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## Introduction

In this session, we propose to create a very first model for Neural Machine Translation

### I. Tokenization

#### Exercise 1:

**Q1: Explain in a few words the goal and the algorithm of BPE.**

- The Goal: *sub-word tokenization; in fact, “Byte-Pair Encoding (BPE) is an unsupervised sub-word tokenization technique, commonly used in neural machine translation and other NLP tasks.”<sup>1</sup> <sup>2</sup> Words in Languages are built up of different sub-words and taking those sub-words enhance the quality of embeddings on a NMT.*
- The Algorithm: *It is a data compression algorithm; it “iteratively replaces the most frequent pair of bytes in a sequence with a single, unused byte.”<sup>3</sup>*

**Q2: Prepare 3 BPE models, associated with 3 code sizes: 16k, 32k and 48k.  
 What are the exact amount of code done for each one?**

After prepare the model we have :

```
! ls ./codes/ -ltr

total 1032
-rw-r--r-- 1 root root 160388 Jan 31 14:34 codes_files_16k.bpe
-rw-r--r-- 1 root root 345768 Jan 31 14:36 codes_file_32k.bpe
-rw-r--r-- 1 root root 543107 Jan 31 14:38 codes_file_48k.bpe
```

- Amount of code for 16k : 16001 ( 16k + one line for the version )

```
15998 alk aline</w>
15999 al ?</w>
16000 affin ité</w>
16001 ab ond
16002
```

- Amount of code for 32k: 32001 ( 32k + one line for the version )

```
31998 pow er,</w>
31999 pover ty.</w>
32000 pousoir</w>
32001 poursuivre</w>
32002
```

<sup>1</sup> *Investigating the Effectiveness of BPE: The Power of Shorter Sequences*, Matthias Galle

<sup>2</sup> See Annex figure 1 for the illustration.

<sup>3</sup> *Neural Machine Translation of Rare Words with Subword Units*, Rico Sennrich and Barry Haddow and Alexandra Birch School of Informatics, University of Edinburgh

- Amount of code for 48k : 48001 (48k + one line for the version )

```
47998 moder ation</w>
47999 mobil is
48000 mo te</w>
48001 mo s</w>
48002
```

Since I used the syntax :

```
# First 16k BPE model
! subword-nmt learn-joint-bpe-and-vocab --input ./drive/MyDrive/train.fr ./drive/MyDrive/train.en -s 16000 -o ./codes/codes_files_16k.bpe --write-vocabulary
# First 32k BPE model
! subword-nmt learn-joint-bpe-and-vocab --input ./drive/MyDrive/train.fr ./drive/MyDrive/train.en -s 32000 -o ./codes/codes_file_32k.bpe --write-vocabulary
# Third 48k BPE model
! subword-nmt learn-joint-bpe-and-vocab --input ./drive/MyDrive/train.fr ./drive/MyDrive/train.en -s 48000 -o ./codes/codes_file_48k.bpe --write-vocabulary
```

The vocabs file has been created with the number of occurrences behind each subwords. For example

```
1 the 50039
2 of 36050
3 and 23687
```

### Q3: Open the code files compare then, what can you conclude?

After opening the different codes\_files, the observation is clear: codes\_files\_16k is included in codes\_files\_32k which is also included in code\_files\_48k. Then the more is the number of iterations on BPE, the more the sub-word tokenizer will be.

### Q4: Generate 3 datasets (i.e. train, dev, test and vocabularies) associated to the 3 models, compare the amount of data.

To generate we apply our different models to the train, dev, test and we get the vocab of train.

For Each model we have :

- 2 train : fr and en.
- 2 dev : fr and en
- 2 test : fr and en
- 2 vocab: fr and en.

