Text Analytics

MODULE 3: GET THE TEXT DATA READY FOR ANALYSIS

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Objectives

At the end of this module, you can:

- Define the metadata and corpus to be imported into TA repository
- Identify preprocessing steps of text data typically required for TA tasks
- Develop term-document frequency matrix to enable lookup of text and documents within the corpus

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Outline

- Overview of task
- Text preprocessing
- From text to word – tokenization, stemming, stopword removal
- Convert text to term-document frequency matrix (indexing)

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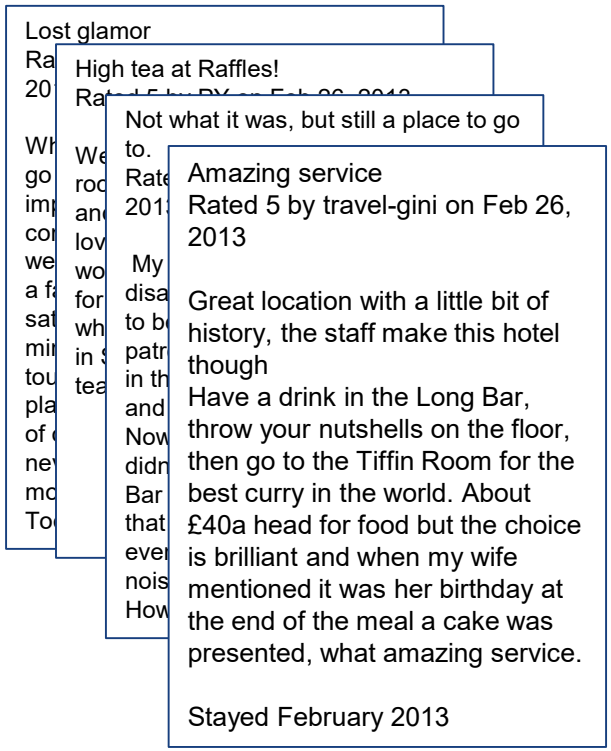
The whole task here is…

Documents



Term Document Matrix

	amazing	service	lost	glamour	disappoint	brilliant	super	expensive	noisy	…
Doc1	1	1	0	0	0	1	0	0	0	
Doc2	0	0	1	1	1	0	0	1	0	
Doc3	0	0	0	1	0	0	1	0	0	
Doc4	0	0	0	0	2	0	0	1	1	
…										

