Long Short Term Memory (LSTM)

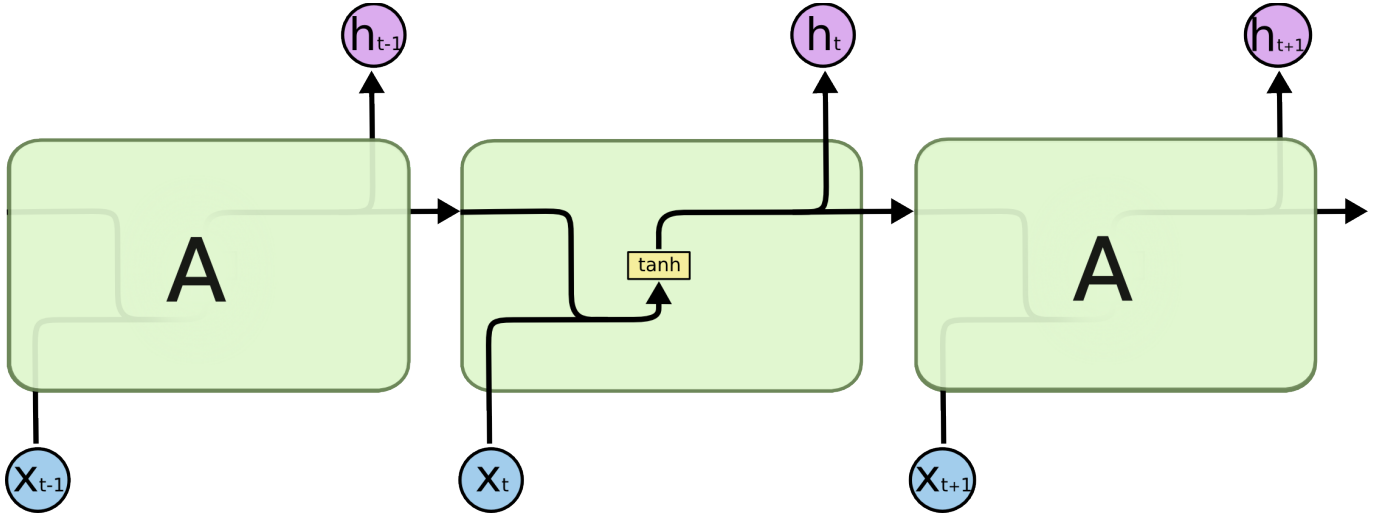
Shusen Wang

LSTM Model

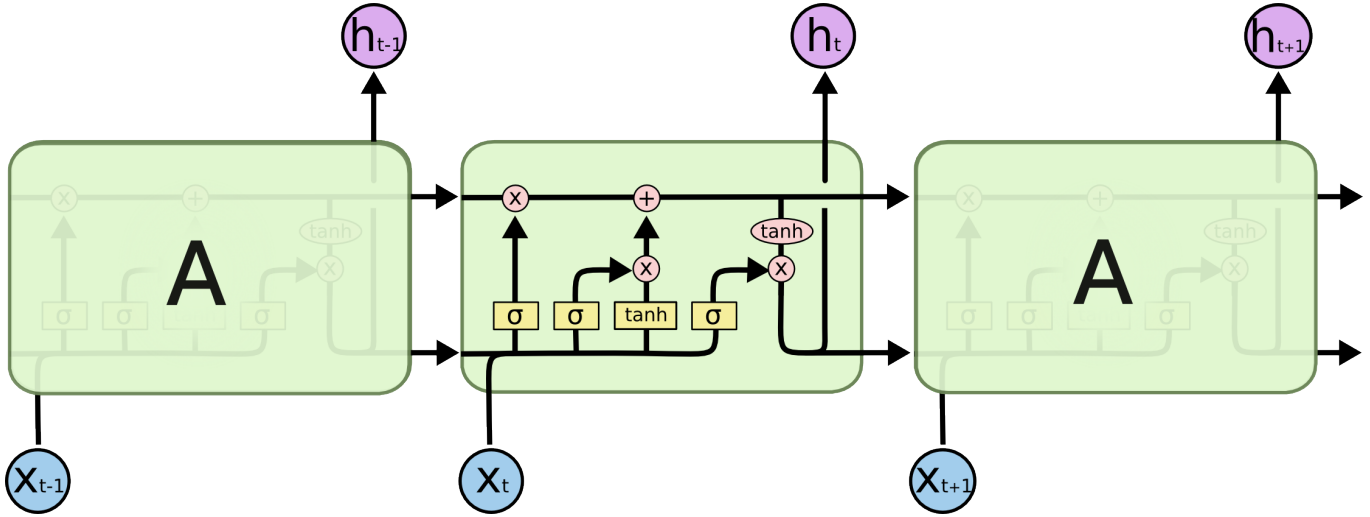
Reference

- Hochreiter and Schmidhuber. Long short-term memory. *Neural computation,* 1997.