The model with the size 48k have the biggest corresponding files and the smallest on the 16k.

```
[17] ! ls ./transformer_model_16k/ -ltr
total 18424
-rw-r--r-- 1 root root 138822 Jan 31 14:35 vocab_16k.fr
-rw-r--r-- 1 root root 120557 Jan 31 14:35 vocab_16k.en
-rw-r--r-- 1 root root 9583101 Jan 31 14:39 train.BPE.fr
-rw-r--r-- 1 root root 8232181 Jan 31 14:39 train.BPE.en
-rw-r--r-- 1 root root 191255 Jan 31 14:39 dev.BPE.fr
-rw-r--r-- 1 root root 166582 Jan 31 14:39 dev.BPE.en
-rw-r--r-- 1 root root 187020 Jan 31 14:39 test.BPE.fr
-rw-r--r-- 1 root root 160269 Jan 31 14:39 test.BPE.en
-rw-r--r-- 1 root root 38676 Jan 31 14:39 vocab.fr
-rw-r--r-- 1 root root 31494 Jan 31 14:39 vocab.en
```

```
! ls ./transformer_model_32k/ -ltr
total 19668
-rw-r--r-- 1 root root 263188 Jan 31 14:36 vocab_32k.fr
-rw-r--r-- 1 root root 223524 Jan 31 14:36 vocab_32k.en
-rw-r--r-- 1 root root 10145061 Jan 31 14:42 train.BPE.fr
-rw-r--r-- 1 root root 8685853 Jan 31 14:42 train.BPE.en
-rw-r--r-- 1 root root 203273 Jan 31 14:42 dev.BPE.fr
-rw-r--r-- 1 root root 176695 Jan 31 14:42 dev.BPE.en
-rw-r--r-- 1 root root 199050 Jan 31 14:42 test.BPE.fr
-rw-r--r-- 1 root root 169707 Jan 31 14:42 test.BPE.en
-rw-r--r-- 1 root root 28948 Jan 31 14:42 vocab.fr
-rw-r--r-- 1 root root 23957 Jan 31 14:43 vocab.en

[19] ! ls ./transformer_model_48k/ -ltr
total 20680
-rw-r--r-- 1 root root 378642 Jan 31 14:38 vocab_48k.fr
-rw-r--r-- 1 root root 317135 Jan 31 14:38 vocab_48k.en
-rw-r--r-- 1 root root 10564341 Jan 31 14:43 train.BPE.fr
-rw-r--r-- 1 root root 9061123 Jan 31 14:43 train.BPE.en
-rw-r--r-- 1 root root 212447 Jan 31 14:43 dev.BPE.fr
-rw-r--r-- 1 root root 184918 Jan 31 14:43 dev.BPE.en
-rw-r--r-- 1 root root 207372 Jan 31 14:43 test.BPE.fr
-rw-r--r-- 1 root root 177339 Jan 31 14:43 test.BPE.en
-rw-r--r-- 1 root root 24989 Jan 31 14:43 vocab.fr
-rw-r--r-- 1 root root 21131 Jan 31 14:43 vocab.en
```

## II. Data file configuration:

This is the content of my data.yml for the model\_32k:

```
1 model_dir: transformer_model_32k/run/
2
3 data:
4   train_features_file: transformer_model_32k/train.BPE.fr
5   train_labels_file: transformer_model_32k/train.BPE.en
6   eval_features_file: /content/drive/MyDrive/data_translation/ep7_dev.BPE.fr
7   eval_labels_file: /content/drive/MyDrive/data_translation/ep7_dev.BPE.en
8   source_vocabulary: transformer_model_32k/vocab.fr
9   target_vocabulary: transformer_model_32k/vocab.en
10
11 train:
12   batch_size: 1024
13   save_checkpoints_steps: 1000
14   maximum_features_length: 50
15   maximum_labels_length: 50
16
17 eval:
18   eval_delay: 3600 # Every 1 hour
19   external_evaluators: BLEU
20   export_on_best: BLEU
21 infer:
22   batch_size: 32
```

It is the same for the 2 other models only the path location of the file is changing according to the model. And the command used to train the model is :

```
# Training
! onmt-main --model_type Transformer --config ./drive/MyDrive/data.yml --auto_config train --with_eval --num_gpus 1
```

```
# Training 32k
! onmt-main --model_type Transformer --config ./drive/MyDrive/data_32k.yml --auto_config train --with_eval --num_gpus 1

# Training 48k
! onmt-main --model_type Transformer --config ./drive/MyDrive/data_48k.yml --auto_config train --with_eval --num_gpus 1
```

I had to save the model every time on my local drive to avoid loosing the training process. Indeed after 12 hours google colab stop the session. To continue the training model I just added the number of step to the files data.yml then train again.

### III. Translate the model obtained.

```
# inference (Translation)
! onmt-main --config ./drive/MyDrive/data.yml --auto_config infer --features_file ./transformer_model_16k/test.BPE.fr --predictions_file /content/transformer_model_16k/test_pred.BPE.en

# inference (Translation)
! onmt-main --config ./drive/MyDrive/data_32k.yml --auto_config infer --features_file ./transformer_model_32k/test.BPE.fr --predictions_file /content/transformer_model_32k/test_pred.BPE.en

# inference (Translation)
! onmt-main --config ./drive/MyDrive/data_48k.yml --auto_config infer --features_file ./transformer_model_48k/test.BPE.fr --predictions_file /content/transformer_model_48k/test_pred.BPE.en
```

