

# CS7015 (Deep Learning) : Lecture 15

## Encoder Decoder Models, Attention Mechanism

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# Module : Introduction to Encoder Decoder Models

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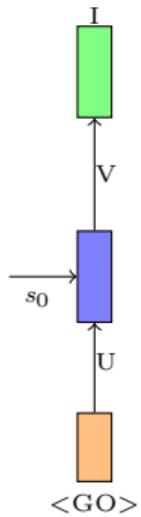
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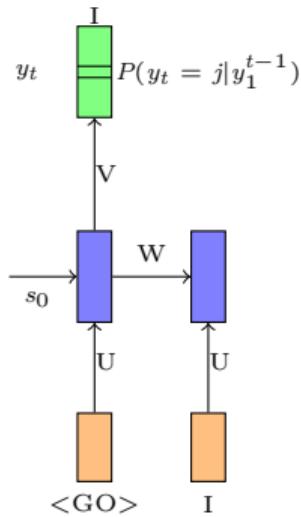
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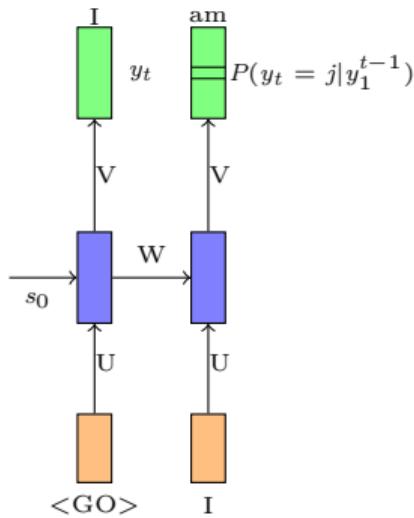
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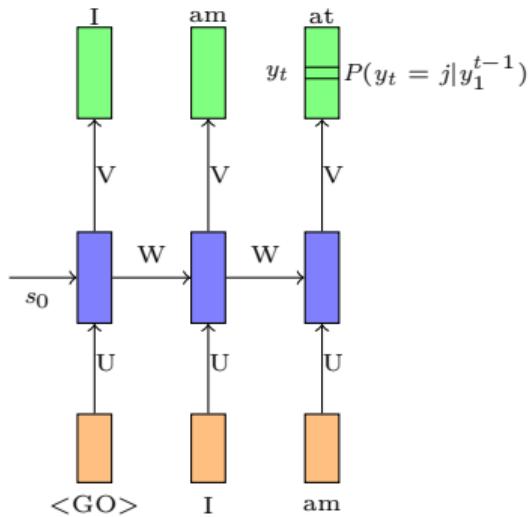
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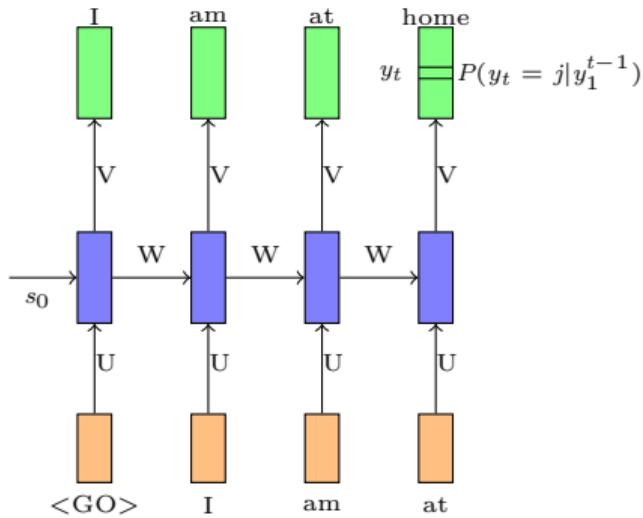
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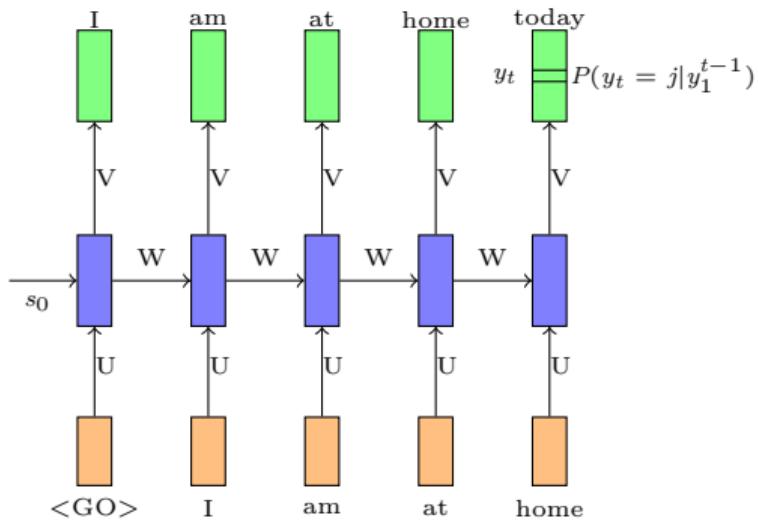
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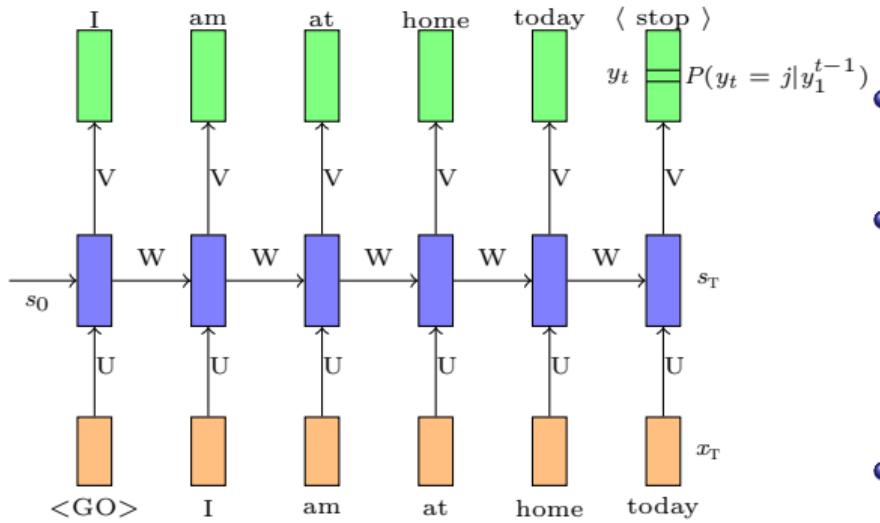
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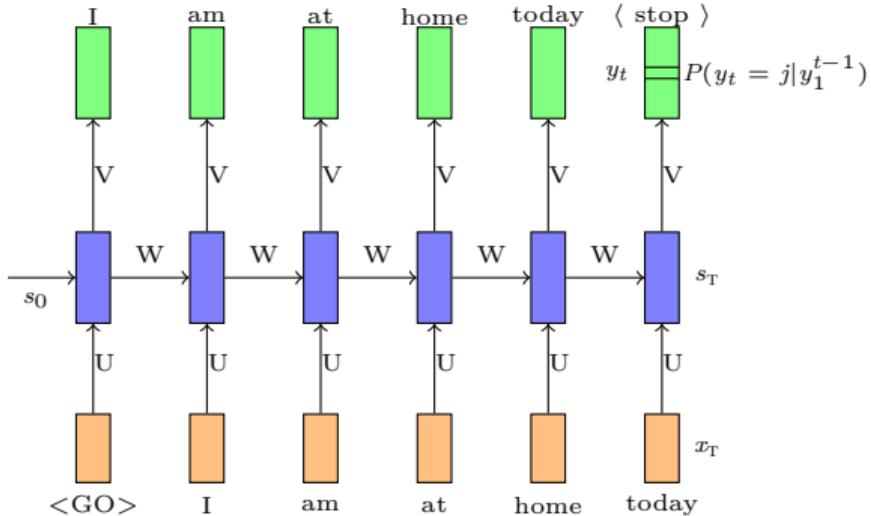


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where  $j \in V$  and  $V$  is the set of all vocabulary words

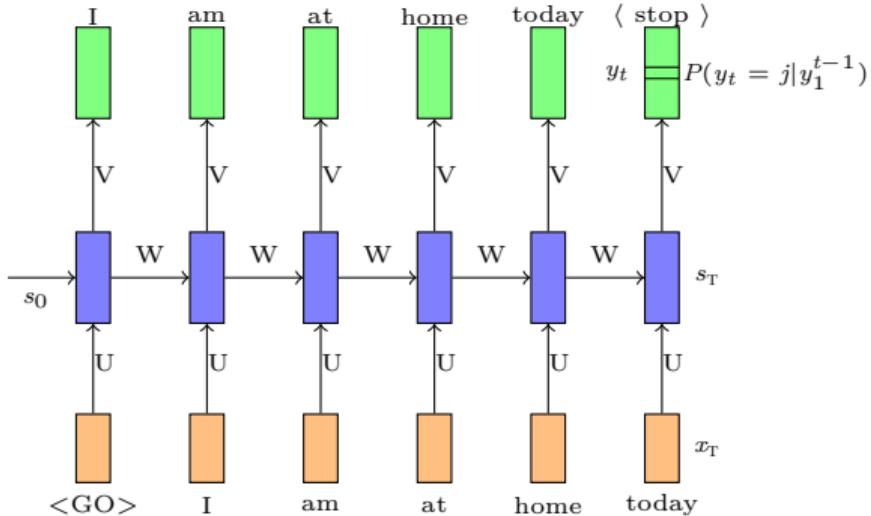
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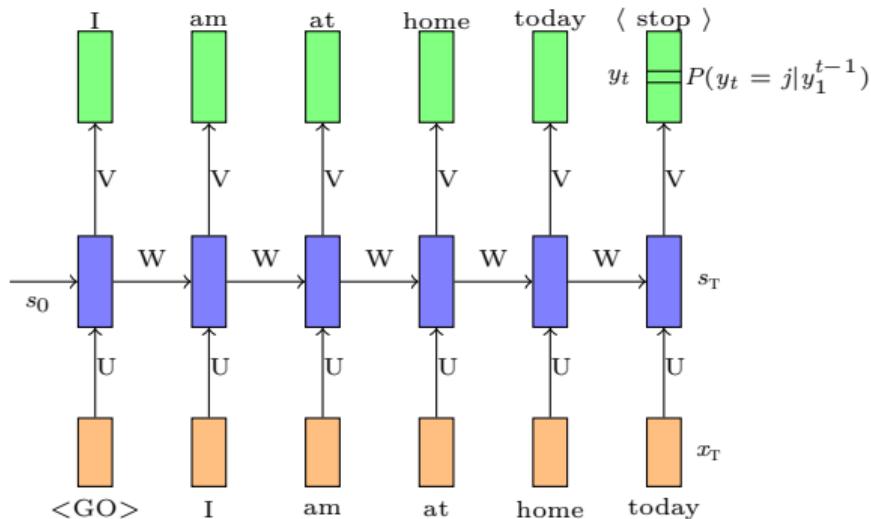
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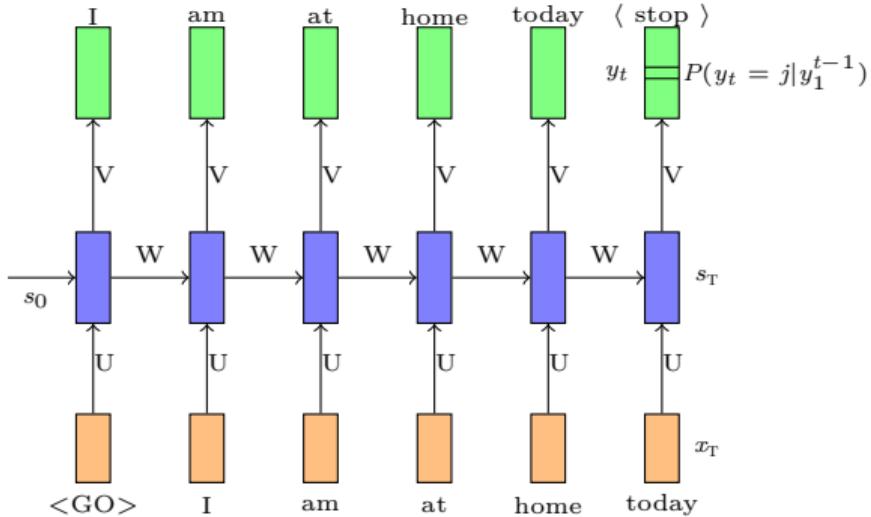
$$P(y_t = j | y_1^{t-1}) = \text{softmax}(Vs_t + c)_j$$

- In other words we compute

$$\begin{aligned} P(y_t = j | y_1^{t-1}) &= P(y_t = j | s_t) \\ &= \text{softmax}(Vs_t + c)_j \end{aligned}$$



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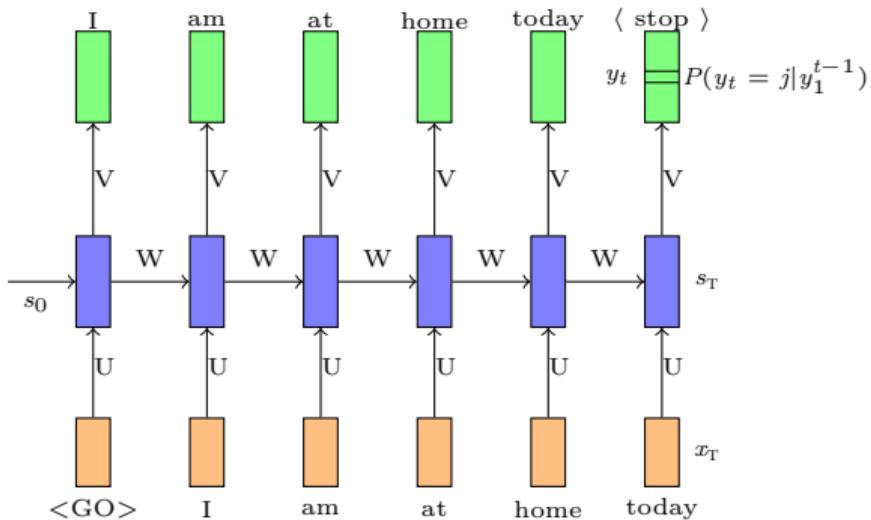
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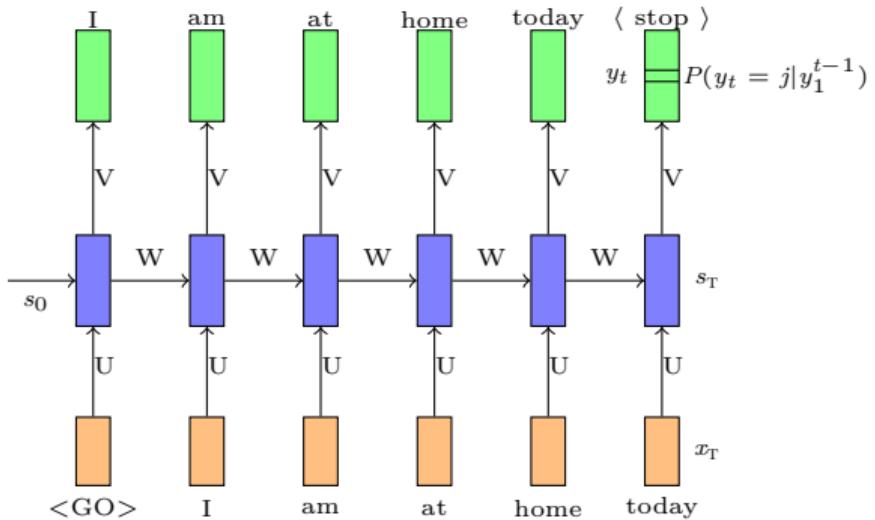
- Notice that the recurrent connections ensure that  $s_t$  has information about  $y_1^{t-1}$

- **Data:** All sentences from any large corpus (say wikipedia)



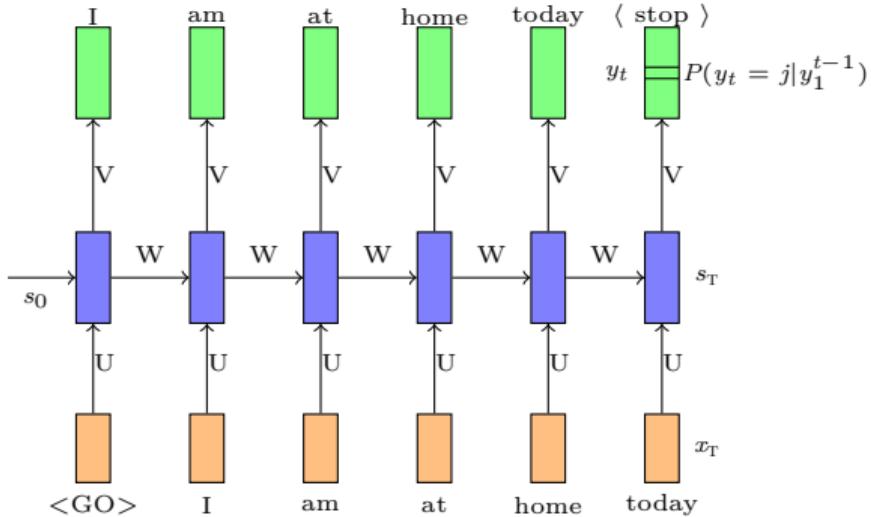
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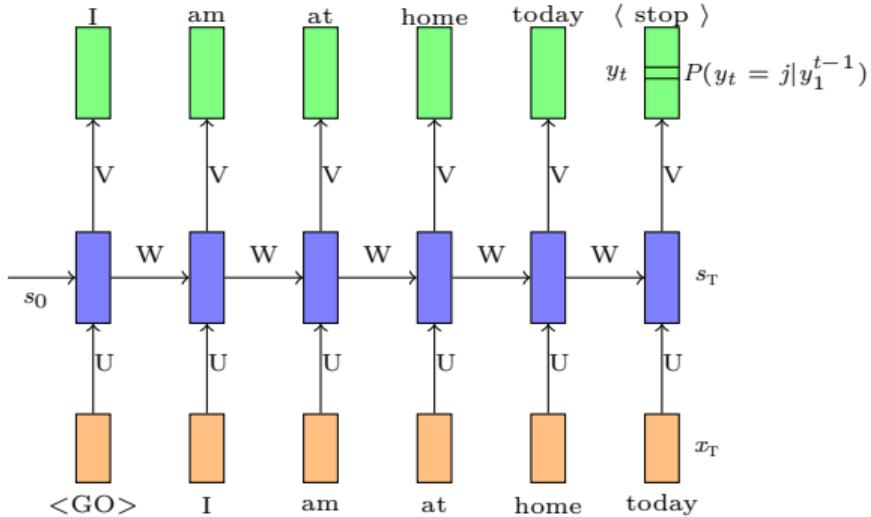


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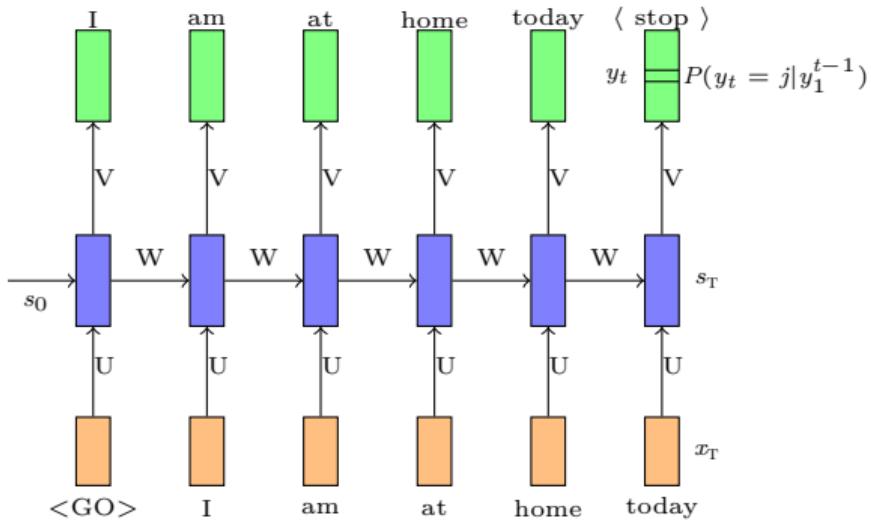
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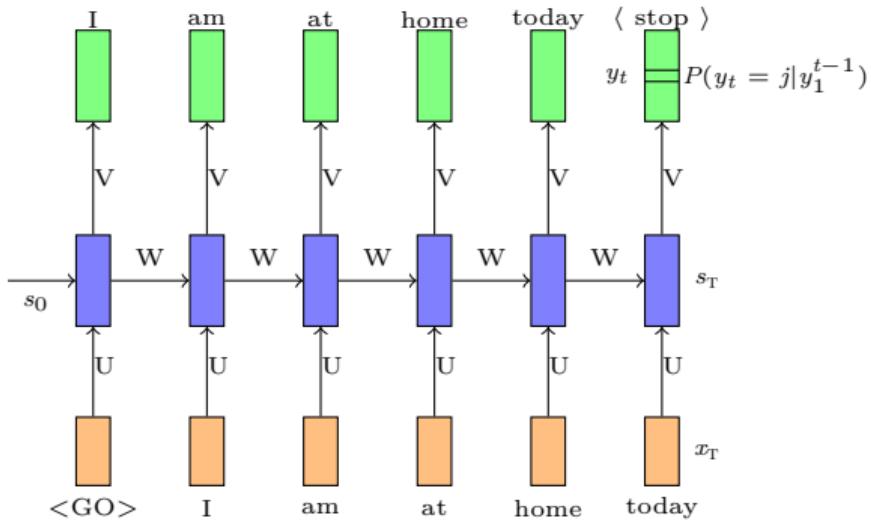
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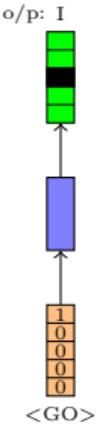
$$\mathcal{L}(\theta) = \sum_{t=1}^T \mathcal{L}_t(\theta)$$

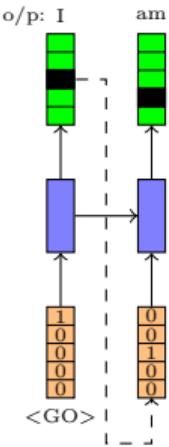
$$\mathcal{L}_t(\theta) = -\log P(y_t = \ell_t | y_1^{t-1})$$

where  $\ell_t$  is the true word at time step  $t$

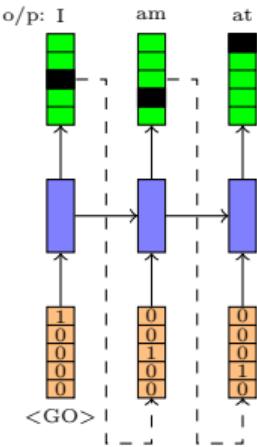
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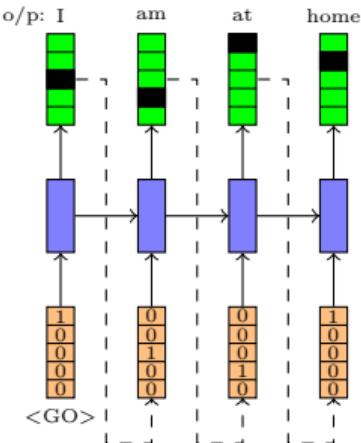




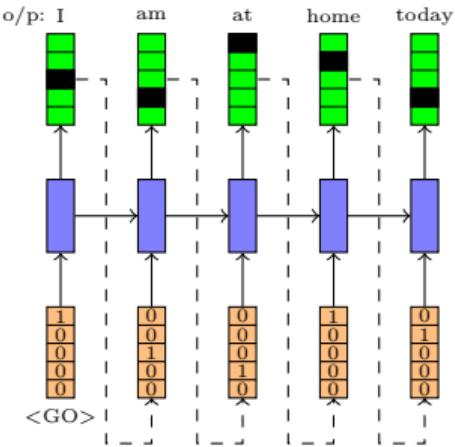
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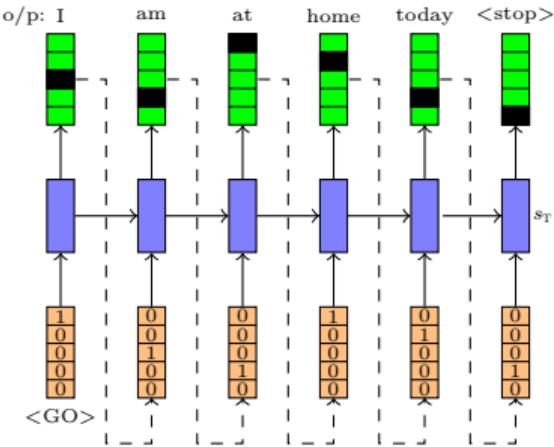
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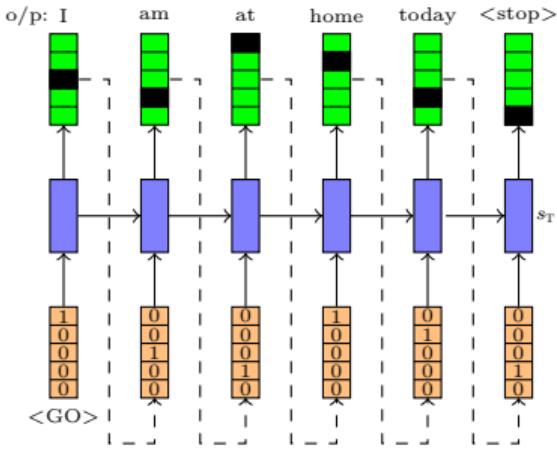
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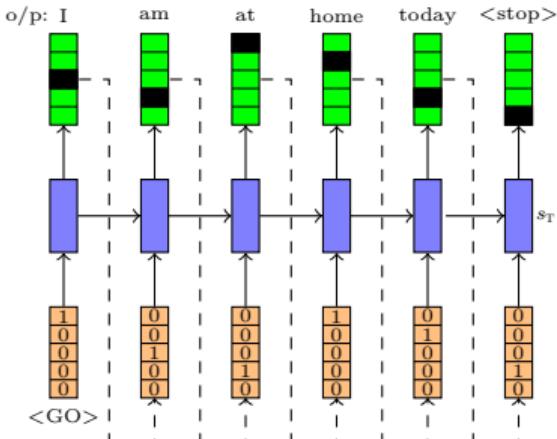


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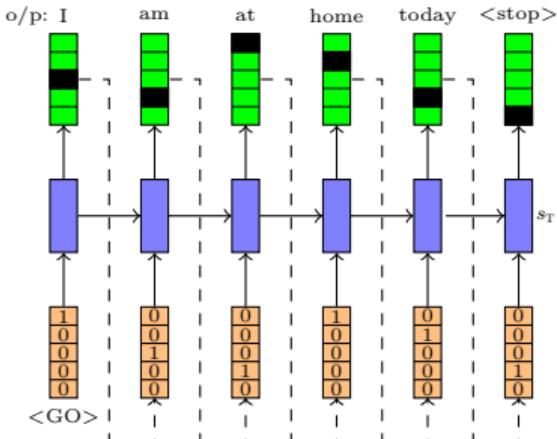


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- Let  $j$  be the index of the word which has been assigned the max probability at time step  $t - 1$
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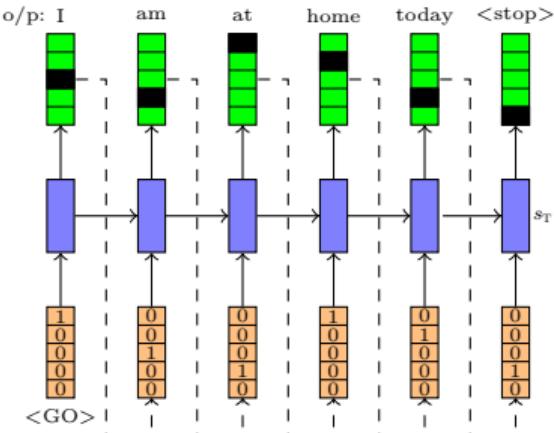
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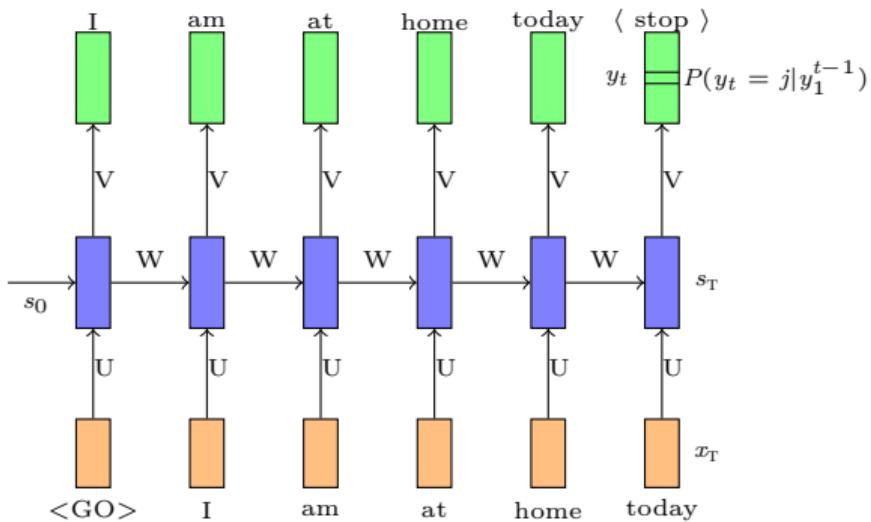
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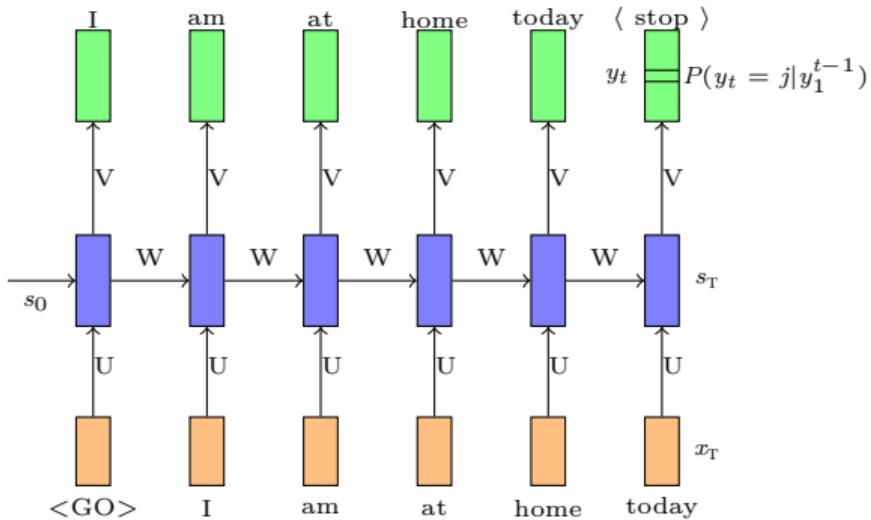
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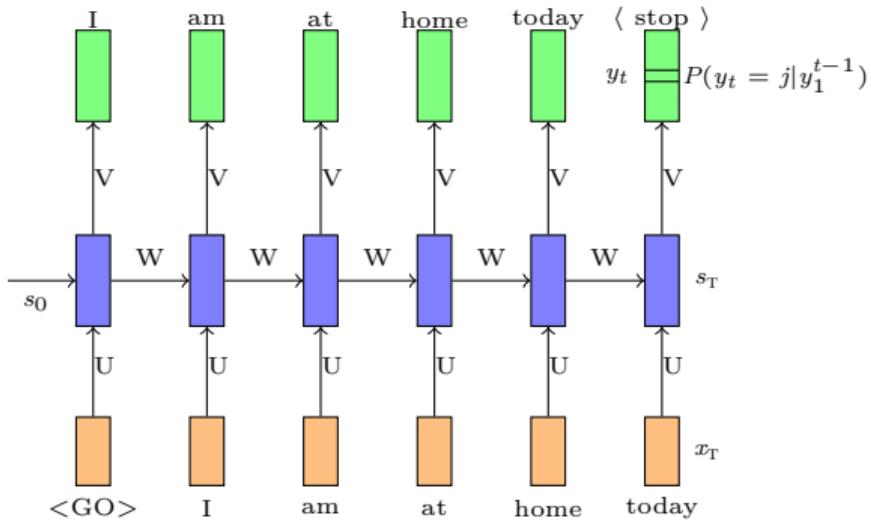
- $x_t$  is essentially a one-hot vector ( $e(v_j)$ ) representing the  $j^{th}$  word in the vocabulary
- In practice, instead of one hot representation we use a pre-trained word embedding of the  $j^{th}$  word

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- We will return back to this later

- Before moving on we will see a compact way of writing the function computed by RNN, GRU and LSTM

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- Before moving on we will see a compact way of writing the function computed by RNN, GRU and LSTM
- We will use these notations going forward

- So far we have seen how to model the conditional probability distribution  $P(y_t|y_1^{t-1})$

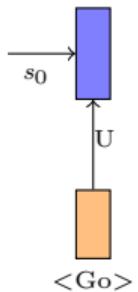
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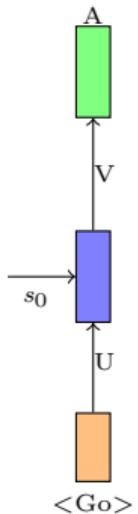


A man throwing  
a frisbee in a park



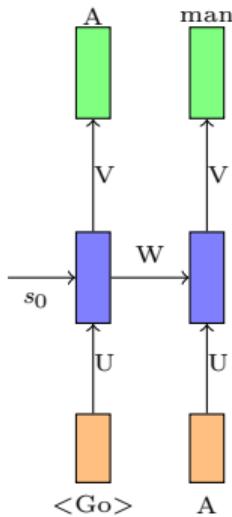
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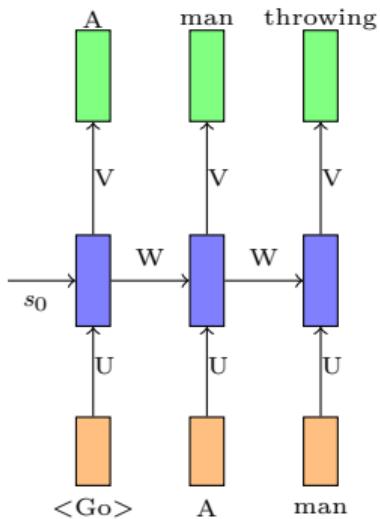
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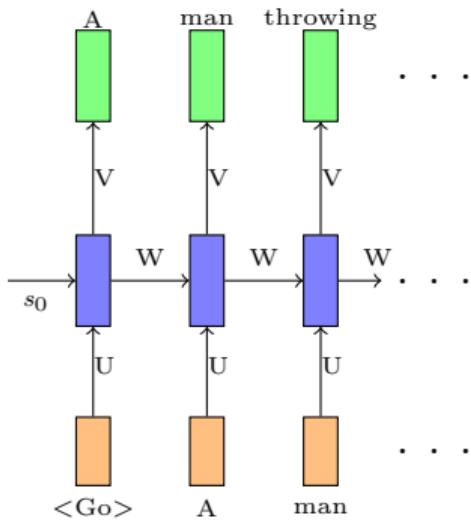
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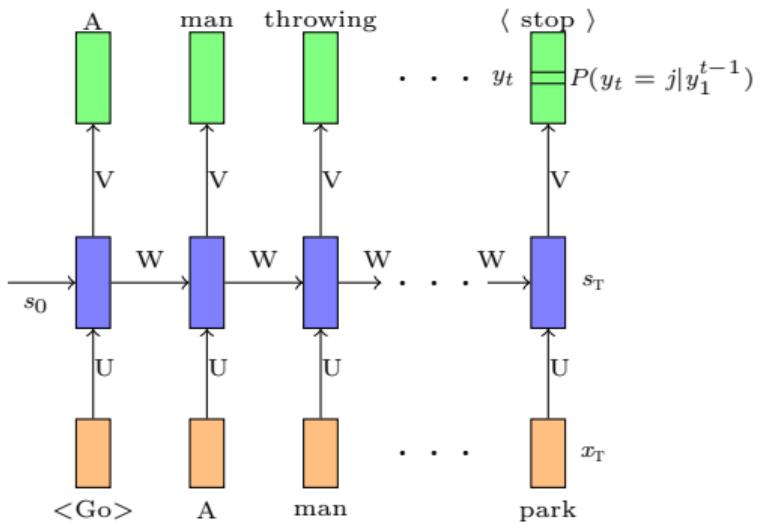
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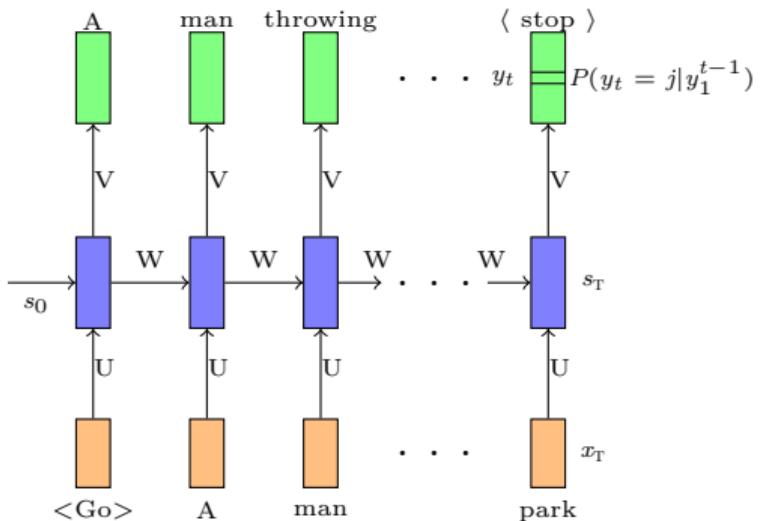
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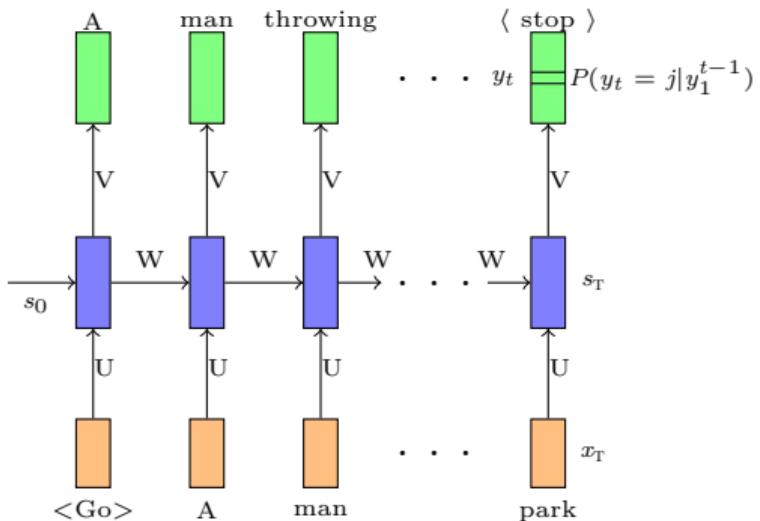
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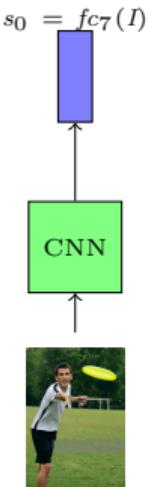


