Day 2 Lecture 6

Recurrent Neural Networks

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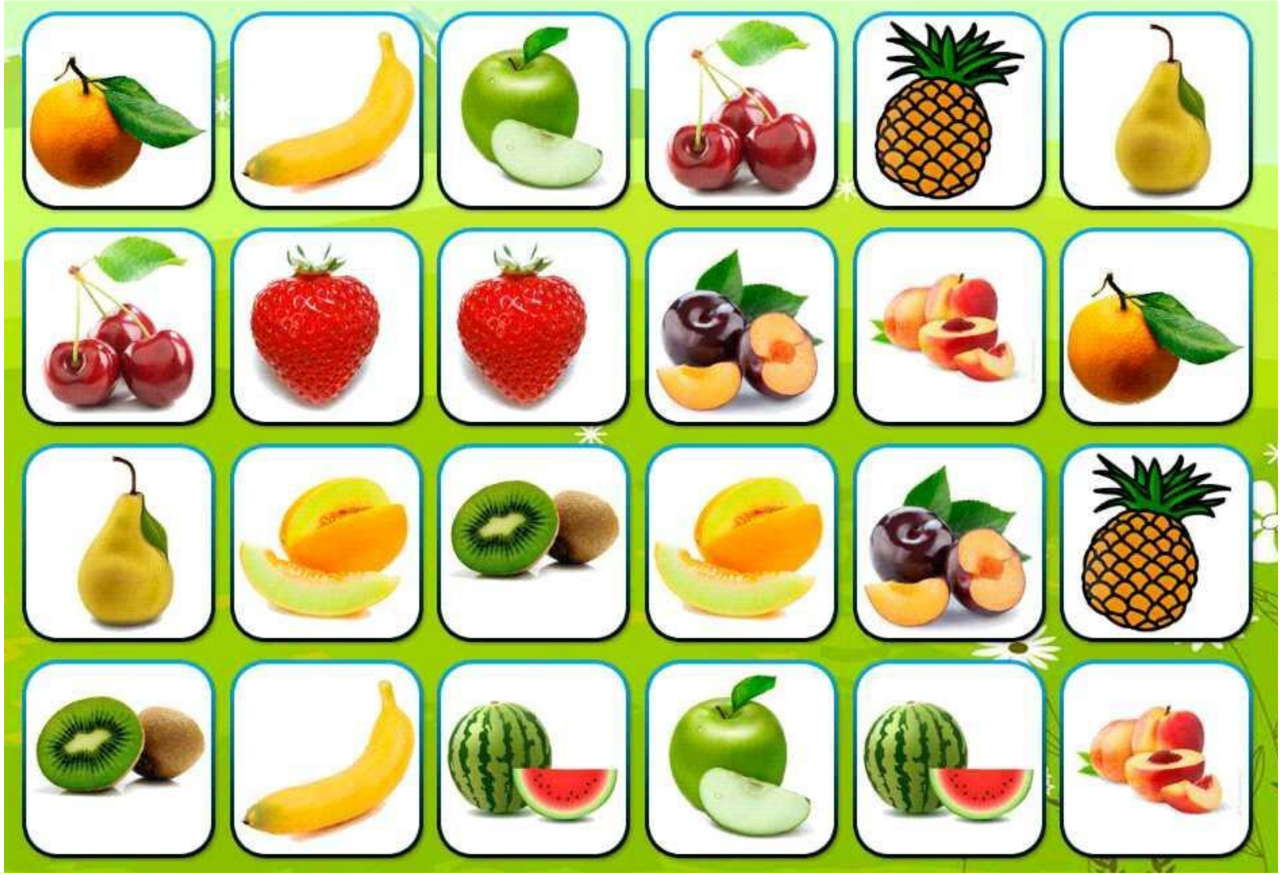
Acknowledgments

Santi Pascual

TALP Research Center

General idea

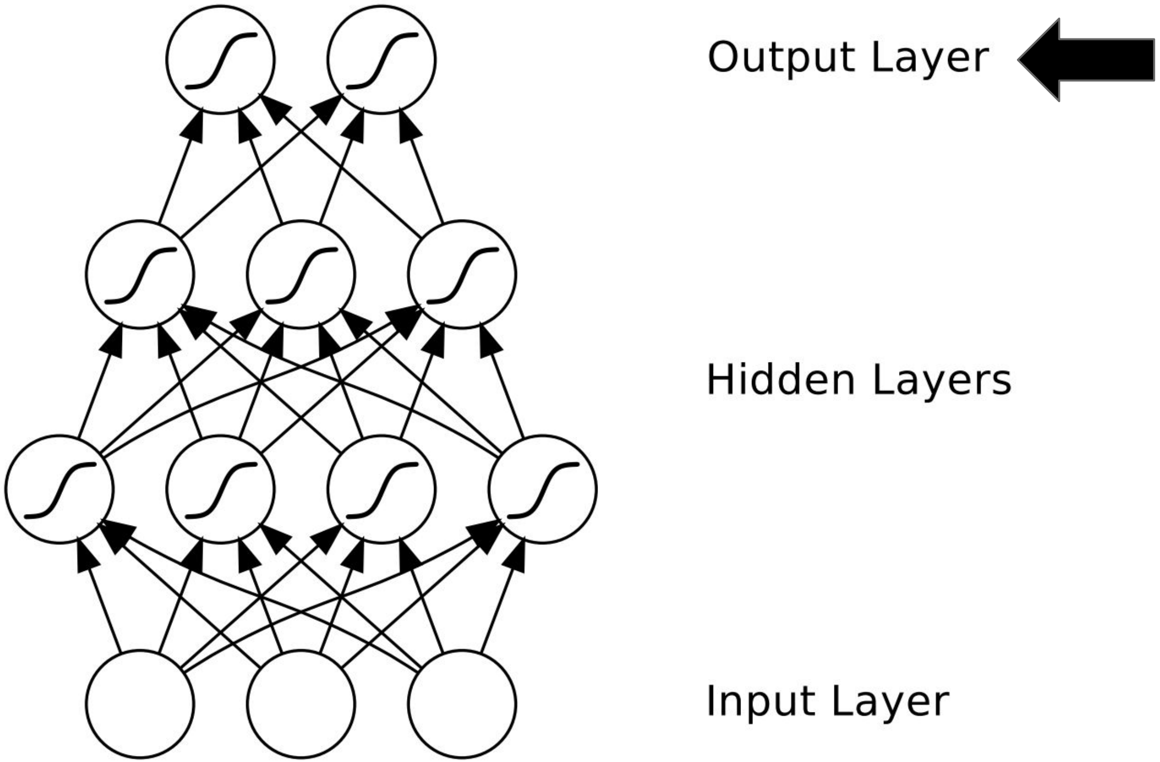


ConvNet

General idea

ConvNet

Multilayer Perceptron

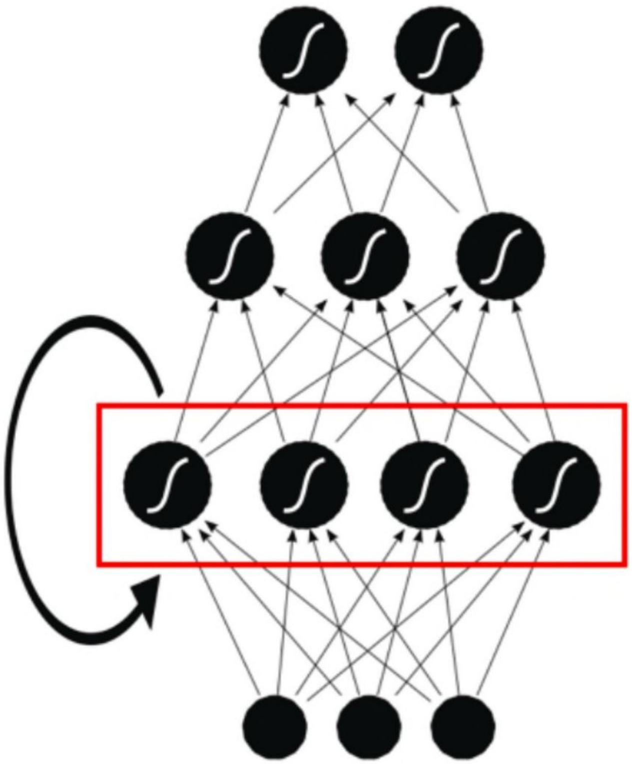


The output depends ONLY on the current input.

Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

Recurrent Neural Network (RNN)

The hidden layers and the output depend from previous states of the hidden layers



Alex Graves, “Supervised Sequence Labelling with Recurrent Neural Networks”

Recurrent Neural Network (RNN)

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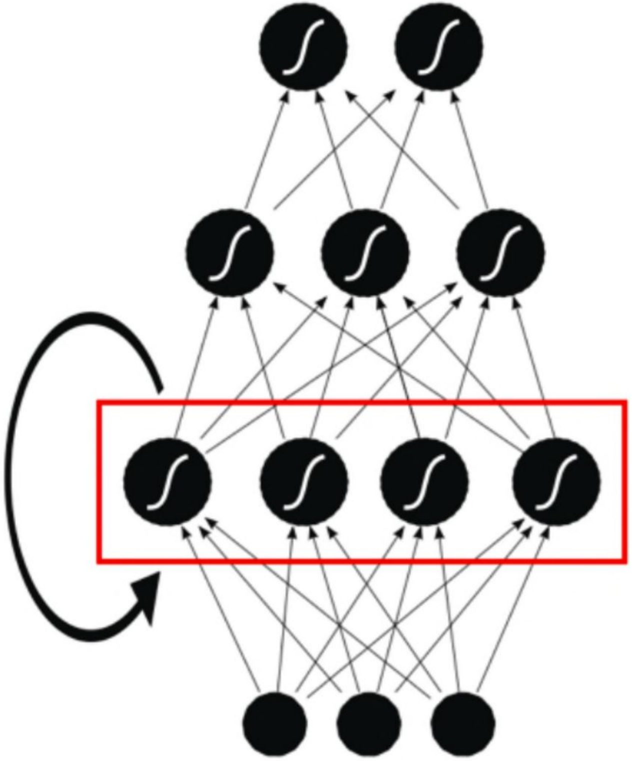
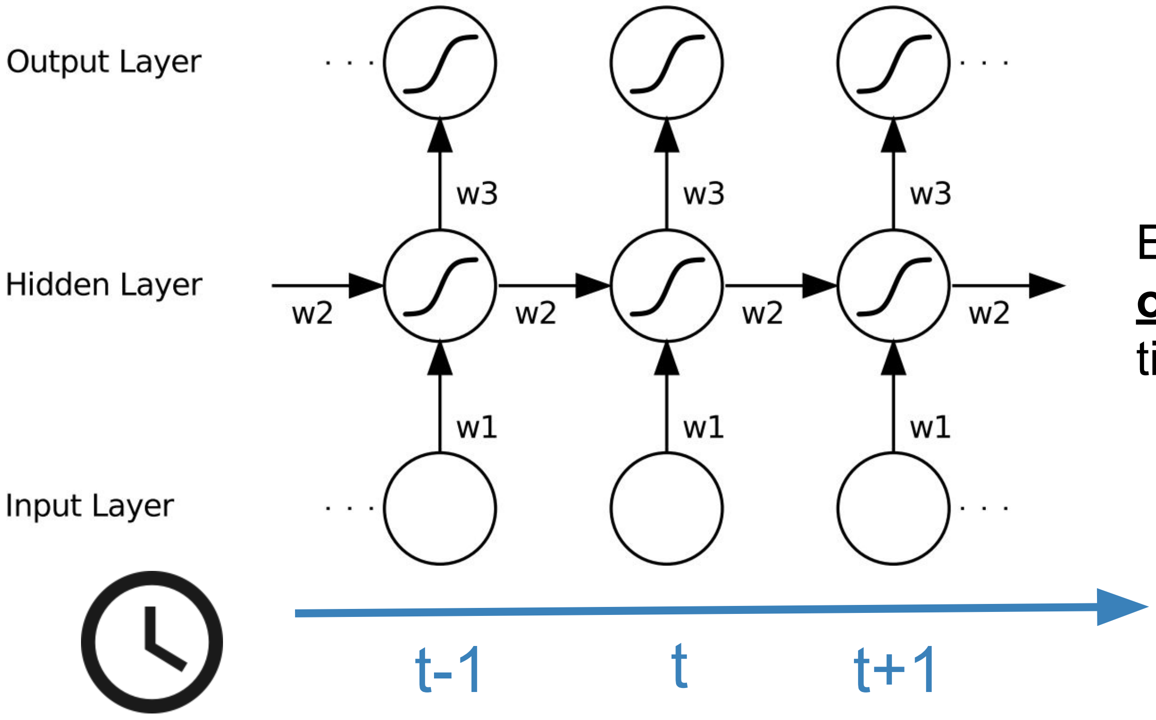


Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

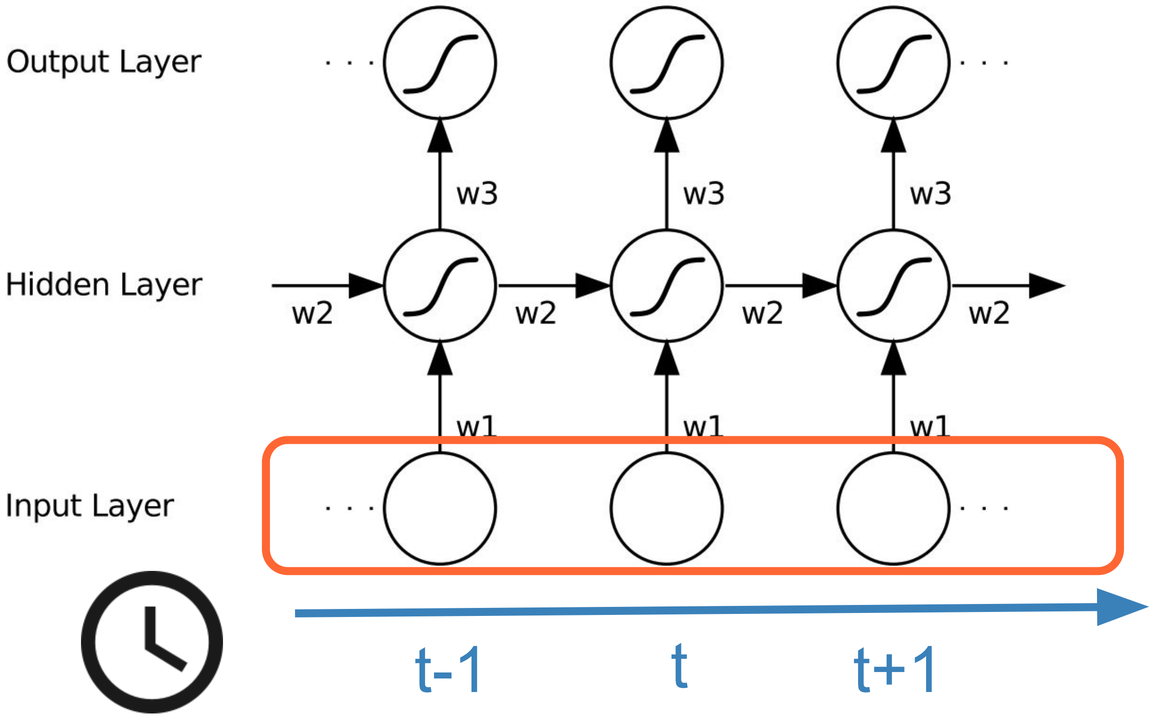
Recurrent Neural Networks (RNN)



Each node represents **a layer of neurons** at a single timestep.

Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

Recurrent Neural Networks (RNN)

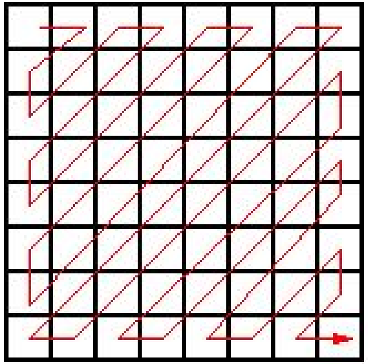


The input is a **<u>SEQUENCE</u> x(t)** of any length.

Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

Recurrent Neural Networks (RNN)

Common visual sequences:



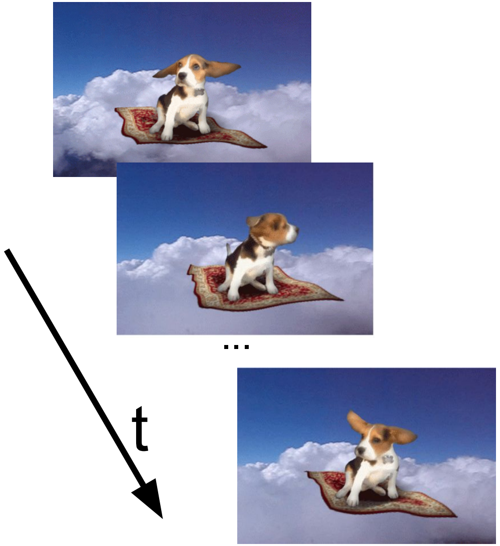
The input is a **SEQUENCE x(t)** of any length.

