

```

1 # =====
2 # importing libraries
3 # =====
4
5 import tensorflow as tf
6 from tensorflow.keras.layers import Input, Dense, Embedding, GRU
7 from tensorflow.keras.models import Model
8 from tensorflow.keras.callbacks import EarlyStopping
9 from tensorflow.keras.preprocessing.text import Tokenizer
10 from tensorflow.keras.preprocessing.sequence import pad_sequences
11 from tensorflow.keras.utils import to_categorical
12 from sklearn.model_selection import train_test_split
13 from tensorflow.keras.optimizers import Adam
14 import numpy as np
15 import unicodedata
16 import re
17 import matplotlib.pyplot as plt
18 %matplotlib inline
19
20 # =====
21 # problem_set_1
22 # =====
23
24 def scaled_dot_product_attention(query, key, value):
25     """
26     Compute the scaled dot product attention.
27     Arguments:
28     query: tensor with shape (batch_size, input_sequence_length, query_dim)
29     key: tensor with shape (batch_size, input_sequence_length, key_dim)
30     value: tensor with shape (batch_size, input_sequence_length, value_dim)
31
32     Returns:
33     output: tensor with shape (batch_size, input_sequence_length, value_dim)
34     """
35     if query.ndim > 3:
36         query = np.reshape(query, (query.shape[0], query.shape[1], -1))
37     if key.ndim > 3:
38         key = np.reshape(key, (key.shape[0], key.shape[1], -1))
39     if value.ndim > 3:
40         value = np.reshape(value, (value.shape[0], value.shape[1], -1))
41
42     dot_product = np.matmul(query, key.transpose(0, 2, 1))
43     scaled_dot_product = dot_product / np.sqrt(query.shape[-1])
44     attention_scores = np.exp(scaled_dot_product)
45     attention_weights = attention_scores / np.sum(attention_scores, axis=-1, keepdims=True)
46     output = np.matmul(attention_weights, value)
47     return output
48
49 def split_heads(x, num_heads):
50     """
51     Compute Split Heads
52     Arguments:
53     x: tensor of shape (batch_size, input_sequence_length, num_heads * query_dim/key_dim/value_dim)
54     num_heads: integer
55
56     Returns:
57     output: tensor with shape (batch_size, input_sequence_length, num_heads, -1)
58     """
59     batch_size, input_sequence_length, concatenated_dim = x.shape
60     head_dim = concatenated_dim // num_heads
61     reshaped_tensor = np.reshape(x, (batch_size, input_sequence_length, num_heads, head_dim))

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62     return reshaped_tensor
63
64 def multi_head_scaled_attention(query, key, value, num_heads, W_q, W_k, W_v):
65     """
66     Compute the multi-head attention.
67     Arguments:
68     query: tensor with shape (batch_size, input_sequence_length, query_dim)
69     key: tensor with shape (batch_size, input_sequence_length, key_dim)
70     value: tensor with shape (batch_size, input_sequence_length, value_dim)
71     num_heads: integer
72     W_q: matrix with shape (query_dim, num_heads * query_dim)
73     W_k: matrix with shape (key_dim, num_heads * key_dim)
74     W_v: matrix with shape (value_dim, num_heads * value_dim)
75
76     Returns:
77     output: tensor with shape (batch_size, input_sequence_length, num_heads * value_dim)
78     """
79     projected_query = np.matmul(query, W_q)
80     projected_key = np.matmul(key, W_k)
81     projected_value = np.matmul(value, W_v)
82     query_heads = split_heads(projected_query, num_heads)
83     key_heads = split_heads(projected_key, num_heads)
84     value_heads = split_heads(projected_value, num_heads)
85     attention_heads = scaled_dot_product_attention(query_heads, key_heads, value_heads)
86     concatenated_attention = np.reshape(attention_heads, (query.shape[0], query.shape[1], -1))
87     return concatenated_attention
88
89 # Testing out with following input values
90 input_seq_len=5 # Maximum length of the input sequence