LSTM Networks



Simple RNN

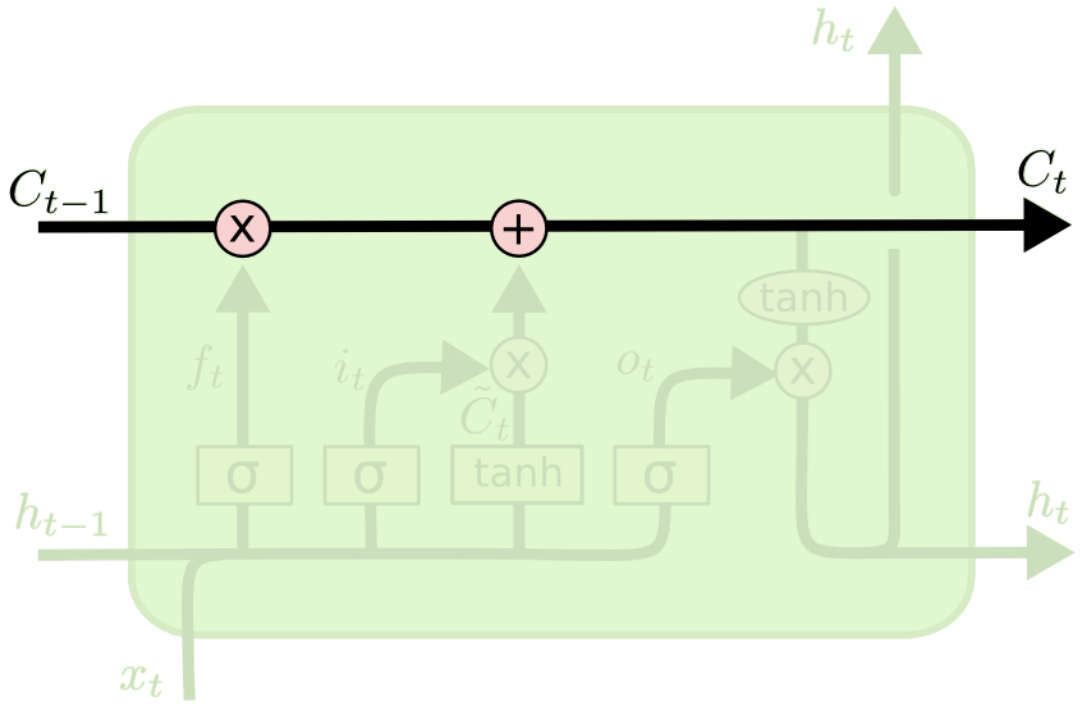


LSTM

Figures are from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Conveyor Belt

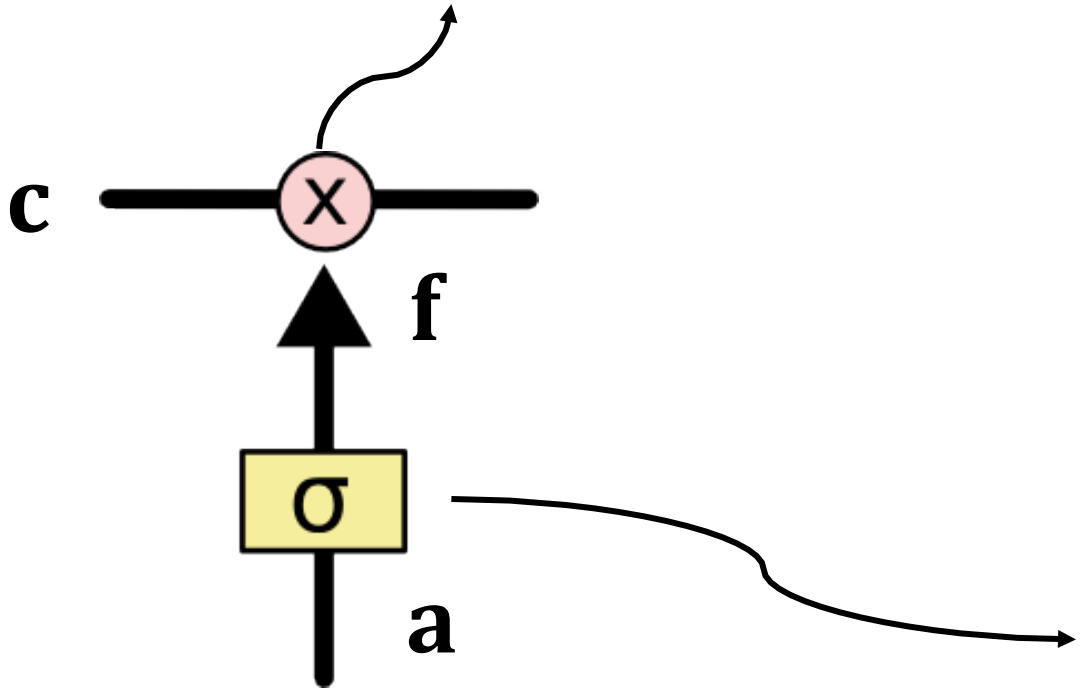
- Conveyor belt: the past information directly flows to the future.

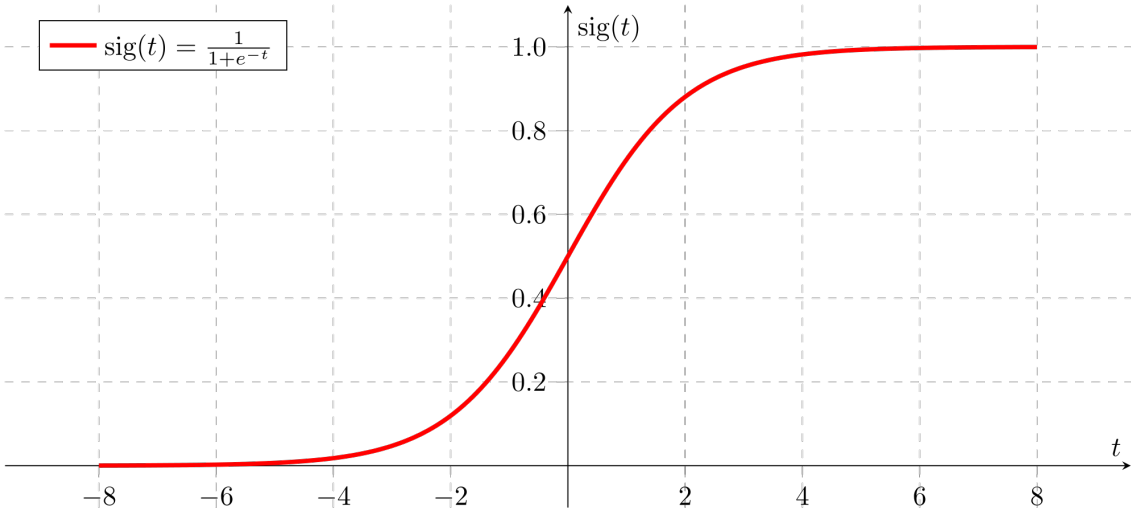


The Figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Forget Gate

Elementwise multiplication of 2 vectors.





