Intel Nervana™ AI Academy

RECURRENT NEURAL NETWORKS (RNNS)

ISSUE: VARIABLE LENGTH SEQUENCES OF WORDS

- With images, we forced them into a specific input dimension
- Not obvious how to do this with text
- For example, classify tweets as positive, negative, or neutral
- Tweets can have a variable number of words
- What to do?

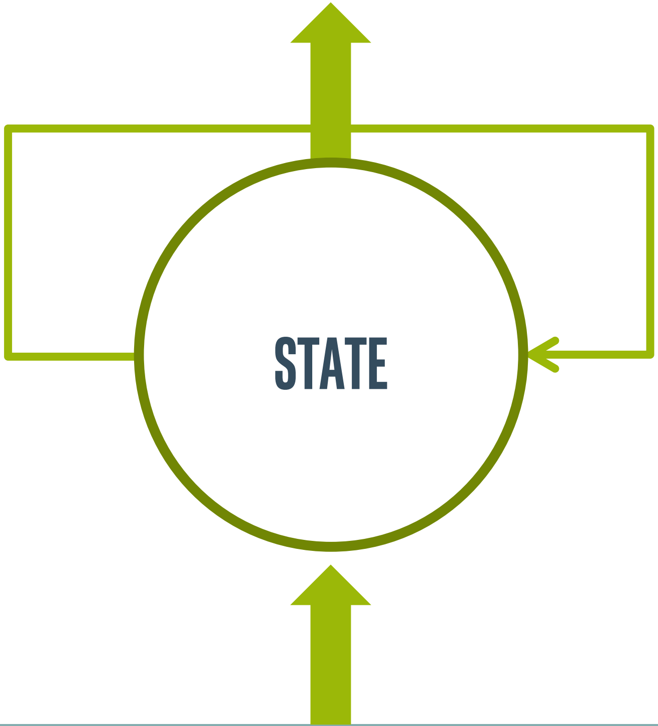
ISSUE: ORDERING OF WORDS IS IMPORTANT

- Want to do better than “bag of words” implementations
- Ideally, each word is processed or understood in the appropriate context
- Need to have some notion of “context”
- Words should be handled differently depending on “context”
- Also, each word should update the context

IDEA: USE THE NOTION OF "RECURRENCE"

- Input words one by one
- Network outputs two things:
  - Prediction: What would be the prediction if the sequence ended with that word
  - State: Summary of everything that happened in the past
- This way, can handle variable lengths of text
- The response to a word depends on the words that preceded it

IDEA: USE THE NOTION OF "RECURRENCE"



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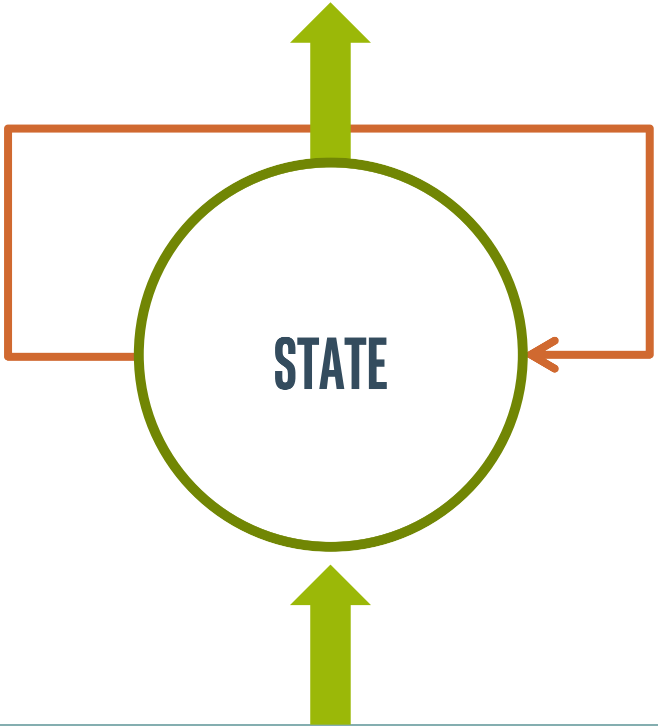

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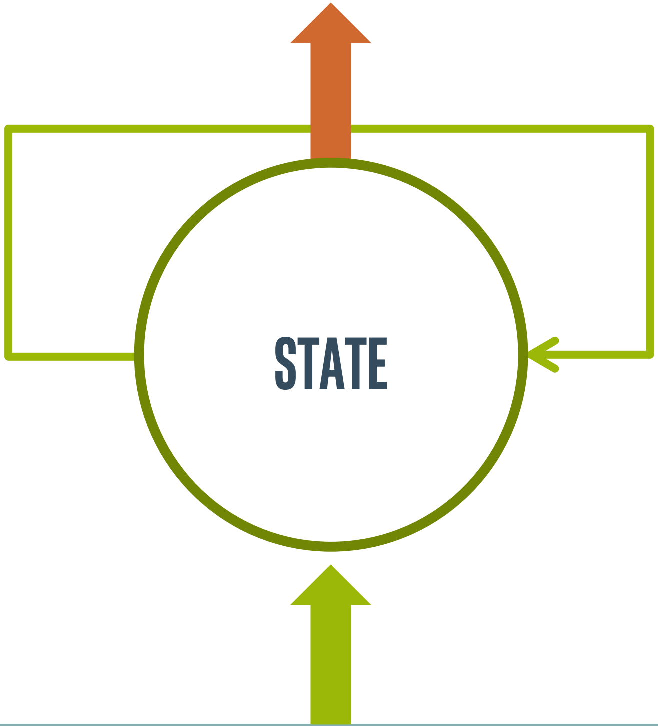

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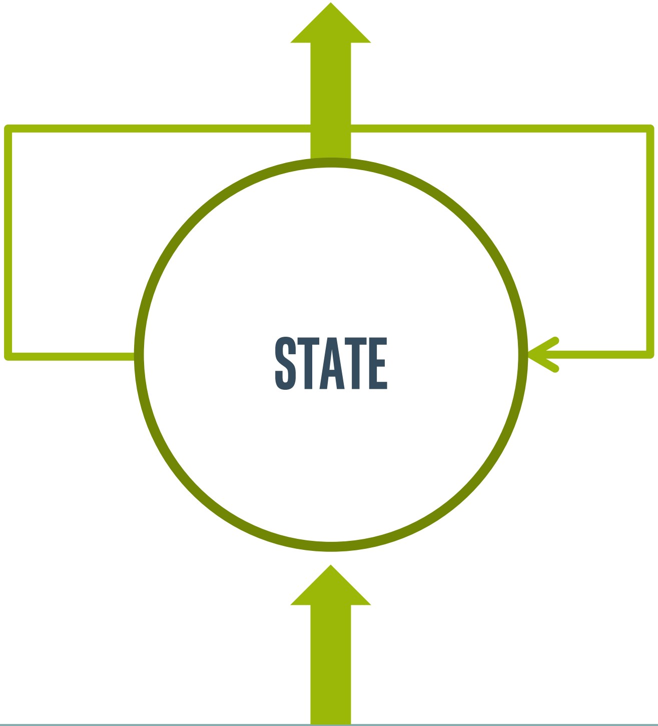
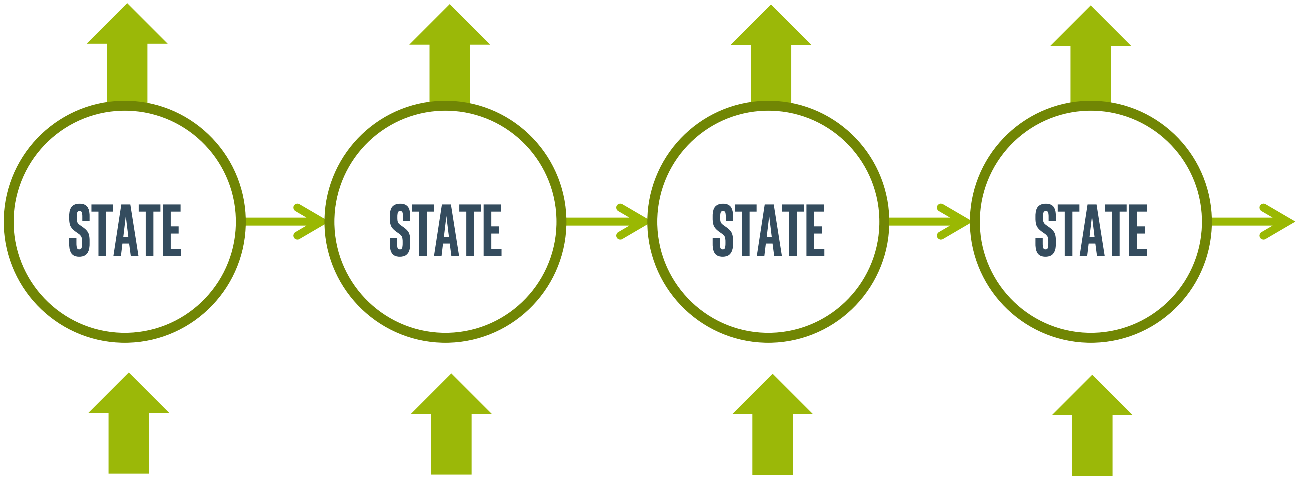
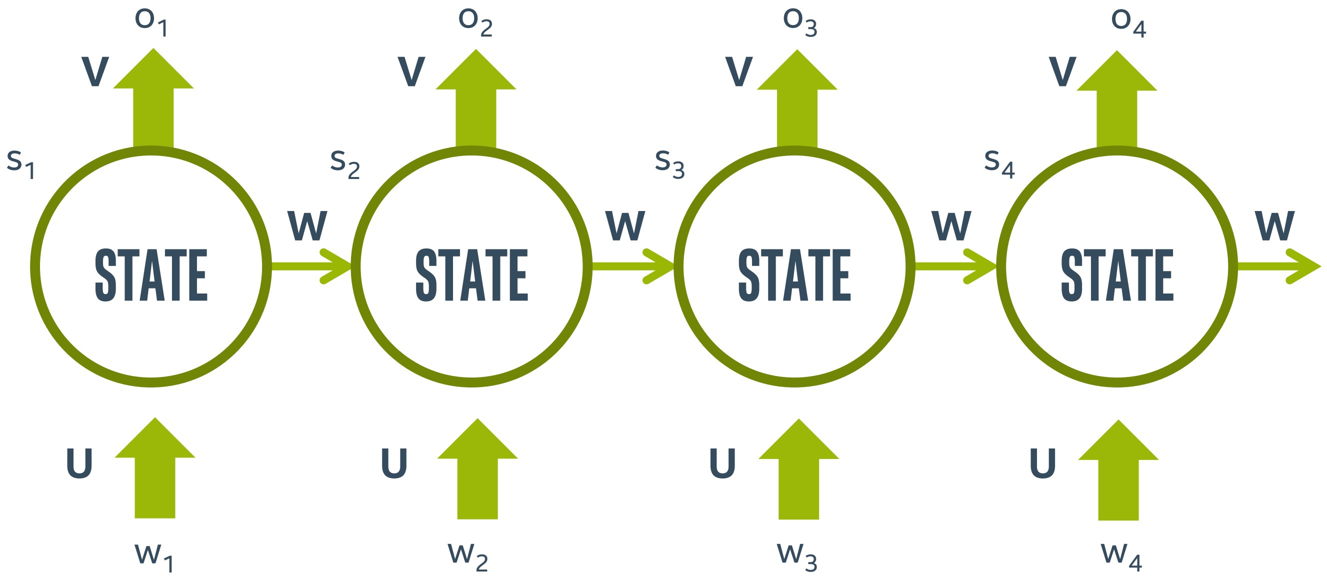


