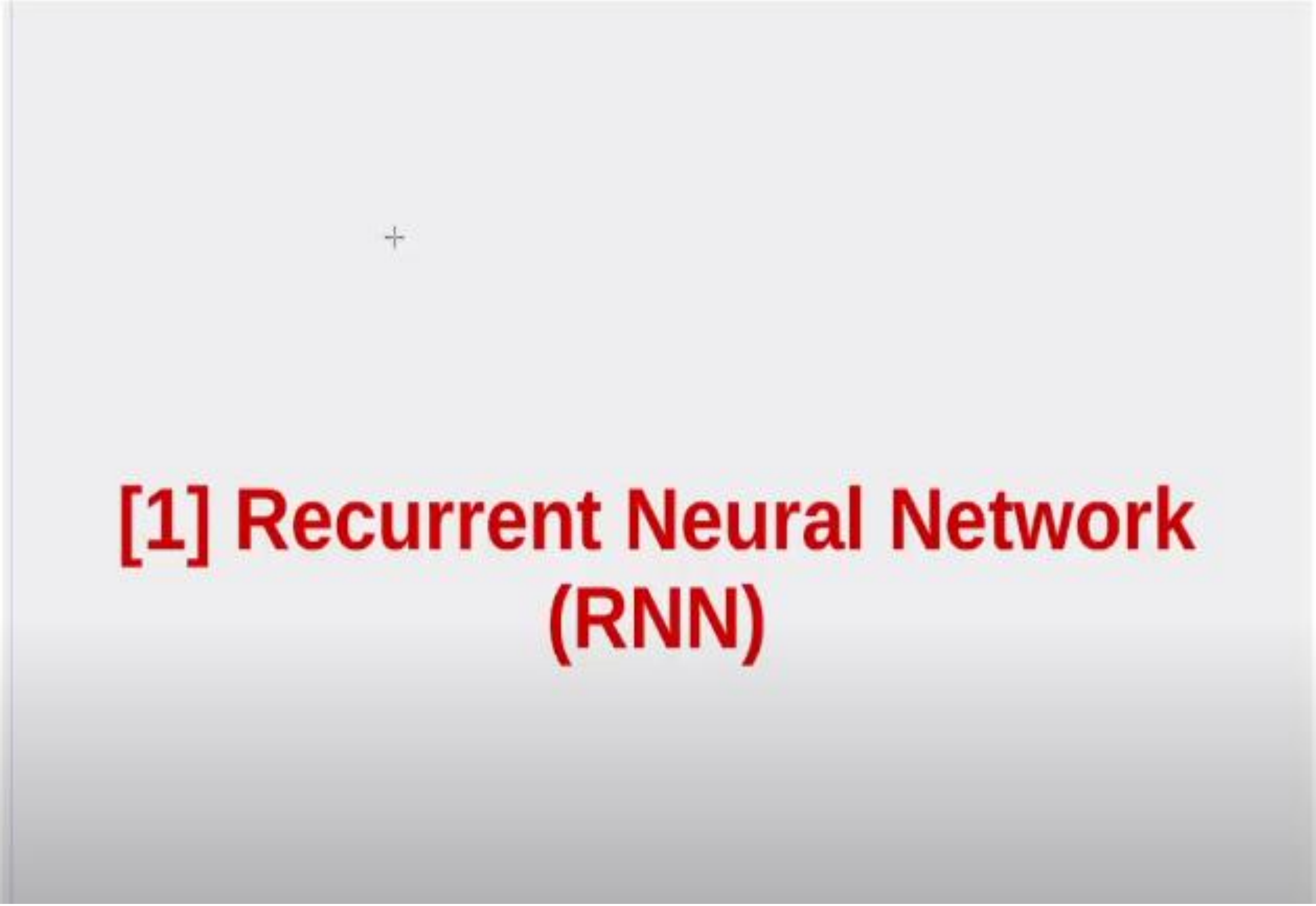


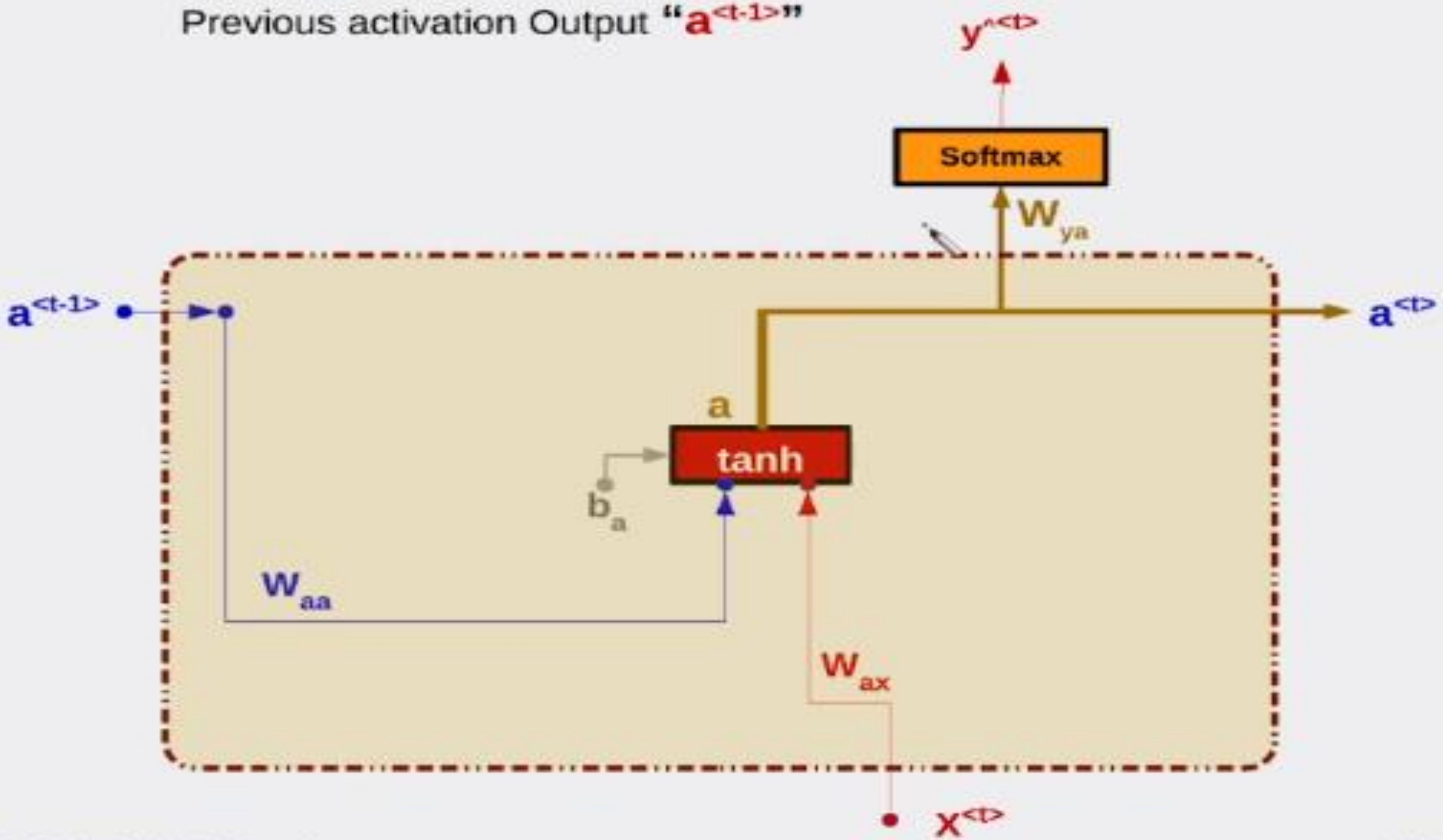
[1] Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN)

Output of Activation Function at time t; "$a^{<t>}$" depends on BOTH:-

Input "$X^{<t>}$" and

Previous activation Output "$a^{<t-1>}$"



