CS7015 (Deep Learning) : Lecture 16

Encoder Decoder Models, Attention Mechanism

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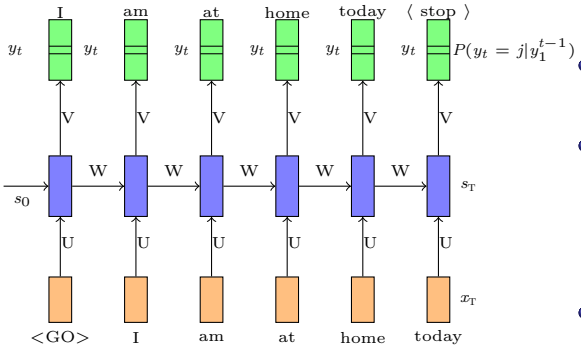
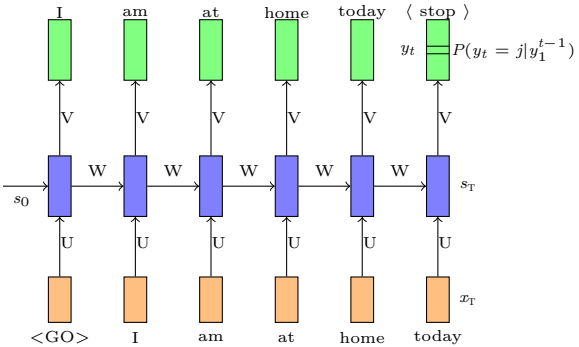
Module 16.1: Introduction to Encoder Decoder Models



- We will start by revisiting the problem of language modeling
- Informally, given '$t-i$' words we are interested in predicting the t^{th} word
- More formally, given $y_1, y_2, ..., y_{t-1}$ we want to find

$$y^* = argmax\ P(y_t|y_1, y_2, ..., y_{t-1})$$

- Let us see how we model $P(y_t|y_1, y_2...y_{t-1})$ using a RNN
- We will refer to $P(y_t|y_1, y_2...y_{t-1})$ by shorthand notation: $P(y_t|y_1^{t-1})$



- We are interested in

$$P(y_t = j|y_1, y_2 \ldots y_{t-1})$$

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

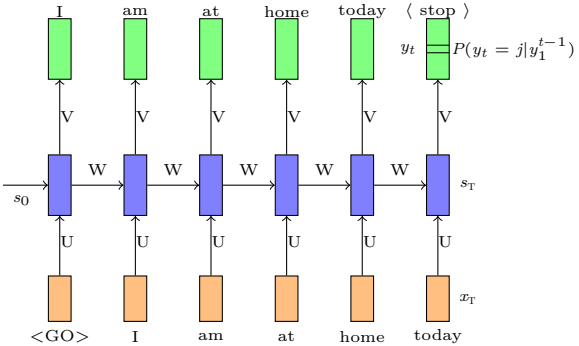
- Using an RNN we compute this as

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

- In other words we compute

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

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



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:**

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

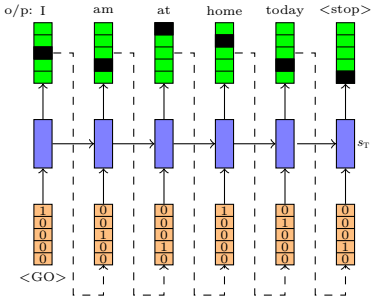
$$P(y_t = j|y_1^{t-1}) = softmax(Vs_t + c)_j$$

- **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 ℓ_t is the true word at time step t



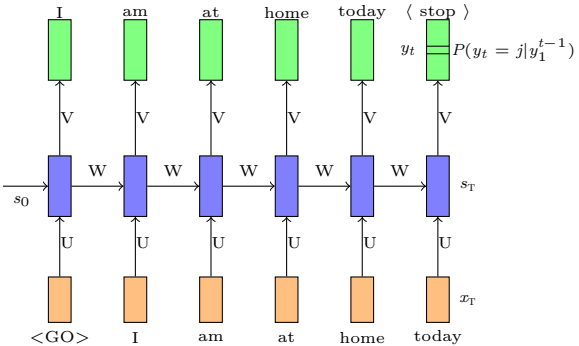
- What is the input at each time step?
- It is simply the word that we predicted at the previous time step
- In general

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

- Let j be the index of the word which has been assigned the max probability at time step $t-1$

$$x_t = e(v_j)$$

- x_t is essentially a one-hot vector $(e(v_j))$representing the j^{th} word in the vocabulary
- In practice, instead of one hot representation we use a pre-trained word embedding of the j^{th} word



- Notice that s_0 is not computed but just randomly initialized
- We learn it along with the other parameters of RNN (or LSTM or GRU)
- We will return back to this later

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

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

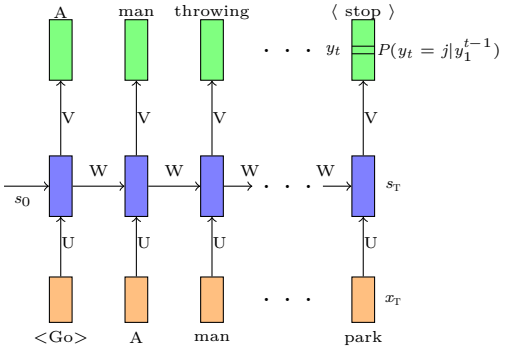
$$\tilde{s}_t = \sigma(W\ h_{t-1} + U x_t + b)$$
$$s_t = f_t \odot\ s_{t-1} + i_t \odot \tilde{s}_t$$
$$h_t = o_t \odot \sigma(s_t)$$

