# Report for assignment 5 by Linsen Li

### 1. Description of data set

This task is to build a machine translation model to translate English to Germany. We download the data set from the website and store it in a txt file. We have chosen the number of 30000 English-to-Germany pairs from the txt file. The following figure shows some examples of the data set (the left is English and the right is Germany):

```
# Show these pair of data
for i in range(3000, 3010):
    print('[' + clean_pairs[i, 0] + '] => [' + clean_pairs[i, 1] + ']')

[tom is spirited] => [tom ist temperamentvoll]
[tom is stalking me] => [tom stalkt mich]
[you broke your leg] => [du hast dir das bein gebrochen]
[its a good school] => [das ist eine gute schule]
[tom will continue] => [tom wird weitermachen]
[the signal was red] => [das signal war rot]
[tom is marys son] => [tom ist der sohn marias]
[what did you learn] => [was haben sie gelernt]
[tom is undressing] => [tom entkleidet sich]
[youve upset tom] => [du hast tom verargert]
```

Figure1: 10 examples of the English-to-Germany pairs

Then we split the data into training set, validation set and test set:

```
# Split the data into train,val,test
np.random.shuffle(clean_pairs)
training, test = clean_pairs[:27000,:], clean_pairs[27000:,:]
np.random.shuffle(training)
train, val = training[:25000,:], training[25000:,:]
print('The shape of training set is' + str(train.shape))
print('The shape of validation set is' + str(val.shape))
print('The shape of test set is' + str(test.shape))
The shape of training set is(25000, 2)
The shape of validation set is(2000, 2)
The shape of test set is(3000, 2)
```

Figure 2: The shape of training set, validation set and test set

# 2. Description of the model

#### 2.1 Seq2seq models

For the Seq2seq models, we build encoder and decoder separately. Then we connect these two parts and formulate our Seq2seq models.

#### 2.1.1 Seg2seg models with LSTM

We use loss function as 'categorical\_crossentropy' with the default learning rate 0.001. We choose optimizer as 'rmsprop'. The following is the summary and structure of the model:

Layer (type)	Output Shape	Param #	Connected to
encoder_input_x (InputLayer)	(None, None, 28)	0	
decoder_input_x (InputLayer)	(None, None, 30)	0	
encoder (Model)	[(None, 512), (None,	583680	encoder_input_x[0][0]
decoder_lstm (LSTM)	[(None, None, 512),	1112064	decoder_input_x[0][0] encoder[1][0] encoder[1][1]
decoder_dense (Dense)	(None, None, 30)	15390	decoder_lstm[1][0]

Figure 3: The summary of the Seq2seq model with LSTM

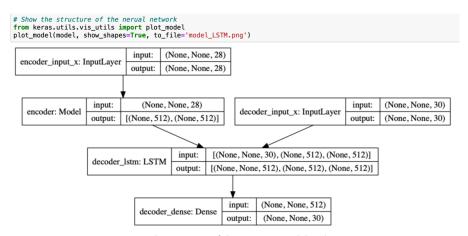


Figure 4: The structure of the Seq2seq model with LSTM

We train the model for 100 epochs, and get the following loss plot:

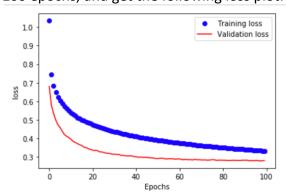


Figure5: The loss plot of the Seq2seq model with LSTM

We test the BLEU score on the validation set, and get the BLEU score:

```
# Compute the BLEU on validation set
blue_score(input_val_texts, target_val_texts)
Average BLEU score 0.1134
```

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Figure 6: The BLEU score of the Seq2seq model with LSTM on validation set

#### 2.1.2 Seq2seq models with GRU

We use loss function as 'categorical\_crossentropy' with the default learning rate 0.001. We choose optimizer as 'rmsprop'. The following is the summary and structure of the model:

Layer (type)	Output Shape	Param #	Connected to
Encoder_Input (InputLayer)	(None, None, 28)	0	
Decoder_Input (InputLayer)	(None, None, 30)	0	
Encoder_GRU (GRU)	[(None, 256), (None,	218880	Encoder_Input[0][0]
Decoder_GRU (GRU)	[(None, None, 256),	220416	Decoder_Input[0][0] Encoder_GRU[0][1]
DecoderOutput (Dense)	(None, None, 30)	7710	Decoder_GRU[0][0]
 Total params: 447,006 Trainable params: 447,006 Non-trainable params: 0		======	

Figure 6: The summary of the Seq2seq model with GRU

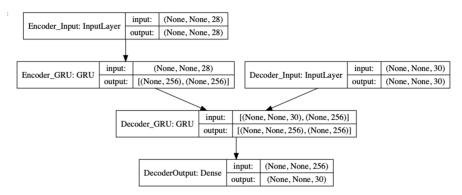


Figure7: The structure of the Seq2seq model with GRU

We train the model for 50 epochs, and get the following loss plot:

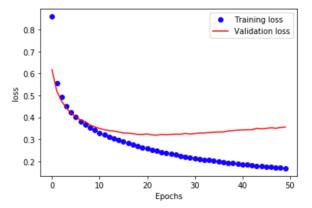


Figure8: The loss plot of the Seq2seq model with GRU

We test the BLEU score on the validation set, and get the BLEU score:

```
: # Compute the BLEU on validation set
blue_score(input_val_texts, target_val_texts)

Average BLEU score 0.1024
```

