

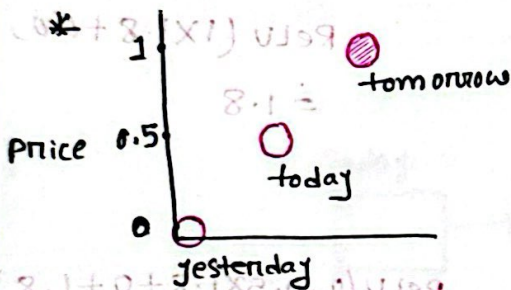
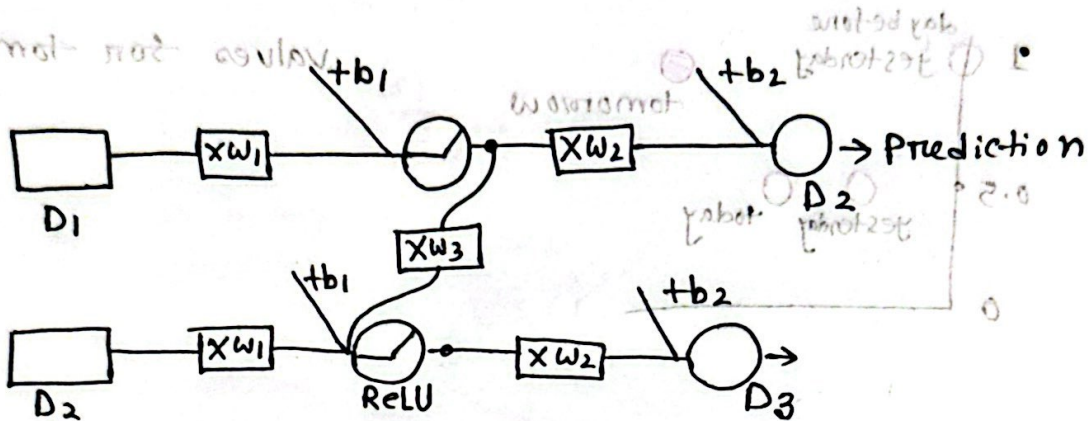
TOPIC NAME: Recurrent Neural Network

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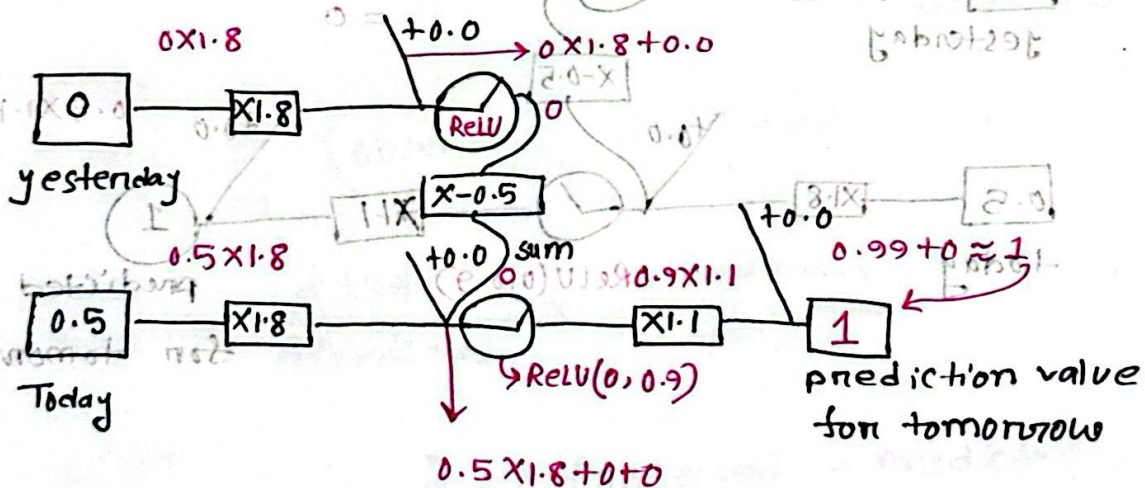
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Steps of RNN (Forward Pass)



