The LSTM architecture

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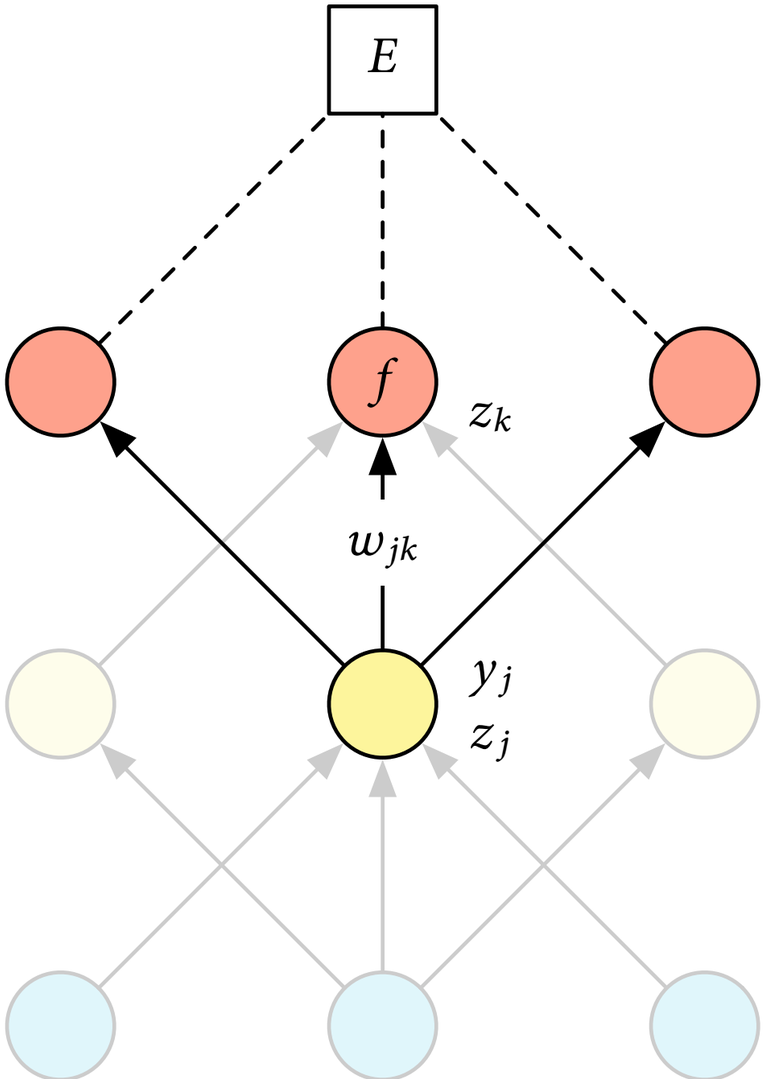
Challenges with recurrent neural networks

- In principle, recurrent neural networks are capable of learning long-distance dependencies in input sequences.
- In practice, training recurrent neural networks is challenging due to the large depth of the unrolled networks.

Vanishing and exploding gradients



$$\delta_k = \frac{\partial E}{\partial z_k} = \frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial z_k} = \frac{\partial E}{\partial y_k} f'(z_k)$$

$$\delta_j = \frac{\partial E}{\partial z_j} = \frac{\partial y_j}{\partial z_j}\sum_k \frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial y_j} = f'(z_j)\sum_k \delta_k w_{jk}$$

Vanishing and exploding gradients

- Gradients either grow or shrink exponentially with the depth of the network – until they explode or vanish.

- This problem is especially prominent in recurrent networks, whose unrolled computation graphs can be very deep.

- Research on recurrent networks has proposed various methods to mitigate this problem.

  weight scaling and clipping, specialised architectures

Long Short-Term Memory (LSTM)

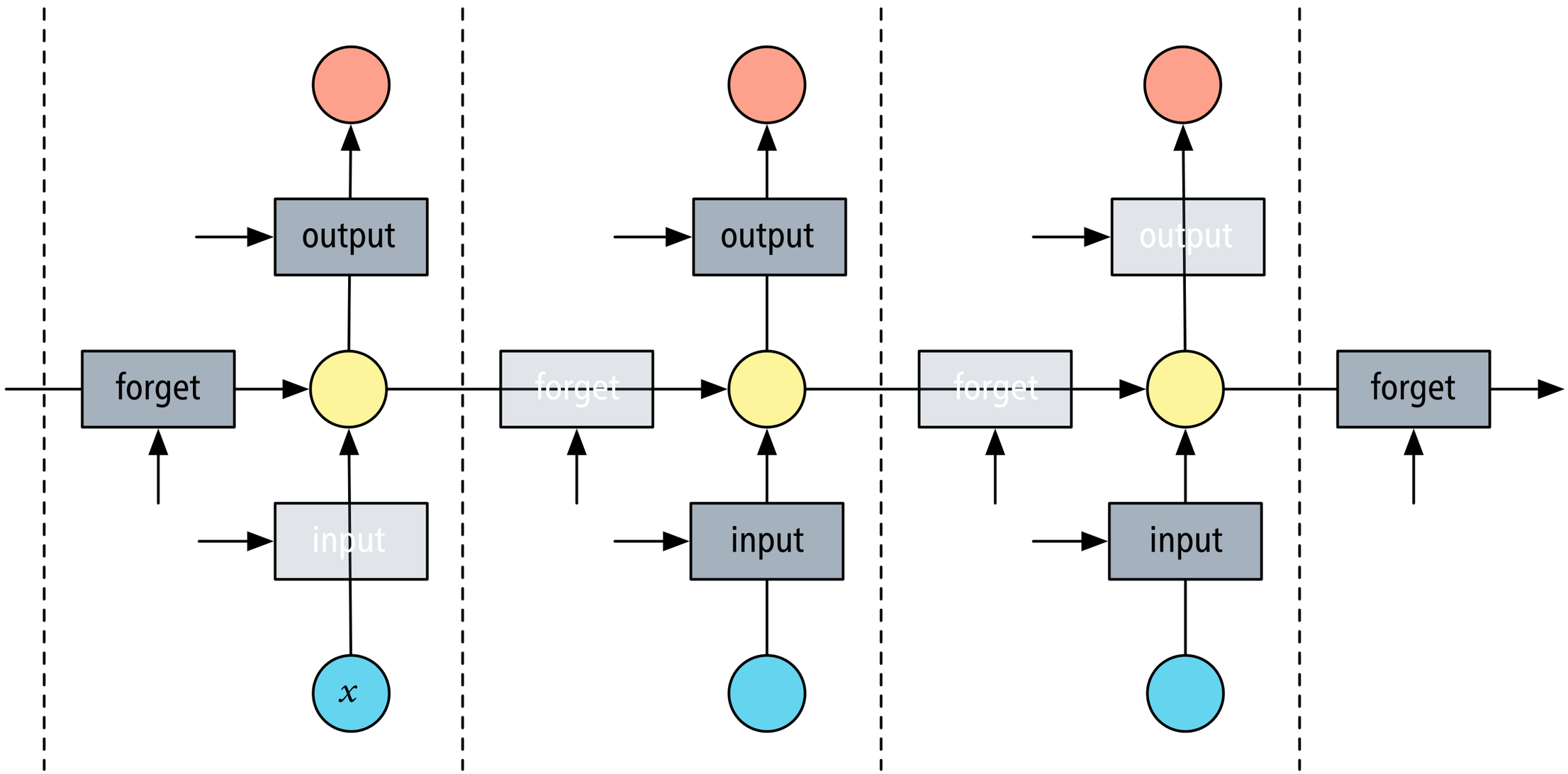
- The **Long Short-Term Memory (LSTM)** architecture was specifically designed to adress the vanishing gradients problem.
  - Metaphor: The hidden state of the neural network can be considered as a short-term memory.
  - The LSTM architecture tries to make this short-term memory last as long as possible by preventing vanishing gradients.

