

Subword

2110572: Natural Language Processing Systems

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Outline

- Introduction
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Introduction



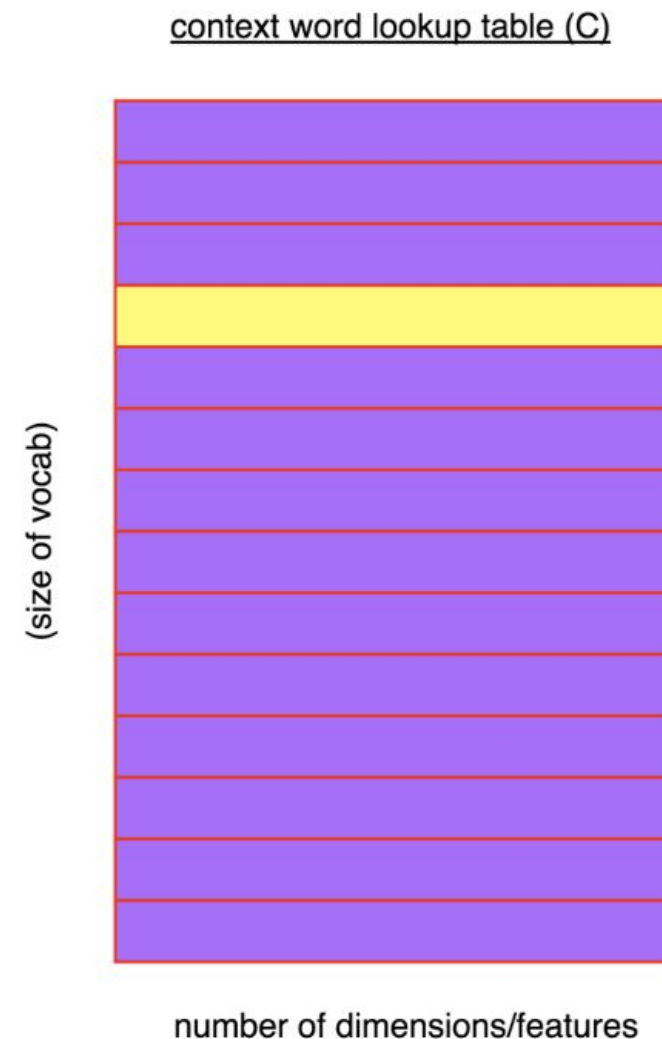
Introduction

Problem:

- 1) out-of-vocab
- 2) large vocabulary size

Solution: subword embedding

- 1) Byte-Pair Encoding (BPE)
- 2) WordPiece
- 3) Unigram
- 4) Sentencepiece



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Byte-Pair Encoding (BPE)

+ Byte-Pair Encoding (BPE)

BPE was introduced in Neural Machine Translation of Rare Words with Subword Units (Sennrich et al., 2015).

Used in GPT-2, Roberta, and even ChatGPT

Relies on a pre-tokenizer that splits the training data into words.

Next, BPE creates a base vocabulary consisting of all symbols that occur in the set of unique words and learns merge rules to form a new symbol from two symbols of the base vocabulary (similar to huffman coding; frequencies).



BPE example(1 sentence)

- aaabdaaaba
- **Z**abd**Z**abac
 - Z=aa
- Z**Y**dZ**Y**ac
 - Y=ab
 - Z=aa
- **X**d**X**ac
 - X=ZY
 - Y=ab
 - Z=aa
- พร[ั]ว และ ข[ั]ว นั้[ั]ง บ[ั]น ร[ั]ว ดู ข[ั]ว ค[ั]ร[ั]ว บ[ั]น ด[ั]ว
- พร[ั]**x** และ ข[ั]**x** นั้[ั]ง บ[ั]น ร[ั]**x** ดู ข[ั]**x** ค[ั]ร[ั]**x** บ[ั]น ด[ั]**x**
 - **x**=าว
- พ[ั]**y** และ ข[ั]**x** นั้[ั]ง บ[ั]น **y** ดู ข[ั]**x** ค[ั]**y** บ[ั]น ด[ั]**x**
 - **x**=าว
 - **y**=ร[ั]**x**
- พ[ั]**y** และ ข[ั]**x** นั้[ั]ง **z** **y** ดู ข[ั]**x** ค[ั]**y** **z** ด[ั]**x**
 - **x**=าว
 - **y**=ร[ั]**x**
 - **z**=บ[ั]น



