Deep Learning Practice - NLP

Tokenisation, HF Tokenizers

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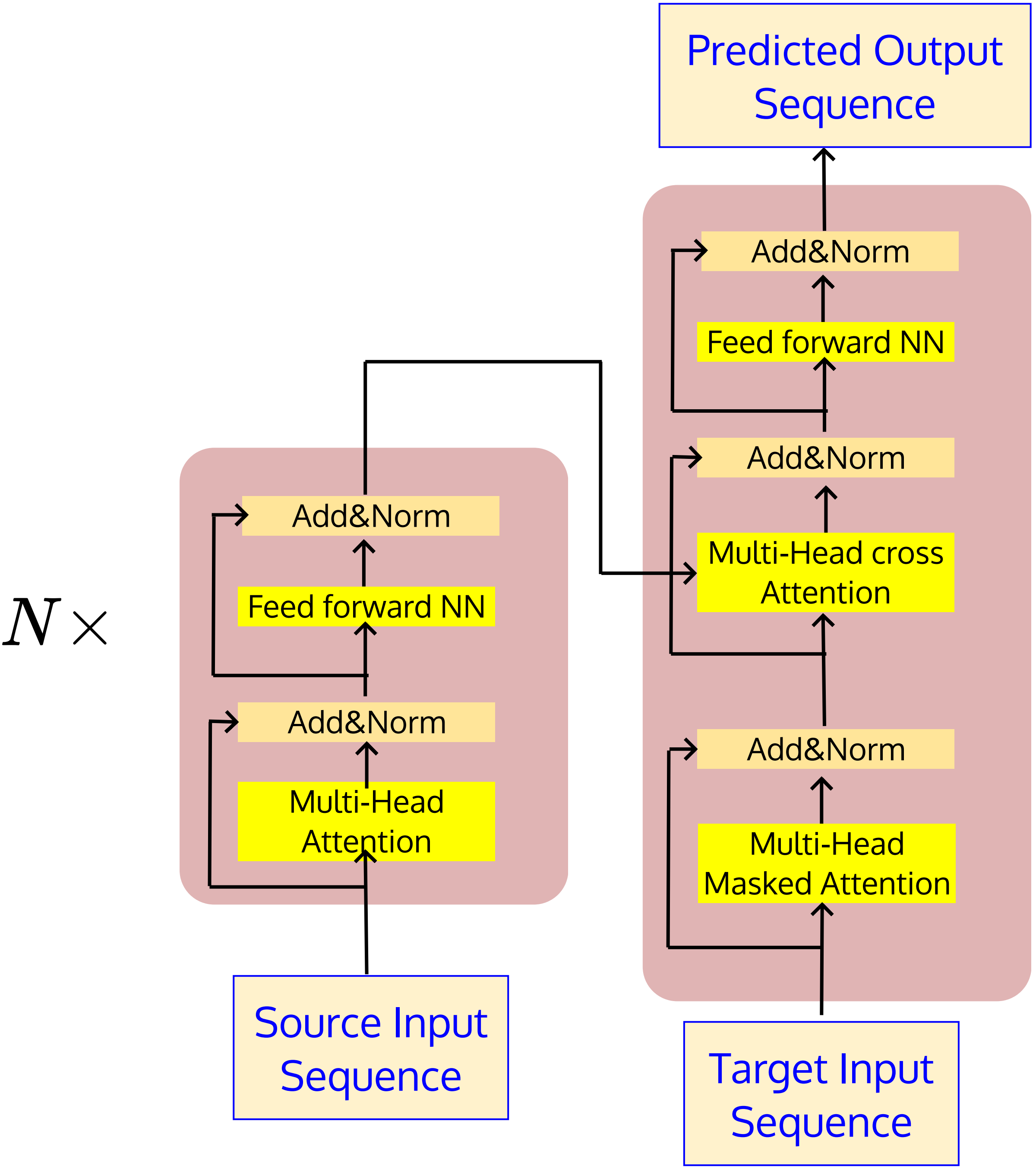


Recall that the transformer is a simple encoder-decoder model with attention mechanism at its core

The input is a sequence of words in the source language

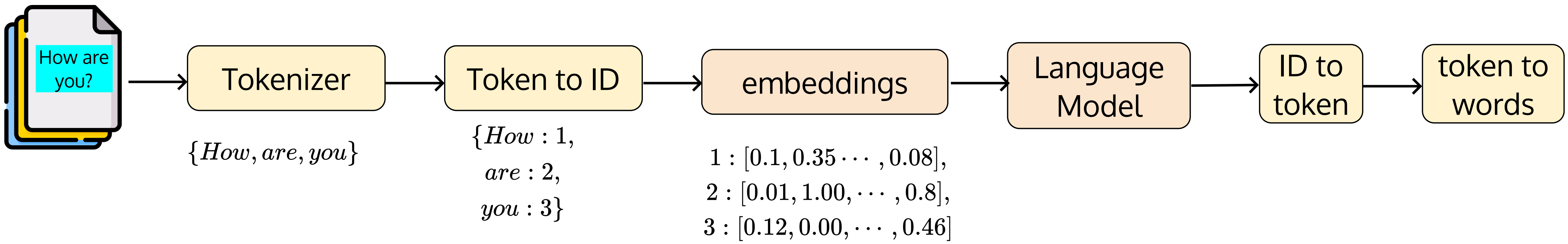
`I am reading a book`

The output is also a sequence of words in the target language

`Naan oru puthagathai padiththu kondirukiren`

The lengths of the input and output sequences need not be the same

Tokenizer in the Training pipeline



The tokenizer simply splits the input sequence into tokens.

A simple approach is to use whitespace for splitting the text.

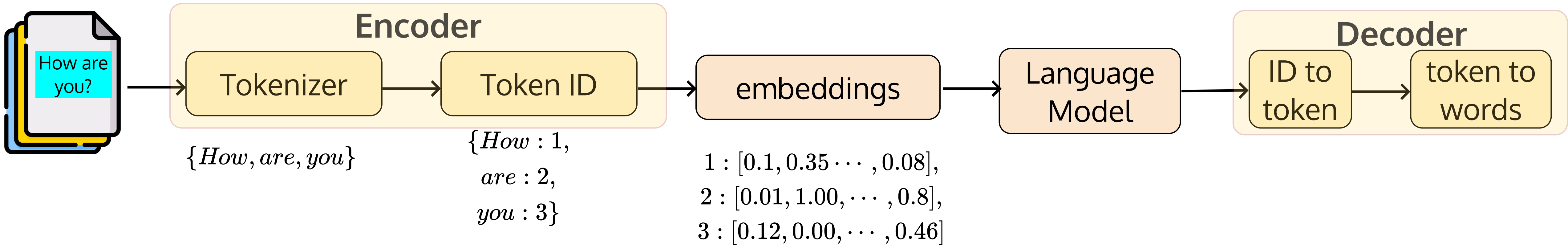
Each token is associated with a unique ID.

Each ID is associated with a unique embedding vector.

The model then takes these embeddings and predicts token IDs.

During inference, the predicted token IDs are converted back to tokens (and then to words).

Tokenizer in the Training pipeline



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Each token is associated with a unique ID.

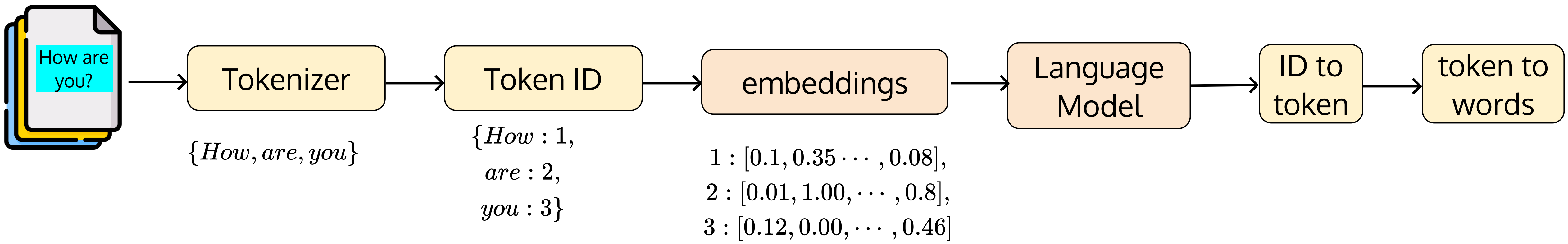
Each ID is associated with a unique embedding vector.

The model then takes these embeddings and predicts token IDs.

During inference, the predicted token IDs are converted back to tokens (and then to words).

The tokenizer essentially contains two components: the encoder, which converts input word (token) to a token id, and the decoder, which performs the reverse operation.

Tokenizer in the Training pipeline



The size of the vocabulary determines the size of the embedding table

The question then is how do we build (learn) a vocabulary $\mathcal{V}$ from a large corpus that contains billions of sentences?

We can split the text into words using whitespace (now called pre-tokenization) and add all unique words in the corpus to the vocabulary.

We also include special tokens such as ‹go›,‹stop›,‹mask›,‹sep›,‹cls› and others to the vocabulary based on the type of downstream tasks and the architecture (GPT/BERT) choice

Some Questions

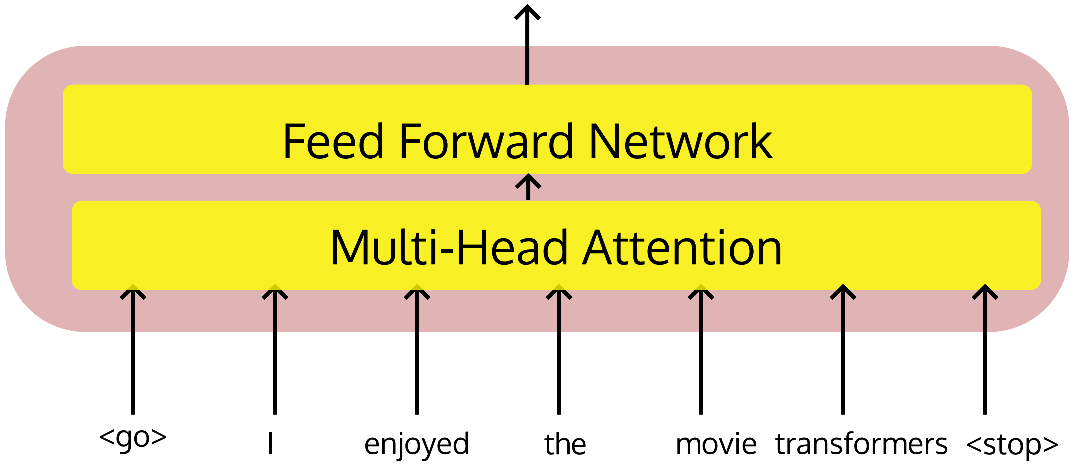
Is spliting the input text into words using whitespace a good approach?

If so, do we treat the words "enjoy" and "enjoyed" as separate tokens?

What about languages like Japanese, which do not use any word delimiters like space?

Why not treat each individual character in a language as a token in the vocabulary?

Finally, what are good tokens?



映画『トランスフォーマー』を楽しく見ました

Challenges in building a vocabulary

What should be the size of vocabulary?

Larger the size, larger the size of embedding matrix and greater the complexity of computing the softmax probabilities. What is the optimal size?

Out-of-vocabulary

If we limit the size of the vocabulary (say, 250K to 50K) , then we need a mechanism to handle out-of-vocabulary (OOV) words. How do we handle them?

Handling misspelled words in corpus

Often, the corpus is built by scraping the web. There are chances of typo/spelling errors. Such erroneous words should not be considered as unique words.

