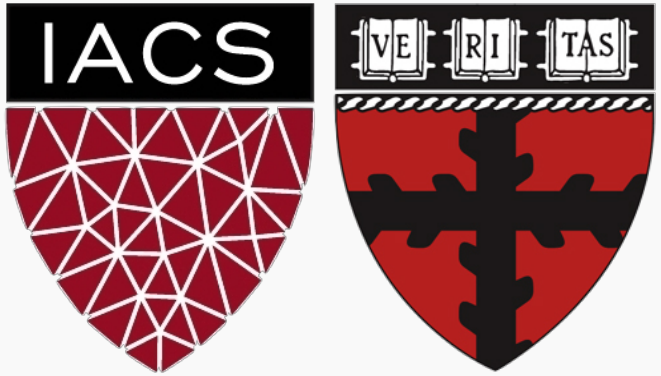
Lecture 11: Recurrent Neural Networks 2

CS109B Data Science 2

Pavlos Protopapas and Mark Glickman



Outline

- Forgetting, remembering and updating (review)
- Gated networks, LSTM and GRU
- RNN Structures
- Bidirectional
- Deep RNN
- Sequence to Sequence
- Teacher Forcing
- Attention models

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- **Forgetting, remembering and updating (review)**
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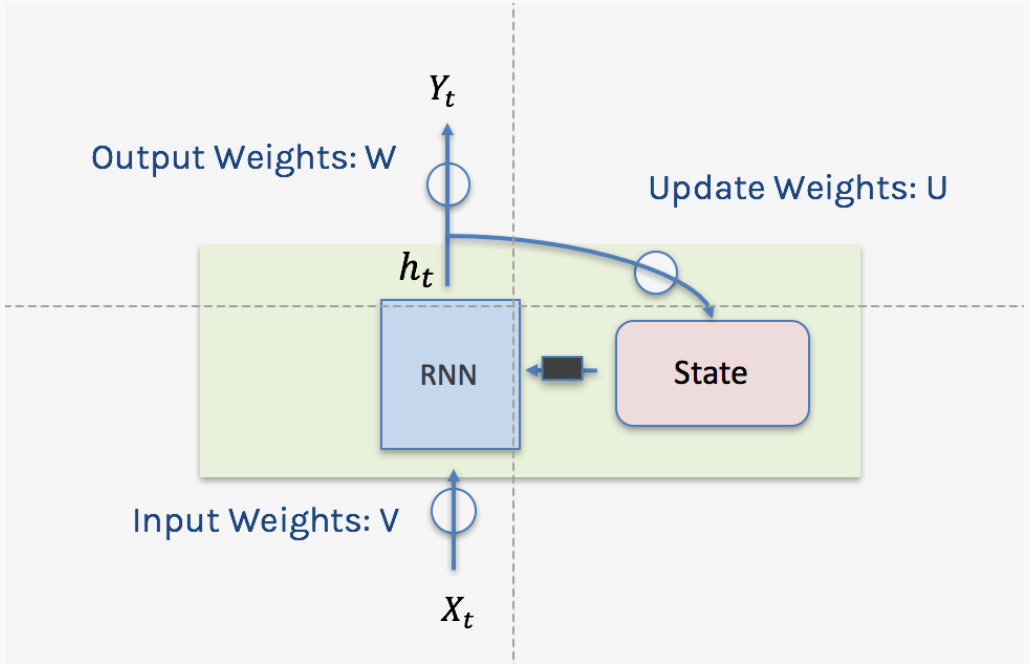
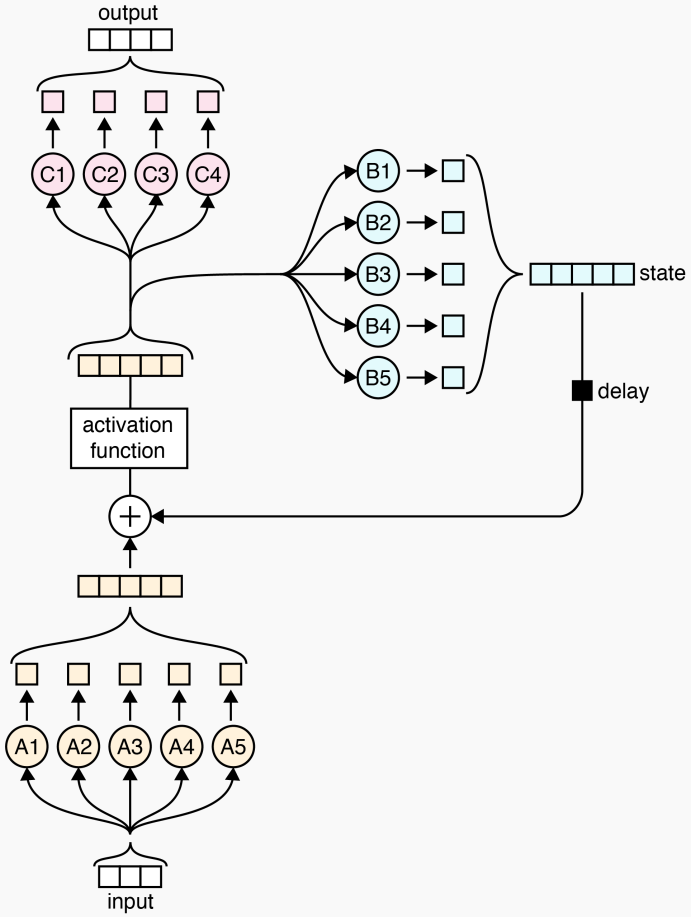
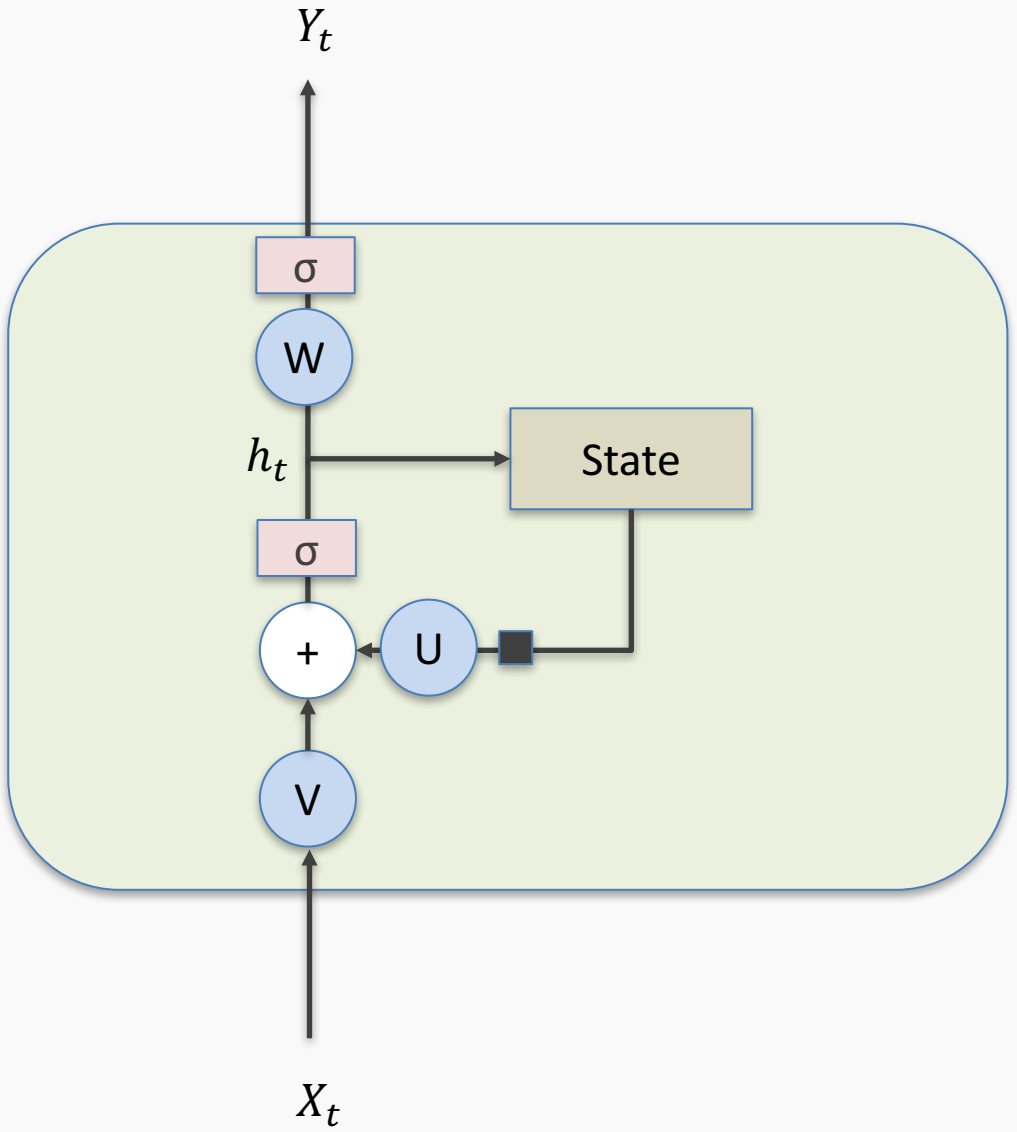
Notation

