92586 Computational Linguistics

Lesson 16. From document representations, towards sequences

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Previously

- Training and loading (existing) embeddings
- Visualisation

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Chapters 6 and 7 of Lane et al. (2019)

Doc2vec

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Objective Computing a vectorial representation of a document.

Le and Mikolov (2014); (Lane et al., 2019, p. 215)

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- A unique ID of the sentence/paragraph/document

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- 1 target word

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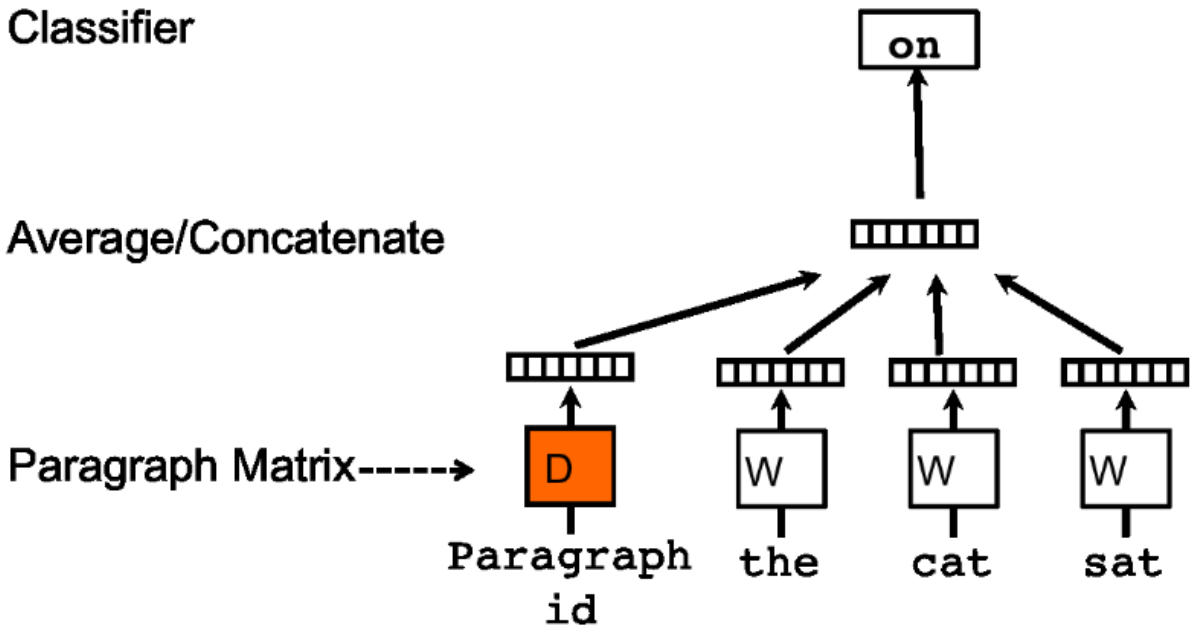
- The paragraph vector is unique among all documents
- The word vectors are shared among all documents
- The document vector is computed **on the fly**

Le and Mikolov (2014); (Lane et al., 2019, p. 215)

Doc2vec

Distributed Memory Model of Paragraph Vectors (PV-DM)

Derived from CBOW



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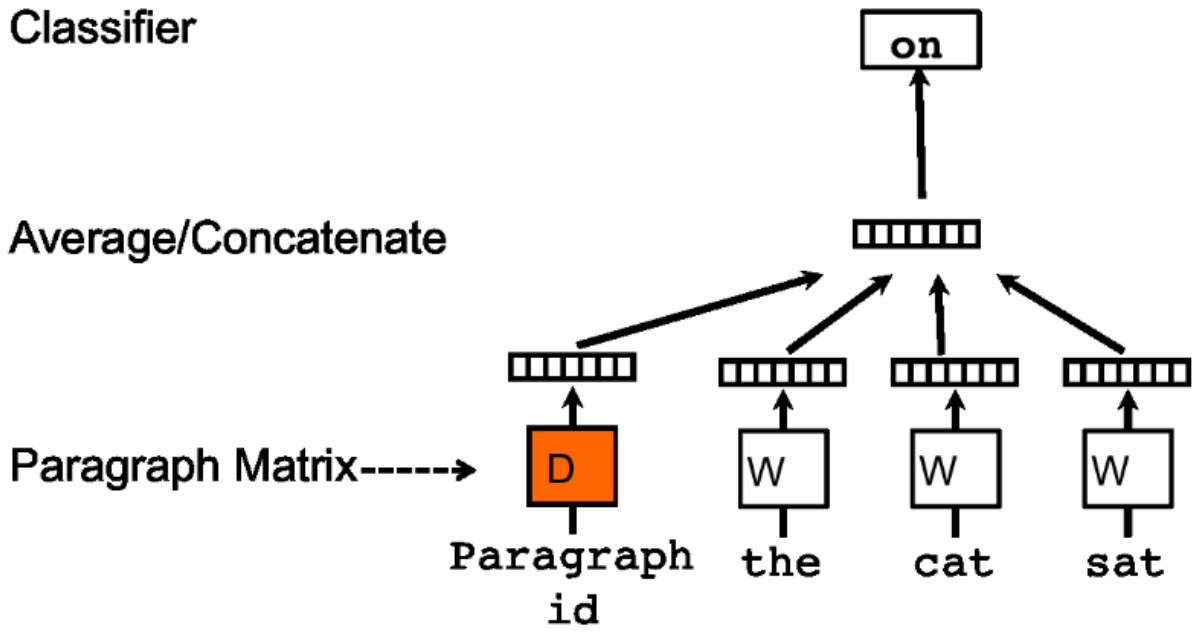

