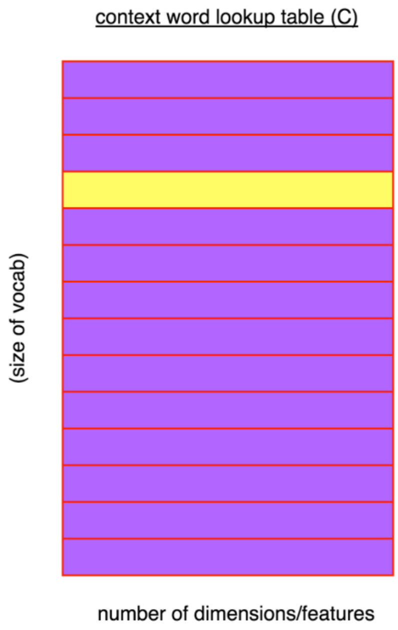
Subword

Introduction

- Problem: only one representation for all unknown words
- Solution: subword embedding
  - 1) Byte-Pair Encoding (BPE)
  - 2) Wordpiece
  - 3) Unigram
  - 4) Sentencepiece



1) Byte-Pair Encoding (BPE)

- Byte-Pair Encoding (BPE) was introduced in Neural Machine Translation of Rare Words with Subword Units (Sennrich et al., 2015).
- Used in GPT-2, Roberta

- 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

พราว และ ขาว นั่ง บน ราว ดู ข่าว คราว บน ดาว

พร**x** และ ข**x** นั่ง บน ร**x** ดู ข่**x** คร**x** บน ด**x**

x=าว

พ**y** และ ข**x** นั่ง บน **y** ดู ข่**x** ค**y** บน ด**x**

x=าว

y=ร**x**

พ**y** และ ข**x** นั่ง **z** **y** ดู ข่**x** ค**y** **z** ด**x**

x=าว

y=รx

z=บน

BPE - train (corpus)

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)
```

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

BPE - using

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)

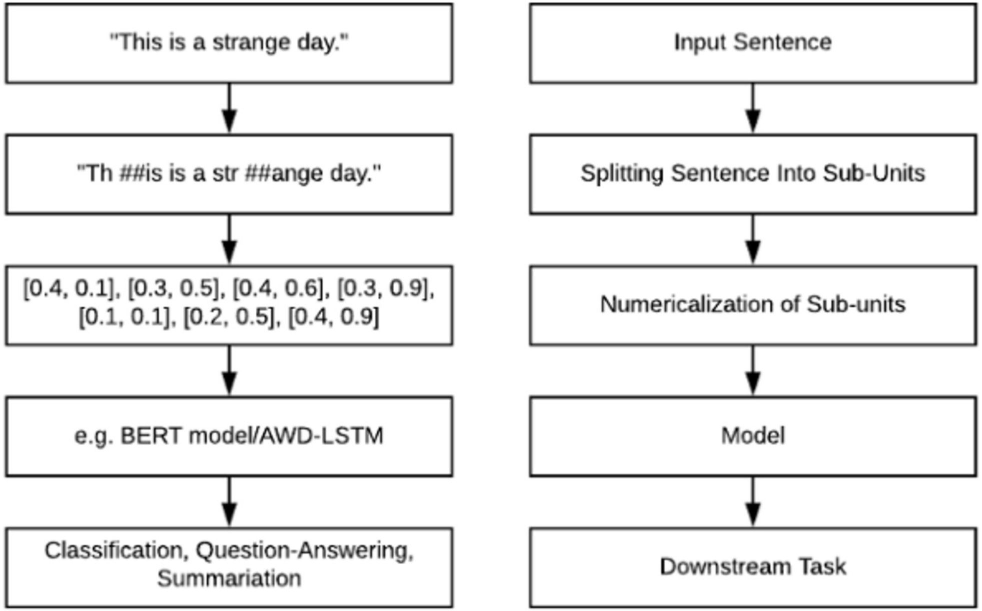
2) wordpiece

- 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 BERT, DistilBERT, and Electra.
- There are 2 types of tokens: start token (no ##), and continuing token (##)



https://jacky2wong.medium.com/understanding-sentencepiece-under-standing-sentence-piece-ac8da59f6b08

wordpiece - train

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
```

so the initial vocabulary will be `["b", "h", "p", "##g", "##n", "##s", "##u"]` (if we forget about special tokens for

wordpiece - train (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 - using

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”]

