Neural Network and Deep Learning



Recurrent Neural Network

Sequential Data

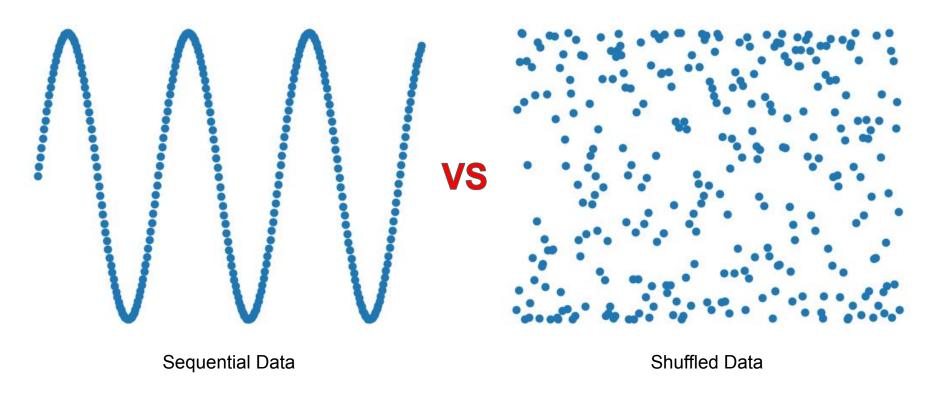
Sequential data refers to data where the order of the elements matters.

Time series data: Stock prices, temperature readings over time, where the order of the data points indicates the progression of time.

Natural language: Words or sentences, where the order determines the meaning (e.g., "The cat sat" is different from "Sat the cat").

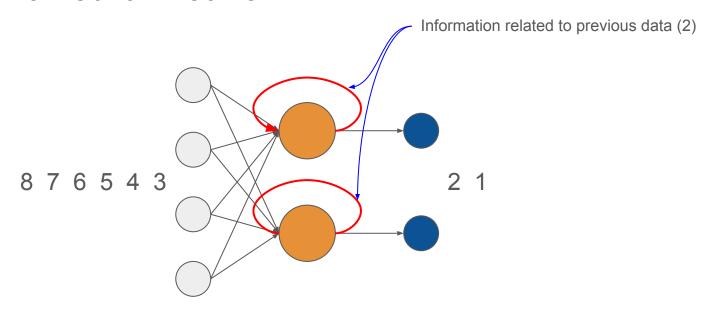
Video data: A series of frames, where each frame is connected to the previous and next to form a coherent motion.