91 d_q=8           # Dimensionality of the linearly projected queries
92 d_k=8           # Dimensionality of the linearly projected keys
93 d_v=8           # Dimensionality of the linearly projected values
94 batch_size=64  # Batch size from the training process
95 num_heads=8    # Number of self-attention heads
96 query = np.random.randn(batch_size, input_seq_len, d_q) # generating input query matrix
97 key = np.random.randn(batch_size, input_seq_len, d_k)   # generating input key matrix
98 value = np.random.randn(batch_size, input_seq_len, d_v) # generating input value matrix
99 W_q = np.random.randn(d_q, num_heads*d_q) # for generating num head projection matrices for queries
100 W_k = np.random.randn(d_k, num_heads*d_k) # for generating num head projection matrices for keys
101 W_v = np.random.randn(d_v, num_heads*d_v) # for generating num head projection matrices for values
102
103 # Testing code of scaled dot product attention
104 attention=scaled_dot_product_attention(query, key, value)
105 print("Scaled Dot Product Attention:", attention)
106 print("Scaled Dot Product Attention Shape:", attention.shape)
107
108 # Testing code of multi head scaled attention
109 multi_head_attention=multi_head_scaled_attention(query, key, value, num_heads, W_q, W_k, W_v)
110 print("Multi Head Scaled Attention", multi_head_attention)
111 print("Multi Head Scaled Attention Shape:", multi_head_attention.shape)
112
113 # =====
114 # problem_set_2
115 # =====
116
117 start_token = 'sos'
118 end_token = 'eos'
119 oov_token = 'unk'
120 BATCH_SIZE = 32
121 EPOCHS = 31
122 GRU_UNITS = 256

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124 def txt_pre_processing(txt:str)->str:
125     txt = txt.lower().strip()
126     txt = unicodedata.normalize('NFKD',txt).encode('ascii','ignore').decode('utf-8')
127     txt = re.sub(pattern=r'[^sa-z\d\.\?\!\,]', repl='', string=txt)
128     txt = re.sub(pattern=r'([\.\?\!\,])', repl=r' \1 ', string=txt)
129     txt = re.sub(pattern=r'\s+', repl=r' ', string=txt).strip()
130     txt = start_token + ' ' + txt + ' ' + end_token
131     return txt
132
133 def load_data() -> tuple:
134     context : list = list()
135     target : list = list()
136     with open(file='./eng-fra.txt',mode='r',encoding='utf-8') as inputstream:
137         for text in inputstream:
138             lines = text.replace('\n','').replace('\r','').split('\t')
139             eng_txt = lines[0]
140             fr_txt = lines[1]
141             eng_txt = txt_pre_processing(txt=eng_txt)
142             fr_txt = txt_pre_processing(txt=fr_txt)
143             context.append(eng_txt)
144             target.append(fr_txt)
145     context = np.array(context)
146     target = np.array(target)
147     return context,target
148
149 eng_sentences,fr_sentences = load_data()
150 shuffling_indices = np.arange(len(eng_sentences))
151 np.random.shuffle(shuffling_indices)
152 eng_sentences = eng_sentences[shuffling_indices]
153 fr_sentences = fr_sentences[shuffling_indices]
154
155 max_seq_length = max([len(x.split(' ')) for x in eng_sentences])
156
157 eng_tokenizer = Tokenizer()
158 eng_tokenizer.fit_on_texts(eng_sentences)
159 eng_vocab_words = eng_tokenizer.word_index.keys()
160 eng_tokenizer.word_index[oov_token] = len(eng_tokenizer.word_index) + 1
161 eng_vocab_size = len(eng_tokenizer.word_index) + 1
162
163 fr_tokenizer = Tokenizer()
164 fr_tokenizer.fit_on_texts(fr_sentences)
165 fr_vocab_size = len(fr_tokenizer.word_index) + 1
166
167 eng_sequences = eng_tokenizer.texts_to_sequences(eng_sentences)
168 fr_sequences = fr_tokenizer.texts_to_sequences(fr_sentences)
169
170 eng_sequences = pad_sequences(eng_sequences,maxlen=max_seq_length,padding='post')
171 fr_sequences = pad_sequences(fr_sequences,maxlen=max_seq_length,padding='post')
172
173 split_80_20: int = int(eng_sequences.shape[0]*0.8)
