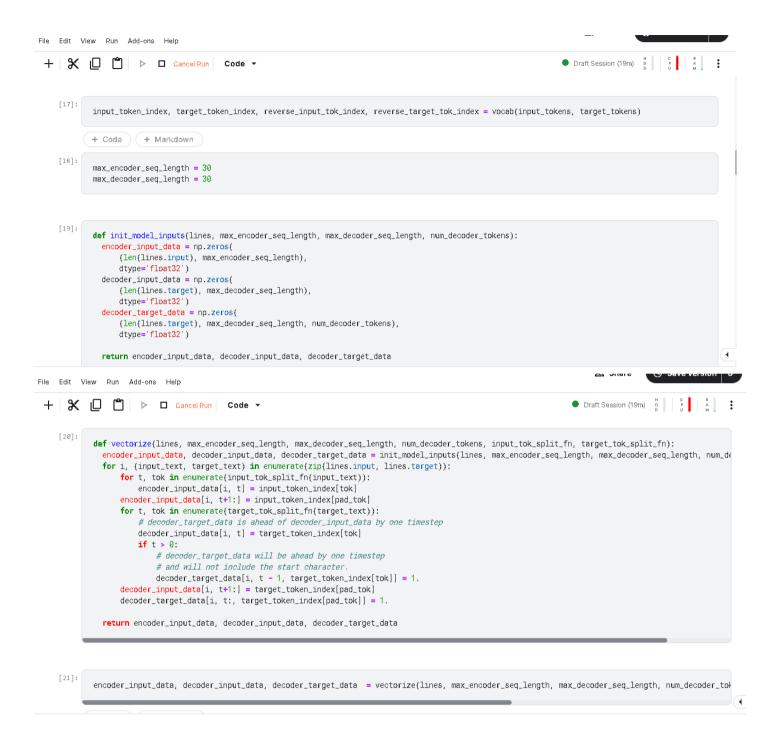






```
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           def vocab(input_tokens, target_tokens):
             input_token_index = {}
             target_token_index = {}
             for i, tok in enumerate(special_tokens):
              input_token_index[tok] = i
              target_token_index[tok] = i
            offset = len(special_tokens)
             for i, tok in enumerate(input_tokens):
              input_token_index[tok] = i+offset
             for i, tok in enumerate(target_tokens):
              target_token_index[tok] = i+offset
             # Reverse-lookup token index to decode sequences back to something readable.
             reverse_input_tok_index = dict{
                (i, tok) for tok, i in input_token_index.items())
             reverse_target_tok_index = dict(
                (i, tok) for tok, i in target_token_index.items())
             \textbf{return} \ \texttt{input\_token\_index}, \ \texttt{target\_token\_index}, \ \texttt{reverse\_input\_tok\_index}, \ \texttt{reverse\_target\_tok\_index}
```



```
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    Draft Session (48m)

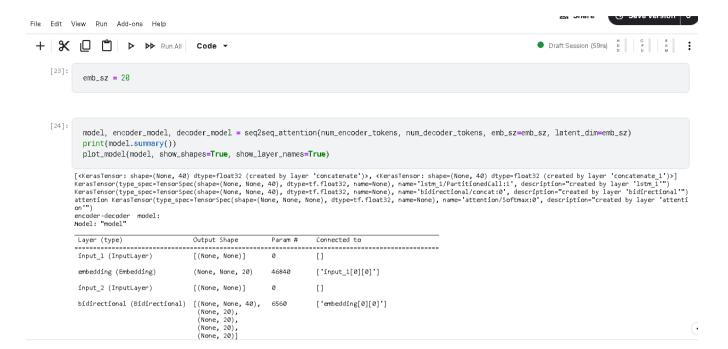
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             def seq2seq_attention(num_encoder_tokens, num_decoder_tokens, emb_sz, latent_dim):
                 # Define an input sequence and process it
                 encoder_inputs = Input(shape=(None,), dtype='float32')
                 encoder_inputs_ = Embedding(num_encoder_tokens, emb_sz, mask_zero=True)(encoder_inputs)
                 encoder = Bidirectional(LSTM(latent_dim, return_state=True, return_sequences=True)) # Bi LSTM
                 encoder_outputs, state_f_h, state_f_c, state_b_h, state_b_c = encoder(encoder_inputs_)# Bi LSTM
                 \verb|state_h| = \verb|Concatenate()([state_f_h, state_b_h]) # Bi LSTM| \\
                 state_c = Concatenate()([state_f_c, state_b_c])# Bi LSTM
                 # We discard 'encoder_outputs' and only keep the states
                 encoder_states = [state_h, state_c] # Bi GRU, LSTM, BHi LSTM
                 print(encoder_states)
                 decoder_inputs = Input(shape=(None,))
decoder_inputs_ = Embedding(num_decoder_tokens, emb_sz, mask_zero=True)(decoder_inputs)
                 # We set up our decoder to return full output sequences,
# and to return internal states as well. We don't use the
                  # return states in the training model, but we will use them in inference
                 {\tt decoder\_lstm = LSTM(latent\_dim*2, return\_sequences=True, return\_state=True) \# \textit{Bi LSTM}}
                 decoder_outputs, _, _ = decoder_lstm(decoder_inputs_, initial_state=encoder_states)
