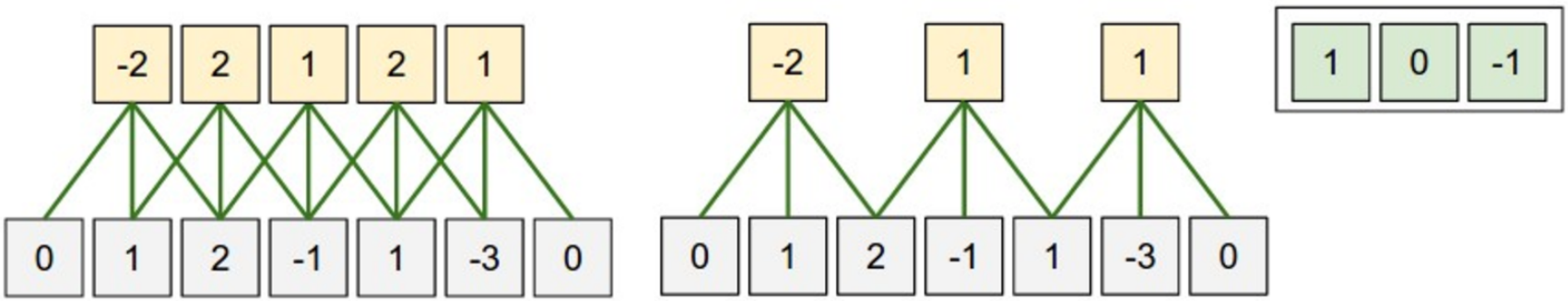

Illustration of spatial arrangement. In this example there is only one spatial dimension (x-axis), one neuron with a receptive field size of F = 3, the input size is W = 5, and there is zero padding of P = 1. **Left:** The neuron strided across the input in stride of S = 1, giving output of size (5 - 3 + 2)/1+1 = 5. **Right:** The neuron uses stride of S = 2, giving output of size (5 - 3 + 2)/2+1 = 3. Notice that stride S = 3 could not be used since it wouldn't fit neatly across the volume. In terms of the equation, this can be determined since (5 - 3 + 2) = 4 is not divisible by 3.

The neuron weights are in this example [1,0,-1] (shown on very right), and its bias is zero. These weights are shared across all yellow neurons (see parameter sharing below).

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- This worked out so because our receptive fields were 3 and we used zero padding of 1
- If there was no zero-padding used, then the output volume would have had spatial dimension of 3
- In general, setting zero padding to be $P = (F - 1)/2$ when the stride is $S = 1$ ensures that the input volume and output volume will have the same size spatially.

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- Not an integer, indicating that the neurons don?t fit neatly and symmetrically across the input.

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- The Conv layer output volume had size $[55 \times 55 \times 96]$
- Each of the $55 * 55 * 96$ neurons in this volume was connected to a region of size $[11 \times 11 \times 3]$ in the input volume

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- We are going to constrain the neurons in each depth slice to use the same weights and bias.
- With this parameter sharing scheme, the first Conv Layer would now have only 96 unique set of weights (one for each depth slice), for a total of 96*11*11*3 = 34,848 unique weights, or 34,944 parameters (+96 biases).

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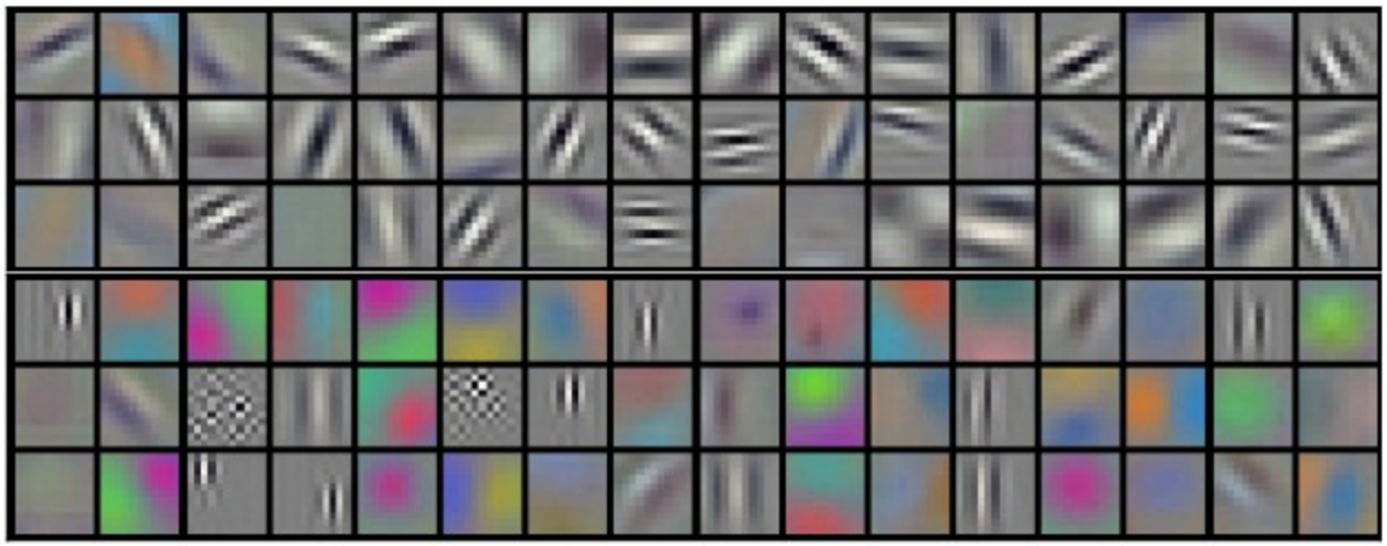
- Notice that if all neurons in a single depth slice are using the same weight vector, then the forward pass of the CONV layer can in each depth slice be computed as a convolution of the neuron?s weights with the input volume
- This is why it is common to refer to the sets of weights as a filter (or a kernel), that is convolved with the input