- Each column in the paragraph matrix is a vector representing one paragraph

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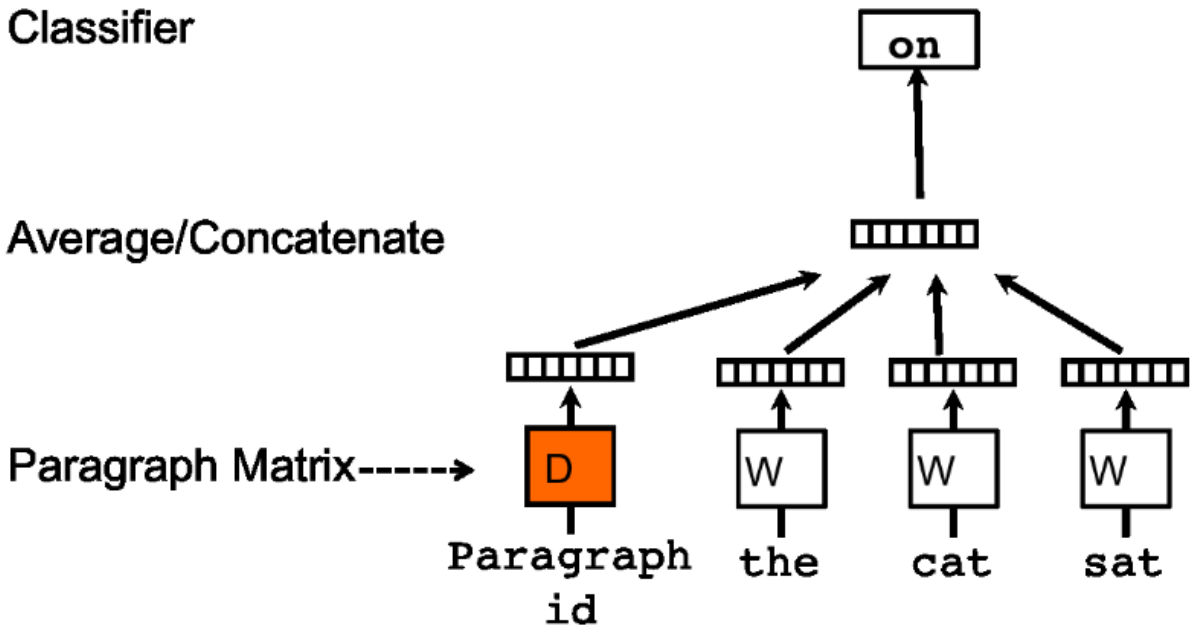
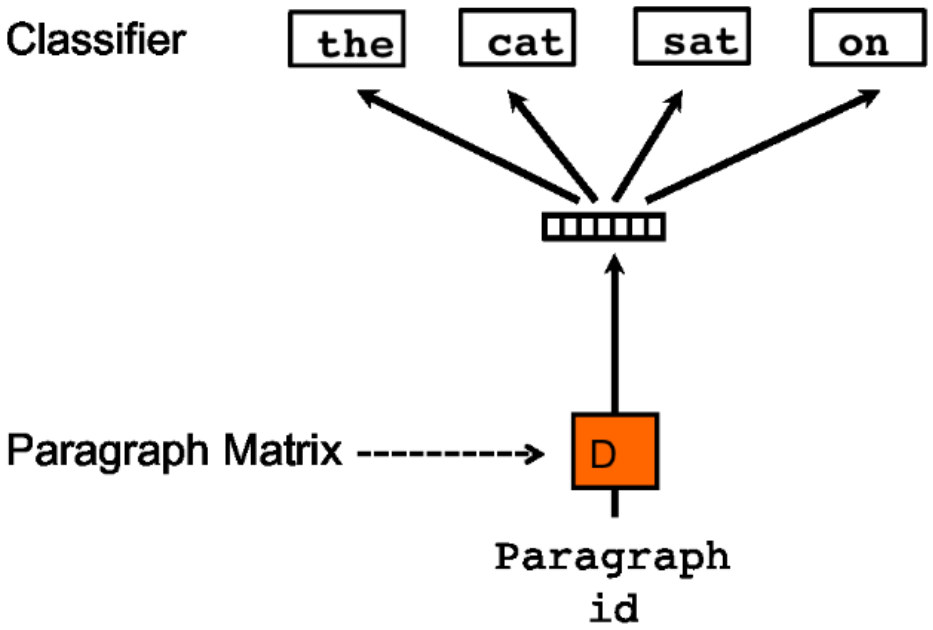


- Each column in the paragraph matrix is a vector representing one paragraph
- We can average or concatenate the word and paragraph vectors

Doc2vec

Distributed Bag of Words version of Paragraph Vector (PV-DBOW)

Similar to skip-gram



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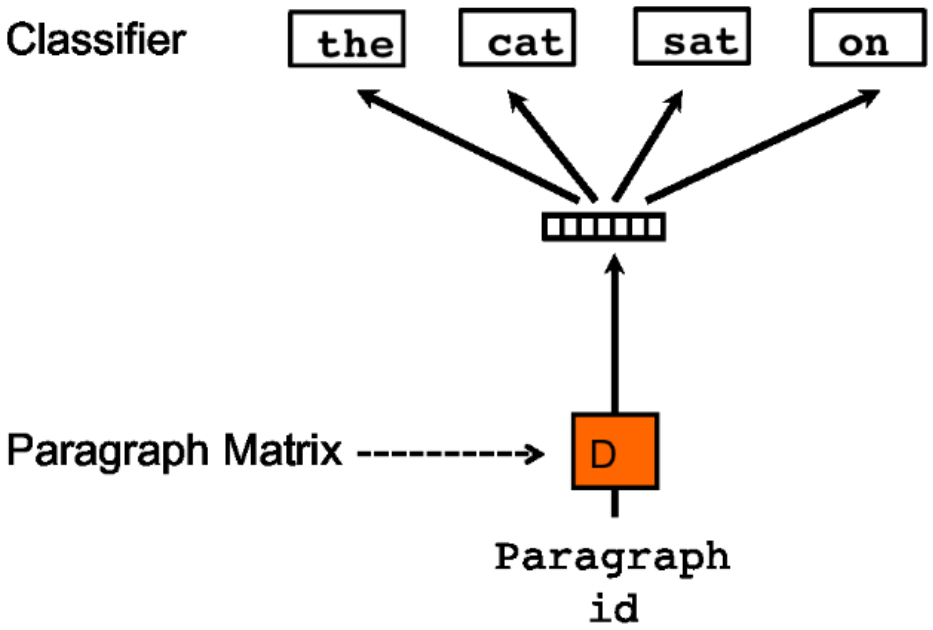

- Iteration: a text window and a random word from the text window are sampled, forming a classification task given the paragraph vector.
- No word vectors: faster + lower memory requirements

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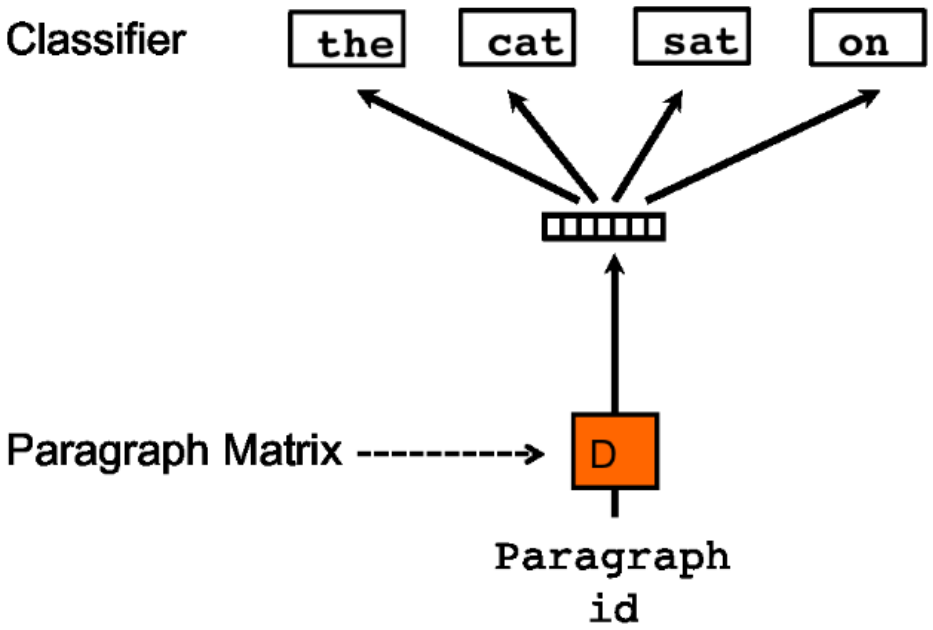

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Let us see

Prologue to CNN and RNN

Prologue

- We have learned to build embedding spaces for words and texts

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We will start heading towards text generation

