



Deep Computer Vision Using Convolutional Neural Networks

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Developing Curricula for Artificial Intelligence and Robotics (DeCAIR) 618535-EPP-1-2020-1-JO-EPPKA2-CBHE-JP

Reference

Chapter 14: Deep Computer Vision Using Convolutional Neural Networks



- Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow, O'Reilly, 3rd Edition, 2022
 - Material: https://github.com/ageron/handson-ml3

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- 3. Pooling layer
- 4. CNN architectures
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1. Introduction

 YouTube Video: Convolutional Neural Networks (CNNs) explained from Deeplizard

https://youtu.be/YRhxdVk_sls

1. Introduction

- Convolutional neural networks (CNNs) emerged from the study of the brain's visual cortex.
- Many neurons in the visual cortex have a small local receptive field.



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2. Convolutional Layer

- Neurons in one layer are not connected to every single pixel/neuron in the previous layer, but only to pixels/neurons in their receptive fields.
- This architecture allows the network to concentrate on **lowlevel features** in one layer, then assemble them into **higher-level features** in the next layer.
- Each layer is represented in **2D**.



2. Convolutional Layer

- f_h and f_w are the height and width of the receptive field.
- Zero padding: In order for a layer to have the same height and width as the previous layer, it is common to add zeros around the inputs.



2.1 Filters

- A neuron's weights can be represented as a small image the size of the receptive field, called filters.
- When all neurons in a layer use the same line filters, we get the **feature maps** on the top.



2.2 Stacking Feature Maps

- In reality, each layer is 3D composed of several feature maps of equal sizes.
- Within one feature map, all neurons share the same parameters, but different feature maps may have different parameters.
- Once the CNN has learned to recognize a pattern in one location, it can recognize it in any other location.



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3. Pooling Layer

- Its goal is to **subsample** (i.e., shrink) the input image in order to reduce the computational load, the memory usage, and the number of parameters.
- It aggregates the inputs using max or mean.



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4. CNN Architectures

 Stack few convolutional layers (each one generally followed by a ReLU layer), then a pooling layer, then another few convolutional layers, then another pooling layer, and so on. The image gets smaller and smaller, but it also gets deeper and deeper. At the end, a dense NN is added.



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5. Example – Fashion MNIST



6. Exercise

14.9. Build your own CNN from scratch and try to achieve the highest possible accuracy on MNIST.

Summary

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