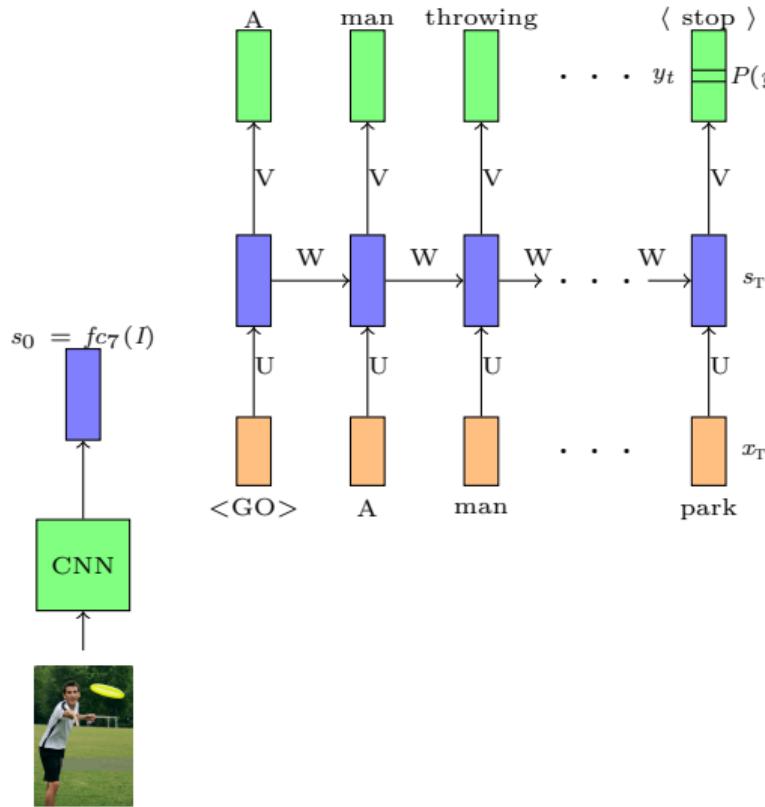
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- Notice that  $P(y_t | y_1^{t-1}, I)$  is again a conditional distribution

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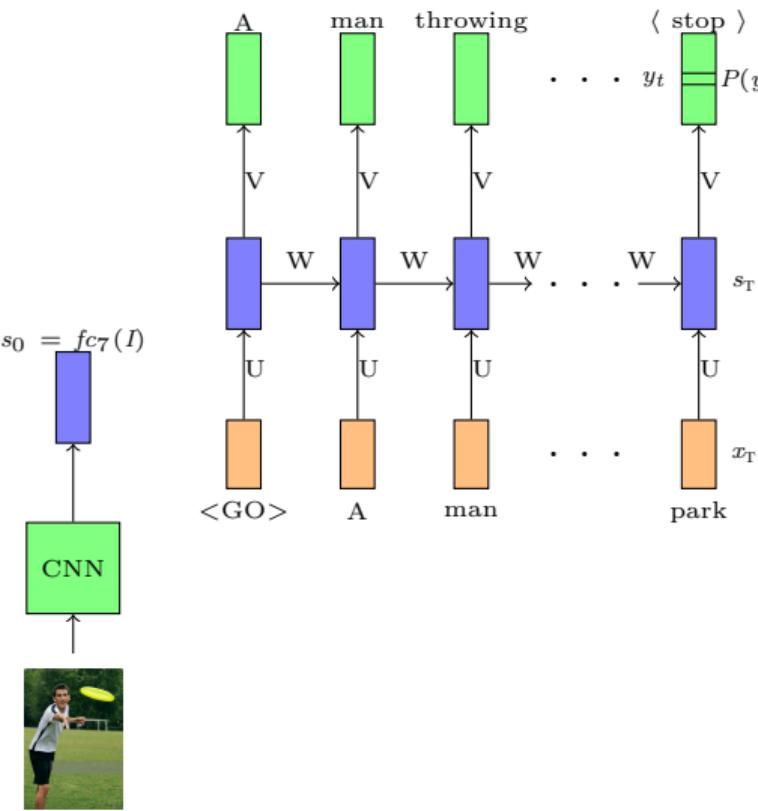




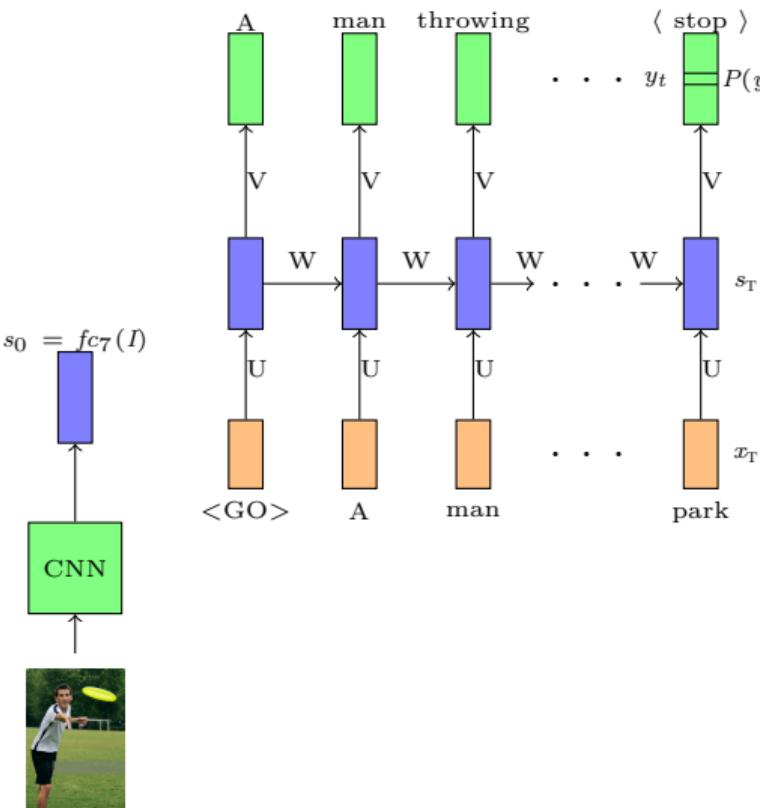
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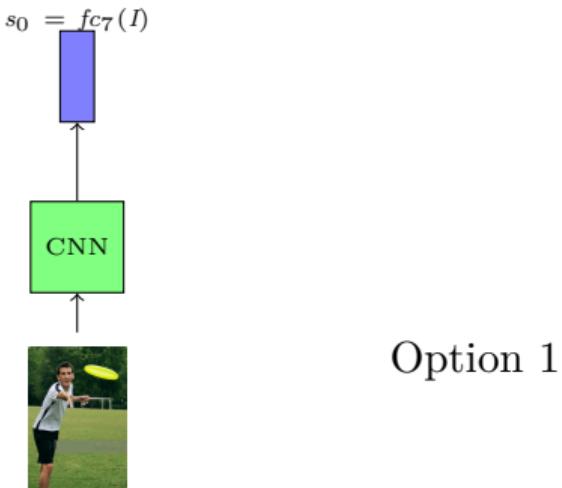


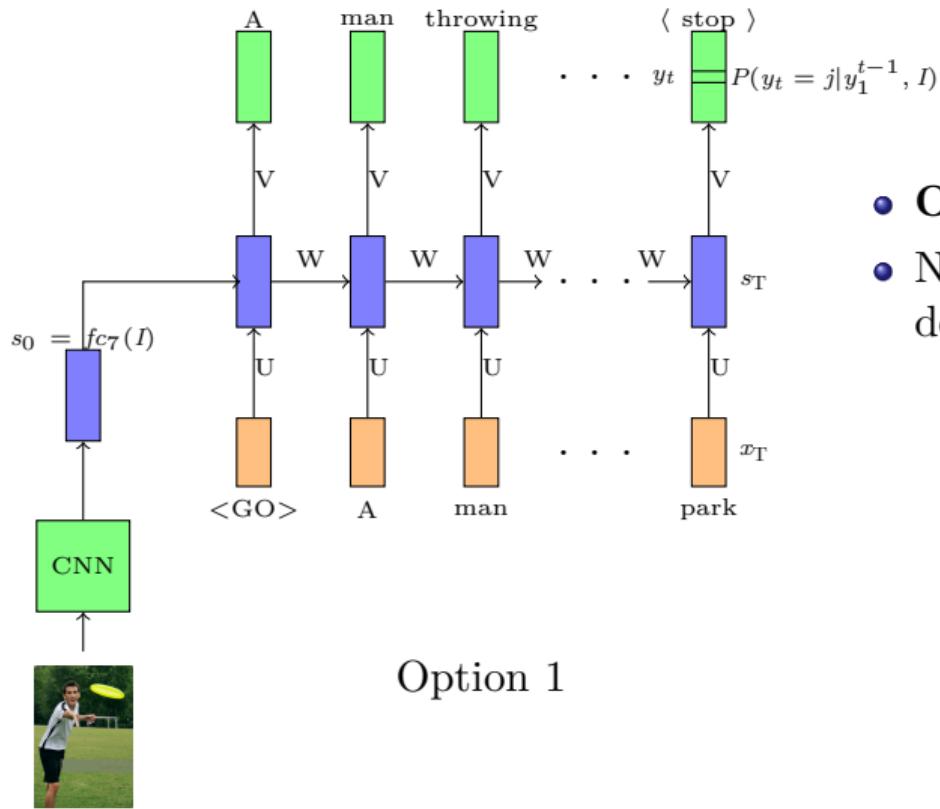
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- where  $f_{c7}(I)$  is the representation obtained from the  $f_{c7}$  layer of an image

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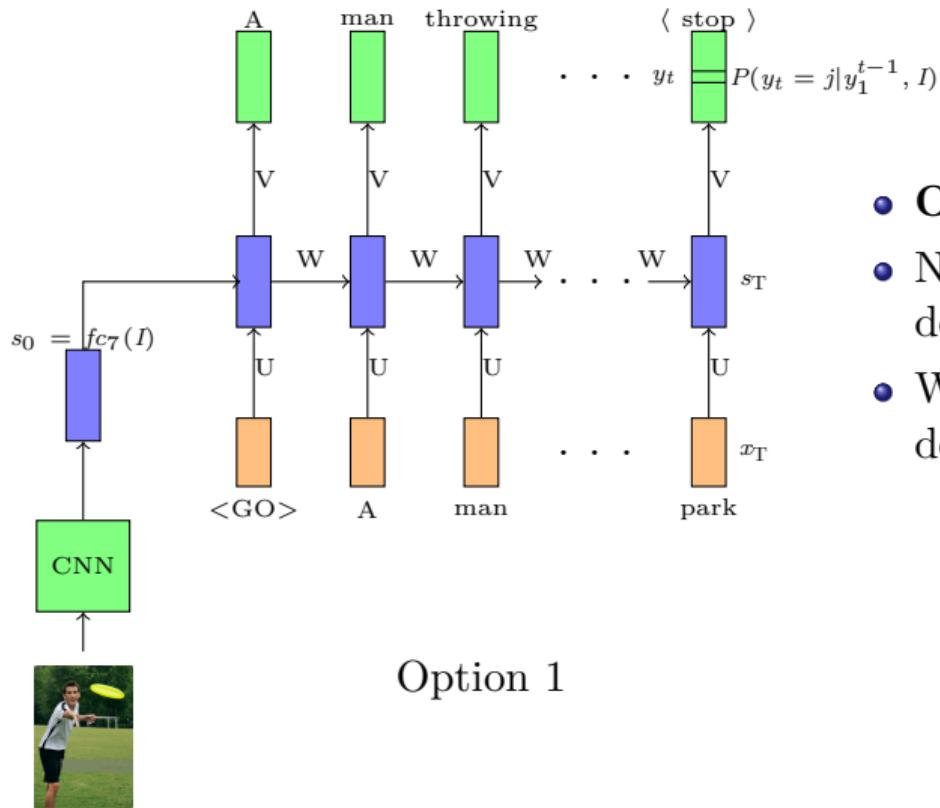
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- Let us see two such options

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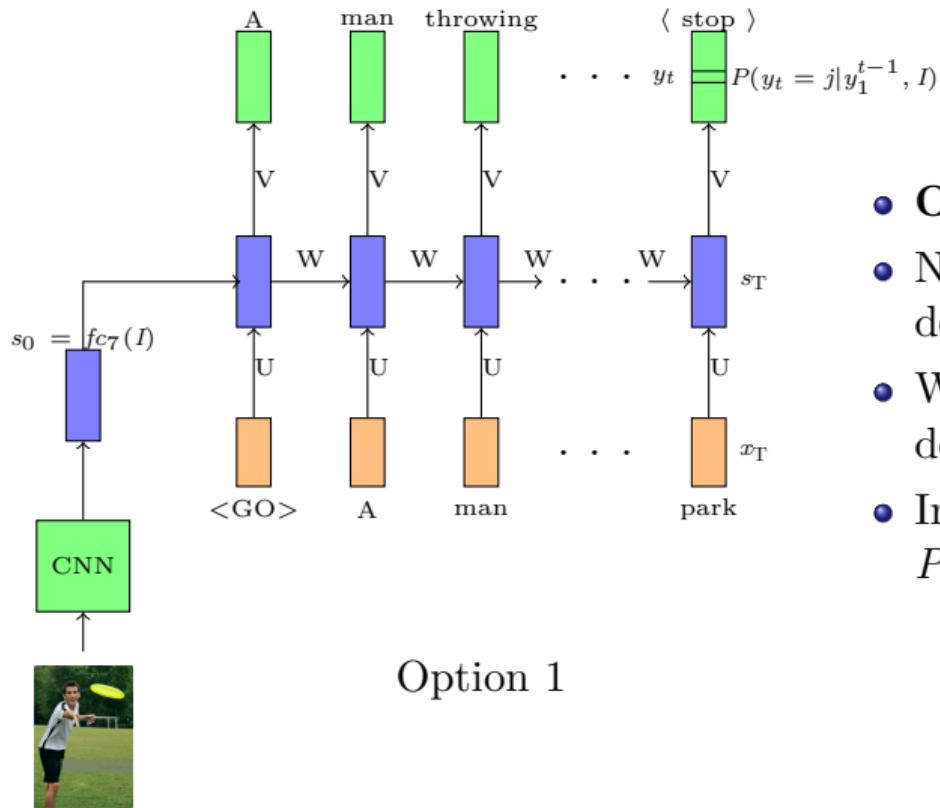




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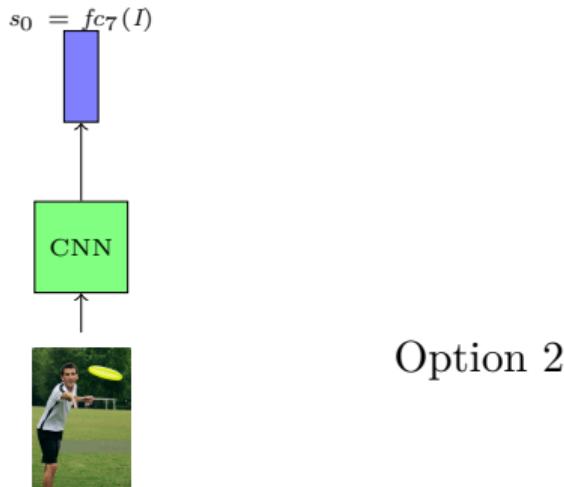
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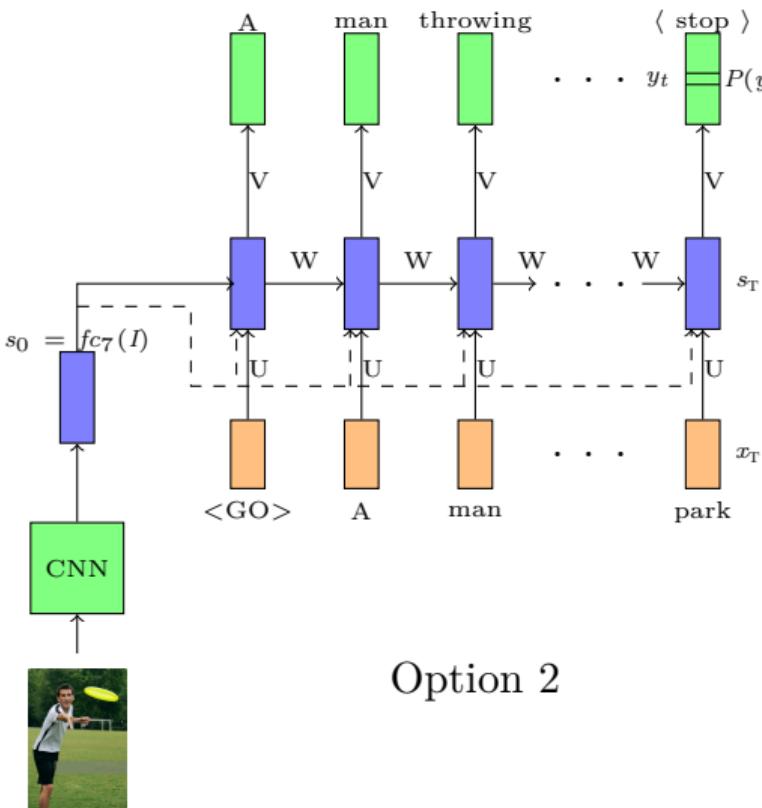


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- In other words, we are computing  $P(y_t = j | s_t, f_{c7}(I))$

- **Option 2:** Another more explicit way of doing this is to compute

$$s_t = RNN(s_{t-1}, [x_t, f_{c7}(I)])$$



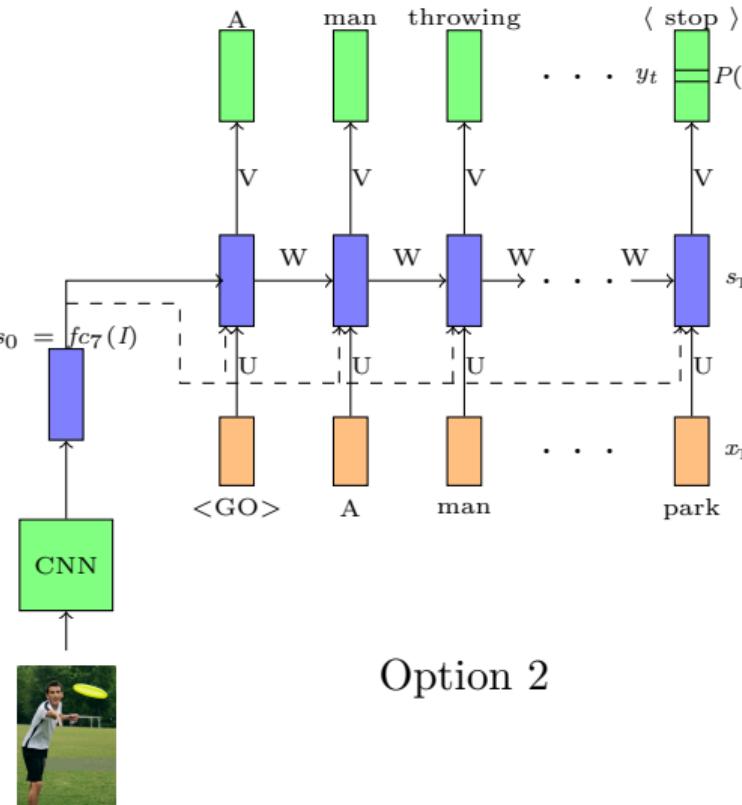


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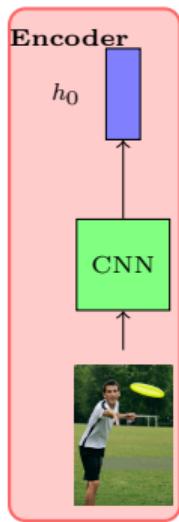
$$y_t \sim P(y_t = j | y_1^{t-1}, I)$$

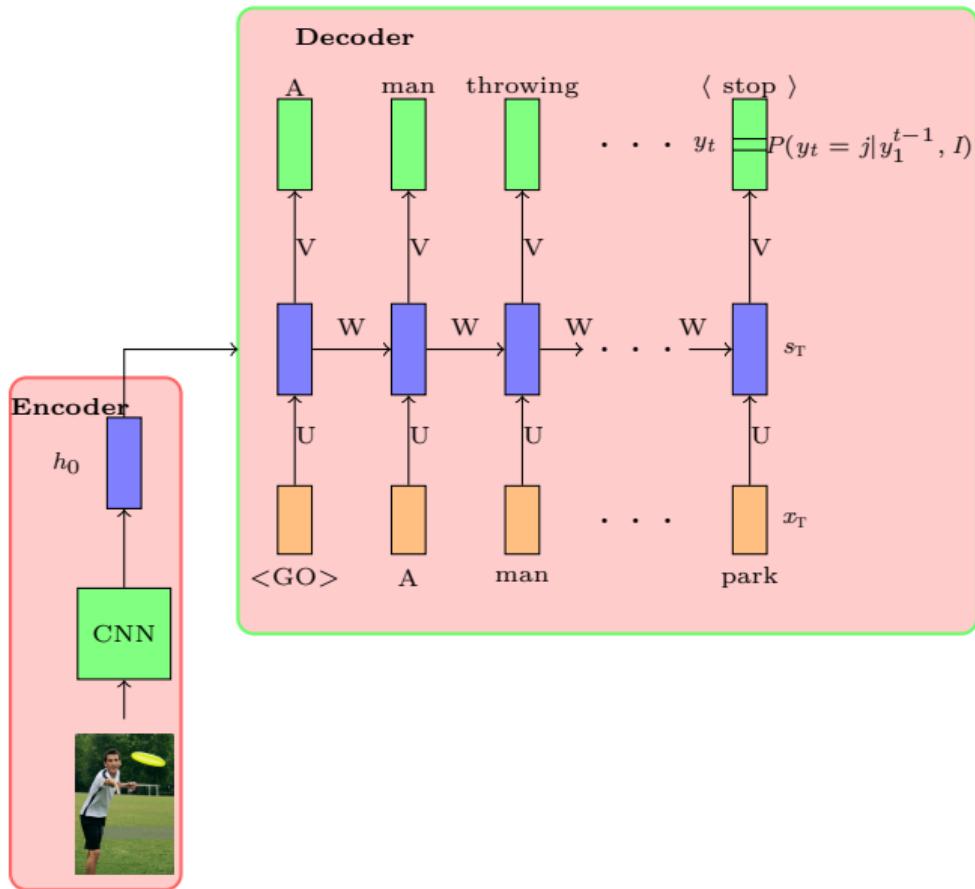
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- In other words we are explicitly using  $f_{c7}(I)$  to compute  $s_t$  and hence  $P(y_t = j)$
- You could think of other ways of conditioning  $P(y_t = j)$  on  $f_{c7}$

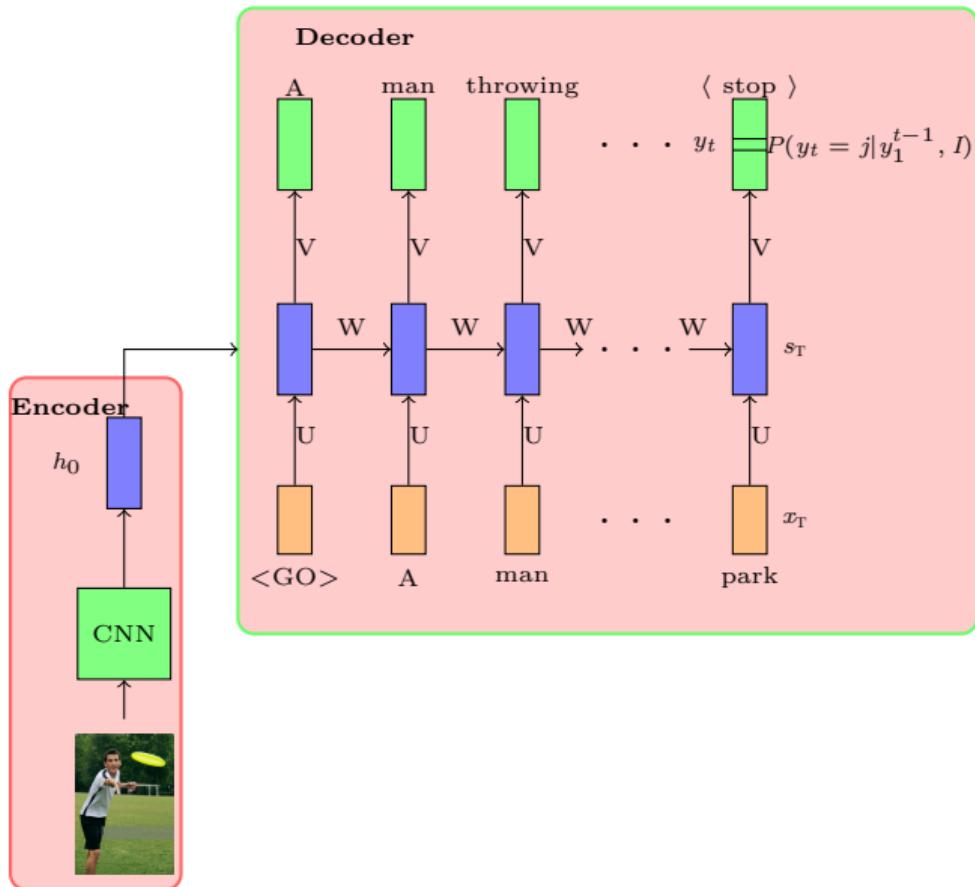
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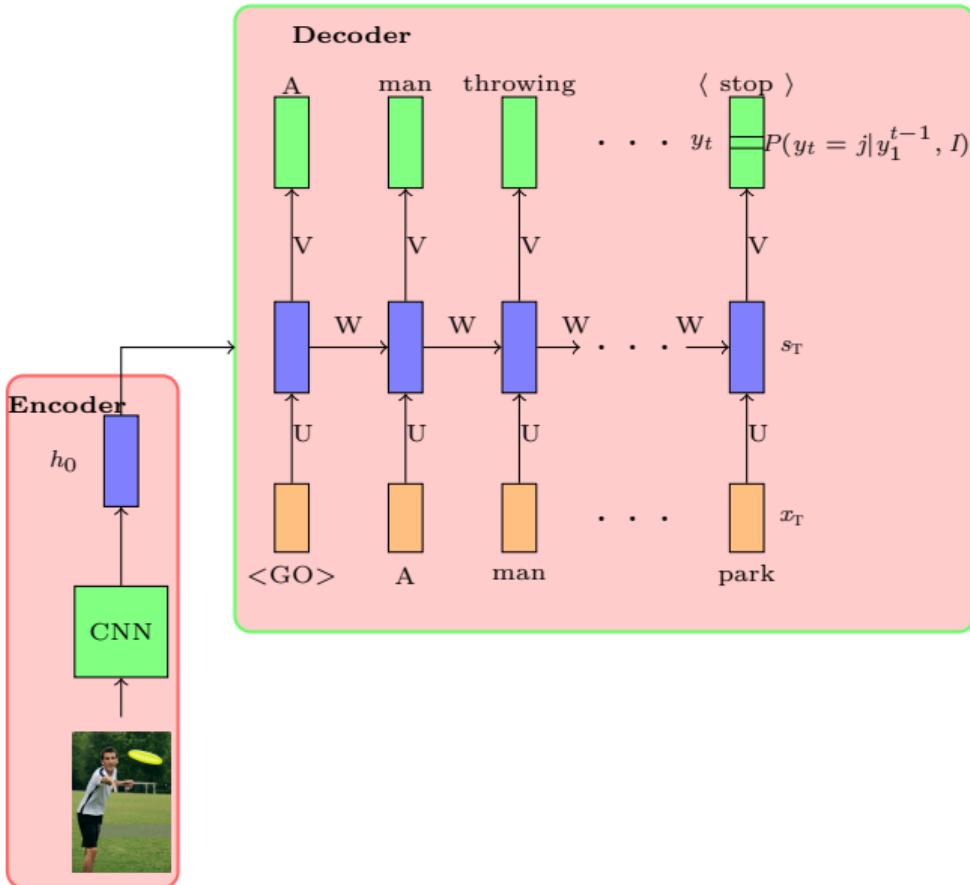




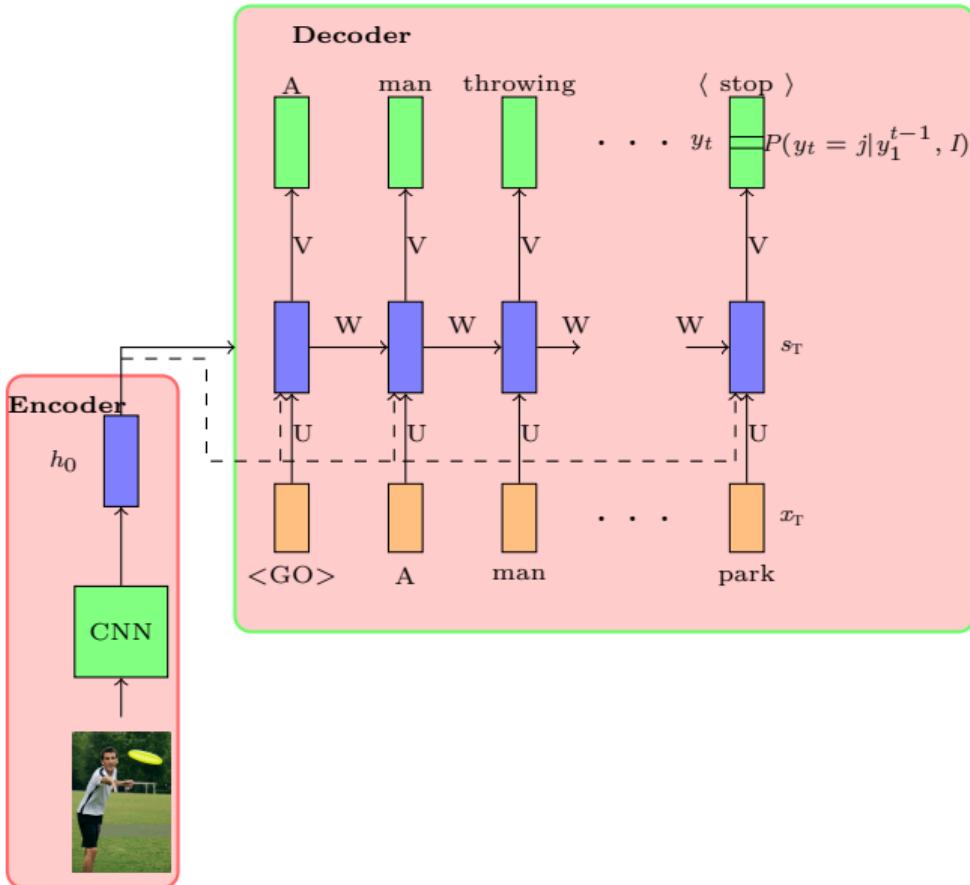
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- Both the encoder and decoder use a neural network
- Alternatively, the encoder's output can be fed to every step of the decoder

# Module : Applications of Encoder Decoder models

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A man throwing . . . < stop >

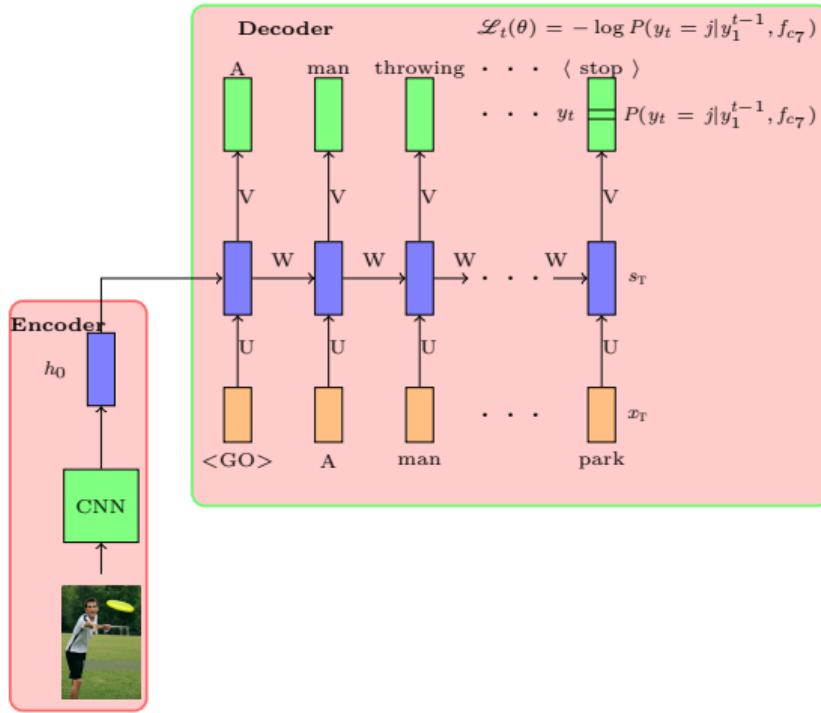


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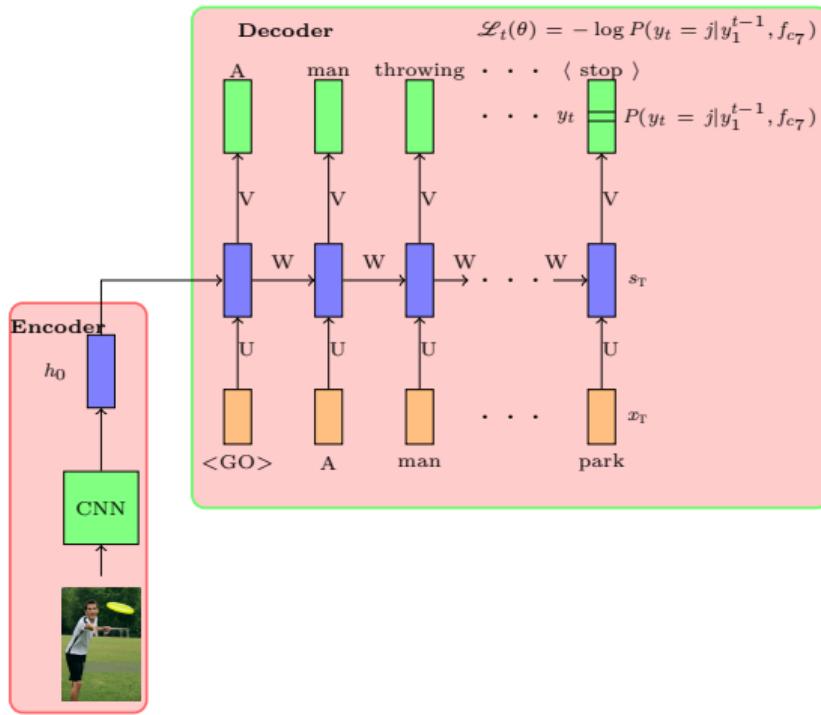
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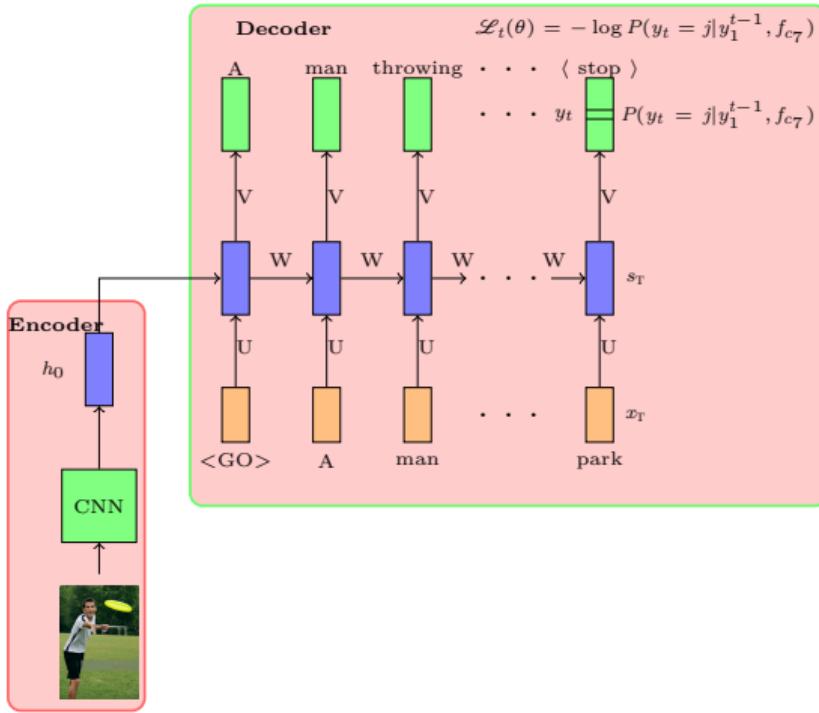


