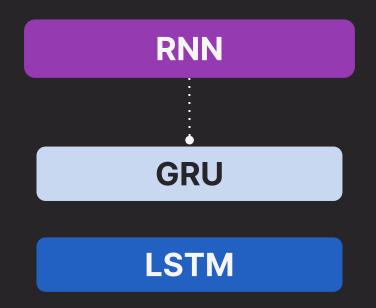




#### **Advanced RNN**

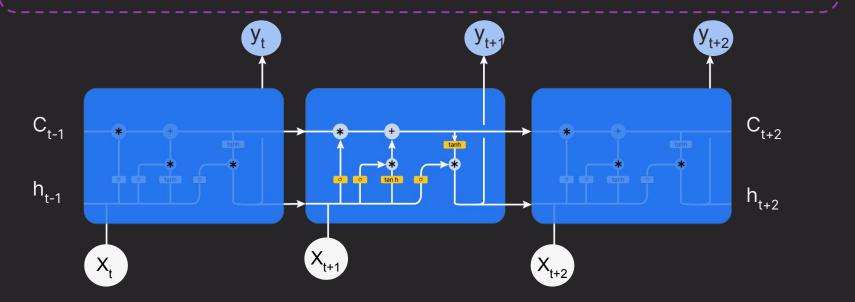






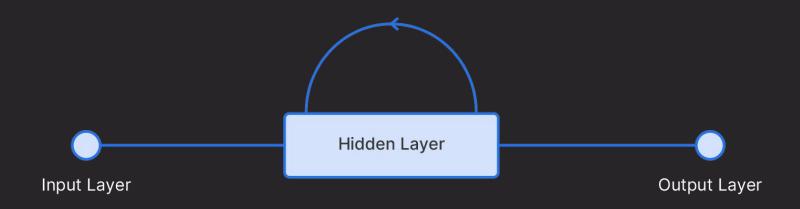
#### Introduction to LSTM

Long Short Term Memory (LSTM) excels at capturing long-term dependencies making it ideal for sequence prediction.





