CS7015 (Deep Learning) : Lecture 16

Encoder Decoder Models, Attention Mechanism

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Module 16.1: Introduction to Encoder Decoder Models

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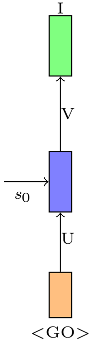

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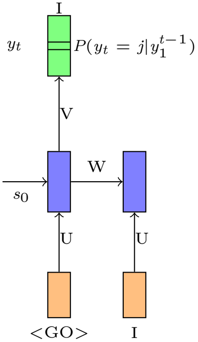

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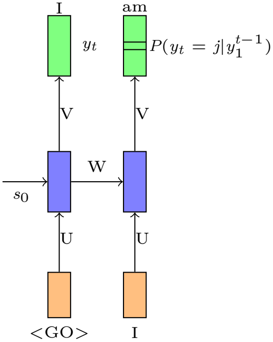

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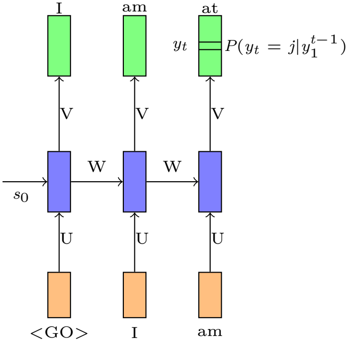

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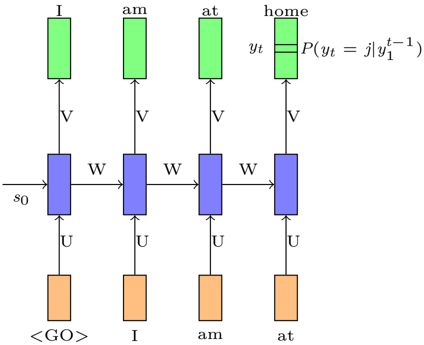

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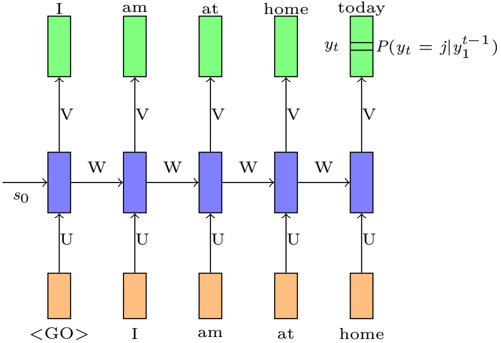

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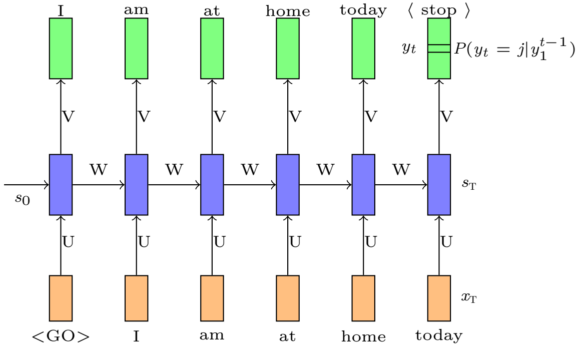

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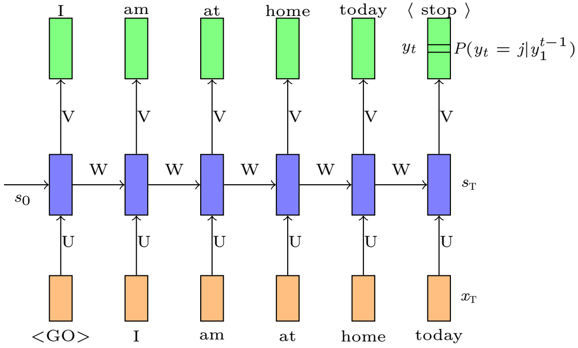

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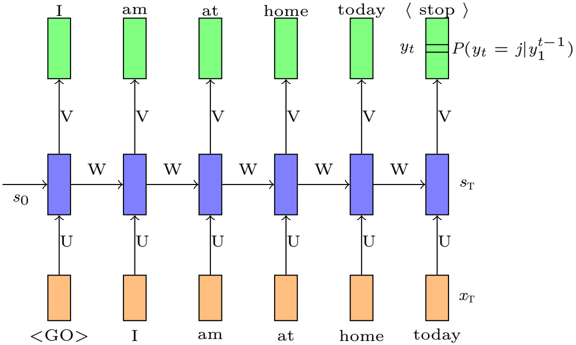
where $j \in V$ and V is the set of all vocabulary words



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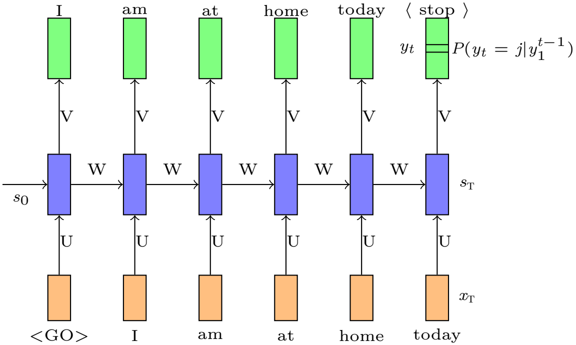

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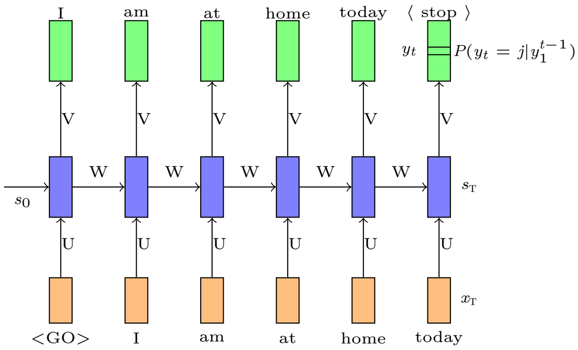

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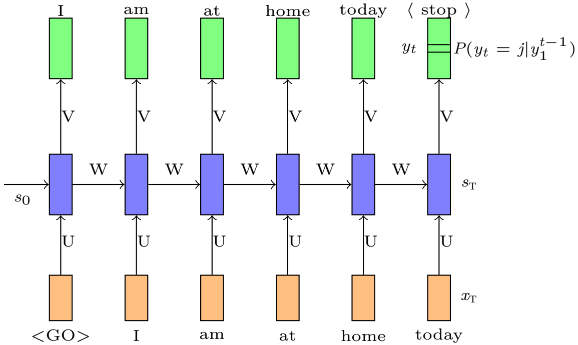
- Notice that the recurrent connections ensure that s_t has information about y_1^{t-1}



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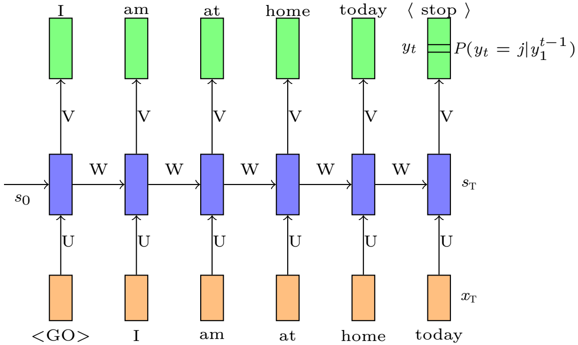
India, officially the Republic of India, is a country in South Asia. It is the seventh-largest country by area, ...

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



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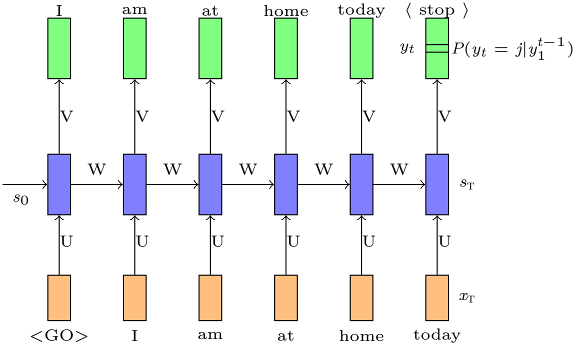

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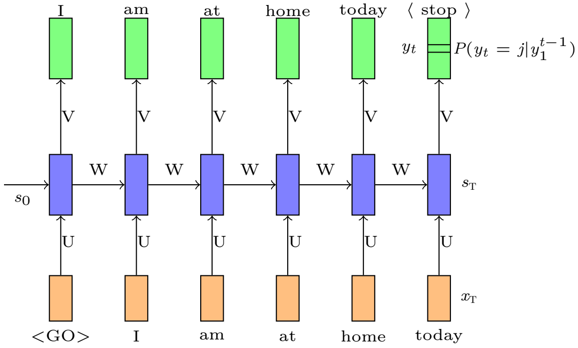

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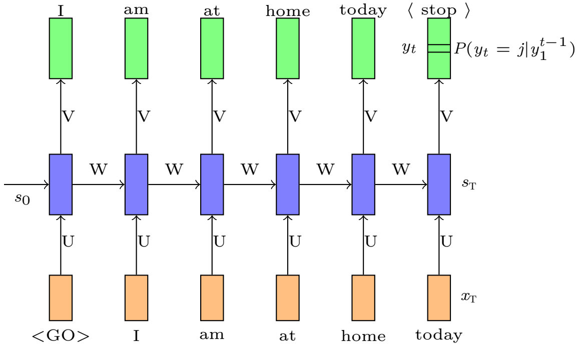

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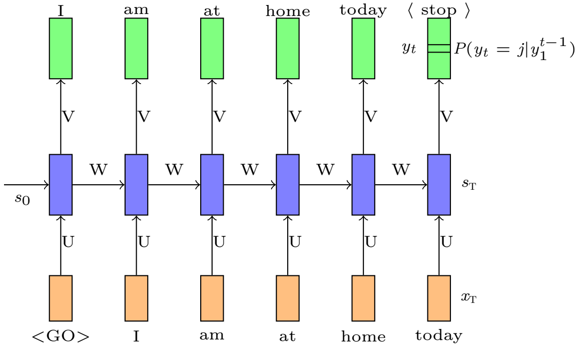

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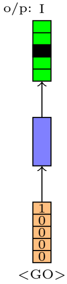
$$\mathscr{L}(\theta) = \sum_{t=1}^{T} \mathscr{L}_t(\theta)$$

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

where ℓ_t is the true word at time step t

- What is the input at each time step?



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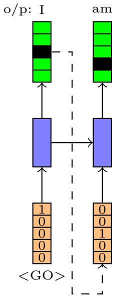

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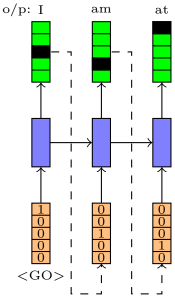

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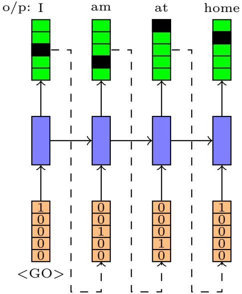

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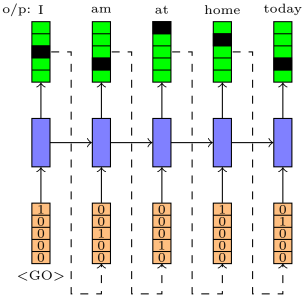

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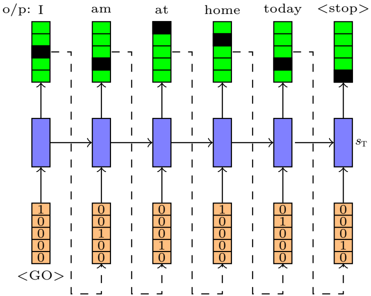

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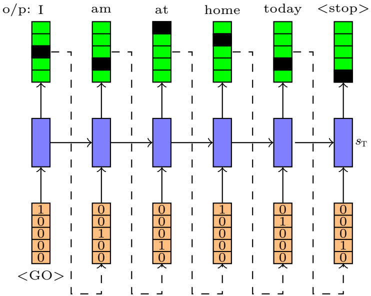

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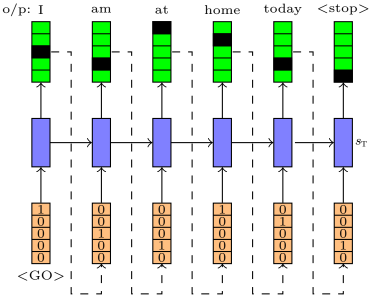

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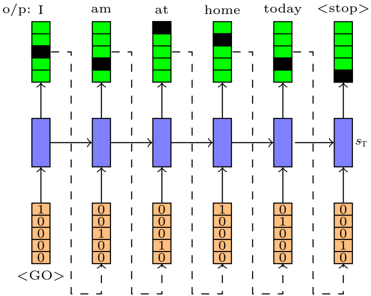

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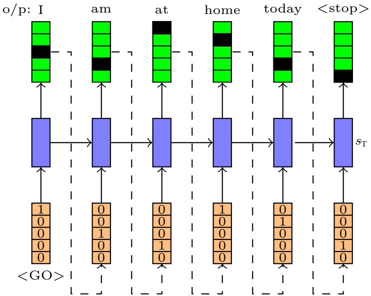

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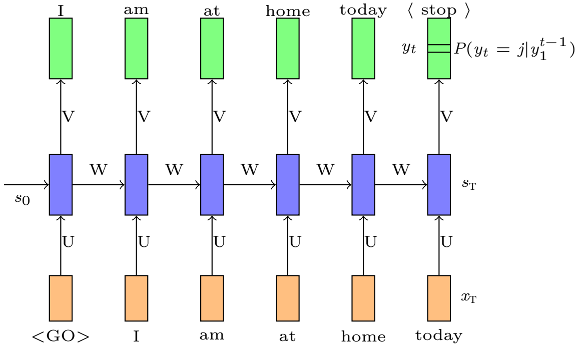
- In practice, instead of one hot representation we use a pre-trained word embedding of the j^{th} word



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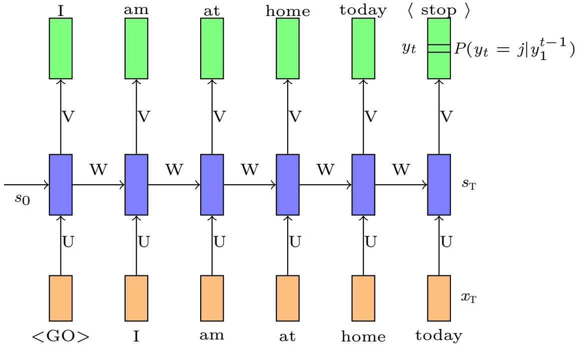

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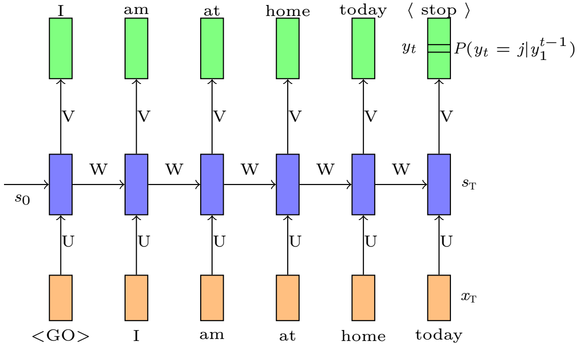

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- We will return back to this later

- 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

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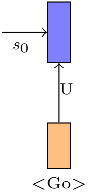
- What if we want to generate a sentence given an image?

A man throwing
a frisbee in a park



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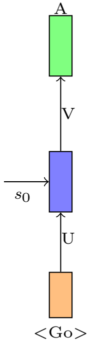

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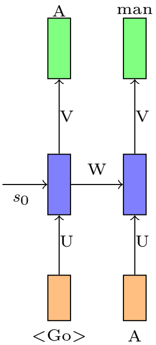

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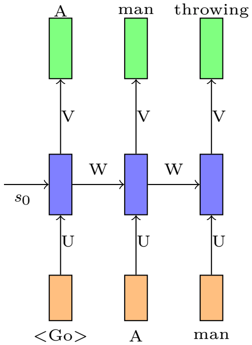

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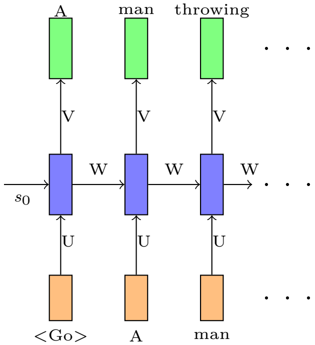

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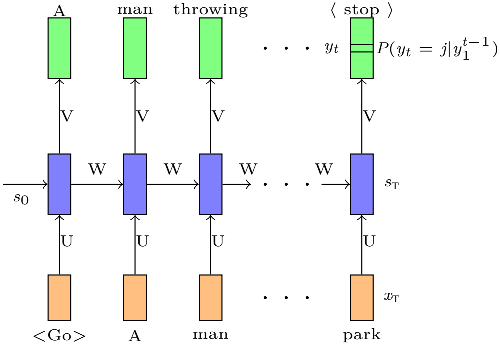

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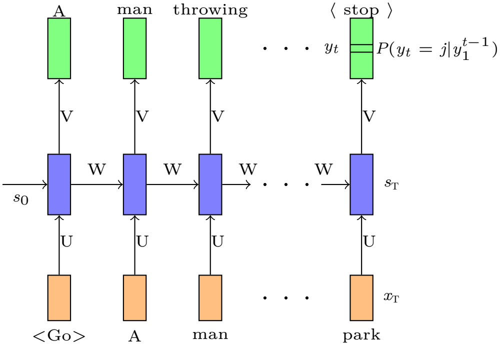

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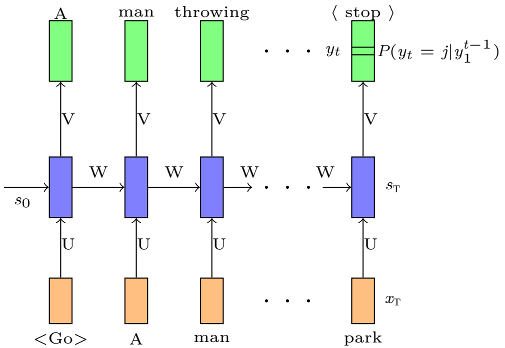

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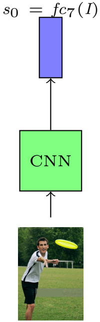
- Notice that $P(y_t|y_1^{t-1}, I)$ is again a conditional distribution



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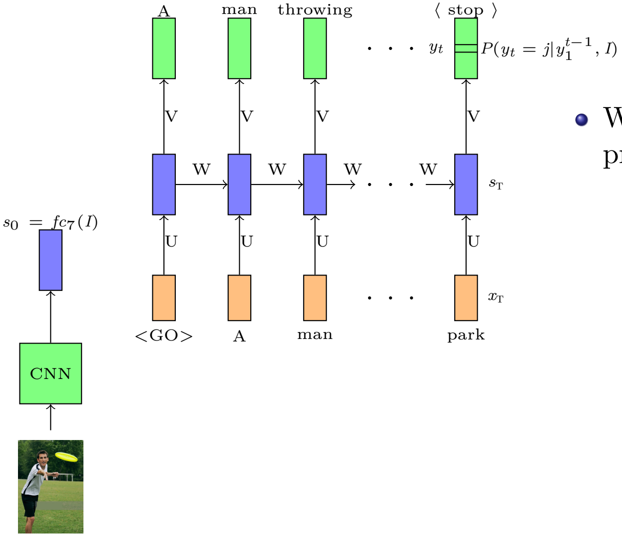