Sigmoid function: between 0 and 1.

LSTM: Forget Gate

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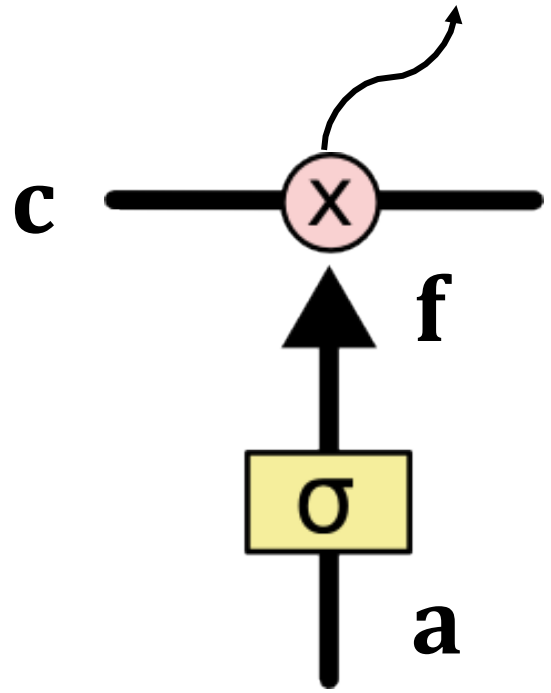
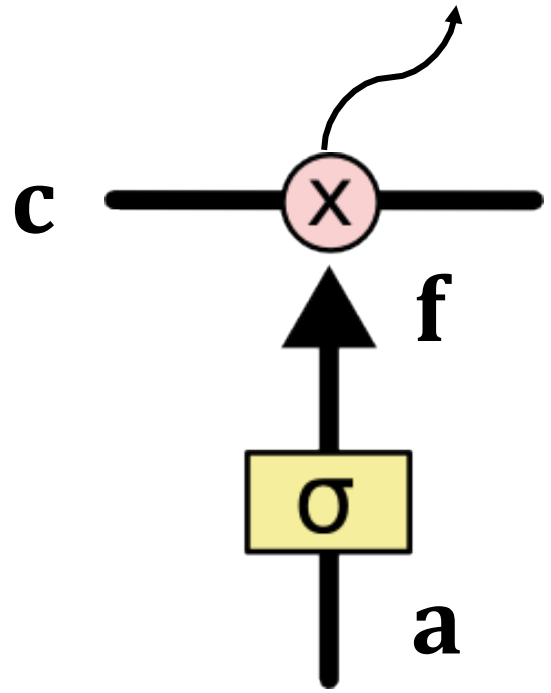


$$\sigma\left(\begin{bmatrix}1\\3\\0\\-2\end{bmatrix}\right) = \begin{bmatrix}0.73\\0.95\\0.5\\0.12\end{bmatrix}$$

a **f**

LSTM: Forget Gate

Elementwise multiplication of 2 vectors.



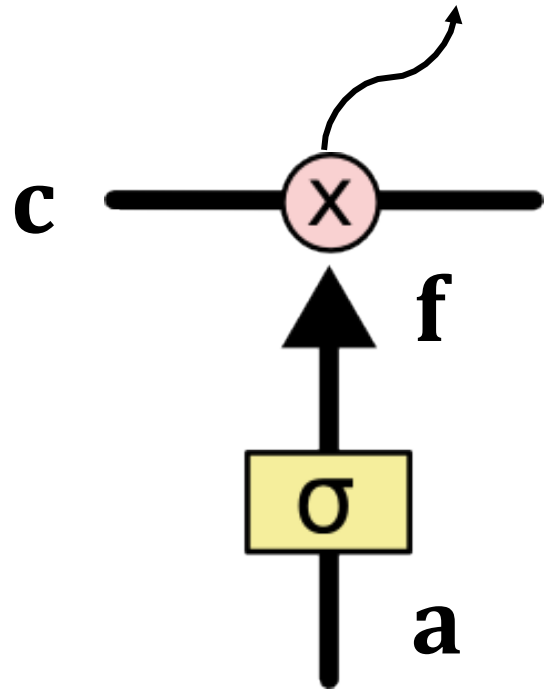
$$\begin{bmatrix} 0.9 \\ 0.2 \\ -0.5 \\ -0.1 \end{bmatrix} \circ \begin{bmatrix} 0.5 \\ 0 \\ 1 \\ 0.8 \end{bmatrix} = \begin{bmatrix} 0.45 \\ 0 \\ -0.5 \\ -0.08 \end{bmatrix}$$

c **f** **output**

LSTM: Forget Gate

- Forget gate (**f**): a vector (the same shape as **c** and **h**).
  - A value of zero means "let nothing through".
  - A value of one means "let everything through!"

Elementwise multiplication of 2 vectors.