BPE - training

Example corpus

```
("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
```

The most frequent symbol pair is "u" followed by "g", occurring $10 + 5 + 5 = 20$ times in total. Thus, the first merge rule the tokenizer learns is to group all "u" symbols followed by a "g" symbol together. Next, "ug" is added to the vocabulary.

```
("h" "ug", 10), ("p" "ug", 5), ("p" "u" "n", 12), ("b" "u" "n", 4), ("h" "ug" "s", 5)
```




BPE - usage

```
("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
```

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Tokenization algorithm

Tokenization follows the training process closely, in the sense that new inputs are tokenized by applying the following steps:

1. Normalization
2. Pre-tokenization
3. Splitting the words into individual characters
4. Applying the merge rules learned in order on those splits

Let's take the example we used during training, with the three merge rules learned:

```
("u", "g") -> "ug"  
("u", "n") -> "un"  
("h", "ug") -> "hug"
```

How to use

- bug = ["b", "ug"] ("b" in dict)
- mug = ["UNK", "ug"] ("m" not in dict)
- thug = ["UNK", "hug"] ("t" not in dict)



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Wordpiece



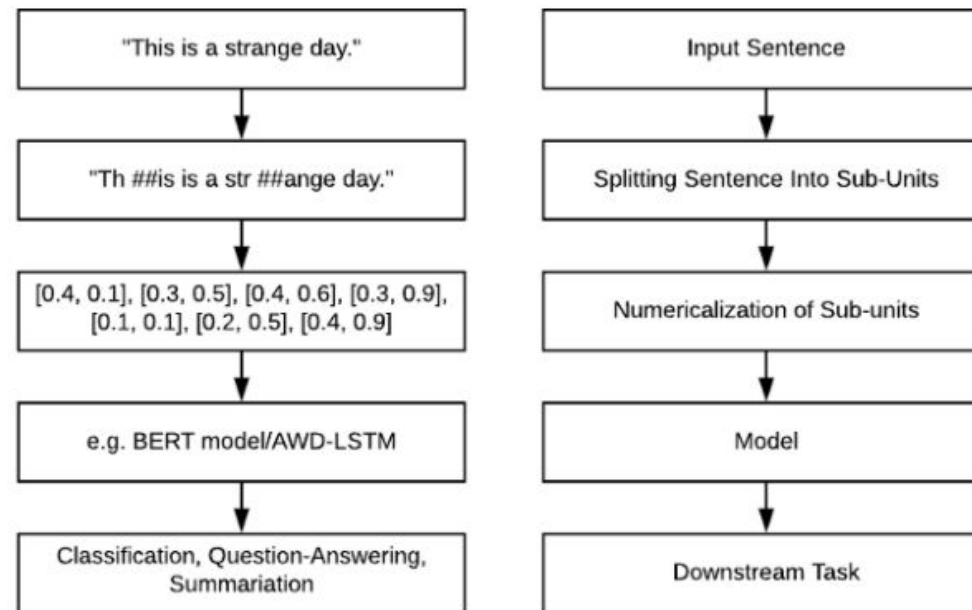
WordPiece

- Google NMT(GNMT) uses a variant of this
 - V1: wordpiece model
 - V2: sentencepiece model
- Rather than char n-gram count, uses a greedy approximation to maximizing language model log likelihood to choose the pieces (add n-gram that maximally reduces perplexity)
- Like BPE, WordPiece learns merge rules. The main difference is the way the pair to be merged is selected. **Instead of selecting the most frequent pair, WordPiece computes a score for each pair, using the following formula:**

$$\text{score} = (\text{freq_of_pair}) / (\text{freq_of_first_element} \times \text{freq_of_second_element})$$

+ WordPiece (cont.)

- WordPiece is the subword tokenization algorithm used for models such as BERT, DistilBERT, and Electra.
- There are 2 types of tokens: start token (no ##), and continuing token (##)



+ WordPiece - training

Corpus

```
("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
```

The splits here will be:

```
("h" "##u" "##g", 10), ("p" "##u" "##g", 5), ("p" "##u" "##n", 12), ("b" "##u" "##n", 4), ("h" "##u" "##g", 5)
```

so the initial vocabulary will be ["b", "h", "p", "##g", "##n", "##s", "##u"]

+ WordPiece - training (cont.)

