ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Natural Language Processing with Convolutional Neural Networks

2024–25

Ion Androutsopoulos

http://www.aueb.gr/users/ion/

Contents

- Quick background: Convolutional Neural Networks (CNNs) in Computer Vision.
- Image to text generation with CNN encoders and RNN decoders.
- Text processing with CNNs.

Convolutions on images

Averaging each pixel with its neighboring values blurs an image:

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

From the blog post "Understanding Convolutional Neural Networks for NLP" of Denny Britz, 2015. http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

Convolutions on images

Input

-1	**1**	-1	-1	-1	-1
1	**1**	**1**	-1	-1	-1
-1	**1**	-1	-1	-1	-1
-1	-1	-1	**1**	-1	**1**
-1	-1	-1	-1	**1**	-1
-1	-1	-1	**1**	-1	**1**

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

- **Input: black/white image** with pixel values -1 or +1.
- **Check** if the **input contains any crosses** and report **where**.

Convolutions on images

Input | **Kernel (Filter)** | **Feature Map**

Input:

-1	**1**	-1	-1	-1	-1
1	**1**	**1**	-1	-1	-1
-1	**1**	-1	-1	-1	-1
-1	-1	-1	**1**	-1	**1**
-1	-1	-1	-1	**1**	-1
-1	-1	-1	**1**	-1	**1**

Kernel (Filter):

-1	1	-1
1	1	1
-1	1	-1

Input:

-1	**1**	-1	-1	-1	-1
1	**1**	**1**	-1	-1	-1
-1	**1**	-1	-1	-1	-1
-1	-1	-1	**1**	-1	**1**
-1	-1	-1	-1	**1**	-1
-1	-1	-1	**1**	-1	**1**

Kernel (Filter):

-1	1	-1
1	1	1
-1	1	-1

Feature Map:

9

Convolutions on images

Input | **Kernel (Filter)** | **Feature Map**

-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

-1	1	-1
1	1	1
-1	1	-1

-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

-1	1	-1
1	1	1
-1	1	-1

9	

-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

-1	1	-1
1	1	1
-1	1	-1

9	-1

Convolutions on images

Input

-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

9	-1	1

- **Let *X*** be the part of the input where we apply the kernel (filter).
- **Let *W*** be the kernel.
- The resulting **feature** of the feature map is: $\sum_{i=1}^{3}\sum_{j=1}^{3} \boldsymbol{W_{i,j}\, X_{i,j}}$
- In practice, we would also use an **activation function** and **bias term**: $f\left(\sum_{i=1}^{3}\sum_{j=1}^{3} W_{i,j}X_{i,j} + b\right)$

Convolutions on images

Input

-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

9	-1	1

...

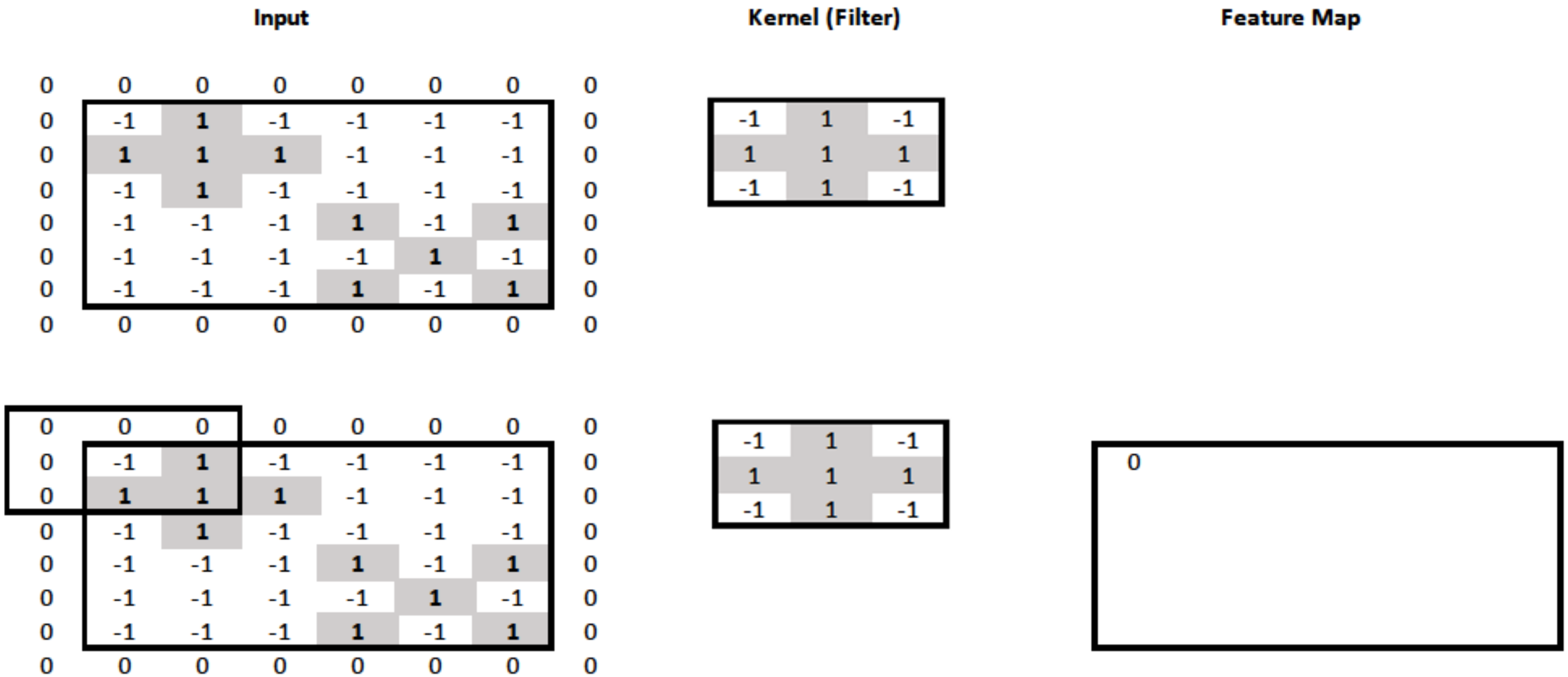
-1	1	-1	-1	-1	-1
1	1	1	-1	-1	-1
-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1
-1	-1	-1	-1	1	-1
-1	-1	-1	1	-1	1

-1	1	-1
1	1	1
-1	1	-1

9	-1	1	-1
-1	-1	-1	-5
1	-1	-1	5
-1	-5	5	-7

- We can think of the resulting **feature map as a new "image"** that indicates the **position(s) of the cross(es)** in the original image.
  - No need to have the crosses at particular parts of the image.
- The new "image" is **4x4 instead of 6x6**, because the **kernel could not slide outside the boundaries** of the original image.

Wide convolutions on images



- We can **pad** the surrounding of the image with zeros, to allow the kernel to slide outside the image boundaries.
- We can now obtain a **feature map** with the **same resolution as the input** image (6x6).

Wide convolutions on images

Input

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

-1	1	-1
1	1	1
-1	1	-1

0

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

-1	1	-1
1	1	1
-1	1	-1

0	-2

Wide convolutions on images

Input

0	0	0	0	0	0	0	0
0	-1	**1**	-1	-1	-1	-1	0
0	**1**	**1**	**1**	-1	-1	-1	0
0	-1	**1**	-1	-1	-1	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	-1	-1	-1	-1	**1**	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	0	0	0	0	0	0	0

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

0	-2	0			

...

0	0	0	0	0	0	0	0
0	-1	**1**	-1	-1	-1	-1	0
0	**1**	**1**	**1**	-1	-1	-1	0
0	-1	**1**	-1	-1	-1	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	-1	-1	-1	-1	**1**	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	0	0	0	0	0	0	0

-1	1	-1
1	1	1
-1	1	-1

0	-2	0	-4	-2	-2
-2					

0	0	0	0	0	0	0	0
0	-1	**1**	-1	-1	-1	-1	0
0	**1**	**1**	**1**	-1	-1	-1	0
0	-1	**1**	-1	-1	-1	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	-1	-1	-1	-1	**1**	-1	0
0	-1	-1	-1	**1**	-1	**1**	0
0	0	0	0	0	0	0	0

-1	1	-1
1	1	1
-1	1	-1

0	-2	0	-4	-2	-2
-2	9				

Wide convolutions on images

Input

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Kernel (Filter)

-1	1	-1
1	1	1
-1	1	-1

Feature Map

0	-2	0	-4	-2	-2
-2	9	-1			

...