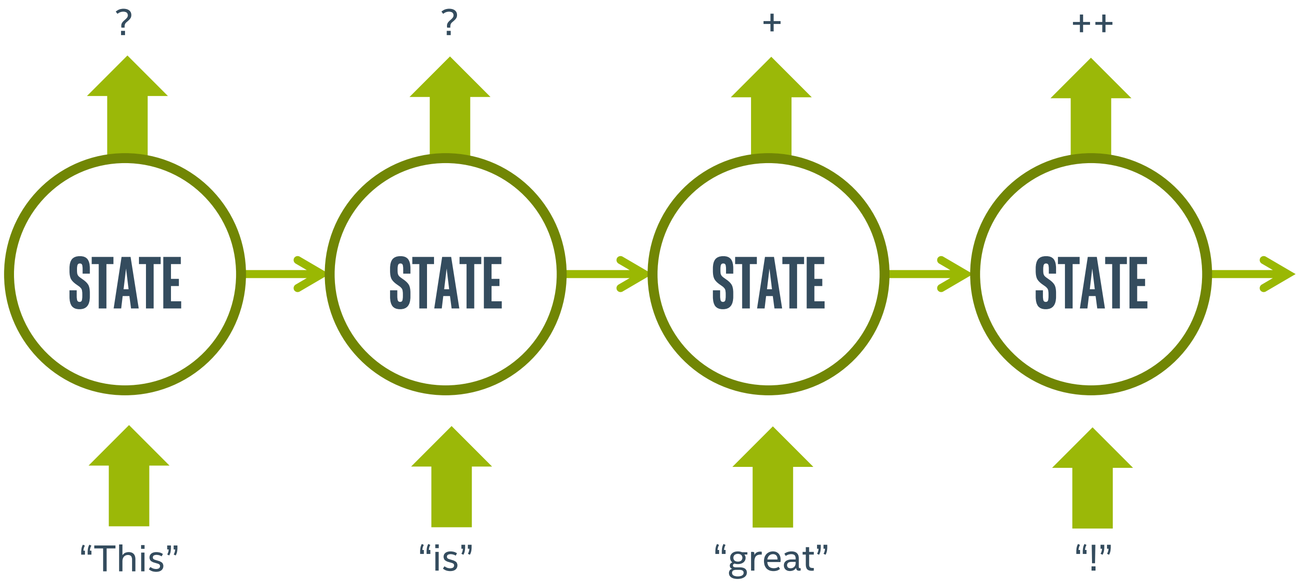
“UNROLLING” THE RNN



"UNROLLING" THE RNN

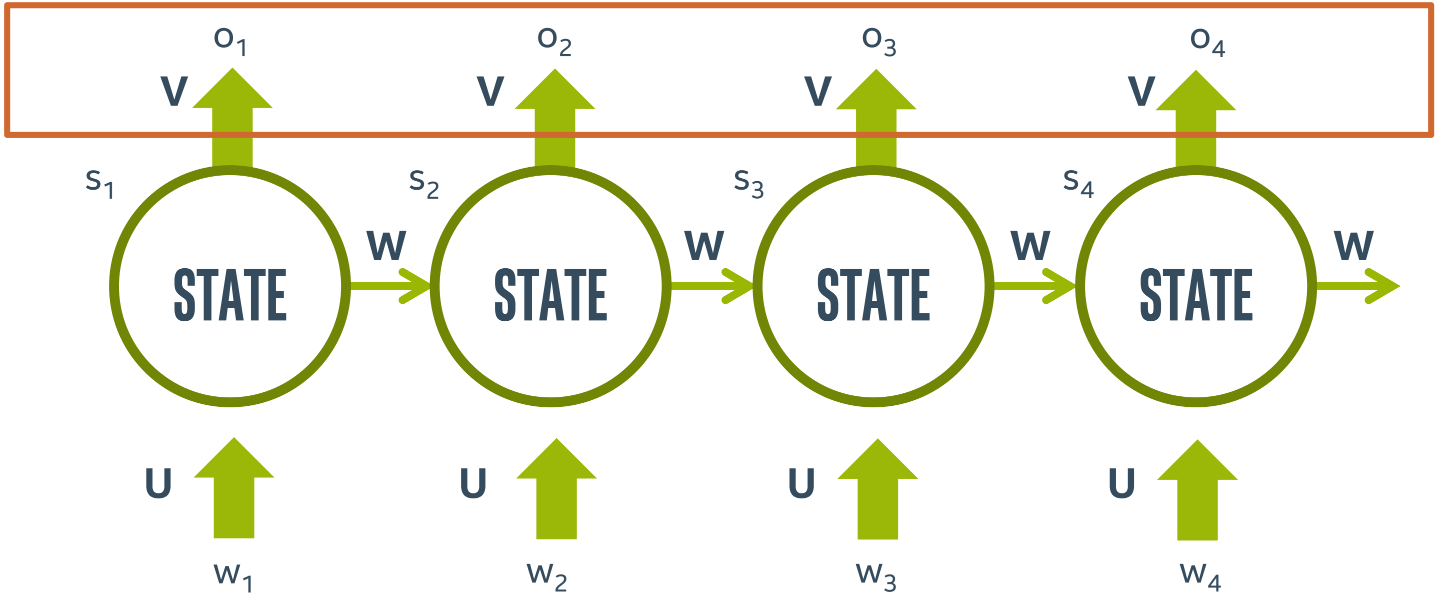


"UNROLLING" THE RNN



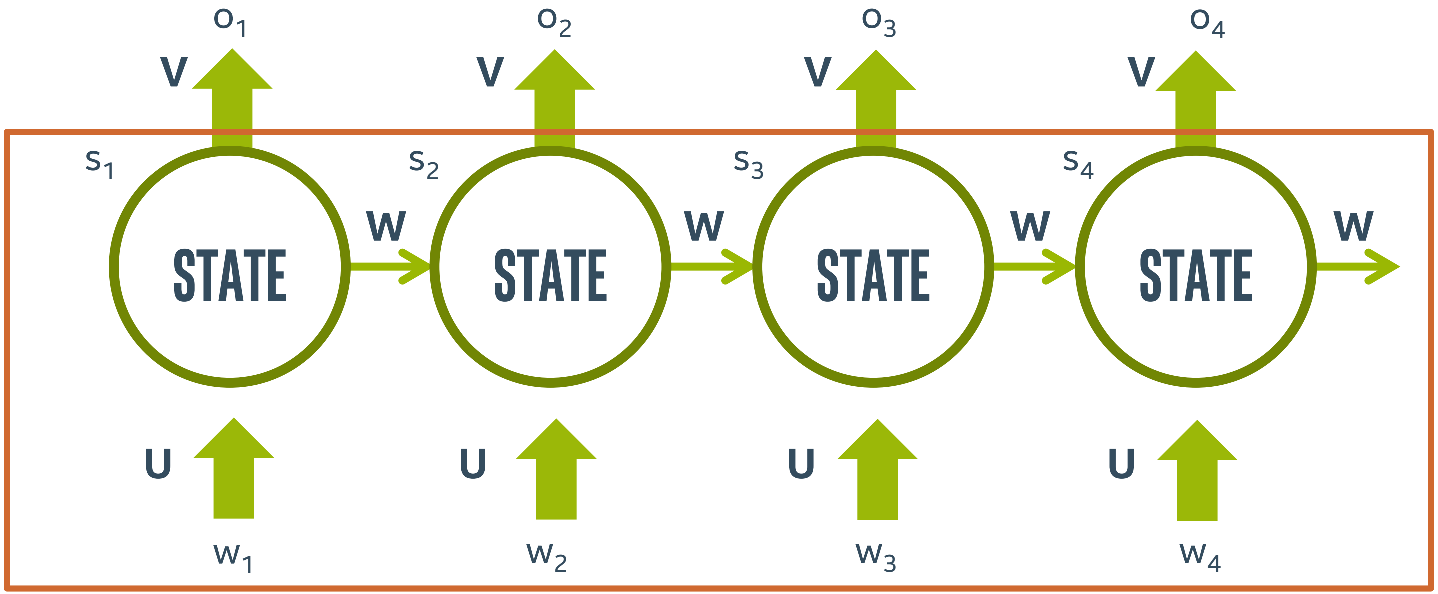
"UNROLLING" THE RNN

In Keras, this part is accomplished by a subsequent Dense layer.



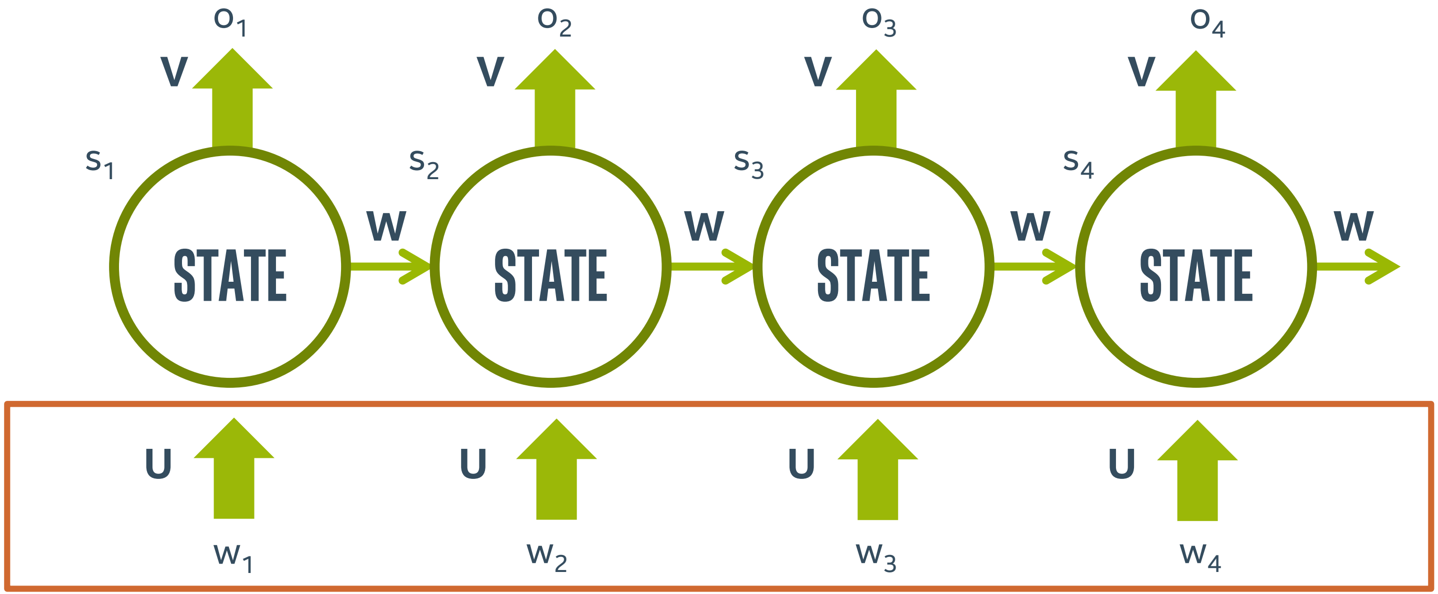
“UNROLLING” THE RNN

This part is the core RNN.



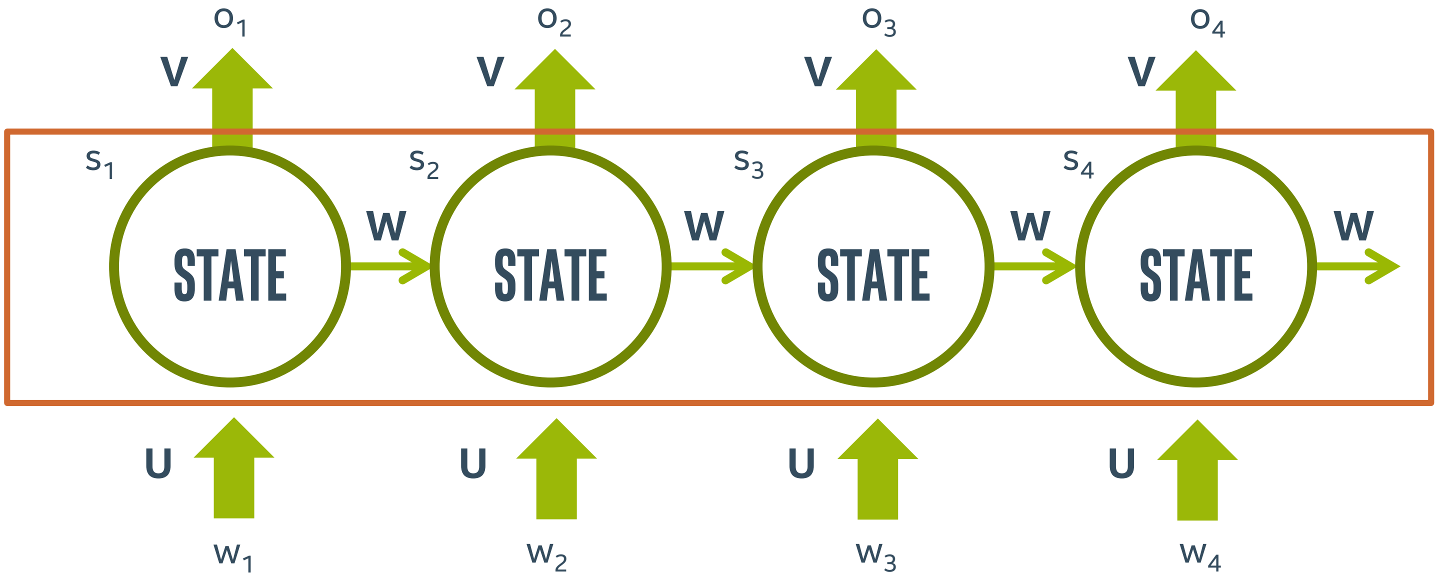
“UNROLLING” THE RNN

Keras calls this part the “kernel” (e.g. `kernel_initializer`,...).



"UNROLLING" THE RNN

Keras calls this part "recurrent" (`recurrent_initializer,...`).



PRACTICAL DETAILS

- Often, we train on just the ”final” output and ignore the intermediate outputs
- Slight variation called Backpropagation Through Time (BPTT) is used to train RNNs
- Sensitive to length of sequence (due to “vanishing/exploding gradient” problem)
- In practice, we still set a maximum length to our sequences
  - If input is shorter than maximum, we “pad” it
  - If input is longer than maximum, we truncate

OTHER USES OF RNNS

- We have focused on text/words as application
- But, RNNs can be used for other sequential data
  - Time-Series Data
  - Speech Recognition
  - Sensor Data
  - Genome Sequences

WEAKNESSES OF RNNS

- Nature of state transition means it is hard to keep information from distant past in current memory without reinforcement
- In the next lecture, we will introduce LSTMs, which have a more complex mechanism for updated the state

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LSTM (LONG-SHORT TERM MEMORY) RNNS