Sequential Data

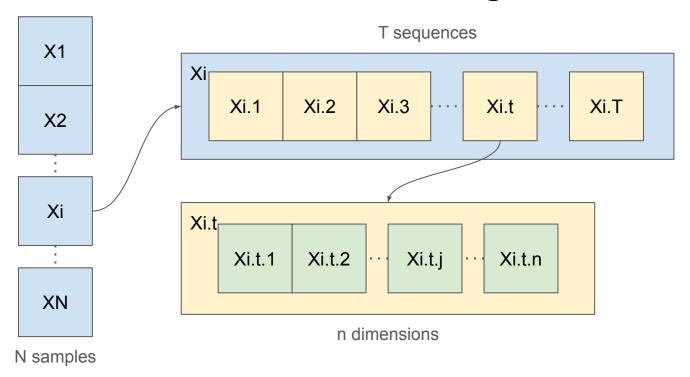


Recurrent Neural Network

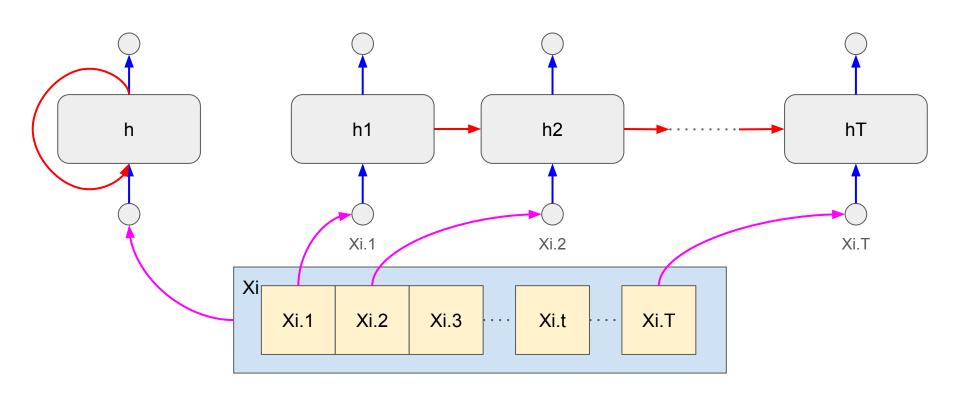
Recurrent Neural Network



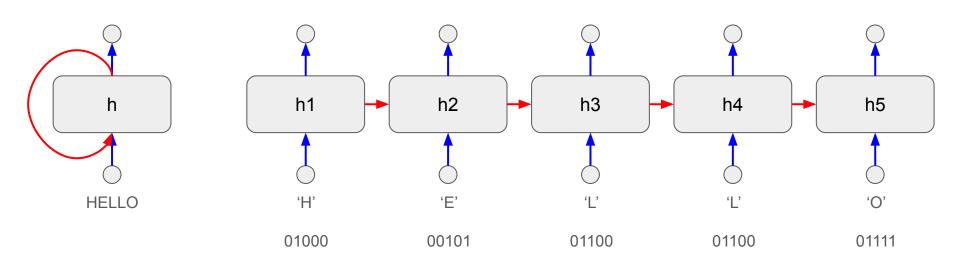
Recurrent Neural Network – Unfolding



Recurrent Neural Network – Unfolding

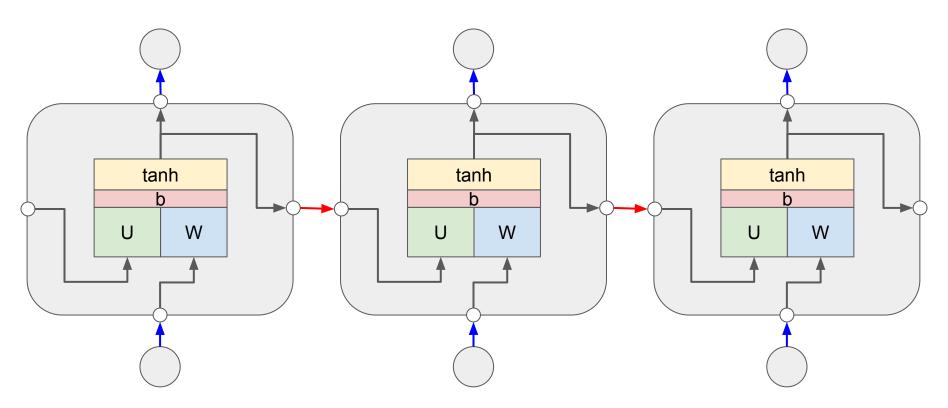


Recurrent Neural Network



Sequence length = 5 Dimension = 5

Recurrent Neural Network



Recurrent Neural Network – Example

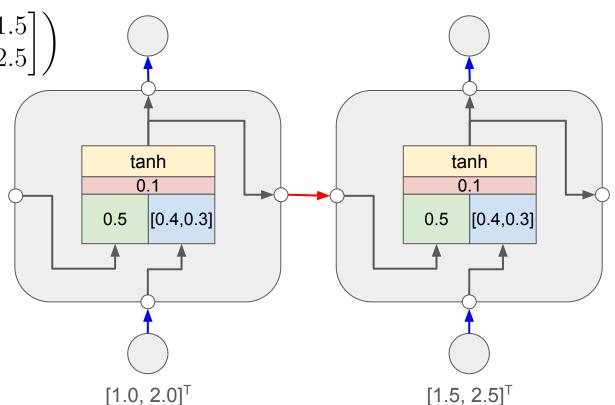
$$X = (x_1, x_2) = \left(\begin{bmatrix} 1.0 \\ 2.0 \end{bmatrix}, \begin{bmatrix} 1.5 \\ 2.5 \end{bmatrix}\right)$$

