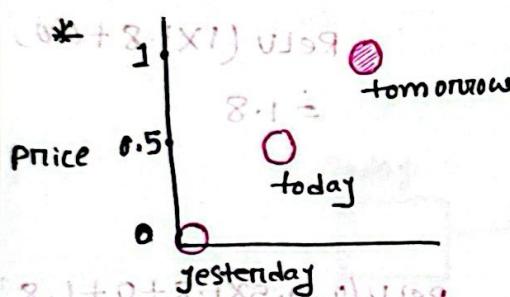
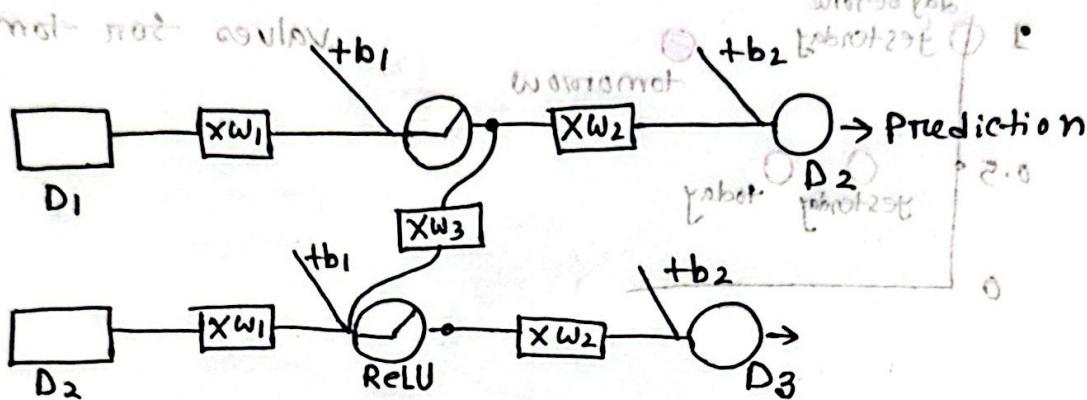
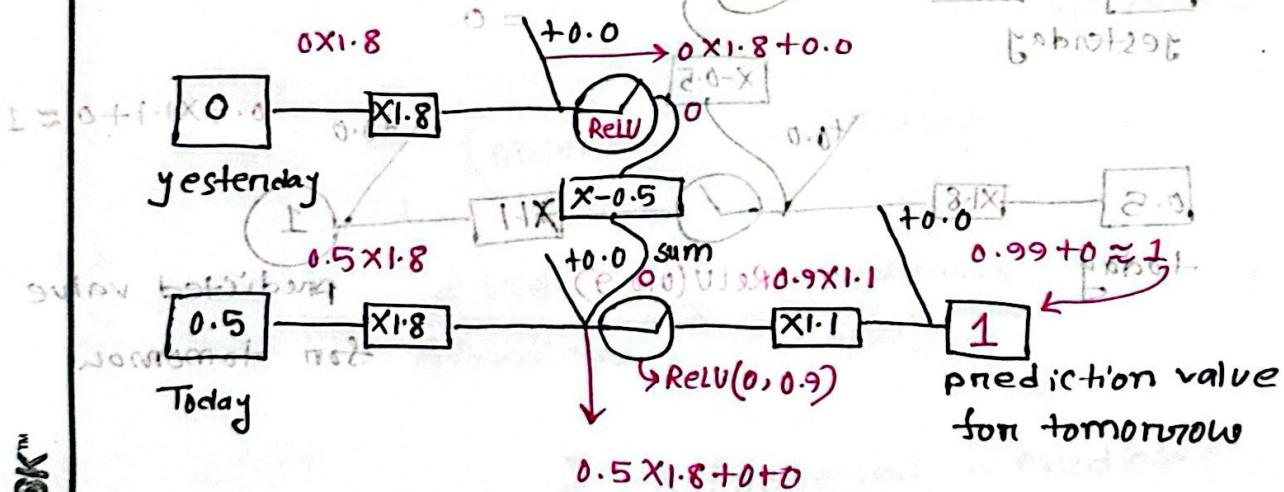