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

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

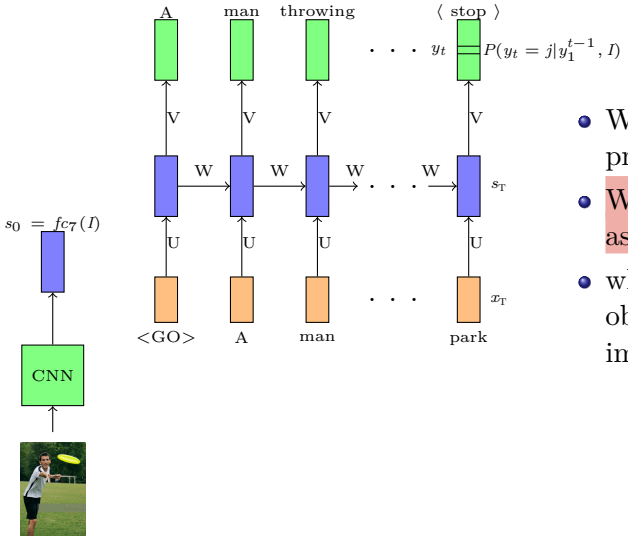
$$h_t, s_t = \text{LSTM}(\ h_{t-1}, s_{t-1}, x_t)$$

- 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



A man throwing a frisbee in a park

- So far we have seen how to model the conditional probability distribution $P(y_t|y_1^{t-1})$
- More informally, we have seen how to generate a sentence given previous words
- What if we want to generate a sentence given an image?
- 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
- Notice that $P(y_t|y_1^{t-1}, I)$ is again a conditional distribution

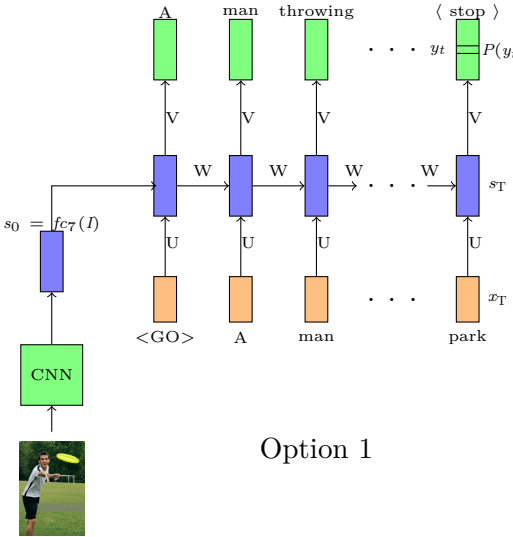


- Earlier we modeled $P(y_t|y_1^{t-1})$ as

$$P(y_t|y_1^{t-1}) = P(y_t = j|s_t)$$

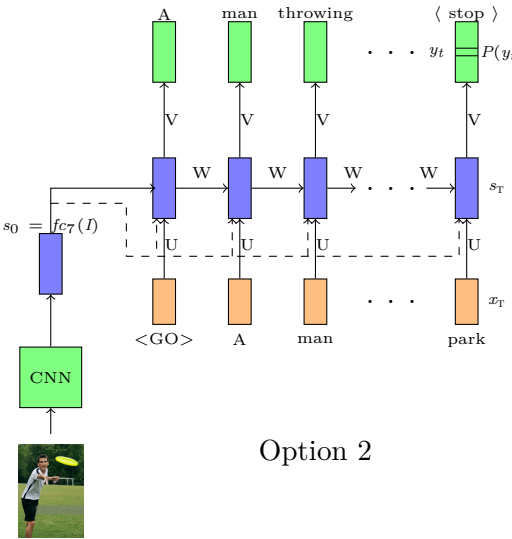
- Where s_t was a state capturing all the previous words
- We could now model $P(y_t = j|y_1^{t-1}, I)$ as $P(y_t = j|s_t, fc_7(I))$
- where $fc_7(I)$ is the representation obtained from the fc_7 layer of an image

- There are many ways of making $P(y_t = j)$ conditional on $f_{c_7}(I)$
- Let us see two such options



Option 1

- **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 $P(y_t = j|s_t, f_{c_7}(I))$