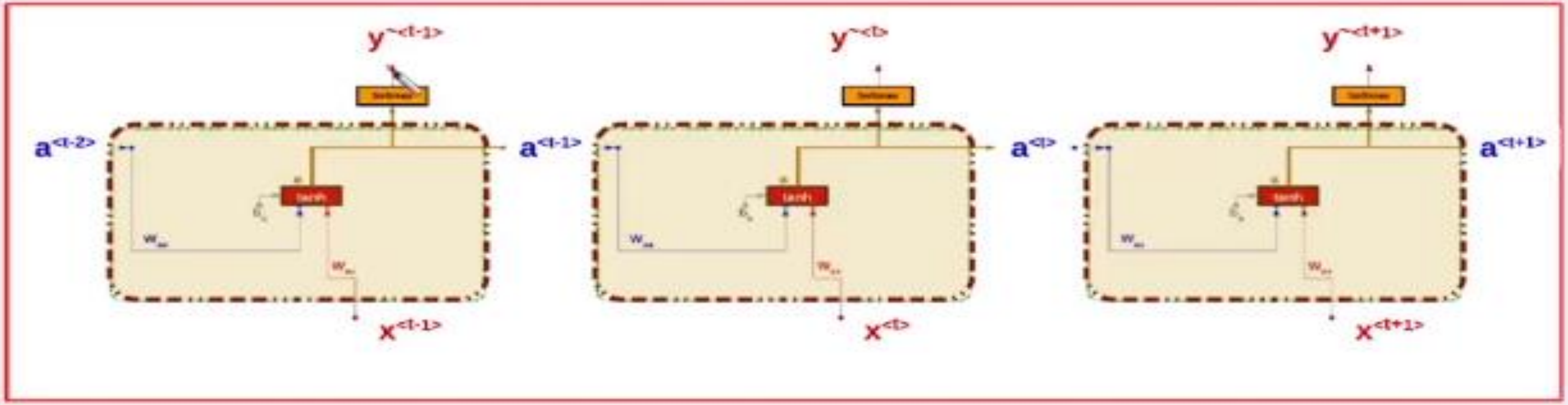
Recurrent Neural Network (RNN)

Output of Activation Function at time t; **“$a^{<t>}$”** depends on BOTH:-

Input **“$X^{<t>}$”** and

Previous activation Output **“$a^{<t-1>}$”**

Inputs at time t-1 , t , t+1

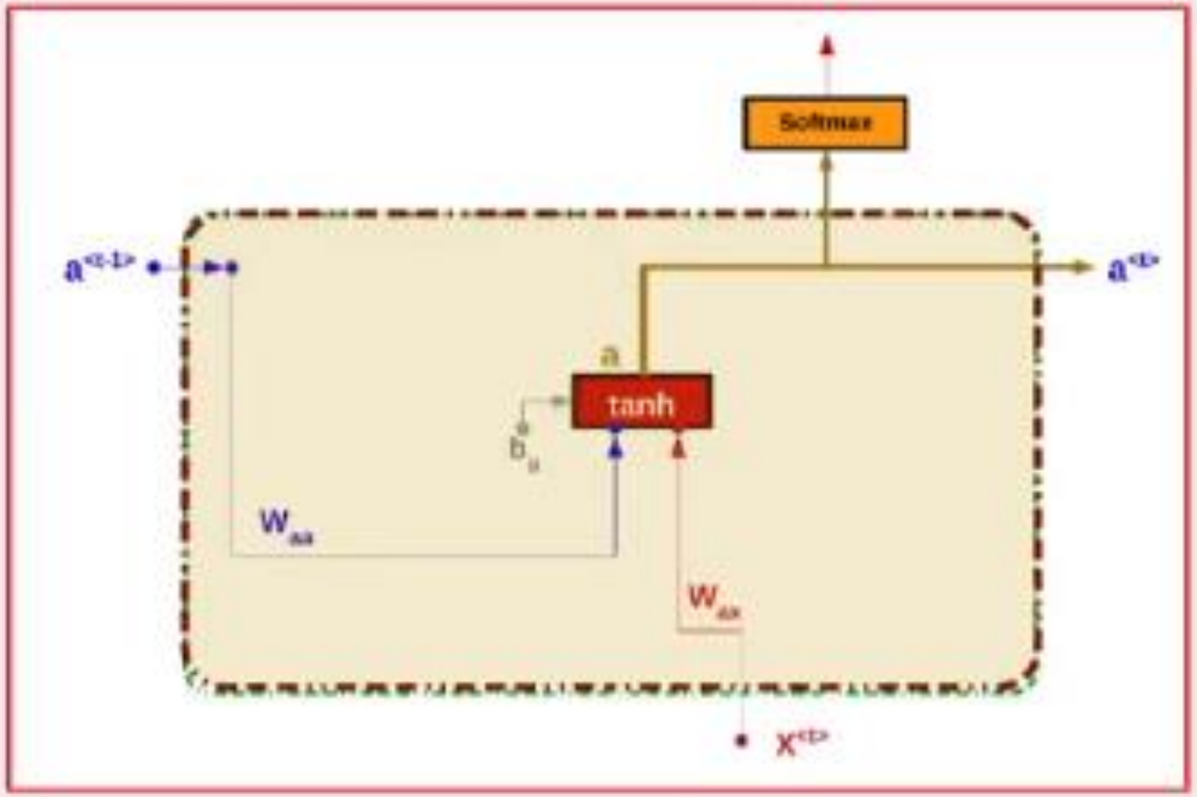


Recurrent Neural Network (RNN)

$$a^{<1>} = F^n\,(\overbrace{W_{aa}a^{<0>}}^{\text{From Prev.}} + \overbrace{W_{ax}x^{<1>}}^{\text{Current I/P}} + b_a)$$

$$y^{\wedge<1>} = F^n\,(W_{ya}\,a^{<1>} + b_y)$$

Non Linearity

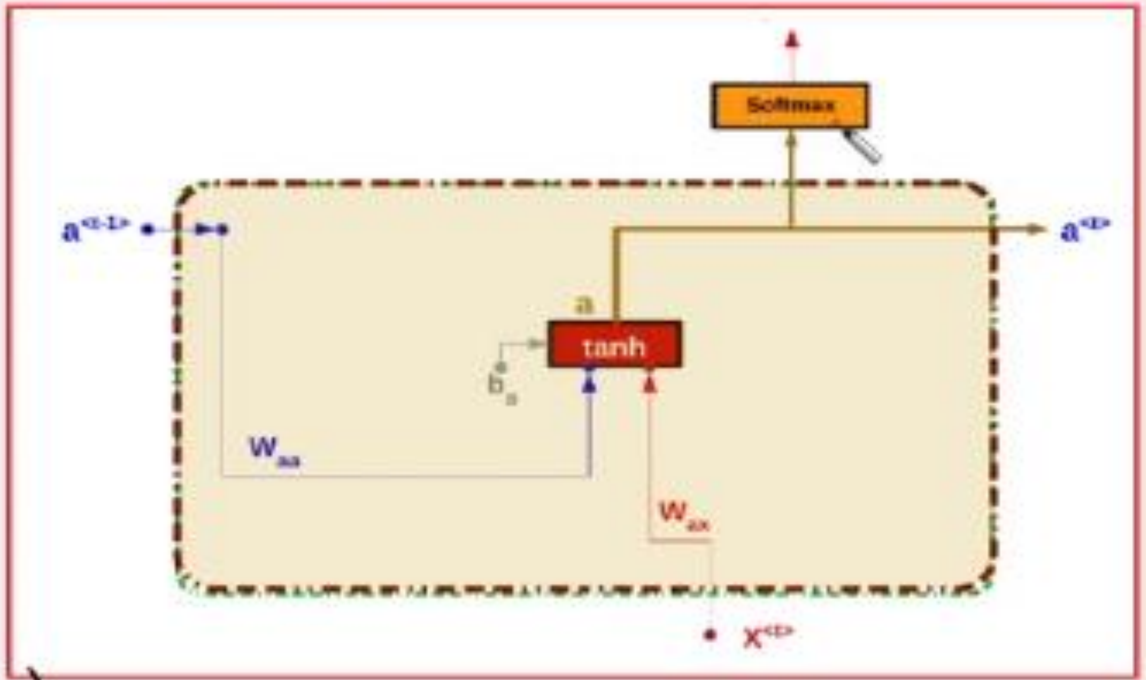


Recurrent Neural Network (RNN)

$$a^{<1>} = F^n\,(\overbrace{W_{aa}a^{<0>}}^{\text{From Prev.}} + \overbrace{W_{ax}x^{<1>}}^{\text{Current I/P}} + b_a)$$

$$y^{\wedge<1>} = F^n\,(W_{ya}\,a^{<1>} + b_y)$$

Non Linearity



$$a^{<1>} = \textbf{tanh}\,(W_{aa}a^{<0>} + W_{ax}x^{<1>} + b_a)$$ May be tanh, ReLU, ...

$$y^{\wedge<1>} = \textbf{Softmax}\,(W_{ya}\,a^{<1>} + b_y)$$ Segmoid for Binary O/P, Softmax for Multi-Class O/P

$$a^{<t>} = \textbf{tanh}\,(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)$$ May be tanh, ReLU, ...