Using conventional and convenient notation

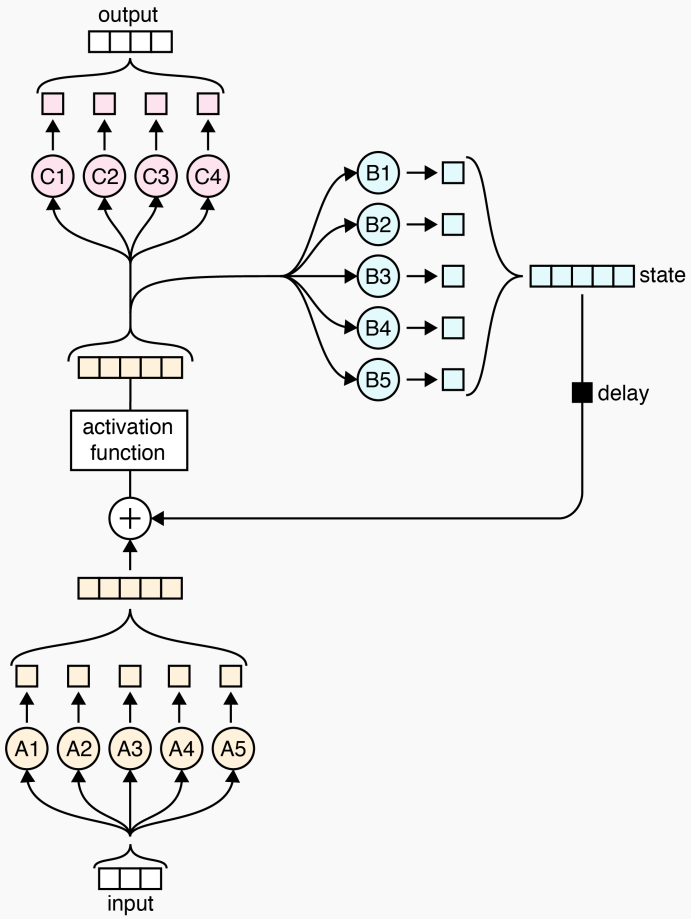


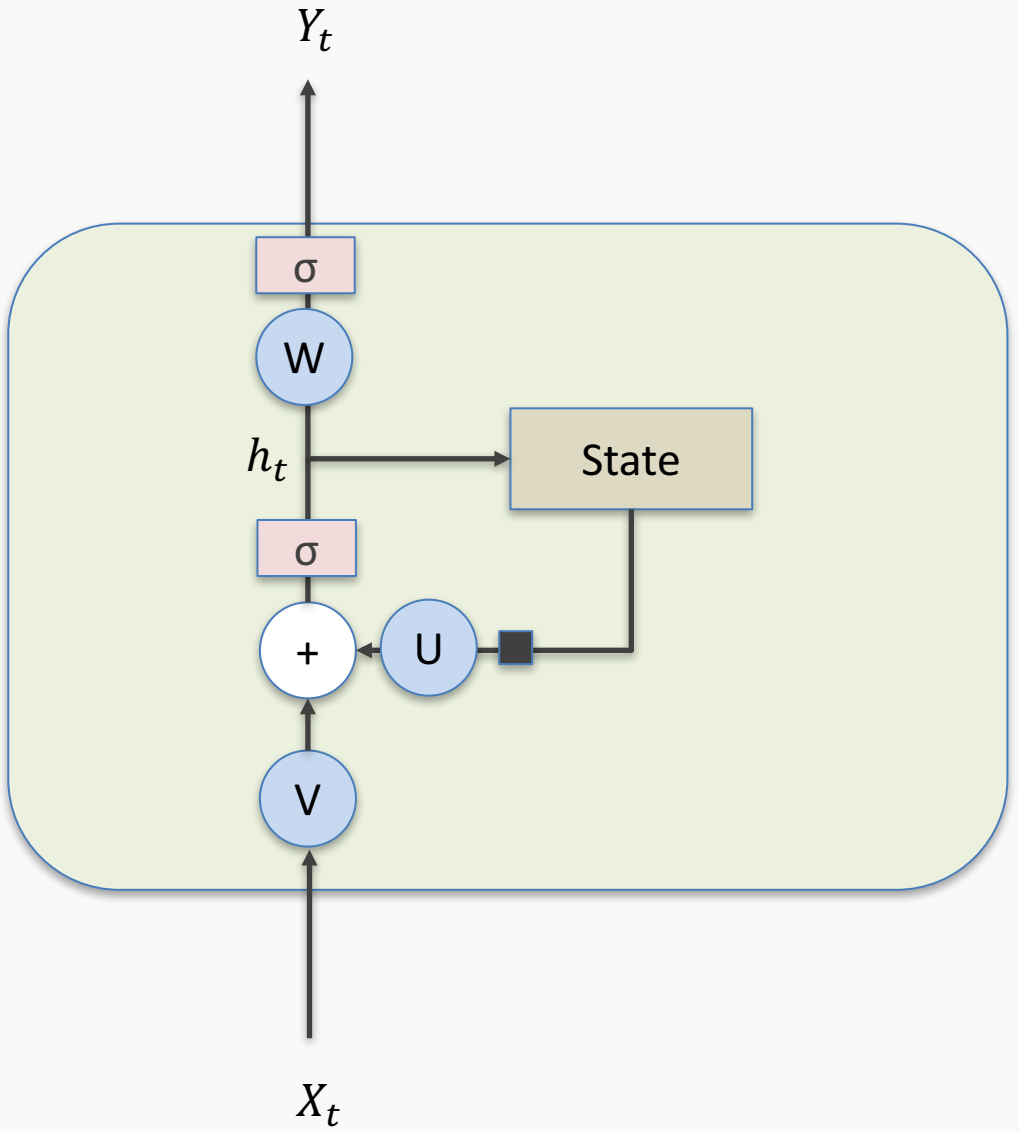
Simple RNN again



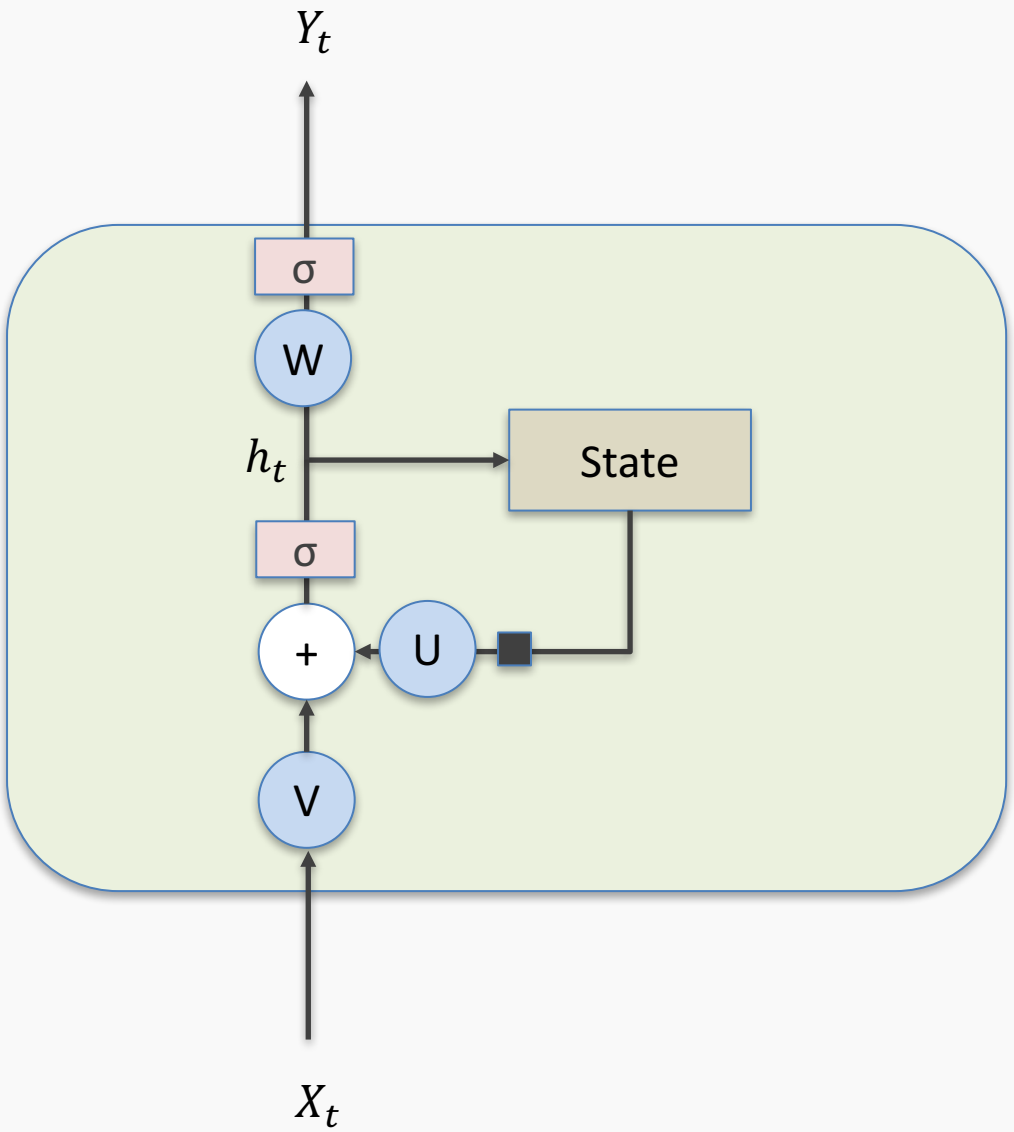


Simple RNN again

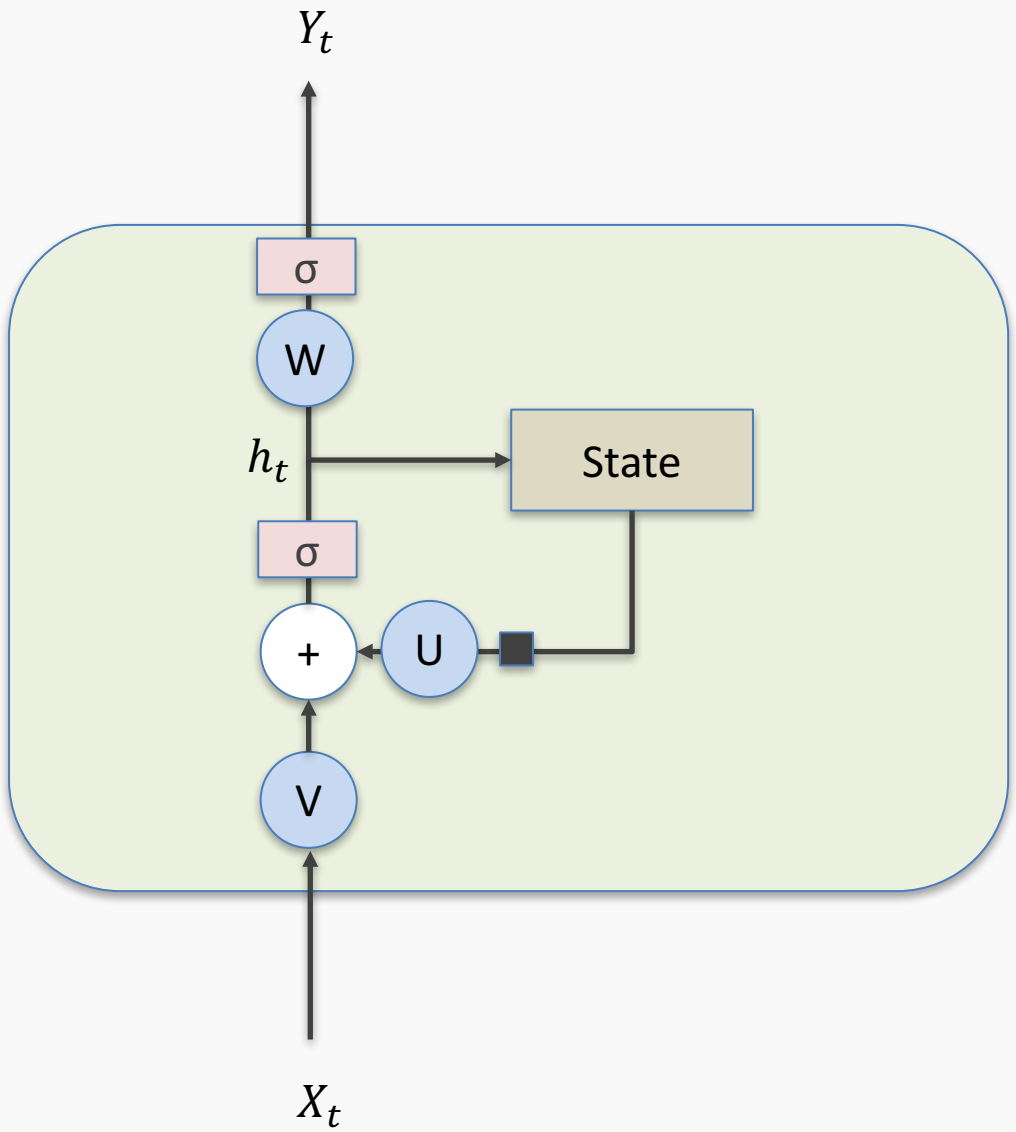




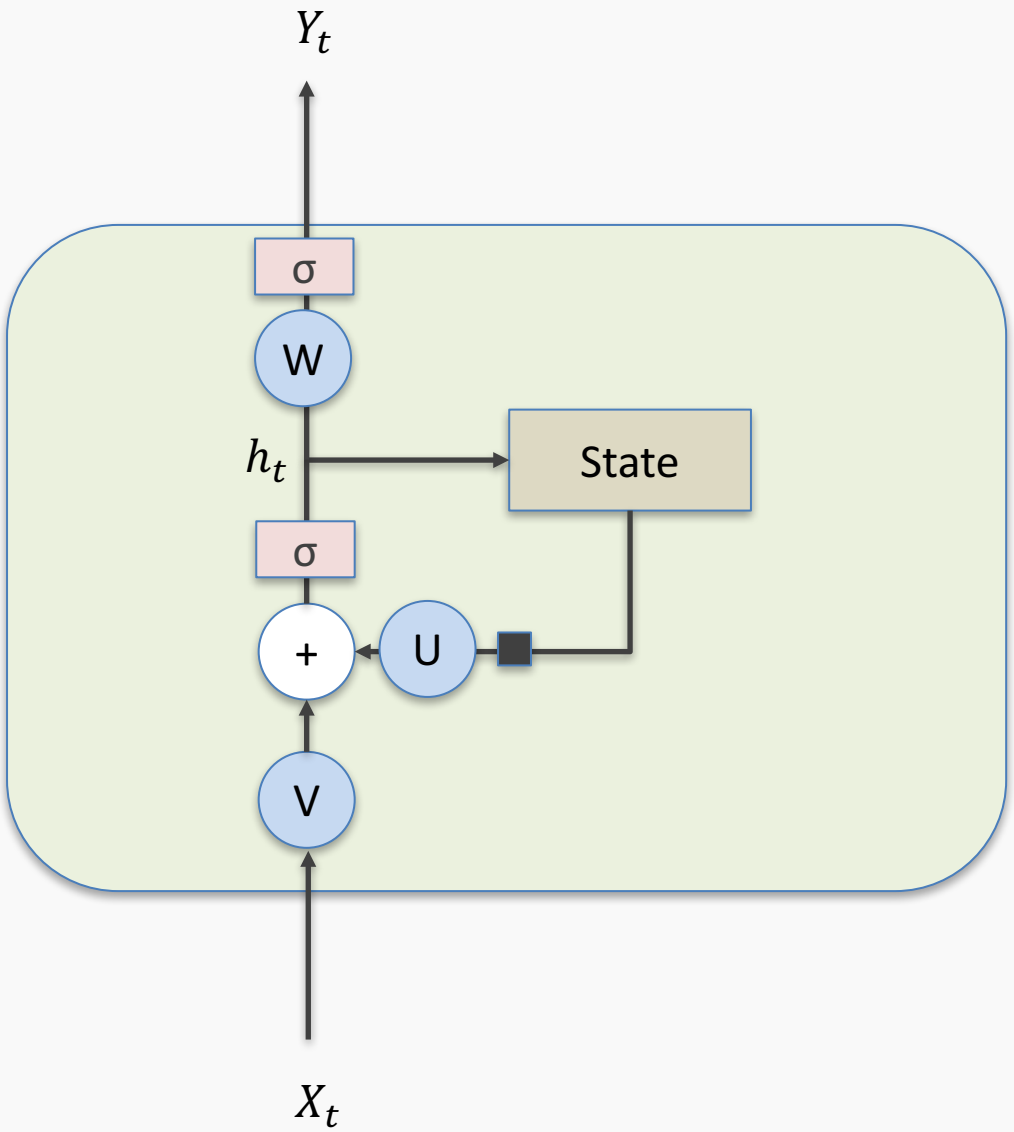
Simple RNN again: **Memories**

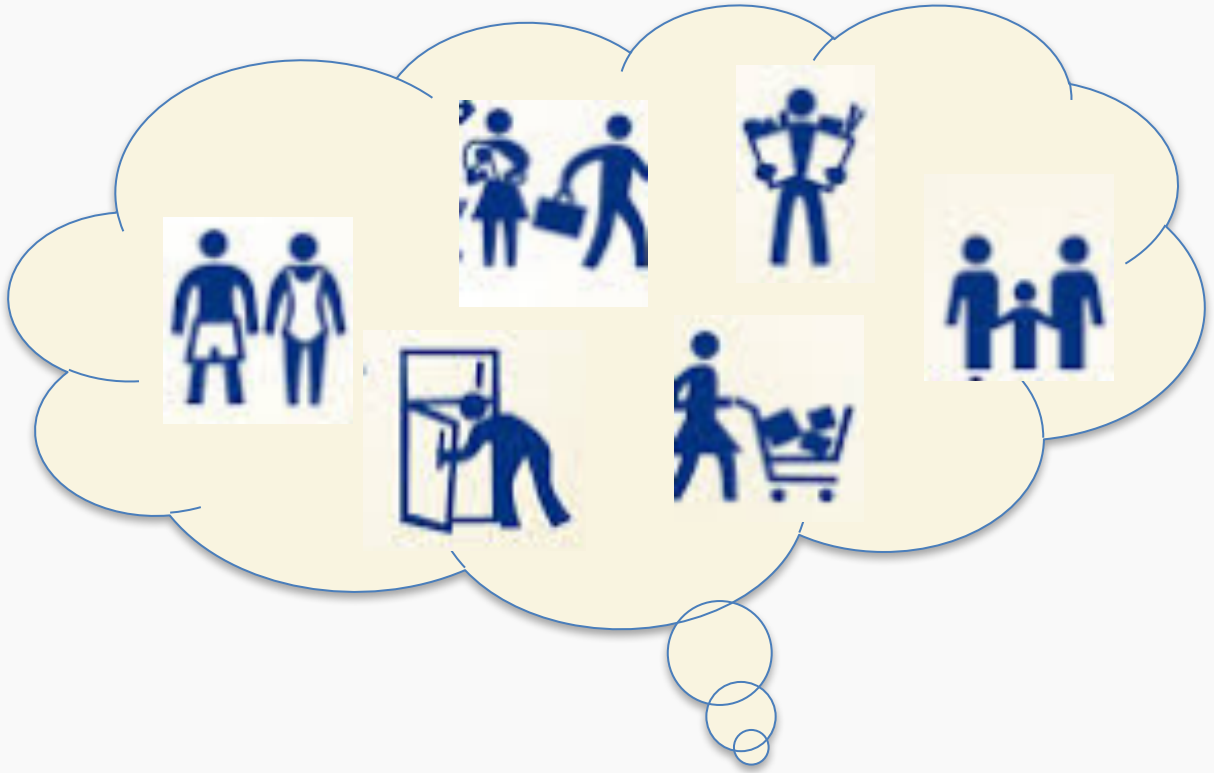


Simple RNN again: **Memories - Forgetting**

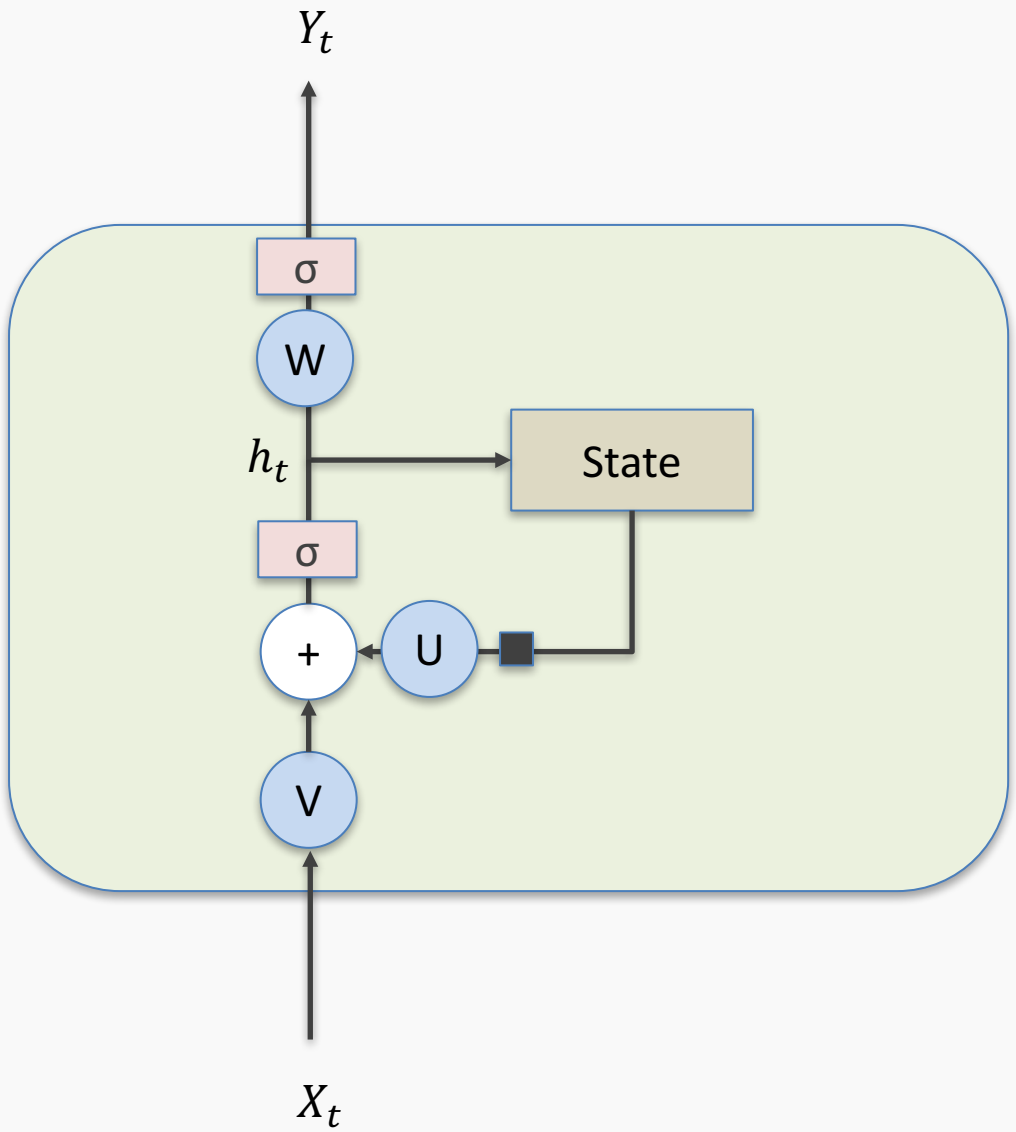


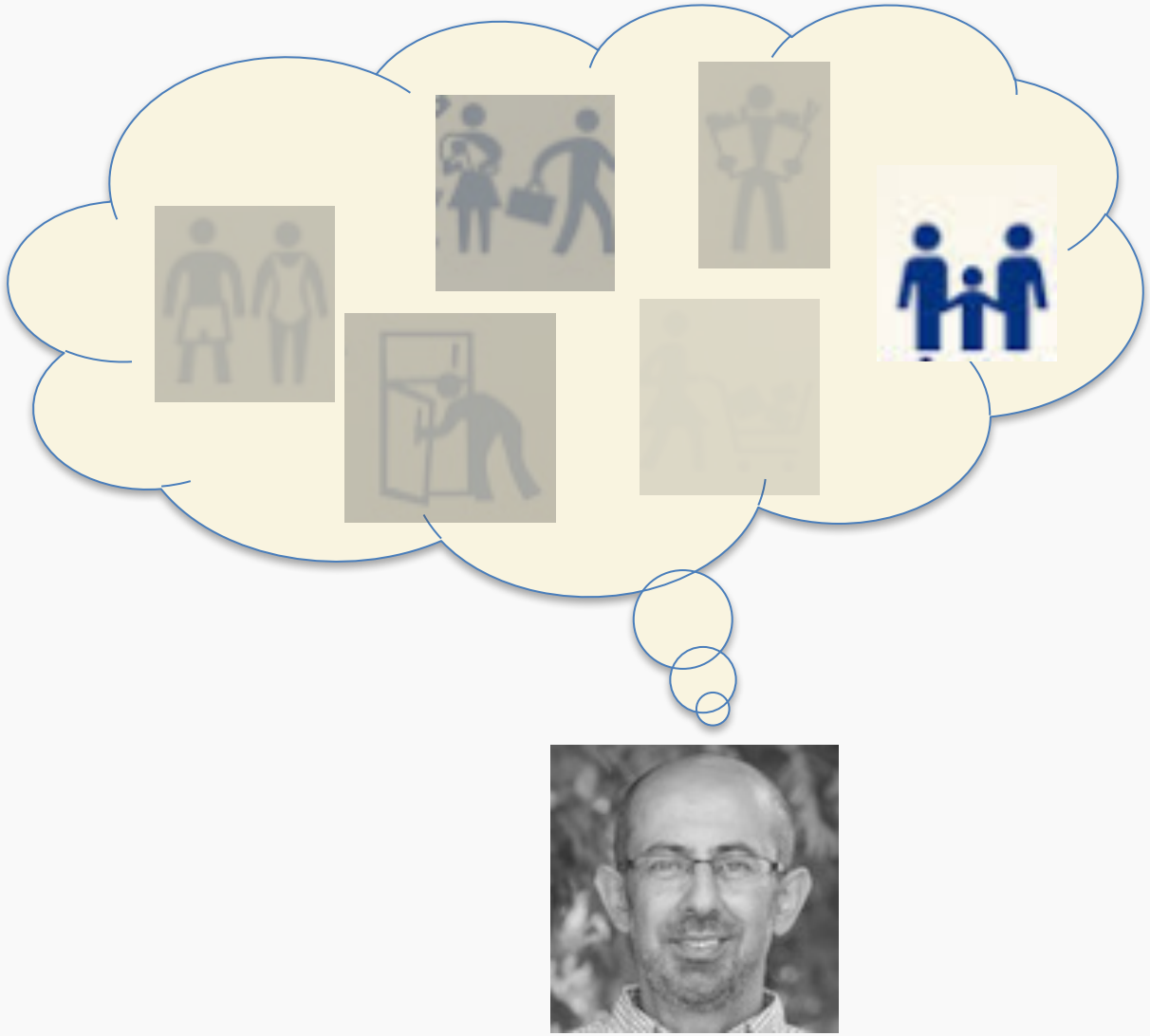
