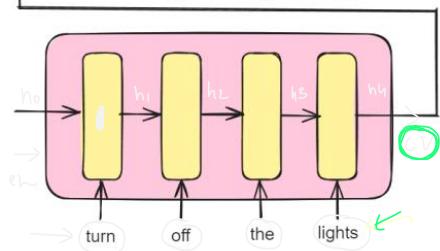
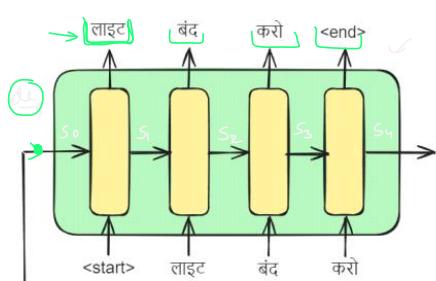


Recap

16 January 2024 16:10



turn off me why → बिल्डर + करो

[NMT]

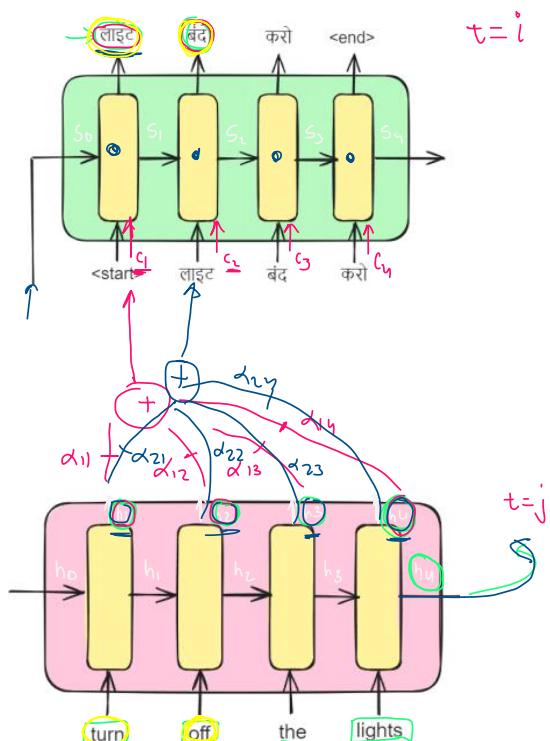
new user - I understand

sentence > 30 words
paragraph
document

bilstm
stacked lstm

translation

bottleneck → Attention mechanism



$c_1 \ c_2 \ c_3 \ c_4$

$$4 \times 4 = 16$$

Weighted sum

$$c_i^* = \sum_{j=1}^4 \alpha_{ij} h_j$$

$\alpha \rightarrow$ alignment score

$$c_1 = \underline{\alpha_{11} h_1} + \alpha_{12} h_2 + \alpha_{13} h_3 + \alpha_{14} h_4$$

$$c_2 = \alpha_{21} h_1 + \underline{\alpha_{22} h_2} + \alpha_{23} h_3 + \alpha_{24} h_4$$

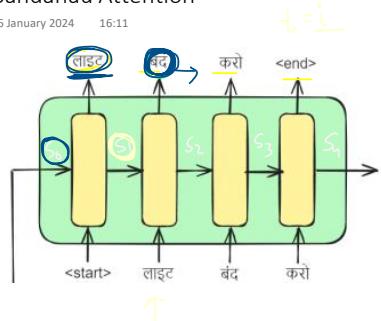
$\alpha \rightarrow$ find out

Bahdanau
attention
architecture

Luong
attention

Bahdanau Attention

16 January 2024 16:11



alignment score

given

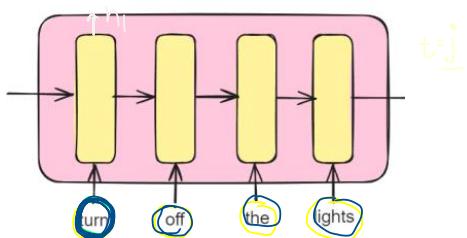
$$\underline{\alpha_j} = \sum \underline{\alpha_{ij}} h_j$$

alignment

$$\underline{\alpha_{11}} \rightarrow \text{turn} \rightarrow \underline{\text{turn}}$$

$$\underline{\alpha_{12}} \rightarrow \text{off} \rightarrow \underline{\text{off}}$$

decode
→ prev hidden
state



$$\underline{\alpha_{11}} = f(h_1, s_0) \quad \underline{\alpha_{21}} = f(h_2, s_1)$$