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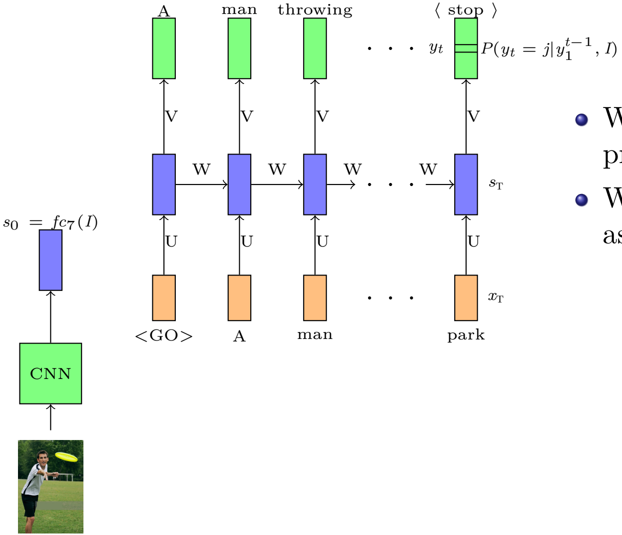

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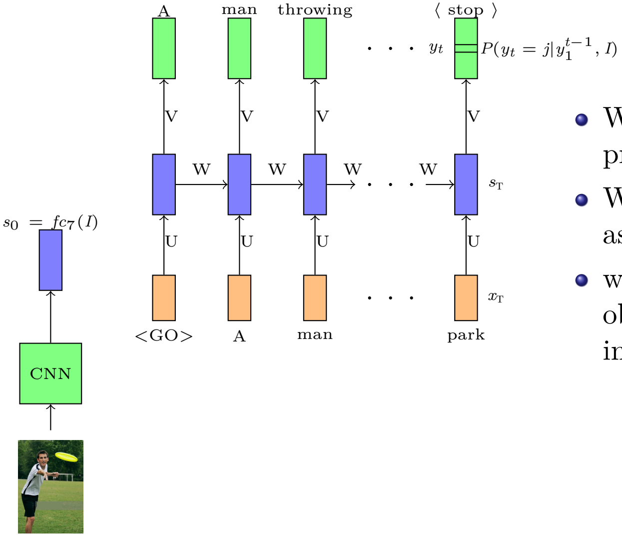

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- where $fc_7(I)$ is the representation obtained from the fc_7 layer of an image

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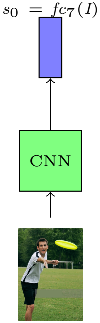
- Let us see two such options

- **Option 1:** Set $s_0 = f_{c_7}(I)$



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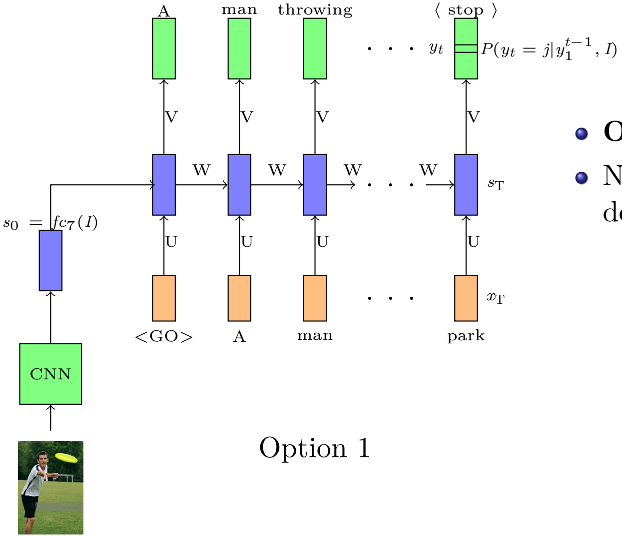

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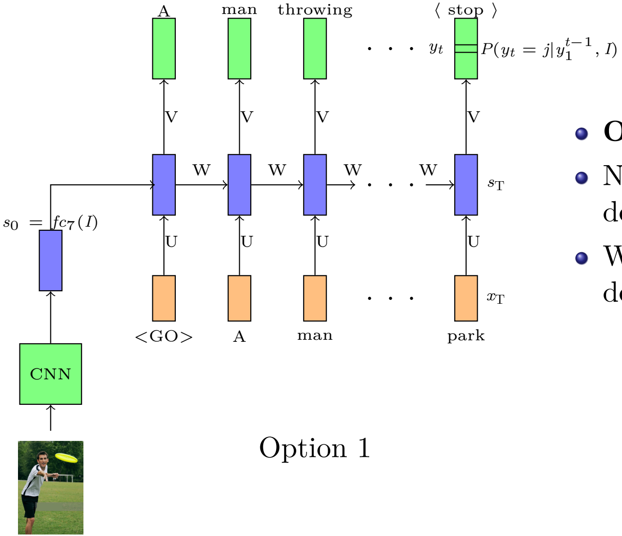

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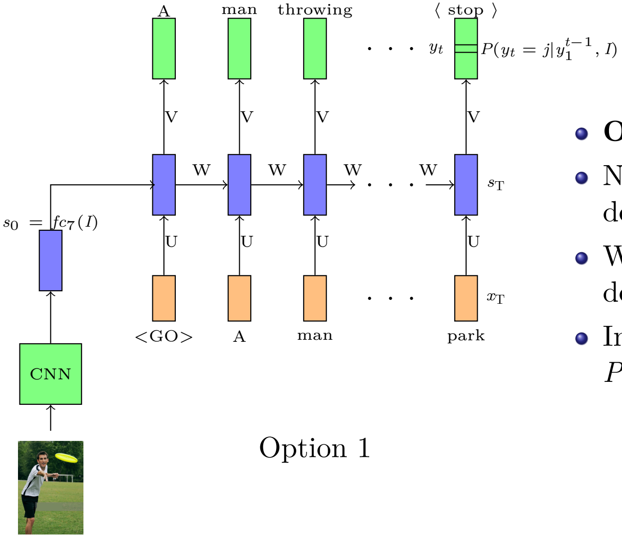

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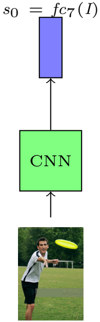
- We can thus say that $P(y_t = j)$ depends on $f_{c_7}(I)$
- In other words, we are computing $P(y_t = j|s_t, f_{c_7}(I))$

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

$$s_t = RNN(s_{t-1}, [x_t, f_{c_7}(I))]$$



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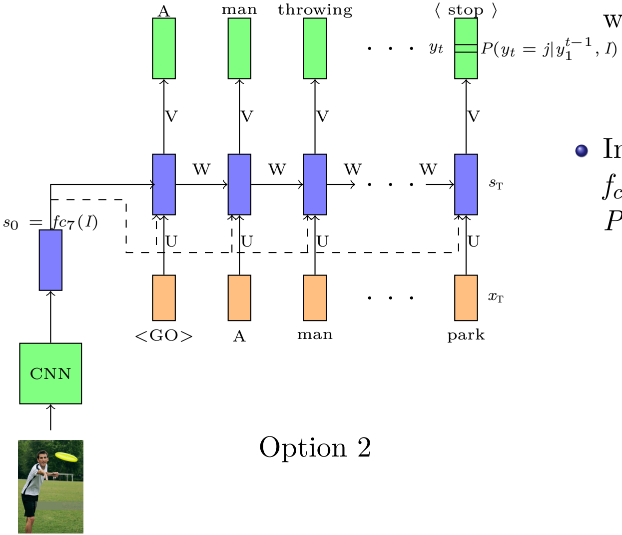

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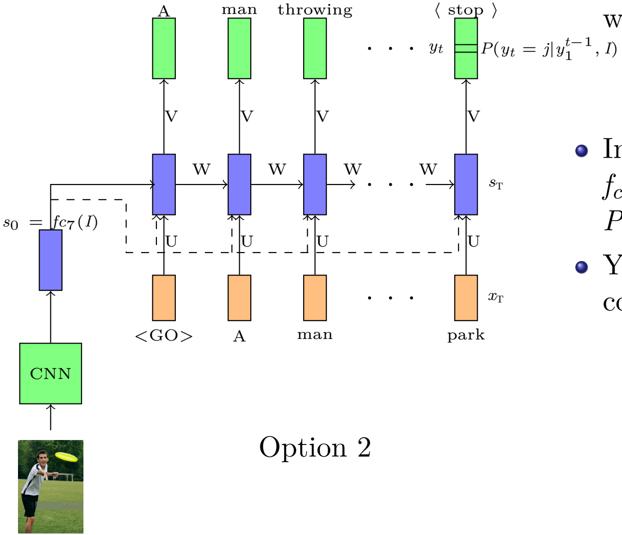

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- You could think of other ways of conditioning $P(y_t = j)$ on f_{c_7}

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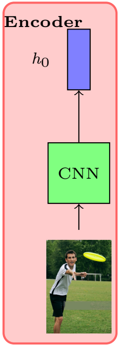

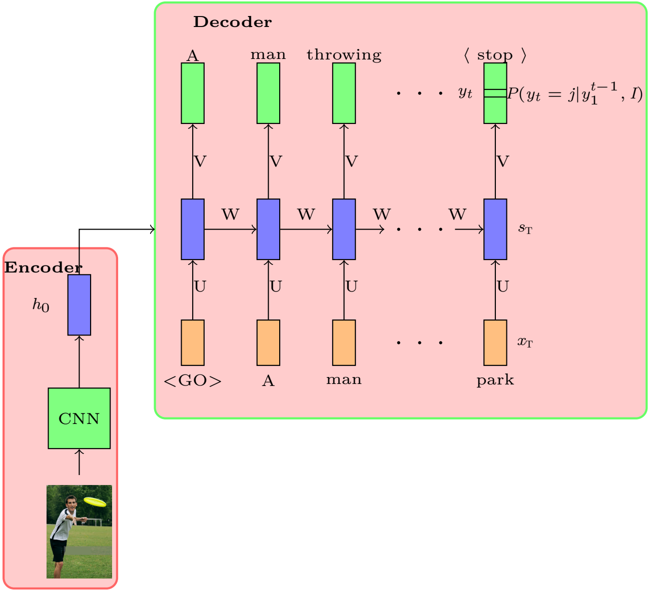

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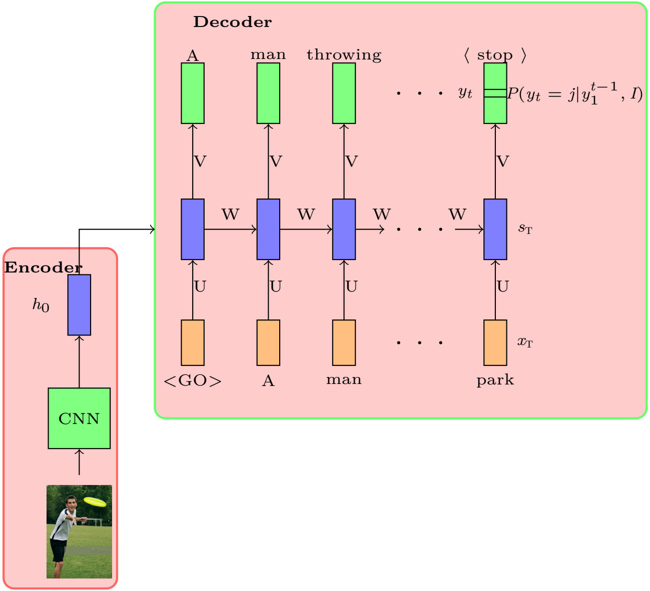

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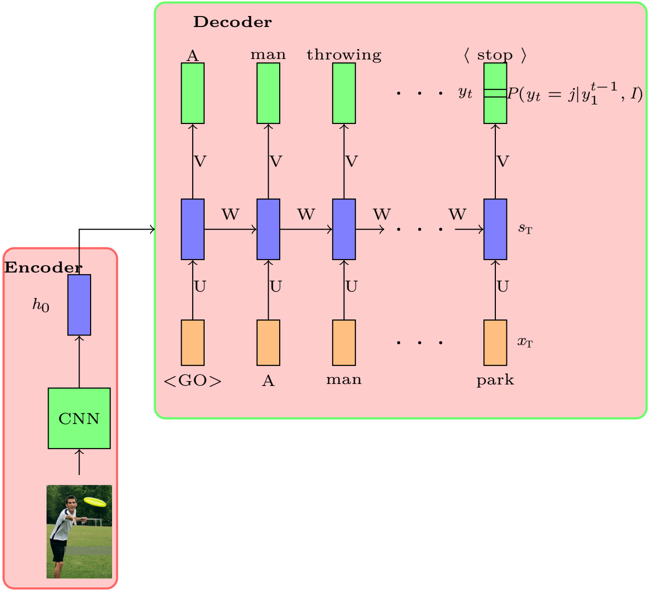

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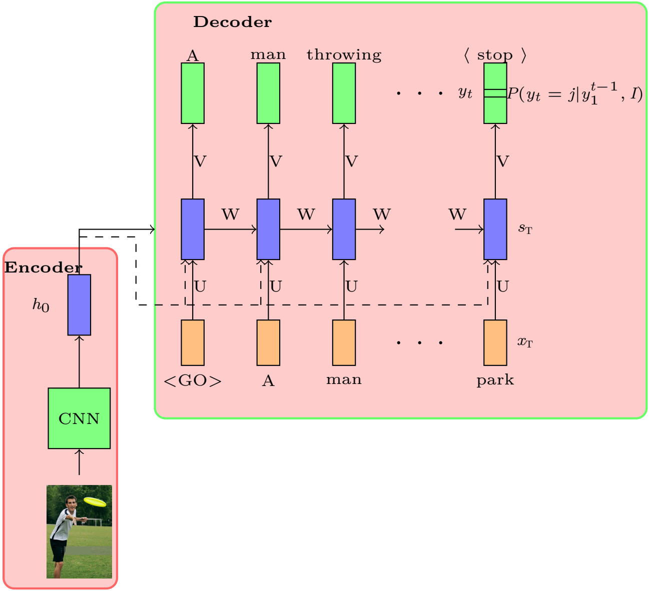

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- Alternatively, the encoder's output can be fed to every step of the decoder

Module 16.2: Applications of Encoder Decoder models

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A man throwing $\cdots$ $\langle$ stop $\rangle$

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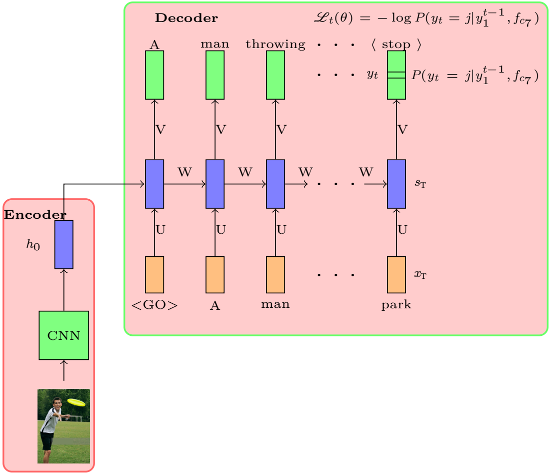

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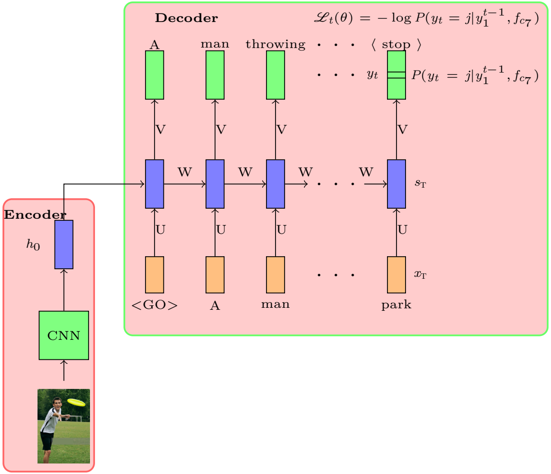

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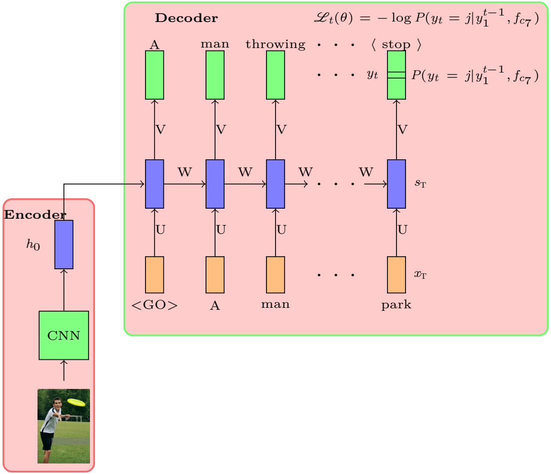

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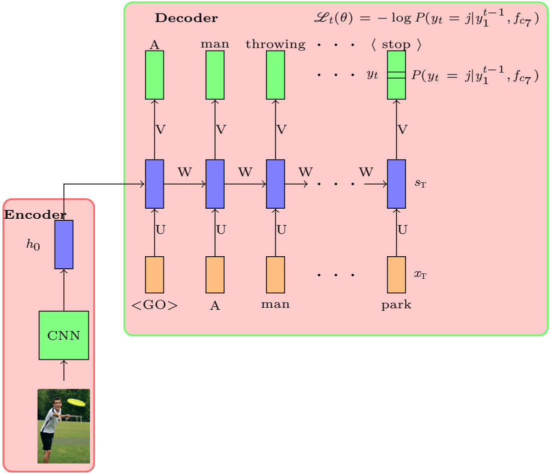

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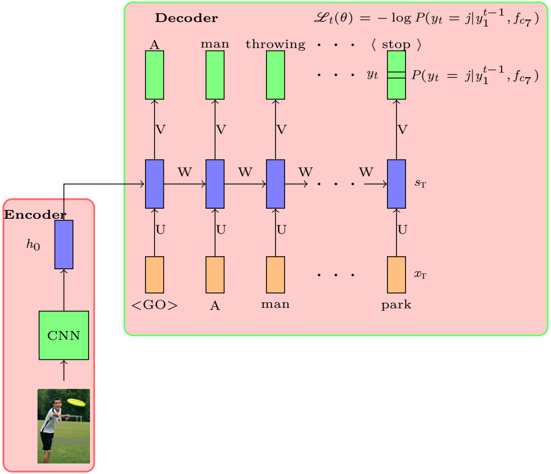

