Neural Networks for sequential data

29 January, 2020

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ISP course on sequential data processing

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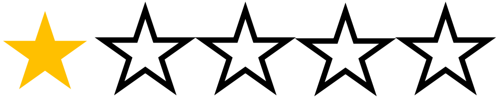
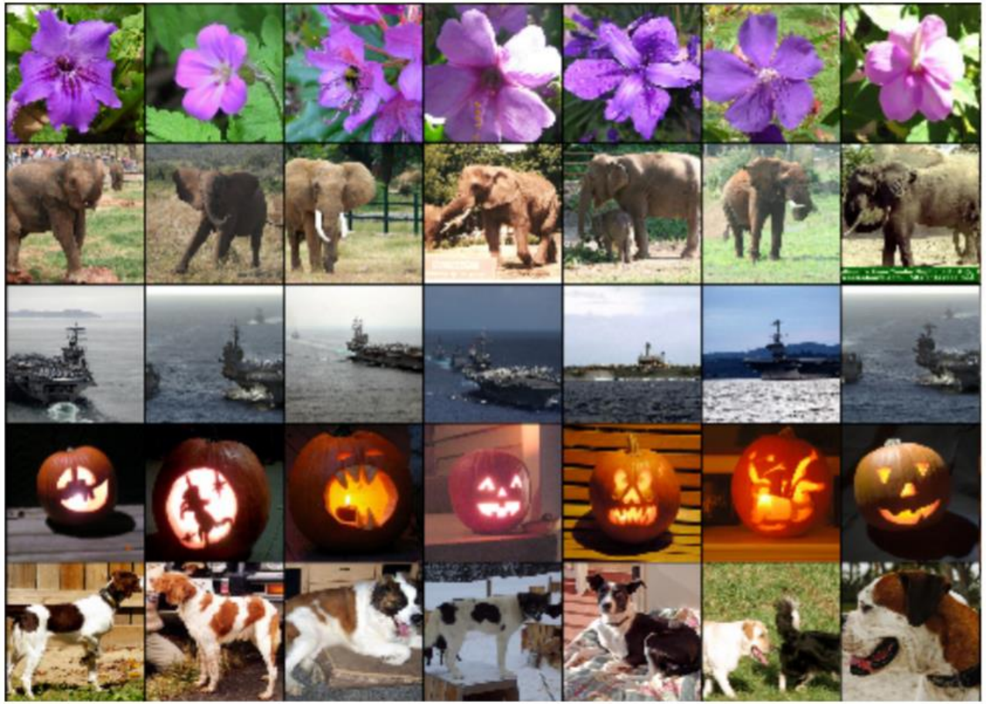
- → **Why bother about Neural Networks for sequential data?**
- → How to do Neural Networks for sequential data?

Complex sequence data examples

Speech recognition		→	“The quick brown fox jumped over the lazy dog.”
Sentiment classification	“There is nothing to like in this movie.”	→	
DNA sequence analysis	AGCCCCTGTGAGGAACTAG	→	AGCCCCTGTGAGGAACTAG
Machine translation	Voulez-vous chanter avec moi?	→	Do you want to sing with me?
Video activity recognition		→	Running

Adopted from Andrew Ng

Why bother with deep learning: Deep learning is better, then a human



Human error percentage is

5.1%

DL error percentage is

3.57%

https://arxiv.org/pdf/1705.02498.pdf
https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/
http://www.image-net.org/papers/imagenet_cvpr09.pdf

Classic approach to Machine Learning

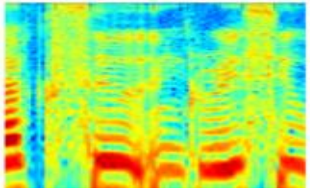
Data → Features → Learning

Image

Features

Recognition

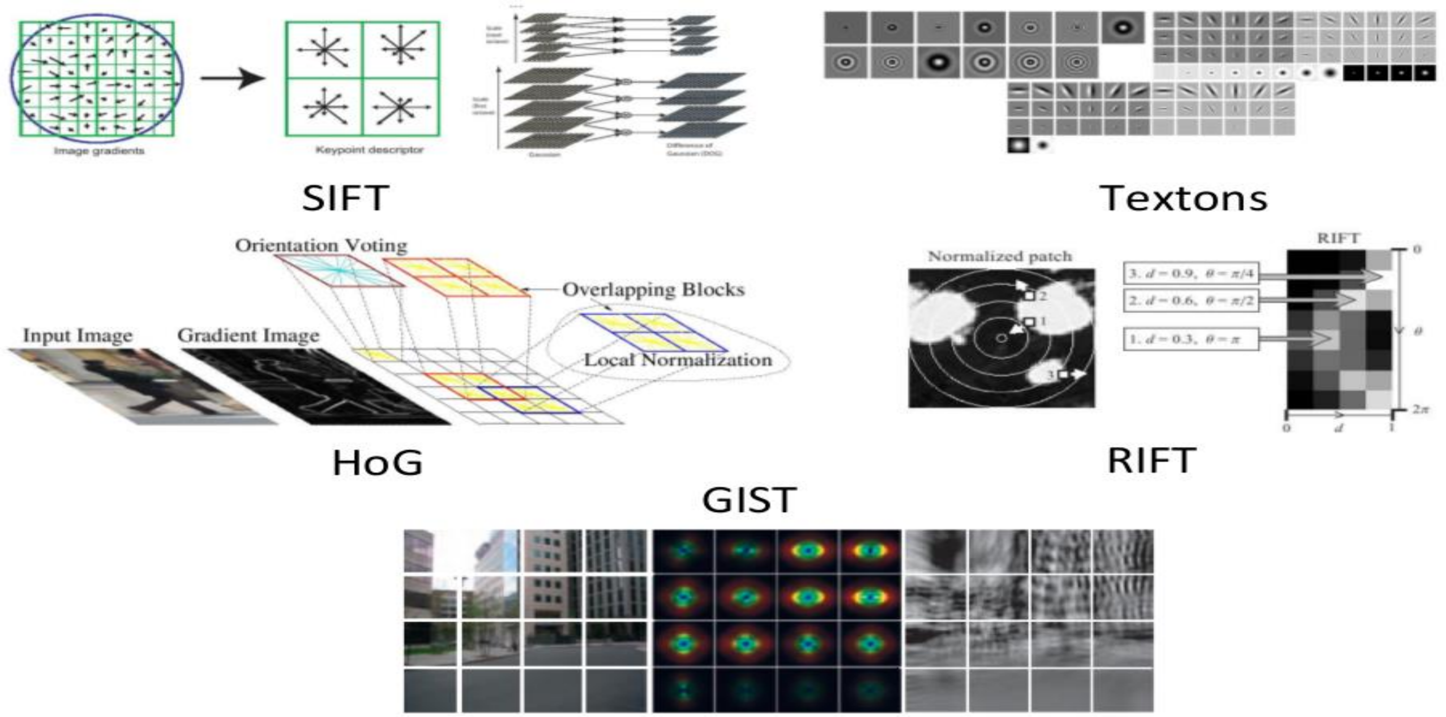
Speech



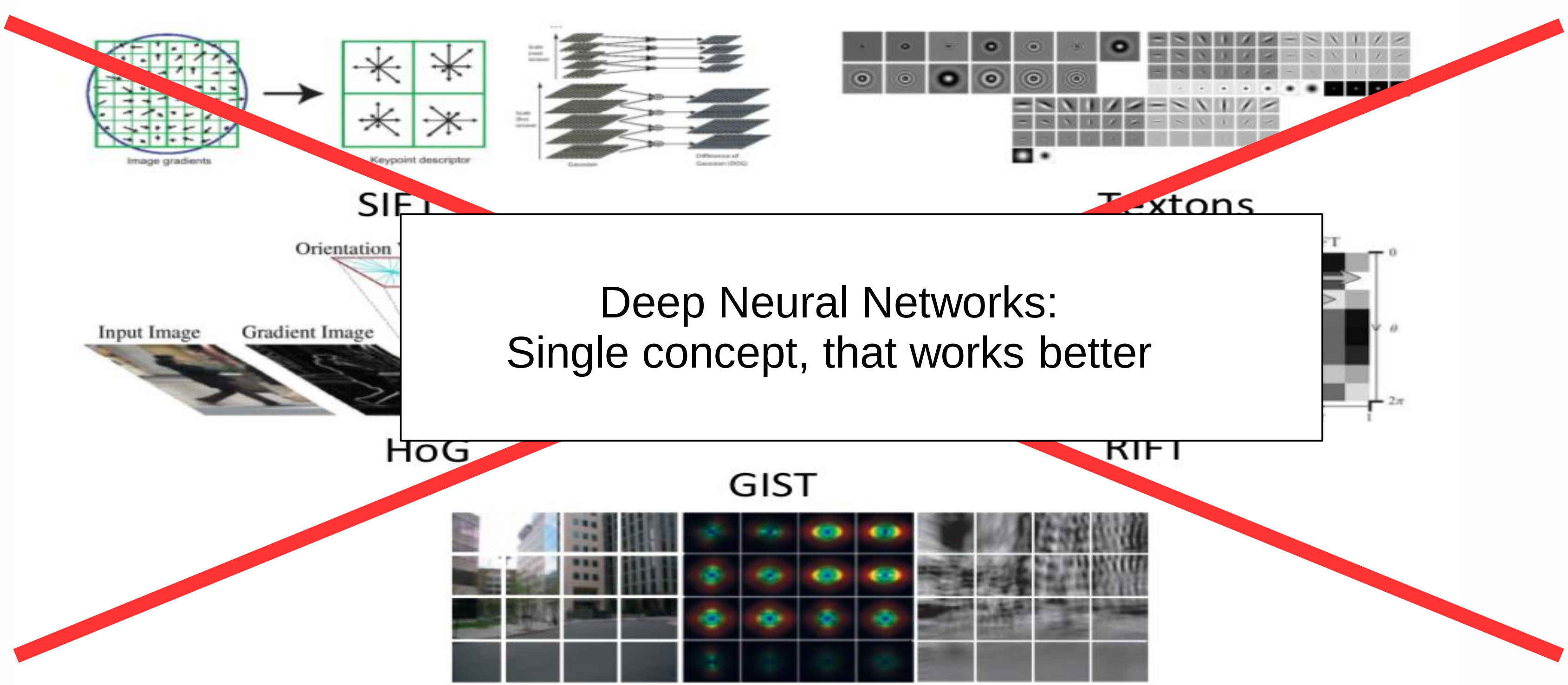
Features

Recognition

An art of feature construction



No art now, just engineering



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Why and how Deep learning works

