ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 15. Convolutions in Text

Alberto Barrón-Cedeño
a.barron@unibo.it

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Quick Keras Reminder

Keras

Sequential()

- Python class
- Neural network abstraction
- Grants access to the basic Keras API

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- Applies backpropagation (weight adjustment)

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Some "cooking" hyperparameters

epochs	number of iterations over the data
batch_size	number of instances before adjusting
optmizer	function

Prologue to CNN and RNN

Prologue

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We will start heading towards text generation

Words have relations and influence each other

Word order

s_1 = The dog chased the cat.
s_2 = The cat chased the dog.

(Lane et al., 2019, p. 220)

Words have relations and influence each other

Word order

$$s_1 = \text{The dog chased the cat.}$$
$$s_2 = \text{The cat chased the dog.}$$

$$sim(tfidf(s_1), tfidf(s_2)) = 1$$

(Lane et al., 2019, p. 220)

Words have relations and influence each other

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$s =$ His mother, besides her son's willingness to amend the issue, decided to punish him

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Consider the position of words
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→ fixed-width window

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convolutional neural networks

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convolutional neural networks

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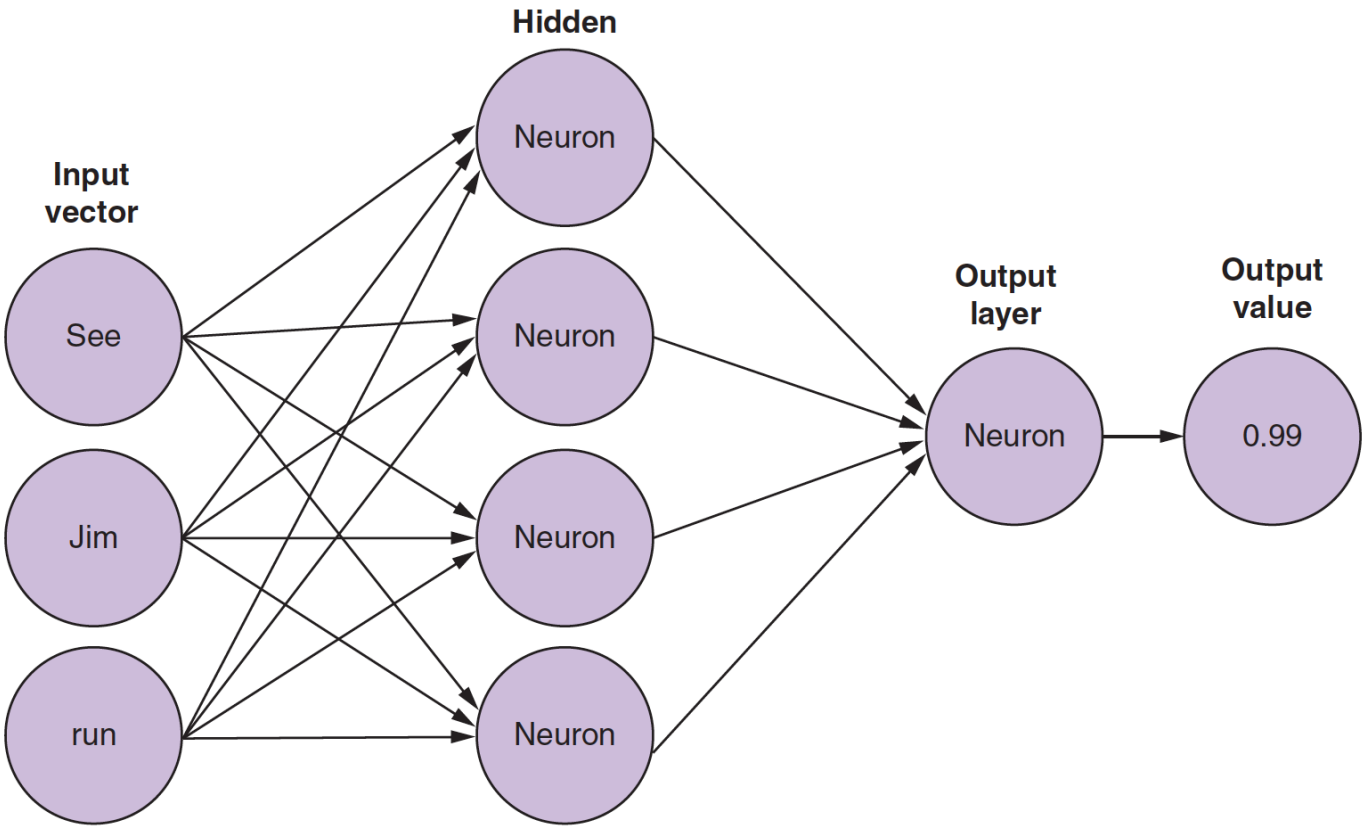
recurrent neural networks

(Lane et al., 2019, p. 220)

Multiple Input Words



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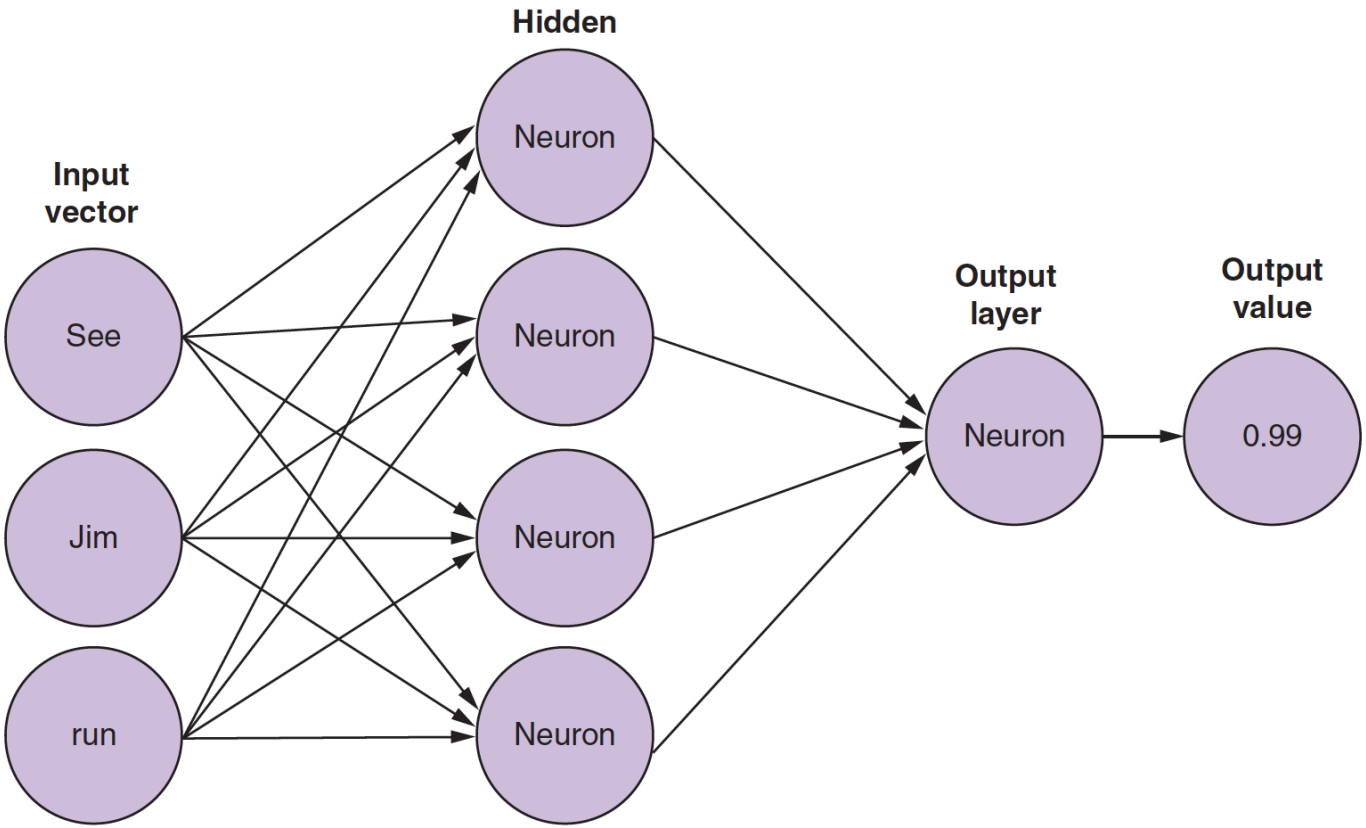

