

Sequence models

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Applications

- Speech recognition
 - Input: sequence of pressure values
 - Output: sequence of words
- Music generation
 - Input: 0
 - Output sequence of notes
- Sentiment classification
 - Input: sequence of words
 - Output: rating (1-5)
- Machine translation
 - Input: sequence of words
 - Output: sequence of words
- Video activity recognition, summarization, etc.:
 - Input: sequence of pictures
 - Output: labels, sequence of words, etc.
- DNA sequence analysis:
 - Input: AGCCCT...
 - Output: eg. sequence of A,G,C,T which corresponds to a protein

Representation

- **x**: Hello World

$$x^{<1>} \quad x^{<2>}$$

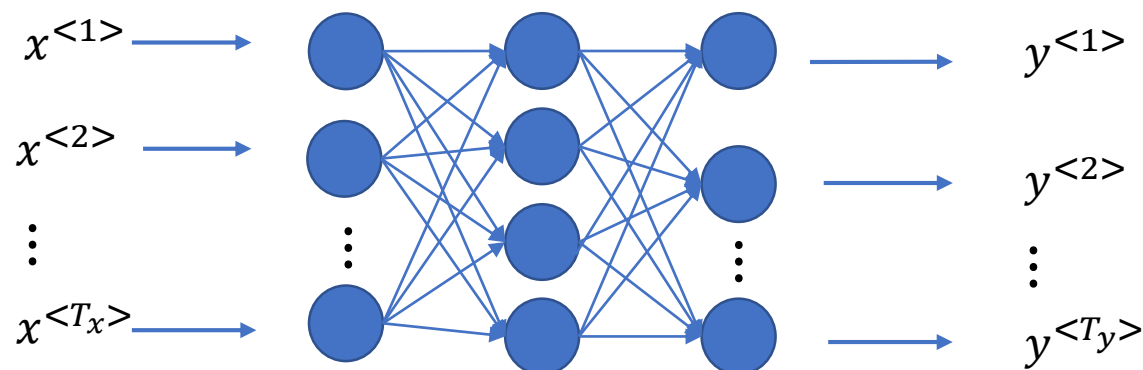
- Or character level: $x^{<1>} = h$, $x^{<2>} = e$, $x^{<3>} = l \dots$

- Vocabulary: list of words or characters:

$$\begin{bmatrix} a \\ b \\ \vdots \end{bmatrix} \text{ or } \begin{bmatrix} a \\ and \\ \vdots \end{bmatrix}$$

- We encode the characters or words with the position index in the vocabulary (after pre-processing)
- Input: one-hot encoded indexes or it's lower dimensional embedding
- Song: vocabulary of notes

Neural network

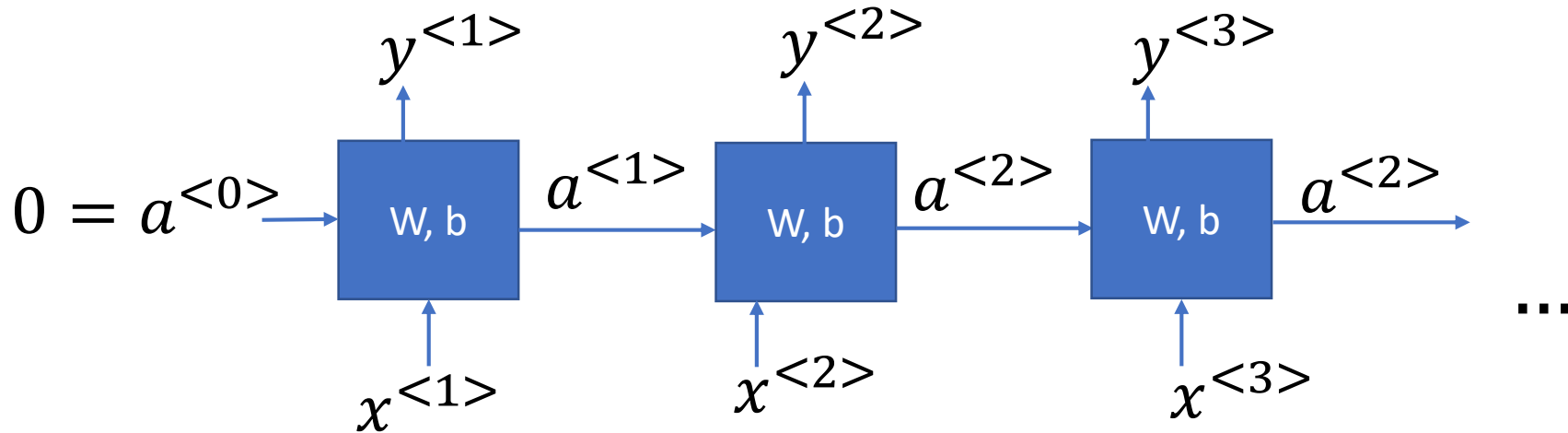


- Different input and output sizes:
 - Text sizes will vary example by example
 - Find the maximal text, pad with zeros the others (not too good)
- Bigger problem: doesn't share learned features across different positions of the text

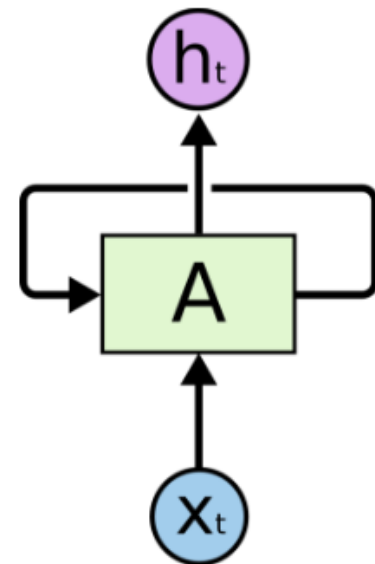
Apple is good for your health. Apple juice is cheap.