Open Vocabulary problem

A new word can be constructed (say,in agglutinative languages) by combining existing words . The vocabulary, in principle, is infinite (that is, names,numbers,..) which makes a task like machine translation challenging

Module 1 : Tokenization algorithms

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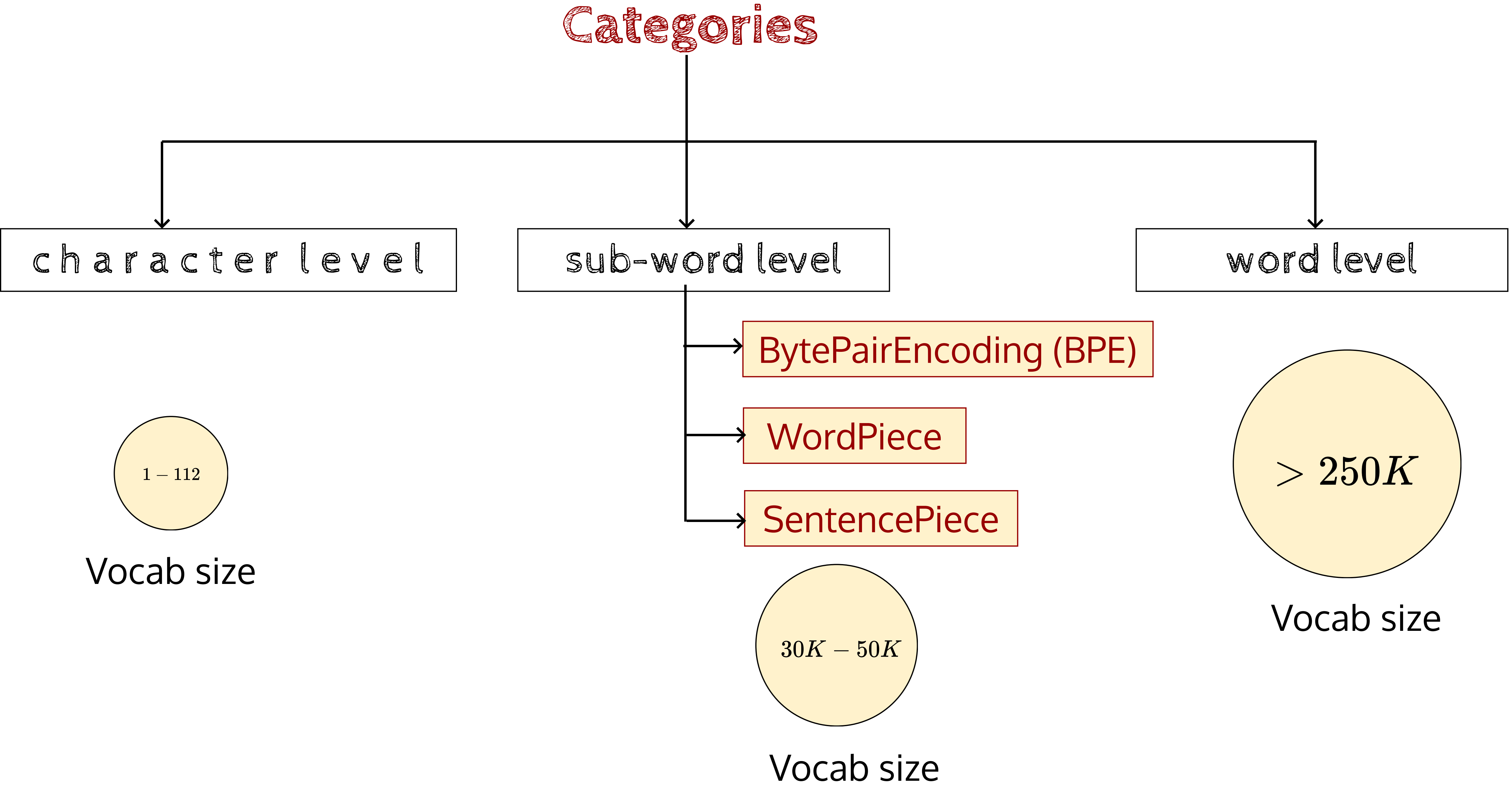
Wishlist

Moderate-sized Vocabulary

Efficiently handle unknown words during inference

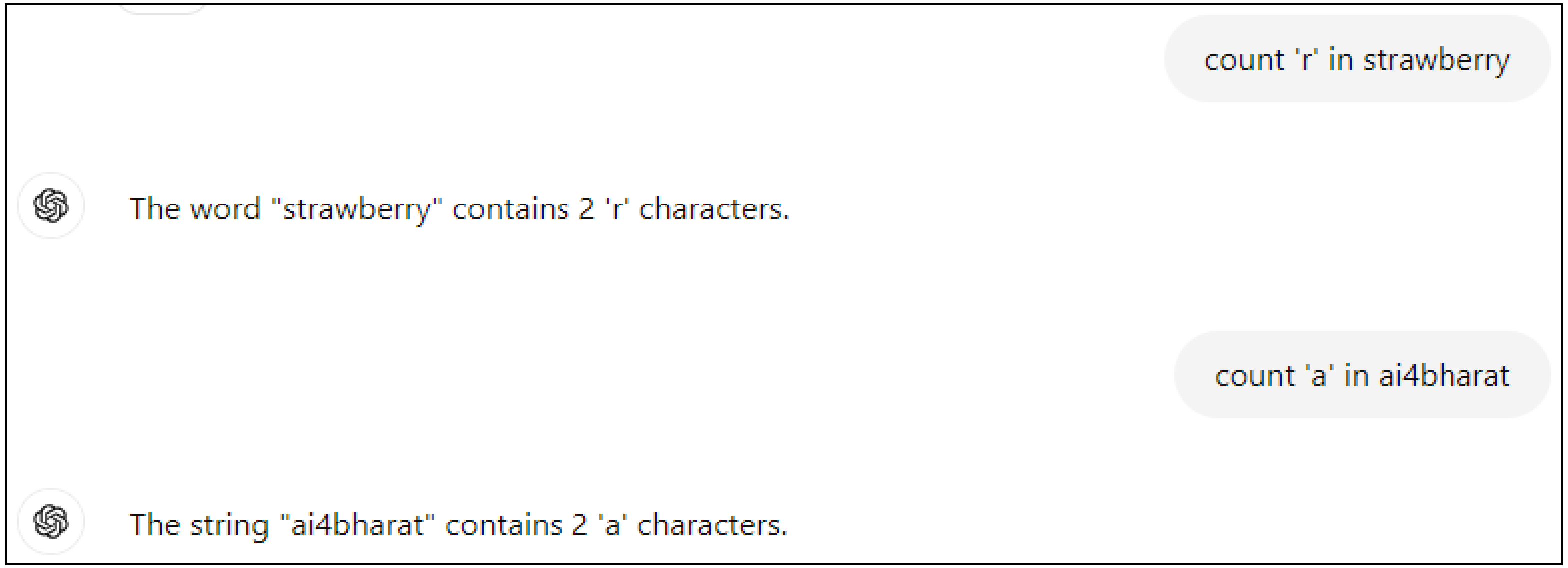
Be language agnostic

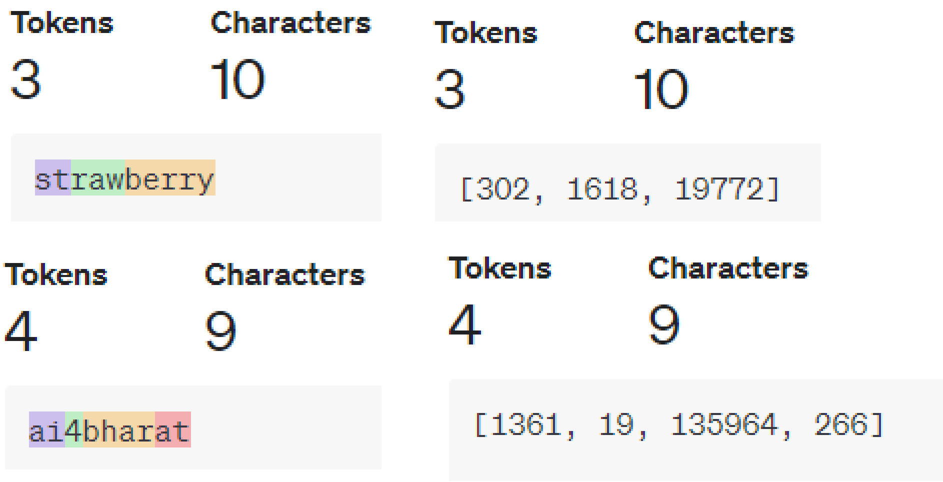


Categories
character level
sub-word level
word level
BytePairEncoding (BPE)
WordPiece
SentencePiece
$1-112$
Vocab size
$30K-50K$
Vocab size
$>250K$
Vocab size

Complexities of subword tokenization [Andrej Karpathy]

- Why can't LLMs spell words? Tokenization.
- Why can't LLMs do super simple string processing tasks like reversing a string? Tokenization.
- Why are LLMs not good at non-English languages (e.g. Japanese)? Tokenization.
- Why are LLMs bad at simple arithmetic? Tokenization.
- Why did GPT-2 have trouble coding in Python? Tokenization.
-
-
- What is the real root of suffering? Tokenization.





Module 1.1 : Byte Pair Encoding

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General Pre-processing steps

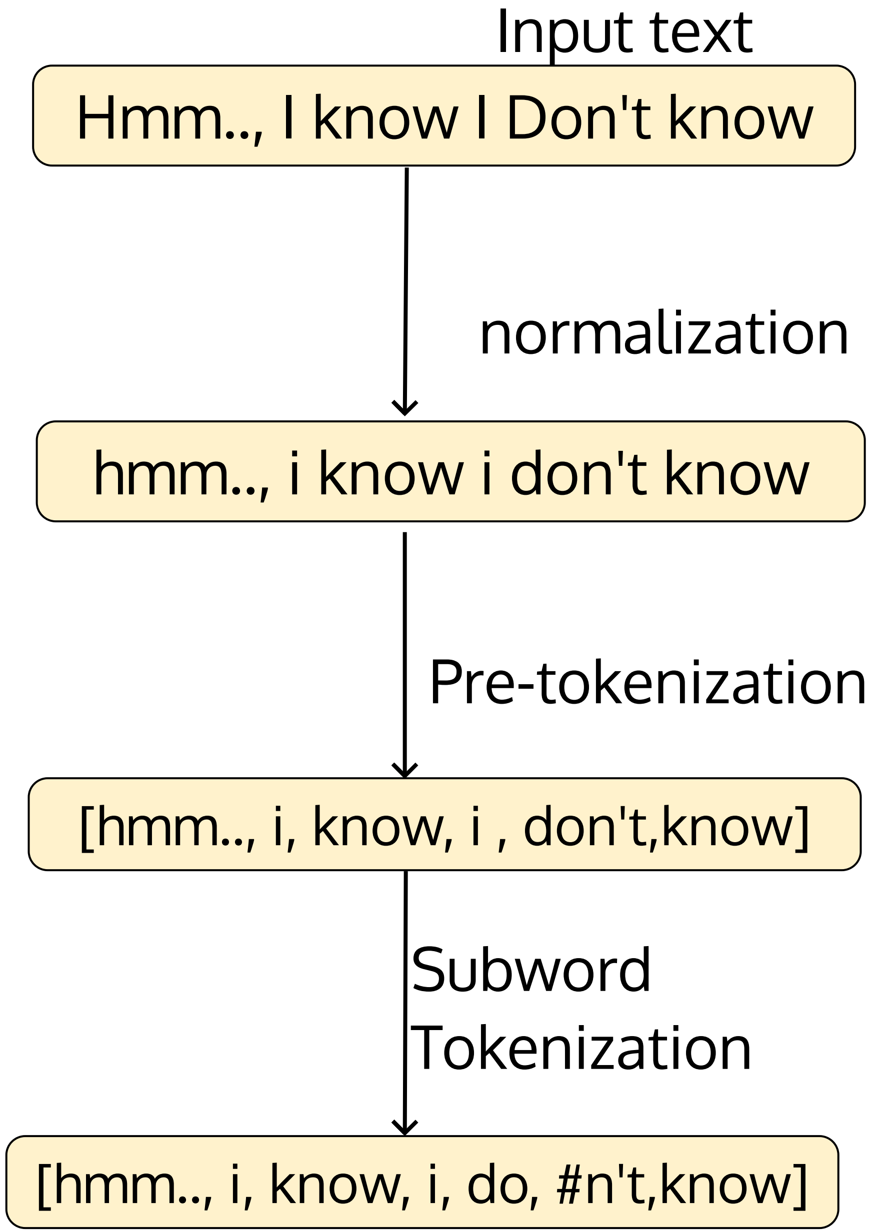
The tokenization schemes follow a sequence of steps to learn the vocabulary.