$$W = \begin{bmatrix} 0.4, 0.3 \end{bmatrix}$$

$$U = 0.5$$

$$b = 0.1$$

$$h_0 = 0$$



Recurrent Neural Network – Example

$$X = (x_1, x_2) = \begin{pmatrix} \begin{bmatrix} 1.0 \\ 2.0 \end{bmatrix}, \begin{bmatrix} 1.5 \\ 2.5 \end{bmatrix} \end{pmatrix}$$

$$W = \begin{bmatrix} 0.4, 0.3 \end{bmatrix} \qquad h_1 = \tanh(Uh_0 + Wx_1 + b)$$

$$U = 0.5 \qquad \qquad = \tanh(0.5 \cdot 0 + \begin{bmatrix} 0.4, 0.3 \end{bmatrix} \cdot \begin{bmatrix} 1.0, 2.0 \end{bmatrix}^{\top} + 0.1)$$

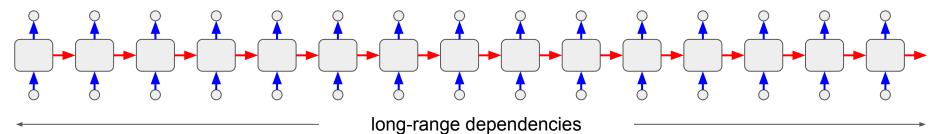
$$h_0 = 0 \qquad \qquad = \tanh(1.1) \approx 0.8005$$