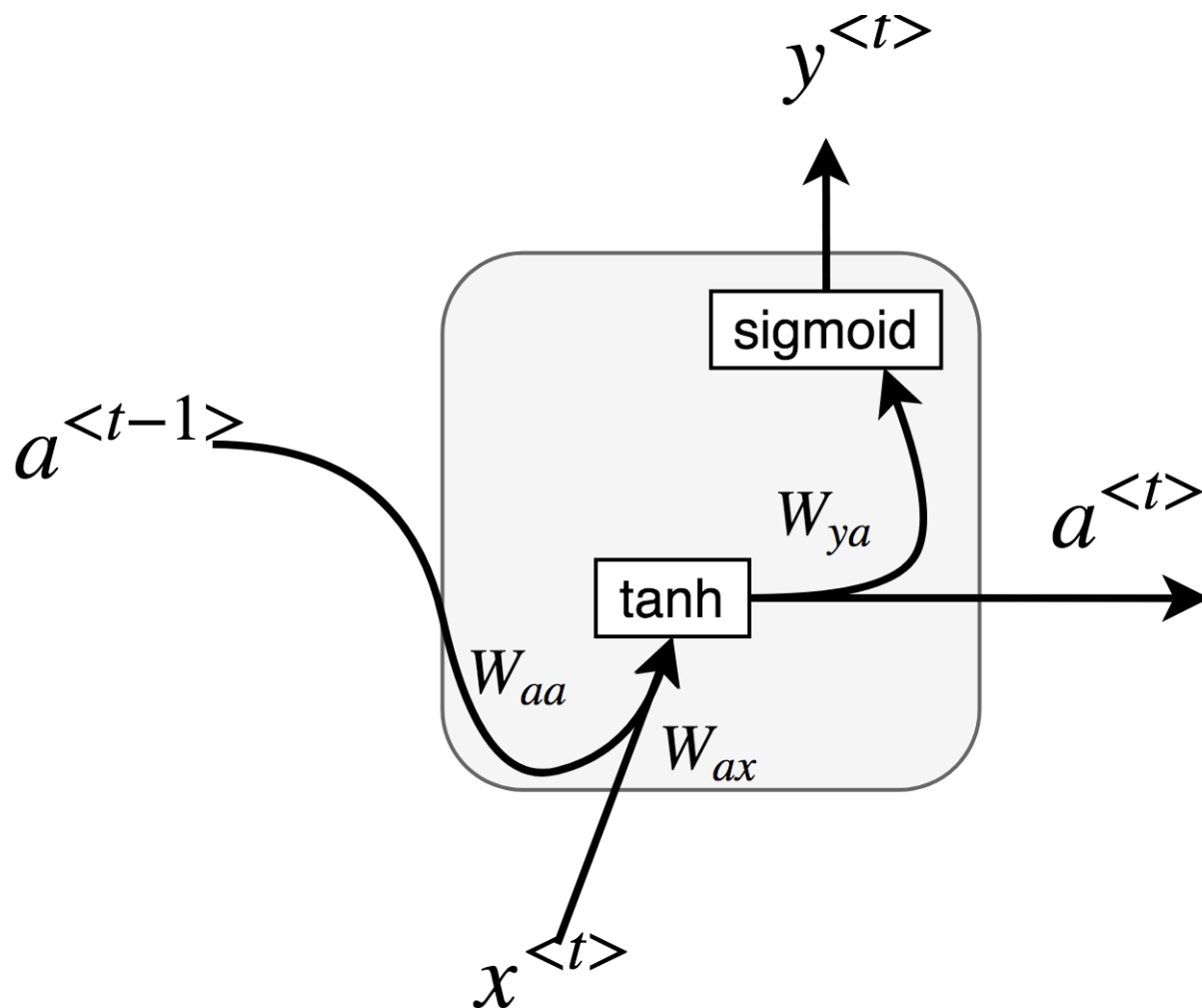
You learned in position 1 that apple is a fruit (found some weights). In position 7 you can't use the weights from position 1, you would have to learn the same weights again.

Recurrent neural networks (RNNs)



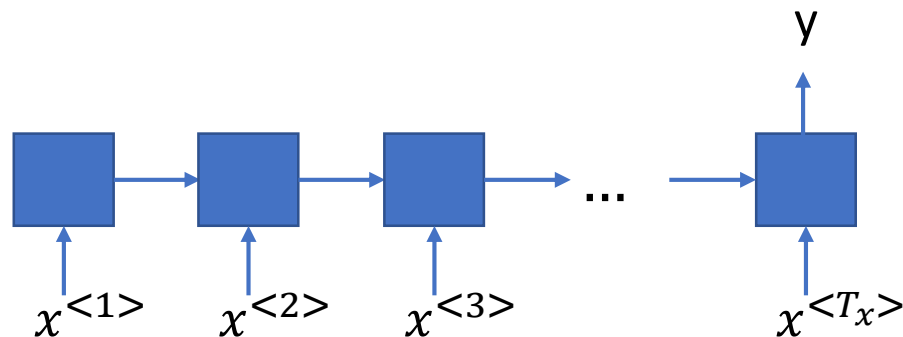
- $a^{<1>} = g(W_{aa}a^{<0>} + W_{ax}x^{<1>} + b_a)$
- $y^{<1>} = g(W_{ya}a^{<1>} + b_y)$
- $a^{<2>} = g(W_{aa}a^{<1>} + W_{ax}x^{<2>} + b_a)$
- $y^{<2>} = g(W_{ya}a^{<2>} + b_y)$
- ...



