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Text preprocessing

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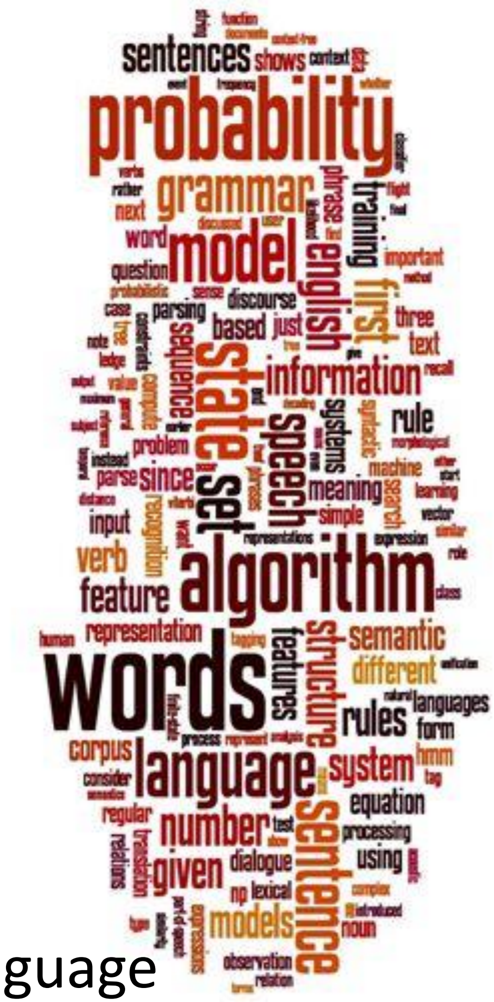
Natural language processing, Edition 2024

Lecture outline

- Text preprocessing and normalization



Read Chapter 2 in
Daniel Jurafsky & James H. Martin. Speech and Language Processing, 3rd edition draft, 2024.

Some slides from this source

Basic text preprocessing for the (classical) NLP pipeline

- document → paragraphs → sentences → words
- words and sentences ← POS tagging
- sentences ← syntactical and grammatical analysis

- still present in neural pipeline, but also splits word into tokens

Text preprocessing

LooL :-)

- text normalization: transformation into a standard (canonic) form or any useful form, e.g., from non-standard language to standard
  - upper/lower casing
  - rediacritisation (e.g., for Slovene)
  - notation of acronyms
  - standard form of dates, time, and numbers
  - stress marks, quotation marks, punctuation,
  - non-informative words
  - spelling, e.g., US or GB
  - emoticons, emoji, hashtags, web links
  - editing and presentation markup, e.g., html tags
  - spelling correction
  - (subword) tokenization
  - lemmatization and stemming
- other forms of text preparation, e.g., extraction from PDFs, structured files like XML, web crawl, etc.


Primary quotation marks
in European languages
„x“
”x”
(also »x»)
«x»
”x”
(also »x»)
„x“
«x»
(“x” for names)
«X»
‘x’
“x”
(‘x’ preferred
in the UK;
“x” preferred
in the US)
„x“
»x«
„x”
rarely:
«x»
«X»
«x»
„x“
„x“
»x«
„x”
„x”
« x »
(with spaces)
«x»
«X»
(but “x” is
recommended
by El País)
in Brazil:
“x”
«X»
“X”
„x“
„x“
«X»
“X”
more maps at
jakubmarian.com

Token, type, term

- A *token* is an instance of a sequence of characters in some text processing task that are grouped together as a useful semantic unit for processing.
- A *type* is the class of all tokens containing the same character sequence.
- A *term* is a (perhaps normalized) type that is included in the system's dictionary.
- *To sleep perchance to dream*,
- 5 tokens, 4 types (2 instances of *to*)
- if *to* is omitted from the index (as a stop word), then there will be only 3 terms: *sleep*, *perchance*, and *dream*

- Warning: neural processing brings some ambiguity what is a (subword) token, e.g., ambiguity -> ambig #u #ity

Is the tokenization this simple?

```
## tokenizing a piece of text
doc = "I wrote this sentence"
for i, w in enumerate(doc.split(" ")):
    print("Token " + str(i) + ": " + w)
```

```
Token 0: I
Token 1: wrote
Token 2: this
Token 3: sentence
```

How many words?

N = number of tokens

V = vocabulary = set of types, **|*V*|** is the size of vocabulary

Heaps Law = Herdan's Law: $|V| = kN^{\beta}$ where often .67 < β < .75

i.e., vocabulary size grows with > square root of the number of word tokens

	Tokens = N	**Types = |V|**
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
COCA, edition 2010	440 million	2 million
Google N-grams	1 trillion	13+ million

Corpora

- Words don't appear out of nowhere.
- A text is produced by a specific writer(s), at a specific time, in a specific variety of a specific language, for a specific function.