174 X_train,y_train = eng_sequences[:split_80_20,:],fr_sequences[:split_80_20]
175 X_test,y_test = eng_sequences[split_80_20:,:],fr_sequences[split_80_20:]
176 y_train = to_categorical(y_train,num_classes=fr_vocab_size)
177 y_test = to_categorical(y_test,num_classes=fr_vocab_size)
178
179 # =====
180 # Load Glove Embedding
181 # =====
182 glove_embeddings_mapping : dict = dict()
183 glove_embeddings_size = 50
184 with open(file='./glove.6B.50d.txt',mode='r',encoding='utf-8') as inputstream:

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183     for text in inputstream:
184         text = text.split()
185         glove_embeddings_mapping[text[0]] = np.asarray(text[1:],dtype='float32')
186
187
188
189 # =====
190 # Glove Matrix
191 # =====
192 glove_embedding_matrix = np.zeros(shape=(eng_vocab_size,glove_embeddings_size))
193 for txt,idx in eng_tokenizer.word_index.items():
194     if txt in glove_embeddings_mapping:
195         glove_embedding_matrix[idx] = glove_embeddings_mapping[txt]
196
197 # =====
198 # enc + dec
199 # =====
200 encoder_inputs = Input(shape=(None,))
201 encoder_embedding = Embedding(input_dim=eng_vocab_size,output_dim=glove_embeddings_size,weights=[glove_embedding_matrix],trainable=False)(encoder_inputs)
202 encoder_gru = GRU(GRU_UNITS,return_state=True)
203 encoder_outputs,encoder_state = encoder_gru(encoder_embedding)
204 decoder_inputs = Input(shape=(None,))
205 decoder_embedding = Embedding(input_dim=fr_vocab_size,output_dim=glove_embeddings_size)(decoder_inputs)
206 decoder_gru = GRU(GRU_UNITS,return_sequences=True,return_state=True)
207 decoder_outputs,_ = decoder_gru(decoder_embedding,initial_state=encoder_state)
208 decoder_dense = Dense(fr_vocab_size,activation='softmax')
209 decoder_outputs = decoder_dense(decoder_outputs)
210 model = Model([encoder_inputs,decoder_inputs],decoder_outputs)
211 model.compile(optimizer=Adam(learning_rate=3e-5,epsilon=1e-07,),loss='categorical_crossentropy',metrics=['accuracy'])
212
213 # =====
214 # Testing Translation
215 # =====
216 test_sentence = X_test[-1].reshape(1,-1)
217 translations_tracking : dict = dict()
218 history_translations_tracking : dict = {
219     'loss' : list(),
220     'val_loss' : list(),
221     'accuracy' : list(),
222     'val_accuracy' : list(),
223 }
224 history_tracking : dict = {
225     'loss' : list(),
226     'val_loss' : list(),
227     'accuracy' : list(),
228     'val_accuracy' : list(),
229 }
230
231 for epoch in range(EPOCHS):
232     history = model.fit([X_train,X_train],y_train,epochs=1,batch_size=BATCH_SIZE,validation_data=([X_test,X_test],y_test))
233     history_tracking['loss'].append(history.history['loss'])
234     history_tracking['val_loss'].append(history.history['val_loss'])
235     history_tracking['accuracy'].append(history.history['accuracy'])
236     history_tracking['val_accuracy'].append(history.history['val_accuracy'])
237     if epoch == 0 or epoch % 5 == 0:
238         curr_trans = model.predict([test_sentence,test_sentence],batch_size=1)
239         translations_tracking[epoch] = {
240             'correct' : eng_tokenizer.sequences_to_texts([test_sentence[0]]),
241             'translated' : fr_tokenizer.sequences_to_texts([np.argmax(curr_trans,axis=-1)[0]]),
242         }
243         history_translations_tracking['loss'].append(history.history['loss'])
244         history_translations_tracking['val_loss'].append(history.history['val_loss'])
245         history_translations_tracking['accuracy'].append(history.history['accuracy'])

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246     history_translations_tracking['val_accuracy'].append(history.history['val_accuracy'])
247     else:
248         continue
249
250 # =====
251 # Plotting training and the testing loss for 0th and multiple of 5 epoch.