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

-1	1	-1
1	1	1
-1	1	-1

0	-2	0	-4	-2	-2
-2	9	-1	1	-1	-2
0	-1	-1	-1	-5	0
-4	1	-1	-1	5	-2
-2	-1	-5	5	-7	4
-2	-2	0	-2	4	-2

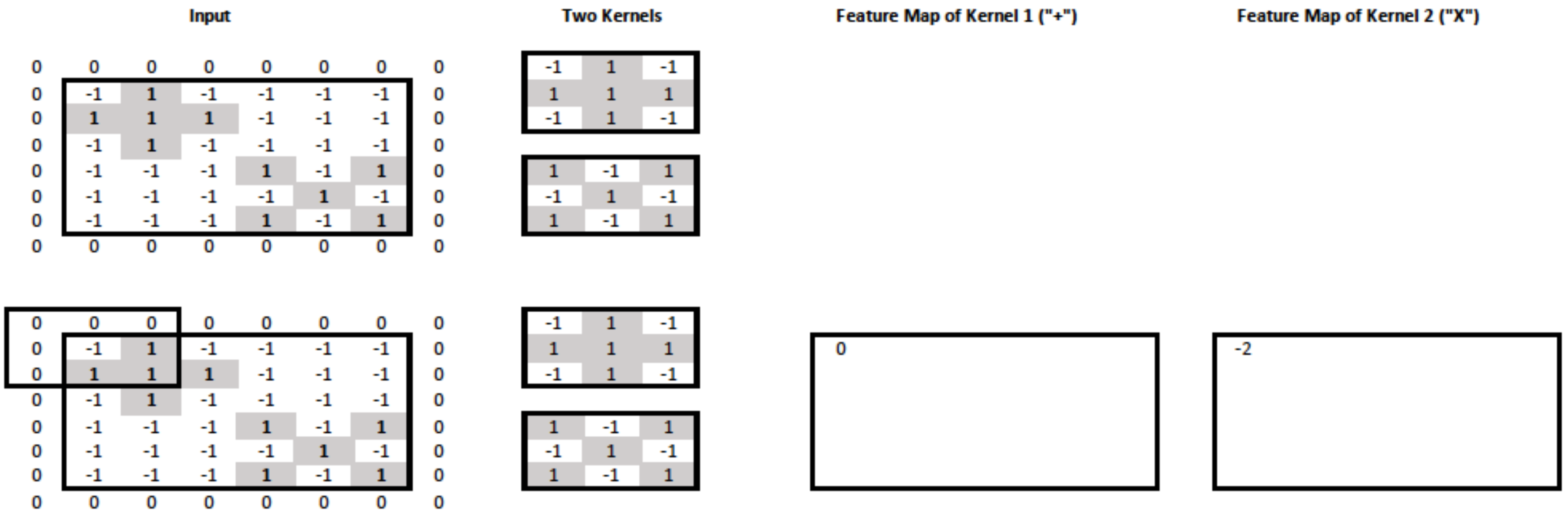
- $\boldsymbol{X}$: **entire input** image. $\boldsymbol{F}$: **feature map**.
- $\boldsymbol{W}$: **kernel**, but with rows and columns numbered $-1, 0, 1$.
- **Feature map values**: $F_{i,j} = \sum_{k=-1}^{1} \sum_{l=-1}^{1} W_{k,l}\, X_{i+k,j+l}$
- In practice: $F_{i,j} = f\left(\sum_{k=-1}^{1} \sum_{l=-1}^{1} W_{k,l}\, X_{i+k,j+l} + b\right)$

Convolution or cross-correlation?

Optional study

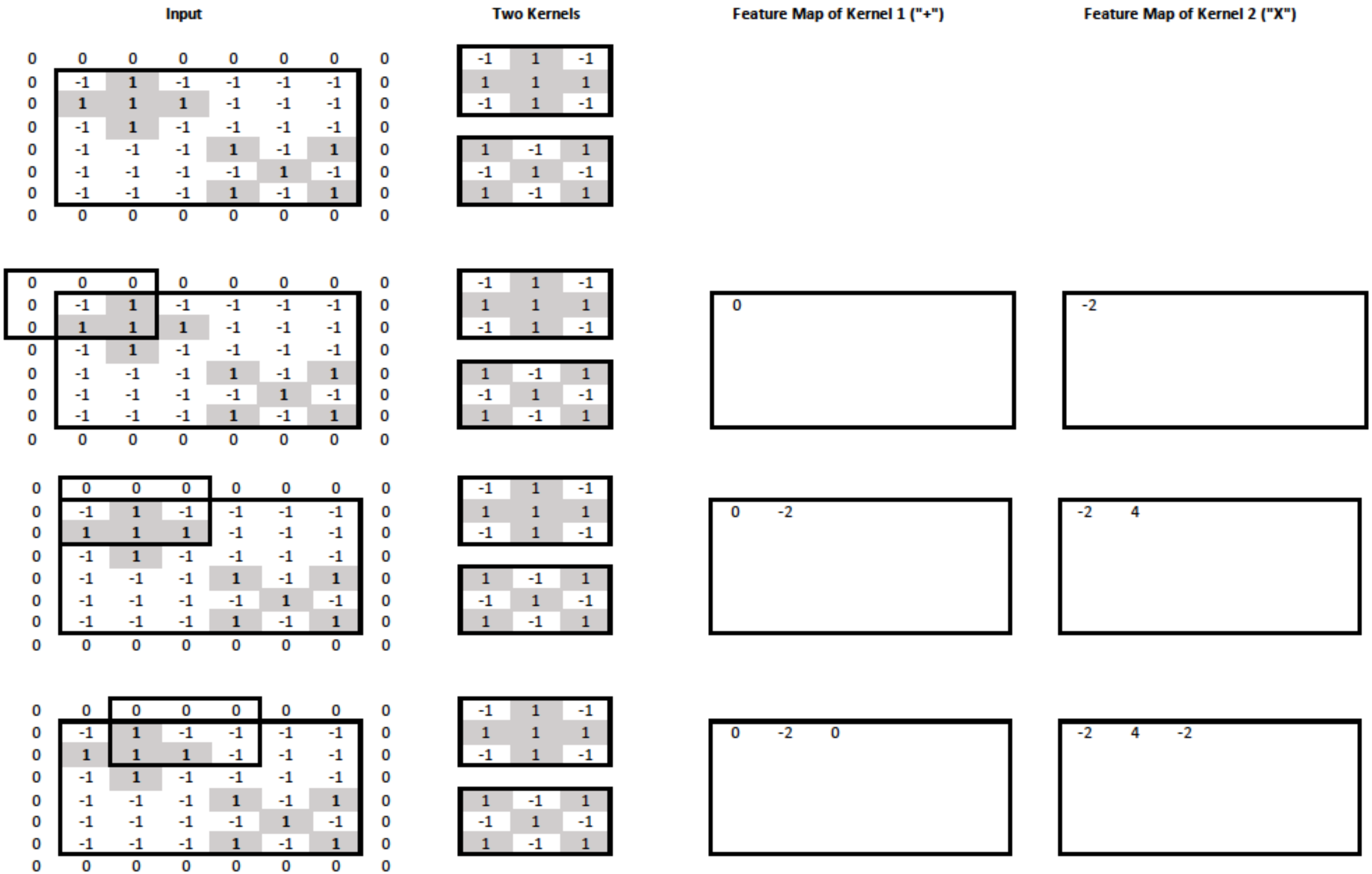
- **Cross-correlation**: $F_{i,j} = \sum_{k=-\infty}^{+\infty} \sum_{l=-\infty}^{+\infty} W_{k,l} X_{i+k,j+l}$
- **Convolution**: $F_{i,j} = \sum_{k=-\infty}^{+\infty} \sum_{l=-\infty}^{+\infty} W_{k,l} X_{i-k,j-l} = W * X$
- We are **actually computing cross-correlations**, not convolutions.
  - The **cross-correlations** we compute are **equal to convolutions with the kernel (or the image) flipped** both vertically and horizontally.
    - Convolution is like cross-correlation, but flips one of the two signals. We don't flip the kernel inside the *cross-correlation*, which is equivalent to giving the kernel already flipped to the *convolution*; the convolution will flip the kernel once more, ending up using the kernel without flipping.
  - So we actually compute **convolutions with flipped kernels** or **cross-correlations with the original kernels**.
  - The **example kernels were symmetric**, so no difference.
  - **In CNNs** (Convolutional Neural Networks), the **kernels are learned**, so **we don't care** if they are flipped in the "convolutions" we compute.
  - So we usually say **CNNs "compute convolutions"**, though we actually use the formulae of cross-correlations.

Two kernels



- We now want to **check the input image for crosses and "X"s**.
- We use **two kernels**, one for crosses, one for "X"s.

Two kernels


Input
Two Kernels
Feature Map of Kernel 1 ("+")
Feature Map of Kernel 2 ("X")
0 0 0 0 0 0 0 0
0 -1 1 -1 -1 -1 -1 0
0 1 1 1 -1 -1 -1 0
0 -1 1 -1 -1 -1 -1 0
0 -1 -1 -1 1 -1 1 0
0 -1 -1 -1 -1 1 -1 0
0 -1 -1 -1 1 -1 1 0
0 0 0 0 0 0 0 0
-1 1 -1
1 1 1
-1 1 -1
1 -1 1
-1 1 -1
1 -1 1
0
-2
0 -2
-2 4
0 -2 0
-2 4 -2

Two kernels

We can **think of the two feature maps as two "channels" of the new image**, one for "+" info, one for "X" info.