## STEPS OF RNN (Forward Pass)

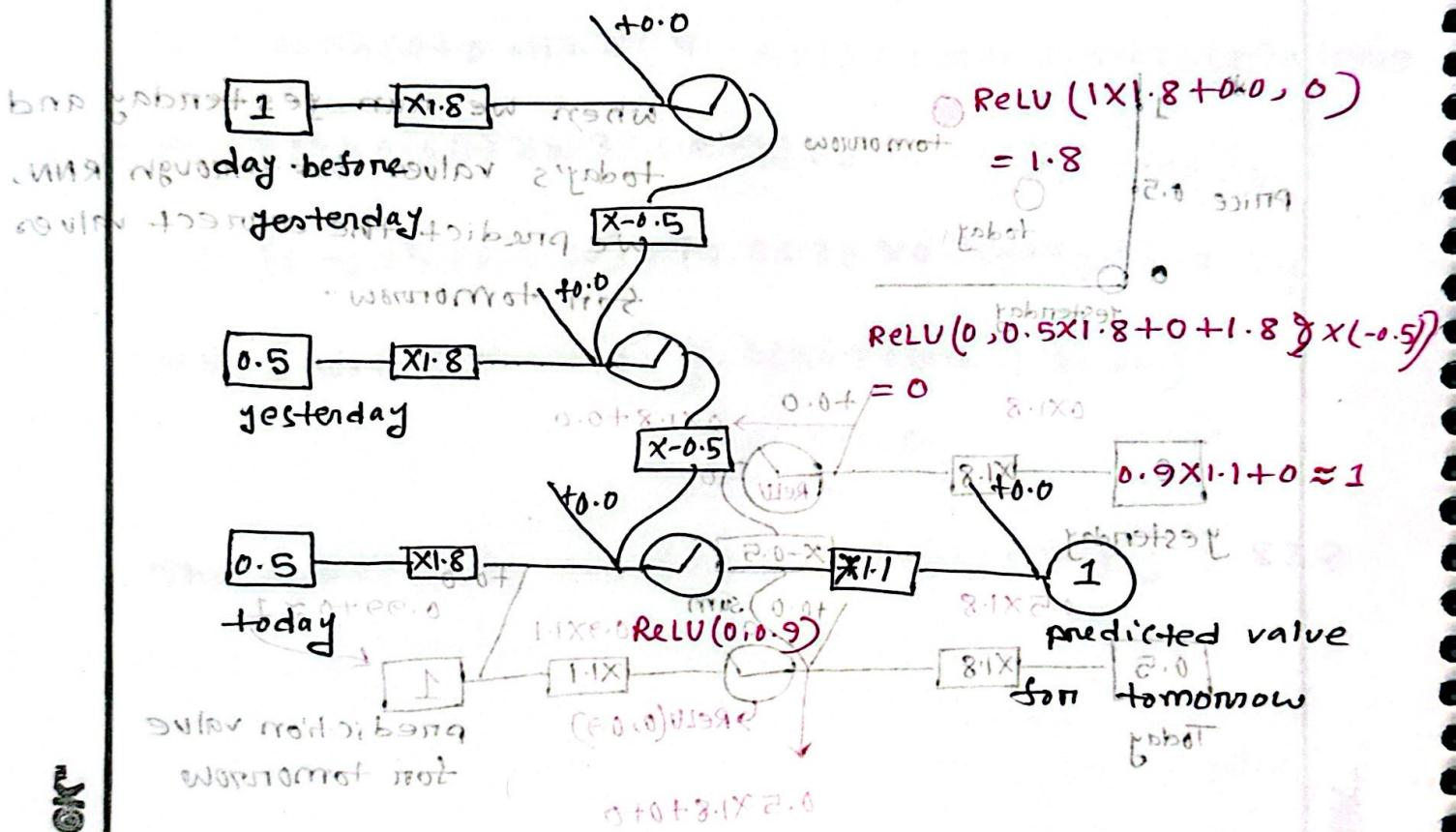
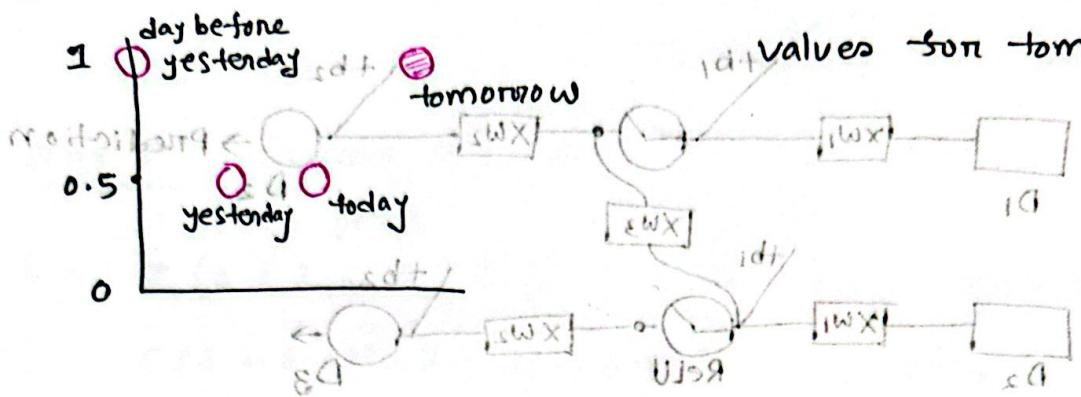
Normal not conv