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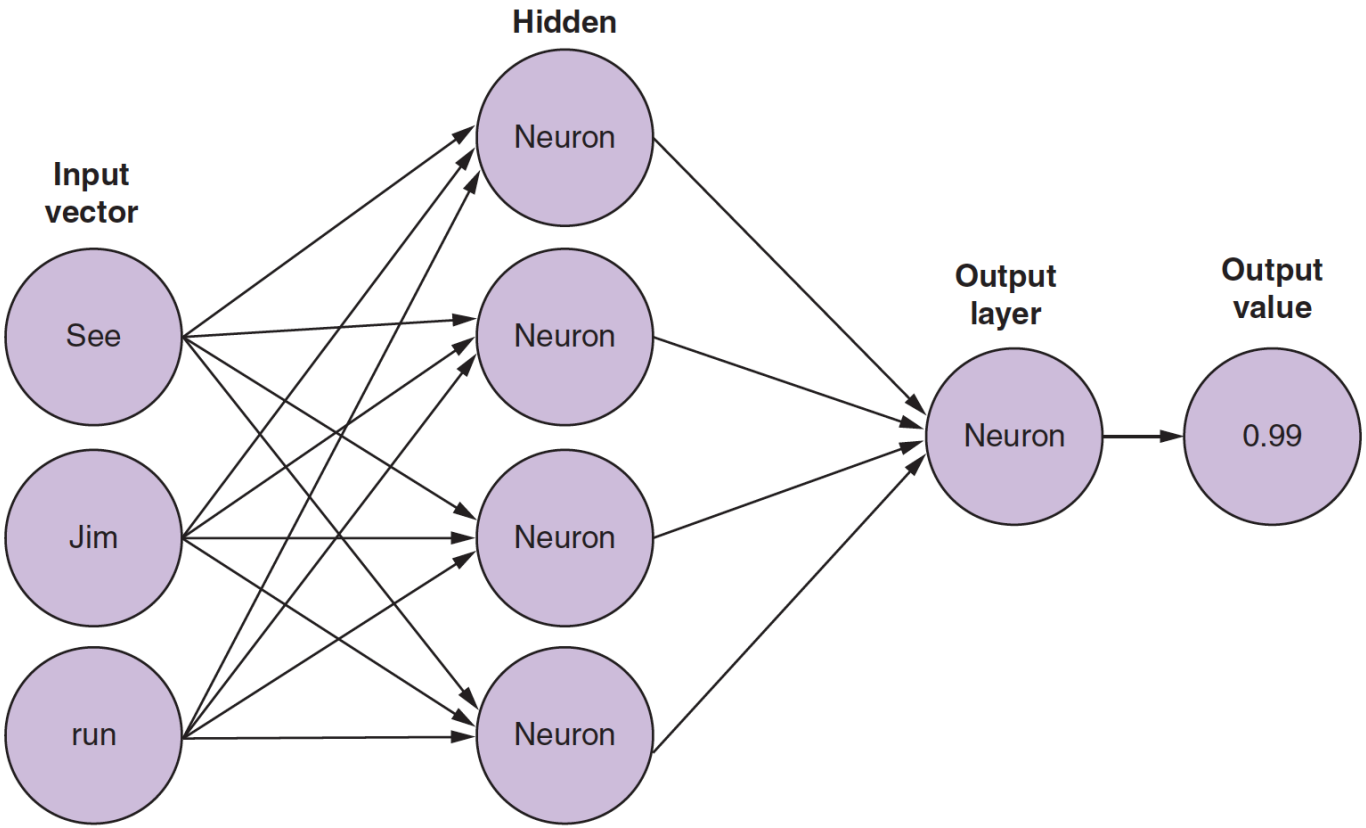

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  - one-hot vector

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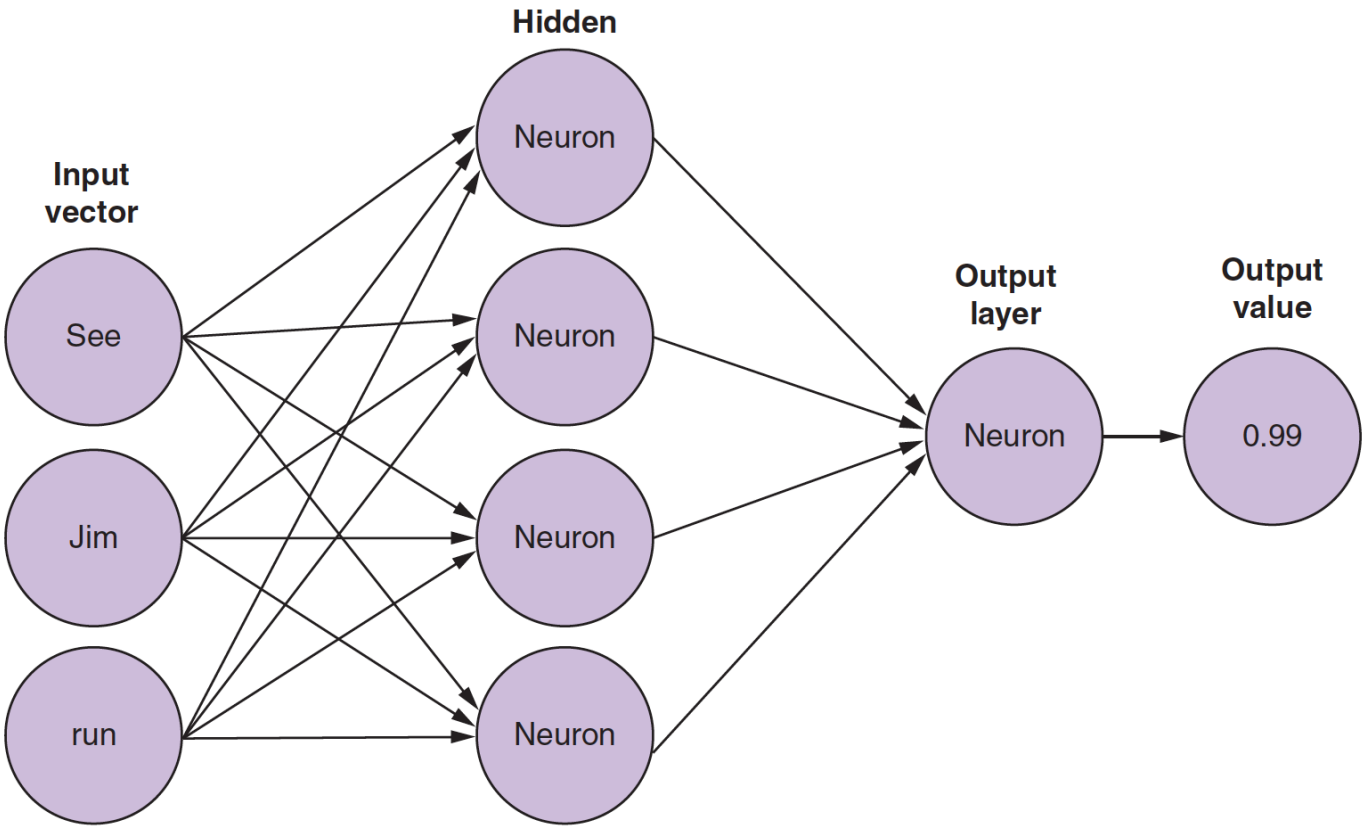