Input | Two Kernels | Feature Map of Kernel 1 ("+") | Feature Map of Kernel 2 ("X")

Step 1

Input:

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Two Kernels:

-1	1	-1
1	1	1
-1	1	-1

1	-1	1
-1	1	-1
1	-1	1

Feature Map of Kernel 1 ("+"):

0	-2	0	-4	-2	-2
-2					

Feature Map of Kernel 2 ("X"):

-2	4	-2	2	0	0
4					

Step 2

Input:

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Two Kernels:

-1	1	-1
1	1	1
-1	1	-1

1	-1	1
-1	1	-1
1	-1	1

Feature Map of Kernel 1 ("+"):

0	-2	0	-4	-2	-2
-2	9				

Feature Map of Kernel 2 ("X"):

-2	4	-2	2	0	0
4	-7				

Step 3

Input:

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Two Kernels:

-1	1	-1
1	1	1
-1	1	-1

1	-1	1
-1	1	-1
1	-1	1

Feature Map of Kernel 1 ("+"):

0	-2	0	-4	-2	-2
-2	9	-1			

Feature Map of Kernel 2 ("X"):

-2	4	-2	2	0	0
4	-7	3			

...

Final step

Input:

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Two Kernels:

-1	1	-1
1	1	1
-1	1	-1

1	-1	1
-1	1	-1
1	-1	1

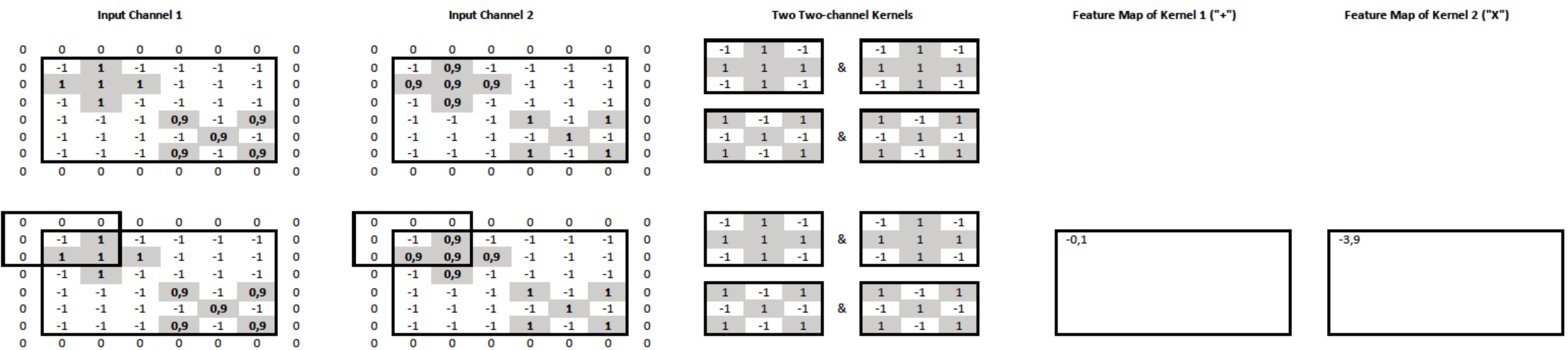
Feature Map of Kernel 1 ("+"):

0	-2	0	-4	-2	-2
-2	9	-1	1	-1	-2
0	-1	-1	-1	-5	0
-4	1	-1	-1	5	-2
-2	-1	-5	5	-7	4
-2	-2	0	-2	4	-2

Feature Map of Kernel 2 ("X"):

-2	4	-2	2	0	0
4	-7	3	-3	-1	0
-2	3	-1	-1	3	-2
2	-3	-1	3	-7	4
0	-1	3	-7	9	-6
0	0	-2	4	-6	4

Two input channels too

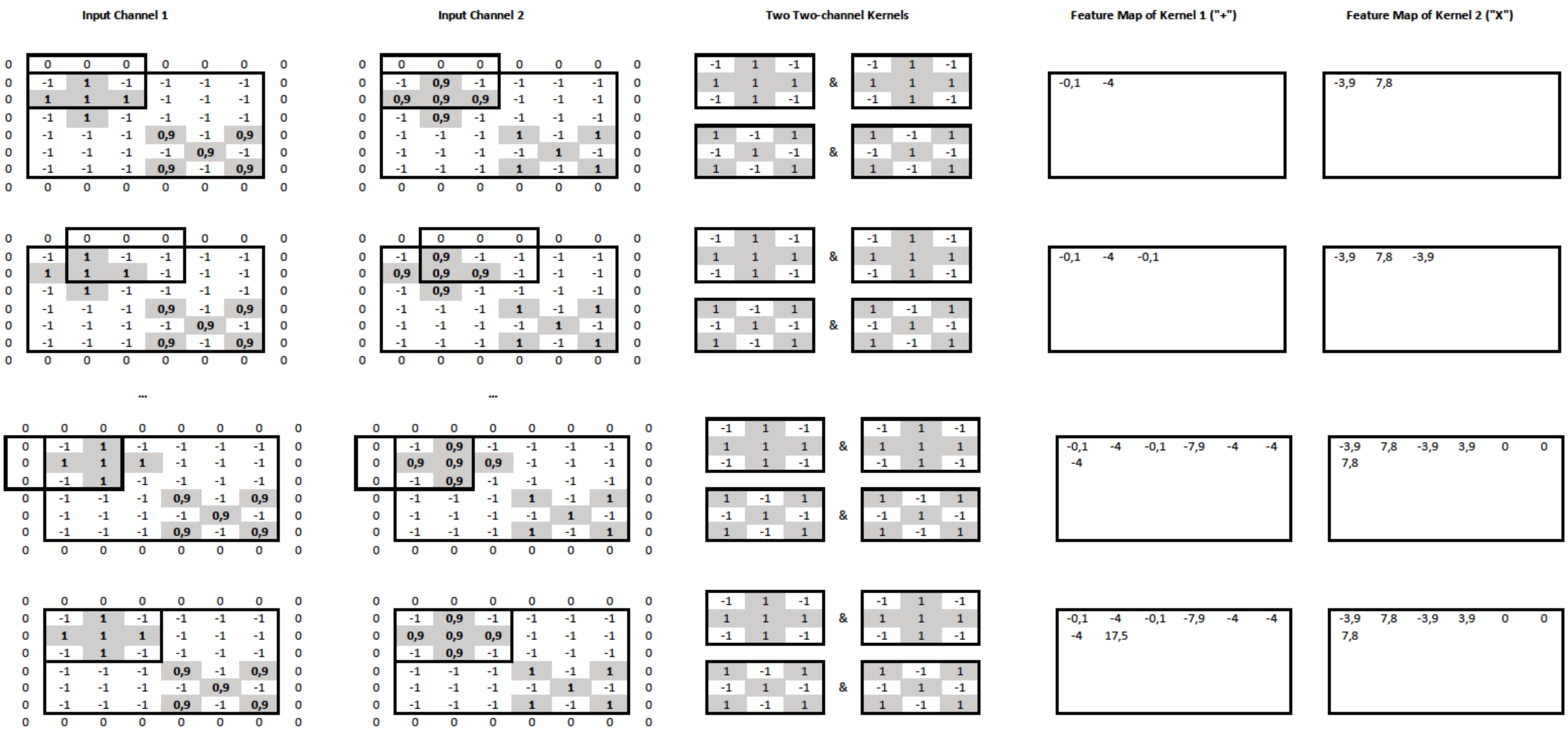


- The **input image** now also has **two channels** (e.g., from grayscale and depth cameras). **Each kernel** now operates on **both input channels**.
  - It has **two slices**, one per input channel ($c = 1, c = 2$).
- We have **two kernels**, so the **output** also has **two channels**.
- At the output feature map of kernel $W^{(m)}$, the value at cell (i, j) is:

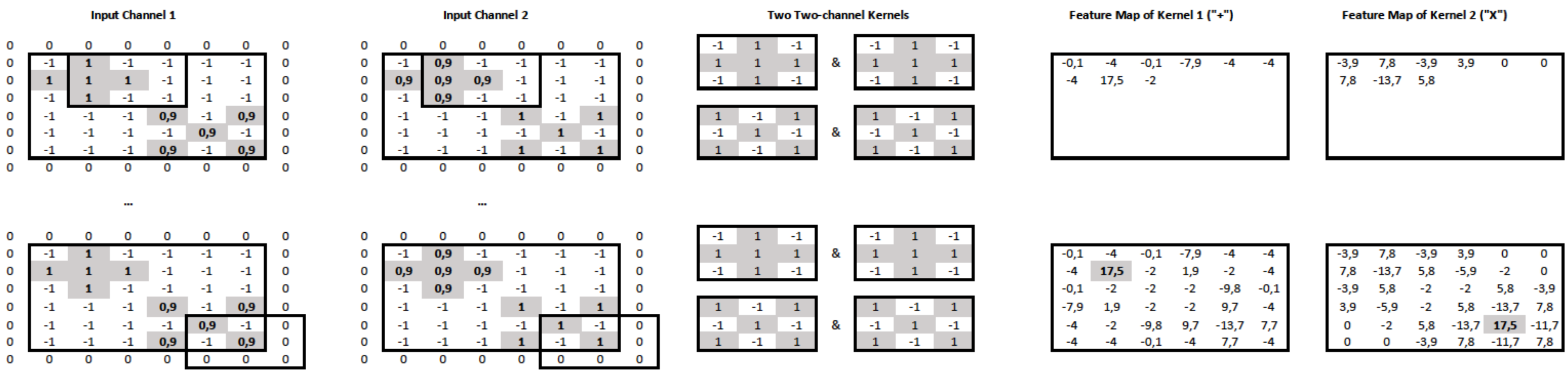
$$F_{i,j,m} = \sum_{k=-1}^{1} \sum_{l=-1}^{1} \sum_{c=1}^{2} W_{k,l,c}^{(m)} X_{i+k,j+l,c}$$

- In practice, we would also have an activation function and bias term.

