LSTM and GRU

EE6350: Artificial Intelligence

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Lecture Outline

1. Problems with RNNs
2. LSTM
    a. The Core Idea
    b. Step-by-Step LSTM Walk Through
    c. PyTorch Implementation
3. Gated Recurrent Unit (GRU)
    a. PyTorch Implementation

Problems with RNNs

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

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Problems with RNNs

- RNNs brings the previous information to present task. However, RNNs fail to learn long term dependencies.
- E.g., “I grew up in France … **<a lot of text>** … **I speak fluent <u>French</u>**”(Here is the underlined word is the one we are going to predict).
- Recent text suggests the next work should be a name of a **language.**
- **But which language?**

Solution: LSTM - **Long Short Term Memory** Networks

LSTM

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

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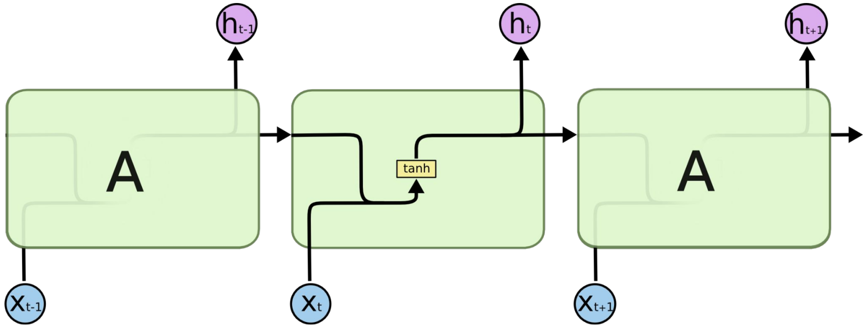
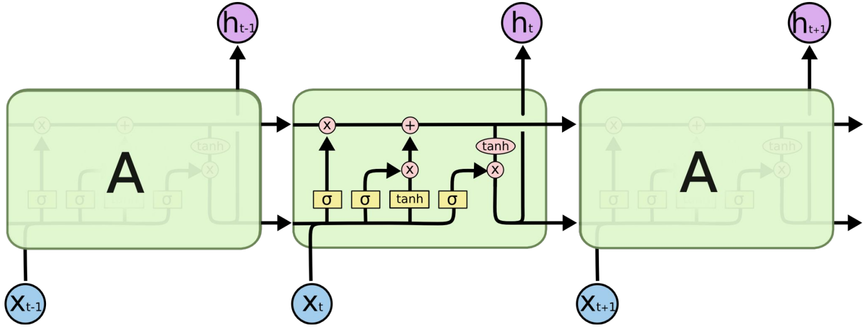
LSTM

- LSTMs got the capability to learn long-term dependencies.
- It has been introduced by **Hochreiter & Schmidhuber (1997).**