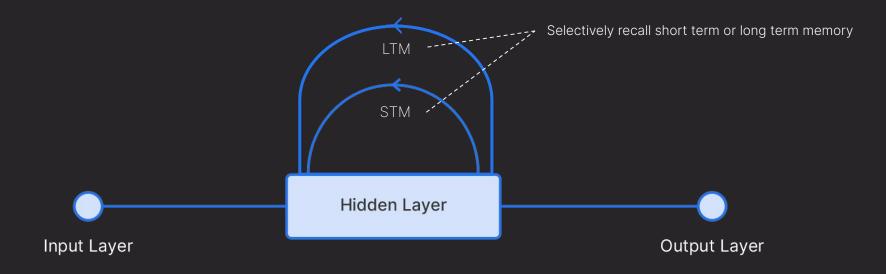
#### Introduction to LSTM



Structure of a Simple RNN

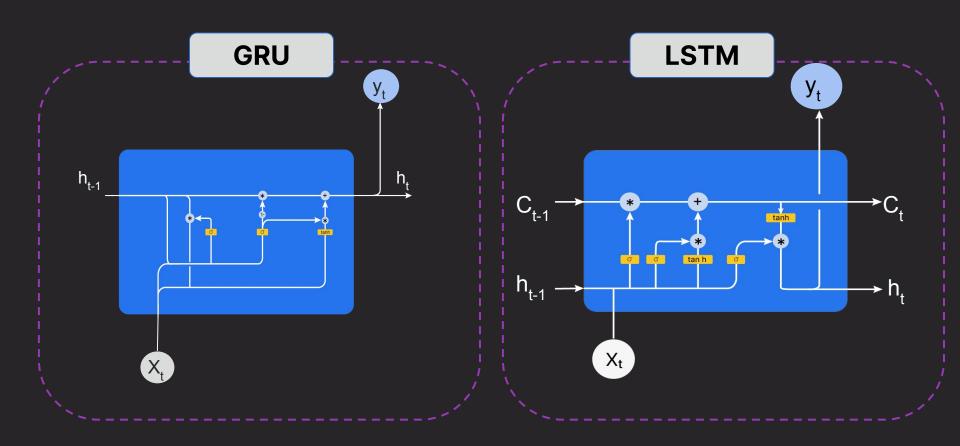


#### **Introduction to LSTM**

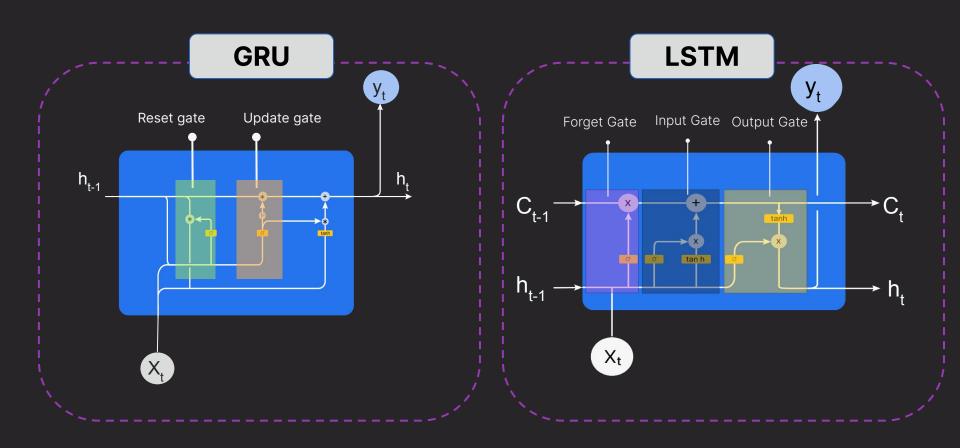


Structure of LSTM

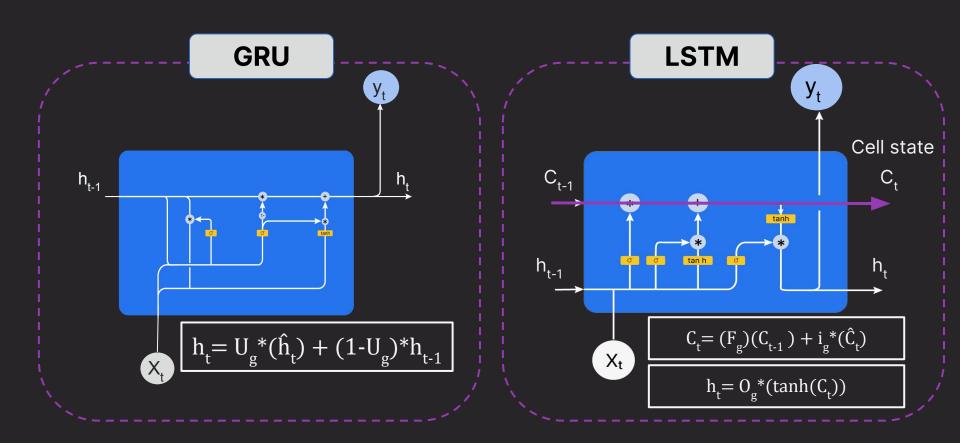






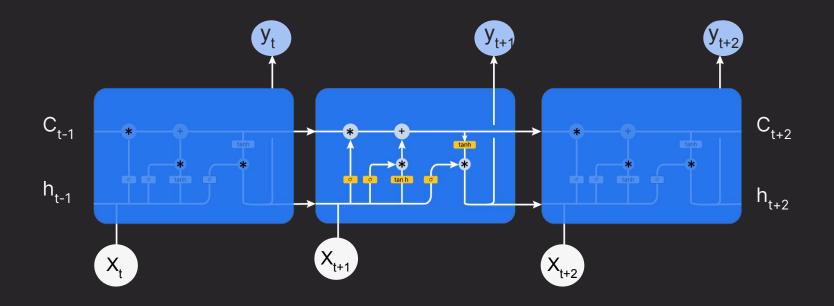






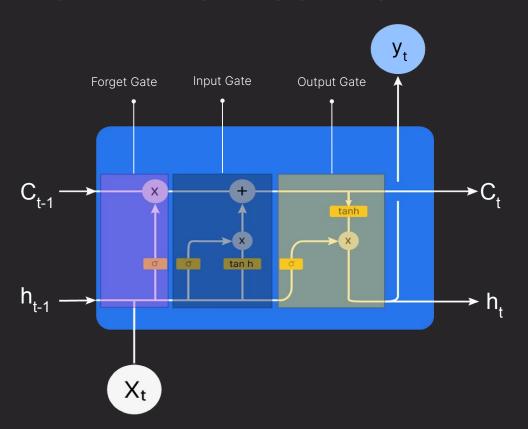


