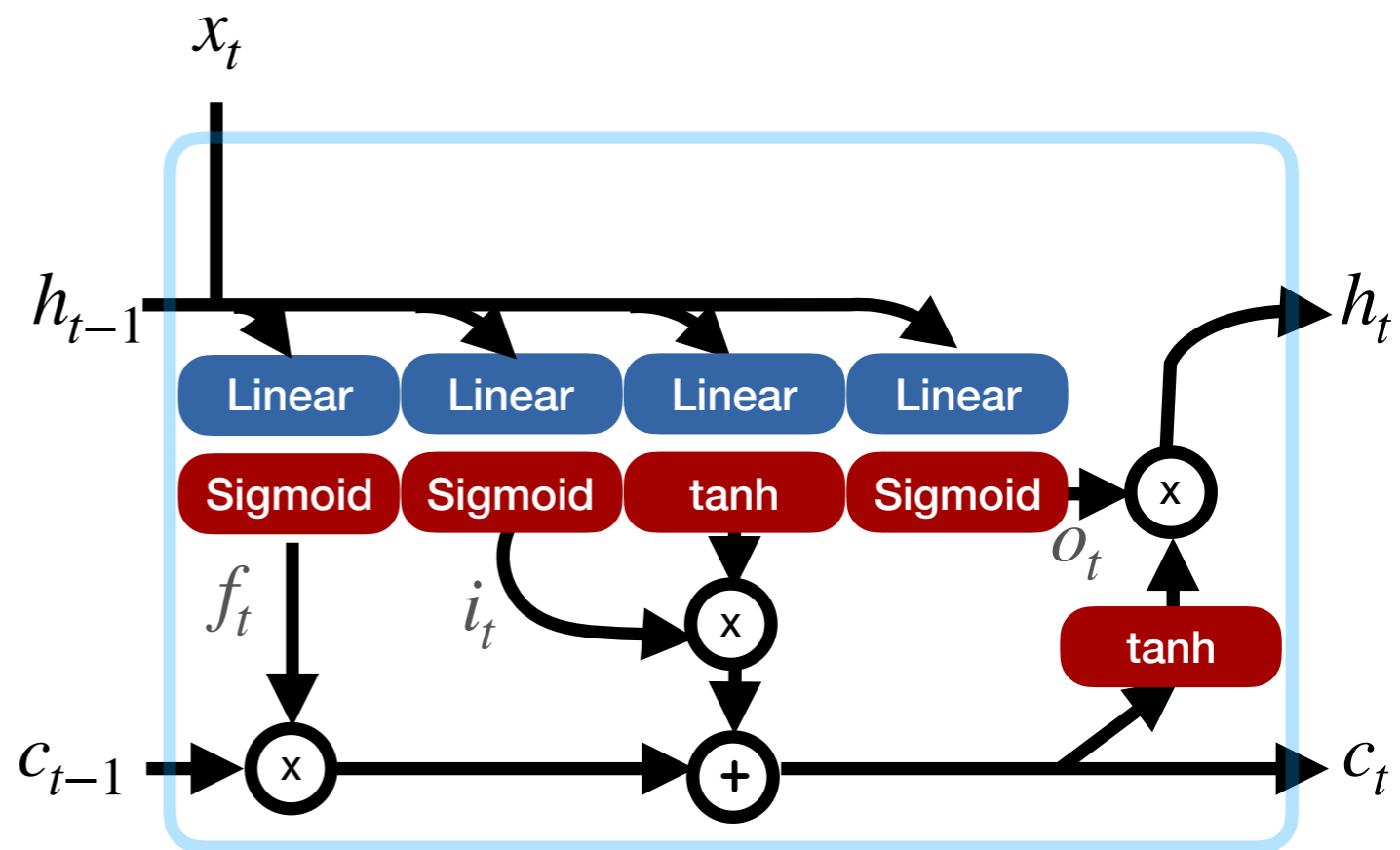


# LSTMs and GRUs

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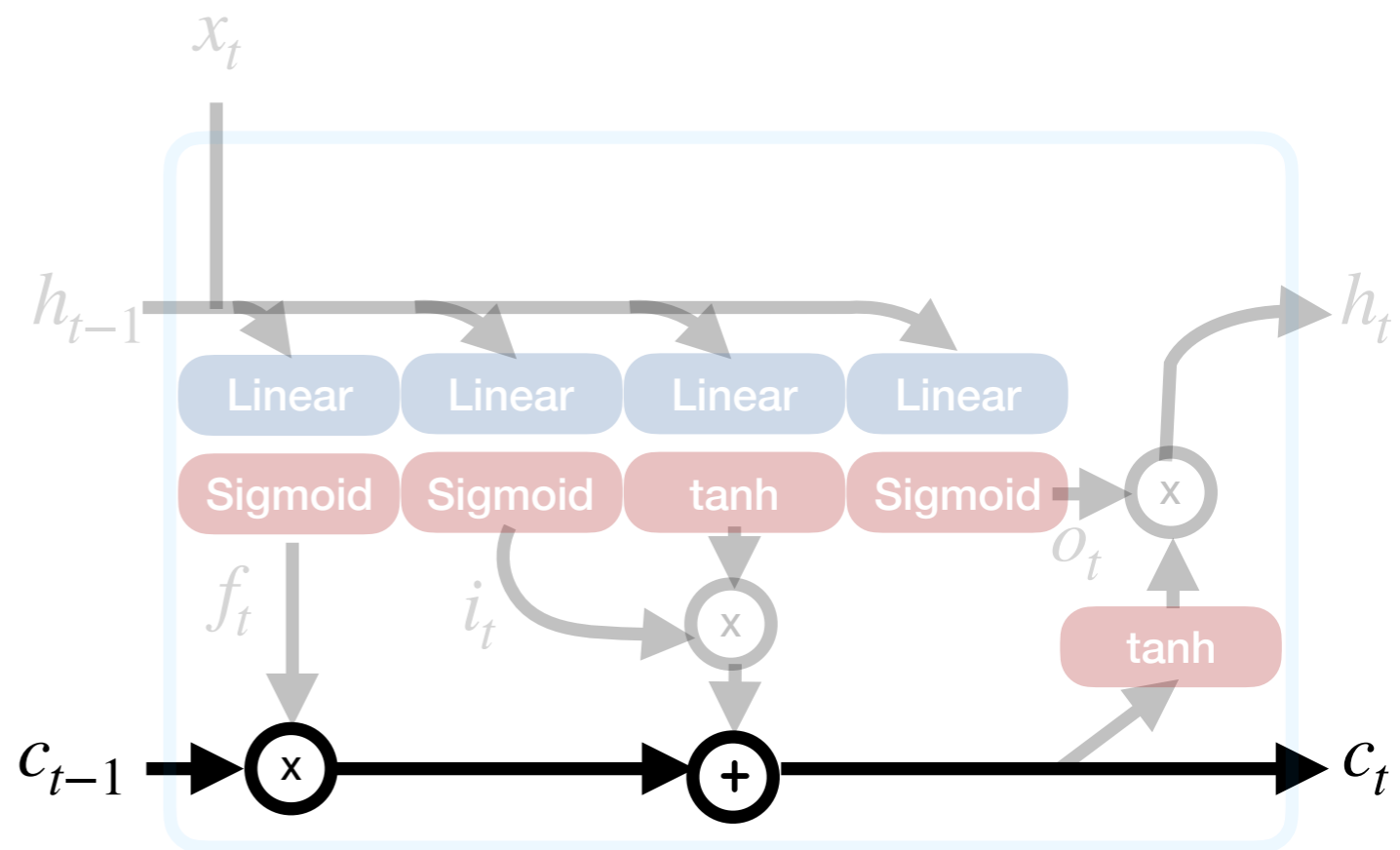
# Long short-term memory

- Two recurrent connections
- Long-term  $c$
- Short term  $h$
- Input  $x$
- Output  $h$