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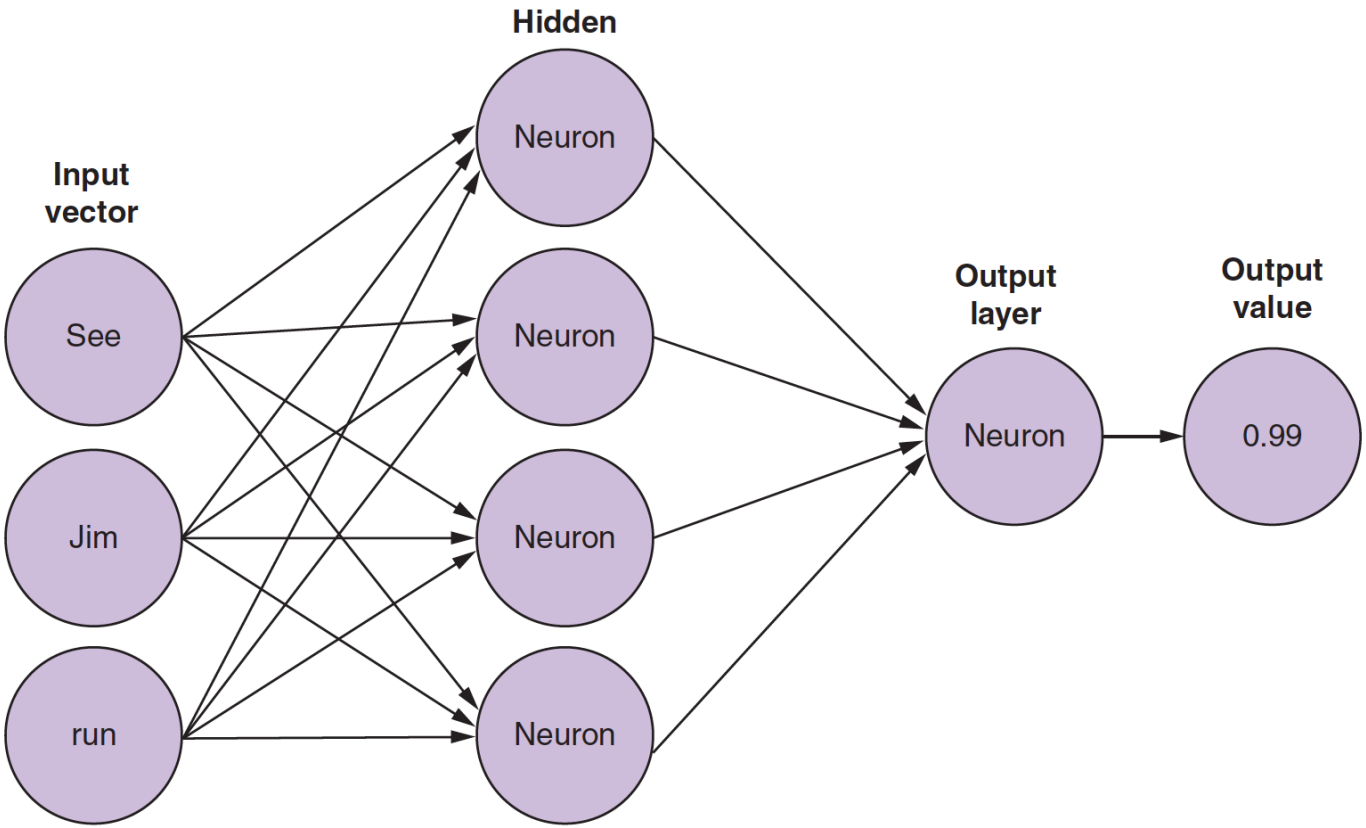

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`See Jim run` $\neq$ `run See Jim` (!)

CNN

Convolutional Neural Networks

Sliding —or convolving[1]— a window over the sample

[1] To roll or wind together (Webster's) (Lane et al., 2019, p. 222)

Convolutional Neural Networks

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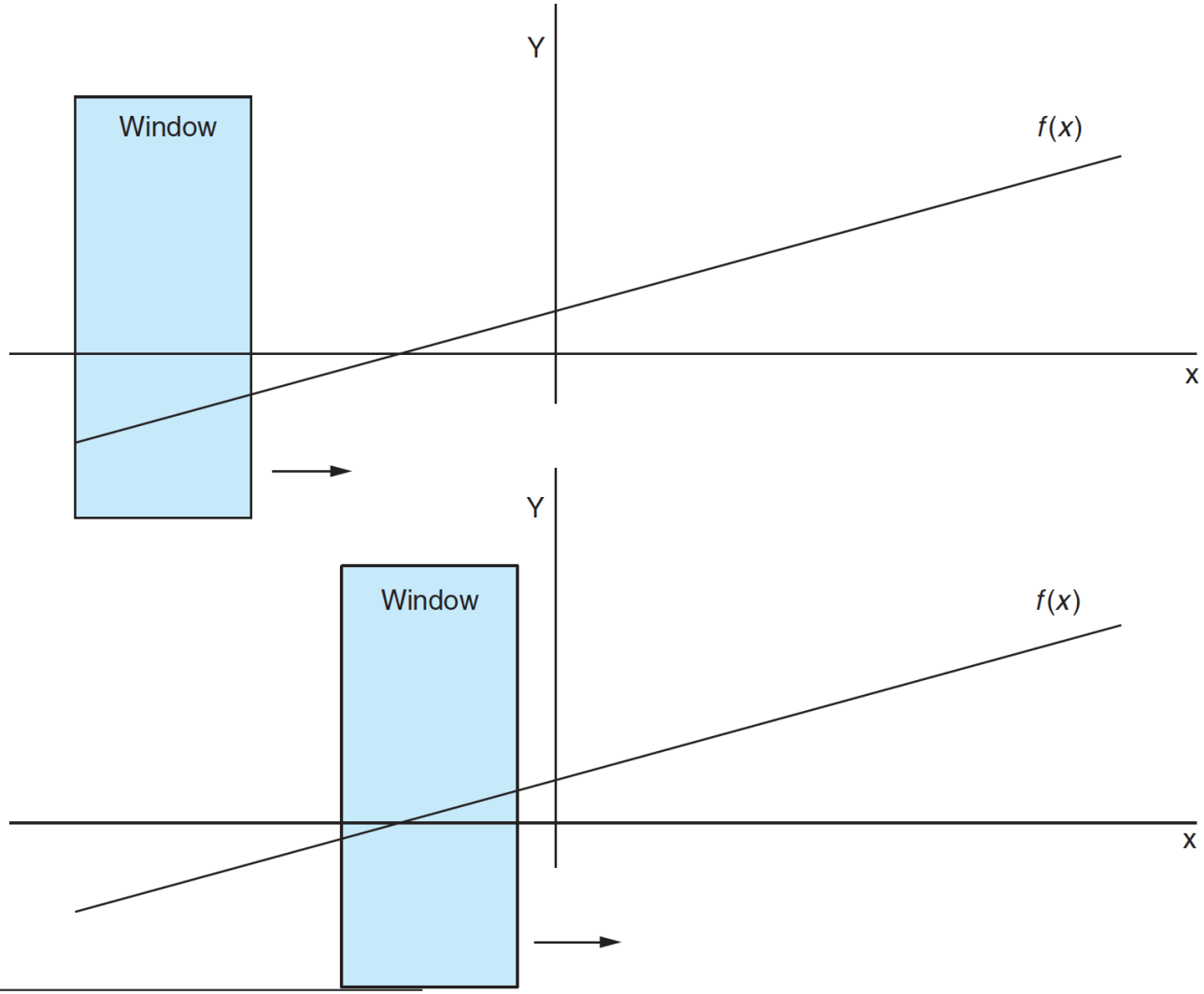

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Convolutional Neural Networks

