Encoder Decoder Models

# DSE 5251 DEEP LEARNING

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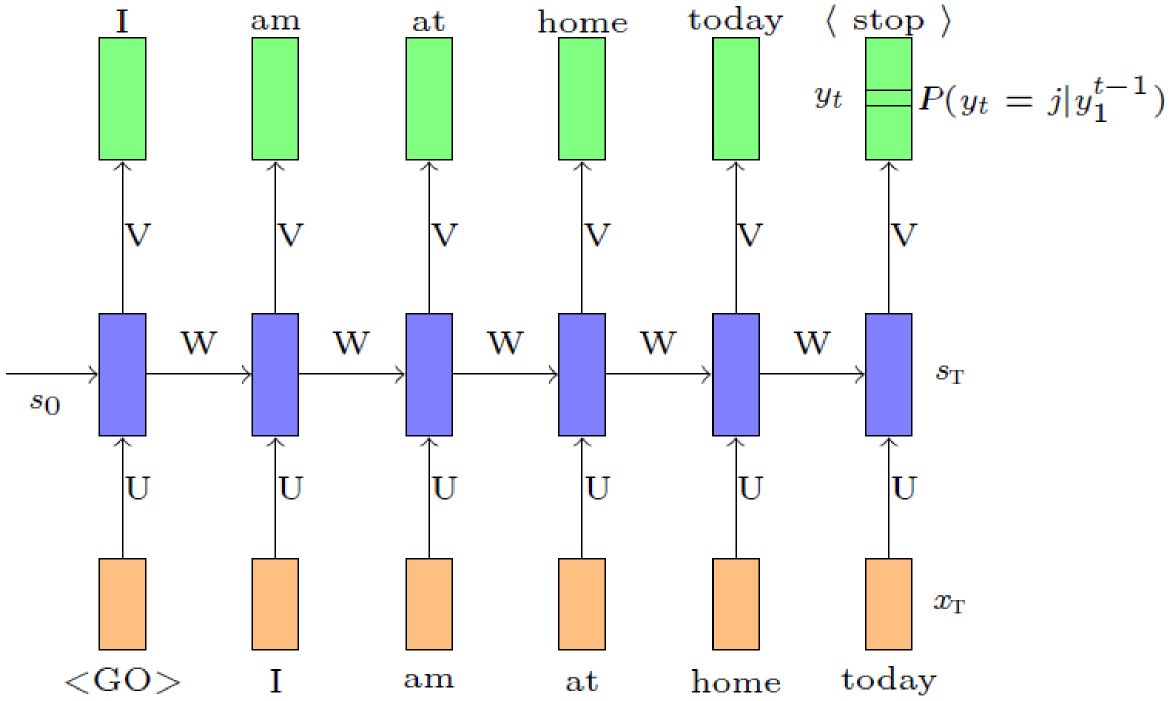
MIT Manipal

# Encoder Decoder Models : Introduction

- Language Modeling:
  Given the t-i words predict the $t^{th}$ word




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

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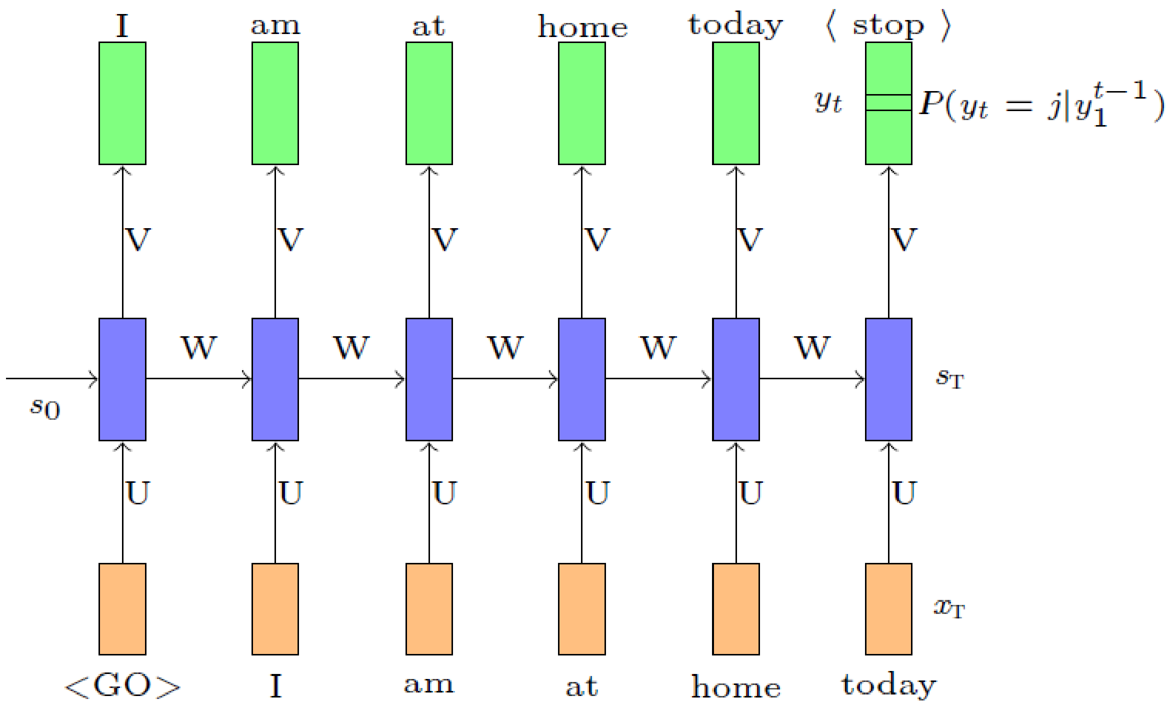


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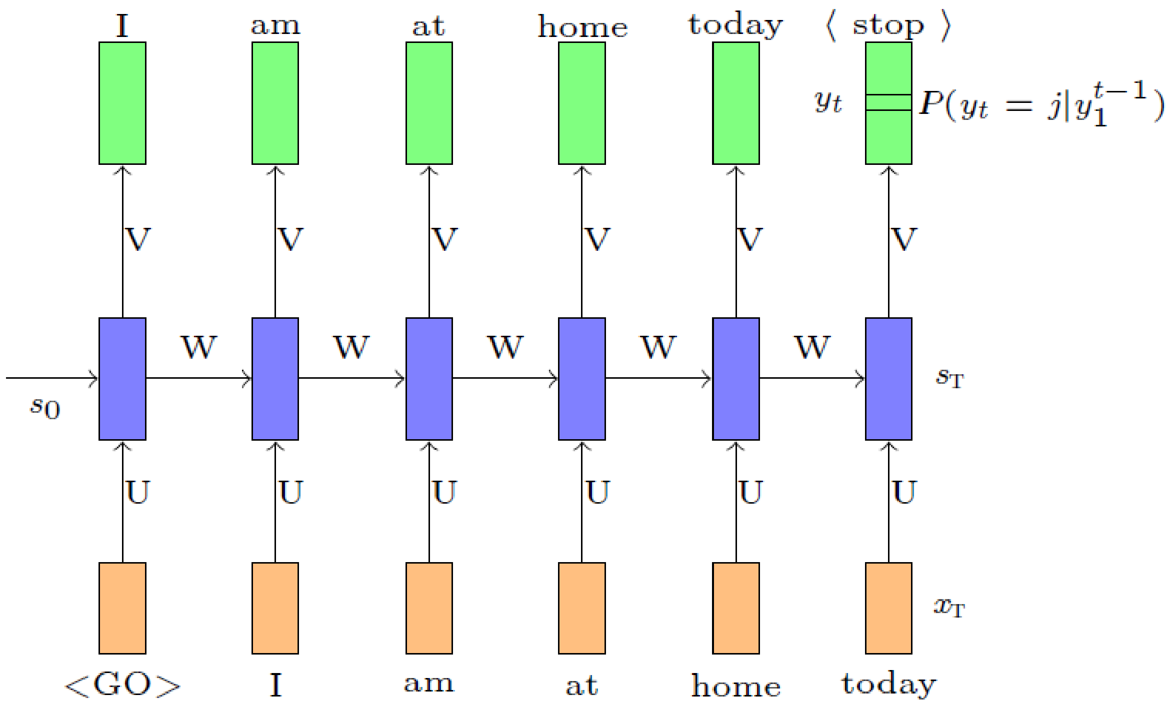


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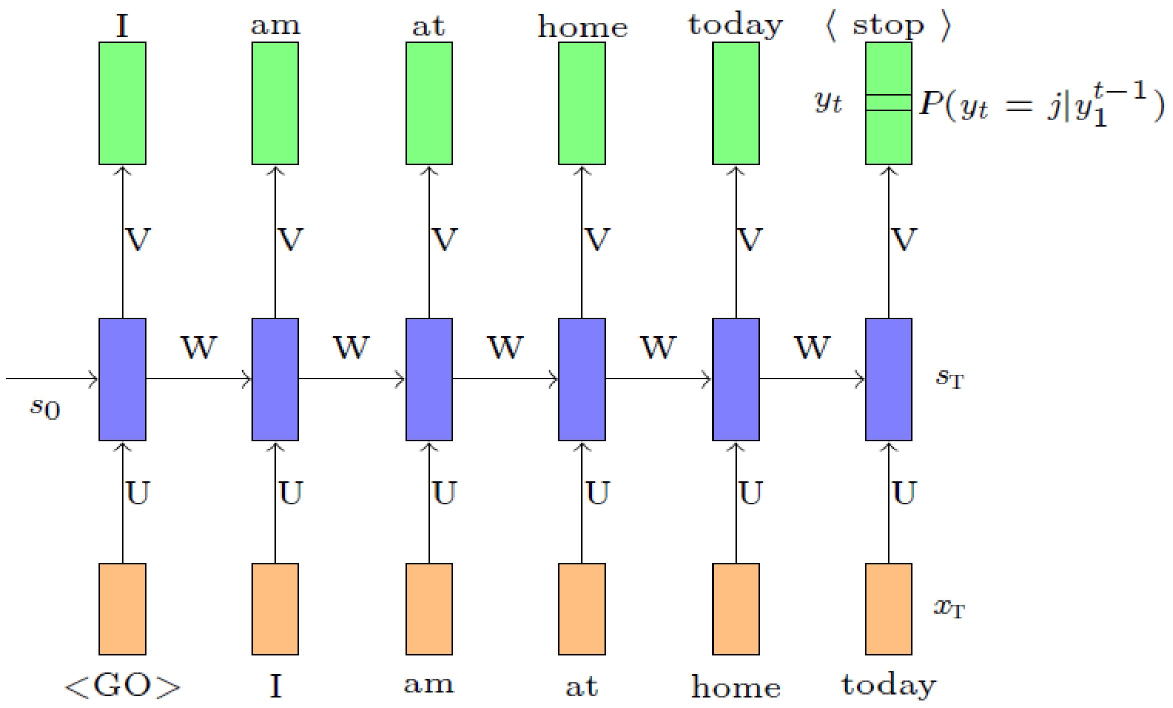


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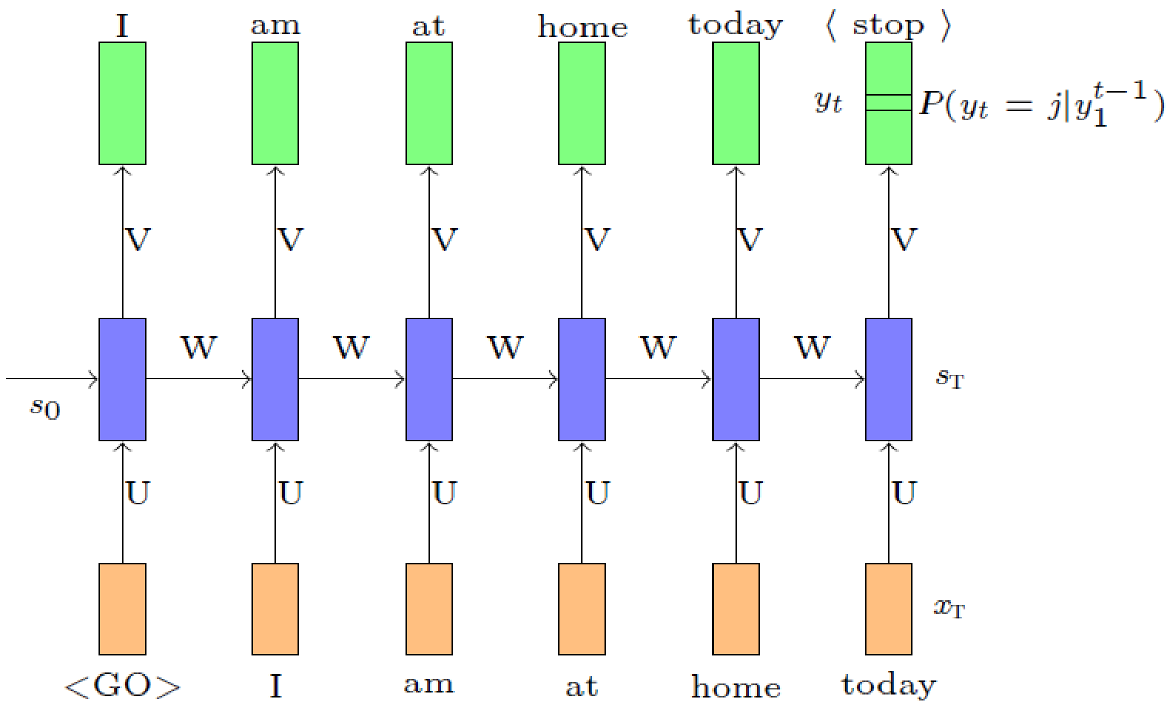


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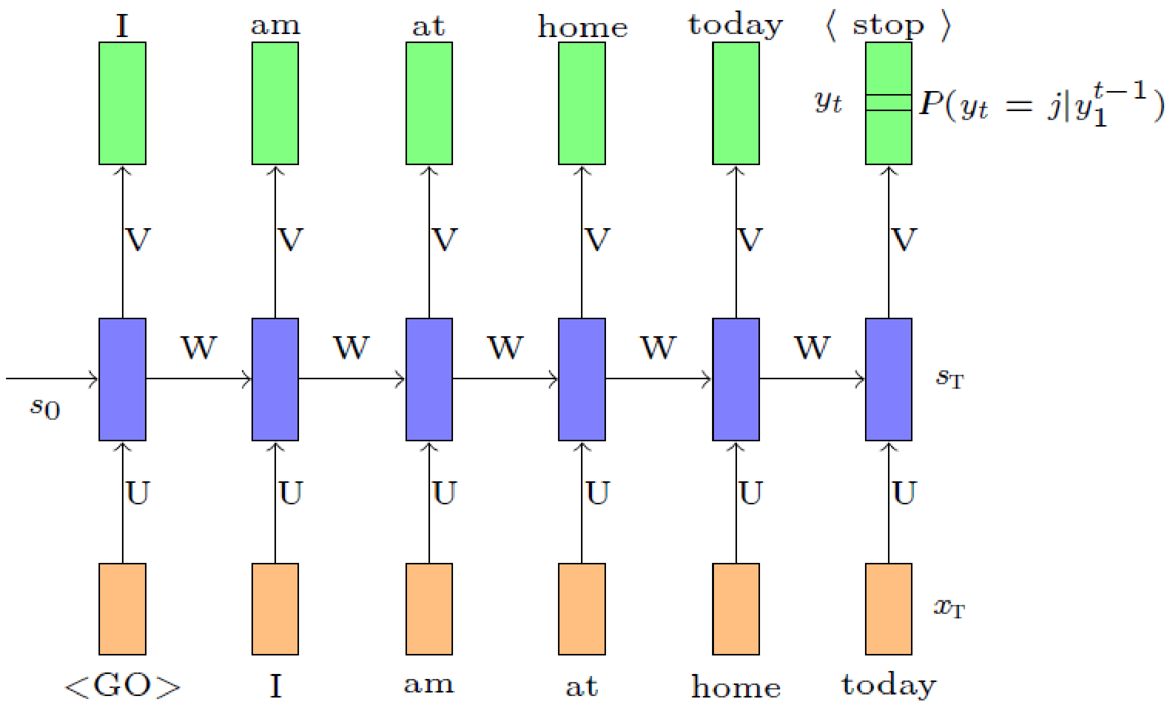
j$^{th}$ word in the vocabulary

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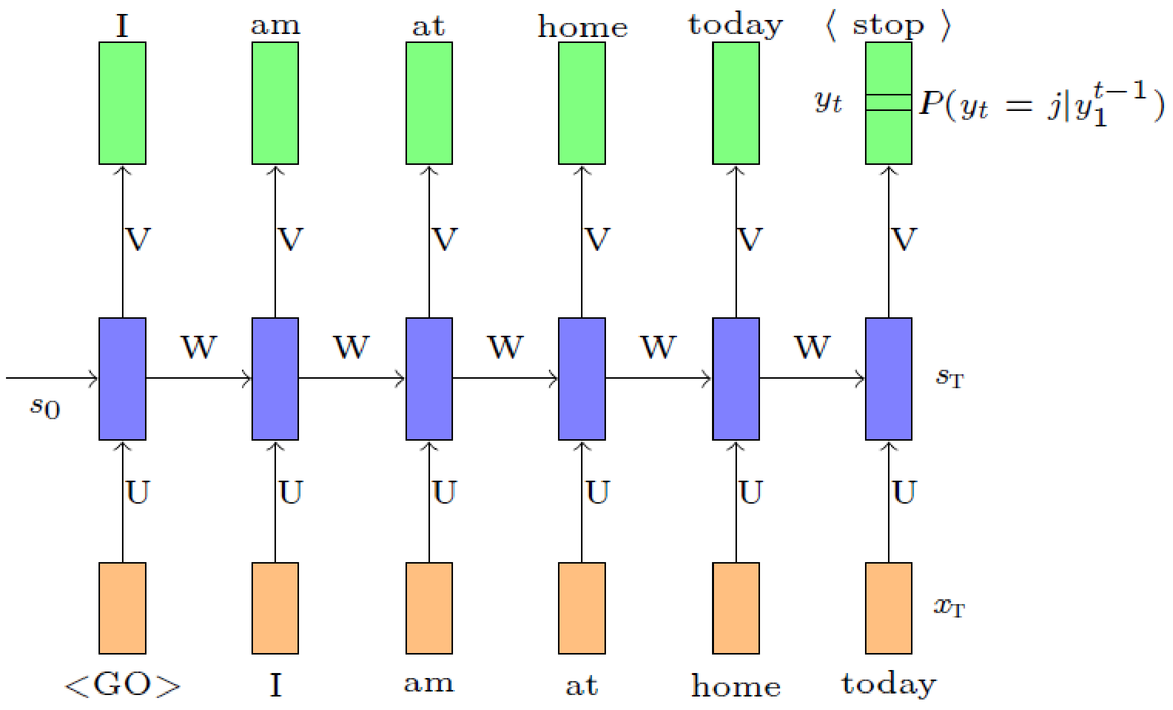
Using an RNN we will compute this as:

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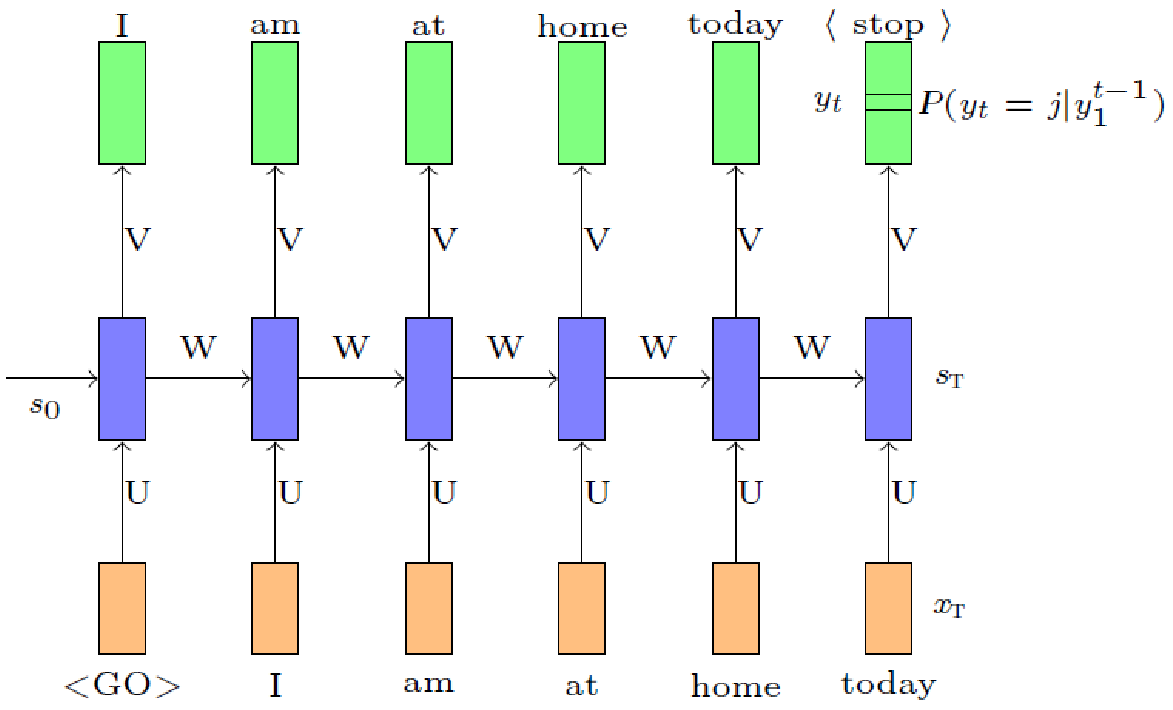
$$P(y_t = j | y_1^{t-1}) = softmax(Vs_t + c)_j$$

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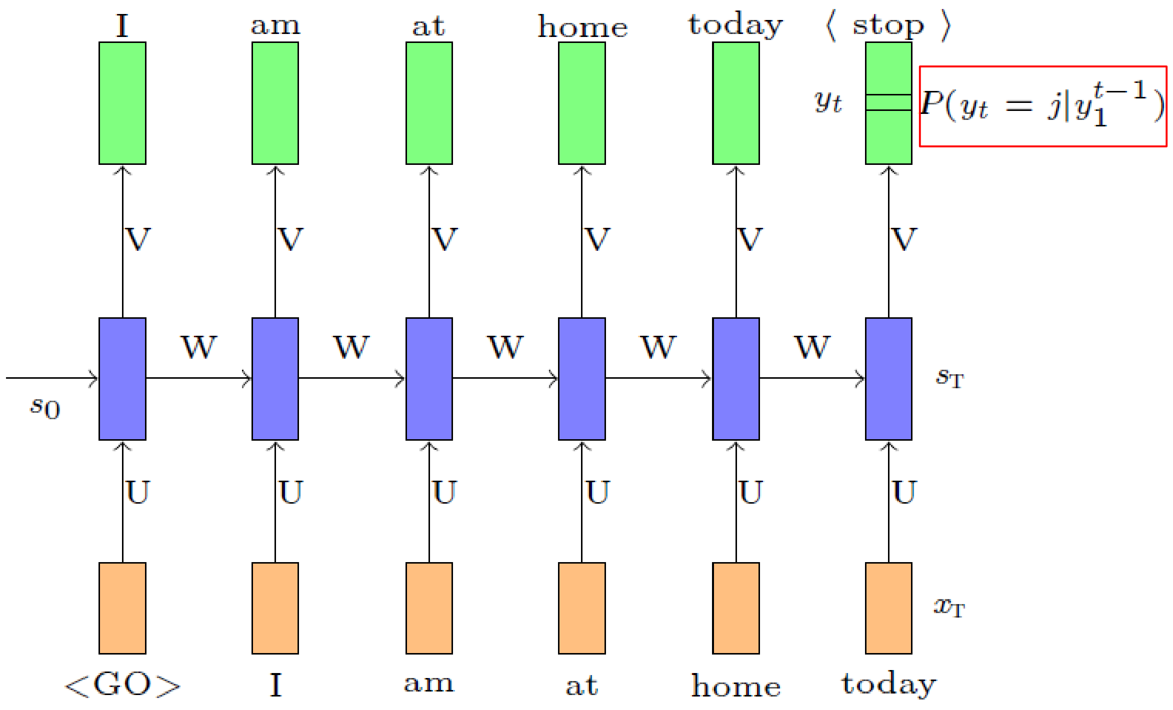


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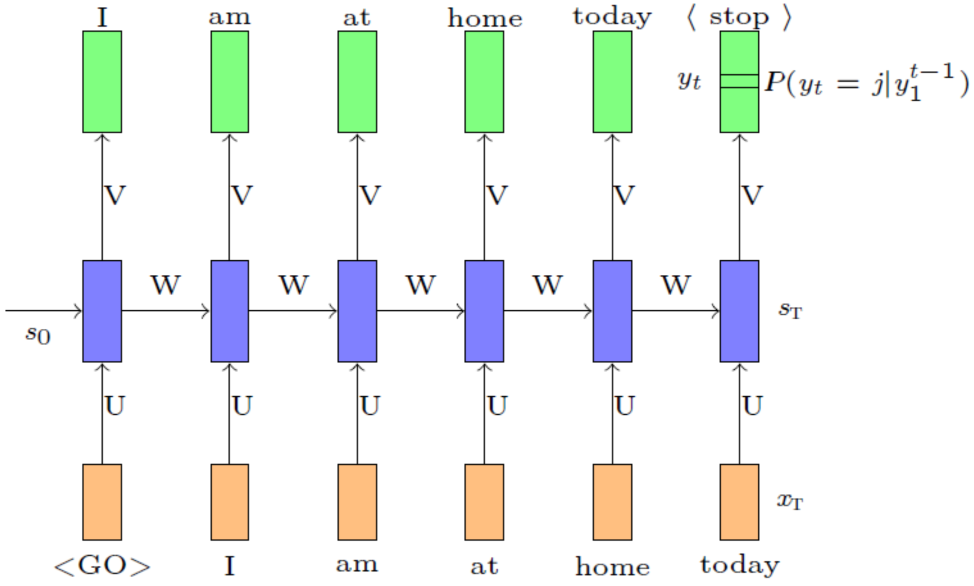


Data: India, officially the Republic of India, is a country in South Asia. It is the seventh-largest country by area, .....