- Availability of Graphical processing units (GPU)

- Large scale “big” data

- Open-source libraries

- Complex structured data

Complex sequence data examples

		Large data set	Structured data
Speech recognition		+	+
Sentiment classification	“There is nothing to like in this movie.”	+	+
DNA sequence analysis	AGCCCCTGTGAGGAACTAG	+	+
Machine translation	Voulez-vous chanter avec moi?	+	+
Video activity recognition		+	+

- → Why bother about Neural Networks for sequential data?
- → **How to do Neural Networks for sequential data?**

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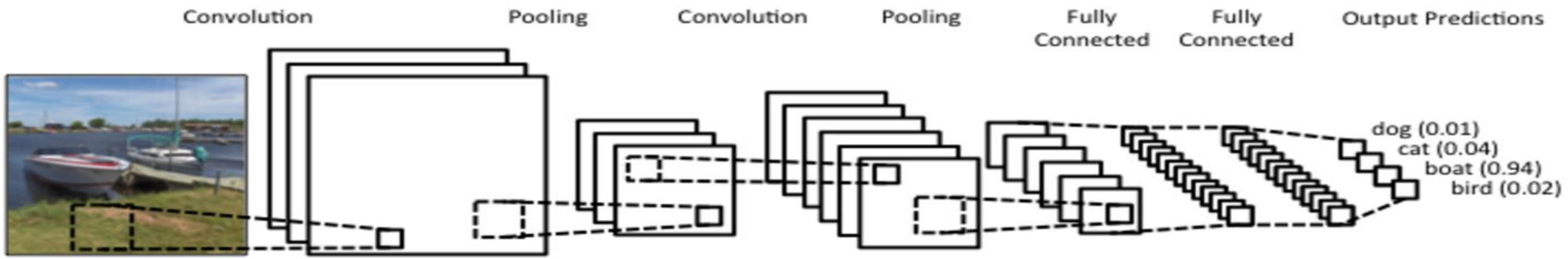
Convolutional Neural Networks

- Mathematical definition: combination of simple transformations
- There can be a lot of layers
- Convolutional layers help



https://playground.tensorflow.org/

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Convolutional Neural Networks

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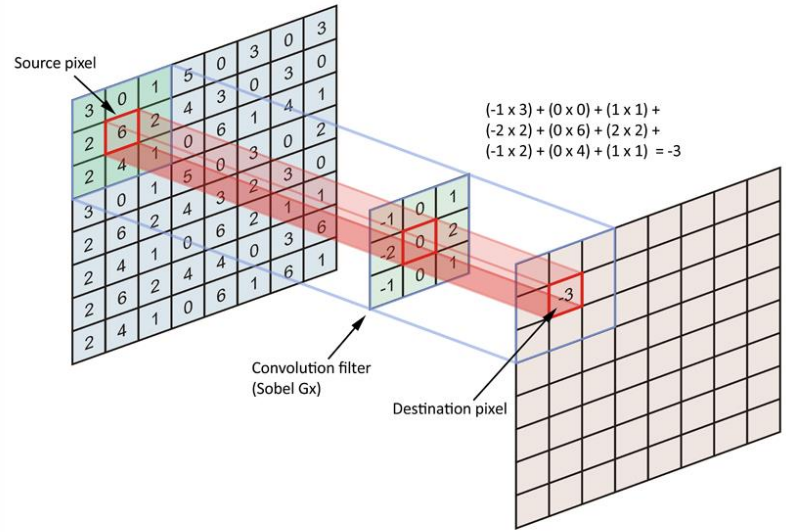
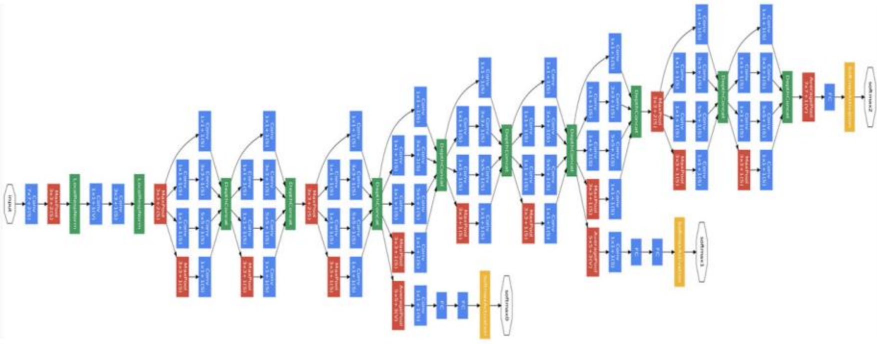
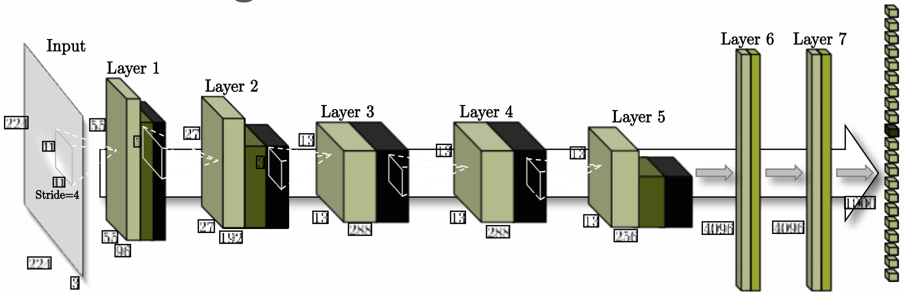


Single convolutional layer

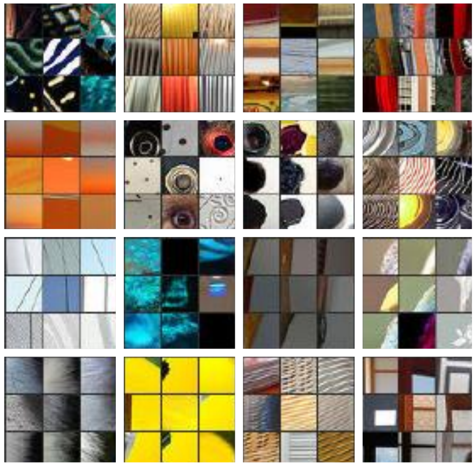


GoogLeNet architecture

Flow of data through Convolutional Neural Network



Layer 1

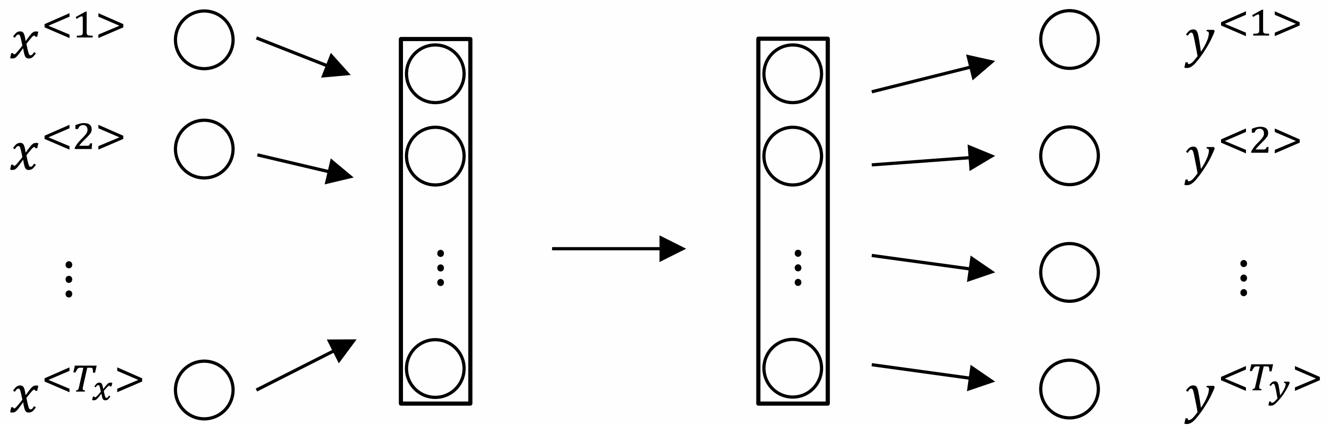


Layer 2

Layer 5

[Zeiler Fergus 14]

Why not a standard fully-connected or convolutional network?