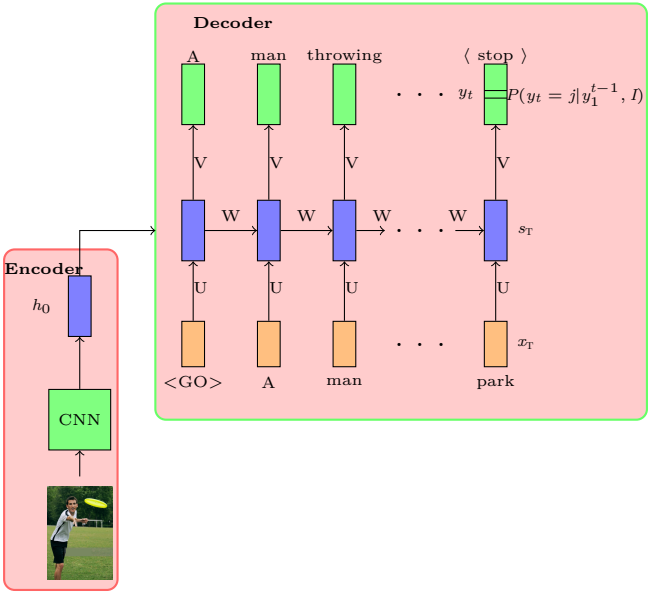


Option 2

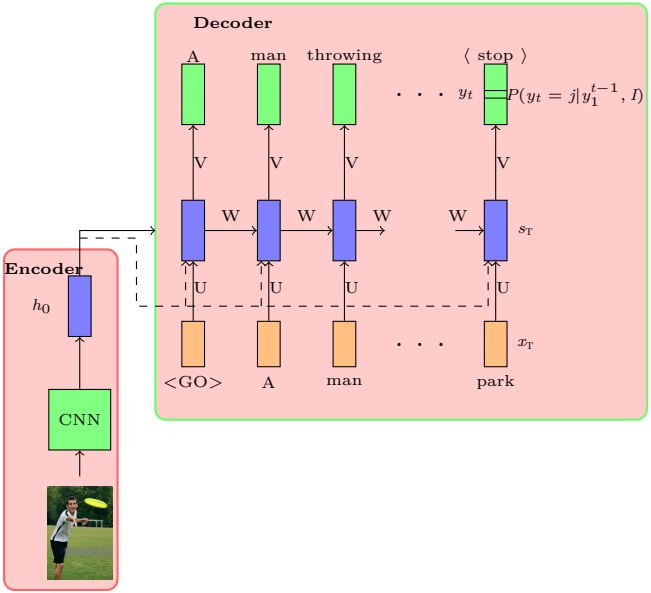
- **Option 2:** Another more explicit way of doing this is to compute

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

- In other words we are explicitly using $f_{c_7}(I)$ to compute s_t and hence $P(y_t = j)$
- You could think of other ways of conditioning $P(y_t = j)$ on f_{c_7}



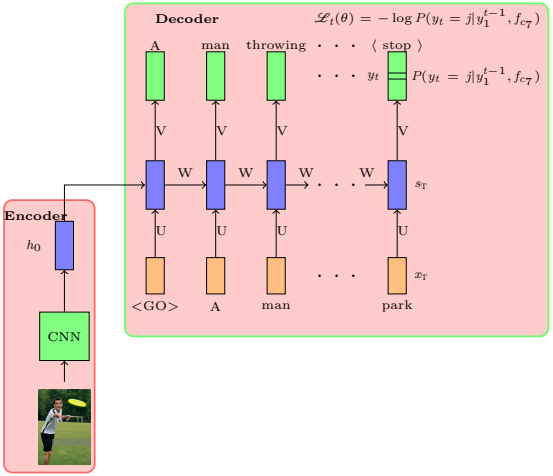
- Let us look at the full architecture
- A CNN is first used to **encode** the image
- A RNN is then used to decode (generate) a sentence from the encoding
- This is a typical **encoder decoder architecture**
- Both the encoder and decoder use a neural network



- Let us look at the full architecture
- A CNN is first used to **encode** the image
- A RNN is then used to decode (generate) a sentence from the encoding
- This is a typical **encoder decoder architecture**
- Both the encoder and decoder use a neural network
- Alternatively, the encoder's output can be fed to every step of the decoder

Module 16.2: Applications of Encoder Decoder models

- For all these applications we will try to answer the following questions
- What kind of a network can we use to encode the input(s)? (What is an appropriate encoder?)
- What kind of a network can we use to decode the output? (What is an appropriate decoder?)
- What are the parameters of the model ?
- What is an appropriate loss function ?



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

$$s_0 = CNN(x_i)$$

  - **Decoder:**

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

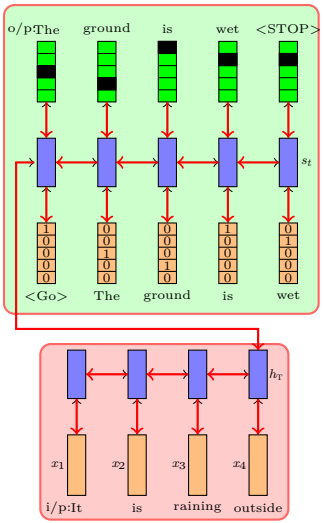
$$P(y_t|y_1^{t-1}, I) = softmax(Vs_t + b)$$

- **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

o/p : The ground is wet



i/p : It is raining outside

- **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:**

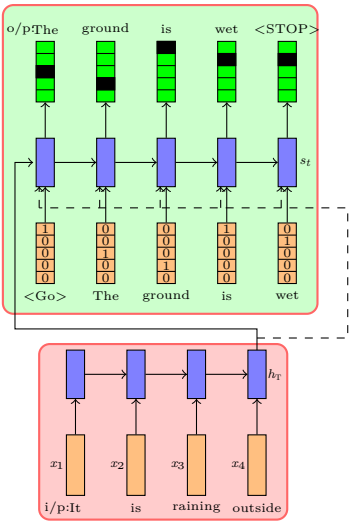
$$s_0 = h_T \quad (T \text{ is length of input})$$
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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 : The ground is wet



i/p : It is raining outside

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

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

  - **Decoder:**

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

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

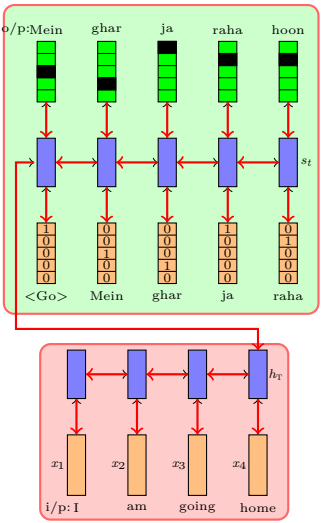
$$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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 : 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 1):**
  - **Encoder:**

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

  - **Decoder:**

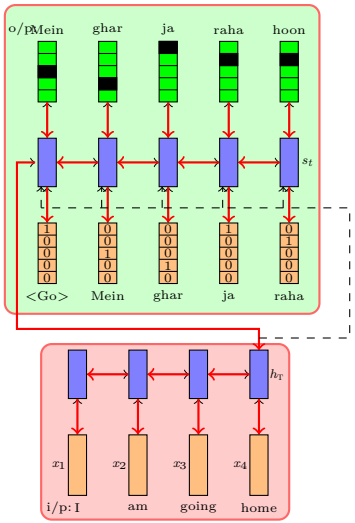
$$s_0 = h_T \quad (T \text{ is length of input})$$
$$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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
- **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:**