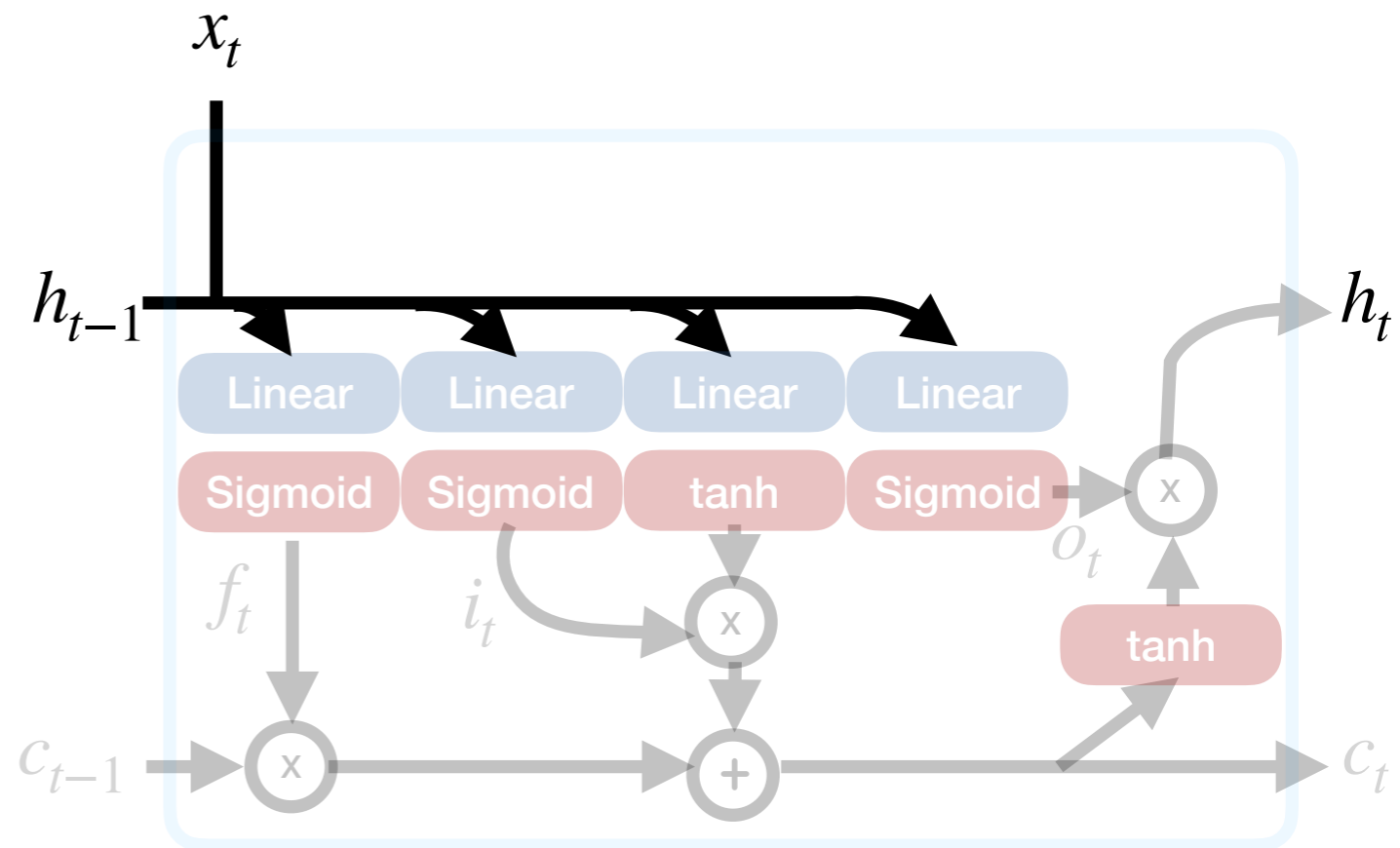
# Cell state

- Cell state  $c$
- Only multiplication and addition
- Shortcut
  - Similar to ResNets