Problems:

- Inputs, outputs can be different lengths in different examples
- Doesn’t share features learned across different positions of text

Adopted from Andrew Ng

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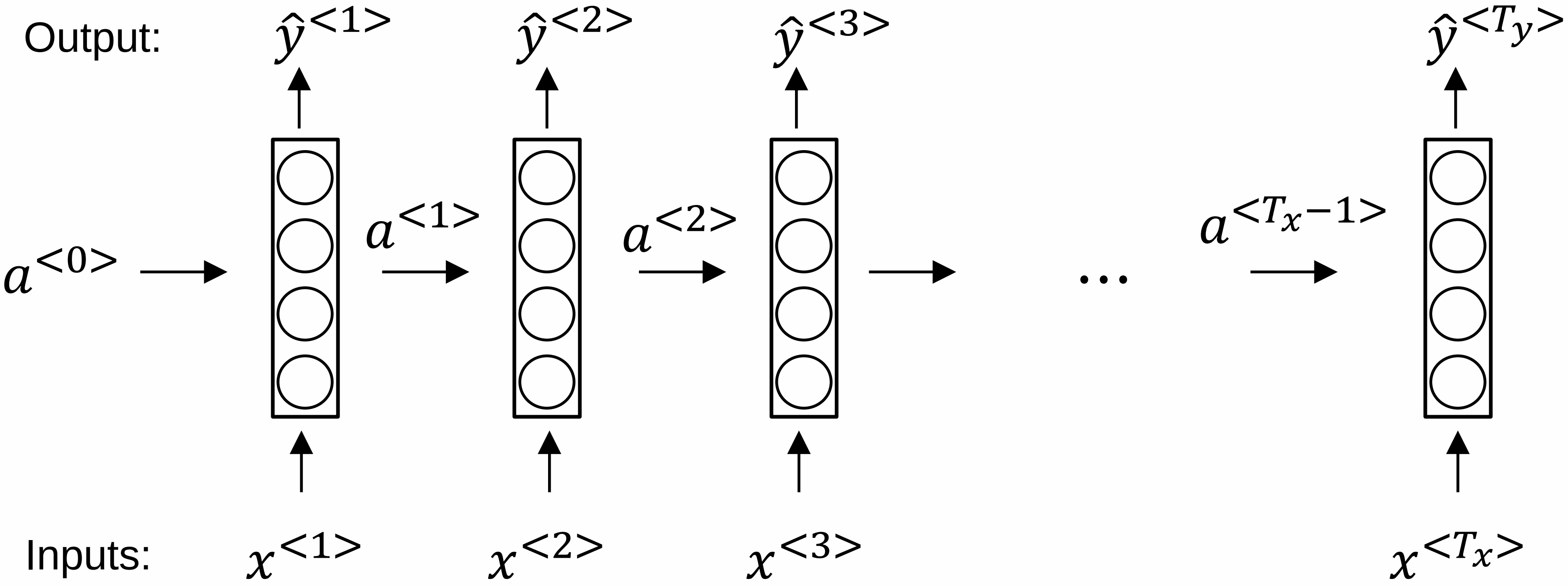
Forward propagation through Recurrent Neural Network



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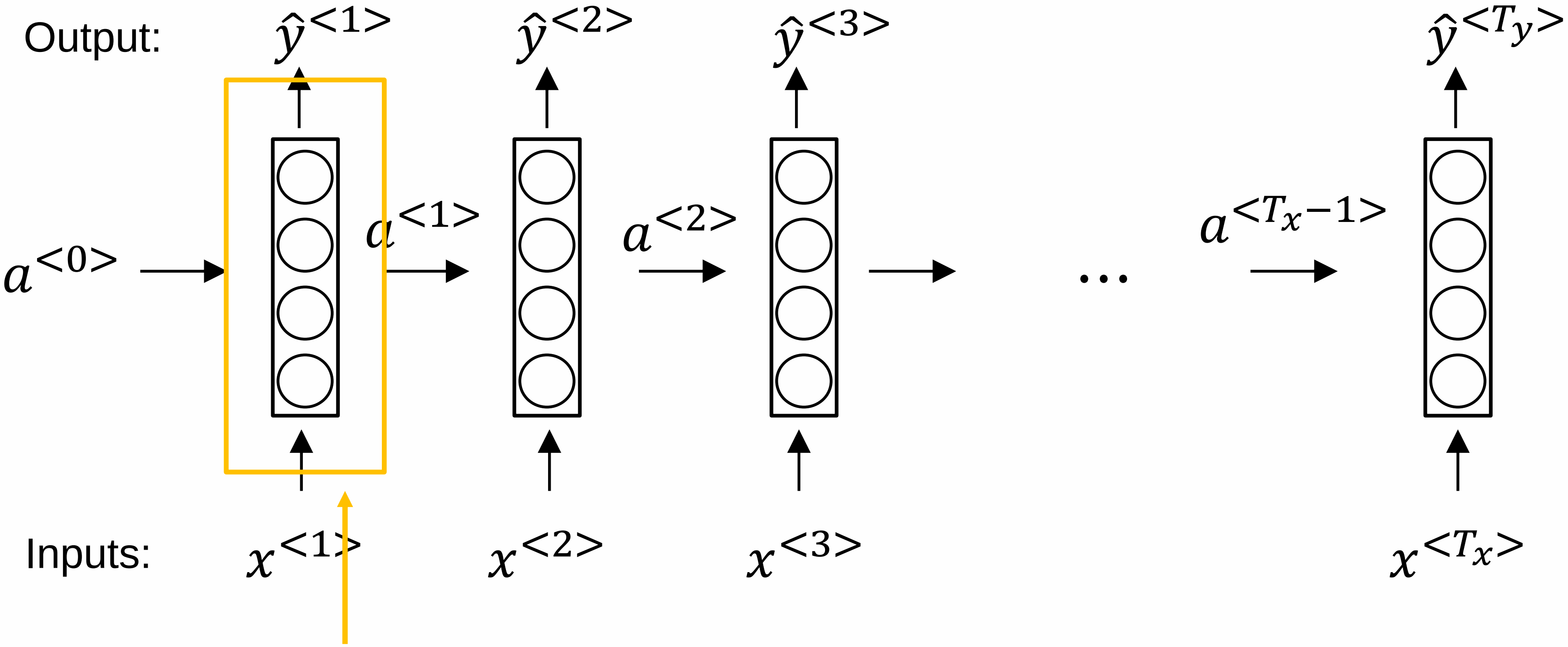
Forward propagation through Recurrent Neural Network



Processing unit is the same for all time moments.
Units has parameters we want to learn!

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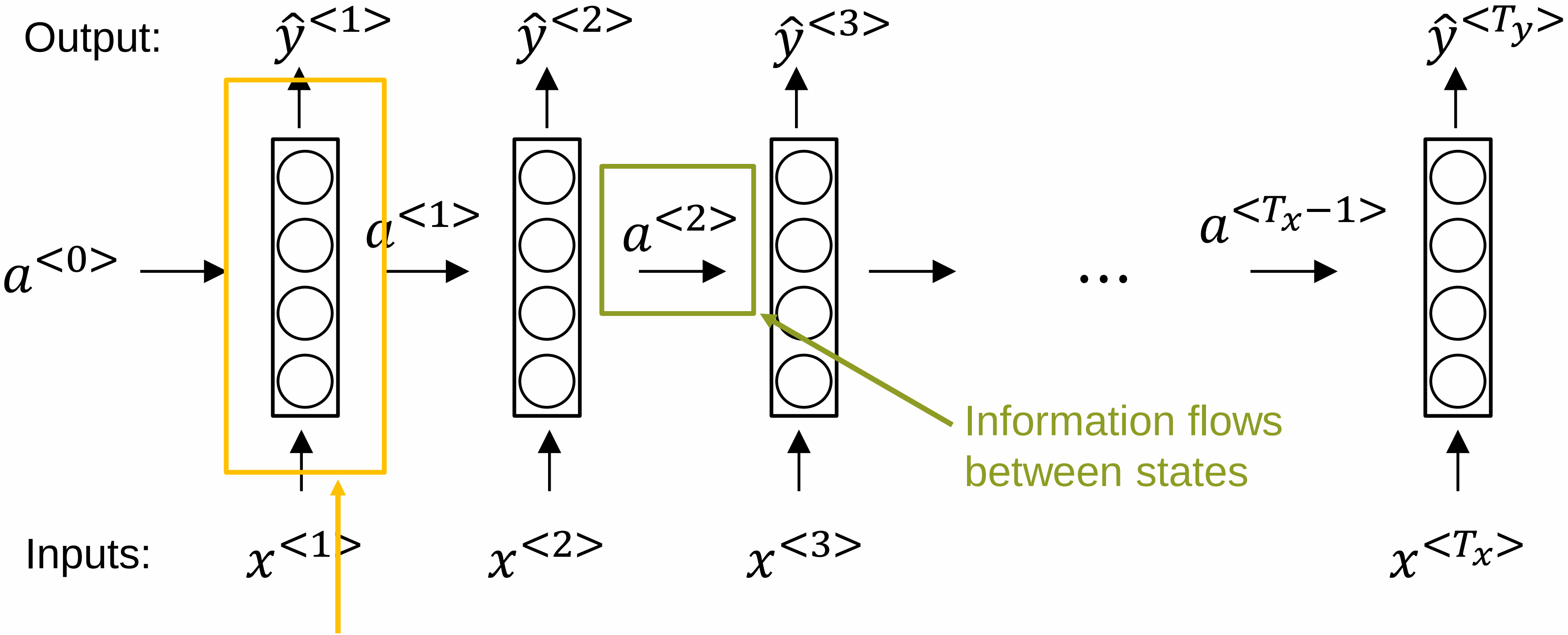