Memory cell and gating mechanism

The crucial innovation in an LSTM is the design of its memory cell.

- Information is written into the cell if its INPUT gate is open.
- Information stays in the cell as long as its FORGET gate is closed.
- Information is read from the cell if its READ gate is open.

Information flow in an LSTM



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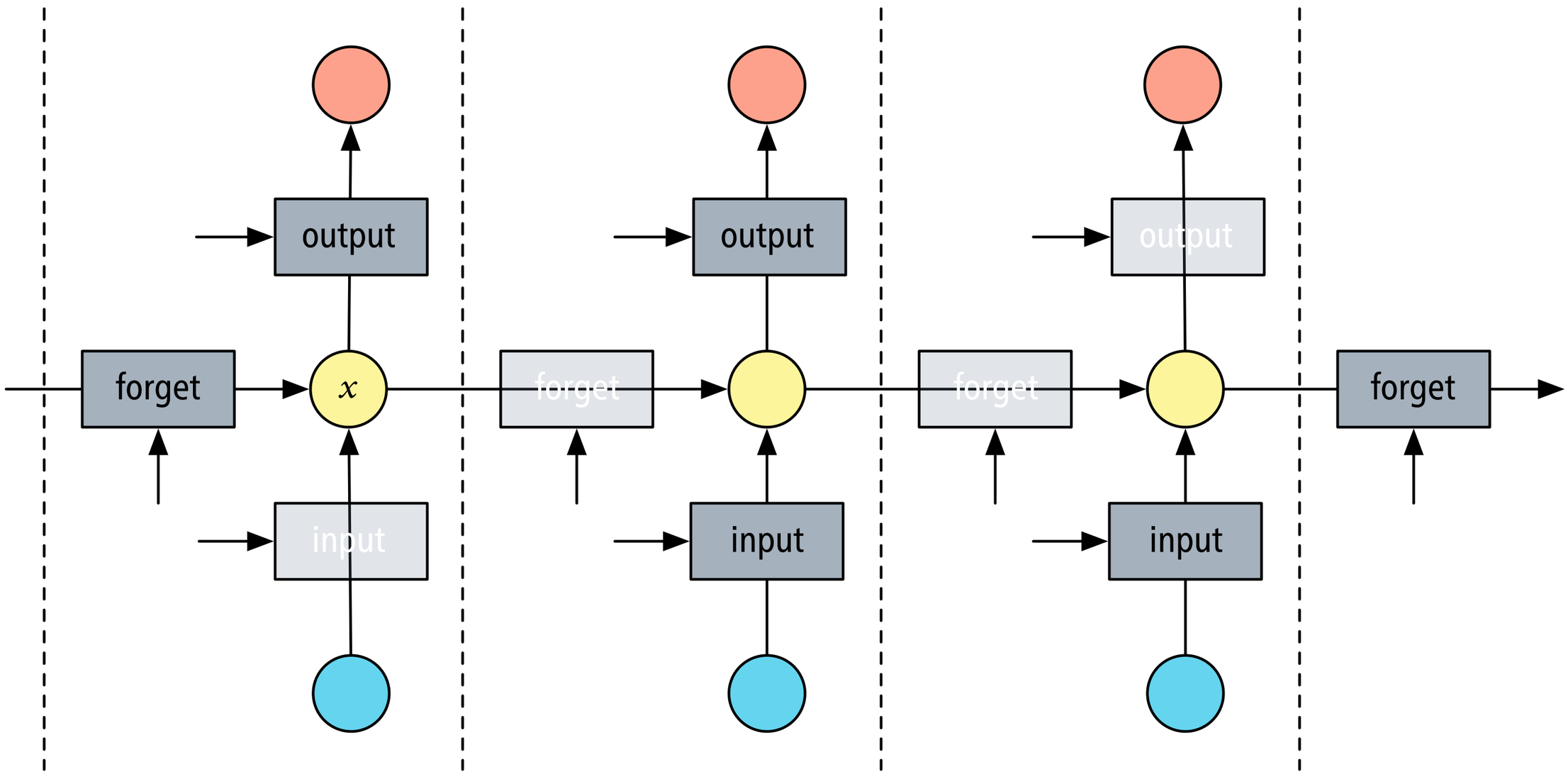
Information flow in an LSTM



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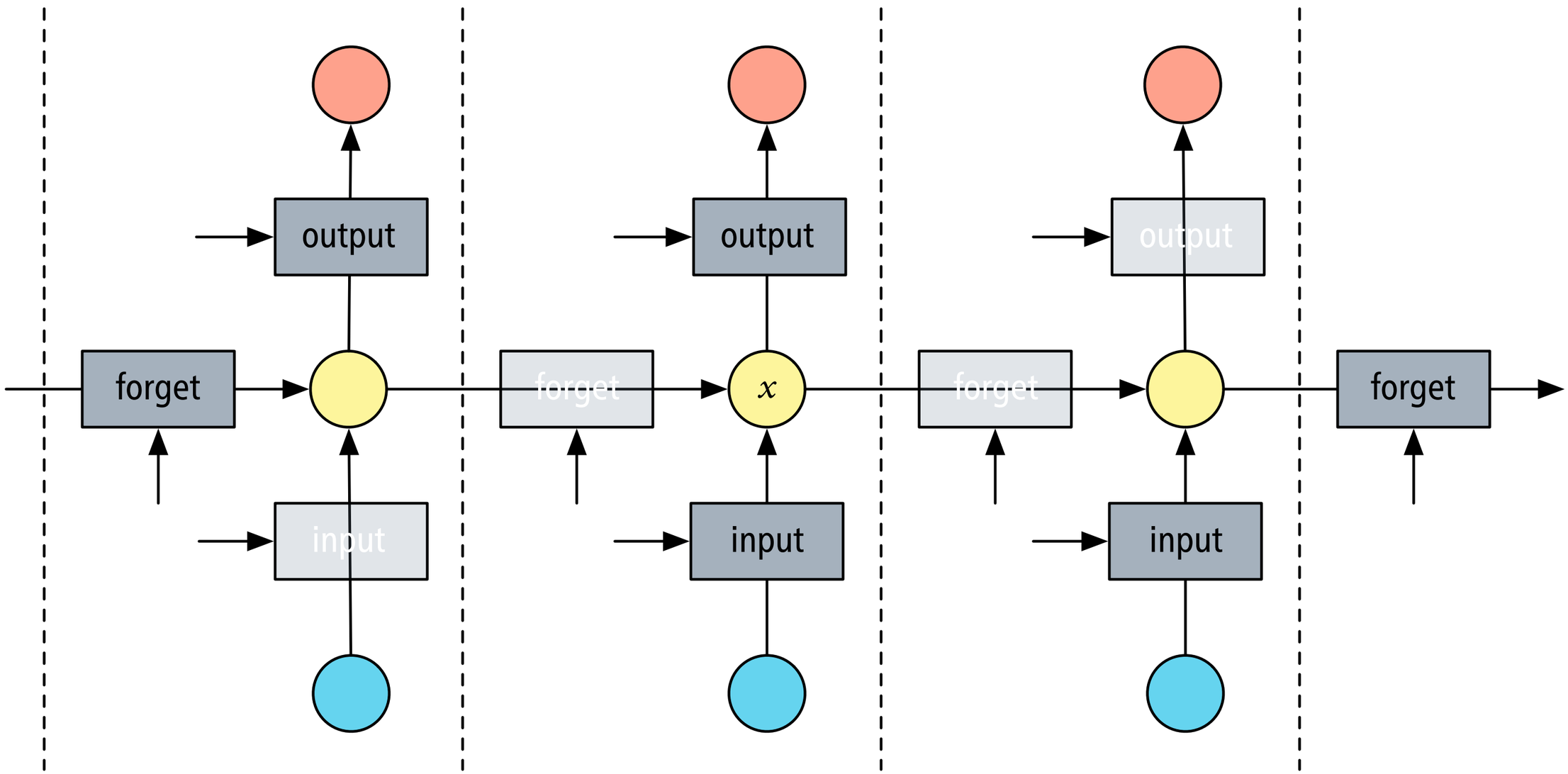
Information flow in an LSTM