$$h_2 = \tanh(Uh_1 + Wx_2 + b)$$

$$= \tanh(0.5 \cdot 0.8005 + [0.4, 0.3] \cdot [1.5, 2.5]^{\top} + 0.1)$$

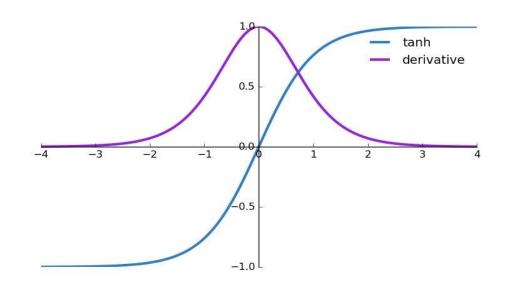
$$= \tanh(1.85) \approx 0.9516$$

Recurrent Neural Network – Disadvantage

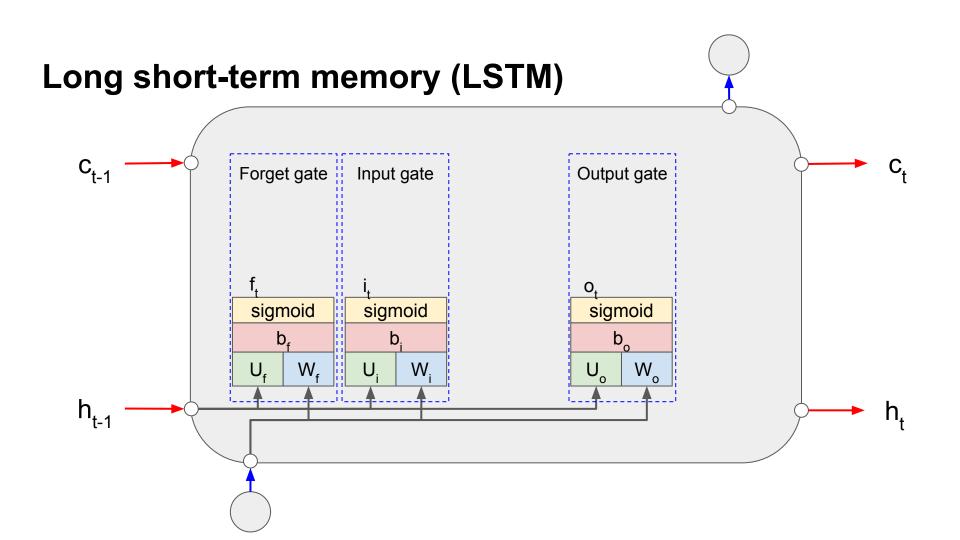


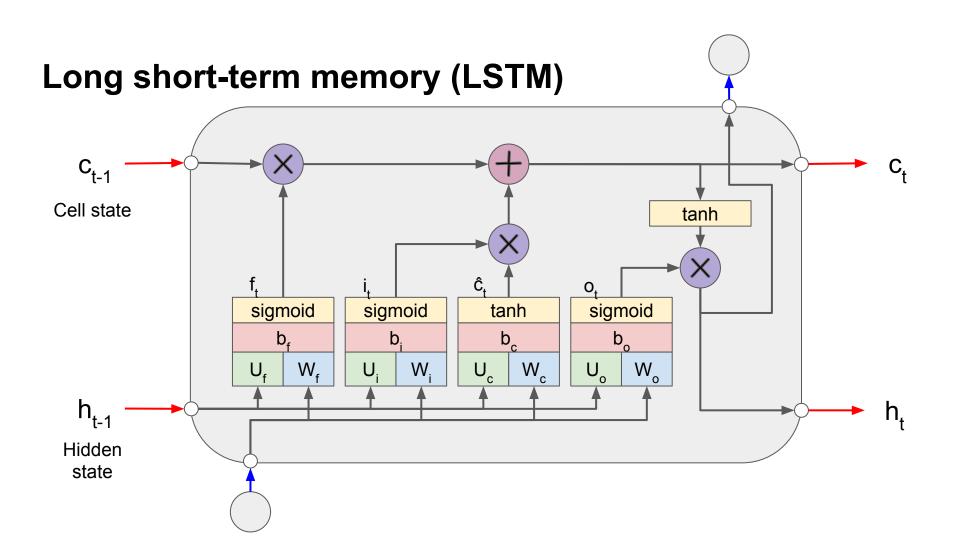
Definition: Long-range dependencies refer to relationships or patterns in data that span over many time steps.

The vanishing gradient problem is particularly pronounced in RNNs when dealing with long-range dependencies.



Long short-term memory (LSTM)





Long short-term memory (LSTM)

Forget gate: Determines which information from the previous cell state should be discarded to forget irrelevant data.

Input gate: Controls how much new information from the current input and previous hidden state is added to the cell state.

Output gate: Regulates what part of the cell state is output as the hidden state for the next time step.

Long short-term memory (LSTM)

$$\begin{split} f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) & \text{Forget gate} \\ i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) & \text{Input gate} \\ o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) & \text{Output gate} \\ \hat{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) & \text{Cell input node} \\ c_t &= f_t \odot c_{t-1} + i_t \odot \hat{c}_t & \text{Cell state} \\ h_t &= o_t \odot \tanh(c_t) & \text{Hidden state} \end{split}$$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0, \quad c_0 = 0$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$
 $W_o = [0.6, 0.9], \quad U_o = [0.4]$
 $W_c = [0.5, 0.8], \quad U_c = [0.3]$
 $b_f = 0.1, \quad b_i = 0.2$
 $b_o = 0.3, \quad b_c = 0.0$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0, \quad c_0 = 0$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$
 $W_o = [0.6, 0.9], \quad U_o = [0.4]$
 $W_c = [0.5, 0.8], \quad U_c = [0.3]$
 $b_f = 0.1, \quad b_i = 0.2$
 $b_o = 0.3, \quad b_c = 0.0$

$$f_1 = \sigma(W_f x_1 + U_f h_0 + b_f)$$

$$= \sigma([0.2, 0.4] \cdot [0.1, 0.2] + 0.5 \cdot 0 + 0.1)$$

$$= \sigma(0.02 + 0.08 + 0.1)$$

$$= \sigma(0.2)$$

$$f_1 \approx 0.55$$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0, \quad c_0 = 0$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$
 $W_o = [0.6, 0.9], \quad U_o = [0.4]$
 $W_c = [0.5, 0.8], \quad U_c = [0.3]$
 $b_f = 0.1, \quad b_i = 0.2$
 $b_o = 0.3, \quad b_c = 0.0$

$$i_1 = \sigma(W_i x_1 + U_i h_0 + b_i)$$

$$= \sigma([0.3, 0.7] \cdot [0.1, 0.2] + 0.6 \cdot 0 + 0.2)$$

$$= \sigma(0.03 + 0.14 + 0.2)$$

$$= \sigma(0.37)$$

$$i_1 \approx 0.59$$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0, \quad c_0 = 0$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$
 $W_o = [0.6, 0.9], \quad U_o = [0.4]$
 $W_c = [0.5, 0.8], \quad U_c = [0.3]$
 $b_f = 0.1, \quad b_i = 0.2$
 $b_o = 0.3, \quad b_c = 0.0$