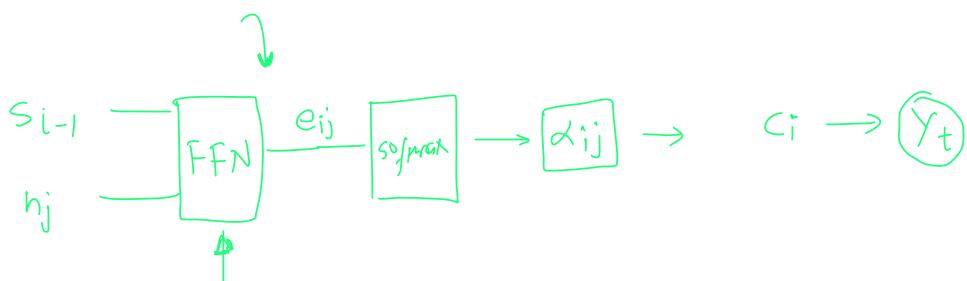
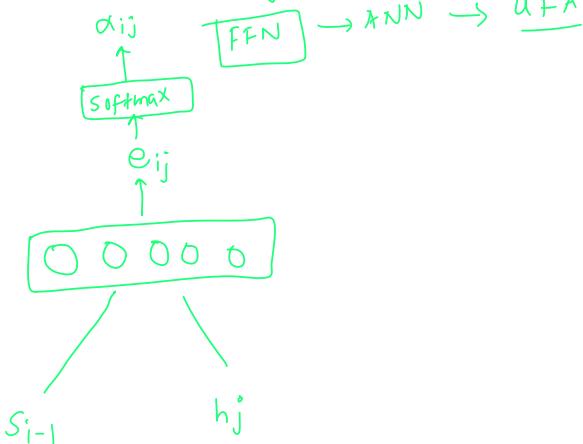
$$\rightarrow \underline{\alpha_{ij}} = \underline{\alpha_{ij}}(h_j, s_{i-1})$$

approximate

$$\underline{\alpha_{ij}} = \underline{\alpha_{ij}}(\text{math func})$$

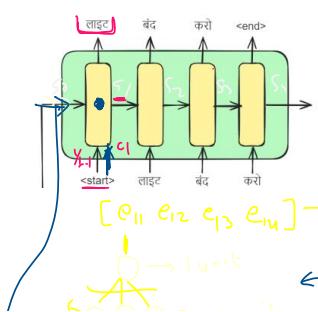
→ the
encoded
hidden

deal
prev
hidden
state



$$s_0, Y_{t-1}, c_1 \rightarrow \text{lstm} \rightarrow Y_t (\underline{\text{लाइट}}) [S_1]$$

