Text as Data: Computational Text Analysis

Week 2:
Natural Language Processing: Building Pre-Processing Pipeline, POS Tagging, NER + Building Dictionaries

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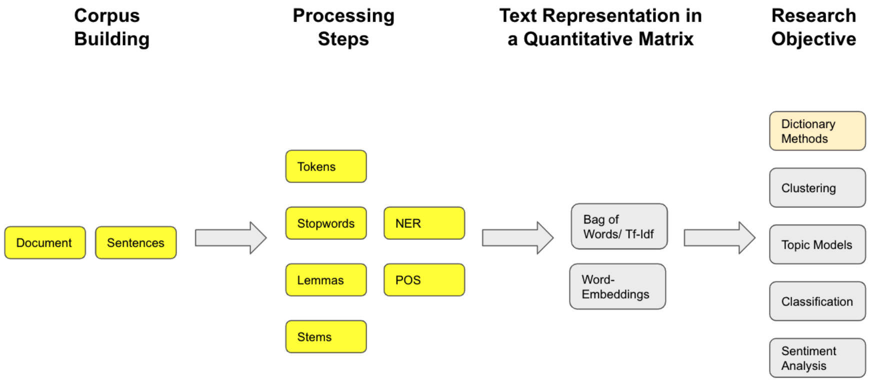
Overview from Text to Data[1]



[1] Some of the slides are based on Federico Nanni's course of Computational Text Analysis at U Mannheim

Recap - What have we learned until now?

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- Naive vs NLTK Tokenizer

Today

- Further on Text Pre-Processing (Stemming, Lemmatization)

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- The Power of Counting Words

Pre-Processing Example

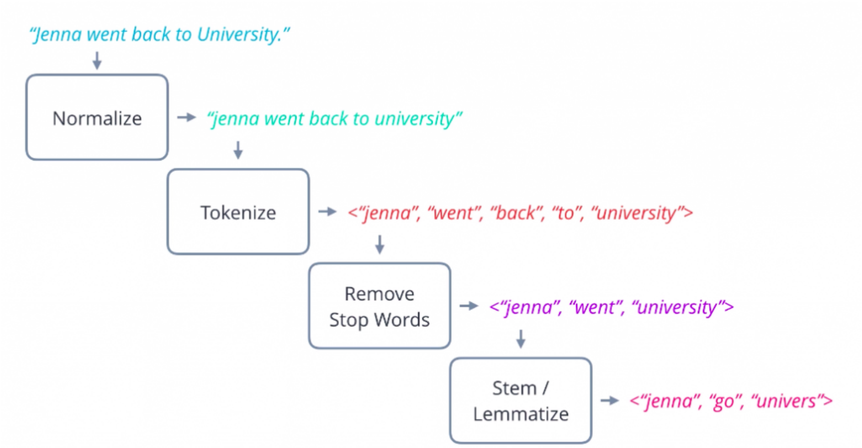

Image source: `https://eng.ftech.ai/`

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Separating single words, starting from a string (which could be a document, a sentence, a tweet) $\rightarrow$ they will become tokens.

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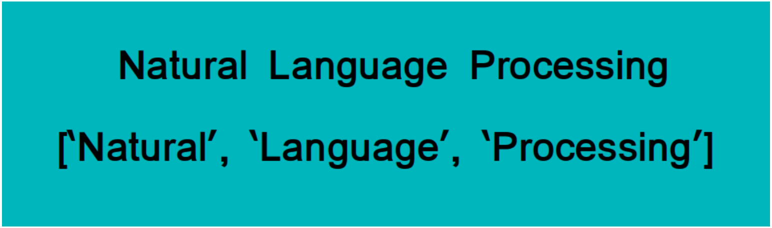

Image source: Analytics Vidha

Lemmatization

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- took $\rightarrow$ take

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- mice $\rightarrow$ mouse
- took $\rightarrow$ take
- studying $\rightarrow$ study
- fishes $\rightarrow$ fish

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Sample text: Such an analysis can reveal features that are not easily visible from the variations in the individual genes and can lead to a picture of expression that is more biologically transparent and accessible to interpretation

Lovins stemmer: such an analys can reve featur that ar not eas vis from th vari in th individu gen and can lead to a pictur of expres that is mor biolog transpar and acces to interpres

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Paice stemmer: such an analys can rev feat that are not easy vis from the vary in the individ gen and can lead to a pict of express that is mor biolog transp and access to interpret

Image source: Schütze et al (2008)

Lemmatization and Stemming

The goal of both stemming and lemmatization is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form. - Schütze et al (2008)

Word-Sense-Disambiguation

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With Word-Sense-Disambiguation we establish which sense of a word is used in a sentence, when a word is ambiguous and can have several meanings.