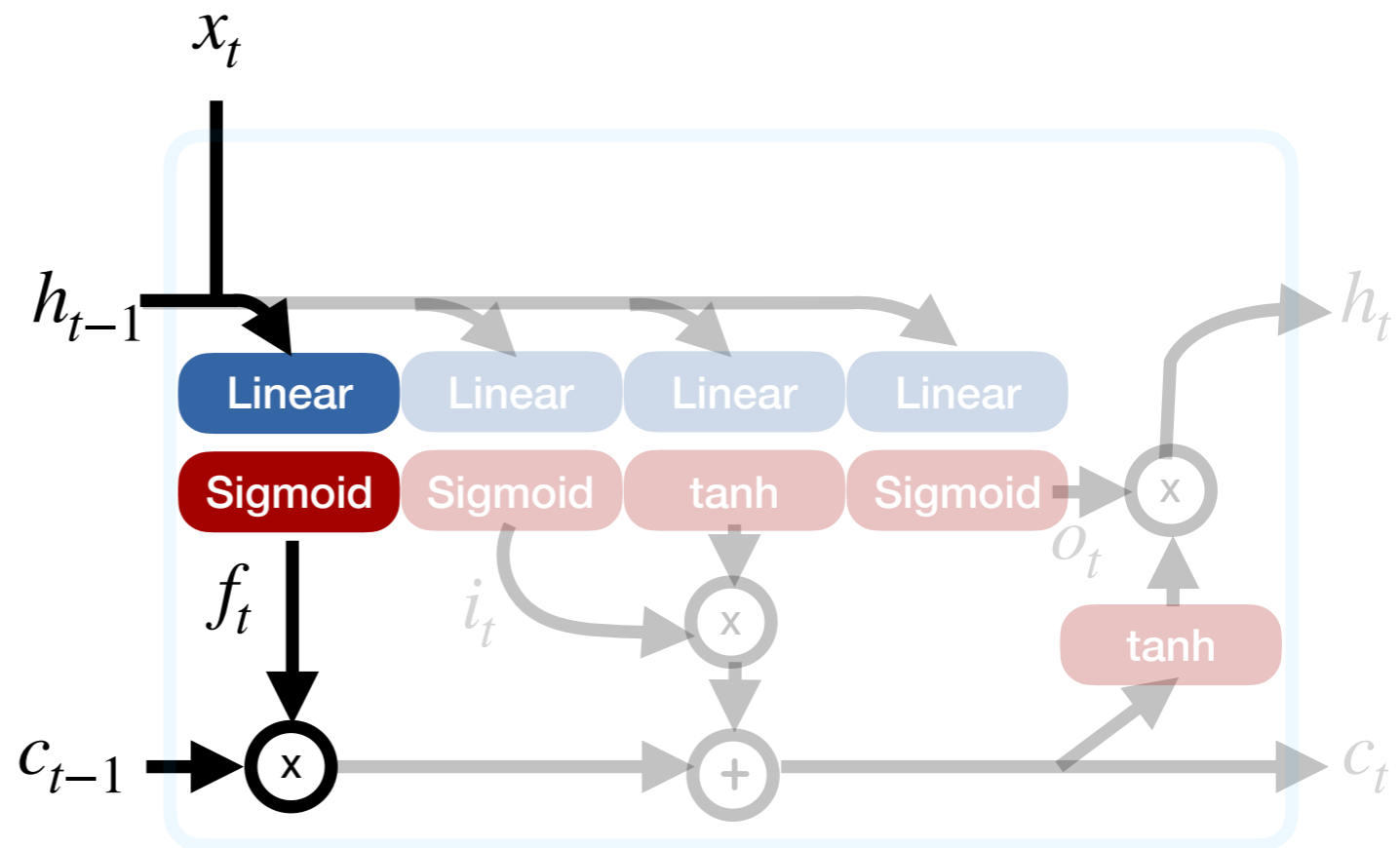
# Input

- Input
- $x$
- Previous  $h$



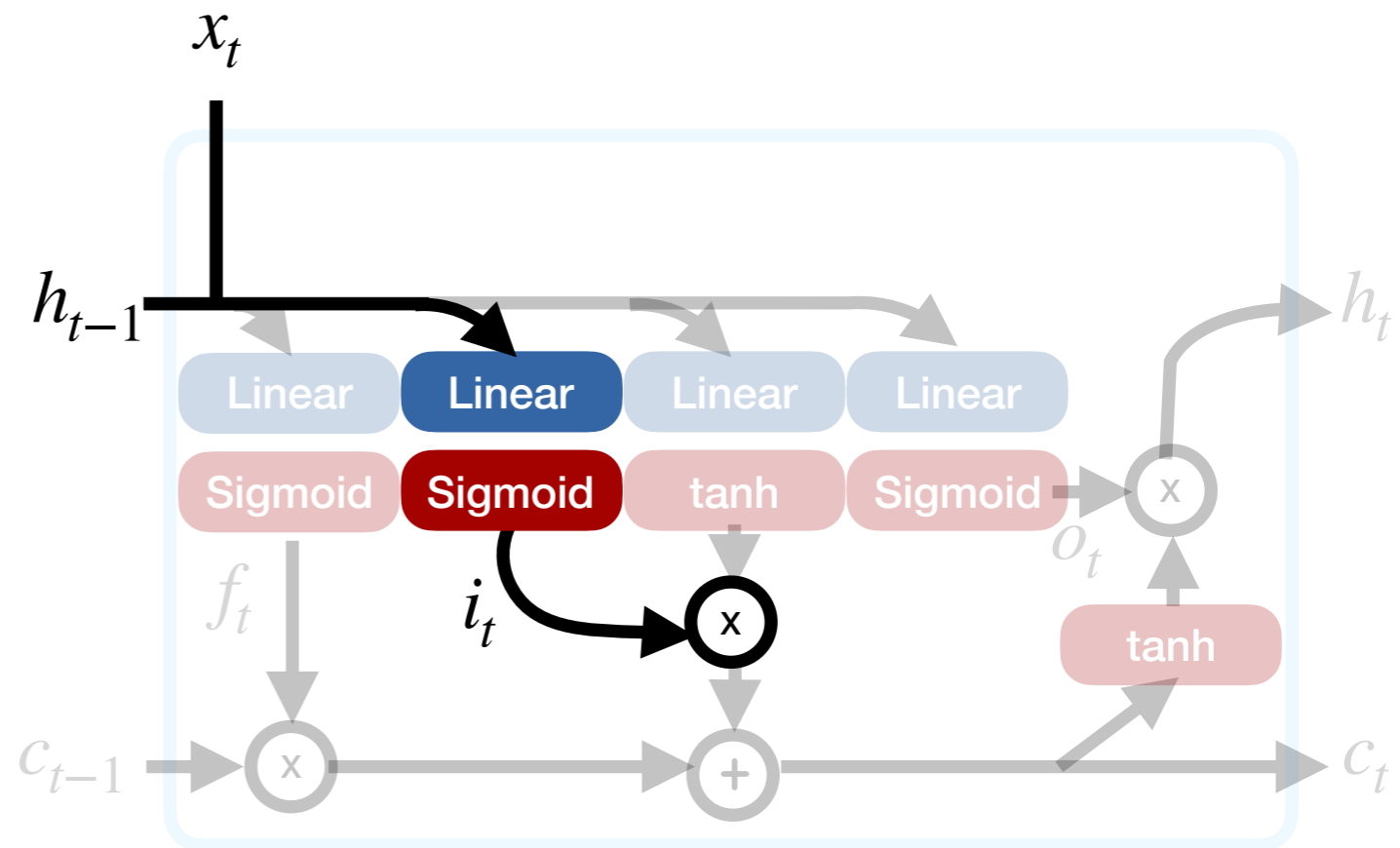