$$o_1 = \sigma(W_o x_1 + U_o h_0 + b_o)$$

$$= \sigma([0.6, 0.9] \cdot [0.1, 0.2] + 0.4 \cdot 0 + 0.3)$$

$$= \sigma(0.06 + 0.18 + 0.3)$$

$$= \sigma(0.54)$$

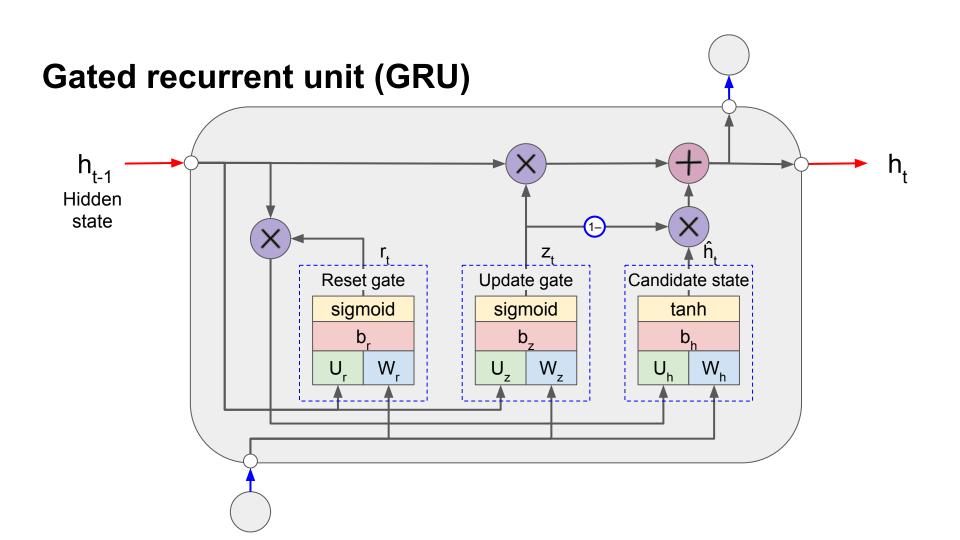
$$o_1 \approx 0.63$$

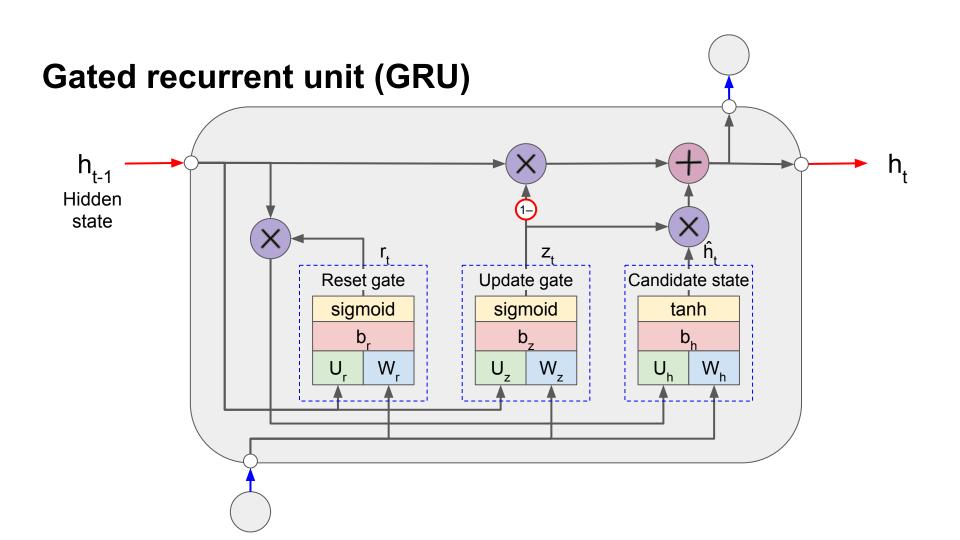
$$x_1 = [0.1, 0.2]$$
 $h_0 = 0, \quad c_0 = 0$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$
 $W_o = [0.6, 0.9], \quad U_o = [0.4]$
 $W_c = [0.5, 0.8], \quad U_c = [0.3]$
 $b_f = 0.1, \quad b_i = 0.2$
 $b_o = 0.3, \quad b_c = 0.0$