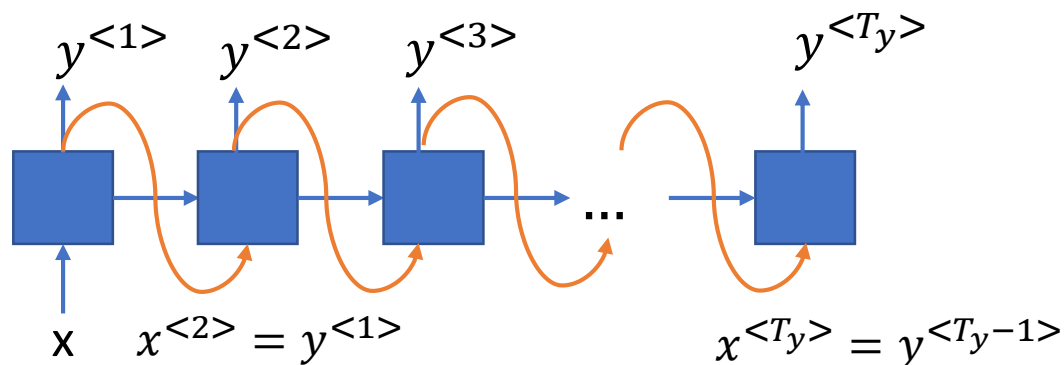


RNN architectures

- Many-to-one (e.g. sentiment classification)

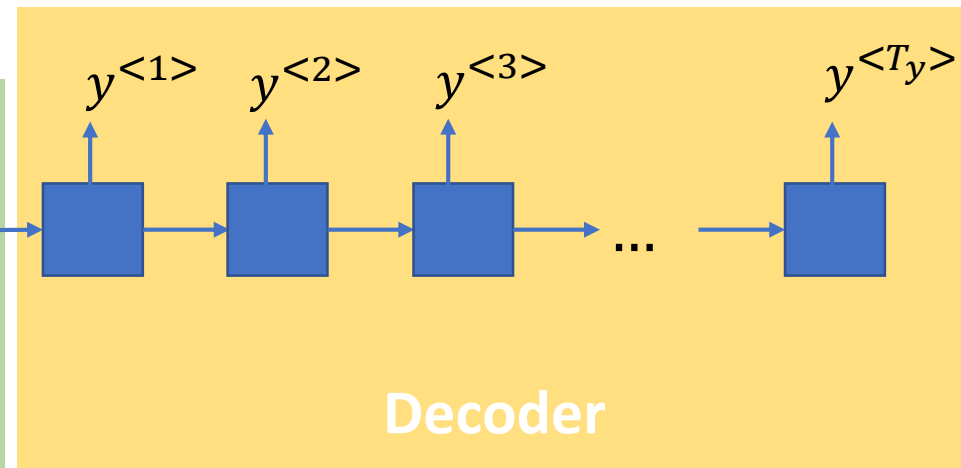
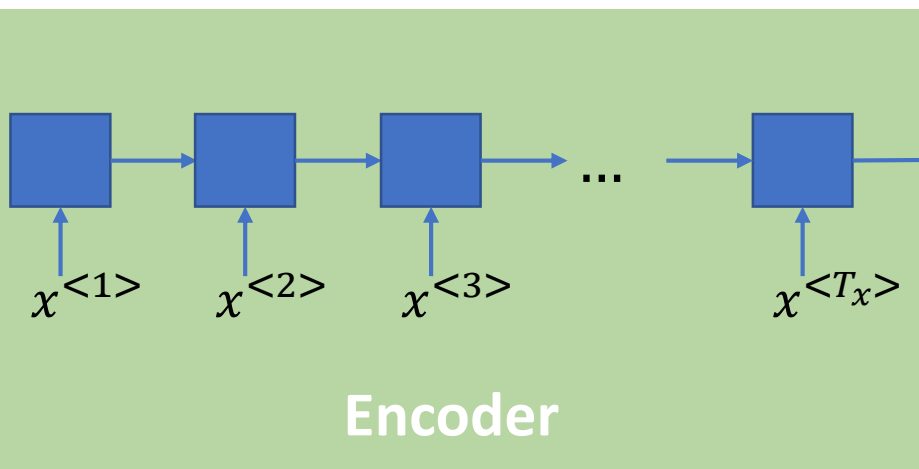
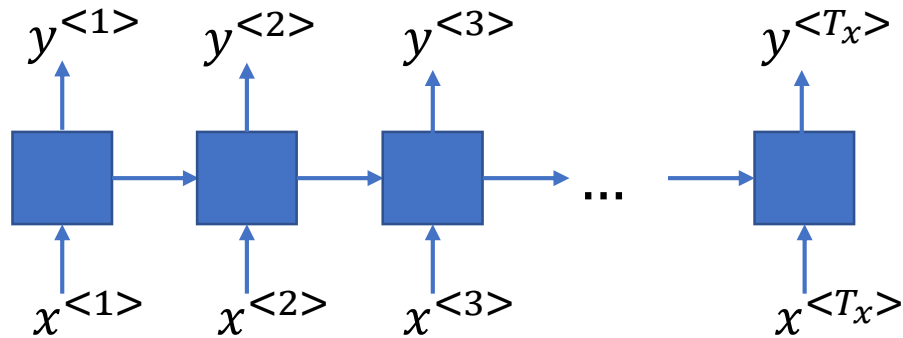