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LSTM: Forget Gate

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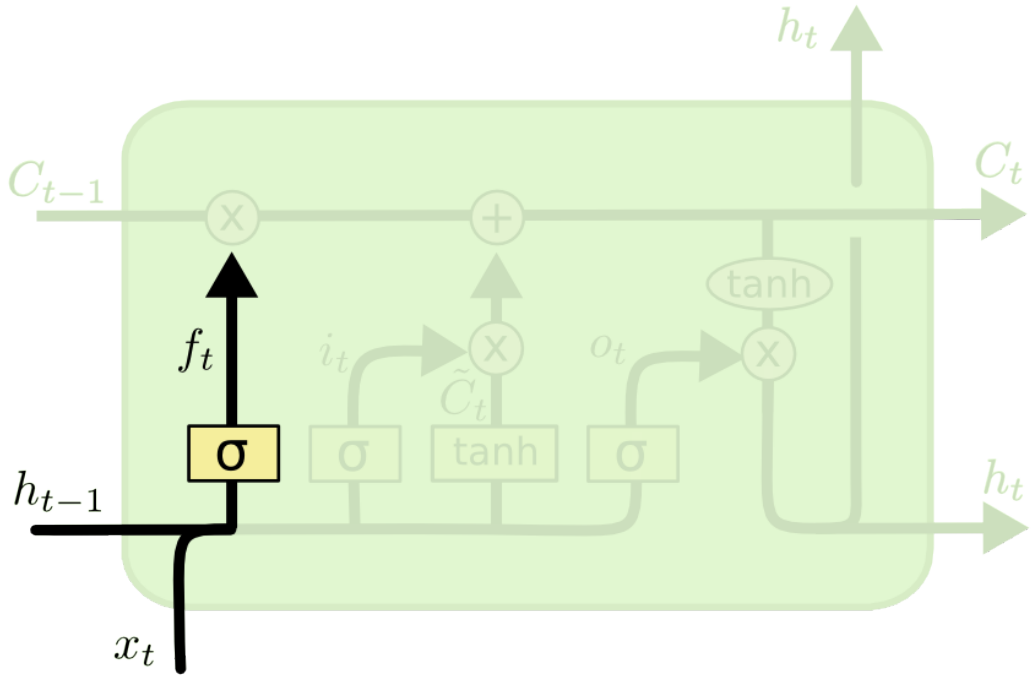
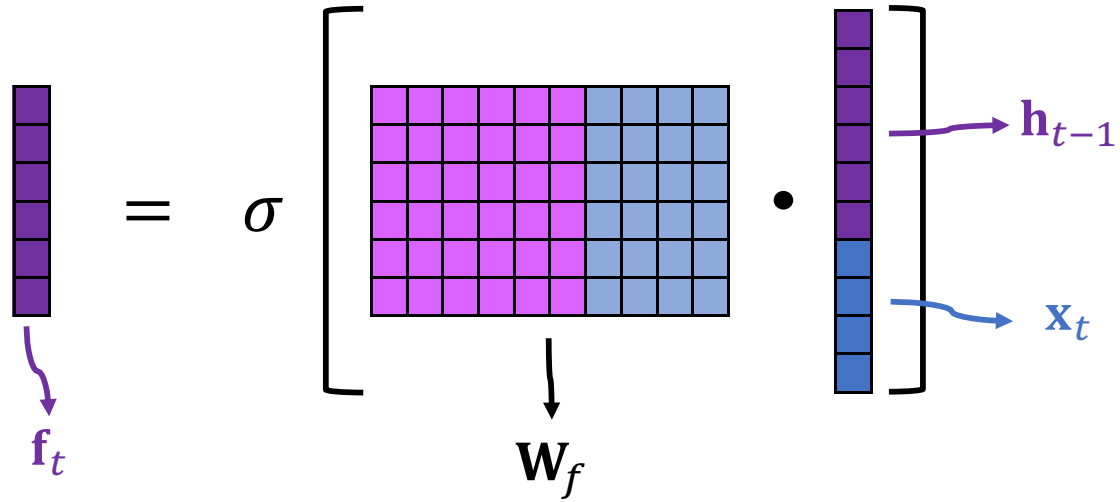
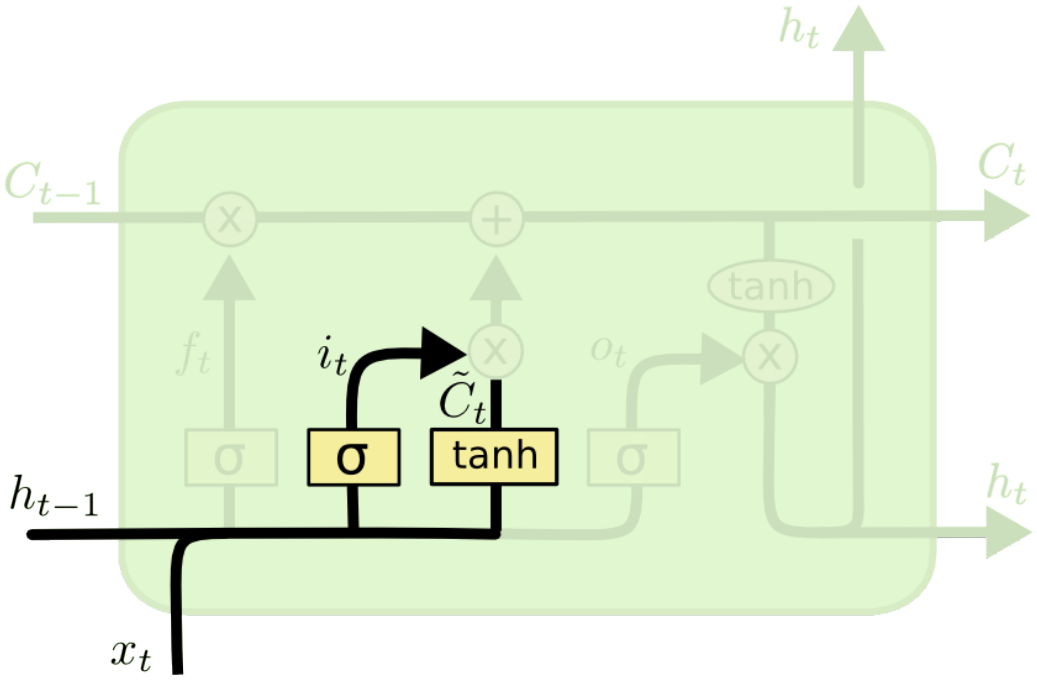




The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Input Gate

- Input gate ($\mathbf{i}_t$): decides which values of the conveyor belt we'll update.