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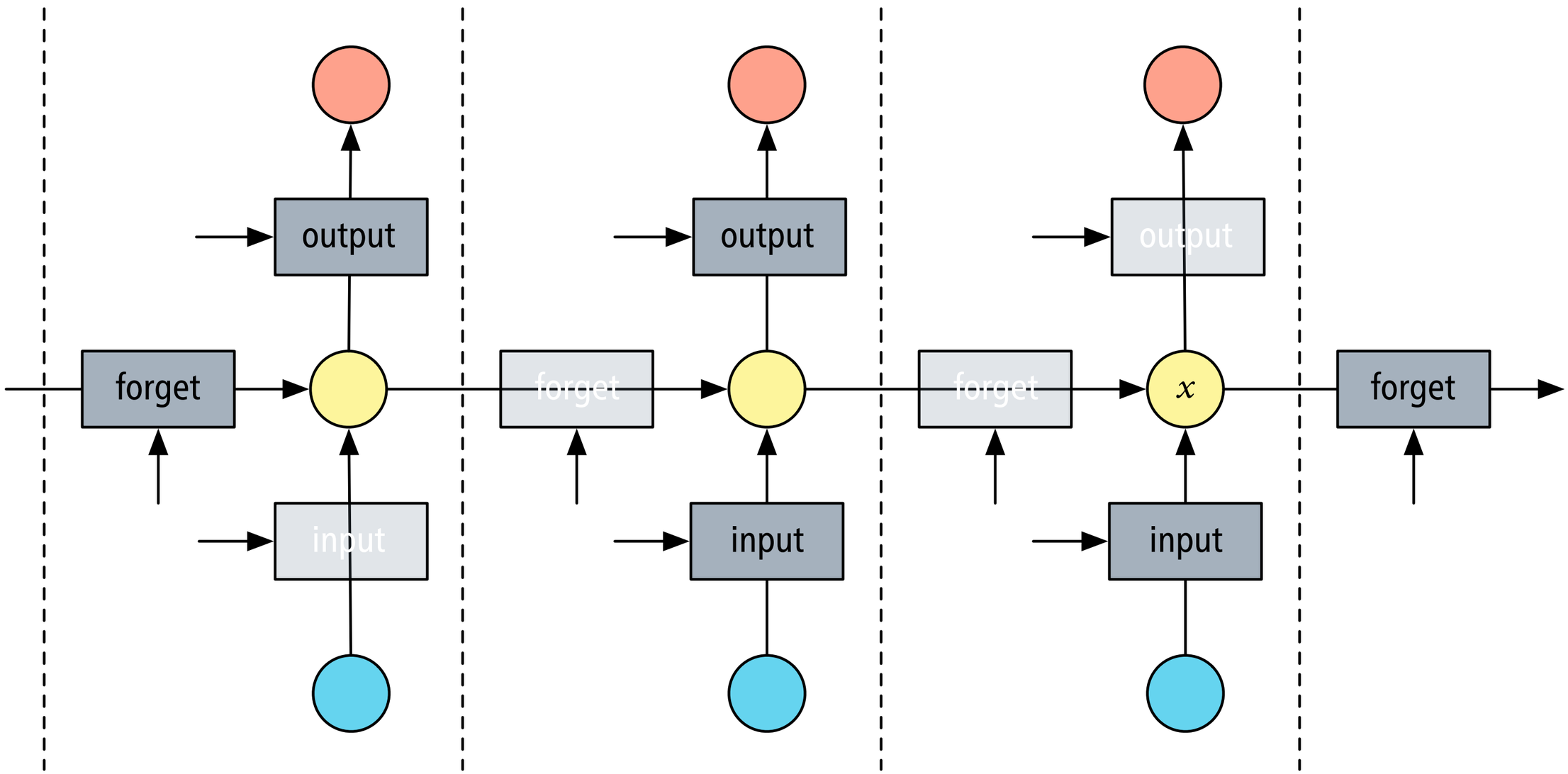
Information flow in an LSTM



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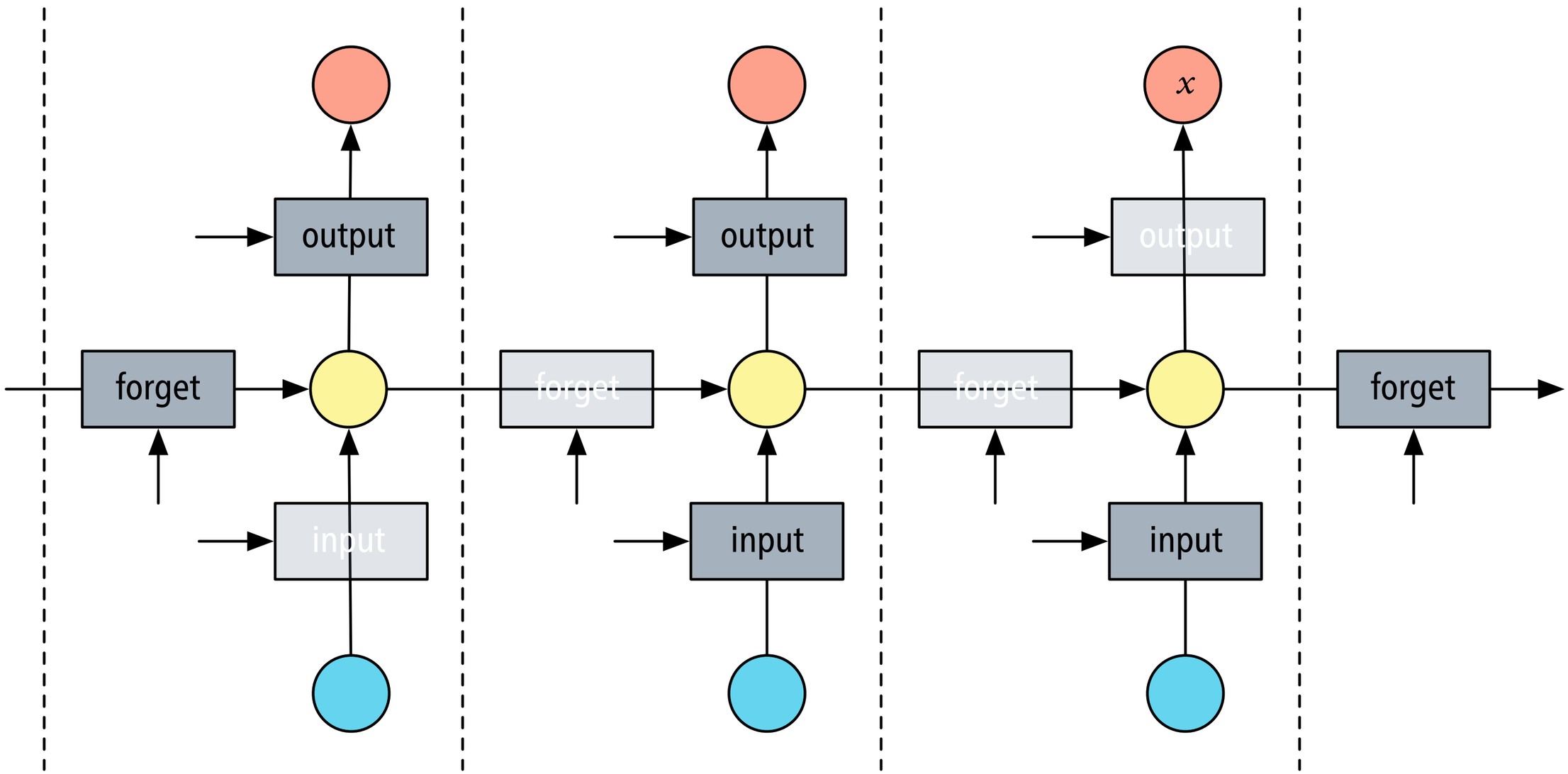
Information flow in an LSTM



