## **Text Normalization**

SLP3 Ch 2; INLP Ch 4.3.1

### **Text Normalization**

- Every NLP task requires text normalization:
  - Tokenizing (segmenting) words
  - Normalizing word formats
  - Segmenting sentences

## **Word Tokenization**

## Space-based tokenization

- A very simple way to tokenize
  - For language that use space characters between words
    - Arabic, Cyrillic, Greek, Latin, etc., based writing systems
  - Segment off a token between instances of spaces (and punctuations)
- Example
  - Sentence:
    - I love natural language processing, too.
  - Tokenized:
    - I\_love\_natural\_language\_processing\_too
    - Represent the delimiter string as "\_"

### Issues in tokenization

- Can't just blindly remove punctuation:
  - m.p.h., Ph.D., AT&T, cap'n
  - Prices (\$45.55)
  - Dates (01/02/06)
  - URLs (https://www.shanghaitech.edu.cn)
  - Hashtags (#nlproc)
  - Email addresses (someone@shanghaitech.edu.cn)
- Clitic: a word that doesn't stand on its own
  - "are" in we're, French "je" in j'ai, "le" in l'honneur
- When should multiword expressions (MWE) be words?
  - New York, rock 'n' roll

## Tokenization in Natural Language Toolkit (NLTK)

Bird, Loper and Klein (2009), Natural Language Processing with Python. O'Reilly

Sentence:

Expected output:

Words with optional internal hyphens:

- Abbreviations:
  U.S.A.
- Currency and percentages: \$12.40
- ► Ellipsis:
- ▶ Separate tokens:
  ][.,;"'?():-\_`

## Tokenization in Natural Language Toolkit (NLTK)

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#### Idea:

- Write a pattern matching all possible tokens but matching none of non-tokens.
- Output all non-overlapping matches.
- Tool: regular expression (RE)
  - Words with optional internal hyphens:
    - Pattern in RE: \w+(-\w+)\*
    - Strings accepted:
      - That, poster-print, costs
    - Strings rejected:
      - ▶ U.S.A., \$12.40, ...
      - ▶ non-, -ly, AT&T

\w = any word character

 $= [a-zA-Z0-9_]$ 

- + = match 1 or more times
- = match 0 or more times
- (...) is a group (followed by + or \*)



## Tokenization in Natural Language Toolkit (NLTK)

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#### Abbreviations:

- Pattern: ([A-Z]\.)+
- Strings accepted: U.S.A.
- String rejected: UU.S.A, I
- Currency and percentages:
  - Pattern: \\$?\d+(\.\\d+)?%?
  - String accepted: \$12.40
  - String rejected: \$.4, 1.4.0, 1%
- ▶ Ellipsis:
  - ▶ Pattern: \.\.\.
  - String accepted: ...
- Separate tokens:
  - Pattern: [][.,;"'?():-\_`]

[A-Z] = uppercased char

 $\frac{d}{d} = digit = [0-9]$ 

In RE, some characters (e.g., ^\$.?+\*()[]) have special meaning. They should be escaped to match them.

- + = match 1 or more times
- ? = match 0 or 1 time

## Tokenization in languages without spaces

- Many languages (like Chinese, Japanese, Thai) don't use spaces to separate words!
- Same for compound nouns in some western languages
  - Example: German:
     Freundschaftsbezeigungen (demonstration of friendship)
  - Example: hashtags in social media: #TrueLoveInFourWords

### How to do word tokenization in Chinese?

- Sentence: 姚明进入总决赛
- ▶ 姚明/进入/总决赛
- ▶ 姚/明/进入/总/决赛
- Typically cast as sequence labeling + supervised learning (to be discussed later)
- ▶ 姚/明/进/入/总/决/赛 single-character segmentation

### Subword tokenization

- Tokens can be parts of words as well as whole words
  - Use the data to tell us how to tokenize
- Three common algorithms:
  - Byte-Pair Encoding (BPE) (Sennrich et al., 2016)
  - Unigram language modeling tokenization (Kudo, 2018)
  - WordPiece (Schuster and Nakajima, 2012)
- All have 2 parts:
  - A token learner that takes a raw training corpus and induces a vocabulary (a set of tokens).
  - A token segmenter that takes a raw test sentence and tokenizes it according to that vocabulary



## Byte Pair Encoding (BPE) token learner

Let vocabulary be the set of all individual characters

$$= \{A, B, C, D, ..., a, b, c, d....\}$$

- Repeat:
  - Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', 'B')
  - Add a new merged symbol 'AB' to the vocabulary
  - Replace every adjacent 'A' 'B' in the corpus with 'AB'.
- Until k merges have been done.