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

$$s_t = \sigma(Ws_{t-1} + Ux_t + b)$$

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

- **Parameters:** $U, V, W, b, c$
- **Loss:**

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

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

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

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# Encoder Decoder Models : Introduction

- <u>Shorthand notations:</u>

$$s_t = \sigma(U x_t + W s_{t-1} + b)$$

$$\tilde{s}_t = \sigma(W(o_t \odot s_{t-1}) + U x_t + b)$$
$$s_t = i_t \odot s_{t-1} + (1 - i_t) \odot \tilde{s}_t$$

$$\tilde{s}_t = \sigma(W h_{t-1} + U x_t + b)$$
$$s_t = f_t \odot s_{t-1} + i_t \odot \tilde{s}_t$$
$$h_t = o_t \odot \sigma(s_t)$$

$$s_t = \mathrm{RNN}(s_{t-1}, x_t)$$

$$s_t = \mathrm{GRU}(s_{t-1}, x_t)$$

$$h_t, s_t = \mathrm{LSTM}(h_{t-1}, s_{t-1}, x_t)$$

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# Encoder Decoder Models : Introduction

Task: generate a sentence given an image

A man throwing
a frisbee in a park

We are now interested in $P(y_t|y_1^{t-1}, I)$ instead of $P(y_t|y_1^{t-1})$ where $I$ is an image

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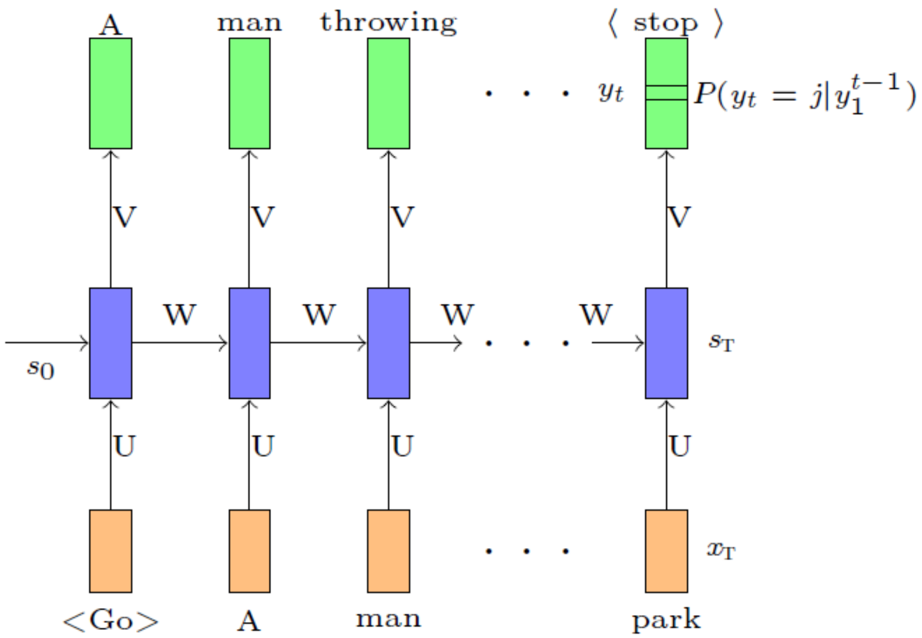


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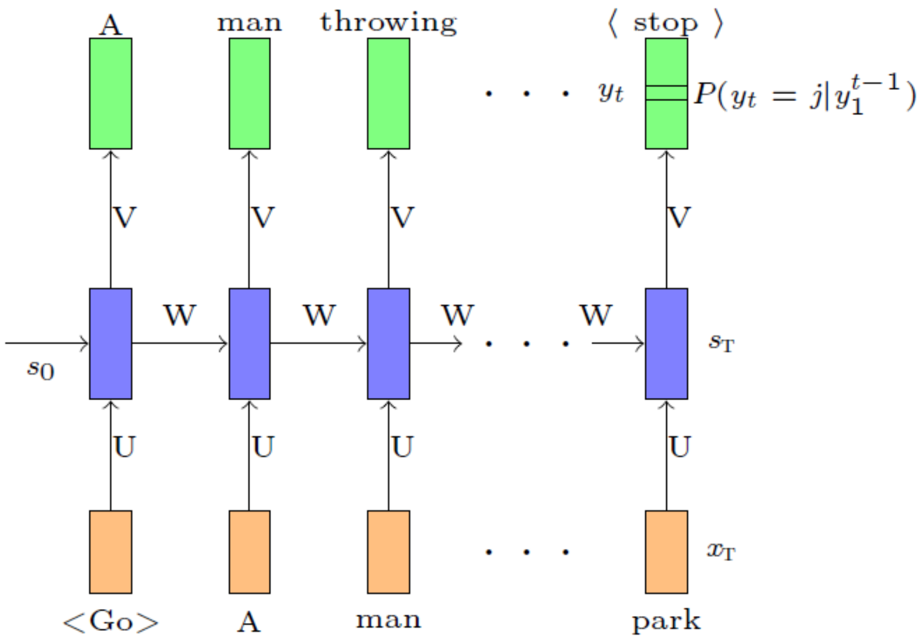


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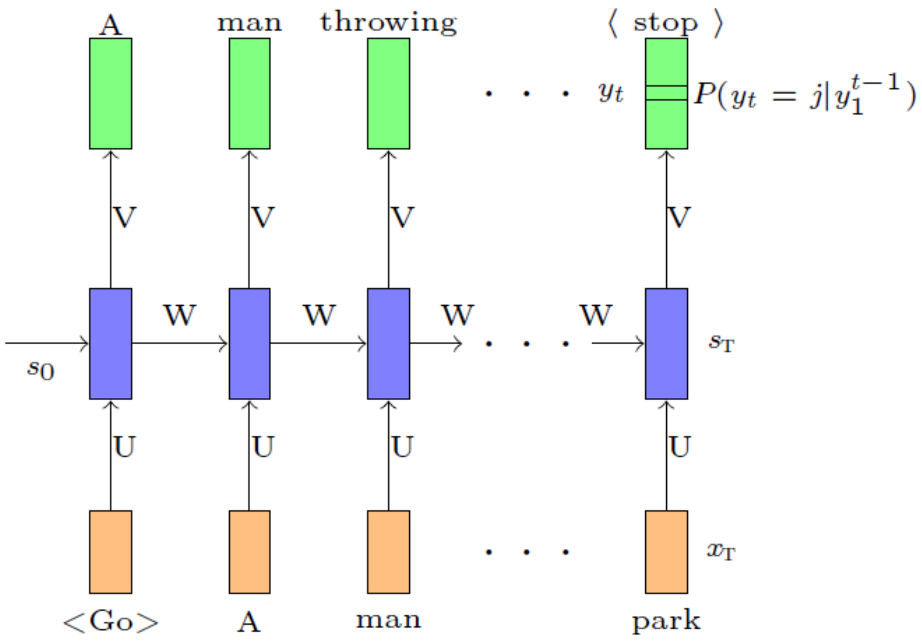


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- We could now model $P(y_t = j|y_1^{t-1}, I)$ as $P(y_t = j|s_t, f_{c_7}(I))$

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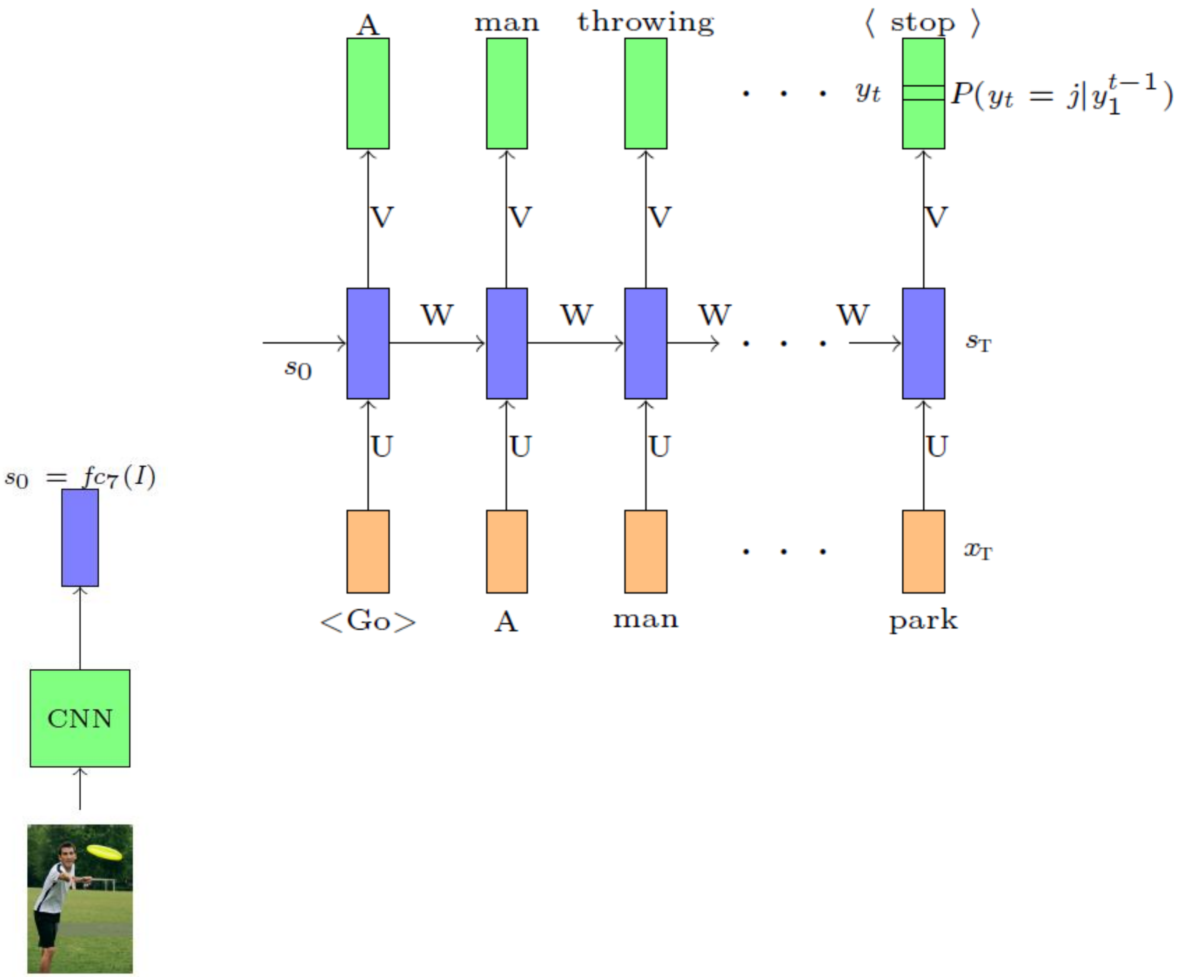


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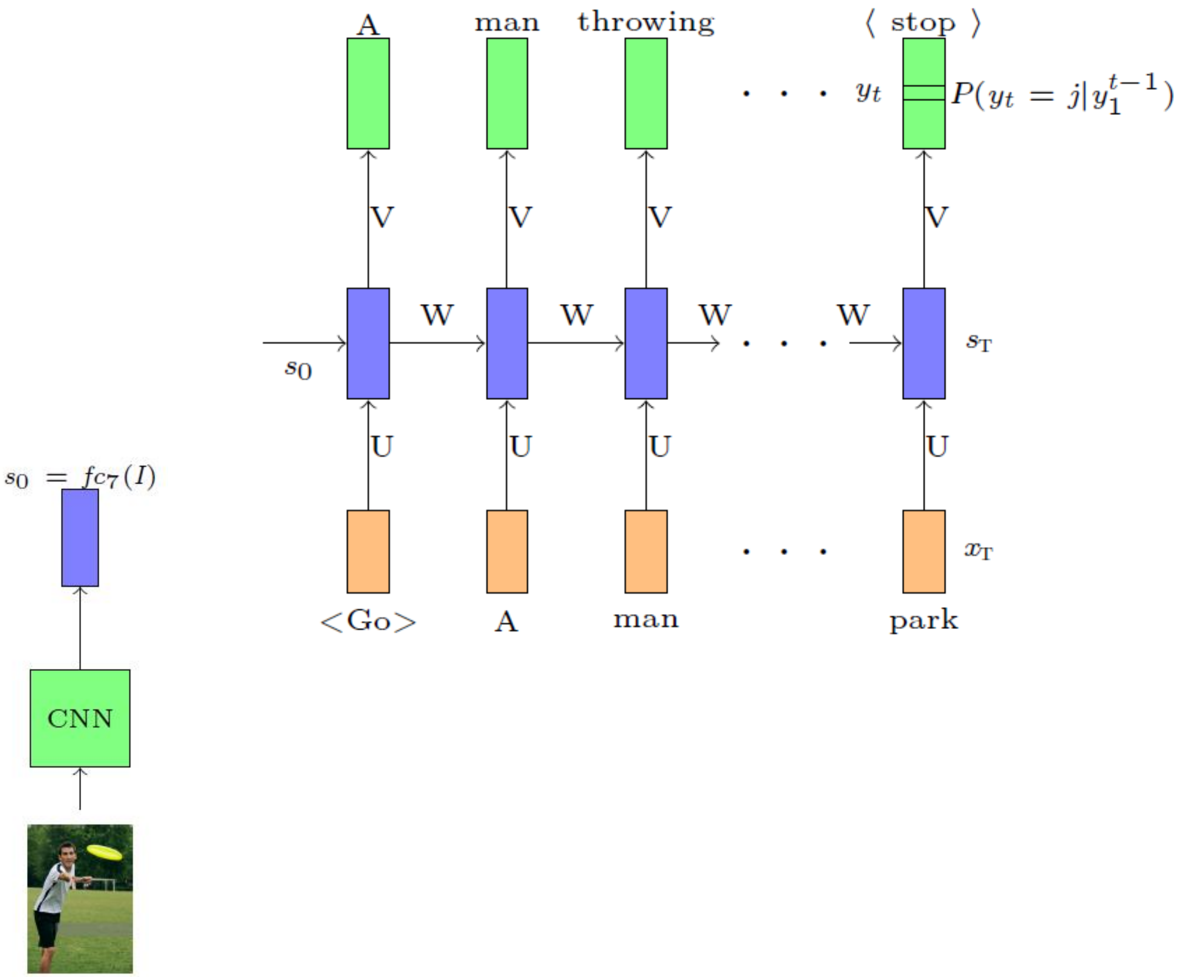


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- where $fc_7(I)$ is the representation obtained from the $fc_7$ layer of an image

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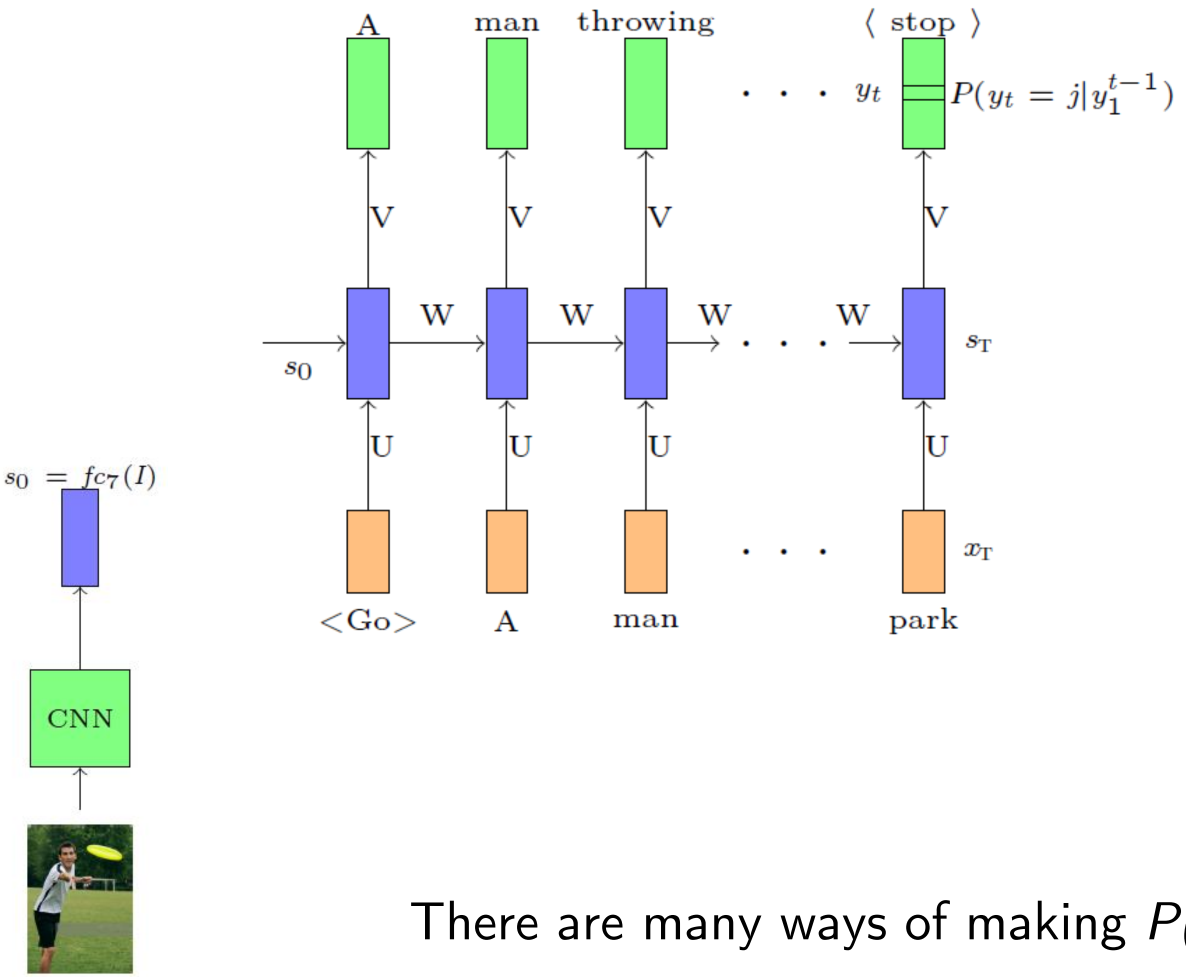


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There are many ways of making $P(y_t = j)$ conditional on $f_{c7}(I)$

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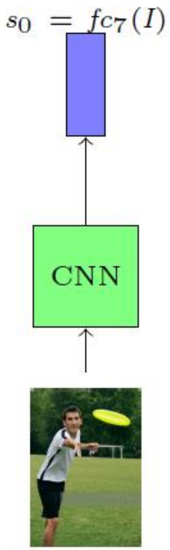


**Option 1:** Set $s_0 = f_{c_7}(I)$

Now $s_0$ and hence all subsequent $s_t$'s depend on $f_{c_7}(I)$

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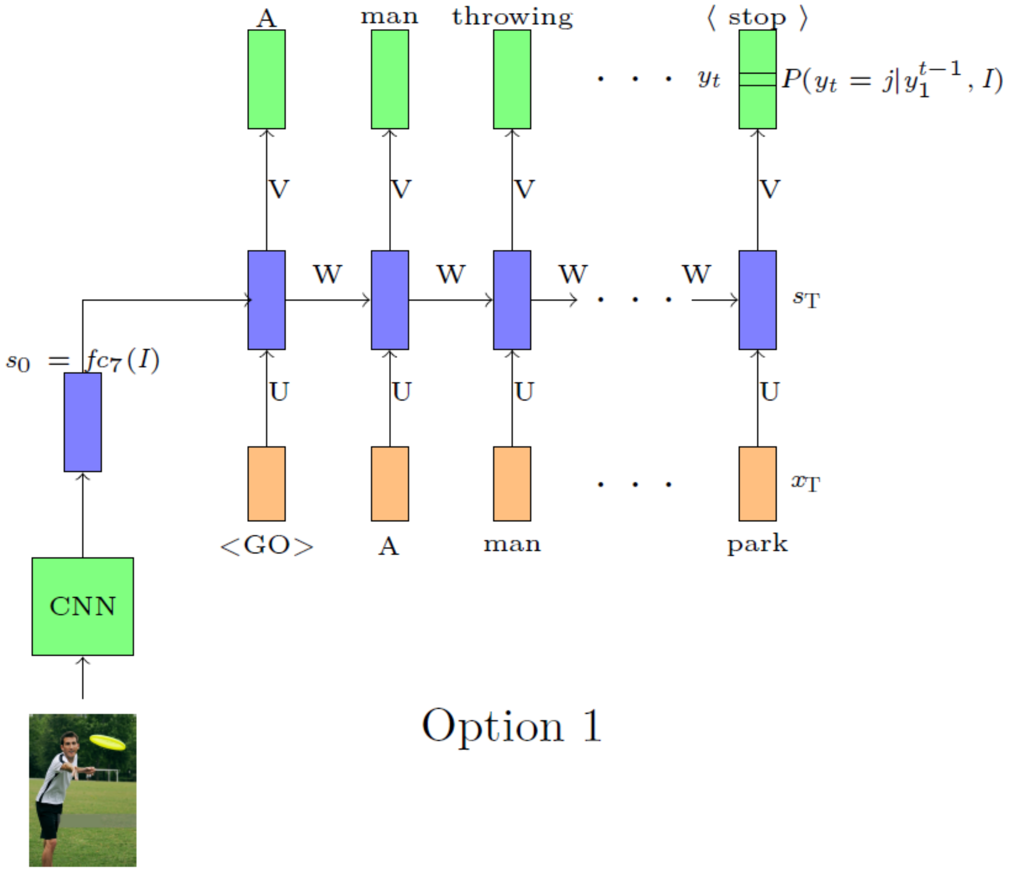


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**Option 1:** Set $s_0 = f_{c_7}(I)$

Now $s_0$ and hence all subsequent $s_t$'s depend on $f_{c_7}(I)$

We can thus say that $P(y_t = j)$ depends on $f_{c_7}(I)$

In other words, we are computing $P(y_t = j | s_t, f_{c_7}(I))$

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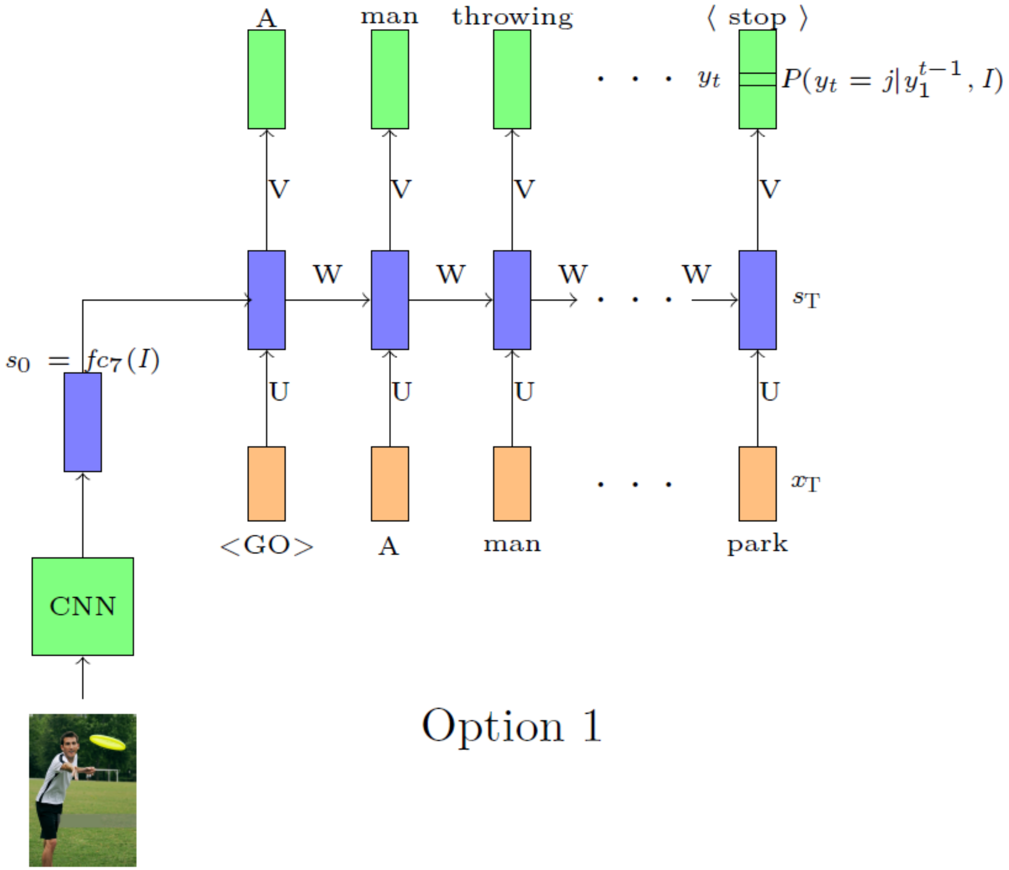