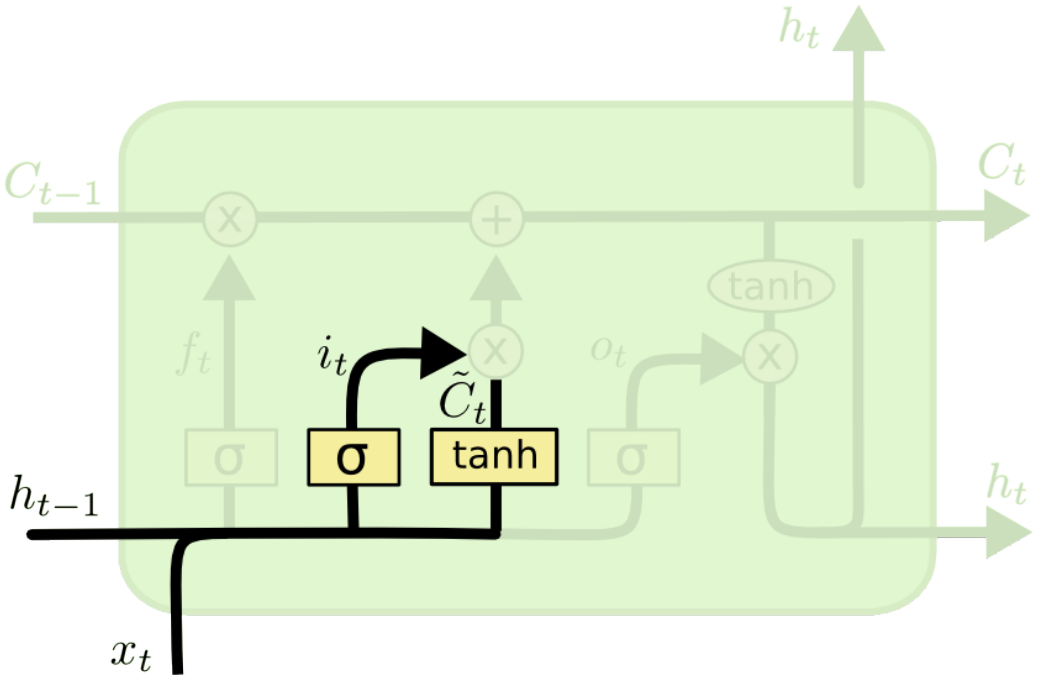


$$\mathbf{i}_t = \sigma\left[\mathbf{W}_i \cdot \begin{bmatrix}\mathbf{h}_{t-1} \\ \mathbf{x}_t\end{bmatrix}\right]$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: New Value

- New value ($\tilde{\mathbf{c}}_t$): to be added to the conveyor belt.

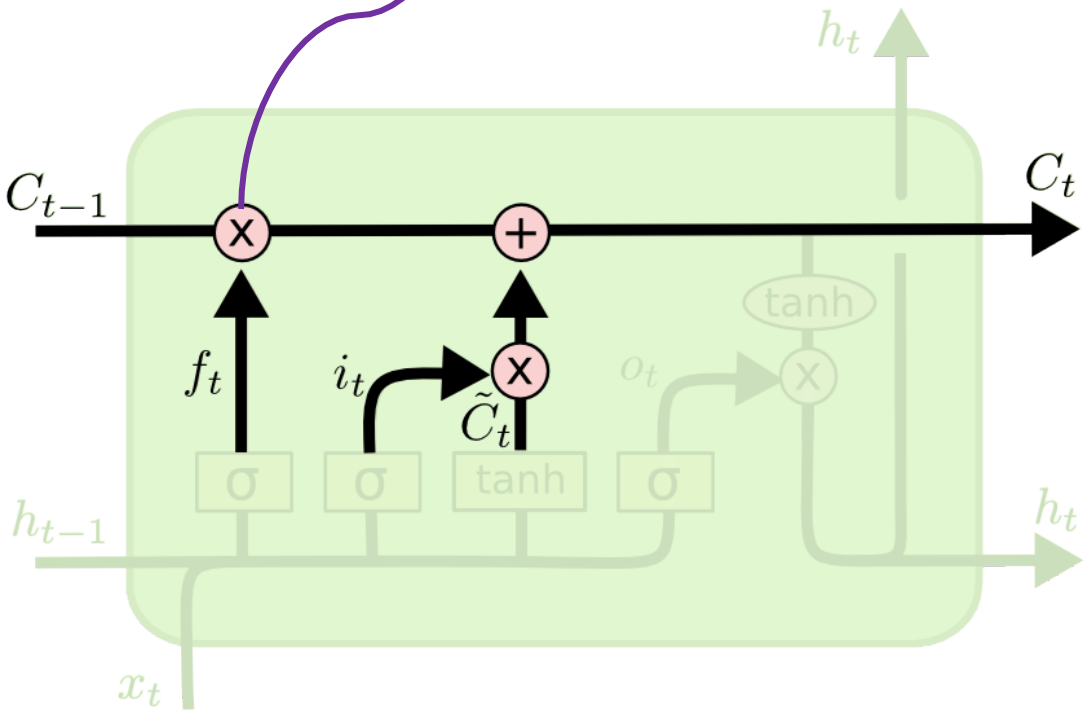


$$\tilde{\mathbf{c}}_t = \tanh\left[\mathbf{W}_c \cdot \begin{bmatrix} \mathbf{h}_{t-1} \\ \mathbf{x}_t \end{bmatrix}\right]$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update the Conveyor Belt