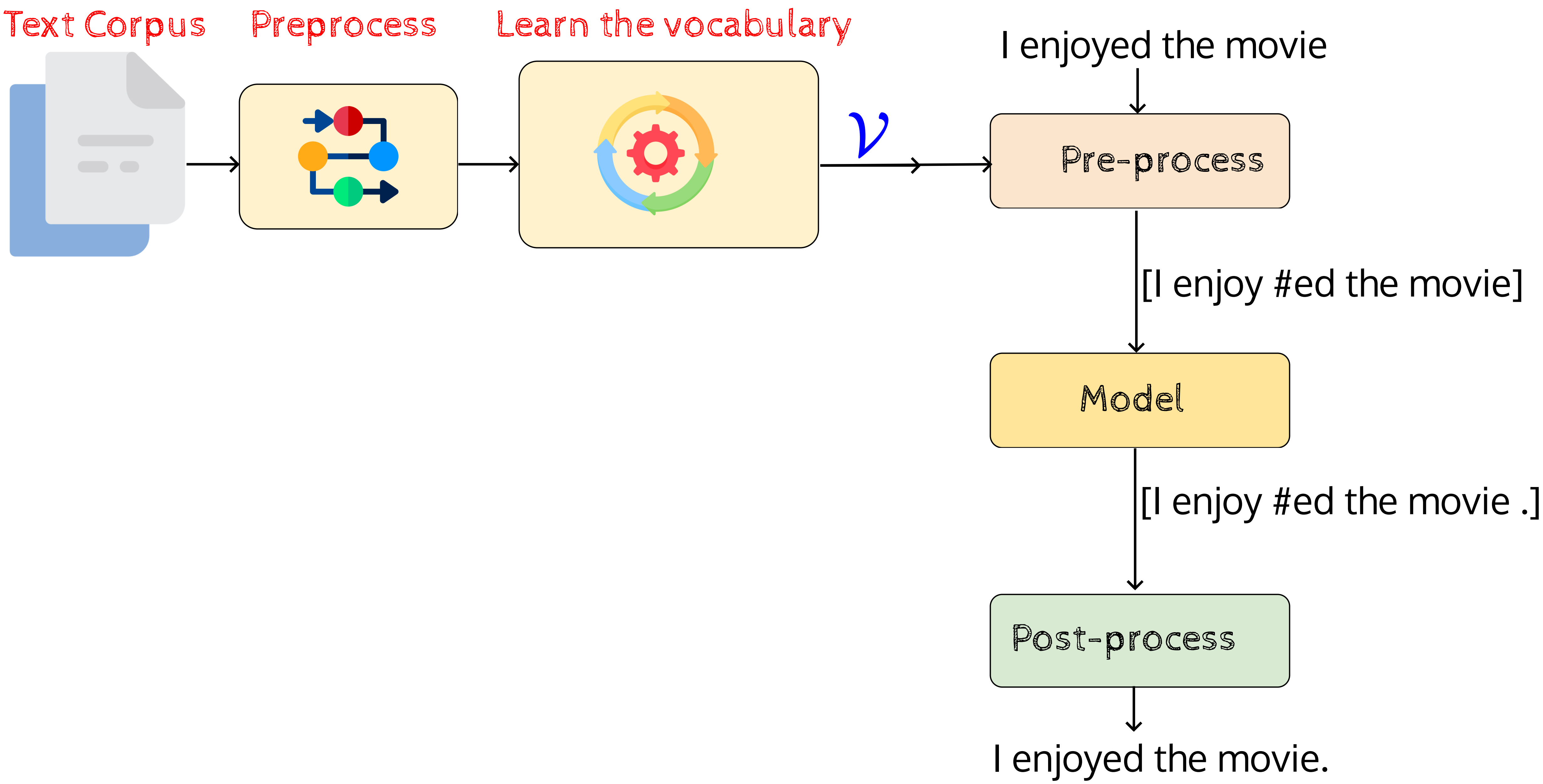
The input text corpus is often built by scraping web pages and ebooks.

First the text is normalized, which involves operations such as treating cases, removing accents, eliminating multiple whitespaces, handling HTML tags, etc.

Splitting the text by whitespace was traditionally called tokenization. However, when it is used with a sub-word tokenization algorithm, it is called pre-tokenization.

Learn the vocabulary (called training) using these words




Text Corpus
Preprocess
Learn the vocabulary
$\mathcal{V}$
I enjoyed the movie
Pre-process
[I enjoy #ed the movie]
Model
[I enjoy #ed the movie .]
Post-process
I enjoyed the movie.

Algorithm

Start with a dictionary that contains words and their counts

Append a special symbol </w> at the end of each word in the dictionary

Set required number of merges (a hyperparameter)

Initialize the character-frequency table (base vocabulary)

Get the frequency count for a pair of characters

Merge pairs with maximum occurrence

```
import re, collections

def get_stats(vocab):
  pairs = collections.defaultdict(int)
  for word, freq in vocab.items():
    symbols = word.split()
    for i in range(len(symbols)-1):
      pairs[symbols[i],symbols[i+1]] += freq
  return pairs

def merge_vocab(pair, v_in):
  v_out = {}
  bigram = re.escape(' '.join(pair))
  p = re.compile(r'(?<!\S)' + bigram + r'(?!\S)')
  for word in v_in:
        w_out = p.sub(''.join(pair), word)
        v_out[w_out] = v_in[word]
  return v_out

vocab = {'l o w </w>' : 5, 'l o w e r </w>' : 2,
'n e w e s t </w>':6, 'w i d e s t </w>':3}
num_merges = 10

for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
print(best)
```

Example

knowing the name of something is different from knowing something. knowing something about everything isn't bad

Word
'k n o w i n g </w>'
't h e </w>
'n a m e </w>
'o f </w>'
's o m e t h i n g </w>
'i s </w>'
'd i f f e r e n t </w>'
'f r o m </w>'
's o m e t h i n g . </w>'
'a b o u t </w>'
'e v e r y t h i n g </w>'
"i s n ' t </w>
'b a d </w>'

‹/w› identifies the word boundary.

Objective: Find most frequently occurring byte-pair

Example

knowing the name of something is different from knowing something. knowing something about everything isn't bad

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

‹/w› identifies the word boundary.

Objective: Find most frequently occurring byte-pair

Let's count the word frequencies first.

We can count character frequencies from the table

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Initial token count

Character	Frequency
'k'	3

We could infer that "k" has occurred three times by counting the frequency of occurrence of words having the character "k" in it.

In this corpus, the only word that contains "k" is the word "knowing" and it has occurred three times.

⋮ ⋮

Word count

Word	Frequency
'k n o w i n g </w>'	3 $2 * 3 = 6$
't h e </w>	1
'n a m e </w>	1 $1 * 1 = 1$
'o f </w>'	1
's o m e t h i n g </w>	2 $1 * 2 = 2$
'i s </w>'	1
'd i f f e r e n t </w>'	1 $1 * 1 = 1$
'f r o m </w>'	1
's o m e t h i n g . </w>'	1 $1 * 1 = 1$
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1 $1 * 1 = 1$
"i s n ' t </w>	1 $1 * 1 = 1$
'b a d </w>'	1

Vocab size:13

Initial token count

Character	Frequency
'k'	3

Character	Frequency
'k'	3
'n'	13
⋮	⋮

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Vocab size:13

Initial token count

Character	Frequency
'k'	3

Character	Frequency
'k'	3
'n'	13

Character	Frequency
'k'	3
'n'	13
'o'	9

Character	Frequency
'k'	3
'n'	13
'o'	9
⋮	⋮
'</w>'	3+1+1+1+2+...+1=16

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Vocab size:13

Initial tokens and count

Character	Frequency
'k'	3

Character	Frequency
'k'	3
'n'	13

Character	Frequency
'k'	3
'n'	13
'o'	9

Character	Frequency
'k'	3
'n'	13
'o'	9
⋮	⋮
'</w>'	3+1+1+1+2+...+1=16

Character	Frequency
'k'	3
'n'	13
'o'	9
⋮	⋮
'</w>'	16
⋮	⋮
"""	1

Initial Vocab Size :22

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o')	3

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	$3 + 2 + 1 + 1 = 7$

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	7
('n', 'g')	7
('g', '</w>')	6
('t', 'h')	5
('h', 'e')	1
('e', '</w>'	2
⋮	⋮
('a', 'd')	1
('d', '</w>')	1

Initial Vocabulary

Character	Frequency
'k'	3
'n'	13
'o'	9
'i'	10
'</w>'	16
⋮	⋮
"""	1

"in"	7

Merge the most commonly occurring pair :

$$(i, n) \rightarrow in$$

Word count

Word	Frequency
'k n o w i n g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h i n g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h i n g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h i n g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	7
('n', 'g')	7
('g', '</w>')	6
('t', 'h')	5
('h', 'e')	1
('e', '</w>'	2
⋮	⋮
('a', 'd')	1
('d', '</w>')	1

Updated Vocabulary

Character	Frequency
'k'	3
'n'	13 -7 = 6
'o'	9
'i'	10-7 = 3
'</w>'	16
⋮	⋮
"'"	1

"in"	7

Added new token

Merge the most commonly occurring pair

Update token count

Word count

Word	Frequency
'k n o w in g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h in g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h in g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h in g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	7
('n', 'g')	7
('g', '</w>')	6
('t', 'h')	5
('h', 'e')	1
('e', '</w>'	2
⋮	⋮
('a', 'd')	1
('d', '</w>')	1

Updated vocabulary

Character	Frequency
'k'	3
'n'	6
'o'	9
'i'	3
'</w>'	16
⋮	⋮
"""	1
'g': 7	7
"in"	7

Now, treat "in" as a single token and repeat the steps.