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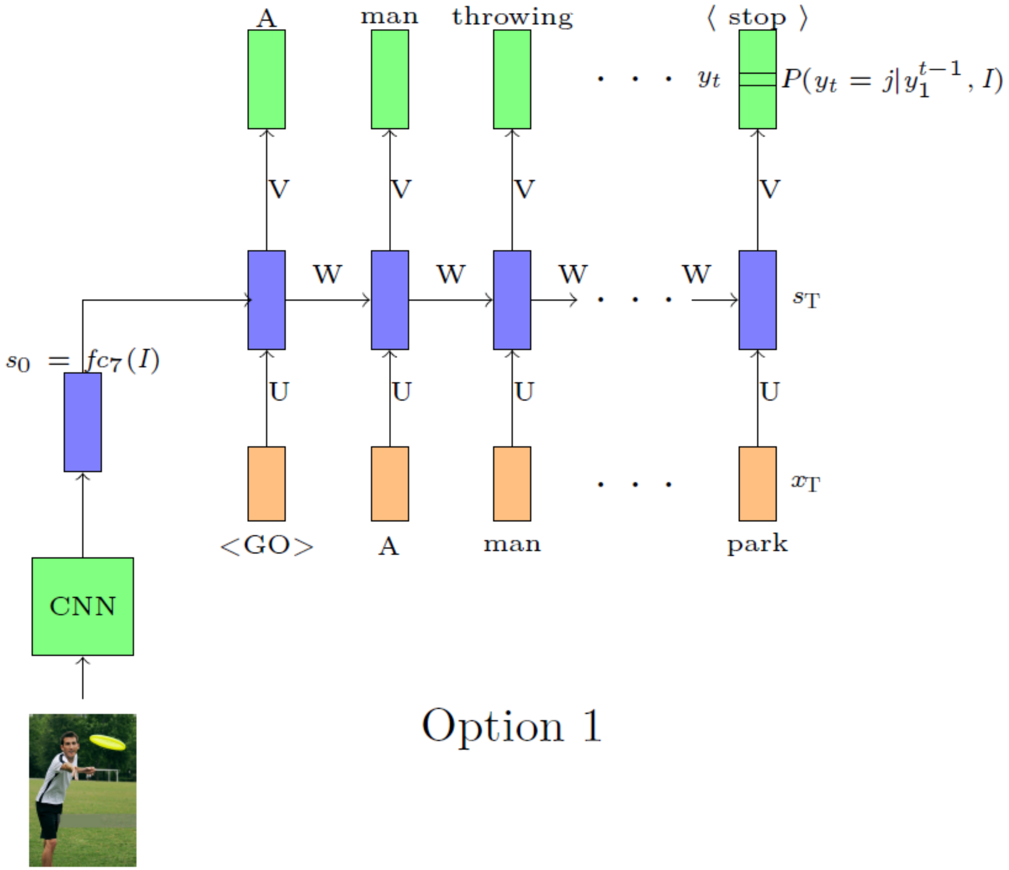


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Fully connected layer #7 in CNN (here, AlexNet)

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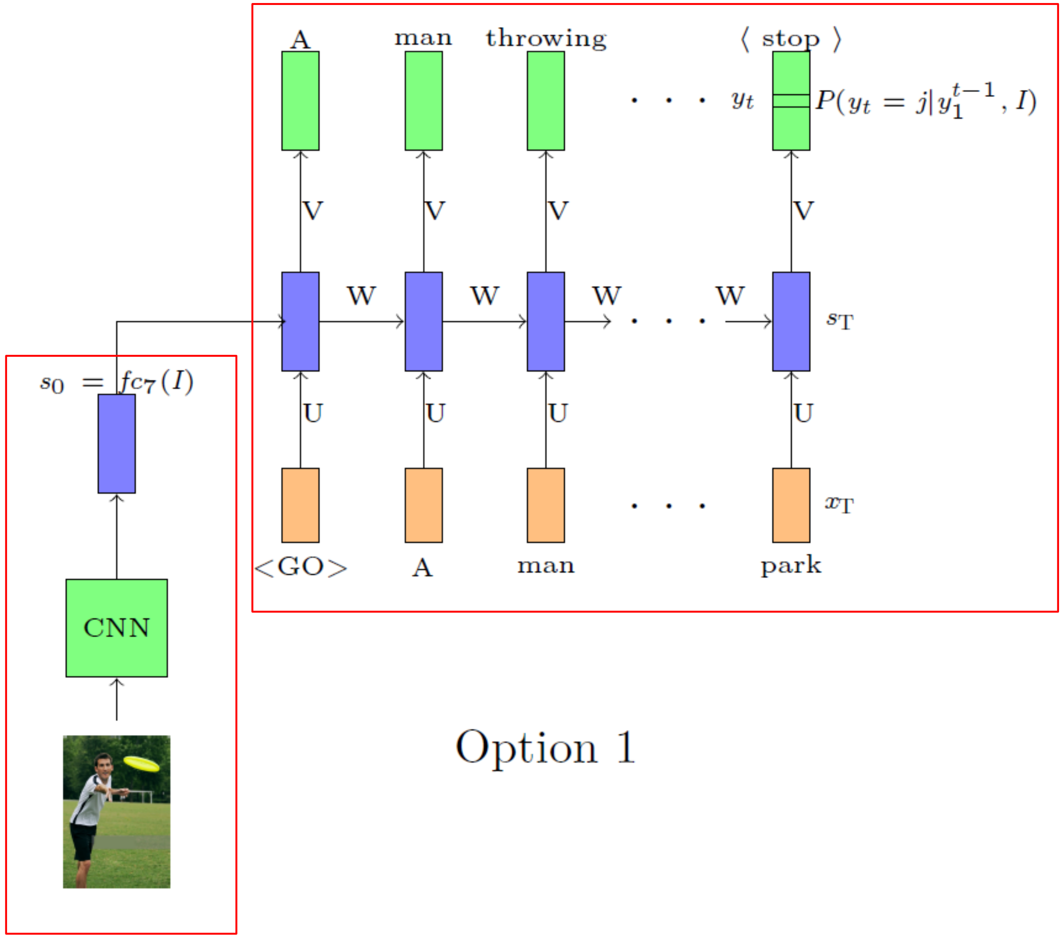


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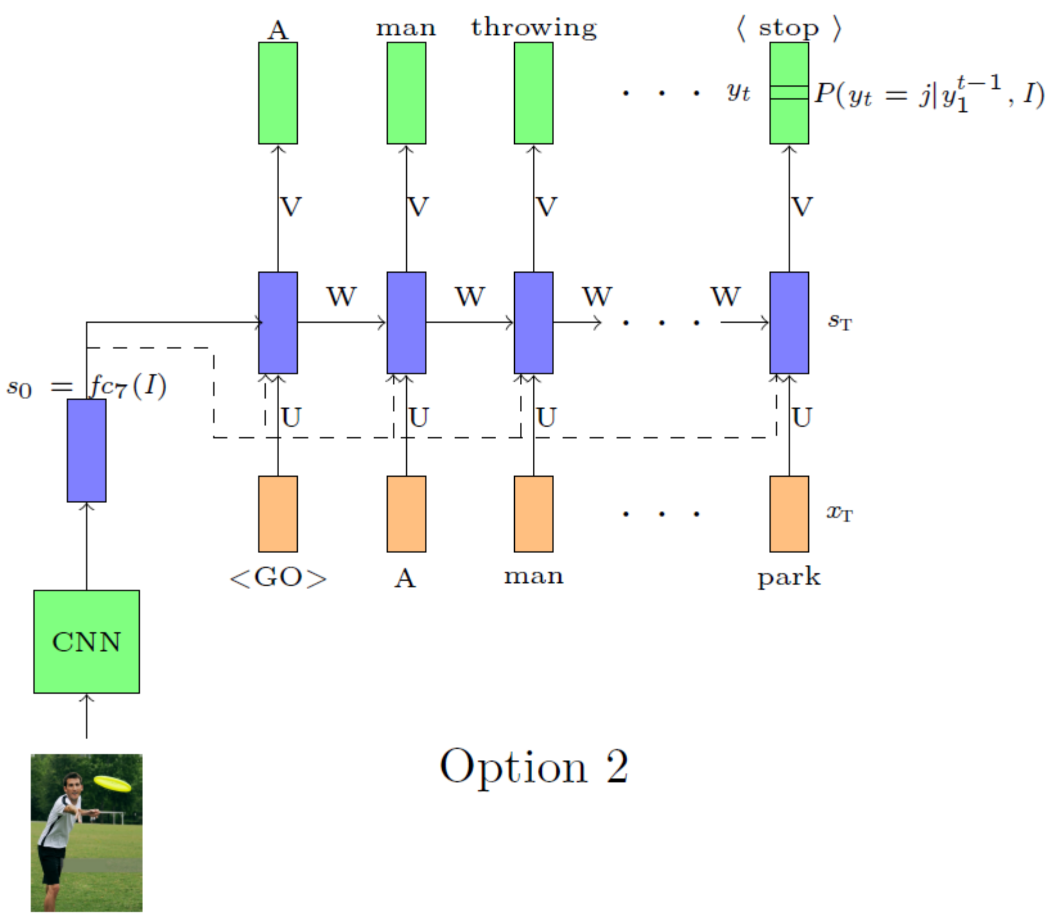


Option 2

**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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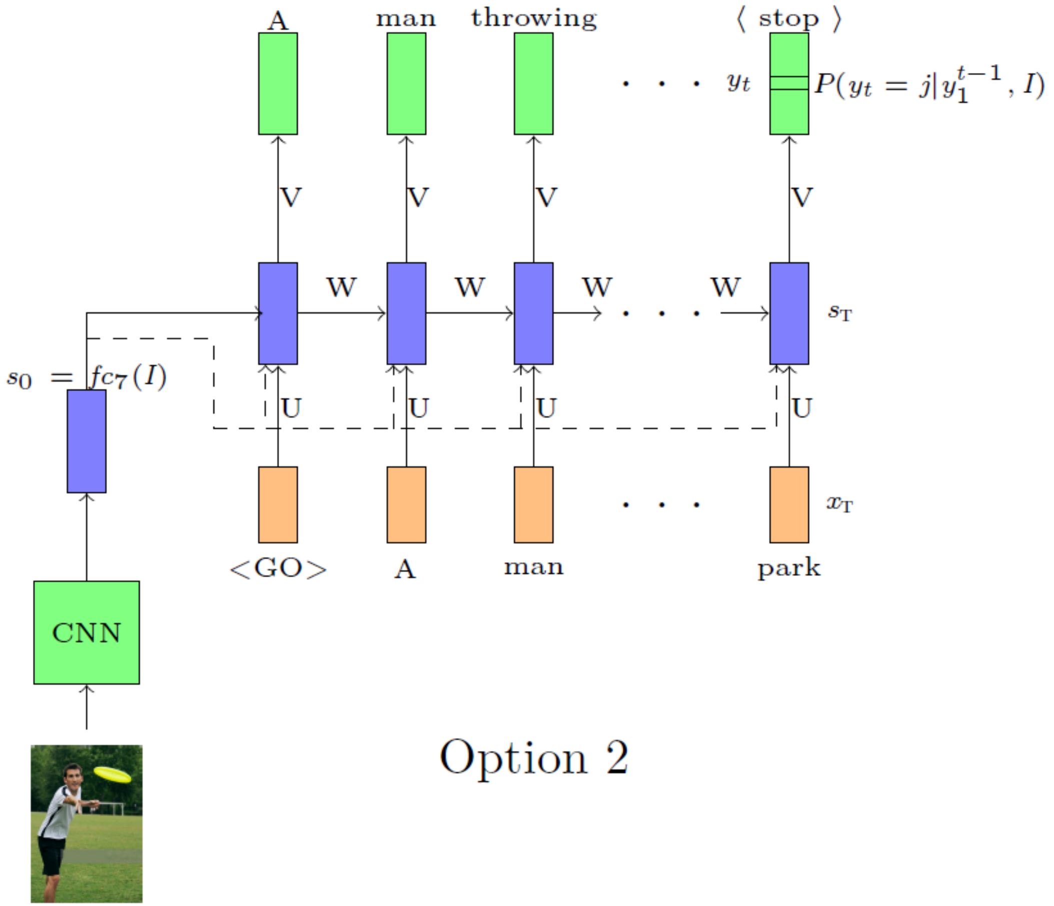


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$$s_t = RNN(s_{t-1}, [x_t, f_{c_7}(I)])$$

In other words we are explicitly using $f_{c_7}(I)$ to compute $s_t$ and hence $P(y_t = j)$

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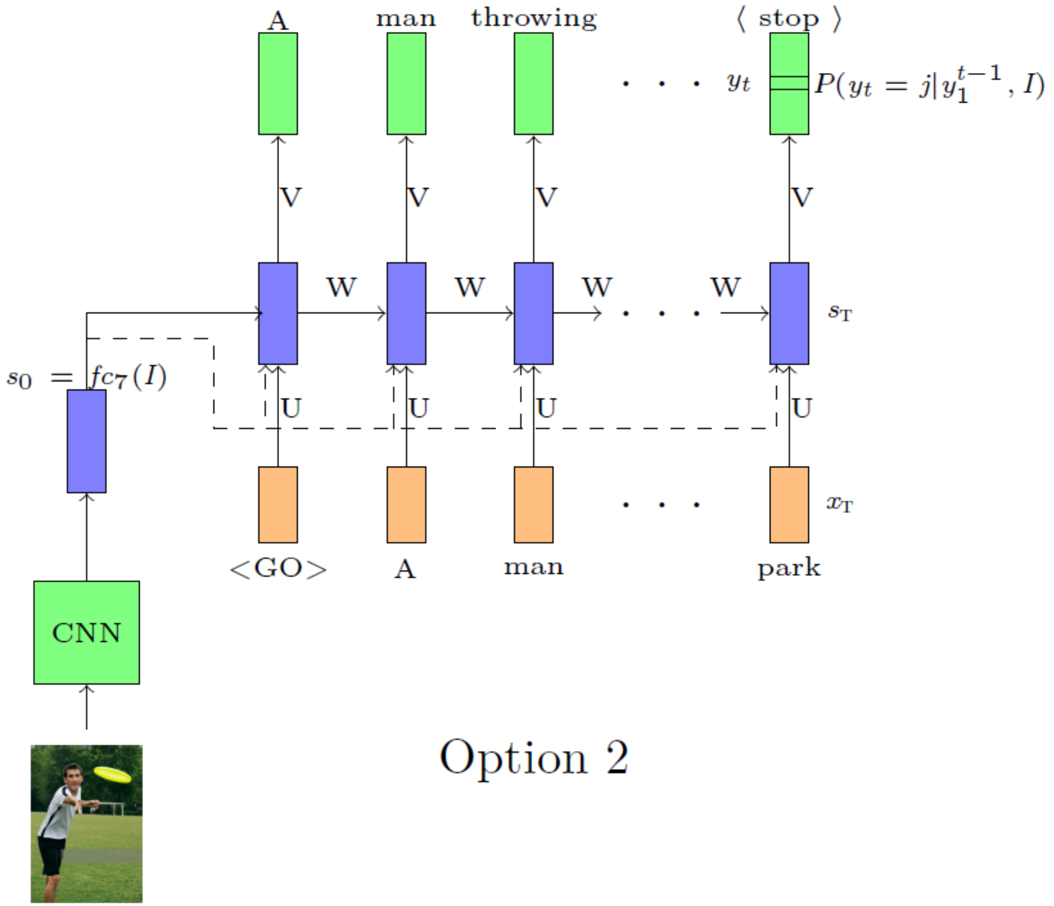


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The o/p of CNN is concatenated with the input embedding and then fed to the RNN as input at each time step.

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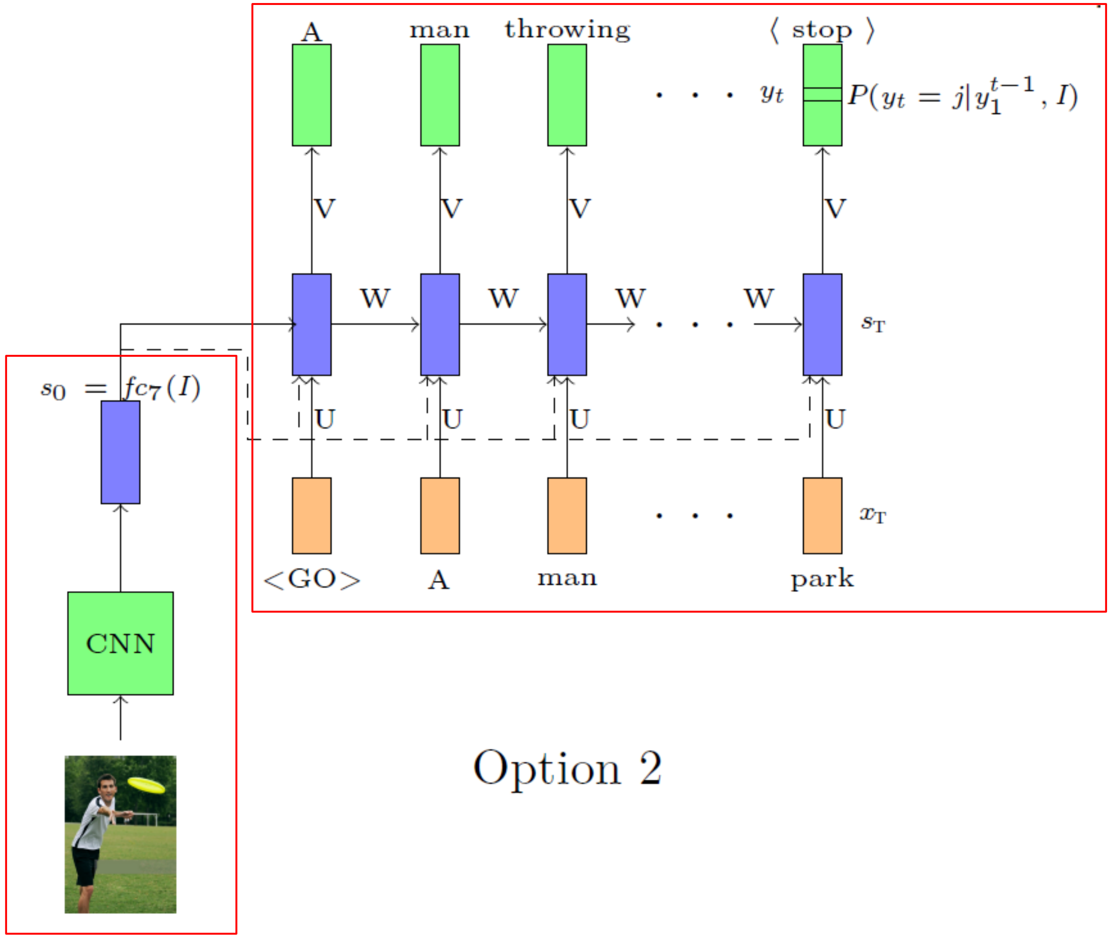


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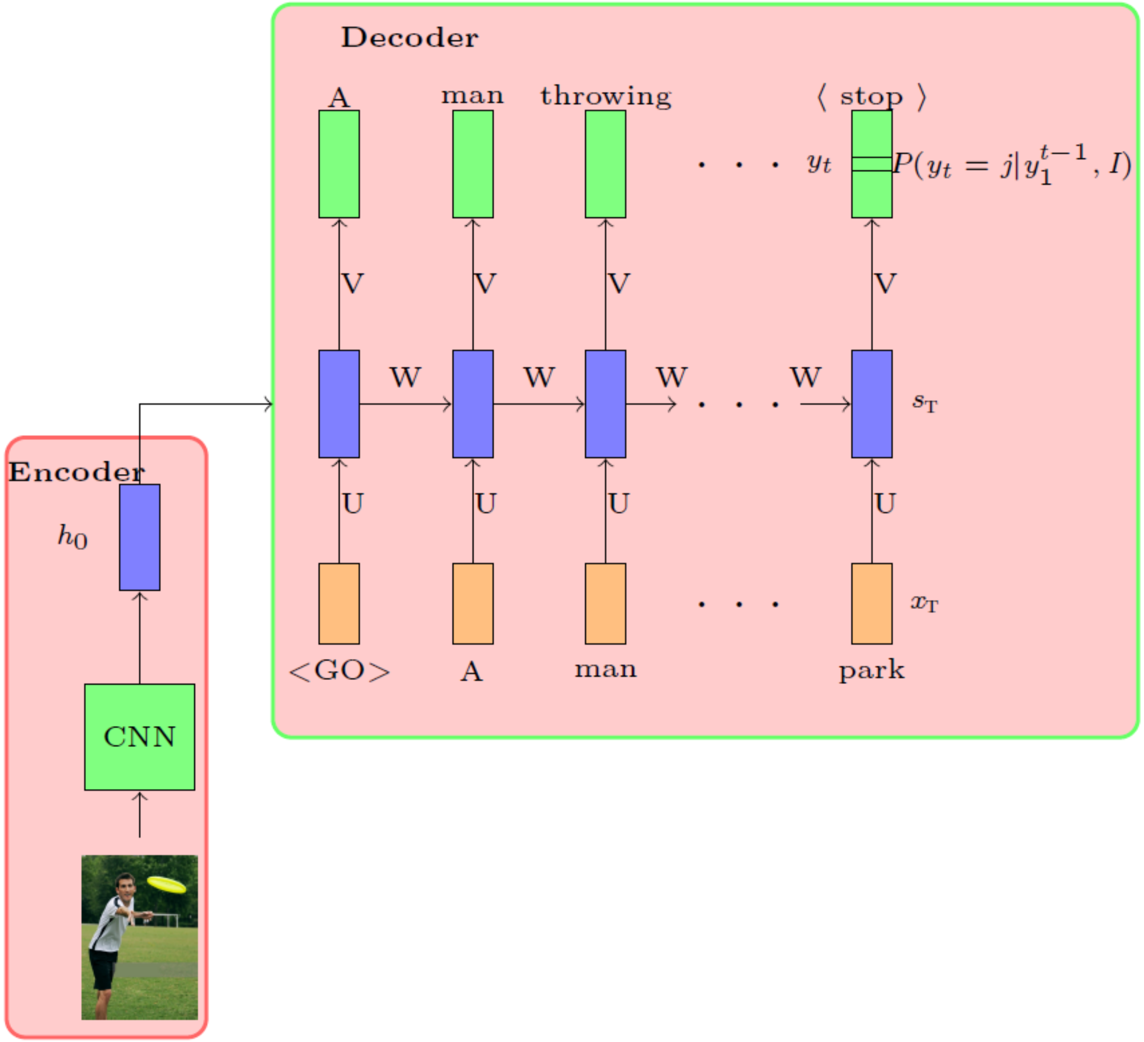


- This is typical **encoder decoder** architecture

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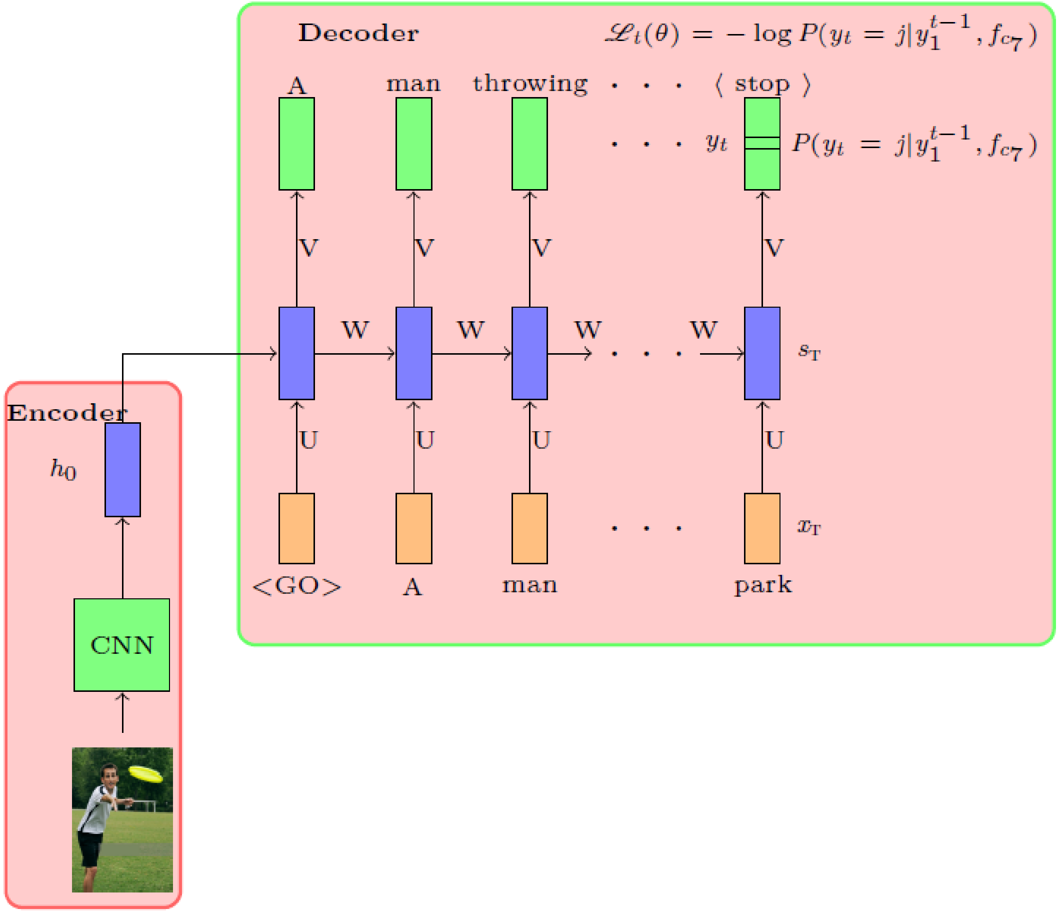
# Applications of Encoder Decoder Models: Image Captioning