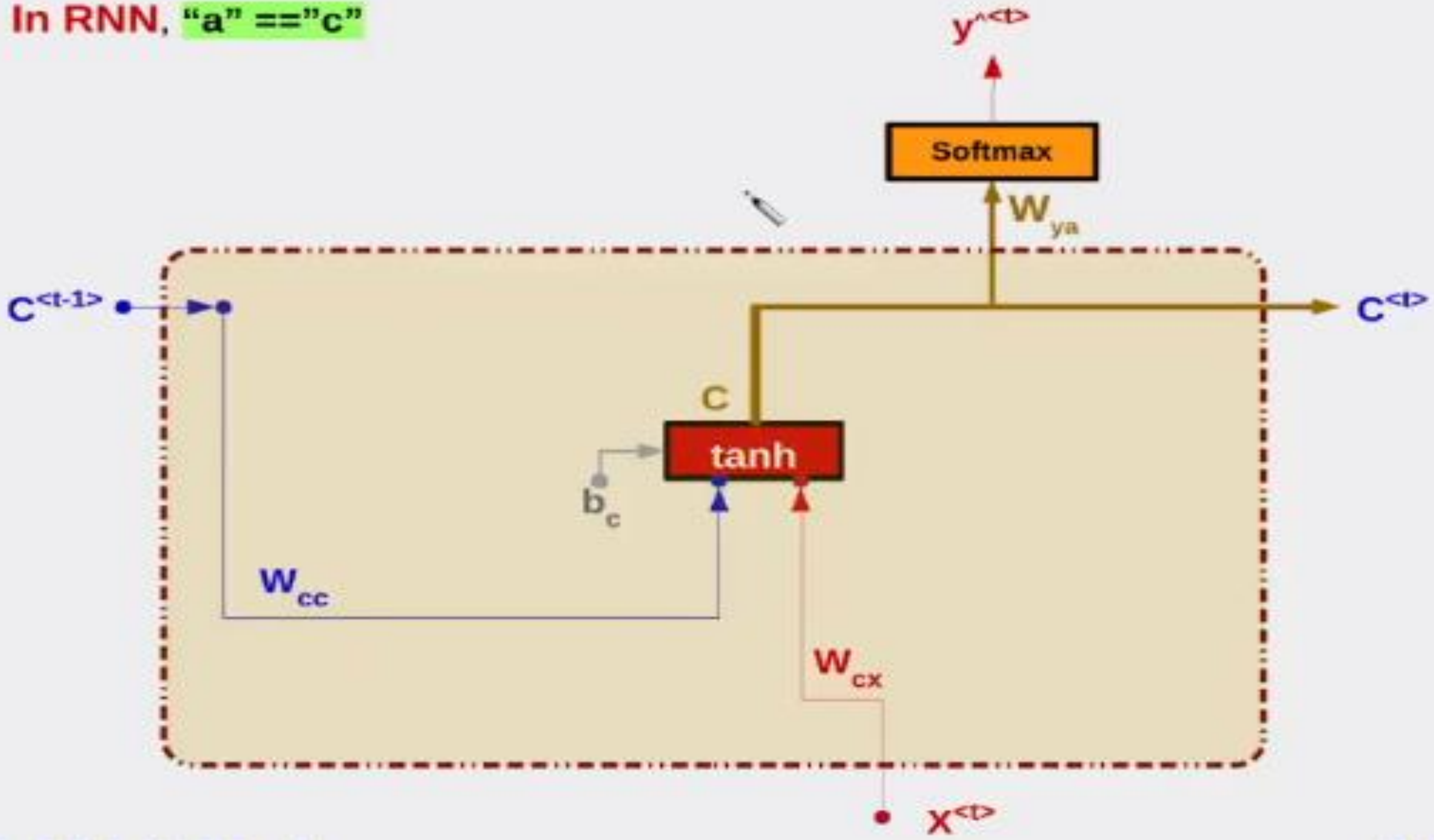
$$y^{\wedge<t>} = \textbf{Softmax}\,(W_{ya}\,a^{<t>} + b_y)$$ Segmoid for Binary O/P, Softmax for Multi-Class O/P

[2] Gated Recurrent Unit (GRU)

From RNN to GRU

Define **Memory** Cell "**C**" in addition to Output of **Activation** function "**a**".

In RNN, **"a" ==”c”**



From RNN to GRU

[1] Adding Update Gate G_u

Value of CURRENT Memory Cell $C^{<t>}$=

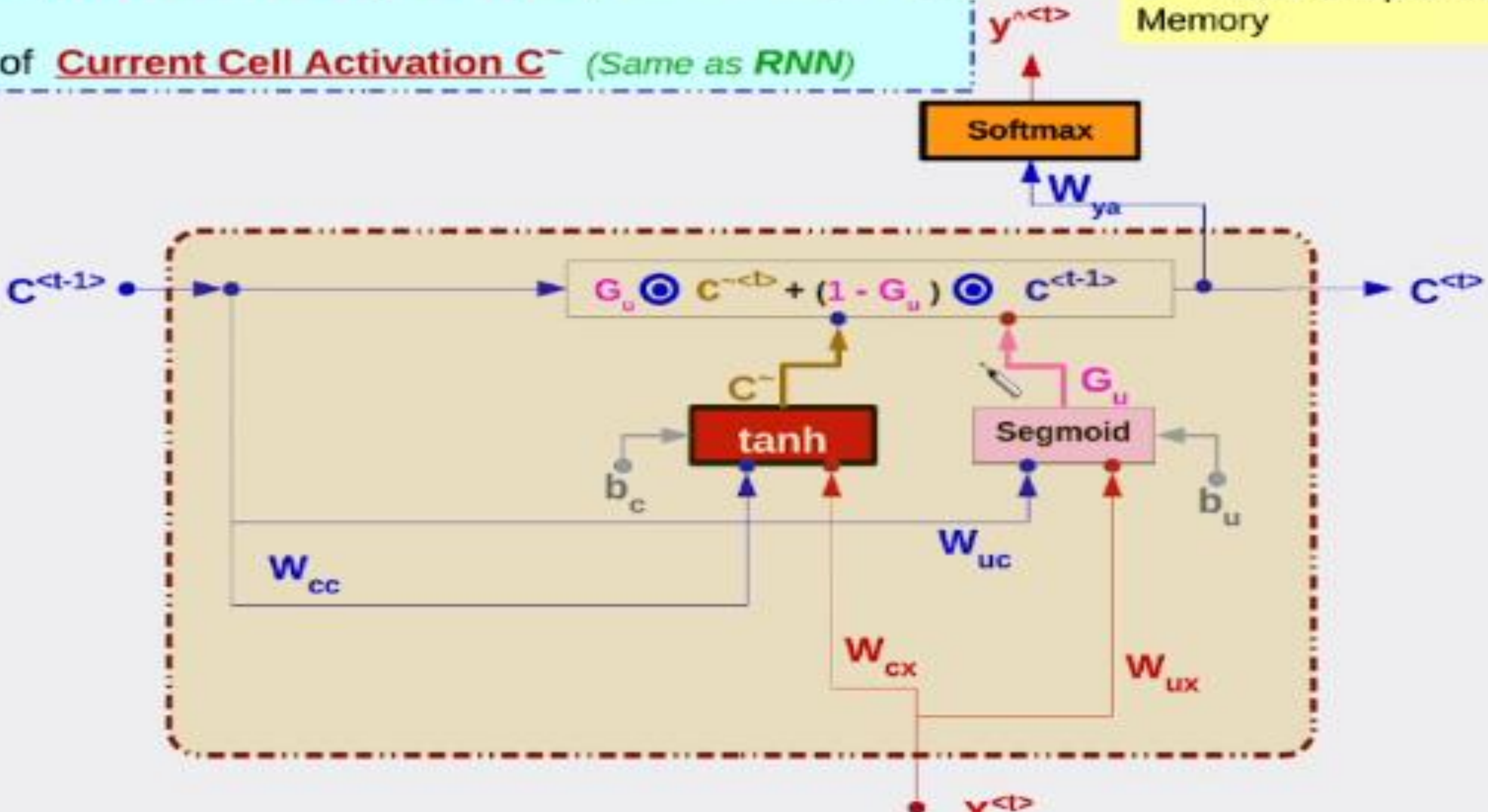
Percentage of Previous Memory Cell $C^{<t-1>}$ *(Not Affected by $X^{<t>}$)*