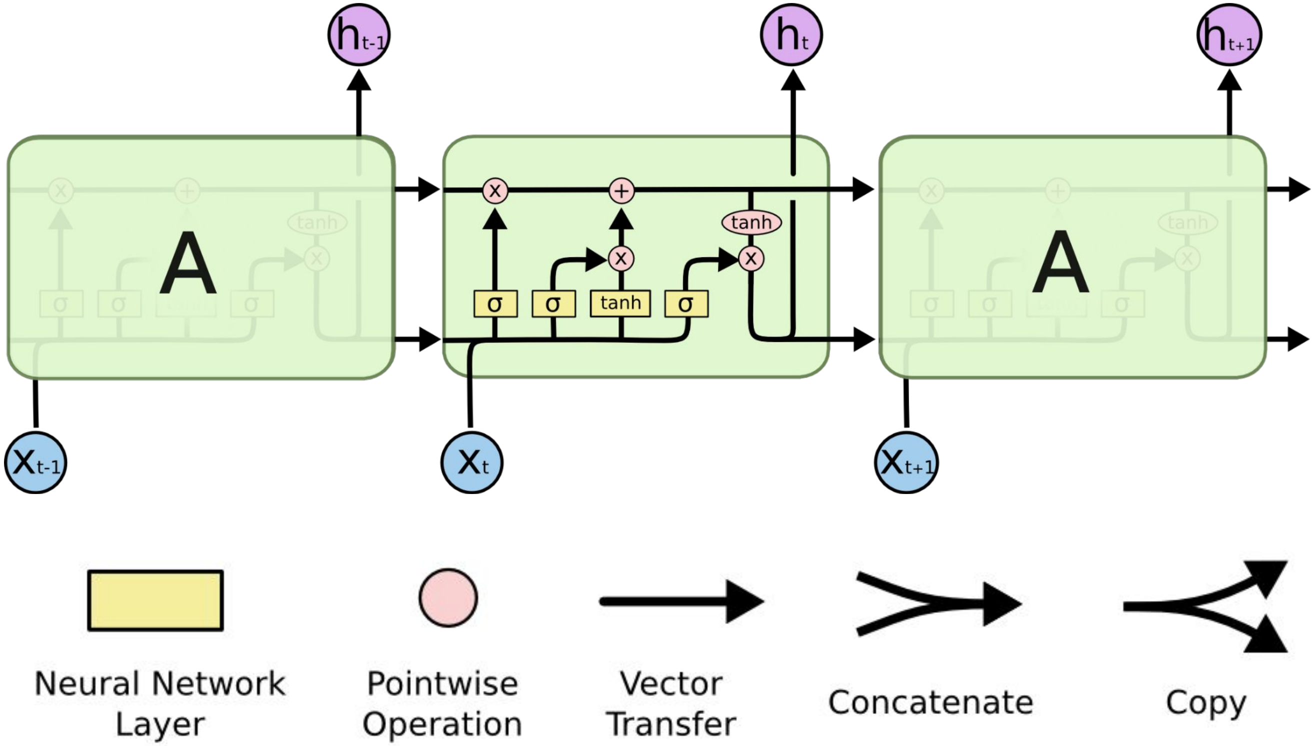
Repeating Module in Standard RNN



Repeating Module in LSTM

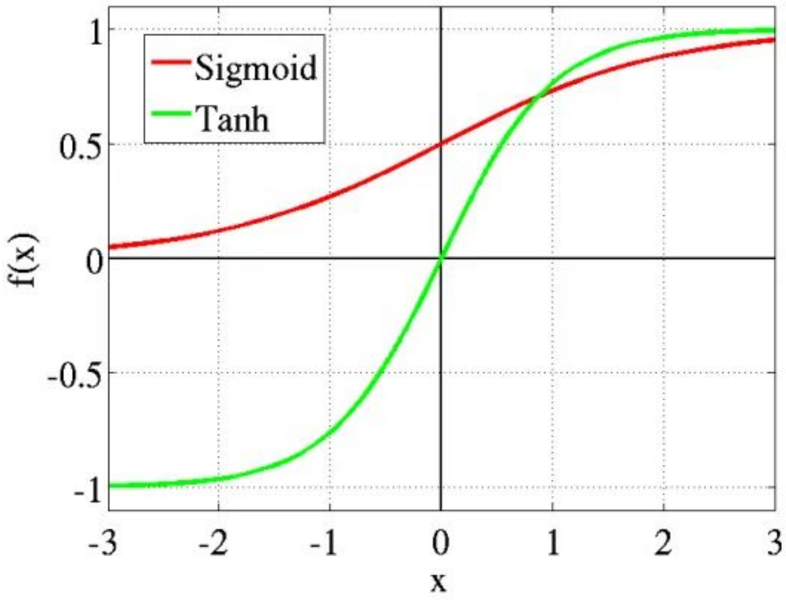
LSTM

4-Layers in LSTM instead of one in standard RNN.



