Text Data in Business and Economics

Basel University - Autumn 2023

3. Tokenization

Today

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- Output (tokens, n-grams):
  - A sequence, W_i, containing a list of tokens in document i – words or word pieces for use in natural language processing
  - A document-term matrix, X, containing statistics about word/phrase frequencies in those documents.

Goals of Tokenization

To summarize: A major goal of tokenization is to produce features that are

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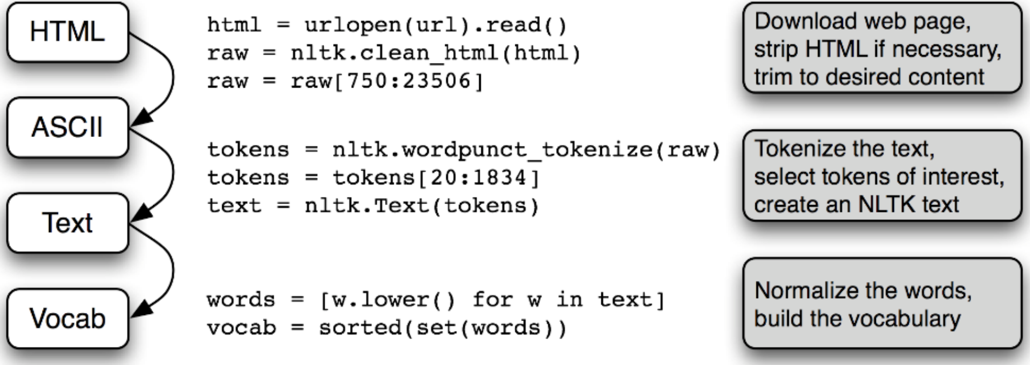
Two broad approaches:

1. convert documents to vectors, usually frequency distributions over pre-processed n-grams.
2. convert documents to sequences of tokens, for inputs to sequential models.

A Standard Tokenization Pipeline



Source: NLTK Book, Chapter 3.

Segmenting paragraphs/sentences

- Many tasks should be done on sentences, rather than corpora as a whole.
  - spaCy does a good (but not perfect) job of splitting sentences, while accounting for periods on abbreviations, etc.
- There isn't a grammar-based paragraph tokenizer.
  - most corpora have new paragraphs annotated.
  - or use line breaks.

Pre-processing

- An important piece of the “art” of text analysis is deciding what data to throw out.
  - Uninformative data add noise and reduce statistical precision.
  - They are also computationally costly.
- Pre-processing choices can affect down-stream results, especially in unsupervised learning tasks (Denny and Spirling 2017).
  - some features are more interpretable: “judge has” / “has discretion” vs “judge has discretion”.

Capitalization

- Removing capitalization is a standard corpus normalization technique
  - usually the capitalized/non-capitalized version of a word are equivalent – e.g. words showing up capitalized at beginning of sentence
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  - needed for sentence splitting, part-of-speech tagging,named entity recognition, syntactic/semantic parsing.

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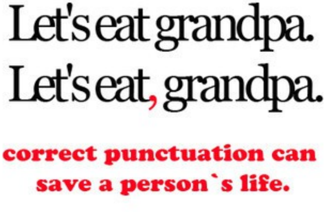
- For some tasks, capitalization is important
  - needed for sentence splitting, part-of-speech tagging,named entity recognition, syntactic/semantic parsing.
  - For sequence data, e.g. language modeling. To generate believable text, need to keep everything.

Punctuation



Source: Chris Bail text data slides.

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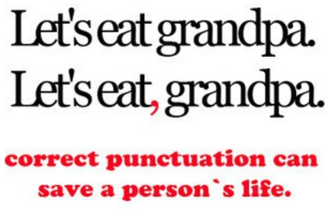

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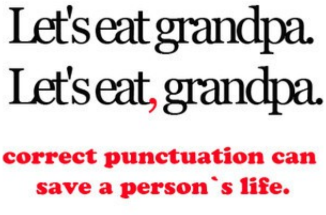

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Inclusion of punctuation depends on your task:

- if you are vectorizing the document as a bag of words or bag of n-grams, punctuation won't be needed.
- like capitalization, punctuation is needed for annotations (sentence splitting, parts of speech, syntax, roles, etc) or for text generators.