+

Percentage of Current Cell Activation $C^{\sim}$ *(Same as **RNN**)*

$C^{\sim}$ Candidate Value of Updated Memory

C Value of Updated Memory



From RNN to GRU

[1] Adding Update Gate G_u

Value of G_u is based on:

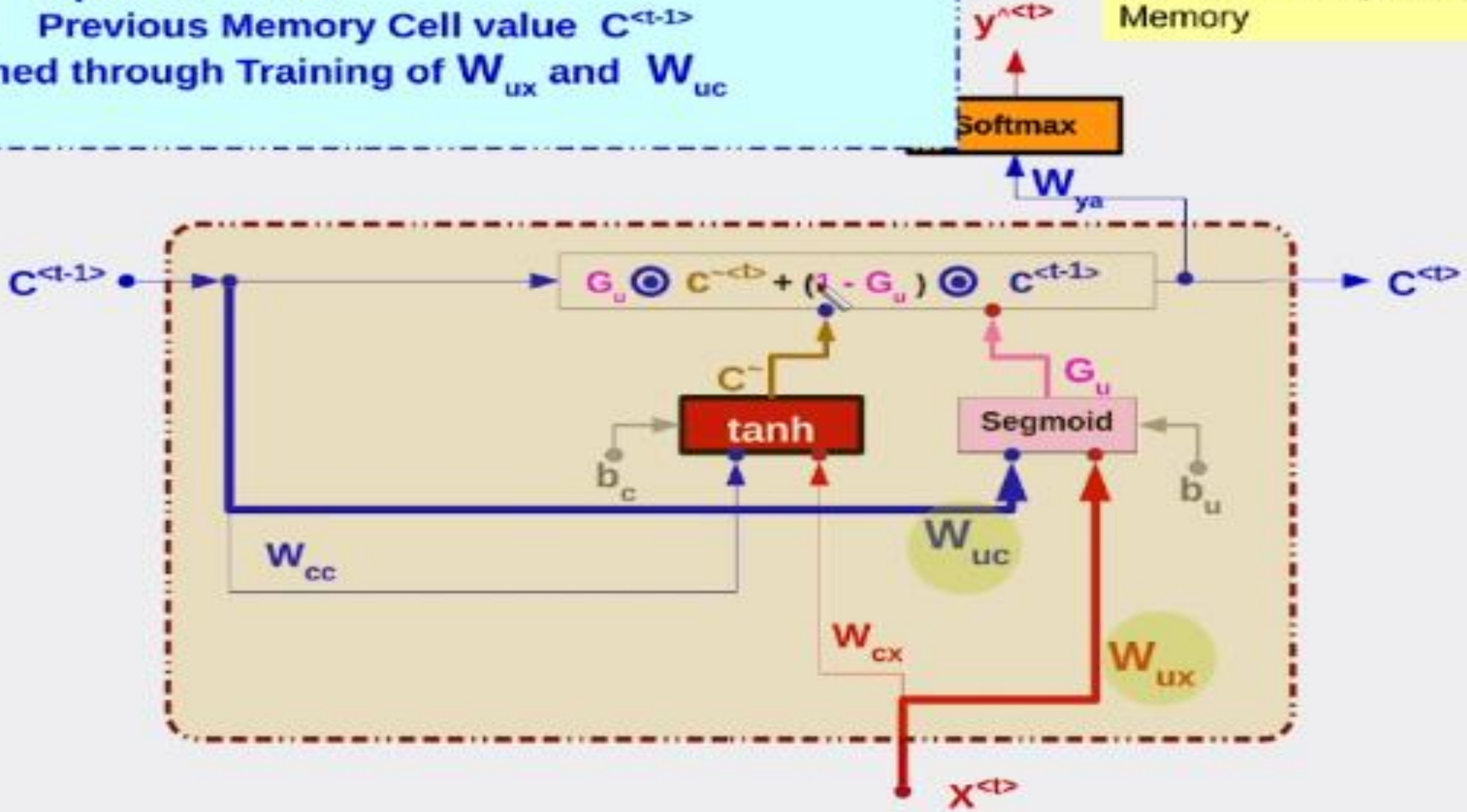
Input $X^{<t>}$ and

Previous Memory Cell value $C^{<t-1>}$

G_u is obtained through Training of W_{ux} and W_{uc}

$C^{\sim}$ Candidate Value of Updated Memory

C Value of Updated Memory



From RNN to GRU

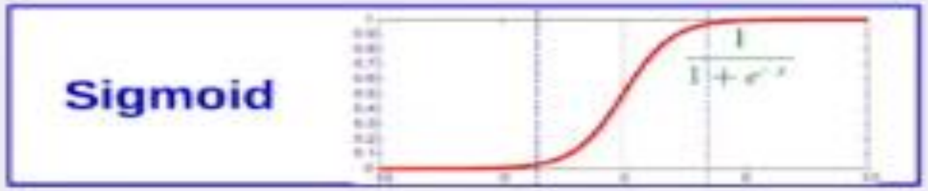