$$\hat{c}_1 = \tanh(W_c x_1 + U_c h_0 + b_c)
= \tanh([0.5, 0.8] \cdot [0.1, 0.2] + 0.3 \cdot 0 + 0.0)
= \tanh(0.05 + 0.16)
= \tanh(0.21)
\hat{c}_1 \approx 0.21$$

$$x_1 = [0.1, 0.2]$$
 $c_1 = f_1 \odot c_0 + i_1 \odot \hat{c}_1$
 $h_0 = 0, \quad c_0 = 0$ $= 0.55 \odot 0 + 0.59 \odot 0.21$
 $W_f = [0.2, 0.4], \quad U_f = [0.5]$ $c_1 \approx 0.12$
 $W_i = [0.3, 0.7], \quad U_i = [0.6]$ $h_1 = o_1 \odot \tanh(c_1)$
 $w_o = [0.63 \odot \tanh(0.12))$
 $w_c = [0.5, 0.8], \quad U_c = [0.3]$ $h_1 \approx 0.076$
 $b_f = 0.1, \quad b_i = 0.2$ $h_1 \approx 0.076$

Gated recurrent unit (GRU)





Gated recurrent unit (GRU)

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$

$$\hat{h}_t = \phi(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$$

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

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

Update gate

Reset gate

Candidate state

Hidden state

```
x_1 = [0.1, 0.2]
 h_0 = 0
W_r = [0.2, 0.4], \quad U_r = [0.5]
W_z = [0.3, 0.7], \quad U_z = [0.6]
W_h = [0.6, 0.9], \quad U_h = [0.4]
 b_r = 0.1, \quad b_z = 0.2
 b_h = 0.3
```

$$x_1 = [0.1, 0.2]$$
 $r_1 = \sigma(W_r \cdot x_1 + U_r \cdot h_0 + b_r)$
 $h_0 = 0$ $= \sigma([0.2, 0.4] \cdot [0.1, 0.2] + 0.5 \cdot 0 + 0.1)$
 $W_r = [0.2, 0.4], \quad U_r = [0.5]$ $= \sigma(0.02 + 0.08 + 0.1)$
 $W_z = [0.3, 0.7], \quad U_z = [0.6]$ $r_1 \approx 0.55$
 $W_h = [0.6, 0.9], \quad U_h = [0.4]$
 $b_r = 0.1, \quad b_z = 0.2$
 $b_h = 0.3$

