# CS 349: AI-II

## Encoder Decoder Models, Attention Mechanism

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# *Introduction to Encoder Decoder Models*

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

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$$L(\theta) = \sum_{t=1}^{T} L_t(\theta)$$
$$L_t(\theta) = -\log P(y_t = \ell_t | y_1^{t-1})$$

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

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

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- We will return back to this later

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- We will use these notations going forward

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

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

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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

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

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

# Applications of Encoder Decoder models

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  - **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:**

$$L(\theta) = \sum_{i=1}^{T} L_t(\theta) = -\sum_{t=1}^{T} \log P(y_t = \ell|y_1^{t-1}, I)$$

- **Algorithm:** Gradient descent with backpropagation

o/p : The ground is wet

- **Task:** Textual entailment

i/p : It is raining outside

o/p : The ground is wet

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

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- **Task:** Textual entailment
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$$h_t = RNN(h_{t-1}, x_{it})$$

i/p : It is raining outside

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

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

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

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

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

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- **Algorithm:** Gradient descent with backpropagation

o/p : The ground is wet

- **Task:** Textual entailment

i/p : It is raining outside

o/p : The ground is wet

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

i/p : It is raining outside

o/p : The ground is wet

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

i/p : It is raining outside

o/p : The ground is wet

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

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

i/p : It is raining outside

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:**

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

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

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

o/p : The ground is wet

i/p : It is raining outside

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

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

o/p : The ground is wet

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- **Task:** Textual entailment
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- **Algorithm:** Gradient descent with backpropagation

o/p : Mein ghar ja raha hoon

- **Task:** Machine translation

i/p : I am going home

o/p : Mein ghar ja raha hoon

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

i/p : I am going home

o/p : Mein ghar ja raha hoon

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

i/p : I am going home

o/p : Mein ghar ja raha hoon

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

i/p : I am going home

o/p : Mein ghar ja raha hoon

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

o/p : Mein ghar ja raha hoon

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

  - **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:**

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

- **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:**

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

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O/p: White

- **Task:** Image Question Answeing

Question: What is the bird's color

O/p: White

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

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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
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o/p : A man walking on a rope

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o/p: Surya Namaskar

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o/p: I am fine

- **Task:** Dialog

i/p: How are you

o/p: I am fine

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- And the list continues ...

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- Encoder decoder models can be made even more expressive by adding an "attention" mechanism

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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

# A Quick Recap

- Discussed Encoder-Decoder Model
    - Encoder can be any NN
    - Decoder can be any NN
    - Depends upon the applications
- Have seen different variants of Encoder-decoder for several applications
    - NLP and Computer Vision

- Most of the problems can be converted into sequence transformation

# Attention Mechanism

o/p : I am going home

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

i/p : Main ghar ja raha hoon

Option 2

o/p : I am going home

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

i/p : Main ghar ja raha hoon

Option 2

o/p : I am going home

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Option 2

- 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

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- The encoder reads the sentences only once and encodes it
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- Is this how humans translate a sentence ?

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i/p : Main ghar ja raha hoon

Option 2

- 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

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$t_4$ : [ 0 1 0 0 0 ]

i/p : Main ghar ja raha hoon

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- 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

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

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i/p : Main ghar ja raha hoon

Option 2

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

o/p : I am going home

i/p : Main ghar ja raha hoon

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- We either feed in the encoder information only once(at $s_0$)

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- Or we feed the same encoder information at each time step

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- Now suppose an oracle told you which words to focus on at a given time-step $t$

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

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
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hoon

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

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

o/p: I
am
going
home
<STOP>
<Go>
I
am
going
home
$c_t$
$a_{1,2}$
$a_{2,2}$
$a_{3,2}$
$a_{4,2}$
$a_{5,2}$
$h_i$
$x_1$
$x_2$
$x_3$
$x_4$
$x_4$
i/p:Main
ghar
ja
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- Of course in practice we will not have this oracle

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- We can normalize these weights by using the softmax function

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

o/p: I
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$x_3$
$x_4$
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i/p:Main
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raha
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$a_{4,2}$
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- These parameters will be learned along with the other parameters of the encoder and decoder

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- It is hard to get such annotated data
- Then how would this model work in the absence of such data ?

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- 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)

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- **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)

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

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

# Attention over images

A man throwing
a frisbee in a park

- How do we model an attention mechanism for images?

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- But for images we typically use representation from one of the fully connected layers
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- So then what is the input to the attention mechanism?

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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.]

# Hierarchical Attention

- 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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- Thus what we have here is a "sequence of sequences" as input
- Can you think of an encoder for such a sequence of sequences?

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- 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

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- **Algorithm:** Gradient Descent with backpropagation

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- Let us see how to model this

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$$\alpha_{ij} = \frac{exp(u_{ij}^T u_w)}{\sum_t exp(u_{it}^T u_w)}$$

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

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$$\alpha_{ij} = \frac{exp(u_{ij}^T u_w)}{\sum_t exp(u_{it}^T u_w)}$$

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

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

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

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- **Loss:** cross entropy

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

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

## Resources: Acknowledgement

- Stanford Deep Learning for NLP Lectures

***Thank you for your Attention!***