Corpora vary along dimension like

- **Language**: 7097 languages in the world
- **Variety**, like African American Language varieties.
  - AAL Twitter posts might include forms like "*iont" (I don't)*
- **Code switching**, e.g., Spanish/English, Hindi/English:

S/E: Por primera vez veo a @username actually being hateful! It was beautiful:)

[For the first time I get to see @username actually being hateful! it was beautiful:)]

H/E: dost tha or ra- hega ... dont wory ... but dherya rakhe

[“he was and will remain a friend ... don’t worry ... but have faith”]

- **Genre:** newswire, fiction, non-fiction, scientific articles, Wikipedia
- **Author demographics**: writer's age, gender, race, socioeconomic status, etc.

Corpus datasheets

- **Motivation**: Why was the corpus collected, by whom, and who funded it?
- **Situation**: In what situation was the text written?
- **Collection process**: If it is a subsample how was it sampled? Was there consent? Pre-processing?
- **+Annotation process, language variety, speaker demographics**

- See, e.g., corpora on Clarin.si

Text Normalization

- Most NLP task need text normalization:
  1. Segmenting/tokenizing words in running text
  2. Normalizing word formats
  3. Segmenting sentences in running text

Simple Tokenization in UNIX

- (Inspired by Ken Church's UNIX for Poets.)
- Given a text file, output the word tokens and their frequencies
- Command tr (translate)

```
tr -sc 'A-Za-z' '\n' < shakes.txt      Change all non-alpha to newlines
     | sort                            Sort in alphabetical order
     | uniq -c                         Merge and count each type
```

```
1945 A
  72 AARON
  19 ABBESS
   5 ABBOT
 ... ...
```

```
25 Aaron
 6 Abate
 1 Abates
 5 Abbess
 6 Abbey
 3 Abbot
.... …
```

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; (http://www.stanford.edu),
  - hashtags (#nlproc),
  - email addresses (someone@cs.colorado.edu).
- Clitics: a part of a word that can't stand on its own
  - we're → we are
  - French j'ai, l'honneur
  - Slovene: a b’ šlo
- Can "Multiword Expressions (MWE) be words?
  - New York, rock ’n’ roll

Issues in Tokenization

- Finland’s capital → Finland Finlands Finland’s *?*
- what’re, I’m, isn’t → What are, I am, is not
- Hewlett-Packard → Hewlett Packard ?
- state-of-the-art → state of the art ?
- Lowercase → lower-case lowercase lower case ?
- San Francisco → one token or two?
- m.p.h., PhD. → ??

Tokenization in NLTK

Bird et al. (2009)

```
>>> text = ’That U.S.A. poster-print costs $12.40...’
>>> pattern = r’’’(?x)    # set flag to allow verbose regexps
...     ([A-Z]\.)+        # abbreviations, e.g. U.S.A.
...   | \w+(-\w+)*        # words with optional internal hyphens
...   | \$?\d+(\.\d+)?%?  # currency and percentages, e.g. $12.40, 82%
...   | \.\.\.            # ellipsis
...   | [][.,;"’?():-_‘]  # these are separate tokens; includes ], [
... ’’’
>>> nltk.regexp_tokenize(text, pattern)
[’That’, ’U.S.A.’, ’poster-print’, ’costs’, ’$12.40’, ’...’]
```

Tokenization: language issues

- French
  - ***L'ensemble*** $\rightarrow$ one token or two?
    - ***L*** ? ***L’*** ? ***Le*** ?
    - Want ***l’ensemble*** to match with ***un ensemble***
- German noun compounds are not segmented
  - ***Lebensversicherungsgesellschaftsangestellter***
  - ‘life insurance company employee’
  - German information retrieval needs **compound splitter**

Word Tokenization in Chinese

- Also called **Word Segmentation**
- Chinese words are composed of characters called **hanzi**
- Each one represents a meaning unit called a morpheme.
  - Characters are generally 1 syllable and 1 morpheme.
  - Average word is 2.4 characters long.
- But deciding what counts as a word is complex and not agreed upon
- Standard baseline segmentation algorithm:
  - Maximum Matching (also called Greedy)
- So in Chinese it's common not to do word segmentation at all
- But in Thai and Japanese, it's required
- The standard algorithms are neural sequence models trained by supervised machine learning.