Word-Sense-Disambiguation

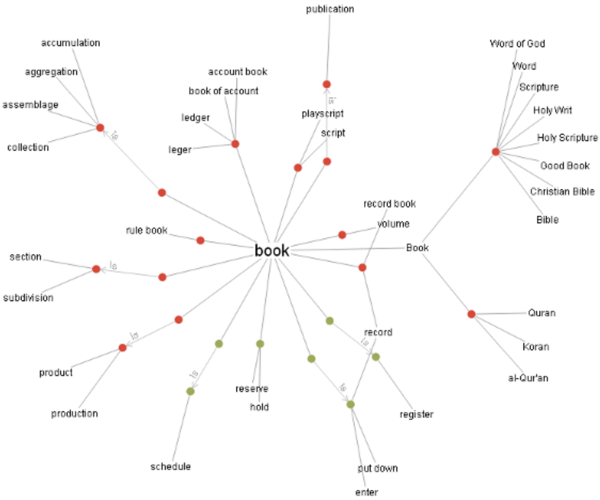

Image source: Open Science

Word-Sense-Disambiguation

Sentence 1: I can hear bass/frequency sound.
Sentence 2: He likes to eat grilled bass/fish

Employ WordNet and apply Lesk algorithm:

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We want to select the best sense for a word in a given context!

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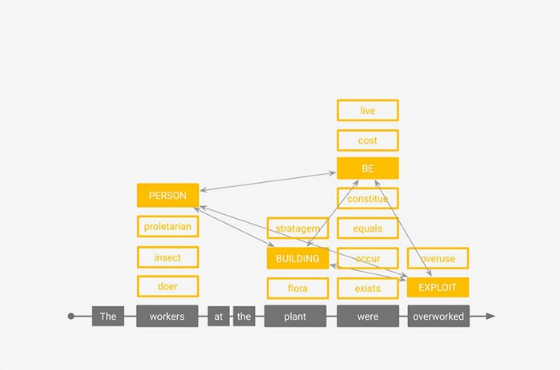

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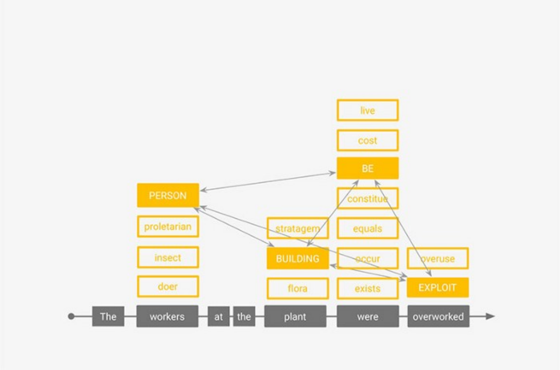

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- Assumption - words in a sentence should be part of a shared topic

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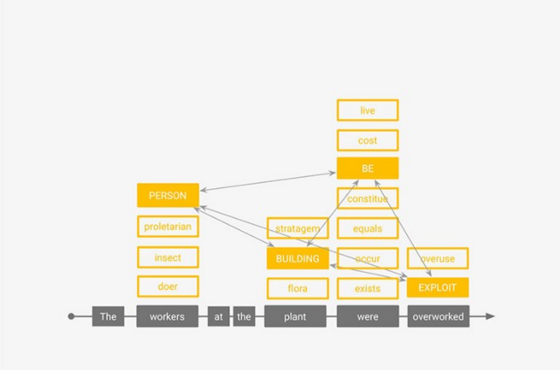