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



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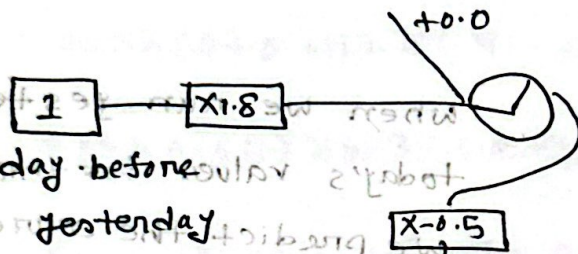
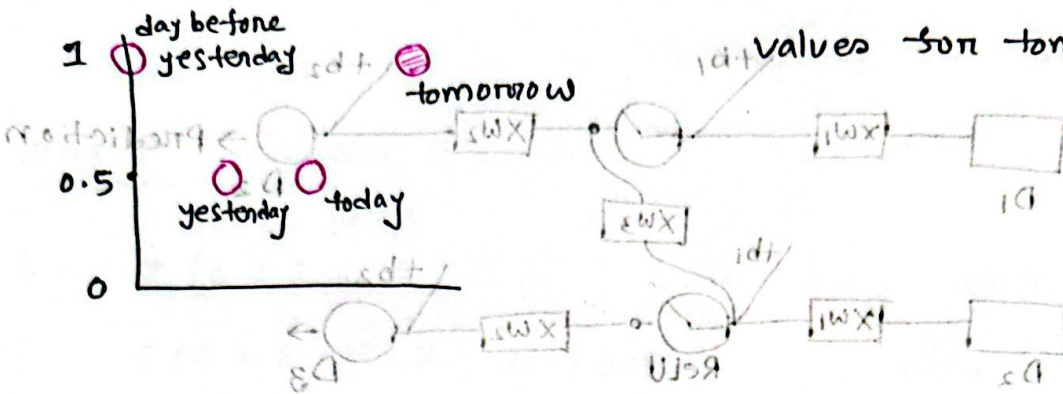
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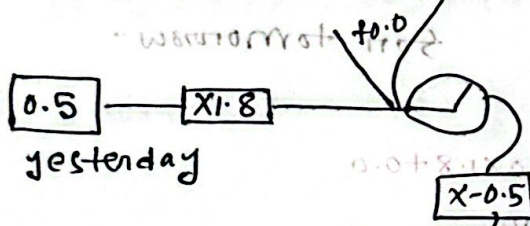
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we predict the correct

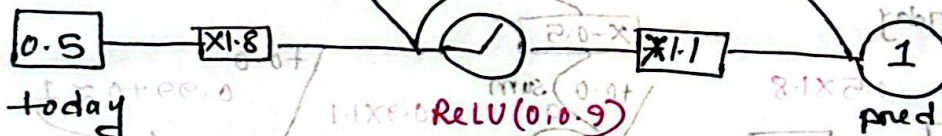
values for tomorrow.