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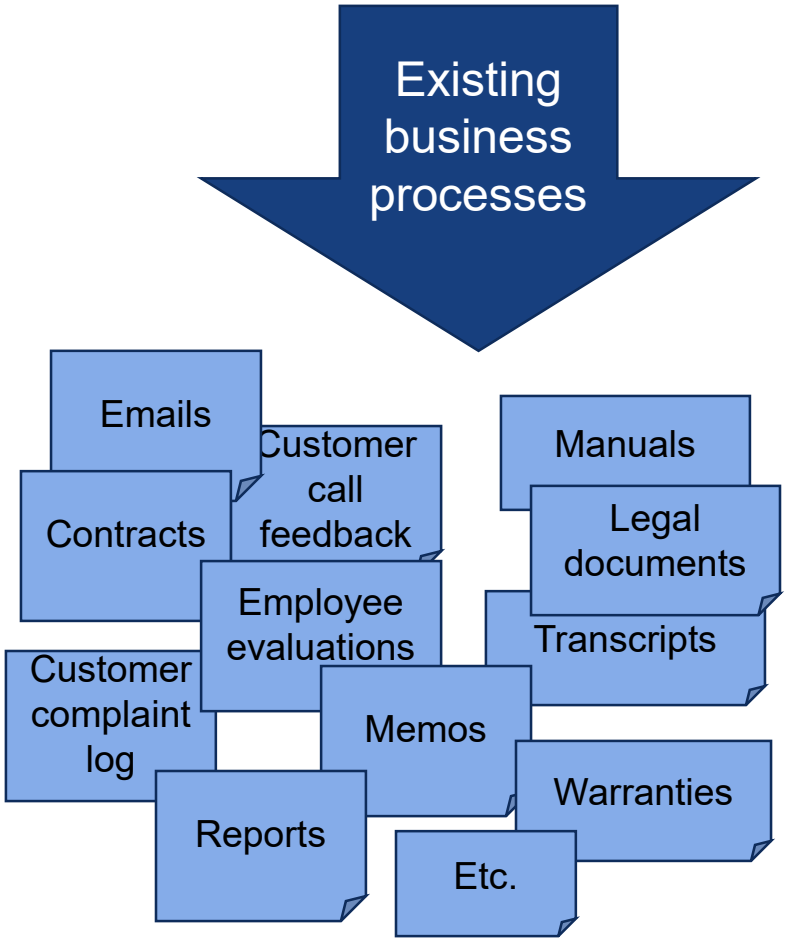
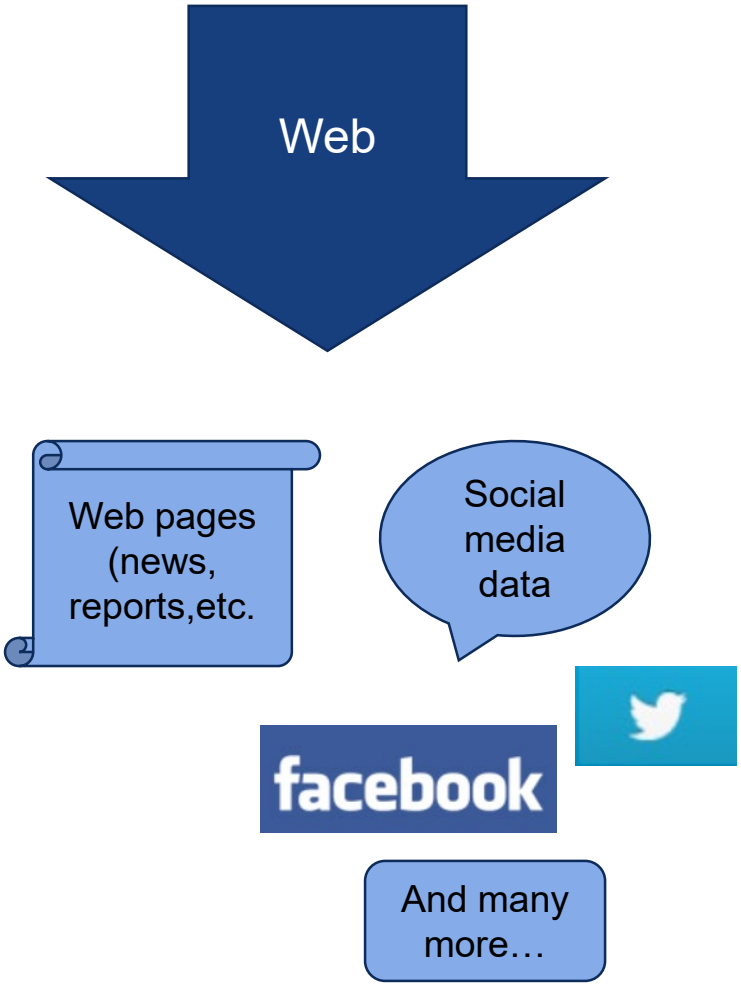
Sources of Text Data