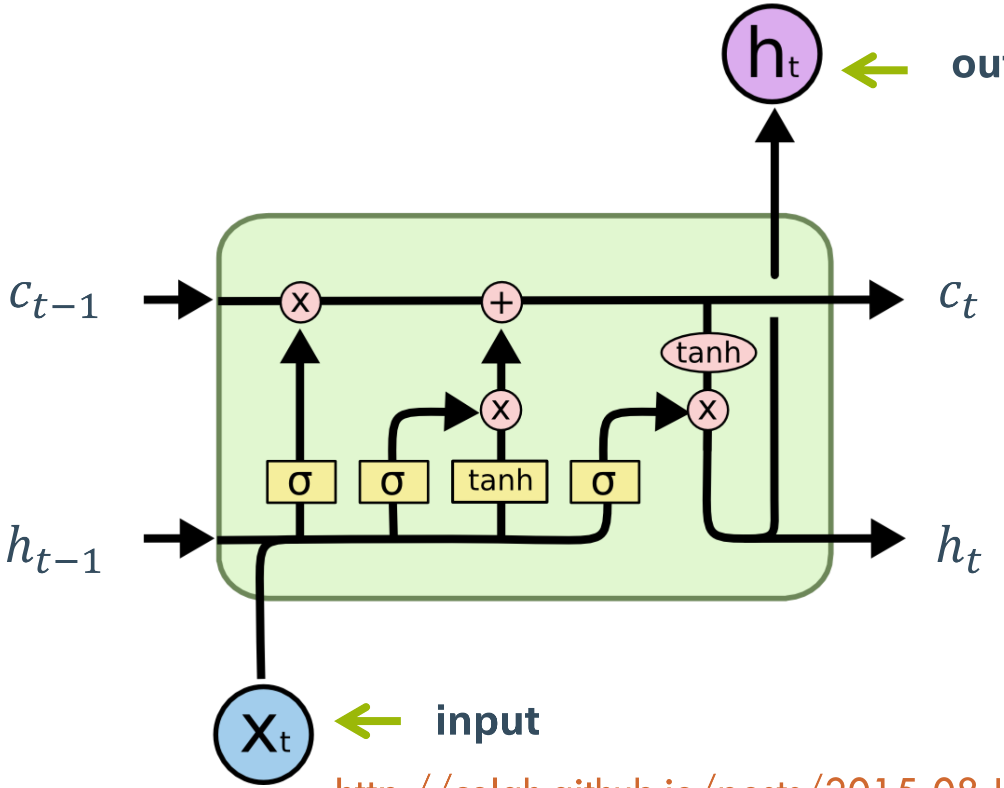
ISSUE: STANDARD RNNS HAVE POOR MEMORY

- Transition Matrix necessarily weakens signal
- Need a structure that can leave some dimensions unchanged over many steps
- This is the problem addressed by so-called Long-Short Term Memory RNNs (LSTM)

IDEA: MAKE "REMEMBERING" EASY

- Define a more complicated update mechanism for the changing of the internal state
- By default, LSTMs remember the information from the last step
- Items are overwritten as an active choice

LSTM DIAGRAM



output

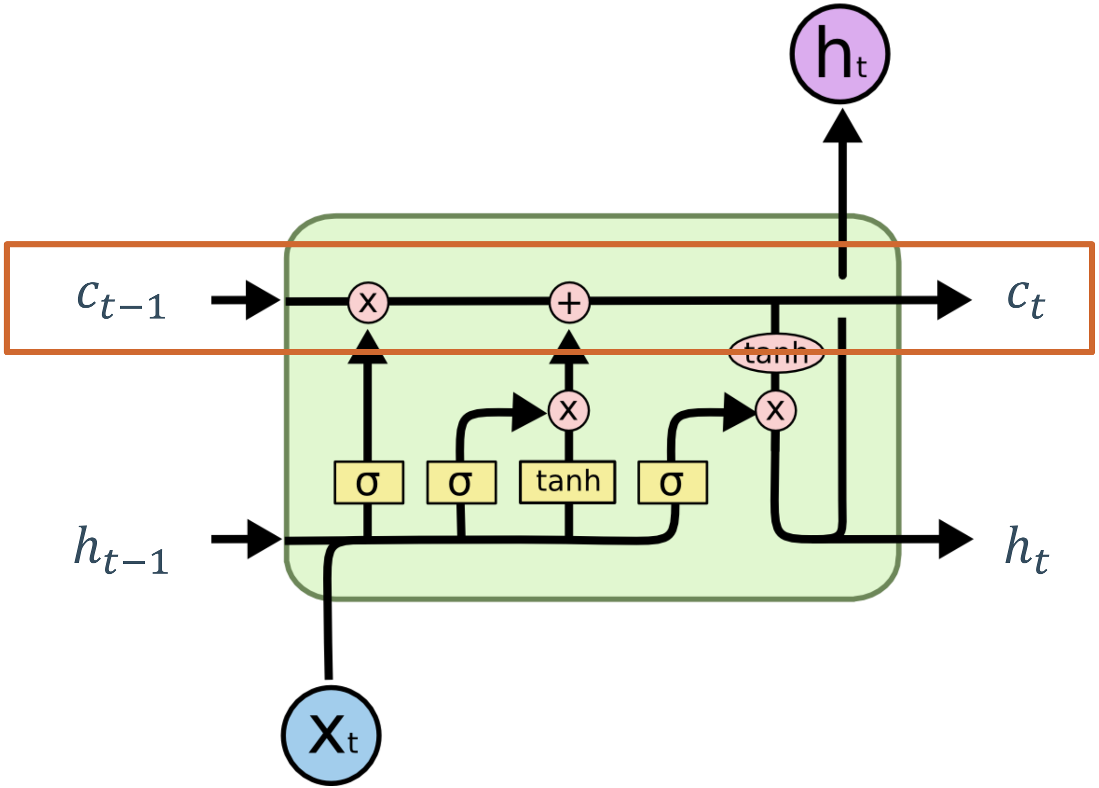
cell state

output (which also feeds into next unit)

input

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

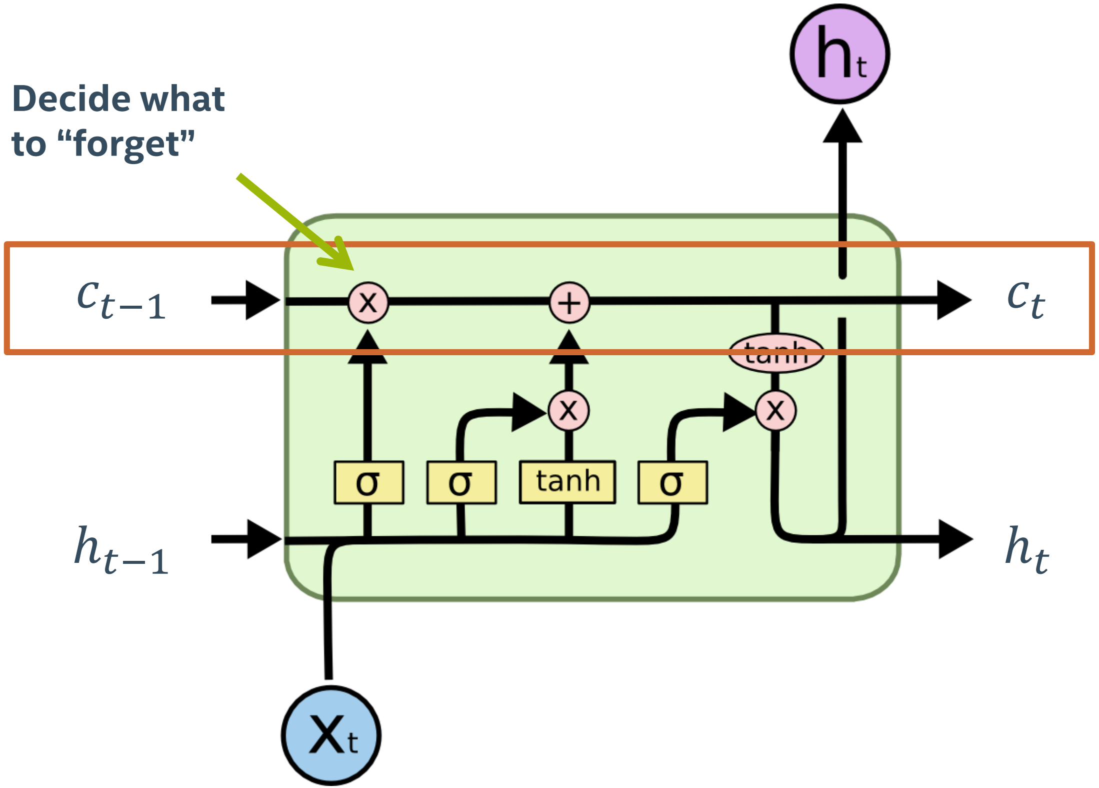
LSTM DIAGRAM



cell state gets updated in two stages

LSTM DIAGRAM

Decide what
to "forget"