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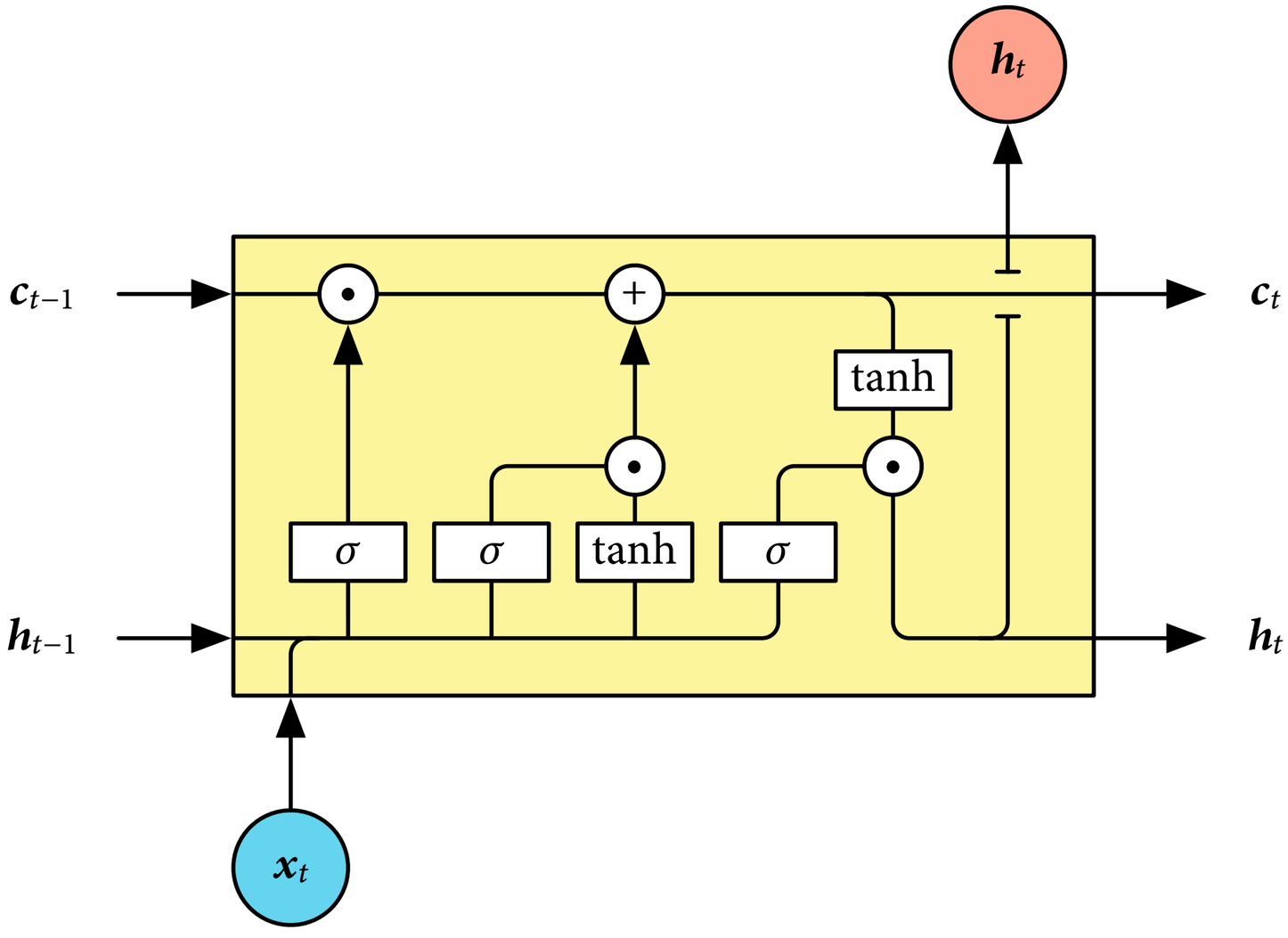
Gating mechanism

$$\begin{bmatrix}1\\2\\3\\4\end{bmatrix} \odot \begin{bmatrix}0\\1\\1\\0\end{bmatrix} + \begin{bmatrix}5\\6\\7\\8\end{bmatrix} \odot \begin{bmatrix}1\\0\\0\\1\end{bmatrix} = \begin{bmatrix}5\\2\\3\\8\end{bmatrix}$$

$\boldsymbol{h}_{t-1}$ $\boldsymbol{g}$ $\boldsymbol{x}_t$ $1-\boldsymbol{g}$ $\boldsymbol{h}_t$

The gating masks $\boldsymbol{g}$ are learned values between 0 and 1.

