NLP TP5 REPORT

Machine Translation English to French

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GROUP 01



INTRODUCTION

Machine translation (MT) refers to fully automated software that can translate source content into target languages. Humans may use MT to help them render text and speech into another language, or the MT software may operate without human intervention.

We will build Neural network architecture (GRU) to train the algorithm translate from English to French. We will use keras library to build Neural Network and then obtain the translation.

DATASET

The most common datasets used for machine translation are from <u>WMT</u>. However, that will take a long time to train a neural network on. We'll be using a dataset we created for this project that contains a small vocabulary. We'll be able to train your model in a reasonable time with this dataset.

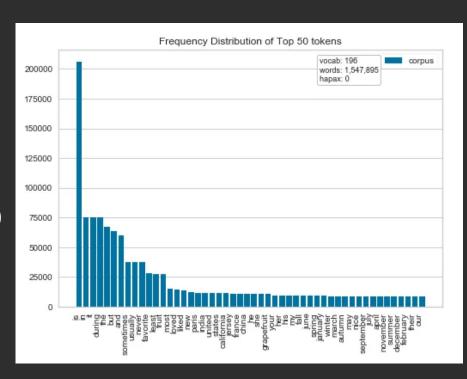
Overview of our dataset

```
small_vocab_en Line 1: new jersey is sometimes quiet during autumn , and it is snowy in april .
small_vocab_fr Line 1: new jersey est parfois calme pendant l' automne , et il est neigeux en avril .
small_vocab_en Line 2: the united states is usually chilly during july , and it is usually freezing in november .
small_vocab_fr Line 2: les Āctats-unis est gĀcnĀcralement froid en juillet , et il gĀ"le habituellement en novembre .
```

 The `small_vocab_en` file contains English sentences with their French translations in the `small_vocab_fr` file.

Vocabulary

our dataset has 1823250
 English words with 227
 unique words and
 1961295 French words
 with 355 unique words.



Data Preprocessing

Tokenization

 map words to ids in order to make them comprehensible to machine learning algorithms.

```
Sequence 1 in x
Input: The quick brown fox jumps over the lazy dog .
Output: [1, 2, 4, 5, 6, 7, 1, 8, 9]
Sequence 2 in x
Input: By Jove , my quick study of lexicography won a prize .
Output: [10, 11, 12, 2, 13, 14, 15, 16, 3, 17]
Sequence 3 in x
Input: This is a short sentence .
Output: [18, 19, 3, 20, 21]
```

Padding

• Make sure all the English and french sequences have the same length.

```
Sequence 1 in x
   Input: [1 2 4 5 6 7 1 8 9]
   Output: [1 2 4 5 6 7 1 8 9 0]

Sequence 2 in x
   Input: [10 11 12 2 13 14 15 16 3 17]
   Output: [10 11 12 2 13 14 15 16 3 17]

Sequence 3 in x
   Input: [18 19 3 20 21]

Output: [18 19 3 20 21 0 0 0 0 0]
```

Preprocessed Data

```
Data Preprocessed
Max English sentence length: 15
Max French sentence length: 21
English vocabulary size: 199
French vocabulary size: 345
```

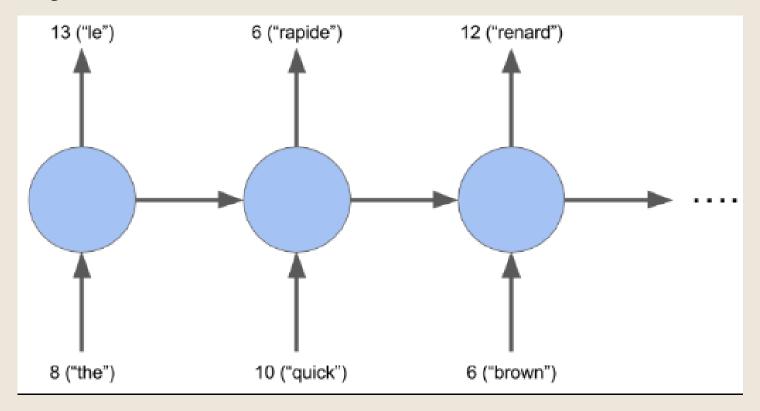
Models Training, Evaluation and Validation

- We have implemented three model architectures.
- Models are evaluated by the categorical cross entropy on validation data.

