Guidelines in Selecting Appropriate Text Preprocessing Methods

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Slides on GitHub: `https://tinyurl.com/csp-2021-chai`

Why is **data** preprocessing important?

- Data scientists spend more than 50% of their work time on data preprocessing, i.e., preparing the data for analysis.

  – *The New York Times* (Lohr, 2014)

- Although time-consuming, data preprocessing is worth the efforts. Real-life data are messier than people think! (Chai, 2020) Adequately preprocessed data are key to success in modeling.

- Data can be structured (numeric) and/or unstructured (text).
- There is no one-size-fits-all solution for data preprocessing!

Why is **text** preprocessing important?

- “Merrill Lynch recently estimated that more than 80% of all potentially useful business information is unstructured data.” (Gharehchopogh and Khalifelu, 2011)

- Text data also require appropriate preprocessing, to prepare the corpus for machine learning and text mining models. (Kalra and Aggarwal, 2018)

- Webscraped text often contains lots of HTML formats.
  $\Rightarrow$ Remove using Python `BeautifulSoup` or R `textclean`.
- Application-specific formats: e.g. [10:23 PM] in chat messages
  $\Rightarrow$ Remove these formats using regular expressions.

Text preprocessing is more important than it seems!

- Text preprocessing details affect **reproducibility.** (Roy et al., 2018)
- Removing stopwords: Which words are regarded as stopwords? Obvious words: “I”, “the”, etc. What about non-obvious words? e.g. Is “algorithm” a stopword in a computer science corpus?

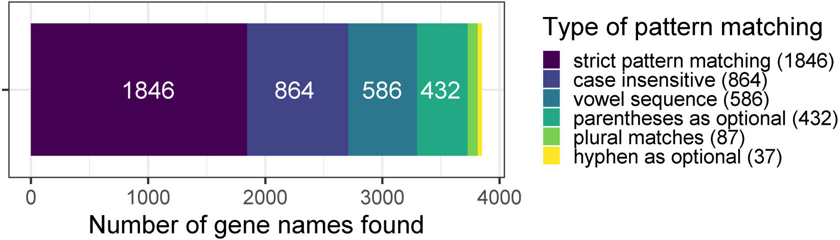
- Trieschnigg et al. (2007): **Tokenization decisions** can contribute more to system performance than the text model itself.

- Text string `NF-`κ` B/CD28-responsive` can be tokenized in many ways, resulting in different precision for document retrieval:
  - `nf `κ` b cd responsive`: 32% precision
  - `NF-`κ` B/CD28-responsive` (non-whitespace): 17%
  - `nf kappa nfkappa b cd 28 respons bcd28respons`: 40%

Tokenization Choices Matter: Another Example

- Tokenization choices of the gene name *alpha-2-macroglobulin* lead to different results of pattern matching in biomedical text.

Official gene name: alpha-2-macroglobulin



Data from Table 2 in (Cohen et al., 2002)

Text Preprocessing: Resources $\neq$ Guidelines

- Lots of resources:
  - NLTK in Python (Natural Language Toolkit) (Bird et al., 2009)
  - R packages: `stringr`, `quanteda`, `textclean`, `tm`, etc.
  - SAS Text Miner, Microsoft Azure Machine Learning Studio
- But most are for implementation (**how**), not for guidelines (**why**).
- Unanswered questions include and are not limited to:
  - Which methods are better for which text applications?
  - How to improve the current text preprocessing pipeline?
  - What are the potential risks of a specific method?

Structure of this talk: Text Preprocessing Methods

- Discuss several commonly-used methods
  Explain the advantages and potential issues
- Review specific examples of text analysis
  How preprocessing decisions contribute to the modeling
- Discussion and key takeaways

- But before we get into the methods, let's talk about the recent advances in natural language processing.

Recent Advances in Natural Language Processing

- Lots of pretrained word embeddings for text models: `word2vec` (Mikolov et al., 2013), `GloVe` (Pennington et al., 2014), `BERT` (Devlin et al., 2018), `ELMo` (Peters et al., 2018), etc.
- Word embeddings map words to vectors using a large corpus.
- Helpful for text models and support in multiple languages.