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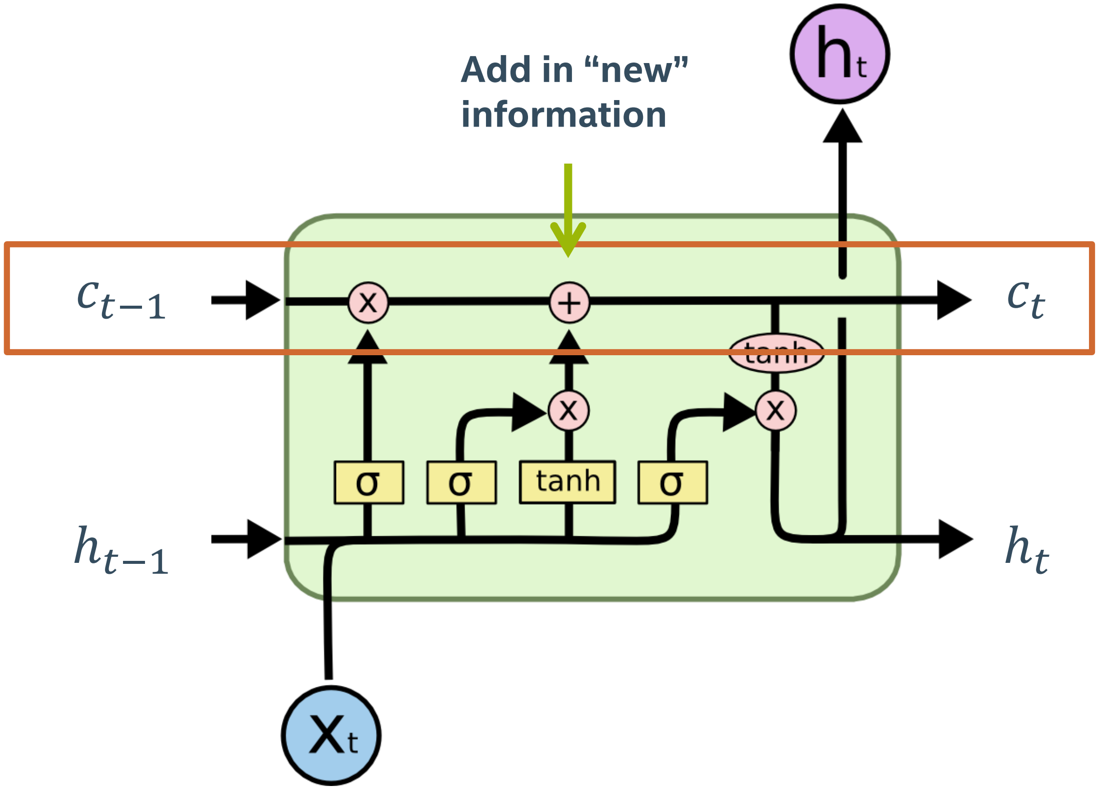
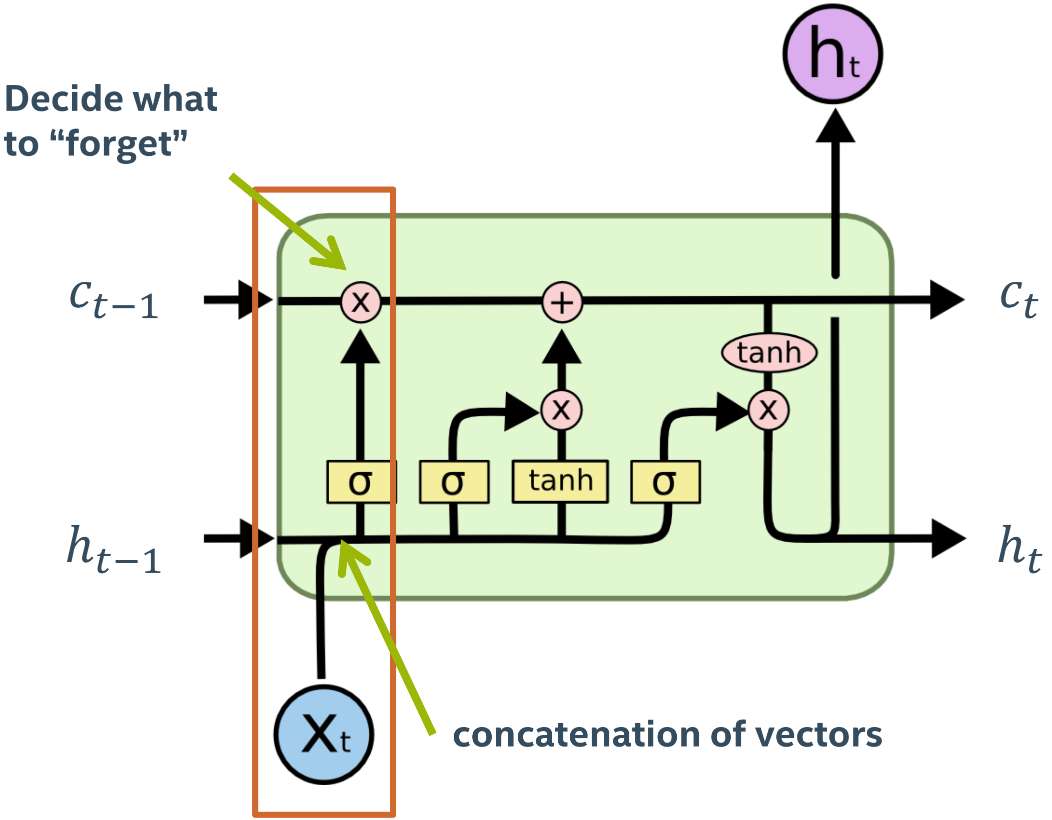
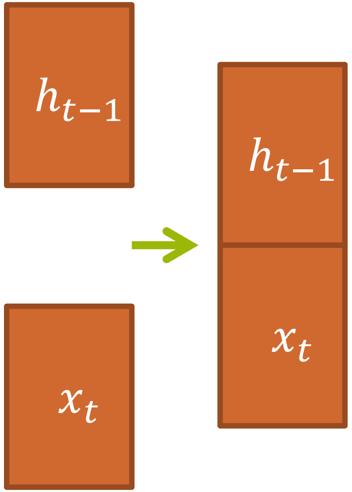


cell state gets updated in two stages

LSTM DIAGRAM

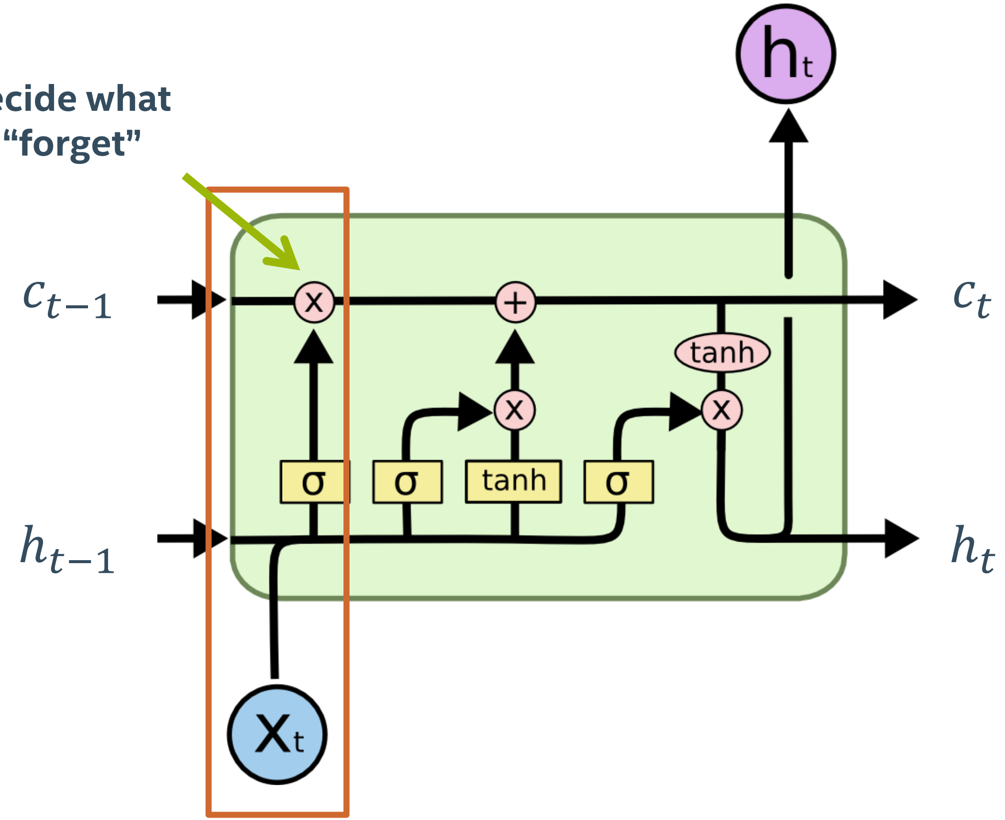




$[h_{t-1}, x_t]$

LSTM DIAGRAM

Decide what to “forget”