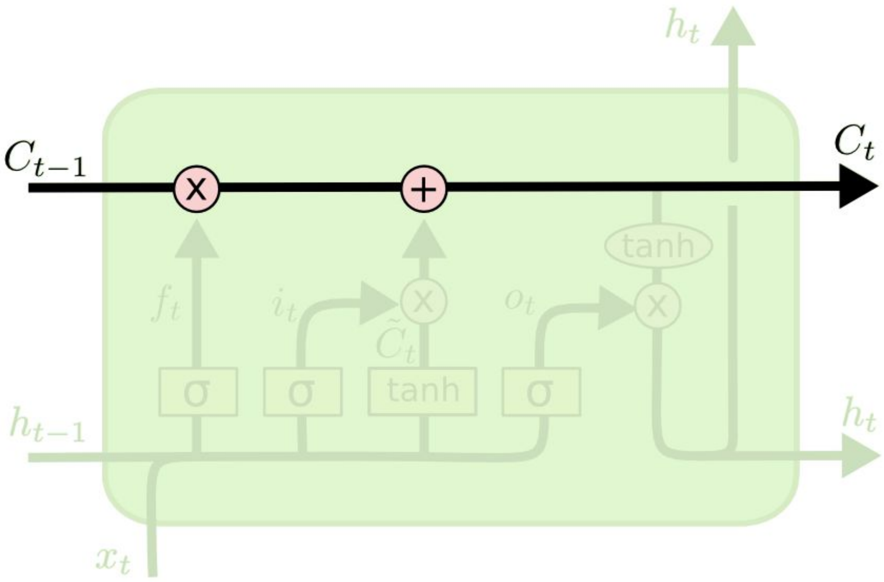
Recap

Sigmoid Vs Tanh Activation Functions



LSTM: The Core Idea

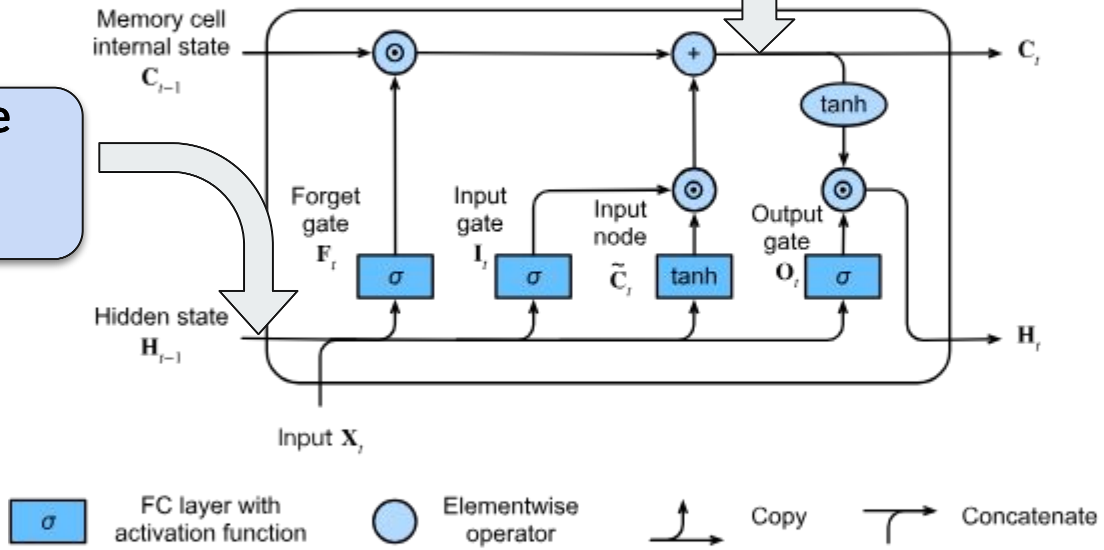
- Key in LSTM: **Cell State**
- Runs straight down the entire chain with only some **minor linear interactions.**
- In LSTM there are 3 gates to **protect and control the cell state.**



LSTM: The Core Idea

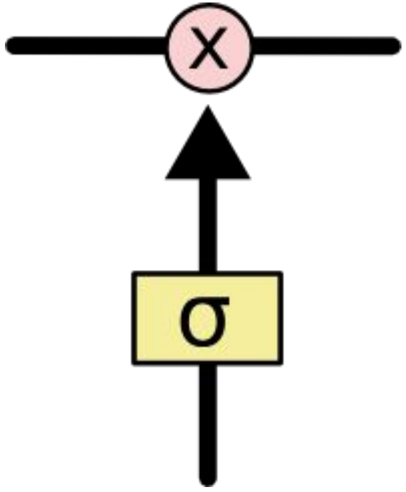
Represents the long-term memory

Represents the short-term memory



LSTM: The Core Idea

- LSTM remove or add information to the cell state through the structures called GATES.
- Gates optionally let information through.
- Consist of sigmoid neural network layer and pointwise multiplication.



LSTM: Step-by-Step LSTM Walk Through

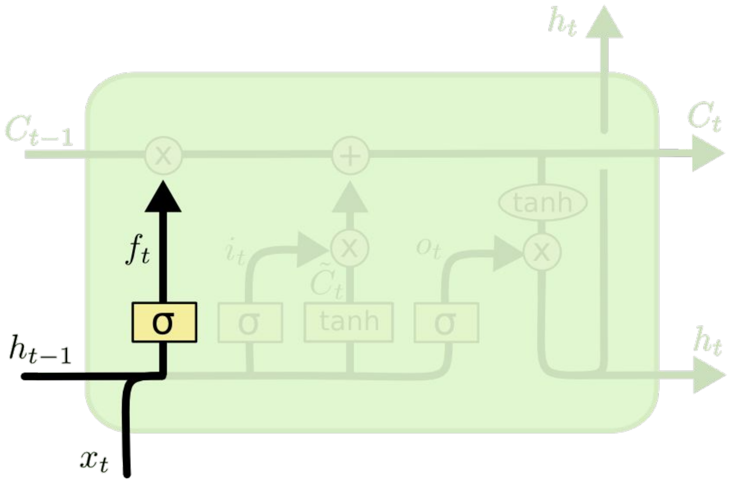
1

Step: 01

Purpose: Decide what information to throw away from the sell state.