#### **LSTM Architecture**



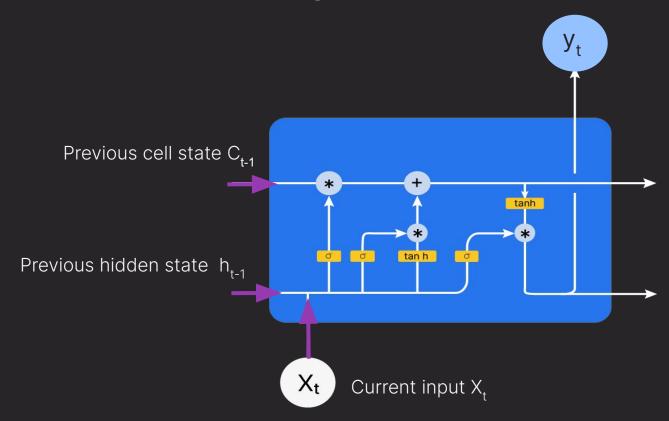


#### **LSTM Architecture**

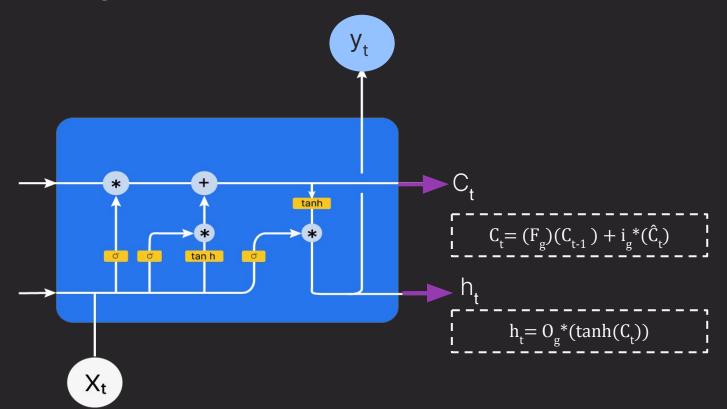


- **Forget Gate**: Decides informations to discard from the cell state
- Input Gate: Decides new information to add to the cell state.
- Output Gate: Determines the current time step's hidden state (h<sub>+</sub>).