- **Task:** Image captioning
- **Data:** $\{x_i = image_i, \ y_i = caption_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**

$$s_0 = CNN(x_i)$$

  - **Decoder:**

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

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

Represents the input embedding of the output obtained at time step t-1

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

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

- **Algorithm:** Gradient descent with backpropagation

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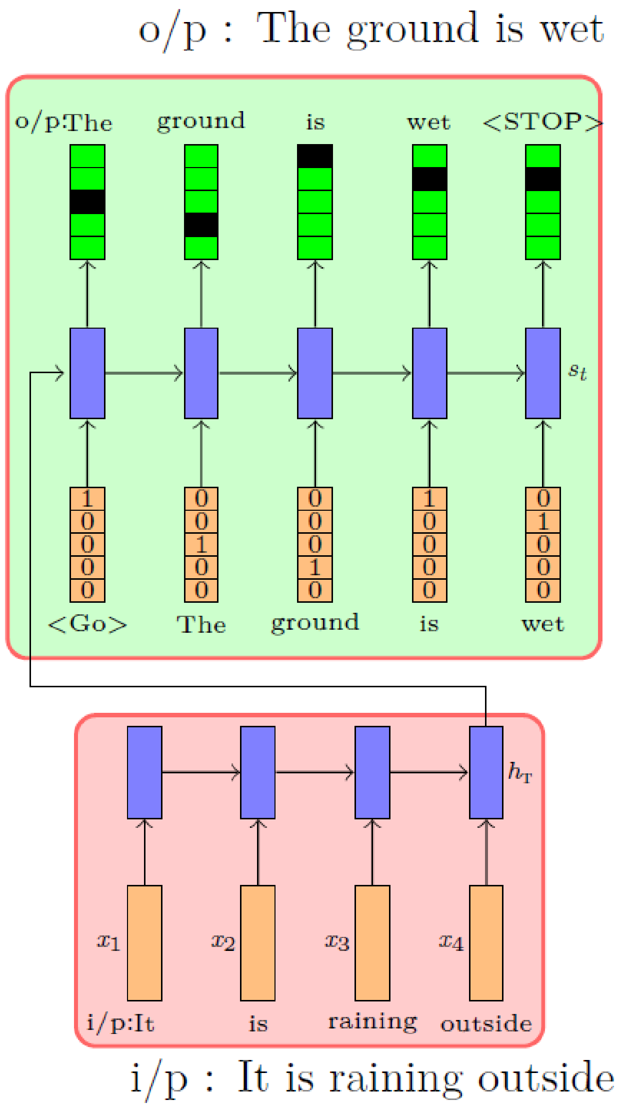
# Applications of Encoder Decoder Models: Textual Entailment




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

- **Task:** Textual entailment
- **Data:** $\{x_i = premise_i,\ y_i = hypothesis_i\}_{i=1}^{N}$
- **Model (Option 1):**
  - **Encoder:**

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

  - **Decoder:**

$$s_0 = h_T \quad (T \textit{ is length of input})$$
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

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

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

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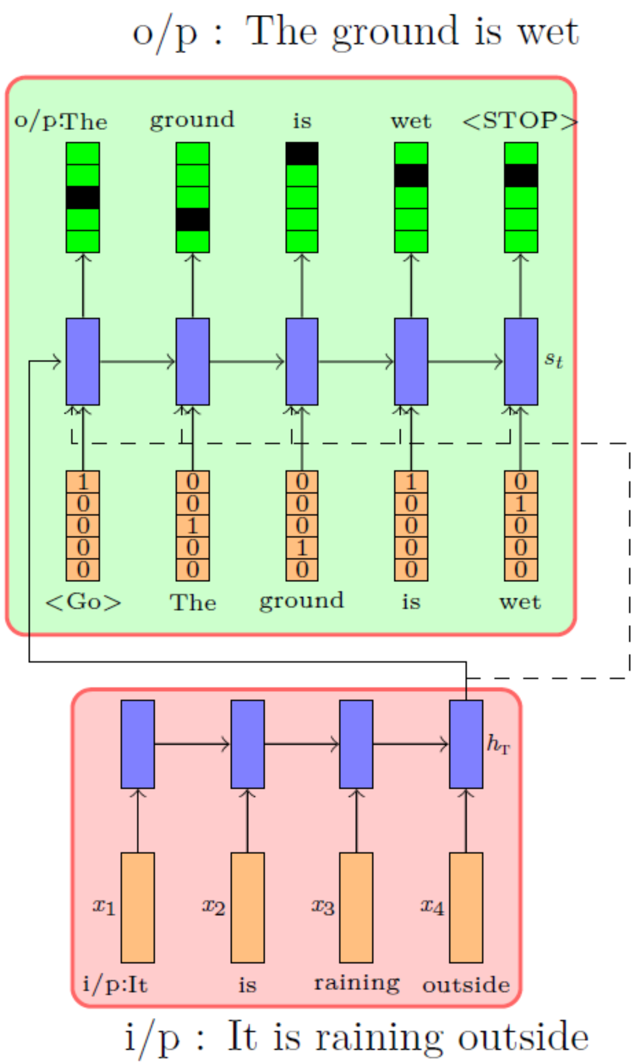



- **Task:** Textual entailment
- **Data:** $\{x_i = premise_i,\ y_i = hypothesis_i\}_{i=1}^{N}$
- **Model** $\boxed{\textbf{(Option 2}}$**):**
  - **Encoder:**

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

  - **Decoder:**

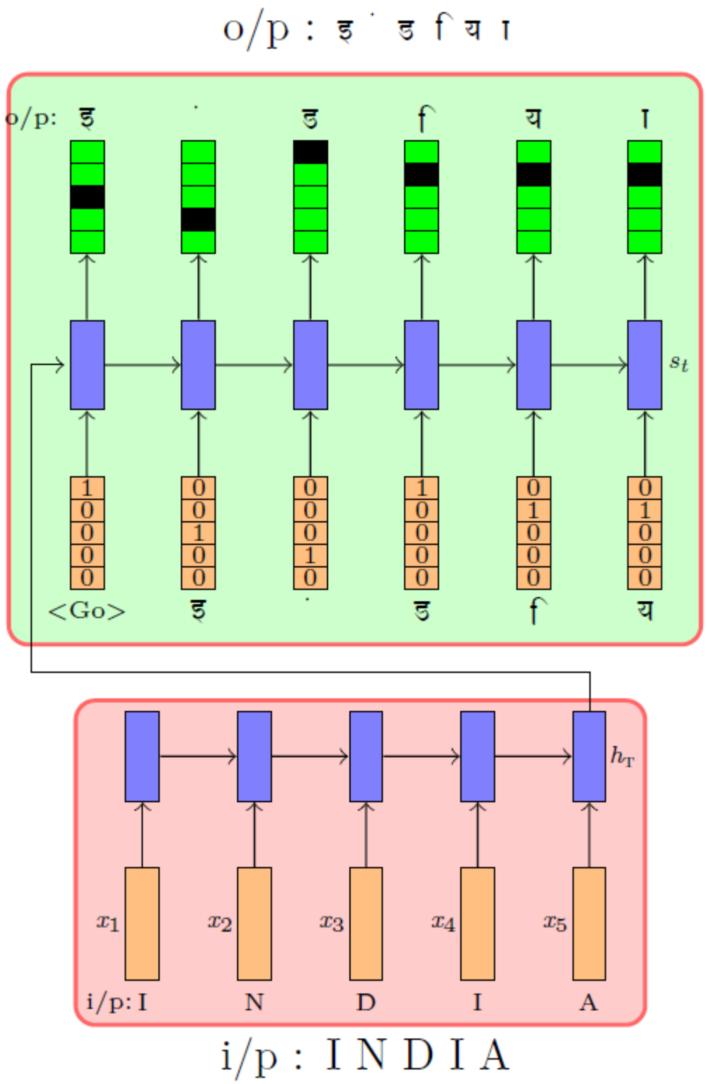
$$s_0 = h_T \quad (T \text{ is length of input})$$
$$s_t = RNN(s_{t-1}, [h_T, e(\hat{y}_{t-1})])$$
$$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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

# Applications of Encoder Decoder Models: Transliteration

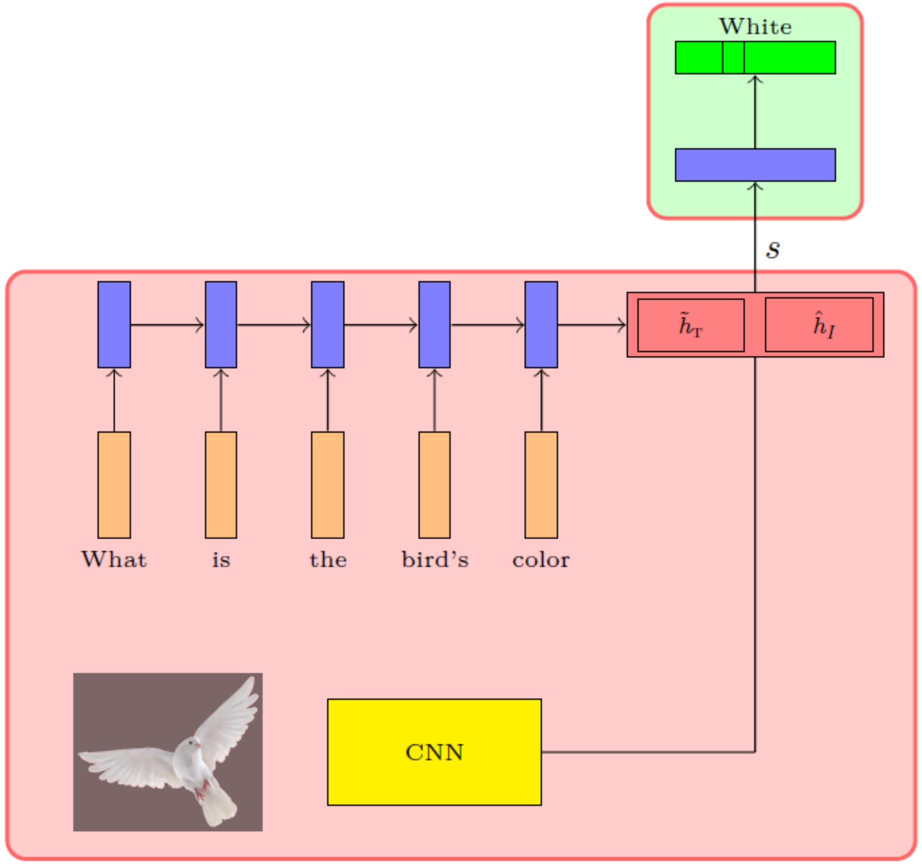



Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

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

# Applications of Encoder Decoder Models: Image Question Answering

O/p: White




Question: What is the bird's color

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

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

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

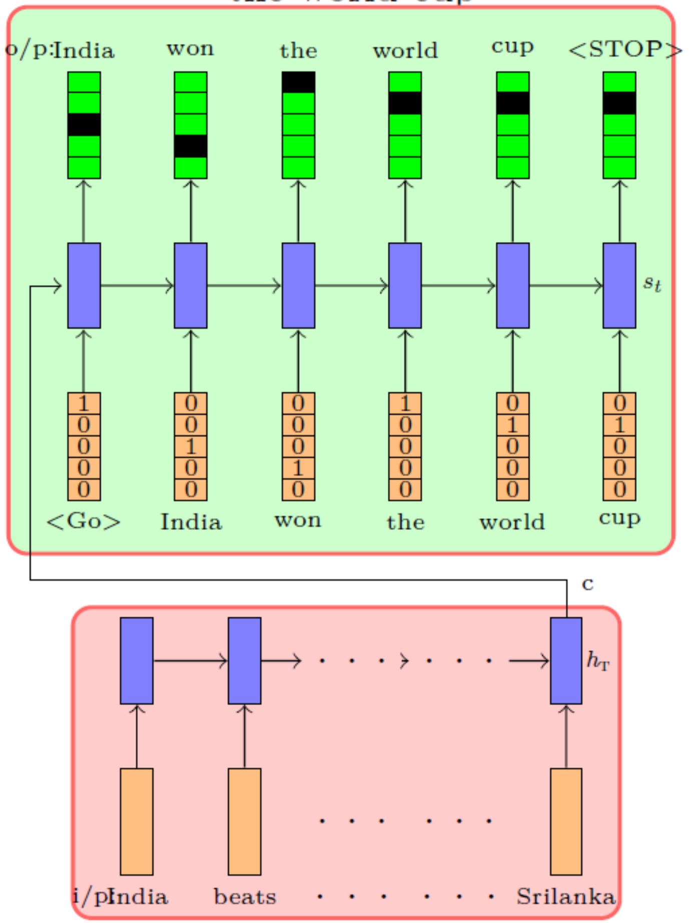
  $$\mathscr{L}(\theta) = -\log P(y = \ell | I, q)$$

- **Algorithm:** Gradient descent with backpropagation

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Applications of Encoder Decoder Models: Document Summarization

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

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

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

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

  - **Decoder:**

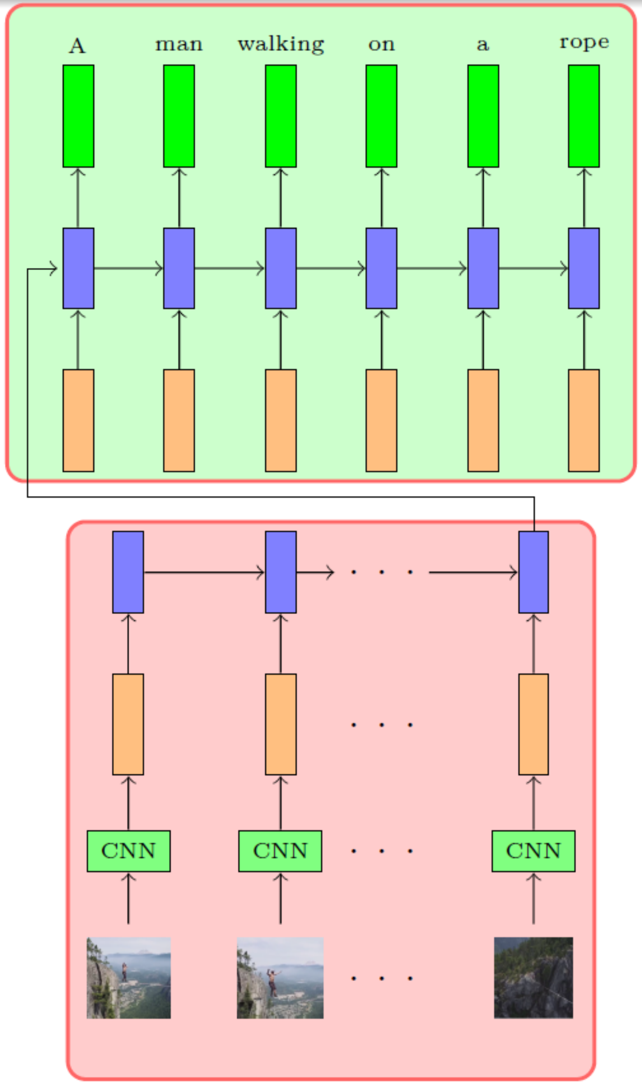
$$s_0 = h_T$$
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

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

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

- **Algorithm:** Gradient descent with backpropagation

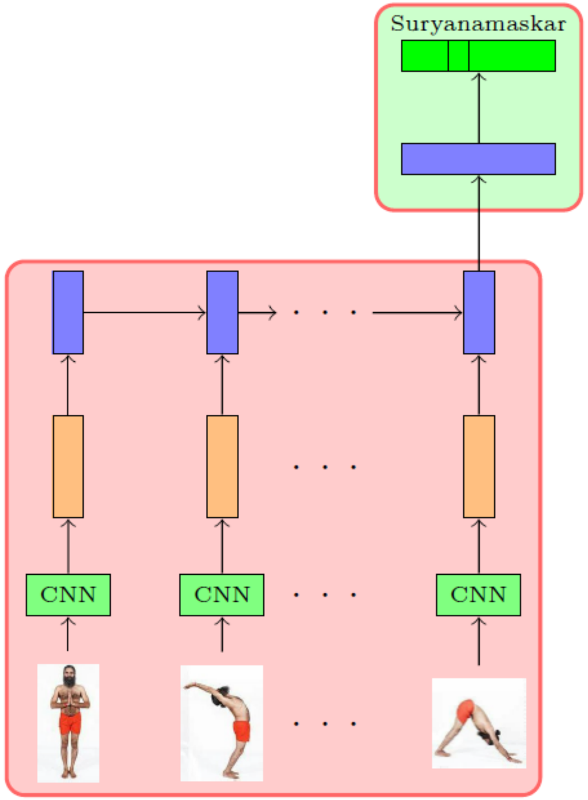
# Applications of Encoder Decoder Models: Video Captioning




- **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:**
    $$s_0 = h_T$$
    $$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
    $$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$
- **Parameters:** $U_{dec}$, $W_{dec}$, $V$, $b$, $W_{conv}$, $U_{enc}$, $W_{enc}$, $b$
- **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

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

o/p: Surya Namaskar

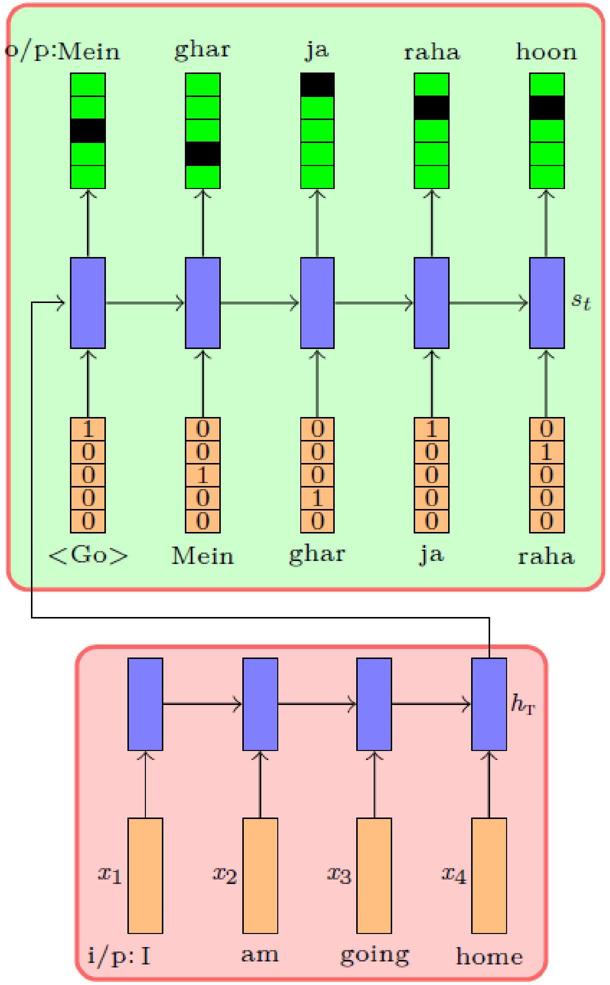



- **Task:** Video Classification
- **Data:** $\{x_i = Video_i,\ y_i = Activity_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**
  $$h_t = RNN(h_{t-1}, CNN(x_{it}))$$
  - **Decoder:**
  $$s = h_T$$
  $$P(y|I) = softmax(Vs + b)$$
- **Parameters:** $V,\ b,\ W_{conv},\ U_{enc},\ W_{enc}, b$
- **Loss:**
  $$\mathscr{L}(\theta) = -\log P(y = \ell | Video)$$
- **Algorithm:** Gradient descent with backpropagation

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Applications of Encoder Decoder Models: Machine Translation

o/p : Mein ghar ja raha hoon




i/p : I am going home

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Applications of Encoder Decoder Models: Machine Translation

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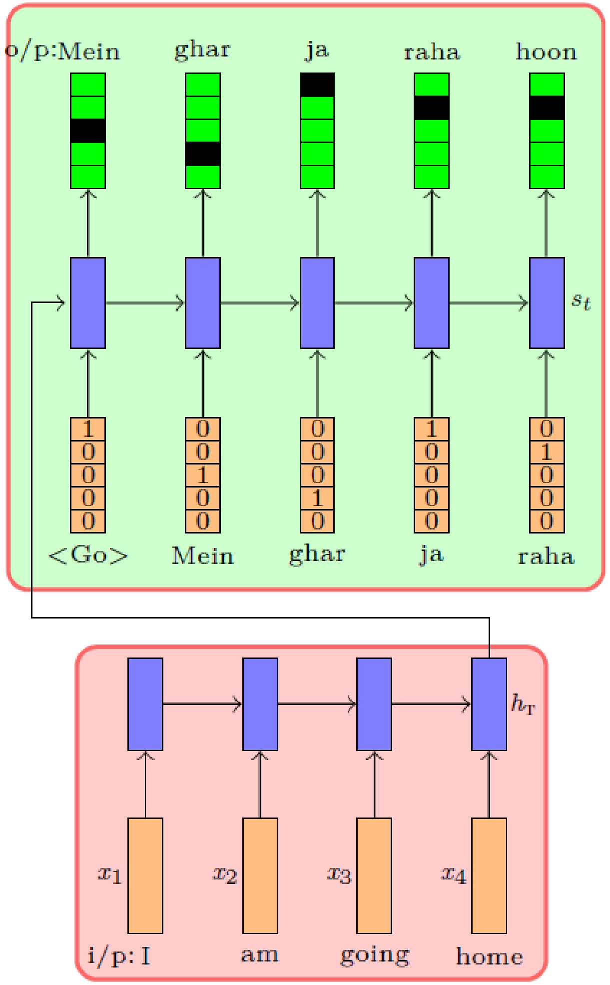



i/p : I am going home

- **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:**

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

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

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

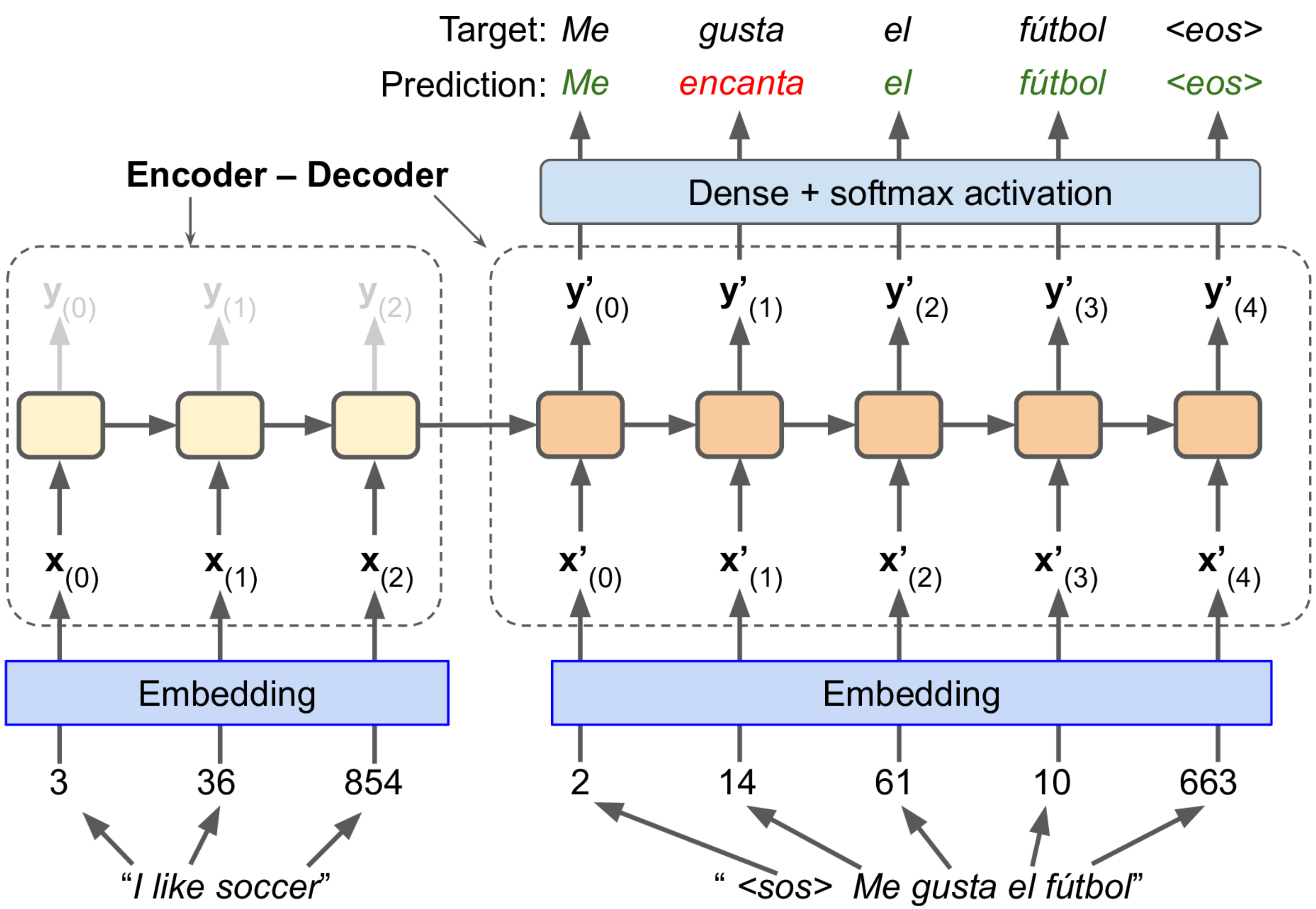
- **Parameters:** $U_{dec},\ V,\ W_{dec},\ U_{enc},\ W_{enc},\ b$
- **Loss:**

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

- **Algorithm:** Gradient descent with backpropagation

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Applications of Encoder Decoder Models: Machine Translation




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Machine Translation as Conditional Learning Problem

- $Y = P(y1, y2, y3 \ldots, yn \mid x1, x2. \ldots., xm)$

- Jane visitr l'Afrique en Septembre (x:French)
  - Jane is visiting Africa in September (y: English)
  - Jane is going to be visiting Africa in September September (y: English)
  - In September, Jane will visit Africa.