Numbers

- for bag of words/phrases:
  - drop numbers, or replace with a special character (e.g. #)
- for language models:
  - just treat them like letters.

Drop Stopwords?

a	an	and	are	as	at	be	by	for	from
has	he	in	is	it	its	of	on	that	the
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- What about "not guilty"?
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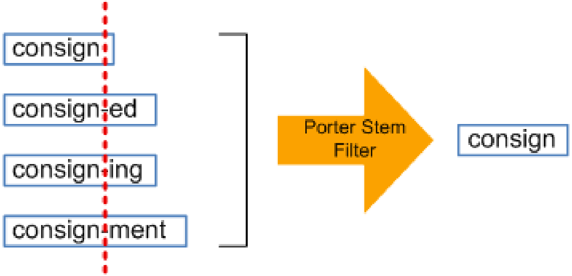
- What about "not guilty"?
- Legal "memes" often contain stopwords:
  - "beyond a reasonable doubt"
  - "with all deliberate speed"
- can drop stopwords by themselves, but keep them as part of phrases.
- can filter out words and phrases using part-of-speech tags (later).

Stemming/lemmatizing



- Effective dimension reduction with little loss of information.
- Lemmatizer produces real words, but N-grams won't make grammatical sense
  - e.g., "judges have been ruling" would become "judge have be rule"

Tokenization: Overview

Pre-Processing Text

Counts and Frequencies

N-Grams

Parts of Speech

Tokens

The most basic unit of representation in a text.

- characters: documents as sequence of individual letters {h,e,l,l,o, ,w,o,r,l,d}

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- characters: documents as sequence of individual letters $\{$h,e,l,l,o, ,w,o,r,l,d$\}$
- words: split on white space $\{$hello, world$\}$
- n-grams: learn a vocabulary of phrases and tokenize those: "Basel University $\rightarrow$ basel_university"

Bag-of-words representation

Say we want to convert a corpus D to a matrix X:

- In the "bag-of-words" representation, a row of X is just the frequency distribution over words in the document corresponding to that row.

- more generally, "bag of terms" representation refers to counts over any informative features – e.g. n-grams, syntax features, etc.

Counts and frequencies

- **Document counts**: number of documents where a token appears.
- **Term counts**: number of total appearances of a token in corpus.
- **Term frequency**:

$$\text{Term Frequency of } w \text{ in document } d = \frac{\text{Count of } w \text{ in document } d}{\text{Total tokens in document } d}$$

Application: Ranking Partisan language

Monroe et al (2009), "Fightin' Words"

- This paper systematically explores a number of methods for identifying words that are distinctive of groups of speakers
  - in this case, whether U.S. congressmen are Republicans or Democrats.

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  - in this case, whether U.S. congressmen are Republicans or Democrats.
- First, they separate speeches by topic using latent dirichlet allocation (next lectures).
  - they then test a number of methods for ranking partisanship of words.