# Forget gate

- Forget gate  $f$
- Clears cell state



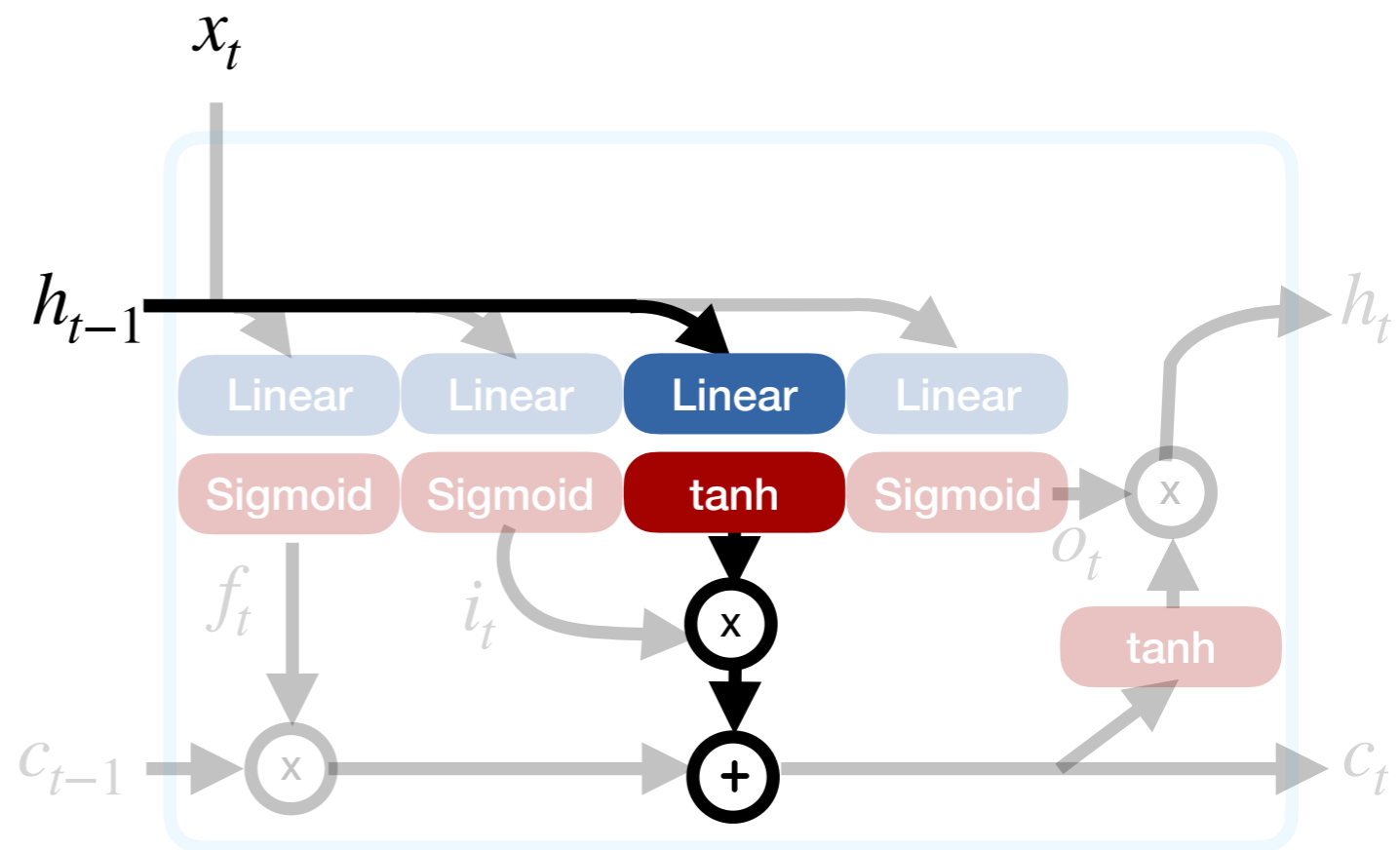
# Input gate

- Input gate  $i$