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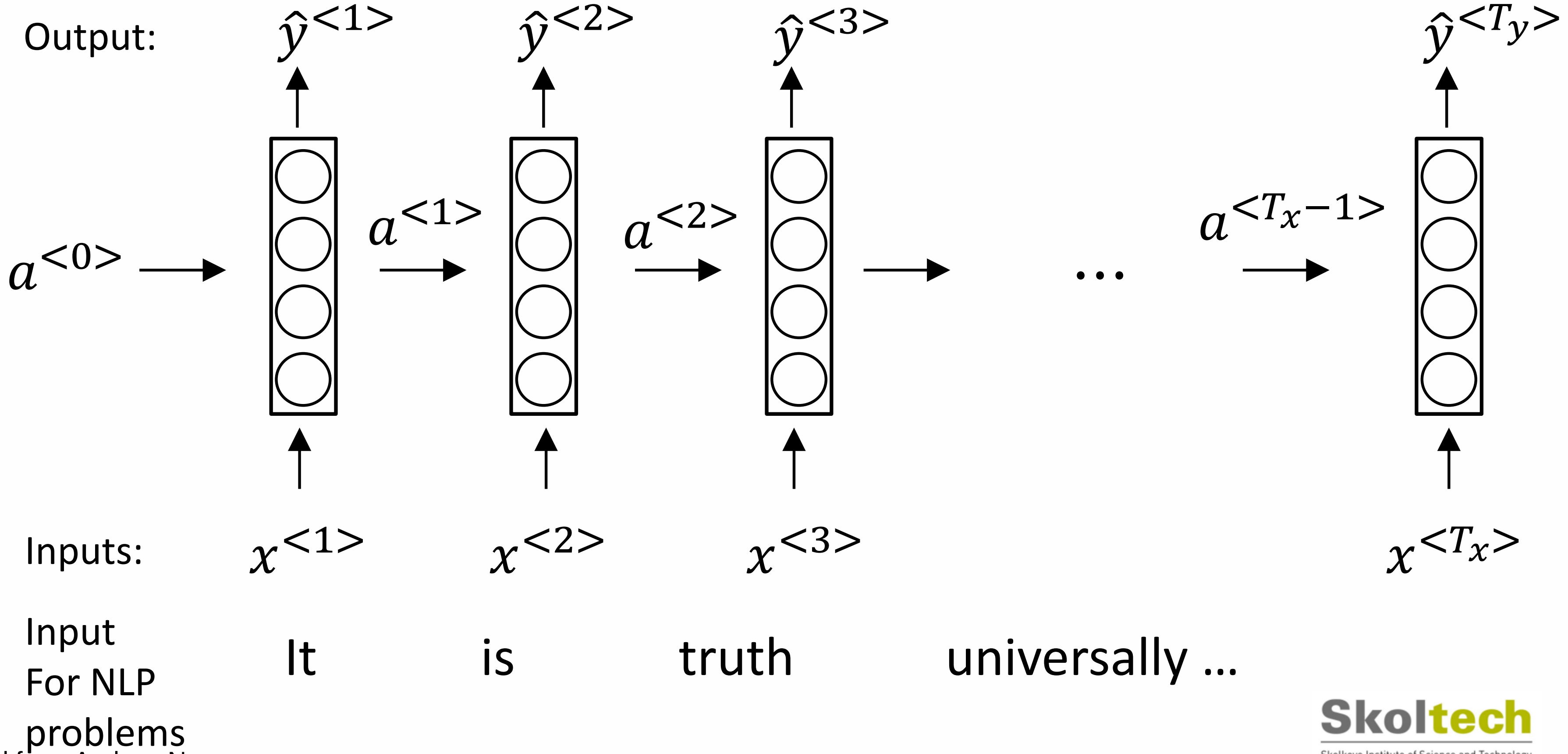

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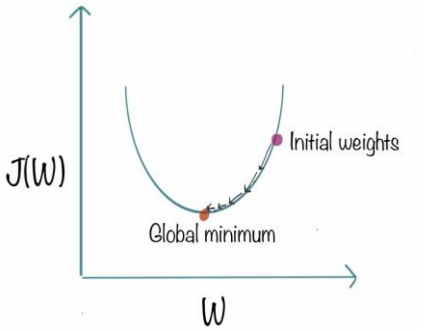
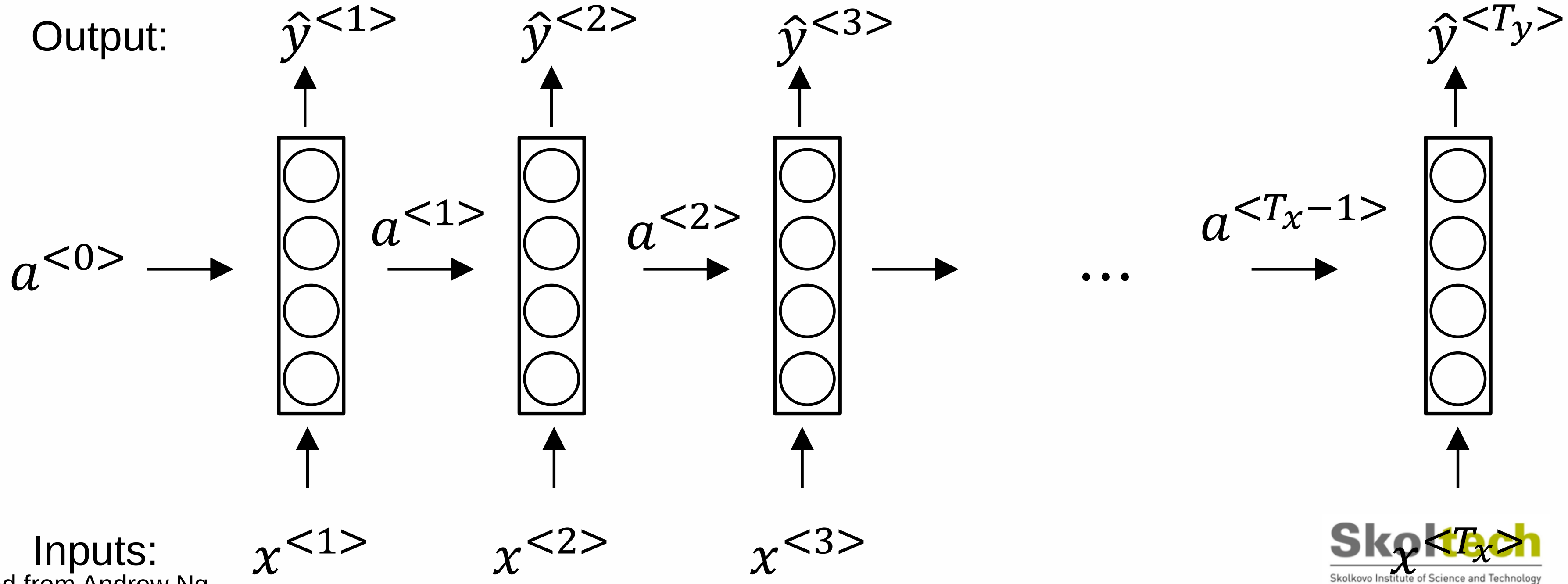
Backward propagation through Recurrent Neural Network

- Our loss function is $\mathcal{L}^{<t>}(\hat{y}^{<t>}, y^{<t>})$
- We want to estimate parameters, so we need derivatives!

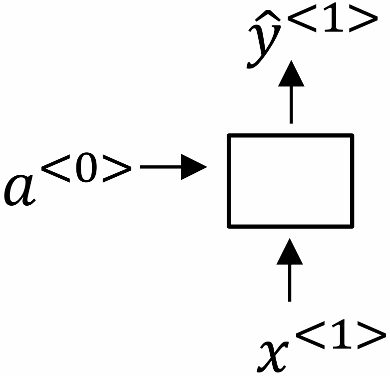




Adopted from Andrew Ng

Zoo of RNN (Recurrent Neural Network) models

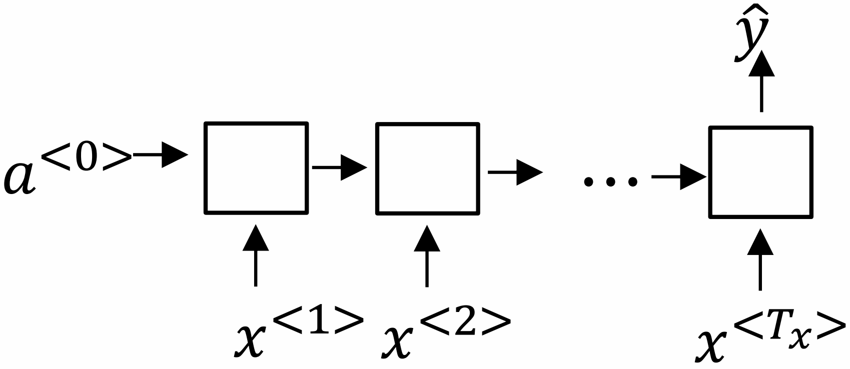
One to one



We have a separate input & output each time

- Image classification from cameras

Many to one



We have a single output for a sequence

- Sentiment of a sentence: good or bad review?