when we run yesterday and today's values through RNN, we predict the correct values for tomorrow.



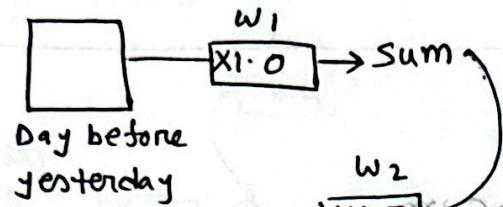
\* We predict the correct values for tomorrow.



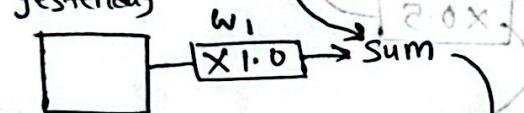
TOPIC NAME: RNN BackpropagationDAY: 1 / 1  
TIME: 10:00 / 10:00  
DATE: 1/1/2023

## RNN Backpropagation

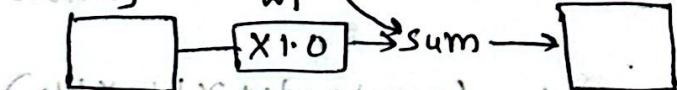
$$\text{Predicted value} = \sum_{i=1}^n w_i x_i + b$$



yesterday



Today not yet



$$(w_1 x_{\text{today}}) + (w_2 x_{\text{yesterday}}) = b \text{ predicted value}$$

Son tomorrow

### Analyse

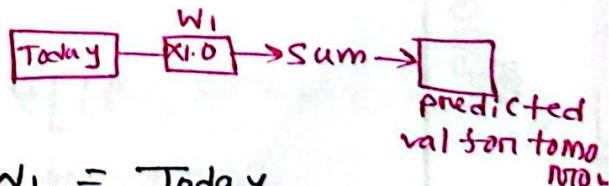
$$SSR = \sum_{i=1}^n (\text{observed}_i - \text{predicted}_i)^2$$

$$\frac{dSSR}{dw_1} = \frac{dSSR}{d\text{Predicted}} \times \frac{d\text{Predicted}}{dw_1}$$

$$\frac{dSSR}{d\text{Predicted}} = \sum_{i=1}^n -2 (\text{observed}_i - \text{predicted}_i)$$

$$\text{predicted} = \text{Today} \times w_1$$

$$\frac{d\text{Predicted}}{dw_1} = \frac{d}{dw_1} \text{Today} \times w_1 = \text{Today}$$