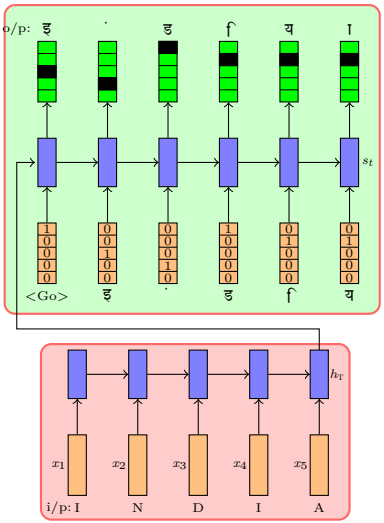
$$s_0 = h_T \quad (T \text{ is length of input})$$
$$s_t = RNN(s_{t-1}, [h_T, e(\hat{y}_{t-1})])$$
$$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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 : 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:**

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

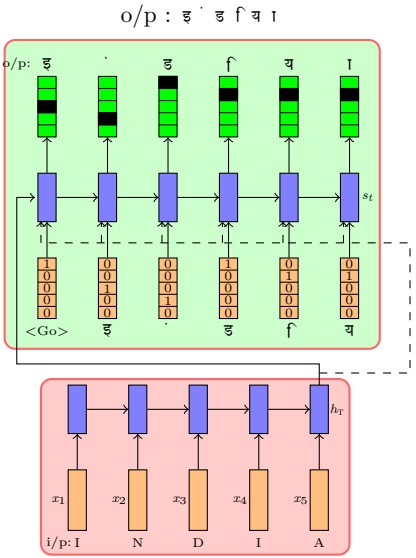
  - **Decoder:**

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

- **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



- **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:**

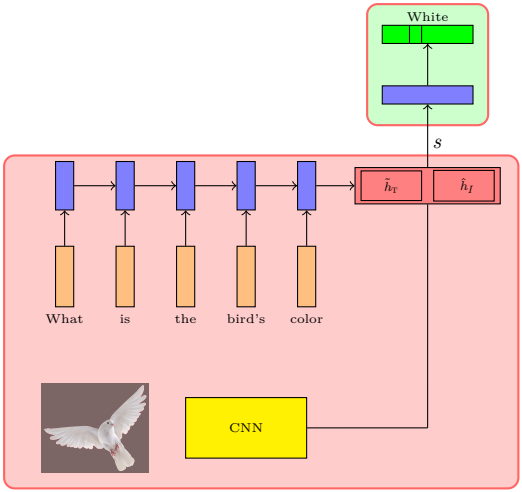
$$s_0 = h_T \quad (T \text{ is length of input})$$
$$s_t = RNN(s_{t-1}, [e(\hat{y}_{t-1}), h_T])$$
$$P(y_t | y_1^{t-1}, x) = softmax(Vs_t + b)$$

- **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



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:**

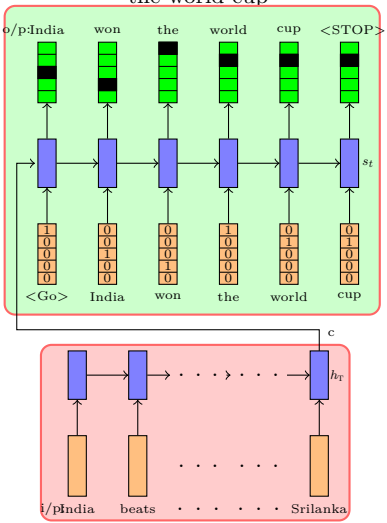
    $$\hat{h}_I = CNN(I),\ \tilde{h}_t = RNN(\tilde{h}_{t-1}, q_{it})$$

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

o/p : India won the world cup



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

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

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

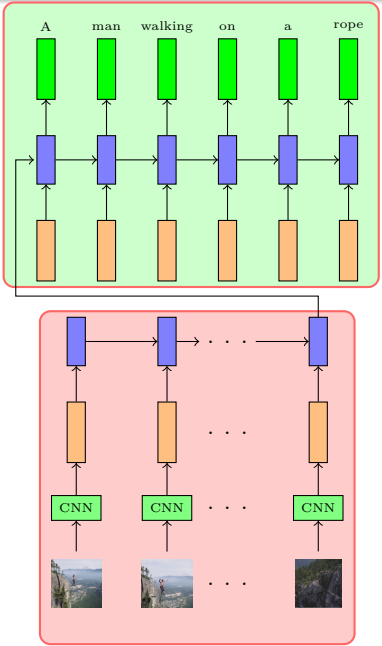
  - **Decoder:**

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

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

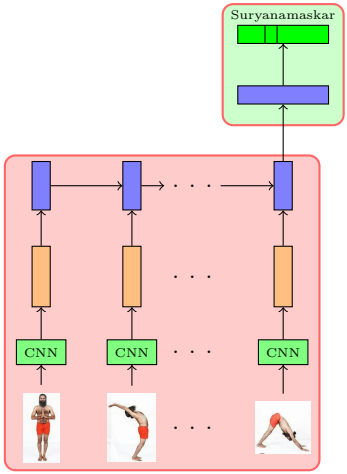
$$\mathscr{L}(\theta) = \sum_{i=1}^{T} \mathscr{L}_t(\theta) = -\sum_{t=1}^{T} \log P(y_t = \ell_t|y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