- $Y_{argmax(y1,..yn)} = P(y1, y2, y3 \ldots, yn \mid x1, x2. \ldots., xm)$

# Beam Search

**"Comment vas-tu?" – How are you?**
**"Comment vas-tu jouer?" – How will you play?**
*Model could output "How will you?"*

- Since model greedily outputs the most likely word at each step, it ended with suboptimal translation
- Can model go back and correct mistakes?
- **Beam Search**
  - Keeps track of a short list of the k most promising sentences
  - Parameter k is beam width
  - At each decoder step it tries to extend them by 1 word
- **Step 1:** First word could be "How" (Prob: 75%), "what" or "you"
- **Step 2:** 3 copies of model made to find the next word
- **Step 3:** First model will look for next word after "How" by computing conditional probabilities
  - Output could be "will (Prob:36%) "are", "do",
- **Step 4:** Compute the probabilities of each of the two word sentences the model considered and so on
- Advantage is that good translation for fairly short sentences can be obtained
- Disadvantage – really bad at translating long sentences.
- Due to limited short term memory, let to **ATTENTION MECHANISM**

# Attention Mechanism (Bahdanau et al , 2014)

- Technique that allowed the decoder to focus on the appropriate words at each time steps
- Ensures that the path to from an input word to its translation is much shorter
- For instance , at the time step where the decoder needs to output the word 'lait' it focusses on the word "milk"
- Path from input word to translation is smaller, so not affected by the short term limitations of RNNS
- **Visual Attention**
  - For example : Generating image captions using visual attentions
  - CNN processes image and outputs some feature maps
  - Then decoder RNN with attention generates the caption , one word at a time
- **Leads to Explainability (Ribeiro et al. 2016)**
  - **What led the model to produce its output**
  - **Which leads to fairness in results**
    - **Google apologizes after its Vision AI produced racist results**

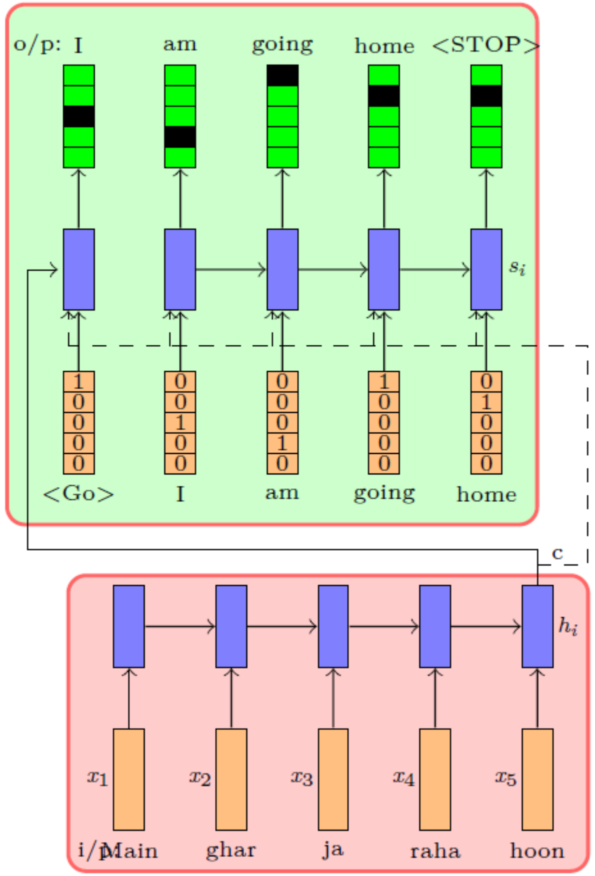
# Attention Mechanism (Bahdanau et al , 2014)

- Attention is proposed as a method to both align and translate.
  - **Alignment**
    - is the problem in machine translation that identifies which parts of the input sequence are relevant to each word in the output
  - **translation**
    - is the process of using the relevant information to select the appropriate output
- *"... we introduce an extension to the encoder–decoder model which learns to align and translate jointly. Each time the proposed model generates a word in a translation, it (soft-)searches for a set of positions in a source sentence where the most relevant information is concentrated. The model then predicts a target word based on the context vectors associated with these source positions and all the previous generated target words."*
  - Neural Machine Translation by Jointly Learning to Align and Translate, 2015.

# Attention Mechanism: Introduction

**Task:** Machine translation

o/p : I am going home

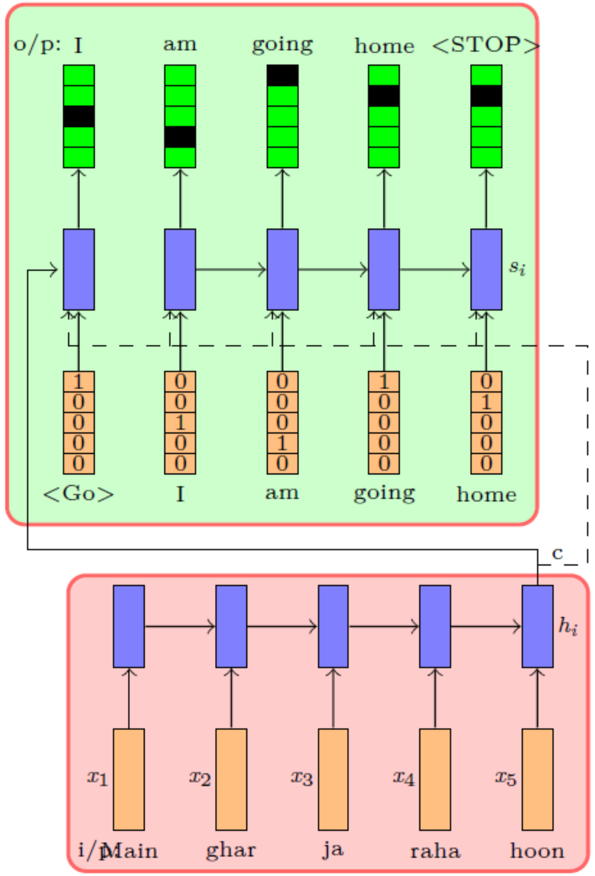



i/p : Main ghar ja raha hoon

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

**Task:** Machine translation

o/p : I am going home




i/p : Main ghar ja raha hoon

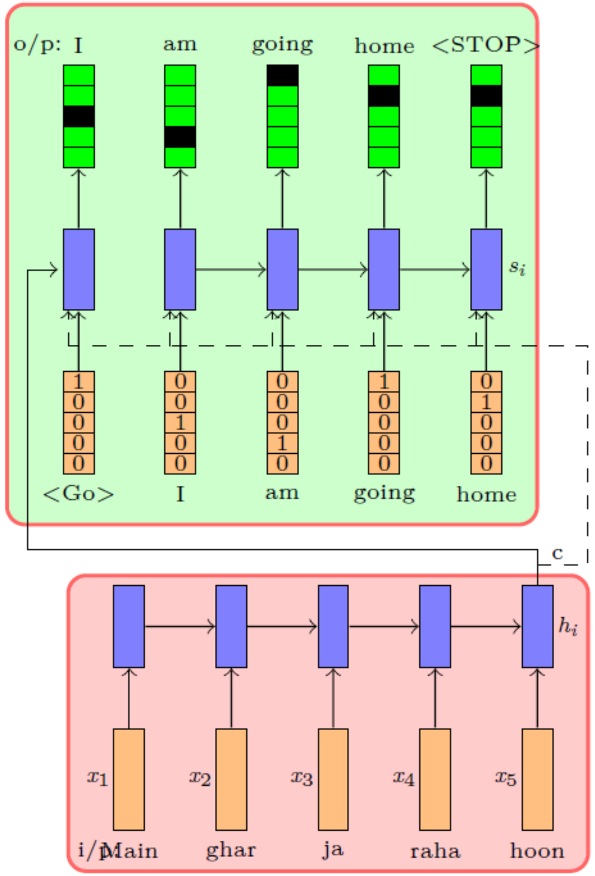
- In a typical encoder decoder network, each time step of the decoder uses the information obtained from the last time step of the encoder.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Attention Mechanism: Introduction

**Task:** Machine translation

o/p : I am going home




i/p : Main ghar ja raha hoon

- In a typical encoder decoder network, each time step of the decoder uses the information obtained from the last time step of the encoder.
- However, the translation would be effective if the network could focus/or pay attention to specific input word that would contribute to the prediction.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Attention Mechanism: Introduction

- Consider the task of machine translation:

$$\text{o/p : I am going home}$$

$$\text{i/p : Main ghar ja raha hoon}$$

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

While predicting each word in the o/p we would like our model to mimic humans and focus on specific words in the i/p

o/p : I am going home

$t_1$ : [ 1 0 0 0 0 ]

i/p : Main ghar ja raha hoon

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Attention Mechanism: Introduction

While predicting each word in the o/p we would like our model to mimic humans and focus on specific words in the i/p

$$\text{o/p} : \text{I am going home}$$

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

$$t_2 : [\ 0\ 0\ 0\ 0\ 1\ ]$$

$$\text{i/p} : \text{Main ghar ja raha hoon}$$

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

While predicting each word in the o/p we would like our model to mimic humans and focus on specific words in the i/p

$$\text{o/p : I am going home}$$

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

$$t_2 : [\ 0\ 0\ 0\ 0\ 1\ ]$$

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

$$\text{i/p : Main ghar ja raha hoon}$$

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Attention Mechanism: Introduction

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 ]

$t_4$ : [ 0 1 0 0 0 ]

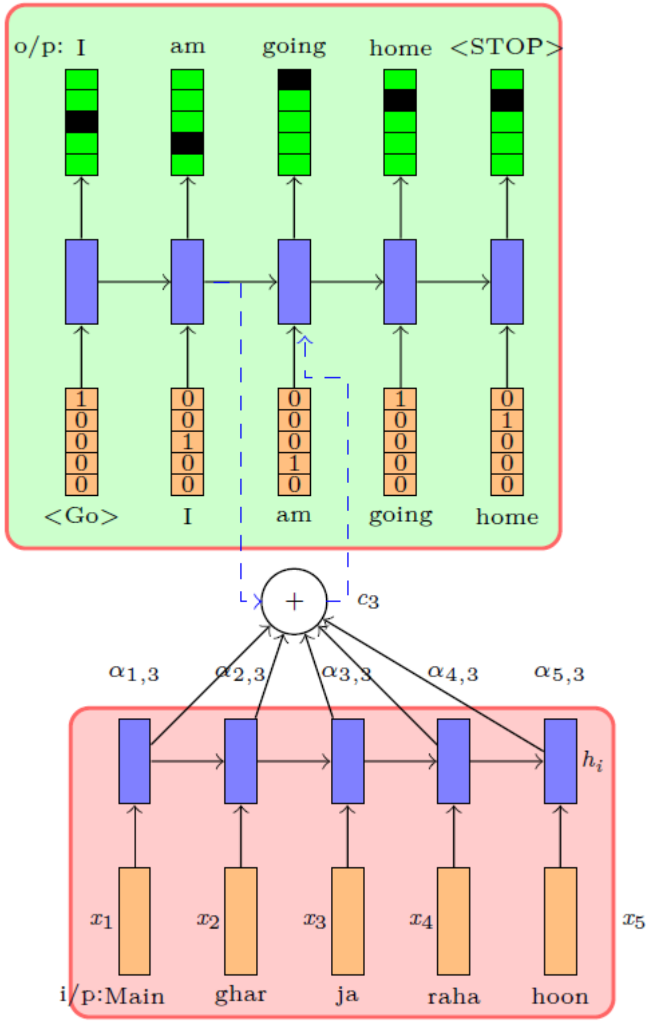
i/p : Main ghar ja raha hoon

- Essentially, at each time step, a distribution on the input words must be introduced.
- This distribution tells the model how much attention to pay to each input words at each time step.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

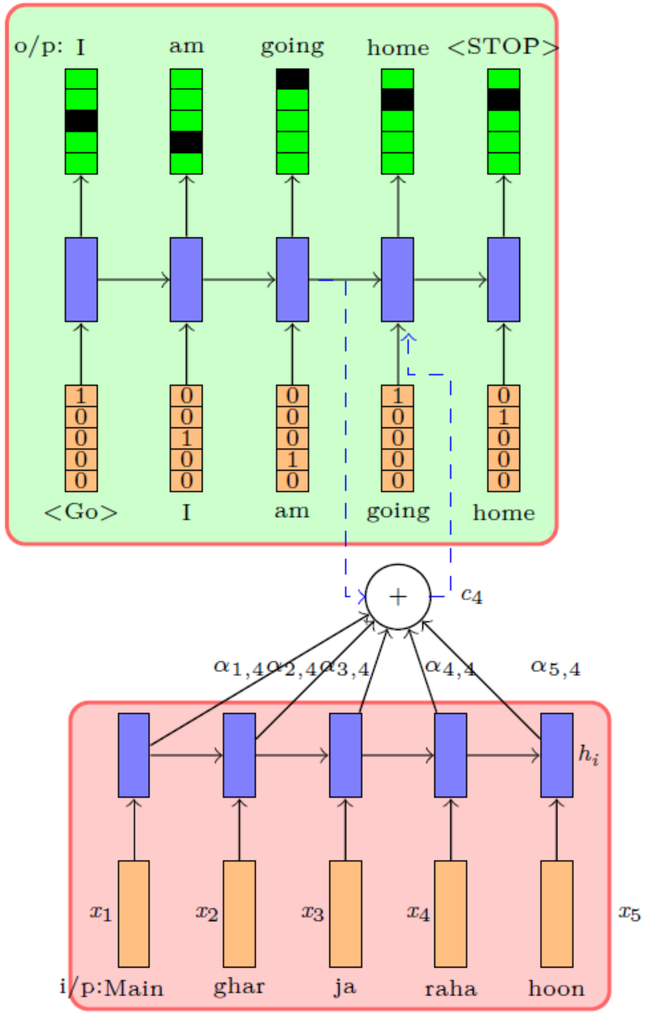
# Encoder Decoder with Attention Mechanism

**Task:** Machine translation




- To do this, we could just take a weighted average of the corresponding word representations and feed it to the decoder

**Task:** Machine translation

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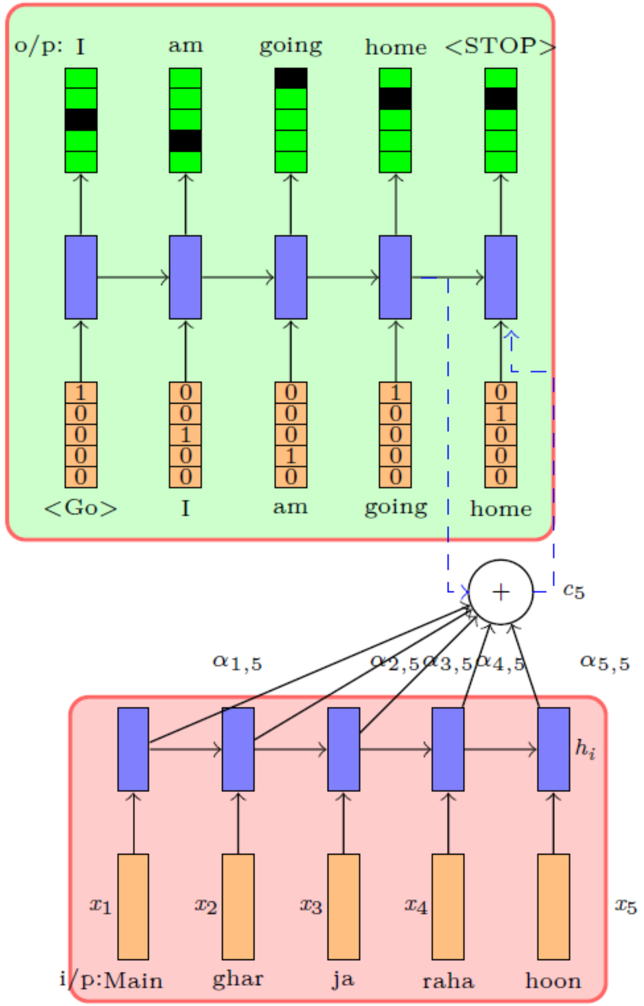
Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation

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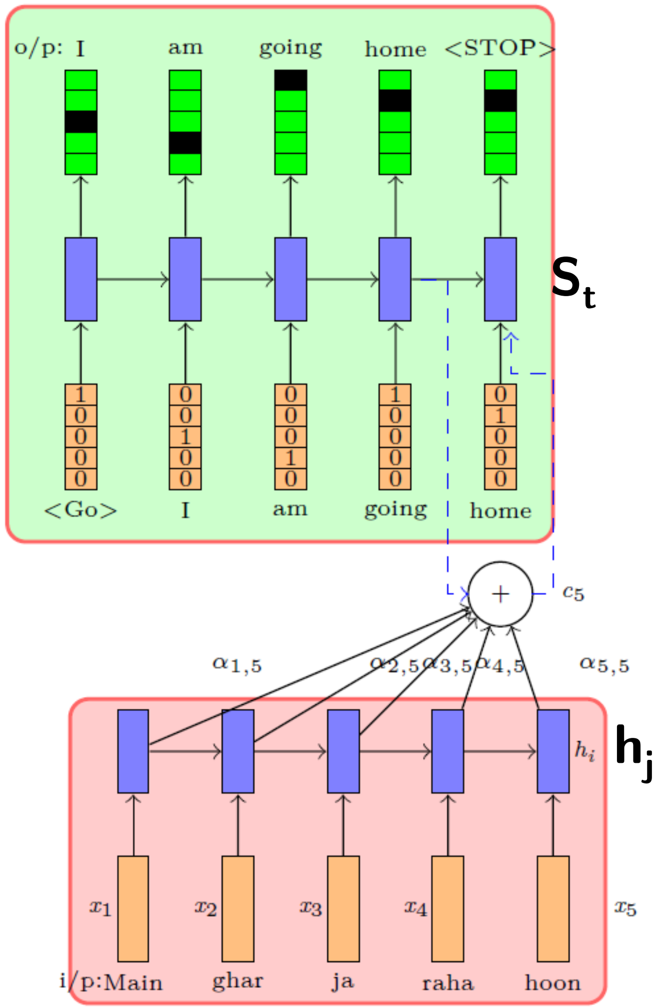
# Encoder Decoder with Attention Mechanism

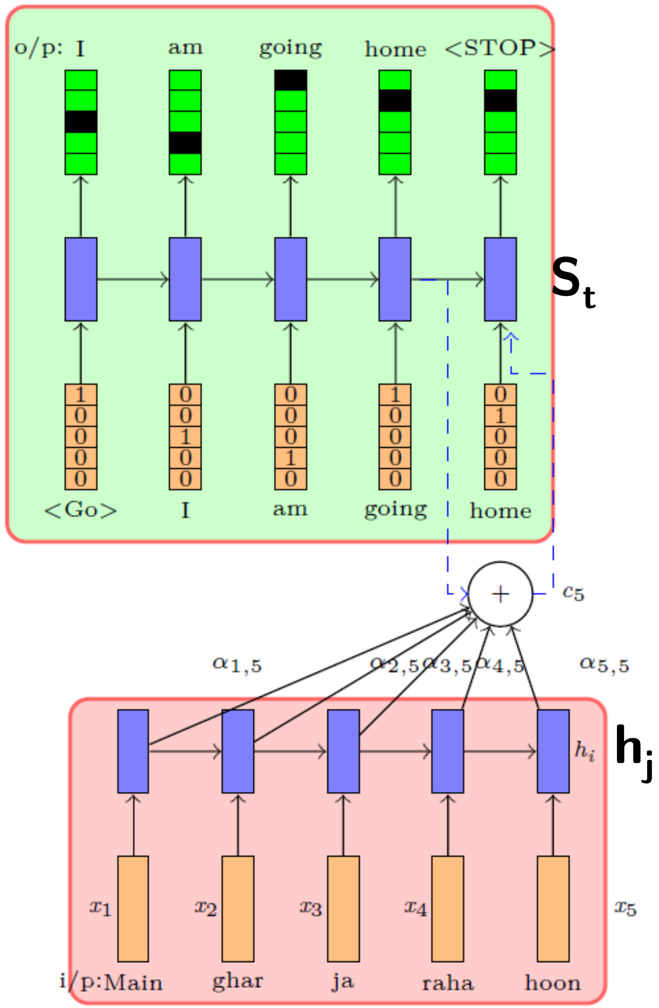
**Task:** Machine translation




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation

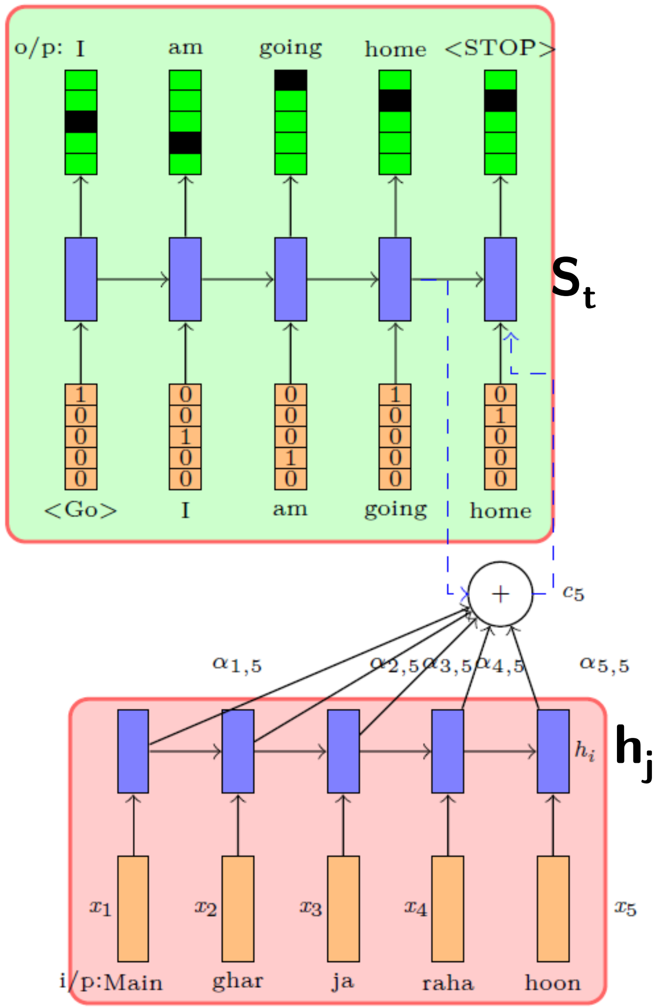



- To enable the network to focus on certain data we define the following function:

