Convolutional Neural Network

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Week 9

ECEGR4750 - Introduction to Machine Learning
Seattle University

November 20, 2023

Recap and Updates

- Lab Take Home Assignment due next Wednesday 11/22/23 at 11.59pm
- Office Hours: please email me your desired timeslot and to make appointments
- Final Homework 5 due: 12/1/23 at 11.59pm
- Final week of class: review + in class "exam" on 11/30/23 as bonus
- Final project due: 12/8/23 at 11.59pm
- Additional reading: link (a very good lecture and class)

Overview

1. Introduction

2. Layers of a CNN
   - Convolutional Layer
   - Pooling Layer
   - Flattening / Fully-Connected Layer
   - CNN Architecture

Convolutional Neural Network (CNN or ConvNet)

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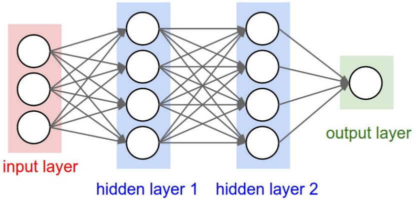

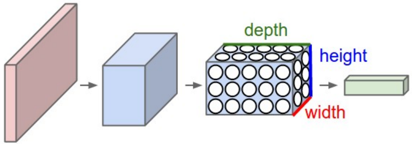

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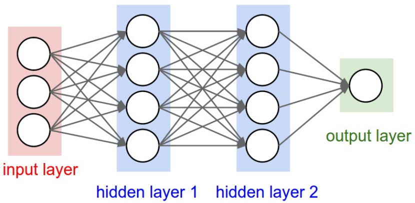

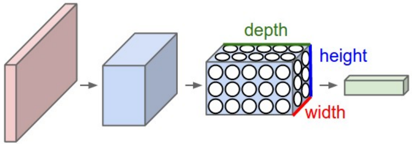

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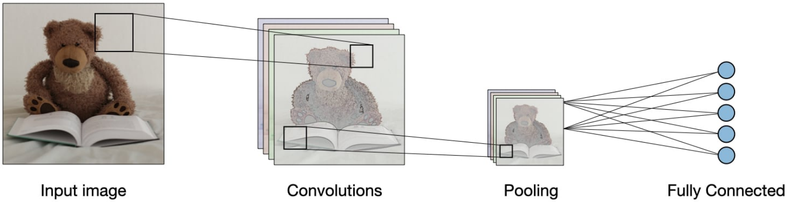
- The neurons in CNN are arranged in 3D (width, depth, height). (e.g: the red input layer has width = horizontal pixels, height = vertical pixels, depth = R, G, B channels)

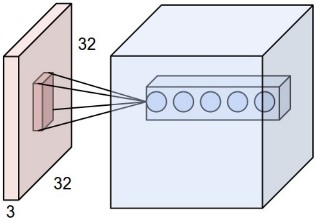
Layers of a CNN

1. **Convolutional Layer** (CONV)
2. **Pooling Layer** (POOL)
3. **Fully-Connected Layer** (FC)
4. **Activation Layer (usually ReLU)** (RELU)



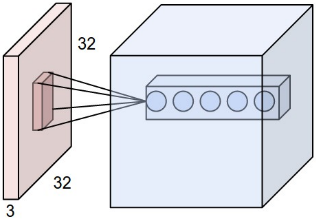
Convolutional Layer

Core building block of a CNN that does most of the computational heavy lifting.



Convolutional Layer

Local Connectivity



Each neuron is connected to only a local region (along width and height in the 2D space), but fully along the depth axis, of the input volume. The spatial extent is called the **receptive field** or the filter size.

Red input volume: 32x32x3. Blue convolutional layer with receptive field: 5x5. Each neuron in the CONV layer will have 5x5x3 weights.

Convolutional Layer

Spatial Arrangement

Hyperparameters:

1. **Depth**. Depth of the convolutional layer. Corresponds to the number of filters we are using, each learning to look for something different in the input, such as: oriented edges, blobs of color, etc. The set of neurons that are all looking at the same region of the input is called the *depth column*.
2. **Receptive Field (Kernel / Filter) Size**. The width and height of the kernel or filter that slides across the input volume..
3. **Stride**. Stride in which we slide the filter. If stride is 1, we move 1 pixel at a time. Usually stride is set to 2.
4. **Zero Padding**. Pad the input volume with zeroes around the border.