Back to the roots: image recognition

- Input: pixels of an image
- Output: the image contains x

https://blogs.nvidia.com/wp-content/uploads/2019/04/ADAS-IMG_0052.jpg

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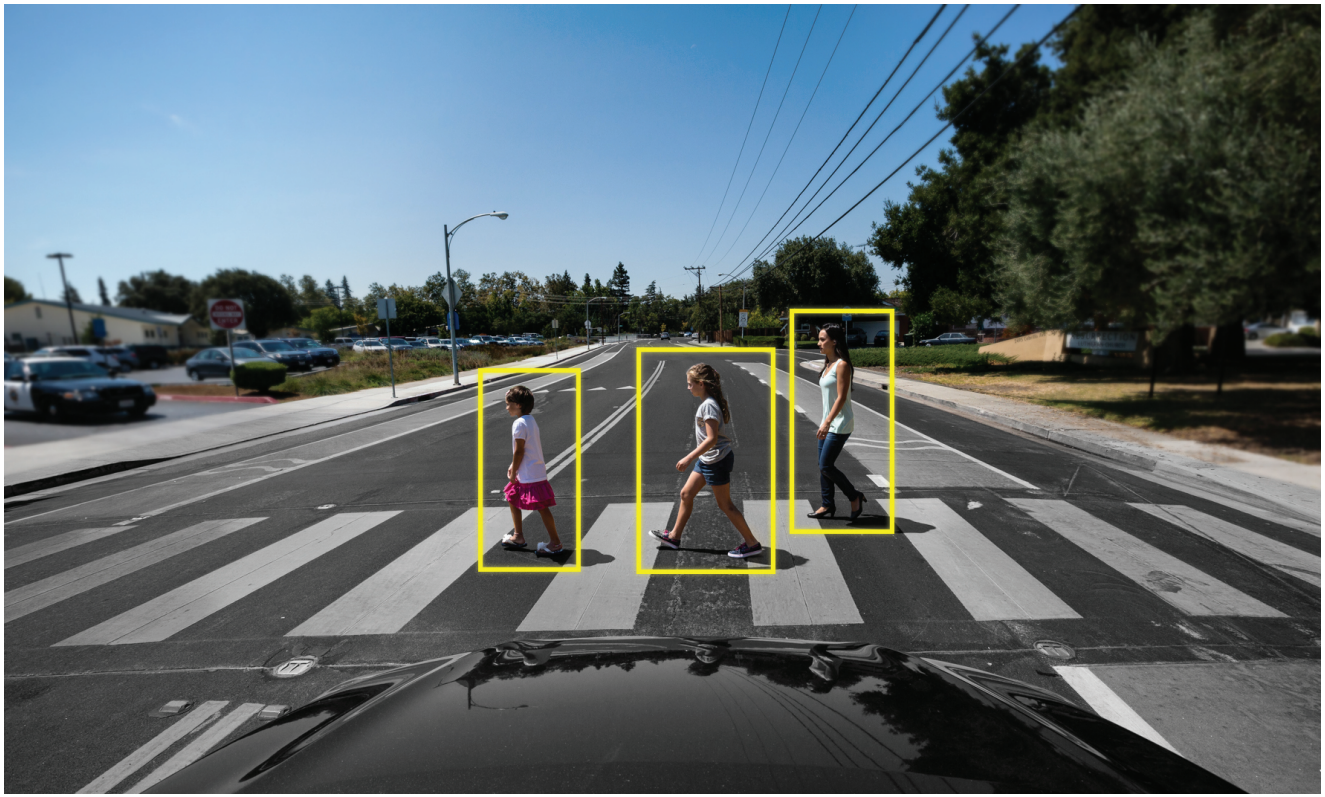

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Convolutional Neural Networks

When the input is an image

- B&W: [0,1] (with a smooth binariser)
- Grayscaled: [0, 255]
- Colour: R: [0, 255] G: [0, 255] B: [0, 255]

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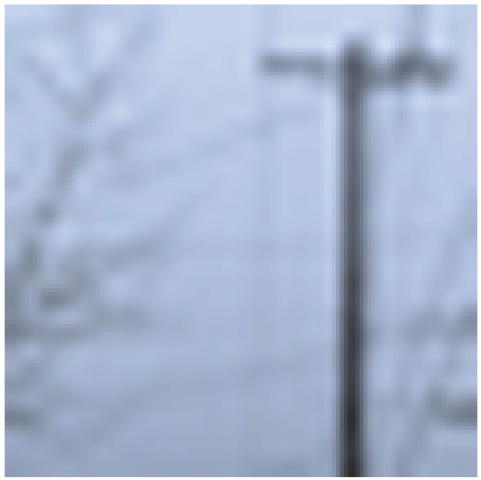

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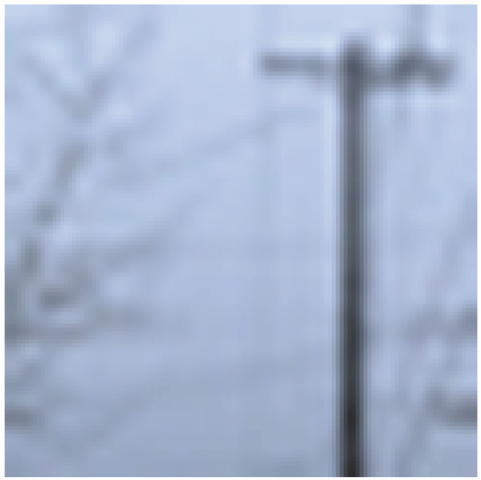

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5	103	112	109	98	100	93	111	112	115	113	117	117	117	116	116	112	118	116	114	110	41	81	110	102	119	114	119	117
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7	111	111	109	105	103	110	103	103	106	111	115	115	114	110	107	103	113	114	115	115	48	87	105	105	114	111	116	115
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24	60	66	82	92	90	90	87	90	94	94	94	94	93	94	92	93	94	95	95	81	0	76	90	92	81	77	65	58
25	87	81	83	86	87	84	90	92	92	92	92	92	92	92	91	92	92	91	92	77	4	73	91	92	81	95	96	95
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27	81	86	88	91	89	89	89	89	89	88	88	89	89	89	84	83	79	80	87	74	0	60	89	77	90	91	90	89

(Lane et al., 2019, p. 223)

Convolutional Neural Networks

When the input is an image

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$\rightarrow$ Sliding over fragments of the image

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The convolution defines a set of filters (aka kernels) to do just that

An image is just a bunch of numbers

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→ Sliding over fragments of the image

The convolution defines a set of filters (aka kernels) to do just that

- Take "snapshots" of different areas of the image
- Process them, one at a time

Stride

- The distance "traveled" when sliding
- Yet another parameter
- Never bigger than the size of the filter $\rightarrow$ overlapping areas

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Sounds familiar?

Convolutional Neural Networks

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Convolutional Neural Networks

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- $n \times m$ surfaces

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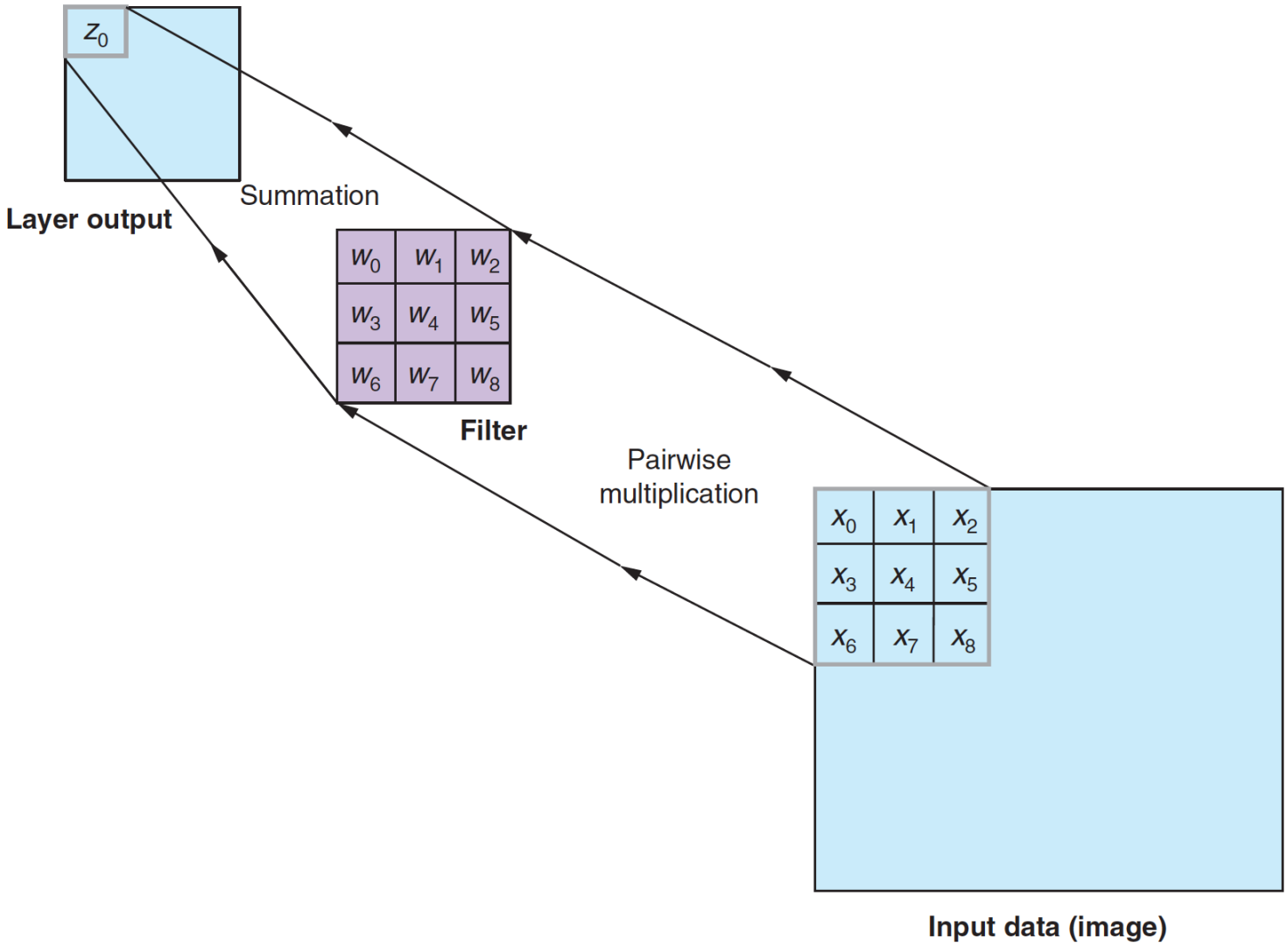
- Typically $n = m = 3$ (often $n \neq m$)
- Includes a set of weights (fix for the whole image)
- Includes an activation function: usually ReLU