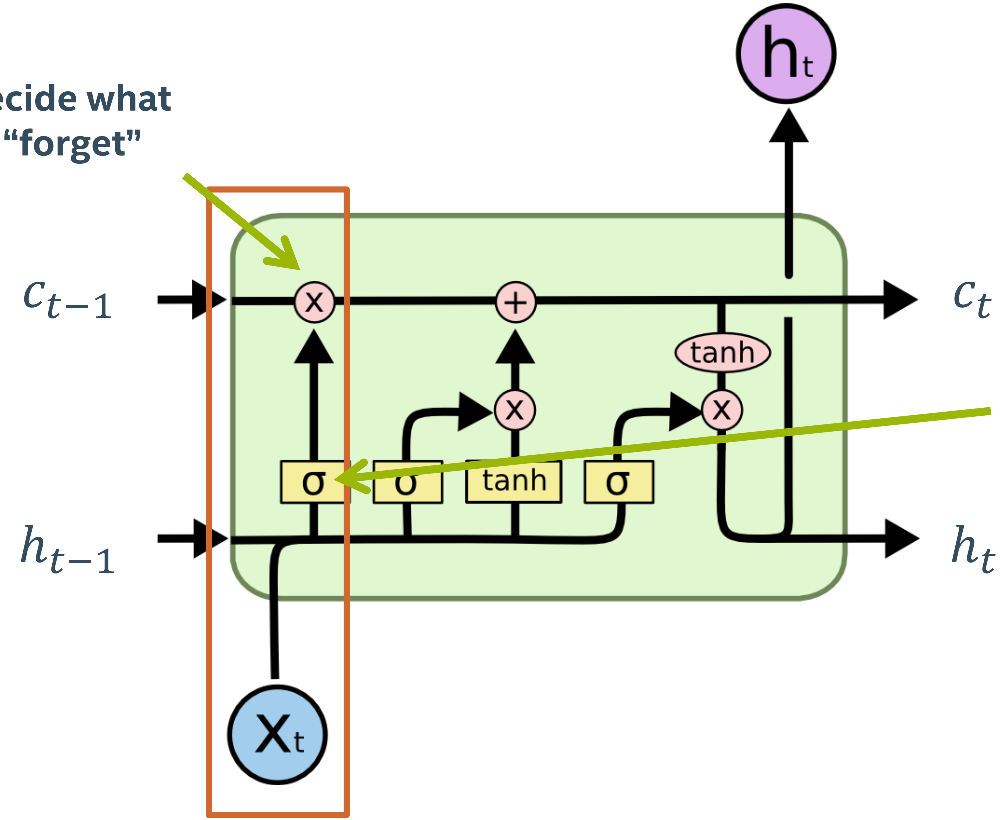


$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$$

based on previous output and current input

LSTM DIAGRAM

Decide what to "forget"



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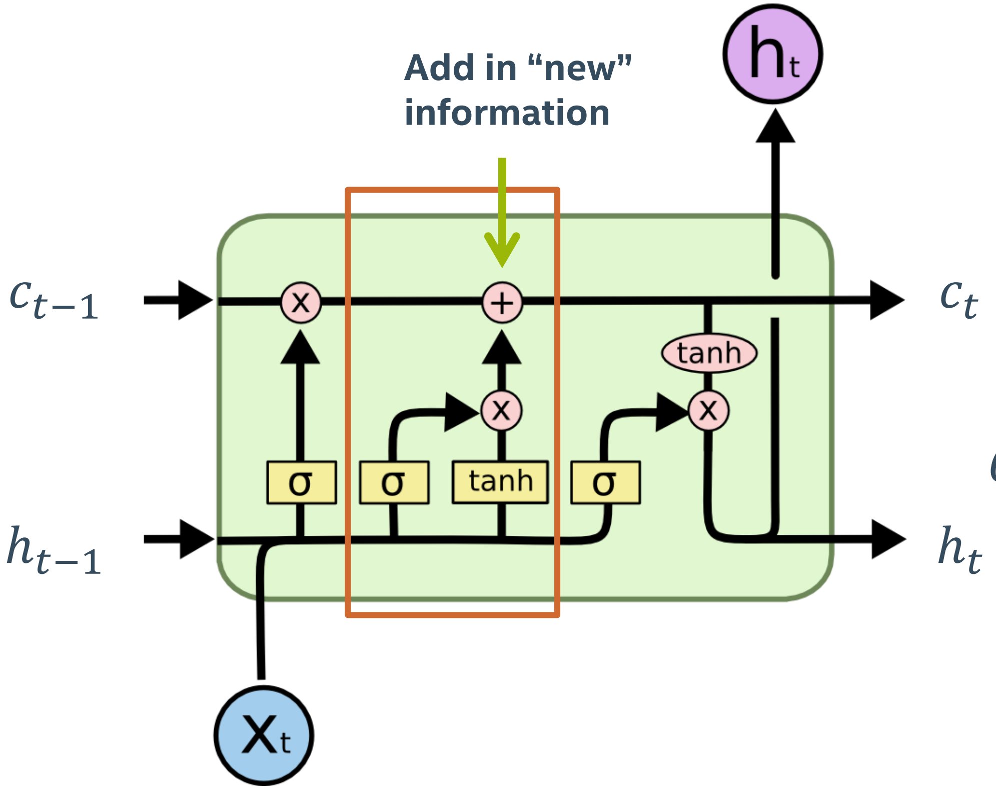
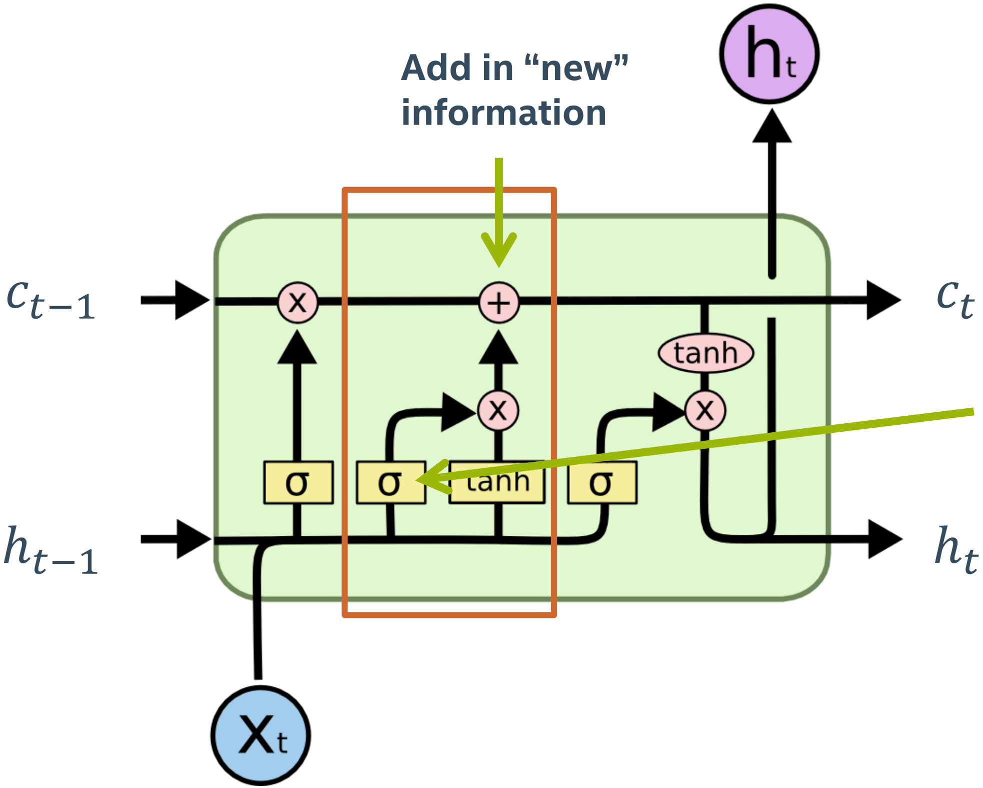


$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$C_t' = tanh(W_C[h_{t-1}, x_t] + b_C)$$

LSTM DIAGRAM



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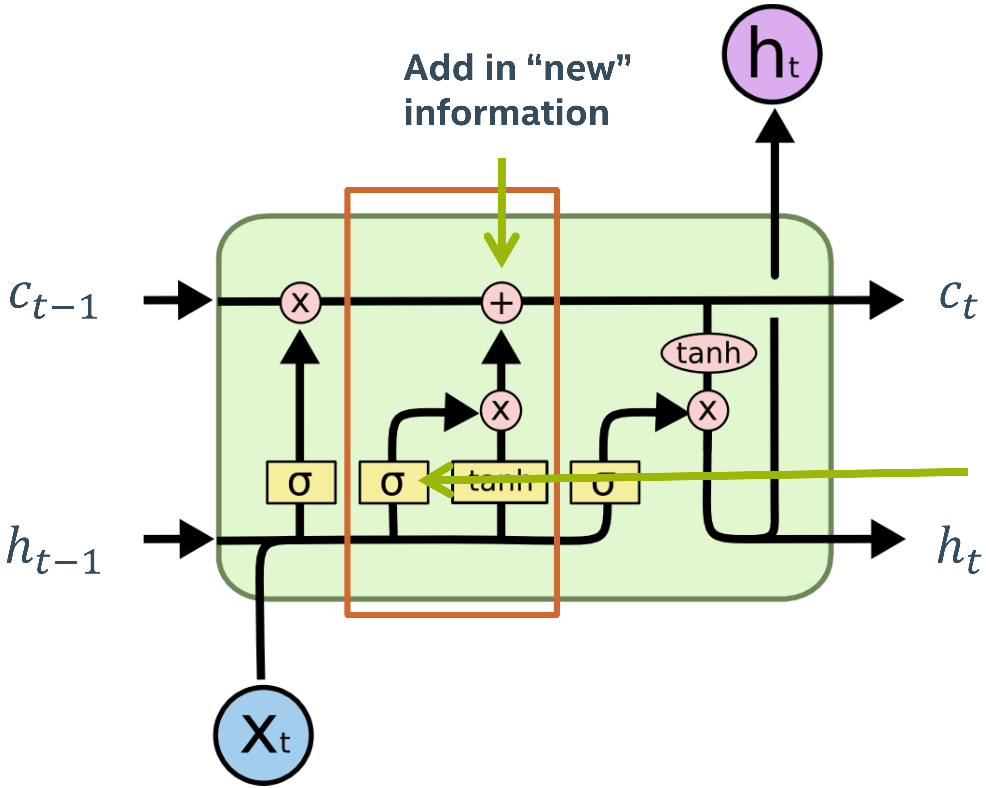