Simple RNN again: **New Events**



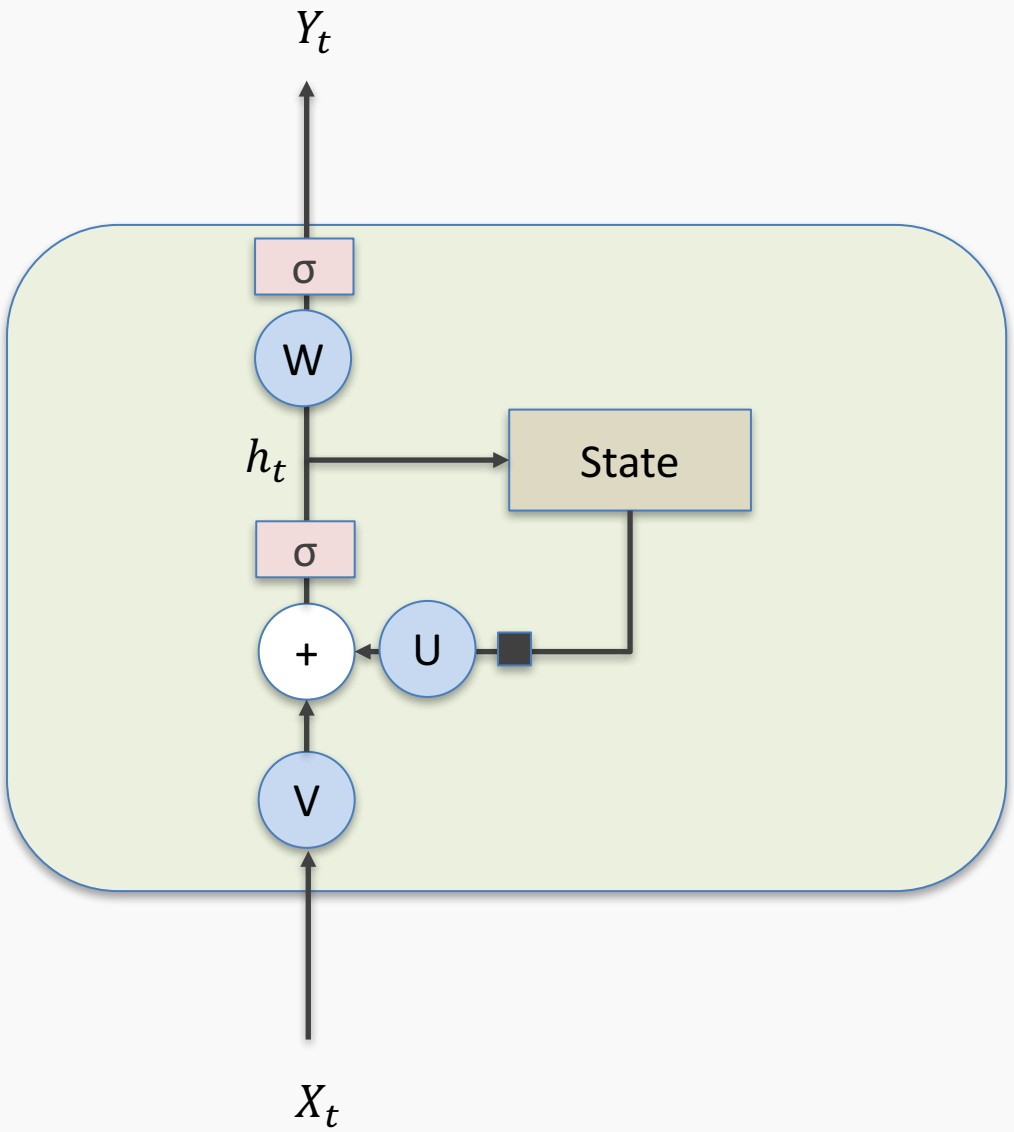


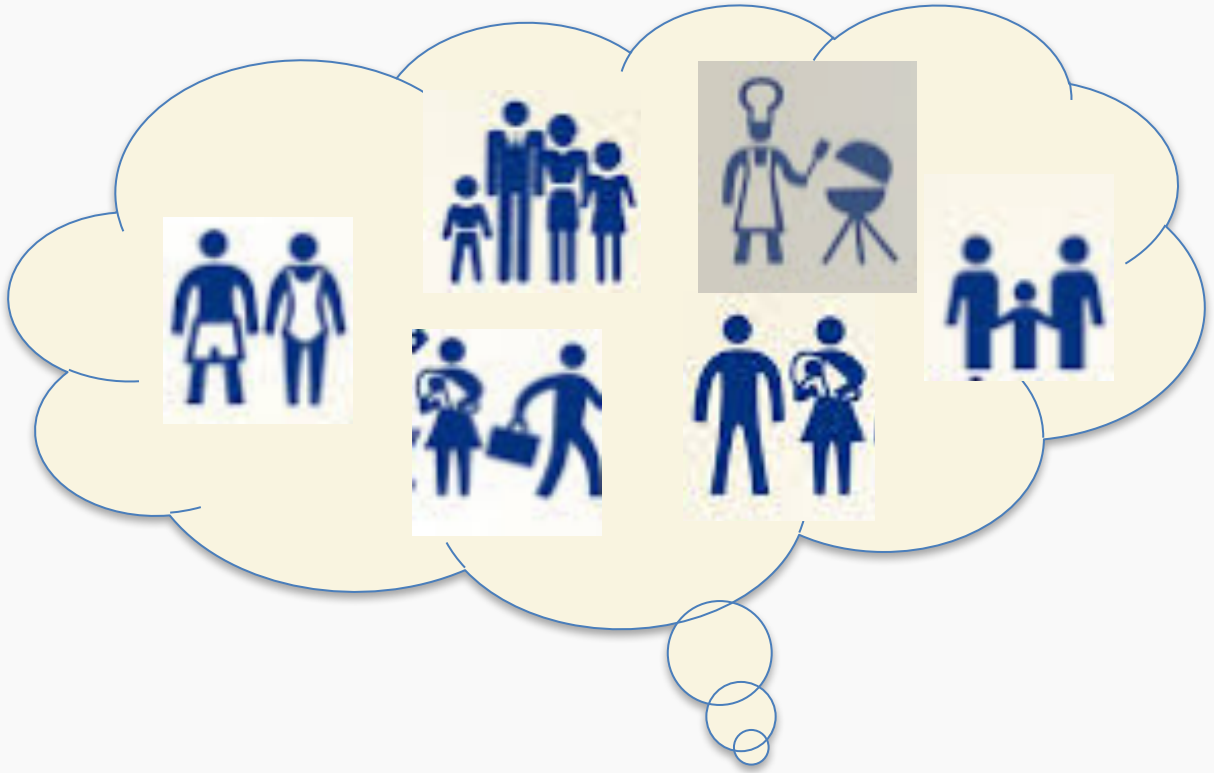
Simple RNN again: **New Events Weighted**



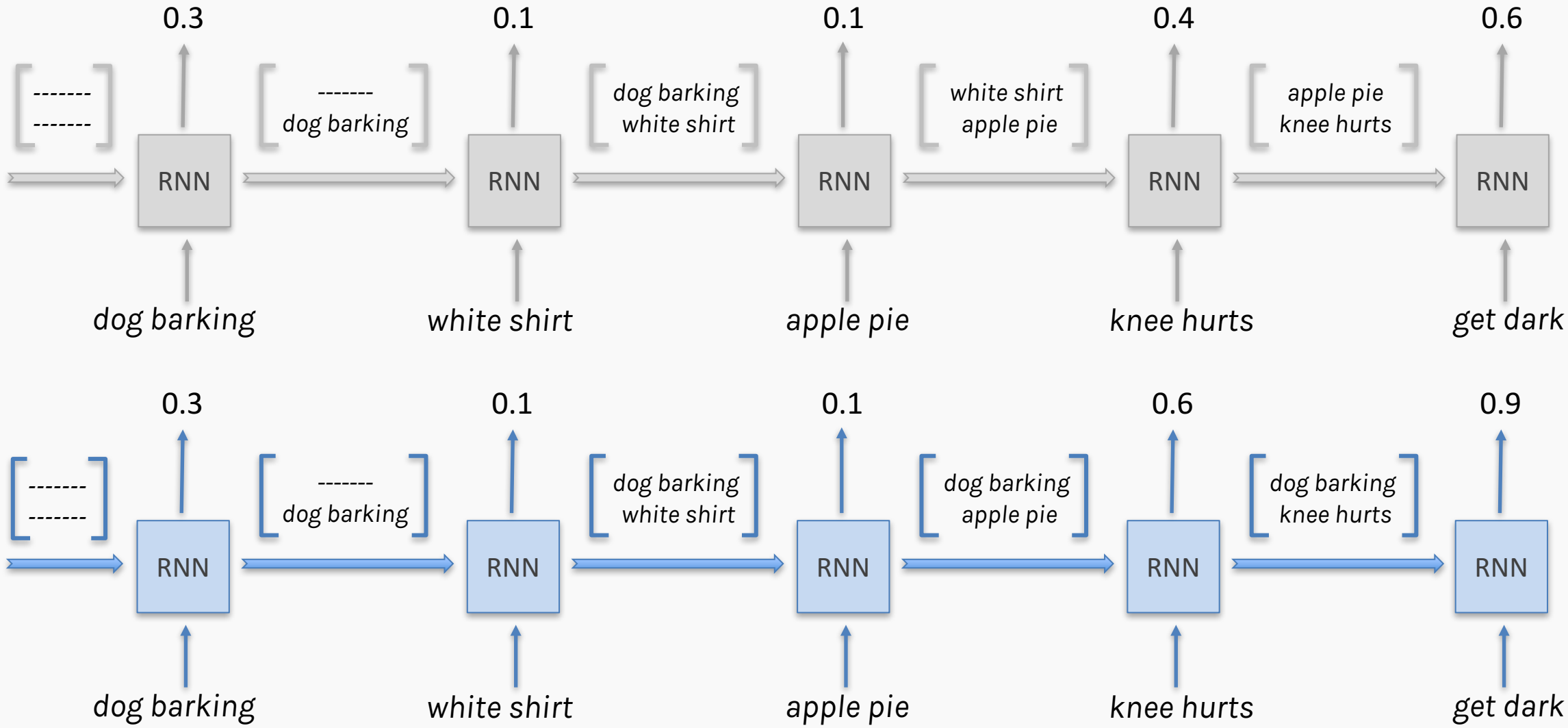


Simple RNN again: **Updated memories**





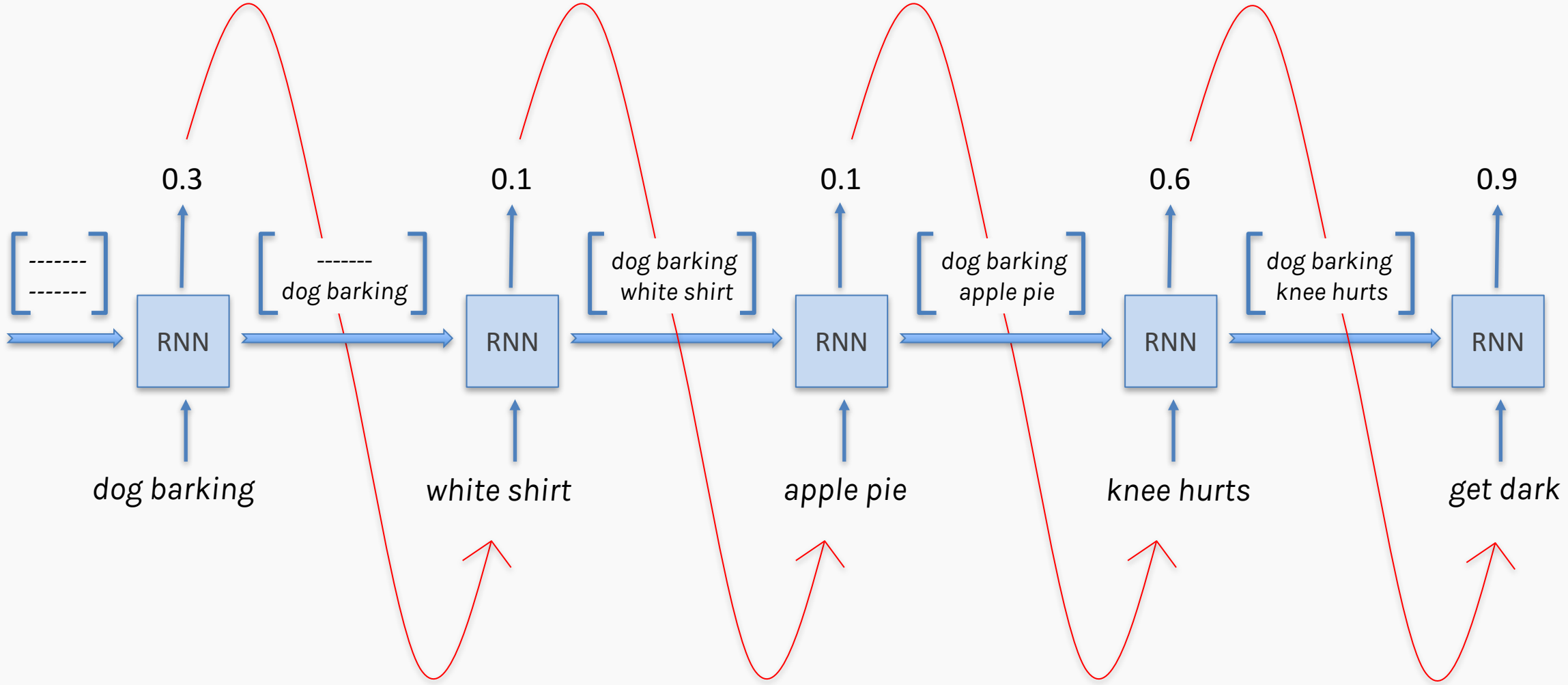
RNN + Memory


0.3
0.1
0.1
0.4
0.6

----
dog barking
dog barking
white shirt
apple pie
white shirt
apple pie
apple pie
knee hurts
RNN
RNN
RNN
RNN
RNN
dog barking
white shirt
apple pie
knee hurts
get dark
0.3
0.1
0.1
0.6
0.9

