

FINAL NLP CLASS PROJECT REPORT

BBC News Analysis

Mahsa Ghaderan

Supervise by

Dr Sauleh Etemadi

 $\mathrm{June}\ 23,\ 2021$

Department of Computer Engineering
Iran University of Science and Technology

Contents

A Appendix Title

Li	st of Figures	
Lis	st of Tables	
Lis	st of Acronyms	
1	Word2Vec 1.1 Iran News 1.2 Art News 1.3 Sport News 1.4 Economic News 1.5 Science News	1 1 2 2 2 2 3
2	Tokeniation 2.1 Sub-word Level 2.2 Word Level	5 5
3	Parsing	9
4	Language Model	11
Bi	ibliography	13
Aı	ppendices	15

17

List of Figures

Figure 1.1	Sub-words vocab example]
Figure 1.2	Sub-words vocab example	2
Figure 1.3	Sub-words vocab example	2
Figure 1.4	Sub-words vocab example	3
Figure 1.5	Sub-words vocab example	
T. 0.4		,
Figure 2.1	Sub-words vocab example	(

List of Tables

Word2Vec

In this part I used assignment2 from cs224n, 2021 Stanford NLP course as my base code. Different Word2Vec models are trained for each label which exist in BBC data set. Headline is concatenated with body of each news for as input text for the model. Each models trains for 40000 iteration. It took about 5 hours for each label. Wights of models are saved is "models/word2vec" directory. Most 30 repeated words are chosen from each label. Images - , - , - and - shows distribution of each model on a 2D map.

1.1 Iran News

After training word2vec model we exoect to see words with same meaning appear near to ech other and words with far meaning and context place far from others on each map.

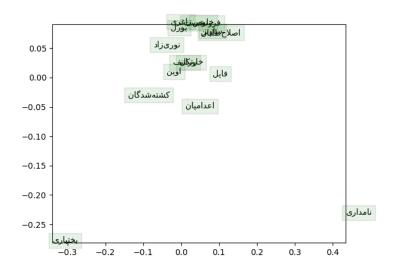


Figure 1.1: Sub-words vocab example

1.2 Art News

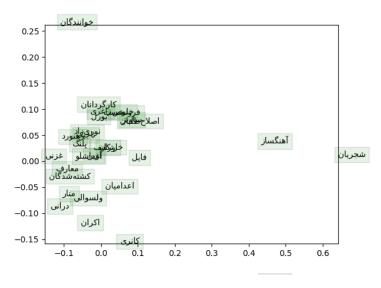


Figure 1.2: Sub-words vocab example

1.3 Sport News

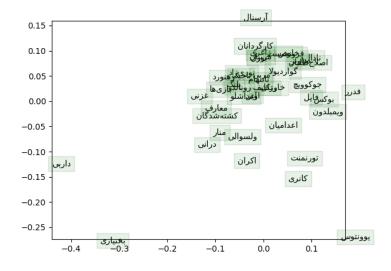


Figure 1.3: Sub-words vocab example

1.4 Economic News

In map 1.4 words in car and it's factory are gathered in the left part of the image.

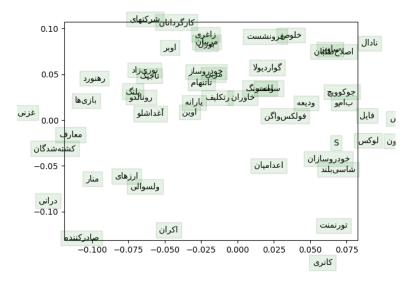


Figure 1.4: Sub-words vocab example

1.5 Science News

At map 1.5 words are overlapped and it's not easy to distinguish them. Equivalent of two words Astronauts and UFO persia are in same context and located almost near to each other and far from others. Two other words are composer and name of a popular Iranian singer, Shajarian, are placed next to each other.

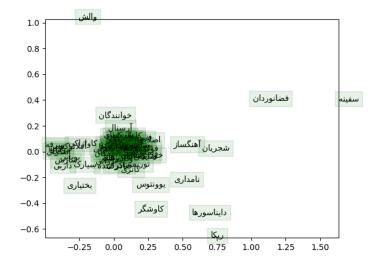


Figure 1.5: Sub-words vocab example

Tokeniation

SentencePiece is an unsupervised text tokenizer and detokenizer python project, which mainly used for text generation tass. This part is mainly based on this packet. It use a model to train what tokens are best to tokenizing a given corpus. In this part 2 different methods of tokenization in implemented. First is tokenizing words and subwords, in this methods model looking for most repeated words and sub-words and even letter. As a result we can see almost every word in final version of chosen tokens. On the contrary the second method is just tokenizing words, this models looking for most repeated words.