[1] Adding Update Gate G_u

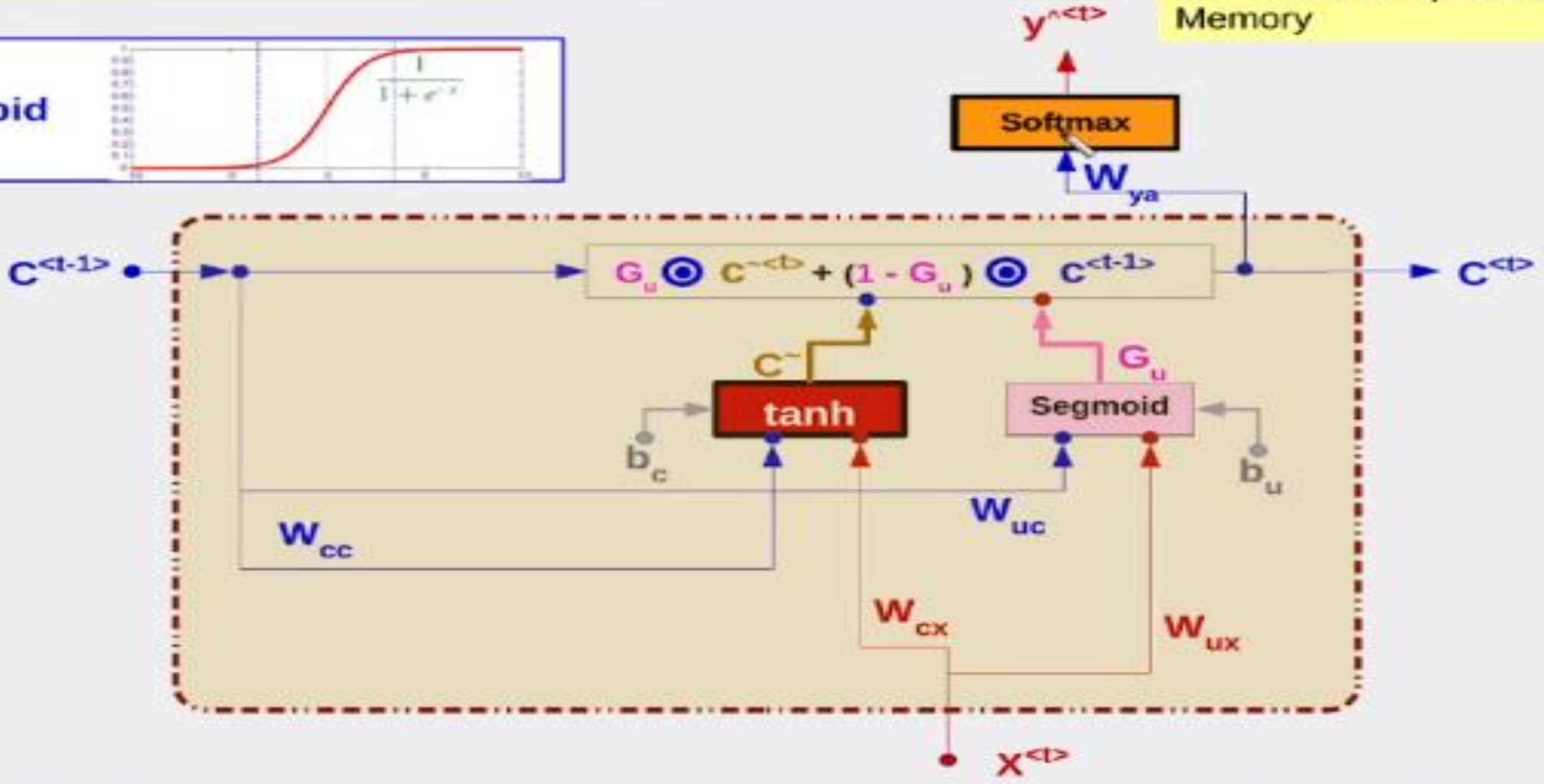
If G_u = 0 , **Keep** Memory Value "$C^{<t>}$" **Same as** Previous Value "$C^{<t-1>}$"

If G_u = 1 , **Forget** Previous Memory Value "$C^{<t-1>}$"

$C^{\sim}$ Candidate Value of Updated Memory

C Value of Updated Memory





From RNN to GRU

$G_u = \textbf{Sigmoid}\,(W_{uc}c^{<t-1>} + W_{ux}x^{<t>} + b_u)$

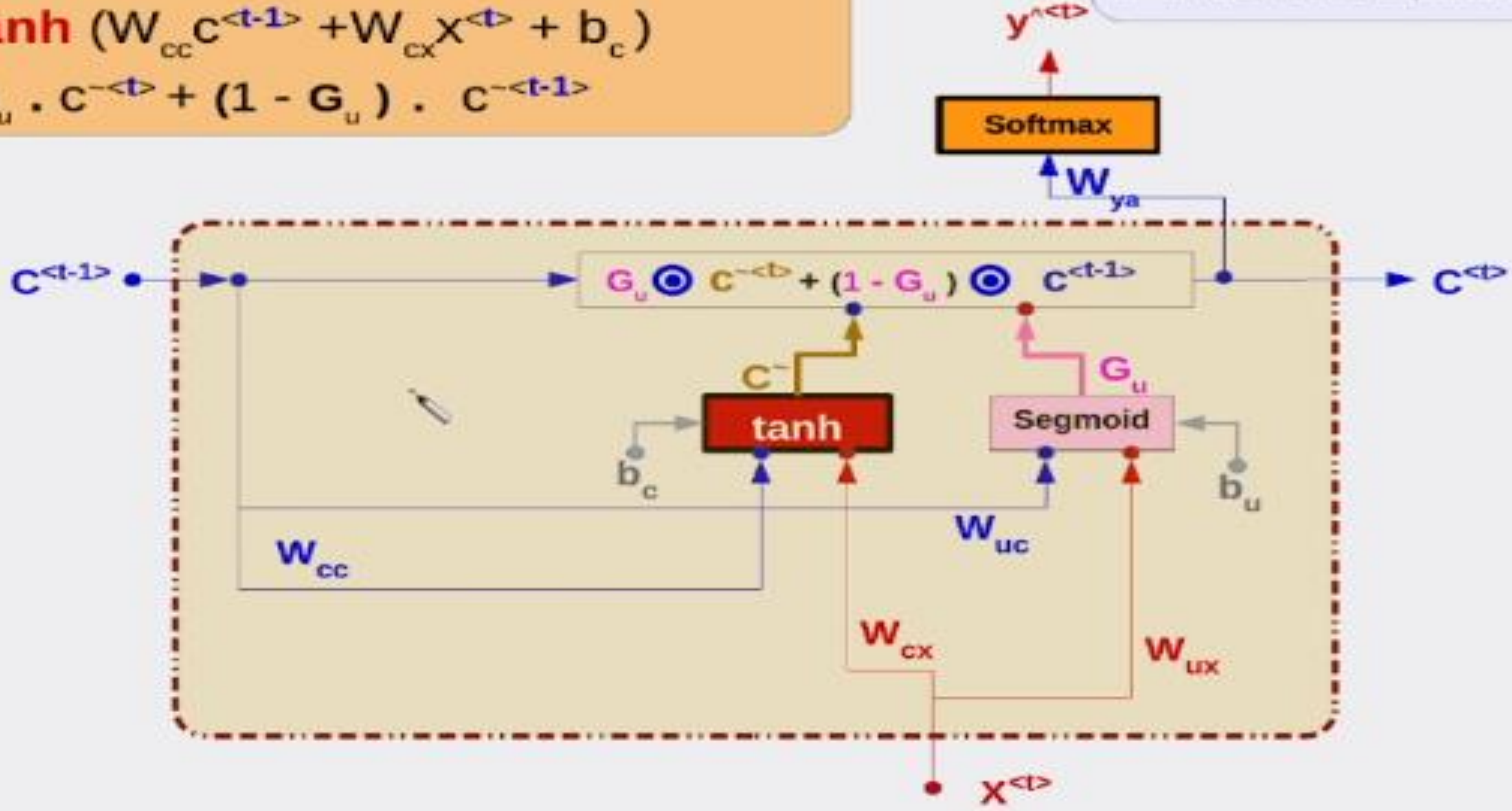
$c^{\sim<t>} = \textbf{tanh}\,(W_{cc}c^{<t-1>} + W_{cx}x^{<t>} + b_c)$