- We still need to learn text preprocessing methods, because **word embeddings are not a panacea**, i.e., have some limitations.
  - Tokenization is required to break a text string into tokens (words).
  - Some minority languages (e.g. Tibetan) are not supported yet.[1]
  - To add extra words (e.g. company-specific acronyms), we may need to retrain the word embeddings. (Wilson et al., 2020)

[1] `https://github.com/google-research/bert/blob/master/multilingual.md`

Tokenization: Implementation

- Convert a text string into a sequence of words (tokens)
- Whitespace is not the only separator. (Clough, 2001)
- Tools: Python `nltk.tokenize`, R `str_split` in `stringr`

- Example 1: “Statistics is fun” ⇒ “Statistics”, “is”, “fun”
- Example 2: “I downloaded this software on-the-fly”
  Does “on-the-fly” count as one word or three words?

- We need to **decide which characters count as separators.**
- Examine abbreviations and non-standard punctuation usage, especially in biomedical text. (Díaz and López, 2015)
- And most importantly, be clear and consistent with the definitions.

Tokenization: Need Precise Definitions

- **Lexical richness** measures the quality of vocabulary in a corpus (Malvern and Richards, 2012). It can be defined by

$$\textbf{type-token ratio} = \frac{\text{the number of types (distinct words)}}{\text{the number of tokens (total words)}}$$

- But the terms “type” and “token” are loosely defined.
  e.g. “don’t” vs “do not”, “New_York” vs “New York”

- Some researchers try various definitions and select one that produces a statistically significant result. (Cohen et al., 2019)
- **P-hacking hurts reproducibility in research!** (Head et al., 2015)
- Good practice: Give the precise definition of “type” and “token”

Tokenization: Compound Words

- Compound words in languages with whitespace between tokens
  - “White House” in English, “sin embargo” (however) in Spanish, “parce que” (because) in French (Barrett and Weber-Jahnke, 2011)
  - In Arabic, a word has up to four independent tokens. (Attia, 2007)

- Traditional approach: Find the terms that are statistically and practically significant (Blei and Lafferty, 2009)
- Modern approach: Leverage contextualized word representations to find the compound words (Shwartz and Dagan, 2019)

- CJK (Chinese, Japanese, Korean) do not have whitespaces, and a word can also contain multiple tokens.
- Possible to train a neural network model on known words, and update the model based on new information. (Hiraoka et al., 2019)

Handling Punctuation

- Easiest way is to remove all punctuation from the text corpus.
  - Acceptable for information retrieval & topic modeling, where we focus on text rather than sentence (Korde and Mahender, 2012).
  - Inappropriate for applications that require sentence segmentation!

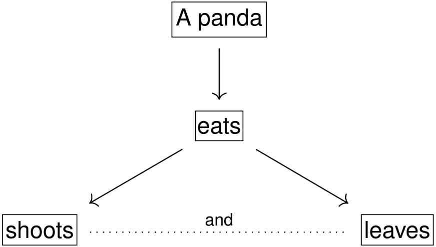
- **Punctuation provides syntactic information for parsing.**
- Categories: sentence-final, sentence-internal, word-internal
- Part-of-speech tagging needs to identify sentence boundaries first.
- Sentences are necessary for end-use applications, such as: **text summarization, machine translation, question answering.** (Patil et al., 2015; Kim and Zhu, 2019; Li and Croft, 2001)

Punctuation Serves as Discourse Markers

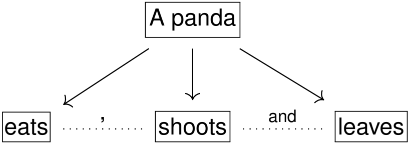
Discourse parsing needs punctuation to identify relations between text.

