
Introduction to Convolutional Neural Networks

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Topics to cover today

- **Convolution operation: kernel size, stride, padding**
- **Pooling Operation: kernel size, type of pooling**
- **Implementations in PyTorch**

Dealing with images

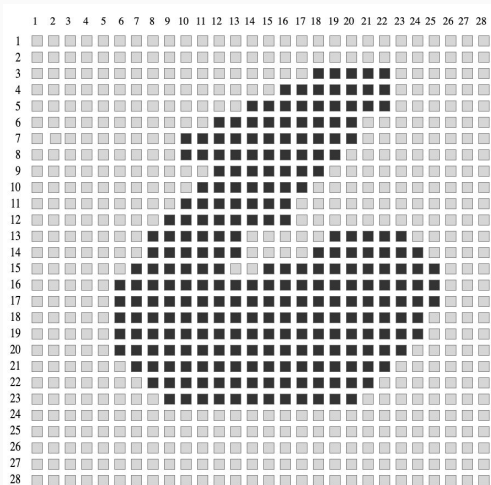
MNIST Dataset

MNIST Dataset: Dataset of handwritten digits. Each image represented as 28 x 28 binary pixels. Thus, dimension: (1 x 28 x 28)

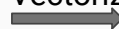
Flatten the image to get a 784 dimensional vector representing each image.

In general, an image has dimensions (C x H x W), where C, H, and W are for channels, height and width.

For color images, C = 3 (R, G, and B)



Vectorize



Pixel 1

Pixel 2

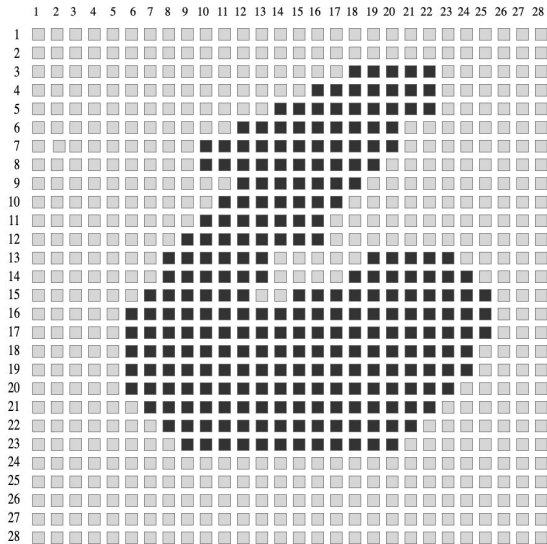
Pixel 782

Pixel 783

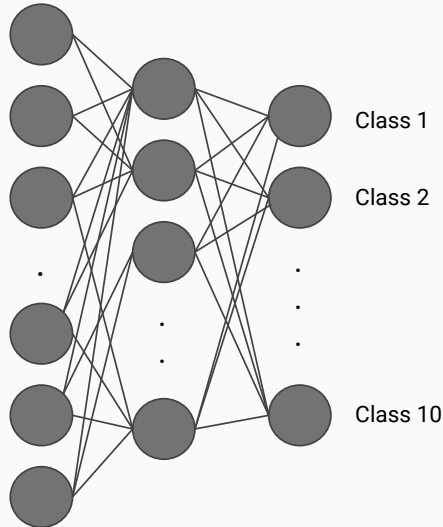
Pixel 784

Dealing with images

Feeding the data to a model



Vectorize



Dealing with images

Feeding the data to a model

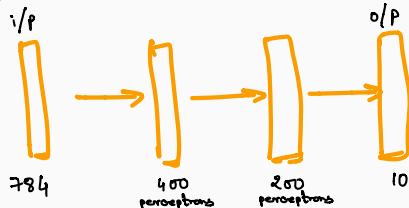
Demo: <https://colab.research.google.com/drive/1PYUjTKM1SidodJNyIRJepVsy1L5L1OiM>

Disadvantages of vectorizing images

- Loses spatial information inherent to the image
- High resolution images lead to very high number of parameters

Exercise:

How many trainable parameters does the following model have?