Still image + Spatial scan

(zigzag, row, column)

Recurrent Neural Networks (RNN)

Common visual sequences:

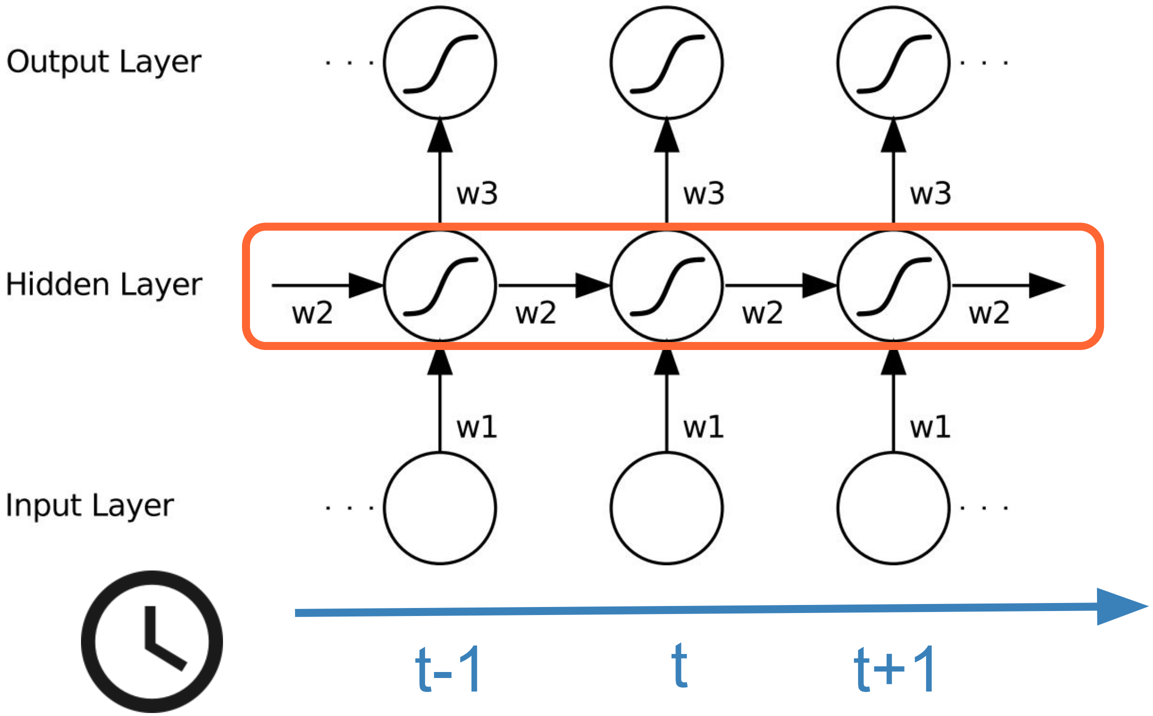


The input is a **<u>SEQUENCE</u> x(t)** of any length.

Video

Temporal sampling

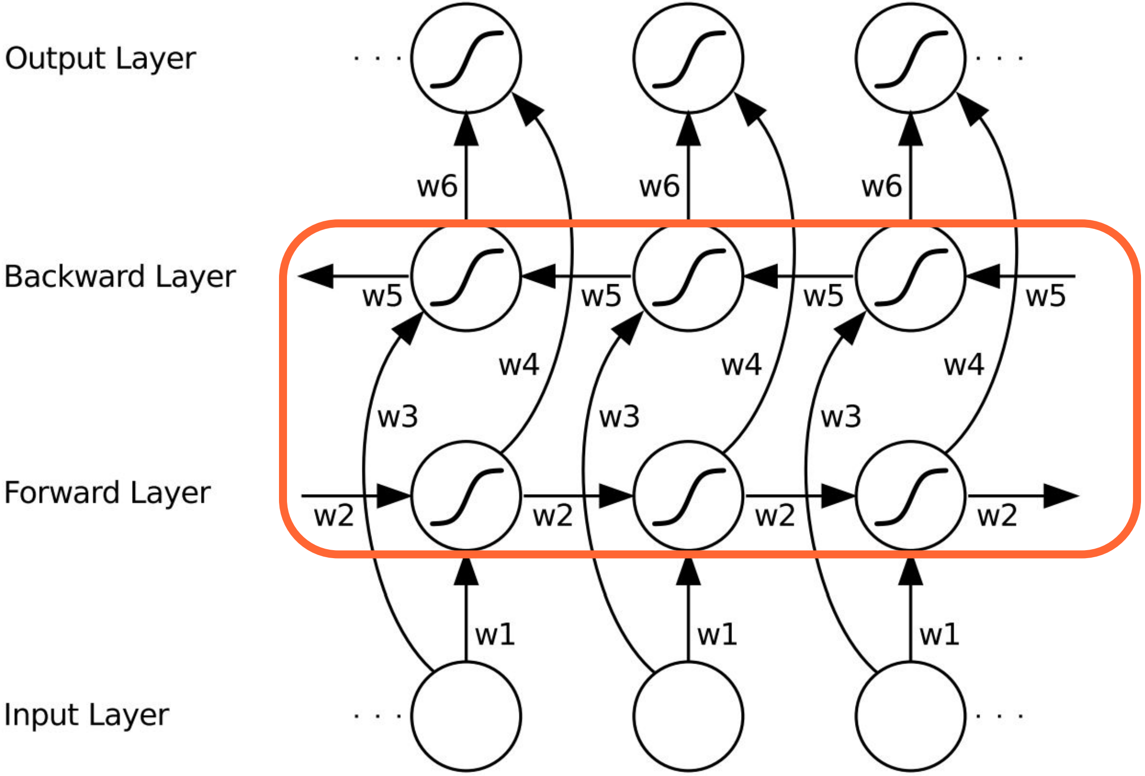
Recurrent Neural Networks (RNN)



Must learn weights w2; in addition to w1 & w3.

Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

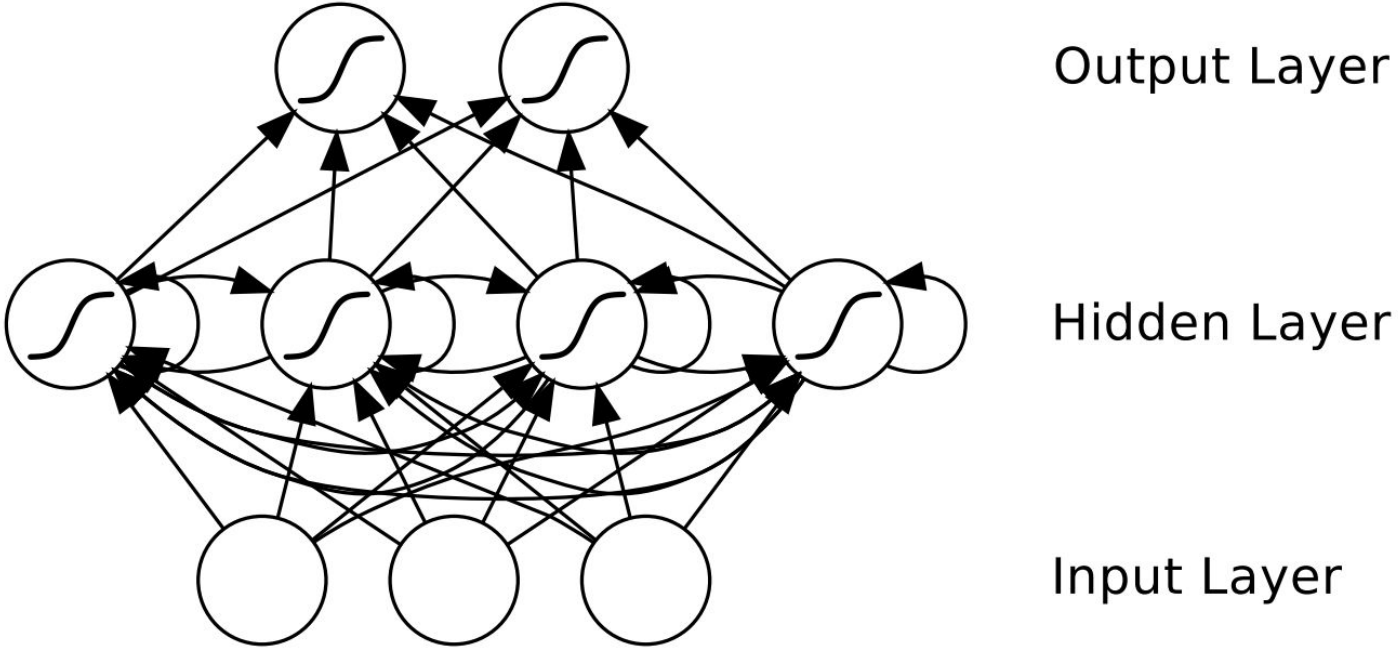
Bidirectional RNN (BRNN)



Must learn weights w2, w3, w4 & w5; in addition to w1 & w3.