$$x_{1} = [0.1, 0.2]$$

$$b_{0} = 0$$

$$W_{r} = [0.2, 0.4], \quad U_{r} = [0.5]$$

$$W_{z} = [0.3, 0.7], \quad U_{z} = [0.6]$$

$$W_{h} = [0.6, 0.9], \quad U_{h} = [0.4]$$

$$b_{r} = 0.1, \quad b_{z} = 0.2$$

$$b_{h} = 0.3$$

$$z_{1} = \sigma(W_{z} \cdot x_{1} + U_{z} \cdot h_{0} + b_{z})$$

$$= \sigma([0.3, 0.7] \cdot [0.1, 0.2] + 0.6 \cdot 0 + 0.2)$$

$$= \sigma(0.03 + 0.14 + 0.2)$$

$$z_{1} = 0.59$$

$$x_{1} = [0.1, 0.2]$$

$$h_{0} = 0$$

$$W_{r} = [0.2, 0.4], \quad U_{r} = [0.5]$$

$$W_{z} = [0.3, 0.7], \quad U_{z} = [0.6]$$

$$W_{h} = [0.6, 0.9], \quad U_{h} = [0.4]$$

$$b_{r} = 0.1, \quad b_{z} = 0.2$$

$$h_{1} = \tanh(W_{h} \cdot x_{1} + U_{h} \cdot (r_{1} \odot h_{0}) + b_{h})$$

$$= \tanh([0.6, 0.9] \cdot [0.1, 0.2]$$

$$+ 0.4 \cdot (0.5498 \odot 0) + 0.3)$$

$$= \tanh(0.06 + 0.18 + 0.3)$$

$$\hat{h}_{1} \approx 0.49$$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0$
 $W_r = [0.2, 0.4], \quad U_r = [0.5]$
 $W_z = [0.3, 0.7], \quad U_z = [0.6]$
 $W_h = [0.6, 0.9], \quad U_h = [0.4]$
 $b_r = 0.1, \quad b_z = 0.2$
 $b_h = 0.3$

$$h_1 = z_1 \odot h_0 + (1 - z_1) \odot \hat{h}_1$$

$$= 0.5914 \odot 0 + (1 - 0.5914) \odot 0.4910$$

$$= 0 + (1 - 0.5914) \odot 0.4910$$

$$h_1 \approx 0.20$$

$$x_1 = [0.1, 0.2]$$
 $h_0 = 0$
 $W_r = [0.2, 0.4], \quad U_r = [0.5]$
 $W_z = [0.3, 0.7], \quad U_z = [0.6]$
 $W_h = [0.6, 0.9], \quad U_h = [0.4]$
 $b_r = 0.1, \quad b_z = 0.2$
 $b_h = 0.3$

$$h_1 = (1 - z_1) \odot h_0 + z_1 \odot \hat{h}_1$$

$$= (1 - 0.5914) \odot 0 + 0.5914 \odot 0.4910$$

$$= 0 + 0.5914 \odot 0.4910$$

$$h_1 \approx 0.29$$

Hands On

Compute the **RNN** cell manually using the equations provided, with **2-dimensional input x for 3 time-step**

$$X = (x_1, x_2, x_3) = \left(\begin{bmatrix} -1.0 \\ 1.0 \end{bmatrix}, \begin{bmatrix} 1.0 \\ -1.0 \end{bmatrix}, \begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}\right)$$

$$W = \begin{bmatrix} 0.4, 0.3 \end{bmatrix}$$

$$U = 0.5$$

$$b = 0.1$$

$$h_0 = 0$$

Hands On

Compute the **LSTM** cell manually using the equations provided, with **2-dimensional input x for 2 time-step**

$$X = (x_1, x_2) = \begin{pmatrix} \begin{bmatrix} -1.0 \\ 1.0 \end{bmatrix}, \begin{bmatrix} 1.0 \\ -1.0 \end{bmatrix}, \\ h_0 = 0, \quad c_0 = 0 \\ W_f = \begin{bmatrix} 0.2, 0.4 \end{bmatrix}, \quad U_f = \begin{bmatrix} 0.5 \end{bmatrix} \\ W_i = \begin{bmatrix} 0.3, 0.7 \end{bmatrix}, \quad U_i = \begin{bmatrix} 0.6 \end{bmatrix} \\ W_o = \begin{bmatrix} 0.6, 0.9 \end{bmatrix}, \quad U_o = \begin{bmatrix} 0.4 \end{bmatrix} \\ W_c = \begin{bmatrix} 0.5, 0.8 \end{bmatrix}, \quad U_c = \begin{bmatrix} 0.3 \end{bmatrix} \\ b_f = 0.1, \quad b_i = 0.2 \\ b_o = 0.3, \quad b_c = 0.0$$

Hands On

Compute the **GRU** cell manually using the equations provided, with **2-dimensional input x for 2 time-step**

$$X = (x_1, x_2) = \begin{pmatrix} \begin{bmatrix} -1.0 \\ 1.0 \end{bmatrix}, \begin{bmatrix} 1.0 \\ -1.0 \end{bmatrix}, \end{pmatrix}$$

$$h_0 = 0$$

$$W_r = [0.2, 0.4], \quad U_r = [0.5]$$

$$W_z = [0.3, 0.7], \quad U_z = [0.6]$$

$$W_h = [0.6, 0.9], \quad U_h = [0.4]$$

$$b_r = 0.1, \quad b_z = 0.2$$

$$b_h = 0.3$$