- Allows state update



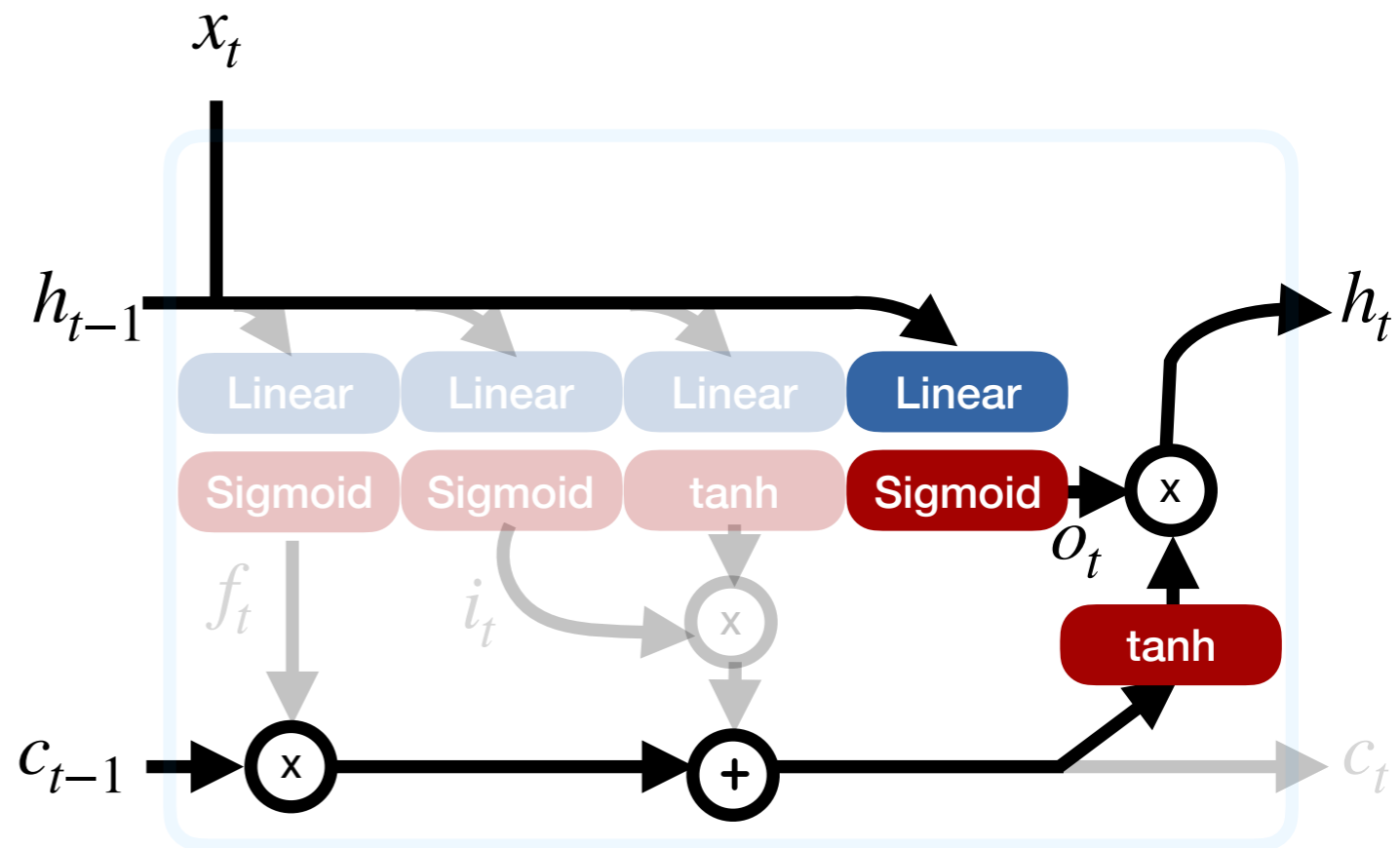
# State update

- State update
- tanh