optionally let information through

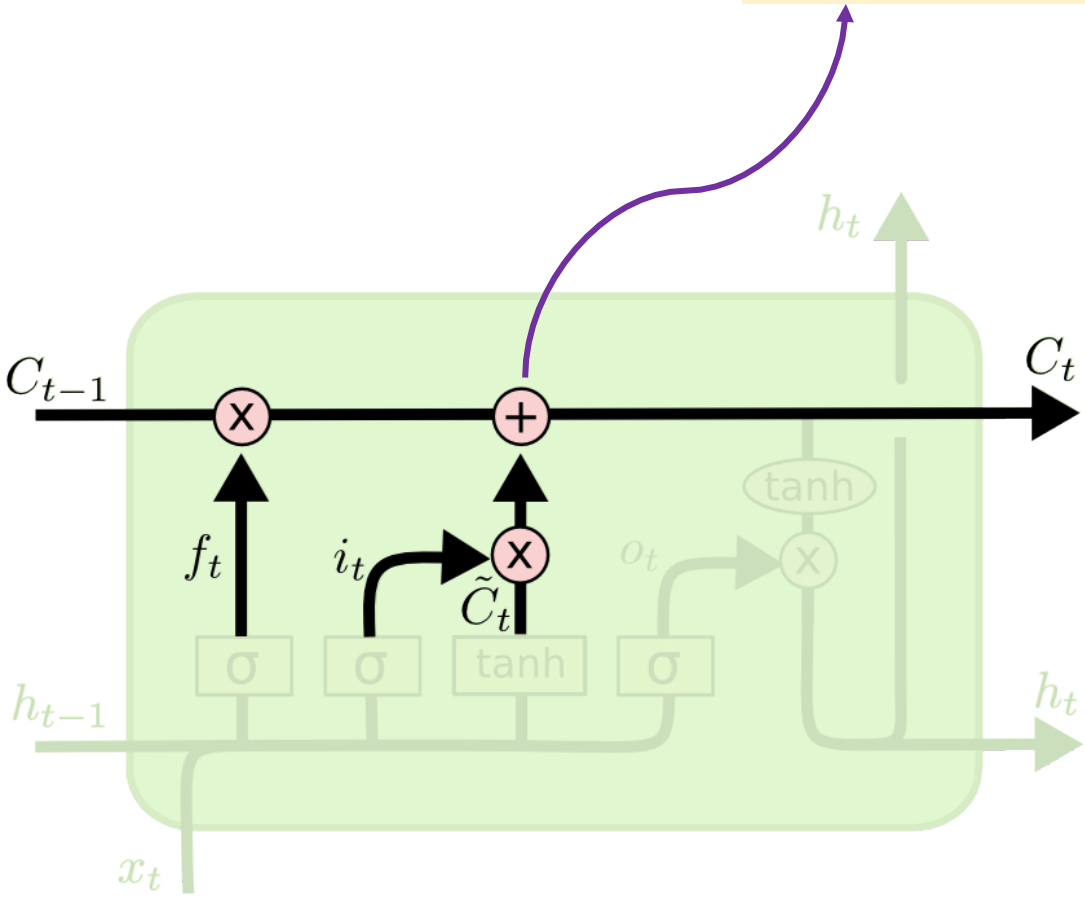


$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update the Conveyor Belt

add new value

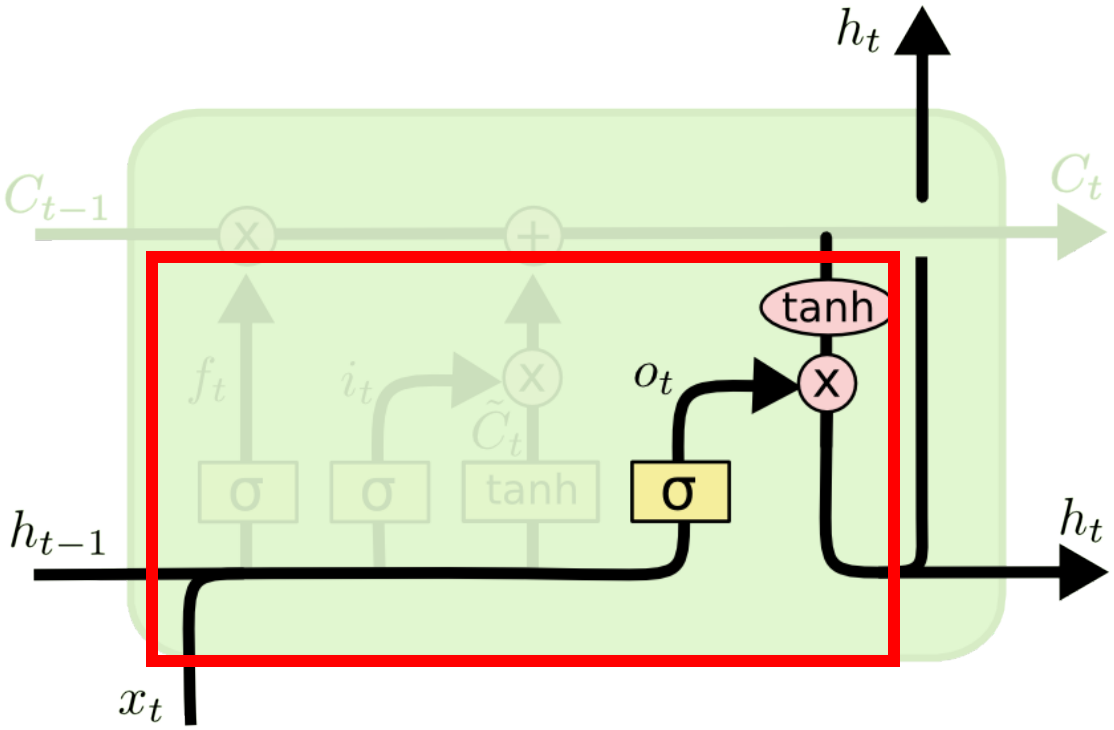


$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Output Gate

- Output gate ($\mathbf{o}_t$): decide what flows from the conveyor belt C_{t-1} to the state h_t.