Convolutional Layer

Spatial Arrangement

Number of Output Neurons

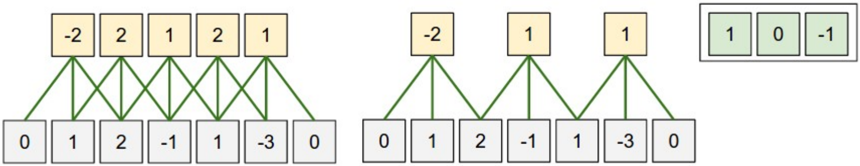
$$\frac{W - F + 2P}{S} + 1$$

where:

- W: input volume size
- F: receptive field size
- P: amount of zero padding
- S: stride

These parameters have to be carefully selected such that the number of the output neurons is an integer.

Input volume: grey. Kernel: green. Output volume: yellow.



Left:

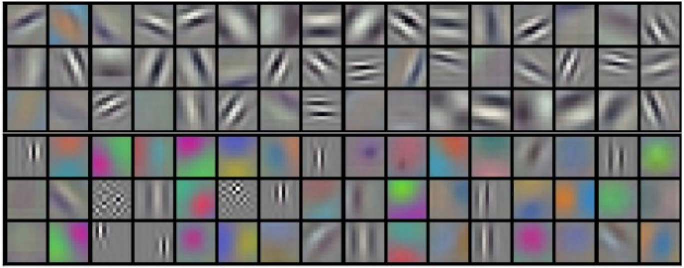
- Input size $W = 5$
- Receptive field $F = 3$
- Zero Padding $P = 1$
- Stride $S = 1$
- Output size $\frac{5-3+2}{1} + 1 = 5$

Right:

- Input size $W = 5$
- Receptive field $F = 3$
- Zero Padding $P = 1$
- Stride $S = 2$
- Output size $\frac{5-3+2}{2} + 1 = 3$

Neurons from a single 2D slice of depth '*depth slice*' share the same parameters (weights and biases).

ImageNet Challenge 2012 winner, Krizhevsky et al. with output volume of 55x55x96 and receptive field of 11x11x3. Each of the 96 filters below is 11x11x3, and each one is shared by the 55x55 neurons in one depth slice.



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Convolutional Layer

Parameter Sharing

Parameter sharing make sense when:
Detecting a horizontal edge is important at some location in the image, it should be useful at some other location as well (translational invariance). There is no need to relearn to detect a horizontal edge at every one of the distinct locations.

Parameter sharing doesn't make sense when:
The input images to a CNN have some specific centered structure. For example, when the input are faces that have been centered in the image. Eye-specific or hair-specific features should be learned in different spatial locations. In this case, the parameter sharing scheme is relaxed and the layer is called a **Locally-Connected Layer**.

Convolutional Layer

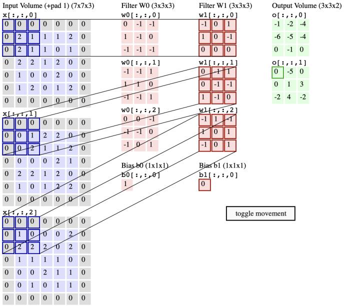
Summary

1. Accepts an input volume of size $W_1 \times H_1 \times D_1$
2. Requires 4 hyperparameters:
    1. Receptive field size F_w (kernel width) $\times F_h$ (kernel height)
    2. Amount of zero padding P
    3. Stride S
    4. Number of filters K
3. Produces an output volume of size $W_2 \times H_2 \times D_2$ where:
    - $W_2 = \frac{W_1 - F_w + 2P}{S} + 1$
    - $H_2 = \frac{H_1 - F_h + 2P}{S} + 1$
    - $D_2 = K$
4. With parameters sharing:
    1. Number of weights per filter: $F_w \cdot F_h \cdot D_1$
    2. Total weights: $(F_w \cdot F_h \cdot D_1) \cdot K$ and K biases
5. Common hyperparameter setting: $F_w = F_h = 3$, $S = 1$, $P = 1$

Convolutional Layer

Computation

The visualization below iterates over the output activations (green), and shows that each element is computed by elementwise multiplying the highlighted input (blue) with the filter (red), summing it up, and then offsetting the result by the bias.