- One-to-many (e.g. music generation)



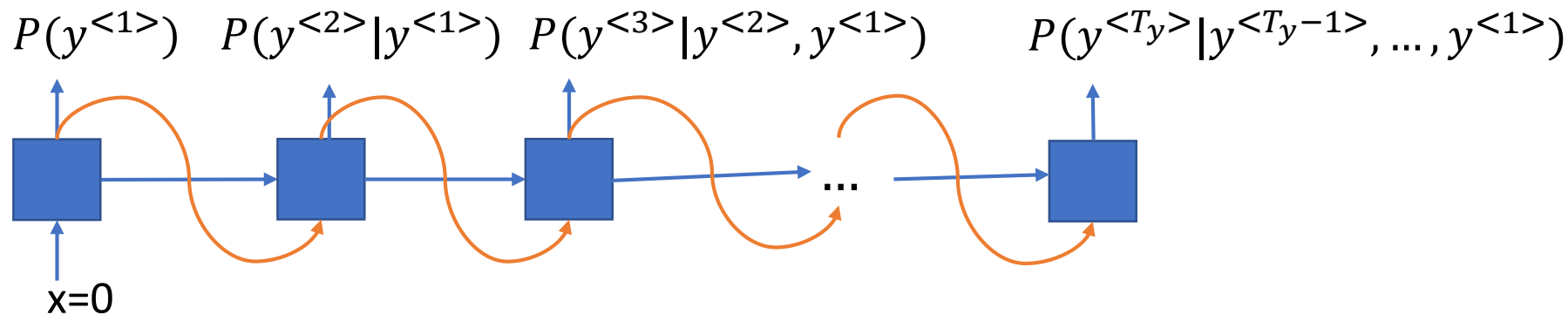
RNN architectures

- Many-to-many: 2 case: $T_x = T_y$ or $T_x \neq T_y$



Language modelling

- Language model: $P(\text{sentences})$
- Language model with RNN:



$$P(y^{<1>}, y^{<2>}, \dots, y^{<T_y>}) =$$

$$P(y^{<1>}) P(y^{<2>} | y^{<1>}) P(y^{<3>} | y^{<2>} y^{<1>}) \dots P(y^{<T_y>} | y^{<T_y-1>}, \dots)$$

Backpropagation


- Loss function:

$$L^{<t>}(\hat{y}^{<t>}, y^{<t>}) = - \sum_k y_k^{<t>} \log \hat{y}_k^{<t>}$$

$$L = \sum_{t=1}^{T_y} L^{<t>}(\hat{y}^{<t>}, y^{<t>})$$

- RNN: $a^{<t>} = g(W_{aa}a^{<t-1>} + W_{ax}x^{<t-1>} + b_a)$

- Let's say we know: $\frac{\partial L}{\partial a^{<t>}} = \frac{\partial L}{\partial y^{<t>}} \frac{\partial y^{<t>}}{\partial a^{<t>}}$

- We need: $\frac{\partial L}{\partial W_{aa}}, \frac{\partial L}{\partial W_{ax}}, \frac{\partial L}{\partial b_a}$  $\frac{\partial L^{<t>}}{\partial W_{aa}} = \frac{\partial L^{<t>}}{\partial a^{<t>}} \frac{\partial a^{<t>}}{\partial W_{aa}}$

$$\frac{\partial a^{<t>}}{\partial W_{aa}} = g'(a^{<t>}) \cdot \left(a^{<t-1>} + W_{aa} \frac{\partial L}{\partial a^{<t-1>}} \right) \img alt="blue arrow pointing right" data-bbox="828 781 891 818"/> \text{Backprop through time}$$

- When we train we have to do backpropagation through time
- Long sentences: vanishing gradient problem
- Vanishing gradient: g' small, $(g')^N \rightarrow 0$ (long sentence = big N)
- Similar to very deep networks
- ResNet: skip connection (linear information flow)

$$F(x) \rightarrow F(x) + x$$
$$F'(x) \frac{\partial L}{\partial x} \rightarrow F'(x) \frac{\partial L}{\partial x} + \frac{\partial L}{\partial x}$$

- NEW architectures instead of RNN with linear information flow

Gate recurrent unit (GRU)

- New hidden variable: c = memory cell
- Candidate value: $\tilde{c} = g(W_{cc}c^{<t-1>} + W_{cx}x^{<t>} + b_c)$
- Update gate: $\Gamma_u = \sigma(W_{uc}c^{<t-1>} + W_{ux}x^{<t>} + b_u)$
- Update rule: $c^{<t>} = \Gamma_u \cdot \tilde{c} + (1 - \Gamma_u) \cdot c^{<t-1>}$
- Activation: simply $a^{<t>} = c^{<t>}$
- Example: c_0 = plural (0) / singular (1)