Two input channels too



Two input channels too



- We now have a mechanism, a "**convolutional layer**", that maps an **input image of any number of channels** to a new **output "image" of any number of channels** (feature maps).
  - The **kernels** will have **as many slices as the input channels**.
  - The **number of kernels** will be **equal to the number of output channels**.
- We can **stack** multiple **convolutional layers**.
  - Each one will operate on the "image" produced by the previous layer.
  - **All kernels** will be randomly initialized and **learned via backpropagation**.

Max-pooling

Feature Map of Kernel 1 ("+") | **Feature Map of Kernel 2 ("X")** | **Max-Pooling (2,2) with Stride (2,2)**

-0,1	-4	-0,1	-7,9	-4	-4
-4	**17,5**	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	**17,5**	-11,7
0	0	-3,9	7,8	-11,7	7,8

17,5	

7,8	

-0,1	-4	-0,1	-7,9	-4	-4
-4	**17,5**	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	**17,5**	-11,7
0	0	-3,9	7,8	-11,7	7,8

17,5	1,9

7,8	5,8

-0,1	-4	-0,1	-7,9	-4	-4
-4	**17,5**	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	**17,5**	-11,7
0	0	-3,9	7,8	-11,7	7,8

17,5	1,9	-2

7,8	5,8	0

- We keep the **max value of each window**, separately from each channel.
- The **stride** determines **how much the window shifts** vertically & horizontally.

Max-pooling

Feature Map of Kernel 1 ("+")

-0,1	-4	-0,1	-7,9	-4	-4
-4	**17,5**	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

Feature Map of Kernel 2 ("X")

-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	**17,5**	-11,7
0	0	-3,9	7,8	-11,7	7,8

Max-Pooling (2,2) with Stride (2,2)

17,5	1,9	-2
1,9		

7,8	5,8	0
5,8		

...

...

-0,1	-4	-0,1	-7,9	-4	-4
-4	**17,5**	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

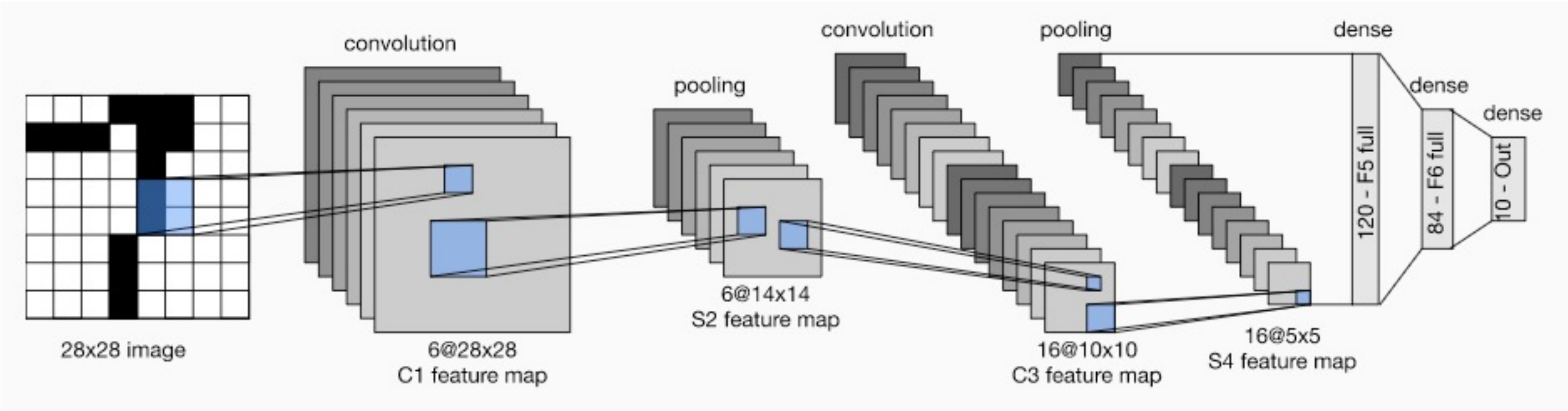
-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	**17,5**	-11,7
0	0	-3,9	7,8	-11,7	7,8

17,5	1,9	-2
1,9	-2	9,7
-2	9,7	7,7

7,8	5,8	0
5,8	5,8	7,8
0	7,8	**17,5**

- **Max-pooling** layers are usually placed **between stacked convolutional layers**.

Stacking convolution, pooling, dense layers



LeNet architecture as illustrated in *Dive into Deep Learning* by Zhang et al. (https://d2l.ai/chapter_convolutional-neural-networks/lenet.html).

- Max-pooling gradually **reduces the resolution at higher layers**, **allowing us to use more channels** (for the same total number of trainable parameters/layer).
- It also helps **increase more quickly the receptive field**.

Input Channel 1

0	0	0	0	0	0	0	0
0	-1	1	-1	-1	-1	-1	0
0	1	1	1	-1	-1	-1	0
0	-1	1	-1	-1	-1	-1	0
0	-1	-1	-1	0,9	-1	0,9	0
0	-1	-1	-1	-1	0,9	-1	0
0	-1	-1	-1	0,9	-1	0,9	0
0	0	0	0	0	0	0	0

Input Channel 2

0	0	0	0	0	0	0	0
0	-1	0,9	-1	-1	-1	-1	0
0	0,9	0,9	0,9	-1	-1	-1	0
0	-1	0,9	-1	-1	-1	-1	0
0	-1	-1	-1	1	-1	1	0
0	-1	-1	-1	-1	1	-1	0
0	-1	-1	-1	1	-1	1	0
0	0	0	0	0	0	0	0

Two Two-channel Kernels

-1	1	-1	&	-1	1	-1
1	1	1		1	1	1
-1	1	-1		-1	1	-1

1	-1	1	&	1	-1	1
-1	1	-1		-1	1	-1
1	-1	1		1	-1	1

Feature Map of Kernel 1 ("+")

-0,1	-4	-0,1	-7,9	-4	-4
-4	17,5	-2	1,9	-2	-4
-0,1	-2	-2	-2	-9,8	-0,1
-7,9	1,9	-2	-2	9,7	-4
-4	-2	-9,8	9,7	-13,7	7,7
-4	-4	-0,1	-4	7,7	-4

Feature Map of Kernel 2 ("X")

-3,9	7,8	-3,9	3,9	0	0
7,8	-13,7	5,8	-5,9	-2	0
-3,9	5,8	-2	-2	5,8	-3,9
3,9	-5,9	-2	5,8	-13,7	7,8
0	-2	5,8	-13,7	17,5	-11,7
0	0	-3,9	7,8	-11,7	7,8

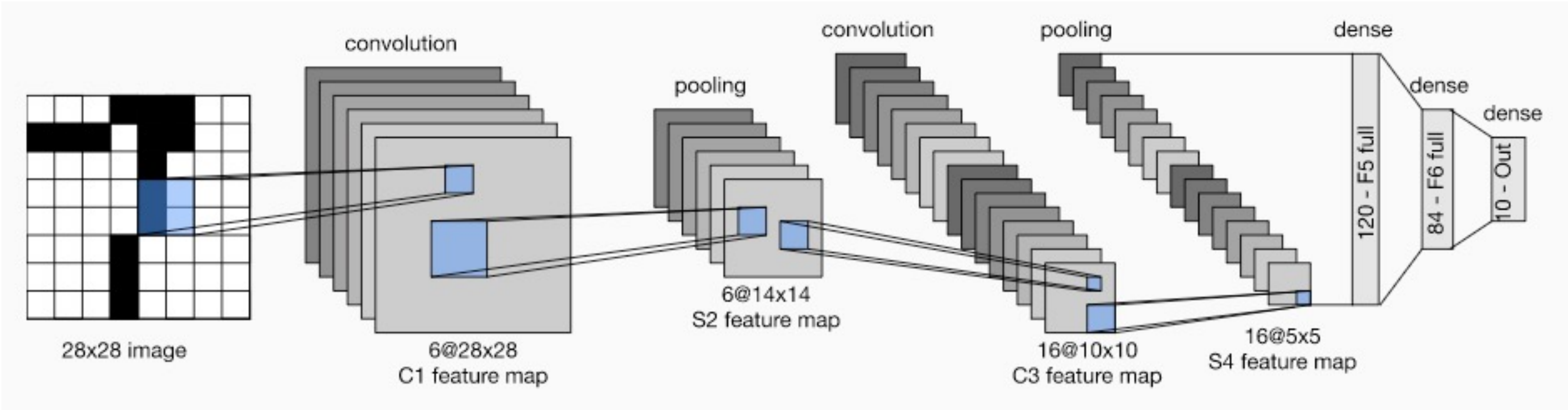
Max-Pooling (2,2) with Stride (2,2)

17,5	1,9	-2
1,9	-2	9,7
-2	9,7	7,7

7,8	5,8	0
5,8	5,8	7,8
0	7,8	17,5

- **Each feature of the max-pooled feature maps** is derived from (is "looking at") **4 features of the pre-pooled** feature maps, and **16 features of the input**.
- **By stacking** convolution and pooling layers, we can get **features that are increasingly aware of larger parts of the input** (larger "**receptive field**").