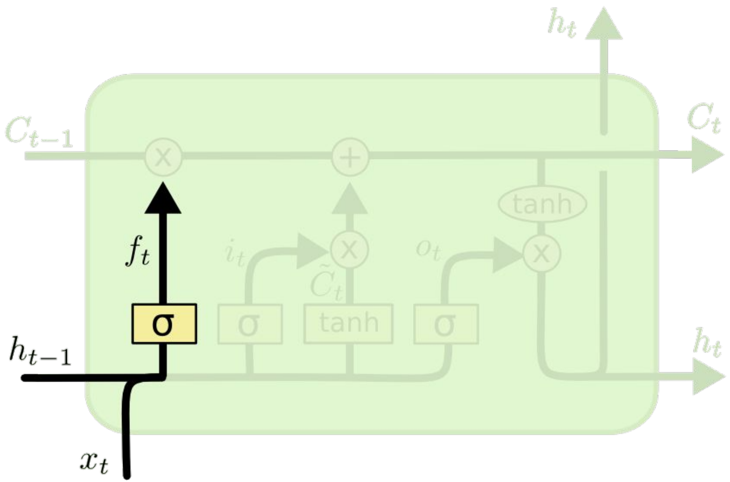
Done using "**Forget Gate Layer**".

Identify what percentage of the long-term memory will be remembered...



LSTM: Step-by-Step LSTM Walk Through

1



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

1

LSTM: Step-by-Step LSTM Walk Through

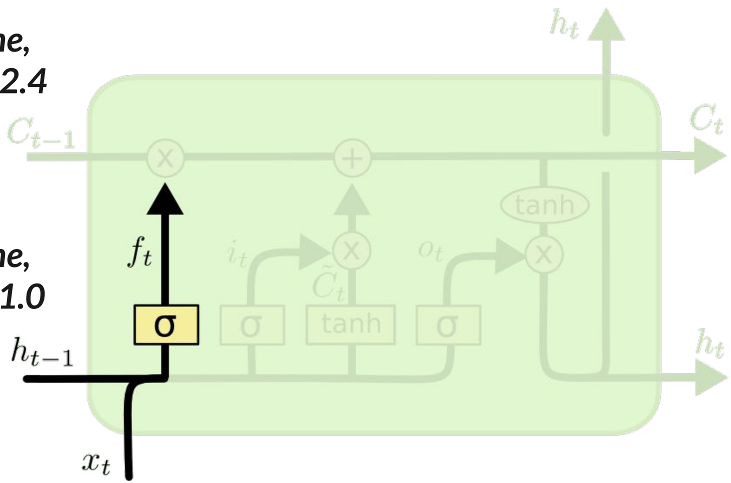
f_t

0.98

0.02

Assume,
$C_{t-1} = 2.4$

Assume,
$h_{t-1} = 1.0$



$x_t = 1.2, 1.5, 2.7, 5.3...$

Values for illustration purposes only. Not associated with any actual example/calculation. Furthermore, under the actual scenarios computation are happening as matrix multiplications.

1

LSTM: Step-by-Step LSTM Walk Through

Example: Predict next word based on previous information.

- Cell state might include the gender of the present subject. So that the correct pronoun can be used.
- Once found a new subject, we want to **forget the gender of the old subject.**

E.g.,
Mr. Sam is a teacher and **he** has a daughter. **She** is 6 years old and **her**…

2

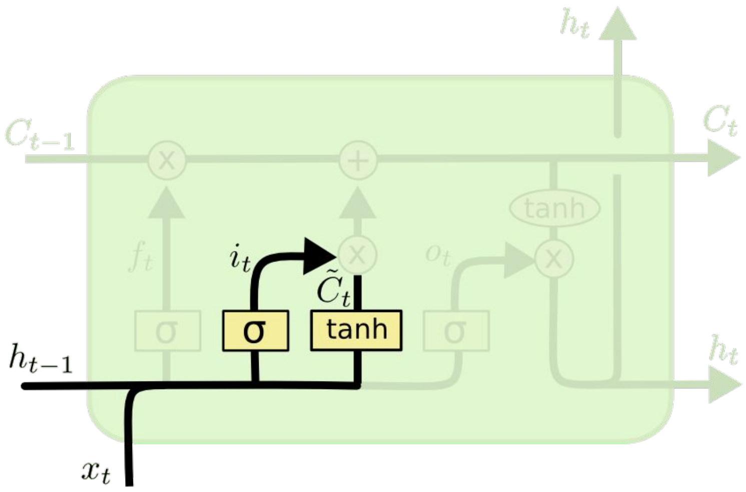
LSTM: Step-by-Step LSTM Walk Through

Step: 02

Purpose: Decide what new information we are going to store in the cell state.