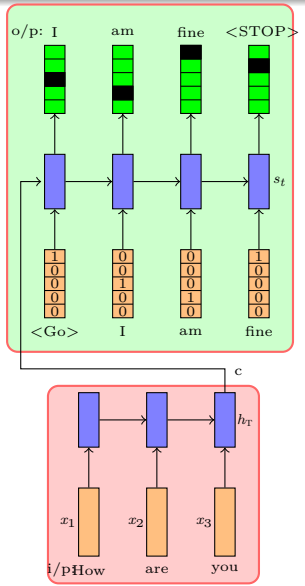


- **Task:** Video Captioning
- **Data:** $\{x_i = video_i,\ y_i = desc_i\}_{i=1}^{N}$
- **Model:**
  - **Encoder:**
    $$h_t = RNN(h_{t-1}, CNN(x_{it}))$$
  - **Decoder:**
    $$s_0 = h_T$$
    $$s_t = RNN(s_{t-1}, e(\hat{y}_{t-1}))$$
    $$P(y_t|y_1^{t-1}, x) = softmax(Vs_t + b)$$
- **Parameters:**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

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



i/p: How are you

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

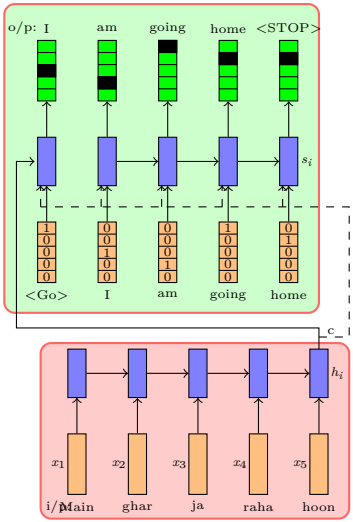
$$\mathscr{L}(\theta) = \sum_{i=1}^{T} \mathscr{L}_t(\theta) = -\sum_{t=1}^{T} \log P(y_t = \ell_t|y_1^{t-1}, x)$$

- **Algorithm:** Gradient descent with backpropagation

- And the list continues ...
- 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
- 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

t_1 : [1 0 0 0 0]

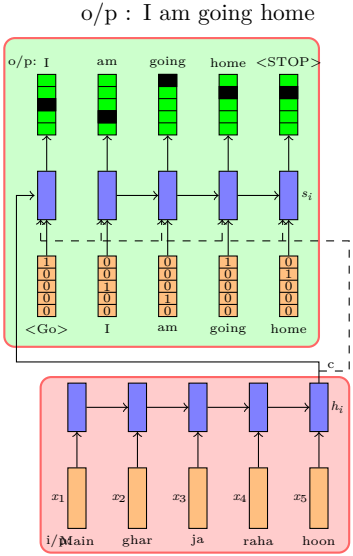
t_2 : [0 0 0 0 1]

t_3 : [0 0 0.5 0.5 0]

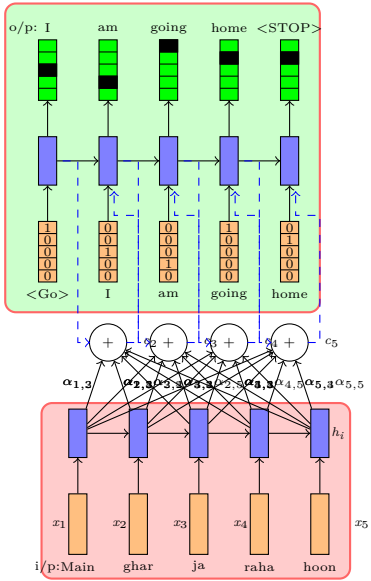
t_4 : [0 1 0 0 0]

i/p : Main ghar ja raha hoon

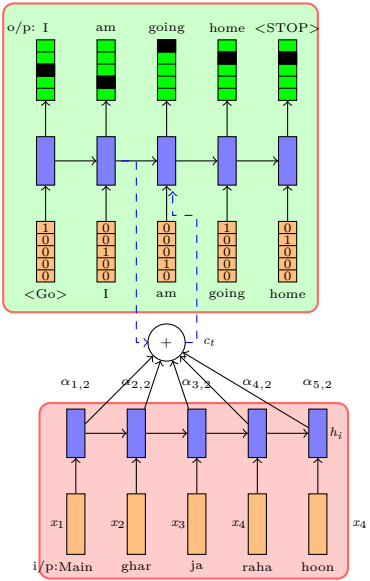
- Humans try to produce each word in the output by focusing only on certain words in the input
- Essentially at each time step we come up with a distribution on the input words
- This distribution tells us how much attention to pay to each input words at each time step
- Ideally, at each time-step we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



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



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

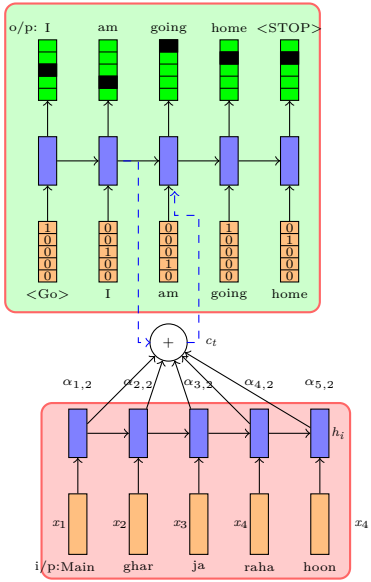


- Of course in practice we will not have this oracle
- The machine will have to learn this from the data
- To enable this we define a function