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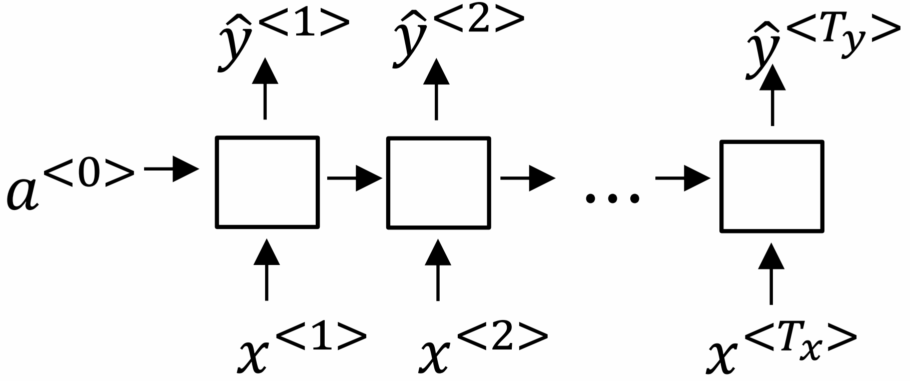
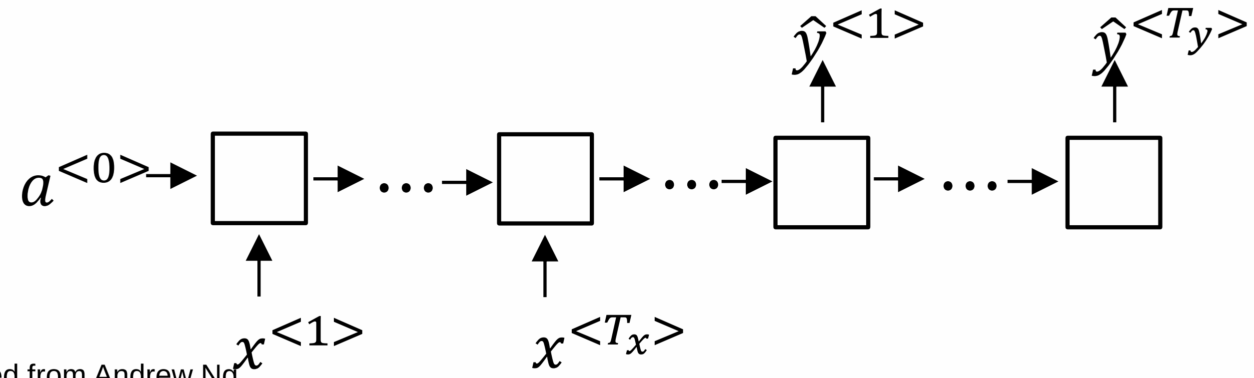
Zoo of RNN (Recurrent Neural Network) models

Many to many



- Time series prediction
- Anomaly detection



- Translation

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Forward propagation through Recurrent Neural Network

Initial sequence:

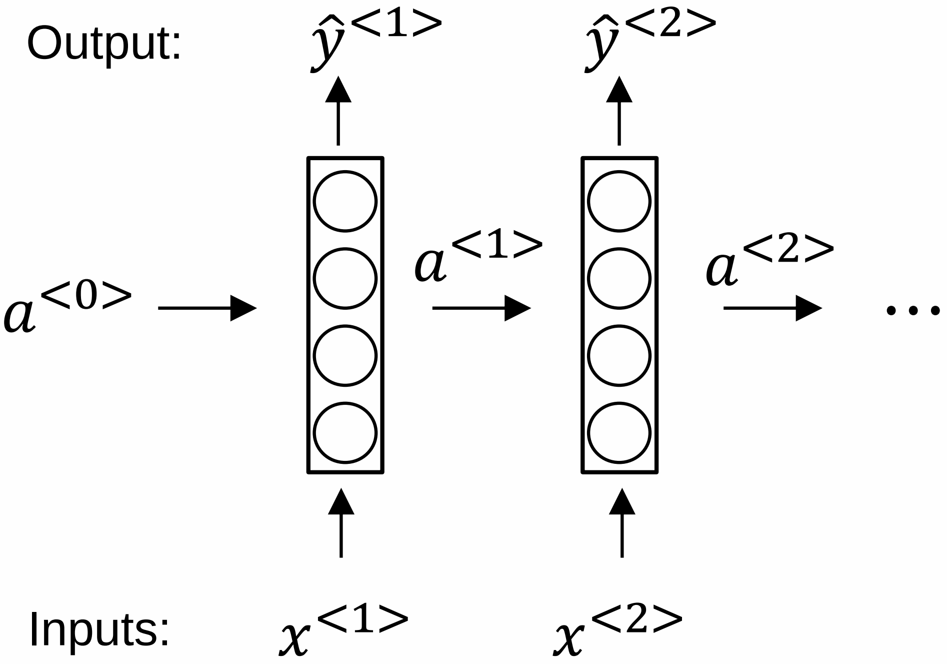
$$x^{<1:n>} = x^{<1>}, x^{<2>}, \dots, x^{<T>}, x_i \in \mathbb{R}^{d_{in}}$$

For each input $x_{1:i}$ we get an output y_i:

$$y^{<i>} = RNN(x^{<1:i>}), y^{<i>} \in \mathbb{R}^{d_{out}}$$

For the whole sequence $x^{<1:n>}$:

$$y^{<1:n>} = RNN^*(x^{<1:n>}), y^{<i>} \in \mathbb{R}^{d_{out}}$$



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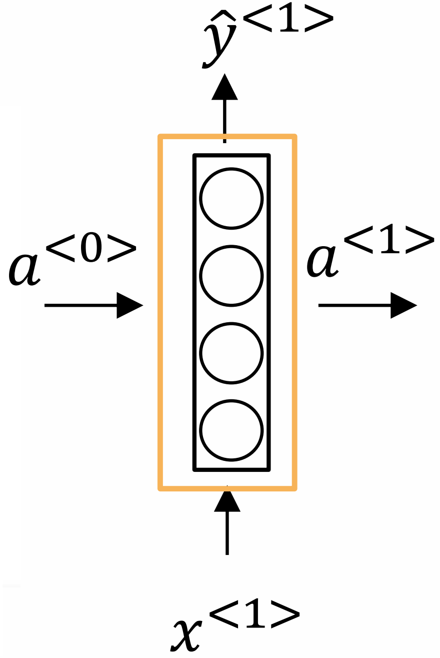
Selection of RNN architecture

Simplest RNN unit: what is going on inside yellow rectangle?

- $RNN^*(x^{<1:n>}, a^{<0>}) = y^{<1:n>}$
- $y^{<i>} = g(W^{out}[a^{<i>}, x^{<i>}] + b)$



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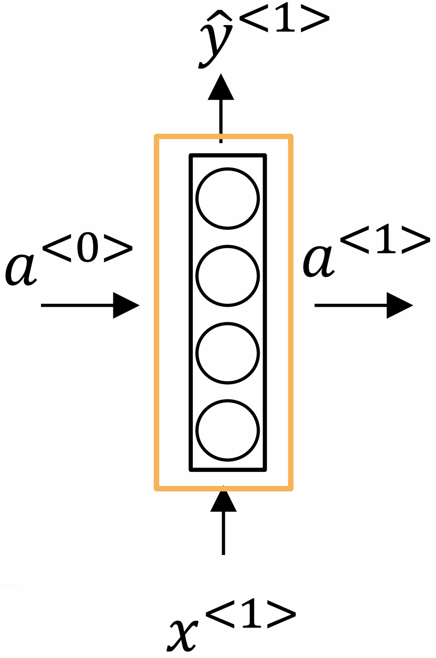
- $RNN^*(x^{<1:n>}, a^{<0>}) = y^{<1:n>}$
- $y^{<i>} = g(W^{out}[a^{<i>}, x^{<i>}] + b)$
- R is a recursive activation function. It depends on inputs $x^{<t>}$ and output of the previous state $a_{<t-1>}$ (vector of the previous state)
- $a^{<i>} = R(a^{<i-1>}, x^{<i>})$
- $R(a^{<i-1>}, x^{<i>}) = g(W^{hid}[a^{<i-1>}, x^{<i>}] + b)$, $[a^{<i>}, x^{<i>}]$ is the concatenation of $a^{<i>}$ and $x^{<i>}$
- $x^{<i>} \in \mathbb{R}^{d_{in}}, y^{<i>} \in \mathbb{R}^{d_{out}}, a^{<i>} \in \mathbb{R}^{d_{hid}}$