Words in preprocessing

- Lexical analysis (tokenizer, word segmented), not just spaces
- 1,999.00€   1.999,00€!
- Ravne na Koroškem
- Port-au-prince

- Rules, finite automata, statistical models, dictionaries (of proper names), lexicons, ML models

Subword Encoding tokenization

- Learn tokenization based on statistics
- Relevant for modern neural networks
- Use the data to tell us how to tokenize.
- **Subword tokenization** (because tokens are often parts of words)
- Can include common morphemes like *-est* or *-er*.
  - (A morpheme is the smallest meaning-bearing unit of a language; *unlikeliest* has morphemes *un-*, *likely*, and *-est*.)
- Relevant for all languages, but crucial for morphologically-rich languages such as Slovene
- What happens if subword tokenization is inadequate?

Subword tokenization

- Common algorithms:
  - Byte-Pair Encoding (BPE) (Sennrich et al., 2016)
  - WordPiece (Schuster and Nakajima, 2012)
- Both 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)

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 training corpus (say ‘A’, ‘B’),
  - adds a new merged symbol ‘AB’ to the vocabulary
  - replace every adjacent ’A’ ’B’ in corpus with ‘AB’.
- Until *k* merges have been done.

BPE token learner algorithm

function BYTE-PAIR ENCODING(strings C, number of merges k) **returns** vocab V

$V \leftarrow$ all unique characters in C # initial set of tokens is characters
for $i = 1$ **to** k **do** # merge tokens til k times
  $t_L, t_R \leftarrow$ Most frequent pair of adjacent tokens in C
  $t_{NEW} \leftarrow t_L + t_R$ # make new token by concatenating
  $V \leftarrow V + t_{NEW}$ # update the vocabulary
  Replace each occurrence of t_L, t_R in C with t_{NEW} # and update the corpus
return V

BPE in use

- Most subword algorithms are run inside white-space separated tokens.
- So first add a special end-of-word symbol '__' before whitespace in training corpus
- Next, separate into letters.

BPE token learner

An example corpus :(

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

Add end-of-word tokens and segment:

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

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

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

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 learner algorithm

- 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_"

Term normalization

- Why we need to “normalize” terms
  - Information Retrieval (IR): indexed text & query terms must have the same form.
    - We want to match ***U.S.A.*** and ***USA***
    - uhhuh or uh-huh
    - Fed or fed
    - am, is be, are
- We implicitly define equivalence classes of terms
  - e.g., deleting periods in a term
- Alternative: asymmetric expansion:
  - Enter: ***window*** Search: ***window, windows***
  - Enter: ***windows*** Search: ***Windows, windows, window***
  - Enter: ***Windows*** Search: ***Windows***
- Potentially more powerful, but less efficient

Case folding

- Applications like IR: reduce all letters to lower case
  - Since users tend to use lower case
  - Possible exception: upper case in mid-sentence?
    - e.g., ***General Motors***
    - ***Fed*** vs. ***fed***
    - ***SAIL*** vs. ***sail***
- For many uses case is helpful
  - sentiment analysis, machine translation (MT), information extraction
  - ***US*** versus ***us*** is important

Lemmatization

- Reduce inflections or variant forms to base form
  - *am, are, is* $\rightarrow$ *be*
  - *car, cars, car's, cars'* $\rightarrow$ *car*
- *the boy's cars are different colors* $\rightarrow$ *the boy car be different color*
- Lemmatization: have to find correct dictionary headword form
- Machine translation
  - Slovene hočem (‘I want’), hočeš (‘you want’) have the same lemma as hoteti ‘want’

Lemmatization

- Lemmatization is the process of grouping together the different inflected forms of a word so they can be analyzed as a single item.
- Lemmatization difficulty is language dependent i.e., depends on morphology
- *English*
  - *walk, walked, walking, walks, ne pa walker*
  - *go, goes, going, gone, went*
- *Slovene*
  - *priti, pridem, prideš, pride, prideva, prideta, pridejo, pridemo, pridete, pridejo, ne pa prihod, prihodnost, prihajanje, prišlec*
  - *vlak, vlaka, vlaku, vlakom, vlakov,vlakoma,vlakih,vlaki, vlake*
  - *jaz, mene, meni, mano*
  - *Gori na gori gori!*
  - *Gori, na gori gori!*
- Use rules, dictionaries, lexicons, machine learning models
- Ambiguity resolution may be difficult

  Meni je vzel z mize (zapestnico).
- Quick solutions and heuristics, in English just remove suffixes: *–ing, -ation, -ed, …*
- essential approach for morphologically rich languages (Slavic, Arabic, Turkish, Spanish, etc)

Morphology

- Morphemes:
  - Small meaningful units that make up words
  - **Stems**: The core meaning-bearing units
  - **Affixes**: Bits and pieces 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*.