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

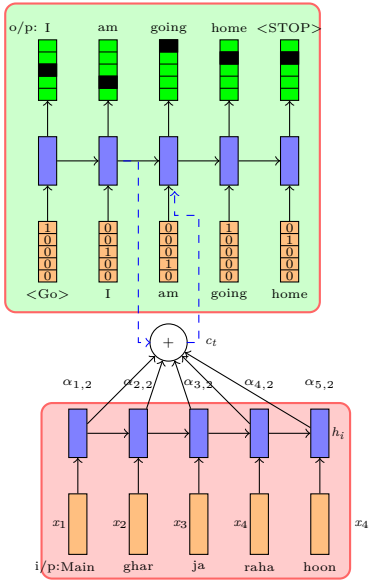
- This quantity captures the importance of the j^{th} input word for decoding the t^{th} output word (we will see the exact form of f_{ATT} later)
- We can normalize these weights by using the softmax function

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



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

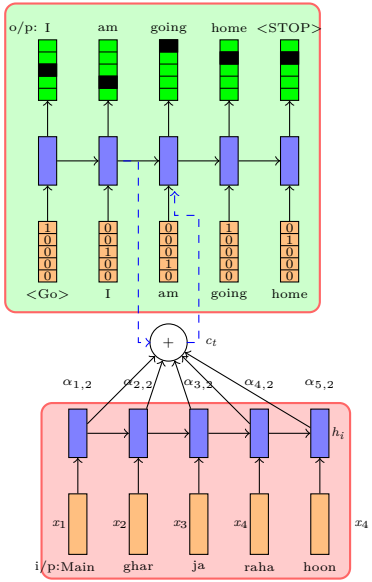
- α_{jt} denotes the probability of focusing on the j^{th} word to produce the t^{th} output word
- We are now trying to learn the α's instead of an oracle informing us about the α's
- Learning would always involve some parameters
- So let's define a parametric form for α's



- From now on we will refer to the decoder RNN's state at the t-th timestep as s_t and the encoder RNN's state at the j-th time step as c_j
- Given these new notations, one (among many) possible choice for f_{ATT} is

$$e_{jt} = V_{att}^T \tanh(U_{att} s_{t-1} + W_{att} c_j)$$

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

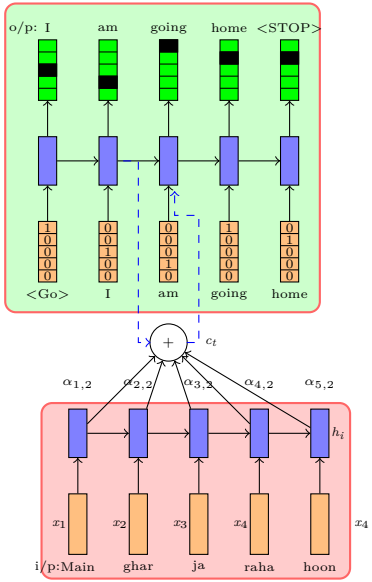


- Wait a minute !
- This model would make a lot of sense if were given the true α's at training time

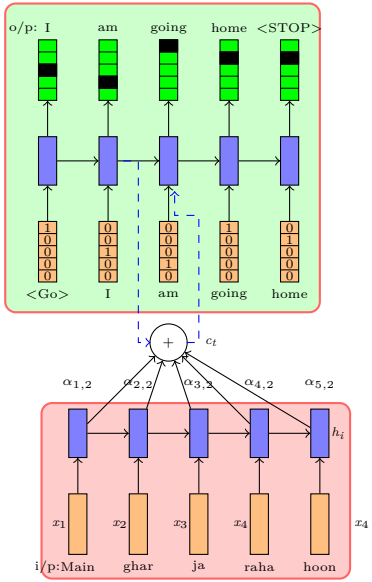
$$\alpha_{tj}^{true} = [0, 0, 0.5, 0.5, 0]$$

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

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

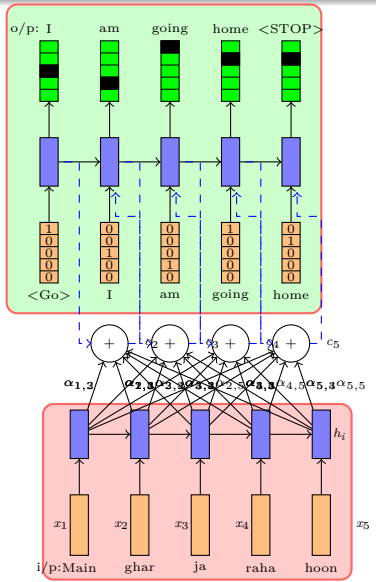


- For example, in our translation example we would want someone to manually annotate the source words which contribute to every target word
- It is hard to get such annotated data
- Then how would this model work in the absence of such data ?



- It works because it is a better modeling choice
- This is a more informed model
- We are essentially asking the model to approach the problem in a better (more natural) way
- Given enough data it should be able to learn these attention weights just as humans do
- That's the hope (and hope is a good thing)
- And in practice indeed these models work better than the vanilla encoder decoder models

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



- **Task:** Machine Translation
- **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 ?
- 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)

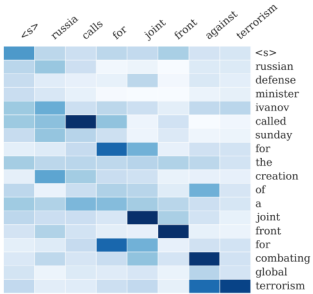


Figure: Example output of attention-based summarization system [Rush et al. 2015.]