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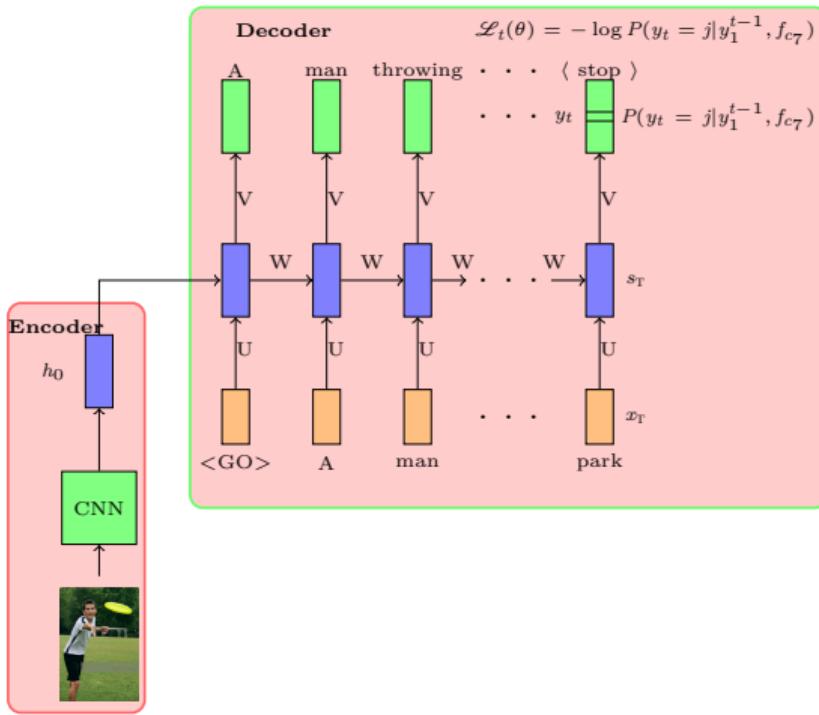
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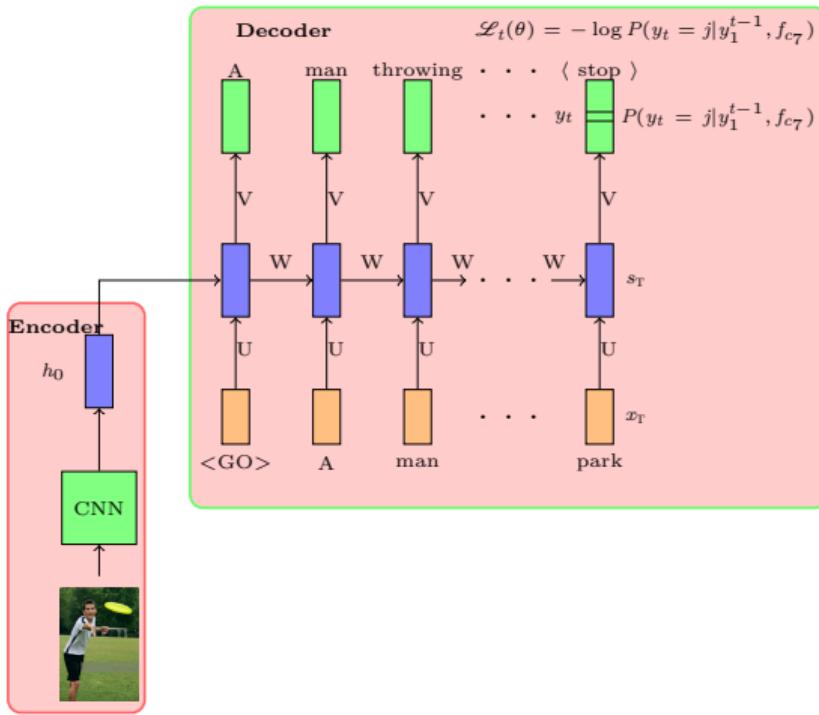
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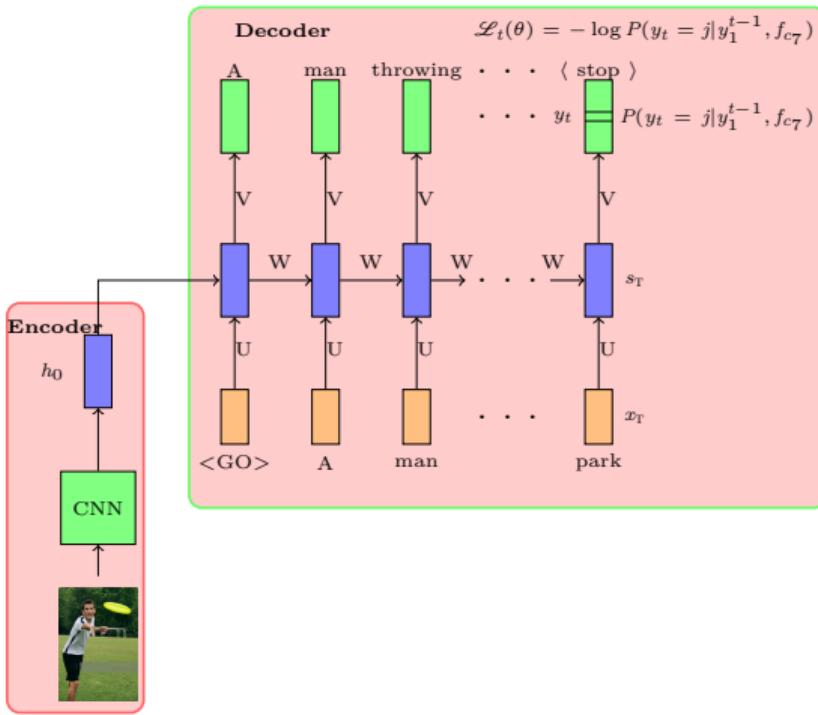
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- **Algorithm:** Gradient descent with backpropagation

o/p : The ground is wet

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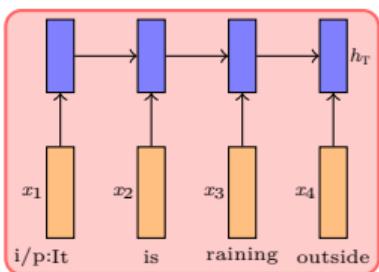
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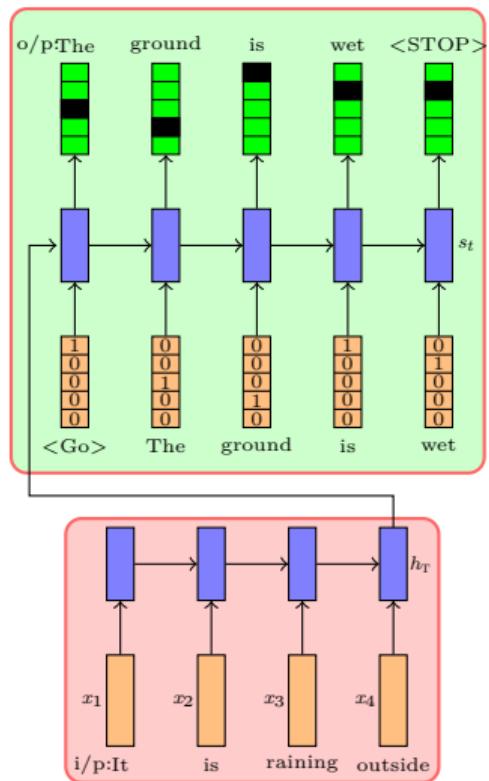
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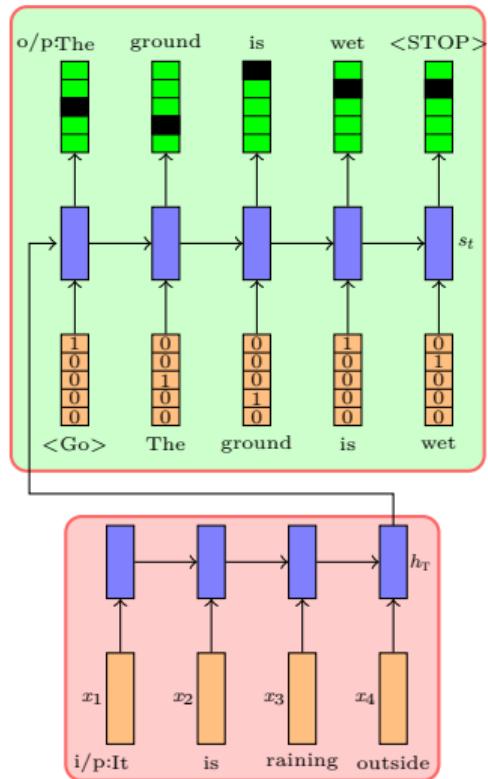
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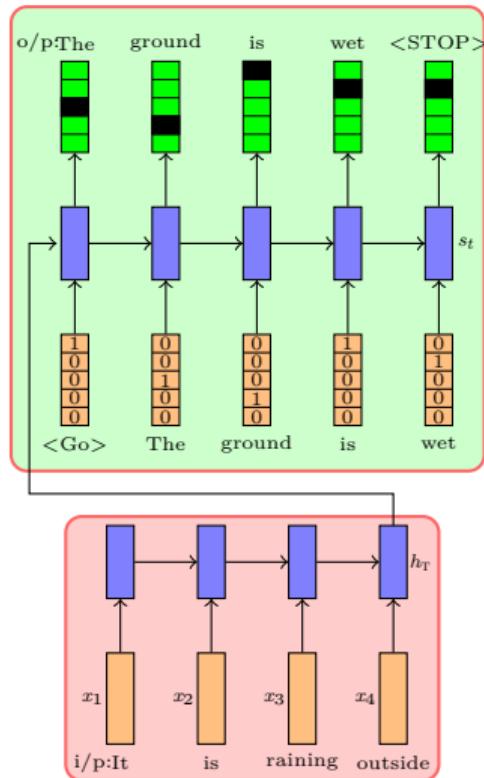
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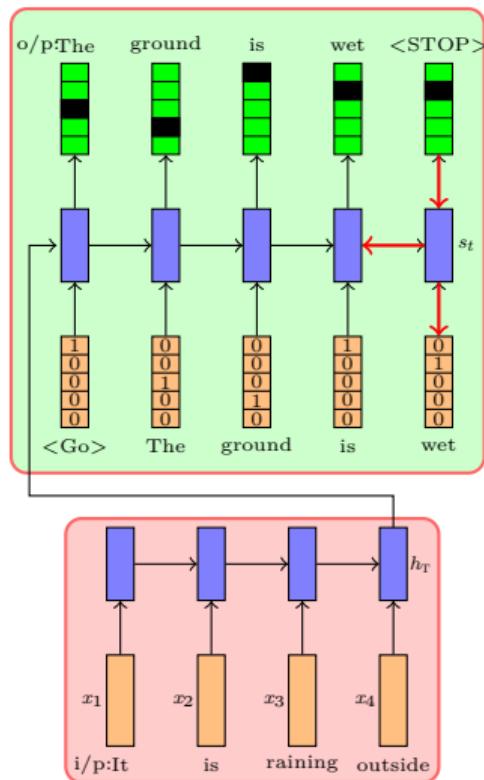
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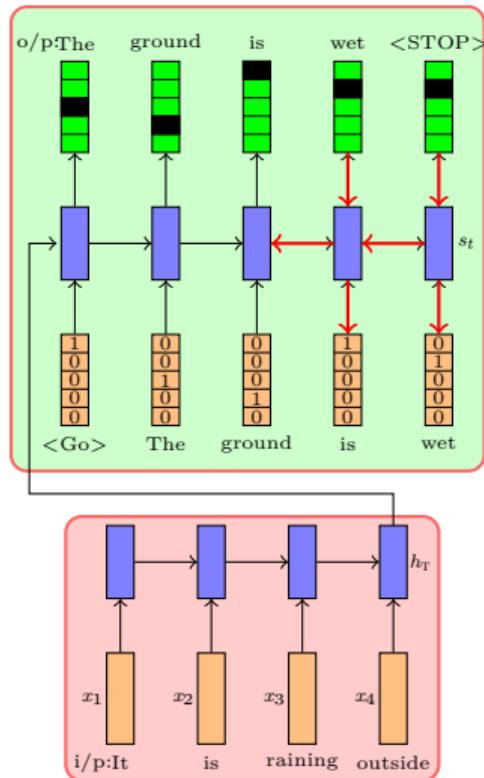
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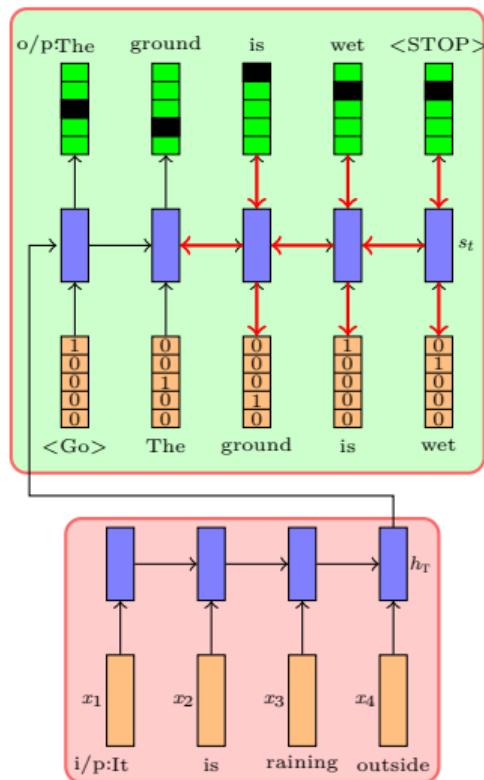
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

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$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

*o/p* : The ground is wet



*i/p* : It is raining outside

- **Task:** Textual entailment
- **Data:**  $\{x_i = \text{premise}_i, y_i = \text{hypothesis}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

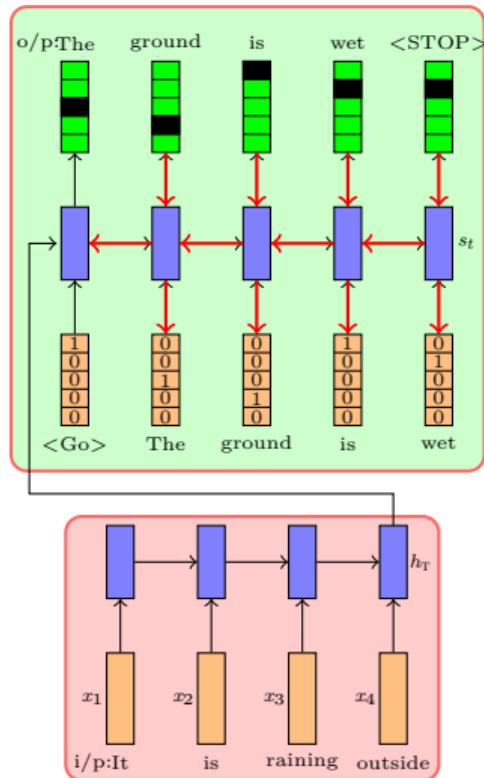
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

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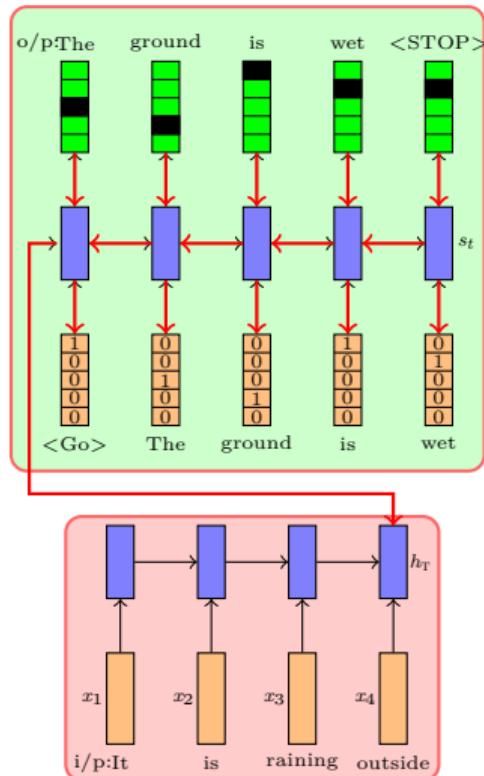
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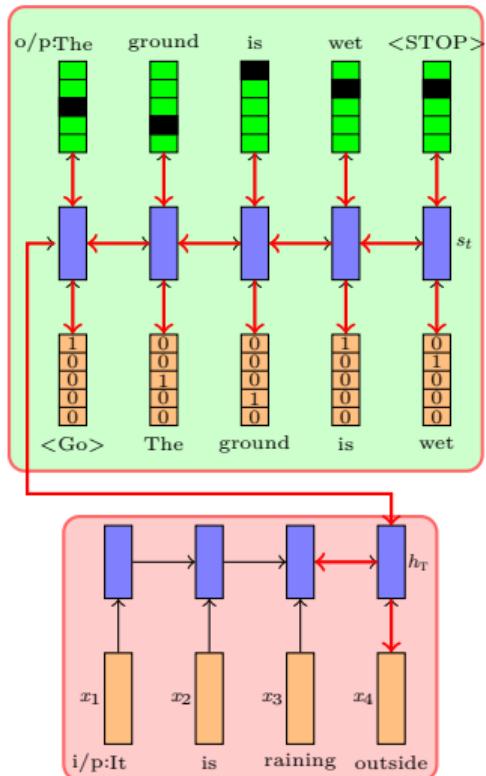
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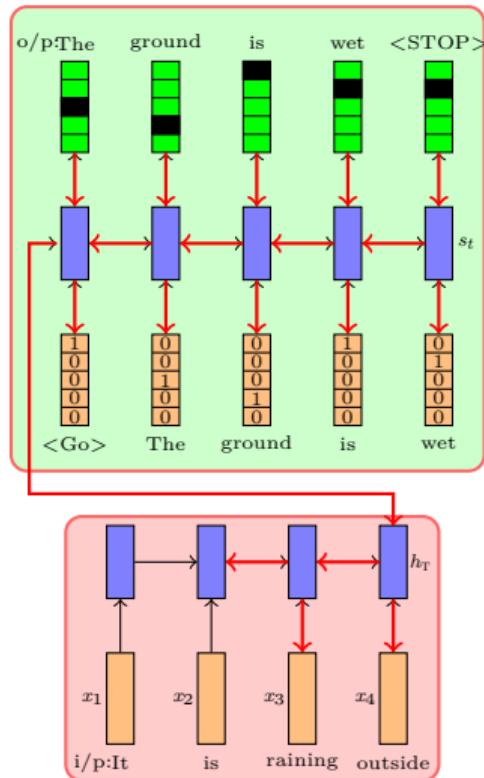
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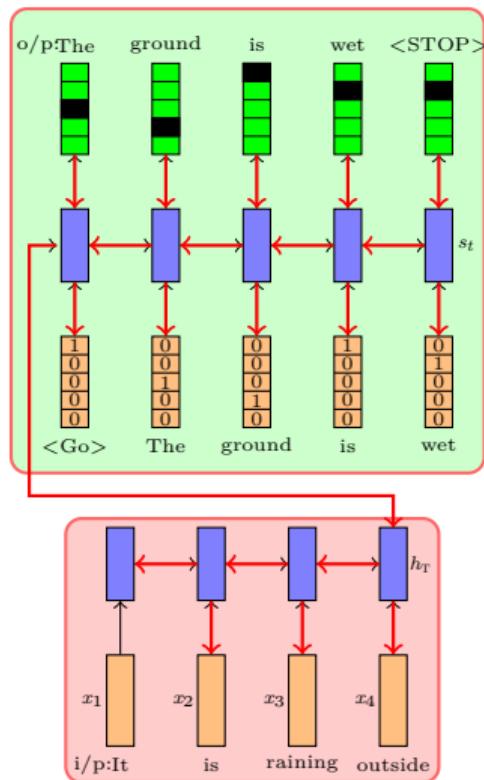
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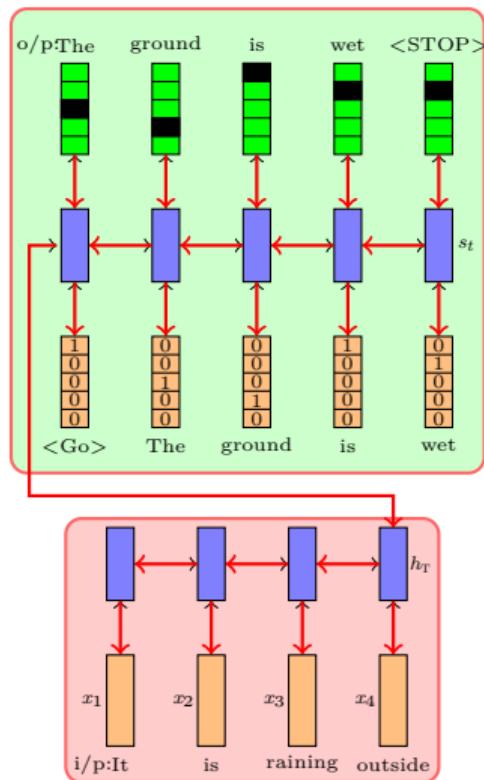
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- **Algorithm:** Gradient descent with backpropagation

o/p : The ground is wet

- **Task:** Textual entailment

i/p : It is raining outside

o/p : The ground is wet

- **Task:** Textual entailment

- **Data:**  $\{x_i = premise_i, y_i = hypothesis_i\}_{i=1}^N$

i/p : It is raining outside

o/p : The ground is wet

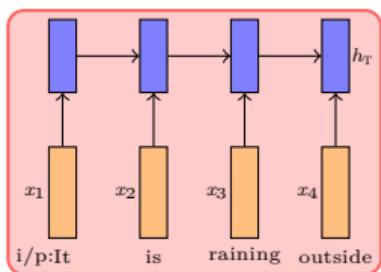
- **Task:** Textual entailment
- **Data:**  $\{x_i = \text{premise}_i, y_i = \text{hypothesis}_i\}_{i=1}^N$
- **Model (Option 2):**

i/p : It is raining outside

o/p : The ground is wet

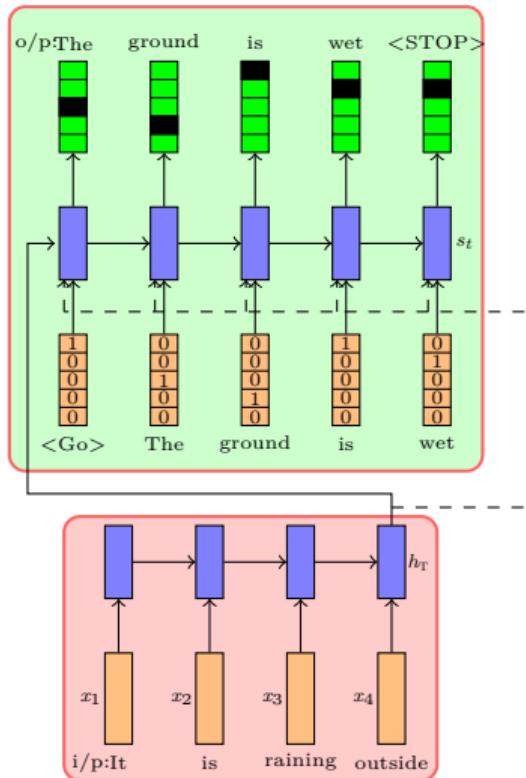
- **Task:** Textual entailment
- **Data:**  $\{x_i = \text{premise}_i, y_i = \text{hypothesis}_i\}_{i=1}^N$
- **Model (Option 2):**
  - **Encoder:**

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i/p : It is raining outside

*o/p* : The ground is wet



*i/p* : It is raining outside

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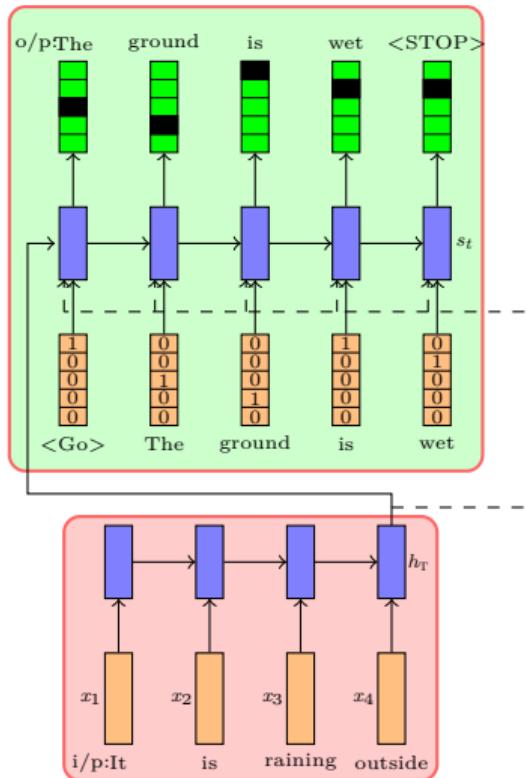
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$$P(y_t | y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

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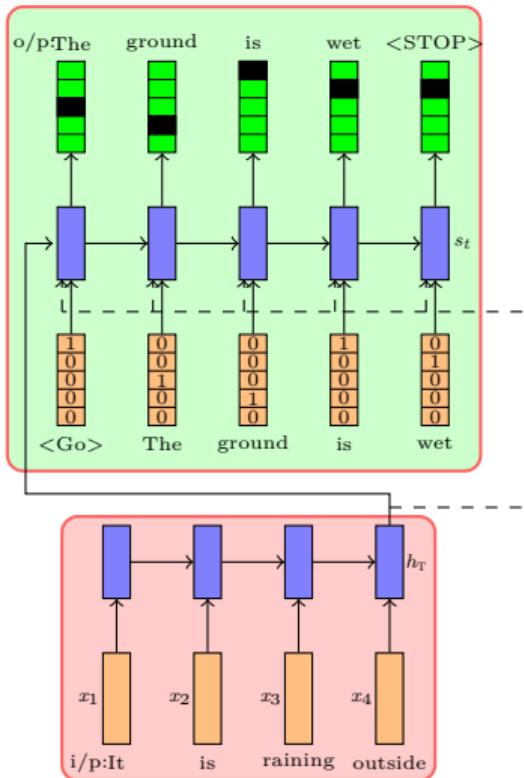
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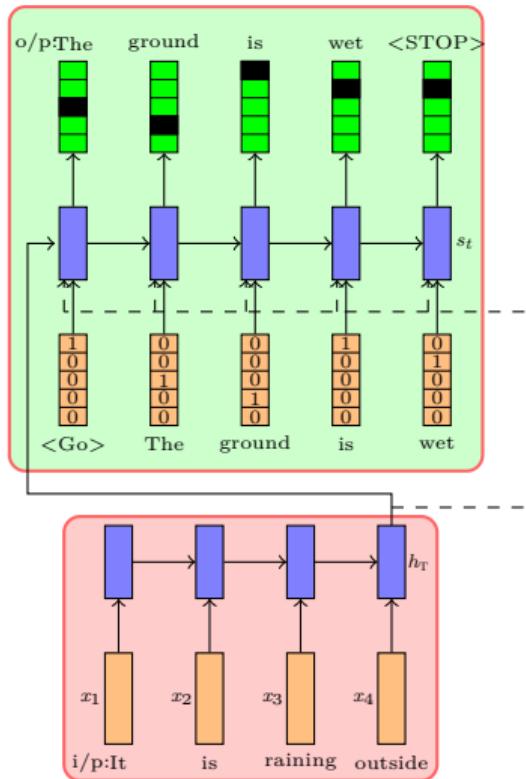
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- **Algorithm:** Gradient descent with backpropagation

o/p : Mein ghar ja raha hoon

- **Task:** Machine translation

i/p : I am going home

o/p : Mein ghar ja raha hoon

- **Task:** Machine translation

- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$

i/p : I am going home

o/p : Mein ghar ja raha hoon

- **Task:** Machine translation
- **Data:**  $\{x_i = source_i, y_i = target_i\}_{i=1}^N$
- **Model (Option 1):**

i/p : I am going home

o/p : Mein ghar ja raha hoon

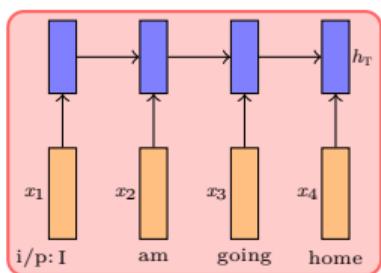
- **Task:** Machine translation

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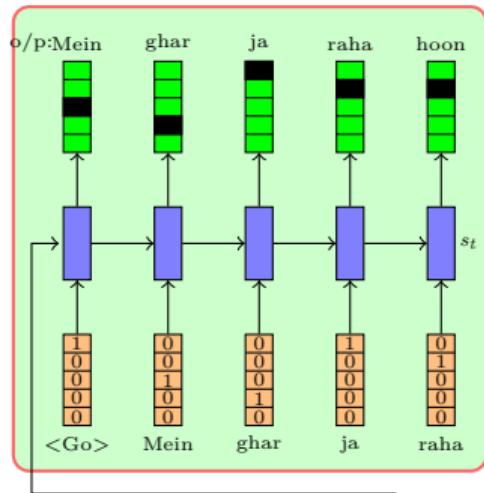
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i/p : I am going home

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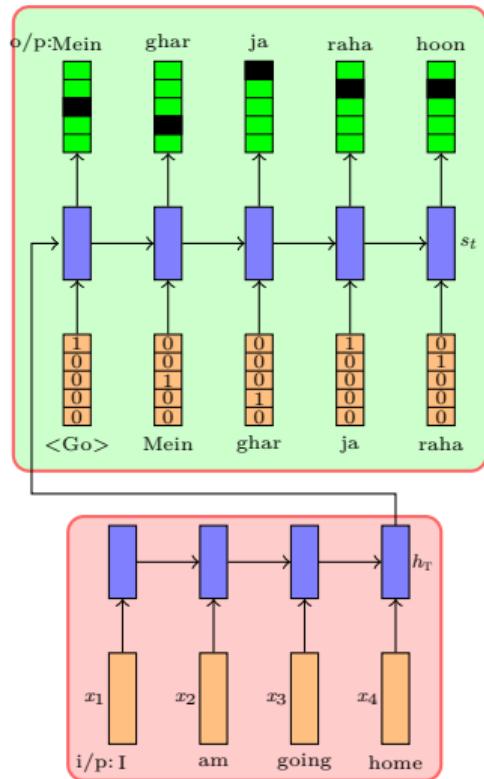
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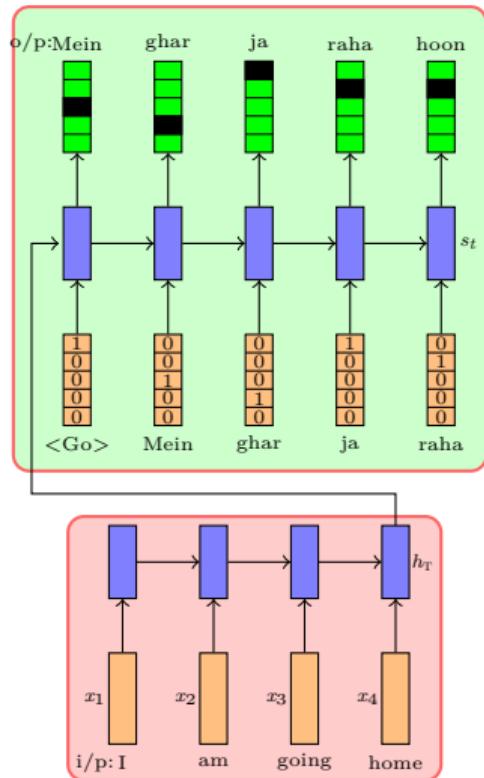
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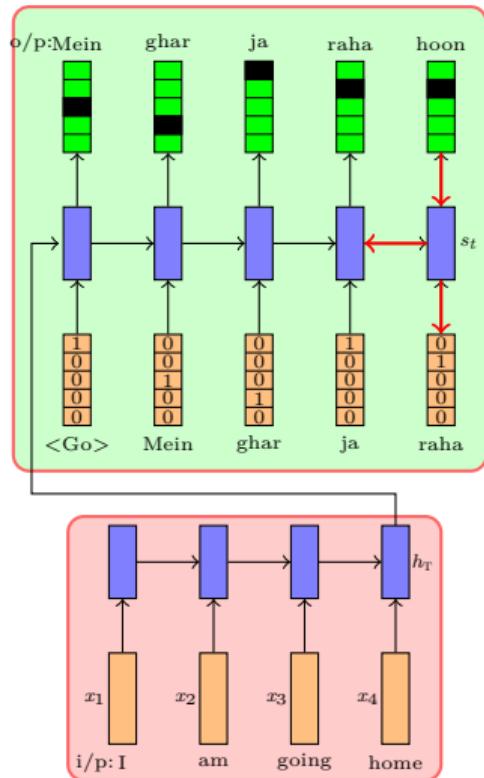
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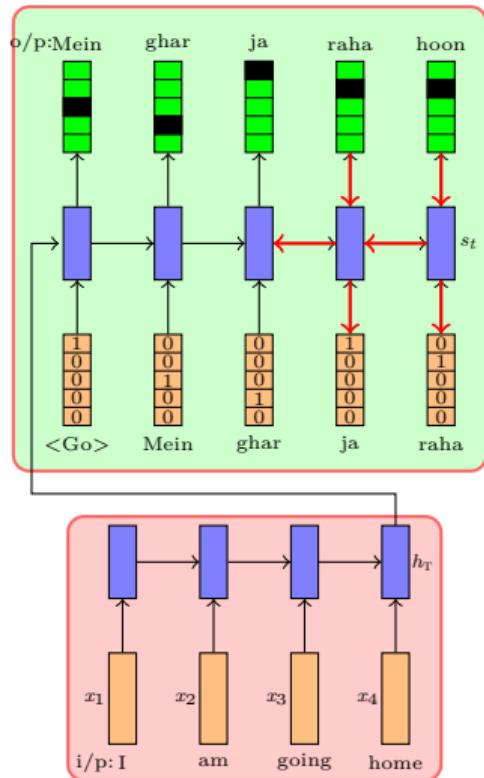
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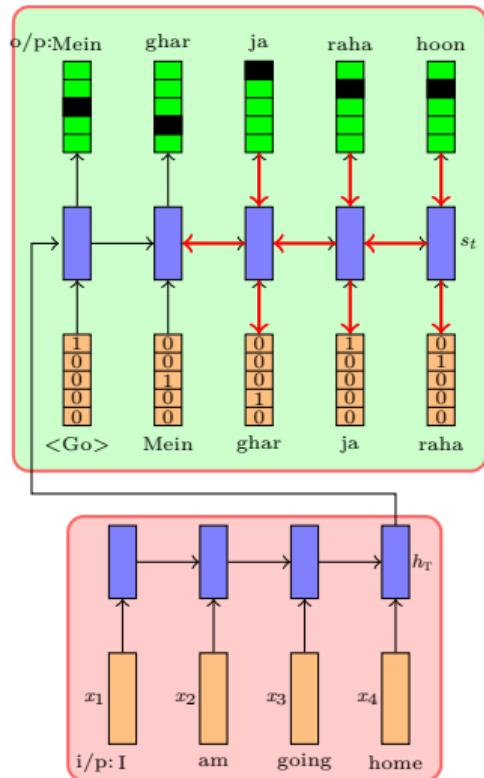
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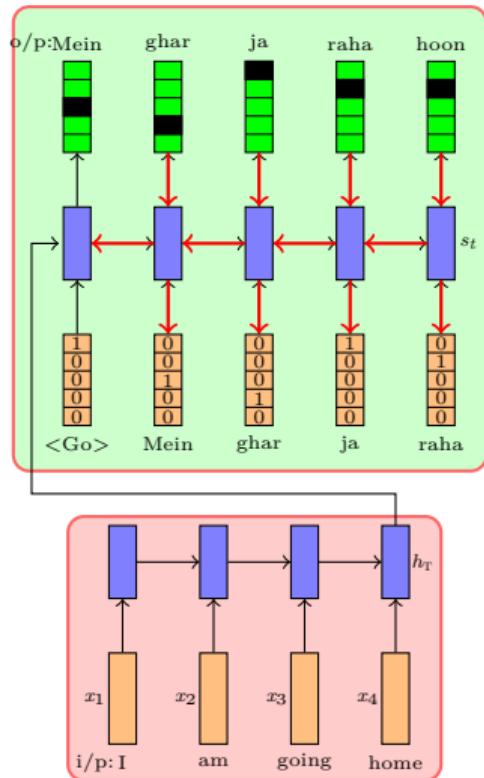
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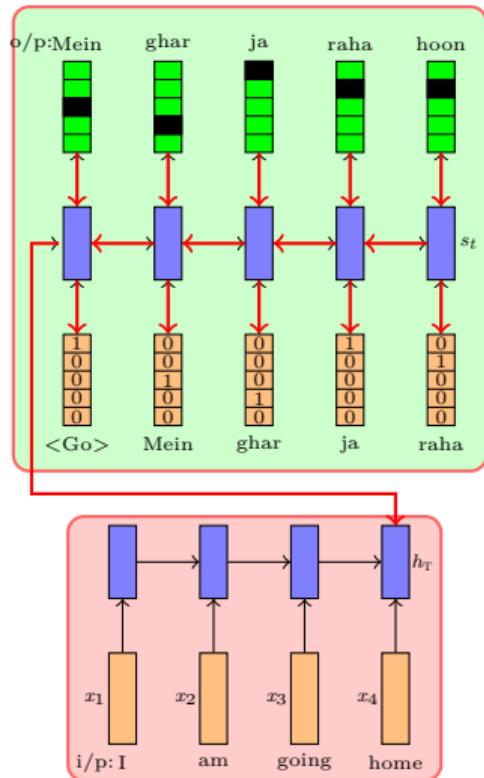
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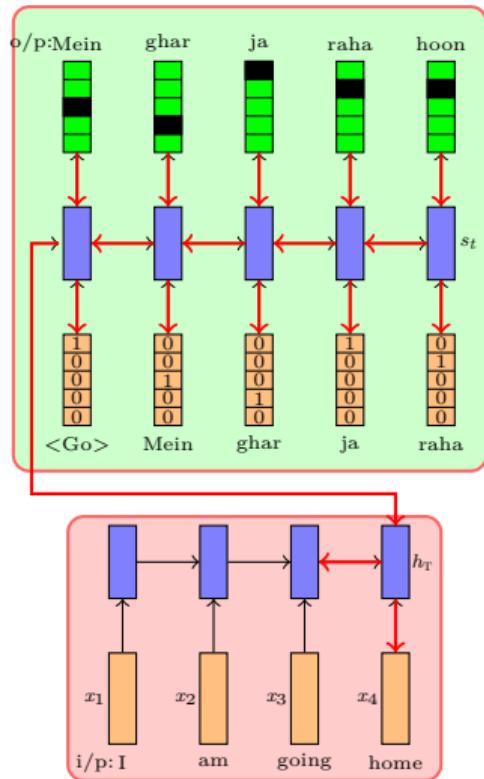
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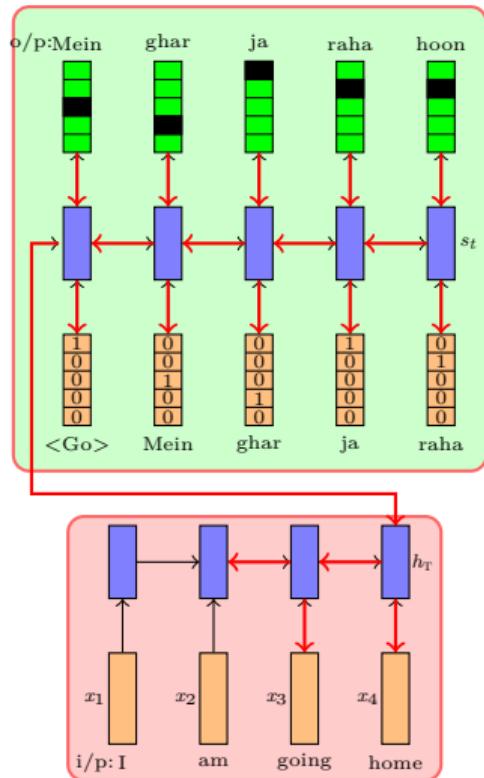
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