Corpus

```
("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
```

From initial vocab ["b", "h", "p", "##g", "##n", "##s", "##u"]

the best score goes to the pair ("##g", "##s") — the only one without a "##u" — at 1 / 20, and the first merge learned is ("##g", "##s") -> ("##gs")

Vocabulary: ["b", "h", "p", "##g", "##n", "##s", "##u", "##gs"]

Corpus: ("h" "##u" "##g", 10), ("p" "##u" "##g", 5), ("p" "##u" "##n", 12), ("b" "##u" "##n", 4), ("h" "##u" "##gs", 5)

WordPiece - usage

Tokenization differs in WordPiece and BPE in that WordPiece only saves the final vocabulary, not the merge rules learned.

```
Vocabulary: ["b", "h", "p", "##g", "##n", "##s", "##u", "##gs", "hu", "hug"]
```

How to use: “the longest subword”

- hugs = [“hug”, “##s”]

If not possible to find subwords, tokenize the **whole** word as UNK.

- mug = [“UNK”]
- bum = [“UNK”] ~~(not [“b”, “##u”, UNK])~~

WordPiece - usage

Tokenization differs in WordPiece and BPE in that WordPiece only saves the final vocabulary, not the merge rules learned.

```
Vocabulary: ["b", "h", "p", "##g", "##n", "##s", "##u", "##gs", "hu", "hug"]
```

if we use the vocabulary learned in the example above, for the word "hugs" the **longest** subword starting from the beginning that is inside the vocabulary is "hug", so we split there and get ["hug", "##s"]. We then continue with "##s", which is in the vocabulary, so the tokenization of "hugs" is ["hug", "##s"].

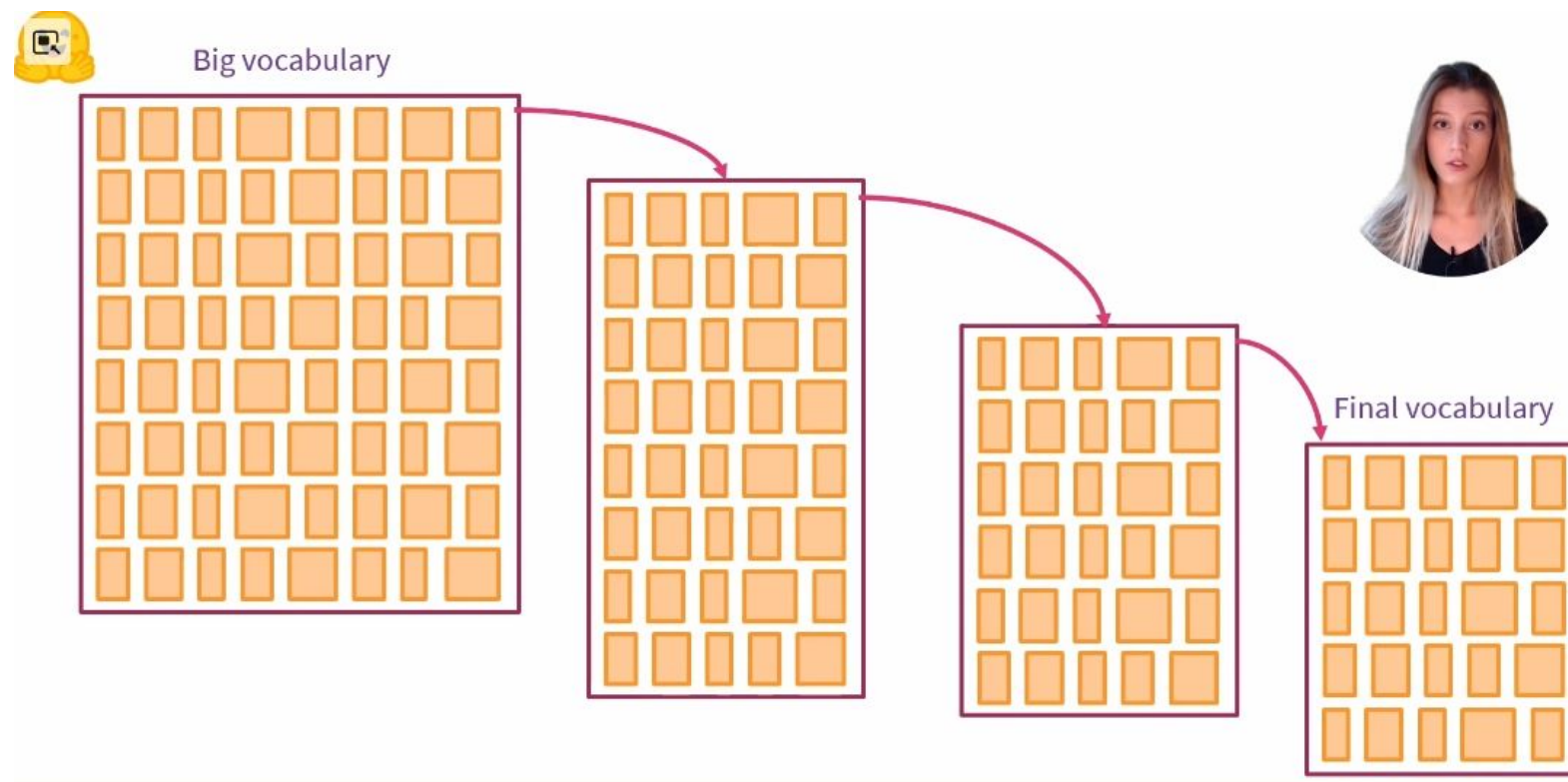
When the tokenization gets to a stage where it's not possible to find a subword in the vocabulary, the whole word is tokenized as unknown — so, for instance, "mug" would be tokenized as ["[UNK]"], as would "bum" (even if we can begin with "b" and "##u", "##m" is not the vocabulary, and the resulting tokenization will just be ["[UNK]"], not ["b", "##u", "[UNK]"). This is another difference from BPE, which would only classify the individual characters not in the vocabulary as unknown.