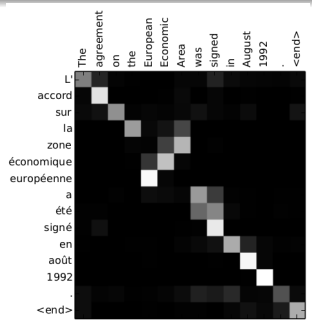
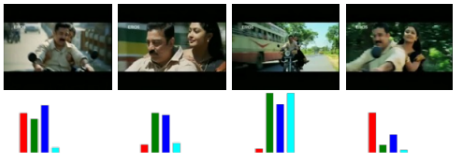
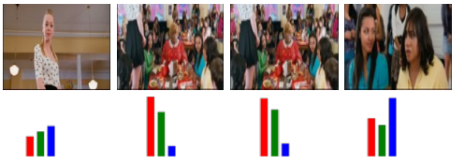
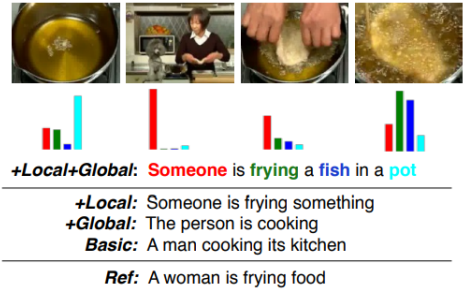


Figure: Example output of attention-based neural machine translation model [Cho et al. 2015].

- 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)







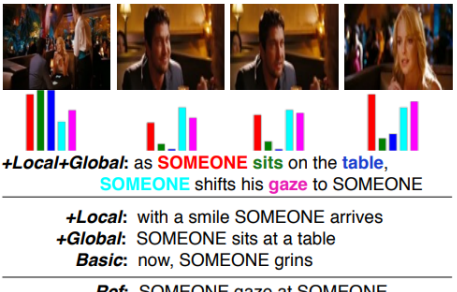
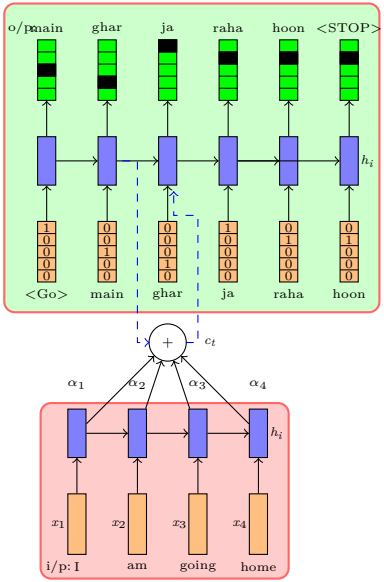


Figure: Example output of attention-based video captioning system [Yao et al. 2015.]

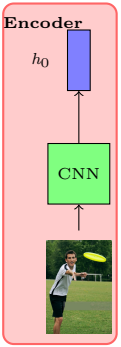
Module 16.4: Attention over images

A man throwing
a frisbee in a park

- How do we model an attention mechanism for images?

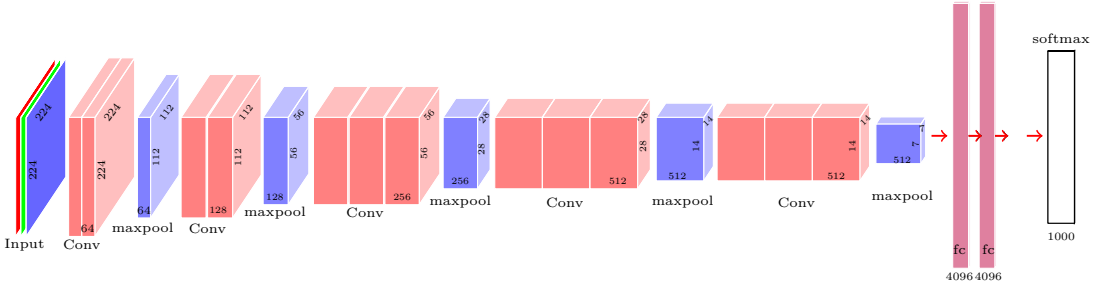


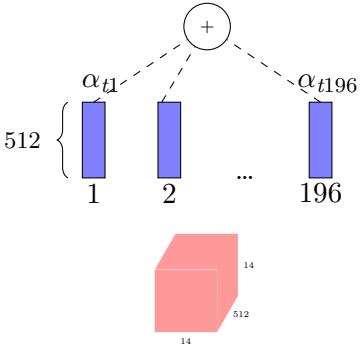
- How do we model an attention mechanism for images?
- In the case of text we have a representation for every location (time step) of the input sequence



- 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
- 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
- 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)
- 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

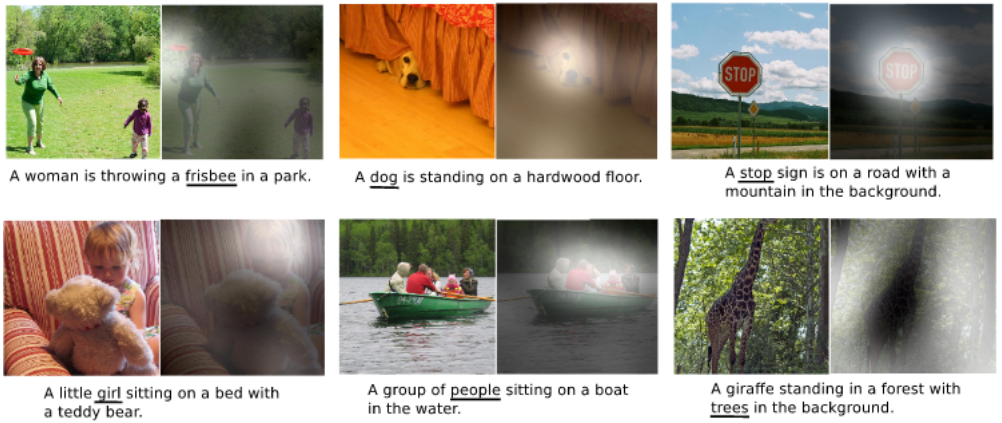


Figure: Examples of the attention-based model attending to the correct object (*white* indicates the attended regions,*underlines* indicates the corresponding word) [Kyunghyun Cho et al. 2015.]