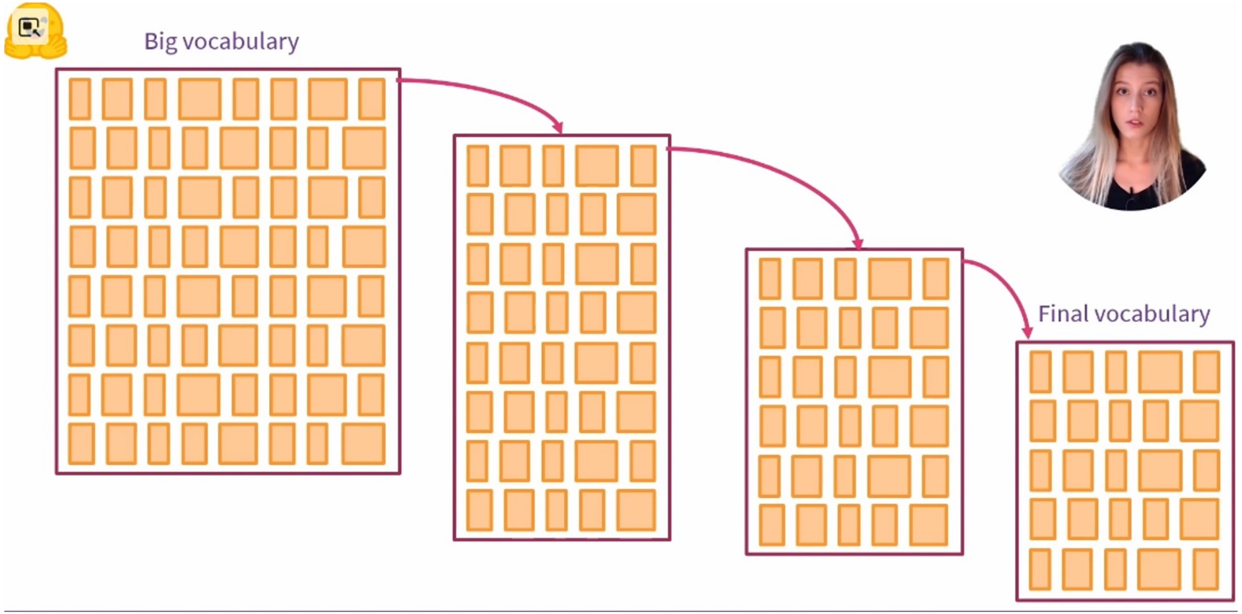
If not possible to find subwords, tokenize the whole word as UNK.

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

https://youtu.be/TGZfZVuF9Yc

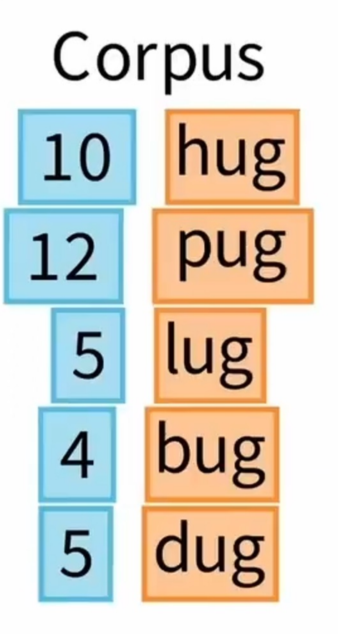
3) unigram

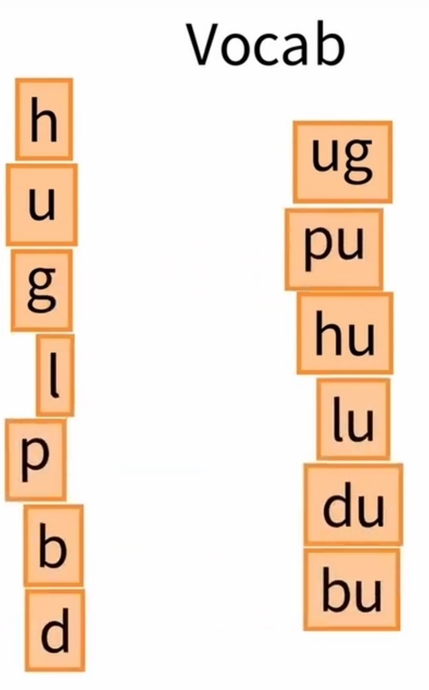
Start with a big vocab and reduce it based on unigram LM loss

