

Deep Learning Chapter 4 Tensorflow

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Chapter 3: Convolutional Neural Network

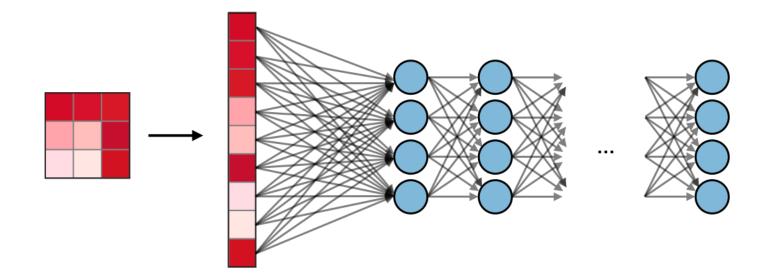
- 1. Convolutional operator
- 2. History of CNN
- 3. Layers in CNN
- 4. Deep Convolutional Models
- 5. Applications of CNN
- 6. Practice



Learning Objectives

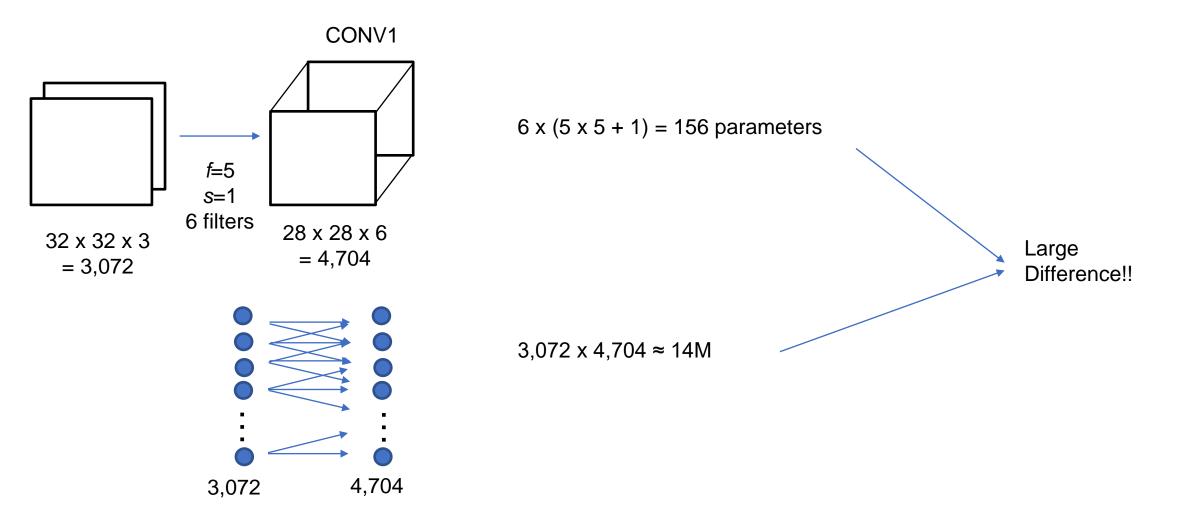
- ✓ Be able to explain what a convolutional layer does and how it's different from a fullyconnected layer
- ✓ Understand the assumptions and trade-offs that are being made when using convolutional architectures
- ✓ Be able to build a convolutional architecture using Tensorflow 2.0 and Keras Layers
- \checkmark Be able to use Keras to train a model on a dataset
- ✓ Implement either network together

The fully connected layer (FC) operates on a flattened input where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures and can be used to optimize objectives such as class scores.