Words have relations and influence each other

Word order

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

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

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recurrent neural networks

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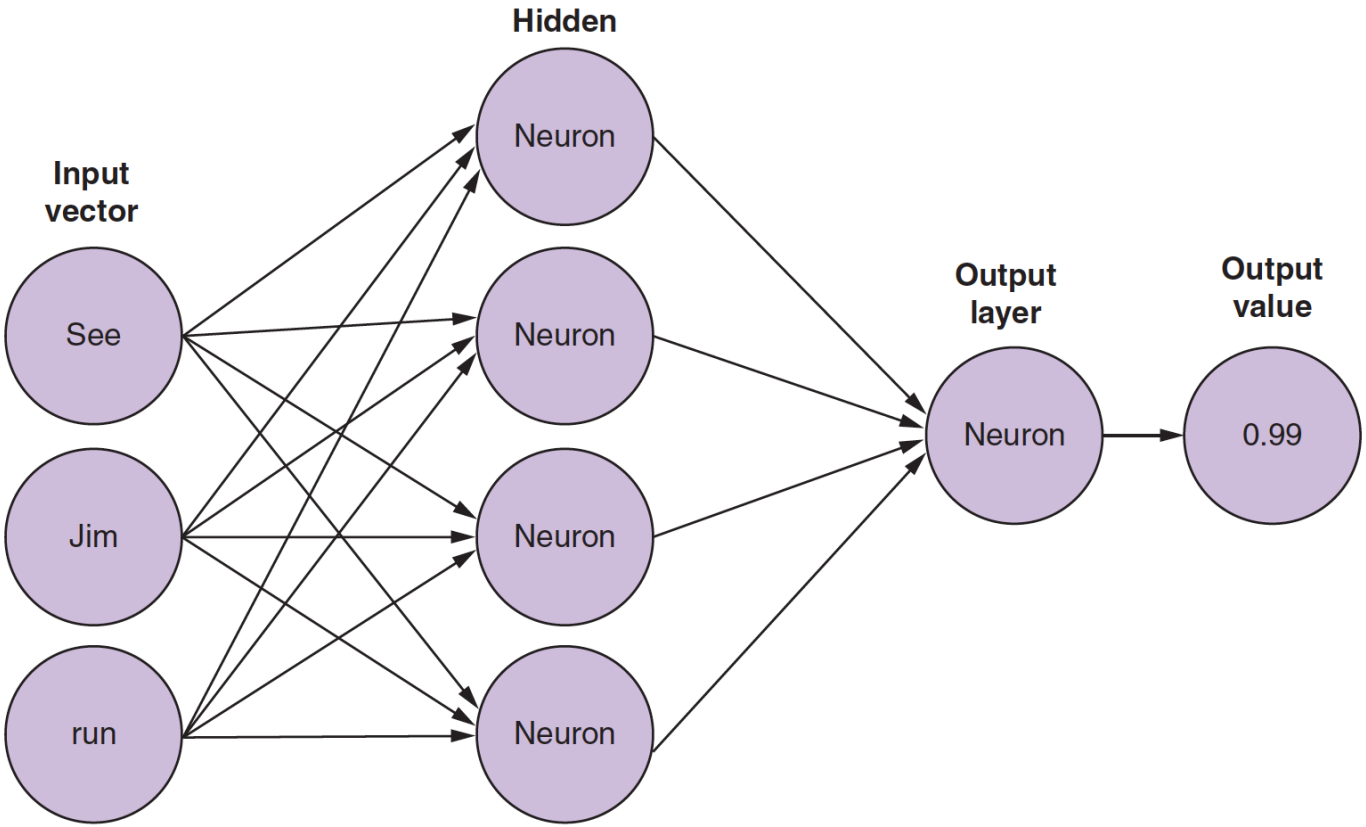
Multiple Input Words



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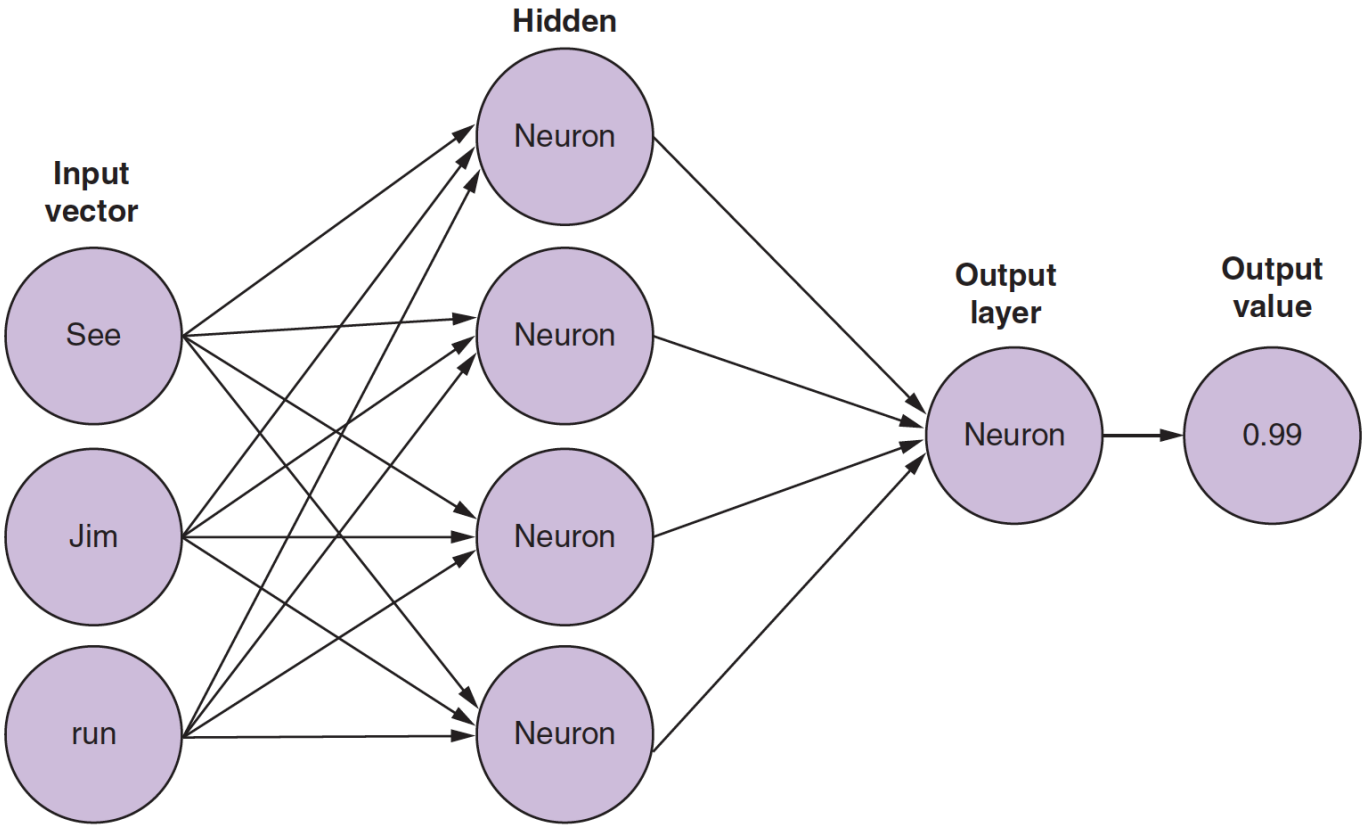