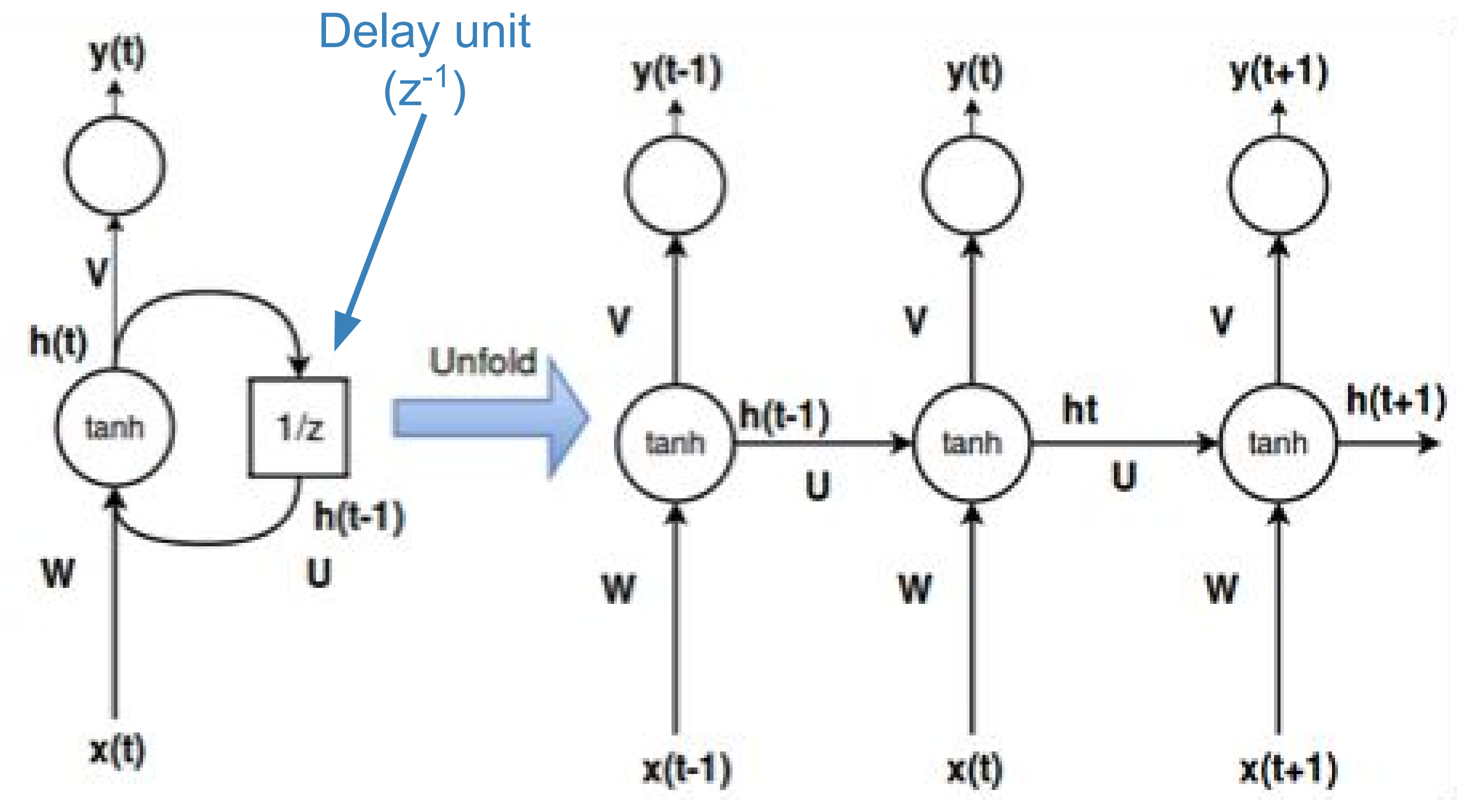
Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

Bidirectional RNN (BRNN)



Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”]

Formulation: One hidden layer

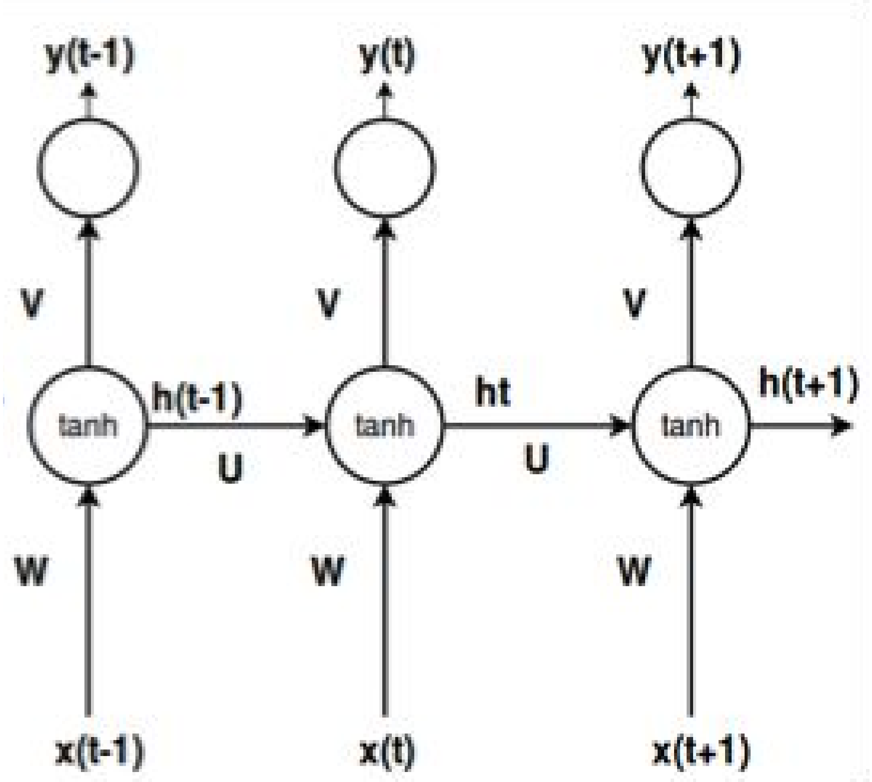


Formulation: One hidden layer

$$\mathbf{y}_t = f(\mathbf{V} \cdot \mathbf{h}_t + \mathbf{b}_v)$$

$$\mathbf{h}_t = g(\mathbf{W} \cdot \mathbf{x}_t + \underbrace{\boxed{\mathbf{U} \cdot \mathbf{h}_{t-1}}}_{\text{Recurrence}} + \mathbf{b}_h)$$

$$\mathbf{x}_t \in \mathbb{R}^n$$



Formulation: Multiple hidden layers

Single layer (1)

$$\mathbf{h}_t = g(\mathbf{W} \cdot \mathbf{x}_t + \boxed{\mathbf{U} \cdot \mathbf{h}_{t-1}} + \mathbf{b}_h)$$

Recurrence

Multiple layers (T)

$$\mathbf{h}_t = g(\mathbf{W} \cdot \mathbf{x}_t + \boxed{\mathbf{U} \cdot g(\cdots g(\mathbf{W} \cdot \mathbf{x}_{t-T} + \mathbf{U} \cdot \mathbf{h}_{t-T} + \mathbf{b}_h) \cdots)} + \mathbf{b}_h)$$

RNN problems

Long term memory vanishes because of the T nested multiplications by U.