----
dog barking
dog barking
white shirt
dog barking
apple pie
dog barking
knee hurts
RNN
RNN
RNN
RNN
RNN
dog barking
white shirt
apple pie
knee hurts
get dark

RNN + Memory + Output



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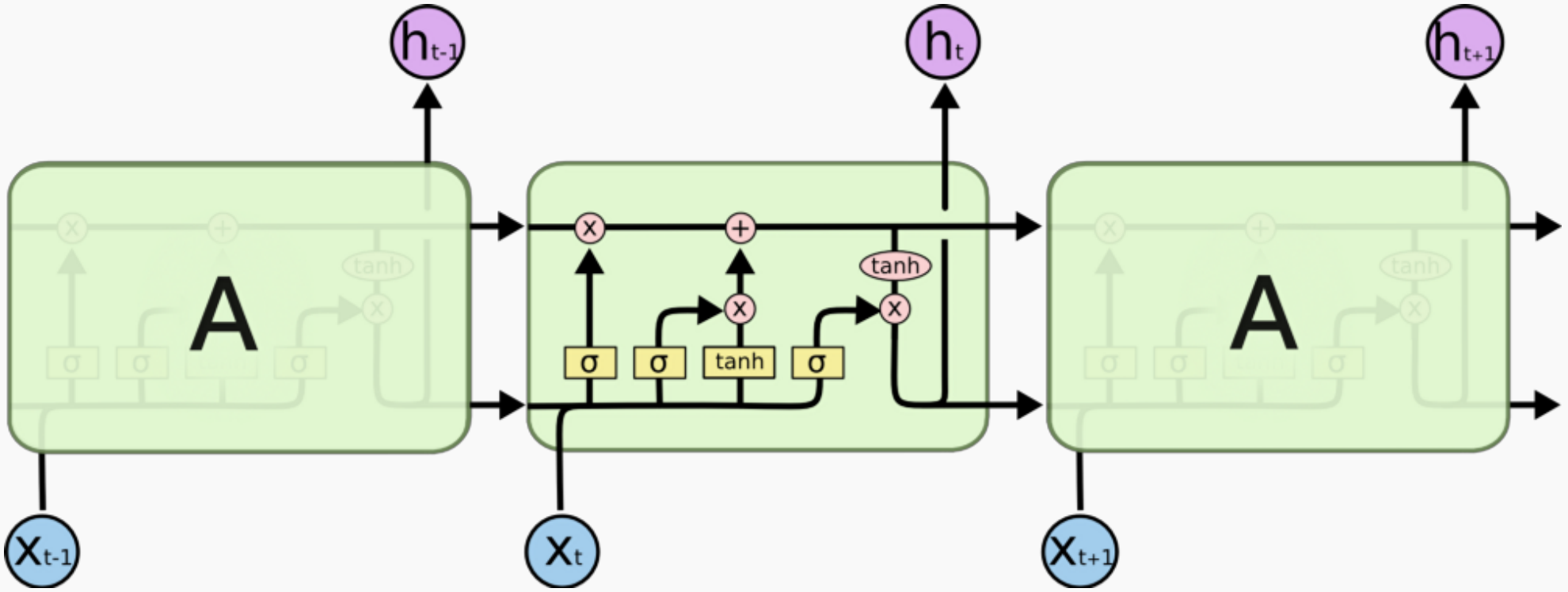
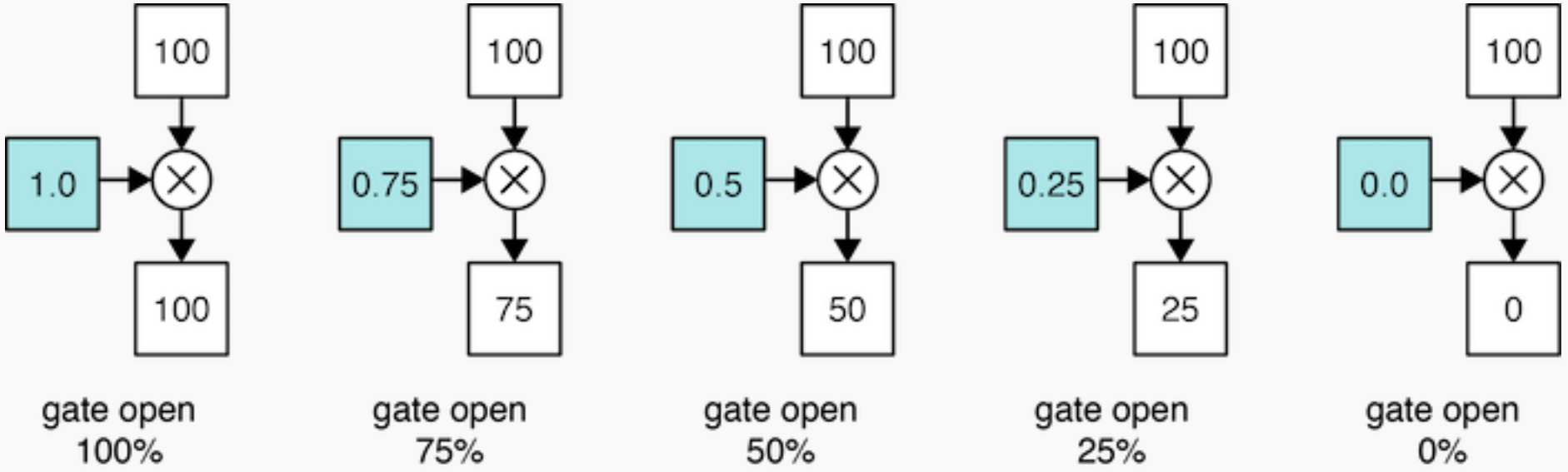
LSTM: Long short term memory



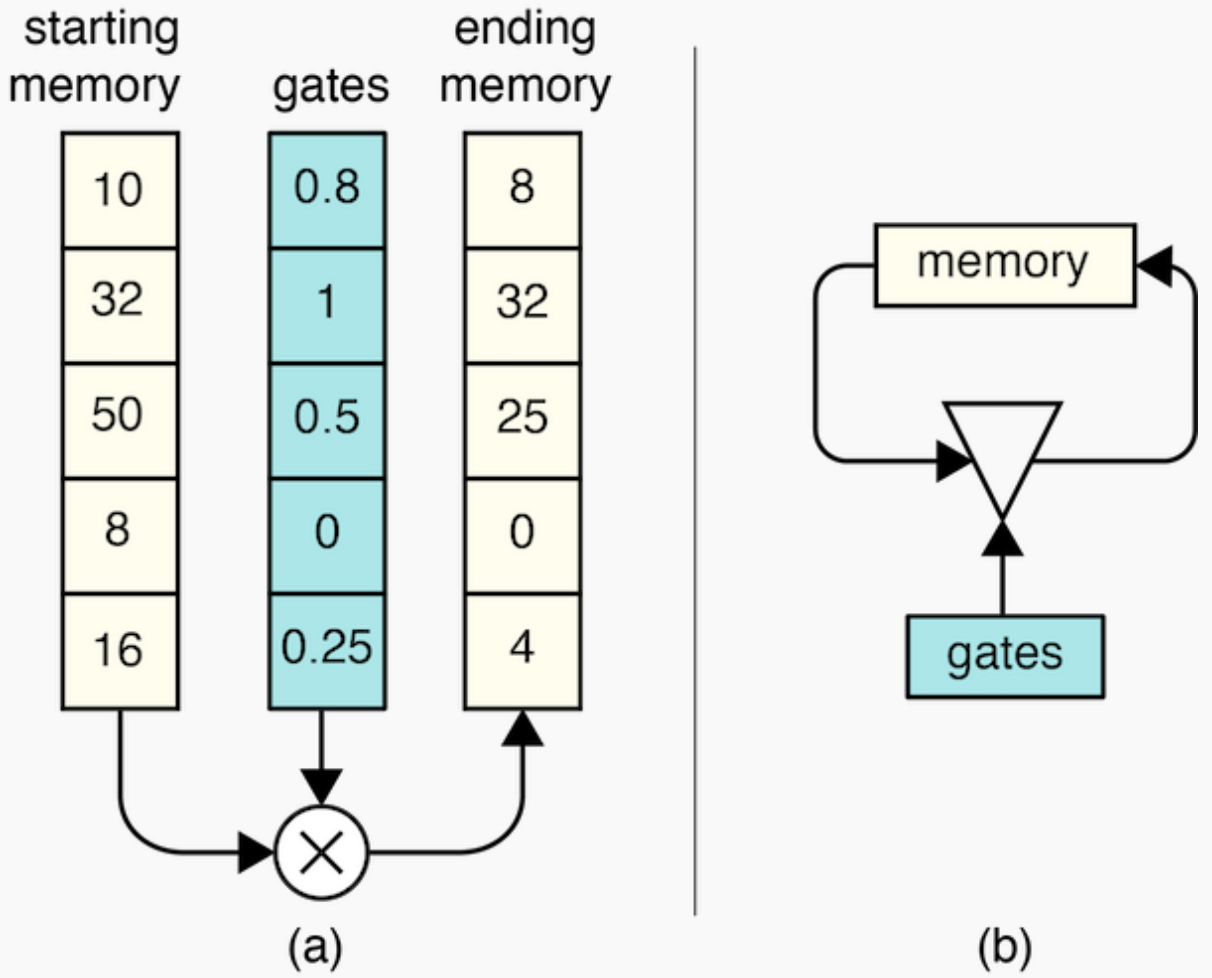
Gates

A key idea in the LSTM is a mechanism called a gate.



Forgetting

Each value is multiplied by a gate, and the result is stored back into the memory.



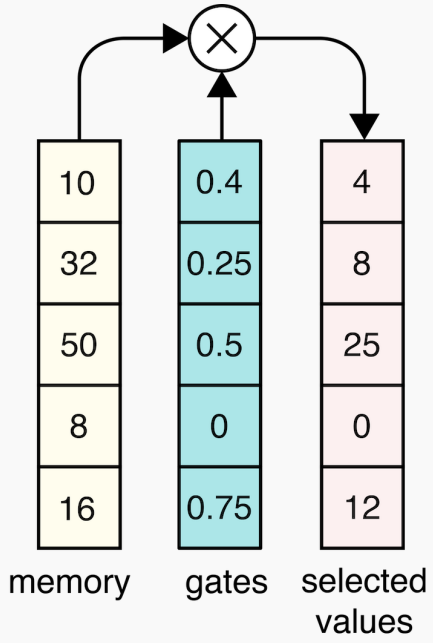
Remembering

Remembering involves two steps.

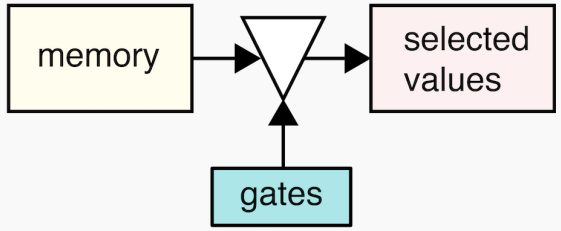
1. We determine how much of each new value we want to remember and we use gates to control that.

2. Remember the gated values, we merely add them in to the existing contents of the memory.

Remembering (cont)



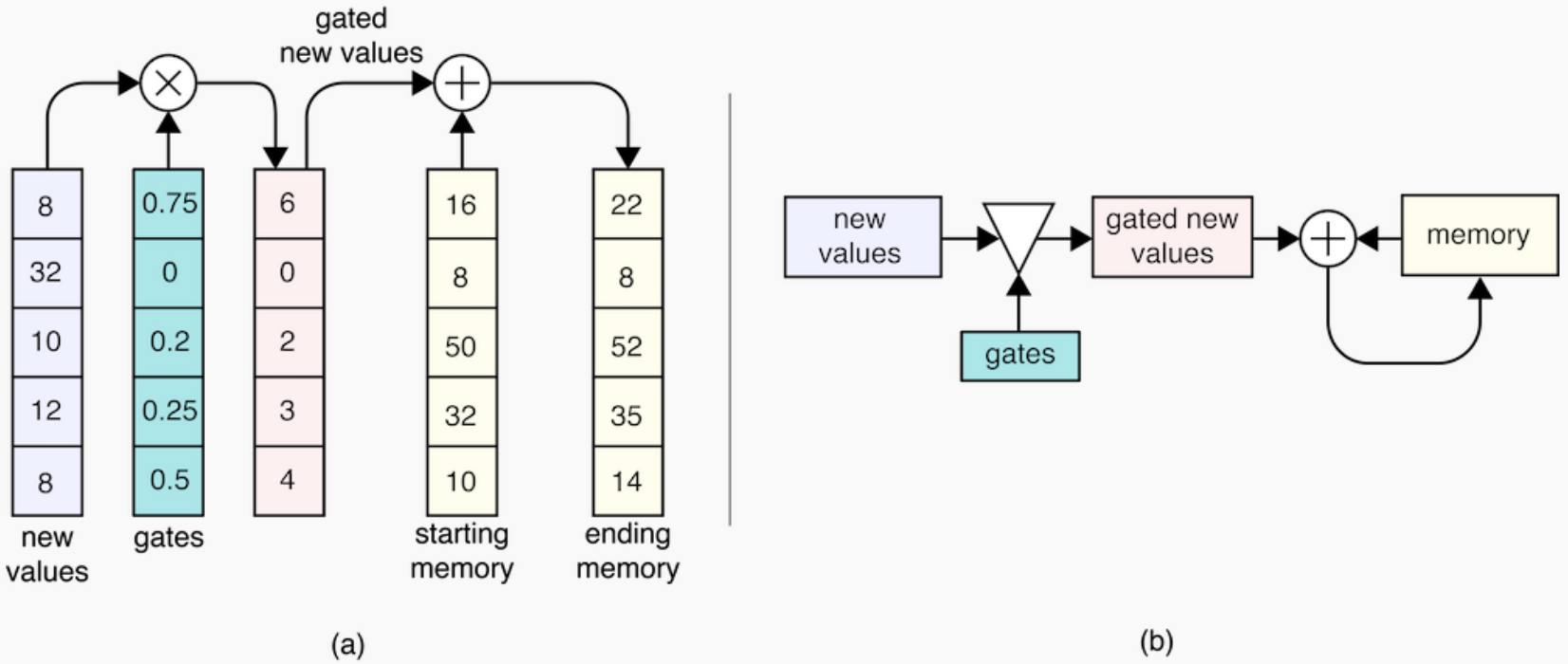
(a)