*o/p* : Mein ghar ja raha hoon



*i/p* : I am going home

- **Task:** Machine translation

- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

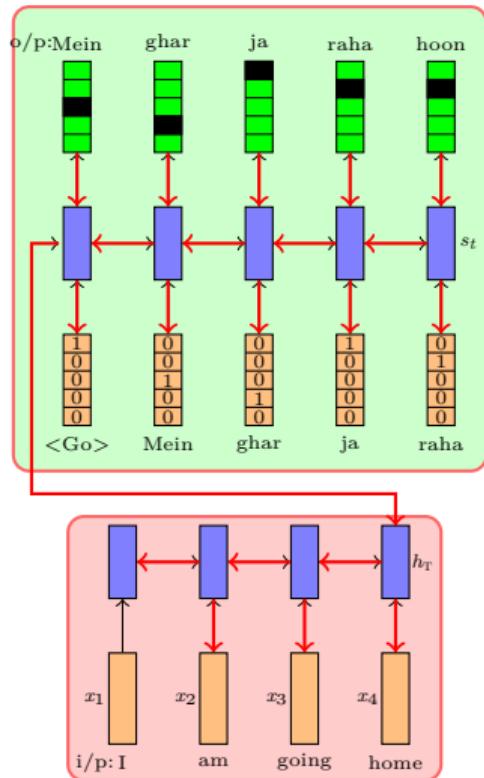
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

*o/p* : Mein ghar ja raha hoon



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- **Task:** Machine translation

- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$

- **Model (Option 1):**

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$$h_t = RNN(h_{t-1}, x_{it})$$

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$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

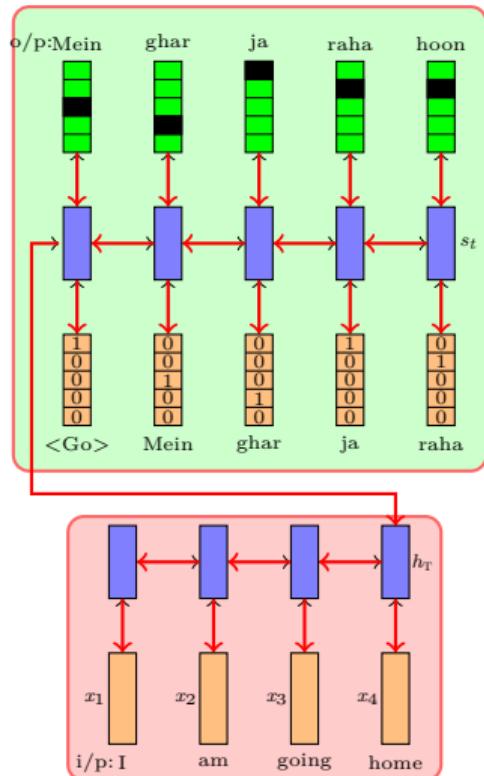
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

*o/p* : Mein ghar ja raha hoon



*i/p* : I am going home

- **Task:** Machine translation

- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

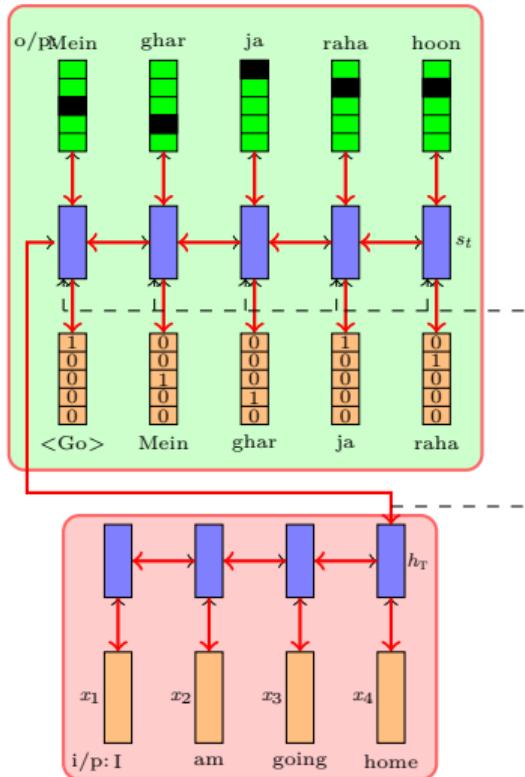
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

o/p : Mein ghar ja raha hoon



i/p : I am going home

- **Task:** Machine translation

- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$

- **Model (Option 2):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, [h_T, e(\hat{y}_{t-1})])$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

o/p : इंडिया

- **Task:** Transliteration

i/p : INDIA

o/p : इंडिया

- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

i/p : INDIA

o/p : इंडिया

- **Task:** Transliteration
- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$
- **Model (Option 1):**

i/p : INDIA

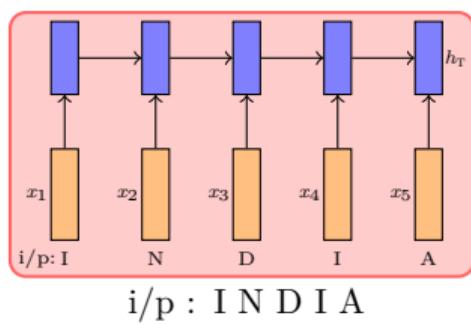
- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 1):**

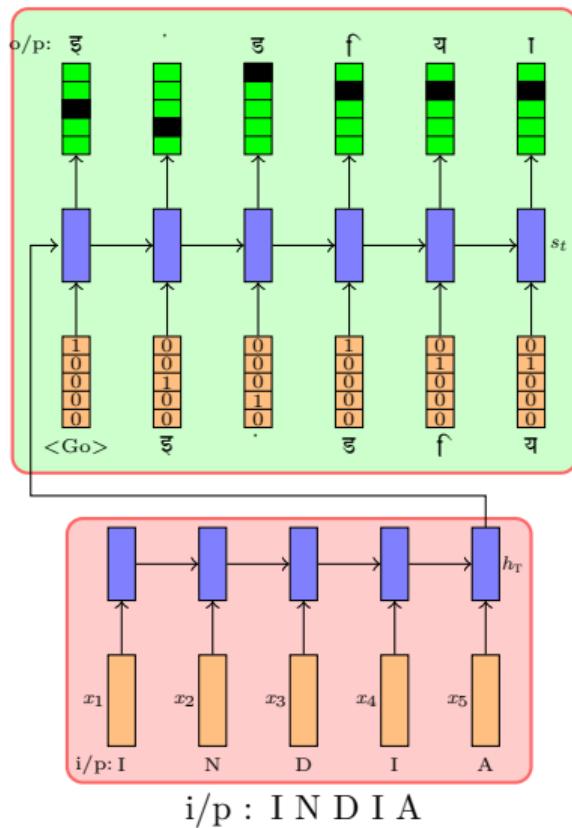
- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$



i/p : I N D I A

O/P : ଇ ଟ ଫ୍ୟ ଏ



- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

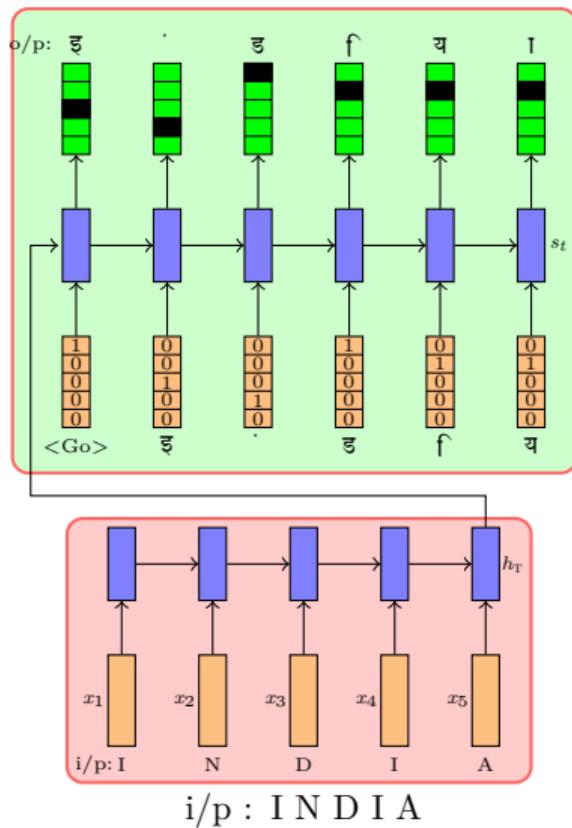
- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

O/P : ଇ ଟ ଫ୍ୟ ଏ



- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

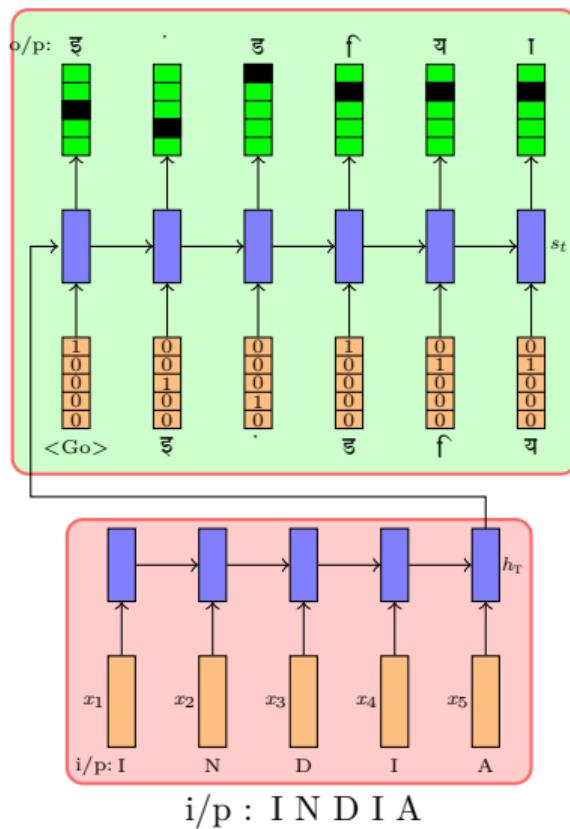
$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t | y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

O/P : ଇ ଟ ଫ୍ୟ ଏ



- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

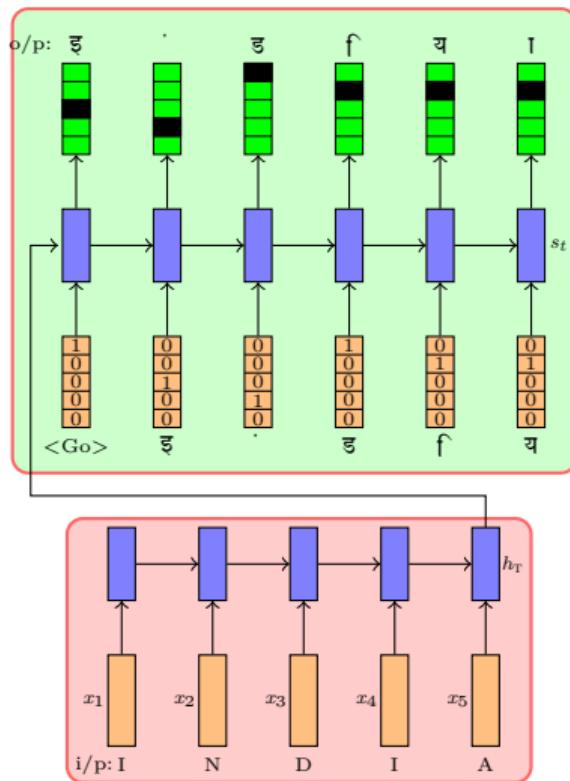
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_i(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$



- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 1):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

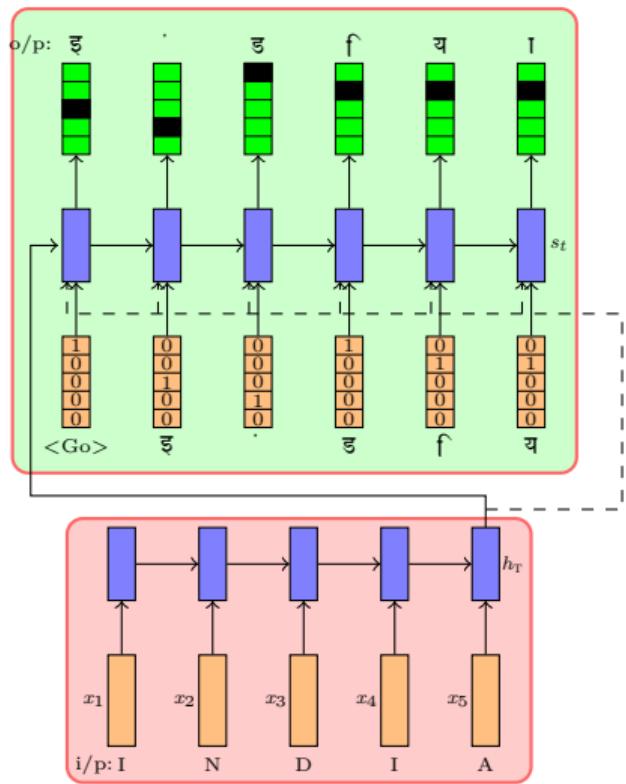
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

O/P : ଇ ଟ ଫ୍ୟ ଏ



- **Task:** Transliteration

- **Data:**  $\{x_i = \text{srcword}_i, y_i = \text{tgtword}_i\}_{i=1}^N$

- **Model (Option 2):**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

$$s_0 = h_T \quad (T \text{ is length of input})$$

$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), h_T])$$

$$P(y_t | y_1^{t-1}, x) = \text{softmax}(V s_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

O/p: White

- **Task:** Image Question Answering



Question: What  
is the bird's color

O/p: White

- **Task:** Image Question Answering
- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$



Question: What  
is the bird's color

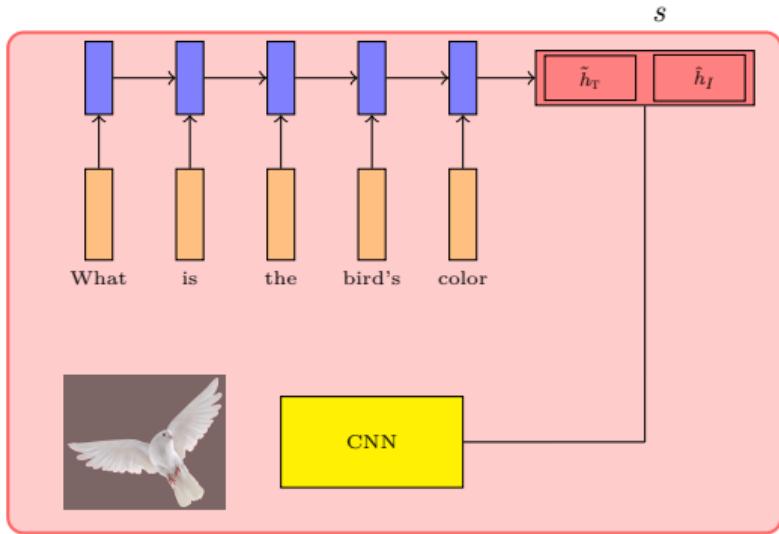
O/p: White

- **Task:** Image Question Answering
- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$
- **Model:**



Question: What  
is the bird's color

O/p: White



Question: What  
is the bird's color

- **Task:** Image Question Answering

- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$

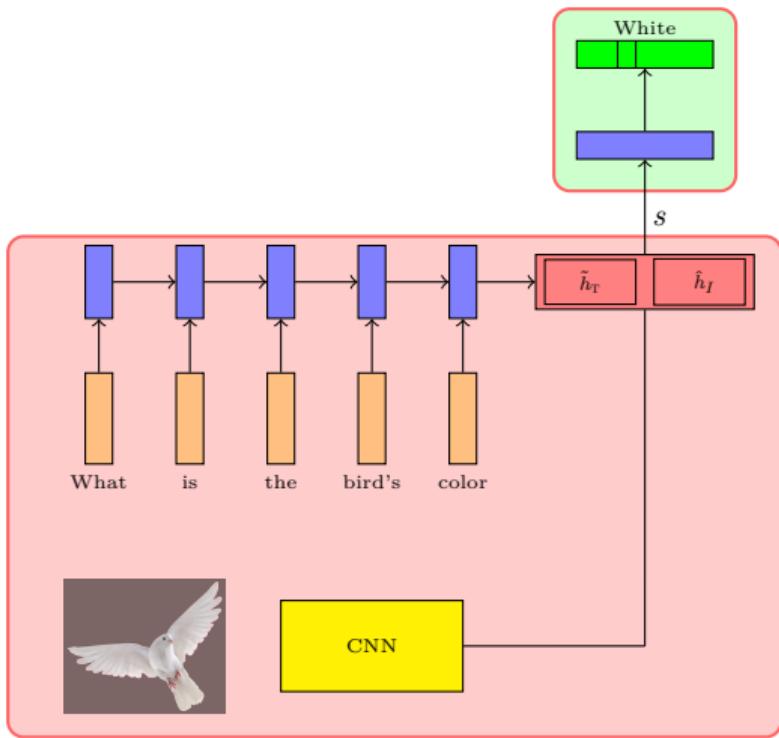
- **Model:**

- **Encoder:**

$$\hat{h}_I = CNN(I), \quad \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

$$s = [\tilde{h}_T; \hat{h}_I]$$

O/p: White



Question: What  
is the bird's color

- **Task:** Image Question Answering

- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$

- **Model:**

- **Encoder:**

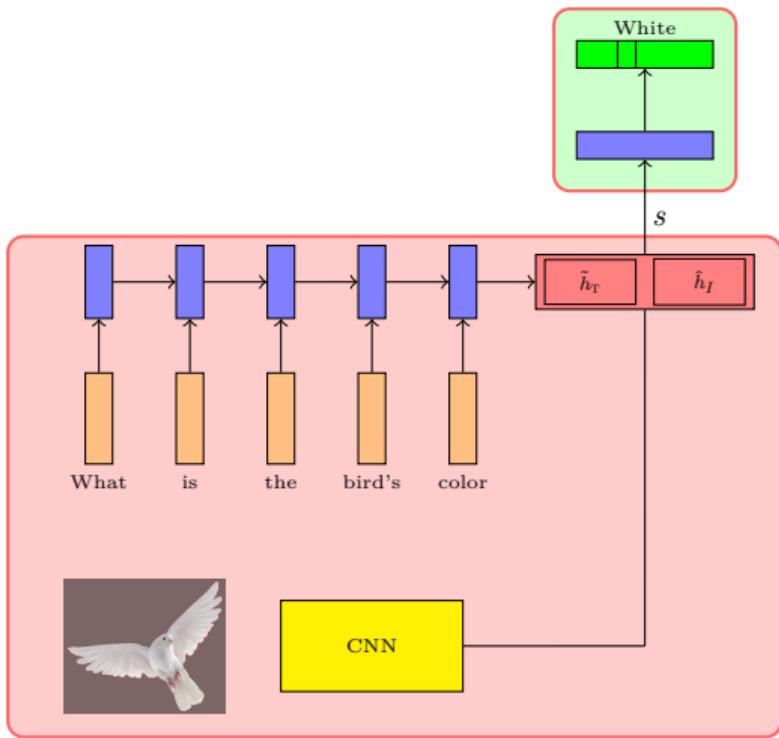
$$\hat{h}_I = CNN(I), \quad \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

$$s = [\tilde{h}_T; \hat{h}_I]$$

- **Decoder:**

$$P(y|q, I) = softmax(Vs + b)$$

O/p: White



Question: What  
is the bird's color

- **Task:** Image Question Answering

- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$

- **Model:**

- **Encoder:**

$$\hat{h}_I = CNN(I), \quad \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

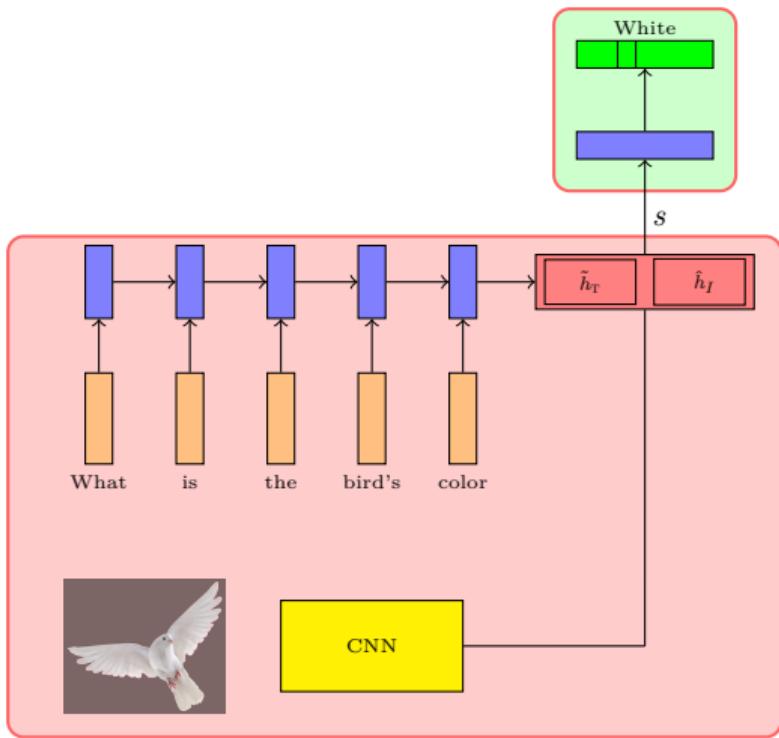
$$s = [\tilde{h}_T; \hat{h}_I]$$

- **Decoder:**

$$P(y|q, I) = softmax(Vs + b)$$

- **Parameters:**  $V, b, U_q, W_q, W_{conv}, b$

O/p: White



Question: What  
is the bird's color

- **Task:** Image Question Answering

- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$

- **Model:**

- **Encoder:**

$$\hat{h}_I = CNN(I), \quad \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

$$s = [\tilde{h}_T; \hat{h}_I]$$

- **Decoder:**

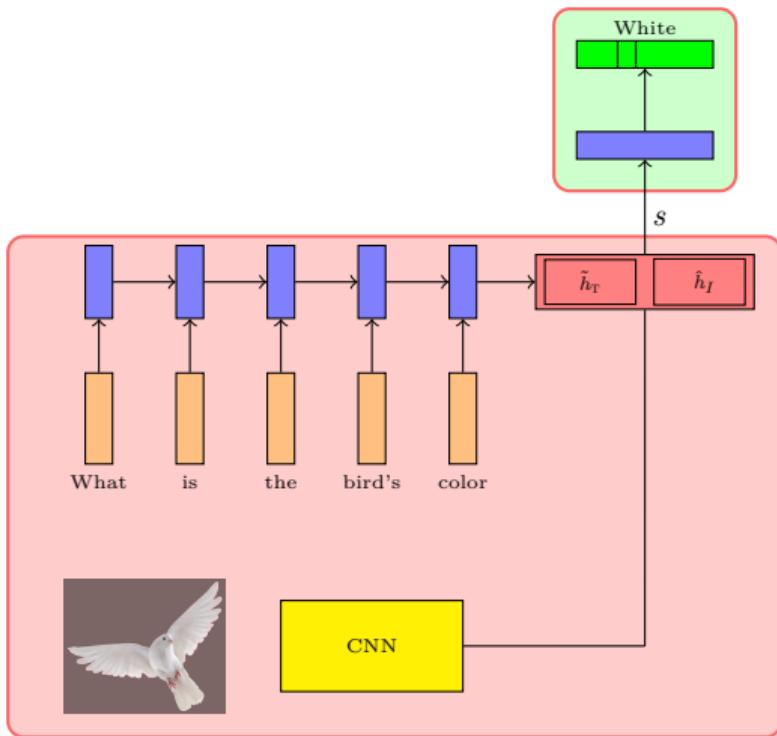
$$P(y|q, I) = softmax(Vs + b)$$

- **Parameters:**  $V, b, U_q, W_q, W_{conv}, b$

- **Loss:**

$$\mathcal{L}(\theta) = -\log P(y = \ell | I, q)$$

O/p: White



Question: What  
is the bird's color

- **Task:** Image Question Answering

- **Data:**  $\{x_i = \{I, q\}_i, y_i = Answer_i\}_{i=1}^N$

- **Model:**

- **Encoder:**

$$\hat{h}_I = CNN(I), \quad \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

$$s = [\tilde{h}_T; \hat{h}_I]$$

- **Decoder:**

$$P(y|q, I) = softmax(Vs + b)$$

- **Parameters:**  $V, b, U_q, W_q, W_{conv}, b$

- **Loss:**

$$\mathcal{L}(\theta) = -\log P(y = \ell|I, q)$$

- **Algorithm:** Gradient descent with backpropagation

o/p : India won  
the world cup

- **Task:** Document Summarization

i/p : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

o/p : India won  
the world cup

- **Task:** Document Summarization
- **Data:**  $\{x_i = Document_i, y_i = Summary_i\}_{i=1}^N$

i/p : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

o/p : India won  
the world cup

- **Task:** Document Summarization
- **Data:**  $\{x_i = Document_i, y_i = Summary_i\}_{i=1}^N$
- **Model:**

i/p : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

i/p : India won  
the world cup

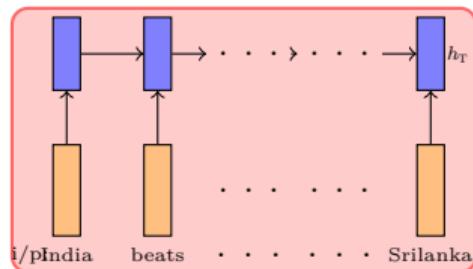
- **Task:** Document Summarization

- **Data:**  $\{x_i = Document_i, y_i = Summary_i\}_{i=1}^N$

- **Model:**

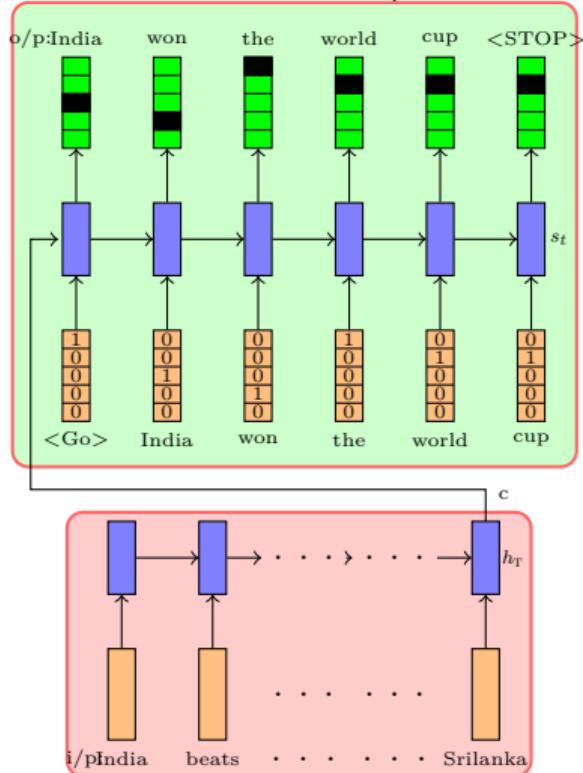
- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$



i/p : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

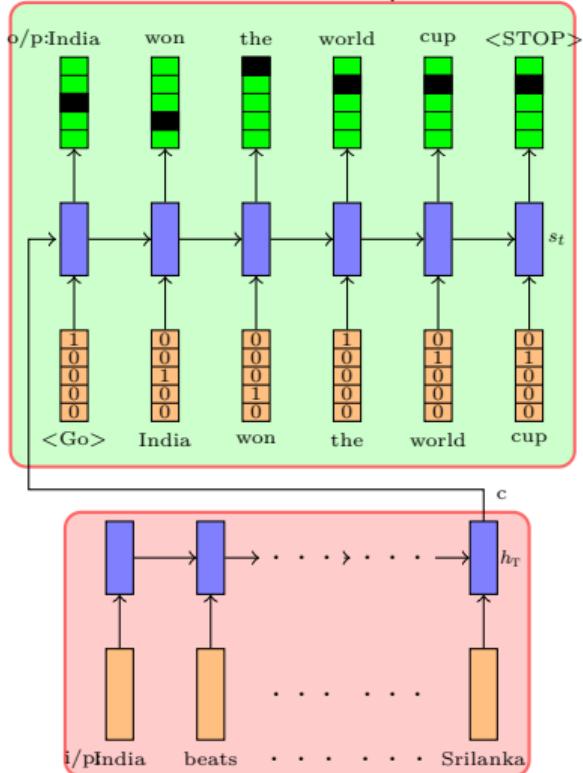
*o/p* : India won  
the world cup



*i/p* : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

- **Task:** Document Summarization
- **Data:**  $\{x_i\}_{i=1}^N = Document_i, y_i = Summary_i$
- **Model:**
  - **Encoder:**
$$h_t = RNN(h_{t-1}, x_{it})$$
  - **Decoder:**
$$s_0 = h_T$$
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

*o/p* : India won  
the world cup



- **Task:** Document Summarization

- **Data:**  $\{x_i\}_{i=1}^N = \text{Document}_i, y_i = \text{Summary}_i$

- **Model:**

- **Encoder:**

$$h_t = RNN(h_{t-1}, x_{it})$$

- **Decoder:**

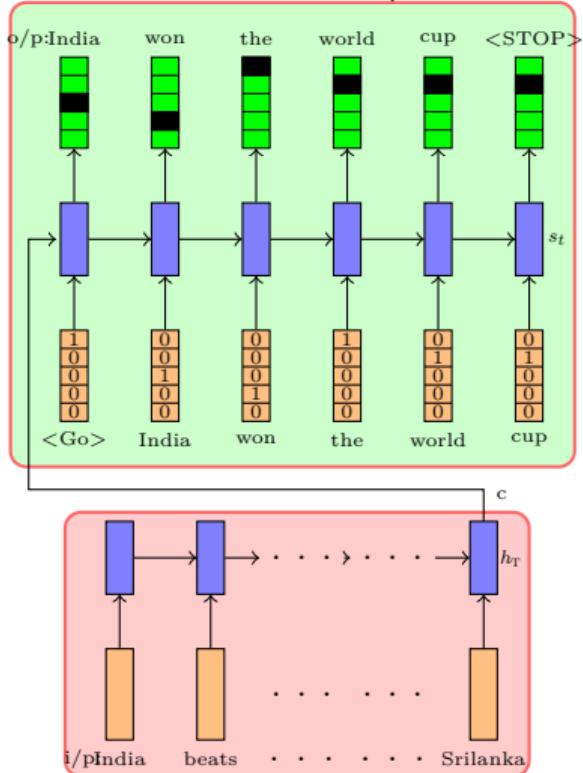
$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

*o/p* : India won  
the world cup



*i/p* : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

- **Task:** Document Summarization

- **Data:**  $\{x_i\}_{i=1}^N = Document_i, y_i = Summary_i$

- **Model:**

- **Encoder:**

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- **Decoder:**

$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

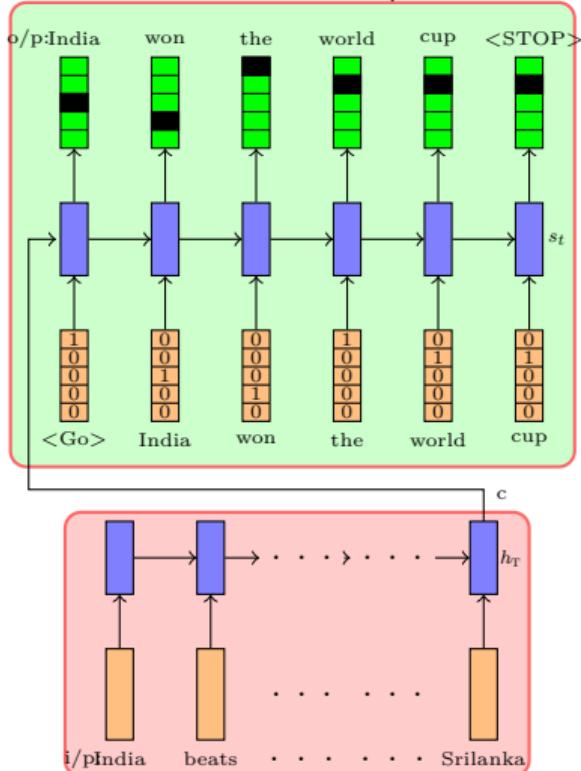
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$

*o/p* : India won  
the world cup



*i/p* : India beats Srilanka to win ICC WC 2011.  
Dhoni and Gambhir's half centuries help beat SL

- **Task:** Document Summarization
- **Data:**  $\{x_i\}_{i=1}^N = Document_i, y_i = Summary_i$
- **Model:**
  - **Encoder:**  $h_t = RNN(h_{t-1}, x_{it})$
  - **Decoder:**  $s_0 = h_T$   
 $s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$   
 $P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$
- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$
- **Loss:**  $\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$
- **Algorithm:** Gradient descent with backpropagation

o/p : A man walking on a rope

• **Task:** Video Captioning



...



o/p : A man walking on a rope

- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$



...



o/p : A man walking on a rope

- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$
- **Model:**



...