# Output

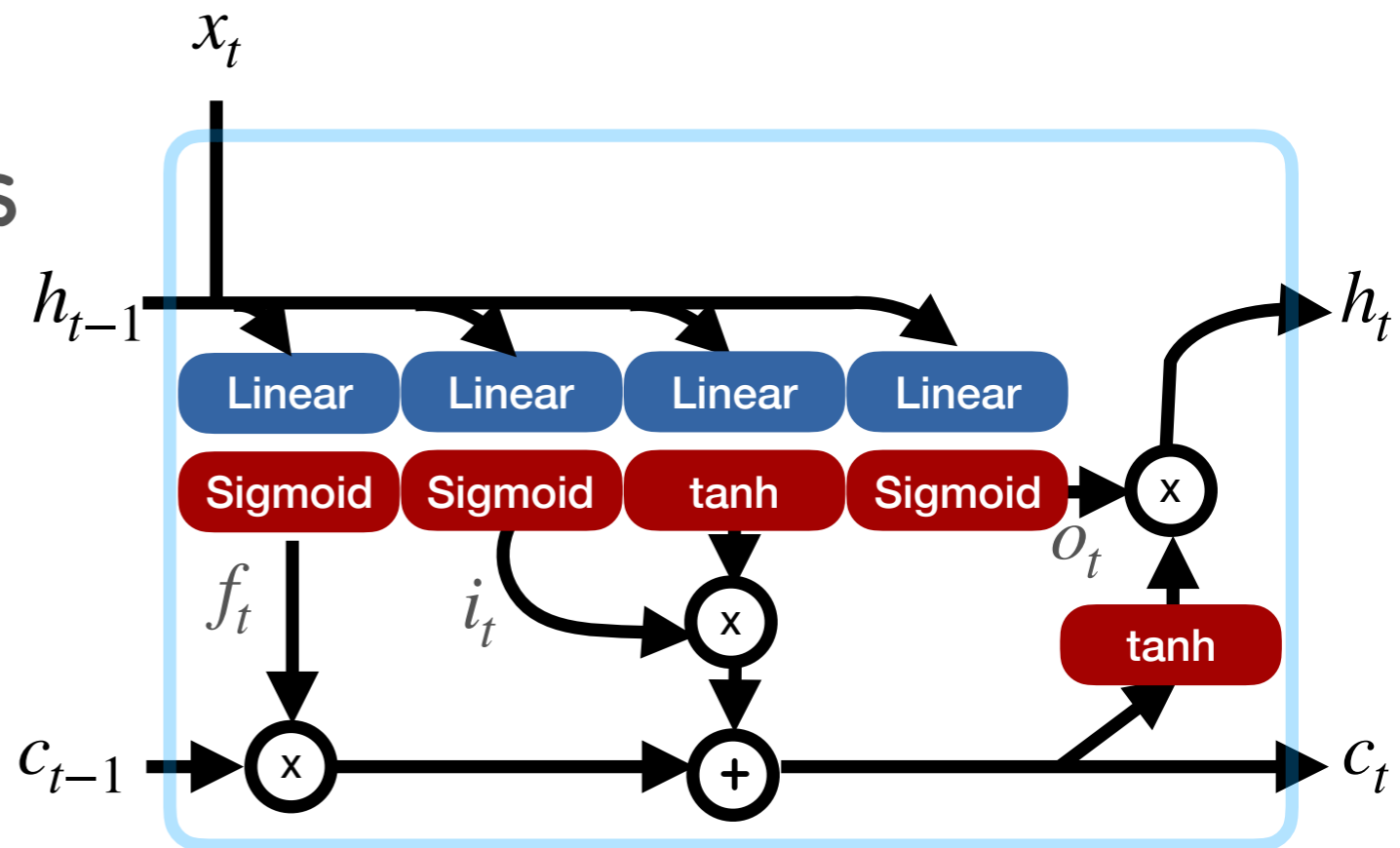
- Output gate  $o$
- Produce an output?
- Output  $h$
- $\tanh$  of cell state