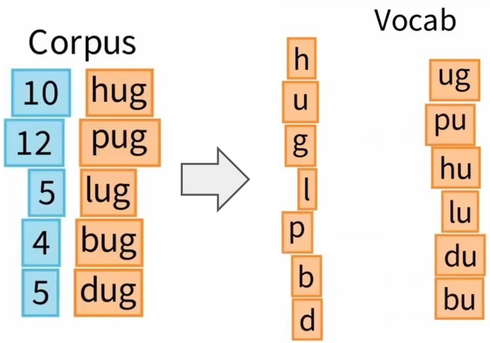


Unigram - training

Initial vocab = all substring of corpus







Unigram - training

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 $\frac{10}{180} \times \frac{36}{180} \times \frac{36}{180} = 2.22e-03$

Choose 1 random

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

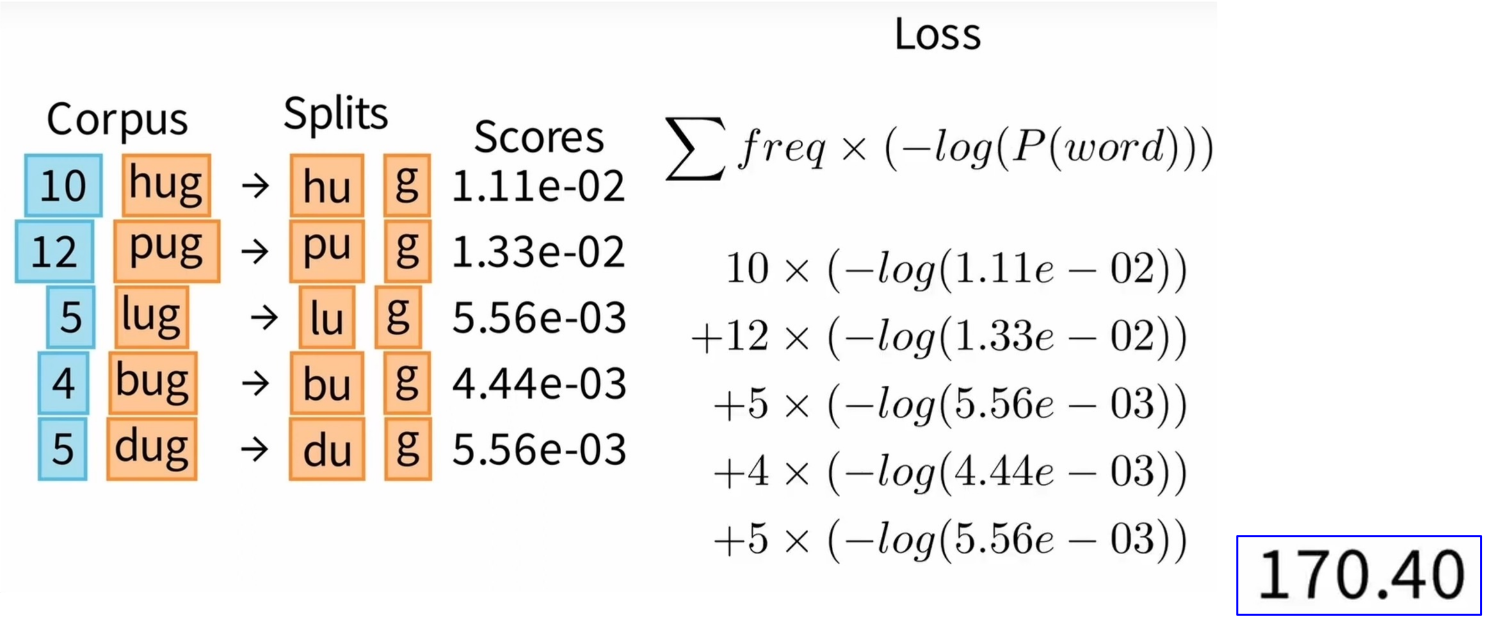
h ug $\frac{10}{180} \times \frac{36}{180} = 1.11e-02$

hug 0

Unigram - training

1st iteration of EM

The E step. Cal loss.