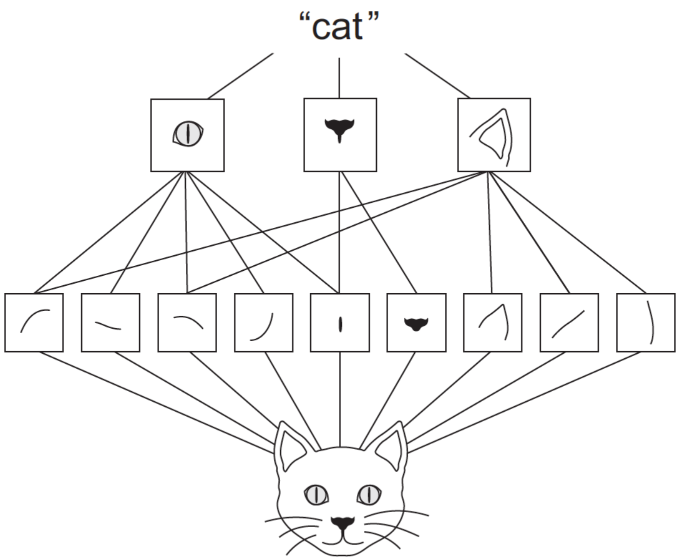
Stacking convolution, pooling, dense layers



LeNet architecture as illustrated in *Dive into Deep Learning* by Zhang et al. (https://d2l.ai/chapter_convolutional-neural-networks/lenet.html).

- **The features of the top feature maps** are concatenated to a **single vector** and **passed to a dense** (fully connected) **layer** or an **MLP** (with hidden layers).
  - To **recognize the digit** (0-9) in an image, the dense layer (or output layer of the MLP) would have **10 neurons with softmax**, and we would use **cross-entropy** loss.
  - To output the **coordinates of the eyes** in images (or video frames) of faces, the **dense layer** (or output layer of the MLP) could have **4 neurons** (x1, y1, x2, y2) with no activation function, and we could use the **mean squared error** as loss. (But better, more advanced models can be used...)
  - The **training examples** would be digit or face **images** (or video frames) **annotated with the correct responses** (digits or coordinates of the eyes).
- In practice we would also include **dropout** layers and **residuals**.

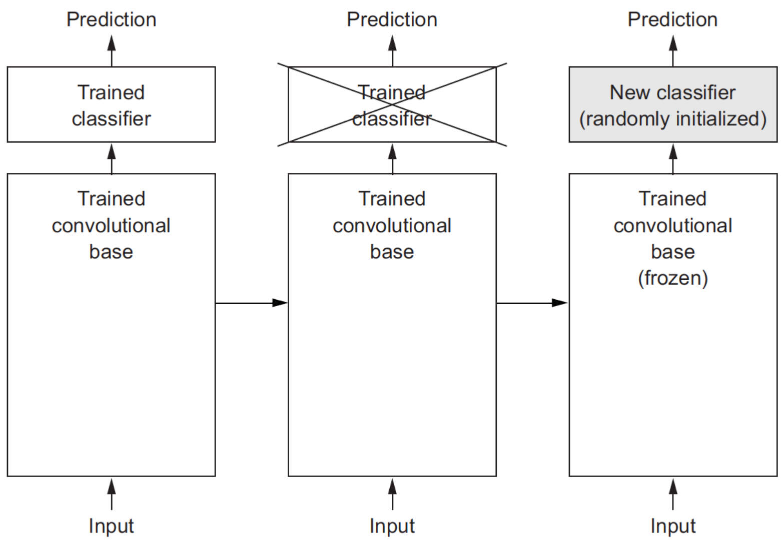
What do the layers learn?



- The kernels of **lower layers** tend to detect **low-level features (e.g., edges of different directions)**. The kernels of **higher layers** tend to detect **higher-level features (e.g., eyes, ears)**.
- **Pre-trained kernels of lower levels** can be useful in many different tasks.

Figure from the recommended book **"Deep Learning with Python"** by F. Chollet, Manning Publications, 1st edition. Also covers Keras. Optionally consult Chapter 5 (Deep Learning for Computer Vision) for ways to visualize what CNN layers learn.
https://www.manning.com/books/deep-learning-with-python
https://www.manning.com/books/deep-learning-with-python-second-edition

Re-using pretrained layers



- In practice, we start with a **CNN pre-trained on a very large dataset**.
  - Often **ImageNet**, 1.4 million images, 1,000 classes (e.g., dogs, cats).
- We **replace the top layers** with a **task-specific classification/regression layer**.
  - We **train the task-specific layer on task-specific data**, keeping the **pre-trained convolutional layers frozen** (no weight updates in the frozen layers).
  - We may then **gradually unfreeze some of the convolutional layers too** (weight updates in both the task-specific layers and the unfrozen convolutional layers).

Figure from the recommended book **"Deep Learning with Python"** by F. Chollet, Manning Publications, 1st edition. Also covers Keras. https://www.manning.com/books/deep-learning-with-python https://www.manning.com/books/deep-learning-with-python-second-edition

Re-using pretrained layers

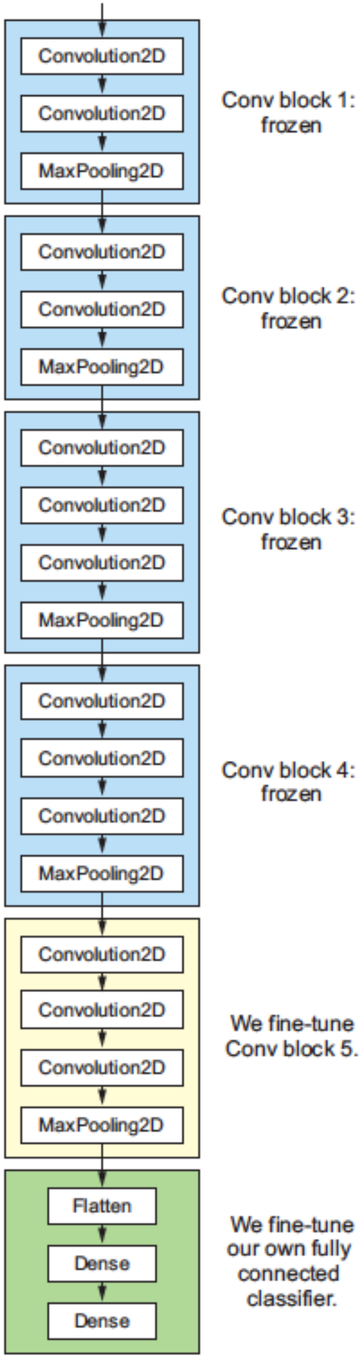


Figure 5.19 Fine-tuning the last convolutional block of the VGG16 network

Figure from the recommended book **"Deep Learning with Python"** by F. Chollet, Manning Publications, 1st edition. Also covers Keras. https://www.manning.com/books/deep-learning-with-python https://www.manning.com/books/deep-learning-with-python-second-edition

Data augmentation

Figure 5.11 Generation of cat pictures via random data augmentation

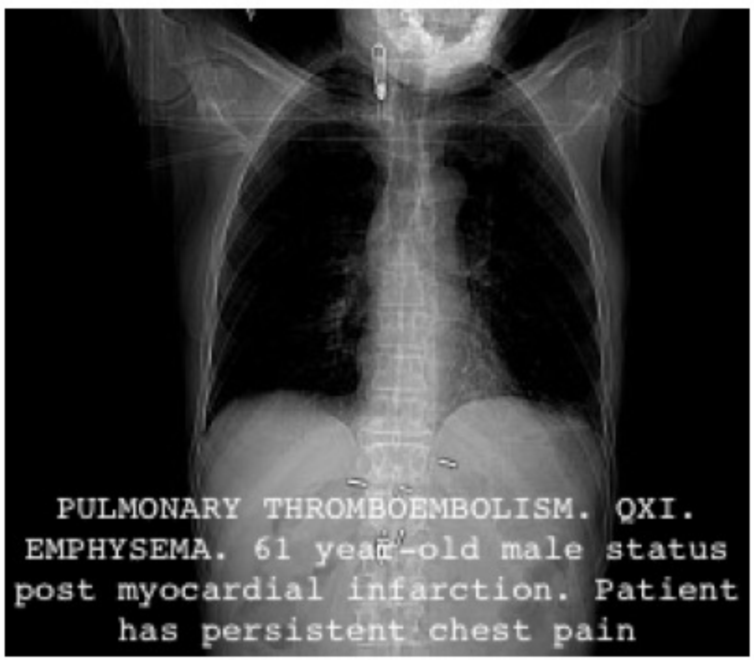
- We can **increase the number of task-specific training examples** by adding artificial training examples.
  - For example, we can **rotate, squeeze, flip** etc. the task-specific **training images**.
  - **Big improvements** usually.
- How do we do **data augmentation for NLP?**