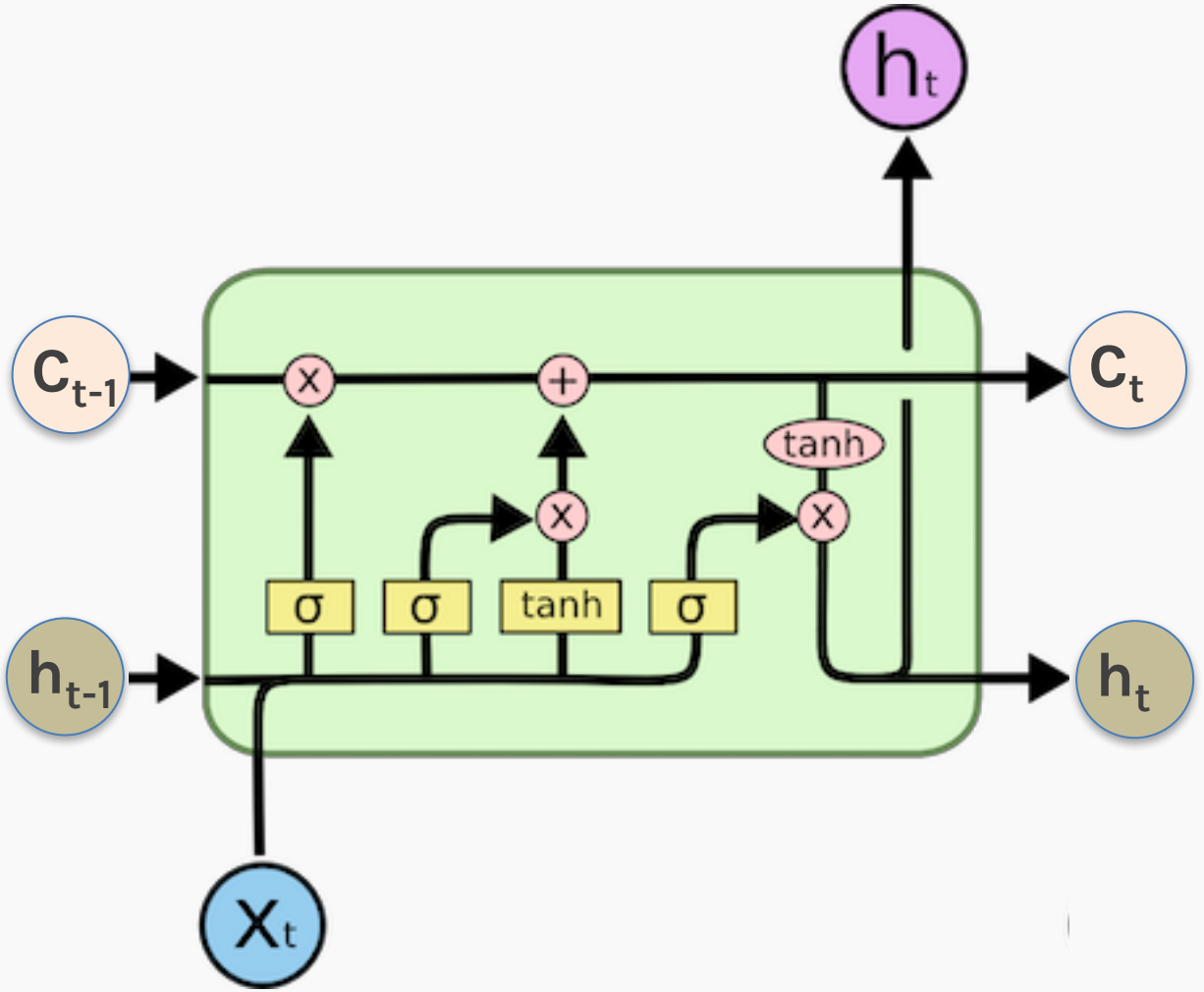
(b)

Updating

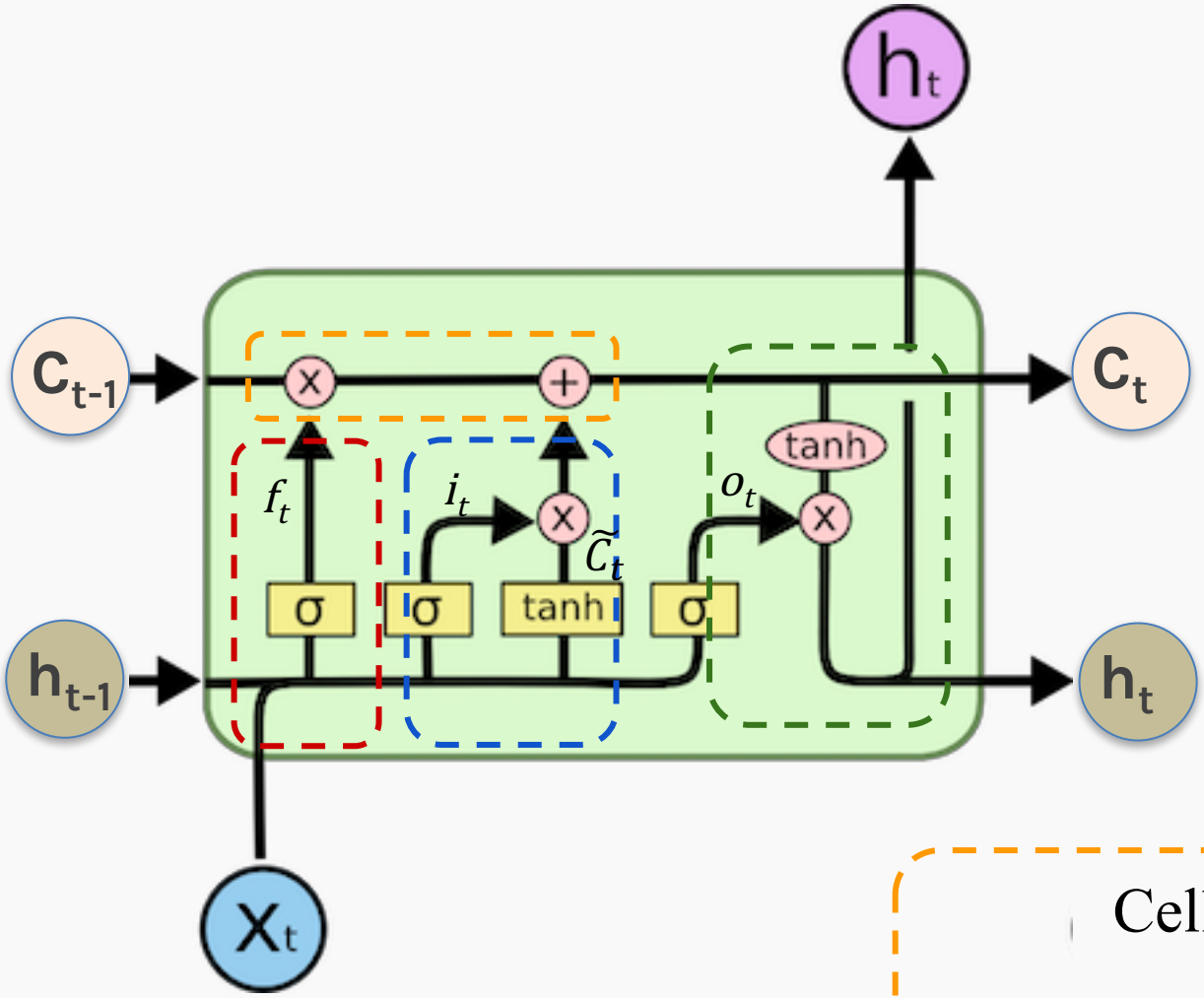
To select from memory we just determine how much of each element we want to use, we apply gates to the memory elements, and the results are a list of scaled memories.



LSTM



Before to really understand LSTM lets see the big picture …



Forget Gate

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

Output Gate

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

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

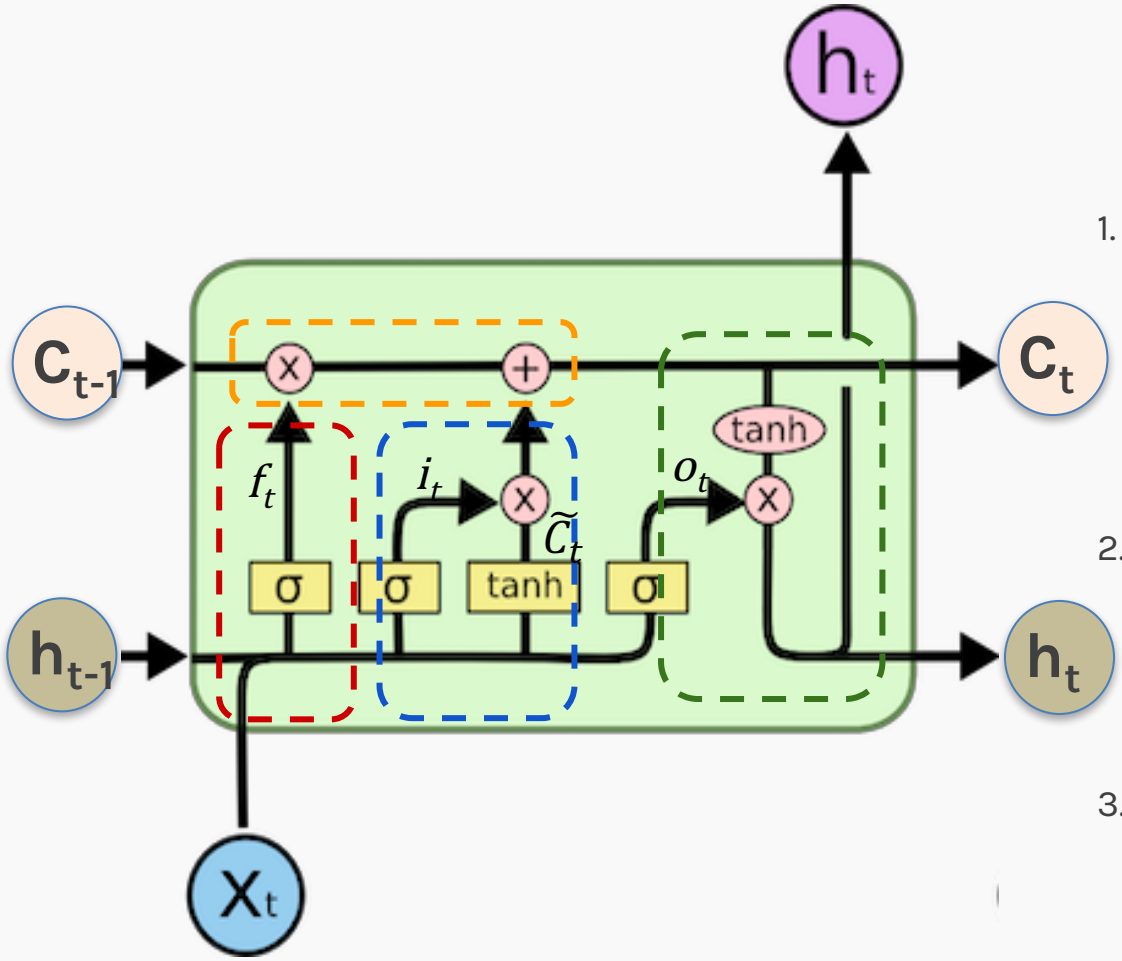
Input Gate

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

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

Cell State

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



1. LSTM are recurrent neural networks with a cell and a hidden state, boths of these are updated in each step and can be thought as memories.

2. Cell states work as a long term memory and the updates depends on the relation between the hidden state in t -1 and the input.

3. The hidden state of the next step is a transformation of the cell state and the output (which is the section that is in general used to calculate our loss, ie information that we want in a short memory).

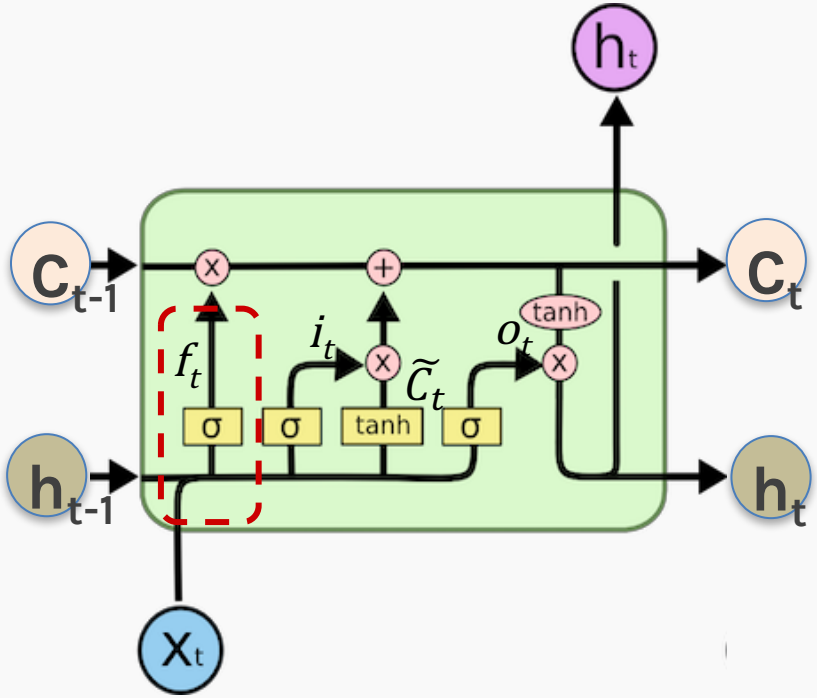
Let's think about my cell state

$$x_t = \begin{bmatrix} \text{👪} & 1 \\ \text{  } & -1 \\ \text{6AM} & 1 \end{bmatrix} \quad h_{t-1} = \begin{bmatrix} \text{😄} & 1 \\ \text{⏱️} & 1 \end{bmatrix} \quad C_{t-1} = \begin{bmatrix} \text{😄} & 0.7 \\ \text{⏱️} & 0.3 \end{bmatrix}$$

Let's predict if I will help you with the homework in time *t*

Forget Gate

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



The forget gate tries to estimate what features of the cell state should be forgotten.

$$f_t = \sigma\left(\begin{bmatrix}1 & -1\\ -1 & 1\end{bmatrix}\begin{bmatrix}\text{😄}\\ \text{⏱}\end{bmatrix} + \begin{bmatrix}1 & 1 & -100\\ 0.1 & 0.1 & -100\end{bmatrix}\begin{bmatrix}\text{👪}\\ \text{🪳}\\ \text{6AM}\end{bmatrix}\right)$$

$$f_t = \sigma\left(\begin{bmatrix}0\\ 0\end{bmatrix} + \begin{bmatrix}-100\\ -100\end{bmatrix}\right)$$

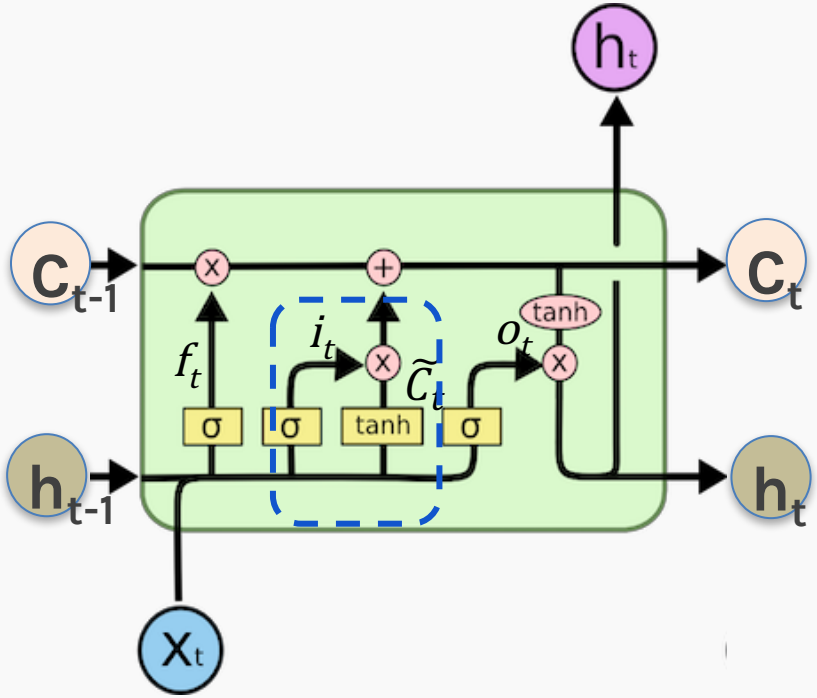
$$\begin{bmatrix}0\\ 0\end{bmatrix}$$

Erase everything!

