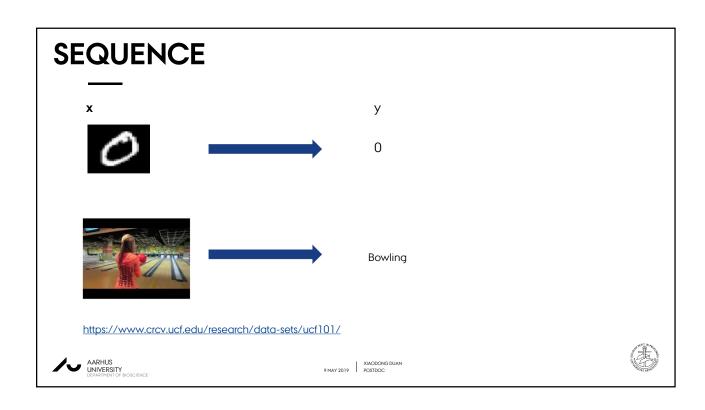
RECURRENT NEURAL NETWORK



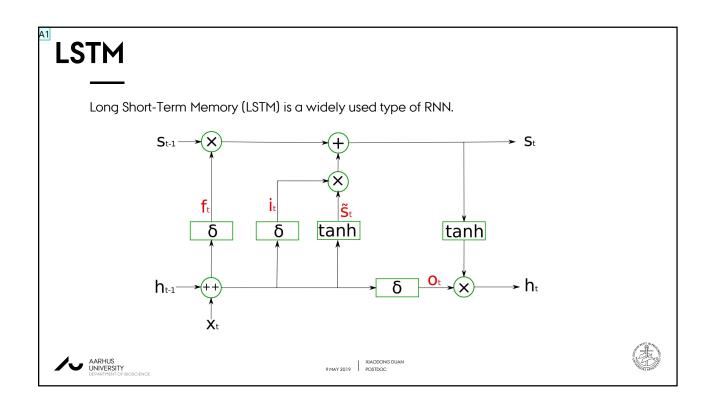
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$\begin{array}{c} \textbf{RNN} \\ \hline \\ \textbf{1. It is with recurrent connections specialized for processing sequential data} \\ \hline \\ \textbf{y}^{(r)} \textbf{v}^{(r)} \\ \hline \\ \textbf{y}^{(r)} \textbf{v}^{(r)} \\ \hline \\ \textbf{v}^{(r)} \\ \hline \\ \textbf{w}^{(r)} \\ \hline \\ \textbf{w}^{(r)} \\ \hline \\ \textbf{w}^{(r)} \\ \hline \\ \textbf{v}^{(r)} \\ \\ \textbf{v}^{(r)} \\ \hline \\ \textbf{v}^{(r)} \\$



A1 Author; 13-05-2019

LSTM

$$f_t = \delta(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f)$$
 $i_t = \delta(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)$
 $o_t = \delta(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o)$
 $\tilde{\mathbf{s}}_t = tanh(\mathbf{W}_s \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_s)$
 $s_t = f_t \times s_{t-1} + i_t \times \tilde{\mathbf{s}}_t$
 $h_t = o_t \times tanh(\mathbf{s}_t)$





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AN EXAMPLE



What is on the wall to the right side of the bookshelf?

 $\underline{https://www.mpi-inf.mpg.de/departments/computer-vision-and-multimodal-computing/research/vision-and-language/visual-turing-challenge/linearch/vision-and-language/visual-turing-challenge/visual-turing-challenge/visual-turing-challenge/visual$



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AN EXAMPLE



What is the colour of the pillow cover?

https://www.mpi-inf.mpq.de/departments/computer-vision-and-multimodal-computing/research/vision-and-language/visual-turing-challenge/





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CONVOLUTIONAL NEURAL NETWORK



0 MAY 2010

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CNN

- 1. It is widely used in image processing.
- 2. The core is the two-dimensional convolution operation.

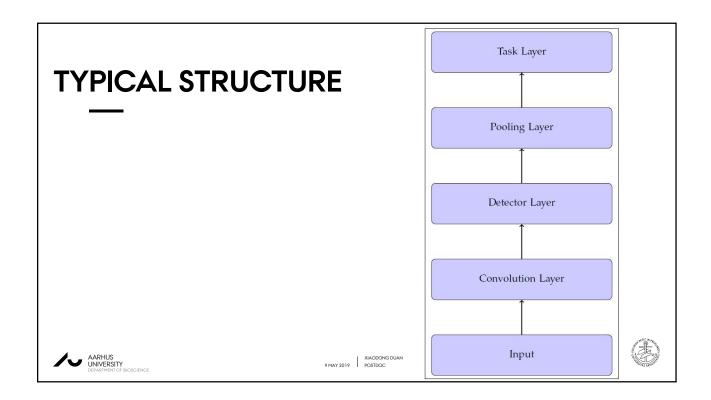
$$S(i,j) = \sum_{m=-M}^{M} \sum_{n=-N}^{N} I(i-m,j-n)K(m,n)$$

- 3. It usually consists of many layers
 - Residual Neural Network (ResNet): 152 layers
 - He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition.* 2016.



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CONVOLUTION LAYER

Zero padding

Filters (Convolution Kernels)

Identity
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\text{Edge detection} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 0 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Strides



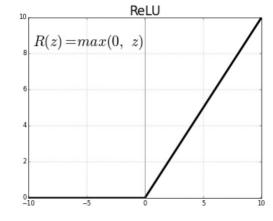
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DETECTOR LAYER

Nonlinear activations

- Increase the non-linearity
- ReLU



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POOLING

- 1. Reducing the spatial dimensions
- 2. Invariant to small translations of the input
- 3. Max pooling

$$\begin{bmatrix} 1 & 2 & 5 & 6 \\ 3 & 4 & 7 & 8 \\ 9 & 8 & 5 & 4 \\ 7 & 6 & 3 & 2 \end{bmatrix} \xrightarrow{\text{Max pool with } 2 \times 2 \text{ filter and stride } 2} \begin{bmatrix} 4 & 8 \\ 9 & 5 \end{bmatrix}$$



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TASK LAYER

- 1. It depends on your application
- 2. Fully connected neural network



E)



Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

ConvNet Configuration					
A	A-LRN	В	С	D	Е
11 weight	11 weight	13 weight	16 weight	16 weight	19 weight
layers	layers	layers	layers	layers	layers
input (224×224 RGB image)					
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	conv3-64
	LRN	conv3-64	conv3-64	conv3-64	conv3-64
maxpool					
conv3-128	conv3-128	conv3-128	conv3-128	conv3-128	conv3-128
		conv3-128	conv3-128	conv3-128	conv3-128
maxpool					
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
			conv1-256	conv3-256	conv3-256
					conv3-256
maxpool					
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
			conv1-512	conv3-512	conv3-512
					conv3-512
maxpool					
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
			conv1-512	conv3-512	conv3-512
					conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					



CNN IN KERAS

- 1. Conv2D(): convolution + relu
- 2. MaxPooling2D()
- 3. Flatten()



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