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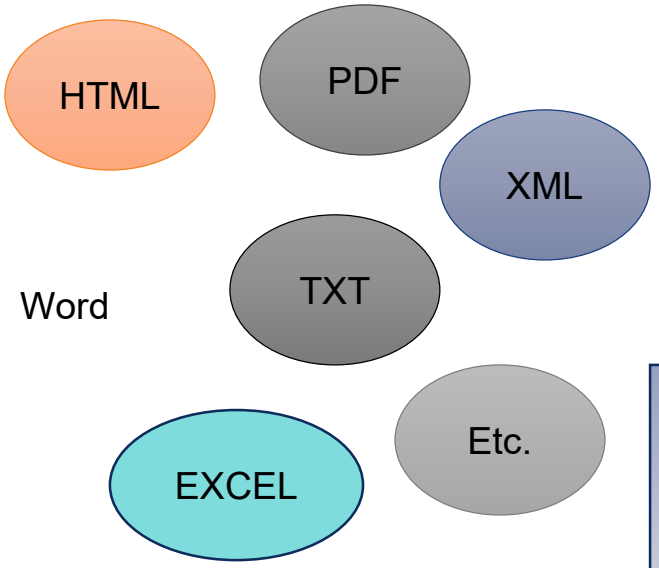
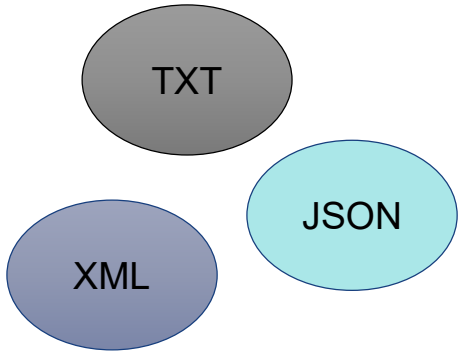
File Preprocessing





—Delete formatting tags
—Remove special characters
—Detect and label different zones
—Determine sentence/paragraph boundaries

Most TA tools provide functionality of importing text from some common formats.

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In a pure text file…

Amazing service

Rated 5 by travel-gini on Feb 26, 2013

Great location with a little bit of history, the staff make this hotel though
Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin Room for the best curry in the world. About £40a head for food but the choice is brilliant and when my wife mentioned it was her birthday at the end of the meal a cake was presented, what amazing service.

Stayed February 2013

…

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XML as Standard Exchange Format

- Popular in industry and text-processing community
- With XML, we can insert tags onto a text to identify its parts.
  - Eg. <*DOC*>, <*SUBJECT*>, <*TOPIC*>, <*TEXT*>, etc.
  - Such tags are very useful as they allow selection/extraction of the parts to generate features for subsequent mining.
- Many word processors allow documents to be saved as XML format

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What would an XML doc look like?