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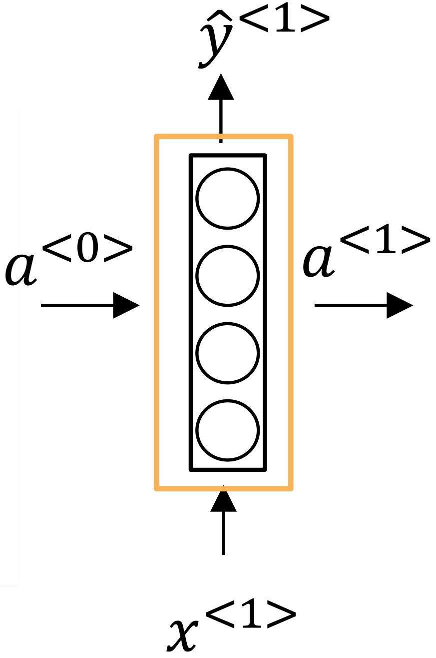
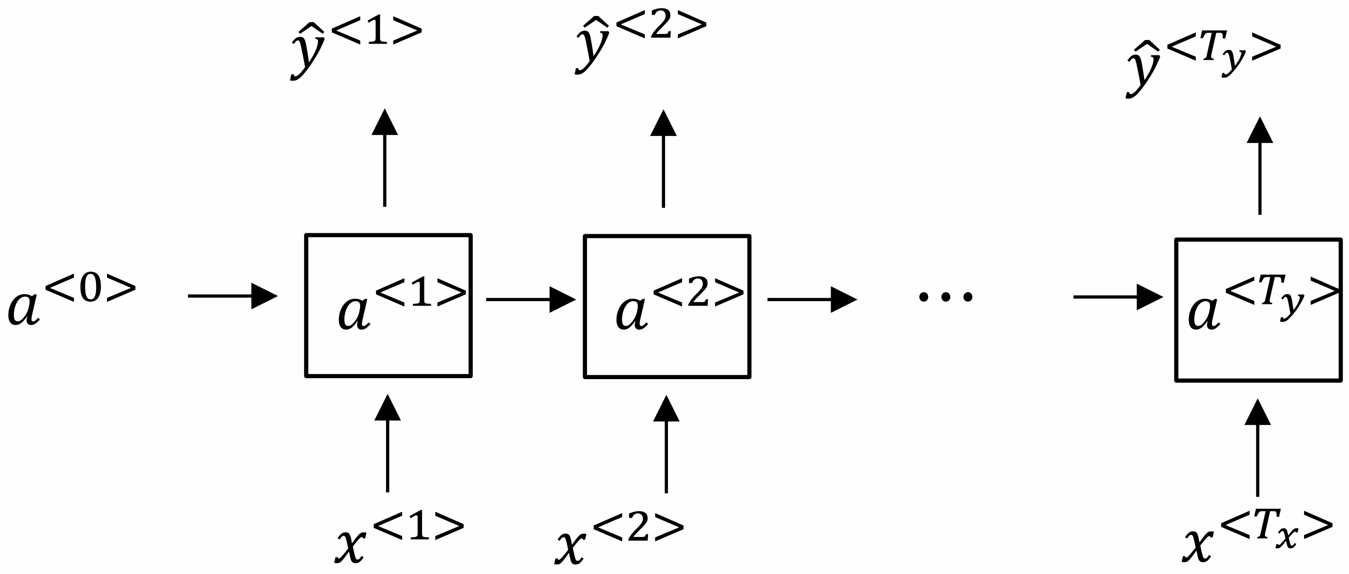
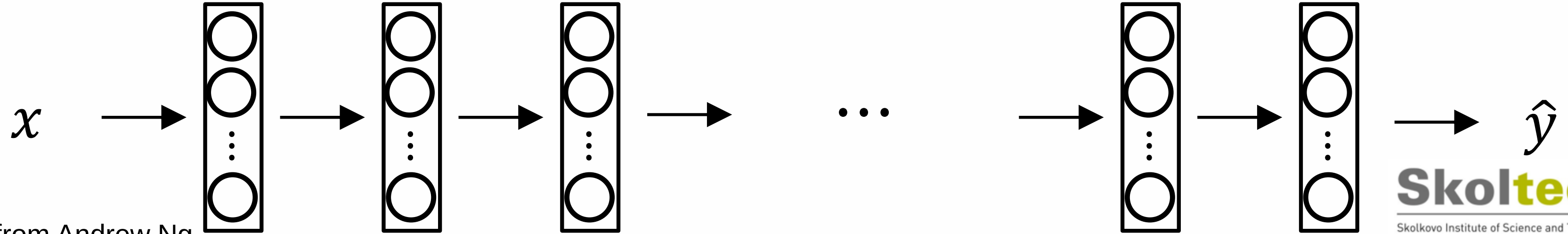
- $x^{<i>} \in \mathbb{R}^{d_{in}}, y^{<i>} \in \mathbb{R}^{d_{out}}, a^{<i>} \in \mathbb{R}^{d_{hid}}$
- Parameters of Neural Network are $W^{hid} \in \mathbb{R}^{(d_{in}+d_{out})\times d_{hid}}, W^{out} \in \mathbb{R}^{d_{hid}\times d_{out}}$