Figure from the recommended book **"Deep Learning with Python"** by F. Chollet, Manning Publications, 1st edition. Also covers data augmentation in Keras.
https://www.manning.com/books/deep-learning-with-python
https://www.manning.com/books/deep-learning-with-python-second-edition

Image captioning

Optional study

(a) General



(b) Biomedical

Possible applications:

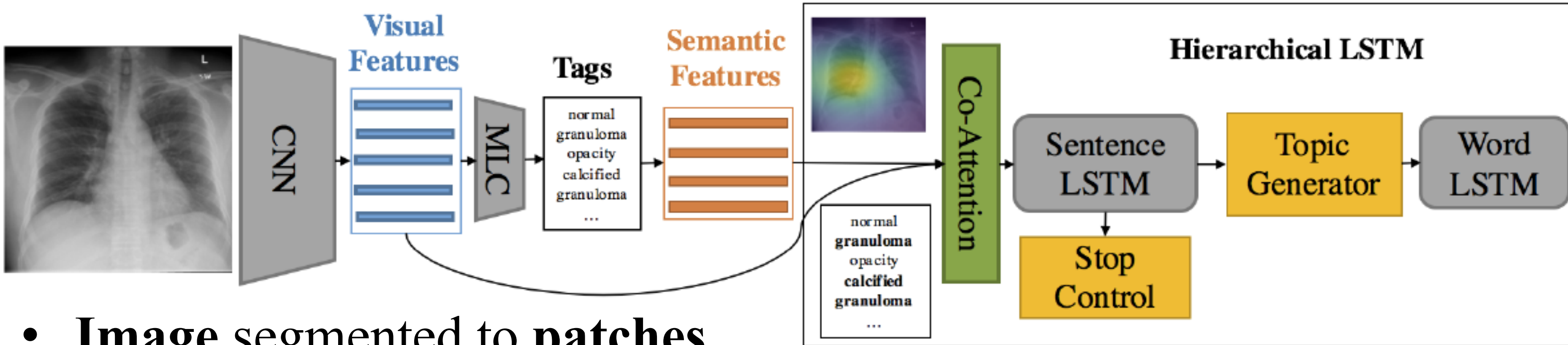
- Image retrieval via captions.
- Eyesight problems.
- Drafting medical reports.

Figure 1: Example of a caption produced by the model of Vinyals et al. (2017) for a non-biomedical image (1a) and an example of a PEIR Radiology image with its associated caption (1b).

From I. Pavlopoulos, V. Kougia, I. Androutsopoulos, "A Survey on Biomedical Image Captioning". https://www.aclweb.org/anthology/W19-1803/

Biomedical image to text generation

Optional study



- **Image** segmented to **patches**.
- **CNN** converts each **patch to a vector**, producing "**visual features**".
- **MLP** ("MLC") **predicts tags** (classes) given the visual features.
- The **word embeddings of the tags** are "**semantic features**".
- **Sentence-level LSTM** produces **sentence embeddings** ("topics").
  - A **stop control** (classifier) decides when to **stop producing sentences**.
  - At each time-step, **attention** over **visual** and **semantic features**.
- For each sentence embedding, **word-level LSTM produces words**.

B. Jing, P. Xie, E.P. Xing, "On the Automatic Generation of Medical Imaging Reports", ACL 2018 (http://www.aclweb.org/anthology/P18-1240).

Convolutions on text

Let's **pretend** that we know what the **dimensions** of the word **embeddings represent**, and that the dimensions are **binary**.

Words	Embeddings			
	Subject	Positive	Stress	Quantity
I	**1**	0	0	0
like	0	**1**	0	0
this	0	0	0	0
movie	0	0	0	0
very	0	0	**1**	0
much	0	0	0	**1**
!	0	0	**1**	0

2

Filter for "I like", "we admire"…			
1	0	0	0
0	**1**	0	0

Filter for "very much", "so much"…			
0	0	**1**	0
0	0	0	**1**

Convolutions on text

Let's **pretend** that we know what the **dimensions** of the word **embeddings represent**, and that the dimensions are **binary**.

Words	Embeddings			
	Subject	Positive	Stress	Quantity
I	**1**	0	0	0
like	0	**1**	0	0
this	0	0	0	0
movie	0	0	0	0
very	0	0	**1**	0
much	0	0	0	**1**
!	0	0	**1**	0

0

Filter for "I like", "we admire"…			
1	0	0	0
0	**1**	0	0

Filter for "very much", "so much"…			
0	0	**1**	0
0	0	0	**1**

Convolutions on text

Words	Embeddings			
	Subject	Positive	Stress	Quantity
I	**1**	0	0	0
like	0	**1**	0	0
this	0	0	0	0
movie	0	0	0	0
very	0	0	**1**	0
much	0	0	0	**1**
!	0	0	**1**	0

2
0
0
0
0
0

Filter for "I like", "we admire"…			
1	0	0	0
0	**1**	0	0

Filter for "very much", "so much"…			
0	0	**1**	0
0	0	0	**1**

Convolutions on text

Words	Embeddings					
	Subject	Positive	Stress	Quantity		
I	**1**	0	0	0		
like	0	**1**	0	0	2	0
this	0	0	0	0	0	0
movie	0	0	0	0	0	0
very	0	0	**1**	0	0	0
much	0	0	0	**1**	0	
!	0	0	**1**	0	0	

Filter for "I like", "we admire"…			
1	0	0	0
0	**1**	0	0

Filter for "very much", "so much"…			
0	0	**1**	0
0	0	0	**1**

Convolutions on text

Words	Embeddings			
	Subject	Positive	Stress	Quantity
I	**1**	0	0	0
like	0	**1**	0	0
this	0	0	0	0
movie	0	0	0	0
very	0	0	**1**	0
much	0	0	0	**1**
!	0	0	**1**	0

2	0
0	0
0	0
0	0
0	2
0	

Filter for “I like”, “we admire”…			
1	0	0	0
0	**1**	0	0

Filter for “very much”, “so much”…			
0	0	**1**	0
0	0	0	**1**

Convolutions on text

Words	Embeddings			
	Subject	Positive	Stress	Quantity
I	**1**	0	0	0
like	0	**1**	0	0
this	0	0	0	0
movie	0	0	0	0
very	0	0	**1**	0
much	0	0	0	**1**
!	0	0	**1**	0