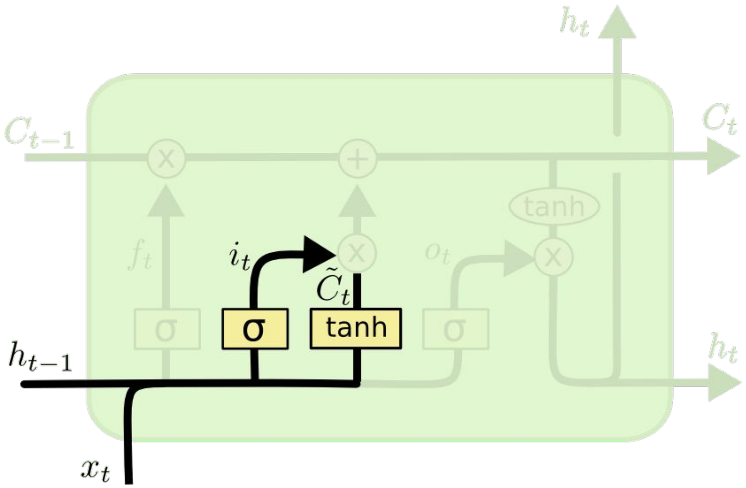
Done using two parts:

- **Input Gate Layer (Sigmoid)**: Decides which values we'll update.
- Next the **tanh layer** creates a vector of new candidate values that could be added to the state.



2

LSTM: Step-by-Step LSTM Walk Through



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

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

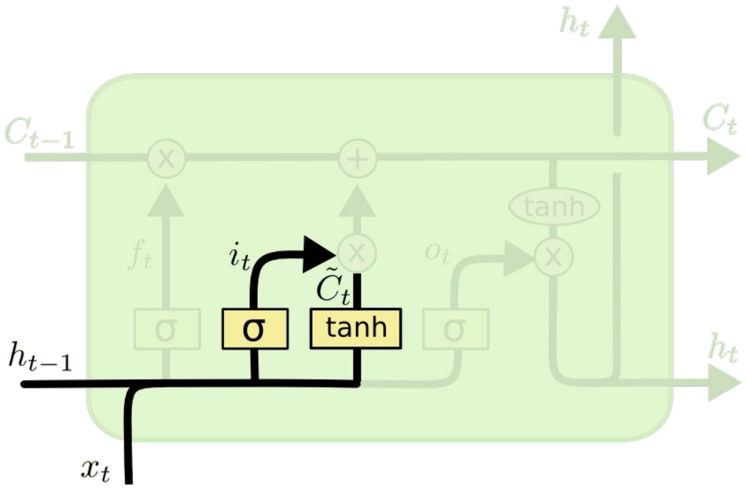
LSTM: Step-by-Step LSTM Walk Through

2

i_t

0.98

0.02



$\tilde{C}_t$

0.85

Values for illustration purposes only. Not associated with any actual example/calculation. Furthermore, under the actual scenarios computation are happening as matrix multiplications.

LSTM: Step-by-Step LSTM Walk Through

2

Example: Predict next word based on previous information.

- Cell state might include the gender of the present subject. So that the correct pronoun can be used.
- Once found a new subject, we want to forget the gender of the old subject.
- **Add the gender of the new subject to the cell state to replace the old one we are forgetting.**

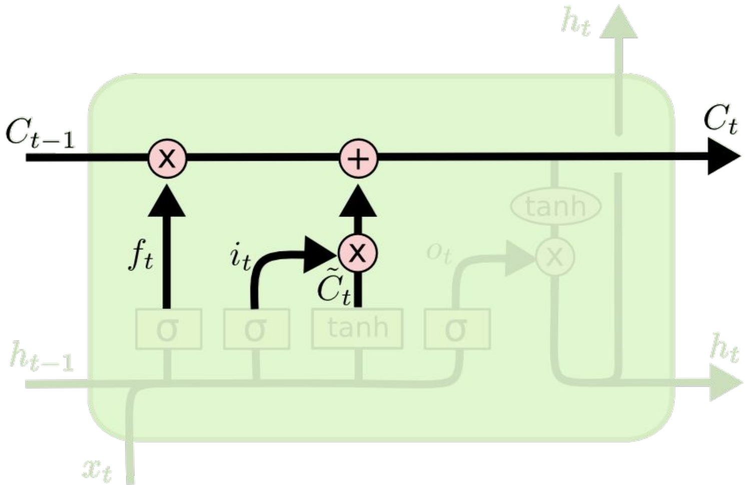
E.g.,
Mr. Sam is a teacher and **he** has a daughter. **She** is 6 years old and **her**…