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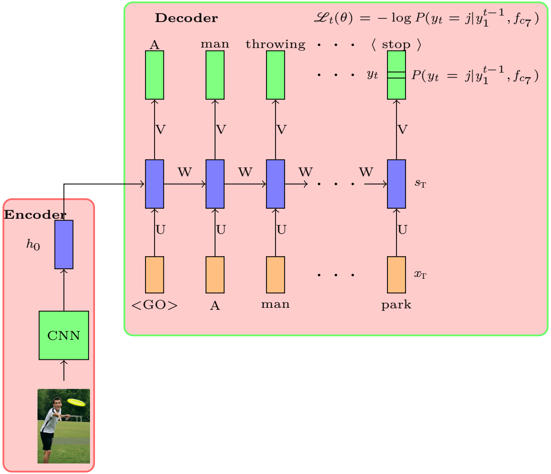

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- **Algorithm:** Gradient descent with backpropagation

o/p : The ground is wet

- **Task:** Textual entailment

i/p : It is raining outside

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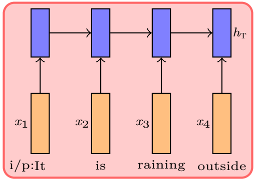

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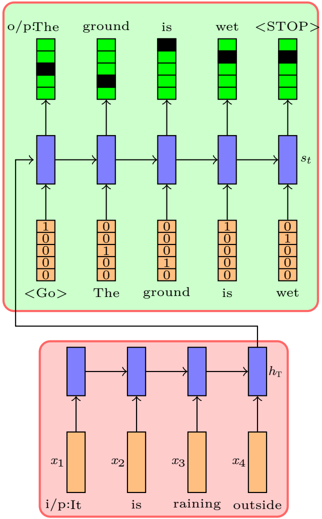

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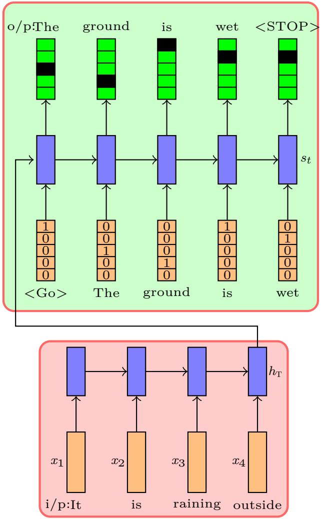

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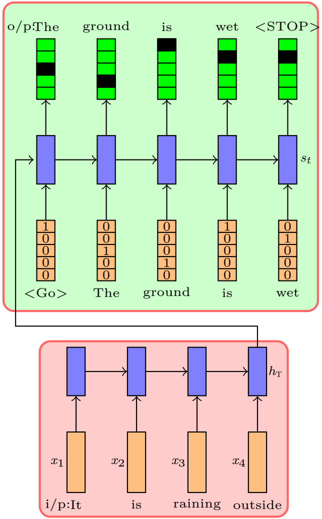

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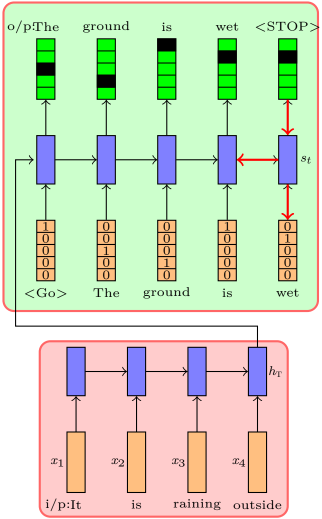

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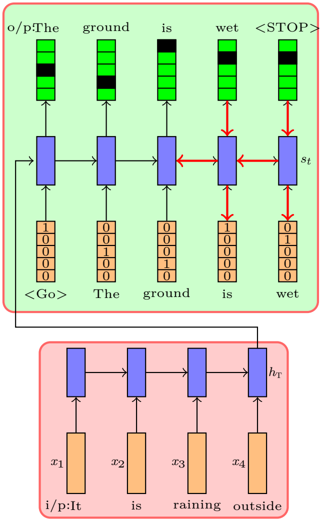

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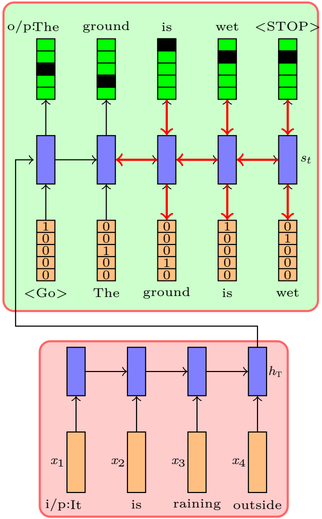
o/p : The ground is wet



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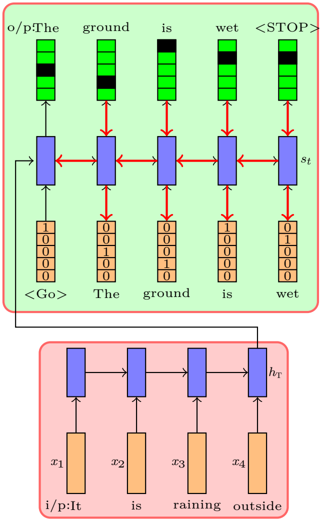

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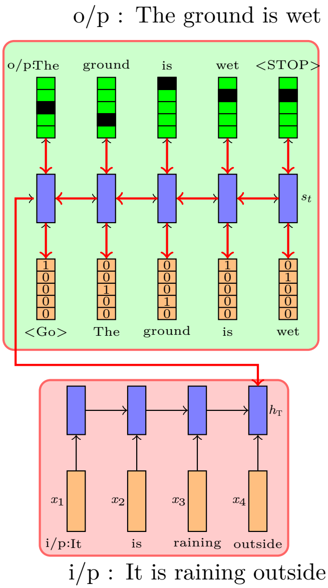

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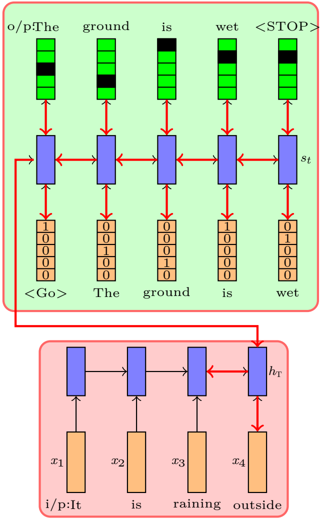

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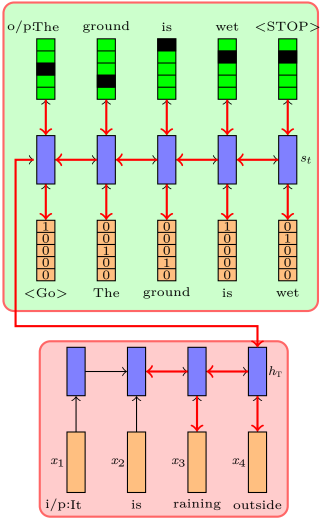

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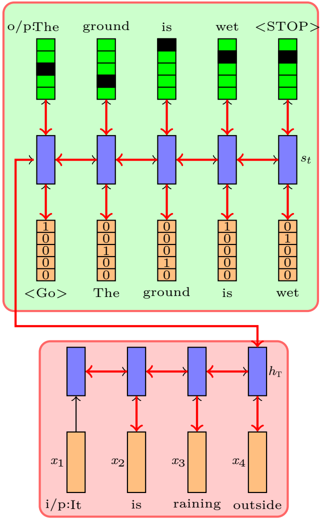

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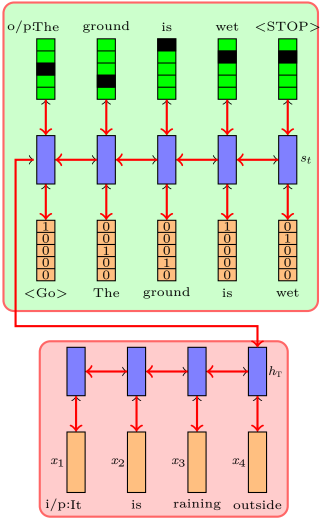

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i/p : It is raining outside

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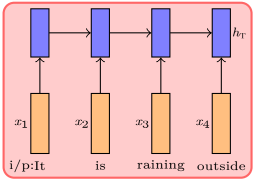
i/p : It is raining outside

o/p : The ground is wet



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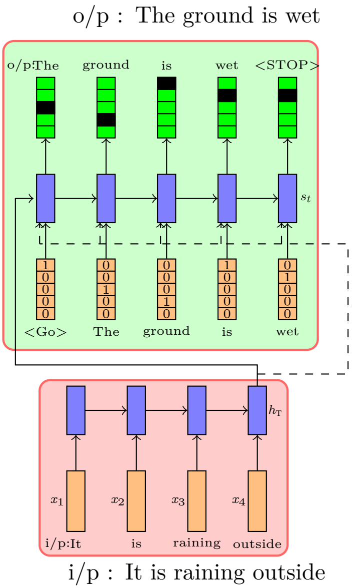

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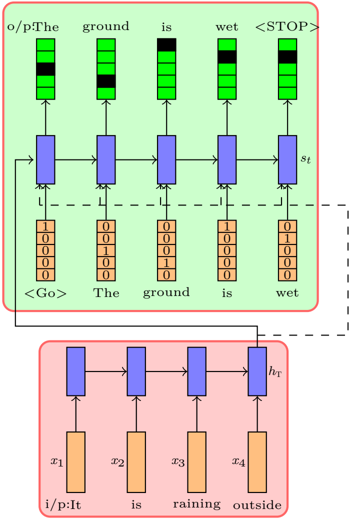

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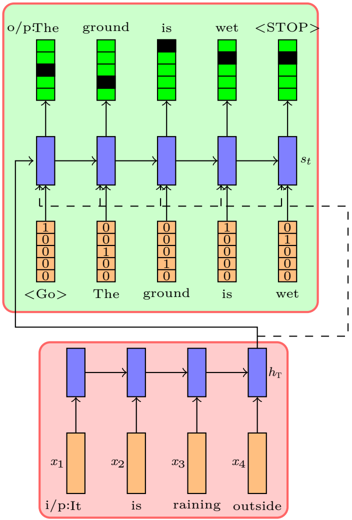

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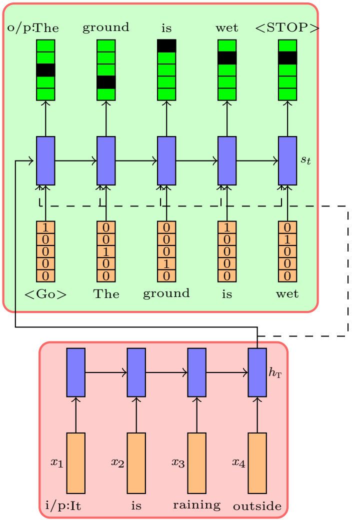

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o/p : Mein ghar ja raha hoon

- **Task:** Machine translation

i/p : I am going home

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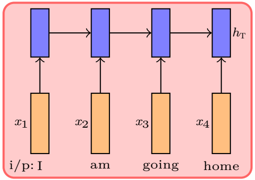

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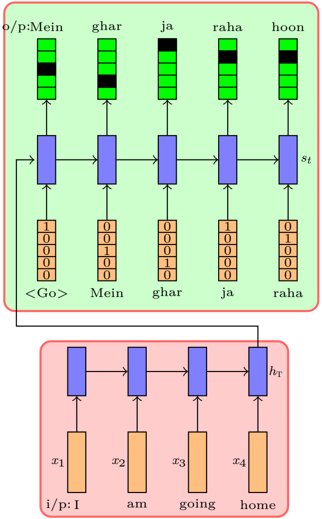

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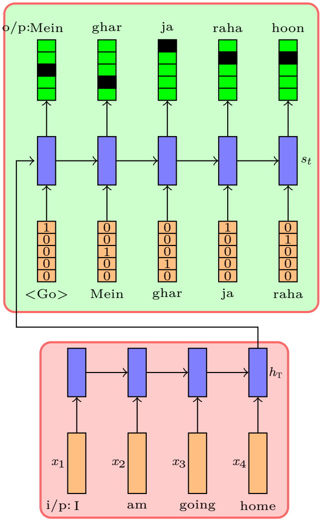

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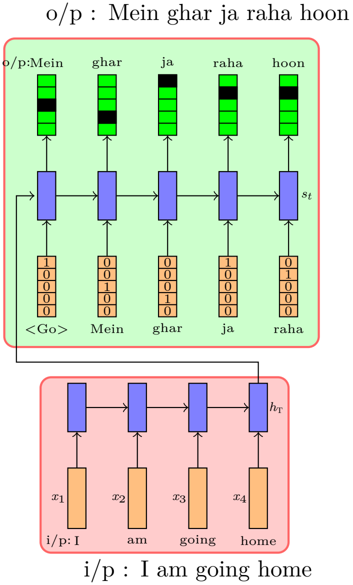

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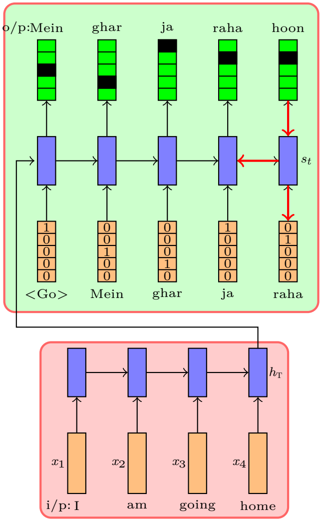

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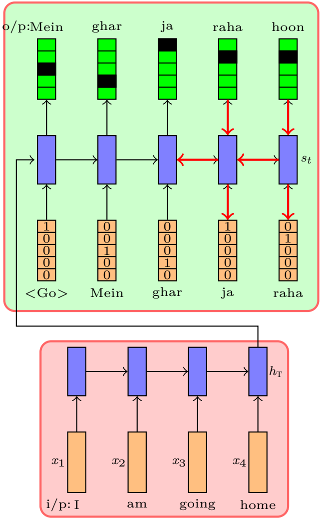

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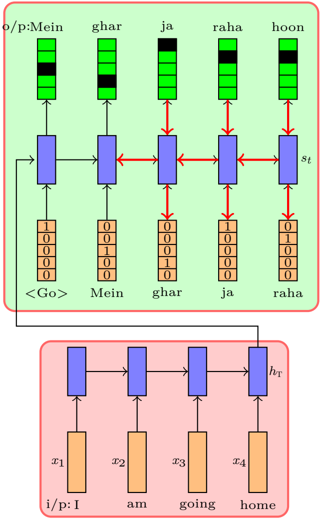

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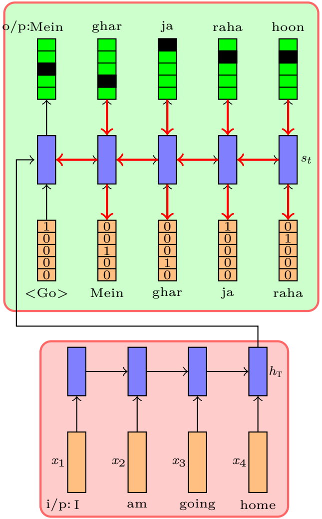

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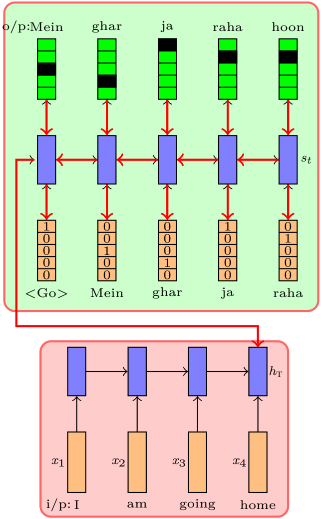

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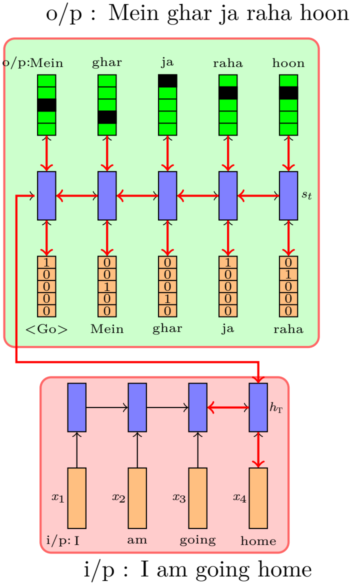


- **Task:** Machine translation
- **Data:** $\{x_i = source_i,\ y_i = target_i\}_{i=1}^{N}$
- **Model (Option 1):**
  - **Encoder:**

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

  - **Decoder:**

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

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

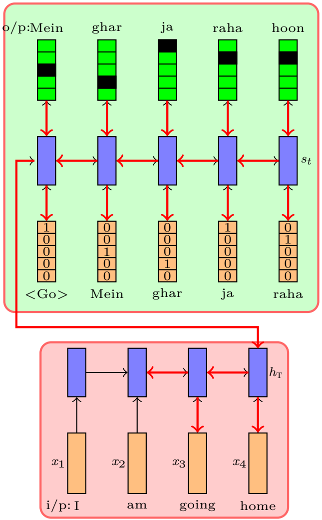
$$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$

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

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

- **Algorithm:** Gradient descent with backpropagation

o/p : Mein ghar ja raha hoon



i/p : I am going home

- **Task:** Machine translation
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- **Model (Option 1):**
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- **Parameters:** $U_{dec},\ V,\ W_{dec},\ U_{enc},\ W_{enc}, b$
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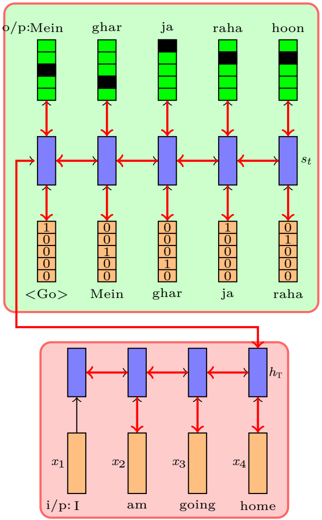

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- **Algorithm:** Gradient descent with backpropagation

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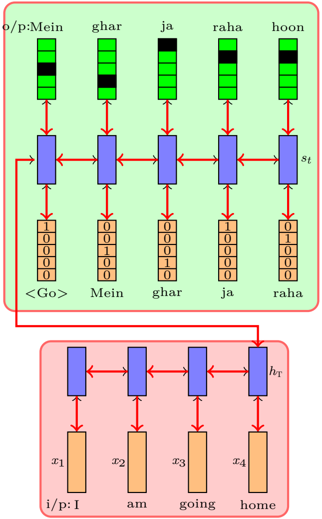

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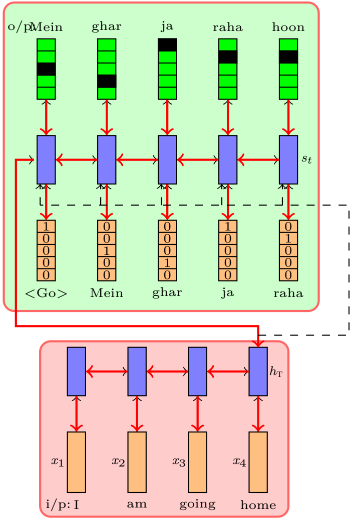
o/p : Mein ghar ja raha hoon



i/p : I am going home

- **Task:** Machine translation
- **Data:** $\{x_i = source_i,\ y_i = target_i\}_{i=1}^{N}$
- **Model (Option 2):**
  - **Encoder:**