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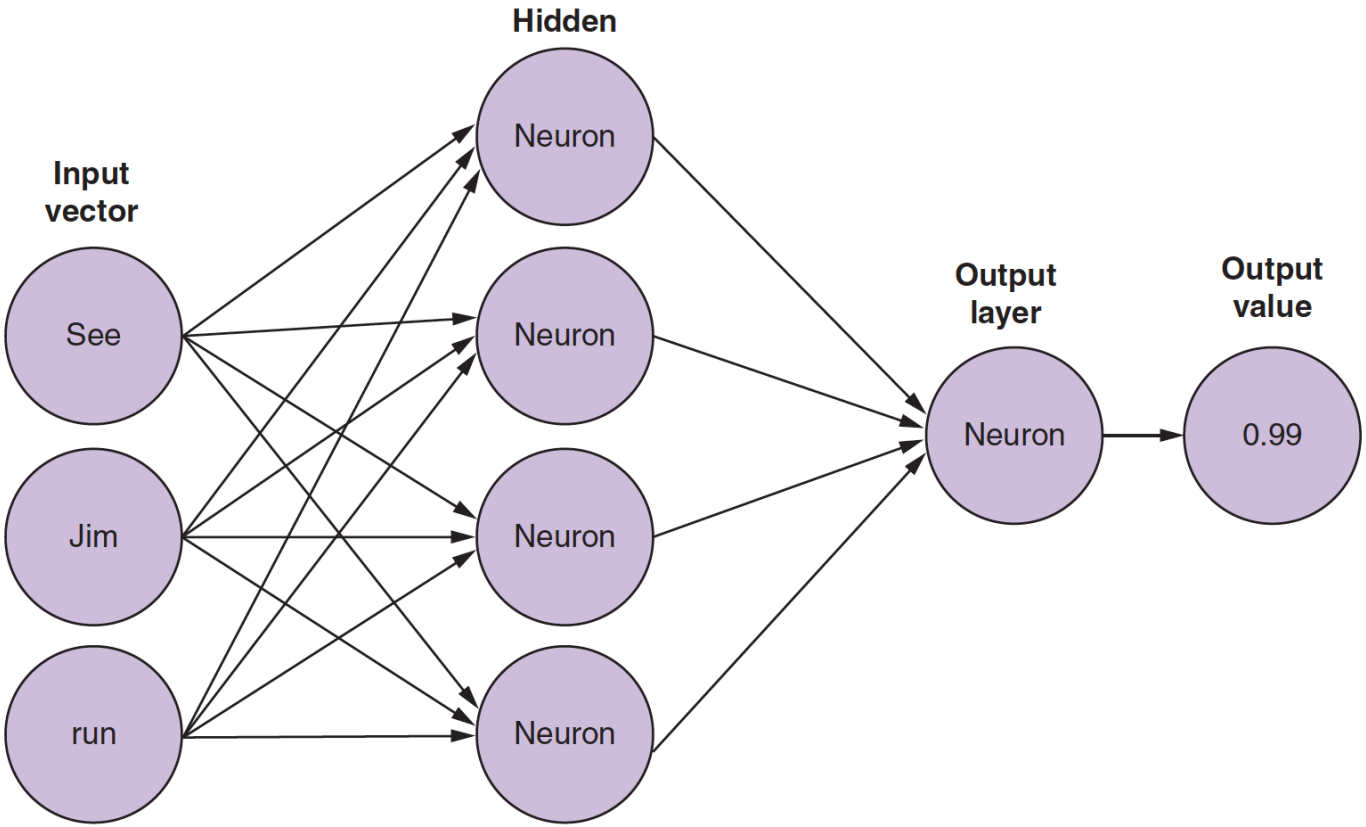

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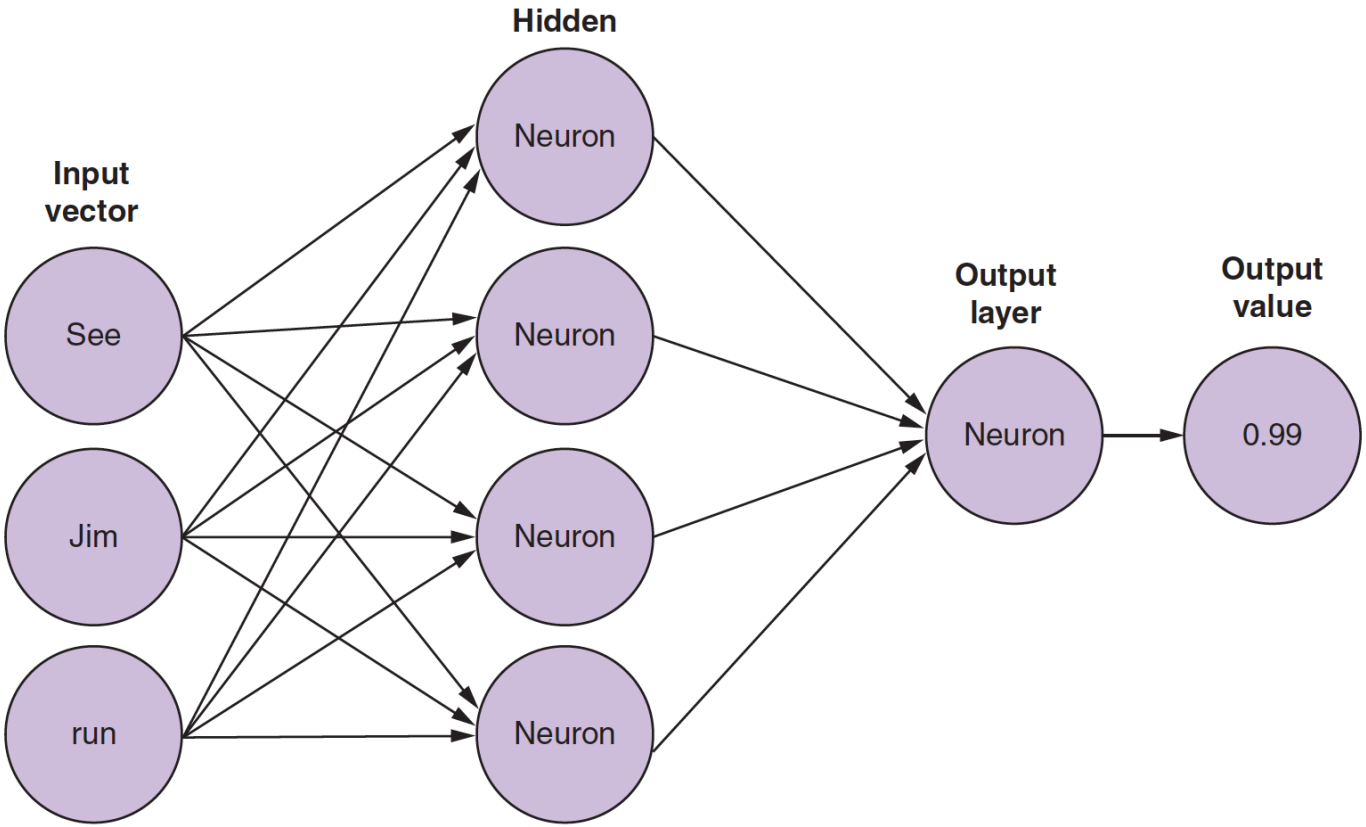