A look inside an LSTM cell



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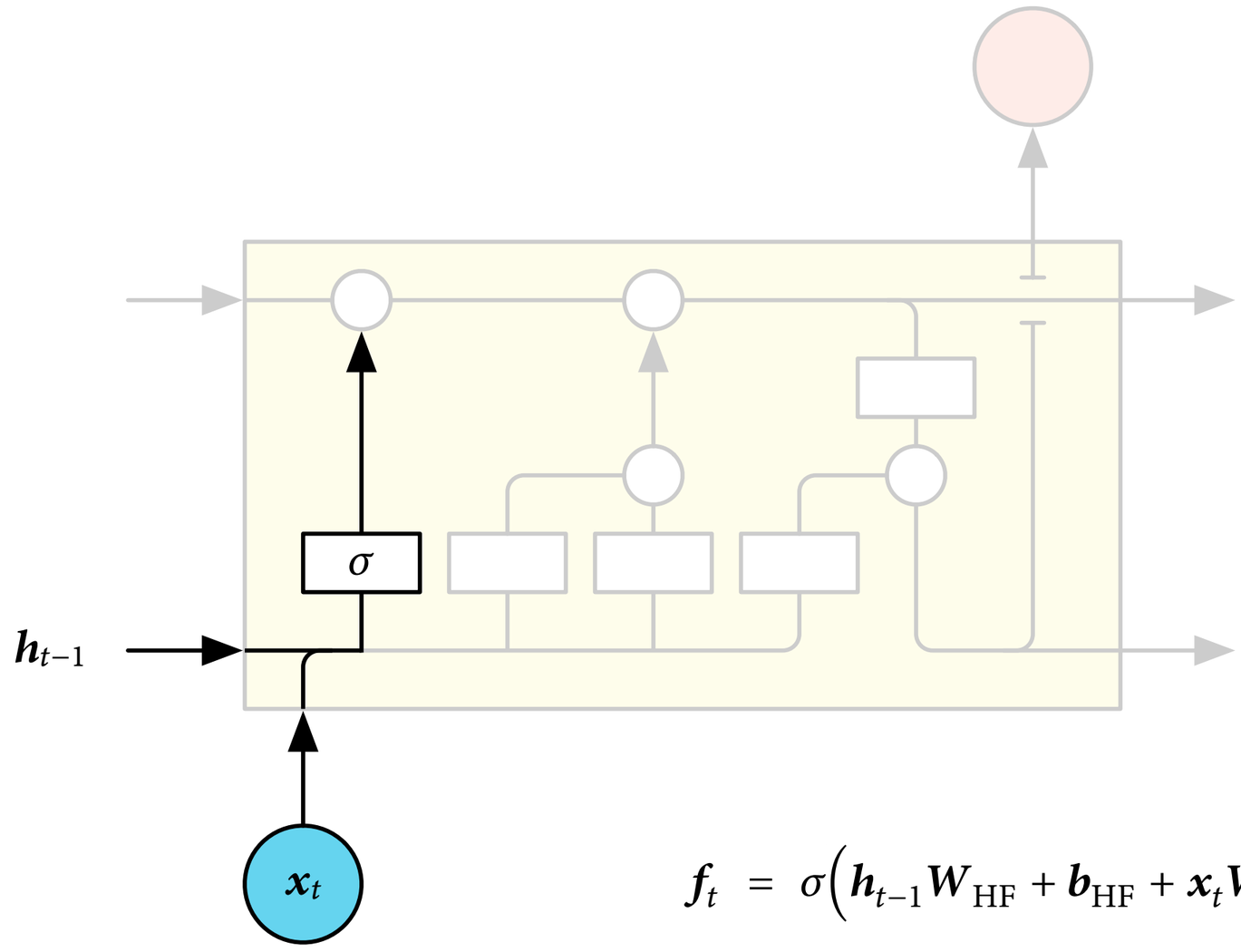
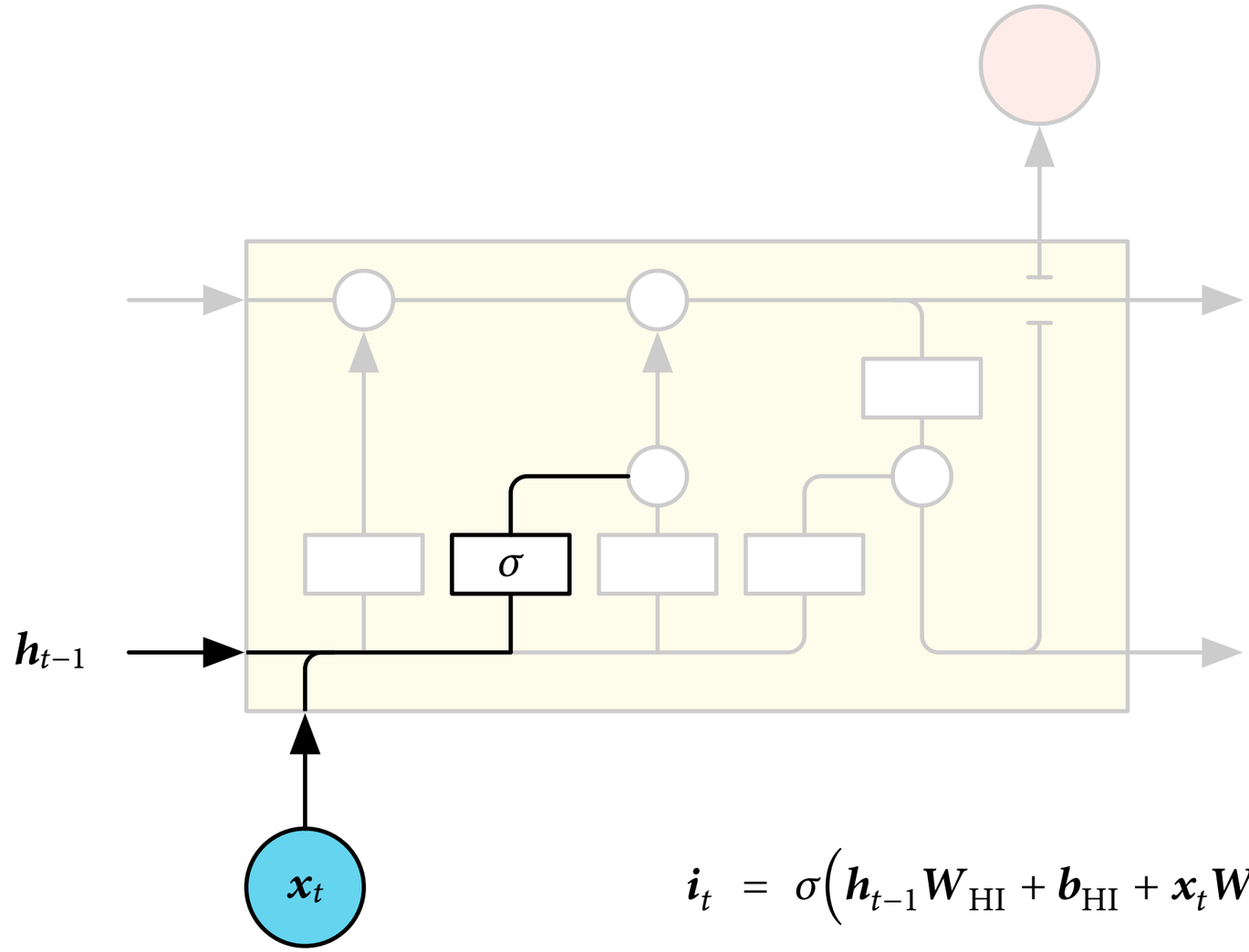
Forget gate



$$f_t = \sigma\left(h_{t-1}W_{\mathrm{HF}} + b_{\mathrm{HF}} + x_t W_{\mathrm{XF}} + b_{\mathrm{XF}}\right)$$

Attribution: Chris Olah

Input gate



$$i_t = \sigma\left(h_{t-1}W_{\mathrm{HI}} + b_{\mathrm{HI}} + x_t W_{\mathrm{XI}} + b_{\mathrm{XI}}\right)$$