$$z = \max(sum(x * w), 0)$$

Convolutional Neural Networks

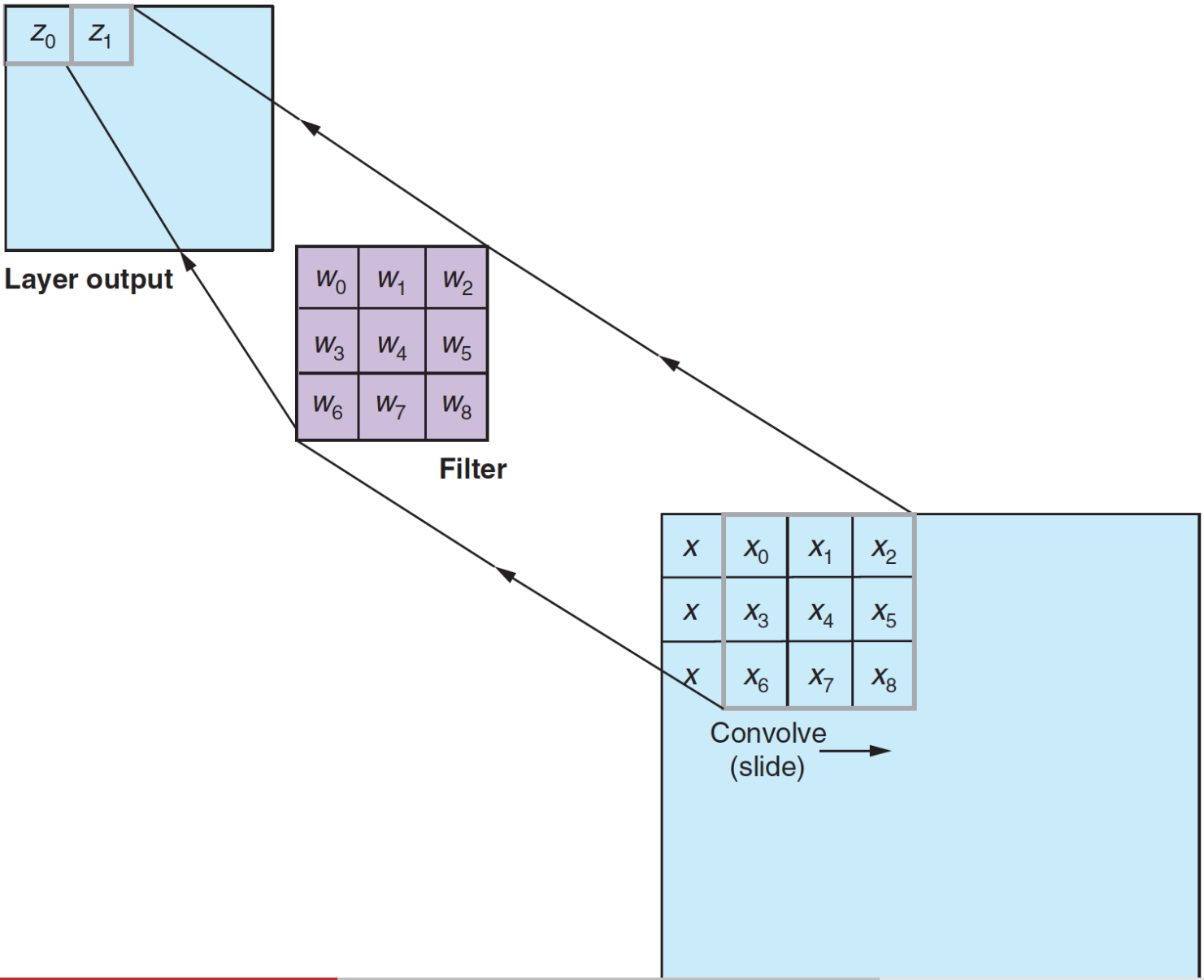
Convolutional step



(Lane et al., 2019, p. 225)

Convolutional Neural Networks

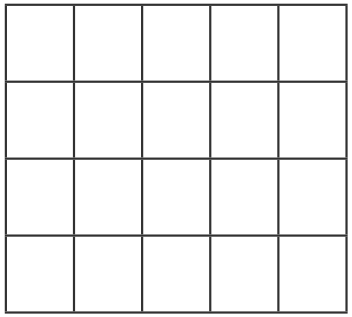
Convolution



- k filters exist which carry out different operations
- Every filter will produce a new image, combination of source and filter

Convolutional Neural Networks

Padding



input

Convolutional Neural Networks

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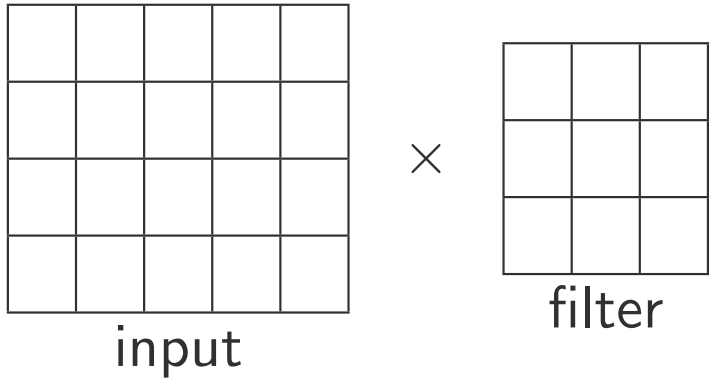

Convolutional Neural Networks

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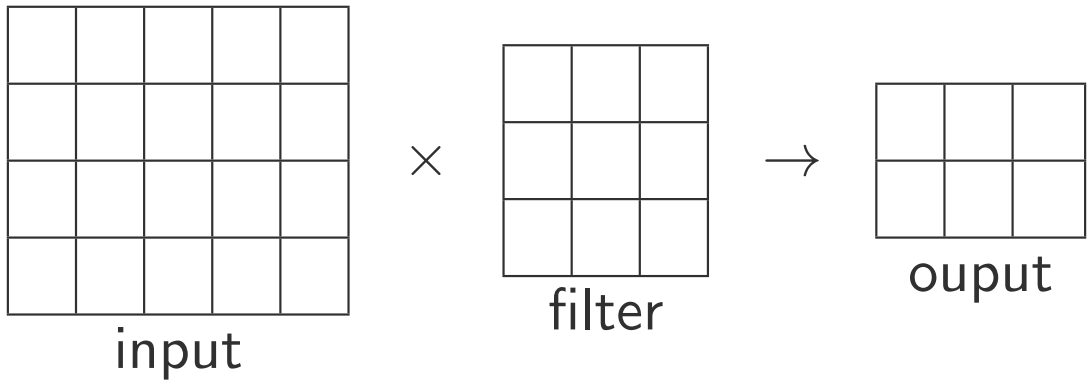