Until this part entire headline and body of each news are both covered in the corpus but from this part English values are removed from corpus so tokenization and language generation will focus on Persian.

The corpus is shuffled 5 times and separated to train and test data. Also tokenization is applied on 4 different vocab size due to possible SentencePiece size and performance of output model is evaluated against these vocab size. In the following section, we discuss about effects of vocab size from very small value increasing to a large value.

2.1 Sub-word Level

At first i train tokenizer model on sub-words. It means model not only pays attention to words, but also pays attention to sub-words during training time.

When the vocab size is 1000, it is too small for such a corpus and due to model type, model focuce on smaller sub-words rather than meaning full words. In final choosedvocab, almost every character in source language exists. So when we tokenize a text there wouldn't be any <unk> token and most words break into sub-words.

As vocab size increases model learns more complicated sub-words and less meaning-less characters and sub-words. Bot the negative point is as the vocab size increases it would be harder for models to learn task and the positive point is more context will be save after tokenization.

Another point is SentencePiece can discriminate between statrting token and not starting token and ending token of a word in this mode. As we can see in 2.1 the are different form of one token.

```
""<unk>": 3, "": 4, "o": 5, ".": 6, "_": 7,
"": 8, """: 9, "p": 10, "p": 11, "p": 12,
"p": 13, "p": 14, "p": 15, "p": 16, "p": 17,
"p: 13, "p": 19, "p": 20, "p": 21, "p": 22,
"p": 21, "p": 22, "p": 22, "p": 22,
"p": 23, "p": 24, "p": 25, "p": 31, "p": 32,
"p": 33, "p": 34, "p": 35, "p": 36, "p": 37,
"p": 38, "p": 39, "p": 40, "p": 41, "p": 42,
"p": 43, "p": 44, "p": 44, "p": 47,
```

Figure 2.1: Sub-words vocab example

2.2 Word Level

In this part, i used word level tokenization, in this experience there exist <unk> token due to vocab size and model dealing with choosing best token in order to minimize <unk> token in unseen text.

Same as previous experiment, data-set is divided into train and test set and 5 different shuffled corpus is saved, this help us to have a better evaluation on each vocab size. Four different vocab size is defined as follow: 1000, 5000, 10000, 15000. Number of <unk> token and percent of that over each corpus and vocab is reported in "report/tokenization" directory and each model and output on test set is saved in "src/tokenization/working-dir/words-out". percent of each vocab size is presented in table 2.2.

	word-level					
corpus	1	2	3	4	5	AVG
1000	0.44	0.44	0.44	0.43	0.44	0.44
5000	0.20	0.20	0.20	0.20	0.20	0.21
10000	0.14	0.14	0.14	0.14	0.15	0.15
15000	0.12	0.12	0.12	0.12	0.14	0.13

As it is illustrated in table 2.2, number of <unk> token increase by vocab size reduction. the fewer <unk> token, the fewer information loss. On the other the larger vocab size leads into more amount of computation for future task. As we saw it is a trade of between these to parameters, in my opinion best vocab size due to this corpus is 10000. It has reasonable <unk> token and it may need less computation rather than 15000 vocab size.

Parsing

Language Model

Language model neural network artichecture is adopt from pytorch/examples project. Tokenizer codes and models are replaced with Part 2 and vocab for Language Modeling is construct in part 2. In this part the corpus is divided into three part, train set, dev set and test set. LanguageModel is trained on each label separately to evaluate capability of each model to generate specific news. Models are saved in "models/lm" directory.

Bibliography

- [1] D. Evans, P. Gruba, and J. Zobel, *How to write a better thesis*. Melbourne Univ. Publishing, 2011.
- [2] H. Kopka and P. Daly, "A guide to ${\Delta TeX}-document$," Journal name, 1995.

Appendices

Appendix A

Appendix Title

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

This is the second paragraph. Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.