Word count

Word	Frequency
'k n o w in g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h in g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h in g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h in g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
~~('w', 'i')~~	~~3~~
('w','in')	3
('in', 'g')	7
('g', '</w>')	6
('t', 'h')	5
('h', 'e')	1
('e', '</w>'	2
⋮	⋮
('a', 'd')	1
('d', '</w>')	1

Updated vocabulary

Character	Frequency
'k'	3
'n'	6
'o'	9
'i'	3
'</w>'	16
⋮	⋮
"'"	1
'g': 7	7
"in"	7
"ing"	7

Note, at iteration 4, we treat (w,in) as a pair instead of (w,i)

Therefore, the new byte pairs are (w,in):3,(in,g):7, (h,in):4

Word count

Word	Frequency
'k n o w in g </w>'	3
't h e </w>	1
'n a m e </w>	1
'o f </w>'	1
's o m e t h in g </w>	2
'i s </w>'	1
'd i f f e r e n t </w>'	1
'f r o m </w>'	1
's o m e t h in g . </w>'	1
'a b o u t </w>'	1
'e v e r y t h in g </w>'	1
"i s n ' t </w>	1
'b a d </w>'	1

Byte-Pair count

Word	Frequency
('k', 'n')	3
('n', 'o'	3
('o', 'w')	3
('w', 'in')	3
('h', 'in')	4
('in', 'g')	7
('g', '</w>')	6
('t', 'h')	5
('h', 'e')	1
('e', '</w>'	2
⋮	⋮
('a', 'd')	1
('d', '</w>')	1

Updated vocabulary

Character	Frequency
'k'	3
'n'	6
'o'	9
'i'	3
'</w>'	16
⋮	⋮
"""	1
'g': 7	7
"in"	7
"ing"	7

Of all these pairs, merge most frequently occurring byte-pairs which turns out to be "ing"

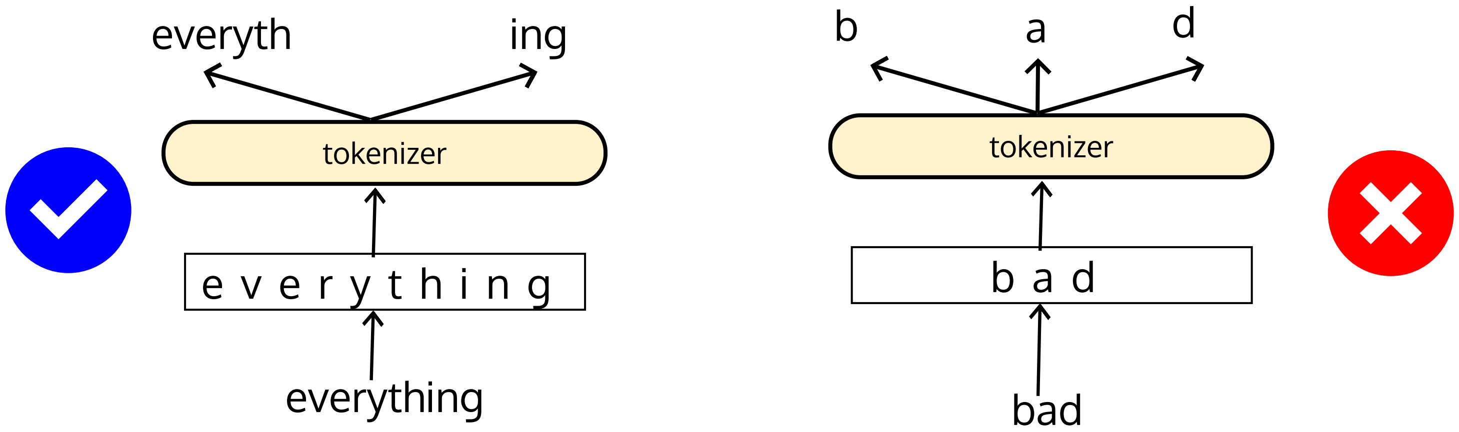
Now, treat "ing" as a single token and repeat the steps

After 45 merges

Tokens
'k'
'n'
'o'
'i'
'</w>'
⋮
'in'
'ing'
⋮
'k n o w i n g </w>'
't h e </w>'
'n a m e </w>'
'o f </w>'
's o m e t h i n g </w>'
'i s </w>'
'd i f f e r e n t </w>'
'f r o m </w>'
's o m e t h i n g . </w>'
'a b o u t </w>'
'e v e r y t h'
"i s n ' t </w>'
'b a d </w>'

The final vocabulary contains initial vocabulary and all the merges (in order). The rare words are broken down into two or more subwords

At test time, the input word is split into a sequence of characters, and the characters are merged into larger known symbols



The pair ('i','n') is merged first and follwed by the pair ('in','g')

The algorithm offers a way to adjust the size of the vocabulary as a function of the number of merges.

For a larger corpus, we often end up with a vocabulary whose size is smaller than considering individual words as tokens

BPE for non-segmented languages

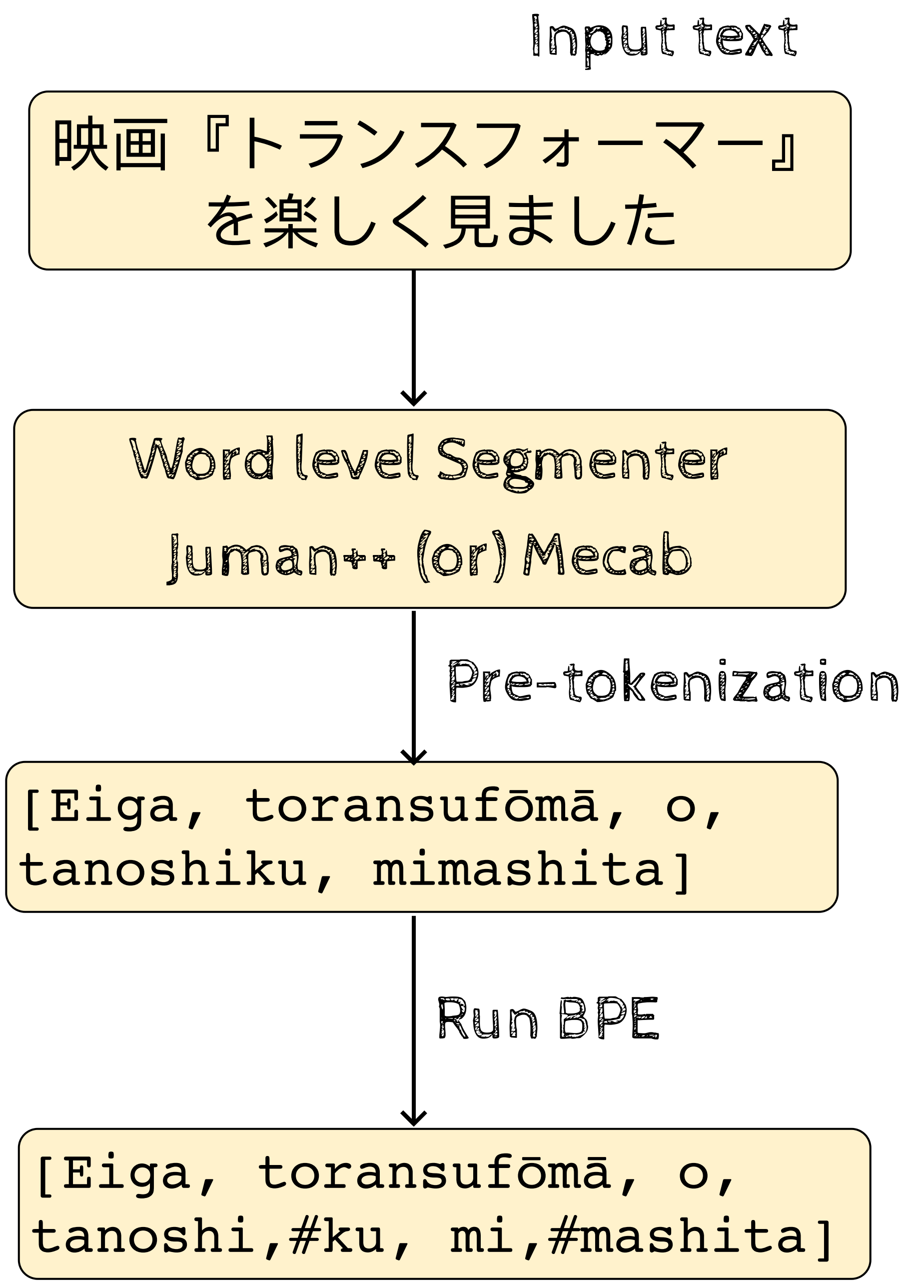
Languages such as Japanese and Korean are non-segmented

However, BPE requires space-separated words

How do we apply BPE for non-segmented languages then?

In practice, we can use language specific morphology based word segmenters such as Juman++ for Japanese (as shown in the figure on the right)

However, in the case of multilingual translation, having a language agnostic tokenizer is desirable.



Example:

$$\mathcal{V} = \{a, b, c, \cdots, z, lo, he\}$$

Tokenize the text "hello lol"

[h e l l o] , [l o l]

search for the byte-pair 'lo', if present merge

Yes. Therefore, Merge

[h e l lo], [lo l]

search for the byte-pair 'he', if present merge

Yes. Therefore, Merge

[he l lo], [lo l]

return the text after merge

he #l #lo, lo #l

Module 1.2 : WordPiece

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In BPE we merged a pair of tokens which has the highest frequency of occurence.

What if there are more pairs that are occurring with the same frequency, for example ('i','n') and ('n','g')?

Take the frequency of occurrence of individual tokens in the pair into account

$$score = \frac{count(\alpha,\beta)}{count(\alpha)count(\beta)}$$

Now we can select a pair of tokens where the individual tokens are less frequent in the vocabulary

The WordPiece algorithm uses this score to merge the pairs.

Word	Frequency
('k', 'n')	3
('n', 'o')	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	7
('n', 'g')	7
('g', '.')	1
('t', 'h')	5
('h', 'e')	1
('e', '</w>')	2
⋮	⋮
('a', 'd')	1

Word count

Word	Frequency
'k n o w i n g'	3
't h e '	1
'n a m e '	1
'o f '	1
's o m e t h i n g '	2
'i s '	1
'd i f f e r e n t '	1
'f r o m '	1
's o m e t h i n g. '	1
'a b o u t '	1
'e v e r y t h i n g '	1
"i s n ' t '	1
'b a d '	1

Initial Vocab Size :22

Character	Frequency
'k'	3
'#n'	13
'#o'	9
⋮	⋮
't'	16
'#h'	5
"'"	1
⋮	⋮

Subwords are identified by prefix ## (we use single # for illustration)

knowing k #n #o #w #i #n #g

Word count

Word	Frequency
'k n o w i n g'	3
't h e '	1
'n a m e '	1
'o f '	1
's o m e t h i n g '	2
'i s '	1
'd i f f e r e n t '	1
'f r o m '	1
's o m e t h i n g. '	1
'a b o u t '	1
'e v e r y t h i n g '	1
"i s n ' t '	1
'b a d '	1

