ATTENTION MECHANISM

What is Attention?

In psychology, attention is the cognitive process of selectively concentrating on one or a few things while ignoring others.

A neural network is considered to be an effort to mimic human brain actions in a simplified manner. Attention Mechanism is also an attempt to implement the same action of selectively concentrating on a few relevant things while ignoring others in deep neural networks.

Let me explain what this means. Let's say you are seeing a group photo of your first school. Typically, there will be a group of children sitting across several rows, and the teacher will sit somewhere in between. Now, if anyone asks the question, "How many people are there?", how will you answer it?

Simply by counting heads, right? You don't need to consider any other things in the photo. Now, if anyone asks a different question, "Who is the teacher in the photo?", your brain knows exactly what to do. It will simply start looking for the features of an adult in the photo. The rest of the features will simply be ignored. **This is the 'Attention' that our brain is very adept at implementing.**

How Attention Mechanism was Introduced in Deep Learning

The attention mechanism emerged as an improvement over the encoder decoder-based neural machine translation system in natural language processing (NLP). Later, this mechanism, or its variants, was used in other applications, including computer vision, speech processing, etc.

Before **Bahdanau et al** proposed the first Attention model in 2015, neural machine translation was based on encoder-decoder RNNs/LSTMs. Both encoder and decoder are stacks of LSTM/RNN units. It works in the two following steps:

1. **The encoder LSTM is used to process the entire input sentence and encode it into a context vector**, which is the last hidden state of the LSTM/RNN. This is expected to be a good summary of the input sentence. All the intermediate states of the encoder are ignored, and the final state id supposed to be the initial hidden state of the decoder
2. **The decoder LSTM or RNN units produce the words in a sentence one after another**

In short, there are two RNNs/LSTMs. One we call the encoder – this reads the input sentence and tries to make sense of it, before summarizing it. It passes the summary (context vector) to the decoder which translates the input sentence by just seeing it.

The main drawback of this approach is evident. If the encoder makes a bad summary, the translation will also be bad. And indeed it has been observed that the encoder creates a bad

summary when it tries to understand longer sentences. It is called the **long-range dependency problem of RNN/LSTMs.**

RNNs cannot remember longer sentences and sequences due to the vanishing/exploding gradient problem. It can remember the parts which it has just seen. Even Cho et al (2014), who proposed the encoder-decoder network, demonstrated that **the performance of the encoder-decoder network degrades rapidly as the length of the input sentence increases.**

Although an LSTM is supposed to capture the long-range dependency better than the RNN, it tends to become forgetful in specific cases. Another problem is that there is no way to give more importance to some of the input words compared to others while translating the sentence.

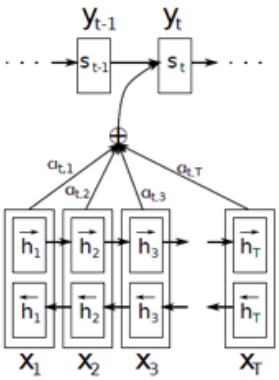
Now, let's say, we want to predict the next word in a sentence, and its context is located a few words back. Here's an example – **"Despite originally being from Uttar Pradesh, as he was brought up in Bengal, he is more comfortable in Bengali".** In these groups of sentences, if we want to predict the word **"Bengali**", the phrase **"brought up"** and **"Bengal"-** these two should be given more weight while predicting it. And although **Uttar Pradesh** is another state's name, it should be "ignored".

So is there any way we can keep all the relevant information in the input sentences intact while creating the context vector?

Bahdanau et al (2015) came up with a simple but elegant idea where they suggested that not only can all the input words be taken into account in the context vector, but relative importance should also be given to each one of them.

So, whenever the proposed model generates a sentence, it searches for a set of positions in the encoder hidden states where the most relevant information is available. This idea is called 'Attention'.

Understanding the Attention Mechanism



This is the diagram of the Attention model shown in Bahdanau's paper. The Bidirectional LSTM used here generates a sequence of annotat*ions (h1, h2,….., hTx)* for each input sentence. All the vectors h1,h2.., etc., used in their work are basically the concatenation of forward and backward hidden states in the encoder.

$$h_j = \left[\overrightarrow{h}_j^\top ; \overleftarrow{h}_j^\top \right]^\top$$

To put it in simple terms, all the vectors h1,h2,h3…., hTx are representations of Tx number of words in the input sentence. In the simple encoder and decoder model, only the last state of the encoder LSTM was used (hTx in this case) as the context vector.