$t=2$



↳ encoded sentence
 $\hookrightarrow h_1, h_2, h_3, h_4$

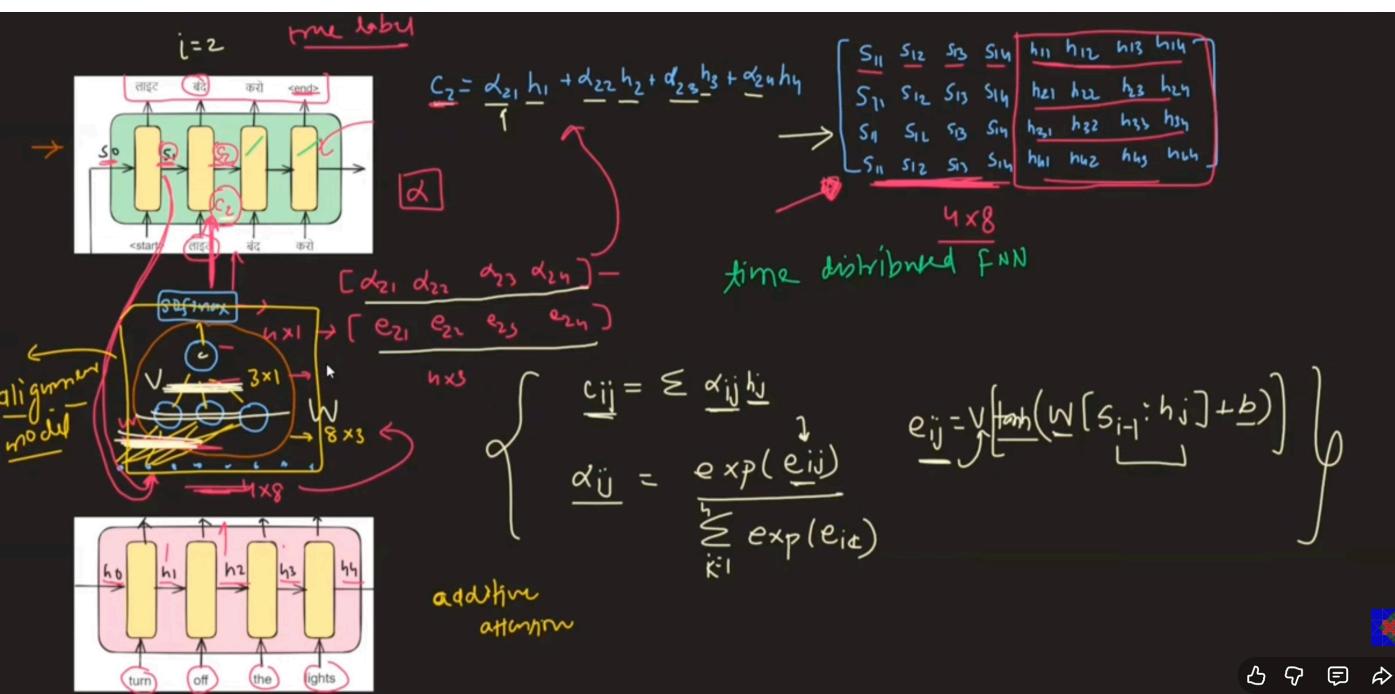
$(S_{i-1}) h_j$

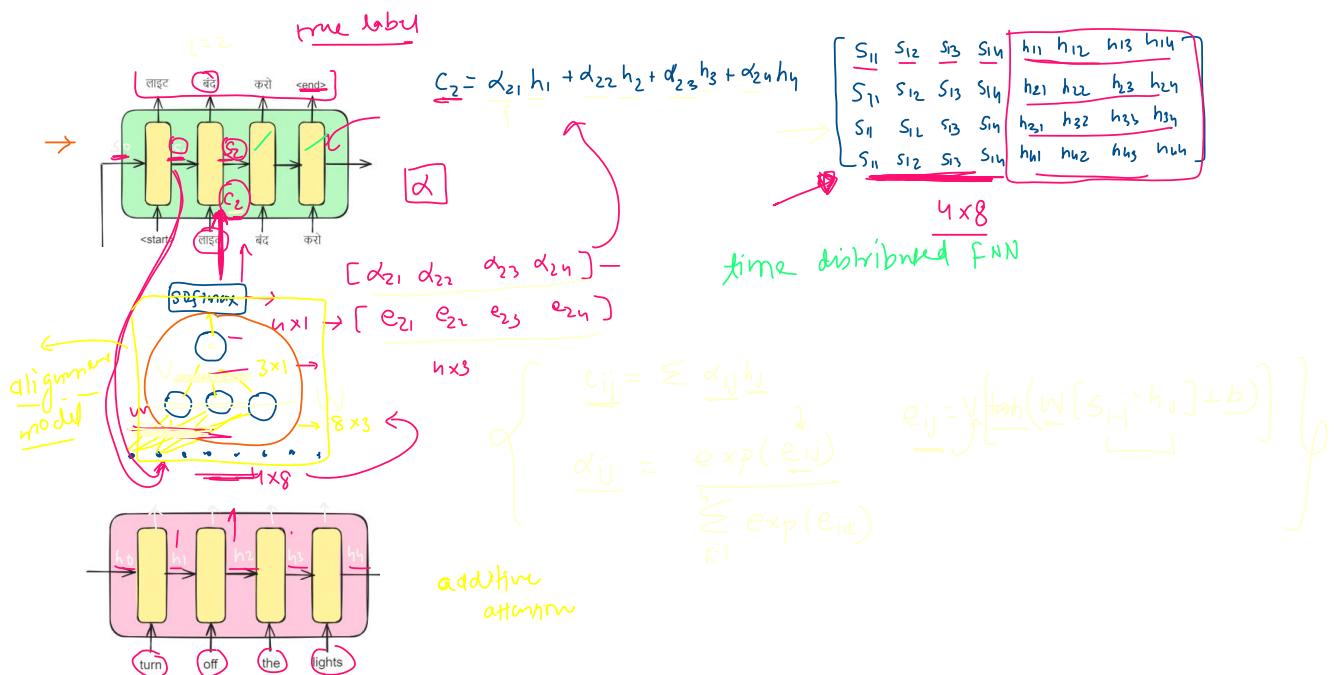
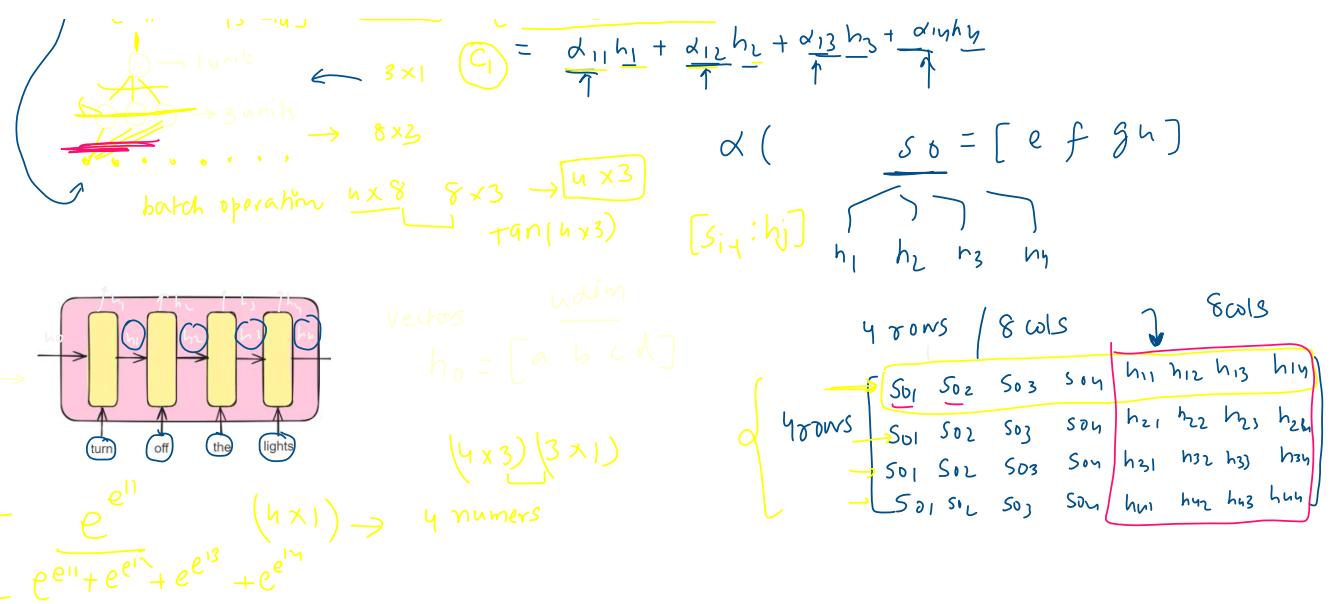
$$s_0 = [e + g h]$$

$$c_1 = \sum \underline{\alpha_{ij}} h_j$$

$$\rightarrow [\underline{\alpha_{11}} \underline{\alpha_{12}} \underline{\alpha_{13}} \underline{\alpha_{14}}]$$