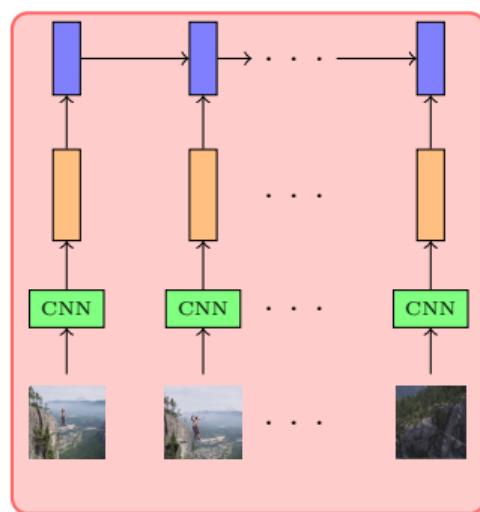


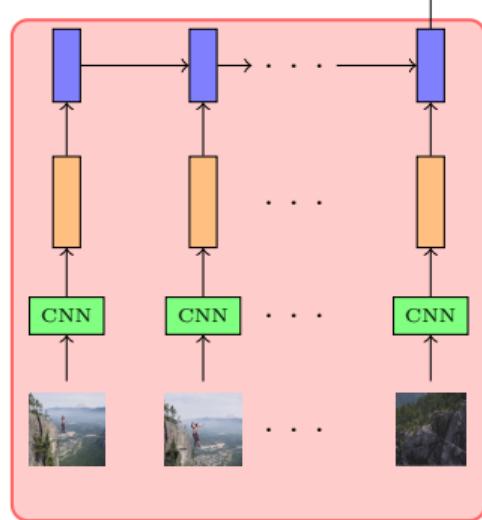
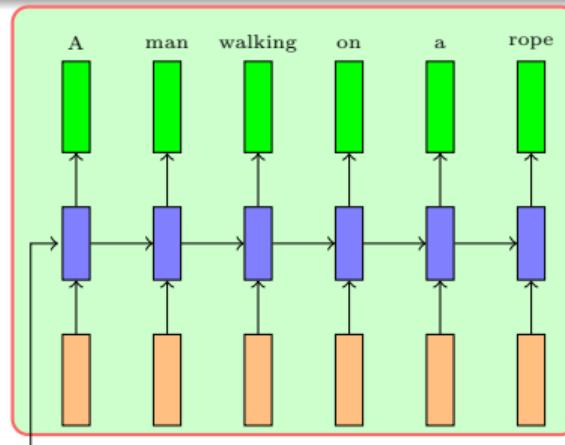
o/p : A man walking on a rope

- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$
- **Model:**

- **Encoder:**

$$h_t = RNN(h_{t-1}, CNN(x_{it}))$$





- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$

- **Model:**

- **Encoder:**

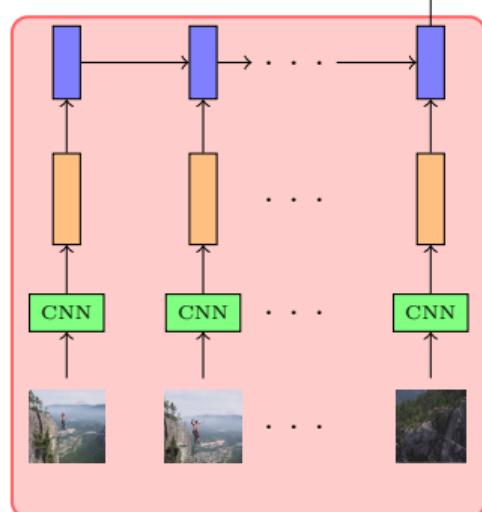
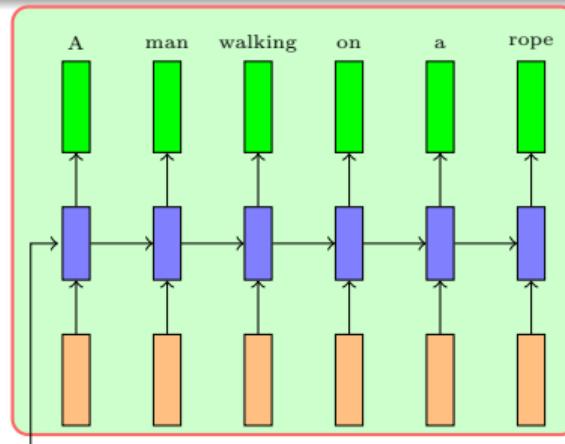
$$h_t = RNN(h_{t-1}, CNN(x_{it}))$$

- **Decoder:**

$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$



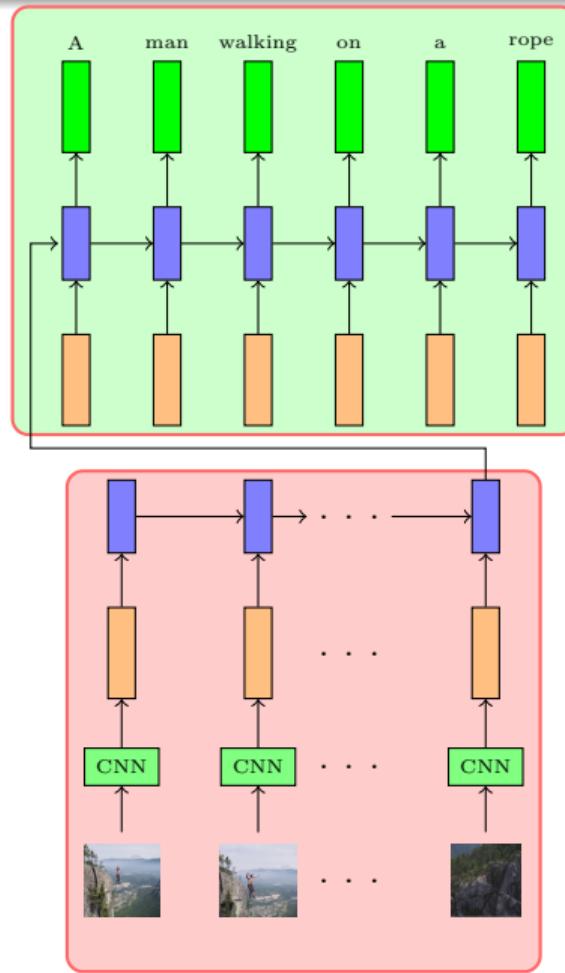
- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$
- **Model:**
  - **Encoder:**

$$h_t = RNN(h_{t-1}, CNN(x_{it}))$$
  - **Decoder:**

$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$
- **Parameters:**  $U_{dec}, W_{dec}, V, b, W_{conv}, U_{enc}, W_{enc}, b$



- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$
- **Model:**
  - **Encoder:**

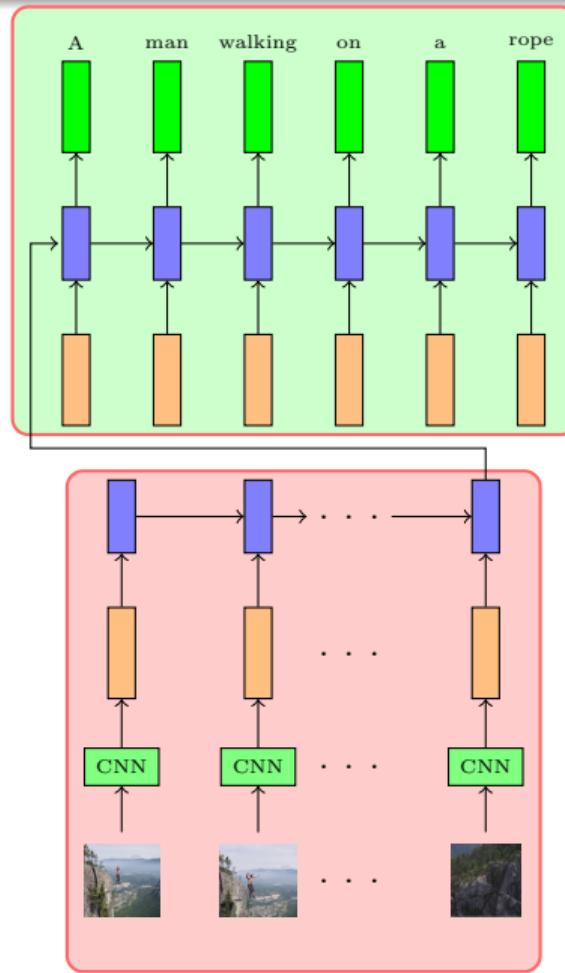
$$h_t = RNN(h_{t-1}, CNN(x_{it}))$$
  - **Decoder:**

$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$
- **Parameters:**  $U_{dec}, W_{dec}, V, b, W_{conv}, U_{enc}, W_{enc}, b$
- **Loss:**

$$\mathcal{L}(\theta) = \sum_{i=1}^T \mathcal{L}_t(\theta) = - \sum_{t=1}^T \log P(y_t = \ell_t | y_1^{t-1}, x)$$



- **Task:** Video Captioning
- **Data:**  $\{x_i = \text{video}_i, y_i = \text{desc}_i\}_{i=1}^N$
- **Model:**
  - **Encoder:**

$$h_t = RNN(h_{t-1}, CNN(x_{it}))$$
  - **Decoder:**

$$s_0 = h_T$$

$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

$$P(y_t|y_1^{t-1}, x) = \text{softmax}(Vs_t + b)$$
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- **Loss:**

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- **Algorithm:** Gradient descent with backpropagation

o/p: Surya Namaskar

- **Task:** Video Classification



- **Task:** Video Classification

- **Data:**  $\{x_i = \text{Video}_i, y_i = \text{Activity}_i\}_{i=1}^N$



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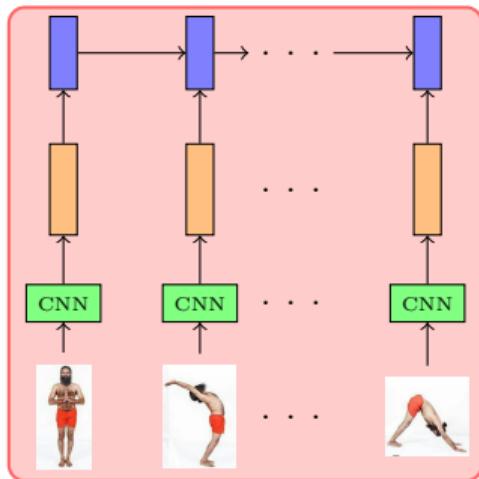
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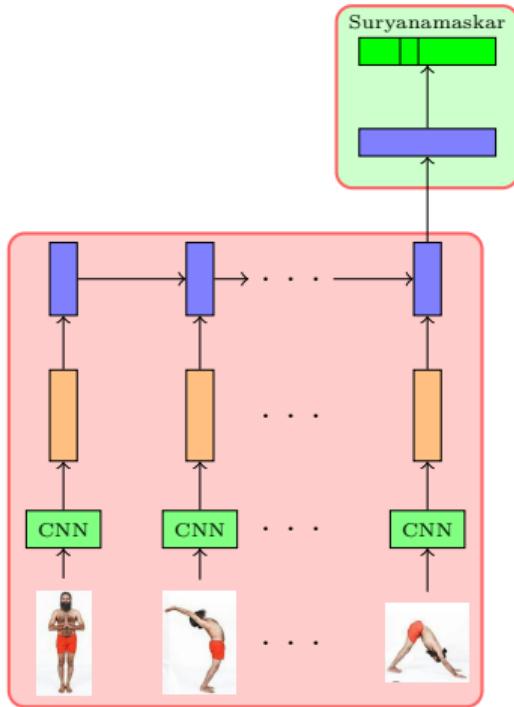
- **Model:**

- **Encoder:**

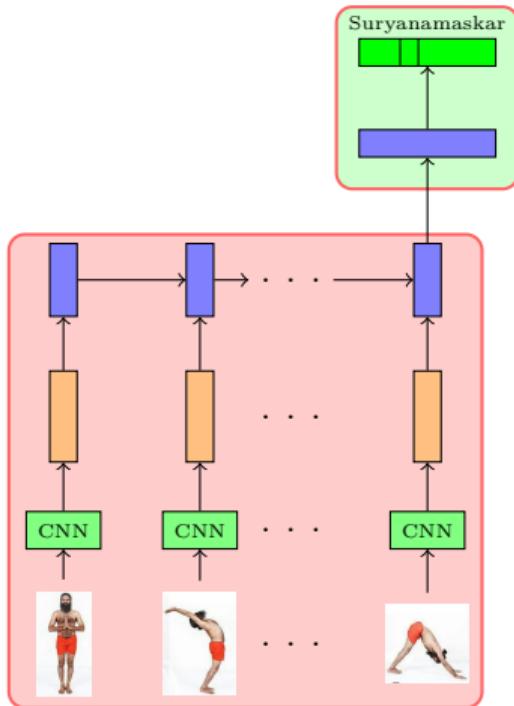
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o/p: Surya Namaskar



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- **Data:**  $\{x_i = \text{Video}_i, y_i = \text{Activity}_i\}_{i=1}^N$
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$$s = h_T$$
$$P(y|I) = \text{softmax}(Vs + b)$$



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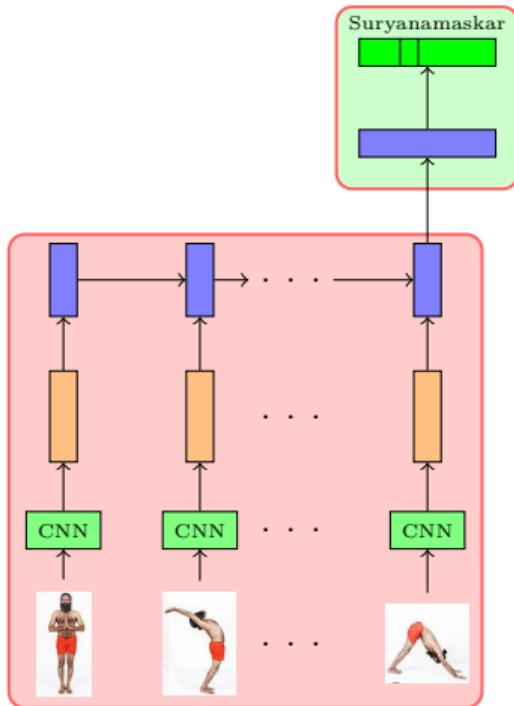
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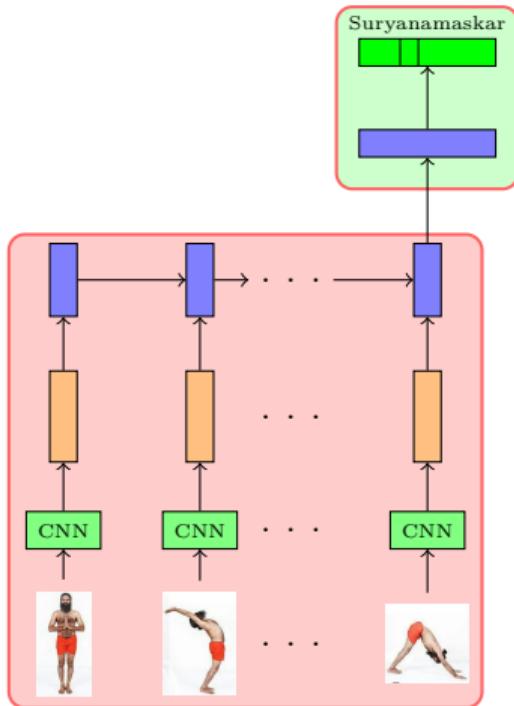
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- **Parameters:**  $V, b, W_{conv}, U_{enc}, W_{enc}, b$

- **Loss:**

$$\mathcal{L}(\theta) = -\log P(y = \ell | \text{Video})$$

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o/p: I am fine

• **Task:** Dialog

i/p: How are you

o/p: I am fine

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- **Data:**  $\{x_i = Utterance_i, y_i = Response_i\}_{i=1}^N$

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i/p: How are you

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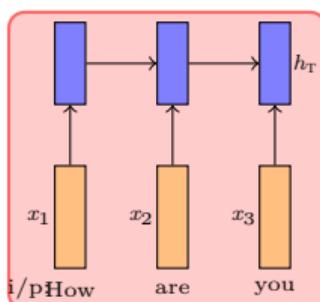
- **Task:** Dialog

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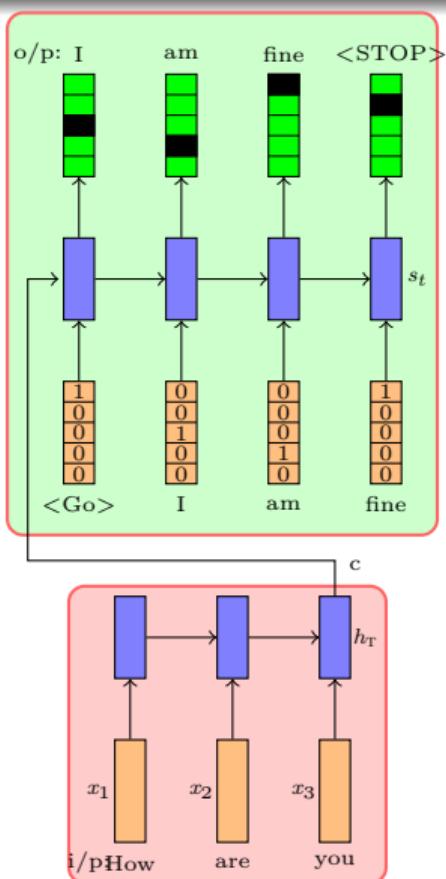
- **Model:**

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i/p: How are you



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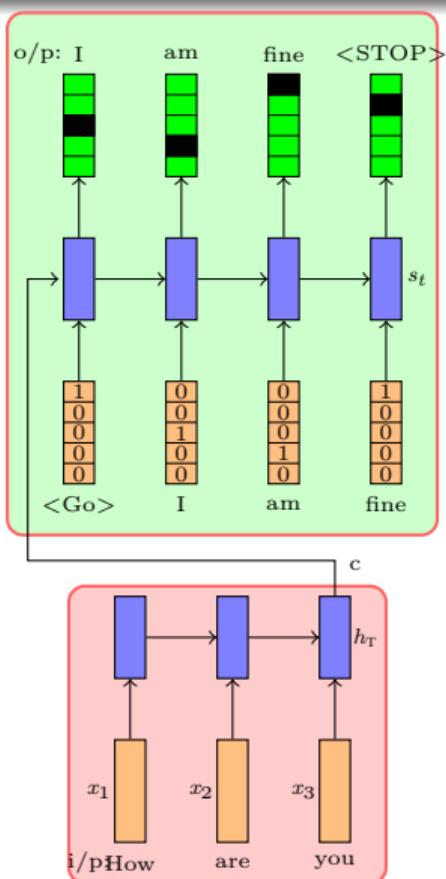
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$$s_0 = h_T \quad (T \text{ is length of input})$$

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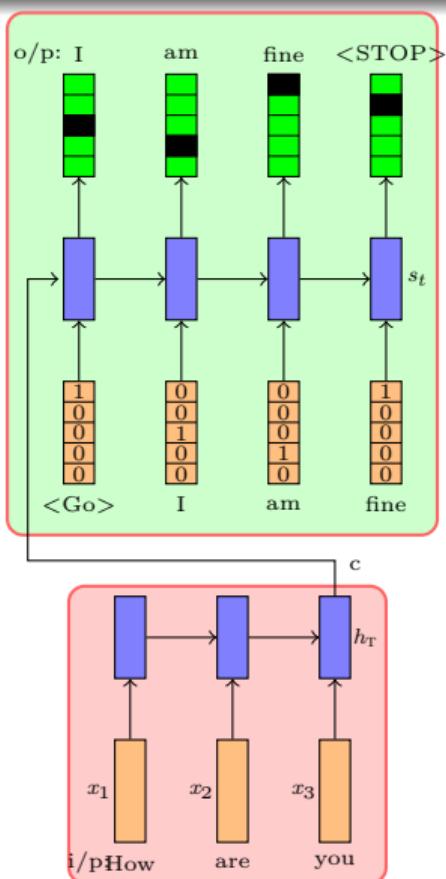
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- **Parameters:**  $U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b$



i/p: How are you

- **Task:** Dialog

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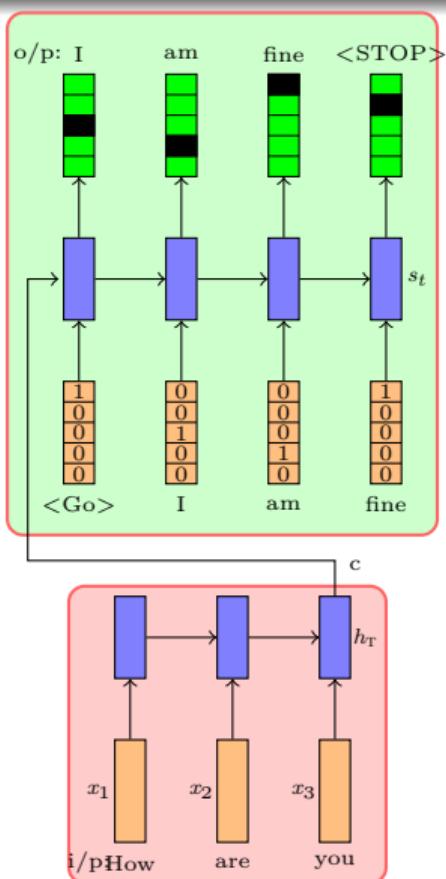
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- **Parameters:**  $U_{dec}$ ,  $V$ ,  $W_{dec}$ ,  $U_{enc}$ ,  $W_{enc}$ ,  $b$

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- **Algorithm:** Gradient descent with backpropagation

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- Try picking a problem from your domain and see if you can model it using the encoder decoder paradigm
- Encoder decoder models can be made even more expressive by adding an “attention” mechanism
- We will first motivate the need for this and then explain how to model it

# Module : Attention Mechanism

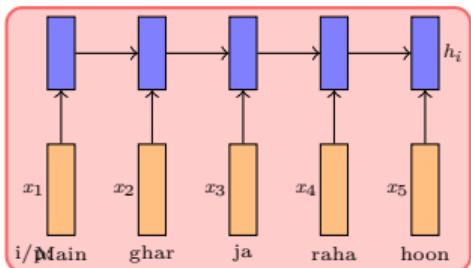
o/p : I am going home

- Let us motivate the task of attention with the help of MT

i/p : Main ghar ja raha hoon

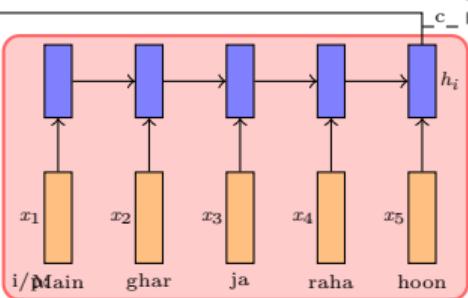
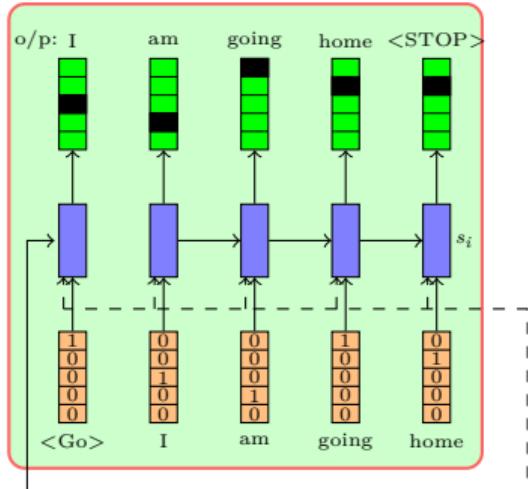
o/p : I am going home

- Let us motivate the task of attention with the help of MT
- The encoder reads the sentences only once and encodes it



i/p : Main ghar ja raha hoon

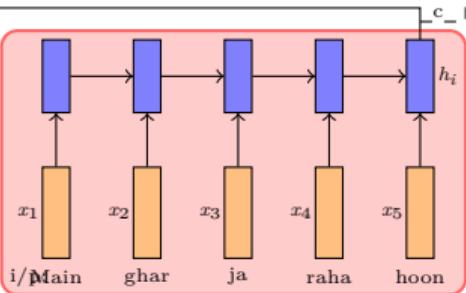
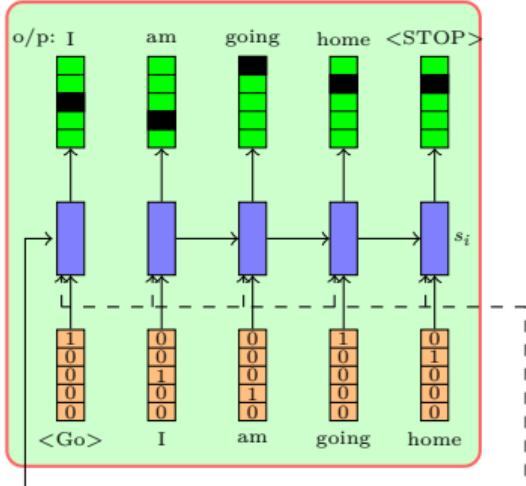
o/p : I am going home



i/p : Main ghar ja raha hoon

- Let us motivate the task of attention with the help of MT
- The encoder reads the sentences only once and encodes it
- At each timestep the decoder uses this embedding to produce a new word

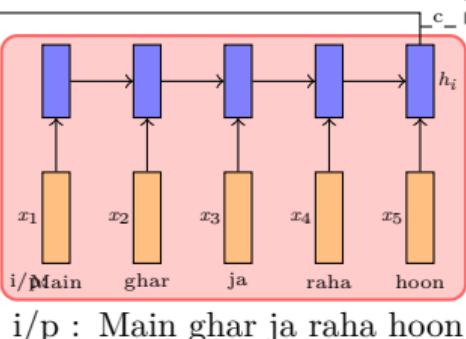
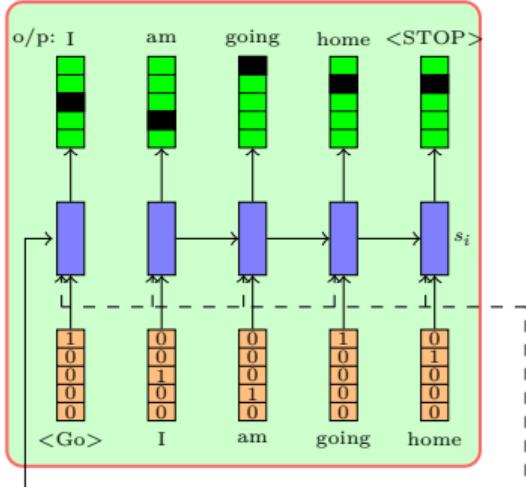
o/p : I am going home



i/p : Main ghar ja raha hoon

- Let us motivate the task of attention with the help of MT
- The encoder reads the sentences only once and encodes it
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- Is this how humans translate a sentence ?

o/p : I am going home



i/p : Main ghar ja raha hoon

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- The encoder reads the sentences only once and encodes it
- At each timestep the decoder uses this embedding to produce a new word
- Is this how humans translate a sentence ?  
Not really!

o/p : I am going home

- Humans try to produce each word in the output by focusing only on certain words in the input

i/p : Main ghar ja raha hoon

o/p : I am going home

- Humans try to produce each word in the output by focusing only on certain words in the input
- Essentially at each time step we come up with a distribution on the input words

i/p : Main ghar ja raha hoon

o/p : I am going home

$t_1 : [ 1 \ 0 \ 0 \ 0 \ 0 ]$

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i/p : Main ghar ja raha hoon

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$t_1 : [ 1 \ 0 \ 0 \ 0 \ 0 ]$

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i/p : Main ghar ja raha hoon

o/p : I am **going** home

$t_1 : [ 1 \ 0 \ 0 \ 0 \ 0 ]$

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$t_3 : [ 0 \ 0 \ 0.5 \ 0.5 \ 0 ]$

- Humans try to produce each word in the output by focusing only on certain words in the input
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i/p : Main ghar **ja raha** hoon

o/p : I am going **home**

$t_1 : [1 \ 0 \ 0 \ 0 \ 0]$

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$t_4 : [0 \ 1 \ 0 \ 0 \ 0]$

i/p : Main **ghar** ja raha hoon

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o/p : I am going home

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- Humans try to produce each word in the output by focusing only on certain words in the input
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- This distribution tells us how much attention to pay to each input words at each time step

o/p : I am going home

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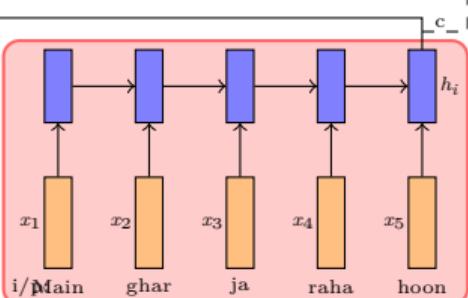
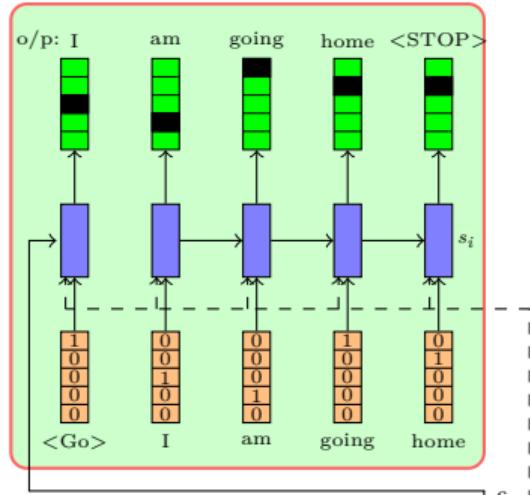
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- Humans try to produce each word in the output by focusing only on certain words in the input
- Essentially at each time step we come up with a distribution on the input words
- This distribution tells us how much attention to pay to each input words at each time step
- Ideally, at each time-step we should feed only this relevant information (i.e. encodings of relevant words) to the decoder

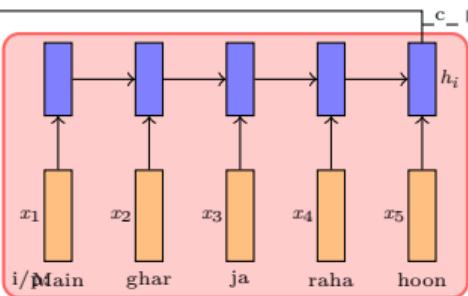
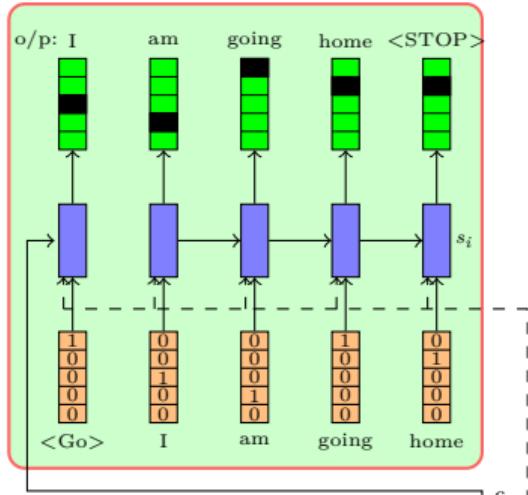
o/p : I am going home



i/p : Main ghar ja raha hoon

- Let us revisit the decoder that we have seen so far

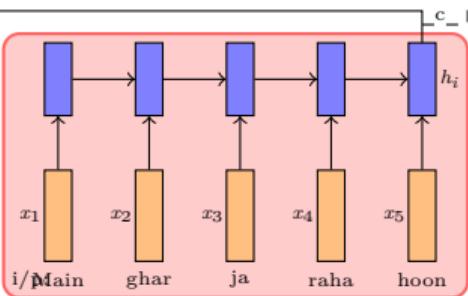
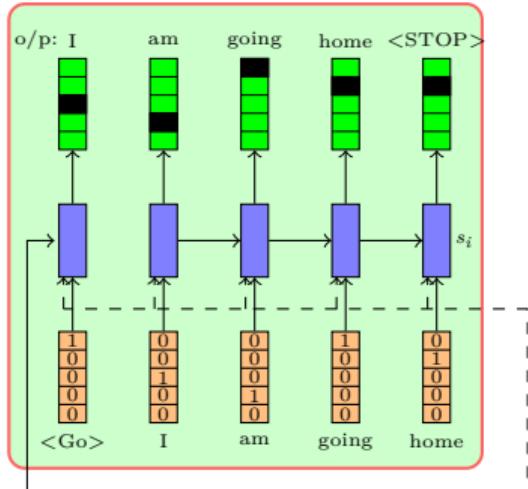
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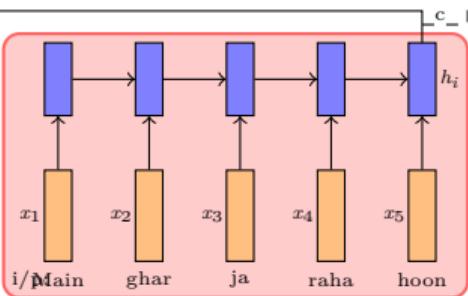
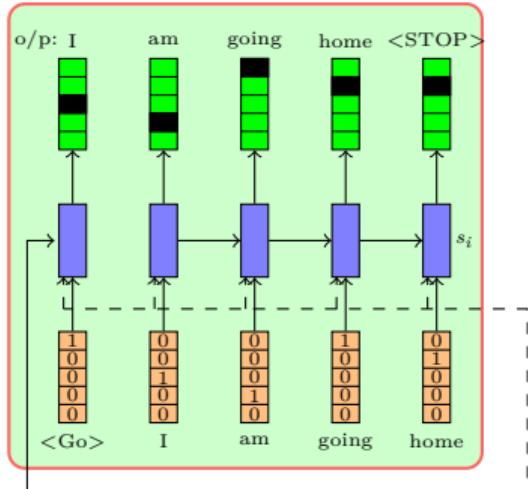
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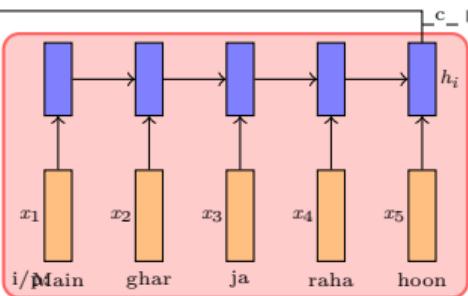
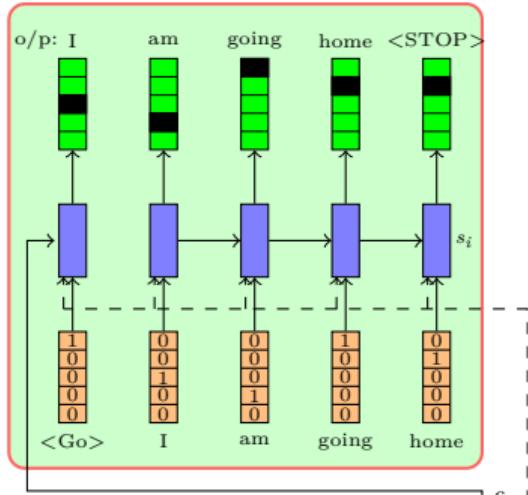
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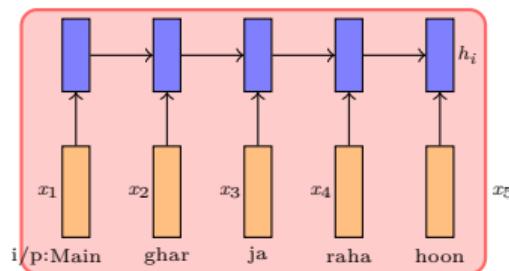
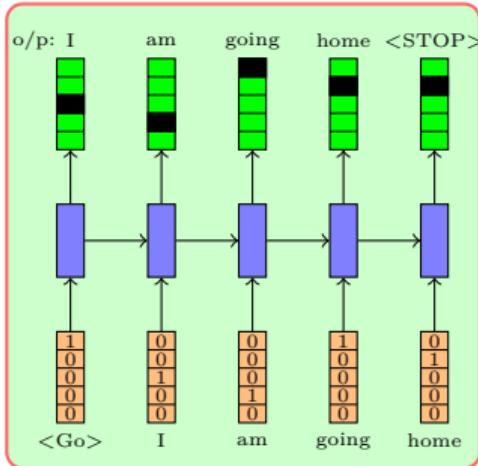
- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at  $s_0$ )
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- Now suppose an oracle told you which words to focus on at a given time-step  $t$

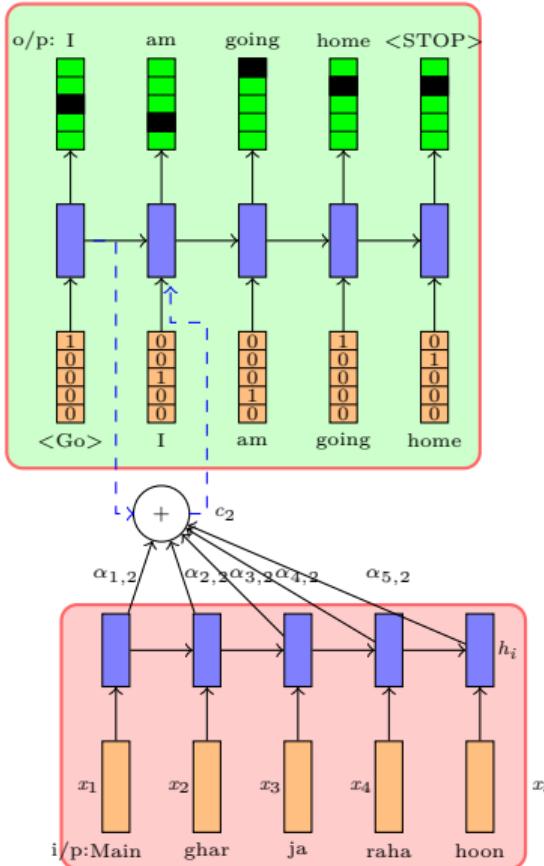
o/p : I am going home



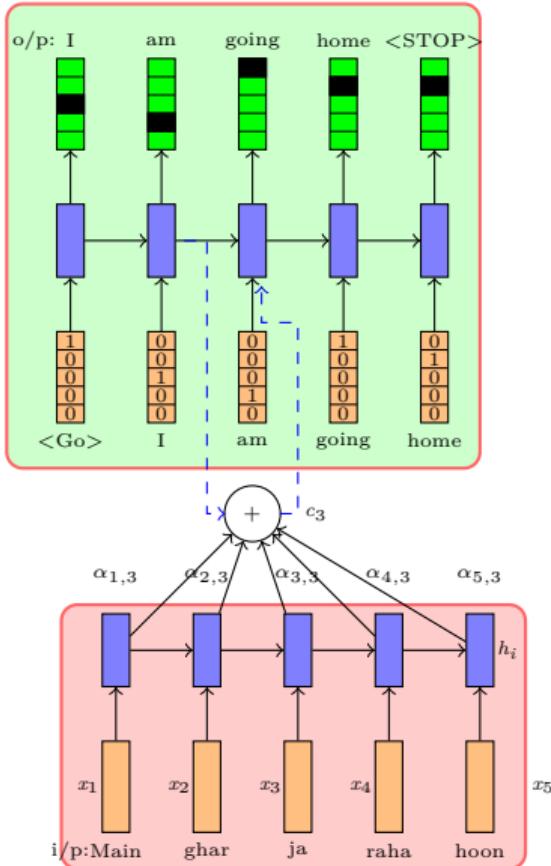
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- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at  $s_0$ )
- Or we feed the same encoder information at each time step
- Now suppose an oracle told you which words to focus on at a given time-step  $t$
- Can you think of a smarter way of feeding information to the decoder?

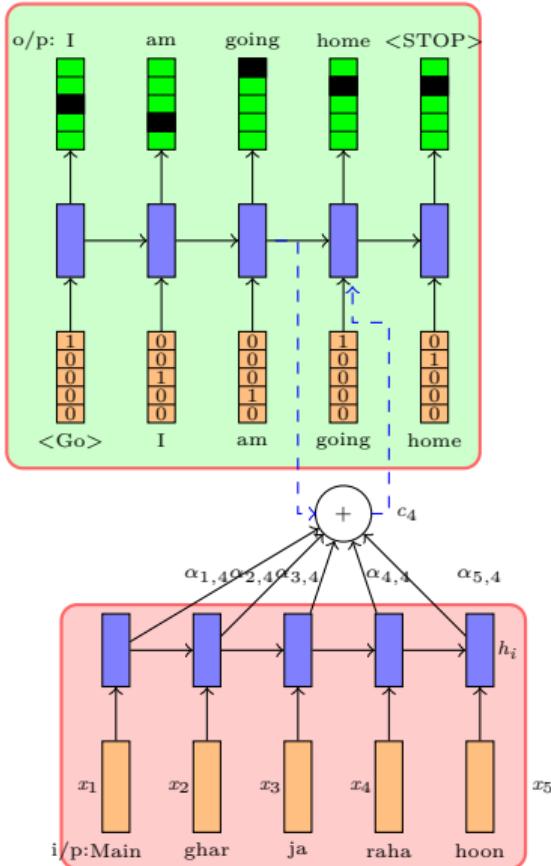




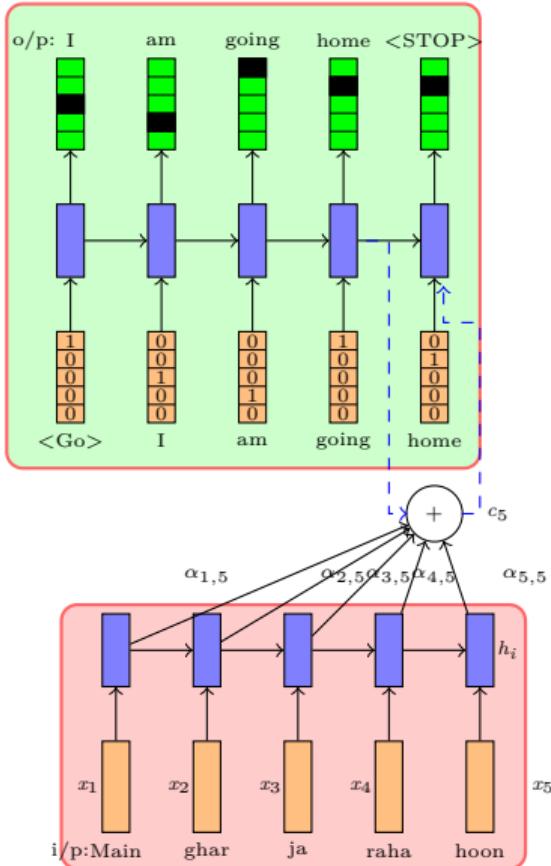
- We could just take a weighted average of the corresponding word representations and feed it to the decoder



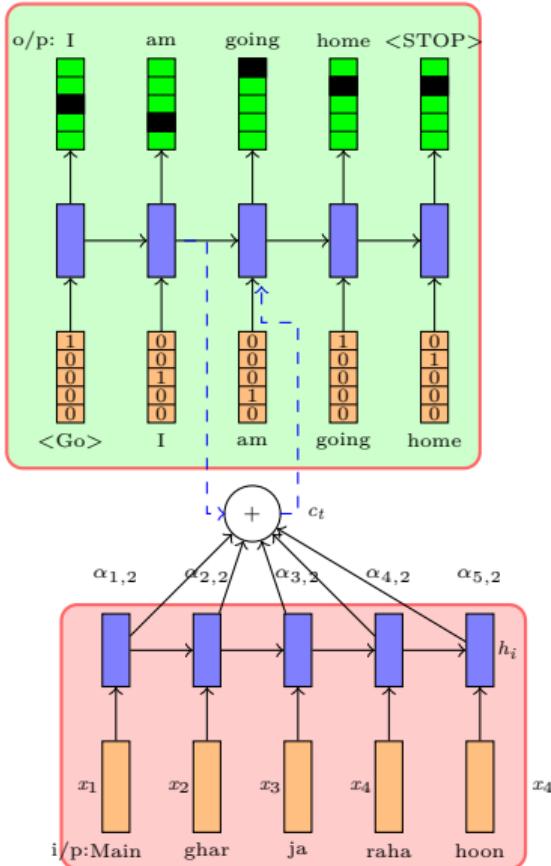
- We could just take a weighted average of the corresponding word representations and feed it to the decoder
- For example at timestep 3, we can just take a weighted average of the representations of 'ja' and 'raha'

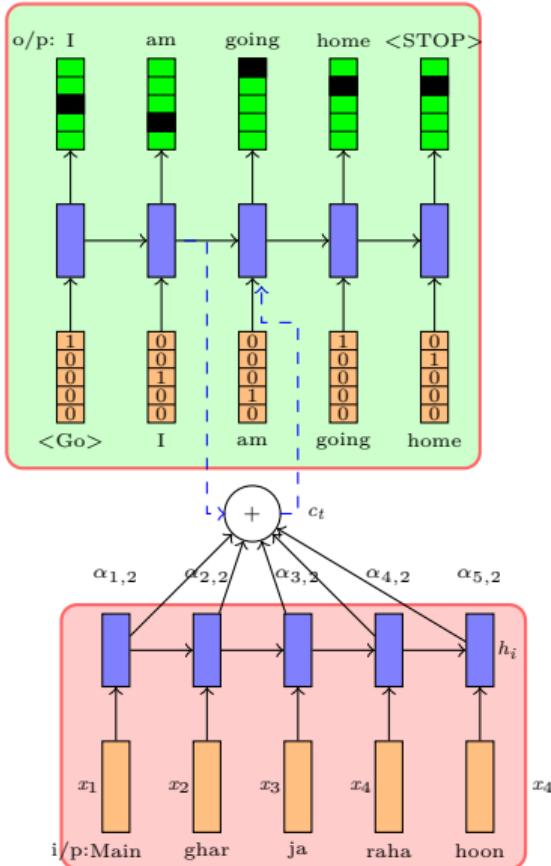


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- Intuitively this should work better because we are not overloading the decoder with irrelevant information (about words that do not matter at this time step)

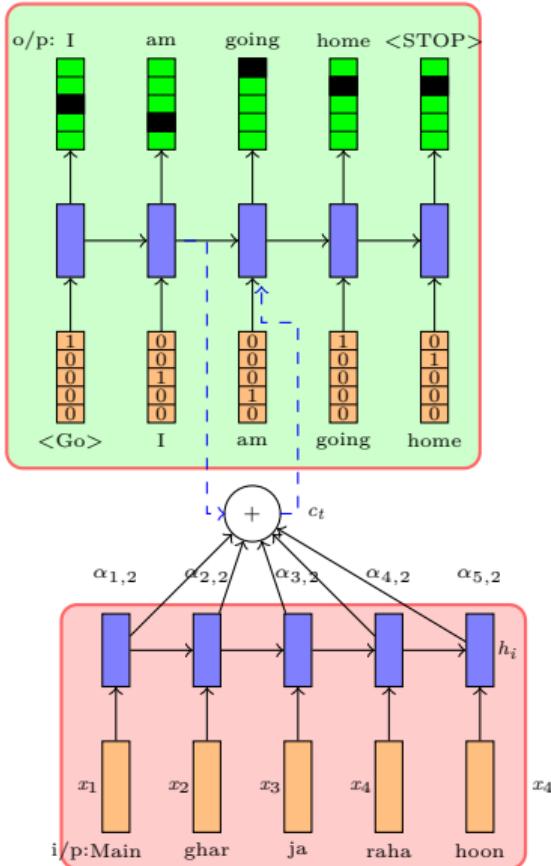


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- For example at timestep 3, we can just take a weighted average of the representations of 'ja' and 'raha'
- Intuitively this should work better because we are not overloading the decoder with irrelevant information (about words that do not matter at this time step)
- How do we convert this intuition into a model ?