$c^{<t>} = G_u \,.\, c^{\sim<t>} + (1 - G_u) \,.\, c^{\sim<t-1>}$

$C^{\sim}$ is the Candidate Update

G_u is the Update Gate

C is the Actual Update

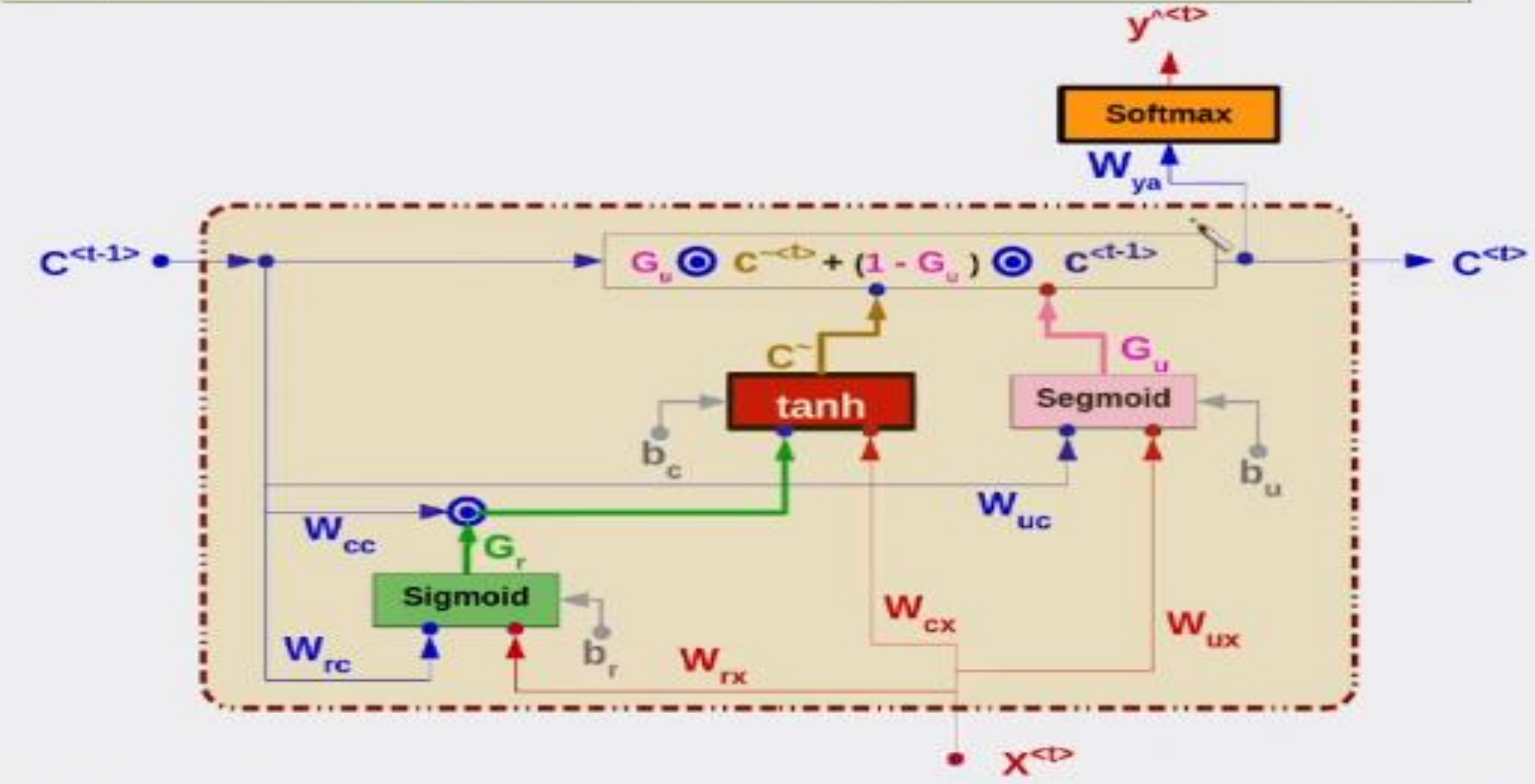


From RNN to GRU

[2] Adding Relevance Gate G_r

If $G_r = 1$, $C^{<t-1>}$ is Relevant to update Candidate Memory cell value “$C^{\sim}$

If $G_r = 0$, $C^{<t-1>}$ is IrRelevant to update Candidate Memory cell value “$C^{\sim}$



From RNN to GRU

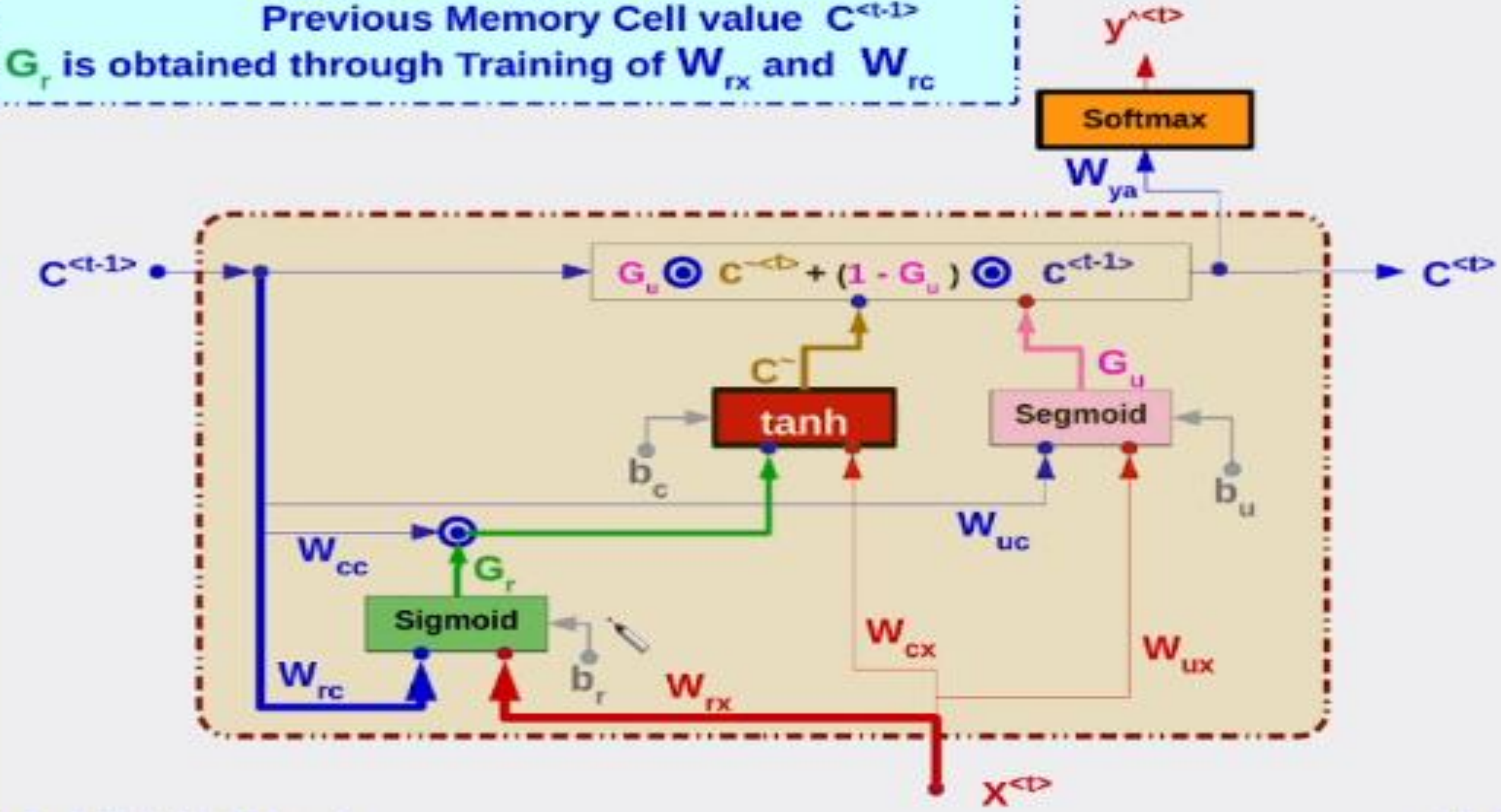
[2] Adding Relevance Gate G_r

Value of G_r is based on:

