Generative Artificial Intelligence

Sub-word Tokenization

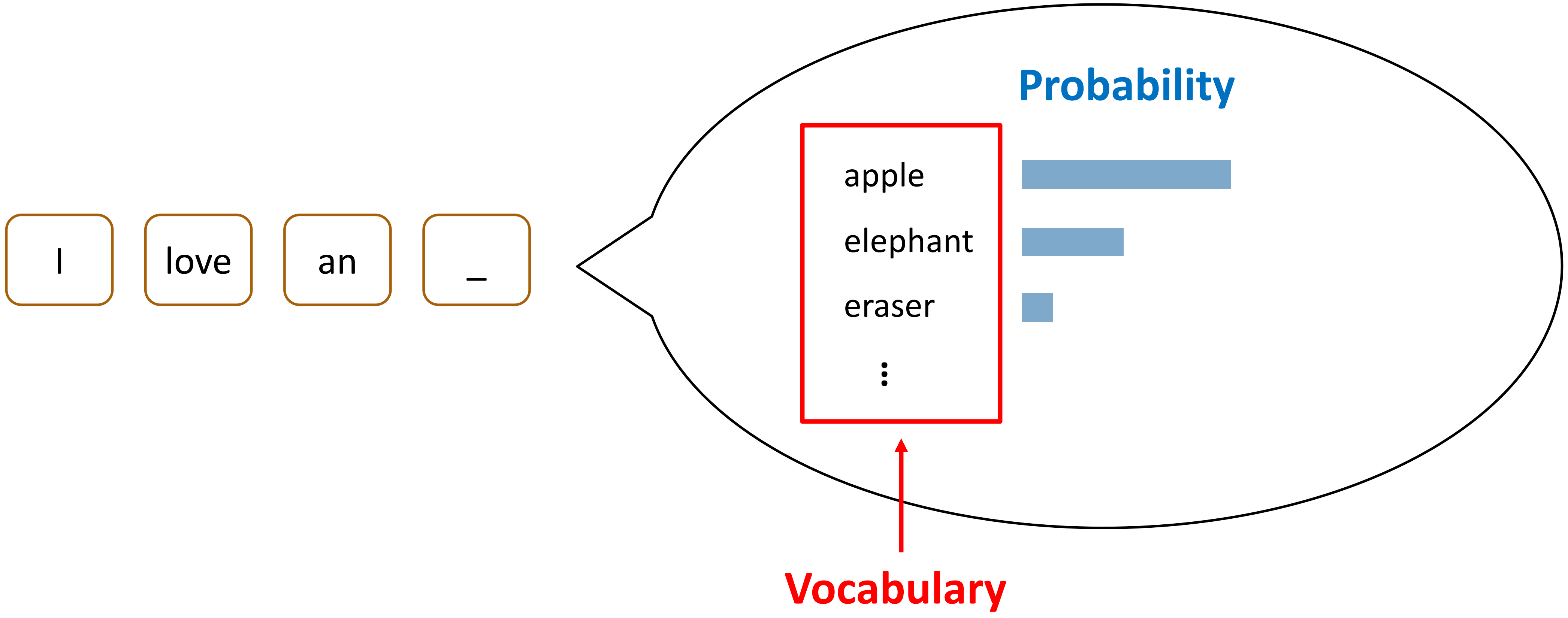
Outline

Recap

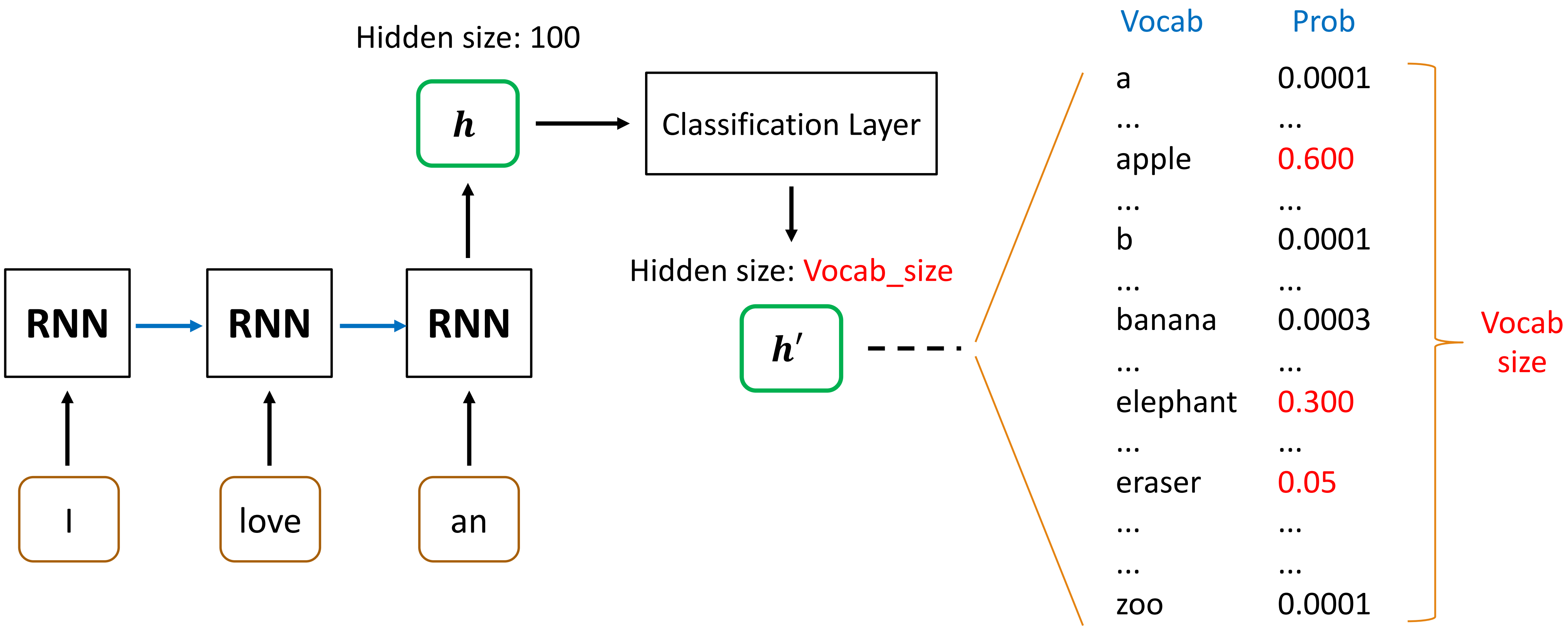
Word Segmentation

Sub-word Tokenization

Recap: Word Representations



Recap: Word Representations (Details)



Basic Pipeline of Natural Language Processing

Build the vocabulary

↓

Learn the representations (Training)

↓

Perform predictions (Testing)

How to build the vocabulary?

- Segment words based on delimiters (e.g., white spaces).
- Then we can collect the words from training corpora.

I love apples. I like apples and pineapples.

(You can also perform stemming after word segmentation!)

Vocabulary

Word	ID
and	0
apples	1
I	2
like	3
love	4
pineapples	5
.	6
<UNK>	7

Unknown words (not shown up in the training corpora)

Issues of Delimiter-based Segmentation

- Only work for Western languages.
  - Cannot work for Chinese, Japanese, ...
- Cannot handle unseen words (not shown up in the training corpora)
  - A misspelled word contains morphological information but become an unknown word.

Issues of Delimiter-based Segmentation (Continued.)

- For machine translation, there is not always a 1-to-1 correspondence between source and target words since compound words may exist in target language.

- For example, sewage water treatment plant (English) -> Abwasserbehandlungsanlage (German)

$\underbrace{\text{Abwasser}}_{\text{sewage water}}\underbrace{\text{behandlungs}}_{\text{treatment}}\underbrace{\text{anlage}}_{\text{plant/facility}}$ (German)

Sub-word units are favored.

Common Sub-word Tokenization Algorithms

- Byte Pair Encoding (BPE) (Sennrich et al., 2016)[1]
- WordPiece (Schuster and Nakajima, 2012)[2]
- Unigram Language Model (Kudo, 2018)[3]

[1] Sennrich, Rico, Barry Haddow, and Alexandra Birch. "Neural Machine Translation of Rare Words with Subword Units." Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL), 2016.
[2] Schuster, Mike, and Kaisuke Nakajima. "Japanese and korean voice search." 2012 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2012.
[3] Kudo, Taku. "Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates." Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL). 2018.

Segmentation vs. Tokenization

- All tokenization is segmentation, but not all segmentation is tokenization.
- Segmentation can be:
  - Word segmentation from a sentence
  - Sentence segmentation from a document
- Tokenization can be:
  - Word segmentation from a sentence (then `words` become `tokens`)
  - Sub-word tokenization from a word or sentence

Sub-word Tokenization (1)

- Given a training corpus, we first turn each word into a sequence of characters (separated by spaces)

Training corpus

low low low low low lower lower newest newest newest newest newest newest widest widest widest

Word	Frequency
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

- </w> is a special end-of-word symbol, allowing us to restore the original tokenization.