ignoring the prefix

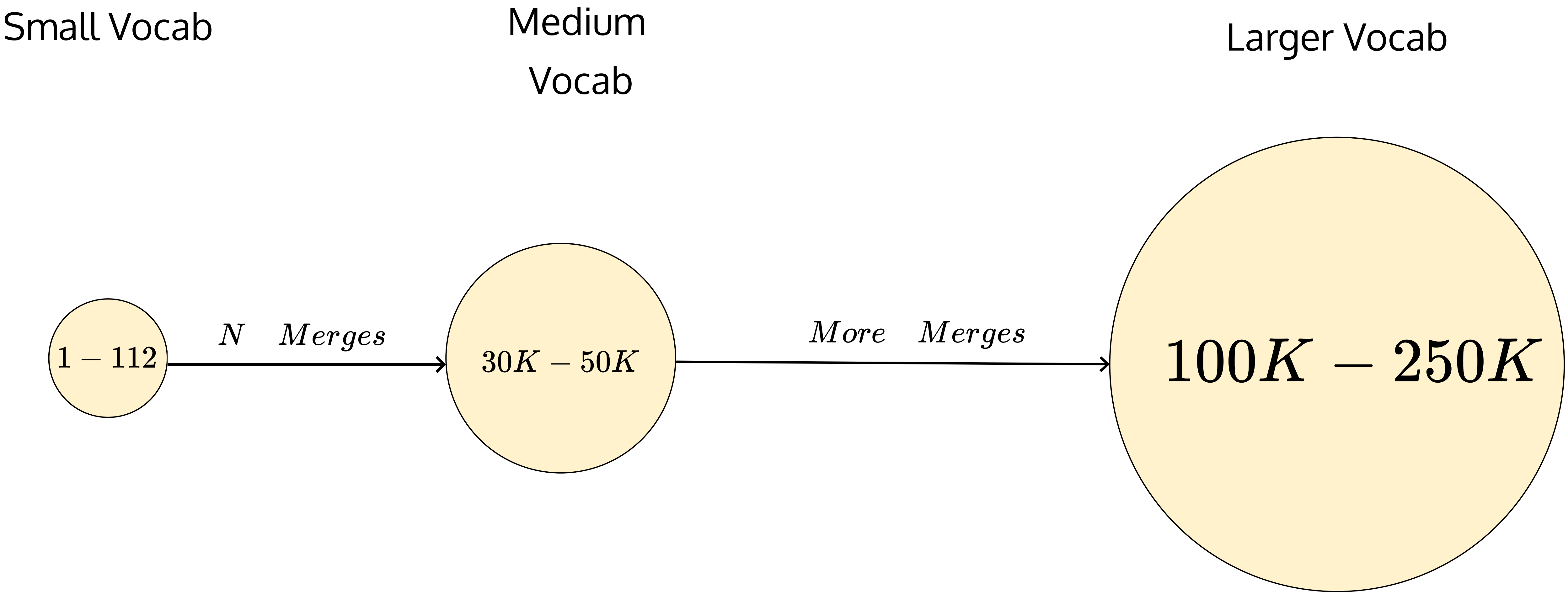
Word	Frequency
('k', 'n')	3
('n', 'o')	3
('o', 'w')	3
('w', 'i')	3
('i', 'n')	7
('n', 'g')	7
('g', '.')	1
('t', 'h')	5
('h', 'e')	1
('e', '</w>')	2
⋮	⋮
('a', 'd')	1

Freq of 1st element	Freq of 2nd element	score
'k':3	'n':13	0.076
'n':13	'o':9	0.02
'o':9	'w':3	0.111
'i':10	'n':13	0.05
'n':13	'g':7	0.076
't':8	'h':5	0.125
'a':3	'd':2	0.16

Now, merging is based on the score of each byte pair.

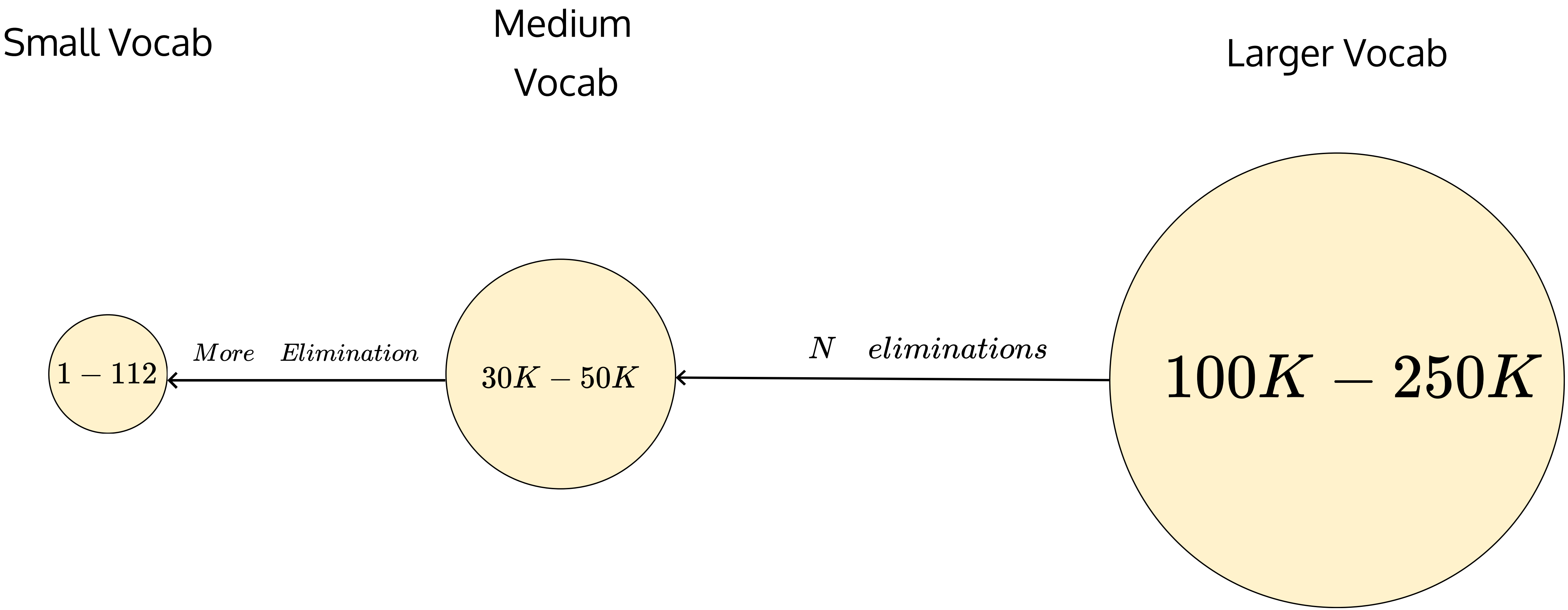
$$score = \frac{count(\alpha,\beta)}{count(\alpha)count(\beta)}$$

Merge the pair with highest score



We start with a character level vocab and keep merging until a desired vocabulary size is reached

Well, we can do the reverse as well.



We start with word level vocab and keep eliminating words until a desired vocabulary size is reached

That's what we will see next.

Module 1.3 : SentencePiece

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A given word can have numerous subwords.

For instance, the word "X=hello" can be segmented in multiple ways (by BPE) even with the same vocabulary

$\mathcal{V}$={h,e,l,l,o,he,el,lo,ll,hell}

$$\mathbf{x_1} = he, ll, o \qquad \mathbf{x_2} = h, el, lo$$

$$\mathbf{x_3} = he, l, lo \qquad \mathbf{x_4} = hell, o$$

however, following the merge rule, BPE outputs : he, l, lo

On the other hand, if

$\mathcal{V}$={h,e,l,l,o,el,he,lo,ll,hell}

then BPE outputs: h, el, lo

Therefore, we say BPE is greedy and deterministic (we can use BPE-Dropout [Ref] to make it stochastic)

The probabilistic approach is to find the subword sequence $\mathbf{x}^* \in \{\mathbf{x_1}, \mathbf{x_2}, \cdots, \mathbf{x_k}\}$ that maximizes the likelihood of the word X

$\boxed{X} \longleftarrow \boxed{\text{All possible subwords of } X}$

observed

hidden

The word X in sentencepiece means a sequence of characters or words (without spaces)

Therefore, it can be applied to languages (like Chinese and Japanese) that do not use any word delimiters in a sentence.

Let $\mathbf{x}$ denote a subword sequence of length n.

$$\mathbf{x} = (x_1, x_2, \dots, x_n)$$

then the probability of the subword sequence (with unigram LM) is simply

$$P(\mathbf{x}) = \prod_{i=1}^{n} P(x_i)$$

$$\sum_{x \in \mathcal{V}} p(x) = 1$$

the objective is to find the subword sequence for the input sequence X (from all possible segmentation candidates of $S(X)$) that maximizes the (log) likelihood of the sequence

$$\mathbf{x}^* = \arg\max_{\mathbf{x} \in S(X)} P(\mathbf{x})$$

We can use Viterbi decoding to find $\mathbf{x}^*$.

Then, for all the sequences in the dataset D, we define the likelihood function as

$$\mathcal{L} = \sum_{s=1}^{|D|} \log(P(X^s))$$

$$= \sum_{s=1}^{|D|} \log\left(\sum_{\mathbf{x} \in S(X^s)} P(\mathbf{x})\right)$$

Recall that the subwords $p(x_i)$ are hidden (latent) variables.

Therefore, given the vocabulary $\mathcal{V}$, Expectation-Maximization (EM) algorithm could be used to maximize the likelihood

Let $X =$ "knowing" and a few segmentation candidates be $S(X) = \{`k, now, ing`, `know, ing`, `knowing`\}$

Given the unigram language model we can calculate the probabilities of the segments as follows

$$p(\mathbf{x_1} = k, now, ing) = p(k)p(now)p(ing)$$

$$= \frac{3}{16} \times \frac{3}{16} \times \frac{7}{16} = \frac{63}{4096}$$

$$p(\mathbf{x_2} = know, ing) = p(know)p(ing) = \frac{21}{256} = \frac{336}{4096}$$

$$p(\mathbf{x_3} = knowing) = p(knowing) = \frac{3}{16} = \frac{768}{4096}$$

$$\boxed{\mathbf{x}^* = \arg\max_{\mathbf{x} \in S(X)} P(\mathbf{x}) = \mathbf{x_3}}$$

In practice, we use Viterbi decoding to find $\mathbf{x}^*$ instead of enumerating all possible segments

Word	Frequency
'knowing'	3
'the'	1
'name'	1
'of'	1
'something'	2
'is'	1
'different'	1
'from'	1
'something.'	1
'about'	1
'everything'	1
"isn't"	1
'bad'	1

Unigram model favours the segmentation with least number of subwords

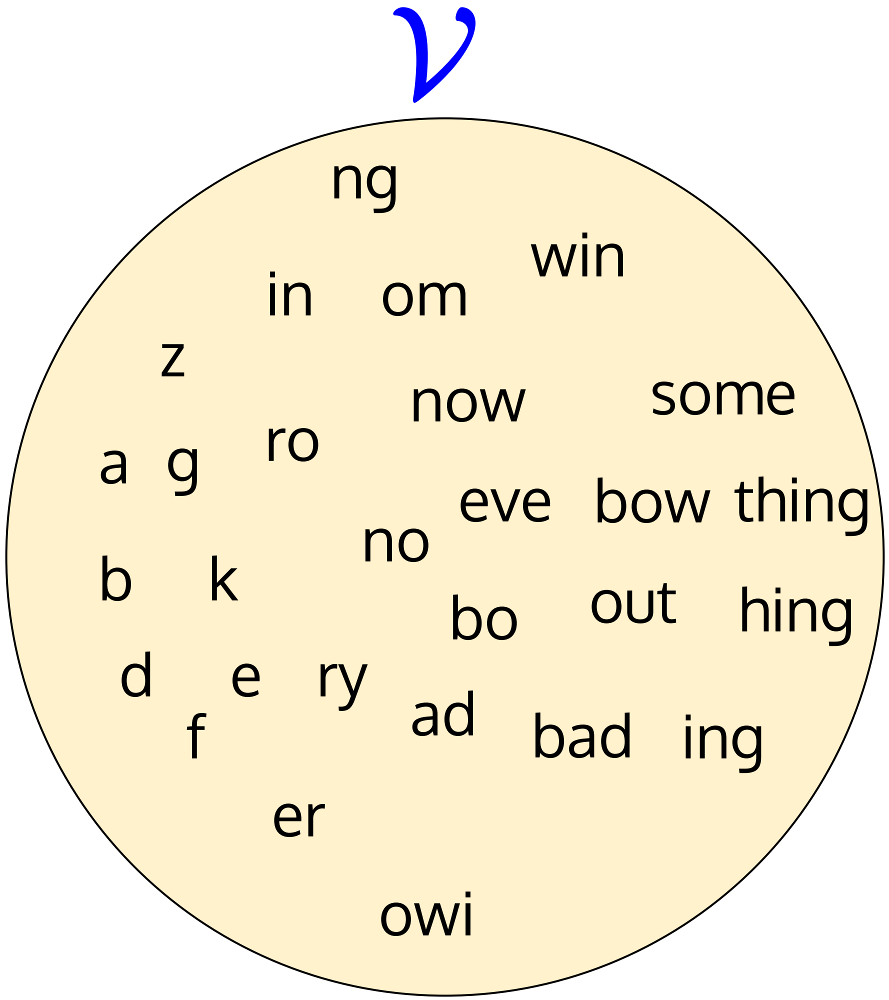
Algorithm

Set the desired vocabulary size

1. Construct a reasonably large seed vocabulary using BPE or Extended Suffix Array algorithm.
2. **E-Step:**

   Estimate the probability for every token in the given vocabulary using frequency counts in the training corpus
3. **M-Step:**