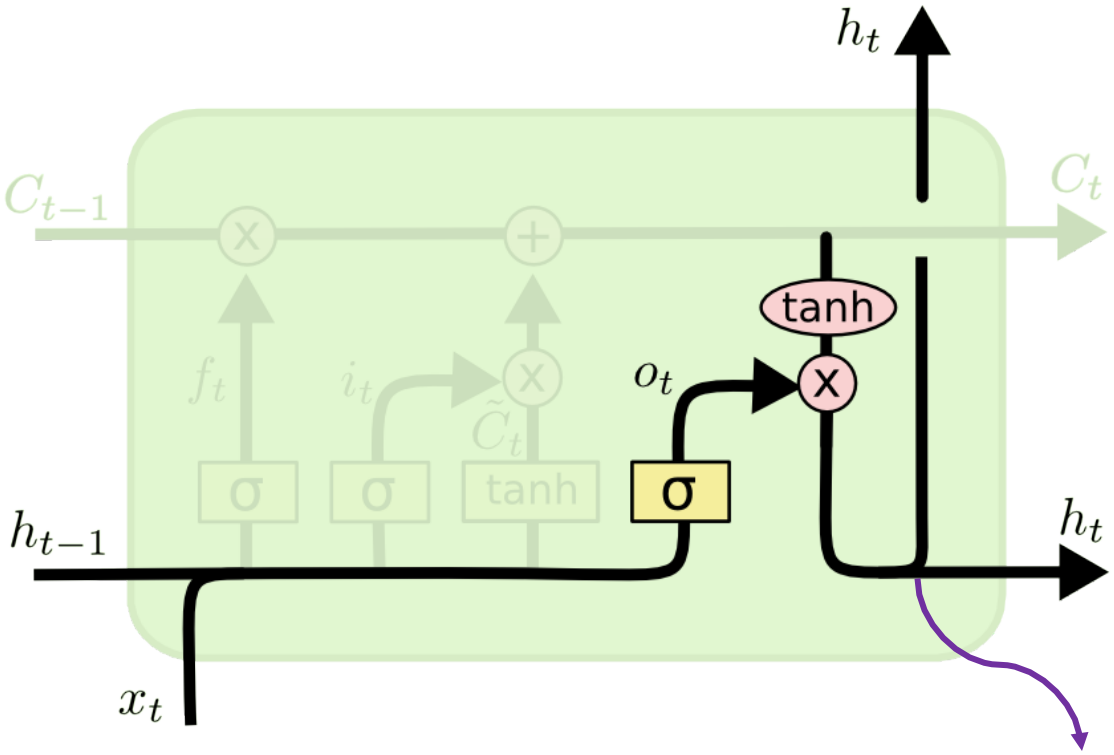


$$\mathbf{o}_t = \sigma\left(\mathbf{W}_o \cdot \begin{bmatrix} \mathbf{h}_{t-1} \\ \mathbf{x}_t \end{bmatrix}\right)$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update State

- State ($\mathbf{h}_t$): the output of LSTM.

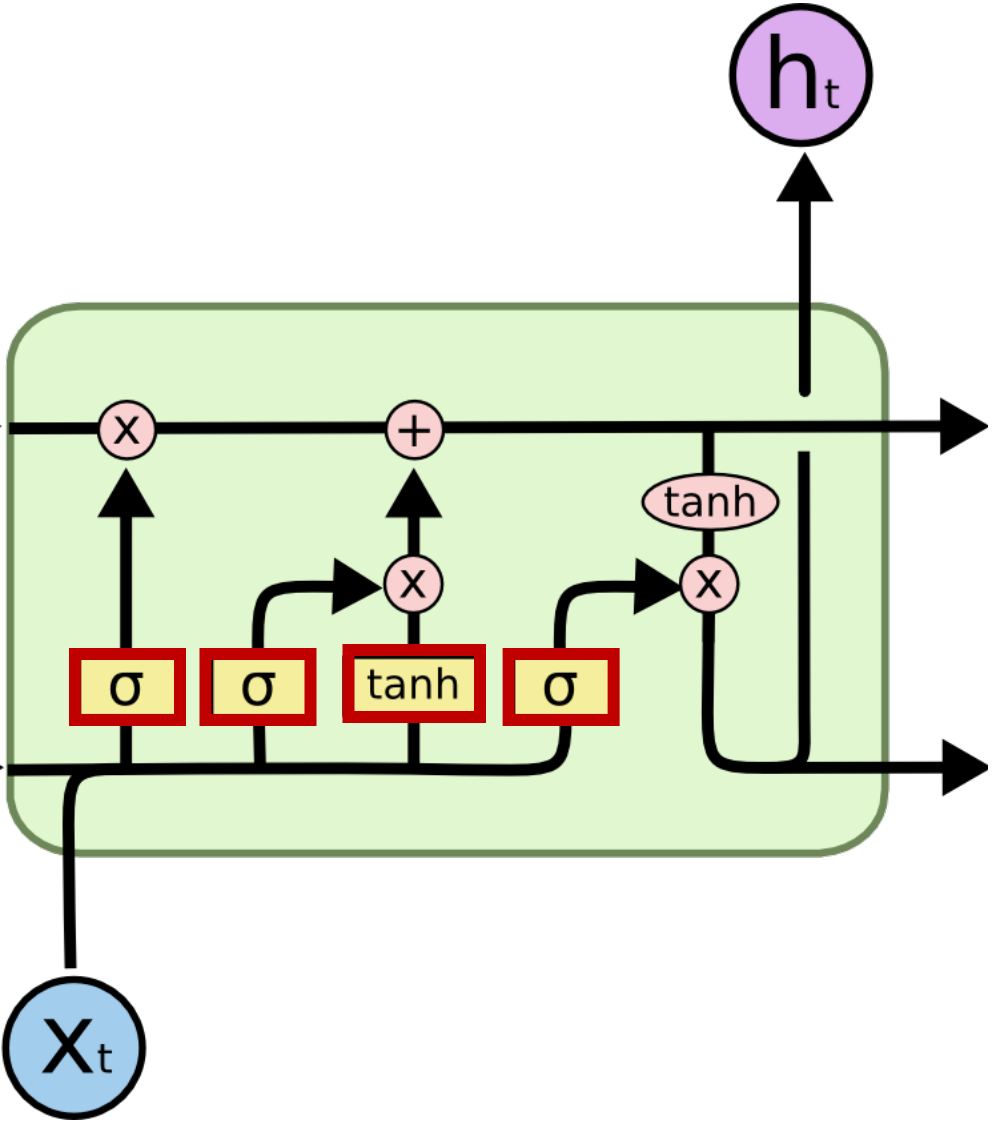


Two copies of h_t

$$\mathbf{h}_t = \mathbf{o}_t \circ \tanh\left[\mathbf{c}_t\right]$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Number of Parameters