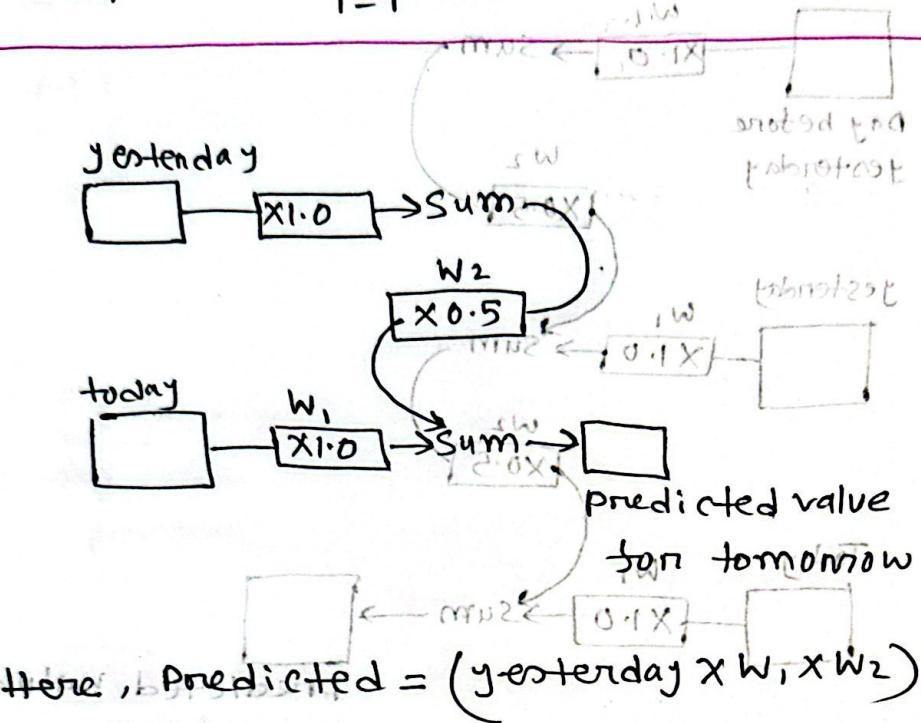


predicted value tomorrow

GOOD LUCK

TOPIC NAME: Linear RegressionDAY: 1 / 1  
TIME: 10:00 AM / 10:30 AM  
DATE: 1/1/2023

$$\frac{dSSR}{dW_1} = \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times \text{Today}_i$$



$$\text{Here, Predicted} = (\text{yesterday} \times w_1 \times w_2) + (\text{Today} \times w_1)$$

$$\frac{d\text{Predicted}}{dW_1} = \frac{d}{dW_1} ((\text{yesterday} \times w_1 \times w_2) + (\text{Today} \times w_1))$$

$$= (\text{yesterday} \times w_2) + \text{Today}$$

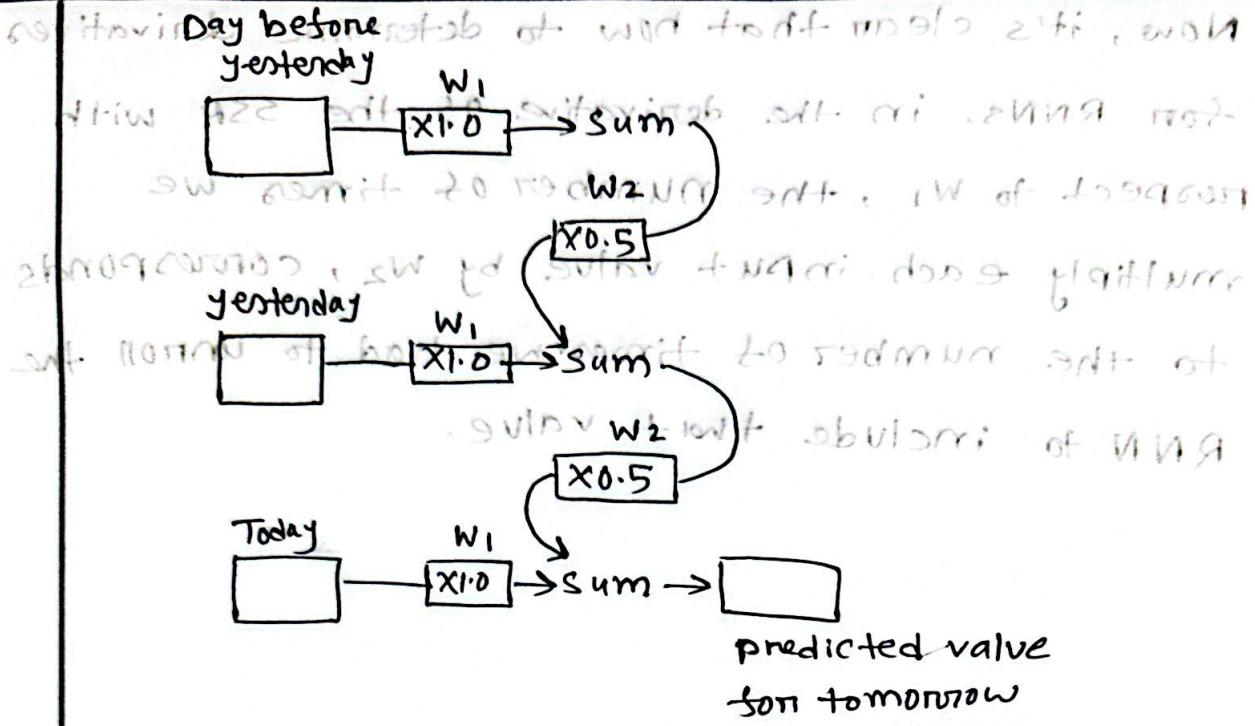
$$\frac{dSSR}{dW_1} = \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times [(\text{yesterday} \times w_2) + \text{Today}]$$