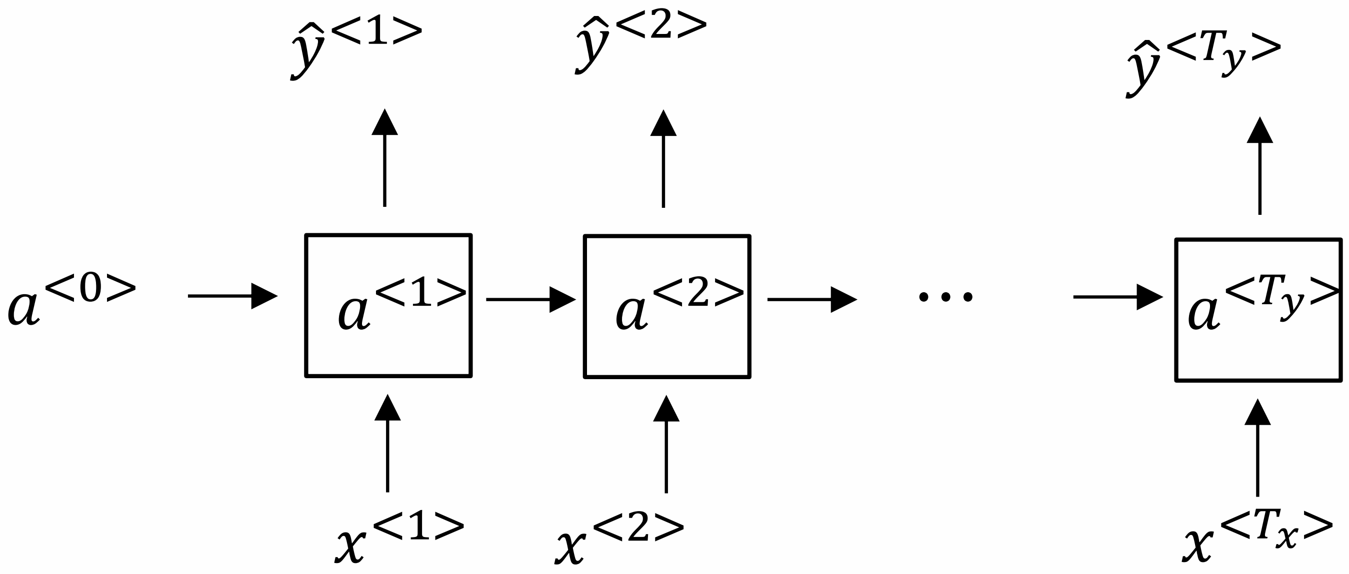
Gradient vanish and/or explode





Adopted from Andrew Ng

Gradient vanish and/or explode



Neural networks forget fast, and it is hard to learn long-term dependencies

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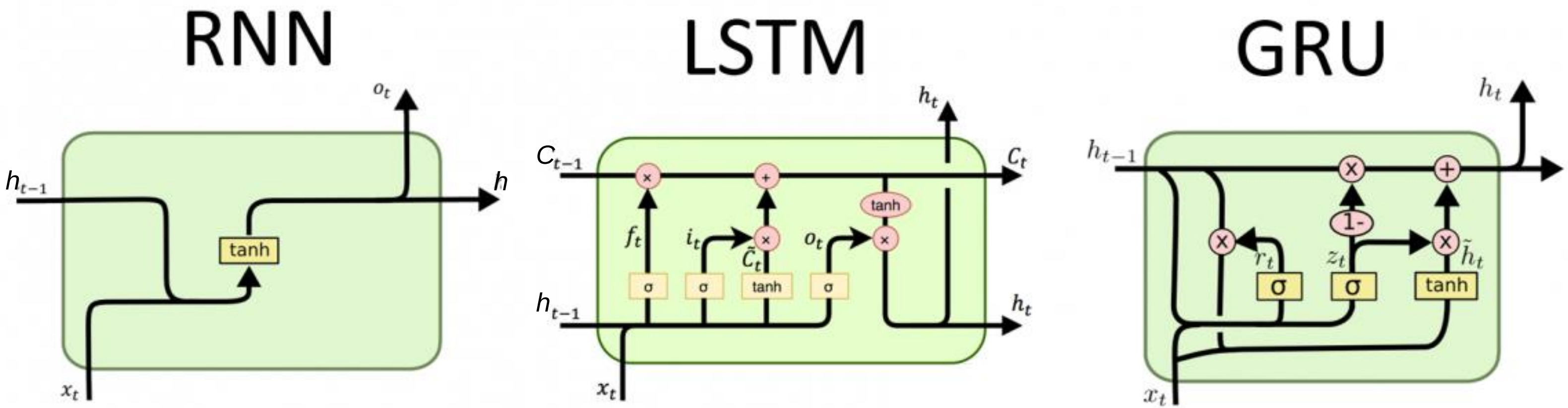
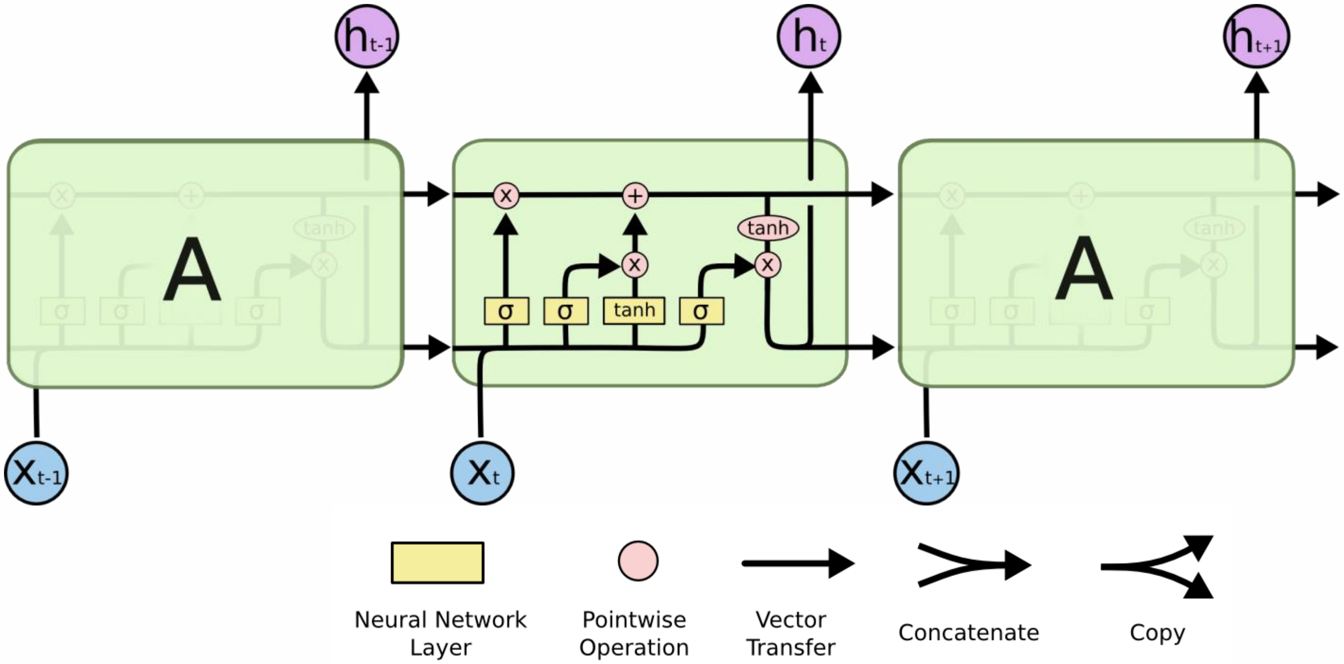
Better RNN units: LSTM and GRU

- LSTM: long short term memory
- GRU: Gated recurrent unit



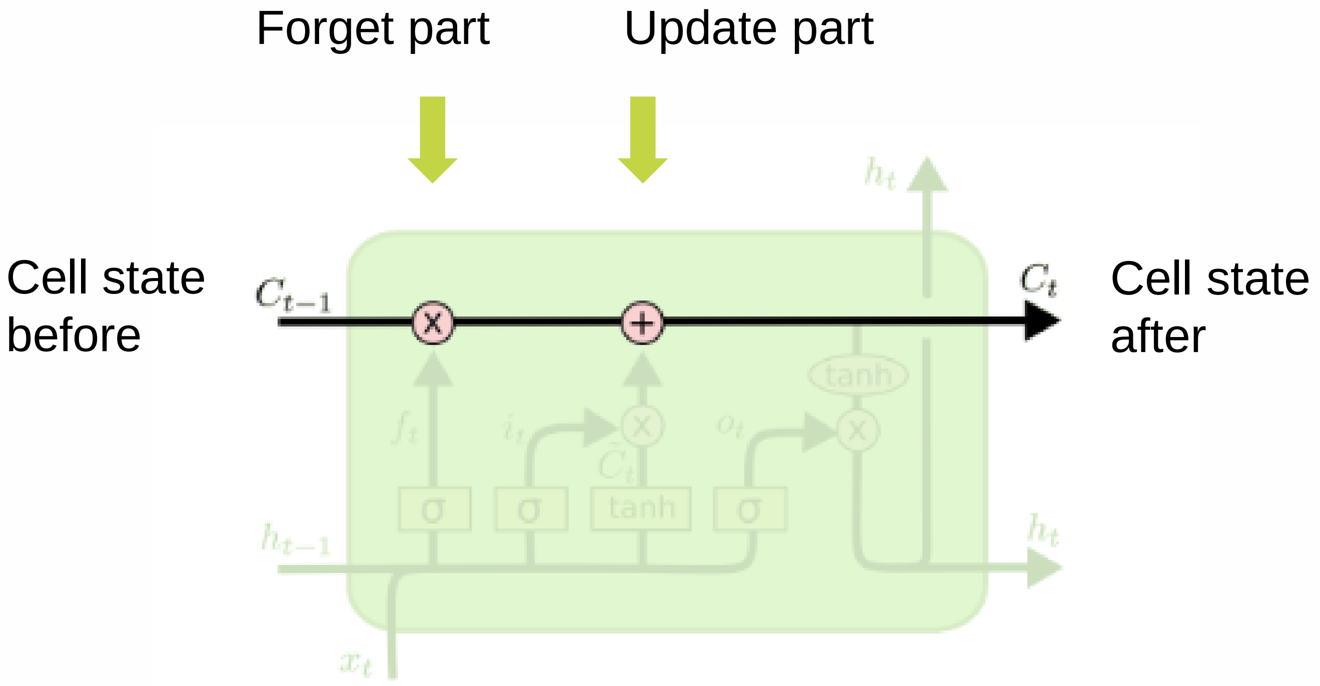
Details on how LSTM works

Remembering information for long periods of time is practically the default behavior of LSTM



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long term memory part – Cell state



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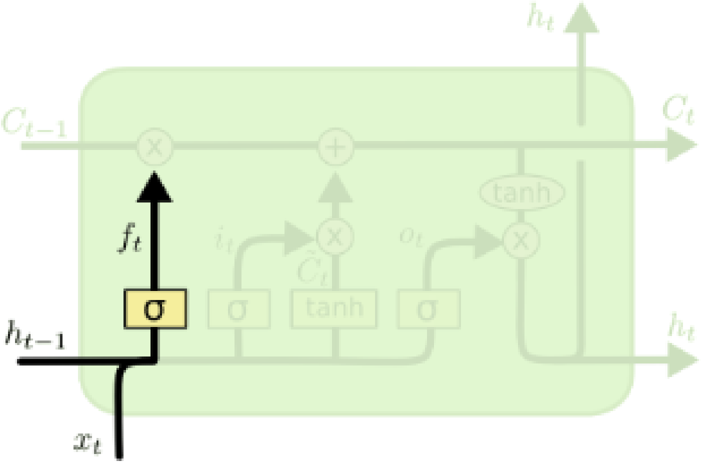
Forget part

Identify how much should we forget:
sigmoid returns value between 0 and 1

hidden
state (a)



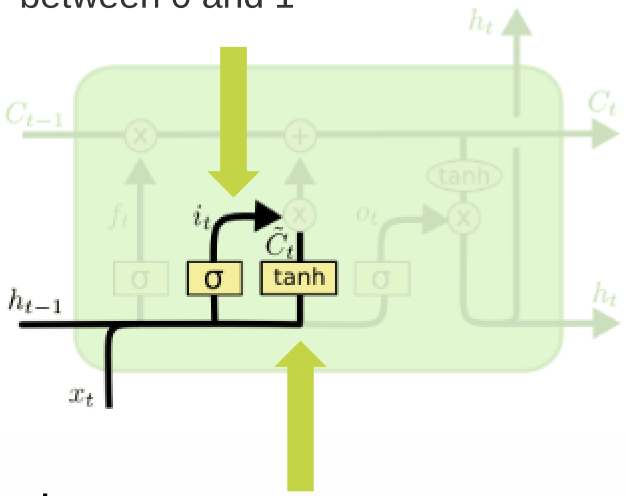
inputs

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

Update part

Identify how much should we update: sigmoid returns value between 0 and 1

hidden state (a)



inputs

What update we do

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

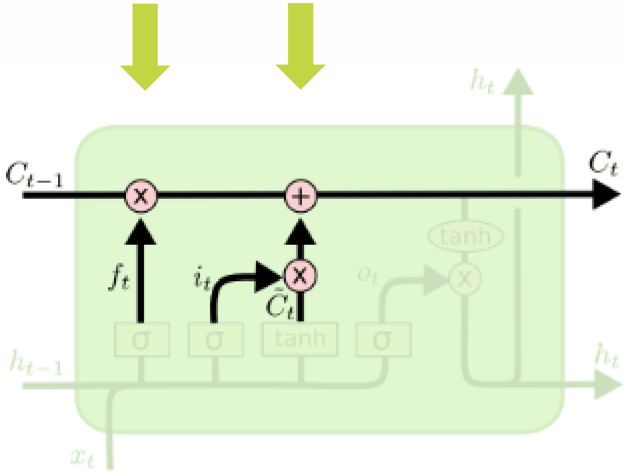
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Long term memory part – Cell state