Parameter Reduction



Example filters learned by Krizhevsky et al. Each of the 96 filters shown here is of size [11x11x3], and each one is shared by the 55*55 neurons in one depth slice. Notice that the parameter sharing assumption is relatively reasonable: If detecting a horizontal edge is important at some location in the image, it should intuitively be useful at some other location as well due to the translationally-invariant structure of images. There is therefore no need to relearn to detect a horizontal edge at every one of the 55*55 distinct locations in the Conv layer output volume.

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- A depth slice, or equivalently an activation map at depth d would be the activations X[:,:,d].

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- Suppose further that we use no zero padding ($P = 0$), that the filter size is $F = 5$, and that the stride is $S = 2$.
- The output volume would therefore have spatial size $(11 - 5)/2 + 1 = 4$, giving a volume with width and height of 4

Conv Layer Example

The activation map in the output volume (call it V), would then look as follows

V[0,0,0] = np.sum(X[:5,:5,:] * W0) + b0

V[1,0,0] = np.sum(X[2:7,:5,:] * W0) + b0

V[2,0,0] = np.sum(X[4:9,:5,:] * W0) + b0

V[3,0,0] = np.sum(X[6:11,:5,:] * W0) + b0

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- we are using the same weight and bias (due to parameter sharing), and where the dimensions along the width are increasing in steps of 2 (i.e. the stride).

Conv Layer Example

To construct a second activation map in the output volume, we would have:
V[0,0,1] = np.sum(X[:5,:5,:] * W1) + b1
V[1,0,1] = np.sum(X[2:7,:5,:] * W1) + b1
V[2,0,1] = np.sum(X[4:9,:5,:] * W1) + b1
V[3,0,1] = np.sum(X[6:11,:5,:] * W1) + b1
V[0,1,1] = np.sum(X[:5,2:7,:] * W1) + b1 (example of going along y)

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Conv Layer Example

- where we see that we are indexing into the second depth dimension in V (at index 1) because we are computing the second activation map, and that a different set of parameters (W1) is now used.
- Additionally, recall that these activation maps are often followed elementwise through an activation function such as ReLU.

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- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.

Summary Conv Layer

- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
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  - With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
  - In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Convolution Demo

Conv Demo
http://cs231n.github.io/convolutional-networks/

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- Every MAX operation would in this case be taking a max over 4 numbers . The depth dimension remains unchanged.

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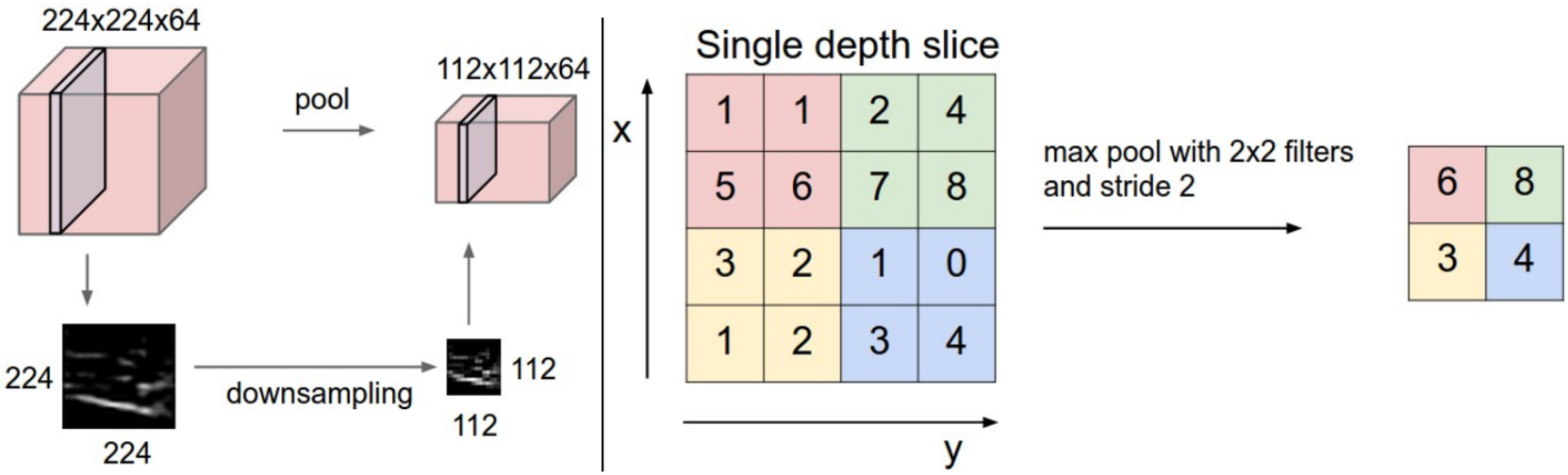
- Note that it is not common to use zero-padding for Pooling layers