Convolutional Neural Networks

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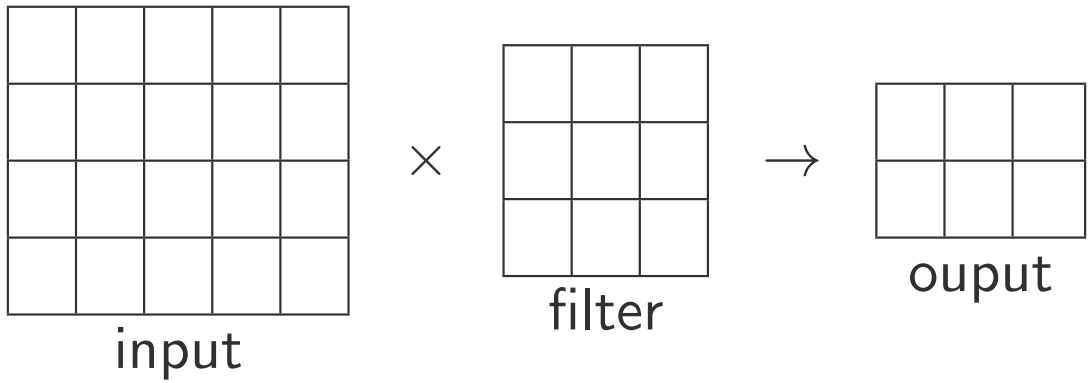

We are producing smaller images

"I don't care": Keras' argument `padding='valid'`

Convolutional Neural Networks

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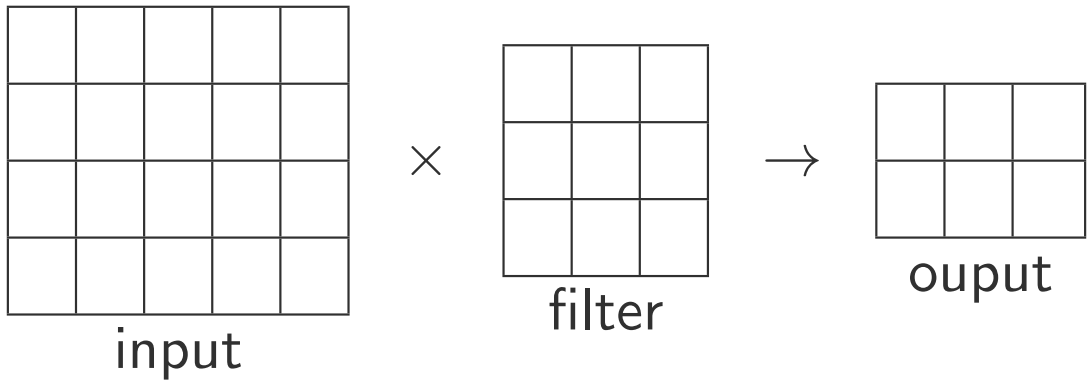

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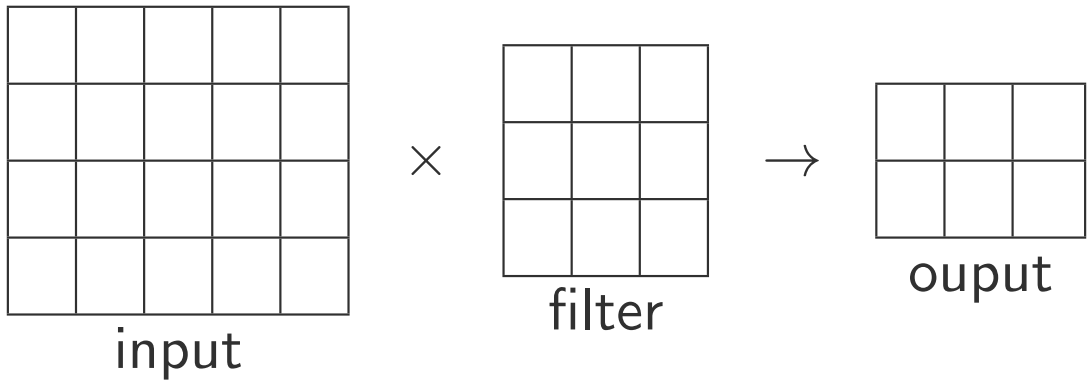

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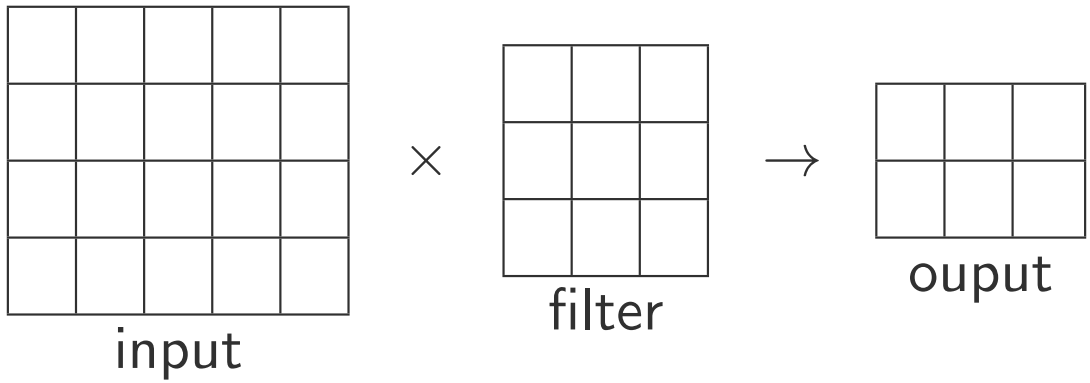

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In NLP we care

Convolutional Neural Networks

Pipeline

Input: an image, text

Output: a class, a real number

- Produce k new images through k filters

Convolutional Neural Networks

Pipeline

Input: an image, text

Output: a class, a real number

- Produce k new images through k filters
- Wire the filtered images to a feed-forward network

Convolutional Neural Networks

Pipeline

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What is learned

- Good filters
- "Standard" weights

Convolutional Neural Networks

Keras premier

```
from keras.models import Sequential
from keras.layers import Conv1D

model = Sequential()

model.add(Conv1D(filters=16,
                 kernel_size=3,
                 padding='same',
                 activation='relu',
                 strides=1,
                 input_shape=(100, 300))
)
```

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- Sliding —or convolving— a window over the sample

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- At the end, we can plug a "standard" fully-connected NN

CNNs for NLP

Back to Text

- In images both vertical and horizontal relationships are relevant

[2] l2r or r2l; for some languages it's the vertical direction that matters (e.g., Japanese) (Lane et al., 2019, p. 229)

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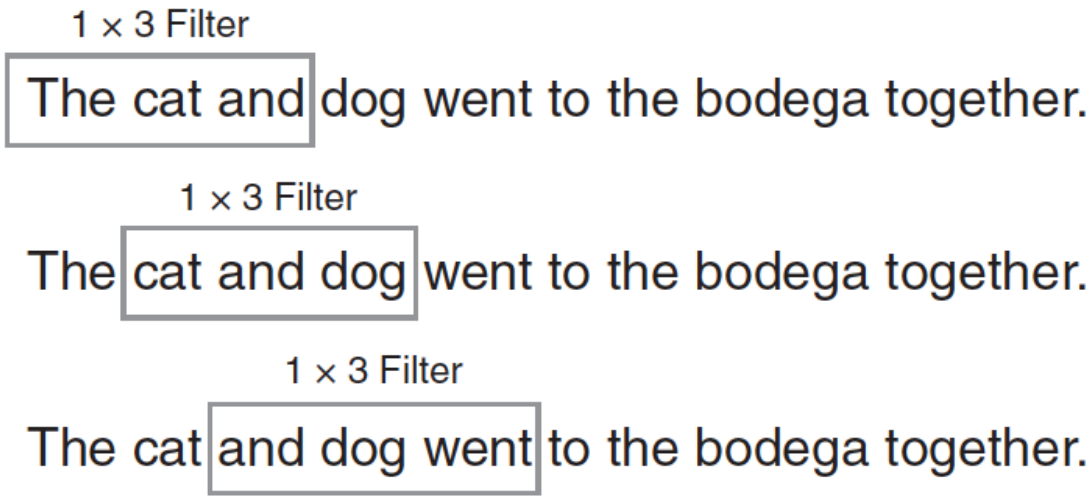
- In images both vertical and horizontal relationships are relevant
- In text only horizontal ones do[2]
- We need "1D" filters