Input $X^{<t>}$ and

Previous Memory Cell value $C^{<t-1>}$

G_r is obtained through Training of W_{rx} and W_{rc}



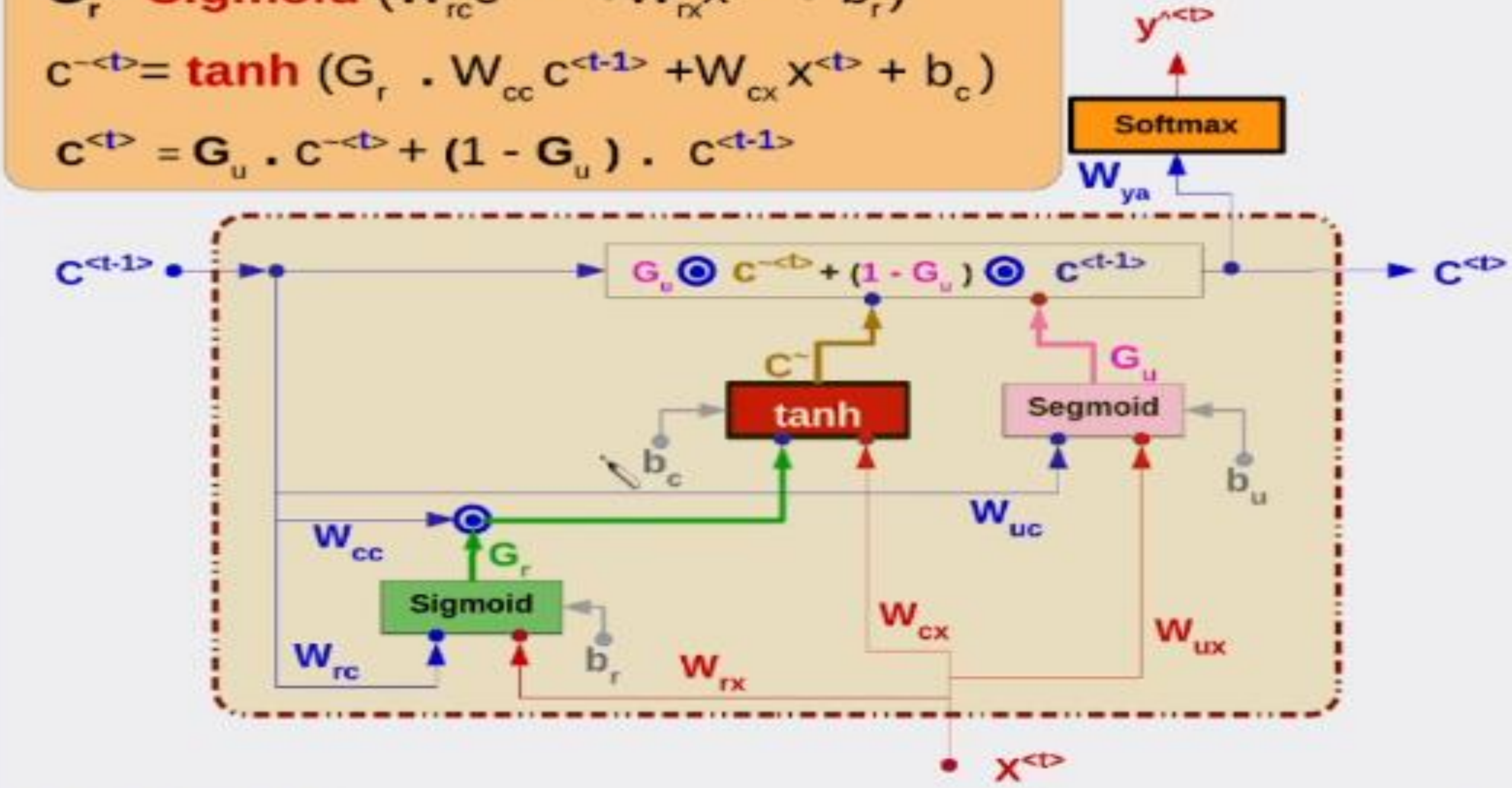
From RNN to GRU

$$G_u = \text{Sigmoid}\ (W_{uc} c^{<t-1>} + W_{ux} x^{<t>} + b_u)$$

$$G_r = \text{Sigmoid}\ (W_{rc} c^{<t-1>} + W_{rx} x^{<t>} + b_r)$$

$$c^{\sim<t>} = \tanh\ (G_r\ .\ W_{cc}\, c^{<t-1>} + W_{cx}\, x^{<t>} + b_c)$$

$$c^{<t>} = G_u\ .\ c^{\sim<t>} + (1 - G_u)\ .\ c^{<t-1>}$$



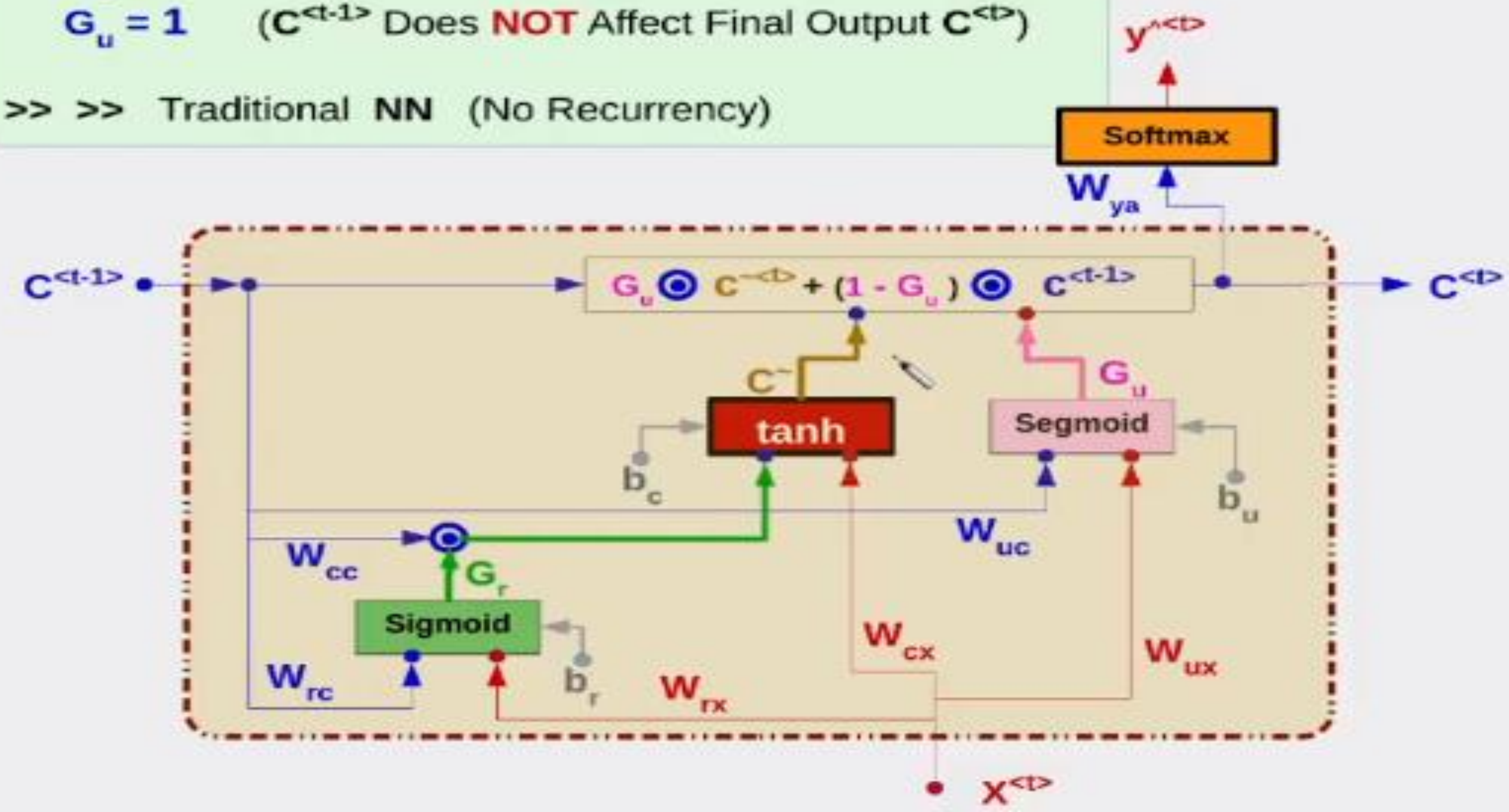
From RNN to GRU

IF

$G_r = 0$ ($C^{<t-1>}$ Does NOT Affect tanh Output $C^{\sim}$)

$G_u = 1$ ($C^{<t-1>}$ Does NOT Affect Final Output $C^{<t>}$)

>> >> Traditional **NN** (No Recurrency)