Figure9: The BLEU score of the Seq2seq model with GRU on validation set

#### 2.1.3 Seg2seg models with SimpleRNN

We use loss function as 'categorical\_crossentropy' with the default learning rate 0.001. We choose optimizer as 'rmsprop'. The following is the summary and structure of the model:

Layer (type)	Output Shape	Param #	Connected to
encoder_input_x (InputLayer)	(None, None, 28)	0	
decoder_input_x (InputLayer)	(None, None, 30)	0	
encoder (Model)	[(None, 256), (None,	72960	encoder_input_x[0][0]
decoder_RNN (LSTM)	[(None, None, 256),	293888	decoder_input_x[0][0] encoder[1][0] encoder[1][1]
decoder_dense (Dense)	(None, None, 30)	7710	decoder_RNN[1][0]
Total params: 374,558 Trainable params: 374,558 Non-trainable params: 0			

Figure 10: The summary of the Seq2seq model with SimpleRNN

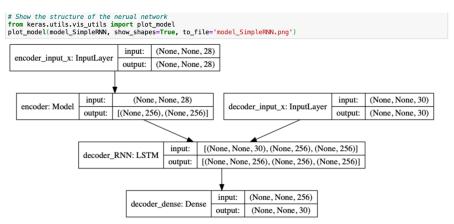


Figure 11: The structure of the Seq2seq model with SimpleRNN

We train the model for 50 epochs, and get the following loss plot:

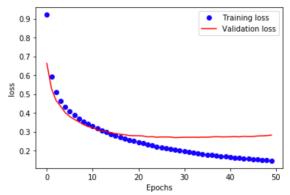


Figure 12: The loss plot of the Seq2seq model with SimpleRNN

We test the BLEU score on the validation set, and get the BLEU score:

```
# Compute the BLEU on validation set
blue_score(input_val_texts, target_val_texts)
```

Average BLEU score 0.0877

Figure 13: The BLEU score of the Seq2seq model with SimpleRNN on validation set

## 2.1.4 Seq2seq models conclusion

We have tried Seq2seq model with different RNN cells: LSTM, GRU and simple RNN. We find that LSTM performs the best on BLEU score.

### 2.2 Seg2seg models with attention

We use loss function as 'categorical\_crossentropy' with the default learning rate 0.001. We choose optimizer as 'rmsprop'. The following is the summary and structure of the model:

Output Shape	!	Param #	Connected to
(None, None,	30)	0	
(None, None,	28)	0	
(None, None,	512)	1112064	input_4[0][0]
[(None, None	, 512),	583680	input_3[0][0]
(None, None,	512)	0	lstm_7[0][0]
(None, None,	512)	0	bidirectional_11[0][0]
(None, None,	None)	0	dropout_7[0][0] dropout_6[0][0]
(None, None,	None)	0	dot_3[0][0]
(None, None,	512)	0	activation_2[0][0] dropout_6[0][0]
(None, None,	1024)	0	dot_4[0][0] dropout_7[0][0]
(None, None,	30)	30750	concatenate_16[0][0]
	(None, None,	Output Shape (None, None, 30) (None, None, 28) (None, None, 512) [(None, None, 512), (None, None, 512) (None, None, 512) (None, None, None) (None, None, None) (None, None, 1024) (None, None, 1024) (None, None, 30)	(None, None, 30) 0 (None, None, 28) 0 (None, None, 512) 1112064 [(None, None, 512), 583680 (None, None, 512) 0 (None, None, 512) 0 (None, None, None) 0

Figure14: The summary of the Seq2seq model with attention

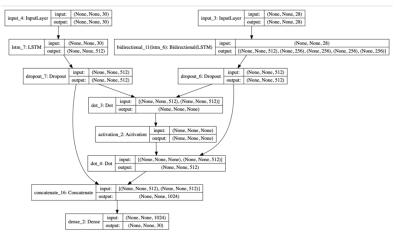


Figure 15: The structure of the Seq2seq model with attention

We train the model for 50 epochs, and get the following loss plot:

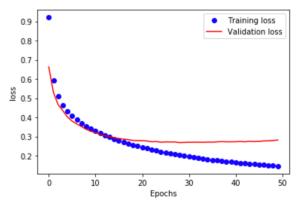


Figure 16: The loss plot of the Seq2seq model with attention

### 3. Compare model on test set

Since previously we have found out that LSTM performs the best on BLEU score on validation set. So, we choose LSTM as our best Seq2seq model. In order to improve the Seq2seq model, we change it to Bi-LSTM. Note that we can only use Bi-direction LSTM for the encoder part. At last we get our best Seq2seq model. We use this to compare with the attention model on test set, the result is following:



Figure 17: The BLEU on test set

The result show that the Seq2seq with attention performs better than normal Seq2seq.

# 4. Show some translation examples

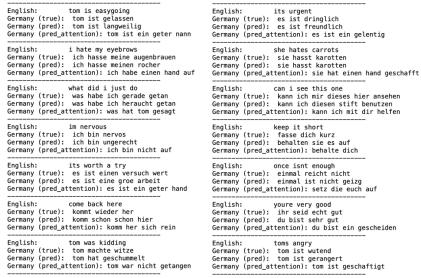


Figure 18: Some translation examples