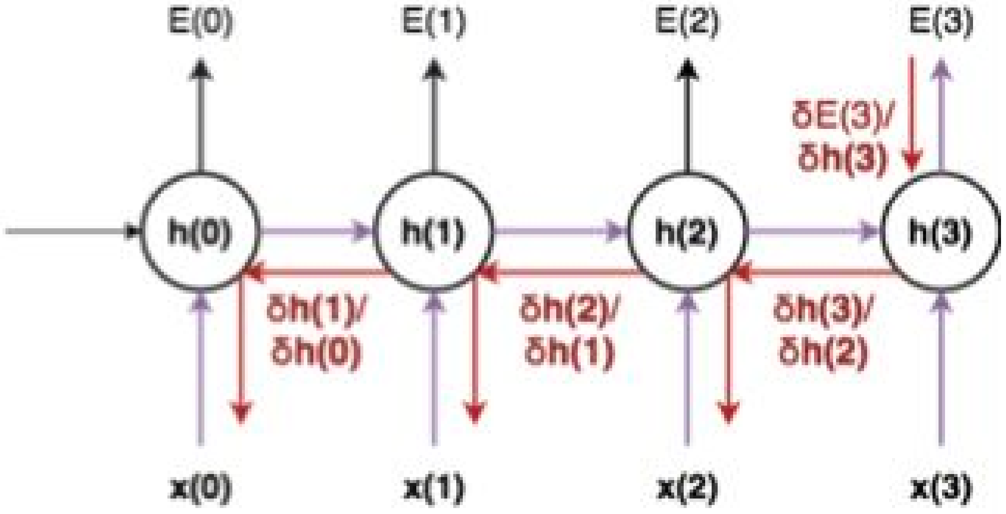
$$\mathbf{h}_t = g(\mathbf{W} \cdot \mathbf{x}_t + \boxed{\mathbf{U}} \cdot g(\cdot \boxed{\cdot} \cdot g(\mathbf{W} \cdot \mathbf{x}_{t-T} + \boxed{\mathbf{U}} \cdot \mathbf{h}_{t-T} + \mathbf{b}_h) \cdots) + \mathbf{b}_h)$$

...

RNN problems

During training, gradients may explore or vanish because of temporal depth.

Example: Back-propagation in time with 3 steps.



Long Short-Term Memory (LSTM)

Stanford NLP Group
@stanfordnlp

Seguint

LSTMs are really mainstream now … just referenced in the @Apple #WWDC2016 keynote for iOS QuickType auto-completion

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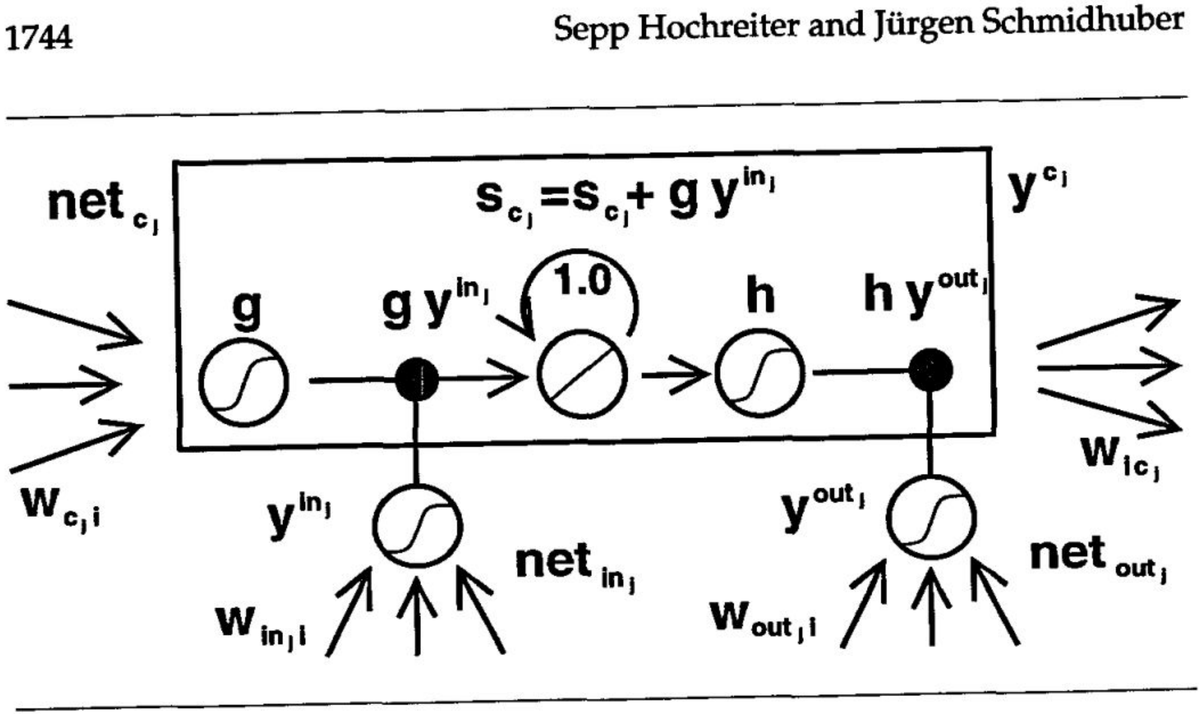
Long Short-Term Memory (LSTM)



Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9, no. 8 (1997): 1735-1780.

Long Short-Term Memory (LSTM)

Based on a standard RNN whose neuron activates with *tanh*...

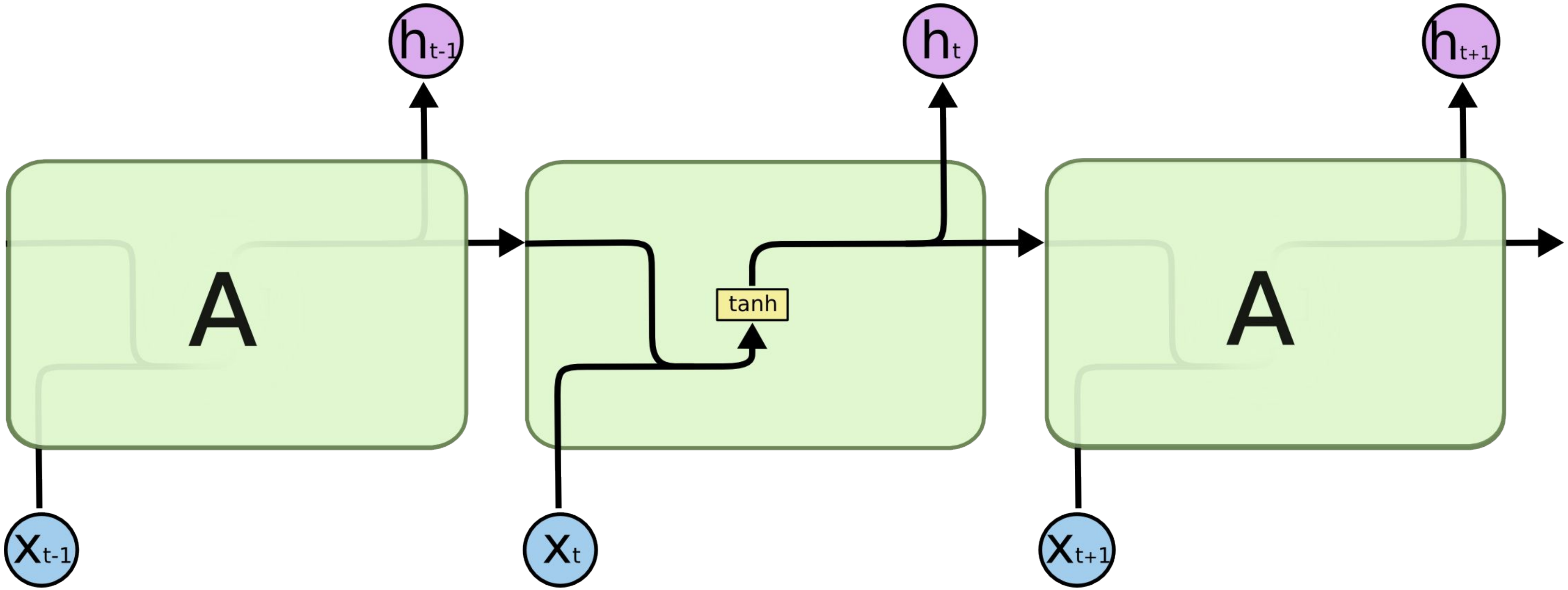


Figure: Cola's blog, "Understanding LSTM Networks" (2015)

Long Short-Term Memory (LSTM)

...three more *sigmoid* neural layers are added.