   Use Viterbi algorithm to segment the corpus and return optimal segments that maximizes the (log) likelihood.
4. Compute the likelihood for each new subword from optimal segments
5. Shrink the vocabulary size by removing top $x\%$ of subwords that have the smallest likelihood.
6. Repeat step 2 to 5 until desired vocabulary size is reached



Let us consider segmenting the word "whereby" using Viterbi decoding

Forward algorithm

$\underline{w}here by$

w

-4.29

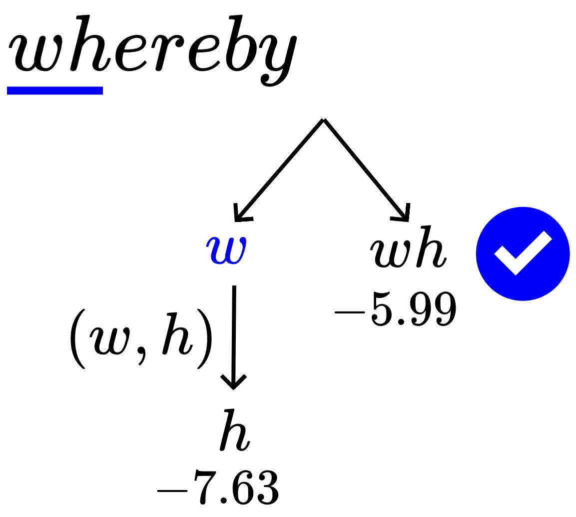
w

Iterate over every position in the given word

output the segment which has the highest likelihood

$t = 1$

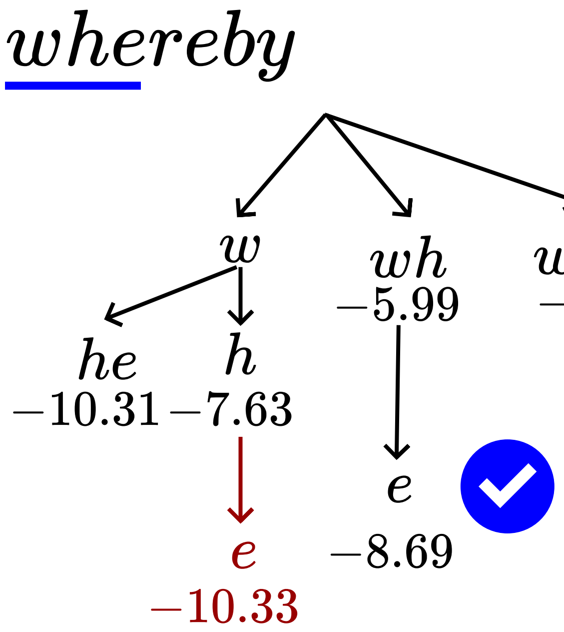
Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13



At this position, the posible segmentations of the slice "wh" are (w,h) and (wh)

Compute the log-likelihood for both and output the best one.

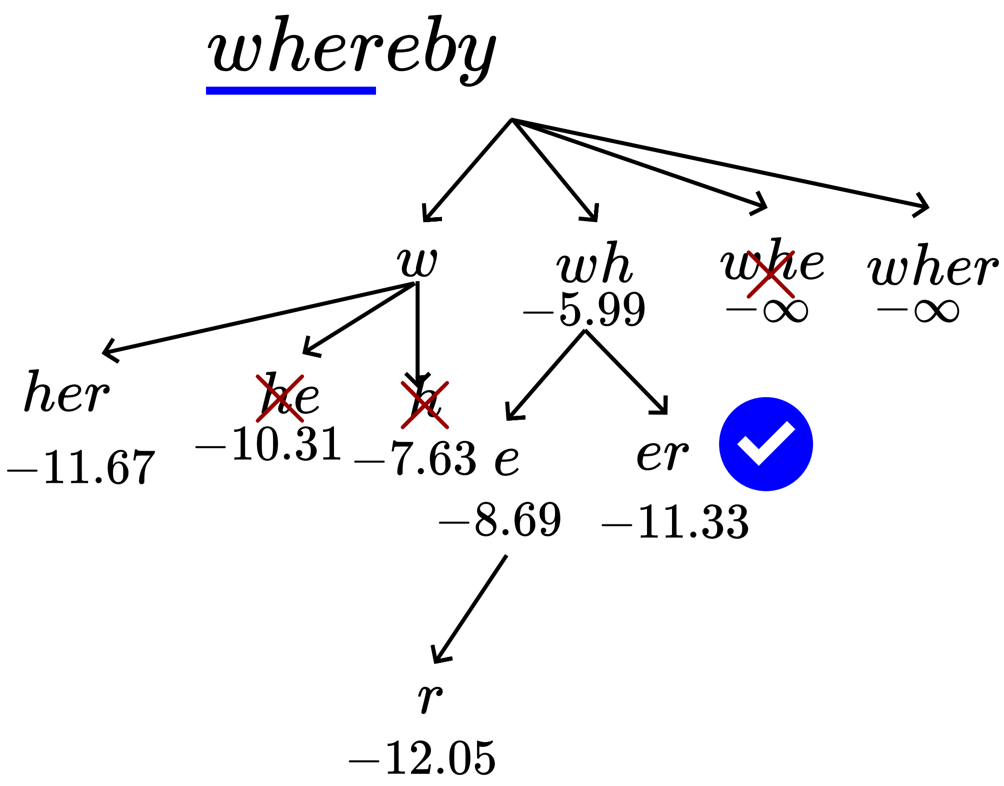
Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13



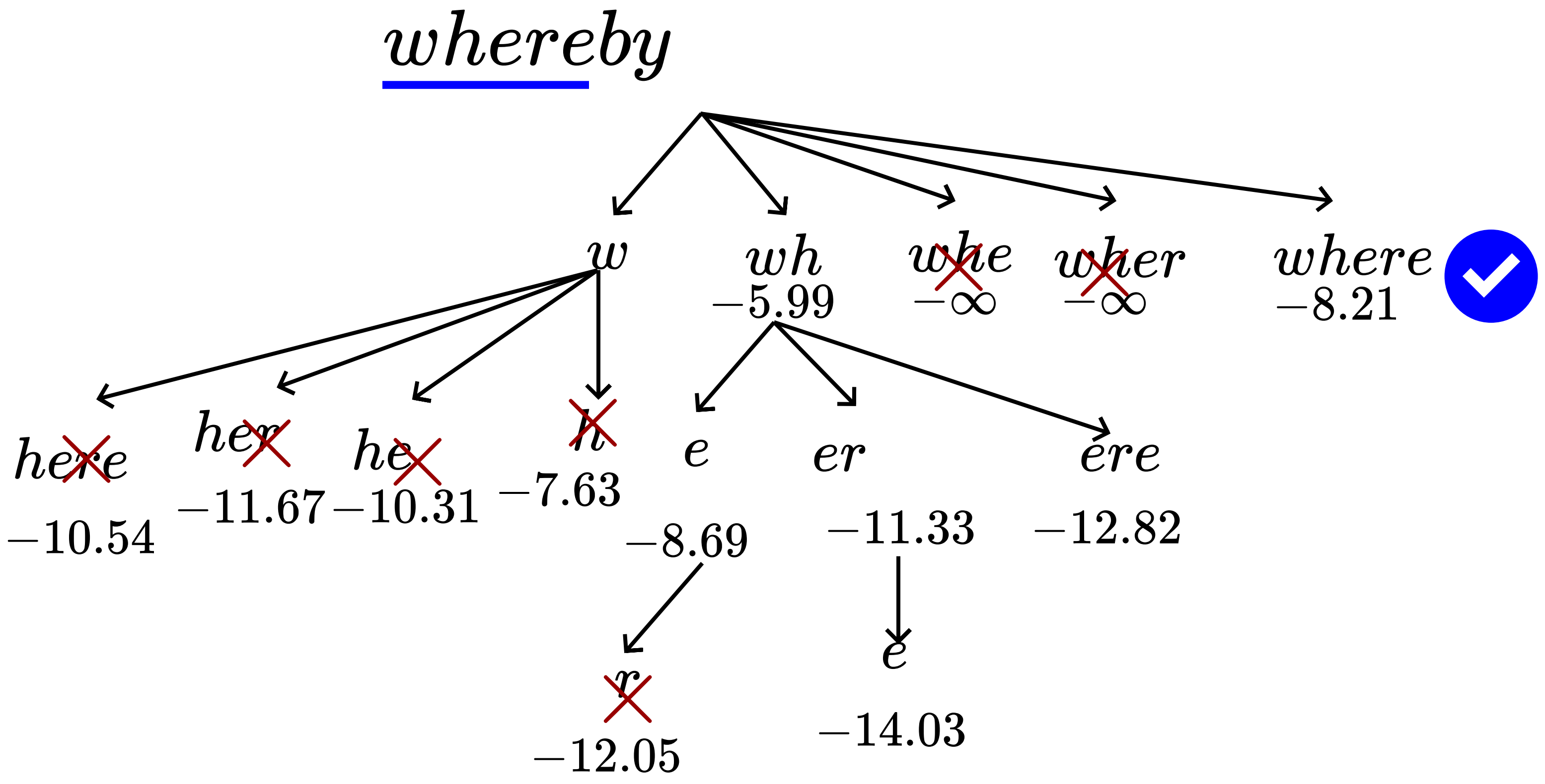
We do not need to compute the likelihood of (w,h,e) as we already ruled out (w,h) in favor of (wh). We display it for completeness

Of these, (wh,e) is the best segmentation that maximizes the likelihood.