Input Gate

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

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



The input gate layer works in a similar way that the forget layer, the input gate layer estimates the degree of confidence of $\tilde{C}_t$. $\tilde{C}_t$ is a new estimation of the cell state.

Let's say that my input gate estimation is: $i_t = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

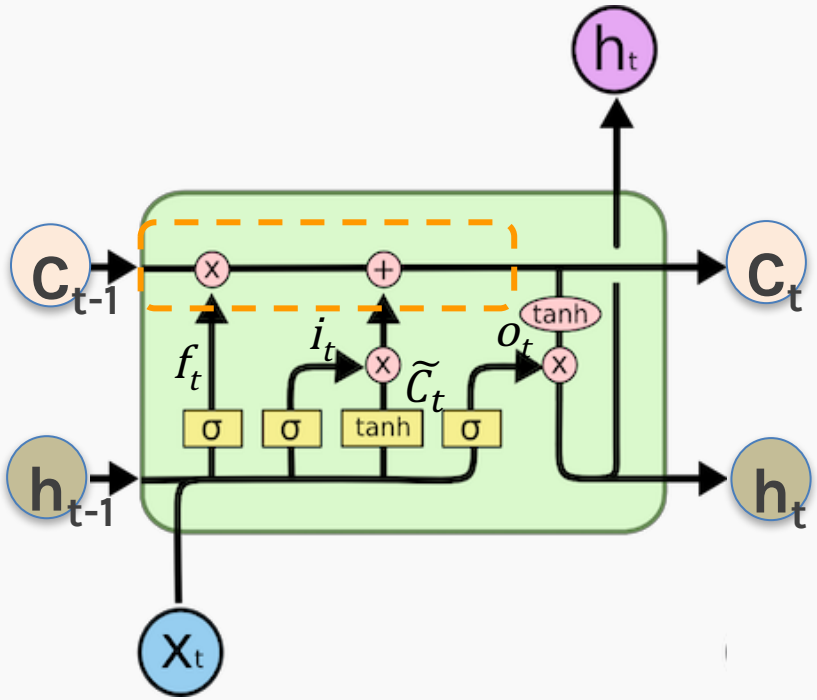
$$\tilde{C}_t = \tanh\left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 😄 \\ ⏰ \end{bmatrix} + \begin{bmatrix} 10 & 1 & -1 \\ -1 & 1 & 10 \end{bmatrix} \begin{bmatrix} 👪 \\ 🪳 \\ 6AM \end{bmatrix} \right)$$

$$\tilde{C}_t = \tanh\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 10 \\ 10 \end{bmatrix} \right)$$

$$\begin{bmatrix} 😄 \\ ⏰ \end{bmatrix}$$

Cell state

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



After the calculation of forget gate and input gate we can update our new cell state.

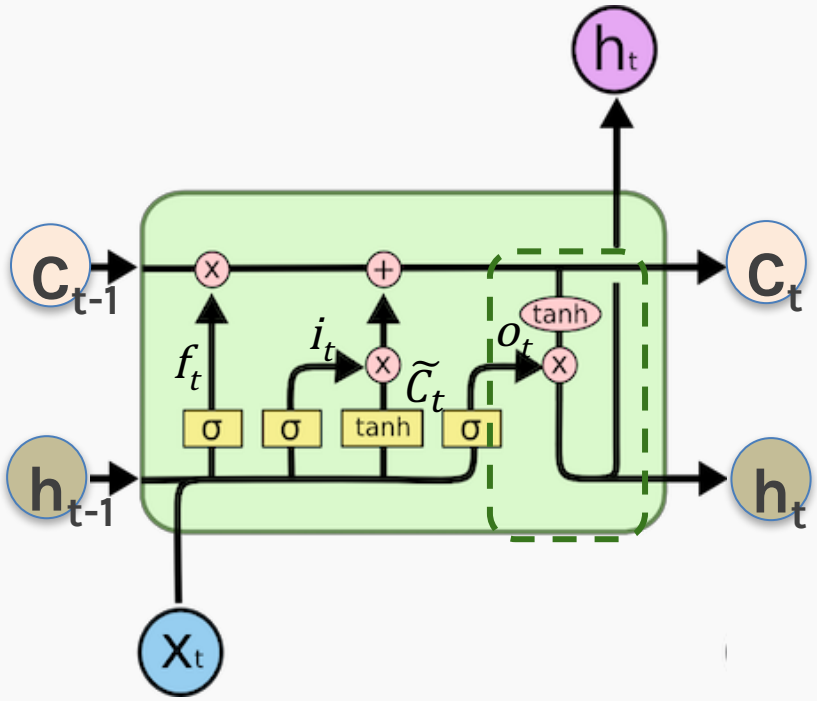
$$C_t = \underbrace{\begin{bmatrix}0\\0\end{bmatrix} * \begin{bmatrix}😄 & 0.7\\ ⏱ & 0.3\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} * \begin{bmatrix}😄 & 1\\ ⏱ & 1\end{bmatrix}}$$

$$C_t = \begin{bmatrix}😄 & 1\\ ⏱ & 1\end{bmatrix}$$

Output gate

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

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



- The output gate layer is calculated using the information of the input *x* in time *t* and hidden state of the last step.
- It is important to notice that the hidden state used in the next step is obtained using the output gate layer which is usually the function that we optimize.

$$o_t = \sigma\left(\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 😄 & 1 \\ ⏱ & 1 \end{bmatrix} + \begin{bmatrix} 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 👥 & 1 \\ 🪳 & -1 \\ 6AM & 1 \end{bmatrix} \right)$$

$$o_t \approx 0.9$$

$$h_t \approx 0.9 * \begin{bmatrix} 😄 & 1 \\ ⏱ & 1 \end{bmatrix} = \begin{bmatrix} 😄 & 0.9 \\ ⏱ & 0.9 \end{bmatrix}$$

GRU

A variant of the LSTM is called the Gated Recurrent Unit, or GRU.

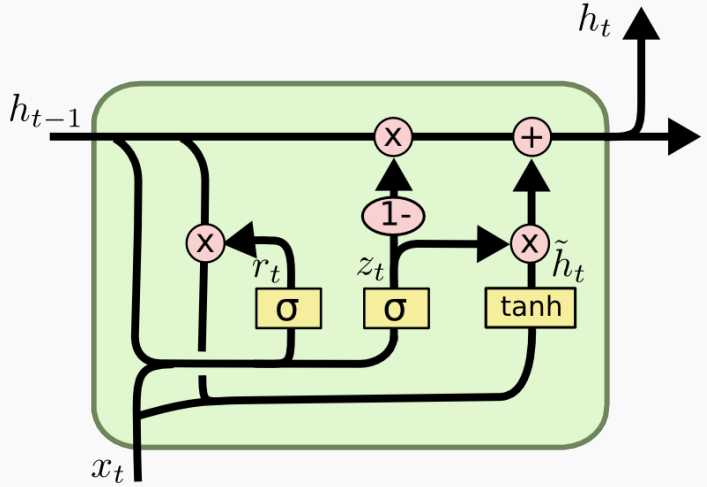
The GRU is like an LSTM but with some simplifications.

1. **The forget and input gates are combined into a single gate**
2. **No cell state**

Since there's a bit less work to be done, a GRU can be a bit faster than an LSTM. It also usually produces results that are similar to the LSTM.

Note: Worthwhile to try both the LSTM and GRU to see if either provides more accurate results for a data set.

GRU (cont)

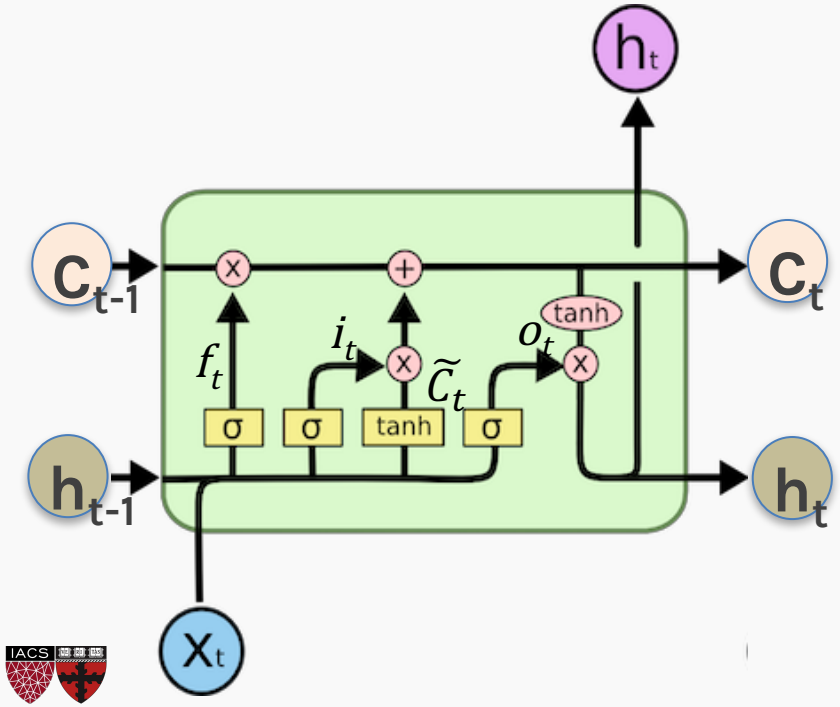


$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$




HARVARD
E
U
AS
HARD

wcct! = we can calculate this!

To optimize my parameters i basically need to do:
Let's calculate all the derivatives in some time t!

$$W = W - \eta \frac{\partial \mathcal{L}}{\partial W}$$

$$\frac{\partial \mathcal{L}}{\partial W_f} = \frac{\partial \mathcal{L}}{\partial C^t} \underbrace{\frac{\partial C^t}{\partial f^t}}_{C^{t-1}} \overbrace{\frac{\partial f^t}{\partial W_f}}^{\text{wcct!}}$$

$$\frac{\partial \mathcal{L}}{\partial W_c} = \frac{\partial \mathcal{L}}{\partial C^t} \underbrace{\frac{\partial C^t}{\partial (i^t \odot \hat{C}^t)}}_{1} \overbrace{\frac{\partial (i^t \odot \hat{C}^t)}{\partial W_c}}^{\text{wcct!}}$$

$$\frac{\partial \mathcal{L}}{\partial W_i} = \frac{\partial \mathcal{L}}{\partial C^t} \underbrace{\frac{\partial C^t}{\partial (i^t \odot \hat{C}^t)}}_{1} \overbrace{\frac{\partial (i^t \odot \hat{C}^t)}{\partial W_i}}^{\text{wcct!}}$$

$$\frac{\partial \mathcal{L}}{\partial W_o} = \frac{\partial \mathcal{L}}{\partial h^t} \underbrace{\frac{\partial h^t}{\partial o^t}}_{\tanh C^t} \overbrace{\frac{\partial o^t}{\partial W_o}}^{\text{wcct!}}$$

So… every derivative is wrt the cell state or the hidden state

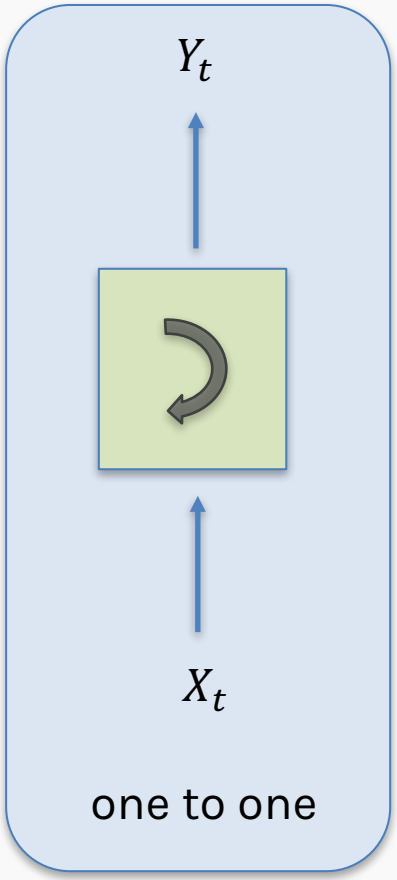
Let's calculate the cell state and the hidden state

$$\frac{\partial \mathcal{L}}{\partial h^{t-1}} = \frac{\partial \mathcal{L}}{\partial C^t}\left(\frac{\partial C^t}{\partial f^t}\frac{\partial f^t}{\partial h^t} + \frac{\partial C^t}{\partial (i^t \odot \hat{C}^t)}\frac{\partial (i^t \odot \hat{C}^t)}{\partial h^t}\right) + \frac{\partial \mathcal{L}}{\partial h^t}\frac{\partial h^t}{\partial o^t}\frac{\partial o^t}{\partial h^{t-1}}$$

$$\frac{\partial \mathcal{L}}{\partial C^t} = \underbrace{\frac{\partial \mathcal{L}}{\partial (f^{t+1} \odot C^t + i^{t+1} \odot \hat{C}^t)}}\underbrace{\frac{\partial (f^{t+1} \odot C^t + i^{t+1} \odot \hat{C}^t)}{\partial C^t}}$$

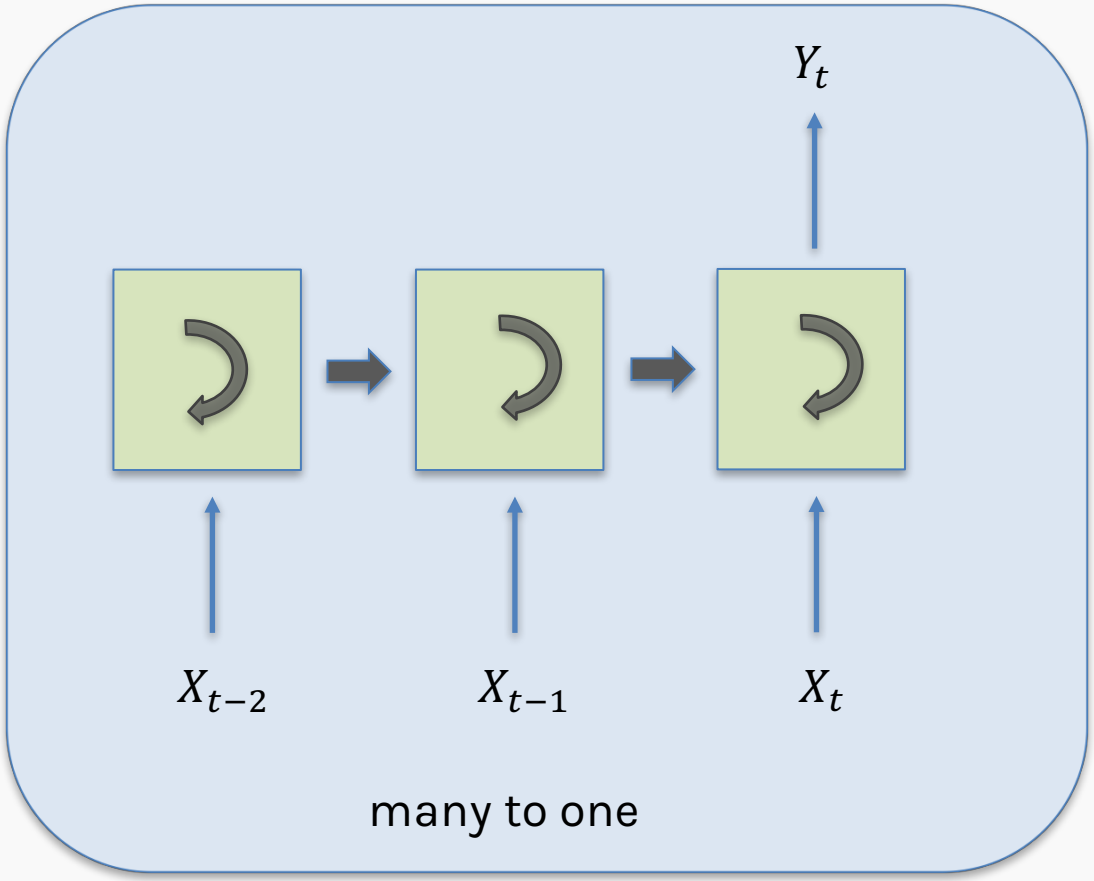
$$\left(\frac{\partial \mathcal{L}}{\partial C^{t+1}} + \frac{\partial \mathcal{L}}{\partial h^{t+1}}\frac{\partial h^{t+1}}{\partial C^{t+1}}\right) \odot f^{t+1}$$