252 # =====
253 fig,axs = plt.subplots(2,1,figsize=(10,13))
254 axs[0].plot(history_translations_tracking['loss'])
255 axs[0].plot(history_translations_tracking['val_loss'])
256 axs[0].title.set_text('Enc + Dec Training Loss vs Validation Loss')
257 axs[0].set_xlabel('Epochs')
258 axs[0].set_ylabel('Loss')
259 axs[0].legend(['Train', 'Val'])
260 axs[1].plot(history_translations_tracking['accuracy'])
261 axs[1].plot(history_translations_tracking['val_accuracy'])
262 axs[1].title.set_text('Enc + Dec Training Accuracy vs Validation Accuracy')
263 axs[1].set_xlabel('Epochs')
264 axs[1].set_ylabel('Accuracy')
265 axs[1].legend(['Train', 'Val'])
266
267 # =====
268 # Plotting training and the testing loss for each epoch.
269 # =====
270 fig,axs = plt.subplots(2,1,figsize=(10,13))
271 axs[0].plot(history_tracking['loss'])
272 axs[0].plot(history_tracking['val_loss'])
273 axs[0].title.set_text('Enc + Dec Training Loss vs Validation Loss')
274 axs[0].set_xlabel('Epochs')
275 axs[0].set_ylabel('Loss')
276 axs[0].legend(['Train', 'Val'])
277 axs[1].plot(history_tracking['accuracy'])
278 axs[1].plot(history_tracking['val_accuracy'])
279 axs[1].title.set_text('Enc + Dec Training Accuracy vs Validation Accuracy')
280 axs[1].set_xlabel('Epochs')
281 axs[1].set_ylabel('Accuracy')
282 axs[1].legend(['Train', 'Val'])
```

```
scaled_dot_product_attention -> query.shape = (64, 5, 8)
scaled_dot_product_attention -> key.shape = (64, 5, 8)
scaled_dot_product_attention -> value.shape = (64, 5, 8)
scaled_dot_product_attention -> dot_product.shape = (64, 5, 5)
scaled_dot_product_attention -> scaled_dot_product.shape = (64, 5, 5)
scaled_dot_product_attention -> attention_scores.shape = (64, 5, 5)
scaled_dot_product_attention -> attention_weights.shape = (64, 5, 5)
scaled_dot_product_attention -> output.shape = (64, 5, 8)
Scaled Dot Product Attention: [[[ 0.32049449 -0.26037721  0.57715652 ...  0.67257267  0.57302852
  0.42918147]
 [ 0.18361762 -0.1615577  0.74465832 ...  0.67088495  0.83321277
  0.41839623]
 [ 0.25670707 -0.6283299  1.1702535 ...  0.57414191  0.20628595
  0.47909316]
 [ 0.48596639  0.07771385 -0.16564297 ...  0.78107628  1.00761391
  0.33899313]
 [ 0.34698335  0.26430095 -0.43351202 ...  0.86874091  1.03004984
  0.3646912 ]]

[[[ 0.09733811  0.29871887 -0.04301486 ... -0.49032091  0.20637658
  -0.06015095]
 [ 0.21399615  0.27831926  0.10238223 ... -0.40469542  0.24720898
  0.27278054]
 [-0.03270254  0.40088035  0.07822751 ... -0.6222459  0.50397853
  0.1627915 ]]
 [-0.09250097  0.37620038 -0.12072245 ... -0.64427094  0.31387475
  -0.24786255]
 [ 0.10300623  0.21843467 -0.07129473 ... -0.4805931  0.25780556
  -0.09008697]]]

[[[ 0.7587503 -1.22443682  0.6396305 ...  0.1048958  0.7339676
  -0.41744447]
 [ 0.37518944 -0.4003244  0.29736823 ...  0.0821836  0.39091867
  -0.3322847 ]]
 [ 0.63708029  0.02857291 -0.17430152 ... -0.12008221  0.69168012
  -0.51092033]
 [ 0.63177876 -0.2736909 -0.25066728 ...  0.12965289  1.15408735
  -0.82825644]
 [ 0.27850985 -0.45713751 -0.33024877 ...  0.18237319  0.75179257
  -0.59662702]]]

...