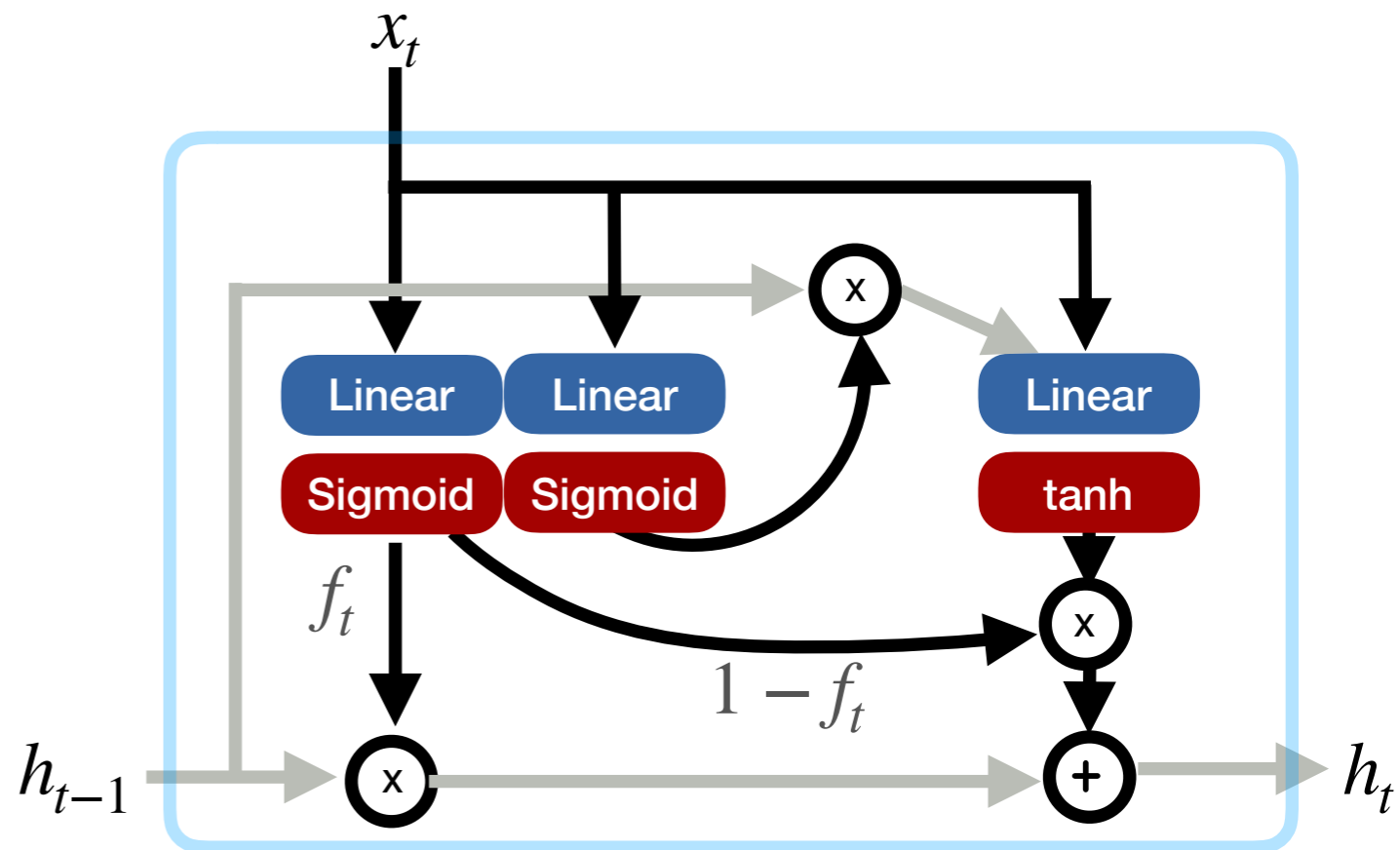
# LSTMs

- Can learn to keep state for up to 100 time steps
- Fewer vanishing gradients
- Short cut