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Unigram

+ Unigram

Start with a big vocab and reduce it based on a unigram LM loss





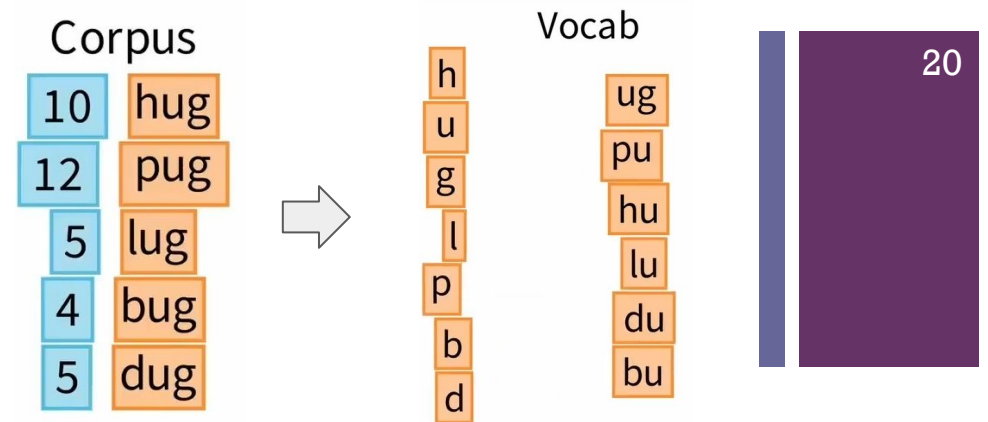
Unigram - training

Initial vocab = **all** substring of corpus

Corpus	
10	hug
12	pug
5	lug
4	bug
5	dug

Vocab	
h	ug
u	pu
g	hu
l	lu
p	du
b	bu
d	

+ Unigram - training (cont.)



1st iteration of EM

The E step. Select the split for each word in the corpus with highest prob.