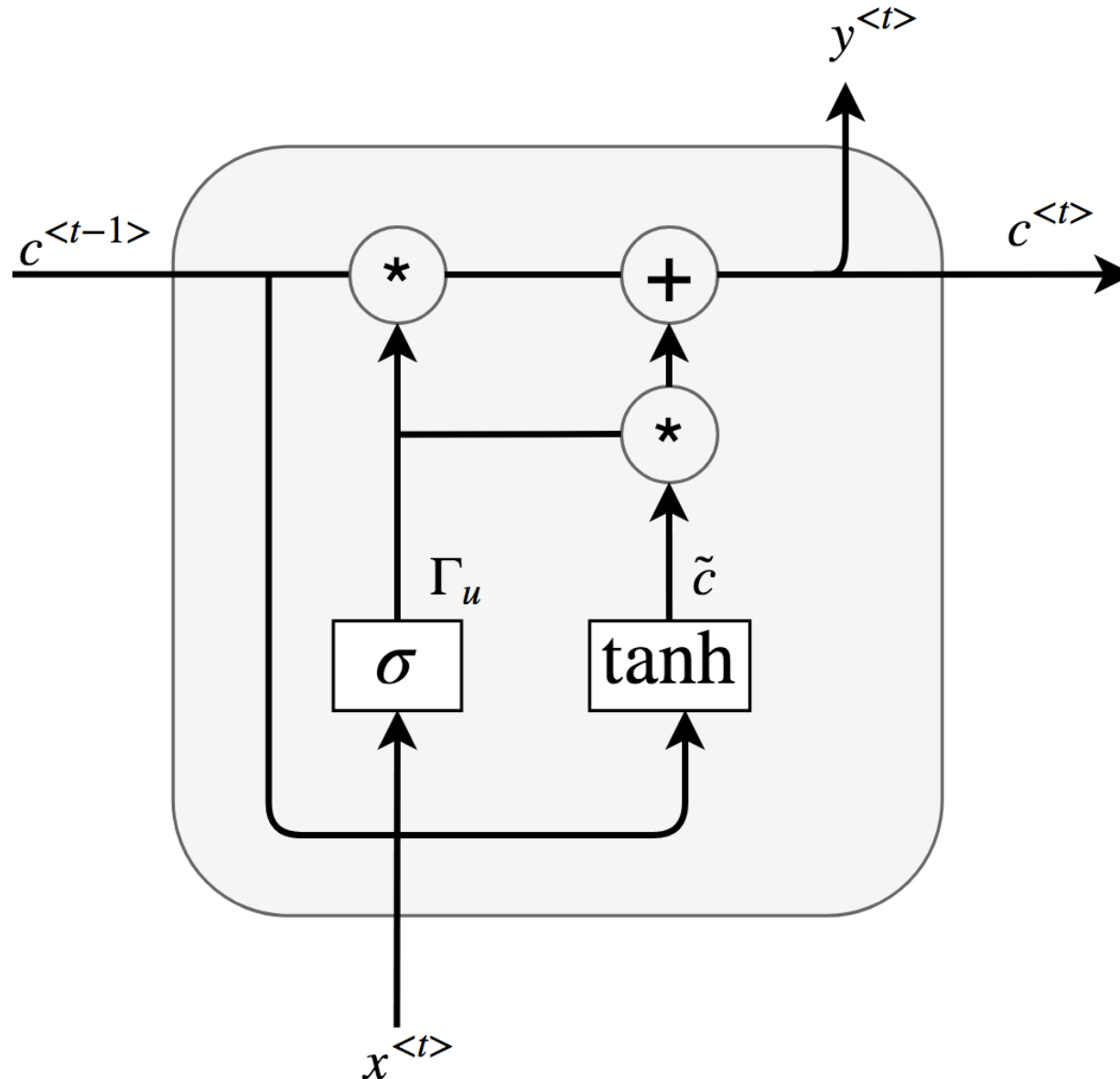
$$\begin{array}{ccc} \Gamma_u = 0 & \Gamma_u = 1 & \Gamma_u = 0 \\ c_0^{<1>} = 0 & c_0^{<2>} = 1 & c_0^{<3>} = 1 \end{array}$$

$$\begin{array}{cc} \Gamma_u = 0 & \Gamma_u = 0 \\ c_0^{<7>} = 1 & c_0^{<8>} = 1 \end{array}$$

$$\begin{array}{c} \Gamma_u = 1 \\ c_0^{<12>} = 0 \end{array}$$

The cat, who belongs to my friend, was red. The other cats ...

Gate recurrent unit (GRU)