But Bahdanau et al put emphasis on embeddings of all the words in the input (represented by hidden states) while creating the context vector. They did this by simply taking a weighted sum of the hidden states.

Now, the question is how should the weights be calculated? Well, the weights are also learned by a feed-forward neural network and I've mentioned their mathematical equation below.

The context vector ci for the output word yi is generated using the weighted sum of the annotations:

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j .$$

The weights αij are computed by a softmax function given by the following equation:

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)},$$

This equation helps to sum up the alpha value to 1.

$$e_{ij} = a(s_{i-1}, h_j)$$

eij is the output score of a feedforward neural network described by the function **a** that attempts to capture the alignment between input at **j** and output at **i**.

Basically, if the encoder produces **Tx** number of "annotations" (the hidden state vectors) each having dimension **d,** then the input dimension of the feedforward network is **(Tx , 2d)** (assuming

the previous state of the decoder also has **d** dimensions and these two vectors are concatenated)**.** This input is multiplied with a matrix **Wa** of **(2d, 1)** dimensions (of course followed by addition of the bias term) to get scores **eij (having a dimension (Tx , 1))**.

On the top of these **eij** scores, a tan hyperbolic function is applied followed by a softmax to get the normalized alignment scores for output j:

$$E = I\,[Tx*2d] * Wa\,[2d * 1] + B[Tx*1]$$

$$\alpha = softmax(tanh(E))$$