LSTM: Step-by-Step LSTM Walk Through

Step: 03

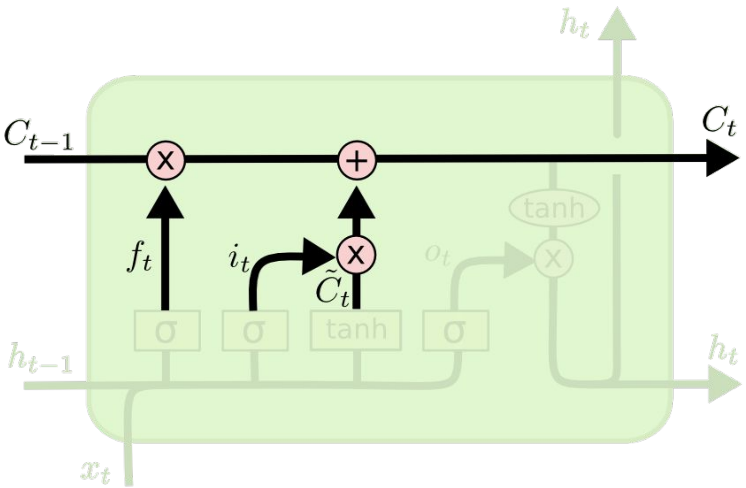
Purpose: The old cell state c_{t-1} will be updated into the new cell state c_t.

- In the previous two stages we have decided what to forget and what to be added to the cell state.



3

LSTM: Step-by-Step LSTM Walk Through



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

LSTM: Step-by-Step LSTM Walk Through

3

f_t

0.98

0.02

i_t

0.98

0.02

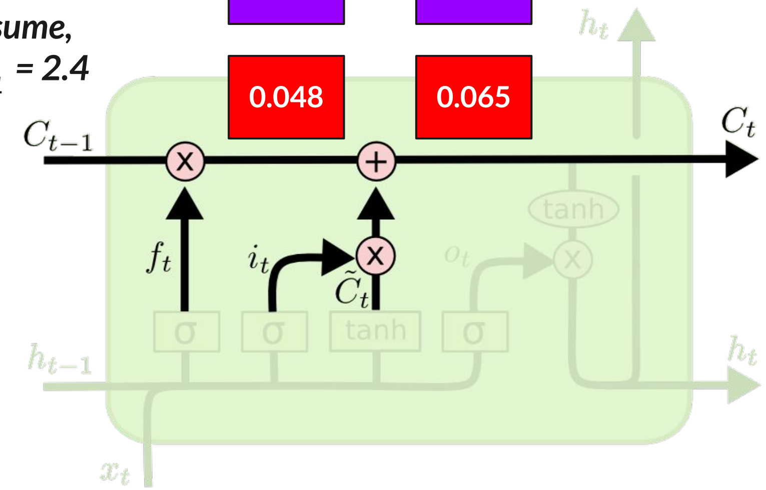
Assume,
C_{t-1} = 2.4

2.352

3.185

0.048

0.065



$\tilde{C}_t$

0.85

Values for illustration purposes only. Not associated with any actual example/calculation. Furthermore, under the actual scenarios computation are happening as matrix multiplications.

3

LSTM: Step-by-Step LSTM Walk Through

Example: Predict next word based on previous information.

- Cell state might include the gender of the present subject. So that the correct pronoun can be used.
- Once found a new subject, we want to forget the gender of the old subject.
- Add the gender of the new subject to the cell state to replace the old one we are forgetting.
- **This is actually where we drop the information about the old subject's gender and add the new information.**

E.g.,
Mr. Sam is a teacher and **he** has a daughter. **She** is 6 years old and **her**…