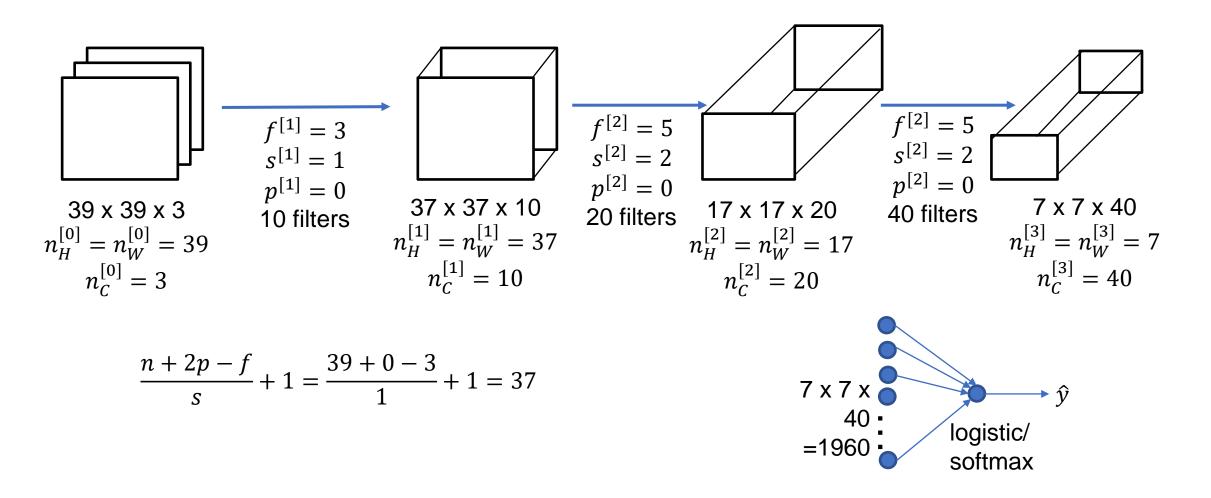






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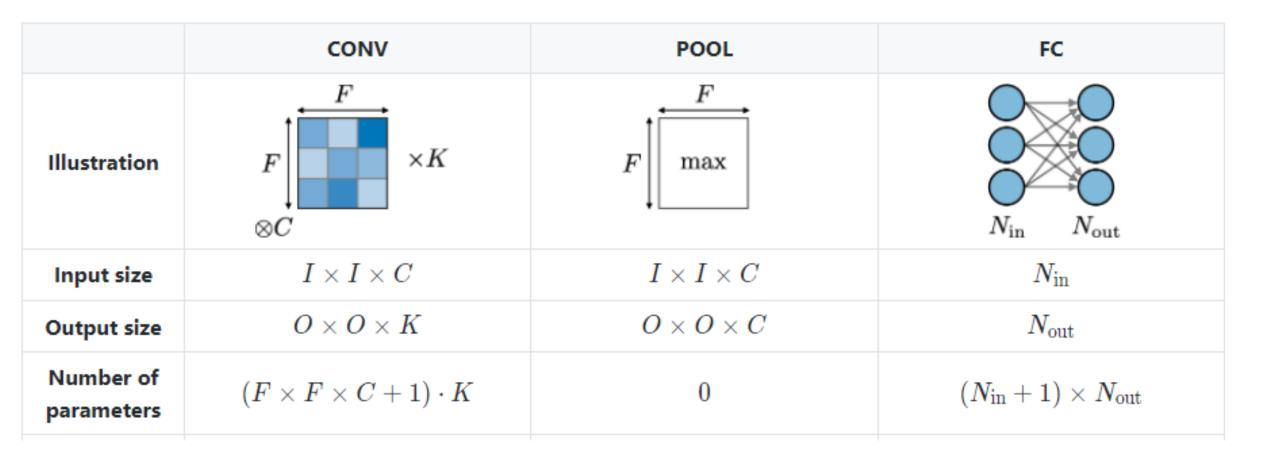
Example



3.4 Deep Convolutional Models Example Conv2D MaxPooling2D Conv2D $f^{[1]} = 3$ pool_size=2 $f^{[3]} = 3$ $s^{[1]} = 1$ $s^{[3]} = 1$ 28 x 28 x 1 $28 \times 28 \times 1 \qquad p^{[1]} = 0 \qquad 26 \times 26 \times 32$ $n_{H}^{[0]} = n_{W}^{[0]} = 28 \qquad 32 \text{ filters} n_{H}^{[1]} = n_{W}^{[1]} = 26$ 13 x 13 x 32 $p^{[3]} = 0$ 11 x 11 x 64 $n_{H}^{[2]} = n_{W}^{[2]} = 13$ 64 filters $n_H^{[3]} = n_W^{[3]} = 11$ $n_{C}^{[0]} = 1$ $n_c^{[1]} = 32$ $n_c^{[2]} = 32$ $n_c^{[3]} = 32$ $\frac{n+2p-f}{r} + 1 = \frac{28+0-3}{1} + 1 = 26$ Conv2D MaxPooling2D Flatten Ŷ $f^{[5]} = 3$ pool_size=2 3 x 3 x logistic/ $s^{[5]} = 1$ 3 x 3 x 128 128 =1152 5 x 5 x 64 $\begin{array}{c} 5 \times 5 \times 64 \\ n_{H}^{[4]} = n_{W}^{[4]} = 5 \\ n_{L}^{[4]} = 64 \end{array} \begin{array}{c} p^{[5]} = 0 \\ 128 \text{ filters} \end{array} \begin{array}{c} n_{H}^{[5]} = n_{W}^{[5]} = 3 \\ n_{C}^{[5]} = 128 \end{array}$ softmax 115 10 $n_{C}^{[4]}=64$ 2

Complexity





Visualization example



https://www.cs.ryerson.ca/~aharley/vis/conv/

https://poloclub.github.io/cnn-explainer/

These slides are provided by Minhhuy Le, ICSLab, Phenikaa Uni.