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

  - **Decoder:**

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

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

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

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

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

- **Algorithm:** Gradient descent with backpropagation

o/p : इं डि या

- **Task:** Transliteration

i/p : I N D I A

o/p : इ ं ड ि य ा

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i,\ y_i = tgtword_i\}_{i=1}^{N}$

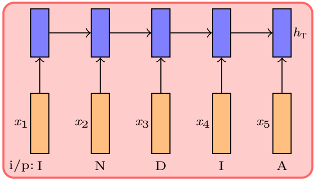
i/p : I N D I A

o/p : इ ं ड ि य ा

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i,\ y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**

i/p : I N D I A

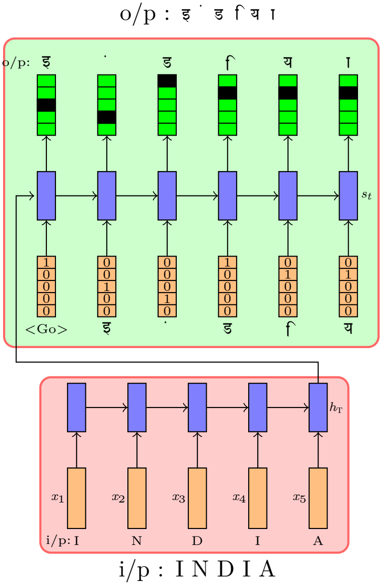
o/p : इंडिया



i/p : I N D I A

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i,\ y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**
  - **Encoder:**

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



- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i, \ y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**
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$$h_t = RNN(h_{t-1}, x_{it})$$

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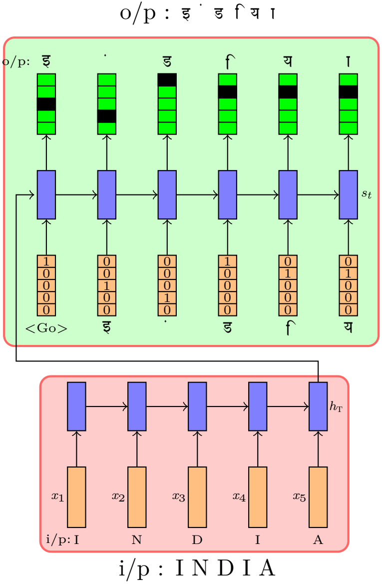

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i,\ y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**
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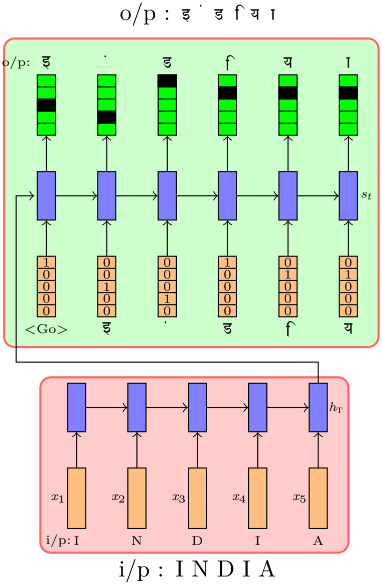
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$

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

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



- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i, \;\; y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**
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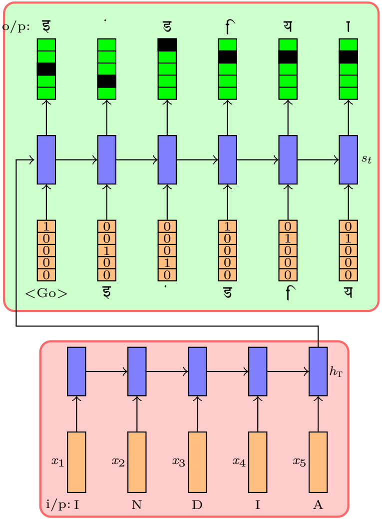
$$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$

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

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

o/p : इ ं ड ि य ा



i/p : I N D I A

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i, \; y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 1):**
  - **Encoder:**

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

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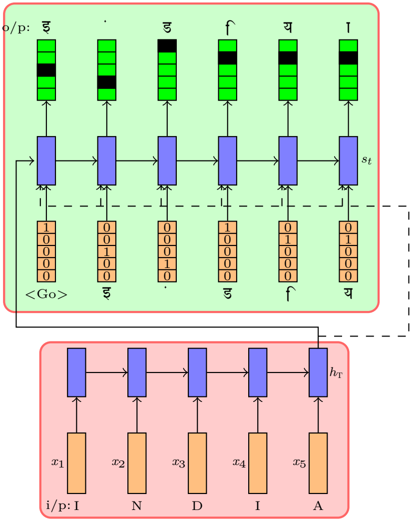
- **Parameters:** $U_{dec}, \; V, \; W_{dec}, \; U_{enc}, \; W_{enc}, b$
- **Loss:**

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

- **Algorithm:** Gradient descent with backpropagation

o/p : इ ं ड ि य ा



i/p : I N D I A

- **Task:** Transliteration
- **Data:** $\{x_i = srcword_i, \ y_i = tgtword_i\}_{i=1}^{N}$
- **Model (Option 2):**
  - **Encoder:**
  $$h_t = RNN(h_{t-1}, x_{it})$$
  - **Decoder:**
  $$s_0 = h_T \quad (T \textit{ is length of input})$$
  $$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), h_T])$$
  $$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$
- **Parameters:** $U_{dec}, \ V, \ W_{dec}, \ U_{enc}, \ W_{enc}, b$
- **Loss:**
$$\mathscr{L}(\theta) = \sum_{i=1}^{T} \mathscr{L}_t(\theta) = -\sum_{t=1}^{T} \log P(y_t = \ell_t | y_1^{t-1}, x)$$
- **Algorithm:** Gradient descent with backpropagation

O/p: White

- **Task:** Image Question Answeing

Question: What
is the bird's color

O/p: White

Question: What is the bird's color

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

O/p: White

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

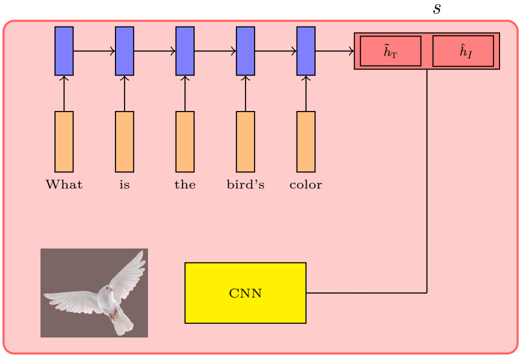
Question: What is the bird's color

O/p: White

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

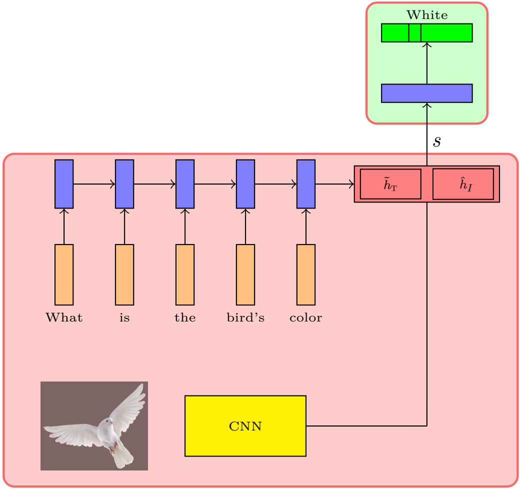
    $$\hat{h}_I = CNN(I),\ \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

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



Question: What is the bird's color

O/p: White



Question: What is the bird's color

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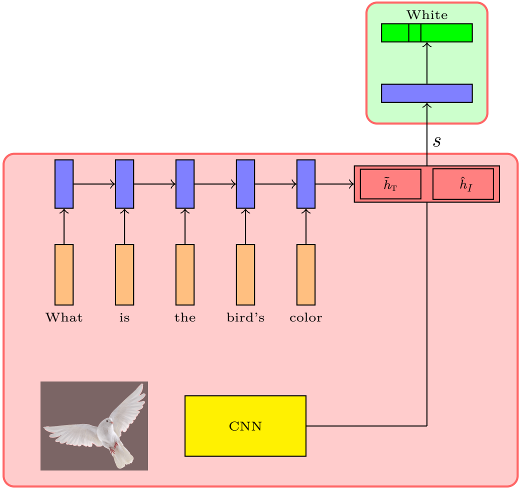
- **Data:** $\{x_i = \{I, q\}_i, \ y_i = Answer_i\}_{i=1}^N$
- **Model:**
  - **Encoder:**

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

    $$s = [\tilde{h}_T; \hat{h}_I]$$
  - **Decoder:**

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

O/p: White



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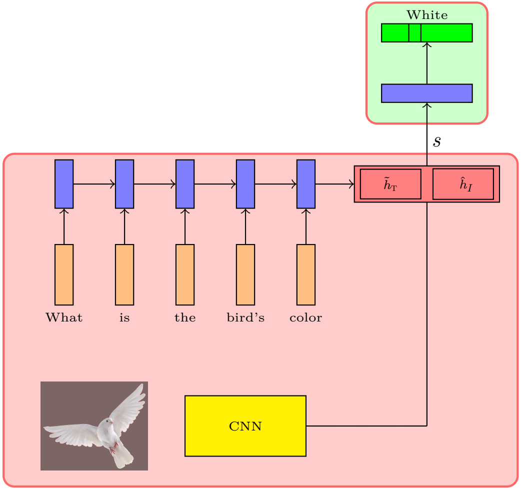
  - **Decoder:**

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

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

O/p: White



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

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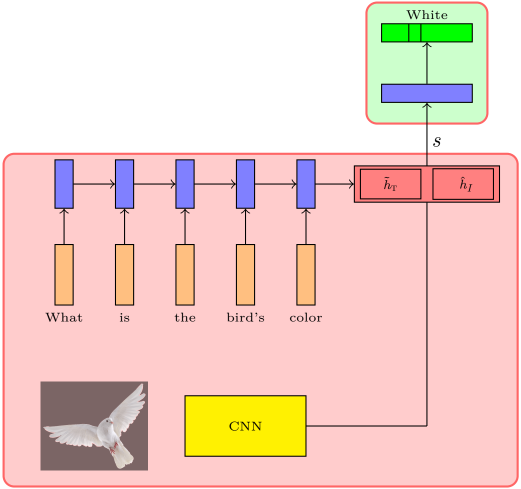
O/p: White



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- **Loss:**

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- **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
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- **Data:** $\{x_i = Document_i, \ y_i = Summary_i\}_{i=1}^{N}$
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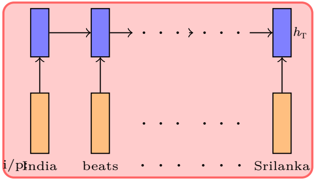
Dhoni and Gambhir's half centuries help beat SL

o/p : India won
the world cup

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

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



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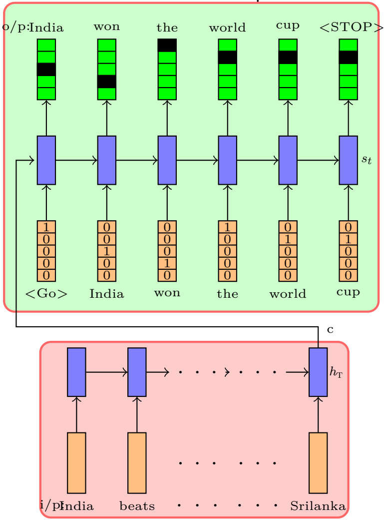

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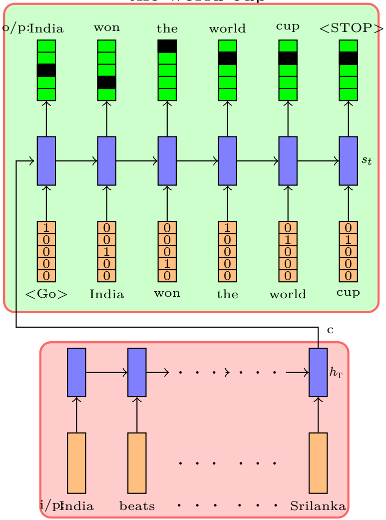
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

o/p : India won
the world cup



i/p : India beats Srilanka to win ICC WC 2011.
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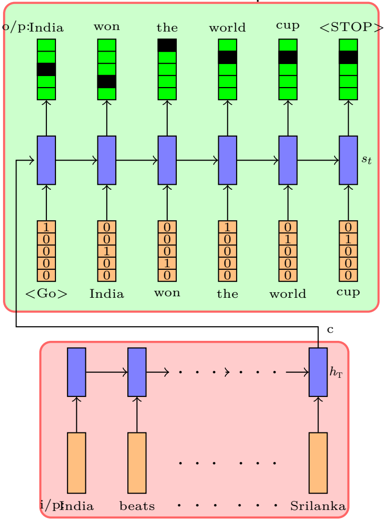
- **Parameters:** U_{dec}, V, W_{dec}, U_{enc}, W_{enc}, b

o/p : India won the world cup



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o/p : India won
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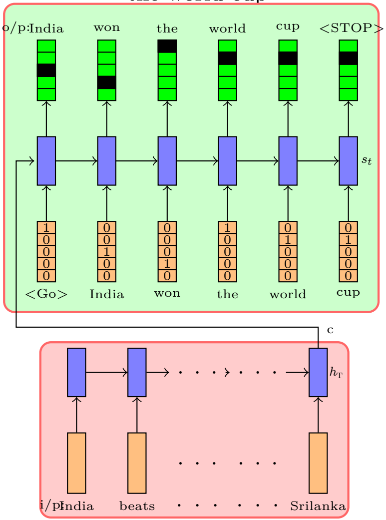

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- **Algorithm:** Gradient descent with backpropagation

o/p : A man walking on a rope

- **Task:** Video Captioning

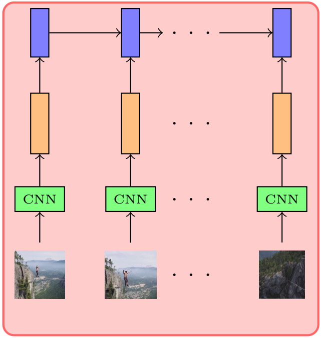
o/p : A man walking on a rope

- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$

o/p : A man walking on a rope

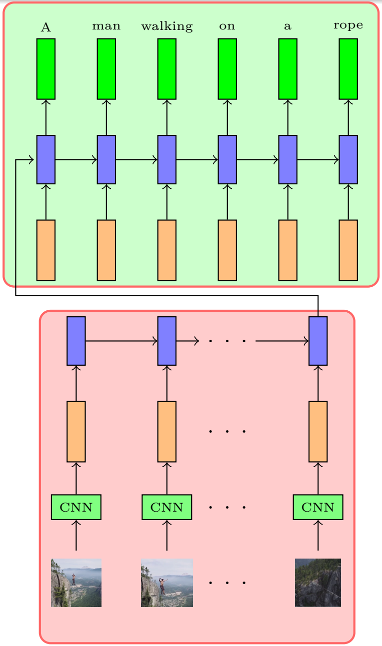
- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$
- **Model:**

o/p : A man walking on a rope



- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**

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



- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**

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

  - **Decoder:**

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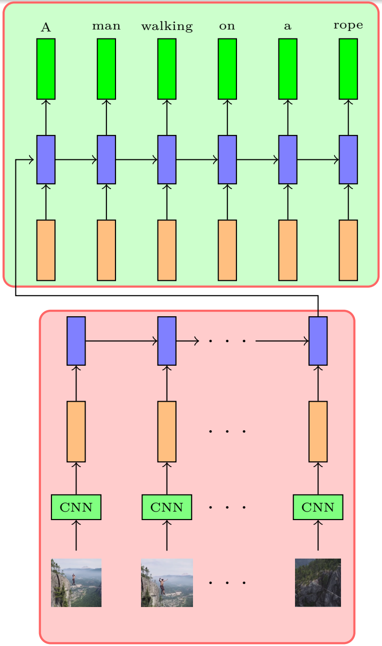
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$



- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**

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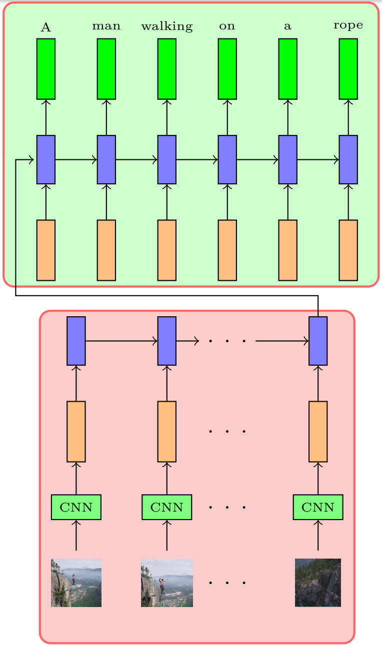
- **Parameters:** U_{dec}, W_{dec}, V, b, W_{conv}, U_{enc}, W_{enc}, b



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- **Parameters:** U_{dec}, W_{dec}, V, b, W_{conv}, U_{enc}, W_{enc}, b
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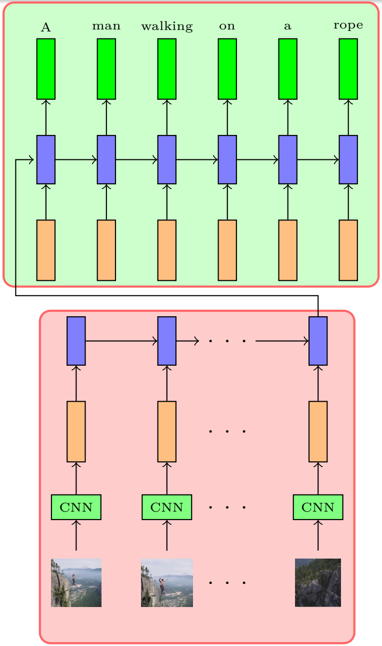
$$\mathscr{L}(\theta) = \sum_{i=1}^{T} \mathscr{L}_t(\theta) = -\sum_{t=1}^{T} \log P(y_t = \ell_t|y_1^{t-1}, x)$$



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o/p: Surya Namaskar

- **Task:** Video Classification

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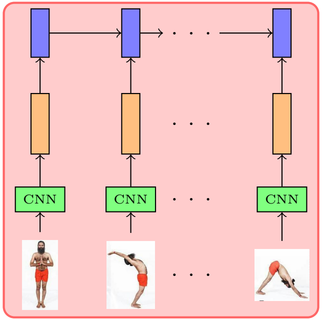
- **Task:** Video Classification
- **Data:** $\{x_i = Video_i,\ y_i = Activity_i\}_{i=1}^{N}$

o/p: Surya Namaskar

- **Task:** Video Classification
- **Data:** $\{x_i = Video_i,\ y_i = Activity_i\}_{i=1}^{N}$
- **Model:**

o/p: Surya Namaskar



- **Task:** Video Classification
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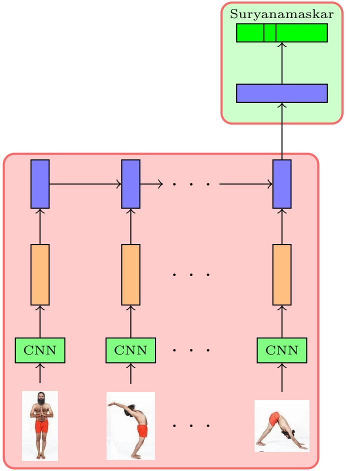
  - **Encoder:**