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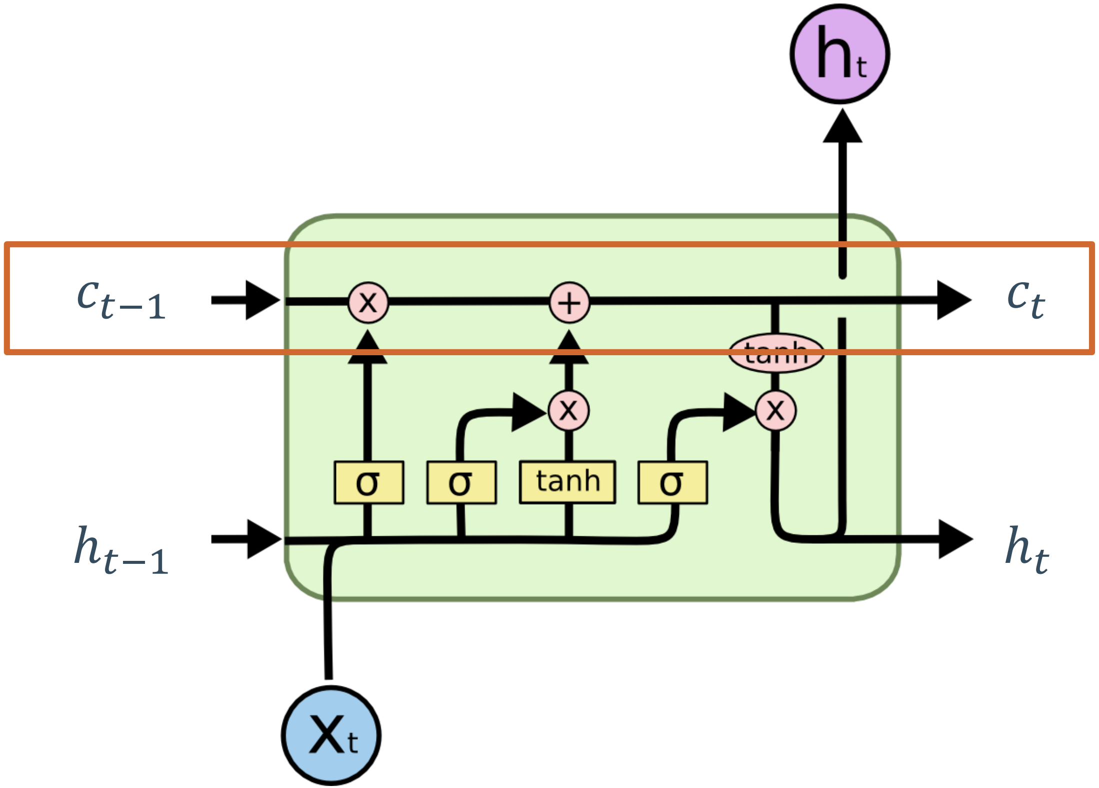
LSTM DIAGRAM



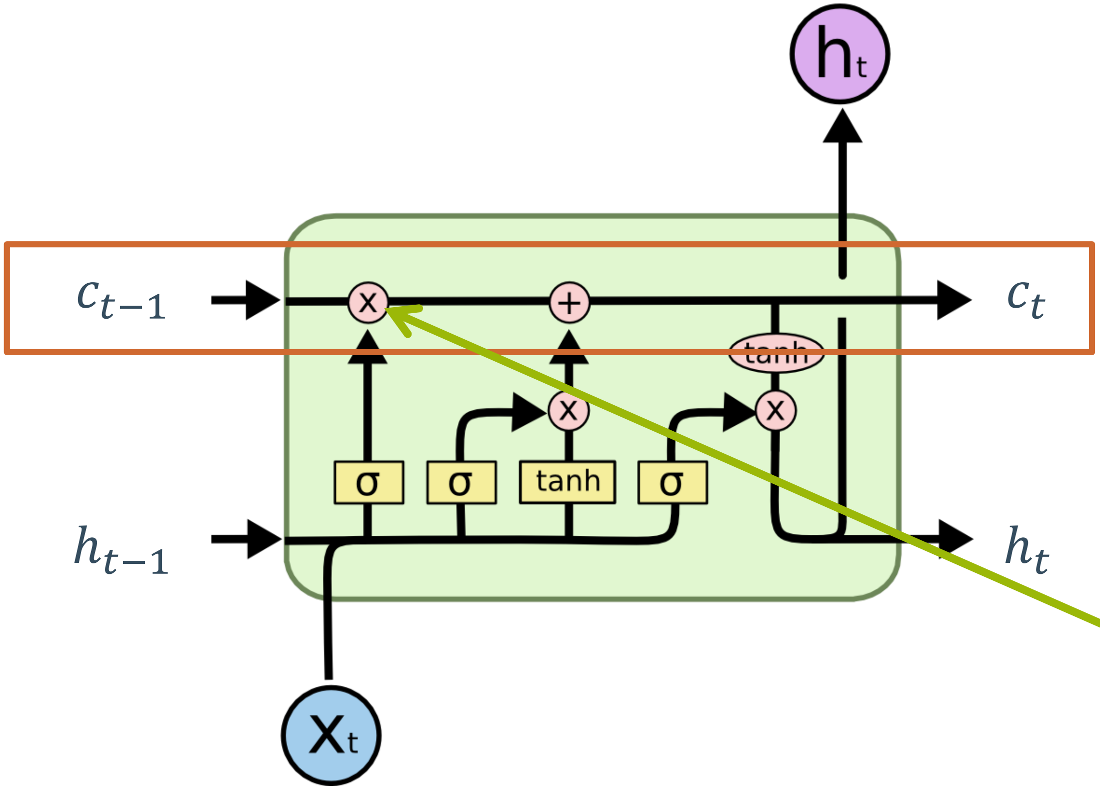
Note: '∗' represents element-wise multiplication

$$C_t = f_i * C_{t-1} + i_t * C_t'$$

forget the old (or not)

add the new (or not)

LSTM DIAGRAM



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$$C_t = f_i * C_{t-1} + i_t * C'_t$$

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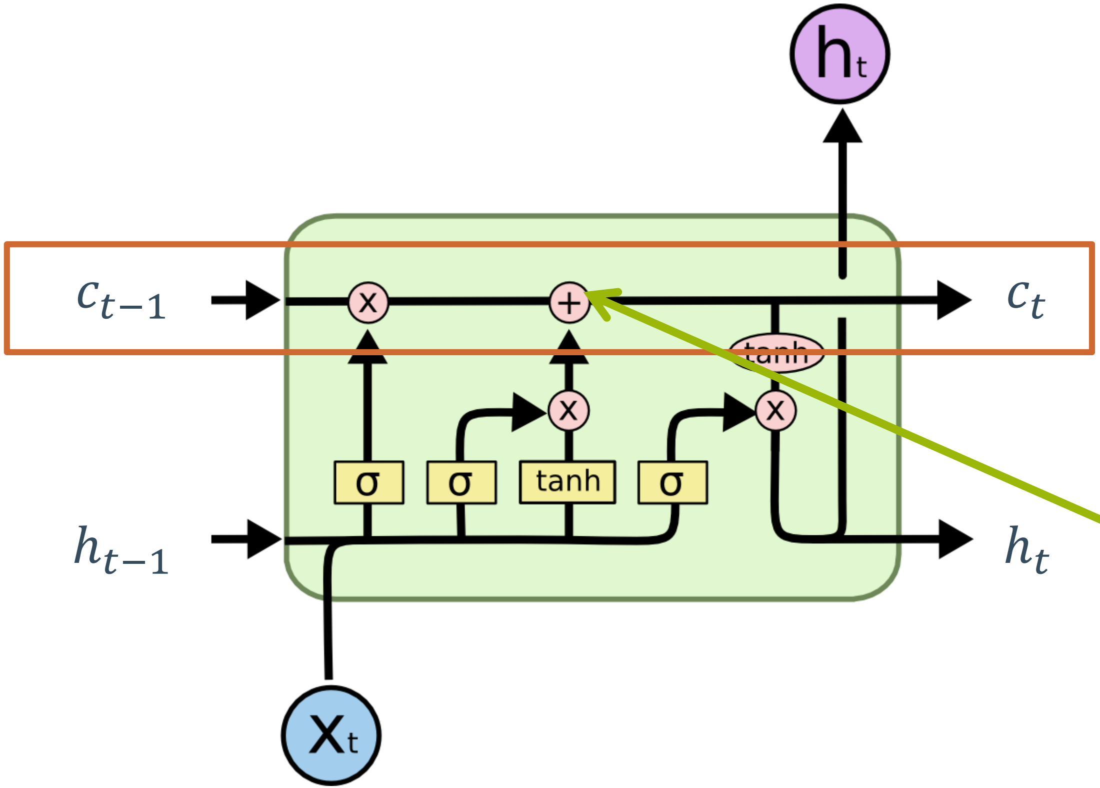
LSTM DIAGRAM