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation



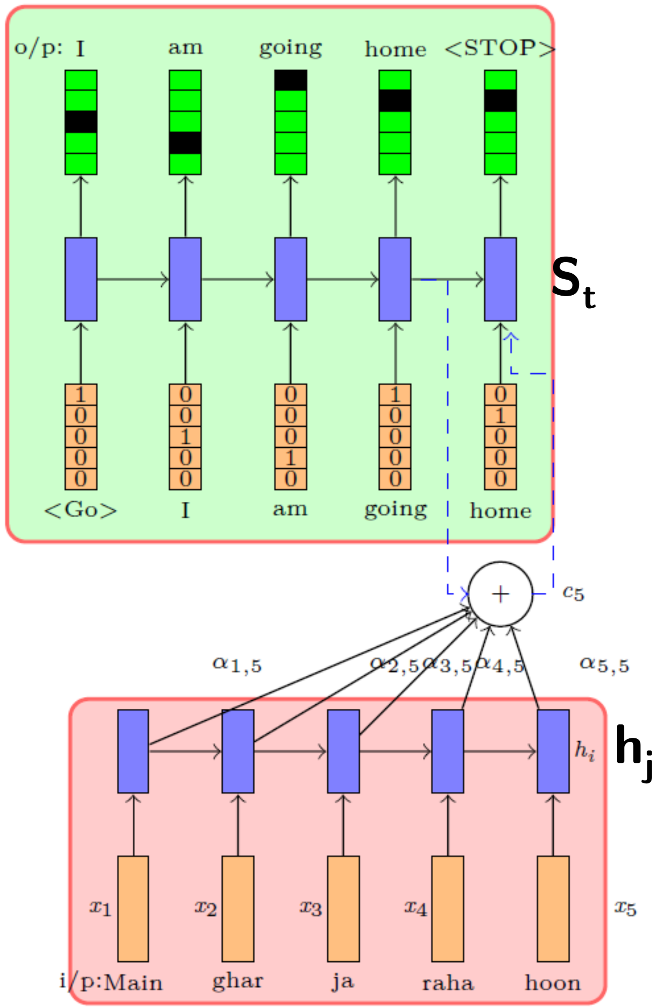

- To enable the network to focus on certain data we define the following function:

$$e_{jt} = f_{ATT}(s_{t-1}, \mathbf{h_j})$$

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation




- To enable the network to focus on certain data we define the following function:

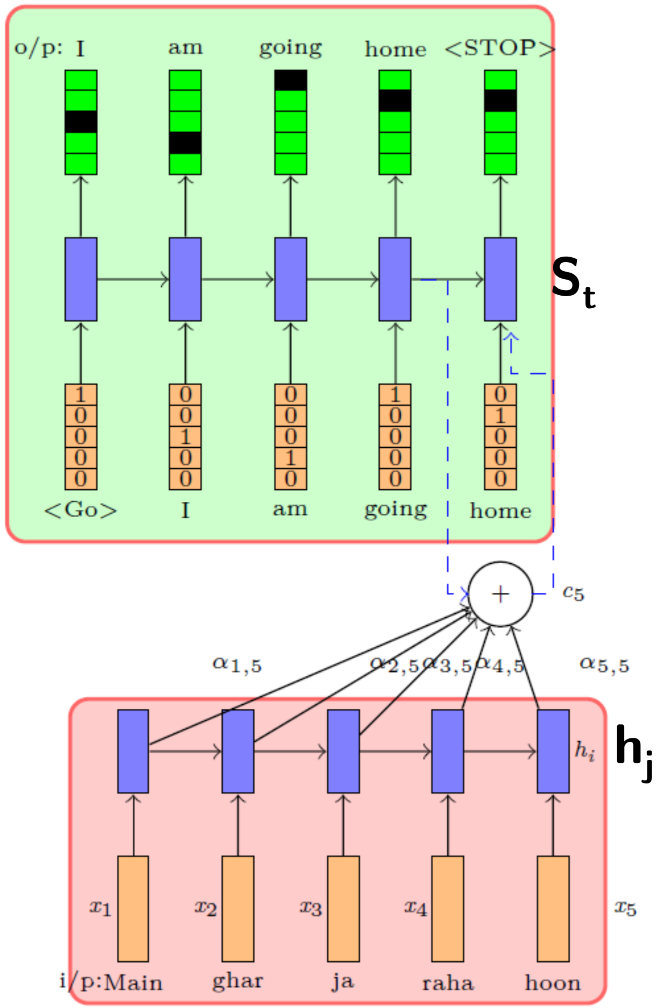
$$e_{jt} = f_{ATT}(s_{t-1}, \mathbf{h_j})$$

Can be considered as a separate feed forward network

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation




- To enable the network to focus on certain data we define the following function:

$$e_{jt} = f_{ATT}(s_{t-1}, \mathbf{h_j}) \longrightarrow$$

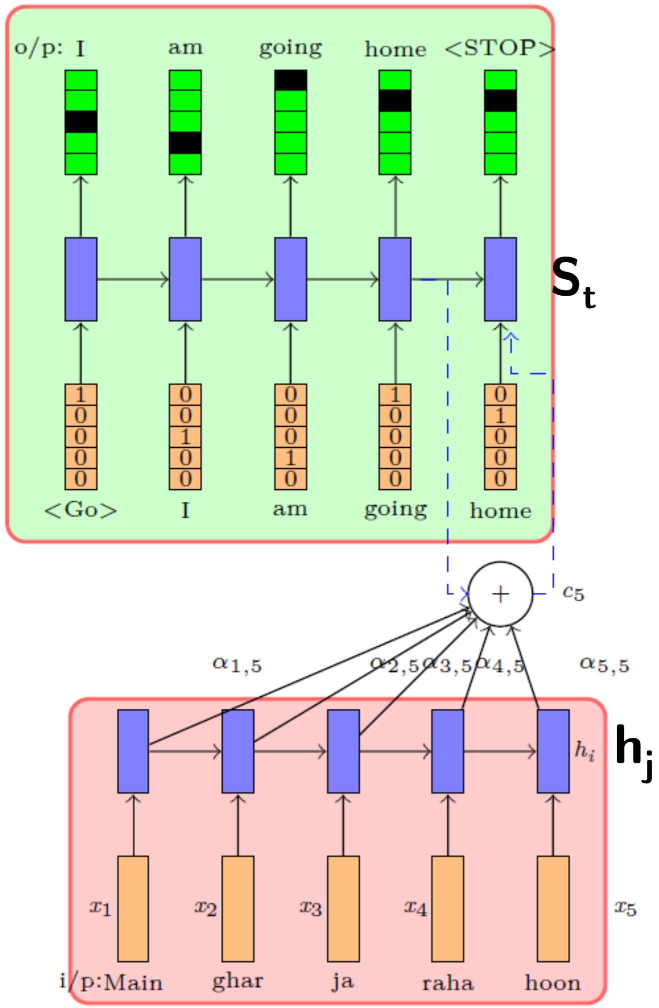
Can be considered as a separate feed forward network

- This quantity captures the importance of the $j^{th}$ input word for decoding the $t^{th}$ output word.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation

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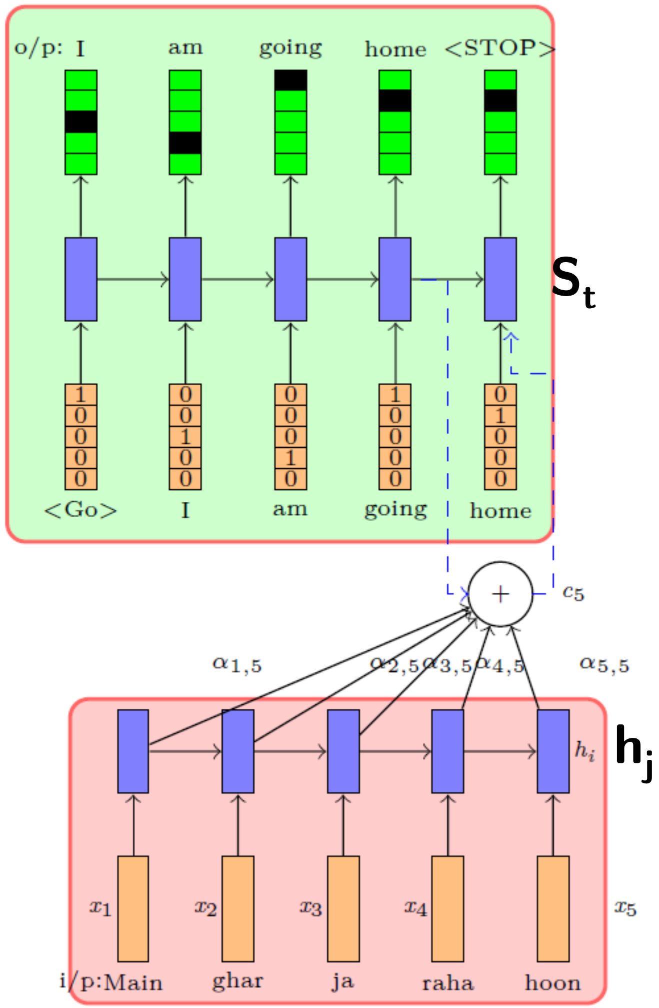
Can be considered as a separate feed forward network

- This quantity captures the importance of the $j^{th}$ input word for decoding the $t^{th}$ output word.

- We could compute $\alpha_{jt}$ by normalizing these weights using the softmax function.

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation

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Can be considered as a separate feed forward network

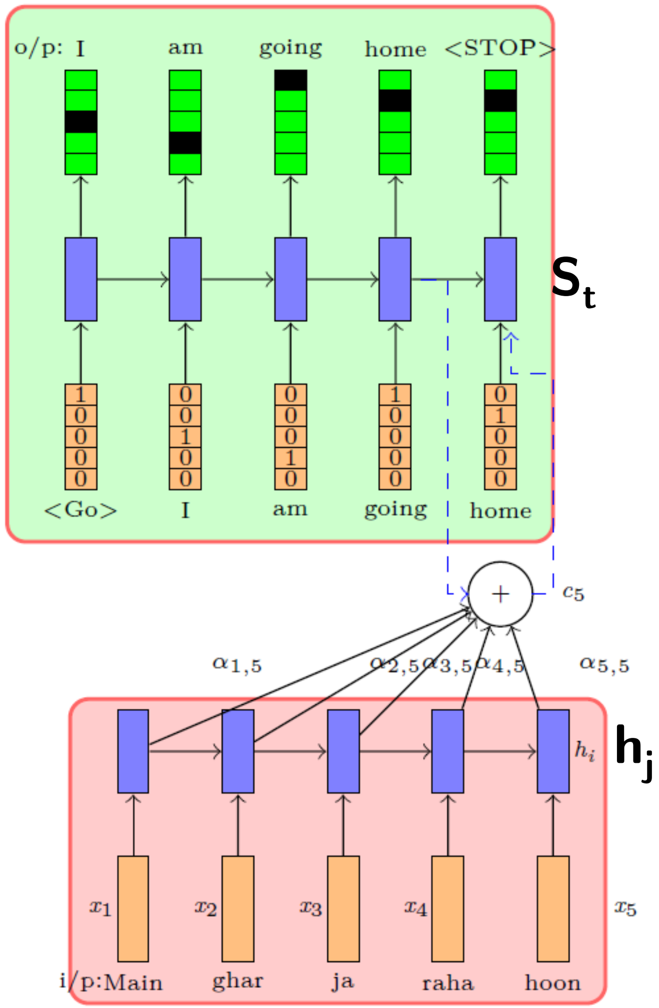
- This quantity captures the importance of the $j^{th}$ input word for decoding the $t^{th}$ output word.

- We could compute $\alpha_{jt}$ by normalizing these weights using the softmax function.

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

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

**Task:** Machine translation

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Can be considered as a separate feed forward network

- This quantity captures the importance of the j^th input word for decoding the t^th output word.

- We could compute $\alpha_{jt}$ by normalizing these weights using the softmax function.

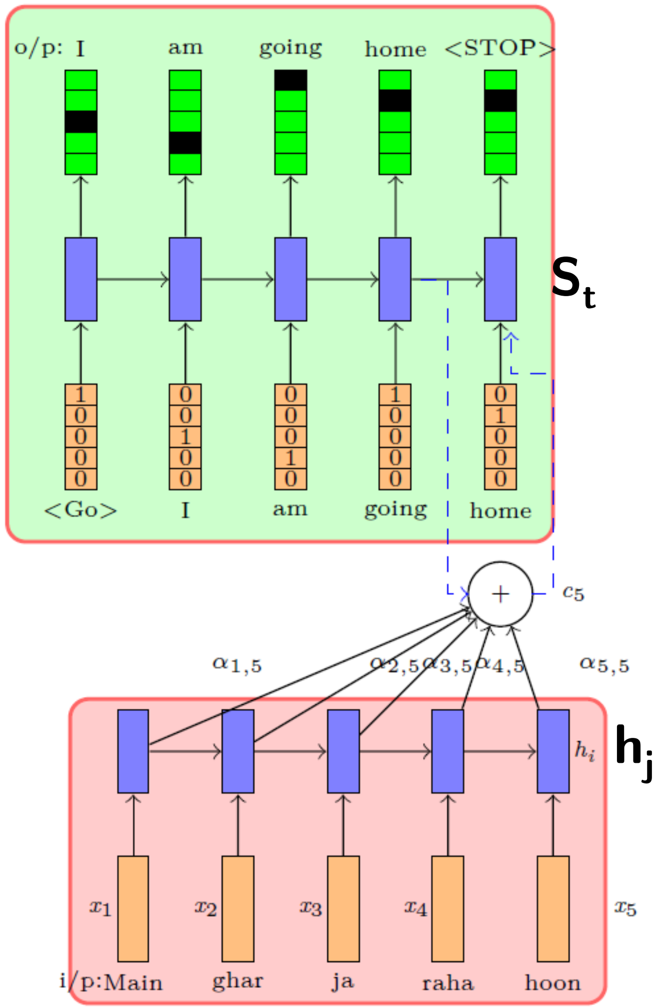
$$\alpha_{jt} = \frac{exp(e_{jt})}{\sum_{j=1}^{M} exp(e_{jt})}$$

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

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation

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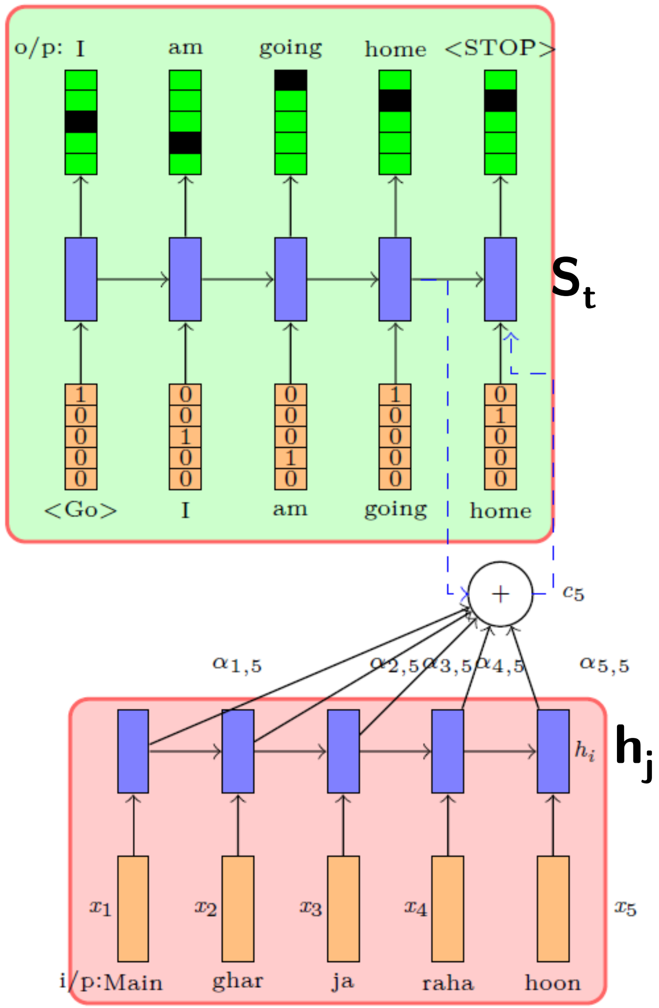


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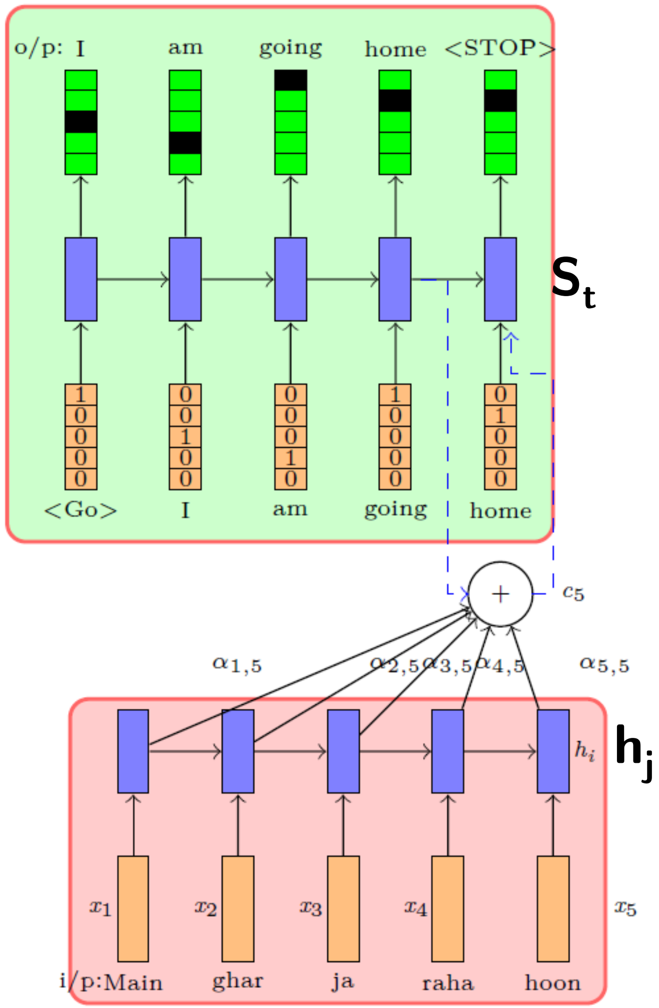


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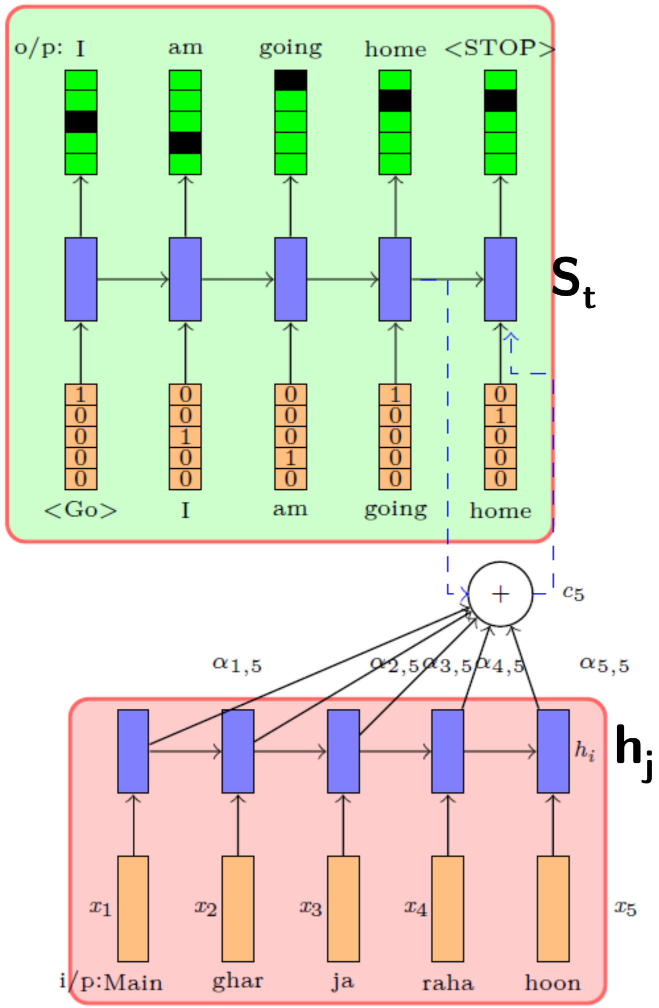


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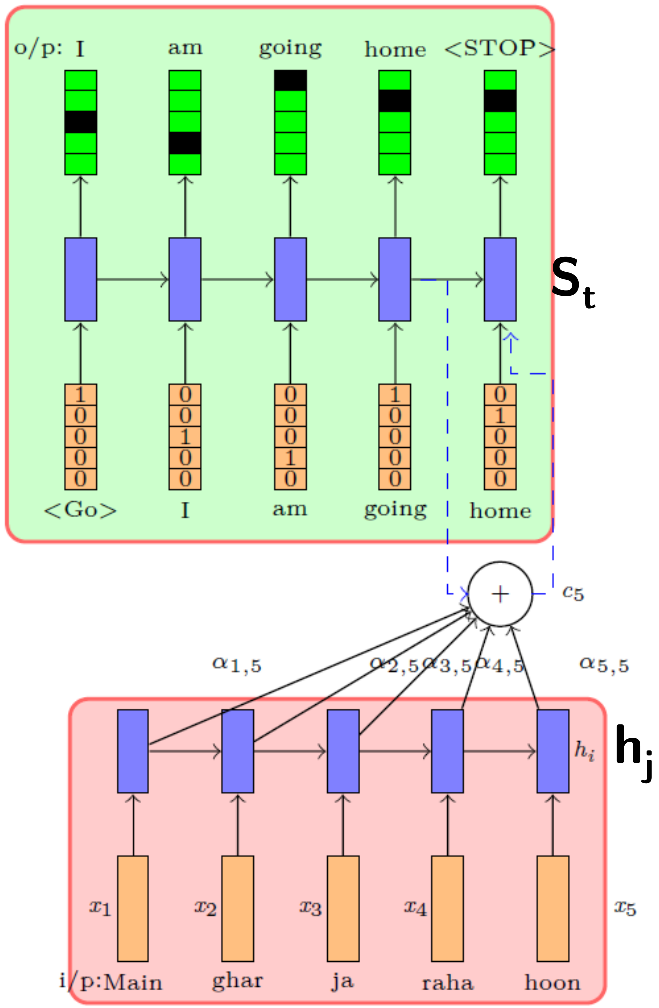


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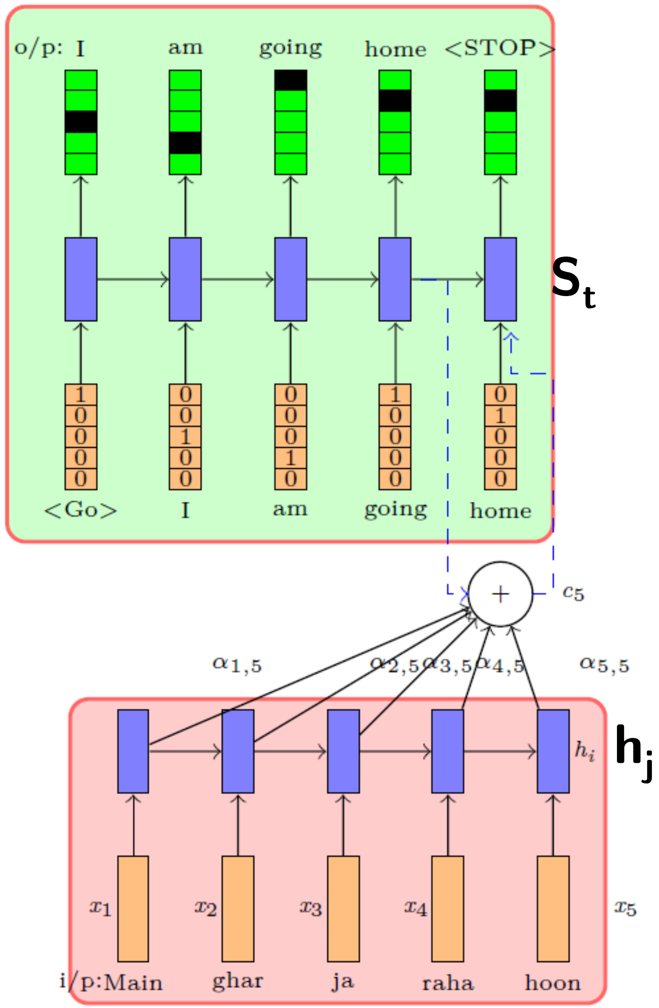
**Task:** Machine translation

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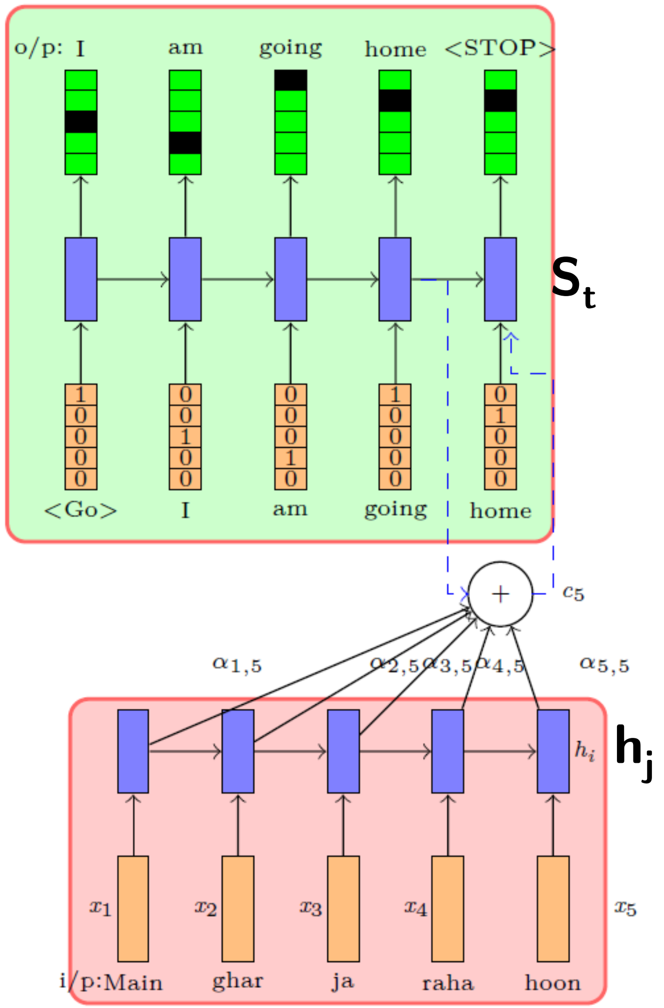
Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

**Task:** Machine translation




- To enable the network to focus on certain data we define the following function:

$$e_{jt} = f_{ATT}(s_{t-1}, \mathbf{h_j})$$

- This quantity captures the importance of the $j^{th}$ input word for decoding the $t^{th}$ output word.