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<REVIEWS>
    <REVIEW>
        <TITLE>Amazing service</TITLE>
        <RATING>5</RATING>
        <DATE>26/02/2013</DATE>
        <BY>travel-gini</BY>
        <CONTENT>Great location with a little bit of history, the staff make this hotel though
    Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin Room for the best
    curry in the world. About £40a head for food but the choice is brilliant and when my wife mentioned it
    was her birthday at the end of the meal a cake was presented, what amazing service. Stayed
    February 2013 </CONTENT>
    </REVIEW>
    …
</REVIEWS>
```


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Or as JSON format

{

"title": "Amazing service",

"rating": 5,

"date": "26/02/2013",

"by": "travel-gini",

"content": "Great location with a little bit of history, the staff make this hotel though Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin Room for the best curry in the world. About £40a head for food but the choice is brilliant and when my wife mentioned it was her birthday at the end of the meal a cake was presented, what amazing service. Stayed February 2013"

}

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From Text to Words

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Tokenization

- To break a stream of characters into tokens

Great location with a little bit of history.

Great | location | with | a | little | bit | of | history | .

- This is known as unigram model – every token is a single word.
- There are also bigram, trigram models, where each token is composed of two/three words.

Great location | location with | with a | a little | little bit

bit of | of history | history .

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Tokenization Challenges

- Tokenization is done by identifying token delimiters
  - Whitespace characters such as ***space, tab, newline***
  - Punctuation characters like ***( ) < > ! ? “ ”***
  - Other characters ***. , : - ‘ ’*** etc.
- It seems simple, but…
  - ***. , :*** between numbers are part of the number

    12.34 12,345 12:34
  - **.** can be part of an abbreviation or end of a sentence

    U.S.A. Dr.
  - **’** can be a closing internal quote, indicate a possessive, or be part of another token

    My friend’s isn’t

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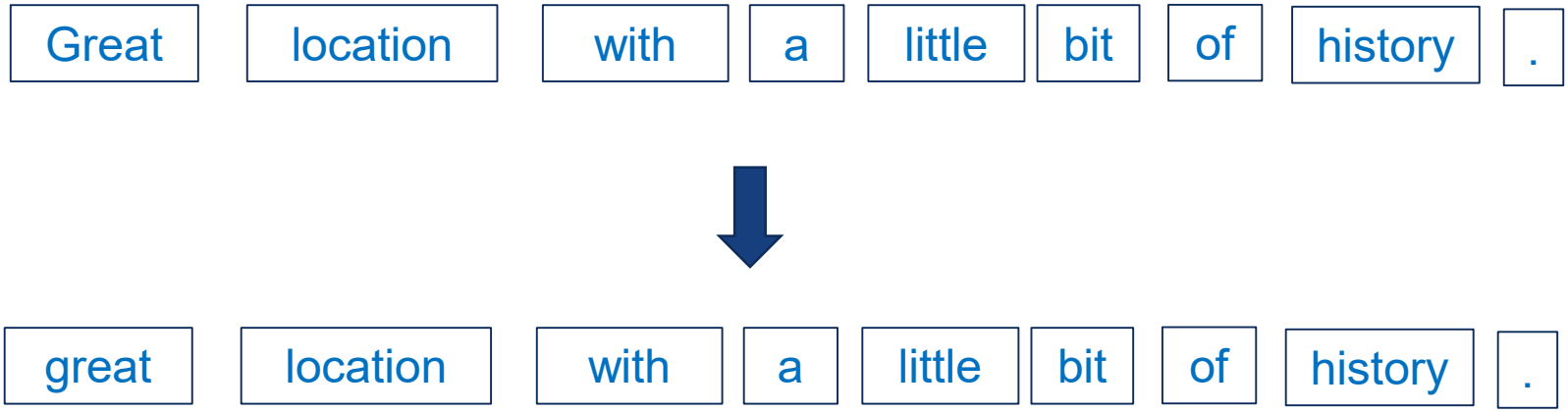
Case Lowering

- Also known as **case normalization**, to convert all tokens to lower case to remove the variation of words due to case differences.



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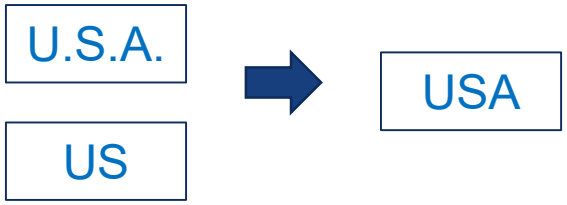
Stemming/Lemmatization

- A word may come in varied forms and therefore need to be converted into a standard form
  - **Inflectional** stemming (no change of POS) -- **Lemmatization**
  - **Derivational** Stemming (with change of POS)
  - Other normalisation (including case normalisation)



- Stemming can reduce the number of distinct features in a text corpus and increase the frequency of occurrence of some individual features.

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How much stemming should be done?

- An inflectional stemmer needs to be partly rule-based and partly dictionary-based.
- Derivational stemming is more aggressive and therefore can reduce the number of features in a corpus drastically. However meaning might be lost in the stemming process.

Too aggressive stemming can result in loss of meaning and non-legitimate words without the support of a dictionary.