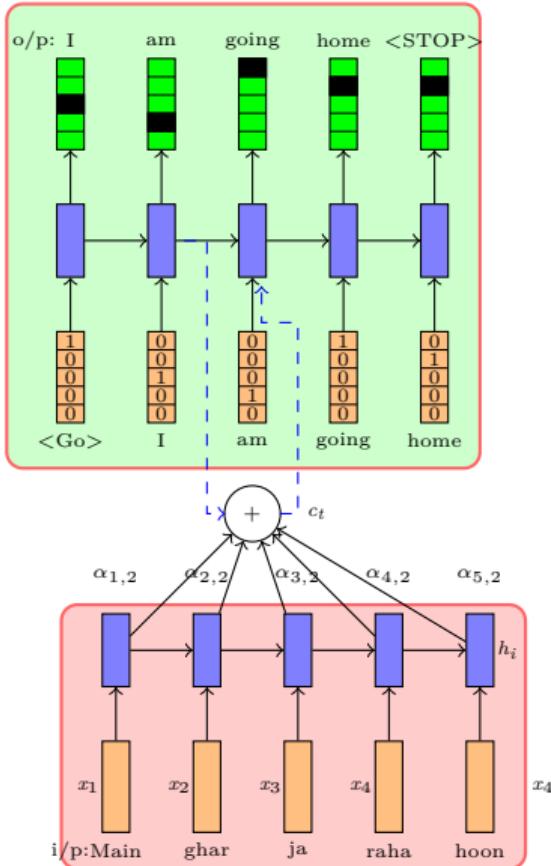




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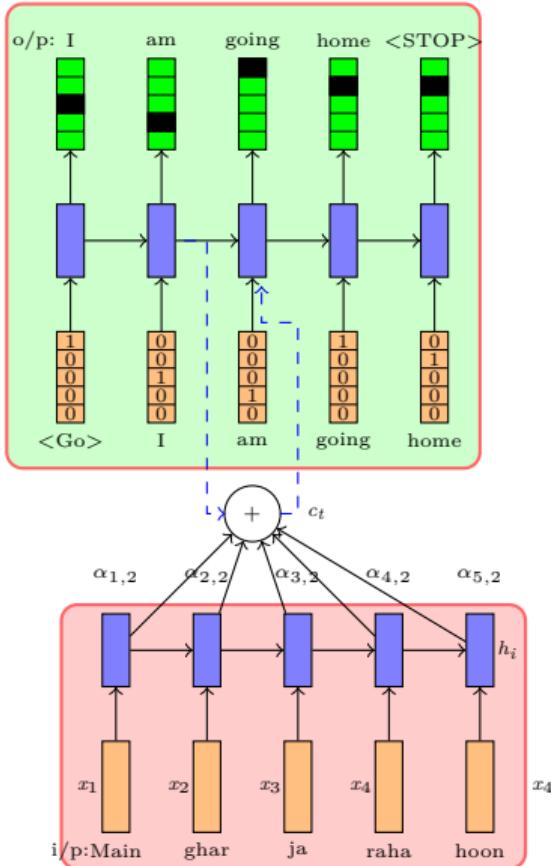


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- The machine will have to learn this from the data



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- The machine will have to learn this from the data
- To enable this we define a function

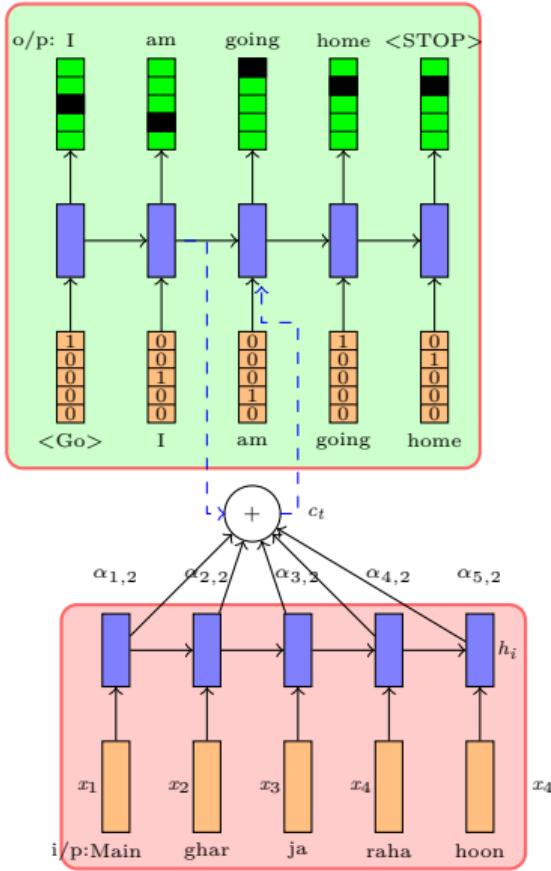
$$e_{jt} = f_{ATT}(s_{t-1}, c_j)$$



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- To enable this we define a function

$$e_{jt} = f_{ATT}(s_{t-1}, c_j)$$

- This quantity captures the importance of the  $j^{th}$  input word for decoding the  $t^{th}$  output word (we will see the exact form of  $f_{ATT}$  later)

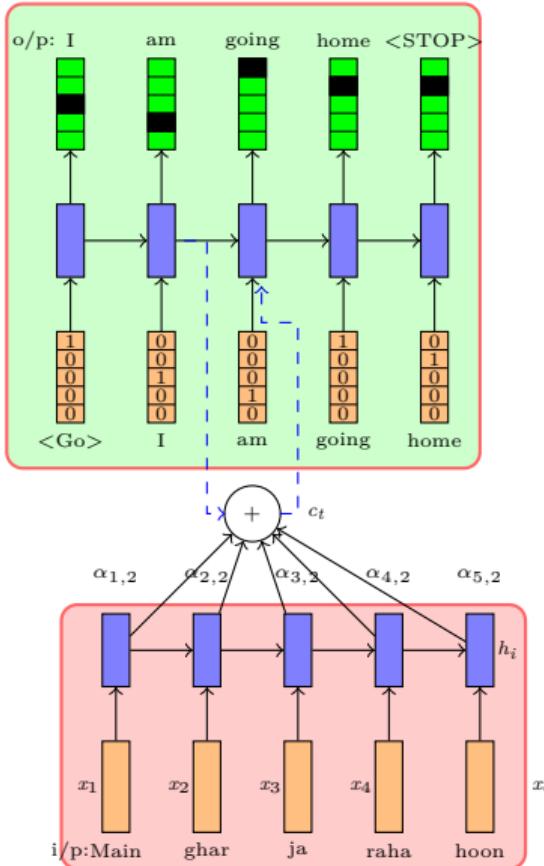


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- The machine will have to learn this from the data
- To enable this we define a function

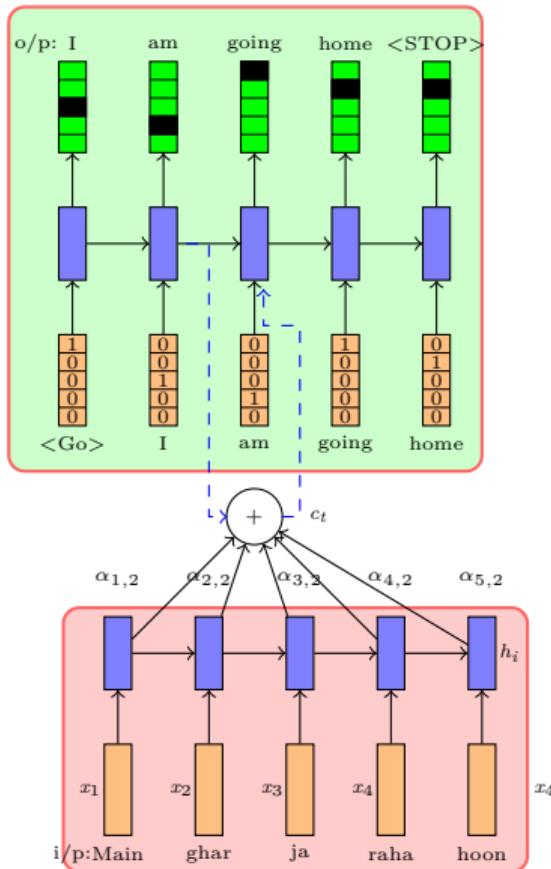
$$e_{jt} = f_{ATT}(s_{t-1}, c_j)$$

- This quantity captures the importance of the  $j^{th}$  input word for decoding the  $t^{th}$  output word (we will see the exact form of  $f_{ATT}$  later)
- We can normalize these weights by using the softmax function

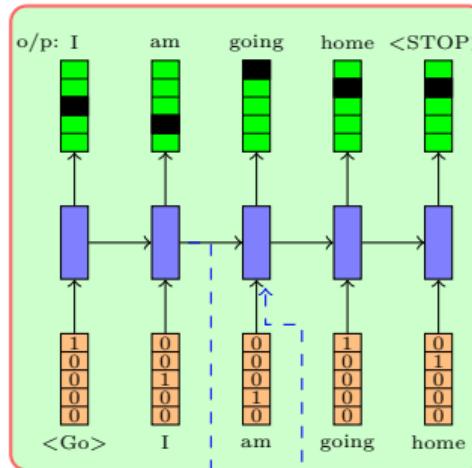
$$\alpha_{jt} = \frac{\exp(e_{jt})}{\sum_{j=1}^M \exp(e_{jt})}$$



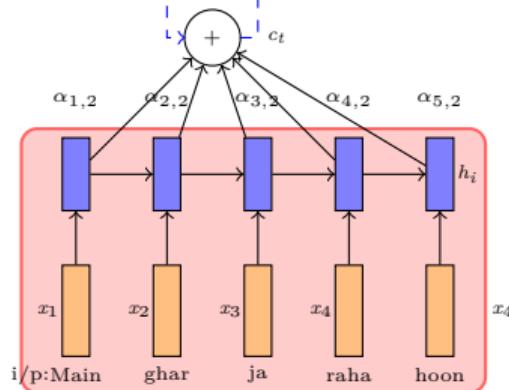
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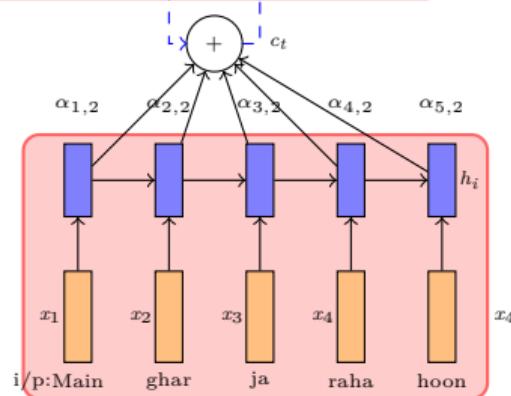
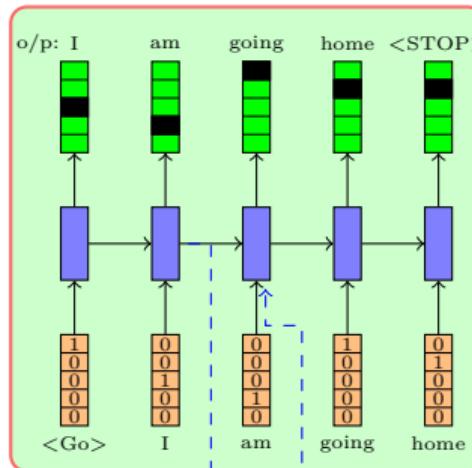
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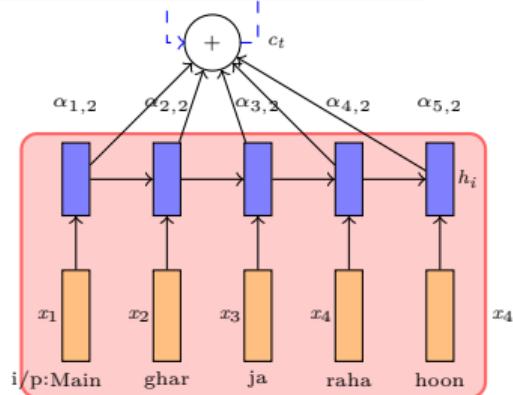
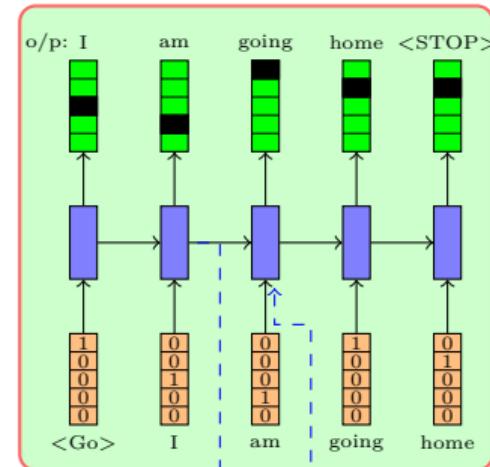
- $\alpha_{jt}$  denotes the probability of focusing on the  $j^{th}$  word to produce the  $t^{th}$  output word



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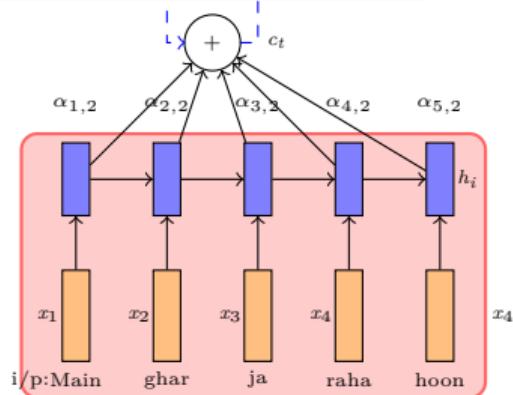
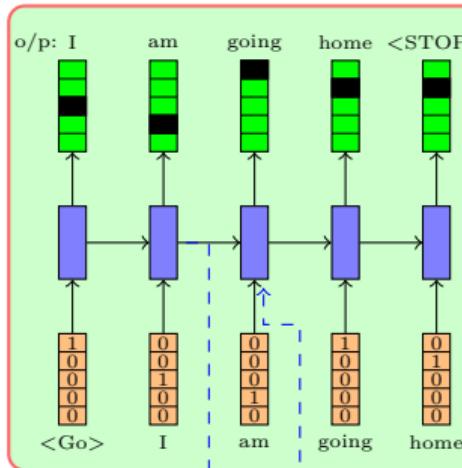
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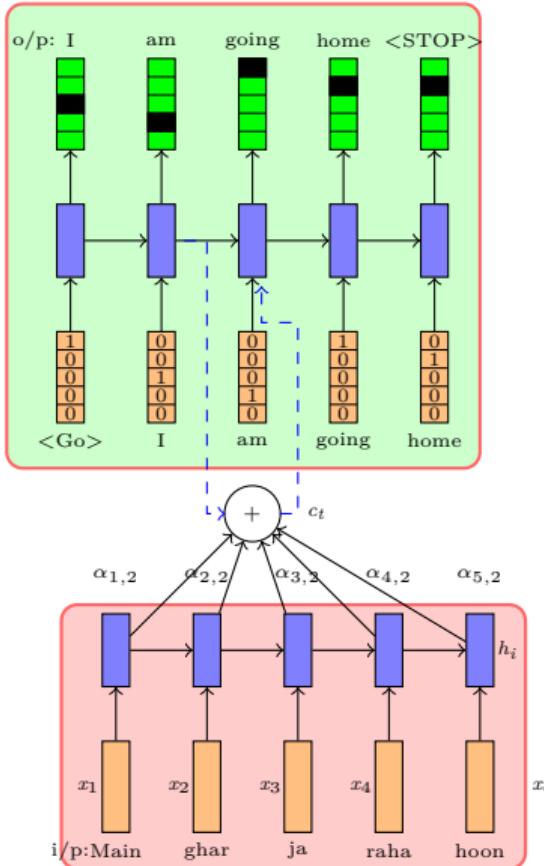
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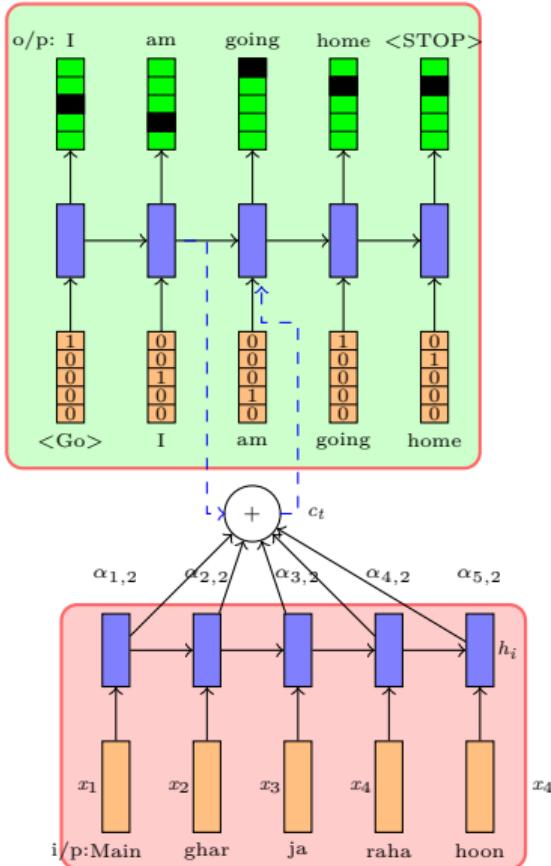
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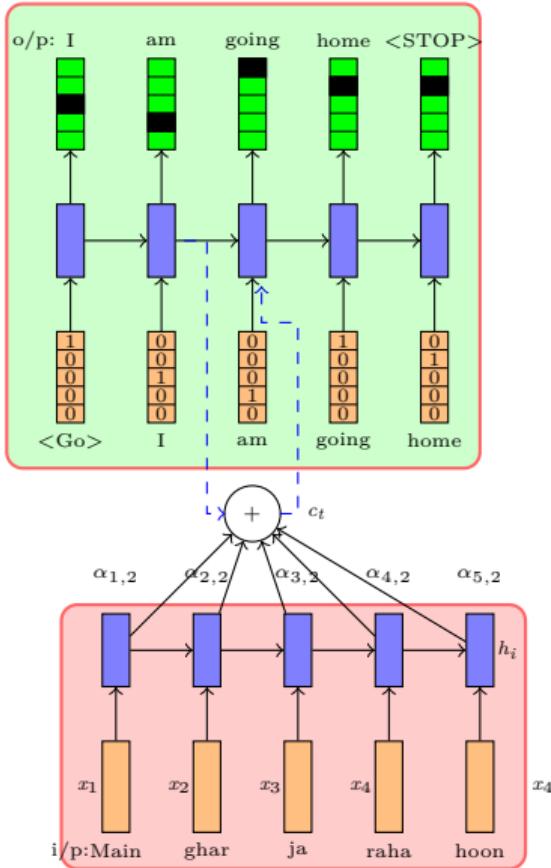


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- Learning would always involve some parameters
- So let's define a parametric form for  $\alpha$ 's



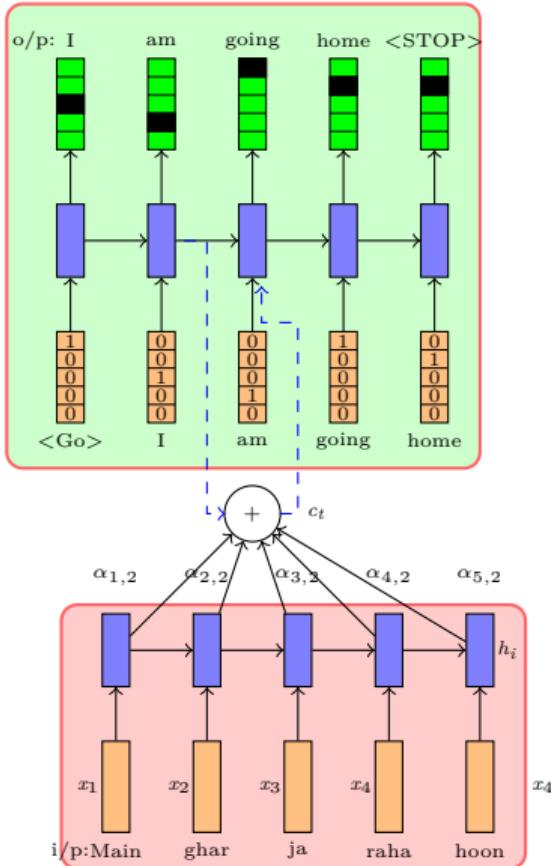


- From now on we will refer to the decoder RNN's state at the  $t$ -th timestep as  $s_t$  and the encoder RNN's state at the  $j$ -th time step as  $c_j$



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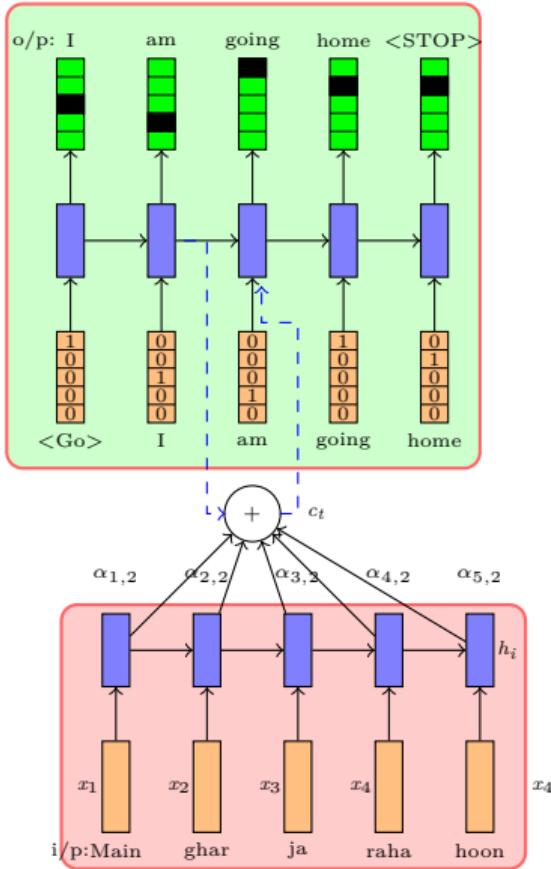
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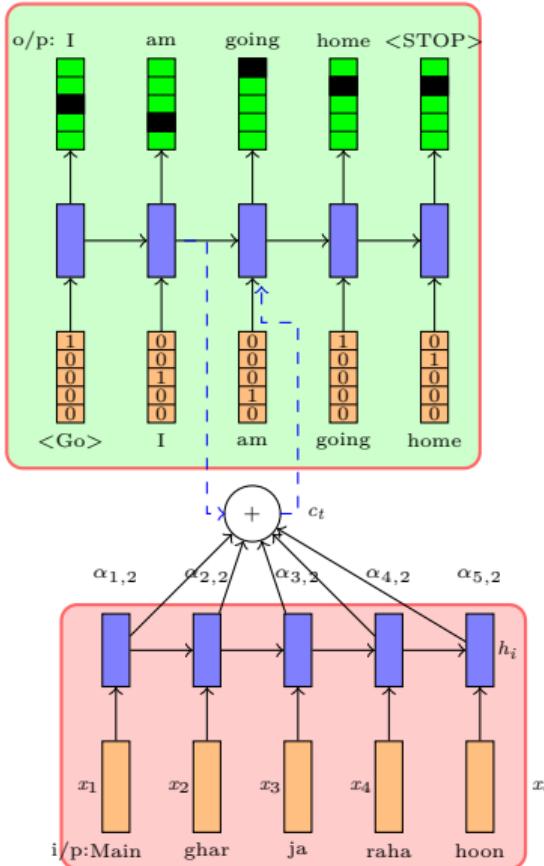
- $V_{att} \in \mathbb{R}^d$ ,  $U_{att} \in \mathbb{R}^{d \times d}$ ,  $W_{att} \in \mathbb{R}^{d \times d}$  are additional parameters of the model



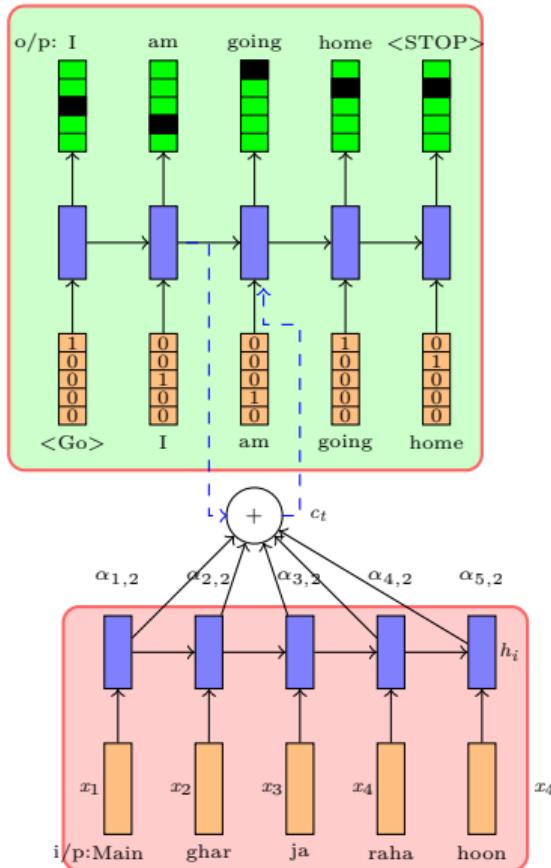
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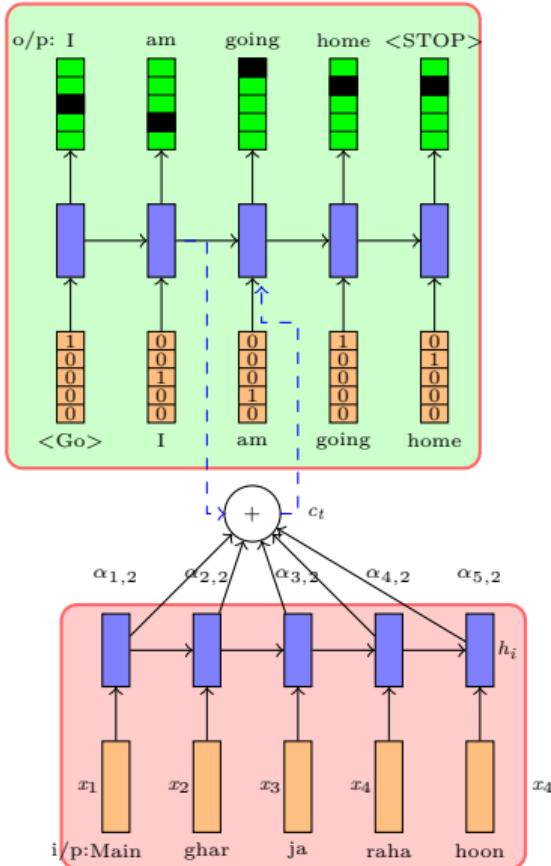
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- $V_{att} \in \mathbb{R}^d$ ,  $U_{att} \in \mathbb{R}^{d \times d}$ ,  $W_{att} \in \mathbb{R}^{d \times d}$  are additional parameters of the model
- These parameters will be learned along with the other parameters of the encoder and decoder



• Wait a minute !

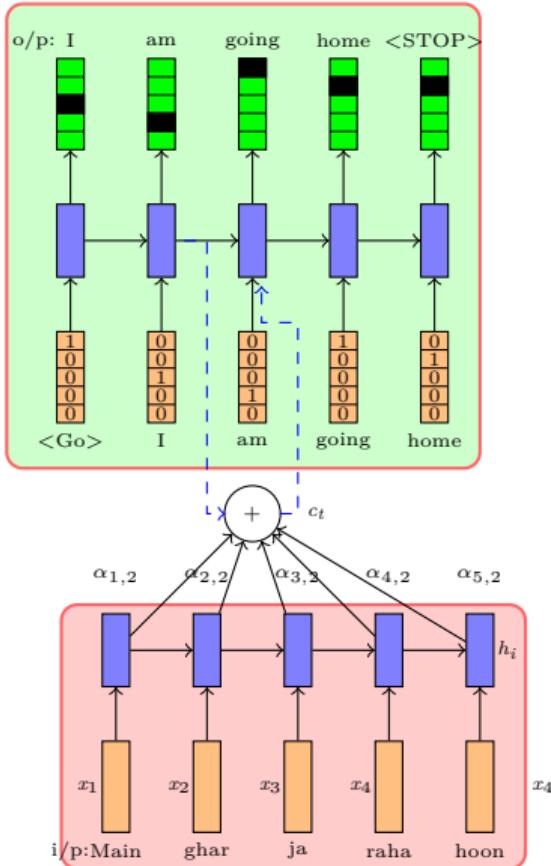




- Wait a minute !
- This model would make a lot of sense if we were given the true  $\alpha$ 's at training time

$$\alpha_{tj}^{true} = [0, 0, 0.5, 0.5, 0]$$

$$\alpha_{tj}^{pred} = [0.1, 0.1, 0.35, 0.35, 0.1]$$

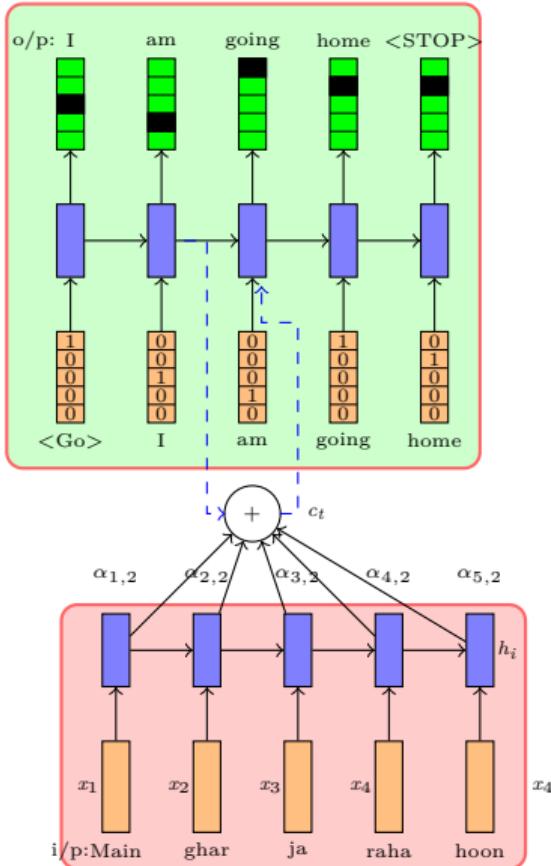


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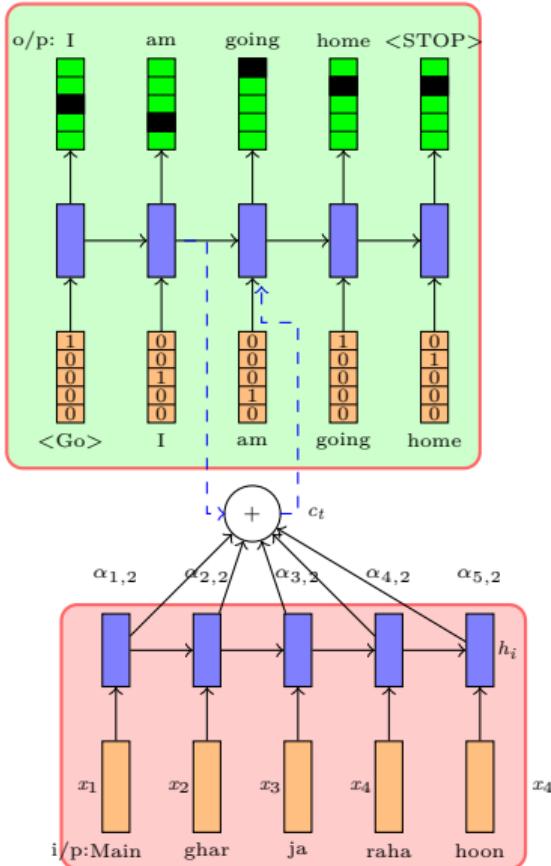


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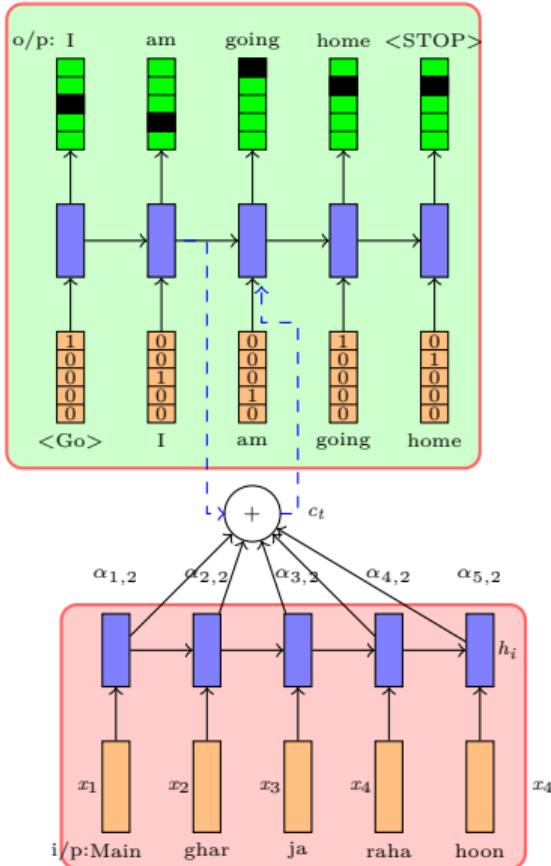
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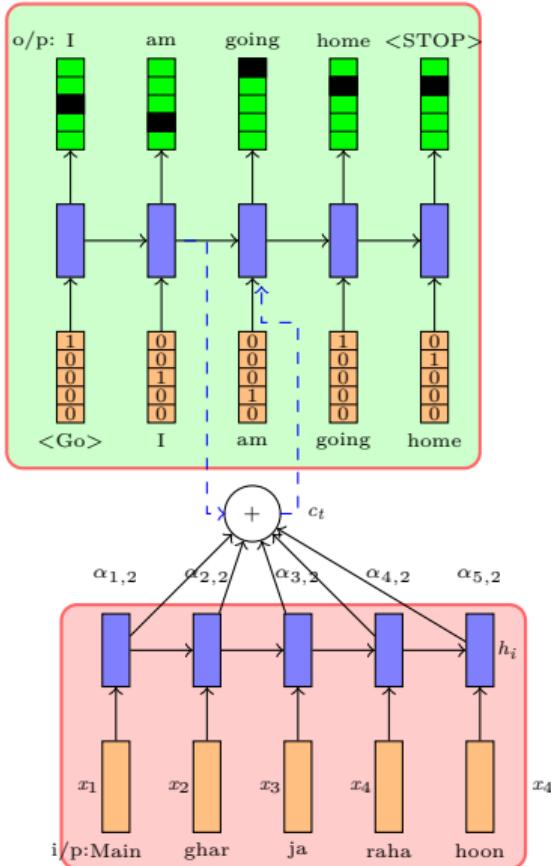
- We could then minimize  $\mathcal{L}(\alpha^{true}, \alpha^{pred})$  in addition to  $\mathcal{L}(\theta)$  as defined earlier
- But in practice it is very hard to get  $\alpha^{true}$



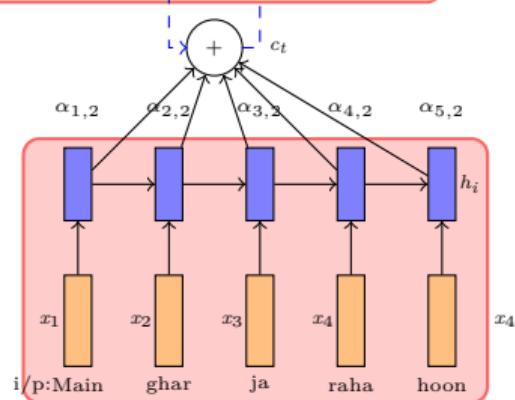
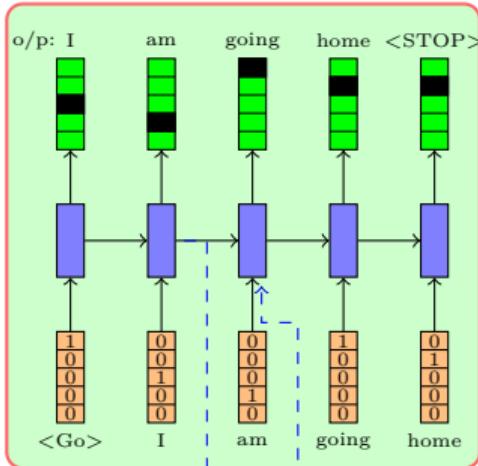
- For example, in our translation example we would want someone to manually annotate the source words which contribute to every target word



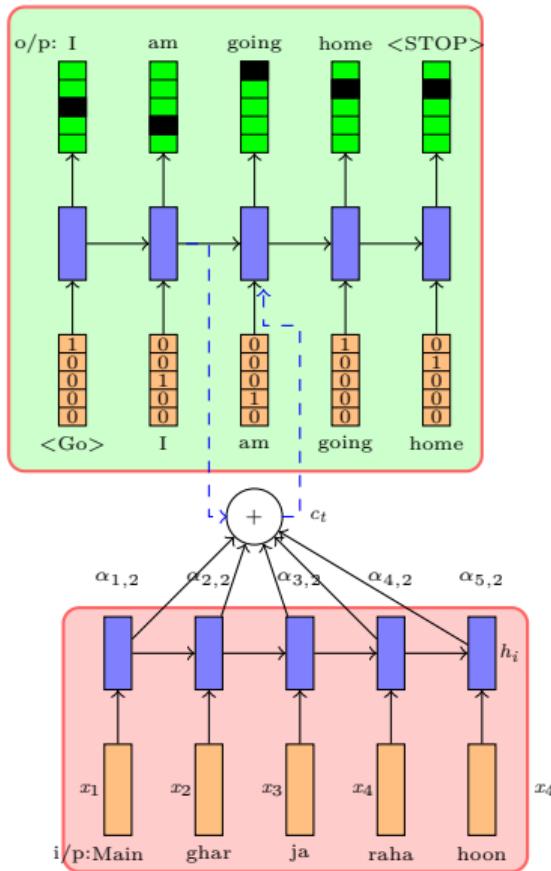
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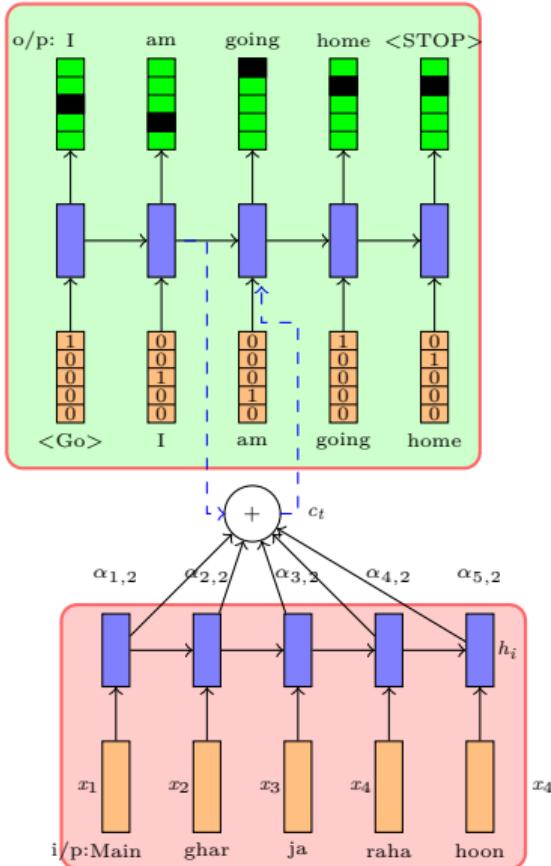


- For example, in our translation example we would want someone to manually annotate the source words which contribute to every target word
- It is hard to get such annotated data
- Then how would this model work in the absence of such data ?