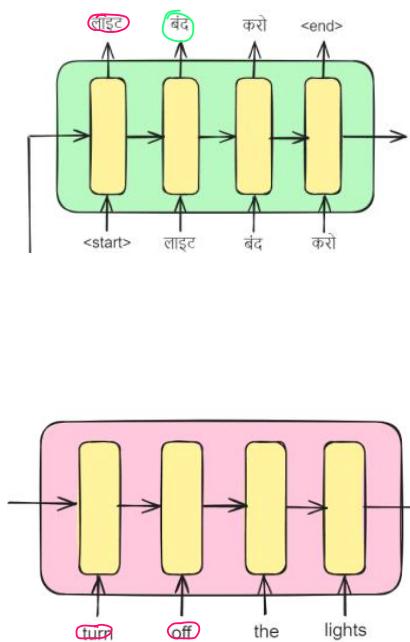
$$c_1 = \frac{\underline{\alpha_{11}}}{\sum} h_1 + \frac{\underline{\alpha_{12}}}{\sum} h_2 + \frac{\underline{\alpha_{13}}}{\sum} h_3 + \frac{\underline{\alpha_{14}}}{\sum} h_4$$





Luong Attention

17 January 2024 00:09



parameters → slow

$$c_i = \sum \alpha_{ij} h_j \rightarrow \text{FPN} \quad q = [V \tan(w[s_{i-1}; h_i] + b)]^T$$

$$\alpha_{ij} = f(s_{i-1}, h_j) \times$$

$$\alpha_{ij} = f(s_i, h_j) \rightarrow [s_i^T \cdot h_j] \rightarrow \text{dot product}$$

↑ current ① diff

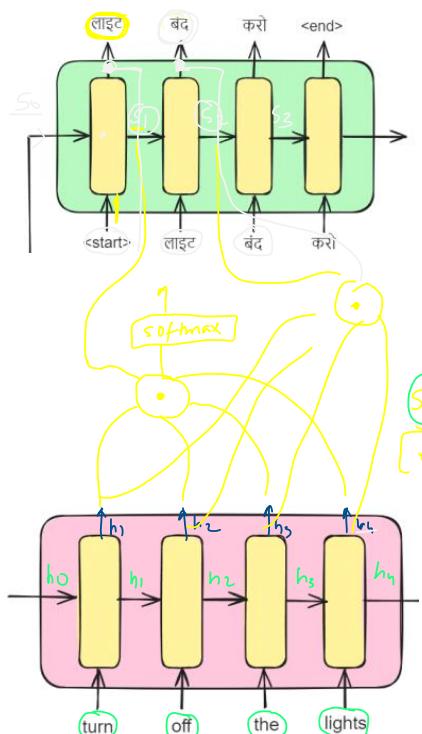
↑ update info $s_i = [a \ b \ c \ d]$

↑ dynamic $h_j = [e \ f \ g \ h]$

↑ adjust $\alpha_{ij} = [ae + bf + cg + dh]$

↑ softmax $\text{softmax} \leftarrow [e_{ij}]$

↑ slow → attention



$$s_i: s_1 \rightarrow \underbrace{\text{softmax}}_{\text{output}}$$

$$[e_{11} \ e_{12} \ e_{13} \ e_{14}] \rightarrow \alpha_{11} \ \alpha_{12} \ \alpha_{13} \ \alpha_{14} \rightarrow \sum \alpha_{ij} h_j$$

$$e_{11} \ e_{12} \ e_{13} \ e_{14} \rightarrow \alpha_{11} \ \alpha_{12} \ \alpha_{13} \ \alpha_{14} \rightarrow \sum \alpha_{ij} h_j$$

Here in Luong , we made two changes , instead of providing context vector in input we are providing it in output , also it changes how alignment score is calculated now instead of neural network we are using dot product , also we are using current decoder hidden state and input to calculate (which is more dynamic)

Due to dot product involvement it is also called multiplicative attention.