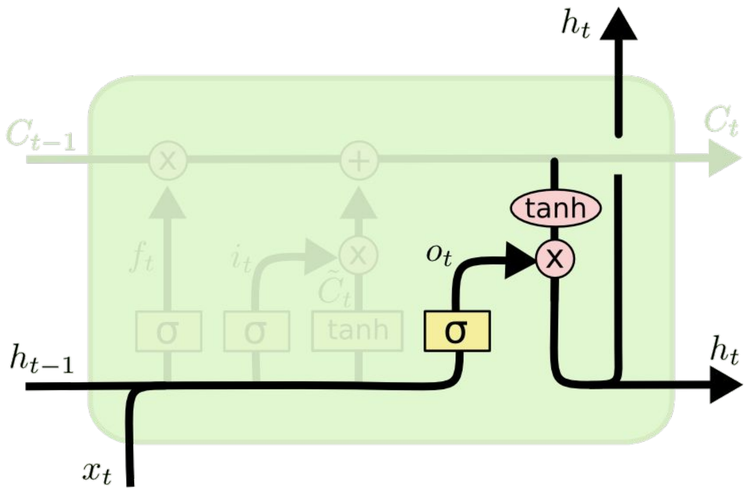
LSTM: Step-by-Step LSTM Walk Through

4

Step: 03

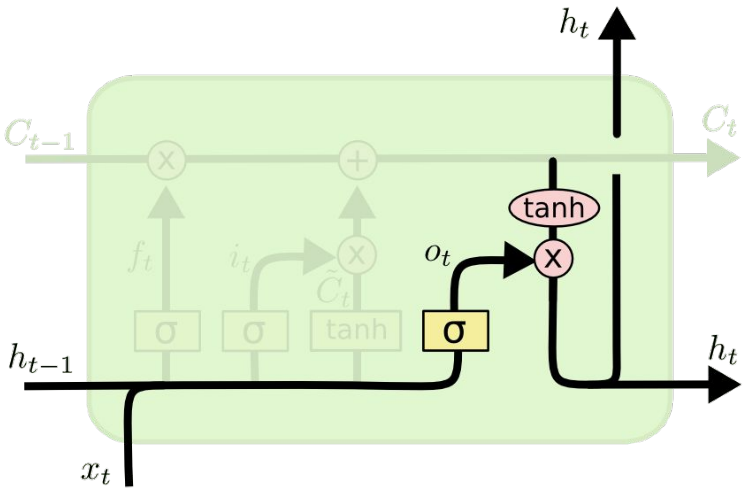
Purpose: Decide what to output.

- Output based on the the cell state (But will be a filtered version).
- This is also known as the **Output Gate.**



4

LSTM: Step-by-Step LSTM Walk Through



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

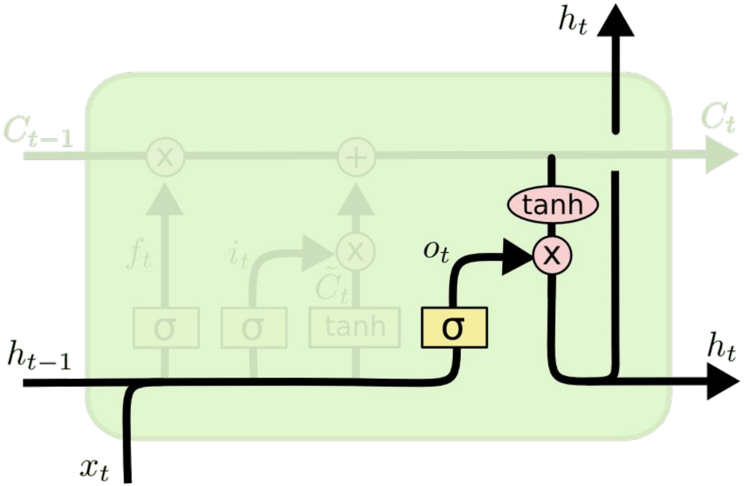
$$h_t = o_t * \tanh\left(C_t\right)$$

LSTM: Step-by-Step LSTM Walk Through

4

o_t

0.92



Values for illustration purposes only. Not associated with any actual example/calculation. Furthermore, under the actual scenarios computation are happening as matrix multiplications.

$h_t = 0.92 \times \tanh(3.185) = 0.91$

3

LSTM: Step-by-Step LSTM Walk Through

Example: Predict next word based on previous information.

- Cell state might include the gender of the present subject. So that the correct pronoun can be used.
- Once found a new subject, we want to forget the gender of the old subject.
- Add the gender of the new subject to the cell state to replace the old one we are forgetting.
- This is actually where we drop the information about the old subject's gender and add the new information.
- **Output whether subject is singular or plural so that we know what form a verb should be conjugated into if that's what follows next.**

E.g.,
Mr. Sam is a teacher and **he** has a daughter. **She** is 6 years old and **her**…

LSTM: PyTorch Implementation

CLASS torch.nn.LSTM(*self*, *input_size*, *hidden_size*, *num_layers=1*, *bias=True*, *batch_first=False*, *dropout=0.0*, *bidirectional=False*, *proj_size=0*, *device=None*, *dtype=None*) [SOURCE]

Parameters

- **input_size** – The number of expected features in the input *x*
- **hidden_size** – The number of features in the hidden state *h*
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two LSTMs together to form a *stacked LSTM*, with the second LSTM taking in outputs of the first LSTM and computing the final results. Default: 1
- **bias** – If `False`, then the layer does not use bias weights *b_ih* and *b_hh*. Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (*batch, seq, feature*) instead of (*seq, batch, feature*). Note that this does not apply to hidden or cell states. See the Inputs/Outputs sections below for details. Default: `False`
- **dropout** – If non-zero, introduces a *Dropout* layer on the outputs of each LSTM layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional LSTM. Default: `False`
- **proj_size** – If `> 0`, will use LSTM with projections of corresponding size. Default: 0