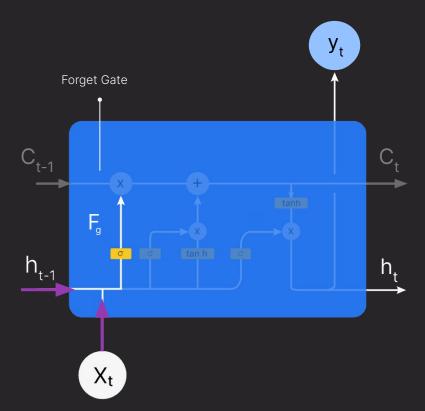






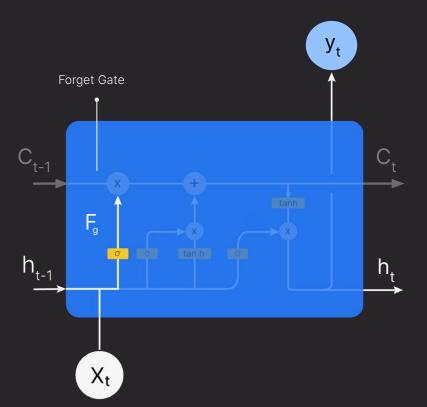






$$F_g = \sigma(W_f[X_t, h_{t-1}] + b_f)$$

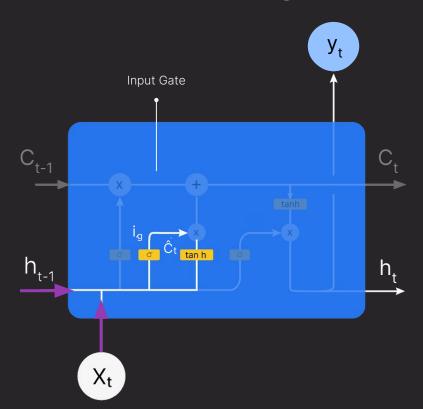




$$F_{g} = \sigma(W_{f}[X_{t}, h_{t-1}] + b_{f})$$

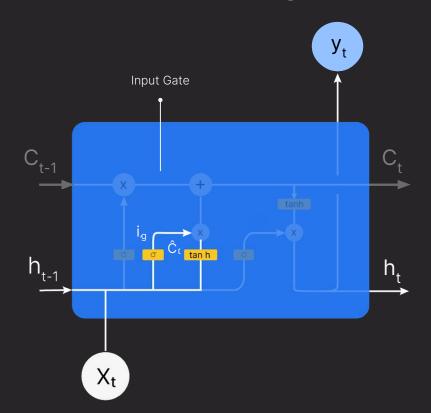
- Outputs → Between 0 and 1
- **0** → "Forget this completely"
- 1 → "Keep this entirely"

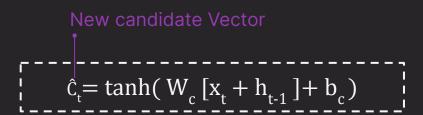




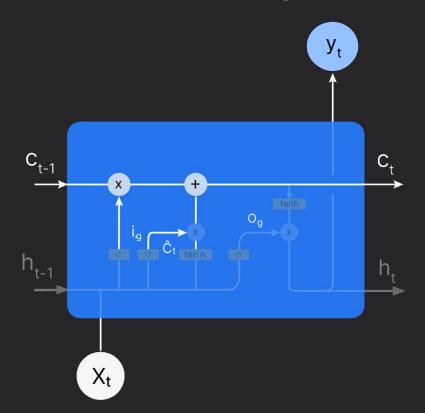
$$i_g = \sigma(W_i[x_t, h_{t-1}] + b_i)$$







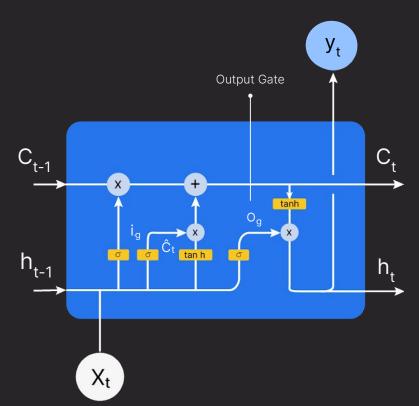




Update the cell state:

$$C_{t} = (F_{g})(C_{t-1}) + i_{g}^{*}(\hat{c}_{t})$$



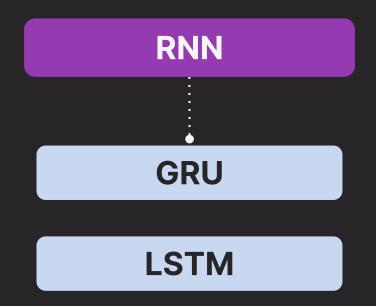


```
O_{g} = \sigma(W_{o}[X_{t}, h_{t-1}] + b_{o})
h_{t} = O_{g} * (tanh(C_{t}))
```

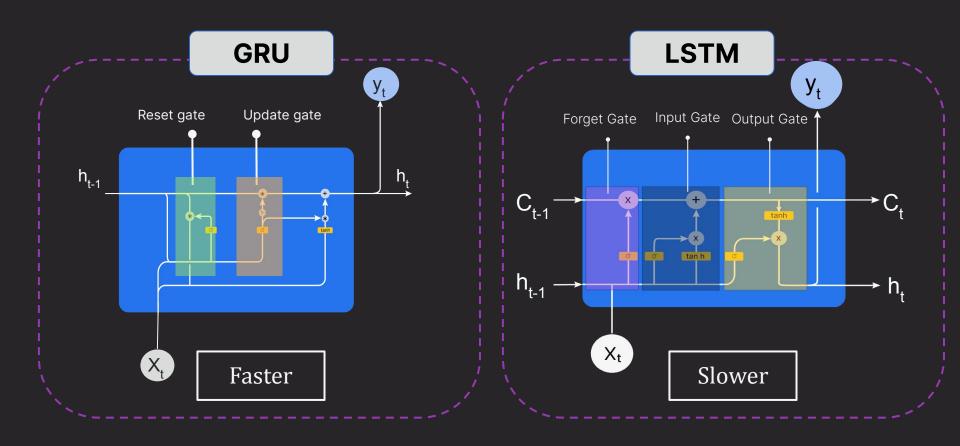


#### **Advanced RNN**











#### **Up Next:** LSTM in Jupyter