                 # Equation (7) with 'dot' score from Section 3.1 in the paper.
# Note that we reuse Softmax-activation layer instead of writing tensor calculation
                 print(decoder_outputs)
  5.
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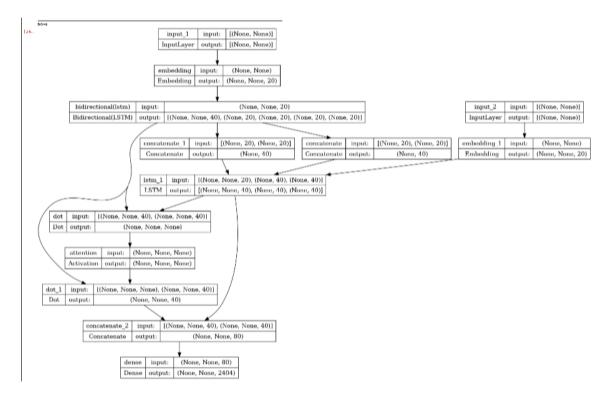
    Draft Session (51m)

                                             oritmax-activation layer instead or writing tensor calculation
                    print(decoder_outputs)
                    print(encoder_outputs)
                    att_dot = Dot(axes=[2, 2])
                    attention = att_dot([decoder_outputs, encoder_outputs])
                    att_activation = Activation('softmax', name='attention')
attention = att_activation(attention)
                    print('attention', attention)
                    context_dot = Dot(axes=[2,1])
                    context = context_dot([attention, encoder_outputs])
                    att_context_concat = Concatenate()
                    decoder_combined_context = att_context_concat([context, decoder_outputs])
                    # Has another weight + tanh layer as described in equation (5) of the paper
                    decoder_dense = Dense(num_decoder_tokens, activation='softmax')
                     #decoder outputs = decoder dense(decoder outputs)
                    decoder_outputs = decoder_dense(decoder_combined_context)
                    # Define the model that will turn
# `encoder_input_data` & `decoder_input_data` into `decoder_target_data`
                    model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
                    {\tt model.compile(optimizer=tf.keras.optimizers.Adam(1r=0.00001),\ loss='categorical\_crossentropy',\ metrics=['acc'])}
                    print('encoder-decoder model:')
                    print(model.summary())
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    Draft Session (57m)
    Draft Session (57m)

                     print(encoder_inputs)
                     print(encoder_outputs)
                     print(encoder_states)
                      encoder_model = Model(encoder_inputs, [encoder_outputs] + encoder_states)
                     decoder_encoder_inputs = Input(shape=(None, latent_dim*2,))
                     decoder_state_input_h = Input(shape=(latent_dim*2,))# Bi LSTM
                      decoder_state_input_c = Input(shape=(latent_dim*2,)) # Bi LSTM
                      decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]
                     decoder_outputs, state_h, state_c = decoder_lstm(decoder_inputs_, initial_state=decoder_states_inputs)
decoder_states = [state_h, state_c]
                     attention = att_dot([decoder_outputs, decoder_encoder_inputs])
                     attention = att_activation(attention)
                      context = context_dot([attention, decoder_encoder_inputs])
                     decoder_combined_context = att_context_concat([context, decoder_outputs])
                     decoder_outputs = decoder_dense(decoder_combined_context)
                     decoder_model = Model(
                          [decoder_inputs, decoder_encoder_inputs] + decoder_states_inputs,
                          [decoder_outputs, attention] + decoder_states)
                      return model, encoder_model, decoder_model
```





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      [25]:
                 model.fit([encoder_input_data, decoder_input_data], decoder_target_data,
                                batch_size=32.