2	0
0	0
0	0
0	0
0	2
0	0

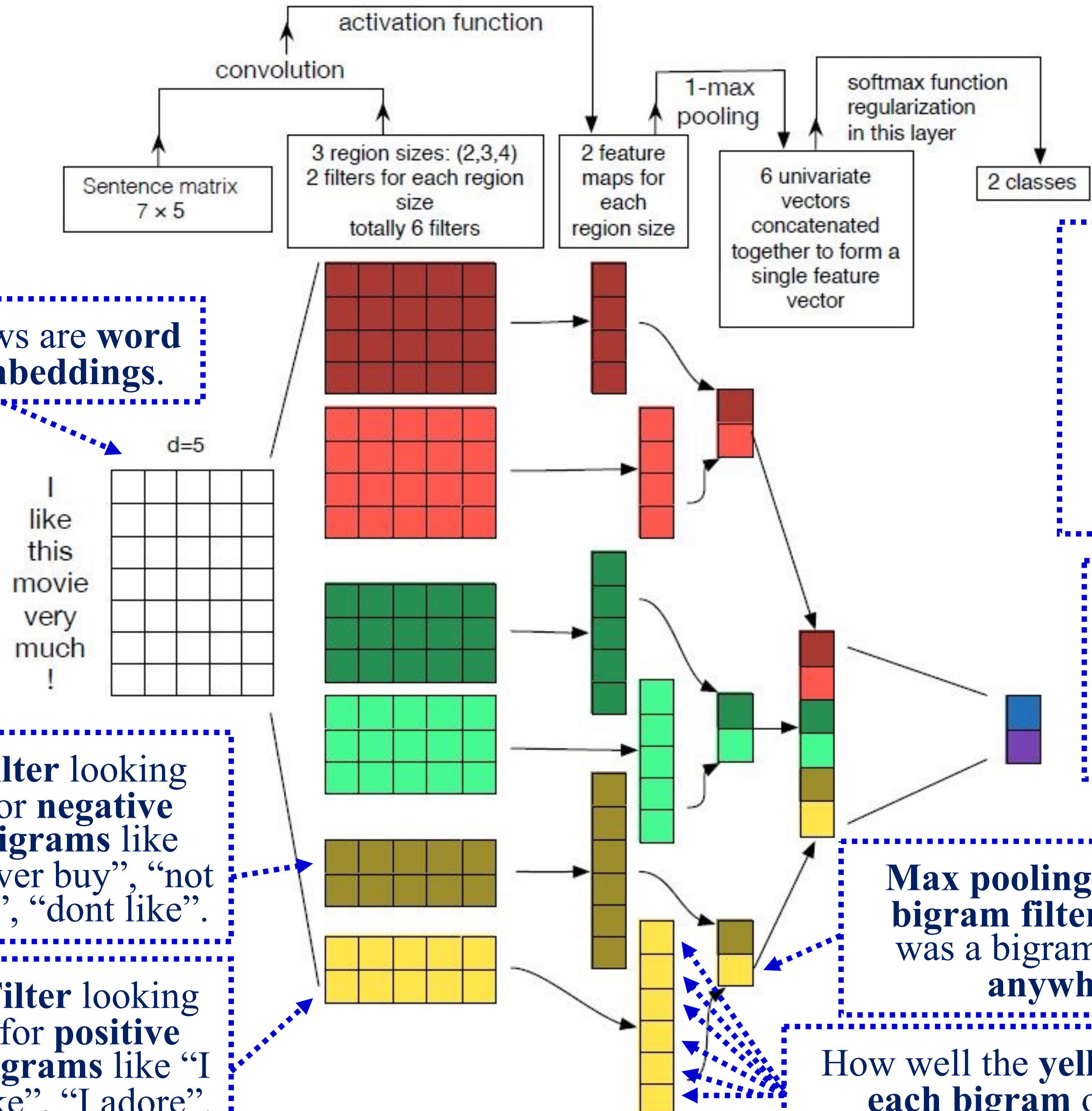
global max pooling → 2 2

Best scores of the two filters: to what extent they **match anywhere** in the sentence.

Filter for “I like”, “we admire”…			
1	0	0	0
0	**1**	0	0

Filter for “very much”, “so much”…			
0	0	**1**	0
0	0	0	**1**

Convolutional Neural Networks



Rows are **word embeddings**.

From "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification", Zhang et al., 2015. http://arxiv.org/abs/1510.03820

The **numbers in each filter** are learned by **backpropagation**. The **embeddings** can also be learned during backpropagation.

Filter looking for **negative bigrams** like "never buy", "not get", "dont like".

Filter looking for **positive bigrams** like "I like", "I adore".

Max pooling: Max score of the **yellow bigram filter**. Best evidence that there was a bigram like "I like" or "I adore" **anywhere** in the sentence.

How well the **yellow bigram filter** matched **each bigram** of the sentence (**scores**).

Convolutions on text – closer to reality

Words	Embeddings			
	d_1	d_2	d_3	d_4
I	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
like	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
this	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
movie	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
very	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$
much	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$
!	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$

$\mathrm{ReLU}(wx + b)$

$x^T = \langle x_{1,1}, x_{1,2}, x_{1,3}, \dots, x_{2,3}, x_{2,4} \rangle$

A bigram filter			
$w_{1,1}$	$w_{1,2}$	$w_{1,3}$	$w_{1,4}$
$w_{2,1}$	$w_{2,2}$	$w_{2,3}$	$w_{2,4}$

$w = \langle w_{1,1}, w_{1,2}, w_{1,3}, \dots, w_{2,3}, w_{2,4} \rangle$

b

Convolutions on text – closer to reality

Words	**Embeddings**			
	d_1	d_2	d_3	d_4
I	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
like	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
this	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
movie	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
very	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$
much	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$
!	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$

$\text{ReLU}(wx + b)$

$x^T = \langle x_{2,1}, x_{2,2}, x_{2,3}, \dots, x_{3,3}, x_{3,4} \rangle$

A bigram filter			
$w_{1,1}$	$w_{1,2}$	$w_{1,3}$	$w_{1,4}$
$w_{2,1}$	$w_{2,2}$	$w_{2,3}$	$w_{2,4}$

$w = \langle w_{1,1}, w_{1,2}, w_{1,3}, \dots, w_{2,3}, w_{2,4} \rangle$

b

Now applying **three** bigram filters

Words	Embeddings			
	d_1	d_2	d_3	d_4
I	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
like	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
this	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
movie	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
very	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$
much	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$
!	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$

$$h_2 = \text{ReLU}(Wx + b) \in \mathbb{R}^{3\times 1}$$

$$x^T = \langle x_{2,1}, x_{2,2}, \dots, x_{3,3}, x_{3,4} \rangle \in \mathbb{R}^{1\times 8}$$

$$W = \begin{bmatrix} w_{1,1,1} & w_{1,1,2} & w_{1,1,3} & \dots & w_{1,2,3} & w_{1,2,4} \\ w_{2,1,1} & w_{2,1,2} & w_{2,1,3} & \dots & w_{2,2,3} & w_{2,2,4} \\ w_{3,1,1} & w_{3,1,2} & w_{3,1,3} & \dots & w_{3,2,3} & w_{3,2,4} \end{bmatrix} \in \mathbb{R}^{3\times 8} \qquad b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \in \mathbb{R}^{3\times 1}$$

Applying 3 bigram filters

Words	Embeddings			
	d_1	d_2	d_3	d_4
I	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
like	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
this	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
movie	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
very	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$
much	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$
!	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$

$$h_2 = \langle h_{2,1}, h_{2,2}, h_{2,3} \rangle^T \in \mathbb{R}^{3\times 1}$$

$$W = \begin{bmatrix} w_{1,1,1} & w_{1,1,2} & w_{1,1,3} & \cdots & w_{1,2,3} & w_{1,2,4} \\ w_{2,1,1} & w_{2,1,2} & w_{2,1,3} & \cdots & w_{2,2,3} & w_{2,2,4} \\ w_{3,1,1} & w_{3,1,2} & w_{3,1,3} & \cdots & w_{3,2,3} & w_{3,2,4} \end{bmatrix} \in \mathbb{R}^{3\times 8}$$

$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \in \mathbb{R}^{3\times 1}$$

Applying 3 bigram filters

$$h^{max} = \langle \max(h_{*,1}), \max(h_{*,2}), \max(h_{*,3}) \rangle^T$$

global max pooling

Feature vector sent to a classifier, regressor, etc.

Words	Embeddings			
	d_1	d_2	d_3	d_4
I	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
like	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
this	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
movie	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
very	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$
much	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$
!	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$

$$h_1 = \langle h_{1,1}, h_{1,2}, h_{1,3} \rangle^T$$
$$h_2 = \langle h_{2,1}, h_{2,2}, h_{2,3} \rangle^T$$
$$h_3 = \langle h_{3,1}, h_{3,2}, h_{3,3} \rangle^T$$
$$h_4 = \langle h_{4,1}, h_{4,2}, h_{4,3} \rangle^T$$

...

$$h_7 = \langle h_{7,1}, h_{7,2}, h_{7,3} \rangle^T$$

$$W = \begin{bmatrix} w_{1,1,1} & w_{1,1,2} & w_{1,1,3} & \cdots & w_{1,2,3} & w_{1,2,4} \\ w_{2,1,1} & w_{2,1,2} & w_{2,1,3} & \cdots & w_{2,2,3} & w_{2,2,4} \\ w_{3,1,1} & w_{3,1,2} & w_{3,1,3} & \cdots & w_{3,2,3} & w_{3,2,4} \end{bmatrix} \in \mathbb{R}^{3\times 8} \qquad b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \in \mathbb{R}^{3\times 1}$$

Stacked CNNs for classification/regression

$$h^{max} = \left\langle \max\left(h_{*,1}^{(4)}\right), \max\left(h_{*,2}^{(4)}\right), \dots, \max(h_{*,m}^{(4)}) \right\rangle^T \in \mathbb{R}^{1\times m}$$

Feature vector sent to a document classifier or regressor (e.g., MLP).