$$\text{ReLU}(1 \times 1.8 + 0.0, 0) = 1.8$$



$$\text{ReLU}(0.5 \times 1.8 + 0.0 + 1.8 \times (-0.5)) = 0$$



$$0.9 \times 1.1 + 0.0 \approx 1$$

predicted value for tomorrow

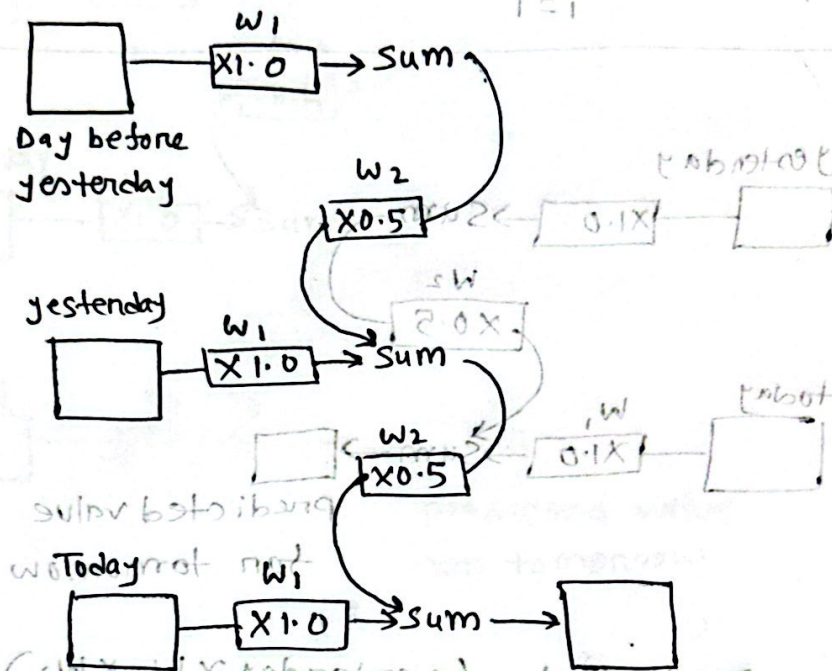
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RNN Backpropagation



Analyse

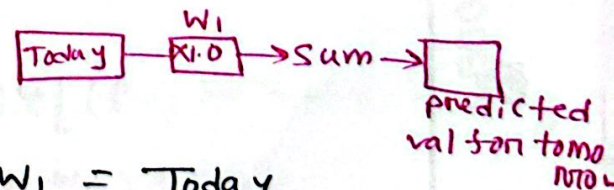
$$SSR = \sum_{i=1}^n (\text{observed}_i - \text{predicted}_i)^2$$

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

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

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

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

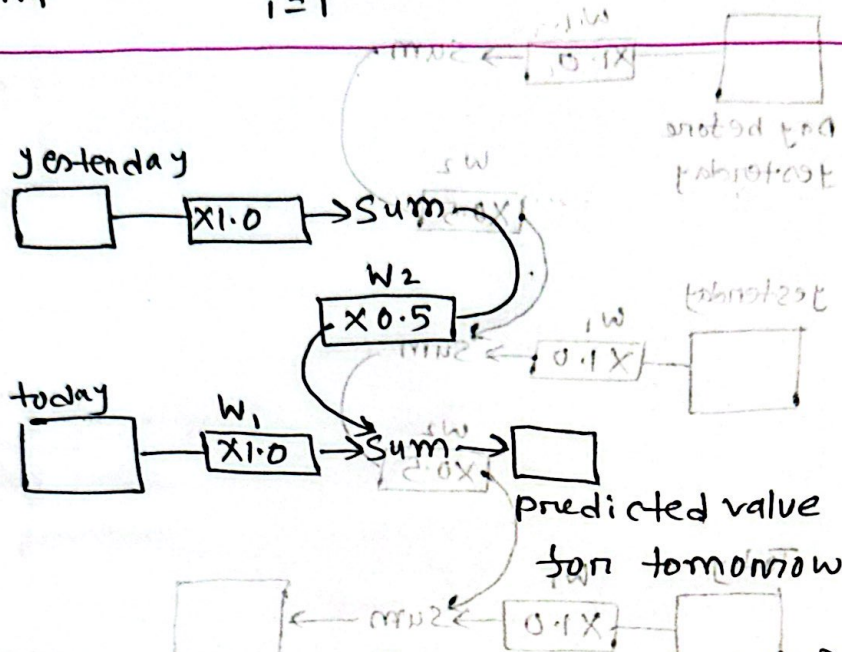


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$$\frac{dSSR}{dw_1} = \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times \text{Today}_i$$



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

$$\frac{d\text{Predicted}}{dw_1} = \frac{d}{dw_1} ((\text{yesterday} \times w_1 \times w_2) + (\text{Today} \times w_1))$$

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

$$\frac{dSSR}{dw_1} = \sum_{i=1}^n -2(\text{Observed}_i - \text{Predicted}_i) \times [\text{Yesterday}_i \times w_2 + \text{Today}_i]$$