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

o/p: Surya Namaskar



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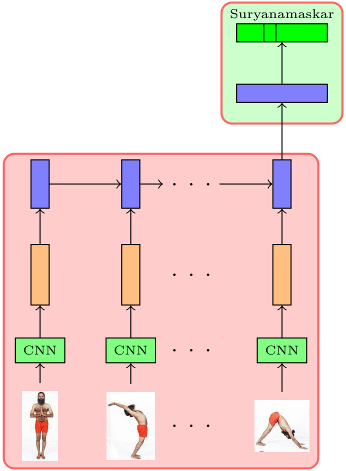
$$s = h_T$$

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

o/p: Surya Namaskar



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- **Data:** $\{x_i = Video_i,\ y_i = Activity_i\}_{i=1}^N$
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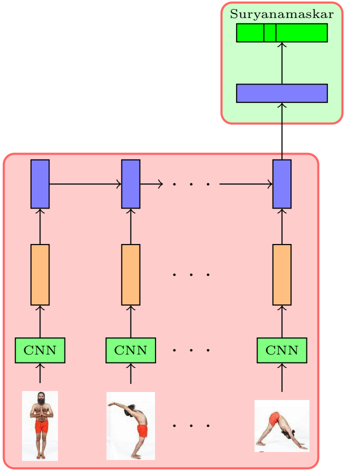
- **Parameters:** $V,\ b,\ W_{conv},\ U_{enc},\ W_{enc}, b$

o/p: Surya Namaskar



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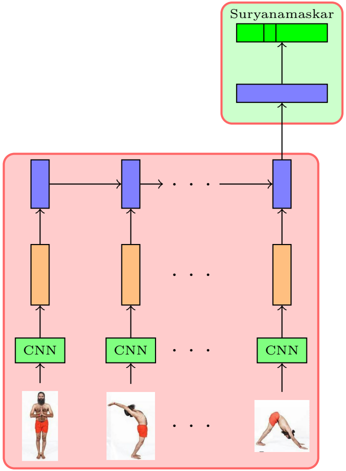

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o/p: I am fine

- **Task:** Dialog

i/p: How are you

o/p: I am fine

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

i/p: How are you

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- **Model:**

i/p: How are you

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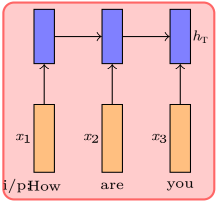

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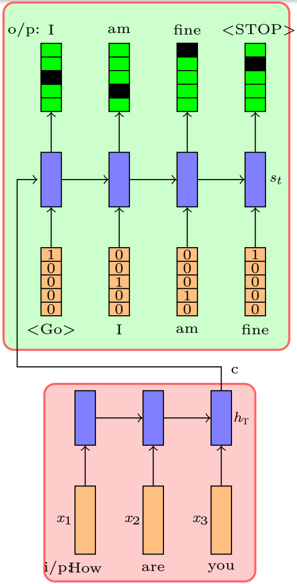

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  $$s_0 = h_T \quad (T \text{ is length of input})$$
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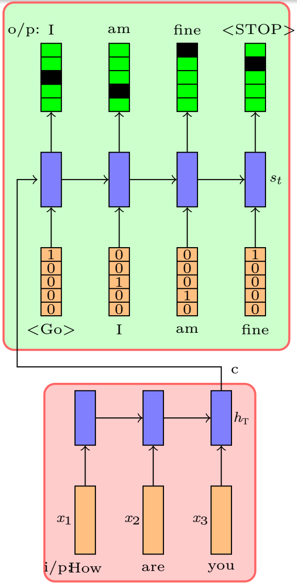

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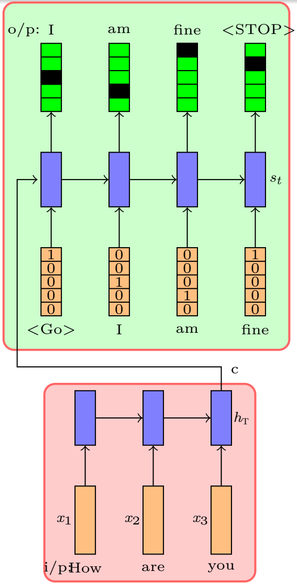

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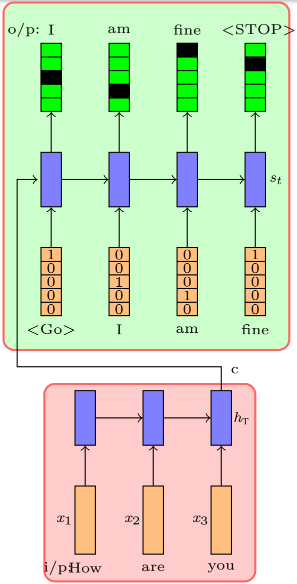

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- **Algorithm:** Gradient descent with backpropagation

- And the list continues ...

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- Try picking a problem from your domain and see if you can model it using the encoder decoder paradigm

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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

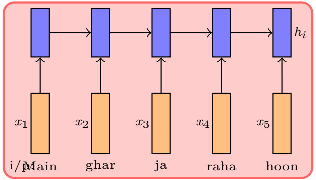
Module 16.3: Attention Mechanism

o/p : I am going home

i/p : Main ghar ja raha hoon

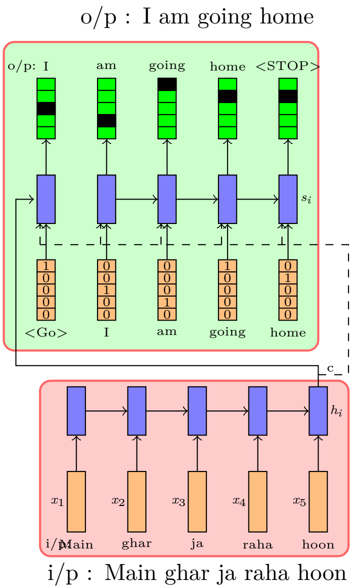
- Let us motivate the task of attention with the help of MT

o/p : I am going home



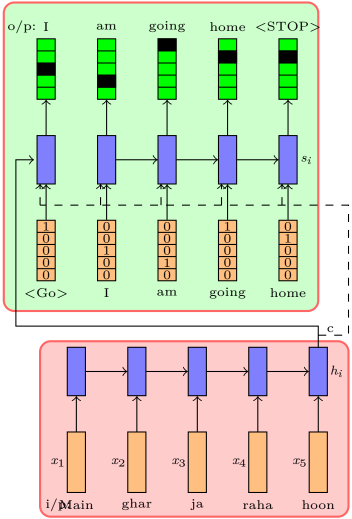
i/p : Main ghar ja raha hoon

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



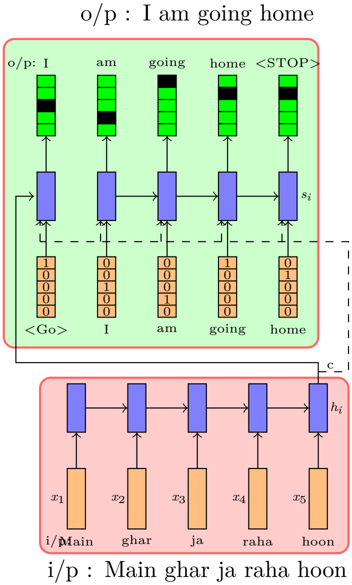
- Let us motivate the task of attention with the help of MT
- The encoder reads the sentences only once and encodes it
- At each timestep the decoder uses this embedding to produce a new word

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
- At each timestep the decoder uses this embedding to produce a new word
- Is this how humans translate a sentence ?



- 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
- Is this how humans translate a sentence ? Not really!

o/p : I am going home

i/p : Main ghar ja raha hoon

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

o/p : I am going home

i/p : Main ghar ja raha hoon

- 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

o/p : I am going home

t_1 : [1 0 0 0 0]

i/p : Main ghar ja raha hoon

- Humans try to produce each word in the output by focusing only on certain words in the input
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o/p : I am going home

t_1 : [1 0 0 0 0]

t_2 : [0 0 0 0 1]

i/p : Main ghar ja raha hoon

- 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

o/p : I am going home

t_1 : [1 0 0 0 0]

t_2 : [0 0 0 0 1]

t_3 : [0 0 0.5 0.5 0]

i/p : Main ghar ja raha hoon

- Humans try to produce each word in the output by focusing only on certain words in the input
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o/p : I am going home

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t_3 : [0 0 0.5 0.5 0]

t_4 : [0 1 0 0 0]

i/p : Main ghar ja raha hoon

- Humans try to produce each word in the output by focusing only on certain words in the input
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o/p : I am going home

t_1 : [1 0 0 0 0]

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i/p : Main ghar ja raha hoon

- 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

o/p : I am going home

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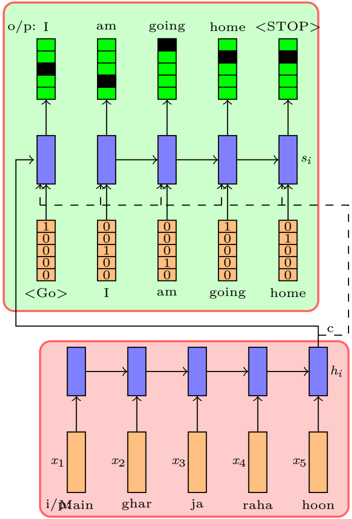
i/p : Main ghar ja raha hoon

- 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

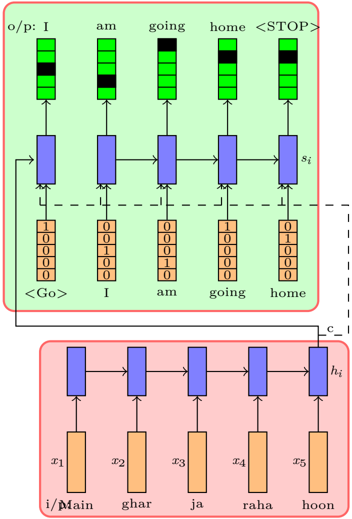
o/p : I am going home



i/p : Main ghar ja raha hoon

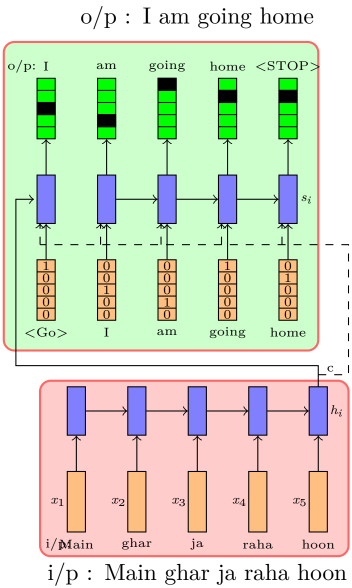
- Let us revisit the decoder that we have seen so far

o/p : I am going home



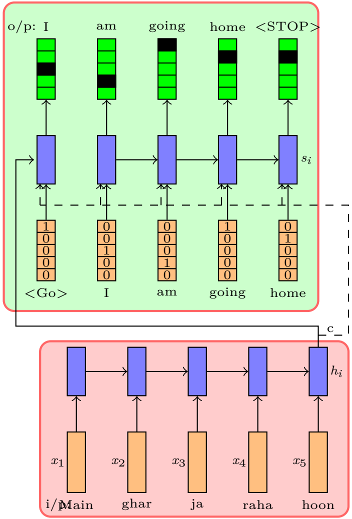
i/p : Main ghar ja raha hoon

- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at s_0)



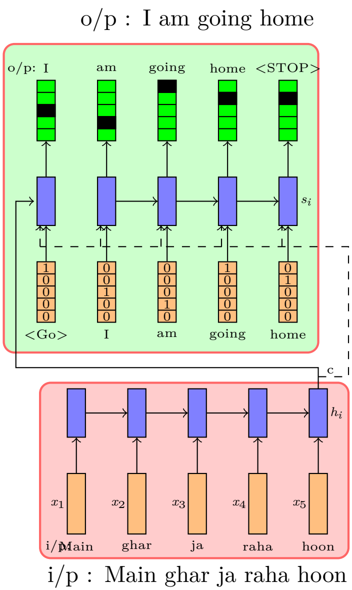
- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at s_0)
- Or we feed the same encoder information at each time step

o/p : I am going home

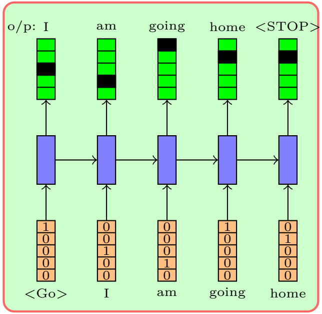


i/p : Main ghar ja raha hoon

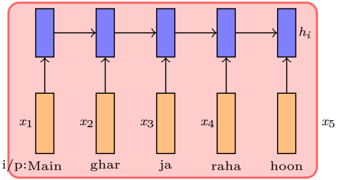
- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at s_0)
- Or we feed the same encoder information at each time step
- Now suppose an oracle told you which words to focus on at a given time-step t



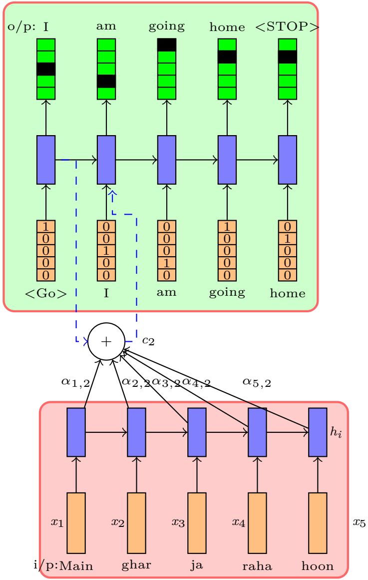
- Let us revisit the decoder that we have seen so far
- We either feed in the encoder information only once(at s_0)
- Or we feed the same encoder information at each time step
- Now suppose an oracle told you which words to focus on at a given time-step t
- Can you think of a smarter way of feeding information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



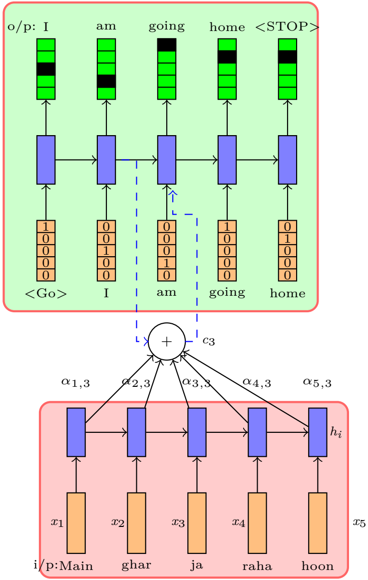
o/p: I
am
going
home
<STOP>
<Go>
I
am
going
home



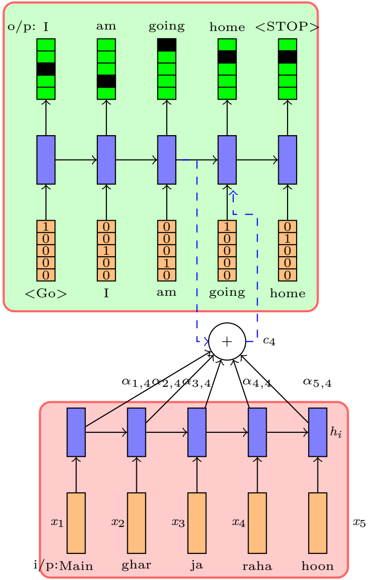
h_i
x_1
x_2
x_3
x_4
x_5
i/p:Main
ghar
ja
raha
hoon



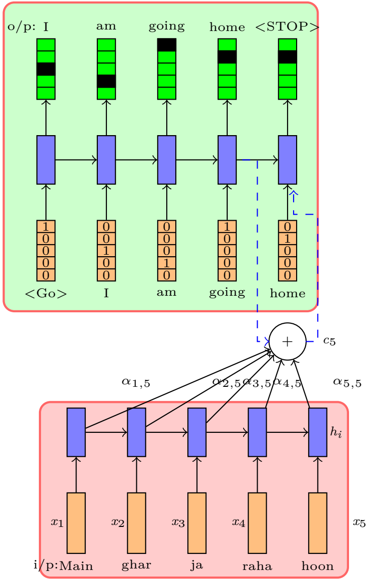
- We could just take a weighted average of the corresponding word representations and feed it to the decoder



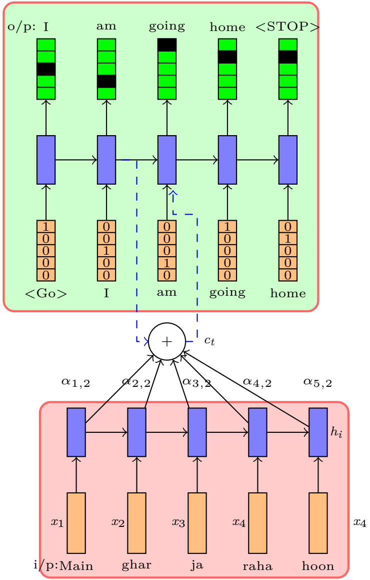
- We could just take a weighted average of the corresponding word representations and feed it to the decoder
- For example at timestep 3, we can just take a weighted average of the representations of 'ja' and 'raha'

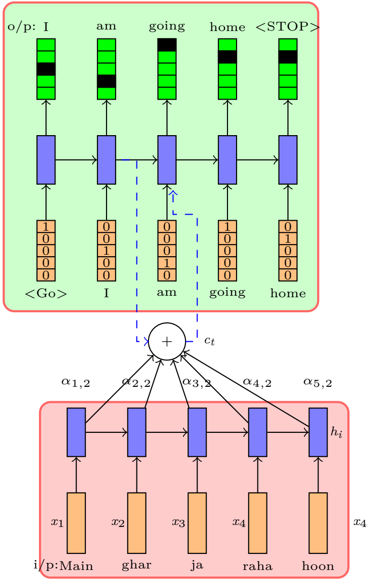


- We could just take a weighted average of the corresponding word representations and feed it to the decoder
- For example at timestep 3, we can just take a weighted average of the representations of 'ja' and 'raha'
- Intuitively this should work better because we are not overloading the decoder with irrelevant information (about words that do not matter at this time step)

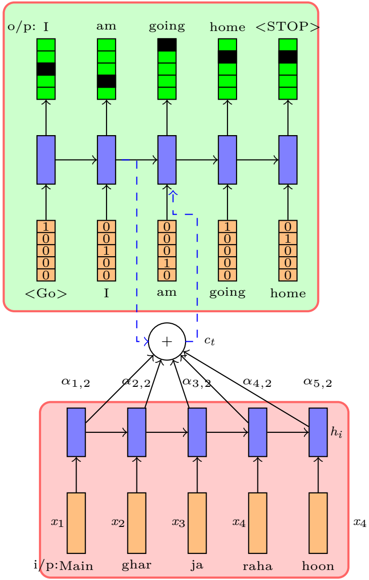


- We could just take a weighted average of the corresponding word representations and feed it to the decoder
- For example at timestep 3, we can just take a weighted average of the representations of 'ja' and 'raha'
- Intuitively this should work better because we are not overloading the decoder with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