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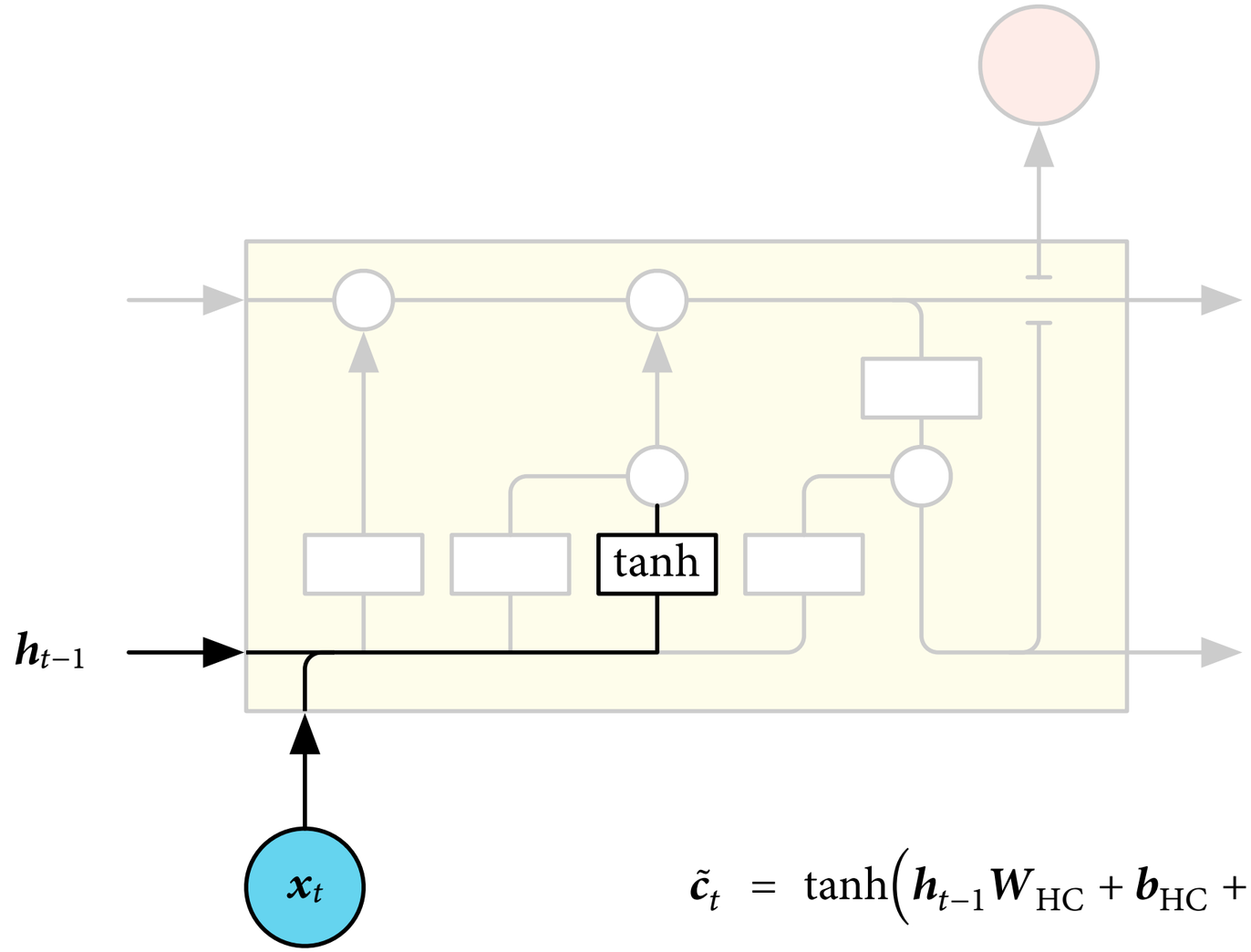
Update candidate



$$\tilde{c}_t = \tanh\left(h_{t-1}W_{\mathrm{HC}} + b_{\mathrm{HC}} + x_t W_{\mathrm{XC}} + b_{\mathrm{XC}}\right)$$

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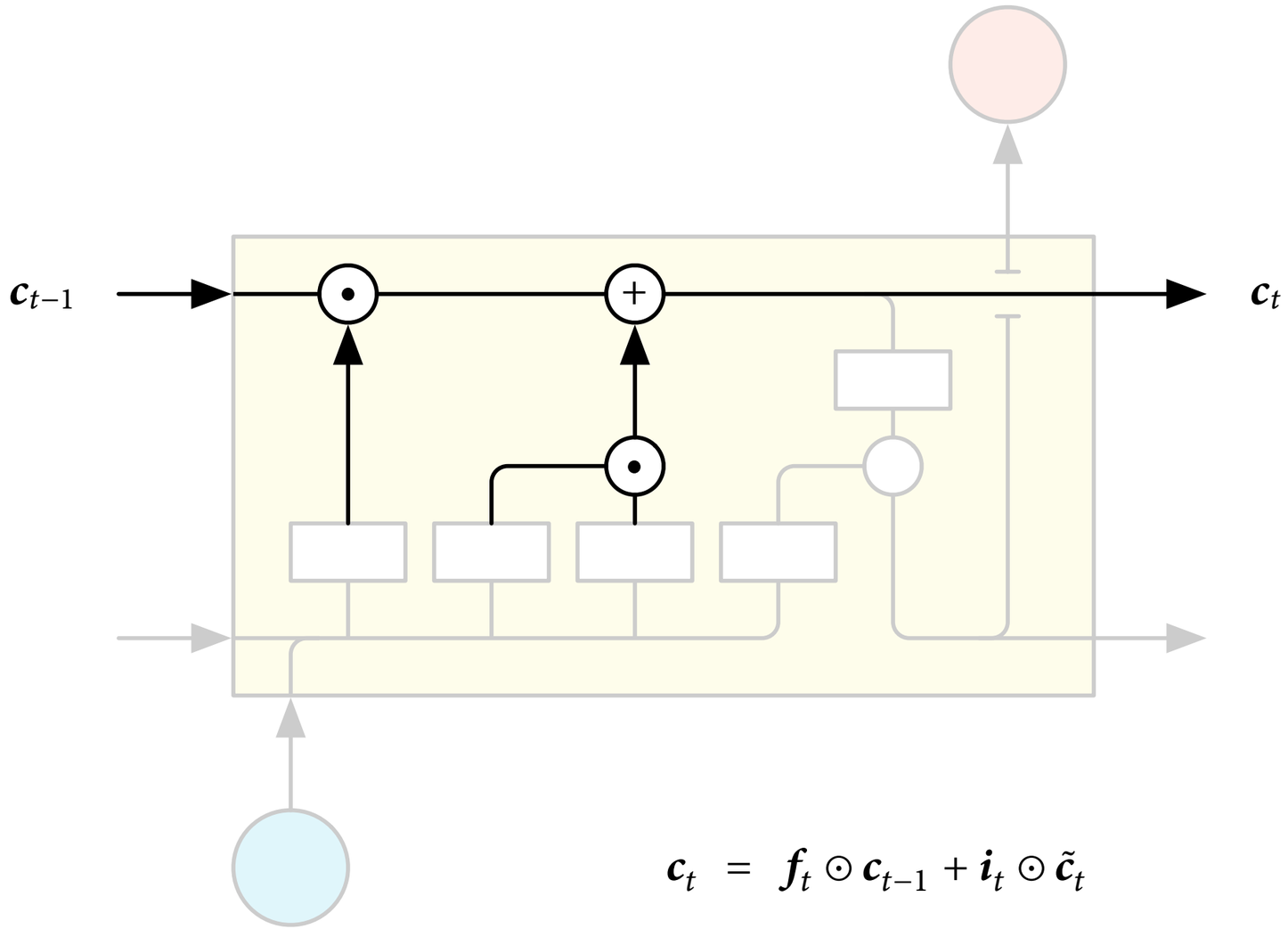
Memory cell update



