

1	2	3	4	5	?
6	7	8	9	10	
11	12	13	14	15	
16	17	18	19	20	
21	22	23	24	25	

2×2
max pool

7	9
17	19

2×2
convolution

$$7 \cdot a_1 + 9 \cdot a_2 + 17 \cdot a_3 + 19 \cdot a_4$$

max pooling helps increase receptive field

LeNet

Input: 32×32 grayscale image $\Rightarrow 1 \times 32 \times 32$ depth
 Layer 1: Convolution: 1 input channel, 6 output channels,
 kernel size = 5, padding = 2 $\Rightarrow 6 \times 32 \times 32$

Layer 2: activation function: sigmoid

Layer 3: average pooling: kernel size 2×2 , stride 2×2
 $\Rightarrow 6 \times 16 \times 16$

Layer 4: convolve on 6 channels of input of 16
 channels of input, kernel size = 5,
 no padding \Rightarrow resolution decreases $\Rightarrow 16 - 4 = 12$

Layer 5: another sigmoid

Layer 6: average pooling: kernel size 2×2 , stride 2×2
 \Rightarrow half resolution $\Rightarrow 16 \times 5 \times 5$

At some point, transform the convolutional layer linear

representation:

Layer 7: flatten \Rightarrow vector of dim $16 \cdot 5 \cdot 5 = 16 \cdot 25 = 400$

Deeper for classification CNN:

- bunch of convolutions and pooling layers
 - flatten layer \Rightarrow from "image" to vector
 - MCP that outputs as many values as there are classes
-

First linear regression: $\hat{y} = a_1 \cdot x_1 + a_2 \cdot x_2 + b$

Second linear regression: $z = c \cdot \hat{y} + d$

$$z = c(a_1 \cdot x_1 + a_2 \cdot x_2 + b) + d$$

$$= \underbrace{a_1 c}_{m} \cdot x_1 + \underbrace{a_2 c}_{n} \cdot x_2 + \underbrace{bc + d}_{p}$$

same thing

$$= m \cdot x_1 + n \cdot x_2 + p$$

between layers of linear "stuff": non-linear activation function!

$$y = \frac{1}{1 + e^{-x}}$$