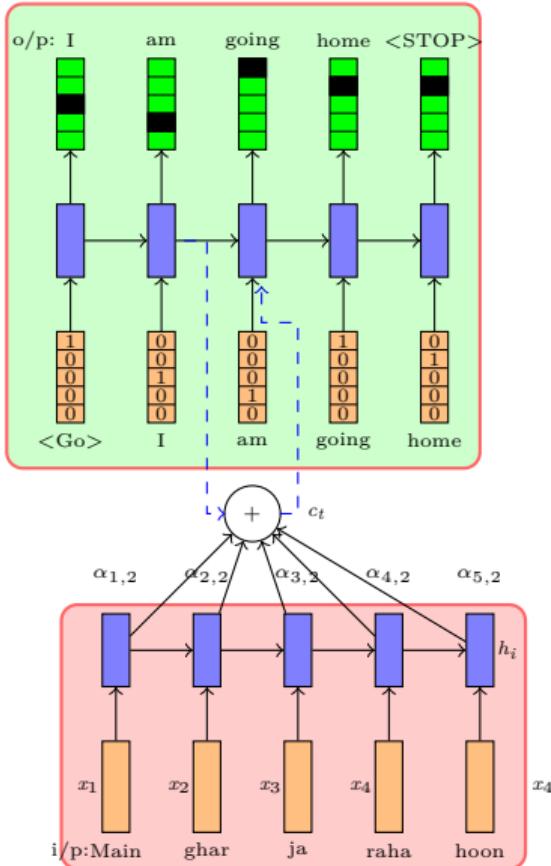


- It works because it is a better modeling choice

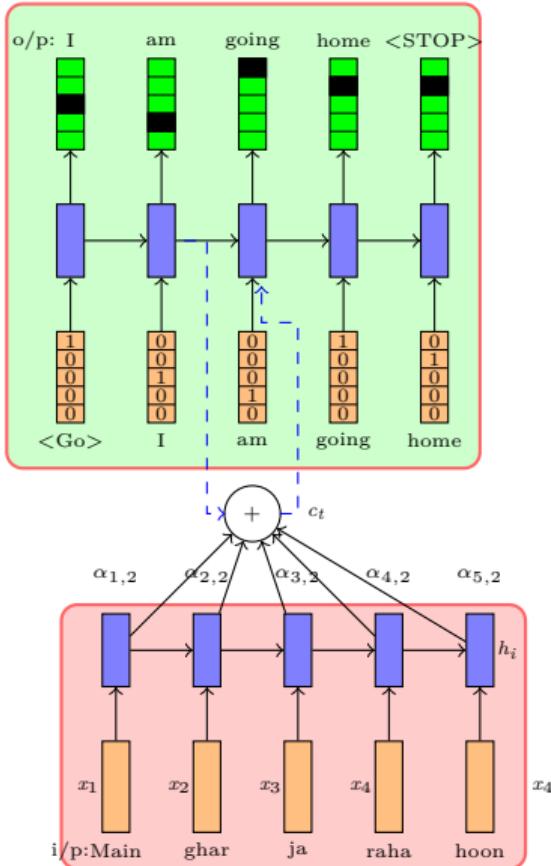




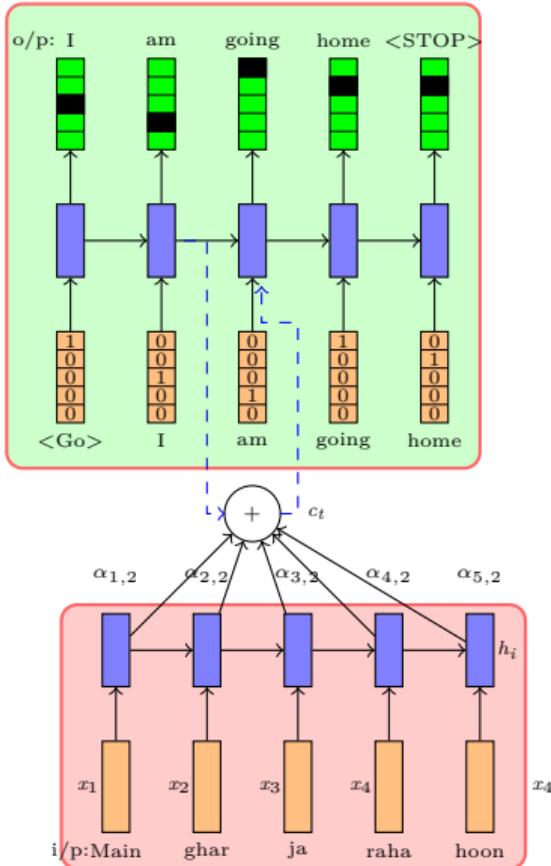
- It works because it is a better modeling choice
- This is a more informed model



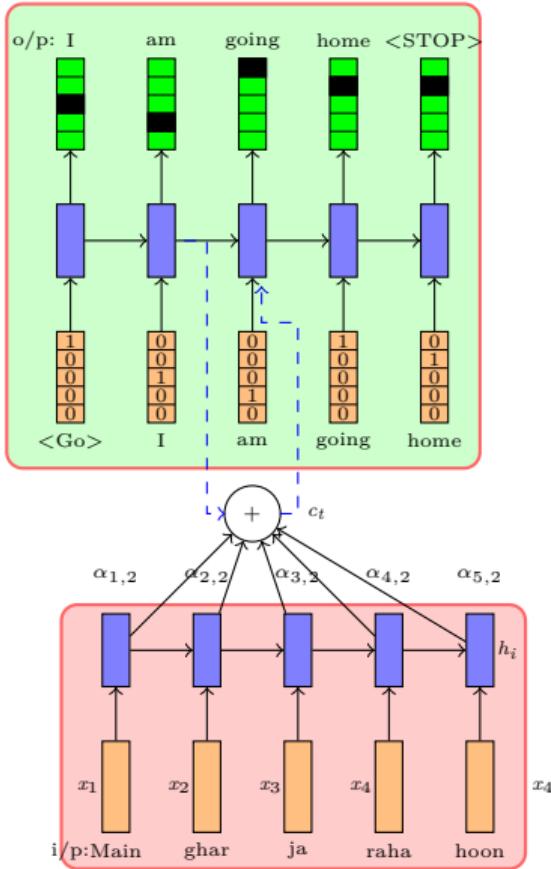
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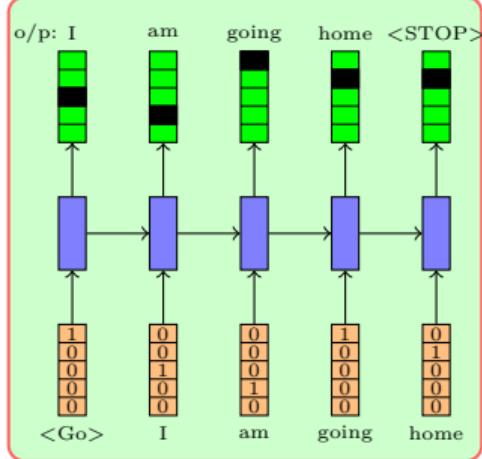


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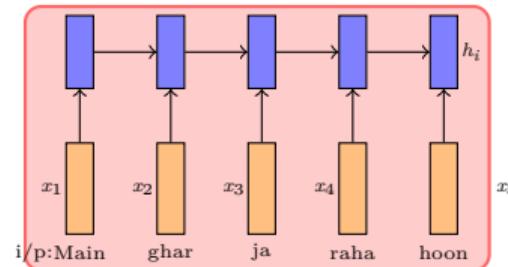


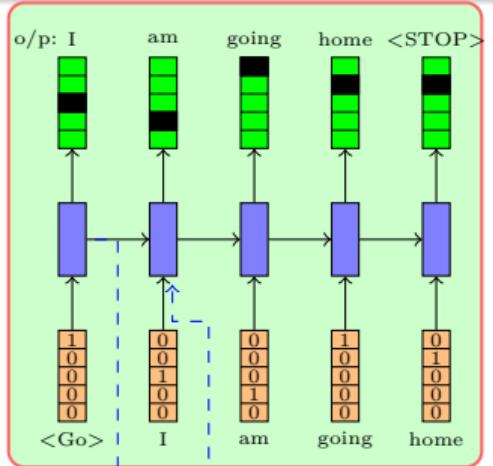
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- Given enough data it should be able to learn these attention weights just as humans do
- That's the hope (and hope is a good thing)
- And in practice indeed these models work better than the vanilla encoder-decoder models

Let us revisit the MT model that we saw earlier and answer the same set of questions again (data, encoder, decoder, loss, training algorithm)

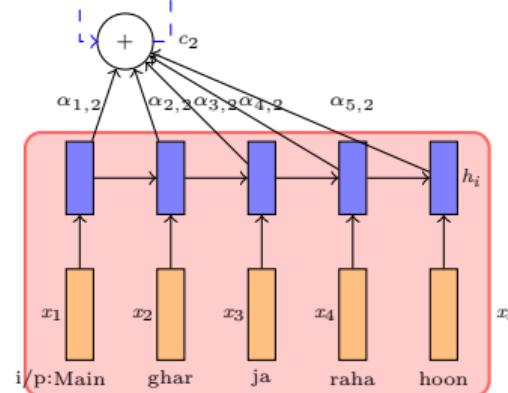


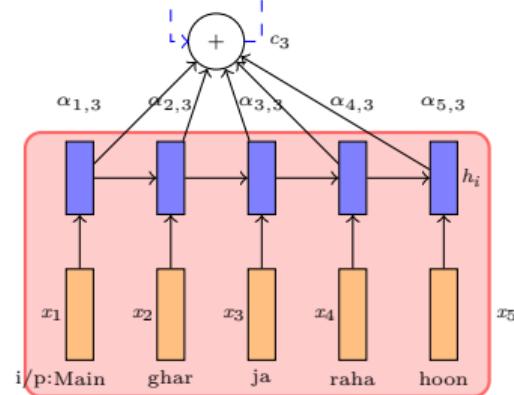
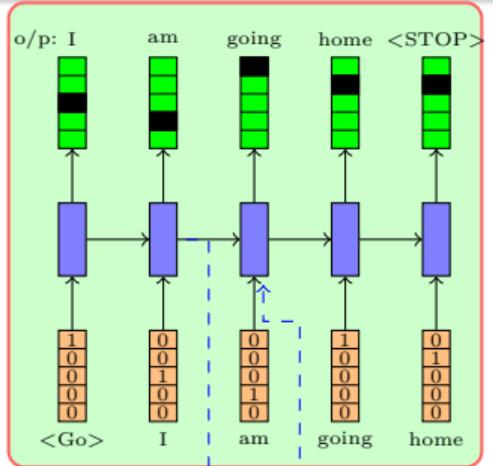
- **Task:** Machine Translation





- **Task:** Machine Translation
- **Data:**  $\{x_i = \text{source}_i, y_i = \text{target}_i\}_{i=1}^N$





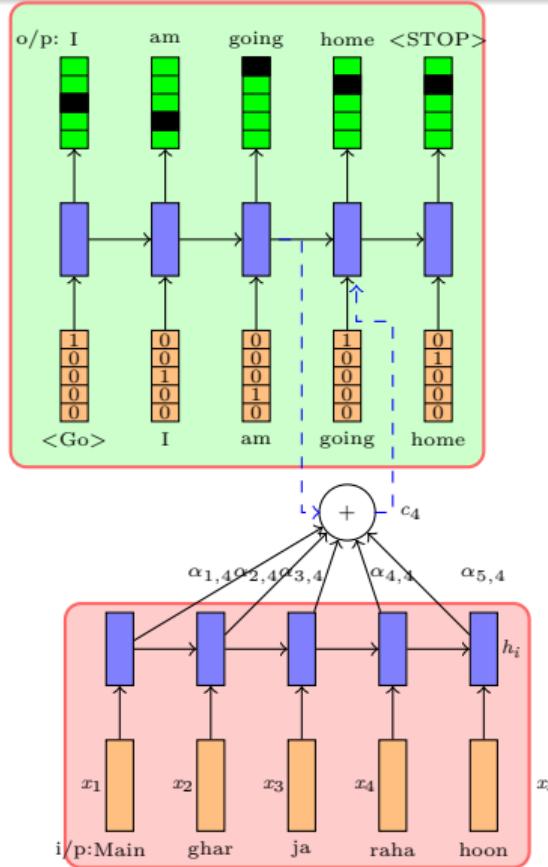
- **Task:** Machine Translation

- **Data:**  $\{x_i = source_i, y_i = target_i\}_{i=1}^N$

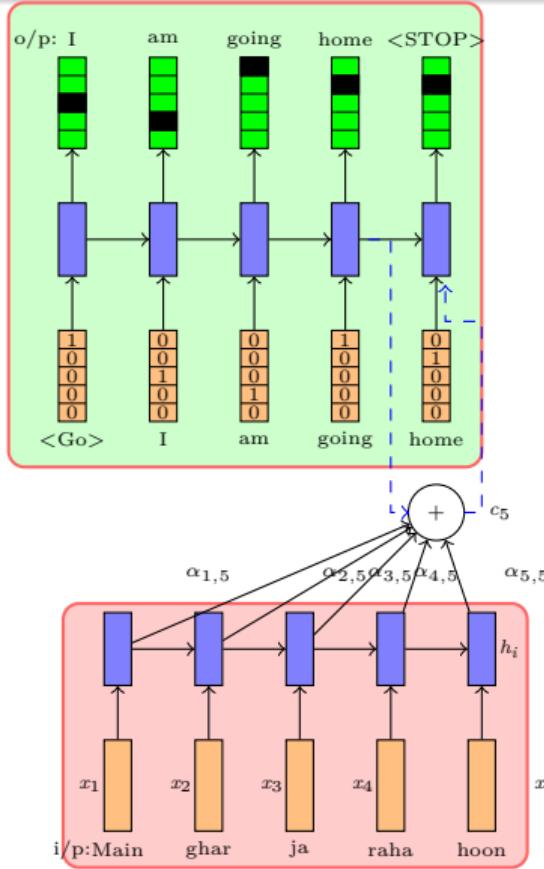
- **Encoder:**

$$h_t = RNN(h_{t-1}, x_t)$$

$$s_0 = h_T$$



- **Task:** Machine Translation
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- **Task:** Machine Translation

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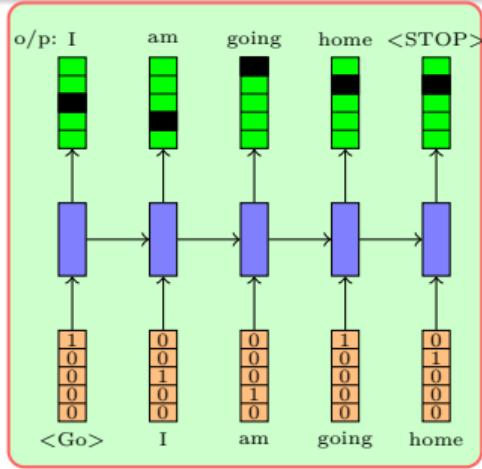
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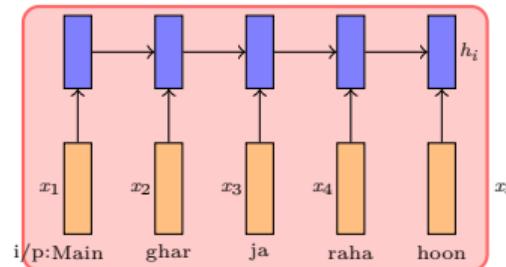
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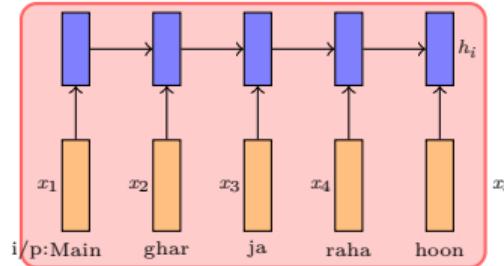
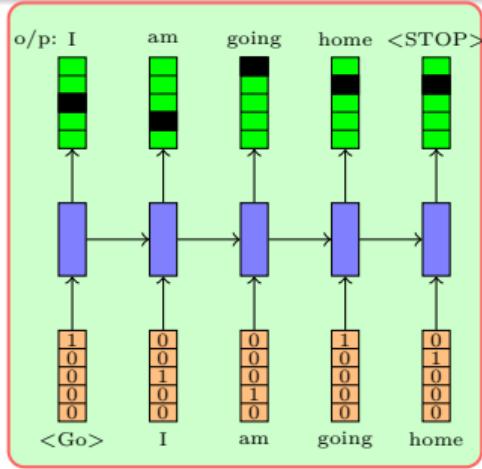
$$s_0 = h_T$$

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$$e_{jt} = V_{attn}^T \tanh(U_{attn} h_j + W_{attn} s_t)$$

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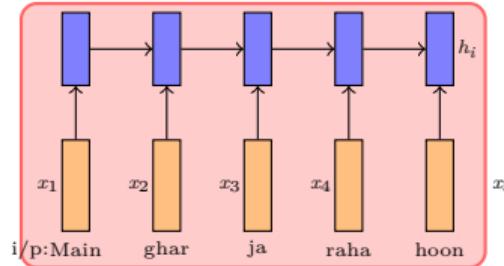
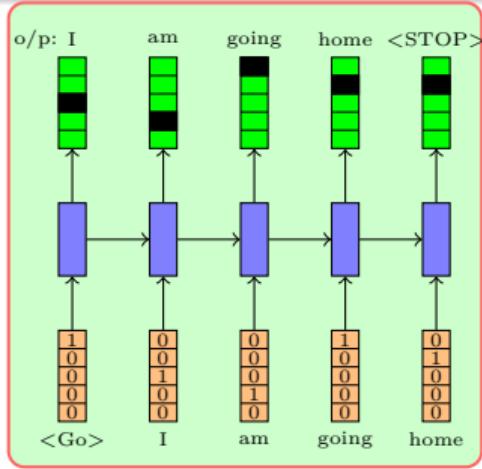
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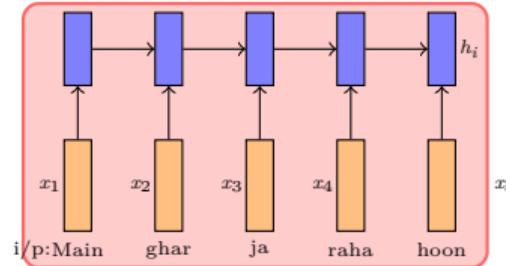
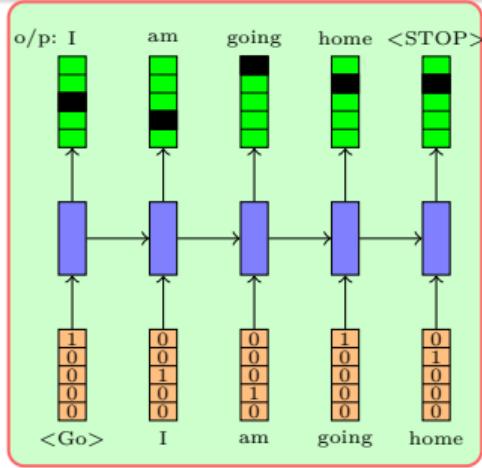
- **Decoder:**

$$e_{jt} = V_{attn}^T \tanh(U_{attn} h_j + W_{attn} s_t)$$

$$\alpha_{jt} = \text{softmax}(e_{jt})$$

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$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), c_t])$$



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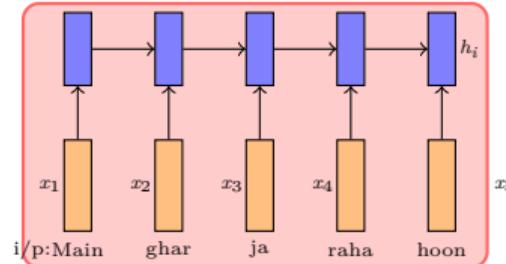
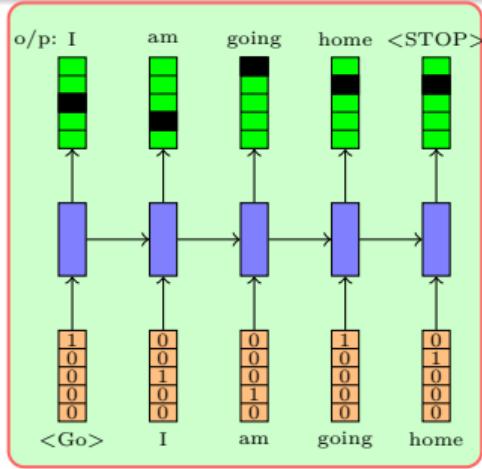
$$\alpha_{jt} = \text{softmax}(e_{jt})$$

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$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), c_t])$$

$$\ell_t = \text{softmax}(Vs_t + b)$$

- **Parameters:**  $U_{dec}$ ,  $V$ ,  $W_{dec}$ ,  $U_{enc}$ ,  $W_{enc}$ ,  $b$ ,  $U_{attn}$ ,  $V_{attn}$



- **Task:** Machine Translation

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$$e_{jt} = V_{attn}^T \tanh(U_{attn} h_j + W_{attn} s_t)$$

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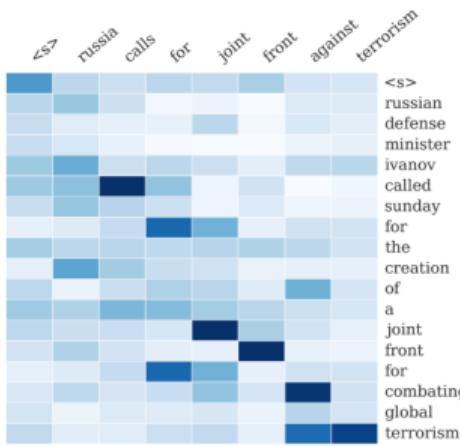
- **Loss and Algorithm** remains same

You can try adding an attention component to all the other encoder decoder models that we discussed earlier and answer the same set of questions (data, encoder, decoder, loss, training algorithm)

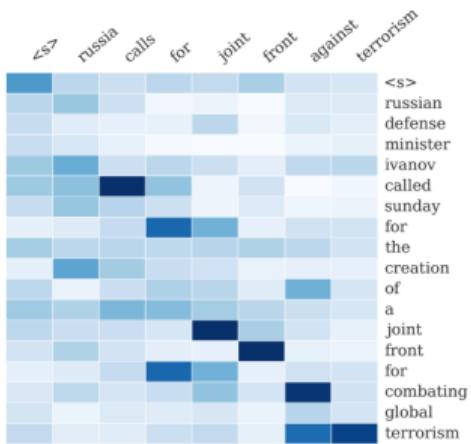
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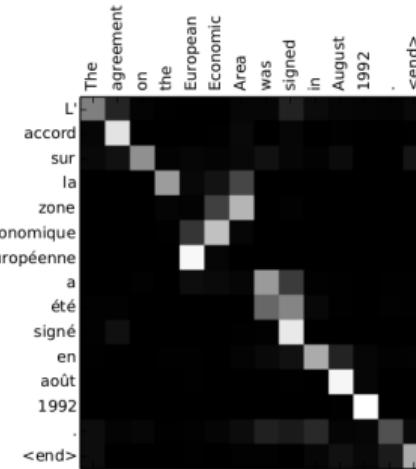
- Can we check if the attention model actually learns something meaningful ?
- In other words does it really learn to focus on the most relevant words in the input at the  $t$ -th timestep ?
- We can check this by plotting the attention weights as a heatmap (we will see some examples on the next slide)



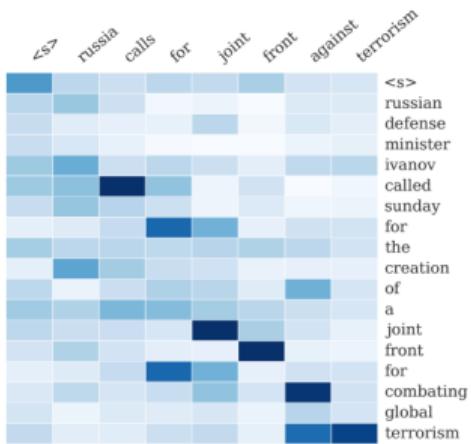
**Figure:** Example output of attention-based summarization system [Rush et al. 2015.]



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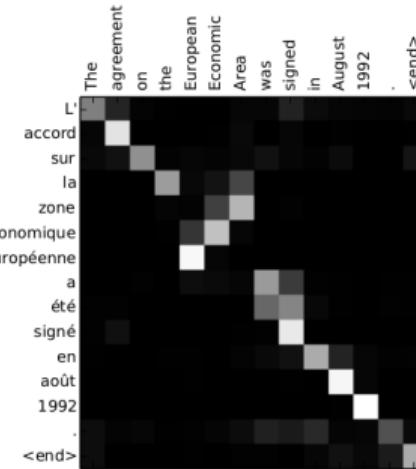


**Figure:** Example output of attention-based neural machine translation model [Cho et al. 2015].

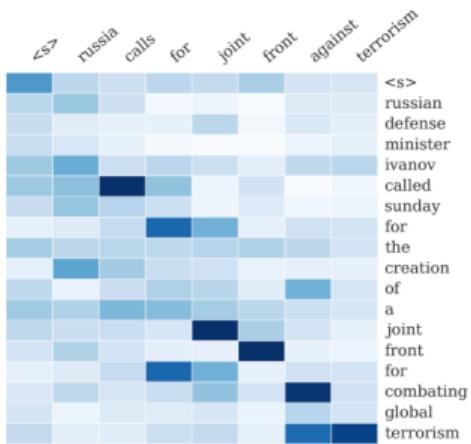


**Figure:** Example output of attention-based summarization system [Rush et al. 2015.]

- The heat map shows a soft alignment between the input and the generated output.

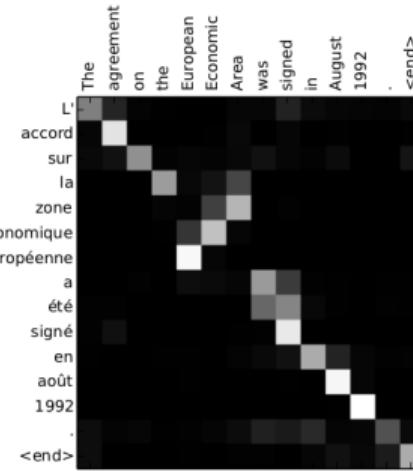


**Figure:** Example output of attention-based neural machine translation model [Cho et al. 2015].



**Figure:** Example output of attention-based summarization system [Rush et al. 2015.]

- The heat map shows a soft alignment between the input and the generated output.
- Each cell in the heat map corresponds to  $\alpha_{tj}$  (i.e., the importance of the  $j^{th}$  input word for predicting the  $t^{th}$  output word as determined by the model)



**Figure:** Example output of attention-based neural machine translation model [Cho et al. 2015].



+**Local+Global**: A **man** and a **woman** are **talking** on the **road**

**Ref:** A man and a woman ride a motorcycle



+**Local+Global**: **Someone** is **frying** a **fish** in a **pot**

+**Local**: Someone is frying something

+**Global**: The person is cooking

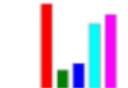
**Basic**: A man cooking its kitchen

**Ref:** A woman is frying food



+**Local+Global**: the **girl** **grins** at **him**

**Ref:** SOMEONE and SOMEONE swap a look



+**Local+Global**: as **SOMEONE** sits on the **table**,  
**SOMEONE** shifts his **gaze** to **SOMEONE**

+**Local**: with a smile SOMEONE arrives

+**Global**: SOMEONE sits at a table

**Basic**: now, SOMEONE grins

**Ref:** SOMEONE gaze at SOMEONE

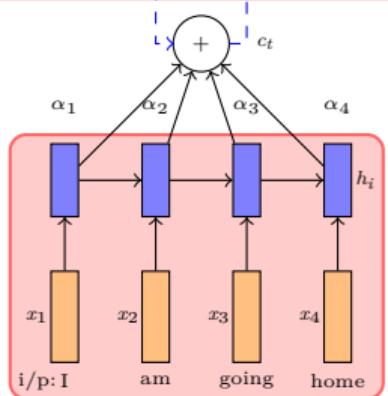
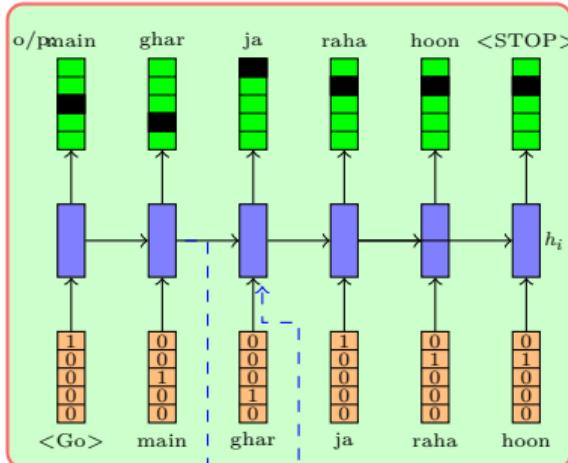
Figure: Example output of attention-based video captioning system [Yao et al. 2015.]

# Module : Attention over images

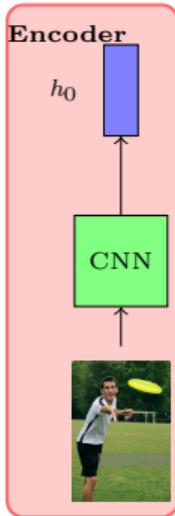


A man throwing  
a frisbee in a park

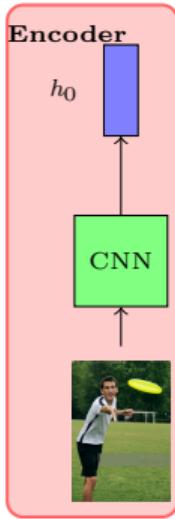
- How do we model an attention mechanism for images?



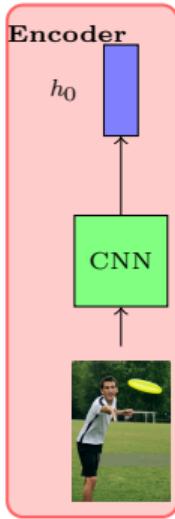
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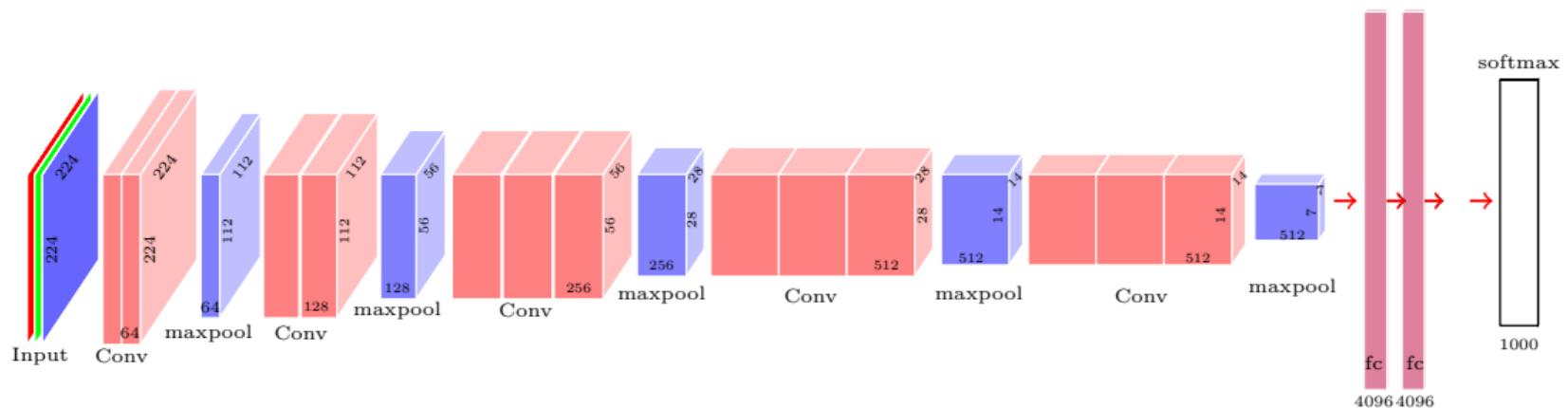


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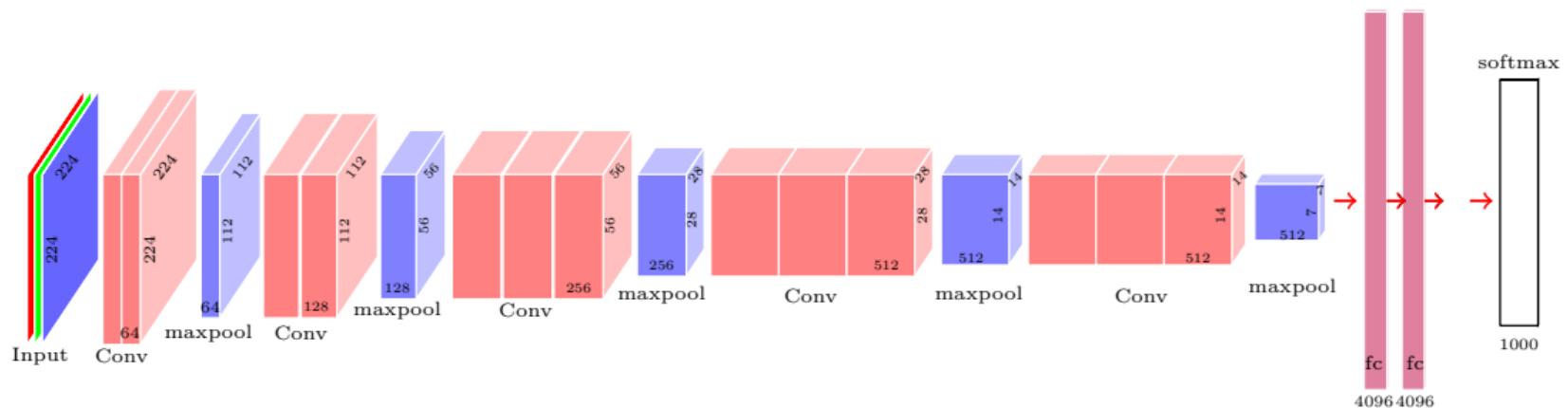


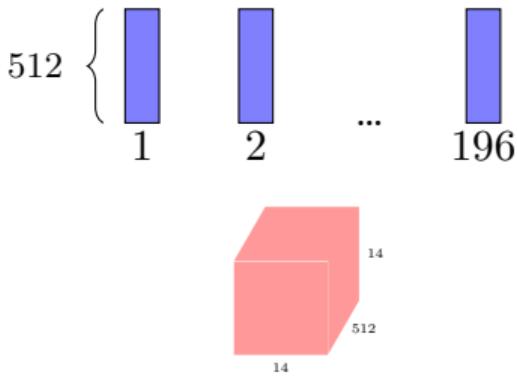
- How do we model an attention mechanism for images?
- In the case of text we have a representation for every location (time step) of the input sequence
- But for images we typically use representation from one of the fully connected layers
- This representation does not contain any location information
- So then what is the input to the attention mechanism?