- We could compute $\alpha_{jt}$ by normalizing these weights using the softmax function.

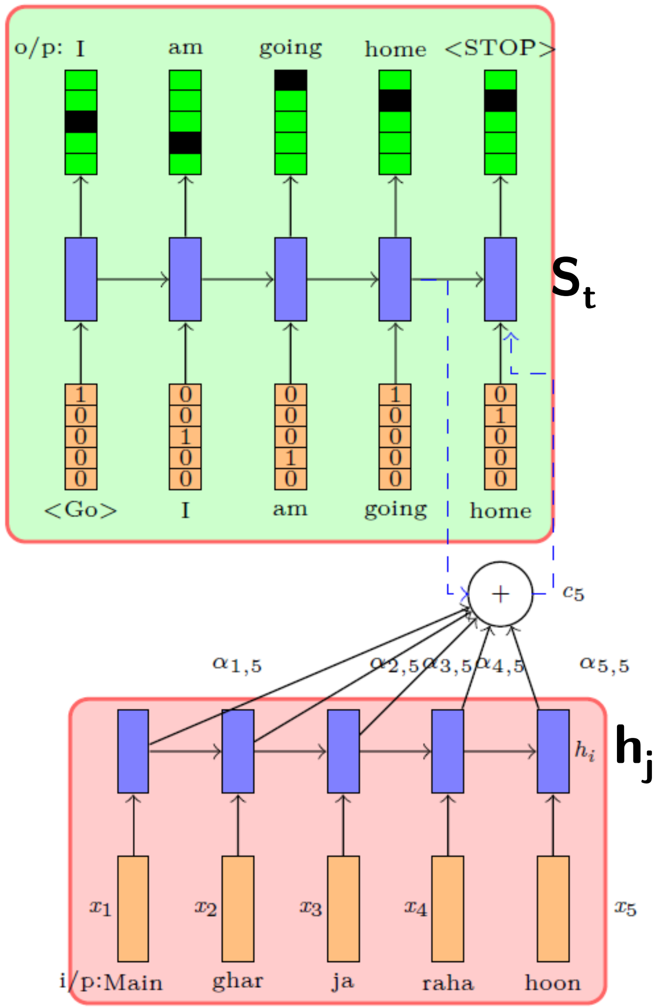
$$\alpha_{jt} = \frac{exp(e_{jt})}{\sum_{j=1}^{M} exp(e_{jt})}$$

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

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation




- Introducing the parametric form of $\alpha$ :

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

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

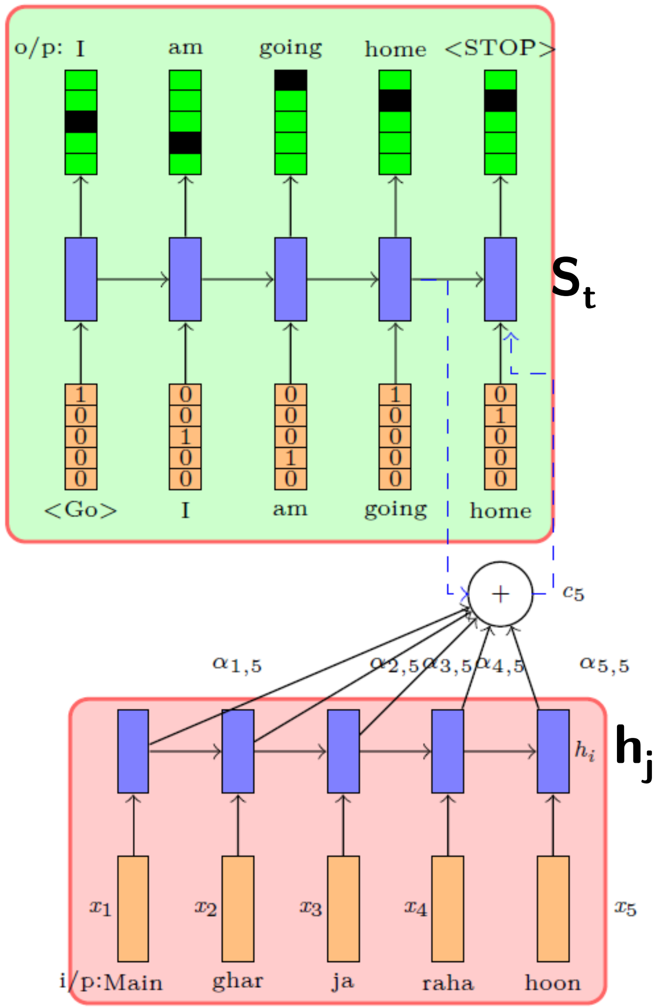
$$\boxed{c_t = \sum_{j=1}^{T} \alpha_{jt} h_j}$$

- Where, $c_t$ (context) gives a weighted sum over the inputs.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Encoder Decoder with Attention Mechanism

**Task:** Machine translation



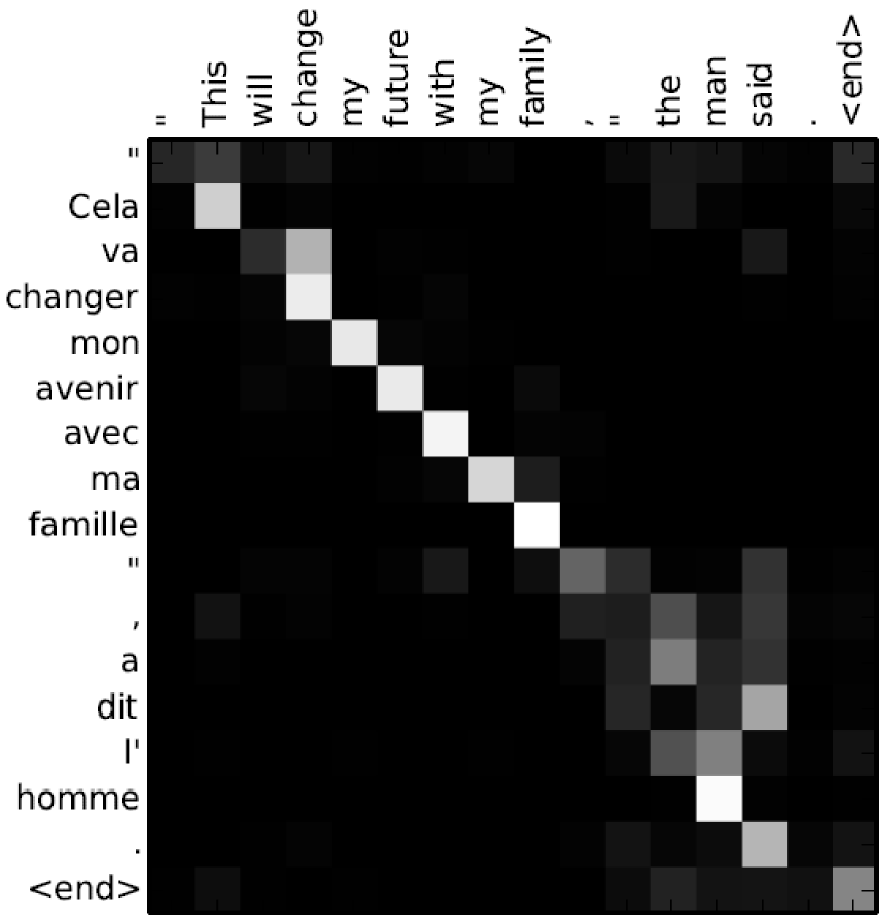

- **Data:** $\{x_i = source_i,\ y_i = target_i\}_{i=1}^{N}$
- **Encoder:**

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

- **Decoder:**

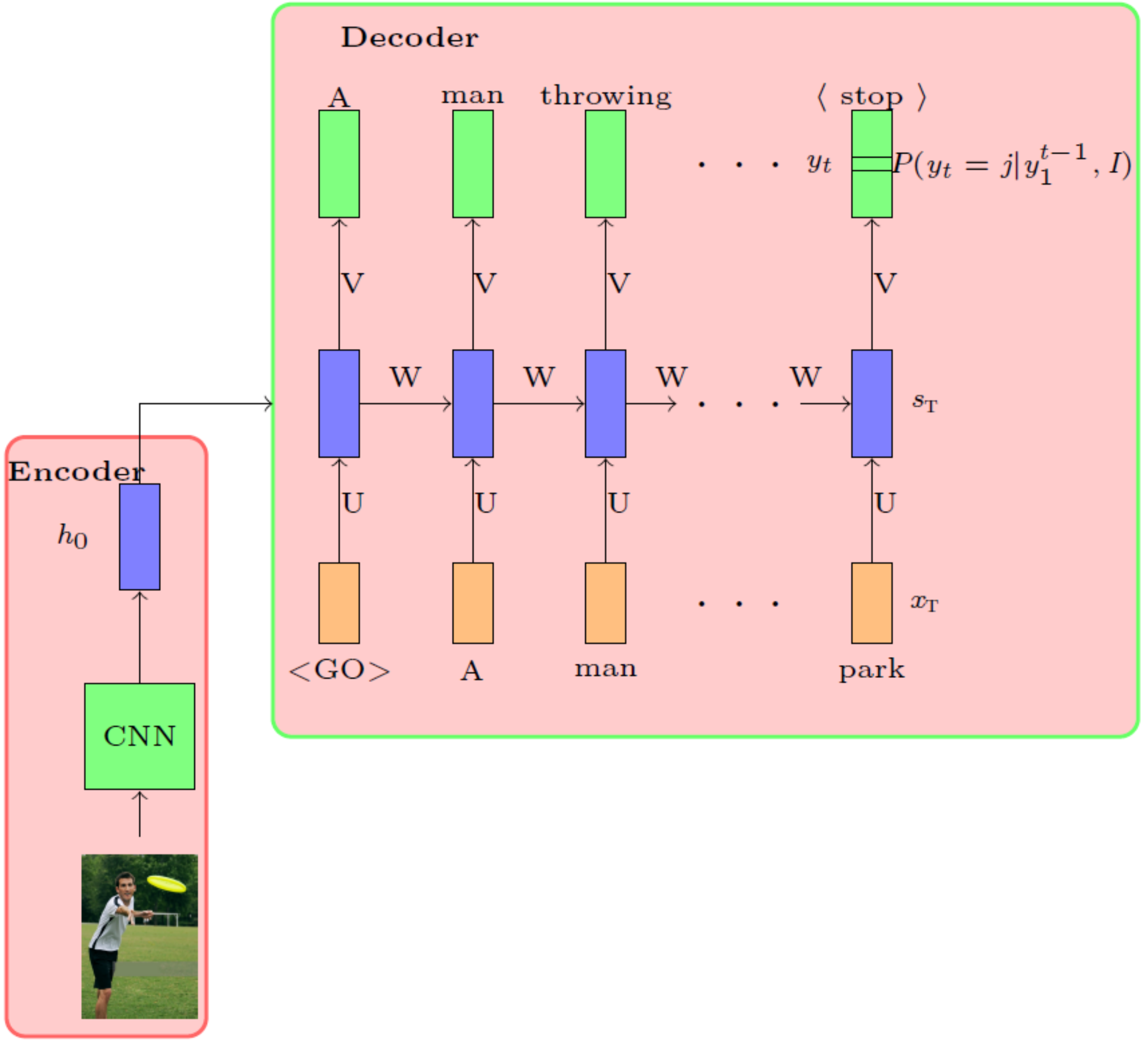
$$e_{jt} = V_{attn}^{T} tanh(U_{attn} h_j + W_{attn} s_t)$$
$$\alpha_{jt} = softmax(e_{jt})$$
$$c_t = \sum_{j=1}^{T} \alpha_{jt} h_j$$
$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), c_t])$$
$$\ell_t = softmax(V s_t + b)$$

- **Parameters:** $U_{dec},\ V,\ W_{dec},\ U_{enc},\ W_{enc},\ b,\ U_{attn},\ V_{attn}$
- **Loss** and **Algorithm** remains same




Example output of attention-based neural machine translation model
Bahdanau et al. 2015

# Attention over Images




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

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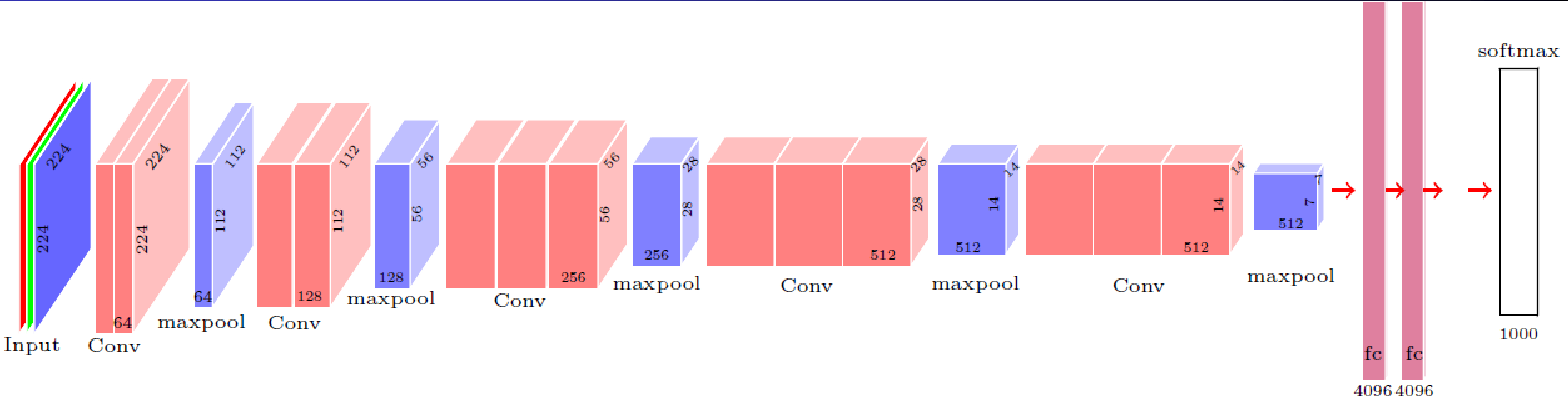
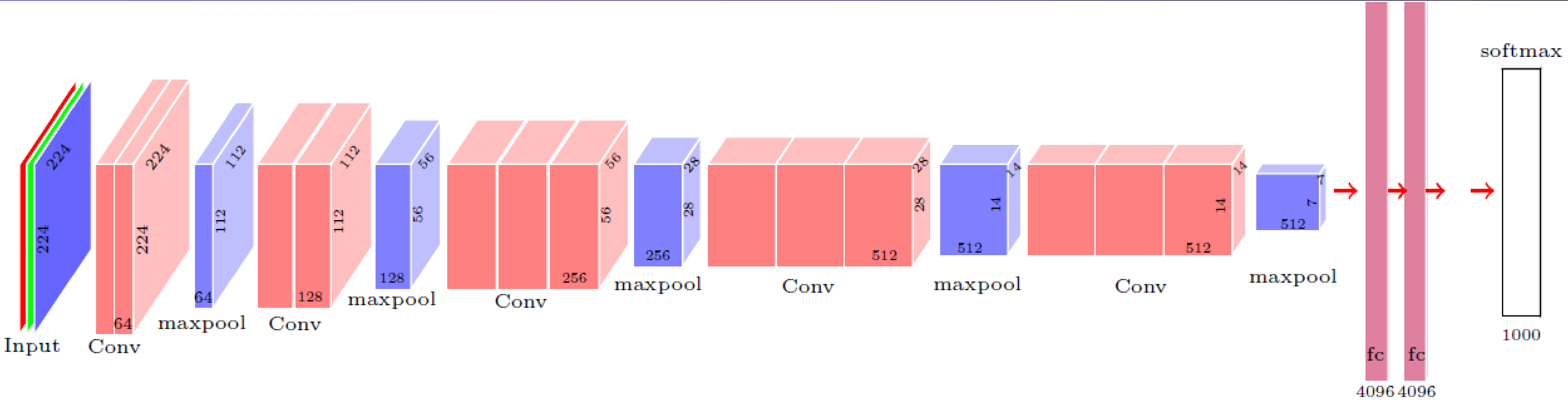
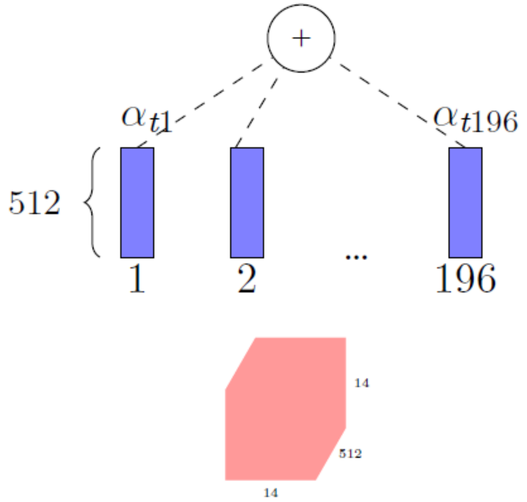



- For a CNN (eg: VGG-16) we would consider the convolution layer to be an input to the decoder, instead of the fully connected layers.
- This is because, the information about the image is contained in the feature maps in the convolution layer.
- Therefore, we could add attention weights to each pixel of the feature map volume to make the model focus on a particular pixel or region in the image.

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Attention over Images

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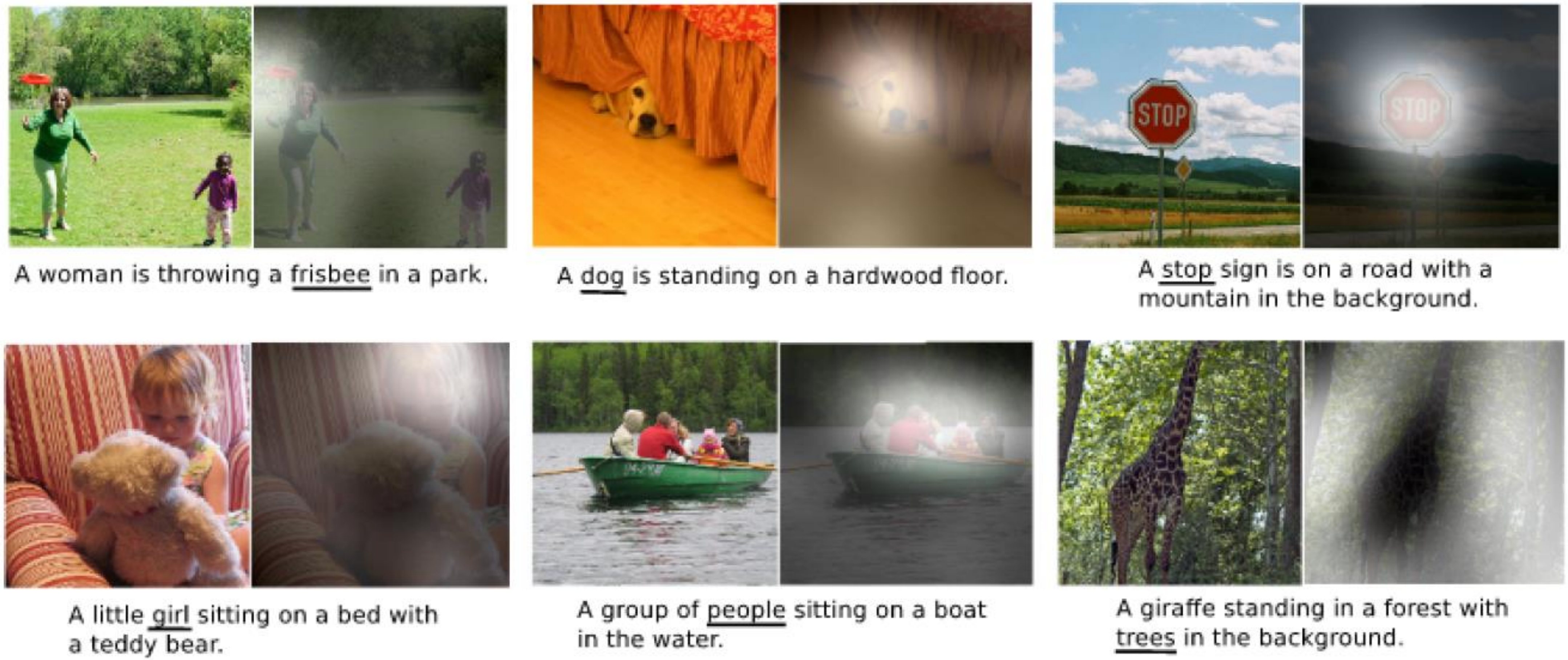


Figure: Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicates the corresponding word) [Kyunghyun Cho et al. 2015.]

# Evaluation of Machine Translation: BLUE score

- Bilingual Evaluation Understudy (BLUE) is a score for comparing a candidate translation of text to one or more reference translations.
- Correlates to human judgment of quality
- Scores are calculated for individual translated segments by comparing them with a set of good quality reference translations.
- Scores are then averaged over the whole corpus to reach an estimate of the translation's overall quality.
- Intelligibility or grammatical correctness are not taken into account
- Number between 0 and 1

# Evaluation of Machine Translation: BLUE score

German: Ich bin zur Zeit nicht im Büro

Reference English: I am currently out of the office

MT English: $\boxed{\text{am am am am am am}}$

Precision *(uni-gram)*:

$$p_1 = \frac{(1 + 1 + 1 + 1 + 1 + 1)}{6} = 1$$

# Evaluation of Machine Translation: BLUE score

German: Ich bin zur Zeit nicht im Büro

Reference English: I am currently out of the office

MT English: am am am am am am

Modified Precision *(uni-gram)*:

$$p_1 = \frac{(1 + 0 + 0 + 0 + 0 + 0)}{6} = 0.16$$

# Evaluation of Machine Translation: BLUE score

German: Ich bin zur Zeit nicht im Büro

Reference English: I am currently out of the office

MT English: I am currently not in the office

Modified Precision *(unigram)*:

$$p_1 = \frac{1+1+1+0+0+1+1}{7} = \frac{5}{7} = 0.71$$

Modified Precision *(bi-gram)*:

English: (I am), (am currently), (currently out), (out, of), (of the), (the office)

MT English: (I am), (am currently), (currently not), (not in), (in the), (the office)

$$p_2 = \frac{1+1+1+0+0+1}{6} = \frac{4}{6} = 0.66$$

# Evaluation of Machine Translation: BLUE score

German: Ich bin zur Zeit nicht im Büro

Reference English: I am currently out of the office

MT English: I am

Modified Precision (unigram): $p_1 = 1$

Modified Precision (bigram): $p_2 = 1$

Modifier Precision (n-gram): $p_n = 1$

# Evaluation of Machine Translation: BLUE score

German: Ich bin zur Zeit nicht im Büro

Reference English: I am currently out of the office

MT English: I am

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-r/c)} & if\ c \leq r \end{cases}$$

Brievity Penalty

$$\boxed{\text{Bleu Score} = BP \cdot e^{\left(\frac{1}{N}\sum_{n=1}^{N} P_n\right)}}$$

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# Evaluation of machine translation

## NIST

- n-gram precision
  - counts how many (i=1,...,4) grams match their n-gram counterpart in the reference translations.
- BLEU simply calculates n-gram precision adding equal weight to each segment
- NIST also calculates how informative a particular n-gram is.
- when a correct n-gram is found, the rarer that n-gram is, the more weight it will be given

# Evaluation of machine translation

- **WORD ERROR RATE**
  - metric based on the Levenshtein distance at the word level.
  - based on the calculation of the number of words that differ between a piece of machine-translated text and a reference translation.
- **METEOR** (**Metric for Evaluation of Translation with Explicit ORdering**)
  - Recall – the proportion of the matched n-grams out of the total number of n-grams in the reference translation
  - based on the harmonic mean of unigram precision and recall, with recall weighted higher than precision
  - Features include stemming and synonymy matching along with exact word matching
- **LEPOR** (**Le**ngth Penalty, **P**recision, n-gram **Po**sition difference Penalty and **R**ecall)
  - **Language Independent – overcomes language bias problem**
  - factors of
    - enhanced length penalty – Translator is punished if longer or shorter than the reference translation
    precision - score reflects the accuracy of the hypothesis translation
    - recall - score reflects the loyalty of the hypothesis translation to the reference translation or source language.
    - n-gram word order penalty- is designed for the different position orders between the hypothesis translation and reference translation.