Function to map ids back to words.

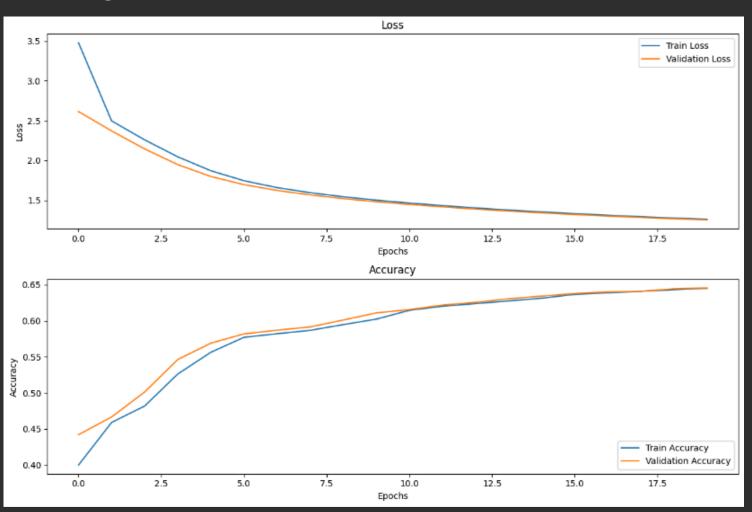
```
def logits_to_text(logits, tokenizer):
    index_to_words = {id: word for word, id in tokenizer.word_index.items()}
    index_to_words[0] = '<PAD>'
    return ' '.join([index_to_words[prediction] for prediction in np.argmax(logits, 1) if index_to_words[prediction]!='<PAD>'] )
print('`logits_to_text` function loaded.')
```

Model 1: Basic RNN with Time Distributed Layer



Layer (type)	Output Shape	Param #	
input_layer (InputLayer)	[(None, 21, 1)]	θ	
LSTM_layer (LSTM)	(None, 21, 64)	16896	
Dense_layer (TimeDistribut ed)	(None, 21, 345)	22425	
Total params: 39321 (153.60 KB) Trainable params: 39321 (153.60 KB) Non-trainable params: 0 (0.00 Byte)			

Learning curves:

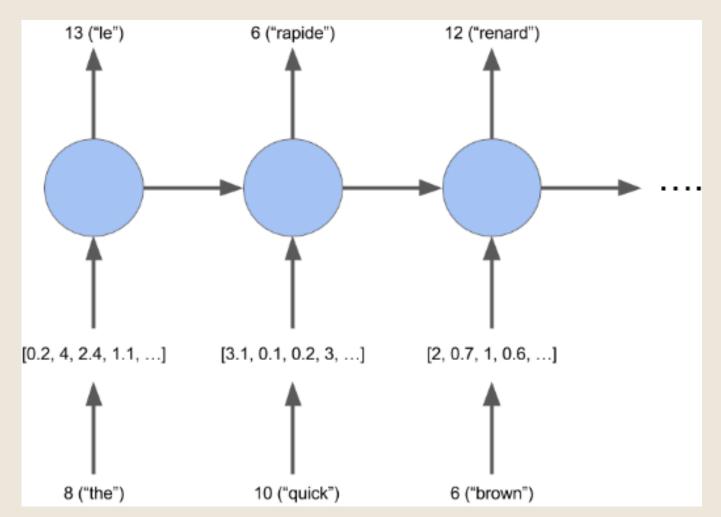


- Accuracy and loss are converging properly, we have achieved a validation accuracy of 64%, we will try other improved architectures and maybe training on more epochs would be also useful
- when it comes to the variance between validation and training sets, it's approximately not at all variance