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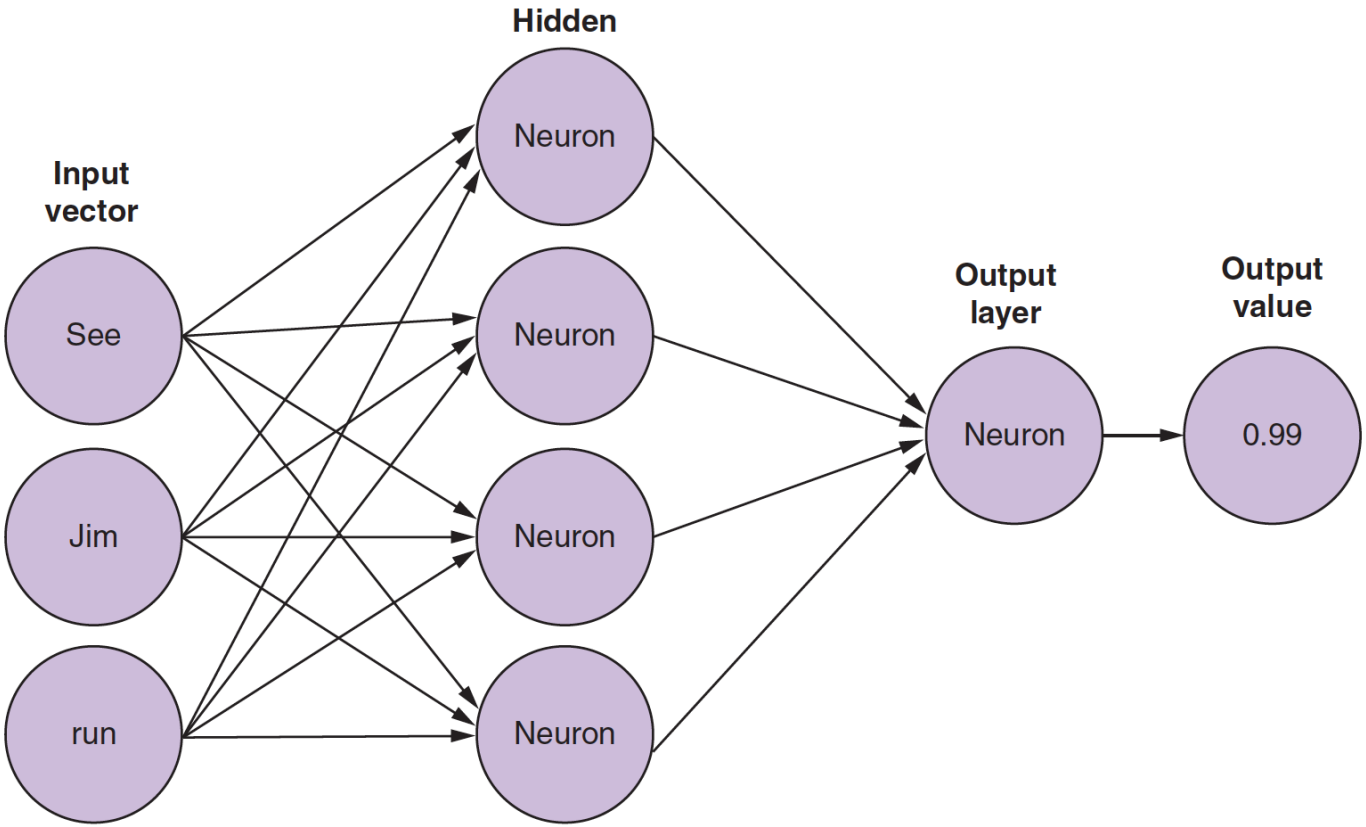

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`See Jim run` $\neq$ `run See Jim` (!)

Back to Keras

Sequential()

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

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Some "cooking" hyperparameters

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

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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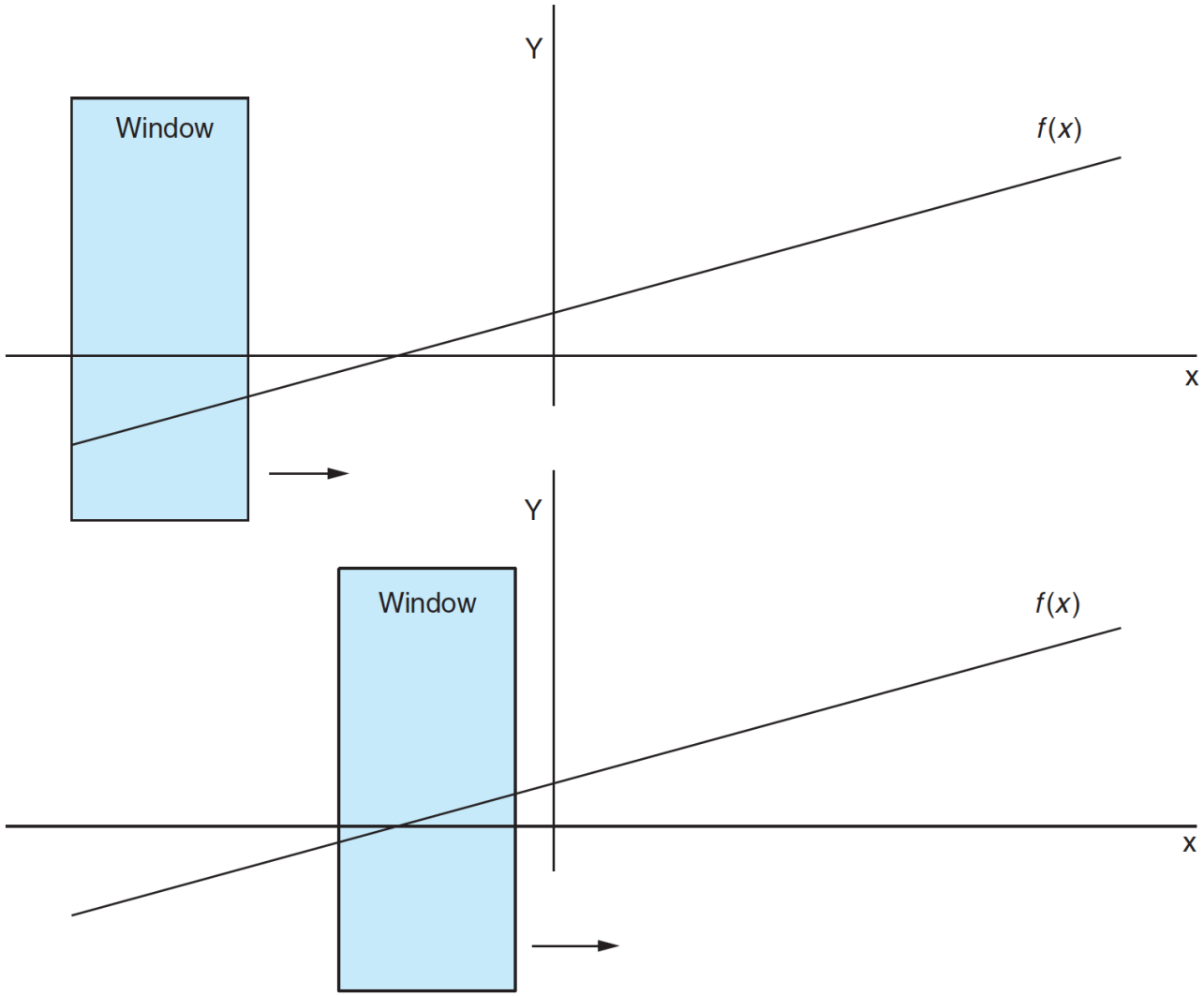

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Convolutional Neural Networks