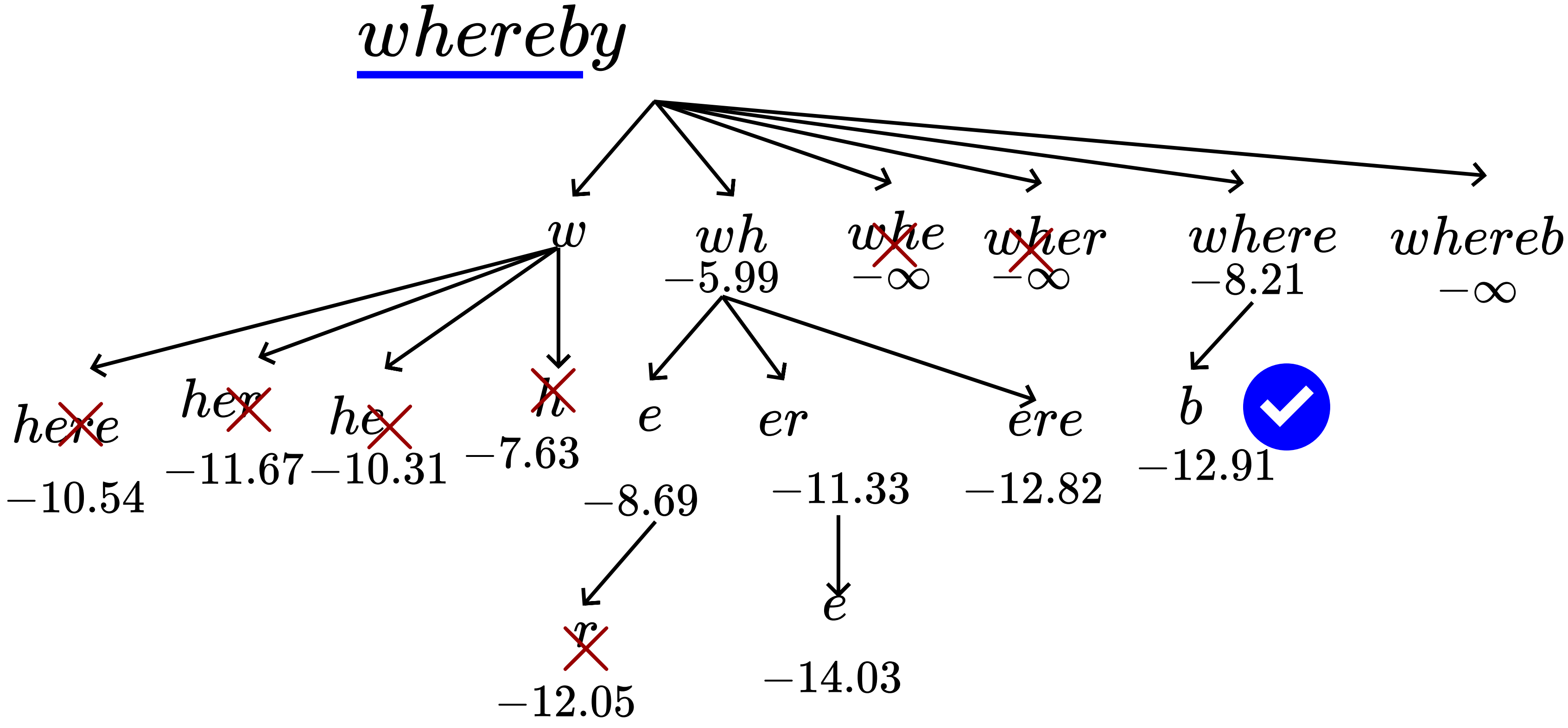
Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13



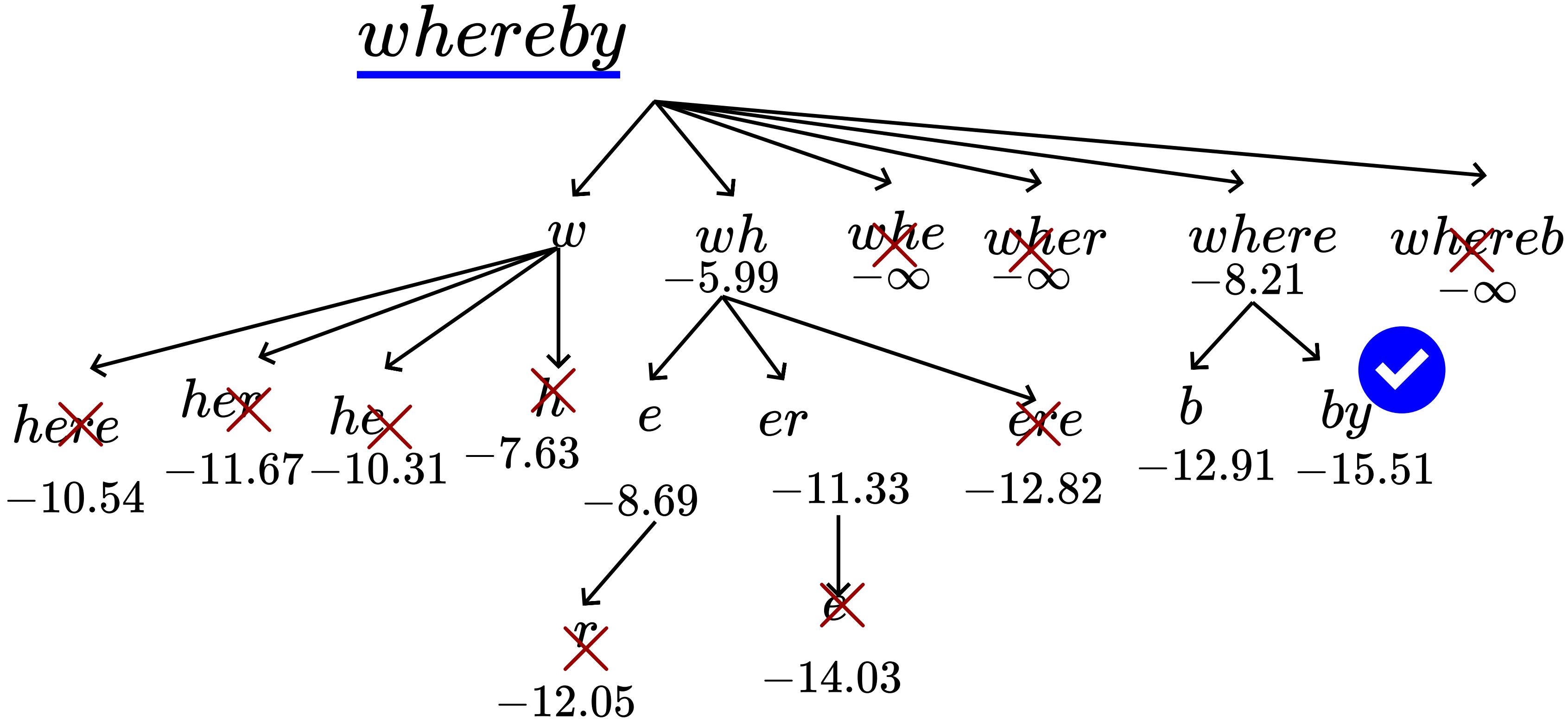
Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13



Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13

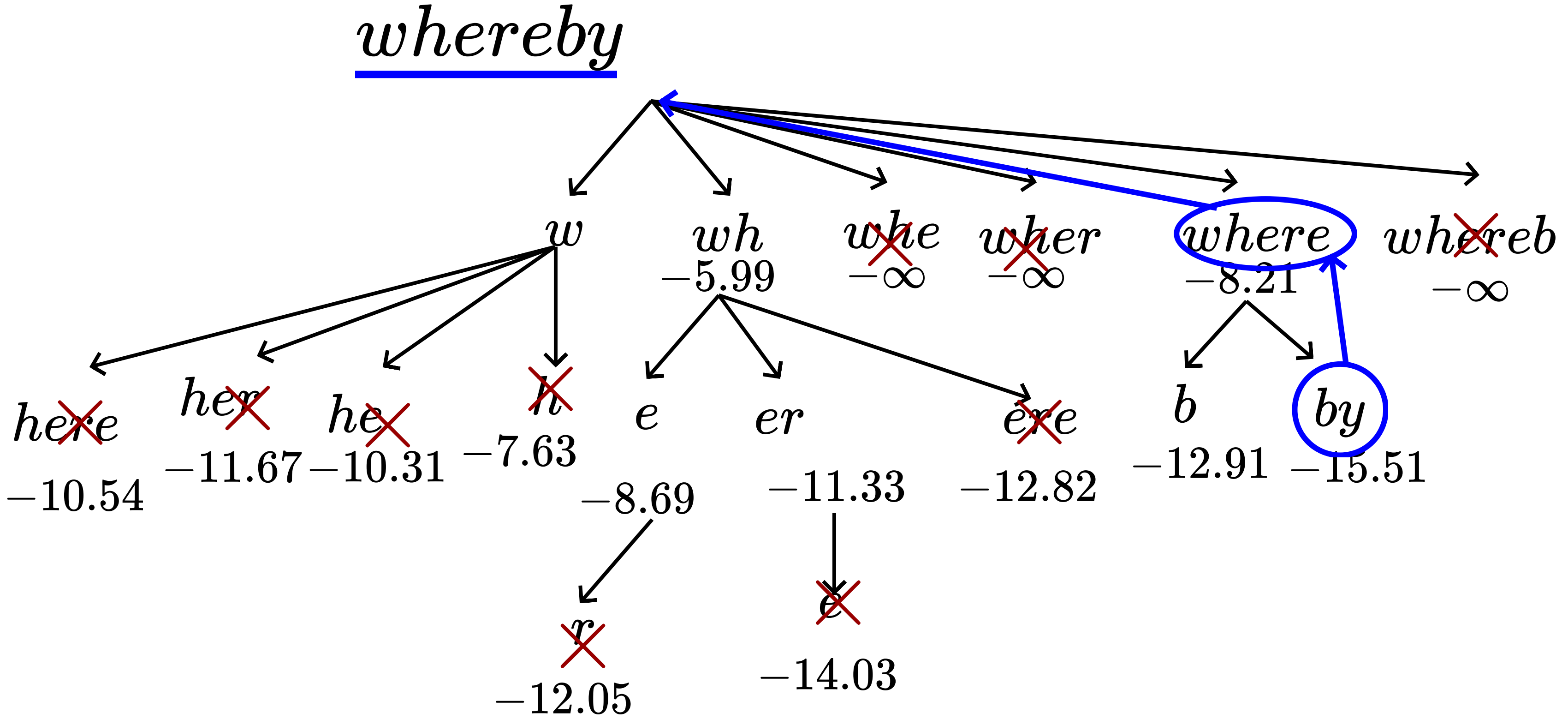


Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13



Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13

Backtrack



Token	log(p(x))
b	-4.7
e	-2.7
h	-3.34
r	-3.36
w	-4.29
wh	-5.99
er	-5.34
where	-8.21
by	-7.34
he	-6.02
ere	-6.83
here	-7.84
her	-7.38
re	-6.13

The best segmentation of the word "whereby" that maximizes the likelihood is "where,by"

We can follow the same procedure for languages that do not use any word delimiters in a sentence.