```
[[6]]
battery life portability accessories style

[[7]]
   ability  store    music     ability  create playlists

[[8]]
portability capacity sound quality durability
```

```
[[6]]
batteri life portabl accessori style

[[7]]
   abil  store    music     abil  creat playlist

[[8]]
portabl capac sound qualiti durabl
```


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Stemmers

- Some well-known stemming algorithms for English
  - Lovins Stemmer by Julie Beth Lovins, 1968
    - single pass, longest-match
    - removing the longest suffix, ensuring the remaining stem is at least 3 characters long
    - reforming the stem through recoding transformations
  - Porter Stemmer by Martin Porter, 1980
    - Widely used, with implementations in various languages available online (C, java, Perl, python, C#, VB, Javascript, Tcl, Ruby, etc.)
  - Snowball by Porter, a framework for writing Stemming algorithms

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Stopword Removal

- Some words are extremely common. They appear in almost all documents and carry little meaning. They are of limited use in text analytics applications.
  - Functional words (conjunctions, prepositions, determiners, or pronouns) like *the, of, to, and, it*, etc.
  - A stopword list can be constructed to exclude them from analysis.
  - **Depending on the domain**, other words may need to be included in the stopword list.

great	location	with	a	little	bit	of	history	.

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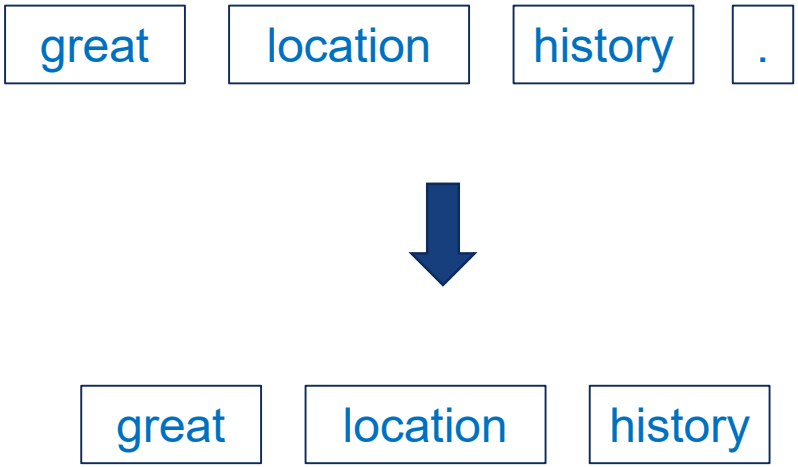
Further clean-up

- Punctuation removal
- Number removal, etc.



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Indexing

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Indexing

- Many text mining applications are based on vector representation of documents (*term-document matrix* or *document-term matrix*) using "bag-of-words" approach

$$\begin{array}{c|cccc} & T_1 & T_2 & \cdots & T_t \\ D_1 & w_{11} & w_{21} & \cdots & w_{t1} \\ D_2 & w_{12} & w_{22} & \cdots & w_{t2} \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ D_n & w_{1n} & w_{2n} & \cdots & w_{tn} \end{array}$$

T: term
D: document
w: **weight** of the term

- Usually only content words (adjectives, adverbs, nouns, and verbs) are used as vector features.

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Term Weighting

- Binary
  - 0 or 1, simply indicating whether a word has occurred in the document (but that's not very helpful).
- Frequency-based
  - *term frequency*, the frequency of words in the document, which provides additional information that can be used to contrast with other documents.

	amazing	service	lost	glamour	disappoint	brilliant	super	expensive	noisy	…
Doc1	1	1	0	0	0	1	0	0	0	
Doc2	0	0	1	1	1	0	0	1	0	
Doc3	0	0	0	1	0	0	1	0	0	
Doc4	0	0	0	0	2	0	0	1	1	
…										

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Frequent Word List

- With frequency-based TDM, a list of words and their frequencies in the corpus can be generated
  - *Global frequency* – how many times a word appears in the corpus