global max pooling

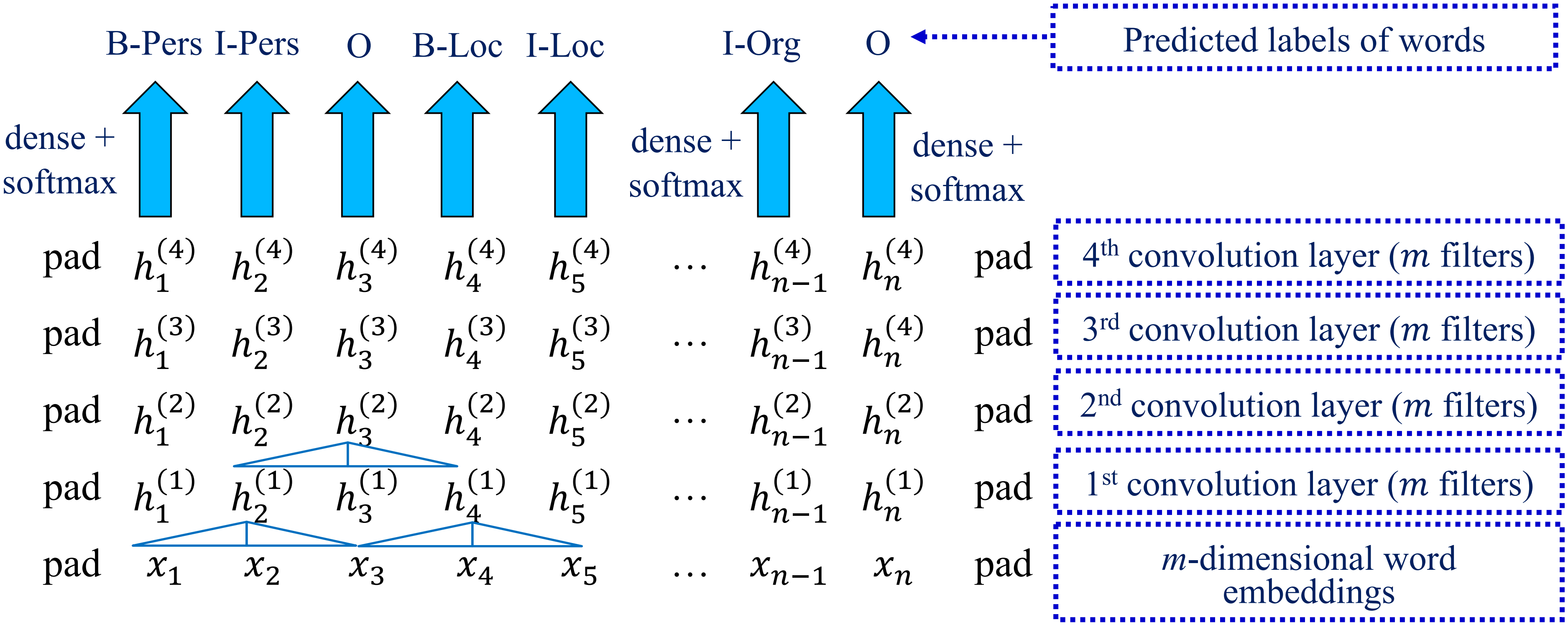
pad	$h_1^{(4)}$	$h_2^{(4)}$	$h_3^{(4)}$	$h_4^{(4)}$	$h_5^{(4)}$	$\dots$	$h_{n-1}^{(4)}$	$h_n^{(4)}$	pad	4th convolution layer (m filters)
pad	$h_1^{(3)}$	$h_2^{(3)}$	$h_3^{(3)}$	$h_4^{(3)}$	$h_5^{(3)}$	$\dots$	$h_{n-1}^{(3)}$	$h_n^{(4)}$	pad	3rd convolution layer (m filters)
pad	$h_1^{(2)}$	$h_2^{(2)}$	$h_3^{(2)}$	$h_4^{(2)}$	$h_5^{(2)}$	$\dots$	$h_{n-1}^{(2)}$	$h_n^{(2)}$	pad	2nd convolution layer (m filters)
pad	$h_1^{(1)}$	$h_2^{(1)}$	$h_3^{(1)}$	$h_4^{(1)}$	$h_5^{(1)}$	$\dots$	$h_{n-1}^{(1)}$	$h_n^{(1)}$	pad	1st convolution layer (m filters)
pad	x_1	x_2	x_3	x_4	x_5	$\dots$	x_{n-1}	x_n	pad	m-dimensional word embeddings

$$h_i^{(1)} = \text{ReLU}\left(W^{(1)}[x_{i-1}; x_i; x_{i+1}] + b^{(1)}\right) + x_i \in \mathbb{R}^{m\times 1}$$

$$h_i^{(j)} = \text{ReLU}\left(W^{(j)}\left[h_{i-1}^{(j-1)}; h_i^{(j-1)}; h_{i+1}^{(j-1)}\right] + b^{(j)}\right) + h_i^{(j-1)} \in \mathbb{R}^{m\times 1}$$

Residual (shortcut) connection, needed when stacking many CNNs (or RNNs).

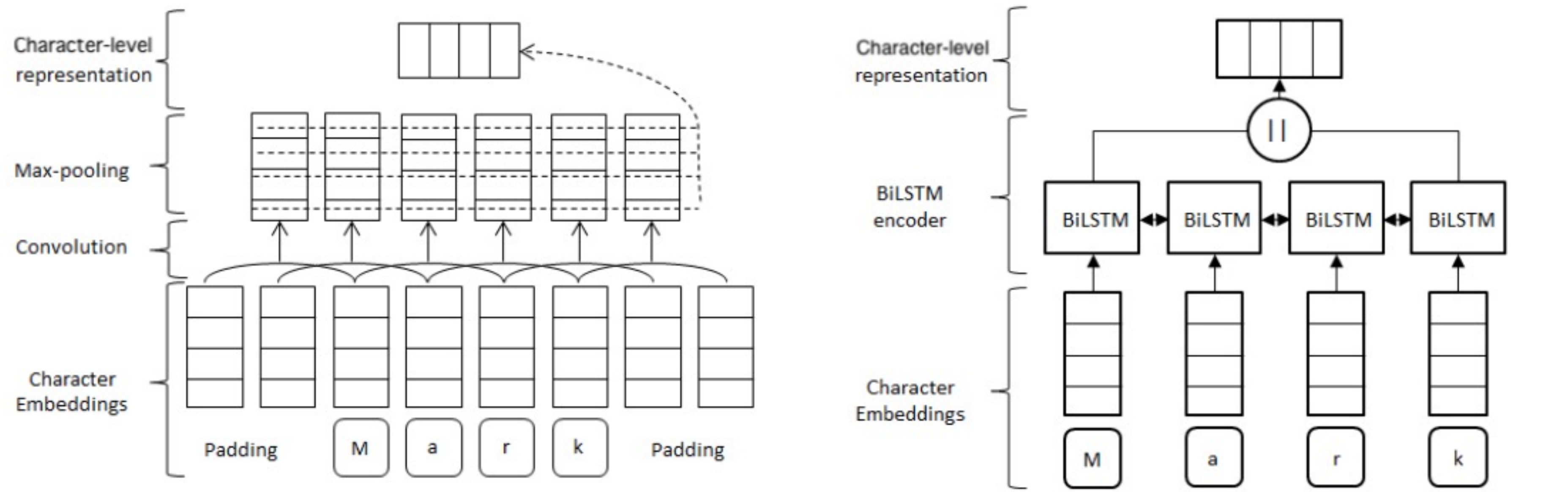
Stacked CNNs for token classification



$$h_i^{(1)} = \mathrm{ReLU}\left(W^{(1)}[x_{i-1}; x_i; x_{i+1}] + b^{(1)}\right) + x_i \in \mathbb{R}^{m\times 1}$$

$$h_i^{(j)} = \mathrm{ReLU}\left(W^{(j)}\left[h_{i-1}^{(j-1)}; h_i^{(j-1)}; h_{i+1}^{(j-1)}\right] + b^{(j)}\right) + h_i^{(j-1)} \in \mathbb{R}^{m\times 1}$$

CNNs/RNNs that produce word embeddings from character embeddings



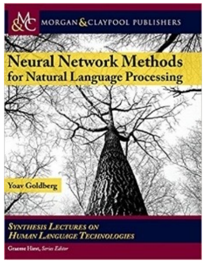
(CNN-based character-level word representation) (LSTM-based character-level word representation)

Figure 2: Character-level word representations. This figure is also adapted from Reimers and Gurevych (2017a).

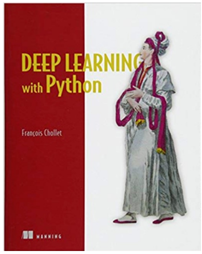
Z. Zhai, D.Q. Nguyen and K. Verspoor, "Comparing CNN and LSTM Character-Level Embeddings in BiLSTM-CRF Models for Chemical and Disease Named Entity Eecognition". 9th Int. Workshop on Health Text Mining and Information Analysis, Brussels, Belgium, 2018. http://aclweb.org/anthology/W18-5605

Recommended reading

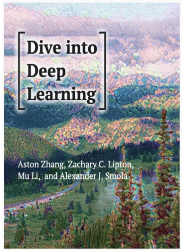
- Y. Goldberg, *Neural Network Models for Natural Language Processing*, Morgan & Claypool Publishers, 2017.
  - Mostly Chapter 13.



- Jurafsky and Martin's, *Speech and Language Processing* is being revised (3rd edition) to include DL methods.
  - http://web.stanford.edu/~jurafsky/slp3/ (free draft)
- F. Chollet, *Deep Learning in Python*, 1st edition, Manning Publications, 2017.
  - 1st edition freely available (and sufficient for this part of the course): https://www.manning.com/books/deep-learning-with-python
  - See Chapter 6 for CNNs in Computer Vision.
  - 2nd edition (2022) now available, requires payment. Highly recommended.



Recommended reading – continued



- A. Zhang et al., *Dive into Deep Learning*.
  - Freely available at: https://d2l.ai/
  - See Chapter 6 for CNNs.
- See also the recommended reading and resources of the previous parts (NLP with MLPs, RNNs) of this course.