[[[ 0.86287874  0.87762199 -0.31237313 ...  0.47403448 -0.52667169
  0.22082798]
 [ 0.47433115 -0.07577435  0.0274051 ... -0.34456309  0.14853777
  0.38885748]
 [ 0.29648921  0.24600455  0.19818333 ... -0.01334004  0.22414259
  0.57022444]
 [ 0.15305594 -0.08036415  0.11077052 ... -0.22036802 -0.18909445
  0.49740526]
 [ 0.23558292  0.16375332  0.17607076 ... -0.04813029  0.0650367
  0.55424271]]]

[[[ 0.43266217  0.45181045 -0.53921716 ...  0.82770425 -0.03493847
  -0.54090625]
 [ 0.48486403  0.17985689 -0.11505856 ...  0.28442258  0.11320648
  -0.28030211]
```

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0.55424271]]
[[ 0.43266217 0.45181045 -0.53921716 ... 0.82770425 -0.03493847
-0.54090625]
[ 0.48486403 0.17985689 -0.11505856 ... 0.28442258 0.11320648
-0.28030211]
[ 0.3152738 0.29972283 -0.48899666 ... 0.65538579 -0.0623106
0.28312533]
[ 0.03627946 0.23007976 0.17741296 ... 1.18159433 -0.1205346
0.11506042]
[ 0.71147901 0.5041412 -0.70295973 ... 0.46050544 0.09043237
-1.04158201]]

[[-0.74940332 0.36280141 0.26116175 ... -0.57908213 -0.21421493
0.25120602]
[-0.39935223 0.46270689 -0.05223337 ... -0.3855749 -0.31565068
-0.06946156]
[-0.15002964 0.7667206 -0.49081544 ... -1.1160412 0.05242817
-0.11869961]
[-0.24597695 0.38134416 -0.43823219 ... -0.56154394 -0.35290235
-0.18280336]
[-0.37389065 0.85254153 -0.22990709 ... -1.00939112 -0.01977578
-0.0021528 ]]

Scaled Dot Product Attention Shape: (64, 5, 8)
=====
multi_head_scaled_attention -> projected_query.shape = (64, 5, 64)
multi_head_scaled_attention -> projected_key.shape = (64, 5, 64)
multi_head_scaled_attention -> projected_value.shape = (64, 5, 64)
multi_head_scaled_attention -> query_heads.shape = (64, 5, 8, 8)
multi_head_scaled_attention -> key_heads.shape = (64, 5, 8, 8)
multi_head_scaled_attention -> value_heads.shape = (64, 5, 8, 8)
scaled_dot_product_attention -> query.shape = (64, 5, 64)
scaled_dot_product_attention -> key.shape = (64, 5, 64)