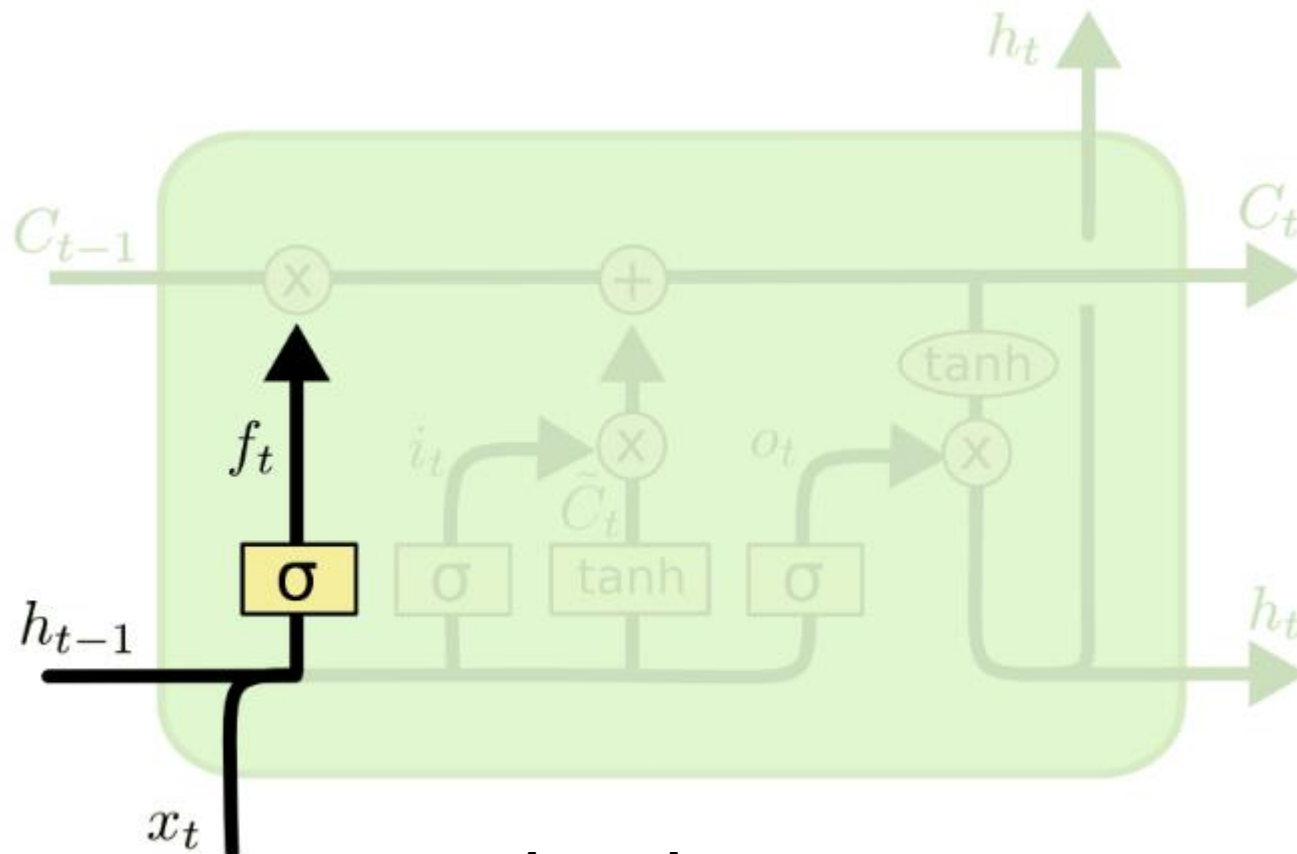


Long short-term memory (LSTM)

- GRU is a simpler model which is able to learn long-term dependencies
- More powerful model is LSTM
- Solves the vanishing problem very similarly: linear information flow through time
- Candidate value: $\tilde{c} = g(W_{cc}c^{<t-1>} + W_{cx}x^{<t>} + b_c)$
- It uses more gates:
 - Update gate: $\Gamma_u = \sigma(W_{uc}c^{<t-1>} + W_{ux}x^{<t>} + b_u)$
 - Forget gate: $\Gamma_f = \sigma(W_{fc}c^{<t-1>} + W_{fx}x^{<t>} + b_f)$
 - Output gate: $\Gamma_o = \sigma(W_{oc}c^{<t-1>} + W_{ox}x^{<t>} + b_o)$
- Update rule: $c^{<t>} = \Gamma_u \cdot \tilde{c} + \Gamma_f \cdot c^{<t-1>}$
- Activation: $a^{<t>} = \Gamma_o \cdot c^{<t>}$

Long short-term memory (LSTM)

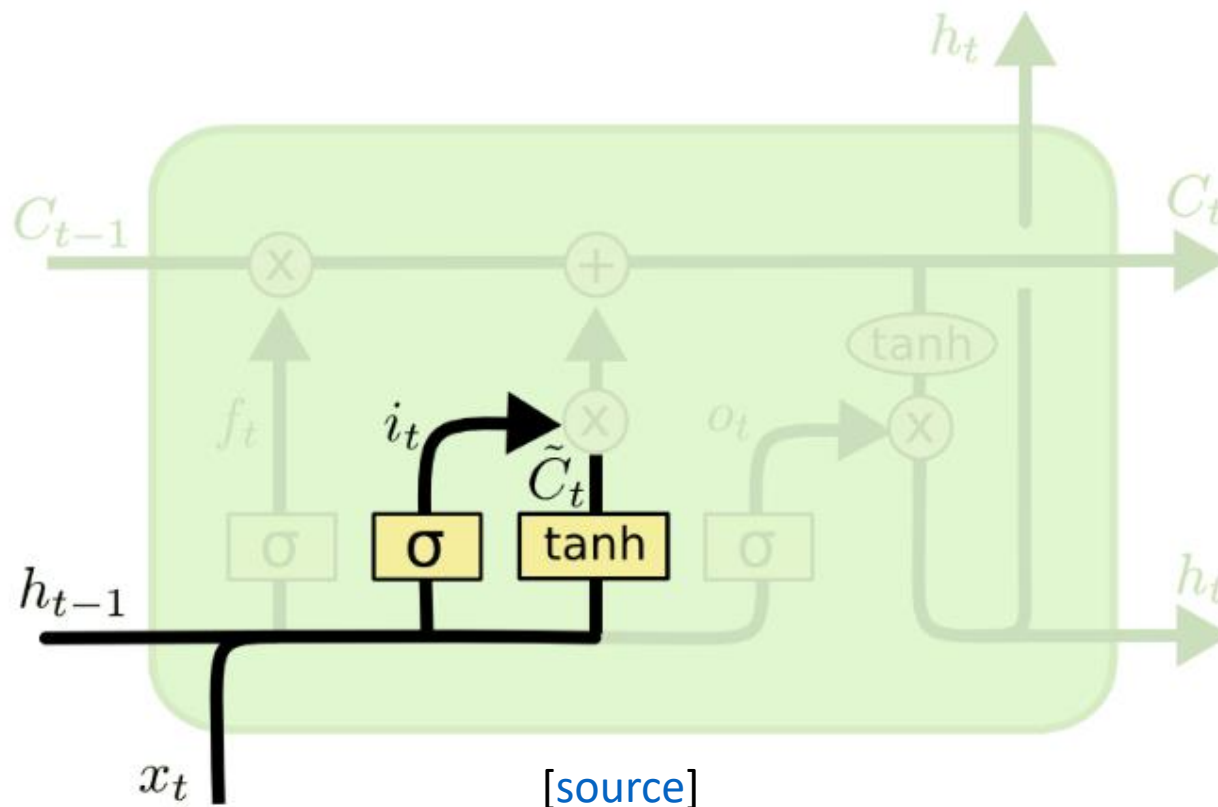
- Forget gate:
 - New parameters which control what information we forget