Relative Frequency of Words

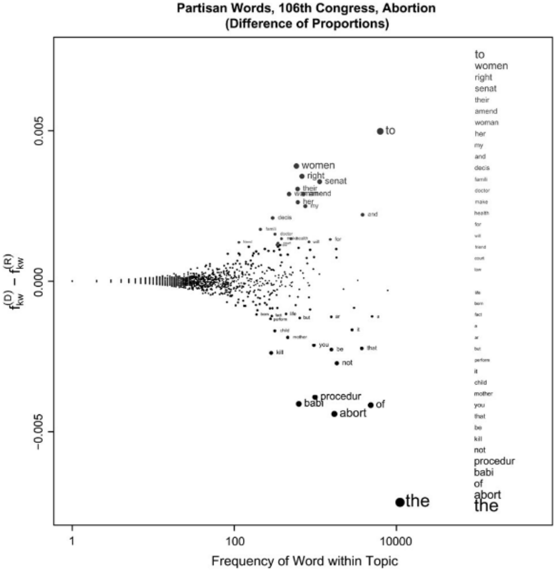

Fig. 1 Feature evaluation and selection using $f_{kw}^{(D)} - f_{kw}^{(R)}$. Plot size is proportional to evaluation weight, $|f_{kw}^{(D)} - f_{kw}^{(R)}|$. The top 20 Democratic and Republican words are labeled and listed in rank order to the right. The results are almost identical for two other measures discussed in the text: unlogged *tf.idf* and frequency-weighted WordScores.

Questions

- drop stopwords?
- try n-grams?
- How robust across topics?
- Is this useful for anything besides description?

Others?

Building a vocabulary

- An important featurization step is to build a vocabulary of words:
  - Compute document frequencies for all words
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- Can also impose more complex thresholds, e.g.:
  - appears twice in at least 20 documents
  - appears in at least 3 documents in at least 5 years
- Assign numerical identifiers to tokens to increase speed and reduce disk usage.

TF-IDF Weighting

- TF/IDF: "Term-Frequency / Inverse-Document-Frequency."
- The formula for word w in document k:

$$\underbrace{\frac{\text{Count of } w \text{ in } k}{\text{Total word count of } k}}_{\text{Term Frequency}} \times \underbrace{\log(\frac{\text{Number of documents in } D}{\text{Count of documents containing } w})}_{\text{Inverse Document Frequency}}$$

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- The formula up-weights relatively rare words that do not appear in all documents.
  - These words are probably more distinctive of topics or differences between documents.
  - Example: A document contains 100 words, and the word appears 3 times in the document. The TF is .03. The corpus has 100 documents, and the word appears in 10 documents. the IDF is $\log(100/10) \approx 2.3$, so the TF-IDF for this document is $.03 \times 2.3 = .07$. Say the word appears in 90 out of 100 documents: Then the IDF is 0.105, with TF-IDF for this document equal to .003.

scikit-learn's TfidfVectorizer

https://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

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>>> from sklearn.feature_extraction.text import TfidfVectorizer
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- `corpus` is a sequence of strings, e.g. pandas data-frame columns.
- pre-processing options: strip accents, lowercase, drop stopwords,
- n-grams: can produce phrases up to length n (words or characters).
- vocab options: min/max frequency, vocab size
- post-processing: binary, l2 norm, (smoothed) idf weighting, etc

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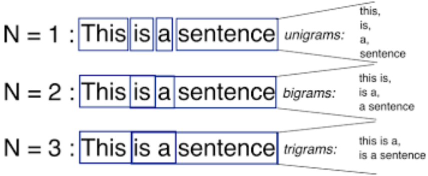
- Could add log counts, quadratics in counts, etc.
- Could also add pairwise interactions between word counts/frequencies.
- These often are not done much because of the dimensionality problem.
  - could use feature selection or principal components to help deal with that.

What are N-grams

- N-grams are phrases, sequences of words up to length N.
  - bigrams, trigrams, quadgrams, etc.



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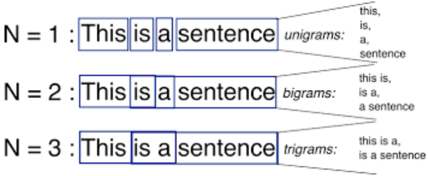

- Google Developers recommend **tf-idf-weighted bigrams** as a baseline specification for text classification tasks.
  - ideal for fewer, longer documents.

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  - filtering out uninformative n-grams is necessary.
- Google Developers say that a feature space with $P = 20,000$ will work well for descriptive and prediction tasks.
  - I have gotten good performance with 10K or even 2K features.
  - For supervised learning tasks, a decent baseline is to build a vocabulary of 60K, then use feature selection to get down to 10K.