Forget part

Update part

Cell state before

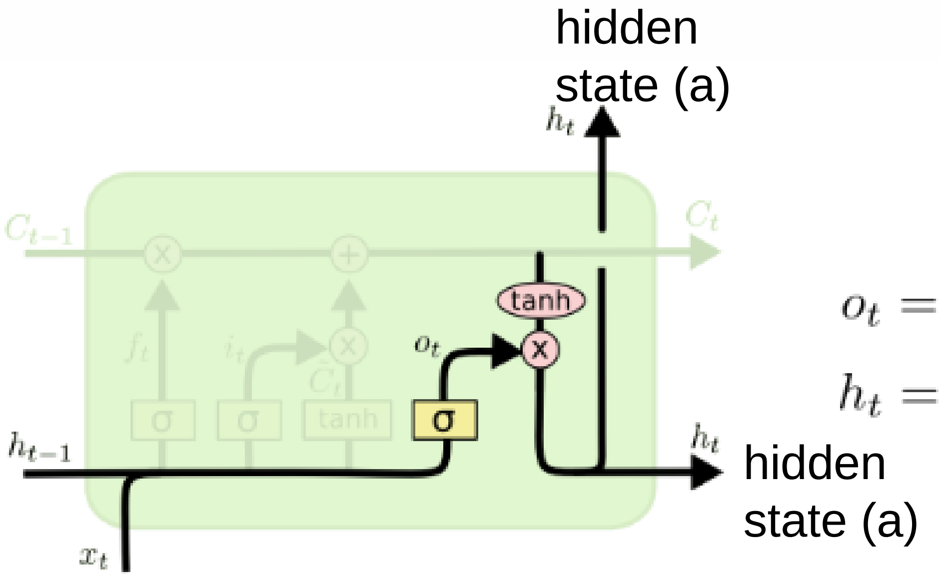


Cell state after

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

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Update everything else



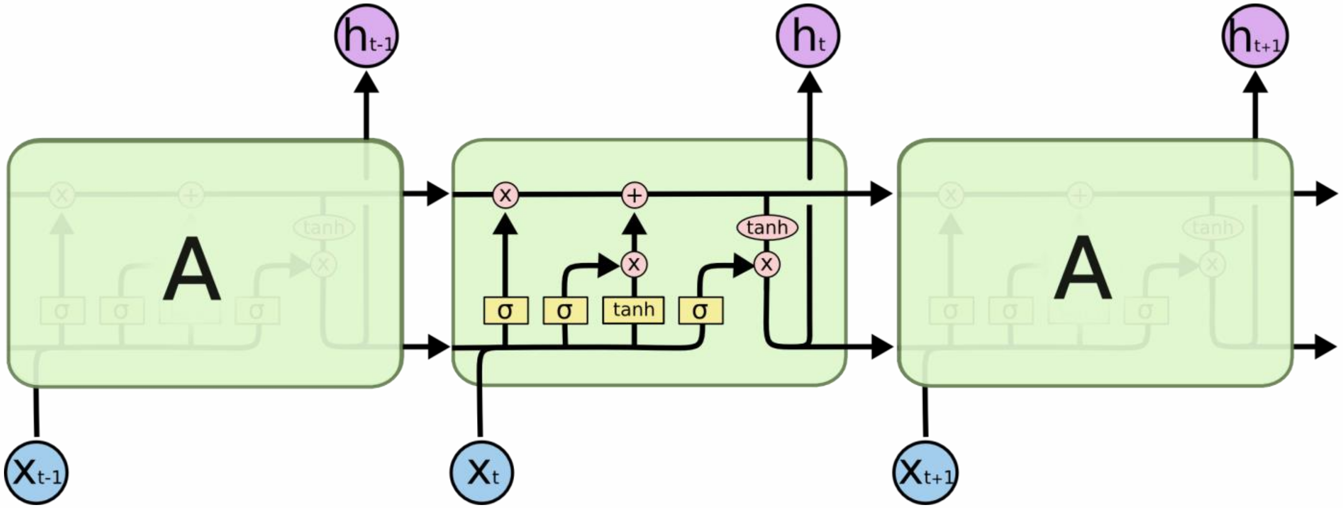
$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

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

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Details on how LSTM works

- There are cell and hidden (activation) states
- LSTM block forgets and updates cell state during processing at one block



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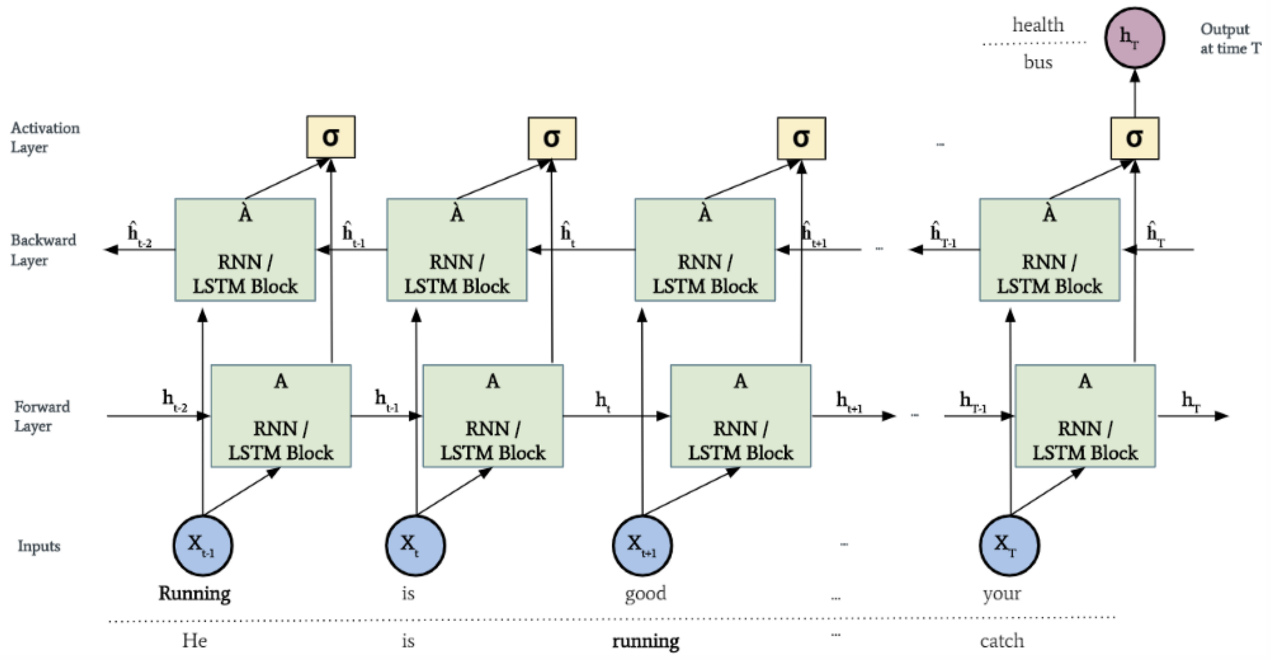
Other architectures: bidirectional LSTM

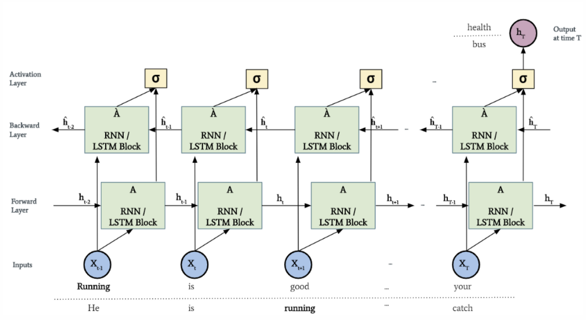


https://mc.ai/review-generation-using-bidirectional-long-short-term-memorylstm/

Other architectures: bidirectional LSTM

Bidirectional LSTM are useful when we benefit from the future data:

- handwriting recognition
- speech recognition
- protein Structure Prediction (bioinformatics)



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Take-home messages

- For some types of data classic methods fail:
  we need to learn a representation i.e. extract features automatically

- Neural Networks provide enough flexibility for this problem for various data types

- The basic architecture is Recurrent Neural Network RNN

- But we can do better in terms of keeping the necessary information with LSTM and GRU blocks/architectures

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