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Words are represented with word embeddings: vectors

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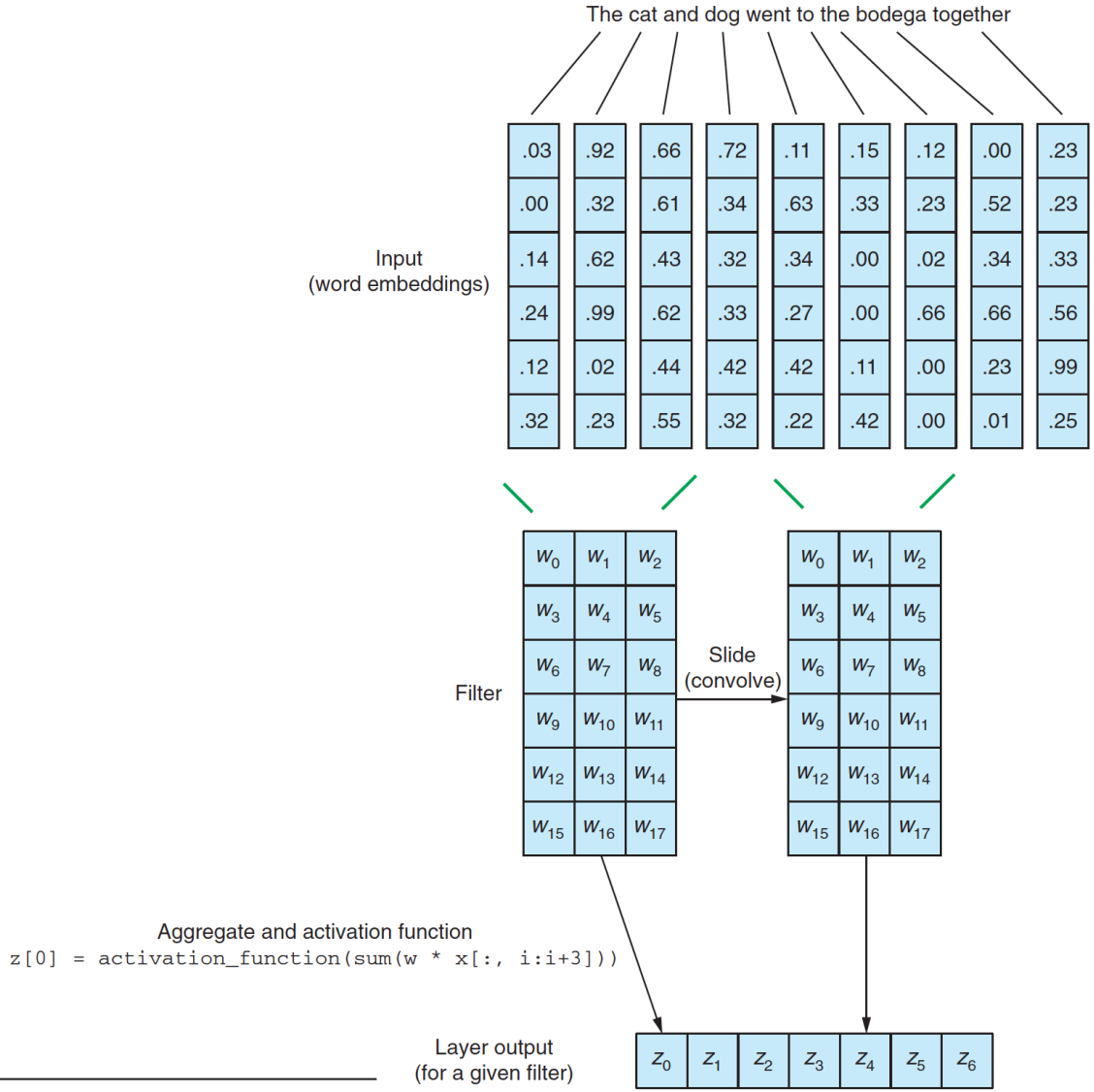

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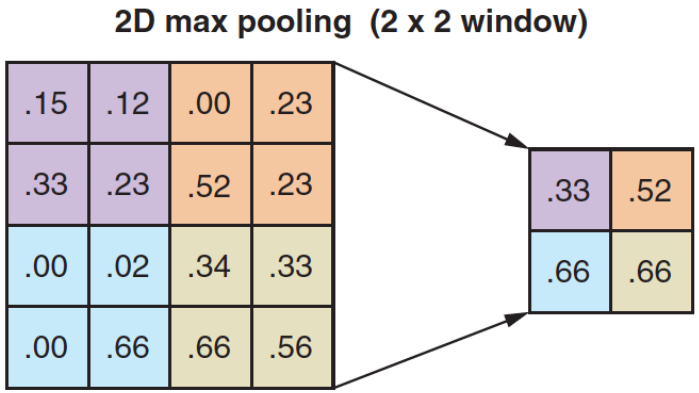

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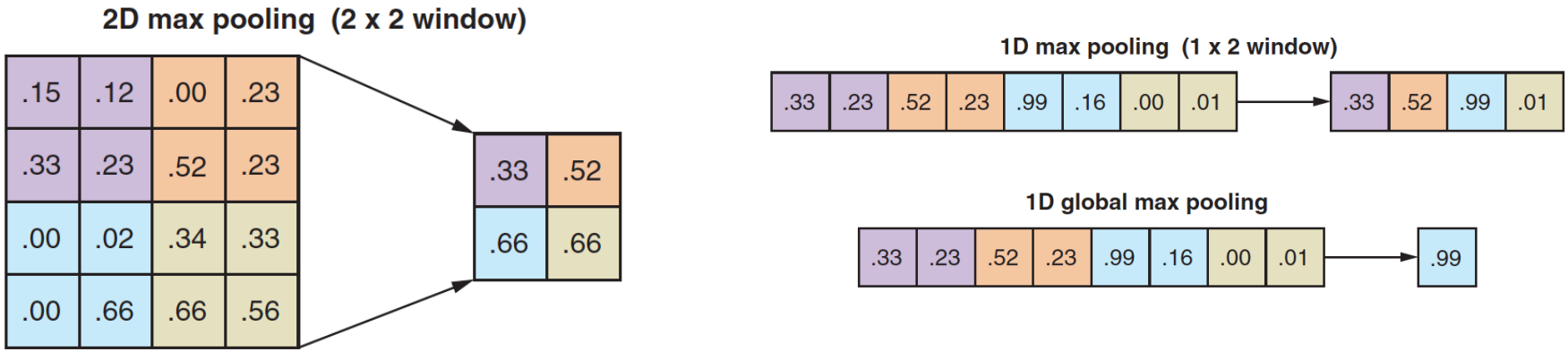