Sub-word Tokenization (1)

- Initialize the vocabulary with the existing characters:

low low low low low lower lower newest newest newest newest newest newest widest widest widest

⬇

Initial vocab: </w>, d, e, i, l, n, o, r, s, t, w

Sub-word Tokenization (2)

- Find the character **pair** with the highest frequency

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w $\boxed{\text{e s}}$ t </w>	6
w i d $\boxed{\text{e s}}$ t </w>	3

Found "e s" with the highest frequency 6+3=9

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w

Sub-word Tokenization (3)

- Add the pair with the highest frequency to the vocab

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w $\boxed{\text{e s}}$ t </w>	6
w i d $\boxed{\text{e s}}$ t </w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es

Sub-word Tokenization (4)

- Merge the characters by replacing all words in the corpus with the newly added pair.

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w **es** t </w>	6
w i d **es** t </w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es

Sub-word Tokenization (2)

Repeated (2)-(4) according to `num_merges`

- Find the character **pair** with the highest frequency

Word	**Frequency**
l o w </w>	5
l o w e r </w>	2
n e w $\boxed{\text{es t}}$ </w>	6
w i d $\boxed{\text{es t}}$ </w>	3

Found “es t” with the highest frequency 6+3=9

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es

Sub-word Tokenization (3)

Repeated (2)-(4)
according to `num_merges`

- Add the pair with the highest frequency to the vocab

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w es t </w>	6
w i d es t </w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es est

Sub-word Tokenization (4)

Repeated (2)-(4)
according to `num_merges`

- Merge the characters by replacing all words in the corpus with the newly added pair.

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w **est** </w>	6
w i d **est** </w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est

Sub-word Tokenization (2)

Repeated (2)-(4) according to `num_merges`

- Find the character **pair** with the highest frequency

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w est </w>	6
w i d est </w>	3

Found “est </w>” with the highest frequency 6+3=9

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est

Sub-word Tokenization (3)

Repeated (2)-(4) according to `num_merges`

- Add the pair with the highest frequency to the vocab

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w est </w>	6
w i d est </w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>

Sub-word Tokenization (4)

Repeated (2)-(4) according to `num_merges`

- Merge the characters by replacing all words in the corpus with the newly added pair.

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w **est</w>**	6
w i d **est</w>**	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>

Sub-word Tokenization (2)

Repeated (2)-(4) according to \`num_merges\`

- Find the character **pair** with the highest frequency

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w est</w>	6
w i d est</w>	3

Found “l o” with the highest frequency 5+2=7

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>

Sub-word Tokenization (3)

Repeated (2)-(4) according to `num_merges`

- Add the pair with the highest frequency to the vocab

Word	Frequency
l o w </w>	5
l o w e r </w>	2
n e w est</w>	6
w i d est</w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>, lo

Sub-word Tokenization (4)

Repeated (2)-(4)
according to `num_merges`

- Merge the characters by replacing all words in the corpus with the newly added pair.

Word	Frequency
lo w </w>	5
lo w e r </w>	2
n e w est</w>	6
w i d est</w>	3

Current Vocabulary: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>, lo

Finish Sub-word Leaning

- Assume `num_merges`=4 (we just repeated four times.)
- `num_merges` is a hyperparameter that you need to set for BPE.
- The learned vocabulary is: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>, lo

Tokenization with Learned BPE

- **The learned vocabulary** is: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>, lo
- We first turn each word into a sequence of characters with </w> placed at the end of a word, same as the first step during the learning phase.
- Then we can merge the characters according to **the learned vocabulary**.
- Examples:

l o w </w> → lo | w | </w>

w i d e s t </w> → w | i | d | est</w>

Properties of BPE

- The final learned vocabulary size = **initial** size + `num_merges`

  Initial vocab: </w>, d, e, i, l, n, o, r, s, t, w

  Learned vocab: </w>, d, e, i, l, n, o, r, s, t, w, es, est, est</w>, lo

- This algorithm is based on statistics, so frequent sub-word units in provided corpora will be put to the learned vocabulary.

Why do we need Sub-word Tokenization?

- With sub-word tokenization algorithms, we can handle representations for unknown words (or mis-spelled words / compound words).
- In machine translation, the compound word issues between source and target languages can be alleviated.
- State-of-the-art pre-trained language models (e.g., GPT-3, BERT) adopt sub-word tokenization algorithms before pre-training.

Limitations of Sub-word Tokenization

- (Not many disadvantages for sub-word tokenization)
- The hyperparameter `num_merges` needs to be tuned.
- Once the learned vocabulary is created, it becomes fixed. The algorithm needs to be re-run after adding new data.

Thank you!

Sub-word Tokenization

Generative Artificial Intelligence