Prediction:

elle fruit préféré est la mais mais son préféré est la

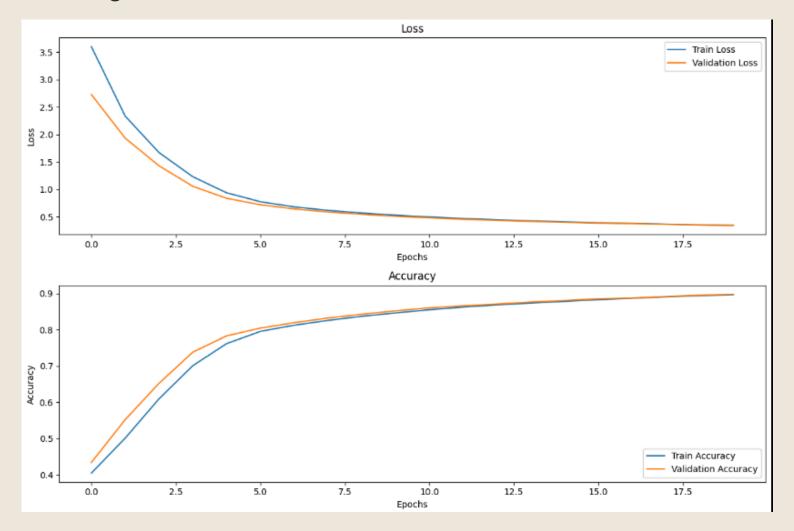
Model 2: Basic RNN with Time Distributed Layer and Embedding



Model: "Embedding_LSTM"			
Layer (type)	Output Shape	Param #	
input_layer (InputLayer)	[(None, 21)]	θ	
Embedding_layer (Embedding)	(None, 21, 256)	51200	
LSTM_layer (LSTM)	(None, 21, 64)	82176	
Dense_layer (TimeDistribut ed)	(None, 21, 345)	22425	
Total params: 155801 (608.60 KB) Trainable params: 155801 (608.60 KB) Non-trainable params: 0 (0.00 Byte)			

 Validation Accuracy is now 84%, we notice that this is a huge improvement after adding just the embedding layer.

Learning curves:



Prediction:

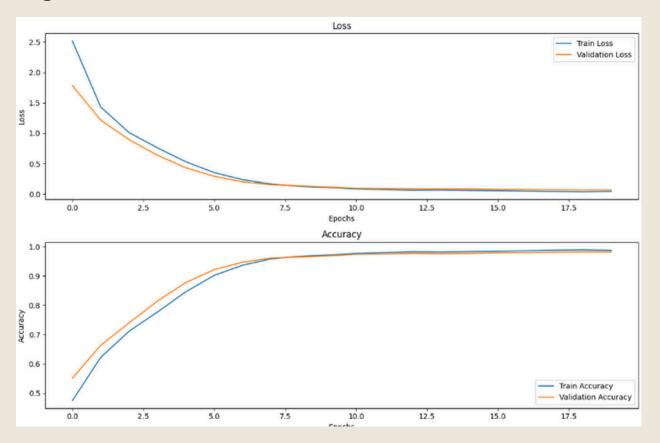
• Better prediction compared to the first model.

Model 3: bi-LSTM encoder LSTM decoder

 We tried to improve more in the model architecture and this encoder decoder based architecture gave us the best results: validation accuracy of 98% after 20 epochs, although the training time was 3 hours.

```
Model: "sequential"
Layer (type)
                              Output Shape
                                                         Param #
 Embedding layer (Embedding (None, 21, 256)
                                                         51200
Bi LSTM encoder (Bidirecti
                             (None, 512)
                                                         1050624
onal)
Glue (RepeatVector)
                              (None, 21, 512)
LSTM decoder (LSTM)
                              (None, 21, 256)
                                                         787456
Dense (TimeDistributed)
                              (None, 21, 345)
                                                         88665
```

Learning curves:



Prediction:

• It has predicted correctly the whole sentence comparing to the previous models that mispredicted some words.