RNN Structures



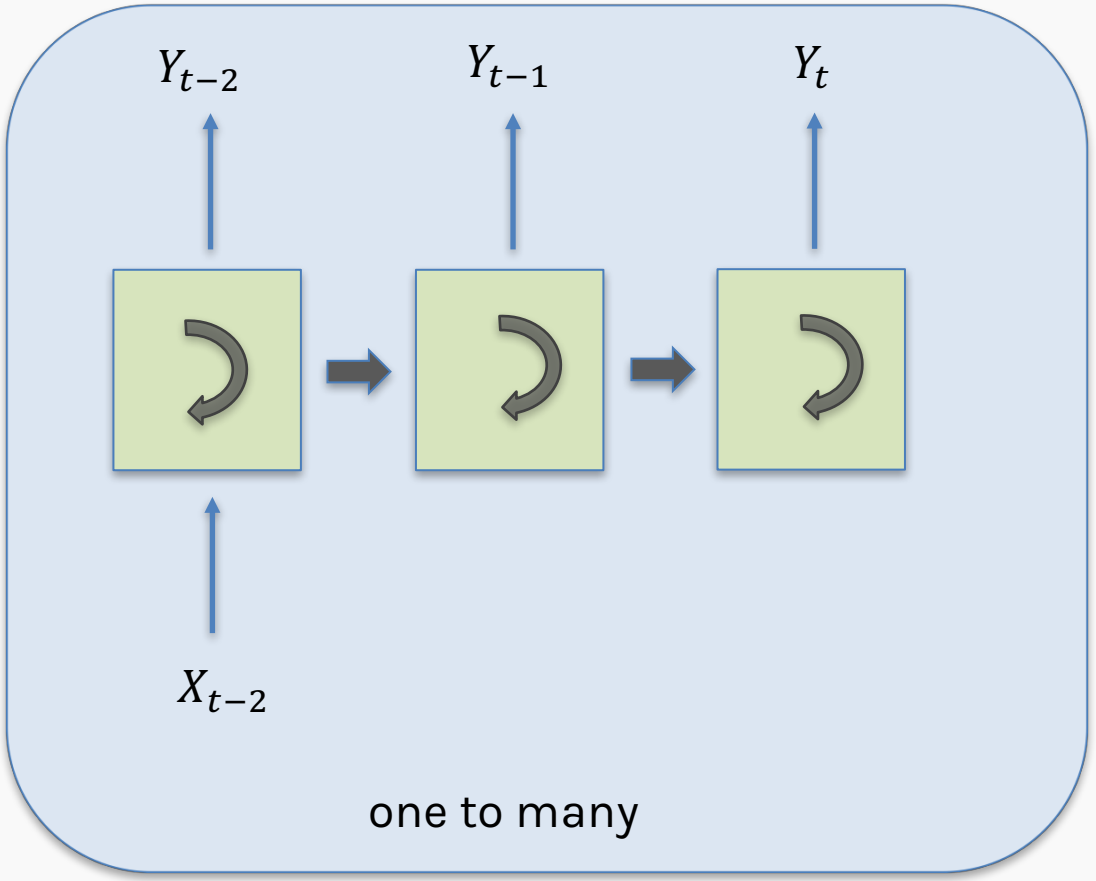
- The **one to one** structure is useless.
- It takes a single input and it produces a single output.
- Not useful because the RNN cell is making little use of its unique ability to remember things about its input sequence

RNN Structures (cont)



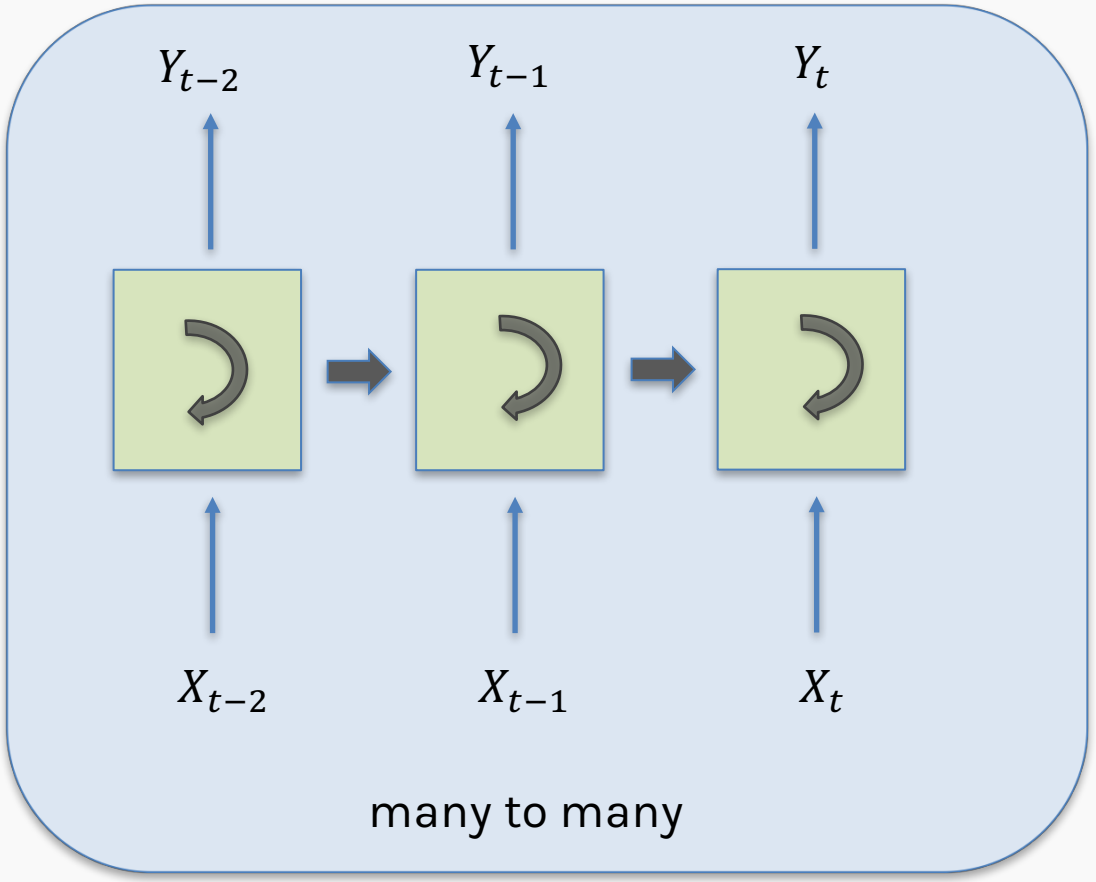
The **many to one** structure reads in a sequence and gives us back a single value.
Example: Sentiment analysis, where the network is given a piece of text and then reports on some quality inherent in the writing. A common example is to look at a movie review and determine if it was positive or negative. (see lab on Thursday)

RNN Structures (cont)



The **one to many** takes in a single piece of data and produces a sequence.
For example we give it the starting note for a song, and the network produces the rest of the melody for us.

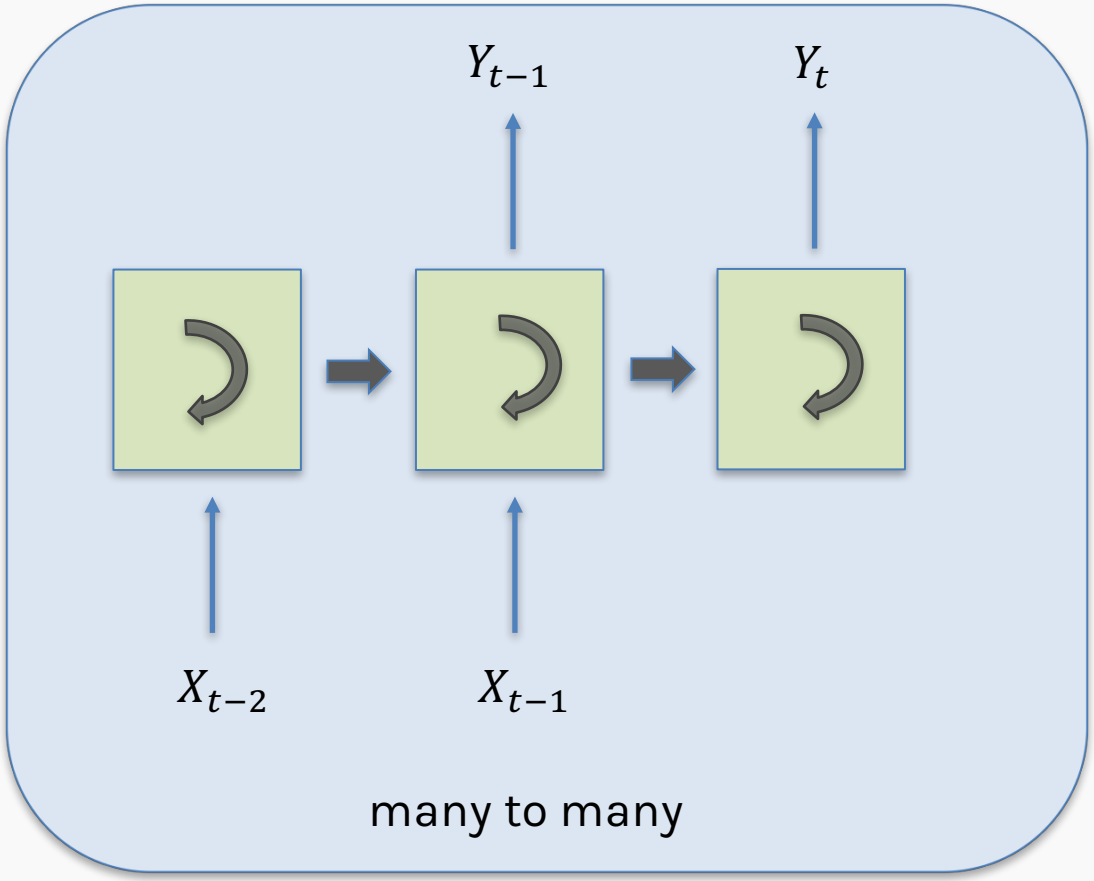
RNN Structures (cont)



The **many to many** structures are in some ways the most interesting.

Example: Predict if it will rain given some inputs.

RNN Structures (cont)



This form of **many to many** can be used for machine translation.

For example, the English sentence:
"The black dog jumped over the cat"
In Italian as:
"Il cane nero saltò sopra il gatto"
In the Italia, the adjective "nero" (black) follows the noun "cane" (dog), so we need to have some kind of buffer so we can produce the words in their proper English.

Bidirectional

RNNs (LSTMs and GRUs) are designed to analyze sequence of values.

For example: *Srivatsan said he needs a vacation.*

he here means *Srivatsan* and we know this because the word *Srivatsan* was before the word *he.*

However consider the following sentence:

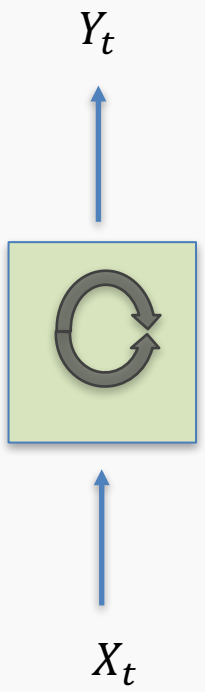
He needs to work harder, Pavlos said about Srivatsan.

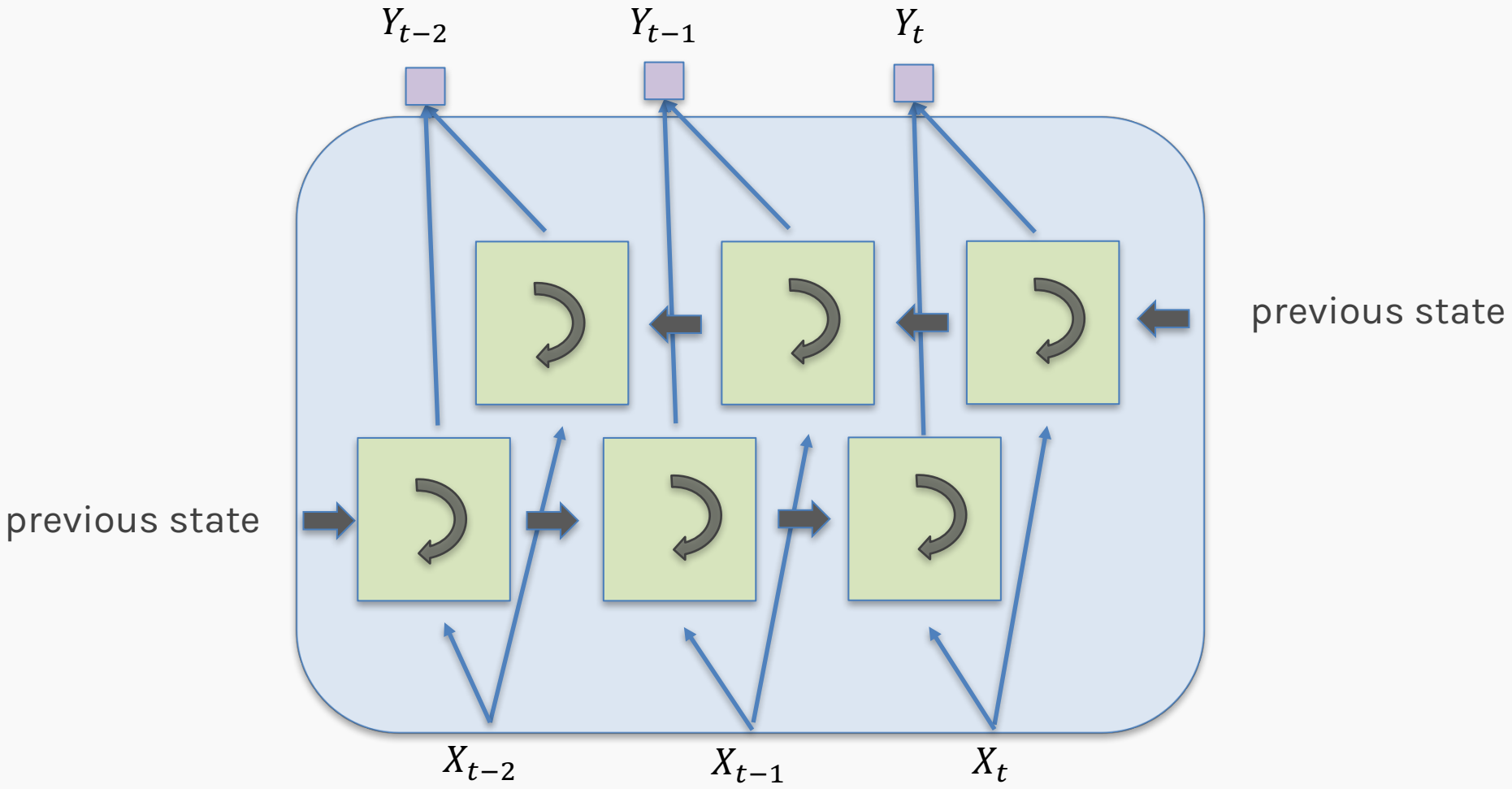
He here comes before *Srivatsan* and therefore the order has to be reversed or combine forward and backward.

These are called bidirectional RNN or **BRNN** or bidirectional LSTM or **BLSTM** when using LSTM units (BGRU etc).