- Well, instead of the fc7 representation we use the output of one of the convolution layers which has spatial information



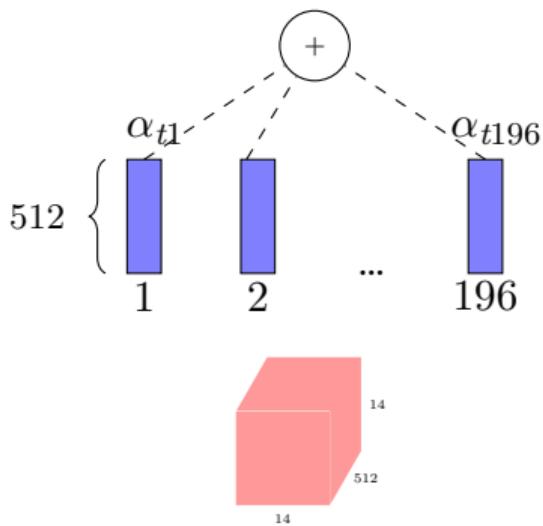
- Well, instead of the fc7 representation we use the output of one of the convolution layers which has spatial information
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- For example the output of the 5<sup>th</sup> convolutional layer of VGGNet is a  $14 \times 14 \times 512$  size feature map
- We could think of this as 196 locations (each having a 512 dimensional representation)
- The model will then learn an attention over these locations (which in turn correspond to actual locations in the images)



- Let us look at some examples of attention over images for the task of image captioning



A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.



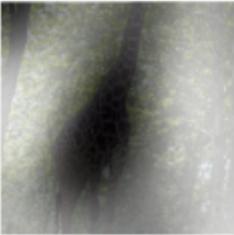
A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.



A group of people sitting on a boat in the water.



A giraffe standing in a forest with trees in the background.

**Figure:** Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicates the corresponding word) [Kyunghyun Cho et al. 2015.]

# Module : Hierarchical Attention

## Context

U: Can you suggest a good movie?

B: Yes, sure. How about Logan?

U: Okay, who is the lead actor?

## Response

B: Hugh Jackman, of course

- Consider a dialog between a user ( $u$ ) and a bot ( $B$ )

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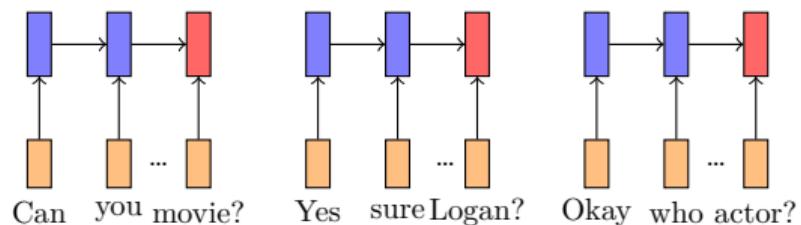
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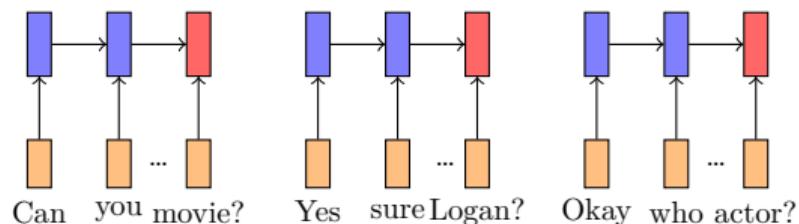
- Consider a dialog between a user ( $u$ ) and a bot ( $B$ )
- The dialog contains a sequence of utterances between the user and the bot
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- Thus what we have here is a “sequence of sequences” as input
- Can you think of an encoder for such a sequence of sequences?

- We could think of a two level hierarchical RNN encoder

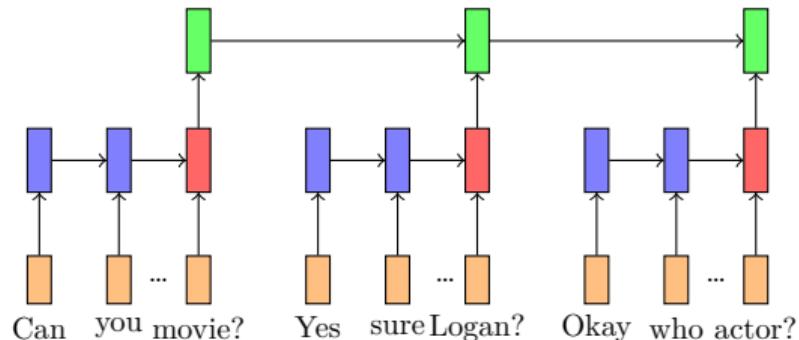
- We could think of a two level hierarchical RNN encoder
- The first level RNN operates on the sequence of words in each utterance and gives us a representation

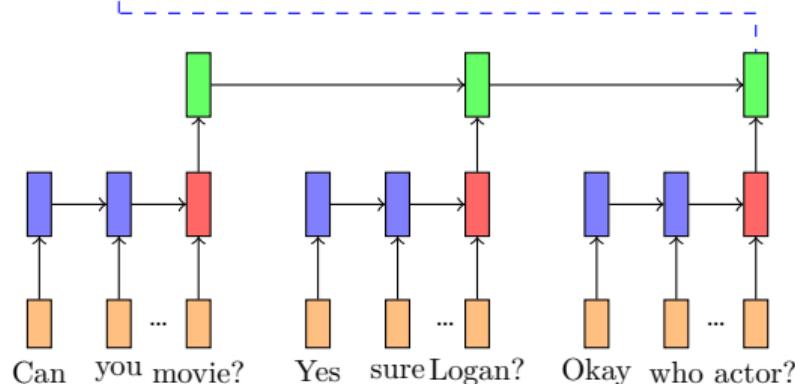
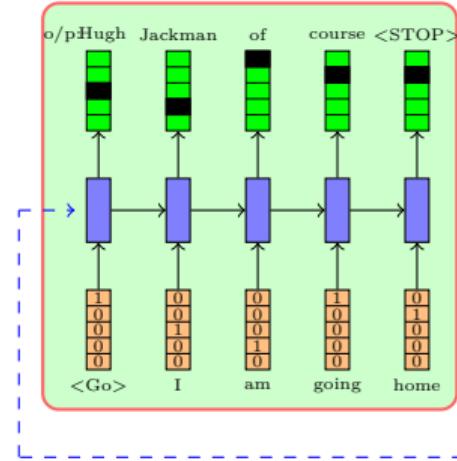


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- We now have a sequence of utterance representations (red vectors in the image)
- We can now have another RNN which encodes this sequence and gives a single representations for the sequences of utterances
- The decoder can then produce an output sequence conditioned on this utterance

Politics is the process of making decisions applying to all members of each group.

More narrowly, it refers to achieving and ...

- Let us look at another example

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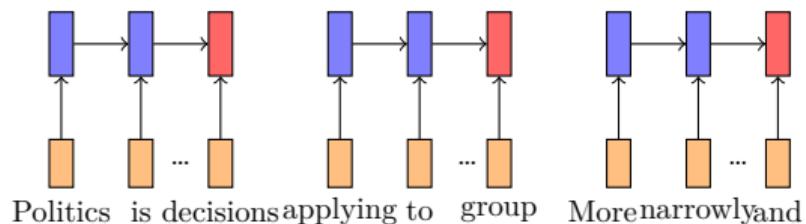
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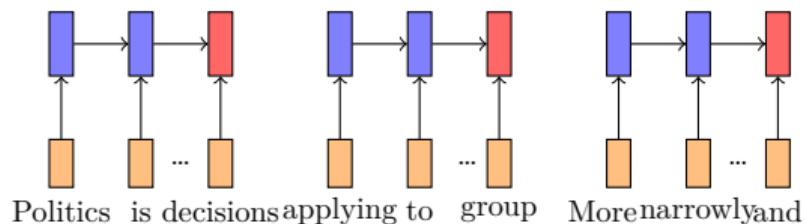
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- Consider the task of document classification or summarization
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- We can again use a hierarchical RNN to model this



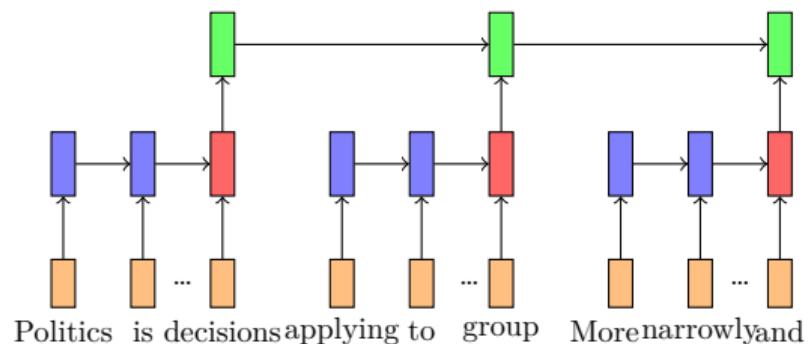
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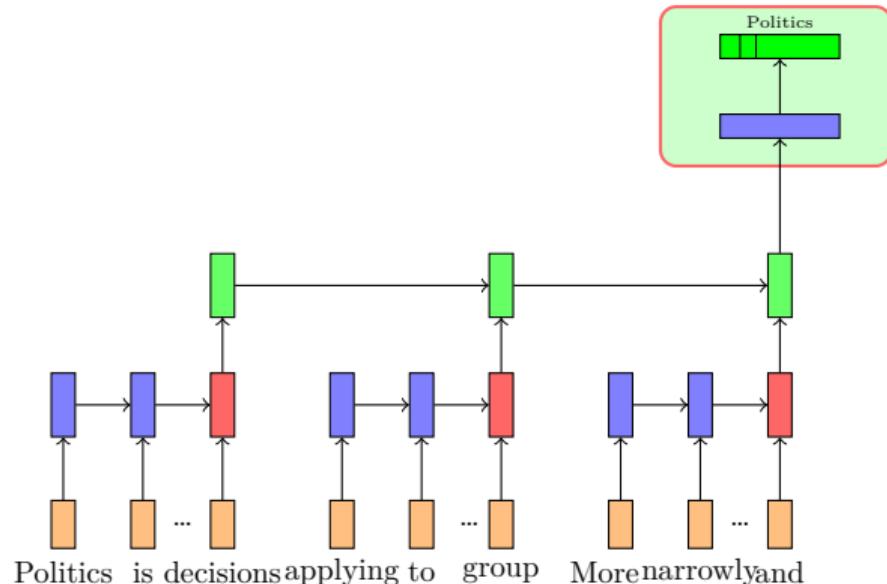
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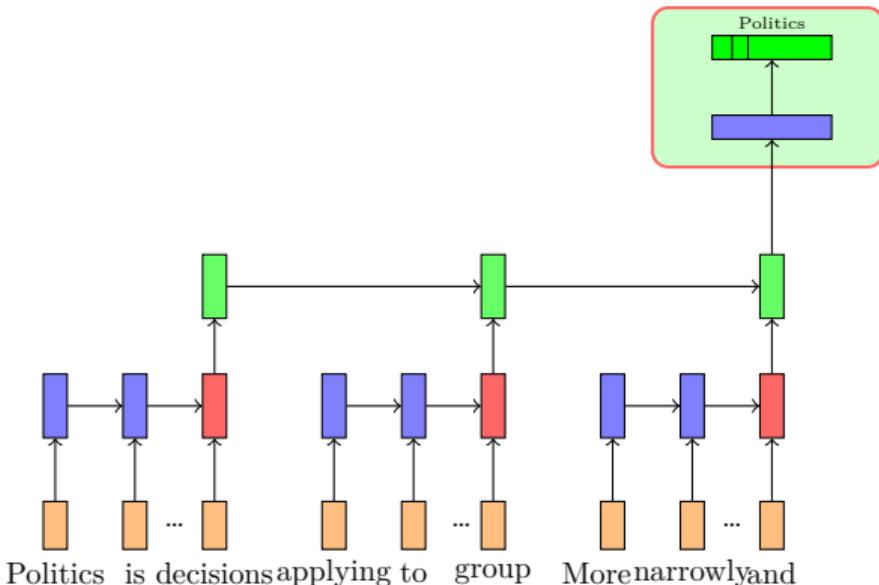
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- Data:  $\{Document_i, class_i\}_{i=1}^N$

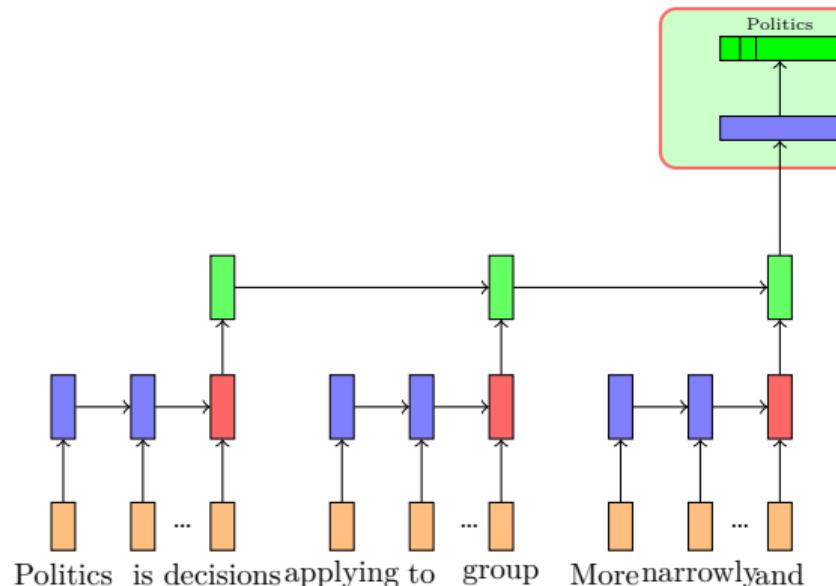


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- **Data:**  $\{Document_i, class_i\}_{i=1}^N$
- **Word level (1) encoder:**

$$h_{ij}^1 = RNN(h_{ij-1}^1, w_{ij})$$

$$s_i = h_{iT_i}^1 \quad [T \text{ is length of sentence } i]$$



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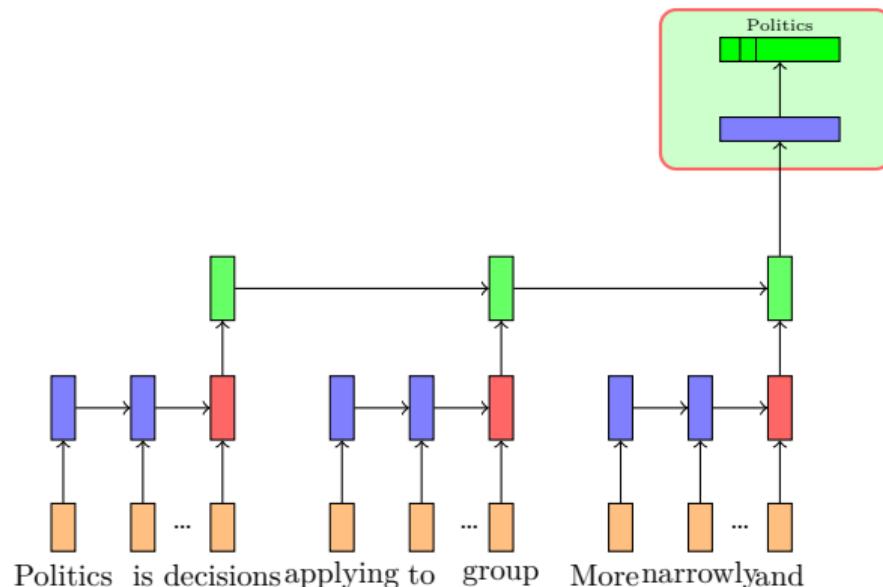
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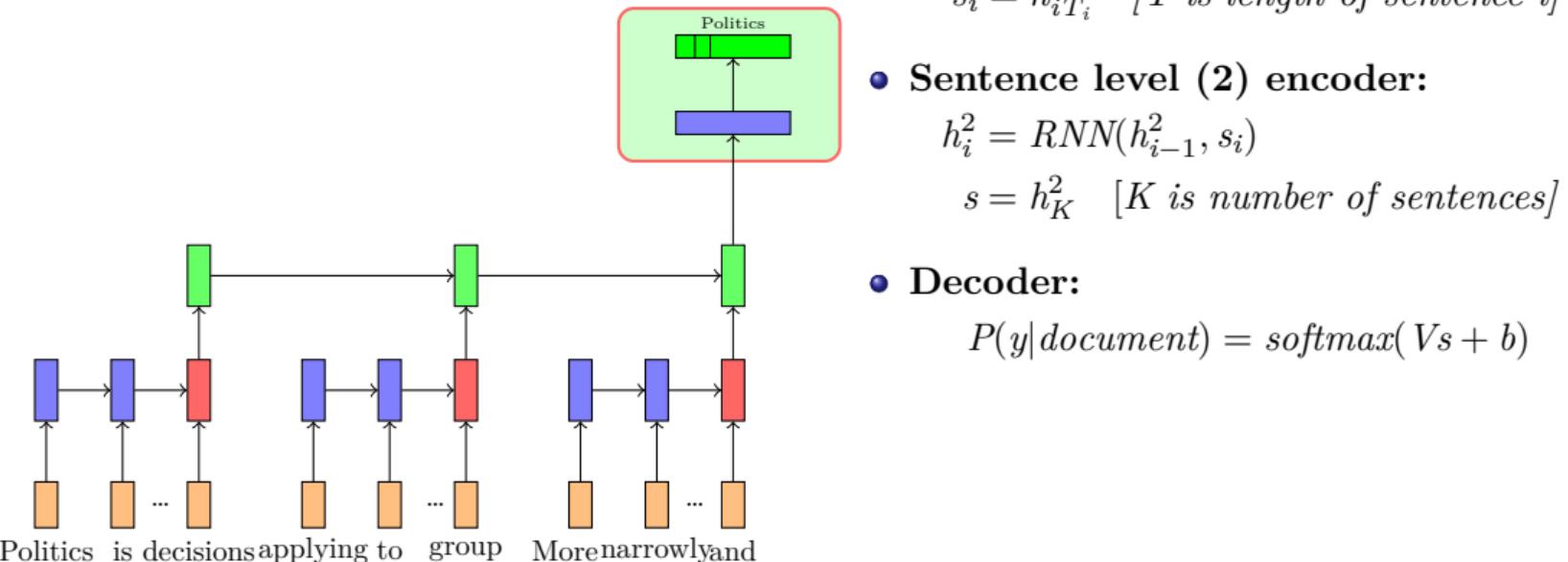
- **Sentence level (2) encoder:**

$$h_i^2 = RNN(h_{i-1}^2, s_i)$$

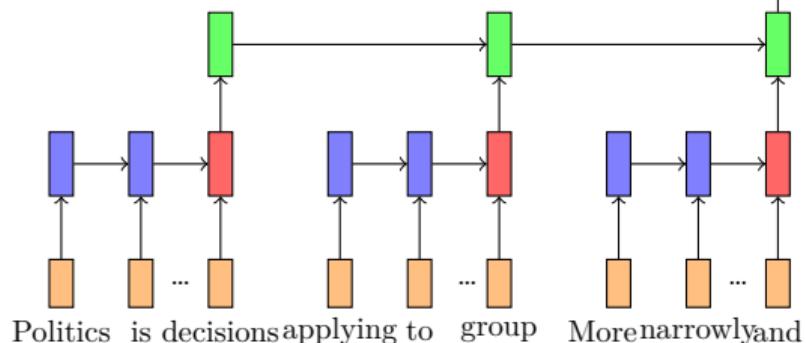
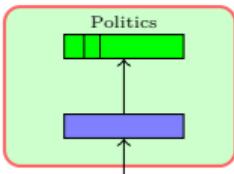
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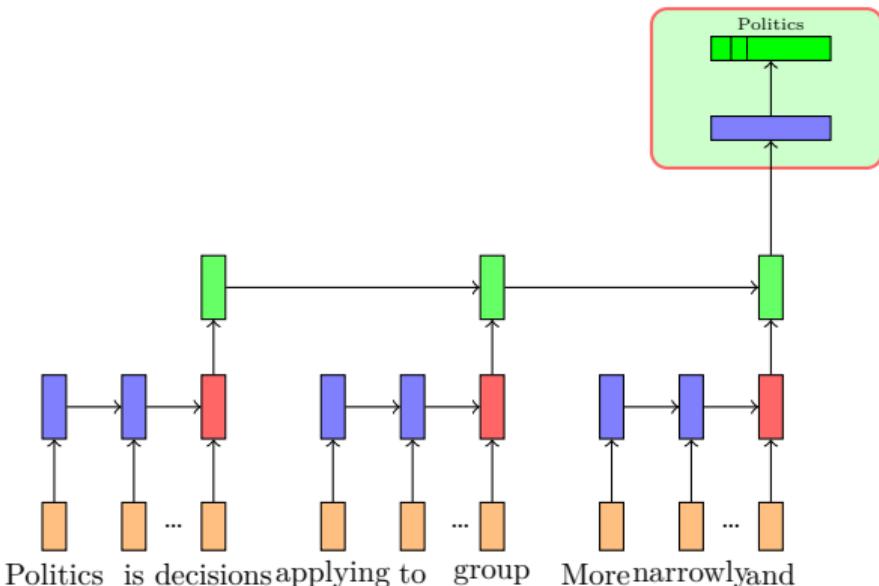
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$$s = h_K^2 \quad [K \text{ is number of sentences}]$$
- **Decoder:**  

$$P(y|document) = softmax(Vs + b)$$
- **Params:**  $W_{enc}^1, U_{enc}^1, W_{enc}^2, U_{enc}^2, V, b$

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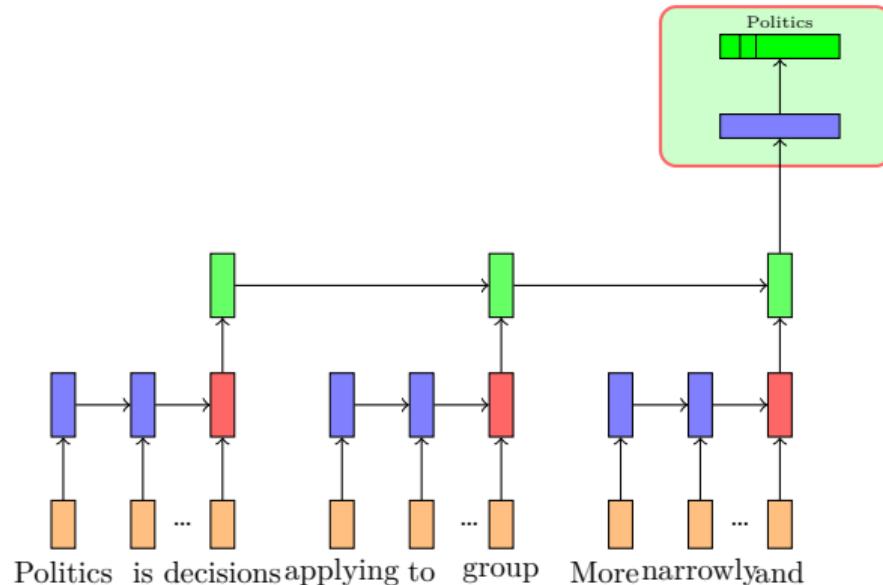
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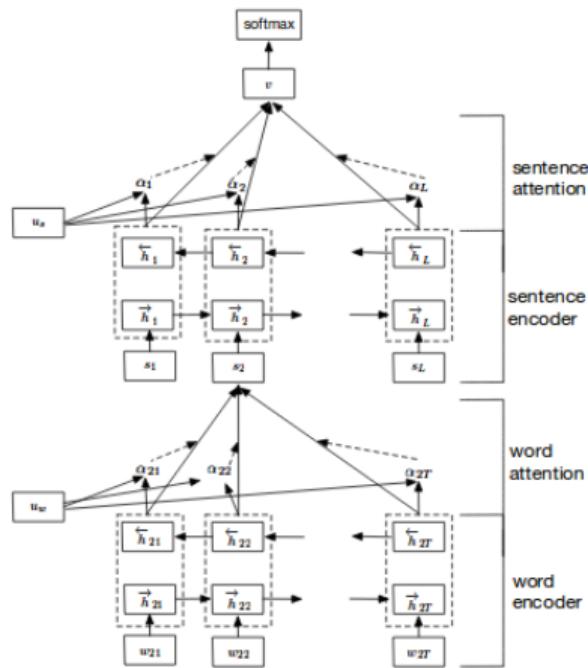
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- **Loss:** Cross Entropy
- **Algorithm:** Gradient Descent with backpropagation

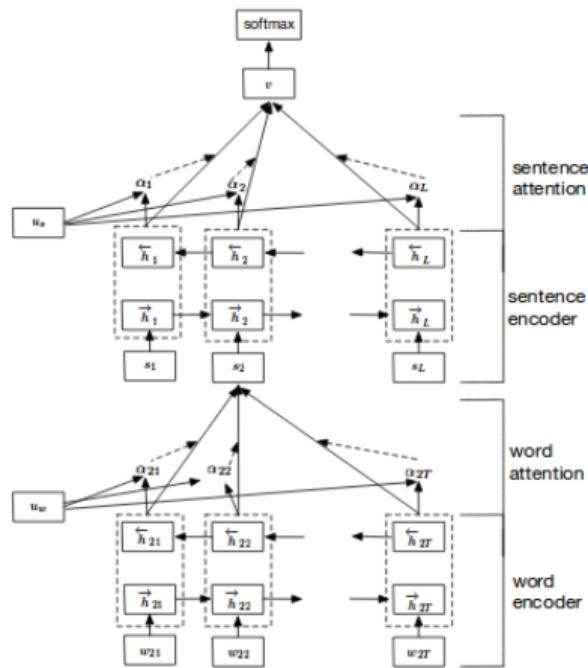
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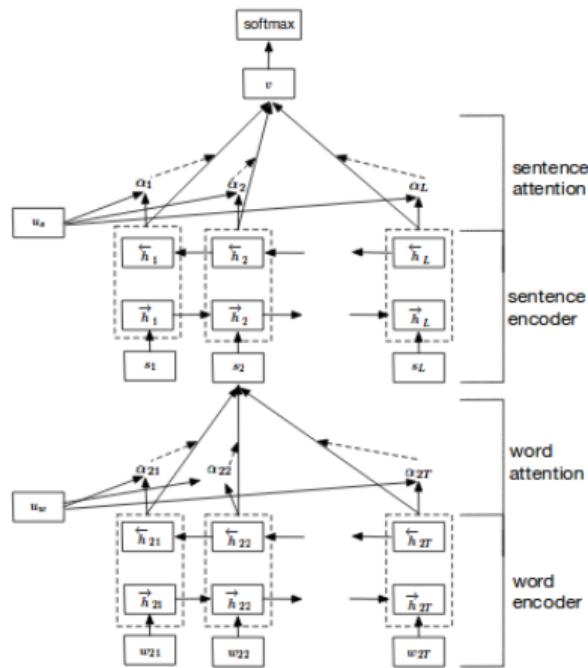
**Figure:** Hierarchical Attention Network  
[Yang et al.]

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[Yang et al.]

- How would you model attention in such a hierarchical encoder decoder model ?
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- Then we need to attend to important (most informative) sentences in a document
- Let us see how to model this

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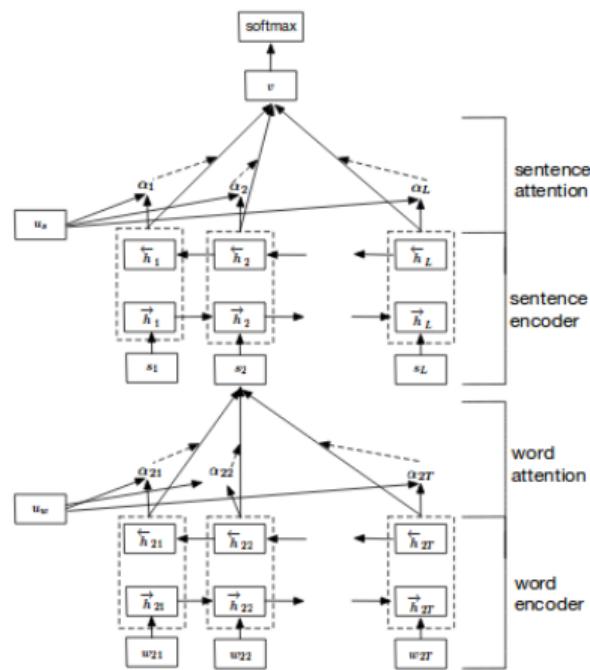
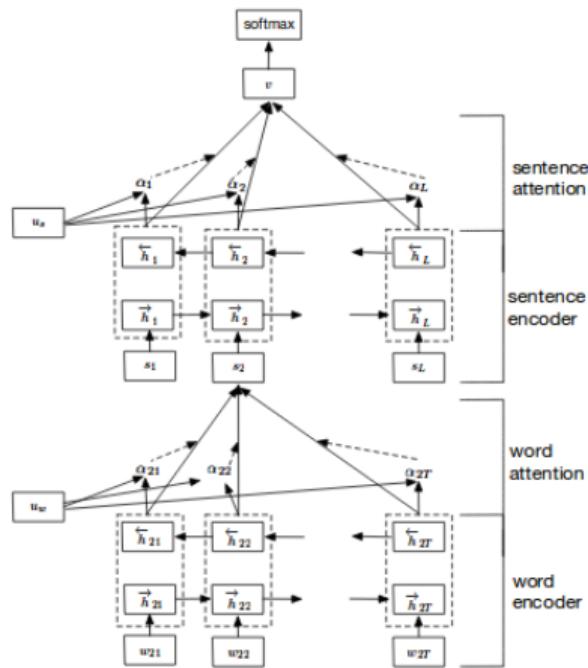


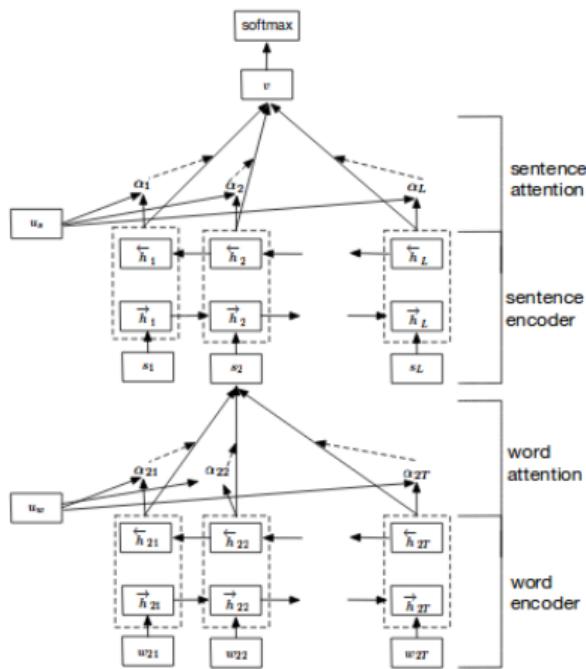
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$$\begin{aligned}
 h_{ij} &= RNN(h_{ij-1}, w_{ij}) \\
 u_{ij} &= \tanh(W_w h_{ij} + b_w) \\
 \alpha_{ij} &= \frac{\exp(u_{ij}^T u_w)}{\sum_t \exp(u_{it}^T u_w)} \\
 s_i &= \sum_j \alpha_{ij} h_{ij}
 \end{aligned}$$



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$$s_i = \sum_j \alpha_{ij} h_{ij}$$

- **Sentence level (2) encoder:**

$$h_i = RNN(h_{i-1}, s_i)$$

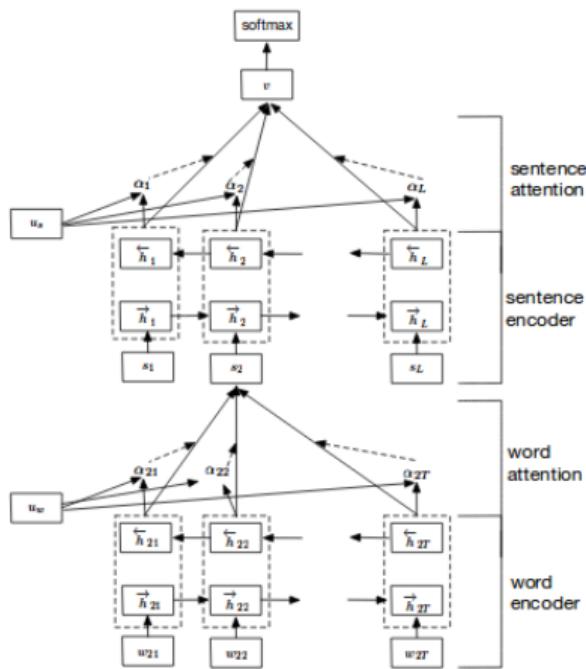
$$u_i = \tanh(W_s h_i + b_s)$$

$$\alpha_i = \frac{\exp(u_i^T u_s)}{\sum_i \exp(u_i^T u_s)}$$

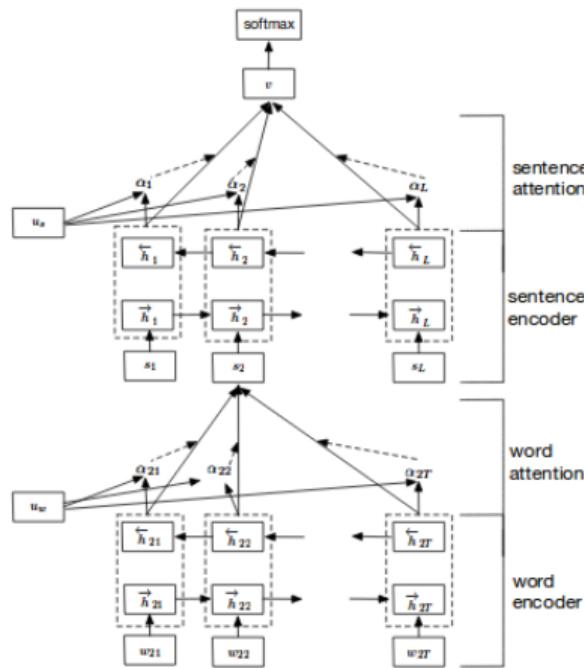
$$s = \sum_i \alpha_i h_i$$

## • Decoder:

$$P(y|document) = \text{softmax}(Vs + b)$$



**Figure:** Hierarchical Attention Network  
[Yang et al..]



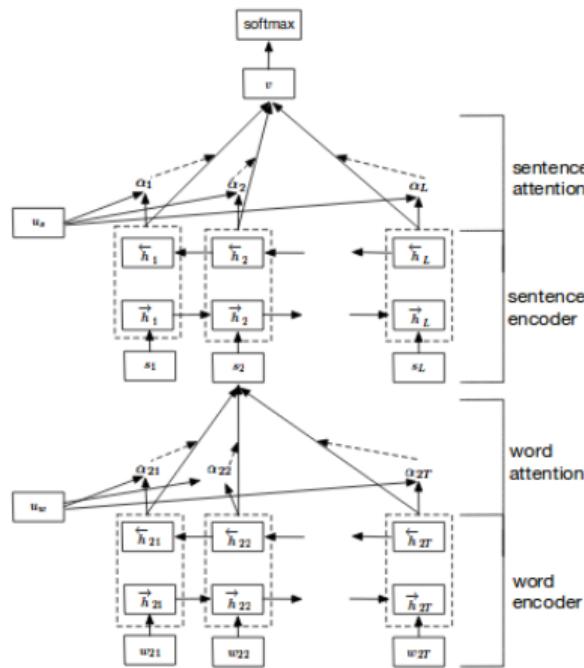
## • Decoder:

$$P(y|document) = \text{softmax}(Vs + b)$$

## • Parameters:

$$W_w, W_s, V, b_w, b_s, b, u_w, u_s$$

**Figure:** Hierarchical Attention Network  
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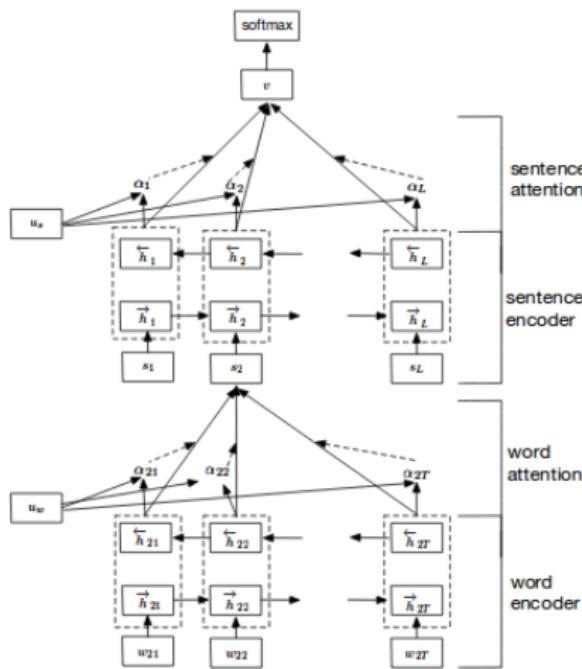
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- **Loss:** cross entropy



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[Yang et al..]

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- **Loss:** cross entropy

- **Algorithm:** Gradient Descent and backpropagation