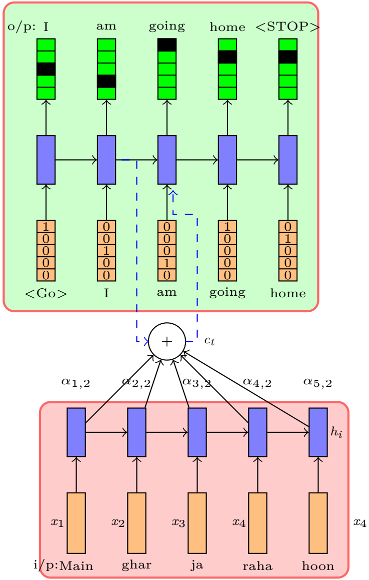

o/p: I
am
going
home
<STOP>
1 0 0 0 0
0 0 1 0 0
0 0 0 1 0
1 0 0 0 0
0 1 0 0 0
<Go>
I
am
going
home
+
c_t
$\alpha_{1,2}$
$\alpha_{2,2}$
$\alpha_{3,2}$
$\alpha_{4,2}$
$\alpha_{5,2}$
h_i
x_1
x_2
x_3
x_4
x_4
i/p:Main
ghar
ja
raha
hoon



- Of course in practice we will not have this oracle



- Of course in practice we will not have this oracle
- The machine will have to learn this from the data



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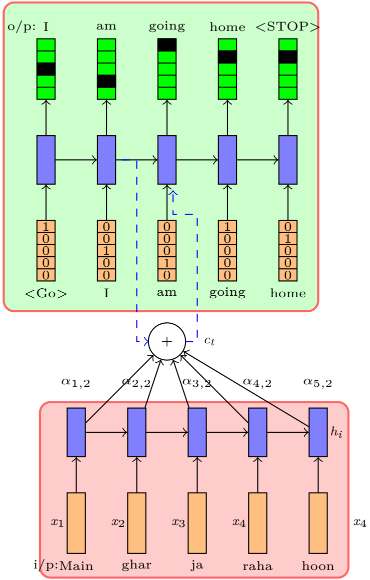
- The machine will have to learn this from the data
- To enable this we define a function

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



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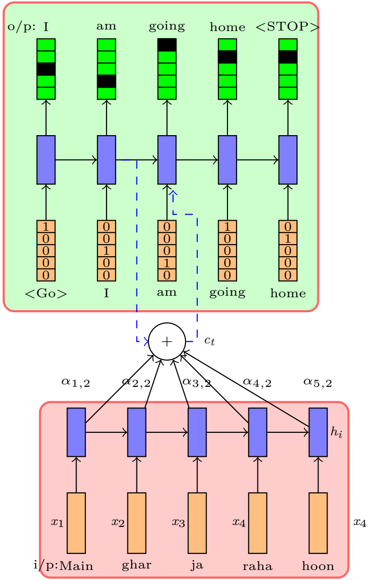

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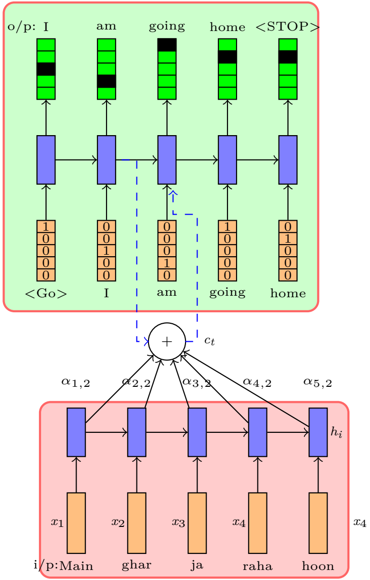
- We can normalize these weights by using the softmax function

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



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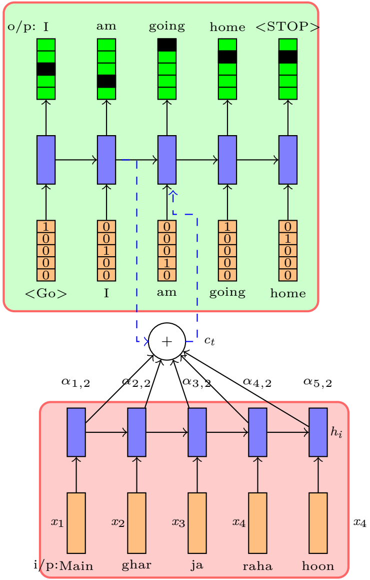

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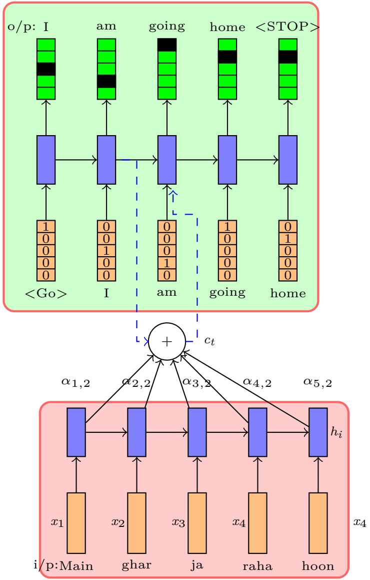

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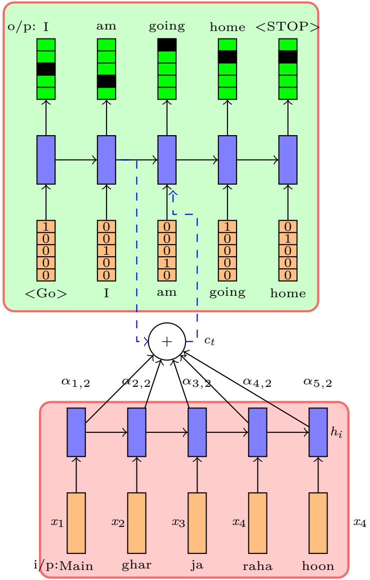

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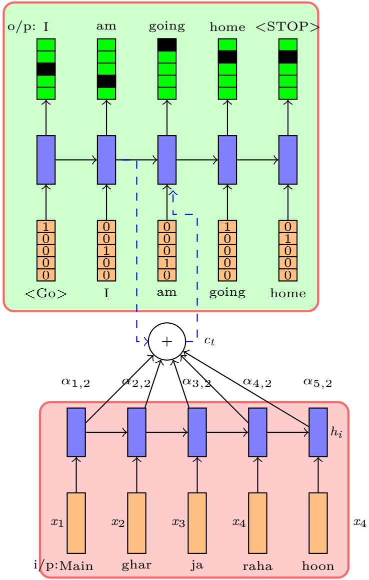

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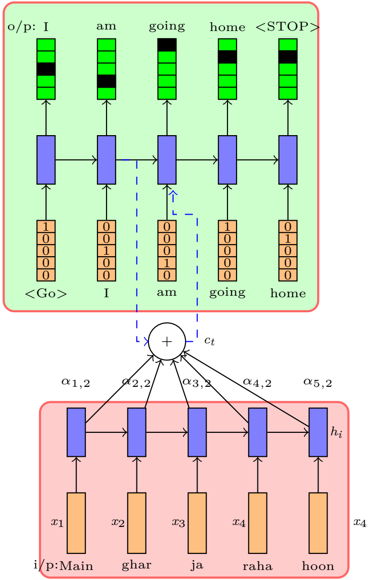

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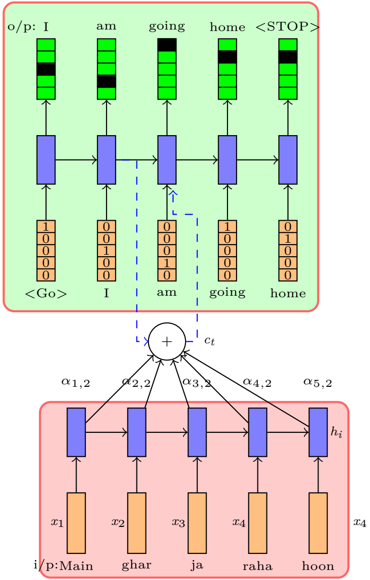
- So let's define a parametric form for α's



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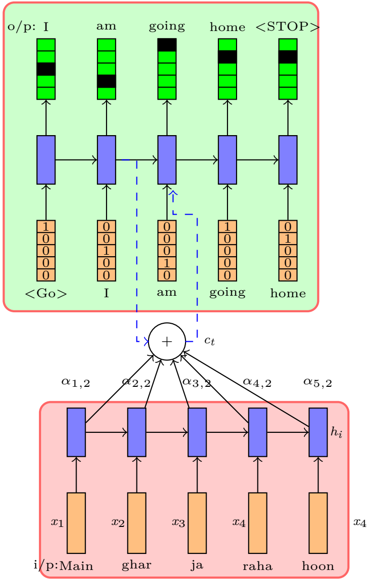

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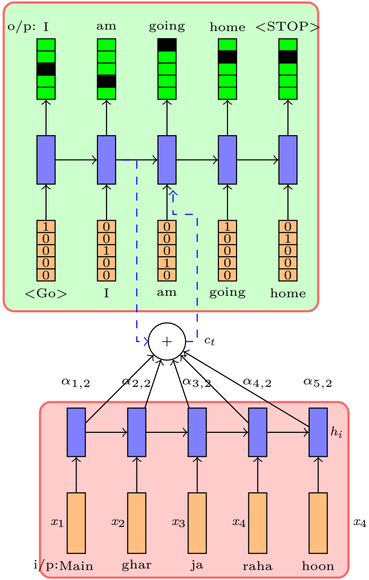

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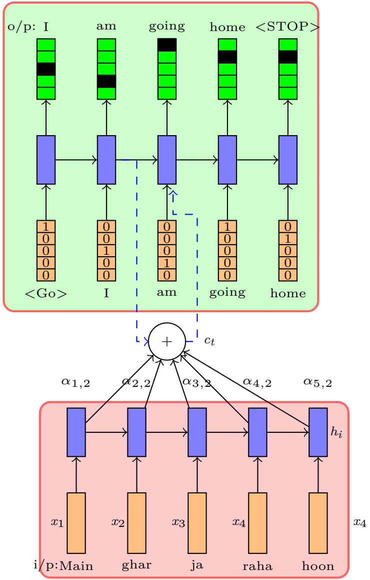

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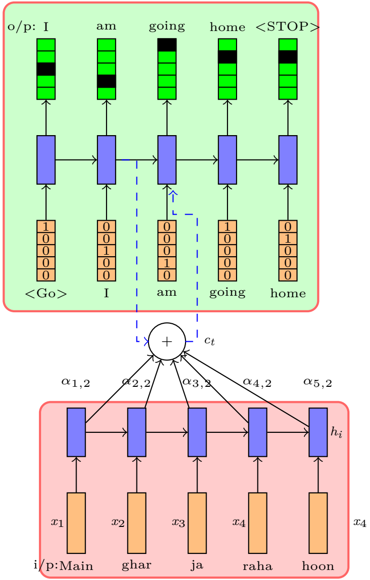

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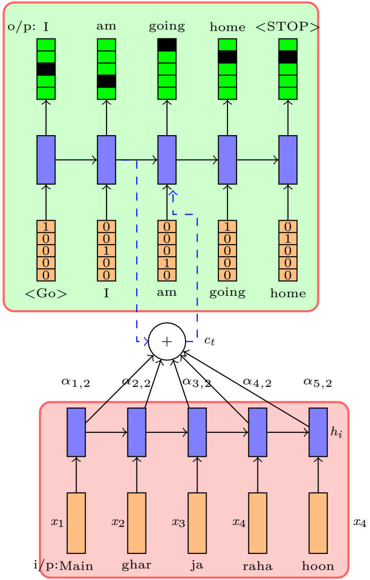
- These parameters will be learned along with the other parameters of the encoder and decoder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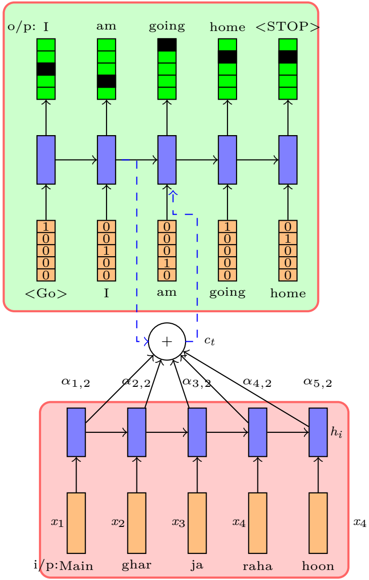

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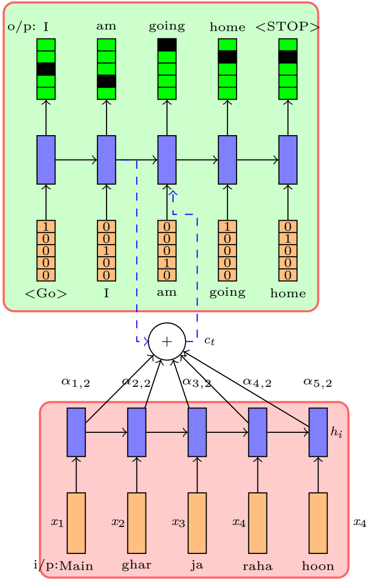

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- This model would make a lot of sense if were given the true α's at training time

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

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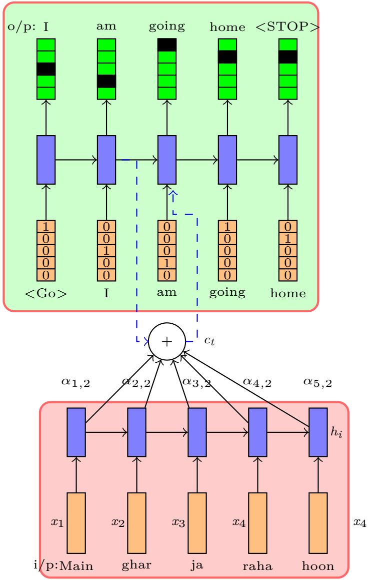

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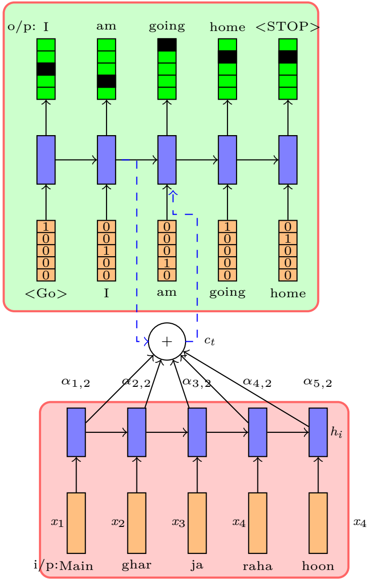

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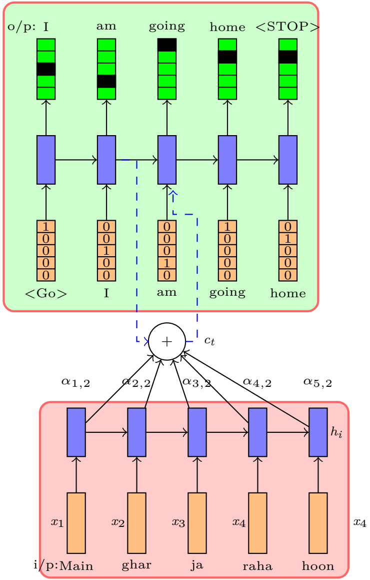
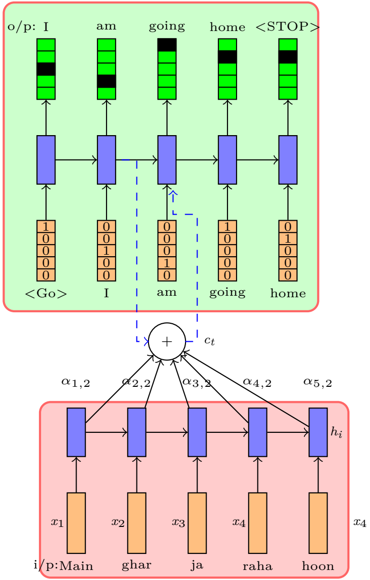
- But in practice it is very hard to get α^{true}



- 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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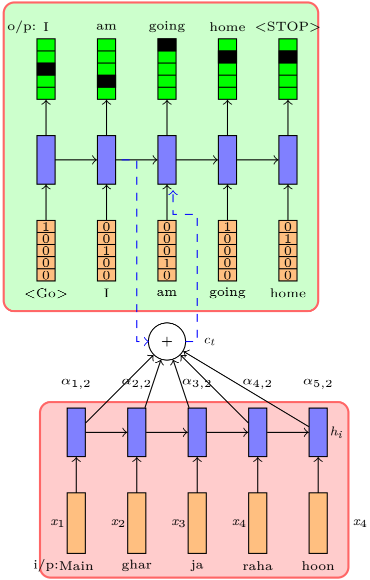
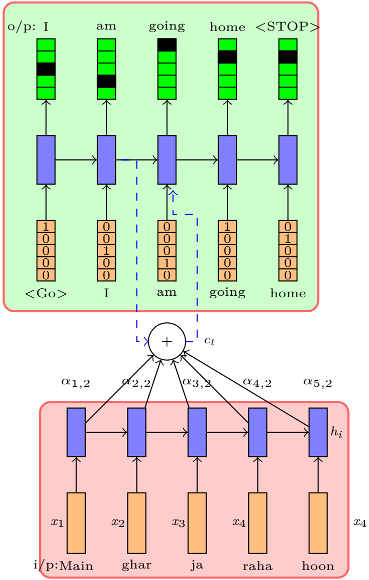


- For example, in our translation example we would want someone to manually annotate the source words which contribute to every target word
- It is hard to get such annotated data
- Then how would this model work in the absence of such data ?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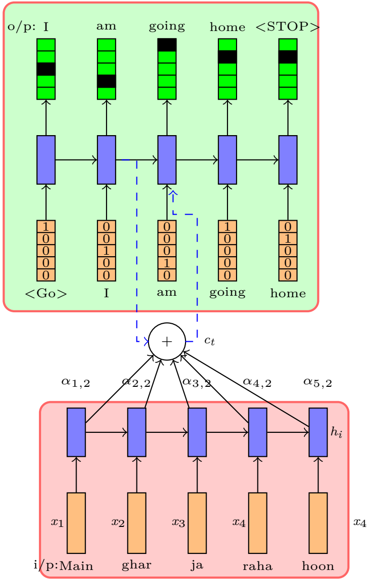

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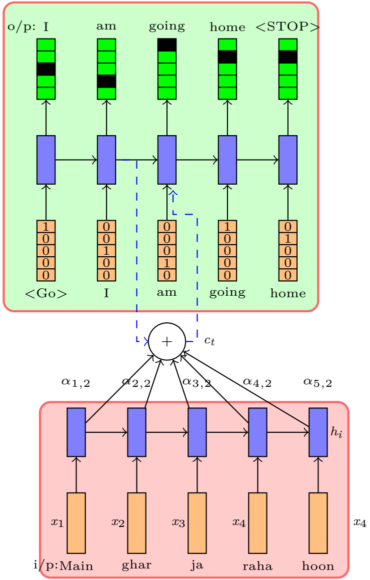

