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`
    - "␣": delimiter

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

An example sentence

- Sentence:

  That U.S.A. poster-print costs $12.40...?

- Expected output:

  That␣U.S.A.␣poster-print␣costs␣$12.40␣...␣?

  - Words with optional internal hyphens: That, poster-print, costs
  - Abbreviations: U.S.A.
  - Currency and percentages: $12.40
  - Ellipsis: ...
  - Separate tokens:][.,;”’?():-_`

Tokenization with regular expressions

- 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 with regular expressions

- 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

`\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

Tokenization in languages without spaces

- Sentence: 姚明进入总决赛
- Multiple ways of tokenization
  - 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)

single-character segmentation

- Ambiguity
  - 南京市长江大桥

Bai du 百科

江大桥是一个网络流行用语，指的是“从未在公共场合露面，但手握重权，同时任职多市市长的中国政界传奇人物”

Subword tokenization

- Subword tokens can be parts of words as well as whole words
- Advantages
  - Subwords are sometimes meaningful
    - prefix, postfix, stem, …
    - Ex: postprocessing → post, process, ing
  - Much smaller vocabulary
  - Avoiding out-of-vocabulary (OOV) words
  - Can be automatically learned from data

Subword tokenization

- 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.

BPE token learner

- Original corpus:

low low low low low lowest lowest newer newer newer newer newer newer wider wider wider new new

- Usually run inside space-separated tokens.
- First add end-of-word tokens "_"
  - So we can differentiate **est** in **<u>est</u>ate** and **small<u>est</u>**
- Resulting vocabulary:

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w
2	l o w e s t _	
6	n e w e r _	
3	w i d e r _	
2	n e w _	

BPE token learner

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w
2	l o w e s t _	
6	n e w e r _	
3	w i d e r _	
2	n e w _	

- Merge `e r` to `er`

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2	l o w e s t _	
6	n e w er _	
3	w i d er _	
2	n e w _	

BPE token learner

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2	l o w e s t _	
6	n e w er _	
3	w i d er _	
2	n e w _	

- Merge er _ to er_

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_
2	l o w e s t _	
6	n e w er_	
3	w i d er_	
2	n e w _	

BPE token learner

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_
2	l o w e s t _	
6	n e w er_	
3	w i d er_	
2	n e w _	

- Merge n e to ne

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne
2	l o w e s t _	
6	ne w er_	
3	w i d er_	
2	ne w _	

BPE token learner

- 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
(new, er_)	_, 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 "l o w e r _" 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

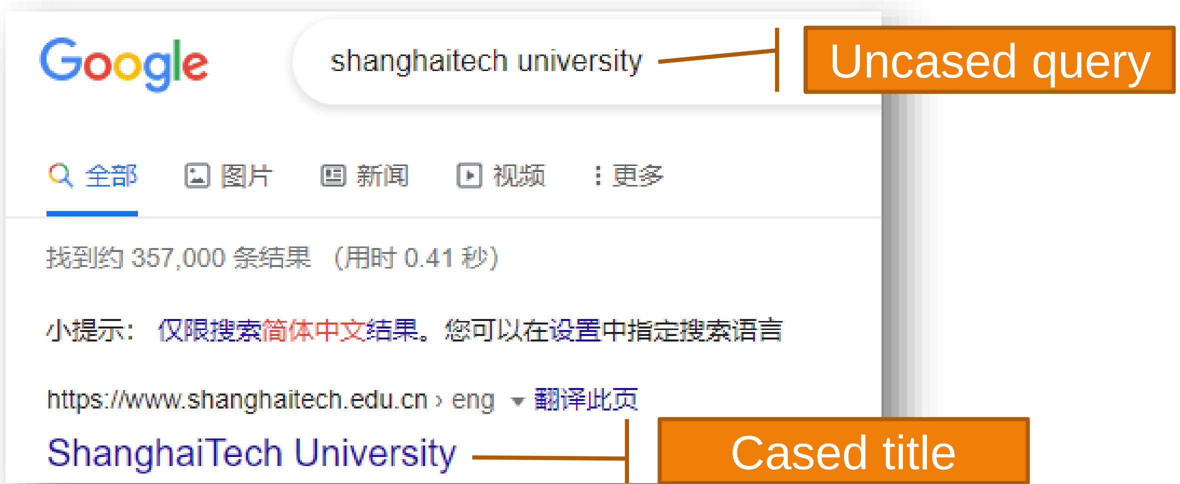
Word Normalization

Word normalization

- Putting words/tokens in a standard format
  - U.S.A. or USA
  - uhhuh or uh-huh
  - Putting or putting
  - 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
  - am, are, is → be
  - car, cars, car's, cars' → car
  - Spanish quiero (‘I want’), quieres (‘you want’)
  → querer ‘want’
- Example
  - He is reading detective stories
  → He be read detective story
- A simple method: dictionary matching

Lemmatization done by Morphological Parsing

- Morphemes:
  - The small meaningful units that make up words
  - Stems: The core meaning-bearing units
    - Can be used to recover the lemma
  - 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

$$
\begin{aligned}
\text{ATIONAL} &\rightarrow \text{ATE} \quad \text{(e.g., relational} \rightarrow \text{relate)} \\
\text{ING} &\rightarrow \epsilon \quad \text{if stem contains vowel (e.g., motoring} \rightarrow \text{motor)} \\
\text{SSES} &\rightarrow \text{SS} \quad \text{(e.g., grasses} \rightarrow \text{grass)}
\end{aligned}
$$

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
    - So a period is classified as either part of a word or a sentence-boundary.
  - Sentence segmentation can then often be done by rules based on this tokenization.
    - Ex: punctuation, capitalization

Summary

Text Normalization

- Word tokenization
  - Regular expression, BPE
- Word normalization
  - Lemmatization, stemming
- Sentence segmentation