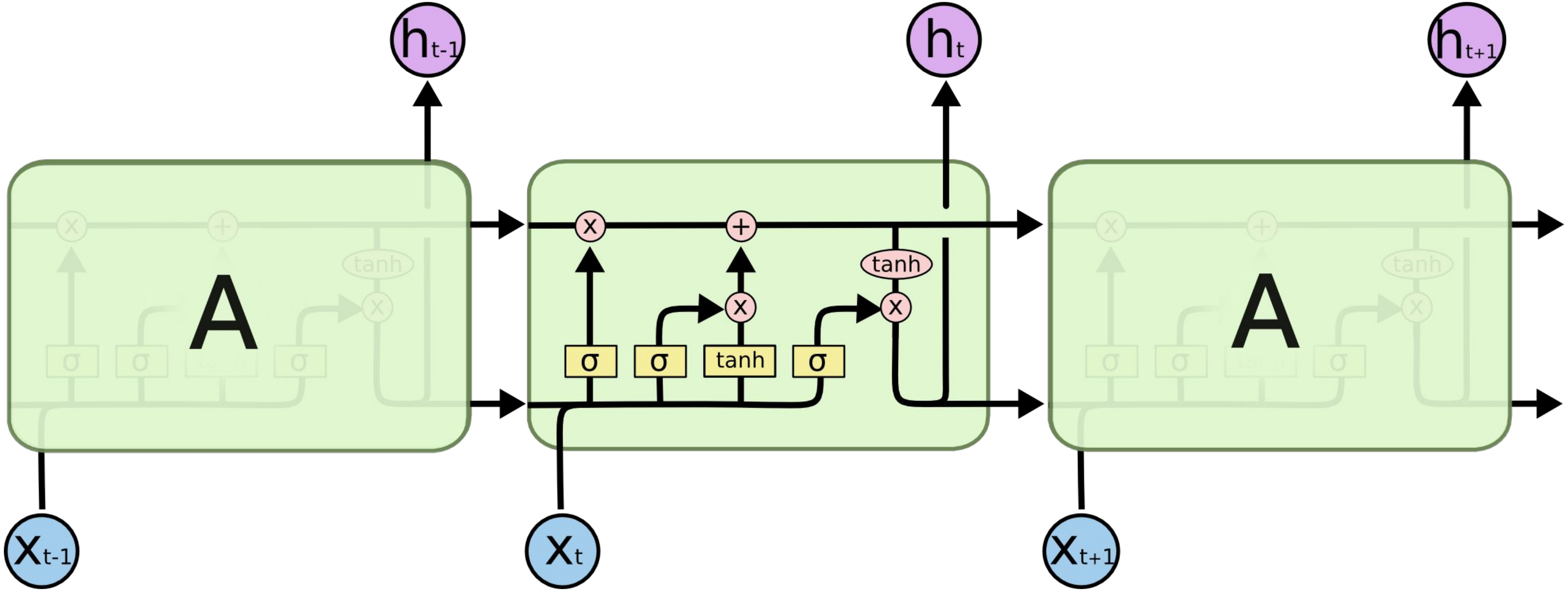


Figure: Cola's blog, "Understanding LSTM Networks" (2015)

Long Short-Term Memory (LSTM)

$\mathbf{C_t}$ is the cell state, which flows through the entire chain.

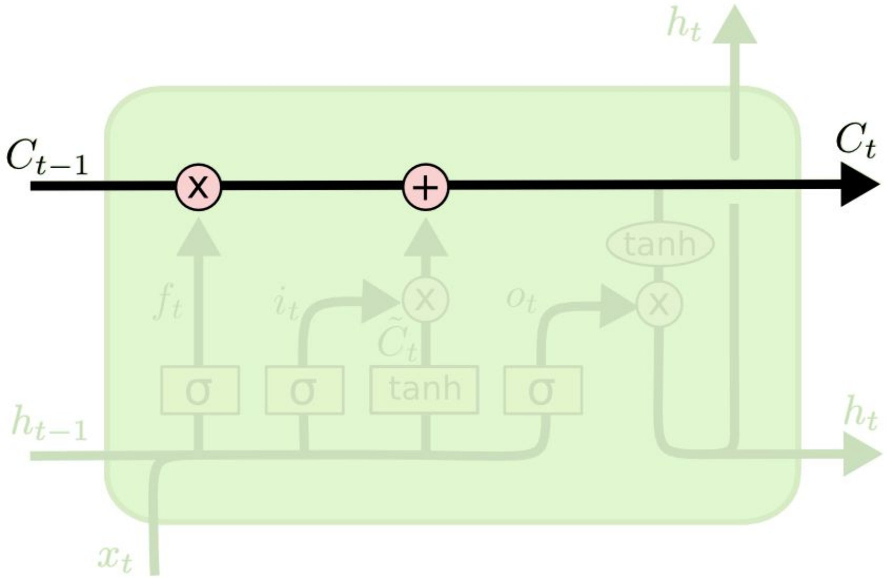
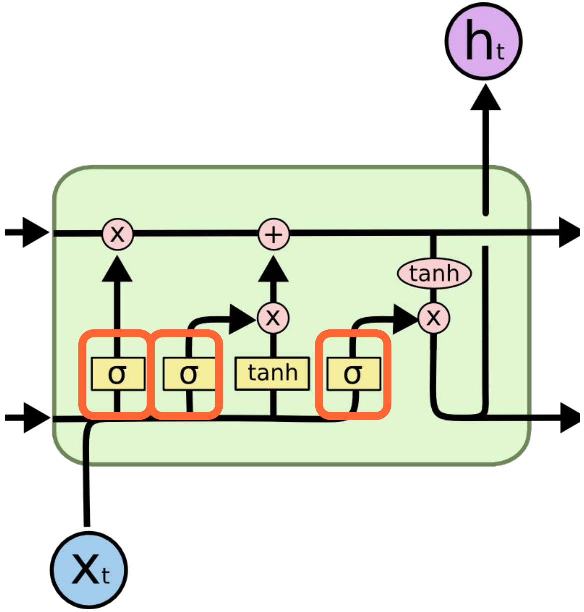
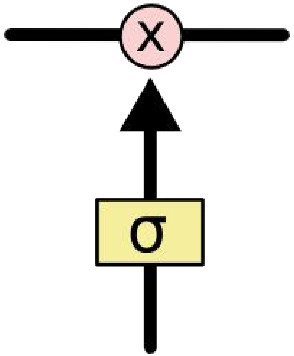


Figure: Cola's blog, [“Understanding LSTM Networks”](#) (2015)

Long Short-Term Memory (LSTM)

The three **gates** are governed by sigmoids [0,1], which define how much of their input must go through.





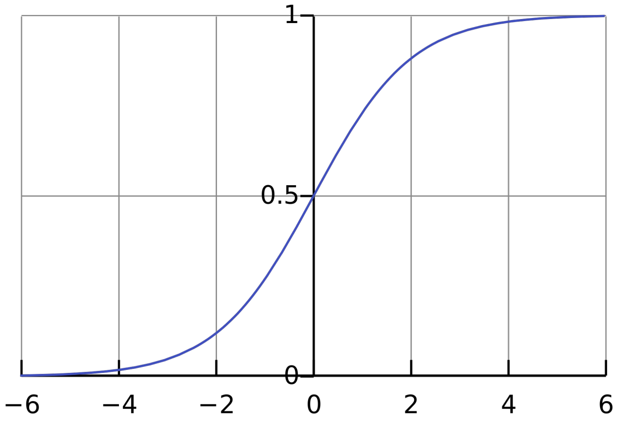
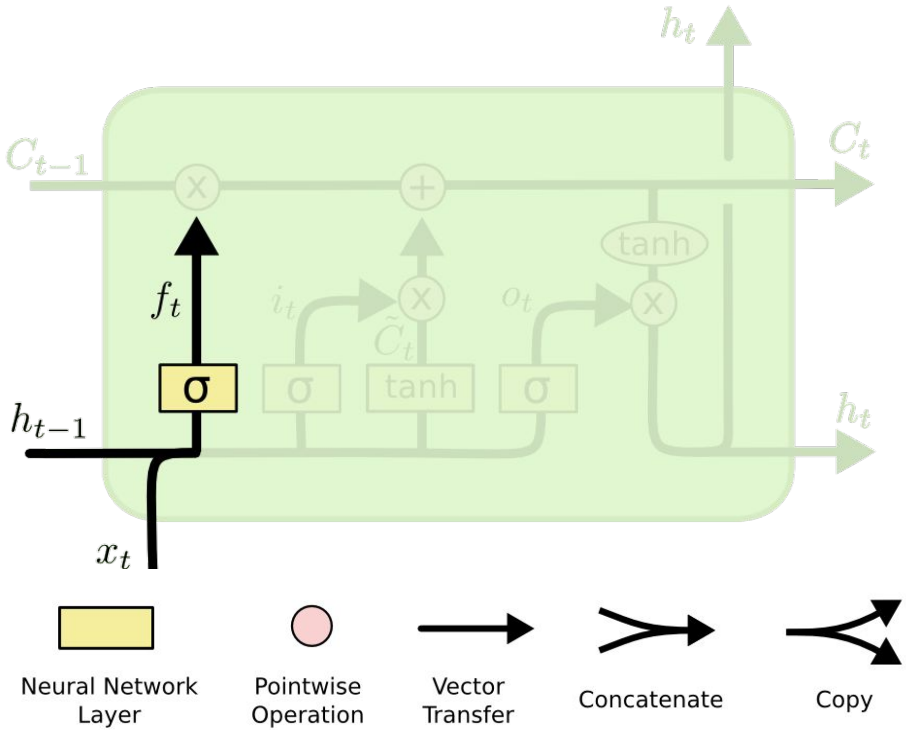