Convolution operation

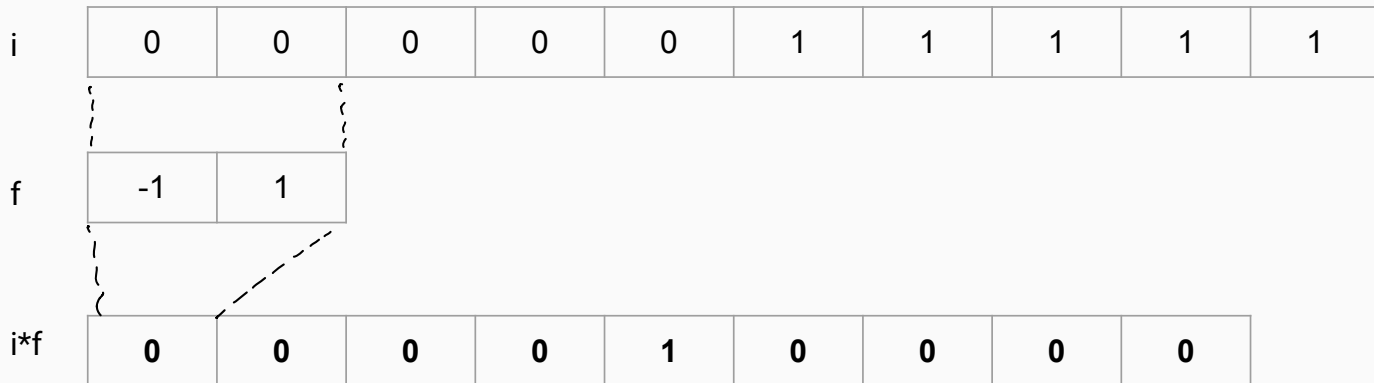
Discrete 1-d convolution

Given two signals, $i(t)$ and $f(t)$, their convolution is mathematically defined as