See Full Animation Here

Mathematically, the convolution operation is expressed as:

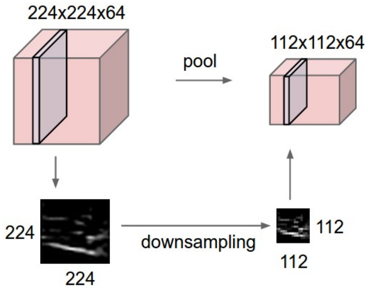
$$Output = (I * K)(i, j) = \sum_{m=0}^{F_w} \sum_{n=0}^{F_h} I(i + m, j + n)K(m, n)$$

where: I = image
K = kernel
F_w = kernel width
F_h = kernel height

Pooling Layer

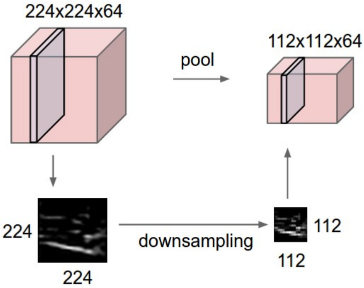
Pooling layer is inserted in-between successive Convolutional layers to:

- Progressively reduce the spatial size of the representation
- Reduce the amount of parameters and computation in the network
- Control overfitting



Pooling Layer

Spatial Arrangement



1. Pooling layer downsamples the volume independently in each depth slice. The **hyperparameters** are:
   1. **Spatial Extent** F
   2. **Stride** S
   3. Typically there is no zero padding in the input of a pooling layer
   4. In practice, $F = 3$, $S = 2$ or $F = 2$, $S = 2$ are commonly used.

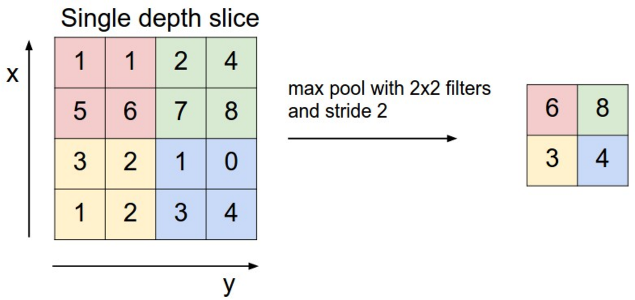
Pooling Layer

Summary

1. Accepts an input volume of size $W_1 \times H_1 \times D_1$
2. Requires 2 hyperparameters:
    1. Receptive field size F
    2. Stride S
3. Produces an output volume of size $W_2 \times H_2 \times D_2$ where:
    - $W_2 = \frac{W_1 - F}{S} + 1$
    - $H_2 = \frac{H_1 - F}{S} + 1$
    - $D_2 = D_1$
4. Common hyperparameter setting: $F = 3$, $S = 2$, or $F = 2$, $S = 2$

Pooling Layer

Computation



The most common downsampling operation is *max*, which yields **max-pooling** method, which is proven to be better than *average-pooling* or *L2-norm pooling*.

Pooling Layer

No pooling

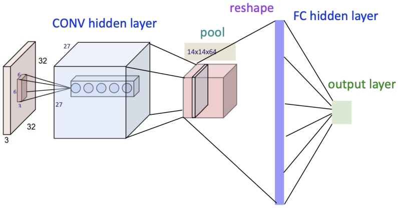
Striving for Simplicity: The All Convolutional Net proposes to discard the pooling layer. To reduce the size of the representation, they proposed using a larger stride once in a while. Discarding pooling is importnat in training good generative models such as VAE or GANs.

Flattening / Fully-Connected Layer

The last layer of a CNN is typically a Fully-Connected Layer. This can be achieved by flattening the output of the last pooling or convolutional layer into a one-dimensional neurons.

Flattening means stacking all rows of each 2D layer at the end of each other, followed by the next 2D layer, and so on.

Finally, this Fully-Connected layer can be passed into a sigmoid activation to return a class prediction.