  - *Document frequency* – how many unique documents contain the word

- This list, sorted by frequency, can give us a rough idea of what the corpus is about.

- Word Cloud is a nice visualization of such information.

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Word Cloud: another example

- Generated from http://worditout.com/word-cloud/make-a-new-one

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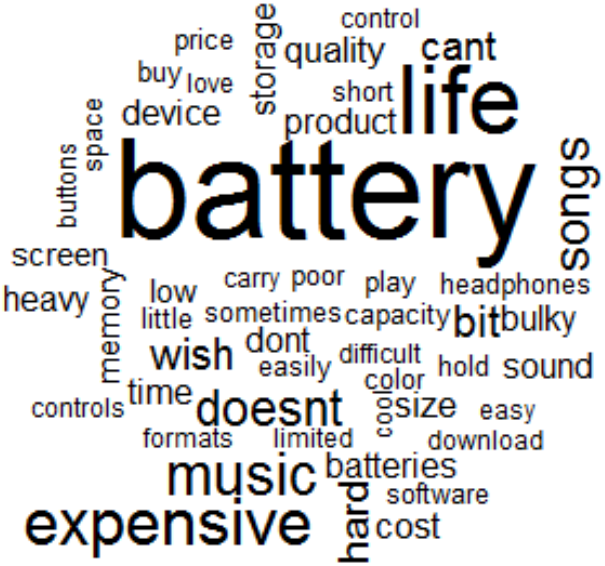
Contrasting Two Groups

- "What do you like most…"

- "What do you like least…"



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Other Weighting Methods

- Normalized frequency
  - To deal with varied document length, since a long document definitely has more occurrences of terms than a short document

$$normalized\_frequency = \frac{frequency\ of\ a\ term\ in\ a\ document}{total\ number\ of\ terms\ in\ the\ document}$$

- ***tf-idf***
  - To modify the frequency of a word in a document by the perceived importance of the word(the *inverse document frequency)*, widely used in information retrieval
    - When a word appears in many documents, it's considered unimportant.
    - When the word is relatively unique and appears in few documents, it's important.

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tf-idf Indexing

- *tf-idf* weighting :

$$tf\text{-}idf_{t,d} = tf_{t,d} * idf_t$$

  - $tf_{t,d}$: *term frequency* – number of occurrences of term t in document d
  - idf_t : *inverted document frequency* of term t

$$idf_t = \log \frac{N}{df_t}$$

N : the total number of documents in the corpus

df_t : the document frequency of term t, i.e., the number of documents that contain the term.

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tf-idf Indexing – An Example

Note that in this example, stopwords and very common words are not removed, and terms are not reduced to root terms.

TERM VECTOR MODEL BASED ON $w_i = tf_i * IDF_i$

Query, Q: "gold silver truck"
D_1: "Shipment of gold damaged in a fire"
D_2: "Delivery of silver arrived in a silver truck"
D_3: "Shipment of gold arrived in a truck"
$D = 3$; $IDF = \log(D/df_i)$

		Counts, tf_i						Weights, $w_i = tf_i * IDF_i$			
Terms	Q	D_1	D_2	D_3	df_i	D/df_i	IDF_i	Q	D_1	D_2	D_3
a	0	1	1	1	3	3/3 = 1	0	0	0	0	0
arrived	0	0	1	1	2	3/2 = 1.5	0.1761	0	0	0.1761	0.1761
damaged	0	1	0	0	1	3/1 = 3	0.4771	0	0.4771	0	0
delivery	0	0	1	0	1	3/1 = 3	0.4771	0	0	0.4771	0
fire	0	1	0	0	1	3/1 = 3	0.4771	0	0.4771	0	0
gold	1	1	0	1	2	3/2 = 1.5	0.1761	0.1761	0.1761	0	0.1761
in	0	1	1	1	3	3/3 = 1	0	0	0	0	0
of	0	1	1	1	3	3/3 = 1	0	0	0	0	0
silver	1	0	2	0	1	3/1 = 3	0.4771	0.4771	0	0.9542	0
shipment	0	1	0	1	2	3/2 = 1.5	0.1761	0	0.1761	0	0.1761
truck	1	0	1	1	2	3/2 = 1.5	0.1761	0.1761	0	0.1761	0.1761

http://www.miislita.com/term-vector/term-vector-3.html

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Alternative Representation of TDM

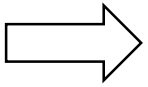
- The resulting term document matrix is expected to have most of the values to be zero, since typically a document will only contain a small subset of the vocabulary in a corpus