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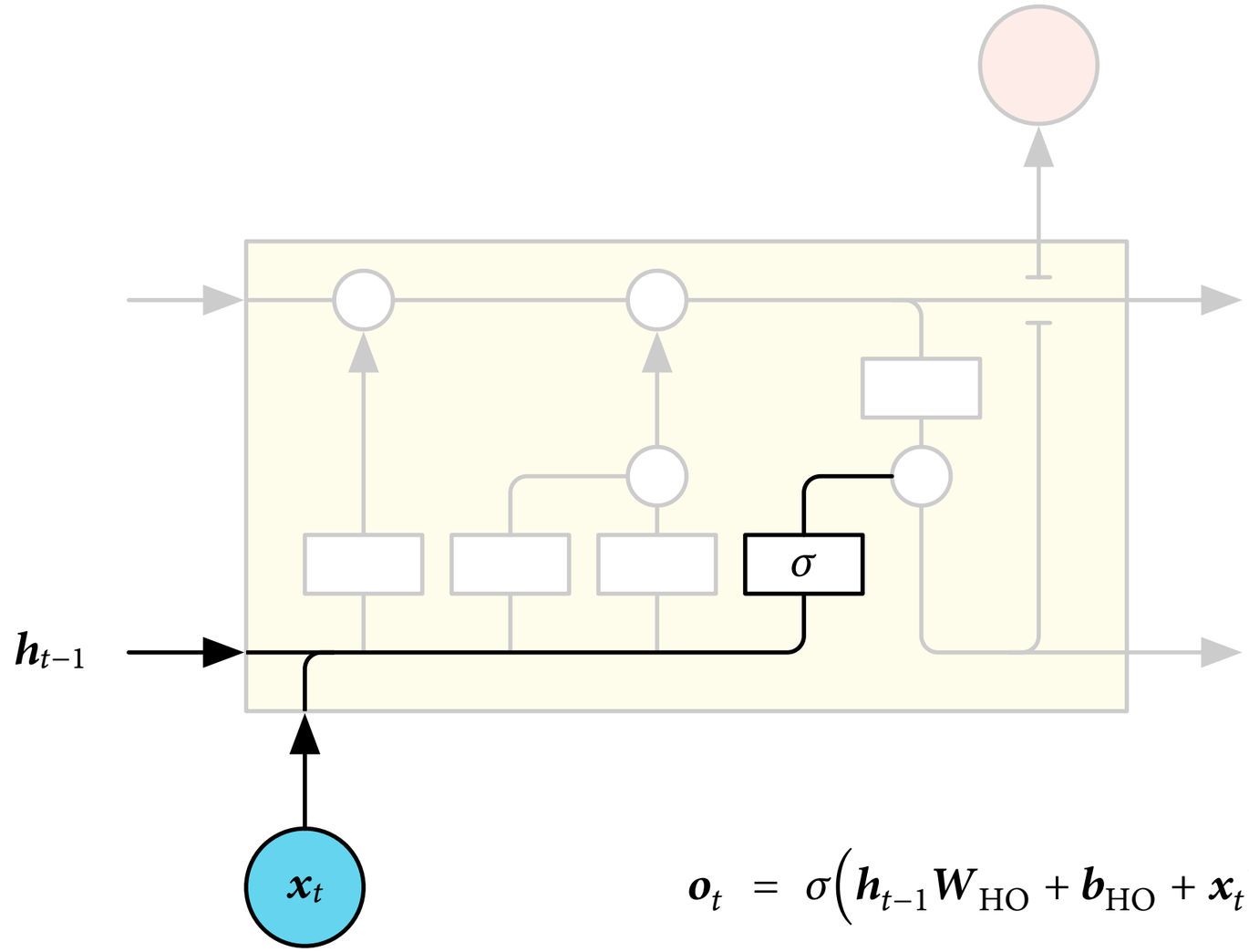
Output gate



$$o_t = \sigma\left(h_{t-1}W_{\mathrm{HO}} + b_{\mathrm{HO}} + x_t W_{\mathrm{XO}} + b_{\mathrm{XO}}\right)$$

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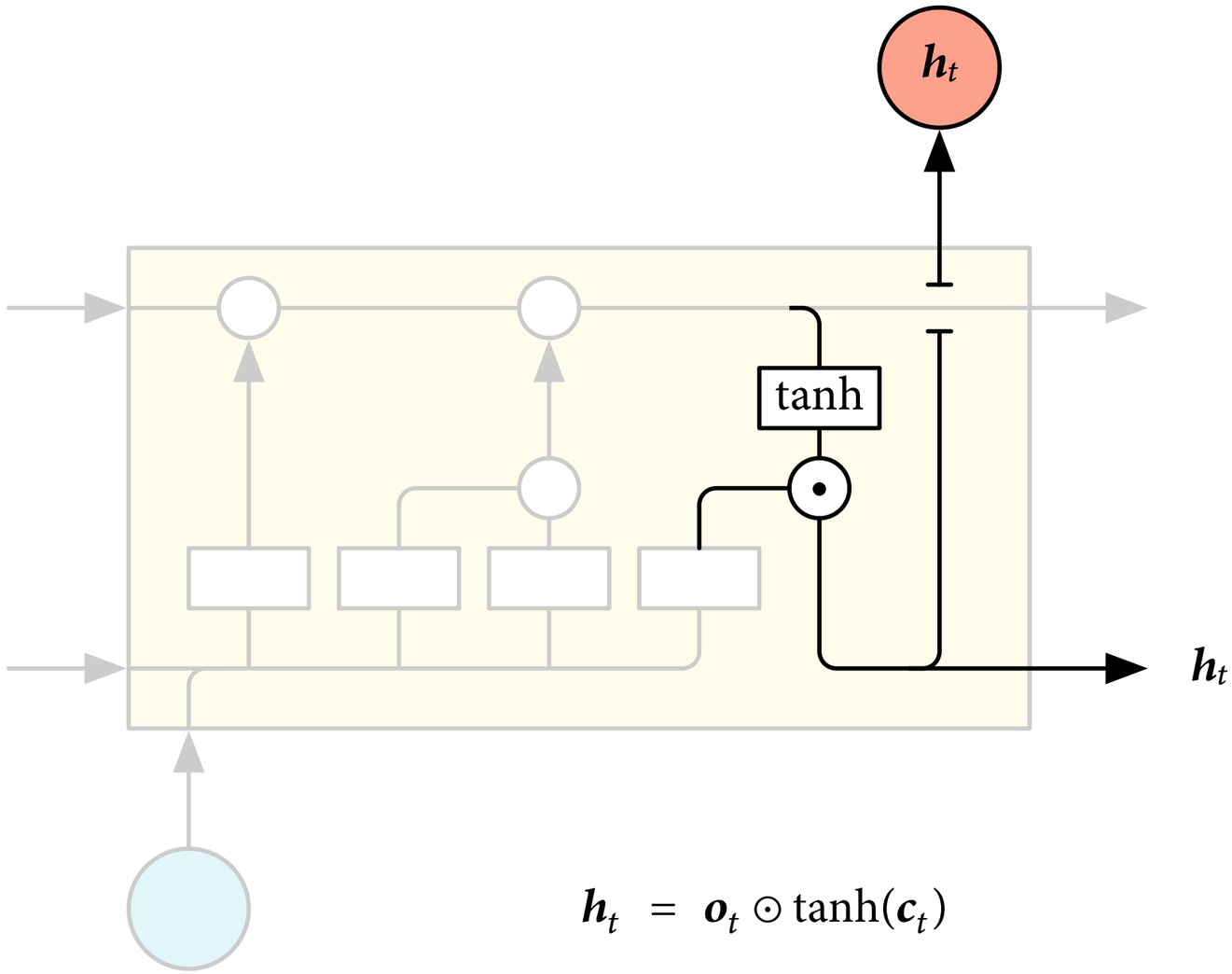
Output