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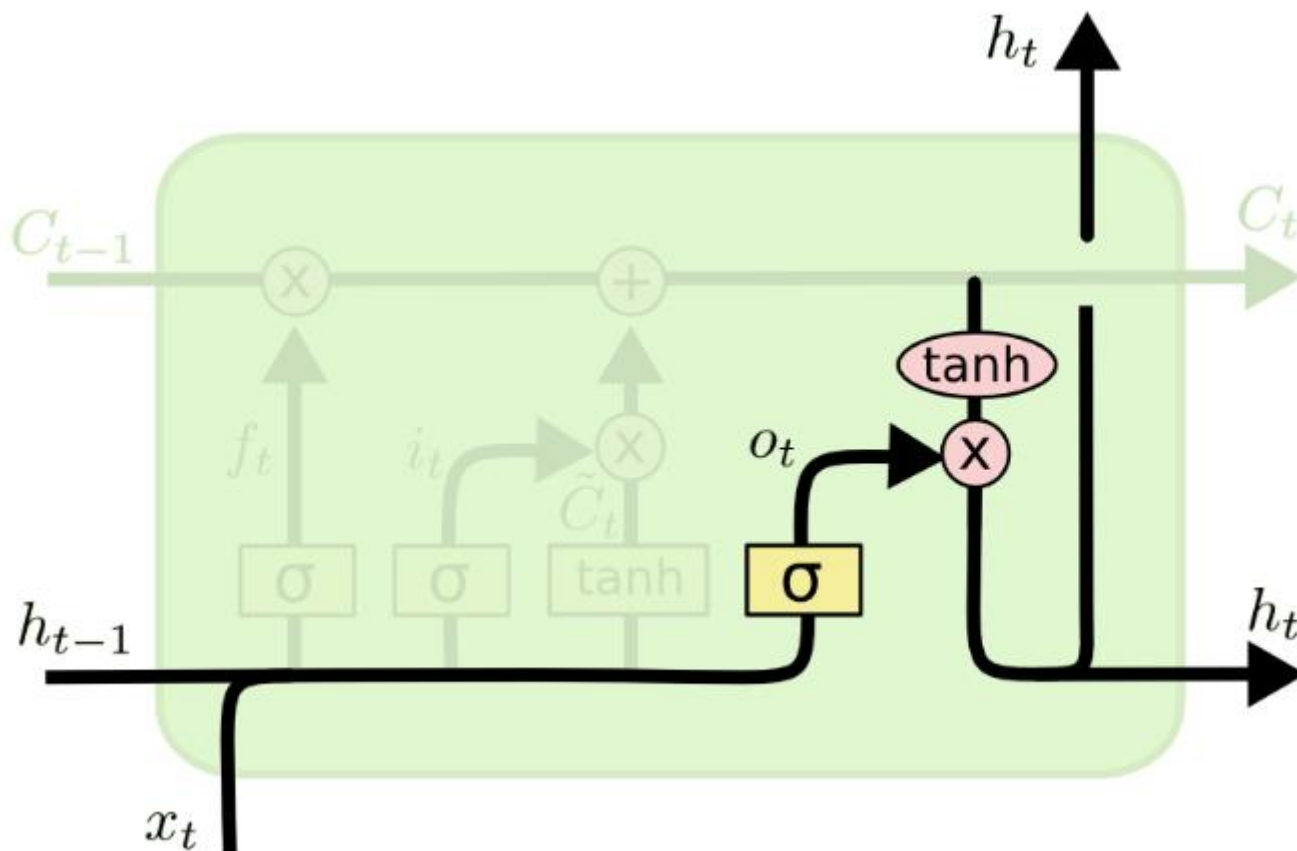
Long short-term memory (LSTM)

- We learn parameters for a candidate value: new c vector
- We also learn parameters for an update gate: how much information we want to store