**Task:** Chat Bot

**Context**

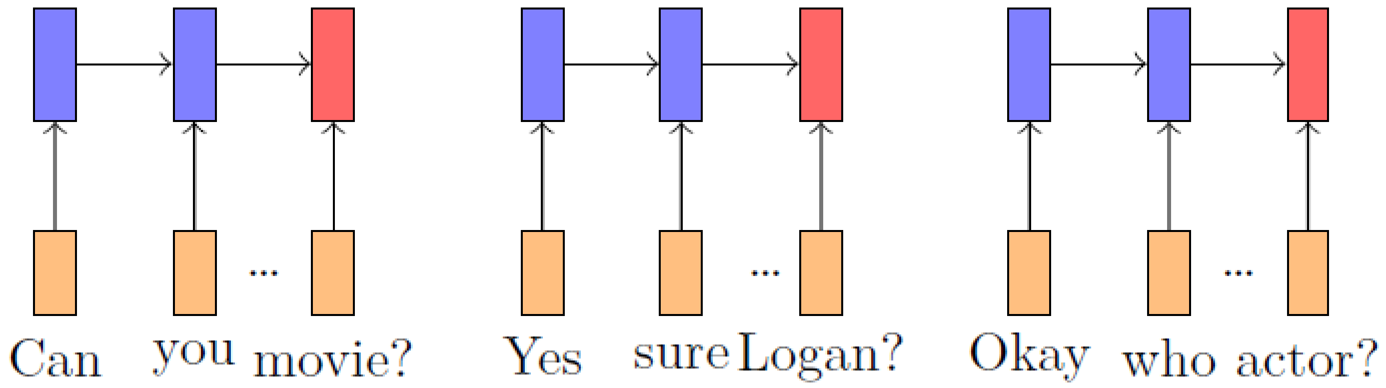
U: Can you suggest a good movie?

B: Yes, sure. How about Logan?

U: Okay, who is the lead actor?

**Response**

B: Hugh Jackman, of course




Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

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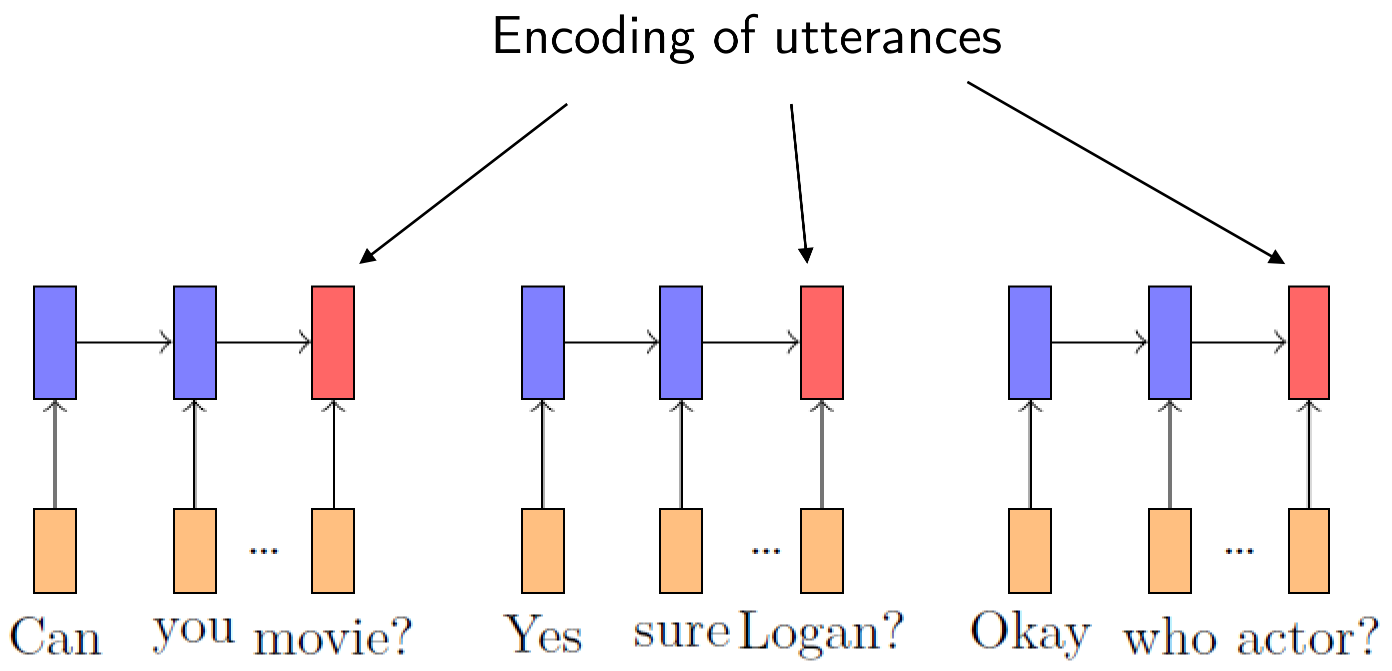


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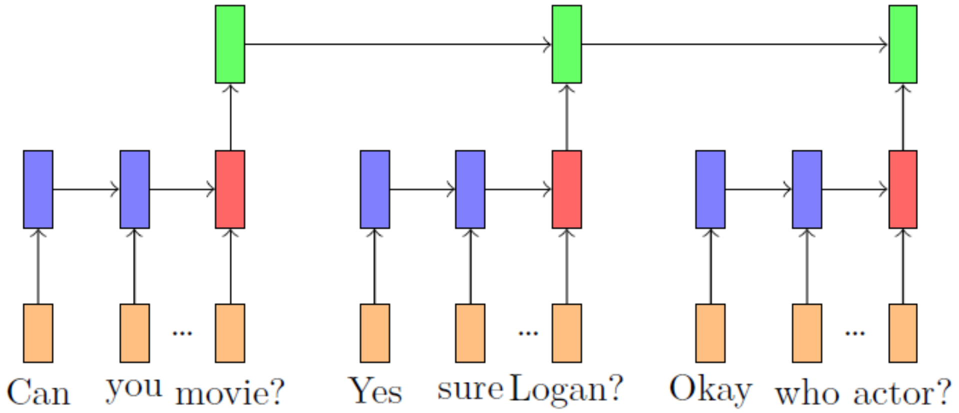


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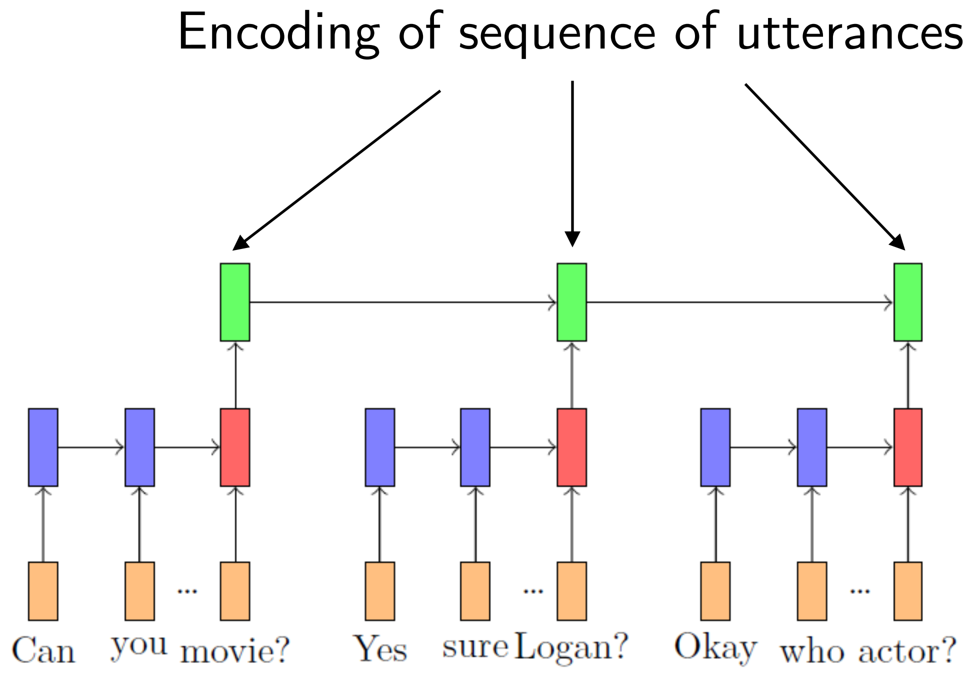


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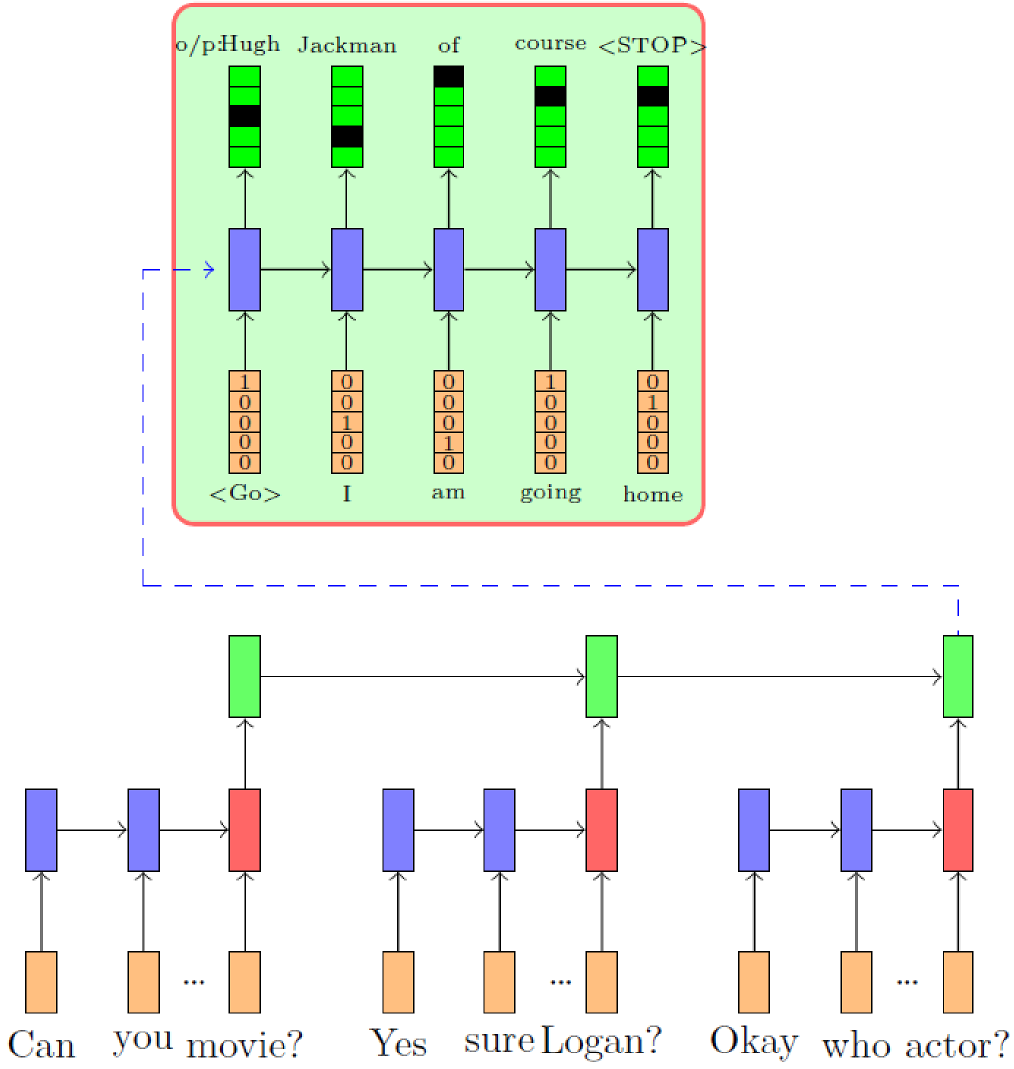
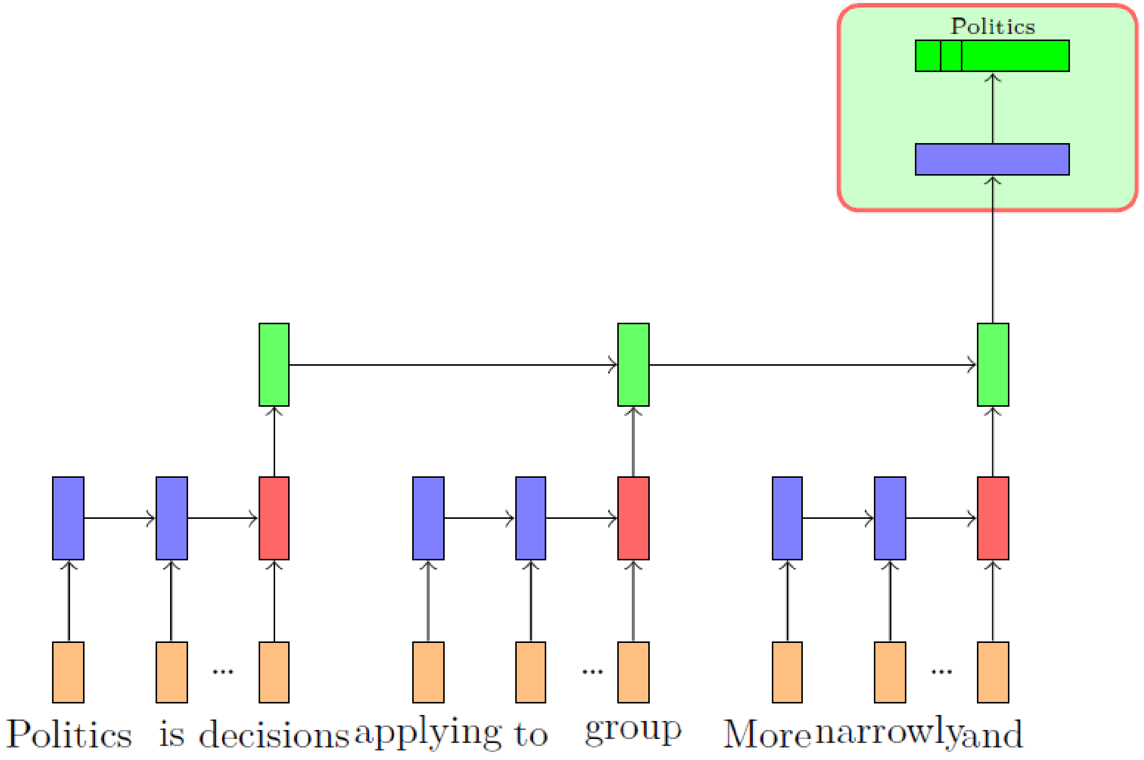



Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Hierarchical Attention : Introduction to Hierarchical Models

**Task:** Document Summarization

> Politics is the process of making decisions applying to all members of each group. More narrowly, it refers to achieving and ...



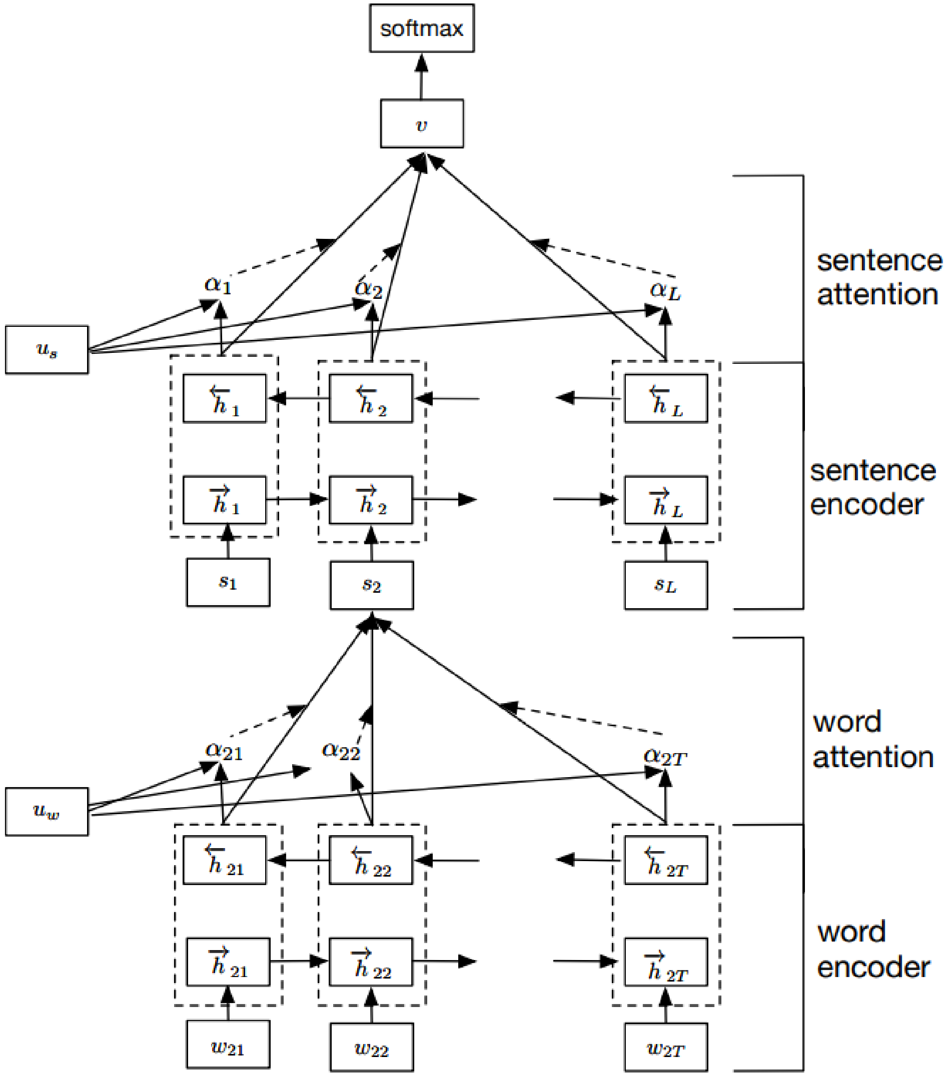

- **Data:** $\{Document_i, class_i\}_{i=1}^{N}$
- **Word level (1) encoder:**
  $$h^1_{ij} = RNN(h^1_{ij-1}, w_{ij})$$
  $$s_i = h^1_{iT_i} \quad [T \textit{ is length of sentence } i]$$
- **Sentence level (2) encoder:**
  $$h^2_i = RNN(h^2_{i-1}, s_i)$$
  $$s = h^2_K \quad [K \textit{ is number of sentences}]$$
- **Decoder:**
  $$P(y|document) = softmax(Vs + b)$$
- **Params:** $W^1_{enc}, U^1_{enc}, W^2_{enc}, U^2_{enc}, V, b$
- **Loss:** Cross Entropy
- **Algorithm:** Gradient Descent with backpropagation

Source: CS7015 Deep Learning, Dept. of CSE, IIT Madras

# Document Classification using Hierarchical Attention Networks

- To understand the main message of a document
  - Not every word in a sentence and every sentence in a document are equally important
- Meaning of word depends on context
  - For example - "The bouquet of flowers is pretty" vs. "The food is pretty bad".
- HAN
  - considers the hierarchical structure of documents (document - sentences - words)
  - Includes an attention mechanism that is able to find the most important words and sentences in a document while taking the context into consideration

# Hierarchical Attention Networks




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

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

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

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

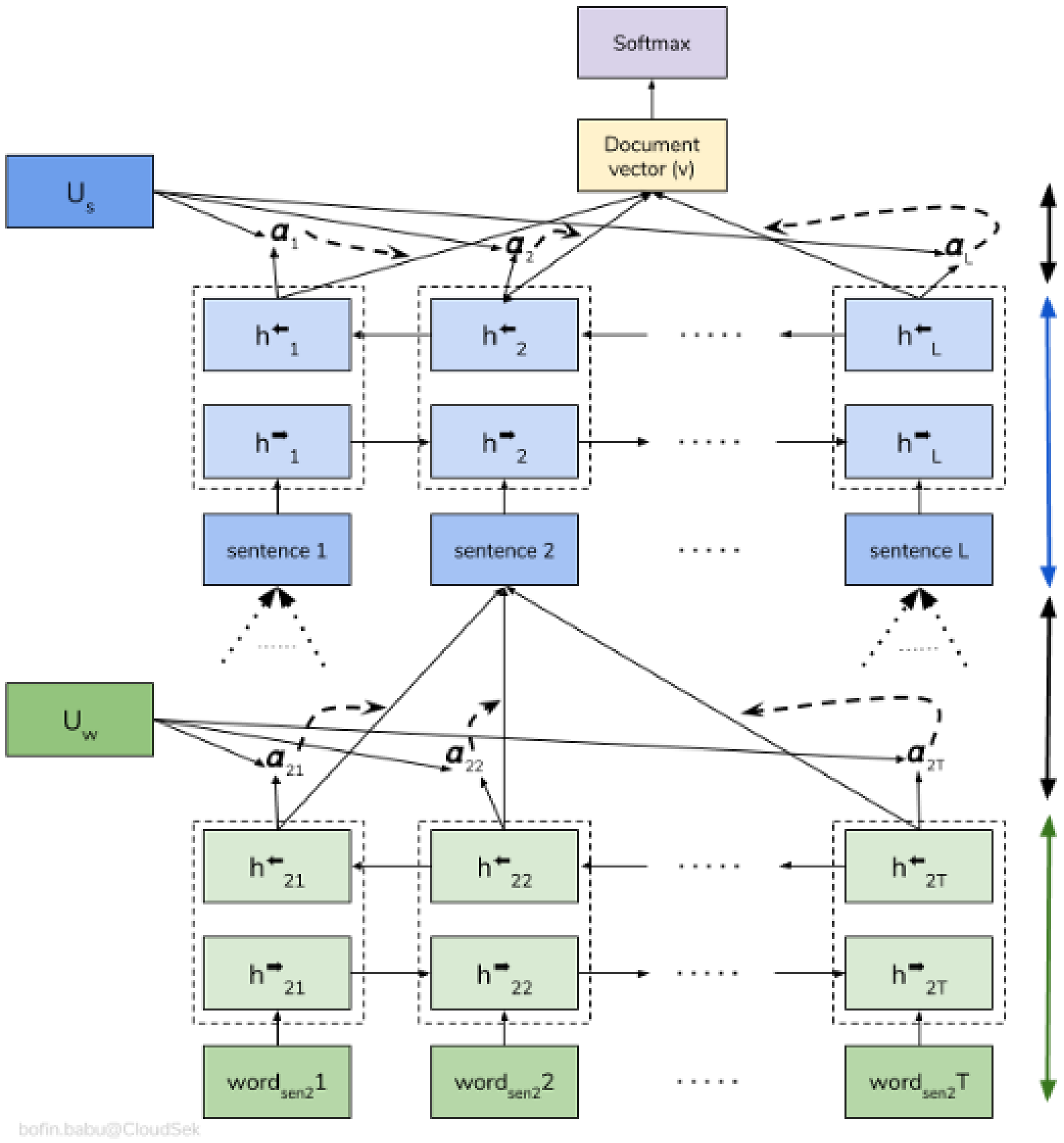
- **Decoder:**

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

- **Parameters:** $W_w, W_s, V, b_w, b_s, b, u_w, u_s$
- **Loss:** cross entropy
- **Algorithm:** Gradient Descent and backpropagation

Yang et al. Hierarchical Attention Networks for Document Classification, Proceedings of NAACL-HLT 2016

# Hierarchical Attention Networks (Yang et al. 2016)




**Sentence attention**

$U_s$: sentence context vector

**Sentence encoder**

**Word attention**

$\alpha$ : importance weight
$U_w$ : word context vector (what is the informative word?)

**Word encoder**

h→ : forward hidden state
h← : backward hidden state
$word_{sen2}1$ : The first word in sentence 2

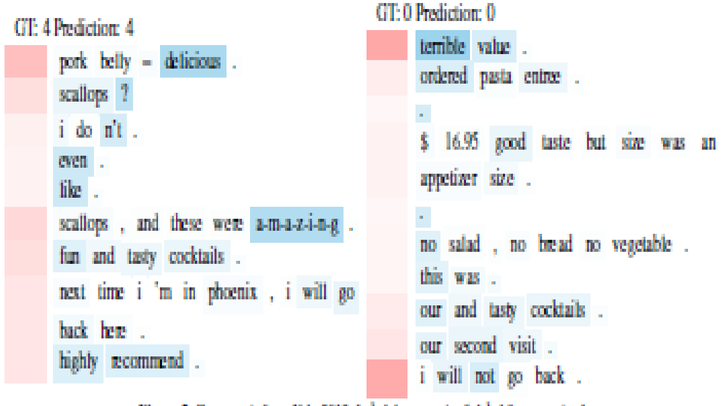



Figure 5: Documents from Yelp 2013. Label 4 means star 5, label 0 means star 1.

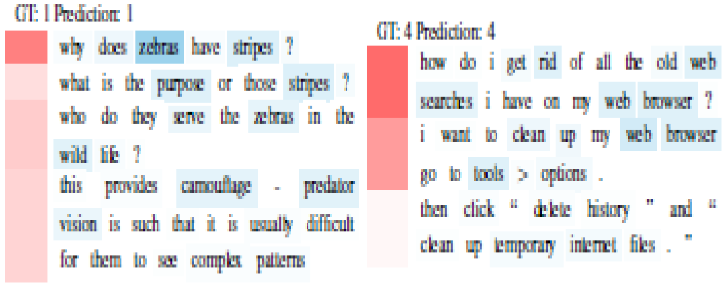



Figure 6: Documents from Yahoo Answers. Label 1 denotes Science and Mathematics and label 4 denotes Computers and Internet.