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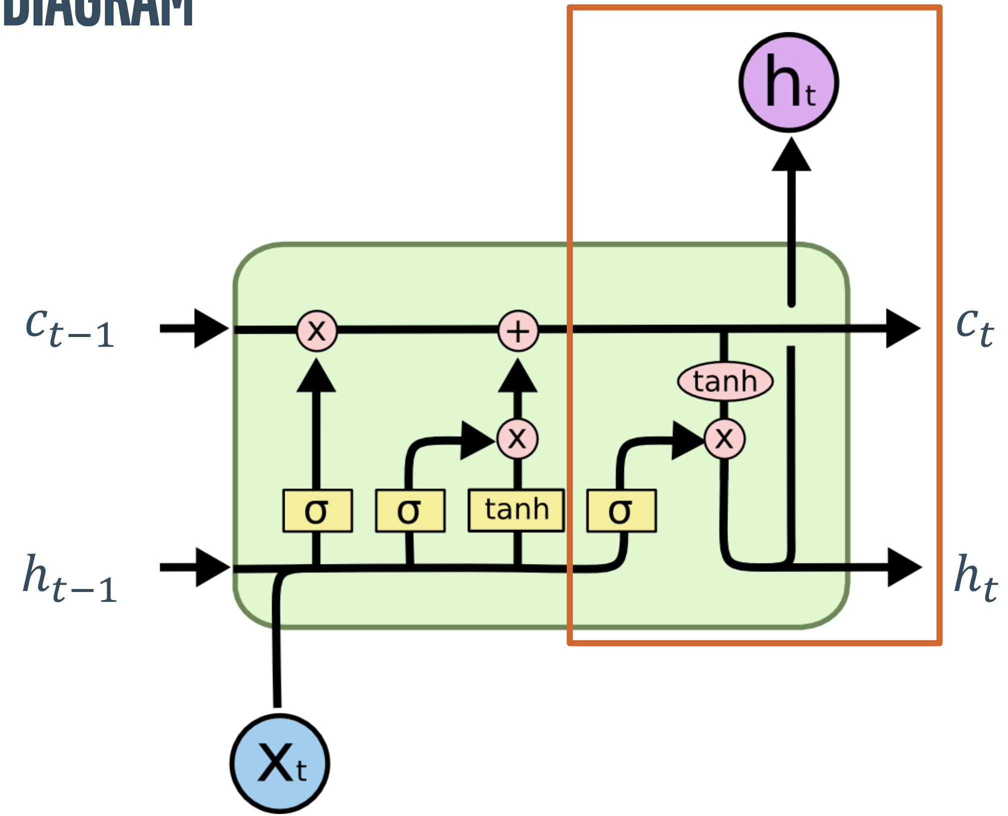
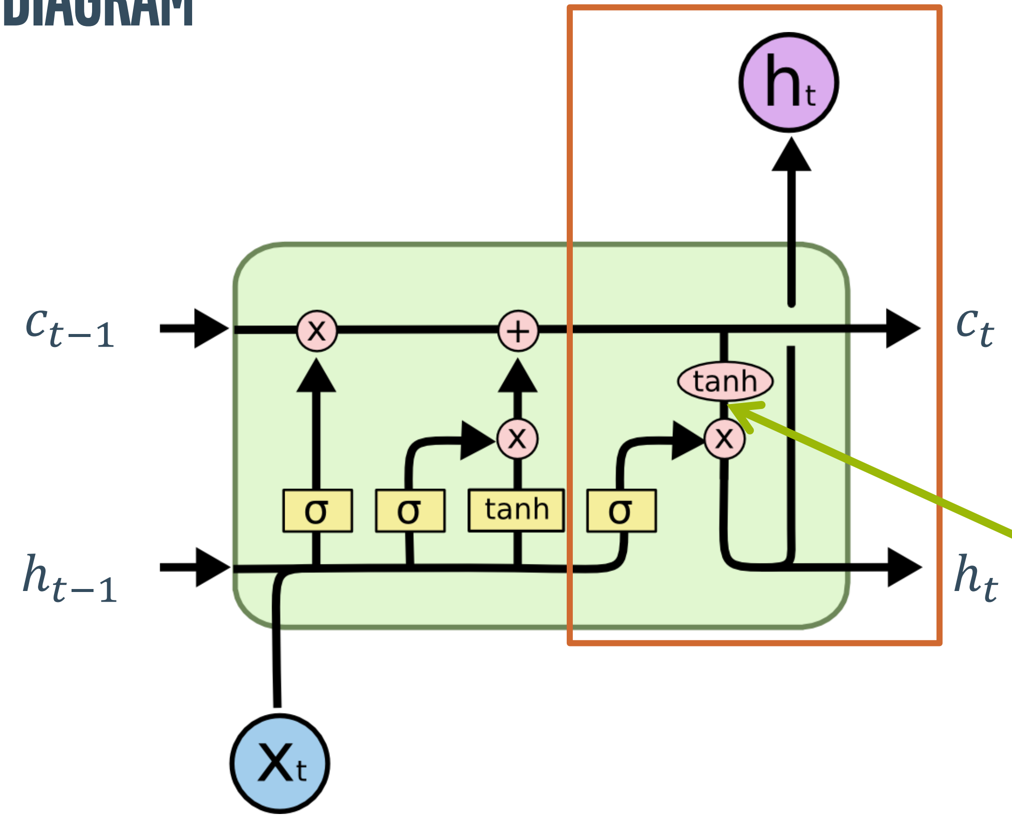


Final stage computes the output

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

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

LSTM DIAGRAM



Final stage computes the output

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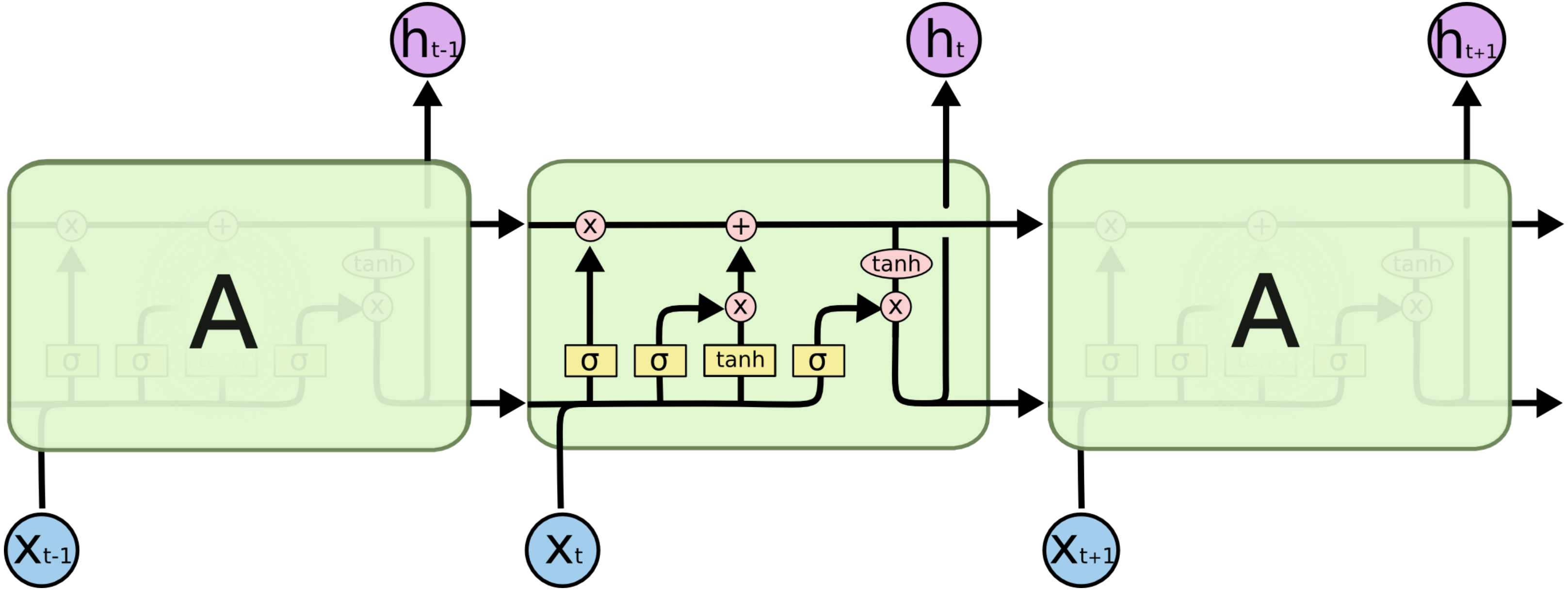
$$h_t = o_t * \tanh(C_t)$$

Note: No weights here

LSTM UNROLLED



FINAL POINTS

- This is the most common version of LSTM, but there are many different “flavors”
  - Gated Recurrent Unit (GRU)
  - Depth-Gated RNN
- LSTMs have considerably more parameters than plain RNNs
- Most of the big performance improvements in NLP have come from LSTMs, not plain RNN

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