                                epochs=100)
              Epoch 1/100
              Epoch 2/100
              117/117 [=============== ] - 12s 106ms/step - loss: 5.2753 - acc: 0.1241
              Epoch 3/100
              117/117 [================ ] - 12s 103ms/step - loss: 5.0216 - acc: 0.1708
              Epoch 4/100
              117/117 [================== ] - 12s 107ms/step - loss: 4.8021 - acc: 0.2277
              Epoch 5/100
              117/117 [================== ] - 13s 108ms/step - loss: 4.6844 - acc: 0.2441
              Epoch 6/100
              117/117 [================ ] - 12s 106ms/step - loss: 4.6001 - acc: 0.2549
              Epoch 7/100
              117/117 [================ ] - 13s 107ms/step - loss: 4.5283 - acc: 0.2603
              Epoch 8/100
              117/117 [================= ] - 12s 105ms/step - loss: 4.4614 - acc: 0.2659
              Epoch 9/100
              File Edit View Run Add-ons Help
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        def decode_sequence_attention(input_seq, sep=' ');
            # Encode the input as state vectors.
encoder_outputs, h, c = encoder_model.predict(input_seq)
            states_value = [h,c]
# Generate empty target sequence of length 1.
           \label{target_seq} \begin{array}{l} target\_seq = np.zeros((1,1)) \\ \textit{\# Populate the first character of target sequence with the start character.} \end{array}
           target_seq[0, 0] = target_token_index[st_tok]
# Sampling loop for a batch of sequences
# (to simplify, here we assume a batch of size 1),
stop_condition = False
           decoded_sentence = ''
attention_density = []
            while not stop_condition:
              cends step_condition.
output_tokens, attention, h, c = decoder_model.predict(
    [target_seq, encoder_outputs] + states_value\
attention_density.append(attention[0][0])# attention is max_sent_len x 1 since we have num_time_steps = 1 for the output
               # Sample a toke
               sampled_token_index = np.argmax(output_tokens[8, -1, :])
sampled_tok = reverse_target_tok_index[sampled_token_index]
```

decoded_sentence += sep + sampled_tok
if (sampled_tok == end_tok or
 len(decoded_sentence) > 52):
 stop_condition = True

Update the target sequence (of length 1). target_seq = np.zeros($\{1,1\}$) target_seq[θ , θ] = sampled_token_index

states_value = [h, c]
attention_density = np.array(attention_density)
return decoded_sentence, attention_density

```
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                                                                                                                                                              ● Draft Session (1h:5m) 불 불 불 산 🌣 🚼
 + | X □ 🗂 | > ▶ Run All | Code →
     [27]: lines.input[0]
     [27]: 'hi COMMA how are you doing'
     [28]:
             word_decoded_sents = []
for seq_index in range(108): #[14077,20122,40035,40064, 40056, 40068, 40090, 40095, 40100, 40119, 40131, 40136, 40150, 40153]:
   input_seq = encoder_input_data[seq_index: seq_index + 1]
   decoded_sentence, attention = decode_sequence_attention(input_seq)
   print('-')
                 print('Tinput sentence:', lines.input[seq_index: seq_index + 1])
print('Decoded sentence:', decoded_sentence)
word_decoded_sents.append(decoded_sentence)
           ۶.,
  [29]:
             def calculate_WER_sent(gt, pred):
                  calculate_WER('calculating wer between two sentences', 'calculate wer between two sentences')
                  gt_words = gt.lower().split(' ')
                  pred_words = pred.lower().split(' ')
                   d = np.zeros\{((len(gt_words) + 1), (len(pred_words) + 1)), \ dtype=np.uint8) \\ for i in renge(len(gt_words) + 1): 
                       for j in range(len(pred_words) + 1):
   if i == 0:
                               d[B][j] = j
                            elif j == B:
                              d[i][0] = i
                  for i in range(1, len(gt_words) + 1):
                       for j in range(1, len(pred_words) + 1):
                           if gt_words[i - 1] == pred_words[j - 1]:
                                d[i][j] = d[i-1][j-1]
                            else:
                               substitution = d[i-1][j-1]+1
                                insertion = d[i][j-1]+1
deletion = d[i-1][j]+1
                                d[i][j] = min(substitution, insertion, deletion)
                  return d[len(gt_words)][len(pred_words)]
             def celculate_WER(gt, pred):
                   perem gt: list of sentences of the ground truth
                   perem pred: list of sentences of the predictions
                  both lists must have the same length
                  :return: eccumulated WER
                  WER = B
                  nb_w = B
                  for i in renge(len(gt)):
                       \textit{Aprint}(\textit{gt[i]})
                       Aprint(pred[i])
                      WER += celculete_WER_sent(gt[i], pred[i])
nb_w += len(gt[i])
                  return WER / nb_w
```