### V. Detokenization

```
# detokenization
cat ./transformer_model_16k/test_pred.BPE.en | sed "s/@@ //g" > ./transformer_model_16k/test.en
cat ./transformer_model_32k/test_pred.BPE.en | sed "s/@@ //g" > ./transformer_model_32k/test.en
cat ./transformer_model_48k/test_pred.BPE.en | sed "s/@@ //g" > ./transformer_model_48k/test.en
```

### VI. Evaluation Using BLEU

Using the script multi-bleu.pl

	Model 16k	Model 32k	Model 48k
BLEU Score %	27.8	27.3	27.1

So the model BPE 48k is the one with the smallest Bleu Score

#### Exercice 2:

#### Q1: translate and evaluate the EMEA\_tst file. What is the BLEU score?:

In the Evaluation above we used the ep7\_test. Now using EMEA\_tst file we have :

	Model 16k	Model 32k	Model 48k
BLEU Score %	30.1	30.3	30.5

For example this is how we compute the evaluation for the this model\_16k

```
# Evaluation Using BLEU 16k
! perl ./multi-bleu.perl /content/transformer_model_16k/train.en.bpe < ./transformer_model_16k/test.en

BLEU = 30.11, 8.2/0.3/0.1/0.0 (BP=0.395, ratio=0.518, hyp_len=19499, ref_len=37618)
It is not advisable to publish scores from multi-bleu.perl. The scores depend on your tokenizer, which is unlikely to be repro
```

**Q2: re-launch the training process by using EMEA\_dev file as valid file and re-translate and re-evaluate the EMEA\_tst and ep7\_tst files. Is there a strong difference between the two experiments?**

First we used Ep7 as validation file.

Now we use the use of EMEA\_dev ( Changing the input validation on data.yml).

Using only the model 16k we have the following results :

BLEU Score %	Evaluation of EP7_tst	Evaluation of EMEA_tst
Valid : EP7_dev	27.6	30.6
Valid = EMEA_dev	21.3	20.2

No the difference is not that strong.

**Q3: Re-evaluate all the translations using other metrics often used for Machine Translation. Choose two other metrics, score the files, explain why you chose them and explain them.**

First we are using the script mteval-v14c.pl

Then we will choose AMBER (Modified BLEU, Enhanced Ranking Metric ), which is based on the metric BLEU but incorporates recall, extra penalties, and some text processing variants.

AMBER %	Evaluation of EP7_tst	Evaluation of EMEA_tst
Valid = EP7_dev	30.6	30.2
Valid = EMEA_dev	26.8	22.9

Finally we will choose METEOR (Metric for Evaluation of Translation with Explicit Ordering), which is by far the most widely employed human-targeted metric in MT. I

METEOR Score %	Evaluation of EP7_tst	Evaluation of EMEA_tst
Valid = EP7_dev	29.5	30.9
Valid = EMEA_dev	27.6	26.7

**References:**

## 1. The script :

[https://colab.research.google.com/drive/1YFODjXY06FhmhJguHKdbTbQ2\\_0tzVTWr?authuser=3#scrollTo=9ceKWm01Avbq](https://colab.research.google.com/drive/1YFODjXY06FhmhJguHKdbTbQ2_0tzVTWr?authuser=3#scrollTo=9ceKWm01Avbq)

**Annex:****Figure 1: The foundation of NLP-Subword Model****Byte Pair Encoding**

- A word segmentation algorithm:

- Start with a vocabulary of characters
- Most frequent ngram pairs ↠ a new ngram

Dictionary

5 low  
2 lower  
6 newest  
3 widest

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es

Add a pair (e, s) with freq 9

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(Example from Sennrich)

**Byte Pair Encoding**

- A word segmentation algorithm:

- Start with a vocabulary of characters
- Most frequent ngram pairs ↠ a new ngram

Dictionary

5 low  
2 lower  
6 newest  
3 widest

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es, est

Add a pair (es, t) with freq 9

22

(Example from Sennrich)

**Byte Pair Encoding**

- A word segmentation algorithm:

- Start with a vocabulary of characters
- Most frequent ngram pairs ↠ a new ngram

Dictionary

5 lo w  
2 lo w e r  
6 n e w e st  
3 wi d e st

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es, est, lo

Add a pair (l, o) with freq 7

23

(Example from Sennrich)

**Byte Pair Encoding**

- Have a target vocabulary size and stop when you reach it

- Do deterministic longest piece segmentation of words
- Segmentation is only within words identified by some prior tokenizer (commonly Moses tokenizer for MT)

- Automatically decides vocab for system

- No longer strongly “word” based in conventional way

Top places in WMT 2016!  
Still widely used in WMT 2018

<https://github.com/rsennrich/nematus>

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<sup>4</sup> Source : <https://www.programmersought.com/article/47414443821/>