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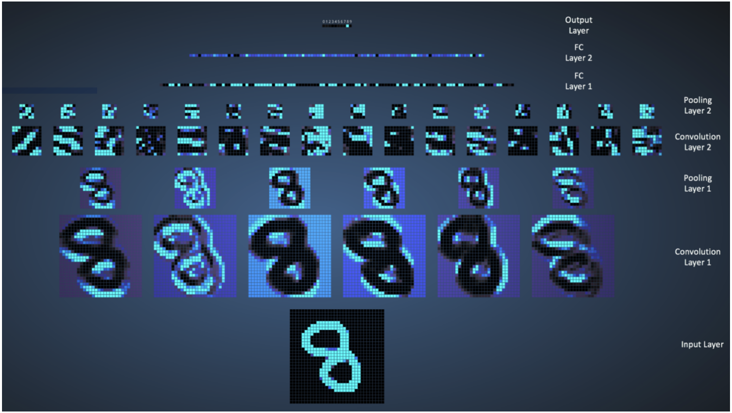
Gradient-Based Learning Applied to Document Recognition - LeCun et al. (1998)



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ImageNet Classification with Deep Neural Networks - Krizhevksy et al. (2012)

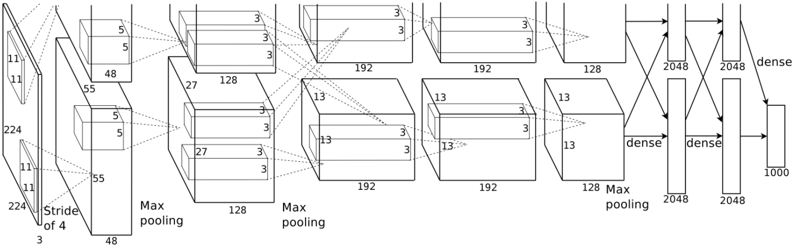

Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

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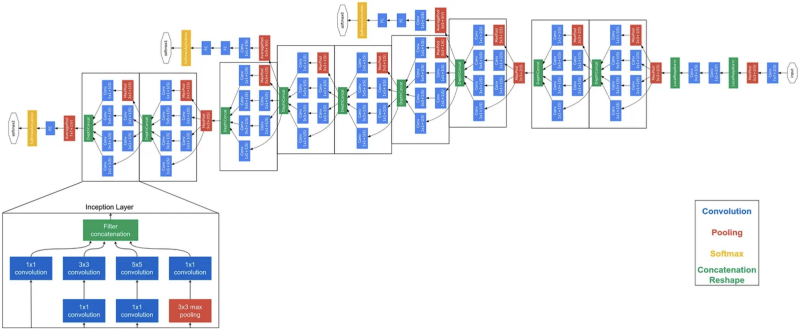
Some Examples

GoogLeNet

Going Deeper with Convolutions - Szegedy et al. (2014)

- Motivated by multiscale nature of images
- Uses large kernel for global features and small kernels for local features



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Some Examples

ResNet

Deep Residual Learning for Image Recognition - He et al. (2015)

- Motivated by the gradient explosion and vanishing problems from training deep networks.
- Identified shortcuts by skipping one or more layers.

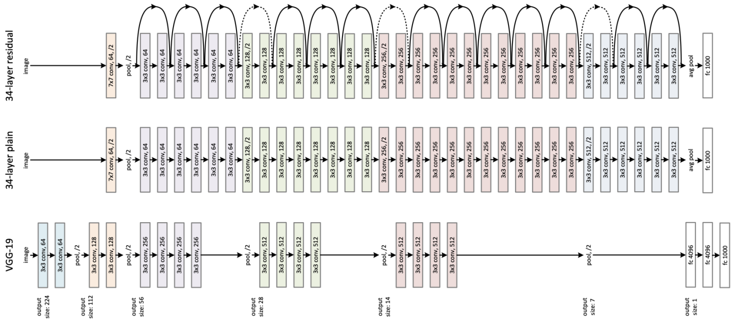

Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

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References

Fei-Fei Li, Yunzhu Li, Ruohan Gao (2023)
CSE231n Deep Learning for Computer Vision
Stanford University

Kevin Jamieson and Simon Du (2023)
CSE 446/546 Machine Learning
University of Washington