$$= \frac{1}{n} \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times [(\text{yesterday} \times w_2) + \text{Today}]$$

$$= \frac{1}{n} \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times \text{y}_{\text{robot}}$$

$$\text{y}_{\text{robot}} = w \times \text{Today} \times \frac{6}{100} = \frac{6 \times \text{Today}}{100}$$

GOOD LUCK!  
Best of luck for  
your  
exams

TOPIC NAME: Linear RegressionDAY: 1 / 1  
TIME: 10:00 / 10:00

here,

$$\text{predicted} = \{ [( \text{Day before yesterday} \times w_1 \times w_2 ) + ( \text{yesterday} \times w_1 ) \times w_2 ] + ( \text{Today} \times w_1 ) \}$$

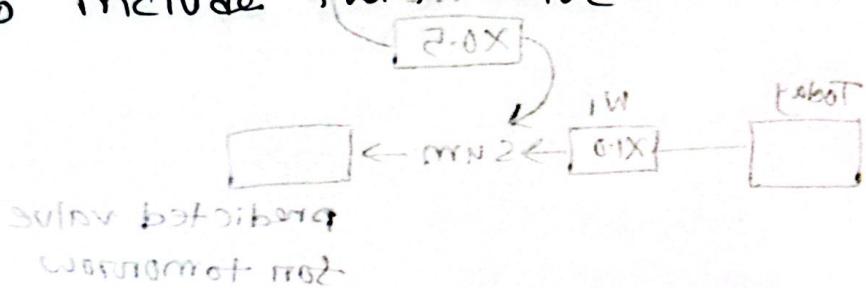
$$\frac{d \text{predicted}}{d w_1} = \frac{d}{d w_1} [ ( \text{Day before yesterday} \times w_1 \times w_2^2 ) + ( \text{yesterday} \times w_1 \times w_2 ) + ( \text{Today} \times w_1 ) ]$$

$$= ( \text{Day before yesterday} \times w_2^2 ) + ( \text{yesterday} \times w_2 ) + \text{Today}$$

$$\frac{d \text{SSR}}{d w_1} = \frac{d \text{SSR}}{d \text{predicted}} \times \frac{d \text{predicted}}{d w_1}$$

$$= \sum_{i=1}^n -2 \times (\text{observed} - \text{predicted}) \times [ ( \text{Day before yesterday} \times w_2^2 ) + ( \text{yesterday} \times w_2 ) + \text{Today} ]$$

Now, it's clear that how to determine derivatives for RNNs. in the derivative of the SSR with respect to  $w_1$ , the number of times we multiply each input value by  $w_2$ , corresponds to the number of times we had to unroll the RNN to include that value.



$$(w \times \text{tabot}) + (s_w \times (w \times \text{tabot} \text{ and } \partial)) \{ = \text{tabot} \\ (w \times \text{tabot}) + \{ s_w \times$$

$$(\text{tabot}) + (s_w \times (w \times (\text{tabot} \text{ and } \partial))) \frac{\partial}{\partial w} = \frac{\text{tabot}}{s_w} \\ [ (w \times \text{tabot}) + (s_w \times w \times$$

$$(\text{tabot}) + (s_w \times \text{tabot} \text{ and } \partial) ] + (s_w \times \text{tabot} \text{ and } \partial) =$$

$$\frac{\text{tabot}}{s_w} \times \frac{922b}{\text{tabot}} = \frac{922b}{s_w}$$

$$[ \text{tabot} + (s_w \times \text{tabot}) + (s_w \times$$