De-Confounded Feature Selection

- What if a feature is important due to a confounding correlation?
  - e.g. in “Fightin Words” paper: say there are more republicans in congress over time, and the word “kill” coincidentally becomes more popular over time.
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  - can be done with other groups as well – e.g., compare legislators from the same state.
  - can also de-mean the outcome
- What if you want to de-mean by both year and state?
  - $\rightarrow$ take residuals from linear regression of each variable (outcome and predictor) on the category dummies.
  - That is:
    - regress $Y_i = \text{FE}_1 + \text{FE}_2 + \epsilon_i$ and $x_i^w = \text{FE}_1 + \text{FE}_2 + \epsilon_i, \forall w$,
    - take residuals $\tilde{Y}_i = Y_i - \hat{Y}_i$ and $\tilde{x}_i^w = x_i^w - \hat{x}_i^w$
  - Then use residuals as variables, in feature selection step or in machine learning task.

Collocations are Familiar N-grams

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  - Non-modifiable: cannot modify with additional words or grammar: (e.g., "kick around the bucket", "kick the buckets")
- But the reduction methods so far do not help identify collocations.

Point-wise mutual information

- A metric for identifying collocations is point-wise mutual information:

$$\mathrm{PMI}(w_1, w_2) = \frac{\Pr(w_1\_w_2)}{\Pr(w_1)\Pr(w_2)}$$
$$= \frac{\text{Prob. of collocation, actual}}{\text{Prob. of collocation, if independent}}$$

  where w_1 and w_2 are words in the vocabulary, and w_1, w_2 is the N-gram $w_1\_w_2$.
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- Generalizes to longer phrases (length N) as the geometric mean of the probabilities:

$$\frac{\Pr(w_1, \ldots, w_N)}{\prod_{i=1}^{n} \sqrt[n]{\Pr(w_i)}}$$

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- Warning: Rare words that appear together once or twice will have high PMI.
  - Address this with minimum frequency thresholds.

Parts of speech tags

- Parts of speech (POS) tags provide useful word categories corresponding to their functions in sentences:
  - Eight main parts of speech: verb (VB), noun (NN), pronoun (PR), adjective (JJ), adverb (RB), determinant (DT), preposition (IN), conjunction (CC).
  - The Penn TreeBank POS tag set (used in many applications) has 36 tags: `https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html`

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  - For sentiment, adjectives are usually most important.
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- In particular, noun phrases are often informative features – spaCy can do fast noun phrase chunking.
- Can count parts of speech tags as features – e.g., using more adjectives, or using more passive verbs.
- POS n-gam frequencies (e.g. NN, NV, VN, ...), like function words, are good stylistic features for authorship detection.
  - not biased by topics/content

Named Entity Recognition

- refers to the task of identifying named entities such as "Basel University" and "Marie Curie", which can be used as tokens.

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- detecting the type requires a trained model (e.g. spaCy):

Type	Tag	Sample Categories	Example sentences
People	PER	people, characters	**Turing** is a giant of computer science.
Organization	ORG	companies, sports teams	The **IPCC** warned about the cyclone.
Location	LOC	regions, mountains, seas	The **Mt. Sanitas** loop is in **Sunshine Canyon**.
Geo-Political Entity	GPE	countries, states, provinces	**Palo Alto** is raising the fees for parking.
Facility	FAC	bridges, buildings, airports	Consider the **Golden Gate Bridge**.
Vehicles	VEH	planes, trains, automobiles	It was a classic **Ford Falcon**.

Figure 18.1 A list of generic named entity types with the kinds of entities they refer to.

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- Typically, have to choose a vocabulary for featurizing a document.
  - e.g., top 10K words by frequency
- what to do with the words that get dropped out?
  - drop them
  - replace with "unknown" token
  - replace with part-of-speech tag
  - replace with in-vocab hypernym (from WordNet)