(Ji and Eisenstein, 2014)

- “A panda eats shoots and leaves.” (without comma)



- “A panda eats, shoots and leaves.” (with comma)



– *Eats, Shoots & Leaves: The zero tolerance approach to punctuation* by Truss (2004)

Removing Punctuation

- If we decide to remove punctuation from the corpus, using regular expressions is straightforward.
- Python and R both provide the list of punctuation symbols:

  `!"#$\%&'()*+,-./:;<=>?@[\]^_`{|}~`

- Beware of word-internal punctuation for contractions
- Predefined list to split contractions[2] (e.g. "don't" ⇒ "do not")
- Python `pycontractions` provides higher precision with context e.g. Does "I'd" map to "I would" or "I had"? (Beaver, 2019)

- Consider retaining emoticons (:-), :p) with Python NLTK's `TweetTokenizer()`, especially in social media data

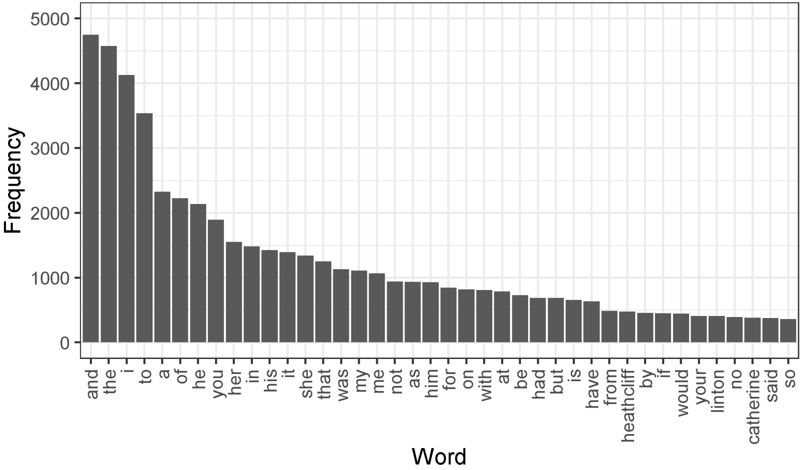
[2] https://gist.github.com/nealrs/96342d8231b75cf4bb82

Removing Stopwords: Overview

- Stopwords are the words that **do not distinguish one document from another in the corpus.** (Ferilli et al., 2014)
  - General: prepositions (“at”), pronouns (“you”), articles (“the”), etc.
  - Domain-specific: “method”, “problem”, “algorithm” in a corpus of machine learning papers (Fan et al., 2017)
- **Don’t just regard stopwords as “noise”.**
  Every word has semantic meaning, no matter how little.
- Stopwords are identified from a predefined list, or from corpus:
  - TF-IDF (term frequency – inverse document frequency)
  - Entropy (information theory) (Gerlach et al., 2019)
  - Kullback-Leibler (KL) divergence (Sarica and Luo, 2020)
- Especially useful for text corpora with technical content

English Classic Novel: *Wuthering Heights*

- Most frequent words are stopwords: and, the, I, etc.
- Zipf's law: The frequency distribution is right-skewed. (Zipf, 1949)



Existing Stopword Lists

- Python NLTK (127 English words, supports 23 languages)
- R package `stopwords` (175 English words, 231 German words)
- List of $\sim$ 500 removes 40-50% of corpus. (Schofield et al., 2017)

- Project Gutenberg: 60,000+ publicly available e-books[3]
- Choose an e-book of general content (e.g. *Alice's Adventures in Wonderland*) to filter out non-technical words from a technical database. (Brooke et al., 2015)

- **Recommendation: Start with a smaller stopword list, then gradually add more stopwords if necessary.**
- Words removed do not return to the text model later.

[3] `https://www.gutenberg.org/`

Removing Stopwords: Known Issues

- Beware: Unintentional removal of important information
  e.g. “The The” (a band), “to be or not to be” from *Hamlet*
  e.g. “Chemistry is not easy.” ⇒ “Chemistry easy.” (Really?)
- Most stopword lists contain negation (“no”, “not”, “isn’t”, etc.).
  At a minimum, remove these terms to **preserve negation**!

- Stopwords have syntactic information for **dependency parsing.**[4]
- Patterns of stopword usage help in **authorship attribution** (Arun et al., 2009) and **plagiarism detection** (Stamatatos, 2011).
- Feature: How often pronouns are used for a specific name [5]
- Feature: A person ⇒ “he/she” or “he (she)” or else?