Dealing with complex morphology is sometimes necessary

- Some languages requires complex morpheme segmentation
  - Turkish
  - Uygarlastiramadiklarimizdanmissinizcasina
  - `(behaving) as if you are among those whom we could not civilize’
  - Uygar `civilized’ + las `become’
    + tir `cause’ + ama `not able’
    + dik `past’ + lar ‘plural’
    + imiz ‘p1pl’ + dan ‘abl’
    + mis ‘past’ + siniz ‘2pl’ + casina ‘as if’

Stemming

- stem: the root or main part of a word, to which inflections or formative elements are added
- in English
- simple solution: remove affixes

***for example compressed and compression are both accepted as equivalent to compress*.**

for exampl compress and compress ar both accept as equival to compress

- Stemmer operates on a single word *without* knowledge of the context, and therefore cannot discriminate between words which have different meanings depending on part of speech (meeting: a lemma is to meet or a meeting). Speed!
- Potter algorithm
- rare nowadays

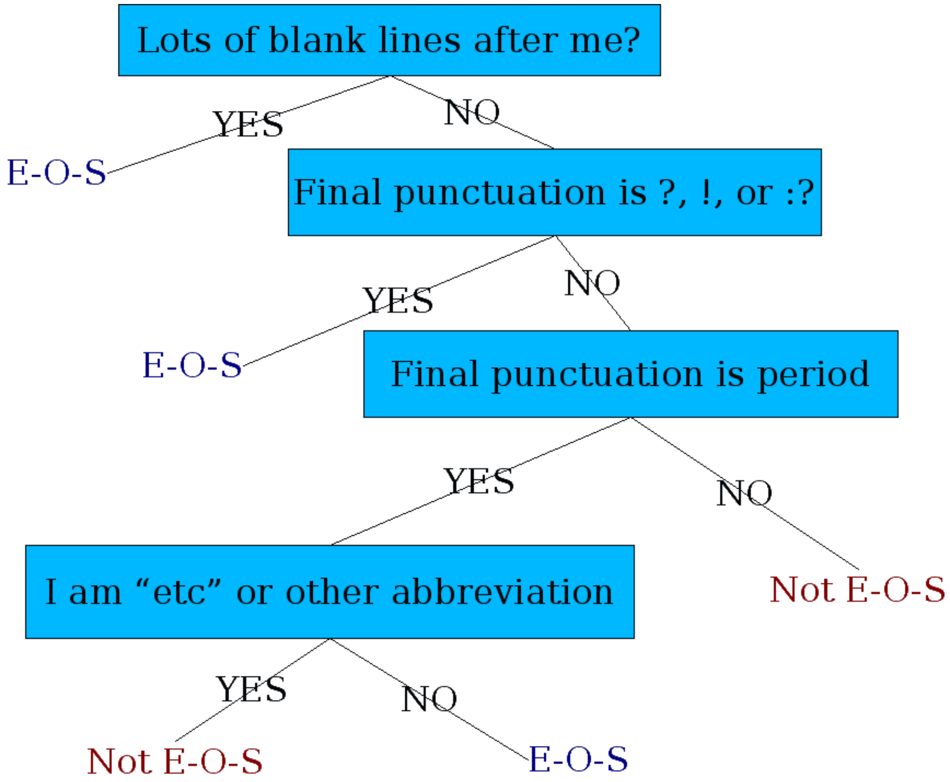
Sentences

- sentence delimiters – punctuation marks and capitalization are insufficient
- E.g., remains of 1. Timbuktu from 5c BC, were discovered by dr. Barth.
- Regular expressions, rules, manually segmented corpora

Sentence segmentation

- !, ? are relatively unambiguous
- Period "." is quite ambiguous
  - Sentence boundary
  - Abbreviations like Inc. or Dr.
  - Numbers like .02% or 4.3
- Build a binary ML classifier
  - Looks at a "."
  - Decides EndOfSentence/NotEndOfSentence
  - Classifiers: hand-written rules, regular expressions, or machine-learning

Determining if a word is end-of-sentence: a Decision Tree



More sophisticated features

- Case of word with “.”: Upper, Lower, Cap, Number
- Case of word after “.”: Upper, Lower, Cap, Number

- Numeric features
  - Length of word with “.”
  - Probability(word with “.” occurs at end-of-s)
  - Probability(word after “.” occurs at beginning-of-s)

Tools

- every NLP library has a tokenizer, sentence delimiter, lemmatizer, e.g., NLTK, spaCy, Gensim

- for Slovene: CLASSLA-Stanza
- https://www.cjvt.si/viri/
- https://github.com/clarinsi
- for nonstandard Slovene (twits, forum messages)
  - ***Nikola Ljubešić, Tomaž Erjavec, Darja Fišer:*** Orodja za procesiranje nestandardne slovenščine. V Fišer, D. (ur). 2018. Viri, orodja in metode za analizo spletne slovenščine. Ljubljana: Znanstveni založbi Filozofske fakultete Univerze v Ljubljani.