#parameters: 4 times as many as SimpleRNN

- 4 parameter matrices, each of which has
  - `#rows: shape(h)`
  - `#cols: shape(h)+shape(x)`

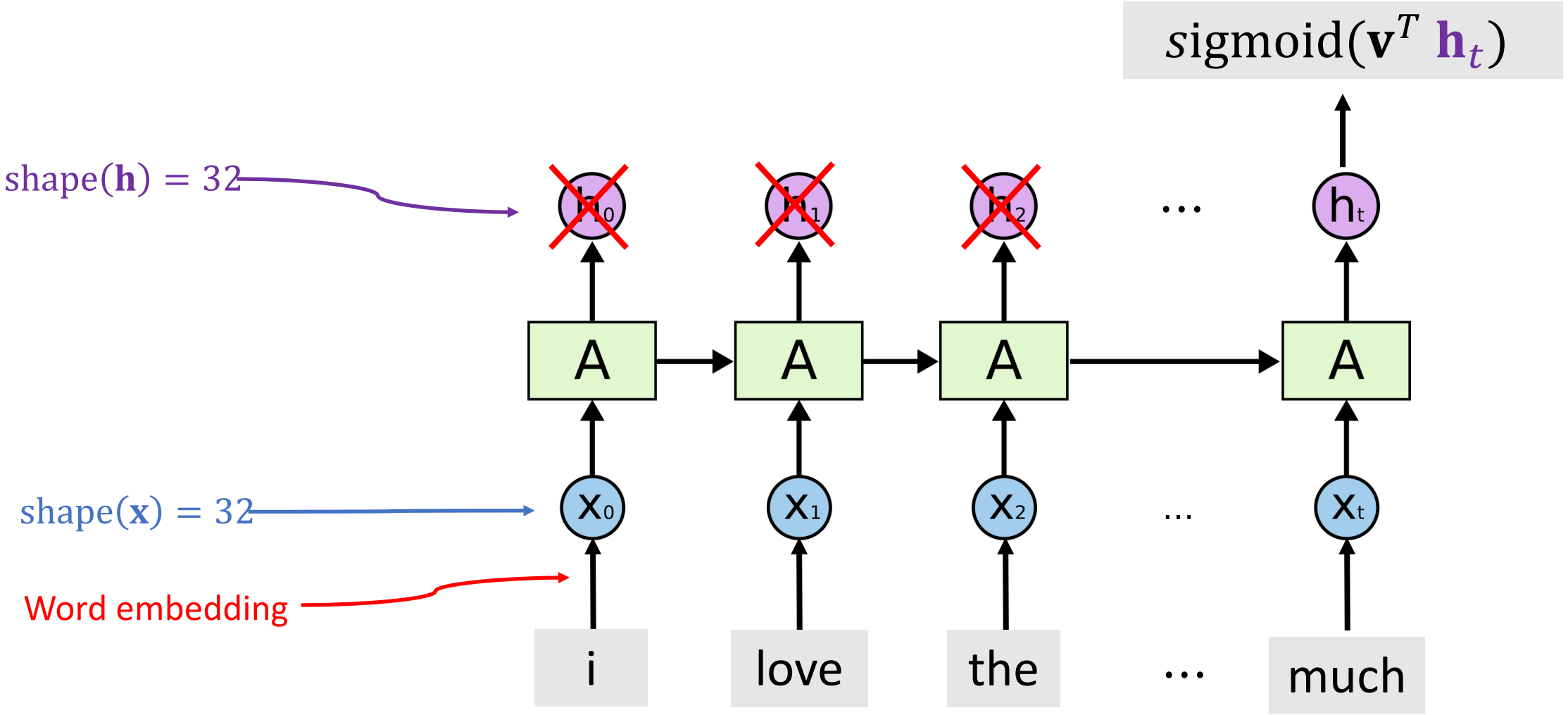
- #parameter (do not count intercept):

`4 × shape(h) × [shape(h)+shape(x)]`

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM Using Keras

LSTM for IMDB Review



LSTM for IMDB Review

```
from keras.models import Sequential
from keras.layers import LSTM, Embedding, Dense, Flatten

vocabulary = 10000
embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(LSTM(state_dim, return_sequences=False))
model.add(Dense(1, activation='sigmoid'))
```

Replace “SimpleRNN” by “LSTM”.

```
model.summary()
```

LSTM for IMDB Review

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
lstm_1 (LSTM)	(None, 32)	8320
dense_1 (Dense)	(None, 1)	33

Total params: 328,353
Trainable params: 328,353
Non-trainable params: 0

LSTM for IMDB Review

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
lstm_1 (LSTM)	(None, 32)	8320
dense_1 (Dense)	(None, 1)	33

embedding_dim

number of words

vocabulary ×embedding_dim

Total params: 328,353
Trainable params: 328,353
Non-trainable params: 0

#parameters in LSTM:

- $8320 = 2080 \times 4$
- $2080 = 32 \times (32 + 32) + 32$

$\text{shape}(\mathbf{h}) = 32$

$\text{shape}(\mathbf{x})$

LSTM for IMDB Review

- Training Accuracy: 91.8%
- Validation Accuracy: 88.7%
- Test Accuracy: 88.6%

Substantial improvement over SimpleRNN (whose test accuracy is 84%).

LSTM Dropout

Zhiqiu:

Dropout does not improve the accuracy because the overfitting is caused by the number of parameters in the embedding layer.

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from keras.layers import LSTM, Embedding, Dense, Flatten

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embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(LSTM(state_dim, return_sequences=False, dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

model.summary()
```

Summary

- LSTM uses a “conveyor belt” to get longer memory than SimpleRNN.

Summary

- LSTM uses a "conveyor belt" to get longer memory than SimpleRNN.
- Each of the following blocks has a parameter matrix:
  - Forget gate.
  - Input gate.
  - New values.
  - Output gate.
- Number of parameters:

$$4 \times \text{shape}(\mathbf{h}) \times [\text{shape}(\mathbf{h}) + \text{shape}(\mathbf{x})].$$

Thank You!