scaled_dot_product_attention -> value.shape = (64, 5, 64)
scaled_dot_product_attention -> dot_product.shape = (64, 5, 5)
scaled_dot_product_attention -> scaled_dot_product.shape = (64, 5, 5)
scaled_dot_product_attention -> attention_scores.shape = (64, 5, 5)
scaled_dot_product_attention -> attention_weights.shape = (64, 5, 5)
scaled_dot_product_attention -> output.shape = (64, 5, 64)
Multi Head Scaled Attention [[[-1.10576549 3.34213618 -1.09227605 ... -2.68362801 6.71951716
-5.0379075 ]
[ 3.22571549 2.00964825 0.1544249 ... 0.82026753 0.87772739
-0.92102584]
[-0.87755784 3.38009532 -1.03371098 ... -2.5147299 6.48268136
-4.89333112]
[ 0.27984611 0.02480872 0.18258911 ... 1.84044702 2.14403798
1.59627869]
[ 0.54358086 0.57503965 -0.25579966 ... 2.9502067 -1.85284197
1.1064349 ]]

[[-1.62861208 2.4619379 -0.34590429 ... 0.69778489 -1.30499806
-1.25729776]
[-1.57034696 2.40017486 -0.32376202 ... 0.68566511 -1.31363848
-1.1969879 ]
[ 1.22332422 -0.65744974 0.73922393 ... 0.08230363 -1.75732589
1.74940991]
[-1.40826917 2.15407997 -0.25886037 ... 0.65065985 -1.33491208
-0.96892455]
[-0.7867873 -0.87297427 0.14740872 ... 0.91474751 -0.61873359

```

```
[[-1.62861208  2.4619379 -0.34590429 ...  0.69778489 -1.30499806
-1.25729776]
[-1.57034696  2.40017486 -0.32376202 ...  0.68566511 -1.31363848
-1.1969879 ]
[ 1.22332422 -0.65744974  0.73922393 ...  0.08230363 -1.75732589
1.74940991]
[-1.40826917  2.15407997 -0.25886037 ...  0.65065985 -1.33491208
-0.96892455]
[-0.7867873  -0.87297427  0.14240872 ...  0.91474751 -0.61873359
2.09101434]]
```

```
[[-1.55576017 -1.48412891  1.33913957 ... -2.67502232  3.59819332
-0.08224043]
[-1.32251771 -2.57036847  0.92133628 ... -1.97955463  2.12090305
0.83482006]
[ 3.09096162  6.41962885  0.3837507 ...  1.30014462  0.14192193
-3.75912086]
[ 3.15971335  6.48500103  0.40526569 ...  1.25974027  0.20453632
-3.86178132]
[ 0.63945916 -1.1304109 -0.74444328 ...  1.86229298 -2.94315723
1.91299072]]
```

...

```