### Original corpus:

low low low low lowest lowest newer newer

- Usually run inside space-separated tokens.
- First add end-of-word tokens "\_"
  - So we can differentiate est in estate and smallest
- Resulting vocabulary:

```
      corpus

      5
      1 o w __
      _, d, e, i, 1, n, o, r, s, t, w

      2
      1 o w e s t __

      6
      n e w e r __

      3
      w i d e r __

      2
      n e w __
```

#### corpus

#### vocabulary

\_, d, e, i, l, n, o, r, s, t, w

### Merge e r to er

#### corpus

#### vocabulary

\_, d, e, i, l, n, o, r, s, t, w, er

#### corpus

- 5 1 o w \_
- 2 lowest\_
- 6 newer\_
- 3 wider  $\_$
- 2 new\_

#### vocabulary

\_, d, e, i, l, n, o, r, s, t, w, er

### Merge er \_ to er\_

#### corpus

- 5 low\_
- 2 lowest\_
- 6 newer\_
- 3 wider\_
- 2 new\_

#### vocabulary

\_\_, d, e, i, l, n, o, r, s, t, w, er, er\_\_

#### corpus

- 5 low \_
- 2 lowest\_
- 6 newer\_
- 3 wider\_
- 2 new\_

#### vocabulary

 $\_$ , d, e, i, l, n, o, r, s, t, w, er, er $\_$ 

### Merge n e to ne

#### corpus

- 5 1 o w \_
- 2 lowest\_
- 6 ne w er\_
- 3 wider\_
- 2 ne w \_

#### vocabulary

\_\_, d, e, i, l, n, o, r, s, t, w, er, er\_\_, ne

The next merges are:

```
      Merge
      Current Vocabulary

      (ne, w)
      __, d, e, i, l, n, o, r, s, t, w, er, er__, ne, new

      (l, o)
      __, d, e, i, l, n, o, r, s, t, w, er, er__, ne, new, lo

      (lo, w)
      __, d, e, i, l, n, o, r, s, t, w, er, er__, ne, new, lo, low, newer__

      (low, __)
      __, d, e, i, l, n, o, r, s, t, w, er, er__, ne, new, lo, low, newer__, low__
```

## BPE token segmenter algorithm

The learned vocabulary:

```
__, d, e, i, l, n, o, r, s, t, w, er, er__, ne, new, lo, low, newer__, low__
```

- On the test data, run each merge learned from the training data:
  - Greedily, in the order we learned them
  - (test frequencies don't play a role)
- So: merge every e r to er, then merge er \_ to er\_, etc.
- Result:
  - Test set "n e w e r \_ " would be tokenized as a full word
  - Test set "lower\_" would be two tokens: "low er\_"

## Properties of BPE tokens

- Usually include frequent words and frequent subwords
  - Which are often morphemes like -est or -er
- A morpheme is the smallest meaning-bearing unit of a language
  - unbreakable has 3 morphemes un-, -break-, and -able

## **Word Normalization**

### Word normalization

- Putting words/tokens in a standard format
  - ▶ U.S.A. or USA
  - uhhuh or uh-huh
  - Fed or fed
  - am, is, be, are

## Case folding

- Reduce all letters to lower case
- Good in some scenarios
  - Information retrieval: users tend to use lower case
  - Example:



- Not good in others
  - Example: General Motors, Fed, US

### Lemmatization

- Represent all words as their lemma, their shared root= dictionary headword form
  - $\blacktriangleright$  am, are, is  $\rightarrow$  be
  - ▶ car, cars, car's, cars' → car
  - Spanish quiero ('I want'), quieres ('you want')
    - → querer 'want'
  - He is reading detective stories
    - → He be read detective story

## Lemmatization done by Morphological Parsing

- Morphemes:
  - The small meaningful units that make up words
  - Stems: The core meaning-bearing units
  - Affixes: Parts that adhere to stems, often with grammatical functions
- Morphological Parsers:
  - Parse cats into two morphemes cat and s
  - Parse Spanish amaren ('if in the future they would love') into morpheme amar 'to love', and the morphological features 3PL and future subjunctive.
- We will talk about parsing later.

## Stemming

- Reduce terms to stems, chopping off affixes crudely
  - A simple and crude alternative to lemmatization
- Porter Stemmer
  - Based on a series of rewrite rules run in series
    - A cascade, in which output of each pass fed to next pass
  - Some sample rules

```
ATIONAL \rightarrow ATE (e.g., relational \rightarrow relate)

ING \rightarrow \epsilon if stem contains vowel (e.g., motoring \rightarrow motor)

SSES \rightarrow SS (e.g., grasses \rightarrow grass)
```

## Stemming

- Reduce terms to stems, chopping off affixes crudely
  - A simple and crude alternative to lemmatization
- Example
  - Sentence:
    - This was not the map we found in Billy Bones's chest.
  - Stemming:
    - Thi wa not the map we found in Billi Bone s chest.
  - Lemmatizing:
    - This be not the map we find in Billy Bones 's chest.

# Sentence Segmentation

## Sentence segmentation

- !, ? mostly unambiguous but period "." is very ambiguous
  - Sentence boundary
  - Abbreviations like Inc. or Dr.
  - Numbers like .02% or 4.3
- Common algorithm
  - Tokenize first: use rules or ML to classify a period as either
     (a) part of the word or (b) a sentence-boundary.
    - An abbreviation dictionary can help
  - Sentence segmentation can then often be done by rules based on this tokenization.

# Summary

### **Text Normalization**

- Word tokenization
- Word normalization
- Sentence segmentation
- Methodology: Rules + ML