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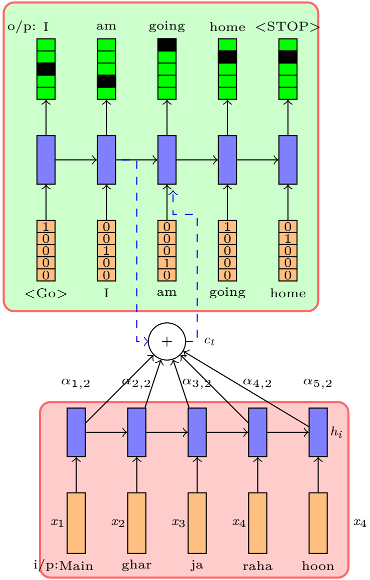

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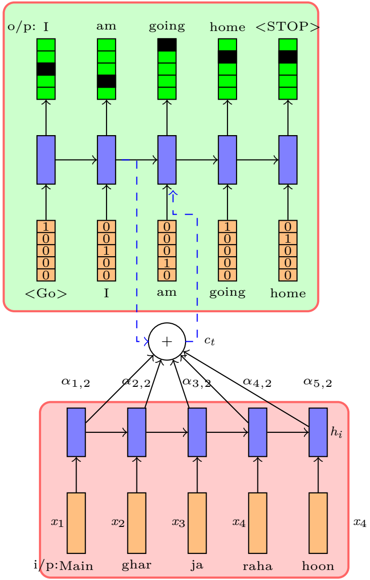

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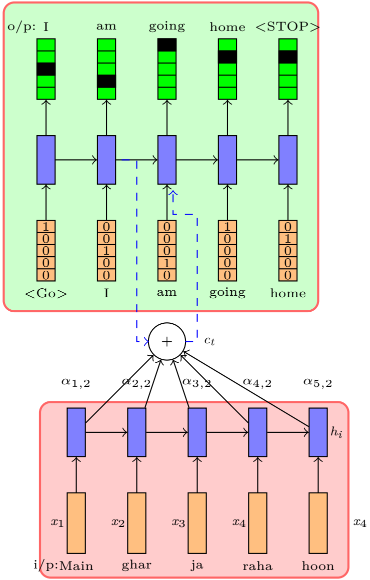

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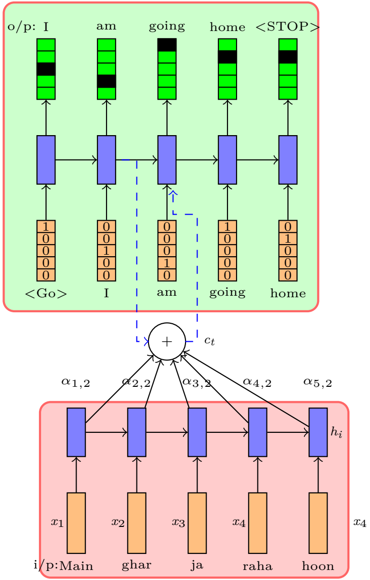

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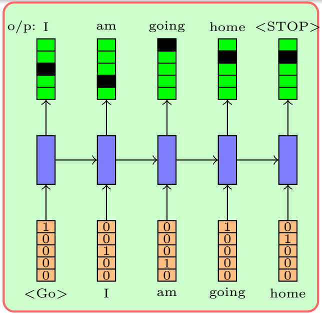
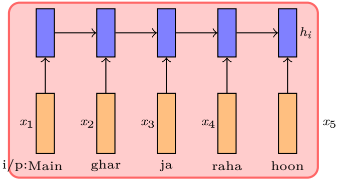
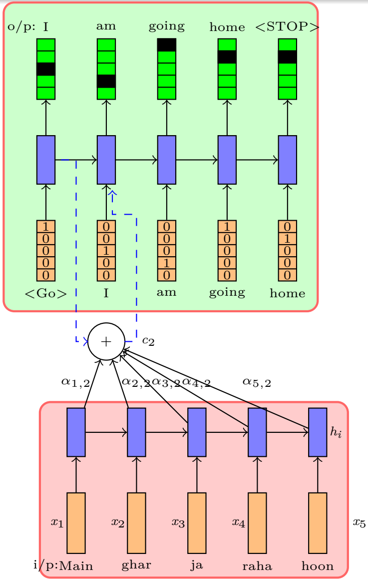
- And in practice indeed these models work better than the vanilla encoder decoder models

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



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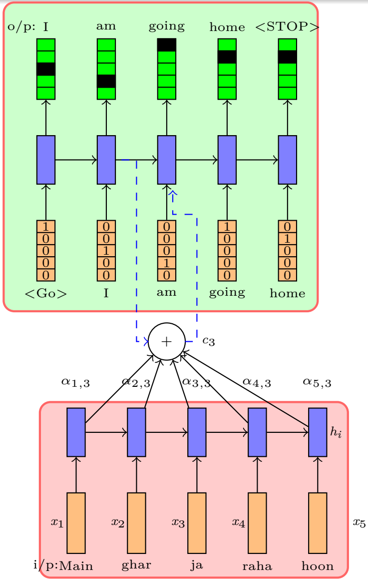

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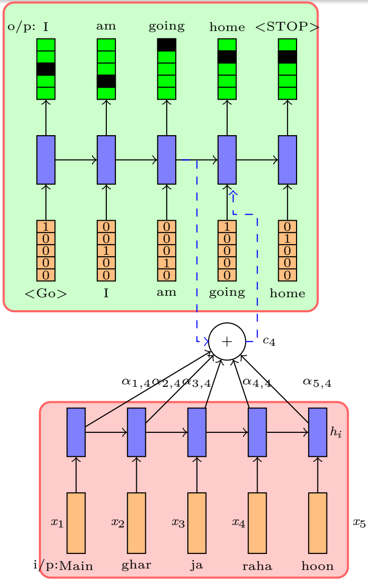

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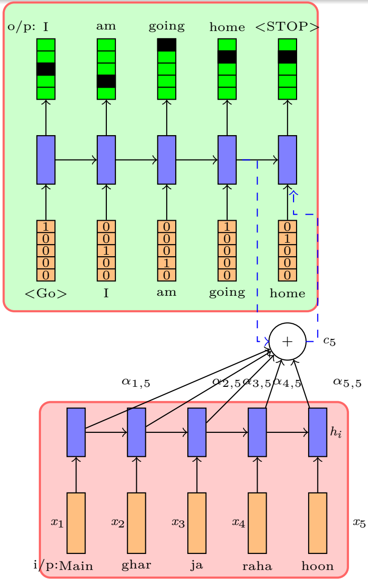

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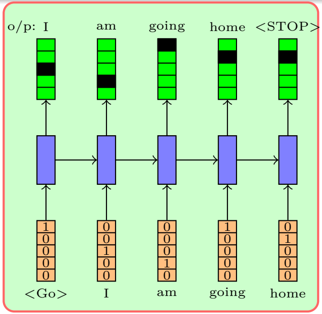

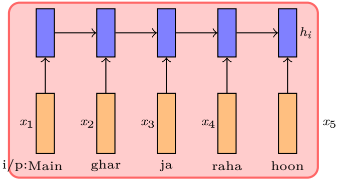

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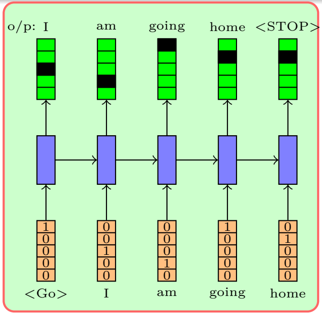

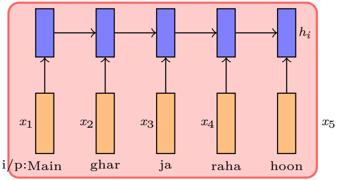

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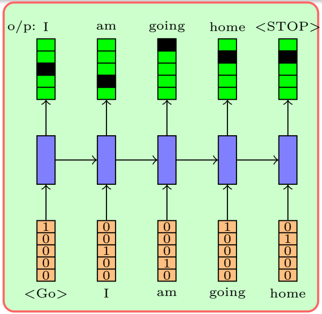

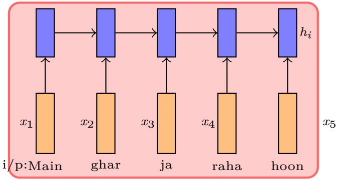

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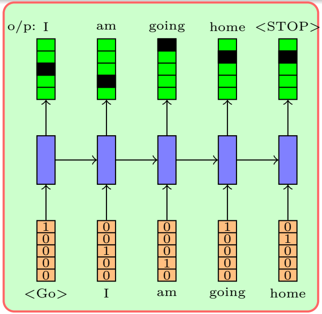

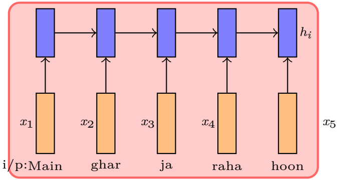

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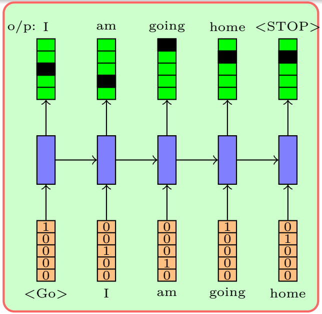
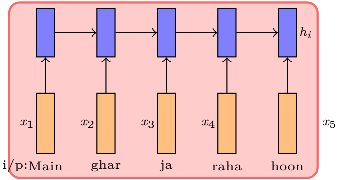
$$\ell_t = softmax(Vs_t + b)$$

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





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

$$h_t = RNN(h_{t-1}, x_t)$$
$$s_0 = h_T$$

- **Decoder:**

$$e_{jt} = V_{attn}^T tanh(U_{attn}h_j + W_{attn}s_t)$$
$$\alpha_{jt} = softmax(e_{jt})$$
$$c_t = \sum_{j=1}^{T} \alpha_{jt}h_j$$
$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), c_t])$$
$$\ell_t = softmax(Vs_t + b)$$

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

- Can we check if the attention model actually learns something meaningful ?

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- In other words does it really learn to focus on the most relevant words in the input at the t-th timestep ?

- 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)

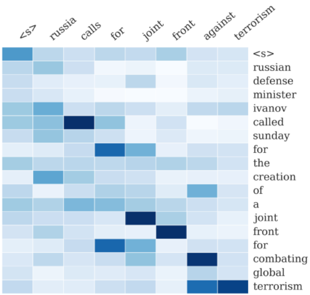
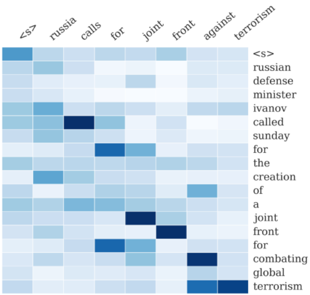


Figure: Example output of attention-based summarization system [Rush et al. 2015.]



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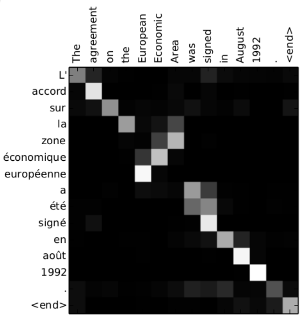


Figure: Example output of attention-based neural machine translation model [Cho et al. 2015].

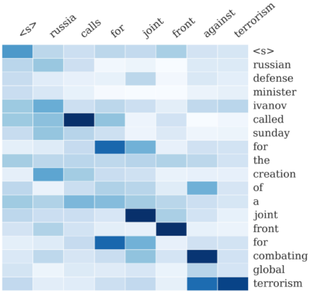


Figure: Example output of attention-based summarization system [Rush et al. 2015.]

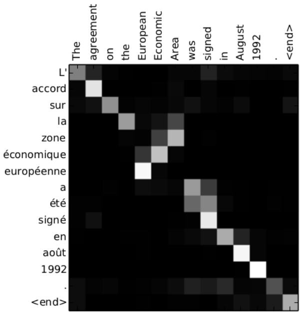
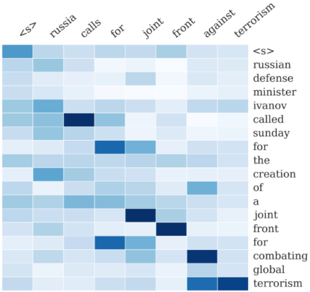


Figure: Example output of attention-based neural machine translation model [Cho et al. 2015].

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



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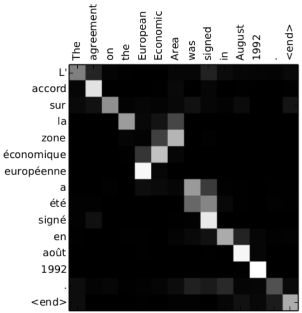


Figure: Example output of attention-based neural machine translation model [Cho et al. 2015].

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

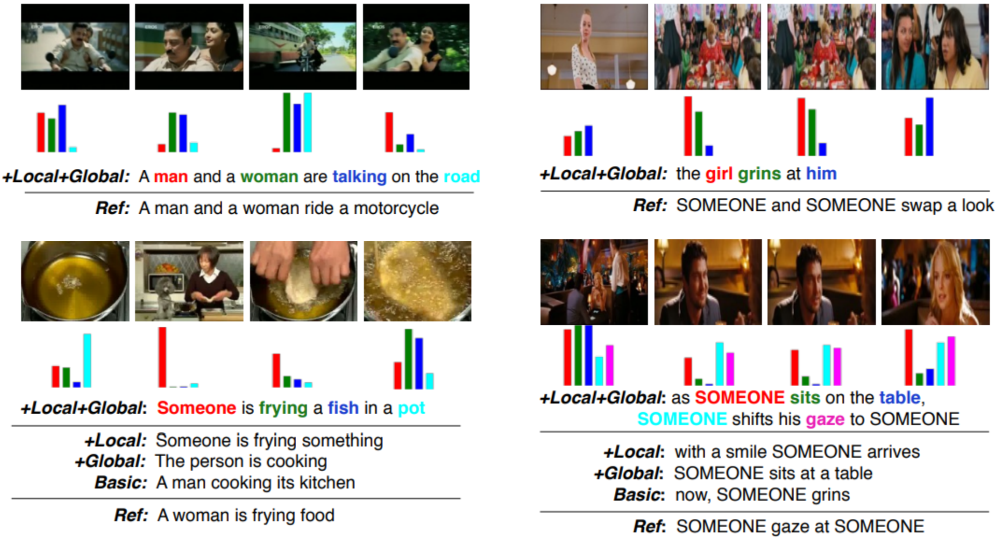
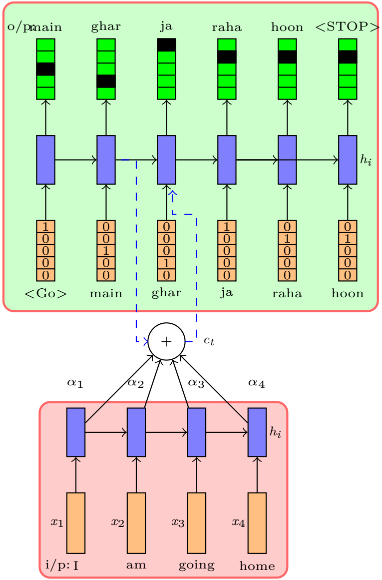


Figure: Example output of attention-based video captioning system [Yao et al. 2015.]

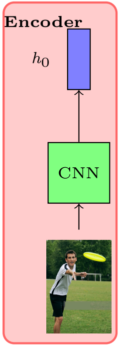
Module 16.4: Attention over images

A man throwing
a frisbee in a park

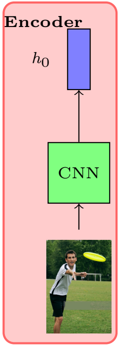
- How do we model an attention mechanism for images?



- 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



- 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



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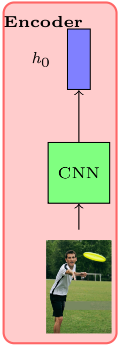
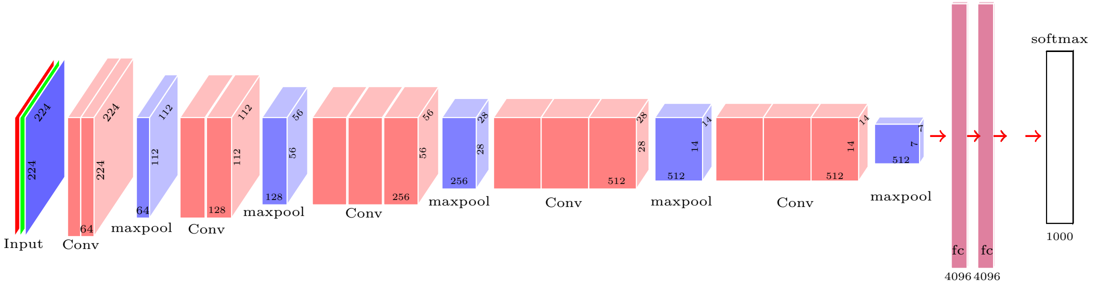
- But for images we typically use representation from one of the fully connected layers
- This representation does not contain any location information

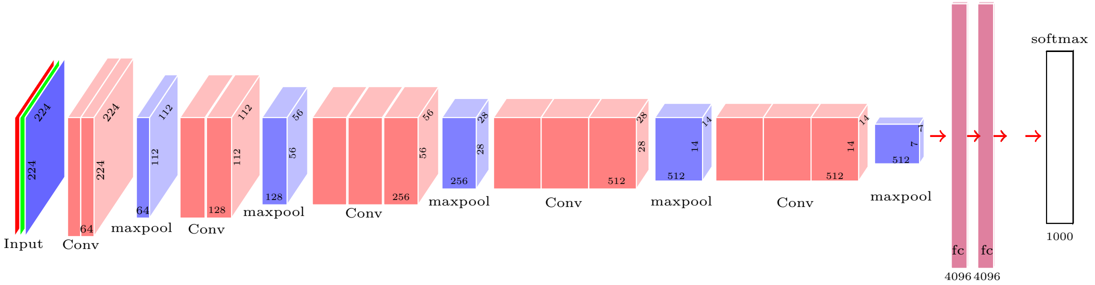


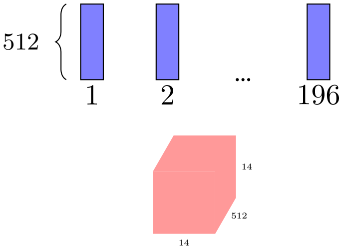
- How do we model an attention mechanism for images?
- In the case of text we have a representation for every location (time step) of the input sequence
- But for images we typically use representation from one of the fully connected layers
- This representation does not contain any location information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

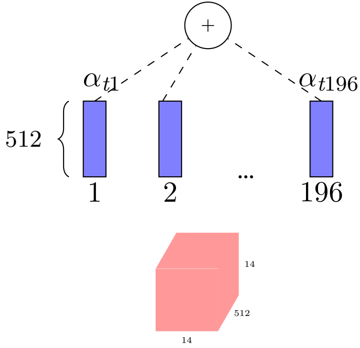


- Well, instead of the fc7 representation we use the output of one of the convolution layers which has spatial information
- For example the output of the 5^{th} convolutional layer of VGGNet is a $14 \times 14 \times 512$ size feature map





- Well, instead of the fc7 representation we use the output of one of the convolution layers which has spatial information
- For example the output of the 5^{th} 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)



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- For example the output of the 5^{th} 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

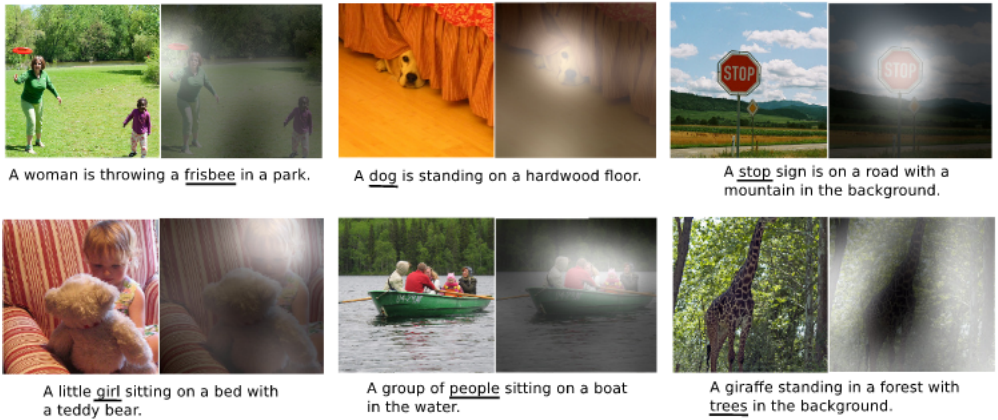

Figure: Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicates the corresponding word) [Kyunghyun Cho et al. 2015.]