[4] (Elming et al., 2013; Poria et al., 2014)

[5] (Sánchez-Vega et al., 2019)

Stemming and Lemmatization: Overview

- Both stemming and lemmatization normalize words to their base forms for vocabulary consolidation. (Manning et al., 2008)
- A word may have inflectional or derivational morphemes.
  - Inflectional: enjoy (verb) → enjoy**s**, enjoy**ed** (verb)
  - Derivational: enjoy (verb) → enjoy**able** (adjective)
  - Derivations change the word's part-of-speech; inflections do not.[6]
- Vocabulary consolidation decreases noise in the corpus e.g. worry, worries, worried, worrying → worri
- Improves performance for **text classification** (Biba and Gjati, 2014) and **information retrieval** (Rajput and Khare, 2015)
- But risks losing **semantic information in word variations** Some sentiments and named entities may be destroyed (Bao et al., 2014; Cambria et al., 2017)

[6] https://blogs.umass.edu/anyman/files/2020/04/Inflectional-vs.-Derivational-Morphemes.pdf

Stemming and Lemmatization: Comparison

- Stemming uses suffix rules to return each word to its root (stem), and removes both inflectional and derivational variations.
- Stemming algorithms: Porter (1980), Lovins (1968), Lancaster[7]
- Fast and requires less context, but creates tokens (not real words) e.g. challenge → **challeng**, president → **presid**

- Lemmatization maps a word's inflected forms to its lemma, and considers the part-of-speech. (Bergmanis and Goldwater, 2018)
- Tool: Python NLTK `WordNetLemmatizer`
- Isolated word: return the most common lemma or multiple options
- Helpful in morphologically rich languages (e.g. Turkish, Finnish), where word changes indicate subject / verb / object / etc. (Tsarfaty et al., 2010)

[7] (Paice and Hooper, 2005)

Stemming and Lemmatization: Potential Risks

- **Over-consolidation**: Words of different meanings → same token
  "computer", "computation" → "comput" (R package `SnowballC`)
- Some words have multiple lemmas, and context is needed.
  "leaves" → "leave" (verb, or noun as days off from a job)
  "leaves" → "leaf" (noun, as on the tree)

- **Sentiment analysis**: Positive & negative words grouped together[8]
  "objective" (positive), "objection" (negative) → "object"
- **Named entity recognition**: Entities may become unrecognizable
  "Guns N' Roses" → "gun n rose" (Cambria et al., 2017)

[8] (Ghazvinian, 2011)

N-Gramming: Retain Word Order

- N-gramming creates n-grams as phrases of *n* consecutive words, with a moving window of length *n* across the text.[9]
- Some n-grams are **multi-word expressions**, and should be retained as a single token. e.g. New Jersey, Black Lives Matter

- Word order is important in languages with few inflections. English: “dog bites man” vs “man bites dog” (Haspelmath, 1996)
- Languages with lots of inflections ⇒ word order rarely matters Latin: Noun as subject has a different form than noun as object. But word order info is still helpful for context. (Beier et al., 2011)

[9] (Gries and Mukherjee, 2010)

Detecting Multi-Word Expressions: Methods

- **Practical significance**: Threshold of raw frequency
  Microsoft Azure ML Studio sets 5 times as the default threshold.[10]
  Threshold of 100 times for a corpus of ∼1 billion words[11]
- **Statistical significance**: Conditional probability (Chai, 2017)
  Bi-gram $w_1 w_2$ is a multi-word expression when $P(w_2|w_1) > P(w_2)$
- **Conditional random fields** (Lafferty et al., 2001; Maldonado et al., 2017)
  Undirected probabilistic graphical model for pattern recognition
- **Retrain word embeddings** to identify multi-word expressions
  Still a growing field in deep learning. (Ashok et al., 2019)
  Tokenizing multi-word expressions does not negatively impact machine translation of single words. (Otani et al., 2020)

[10] `https://tinyurl.com/microsoft-n-grams`

[11] (Berberich and Bedathur, 2013)