$$(i * f)(T) = \sum_{t=0}^T i(t)f(T - t)$$

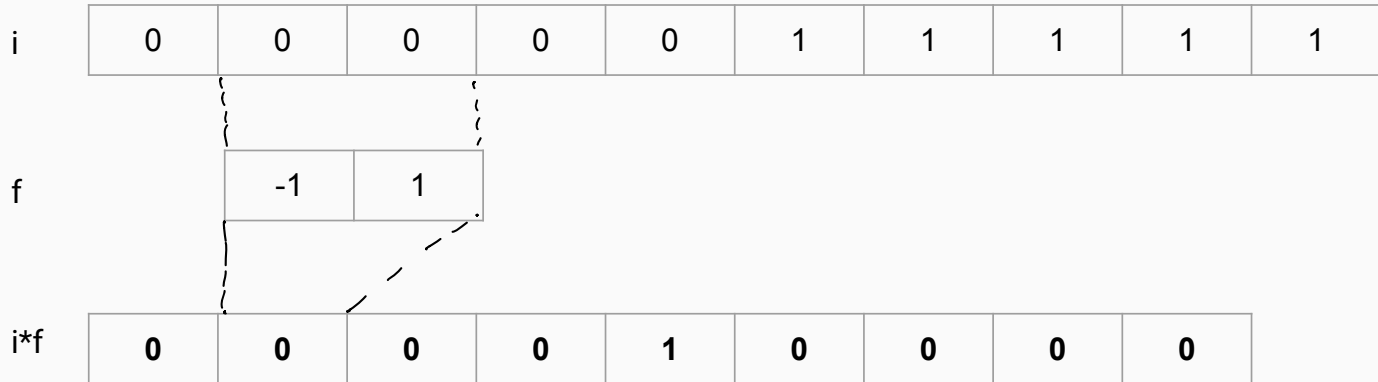
Convolution operation

Discrete 1-d convolution



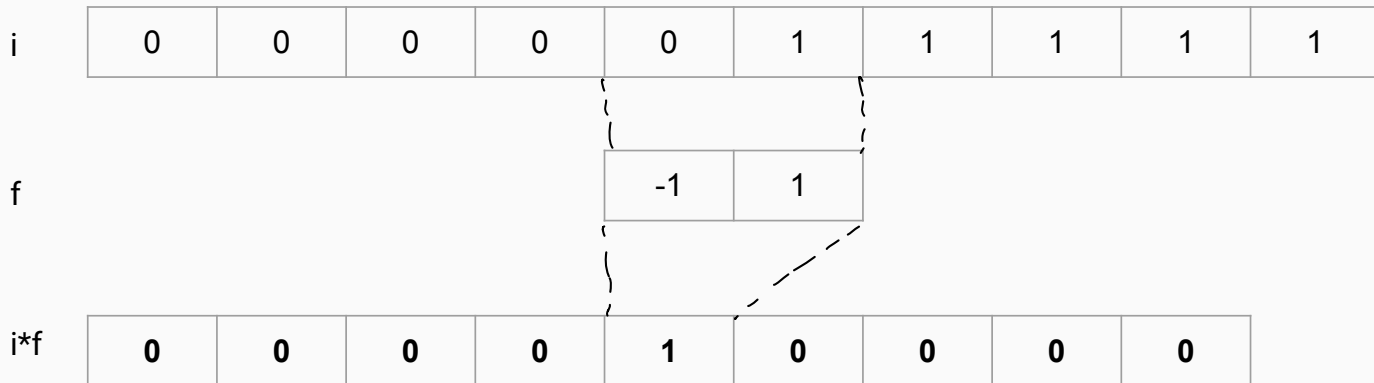
Convolution operation

Discrete 1-d convolution



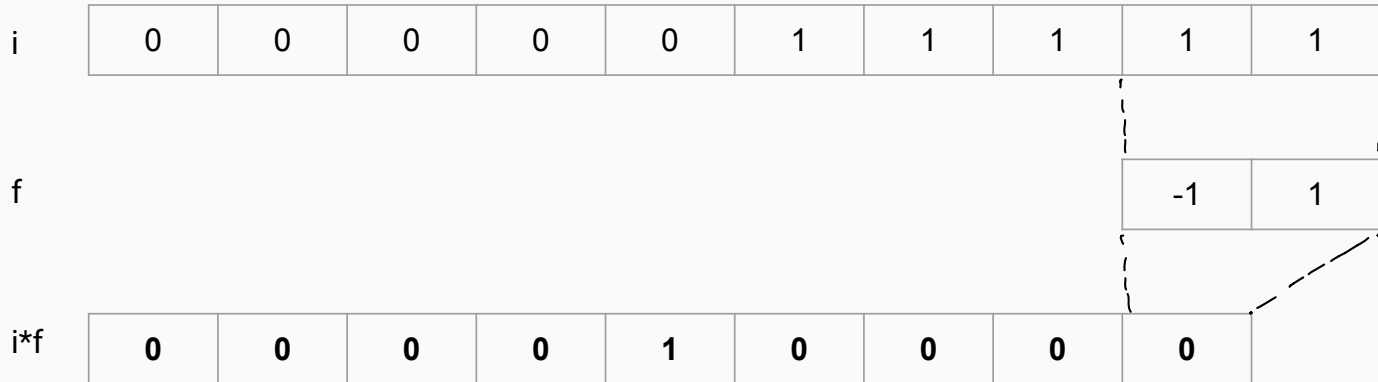
Convolution operation

Discrete 1-d convolution



Convolution operation

Discrete 1-d convolution



Convolution operation

Discrete 2-d convolution

$$\begin{array}{c} i \\ \begin{array}{|c|c|c|} \hline 0 & 80 & 40 \\ \hline 20 & 40 & 0 \\ \hline 0 & 0 & 40 \\ \hline \end{array} \end{array} * \begin{array}{c} f \\ \begin{array}{|c|c|} \hline 0 & 0.25 \\ \hline 0.5 & 1 \\ \hline \end{array} \end{array}$$