Vocab

h	10/180	ug	36/180
u	36/180	pu	12/180
g	36/180	hu	10/180
l	5/180	lu	5/180
p	12/180	du	5/180
b	4/180	bu	4/180
d	5/180		

Possible splits for "hug"

$$h \ u \ g \quad \frac{10}{180} \times \frac{36}{180} \times \frac{36}{180} = 2.22e - 03$$

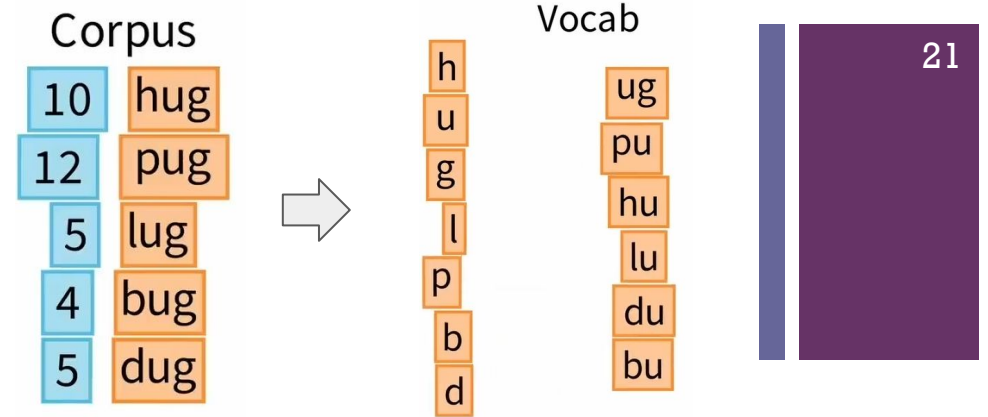
Choose 1 randomly

$$hu \ g \quad \frac{10}{180} \times \frac{36}{180} = 1.11e - 02$$

$$h \ ug \quad \frac{10}{180} \times \frac{36}{180} = 1.11e - 02$$

hug 0

+ Unigram - training (cont.)



1st iteration of EM

The E step. Calculate loss.

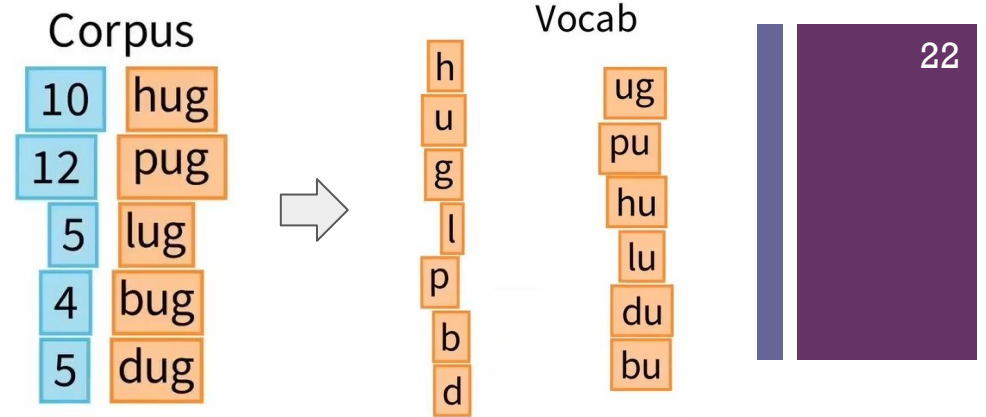
Loss				
Corpus	Splits	Scores		
10 hug	→ hu g	1.11e-02		
12 pug	→ pu g	1.33e-02		
5 lug	→ lu g	5.56e-03		
4 bug	→ bu g	4.44e-03		
5 dug	→ du g	5.56e-03		

$$\sum freq \times (-\log(P(word)))$$

$$\begin{aligned}
 &10 \times (-\log(1.11e-02)) \\
 &+ 12 \times (-\log(1.33e-02)) \\
 &+ 5 \times (-\log(5.56e-03)) \\
 &+ 4 \times (-\log(4.44e-03)) \\
 &+ 5 \times (-\log(5.56e-03))
 \end{aligned}$$

170.40

+ Unigram - training (cont.)