[ [ 0.24413171 -1.77120864 -0.81233591 ...  3.21259207  0.43097956
3.25990132]
[ 0.44533161 -1.31569924 -0.64796026 ...  3.1800236  0.6045574
3.15987864]
[ 3.36655761  5.2973567  1.75064552 ...  2.6728601  3.14037056
1.69081288]
[ 0.44809837  2.81245393  1.1168635 ...  0.36076492  2.42829345
0.52082055]
[ 0.31718308 -1.56516213 -0.7300772 ...  3.15089861  0.52540473
3.18531628]]
```

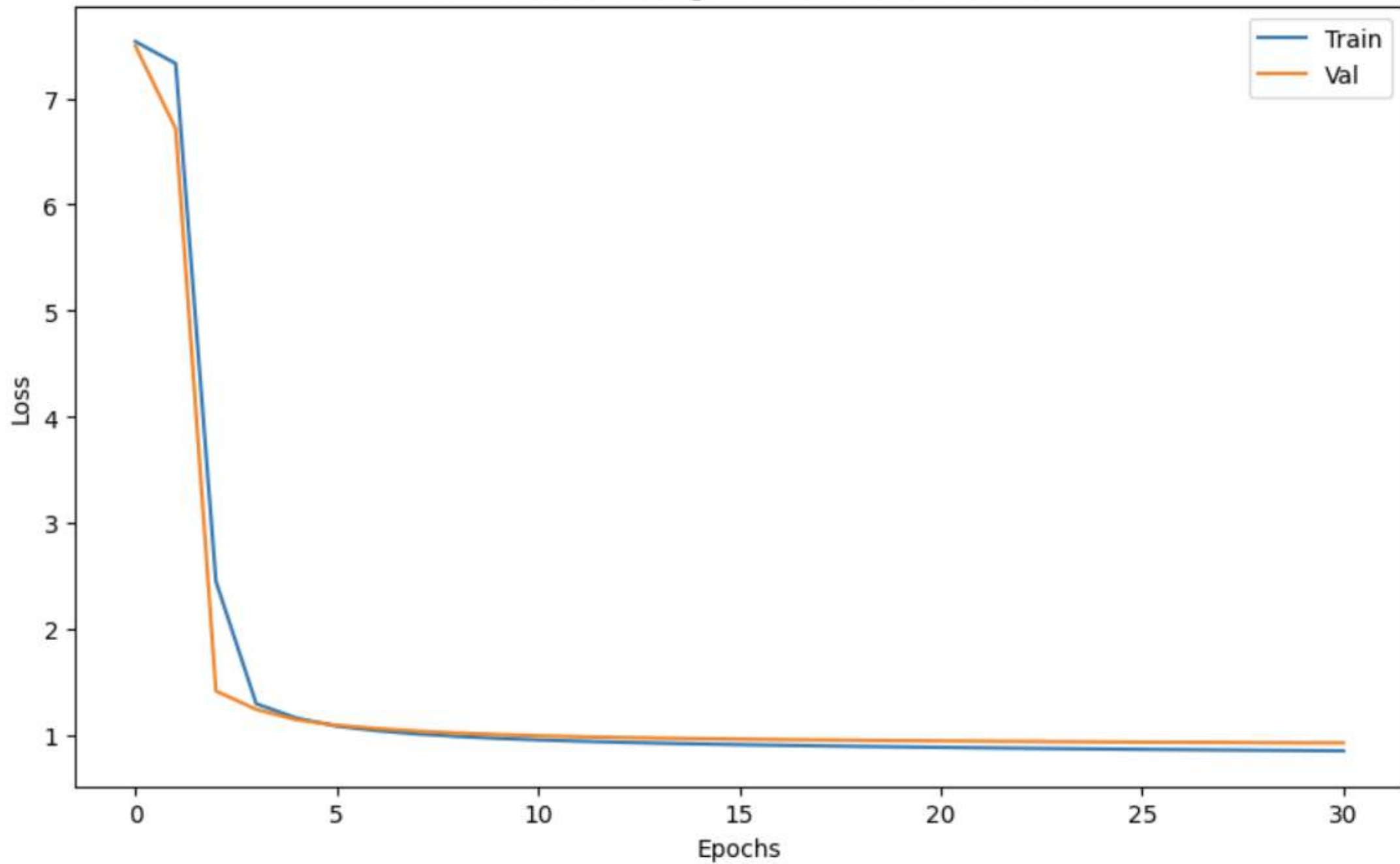
```
[[-1.24195709 -2.40513444 -1.60342133 ...  1.48904369 -1.28392825
-0.10417113]
[-0.81987015  0.92844469 -1.38007812 ...  3.57147195 -2.95665296
0.46726103]
[ 0.57122004  3.08912381  1.53377398 ... -0.19168696  1.3939471
2.0800465 ]
[ 0.43263325 -1.89560183 -0.88595476 ... -1.41954168  0.23889672
-2.32849922]
[ 0.06658936  1.62020413  0.57646473 ...  0.43944132  0.44043603
1.38041953]]
```

```
[[-2.50422211 -6.10252394  2.15616899 ... -0.12749075 -3.05709315
7.06989817]
[ 1.69929339 -0.96767492  0.82998026 ... -0.24005252 -3.79681386
3.28837821]
[ 1.69927007 -0.96770342  0.82998759 ... -0.24005192 -3.79680972
3.28839911]
[-2.02190098 -2.43940498 -1.85465602 ... -1.69335101 -0.39778574
-2.53800194]
[ 1.04684875 -1.76242162  1.03499092 ... -0.22269616 -3.68103031
3.87253629]]]
```

Multi Head Scaled Attention Shape: (64, 5, 64)


```
Epoch 0: {'correct': ['sos how are you eos'], 'translated': ['sos']}
Epoch 5: {'correct': ['sos how are you eos'], 'translated': ['sos ca eos']}
Epoch 10: {'correct': ['sos how are you eos'], 'translated': ['sos comment il eos']}
Epoch 15: {'correct': ['sos how are you eos'], 'translated': ['sos comment allez eos']}
Epoch 20: {'correct': ['sos how are you eos'], 'translated': ['sos comment allez eos']}
Epoch 25: {'correct': ['sos how are you eos'], 'translated': ['sos comment allez vous eos']}
Epoch 30: {'correct': ['sos how are you eos'], 'translated': ['sos comment allez vous eos']}
```

Enc + Dec Training Loss vs Validation Loss



Enc + Dec Training Accuracy vs Validation Accuracy