Pooling



Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. **Left:** In this example, the input volume of size [224x224x64] is pooled with filter size 2, stride 2 into output volume of size [112x112x64]. Notice that the volume depth is preserved. **Right:** The most common downsampling operation is max, giving rise to **max pooling**, here shown with a stride of 2. That is, each max is taken over 4 numbers (little 2x2 square).

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- Discarding pooling layers has also been found to be important in training good generative models, such as variational autoencoders (VAEs) or generative adversarial networks (GANs).
- It seems likely that future architectures will feature very few to no pooling layers.

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- Their activations can hence be computed with a matrix multiplication followed by a bias offset.

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- How these are commonly stacked together to form entire ConvNets?

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- INPUT $->$ [CONV $->$ RELU $->$ CONV $->$ RELU $->$ POOL]*3 $->$ [FC $->$ RELU]*2 $->$ FC Here we see two CONV layers stacked before every POOL layer.
- This is generally a good idea for larger and deeper networks, because multiple stacked CONV layers can develop more complex features of the input volume before the destructive pooling operation.

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- Intuitively, stacking CONV layers with tiny filters as opposed to having one CONV layer with big filters allows us to express more powerful features of the input, and with fewer parameters.
- As a practical disadvantage, we might need more memory to hold all the intermediate CONV layer results if we plan to do backpropagation.

ImageNet

- In practice: use whatever works best on ImageNet.

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- Instead of rolling your own architecture for a problem, you should look at whatever architecture currently works best on ImageNet, download a pretrained model and finetune it on your data.

Layer Sizing Patterns

- The input layer (that contains the image) should be divisible by 2 many times. Common numbers include 32 (e.g. CIFAR-10), 64, 96 (e.g. STL-10), or 224 (e.g. common ImageNet ConvNets), 384, and 512.

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- That is, when $F = 3$, then using $P = 1$ will retain the original size of the input.
- When $F = 5, P = 2$.
- For a general F, it can be seen that $P = (F - 1)/2$ preserves the input size.

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- Note that this discards exactly 75% of the activations in an input volume (due to downsampling by 2 in both width and height).

Reducing sizing headaches

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- In an alternative scheme where we use strides greater than 1 or don?t zero-pad the input in CONV layers, we would have to very carefully keep track of the input volumes throughout the CNN architecture and make sure that all strides and filters work out, and that the ConvNet architecture is nicely and symmetrically wired.

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- Additionally, stride 1 allows us to leave all spatial down-sampling to the POOL layers, with the CONV layers only transforming the input volume depth-wise.

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- If the CONV layers were to not zero-pad the inputs and only perform valid convolutions, then the size of the volumes would reduce by a small amount after each CONV, and the information at the borders would be washed away too quickly.

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- This amounts to a total of about 10 million activations, or 72MB of memory (per image, for both activations and gradients).
- Since GPUs are often bottlenecked by memory, it may be necessary to compromise.

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- For example, one compromise might be to use a first CONV layer with filter sizes of 7×7 and stride of 2 (as seen in a ZF net).
- As another example, an AlexNet uses filter sizes of 11×11 and stride of 4.

Case Studies

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- The Network had a very similar architecture to LeNet, but was deeper, bigger, and featured Convolutional Layers stacked on top of each other

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- ZF Net: The ILSVRC 2013 winner was a Convolutional Network from Matthew Zeiler and Rob Fergus. It was an improvement on AlexNet by tweaking the architecture hyperparameters, in particular by expanding the size of the middle convolutional layers and making the stride and filter size on the first layer smaller.

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- GoogLeNet: The ILSVRC 2014 winner was a Convolutional Network from Szegedy et al. from Google. Its main contribution was the development of an Inception Module that dramatically reduced the number of parameters in the network (4M, compared to AlexNet with 60M).

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- ResNet: Residual Network developed by Kaiming He et al. was the winner of ILSVRC 2015.
- ResNets are currently by far state of the art Convolutional Neural Network models and are the default choice for using ConvNets in practice (as of May 10, 2016).