1st iteration of EM

The M step. Remove the tokens that least impacts the loss (remove p% at a time)

Try removing **ug**

Loss is still the same

Removing any token results in the same loss so choose randomly again

Vocab

h	10/180	ug	36/180
u	36/180	pu	12/180
g	36/180	hu	10/180
l	5/180	lu	5/180
p	12/180	du	5/180
b	4/180	bu	4/180
d	5/180		

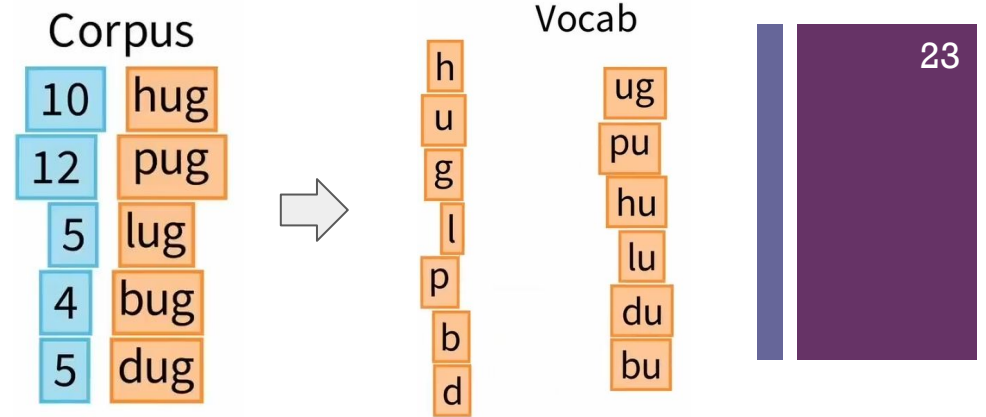
Corpus

10	hug	→	hu	g	1.11e-02
12	pug	→	pu	g	1.33e-02
5	lug	→	lu	g	5.56e-03
4	bug	→	bu	g	4.44e-03
5	dug	→	du	g	5.56e-03

Loss 170.40

	Loss
With all vocabulary	170.4
Without	ug 170.4
	pu 170.4
	hu 170.4
	lu 170.4
	du 170.4
	bu 170.4

+ Unigram - training (cont.)



2nd iteration of EM

The E step. Select the split for each word in the corpus with highest prob.

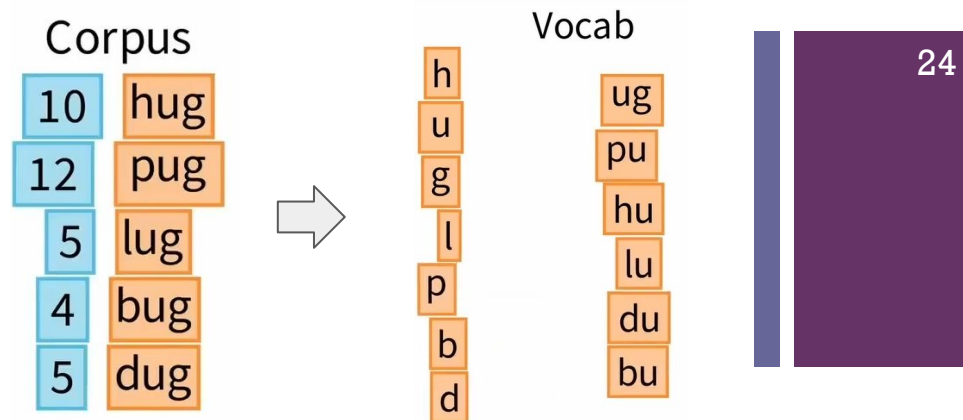
Vocab

h	10/144	pu	12/144
u	36/144	hu	10/144
g	36/144	lu	5/144
l	5/144	du	5/144
p	12/144	bu	4/144
b	4/144		
d	5/144		

Possible splits for "hug"

h	u	g	$\frac{10}{144} \times \frac{36}{144} \times \frac{36}{144} = 4.34e - 03$
hu	g	$(10/144) * (36/144) = 1.7e-02$	
h	ug	$\frac{10}{144} \times 0 = 0.00e + 00$	
hug		$0 = 0.00e + 00$	

+ Unigram - training (cont.)



2nd iteration of EM

The E step. Calculate loss.