Detecting Multi-Word Expressions: Applications

- Bag-of-words models: Disregards grammar and word order
- **Topic modeling, text classification, information retrieval**
- Multi-word expressions produce stronger signals.[12]

- Natural language processing tasks where context is required
- **Word sense disambiguation**: Determine which meaning of the word is used in a given context (Finlayson and Kulkarni, 2011)
- **Machine translation**: Improves translation accuracy (Tan and Pal, 2014) and extends to multi-lingual corpora (Han et al., 2020)
- **Psycholinguistics** (linguistics + psychology): Idiom usage reflects mental representation (Müller, 2011)

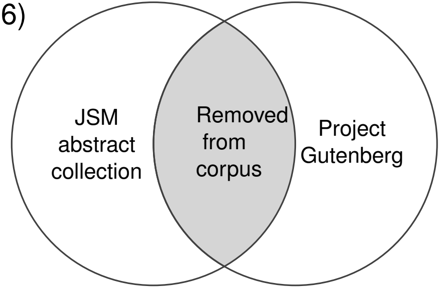
[12] (Blei and Lafferty, 2009)

Example 1: JSM Abstract Dataset – Preprocessing

- Dataset: 3000+ abstracts and 700+ sessions from JSM 2015
  JSM (Joint Statistical Meetings) is a large global conference.
- Lots of technical terms: e.g. maximum likelihood estimation
- **Extract technical terms for conference session scheduling**

Stopword removal process: (Bi, 2016)

1. Stem and n-gram the JSM dataset.
2. Stem and n-gram an e-book from Project Gutenberg.
3. Remove anything from 1. that exists in 2.



Example 1: JSM Abstract Dataset – Applications

- Topic models: Six topics found by LDA (latent Dirichlet allocation)
  Spatial stats, clinical trials, Bayesian, genomics, hypothesis tests
- Conference session scheduling:
  Minimize the overlap of sessions with similar topics
  People interested in a topic can join many relevant sessions
- Abstracts often include keywords from authors, but an automated system is still needed for session scheduling. (Sweeney, 2020)
- **Virtual conferences: Scheduling is still a challenge!** [13]
  Without physical restrictions, but need to account for other factors.
  Availability of on-demand recordings may change the equation.

[13] (Patro et al., 2020)

Example 2: Social Media Data – Preprocessing

- Twitter: Twitter developer API, Python `tweepy`, R `twitteR`
- Webscraping: Python `scrapy`, R `rvest`, webscraper.io, etc.

- Remove HTML tags: Python `BeautifulSoup`, R `textclean`
- Remove leading and trailing whitespaces for each message
- Python NLTK `TweetTokenizer()`[14] retains hashtags (`#hashtag`), mentions (`@username`), and emoticons (`:-D`)

- Text normalization: Consider splitting Internet slang abbreviations e.g. cu = see you, idk = I don't know (Pennell and Liu, 2011)
- Dependency parsing: Beware of nonstandard spellings and punctuation usage (Blodgett et al., 2018)

[14] https://www.nltk.org/api/nltk.tokenize.html

Example 2: Social Media Data – Applications

- **COVID-19**: Information spreading (Cinelli et al., 2020)
  Twitter dataset with daily updates (Banda et al., 2020)[15]
  COVID-Twitter-BERT: Pretrained large corpus (Müller et al., 2020)[16]
- **Analyze the impact of recent events**:
  Black Lives Matter (Giorgi et al., 2020)
  2020 US presidential election (Chen et al., 2020)
  National Disaster Situational Awareness (Karami et al., 2020)
- But applications cannot be done without **text preprocessing**.
  Data need to be preprocessed to be ready for text model input.

[15] https://github.com/thepanacealab/covid19_twitter

[16] https://github.com/digitalepidemiologylab/covid-twitter-bert

Example 3: Text with Numerical Ratings – Data

- Employee satisfaction survey: (Chai, 2019)
  Ratings from **1 (least satisfied)** to **10 (most satisfied)**
  Text comment to explain why you made the rating
- Best: Combined analysis in text and numerical data

- Need to **preserve negation terms** while removing stopwords.
  "No clear path to promotion" ⇒ "Clear path promotion"?
  Negation terms should be excluded from the stopword list.