Bidirectional (cond)

symbol for a BRNN



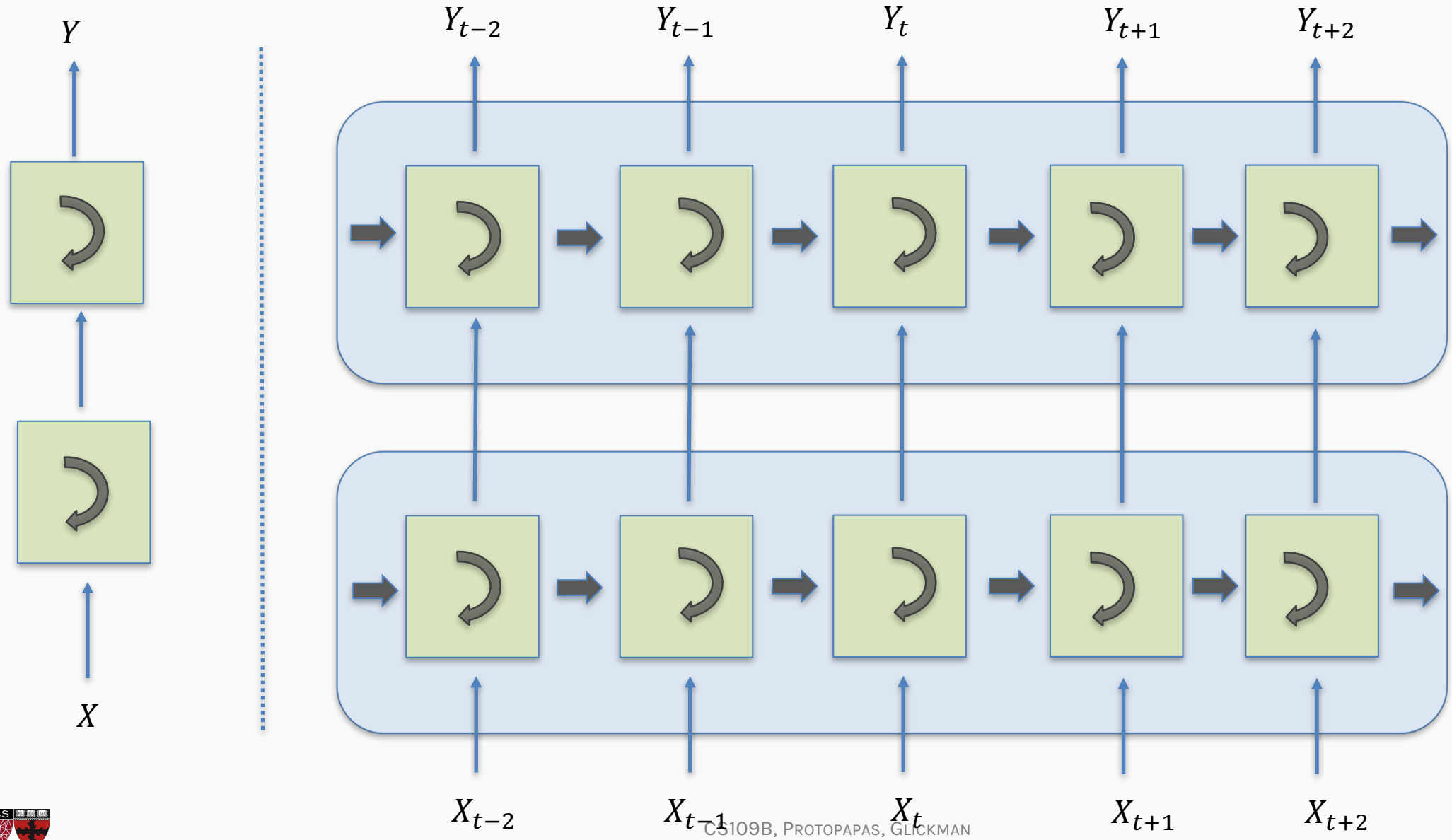


Deep RNN

LSTM units can be arranged in layers, so that each the output of each unit is the input to the other units. This is called **a deep RNN**, where the adjective “deep” refers to these multiple layers.

- Each layer feeds the LSTM on the next layer
- First time step of a feature is fed to the first LSTM, which processes that data and produces an output (and a new state for itself).
- That output is fed to the next LSTM, which does the same thing, and the next, and so on.
- Then the second time step arrives at the first LSTM, and the process repeats.

Deep RNN

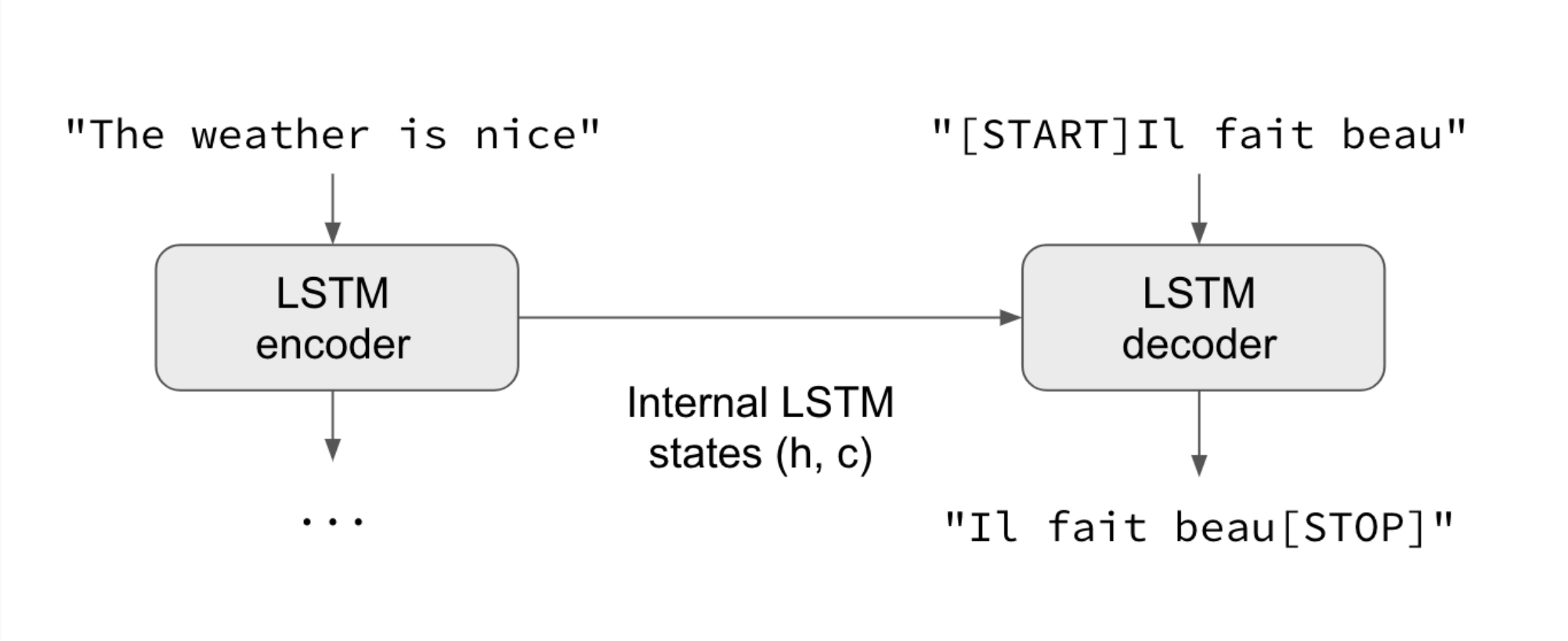


Sequence to Sequence

Sebastien lived in France.

Seq2seq model learns from variable sequence input fixed length sequence output. It uses two LSTM model, one learns vector representation from input sequence of fixed dimensionality and another LSTM learns to decode from this input vector to target sequence.

Sequence to Sequence (cont)



What is Teacher Forcing (cont)

Models that have recurrent connections from their outputs leading back into the model may be trained with teacher forcing.

— Page 372, Deep Learning, 2016.

Teacher forcing is a procedure [...] in which during training the model receives the ground truth output y(t) as input at time t + 1.

— Page 372, Deep Learning, 2016.

What is Teacher Forcing (cont)

Given the following input sequence:

"The wheels on the bus go round and round."

In this task we want to train a model to generate the next word in the sequence given the previous sequence of words.

We add a token to signal the start of the sequence and another to signal the end of the sequence. We will use "*[START]*" and "*[END]*" respectively.

"**[START]** The wheels on the bus go round and round **[END]**

What is Teacher Forcing (cont)

Imagine the model generates the word "*A*", but of course, we expected "*The*".

The model is off track and is going to get punished for every subsequent word it generates. This makes learning slower and the model unstable.

Instead, we can use teacher forcing.

In the first example when the model generated "***A***" as output, we can discard this output after calculating error and feed in "***The***" as part of the input on the subsequent time step.

What is Teacher Forcing (cont)

In the first example when the model generated "***A***" as output, we can discard this output after calculating error and feed in "***The***" as part of the input on the subsequent time step.

[START], ?

[START], The, wheels ?

[START], The, wheels, on , ?

[START], The, wheels, on , the, ?

…

REMEMBER: ONLY IN TRAINING TIME

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Attention models

Sebastien lived in France.

Back in Sebastien's days at France, he lived in the city of Paris, a city of great beauty and filled with love and beautiful art, and he spoke French, a language with great history and the national language of France.

Back in Sebastien's days at France, =>

he lived in the city of Paris, =>

a city of great beauty and filled with love and beautiful art, =>

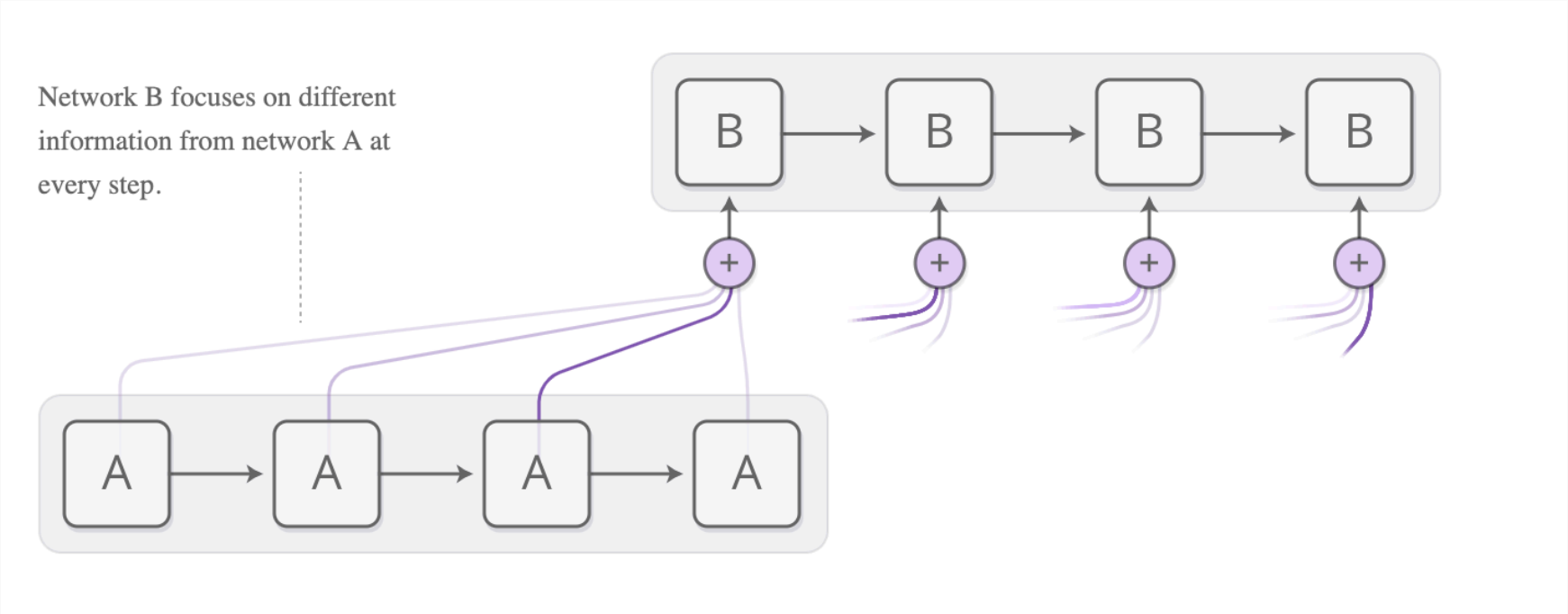
and he spoke French, a language with great history and the national language of France.

Attention models

When translating a sentence, you pay attention to the word that is presently translated.

When transcribing an audio recording, you listen carefully to the segment you are actively writing down.

To describe the room you are in, you describe the objects in that room.



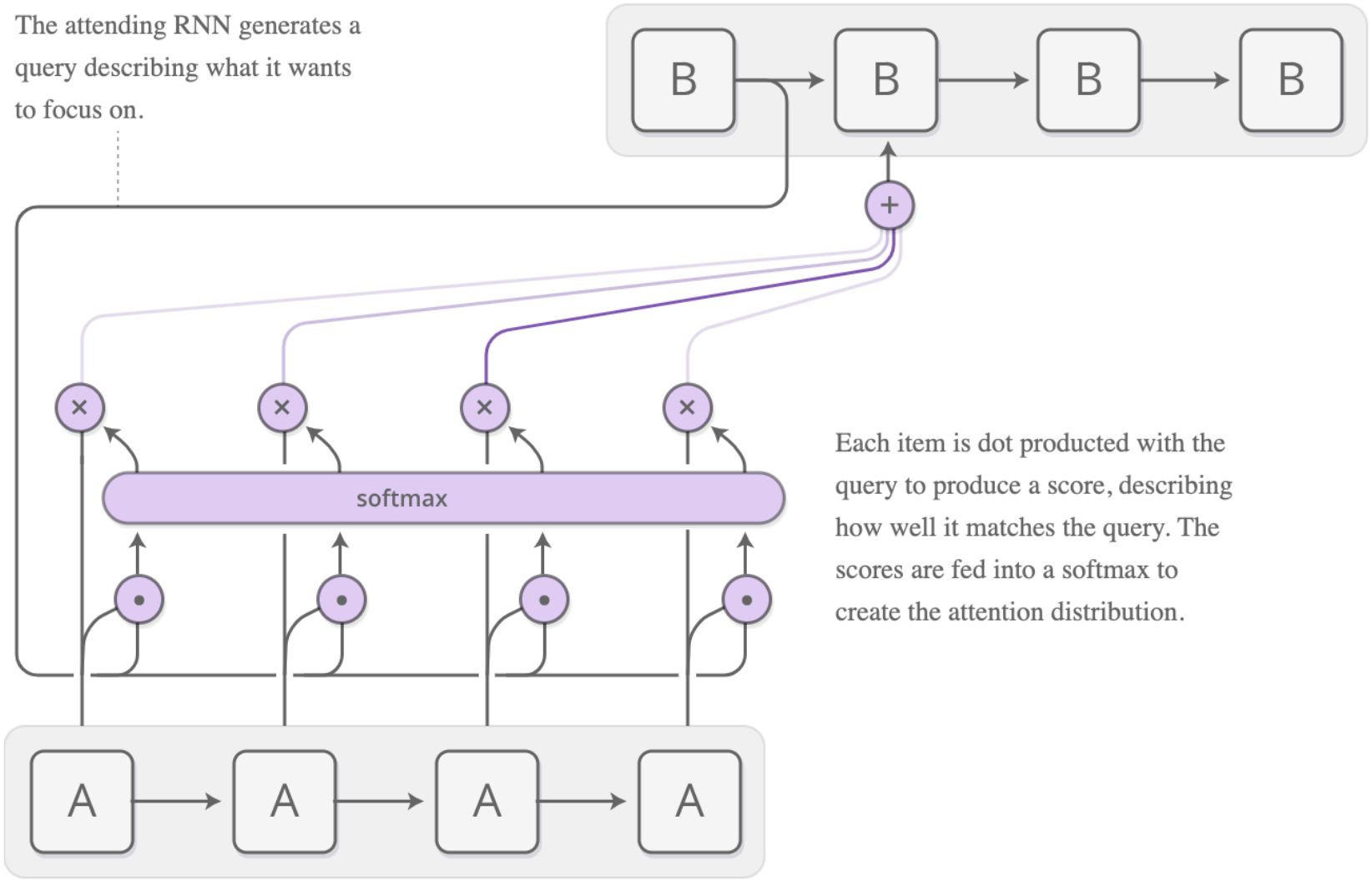
https://distill.pub/2016/augmented-rnns/

Attention models (cont)

This attention is generated with content-based attention. The attending RNN generates a query describing what it wants to focus on. Each item is multiplied (dot product) with the query to produce a score, describing how well it matches the query. The scores are fed into a softmax to create the attention distribution.

Source – https://github.com/google/seq2seq

Attention models (cont)



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