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

$$\text{Predicted} = w_1 \times \text{Today} + w_2 \times \text{Yesterday}$$

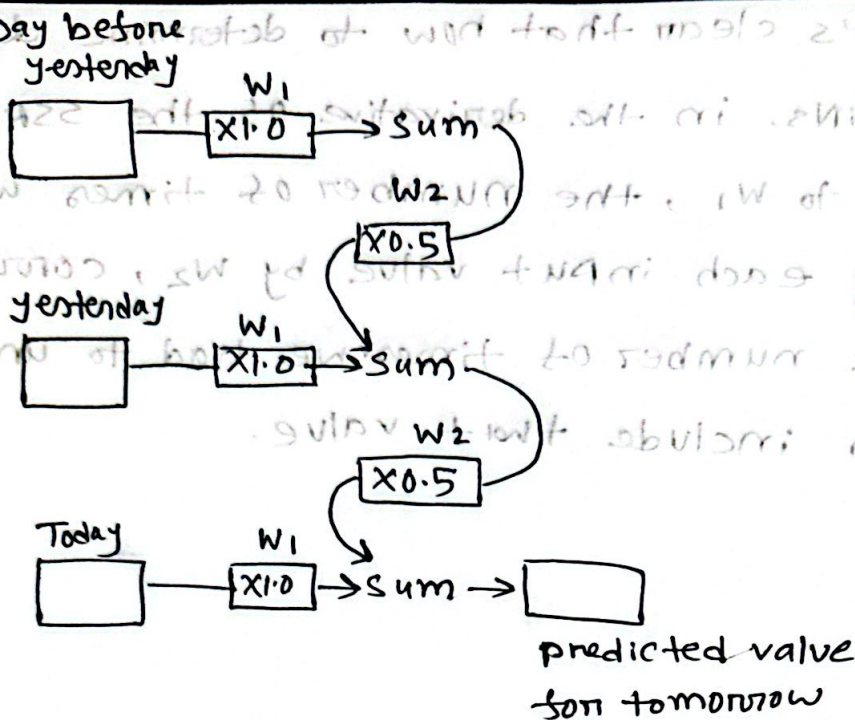
$$\frac{d\text{Predicted}}{dw_1} = \text{Today}$$

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here,

$$\text{Predicted} = \{ [(\text{Day before yesterday} \times W_1 \times W_2) + (\text{yesterday} \times W_1) \times W_2] + (\text{Today} \times W_1)$$

$$\frac{d \text{Predicted}}{d W_1} = \frac{d}{d W_1} [(\text{Day before yesterday} \times W_1 \times W_2^2) + (\text{yesterday} \times W_1 \times W_2) + (\text{Today} \times W_1)]$$

$$= (\text{Day before yesterday} \times W_2^2) + (\text{yesterday} \times W_2) + \text{Today}$$

$$\frac{d \text{SSR}}{d W_1} = \frac{d \text{SSR}}{d \text{Predicted}} \times \frac{d \text{Predicted}}{d W_1}$$

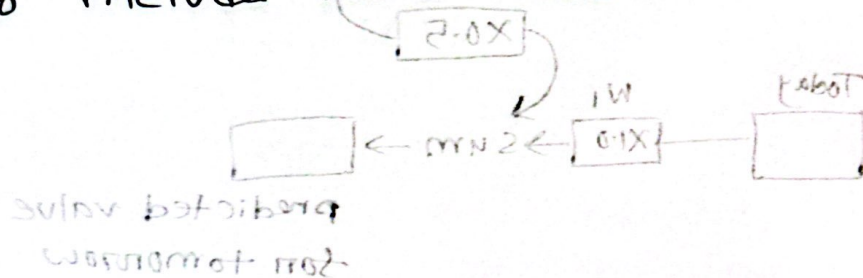
$$= \sum_{i=1}^n -2 \times (\text{Observed} - \text{Predicted}) \times [(\text{Day before yesterday} \times W_2^2) + (\text{yesterday} \times W_2) + \text{Today}]$$

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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.



$$[w_2] + (w_1 \times w_2)$$

$$[w_2] + (w_1 \times w_2)$$

$$\frac{9.226}{9.226} \times \frac{9.226}{9.226} = \frac{9.226}{9.226}$$

$$[w_2] + (w_1 \times w_2)$$