- Data often contain possible errors.
  "Love my work – very varied." ⇒ rating 1?
  Common reason: **Confusion with rating scale** (Fisher, 2013)
  The respondent meant 10 (most satisfied) but reverted the scale.

Example 3: Text with Numerical Ratings – Modeling

- How to **detect potential rating errors** in the survey?
- **Method 1: Leverage the text response** (i.e., text mining)
  Predict the rating from the text comment with supervised methods
  Large discrepancy between predicted rating and actual rating
  $\Rightarrow$ Flag as potential error and examine the record
- **Method 2: Leverage other ratings** in the same dataset
  Predict the overall rating from the ratings of each item
  e.g. EM (expectation maximization) algorithm (Fisher and Lee, 2011)
  Also check for large discrepancies between predicted and actual

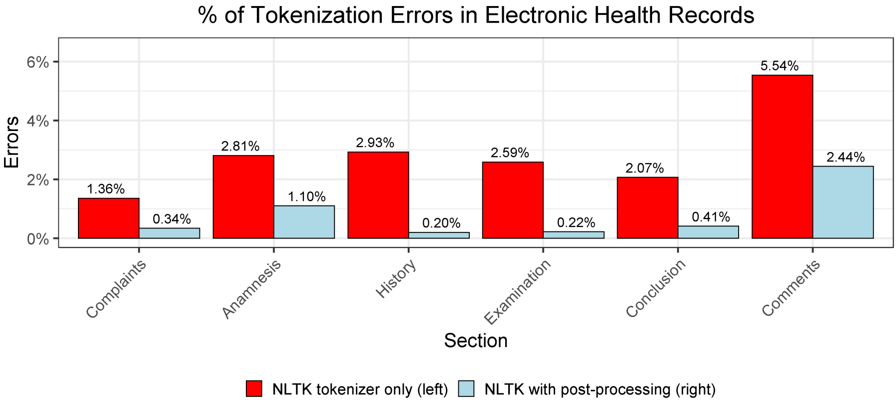
Example 4: Biomedical Data

- Pretrained word embeddings for biomedical text
  Gradually increasing in popularity (Wang et al., 2018)
  BioBERT (Lee et al., 2020): Pretrained on PubMed and PMC
- Challenge: Word vectors don't reflect internal structure of words.
  e.g. "**delta**proteobacteria" and "**beta**proteobacteria" are related.
  $\Rightarrow$ Leverage subword info. in pretraining (Zhang et al., 2019)

- Tokenizing biomedical text includes **Greek letter normalization** and **break point identification** (Jiang and Zhai, 2007)
- Both MIP-**1**-α and MIP-**1**α should tokenize to `MIP 1 alpha`
- Text string NF-κ B/CD28-responsive (Trieschnigg et al., 2007)
  - nf κ b cd responsive: 32% precision in document retrieval
  - `nf kappa nfkappa b cd 28 respons bcd28respons`: 40%

Example 4: Biomedical Data

- NLTK tokenizer + post-processing ⇒ fewer tokenization errors



Data from Table 1 in (Grön and Bertels, 2018)

Discussion

- Different applications require different preprocessing methods.
- Bag-of-words models: Acceptable to remove punctuation, remove stopwords, stem and lemmatize the corpus.
    - **Topic modeling, text classification, information retrieval**, etc.
- Other applications that require more context: Need to reconsider whether each text preprocessing step is appropriate.
    - **Dependency parsing, machine translation, text summarization, question answering**, etc.
- Detecting multi-word expressions is a challenging problem, even with the help of word embeddings. (Park and Tsvetkov, 2019)

Key Takeaways

- Text preprocessing prepares the corpus for analysis, so this directly affects data quality in modeling.
- Document the decisions made in the process (Nugent, 2020)
- **Exclude negation terms from the stopword list!** Don't accidentally remove negation from the corpus.
- Word embeddings are useful, but not a panacea solution. A non-trivial prerequisite: Tokenize the corpus into words
- Need to learn text preprocessing basics to make better decisions.

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