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- Assumption - words in a sentence should be part of a shared topic
- Algorithm 1. check a sentence, 2. "selects the senses whose definitions have the maximum overlap (the highest number of common words)" (SAP 2015)

Part-of-Speech-Tagging

The process of classifying words into their parts of speech and labeling them accordingly is known as part-of-speech (POS) tagging. - Schütze et al (2008)

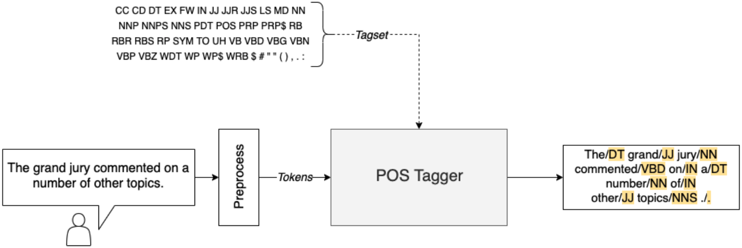

Image source: Devopedia 2019

Part-of-Speech-Tagging

One of the main problems are ambiguity.

They **refuse** to **permit** us to **obtain** the **refuse permit.**

Part-of-Speech-Tagging

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They **refuse/VERB** to **permit/VERB** us to **obtain/VERB** the **refuse/NOUN permit/NOUN.**

Part-of-Speech-Tagging

Statistical POS tagging - we attach descriptive tags to each token to show which parts of speech are these tokens associated to. Tags are usually: verbs, noun, adjectives, etc.

Time/Noun flies like an arrow

- Capital: Yes
- Length: 4
- Prefix: No
- Suffix: No
- Beginning of Sentence: Yes

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→ Hidden Markov Model - using both tag sequence probabilities and word frequency measurements.

Named Entity Recognition

NER seeks to locate and classify pieces of text into predefined categories such as the names of:

- persons
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- expressions of times
- quantities
- monetary values
- percentages

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Named Entity Recognition

First of all, regular expression to extract:

- telephone numbers
- E-mails
- Dates
- Prices
- Locations (e.g., word + "river" indicates a river $\rightarrow$ Hudson river)

Named Entity Recognition

Then, gazetteers with list of proper names of:

- Person
- Location
- Organization

Named Entity Recognition

Then, context patterns, such as:

- PERSON earns [Money]
- PERSON joined [ORGANIZATION]
- PERSON fly to [LOCATION]

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Remember to always validate!

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  - Reliability (split-half test)

The Power of Counting

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- Remove infrequently used terms to improve performance (Denny and Spirling 2018)
- Sentiment Analysis using word counts of pre-defined dictionaries (Young and Soroka 2012)

The Power of Counting

Nielsen, Richard. 2019. "What Counting Words Can Teach Us About Middle East Politics" APSA MENA Newsletter Volume 2, Issue 2, Fall 2019.

Question: "Why do Salafi women cite the hadith and Quran only half as often as men when they write online?" (Nielsen 2019)

- Male Preachers use "God" more than women

Table 1 Men Use Hadith-Related Phrases More Than Women

	% of Documents Using Term		% of All Words	
Term	Men	Women	Men	Women
allāh	95	85	3.02	1.60
ṣalā allāh	67	32	0.50	0.21
raḍī allāh	50	20	0.18	0.10
ḥadīth	64	39	0.30	0.14
qāl/yaqūl (al-)rasūl	30	10	0.047	0.026
Ibn Taymiyya	23	3	0.030	0.006
al-Bukhari	41	10	0.098	0.030
al-Bayhaqi	17	1	0.013	0.001
Abu Hurayra	29	4	0.048	0.008
al-Tabarani	16	1	0.014	0.002
Abu Dawud	29	4	0.043	0.006

Note: This table counts the use of hadith-related phrases in 3,470 documents (1,306,641 words) by women and 17,854 documents (74,991,711 words) by men on saaid.net. The left two columns show the percentage of men's and women's documents that contain each phrase. The right two columns show the percentage of men's and women's words devoted to each phrase. All gender differences are statistically significant at the .05 percent level.

Image source: Nielsen (2020)

References 1/2

- Denny, M. J. and Spirling, A., 2018. Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It. Political Analysis 26(2), pp. 168–189
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