3.5 Applications of CNN

MNIST

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Test accuracy: 0.991	u
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Epoch 1/5	
938/938 [===============================	
Epoch 2/5	
938/938 [
Epoch 3/5	
938/938 [=====	
Epoch 4/5	
938/938 [====================================	

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Layer (type)	Output Shape	Param # E
input_1 (InputLayer)	[(None, 28, 28, 1)]	0
conv2d (Conv2D)	(None, 26, 26, 32)	320
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
<pre>max_pooling2d_1 (MaxPooling2</pre>	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 128)	73856
flatten (Flatten)	(None, 1152)	0
uense (Dense)	(None, 10)	11530

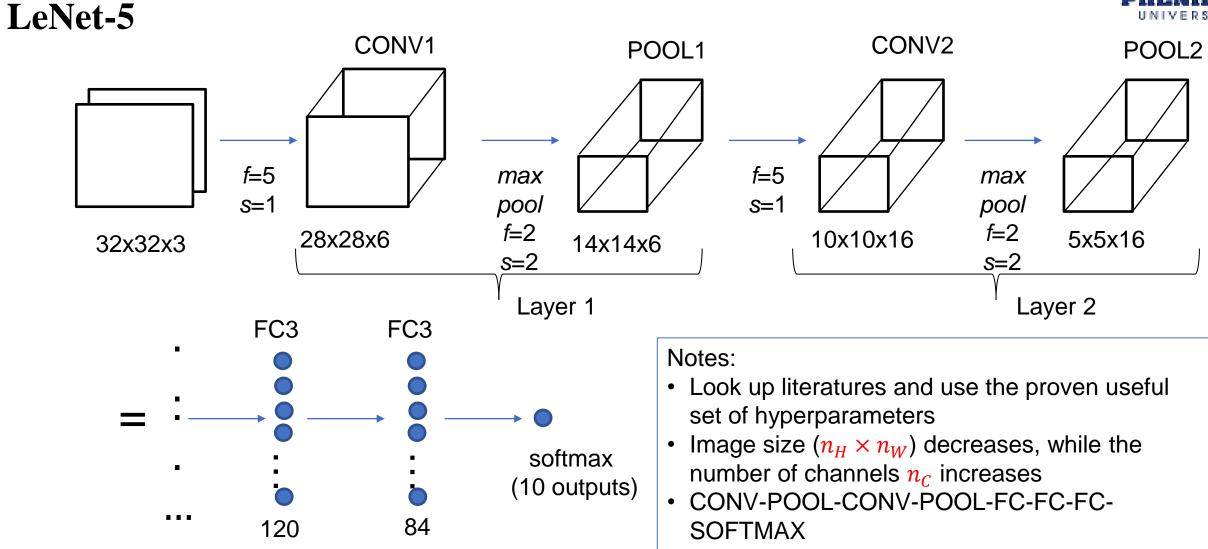
Total params: 104,202 Trainable params: 104,202 Non-trainable params: 0

Epoch 1/5
938/938 [=============] - 44s 47ms/step - loss: 0.1606 - accuracy: 0.9495
Epoch 2/5
938/938 [===========] - 43s 46ms/step - loss: 0.0444 - accuracy: 0.9860
Epoch 3/5
938/938 [===========] - 43s 46ms/step - loss: 0.0309 - accuracy: 0.9906
Epoch 4/5
938/938 [===========] - 45s 48ms/step - loss: 0.0227 - accuracy: 0.9931
Epoch 5/5
938/938 [===========] - 46s 49ms/step - loss: 0.0176 - accuracy: 0.9946

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3.5 Applications of CNN



3.5 Applications of CNN

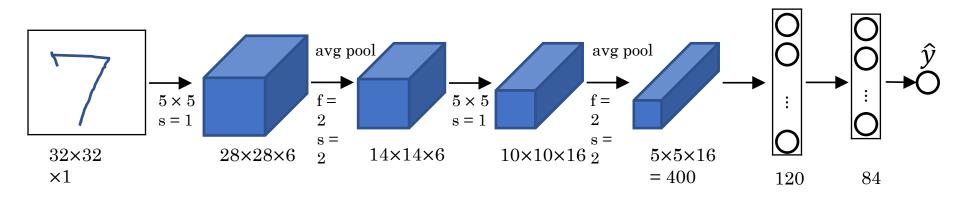
LeNet-5



	Activation Shape	Activation Size	# Parameters
Input	(32, 32, 3)	3,072	0
CONV1 (f=5, s=1)	(28, 28, 8)	6,272	208
POOL1	(14, 14, 8)	1,568	0
CONV2 (f=5, s=1)	(10, 10, 16)	1,600	416
POOL2	(5, 5, 16)	400	0
FC3	(120, 1)	120	48,001
FC4	(84, 1)	84	10,081
Softmax	(10, 1)	10	841



3.5 Applications of CNN LeNet-5



- 60K parameters (small by modern standards)
- n_H , n_W decreased with layers, n_C increased
- CONV POOL CONV POOL FC FC Output

[LeCun et al., 1998. Gradient-based learning applied to document recognition]