```
<<DocumentTermMatrix (documents: 1000, terms: 17887)>>
Non-/sparse entries: 92858/17794142
Sparsity           : 99%
Maximal term length: 56
Weighting          : term frequency (tf)
```

- It saves memory to store the matrix as a set of sparse vectors, where a row is represented by a list of pairs, (ColumnNumber, Value)

Matrix

0	5	2	0
4	0	0	0
3	1	0	6



Sparse Vectors

(2, 5) (3, 2)
(1, 4)
(1, 3) (2, 1) (4, 6)

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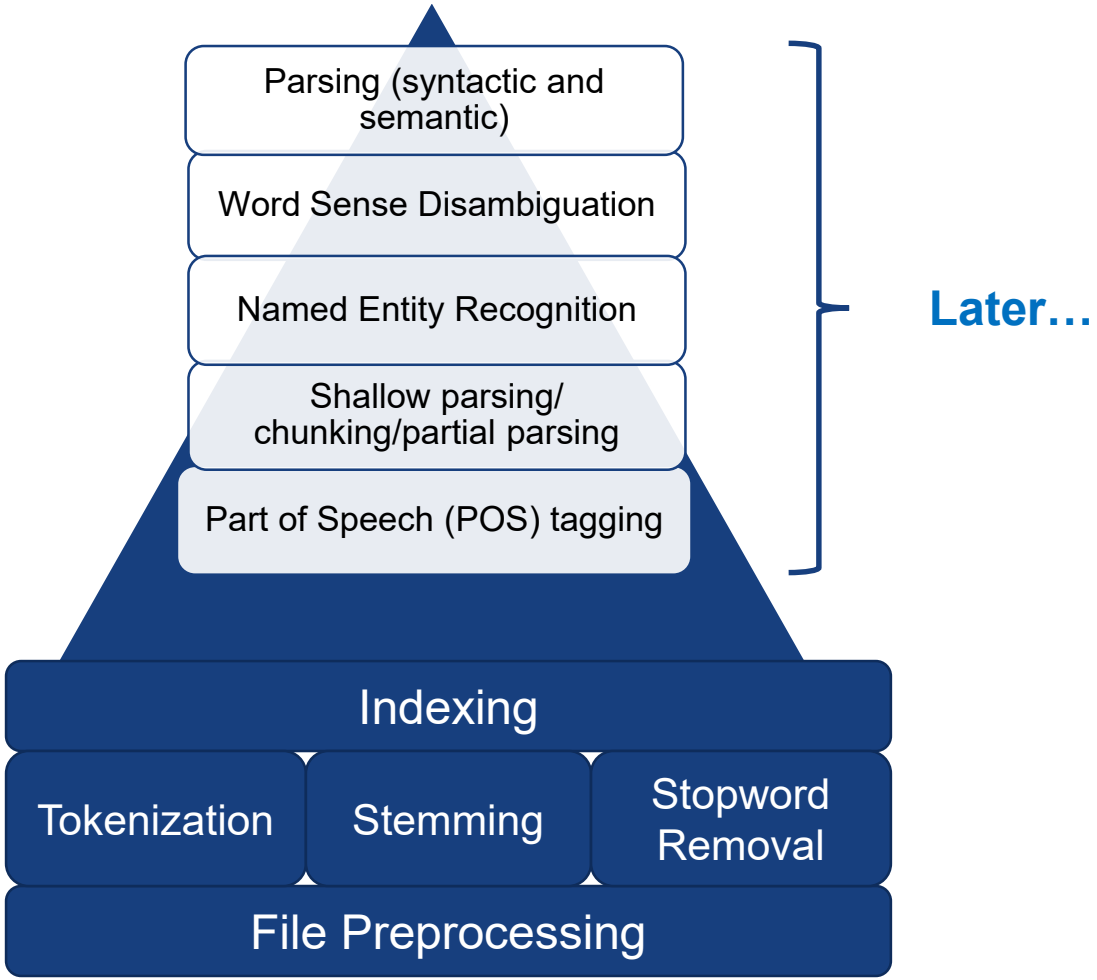
Summary



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Reference & Resources

- Jurafsky, Dan. *Speech & language processing*. Pearson Education India, 2000. (continuously updated)
- Weiss, Indurkhya, & Zhang. Chapter 2 “From Textual Information to Numerical Vectors”, *Fundamentals of Predictive Text Mining*, Springer, 2010.
- List of online word cloud generators
  - http://www.techlearning.com/default.aspx?tabid=67&entryid=364

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