Module 2 : HF Tokenizers

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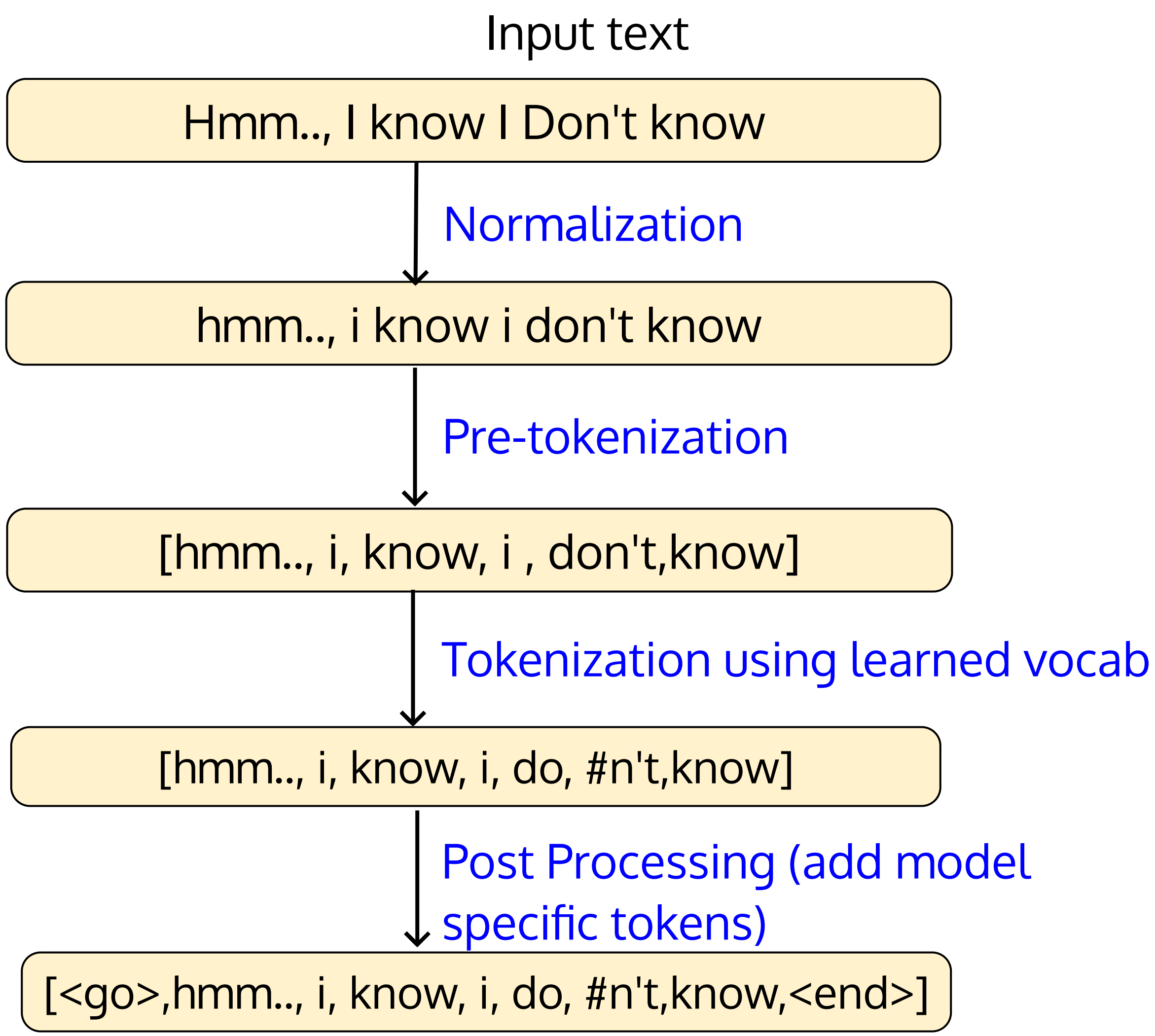
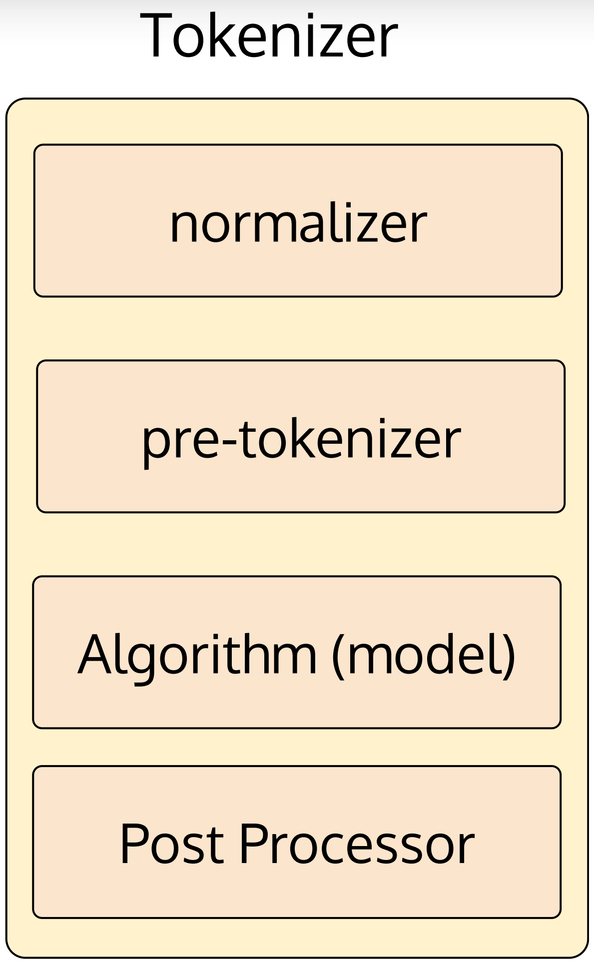
Recall the general Pre-processing pipeline



HF tokenizers module provides a class that encapsulates all of these components

```python
from tokenizers import Tokenizer
```



HF tokenizers module provides a class that encapsulates all of these compoents

```python
from tokenizers import Tokenizer
```

We can customize each step of the tokenizer pipeline

via the setter and getter properties of the class (just like a plug-in)

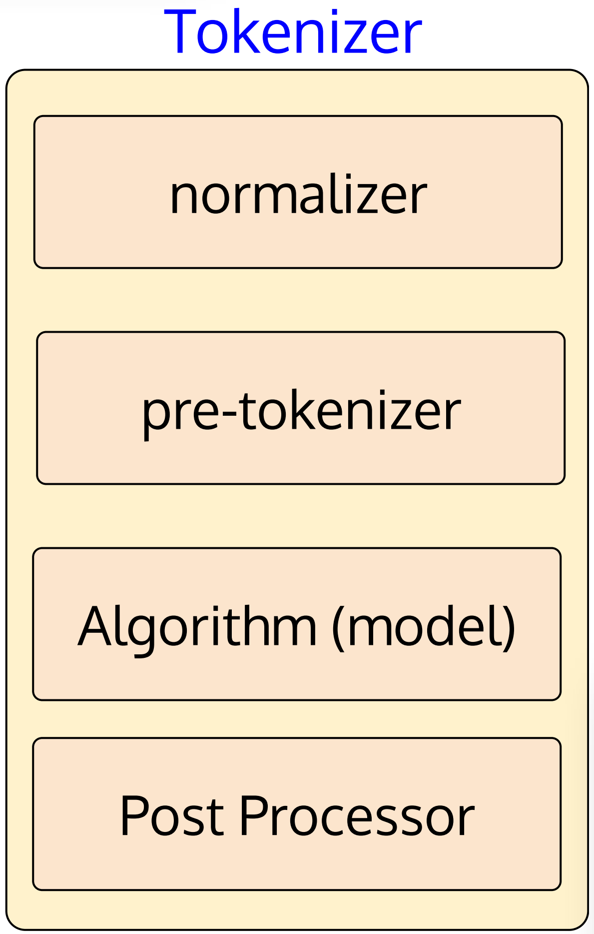
Choices

LowerCase, StripAccents

WhiteSpace, Regex, BERTlike

BPE,WordPiece..

Insert model specific tokens



Property (getter and setter,del)

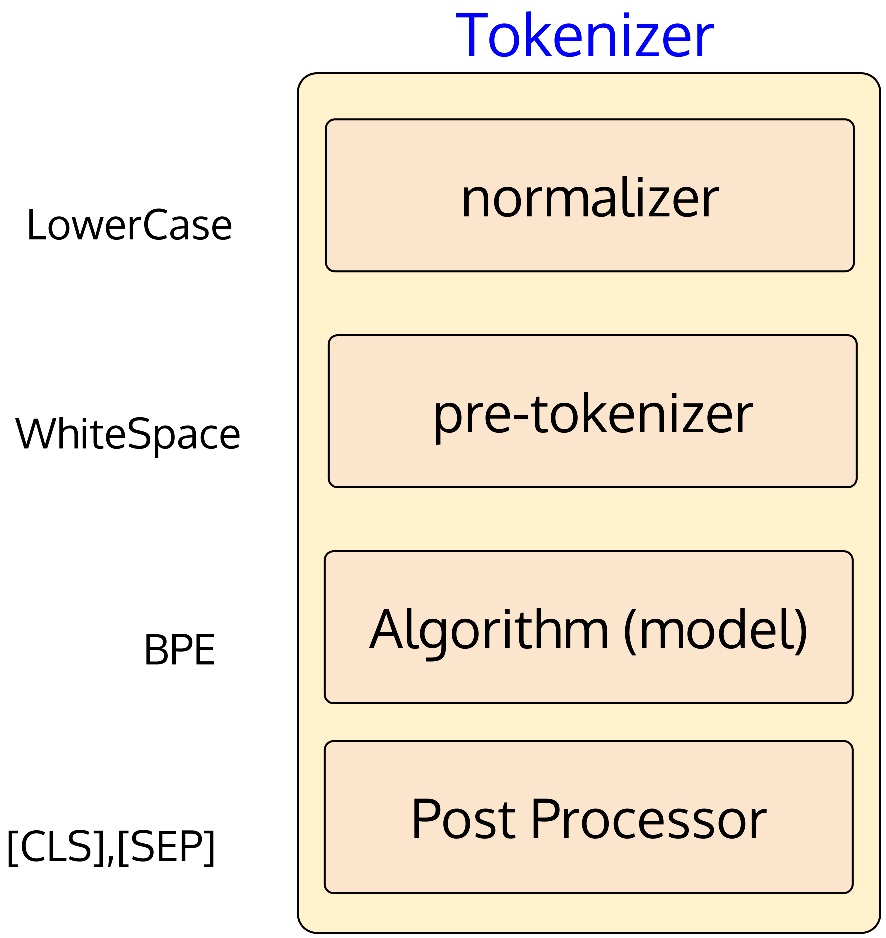
1. `model`
2. `normalizer`
3. `pre_tokenizer`
4. `post_processor`
5. `padding (no setter)`
6. `truncation (no setter)`
7. `decoder`

```python
tokenizer = Tokenizer(BPE())
#doesn't matter  order in which the properties are set
tokenizer.pre_tokenizer = Whitespace()
tokenizer.normalizer = Lowercase()
```

Learning the vocabualty

Provides set of methods for training (learn the vocabulary), encoding input and decoding predictions and so on

```
tokenizer = Tokenizer(BPE())
#doesn't matter  order in which the properties are set
tokenizer.pre_tokenizer = Whitespace()
tokenizer.normalizer = Lowercase()
```



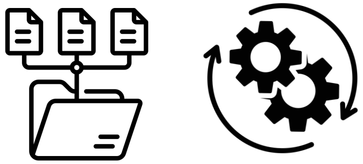
Methods

1. `add_special_tokens(str,AddedToken)`
    - `no token_ids are assigned`
2. `add_tokens()`
3. `enable_padding(), enable_truncation()`
4. **`encode(seq,pair,is_pretokenized), encode_batch()`**
5. **`decode(),decode_batch()`**
6. `from_file(.json) # serialized local  json file`
7. `from_pretrained(.json) # from hub`
8. **`get_vocab(), get_vocab_size()`**
9. `id_to_token(), token_to_id()`
10. `post_process()`
11. **`train(files), train_from_iterator(dataset)`**

```python
# Core Class
class tokenizers.Tokenizer
```

Object

Tokenizer



List of strings (text)

(vocab_size, special_tokens,prefix,..)

`.train_from_iterator(dataset, trainer)`

We do not need to call each of these methods sequentially to build a tokenizer

After setting Normalizer and Pre-Tokenizer, we just need to call the train methods to build the vocabulary

Once the training is complete, we can call methods such as `encode` for encoding the input string

What should be the output if we call `encode_batch` method?

Encoding Class

Assume that the tokenizer has been trained (i.e., learned the vocabulary)

Object

['This is great','tell me a joke'] → Tokenizer → {input_ids, attention_mask, type_ids, ..}

The output is a dictionary that contains not only `input_ids` but also optional outputs like `attention_mask`, `type_ids` (which we will learn about in the next lecture)

We can customize the output behaviour by passing the instance of Encoding object to the *post_process()* methods of Tokenizer (it is used internally, we can just set the desired formats in the optional parameters like "pair" in `encode()`)

```
encoding = Encoding()
tokenizer.post_process(encoding,pair=True)
```

Customization

It is possible to customize each component as desired. However, we will not go into details in this course.

The takeaway is that we can build and train a tokenizer on any dataset (regardless of size) in 6 to 8 lines of code!