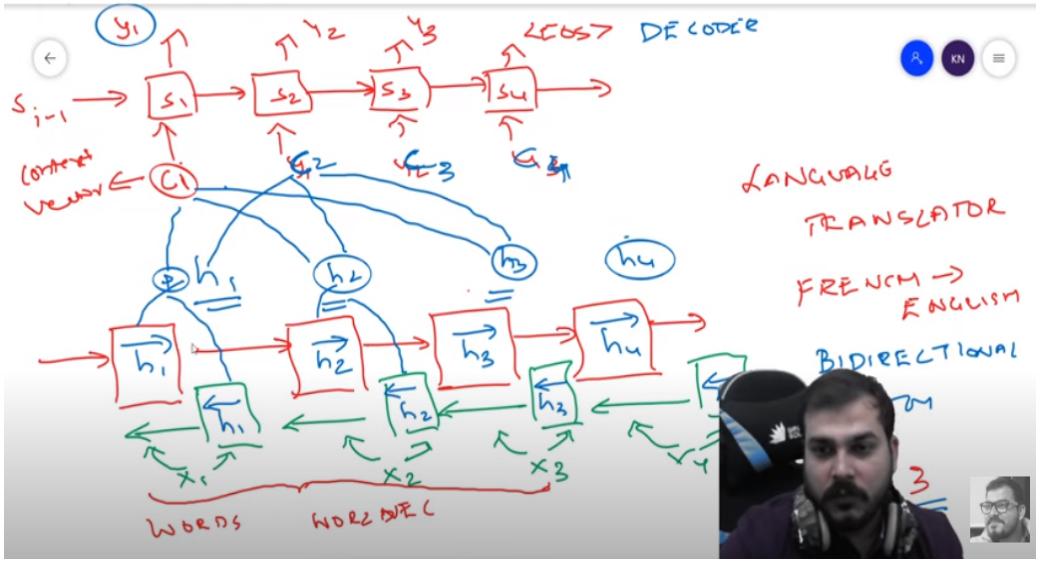
$$C = IT * \alpha$$

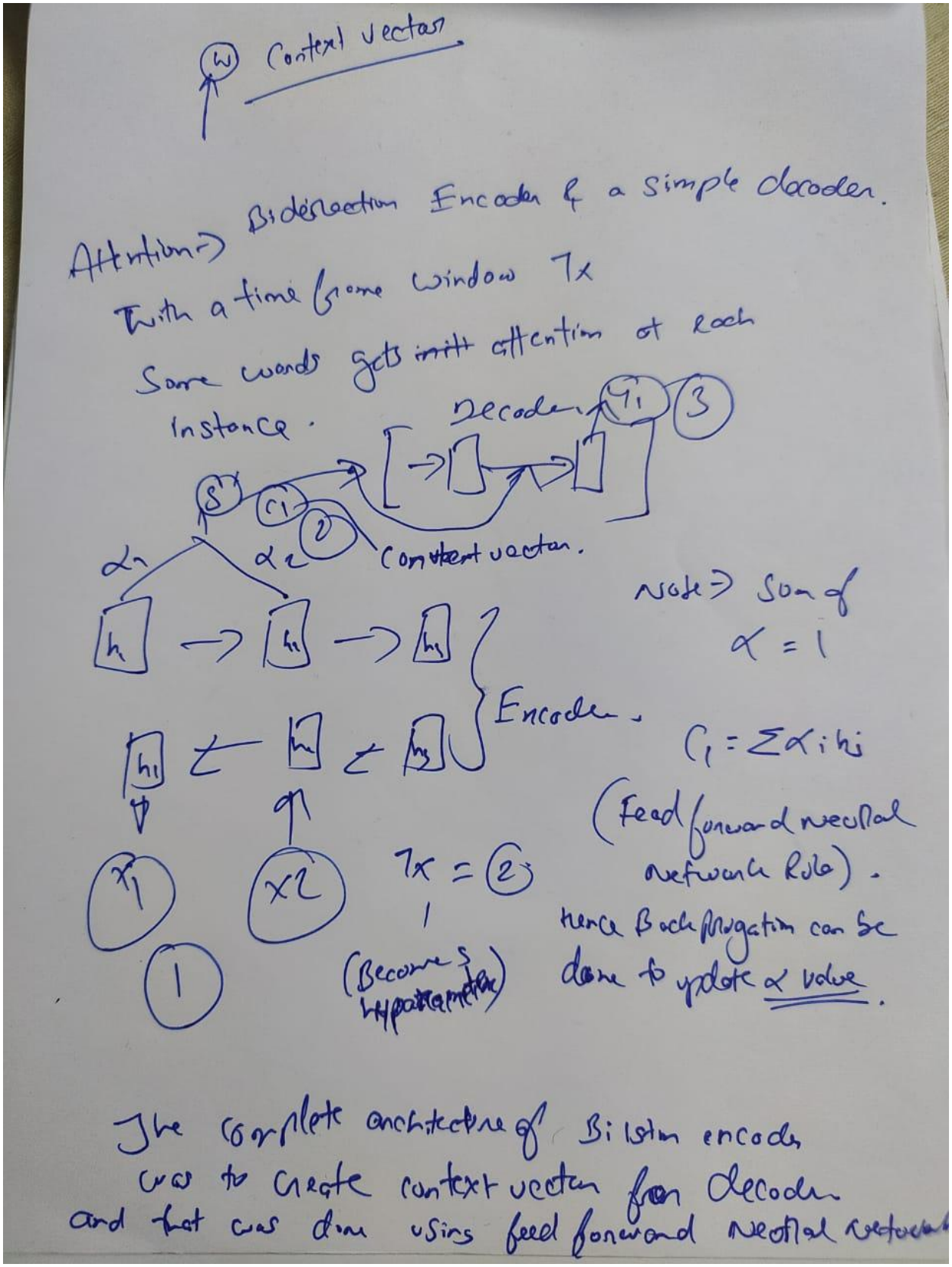
So, **α** is a (Tx, 1) dimensional vector and its elements are the weights corresponding to each word in the input sentence.

Let **α** is **[0.2, 0.3, 0.3, 0.2]** and the input sentence is **"I am doing it".** Here, the context vector corresponding to it will be:

C=0.2*I"I" + 0.3*I"am" + 0.3*I"doing" + + 0.3*I"it" [**Ix** is the hidden state corresponding to the word **x**]

KRISH NAIK
ENCODER - DECODER
BI-DIRECTIONAL LSTM IN ENCODER





Alpha is given to the sigmoid function so that all alpha sums up to 1.

Code:

```
#LSTM 3
encoder_lstm3=LSTM(latent_dim, return_state=True, return_sequences=True)

encoder_outputs, state_h, state_c= encoder_lstm3(encoder_output2)

# Set up the decoder.
decoder_inputs = Input(shape=(None,))
dec_emb_layer = Embedding(y_voc_size, latent_dim,trainable=True)

dec_emb = dec_emb_layer(decoder_inputs)

#LSTM using encoder_states as initial state
decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)

decoder_outputs,decoder_fwd_state, decoder_back_state =
decoder_lstm(dec_emb,initial_state=[state_h, state_c])

#Attention Layer
Attention layer attn_layer = AttentionLayer(name='attention_layer')
attn_out, attn_states = attn_layer([encoder_outputs, decoder_outputs])

# Concat attention output and decoder LSTM output
decoder_concat_input = Concatenate(axis=-1, name='concat_layer')([decoder_outputs,
attn_out])

#Dense layer
decoder_dense = TimeDistributed(Dense(y_voc_size, activation='softmax'))
decoder_outputs = decoder_dense(decoder_concat_input)

# Define the model
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
model.summary()
```