Module 16.5: 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)

Context

U: Can you suggest a good movie?

B: Yes, sure. How about Logan?

U: Okay, who is the lead actor?

Response

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- Consider a dialog between a user (u) and a bot (B)
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- Consider a dialog between a user (u) and a bot (B)
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- Consider a dialog between a user (u) and a bot (B)
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- Thus what we have here is a "sequence of sequences" as input

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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
- Each utterance in turn is a sequence of words
- 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

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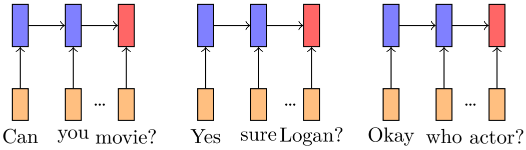
- The first level RNN operates on the sequence of words in each utterance and gives us a representation



- We could think of a two level hierarchical RNN encoder
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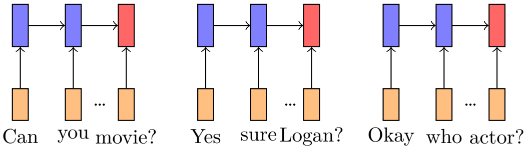
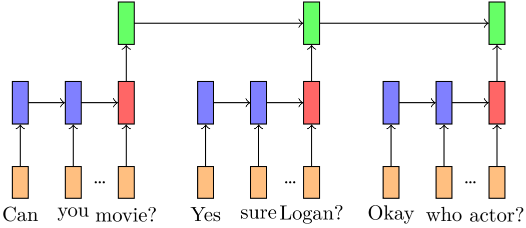
- We now have a sequence of utterance representations (red vectors in the image)





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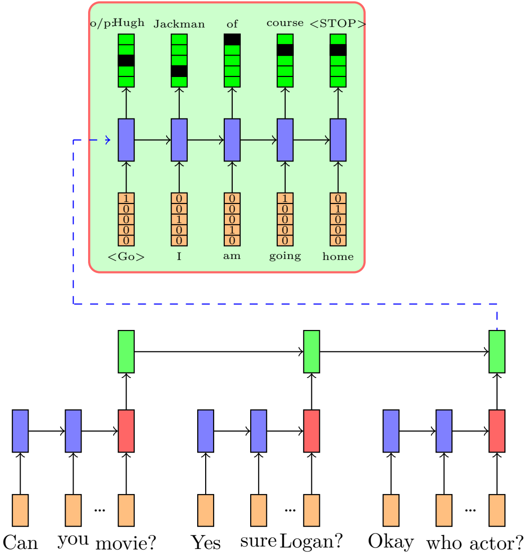

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- The decoder can then produce an output sequence conditioned on this utterance

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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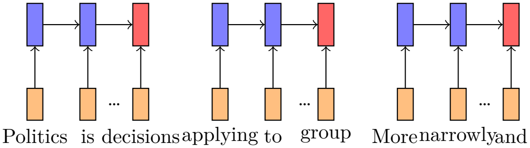

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- Consider the task of document classification or summarization
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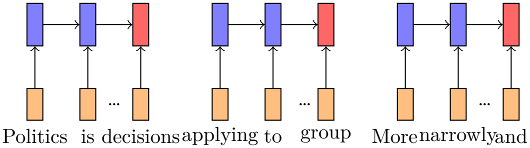

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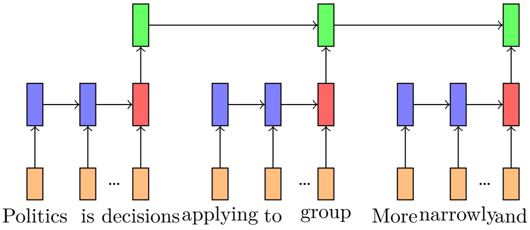

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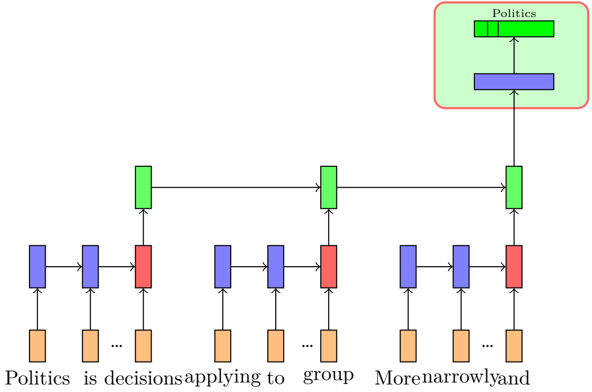

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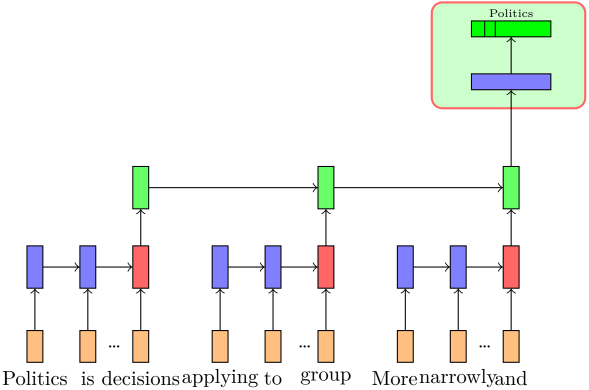

- **Data:** $\{Document_i, class_i\}_{i=1}^{N}$

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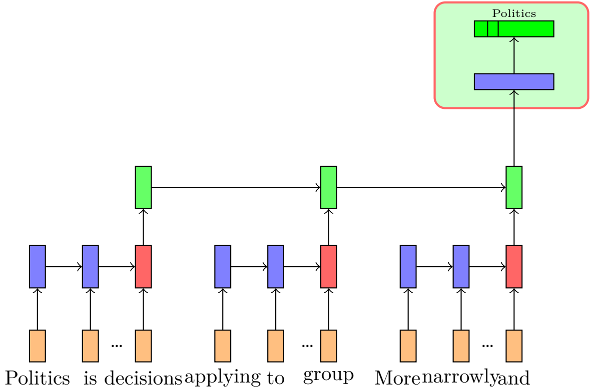

- **Data:** $\{Document_i, class_i\}_{i=1}^{N}$
- **Word level (1) encoder:**

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

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

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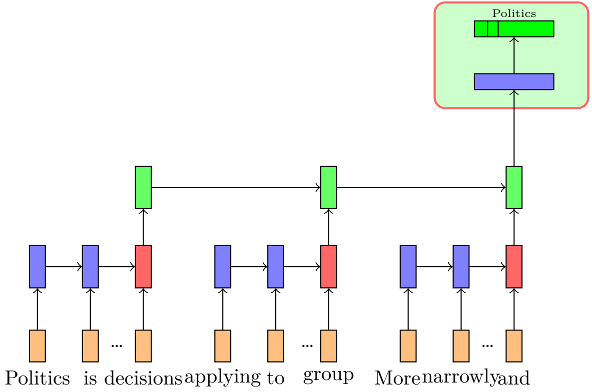

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- **Sentence level (2) encoder:**

$$h^2_i = RNN(h^2_{i-1}, s_i)$$

$$s = h^2_K \quad [K \text{ is number of sentences}]$$

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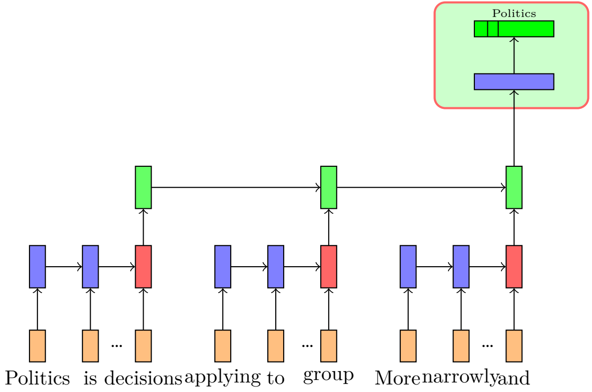

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- **Sentence level (2) encoder:**

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

$$s = h_K^2 \quad [K \textit{ is number of sentences}]$$

- **Decoder:**

$$P(y|document) = softmax(Vs + b)$$

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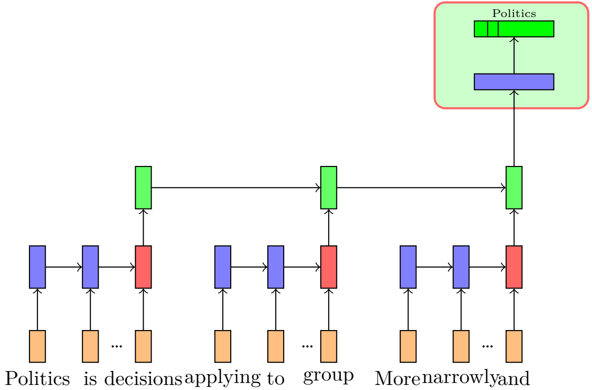

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- **Params:** $W^1_{enc}, U^1_{enc}, W^2_{enc}, U^2_{enc}, V, b$

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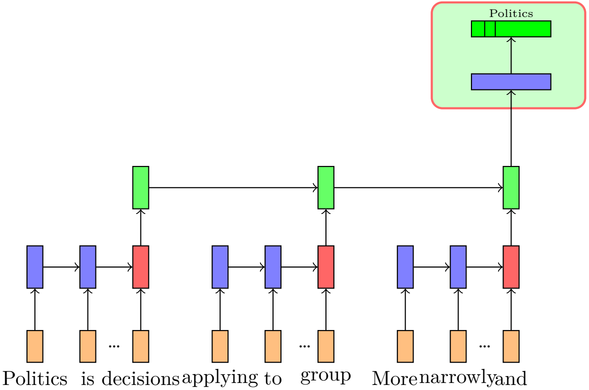

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- **Params:** $W_{enc}^1, U_{enc}^1, W_{enc}^2, U_{enc}^2, V, b$
- **Loss:** Cross Entropy

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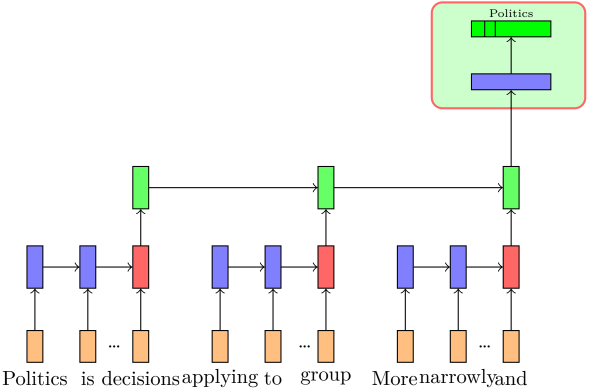

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- **Params:** $W^1_{enc}, U^1_{enc}, W^2_{enc}, U^2_{enc}, V, b$
- **Loss:** Cross Entropy
- **Algorithm:** Gradient Descent with backpropagation

- How would you model attention in such a hierarchical encoder decoder model ?

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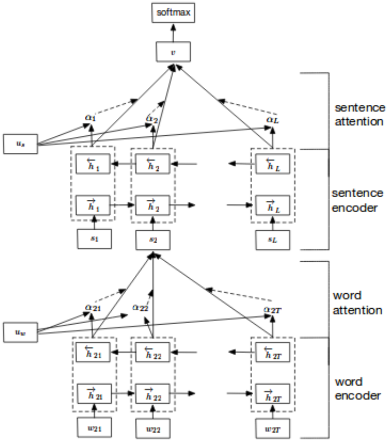
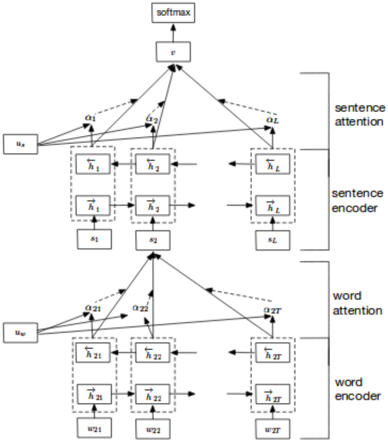


Figure: Hierarchical Attention Network [Yang et al.]

- How would you model attention in such a hierarchical encoder decoder model ?
- We need attention at two levels
- First we need to attend to important (most informative) words in a sentence



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- How would you model attention in such a hierarchical encoder decoder model ?
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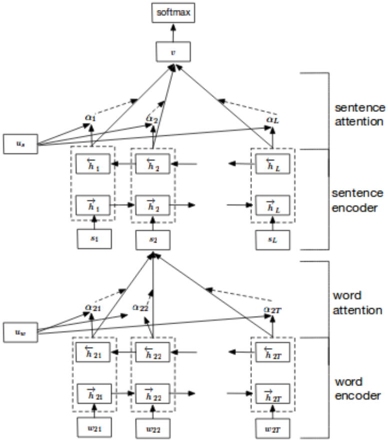

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- Then we need to attend to important (most informative) sentences in a document
- Let us see how to model this

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

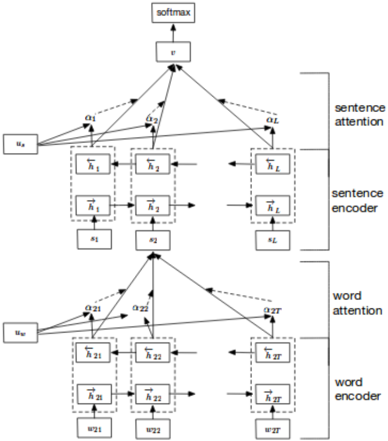


Figure: Hierarchical Attention Network [Yang et al.]

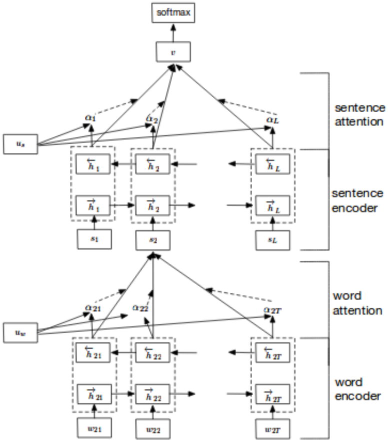
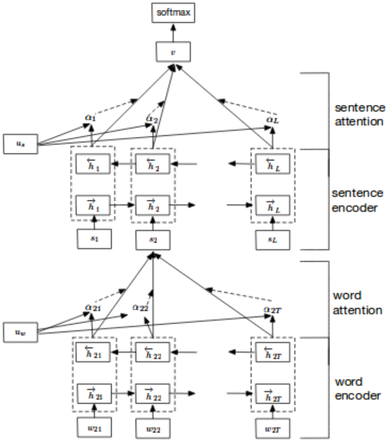


Figure: Hierarchical Attention Network [Yang et al.]

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

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



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

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

$$h_i = RNN(h_{i-1}, s_i)$$
$$u_i = tanh(W_s h_i + b_s)$$
$$\alpha_i = \frac{exp(u_i^T u_s)}{\sum_i exp(u_i^T u_s)}$$
$$s = \sum_i \alpha_i h_i$$

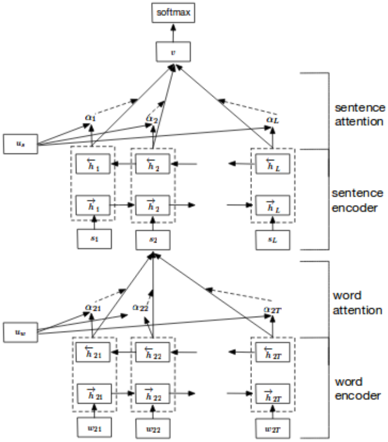
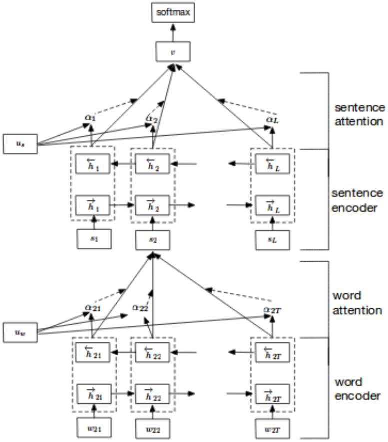


Figure: Hierarchical Attention Network [Yang et al..]

- **Decoder:**

$$P(y|document) = softmax(Vs + b)$$



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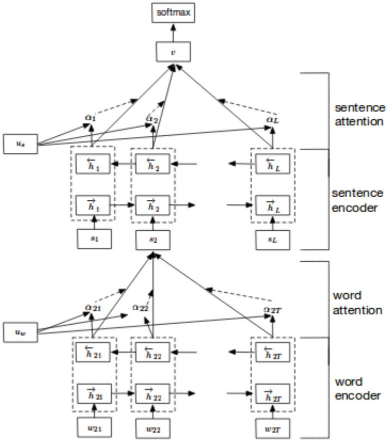
- **Parameters:**
W_w, W_s, V, b_w, b_s, b, u_w, u_s



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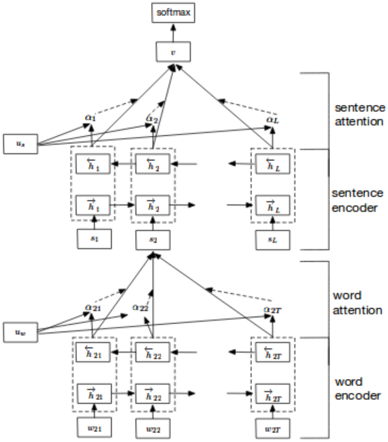

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