Figure: Cola’s blog, “Understanding LSTM Networks” (2015)

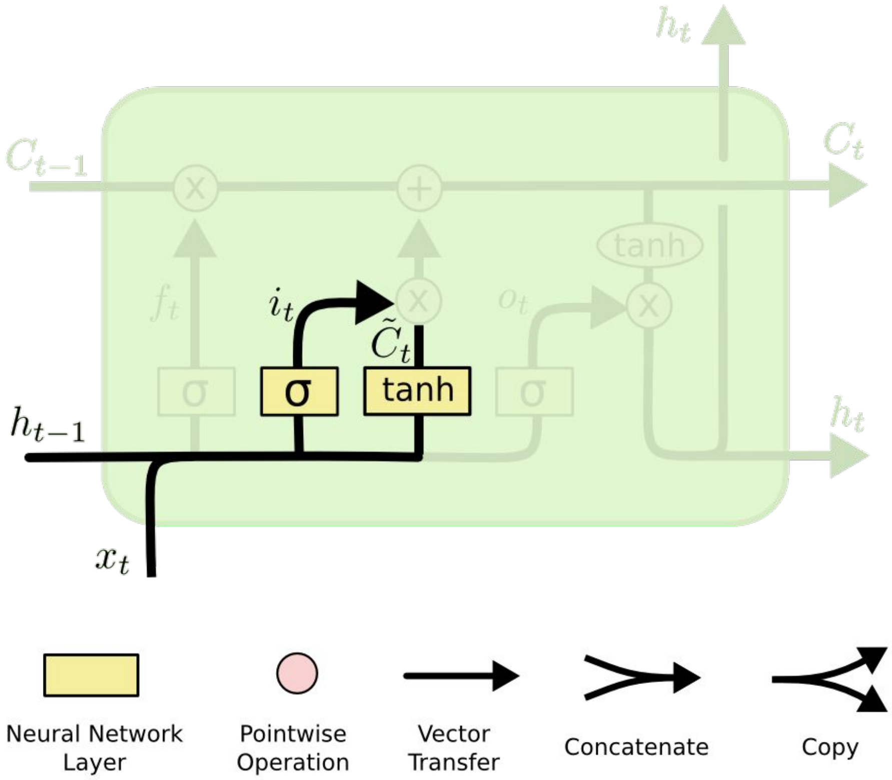
Long Short-Term Memory (LSTM)



Forget Gate:

$$f_t = \sigma\left(W_f \cdot \underbrace{[h_{t-1}, x_t]}_{\text{Concatenate}} + b_f\right)$$

Long Short-Term Memory (LSTM)



Input Gate Layer

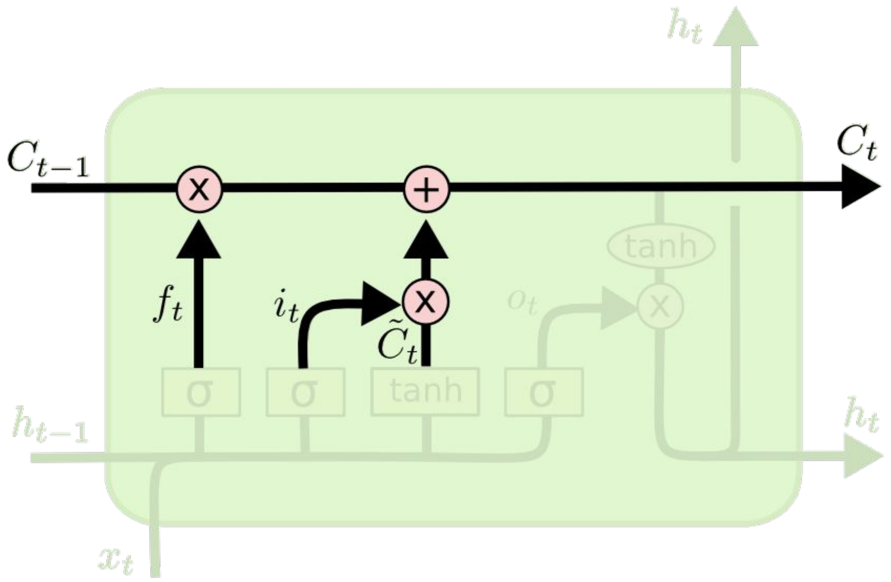
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

New contribution to cell state

$$\tilde{C}_t = \underbrace{\tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)}_{\text{Classic neuron}}$$

Figure: Cola's blog, "Understanding LSTM Networks" (2015) / Slide: Alberto Montes

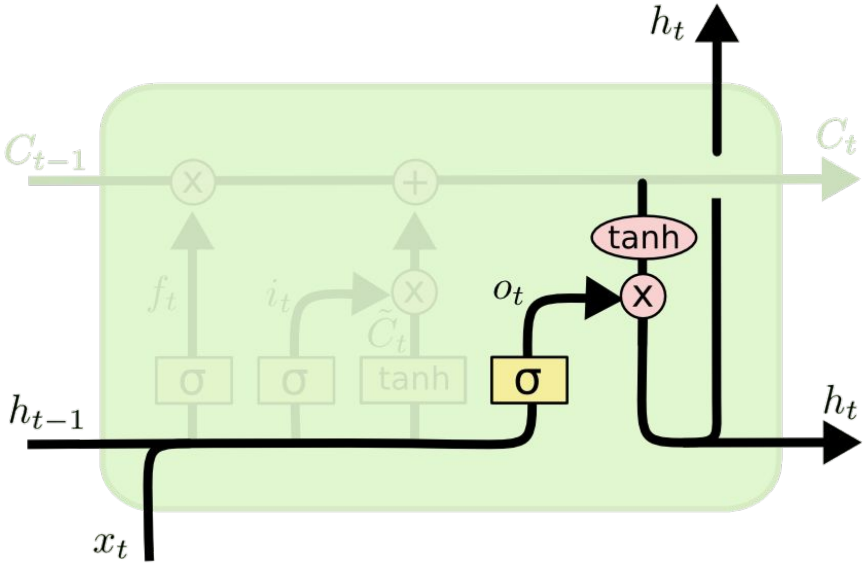
Long Short-Term Memory (LSTM)



Update Cell State (memory):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Long Short-Term Memory (LSTM)



Output Gate Layer

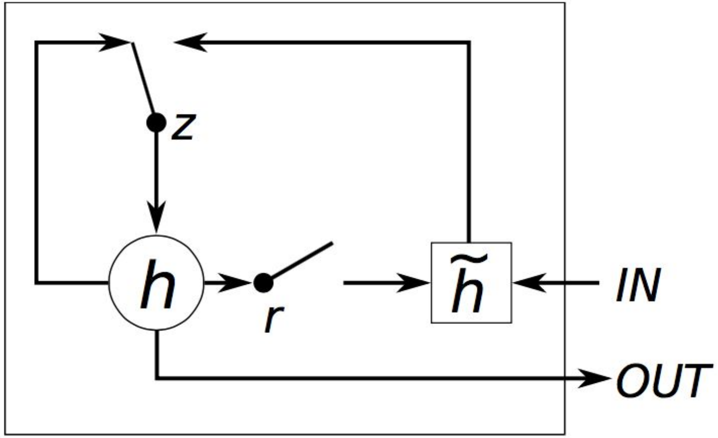
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Figure: Cola's blog, "Understanding LSTM Networks" (2015) / Slide: Alberto Montes