$$h_t = o_t \odot \tanh(c_t)$$

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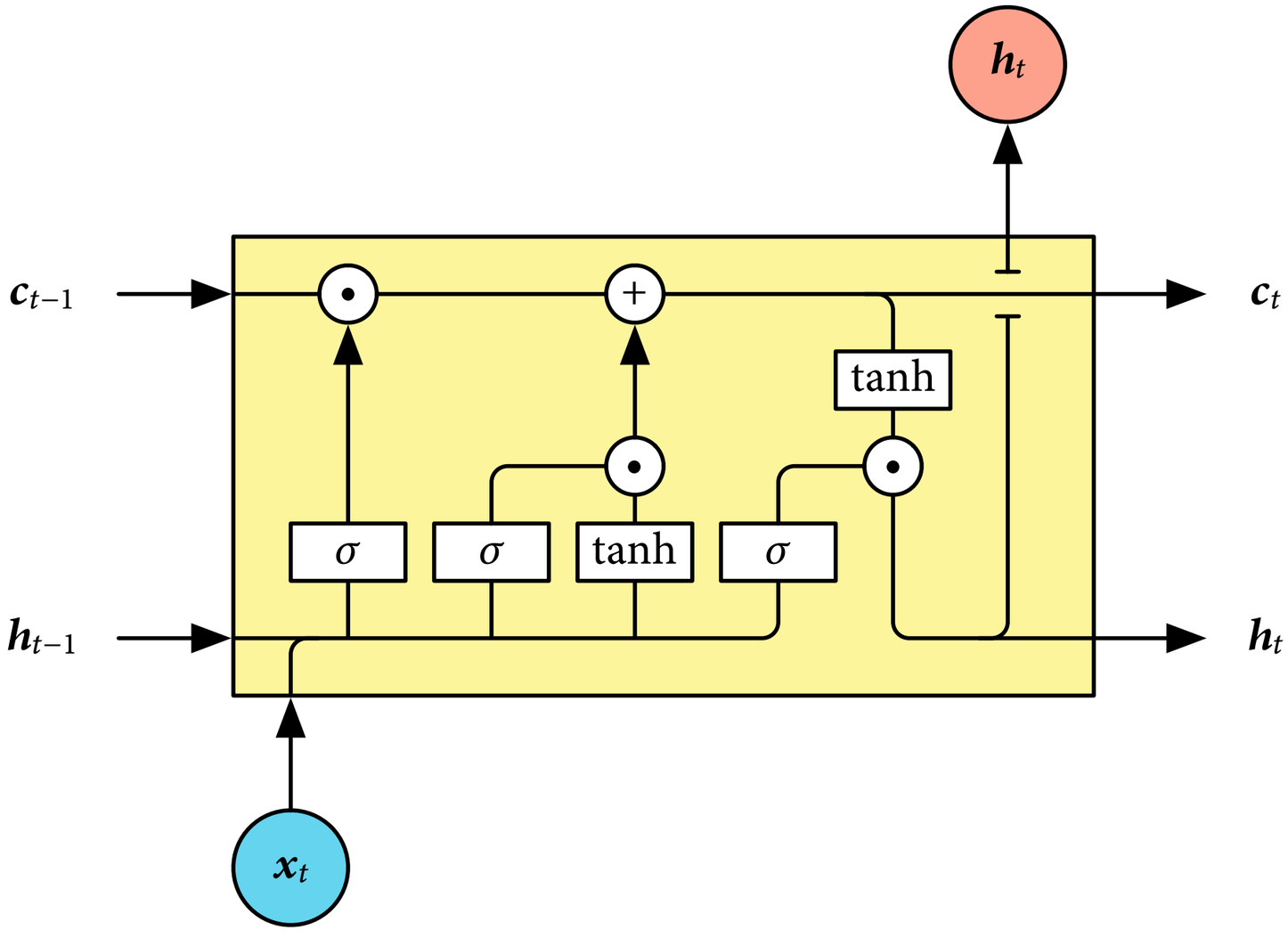
A look inside an LSTM cell



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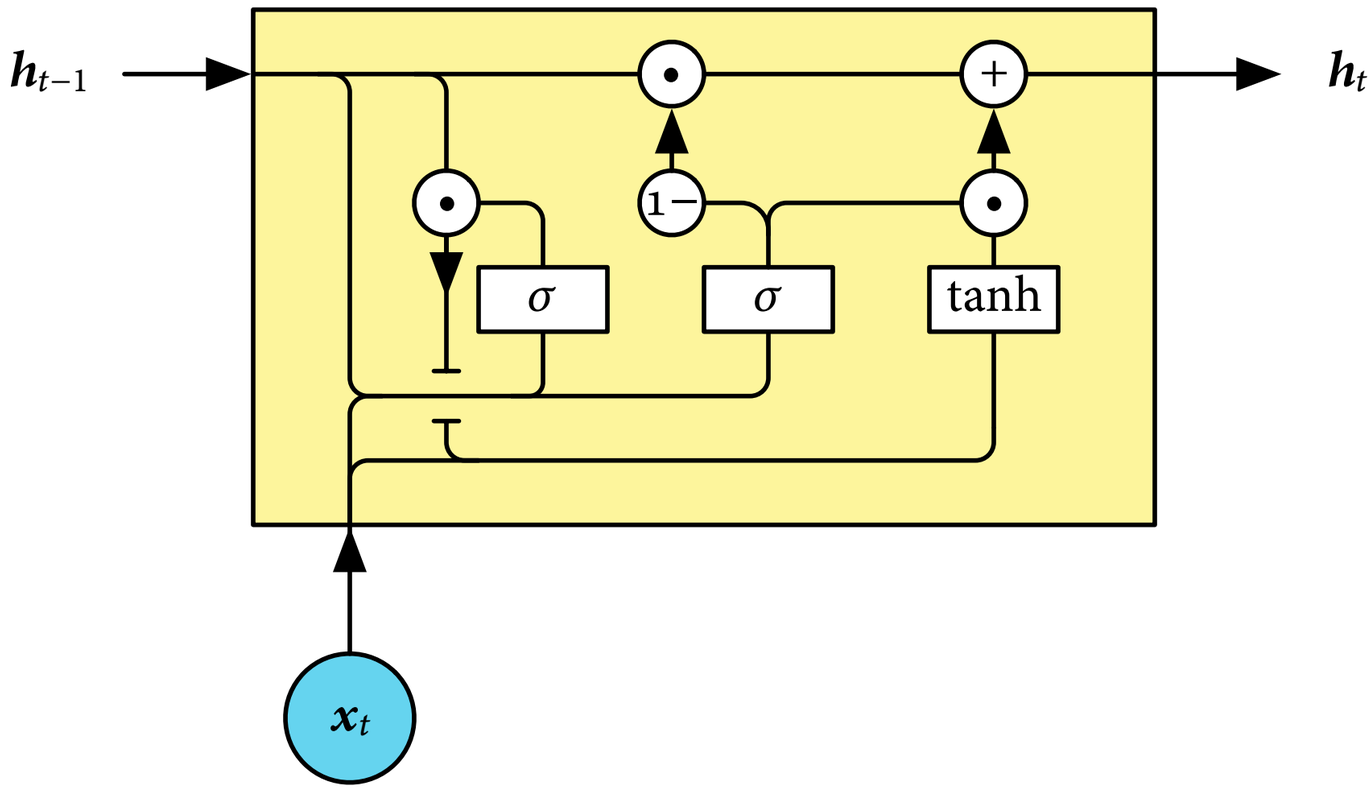
Gated Recurrent Unit (GRU)



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