Vocab

h	10/144
u	36/144
g	36/144
l	5/144
p	12/144
b	4/144
d	5/144

pu	12/144
hu	10/144
lu	5/144
du	5/144
bu	4/144

Corpus

10	hug
12	pug
5	lug
4	bug
5	dug

Splits

hu	g
pu	g
lu	g
bu	g
du	g

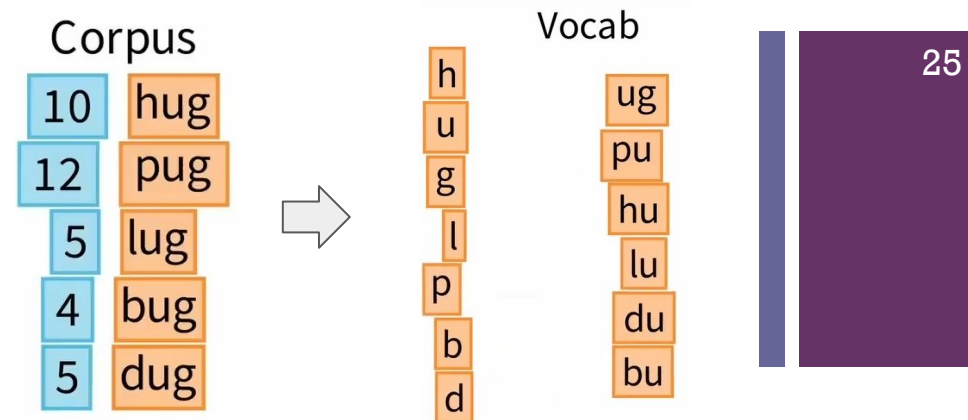
Scores

1.7e-02
2.08e-02
8.68e-03
6.94e-03
8.68e-03

Loss

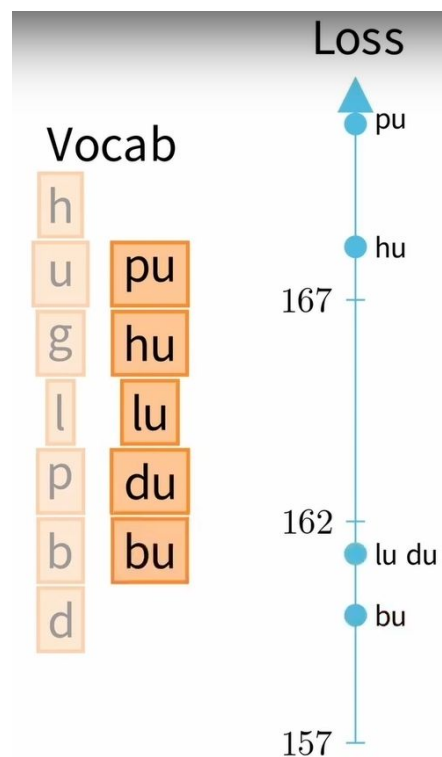
168.20

+ Unigram - training (cont.)



2nd iteration of EM

The M step. Remove the tokens that least impacts the loss (remove $p\%$ at a time)





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SentencePiece



SentencePiece

- SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing (Kudo et al., 2018)
- It aims to solve 2 issues.
- Issue 1: Which one should be the correct detokenization?
 - Tokenize(“World.”) == Tokenize(“World.”)
- Issue 2: End-to-End to avoid the need of language-specific tokenization.

WangchanBERTa We name our pretrained language models according to their architectures, tokenizers and the datasets on which they are trained on. The models can be found on HuggingFace¹².

	Architecture	Dataset	Tokenizer
wangchanberta-base-wiki-spm	RoBERTa-base	Wikipedia-only	SentencePiece
wangchanberta-base-wiki-newmm	RoBERTa-base	Wikipedia-only	word (newmm)
wangchanberta-base-wiki-ssg	RoBERTa-base	Wikipedia-only	syllable (ssg)
wangchanberta-base-wiki-sefr	RoBERTa-base	Wikipedia-only	SEFR
wangchanberta-base-att-spm-uncased	RoBERTa-base	Assorted Thai Texts	SentencePiece

Table 3: WangchanBERTa model names

+ SentencePiece (cont.)

Introduces “_ (U+2581)” to preserve whitespace for detokenization

For the sake of clarity, SentencePiece first escapes the whitespace with a meta symbol _ (U+2581), and tokenizes the input into an arbitrary subword sequence, for example:

- **Raw text:** Hello_world.
- **Tokenized:** [Hello] [_wor] [ld] [.]

As the whitespace is preserved in the tokenized text, we can detokenize the tokens without any ambiguities with the following Python code.

```
detok = ''.join(tokens).replace('_', ' ')
```

Feature	SentencePiece
Supported algorithm	BPE, unigram, char, word

<https://github.com/google/sentencepiece>