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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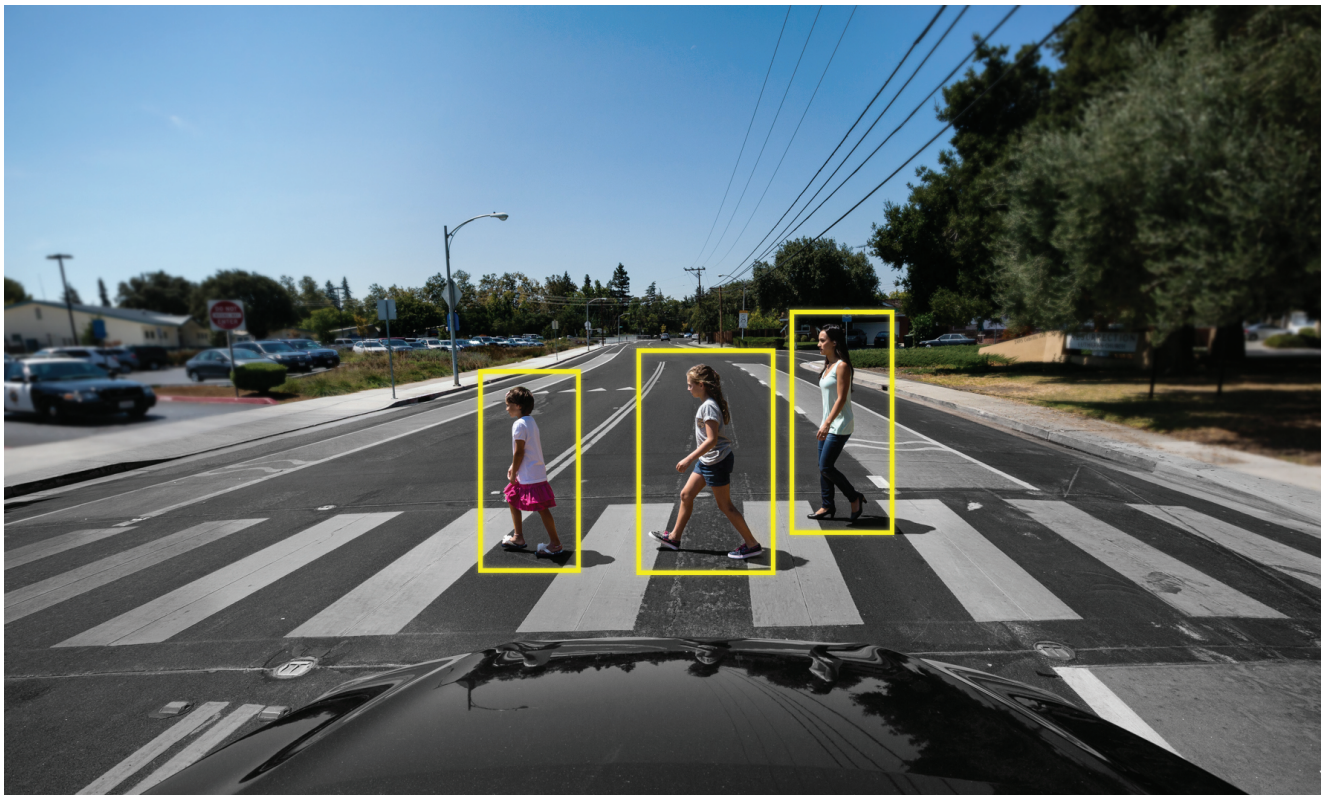

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Convolutional Neural Networks

When the input is an image

- B&W: [0,1] (with a smooth binariser)
- Grayscaled: [0, 255]
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(Lane et al., 2019, p. 223)

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	0	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	26	27
0	120	119	118	108	103	111	113	115	111	117	120	120	120	119	121	114	118	120	120	120	121	121	121	115	100	120	118	117
1	111	109	111	106	107	118	120	110	106	117	120	119	119	119	121	114	118	119	118	119	118	114	119	109	102	122	114	117
2	109	114	121	116	108	119	118	104	111	119	119	119	119	119	119	110	119	121	122	124	73	92	128	100	87	119	115	119
3	109	102	114	117	108	116	108	111	117	118	118	117	119	117	118	79	75	80	76	87	36	63	86	51	55	72	91	120
4	108	110	100	116	111	95	104	110	114	117	117	117	117	117	117	106	107	108	94	90	42	54	70	62	86	70	96	118
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19	60	71	77	77	80	88	92	91	93	96	96	101	100	101	100	98	101	101	104	92	13	64	93	89	81	89	81	79
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21	92	80	88	99	100	98	100	100	100	97	98	97	97	96	92	91	92	93	96	87	13	79	105	95	98	96	89	100
22	77	80	88	92	96	97	96	95	93	92	93	92	92	92	91	94	96	95	98	89	12	79	103	91	100	89	98	104
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26	87	88	88	83	85	91	91	89	90	91	92	91	91	91	89	90	92	90	89	73	8	66	92	83	84	92	91	91
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

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$\rightarrow$ **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

Convolutional Neural Networks

Strides and filters

Stride

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

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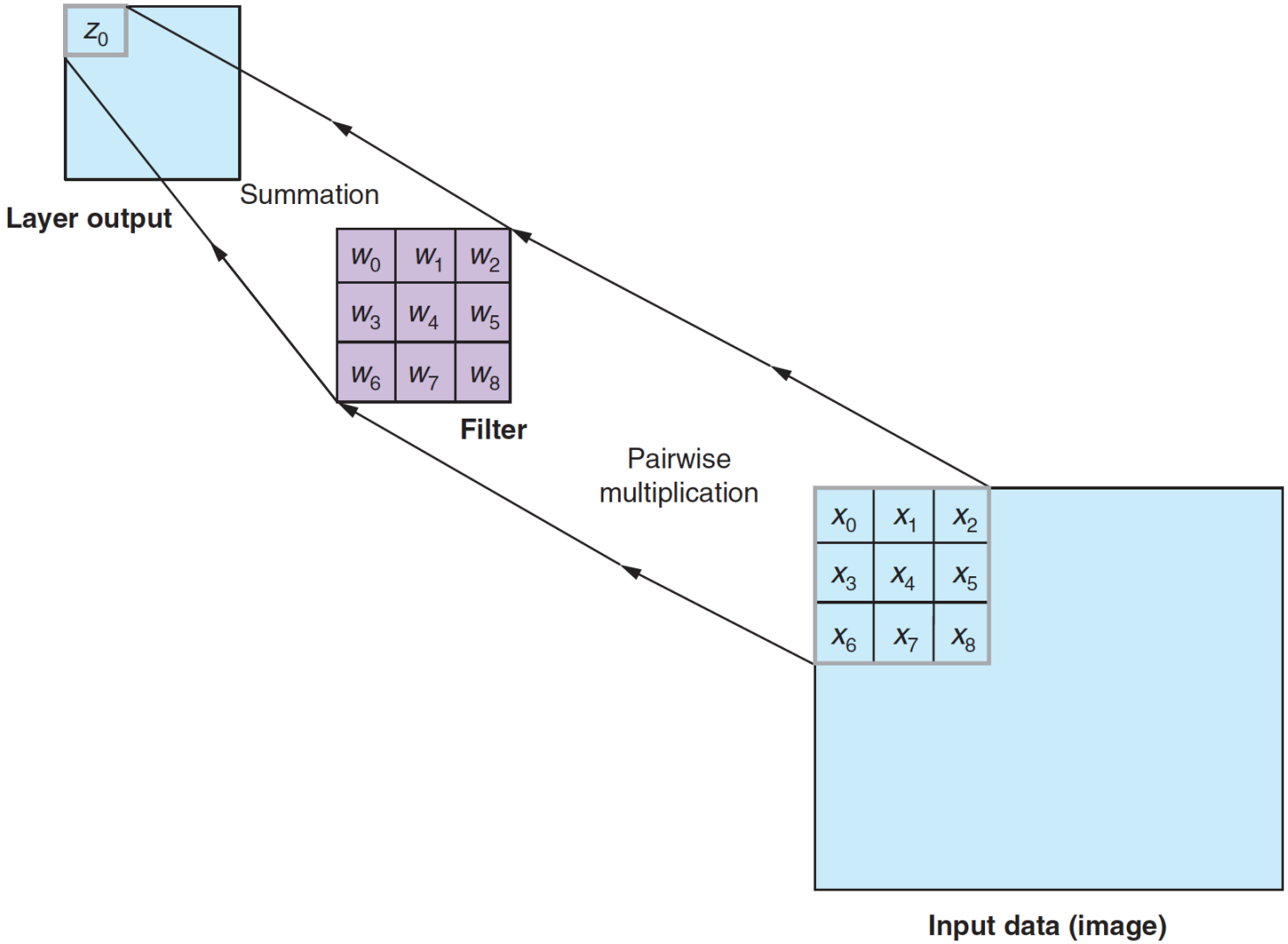
- Typically $n = m = 3$ (often $n \neq m$)
- Includes a set of weights (fix for the whole image)
- Includes an activation function: usually ReLU