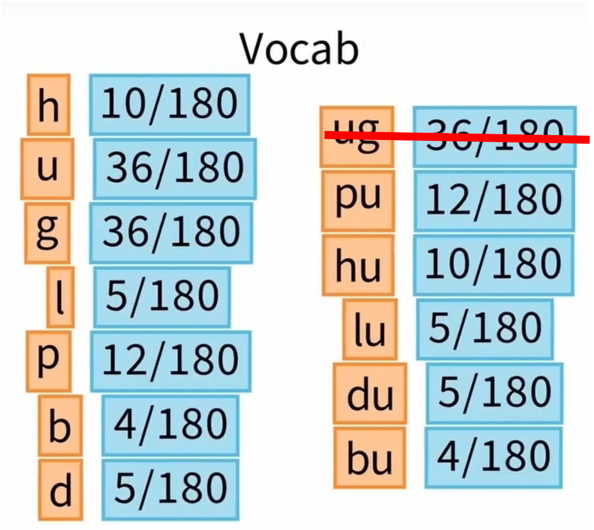


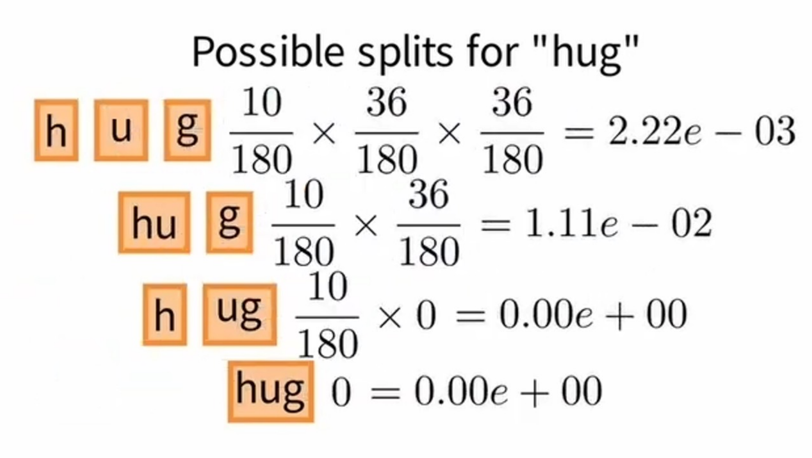
Unigram - training

1st iteration of EM

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

Try removing **ug**



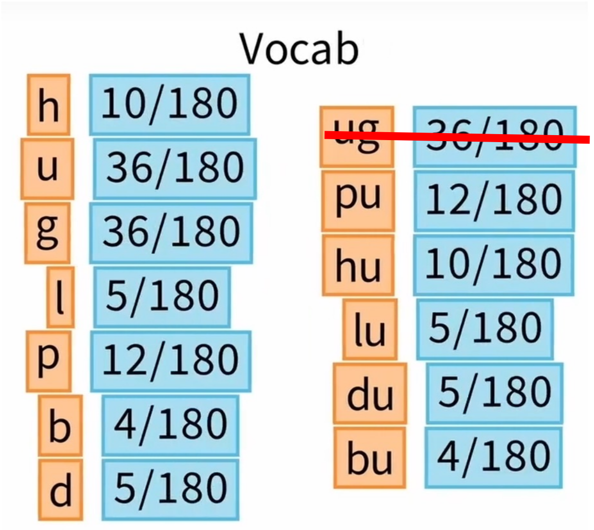


Unigram - training

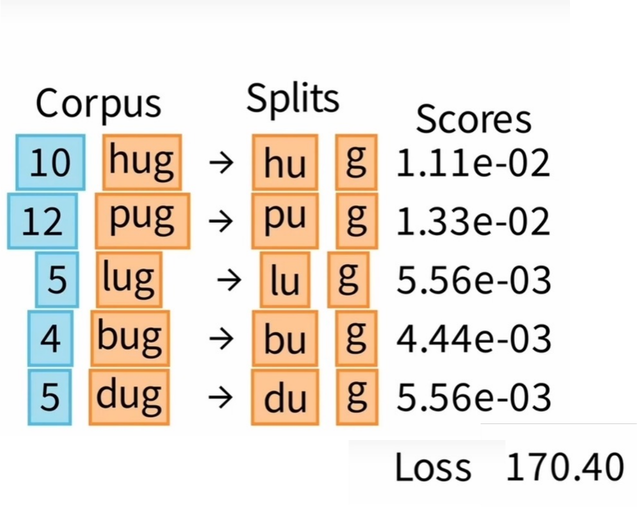
1st iteration of EM

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

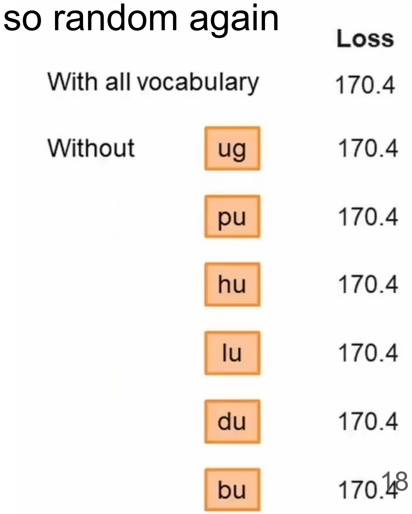
Try removing **ug**



Loss still the same



Removing any token results in the same loss so random again



Unigram - training

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) = 17e-03

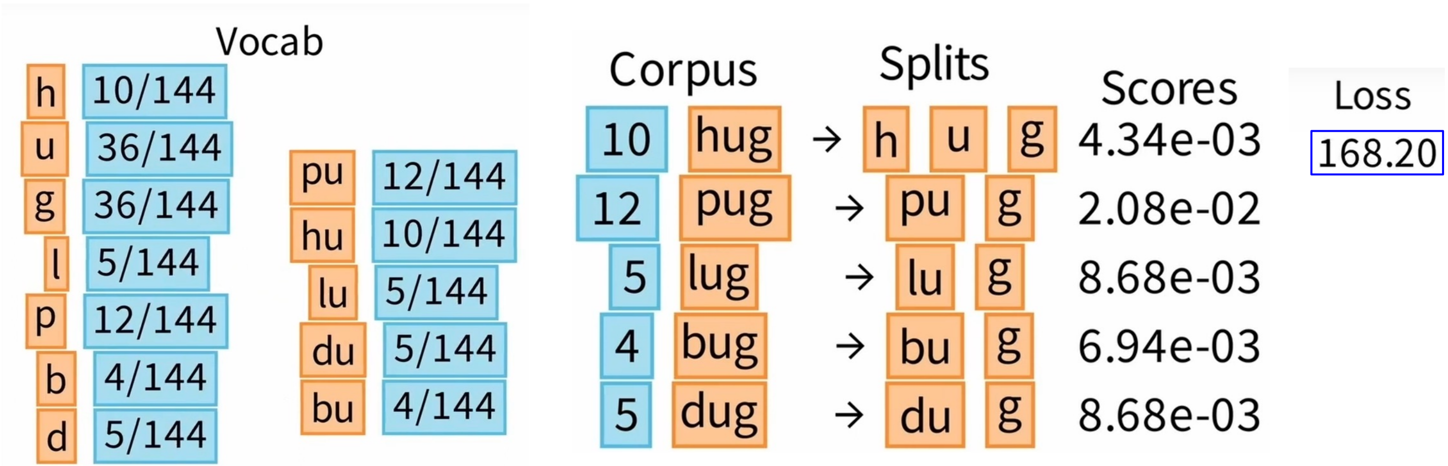
h ug $\frac{10}{144} \times 0 = 0.00e+00$

hug $0 = 0.00e+00$

Unigram - training

2nd iteration of EM

The E step. Calculate loss

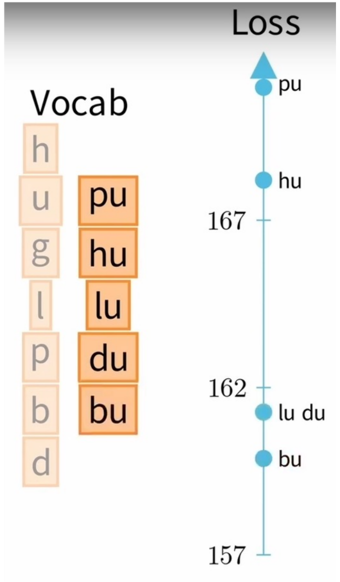


* Remark: the example is incorrect a bit, (“hu”, “g”) should be used instead of (“h”, “u”, “g”)

Unigram - training

2nd iteration of EM

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



Removing bu gives the least loss so
bu is removed

4) 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.
- Issue1: Which one should a correct denomalization?
  - Tokenize(“World.”) == Tokenize(“World_.”)
- Issue2: 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 HuggingFace[12].

	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

https://aclanthology.org/D18-2012.pdf

4) 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