Convolution operation

Discrete 2-d convolution

i

0	80	40
20	40	0
0	0	40

$*$

f

1	0.5
0.25	0

$=$

$$1 \times 0 + 0.5 \times 80 + 0.25 \times 20 + 0 \times 40$$

↓

45	

Convolution operation

Discrete 2-d convolution

i

0	80	40
20	40	0
0	0	40

$*$

f

1	0.5
0.25	0

$=$

45	110

Convolution operation

Discrete 2-d convolution

$$\begin{array}{|c|c|c|} \hline & i & \\ \hline 0 & 80 & 40 \\ \hline 20 & 40 & 0 \\ \hline 0 & 0 & 40 \\ \hline \end{array} * \begin{array}{|c|c|} \hline 1 & 0.5 \\ \hline 0.25 & 0 \\ \hline \end{array} = \begin{array}{|c|c|} \hline 45 & 110 \\ \hline 40 & \\ \hline \end{array}$$

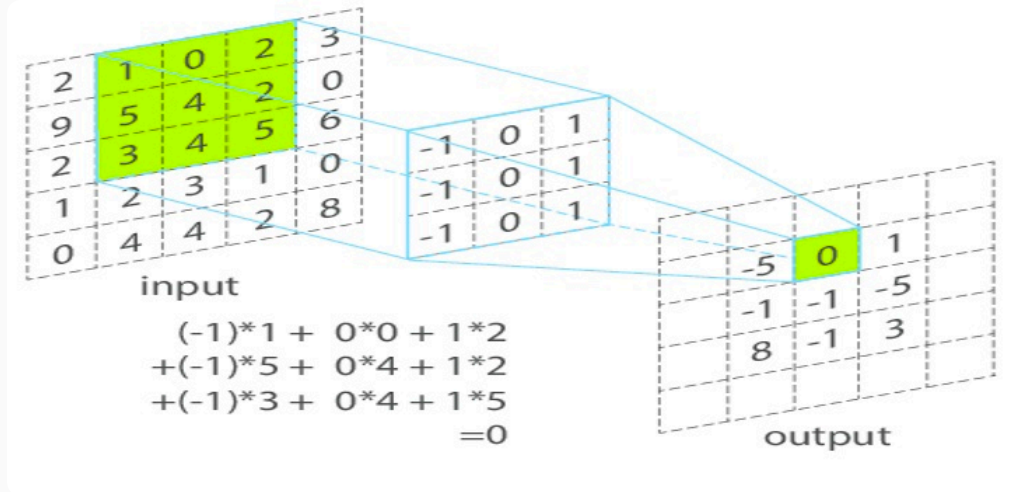
Convolution operation

Discrete 2-d convolution

$$\begin{array}{c} i \\ \begin{array}{|c|c|c|} \hline 0 & 80 & 40 \\ \hline 20 & 40 & 0 \\ \hline 0 & 0 & 40 \\ \hline \end{array} \\ 3 \times 3 \end{array} * \begin{array}{c} f \\ \begin{array}{|c|c|} \hline 1 & 0.5 \\ \hline 0.25 & 0 \\ \hline \end{array} \\ 2 \times 2 \end{array} = \begin{array}{c} i * f \\ \begin{array}{|c|c|} \hline 45 & 110 \\ \hline 40 & 40 \\ \hline \end{array} \\ 2 \times 2 \end{array}$$