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

Convolutional Neural Networks

Convolutional step



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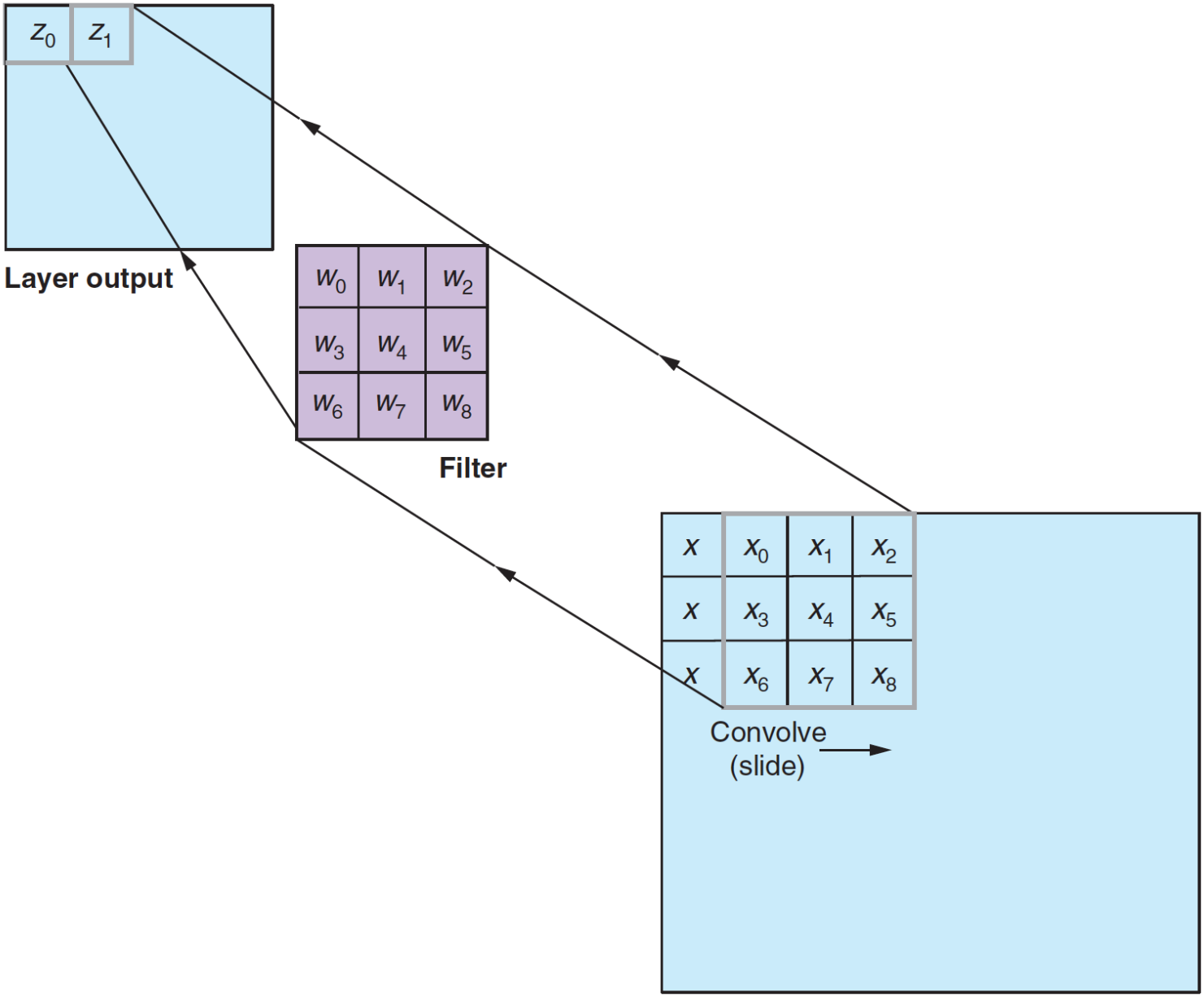
Convolutional Neural Networks