Gated Recurrent Unit (GRU)

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

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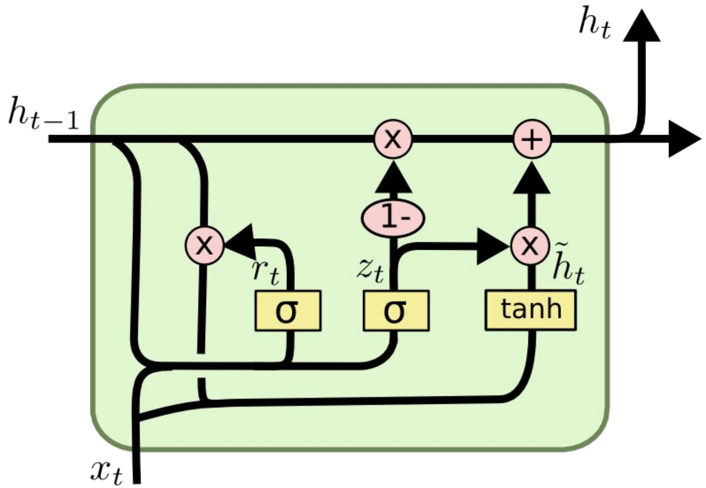
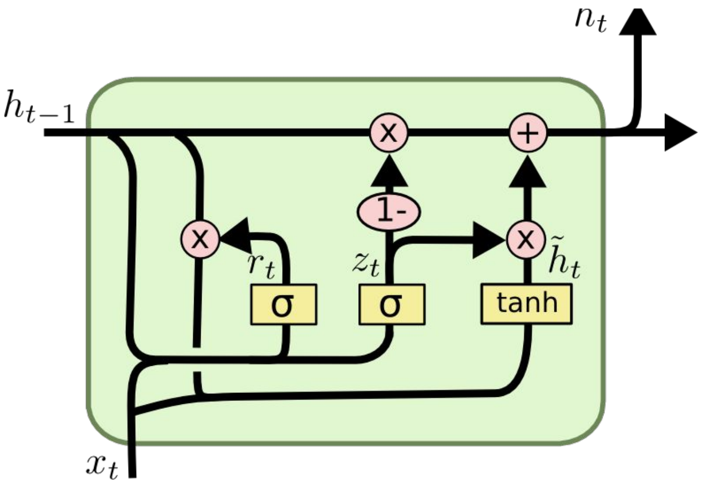
GRU

- Combines the forget and input gates to single update gate.
- Also merges the cell state and the hidden state.
- Ultimately the GRU model has become much simpler than the LSTM.



GRU

Try to investigate how these functions have been derived and overall working of GRU...



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

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

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

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

GRU: PyTorch Implementation

CLASS torch.nn.GRU(*self, input_size, hidden_size, num_layers=1, bias=True, batch_first=False, dropout=0.0, bidirectional=False, device=None, dtype=None*) [SOURCE]

Parameters

- **input_size** – The number of expected features in the input *x*
- **hidden_size** – The number of features in the hidden state *h*
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two GRUs together to form a *stacked GRU*, with the second GRU taking in outputs of the first GRU and computing the final results. Default: 1
- **bias** – If `False`, then the layer does not use bias weights *b_ih* and *b_hh*. Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (*batch, seq, feature*) instead of (*seq, batch, feature*). Note that this does not apply to hidden or cell states. See the Inputs/Outputs sections below for details. Default: `False`
- **dropout** – If non-zero, introduces a *Dropout* layer on the outputs of each GRU layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional GRU. Default: `False`

LSTM vs GRU

Investigate the differences between the LSTM and GRU architectures and their advantages and disadvantages…

Recommended Reading: Chung, J., Gulcehre, C., Cho, K. and Bengio, Y., 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

References

1. C. Olah, “Understanding LSTM Networks,” Github.io, Aug. 27, 2015. https://colah.github.io/posts/2015-08-Understanding-LSTMs/
2. S. SHARMA, “Activation Functions in Neural Networks,” Medium, Sep. 06, 2017. https://towardsdatascience.com/activation-functions-neural-networks-1cbd9f8d91d6
3. “Long Short-Term Memory (LSTM), Clearly Explained,” www.youtube.com. https://youtu.be/YCzL96nL7j0 (accessed Apr. 05, 2024).
4. “9.2. Long Short Term Memory (LSTM) — Dive into Deep Learning 0.14.4 documentation,” d2l.ai. https://d2l.ai/chapter_recurrent-modern/lstm.html.

Thank You