LSTM as a layer

During one time step t, the LSTM

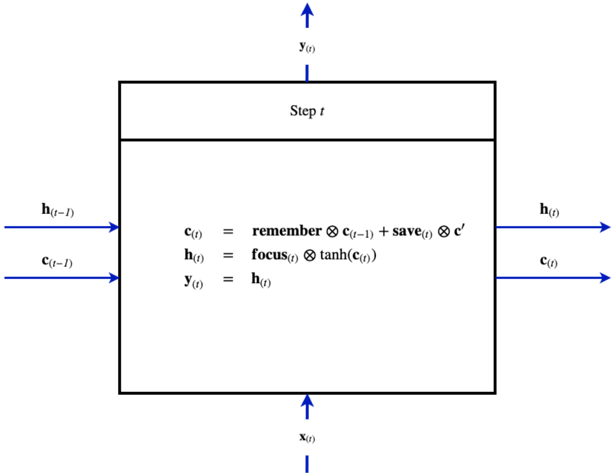
- Takes input element $\mathbf{x}_{(t)}$
- Updates long term memory $\mathbf{c}_{(t)}$
- Updates control state $\mathbf{h}_{(t)}$
- Optionally outputs $\mathbf{y}_{(t)}$

The three separate computations are functions of

- the previous short term state $\mathbf{h}_{(t-1)}$,
- previous long term state $\mathbf{c}_{(t-1)}$
- and the current input $x_{(t)}$.

$$\mathbf{y}_{(t)}, \mathbf{h}_{(t)}, \mathbf{c}_{(t)} = f(\mathbf{x}_{(t)}, \mathbf{h}_{(t-1)}, \mathbf{c}_{(t-1)})$$

LSTM



$$\begin{aligned}
\mathbf{c}_{(t)} &= \mathbf{remember} \otimes \mathbf{c}_{(t-1)} + \mathbf{save}_{(t)} \otimes \mathbf{c}' \\
\mathbf{h}_{(t)} &= \mathbf{focus}_{(t)} \otimes \tanh(\mathbf{c}_{(t)}) \\
\mathbf{y}_{(t)} &= \mathbf{h}_{(t)}
\end{aligned}$$

$\mathbf{remember}, \mathbf{focus}, \mathbf{save}$ are *gates*

- That control different aspects of the update process

Conclusion

This was a high level introduction to the LSTM API.

It is similar to a vanilla RNN but separates responsibility

- For short-term transition control
- And long term memory and output
- Using an additional variable $\mathbf{c}_{(t)}$

It will turn out that the gates are specially designed to combat the problem of vanishing/exploding gradients.

In [ ]:

```
print("Done")
```