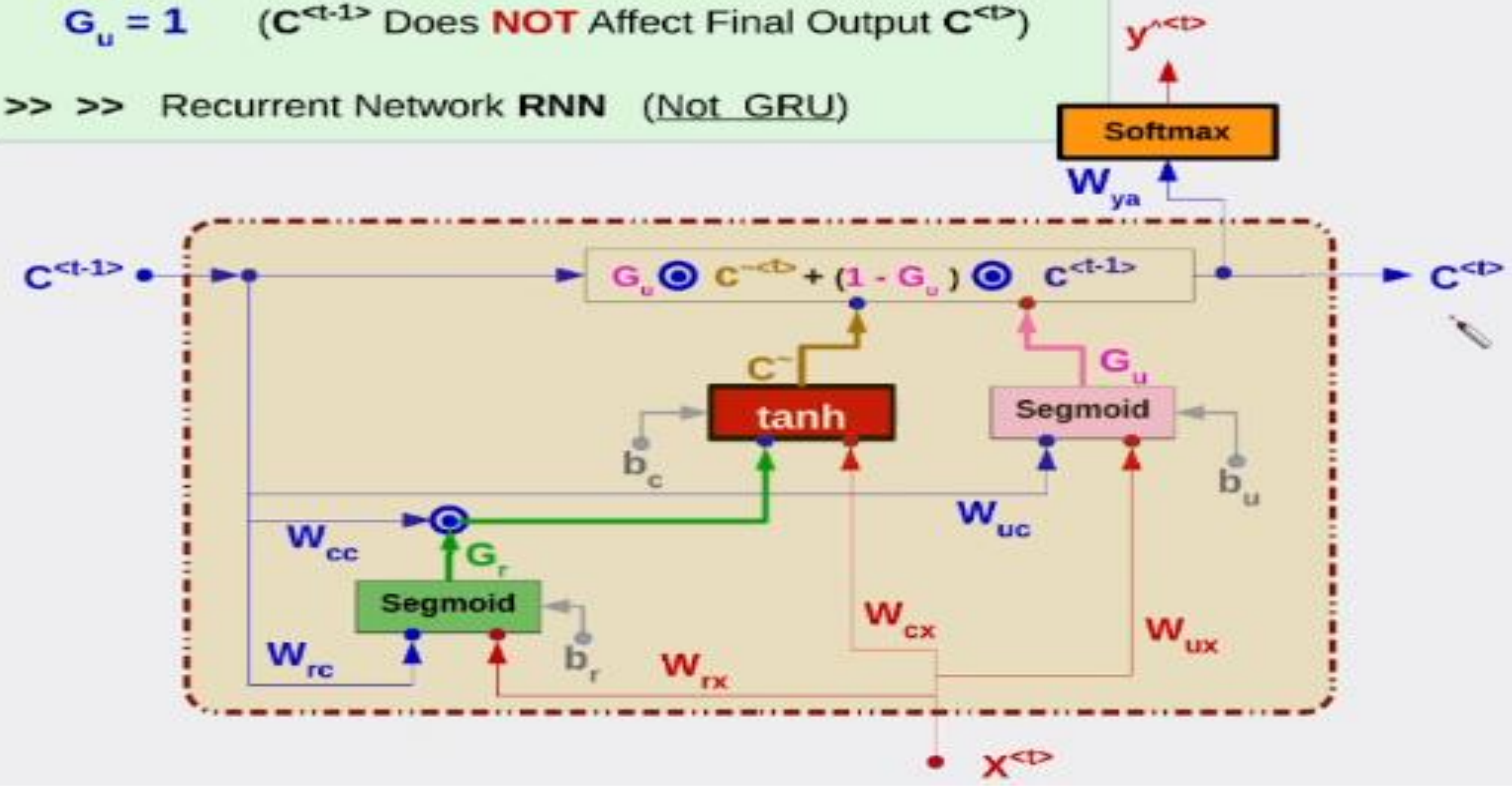
From RNN to GRU

IF

$G_r = 1$ ($C^{<t-1>}$ **Affects** tanh Output $C^{\sim}$)

$G_u = 1$ ($C^{<t-1>}$ Does NOT Affect Final Output $C^{<t>}$)

>> >> Recurrent Network **RNN** (Not GRU)



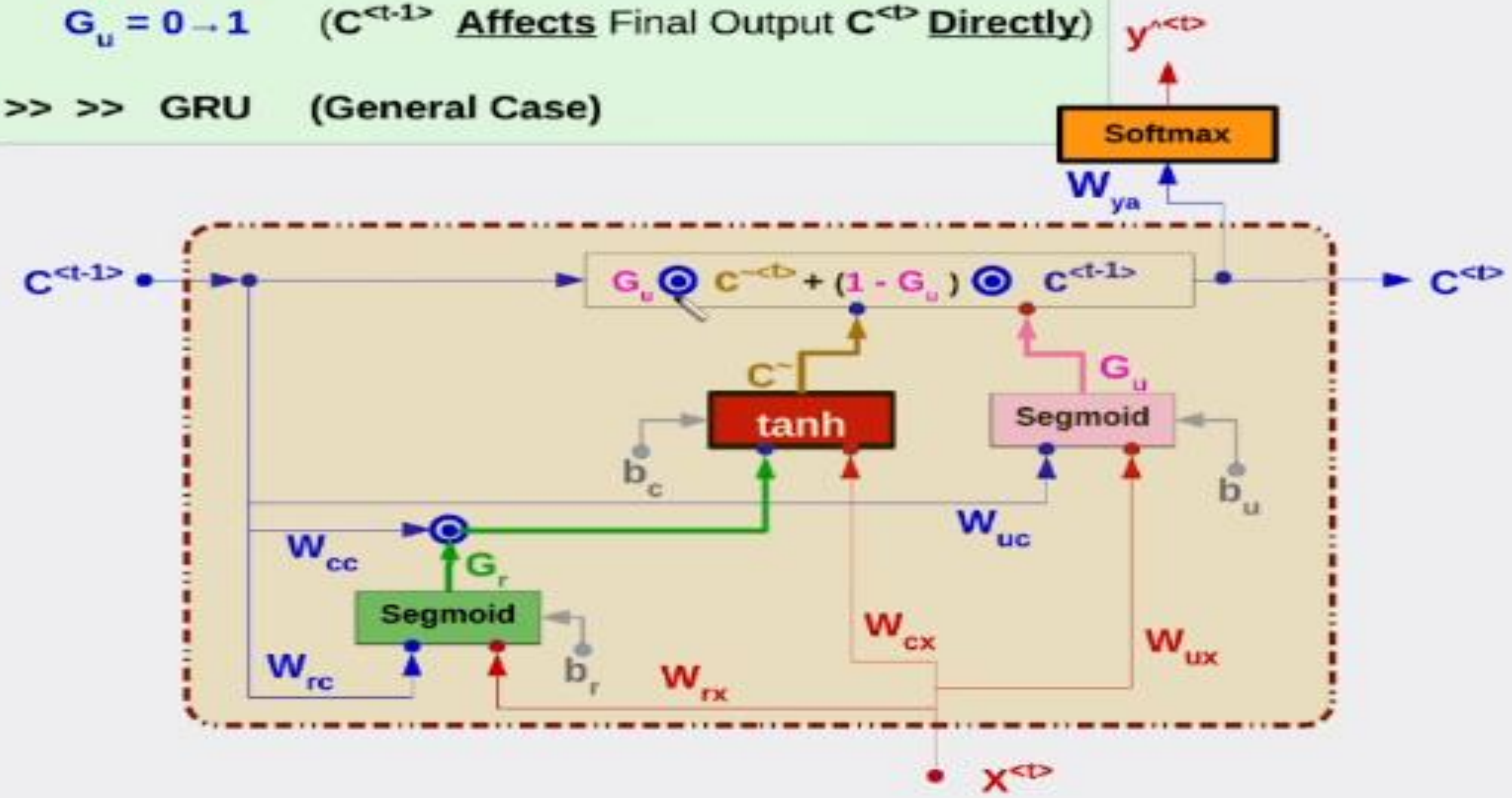
From RNN to GRU

IF

$G_r = 0 \to 1$ ($C^{<t-1>}$ **Affects** tanh Output $C^{\sim}$)

$G_u = 0 \to 1$ ($C^{<t-1>}$ **Affects** Final Output $C^{<t>}$ **Directly**)

>> >> GRU (General Case)



[3] Long Short Term Memory (LSTM)