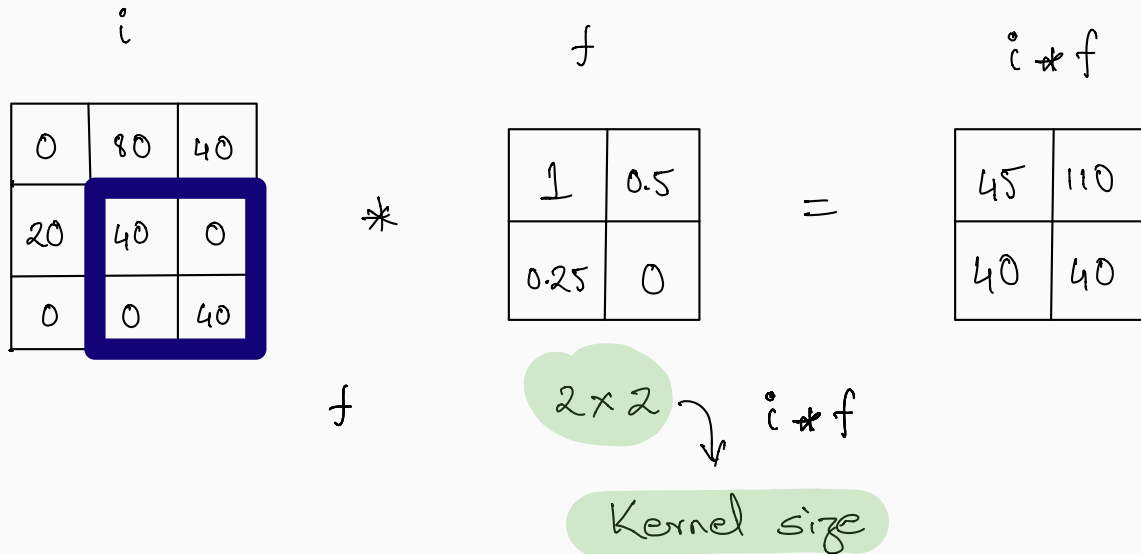
Convolution operation

Discrete 2-d convolution : another example



Convolution operation

Discrete 2-d convolution : **Kernel size**



Convolution operation

Discrete 2-d convolution : **Stride**

i

→

0	80	40
20	40	0
0	0	40

Stride = 1

*

1	0.5
0.25	0

2x2

=

45	110
40	40

Convolution operation

Discrete 2-d convolution : **Padding**

- What if we want the output size to be the same as the input size?
- Also, note that the filter isn't able to reach the corners of our input.

Padding allows us to do these things.

Convolution operation

Discrete 2-d convolution : Padding

i

0	0	0	0	0
0	0	80	40	0
0	20	40	0	0
0	0	0	40	0
0	0	0	0	0

*

f

0	0.25
0.5	1

=

What will be
the output??

Convolution operation

Discrete 2-d convolution : Padding

i

0	0	0	0	0
0	0	80	40	0
0	20	40	0	0
0	0	0	40	0
0	0	0	0	0

*

f

0	0.25	0
0.25	0.5	1
0	0	0.25

=

90	80	40
50	55	?
?	?	?

(this assumes
stride = ?)

Convolution operation

Discrete 2-d convolution : Padding

i

0	0	0	0	0
0	0	80	40	0
0	20	40	0	0
0	0	0	40	0
0	0	0	0	0

*

f

0	0.25	0
0.25	0.5	1
0	0	0.25

=

?

What if the stride is 2 ?

Convolution operation

Discrete 2-d convolution

Output size formula:

$$O = \left\lfloor \frac{i + 2p - k}{s} \right\rfloor + 1$$

↑
floor function

i : square input size

p : square padding

k : square kernel

s : square stride

Pooling operation

- Pooling reduces the input size
- Pooling is performed on non-overlapping neighborhoods

Pooling operation

Max pooling

10	15	10	20
10	5	0	30
5	15	20	25
15	10	25	20

max pooling
2x2 →

10	

Pooling operation

Max pooling

10	15	10	20
10	5	0	30
5	15	20	25
15	10	25	20

max pooling
2x2 →

10	30

Pooling operation

Max pooling

10	15	10	20
10	5	0	30
5	15	20	25
15	10	25	20

max pooling
2x2 →

10	30
15	

Pooling operation

Max pooling

10	15	10	20
10	5	0	30
5	15	20	25
15	10	25	20

max pooling
2x2 →

10	30
15	25

Pooling operation

Average pooling

10	15	10	20
10	5	0	30
5	15	20	25
15	10	25	20

avg pooling
2x2 →

10	15
13.75	22.5

Advantages of convolution and pooling operations

- Local connectivity
- Parameter sharing
- Translation invariance (due to pooling)