Gated Recurrent Unit (GRU)

Similar performance as LSTM with less computation.



$$u_i = \sigma\left(W^{(u)}x_i + U^{(u)}h_{i-1} + b^{(u)}\right) \quad (1)$$

$$r_i = \sigma\left(W^{(r)}x_i + U^{(r)}h_{i-1} + b^{(r)}\right) \quad (2)$$

$$\tilde{h}_i = \tanh\left(Wx_i + r_i \circ Uh_{i-1} + b^{(h)}\right) \quad (3)$$

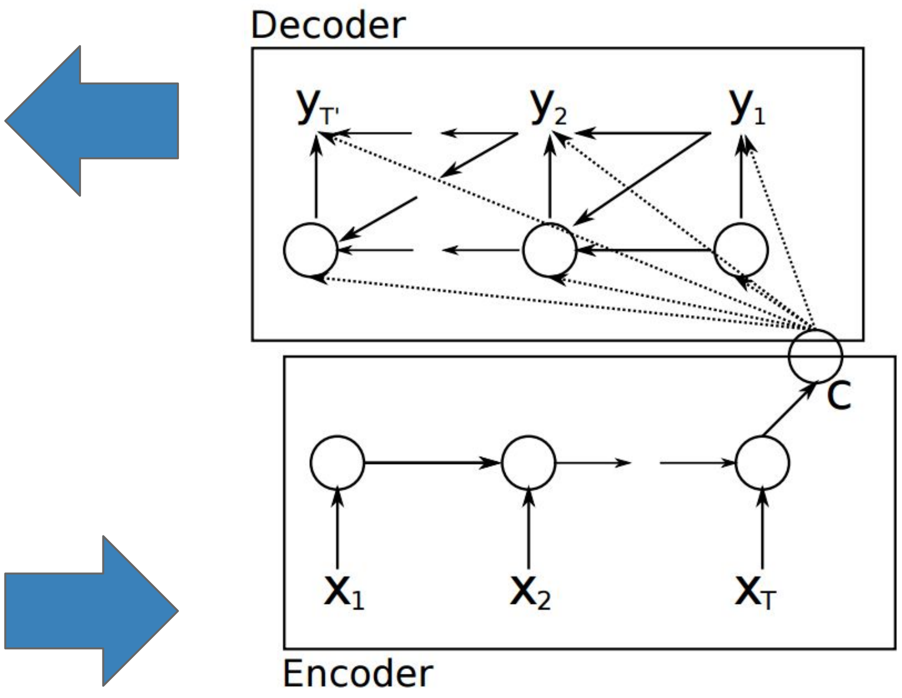
$$h_i = u_i \circ \tilde{h}_i + (1 - u_i) \circ h_{i-1} \quad (4)$$

Cho, Kyunghyun, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

Applications: Machine Translation

Language OUT

Language IN



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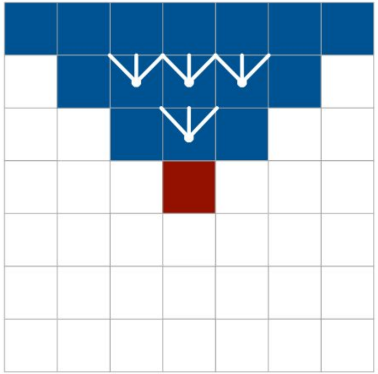
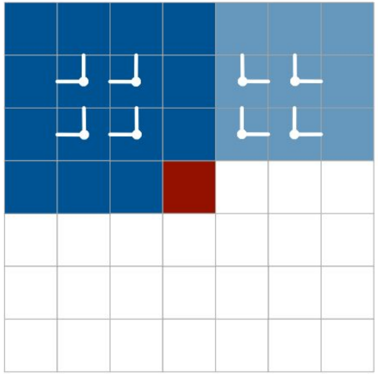
Applications: Image Classification

RowLSTM



Diagonal BiLSTM

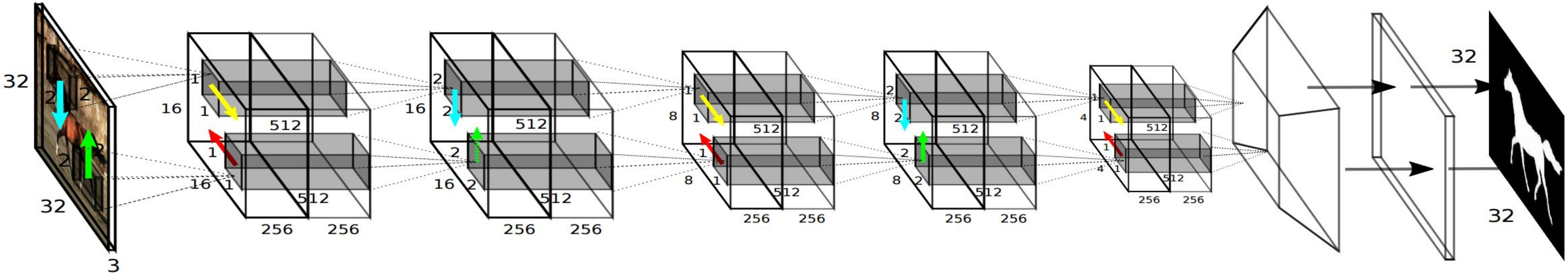


Classification MNIST

Model	NLL Test
DBM 2hl [1]:	≈ 84.62
DBN 2hl [2]:	≈ 84.55
NADE [3]:	88.33
EoNADE 2hl (128 orderings) [3]:	85.10
EoNADE-5 2hl (128 orderings) [4]:	84.68
DLGM [5]:	≈ 86.60
DLGM 8 leapfrog steps [6]:	≈ 85.51
DARN 1hl [7]:	≈ 84.13
MADE 2hl (32 masks) [8]:	86.64
DRAW [9]:	≤ 80.97
Diagonal BiLSTM (1 layer, $h = 32$):	**80.75**
Diagonal BiLSTM (7 layers, $h = 16$):	**79.20**

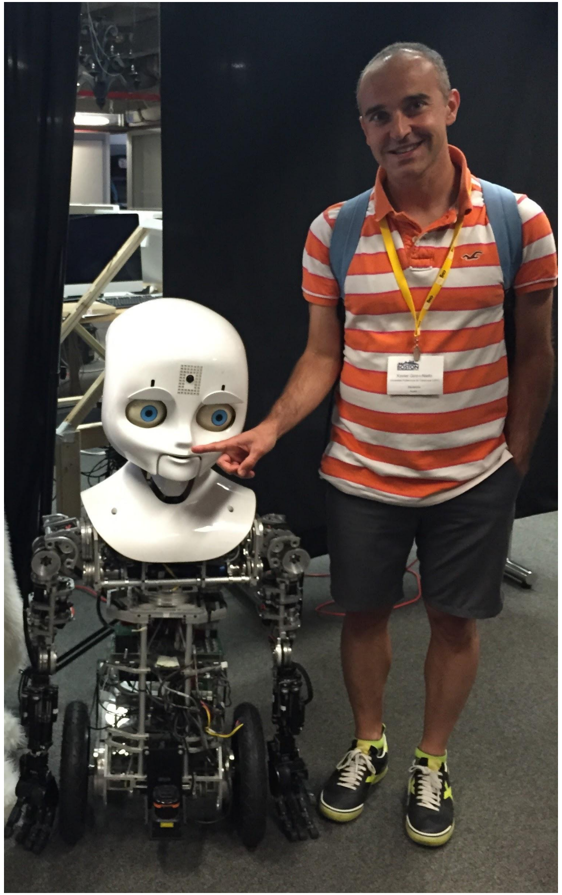
van den Oord, Aaron, Nal Kalchbrenner, and Koray Kavukcuoglu. "Pixel Recurrent Neural Networks." arXiv preprint arXiv:1601.06759 (2016).

Applications: Segmentation



Francesco Visin, Marco Ciccone, Adriana Romero, Kyle Kastner, Kyunghyun Cho, Yoshua Bengio, Matteo Matteucci, Aaron Courville, [“ReSeg: A Recurrent Neural Network-Based Model for Semantic Segmentation”](). DeepVision CVPRW 2016.

Thanks ! Q&A ?



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