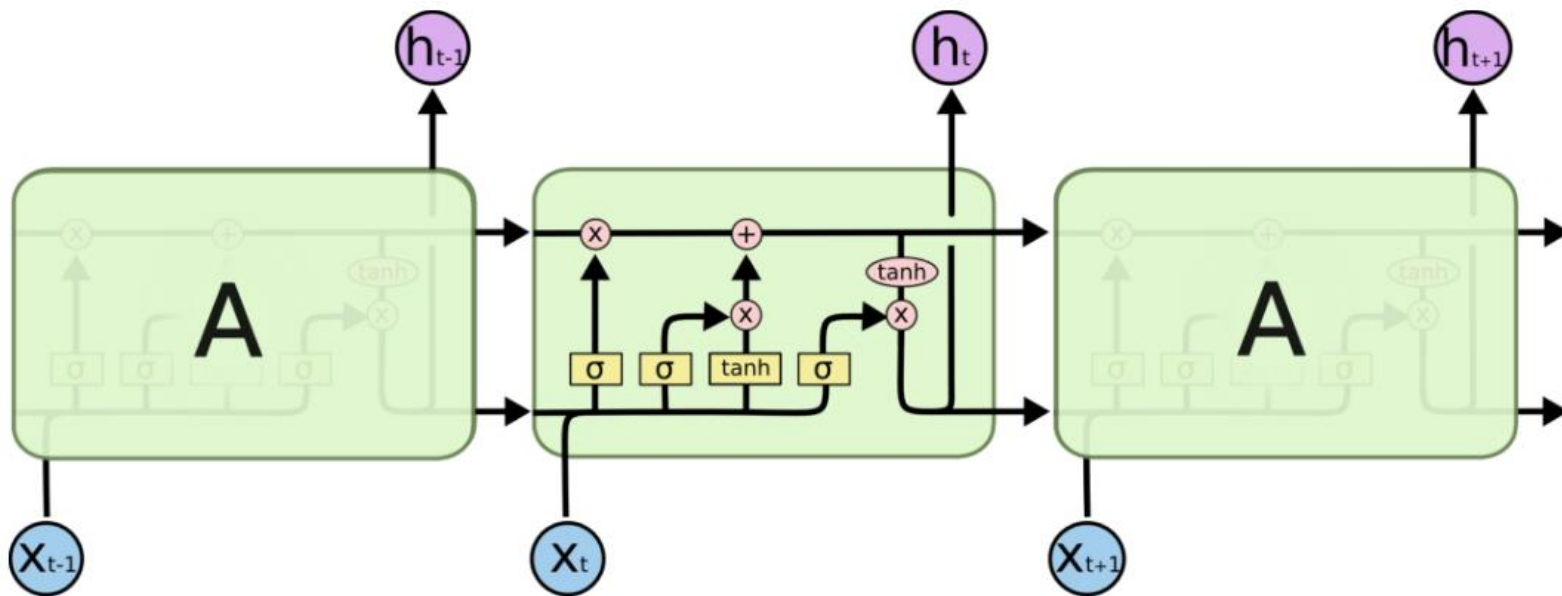
Long short-term memory (LSTM)

- Output gate: what information we want to the cell to output
- This gate also has learned parameters



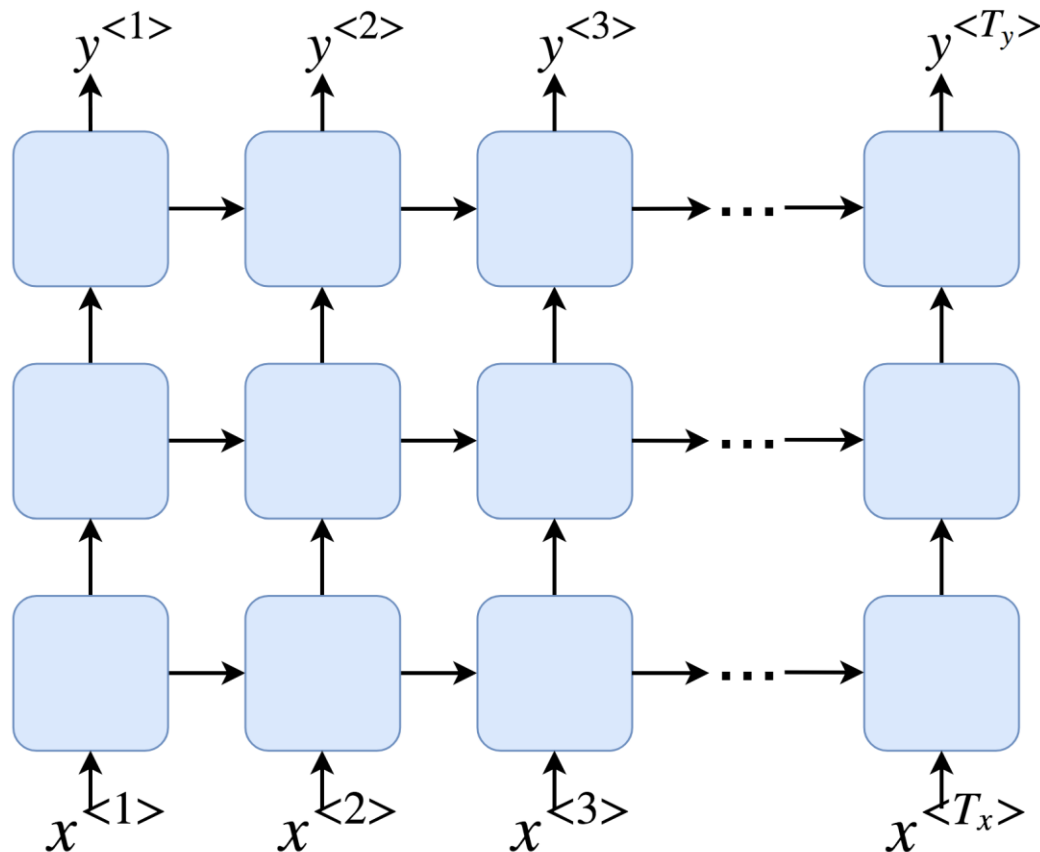
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- The full LSTM cell



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- We can stack RNN, GRU or LSTM cells in top of each other
- Typically a few cell (e.g. LSTM contains 4 “layers” => few layer is a deep network)



Demo notebooks

- Music generation:

https://github.com/qati/DeepLearningCourse/blob/master/demo_notebooks/lecture_09/piano.ipynb

- Tweet generation:

https://github.com/qati/DeepLearningCourse/blob/master/demo_notebooks/lecture_09/tweets.ipynb