Module 16.5: Hierarchical Attention

Context

U: Can you suggest a good movie?

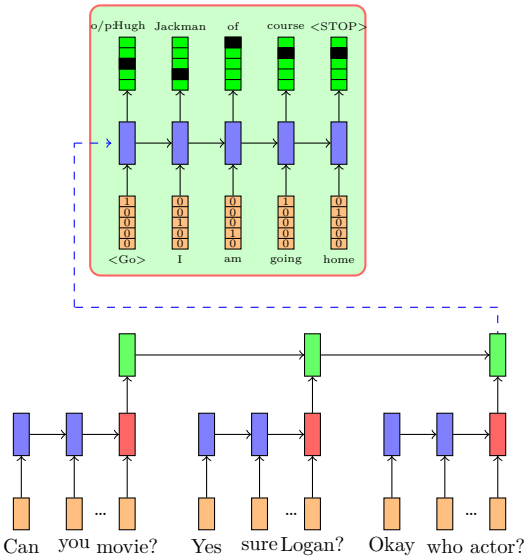
B: Yes, sure. How about Logan?

U: Okay, who is the lead actor?

Response

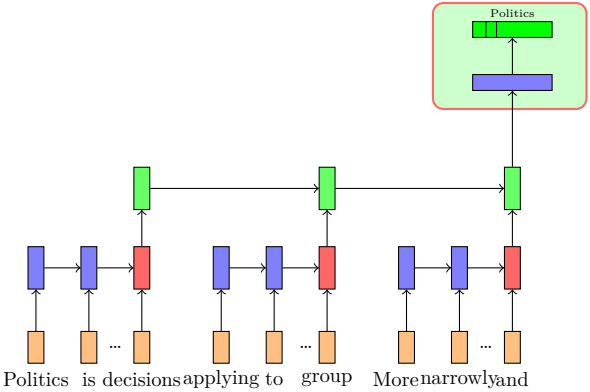
B: Hugh Jackman, of course

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



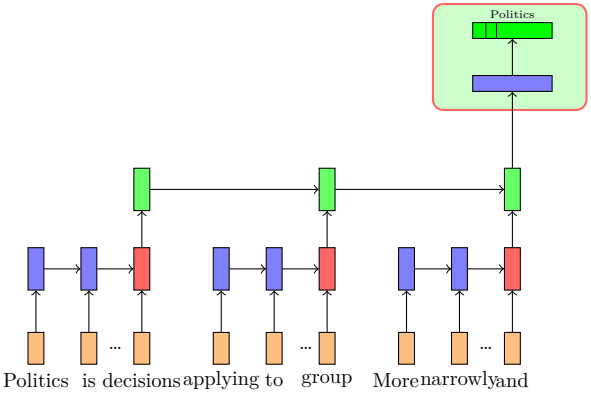
- We could think of a two level hierarchical RNN encoder
- The first level RNN operates on the sequence of words in each utterance and gives us a representation
- We now have a sequence of utterance representations (red vectors in the image)
- We can now have another RNN which encodes this sequence and gives a single representations for the sequences of utterances
- The decoder can then produce an output sequence conditioned on this utterance

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



- Let us look at another example
- Consider the task of document classification or summarization
- A document is a sequence of sentences
- Each sentence in turn is a sequence of words
- We can again use a hierarchical RNN to model this

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:**

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

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

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

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

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

- **Decoder:**

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

- **Params:** $W_{enc}^1,\ U_{enc}^1,\ W_{enc}^2,\ U_{enc}^2,\ V, b$
- **Loss:** Cross Entropy
- **Algorithm:** Gradient Descent with backpropagation

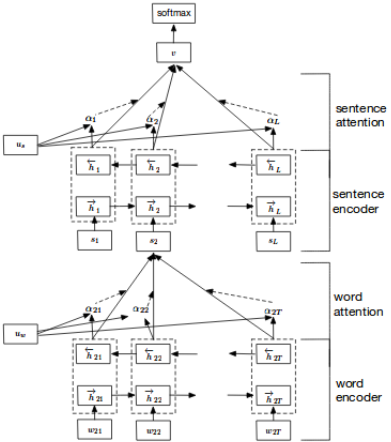


Figure: Hierarchical Attention Network [Yang et al.]

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

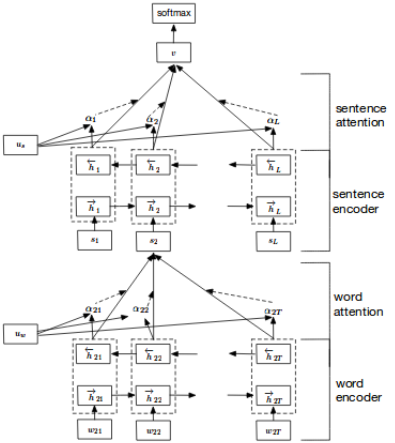


Figure: Hierarchical Attention Network [Yang et al.]

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

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

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

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

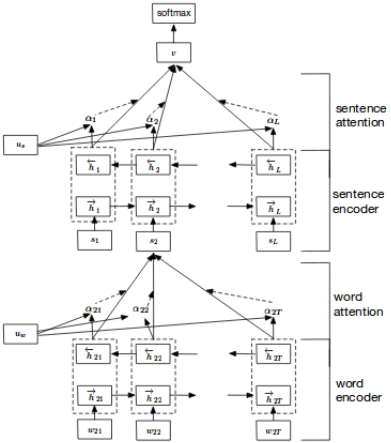


Figure: Hierarchical Attention Network [Yang et al..]

- **Decoder:**

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

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