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Max vs Average Pooling

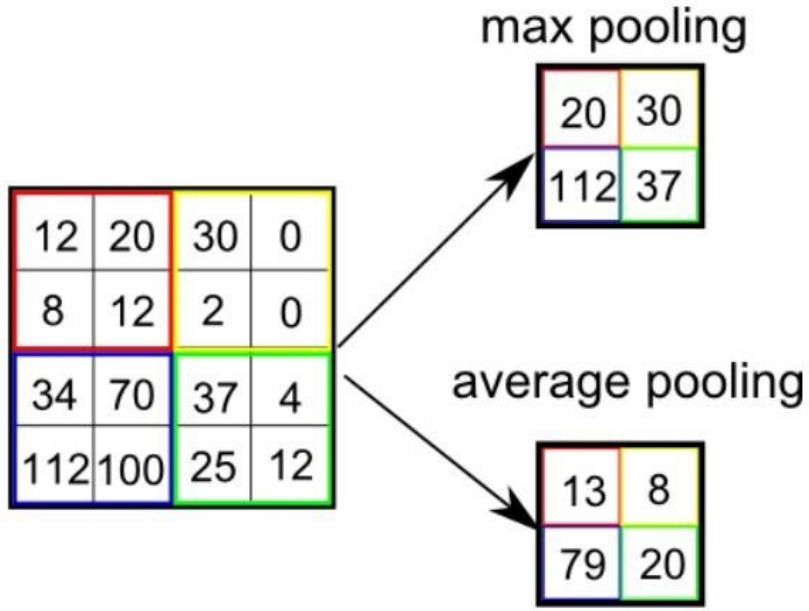

Image borrowed from
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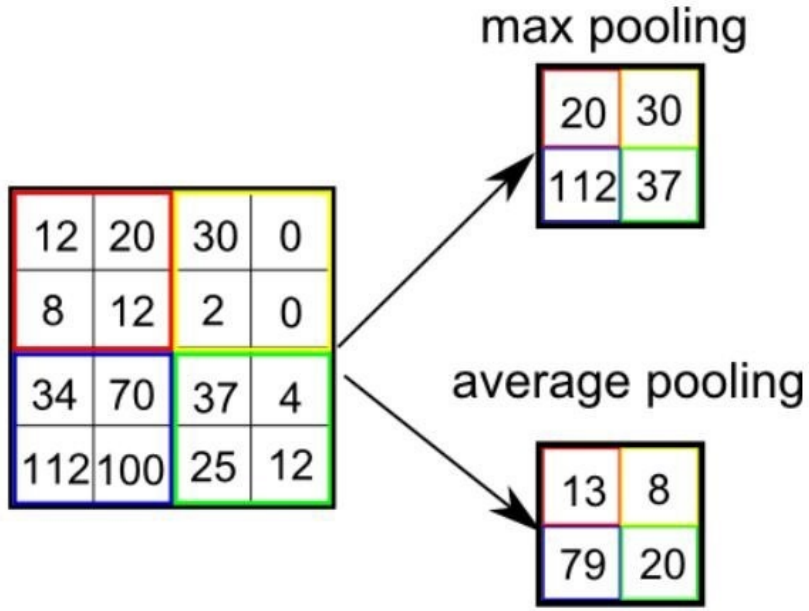

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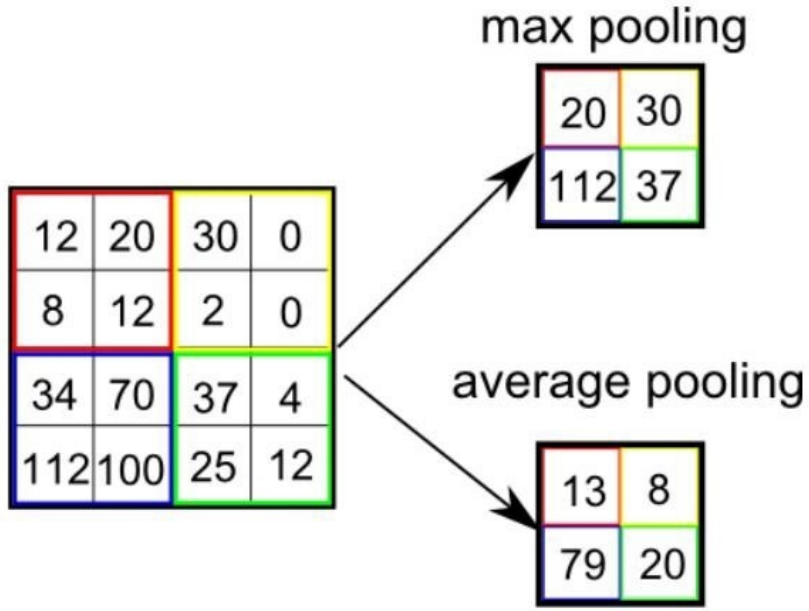

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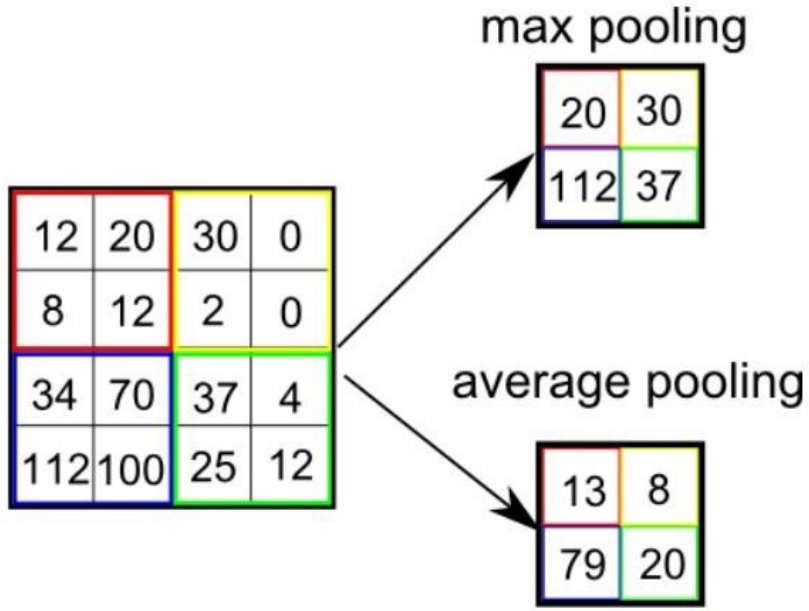

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This is a crude semantic representation of the text

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- Chosen randomly on each pass

Photogram from the film "The Platform" (2019)

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Image borrowed from `https://blog.mapillary.com`

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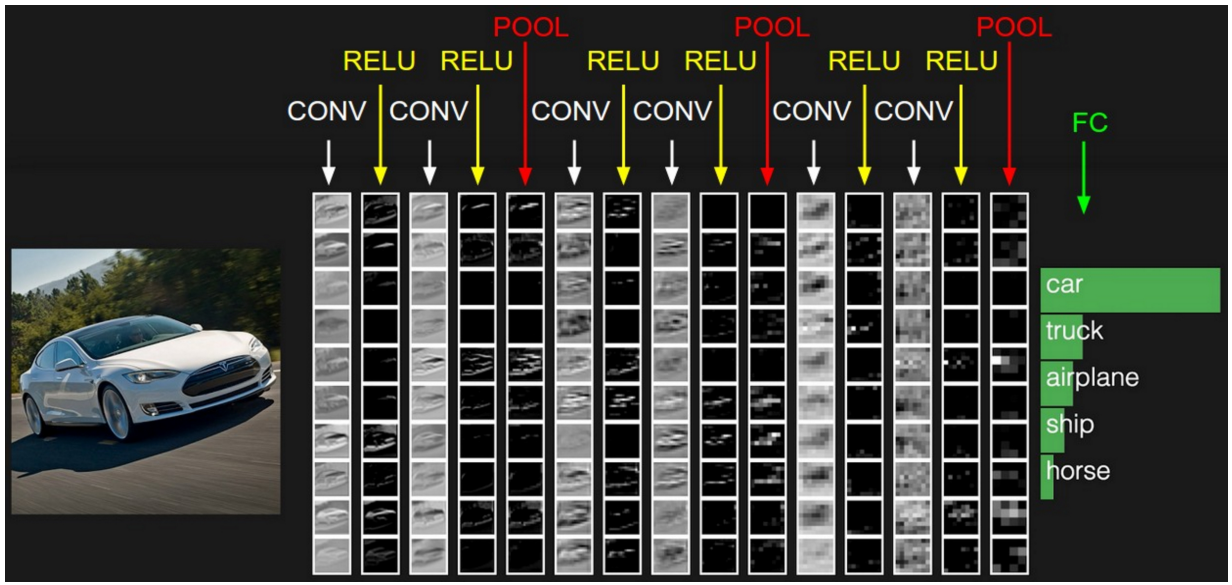

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Next time

- Recurrent Neural Networks

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.