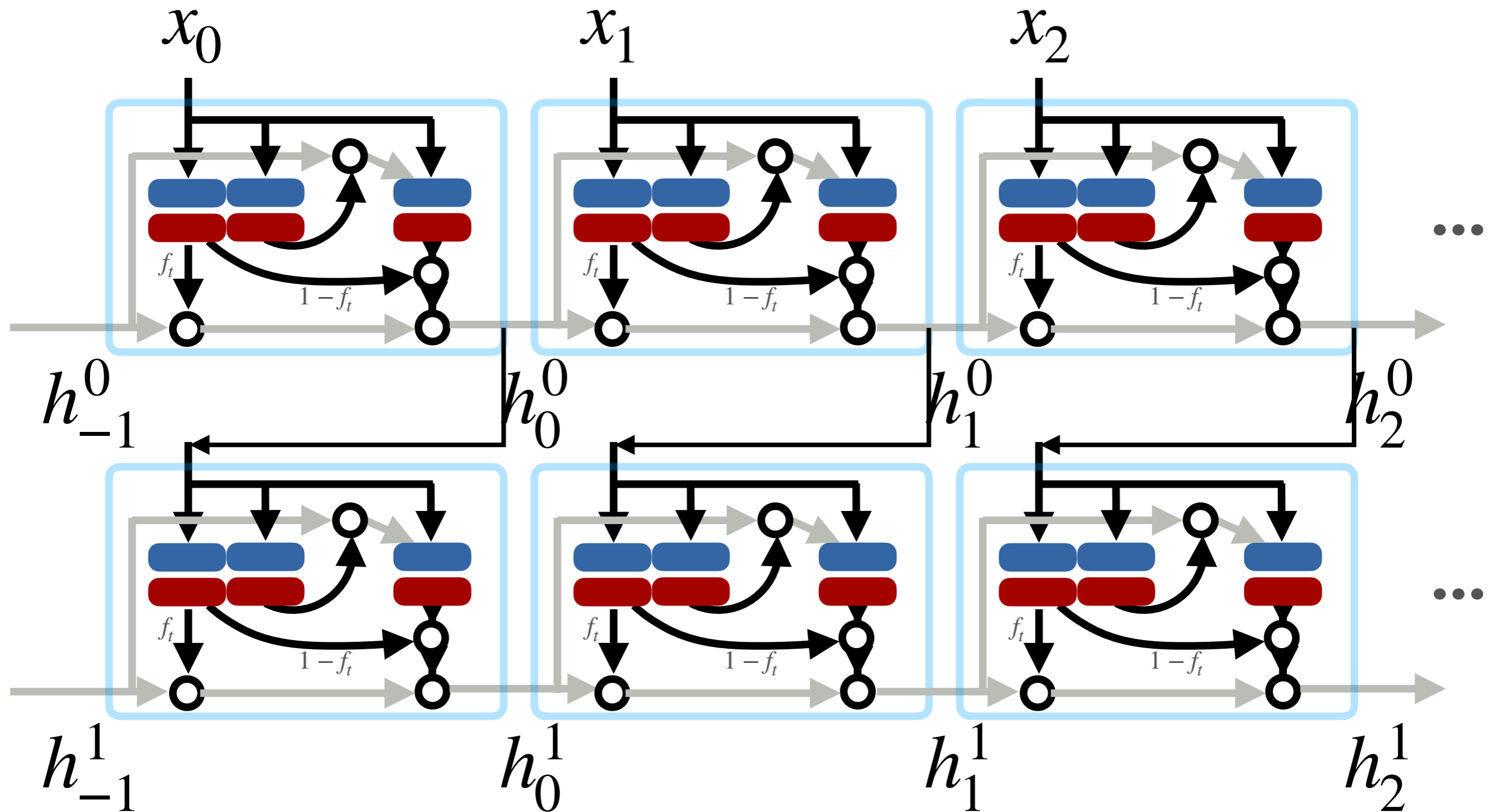


# Gated Recurrent Units

- Simpler LSTM
- Single state
- Fewer gates
- Similar performance



# LSTM/GRU Networks

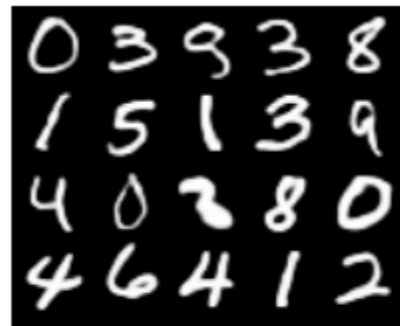


# LSTM / GRU applications

- Hand writing synthesis
- Natural language processing
- Image generation



Image source: Demo by Alex Graves  
<http://www.cs.toronto.edu/~graves/>



hi how are you?

salut comment ca va?

Image source: Gregor et al., <https://arxiv.org/pdf/1502.04623.pdf>

- Generating Sequences With Recurrent Neural Networks, Graves, arXiv 2013
- Sequence to Sequence Learning with Neural Networks, Sutskever et al., NIPS 2014
- DRAW: A Recurrent Neural Network For Image Generation, Gregor et al., ICML 2015