Convolution



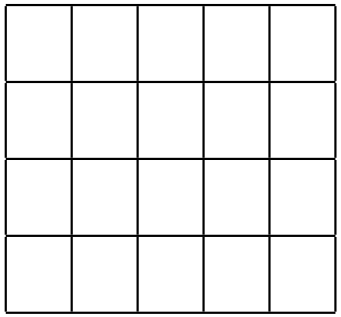
Convolutional Neural Networks

Producing multiple images

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

Convolutional Neural Networks

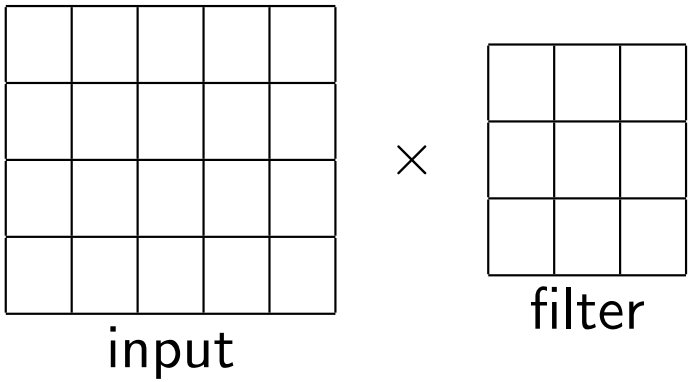
Padding



input

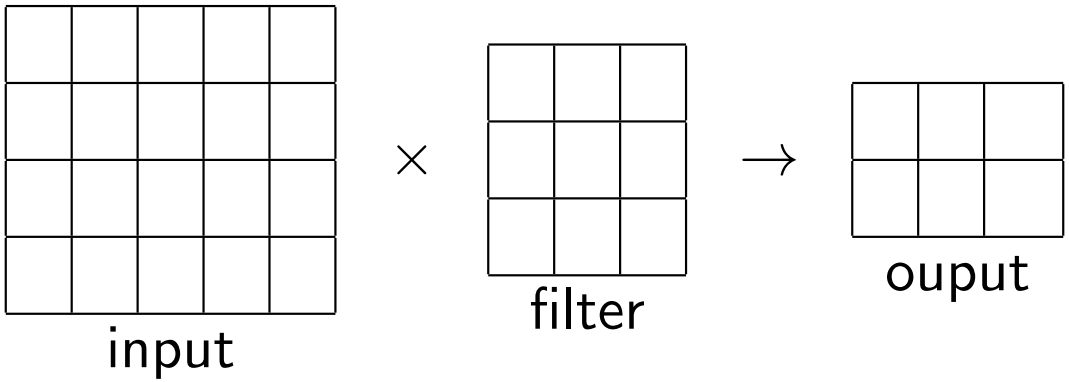
Convolutional Neural Networks

Padding



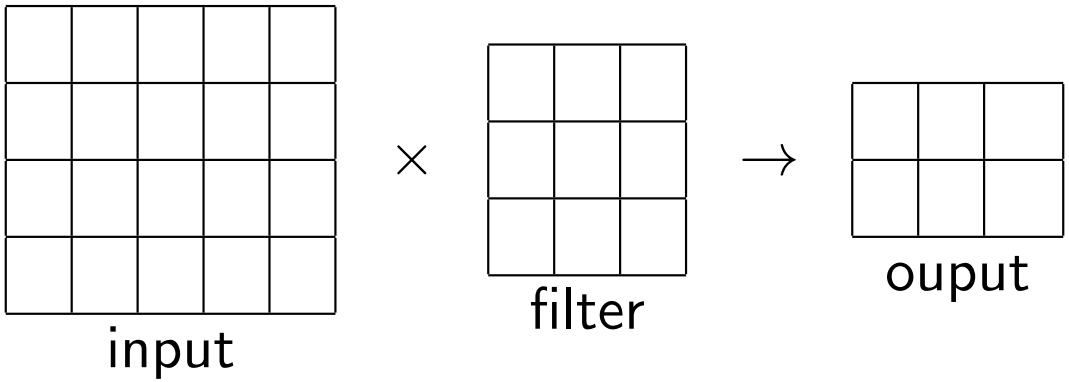
Convolutional Neural Networks

Padding



Convolutional Neural Networks

Padding

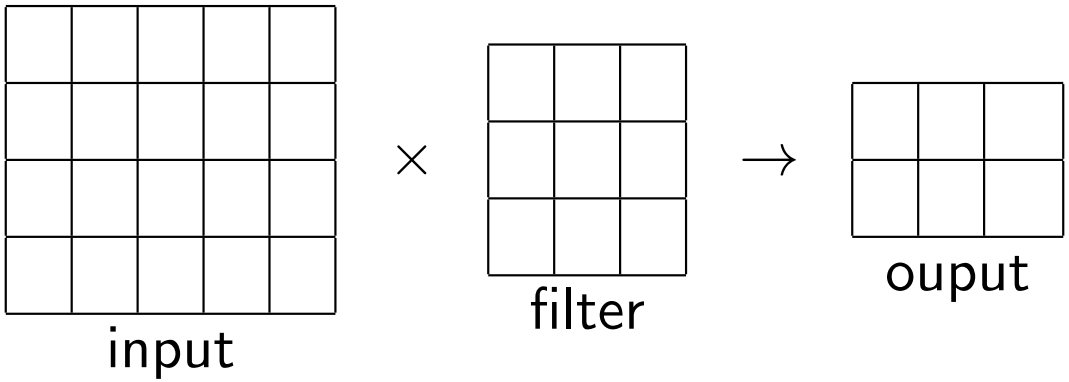


We are producing smaller images

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

Convolutional Neural Networks

Padding



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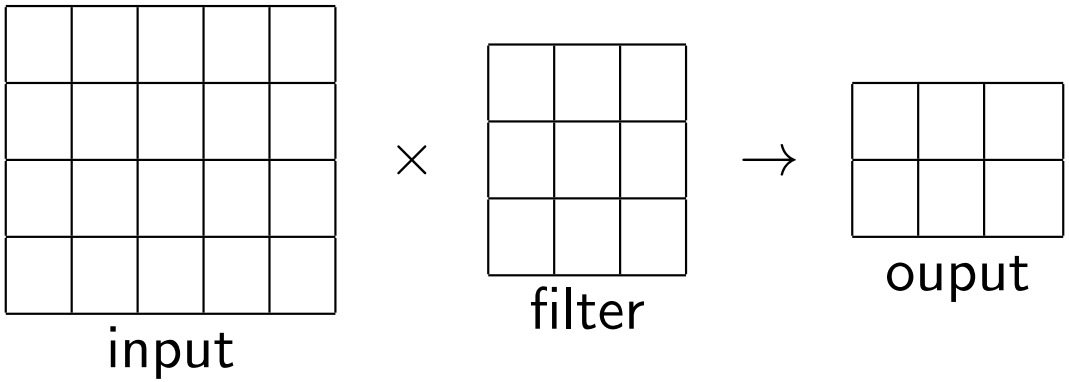
"I don't care": Keras' argument `padding='valid'`
The edges of the image are undersampled

Convolutional Neural Networks

Padding



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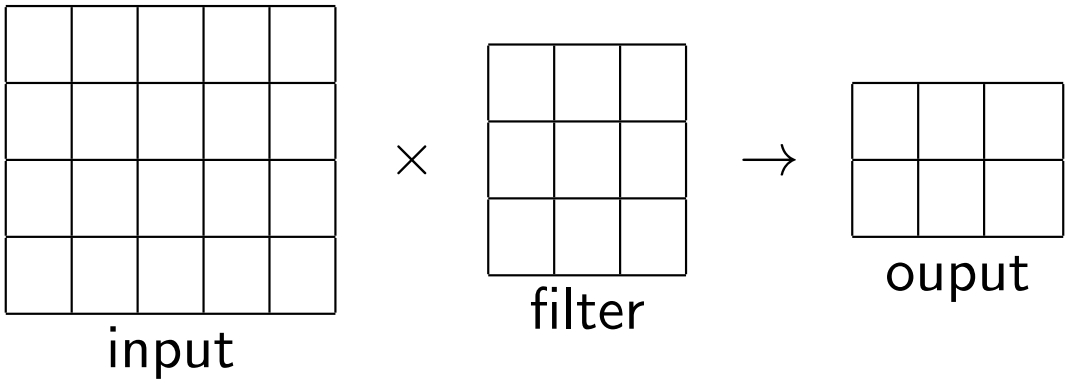
"I do care": Keras' padding argument `padding='same'`

Convolutional Neural Networks

Padding



We are producing smaller images

"I don't care": Keras' argument `padding='valid'`
The edges of the image are undersampled

"I do care": Keras' padding argument `padding='same'`

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

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
- Proceed as usual

Convolutional Neural Networks

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We can add multiple convolution layers

A full path of learning layers and abstractions

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A full path of learning layers and abstractions

- Edges

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- Edges
- Shapes

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- Edges
- Shapes
- Colours

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- Edges
- Shapes
- Colours
- **Concepts**

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Input: an image, text

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A full path of learning layers and abstractions

- Edges
- Shapes
- Colours
- **Concepts**

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))
)
```

Next time

- CNNs for NLP

References

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

Le, Q. V. and T. Mikolov
2014. Distributed representations of sentences and documents.